Oracle® Machine Learning for Python

User's Guide

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Oracle Machine Learning for Python User's Guide, Release 2.0

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Preface

This publication describes Oracle Machine Learning for Python (OML4Py) and how to use it.

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Audience

Related Resources

Related documentation is in the following publications:

- *Oracle Machine Learning for Python API Reference*
- *Oracle Machine Learning for Python Known Issues*
- *Oracle Machine Learning for Python Licensing Information User Manual*
- *REST API for Embedded Python Execution*
- Get Started with Notebooks for Data Analysis and Data Visualization in *Using Oracle Machine Learning Notebooks*
- Oracle Machine Learning AutoML User Interface
- *REST API for Oracle Machine Learning Services*

For more information, see these Oracle resources:

- Oracle Machine Learning Technologies
- Oracle Autonomous Database

Conventions

The following text conventions are used in this document:

Convention	Meaning
boldface	Boldface type indicates graphical user interface elements associated with an action, or terms defined in text or the glossary.
italic	Italic type indicates book titles, emphasis, or placeholder variables for which you supply particular values.

Convention	Meaning
`monospace`	Monospace type indicates commands within a paragraph, URLs, code in examples, text that appears on the screen, or text that you enter.

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About Oracle Machine Learning for Python

The following topics describe Oracle Machine Learning for Python (OML4Py) and its advantages for the Python user.

- What Is Oracle Machine Learning for Python?
  Oracle Machine Learning for Python (OML4Py) enables you to run Python commands for data transformations and for statistical, machine learning, and graphical analysis on data stored in or accessible through an Oracle database using a Python API. The OML4Py supports running user-defined Python functions through the database spawned and controlled Python engines, with optional built-in data-parallelism and task-parallelism. This embedded execution functionality enables invoking user-defined functions from SQL, and on ADB, REST. The OML4Py supports Automated Machine Learning (AutoML) for algorithm and feature selection, and model tuning and selection. You can augment the Python included functionality with third-party packages from the Python ecosystem.
- Advantages of Oracle Machine Learning for Python
  Using OML4Py to prepare and analyze data in or accessible to an Oracle database has many advantages for a Python user.
- Manipulate database tables and views using familiar Python functions and syntax
  With the transparency layer classes, you can manipulate database tables and views using familiar Python functions and syntax, For example, using DataFrame proxy objects that map to database data, users can invoke overloaded Pandas functions that transparently generate SQL that runs in the database, using the database as a high-performance compute engine.
- About the Python Components and Libraries in OML4Py
  OML4Py requires an installation of Python, the specified Python libraries, as well as the OML4Py components.

1.1 What Is Oracle Machine Learning for Python?

Oracle Machine Learning for Python (OML4Py) enables you to run Python commands for data transformations and for statistical, machine learning, and graphical analysis on data stored in or accessible through an Oracle database using a Python API. The OML4Py supports running user-defined Python functions through the database spawned and controlled Python engines, with optional built-in data-parallelism and task-parallelism. This embedded execution functionality enables invoking user-defined functions from SQL, and on ADB, REST. The OML4Py supports Automated Machine Learning (AutoML) for algorithm and feature selection, and model tuning and selection. You can augment the Python included functionality with third-party packages from the Python ecosystem.

OML4Py is a Python module that enables Python users to manipulate data in database tables and views using Python syntax. OML4Py functions and methods transparently translate a select set of Python functions into SQL for in-database execution.

OML4Py is available in the Python interpreter in Oracle Machine Learning Notebooks in your Oracle Autonomous Database. For more information, see Get Started with Notebooks for Data Analysis and Data Visualization in *Using Oracle Machine Learning Notebooks*.

Designed for problems involving both large and small volumes of data, OML4Py integrates Python with the database. With OML4Py, you can do the following:

- Run overloaded Python functions and use native Python syntax to manipulate in-database data, without having to learn SQL.
- Use Automated Machine Learning (AutoML) to enhance user productivity and machine learning results through automated algorithm and feature selection, as well as model tuning and selection.
- Use Embedded Python Execution to run user-defined Python functions in Python engines spawned and managed by the database environment. The user-defined functions and data are automatically loaded to the engines as required, and when data-parallel and task-parallel execution is enabled. Develop, refine, and deploy user-defined Python functions and machine learning models that leverage the parallelism and scalability of the database to automate data preparation and machine learning.
- Use a natural Python interface to build in-database machine learning models.

1.2 Advantages of Oracle Machine Learning for Python

Using OML4Py to prepare and analyze data in or accessible to an Oracle database has many advantages for a Python user.

With OML4Py, you can do the following:

- **Operate on database data without using SQL**

  OML4Py transparently translates many standard Python functions into SQL. With OML4Py, you can create Python proxy objects that access, analyze, and manipulate data that resides in the database. OML4Py can automatically optimize the SQL by taking advantage of column indexes, query optimization, table partitioning, and database parallelism.

  OML4Py overloaded functions are available for many commonly used Python functions, including those on Pandas data frames for in-database execution.

  See Also: Manipulate database tables and views using familiar Python functions and syntax

- **Automate common machine learning tasks**

  By using Oracle's advanced Automated Machine Learning (AutoML) technology, both data scientists and beginner machine learning users can automate common machine learning modeling tasks such as algorithm selection and feature selection, and model tuning and selection, all of which leverage the parallel processing and scalability of the database.

  See Also: About Automated Machine Learning

- **Minimize data movement**

  By keeping data in the database whenever possible, you eliminate the time involved in transferring the data to your client Python engine and the need to store the data locally. You also eliminate the need to manage the locally stored data, which includes tasks such as distributing the data files to the appropriate locations, synchronizing the data with changes that are made in the production database, and so on.

  See Also: About Moving Data Between the Database and a Python Session

- **Keep data secure**

  By keeping the data in the database, you have the security, scalability, reliability, and backup features of the database for managing the data.

- **Use the power of the database**

By operating directly on data in the database, you can use the memory and processing power of the database and avoid the memory constraints of your client Python engine.

- **Use current data**

  As data is refreshed in the database, you have immediate access to current data.

- **Save Python objects to a datastore in the database**

  You can save Python objects to an OML4Py datastore for future use and for use by others.

  See Also: About OML4Py Datastores

- **Build and store native Python models in the database**

  Using Embedded Python Execution, you can build native Python models and store and manage them in an OML4Py datastore.

  You can also build in-database models, with, for example, an `oml` class such as the Decision Tree class `oml.dt`. These in-database models have proxy objects that reference the actual models. Keeping with normal Python behavior, when the Python engine terminates, all in-memory objects, including models, are lost. To prevent an in-database model created using OML4Py from being deleted when the database connection is terminated, you must store its proxy object in a datastore.

  See Also: About Machine Learning Classes and Algorithms

- **Score data**

  For most of the OML4Py machine learning classes, you can use the `predict` and `predict_proba` methods of the model object to score new data.

  For these OML4Py in-database models, you can also use the SQL `PREDICTION` function on the model proxy objects, which scores directly in the database. You can use in-database models directly from SQL if you prepare the data properly. For open source models, you can use Embedded Python Execution and enable data-parallel execution for performance and scalability.

- **Run user-defined Python functions in embedded Python engines**

  Using OML4Py Embedded Python Execution, you can store user-defined Python functions in the OML4Py script repository, and run those functions in Python engines spawned by the database environment. When a user-defined Python function runs, the database starts, controls, and manages one or more Python engines that can run in parallel. With the Embedded Python Execution functionality, you can do the following:

  – Use a select set of Python packages in user-defined functions that run in embedded Python engines

  – Use other Python packages and third-party package in user-defined Python functions that run in embedded Python engines

  – Operationalize user-defined Python functions for use in production applications and eliminate porting Python code and models into SQL, and on ADB, REST; avoid reinventing code to integrate Python results into existing applications

  – Seamlessly leverage your Oracle database as a high-performance computing environment for user-defined Python functions, providing data parallelism and resource management

  – Perform parallel simulations, for example, Monte Carlo analysis, using the `oml.index_apply` function

  – Generate JSON images, PNG images and XML representations of both structured and image data, which can be used by Python clients and SQL-based applications. PNG

images and structured data can be used for Python clients and applications that use REST APIs.

See Also: About Embedded Python Execution

1.3 Manipulate database tables and views using familiar Python functions and syntax

With the transparency layer classes, you can manipulate database tables and views using familiar Python functions and syntax, For example, using DataFrame proxy objects that map to database data, users can invoke overloaded Pandas functions that transparently generate SQL that runs in the database, using the database as a high-performance compute engine.

The OML4Py transparency layer does the following:

- Enables creating tables and views from `pandas.DataFrame` and getting proxy objects to tables and views.
- Overloads specific Python functions that transparently translate functionality to SQL
- Leverages proxy objects for database data
- Uses familiar Python syntax to manipulate database data

The following table lists the transparency layer functions for getting and creating proxy objects and tables/views.

Table 1-1 Transparency Layer Functions for getting and creating proxy objects and tables/views

Function	Description
`oml.create`	Creates a table in a the database schema from a Python data set.
`oml_object``.pull`	Creates a local Python object that contains a copy of data fetched from database object referenced by the `oml` object.
`oml.push`	Pushes data from a Python session into an object in a database schema.
`oml.sync`	Creates a `DataFrame` proxy object in Python that represents a database table or view.
`oml.dir`	Return the names of `oml` objects in the Python session workspace.
`oml.drop`	Drops a persistent database table or view.

Transparency layer proxy classes map SQL data types or objects to corresponding Python types. The classes provide Python functions and operators that are the same as those on the mapped Python types. The following table lists the transparency layer data type classes.

Table 1-2 Transparency Layer Data Type Classes

Class	Description
`oml.Boolean`	A boolean series data class that represents a single column of 0, 1, and NULL values in database data.
`oml.Bytes`	A binary series data class that represents a single column of `RAW` or `BLOB` database data types.
`oml.Float`	A numeric series data class that represents a single column of `NUMBER`, `BINARY_DOUBLE`, or `BINARY_FLOAT` database data types.

Table 1-2 (Cont.) Transparency Layer Data Type Classes

Class	Description
`oml.String`	A character series data class that represents a single column of `VARCHAR2`, `CHAR`, or `CLOB` database data types.
`oml.DataFrame`	A tabular `DataFrame` class that represents multiple columns of `oml.Boolean`, `oml.Bytes`, `oml.Float`, and `oml.String` data.
`oml.Integer`	A data class that represents a single column of `NUMBER(*,0)` data in the database.
`oml.Datetime`	A series date class that represents a single column of `TIMESTAMP` or `TIMESTAMP WITH TIME ZONE` in Oracle Database. `oml.Timezone` A time class that is used with `oml.Datetime` to support `TIME STAMP WITH TIME ZONE`. `oml.Timedelta` A time class that represents a single column series of differences between two dates or times, or `INTERVAL DAY TO SECOND` in Oracle Database.
`oml.Timezone`	A time class that is used with `oml.Datetime` to support `TIME STAMP WITH TIME ZONE`.
`oml.Timedelta`	A time class that represents a single column series of differences between two dates or times, or `INTERVAL DAY TO SECOND` in Oracle Database.

The following table lists the mappings of Python data types for both the reading and writing of data between Python and the database.

Table 1-3 Python and SQL Data Type Equivalencies

Database Read	Python Data Types	Database Write
N/A	`Bool`	If `oranumber == True`, then `NUMBER` (the default), else `BINARY_DOUBLE`.
`BLOB`	`bytes`	`BLOB`
`RAW`		`RAW`
`BINARY_DOUBLE`	`float`	If `oranumber == True`, then `NUMBER` (the default), else `BINARY_DOUBLE`.
`BINARY_FLOAT`		
`NUMBER`		
`CHAR`	`str`	`CHAR`
`CLOB`		`CLOB`
`VARCHAR2`		`VARCHAR2`
`NUMBER(*,0)`	`int`	`NUMBER(*,0)`
`TIMESTAMP` or `TIMESTAMP WITH TIME ZONE`	`datetime.datetime`	`TIMESTAMP` or `TIMESTAMP WITH TIME ZONE`
`TIMESTAMP WITH TIME ZONE`	`datetime.timezone`	`TIMESTAMP WITH TIME ZONE`
`INTERVAL DAY TO SECOND`	`datetime.timedelta`	`INTERVAL DAY TO SECOND`

1.4 About the Python Components and Libraries in OML4Py

OML4Py requires an installation of Python, the specified Python libraries, as well as the OML4Py components.

- In Oracle Autonomous Database, OML4Py is already installed. The OML4Py installation includes Python, additional required Python libraries, and the OML4Py server components. A Python interpreter is included with Oracle Machine Learning Notebooks in Autonomous Database.
- You can install third-party Python libraries in a conda environment through a conda interpreter for use within OML Notebooks sessions and OML4Py embedded execution invocations.

Python Version in Current Release of OML4Py

The current release of OML4Py is based on Python 3.12.0.

This version is in the current release of Oracle Autonomous Database.

Required Python Libraries

The following Python libraries must be included.

- `oracledb 1.4.0`
- `cycler 0.10.0`
- `joblib 1.1.0`
- `kiwisolver 1.1.0`
- `matplotlib 3.7.2`
- `numpy 1.26.0`
- `pandas 2.1.1`
- `Pillow-8.2.0`
- `pyparsing 2.4.0`
- `python-dateutil 2.8.1`
- `pytz 2022.1`
- `scikit-learn 1.2.1`
- `scipy 1.11.3`
- `six 1.13.0`
- `threadpoolctl 3.1.0`

All the above libraries are included with Python in the current release of Oracle Autonomous Database.

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Install Third-Party Packages

Oracle Machine Learning Notebooks in the Autonomous Database provides a conda interpreter to install third-party Python libraries in a conda environment for use within OML Notebooks sessions and OML4Py embedded execution invocations. Conda is an open-source package and environment management system that enables the use of environments containing third-party Python libraries.

Administrators create conda environments and install packages that can then be accessed by non-administrator users and loaded into their OML Notebooks session. The conda environments can be used by OML4Py Python, SQL, and REST APIs.

> **Note:**
>
> - None of the OML features that come with ADB require the customer to install any additional third-party software via the conda feature.
> - When installing third-party software using the conda feature, vulnerability management and license compliance of that software is the sole responsibility of the customer who installed it, not Oracle.

Topics:

2.1 Conda Commands

This topic contains common commands used by ADMIN while creating and testing conda environments in Autonomous Databases. Conda is an open-source package and environment

management system that enables the use of environments containing third-party Python libraries.

Refer to Conda Interpreter Commands for a table of supported conda commands.

Conda Help

To get help for conda commands, run the command name followed by the `--help` flag.

> **Note:**
>
> The conda command is not run explicitly because the `%conda` interpreter provides the conda context.

- Get help for all conda commands

```
%conda

--help
```

- Get help for a specific conda command. Run the following command to get help with the `install` command:

```
%conda

install --help
```

Conda Info

The `info` command displays information about the conda installation, including the conda version and available channels.

```
%conda

info
```

Conda Search

The `search` command allows the user to search for packages and display associated information, including the package version and the channel where it resides.

- Search for a specific package. Run the following command to search for the package `scikit-learn`.

```
%conda

search scikit-learn
```

- Search for packages containing 'scikit' in the package name.

```
%conda

search '*scikit*'
```

- Search for a specific version of a package.

```
%conda

search 'numpy==1.12'


%conda

search 'numpy>=1.12'
```

- Search for a specific version on a specific channel.

```
%conda

search conda-forge::numpy
```

Enhanced Conda Commands

A set of enhanced conda commands in the conda environment lifecycle management package `env-lcm` supports the management of environments saved to Object Storage, including uploading, downloading, listing, and deleting available environments.

Help for conda lifecycle environment commands.

```
%conda

env-lcm --help


Usage: conda-env-lcm [OPTIONS] COMMAND [ARGS]...

  ADB-S Command Line Interface (CLI) to manage persistence of conda
  environments

Options:
  -v, --version  Show the version and exit.
  --help         Show this message and exit.

Commands:
  delete           Delete a saved conda environment
  download         Download a saved conda environment
  import           Create or update a conda environment from saved metadata
  list-local-envs  List locally available environments for use
  list-saved-envs  List saved conda environments
  upload           Save conda environment for later use
```

Creating Conda Environments

This section demonstrates creating and installing packages to a conda environment, then removing the environment. Here commonly used options available for environment creation and testing are illustrated. The environment exists for the duration of the notebook session and does not persist between sessions unless it is saved to Object Storage. For instructions that include both creating and persisting an environment for OML users, refer to Administrative task to create and save the conda environments. As an ADMIN user:

1. Use the create command to create an environment `myenv` and install the Python keras package.
2. Verify that the new environment is created, and activate the environment.
3. Install, then uninstall an additional Python package, pytorch, in the environment.
4. Deactivate and remove the environment.

> **Note:**
>
> The ADMIN user can access the conda environment from Python and R, but does not have the capability to run embedded Python and R execution commands.

For help with the conda `create` command, enter `create --help` in a `%conda` paragraph.

List Environments

Start by listing the environments available by default. Conda contains default environments with some core system libraries and conda dependencies. The active environment is marked with an asterisk (*).

```
%conda

env list


# conda environments:
#
base                  * /usr
conda-pack-env          /usr/envs/conda-pack-env
```

Create Conda Environment

Create conda environment called `myenv` with Python 3.10 for OML4Py compatibility and install the keras package.

```
%conda

create -n myenv python=3.10 keras
```

Verify Environment Creation

Verify the myenv environment is in the list of environments. The asterisk (*) indicates active environments. The new environment is created but not activated.

```
%conda

env list


# conda environments:
#
myenv                   /u01/.conda/envs/myenv
```

```
base                  * /usr
conda-pack-env          /usr/envs/conda-pack-env
```

Activate the Environment

Activate the myenv environment and list the environments to verify the activation. The asterisk (*) next to the environment name confirms the activation.

```
%conda

activate myenv


Conda environment 'myenv' activated
```

List the environments available by default.

```
%conda

env list


# conda environments:
#
myenv                 * /u01/.conda/envs/myenv
base                    /usr
conda-pack-env          /usr/envs/conda-pack-env
```

Installing and Uninstalling Libraries

The ADMIN user can install and uninstall libraries into an environment using the `install` and `uninstall` commands. For help with the conda `install` and `uninstall` commands, type `install --help` and `uninstall --help` in a `%conda` paragraph.

> **Note:**
>
> When conda installs a package into an environment, it also installs any required dependencies. As shown here, it's possible to install packages to an existing environment. As a best practice, to avoid dependency conflicts, simultaneously install all the packages you need in a specific environment.

Install Additional Packages

Install the pytorch package into the activated myenv environment.

```
%conda

install pytorch
```

List Packages in the Current Environment

List the packages installed in the current environment, and confirm that keras and pytorch are installed.

```
%conda

list
```

The output is similar to the following:

```
# packages in environment at /u01/.conda/envs/myenv:
#
# Name                    Version                   Build  Channel
_libgcc_mutex             0.1                        main
_openmp_mutex             5.1                       1_gnu
blas                      1.0                         mkl
.
.
.
fftw                      3.3.9                h27cfd23_1
future                    0.18.2           py310h06a4308_1
intel-openmp              2021.4.0           h06a4308_3561
keras                     2.10.0           py310h06a4308_0
keras-preprocessing       1.1.2               pyhd3eb1b0_0
ld_impl_linux-64          2.38                 h1181459_1
libffi                    3.3                  he6710b0_2
libgcc-ng                 11.2.0               h1234567_1
.
.
.
numpy-base                1.23.3           py310h8e6c178_1
openssl                   1.1.1s               h7f8727e_0
pip                       22.2.2           py310h06a4308_0
pycparser                 2.21                    pypi_0    pypi
python                    3.10.6               haa1d7c7_1
pytorch                   1.10.2          cpu_py310h6894f24_0
readline                  8.2                  h5eee18b_0
.
.
.
xz                        5.2.6                h5eee18b_0
zlib                      1.2.13               h5eee18b_0
```

The output above has been truncated and does not show the complete list of packages.

Uninstall Package

Libraries can be uninstalled from an environment using the uninstall command. Let's uninstall the pytorch package from the current environment.

```
%conda

uninstall pytorch
```

Verify Package was Uninstalled

List packages in current environment and verify that the pytorch package was uninstalled.

```
%conda

list
```

The output shown below does not contain the `pytorch` package.

```
# packages in environment at /u01/.conda/envs/myenv:
#
# Name                    Version                   Build  Channel
_libgcc_mutex             0.1                        main
_openmp_mutex             5.1                       1_gnu
blas                      1.0                         mkl
bzip2                     1.0.8                h7b6447c_0
ca-certificates           2022.10.11           h06a4308_0
certifi                   2022.9.24        py310h06a4308_0
cffi                      1.15.1           py310h74dc2b5_0
fftw                      3.3.9                h27cfd23_1
future                    0.18.2           py310h06a4308_1
intel-openmp              2021.4.0           h06a4308_3561
keras                     2.10.0           py310h06a4308_0
keras-preprocessing       1.1.2              pyhd3eb1b0_0
ld_impl_linux-64          2.38                 h1181459_1
libffi                    3.3                  he6710b0_2
libgcc-ng                 11.2.0               h1234567_1
libgfortran-ng            11.2.0               h00389a5_1
libgfortran5              11.2.0               h1234567_1
libgomp                   11.2.0               h1234567_1
libstdcxx-ng              11.2.0               h1234567_1
libuuid                   1.0.3                h7f8727e_2
mkl                       2021.4.0           h06a4308_640
mkl-service               2.4.0            py310h7f8727e_0
mkl_fft                   1.3.1            py310hd6ae3a3_0
mkl_random                1.2.2            py310h00e6091_0
ncurses                   6.3                  h5eee18b_3
ninja                     1.10.2               h06a4308_5
ninja-base                1.10.2               hd09550d_5
numpy                     1.23.3           py310hd5efca6_1
numpy-base                1.23.3           py310h8e6c178_1
openssl                   1.1.1s               h7f8727e_0
pip                       22.2.2           py310h06a4308_0
pycparser                 2.21                     pypi_0    pypi
python                    3.10.6               haa1d7c7_1
readline                  8.2                  h5eee18b_0
scipy                     1.9.3            py310hd5efca6_0
setuptools                65.5.0           py310h06a4308_0
six                       1.16.0             pyhd3eb1b0_1
sqlite                    3.39.3               h5082296_0
tk                        8.6.12               h1ccaba5_0
typing-extensions         4.3.0            py310h06a4308_0
typing_extensions         4.3.0            py310h06a4308_0
tzdata                    2022f                h04d1e81_0
wheel                     0.37.1             pyhd3eb1b0_0
```

```
xz                        5.2.6                h5eee18b_0
zlib                      1.2.13               h5eee18b_0
```

Removing Environments

If you don't intend to upload the environment to Object Storage for the OML users in the database, you can simply exit the notebook session and it will go out of scope. Alternatively, it can be explicitly removed using the env remove command. Remove the myenv environment and verify it was removed. A best practice is to deactivate the environment prior to removal. For help on the `env remove` command, type `env remove --help` in the `%conda` interpreter.

- Deactivate the environment.

  ```
  %conda

  deactivate


  Conda environment deactivated
  ```

- Remove the environment.

  ```
  %conda

  env remove -n myenv
  ```

  List the environment to see if the environment is removed or not.

  ```
  env list


  # conda environments:
  #
  myrenv                   /u01/.conda/envs/myrenv
  base                  *  /usr
  conda-pack-env           /usr/envs/conda-pack-env
  ```

  Remove all packages in environment `/u01/.conda/envs/myenv`.

Specify Packages for Installation

Install Packages from the conda-forge Channel

Conda channels are the locations where packages are stored. They serve as the base for hosting and managing packages. Conda packages are downloaded from remote channels, which are URLs to directories containing conda packages. The conda command searches a set of channels. By default, packages are automatically downloaded and updated from the default channel. The conda-forge channel is free for all to use. You can modify what remote channels are automatically searched. You might want to do this to maintain a private or internal channel. We use the conda-forge channel, a community channel made up of thousands of contributors, in the following examples.

- Install a specific version of a Package.

  To install a specific version of a package, use <`package_name`>=<`version`>.

- Create an environment using conda-forge.

```
%conda

create -n mychannelenv -c conda-forge python=3.10

activate mychannelenv
```

- Install a package from conda-forge by specifying the channel.

```
%conda

install scipy --channel conda-forge
```

- Install a specific version of a package.

```
%conda

install scipy=0.15.0
```

2.2 Administrative Tasks for Creating and Saving a Conda Environment

In OML Notebooks, user ADMIN can manage the lifecycle of the OML user's conda environments, including creating and deleting environments and installing and deleting packages.

The conda environments created by user ADMIN are stored in an Object Storage bucket folder associated with the Autonomous Database instance. OML users can download these conda environments using enhanced conda commands. Conda environments are available after they are downloaded and activated using the download and activate functions in a `%conda` paragraph. An activated environment is available until it is deactivated.

Create a Conda enviroment

As an ADMIN user in an OML notebook, specify a conda interpreter in a paragraph using `%conda`, then use the `create` command to create a conda environment named *sbenv* to install the seaborn package. Specify the Python version using the `python` parameter. Here, Python 3.10 is used for compatibility with OML4Py.

> **Note:**
>
> When conda installs a package into an environment, it also installs any required dependencies. As a best practice, to avoid dependency conflicts, simultaneously install all the packages you need in a specific environment.

> **Note:**
>
> Specify `python=3.10.8` when creating a conda environment for a 3rd-party package to avoid inconsistencies.

```
%conda

create -n sbenv python==3.10.8 seaborn
```

Upload the environment to Object Storage

Upload the environment to the Object Storage associated with the Autonomous Database instance. Here you provide an environment description and a tag corresponding to an application name, OML4Py.

```
%conda

upload sbenv --description 'Conda environment with seaborn' -t application
"OML4PY"


Uploading conda environment sbenv
Upload successful for conda environment sbenv
```

The environment is now available for an OML user to download. The uploaded environment will persist in Object Storage until it is deleted. The application tag is required for use with embedded execution. For example, OML4Py embedded Python execution works with conda environments containing the OML4Py tag, and OML4R embedded R execution works with conda environments containing the OML4R tag.

There is one Object Storage bucket for each data center region. The conda environments are saved to a folder in Object Storage corresponding to the tenancy and database. The folder is managed by Autonomous Database and only available to users through OML Notebooks. There is an 8G maximum size for a single conda environment, and no size limit on Object Storage.

Logged in as a non-administrator user, specify the conda interpreter in a notebook paragraph using `%conda`. Get the list of environments saved in Object Storage using the `list-saved-envs` command.

```
%conda

list-saved-envs
```

Provide the environment name as an argument to the `-e` parameter and request a list of packages installed in the environment.

```
%conda

list-saved-envs -e sbenv --installed-packages
```

The output is similar to the following:


```
{
  "name": "sbenv",
  "size": "1.7 GiB",
  "description": "Conda environment with seaborn",
  "tags": {
    "application": "OML4PY"
  },
  "number_of_installed_packages": 78,
  "installed_packages": [
    "blas-1.0-mkl",
    "bottleneck-1.3.5-py39h7deecbd_0",
    "brotli-1.0.9-h5eee18b_7",
    "brotli-bin-1.0.9-h5eee18b_7",
    "ca-certificates-2022.07.19-h06a4308_0",
    "certifi-2022.9.14-py39h06a4308_0",
    "cycler-0.11.0-pyhd3eb1b0_0",
    "dbus-1.13.18-hb2f20db_0",
    "expat-2.4.4-h295c915_0",
    "fftw-3.3.9-h27cfd23_1",
    "fontconfig-2.13.1-h6c09931_0",
    "fonttools-4.25.0-pyhd3eb1b0_0",
    "freetype-2.11.0-h70c0345_0",
    "giflib-5.2.1-h7b6447c_0",
    "glib-2.69.1-h4ff587b_1",
    "gst-plugins-base-1.14.0-h8213a91_2",
    "gstreamer-1.14.0-h28cd5cc_2",
    "icu-58.2-he6710b0_3",
    "intel-openmp-2021.4.0-h06a4308_3561",
    "jpeg-9e-h7f8727e_0",
    "kiwisolver-1.4.2-py39h295c915_0",
    "lcms2-2.12-h3be6417_0",
    "ld_impl_linux-64-2.38-h1181459_1",
    "lerc-3.0-h295c915_0",
    "libbrotlicommon-1.0.9-h5eee18b_7",
    "libbrotlidec-1.0.9-h5eee18b_7",
    "libbrotlienc-1.0.9-h5eee18b_7",
    "libdeflate-1.8-h7f8727e_5",
    "libffi-3.3-he6710b0_2",
    "libgcc-ng-11.2.0-h1234567_1",
    "libgfortran-ng-11.2.0-h00389a5_1",
    "libgfortran5-11.2.0-h1234567_1",
    "libpng-1.6.37-hbc83047_0",
    "libstdcxx-ng-11.2.0-h1234567_1",
    "libtiff-4.4.0-hecacb30_0",
    "libuuid-1.0.3-h7f8727e_2",
    "libwebp-1.2.2-h55f646e_0",
    "libwebp-base-1.2.2-h7f8727e_0",
    "libxcb-1.15-h7f8727e_0",
    "libxml2-2.9.14-h74e7548_0",
    "lz4-c-1.9.3-h295c915_1",
    "matplotlib-3.5.2-py39h06a4308_0",
    "matplotlib-base-3.5.2-py39hf590b9c_0",
    "mkl-2021.4.0-h06a4308_640",
    "mkl-service-2.4.0-py39h7f8727e_0",
```

```
    "mkl_fft-1.3.1-py39hd3c417c_0",
    "mkl_random-1.2.2-py39h51133e4_0",
    "munkres-1.1.4-py_0",
    "ncurses-6.3-h5eee18b_3",
    "numexpr-2.8.3-py39h807cd23_0",
    "numpy-1.22.3-py39he7a7128_0",
    "numpy-base-1.22.3-py39hf524024_0",
    "openssl-1.1.1q-h7f8727e_0",
    "packaging-21.3-pyhd3eb1b0_0",
    "pandas-1.4.4-py39h6a678d5_0",
    "pcre-8.45-h295c915_0",
    "pillow-9.2.0-py39hace64e9_1",
    "pip-22.1.2-py39h06a4308_0",
    "pyparsing-3.0.9-py39h06a4308_0",
    "pyqt-5.9.2-py39h2531618_6",
    "python-3.9.0-hdb3f193_2",
    "python-dateutil-2.8.2-pyhd3eb1b0_0",
    "pytz-2022.1-py39h06a4308_0",
    "qt-5.9.7-h5867ecd_1",
    "readline-8.1.2-h7f8727e_1",
    "scipy-1.7.3-py39h6c91a56_2",
    "seaborn-0.11.2-pyhd3eb1b0_0",
    "setuptools-63.4.1-py39h06a4308_0",
    "sip-4.19.13-py39h295c915_0",
    "six-1.16.0-pyhd3eb1b0_1",
    "sqlite-3.39.2-h5082296_0",
    "tk-8.6.12-h1ccaba5_0",
    "tornado-6.2-py39h5eee18b_0",
    "tzdata-2022c-h04d1e81_0",
    "wheel-0.37.1-pyhd3eb1b0_0",
    "xz-5.2.5-h7f8727e_1",
    "zlib-1.2.12-h5eee18b_3",
    "zstd-1.5.2-ha4553b6_0"
  ]
}
```

Delete an environment saved in an Object Storage

Use the `delete` command to delete an environment saved in an Object Storage.

> **Note:**
>
> Only user ADMIN can delete an environment saved in an Object Storage.

```
%conda

delete sbenv


Deleting conda environment sbenv
Deletion successful for conda environment sbenv
```

2.3 OML User Tasks for Downloading an Available Conda Environment

Once user ADMIN installs the environment in Object Storage in the Autonomous Database, as an OML user, you can download, activate, and use it in Python paragraphs in notebooks and with embedded execution.

List all environments persisted in Object Storage

Get the list of environments saved in Object Storage using the `list-saved-envs` command.

```
%conda

list-saved-envs
```

Get information on a named environment persisted in Object Storage

Provide the environment name as an argument to the `-e` parameter and request information on the environment.

```
%conda

list-saved-envs -e sbenv
```

The output is similar to the following:

```
{
  "name": "sbenv",
  "size": "1.2 GiB",
  "description": "Conda environment with seaborn",
  "tags": {
    "application": "OML4PY"
  },
  "number_of_installed_packages": 60
}
```

Download and activate the environment

Use the `download` command to download an environment from Object Storage. To activate the downloaded environment, use the `activate` command.

> **Note:**
>
> The paragraph that contains the download command must be the first paragraph in the notebook.

```
%conda
```

```
download sbenv
activate sbenv


Downloading conda environment sbenv
Download successful for conda environment sbenv
```

List the packages available in the environment

Get the list of all the packages in an active environment using the `list` command.

```
%conda

list
```

The output is similar to the following:

```
# packages in environment at /u01/.conda/envs/sbenv:
#
# Name                    Version                   Build  Channel
blas                      1.0                         mkl
bottleneck                1.3.5           py39h7deecbd_0
brotli                    1.0.9                h5eee18b_7
brotli-bin                1.0.9                h5eee18b_7
ca-certificates           2022.07.19           h06a4308_0
certifi                   2022.9.14       py39h06a4308_0
cycler                    0.11.0            pyhd3eb1b0_0
dbus                      1.13.18              hb2f20db_0
expat                     2.4.4                h295c915_0
fftw                      3.3.9                h27cfd23_1
fontconfig                2.13.1               h6c09931_0
fonttools                 4.25.0            pyhd3eb1b0_0
freetype                  2.11.0               h70c0345_0
giflib                    5.2.1                h7b6447c_0
glib                      2.69.1               h4ff587b_1
gst-plugins-base          1.14.0               h8213a91_2
gstreamer                 1.14.0               h28cd5cc_2
icu                       58.2                 he6710b0_3
intel-openmp              2021.4.0          h06a4308_3561
jpeg                      9e                   h7f8727e_0
kiwisolver                1.4.2           py39h295c915_0
lcms2                     2.12                 h3be6417_0
ld_impl_linux-64          2.38                 h1181459_1
lerc                      3.0                  h295c915_0
libbrotlicommon           1.0.9                h5eee18b_7
libbrotlidec              1.0.9                h5eee18b_7
libbrotlienc              1.0.9                h5eee18b_7
libdeflate                1.8                  h7f8727e_5
libffi                    3.3                  he6710b0_2
libgcc-ng                 11.2.0               h1234567_1
libgfortran-ng            11.2.0               h00389a5_1
libgfortran5              11.2.0               h1234567_1
libpng                    1.6.37               hbc83047_0
libstdcxx-ng              11.2.0               h1234567_1
libtiff                   4.4.0                hecacb30_0
```

```
libuuid                   1.0.3              h7f8727e_2
libwebp                   1.2.2              h55f646e_0
libwebp-base              1.2.2              h7f8727e_0
libxcb                    1.15               h7f8727e_0
libxml2                   2.9.14             h74e7548_0
lz4-c                     1.9.3              h295c915_1
matplotlib                3.5.2           py39h06a4308_0
matplotlib-base           3.5.2           py39hf590b9c_0
mkl                       2021.4.0          h06a4308_640
mkl-service               2.4.0           py39h7f8727e_0
mkl_fft                   1.3.1           py39hd3c417c_0
mkl_random                1.2.2           py39h51133e4_0
munkres                   1.1.4                    py_0
ncurses                   6.3                h5eee18b_3
numexpr                   2.8.3           py39h807cd23_0
numpy                     1.22.3          py39he7a7128_0
numpy-base                1.22.3          py39hf524024_0
openssl                   1.1.1q             h7f8727e_0
packaging                 21.3              pyhd3eb1b0_0
pandas                    1.4.4           py39h6a678d5_0
pcre                      8.45               h295c915_0
pillow                    9.2.0           py39hace64e9_1
pip                       22.1.2          py39h06a4308_0
pyparsing                 3.0.9           py39h06a4308_0
pyqt                      5.9.2           py39h2531618_6
python                    3.9.0              hdb3f193_2
python-dateutil           2.8.2             pyhd3eb1b0_0
pytz                      2022.1          py39h06a4308_0
qt                        5.9.7              h5867ecd_1
readline                  8.1.2              h7f8727e_1
scipy                     1.7.3           py39h6c91a56_2
seaborn                   0.11.2            pyhd3eb1b0_0
setuptools                63.4.1          py39h06a4308_0
sip                       4.19.13         py39h295c915_0
six                       1.16.0            pyhd3eb1b0_1
sqlite                    3.39.2             h5082296_0
tk                        8.6.12             h1ccaba5_0
tornado                   6.2             py39h5eee18b_0
tzdata                    2022c              h04d1e81_0
wheel                     0.37.1            pyhd3eb1b0_0
xz                        5.2.5              h7f8727e_1
zlib                      1.2.12             h5eee18b_3
zstd                      1.5.2              ha4553b6_0
```

Example 2-1 Create a visualization using seaborn

The following example shows the use of the available packages in the installed and activated environment. It imports `pandas, seaborn, and matplotlib` packages and loads the `iris` dataset from the seaborn library as a pandas dataframe. The `pairplot` seaborn function plots the pair-wise relationship between all the variables of the dataset.

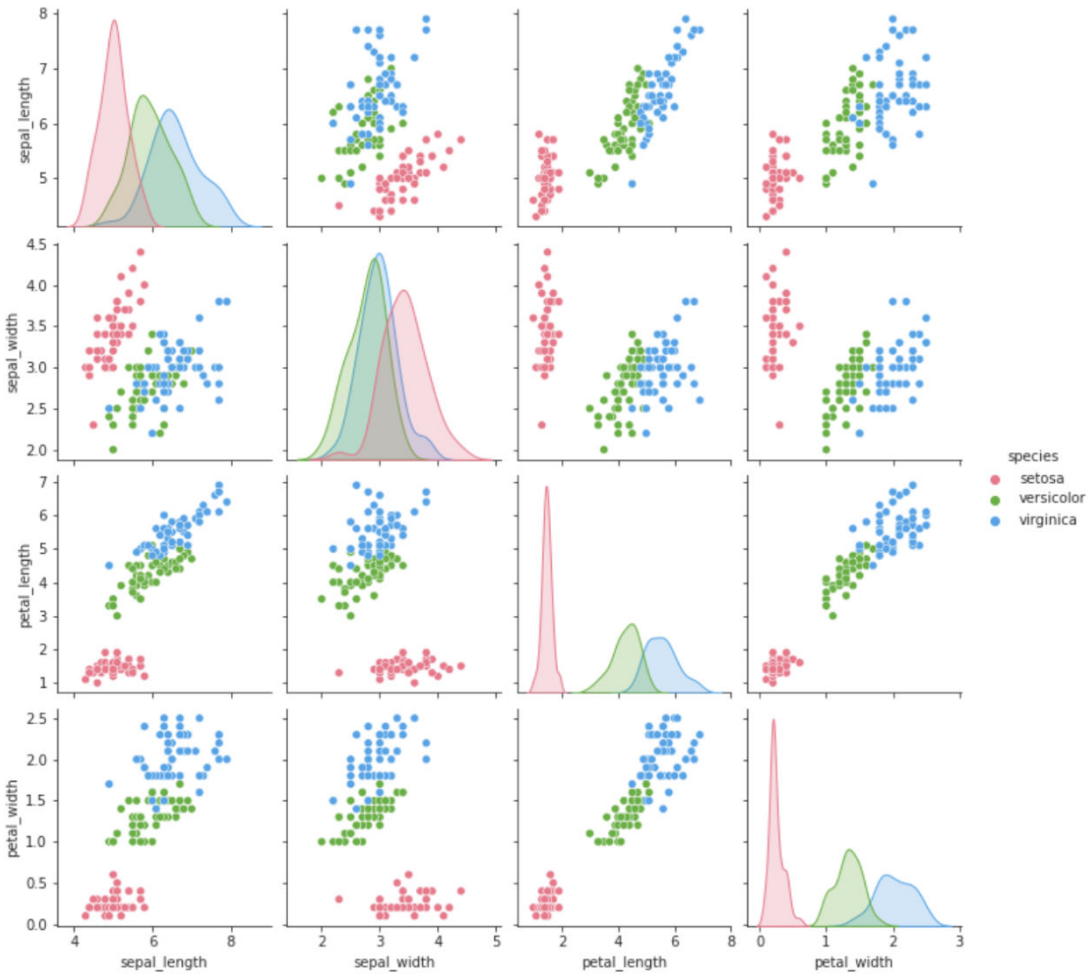
```
%python

import pandas as pd
import seaborn as sb
from matplotlib import pyplot as plt
```

```
df = sb.load_dataset('iris')
sb.set_style("ticks")
sb.pairplot(df,hue = 'species',diag_kind = "kde",kind = "scatter",palette =
"husl")
plt.show()
```

The output of the example is the following.

Figure 2-1 Iris pair plot



Example 2-2 Create a string representation of the function and save it to the OML4Py script repository

With OML4Py, functions are saved to the script repository using their string definition representation so they can be run in embedded Python execution. Create a function `sb_plot`, after verifying the function behaves as expected, provide it as a string (within triple quotes for formatting), and save it to the OML4Py script repository. Use the `oml.script.create` function to store a single user-defined Python function in the OML4Py script repository. The parameter

"sb_plot" is a string that specifies the name of the user-defined function. The parameter func=sb_plot is the Python function to run.

```
%python

sb_plot = """def sb_plot():
    import pandas as pd
    import seaborn as sb
    from matplotlib import pyplot as plt
    df = sb.load_dataset('iris')
    sb.set_style("ticks")
    sb.pairplot(df,hue = 'species',diag_kind = "kde",kind = "scatter",palette
= "husl")
    plt.show()"""

oml.script.create("sb_plot", func=sb_plot)
```

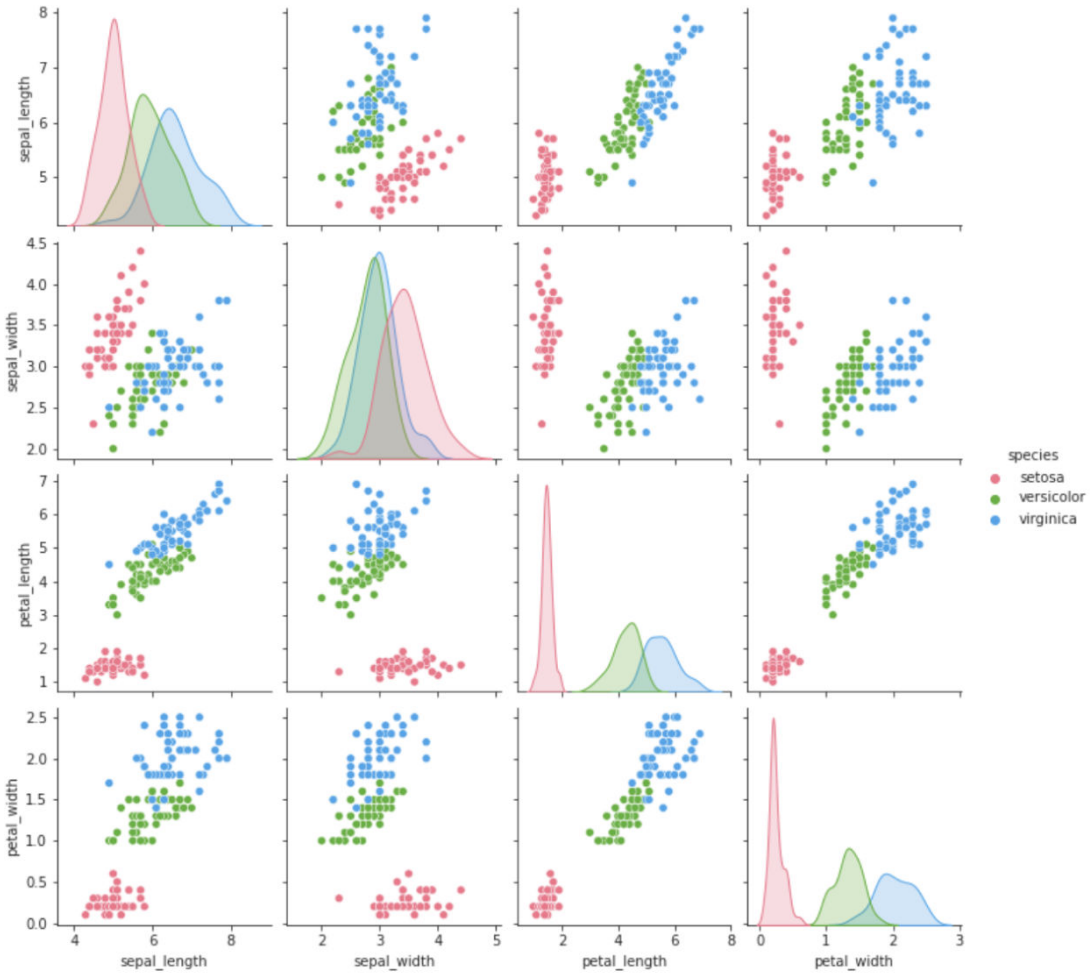
Use the Python API for embedded Python execution to run the user-defined Python function you saved in the script repository.

```
%python

oml.do_eval(func="sb_plot", graphics=True)
```

The output of the example is the following:

Figure 2-2 Iris pair plot



Deactivate the current environment

Use the `deactivate` command to deactivate an enviroment.

> **Note:**
>
> At a given time, only one active environment is supported. So, a newly activated environment would replace an old environment. As a best practice, deactivate an environment before logging off.

```
%conda

deactivate


Conda environment deactivated
```

2.4 Using Conda Environments with Embedded Python Execution

This topic explains the usage of conda environments by running user-defined functions (UDFs) in SQL and REST APIs for embedded Python execution.

Running UDFs in the SQL and REST APIs for embedded Python execution

The conda environments can be used by OML4Py Python, SQL, and REST APIs. To use the SQL and REST API for embedded Python execution, the following information is needed.

1. The token URL from the OML service console in Autonomous Database. For more information on how to obtain the token URL and set the access token see Access and Authorization Procedures and Functions (Autonomous Database).
2. A script containing a user-defined Python function in the Oracle Machine Learning for Python (OML4Py) script repository. For information on creating a script and saving it to the script repository, see About Embedded Python Execution and the Script Repository.

> **Note:**
>
> To use a conda environment when calling OML4Py script execution endpoints, specify the conda environment in the `env_name` field when using SQL, and the `envName` field when using REST.

Run the Python UDF using the SQL API for embedded Python execution - Asynchronous mode

Run a `SELECT` statement that calls the `pyqEval` function. The `PAR_LST` argument specifies the special control argument `oml_graphics_flag` to `true` so that the web server can capture images rendered in the invoked script, the `oml_async_flag` is set to true to submit the job asynchronously. In the `OUT_FMT` argument, the string 'PNG', specifies that the table returns the response in a table with fixed columns (including an image bytes column). The `SCR_NAME` parameter specifies the function `sb_plot` stored in the script repository. The `ENV_NAME` specifies the environment name `mysbenv` in which the script is called.

```
%script

set long 2000

SELECT * FROM table(pyqEval(
    par_lst => '{"oml_graphics_flag":true, "oml_async_flag":true}',
    out_fmt => 'PNG',
    scr_name => 'sb_plot',
    scr_owner=> NULL,
    env_name => 'mysbenv'));
```

The output is similar to the following:

```
NAME VALUE
--------------------------
```

```
            https://gcc59e2cf7a6f5f-oml4.adb-compdev1.us-
phoenix-1.oraclecloudapps.com/oml/api/py-scripts/v1/jobs/b82947a7-ec3a-4ca6-
bf86-54b3f2b3a4b0
```

Get the job status

Poll the job status using the pyqJobStatus function. If the job is still running, the return value will note that the job is still running. When the job completes, a job ID and result location are returned.

```
%script

set long 1000
SELECT VALUE from pyqJobStatus(job_id => 'b82947a7-ec3a-4ca6-
bf86-54b3f2b3a4b0');
```

The output returns a job ID:

```
NAME VALUE
---------------------------
            https://gcc59e2cf7a6f5f-oml4.adb-compdev1.us-
phoenix-1.oraclecloudapps.com/oml/api/py-scripts/v1/jobs/b82947a7-ec3a-4ca6-
bf86-54b3f2b3a4b0/result
```

Retrieve the result

```
%script

set long 500
SELECT NAME, ID, VALUE, dbms_lob.substr(image,100,1) image FROM
pyqJobResult(job_id => 'b82947a7-ec3a-4ca6-bf86-54b3f2b3a4b0',
out_fmt=>'PNG');
```

The output is similar to the following:

```
NAME ID VALUE IMAGE
---------------------------
           1
[{"0":0.0,"1":0.0,"2":0.2333333333,"accuracy":0.2333333333,"macro
avg":0.0777777778,"weighted avg":0.0544444444},
{"0":0.0,"1":0.0,"2":1.0,"accuracy":0.2333333333,"macro
avg":0.3333333333,"weighted avg":0.2333333333},
{"0":0.0,"1":0.0,"2":0.3783783784,"accuracy":0.2333333333,"macro
avg":0.1261261261,"weighted avg":0.0882882883},
{"0":11.0,"1":12.0,"2":7.0,"accuracy":0.2333333333,"macro avg":30.0,"weighted
avg":30.0}]
89504E470D0A1A0A0000000D494844520000046A000003E80806000000668185B000000397445
5874536F667477617265004D6174706C6F746C69622076657273696F6E332E362E322C20687474
70733A2F2F6D6174706C6F746C69622E6F72672F28E8
```

Run the Python UDF using the REST API for embedded Python execution

The following example runs the script named `sb_plot` in the OML4Py REST API for embedded Python execution. The environment name parameter `envName` is set to `mysbenv`. The `graphicsFlag` parameter is set to `true` to return the PNG image and the data from the function in JSON format.

```
$ curl -i -X POST --header "Authorization: Bearer ${token}" \
--header 'Content-Type: application/json' --header 'Accept: application/json'
\
-d '{"envName":"mysbenv", "graphicsFlag":true, "service":"LOW"}' \
"${omlserver}/oml/api/py-scripts/v1/do-eval/sb_plot"
```

The output is similar to the following:

```
NAME ID VALUE IMAGE
---------------------------
1 [{"0":0.0,"1":0.0,"2":0.2333333333,"accuracy":0.2333333333,"macro
avg":0.0777777778,"weighted avg":0.0544444444},
{"0":0.0,"1":0.0,"2":1.0,"accuracy":0.2333333333,"macro
avg":0.3333333333,"weighted avg":0.2333333333},
{"0":0.0,"1":0.0,"2":0.3783783784,"accuracy":0.2333333333,"macro
avg":0.1261261261,"weighted avg":0.0882882883},
{"0":11.0,"1":12.0,"2":7.0,"accuracy":0.2333333333,"macro avg":30.0,"weighted
avg":30.0}]
89504E470D0A1A0A0000000D494844520000046A000003E808060000008668185B000000397445
5874536F667477617265004D6174706C6F746C6962207665727369 6F6E332E362E322C20687474
70733A2F2F6D6174706C6F746C69622E6F72672F28E8
```

3

Get Started with Oracle Machine Learning for Python

Learn how to use OML4Py in Oracle Machine Learning Notebooks and how to move data between the local Python session and the database.

These actions are described in the following topics.

- Use OML4Py with Oracle Autonomous Database
- Move Data Between the Database and a Python Session
- Save Python Objects in the Database
- Use OML4Py with Oracle Autonomous Database
  OML4Py is available through the Python interpreter in Oracle Machine Learning Notebooks in Oracle Autonomous Database.
- Move Data Between the Database and a Python Session
  With OML4Py functions, you can interact with data structures in a database schema.
- Save Python Objects in the Database
  You can save Python objects in OML4Py datastores, which persist in the database.

3.1 Use OML4Py with Oracle Autonomous Database

OML4Py is available through the Python interpreter in Oracle Machine Learning Notebooks in Oracle Autonomous Database.

For more information, see Get Started with Notebooks for Data Analysis and Data Visualization in *Using Oracle Machine Learning Notebooks*.

3.2 Move Data Between the Database and a Python Session

With OML4Py functions, you can interact with data structures in a database schema.

In your Python session, you can move data to and from the database and create temporary or persistent database tables. The OML4Py functions that perform these actions are described in the following topics.

- About Moving Data Between the Database and a Python Session
- Push Local Python Data to the Database
- Pull Data from the Database to a Local Python Session
- Create a Python Proxy Object for a Database Object
- Create a Persistent Database Table from a Python Data Set
- About Moving Data Between the Database and a Python Session
  Using the functions described in this topic, you can move data between the your local Python session and an Oracle database schema.

- Push Local Python Data to the Database
  Use the `oml.push` function to push data from your local Python session to a temporary table in your Oracle database schema.
- Pull Data from the Database to a Local Python Session
  Use the `pull` method of an `oml` proxy object to create a Python object in your local Python session.
- Create a Python Proxy Object for a Database Object
  Use the `oml.sync` function to create a Python object as a proxy for a database table, view, or SQL statement.
- Create a Persistent Database Table from a Python Data Set
  Use the `oml.create` function to create a persistent table in your database schema from data in your Python session.

3.2.1 About Moving Data Between the Database and a Python Session

Using the functions described in this topic, you can move data between the your local Python session and an Oracle database schema.

The following functions create proxy `oml` Python objects from database objects, create database tables from Python objects, list the objects in the workspace, and drop tables and views.

Function	Definition
`oml.create`	Creates a persistent database table from a Python data set.
`oml.cursor`	Returns a `cx_Oracle cursor` object for the current OML4Py database connection.
`oml.dir`	Returns the names of the `oml` objects in the workspace.
`oml.drop`	Drops a persistent database table or view.
`oml_object``.pull`	Creates a local Python object that contains a copy of the database data referenced by the `oml` object.
`oml.push`	Pushes data from the OML Notebooks Python session memory into a temporary table in the database.
`oml.sync`	Creates an `oml.DataFrame` proxy object in Python that represents a database table, view, or query.

With the `pull` method of an `oml` object, you can create a local Python object that contains a copy of the database data represented by an `oml` proxy object.

The `oml.push` function implicitly coerces Python data types to `oml` data types and the `pull` method on `oml` objects coerces `oml` data types to Python data types.

With the `oml.create` function, you can create a persistent database table and a corresponding `oml.DataFrame` proxy object from a Python data set.

With the `oml.sync` function, you can synchronize the metadata of a database table or view with the `oml` object representing the database object.

With the `oml.cursor` function, you can create a `cx_Oracle cursor` object for the current database connection. You can user the `cursor` to run queries against the database, as shown in Example 3-6.

3.2.2 Push Local Python Data to the Database

Use the `oml.push` function to push data from your local Python session to a temporary table in your Oracle database schema.

The `oml.push` function creates a temporary table in the user's database schema and inserts data into the table. It also creates and returns a corresponding proxy `oml.DataFrame` object that references the table in the Python session. The table exists as long as an `oml` object exists that references it, either in the Python session memory or in an OML4Py datastore.

The syntax of the `oml.push` function is the following:

```
oml.push(x, oranumber=True, dbtypes=None)
```

The `x` argument may be a `pandas.DataFrame` or a list of tuples of equal size that contain the data for the table. For a list of tuples, each tuple represents a row in the table and the column names are set to COL1, COL2, and so on.

The SQL data types of the columns are determined by the following:

- OML4Py determines default column types by looking at 20 random rows sampled from the table. For tables with less than 20 rows, it uses all rows in determining the column type.

  If the values in a column are all `None`, or if a column has inconsistent data types that are not `None` in the sampled rows, then a default column type cannot be determined and a `ValueError` is raised unless a SQL type for the column is specified by the `dbtypes` argument.
- For numeric columns, the `oranumber` argument, which is a `bool`, determines the SQL data type. If `True` (the default), then the SQL data type is `NUMBER`. If `False`, then the data type is `BINARY_DOUBLE`.

  If the data in `x` contains `NaN` values, then you should set `oranumber` to `False`.
- For string columns, the default type is `VARCHAR2(4000)`.
- For bytes columns, the default type is `BLOB`.

With the `dbtypes` argument, you can specify the SQL data types for the table columns. The values of `dbtypes` may be either a `dict` that maps `str` to `str` values or a list of `str` values. For a `dict`, the keys are the names of the columns.

Example 3-1 Pushing Data to a Database Table

This example creates `pd_df`, a `pandas.core.frame.DataFrame` object with columns of various data types. It pushes `pd_df` to a temporary database table, which creates the `oml_df` object, which references the table. It then pulls the data from the `oml_df` object to the `df` object in local memory.

```
import oml
import pandas as pd

pd_df = pd.DataFrame({'numeric': [1, 1.4, -4, 3.145, 5, None],
                      'string' : [None, None, 'a', 'a', 'a', 'b'],
                      'bytes' : [b'a', b'b', b'c', b'c', b'd', b'e']})

# Push the data set to a database table with the specified dbtypes
```

```
# for each column.
oml_df = oml.push(pd_df, dbtypes = {'numeric': 'BINARY_DOUBLE',
                                    'string':'CHAR(1)',
                                    'bytes':'RAW(1)'})

# Display the data type of oml_df.
type(oml_df)

# Pull the data from oml_df into local memory.
df = oml_df.pull()

# Display the data type of df.
type(df)

# Create a list of tuples.
lst = [(1, None, b'a'), (1.4, None, b'b'), (-4, 'a', b'c'),
       (3.145, 'a', b'c'), (5, 'a', b'd'), (None, 'b', b'e')]

# Create an oml.DataFrame using the list.
oml_df2 = oml.push(lst, dbtypes = ['BINARY_DOUBLE','CHAR(1)','RAW(1)'])

type(oml_df2)
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>>
>>> pd_df = pd.DataFrame({'numeric': [1, 1.4, -4, 3.145, 5, None],
...                       'string' : [None, None, 'a', 'a', 'a', 'b'],
...                       'bytes' : [b'a', b'b', b'c', b'c', b'd', b'e']})
>>>
>>> # Push the data set to a database table with the specified dbtypes
... # for each column.
... oml_df = oml.push(pd_df, dbtypes = {'numeric': 'BINARY_DOUBLE',
...                                     'string':'CHAR(1)',
...                                     'bytes':'RAW(1)'})
>>>
>>> # Display the data type of oml_df.
... type(oml_df)
<class 'oml.core.frame.DataFrame'>
>>>
>>> # Pull the data from oml_df into local memory.
... df = oml_df.pull()
>>>
>>> # Display the data type of df.
... type(df)
<class 'pandas.core.frame.DataFrame'>
>>>
>>> # Create a list of tuples.
... lst = [(1, None, b'a'), (1.4, None, b'b'), (-4, 'a', b'c'),
...        (3.145, 'a', b'c'), (5, 'a', b'd'), (None, 'b', b'e')]
>>>
>>> # Create an oml.DataFrame using the list.
... oml_df2 = oml.push(lst, dbtypes = ['BINARY_DOUBLE','CHAR(1)','RAW(1)'])
```

```
>>>
>>> type(oml_df2)
<class 'oml.core.frame.DataFrame'>
```

3.2.3 Pull Data from the Database to a Local Python Session

Use the `pull` method of an `oml` proxy object to create a Python object in your local Python session.

> **Note:**
>
> You can pull data to a local `pandas.DataFrame` only if the data can fit into the local Python session memory. Also, even if the data fits in memory but is still very large, you may not be able to perform many, or any, Python functions in the local Python session.

Example 3-2 Pulling Data into Local Memory

This example loads the iris data set and creates the IRIS database table and the `oml_iris` proxy object that references that table. It displays the type of the `oml_iris` object, then pulls the data from it to the `iris` object in local memory and displays its type.

```
import oml
from sklearn.datasets import load_iris
import pandas as pd

iris = load_iris()
x = pd.DataFrame(iris.data, columns = ['SEPAL_LENGTH','SEPAL_WIDTH',
'PETAL_LENGTH','PETAL_WIDTH'])
y = pd.DataFrame(list(map(lambda x: {0: 'setosa', 1: 'versicolor', 2:
'virginica'}[x], iris.target)), columns = ['SPECIES'])
iris_df = pd.concat([x, y], axis=1)

oml_iris = oml.create(iris_df, table = 'IRIS')

# Display the data type of oml_iris.
type(oml_iris)

# Pull the data from oml_iris into local memory.
iris = oml_iris.pull()

# Display the data type of iris.
type(iris)

# Drop the IRIS database table.
oml.drop('IRIS')
```

Listing for This Example

```
>>> import oml
>>> from sklearn.datasets import load_iris
```

```
>>> import pandas as pd
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
>>> iris = datasets.load_iris()

>>> iris = load_iris()
>>> x = pd.DataFrame(iris.data, columns = ['SEPAL_LENGTH','SEPAL_WIDTH',
'PETAL_LENGTH','PETAL_WIDTH'])
>>> y = pd.DataFrame(list(map(lambda x: {0: 'setosa', 1: 'versicolor', 2:
'virginica'}[x], iris.target)), columns = ['SPECIES'])
>>> iris_df = pd.concat([x, y], axis=1)

>>> oml_iris = oml.create(iris_df, table = 'IRIS')

>>>
>>> # Display the data type of oml_iris.
... type(oml_iris)
<class 'oml.core.frame.DataFrame'>
>>>
>>> # Pull the data from oml_iris into local memory.
... iris = oml_iris.pull()
>>>
>>> # Display the data type of iris.
... type(iris)
<class 'pandas.core.frame.DataFrame'>
>>>
>>> # Drop the IRIS database table.
... oml.drop('IRIS')
```

3.2.4 Create a Python Proxy Object for a Database Object

Use the `oml.sync` function to create a Python object as a proxy for a database table, view, or SQL statement.

The `oml.sync` function returns an `oml.DataFrame` object or a dictionary of `oml.DataFrame` objects. The `oml.DataFrame` object returned by `oml.sync` is a proxy for the database object.

You can use the proxy `oml.DataFrame` object to select data from the table. When you run a Python function that selects data from the table, the function returns the current data from the database object. However, if some application has added a column to the table, or has otherwise changed the metadata of the database object, the `oml.DataFrame` proxy object does not reflect such a change until you again invoke `oml.sync` for the database object.

> **Tip:**
>
> To conserve memory resources and save time, you should only create proxies for the tables that you want to use in your Python session.

You can use the `oml.dir` function to list the `oml.DataFrame` proxy objects in the environment for a schema.

The syntax of the `oml.sync` function is the following:

```
oml.sync(schema=None, regex_match=False, table=None, view=None, query=None)
```

The `schema` argument in `oml.sync` specifies the name of the schema where the database object exists. If `schema=None`, which is the default, then the current schema is used.

To create an `oml.DataFrame` object for a table, use the `table` parameter. To create one for a view, use the `view` parameter. To create one for a SQL `SELECT` statement, use the `query` parameter. You can only specify one of these parameters in an `oml.sync` invocation: the argument for one of the parameters must be a string and the argument for each of the other two parameters must be `None`.

Creating a proxy object for a query enables you to create an `oml.DataFrame` object without creating a view in the database. This can be useful when you do not have the `CREATE VIEW` system privilege for the current schema. You cannot use the `schema` parameter and the `query` parameter in the same `ore.sync` invocation.

With the `regex_match` argument, you can specify whether the value of the `table` or `view` argument is a regular expression. If `regex_match=True`, then `oml.sync` creates `oml.DataFrame` objects for each database object that matches the pattern. The matched tables or views are returned in a `dict` with the table or view names as keys.

Example 3-3 Creating a Python Object for a Database Table

This example creates an `oml.DataFrame` Python object as a proxy for a database table. For this example, the table COFFEE exists in the user's schema.

```
import oml

# Create the Python object oml_coffee as a proxy for the
# database table COFFEE.
oml_coffee = oml.sync(table = 'COFFEE')
type(oml_coffee)

# List the proxy objects in the schema.
oml.dir()

oml_coffee.head()
```

Listing for This Example

```
>>> import oml
>>>
>>> # Create the Python object oml_coffee as a proxy for the
... # database table COFFEE.
... oml_coffee = oml.sync(table = 'COFFEE')
>>> type(oml_coffee)
<class 'oml.core.frame.DataFrame'>
>>>
>>> # List the proxy objects in the schema.
... oml.dir()
['oml_coffee']
>>>
>>> oml_coffee.head()
```

```
   ID COFFEE WINDOW
0   1    esp      w
1   2    cap      d
2   3    cap      w
3   4    kon      w
4   5    ice      w
```

Example 3-4 Using the regex_match Argument

This example uses the `regex_match` argument in creating a `dict` object that contains `oml.DataFrame` proxy objects for tables whose names start with C. For this example, the COFFEE and COLOR tables exist in the user's schema and are the only tables whose names start with C.

```
# Create a dict of oml.DataFrame proxy objects for tables
# whose names start with 'C'.
oml_cdat = oml.sync(table="^C", regex_match=True)

oml_cdat.keys()
oml_cdat['COFFEE'].columns
oml_cdat['COLOR'].columns
```

Listing for This Example

```
>>> # Create a dict of oml.DataFrame proxy objects for tables
... # whose names start with 'C'.
... oml_cdat = oml.sync(table="^C", regex_match=True)
>>>
>>> oml_cdat.keys()
dict_keys(['COFFEE', 'COLOR']
>>> oml_cdat['COFFEE'].columns
['ID', 'COFFEE', 'WINDOW']
>>> oml_cdat['COLOR'].columns
['REGION', 'EYES', 'HAIR', 'COUNT']
```

Example 3-5 Synchronizing an Updated Table

This example uses `oml.sync` to create an `oml.DataFrame` for the database table COFFEE. For the example, the new column BREW has been added to the database table by some other database process after the first invocation of `oml.sync`. Invoking `oml.sync` again synchronizes the metadata of the `oml.DataFrame` with those of the table.

```
oml_coffee =  oml.sync(table = "COFFEE")
oml_coffee.columns

# After a new column has been inserted into the table.
oml_coffee =  oml.sync(table = "COFFEE")
oml_coffee.columns
```

Listing for This Example

```
>>> oml_coffee =  oml.sync(table = "COFFEE")
>>> oml_coffee.columns
['ID', 'COFFEE', 'WINDOW']
```

```
>>>
>>> # After a new column has been inserted into the table.
... oml_coffee =  oml.sync(table = "COFFEE")
>>> oml_coffee.columns
['ID', 'COFFEE', 'WINDOW', 'BREW']
```

3.2.5 Create a Persistent Database Table from a Python Data Set

Use the `oml.create` function to create a persistent table in your database schema from data in your Python session.

The `oml.create` function creates a table in the database schema and returns an `oml.DataFrame` object that is a proxy for the table. The proxy `oml.DataFrame` object has the same name as the table.

> **Note:**
>
> When creating a table in Oracle Machine Learning for Python, if you use lowercase or mixed case for the name of the table, then you must use the same lowercase or mixed case name in double quotation marks when using the table in a SQL query or function. If, instead, you use an all uppercase name when creating the table, then the table name is case-insensitive: you can use uppercase, lowercase, or mixed case when using the table without using double quotation marks. The same is true for naming columns in a table.

You can delete the persistent table in a database schema with the `oml.drop` function.

> **Caution:**
>
> Use the `oml.drop` function to delete a persistent database table. Use the `del` statement to remove an `oml.DataFrame` proxy object and its associated temporary table; `del` does not delete a persistent table.

The syntax of the `oml.create` function is the following:

```
oml.create(x, table, oranumber=True, dbtypes=None, append=False)
```

The `x` argument is a `pandas.DataFrame` or a list of tuples of equal size that contain the data for the table. For a list of tuples, each tuple represents a row in the table and the column names are set to COL1, COL2, and so on. The `table` argument is a string that specifies a name for the table.

The SQL data types of the columns are determined by the following:

- OML4Py determines default column types by looking at 20 random rows sampled from the table. For tables with less than 20 rows, it uses all rows in determining the column type.

  If the values in a column are all `None`, or if a column has inconsistent data types that are not `None` in the sampled rows, then a default column type cannot be determined and a `ValueError` is raised unless a SQL type for the column is specified by the `dbtypes` argument.

- For numeric columns, the `oranumber` argument, which is a `bool`, determines the SQL data type. If `True` (the default), then the SQL data type is NUMBER. If `False`, then the data type is BINARY DOUBLE.

  If the data in `x` contains NaN values, then you should set `oranumber` to `False`.
- For string columns, the default type is VARCHAR2(4000).
- For bytes columns, the default type is BLOB.

With the `dbtypes` parameter, you can specify the SQL data types for the table columns. The values of `dbtypes` may be either a `dict` that maps `str` to `str` values or a list of `str` values. For a `dict`, the keys are the names of the columns. The `dbtypes` parameter is ignored if the `append` argument is `True`.

The `append` argument is a `bool` that specifies whether to append the `x` data to an existing table.

Example 3-6 Creating Database Tables from a Python Data Set

This example creates a `cursor` object for the database connection, creates a `pandas.core.frame.DataFrame` with columns of various data types, then creates a series of tables using different `oml.create` parameters and shows the SQL data types of the table columns.

```
import oml

# Create a cursor object for the current OML4Py database
# connection to run queries and get information from the database.
cr = oml.cursor()

import pandas as pd

df = pd.DataFrame({'numeric': [1, 1.4, -4, 3.145, 5, 2],
                   'string' : [None, None, 'a', 'a', 'a', 'b'],
                   'bytes' : [b'a', b'b', b'c', b'c', b'd', b'e']})

# Get the order of the columns
df.columns

# Create a table with the default parameters.
oml_df1 = oml.create(df, table = 'tbl1')

# Show the default SQL data types of the columns.
_ = cr.execute("select data_type from all_tab_columns where table_name =
'tbl1'")
cr.fetchall()

# Create a table with oranumber set to False.
oml_df2 = oml.create(df, table = 'tbl2', oranumber = False)

# Show the SQL data typea of the columns.
_ = cr.execute("select data_type from all_tab_columns where table_name =
'tbl2'")
cr.fetchall()

# Create a table with dbtypes specified as a dict mapping column names
# to SQL data types.
oml_df3 = oml.create(df, table = 'tbl3',
```

```
                    dbtypes = {'numeric': 'BINARY_DOUBLE',
                               'bytes':'RAW(1)'})

# Show the SQL data types of the columns.
_ = cr.execute("select data_type from all_tab_columns where table_name =
'tbl3'")
cr.fetchall()

# Create a table with dbtypes specified as a list of SQL data types
# matching the order of the columns.
oml_df4 = oml.create(df, table = 'tbl4',
                    dbtypes = ['BINARY_DOUBLE','VARCHAR2','RAW(1)'])

# Show the SQL data type of the columns.
_ = cr.execute("select data_type from all_tab_columns where table_name =
'tbl4'")
cr.fetchall()

# Create a table from a list of tuples.
lst = [(1, None, b'a'), (1.4, None, b'b'), (-4, 'a', b'c'),
       (3.145, 'a', b'c'), (5, 'a', b'd'), (None, 'b', b'e')]
oml_df5 = oml.create(lst, table = 'tbl5',
                    dbtypes = ['BINARY_DOUBLE','CHAR(1)','RAW(1)'])

# Close the cursor
cr.close()

# Drop the tables.
oml.drop('tbl1')
oml.drop('tbl2')
oml.drop('tbl3')
oml.drop('tbl4')
oml.drop('tbl5')
```

Listing for This Example

```
>>> import oml
>>>
>>> # Create a cursor object for the current OML4Py database
... # connection to run queries and get information from the database.
... cr = oml.cursor()
>>>
>>> import pandas as pd
>>>
>>> df = pd.DataFrame({'numeric': [1, 1.4, -4, 3.145, 5, 2],
...                    'string' : [None, None, 'a', 'a', 'a', 'b'],
...                    'bytes' : [b'a', b'b', b'c', b'c', b'd', b'e']})
>>>
>>> # Get the order of the columns.
... df.columns
Index(['numeric', 'string', 'bytes'], dtype='object')
>>>
>>> # Create a table with the default parameters.
... oml_df1 = oml.create(df, table = 'tbl1')
>>>
```

```
>>> # Show the default SQL data types of the columns.
... _ = cr.execute("select data_type from all_tab_columns where table_name =
'tbl1'")
>>> cr.fetchall()
[('NUMBER',), ('VARCHAR2',), ('BLOB',)]
>>>
>>> # Create a table with oranumber set to False.
... oml_df2 = oml.create(df, table = 'tbl2', oranumber = False)
>>>
>>> # Show the SQL data types of the columns.
... _ = cr.execute("select data_type from all_tab_columns where table_name =
'tbl2'")
>>> cr.fetchall()
[('BINARY_DOUBLE',), ('VARCHAR2',), ('BLOB',)]
>>>
>>> # Create a table with dbtypes specified as a dict mapping column names
... # to SQL data types.
... oml_df3 = oml.create(df, table = 'tbl3',
...                      dbtypes = {'numeric': 'BINARY_DOUBLE',
...                                 'bytes':'RAW(1)'})
>>>
>>> # Show the SQL data type of the columns.
... _ = cr.execute("select data_type from all_tab_columns where table_name =
'tbl3'")
>>> cr.fetchall()
[('BINARY_DOUBLE',), ('VARCHAR2',), ('RAW',)]
>>>
>>> # Create a table with dbtypes specified as a list of SQL data types
... # matching the order of the columns.
... oml_df4 = oml.create(df, table = 'tbl4',
...                      dbtypes = ['BINARY_DOUBLE','CHAR(1)', 'RAW(1)'])
>>>
>>> # Show the SQL data type of the columns
... _ = cr.execute("select data_type from all_tab_columns where table_name =
'tbl4'")
>>> cr.fetchall()
[('BINARY_DOUBLE',), ('CHAR',), ('RAW',)]
>>>
>>> # Create a table from a list of tuples.
... lst = [(1, None, b'a'), (1.4, None, b'b'), (-4, 'a', b'c'),
...        (3.145, 'a', b'c'), (5, 'a', b'd'), (None, 'b', b'e')]
>>> oml_df5 = oml.create(lst, table ='tbl5',
...                      dbtypes = ['BINARY_DOUBLE','CHAR(1)','RAW(1)'])
>>>
>>> # Show the SQL data type of the columns.
... _ = cr.execute("select data_type from all_tab_columns where table_name =
'tbl5'")
>>> cr.fetchall()
[('BINARY_DOUBLE',), ('CHAR',), ('RAW',)]
>>>
>>> # Close the cursor.
... cr.close()
>>>
>>> # Drop the tables
... oml.drop('tbl1')
>>> oml.drop('tbl2')
```

```
>>> oml.drop('tbl3')
>>> oml.drop('tbl4')
>>> oml.drop('tbl5')
```

3.3 Save Python Objects in the Database

You can save Python objects in OML4Py datastores, which persist in the database.

You can grant or revoke read privilege access to a datastore or its objects to one or more users. You can restore the saved objects in another Python session.

The following topics describe the OML4Py functions for creating and managing datastores:

- About OML4Py Datastores
- Save Objects to a Datastore
- Load Saved Objects From a Datastore
- Get Information About Datastores
- Get Information About Datastore Objects
- Delete Datastore Objects
- Manage Access to Stored Objects

- About OML4Py Datastores
  In an OML4Py datastore, you can store Python objects, which you can then use in subsequent Python sessions; you can also make them available to other users or programs.
- Save Objects to a Datastore
  The `oml.ds.save` function saves one or more Python objects to a datastore.
- Load Saved Objects From a Datastore
  The `oml.ds.load` function loads one or more Python objects from a datastore into a Python session.
- Get Information About Datastores
  The `oml.ds.dir` function provides information about datastores.
- Get Information About Datastore Objects
  The `oml.ds.describe` function provides information about the objects in a datastore.
- Delete Datastore Objects
  The `oml.ds.delete` function deletes datastores or objects in a datastore.
- Manage Access to Stored Objects
  The `oml.grant` and `oml.revoke` functions grant or revoke the read privilege to datastores or to user-defined Python functions in the script repository.

3.3.1 About OML4Py Datastores

In an OML4Py datastore, you can store Python objects, which you can then use in subsequent Python sessions; you can also make them available to other users or programs.

Python objects, including OML4Py proxy objects, exist only for the duration of the current Python session unless you explicitly save them. You can save a Python object, including `oml` proxy objects, to a named datastore and then load that object in a later Python session, including an Embedded Python Execution session. OML4Py creates the datastore in the user's

database schema. A datastore, and the objects it contains, persist in the database until you delete them.

You can grant or revoke read privilege permission to another user to a datastore that you created or to objects in a datastore.

OML4Py has Python functions for managing objects in a datastore. It also has PL/SQL procedures for granting or revoking the read privilege and database views for listing available datastores and their contents.

Using a datastore, you can do the following:

- Save OML4Py and other Python objects that you create in one Python session and load them in another Python session.
- Pass arguments to Python functions for use in Embedded Python Execution.
- Pass objects for use in Embedded Python Execution. You could, for example, use the `oml.glm` class to build an Oracle Machine Learning model and save it in a datastore. You could then use that model to score data in the database through Embedded Python Execution.

Python Interface for Datastores

The following table lists the Python functions for saving and managing objects in a datastore.

Function	Description
`oml.ds.delete`	Deletes one or more datastores or Python objects from a datastore.
`oml.ds.dir`	Lists the datastores available to the current user.
`oml.ds.load`	Loads Python objects from a datastore into the user's session.
`oml.ds.save`	Saves Python objects to a named datastore in the user's database schema.

The following table lists the Python functions for managing access to datastores and datastore objects.

Function	Description
`oml.grant`	Grants read privilege permission to another user to a datastore or a user-defined Python function in the script repository owned by the current user.
`oml.revoke`	Revokes the read privilege permission that was granted to another user to a datastore or a user-defined Python function in the script repository owned by the current user.

3.3.2 Save Objects to a Datastore

The `oml.ds.save` function saves one or more Python objects to a datastore.

OML4Py creates the datastore in the current user's schema.

The syntax of `oml.ds.save` is the following:

```
oml.ds.save(objs, name, description=' ', grantable=None,
                      overwrite=False, append=False, compression=False)
```

The `objs` argument is a `dict` that contains the name and object pairs to save to the datastore specified by the `name` argument.

With the `description` argument, you can provide some descriptive text that appears when you get information about the datastore. The `description` parameter has no effect when used with the `append` parameter.

With the `grantable` argument, you can specify whether the read privilege to the datastore may be granted to other users.

If you set the `overwrite` argument to `TRUE`, then you can replace an existing datastore with another datastore of the same name.

If you set the `append` argument to `TRUE`, then you can add objects to an existing datastore. The `overwrite` and `append` arguments are mutually exclusive.

If you set compression to `True`, then the serialized Python objects are compressed in the datastore.

Example 3-7 Saving Python Objects to a Datastore

This example demonstrates creating datastores.

```
import oml
from sklearn import datasets
from sklearn import linear_model
import pandas as pd

# Load three data sets and create oml.DataFrame objects for them.
wine = datasets.load_wine()
x = pd.DataFrame(wine.data, columns = wine.feature_names)
y = pd.DataFrame(wine.target, columns = ['Class'])

# Create the database table WINE.
oml_wine = oml.create(pd.concat([x, y], axis=1), table = 'WINE')
oml_wine.columns

diabetes = datasets.load_diabetes()
x = pd.DataFrame(diabetes.data, columns=diabetes.feature_names)
y = pd.DataFrame(diabetes.target, columns=['disease_progression'])
oml_diabetes = oml.create(pd.concat([x, y], axis=1),
                                    table = "DIABETES")
oml_diabetes.columns

boston = datasets.load_boston()
x = pd.DataFrame(boston.data, columns = boston.feature_names.tolist())
y = pd.DataFrame(boston.target, columns = ['Value'])
oml_boston = oml.create(pd.concat([x, y], axis=1), table = "BOSTON")
oml_boston.columns

# Save the wine Bunch object to the datastore directly,
# along with the oml.DataFrame proxy object for the BOSTON table.
oml.ds.save(objs={'wine':wine, 'oml_boston':oml_boston},
            name="ds_pydata", description = "python datasets")

# Save the oml_diabetes proxy object to an existing datastore.
oml.ds.save(objs={'oml_diabetes':oml_diabetes},
                  name="ds_pydata", append=True)

# Save the oml_wine proxy object to another datastore.
```

```
oml.ds.save(objs={'oml_wine':oml_wine},
            name="ds_wine_data", description = "wine dataset")

# Create regression models using sklearn and oml.
# The regr1 linear model is a native Python object.
regr1 = linear_model.LinearRegression()
regr1.fit(boston.data, boston.target)
# The regr2 GLM model is an oml object.
regr2 = oml.glm("regression")
X = oml_boston.drop('Value')
y = oml_boston['Value']
regr2 = regr2.fit(X, y)

# Save the native Python object and the oml proxy object to a datastore
# and allow the read privilege to be granted to them.
oml.ds.save(objs={'regr1':regr1, 'regr2':regr2},
            name="ds_pymodel", grantable=True)

# Grant the read privilege to the datastore to every user.
oml.grant(name="ds_pymodel", typ="datastore", user=None)

# List the datastores to which the read privilege has been granted.
oml.ds.dir(dstype="grant")
```

Listing for This Example

```
>>> import oml
>>> from sklearn import datasets
>>> from sklearn import linear_model
>>> import pandas as pd
>>>
>>> # Load three data sets and create oml.DataFrame objects for them.
>>> wine = datasets.load_wine()
>>> x = pd.DataFrame(wine.data, columns = wine.feature_names)
>>> y = pd.DataFrame(wine.target, columns = ['Class'])
>>>
>>> # Create the database table WINE.
... oml_wine = oml.create(pd.concat([x, y], axis=1), table = 'WINE')
>>> oml_wine.columns
['alcohol', 'malic_acid', 'ash', 'alcalinity_of_ash', 'magnesium',
'total_phenols', 'flavanoids', 'nonflavanoid_phenols', 'proanthocyanins',
'color_intensity', 'hue', 'od280/od315_of_diluted_wines', 'proline', 'Class']
>>>
>>> diabetes = datasets.load_diabetes()
>>> x = pd.DataFrame(diabetes.data, columns=diabetes.feature_names)
>>> y = pd.DataFrame(diabetes.target, columns=['disease_progression'])
>>> oml_diabetes = oml.create(pd.concat([x, y], axis=1),
...                           table = "DIABETES")
>>> oml_diabetes.columns
['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6',
'disease_progression']
>>>
>>> boston = datasets.load_boston()
>>> x = pd.DataFrame(boston.data, columns = boston.feature_names.tolist())
>>> y = pd.DataFrame(boston.target, columns = ['Value'])
```

```
>>> oml_boston = oml.create(pd.concat([x, y], axis=1), table = "BOSTON")
>>> oml_boston.columns
['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
'PTRATIO', 'B', 'LSTAT', 'Value']
>>>
>>> # Save the wine Bunch object to the datastore directly,
... # along with the oml.DataFrame proxy object for the BOSTON table.
... oml.ds.save(objs={'wine':wine, 'oml_boston':oml_boston},
...             name="ds_pydata", description = "python datasets")
>>>
>>> # Save the oml_diabetes proxy object to an existing
datastore.
... oml.ds.save(objs={'oml_diabetes':oml_diabetes},
...                   name="ds_pydata", append=True)
>>>
>>> # Save the oml_wine proxy object to another datastore.
... oml.ds.save(objs={'oml_wine':oml_wine},
...             name="ds_wine_data", description = "wine dataset")
>>>
>>> # Create regression models using sklearn and oml.
... # The regr1 linear model is a native Python object.
... regr1 = linear_model.LinearRegression()
>>> regr1.fit(boston.data, boston.target)
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
>>> # The regr2 GLM model is an oml proxy object.
... regr2 = oml.glm("regression")
>>> X = oml_boston.drop('Value')
>>> y = oml_boston['Value']
>>> regr2 = regr2.fit(X, y)
>>>
>>> # Save the native Python object and the oml proxy object to a datastore
... # and allow the read privilege to be granted to them.
... oml.ds.save(objs={'regr1':regr1, 'regr2':regr2},
...             name="ds_pymodel", grantable=True)
>>>
>>> # Grant the read privilege to the ds_pymodel datastore to every user.
... oml.grant(name="ds_pymodel", typ="datastore", user=None)
>>>
>>> # List the datastores to which the read privilege has been granted.
... oml.ds.dir(dstype="grant")
  datastore_name grantee
0     ds_pymodel  PUBLIC
```

3.3.3 Load Saved Objects From a Datastore

The `oml.ds.load` function loads one or more Python objects from a datastore into a Python session.

The syntax of `oml.ds.load` is the following:

```
oml.ds.load(name, objs=None, owner=None, to_globals=True)
```

The `name` argument specifies the datastore that contains the objects to load.

With the `objs` argument, you identify a specific object or a list of objects to load.

With the boolean `to_globals` parameter, you can specify whether the objects are loaded to a global workspace or to a dictionary object. If the argument to `to_globals` is `True`, then `oml.ds.load` function loads the objects into the global workspace. If the argument is `False`, then the function returns a `dict` object that contains pairs of object names and values.

The `oml.ds.load` function raises a `ValueError` if the `name` argument is an empty string or if the owner of the datastore is not the current user and the read privilege for the datastore has not been granted to the current user.

Example 3-8 Loading Objects from Datastores

This example loads objects from datastores. For the creation of the datastores used in this example, see Example 3-7.

```
import oml

# Load all Python objects from a datastore to the global workspace.
sorted(oml.ds.load(name="ds_pydata"))

# Load the named Python object from the datastore to the global workspace.
oml.ds.load(name="ds_pymodel", objs=["regr2"])

# Load the named Python object from the datastore to the user's workspace.
oml.ds.load(name="ds_pymodel", objs=["regr1"], to_globals=False)
```

Listing for This Example

```
>>> import oml
>>>
>>> # Load all Python objects from a datastore to the current workspace.
... sorted(oml.ds.load(name="ds_pydata"))
['oml_boston', 'oml_diabetes', 'wine']
>>>
>>> # Load the named Python object from the datastore to the global workspace.
... oml.ds.load(name="ds_pymodel", objs=["regr2"])
['regr2']
>>>
>>> # Load the named Python object from the datastore to the user's workspace.
... oml.ds.load(name="ds_pymodel", objs=["regr1"], to_globals=False)
{'regr1': LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1,
normalize=False)}
```

3.3.4 Get Information About Datastores

The `oml.ds.dir` function provides information about datastores.

The syntax of `oml.ds.dir` is the following:

```
oml.ds.dir(name=None, regex_match=False, dstype='user')
```

Use the `name` parameter to get information about a specific datastore.

Optionally, you can use the `regex_match` and `dstype` parameters to get information about datastores with certain characteristics. The valid arguments for `dstype` are the following:

Argument	Description
`all`	Lists all of the datastores to which the current user has the read privilege.
`grant`	Lists the datastores for which the current user has granted read privilege to other users.
`granted`	Lists the datastores for which other users have granted read privilege to the current user.
`grantable`	Lists the datastores that the current user can grant the read privilege to.
`user`	Lists the datastores created by current user.
`private`	Lists the datastores that the current user cannot grant the read privileges to.

The `oml.ds.dir` function returns a `pandas.DataFrame` object that contains different columns depending on which `dstype` argument you use. The following table lists the arguments and the columns returned for the values supplied.

dstype Argument	Columns in the DataFrame Returned

`user`
`private`
`grantable`
	DSNAME, which contains the datastore name
	NOBJ, which contains the number of objects in the datastore
	DSIZE, which contains the size in bytes of each object in the datastore
	CDATE, which contains the creation date of the datastore
	DESCRIPTION, which contains the optional description of the datastore

`all` `granted`	All of the columns returned by the `user`, `private`, and `grantable` values, plus this additional column: DSOWNER, which contains the owner of the datastore
`grant`	DSNAME, which contains the datastore name GRANTEE, which contains the name of the user to which the read privilege to the datastore has been granted by the current session user

Example 3-9 Getting Information About Datastores

This example demonstrates using different combinations of arguments to the `oml.ds.dir` function. It demonstrates using `oml.dir` to list some or all of the datastores. For the creation of the datastores used in this example, see Example 3-7.

```
import oml

# Show all saved datastores.
oml.ds.dir(dstype="all")[['owner', 'datastore_name', 'object_count']]

# Show datastores to which other users have been granted the read
# privilege.
oml.ds.dir(dstype="grant")

# Show datastores whose names match a pattern.
```

```
oml.ds.dir(name='pydata', regex_match=True)\
          [['datastore_name', 'object_count']]
```

Listing for This Example

```
>>> import oml
>>>
>>> # Show all saved datastores.
... oml.ds.dir(dstype="all")[['owner', 'datastore_name', 'object_count']]
     owner  datastore_name  object_count
0  OML_USER      ds_pydata             3
1  OML_USER     ds_pymodel             2
2  OML_USER   ds_wine_data             1
>>>
>>> # Show datastores to which other users have been granted the read
>>> # privilege.
... oml.ds.dir(dstype="grant")
  datastore_name grantee
0     ds_pymodel  PUBLIC
>>>
>>> oml.ds.dir(name='pydata', regex_match=True)\
...           [['datastore_name', 'object_count']]
  datastore_name  object_count
0      ds_pydata             3
```

3.3.5 Get Information About Datastore Objects

The `oml.ds.describe` function provides information about the objects in a datastore.

The syntax of `oml.ds.describe` is the following:

```
oml.ds.describe(name, owner=None))
```

The `name` argument is a string that specifies the name of a datastore.

The `owner` argument is a string that specifies the owner of the datastore or `None` (the default). If you do not specify the owner, then the function returns information about the datastore if it is owned by the current user.

The `oml.ds.describe` function returns a `pandas.DataFrame` object, each row of which represents an object in the datastore. The columns of the `DataFrame` are the following:

- object_name, which specifies the name of the object
- class, which specifies the class of the object
- size, which specifies the size of the object in bytes
- length, which specifies the length of the object
- row_count, which specifies the rows of the object
- col_count, which specifies the columns of the object

This function raises a `ValueError` if the following occur:

- The current user is not the owner of the datastore and has not been granted read privilege for the datastore.

- The datastore does not exist.

Example 3-10 Getting Information About Datastore Objects

This example demonstrates the using the `oml.ds.describe` function. For the creation of the datastore used in this example, see Example 3-7.

```
import oml

# Describe the contents of the ds_pydata datastore.
oml.ds.describe(name='ds_pydata')
oml.ds.describe(name="ds_pydata")[['object_name', 'class']]
```

Listing for This Example

```
>>> import oml
>>>
>>> # Describe the contents of the ds_pydata datastore.
... oml.ds.describe(name='ds_pydata')
    object_name          class   size  length  row_count  col_count
0    oml_boston  oml.DataFrame   1073     506        506         14
1  oml_diabetes  oml.DataFrame    964     442        442         11
2          wine          Bunch  24177       5          1          5
>>> oml.ds.describe(name="ds_pydata")[['object_name', 'class']]
    object_name          class
0    oml_boston  oml.DataFrame
1  oml_diabetes  oml.DataFrame
2          wine          Bunch
```

3.3.6 Delete Datastore Objects

The `oml.ds.delete` function deletes datastores or objects in a datastore.

Use the `oml.ds.delete` function to delete one or more datastores in your database schema or to delete objects in a datastore.

The syntax of `oml.ds.delete` is the following:

```
oml.ds.delete(name, objs=None, regex_match=False)
```

The argument to the `name` parameter may be one of the following:

- A string that specifies the name of the datastore to modify or delete, or a regular expression that matches the datastores to delete.
- A list of `str` objects that name the datastores from which to delete objects.

The `objs` parameter specifies the objects to delete from a datastore. The argument to the `objs` parameter may be one of the following:

- A string that specifies the object to delete from one or more datastores, or a regular expression that matches the objects to delete.
- `None` (the default), which deletes the entire datastore or datastores.

The `regex_match` parameter is a `bool` that indicates whether the `name` or `objs` arguments are regular expressions. The default value is `False`. The `regex_match` parameter operates as follows:

- If `regex_match=False` and if `name` is not `None`, and:
  - If `objs=None`, then `oml.ds.delete` deletes the datastore or datastores specified in the `name` argument.
  - If you specify one or more datastores with the `name` argument and one or more datastore objects with the `objs` argument, then `oml.ds.delete` deletes the specified Python objects from the datastores.
- If `regex_match=True` and:
  - If `objs=None`, then `oml.ds.delete` deletes the datastores you specified in the `name` argument.
  - If the `name` argument is a string and you specify one or more datastore objects with the `objs` argument, then `oml.ds.delete` deletes from the datastore the objects whose names match the regular expression specified in the `objs` argument.
  - If the `name` argument is a list of `str` objects, then the `objs` argument must be a list of `str` objects of the same length as `name`, and `oml.ds.delete` deletes from the datastores the objects whose names match the regular expressions specified in `objs`.

This function raises an error if the following occur:

- A specified datastore does not exist.
- Argument `regex_match` is `False` and argument `name` is a list of `str` objects larger than 1 and argument `objs` is not `None`.
- Argument `regex_match` is `True` and arguments `name` and `objs` are lists that are not the same length.

Example 3-11 Deleting Datastore Objects

This example demonstrates the using the `oml.ds.delete` function. For the creation of the datastores used in this example, see Example 3-7.

```
import oml

# Show the existing datastores.
oml.ds.dir()

# Show the Python objects in the ds_pydata datastore.
oml.ds.describe(name='ds_pydata')

# Delete some objects from the datastore.
oml.ds.delete(name="ds_pydata", objs=["wine", "oml_boston"])

# Delete a datastore.
oml.ds.delete(name="ds_pydata")

# Delete all datastores whose names match a pattern.
oml.ds.delete(name="_pymodel", regex_match=True)

# Show the existing datastores again.
oml.ds.dir()
```

Listing for This Example

```
>>> import oml
>>>
>>> # Show the existing datastores.
... oml.ds.dir()
  datastore_name  object_count  size                date      description
0      ds_pydata             3  26214 2019-05-18 21:04:06  python datasets
1     ds_pymodel             2   6370 2019-05-18 21:08:18             None
2   ds_wine_data             1   1410 2019-05-18 21:06:53     wine dataset
>>>
>>> # Show the Python objects in the ds_pydata datastore.
... oml.ds.describe(name='ds_pydata')
    object_name          class  size  length  row_count  col_count
0    oml_boston  oml.DataFrame  1073     506        506         14
1  oml_diabetes  oml.DataFrame   964     442        442         11
2          wine          Bunch  24177       5          1          5
>>>
>>> # Delete some objects from a datastore.
... oml.ds.delete(name="ds_pydata", objs=["wine", "oml_boston"])
{'wine', 'oml_boston'}
>>>
>>> # Delete a datastore.
... oml.ds.delete(name="ds_pydata")
'ds_pydata'
>>>
>>> # Delete all datastores whose names match a pattern.
... oml.ds.delete(name="_pymodel", regex_match=True)
{'ds_pymodel'}
>>>
>>> # Show the existing datastores again.
... oml.ds.dir()
  datastore_name  object_count  size                date   description
0   ds_wine_data             1  1410 2019-05-18 21:06:53  wine dataset
```

3.3.7 Manage Access to Stored Objects

The `oml.grant` and `oml.revoke` functions grant or revoke the read privilege to datastores or to user-defined Python functions in the script repository.

The `oml.grant` function grants the read privilege to another user to a datastore or to a user-defined Python function in the OML4Py script repository. The `oml.revoke` function revokes that privilege.

The syntax of these functions is the following:

```
oml.grant(name, typ='datastore', user=None)
oml.revoke(name, typ='datastore', user=None)
```

The `name` argument is a string that specifies the name of the user-defined Python function in the script repository or the name of a datastore.

The `typ` parameter must be specified. The argument is a string that is either `'datastore'` or `'pyqscript'`.

The `user` argument is a string that specifies the user to whom read privilege to the named datastore or user-defined Python function is granted or from whom it is revoked, or `None` (the default). If you specify `None`, then the read privilege is granted to or revoked from all users.

Example 3-12 Granting and Revoking Access to Datastores

This example displays the datastores to which the read privilege has been granted to all users. It revokes read privilege from the `ds_pymodel` datastore and displays the datastores with public read privilege again. It next grants the read privilege to the user SH and finally displays once more the datastores to which read privilege has been granted. For the creation of the datastores used in this example, see Example 3-7.

```
import oml

# Show datastores to which other users have been granted read privilege.
oml.ds.dir(dstype="grant")

# Revoke the read privilege from every user.
oml.revoke(name="ds_pymodel", typ="datastore", user=None)

# Again show datastores to which read privilege has been granted.
oml.ds.dir(dstype="grant")

# Grant the read privilege to the user SH.
oml.grant(name="ds_pymodel", typ="datastore", user="SH")

oml.ds.dir(dstype="grant")
```

Listing for This Example

```
>>> import oml
>>>
>>> # Show datastores to which other users have been granted read privilege.
... oml.ds.dir(dstype="grant")
  datastore_name grantee
0     ds_pymodel  PUBLIC
>>>
>>> # Revoke the read privilege from every user.
... oml.revoke(name="ds_pymodel", typ="datastore", user=None)
>>>
>>> # Again show datastores to which read privilege has been granted to other
users.
... oml.ds.dir(dstype="grant")
Empty DataFrame
Columns: [datastore_name, grantee]
Index: []
>>>
>>> # Grant the read privilege to the user SH.
... oml.grant(name="ds_pymodel", typ="datastore", user="SH")
>>>
>>> oml.ds.dir(dstype="grant")
  datastore_name grantee
0     ds_pymodel      SH
```

Example 3-13 Granting and Revoking Access to User-Defined Python Functions

This example grants the read privilege to the MYLM user-defined Python function to the user SH and then revokes that privilege. For the creation of the user-defined Python functions used in this example, see Example 7-11.

```
# List the user-defined Python functions available only to the current user.
oml.script.dir(sctype='user')

# Grant the read privilege to the MYLM user-defined Python function to the
user SH.
oml.grant(name="MYLM", typ="pyqscript", user="SH")

# List the user-defined Python functions to which read privilege has been
granted.
oml.script.dir(sctype="grant")

# Revoke the read privilege to the MYLM user-defined Python function from the
user SH.
oml.revoke(name="MYLM", typ="pyqscript", user="SH")

# List the granted user-defined Python functions again to see if the
revocation was successful.
oml.script.dir(sctype="grant")
```

Listing for This Example

```
>>> # List the user-defined Python functions available only to the current
user.
oml.script.dir(sctype='user')
   name                                                script
0  MYLM  def build_lm1(dat):\n  from sklearn import lin...
>>>
>>># Grant the read privilege to the MYLM user-defined Python function to the
user SH.
...oml.grant(name="MYLM", typ="pyqscript", user="SH")
>>>
>>> # List the user-defined Python functions to which read privilege has been
granted.
... oml.script.dir(sctype="grant")
   name grantee
0  MYLM      SH
>>>
>>> # Revoke the read privilege to the MYLM user-defined Python function from
the user SH.
... oml.revoke(name="MYLM", typ="pyqscript", user="SH")
>>>
>>> # List the granted user-defined Python functions again to see if the
revocation was successful.
... oml.script.dir(sctype="grant")
Empty DataFrame
Columns: [name, grantee]
Index: []
```

4
Prepare and Explore Data

Use OML4Py methods to prepare data for analysis and to perform exploratory analysis of the data.

Methods of the OML4Py data type classes make it easier for you to prepare very large enterprise database-resident data for modeling. These methods are described in the following topics.

- Prepare Data
  Using methods of OML4Py data type classes, you can prepare data for analysis in the database, as described in the following topics.
- Explore Data
  OML4Py provides methods that enable you to perform exploratory data analysis and common statistical operations.
- Render Graphics
  OML4Py provides functions for rendering graphical displays of data.

4.1 Prepare Data

Using methods of OML4Py data type classes, you can prepare data for analysis in the database, as described in the following topics.

- About Preparing Data in the Database
  OML4Py data type classes have methods that enable you to use Python to prepare database data for analysis.
- Select Data
  A typical step in preparing data for analysis is selecting or filtering values of interest from a larger data set.
- Combine Data
  You can join data from `oml.DataFrame` objects that represent database tables by using the `append`, `concat`, and `merge` methods.
- Clean Data
  In preparing data for analysis, a typical step is to transform data by dropping some values.
- Split Data
  Sample and randomly partition data with the `split` and `KFold` methods.

4.1.1 About Preparing Data in the Database

OML4Py data type classes have methods that enable you to use Python to prepare database data for analysis.

You can perform data preparation operations on large quantities of data in the database and then continue operating on that data in-database or pull a subset of the results to your local Python session where, for example, you can use third-party Python packages to perform other operations.

The following table lists methods with which you can perform common data preparation tasks and indicates whether the OML4Py data type class supports the method.

Table 4-1 Methods Supported by Data Types

Method	Description	oml.Boolean	oml.Bytes	oml.Float	oml.String	oml.DataFrame	oml.Datatime	oml.Timezone	oml.Timedelta	oml.Integer
`append`	Appends another `oml` data object of the same class to an `oml` object.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`ceil`	Computes the ceiling of each element in an `oml.Float` series data object.	⊗	⊗	✓	⊗	⊗	⊗	⊗	⊗	⊗
`concat`	Combines an `oml` data object column-wise with one or more other data objects.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`count_pattern`	Counts the number of occurrences of a pattern in each string.	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗	⊗
`create_view`	Creates an Oracle Database view for the data represented by the OML4Py data object.	⊗	⊗	⊗	⊗	✓	✓	✓	✓	✓
`dot`	Calculates the inner product of the current `oml.Float` object with another `oml.Float`, or does matrix multiplication with an `oml.DataFrame`.	⊗	⊗	✓	⊗	⊗	⊗	⊗	⊗	✓
`drop`	Drops specified columns in an `oml.DataFrame`.	⊗	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗
`drop_duplicates`	Removes duplicated elements from an `oml` series data object or duplicated rows from an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`dropna`	Removes missing elements from an `oml` series data object, or rows containing missing values from an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 4-1 (Cont.) Methods Supported by Data Types

Method	Description	oml.Boolean	oml.Bytes	oml.Float	oml.String	oml.DataFrame	oml.Datatime	oml.Timezone	oml.Timedelta	oml.Integer
`exp`	Computes element-wise `e` to the power of values in an `oml.Float` series data object.	⊗	⊗	✓	⊗	⊗	⊗	⊗	⊗	✓
`find`	Finds the lowest index in each string in which a substring is found that is greater than or equal to a start index.	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗	⊗
`floor`	Computes the floor of each element in an `oml.Float` series data object.	⊗	⊗	✓	⊗	⊗	⊗	⊗	⊗	⊗
`head`	Returns the first *n* elements of an `oml` series data object or the first *n* rows of an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`KFold`	Splits the `oml` data object randomly into *k* consecutive folds.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`len`	Computes the length of each string in an `oml.Bytes` or `oml.String` series data object.	⊗	✓	⊗	✓	⊗	⊗	⊗	⊗	⊗
`log`	Calculates an element-wise logarithm, to the given base, of values in the `oml.Float` series data object.	⊗	⊗	✓	⊗	⊗	⊗	⊗	⊗	✓
`materialize`	Pushes the contents represented by an OML4Py proxy object (a view, a table, and so on) into a table in Oracle Database.	⊗	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗
`merge`	Joins another `oml.DataFrame` to an `oml.DataFrame`.	⊗	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗
`replace`	Replaces an existing value with another value.	⊗	⊗	✓	✓	✓	✓	⊗	⊗	✓

Table 4-1 (Cont.) Methods Supported by Data Types

Method	Description	oml.Boolean	oml.Bytes	oml.Float	oml.String	oml.DataFrame	oml.Datatime	oml.Timezone	oml.Timedelta	oml.Integer
`rename`	Renames columns of an `oml.DataFrame`.	⊗	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗
`round`	Rounds `oml.Float` values to the specified decimal place.	⊗	⊗	✓	⊗	⊗	⊗	⊗	⊗	⊗
`select_types`	Returns the subset of columns that are included or excluded based on their `oml` data type.	⊗	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗
`split`	Splits an `oml` data object randomly into multiple sets.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`sqrt`	Computes the square root of each element in an `oml.Float` series data object.	⊗	⊗	✓	⊗	⊗	⊗	⊗	⊗	✓
`tail`	Returns the last *n* elements of an `oml` series data object or the last *n* rows of an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓

4.1.2 Select Data

A typical step in preparing data for analysis is selecting or filtering values of interest from a larger data set.

The examples in this section demonstrate selecting data from an `oml.DataFrame` object by rows, by columns, and by value.

The examples use the `oml_iris` object created by the following code, which imports the `sklearn.datasets` package and loads the `iris` data set. It creates the `x` and `y` variables, and then creates the persistent database table IRIS and the `oml.DataFrame` object `oml.iris` as a proxy for the table.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data, columns = ['Sepal_Length','Sepal_Width',
                                       'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x: {0: 'setosa', 1: 'versicolor',
                                     2:'virginica'}[x], iris.target)),
```

```
                columns = ['Species'])

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
```

The examples are in the following topics:

- Select the First or Last Number of Rows
- Select Data by Column
- Select Data by Value

Select the First or Last Number of Rows

The `head` and `tail` methods return the first or last number of elements.

The default number of rows selected is 5.

Example 4-1 Selecting the First and Last Number of Rows

This example selects rows from the `oml.DataFrame` object `oml_iris`. It displays the first five rows and ten rows of `oml_iris` and then the last five and ten rows.

```
# Display the first 5 rows.
oml_iris.head()

# Display the first 10 rows.
oml_iris.head(10)

# Display the last 5 rows.
oml_iris.tail()

# Display the last 10 rows.
oml_iris.tail(10)
```

Listing for This Example

```
>>> # Display the first 5 rows.
... oml_iris.head()
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width Species
0           5.1          3.5           1.4          0.2  setosa
1           4.9          3.0           1.4          0.2  setosa
2           4.7          3.2           1.3          0.2  setosa
3           4.6          3.1           1.5          0.2  setosa
4           5.0          3.6           1.4          0.2  setosa
>>>
>>> # Display the first 10 rows.
... oml_iris.head(10)
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width Species
0           5.1          3.5           1.4          0.2  setosa
1           4.9          3.0           1.4          0.2  setosa
2           4.7          3.2           1.3          0.2  setosa
3           4.6          3.1           1.5          0.2  setosa
4           5.0          3.6           1.4          0.2  setosa
5           5.4          3.9           1.7          0.4  setosa
6           4.6          3.4           1.4          0.3  setosa
```

```
7           5.0          3.4           1.5          0.2  setosa
8           4.4          2.9           1.4          0.2  setosa
9           4.9          3.1           1.5          0.1  setosa
>>>
>>> # Display the last 5 rows.
... oml_iris.tail()
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width    Species
0           6.7          3.0           5.2          2.3  virginica
1           6.3          2.5           5.0          1.9  virginica
2           6.5          3.0           5.2          2.0  virginica
3           6.2          3.4           5.4          2.3  virginica
4           5.9          3.0           5.1          1.8  virginica

>>>
>>> # Display the last 10 rows.
... oml_iris.tail(10)
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width    Species
0           6.7          3.1           5.6          2.4  virginica
1           6.9          3.1           5.1          2.3  virginica
2           5.8          2.7           5.1          1.9  virginica
3           6.8          3.2           5.9          2.3  virginica
4           6.7          3.3           5.7          2.5  virginica
5           6.7          3.0           5.2          2.3  virginica
6           6.3          2.5           5.0          1.9  virginica
7           6.5          3.0           5.2          2.0  virginica
8           6.2          3.4           5.4          2.3  virginica
9           5.9          3.0           5.1          1.8  virginica
```

Select Data by Column

Example 4-2 Selecting Data by Columns

The example selects two columns from `oml_iris` and creates the `oml.DataFrame` object `iris_projected1` with them. It then displays the first three rows of `iris_projected1`. The example also selects a range of columns from `oml_iris`, creates `iris_projected2`, and displays its first three rows. Finally, the example selects columns from `oml_iris` by data types, creates `iris_projected3`, and displays its first three rows.

```
# Select all rows with the specified column names.
iris_projected1 = oml_iris[:, ["Sepal_Length", "Petal_Length"]]
iris_projected1.head(3)

# Select all rows with columns whose indices are in the range [1, 4).
iris_projected2 = oml_iris[:, 1:4]
iris_projected2.head(3)

# Select all rows with columns of oml.String data type.
iris_projected3 = oml_iris.select_types(include=[oml.String])
iris_projected3.head(3)
```

Listing for This Example

```
>>> # Select all rows with specified column names.
... iris_projected1 = oml_iris[:, ["Sepal_Length", "Petal_Length"]]
>>> iris_projected1.head(3)
```

```
   Sepal_Length  Petal_Length
0           5.1           1.4
1           4.9           1.4
2           4.7           1.3
>>>
>>> # Select all rows with columns whose indices are in range [1, 4).
... iris_projected2 = oml_iris[:, 1:4]
>>> iris_projected2.head(3)
   Sepal_Width  Petal_Length  Petal_Width
0          3.5           1.4          0.2
1          3.0           1.4          0.2
2          3.2           1.3          0.2
>>>
>>> # Select all rows with columns of oml.String data type.
... iris_projected3 = oml_iris.select_types(include=[oml.String])
>>> iris_projected3.head(3)
  Species
0  setosa
1  setosa
2  setosa
```

Select Data by Value

Example 4-3 Selecting Data by Value

This example filters `oml_iris` to produce `iris_of_filtered1`, which contains the values from the rows of `oml_iris` that have a petal length of less than 1.5 and that are in the Sepal_Length and Petal_Length columns. The example also filters the data using conditions, so that `oml_iris_filtered2` contains the values from `oml_iris` that have a petal length of less than 1.5 or a sepal length equal to 5.0 and `oml_iris_filtered3` contains the values from `oml_iris` that have a petal length of less than 1.5 and a sepal length larger than 5.0.

```
# Select sepal length and petal length where petal length
# is less than 1.5.
oml_iris_filtered1 = oml_iris[oml_iris["Petal_Length"] < 1.5,
                                      ["Sepal_Length", "Petal_Length"]]
len(oml_iris_filtered1)
oml_iris_filtered1.head(3)

### Using the AND and OR conditions in filtering.
# Select all rows in which petal length is less than 1.5 or sepal length
# sepal length is 5.0.
oml_iris_filtered2 = oml_iris[(oml_iris["Petal_Length"] < 1.5) |
                              (oml_iris["Sepal_Length"] == 5.0), :]
len(oml_iris_filtered2)
oml_iris_filtered2.head(3)

# Select all rows in which petal length is less than 1.5 and
# sepal length is larger than 5.0.
oml_iris_filtered3 = oml_iris[(oml_iris["Petal_Length"] < 1.5) &
                              (oml_iris["Sepal_Length"] > 5.0), :]
len(oml_iris_filtered3)
oml_iris_filtered3.head()
```

Listing for This Example

```
>>> # Select sepal length and petal length where petal length
... # is less than 1.5.
... oml_iris_filtered1 = oml_iris[oml_iris["Petal_Length"] < 1.5,
...                                        ["Sepal_Length", "Petal_Length"]]
>>> len(oml_iris_filtered1)
24
>>> oml_iris_filtered1.head(3)
   Sepal_Length  Petal_Length
0           5.1           1.4
1           4.9           1.4
2           4.7           1.3
>>>
>>> ### Using the AND and OR conditions in filtering.
... # Select all rows in which petal length is less than 1.5 or
... # sepal length is 5.0.
... oml_iris_filtered2 = oml_iris[(oml_iris["Petal_Length"] < 1.5) |
...                                (oml_iris["Sepal_Length"] == 5.0), :]
>>> len(oml_iris_filtered2)
30
>>> oml_iris_filtered2.head(3)
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width Species
0           5.1          3.5           1.4          0.2  setosa
1           4.9          3.0           1.4          0.2  setosa
2           4.7          3.2           1.3          0.2  setosa
>>>
>>> # Select all rows in which petal length is less than 1.5
... # and sepal length is larger than 5.0.
... oml_iris_filtered3 = oml_iris[(oml_iris["Petal_Length"] < 1.5) &
...                                (oml_iris["Sepal_Length"] > 5.0), :]
>>> len(oml_iris_filtered3)
7
>>> oml_iris_filtered3.head()
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width Species
0           5.1          3.5           1.4          0.2  setosa
1           5.8          4.0           1.2          0.2  setosa
2           5.4          3.9           1.3          0.4  setosa
3           5.1          3.5           1.4          0.3  setosa
4           5.2          3.4           1.4          0.2  setosa
```

4.1.3 Combine Data

You can join data from `oml.DataFrame` objects that represent database tables by using the `append`, `concat`, and `merge` methods.

Examples of using these methods are in the following topics.

- Append Data from One Object to Another Object
- Combine Two Objects
- Join Data From Two Objects

Append Data from One Object to Another Object

Use the `append` method to join two objects of the same data type.

Example 4-4 Appending Data from Two Tables

This example first appends the `oml.Float` series object `num1` to another `oml.Float` series object, `num2`. It then appends an `oml.DataFrame` object to another `oml.DataFrame` object, which has the same column types.

```
import oml
import pandas as pd

df = pd.DataFrame({"id" : [1, 2, 3, 4, 5],
                   "val" : ["a", "b", "c", "d", "e"],
                   "ch" : ["p", "q", "r", "a", "b"],
                   "num" : [4, 3, 6.7, 7.2, 5]})
oml_df = oml.push(df)

# Append an oml.Float series object to another.
num1 = oml_df['id']
num2 = oml_df['num']
num1.append(num2)

# Append an oml.DataFrame object to another.
x = oml_df[['id', 'val']] # 1st column oml.Float, 2nd column oml.String
y = oml_df[['num', 'ch']] # 1st column oml.Float, 2nd column oml.String
x.append(y)
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>>
>>> df = pd.DataFrame({"id" : [1, 2, 3, 4, 5],
...                    "val" : ["a", "b", "c", "d", "e"],
...                    "ch" : ["p", "q", "r", "a", "b"],
...                    "num" : [4, 3, 6.7, 7.2, 5]})
>>> oml_df = oml.push(df)
>>>
>>> # Append an oml.Float series object to another.
... num1 = oml_df['id']
>>> num2 = oml_df['num']
>>> num1.append(num2)
[1, 2, 3, 4, 5, 4, 3, 6.7, 7.2, 5]
>>>
>>> # Explicitly convert oml.Integer to oml.Float
>>> oml.Float(num1).append(num2)
>>> # Append an oml.DataFrame object to another.
... x = oml_df[['id', 'val']] # 1st column oml.Float, 2nd column oml.String
>>> y = oml_df[['num', 'ch']] # 1st column oml.Float, 2nd column oml.String
>>> x.append(y)
    id val
0  1.0   a
1  2.0   b
2  3.0   c
3  4.0   d
4  5.0   e
5  4.0   p
```

```
6  3.0   q
7  6.7   r
8  7.2   a
9  5.0   b
```

Combine Two Objects

Use the `concat` method to combine columns from one object with those of another object. The `auto_name` argument of the `concat` method controls whether to invoke automatic name conflict resolution. You can also perform customized renaming by passing in a dictionary mapping strings to objects.

To combine two objects with the `concat` method, both objects must represent data from the same underlying database table, view, or query.

Example 4-5 Combining Data Column-Wise

This example first combines the two `oml.DataFrame` objects `x` and `y` column-wise. It then concatenates object `y` with the `oml.Float` series object `w`.

```
import oml
import pandas as pd
from collections import OrderedDict

df = pd.DataFrame({"id" : [1, 2, 3, 4, 5],
                   "val" : ["a", "b", "c", "d", "e"],
                   "ch" : ["p", "q", "r", "a", "b"],
                   "num" : [4, 3, 6.7, 7.2, 5]})
oml_df = oml.push(df)

# Create two oml.DataFrame objects and combine the objects column-wise.
x = oml_df[['id', 'val']]
y = oml_df[['num', 'ch']]
x.concat(y)

# Create an oml.Float object with the rounded exponential of two times
# the values in the num column of the oml_df object, then
# concatenate it with the oml.DataFrame object y using a new column name.
w = (oml_df['num']*2).exp().round(decimals=2)
y.concat({'round(exp(2*num))':w})

# Concatenate object x with multiple objects and turn on automatic
# name conflict resolution.
z = oml_df[:,'id']
x.concat([z, w, y], auto_name=True)

# Concatenate multiple oml data objects and perform customized renaming.
x.concat(OrderedDict([('ID',z), ('round(exp(2*num))',w), ('New_',y)]))
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from collections import OrderedDict
>>>
>>> df = pd.DataFrame({"id" : [1, 2, 3, 4, 5],
```

```
...                     "val" : ["a", "b", "c", "d", "e"],
...                     "ch" : ["p", "q", "r", "a", "b"],
...                     "num" : [4, 3, 6.7, 7.2, 5]})
>>> oml_df = oml.push(df)

>>> # Create two oml.DataFrame objects and combine the objects column-wise.
... x = oml_df[['id', 'val']]
>>> y = oml_df[['num', 'ch']]
>>> x.concat(y)
   id val  num  ch
0   1   a  4.0   p
1   2   b  3.0   q
2   3   c  6.7   r
3   4   d  7.2   a
4   5   e  5.0   b
>>>
>>> # Create an oml.Float object with the rounded exponential of two times
... # the values in the num column of the oml_df object, then
... # concatenate it with the oml.DataFrame object y using a new column name.
... w = (oml_df['num']*2).exp().round(decimals=2)
>>> y.concat({'round(exp(2*num))':w})
   num ch round(exp(2*num))
0  4.0  p           2980.96
1  3.0  q            403.43
2  6.7  r         660003.22
3  7.2  a        1794074.77
4  5.0  b          22026.47
>>>
>>> # Concatenate object x with multiple objects and turn on automatic
... # name conflict resolution.
... z = oml_df[:,'id']
>>> x.concat([z, w, y], auto_name=True)
  id  val  id3         num  num5  ch
0  1    a    1     2980.96   4.0  p
1  2    b    2      403.43   3.0  q
2  3    c    3   660003.22   6.7  r
3  4    d    4  1794074.77   7.2  a
4  5    e    5    22026.47   5.0  b
>>>
>>> # Concatenate multiple oml data objects and perform customized renaming.
... x.concat(OrderedDict([('ID',z), ('round(exp(2*num))',w), ('New_',y)]))
  id  val  ID  round(exp(2*num))  New_num  New_ch
0  1    a   1           2980.96      4.0       p
1  2    b   2            403.43      3.0       q
2  3    c   3         660003.22      6.7       r
3  4    d   4        1794074.77      7.2       a
4  5    e   5          22026.47      5.0       b
```

Join Data From Two Objects

Use the `merge` method to join data from two objects.

Example 4-6 Joining Data from Two Tables

This example first performs a cross join on the `oml.DataFrame` objects `x` and `y`, which creates the `oml.DataFrame` object `xy`. The example performs a left outer join on the first four rows of `x`

with the `oml.DataFrame` object other on the shared column id and applies the suffixes `.l` and `.r` to column names on the left and right side, respectively. The example then performs a right outer join on the id column on the left side object `x` and the num column on the right side object `y`.

```
import oml
import pandas as pd

df = pd.DataFrame({"id" : [1, 2, 3, 4, 5],
                   "val" : ["a", "b", "c", "d", "e"],
                   "ch" : ["p", "q", "r", "a", "b"],
                   "num" : [4, 3, 6.7, 7.2, 5]})
oml_df = oml.push(df)

x = oml_df[['id', 'val']]
y = oml_df[['num', 'ch']]

# Perform a cross join.
xy = x.merge(y)
xy

# Perform a left outer join.
x.head(4).merge(other=oml_df[['id', 'num']], on="id",
                suffixes=['.l','.r'])

# Perform a right outer join.
x.merge(other=y, left_on="id", right_on="num", how="right")
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>>
>>> df = pd.DataFrame({"id" : [1, 2, 3, 4, 5],
...                    "val" : ["a", "b", "c", "d", "e"],
...                    "ch" : ["p", "q", "r", "a", "b"],
...                    "num" : [4, 3, 6.7, 7.2, 5]})
>>> oml_df = oml.push(df)
>>>
>>> x = oml_df[['id', 'val']]
>>> y = oml_df[['num', 'ch']]
>>>
>>> # Perform a cross join.
... xy = x.merge(y)
>>> xy
    id_l val_l  num_r ch_r
0      1     a    4.0    p
1      1     a    3.0    q
2      1     a    6.7    r
3      1     a    7.2    a
4      1     a    5.0    b
5      2     b    4.0    p
6      2     b    3.0    q
7      2     b    6.7    r
8      2     b    7.2    a
```

```
9      2     b    5.0    b
10     3     c    4.0    p
11     3     c    3.0    q
12     3     c    6.7    r
13     3     c    7.2    a
14     3     c    5.0    b
15     4     d    4.0    p
16     4     d    3.0    q
17     4     d    6.7    r
18     4     d    7.2    a
19     4     d    5.0    b
20     5     e    4.0    p
21     5     e    3.0    q
22     5     e    6.7    r
23     5     e    7.2    a
24     5     e    5.0    b
>>>
>>> # Perform a left outer join.
... x.head(4).merge(other=oml_df[['id', 'num']], on="id",
...                 suffixes=['.l','.r'])
   id val.l  num.r
0   1     a    4.0
1   2     b    3.0
2   3     c    6.7
3   4     d    7.2
>>>
>>> # Perform a right outer join.
... x.merge(other=y, left_on="id", right_on="num", how="right")
   id_l val_l  num_r ch_r
0   3.0     c    3.0    q
1   4.0     d    4.0    p
2   5.0     e    5.0    b
3   NaN  None    6.7    r
4   NaN  None    7.2    a
```

4.1.4 Clean Data

In preparing data for analysis, a typical step is to transform data by dropping some values.

You can filter out unneeded data by using the `drop`, `drop_duplicates`, and `dropna` methods.

Example 4-7 Filtering Data

This example demonstrates ways of dropping columns with the `drop` method, dropping missing values with the `dropna` method, and dropping duplicate values with the `drop_duplicates` method.

```
import pandas as pd
import oml

df = pd.DataFrame({'numeric': [1, 1.4, -4, -4, 5.432, None, None],
                   'string1' : [None, None, 'a', 'a', 'a', 'b', None],
                   'string2': ['x', None, 'z', 'z', 'z', 'x', None]})
oml_df = oml.push(df, dbtypes = {'numeric': 'BINARY_DOUBLE',
                                 'string1':'CHAR(1)',
                                 'string2':'CHAR(1)'})
```

```
# Drop rows with any missing values.
oml_df.dropna(how='any')

# Drop rows in which all column values are missing.
oml_df.dropna(how='all')

# Drop rows in which any numeric column values are missing.
oml_df.dropna(how='any', subset=['numeric'])

# Drop duplicate rows.
oml_df.drop_duplicates()

# Drop rows that have the same value in column 'string1' and 'string2'.
oml_df.drop_duplicates(subset=['string1', 'string2'])

# Drop column 'string2'
oml_df.drop('string2')
```

Listing for This Example

```
>>> import pandas as pd
>>> import oml
>>>
>>> df = pd.DataFrame({'numeric': [1, 1.4, -4, -4, 5.432, None, None],
...                    'string1' : [None, None, 'a', 'a', 'a', 'b', None],
...                    'string2': ['x', None, 'z', 'z', 'z', 'x', None]})
>>> oml_df = oml.push(df, dbtypes = {'numeric': 'BINARY_DOUBLE',
...                                  'string1':'CHAR(1)',
...                                  'string2':'CHAR(1)'})
>>>
>>> # Drop rows with any missing values.
... oml_df.dropna(how='any')
   numeric string1 string2
0   -4.000       a       z
1   -4.000       a       z
2    5.432       a       z
>>>
>>> # Drop rows in which all column values are missing.
... oml_df.dropna(how='all')
   numeric string1 string2
0    1.000    None       x
1    1.400    None    None
2   -4.000       a       z
3   -4.000       a       z
4    5.432       a       z
5      NaN       b       x
>>>
>>> # Drop rows in which any numeric column values are missing.
... oml_df.dropna(how='any', subset=['numeric'])
   numeric string1 string2
0    1.000    None       x
1    1.400    None    None
2   -4.000       a       z
3   -4.000       a       z
```

```
4    5.432       a       z
>>>
>>> # Drop duplicate rows.
... oml_df.drop_duplicates()
   numeric string1 string2
0    5.432       a       z
1    1.000    None       x
2   -4.000       a       z
3      NaN       b       x
4    1.400    None    None
5      NaN    None    None
>>>
>>> # Drop rows that have the same value in columns 'string1' and 'string2'.
... oml_df.drop_duplicates(subset=['string1', 'string2'])
   numeric string1 string2
0     -4.0       a       z
1      1.4    None    None
2      1.0    None       x
3      NaN       b       x
>>>
>>> # Drop the column 'string2'.
... oml_df.drop('string2')
   numeric string1
0    1.000    None
1    1.400    None
2   -4.000       a
3   -4.000       a
4    5.432       a
5      NaN       b
6      NaN    None
```

4.1.5 Split Data

Sample and randomly partition data with the `split` and `KFold` methods.

In analyzing large data sets, a typical operation is to randomly partition the data set into subsets for training and testing purposes, which you can do with these methods. You can also sample data with the `split` method.

Example 4-8 Splitting Data into Multiple Sets

This example demonstrates splitting data into multiple sets and into k consecutive folds, which can be used for k-fold cross-validation.

```
import oml
import pandas as pd
from sklearn import datasets

digits = datasets.load_digits()
pd_digits = pd.DataFrame(digits.data,
                         columns=['IMG'+str(i) for i in
                         range(digits['data'].shape[1])])
pd_digits = pd.concat([pd_digits,
                       pd.Series(digits.target,
                                 name = 'target')],
                                 axis = 1)
```

```
oml_digits = oml.push(pd_digits)

# Sample 20% and 80% of the data.
splits = oml_digits.split(ratio=(.2, .8), use_hash = False)
[len(split) for split in splits]

# Split the data into four sets.
splits = oml_digits.split(ratio = (.25, .25, .25, .25),
                          use_hash = False)
[len(split) for split in splits]

# Perform stratification on the target column.
splits = oml_digits.split(strata_cols=['target'])
[split.shape for split in splits]

# Verify that the stratified sampling generates splits in which
# all of the different categories of digits (digits 0~9)
# are present in each split.
[split['target'].drop_duplicates().sort_values().pull()
for split in splits]

# Hash on the target column.
splits = oml_digits.split(hash_cols=['target'])
[split.shape for split in splits]

# Verify that the different categories of digits (digits 0~9) are present
# in only one of the splits generated by hashing on the category column.
[split['target'].drop_duplicates().sort_values().pull()
for split in splits]

# Split the data randomly into 4 consecutive folds.
folds = oml_digits.KFold(n_splits=4)
[(len(fold[0]), len(fold[1])) for fold in folds]
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> digits = datasets.load_digits()
>>> pd_digits = pd.DataFrame(digits.data,
...                          columns=['IMG'+str(i) for i in
...                          range(digits['data'].shape[1])])
>>> pd_digits = pd.concat([pd_digits,
...                        pd.Series(digits.target,
...                                  name = 'target')],
...                                  axis = 1)
>>> oml_digits = oml.push(pd_digits)
>>>
>>> # Sample 20% and 80% of the data.
... splits = oml_digits.split(ratio=(.2, .8), use_hash = False)
>>> [len(split) for split in splits]
[351, 1446]
>>>
```

```
>>> # Split the data into four sets.
... splits = oml_digits.split(ratio = (.25, .25, .25, .25),
...                           use_hash = False)
>>> [len(split) for split in splits]
[432, 460, 451, 454]
>>>
>>> # Perform stratification on the target column.
... splits = oml_digits.split(strata_cols=['target'])
>>> [split.shape for split in splits]
[(1285, 65), (512, 65)]
>>>
>>> # Verify that the stratified sampling generates splits in which
... # all of the different categories of digits (digits 0~9)
... # are present in each split.
... [split['target'].drop_duplicates().sort_values().pull()
... for split in splits]
[[0, 1, 2, 3, 4, 5, 6, 7, 8, 9], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]]
>>>
>>> # Hash on the target column
... splits = oml_digits.split(hash_cols=['target'])
>>> [split.shape for split in splits]
[(899, 65), (898, 65)]
>>>
>>> # Verify that the different categories of digits (digits 0~9) are present
... # in only one of the splits generated by hashing on the category column.
... [split['target'].drop_duplicates().sort_values().pull()
... for split in splits]
[[0, 1, 3, 5, 8], [2, 4, 6, 7, 9]]
>>>
>>> # Split the data randomly into 4 consecutive folds.
... folds = oml_digits.KFold(n_splits=4)
>>> [(len(fold[0]), len(fold[1])) for fold in folds]
[(1352, 445), (1336, 461), (1379, 418), (1325, 472)]
```

4.2 Explore Data

OML4Py provides methods that enable you to perform exploratory data analysis and common statistical operations.

These methods are described in the following topics.

- About the Exploratory Data Analysis Methods
  OML4Py provides methods that enable you to perform exploratory data analysis.
- Correlate Data
  Use the `corr` method to perform Pearson, Spearman, or Kendall correlation analysis across columns where possible in an `oml.DataFrame` object.
- Cross-Tabulate Data
  Use the `crosstab` method to perform cross-column analysis of an `oml.DataFrame` object and the `pivot_table` method to convert an `oml.DataFrame` to a spreadsheet-style pivot table.
- Mutate Data
  In preparing data for analysis, a typical operation is to mutate data by reformatting it or deriving new columns and adding them to the data set.

- Sort Data
  The `sort_values` function enables flexible sorting of an `oml.DataFrame` along one or more columns specified by the `by` argument, and returns an `oml.DataFrame`.
- Summarize Data
  The `describe` method calculates descriptive statistics that summarize the central tendency, dispersion, and shape of the data in each column.
- Date, Time, and Integer Data
  OML4Py provides the data types that enable you to manipulate date, time and integer.

4.2.1 About the Exploratory Data Analysis Methods

OML4Py provides methods that enable you to perform exploratory data analysis.

The following table lists methods of OML4Py data type classes with which you can perform common statistical operations and indicates whether the class supports the method.

Table 4-2 Data Exploration Methods Supported by Data Type Classes

Method	Description	oml.Boolean	oml.Bytes	oml.Float	oml.String	oml.DataFrame	oml.Datetime	oml.Timedelta	oml.Timezone	oml.Integer
`corr`	Computes pairwise correlation between all columns in an `oml.DataFrame` where possible, given the type of coefficient.	⊗	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗
`count`	Computes the number of elements that are not NULL in the series data object or in each column of an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`crosstab`	Computes a cross-tabulation of two or more columns in an `oml.DataFrame`.	⊗	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗
`cumsum`	Computes the cumulative sum after an `oml.Float` series data object is sorted, or of each float or Boolean column after an `oml.DataFrame` object is sorted.	⊗	⊗	✓	⊗	✓	⊗	⊗	⊗	✓

Table 4-2 (Cont.) Data Exploration Methods Supported by Data Type Classes

Method	Description	oml.Boolean	oml.Bytes	oml.Float	oml.String	oml.DataFrame	oml.Datetime	oml.Timedelta	oml.Timezone	oml.Integer
`describe`	Computes descriptive statistics that summarize the central tendency, dispersion, and shape of an `oml` series data distribution, or of each column in an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`kurtosis`	Computes the kurtosis of the values in an `oml.Float` series data object, or for each float column in an `oml.DataFrame`.	⊗	⊗	✓	⊗	✓	⊗	⊗	⊗	✓
`max`	Returns the maximum value in a series data object or in each column in an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`mean`	Computes the mean of the values in an `oml.Float` series object, or for each float or Boolean column in an `oml.DataFrame`.	⊗	⊗	✓	⊗	✓	⊗	⊗	⊗	✓
`median`	Computes the median of the values in an `oml.Float` series object, or for each float column in an `oml.DataFrame`.	⊗	⊗	✓	⊗	✓	⊗	⊗	⊗	✓
`min`	Returns the minimum value in a series data object or of each column in an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`nunique`	Computes the number of unique values in a series data object or in each column of an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 4-2 (Cont.) Data Exploration Methods Supported by Data Type Classes

Method	Description	oml.Boolean	oml.Bytes	oml.Float	oml.String	oml.DataFrame	oml.Datetime	oml.Timedelta	oml.Timezone	oml.Integer
`pivot_table`	Converts an `oml.DataFrame` to a spreadsheet-style pivot table.	⊗	⊗	⊗	⊗	✓	⊗	⊗	⊗	⊗
`sort_values`	Sorts the values in a series data object or sorts the rows in an `oml.DataFrame`.	✓	✓	✓	✓	✓	✓	✓	✓	✓
`skew`	Computes the skewness of the values in an `oml.Float` data series object or of each float column in an `oml.DataFrame`.	⊗	⊗	✓	⊗	✓	⊗	⊗	⊗	✓
`std`	Computes the standard deviation of the values in an `oml.Float` data series object or in each float or Boolean column in an `oml.DataFrame`.	⊗	⊗	✓	⊗	✓	⊗	⊗	⊗	✓
`sum`	Computes the sum of the values in an `oml.Float` data series object or of each float or Boolean column in an `oml.DataFrame`.	⊗	⊗	✓	⊗	✓	⊗	⊗	⊗	✓

4.2.2 Correlate Data

Use the `corr` method to perform Pearson, Spearman, or Kendall correlation analysis across columns where possible in an `oml.DataFrame` object.

For details about the function arguments, invoke `help(oml.DataFrame.corr)` or see *Oracle Machine Learning for Python API Reference*.

Example 4-9 Performing Basic Correlation Calculations

This example first creates a temporary database table, with its corresponding proxy `oml.DataFrame` object `oml_df1`, from the `pandas.DataFrame` object `df`. It then verifies the correlation computed between columns A and B, which gives 1, as expected. The values in B are twice the values in A element-wise. The example also changes a value field in `df` and creates a `NaN` entry. It then creates a temporary database table, with the corresponding proxy

`oml.DataFrame` object `oml_df2`. Finally, it invokes the `corr` method on `oml_df2` with `skipna` set to `True` (the default) and then `False` to compare the results.

```
import oml
import pandas as pd

df = pd.DataFrame({'A': range(4), 'B': [2*i for i in range(4)]})
oml_df1 = oml.push(df)

# Verify that the correlation between column A and B is 1.
oml_df1.corr()

# Change a value to test the change in the computed correlation result.
df.loc[2, 'A'] = 1.5

# Change an entry to NaN (not a number) to test the 'skipna'
# parameter in the corr method.
df.loc[1, 'B'] = None

# Push df to the database using the floating point column type
# because NaNs cannot be used in Oracle numbers.
oml_df2 = oml.push(df, oranumber=False)

# By default, 'skipna' is True.
oml_df2.corr()
oml_df2.corr(skipna=False)
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>>
>>> df = pd.DataFrame({'A': range(4), 'B': [2*i for i in range(4)]})
>>> oml_df1 = oml.push(df)
>>>
>>> # Verify that the correlation between column A and B is 1.
... oml_df1.corr()
   A  B
A  1  1
B  1  1
>>>
>>> # Change a value to test the change in the computed correlation result.
... df.loc[2, 'A'] = 1.5
>>>
>>> # Change an entry to NaN (not a number) so to test the 'skipna'
... # parameter in the corr method.
... df.loc[1, 'B'] = None
>>>
>>> # Push df to the database using the floating point column type
... # because NaNs cannot be used in Oracle numbers.
... oml_df2 = oml.push(df, oranumber=False)
>>>
>>> # By default, 'skipna' is True.
... oml_df2.corr()
          A         B
```

```
A  1.000000  0.981981
B  0.981981  1.000000
>>> oml_df2.corr(skipna=False)
     A    B
A  1.0  NaN
B  NaN  1.0
```

4.2.3 Cross-Tabulate Data

Use the `crosstab` method to perform cross-column analysis of an `oml.DataFrame` object and the `pivot_table` method to convert an `oml.DataFrame` to a spreadsheet-style pivot table.

Cross-tabulation is a statistical technique that finds an interdependent relationship between two columns of values. The `crosstab` method computes a cross-tabulation of two or more columns. By default, it computes a frequency table for the columns unless a column and an aggregation function have been passed to it.

The `pivot_table` method converts a data set into a pivot table. Due to the database 1000 column limit, pivot tables with more than 1000 columns are automatically truncated to display the categories with the most entries for each column value.

For details about the method arguments, invoke `help(oml.DataFrame.crosstab)` or `help(oml.DataFrame.pivot_table)`, or see *Oracle Machine Learning for Python API Reference*.

Example 4-10 Producing Cross-Tabulation and Pivot Tables

This example demonstrates the use of the `crosstab` and `pivot_table` methods.

```
import pandas as pd
import oml

x = pd.DataFrame({
     'GENDER': ['M', 'M', 'F', 'M', 'F', 'M', 'F', 'F',
                None, 'F', 'M', 'F'],
     'HAND': ['L', 'R', 'R', 'L', 'R', None, 'L', 'R',
              'R', 'R', 'R', 'R'],
     'SPEED': [40.5, 30.4, 60.8, 51.2, 54, 29.3, 34.1,
               39.6, 46.4, 12, 25.3, 37.5],
     'ACCURACY': [.92, .94, .87, .9, .85, .97, .96, .93,
                  .89, .84, .91, .95]
    })
x = oml.push(x)

# Find the categories that the most entries belonged to.
x.crosstab('GENDER', 'HAND').sort_values('count', ascending=False)

# For each gender value and across all entries, find the ratio of entries
# with different hand values.
x.crosstab('GENDER', 'HAND', pivot = True, margins = True, normalize = 0)

# Find the mean speed across all gender and hand combinations.
x.pivot_table('GENDER', 'HAND', 'SPEED')

# Find the median accuracy and speed for every gender and hand combination.
x.pivot_table('GENDER', 'HAND', aggfunc = oml.DataFrame.median)
```

```
# Find the max and min speeds for every gender and hand combination and
# across all combinations.
x.pivot_table('GENDER', 'HAND', 'SPEED',
              aggfunc = [oml.DataFrame.max, oml.DataFrame.min],
              margins = True)
```

Listing for This Example

```
>>> import pandas as pd
>>> import oml
>>>
>>> x = pd.DataFrame({
...       'GENDER': ['M', 'M', 'F', 'M', 'F', 'M', 'F', 'F',
...                  None, 'F', 'M', 'F'],
...       'HAND': ['L', 'R', 'R', 'L', 'R', None, 'L', 'R',
...                'R', 'R', 'R', 'R'],
...       'SPEED': [40.5, 30.4, 60.8, 51.2, 54, 29.3, 34.1,
...                 39.6, 46.4, 12, 25.3, 37.5],
...       'ACCURACY': [.92, .94, .87, .9, .85, .97, .96, .93,
...                    .89, .84, .91, .95]
...     })
>>> x = oml.push(x)
>>>
>>> # Find the categories that the most entries belonged to.
... x.crosstab('GENDER', 'HAND').sort_values('count', ascending=False)
  GENDER  HAND  count
0      F     R      5
1      M     L      2
2      M     R      2
3      M  None      1
4      F     L      1
5   None     R      1
>>>
>>> # For each gender value and across all entries, find the ratio of entries
... # with different hand values.
... x.crosstab('GENDER', 'HAND', pivot = True, margins = True, normalize = 0)
  GENDER  count_(L)  count_(R)  count_(None)
0   None   0.000000   1.000000      0.000000
1      F   0.166667   0.833333      0.000000
2      M   0.400000   0.400000      0.200000
3    All   0.250000   0.666667      0.083333
>>>
>>> # Find the mean speed across all gender and hand combinations.
... x.pivot_table('GENDER', 'HAND', 'SPEED')
  GENDER  mean(SPEED)_(L)  mean(SPEED)_(R)  mean(SPEED)_(None)
0   None              NaN            46.40                 NaN
1      F            34.10            40.78                 NaN
2      M            45.85            27.85                29.3
>>>
>>> # Find the median accuracy and speed for every gender and hand
combination.
... x.pivot_table('GENDER', 'HAND', aggfunc = oml.DataFrame.median)
  GENDER  median(ACCURACY)_(L)  median(ACCURACY)_(R)
median(ACCURACY)_(None)  \
```

```
0   None                   NaN                0.890
NaN
1      F                0.96                0.870
NaN
2      M                0.91                0.925
0.97

   median(SPEED)_(L)  median(SPEED)_(R)  median(SPEED)_(None)
0                NaN              46.40                   NaN
1              34.10              39.60                   NaN
2              45.85              27.85                  29.3
>>>
>>> # Find the max and min speeds for every gender and hand combination and
... # across all combinations.
... x.pivot_table('GENDER', 'HAND', 'SPEED',
...                aggfunc = [oml.DataFrame.max, oml.DataFrame.min],
...                margins = True)
  GENDER  max(SPEED)_(L)  max(SPEED)_(R)  max(SPEED)_(None)
max(SPEED)_(All)  \
0   None             NaN            46.4                 NaN
46.4
1      F            34.1            60.8                 NaN
60.8
2      M            51.2            30.4                29.3
51.2
3    All            51.2            60.8                29.3
60.8

   min(SPEED)_(L)  min(SPEED)_(R)  min(SPEED)_(None)  min(SPEED)_(All)
0             NaN            46.4                NaN              46.4
1            34.1            12.0                NaN              12.0
2            40.5            25.3               29.3              25.3
3            34.1            12.0               29.3              12.0
```

4.2.4 Mutate Data

In preparing data for analysis, a typical operation is to mutate data by reformatting it or deriving new columns and adding them to the data set.

These examples demonstrate methods of formatting data and deriving columns.

```
import pandas as pd
import oml

# Create a shopping cart data set.
shopping_cart = pd.DataFrame({
  'Item_name': ['paper_towel', 'ground_pork', 'tofu', 'eggs',
                'pork_loin', 'whole_milk', 'egg_custard'],
  'Item_type': ['grocery', 'meat', 'grocery', 'dairy', 'meat',
                'dairy', 'bakery'],
  'Quantity': [1, 2.6, 4, 1, 1.9, 1, 1],
  'Unit_price': [1.19, 2.79, 0.99, 2.49, 3.19, 2.5, 3.99]
  })
oml_cart = oml.push(shopping_cart)
oml_cart
```

```
# Add a column 'Price' multiplying 'Quantity' with 'Unit_price',
# rounded to 2 decimal places.
price = oml_cart['Quantity']*(oml_cart['Unit_price'])
type(price)
price
oml_cart = oml_cart.concat({'Price': price.round(2)})

# Count the pattern 'egg' in the 'Item_name' column.
egg_pattern = oml_cart['Item_name'].count_pattern('egg')
type(egg_pattern)
oml_cart.concat({'Egg_pattern': egg_pattern})

# Find the start index of substring 'pork' in the 'Item_name' column.
pork_startInd = oml_cart['Item_name'].find('pork')
type(pork_startInd)
oml_cart.concat({'Pork_startInd': pork_startInd})

# Check whether items are of grocery category.
is_grocery=oml_cart['Item_type']=='grocery'
type(is_grocery)
oml_cart.concat({'Is_grocery': is_grocery})

# Calculate the length of item names.
name_length=oml_cart['Item_name'].len()
type(name_length)
oml_cart.concat({'Name_length': name_length})

# Get the ceiling, floor, exponential, logarithm and square root
# of the 'Price' column.
oml_cart['Price'].ceil()
oml_cart['Price'].floor()
oml_cart['Price'].exp()
oml_cart['Price'].log()
oml_cart['Price'].sqrt()
```

Listing for This Example

```
>>> import pandas as pd
>>> import oml
>>>
>>> # Create a shopping cart data set.
... shopping_cart = pd.DataFrame({
...   'Item_name': ['paper_towel', 'ground_pork', 'tofu', 'eggs',
...                 'pork_loin', 'whole_milk', 'egg_custard'],
...   'Item_type': ['grocery', 'meat', 'grocery', 'dairy', 'meat',
...                 'dairy', 'bakery'],
...   'Quantity': [1, 2.6, 4, 1, 1.9, 1, 1],
...   'Unit_price': [1.19, 2.79, 0.99, 2.49, 3.19, 2.5, 3.99]
...   })
>>> oml_cart = oml.push(shopping_cart)
>>> oml_cart
     Item_name Item_type  Quantity  Unit_price
0  paper_towel   grocery       1.0        1.19
1  ground_pork      meat       2.6        2.79
```

```
2         tofu   grocery       4.0        0.99
3         eggs     dairy       1.0        2.49
4    pork_loin      meat       1.9        3.19
5   whole_milk     dairy       1.0        2.50
6  egg_custard    bakery       1.0        3.99
>>>
>>> # Add a column 'Price' multiplying 'Quantity' with 'Unit_price',
... # rounded to 2 decimal places.
... price = oml_cart['Quantity']*(oml_cart['Unit_price'])
>>> type(price)
<class 'oml.core.float.Float'>
>>> price
[1.19, 7.254, 3.96, 2.49, 6.061, 2.5, 3.99]
>>> oml_cart = oml_cart.concat({'Price': price.round(2)})
>>>
>>> # Count the pattern 'egg' in the 'Item_name' column.
... egg_pattern = oml_cart['Item_name'].count_pattern('egg')
>>> type(egg_pattern)
<class 'oml.core.float.Float'>
>>> oml_cart.concat({'Egg_pattern': egg_pattern})
     Item_name Item_type  Quantity  Unit_price  Price  Egg_pattern
0  paper_towel   grocery       1.0        1.19   1.19            0
1  ground_pork      meat       2.6        2.79   7.25            0
2         tofu   grocery       4.0        0.99   3.96            0
3         eggs     dairy       1.0        2.49   2.49            1
4    pork_loin      meat       1.9        3.19   6.06            0
5   whole_milk     dairy       1.0        2.50   2.50            0
6  egg_custard    bakery       1.0        3.99   3.99            1
>>>
>>> # Find the start index of substring 'pork' in the 'Item_name' column.
... pork_startInd = oml_cart['Item_name'].find('pork')
>>> type(pork_startInd)
<class 'oml.core.float.Float'>
>>> oml_cart.concat({'Pork_startInd': pork_startInd})
     Item_name Item_type  Quantity  Unit_price  Price  Pork_startInd
0  paper_towel   grocery       1.0        1.19   1.19             -1
1  ground_pork      meat       2.6        2.79   7.25              7
2         tofu   grocery       4.0        0.99   3.96             -1
3         eggs     dairy       1.0        2.49   2.49             -1
4    pork_loin      meat       1.9        3.19   6.06              0
5   whole_milk     dairy       1.0        2.50   2.50             -1
6  egg_custard    bakery       1.0        3.99   3.99             -1
>>>
>>> # Check whether items are of grocery category.
... is_grocery=oml_cart['Item_type']=='grocery'
>>> type(is_grocery)
<class 'oml.core.boolean.Boolean'>
>>> oml_cart.concat({'Is_grocery': is_grocery})
     Item_name Item_type  Quantity  Unit_price  Price  Is_grocery
0  paper_towel   grocery       1.0        1.19   1.19        True
1  ground_pork      meat       2.6        2.79   7.25       False
2         tofu   grocery       4.0        0.99   3.96        True
3         eggs     dairy       1.0        2.49   2.49       False
4    pork_loin      meat       1.9        3.19   6.06       False
5   whole_milk     dairy       1.0        2.50   2.50       False
6  egg_custard    bakery       1.0        3.99   3.99       False
```

```
>>>
>>> # Calculate the length of item names.
... name_length=oml_cart['Item_name'].len()
>>> type(name_length)
<class 'oml.core.float.Float'>
>>> oml_cart.concat({'Name_length': name_length})
     Item_name Item_type  Quantity  Unit_price  Price  Name_length
0  paper_towel   grocery       1.0        1.19   1.19           11
1  ground_pork      meat       2.6        2.79   7.25           11
2         tofu   grocery       4.0        0.99   3.96            4
3         eggs     dairy       1.0        2.49   2.49            4
4    pork_loin      meat       1.9        3.19   6.06            9
5   whole_milk     dairy       1.0        2.50   2.50           10
6  egg_custard    bakery       1.0        3.99   3.99           11
>>>
>>> # Get the ceiling, floor, exponential, logarithm and square root
... # of the 'Price' column.
... oml_cart['Price'].ceil()
[2, 8, 4, 3, 7, 3, 4]
>>> oml_cart['Price'].floor()
[1, 7, 3, 2, 6, 2, 3]
>>> oml_cart['Price'].exp()
[3.2870812073831184, 1408.1048482046956, 52.45732594909905,
12.061276120444719, 428.37543685928694, 12.182493960703473, 54.05488936332659]
>>> oml_cart['Price'].log()
[0.173953307123438, 1.9810014688665833, 1.3762440252663892,
0.9122827104766162, 1.801709800081223, 0.9162907318741551, 1.3837912309017721]
>>> oml_cart['Price'].sqrt()
[1.0908712114635715, 2.692582403567252, 1.98997487421324, 1.57797338380595,
2.4617067250182343, 1.5811388300841898, 1.997498435543818]
```

4.2.5 Sort Data

The `sort_values` function enables flexible sorting of an `oml.DataFrame` along one or more columns specified by the `by` argument, and returns an `oml.DataFrame`.

Example 4-11 Sorting Data

The following example demonstrates these operations.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

# Create the IRIS database table and the proxy object for the table.
```

```
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Modify the data set by replacing a few entries with NaNs to test
#  how the na_position parameter works in the sort_values method.
Iris = oml_iris.pull()
Iris['Sepal_Width'].replace({3.5: None}, inplace=True)
Iris['Petal_Length'].replace({1.5: None}, inplace=True)
Iris['Petal_Width'].replace({2.3: None}, inplace=True)

# Create another table using the changed data.
oml_iris2 =  oml.create(Iris, table = 'IRIS2')

# Sort the data set first by Sepal_Length then by Sepal_Width
# in descending order and display the first 5 rows of the
# sorted result.
oml_iris2.sort_values(by = ['Sepal_Length', 'Sepal_Width'],
                          ascending=False).head()

# Display the last 5 rows of the data set.
oml_iris2.tail()

# Sort the last 5 rows of the iris data set first by Petal_Length
# then by Petal_Width. By default, rows with NaNs are placed
# after the other rows when the sort keys are the same.
oml_iris2.tail().sort_values(by = ['Petal_Length', 'Petal_Width'])

# Sort the last 5 rows of the iris data set first by Petal_Length
# and then by Petal_Width. When the values in these two columns
# are the same, place the row with a NaN before the other row.
oml_iris2.tail().sort_values(by = ['Petal_Length', 'Petal_Width'],
                                 na_position = 'first')

oml.drop('IRIS')
oml.drop('IRIS2')
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Modify the data set by replacing a few entries with NaNs to test
```

```
... # how the na_position parameter works in the sort_values method.
... Iris = oml_iris.pull()
>>> Iris['Sepal_Width'].replace({3.5: None}, inplace=True)
>>> Iris['Petal_Length'].replace({1.5: None}, inplace=True)
>>> Iris['Petal_Width'].replace({2.3: None}, inplace=True)
>>>
>>> # Create another table using the changed data.
... oml_iris2 =  oml.create(Iris, table = 'IRIS2')
>>>
>>> # Sort the data set first by 'Sepal_Length' then by 'Sepal_Width'
... # in descending order and displays the first 5 rows of the
... # sorted result.
... oml_iris2.sort_values(by = ['Sepal_Length', 'Sepal_Width'],
...                            ascending=False).head()
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width    Species
0           7.9          3.8           6.4          2.0  virginica
1           7.7          3.8           6.7          2.2  virginica
2           7.7          3.0           6.1          NaN  virginica
3           7.7          2.8           6.7          2.0  virginica
4           7.7          2.6           6.9          NaN  virginica
>>>
>>> # Display the last 5 rows of the data set.
... oml_iris2.tail()
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width    Species
0           6.7          3.0           5.2          NaN  virginica
1           6.3          2.5           5.0          1.9  virginica
2           6.5          3.0           5.2          2.0  virginica
3           6.2          3.4           5.4          NaN  virginica
4           5.9          3.0           5.1          1.8  virginica
>>>
>>> # Sort the last 5 rows of the iris data set first by 'Petal_Length'
... # then by 'Petal_Width'. By default, rows with NaNs are placed
... # after  the other rows when the sort keys are the same.
... oml_iris2.tail().sort_values(by = ['Petal_Length', 'Petal_Width'])
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width    Species
0           6.3          2.5           5.0          1.9  virginica
1           5.9          3.0           5.1          1.8  virginica
2           6.5          3.0           5.2          2.0  virginica
3           6.7          3.0           5.2          NaN  virginica
4           6.2          3.4           5.4          NaN  virginica
>>>
>>> # Sort the last 5 rows of the iris data set first by 'Petal_Length'
... # and then by 'Petal_Width'. When the values in these two columns
... # are the same, place the row with a NaN before the other row.
... oml_iris2.tail().sort_values(by = ['Petal_Length', 'Petal_Width'],
...                               na_position = 'first')
   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width    Species
0           6.3          2.5           5.0          1.9  virginica
1           5.9          3.0           5.1          1.8  virginica
2           6.7          3.0           5.2          NaN  virginica
3           6.5          3.0           5.2          2.0  virginica
4           6.2          3.4           5.4          NaN  virginica
>>>
>>> oml.drop('IRIS')
>>> oml.drop('IRIS2')
```

4.2.6 Summarize Data

The `describe` method calculates descriptive statistics that summarize the central tendency, dispersion, and shape of the data in each column.

You can also specify the types of columns to include or exclude from the results.

With the `sum` and `cumsum` methods, you can compute the sum and cumulative sum of each Float or Boolean column of an `oml.DataFrame`.

The `describe` method supports finding the following statistics:

- Mean, minimum, maximum, median, top character, standard deviation
- Number of not-Null values, unique values, top characters
- Percentiles between 0 and 1

Example 4-12 Calculating Descriptive Statistics

The following example demonstrates these operations.

```
import pandas as pd
import oml

df = pd.DataFrame({'numeric': [1, 1.4, -4, 3.145, 5, None],
                   'string' : [None, None, 'a', 'a', 'a', 'b'],
                   'bytes' : [b'a', b'b', b'c', b'c', b'd', b'e']})

oml_df = oml.push(df, dbtypes = {'numeric': 'BINARY_DOUBLE',
                                 'string':'CHAR(1)',
                                 'bytes':'RAW(1)'})

# Combine a Boolean column with oml_df.
oml_bool = oml_df['numeric'] > 3
oml_df = oml_df.concat(oml_bool)
oml_df.rename({'COL4':'boolean'})

# Describe all of the columns.
oml_df.describe(include='all')

# Exclude Float columns.
oml_df.describe(exclude=[oml.Float])

# Get the sum of values in each Float or Boolean column.
oml_df.sum()

# Find the cumulative sum of values in each Float or Boolean column
# after oml_df is sorted by the bytes column in descending order.
oml_df.cumsum(by = 'bytes', ascending = False)

# Compute the skewness of values in the Float columns.
oml_df.skew()

# Find the median value of Float columns.
oml_df.median()
```

```
# Calculate the kurtosis of Float columns.
oml_df.kurtosis()
```

Listing for This Example

```
>>> import pandas as pd
>>> import oml
>>>
>>> df = pd.DataFrame({'numeric': [1, 1.4, -4, 3.145, 5, None],
...                    'string' : [None, None, 'a', 'a', 'a', 'b'],
...                    'bytes' : [b'a', b'b', b'c', b'c', b'd', b'e']})
>>>
>>> oml_df = oml.push(df, dbtypes = {'numeric': 'BINARY_DOUBLE',
...                                  'string':'CHAR(1)',
...                                  'bytes':'RAW(1)'})
>>>
>>> # Combine a Boolean column with oml_df.
... oml_bool = oml_df['numeric'] > 3
>>> oml_df = oml_df.concat(oml_bool)
>>> oml_df.rename({'COL4':'boolean'})
  bytes  numeric string  boolean
0  b'a'    1.000   None    False
1  b'b'    1.400   None    False
2  b'c'   -4.000      a    False
3  b'c'    3.145      a     True
4  b'd'    5.000      a     True
5  b'e'      NaN      b     True
>>>
>>> # Describe all of the columns.
... oml_df.describe(include='all')
       bytes   numeric string boolean
count      6  5.000000      4       6
unique     5       NaN      2       2
top     b'c'       NaN      a   False
freq       2       NaN      3       3
mean     NaN  1.309000    NaN     NaN
std      NaN  3.364655    NaN     NaN
min      NaN -4.000000    NaN     NaN
25%      NaN  1.000000    NaN     NaN
50%      NaN  1.400000    NaN     NaN
75%      NaN  3.145000    NaN     NaN
max      NaN  5.000000    NaN     NaN
>>>
>>> # Exclude Float columns.
... oml_df.describe(exclude=[oml.Float])
       bytes string boolean
count      6      4       6
unique     5      2       2
top     b'c'      a   False
freq       2      3       3
>>>
>>> # Get the sum of values in each Float or Boolean column.
... oml_df.sum()
numeric    6.545
boolean    3.000
```

```
dtype: float64
>>>
>>> # Find the cumulative sum of values in each Float or Boolean column
... # after oml_df is sorted by the bytes column in descending order.
... oml_df.cumsum(by = 'bytes', ascending = False)
   numeric  boolean
0      NaN        1
1    5.000        2
2    1.000        2
3    4.145        3
4    5.545        3
5    6.545        3
>>>
>>> # Compute the skewness of values in the Float columns.
... oml_df.skew()
numeric   -0.683838
dtype: float64
>>>
>>> # Find the median value of Float columns.
... oml_df.median()
numeric    1.4
dtype: float64
>>>
>>> # Calculate the kurtosis of Float columns.
... oml_df.kurtosis()
numeric   -0.582684
dtype: float64
```

4.2.7 Date, Time, and Integer Data

OML4Py provides the data types that enable you to manipulate date, time and integer.

The following newly added data types are now supported in OML4Py:

- `oml.Datetime`
- `oml.Timezone`
- `oml.Timedelta`
- `oml.Integer`

For information on the attributes and methods of `oml.Datetime`, `oml.Timezone`, `oml.Timedelta` and `oml.Integer`, see *Oracle Machine Learning for Python API Reference*.

oml.Datetime

To create a date, you can use the datetime class of the datetime module, which is included in OML4Py.

The datetime class requires three parameters: `year`, `month`, and `day`. It also contains optional parameters for time and timezone that includes `hour`, `minute`, `second`, `microsecond`, and `tzone`.

Example 4-13 Using the oml.Datetime Function

This example creates a proxy object from a table with DATE column.

```
import oml
import pandas as pd
import numpy as np
import datetime
from datetime import datetime, timezone, timedelta
SALES = oml.sync(schema="SH", table="SALES")
z.show(SALES.head())

# Use the following command to compute the statistics on table columns:
pd.set_option('display.max_columns', 50)
pd.set_option('display.width', 1000)
SALES.describe(include='all')

# Use the following command to compute statistics on DATE column TIME_ID:
SALES['TIME_ID'].describe()

# Use the following command to extract date-related features:
date = SALES['TIME_ID']
SALES2 = SALES.concat({'YEAR': date.year, 'MONTH': date.month})
SALES2.head()
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> import numpy as np
>>> import datetime
>>> from datetime import datetime, timezone, timedelta
>>> SALES = oml.sync(schema="SH", table="SALES")
>>> z.show(SALES.head())
>>>  PROD_ID  CUST_ID    TIME_ID              CHANNEL_ID  PROMO_ID
QUANTITY_SOLD  AMOUNT_SOLD
     13       524        1998-01-20 00:00:00  2           999
1.0            1205.99
     13       2128       1998-04-05 00:00:00  2           999
1.0            1250.25
     13       3212       1998-04-05 00:00:00  2           999
1.0            1250.25
     13       3375       1998-04-05 00:00:00  2           999
1.0            1250.25
     13       5204       1998-04-05 00:00:00  2           999
1.0            1250.25
>>> pd.set_option('display.max_columns', 50)
>>> pd.set_option('display.width', 1000)
>>> SALES.describe(include='all')
>>>          PROD_ID         CUST_ID             TIME_ID
CHANNEL_ID         PROMO_ID    QUANTITY_SOLD        AMOUNT_SOLD
count  918843.000000   918843.000000              918843
918843.000000    918843.000000         918843.0      918843.000000
unique NaN            NaN                           1460
NaN              NaN               NaN                NaN
top    NaN            NaN            2001-10-18 00:00:00
```

```
NaN              NaN               NaN               NaN
freq   NaN            NaN                          2940
NaN              NaN               NaN               NaN
mean   78.183945      7289.807720                    NaN
2.861603       976.396093             1.0         106.879882
std    49.008014      8948.653221                    NaN
0.686874       121.829887             0.0         259.780490
min    13.000000      2.000000                       NaN
2.000000        33.000000             1.0           6.400000
25%    31.000000      2383.000000                    NaN
2.000000       999.000000             1.0          17.380000
50%    48.000000      4927.000000                    NaN
3.000000       999.000000             1.0          34.240000
75%   127.000000      9163.000000                    NaN
3.000000       999.000000             1.0          53.890000
max   148.000000    101000.000000                    NaN
9.000000       999.000000             1.0        1782.720000
>>> SALES['TIME_ID'].describe()
>>> count                  918843
    unique                   1460
    top       2001-10-18 00:00:00
    freq                     2940
    Name: TIME_ID, dtype: object
>>> date = SALES['TIME_ID']
>>> SALES2 = SALES.concat({'YEAR': date.year, 'MONTH': date.month})
>>> SALES2.head()
>>> PROD_ID  CUST_ID    TIME_ID  CHANNEL_ID  PROMO_ID  QUANTITY_SOLD
AMOUNT_SOLD  YEAR  MONTH
0        13      524 1998-01-20           2       999            1.0
1205.99  1998      1
1        13     2128 1998-04-05           2       999            1.0
1250.25  1998      4
2        13     3212 1998-04-05           2       999            1.0
1250.25  1998      4
3        13     3375 1998-04-05           2       999            1.0
1250.25  1998      4
4        13     5204 1998-04-05           2       999            1.0
1250.25  1998      4
```

Example 4-14 Using the oml.Datetime Function

This example creates a datetime object with the year, month, day, then creates a temporary proxy object using `oml.push`. The `oml.push` function requires a data frame or list as input, so the date object is converted to a list. The resulting object is an object of class `oml.Datetime`.

```
import oml
import pandas as pd
import numpy as np

import datetime
from datetime import datetime, timezone, timedelta

d1 = datetime(year=2004, month=7, day=24)

print ('d1:', d1)
print('d1 year:', d1.year)
```

```
print('d1 month:', d1.month)
d1_lst = [d1]
D1 = oml.push(d1_lst)

print ('type', type(D1))
print ('D1:', D1)
print ('year:', D1.year)
print ('month:', D1.month)
print ('day:', D1.day)
d2 = datetime.fromisoformat('2004-07-24 00:05:23+04:00')
d2_lst=[d2]

D2 = oml.push(d2_lst)

print('D2', D2)
print('type', type(D2))
D2.strftime()
D2.strftime()
d3 = "14-Jul-05 20:01:01"
d3_lst = [d3]
D3 = oml.push(d3_lst)
oml.Datetime.strptime(D3, "DD-Mon-RR HH24:MI:SS")
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> import numpy as np

>>> import datetime
>>> from datetime import datetime, timezone, timedelta

>>> d1 = datetime(year=2004, month=7, day=24)

>>> print ('d1:', d1)
>>> d1: 2004-07-24 00:00:00
>>> print('d1 year:', d1.year)
>>> d1 year: 2004
>>> print('d1 month:', d1.month)
>>> d1 month: 7

>>> d1_lst = [d1]
>>> D1 = oml.push(d1_lst)

>>> print ('type', type(D1))
>>> type <class 'oml.core.datetime.Datetime'>
>>> print ('D1:', D1)
>>> D1: [datetime.datetime(2004, 7, 24, 0, 0)]
>>> print ('year:', D1.year)
>>> year: [2004]
>>> print ('month:', D1.month)
>>> month: [7]
>>> print ('day:', D1.day)
>>> day: [24]
```

```
>>> d2 = datetime.fromisoformat('2004-07-24 00:05:23+04:00')
>>> d2_lst=[d2]
>>> D2 = oml.push(d2_lst)
>>> print('D2', D2)
>>> D2 [datetime.datetime(2004, 7, 24, 0, 5, 23,
tzinfo=datetime.timezone(datetime.timedelta(seconds=14400)))]
>>> print('type', type(D2))
>>> type <class 'oml.core.datetime.Datetime'>

>>> D2.strftime()
>>> ['2004-07-24 00:05:23+04:00']
>>> d3 = "14-Jul-05 20:01:01"
>>> d3_lst = [d3]

>>> D3 = oml.push(d3_lst)

>>> oml.Datetime.strptime(D3, "DD-Mon-RR HH24:MI:SS")
>>> [datetime.datetime(2005, 7, 14, 20, 1, 1)]
```

oml.Timedelta

`oml.Timedelta` objects represent a span of time, which can be used to perform simple arithmetic operations on `oml.Datetime` objects. The `oml.Timedelta` objects can be multiplied by an integer value or a floating point value. Subtracting dates creates an `oml.Timedelta` object that can be added, subtracted, or multiplied by a `oml.Timedate` object to produce another date.

Example 4-15 Using the oml.Timedelta Function

This example creates a time-based reference using the current date and time, and creates an `oml.Timedelta` object named DELT1 to determine a past and future dates.

```
import oml
import pandas as pd
import numpy as np

import datetime
from datetime import datetime, timezone, timedelta
today = datetime.now()
print('today:', today)

delt1 = timedelta(days=1, hours=2, seconds=5)
print('delt1:', delt1)

dat = pd.DataFrame({'datetime': [today], 'timedelta': [delt1]})
DAT = oml.push(dat, dbtypes = ['TIMESTAMP', 'INTERVAL DAY TO SECOND'])

TODAY = DAT['datetime']
DELT1 = DAT['timedelta']

print('TODAY:', today)
print('DELT1:', DELT1)
past_date1 = TODAY - DELT1
print('past date 1:', past_date1)

past_date2 = TODAY - (DELT1 *3)
```

```
print('past date 2:', past_date2)

future_date1 = TODAY + DELT1
print('future date 1:', future_date1)

future_date2 = TODAY + (DELT1 *3)
print('future date 2:', future_date2)
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> import numpy as np

>>> import datetime
>>> from datetime import datetime, timezone, timedelta
>>> today = datetime.now()
>>> print('today:', today)
>>> today: 2022-12-27 06:00:14.555899

>>> delt1 = timedelta(days=1, hours=2, seconds=5)
>>> print('delt1:', delt1)
>>> delt1: 1 day, 2:00:05

>>> dat = pd.DataFrame({'datetime': [today], 'timedelta': [delt1]})
>>> DAT = oml.push(dat, dbtypes = ['TIMESTAMP', 'INTERVAL DAY TO SECOND'])

>>> TODAY = DAT['datetime']
>>> DELT1 = DAT['timedelta']

>>> print('TODAY:', today)
>>> TODAY: 2022-12-27 06:00:14.555899
>>> print('DELT1:', DELT1)
>>> DELT1: [datetime.timedelta(days=1, seconds=7205)]
>>> past_date1 = TODAY - DELT1
>>> print('past date 1:', past_date1)
>>> past date 1: [datetime.datetime(2022, 12, 26, 4, 0, 9, 555899)]
>>> past_date2 = TODAY - (DELT1 *3)
>>> print('past date 2:', past_date2)
>>> past date 2: [datetime.datetime(2022, 12, 23, 23, 59, 59, 555899)]

>>> future_date1 = TODAY + DELT1
>>> print('future date 1:', future_date1)
>>> future date 1: [datetime.datetime(2022, 12, 28, 8, 0, 19, 555899)]

>>> future_date2 = TODAY + (DELT1 *3)
>>> print('future date 2:', future_date2)
>>> future date 2: [datetime.datetime(2022, 12, 30, 12, 0, 29, 555899)]
```

oml.Integer

The `oml.Integer` class represents the integer data type.

Example 4-16 Using the oml.Integer Function

This example creates an oml.Integer object named INTEGER1 to represent the integer data type.

```
import oml
import pandas as pd
integer1 = oml.push(pd.DataFrame({'INTEGER': [0, -12, 1234, 40, 95]}),
dbtypes = "NUMBER(*, 0)")
integer1
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> integer1 = oml.push(pd.DataFrame({'INTEGER': [0, -12, 1234, 40, 95]}),
dbtypes = "NUMBER(*, 0)")
>>> integer1
       INTEGER
0        0
1      -12
2     1234
3       40
4       95
```

Compare two `oml.Datetime` columns in a proxy object using standard arithmetic comparison operators.

Example 4-17 Using value comparison Function

This example compares two `oml.Datetime` columns in a proxy object using standard arithmetic comparison operators.

```
d1 = datetime(2005, 7, 14, 5, 10, 30)
d2 = datetime(2004, 6, 30, 1, 22, 46)
d3 = datetime(2003, 12, 10, 12, 50, 25)
d4 = datetime(2002, 3, 20, 20, 42, 59)

d3 = pd.DataFrame({'X': [d1, d2], 'Y': [d3,
d4]})
D3 = oml.push(d3, dbtypes = ['TIMESTAMP', 'TIMESTAMP'])

print(D3)
D4 = D3['X']
D5 = D3['Y']

print("D4:", D4)
print("D4 type:", type(D4))

print("D5:", D5)
print("D5 type:", type(D5))

print(D4 == D5)
```

```
print(D4 != D5)

print(D4 > D5)

print(D4 >= D5)

print(D4 < D5)

print(D4 <= D5)

print("max:", D3['X'].max())
print("min:", D3['Y'].min())
```

Listing for This Example

```
>>> d1 = datetime(2005, 7, 14, 5, 10, 30)
>>> d2 = datetime(2004, 6, 30, 1, 22, 46)
>>> d3 = datetime(2003, 12, 10, 12, 50, 25)
>>> d4 = datetime(2002, 3, 20, 20, 42, 59)

>>> d3 = pd.DataFrame({'X': [d1, d2], 'Y': [d3,
d4]})
>>> D3 = oml.push(d3, dbtypes = ['TIMESTAMP', 'TIMESTAMP'])

>>> print(D3)
>>>                   X                   Y
>>> 0 2005-07-14 05:10:30 2003-12-10 12:50:25
>>> 1 2004-06-30 01:22:46 2002-03-20 20:42:59
>>> D4 = D3['X']
>>> D5 = D3['Y']

>>> print("D4:", D4)
>>> print("D4 type:", type(D4))
>>> D4: [datetime.datetime(2005, 7, 14, 5, 10, 30), datetime.datetime(2004,
6, 30, 1, 22, 46)]
>>> D4 type: <class 'oml.core.datetime.Datetime'>

>>> print("D5:", D5)
>>> print("D5 type:", type(D5))
>>> D5: [datetime.datetime(2003, 12, 10, 12, 50, 25), datetime.datetime(2002,
3, 20, 20, 42, 59)]
>>> D5 type: <class 'oml.core.datetime.Datetime'>

>>> print(D4 == D5)
>>> [False, False]

>>> print(D4 != D5)
>>> [True, True]

>>> print(D4 > D5)
>>> [True, True]

>>> print(D4 >= D5)
```

```
>>> [True, True]

>>> print(D4 < D5)
>>> [False, False]

>>> print(D4 <= D5)
>>> [False,
False]

                        >>> [True, True] [True, True] [True, True] [False,
False] [False,

>>> print("max:", D3['X'].max())
>>> max: 2005-07-14 05:10:30
>>> print("min:", D3['Y'].min())
>>> min: 2002-03-20 20:42:59
```

Value Replacement

This function updates the elements of an `oml.Datetime` object, such as year, month, and day.

Example 4-18 Using value replacement function

```
D4 = D3['X'].replace(year=2000)
print("D4:", D4)

D5 = D3['X'].replace(month=11)
print("D5:", D5)

D6 = D3['X'].replace(day=6)
print("D6:", D6)
```

Listing for This Example

```
>>> D4 = D3['X'].replace(year=2000)
>>> print("D4:", D4)
>>> D4: [datetime.datetime(2000, 7, 14, 5, 10, 30), datetime.datetime(2000,
6, 30, 1, 22, 46)]

>>> D5 = D3['X'].replace(month=11)
>>> print("D5:", D5)
>>> D5: [datetime.datetime(2005, 11, 14, 5, 10, 30), datetime.datetime(2004,
11, 30, 1, 22, 46)]

>>> D6 = D3['X'].replace(day=6)
>>> print("D6:", D6)
>>> D6: [datetime.datetime(2005, 7, 6, 5, 10, 30), datetime.datetime(2004, 6,
6, 1, 22, 46)]
```

4.3 Render Graphics

OML4Py provides functions for rendering graphical displays of data.

The `oml.boxplot` and `oml.hist` functions compute the statistics necessary to generate box and whisker plots or histograms in-database for scalability and performance.

OML4Py uses the `matplotlib` library to render the output. You can use methods of `matplotlib.pyplot` to customize the created images and `matplotlib.pyplot.show` to show the images. By default, rendered graphics have the same properties as those stored in `matplotlib.rcParams`.

For the parameters of the `oml.boxplot` and `oml.hist` functions, invoke `help(oml.boxplot)` or `help(oml.hist)`, or see *Oracle Machine Learning for Python API Reference*.

Generate a Box Plot

Use the `oml.boxplot` function to generate a box and whisker plot for every column of *x* or for every column object in *x*.

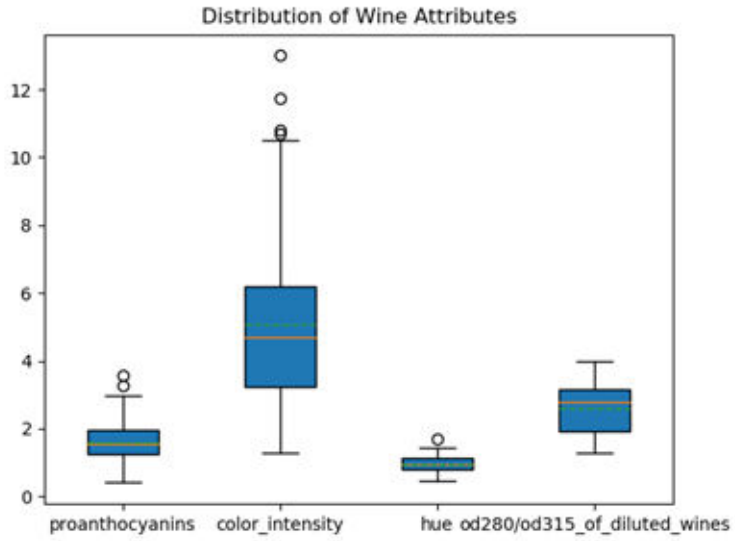
Example 4-19 Using the oml.boxplot Function

This example first loads the wine data set from `sklearn` and creates the `pandas.DataFrame` object `wine_data`. It then creates a temporary database table, with its corresponding proxy `oml.DataFrame` object `oml_wine`, from `wine_data`. It draws a box and whisker plot on every column with the index ranging from 8 to 12 (not including 12) in `oml_wine`. The arguments `showmeans` and `meanline` are set to `True` to show the arithmetic means and to render the mean as a line spanning the full width of the box. The argument `patch_artist` is set to `True` to have the boxes drawn with Patch artists.

```
import oml
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets

wine = datasets.load_wine()
wine_data = pd.DataFrame(wine.data, columns = wine.feature_names)
oml_wine = oml.push(wine_data)
oml.graphics.boxplot(oml_wine[:,8:12], showmeans=True,
                     meanline=True, patch_artist=True,
                     labels=oml_wine.columns[8:12])
plt.title('Distribution of Wine Attributes')
plt.show()
```

The output of the example is the following.



The image shows a box and whisker plot for each of the four columns of the wine data set: Proanthocyanins, Color intensity, Hue, and OD280/OD315 of diluted wines. The boxes extend from the lower to upper quartile values of the data, with a solid orange line at the median. The whiskers that extend from the box show the range of the data. The caps are the horizontal lines at the ends of the whiskers. Flier or outlier points are those past the ends of the whiskers. The mean is shown as a green dotted line spanning the width of the each box.

Generate a Histogram

Use the `oml.hist` function to compute and draw a histogram for every data set column contained in *x*.

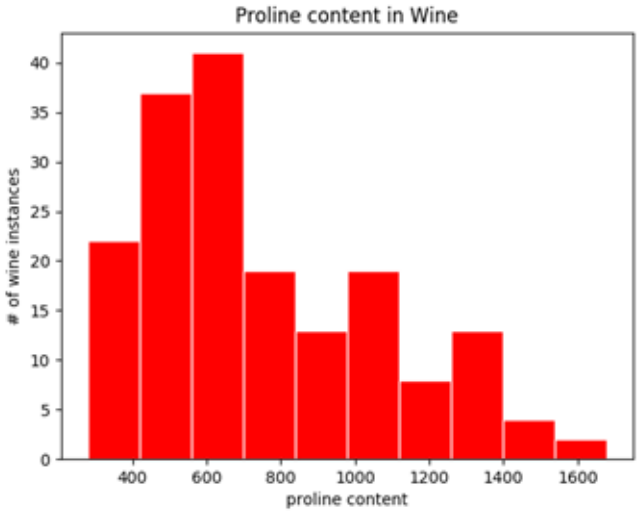
Example 4-20 Using the oml.hist Function

This example first loads the wine data set from `sklearn` and creates the `pandas.DataFrame` object `wine_data`. It then creates a temporary database table, with its corresponding proxy `oml.DataFrame` object `oml_wine`, from `wine_data`. Next it draws a histogram on the proline column of `oml_wine`. The argument `bins` specifies generating ten equal-width bins. Argument `color` specifies filling the bars with the color purple. Arguments `linestyle` and `edgecolor` are set to draw the bar edges as solid lines in pink.

```
import oml
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_wine

wine = load_wine()
wine_data = pd.DataFrame(wine.data, columns = wine.feature_names)
oml_wine = oml.push(wine_data)
oml.graphics.hist(oml_wine['proline'], bins=10, color='red',
                  linestyle='solid', edgecolor='white')
plt.title('Proline content in Wine')
plt.xlabel('proline content')
plt.ylabel('# of wine instances')
plt.show()
```

The output of the example is the following.



The image shows a traditional bar-type histogram for the Proline column of the wine data set. The range of proline values is divided into 10 bins of equal size. The height of the rectangular bar for each bin indicates the number of wine instances in each bin. The bars are red with solid white edges.

5

OML4Py Classes That Provide Access to In-Database Machine Learning Algorithms

OML4Py has classes that provide access to in-database Oracle Machine Learning algorithms.

These classes are described in the following topics.

- About Machine Learning Classes and Algorithms
  These classes provide access to in-database machine learning algorithms.
- About Model Settings
  You can specify settings that affect the characteristics of a model.
- Shared Settings
  These settings are common to all of the OML4Py machine learning classes.
- Export Oracle Machine Learning for Python Models
  You can export an `oml` model from Python and then score it in SQL.
- Automatic Data Preparation
  Oracle Machine Learning for Python supports Automatic Data Preparation (ADP) and user-directed general data preparation.
- Model Explainability
  Use the OML4Py Explainability module to identify the important features that impact a trained model's predictions.
- Attribute Importance
  The `oml.ai` class computes the relative attribute importance, which ranks attributes according to their significance in predicting a classification or regression target.
- Association Rules
  The `oml.ar` class implements the Apriori algorithm to find frequent itemsets and association rules, all as part of an association model object.
- Decision Tree
  The `oml.dt` class uses the Decision Tree algorithm for classification.
- Expectation Maximization
  The `oml.em` class uses the Expectation Maximization (EM) algorithm to create a clustering model.
- Explicit Semantic Analysis
  The `oml.esa` class extracts text-based features from a corpus of documents and performs document similarity comparisons.
- Generalized Linear Model
  The `oml.glm` class builds a Generalized Linear Model (GLM) model.
- k-Means
  The `oml.km` class uses the *k*-Means (KM) algorithm, which is a hierarchical, distance-based clustering algorithm that partitions data into a specified number of clusters.
- Naive Bayes
  The `oml.nb` class creates a Naive Bayes (NB) model for classification.

- Neural Network
  The `oml.nn` class creates a Neural Network (NN) model for classification and regression.
- Random Forest
  The `oml.rf` class creates a Random Forest (RF) model that provides an ensemble learning technique for classification.
- Singular Value Decomposition
  Use the `oml.svd` class to build a model for feature extraction.
- Support Vector Machine
  The `oml.svm` class creates a Support Vector Machine (SVM) model for classification, regression, or anomaly detection.
- Non-Negative Matrix Factorization
  The `oml.nmf` class creates a Non-Negative Matrix Factorization (NMF) model for feature extraction.
- Exponential Smoothing Method
  The `oml.esm` function uses the Exponential Smoothing Method (ESM) algorithm to create a time series model.
- XGBoost
  The `oml.xgb` class supports the in-database scalable gradient tree boosting algorithm for both classification, regression specifications, ranking models, and survival models. It makes available the open source gradient boosting framework. It prepares the categorical encoding and missing value replacement from the OML infrastructure, calls the in-database XGBoost, builds and persists a model as a first-class database model object, and supports using the model for prediction.

5.1 About Machine Learning Classes and Algorithms

These classes provide access to in-database machine learning algorithms.

Algorithm Classes

Class	Algorithm	Function of Algorithm	Description
`oml.ai`	Minimum Description Length	Attribute importance for classification or regression	Ranks attributes according to their importance in predicting a target.
`oml.ar`	Apriori	Association rules	Performs market basket analysis by identifying co-occurring items (frequent itemsets) within a set.
`oml.dt`	Decision Tree	Classification	Extracts predictive information in the form of human-understandable rules. The rules are if-then-else expressions; they explain the decisions that lead to the prediction.
`oml.em`	Expectation Maximization	Clustering	Performs probabilistic clustering based on a density estimation algorithm.
`oml.esa`	Explicit Semantic Analysis	Feature extraction	Extracts text-based features from a corpus of documents. Performs document similarity comparisons.
`oml.glm`	Generalized Linear Model	Classification Regression	Implements logistic regression for classification of binary targets and linear regression for continuous targets.

Class	Algorithm	Function of Algorithm	Description
`oml.km`	*k*-Means	Clustering	Uses unsupervised learning to group data based on similarity into a predetermined number of clusters.
`oml.nb`	Naive Bayes	Classification	Makes predictions by deriving the probability of a prediction from the underlying evidence, as observed in the data.
`oml.nn`	Neural Network	Classification Regression	Learns from examples and tunes the weights of the connections among the neurons during the learning process.
`oml.rf`	Random Forest	Classification	Provides an ensemble learning technique for classification of data.
`oml.svd`	Singular Value Decomposition	Feature extraction	Performs orthogonal linear transformations that capture the underlying variance of the data by decomposing a rectangular matrix into three matrices.
`oml.svm`	Support Vector Machine	Anomaly detection Classification Regression	Builds a model that is a profile of a class, which, when the model is applied, identifies cases that are somehow different from that profile.
`oml.nmf`	Non-Negative Matrix Factorization	Clustering	A state of the art feature extraction algorithm used when there are many attributes and the attributes are ambiguous or have weak predictability.
`oml.xgb`	XGBoost	Classification Regression	Can be used as a stand-alone predictor or incorporate it into real-world production pipelines for a wide range of problems such as ad click-through rate prediction, hazard risk prediction, web text classification, and so on.

Repeatable Results

You can use the `case_id` parameter in the `fit` method of the OML4Py machine learning algorithm classes to achieve repeatable sampling, data splits (train and held aside), and random data shuffling.

Persisting Models

In-database models created through the OML4Py API exist as temporary objects that are dropped when the database connection ends unless you take one of the following actions:

- Save a default-named model object in a datastore, as in the following example:

```
regr2 = oml.glm("regression")
oml.ds.save(regr2, 'regression2')
```

- Use the `model_name` parameter in the `fit` function when building the model, as in the following example:

```
regr2 = regr2.fit(X, y, model_name = 'regression2')
```

- Change the name of an existing model using the `model_name` function of the model, as in the following example:

```
regr2(model_name = 'myRegression2')
```

To drop a persistent named model, use the `oml.drop` function.

Creating a Model from an Existing In-Database Model

You can create an OML4Py model as a proxy object for an existing in-database machine learning model. The in-database model could have been created through OML4Py, OML4SQL, or OML4R. To do so, when creating the OML4Py, specify the name of the existing model and, optionally, the name of the owner of the model, as in the following example.

```
ar_mod = oml.ar(model_name = 'existing_ar_model', model_owner = 'SH',
**setting)
```

An OML4Py model created this way persists until you drop it with the `oml.drop` function.

Scoring New Data with a Model

For most of the OML4Py machine learning classes, you can use the `predict` and `predict_proba` methods of the model object to score new data.

For in-database models, you can use the SQL `PREDICTION` function on model proxy objects, which scores directly in the database. You can use in-database models directly from SQL if you prepare the data properly. For open source models, you can use Embedded Python Execution and enable data-parallel execution for performance and scalability.

Deploying Models Through a REST API

The REST API for Oracle Machine Learning Services provides REST endpoints hosted on an Oracle Autonomous Database instance. These endpoints allow you to store OML models along with their metadata, and to create scoring endpoints for the models.

5.2 About Model Settings

You can specify settings that affect the characteristics of a model.

Some settings are general, some are specific to an Oracle Machine Learning function, and some are specific to an algorithm.

All settings have default values. If you want to override one or more of the settings for a model, then you must specify the settings with the `**params` parameter when instantiating the model or later by using the `set_params` method of the model.

For the `_init_` method, the argument can be key-value pairs or a `dict`. Each list element's name and value refer to a machine learning algorithm parameter setting name and value, respectively. The setting value must be numeric or a string.

The argument for the `**params` parameter of the `set_params` method is a `dict` object mapping a `str` to a `str`. The key should be the name of the setting, and the value should be the new setting.

Example 5-1 Specifying Model Settings

This example shows the creation of an Expectation Maximization (EM) model and the changing of a setting. For the complete code of the EM model example, see Example 5-10.

```
# Specify settings.
setting = {'emcs_num_iterations': 100}
# Create an EM model object
em_mod = em(n_clusters = 2, **setting)

# Intervening code not shown.

# Change the random seed and refit the model.
em_mod.set_params(EMCS_RANDOM_SEED = '5').fit(train_dat)
```

5.3 Shared Settings

These settings are common to all of the OML4Py machine learning classes.

The following table lists the settings that are shared by all OML4Py models.

Table 5-1 Shared Model Settings

Setting Name	Setting Value	Description
ODMS_DETAILS	ODMS_ENABLE ODMS_DISABLE	Helps to control model size in the database. Model details can consume significant disk space, especially for partitioned models. The default value is ODMS_ENABLE. If the setting value is ODMS_ENABLE, then model detail tables and views are created along with the model. You can query the model details using SQL. If the value is ODMS_DISABLE, then model detail tables are not created and tables relevant to model details are also not created. The reduction in the space depends on the algorithm. Model size reduction can be on the order of 10x .
ODMS_MAX_PARTITIONS	1 < *value* <= 1000000	Controls the maximum number of partitions allowed for a partitioned model. The default is 1000.
ODMS_MISSING_VALUE_TREATMENT	ODMS_MISSING_VALUE_AUTO ODMS_MISSING_VALUE_MEAN_MODE ODMS_MISSING_VALUE_DELETE_ROW	Indicates how to treat missing values in the training data. This setting does not affect the scoring data. The default value is ODMS_MISSING_VALUE_AUTO. ODMS_MISSING_VALUE_MEAN_MODE replaces missing values with the mean (numeric attributes) or the mode (categorical attributes) both at build time and apply time where appropriate. ODMS_MISSING_VALUE_AUTO performs different strategies for different algorithms. When ODMS_MISSING_VALUE_TREATMENT is set to ODMS_MISSING_VALUE_DELETE_ROW, the rows in the training data that contain missing values are deleted. However, if you want to replicate this missing value treatment in the scoring data, then you must perform the transformation explicitly. The value ODMS_MISSING_VALUE_DELETE_ROW is applicable to all algorithms.

Table 5-1 (Cont.) Shared Model Settings

Setting Name	Setting Value	Description
ODMS_PARTITION_BUILD_TYPE	ODMS_PARTITION_BUILD_INTRA ODMS_PARTITION_BUILD_INTER ODMS_PARTITION_BUILD_HYBRID	Controls the parallel building of partitioned models. ODMS_PARTITION_BUILD_INTRA builds each partition in parallel using all slaves. ODMS_PARTITION_BUILD_INTER builds each partition entirely in a single slave, but multiple partitions may be built at the same time because multiple slaves are active. ODMS_PARTITION_BUILD_HYBRID combines the other two types and is recommended for most situations to adapt to dynamic environments. This is the default value.
ODMS_PARTITION_COLUMNS	Comma separated list of machine learning attributes	Requests the building of a partitioned model. The setting value is a comma-separated list of the machine learning attributes to be used to determine the in-list partition key values. These attributes are taken from the input columns, unless an XFORM_LIST parameter is passed to the model. If XFORM_LIST parameter is passed to the model, then the attributes are taken from the attributes produced by these transformations.
ODMS_TABLESPACE_NAME	*tablespace_name*	Specifies the tablespace in which to store the model. If you explicitly set this to the name of a tablespace (for which you have sufficient quota), then the specified tablespace storage creates the resulting model content. If you do not provide this setting, then the your default tablespace creates the resulting model content.
ODMS_SAMPLE_SIZE	0 < *value*	Determines how many rows to sample (approximately). You can use this setting only if ODMS_SAMPLING is enabled. The default value is system determined.
ODMS_SAMPLING	ODMS_SAMPLING_ENABLE ODMS_SAMPLING_DISABLE	Allows the user to request sampling of the build data. The default is ODMS_SAMPLING_DISABLE.
ODMS_TEXT_MAX_FEATURES	1 <= *value*	The maximum number of distinct features, across all text attributes, to use from a document set passed to the model. The default is 3000. An oml.esa model has the default value of 300000.
ODMS_TEXT_MIN_DOCUMENTS	Non-negative value	This text processing setting controls how many documents a token needs to appear in to be used as a feature. The default is 1. An oml.esa model has the default value of 3.
ODMS_TEXT_POLICY_NAME	The name of an Oracle Text POLICY created using CTX_DDL.CREATE_POLICY.	Affects how individual tokens are extracted from unstructured text. For details about CTX_DDL.CREATE_POLICY, see *Oracle Text Reference*.
PREP_AUTO	PREP_AUTO_ON PREP_AUTO_OFF	This data preparation setting enables fully automated data preparation. The default is PREP_AUTO_ON.

Table 5-1 (Cont.) Shared Model Settings

Setting Name	Setting Value	Description
PREP_SCALE_2DNUM	pPREP_SCALE_STDDEV PREP_SCALE_RANGE	This data preparation setting enables scaling data preparation for two-dimensional numeric columns. PREP_AUTO must be OFF for this setting to take effect. The following are the possible values: PREP_SCALE_STDDEV: A request to divide the column values by the standard deviation of the column and is often provided together with PREP_SHIFT_MEAN to yield z-score normalization. PREP_SCALE_RANGE: A request to divide the column values by the range of values and is often provided together with PREP_SHIFT_MIN to yield a range of [0,1].
PREP_SCALE_NNUM	PREP_SCALE_MAXABS	This data preparation setting enables scaling data preparation for nested numeric columns. PREP_AUTO must be OFF for this setting to take effect. If specified, then the valid value for this setting is PREP_SCALE_MAXABS, which yields data in the range of [-1,1].
PREP_SHIFT_2DNUM	PREP_SHIFT_MEAN PREP_SHIFT_MIN	This data preparation setting enables centering data preparation for two-dimensional numeric columns. PREP_AUTO must be OFF for this setting to take effect. The following are the possible values: PREP_SHIFT_MEAN: Results in subtracting the average of the column from each value. PREP_SHIFT_MIN: Results in subtracting the minimum of the column from each value.

5.4 Export Oracle Machine Learning for Python Models

You can export an oml model from Python and then score it in SQL.

Export a Model

With the export_sermodel function of an OML4Py algorithm model, you can export the model in a serialized format. You can then score that model in SQL. To save a model to a permanent table, you must pass in a name for the new table. If the model is partitioned, then you can optionally select an individual partition to export; otherwise all partitions are exported.

> **Note:**
>
> Any data transformations you apply to the data for model building you must also apply to the data for scoring with the imported model.

Example 5-2 Export a Trained oml.svm Model to a Database Table

This example creates the x and y variables using the iris data set. It then creates the persistent database table IRIS and the oml.DataFrame object oml_iris as a proxy for the table.

This example preprocesses the `iris` data set and splits the data set into training data and test data. It then fits an `oml.svm` model according to the training data of the data set, and saves the fitted model in a serialized format to a new table named svm_sermod in the database.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

try:
    oml.drop('IRIS')
    oml.drop('IRIS_TEST_DATA')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

df = oml.sync(table = "IRIS").pull()

# Add a case identifier column.
df.insert(0, 'ID', range(0,len(df)))

# Create training data and test data.
IRIS_TMP = oml.push(df).split()
train_x = IRIS_TMP[0].drop('Species')
train_y = IRIS_TMP[0]['Species']
test_dat = IRIS_TMP[1]

# Create the iris_test_data database table.
oml_test_dat = oml.create(test_dat.pull(), table = "IRIS_TEST_DATA")

# Create an oml SVM model object.
svm_mod = oml.svm('classification',
                  svms_kernel_function =
                    'dbms_data_mining.svms_linear')

# Fit the SVM model with the training data.
svm_mod = svm_mod.fit(train_x, train_y, case_id = 'ID')

# Export the oml.svm model to a new table named 'svm_sermod'
# in the database.
svm_export = svm_mod.export_sermodel(table='svm_sermod')
type(svm_export)

# Show the first 10 characters of the BLOB content from the
```

```
# model export.
svm_export.pull()[0][1:10]
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
...    oml.drop('IRIS_TEST_DATA')
...except:
...    pass
>>> # Create the IRIS database table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> df = oml.sync(table = "IRIS").pull()
>>>
>>> # Add a case identifier column.
... df.insert(0, 'ID', range(0,len(df)))
>>>
>>> # Create training data and test data.
... IRIS_TMP = oml.push(df).split()
>>> train_x = IRIS_TMP[0].drop('Species')
>>> train_y = IRIS_TMP[0]['Species']
>>> test_dat = IRIS_TMP[1]
>>>
>>> # Create the iris_test_data database table.
... oml_test_dat = oml.create(test_dat.pull(), table = "IRIS_TEST_DATA")
>>>
>>> # Create an oml SVM model object.
... svm_mod = oml.svm('classification',
...                   svms_kernel_function =
                        'dbms_data_mining.svms_linear')
>>>
>>> # Fit the SVM model with the training data.
... svm_mod = svm_mod.fit(train_x, train_y, case_id='ID')
>>>
>>> # Export the oml.svm model to a new table named 'svm_sermod'
... # in the database.
... svm_export = svm_mod.export_sermodel(table='svm_sermod')
>>> type(svm_export)
<class 'oml.core.bytes.Bytes'>
>>>
```

```
>>> # Show the first 10 characters of the BLOB content from the
... # model export.
... svm_export.pull()[0][1:10]
b'\xff\xfc|\x00\x00\x02\x9c\x00\x00'
```

Import a Model

In SQL, you can import the serialized format of an OML4Py model into an Oracle Machine Learning for SQL model with the `DBMS_DATA_MINING.IMPORT_SERMODEL` procedure. To that procedure, you pass the BLOB content from the table to which the model was exported and the name of the model to be created. The import procedure provides the ability to score the model. It does not create model views or tables that are needed for querying model details. You can use the SQL function `PREDICTION` to apply the imported model to the test data and get the prediction results.

Example 5-3 Import a Serialized SVM Model as an OML4SQL Model in SQL

This example retrieves the serialized content of the SVM classification model from the svm_sermod table. It uses the `IMPORT_SERMODEL` procedure to create a model named my_iris_svm_classifier with the content from the table. It also predicts test data saved in the iris_test_data table with the newly imported model my_iris_svm_classifier, and compares the prediction results with the target classes.

```
-- After starting SQL*Plus as the OML4Py user.
-- Import the model from the serialized content.

DECLARE
  v_blob blob;

BEGIN
  SELECT SERVAL INTO v_blob FROM "svm_sermod";
  dbms_data_mining.import_sermodel(v_blob, 'my_iris_svm_classifier');
END;
/

-- Set the output column format.
column TARGET_SPECIES format a15
column PREDICT_SPECIES format a15

-- Make predictions and display cases where mod(ID,3) equals 0.
SELECT ID, "Species" AS TARGET_SPECIES,
  PREDICTION(my_iris_svm_classifier USING "Sepal_Length", "Sepal_Width",
             "Petal_Length", "Petal_Width")
             AS PREDICT_SPECIES
             FROM "IRIS_TEST_DATA" WHERE MOD(ID,3) = 0;

-- Drop the imported model
BEGIN
  DBMS_DATA_MINING.DROP_MODEL(model_name => 'my_iris_svm_classifier');
END;
/
```

The prediction produces the following results.

```
ID TARGET_SPECIES PREDICT_SPECIES
-- -------------- ---------------
```

```
 0 setosa         setosa
24 setosa         setosa
27 setosa         setosa
33 setosa         setosa
36 setosa         setosa
39 setosa         setosa
48 setosa         setosa
54 versicolor     versicolor
57 versicolor     versicolor
93 versicolor     versicolor
114 virginica     virginica
120 virginica     virginica
132 virginica     virginica
13 rows selected.
```

5.5 Automatic Data Preparation

Oracle Machine Learning for Python supports Automatic Data Preparation (ADP) and user-directed general data preparation.

The `PREP_*` settings enable you to request fully automated (ADP) or manual data preparation. By default, ADP is enabled (`PREP_AUTO_ON`) . When performed manually, data preparation requirements of each algorithm must be addressed

When you enable ADP, the model uses heuristics to transform the build data according to the requirements of the algorithm. Instead of ADP, you can request that the data be shifted and/or scaled with the `PREP_SCALE_*` and `PREP_SHIFT_*` settings. The transformation instructions are stored with the model and reused whenever the model is applied. The model settings can be viewed in `USER_MINING_MODEL_SETTINGS`.

PREP_* Settings

The values for the `PREP_*` settings are described in the following table.

Table 5-2 title

Setting Name	Setting Value	Description
`PREP_AUTO`	`PREP_AUTO_ON` `PREP_AUTO_OFF`	This setting enables fully automated data preparation. The default is `PREP_AUTO_ON`.
`PREP_SCALE_2DNUM`	`PREP_SCALE_STDDEV` `PREP_SCALE_RANGE`	This setting enables scaling data preparation for two-dimensional numeric columns. `PREP_AUTO` must be `OFF` for this setting to take effect. The following are the possible values. `PREP_SCALE_STDDEV`: A request to divide the column values by the standard deviation of the column and is often provided together with `PREP_SHIFT_MEAN` to yield z-score normalization. `PREP_SCALE_RANGE`: A request to divide the column values by the range of values and is often provided together with `PREP_SHIFT_MIN` to yield a range of [0,1].

Table 5-2 (Cont.) title

Setting Name	Setting Value	Description
PREP_SCALE_NNUM	PREP_SCALE_MAXABS	This setting enables scaling data preparation for nested numeric columns. PREP_AUTO must be OFF for this setting to take effect. If specified, then the valid value for this setting is PREP_SCALE_MAXABS, which yields data in the range of [-1,1].
PREP_SHIFT_2DNUM	PREP_SHIFT_MEAN PREP_SHIFT_MIN	This setting enables centering data preparation for two-dimensional numeric columns. PREP_AUTO must be OFF for this setting to take effect. The following are the possible values: PREP_SHIFT_MEAN: Results in subtracting the average of the column from each value. PREP_SHIFT_MIN: Results in subtracting the minimum of the column from each value.

See Also:

- About Model Settings
- Shared Settings

5.6 Model Explainability

Use the OML4Py Explainability module to identify the important features that impact a trained model's predictions.

Machine Learning Explainability (MLX) is the process of explaining and interpreting machine learning models. The OML MLX Python module supports the ability to help better understand a model's behavior and why it makes its predictions. MLX currently provides model-agnostic explanations for classification and regression tasks where explanations treat the ML model as a black-box, instead of using properties from the model to guide the explanation.

The global feature importance explainer object is the interface to the MLX permutation importance explainer. The global feature importance explainer identifies the most important features for a given model and data set. The explainer is model-agnostic and currently supports tabular classification and regression data sets with both numerical and categorical features.

The algorithm estimates feature importance by evaluating the model's sensitivity to changes in a specific feature. Higher sensitivity suggests that the model places higher importance on that feature when making its predictions than on another feature with lower sensitivity.

For information on the `oml.GlobalFeatureImportance` class attributes and methods, call `help(oml.mlx.GlobalFeatureImportance)` or see *Oracle Machine Learning for Python API Reference*.

Example 5-4 Binary Classification

This example uses the Breast Cancer binary classification data set. Load the data set into the database and a unique case id column.

```
import oml
from oml.mlx import GlobalFeatureImportance
import pandas as pd
import numpy as np
from sklearn import datasets

bc_ds = datasets.load_breast_cancer()
bc_data = bc_ds.data.astype(float)
X = pd.DataFrame(bc_data, columns=bc_ds.feature_names)
y = pd.DataFrame(bc_ds.target, columns=['TARGET'])
row_id = pd.DataFrame(np.arange(bc_data.shape[0]),
                      columns=['CASE_ID'])
df = oml.create(pd.concat([X, y, row_id], axis=1),
                table='BreastCancer')
```

Split the data set into train and test variables.

```
train, test = df.split(ratio=(0.8, 0.2), hash_cols='CASE_ID',
                       seed=32)
X, y = train.drop('TARGET'), train['TARGET']
X_test, y_test = test.drop('TARGET'), test['TARGET']
```

Train a Random Forest model.

```
model = oml.algo.rf(ODMS_RANDOM_SEED=32).fit(X, y, case_id='CASE_ID')
        "RF accuracy score = {:.2f}".format(model.score(X_test, y_test))
```

Create the MLX Global Feature Importance explainer, using the binary `f1` metric.

```
gfi = GlobalFeatureImportance(mining_function='classification',
                              score_metric='f1', random_state=32,
                              parallel=4)
```

Run the explainer to generate the global feature importance. Here we construct an explanation using the train data set and then display the explanation.

```
explanation = gfi.explain(model, X, y, case_id='CASE_ID', n_iter=10)
explanation
```

Drop the BreastCancer table.

```
oml.drop('BreastCancer')
```

Listing for This Example

```
>>> import oml
>>> from oml.mlx import GlobalFeatureImportance
```

```
>>> import pandas as pd
>>> import numpy as np
>>> from sklearn import datasets
>>>
>>> bc_ds = datasets.load_breast_cancer()
>>> bc_data = bc_ds.data.astype(float)
>>> X = pd.DataFrame(bc_data, columns=bc_ds.feature_names)
>>> y = pd.DataFrame(bc_ds.target, columns=['TARGET'])
>>> row_id = pd.DataFrame(np.arange(bc_data.shape[0]),
...                       columns=['CASE_ID'])
>>> df = oml.create(pd.concat([X, y, row_id], axis=1),
...                 table='BreastCancer')
>>>
>>> train, test = df.split(ratio=(0.8, 0.2), hash_cols='CASE_ID',
...                        seed=32)
>>> X, y = train.drop('TARGET'), train['TARGET']
>>> X_test, y_test = test.drop('TARGET'), test['TARGET']
>>>
>>> model = oml.algo.rf(ODMS_RANDOM_SEED=32).fit(X, y, case_id='CASE_ID')
...         "RF accuracy score = {:.2f}".format(model.score(X_test, y_test))
'RF accuracy score = 0.95'
>>>
>>> gfi = GlobalFeatureImportance(mining_function='classification',
...                               score_metric='f1', random_state=32,
...                               parallel=4)
>>>
>>> explanation = gfi.explain(model, X, y, case_id='CASE_ID', n_iter=10)
>>> explanation
Global Feature Importance:
[0] worst concave points: Value: 0.0263, Error: 0.0069
[1] worst perimeter: Value: 0.0077, Error: 0.0027
[2] worst radius: Value: 0.0076, Error: 0.0031
[3] worst area: Value: 0.0045, Error: 0.0037
[4] mean concave points: Value: 0.0034, Error: 0.0033
[5] worst texture: Value: 0.0017, Error: 0.0015
[6] area error: Value: 0.0012, Error: 0.0014
[7] worst concavity: Value: 0.0008, Error: 0.0008
[8] worst symmetry: Value: 0.0004, Error: 0.0007
[9] mean texture: Value: 0.0003, Error: 0.0007
[10] mean perimeter: Value: 0.0003, Error: 0.0015
[11] mean radius: Value: 0.0000, Error: 0.0000
[12] mean smoothness: Value: 0.0000, Error: 0.0000
[13] mean compactness: Value: 0.0000, Error: 0.0000
[14] mean concavity: Value: 0.0000, Error: 0.0000
[15] mean symmetry: Value: 0.0000, Error: 0.0000
[16] mean fractal dimension: Value: 0.0000, Error: 0.0000
[17] radius error: Value: 0.0000, Error: 0.0000
[18] texture error: Value: 0.0000, Error: 0.0000
[19] smoothness error: Value: 0.0000, Error: 0.0000
[20] compactness error: Value: 0.0000, Error: 0.0000
[21] concavity error: Value: 0.0000, Error: 0.0000
[22] concave points error: Value: 0.0000, Error: 0.0000
[23] symmetry error: Value: 0.0000, Error: 0.0000
[24] fractal dimension error: Value: 0.0000, Error: 0.0000
[25] worst compactness: Value: 0.0000, Error: 0.0000
[26] worst fractal dimension: Value: 0.0000, Error: 0.0000
```

```
[27] mean area: Value: -0.0001, Error: 0.0011
[28] worst smoothness: Value: -0.0003, Error: 0.0013

oml.drop('BreastCancer')
```

Example 5-5 Multi-Class Classification

This example uses the Iris multi-class classification data set. Load the data set into the database, adding a unique case id column.

```
import oml
from oml.mlx import GlobalFeatureImportance
import pandas as pd
import numpy as np
from sklearn import datasets

iris_ds = datasets.load_iris()
iris_data = iris_ds.data.astype(float)
X = pd.DataFrame(iris_data, columns=iris_ds.feature_names)
y = pd.DataFrame(iris_ds.target, columns=['TARGET'])
row_id = pd.DataFrame(np.arange(iris_data.shape[0]),
                      columns=['CASE_ID'])
df = oml.create(pd.concat([X, y, row_id], axis=1), table='Iris')
```

Split the data set into train and test variables.

```
train, test = df.split(ratio=(0.8, 0.2), hash_cols='CASE_ID',
                       seed=32)
X, y = train.drop('TARGET'), train['TARGET']
X_test, y_test = test.drop('TARGET'), test['TARGET']
```

Train an SVM model.

```
model = oml.algo.svm(ODMS_RANDOM_SEED=32).fit(X, y, case_id='CASE_ID')
"SVM accuracy score = {:.2f}".format(model.score(X_test, y_test))
```

Create the MLX Global Feature Importance explainer, using the `f1_weighted` metric.

```
gfi = GlobalFeatureImportance(mining_function='classification',
                              score_metric='f1_weighted',
                              random_state=32, parallel=4)
```

Run the explainer to generate the global feature importance. Here, we use the test data set. Display the explanation.

```
explanation = gfi.explain(model, X_test, y_test,
                          case_id='CASE_ID', n_iter=10)
explanation
```

Drop the Iris table.

```
oml.drop('Iris')
```

Listing for This Example

```
>>> import oml
>>> from oml.mlx import GlobalFeatureImportance
>>> import pandas as pd
>>> import numpy as np
>>> from sklearn import datasets
>>>
>>> iris_ds = datasets.load_iris()
>>> iris_data = iris_ds.data.astype(float)
>>> X = pd.DataFrame(iris_data, columns=iris_ds.feature_names)
>>> y = pd.DataFrame(iris_ds.target, columns=['TARGET'])
>>> row_id = pd.DataFrame(np.arange(iris_data.shape[0]),
...                       columns=['CASE_ID'])
>>> df = oml.create(pd.concat([X, y, row_id], axis=1), table='Iris')
>>>
>>> train, test = df.split(ratio=(0.8, 0.2), hash_cols='CASE_ID',
...                        seed=32)
>>> X, y = train.drop('TARGET'), train['TARGET']
>>> X_test, y_test = test.drop('TARGET'), test['TARGET']
>>>
>>> model = oml.algo.svm(ODMS_RANDOM_SEED=32).fit(X, y, case_id='CASE_ID')
>>> "SVM accuracy score = {:.2f}".format(model.score(X_test, y_test))
'SVM accuracy score = 0.94'
>>>
>>> gfi = GlobalFeatureImportance(mining_function='classification',
...                               score_metric='f1_weighted',
...                               random_state=32, parallel=4)
>>>
>>> explanation = gfi.explain(model, X_test, y_test,
...                           case_id='CASE_ID', n_iter=10)
>>> explanation
Global Feature Importance:
[0] petal length (cm): Value: 0.3462, Error: 0.0824
[1] petal width (cm): Value: 0.2417, Error: 0.0687
[2] sepal width (cm): Value: 0.0926, Error: 0.0452
[3] sepal length (cm): Value: 0.0253, Error: 0.0152

>>> oml.drop('Iris')
```

Example 5-6 Regression

This example uses the Boston regression data set. Load the data set into the database, adding a unique case id column.

```
import oml
from oml.mlx import GlobalFeatureImportance
import pandas as pd
import numpy as np
from sklearn import datasets

boston_ds = datasets.load_boston()
boston_data = boston_ds.data
X = pd.DataFrame(boston_data, columns=boston_ds.feature_names)
y = pd.DataFrame(boston_ds.target, columns=['TARGET'])
row_id = pd.DataFrame(np.arange(boston_data.shape[0]),
```

```
                        columns=['CASE_ID'])
df = oml.create(pd.concat([X, y, row_id], axis=1), table='Boston')
```

Split the data set into train and test variables.

```
train, test = df.split(ratio=(0.8, 0.2), hash_cols='CASE_ID', seed=32)
X, y = train.drop('TARGET'), train['TARGET']
X_test, y_test = test.drop('TARGET'), test['TARGET']
```

Train a Neural Network regression model.

```
model = oml.algo.nn(mining_function='regression',
                    ODMS_RANDOM_SEED=32).fit(X, y, case_id='CASE_ID')
"NN R^2 score = {:.2f}".format(model.score(X_test, y_test))
```

Create the MLX Global Feature Importance explainer, using the `r2` metric.

```
gfi = GlobalFeatureImportance(mining_function='regression',
                              score_metric='r2', random_state=32,
                              parallel=4)
```

Run the explainer to generate the global feature importance. Here, we use the test data set. Display the explanation.

```
explanation = gfi.explain(model, df, 'TARGET',
                          case_id='CASE_ID', n_iter=10)
explanation
```

Drop the Boston table.

```
oml.drop('Boston')
```

Listing for This Example

```
>>> import oml
>>> from oml.mlx import GlobalFeatureImportance
>>> import pandas as pd
>>> import numpy as np
>>> from sklearn import datasets
>>>
>>> boston_ds = datasets.load_boston()
>>> boston_data = boston_ds.data
>>> X = pd.DataFrame(boston_data, columns=boston_ds.feature_names)
>>> y = pd.DataFrame(boston_ds.target, columns=['TARGET'])
>>> row_id = pd.DataFrame(np.arange(boston_data.shape[0]),
...                       columns=['CASE_ID'])
>>> df = oml.create(pd.concat([X, y, row_id], axis=1), table='Boston')
>>>
>>> train, test = df.split(ratio=(0.8, 0.2), hash_cols='CASE_ID',
...                        seed=32)
>>> X, y = train.drop('TARGET'), train['TARGET']
>>> X_test, y_test = test.drop('TARGET'), test['TARGET']
```

```
>>>
>>> model = oml.algo.nn(mining_function='regression',
..                       ODMS_RANDOM_SEED=32).fit(X, y, case_id='CASE_ID')
>>> "NN R^2 score = {:.2f}".format(model.score(X_test, y_test))
'NN R^2 score = 0.85'
>>>
>>> gfi = GlobalFeatureImportance(mining_function='regression',
...                               score_metric='r2', random_state=32,
...                               parallel=4)
>>>
>>> explanation = gfi.explain(model, df, 'TARGET',
...                           case_id='CASE_ID', n_iter=10)
>>> explanation
Global Feature Importance:
[0] LSTAT: Value: 0.7686, Error: 0.0513
[1] RM: Value: 0.5734, Error: 0.0475
[2] CRIM: Value: 0.5131, Error: 0.0345
[3] DIS: Value: 0.4170, Error: 0.0632
[4] NOX: Value: 0.2592, Error: 0.0206
[5] AGE: Value: 0.2083, Error: 0.0212
[6] RAD: Value: 0.1956, Error: 0.0188
[7] INDUS: Value: 0.1792, Error: 0.0199
[8] B: Value: 0.0982, Error: 0.0146
[9] PTRATIO: Value: 0.0822, Error: 0.0069
[10] TAX: Value: 0.0566, Error: 0.0139
[11] ZN: Value: 0.0397, Error: 0.0081
[12] CHAS: Value: 0.0125, Error: 0.0045

>>> oml.drop('Boston')
```

5.7 Attribute Importance

The `oml.ai` class computes the relative attribute importance, which ranks attributes according to their significance in predicting a classification or regression target.

The `oml.ai` class uses the Minimum Description Length (MDL) algorithm to calculate attribute importance. MDL assumes that the simplest, most compact representation of the data is the best and most probable explanation of the data.

You can use methods of the `oml.ai` class to compute the relative importance of predictor variables when predicting a response variable.

> **Note:**
>
> Oracle Machine Learning does not support the scoring operation for `oml.ai`.

The results of `oml.ai` are the attributes of the build data ranked according to their predictive influence on a specified target attribute. You can use the ranking and the measure of importance for selecting attributes.

For information on the `oml.ai` class attributes and methods, invoke `help(oml.ai)` or see *Oracle Machine Learning for Python API Reference*.

See Also:

- About Model Settings
- Shared Settings

Example 5-7 Ranking Attribute Significance with oml.ai

This example creates the `x` and `y` variables using the iris data set. It then creates the persistent database table IRIS and the `oml.DataFrame` object `oml_iris` as a proxy for the table.

This example demonstrates the use of various methods of the `oml.ai` class.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

try:
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training and test data.
dat = oml.sync(table = 'IRIS').split()
train_x = dat[0].drop('Species')
train _y = dat[0]['Species']
test_dat = dat[1]

# Specify settings.
setting = {'ODMS_SAMPLING':'ODMS_SAMPLING_DISABLE'}

# Create an AI model object.
ai_mod = oml.ai(**setting)

# Fit the AI model according to the training data and parameter
# settings.
ai_mod = ai_mod.fit(train_x, train_y)

# Show the model details.
ai_mod
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
... except:
...    pass
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Create training and test data.
... dat = oml.sync(table = 'IRIS').split()
>>> train_x = dat[0].drop('Species')
>>> train_y = dat[0]['Species']
>>> test_dat = dat[1]
>>>
>>> # Specify settings.
... setting = {'ODMS_SAMPLING':'ODMS_SAMPLING_DISABLE'}
>>>
>>> # Create an AI model object.
... ai_mod = oml.ai(**setting)
>>>
>>> # Fit the AI model according to the training data and parameter
... # settings.
>>> ai_mod = ai_mod.fit(train_x, train_y)
>>>
>>> # Show the model details.
... ai_mod

Algorithm Name: Attribute Importance

Mining Function: ATTRIBUTE_IMPORTANCE

Settings:
                    setting name            setting value
0                      ALGO_NAME              ALGO_AI_MDL
1                   ODMS_DETAILS              ODMS_ENABLE
2  ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
3                  ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
4                      PREP_AUTO                       ON

Global Statistics:
```

```
   attribute name     attribute value
0        NUM_ROWS                 104

Attributes:
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width

Partition: NO

Importance:

       variable  importance  rank
0   Petal_Width    0.615851     1
1  Petal_Length    0.362519     2
2  Sepal_Length    0.042751     3
3   Sepal_Width   -0.155867     4
```

5.8 Association Rules

The `oml.ar` class implements the Apriori algorithm to find frequent itemsets and association rules, all as part of an association model object.

The Apriori algorithm is efficient and scales well with respect to the number of transactions, number of items, and number of itemsets and rules produced.

Use the `oml.ar` class to identify frequent itemsets within large volumes of transactional data, such as in market basket analysis. The results of an association model are the rules that identify patterns of association within the data.

An association rule identifies a pattern in the data in which the appearance of a set of items in a transactional record implies another set of items. The groups of items used to form rules must pass a minimum threshold according to how often they occur (the *support* of the rule) and how often the consequent follows the antecedent (the *confidence* of the rule). Association models generate all rules that have support and confidence greater than user-specified thresholds.

Oracle Machine Learning does not support the scoring operation for association modeling.

For information on the `oml.ar` class attributes and methods, invoke `help(oml.ar)` or see *Oracle Machine Learning for Python API Reference*.

Settings for an Association Rules Model

The following table lists the settings applicable to association rules models.

Table 5-3 Association Rules Models Settings

Setting Name	Setting Value	Description
ASSO_ABS_ERROR	0<ASSO_ABS_ERRORMAX(ASSO_MIN_SUPPORT, ASSO_MIN_CONFIDENCE)	Specifies the absolute error for the association rules sampling. A smaller value of ASSO_ABS_ERROR obtains a larger sample size that gives accurate results but takes longer to compute. Set a reasonable value for ASSO_ABS_ERROR, such as the default value, to avoid too large a sample size. The default value is 0.5 * MAX(ASSO_MIN_SUPPORT, ASSO_MIN_CONFIDENCE).
ASSO_AGGREGATES	NULL	Specifies the columns to aggregate. It is a comma separated list of strings containing the names of the columns for aggregation. The number of columns in the list must be <= 10. You can set ASSO_AGGREGATES if you have specified a column name with ODMS_ITEM_ID_COLUMN_NAME. The data table must have valid column names such as ITEM_ID and CASE_ID which are derived from ODMS_ITEM_ID_COLUMN_NAME. An item value is not mandatory. The default value is NULL. For each item, you may supply several columns to aggregate. However, doing so requires more memory to buffer the extra data and also affects performance because of the larger input data set and increased operations.
ASSO_ANT_IN_RULES	NULL	Sets Including Rules for the antecedent: it is a comma separated list of strings, at least one of which must appear in the antecedent part of each reported association rule. The default value is NULL.
ASSO_ANT_EX_RULES	NULL	Sets Excluding Rules for the antecedent: it is a comma separated list of strings, none of which can appear in the antecedent part of each reported association rule. The default value is NULL.
ASSO_CONF_LEVEL	0 ASSO_CONF_LEVEL 1	Specifies the confidence level for an association rules sample. A larger value of ASSO_CONF_LEVEL obtains a larger sample size. Any value between 0.9 and 1 is suitable. The default value is 0.95.

Table 5-3 (Cont.) Association Rules Models Settings

Setting Name	Setting Value	Description
ASSO_CONS_IN_RULES	NULL	Sets Including Rules for the consequent: it is a comma separated list of strings, at least one of which must appear in the consequent part of each reported association rule. The default value is NULL.
ASSO_CONS_EX_RULES	NULL	Sets Excluding Rules for the consequent: it is a comma separated list of strings, none of which can appear in the consequent part of a reported association rule. You can use the excluding rule to reduce the data that must be stored, but you may be required to build extra models for executing different Including or Excluding Rules. The default value is NULL.
ASSO_EX_RULES	NULL	Sets Excluding Rules applied for each association rule: it is a comma separated list of strings that cannot appear in an association rule. No rule can contain any item in the list. The default value is NULL.
ASSO_IN_RULES	NULL	Sets Including Rules applied for each association rule: it is a comma separated list of strings, at least one of which must appear in each reported association rule, either as antecedent or as consequent The default value NULL, which specifies that filtering is not applied.
ASSO_MAX_RULE_LENGTH	TO_CHAR(2<= *numeric_expr* <=20)	Maximum rule length for association rules. The default value is 4.
ASSO_MIN_CONFIDENCE	TO_CHAR(0<= *numeric_expr* <=1)	Minimum confidence for association rules. The default value is 0.1.
ASSO_MIN_REV_CONFIDENCE	TO_CHAR(0<= *numeric_expr* <=1)	Sets the Minimum Reverse Confidence that each rule should satisfy. The Reverse Confidence of a rule is defined as the number of transactions in which the rule occurs divided by the number of transactions in which the consequent occurs. The value is real number between 0 and 1. The default value is 0.
ASSO_MIN_SUPPORT	TO_CHAR(0<= *numeric_expr* <=1)	Minimum support for association rules. The default value is 0.1.
ASSO_MIN_SUPPORT_INT	TO_CHAR(0<= *numeric_expr* <=1)	Minimum absolute support that each rule must satisfy. The value must be an integer. The default value is 1.

Table 5-3 (Cont.) Association Rules Models Settings

Setting Name	Setting Value	Description
ASSO_CONS_EX_RULES		
ODMS_ITEM_ID_COLUMN_NAME	*column_name*	The name of a column that contains the items in a transaction. When you specify this setting, the algorithm expects the data to be presented in native transactional format, consisting of two columns: • Case ID, either categorical or numeric • Item ID, either categorical or numeric
ODMS_ITEM_VALUE_COLUMN_ NAME	*column_name*	The name of a column that contains a value associated with each item in a transaction. Use this setting only when you have specified a value for ODMS_ITEM_ID_COLUMN_NAME, indicating that the data is presented in native transactional format. If you also use ASSO_AGGREGATES, then the build data must include the following three columns and the columns specified in the AGGREGATES setting. • Case ID, either categorical or numeric • Item ID, either categorical or numeric, specified by ODMS_ITEM_ID_COLUMN_NAME • Item value, either categorical or numeric, specified by ODMS_ITEM_VALUE_COLUMN_ NAME If ASSO_AGGREGATES, Case ID, and Item ID columns are present, then the Item Value column may or may not appear. The Item Value column may specify information such as the number of items (for example, three apples) or the type of the item (for example, macintosh apples).

See Also:

- About Model Settings
- Shared Settings

Example 5-8 Using the oml.ar Class

This example uses methods of the `oml.ar` class.

```
import pandas as pd
from sklearn import datasets
import oml

# Load the iris data set and create a pandas.DataFrame for it.
```

```
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species']))

try:
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training data.
train_dat = oml.sync(table = 'IRIS')

# Specify settings.
setting = {'asso_min_support':'0.1', 'asso_min_confidence':'0.1'}

# Create an AR model object.
ar_mod = oml.ar(**setting)

# Fit the model according to the training data and parameter
# settings.
ar_mod = ar_mod.fit(train_dat)

# Show details of the model.
ar_mod
```

Listing for This Example

```
>>> import pandas as pd
>>> from sklearn import datasets
>>> import oml
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
... except:
...    pass
>>>
>>> # Create the IRIS database table.
```

```
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Create training data.
... train_dat = oml.sync(table = 'IRIS')
>>>
>>> # Specify settings.
... setting = {'asso_min_support':'0.1', 'asso_min_confidence':'0.1'}
>>>
>>> # Create an AR model object.
... ar_mod = oml.ar(**setting)
>>>
>>> # Fit the model according to the training data and parameter
... # settings.
>>> ar_mod = ar_mod.fit(train_dat)
>>>
>>> # Show details of the model.
... ar_mod

Algorithm Name: Association Rules

Mining Function: ASSOCIATION

Settings:
                   setting name                    setting value
0                     ALGO_NAME  ALGO_APRIORI_ASSOCIATION_RULES
1          ASSO_MAX_RULE_LENGTH                                4
2           ASSO_MIN_CONFIDENCE                              0.1
3       ASSO_MIN_REV_CONFIDENCE                                0
4              ASSO_MIN_SUPPORT                              0.1
5          ASSO_MIN_SUPPORT_INT                                1
6                  ODMS_DETAILS                      ODMS_ENABLE
7  ODMS_MISSING_VALUE_TREATMENT         ODMS_MISSING_VALUE_AUTO
8                 ODMS_SAMPLING           ODMS_SAMPLING_DISABLE
9                     PREP_AUTO                              ON

Global Statistics:
     attribute name  attribute value
0     ITEMSET_COUNT         6.000000
1       MAX_SUPPORT         0.333333
2          NUM_ROWS       150.000000
3        RULE_COUNT         2.000000
4 TRANSACTION_COUNT       150.000000

Attributes:
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width
Species

Partition: NO

Itemsets:

   ITEMSET_ID   SUPPORT  NUMBER_OF_ITEMS    ITEM_NAME          ITEM_VALUE
0           1  0.193333                1  Petal_Width  .20000000000000001
```

```
1           2  0.173333               1  Sepal_Width                  3
2           3  0.333333               1      Species             setosa
3           4  0.333333               1      Species         versicolor
4           5  0.333333               1      Species          virginica
5           6  0.193333               2  Petal_Width  .20000000000000001
6           6  0.193333               2      Species             setosa

Rules:

   RULE_ID  NUMBER_OF_ITEMS     LHS_NAME           LHS_VALUE     RHS_NAME  \
0        1                2      Species              setosa  Petal_Width
1        2                2  Petal_Width  .20000000000000001      Species

  RHS_VALUE   SUPPORT  CONFIDENCE  REVCONFIDENCE  LIFT
0      None  0.186667        0.58           1.00     3
1      None  0.186667        1.00           0.58     3
```

5.9 Decision Tree

The `oml.dt` class uses the Decision Tree algorithm for classification.

Decision Tree models are classification models that contain axis-parallel rules. A rule is a conditional statement that can be understood by humans and may be used within a database to identify a set of records.

A decision tree predicts a target value by asking a sequence of questions. At a given stage in the sequence, the question that is asked depends upon the answers to the previous questions. The goal is to ask questions that, taken together, uniquely identify specific target values. Graphically, this process forms a tree structure.

During the training process, the Decision Tree algorithm must repeatedly find the most efficient way to split a set of cases (records) into two child nodes. The `oml.dt` class offers two homogeneity metrics, gini and entropy, for calculating the splits. The default metric is gini.

For information on the `oml.dt` class attributes and methods, invoke `help(oml.dt)` or see *Oracle Machine Learning for Python API Reference*.

Settings for a Decision Tree Model

The following table lists settings that apply to Decision Tree models.

Table 5-4 Decision Tree Model Settings

Setting Name	Setting Value	Description
CLAS_COST_TABLE_NAME	*table_name*	The name of a table that stores a cost matrix for the algorithm to use in building and applying the model. The cost matrix specifies the costs associated with misclassifications. The cost matrix table is user-created. The following are the column requirements for the table. • Column Name: ACTUAL_TARGET_VALUE Data Type: Valid target data type • Column Name: PREDICTED_TARGET_VALUE Data Type: Valid target data type • Column Name: COST Data Type: NUMBER
CLAS_MAX_SUP_BINS	2 <= *a number* <= 2147483647	Specifies the maximum number of bins for each attribute. The default value is 32.
CLAS_WEIGHTS_BALANCED	ON OFF	Indicates whether the algorithm must create a model that balances the target distribution. This setting is most relevant in the presence of rare targets, as balancing the distribution may enable better average accuracy (average of per-class accuracy) instead of overall accuracy (which favors the dominant class). The default value is OFF.
TREE_IMPURITY_METRIC	TREE_IMPURITY_ENTROPY TREE_IMPURITY_GINI	Tree impurity metric for a Decision Tree model. Tree algorithms seek the best test question for splitting data at each node. The best splitter and split value are those that result in the largest increase in target value homogeneity (purity) for the entities in the node. Purity is measured in accordance with a metric. Decision trees can use either gini (TREE_IMPURITY_GINI) or entropy (TREE_IMPURITY_ENTROPY) as the purity metric. By default, the algorithm uses TREE_IMPURITY_GINI.
TREE_TERM_MAX_DEPTH	2 <= *a number* <= 100	Criteria for splits: maximum tree depth (the maximum number of nodes between the root and any leaf node, including the leaf node). The default is 7.
TREE_TERM_MINPCT_NODE	0< = *a number* <= 10	The minimum number of training rows in a node expressed as a percentage of the rows in the training data. The default value is 0.05, indicating 0.05%.

Table 5-4 (Cont.) Decision Tree Model Settings

Setting Name	Setting Value	Description
TREE_TERM_MINPCT_SPLIT	0 < *a number* <= 20	Minimum number of rows required to consider splitting a node expressed as a percentage of the training rows. The default value is 0.1, indicating 0.1%.
TREE_TERM_MINREC_NODE	*A number* >= 0	Minimum number of rows in a node. The default value is 10.
TREE_TERM_MINREC_SPLIT	*A number* > 1	Criteria for splits: minimum number of records in a parent node expressed as a value. No split is attempted if the number of records is below this value. The default value is 20.

See Also:

- About Model Settings
- Shared Settings

Example 5-9 Using the oml.dt Class

This example demonstrates the use of various methods of the `oml.dt` class. In the listing for this example, some of the output is not shown as indicated by ellipses.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

try:
    oml.drop('COST_MATRIX')
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create  training and test data.
dat = oml.sync(table = 'IRIS').split()
```

```
train_x = dat[0].drop('Species')
train_y = dat[0]['Species']
test_dat = dat[1]

# Create a cost matrix table in the database.
cost_matrix = [['setosa', 'setosa', 0],
               ['setosa', 'virginica', 0.2],
               ['setosa', 'versicolor', 0.8],
               ['virginica', 'virginica', 0],
               ['virginica', 'setosa', 0.5],
               ['virginica', 'versicolor', 0.5],
               ['versicolor', 'versicolor', 0],
               ['versicolor', 'setosa', 0.4],
               ['versicolor', 'virginica', 0.6]]
cost_matrix = oml.create(
  pd.DataFrame(cost_matrix,
               columns = ['ACTUAL_TARGET_VALUE',
                          'PREDICTED_TARGET_VALUE', 'COST']),
               table = 'COST_MATRIX')

# Specify settings.
setting = {'TREE_TERM_MAX_DEPTH':'2'}

# Create a DT model object.
dt_mod = oml.dt(**setting)

# Fit the DT model according to the training data and parameter
# settings.
dt_mod.fit(train_x, train_y, cost_matrix = cost_matrix)

# Use the model to make predictions on the test data.
dt_mod.predict(test_dat.drop('Species'),
               supplemental_cols = test_dat[:, ['Sepal_Length',
                                                'Sepal_Width',
                                                'Petal_Length',
                                                'Species']])

# Return the prediction probability.
dt_mod.predict(test_dat.drop('Species'),
               supplemental_cols = test_dat[:, ['Sepal_Length',
                                                'Sepal_Width',
                                                'Species']],
               proba = True)

# Make predictions and return the probability for each class
# on new data.
dt_mod.predict_proba(test_dat.drop('Species'),
                     supplemental_cols = test_dat[:,
                       ['Sepal_Length',
                        'Species']]).sort_values(by = ['Sepal_Length',
                                                       'Species'])

dt_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> try:
...    oml.drop('COST_MATRIX')
...    oml.drop('IRIS')
... except:
...    pass
>>>
>>> # Create training and test data.
... dat = oml.sync(table = 'IRIS').split()
>>> train_x = dat[0].drop('Species')
>>> train_y = dat[0]['Species']
>>> test_dat = dat[1]
>>>
>>> # Create a cost matrix table in the database.
... cost_matrix = [['setosa', 'setosa', 0],
...                ['setosa', 'virginica', 0.2],
...                ['setosa', 'versicolor', 0.8],
...                ['virginica', 'virginica', 0],
...                ['virginica', 'setosa', 0.5],
...                ['virginica', 'versicolor', 0.5],
...                ['versicolor', 'versicolor', 0],
...                ['versicolor', 'setosa', 0.4],
...                ['versicolor', 'virginica', 0.6]]
>>> cost_matrix = oml.create(
...  pd.DataFrame(cost_matrix,
...               columns = ['ACTUAL_TARGET_VALUE',
...                          'PREDICTED_TARGET_VALUE',
...                          'COST']),
...               table = 'COST_MATRIX')
>>>
>>> # Specify settings.
... setting = {'TREE_TERM_MAX_DEPTH':'2'}
>>>
>>> # Create a DT model object.
... dt_mod = oml.dt(**setting)
>>>
>>> # Fit the DT model according to the training data and parameter
... # settings.
```

```
>>> dt_mod.fit(train_x, train_y, cost_matrix = cost_matrix)

Algorithm Name: Decision Tree

Mining Function: CLASSIFICATION

Target: Species

Settings:
                      setting name            setting value
0                        ALGO_NAME       ALGO_DECISION_TREE
1            CLAS_COST_TABLE_NAME "OML_USER"."COST_MATRIX"
2               CLAS_MAX_SUP_BINS                       32
3           CLAS_WEIGHTS_BALANCED                      OFF
4                    ODMS_DETAILS              ODMS_ENABLE
5    ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
6                   ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
7                       PREP_AUTO                       ON
8            TREE_IMPURITY_METRIC       TREE_IMPURITY_GINI
9             TREE_TERM_MAX_DEPTH                        2
10          TREE_TERM_MINPCT_NODE                      .05
11         TREE_TERM_MINPCT_SPLIT                       .1
12          TREE_TERM_MINREC_NODE                       10
13         TREE_TERM_MINREC_SPLIT                       20

Global Statistics:
   attribute name  attribute value
0        NUM_ROWS              104

Attributes:
Petal_Length
Petal_Width

Partition: NO

Distributions:

   NODE_ID TARGET_VALUE  TARGET_COUNT
0        0       setosa            36
1        0   versicolor            35
2        0    virginica            33
3        1       setosa            36
4        2   versicolor            35
5        2    virginica            33

Nodes:

   parent  node.id  row.count  prediction  \
0     0.0        1         36      setosa
1     0.0        2         68  versicolor
2     NaN        0        104      setosa

                                        split  \
0  (Petal_Length <=(2.4500000000000002E+000))
1   (Petal_Length >(2.4500000000000002E+000))
2                                        None
```

```
                                    surrogate  \
0  Petal_Width <=(8.0000000000000004E-001))
1   Petal_Width >(8.0000000000000004E-001))
2                                       None

                                    full.splits
0  (Petal_Length <=(2.4500000000000002E+000))
1   (Petal_Length >(2.4500000000000002E+000))
2                                           (
>>>
>>> # Use the model to make predictions on the test data.
... dt_mod.predict(test_dat.drop('Species'),
...                supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                 'Sepal_Width',
...                                                 'Petal_Length',
...                                                 'Species']])
    Sepal_Length  Sepal_Width  Petal_Length     Species  PREDICTION
0            4.9          3.0           1.4      setosa      setosa
1            4.9          3.1           1.5      setosa      setosa
2            4.8          3.4           1.6      setosa      setosa
3            5.8          4.0           1.2      setosa      setosa
...          ...          ...           ...         ...         ...
44           6.7          3.3           5.7   virginica  versicolor
45           6.7          3.0           5.2   virginica  versicolor
46           6.5          3.0           5.2   virginica  versicolor
47           5.9          3.0           5.1   virginica  versicolor
>>>
>>> # Return the prediction probability.
... dt_mod.predict(test_dat.drop('Species'),
...                supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                 'Sepal_Width',
...                                                 'Species']],
...                proba = True)
    Sepal_Length  Sepal_Width     Species  PREDICTION  PROBABILITY
0            4.9          3.0      setosa      setosa     1.000000
1            4.9          3.1      setosa      setosa     1.000000
2            4.8          3.4      setosa      setosa     1.000000
3            5.8          4.0      setosa      setosa     1.000000
...          ...          ...         ...         ...          ...
44           6.7          3.3   virginica  versicolor     0.514706
45           6.7          3.0   virginica  versicolor     0.514706
46           6.5          3.0   virginica  versicolor     0.514706
47           5.9          3.0   virginica  versicolor     0.514706

>>> # Make predictions and return the probability for each class
>>> # on new data.
>>> dt_mod.predict_proba(test_dat.drop('Species'),
...                      supplemental_cols = test_dat[:,
...                        ['Sepal_Length',
...                         'Species']]).sort_values(by = ['Sepal_Length',
...                                                       'Species'])
    Sepal_Length     Species  PROBABILITY_OF_SETOSA  \
0            4.4      setosa                    1.0
1            4.4      setosa                    1.0
2            4.5      setosa                    1.0
```

```
3            4.8      setosa                    1.0
...          ...         ...                    ...
42           6.7   virginica                    0.0
43           6.9  versicolor                    0.0
44           6.9   virginica                    0.0
45           7.0  versicolor                    0.0

    PROBABILITY_OF_VERSICOLOR  PROBABILITY_OF_VIRGINICA
0                    0.000000                 0.000000
1                    0.000000                 0.000000
2                    0.000000                 0.000000
3                    0.000000                 0.000000
...                       ...                      ...
42                   0.514706                 0.485294
43                   0.514706                 0.485294
44                   0.514706                 0.485294
45                   0.514706                 0.485294
>>>
>>> dt_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])
0.645833
```

5.10 Expectation Maximization

The `oml.em` class uses the Expectation Maximization (EM) algorithm to create a clustering model.

EM is a density estimation algorithm that performs probabilistic clustering. In density estimation, the goal is to construct a density function that captures how a given population is distributed. The density estimate is based on observed data that represents a sample of the population.

For information on the `oml.em` class methods, invoke `help(oml.em)` or see *Oracle Machine Learning for Python API Reference*.

Settings for an Expectation Maximization Model

The following table lists settings for data preparation and analysis for `EM` models.

Table 5-5 Expectation Maximization Settings for Data Preparation and Analysis

Setting Name	Setting Value	Description
EMCS_ATTRIBUTE_FILTER	EMCS_ATTR_FILTER_ENABLE EMCS_ATTR_FILTER_DISABLE	Whether or not to include uncorrelated attributes in the model. When EMCS_ATTRIBUTE_FILTER is enabled, uncorrelated attributes are not included. **Note:** This setting applies only to attributes that are not nested. The default value is system-determined.
EMCS_MAX_NUM_ATTR_2D	TO_CHAR(*numeric_expr* >= 1)	Maximum number of correlated attributes to include in the model. **Note:** This setting applies only to attributes that are not nested (2D). The default value is 50.
EMCS_NUM_DISTRIBUTION	EMCS_NUM_DISTR_BERNOULLI EMCS_NUM_DISTR_GAUSSIAN EMCS_NUM_DISTR_SYSTEM	The distribution for modeling numeric attributes. Applies to the input table or view as a whole and does not allow per-attribute specifications. The options include Bernoulli, Gaussian, or system-determined distribution. When Bernoulli or Gaussian distribution is chosen, all numeric attributes are modeled using the same type of distribution. When the distribution is system-determined, individual attributes may use different distributions (either Bernoulli or Gaussian), depending on the data. The default value is EMCS_NUM_DISTR_SYSTEM.

Table 5-5 (Cont.) Expectation Maximization Settings for Data Preparation and Analysis

Setting Name	Setting Value	Description
EMCS_NUM_EQUIWIDTH_BINS	TO_CHAR(1 <*numeric_expr* <= 255)	Number of equi-width bins that will be used for gathering cluster statistics for numeric columns. The default value is 11.
EMCS_NUM_PROJECTIONS	TO_CHAR(*numeric_expr* >= 1)	Specifies the number of projections to use for each nested column. If a column has fewer distinct attributes than the specified number of projections, then the data is not projected. The setting applies to all nested columns. The default value is 50.
EMCS_NUM_QUANTILE_BINS	TO_CHAR(1 < *numeric_expr* <= 255)	Specifies the number of quantile bins to use for modeling numeric columns with multivalued Bernoulli distributions. The default value is system-determined.
EMCS_NUM_TOPN_BINS	TO_CHAR(1 < *numeric_expr* <= 255)	Specifies the number of top-N bins to use for modeling categorical columns with multivalued Bernoulli distributions. The default value is system-determined.

The following table lists settings for learning for EM models.

Table 5-6 Expectation Maximization Settings for Learning

Setting Name	Setting Value	Description
EMCS_CONVERGENCE_CRITERION	EMCS_CONV_CRIT_HELDASIDE EMCS_CONV_CRIT_BIC	The convergence criterion for EM. The convergence criterion may be based on a held-aside data set or it may be Bayesian Information Criterion. The default value is system determined.
EMCS_LOGLIKE_IMPROVEMENT	TO_CHAR(0 < *numeric_expr* < 1)	When the convergence criterion is based on a held-aside data set (EMCS_CONVERGENCE_CRITERION = EMCS_CONV_CRIT_HELDASIDE), this setting specifies the percentage improvement in the value of the log likelihood function that is required for adding a new component to the model.
EMCS_MODEL_SEARCH	EMCS_MODEL_SEARCH_ENABLE EMCS_MODEL_SEARCH_DISABLE	Enables model search in EM where different model sizes are explored and the best size is selected. The default value is EMCS_MODEL_SEARCH_DISABLE.

Table 5-6 (Cont.) Expectation Maximization Settings for Learning

Setting Name	Setting Value	Description
EMCS_NUM_COMPONENTS	TO_CHAR(*numeric_expr* >= 1)	Maximum number of components in the model. If model search is enabled, the algorithm automatically determines the number of components based on improvements in the likelihood function or based on regularization, up to the specified maximum. The number of components must be greater than or equal to the number of clusters. The default value is 20.
EMCS_NUM_ITERATIONS	TO_CHAR(*numeric_expr* >= 1)	Specifies the maximum number of iterations in the EM algorithm. The default value is 100.
EMCS_RANDOM_SEED	Non-negative integer	Controls the seed of the random generator used in EM. The default value is 0.
EMCS_REMOVE_COMPONENTS	EMCS_REMOVE_COMPS_ENABLE EMCS_REMOVE_COMPS_DISABLE	Allows the EM algorithm to remove a small component from the solution. The default value is EMCS_REMOVE_COMPS_ENABLE.

The following table lists the settings for component clustering for EM models.

Table 5-7 Expectation Maximization Settings for Component Clustering

Setting Name	Setting Value	Description
CLUS_NUM_CLUSTERS	*TO_CHAR(numeric_expr* >= 1)	The maximum number of leaf clusters generated by the algorithm. The algorithm may return fewer clusters than the specified number, depending on the data. but it cannot return more clusters than the number of components, which is governed by algorithm-specific settings. (See Table 5-6.) Depending on these settings, there may be fewer clusters than components. If component clustering is disabled, then the number of clusters equals the number of components. The default value is system-determined.

Table 5-7 (Cont.) Expectation Maximization Settings for Component Clustering

Setting Name	Setting Value	Description
EMCS_CLUSTER_COMPONENTS	EMCS_CLUSTER_COMP_ENABLE EMCS_CLUSTER_COMP_DISABLE	Enables or disables the grouping of EM components into high-level clusters. When disabled, the components themselves are treated as clusters. When component clustering is enabled, model scoring through the SQL CLUSTER function produces assignments to the higher level clusters. When clustering is disabled, the CLUSTER function produces assignments to the original components. The default value is EMCS_CLUSTER_COMP_ENABLE.
EMCS_CLUSTER_THRESH	TO_CHAR(*numeric_expr* >= 1)	Dissimilarity threshold that controls the clustering of EM components. When the dissimilarity measure is less than the threshold, the components are combined into a single cluster. A lower threshold may produce more clusters that are more compact. A higher threshold may produce fewer clusters that are more spread out. The default value is 2.
EMCS_LINKAGE_FUNCTION	EMCS_LINKAGE_SINGLE EMCS_LINKAGE_AVERAGE EMCS_LINKAGE_COMPLETE	Allows the specification of a linkage function for the agglomerative clustering step. EMCS_LINKAGE_SINGLE uses the nearest distance within the branch. The clusters tend to be larger and have arbitrary shapes. EMCS_LINKAGE_AVERAGE uses the average distance within the branch. There is less chaining effect and the clusters are more compact. EMCS_LINKAGE_COMPLETE uses the maximum distance within the branch. The clusters are smaller and require strong component overlap. The default value is EMCS_LINKAGE_SINGLE.

The following table lists the settings for cluster statistics for EM models.

Table 5-8 Expectation Maximization Settings for Cluster Statistics

Setting Name	Setting Value	Description
EMCS_CLUSTER_STATISTICS	EMCS_CLUS_STATS_ENABLE EMCS_CLUS_STATS_DISABLE	Enables or disables the gathering of descriptive statistics for clusters (centroids, histograms, and rules). When statistics are disabled, model size is reduced. The default value is EMCS_CLUS_STATS_ENABLE.
EMCS_MIN_PCT_ATTR_SUPPORT	TO_CHAR(0 < *numeric_expr* < 1)	Minimum support required for including an attribute in the cluster rule. The support is the percentage of the data rows assigned to a cluster that must have non-null values for the attribute. The default value is 0.1.

See Also:

- About Model Settings
- Shared Settings

Example 5-10 Using the oml.em Class

This example creates an EM model and uses some of the methods of the `oml.em` class.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

try:
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training and test data.
dat = oml.sync(table = 'IRIS').split()
```

```
train_dat = dat[0]
test_dat = dat[1]

# Specify settings.
setting = {'emcs_num_iterations': 100}

# Create an EM model object
em_mod = oml.em(n_clusters = 2, **setting)

# Fit the EM model according to the training data and parameter
# settings.
em_mod = em_mod.fit(train_dat)

# Show details of the model.
em_mod

# Use the model to make predictions on the test data.
em_mod.predict(test_dat)

# Make predictions and return the probability for each class
# on new data.
em_mod.predict_proba(test_dat,
  supplemental_cols = test_dat[:,
    ['Sepal_Length', 'Sepal_Width',
     'Petal_Length']]).sort_values(by = ['Sepal_Length',
       'Sepal_Width',  'Petal_Length',
       'PROBABILITY_OF_2', 'PROBABILITY_OF_3'])

# Change the random seed and refit the model.
em_mod.set_params(EMCS_RANDOM_SEED = '5').fit(train_dat)
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
... except:
...    pass
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
```

```
>>> # Create training and test data.
... dat = oml.sync(table = 'IRIS').split()
>>> train_dat = dat[0]
>>> test_dat = dat[1]
>>>
>>> # Specify settings.
... setting = {'emcs_num_iterations': 100}
>>>
>>> # Create an EM model object.
... em_mod = oml.em(n_clusters = 2, **setting)
>>>
>>> # Fit the EM model according to the training data and parameter
... # settings.
>>> em_mod = em_mod.fit(train_dat)
>>>
>>> # Show details of the model.
... em_mod

Algorithm Name: Expectation Maximization

Mining Function: CLUSTERING

Settings:
                     setting name                    setting value
0                       ALGO_NAME  ALGO_EXPECTATION_MAXIMIZATION
1             CLUS_NUM_CLUSTERS                                2
2        EMCS_CLUSTER_COMPONENTS       EMCS_CLUSTER_COMP_ENABLE
3        EMCS_CLUSTER_STATISTICS         EMCS_CLUS_STATS_ENABLE
4            EMCS_CLUSTER_THRESH                              2
5          EMCS_LINKAGE_FUNCTION            EMCS_LINKAGE_SINGLE
6       EMCS_LOGLIKE_IMPROVEMENT                           .001
7           EMCS_MAX_NUM_ATTR_2D                             50
8      EMCS_MIN_PCT_ATTR_SUPPORT                             .1
9              EMCS_MODEL_SEARCH      EMCS_MODEL_SEARCH_DISABLE
10           EMCS_NUM_COMPONENTS                             20
11         EMCS_NUM_DISTRIBUTION          EMCS_NUM_DISTR_SYSTEM
12       EMCS_NUM_EQUIWIDTH_BINS                             11
13           EMCS_NUM_ITERATIONS                            100
14          EMCS_NUM_PROJECTIONS                             50
15              EMCS_RANDOM_SEED                              0
16        EMCS_REMOVE_COMPONENTS       EMCS_REMOVE_COMPS_ENABLE
17                   ODMS_DETAILS                   ODMS_ENABLE
18  ODMS_MISSING_VALUE_TREATMENT        ODMS_MISSING_VALUE_AUTO
19                 ODMS_SAMPLING          ODMS_SAMPLING_DISABLE
20                     PREP_AUTO                             ON

Computed Settings:
                setting name             setting value
0       EMCS_ATTRIBUTE_FILTER  EMCS_ATTR_FILTER_DISABLE
1  EMCS_CONVERGENCE_CRITERION        EMCS_CONV_CRIT_BIC
2      EMCS_NUM_QUANTILE_BINS                         3
3          EMCS_NUM_TOPN_BINS                         3

Global Statistics:
       attribute name  attribute value
0           CONVERGED              YES
```

```
1       LOGLIKELIHOOD         -2.10044
2        NUM_CLUSTERS                2
3      NUM_COMPONENTS                8
4            NUM_ROWS              104
5         RANDOM_SEED                0
6  REMOVED_COMPONENTS               12

Attributes:
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width
Species

Partition: NO

Clusters:

   CLUSTER_ID  CLUSTER_NAME  RECORD_COUNT  PARENT  TREE_LEVEL \
0           1             1           104     NaN           1
1           2             2            68     1.0           2
2           3             3            36     1.0           2
  LEFT_CHILD_ID  RIGHT_CHILD_ID
0           2.0             3.0
1           NaN             NaN
2           NaN             NaN

Taxonomy:

   PARENT_CLUSTER_ID  CHILD_CLUSTER_ID
0                  1               2.0
1                  1               3.0
2                  2               NaN
3                  3               NaN

Centroids:

    CLUSTER_ID ATTRIBUTE_NAME      MEAN  MODE_VALUE  VARIANCE
0            1   Petal_Length  3.721154        None  3.234694
1            1    Petal_Width  1.155769        None  0.567539
2            1   Sepal_Length  5.831731        None  0.753255
3            1    Sepal_Width  3.074038        None  0.221358
4            1        Species       NaN      setosa       NaN
5            2   Petal_Length  4.902941        None  0.860588
6            2    Petal_Width  1.635294        None  0.191572
7            2   Sepal_Length  6.266176        None  0.545555
8            2    Sepal_Width  2.854412        None  0.128786
9            2        Species       NaN  versicolor       NaN
10           3   Petal_Length  1.488889        None  0.033016
11           3    Petal_Width  0.250000        None  0.012857
12           3   Sepal_Length  5.011111        None  0.113016
13           3    Sepal_Width  3.488889        None  0.134159
14           3        Species       NaN      setosa       NaN

Leaf Cluster Counts:
```

```
   CLUSTER_ID  CNT
0           2   68
1           3   36

Attribute Importance:

  ATTRIBUTE_NAME  ATTRIBUTE_IMPORTANCE_VALUE  ATTRIBUTE_RANK
0   Petal_Length                    0.558311               2
1    Petal_Width                    0.556300               3
2   Sepal_Length                    0.469978               4
3    Sepal_Width                    0.196211               5
4        Species                    0.612463               1

Components:

   COMPONENT_ID  CLUSTER_ID  PRIOR_PROBABILITY
0             1           2           0.115366
1             2           2           0.079158
2             3           3           0.113448
3             4           2           0.148059
4             5           3           0.126979
5             6           2           0.134402
6             7           3           0.105727
7             8           2           0.176860

Cluster Hists:

     cluster.id            variable  bin.id  lower.bound  upper.bound  \
0             1        Petal_Length       1         1.00         1.59
1             1        Petal_Length       2         1.59         2.18
2             1        Petal_Length       3         2.18         2.77
3             1        Petal_Length       4         2.77         3.36
...         ...                 ...     ...          ...          ...
137           3         Sepal_Width      11          NaN          NaN
138           3     Species:'Other'       1          NaN          NaN
139           3      Species:setosa       2          NaN          NaN
140           3  Species:versicolor       3          NaN          NaN

         label  count
0       1:1.59     25
1    1.59:2.18     11
2    2.18:2.77      0
3    2.77:3.36      3
...        ...    ...
137          :      0
138          :      0
139          :     36
140          :      0

[141 rows x 7 columns]

Rules:

    cluster.id  rhs.support  rhs.conf  lhr.support  lhs.conf       lhs.var  \
0            1          104  1.000000           93  0.892157   Sepal_Width
1            1          104  1.000000           93  0.892157   Sepal_Width
```

```
2            1          104  1.000000           99  0.892157  Petal_Length
3            1          104  1.000000           99  0.892157  Petal_Length
...        ...          ...       ...          ...       ...           ...
26           3           36  0.346154           36  0.972222  Petal_Length
27           3           36  0.346154           36  0.972222  Sepal_Length
28           3           36  0.346154           36  0.972222  Sepal_Length
29           3           36  0.346154           36  0.972222       Species

    lhs.var.support  lhs.var.conf             predicate
0                93      0.400000    Sepal_Width <= 3.92
1                93      0.400000     Sepal_Width > 2.48
2                93      0.222222   Petal_Length <= 6.31
3                93      0.222222     Petal_Length >= 1
...             ...           ...                    ...
26               35      0.134398     Petal_Length >= 1
27               35      0.094194    Sepal_Length <= 5.74
28               35      0.094194     Sepal_Length >= 4.3
29               35      0.281684        Species = setosa

[30 rows x 9 columns]

>>> # Use the model to make predictions on the test data.
... em_mod.predict(test_dat)
    CLUSTER_ID
0            3
1            3
2            3
3            3
...        ...
42           2
43           2
44           2
45           2

>>> # Make predictions and return the probability for each class
... # on new data.
>>> em_mod.predict_proba(test_dat,
...   supplemental_cols = test_dat[:,
...     ['Sepal_Length', 'Sepal_Width',
...      'Petal_Length']]).sort_values(by = ['Sepal_Length',
...        'Sepal_Width',  'Petal_Length',
...        'PROBABILITY_OF_2', 'PROBABILITY_OF_3'])
    Sepal_Length  Sepal_Width  Petal_Length  PROBABILITY_OF_2  \
0            4.4          3.0           1.3      4.680788e-20
1            4.4          3.2           1.3      1.052071e-20
2            4.5          2.3           1.3      7.751240e-06
3            4.8          3.4           1.6      5.363418e-19
...          ...          ...           ...               ...
43           6.9          3.1           4.9      1.000000e+00
44           6.9          3.1           5.4      1.000000e+00
45           7.0          3.2           4.7      1.000000e+00

    PROBABILITY_OF_3
0       1.000000e+00
1       1.000000e+00
2       9.999922e-01
```

```
3       1.000000e+00
...              ...
43     3.295578e-97
44    6.438740e-137
45     3.853925e-89

>>>
>>> # Change the random seed and refit the model.
... em_mod.set_params(EMCS_RANDOM_SEED = '5').fit(train_dat)

Algorithm Name: Expectation Maximization

Mining Function: CLUSTERING

Settings:
                     setting name                    setting value
0                       ALGO_NAME  ALGO_EXPECTATION_MAXIMIZATION
1              CLUS_NUM_CLUSTERS                               2
2        EMCS_CLUSTER_COMPONENTS       EMCS_CLUSTER_COMP_ENABLE
3        EMCS_CLUSTER_STATISTICS         EMCS_CLUS_STATS_ENABLE
4            EMCS_CLUSTER_THRESH                               2
5          EMCS_LINKAGE_FUNCTION            EMCS_LINKAGE_SINGLE
6       EMCS_LOGLIKE_IMPROVEMENT                           .001
7           EMCS_MAX_NUM_ATTR_2D                              50
8      EMCS_MIN_PCT_ATTR_SUPPORT                              .1
9              EMCS_MODEL_SEARCH      EMCS_MODEL_SEARCH_DISABLE
10           EMCS_NUM_COMPONENTS                              20
11         EMCS_NUM_DISTRIBUTION          EMCS_NUM_DISTR_SYSTEM
12       EMCS_NUM_EQUIWIDTH_BINS                              11
13           EMCS_NUM_ITERATIONS                             100
14          EMCS_NUM_PROJECTIONS                              50
15              EMCS_RANDOM_SEED                               5
16        EMCS_REMOVE_COMPONENTS       EMCS_REMOVE_COMPS_ENABLE
17                   ODMS_DETAILS                   ODMS_ENABLE
18  ODMS_MISSING_VALUE_TREATMENT        ODMS_MISSING_VALUE_AUTO
19                 ODMS_SAMPLING          ODMS_SAMPLING_DISABLE
20                     PREP_AUTO                              ON

Computed Settings:
                setting name             setting value
0       EMCS_ATTRIBUTE_FILTER  EMCS_ATTR_FILTER_DISABLE
1  EMCS_CONVERGENCE_CRITERION        EMCS_CONV_CRIT_BIC
2      EMCS_NUM_QUANTILE_BINS                         3
3          EMCS_NUM_TOPN_BINS                         3

Global Statistics:
       attribute name  attribute value
0           CONVERGED             YES
1       LOGLIKELIHOOD        -1.75777
2        NUM_CLUSTERS               2
3      NUM_COMPONENTS               9
4            NUM_ROWS             104
5         RANDOM_SEED               5
6  REMOVED_COMPONENTS              11

Attributes:
```

```
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width
Species

Partition: NO

Clusters:

   CLUSTER_ID  CLUSTER_NAME  RECORD_COUNT  PARENT  TREE_LEVEL  LEFT_CHILD_ID
\
0           1             1           104     NaN           1
2.0
1           2             2            36     1.0           2
NaN
2           3             3            68     1.0           2
NaN

   RIGHT_CHILD_ID
0             3.0
1             NaN
2             NaN

Taxonomy:

   PARENT_CLUSTER_ID  CHILD_CLUSTER_ID
0                  1               2.0
1                  1               3.0
2                  2               NaN
3                  3               NaN

Centroids:

    CLUSTER_ID ATTRIBUTE_NAME      MEAN  MODE_VALUE  VARIANCE
0            1   Petal_Length  3.721154        None  3.234694
1            1    Petal_Width  1.155769        None  0.567539
2            1   Sepal_Length  5.831731        None  0.753255
3            1    Sepal_Width  3.074038        None  0.221358
4            1        Species       NaN      setosa       NaN
5            2   Petal_Length  1.488889        None  0.033016
6            2    Petal_Width  0.250000        None  0.012857
7            2   Sepal_Length  5.011111        None  0.113016
8            2    Sepal_Width  3.488889        None  0.134159
9            2        Species       NaN      setosa       NaN
10           3   Petal_Length  4.902941        None  0.860588
11           3    Petal_Width  1.635294        None  0.191572
12           3   Sepal_Length  6.266176        None  0.545555
13           3    Sepal_Width  2.854412        None  0.128786
14           3        Species       NaN  versicolor       NaN

Leaf Cluster Counts:

   CLUSTER_ID  CNT
0           2   36
1           3   68
```

```
Attribute Importance:

  ATTRIBUTE_NAME  ATTRIBUTE_IMPORTANCE_VALUE  ATTRIBUTE_RANK
0   Petal_Length                   0.558311               2
1    Petal_Width                   0.556300               3
2   Sepal_Length                   0.469978               4
3    Sepal_Width                   0.196211               5
4        Species                   0.612463               1

Components:

   COMPONENT_ID  CLUSTER_ID  PRIOR_PROBABILITY
0             1           2           0.113452
1             2           2           0.105727
2             3           3           0.114202
3             4           3           0.086285
4             5           3           0.067294
5             6           2           0.124365
6             7           3           0.126975
7             8           3           0.105761
8             9           3           0.155939

Cluster Hists:

     cluster.id            variable  bin.id  lower.bound  upper.bound  \
0             1        Petal_Length       1         1.00         1.59
1             1        Petal_Length       2         1.59         2.18
2             1        Petal_Length       3         2.18         2.77
3             1        Petal_Length       4         2.77         3.36
...         ...                 ...     ...          ...          ...
137           3         Sepal_Width      11          NaN          NaN
138           3     Species:'Other'       1          NaN          NaN
139           3      Species:setosa       3          NaN          NaN
140           3  Species:versicolor       2          NaN          NaN

         label  count
0       1:1.59     25
1    1.59:2.18     11
2    2.18:2.77      0
3    2.77:3.36      3
...        ...    ...
137          :      0
138          :     33
139          :      0
140          :     35

[141 rows x 7 columns]

Rules:

    cluster.id  rhs.support  rhs.conf  lhr.support  lhs.conf       lhs.var  \
0            1          104  1.000000           93  0.894231   Sepal_Width
1            1          104  1.000000           93  0.894231   Sepal_Width
2            1          104  1.000000           99  0.894231  Petal_Length
3            1          104  1.000000           99  0.894231  Petal_Length
```

```
...        ...          ...       ...          ...       ...           ...
26           3           68  0.653846           68  0.955882  Sepal_Length
27           3           68  0.653846           68  0.955882  Sepal_Length
28           3           68  0.653846           68  0.955882       Species
29           3           68  0.653846           68  0.955882       Species

    lhs.var.support  lhs.var.conf             predicate
0                93      0.400000    Sepal_Width <= 3.92
1                93      0.400000     Sepal_Width > 2.48
2                93      0.222222   Petal_Length <= 6.31
3                93      0.222222     Petal_Length >= 1
...             ...           ...                    ...
26               65      0.026013    Sepal_Length <= 7.9
27               65      0.026013    Sepal_Length > 4.66
28               65      0.125809     Species IN 'Other'
29               65      0.125809  Species IN versicolor
```

5.11 Explicit Semantic Analysis

The `oml.esa` class extracts text-based features from a corpus of documents and performs document similarity comparisons.

Explicit Semantic Analysis (ESA) is an unsupervised algorithm for feature extraction. ESA does not discover latent features but instead uses explicit features based on an existing knowledge base.

Explicit knowledge often exists in text form. Multiple knowledge bases are available as collections of text documents. These knowledge bases can be generic, such as Wikipedia, or domain-specific. Data preparation transforms the text into vectors that capture attribute-concept associations.

ESA uses concepts of an existing knowledge base as features rather than latent features derived by latent semantic analysis methods such as Singular Value Decomposition and Latent Dirichlet Allocation. Each row, for example, in a document in the training data maps to a feature, that is, a concept. ESA has multiple applications in the area of text processing, most notably semantic relatedness (similarity) and explicit topic modeling. Text similarity use cases might involve, for example, resume matching, searching for similar blog postings, and so on.

For information on the `oml.esa` class attributes and methods, invoke `help(oml.esa)` or see *Oracle Machine Learning for Python API Reference*.

Settings for an Explicit Semantic Analysis Model

The following table lists settings for ESA models.

Table 5-9 Explicit Semantic Analysis Settings

Setting Name	Setting Value	Description
`ESAS_MIN_ITEMS`	A non-negative number	Determines the minimum number of non-zero entries required in an input row. The default value is 100 for text input and 0 for non-text input.
`ESAS_TOPN_FEATURES`	A positive integer	Controls the maximum number of features per attribute. The default value is `1000`.

Table 5-9 (Cont.) Explicit Semantic Analysis Settings

Setting Name	Setting Value	Description
ESAS_VALUE_THRESHOLD	A non-negative number	Sets the threshold to a small value for attribute weights in the transformed build data. The default value is 1e-8.
FEAT_NUM_FEATURES	TO_CHAR(*numeric_expr* >=1)	The number of features to extract. The default value is estimated by the algorithm. If the matrix rank is smaller than this number, then fewer features are returned.

See Also:

- About Model Settings
- Shared Settings

Example 5-11 Using the oml.esa Class

This example creates an ESA model and uses some of the methods of the `oml.esa` class.

```
import oml
from oml import cursor
import pandas as pd

# Create training data and test data.
dat = oml.push(pd.DataFrame(
  {'COMMENTS':['Aids in Africa: Planning for a long war',
     'Mars rover maneuvers for rim shot',
     'Mars express confirms presence of water at Mars south pole',
     'NASA announces major Mars rover finding',
     'Drug access, Asia threat in focus at AIDS summit',
     'NASA Mars Odyssey THEMIS image: typical crater',
     'Road blocks for Aids'],
     'YEAR':['2017', '2018', '2017', '2017', '2018', '2018', '2018'],
     'ID':[1,2,3,4,5,6,7]})).split(ratio=(0.7,0.3), seed = 1234)
train_dat = dat[0]
test_dat = dat[1]

# Specify settings.
cur = cursor()
cur.execute("Begin ctx_ddl.create_policy('DMDEMO_ESA_POLICY'); End;")
cur.close()

odm_settings = {'odms_text_policy_name': 'DMDEMO_ESA_POLICY',
                '"ODMS_TEXT_MIN_DOCUMENTS"': 1,
                '"ESAS_MIN_ITEMS"': 1}

ctx_settings = {'COMMENTS':
                'TEXT(POLICY_NAME:DMDEMO_ESA_POLICY)(TOKEN_TYPE:STEM)'}
```

```
# Create an oml ESA model object.
esa_mod = oml.esa(**odm_settings)

# Fit the ESA model according to the training data and parameter settings.
esa_mod = esa_mod.fit(train_dat, case_id = 'ID',
                      ctx_settings = ctx_settings)

# Show model details.
esa_mod

# Use the model to make predictions on test data.
esa_mod.predict(test_dat,
                supplemental_cols = test_dat[:, ['ID', 'COMMENTS']])

esa_mod.transform(test_dat,
  supplemental_cols = test_dat[:, ['ID', 'COMMENTS']],
                               topN = 2).sort_values(by = ['ID'])

esa_mod.feature_compare(test_dat,
                        compare_cols = 'COMMENTS',
                        supplemental_cols = ['ID'])

esa_mod.feature_compare(test_dat,
                        compare_cols = ['COMMENTS', 'YEAR'],
                        supplemental_cols = ['ID'])

# Change the setting parameter and refit the model.
new_setting = {'ESAS_VALUE_THRESHOLD': '0.01',
               'ODMS_TEXT_MAX_FEATURES': '2',
               'ESAS_TOPN_FEATURES': '2'}
esa_mod.set_params(**new_setting).fit(train_dat, 'ID', case_id = 'ID',
                   ctx_settings = ctx_settings)

cur = cursor()
cur.execute("Begin ctx_ddl.drop_policy('DMDEMO_ESA_POLICY'); End;")
cur.close()
```

Listing for This Example

```
>>> import oml
>>> from oml import cursor
>>> import pandas as pd
>>>
>>> # Create training data and test data.
... dat = oml.push(pd.DataFrame(
...   {'COMMENTS':['Aids in Africa: Planning for a long war',
...      'Mars rover maneuvers for rim shot',
...      'Mars express confirms presence of water at Mars south pole',
...      'NASA announces major Mars rover finding',
...      'Drug access, Asia threat in focus at AIDS summit',
...      'NASA Mars Odyssey THEMIS image: typical crater',
...      'Road blocks for Aids'],
...      'YEAR':['2017', '2018', '2017', '2017', '2018', '2018', '2018'],
...      'ID':[1,2,3,4,5,6,7]})).split(ratio=(0.7,0.3), seed = 1234)
>>> train_dat = dat[0]
```

```
>>> test_dat = dat[1]
>>>
>>> # Specify settings.
... cur = cursor()
>>> cur.execute("Begin ctx_ddl.create_policy('DMDEMO_ESA_POLICY'); End;")
>>> cur.close()
>>>
>>> odm_settings = {'odms_text_policy_name': 'DMDEMO_ESA_POLICY',
...                 '"ODMS_TEXT_MIN_DOCUMENTS"': 1,
...                 '"ESAS_MIN_ITEMS"': 1}
>>>
>>> ctx_settings = {'COMMENTS':
...                 'TEXT(POLICY_NAME:DMDEMO_ESA_POLICY)(TOKEN_TYPE:STEM)'}
>>>
>>> # Create an oml ESA model object.
... esa_mod = oml.esa(**odm_settings)
>>>
>>> # Fit the ESA model according to the training data and parameter settings.
... esa_mod = esa_mod.fit(train_dat, case_id = 'ID',
...                       ctx_settings =  ctx_settings)
>>>
>>> # Show model details.
... esa_mod

Algorithm Name: Explicit Semantic Analysis

Mining Function: FEATURE_EXTRACTION

Settings:
                     setting name                   setting value
0                       ALGO_NAME  ALGO_EXPLICIT_SEMANTIC_ANALYS
1                 ESAS_MIN_ITEMS                               1
2              ESAS_TOPN_FEATURES                            1000
3            ESAS_VALUE_THRESHOLD                     .00000001
4                    ODMS_DETAILS                    ODMS_ENABLE
5   ODMS_MISSING_VALUE_TREATMENT        ODMS_MISSING_VALUE_AUTO
6                  ODMS_SAMPLING          ODMS_SAMPLING_DISABLE
7          ODMS_TEXT_MAX_FEATURES                        300000
8         ODMS_TEXT_MIN_DOCUMENTS                             1
9           ODMS_TEXT_POLICY_NAME              DMDEMO_ESA_POLICY
10                     PREP_AUTO                             ON

Global Statistics:
   attribute name  attribute value
0        NUM_ROWS                4

Attributes:
COMMENTS
YEAR

Partition: NO

Features:

     FEATURE_ID      ATTRIBUTE_NAME ATTRIBUTE_VALUE  COEFFICIENT
 0            1     COMMENTS.AFRICA            None     0.342997
```

```
 1            1       COMMENTS.AIDS            None     0.171499
 2            1       COMMENTS.LONG            None     0.342997
 3            1   COMMENTS.PLANNING            None     0.342997
...         ...                ...             ...          ...
 24           6    COMMENTS.ODYSSEY            None     0.282843
 25           6     COMMENTS.THEMIS            None     0.282843
 26           6    COMMENTS.TYPICAL            None     0.282843
 27           6                YEAR            2018     0.707107



>>> # Use the model to make predictions on test data.
... esa_mod.predict(test_dat,
...                 supplemental_cols = test_dat[:, ['ID', 'COMMENTS']])
   ID                                          COMMENTS  FEATURE_ID
0   4           NASA announces major Mars rover finding           3
1   6    NASA Mars Odyssey THEMIS image: typical crater           2
2   7                             Road blocks for Aids           5
>>>
>>> esa_mod.transform(test_dat,
...   supplemental_cols = test_dat[:, ['ID', 'COMMENTS']],
...                               topN = 2).sort_values(by = ['ID'])
                                            COMMENTS  TOP_1  TOP_1_VAL  \
 0   4           NASA announces major Mars rover finding      3   0.647065
 1   6    NASA Mars Odyssey THEMIS image: typical crater      2   0.766237
 2   7                             Road blocks for Aids      5   0.759125

    TOP_2  TOP_2_VAL
 0      1   0.590565
 1      2   0.616672
 2      2   0.632604
>>>
>>> esa_mod.feature_compare(test_dat,
                            compare_cols = 'COMMENTS',
                            supplemental_cols = ['ID'])
   ID_A  ID_B  SIMILARITY
0     4     6    0.946469
1     4     7    0.871994
2     6     7    0.954565

>>> esa_mod.feature_compare(test_dat,
...                         compare_cols = ['COMMENTS', 'YEAR'],
...                         supplemental_cols = ['ID'])
    ID_A  ID_B  SIMILARITY
 0     4     6    0.467644
 1     4     7    0.377144
 2     6     7    O.952857

>>> # Change the setting parameter and refit the model.
... new_setting = {'ESAS_VALUE_THRESHOLD': '0.01',
...                'ODMS_TEXT_MAX_FEATURES': '2',
...                'ESAS_TOPN_FEATURES': '2'}
>>> esa_mod.set_params(**new_setting).fit(train_dat, case_id = 'ID',
...                   ctx_settings = ctx_settings)

Algorithm Name: Explicit Semantic Analysis
```

```
Mining Function: FEATURE_EXTRACTION

Settings:
                     setting name                    setting value
0                       ALGO_NAME  ALGO_EXPLICIT_SEMANTIC_ANALYS
1                  ESAS_MIN_ITEMS                               1
2              ESAS_TOPN_FEATURES                               2
3            ESAS_VALUE_THRESHOLD                            0.01
4                    ODMS_DETAILS                     ODMS_ENABLE
5   ODMS_MISSING_VALUE_TREATMENT        ODMS_MISSING_VALUE_AUTO
6                   ODMS_SAMPLING          ODMS_SAMPLING_DISABLE
7          ODMS_TEXT_MAX_FEATURES                               2
8         ODMS_TEXT_MIN_DOCUMENTS                               1
9           ODMS_TEXT_POLICY_NAME              DMDEMO_ESA_POLICY
10                     PREP_AUTO                              ON

Global Statistics:
   attribute name  attribute value
0        NUM_ROWS                4

Attributes:
COMMENTS
YEAR

Partition: NO

Features:

   FEATURE_ID  ATTRIBUTE_NAME  ATTRIBUTE_VALUE  COEFFICIENT
0           1   COMMENTS.AIDS             None     0.707107
1           1       YEAR                  2017     0.707107
2           2   COMMENTS.MARS             None     0.707107
3           2       YEAR                  2018     0.707107
4           3   COMMENTS.MARS             None     0.707107
5           3       YEAR                  2017     0.707107
6           5   COMMENTS.AIDS             None     0.707107
7           5       YEAR                  2018     0.707107

>>>
>>> cur = cursor()
>>> cur.execute("Begin ctx_ddl.drop_policy('DMDEMO_ESA_POLICY'); End;")
>>> cur.close()
```

5.12 Generalized Linear Model

The `oml.glm` class builds a Generalized Linear Model (GLM) model.

GLM models include and extend the class of linear models. They relax the restrictions on linear models, which are often violated in practice. For example, binary (yes/no or 0/1) responses do not have the same variance across classes.

GLM is a parametric modeling technique. Parametric models make assumptions about the distribution of the data. When the assumptions are met, parametric models can be more efficient than non-parametric models.

The challenge in developing models of this type involves assessing the extent to which the assumptions are met. For this reason, quality diagnostics are key to developing quality parametric models.

In addition to the classical weighted least squares estimation for linear regression and iteratively re-weighted least squares estimation for logistic regression, both solved through Cholesky decomposition and matrix inversion, Oracle Machine Learning GLM provides a conjugate gradient-based optimization algorithm that does not require matrix inversion and is very well suited to high-dimensional data. The choice of algorithm is handled internally and is transparent to the user.

GLM can be used to build classification or regression models as follows:

- **Classification**: Binary logistic regression is the GLM classification algorithm. The algorithm uses the logit link function and the binomial variance function.
- **Regression:** Linear regression is the GLM regression algorithm. The algorithm assumes no target transformation and constant variance over the range of target values.

The `oml.glm` class allows you to build two different types of models. Some arguments apply to classification models only and some to regression models only.

For information on the `oml.glm` class attributes and methods, invoke `help(oml.glm)` or see *Oracle Machine Learning for Python API Reference*.

Settings for a Generalized Linear Model

The following table lists the settings that apply to GLM models.

Table 5-10 Generalized Linear Model Settings

Setting Name	Setting Value	Description
`CLAS_COST_TABLE_NAME`	*table_name*	The name of a table that stores a cost matrix for the algorithm to use in scoring the model. The cost matrix specifies the costs associated with misclassifications. The cost matrix table is user-created. The following are the column requirements for the table. • Column Name: ACTUAL_TARGET_VALUE Data Type: Valid target data type • Column Name: PREDICTED_TARGET_VALUE Data Type: Valid target data type • Column Name: COST Data Type: NUMBER
`CLAS_WEIGHTS_BALANCED`	`ON` `OFF`	Indicates whether the algorithm must create a model that balances the target distribution. This setting is most relevant in the presence of rare targets, as balancing the distribution may enable better average accuracy (average of per-class accuracy) instead of overall accuracy (which favors the dominant class). The default value is `OFF`.

Table 5-10 (Cont.) Generalized Linear Model Settings

Setting Name	Setting Value	Description
CLAS_WEIGHTS_TABLE_NAME	*table_name*	The name of a table that stores weighting information for individual target values in GLM logistic regression models. The weights are used by the algorithm to bias the model in favor of higher weighted classes. The class weights table is user-created. The following are the column requirements for the table. • Column Name: TARGET_VALUE Data Type: Valid target data type • Column Name: CLASS_WEIGHT Data Type: NUMBER
GLMS_BATCH_ROWS	0 or a positive integer.	Number of rows in a batch used by the SGD solver. The value of this parameter sets the size of the batch for the SGD solver. An input of 0 triggers a data-driven batch size estimate. The default value is 2000.
GLMS_CONF_LEVEL	TO_CHAR(0< numeric_expr <1)	The confidence level for coefficient confidence intervals. The default confidence level is 0.95.
GLMS_CONV_TOLERANCE	The range is (0, 1) non-inclusive.	Convergence tolerance setting of the GLM algorithm. The default value is system-determined.
GLMS_FTR_GEN_METHOD	GLMS_FTR_GEN_CUBIC GLMS_FTR_GEN_QUADRATIC	Whether feature generation is cubic or quadratic. When you enable feature generation, the algorithm automatically chooses the most appropriate feature generation method based on the data.
GLMS_FTR_GENERATION	GLMS_FTR_GENERATION_ENABLE GLMS_FTR_GENERATION_DISABLE	Whether or not feature generation is enabled for GLM. By default, feature generation is not enabled. **Note:** Note: Feature generation can only be enabled when feature selection is also enabled.
GLMS_FTR_SEL_CRIT	GLMS_FTR_SEL_AIC GLMS_FTR_SEL_ALPHA_INV GLMS_FTR_SEL_RIC GLMS_FTR_SEL_SBIC	Feature selection penalty criterion for adding a feature to the model. When feature selection is enabled, the algorithm automatically chooses the penalty criterion based on the data.
GLMS_FTR_SELECTION	GLMS_FTR_SELECTION_DISABLE	Enable or disable feature selection for GLM. By default, feature selection is not enabled.
GLMS_MAX_FEATURES	TO_CHAR(0 < *numeric_expr* <= 2000)	When feature selection is enabled, this setting specifies the maximum number of features that can be selected for the final model. By default, the algorithm limits the number of features to ensure sufficient memory.
GLMS_NUM_ITERATIONS	A positive integer.	Maximum number of iterations for the GLM algorithm. The default value is system-determined.

Table 5-10 (Cont.) Generalized Linear Model Settings

Setting Name	Setting Value	Description
GLMS_PRUNE_MODEL	GLMS_PRUNE_MODEL_ENABLE GLMS_PRUNE_MODEL_DISABLE	When feature selection is enabled, the algorithm automatically performs pruning based on the data.
GLMS_REFERENCE_CLASS_NAME	*target_value*	The target value used as the reference class in a binary logistic regression model. Probabilities are produced for the other class. By default, the algorithm chooses the value with the highest prevalence (the most cases) for the reference class.
GLMS_RIDGE_REGRESSION	GLMS_RIDGE_REG_ENABLE GLMS_RIDGE_REG_DISABLE	Enable or disable ridge regression. Ridge applies to both regression and classification machine learning functions. When ridge is enabled, prediction bounds are not produced by the PREDICTION_BOUNDS SQL function.
GLMS_RIDGE_VALUE	TO_CHAR(*numeric_expr* > 0)	The value of the ridge parameter. Use this setting only when you have configured the algorithm to use ridge regression. If ridge regression is enabled internally by the algorithm, then the ridge parameter is determined by the algorithm.
GLMS_ROW_DIAGNOSTICS	GLMS_ROW_DIAG_ENABLE GLMS_ROW_DIAG_DISABLE	Enable or disable row diagnostics. By default, row diagnostics are disabled.
GLMS_SOLVER	GLMS_SOLVER_CHOL GLMS_SOLVER_LBFGS_ADMM GLMS_SOLVER_QR GLMS_SOLVER_SGD	Specifies the GLM solver. You cannot select the solver if GLMS_FTR_SELECTION setting is enabled. The default value is system determined. The GLMS_SOLVER_CHOL solver uses Cholesky decomposition. The GLMS_SOLVER_SGD solver uses stochastic gradient descent.
GLMS_SPARSE_SOLVER	GLMS_SPARSE_SOLVER_ENABLE GLMS_SPARSE_SOLVER_DISABLE	Enable or disable the use of a sparse solver if it is available. The default value is GLMS_SPARSE_SOLVER_DISABLE.
ODMS_ROW_WEIGHT_COLUMN_NAME	*column_name*	The name of a column in the training data that contains a weighting factor for the rows. The column datatype must be NUMBER. You can use row weights as a compact representation of repeated rows, as in the design of experiments where a specific configuration is repeated several times. You can also use row weights to emphasize certain rows during model construction. For example, to bias the model towards rows that are more recent and away from potentially obsolete data.

See Also:

- About Model Settings
- Shared Settings

Example 5-12 Using the oml.glm Class

This example demonstrates the use of various methods of the `oml.glm` class. In the listing for this example, some of the output is not shown as indicated by ellipses.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'

try:
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training and test data.
dat = oml.sync(table = 'IRIS').split()
train_x = dat[0].drop('Petal_Width')
train_y = dat[0]['Petal_Width']
test_dat = dat[1]

# Specify settings.
setting = {'GLMS_SOLVER': 'dbms_data_mining.GLMS_SOLVER_QR'}

# Create a GLM model object.
glm_mod = oml.glm("regression", **setting)

# Fit the GLM model according to the training data and parameter
# settings.
glm_mod = glm_mod.fit(train_x, train_y)

# Show the model details.
glm_mod

# Use the model to make predictions on the test data.
glm_mod.predict(test_dat.drop('Petal_Width'),
                supplemental_cols = test_dat[:,
                  ['Sepal_Length', 'Sepal_Width',
                   'Petal_Length', 'Species']])

# Return the prediction probability.
glm_mod.predict(test_dat.drop('Petal_Width'),
                supplemental_cols = test_dat[:,
                  ['Sepal_Length', 'Sepal_Width',
```

```
                  'Petal_Length', 'Species']],
                proba = True)

glm_mod.score(test_dat.drop('Petal_Width'),
              test_dat[:, ['Petal_Width']])

# Change the parameter setting and refit the model.
new_setting = {'GLMS_SOLVER': 'GLMS_SOLVER_SGD'}
glm_mod.set_params(**new_setting).fit(train_x, train_y)
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
... except:
...    pass
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Create training and test data.
... dat = oml.sync(table = 'IRIS').split()
>>> train_x = dat[0].drop('Petal_Width')
>>> train_y = dat[0]['Petal_Width']
>>> test_dat = dat[1]
>>>
>>> # Specify settings.
... setting = {'GLMS_SOLVER': 'dbms_data_mining.GLMS_SOLVER_QR'}
>>>
>>> # Create a GLM model object.
... glm_mod = oml.glm("regression", **setting)
>>>
>>> # Fit the GLM model according to the training data and parameter
... # settings.
>>> glm_mod = glm_mod.fit(train_x, train_y)
>>>
>>> # Show the model details.
... glm_mod

Algorithm Name: Generalized Linear Model
```

```
Mining Function: REGRESSION

Target: Petal_Width

Settings:
                setting name                  setting value
0                    ALGO_NAME  ALGO_GENERALIZED_LINEAR_MODEL
1               GLMS_CONF_LEVEL                           .95
2           GLMS_FTR_GENERATION    GLMS_FTR_GENERATION_DISABLE
3            GLMS_FTR_SELECTION     GLMS_FTR_SELECTION_DISABLE
4                   GLMS_SOLVER                GLMS_SOLVER_QR
5                  ODMS_DETAILS                   ODMS_ENABLE
6  ODMS_MISSING_VALUE_TREATMENT        ODMS_MISSING_VALUE_AUTO
7                 ODMS_SAMPLING          ODMS_SAMPLING_DISABLE
8                     PREP_AUTO                            ON

Computed Settings:
         setting name            setting value
0    GLMS_CONV_TOLERANCE  .0000050000000000000004
1    GLMS_NUM_ITERATIONS                       30
2  GLMS_RIDGE_REGRESSION    GLMS_RIDGE_REG_ENABLE

Global Statistics:
            attribute name  attribute value
0        ADJUSTED_R_SQUARE         0.949634
1                      AIC         -363.888
2                COEFF_VAR          14.6284
3                CONVERGED              YES
4       CORRECTED_TOTAL_DF              103
5         CORRECTED_TOT_SS          58.4565
6            DEPENDENT_MEAN          1.15577
7                 ERROR_DF               98
8        ERROR_MEAN_SQUARE         0.028585
9        ERROR_SUM_SQUARES          2.80131
10                 F_VALUE          389.405
11                   GMSEP         0.030347
12              HOCKING_SP         0.000295
13                     J_P         0.030234
14               MODEL_DF                5
15         MODEL_F_P_VALUE                0
16       MODEL_MEAN_SQUARE           11.131
17       MODEL_SUM_SQUARES          55.6552
18              NUM_PARAMS                6
19                NUM_ROWS              104
20         RANK_DEFICIENCY                0
21            ROOT_MEAN_SQ          0.16907
22                    R_SQ         0.952079
23                    SBIC         -348.021
24 VALID_COVARIANCE_MATRIX              YES
[1 rows x 25 columns]

Attributes:
Petal_Length
Sepal_Length
Sepal_Width
Species
```

```
Partition: NO

Coefficients:

          name       level  estimate
0   (Intercept)        None -0.600603
1  Petal_Length        None  0.239775
2  Sepal_Length        None -0.078338
3   Sepal_Width        None  0.253996
4       Species  versicolor  0.652420
5       Species   virginica  1.010438

Fit Details:
                        name         value
0         ADJUSTED_R_SQUARE  9.496338e-01
1                        AIC -3.638876e+02
2                  COEFF_VAR  1.462838e+01
3        CORRECTED_TOTAL_DF  1.030000e+02
...
21             ROOT_MEAN_SQ  1.690704e-01
22                     R_SQ  9.520788e-01
23                     SBIC -3.480213e+02
24  VALID_COVARIANCE_MATRIX  1.000000e+00

Rank:

6

Deviance:

2.801309

AIC:

-364

Null Deviance:

58.456538

DF Residual:

98.0

DF Null:

103.0

Converged:

True

>>>
>>> # Use the model to make predictions on the test data.
... glm_mod.predict(test_dat.drop('Petal_Width'),
```

```
...                 supplemental_cols = test_dat[:,
...                   ['Sepal_Length', 'Sepal_Width',
...                    'Petal_Length', 'Species']])
    Sepal_Length  Sepal_Width  Petal_Length     Species  PREDICTION
0            4.9          3.0           1.4      setosa    0.113215
1            4.9          3.1           1.5      setosa    0.162592
2            4.8          3.4           1.6      setosa    0.270602
3            5.8          4.0           1.2      setosa    0.248752
...          ...          ...           ...         ...         ...
42           6.7          3.3           5.7   virginica    2.89876
43           6.7          3.0           5.2   virginica    1.893790
44           6.5          3.0           5.2   virginica    1.909457
45           5.9          3.0           5.1   virginica    1.932483

>>> # Return the prediction probability.
... glm_mod.predict(test_dat.drop('Petal_Width'),
...                 supplemental_cols = test_dat[:,
...                   ['Sepal_Length', 'Sepal_Width',
...                    'Petal_Length', 'Species']]),
...                 proba = True)
    Sepal_Length  Sepal_Width     Species  PREDICTION
0            4.9          3.0      setosa    0.113215
1            4.9          3.1      setosa    0.162592
2            4.8          3.4      setosa    0.270602
3            5.8          4.0      setosa    0.248752
...          ...          ...         ...         ...
42           6.7          3.3   virginica    2.089876
43           6.7          3.0   virginica    1.893790
44           6.5          3.0   virginica    1.909457
45           5.9          3.0   virginica    1.932483
>>>
>>> glm_mod.score(test_dat.drop('Petal_Width'),
...               test_dat[:, ['Petal_Width']])
0.951252
>>>
>>> # Change the parameter setting and refit the model.
... new_setting = {'GLMS_SOLVER': 'GLMS_SOLVER_SGD'}
>>> glm_mod.set_params(**new_setting).fit(train_x, train_y)

Algorithm Name: Generalized Linear Model

Mining Function: REGRESSION

Target: Petal_Width

Settings:
                    setting name                    setting value
0                      ALGO_NAME  ALGO_GENERALIZED_LINEAR_MODEL
1                GLMS_CONF_LEVEL                             .95
2             GLMS_FTR_GENERATION    GLMS_FTR_GENERATION_DISABLE
3              GLMS_FTR_SELECTION     GLMS_FTR_SELECTION_DISABLE
4                     GLMS_SOLVER                 GLMS_SOLVER_SGD
5                    ODMS_DETAILS                    ODMS_ENABLE
6  ODMS_MISSING_VALUE_TREATMENT         ODMS_MISSING_VALUE_AUTO
7                   ODMS_SAMPLING           ODMS_SAMPLING_DISABLE
8                      PREP_AUTO                              ON
```

```
Computed Settings:
            setting name          setting value
0        GLMS_BATCH_ROWS                   2000
1    GLMS_CONV_TOLERANCE                  .0001
2    GLMS_NUM_ITERATIONS                   500
3  GLMS_RIDGE_REGRESSION  GLMS_RIDGE_REG_ENABLE
4       GLMS_RIDGE_VALUE                    .01

Global Statistics:
            attribute name  attribute value
0        ADJUSTED_R_SQUARE          0.94175
1                      AIC         -348.764
2                COEFF_VAR          15.7316
3                CONVERGED               NO
4       CORRECTED_TOTAL_DF              103
5         CORRECTED_TOT_SS          58.4565
6            DEPENDENT_MEAN          1.15577
7                 ERROR_DF               98
8        ERROR_MEAN_SQUARE         0.033059
9        ERROR_SUM_SQUARES          3.23979
10                F_VALUE          324.347
11                  GMSEP         0.035097
12              HOCKING_SP         0.000341
13                    J_P         0.034966
14               MODEL_DF                5
15         MODEL_F_P_VALUE                0
16       MODEL_MEAN_SQUARE          10.7226
17       MODEL_SUM_SQUARES           53.613
18              NUM_PARAMS                6
19                NUM_ROWS              104
20         RANK_DEFICIENCY                0
21            ROOT_MEAN_SQ          0.181821
22                    R_SQ          0.944578
23                    SBIC         -332.898
24 VALID_COVARIANCE_MATRIX               NO

[1 rows x 25 columns]

Attributes:
Petal_Length
Sepal_Length
Sepal_Width
Species

Partition: NO

Coefficients:

           name      level  estimate
0   (Intercept)       None -0.338046
1  Petal_Length       None  0.378658
2  Sepal_Length       None -0.084440
3   Sepal_Width       None  0.137150
4       Species  versicolor 0.151916
5       Species  virginica  0.337535
```

```
Fit Details:

                        name          value
0         ADJUSTED_R_SQUARE  9.417502e-01
1                        AIC -3.487639e+02
2                  COEFF_VAR  1.573164e+01
3        CORRECTED_TOTAL_DF  1.030000e+02
...                      ...           ...
21             ROOT_MEAN_SQ  1.818215e-01
22                     R_SQ  9.445778e-01
23                     SBIC -3.328975e+02
24  VALID_COVARIANCE_MATRIX  0.000000e+00

Rank:

6

Deviance:

3.239787

AIC:

-349

Null Deviance:

58.456538

Prior Weights:

1

DF Residual:

98.0

DF Null:

103.0

Converged:

False
```

5.13 *k*-Means

The `oml.km` class uses the *k*-Means (KM) algorithm, which is a hierarchical, distance-based clustering algorithm that partitions data into a specified number of clusters.

The algorithm has the following features:

- Several distance functions: Euclidean, Cosine, and Fast Cosine distance functions. The default is Euclidean.

- For each cluster, the algorithm returns the centroid, a histogram for each attribute, and a rule describing the hyperbox that encloses the majority of the data assigned to the cluster. The centroid reports the mode for categorical attributes and the mean and variance for numeric attributes.

For information on the `oml.km` class attributes and methods, invoke `help(oml.km)` or see *Oracle Machine Learning for Python API Reference*.

Settings for a *k*-Means Model

The following table lists the settings that apply to KM models.

Table 5-11 *k*-Means Model Settings

Setting Name	Setting Value	Description
CLUS_NUM_CLUSTERS	*TO_CHAR(numeric_expr >= 1)*	The maximum number of leaf clusters generated by the algorithm. The algorithm produces the specified number of clusters unless there are fewer distinct data points. The default value is 10.
KMNS_CONV_TOLERANCE	TO_CHAR(0< *numeric_expr* <1)	Minimum Convergence Tolerance for *k*-Means. The algorithm iterates until the minimum Convergence Tolerance is satisfied or until the maximum number of iterations, specified in KMNS_ITERATIONS, is reached. Decreasing the Convergence Tolerance produces a more accurate solution but may result in longer run times. The default Convergence Tolerance is 0.001.
KMNS_DETAILS	KMNS_DETAILS_ALL KMNS_DETAILS_HIERARCHY KMNS_DETAILS_NONE	Determines the level of cluster detail that is computed during the build. KMNS_DETAILS_ALL: Cluster hierarchy, record counts, descriptive statistics (means, variances, modes, histograms, and rules) are computed. KMNS_DETAILS_HIERARCHY: Cluster hierarchy and cluster record counts are computed. This is the default value. KMNS_DETAILS_NONE: No cluster details are computed. Only the scoring information is persisted.
KMNS_DISTANCE	KMNS_COSINE KMNS_EUCLIDEAN	Distance function for *k*-Means. The default distance function is KMNS_EUCLIDEAN.
KMNS_ITERATIONS	TO_CHAR(*positive_numeric_expr*)	Maximum number of iterations for *k*-Means. The algorithm iterates until either the maximum number of iterations is reached or the minimum Convergence Tolerance, specified in KMNS_CONV_TOLERANCE, is satisfied. The default number of iterations is 20.
KMNS_MIN_PCT_ATTR_SUPPORT	TO_CHAR(0< = *numeric_expr* <= 1)	Minimum percentage of attribute values that must be non-null in order for the attribute to be included in the rule description for the cluster. If the data is sparse or includes many missing values, a minimum support that is too high can cause very short rules or even empty rules. The default minimum support is 0.1.

Table 5-11 (Cont.) *k*-Means Model Settings

Setting Name	Setting Value	Description
KMNS_NUM_BINS	TO_CHAR(*numeric_expr* > 0)	Number of bins in the attribute histogram produced by *k*-Means. The bin boundaries for each attribute are computed globally on the entire training data set. The binning method is equi-width. All attributes have the same number of bins with the exception of attributes with a single value, which have only one bin. The default number of histogram bins is 11.
KMNS_RANDOM_SEED	Non-negative integer	Controls the seed of the random generator used during the *k*-Means initialization. It must be a non-negative integer value. The default value is 0.
KMNS_SPLIT_CRITERION	KMNS_SIZE KMNS_VARIANCE	Split criterion for *k*-Means. The split criterion controls the initialization of new *k*-Means clusters. The algorithm builds a binary tree and adds one new cluster at a time. When the split criterion is based on size, the new cluster is placed in the area where the largest current cluster is located. When the split criterion is based on the variance, the new cluster is placed in the area of the most spread-out cluster. The default split criterion is the KMNS_VARIANCE.

See Also:

- About Model Settings
- Shared Settings

Example 5-13 Using the oml.km Class

This example creates a KM model and uses methods of it. In the listing for this example, some of the output is not shown as indicated by ellipses.

```
import oml
import pandas as pd
from sklearn import datasets


# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

try:
```

```
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training and test data.
dat = oml.sync(table = 'IRIS').split()
train_dat = dat[0]
test_dat = dat[1]

# Specify settings.
setting = {'kmns_iterations': 20}

# Create a KM model object and fit it.
km_mod = oml.km(n_clusters = 3, **setting).fit(train_dat)

# Show model details.
km_mod

# Use the model to make predictions on the test data.
km_mod.predict(test_dat,
               supplemental_cols =
                  test_dat[:, ['Sepal_Length', 'Sepal_Width',
                               'Petal_Length', 'Species']])
km_mod.predict_proba(test_dat,
                     supplemental_cols =
                       test_dat[:, ['Species']]).sort_values(by =
                                     ['Species', 'PROBABILITY_OF_3'])

km_mod.transform(test_dat)

km_mod.score(test_dat)
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
... except:
...    pass
```

```
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Create training and test data.
... dat = oml.sync(table = 'IRIS').split()
>>> train_dat = dat[0]
>>> test_dat = dat[1]
>>>
>>> # Specify settings.
... setting = {'kmns_iterations': 20}
>>>
>>> # Create a KM model object and fit it.
... km_mod = omlkm(n_clusters = 3, **setting).fit(train_dat)
>>>
>>> # Show model details.
... km_mod

Algorithm Name: K-Means

Mining Function: CLUSTERING

Settings:
                      setting name            setting value
0                        ALGO_NAME              ALGO_KMEANS
1               CLUS_NUM_CLUSTERS                        3
2             KMNS_CONV_TOLERANCE                     .001
3                    KMNS_DETAILS   KMNS_DETAILS_HIERARCHY
4                   KMNS_DISTANCE          KMNS_EUCLIDEAN
5                  KMNS_ITERATIONS                       20
6       KMNS_MIN_PCT_ATTR_SUPPORT                       .1
7                   KMNS_NUM_BINS                       11
8                KMNS_RANDOM_SEED                        0
9            KMNS_SPLIT_CRITERION            KMNS_VARIANCE
10                   ODMS_DETAILS              ODMS_ENABLE
11  ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
12                 ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
13                     PREP_AUTO                       ON

Global Statistics:
   attribute name  attribute value
0       CONVERGED              YES
1        NUM_ROWS            104.0


Attributes: Petal_Length
Petal_Width
Sepal_Length
Sepal_Width
Species

Partition: NO

Clusters:

   CLUSTER_ID  ROW_CNT  PARENT_CLUSTER_ID  TREE_LEVEL  DISPERSION
```

```
0           1      104                NaN           1    0.986153
1           2       68                1.0           2    1.102147
2           3       36                1.0           2    0.767052
3           4       37                2.0           3    1.015669
4           5       31                2.0           3    1.205363

Taxonomy:

   PARENT_CLUSTER_ID  CHILD_CLUSTER_ID
0                  1               2.0
1                  1               3.0
2                  2               4.0
3                  2               5.0
4                  3               NaN
5                  4               NaN
6                  5               NaN

Leaf Cluster Counts:

   CLUSTER_ID  CNT
0           3   50
1           4   53
2           5   47
>>>
>>> # Use the model to make predictions on the test data.
... km_mod.predict(test_dat, ['Sepal_Length', 'Sepal_Width',
...                           'Petal_Length', 'Species']])
    Sepal_Length  Sepal_Width  Petal_Length     Species  CLUSTER_ID
0            4.9          3.0           1.4      setosa           3
1            4.9          3.1           1.5      setosa           3
2            4.8          3.4           1.6      setosa           3
3            5.8          4.0           1.2      setosa           3
...          ...          ...           ...         ...         ...
38           6.4          2.8           5.6   virginica           5
39           6.9          3.1           5.4   virginica           5
40           6.7          3.1           5.6   virginica           5
41           5.8          2.7           5.1   virginica           5
>>>
>>> km_mod.predict_proba(test_dat,
...                      supplemental_cols =
...                        test_dat[:, ['Species']]).sort_values(by =
...                                      ['Species', 'PROBABILITY_OF_3'])
       Species  PROBABILITY_OF_3  PROBABILITY_OF_4  PROBABILITY_OF_5
0       setosa          0.791267          0.208494          0.000240
1       setosa          0.971498          0.028350          0.000152
2       setosa          0.981020          0.018499          0.000481
3       setosa          0.981907          0.017989          0.000104
...        ...               ...               ...               ...
42   virginica          0.000655          0.316671          0.682674
43   virginica          0.001036          0.413744          0.585220
44   virginica          0.001036          0.413744          0.585220
45   virginica          0.002452          0.305021          0.692527
>>>
>>> km_mod.transform(test_dat)
    CLUSTER_DISTANCE
0           1.050234
```

```
1           0.859817
2           0.321065
3           1.427080
...              ...
42          0.837757
43          0.479313
44          0.448562
45          1.123587
>>>
>>> km_mod.score(test_dat)
-47.487712
```

5.14 Naive Bayes

The `oml.nb` class creates a Naive Bayes (NB) model for classification.

The Naive Bayes algorithm is based on conditional probabilities. Naive Bayes looks at the historical data and calculates conditional probabilities for the target values by observing the frequency of attribute values and of combinations of attribute values.

Naive Bayes assumes that each predictor is conditionally independent of the others. (Bayes' Theorem requires that the predictors be independent.)

For information on the `oml.nb` class attributes and methods, invoke `help(oml.nb)` or see *Oracle Machine Learning for Python API Reference*.

Settings for a Naive Bayes Model

The following table lists the settings that apply to NB models.

Table 5-12 Naive Bayes Model Settings

Setting Name	Setting Value	Description
`CLAS_COST_TABLE_NAME`	*table_name*	The name of a table that stores a cost matrix for the algorithm to use in building the model. The cost matrix specifies the costs associated with misclassifications. The cost matrix table is user-created. The following are the column requirements for the table. • Column Name: ACTUAL_TARGET_VALUE Data Type: Valid target data type • Column Name: PREDICTED_TARGET_VALUE Data Type: Valid target data type • Column Name: COST Data Type: NUMBER
`CLAS_MAX_SUP_BINS`	`2 <=` *a number* `<= 2147483647`	Specifies the maximum number of bins for each attribute. The default value is `32`.
`CLAS_PRIORS_TABLE_NAME`	*table_name*	The name of a table that stores prior probabilities to offset differences in distribution between the build data and the scoring data. The priors table is user-created. The following are the column requirements for the table. • Column Name: TARGET_VALUE Data Type: Valid target data type • Column Name: PRIOR_PROBABILITY Data Type: NUMBER

Table 5-12 (Cont.) Naive Bayes Model Settings

Setting Name	Setting Value	Description
CLAS_WEIGHTS_BALANCED	ON OFF	Indicates whether the algorithm must create a model that balances the target distribution. This setting is most relevant in the presence of rare targets, as balancing the distribution may enable better average accuracy (average of per-class accuracy) instead of overall accuracy (which favors the dominant class). The default value is OFF.
NABS_PAIRWISE_THRESHOLD	TO_CHAR(0 <= *numeric_expr* <= 1)	Value of the pairwise threshold for the NB algorithm. The default value is 0.
NABS_SINGLETON_THRESHOLD	TO_CHAR(0 <= *numeric_expr* <= 1)	Value of the singleton threshold for the NB algorithm. The default value is 0.

See Also:

- About Model Settings
- Shared Settings

Example 5-14 Using the oml.nb Class

This example creates an NB model and uses some of the methods of the `oml.nb` class.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

try:
    oml.drop(table = 'NB_PRIOR_PROBABILITY_DEMO')
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training and test data.
dat = oml.sync(table = 'IRIS').split()

train_x = dat[0].drop('Species')
```

```
train_y = dat[0]['Species']
test_dat = dat[1]

# User specified settings.
setting = {'CLAS_WEIGHTS_BALANCED': 'ON'}

# Create an oml NB model object.
nb_mod = oml.nb(**setting)

# Fit the NB model according to the training data and parameter
# settings.
nb_mod = nb_mod.fit(train_x, train_y)

# Show details of the model.
nb_mod

# Create a priors table in the database.
priors = {'setosa': 0.2, 'versicolor': 0.3, 'virginica': 0.5}
priors = oml.create(pd.DataFrame(list(priors.items()),
                        columns = ['TARGET_VALUE',
                                   'PRIOR_PROBABILITY']),
                        table = 'NB_PRIOR_PROBABILITY_DEMO')

# Change the setting parameter and refit the model
# with a user-defined prior table.
new_setting = {'CLAS_WEIGHTS_BALANCED': 'OFF'}
nb_mod = nb_mod.set_params(**new_setting).fit(train_x,
                                              train_y,
                                              priors = priors)
nb_mod

# Use the model to make predictions on test data.
nb_mod.predict(test_dat.drop('Species'),
               supplemental_cols = test_dat[:, ['Sepal_Length',
                                                'Sepal_Width',
                                                'Petal_Length',
                                                'Species']])
# Return the prediction probability.
nb_mod.predict(test_dat.drop('Species'),
               supplemental_cols = test_dat[:, ['Sepal_Length',
                                                'Sepal_Width',
                                                'Species']],
               proba = True)


# Return the top two most influencial attributes of the highest
# probability class.
nb_mod.predict(test_dat.drop('Species'),
               supplemental_cols = test_dat[:, ['Sepal_Length',
                                                'Sepal_Width',
                                                'Petal_Length',
                                                'Species']],
               topN_attrs = 2)

# Make predictions and return the probability for each class
# on new data.
```

```
nb_mod.predict_proba(test_dat.drop('Species'),
                     supplemental_cols = test_dat[:,
                       ['Sepal_Length',
                        'Species']]).sort_values(by =
                          ['Sepal_Length',
                           'Species',
                           'PROBABILITY_OF_setosa',
                           'PROBABILITY_OF_versicolor'])

# Make predictions on new data and return the mean accuracy.
nb_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop(table = 'NB_PRIOR_PROBABILITY_DEMO')
...    oml.drop('IRIS')
... except:
...    pass
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Create training and test data.
>>> dat = oml.sync(table = 'IRIS').split()
>>> train_x = dat[0].drop('Species')
>>> train_y = dat[0]['Species']
>>> test_dat = dat[1]
>>>
>>> # User specified settings.
... setting = {'CLAS_WEIGHTS_BALANCED': 'ON'}
>>>
>>> # Create an oml NB model object.
... nb_mod = oml.nb(**setting)
>>>
>>> # Fit the NB model according to the training data and parameter
... # settings.
>>> nb_mod = nb_mod.fit(train_x, train_y)
>>>
>>> # Show details of the model.
... nb_mod
```

```
Algorithm Name: Naive Bayes

Mining Function: CLASSIFICATION

Target: Species

Settings:
                    setting name            setting value
0                      ALGO_NAME         ALGO_NAIVE_BAYES
1          CLAS_WEIGHTS_BALANCED                       ON
2        NABS_PAIRWISE_THRESHOLD                        0
3       NABS_SINGLETON_THRESHOLD                        0
4                    ODMS_DETAILS              ODMS_ENABLE
5  ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
6                  ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
7                      PREP_AUTO                       ON

Global Statistics:
   attribute name  attribute value
0        NUM_ROWS              104

Attributes:
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width

Partition: NO

Priors:

   TARGET_NAME TARGET_VALUE  PRIOR_PROBABILITY  COUNT
0      Species       setosa           0.333333     36
1      Species   versicolor           0.333333     35
2      Species    virginica           0.333333     33

Conditionals:

    TARGET_NAME TARGET_VALUE ATTRIBUTE_NAME ATTRIBUTE_SUBNAME
ATTRIBUTE_VALUE  \
0       Species       setosa   Petal_Length              None       ( ;
1.05]
1       Species       setosa   Petal_Length              None     (1.05; 1.2]
2       Species       setosa   Petal_Length              None     (1.2; 1.35]
3       Species       setosa   Petal_Length              None    (1.35; 1.45]
...         ...          ...            ...               ...             ...

152     Species    virginica    Sepal_Width              None    (3.25; 3.35]
153     Species    virginica    Sepal_Width              None    (3.35; 3.45]
154     Species    virginica    Sepal_Width              None    (3.55; 3.65]
155     Species    virginica    Sepal_Width              None    (3.75; 3.85]

     CONDITIONAL_PROBABILITY  COUNT
0                   0.027778      1
1                   0.027778      1
```

```
2                   0.083333      3
3                   0.277778     10
...                      ...    ...
152                 0.030303      1
153                 0.060606      2
154                 0.030303      1
155                 0.060606      2

[156 rows x 7 columns]

>>> # Create a priors table in the database.
... priors = {'setosa': 0.2, 'versicolor': 0.3, 'virginica': 0.5}
>>> priors = oml.create(pd.DataFrame(list(priors.items()),
...                         columns = ['TARGET_VALUE',
...                                    'PRIOR_PROBABILITY']),
...                         table = 'NB_PRIOR_PROBABILITY_DEMO')
>>>
>>> # Change the setting parameter and refit the model
... # with a user-defined prior table.
... new_setting = {'CLAS_WEIGHTS_BALANCED': 'OFF'}
>>> nb_mod = nb_mod.set_params(**new_setting).fit(train_x,
...                                               train_y,
...                                               priors = priors)
>>> nb_mod

Algorithm Name: Naive Bayes

Mining Function: CLASSIFICATION

Target: Species

Settings:
                   setting name                           setting value
0                     ALGO_NAME                       ALGO_NAIVE_BAYES
1        CLAS_PRIORS_TABLE_NAME "OML_USER"."NB_PRIOR_PROBABILITY_DEMO"
2         CLAS_WEIGHTS_BALANCED                                      OFF
3       NABS_PAIRWISE_THRESHOLD                                        0
4      NABS_SINGLETON_THRESHOLD                                        0
5                  ODMS_DETAILS                           ODMS_ENABLE
6  ODMS_MISSING_VALUE_TREATMENT                 ODMS_MISSING_VALUE_AUTO
7                 ODMS_SAMPLING                   ODMS_SAMPLING_DISABLE
8                     PREP_AUTO                                      ON

Global Statistics:
   attribute name  attribute value
0        NUM_ROWS              104

Attributes:
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width

Partition: NO

Priors:
```

```
  TARGET_NAME TARGET_VALUE  PRIOR_PROBABILITY  COUNT
0     Species       setosa                0.2     36
1     Species   versicolor                0.3     35
2     Species    virginica                0.5     33

Conditionals:

    TARGET_NAME TARGET_VALUE ATTRIBUTE_NAME ATTRIBUTE_SUBNAME
ATTRIBUTE_VALUE  \
0       Species       setosa   Petal_Length             None       ( ; 1.05]
1       Species       setosa   Petal_Length             None     (1.05; 1.2]
2       Species       setosa   Petal_Length             None     (1.2; 1.35]
3       Species       setosa   Petal_Length             None    (1.35; 1.45]
...         ...          ...            ...              ...             ...
152     Species    virginica    Sepal_Width             None    (3.25; 3.35]
153     Species    virginica    Sepal_Width             None    (3.35; 3.45]
154     Species    virginica    Sepal_Width             None    (3.55; 3.65]
155     Species    virginica    Sepal_Width             None    (3.75; 3.85]

     CONDITIONAL_PROBABILITY  COUNT
0                   0.027778      1
1                   0.027778      1
2                   0.083333      3
3                   0.277778     10
...                      ...    ...
152                 0.030303      1
153                 0.060606      2
154                 0.030303      1
155                 0.060606      2

[156 rows x 7 columns]

>>> # Use the model to make predictions on test data.
... nb_mod.predict(test_dat.drop('Species'),
...                supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                 'Sepal_Width',
...                                                 'Petal_Length',
...                                                 'Species']])
    Sepal_Length  Sepal_Width  Petal_Length     Species  PREDICTION
0            4.9          3.0           1.4      setosa      setosa
1            4.9          3.1           1.5      setosa      setosa
2            4.8          3.4           1.6      setosa      setosa
3            5.8          4.0           1.2      setosa      setosa
...          ...          ...           ...         ...         ...
42           6.7          3.3           5.7   virginica   virginica
43           6.7          3.0           5.2   virginica   virginica
44           6.5          3.0           5.2   virginica   virginica
45           5.9          3.0           5.1   virginica   virginica

>>> # Return the prediction probability.
>>> nb_mod.predict(test_dat.drop('Species'),
...                supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                 'Sepal_Width',
...                                                 'Species']],
...                proba = True)
```

```
    Sepal_Length  Sepal_Width     Species  PREDICTION  PROBABILITY
0            4.9          3.0      setosa      setosa     1.000000
1            4.9          3.1      setosa      setosa     1.000000
2            4.8          3.4      setosa      setosa     1.000000
3            5.8          4.0      setosa      setosa     1.000000
...           ...          ...         ...         ...          ...
42           6.7          3.3   virginica   virginica     1.000000
43           6.7          3.0   virginica   virginica     0.953848
44           6.5          3.0   virginica   virginica     1.000000
45           5.9          3.0   virginica   virginica     0.932334

>>> # Return the top two most influencial attributes of the highest
... # probability class.
>>> nb_mod.predict(test_dat.drop('Species'),
...                supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                 'Sepal_Width',
...                                                 'Petal_Length',
...                                                 'Species']],
...                topN_attrs = 2)
  Sepal_Length  Sepal_Width Petal_Length    Species PREDICTION \
0          4.9          3.0          1.4     setosa     setosa
1          4.9          3.1          1.5     setosa     setosa
2          4.8          3.4          1.6     setosa     setosa
3          5.8          4.0          1.2     setosa     setosa
... ... ... ... ... ...
42         6.7          3.3          5.7  virginica  virginica
43         6.7          3.0          5.2  virginica  virginica
44         6.5          3.0          5.2  virginica  virginica
45         5.9          3.0          5.1  virginica  virginica
                                  TOP_N_ATTRIBUTES
0 <Details algorithm="Naive Bayes" class="setosa...
1 <Details algorithm="Naive Bayes" class="setosa...
2 <Details algorithm="Naive Bayes" class="setosa...
3 <Details algorithm="Naive Bayes" class="setosa...
...
42 <Details algorithm="Naive Bayes" class="virgin...
43 <Details algorithm="Naive Bayes" class="virgin...
44 <Details algorithm="Naive Bayes" class="virgin...
45 <Details algorithm="Naive Bayes" class="virgin...

>>> # Make predictions and return the probability for each class
... # on new data.
>>> nb_mod.predict_proba(test_dat.drop('Species'),
...                      supplemental_cols = test_dat[:,
...                        ['Sepal_Length',
...                         'Species']]).sort_values(by =
...                            ['Sepal_Length',
...                             'Species',
...                             'PROBABILITY_OF_setosa,
...                             'PROBABILITY_OF_versicolor'])
    Sepal_Length     Species  PROBABILITY_OF_SETOSA  \
0            4.4      setosa           1.000000e+00
1            4.4      setosa           1.000000e+00
2            4.5      setosa           1.000000e+00
3            4.8      setosa           1.000000e+00
...          ...         ...                    ...
```

```
42           6.7   virginica           1.412132e-13
43           6.9  versicolor           5.295492e-20
44           6.9   virginica           5.295492e-20
45           7.0  versicolor           6.189014e-14

     PROBABILITY_OF_VERSICOLOR  PROBABILITY_OF_VIRGINICA
0                 9.327306e-21              7.868301e-20
1                 3.497737e-20              1.032715e-19
2                 2.238553e-13              2.360490e-19
3                 6.995487e-22              2.950617e-21
...                        ...                       ...
42                4.741700e-13              1.000000e+00
43                1.778141e-07              9.999998e-01
44                2.963565e-20              1.000000e+00
45                4.156340e-01              5.843660e-01

>>> # Make predictions on new data and return the mean accuracy.
... nb_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])
0.934783
```

5.15 Neural Network

The `oml.nn` class creates a Neural Network (NN) model for classification and regression.

Neural Network models can be used to capture intricate nonlinear relationships between inputs and outputs or to find patterns in data.

The `oml.nn` class methods build a feed-forward neural network for regression on `oml.DataFrame` data. It supports multiple hidden layers with a specifiable number of nodes. Each layer can have one of several activation functions.

The output layer is a single numeric or binary categorical target. The output layer can have any of the activation functions. It has the linear activation function by default.

Modeling with the `oml.nn` class is well-suited for noisy and complex data such as sensor data. Problems that such data might have are the following:

- Potentially many (numeric) predictors, for example, pixel values
- The target may be discrete-valued, real-valued, or a vector of such values
- Training data may contain errors – robust to noise
- Fast scoring
- Model transparency is not required; models difficult to interpret

Typical steps in Neural Network modeling are the following:

1. Specifying the architecture
2. Preparing the data
3. Building the model
4. Specifying the stopping criteria: iterations, error on a validation set within tolerance
5. Viewing statistical results from the model
6. Improving the model

For information on the `oml.nn` class attributes and methods, invoke `help(oml.nn)` or `help(oml.hist)`, or see *Oracle Machine Learning for Python API Reference*.

Settings for a Neural Network Model

The following table lists settings for NN models.

Table 5-13 Neural Network Models Settings

Setting Name	Setting Value	Description
`CLAS_COST_TABLE_NAME`	*table_name*	The name of a table that stores a cost matrix for the algorithm to use in scoring the model. The cost matrix specifies the costs associated with misclassifications. The cost matrix table is user-created. The following are the column requirements for the table. • Column Name: ACTUAL_TARGET_VALUE Data Type: Valid target data type • Column Name: PREDICTED_TARGET_VALUE Data Type: Valid target data type • Column Name: COST Data Type: NUMBER
`CLAS_WEIGHTS_BALANCED`	`ON` `OFF`	Indicates whether the algorithm must create a model that balances the target distribution. This setting is most relevant in the presence of rare targets, as balancing the distribution may enable better average accuracy (average of per-class accuracy) instead of overall accuracy (which favors the dominant class). The default value is `OFF`.
`NNET_ACTIVATIONS`	A list of the following strings: • `"NNET_ACTIVATIONS_ARCTAN"` • `"NNET_ACTIVATIONS_BIPOLAR_SIG"` • `"NNET_ACTIVATIONS_LINEAR"` • `"NNET_ACTIVATIONS_LOG_SIG"` • `"NNET_ACTIVATIONS_TANH"`	Defines the activation function for the hidden layers. For example, `'"NNET_ACTIVATIONS_BIPOLAR_SIG", "NNET_ACTIVATIONS_TANH"'`. Different layers can have different activation functions. The default value is `"NNET_ACTIVATIONS_LOG_SIG"`. The number of activation functions must be consistent with `NNET_HIDDEN_LAYERS` and `NNET_NODES_PER_LAYER`. **Note:** All quotes are single and two single quotes are used to escape a single quote in SQL statements.
`NNET_HELDASIDE_MAX_FAIL`	A positive integer	With `NNET_REGULARIZER_HELDASIDE`, the training process is stopped early if the network performance on the validation data fails to improve or remains the same for `NNET_HELDASIDE_MAX_FAIL` epochs in a row. The default value is `6`.
`NNET_HELDASIDE_RATIO`	`0 <=` *numeric_expr* `<= 1`	Defines the held ratio for the held-aside method. The default value is `0.25`.
`NNET_HIDDEN_LAYERS`	A non-negative integer	Defines the topology by number of hidden layers. The default value is `1`.

Table 5-13 (Cont.) Neural Network Models Settings

Setting Name	Setting Value	Description
NNET_ITERATIONS	A positive integer	Specifies the maximum number of iterations in the Neural Network algorithm. The default value is 200.
NNET_NODES_PER_LAYER	A list of positive integers	Defines the topology by number of nodes per layer. Different layers can have different number of nodes. The value should be a comma separated list non-negative integers. For example, '10, 20, 5'. The setting values must be consistent with NNET_HIDDEN_LAYERS. The default number of nodes per layer is the number of attributes or 50 (if the number of attributes > 50).
NNET_REG_LAMBDA	TO_CHAR(*numeric_expr* >= 0)	Defines the L2 regularization parameter lambda. This can not be set together with NNET_REGULARIZER_HELDASIDE. The default value is 1.
NNET_REGULARIZER	NNET_REGULARIZER_HELDASIDE NNET_REGULARIZER_L2 NNET_REGULARIZER_NONE	Regularization setting for the Neural Network algorithm. If the total number of training rows is greater than 50000, then the default is NNET_REGULARIZER_HELDASIDE. If the total number of training rows is less than or equal to 50000, then the default is NNET_REGULARIZER_NONE.
NNET_SOLVER	NNET_SOLVER_ADAM NNET_SOLVER_LBFGS	Specifies the method of optimization. The default value is NNET_SOLVER_LBFGS.
NNET_TOLERANCE	TO_CHAR(0 < *numeric_expr* < 1)	Defines the convergence tolerance setting of the Neural Network algorithm. The default value is 0.000001.
NNET_WEIGHT_LOWER_BOUND	A real number	Specifies the lower bound of the region where weights are randomly initialized. NNET_WEIGHT_LOWER_BOUND and NNET_WEIGHT_UPPER_BOUND must be set together. Setting one and not setting the other raises an error. NNET_WEIGHT_LOWER_BOUND must not be greater than NNET_WEIGHT_UPPER_BOUND. The default value is -sqrt(6/(l_nodes+r_nodes)). The value of l_nodes for: • input layer dense attributes is (1+number of dense attributes) • input layer sparse attributes is number of sparse attributes • each hidden layer is (1+number of nodes in that hidden layer) The value of r_nodes is the number of nodes in the layer that the weight is connecting to.
NNET_WEIGHT_UPPER_BOUND	A real number	Specifies the upper bound of the region where weights are initialized. It should be set in pairs with NNET_WEIGHT_LOWER_BOUND and its value must not be smaller than the value of NNET_WEIGHT_LOWER_BOUND. If not specified, the values of NNET_WEIGHT_LOWER_BOUND and NNET_WEIGHT_UPPER_BOUND are system determined. The default value is sqrt(6/(l_nodes+r_nodes)). See NNET_WEIGHT_LOWER_BOUND.

Table 5-13 (Cont.) Neural Network Models Settings

Setting Name	Setting Value	Description
ODMS_RANDOM_SEED	A non-negative integer	Controls the random number seed used by the hash function to generate a random number with uniform distribution. The default values is 0.

See Also:

- About Model Settings
- Shared Settings

Example 5-15 Building a Neural Network Model

This example creates an NN model and uses some of the methods of the `oml.nn` class.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

try:
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training and test data.
dat = oml.sync(table = 'IRIS').split()
train_x = dat[0].drop('Species')
train_y = dat[0]['Species']
test_dat = dat[1]

# Create a Neural Network model object.
nn_mod = oml.nn(nnet_hidden_layers = 1,
                nnet_activations= "'NNET_ACTIVATIONS_LOG_SIG'",
                NNET_NODES_PER_LAYER= '30')

# Fit the NN model according to the training data and parameter
# settings.
```

```
nn_mod = nn_mod.fit(train_x, train_y)

# Show details of the model.
nn_mod

# Use the model to make predictions on test data.
nn_mod.predict(test_dat.drop('Species'),
    supplemental_cols = test_dat[:, ['Sepal_Length', 'Sepal_Width',
                                     'Petal_Length', 'Species']])

nn_mod.predict(test_dat.drop('Species'),
    supplemental_cols = test_dat[:, ['Sepal_Length', 'Sepal_Width',
                                   'Species']], proba = True)

nn_mod.predict_proba(test_dat.drop('Species'),
    supplemental_cols = test_dat[:, ['Sepal_Length',
      'Species']]).sort_values(by = ['Sepal_Length', 'Species',
         'PROBABILITY_OF_setosa', 'PROBABILITY_OF_versicolor'])

nn_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])

# Change the setting parameter and refit the model.
new_setting = {'NNET_NODES_PER_LAYER': '50'}
nn_mod.set_params(**new_setting).fit(train_x, train_y)
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
... except:
...    pass
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Create training and test data.
... dat = oml.sync(table = 'IRIS').split()
>>> train_x = dat[0].drop('Species')
>>> train_y = dat[0]['Species']
>>> test_dat = dat[1]
>>>
```

```
>>> # Create a Neural Network model object.
... nn_mod = oml.nn(nnet_hidden_layers = 1,
...                 nnet_activations= "'NNET_ACTIVATIONS_LOG_SIG'",
...                 NNET_NODES_PER_LAYER= '30')
>>>
>>> # Fit the NN model according to the training data and parameter
... # settings.
... nn_mod = nn_mod.fit(train_x, train_y)
>>>
>>> # Show details of the model.
... nn_mod

Algorithm Name: Neural Network

Mining Function: CLASSIFICATION

Target: Species

Settings:
                     setting name               setting value
0                       ALGO_NAME         ALGO_NEURAL_NETWORK
1          CLAS_WEIGHTS_BALANCED                         OFF
2       LBFGS_GRADIENT_TOLERANCE                 .000000001
3            LBFGS_HISTORY_DEPTH                          20
4            LBFGS_SCALE_HESSIAN  LBFGS_SCALE_HESSIAN_ENABLE
5               NNET_ACTIVATIONS  'NNET_ACTIVATIONS_LOG_SIG'
6        NNET_HELDASIDE_MAX_FAIL                           6
7           NNET_HELDASIDE_RATIO                         .25
8             NNET_HIDDEN_LAYERS                           1
9                NNET_ITERATIONS                         200
10          NNET_NODES_PER_LAYER                          30
11                NNET_TOLERANCE                    .000001
12                  ODMS_DETAILS                ODMS_ENABLE
13  ODMS_MISSING_VALUE_TREATMENT     ODMS_MISSING_VALUE_AUTO
14              ODMS_RANDOM_SEED                           0
15                 ODMS_SAMPLING       ODMS_SAMPLING_DISABLE
16                     PREP_AUTO                          ON

Computed Settings:
       setting name          setting value
0  NNET_REGULARIZER  NNET_REGULARIZER_NONE

Global Statistics:
   attribute name  attribute value
0       CONVERGED              YES
1      ITERATIONS             60.0
2      LOSS_VALUE              0.0
3        NUM_ROWS            102.0


Attributes:
Sepal_Length
Sepal_Width
Petal_Length
Petal_Width
```

```
Partition: NO

Topology:

    HIDDEN_LAYER_ID  NUM_NODE       ACTIVATION_FUNCTION
 0                0        30  NNET_ACTIVATIONS_LOG_SIG

Weights:

      LAYER  IDX_FROM  IDX_TO ATTRIBUTE_NAME ATTRIBUTE_SUBNAME
ATTRIBUTE_VALUE  \
 0        0       0.0       0   Petal_Length              None
None
 1        0       0.0       1   Petal_Length              None
None
 2        0       0.0       2   Petal_Length              None
None
 3        0       0.0       3   Petal_Length              None
None
 ...    ...       ...     ...            ...               ...              ...

 239      1      29.0       2           None              None
None
 240      1       NaN       0           None              None
None
 241      1       NaN       1           None              None
None
 242      1       NaN       2           None              None
None

     TARGET_VALUE     WEIGHT
 0           None -39.836487
 1           None  32.604824
 2           None   0.953903
 3           None   0.714064
 ...          ...        ...
 239    virginica -22.650606
 240       setosa   2.402457
 241   versicolor   7.647615
 242    virginica  -9.493982

[243 rows x 8 columns]



>>> # Use the model to make predictions on test data.
... nn_mod.predict(test_dat.drop('Species'),
...     supplemental_cols = test_dat[:, ['Sepal_Length', 'Sepal_Width',
...                                      'Petal_Length', 'Species']])
     Sepal_Length  Sepal_Width  Petal_Length     Species  PREDICTION
 0            4.9          3.0           1.4      setosa      setosa
 1            4.9          3.1           1.5      setosa      setosa
 2            4.8          3.4           1.6      setosa      setosa
 3            5.8          4.0           1.2      setosa      setosa
...           ...          ...           ...         ...         ...
 44           6.7          3.3           5.7   virginica   virginica
```

```
 45           6.7          3.0           5.2   virginica   virginica
 46           6.5          3.0           5.2   virginica   virginica
 47           5.9          3.0           5.1   virginica   virginica

>>> nn_mod.predict(test_dat.drop('Species'),
...     supplemental_cols = test_dat[:, ['Sepal_Length', 'Sepal_Width',
...                                      'Species']], proba = True)
    Sepal_Length  Sepal_Width     Species  PREDICTION  PROBABILITY
 0           4.9          3.0      setosa      setosa     1.000000
 1           4.9          3.1      setosa      setosa     1.000000
 2           4.8          3.4      setosa      setosa     1.000000
 3           5.8          4.0      setosa      setosa     1.000000
...          ...          ...         ...         ...          ...
 44          6.7          3.3   virginica   virginica     1.000000
 45          6.7          3.0   virginica   virginica     1.000000
 46          6.5          3.0   virginica   virginica     1.000000
 47          5.9          3.0   virginica   virginica     1.000000

>>> nn_mod.predict_proba(test_dat.drop('Species'),
...     supplemental_cols = test_dat[:, ['Sepal_Length',
...       'Species']]).sort_values(by = ['Sepal_Length', 'Species',
...         'PROBABILITY_OF_setosa', 'PROBABILITY_OF_versicolor'])
    Sepal_Length     Species  PROBABILITY_OF_SETOSA  \
 0           4.4      setosa           1.000000e+00
 1           4.4      setosa           1.000000e+00
 2           4.5      setosa           1.000000e+00
 3           4.8      setosa           1.000000e+00
...          ...         ...                    ...
 44          6.7   virginica          4.567318e-218
 45          6.9  versicolor          3.028266e-177
 46          6.9   virginica          1.203417e-215
 47          7.0  versicolor          3.382837e-148

    PROBABILITY_OF_VERSICOLOR  PROBABILITY_OF_VIRGINICA
 0               3.491272e-67             3.459448e-283
 1               8.038930e-58             2.883999e-288
 2               5.273544e-64             2.243282e-293
 3               1.332150e-78             2.040723e-283
...                      ...                       ...
 44              1.328042e-36              1.000000e+00
 45              1.000000e+00              5.063405e-55
 46              4.000953e-31              1.000000e+00
 47              1.000000e+00             2.593761e-121

>>> nn_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])
 0.9375

>>> # Change the setting parameter and refit the model.
... new_setting = {'NNET_NODES_PER_LAYER': '50'}
>>> nn_mod.set_params(**new_setting).fit(train_x, train_y)

Algorithm Name: Neural Network

Mining Function: CLASSIFICATION

Target: Species
```

```
Settings:
                    setting name               setting value
0                       ALGO_NAME         ALGO_NEURAL_NETWORK
1            CLAS_WEIGHTS_BALANCED                         OFF
2         LBFGS_GRADIENT_TOLERANCE                .000000001
3              LBFGS_HISTORY_DEPTH                          20
4              LBFGS_SCALE_HESSIAN  LBFGS_SCALE_HESSIAN_ENABLE
5                 NNET_ACTIVATIONS  'NNET_ACTIVATIONS_LOG_SIG'
6          NNET_HELDASIDE_MAX_FAIL                           6
7             NNET_HELDASIDE_RATIO                         .25
8               NNET_HIDDEN_LAYERS                           1
9                  NNET_ITERATIONS                         200
10           NNET_NODES_PER_LAYER                          50
11                NNET_TOLERANCE                    .000001
12                  ODMS_DETAILS                ODMS_ENABLE
13  ODMS_MISSING_VALUE_TREATMENT     ODMS_MISSING_VALUE_AUTO
14                ODMS_RANDOM_SEED                           0
15                   ODMS_SAMPLING       ODMS_SAMPLING_DISABLE
16                       PREP_AUTO                         ON

Computed Settings:
       setting name          setting value
0  NNET_REGULARIZER  NNET_REGULARIZER_NONE

Global Statistics:
   attribute name  attribute value
0       CONVERGED              YES
1      ITERATIONS             68.0
2      LOSS_VALUE              0.0
3        NUM_ROWS            102.0

Attributes:
Sepal_Length
Sepal_Width
Petal_Length
Petal_Width

Partition: NO

Topology:

    HIDDEN_LAYER_ID  NUM_NODE       ACTIVATION_FUNCTION
 0                0        50  NNET_ACTIVATIONS_LOG_SIG

Weights:

      LAYER  IDX_FROM  IDX_TO ATTRIBUTE_NAME ATTRIBUTE_SUBNAME
ATTRIBUTE_VALUE  \
 0        0       0.0       0   Petal_Length              None
None
 1        0       0.0       1   Petal_Length              None
None
 2        0       0.0       2   Petal_Length              None
None
 3        0       0.0       3   Petal_Length              None
```

```
None
 ...    ...       ...     ...           ...              ...             ...
 399      1      49.0       2          None             None
None
 400      1       NaN       0          None             None
None
 401      1       NaN       1          None             None
None
 402      1       NaN       2          None             None
None

     TARGET_VALUE     WEIGHT
 0           None  10.606389
 1           None -37.256485
 2           None -14.263772
 3           None -17.945173
 ...          ...        ...
 399    virginica -22.179815
 400       setosa  -6.452953
 401   versicolor  13.186332
 402    virginica  -6.973605

[403 rows x 8 columns]
```

5.16 Random Forest

The `oml.rf` class creates a Random Forest (RF) model that provides an ensemble learning technique for classification.

By combining the ideas of bagging and random selection of variables, the Random Forest algorithm produces a collection of decision trees with controlled variance while avoiding overfitting, which is a common problem for decision trees.

For information on the `oml.rf` class attributes and methods, invoke `help(oml.rf)` or see *Oracle Machine Learning for Python API Reference*.

Settings for a Random Forest Model

The following table lists settings for RF models.

Table 5-14 Random Forest Model Settings

Setting Name	Setting Value	Description
CLAS_COST_TABLE_NAME	*table_name*	The name of a table that stores a cost matrix for the algorithm to use in scoring the model. The cost matrix specifies the costs associated with misclassifications. The cost matrix table is user-created. The following are the column requirements for the table. • Column Name: ACTUAL_TARGET_VALUE Data Type: Valid target data type • Column Name: PREDICTED_TARGET_VALUE Data Type: Valid target data type • Column Name: COST Data Type: NUMBER
CLAS_MAX_SUP_BINS	2 <= *a number* <= 254	Specifies the maximum number of bins for each attribute. The default value is 32.
CLAS_WEIGHTS_BALANCED	ON OFF	Indicates whether the algorithm must create a model that balances the target distribution. This setting is most relevant in the presence of rare targets, as balancing the distribution may enable better average accuracy (average of per-class accuracy) instead of overall accuracy (which favors the dominant class). The default value is OFF.
ODMS_RANDOM_SEED	A non-negative integer	Controls the random number seed used by the hash function to generate a random number with uniform distribution. The default values is 0.
RFOR_MTRY	*A number* >= 0	Size of the random subset of columns to consider when choosing a split at a node. For each node, the size of the pool remains the same but the specific candidate columns change. The default is half of the columns in the model signature. The special value 0 indicates that the candidate pool includes all columns.
RFOR_NUM_TREES	1 <= *a number* <= 65535	Number of trees in the forest The default value is 20.
RFOR_SAMPLING_RATIO	0 < *a fraction* <= 1	Fraction of the training data to be randomly sampled for use in the construction of an individual tree. The default is half of the number of rows in the training data.

Table 5-14 (Cont.) Random Forest Model Settings

Setting Name	Setting Value	Description
TREE_IMPURITY_METRIC	TREE_IMPURITY_ENTROPY TREE_IMPURITY_GINI	Tree impurity metric for a decision tree model. Tree algorithms seek the best test question for splitting data at each node. The best splitter and split value are those that result in the largest increase in target value homogeneity (purity) for the entities in the node. Purity is measured in accordance with a metric. Decision trees can use either gini (TREE_IMPURITY_GINI) or entropy (TREE_IMPURITY_ENTROPY) as the purity metric. By default, the algorithm uses TREE_IMPURITY_GINI.
TREE_TERM_MAX_DEPTH	2 <= *a number* <= 100	Criteria for splits: maximum tree depth (the maximum number of nodes between the root and any leaf node, including the leaf node). The default is 16.
TREE_TERM_MINPCT_NODE	0 <= *a number* <= 10	The minimum number of training rows in a node expressed as a percentage of the rows in the training data. The default value is 0.05, indicating 0.05%.
TREE_TERM_MINPCT_SPLIT	0 < *a number* <= 20	Minimum number of rows required to consider splitting a node expressed as a percentage of the training rows. The default value is 0.1, indicating 0.1%.
TREE_TERM_MINREC_NODE	*A number* >= 0	Minimum number of rows in a node. The default value is 10.
TREE_TERM_MINREC_SPLIT	*A number* > 1	Criteria for splits: minimum number of records in a parent node expressed as a value. No split is attempted if the number of records is below this value. The default value is 20.

See Also:

- About Model Settings
- Shared Settings

Example 5-16 Using the oml.rf Class

This example creates an RF model and uses some of the methods of the `oml.rf` class.

```
import oml
import pandas as pd
from sklearn import datasets
```

```
# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

try:
    oml.drop('IRIS')
    oml.drop(table = 'RF_COST')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training and test data.
dat = oml.sync(table = 'IRIS').split()
train_x = dat[0].drop('Species')
train_y = dat[0]['Species']
test_dat = dat[1]

# Create a cost matrix table in the database.
cost_matrix = [['setosa', 'setosa', 0],
               ['setosa', 'virginica', 0.2],
               ['setosa', 'versicolor', 0.8],
               ['virginica', 'virginica', 0],
               ['virginica', 'setosa', 0.5],
               ['virginica', 'versicolor', 0.5],
               ['versicolor', 'versicolor', 0],
               ['versicolor', 'setosa', 0.4],
               ['versicolor', 'virginica', 0.6]]
cost_matrix = \
  oml.create(pd.DataFrame(cost_matrix,
                          columns = ['ACTUAL_TARGET_VALUE',
                                     'PREDICTED_TARGET_VALUE',
                                     'COST']),
             table = 'RF_COST')

# Create an RF model object.
rf_mod = oml.rf(tree_term_max_depth = '2')

# Fit the RF model according to the training data and parameter
# settings.
rf_mod = rf_mod.fit(train_x, train_y, cost_matrix = cost_matrix)

# Show details of the model.
rf_mod

# Use the model to make predictions on the test data.
rf_mod.predict(test_dat.drop('Species'),
               supplemental_cols = test_dat[:, ['Sepal_Length',
```

```
                                                'Sepal_Width',
                                                'Petal_Length',
                                                'Species']])

# Return the prediction probability.
rf_mod.predict(test_dat.drop('Species'),
               supplemental_cols = test_dat[:, ['Sepal_Length',
                                                'Sepal_Width',
                                                'Species']],
               proba = True)


# Return the top two most influencial attributes of the highest
# probability class.
rf_mod.predict_proba(test_dat.drop('Species'),
               supplemental_cols = test_dat[:, ['Sepal_Length',
                                                'Species']],
               topN = 2).sort_values(by = ['Sepal_Length', 'Species'])

rf_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])

# Reset TREE_TERM_MAX_DEPTH and refit the model.
rf_mod.set_params(tree_term_max_depth = '3').fit(train_x, train_y,
cost_matrix)
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
...    oml.drop(table = 'RF_COST')
... except:
...    pass
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Create training and test data.
... dat = oml.sync(table = 'IRIS').split()
>>> train_x = dat[0].drop('Species')
>>> train_y = dat[0]['Species']
>>> test_dat = dat[1]
```

```
>>>
>>> # Create a cost matrix table in the database.
... cost_matrix = [['setosa', 'setosa', 0],
...                ['setosa', 'virginica', 0.2],
...                ['setosa', 'versicolor', 0.8],
...                ['virginica', 'virginica', 0],
...                ['virginica', 'setosa', 0.5],
...                ['virginica', 'versicolor', 0.5],
...                ['versicolor', 'versicolor', 0],
...                ['versicolor', 'setosa', 0.4],
...                ['versicolor', 'virginica', 0.6]]
>>> cost_matrix = \
...   oml.create(pd.DataFrame(cost_matrix,
...                           columns = ['ACTUAL_TARGET_VALUE',
...                                      'PREDICTED_TARGET_VALUE',
...                                      'COST']),
...              table = 'RF_COST')
>>>
>>> # Create an RF model object.
... rf_mod = oml.rf(tree_term_max_depth = '2')
>>>
>>> # Fit the RF model according to the training data and parameter
... # settings.
>>> rf_mod = rf_mod.fit(train_x, train_y, cost_matrix = cost_matrix)
>>>
>>> # Show details of the model.
... rf_mod

Algorithm Name: Random Forest

Mining Function: CLASSIFICATION

Target: Species

Settings:
                     setting name            setting value
0                       ALGO_NAME       ALGO_RANDOM_FOREST
1            CLAS_COST_TABLE_NAME     "OML_USER"."RF_COST"
2               CLAS_MAX_SUP_BINS                       32
3           CLAS_WEIGHTS_BALANCED                      OFF
4                    ODMS_DETAILS             ODMS_ENABLE
5   ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
6                ODMS_RANDOM_SEED                        0
7                   ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
8                       PREP_AUTO                       ON
9                 RFOR_NUM_TREES                       20
10           RFOR_SAMPLING_RATIO                       .5
11          TREE_IMPURITY_METRIC       TREE_IMPURITY_GINI
12           TREE_TERM_MAX_DEPTH                        2
13         TREE_TERM_MINPCT_NODE                      .05
14        TREE_TERM_MINPCT_SPLIT                       .1
15         TREE_TERM_MINREC_NODE                       10
16        TREE_TERM_MINREC_SPLIT                       20

Computed Settings:
  setting name setting value
```

```
0    RFOR_MTRY             2

Global Statistics:
   attribute name  attribute value
0       AVG_DEPTH                2
1   AVG_NODECOUNT                3
2       MAX_DEPTH                2
3   MAX_NODECOUNT                2
4       MIN_DEPTH                2
5   MIN_NODECOUNT                2
6        NUM_ROWS              104

Attributes:
Petal_Length
Petal_Width
Sepal_Length

Partition: NO

Importance:

   ATTRIBUTE_NAME ATTRIBUTE_SUBNAME  ATTRIBUTE_IMPORTANCE
 0   Petal_Length              None              0.329971
 1    Petal_Width              None              0.296799
 2   Sepal_Length              None              0.037309
 3    Sepal_Width              None              0.000000

>>> # Use the model to make predictions on the test data.
... rf_mod.predict(test_dat.drop('Species'),
...                supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                 'Sepal_Width',
...                                                 'Petal_Length',
...                                                 'Species']])
     Sepal_Length  Sepal_Width  Petal_Length     Species  PREDICTION
 0            4.9          3.0           1.4      setosa      setosa
 1            4.9          3.1           1.5      setosa      setosa
 2            4.8          3.4           1.6      setosa      setosa
 3            5.8          4.0           1.2      setosa      setosa
...           ...          ...           ...         ...         ...
42            6.7          3.3           5.7   virginica   virginica
43            6.7          3.0           5.2   virginica   virginica
44            6.5          3.0           5.2   virginica   virginica
45            5.9          3.0           5.1   virginica   virginica

>>> # Return the prediction probability.
... rf_mod.predict(test_dat.drop('Species'),
...                supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                 'Sepal_Width',
...                                                 'Species']],
...                proba = True)
     Sepal_Length  Sepal_Width     Species  PREDICTION  PROBABILITY
 0            4.9          3.0      setosa      setosa     0.989130
 1            4.9          3.1      setosa      setosa     0.989130
 2            4.8          3.4      setosa      setosa     0.989130
 3            5.8          4.0      setosa      setosa     0.950000
...           ...          ...         ...         ...          ...
```

```
42            6.7          3.3   virginica   virginica     0.501016
43            6.7          3.0   virginica   virginica     0.501016
44            6.5          3.0   virginica   virginica     0.501016
45            5.9          3.0   virginica   virginica     0.501016

>>> # Return the top two most influencial attributes of the highest
... # probability class.
>>> rf_mod.predict_proba(test_dat.drop('Species'),
...                supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                 'Species']],
...                topN = 2).sort_values(by = ['Sepal_Length', 'Species'])
     Sepal_Length     Species       TOP_1  TOP_1_VAL       TOP_2  TOP_2_VAL
 0            4.4      setosa      setosa   0.989130  versicolor   0.010870
 1            4.4      setosa      setosa   0.989130  versicolor   0.010870
 2            4.5      setosa      setosa   0.989130  versicolor   0.010870
 3            4.8      setosa      setosa   0.989130  versicolor   0.010870
...           ...         ...         ...        ...         ...        ...
42            6.7   virginica   virginica   0.501016  versicolor   0.498984
43            6.9  versicolor   virginica   0.501016  versicolor   0.498984
44            6.9   virginica   virginica   0.501016  versicolor   0.498984
45            7.0  versicolor   virginica   0.501016  versicolor   0.498984

>>> rf_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])
0.76087

>>> # Reset TREE_TERM_MAX_DEPTH and refit the model.
... rf_mod.set_params(tree_term_max_depth = '3').fit(train_x, train_y,
cost_matrix)

Algorithm Name: Random Forest

Mining Function: CLASSIFICATION

Target: Species
Settings:
                     setting name            setting value
0                       ALGO_NAME       ALGO_RANDOM_FOREST
1            CLAS_COST_TABLE_NAME     "OML_USER"."RF_COST"
2               CLAS_MAX_SUP_BINS                       32
3           CLAS_WEIGHTS_BALANCED                      OFF
4                    ODMS_DETAILS             ODMS_ENABLE
5   ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
6                ODMS_RANDOM_SEED                        0
7                   ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
8                       PREP_AUTO                      ON
9                  RFOR_NUM_TREES                      20
10           RFOR_SAMPLING_RATIO                      .5
11          TREE_IMPURITY_METRIC       TREE_IMPURITY_GINI
12           TREE_TERM_MAX_DEPTH                       3
13         TREE_TERM_MINPCT_NODE                     .05
14        TREE_TERM_MINPCT_SPLIT                      .1
15         TREE_TERM_MINREC_NODE                      10
16        TREE_TERM_MINREC_SPLIT                      20

Computed Settings:
  setting name setting value
```

```
0    RFOR_MTRY             2

Global Statistics:
   attribute name  attribute value
0       AVG_DEPTH                3
1   AVG_NODECOUNT                5
2       MAX_DEPTH                3
3   MAX_NODECOUNT                6
4       MIN_DEPTH                3
5   MIN_NODECOUNT                4
6        NUM_ROWS              104

Attributes:
Petal_Length
Petal_Width
Sepal_Length

Partition: NO

Importance:

  ATTRIBUTE_NAME ATTRIBUTE_SUBNAME  ATTRIBUTE_IMPORTANCE
0   Petal_Length              None              0.501022
1    Petal_Width              None              0.568170
2   Sepal_Length              None              0.091617
3    Sepal_Width              None              0.000000
```

5.17 Singular Value Decomposition

Use the `oml.svd` class to build a model for feature extraction.

The `oml.svd` class creates a model that uses the Singular Value Decomposition (SVD) algorithm for feature extraction. SVD performs orthogonal linear transformations that capture the underlying variance of the data by decomposing a rectangular matrix into three matrices: U, V, and D. Columns of matrix V contain the right singular vectors and columns of matrix U contain the left singular vectors. Matrix D is a diagonal matrix and its singular values reflect the amount of data variance captured by the bases.

The `SVDS_MAX_NUM_FEATURES` constant specifies the maximum number of features supported by SVD. The value of the constant is 2500.

For information on the `oml.svd` class attributes and methods, invoke `help(oml.svd)` or see *Oracle Machine Learning for Python API Reference*.

Settings for a Singular Value Decomposition Model

Table 5-15 Singular Value Decomposition Model Settings

Setting Name	Setting Value	Description
`FEAT_NUM_FEATURES`	`TO_CHAR(`*numeric_expr*`>=1)`	The number of features to extract. The default value is estimated by the algorithm. If the matrix rank is smaller than this number, fewer features are returned.

Table 5-15 (Cont.) Singular Value Decomposition Model Settings

Setting Name	Setting Value	Description
SVDS_OVER_SAMPLING	Range [1, 5000].	Configures the number of columns in the sampling matrix used by the Stochastic SVD solver. The number of columns in this matrix is equal to the requested number of features plus the oversampling setting. TSVDS_SOLVER must be set to SVDS_SOLVER_SSVD or SVDS_SOLVER_STEIGEN.
SVDS_POWER_ITERATIONS	Range [0, 20].	Improves the accuracy of the SSVD solver. The default value is 2. SVDS_SOLVER must be set to SVDS_SOLVER_SSVD or SVDS_SOLVER_STEIGEN.
SVDS_RANDOM_SEED	Range [0 - 4,294,967,296]	The random seed value for initializing the sampling matrix used by the Stochastic SVD solver. The default value is 0. SVDS_SOLVER must be set to SVDS_SOLVER_SSVD or SVDS_SOLVER_STEIGEN
SVDS_SCORING_MODE	SVDS_SCORING_PCA SVDS_SCORING_SVD	Whether to use SVD or PCA scoring for the model. When the build data is scored with SVD, the projections are the same as the U matrix. When the build data is scored with PCA, the projections are the product of the U and D matrices. The default value is SVDS_SCORING_SVD.
SVDS_SOLVER	SVDS_SOLVER_STEIGEN SVDS_SOLVER_SSVD SVDS_SOLVER_TSEIGEN SVDS_SOLVER_TSSVD	Specifies the solver to be used for computing SVD of the data. For PCA, the solver setting indicates the type of SVD solver used to compute the PCA for the data. When this setting is not specified, the solver type selection is data driven. If the number of attributes is greater than 3240, then the default wide solver is used. Otherwise, the default narrow solver is selected. The following are the group of solvers: • Narrow data solvers: for matrices with up to 11500 attributes (TSEIGEN) or up to 8100 attributes (TSSVD). • Wide data solvers: for matrices up to 1 million attributes. For narrow data solvers: • Tall-Skinny SVD uses QR computation TSVD (SVDS_SOLVER_TSSVD) • Tall-Skinny SVD uses eigenvalue computation, TSEIGEN (SVDS_SOLVER_TSEIGEN), which is the default solver for narrow data. For wide data solvers: • Stochastic SVD uses QR computation SSVD (SVDS_SOLVER_SSVD), is the default solver for wide data solvers. • Stochastic SVD uses eigenvalue computations, STEIGEN (SVDS_SOLVER_STEIGEN).
SVDS_TOLERANCE	Range [0, 1]	Defines the minimum value for the eigenvalue of a feature as a share of the first eigenvalue to not prune. Use this setting to prune features. The default value is data driven.

Table 5-15 (Cont.) Singular Value Decomposition Model Settings

Setting Name	Setting Value	Description
SVDS_U_MATRIX_OUTPUT	SVDS_U_MATRIX_ENABLE SVDS_U_MATRIX_DISABLE	Specifies whether to persist the U matrix produced by SVD. The U matrix in SVD has as many rows as the number of rows in the build data. To avoid creating a large model, the U matrix is persisted only when SVDS_U_MATRIX_OUTPUT is enabled. When SVDS_U_MATRIX_OUTPUT is enabled, the build data must include a case ID. If no case ID is present and the U matrix is requested, then an exception is raised. The default value is SVDS_U_MATRIX_DISABLE.

See Also:

- About Model Settings
- Shared Settings

Example 5-17 Using the oml.svd Class

This example uses some of the methods of the `oml.svd` class. In the listing for this example, some of the output is not shown as indicated by ellipses.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

try:
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training and test data.
dat = oml.sync(table = 'IRIS').split()
train_dat = dat[0]
test_dat = dat[1]

# Create an SVD model object.
```

```
svd_mod = oml.svd(ODMS_DETAILS = 'ODMS_ENABLE')

# Fit the model according to the training data and parameter
# settings.
svd_mod = svd_mod.fit(train_dat)

# Show the model details.
svd_mod

# Use the model to make predictions on the test data.
svd_mod.predict(test_dat,
                supplemental_cols = test_dat[:,
                                             ['Sepal_Length',
                                              'Sepal_Width',
                                              'Petal_Length',
                                              'Species']])

# Perform dimensionality reduction and return values for the two
# features that have the highest topN values.
svd_mod.transform(test_dat,
  supplemental_cols = test_dat[:, ['Sepal_Length']],
    topN = 2).sort_values(by = ['Sepal_Length',
                                'TOP_1',
                                'TOP_1_VAL'])
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
... except:
...    pass
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Create training and test data.
... dat = oml.sync(table = 'IRIS').split()
>>> train_dat = dat[0]
>>> test_dat = dat[1]
>>>
>>> # Create an SVD model object.
```

```
... svd_mod = oml.svd(ODMS_DETAILS = 'ODMS_ENABLE')
>>>
>>> # Fit the model according to the training data and parameter
... # settings.
>>> svd_mod = svd_mod.fit(train_dat)
>>>
>>> # Show the model details.
... svd_mod

Algorithm Name: Singular Value Decomposition

Mining Function: FEATURE_EXTRACTION

Settings:
               setting name               setting value
0                      ALGO_NAME  ALGO_SINGULAR_VALUE_DECOMP
1                   ODMS_DETAILS                ODMS_ENABLE
2  ODMS_MISSING_VALUE_TREATMENT     ODMS_MISSING_VALUE_AUTO
3                 ODMS_SAMPLING       ODMS_SAMPLING_DISABLE
4                     PREP_AUTO                          ON
5             SVDS_SCORING_MODE            SVDS_SCORING_SVD
6          SVDS_U_MATRIX_OUTPUT       SVDS_U_MATRIX_DISABLE

Computed Settings:
        setting name                     setting value
0  FEAT_NUM_FEATURES                                 8
1        SVDS_SOLVER              SVDS_SOLVER_TSEIGEN
2     SVDS_TOLERANCE  .00000000000002464695114667847 5

Global Statistics:
    attribute name  attribute value
0   NUM_COMPONENTS                8
1         NUM_ROWS              111
2 SUGGESTED_CUTOFF                1

Attributes:
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width
Species

Partition: NO

Features:

   FEATURE_ID ATTRIBUTE_NAME ATTRIBUTE_VALUE     VALUE
0           1             ID            None  0.996297
1           1   Petal_Length            None  0.046646
2           1    Petal_Width            None  0.015917
3           1   Sepal_Length            None  0.063312
... ... ... ... ...
60          8   Sepal_Width             None -0.030620
61          8       Species          setosa  0.431543
62          8       Species      versicolor  0.566418
63          8       Species       virginica  0.699261
```

```
[64 rows x 4 columns]

D:

   FEATURE_ID      VALUE
0           1  886.737809
1           2   32.736792
2           3   10.043389
3           4    5.270496
4           5    2.708602
5           6    1.652340
6           7    0.938640
7           8    0.452170

V:

        '1'       '2'       '3'       '4'       '5'       '6'       '7' \
0  0.001332  0.156581 -0.317375  0.113462 -0.154414 -0.113058  0.799390
1  0.003692  0.052289  0.316295  0.733040  0.190746  0.022285 -0.046406
2  0.005267 -0.051498 -0.052111  0.527881 -0.066995  0.046461 -0.469396
3  0.015917  0.008741  0.263614  0.244811  0.460445  0.767503  0.262966
4  0.030208  0.550384 -0.358277  0.041807  0.689962 -0.261815 -0.143258
5  0.046646  0.189325  0.766663  0.326363  0.079611 -0.479070  0.177661
6  0.063312  0.790864  0.097964 -0.051230 -0.490804  0.312159 -0.131337
7  0.996297 -0.076079 -0.035940 -0.017429 -0.000960 -0.001908  0.001755
        '8'
0  0.431543
1  0.566418
2  0.699261
3  0.005000
4 -0.030620
5 -0.016932
6 -0.052185
7 -0.001415

>>> # Use the model to make predictions on the test data.
>>> svd_mod.predict(test_dat,
                    supplemental_cols = test_dat[:,
...                                              ['Sepal_Length',
...                                               'Sepal_Width',
...                                               'Petal_Length',
...                                               'Species']])
    Sepal_Length  Sepal_Width  Petal_Length     Species  FEATURE_ID
0            5.0          3.6           1.4    setosa           2
1            5.0          3.4           1.5    setosa           2
2            4.4          2.9           1.4    setosa           8
3            4.9          3.1           1.5    setosa           2
... ... ... ... ... ...
35           6.9          3.1           5.4 virginica           1
36           5.8          2.7           5.1 virginica           1
37           6.2          3.4           5.4 virginica           5
38           5.9          3.0           5.1 virginica           1

>>> # Perform dimensionality reduction and return values for the two
... # features that have the highest topN values.
```

```
>>> svd_mod.transform(test_dat,
...   supplemental_cols = test_dat[:, ['Sepal_Length']],
...     topN = 2).sort_values(by = ['Sepal_Length',
...                                 'TOP_1',
...                                 'TOP_1_VAL'])
    Sepal_Length  TOP_1  TOP_1_VAL  TOP_2  TOP_2_VAL
0            4.4      7   0.153125      3  -0.130778
1            4.4      8   0.171819      2   0.147070
2            4.8      2   0.159324      6  -0.085194
3            4.8      7   0.157187      3  -0.141668
... ... ... ... ... ...
35           7.2      6  -0.167688      1   0.142545
36           7.2      7  -0.176290      6  -0.175527
37           7.6      4   0.205779      3   0.141533
38           7.9      8  -0.253194      7  -0.166967
```

5.18 Support Vector Machine

The `oml.svm` class creates a Support Vector Machine (SVM) model for classification, regression, or anomaly detection.

SVM is a powerful, state-of-the-art algorithm with strong theoretical foundations based on the Vapnik-Chervonenkis theory. SVM has strong regularization properties. Regularization refers to the generalization of the model to new data.

SVM models have a functional form similar to neural networks and radial basis functions, which are both popular machine learning techniques.

SVM can be used to solve the following problems:

- **Classification**: SVM classification is based on decision planes that define decision boundaries. A decision plane is one that separates a set of objects having different class memberships. SVM finds the vectors (“support vectors") that define the separators that give the widest separation of classes.

  SVM classification supports both binary and multiclass targets.
- **Regression**: SVM uses an epsilon-insensitive loss function to solve regression problems.

  SVM regression tries to find a continuous function such that the maximum number of data points lie within the epsilon-wide insensitivity tube. Predictions falling within epsilon distance of the true target value are not interpreted as errors.
- **Anomaly Detection**: Anomaly detection identifies unusual cases in data that is seemingly homogeneous. Anomaly detection is an important tool for detecting fraud, network intrusion, and other rare events that may have great significance but are hard to find.

  Anomaly detection is implemented as one-class SVM classification. An anomaly detection model predicts whether a data point is typical for a given distribution or not.

The `oml.svm` class builds each of these three different types of models. Some arguments apply to classification models only, some to regression models only, and some to anomaly detection models only.

For information on the `oml.svm` class attributes and methods, invoke `help(oml.svm)` or see *Oracle Machine Learning for Python API Reference*.

Support Vector Machine Model Settings

The following table lists settings for SVM models.

Table 5-16 Support Vector Machine Settings

Setting Name	Setting Value	Description
CLAS_COST_TABLE_NAME	*table_name*	The name of a table that stores a cost matrix for the algorithm to use in scoring the model. The cost matrix specifies the costs associated with misclassifications. The cost matrix table is user-created. The following are the column requirements for the table. • Column Name: ACTUAL_TARGET_VALUE Data Type: Valid target data type • Column Name: PREDICTED_TARGET_VALUE Data Type: Valid target data type • Column Name: COST Data Type: NUMBER
CLAS_WEIGHTS_BALANCED	ON OFF	Indicates whether the algorithm must create a model that balances the target distribution. This setting is most relevant in the presence of rare targets, as balancing the distribution may enable better average accuracy (average of per-class accuracy) instead of overall accuracy (which favors the dominant class). The default value is OFF.
CLAS_WEIGHTS_TABLE_NAME	*table_name*	The name of a table that stores weighting information for individual target values in GLM logistic regression models. The weights are used by the algorithm to bias the model in favor of higher weighted classes. The class weights table is user-created. The following are the column requirements for the table. • Column Name: TARGET_VALUE Data Type: Valid target data type • Column Name: CLASS_WEIGHT Data Type: NUMBER
SVMS_BATCH_ROWS	Positive integer	Sets the size of the batch for the SGD solver. This setting applies to SVM models with linear kernel. An input of 0 triggers a data driven batch size estimate. The default value is 20000.
SVMS_COMPLEXITY_FACTOR	TO_CHAR(*numeric_expr* >0)	Regularization setting that balances the complexity of the model against model robustness to achieve good generalization on new data. SVM uses a data-driven approach to finding the complexity factor. Value of complexity factor for SVM algorithm (both Classification and Regression). Default value estimated from the data by the algorithm.
SVMS_CONV_TOLERANCE	TO_CHAR(*numeric_expr* >0)	Convergence tolerance for SVM algorithm. Default is 0.0001.
SVMS_EPSILON	TO_CHAR(*numeric_expr* >0)	Regularization setting for regression, similar to complexity factor. Epsilon specifies the allowable residuals, or noise, in the data. Value of epsilon factor for SVM regression. Default is 0.1.
SVMS_KERNEL_FUNCTION	SVMS_GAUSSIAN SVMS_LINEAR	Kernel for Support Vector Machine. Linear or Gaussian. The default value is SVMS_LINEAR.
SVMS_NUM_ITERATIONS	Positive integer	Sets an upper limit on the number of SVM iterations. The default is system determined because it depends on the SVM solver.

Table 5-16 (Cont.) Support Vector Machine Settings

Setting Name	Setting Value	Description
SVMS_NUM_PIVOTS	Range [1; 10000]	Sets an upper limit on the number of pivots used in the Incomplete Cholesky decomposition. It can be set only for non-linear kernels. The default value is 200.
SVMS_OUTLIER_RATE	TO_CHAR(*0< numeric_expr <1*)	The desired rate of outliers in the training data. Valid for One-Class SVM models only (Anomaly Detection). The default value is 0.01.
SVMS_REGULARIZER	SVMS_REGULARIZER_L1 SVMS_REGULARIZER_L2	Controls the type of regularization that the SGD SVM solver uses. The setting applies only to linear SVM models. The default value is system determined because it depends on the potential model size.
SVMS_SOLVER	SVMS_SOLVER_SGD (Sub-Gradient Descend) SVMS_SOLVER_IPM (Interior Point Method)	Allows the user to choose the SVM solver. The SGD solver cannot be selected if the kernel is non-linear. The default value is system determined.
SVMS_STD_DEV	TO_CHAR(*numeric_expr >0*)	Controls the spread of the Gaussian kernel function. SVM uses a data-driven approach to find a standard deviation value that is on the same scale as distances between typical cases. Value of standard deviation for SVM algorithm. This is applicable only for the Gaussian kernel. The default value is estimated from the data by the algorithm.

See Also:

- About Model Settings
- Shared Settings

Example 5-18 Using the oml.svm Class

This example demonstrates the use of various methods of the `oml.svm` class. In the listing for this example, some of the output is not shown as indicated by ellipses.

```
import oml
import pandas as pd
from sklearn import datasets

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species']))

try:
```

```
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Create training and test data.
dat = oml.sync(table = 'IRIS').split()
train_x = dat[0].drop('Species')
train_y = dat[0]['Species']
test_dat = dat[1]

# Create an SVM model object.
svm_mod = oml.svm('classification',
                  svms_kernel_function =
                  'dbms_data_mining.svms_linear')

# Fit the SVM Model according to the training data and parameter
# settings.
svm_mod.fit(train_x, train_y)

# Use the model to make predictions on test data.
svm_mod.predict(test_dat.drop('Species'),
                supplemental_cols = test_dat[:, ['Sepal_Length',
                                                 'Sepal_Width',
                                                 'Petal_Length',
                                                 'Species']])

# Return the prediction probability.
svm_mod.predict(test_dat.drop('Species'),
                supplemental_cols = test_dat[:, ['Sepal_Length',
                                                 'Sepal_Width',
                                                 'Species']],
                proba = True)
svm_mod.predict_proba(test_dat.drop('Species'),
  supplemental_cols = test_dat[:, ['Sepal_Length',
                                   'Sepal_Width',
                                   'Species']],
  topN = 1).sort_values(by = ['Sepal_Length', 'Sepal_Width'])

svm_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
```

```
...                             {0: 'setosa', 1: 'versicolor',
...                              2:'virginica'}[x], iris.target)),
...                   columns = ['Species'])
>>>
>>> try:
...    oml.drop('IRIS')
... except:
...    pass
>>>
>>> # Create the IRIS database table and the proxy object for the table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Create training and test data.
... dat = oml.sync(table = 'IRIS').split()
>>> train_x = dat[0].drop('Species')
>>> train_y = dat[0]['Species']
>>> test_dat = dat[1]
>>>
>>> # Create an SVM model object.
... svm_mod = oml.svm('classification',
...                    svms_kernel_function =
...                    'dbms_data_mining.svms_linear')
>>>
>>> # Fit the SVM model according to the training data and parameter
... # settings.
>>> svm_mod.fit(train_x, train_y)

Algorithm Name: Support Vector Machine

Mining Function: CLASSIFICATION

Target: Species

Settings:
            setting name                         setting value
0                    ALGO_NAME  ALGO_SUPPORT_VECTOR_MACHINES
1         CLAS_WEIGHTS_BALANCED                           OFF
2                 ODMS_DETAILS                   ODMS_ENABLE
3  ODMS_MISSING_VALUE_TREATMENT       ODMS_MISSING_VALUE_AUTO
4                ODMS_SAMPLING         ODMS_SAMPLING_DISABLE
5                    PREP_AUTO                            ON
6           SVMS_CONV_TOLERANCE                         .0001
7          SVMS_KERNEL_FUNCTION                   SVMS_LINEAR

Computed Settings:
           setting name    setting value
0  SVMS_COMPLEXITY_FACTOR               10
1     SVMS_NUM_ITERATIONS               30
2             SVMS_SOLVER  SVMS_SOLVER_IPM

Global Statistics:
   attribute name  attribute value
0       CONVERGED              YES
1      ITERATIONS               14
2        NUM_ROWS              104
```

```
Attributes:
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width

Partition: NO

COEFFICIENTS:

   TARGET_VALUE ATTRIBUTE_NAME ATTRIBUTE_SUBNAME ATTRIBUTE_VALUE    COEF
0        setosa   Petal_Length              None            None -0.5809
1        setosa    Petal_Width              None            None -0.7736
2        setosa   Sepal_Length              None            None -0.1653
3        setosa    Sepal_Width              None            None  0.5689
4        setosa           None              None            None -0.7355
5    versicolor   Petal_Length              None            None  1.1304
6    versicolor    Petal_Width              None            None -0.3323
7    versicolor   Sepal_Length              None            None -0.8877
8    versicolor    Sepal_Width              None            None -1.2582
9    versicolor           None              None            None -0.9091
10    virginica   Petal_Length              None            None  4.6042
11    virginica    Petal_Width              None            None  4.0681
12    virginica   Sepal_Length              None            None -0.7985
13    virginica    Sepal_Width              None            None -0.4328
14    virginica           None              None            None -5.3180

>>> # Use the model to make predictions on test data.
... svm_mod.predict(test_dat.drop('Species'),
...                 supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                  'Sepal_Width',
...                                                  'Petal_Length',
...                                                  'Species']])
    Sepal_Length  Sepal_Width  Petal_Length     Species  PREDICTION
0            4.9          3.0           1.4      setosa      setosa
1            4.9          3.1           1.5      setosa      setosa
2            4.8          3.4           1.6      setosa      setosa
3            5.8          4.0           1.2      setosa      setosa
...          ...          ...           ...         ...         ...
44           6.7          3.3           5.7   virginica   virginica
45           6.7          3.0           5.2   virginica   virginica
46           6.5          3.0           5.2   virginica   virginica
47           5.9          3.0           5.1   virginica   virginica

>>> # Return the prediction probability.
... svm_mod.predict(test_dat.drop('Species'),
...                 supplemental_cols = test_dat[:, ['Sepal_Length',
...                                                  'Sepal_Width',
...                                                  'Species']],
...                 proba = True)
    Sepal_Length  Sepal_Width     Species  PREDICTION  PROBABILITY
0            4.9          3.0      setosa      setosa     0.761886
1            4.9          3.1      setosa      setosa     0.805510
2            4.8          3.4      setosa      setosa     0.920317
3            5.8          4.0      setosa      setosa     0.998398
...          ...          ...         ...         ...          ...
```

```
44           6.7          3.3   virginica   virginica     0.927706
45           6.7          3.0   virginica   virginica     0.855353
46           6.5          3.0   virginica   virginica     0.799556
47           5.9          3.0   virginica   virginica     0.688024

>>> # Make predictions and return the probability for each class
... # on new data.
>>> svm_mod.predict_proba(test_dat.drop('Species'),
...   supplemental_cols = test_dat[:, ['Sepal_Length',
...                                    'Sepal_Width',
...                                    'Species']],
...   topN = 1).sort_values(by = ['Sepal_Length', 'Sepal_Width'])
    Sepal_Length  Sepal_Width     Species       TOP_1  TOP_1_VAL
0            4.4          3.0      setosa      setosa   0.698067
1            4.4          3.2      setosa      setosa   0.815643
2            4.5          2.3      setosa  versicolor   0.605105
3            4.8          3.4      setosa      setosa   0.920317
...          ...          ...         ...         ...        ...
44           6.7          3.3   virginica   virginica   0.927706
45           6.9          3.1  versicolor  versicolor   0.378391
46           6.9          3.1   virginica   virginica   0.881118
47           7.0          3.2  versicolor      setosa   0.586393

>>> svm_mod.score(test_dat.drop('Species'), test_dat[:, ['Species']])
0.895833
```

5.19 Non-Negative Matrix Factorization

The `oml.nmf` class creates a Non-Negative Matrix Factorization (NMF) model for feature extraction.

Each feature extracted by NMF is a linear combination of the original attribution set. Each feature has a set of non-negative coefficients, which are a measure of the weight of each attribute on the feature. If the argument `allow.negative.scores` is `TRUE`, then negative coefficients are allowed.

Settings for a Non-Negative Matrix Factorization Models

The following table lists settings that apply to Non-Negative Matrix Factorization models.

Table 5-17 Non-Negative Matrix Factorization Model Settings

Setting Name	Setting Value	Description
`NMFS_CONV_TOLERANCE`	`(0< numeric_expr <=0.5)`	Convergence tolerance for NMF algorithm Default is `0.05`
`NMFS_NONNEGATIVE_SCORING`	`NMFS_NONNEG_SCORING_ENABLE` `NMFS_NONNEG_SCORING_DISABLE`	Whether negative numbers should be allowed in scoring results. When set to `NMFS_NONNEG_SCORING_ENABLE`, negative feature values will be replaced with zeros. When set to `NMFS_NONNEG_SCORING_DISABLE`, negative feature values will be allowed. Default is `NMFS_NONNEG_SCORING_ENABLE`

Table 5-17 (Cont.) Non-Negative Matrix Factorization Model Settings

Setting Name	Setting Value	Description
NMFS_NUM_ITERATIONS	(1 <= numeric_expr <=500)	Number of iterations for NMF algorithm Default is 50
NMFS_RANDOM_SEED	(numeric_expr)	Random seed for NMF algorithm. Default is -1.

Example 5-19 Using the oml.nmf Class

This example creates an NMF model and uses some of the methods of the `oml.nmf` class.

```
import oml
import pandas as pd from sklearn import datasets
#For on-premises database follow the below command to connect to the database
oml.connect("<username>","<password>",dsn="dsn")

iris = datasets.load_iris()
x = pd.DataFrame(iris.data, columns = ['Sepal_Length', 'Sepal_Width',
'Petal_Length', 'Petal_Width'])
x.insert(0, "ID", range(1, len(x) + 1))
y = pd.DataFrame(list(map(lambda x: {0: 'setosa', 1: 'versicolor',
2:'virginica'}[x], iris.target)), columns = ['Species'])

z = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

#Create training and test data sets.

train_dat, test_dat = oml.sync(table = "IRIS").split()

#Create a Non-Negative Matrix Factorization model using oml.nmf.

nmf_mod = oml.nmf()

#Fit the model to the training data.

nmf_mod = nmf_mod.fit(train_dat)

#Show the model details.

nmf_mod
#Use the model to make predictions on the test data, returning the
Sepal_Length, Sepal_Width, Petal_Length, and Species columns in the result.

nmf_mod.predict(test_dat, supplemental_cols = test_dat[:, ['Sepal_Length',
'Sepal_Width', 'Petal_Length', 'Species']])

nmf_mod.transform(test_dat, supplemental_cols = test_dat[:,
['Sepal_Length']], topN = 2).sort_values(by = ['Sepal_Length', 'TOP_1',
'TOP_1_VAL'])

#Feature comparison
```

```
nmf_mod.feature_compare(test_dat, compare_cols = ["Sepal_Length",
"Petal_Length"], supplemental_cols = ["Species"])

#Set new parameters and refit the model to produce U matrix output.

new_setting = {'nmfs_conv_tolerance':0.05}
nmf_mod2 = nmf_mod.set_params(**new_setting).fit(train_dat, case_id = "ID")
nmf_mod2
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets

>>> #For on-premises database follow the below command to connect to the
database
>>> oml.connect("<username>","<password>", dsn="<dsn>")

>>> iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data, columns = ['Sepal_Length', 'Sepal_Width',
'Petal_Length', 'Petal_Width'])
>>> x.insert(0, "ID", range(1, len(x) + 1))
>>> y = pd.DataFrame(list(map(lambda x: {0: 'setosa', 1: 'versicolor',
2:'virginica'}[x], iris.target)), columns = ['Species'])

>>> z = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

#Create training and test data sets.

>>> dat = oml.sync(table = "IRIS").split()
>>> train_dat = dat[0]
>>> test_dat = dat[1]

#Create a Non-Negative Matrix Factorization model using oml.nmf.

>>> nmf_mod = oml.nmf()

#Fit the model to the training data.

>>> nmf_mod = nmf_mod.fit(train_dat)

#Show the model details.

>>> nmf_mod

Algorithm Name: Non-Negative Matrix Factorizationx

Mining Function: FEATURE_EXTRACTION

Settings:
                   setting name                    setting value
0                     ALGO_NAME  ALGO_NONNEGATIVE_MATRIX_FACTOR
```

```
1           NMFS_CONV_TOLERANCE                             .05
2      NMFS_NONNEGATIVE_SCORING      NMFS_NONNEG_SCORING_ENABLE
3           NMFS_NUM_ITERATIONS                             50
4              NMFS_RANDOM_SEED                             -1
5                  ODMS_DETAILS                    ODMS_ENABLE
6  ODMS_MISSING_VALUE_TREATMENT         ODMS_MISSING_VALUE_AUTO
7                 ODMS_SAMPLING           ODMS_SAMPLING_DISABLE
8                     PREP_AUTO                             ON

Computed Settings:
              setting name setting value
0        FEAT_NUM_FEATURES             2
1      NMFS_NUM_ITERATIONS             2
2  ODMS_EXPLOSION_MIN_SUPP             1

Global Statistics:
  attribute name attribute value
0      CONVERGED             YES
1     CONV_ERROR       0.0444448
2     ITERATIONS               2
3       NUM_ROWS             111
4    SAMPLE_SIZE             111

Attributes:
ID
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width
Species

Partition: NO

H:

    FEATURE_ID  FEATURE_NAME ATTRIBUTE_NAME ATTRIBUTE_VALUE  COEFFICIENT
0            1             1             ID            None     0.581551
1            1             1   Petal_Length            None     0.355323
2            1             1    Petal_Width            None     0.158492
3            1             1   Sepal_Length            None     0.656558
4            1             1    Sepal_Width            None     0.424101
5            1             1        Species          setosa     0.089560
6            1             1        Species      versicolor     0.534806
7            1             1        Species       virginica     0.539590
8            2             2             ID            None     0.344647
9            2             2   Petal_Length            None     0.506623
10           2             2    Petal_Width            None     0.650077
11           2             2   Sepal_Length            None     0.170237
12           2             2    Sepal_Width            None     0.248640
13           2             2        Species          setosa     0.249221
14           2             2        Species      versicolor     0.042316
15           2             2        Species       virginica     0.093861

W:

    FEATURE_ID  FEATURE_NAME ATTRIBUTE_NAME ATTRIBUTE_VALUE  COEFFICIENT
```

```
0            1             1             ID            None     0.288559
1            1             1   Petal_Length            None    -0.062579
2            1             1    Petal_Width            None    -0.370128
3            1             1   Sepal_Length            None     0.502382
4            1             1    Sepal_Width            None     0.212611
5            1             1        Species      versicolor     0.486970
6            1             1        Species          setosa    -0.113835
7            1             1        Species       virginica     0.450038
8            2             2             ID            None     0.119462
9            2             2   Petal_Length            None     0.578697
10           2             2    Petal_Width            None     0.982575
11           2             2   Sepal_Length            None    -0.238993
12           2             2    Sepal_Width            None     0.082511
13           2             2        Species          setosa     0.353453
14           2             2        Species      versicolor    -0.359264
15           2             2        Species       virginica    -0.275074
```

```
#Use the model to make predictions on the test data, returning the
Sepal_Length, Sepal_Width, Petal_Length, and Species columns in the result.

>>> nmf_mod.predict(test_dat, supplemental_cols = test_dat[:,
['Sepal_Length', 'Sepal_Width', 'Petal_Length', 'Species']])
     Sepal_Length  Sepal_Width  Petal_Length     Species  FEATURE_ID
 0            5.0          3.6           1.4      setosa           2
 1            5.0          3.4           1.5      setosa           2
 2            4.4          2.9           1.4      setosa           2
 3            4.9          3.1           1.5      setosa           2
...           ...          ...           ...         ...         ...
 35           6.9          3.1           5.4   virginica           2
 36           5.8          2.7           5.1   virginica           2
 37           6.2          3.4           5.4   virginica           2
 38           5.9          3.0           5.1   virginica           2

#Transform

>>> nmf_mod.transform(test_dat, supplemental_cols = test_dat[:,
['Sepal_Length']], topN = 2).sort_values(by = ['Sepal_Length', 'TOP_1',
'TOP_1_VAL'])
     Sepal_Length  TOP_1  TOP_1_VAL  TOP_2  TOP_2_VAL
 0            4.4      2   0.464041      1   0.000000
 1            4.4      2   0.482051      1   0.045518
 2            4.8      2   0.475169      1   0.083874
 3            4.8      2   0.510372      1   0.101880
...           ...    ...        ...    ...        ...
 35           7.2      1   0.915012      2   0.850330
 36           7.2      1   0.938112      2   0.745207
 37           7.6      2   0.980757      1   0.864508
 38           7.9      1   1.048287      2   0.947744

#Feature comparison

>>> nmf_mod.feature_compare(test_dat, compare_cols = ["Sepal_Length",
"Petal_Length"], supplemental_cols = ["Species"])
      Species_A  Species_B  SIMILARITY
```

```
 0       setosa     setosa    0.990134
 1       setosa     setosa    0.929516
 2       setosa     setosa    0.976885
 3       setosa     setosa    0.953770
...         ...        ...         ...
 737  virginica  virginica    0.849758
 738  virginica  virginica    0.944063
 739  virginica  virginica    0.983637
 740  virginica  virginica    0.958018

[741 rows x 3 columns]

#Set new parameters and refit tthe model to produce U matrix output.

>>> new_setting = {'nmfs_conv_tolerance':0.05}
>>> nmf_mod2 = nmf_mod.set_params(**new_setting).fit(train_dat, case_id =
"ID")
>>> nmf_mod2

Algorithm Name: Non-Negative Matrix Factorizationx

Mining Function: FEATURE_EXTRACTION

Settings:
                   setting name                    setting value
0                     ALGO_NAME  ALGO_NONNEGATIVE_MATRIX_FACTOR
1           NMFS_CONV_TOLERANCE                             0.05
2      NMFS_NONNEGATIVE_SCORING      NMFS_NONNEG_SCORING_ENABLE
3           NMFS_NUM_ITERATIONS                              50
4              NMFS_RANDOM_SEED                              -1
5                  ODMS_DETAILS                     ODMS_ENABLE
6  ODMS_MISSING_VALUE_TREATMENT         ODMS_MISSING_VALUE_AUTO
7                 ODMS_SAMPLING           ODMS_SAMPLING_DISABLE
8                     PREP_AUTO                              ON

Computed Settings:
              setting name setting value
0        FEAT_NUM_FEATURES             2
1      NMFS_NUM_ITERATIONS             8
2  ODMS_EXPLOSION_MIN_SUPP             1

Global Statistics:
  attribute name attribute value
0      CONVERGED             YES
1     CONV_ERROR       0.0277253
2     ITERATIONS               8
3       NUM_ROWS             111
4    SAMPLE_SIZE             111

Attributes:
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width
Species
```

```
Partition: NO

H:

    FEATURE_ID  FEATURE_NAME ATTRIBUTE_NAME ATTRIBUTE_VALUE   COEFFICIENT
0            1             1   Petal_Length            None  9.889792e-02
1            1             1    Petal_Width            None  1.060984e-01
2            1             1   Sepal_Length            None  1.947197e-01
3            1             1    Sepal_Width            None  5.099539e-01
4            1             1        Species          setosa  7.507257e-01
5            1             1        Species      versicolor  5.773815e-03
6            1             1        Species       virginica  8.136382e-02
7            2             2   Petal_Length            None  6.652922e-01
8            2             2    Petal_Width            None  6.571416e-01
9            2             2   Sepal_Length            None  5.702848e-01
10           2             2    Sepal_Width            None  2.420062e-01
11           2             2        Species          setosa  1.643131e-08
12           2             2        Species      versicolor  5.158020e-01
13           2             2        Species       virginica  4.948837e-01

W:

    FEATURE_ID  FEATURE_NAME ATTRIBUTE_NAME ATTRIBUTE_VALUE  COEFFICIENT
0            1             1   Petal_Length            None    -0.071259
1            1             1    Petal_Width            None    -0.059774
2            1             1   Sepal_Length            None     0.077608
3            1             1    Sepal_Width            None     0.571981
4            1             1        Species      versicolor    -0.144686
5            1             1        Species          setosa     0.947005
6            1             1        Species       virginica    -0.043170
7            2             2   Petal_Length            None     0.392684
8            2             2    Petal_Width            None     0.385395
9            2             2   Sepal_Length            None     0.304214
10           2             2    Sepal_Width            None     0.003195
11           2             2        Species          setosa    -0.221185
12           2             2        Species      versicolor     0.325338
13           2             2        Species       virginica     0.289804
```

5.20 Exponential Smoothing Method

The `oml.esm` function uses the Exponential Smoothing Method (ESM) algorithm to create a time series model.

Exponential Smoothing Methods have been widely used in forecasting for over half a century. It has applications at the strategic, tactical, and operation level. For example, at a strategic level, forecasting is used for projecting return on investment, growth and the effect of innovations. At a tactical level, forecasting is used for projecting costs, inventory requirements, and customer satisfaction. At an operational level, forecasting is used for setting targets and predicting quality and conformance with standards.

In its simplest form, Exponential Smoothing is a moving average method with a single parameter that models an exponentially decreasing effect of past levels on future values. With a variety of extensions, Exponential Smoothing covers a broader class of models than other well-known approaches, such as the Box-Jenkins auto-regressive integrated moving average

(ARIMA) approach. Oracle Machine Learning implements Exponential Smoothing using a state-of-the-art state space method that incorporates a single source of error (SSOE) assumption that provides theoretical and performance advantages.

Settings for an ESM model

The following table lists settings for ESM models.

Table 5-18 ESM Model Settings

Setting Name	Setting Value	Description
EXSM_MODEL	It can take value in set *{EXSM_SIMPLE, EXSM_SIMPLE_MULT, EXSM_HOLT, EXSM_HOLT_DMP, EXSM_MUL_TRND, EXSM_MULTRD_DMP, EXSM_SEAS_ADD, EXSM_SEAS_MUL, EXSM_HW, EXSM_HW_DMP, EXSM_HW_ADDSEA, EXSM_DHW_ADDSEA, EXSM_HWMT, EXSM_HWMT_DMP}*	This setting specifies the model. EXSM_SIMPLE: Simple exponential smoothing model is applied. EXSM_SIMPLE_MULT: Simple exponential smoothing model with multiplicative error is applied. EXSM_HOLT: Holt linear exponential smoothing model is applied. EXSM_HOLT_DMP: Holt linear exponential smoothing model with damped trend is applied. EXSM_MUL_TRND: Exponential smoothing model with multiplicative trend is applied. EXSM_MULTRD_DMP: Exponential smoothing model with multiplicative damped trend is applied. EXSM_SEAS_ADD: Exponential smoothing with additive seasonality, but no trend, is applied. EXSM_SEAS_MUL:Exponential smoothing with multiplicative seasonality, but no trend, is applied. EXSM_HW: Holt-Winters triple exponential smoothing model, additive trend, multiplicative seasonality is applied. EXSM_HW_DMP: Holt-Winters multiplicative exponential smoothing model with damped trend, additive trend, multiplicative seasonality is applied. EXSM_HW_ADDSEA: Holt-Winters additive exponential smoothing model, additive trend, additive seasonality is applied. EXSM_DHW_ADDSEA: Holt-Winters additive exponential smoothing model with damped trend, additive trend, additive seasonality is applied. EXSM_HWMT: Holt-Winters multiplicative exponential smoothing model with multiplicative trend, multiplicative trend, multiplicative seasonality is applied. EXSM_HWMT_DMP: Holt-Winters multiplicative exponential smoothing model with damped multiplicative trend, multiplicative trend, multiplicative seasonality is applied. The default value is EXSM_SIMPLE.

Table 5-18 (Cont.) ESM Model Settings

Setting Name	Setting Value	Description
EXSM_SEASONALITY	positive integer > 1	This setting specifies a positive integer value as the length of seasonal cycle. The value specified must be larger than 1. For example, setting value 4 means that every group of four observations forms a seasonal cycle. This setting is only applicable and must be provided for models with seasonality, otherwise the model throws an error. When EXSM_INTERVAL is not set, this setting applies to the original input time series. When EXSM_INTERVAL is set, this setting applies to the accumulated time series.
EXSM_INTERVAL	It can take value in set *{EXSM_INTERVAL_YEAR, EXSM_INTERVAL_QTR, EXSM_INTERVAL_MONTH,EXSM_INTERVAL_WEEK, EXSM_INTERVAL_DAY, EXSM_INTERVAL_HOUR, EXSM_INTERVAL_MIN,EXSM_INTERVAL_SEC}*	This setting only applies and must be provided when the time column (case_id column) has datetime type. It specifies the spacing interval of the accumulated equally spaced time series. The model throws an error if the time column of input table is of datetime type and setting EXSM_INTERVAL is not provided. The model throws an error if the time column of input table is of oracle number type and setting EXSM_INTERVAL is provided.
EXSM_ACCUMULATE	It can take value in set *{EXSM_ACCU_TOTAL, EXSM_ACCU_STD, EXSM_ACCU_MAX, EXSM_ACCU_MIN, EXSM_ACCU_AVG, EXSM_ACCU_MEDIAN, EXSM_ACCU_COUNT}*	This setting only applies and must be provided when the time column has datetime type. It specifies how to generate the value of the accumulated time series from the input time series.

Table 5-18 (Cont.) ESM Model Settings

Setting Name	Setting Value	Description
EXSM_SETMISSING	It can also specify an option taking value in set *{EXSM_MISS_MIN, EXSM_MISS_MAX, EXSM_MISS_AVG, EXSM_MISS_MEDIAN, EXSM_MISS_LAST, EXSM_MISS_FIRST, EXSM_MISS_PREV, EXSM_MISS_NEXT, EXSM_MISS_AUTO}*.	This setting specifies how to handle missing values, which may come from input data and/or the accumulation process of time series. You can specify either a number or an option. If a number is specified, all the missing values are set to that number. EXSM_MISS_MIN: Replaces missing value with minimum of the accumulated time series. EXSM_MISS_MAX: Replaces missing value with maximum of the accumulated time series. EXSM_MISS_AVG: Replaces missing value with average of the accumulated time series. EXSM_MISS_MEDIAN: Replaces missing value with median of the accumulated time series. EXSM_MISS_LAST: Replaces missing value with last non-missing value of the accumulated time series. EXSM_MISS_FIRST: Replaces missing value with first non-missing value of the accumulated time series. EXSM_MISS_PREV:Replaces missing value with the previous non-missing value of the accumulated time series. EXSM_MISS_NEXT:Replaces missing value with the next non-missing value of the accumulated time series. EXSM_MISS_AUTO:EXSM model treats the input data as an irregular (non-uniformly spaced) time series. If this setting is not provided, EXSM_MISS_AUTO is the default value. In such a case, the model treats the input time series as irregular time series, viewing missing values as gaps.
EXSM_PREDICTION_STEP	It must be set to a number between 1-30.	This setting specifies how many steps ahead the predictions are to be made. If it is not set, the default value is 1: the model gives one-step-ahead prediction. A value greater than 30 results in an error.
EXSM_CONFIDENCE_LEVEL	It must be a number between 0 and 1, exclusive.	This setting specifies the desired confidence level for prediction. The lower and upper bounds of the specified confidence interval is reported. If this setting is not specified, the default confidence level is 95%.

Table 5-18 (Cont.) ESM Model Settings

Setting Name	Setting Value	Description
EXSM_OPT_CRITERION	It takes value in set *{EXSM_OPT_CRIT_LIK, EXSM_OPT_CRIT_MSE, EXSM_OPT_CRIT_AMSE, EXSM_OPT_CRIT_SIG, EXSM_OPT_CRIT_MAE}*.	This setting specifies the desired optimization criterion. The optimization criterion is useful as a diagnostic for comparing models' fit to the same data. EXSM_OPT_CRIT_LIK: Minus twice the log-likelihood of a model. EXSM_OPT_CRIT_MSE: Mean square error of a model. EXSM_OPT_CRIT_AMSE: Average mean square error over user-specified time window. EXSM_OPT_CRIT_SIG: Model's standard deviation of residuals. EXSM_OPT_CRIT_MAE: Mean absolute error of a model. The default value is EXSM_OPT_CRIT_LIK.
EXSM_NMSE	positive integer	This setting specifies the length of the window used in computing the error metric average mean square error (AMSE).

Example 5-20 Using the oml.esm Class

This example creates an ESM model and uses some of the methods of the `oml.esm` class.

```
import oml
import pandas as pd

df = pd.DataFrame({'EVENT': ['A', 'B', 'C', 'D'],
                   'START': ['2021-10-04 13:29:00', '2021-10-07 12:30:00',
                             '2021-10-15 04:20:00', '2021-10-18 15:45:03'],
                   'END':   ['2021-10-08 11:29:06', '2021-10-15 10:30:07',
                             '2021-10-29 05:50:15', '2021-10-22 15:40:03']})

df['START'] = pd.to_datetime(df['START'])
df['END'] = pd.to_datetime(df['END'])
df['DURATION'] = df['END'] - df['START']
df['HOURS'] = df['DURATION'] / pd.Timedelta(hours=1)
df['MINUTES'] = df['DURATION'] / pd.Timedelta(minutes=1)
#For on-premises database follow the below command to connect to the database#
oml.connect("<username>","<password>", dsn="<dsn>")
dat = oml.create(df, table='DF')
train_x = dat[:, 1]
train_y = dat[:, 4]

setting = {'EXSM_INTERVAL':'EXSM_INTERVAL_DAY'}
esm_mod = oml.esm(**setting).fit(train_x, train_y, time_seq = 'START')

esm_mod
train_x = dat[:, 4]
train_y = dat[:, 5]
esm_mod = oml.esm().fit(train_x, train_y, time_seq = 'HOURS')

esm_mod
```

Listing for This Example

```
Create pandas DataFrame with start and end dates for an event. Convert start
and end date columns to datetime, and create new columns that contain
timedelta between the start and end dates. Convert timedelta into total
number of hours and convert timedelta into total number of minutes.

>>> import oml
>>> import pandas as pd

>>> df = pd.DataFrame({'EVENT': ['A', 'B', 'C', 'D'],
                       'START': ['2021-10-04 13:29:00', '2021-10-07 12:30:00',
                                 '2021-10-15 04:20:00', '2021-10-18 15:45:03'],
                       'END':   ['2021-10-08 11:29:06', '2021-10-15 10:30:07',
                                 '2021-10-29 05:50:15', '2021-10-22 15:40:03']})

>>> df['START'] = pd.to_datetime(df['START'])
>>> df['END'] = pd.to_datetime(df['END'])
>>> df['DURATION'] = df['END'] - df['START']
>>> df['HOURS'] = df['DURATION'] / pd.Timedelta(hours=1)
>>> df['MINUTES'] = df['DURATION'] / pd.Timedelta(minutes=1)

>>> #For on-premises database follow the below command to connect to the
database#
>>> oml.connect("<username>","<password>", dsn="<dsn>")
>>> dat = oml.create(df, table='DF')


Using Datetime type

>>> train_x = dat[:, 1]
>>> train_y = dat[:, 4]

>>> setting = {'EXSM_INTERVAL':'EXSM_INTERVAL_DAY'}
>>> esm_mod = oml.esm(**setting).fit(train_x, train_y, time_seq = 'START')

>>> esm_mod

Algorithm Name: Exponential Smoothing

Mining Function: TIME_SERIES

Target: HOURS

Settings:
                     setting name               setting value
0                       ALGO_NAME  ALGO_EXPONENTIAL_SMOOTHING
1                EXSM_ACCUMULATE             EXSM_ACCU_TOTAL
2          EXSM_CONFIDENCE_LEVEL                         .95
3                  EXSM_INTERVAL           EXSM_INTERVAL_DAY
4                       EXSM_NMSE                          3
5         EXSM_OPTIMIZATION_CRIT           EXSM_OPT_CRIT_LIK
6           EXSM_PREDICTION_STEP                          1
7                EXSM_SETMISSING              EXSM_MISS_AUTO
8                    ODMS_BOXCOX          ODMS_BOXCOX_ENABLE
9                   ODMS_DETAILS                ODMS_ENABLE
```

```
10  ODMS_MISSING_VALUE_TREATMENT     ODMS_MISSING_VALUE_AUTO
11                 ODMS_SAMPLING       ODMS_SAMPLING_DISABLE
12                     PREP_AUTO                          ON

Computed Settings:
  setting name setting value
0   EXSM_MODEL   EXSM_SIMPLE

Global Statistics:
       attribute name attribute value
0   -2 LOG-LIKELIHOOD        -21.1618
1                 AIC         48.3236
2                AICC            None
3               ALPHA     0.000100034
4          ALPHA DISC          0.9999
5                AMSE         12175.3
6                 BIC         46.4825
7           CONVERGED             YES
8       INITIAL ALPHA     0.000100034
9       INITIAL LEVEL         179.353
10                MAE          84.403
11                MSE          9843.9
12           NUM_ROWS               4
13              SIGMA         140.313
14                STD         140.313

Attributes:

Partition: NO

Prediction:

    TIME_SEQ       VALUE  PREDICTION      LOWER       UPPER
0 2021-10-04   94.001667  179.352705        NaN         NaN
1 2021-10-07  190.001944  179.344167        NaN         NaN
2 2021-10-15  337.504167  179.345233        NaN         NaN
3 2021-10-18   95.916667  179.361069        NaN         NaN
4 2021-10-19         NaN  179.352712 -95.656158  454.361582


Using Float type

>>> train_x = dat[:, 4]
>>> train_y = dat[:, 5]
>>> esm_mod = oml.esm().fit(train_x, train_y, time_seq = 'HOURS')

>>> esm_mod

Algorithm Name: Exponential Smoothing

Mining Function: TIME_SERIES

Target: MINUTES

Settings:
                     setting name               setting value
```

```
0                     ALGO_NAME  ALGO_EXPONENTIAL_SMOOTHING
1          EXSM_CONFIDENCE_LEVEL                         .95
2                      EXSM_NMSE                           3
3         EXSM_OPTIMIZATION_CRIT          EXSM_OPT_CRIT_LIK
4           EXSM_PREDICTION_STEP                           1
5                EXSM_SETMISSING             EXSM_MISS_AUTO
6                    ODMS_BOXCOX          ODMS_BOXCOX_ENABLE
7                   ODMS_DETAILS                ODMS_ENABLE
8   ODMS_MISSING_VALUE_TREATMENT     ODMS_MISSING_VALUE_AUTO
9                  ODMS_SAMPLING       ODMS_SAMPLING_DISABLE
10                     PREP_AUTO                          ON

Computed Settings:
  setting name setting value
0   EXSM_MODEL     EXSM_HOLT

Global Statistics:
       attribute name attribute value
0   -2 LOG-LIKELIHOOD         4.47424
1                 AIC         1.05153
2                AICC            None
3               ALPHA     0.000104161
4                AMSE       0.0190133
5                BETA     0.000104153
6                 BIC          -2.017
7           CONVERGED             YES
8       INITIAL LEVEL         8.00977
9       INITIAL TREND        0.452033
10             LAMBDA     4.08563e-05
11                MAE         1175.53
12                MSE       0.0266914
13           NUM_ROWS               4
14              SIGMA        0.188649
15                STD        0.188649

Attributes:

Partition: NO

Prediction:

   TIME_SEQ         VALUE    PREDICTION        LOWER         UPPER
0        94   5640.100000   4807.666451          NaN           NaN
1        95   5755.000000   7554.329741          NaN           NaN
2       190  11400.116667  11869.239245          NaN           NaN
3       337  20250.250000  18649.004898          NaN           NaN
4       338           NaN  29301.840039  19894.31833  41663.104953
```

5.21 XGBoost

The `oml.xgb` class supports the in-database scalable gradient tree boosting algorithm for both classification, regression specifications, ranking models, and survival models. It makes available the open source gradient boosting framework. It prepares the categorical encoding and missing value replacement from the OML infrastructure, calls the in-database XGBoost,

builds and persists a model as a first-class database model object, and supports using the model for prediction.

You can use `oml.xgb` as a stand-alone predictor or incorporate it into real-world production pipelines for a wide range of problems such as ad click-through rate prediction, hazard risk prediction, web text classification, and so on.

The `oml.xgb` algorithm takes three types of parameters: general parameters, booster parameters, and task parameters. You set the parameters through the model settings. The algorithm supports most of the settings of the open source XGBoost project. For more information on the supported settings, see XGBoost parameters.

Through `oml.xgb`, OML4Py supports a number of different classification and regression specifications, ranking models, and survival models. Binary and multi-class models are supported under the classification machine learning technique while regression, ranking, count, and survival are supported under the regression machine learning technique.

`oml.xgb` also supports partitioned models and internalizes the data preparation.

Settings for an XGBoost model

The following table lists settings that apply to XGBoost models.

Table 5-19 XGBoost Model Settings

Setting Name	Setting Value	Description
`booster`	A string that is one of the following: • `dart` • `gblinear` • `gbtree`	The booster to use: • `dart` • `gblinear` • `gbtree` The `dart` and `gbtree` boosters use tree-based models whereas `gblinear` uses linear functions. The default value is `gbtree`.
`num_round`	A non-negative integer.	The number of rounds for boosting. The default value is `10`.

For more information on the booster settings, see XGBoost parameters

Example 5-21 Using the oml.xgb Class

This example creates an XGB model and uses some of the methods of the `oml.xgb` class.

```
#Load the iris data from sklearn and combine the target and predictors into a
single DataFrame, which matches the form of a database table.
Use the oml.create function to load this Pandas DataFrame into the databae,
which creates a persistent table and returns a proxy object that you assign
to z.#

import oml
from sklearn import datasets
import pandas as pd

iris = datasets.load_iris()
x = pd.DataFrame(iris.data, columns = ['Sepal_Length', 'Sepal_Width',
'Petal_Length', 'Petal_Width'])
y = pd.DataFrame(list(map(lambda x: {0: 'setosa', 1: 'versicolor',
```

```
2:'virginica'}[x], iris.target)), columns = ['Species'])

#For on-premises database follow the below command to connect to the database#
oml.connect("<username>","<password>", dsn="<dsn>")
z = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

#Create training data and test data.#

dat = oml.sync(table = "IRIS").split()
train_x = dat[0].drop('Species')
train_y = dat[0]['Species']
test_dat = dat[1]

#Classification Example:#

#Create an XGBoost model object.#

setting = {'xgboost_max_depth': '3',
...            'xgboost_eta': '1',
...            'xgboost_num_round': '10'}

xgb_mod = oml.xgb('classification', **setting)

#Fit the XGBoost model to the training data.#

xgb_mod.fit(train_x, train_y)
#Use the model to make predictions on the test data and return the prediction
probabilities for each category in Species.#
xgb_mod.predict(test_dat.drop('Species'), supplemental_cols = test_dat[:,
['Sepal_Length', 'Sepal_Width', 'Species']], proba = True).sort_values(by =
['Sepal_Length', 'Sepal_Width'])
     Sepal_Length  Sepal_Width     Species       TOP_1  TOP_1_VAL
 0            4.4          3.0      setosa      setosa   0.993619
 1            4.4          3.2      setosa      setosa   0.993619
 2            4.5          2.3      setosa      setosa   0.942128
 3            4.8          3.4      setosa      setosa   0.993619
...           ...          ...         ...         ...        ...
 42           6.7          3.3   virginica   virginica   0.996170
 43           6.9          3.1  versicolor  versicolor   0.925217
 44           6.9          3.1   virginica   virginica   0.996170
 45           7.0          3.2  versicolor  versicolor   0.990586

#Create training data and test data.#

dat = oml.sync(table = "IRIS").split()

train_x = dat[0].drop('Sepal_Length')
train_y = dat[0]['Sepal_Length']
test_dat = dat[1]

#Create an XGBoost model object.#

setting = {'xgboost_booster': 'gblinear'}
xgb_mod = oml.xgb('regression', **setting)

#Fit the XGBoost Model according to the training data and parameter settings.#
```

```
xgb_mod.fit(train_x, train_y)
xgb_mod.predict(test_dat.drop('Species'), supplemental_cols = test_dat[:,
['Sepal_Length', 'Sepal_Width', 'Petal_Length', 'Species']]) # doctest:
+NORMALIZE_WHITESPACE, +ELLIPSIS
#Create an XGBoost model object.#

setting = {'xgboost_objective': 'rank:pairwise',
...             'xgboost_max_depth': '3',
...             'xgboost_eta': '0.1',
...             'xgboost_gamma': '1.0',
...             'xgboost_num_round': '4'}

xgb_mod = oml.xgb('regression', **setting)

#Fit the XGBoost Model according to the training data and parameter settings.#

xgb_mod.fit(train_x, train_y)
#Use the model to make predictions on the test data, returning the
Sepal_Length, Sepal_Width, Petal_Length, and Species columns in the result.#

xgb_mod.predict(test_dat.drop('Species'), supplemental_cols = test_dat[:,
['Sepal_Length', 'Sepal_Width', 'Petal_Length', 'Species']])
```

Listing for This Example

```
#Load the iris data from sklearn and combine the target and predictors into a
single DataFrame, which matches the form of a database table.
Use the oml.create function to load this Pandas DataFrame into the databae,
which creates a persistent table and returns a proxy object that you assign
to z.#

>>> import oml
>>> from sklearn import datasets
>>> import pandas as pd

>>> iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data, columns = ['Sepal_Length', 'Sepal_Width',
'Petal_Length', 'Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x: {0: 'setosa', 1: 'versicolor',
2:'virginica'}[x], iris.target)), columns = ['Species'])

>>> #For on-premises database follow the below command to connect to the
database#
>>> oml.connect("<username>","<password>", dsn="<dsn>")
>>> z = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

#Create training data and test data.#

>>> dat = oml.sync(table = "IRIS").split()
>>> train_x = dat[0].drop('Species')
>>> train_y = dat[0]['Species']
>>> test_dat = dat[1]
```

```
#Classification Example:#

#Create an XGBoost model object.#

>>> setting = {'xgboost_max_depth': '3',
...            'xgboost_eta': '1',
...            'xgboost_num_round': '10'}

>>> xgb_mod = oml.xgb('classification', **setting)

#Fit the XGBoost model to the training data.#

>>> xgb_mod.fit(train_x, train_y)

Algorithm Name: XGBOOST
Mining Function: CLASSIFICATION
Target: Species

Settings:
                    setting name            setting value
0                      ALGO_NAME             ALGO_XGBOOST
1          CLAS_WEIGHTS_BALANCED                      OFF
2                   ODMS_DETAILS             ODMS_ENABLE
3   ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
4                  ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
5                      PREP_AUTO                      ON
6                        booster                  gbtree
7                            eta                       1
8                      max_depth                       3
9                    ntree_limit                       0
10                     num_round                      10
11                     objective          multi:softprob

Global Statistics:
  attribute name attribute value
0       NUM_ROWS             104
1       mlogloss        0.024858

Attributes:
Petal_Length
Petal_Width
Sepal_Length
Sepal_Width

Partition: NO

ATTRIBUTE IMPORTANCE:

  PNAME ATTRIBUTE_NAME ATTRIBUTE_SUBNAME ATTRIBUTE_VALUE      GAIN     COVER
\
0  None   Petal_Length             None            None  0.743941
0.560554
1  None    Petal_Width             None            None  0.162191
0.245400
2  None   Sepal_Length             None            None  0.003738
0.044741
```

```
3  None    Sepal_Width              None            None  0.090129
0.149306

   FREQUENCY
0   0.447761
1   0.268657
2   0.119403
3   0.164179

#Use the model to make predictions on the test data and return the prediction
probabilities for each category in Species.#

>>> xgb_mod.predict(test_dat.drop('Species'), supplemental_cols = test_dat[:,
['Sepal_Length', 'Sepal_Width', 'Species']], proba = True).sort_values(by =
['Sepal_Length', 'Sepal_Width'])
     Sepal_Length  Sepal_Width     Species       TOP_1  TOP_1_VAL
 0            4.4          3.0      setosa      setosa   0.993619
 1            4.4          3.2      setosa      setosa   0.993619
 2            4.5          2.3      setosa      setosa   0.942128
 3            4.8          3.4      setosa      setosa   0.993619
...           ...          ...         ...         ...        ...
 42           6.7          3.3   virginica   virginica   0.996170
 43           6.9          3.1  versicolor  versicolor   0.925217
 44           6.9          3.1   virginica   virginica   0.996170
 45           7.0          3.2  versicolor  versicolor   0.990586


#Regression Example:#

#Create training data and test data.#

>>> dat = oml.sync(table = "IRIS").split()

>>> train_x = dat[0].drop('Sepal_Length')
>>> train_y = dat[0]['Sepal_Length']
>>> test_dat = dat[1]

#Create an XGBoost model object.#

>>> setting = {'xgboost_booster': 'gblinear'}
>>> xgb_mod = oml.xgb('regression', **setting)

#Fit the XGBoost Model according to the training data and parameter settings.#

>>> xgb_mod.fit(train_x, train_y)

Algorithm Name: XGBOOST
Mining Function: REGRESSION
Target: Sepal_Length

Settings:
                   setting name            setting value
0                     ALGO_NAME             ALGO_XGBOOST
1                  ODMS_DETAILS              ODMS_ENABLE
2  ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
3                 ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
```

```
4                     PREP_AUTO                     ON
5                       booster                 gblinear
6                   ntree_limit                        0
7                     num_round                       10

Computed Settings:
              setting name setting value
0  ODMS_EXPLOSION_MIN_SUPP             1

Global Statistics:
  attribute name attribute value
0       NUM_ROWS             104
1           rmse        0.364149

Attributes:
Petal_Length
Petal_Width
Sepal_Width
Species

Partition: NO

ATTRIBUTE IMPORTANCE:

  PNAME ATTRIBUTE_NAME ATTRIBUTE_SUBNAME ATTRIBUTE_VALUE    WEIGHT  CLASS
0  None   Petal_Length              None            None  0.335183      0
1  None    Petal_Width              None            None  0.368738      0
2  None    Sepal_Width              None            None  0.249208      0
3  None        Species              None      versicolor -0.197582      0
4  None        Species              None       virginica -0.170522      0

>>> xgb_mod.predict(test_dat.drop('Species'), supplemental_cols = test_dat[:,
['Sepal_Length', 'Sepal_Width', 'Petal_Length', 'Species']]) # doctest:
+NORMALIZE_WHITESPACE, +ELLIPSIS
     Sepal_Length  Sepal_Width  Petal_Length     Species  PREDICTION
 0            4.9          3.0           1.4      setosa    4.797075
 1            4.9          3.1           1.5      setosa    4.818641
 2            4.8          3.4           1.6      setosa    4.963796
 3            5.8          4.0           1.2      setosa    4.979247
...           ...          ...           ...         ...         ...
 42           6.7          3.3           5.7   virginica    6.990700
 43           6.7          3.0           5.2   virginica    6.674599
 44           6.5          3.0           5.2   virginica    6.563977
 45           5.9          3.0           5.1   virginica    6.456711


#Ranking Example:#

#Create an XGBoost model object.#

>>> setting = {'xgboost_objective': 'rank:pairwise',
...            'xgboost_max_depth': '3',
...            'xgboost_eta': '0.1',
...            'xgboost_gamma': '1.0',
...            'xgboost_num_round': '4'}
```

```
>>> xgb_mod = oml.xgb('regression', **setting)

#Fit the XGBoost Model according to the training data and parameter settings.#

>>> xgb_mod.fit(train_x, train_y)
Algorithm Name: XGBOOST
Mining Function: REGRESSION
Target: Sepal_Length

Settings:
                     setting name            setting value
0                       ALGO_NAME             ALGO_XGBOOST
1                    ODMS_DETAILS              ODMS_ENABLE
2   ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
3                   ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
4                       PREP_AUTO                      ON
5                         booster                  gbtree
6                             eta                     0.1
7                           gamma                     1.0
8                       max_depth                       3
9                     ntree_limit                       0
10                    num_round                         4
11                    objective           rank:pairwise

Computed Settings:
              setting name setting value
0  ODMS_EXPLOSION_MIN_SUPP             1

Global Statistics:
  attribute name  attribute value
0       NUM_ROWS              104
1            map                1

Attributes:
Petal_Length
Petal_Width
Sepal_Width
Species

Partition: NO

ATTRIBUTE IMPORTANCE:

  PNAME ATTRIBUTE_NAME ATTRIBUTE_SUBNAME ATTRIBUTE_VALUE      GAIN     COVER
\
0  None   Petal_Length              None            None  0.873855
0.677624
1  None    Petal_Width              None            None  0.083504
0.184802
2  None    Sepal_Width              None            None  0.042641
0.137574

   FREQUENCY
0   0.500000
1   0.285714
2   0.214286
```

```
#Use the model to make predictions on the test data, returning the
Sepal_Length, Sepal_Width, Petal_Length, and Species columns in the result.#

>>> xgb_mod.predict(test_dat.drop('Species'), supplemental_cols = test_dat[:,
['Sepal_Length', 'Sepal_Width', 'Petal_Length', 'Species']])
     Sepal_Length  Sepal_Width  Petal_Length     Species  PREDICTION
 0            4.9          3.0           1.4      setosa    0.243485
 1            4.9          3.1           1.5      setosa    0.243485
 2            4.8          3.4           1.6      setosa    0.243485
 3            5.8          4.0           1.2      setosa    0.310980
...           ...          ...           ...         ...         ...
 42           6.7          3.3           5.7   virginica    0.771761
 43           6.7          3.0           5.2   virginica    0.728637
 44           6.5          3.0           5.2   virginica    0.728637
 45           5.9          3.0           5.1   virginica    0.674835
```

6

Automated Machine Learning

Use the automated algorithm selection, feature selection, and hyperparameter tuning of Automated Machine Learning to accelerate the machine learning modeling process.

Automated Machine Learning in OML4Py is described in the following topics:

- About Automated Machine Learning
  Automated Machine Learning (AutoML) provides built-in data science expertise about data analytics and modeling that you can employ to build machine learning models.
- Algorithm Selection
  The `oml.automl.AlgorithmSelection` class uses the characteristics of the data set and the task to rank algorithms from the set of supported Oracle Machine Learning algorithms.
- Feature Selection
  The `oml.automl.FeatureSelection` class identifies the most relevant feature subsets for a training data set and an Oracle Machine Learning algorithm.
- Model Tuning
  The `oml.automl.ModelTuning` class tunes the hyperparameters for the specified classification or regression algorithm and training data.
- Model Selection
  The `oml.automl.ModelSelection` class automatically selects an Oracle Machine Learning algorithm according to the selected score metric and then tunes that algorithm.

6.1 About Automated Machine Learning

Automated Machine Learning (AutoML) provides built-in data science expertise about data analytics and modeling that you can employ to build machine learning models.

Any modeling problem for a specified data set and prediction task involves a sequence of data cleansing and preprocessing, algorithm selection, and model tuning tasks. Each of these steps require data science expertise to help guide the process to an efficient final model. Automated Machine Learning (AutoML) automates this process with its built-in data science expertise.

OML4Py has the following AutoML capabilities:

- Automated algorithm selection that selects the appropriate algorithm from the supported machine learning algorithms
- Automated feature selection that reduces the size of the original feature set to speed up model training and tuning, while possibly also increasing model quality
- Automated tuning of model hyperparameters, which selects the model with the highest score metric from among several metrics as selected by the user

AutoML performs those common modeling tasks automatically, with less effort and potentially better results. It also leverages in-database algorithm parallel processing and scalability to minimize runtime and produce high-quality results.

> **Note:**
>
> As the `fit` method of the machine learning classes does, the AutoML functions `reduce`, `select`, and `tune` provide a `case_id` parameter that you can use to achieve repeatable data sampling and data shuffling during model building.

The AutoML functionality is also available in a no-code user interface alongside OML Notebooks on Oracle Autonomous Database. For more information, see Oracle Machine Learning AutoML User Interface .

Automated Machine Learning Classes and Algorithms

The Automated Machine Learning classes are the following.

Class	Description
`oml.automl.AlgorithmSelection`	Using only the characteristics of the data set and the task, automatically selects the best algorithms from the set of supported Oracle Machine Learning algorithms. Supports classification and regression functions.
`oml.automl.FeatureSelection`	Uses meta-learning to quickly identify the most relevant feature subsets given a training data set and an Oracle Machine Learning algorithm. Supports classification and regression functions.
`oml.automl.ModelTuning`	Uses a highly parallel, asynchronous gradient-based hyperparameter optimization algorithm to tune the algorithm hyperparameters. Supports classification and regression functions.
`oml.automl.ModelSelection`	Selects the best Oracle Machine Learning algorithm and then tunes that algorithm. Supports classification and regression functions.

The Oracle Machine Learning algorithms supported by AutoML are the following:

Table 6-1 Machine Learning Algorithms Supported by AutoML

Algorithm Abbreviation	Algorithm Name
dt	Decision Tree
glm	Generalized Linear Model
glm_ridge	Generalized Linear Model with ridge regression
nb	Naive Bayes
nn	Neural Network
rf	Random Forest
svm_gaussian	Support Vector Machine with Gaussian kernel
svm_linear	Support Vector Machine with linear kernel

Classification and Regression Metrics

The following tables list the scoring metrics supported by AutoML.

Table 6-2 Binary and Multiclass Classification Metrics

Metric	Description, Scikit-learn Equivalent, and Formula
accuracy	Calculates the rate of correct classification of the target. sklearn.metrics.accuracy_score(*y_true, y_pred, normalize=True, sample_weight=None*) Formula: (tp + tn)/samples
f1_macro	Calculates the f-score or f-measure, which is a weighted average of the precision and recall. The f1_macro takes the unweighted average of per-class scores. sklearn.metrics.f1_score(y_true, y_pred, labels=None, pos_label=1, average='macro', sample_weight=None) Formula: 2 * (precision * recall) / (precision + recall)
f1_micro	Calculates the f-score or f-measure with micro-averaging in which true positives, false positives, and false negatives are counted globally. sklearn.metrics.f1_score(y_true, y_pred, labels=None, pos_label=1, average='micro', sample_weight=None) Formula: 2 * (precision * recall) / (precision + recall)
f1_weighted	Calculates the f-score or f-measure with weighted averaging of per-class scores based on support (the fraction of true samples per class). Accounts for imbalanced classes. sklearn.metrics.f1_score(y_true, y_pred, labels=None, pos_label=1, average='weighted', sample_weight=None) Formula: 2 * (precision * recall) / (precision + recall)
precision_macro	Calculates the ability of the classifier to not label a sample incorrectly. The precision_macro takes the unweighted average of per-class scores. sklearn.metrics.precision_score(y_true, y_pred, labels=None, pos_label=1, average='macro', sample_weight=None) Formula: tp / (tp + fp)
precision_micro	Calculates the ability of the classifier to not label a sample incorrectly. Uses micro-averaging in which true positives, false positives, and false negatives are counted globally. sklearn.metrics.precision_score(y_true, y_pred, labels=None, pos_label=1, average='micro', sample_weight=None) Formula: tp / (tp + fp)

Table 6-2 (Cont.) Binary and Multiclass Classification Metrics

Metric	Description, Scikit-learn Equivalent, and Formula
precision_weighted	Calculates the ability of the classifier to not label a sample incorrectly. Uses weighted averaging of per-class scores based on support (the fraction of true samples per class). Accounts for imbalanced classes. `sklearn.metrics.precision_score(y_true, y_pred, labels=None, pos_label=1, average='weighted', sample_weight=None)` Formula: `tp / (tp + fp)`
recall_macro	Calculates the ability of the classifier to correctly label each class. The recall_macro takes the unweighted average of per-class scores. `sklearn.metrics.recall_score(y_true, y_pred, labels=None, pos_label=1, average='macro', sample_weight=None)` Formula: `tp / (tp + fn)`
recall_micro	Calculates the ability of the classifier to correctly label each class with micro-averaging in which the true positives, false positives, and false negatives are counted globally. `sklearn.metrics.recall_score(y_true, y_pred, labels=None, pos_label=1, average='micro', sample_weight=None)` Formula: `tp / (tp + fn)`
recall_weighted	Calculates the ability of the classifier to correctly label each class with weighted averaging of per-class scores based on support (the fraction of true samples per class). Accounts for imbalanced classes. `sklearn.metrics.recall_score(y_true, y_pred, labels=None, pos_label=1, average='weighted', sample_weight=None)` Formula: `tp / (tp + fn)`

See Also: Scikit-learn classification metrics

Table 6-3 Binary Classification Metrics Only

Metric	Description, Scikit-learn Equivalent, and Formula
f1	Calculates the f-score or f-measure, which is a weighted average of the precision and recall. This metric by default requires a positive target to be encoded as 1 to function as expected. `sklearn.metrics.f1_score(y_true, y_pred, labels=None, pos_label=1, average='binary', sample_weight=None)` Formula: `2 * (precision * recall) / (precision + recall)`

Table 6-3 (Cont.) Binary Classification Metrics Only

Metric	Description, Scikit-learn Equivalent, and Formula
`precision`	Calculates the ability of the classifier to not label a sample positive (1) that is actually negative (0). `sklearn.metrics.precision_score(y_true, y_pred, labels=None, pos_label=1, average='binary', sample_weight=None)` Formula: `tp / (tp + fp)`
`recall`	Calculates the ability of the classifier to label all positive (1) samples correctly. `sklearn.metrics.recall_score(y_true, y_pred, labels=None, pos_label=1, average='binary', sample_weight=None)` Formula: `tp / (tp + fn)`
`roc_auc`	Calculates the Area Under the Receiver Operating Characteristic Curve (roc_auc) from prediction scores. `sklearn.metrics.accuracy_score(y_true, y_pred, normalize=True, sample_weight=None)` See also the definition of receiver operation characteristic.

Table 6-4 Regression Metrics

Metric	Description, Scikit-learn Equivalent, and Formula
`r2`	Calculates the coefficient of determination (R squared). `sklearn.metrics.r2_score(y_true, y_pred, sample_weight=None, multioutput='uniform_average')` See also the definition of coefficient of determination.
`neg_mean_absolute_error`	Calculates the mean of the absolute difference of predicted and true targets (MAE). `sklearn.metrics.mean_absolute_error(y_true, y_pred, sample_weight=None, multioutput='uniform_average')` Formula: $-\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)$

Table 6-4 (Cont.) Regression Metrics

Metric	Description, Scikit-learn Equivalent, and Formula
`neg_mean_squared_error`	Calculates the mean of the squared difference of predicted and true targets. `-1.0 * sklearn.metrics.mean_squared_error(y_true, y_pred, sample_weight=None, multioutput='uniform_average')` Formula: $-\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$
`neg_mean_squared_log_error`	Calculates the mean of the difference in the natural log of predicted and true targets. `sklearn.metrics.mean_squared_log_error(y_true, y_pred, sample_weight=None, multioutput='uniform_average')` Formula: $-\frac{1}{n}\sum_{i=1}^{n}(\log(Y_i) - \log(\hat{Y}_i))^2$
`neg_median_absolute_error`	Calculates the median of the absolute difference between predicted and true targets. `sklearn.metrics.median_absolute_error(y_true, y_pred)` Formula: $-Med(\{Y_i - \hat{Y}_i, 0 \le i < n\})$

See Also: Scikit-learn regression metrics

6.2 Algorithm Selection

The `oml.automl.AlgorithmSelection` class uses the characteristics of the data set and the task to rank algorithms from the set of supported Oracle Machine Learning algorithms.

Selecting the best Oracle Machine Learning algorithm for a data set and a prediction task is non-trivial. No single algorithm works best for all modeling problems. The `oml.automl.AlgorithmSelection` class ranks the candidate algorithms according to how likely each is to produce a quality model. This is achieved by using Oracle advanced meta-learning intelligence learned from a repertoire of data sets with the goal of avoiding exhaustive searches, thereby reducing overall compute time and costs.

The `oml.automl.AlgorithmSelection` class supports classification and regression algorithms. To use the class, you specify a data set and the number of algorithms you want to evaluate.

The `select` method of the class returns a sorted list of the top algorithms and their predicted rank (from best to worst).

For information on the parameters and methods of the class, invoke `help(oml.automl.AlgorithmSelection)` or see *Oracle Machine Learning for Python API Reference*.

Example 6-1 Using the `oml.automl.AlgorithmSelection` Class

This example creates an `oml.automl.AlgorithmSelection` object and then displays the algorithm rankings with their corresponding score metric. You may select the top entry or choose a different model depending on the needs of your particular business problem.

```
import oml
from oml import automl
import pandas as pd
from sklearn import datasets

# Load the breast cancer data set.
bc = datasets.load_breast_cancer()
bc_data = bc.data.astype(float)
X = pd.DataFrame(bc_data, columns = bc.feature_names)
y = pd.DataFrame(bc.target, columns = ['TARGET'])

# Create the database table BreastCancer.
oml_df = oml.create(pd.concat([X, y], axis=1),
                                table = 'BreastCancer')

# Split the data set into training and test data.
train, test = oml_df.split(ratio=(0.8, 0.2), seed = 1234)
X, y = train.drop('TARGET'), train['TARGET']
X_test, y_test = test.drop('TARGET'), test['TARGET']

# Create an automated algorithm selection object with f1_macro as
# the score_metric argument.
asel = automl.AlgorithmSelection(mining_function='classification',
                               score_metric='f1_macro', parallel=4)

# Run algorithm selection to get the top k predicted algorithms and
# their ranking without tuning.
algo_ranking = asel.select(X, y, k=3)

# Show the selected and tuned model.
[(m, "{:.2f}".format(s)) for m,s in algo_ranking]

# Drop the database table.
oml.drop('BreastCancer')
```

Listing for This Example

```
>>> import oml
>>> from oml import automl
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the breast cancer data set.
... bc = datasets.load_breast_cancer()
>>> bc_data = bc.data.astype(float)
>>> X = pd.DataFrame(bc_data, columns = bc.feature_names)
```

```
>>> y = pd.DataFrame(bc.target, columns = ['TARGET'])
>>>
>>> # Create the database table BreastCancer.
>>> oml_df = oml.create(pd.concat([X, y], axis=1),
...                                table = 'BreastCancer')
>>>
>>> # Split the data set into training and test data.
... train, test = oml_df.split(ratio=(0.8, 0.2), seed = 1234)
>>> X, y = train.drop('TARGET'), train['TARGET']
>>> X_test, y_test = test.drop('TARGET'), test['TARGET']
>>>
>>> # Create an automated algorithm selection object with f1_macro as
... # the score_metric argument.
... asel = automl.AlgorithmSelection(mining_function='classification',
...                                  score_metric='f1_macro', parallel=4)
>>>
>>> # Run algorithm selection to get the top k predicted algorithms and
... # their ranking without tuning.
... algo_ranking = asel.select(X, y, k=3)
>>>
>>> # Show the selected and tuned model.
>>> [(m, "{:.2f}".format(s)) for m,s in algo_ranking]
[('svm_gaussian', '0.97'), ('glm_ridge', '0.96'), ('nn', '0.96')]
>>>
>>> # Drop the database table.
... oml.drop('BreastCancer')
```

6.3 Feature Selection

The `oml.automl.FeatureSelection` class identifies the most relevant feature subsets for a training data set and an Oracle Machine Learning algorithm.

In a data analytics application, feature selection is a critical data preprocessing step that has a high impact on both runtime and model performance. The `oml.automl.FeatureSelection` class automatically selects the most relevant features for a data set and model. It internally uses several feature-ranking algorithms to identify the best feature subset that reduces model training time without compromising model performance. Oracle advanced meta-learning techniques quickly prune the search space of this feature selection optimization.

The `oml.automl.FeatureSelection` class supports classification and regression algorithms. To use the `oml.automl.FeatureSelection` class, you specify a data set and the Oracle Machine Learning algorithm on which to perform the feature reduction.

For information on the parameters and methods of the class, invoke `help(oml.automl.FeatureSelection)` or see *Oracle Machine Learning for Python API Reference*.

Example 6-2 Using the `oml.automl.FeatureSelection` Class

This example uses the `oml.automl.FeatureSelection` class. The example builds a model on the full data set and computes predictive accuracy. It performs automated feature selection, filters the columns according to the determined set, and rebuilds the model. It then recomputes predictive accuracy.

```
import oml
from oml import automl
```

```
import pandas as pd
import numpy as np
from sklearn import datasets

# Load the digits data set into the database.
digits = datasets.load_digits()
X = pd.DataFrame(digits.data,
                 columns = ['pixel{}'.format(i) for i
                            in range(digits.data.shape[1])])
y = pd.DataFrame(digits.target, columns = ['digit'])
oml_df = oml.create(pd.concat([X, y], axis=1), table = 'DIGITS')

# Split the data set into train and test.
train, test = oml_df.split(ratio=(0.8, 0.2),
                           seed = 1234, strata_cols='digit')
X_train, y_train = train.drop('digit'), train['digit']
X_test, y_test = test.drop('digit'), test['digit']

# Default model performance before feature selection.
mod = oml.svm(mining_function='classification').fit(X_train,
                                                    y_train)
"{:.2}".format(mod.score(X_test, y_test))

# Create an automated feature selection object with accuracy
# as the score_metric.
fs = automl.FeatureSelection(mining_function='classification',
                             score_metric='accuracy', parallel=4)

# Get the reduced feature subset on the train data set.
subset = fs.reduce('svm_linear', X_train, y_train)
"{} features reduced to {}".format(len(X_train.columns),
                                   len(subset))

# Use the subset to select the features and create a model on the
# new reduced data set.
X_new  = X_train[:,subset]
X_test_new = X_test[:,subset]
mod = oml.svm(mining_function='classification').fit(X_new, y_train)
"{:.2} with {:.1f}x feature reduction".format(
  mod.score(X_test_new, y_test),
  len(X_train.columns)/len(X_new.columns))

# Drop the DIGITS table.
oml.drop('DIGITS')

# For reproducible results, add a case_id column with unique row
# identifiers.
row_id = pd.DataFrame(np.arange(digits.data.shape[0]),
                                columns = ['CASE_ID'])
oml_df_cid = oml.create(pd.concat([row_id, X, y], axis=1),
                        table = 'DIGITS_CID')

train, test = oml_df_cid.split(ratio=(0.8, 0.2), seed = 1234,
                               hash_cols='CASE_ID',
                               strata_cols='digit')
X_train, y_train = train.drop('digit'), train['digit']
```

```
X_test, y_test = test.drop('digit'), test['digit']

# Provide the case_id column name to the feature selection
# reduce function.
subset = fs.reduce('svm_linear', X_train,
                   y_train, case_id='CASE_ID')
"{} features reduced to {} with case_id".format(
                                          len(X_train.columns)-1,
                                          len(subset))

# Drop the tables created in the example.
oml.drop('DIGITS')
oml.drop('DIGITS_CID')
```

Listing for This Example

```
>>> import oml
>>> from oml import automl
>>> import pandas as pd
>>> import numpy as np
>>> from sklearn import datasets
>>>
>>> # Load the digits data set into the database.
... digits = datasets.load_digits()
>>> X = pd.DataFrame(digits.data,
...                  columns = ['pixel{}'.format(i) for i
...                             in range(digits.data.shape[1])])
>>> y = pd.DataFrame(digits.target, columns = ['digit'])
>>> oml_df = oml.create(pd.concat([X, y], axis=1), table = 'DIGITS')
>>>
>>> # Split the data set into train and test.
... train, test = oml_df.split(ratio=(0.8, 0.2),
...                            seed = 1234, strata_cols='digit')
>>> X_train, y_train = train.drop('digit'), train['digit']
>>> X_test, y_test = test.drop('digit'), test['digit']
>>>
>>> # Default model performance before feature selection.
... mod = oml.svm(mining_function='classification').fit(X_train,
...                                                     y_train)
>>> "{:.2}".format(mod.score(X_test, y_test))
'0.92'
>>>
>>> # Create an automated feature selection object with accuracy
... # as the score_metric.
... fs = automl.FeatureSelection(mining_function='classification',
...                              score_metric='accuracy', parallel=4)
>>> # Get the reduced feature subset on the train data set.
... subset = fs.reduce('svm_linear', X_train, y_train)
>>> "{} features reduced to {}".format(len(X_train.columns),
...                                    len(subset))
'64 features reduced to 41'
>>>
>>> # Use the subset to select the features and create a model on the
... # new reduced data set.
... X_new  = X_train[:,subset]
```

```
>>> X_test_new = X_test[:,subset]
>>> mod = oml.svm(mining_function='classification').fit(X_new, y_train)
>>> "{:.2} with {:.1f}x feature reduction".format(
...   mod.score(X_test_new, y_test),
...   len(X_train.columns)/len(X_new.columns))
'0.92 with 1.6x feature reduction'
>>>
>>> # Drop the DIGITS table.
... oml.drop('DIGITS')
>>>
>>> # For reproducible results, add a case_id column with unique row
... # identifiers.
>>> row_id = pd.DataFrame(np.arange(digits.data.shape[0]),
...                                columns = ['CASE_ID'])
>>> oml_df_cid = oml.create(pd.concat([row_id, X, y], axis=1),
...                         table = 'DIGITS_CID')

>>> train, test = oml_df_cid.split(ratio=(0.8, 0.2), seed = 1234,
...                                hash_cols='CASE_ID',
...                                strata_cols='digit')
>>> X_train, y_train = train.drop('digit'), train['digit']
>>> X_test, y_test = test.drop('digit'), test['digit']
>>>
>>> # Provide the case_id column name to the feature selection
... # reduce function.
>>> subset = fs.reduce('svm_linear', X_train,
...                    y_train, case_id='CASE_ID')
... "{} features reduced to {} with case_id".format(
...                                            len(X_train.columns)-1,
...                                            len(subset))
'64 features reduced to 45 with case_id'
>>>
>>> # Drop the tables created in the example.
... oml.drop('DIGITS')
>>> oml.drop('DIGITS_CID')
```

6.4 Model Tuning

The `oml.automl.ModelTuning` class tunes the hyperparameters for the specified classification or regression algorithm and training data.

Model tuning is a laborious machine learning task that relies heavily on data scientist expertise. With limited user input, the `oml.automl.ModelTuning` class automates this process using a highly-parallel, asynchronous gradient-based hyperparameter optimization algorithm to tune the hyperparameters of an Oracle Machine Learning algorithm.

The `oml.automl.ModelTuning` class supports classification and regression algorithms. To use the `oml.automl.ModelTuning` class, you specify a data set and an algorithm to obtain a tuned model and its corresponding hyperparameters. An advanced user can provide a customized hyperparameter search space and a non-default scoring metric to this black box optimizer.

For a partitioned model, if you pass in the column to partition on in the `param_space` argument of the `tune` method, `oml.automl.ModelTuning` tunes the partitioned model's hyperparameters.

For information on the parameters and methods of the class, invoke `help(oml.automl.ModelTuning)` or see *Oracle Machine Learning for Python API Reference*.

Example 6-3 Using the `oml.automl.ModelTuning` Class

This example creates an `oml.automl.ModelTuning` object.

```
import oml
from oml import automl
import pandas as pd
from sklearn import datasets

# Load the breast cancer data set.
bc = datasets.load_breast_cancer()
bc_data = bc.data.astype(float)
X = pd.DataFrame(bc_data, columns = bc.feature_names)
y = pd.DataFrame(bc.target, columns = ['TARGET'])

# Create the database table BreastCancer.
oml_df = oml.create(pd.concat([X, y], axis=1),
                    table = 'BreastCancer')

# Split the data set into training and test data.
train, test = oml_df.split(ratio=(0.8, 0.2), seed = 1234)
X, y = train.drop('TARGET'), train['TARGET']
X_test, y_test = test.drop('TARGET'), test['TARGET']

# Start an automated model tuning run with a Decision Tree model.
at = automl.ModelTuning(mining_function='classification',
                        parallel=4)
results = at.tune('dt', X, y, score_metric='accuracy')

# Show the tuned model details.
tuned_model = results['best_model']
tuned_model

# Show the best tuned model train score and the
# corresponding hyperparameters.
score, params = results['all_evals'][0]
"{:.2}".format(score), ["{}:{}".format(k, params[k])
  for k in sorted(params)]

# Use the tuned model to get the score on the test set.
"{:.2}".format(tuned_model.score(X_test, y_test))

# An example invocation of model tuning with user-defined
# search ranges for selected hyperparameters on a new tuning
# metric (f1_macro).
search_space = {
  'RFOR_SAMPLING_RATIO': {'type': 'continuous',
                          'range': [0.01, 0.5]},
  'RFOR_NUM_TREES': {'type': 'discrete',
                     'range': [50, 100]},
  'TREE_IMPURITY_METRIC': {'type': 'categorical',
                           'range': ['TREE_IMPURITY_ENTROPY',
                           'TREE_IMPURITY_GINI']},}
results = at.tune('rf', X, y, score_metric='f1_macro',
                  param_space=search_space)
score, params = results['all_evals'][0]
```

```
("{:.2}".format(score), ["{}:{}".format(k, params[k])
  for k in sorted(params)])

# Some hyperparameter search ranges need to be defined based on the
# training data set sizes (for example, the number of samples and
# features). You can use placeholders specific to the data set,
# such as $nr_features and $nr_samples, as the search ranges.
search_space = {'RFOR_MTRY': {'type': 'discrete',
                              'range': [1, '$nr_features/2']}}
results = at.tune('rf', X, y,
                  score_metric='f1_macro', param_space=search_space)
score, params = results['all_evals'][0]
("{:.2}".format(score), ["{}:{}".format(k, params[k])
  for k in sorted(params)])

# Drop the database table.
oml.drop('BreastCancer')
```

Listing for This Example

```
>>> import oml
>>> from oml import automl
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the breast cancer data set.
... bc = datasets.load_breast_cancer()
>>> bc_data = bc.data.astype(float)
>>> X = pd.DataFrame(bc_data, columns = bc.feature_names)
>>> y = pd.DataFrame(bc.target, columns = ['TARGET'])
>>>
>>> # Create the database table BreastCancer.
>>> oml_df = oml.create(pd.concat([X, y], axis=1),
...                     table = 'BreastCancer')
>>>
>>> # Split the data set into training and test data.
... train, test = oml_df.split(ratio=(0.8, 0.2), seed = 1234)
>>> X, y = train.drop('TARGET'), train['TARGET']
>>> X_test, y_test = test.drop('TARGET'), test['TARGET']
>>>
>>> # Start an automated model tuning run with a Decision Tree model.
... at = automl.ModelTuning(mining_function='classification',
...                         parallel=4)
>>> results = at.tune('dt', X, y, score_metric='accuracy')
>>>
>>> # Show the tuned model details.
... tuned_model = results['best_model']
>>> tuned_model

Algorithm Name: Decision Tree

Mining Function: CLASSIFICATION

Target: TARGET
```

```
Settings:
                       setting name            setting value
0                         ALGO_NAME       ALGO_DECISION_TREE
1                CLAS_MAX_SUP_BINS                       32
2             CLAS_WEIGHTS_BALANCED                      OFF
3                      ODMS_DETAILS             ODMS_DISABLE
4   ODMS_MISSING_VALUE_TREATMENT  ODMS_MISSING_VALUE_AUTO
5                    ODMS_SAMPLING    ODMS_SAMPLING_DISABLE
6                         PREP_AUTO                       ON
7              TREE_IMPURITY_METRIC       TREE_IMPURITY_GINI
8               TREE_TERM_MAX_DEPTH                        8
9             TREE_TERM_MINPCT_NODE                     3.34
10          TREE_TERM_MINPCT_SPLIT                      0.1
11           TREE_TERM_MINREC_NODE                       10
12          TREE_TERM_MINREC_SPLIT                       20

Attributes:
mean radius
mean texture
mean perimeter
mean area
mean smoothness
mean compactness
mean concavity
mean concave points
mean symmetry
mean fractal dimension
radius error
texture error
perimeter error
area error
smoothness error
compactness error
concavity error
concave points error
symmetry error
fractal dimension error
worst radius
worst texture
worst perimeter
worst area
worst smoothness
worst compactness
worst concavity
worst concave points
worst symmetry
worst fractal dimension

Partition: NO

>>>
>>> # Show the best tuned model train score and the
... # corresponding hyperparameters.
... score, params = results['all_evals'][0]
>>> "{:.2}".format(score), ["{}:{}".format(k, params[k])
...   for k in sorted(params)]
```

```
('0.92', ['CLAS_MAX_SUP_BINS:32', 'TREE_IMPURITY_METRIC:TREE_IMPURITY_GINI',
'TREE_TERM_MAX_DEPTH:7', 'TREE_TERM_MINPCT_NODE:0.05',
'TREE_TERM_MINPCT_SPLIT:0.1'])
>>>
>>> # Use the tuned model to get the score on the test set.
... "{:.2}".format(tuned_model.score(X_test, y_test))
'0.92
>>>
>>> # An example invocation of model tuning with user-defined
... # search ranges for selected hyperparameters on a new tuning
... # metric (f1_macro).
...  search_space = {
...   'RFOR_SAMPLING_RATIO': {'type': 'continuous',
...                           'range': [0.01, 0.5]},
...   'RFOR_NUM_TREES': {'type': 'discrete',
...                      'range': [50, 100]},
...   'TREE_IMPURITY_METRIC': {'type': 'categorical',
...                            'range': ['TREE_IMPURITY_ENTROPY',
...                            'TREE_IMPURITY_GINI']},}
>>> results = at.tune('rf', X, y, score_metric='f1_macro',
>>>                   param_space=search_space)
>>> score, params = results['all_evals'][0]
>>> ("{:.2}".format(score), ["{}:{}".format(k, params[k])
...   for k in sorted(params)])
('0.92', ['RFOR_NUM_TREES:53', 'RFOR_SAMPLING_RATIO:0.4999951',
'TREE_IMPURITY_METRIC:TREE_IMPURITY_ENTROPY'])
>>>
>>> # Some hyperparameter search ranges need to be defined based on the
... # training data set sizes (for example, the number of samples and
... # features). You can use placeholders specific to the data set,
... # such as $nr_features and $nr_samples, as the search ranges.
... search_space = {'RFOR_MTRY': {'type': 'discrete',
...                               'range': [1, '$nr_features/2']}}
>>> results = at.tune('rf', X, y,
...                   score_metric='f1_macro', param_space=search_space)
>>> score, params = results['all_evals'][0]
>>> ("{:.2}".format(score), ["{}:{}".format(k, params[k])
...   for k in sorted(params)])
('0.93', ['RFOR_MTRY:10'])
>>>
>>> # Drop the database table.
... oml.drop('BreastCancer')
```

6.5 Model Selection

The `oml.automl.ModelSelection` class automatically selects an Oracle Machine Learning algorithm according to the selected score metric and then tunes that algorithm.

The `oml.automl.ModelSelection` class supports classification and regression algorithms. To use the `oml.automl.ModelSelection` class, you specify a data set and the number of algorithms you want to tune.

The `select` method of the class returns the best model out of the models considered.

For information on the parameters and methods of the class, invoke `help(oml.automl.ModelSelection)` or see *Oracle Machine Learning for Python API Reference*.

Example 6-4 Using the `oml.automl.ModelSelection` Class

This example creates an `oml.automl.ModelSelection` object and then uses the object to select and tune the best model.

```
import oml
from oml import automl
import pandas as pd
from sklearn import datasets

# Load the breast cancer data set.
bc = datasets.load_breast_cancer()
bc_data = bc.data.astype(float)
X = pd.DataFrame(bc_data, columns = bc.feature_names)
y = pd.DataFrame(bc.target, columns = ['TARGET'])

# Create the database table BreastCancer.
oml_df = oml.create(pd.concat([X, y], axis=1),
                    table = 'BreastCancer')

# Split the data set into training and test data.
train, test = oml_df.split(ratio=(0.8, 0.2), seed = 1234)
X, y = train.drop('TARGET'), train['TARGET']
X_test, y_test = test.drop('TARGET'), test['TARGET']

# Create an automated model selection object with f1_macro as the
# score_metric argument.
ms = automl.ModelSelection(mining_function='classification',
                           score_metric='f1_macro', parallel=4)

# Run model selection to get the top (k=1) predicted algorithm
# (defaults to the tuned model).
select_model = ms.select(X, y, k=1)

# Show the selected and tuned model.
select_model

# Score on the selected and tuned model.
"{:.2}".format(select_model.score(X_test, y_test))

# Drop the database table.
oml.drop('BreastCancer')
```

Listing for This Example

```
>>> import oml
>>> from oml import automl
>>> import pandas as pd
>>> from sklearn import datasets
>>>
>>> # Load the breast cancer data set.
... bc = datasets.load_breast_cancer()
```

```
>>> bc_data = bc.data.astype(float)
>>> X = pd.DataFrame(bc_data, columns = bc.feature_names)
>>> y = pd.DataFrame(bc.target, columns = ['TARGET'])
>>>
>>> # Create the database table BreastCancer.
>>> oml_df = oml.create(pd.concat([X, y], axis=1),
...                     table = 'BreastCancer')
>>>
>>> # Split the data set into training and test data.
... train, test = oml_df.split(ratio=(0.8, 0.2), seed = 1234)
>>> X, y = train.drop('TARGET'), train['TARGET']
>>> X_test, y_test = test.drop('TARGET'), test['TARGET']
>>>
>>> # Create an automated model selection object with f1_macro as the
... # score_metric argument.
... ms = automl.ModelSelection(mining_function='classification',
...                            score_metric='f1_macro', parallel=4)
>>>
>>> # Run the model selection to get the top (k=1) predicted algorithm
... # (defaults to the tuned model).
... select_model = ms.select(X, y, k=1)
>>>
>>> # Show the selected and tuned model.
... select_model

Algorithm Name: Support Vector Machine

Mining Function: CLASSIFICATION

Target: TARGET

Settings:
                     setting name                 setting value
0                       ALGO_NAME  ALGO_SUPPORT_VECTOR_MACHINES
1          CLAS_WEIGHTS_BALANCED                           OFF
2                    ODMS_DETAILS                ODMS_DISABLE
3   ODMS_MISSING_VALUE_TREATMENT       ODMS_MISSING_VALUE_AUTO
4                   ODMS_SAMPLING         ODMS_SAMPLING_DISABLE
5                       PREP_AUTO                           ON
6         SVMS_COMPLEXITY_FACTOR                           10
7            SVMS_CONV_TOLERANCE                        .0001
8           SVMS_KERNEL_FUNCTION               SVMS_GAUSSIAN
9                SVMS_NUM_PIVOTS                          ...
10                  SVMS_STD_DEV          5.3999999999999995

Attributes:
area error
compactness error
concave points error
concavity error
fractal dimension error
mean area
mean compactness
mean concave points
mean concavity
mean fractal dimension
```

```
mean perimeter
mean radius
mean smoothness
mean symmetry
mean texture
perimeter error
radius error
smoothness error
symmetry error
texture error
worst area
worst compactness
worst concave points
worst concavity
worst fractal dimension
worst perimeter
worst radius
worst smoothness
worst symmetry
worst texture
Partition: NO

>>>
>>> # Score on the selected and tuned model.
... "{:.2}".format(select_model.score(X_test, y_test))
'0.99'
>>>
>>> # Drop the database table.
... oml.drop('BreastCancer')
```

7

Embedded Python Execution

Embedded Python Execution is a feature of Oracle Machine Learning for Python that allows you to invoke user-defined Python functions directly in an Oracle database instance.

Embedded Python Execution is described in the following topics:

- About Embedded Python Execution
- Python API for Embedded Python Execution
- REST API for Embedded Python Execution
- SQL API for Embedded Python Execution with Autonomous Database

Embedded Python Execution is available on:

- Oracle Autonomous Database, where pre-installed Python packages can be used, via Python, REST and SQL APIs.
- Oracle Database on premises, ExaCS, ExaC@C, DBCS, and Oracle Database deployed in a compute instance, where the user can custom install third-party packages to use with EPE, via Python and SQL APIs.

- About Embedded Python Execution
  With Embedded Python Execution, you can invoke user-defined Python functions in Python engines spawned and managed by the Oracle database instance.
- Datastores Supporting Embedded Python Execution
  OML4Py includes the datastore views supporting Embedded Python Execution. You can use these datastore views with the Embedded Python Execution APIs to work with the datastores and their contents.
- Script repository for user-defined Python functions supporting EPE
  OML4Py includes the script repository views supporting Embedded Python Execution. You can use these script repository views with the Embedded Python Execution APIs to work with the script repository and their contents.
- Python API for Embedded Python Execution
  You can invoke user-defined Python functions directly in an Oracle database instance by using Embedded Python Execution functions.
- SQL API for Embedded Python Execution with Autonomous Database
  The SQL API for Embedded Python Execution with Autonomous Database provides SQL interfaces for setting authorization tokens, managing access control list (ACL) privileges, executing Python scripts, and synchronously and asynchronously running jobs.

7.1 About Embedded Python Execution

With Embedded Python Execution, you can invoke user-defined Python functions in Python engines spawned and managed by the Oracle database instance.

Embedded Python Execution is available in Oracle Autonomous Database.

In Oracle Autonomous Database, you can use:

- An OML Notebooks Python interpreter session (see Use the Python Interpreter in a Notebook Paragraph)
- REST API for Embedded Python Execution
- Comparison of the Embedded Python Execution APIs
  The table below compares the four Embedded Python Execution APIs.

7.1.1 Comparison of the Embedded Python Execution APIs

The table below compares the four Embedded Python Execution APIs.

The APIs are:

- Embedded Python Execution API
- REST API for Embedded Python Execution (for use with Oracle Autonomous Database)
- SQL API for Embedded Python Execution with Oracle Autonomous Database.

The APIs share many functions, but they differ in some ways because of the different environments. For example, the APIs available for Autonomous Database provide an API for operating in a web environment.

The procedures and functions are part of the `PYQSYS` and `SYS` schemas.

Category	Python API for Embedded Python Execution	REST API for Embedded Python Execution	SQL APIs for Embedded Python Execution

Embedded Python Execution function	`oml.do_eval` function
	See Run a User-Defined Python Function.
		`POST /api/py-scripts/v1/do-eval/{scriptName}`
		See Run a Python Function.
		`POST /api/py-scripts/v1/do-eval/{scriptName}/{ownerName}`
		See Run a Python Function with Script Owner Specified.
			pyqEval Function (Autonomous Database) (Autonomous Database)

Embedded Python Execution function	`oml.table_apply` function
	See Run a User-Defined Python Function on the Specified Data.
		`POST /api/py-scripts/v1/table-apply/{scriptName}`
		See Run a Python Function on Specified Data.
		`POST /api/py-scripts/v1/table-apply/{scriptName}/{ownerName}}`
		See Run a Python Function on Specified Data with Script Owner Specified.
			pyqTableEval Function (Autonomous Database) (Autonomous Database)

Category	Python API for Embedded Python Execution	REST API for Embedded Python Execution	SQL APIs for Embedded Python Execution

Embedded Python Execution function	`oml.group_apply` function
	See Run a Python Function on Data Grouped By Column Values.
		`POST /api/py-scripts/v1/group-apply/{scriptName}`
		See Run a Python Function on Grouped Data.
		`POST /api/py-scripts/v1/group-apply/{scriptName}/{ownerName}`
		See Run a Python Function on Grouped Data with Script Owner Specified.
			pyqGroupEval Function (Autonomous Database)
			(Autonomous Database)

Embedded Python Execution function	`oml.row_apply` function
	See Run a User-Defined Python Function on Sets of Rows.
		`POST /api/py-scripts/v1/row-apply/{scriptName}`
		See Run a Python Function on Chunks of Rows.
		`POST /api/py-scripts/v1/row-apply/{scriptName}/{ownerName}`
		See Run a Python Function on Chunks of Rows with Script Owner Specified.
			pyqRowEval Function (Autonomous Database)
			(Autonomous Database)

Embedded Python Execution function	`oml.index_apply` function
	See Run a User-Defined Python Function Multiple Times.
		`POST /api/py-scripts/v1/index-apply/{scriptName}`
		See Run a Python Function Multiple Times.
		`POST /api/py-scripts/v1/index-apply/{scriptName}/{ownerName}`
		See Run a Python Function Multiple Times with Script Owner Specified.
			pyqIndexEval Function (Autonomous Database)
			(Autonomous Database)

Job status API	NA	`GET /api/py-scripts/v1/jobs/{jobId}` See Retrieve Asynchronous Job Status.	pyqJobStatus Function (Autonomous Database)
Job result API	NA	`GET /api/py-scripts/v1/jobs/{jobId}/result` See Retrieve Asynchronous Job Result.	pyqJobResult Function (Autonomous Database)
Script repository	`oml.script.dir` function See List Available User-Defined Python Functions.	`GET /api/py-scripts/v1/scripts` See List Scripts.	List the scripts by querying the ALL_PYQ_SCRIPTS View and the USER_PYQ_SCRIPTS View.
Script repository	`oml.script.create` function See Create and Store a User-Defined Python Function.	NA	pyqScriptCreate Procedure (Autonomous Database) (Autonomous Database)
Script repository	`oml.script.drop` function See Drop a User-Defined Python Function from the Repository.	NA	pyqScriptDrop Procedure (Autonomous Database) (Autonomous Database)

Category	Python API for Embedded Python Execution	REST API for Embedded Python Execution	SQL APIs for Embedded Python Execution
Script repository	`oml.script.load` function See Load a User-Defined Python Function.	NA	NA (Scripts are loaded in the SQL APIs when the function is called.)
Script repository and datastore	`oml.grant` function See About the Script Repository.	NA	`pyqGrant` procedure (Oracle Autonomous Database)
Script repository and datastore	`oml.revoke` function See About the Script Repository.	NA	`pyqRevoke` procedure (Autonomous Database)
Authorization - Access Control Lists	NA	NA	pyqAppendHostACE Procedure (Autonomous Database)
Authorization - Access Control Lists	NA	NA	pyqRemoveHostACE Procedure (Autonomous Database)
Authorization - Access Control Lists	NA	NA	pyqGetHostACE Function (Autonomous Database)
Authorization - Tokens	NA	See Authenticate.	• pyqSetAuthToken Procedure (Autonomous Database) • NA (on-premises database)
Authorization - Tokens	NA	See Authenticate.	pyqIsTokenSet Function (Autonomous Database)

Note:

An output limit exists on the length function for REST API and SQL APIs for embedded Python execution. A query on the length function with a length of more than 5000 will result in an error with error code 1024 and the error message "Output exceeds maximum length 5000". The limit is set on the `len()` result of the returning python object. For example, `len()` of a pandas.DataFrame is the number of rows, `len()` of a list is the length of the list, etc. If pandas.DataFrame is returned, it cannot have more than 5000 rows. If a list is returned, it should not contain more than 5000 items. This limit can be extended by updating the `OML_OUTPUT_SZLIMIT` in a `%script` paragraph:

```
%script

EXEC sys.pyqconfigset('OML_OUTPUT_SZLIMIT', '8000')
```

7.2 Datastores Supporting Embedded Python Execution

OML4Py includes the datastore views supporting Embedded Python Execution. You can use these datastore views with the Embedded Python Execution APIs to work with the datastores and their contents.

View	Description
ALL_PYQ_DATASTORES View	Contains information about the datastores available to the current user.
ALL_PYQ_DATASTORE_CONTENTS View	Contains information about the objects in the datastores available to the current user.
USER_PYQ_DATASTORES View	Contains information about the datastores owned by the current user.

- ALL_PYQ_DATASTORE_CONTENTS View
  The `ALL_PYQ_DATASTORE_CONTENTS` view contains information about the contents of datastores that are available to the current user.
- ALL_PYQ_DATASTORES View
  The `ALL_PYQ_DATASTORES` view contains information about the datastores that are available to the current user.
- USER_PYQ_DATASTORES View
  The `USER_PYQ_DATASTORES` view contains information about the datastores that are owned by the current user.

7.2.1 ALL_PYQ_DATASTORE_CONTENTS View

The `ALL_PYQ_DATASTORE_CONTENTS` view contains information about the contents of datastores that are available to the current user.

Column	Datatype	Null	Description
DSOWNER	VARCHAR2(128)	NULL permitted	The owner of the datastore.
DSNAME	VARCHAR2(128)	NULL permitted	The name of the datastore.
OBJNAME	VARCHAR2(128)	NULL permitted	The name of an object in the datastore.
CLASS	VARCHAR2(128)	NULL permitted	The class of a Python object in the datastore.
OBJSIZE	NUMBER	NULL permitted	The size of an object in the datastore.
LENGTH	NUMBER	NULL permitted	The length of an object in the datastore. The length is 1 for all objects unless the object is a `list`, `dict`, `pandas.DataFrame`, or `oml.DataFrame`, in which case it is equal to `len(obj)`.
NROW	NUMBER	NULL permitted	The number of rows of an object in the datastore. The number is 1 for all objects except for `pandas.DataFrame` and `oml.DataFrame` objects, in which case it is equal to `len(df)`.
NCOL	NUMBER	NULL permitted	The number of columns of an object in the datastore. The number is `len(obj)` if the object is a `list` or `dict`, `len(obj.columns)` if the object is a `pandas.DataFrame` or `oml.DataFrame`, and 1 otherwise.

Example 7-1 Selecting from the ALL_PYQ_DATASTORE_CONTENTS View

This example selects all columns from the `ALL_PYQ_DATASTORE_CONTENTS` view. For the creation of the datastores in this example, see Example 3-7.

```
SELECT * FROM ALL_PYQ_DATASTORE_CONTENTS
```

```
DSOWNER   DSNAME        OBJNAME       CLASS              OBJSIZE  LENGTH
NROW  NCOL
--------  ------------  ------------  -----------------  -------  ------
----  ----
OML_USER  ds_pydata     oml_boston    oml.DataFrame         1073     506
506    14
OML_USER  ds_pydata     oml_diabetes  oml.DataFrame          964     442
442    11
OML_USER  ds_pydata     wine          Bunch                24177       5
1      5
OML_USER  ds_pymodel    regr1         LinearRegression       706       1
1      1
OML_USER  ds_pymodel    regr2         oml.glm               5664       1
1      1
OML_USER  ds_wine_data  oml_wine      oml.DataFrame      1410     178
178    14
```

7.2.2 ALL_PYQ_DATASTORES View

The `ALL_PYQ_DATASTORES` view contains information about the datastores that are available to the current user.

Column	Datatype	Null	Description
DSOWNER	VARCHAR2(256)	NULL permitted	The owner of the datastore.
DSNAME	VARCHAR2(128)	NULL permitted	The name of the datastore.
NOBJ	NUMBER	NULL permitted	The number of objects in the datastore.
DSSIZE	NUMBER	NULL permitted	The size of the datastore.
CDATE	DATE	NULL permitted	The date on which the datastore was created.
DESCRIPTION	VARCHAR2(2000)	NULL permitted	A description of the datastore.
GRANTABLE	VARCHAR2(1)	NULL permitted	Whether or not the read privilege to the datastore may be granted. The value in this column is either T for True or F for False.

Example 7-2 Selecting from the ALL_PYQ_DATASTORES View

This example selects all columns from the `ALL_PYQ_DATASTORES` view. It then selects only the DSNAME and GRANTABLE columns from the view. For the creation of the datastores in these examples, see Example 3-7.

```
SELECT * FROM ALL_PYQ_DATASTORES;
```

```
DSOWNER    DSNAME          NOBJ    DSSIZE   CDATE       DESCRIPTION       G
--------   ------------   -----   -------   ---------   ---------------   -
OML_USER   ds_pydata           3     26214   18-MAY-19   python datasets   F
OML_USER   ds_pymodel          2      6370   18-MAY-19                     T
OML_USER   ds_wine_data        1      1410   18-MAY-19   wine dataset      F
```

This example selects only the DSNAME and GRANTABLE columns from the view.

```
SELECT DSNAME, GRANTABLE FROM ALL_PYQ_DATASTORES;
```

```
DSNAME       G
----------   -
ds_pydata    F
ds_pymodel   T
ds_wine_data F
```

7.2.3 USER_PYQ_DATASTORES View

The `USER_PYQ_DATASTORES` view contains information about the datastores that are owned by the current user.

Column	Datatype	Null	Description
DSNAME	VARCHAR2(128)	NULL permitted	The name of the datastore.
NOBJ	NUMBER	NULL permitted	The number of objects in the datastore.
DSSIZE	NUMBER	NULL permitted	The size of the datastore.
CDATE	DATE	NULL permitted	The date on which the datastore was created.
DESCRIPTION	VARCHAR2(2000)	NULL permitted	A description of the datastore.
GRANTABLE	VARCHAR2(1)	NULL permitted	Whether or not the read privilege to the datastore may be granted. The value in this column is either T for True or F for False.

Example 7-3 Selecting from the USER_PYQ_DATASTORES View

This example selects all columns from the `USER_PYQ_DATASTORES` view. For the creation of the datastores in these examples, see Example 3-7.

```
SELECT * FROM USER_PYQ_DATASTORES;
```

```
DSNAME       NOBJ   DSSIZE   CDATE       DESCRIPTION       G
----------   ----   ------   ---------   ---------------   -
ds_wine_data    1     1410   18-MAY-19   wine dataset      F
ds_pydata       3    26214   18-MAY-19   python datasets   F
ds_pymodel      2     6370   18-MAY-19                     T
```

This example selects only the DSNAME and GRANTABLE columns from the view.

```
SELECT DSNAME, GRANTABLE FROM USER_PYQ_DATASTORES;
```

```
DSNAME        G
----------    -
ds_wine_data  F
ds_pydata     F
ds_pymodel    T
```

7.3 Script repository for user-defined Python functions supporting EPE

OML4Py includes the script repository views supporting Embedded Python Execution. You can use these script repository views with the Embedded Python Execution APIs to work with the script repository and their contents.

View	Description
ALL_PYQ_SCRIPTS View	Describes the scripts that are available to the current user.
USER_PYQ_SCRIPTS View	Describes the user-defined Python functions in the script repository that are owned by the current user.

- ALL_PYQ_SCRIPTS View
  The `ALL_PYQ_SCRIPTS` view contains information about the user-defined Python functions in the OML4Py script repository that are available to the current user.
- USER_PYQ_SCRIPTS View
  This view contains information about the user-defined Python functions in the OML4Py script repository that are owned by the current user.

7.3.1 ALL_PYQ_SCRIPTS View

The `ALL_PYQ_SCRIPTS` view contains information about the user-defined Python functions in the OML4Py script repository that are available to the current user.

Column	Datatype	Null	Description
`OWNER`	`VARCHAR2(256)`	`NULL` permitted	The owner of the user-defined Python function.
`NAME`	`VARCHAR2(128)`	`NULL` permitted	The name of the user-defined Python function.
`SCRIPT`	`CLOB`	`NULL` permitted	The user-defined Python function.

Example 7-4 Selecting from the ALL_PYQ_SCRIPTS View

This example selects the owner and the name of the user-defined Python function from the `ALL_PYQ_SCRIPTS` view.

```
SELECT owner, name FROM ALL_PYQ_SCRIPTS;
```

```
OWNER      NAME
--------   -----------------
OML_USER   create_iris_table
OML_USER   tmpqfun2
PYQSYS     tmpqfun2
```

This example selects the name of the user-defined Python function and the function definition from the view.

```
SELECT name, script FROM ALL_PYQ_SCRIPTS WHERE name = 'create_iris_table';
```

```
NAME                SCRIPT
-----------------
--------------------------------------------------------------------------
create_iris_table   "def create_iris_table():  from sklearn.datasets import
load_iris ...
```

7.3.2 USER_PYQ_SCRIPTS View

This view contains information about the user-defined Python functions in the OML4Py script repository that are owned by the current user.

Column	Datatype	Null	Description
`NAME`	`VARCHAR2(128)`	`NOT NULL`	The name of the user-defined Python function.
`SCRIPT`	`CLOB`	`NULL` permitted	The user-defined Python function.

Example 7-5 Selecting from the USER_PYQ_SCRIPTS View

This example selects all columns from `USER_PYQ_SCRIPTS`.

```
SELECT * FROM USER_PYQ_SCRIPTS;



NAME                SCRIPT
-----------------
--------------------------------------------------------------------
create_iris_table   "def create_iris_table():    from sklearn.datasets import
load_iris ...
tmpqfun2            "def return_frame():     import numpy as np       import
pickle     ...
```

7.4 Python API for Embedded Python Execution

You can invoke user-defined Python functions directly in an Oracle database instance by using Embedded Python Execution functions.

- About Python API for Embedded Python Execution
- Run a User-Defined Python Function
  Use the `oml.do_eval` function to run a user-defined input function that explicitly retrieves data or for which external data is not required.
- Run a User-Defined Python Function on the Specified Data
  Use the `oml.table_apply` function to run a Python function on data that you specify with the `data` parameter.
- Run a Python Function on Data Grouped By Column Values
  Use the `oml.group_apply` function to group the values in a database table by one or more columns and then run a user-defined Python function on each group.
- Run a User-Defined Python Function on Sets of Rows
  Use the `oml.row_apply` function to chunk data into sets of rows and then run a user-defined Python function on each chunk.
- Run a User-Defined Python Function Multiple Times
  Use the `oml.index_apply` function to run a Python function multiple times in Python engines spawned by the database environment.
- Save and Manage User-Defined Python Functions in the Script Repository
  The OML4Py script repository stores user-defined Python functions for use with Embedded Python Execution functions.

7.4.1 About Python API for Embedded Python Execution

You may choose to run your functions in a data-parallel or task-parallel manner in one or more of these Python engines. In data-parallel processing, the data is partitioned and the same user-defined Python function of each data subset is invoked using one or more Python engines. In task-parallel processing, a user-defined function is invoked multiple times in one or more Python engines with a unique index passed in as an argument; for example, you may use task parallelism for Monte Carlo simulations in which you use the index to set a random seed.

The following table lists the Python functions for Embedded Python Execution.

Function	Description
`oml.do_eval`	Runs a user-defined Python function in a Python engine spawned and managed by the database environment.
`oml.group_apply`	Partitions a database table by the values in one or more columns and runs the provided user-defined Python function on each partition.
`oml.index_apply`	Runs a Python function multiple times, passing in a unique index of the invocation to the user-defined function.
`oml.row_apply`	Partitions a database table into sets of rows and runs the provided user-defined Python function on the data in each set.
`oml.table_apply`	Runs a Python function on data in the database as a single `pandas.DataFrame` in a single Python engine.

About Special Control Arguments

Special control arguments control what happens before or after the running of the function that you pass to an Embedded Python Execution function. You specify a special control argument with the `**kwargs` parameter of a function such as `oml.do_eval`. The control arguments are not passed to the function specified by the `func` argument of that function.

Table 7-1 Special Control Arguments

Argument	Description
`oml_input_type`	Identifies the type of input data object that you are supplying to the `func` argument. The input types are the following: • `pandas.DataFrame` • `numpy.recarray` • `'default'` (the default value) If all columns are numeric, then default type is a 2-dimensional `numpy.ndarray` of type `numpy.float64`. Otherwise, the default type is a `pandas.DataFrame`.
`oml_na_omit`	Controls the handling of missing values in the input data. If you specify `oml_na_omit = True`, then rows that contain missing values are removed from the input data. If all of the rows contain missing values, then the input data is an empty `oml.DataFrame`. The default value is `False`.

About Output

When a user-defined Python function runs in OML4Py, by default it returns the Python objects returned by the function. Also, OML4Py captures all `matplotlib.figure.Figure` objects created by the user-defined Python function and converts them into PNG format.

If `graphics = True`, the Embedded Python Execution functions return `oml.embed.data_image._DataImage` objects. The `oml.embed.data_image._DataImage` class contains Python objects and PNG images. Calling the method `__repr__()` displays the PNG images and prints out the Python object. By default, `.dat` returns the Python object that the user-defined Python function returned; `.img` returns a list containing PNG image data for each figure.

About the Script Repository

Embedded Python Execution includes the ability to create and store user-defined Python functions in the OML4Py script repository, grant or revoke the read privilege to a user-defined Python function, list the available user-defined Python functions, load user-defined Python functions into the Python environment, or drop a user-defined Python function from the script repository.

Along with whatever other actions a user-defined Python function performs, it can also create, retrieve, and modify Python objects that are stored in OML4Py datastores.

In Embedded Python Execution, a user-defined Python function runs in one or more Python engines spawned and managed by the database environment. The engines are dynamically started and managed by the database. From the same user-defined Python function you can get structured data and PNG images.

You can make the user-defined Python function either private or global. A global function is available to any user. A private function is available only to the owner or to users to whom the owner of the function has granted the read privilege.

7.4.2 Run a User-Defined Python Function

Use the `oml.do_eval` function to run a user-defined input function that explicitly retrieves data or for which external data is not required.

The `oml.do_eval` function runs a user-defined Python function in a Python engine spawned and managed by the database environment.

The syntax of the `oml.do_eval` function is the following:

```
oml.do_eval(func, func_owner=None, graphics=False, **kwargs)
```

The `func` argument is the function to run. It may be one of the following:

- A Python function
- A string that is the name of a user-defined Python function in the OML4Py script repository
- A string that defines a Python function
- An `oml.script.script.Callable` object returned by the `oml.script.load` function

The optional `func_owner` argument is a string or `None` (the default) that specifies the owner of the registered user-defined Python function when argument `func` is a registered user-defined Python function name.

The `graphics` argument is a boolean that specifies whether to look for images. The default value is `False`.

With the `**kwargs` parameter, you can pass additional arguments to the `func` function. Special control arguments, which start with `oml_`, are not passed to the function specified by `func`, but instead control what happens before or after the running of the function.

The `oml.do_eval` function returns a Python object or an `oml.embed.data_image._DataImage`. If no image is rendered in the user-defined Python function, `oml.do_eval` returns whatever Python object is returned by the function. Otherwise, it returns an `oml.embed.data_image._DataImage` object.

Example 7-6 Using the oml.do_eval Function

This example defines a Python function that returns a Pandas DataFrame with the columns ID and RES. It then passes that function to the `oml.do_eval` function.

```
import pandas as pd
import oml

def return_df(num, scale):
    import pandas as pd
    id = list(range(0, int(num)))
    res = [i/scale for i in id]
    return pd.DataFrame({"ID":id, "RES":res})

res = oml.do_eval(func=return_df, scale = 100, num = 10)
type(res)

res
```

Listing for This Example

```
>>> import pandas as pd
>>> import oml
>>>
>>> def return_df(num, scale):
...     import pandas as pd
...     id = list(range(0, int(num)))
...     res = [i/scale for i in id]
...     return pd.DataFrame({"ID":id, "RES":res})
...
>>>
>>> res = oml.do_eval(func=return_df, scale = 100, num = 10)
>>> type(res)
<class 'pandas.core.frame.DataFrame'>
>>>
>>> res
   ID  RES
0 0.0 0.00
1 1.0 0.01
2 2.0 0.02
3 3.0 0.03
4 4.0 0.04
5 5.0 0.05
6 6.0 0.06
7 7.0 0.07
8 8.0 0.08
9 9.0 0.09
```

7.4.3 Run a User-Defined Python Function on the Specified Data

Use the `oml.table_apply` function to run a Python function on data that you specify with the `data` parameter.

The `oml.table_apply` function runs a user-defined Python function in a Python engine spawned and managed by the database environment. With the `func` parameter, you can

supply a Python function or you can specify the name of a user-defined Python function in the OML4Py script repository.

The syntax of the function is the following:

```
oml.table_apply(data, func, func_owner=None, graphics=False, **kwargs)
```

The `data` argument is an `oml.DataFrame` that contains the data that the `func` function operates on.

The `func` argument is the function to run. It may be one of the following:

- A Python function
- A string that is the name of a user-defined Python function in the OML4Py script repository
- A string that defines a Python function
- An `oml.script.script.Callable` object returned by the `oml.script.load` function

The optional `func_owner` argument is a string or `None` (the default) that specifies the owner of the registered user-defined Python function when argument `func` is a registered user-defined Python function name.

The `graphics` argument is a boolean that specifies whether to look for images. The default value is `False`.

With the `**kwargs` parameter, you can pass additional arguments to the `func` function. Special control arguments, which start with `oml_`, are not passed to the function specified by `func`, but instead control what happens before or after the execution of the function.

The `oml.table_apply` function returns a Python object or an `oml.embed.data_image._DataImage`. If no image is rendered in the user-defined Python function, `oml.table_apply` returns whatever Python object is returned by the function. Otherwise, it returns an `oml.embed.data_image._DataImage` object.

Example 7-7 Using the oml.table_apply Function

This example builds a regression model using in-memory data, and then uses the `oml.table_apply` function to predict using the model on the first 10 rows of the IRIS table.

```
import oml
import pandas as pd
from sklearn import datasets
from sklearn import linear_model

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()

x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

# Drop the IRIS database table if it exists.
try:
```

```
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Build a regression model using in-memory data.
iris = oml_iris.pull()
regr = linear_model.LinearRegression()
regr.fit(iris[['Sepal_Width', 'Petal_Length', 'Petal_Width']],
         iris[['Sepal_Length']])
regr.coef_

# Use oml.table_apply to predict using the model on the first 10
# rows of the IRIS table.
def predict(dat, regr):
    import pandas as pd
    pred = regr.predict(dat[['Sepal_Width', 'Petal_Length',
                             'Petal_Width']])
    return pd.concat([dat,pd.DataFrame(pred)], axis=1)

res = oml.table_apply(data=oml_iris.head(n=10),
                      func=predict, regr=regr)
res
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>> from sklearn import linear_model
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>>
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> # Drop the IRIS database table if it exists.
... try:
...     oml.drop('IRIS')
... except:
...     pass
>>>
>>> # Create the IRIS database table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Build a regression model using in-memory data.
... iris = oml_iris.pull()
```

```
>>> regr = linear_model.LinearRegression()
>>> regr.fit(iris[['Sepal_Width', 'Petal_Length', 'Petal_Width']],
...          iris[['Sepal_Length']])
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
>>> regr.coef_
array([[ 0.65083716,  0.70913196, -0.55648266]])
>>>
>>> # Use oml.table_apply to predict using the model on the first 10
... # rows of the IRIS table.
... def predict(dat, regr):
... import pandas as pd
... pred = regr.predict(dat[['Sepal_Width', 'Petal_Length',
...                          'Petal_Width']])
... return pd.concat([dat,pd.DataFrame(pred)], axis=1)
...
>>> res = oml.table_apply(data=oml_iris.head(n=10),
...                       func=predict, regr=regr)
>>> res   Sepal_Length  Sepal_Width  Petal_Length  Petal_Width
0           4.6          3.6             1          0.2
1           5.1          2.5             3          1.1
2           6.0          2.2             4          1.0
3           5.8          2.6             4          1.2
4           5.5          2.3             4          1.3
5           5.5          2.5             4          1.3
6           6.1          2.8             4          1.3
7           5.7          2.5             5          2.0
8           6.0          2.2             5          1.5
9           6.3          2.5             5          1.9

      Species         0
0      setosa  4.796847
1  versicolor  4.998355
2  versicolor  5.567884
3  versicolor  5.716923
4  versicolor  5.466023
5  versicolor  5.596191
6   virginica  5.791442
7   virginica  5.915785
8   virginica  5.998775
9   virginica  5.971433
```

7.4.4 Run a Python Function on Data Grouped By Column Values

Use the `oml.group_apply` function to group the values in a database table by one or more columns and then run a user-defined Python function on each group.

The `oml.group_apply` function runs a user-defined Python function in a Python engine spawned and managed by the database environment. The `oml.group_apply` function passes the `oml.DataFrame` specified by the `data` argument to the user-defined `func` function as its first argument. The `index` argument to `oml.group_apply` specifies the columns of the `oml.DataFrame` by which the database groups the data for processing by the user-defined Python function. The `oml.group_apply` function can use data-parallel execution, in which one or more Python engines perform the same Python function on different groups of data.

The syntax of the function is the following.

```
oml.group_apply(data, index, func, func_owner=None, parallel=None,
orderby=None, graphics=False, **kwargs)
```

The `data` argument is an `oml.DataFrame` that contains the in-database data that the `func` function operates on.

The `index` argument is an `oml.DataFrame` object, the columns of which are used to group the data before sending it to the `func` function.

The `func` argument is the function to run. It may be one of the following:

- A Python function
- A string that is the name of a user-defined Python function in the OML4Py script repository
- A string that defines a Python function
- An `oml.script.script.Callable` object returned by the `oml.script.load` function

The optional `func_owner` argument is a string or `None` (the default) that specifies the owner of the registered user-defined Python function when argument `func` is a registered user-defined Python function name.

The `parallel` argument is a boolean, an `int`, or `None` (the default) that specifies the preferred degree of parallelism to use in the Embedded Python Execution job. The value may be one of the following:

- A positive integer greater than or equal to 1 for a specific degree of parallelism
- `False`, `None`, or `0` for no parallelism
- `True` for the default data parallelism

The optional `orderby` argument is an `oml.DataFrame`, `oml.Float`, or `oml.String` that specifies the ordering of the group partitions.

The `graphics` argument is a boolean that specifies whether to look for images. The default value is `False`.

With the `**kwargs` parameter, you can pass additional arguments to the `func` function. Special control arguments, which start with `oml_`, are not passed to the function specified by `func`, but instead control what happens before or after the running of the function.

The `oml.group_apply` function returns a `dict` of Python objects or a `dict` of `oml.embed.data_image._DataImage` objects. If no image is rendered in the user-defined Python function, `oml.group_apply` returns a `dict` of Python object returned by the function. Otherwise, it returns a `dict` of `oml.embed.data_image._DataImage` objects.

Example 7-8 Using the oml.group_apply Function

This example defines some functions and calls `oml.group_apply` for each function.

```
import pandas as pd
from sklearn import datasets
import oml

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
```

```
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

# Drop the IRIS database table if it exists.
try:
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Define a function that counts the number of rows and returns a
# dataframe with the species and the count.
def group_count(dat):
    import pandas as pd
    return pd.DataFrame([(dat["Species"][0], dat.shape[0])],\
                        columns = ["Species", "COUNT"])

# Select the Species column to use as the index argument.
index = oml.DataFrame(oml_iris['Species'])

# Group the data by the Species column and run the user-defined
# function for each species.
res = oml.group_apply(oml_iris, index, func=group_count,
                      oml_input_type="pandas.DataFrame")
res

# Define a function that builds a linear regression model, with
# Petal_Width as the feature and Petal_Length as the target value,
# and that returns the model after fitting the values.
def build_lm(dat):
    from sklearn import linear_model
    lm = linear_model.LinearRegression()
    X = dat[["Petal_Width"]]
    y = dat[["Petal_Length"]]
    lm.fit(X, y)
    return lm

# Run the model for each species and return an objectList in
# dict format with a model for each species.
mod = oml.group_apply(oml_iris[:,["Petal_Length", "Petal_Width",
                                  "Species"]], index, func=build_lm)

# The output is a dict of key-value pairs for each species and model.
type(mod)

# Sort dict by the key species.
{k: mod[k] for k in sorted(mod.keys())}
```

Listing for This Example

```
>>> import pandas as pd
>>> from sklearn import datasets
>>> import oml
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>>
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> # Drop the IRIS database table if it exists.
... try:
...     oml.drop('IRIS')
... except:
...     pass
>>>
>>> # Create the IRIS database table.
... oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Define a function that counts the number of rows and returns a
... # dataframe with the species and the count.
... def group_count(dat):
...     import pandas as pd
...     return pd.DataFrame([(dat["Species"][0], dat.shape[0])],\
...                         columns = ["Species", "COUNT"])
...
>>> # Select the Species column to use as the index argument.
... index = oml.DataFrame(oml_iris['Species'])
>>>
>>> # Group the data by the Species column and run the user-defined
... # function for each species.
... res = oml.group_apply(oml_iris, index, func=group_count,
...                       oml_input_type="pandas.DataFrame")
>>> res
{'setosa':   Species  COUNT
0  setosa     50, 'versicolor':       Species  COUNT
0  versicolor     50, 'virginica':      Species  COUNT
0  virginica     50}
>>>
>>> # Define a function that builds a linear regression model, with
... # Petal_Width  as the feature and Petal_Length as the target value,
... # and that returns the model after fitting the values.
... def build_lm(dat):
...     from sklearn import linear_model
...     lm = linear_model.LinearRegression()
...     X = dat[["Petal_Width"]]
...     y = dat[["Petal_Length"]]
...     lm.fit(X, y)
...     return lm
```

```
...
>>> # Run the model for each species and return an objectList in
... # dict format with a model for each species.
... mod = oml.group_apply(oml_iris[:,["Petal_Length", "Petal_Width",
...                                   "Species"]], index, func=build_lm)
>>>
>>> # The output is a dict of key-value pairs for each species and model.
... type(mod)
<class 'dict'>
>>>
>>> # Sort dict by the key species.
... {k: mod[k] for k in sorted(mod.keys())}
{'setosa': LinearRegression(copy_X=True, fit_intercept=True,
n_jobs=None,normalize=False), 'versicolor': LinearRegression(copy_X=True,
fit_intercept=True, n_jobs=None, normalize=False), 'virginica':
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
normalize=False)}
```

7.4.5 Run a User-Defined Python Function on Sets of Rows

Use the `oml.row_apply` function to chunk data into sets of rows and then run a user-defined Python function on each chunk.

The `oml.row_apply` function passes the `oml.DataFrame` specified by the `data` argument as the first argument to the user-defined `func` Python function. The `rows` argument specifies the maximum number of rows of the `oml.DataFrame` to assign to each chunk. The last chunk of rows may have fewer rows than the number specified.

The `oml.row_apply` function runs the Python function in a database-spawned Python engine. The function can use data-parallel execution, in which one or more Python engines perform the same Python function on different chunks of the data.

The syntax of the function is the following.

```
oml.row_apply(data, func, func_owner=None, rows=1, parallel=None,
graphics=False, **kwargs)
```

The `data` argument is an `oml.DataFrame` that contains the data that the `func` function operates on.

The `func` argument is the function to run. It may be one of the following:

- A Python function
- A string that is the name of a user-defined Python function in the OML4Py script repository
- A string that defines a Python function
- An `oml.script.script.Callable` object returned by the `oml.script.load` function

The optional `func_owner` argument is a string or `None` (the default) that specifies the owner of the registered user-defined Python function when argument `func` is a registered user-defined Python function name.

The `rows` argument is an `int` that specifies the maximum number of rows to include in each chunk.

The `parallel` argument is a boolean, an `int`, or `None` (the default) that specifies the preferred degree of parallelism to use in the Embedded Python Execution job. The value may be one of the following:

- A positive integer greater than or equal to 1 for a specific degree of parallelism
- `False`, `None`, or `0` for no parallelism
- `True` for the default data parallelism

The `graphics` argument is a boolean that specifies whether to look for images. The default value is `True`.

With the `**kwargs` parameter, you can pass additional arguments to the `func` function. Special control arguments, which start with `oml_`, are not passed to the function specified by `func`, but instead control what happens before or after the running of the function.

The `oml.row_apply` function returns a `pandas.DataFrame` or a list of `oml.embed.data_image._DataImage` objects. If no image is rendered in the user-defined Python function, `oml.row_apply` returns a `pandas.DataFrame`. Otherwise, it returns a list of `oml.embed.data_image._DataImage` objects.

Example 7-9 Using the oml.row_apply Function

This example creates the `x` and `y` variables using the iris data set. It then creates the persistent database table IRIS and the `oml.DataFrame` object `oml_iris` as a proxy for the table.

The example builds a regression model based on iris data. It defines a function that predicts the Petal_Width values based on the Sepal_Length, Sepal_Width, and Petal_Length columns of the input data. It then concatenates the Species column, the Petal_Width column, and the predicted Petal_Width as the object to return. Finally, the example calls the `oml.row_apply` function to apply the `make_pred()` function on each 4-row chunk of the input data.

```
import oml
import pandas as pd
from sklearn import datasets
from sklearn import linear_model

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()
x = pd.DataFrame(iris.data,
                 columns = ['Sepal_Length','Sepal_Width',
                            'Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor',
                           2:'virginica'}[x], iris.target)),
                 columns = ['Species'])

# Drop the IRIS database table if it exists.
try:
    oml.drop('IRIS')
except:
    pass

# Create the IRIS database table and the proxy object for the table.
oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')

# Build a regression model to predict Petal_Width using in-memory
```

```
# data.
iris = oml_iris.pull()
regr = linear_model.LinearRegression()
regr.fit(iris[['Sepal_Length', 'Sepal_Width', 'Petal_Length']],
         iris[['Petal_Width']])
regr.coef_

# Define a Python function.
def make_pred(dat, regr):
    import pandas as pd
    import numpy as np
    pred = regr.predict(dat[['Sepal_Length',
                             'Sepal_Width',
                             'Petal_Length']])
    return pd.concat([dat[['Species', 'Petal_Width']],
                      pd.DataFrame(pred,
                                   columns=['Pred_Petal_Width'])],
                                   axis=1)

input_data = oml_iris.split(ratio=(0.9, 0.1), strata_cols='Species')[1]
input_data.crosstab(index = 'Species').sort_values('Species')

res = oml.row_apply(input_data, rows=4, func=make_pred,
                    regr=regr, parallel=2)
type(res)
res
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>> from sklearn import datasets
>>> from sklearn import linear_model
>>>
>>> # Load the iris data set and create a pandas.DataFrame for it.
... iris = datasets.load_iris()
>>> x = pd.DataFrame(iris.data,
...                  columns = ['Sepal_Length','Sepal_Width',
...                             'Petal_Length','Petal_Width'])
>>> y = pd.DataFrame(list(map(lambda x:
...                           {0: 'setosa', 1: 'versicolor',
...                            2:'virginica'}[x], iris.target)),
...                  columns = ['Species'])
>>>
>>> # Drop the IRIS database table if it exists.
... try:
...     oml.drop('IRIS')
... except:
...     pass
>>>
>>> # Create the IRIS database table and the proxy object for the table.
>>> oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
>>>
>>> # Build a regression model to predict Petal_Width using in-memory
... # data.
```

```
... iris = oml_iris.pull()
>>> regr = linear_model.LinearRegression()
>>> regr.fit(iris[['Sepal_Length', 'Sepal_Width', 'Petal_Length']],
...          iris[['Petal_Width']])
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
normalize=False)
>>> regr.coef_
array([[-0.20726607,  0.22282854,  0.52408311]])
>>>
>>> # Define a Python function.
... def make_pred(dat, regr):
...     import pandas as pd
...     import numpy as np
...     pred = regr.predict(dat[['Sepal_Length',
...                              'Sepal_Width',
...                              'Petal_Length']])
...     return pd.concat([dat[['Species', 'Petal_Width']],
...                       pd.DataFrame(pred,
...                                    columns=['Pred_Petal_Width'])],
...                                    axis=1)
>>>
>>> input_data = oml_iris.split(ratio=(0.9, 0.1), strata_cols='Species')[1]
>>> input_data.crosstab(index = 'Species').sort_values('Species')
      SPECIES  count
0      setosa      7
1  versicolor      8
2   virginica      4
>>>  res = oml.row_apply(input_data, rows=4, func=make_pred, regr=regr,
...                      columns=['Species',
...                               'Petal_Width',
...                               'Pred_Petal_Width']))
>>> res = oml.row_apply(input_data, rows=4, func=make_pred,
...                      regr=regr, parallel=2)
>>> type(res)
<class 'pandas.core.frame.DataFrame'>
>>> res
       Species  Petal_Width  Pred_Petal_Width
0       setosa          0.4          0.344846
1       setosa          0.3          0.335509
2       setosa          0.2          0.294117
3       setosa          0.2          0.220982
4       setosa          0.2          0.080937
5   versicolor          1.5          1.504615
6   versicolor          1.3          1.560570
7   versicolor          1.0          1.008352
8   versicolor          1.3          1.131905
9   versicolor          1.3          1.215622
10  versicolor          1.3          1.272388
11   virginica          1.8          1.623561
12   virginica          1.8          1.878132
```

7.4.6 Run a User-Defined Python Function Multiple Times

Use the `oml.index_apply` function to run a Python function multiple times in Python engines spawned by the database environment.

The syntax of the function is the following:

```
oml.index_apply(times, func, func_owner=None, parallel=None, graphics=False,
**kwargs)
```

The `times` argument is an `int` that specifies the number of times to run the `func` function.

The `func` argument is the function to run. It may be one of the following:

- A Python function
- A string that is the name of a user-defined Python function in the OML4Py script repository
- A string that defines a Python function
- An `oml.script.script.Callable` object returned by the `oml.script.load` function

The optional `func_owner` argument is a string or `None` (the default) that specifies the owner of the registered user-defined Python function when argument `func` is a registered user-defined Python function name.

The `parallel` argument is a boolean, an `int`, or `None` (the default) that specifies the preferred degree of parallelism to use in the Embedded Python Execution job. The value may be one of the following:

- A positive integer greater than or equal to 1 for a specific degree of parallelism
- `False`, `None`, or `0` for no parallelism
- `True` for the default data parallelism

The `graphics` argument is a boolean that specifies whether to look for images. The default value is `True`.

With the `**kwargs` parameter, you can pass additional arguments to the `func` function. Special control arguments, which start with `oml_`, are not passed to the function specified by `func`, but instead control what happens before or after the running of the function.

The `oml.index_apply` function returns a list of Python objects or a list of `oml.embed.data_image._DataImage` objects. If no image is rendered in the user-defined Python function, `oml.index_apply` returns a list of the Python objects returned by the user-defined Python function. Otherwise, it returns a list of `oml.embed.data_image._DataImage` objects.

Example 7-10 Using the oml.index_apply Function

This example defines a function that returns the mean of a set of random numbers the specified number of times.

```
import oml
import pandas as pd

def compute_random_mean(index):
    import numpy as np
    import scipy
    from statistics import mean
    np.random.seed(index)
    res = np.random.random((100,1))*10
    return mean(res[1])
res = oml.index_apply(times=10, func=compute_random_mean)
```

```
type(res)
res
```

Listing for This Example

```
>>> import oml
>>> import pandas as pd
>>>
>>> def compute_random_mean(index):
...     import numpy as np
...     import scipy
...     from statistics import mean
...     np.random.seed(index)
...     res = np.random.random((100,1))*10
...     return mean(res[1])
...
>>> res = oml.index_apply(times=10, func=compute_random_mean)
>>> type(res)
<class 'list'>
>>> res
[7.203244934421581, 0.25926231827891333, 7.081478226181048,
5.4723224917572235, 8.707323061773764, 3.3197980530117723,
7.7991879224011464, 9.68540662820932, 5.018745921487388,
0.207519493594015]
```

7.4.7 Save and Manage User-Defined Python Functions in the Script Repository

The OML4Py script repository stores user-defined Python functions for use with Embedded Python Execution functions.

> **Note:**
>
> The user-defined Python functions can be used outside of Embedded Python Execution. You can store functions and reload them back into notebooks or other user-defined functions.

The script repository is a component of the Embedded Python Execution functionality.

The following topics describe the script repository and the Python functions for managing user-defined Python functions:

- About the Script Repository
- Create and Store a User-Defined Python Function
- List Available User-Defined Python Functions
- Load a User-Defined Python Function
- Drop a User-Defined Python Function from the Repository
- About the Script Repository
  Use these functions to store, manage, and use user-defined Python functions in the script repository.

- Create and Store a User-Defined Python Function
  Use the `oml.script.create` function to add a user-defined Python function to the script repository.
- List Available User-Defined Python Functions
  Use the `oml.script.dir` function to list the user-defined Python functions in the OML4Py script repository.
- Load a User-Defined Python Function
  Use the `oml.script.load` function to load a user-defined Python function from the script repository into a Python session.
- Drop a User-Defined Python Function from the Repository
  Use the `oml.script.drop` function to remove a user-defined Python function from the script repository.

7.4.7.1 About the Script Repository

Use these functions to store, manage, and use user-defined Python functions in the script repository.

The following table lists the Python functions for the script repository.

Function	Description
`oml.script.create`	Registers a single user-defined Python function in the script repository.
`oml.script.dir`	Lists the user-defined Python functions present in the script repository.
`oml.script.drop`	Drops a user-defined Python function from the script repository.
`oml.script.load`	Loads a user-defined Python function from the script repository into a Python session.

The following table lists the Python functions for managing access to user-defined Python functions in the script repository, and to datastores and datastore objects.

Function	Description
`oml.grant`	Grants read privilege permission to another user to a datastore or user-defined Python function owned by the current user.
`oml.revoke`	Revokes the read privilege permission that was granted to another user to a datastore or user-defined Python function owned by the current user.

7.4.7.2 Create and Store a User-Defined Python Function

Use the `oml.script.create` function to add a user-defined Python function to the script repository.

With the `oml.script.create` function, you can store a single user-defined Python function in the OML4Py script repository. You can then specify the user-defined Python function as the `func` argument to the Embedded Python Execution functions `oml.do_eval`, `oml.group_apply`, `oml.index_apply`, `oml.row_apply`, and `oml.table_apply`.

You can make the user-defined Python function either private or global. A private user-defined Python function is available only to the owner, unless the owner grants the read privilege to other users. A global user-defined Python function is available to any user.

The syntax of `oml.script.create` is the following:

```
oml.script.create(name, func, is_global=False, overwrite=False)
```

The `name` argument is a string that specifies a name for the user-defined Python function in the Python script repository.

The `func` argument is the Python function to run. The argument can be a Python function or a string that contains the definition of a Python function. You must specify a string in an interactive session if `readline` cannot get the command history.

The `is_global` argument is a boolean that specifies whether to create a global user-defined Python function. The default value is `False`, which indicates that the user-defined Python function is a private function available only to the current session user. When `is_global` is `True`, it specifies that the function is global and every user has the read privilege and the execute privilege to it.

The `overwrite` argument is a boolean that specifies whether to overwrite the user-defined Python function if it already exists. The default value is `False`.

Example 7-11 Using the oml.script.create Function

This example stores two user-defined Python functions in the script repository. It then lists the contents of the script repository using different arguments to the `oml.script.dir` function.

Load the iris dataset as a pandas dataframe from the seaborn library. Use the `oml.create` function to create the IRIS database table and the proxy object for the table.

```
%python

from sklearn import datasets
import pandas as pd
import oml

# Load the iris data set and create a pandas.DataFrame for it.
iris = datasets.load_iris()

# Create objects containing data for the user-defined functions to use.
x = pd.DataFrame(iris.data,
                 columns =
['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width'])
y = pd.DataFrame(list(map(lambda x:
                          {0: 'setosa', 1: 'versicolor', 2:'virginica'}[x],
iris.target)),
                 columns = ['Species'])

# Create the IRIS database table and the proxy object for the table.

try:
  oml.drop(table="IRIS")
except:
  pass

oml_iris = oml.create(pd.concat([x, y], axis=1), table = 'IRIS')
```

Create an user-defined function `build_lm1` and use `oml.script.create` function to store it in the OML4Py script repository. The parameter `"build_lm1"` is a string that specifies the name of the user-defined function. The parameter `func=build_lm1` is the Python function to run. Run the user-defined Python function in embedded Python execution.

```
%python

# Define a function.

build_lm1 = '''def build_lm1(dat):
  from sklearn import linear_model
  regr = linear_model.LinearRegression()
  import pandas as pd
  dat = pd.get_dummies(dat, drop_first=True)
  X = dat[["Sepal_Width", "Petal_Length", "Petal_Width",
"Species_versicolor", "Species_virginica"]]
  y = dat[["Sepal_Length"]]
  regr.fit(X, y)
  return regr'''

# Create a private user-defined Python function.
oml.script.create("build_lm1", func=build_lm1, overwrite=True)

# Run the user-defined Python function in embedded Python execution
res = oml.table_apply(oml_iris, func="build_lm1",
oml_input_type="pandas.DataFrame")

res
res.coef_
```

The output is the following:

```
array([[ 0.49588894,  0.82924391, -0.31515517, -0.72356196, -1.02349781]])
```

Define another user-defined function `build_lm2`, store the function as a global script in the OML4Py script repository. Run the user-defined Python function in embedded Python execution.

```
%python

# Define another function

build_lm2 = '''def build_lm2(dat):
  from sklearn import linear_model
  regr = linear_model.LinearRegression()
  X = dat[["Petal_Width"]]
  y = dat[["Petal_Length"]]
  regr.fit(X, y)
  return regr'''

# Save the function as a global script to the script repository, overwriting
any existing function with the same name.
oml.script.create("build_lm2", func=build_lm2, is_global=True,
overwrite=True)
```

```
res = oml.table_apply(oml_iris, func="build_lm2",
oml_input_type="pandas.DataFrame")
res
```

The output is the following:

```
LinearRegression()
```

List the user-defined Python functions in the script repository available to the current user only.

```
%python

oml.script.dir()
```

The output is similar to the following:

```
                name  ...                date
0          build_lm1  ... 2022-12-15 19:02:44
1          build_mod  ... 2022-12-12 23:02:31
2      myFitMultiple  ... 2022-12-14 22:30:43
3  sample_iris_table  ... 2022-12-14 22:21:24

[4 rows x 4 columns]
```

List all of the user-defined Python functions available to the current user.

```
%python

oml.script.dir(sctype='all')
```

The output is similar to the following:

```
     owner  ...                date
0   PYQSYS  ... 2022-02-11 06:06:44
1   PYQSYS  ... 2022-10-19 16:59:50
2   PYQSYS  ... 2022-10-19 16:59:52
3   PYQSYS  ... 2022-10-19 16:59:53
```

List the user-defined Python functions available to all users.

```
%python

oml.script.dir(sctype='global')
```

The output is similar to the following:

```
                  name  ...                date
```

```
0                GLBLM  ... 2022-02-11 06:06:44
1         RandomRedDots  ... 2022-10-19 16:59:50
2        RandomRedDots2  ... 2022-10-19 16:59:52
3        RandomRedDots3  ... 2022-10-19 16:59:53
4                  TEST  ... 2021-08-13 17:37:02
5                 TEST4  ... 2021-08-13 17:42:49
6             TEST_FUN  ... 2021-08-13 22:38:54
```

7.4.7.3 List Available User-Defined Python Functions

Use the `oml.script.dir` function to list the user-defined Python functions in the OML4Py script repository.

The syntax of the `oml.script.dir` function is the following:

```
oml.script.dir(name=None, regex_match=False, sctype='user')
```

The `name` argument is a string that specifies the name of a user-defined Python function or a regular expression to match to the names of user-defined Python functions in the script repository. When `name` is `None`, this function returns the type of user-defined Python functions specified by argument `sctype`.

The `regex_match` argument is a boolean that indicates whether argument `name` is a regular expression to match. The default value is `False`.

The `sctype` argument is a string that specifies the type of user-defined Python function to list. The value may be one of the following.

- `user`, to specify the user-defined Python functions available to the current user only.
- `grant`, to specify the user-defined Python functions to which the read and execute privilege have been granted by the current user to other users.
- `granted`, to specify the user-defined Python functions to which the read and execute privilege have been granted by other users to the current user.
- `global`, to specify all of the global user-defined Python functions created by the current user.
- `all`, to specify all of the user-defined Python functions available to the current user.

The `oml.script.dir` function returns a `pandas.DataFrame` that contains the columns NAME and SCRIPT and, optionally, the columns OWNER and GRANTEE.

Example 7-12 Using the oml.script.dir Function

This example lists the contents of the script repository using different arguments to the `oml.script.dir` function. For the creation of the user-defined Python functions, see Example 7-11.

```
import oml

# List the user-defined Python functions in the script
# repository available to the current user only.
oml.script.dir()

# List all of the user-defined Python functions available
# to the current user.
```

```
oml.script.dir(sctype='all')

# List the user-defined Python functions available to all users.
oml.script.dir(sctype='global')

# List the user-defined Python functions that contain the letters
# BL and that are available to all users.
oml.script.dir(name="BL", regex_match=True, sctype='all')
```

Listing for This Example

```
>>> import oml
>>>
>>> # List the user-defined Python functions in the script
... # repository available to the current user only.
... oml.script.dir()
   NAME                                              SCRIPT
0  MYLM  def build_lm1(dat):\n    from sklearn import l...
>>>
>>> # List all of the user-defined Python functions available
... to the current user.
... oml.script.dir(sctype='all')
     OWNER    NAME                                                SCRIPT
0    PYQSYS  GLBLM  def build_lm2(dat):\n    from sklearn import l...
1  OML_USER   MYLM  def build_lm1(dat):\n    from sklearn import l...
>>>
>>> # List the user-defined Python functions available to all users.
>>> oml.script.dir(sctype='global')
    NAME                                               SCRIPT
0  GLBLM  def build_lm2(dat):\n    from sklearn import l...
>>>
>>> # List the user-defined Python functions that contain the letters
... # BL and that are available to all users.
... oml.script.dir(name="BL", regex_match=True, sctype='all')
    OWNER   NAME                                             SCRIPT
0  PYQSYS  GLBLM  def build_lm2(dat):\n    from sklearn import l...
```

7.4.7.4 Load a User-Defined Python Function

Use the `oml.script.load` function to load a user-defined Python function from the script repository into a Python session.

The syntax of the function is the following:

```
oml.script.load(name, owner=None)
```

The `name` argument is a string that specifies the name of the user-defined Python function to load from the OML4Py script repository.

The optional `owner` argument is a string that specifies the owner of the user-defined Python function or `None` (the default). If `owner=None`, then this function finds and loads the user-defined Python function that matches `name` in the following order:

1. A user-defined Python function that the current user created.

2. A global user-defined Python function that was created by another user.

The `oml.script.load` function returns an `oml.script.script.Callable` object that references the named user-defined Python function.

Example 7-13 Using the oml.script.load Function

This example loads user-defined Python functions from the script repository and pulls them to the local Python session. For the creation of the user-defined Python functions, see Example 7-11.

```
import oml

# Load the MYLM and GLBLM user-defined Python functions.
MYLM = oml.script.load(name="MYLM")
GMYLM = oml.script.load(name="GLBLM")

# Pull the models to the local Python session.
MYLM(oml_iris.pull()).coef_
GMYLM(oml_iris.pull())
```

Listing for This Example

```
>>> import oml
>>>
>>> # Load the MYLM and GLBLM user-defined Python functions.
>>> MYLM = oml.script.load(name="MYLM")
>>> GMYLM = oml.script.load(name="GLBLM")
>>>
>>> # Pull the models to the local Python session.
... MYLM(oml_iris.pull()).coef_
array([[ 0.49588894, 0.82924391, -0.31515517, -0.72356196, -1.02349781]])
>>> GMYLM(oml_iris.pull())
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1,
         normalize=False)
```

7.4.7.5 Drop a User-Defined Python Function from the Repository

Use the `oml.script.drop` function to remove a user-defined Python function from the script repository.

The `oml.script.drop` function drops a user-defined Python function from the OML4Py script repository.

The syntax of the function is the following:

```
oml.script.drop(name, is_global=False, silent=False)
```

The `name` argument is a string that specifies the name of the user-defined Python function in the script repository.

The `is_global` argument is a boolean that specifies whether the user-defined Python function to drop is a global or a private user-defined Python function. The default value is `False`, which indicates a private user-defined Python function.

The `silent` argument is a boolean that specifies whether to display an error message when `oml.script.drop` encounters an error in dropping the specified user-defined Python function. The default value is `False`.

Example 7-14 Using the oml.script.drop Function

This example drops user-defined Python functions the MYLM private user-defined Python function and the GLBLM global user-defined Python function from the script repository. For the creation of the user-defined Python functions, see Example 7-11.

```
import oml

# List the available user-defined Python functions.
oml.script.dir(sctype="all")

# Drop the private user-defined Python function.
oml.script.drop("MYLM")

# Drop the global user-defined Python function.
oml.script.drop("GLBLM", is_global=True)

# List the available user-defined Python functions again.
oml.script.dir(sctype="all")
```

Listing for This Example

```
>>> import oml
>>>
>>> # List the available user-defined Python functions.
... oml.script.dir(sctype="all")
     OWNER   NAME                                                SCRIPT
0   PYQSYS  GLBLM  def build_lm2(dat):\n  from sklearn import lin...
1 OML_USER   MYLM  def build_lm1(dat):\n  from sklearn import lin...
>>>
>>> # Drop the private user-defined Python function.
... oml.script.drop("MYLM")
>>>
>>> # Drop the global user-defined Python function.
... oml.script.drop("GLBLM", is_global=True)
>>>
>>> # List the available user-defined Python functions again.
... oml.script.dir(sctype="all")
Empty DataFrame
Columns: [OWNER, NAME, SCRIPT]
Index: []
```

7.5 SQL API for Embedded Python Execution with Autonomous Database

The SQL API for Embedded Python Execution with Autonomous Database provides SQL interfaces for setting authorization tokens, managing access control list (ACL) privileges, executing Python scripts, and synchronously and asynchronously running jobs.

The following topics describe the SQL API.

- Access and Authorization Procedures and Functions
  Use the network access control lists (ACL) API to control access by users to external network services and resources from the database. Use the token store API to persist the authorization token issued by a cloud host so it can be used with subsequent SQL calls.
- Embedded Python Execution Functions (Autonomous Database)
  The SQL API for Embedded Python Execution with Autonomous Database functions are described in the following topics.
- Asynchronous Jobs (Autonomous Database)
  When a function is run asynchronously, it's run as a job which can be tracked by using the `pyqJobStatus` and `pyqJobResult` functions.
- Special Control Arguments (Autonomous Database)
  Use the `PAR_LST` parameter to specify special control arguments and additional arguments to be passed into the Python script.
- Output Formats (Autonomous Database)
  The `OUT_FMT` parameter controls the format of output returned by the table functions `pyqEval`, `pyqGroupEval`, `pyqIndexEval`, `pyqRowEval`, `pyqTableEval`, and `pyqJobResult`.

7.5.1 Access and Authorization Procedures and Functions

Use the network access control lists (ACL) API to control access by users to external network services and resources from the database. Use the token store API to persist the authorization token issued by a cloud host so it can be used with subsequent SQL calls.

Use the following to manage ACL privileges. An `ADMIN` user is required.

- pyqAppendHostACE Procedure
- pyqGetHostACE Function
- pyqRemoveHostACE Procedure

Use the following to manage authorization tokens:

- pyqSetAuthToken Procedure
- pyqIsTokenSet Function

Workflow

The typical workflow for using the SQL API for Embedded Python Execution with Autonomous Database is:

1. Connect to PDB as the `ADMIN` user, and add a normal user `OMLUSER` to the ACL list of the cloud host of which the root domain is `adb.us-region-1.oraclecloudapps.com`:

   ```
   exec pyqAppendHostAce('OMLUSER','adb.us-region-1.oraclecloudapps.com');
   ```

2. The OML Rest URLs can be obtained from the Oracle Autonomous Database that is provisioned.

a. Sign into your Oracle Cloud Infrastructure account. You will need your OCI user name and password.

b. Click the hamburger menu and select Autonomous Database instance that is provisioned. For more information on provisioning an Autonomous Database, see: Provision an Oracle Autonomous Database.

c. Click **Service Console** and then click **Devlopment**.

d. Scroll down to **Oracle Machine Learning RESTful Services** tile and click **Copy** to obtain the following URLs for:

   - Obtaining the REST authentication token for REST APIs provided by OML:

     ```
     <oml-cloud-service-location-url>/omlusers/
     ```

The URL `<oml-cloud-service-location-url>` includes the tenancy ID, location, and database name. For example, `https://qtraya2braestch-omldb.adb.us-sanjose-1.oraclecloudapps.com`.

In this example,

- `qtraya2braestch` is the tenancy ID
- `omldb` is the database name
- `us-sanjose-1` is the datacenter region
- `oraclecloudapps.com` is the root domain

3. The Oracle Machine Learning REST API uses tokens to authenticate an Oracle Machine Learning user. To authenticate and obtain an access token, send a POST request to the Oracle Machine Learning User Management Cloud Service REST endpoint `/oauth2/v1/token` with your OML username and password.

```
curl -X POST --header 'Content-Type: application/json' --header 'Accept:
application/json'
-d '{"grant_type":"password", "username":"'${username}'", "password":"'$
{password}'"}'
"<oml-cloud-service-location-url>/omlusers/api/oauth2/v1/token"
```

The example uses the following values:

- `username` is the OML username.
- `password` is the OML user password.
- `oml-cloud-service-location-url` is a variable containing the REST server portion of the Oracle Machine Learning User Management Cloud Service instance URL that includes the tenancy ID, database name, and the location name. You can obtain the omlserver URL from the Development tab in the Service Console of your Oracle Autonomous Database instance.

> **Note:**
>
> When a token expires, all calls to the OML Services REST endpoints with return a message stating that the token has expired along with the HTTP error: `HTTP/1.1 401 Unauthorized`

4. Connect to PDB as `OMLUSER`, set the access token, and run `pyqIndexEval`:

```
exec pyqSetAuthToken('<access token>');
select *
    from table(pyqIndexEval(
        par_lst => NULL,
        out_fmt => '{"ID":"number", "RES":"varchar2(3)"}',
        times_num => 3,
        scr_name => 'idx_ret_df'));

        ID RES
---------- ---
         1 a
         2 b
         3 c

3 rows selected.
```

- pyqAppendHostACE Procedure
  The `pyqAppendHostACE` procedure appends an access control entry (ACE) to the access control list (ACL) of the cloud host. The ACL controls access to the cloud host from the database, and the ACE specifies the connect privilege granted to the specified user name.
- pyqGetHostACE Function
  The `pyqGetHostACE` function gets the existing host access control entry (ACE) for the specified user. An exception is raised if the host ACE doesn't exist for the specified user.
- pyqRemoveHostACE Procedure
- pyqSetAuthToken Procedure
  The `pyqSetAuthToken` procedure sets the access token in the token store.
- pyqIsTokenSet Function
  The `pyqIsTokenSet` function returns whether the authorization token is set or not.

7.5.1.1 pyqAppendHostACE Procedure

The `pyqAppendHostACE` procedure appends an access control entry (ACE) to the access control list (ACL) of the cloud host. The ACL controls access to the cloud host from the database, and the ACE specifies the connect privilege granted to the specified user name.

Syntax

```
PROCEDURE SYS.pyqAppendHostACE(
    username IN VARCHAR2,
    host_root_domain IN VARCHAR2
)
```

Parameter

username - Database user to whom the connect privilege to the cloud host is granted.

host_root_domain - Root domain of the cloud host. For example, if the URL is `https://qtraya2braestch-omldb.adb.us-sanjose-1.oraclecloudapps.com`, the root domain of the cloud host is: `adb.us-sanjose-1.oraclecloudapps.com`.

Example

```
exec pyqAppendHostAce('OMLUSER','adb.us-region-1.oraclecloudapps.com');
```

> **Note:**
>
> OML username is case sensitive

7.5.1.2 pyqGetHostACE Function

The `pyqGetHostACE` function gets the existing host access control entry (ACE) for the specified user. An exception is raised if the host ACE doesn't exist for the specified user.

Syntax

```
FUNCTION sys.pyqGetHostACE(
  p_username IN VARCHAR2
)
```

Parameter

p_username - Database user to look for the host ACE.

Example

If user `OMLUSER` has access to the cloud host, i.e., `ibuwlq4mjqkeils-omlrgpy1.adb.us-region-1.oraclecloudapps.com`, the ADMIN user can run the following to check the user's privileges:

```
SQL> set serveroutput on
DECLARE
    hostname VARCHAR2(4000);
BEGIN
    hostname := pyqGetHostACE('OMLUSER');
    DBMS_OUTPUT.put_line ('hostname: ' || hostname);
END;
/
SQL> hostname: ibuwlq4mjqkeils-omlrgpy1.adb.us-region-1.oraclecloudapps.com
PL/SQL procedure successfully completed.
```

7.5.1.3 pyqRemoveHostACE Procedure

The `pyqRemoveHostACE` procedure removes the existing host access control entry (ACE) from the specified *username*. If an access token was set for the cloud host, the token is also removed. An exception is raised if the host ACE does not exist.

Syntax

```
PROCEDURE SYS.pyqRemoveHostACE(
   username IN  VARCHAR2
)
```

Parameter

username - Database user from whom the connect privilege to the cloud host is revoked.

7.5.1.4 pyqSetAuthToken Procedure

The `pyqSetAuthToken` procedure sets the access token in the token store.

Syntax

```
PROCEDURE SYS.pyqSetAuthToken(
  access_token IN VARCHAR2
)
```

7.5.1.5 pyqIsTokenSet Function

The `pyqIsTokenSet` function returns whether the authorization token is set or not.

Syntax

```
FUNCTION SYS.pyqIsTokenSet() RETURN BOOLEAN
```

Example

The following example shows how to use the `pyqSetAuthToken` procedure and the `pyqIsTokenSet` function.

```
DECLARE
    is_set BOOLEAN;
BEGIN
    pyqSetAuthToken('<access token>');
    is_set := pyqIsTokenSet();
    IF (is_set) THEN
        DBMS_OUTPUT.put_line ('token is set');
    END IF;
END;
/
```

7.5.2 Embedded Python Execution Functions (Autonomous Database)

The SQL API for Embedded Python Execution with Autonomous Database functions are described in the following topics.

Topics

- pyqListEnvs Function (Autonomous Database)
- pyqEval Function (Autonomous Database)
- pyqTableEval Function (Autonomous Database)
- pyqRowEval Function (Autonomous Database)
- pyqGroupEval Function (Autonomous Database)

- pyqIndexEval Function (Autonomous Database)
- pyqGrant Function (Autonomous Database)
- pyqRevoke Function (Autonomous Database)
- pyqScriptCreate Procedure (Autonomous Database)
- pyqScriptDrop Procedure (Autonomous Database)
- pyqListEnvs Function (Autonomous Database)
  The function `pyqListEnvs` when used in Oracle Autonomous Database, lists the environments saved in an Object Storage.
- pyqEval Function (Autonomous Database)
  The function `pyqEval`, when used in Oracle Autonomous Database, calls a user-defined Python function. Users can pass arguments to the user-defined Python function.
- pyqTableEval Function (Autonomous Database)
  The function `pyqTableEval` function when used in Oracle Autonomous Database, runs a user-defined Python function on data from an Oracle Database table.
- pyqRowEval Function (Autonomous Database)
  The function `pyqRowEval` when used in Oracle Autonomous Database, chunks data into sets of rows and then runs a user-defined Python function on each chunk.
- pyqGroupEval Function (Autonomous Database)
  The function `pyqGroupEval` when used in Oracle Autonomous Database, groups data by one or more columns and runs a user-defined Python function on each group.
- pyqIndexEval Function (Autonomous Database)
  The function `pyqIndexEval` when used in Oracle Autonomous Database, runs a user-defined Python function multiple times as required in the Python engines spawned by the database environment.
- pyqGrant Function (Autonomous Database)
  This topic describes the `pyqGrant` function when used in Oracle Autonomous Database.
- pyqRevoke Function (Autonomous Database)
  This topic describes the `pyqRevoke` function when used in Oracle Autonomous Database.
- pyqScriptCreate Procedure (Autonomous Database)
  This topic describes the `pyqScriptCreate` procedure in Oracle Autonomous Database. Use the `pyqScriptCreate` procedure to create a user-defined Python function and add it to the OML4Py script repository.
- pyqScriptDrop Procedure (Autonomous Database)
  This topic describes the `pyqScriptDrop` procedure in Oracle Autonomous Database. Use the `pyqScriptDrop` procedure to remove a user-defined Python function from the OML4Py script repository.

7.5.2.1 pyqListEnvs Function (Autonomous Database)

The function `pyqListEnvs` when used in Oracle Autonomous Database, lists the environments saved in an Object Storage.

Syntax

```
FUNCTION PYQSYS.pyqListEnvs
RETURN SYS.AnyDataSet
```

Example

Issue a query that calls the `pyqListEnvs` function and lists the environments present.

```
select * from table(pyqListEnvs());
```

The output is similar to the following:

```
NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--
{"envs":[{"size":" 1.7 GiB","name":"sbenv","description":"Conda environment
with seaborn","number_of_installed_packages":78,"tags":"appli
cation":"OML4PY"}]}
```

7.5.2.2 pyqEval Function (Autonomous Database)

The function `pyqEval`, when used in Oracle Autonomous Database, calls a user-defined Python function. Users can pass arguments to the user-defined Python function.

The function `pyqEval` does not automatically load the data. Within the user-defined Python function, the user may explicitly access and/or retrieve data using the transparency layer or an ROracle database connection.

Syntax

```
FUNCTION PYQSYS.pyqEval(
    PAR_LST    VARCHAR2,
    OUT_FMT    VARCHAR2,
    SCR_NAME   VARCHAR2,
    SCR_OWNER  VARCHAR2 DEFAULT NULL,
    ENV_NAME   VARCHAR2 DEFAULT NULL
    )
    RETURN SYS.AnyDataSet
```

Parameters

Parameter	Description
`PAR_LST`	A JSON string that contains additional parameters to pass to the user-defined Python function specified by the `SCR_NAME` parameter. Special control arguments, which start with `oml_`, are not passed to the function specified by `SCR_NAME`, but instead control what happens before or after the invocation of the function. For example, to specify the input data type as `pandas.DataFrame`, use: `'{"oml_input_type":"pandas.DataFrame"}'` **See also:** Special Control Arguments (Autonomous Database).

Parameter	Description
OUT_FMT	The format of the output returned by the function. It can be one of the following: • A JSON string that specifies the column names and data types of the table returned by the function. Any image data is discarded. The Python function must return a pandas.DataFrame, a numpy.ndarray, a tuple, or a list of tuples. • The string 'JSON', which specifies that the table returned contains a CLOB that is a JSON string. • The string 'XML', which specifies that the table returned contains a CLOB that is an XML string. The XML can contain both structured data and images, with structured or semi-structured Python objects first, followed by the image or images generated by the Python function. • The string 'PNG', which specifies that the table returned contains a BLOB that has the image or images generated by the Python function. Images are returned as a base 64 encoding of the PNG representation. **See also:** Output Formats (Autonomous Database).
SCR_NAME	The name of a user-defined Python function in the OML4Py script repository.
SCR_OWNER	The owner of the registered Python script. The default value is NULL. If NULL, will search for the Python script in the user's script repository.
ENV_NAME	The name of the conda environment that should be used when running the named user-defined Python function.

This example defines a Python function and stores it in the OML4Py script repository. It calls the pyqEval function on the user-defined Python functions.

In a PL/SQL block, create a Python function that is stored in script repository with the name pyqFun1.

```
begin
    sys.pyqScriptCreate('pyqFun1',
        'def fun_tab():
                import pandas as pd
                names = ["demo_"+str(i) for i in range(10)]
                ids = [x for x in range(10)]
                floats = [float(x)/10 for x in range(10)]
                d = {''ID'': ids, ''NAME'': names, ''FLOAT'': floats}
                scores_table = pd.DataFrame(d)
                return scores_table
',FALSE,TRUE); -- V_GLOBAL, V_OVERWRITE
end;
/
```

Next, call the pyqEval function, which runs the user-defined Python function.

The PAR_LST argument specifies using LOW service level with the special control argument oml_service_level.

In the OUT_FMT argument, the string 'JSON', specifies that the table returned contains a CLOB that is a JSON string.

The SCR_NAME parameter specifies the pyqFun1 function in the script repository as the Python function to call.

The JSON output is a CLOB. You can call `set long [length]` to get more output.

```
set long 500
select *
    from table(pyqEval(
        par_lst => '{"oml_service_level":"LOW"}',
        out_fmt => 'JSON',
        scr_name => 'pyqFun1'));
```

The output is the following.

```
NAME
--------------------------------------------------------------------------------
VALUE
--------------------------------------------------------------------------------
[{"FLOAT":0,"ID":0,"NAME":"demo_0"},{"FLOAT":0.1,"ID":1,"NAME":"demo_1
"},{"FLOAT":0.2,"ID":2,"NAME":"demo_2"},{"FLOAT":0.3,"ID":3,"NAME":"de
mo_3"},{"FLOAT":0.4,"ID":4,"NAME":"demo_4"},{"FLOAT":0.5,"ID":5,"NAME"
:"demo_5"},{"FLOAT":0.6,"ID":6,"NAME":"demo_6"},{"FLOAT":0.7,"ID":7,"N
AME":"demo_7"},{"FLOAT":0.8,"ID":8,"NAME":"demo_8"},{"FLOAT":0.9,"ID":
9,"NAME":"demo_9"}]

1 row selected.
```

Issue another query that invokes the same `pyqFun1` script. The `OUT_FMT` argument specifies a JSON string that contains the column names and data types of the structured table output.

```
select *
    from table(pyqEval(
        par_lst => '{"oml_service_level":"LOW"}',
        out_fmt => '{"ID":"number", "NAME":"VARCHAR2(8)",
"FLOAT":"binary_double"}',
        scr_name => 'pyqFun1'));
```

The output is the following:

```
ID NAME FLOAT
   0 demo_0 0.0
   1 demo_1 0.1
   2 demo_2 0.2
   3 demo_3 0.3
   4 demo_4 0.4
   5 demo_5 0.5
   6 demo_6 0.6
   7 demo_7 0.7
   8 demo_8 0.8
   9 demo_9 0.9


10 rows selected.
```

Use the following code to create the "seaborn" environment based on Python version 3.10 and upload the environment to the object storage owned by the Pluggable Database (PDB).

> **Note:**
>
> Admin privilege is required to create and manage the Conda environments.

```
create -n seaborn python=3.10 seaborn
upload seaborn --overwrite --description 'Python package for seaborn' -t
python 3.10 -t
      application OML4PY
```

The data visualization library 'seaborn' is installed in the environment.

Use the following code to create the script 'test_seaborn_noinp':

```
begin
  sys.pyqScriptCreate('test_seaborn_noinp',
  'def fun_tab():
  import seaborn as sns
  import matplotlib.pyplot as plt
  import numpy as np
  import pandas as pd
  data = np.random.multivariate_normal([0, 0], [[5, 2], [2, 2]],
size=2000)
  data = pd.DataFrame(data, columns=["x", "y"])
  sns.displot(data["x"])
  plt.title("Dist plot")
  plt.show()
  return "hello world" ',FALSE,TRUE); -- V_GLOBAL, V_OVERWRITE
end;
/
```

This example calls the pyqEval function, which runs the specified Python script.

The `PAR_LST` argument specifies capturing images rendered in the script with the special control argument oml_graphics_flag.

In the `OUT_FMT` arguments, the string 'PNG', specifies returning a table with BLOB containing the images generated by the Python function.

The `SCR_NAME` parameter specifies the 'test_seaborn_noinp' script in the script repository as the Python function to call.

The `ENV_NAME` parameter specifies 'seaborn', which is the Conda environment to run the Python function.

```
select *
  from table(pyqEval(
        par_lst => '{"oml_graphics_flag":true}',
        out_fmt => 'PNG',
        scr_name => 'test_seaborn_noinp',
        scr_owner => NULL,
        env_name => 'seaborn'
));
```

The output is the following.

```
NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--

         1
"hello world"

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
Lineplot
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58
74536F667477617265004D6174706C6F746C6962207665727369 6F6E332E332E332C2068747470
73

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000 00F6100000F6101
A8
```

```
3FA7690000682C49444154789CEDDD797C5355FE3FFE579236E9BEB7E942DBB414286B0B2D9482
0A
4AC7023A82A2022E2C83B801A37674147F0A2EDFCF1415114719D119293AC280CC208EC8A050D9
84

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
```

In a PL/SQL block, define the Python function `create_iris_table` and store in the script repository with the name `create_iris_table`, overwriting any existing user-defined Python function stored in the script repository with the same name.

The `create_iris_table` function imports and loads the iris data set, creates two `pandas.DataFrame` objects, and then returns the concatenation of those objects.

```
BEGIN
    sys.pyqScriptCreate('create_iris_table',
        'def create_iris_table():
            from sklearn.datasets import load_iris
            import pandas as pd
            iris = load_iris()
            x = pd.DataFrame(iris.data, columns = ["Sepal_Length",\
                "Sepal_Width", "Petal_Length", "Petal_Width"])
            y = pd.DataFrame(list(map(lambda x: {0:"setosa", 1: "versicolor",\
                2: "virginica"}[x], iris.target)),\
                columns = ["Species"])
            return pd.concat([y, x], axis=1)',
        FALSE, TRUE); -- V_GLOBAL, V_OVERWRITE
   END;
/
CREATE TABLE IRIS AS
(SELECT * FROM pyqEval(
    NULL,
    '{"Species":"VARCHAR2(10)","Sepal_Length":"number",
      "Sepal_Width":"number","Petal_Length":"number",
      "Petal_Width":"number"}',
    'create_iris_table'
));
```

7.5.2.3 pyqTableEval Function (Autonomous Database)

The function `pyqTableEval` function when used in Oracle Autonomous Database, runs a user-defined Python function on data from an Oracle Database table.

Pass data to the user-defined Python function from the table name specified in the `INP_NAM` parameter. Pass arguments to the user-defined Python function with the `PAR_LST` parameter.

The user-defined Python function can return a `boolean`, a `dict`, a `float`, an `int`, a `list`, a `str`, a `tuple` or a `pandas.DataFrame` object. You define the form of the returned value with the `OUT_FMT` parameter.

Syntax

```
FUNCTION PYQSYS.pyqTableEval(
   INP_NAM    VARCHAR2,
   PAR_LST    VARCHAR2,
   OUT_FMT    VARCHAR2,
   SCR_NAME   VARCHAR2,
   SCR_OWNER  VARCHAR2 DEFAULT NULL,
   ENV_NAME   VARCHAR2 DEFAULT NULL
   )
   RETURN SYS.AnyDataSet
```

Parameters

Parameter	Description
`INP_NAM`	The name of a table or view that specifies the data to pass to the Python function specified by the `SCR_NAME` parameter. If using a table or view owned by another user, use the format `<owner name>.<table/view name>`. You must have read access to the specified table or view.
`PAR_LST`	A JSON string that contains additional parameters to pass to the user-defined Python function specified by the `SCR_NAME` parameter. Special control arguments, which start with `oml_`, are not passed to the function specified by `SCR_NAME`, but instead control what happens before or after the invocation of the function. For example, to specify the input data type as `pandas.DataFrame`, use: `'{"oml_input_type":"pandas.DataFrame"}'` **See also:** Special Control Arguments (Autonomous Database).

Parameter	Description
OUT_FMT	The format of the output returned by the function. It can be one of the following: • A JSON string that specifies the column names and data types of the table returned by the function. Any image data is discarded. The Python function must return a pandas.DataFrame, a numpy.ndarray, a tuple, or a list of tuples. • The string 'JSON', which specifies that the table returned contains a CLOB that is a JSON string. • The string 'XML', which specifies that the table returned contains a CLOB that is an XML string. The XML can contain both structured data and images, with structured or semi-structured Python objects first, followed by the image or images generated by the Python function. • The string 'PNG', which specifies that the table returned contains a BLOB that has the image or images generated by the Python function. Images are returned as a base 64 encoding of the PNG representation. **See also:** Output Formats (Autonomous Database).
SCR_NAME	The name of a user-defined Python function in the OML4Py script repository.
SCR_OWNER	The owner of the registered Python script. The default value is NULL. If NULL, will search for the Python script in the user's script repository.
ENV_NAME	The name of the conda environment that should be used when running the named user-defined Python function.

Example

Define the Python function fit_model and store it with the name myLinearRegressionModel as a private function in the script repository, overwriting any existing user-defined Python function stored with that name.

The fit_model function fits a regression model to the input data dat and then saves the fitted model as an object specified by the modelName argument to the datastore specified by the datastoreName argument. The fit_model function returns the fitted model in a string format.

By default, Python objects are saved to a new datastore with the specified datastoreName. To save an object to an existing datastore, either set the overwrite or append argument to True in the oml.ds.save invocation.

```
BEGIN
    sys.pyqScriptCreate('myLinearRegressionModel',
        'def fit_model(dat, modelName, datastoreName):
            import oml
            from sklearn import linear_model
            regr = linear_model.LinearRegression()
            regr.fit(dat.loc[:, ["Sepal_Length", "Sepal_Width", \
                                 "Petal_Length"]],
                     dat.loc[:,["Petal_Width"]])
            oml.ds.save(objs={modelName:regr}, name=datastoreName,
                        overwrite=True)
            return str(regr)',
        FALSE, TRUE); -- V_GLOBAL, V_OVERWRITE
END;
/
```

Use the following code to create the 'test_seaborn_inp' script:

```
begin  sys.pyqScriptCreate('test_seaborn_inp',
         'def fun_tab(dat):
          import seaborn as sns
          import matplotlib.pyplot as plt
          sns.lineplot(x="Sepal_Length", y="Sepal_Width", data=dat)
          plt.title("Iris plot")
          plt.show()
          return "hello world"
          ',FALSE,TRUE); -- V_GLOBAL, V_OVERWRITE
end;
/
```

This example calls the pyqTableEval function, which runs the specified Python function on the specified data set.

`The INP_NAM` argument specifies the data in the IRIS table to pass to the Python function.

`The PAR_LST` argument specifies capturing images rendered in the script with the special control argument oml_graphics_flag.

The `OUT_FMT` arguments specifies returning a table with BLOB containing the images generated by the Python function.

The `SCR_NAME` parameter specifies the 'test_seaborn_inp' script, which is the name in the script repository of the user-defined Python function to invoke.

The `ENV_NAME` parameter specifies 'seaborn', which is a Conda environment created in pyqEval Function (Autonomous Database) .

```
select *
  from table(pyqTableEval(
        inp_nam =>  'IRIS',
        par_lst => '{"oml_graphics_flag":true}',
        out_fmt => 'PNG',
        scr_name => 'test_seaborn_inp',
        scr_owner => NULL,
        env_name => 'seaborn'
));
```

The output is the following.

```
NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
```

```
--

         1
"hello world"

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
Iris plot
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58
74536F667477617265004D6174706C6F746C6962207665727369696F6E332E332E332C2068747470
73

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000000F6100000F6101
A8
3FA7690000B9BC49444154789CECDD797CDC759D3FF0D7F79A2B9399DC499BA44DEF527A41B9CA
61
3945C042576559500AABAC2BE2AE8ABA520459442CBA80E0FA0304517057B60A0B28972C22E5A6
F4

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
```

```
--
IMAGE
--------------------------------------------------------------------------------
--
```

This example uses the IRIS table created in the example shown in `pyqEval` Function (Autonomous Database). Run a `SELECT` statement that invokes the `pyqTableEval` function. The `INP_NAM` parameter of the `pyqTableEval` function specifies the IRIS table as the data to pass to the Python function. The `PAR_LST` parameter specifies the names of the model and datastore to pass to the Python function. The `OUT_FMT` parameter specifies returning the value in XML format and the `SCR_NAME` parameter specifies the `myLinearRegressionModel` function in the script repository as the Python function to invoke. The XML output is a CLOB; you can call `set long [length]` to get more output.

```
SELECT *
FROM table(pyqTableEval(
    inp_nam => 'IRIS',
    par_lst => '{"modelName":"linregr",
                 "datastoreName":"pymodel"}',
out_fmt => 'XML',
scr_name => 'myLinearRegressionModel'));
```

The output is the following:

```
NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--
<root><str>LinearRegression()</str></root>
1 row selected.
```

7.5.2.4 pyqRowEval Function (Autonomous Database)

The function `pyqRowEval` when used in Oracle Autonomous Database, chunks data into sets of rows and then runs a user-defined Python function on each chunk.

The `ROW_NUM` parameter specifies the maximum number of rows to pass to each invocation of the user-defined Python function. The last set of rows may have fewer rows than the number specified.

The user-defined Python function can return a `boolean`, a `dict`, a `float`, an `int`, a `list`, a `str`, a `tuple` or a `pandas.DataFrame` object. You can define the form of the returned value with the `OUT_FMT` parameter.

Syntax

```
FUNCTION PYQSYS.pyqRowEval(
    INP_NAM    VARCHAR2,
    PAR_LST    VARCHAR2,
    OUT_FMT    VARCHAR2,
    ROW_NUM    NUMBER,
```

```
SCR_NAME    VARCHAR2,
SCR_OWNER   VARCHAR2 DEFAULT NULL,
ENV_NAME    VARCHAR2 DEFAULT NULL
)
RETURN SYS.AnyDataSet
```

Parameters

Parameter	Description
INP_NAM	The name of a table or view that specifies the data to pass to the Python function specified by the SCR_NAME parameter. If using a table or view owned by another user, use the format <owner name>.<table/view name>. You must have read access to the specified table or view.
PAR_LST	A JSON string that contains additional parameters to pass to the user-defined Python function specified by the SCR_NAME parameter. Special control arguments, which start with oml_, are not passed to the function specified by SCR_NAME, but instead control what happens before or after the invocation of the function. For example, to specify the input data type as pandas.DataFrame, use: '{"oml_input_type":"pandas.DataFrame"}' **See also:** Special Control Arguments (Autonomous Database).
OUT_FMT	The format of the output returned by the function. It can be one of the following: • A JSON string that specifies the column names and data types of the table returned by the function. Any image data is discarded. The Python function must return a pandas.DataFrame, a numpy.ndarray, a tuple, or a list of tuples. • The string 'JSON', which specifies that the table returned contains a CLOB that is a JSON string. • The string 'XML', which specifies that the table returned contains a CLOB that is an XML string. The XML can contain both structured data and images, with structured or semi-structured Python objects first, followed by the image or images generated by the Python function. • The string 'PNG', which specifies that the table returned contains a BLOB that has the image or images generated by the Python function. Images are returned as a base 64 encoding of the PNG representation. **See also:** Output Formats (Autonomous Database).
ROW_NUM	The number of rows in a chunk. The Python script is executed in each chunk.
SCR_NAME	The name of a user-defined Python function in the OML4Py script repository.
SCR_OWNER	The owner of the registered Python script. The default value is NULL. If NULL, will search for the Python script in the user's script repository.
ENV_NAME	The name of the conda environment that should be used when running the named user-defined Python function.

Example

This example calls the pyqRowEval function, which runs the specified Python script on each chunk of rows in the specified data set.

The INP_NAM argument specifies the data in the IRIS table to pass to the Python function.

The PAR_LST argument specifies capturing images rendered in the script with the special control argument oml_graphics_flag.

The `OUT_FMT` arguments specifies returning a table with BLOB containing the images generated by the Python function.

The `ROW_NUM` argument specifies that 50 rows are included in each invocation of the function specified by SCR_NAME.

The `SCR_NAME` parameter specifies the 'test_seaborn_inp' script, which is created in pyqTableEval Function (Autonomous Database).

The `ENV_NAME` parameter specifies 'seaborn', which is a Conda environment created in pyqEval Function (Autonomous Database) .

```
select *
  from table(pyqRowEval(
        inp_nam =>  'IRIS',
        par_lst => '{"oml_graphics_flag":true}',
        out_fmt => 'PNG',
        row_num => 50,
        scr_name => 'test_seaborn_inp',
        scr_owner => NULL,
        env_name => 'seaborn'
));
```

The output is the following.

```
NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
CHUNK_1
         1
"hello world"

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
```

```
--
Iris plot
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58
74536F667477617265004D6174706C6F746C6962207665727369696F6E332E332E332C2068747470
73

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000000F6100000F6101
A8
3FA769000081254944415478 9CEDDD7774D5F5FD3FF0E767DC99BD13C82081B0041450101C888A
0A
54455B57ADA3167F75B46AF5EBB7DA6FADB5D6E2AAA3B52A6A155A6B69B56A97685DE042050105
8A

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--

CHUNK_2
         1

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
```

```
--
IMAGE
--------------------------------------------------------------------------------
--
"hello world"
Iris plot
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
74536F667477617265004D6174706C6F746C6962207665727369 6F6E332E332E332C2068747470
73
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000 00F6100000F6101
A8
3FA7690000ABB149444154789CECDD79985C65993EFEFB2C55A7BABBBA7A4D6F49670F21210B10
02

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
84C5B093804846C5AF8E4C4445470467181CD1388A0A32114401C71FA88802A318070750190920
92

CHUNK_3

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
```

```
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
         1
"hello world"
Iris plot

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58
74536F667477617265004D6174706C6F746C6962207665727369 6F6E332E332E332C2068747470
73
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000 00F6100000F6101
A8

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
3FA76900008C7149444154789CEDDD77945BD5D536F0E7AA774D2F9EE25EB14D316D3060209862
E2
50120204B009900487040229E00402841843288 1242FA663E7230402015E9AF14B33C5543730B6
71
```

Example

This example loads the Python model `linregr` to predict row chunks of sample iris data. The model is created and saved in the datastore `pymodel`, which is shown in the example for pyqTableEval Function (Autonomous Database).

The example defines a Python function and stores it in the OML4Py script repository. It uses the user-defined Python function to create a database table as the result of the `pyqEval` function. It defines a Python function that runs a prediction function on a model loaded from the OML4Py datastore. It then invokes the `pyqTableEval` function to invoke the function on chunks of rows from the database table.

In a PL/SQL block, define the function `sample_iris_table` and store it in the script repository. The function loads the iris data set, creates two `pandas.DataFrame` objects, and then returns a sample of the concatenation of those objects.

```
BEGIN
    sys.pyqScriptCreate('sample_iris_table',
        'def sample_iris_table(size):
            from sklearn.datasets import load_iris
            import pandas as pd
            iris = load_iris()
            x = pd.DataFrame(iris.data, columns = ["Sepal_Length",\
                           "Sepal_Width","Petal_Length","Petal_Width"])
            y = pd.DataFrame(list(map(lambda x: {0:"setosa", 1: "versicolor",\
                                    2: "virginica"}[x], iris.target)),\
                           columns = ["Species"])
            return pd.concat([y, x], axis=1).sample(int(size))',
        FALSE, TRUE); -- V_GLOBAL, V_OVERWRITE
END;
/
```

Create the `SAMPLE_IRIS` table in the database as the result of a `SELECT` statement, which invokes the `pyqEval` function on the `sample_iris_table` user-defined Python function saved in the script repository with the same name. The `sample_iris_table` function returns an iris data sample of size `size`.

```
CREATE TABLE sample_iris AS
SELECT *
    FROM TABLE(pyqEval(
                '{"size":20}',
                '{"Species":"varchar2(10)","Sepal_Length":"number",
                "Sepal_Width":"number","Petal_Length":"number",
                "Petal_Width":"number"}',
                'sample_iris_table'));
```

Define the Python function `predict_model` and store it with the name `linregrPredict` in the script repository. The function predicts the data in `dat` with the Python model specified by the `modelName` argument, which is loaded from the datastore specified by the `datastoreName` argument. The function also plots the actual petal width values with the predicted values. The predictions are finally concatenated and returned with `dat` as the object that the function returns.

```
BEGIN
    sys.pyqScriptCreate('linregrPredict',
        'def predict_model(dat, modelName, datastoreName):
            import oml
            import pandas as pd
            objs = oml.ds.load(name=datastoreName, to_globals=False)
            pred = objs[modelName].predict(dat[["Sepal_Length",\
```

```
            "Sepal_Width","Petal_Length"]])
            return pd.concat([dat, pd.DataFrame(pred, \
            columns=["Pred_Petal_Width"])], axis=1)',
        FALSE, TRUE); -- V_GLOBAL, V_OVERWRITE
END;
/
```

Run a `SELECT` statement that invokes the `pyqRowEval` function, which runs the specified Python function on each chunk of rows in the specified data set.

The `INP_NAM` argument specifies the data in the `SAMPLE_IRIS` table to pass to the Python function.

The `PAR_LST` argument specifies passing the input data as a pandas. DataFrame with the special control argument `oml_input_type`, along with values for the function arguments `modelName` and `datastoreName`.

In the `OUT_FMT` argument, the JSON string specifies the column names and data types of the structured table output.

The `ROW_NUM` argument specifies that five rows are included in each invocation of the function specified by `SCR_NAME`.

The `SCR_NAME` parameter specifies `linregrPredict`, which is the name in the script repository of the user-defined Python function to invoke.

```
SELECT *
    FROM table(pyqRowEval(
        inp_nam => 'SAMPLE_IRIS',
        par_lst => '{"oml_input_type":"pandas.DataFrame",
                     "modelName":"linregr", "datastoreName":"pymodel"}',
        out_fmt => '{"Species":"varchar2(12)", "Petal_Length":"number",
"Pred_Petal_Width":"number"}',
        row_num => 5,
        scr_name => 'linregrPredict'));
```

The output is the following.

```
Species      Petal_Length   Pred_Petal_Width
setosa                1.2       0.0653133202
versicolor            4.5        1.632087234
setosa                1.3       0.2420812759
setosa                1.9       0.5181904241
setosa                1.4       0.2162518989
setosa                1.4       0.1732424372
setosa                1.5       0.2510460971
setosa                1.3       0.1907951829
versicolor            3.9       1.1999981051
versicolor            4.2       1.4017887483
versicolor              4       1.2332360562
versicolor            4.8        1.765473067
virginica             5.6       2.0095892178
versicolor            4.7       1.5824801232

Species      Petal_Length   Pred_Petal_Width
virginica             5.4       2.0623088225
```

```
versicolor              4.7       1.6524411804
virginica               5.6       1.9919751044
virginica               5.8       2.1206308288
virginica               5.1       1.7983383572
versicolor              4.4       1.3677441077


20 rows selected.
```

Run a `SELECT` statement that invokes the `pyqRowEval` function and return the XML output. Each invocation of script `linregrPredict` is applied to 10 rows of data in the `SAMPLE_IRIS` table. The XML output is a CLOB; you can call `set long [length]` to get more output.

```
set long 300
SELECT *
    FROM table(pyqRowEval(
        inp_nam => 'SAMPLE_IRIS',
        par_lst => '{"oml_input_type":"pandas.DataFrame",
                     "modelName":"linregr", "datastoreName":"pymodel",
"oml_parallel_flag":true, "oml_service_level":"MEDIUM"}',
        out_fmt => 'XML',
        row_num => 10,
        scr_name => 'linregrPredict'));
```

The output is the following:

```
NAME VALUE
       <root><pandas_dataFrame><ROW-pandas_dataFrame><Species>setosa</
Species><Sepal_Length>5</Sepal_Length><Sepal_Width>3.2</
Sepal_Width><Petal_Length>1.2</Petal_Length><Petal_Width>0.2</
Petal_Width><Pred_Petal_Width>0.0653133201897007</Pred_Petal_Width></ROW-
pandas_dataFrame><ROW-pandas_dataFrame><Species>
```

7.5.2.5 pyqGroupEval Function (Autonomous Database)

The function `pyqGroupEval` when used in Oracle Autonomous Database, groups data by one or more columns and runs a user-defined Python function on each group.

The user-defined Python function can return a `boolean`, a `dict`, a `float`, an `int`, a `list`, a `str`, a `tuple` or a `pandas.DataFrame` object. Define the form of the returned value with the `OUT_FMT` parameter.

Syntax

```
FUNCTION PYQSYS.pyqGroupEval(
    INP_NAM    VARCHAR2,
    PAR_LST    VARCHAR2,
    OUT_FMT    VARCHAR2,
    GRP_COL    VARCHAR2,
    ORD_COL    VARCHAR2,
    SCR_NAME   VARCHAR2,
    SCR_OWNER  VARCHAR2 DEFAULT NULL,
    ENV_NAME   VARCHAR2 DEFAULT NULL
```

```
)
RETURN SYS.AnyDataSet
```

Parameters

Parameter	Description
INP_NAM	The name of a table or view that specifies the data to pass to the Python function specified by the SCR_NAME parameter. If using a table or view owned by another user, use the format <owner name>.<table/view name>. You must have read access to the specified table or view.
PAR_LST	A JSON string that contains additional parameters to pass to the user-defined Python function specified by the SCR_NAME parameter. Special control arguments, which start with oml_, are not passed to the function specified by SCR_NAME, but instead control what happens before or after the invocation of the function. For example, to specify the input data type as pandas.DataFrame, use: '{"oml_input_type":"pandas.DataFrame"}' **See also:** Special Control Arguments (Autonomous Database).
OUT_FMT	The format of the output returned by the function. It can be one of the following: • A JSON string that specifies the column names and data types of the table returned by the function. Any image data is discarded. The Python function must return a pandas.DataFrame, a numpy.ndarray, a tuple, or a list of tuples. • The string 'JSON', which specifies that the table returned contains a CLOB that is a JSON string. • The string 'XML', which specifies that the table returned contains a CLOB that is an XML string. The XML can contain both structured data and images, with structured or semi-structured Python objects first, followed by the image or images generated by the Python function. • The string 'PNG', which specifies that the table returned contains a BLOB that has the image or images generated by the Python function. Images are returned as a base 64 encoding of the PNG representation. **See also:** Output Formats (Autonomous Database).
GRP_COL	The names of the grouping columns by which to partition the data. Use commas to separate multiple columns. For example, to group by GENDER and YEAR: "GENDER,YEAR"
ORD_COL	Comma-separated column names to order the input data. For example to order by GENDER: "GENDER" If specified, the input data will first be ordered by the ORD_COL columns and then grouped by the GRP_COL columns.
SCR_NAME	The name of a user-defined Python function in the OML4Py script repository.
SCR_OWNER	The owner of the registered Python script. The default value is NULL. If NULL, will search for the Python script in the user's script repository.
ENV_NAME	The name of the conda environment that should be used when running the named user-defined Python function.

Example

This example calls the pyqGroupEval function, which runs the specified Python script on each partition of data in the specified data set.

The INP_NAM argument specifies the data in the IRIS table to pass to the Python function.

The PAR_LST argument specifies capturing images rendered in the script with the special control argument oml_graphics_flag.

The OUT_FMT arguments specifies returning a table with BLOB containing the images generated by the Python function.

The GRP_COL argument specifies to group the specified data by the 'Species' column.

The SCR_NAME parameter specifies the 'test_seaborn_inp' script, which is created in pyqTableEval Function (Autonomous Database).

The ENV_NAME parameter specifies 'seaborn', which is a Conda environment created in pyqEval Function (Autonomous Database) .

```
select *
  from table(pyqGroupEval(
        inp_nam =>  'IRIS',
        par_lst => '{"oml_graphics_flag":true}',
        out_fmt => 'PNG',
        grp_col => 'Species',
        ord_col => NULL,
        scr_name => 'test_seaborn_inp',
        scr_owner => NULL,
        env_name => 'seaborn'
));
```

The output is the following.

```
NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
GROUP_setosa
         1
"hello world"

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
```

```
--
IMAGE
--------------------------------------------------------------------------------
--
Iris plot
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58
74536F667477617265004D6174706C6F746C6962207665727369696F6E332E332E332C2068747470
73

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000000F6100000F6101
A8
3FA76900006AC6494441547 89CEDDD797854E5DD3EF0FBCC9EC92CD9F7B02624EC088A804B4440
05
AAD2AAB5D4166DD5F7ADDAB75A972AD60D375C706B2D2E588BED5B6A5FFD556AA91B5551145490
45

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--

GROUP_versicolor
         1

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
```

```
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
"hello world"
Iris plot
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
74536F667477617265004D6174706C6F746C6962207665727369 6F6E332E332E332C2068747470
73
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000 00F6100000F6101
A8
3FA76900009E9149444154789CECDD77785CE5993FFCEF2973CE548D7AB124F76E6C03A69966AA
C1

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
B0244E42360B01872CC96F43CC2659922C980D9B42884902A9FB420229904D1CD22064E90EC1A6
19

GROUP_virginica

NAME
--------------------------------------------------------------------------------
--
        ID
```

```
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
         1
"hello world"
Iris plot

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58
74536F667477617265004D6174706C6F746C6962207665727369 6F6E332E332E332C2068747470
73
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000 00F6100000F6101
A8

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
3FA7690000838E49444154789CEDDD797854E5D906F07BF6996496EC7B2010F64D14C1065450C1
05
8A625B6B2D0A56ED82B8B756B12AA245D4AAD5B61FA8B8606BA9AD56DC91E2120465DFF73D0442
42
```

Example

This example uses the IRIS table created in the example shown in pyqEval Function (Autonomous Database).

Define the Python function `group_count` and store it with the name `mygroupcount` in the script repository. The function returns a `pandas.DataFrame` generated on each group of data `dat`. The function also plots the sepal length with the petal length values on each group.

```
BEGIN
    sys.pyqScriptCreate('mygroupcount',
        'def group_count(dat):
        import pandas as pd
        import matplotlib.pyplot as plt
        plt.plot(dat[["Sepal_Length"]], dat[["Petal_Length"]], ".")
        plt.xlabel("Sepal Length")
        plt.ylabel("Petal Length")
        plt.title("{}".format(dat["Species"][0]))
        return pd.DataFrame([(dat["Species"][0], dat.shape[0])],\
        columns = ["Species", "CNT"]) ',
        FALSE, TRUE); -- V_GLOBAL, V_OVERWRITE
END;
/
```

Issue a query that invokes the `pyqGroupEval` function. In the function, the `INP_NAM` argument specifies the data in the IRIS table to pass to the function.

The `PAR_LST` argument specifies the special control argument `oml_input_type`.

The `OUT_FMT` argument specifies a JSON string that contains the column names and data types of the table returned by `pyqGroupEval`.

The `GRP_COL` parameter specifies the column to group by.

The `SCR_NAME` parameter specifies the user-defined Python function stored with the name `mygroupcount` in the script repository.

```
SELECT *
    FROM table(
        pyqGroupEval(
            inp_nam => 'IRIS',
            par_lst => '{"oml_input_type":"pandas.DataFrame"}',
            out_fmt => '{"Species":"varchar2(10)", "CNT":"number"}',
            grp_col => 'Species',
            ord_col => NULL,
            scr_name => 'mygroupcount'));
```

The output is the following:

```
Species CNT
---------- ----------
virginica 50
setosa 50
versicolor 50
3 rows selected.
```

Run the same script with IRIS data and return the XML output. The `PAR_LST` argument specifies the special control argument `oml_graphics_flag` to capture images rendered in the script. Both structured data and images are included in the XML output. The XML output is a CLOB; you can call `set long [length]` to get more output.

```
set long 300
SELECT *
    FROM table(
        pyqGroupEval(
            inp_nam => 'IRIS',
            par_lst => '{"oml_input_type":"pandas.DataFrame",
"oml_graphics_flag":true, "oml_parallel_flag":true",
"oml_service_level":"MEDIUM"}',
            out_fmt => 'XML',
            grp_col => 'Species',
            ord_col => NULL,
            scr_name => 'mygroupcount'));
```

The output is the following.

```
NAME VALUE
virginica <root><Py-data><pandas_dataFrame><ROW-
pandas_dataFrame><Species>virginica</Species><CNT>50</CNT></ROW-
pandas_dataFrame></pandas_dataFrame></Py-data><images><image><img
src="data:image/pngbase64"><!
[CDATA[iVBORw0KGgoAAAANSUhEUgAAAoAAAAHgCAYAAAA10dzkAAAAOXRFWHRTb2Z0d2FyZQBNYXR
wbG90bGliIHZlcnNpb24zLjMu
setosa <root><Py-data><pandas_dataFrame><ROW-
pandas_dataFrame><Species>setosa</Species><CNT>50</CNT></ROW-
pandas_dataFrame></pandas_dataFrame></Py-data><images><image><img
src="data:image/pngbase64"><!
[CDATA[iVBORw0KGgoAAAANSUhEUgAAAoAAAAHgCAYAAAA10dzkAAAAOXRFWHRTb2Z0d2FyZQBNYXR
wbG90bGliIHZlcnNpb24zLjMuMyw
versicolor <root><Py-data><pandas_dataFrame><ROW-
pandas_dataFrame><Species>versicolor</Species><CNT>50</CNT></ROW-
pandas_dataFrame></pandas_dataFrame></Py-data><images><image><img
src="data:image/pngbase64"><!
[CDATA[iVBORw0KGgoAAAANSUhEUgAAAoAAAAHgCAYAAAA10dzkAAAAOXRFWHRTb2Z0d2FyZQBNYXR
wbG90bGliIHZlcnNpb24zLjM
```

Run the same script with IRIS data and get the PNG output. The `PAR_LST` argument specifies the special control argument `oml_graphics_flag` to capture images.

```
column name format a7
column value format a15
column title format a16
column image format a15
SELECT *
    FROM table(
        pyqGroupEval(
            inp_nam => 'IRIS',
            par_lst => '{"oml_input_type":"pandas.DataFrame",
"oml_graphics_flag":true}',
            out_fmt => 'PNG',
```

```
            grp_col => 'Species',
            ord_col => NULL,
            scr_name => 'mygroupcount'));
```

The output is the following:

```
NAME            ID VALUE           TITLE           IMAGE
------- ---------- --------------- --------------- ---------------
GROUP_s          1 [{"Species":"se setosa          89504E470D0A1A0
etosa               tosa","CNT":50}                A0000000D494844
                    ]                              520000028000000
                                                   1E0080600000035
                                                   D1DCE4000000397
                                                   4455874536F6674
                                                   77617265004D617
                                                   4706C6F746C6962
                                                   2076657273696F6
                                                   E332E332E332C20
                                                   6874747073

NAME            ID VALUE           TITLE           IMAGE
------- ---------- --------------- --------------- ---------------

GROUP_v          1 [{"Species":"ve versicolor      89504E470D0A1A0
ersicol             rsicolor","CNT"                A0000000D494844
or                  :50}]                          520000028000000
                                                   1E0080600000035
                                                   D1DCE4000000397
                                                   4455874536F6674
                                                   77617265004D617
                                                   4706C6F746C6962
                                                   2076657273696F6
                                                   E332E332E332C20

NAME            ID VALUE           TITLE           IMAGE
------- ---------- --------------- --------------- ---------------
                                                   6874747073

GROUP_v          1 [{"Species":"vi virginica       89504E470D0A1A0
irginic             rginica","CNT":                A0000000D494844
a                   50}]                           520000028000000
                                                   1E0080600000035
                                                   D1DCE4000000397
                                                   4455874536F6674
                                                   77617265004D617
                                                   4706C6F746C6962
                                                   2076657273696F6
```

7.5.2.6 pyqIndexEval Function (Autonomous Database)

The function `pyqIndexEval` when used in Oracle Autonomous Database, runs a user-defined Python function multiple times as required in the Python engines spawned by the database environment.

Syntax

```
FUNCTION PYQSYS.pyqIndexEval(
    PAR_LST VARCHAR2,
    OUT_FMT VARCHAR2,
    TIMES_NUM NUMBER,
    SCR_NAME VARCHAR2,
    SCR_OWNER VARCHAR2 DEFAULT NULL,
    ENV_NAME VARCHAR2 DEFAULT NULL
)
RETURN SYS.AnyDataSet
```

Parameters

Parameter	Description
PAR_LST	A JSON string that contains additional parameters to pass to the user-defined Python function specified by the SCR_NAME parameter. Special control arguments, which start with oml_, are not passed to the function specified by

Parameter	Description
	`SCR_NAME`, but instead control what happens before or after the invocation of the function. For example, to specify the input data type as `pandas.DataFrame`, use: `'{"oml_input_type":"pandas.DataFrame"}'` **See also:** Special Control Arguments

Parameter	Description
	(Autonomous Database).

Parameter	Description
OUT_FMT	The format of the output returned by the function. It can be one of the following: • A JSON string that specifies the column nam

Parameter	Description
	esanddatatypesofthetableretur nedbythefunction.Anyimageda

Parameter	Description
	tais discarded. The Python function must return a pandas.DataFr

Parameter	Description
	ame, anumpy.ndarray, atuple, oralistoftuples. • Thestring'JS

Parameter	Description
	ON', which specifies that the table return contains a CLOB that i

Parameter	Description
	saJSONstring. The string 'XML', which specifies that the table re

Parameter	Description
	turnedcontainsaCLOBthatisanXMLstring.TheXMLcancontainboot

Parameter	Description
	hstructureddataandimages,withhstructuredorsemi-structured

Parameter	Description
	Python objects first, followed by the image or image generated by

Parameter	Description
	the Python function. • The string 'PNG', which specifies that the beta

Parameter	Description
	blereturnedcontainsaBLOBthathasthe imageorimagesgenerated

Parameter	Description
	by the Python function. Images are returned as base64 encoding of

Parameter	Description
	the PNG representation. **See also:** Output Formats (Autonomous Database).
TIMES_NUM	The number of times to execute the Python script.

Parameter	Description
SCR_NAME	The name of a user-defined Python function in the OML4Py script repository.
SCR_OWNER	The owner of the registered Python script. The default value is NULL. If NULL, will search for the Python script in the user's script repository.

Parameter	Description
ENV_NAME	The name of the conda environment that should be used when running the named user-defined Python function.

Example

This example defines a Python function to use with Conda environment.

Use the following code to create the 'test_seaborn_idx' script:

```
begin
  sys.pyqScriptCreate('test_seaborn_idx',
  'def fun_tab(idx):
  import seaborn as sns
  import matplotlib.pyplot as plt
  import numpy as np
  import pandas as pd
  data = np.random.multivariate_normal([0, 0], [[5, 2], [2, 2]], size=2000)
  data = pd.DataFrame(data, columns=["x", "y"])
  sns.displot(data["x"])
  plt.title("Title {}".format(idx))
  plt.show()
  return idx
  ',FALSE,TRUE); -- V_GLOBAL, V_OVERWRITE
end;
/
```

This example calls the pyqIndexEval function, which runs the specified Python function multiple times.

The `PAR_LST` argument specifies capturing images rendered in the script with the special control argument oml_graphics_flag.

The `OUT_FMT` arguments specifies returning a table with BLOB containing the images generated by the Python function.

The `TIMES_NUM` argument specifies to run the specified script 2 times.

The `SCR_NAME` parameter specifies the 'test_seaborn_idx' script as the Python function to invoke.

The `ENV_NAME` parameter specifies 'seaborn', which is a Conda environment created in pyqEval Function (Autonomous Database) .

```
select *
  from table(pyqIndexEval(
        par_lst => '{"oml_graphics_flag":true}',
        out_fmt => 'PNG',
        times_num => 2,
        scr_name => 'test_seaborn_idx',
        scr_owner => NULL,
        env_name => 'seaborn'
));
```

The output is the following.

```
NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
TIME_1
         1
1

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
```

```
--------------------------------------------------------------------------------
--
Title 1
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58
74536F667477617265004D6174706C6F746C6962207665727369696F6E332E332E332C2068747470
73

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000000F6100000F6101
A8
3FA769000066674944154789CEDDD797C5355FE3FFE579236E9BEB7495BBA52A0AC2D1428C505
94
7E2DA0A3082AA0332083B80C30424747F1A720CE5254441C65649C11706340E68338A283426551
28

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--

TIME_2
         1

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
```

```
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
2
Title 2
89504E470D0A1A0A0000000D4948445200000280000001E0080600000035D1DCE4000000397445
58

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
74536F667477617265004D6174706C6F746C6962207665727369 6F6E332E332E332C2068747470
73
3A2F2F6D6174706C6F746C69622E6F72672FC897B79C0000000970485973000 00F6100000F6101
A8
3FA769000068764944415 4789CEDDD79785355FE3FF0F74DDAA47BBA6FD0D2859DB216A8451495
7E

NAME
--------------------------------------------------------------------------------
--
        ID
----------
VALUE
--------------------------------------------------------------------------------
--
TITLE
--------------------------------------------------------------------------------
--
IMAGE
--------------------------------------------------------------------------------
--
2DC2A8082A220E8A88CA80A3561DADBF19709919500171D491D1914505451CF7A55A2A204BD95A
CA
```

Example

Define the Python function `fit_lm` and store it with the name `myFitMultiple` in the script repository. The function returns a `pandas.DataFrame` containing the index and prediction score of the fitted model on the data sampled from `scikit-learn`'s IRIS dataset.

```
begin
    sys.pyqScriptCreate('myFitMultiple',
```

```
        'def fit_lm(i, sample_size):
            from sklearn import linear_model
            from sklearn.datasets import load_iris
            import pandas as pd

            import random
            random.seed(10)

            iris = load_iris()
            x = pd.DataFrame(iris.data, columns = ["Sepal_Length",\
                        "Sepal_Width","Petal_Length","Petal_Width"])
            y = pd.DataFrame(list(map(lambda x: {0:"setosa", 1: "versicolor",\
                                    2: "virginica"}[x], iris.target)),\
                         columns = ["Species"])
            dat = pd.concat([y, x], axis=1).sample(sample_size)
            regr = linear_model.LinearRegression()
            regr.fit(x.loc[:, ["Sepal_Length", "Sepal_Width", \
                              "Petal_Length"]],
                     x.loc[:,["Petal_Width"]])
            sc = regr.score(dat.loc[:, ["Sepal_Length", "Sepal_Width", \
                              "Petal_Length"]],
                            dat.loc[:,["Petal_Width"]])
            return pd.DataFrame([[i,sc]],columns=["id","score"])
        ',FALSE,TRUE); -- V_GLOBAL, V_OVERWRITE
end;
/
```

Issue a query that invokes the `pyqIndexEval` function. In the function, the `PAR_LST` argument specifies the function argument `sample_size`. The `OUT_FMT` argument specifies a JSON string that contains the column names and data types of the table returned by `pyqIndexEval`. The `TIMES_NUM` parameter specifies the number of times to execute the script. The `SCR_NAME` parameter specifies the user-defined Python function stored with the name `myFitMultiple` in the script repository.

```
select *
    from table(pyqIndexEval(
        par_lst => '{"sample_size":80,
                     "oml_parallel_flag":true",
"oml_service_level":"MEDIUM"}',
        out_fmt => '{"id":"number","score":"number"}',
        times_num => 3,
        scr_name => 'myFitMultiple'));
```

The output is the following:

```
        id score
---------- ----------
         1 .943550631
         2 .927836941
         3 .937196049
3 rows selected.
```

7.5.2.7 pyqGrant Function (Autonomous Database)

This topic describes the `pyqGrant` function when used in Oracle Autonomous Database.

The `pyqGrant` function grants read privilege access to an OML4Py datastore or to a script in the OML4Py script repository.

Syntax

```
pyqGrant (
    V_NAME          VARCHAR2    IN
    V_TYPE          VARCHAR2    IN
    V_USER          VARCHAR2    IN     DEFAULT)
```

Parameters

Parameter	Description
V_NAME	The name of an OML4Py datastore or a script in the OML4Py script repository.
V_TYPE	For a datastore, the type is `datastore`; for script the type is `pyqScript`.
V_USER	The name of the user to whom to grant access.

Example 7-15 Granting Read Access to a script

```
-- Grant read privilege access to Scott.
BEGIN
  pyqGrant('pyqFun1', 'pyqscript', 'SCOTT');
END;
/
```

Example 7-16 Granting Read Access to a datastore

```
-- Grant read privilege access to datastore ds1 to SCOTT.
BEGIN
  pyqGrant('ds1', 'datastore', 'SCOTT');
END;
/
```

Example 7-17 Granting Read Access to a Script to all Users

```
-- Grant read privilege access to script RandomRedDots to all users.
BEGIN
  pyqGrant('pyqFun1', 'pyqscript', NULL);
END;
/
```

Example 7-18 Granting Read Access to a datastore to all Users

```
-- Grant read privilege access to datastore ds1 to all users.
BEGIN
  pyqGrant('ds1', 'datastore', NULL);
```

```
END;
/
```

7.5.2.8 pyqRevoke Function (Autonomous Database)

This topic describes the `pyqRevoke` function when used in Oracle Autonomous Database.

The `pyqRevoke` function revokes read privilege access to an OML4Py datastore or to a script in the OML4Py script repository.

Syntax

```
pyqRevoke (
    V_NAME          VARCHAR2    IN
    V_TYPE          VARCHAR2    IN
    V_USER          VARCHAR2    IN     DEFAULT)
```

Parameters

Parameter	Description
`V_NAME`	The name of an OML4Py datastore or a script in the OML4Py script repository.
`V_TYPE`	For a datastore, the type is `datastore`; for script the type is `pyqScript`.
`V_USER`	The name of the user from whom to revoke access.

Example 7-19 Revoking Read Access to a script

```
-- Revoke read privilege access to script pyqFun1 from SCOTT.
BEGIN
  pyqRevoke('pyqFun1', 'pyqscript', 'SCOTT');
END;
/
```

Example 7-20 Revoking Read Access to a datastore

```
-- Revoke read privilege access to datastore ds1 from SCOTT.
BEGIN
  pyqRevoke('ds1', 'datastore', 'SCOTT');
END;
/
```

Example 7-21 Revoking Read Access to a script from all Users

```
-- Revoke read privilege access to script pyqFun1 from all users.
BEGIN
  pyqRevoke('pyqFun1', 'pyqscript', NULL);
END;
/
```

Example 7-22 Revoking Read Access to a datastore from all Users

```
-- Revoke read privilege access to datastore ds1 from all users.
BEGIN
  pyqRevoke('ds1', 'datastore', NULL);
END;
/
```

7.5.2.9 pyqScriptCreate Procedure (Autonomous Database)

This topic describes the `pyqScriptCreate` procedure in Oracle Autonomous Database. Use the `pyqScriptCreate` procedure to create a user-defined Python function and add it to the OML4Py script repository.

Syntax

```
sys.pyqScriptCreate (
    V_NAME          VARCHAR2    IN
    V_SCRIPT        CLOB        IN
    V_GLOBAL        BOOLEAN     IN     DEFAULT
    V_OVERWRITE     BOOLEAN     IN     DEFAULT)
```

Parameter	Description
`V_NAME`	A name for the user-defined Python function in the OML4Py script repository.
`V_SCRIPT`	The definition of the Python function.
`V_GLOBAL`	`TRUE` specifies that the user-defined Python function is public; `FALSE` specifies that the user-defined Python function is private.
`V_OVERWRITE`	If the script repository already has a user-defined Python function with the same name as `V_NAME`, then `TRUE` replaces the content of that user-defined Python function with `V_SCRIPT` and `FALSE` does not replace it.

Example 7-23 Using the pyqScriptCreate Procedure

This example creates a private user-defined Python function named `pyqFun2` in the OML4Py script repository.

```
BEGIN
  sys.pyqScriptCreate('pyqFun2',
    'def return_frame():
       import numpy as np
       import pickle
       z = np.array([y for y in zip([str(x)+"demo" for x in range(10)],
       [float(x)/10 for x in range(10)],
       [x for x in range(10)],
       [bool(x%2) for x in range(10)],
       [pickle.dumps(x) for x in range(10)],
       ["test"+str(x**2) for x in range(10)])],
       dtype=[("a", "U10"), ("b", "f8"), ("c", "i4"), ("d", "?"),
       ("e", "S20"), ("f", "O")])
       return z');
END;
/
```

This example creates a global user-defined Python function named `pyqFun2` in the script repository and overwrites any existing user-defined Python function of the same name.

```
BEGIN
  sys.pyqScriptCreate('pyqFun2',
    'def return_frame():
       import numpy as np
       import pickle
       z = np.array([y for y in zip([str(x)+"demo" for x in range(10)],
       [float(x)/10 for x in range(10)],
       [x for x in range(10)],
       [bool(x%2) for x in range(10)],
       [pickle.dumps(x) for x in range(10)],
       ["test"+str(x**2) for x in range(10)])],
       dtype=[("a", "U10"), ("b", "f8"), ("c", "i4"), ("d", "?"),
       ("e", "S20"), ("f", "O")])
       return z',
       TRUE,  -- Make the user-defined Python function global.
       TRUE); -- Overwrite any global user-defined Python function
              -- with the same name.
END;
/
```

This example creates a private user-defined Python function named `create_iris_table` in the script repository.

```
BEGIN
  sys.pyqScriptCreate('create_iris_table',
    'def create_iris_table():
       from sklearn.datasets import load_iris
       import pandas as pd
       iris = load_iris()
       x = pd.DataFrame(iris.data, columns = ["Sepal_Length",\
                        "Sepal_Width","Petal_Length","Petal_Width"])
       y = pd.DataFrame(list(map(lambda x: {0:"setosa", 1: "versicolor",\
                                 2: "virginica"}[x], iris.target)),\
                        columns = ["Species"])
       return pd.concat([y, x], axis=1)');
END;
/
```

Display the user-defined Python functions owned by the current user.

```
SELECT * from USER_PYQ_SCRIPTS;
```

```
NAME               SCRIPT
-----------------
-------------------------------------------------------------------------
create_iris_table  def create_iris_table():       from sklearn.datasets
import load_iris ...
pyqFun2            def return_frame():       import numpy as np       import
pickle      ...
```

Display the user-defined Python functions available to the current user.

```
SELECT * from ALL_PYQ_SCRIPTS;
```

```
OWNER     NAME               SCRIPT
--------   -----------------
-----------------------------------------------------------------------
OML_USER   create_iris_table  "def create_iris_table():  from
sklearn.datasets import load_iris ...
OML_USER   pyqFun2            "def return_frame():  import numpy as np
import pickle      ...
PYQSYS     pyqFun2            "def return_frame():  import numpy as np
import pickle      ...
```

7.5.2.10 pyqScriptDrop Procedure (Autonomous Database)

This topic describes the `pyqScriptDrop` procedure in Oracle Autonomous Database. Use the `pyqScriptDrop` procedure to remove a user-defined Python function from the OML4Py script repository.

Syntax

```
sys.pyqScriptDrop (
    V_NAME          VARCHAR2    IN
    V_GLOBAL        BOOLEAN     IN     DEFAULT
    V_SILENT        BOOLEAN     IN     DEFAULT)
```

Parameter	Description
`V_NAME`	A name for the user-defined Python function in the OML4Py script repository.
`V_GLOBAL`	A BOOLEAN that specifies whether the user-defined Python function to drop is a global or a private user-defined Python function. The default value is `FALSE`, which indicates a private user-defined Python function. `TRUE` specifies that the user-defined Python function is public.
`V_SILENT`	A BOOLEAN that specifies whether to display an error message when `sys.pyqScriptDrop` encounters an error in dropping the specified user-defined Python function. The default value is `FALSE`.

Example 7-24 Using the sys.pyqScriptDrop Procedure

This example drops the private user-defined Python function `pyqFun2` from the script repository.

```
BEGIN
  sys.pyqScriptDrop('pyqFun2');
 END;
 /
```

This example drops the global user-defined Python function `pyqFun2` from the script repository.

```
BEGIN
  sys.pyqScriptDrop('pyqFun2', TRUE);
```

```
END;
/
```

7.5.3 Asynchronous Jobs (Autonomous Database)

When a function is run asynchronously, it's run as a job which can be tracked by using the `pyqJobStatus` and `pyqJobResult` functions.

Topics:

- oml_async_flag Argument
  The special control argument `oml_async_flag` determines if a job is run synchronously or asynchronously. The default value is false.
- pyqJobStatus Function
  Use the `pyqJobStatus` function to look up the status of an asynchronous job. If the job is pending, it returns `job is still running` . If the job is completed, the function returns a URL.
- pyqJobResult Function
  Use the `pyqJobResult` function to return the job result.
- Asynchronous Job Example
  The following examples shows how to submit asynchronous jobs with non-XML output and with XML output.

7.5.3.1 oml_async_flag Argument

The special control argument `oml_async_flag` determines if a job is run synchronously or asynchronously. The default value is false.

Set the `oml_async_flag` Argument

- To run a function in synchronous mode, set `oml_async_flag` to `false`.

  In synchronous mode, the SQL API waits for the HTTP call to finish and returns when the HTTP response is ready.

  By default, `pyq*Eval` functions are executed synchronously. The default connection timeout limit is 60 seconds. Synchronous mode is used if `oml_async_flag` is not set or if it's set to `false`.
- To run a function in asynchronous mode, set `oml_async_flag` to `true`.

  In asynchronous mode, the SQL API returns a URL directly after the asynchronous job is submitted to the web server. The URL contains a job ID, which can be used to fetch the job status and result in subsequent SQL calls.

Submit Asynchronous Job Example

This example uses the table `GRADE`, created as follows:

```
CREATE TABLE GRADE (
NAME VARCHAR2(30),
GENDER VARCHAR2(1),
STATUS NUMBER(10),
YEAR NUMBER(10),
SECTION VARCHAR2(1),
SCORE NUMBER(10),
FINALGRADE NUMBER(10)
);

insert into GRADE values('Abbott', 'F', 2, 97, 'A', 90, 87);
insert into GRADE values('Branford', 'M', 1, 98, 'A', 92, 97);
insert into GRADE values('Crandell', 'M', 2, 98, 'B', 81, 71);
insert into GRADE values('Dennison', 'M', 1, 97, 'A', 85, 72);
insert into GRADE values('Edgar', 'F', 1, 98, 'B', 89, 80);
insert into GRADE values('Faust', 'M', 1, 97, 'B', 78, 73);
insert into GRADE values('Greeley', 'F', 2, 97, 'A', 82, 91);
insert into GRADE values('Hart', 'F', 1, 98, 'B', 84, 80);
insert into GRADE values('Isley', 'M', 2, 97, 'A', 88, 86);
insert into GRADE values('Jasper', 'M', 1, 97, 'B', 91, 83);
```

In the following code, the Python function `score_diff` is defined and stored with the name `computeGradeDiff` as a private function in the script repository. The function returns a `pandas.DataFrame` after assigning a new `DIFF` column by computing the difference between the `SCORE` and `FINALGRADE` column of the input data.

```
begin
    sys.pyqScriptCreate('computeGradeDiff','def score_diff(dat):
        import numpy as np
        import pandas as pd
        df = dat.assign(DIFF=dat.SCORE-dat.FINALGRADE)
        return df
    ');
end;
/
```

Run the saved `computeGradeDiff` script as follows:

```
select *
   from table(pyqTableEval(
         inp_nam => 'GRADE',
         par_lst => '{"oml_async_flag":true}',
         out_fmt => NULL,
         scr_name => 'computeGradeDiff',
         scr_owner => NULL
   ));
```

The `VALUE` column of the result contains a URL containing the job ID of the asynchronous job:

```
NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--
https://<oml-cloud-service-location-url>/oml/api/py-scripts/v1/jobs/<job id>
1 row selected.
```

7.5.3.2 pyqJobStatus Function

Use the `pyqJobStatus` function to look up the status of an asynchronous job. If the job is pending, it returns `job is still running` . If the job is completed, the function returns a URL.

Syntax

```
FUNCTION PYQSYS.pyqJobStatus(
  job_id       VARCHAR2
)
RETURN PYQSYS.pyqClobSet
```

Parameters

Parameter	Description
`job_id`	The ID of the asynchronous job.

Example

The following example shows a `pyqJobStatus` call and its output.

```
SQL> select * from pyqJobStatus(
       job_id => '<job id>'
);


NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--
https://<oml-cloud-service-location-url>/oml/api/py-scripts/v1/jobs/<job id>/
result

1 row selected.
```

7.5.3.3 pyqJobResult Function

Use the `pyqJobResult` function to return the job result.

Syntax

```
FUNCTION PYQSYS.pyqJobResult(
  job_id       VARCHAR2,
  out_fmt      VARCHAR2 DEFAULT 'JSON'
)
RETURN SYS.AnyDataSet
```

Parameters

Parameter	Description
`job_id`	The ID of the asynchronous job.
`out_fmt`	The format of the job result. It can be one of the following: • A JSON string that specifies the column names and data types of the table returned by the function. Any image data is discarded. The Python function must return a pandas.DataFrame, a numpy.ndarray, a tuple, or a list of tuples. • The string 'JSON', which specifies that the table returned contains a CLOB that is a JSON string. • The string 'XML', which specifies that the table returned contains a CLOB that is an XML string. The XML can contain both structured data and images, with structured or semi-structured Python objects first, followed by the image or images generated by the Python function. • The string 'PNG', which specifies that the table returned contains a BLOB that has the image or images generated by the Python function. Images are returned as a base 64 encoding of the PNG representation.

Example

The following example shows a `pyqJobResult` call and its output.

```
SQL> select * from pyqJobResult(
    job_id => '<job id>',
    out_fmt =>
'{"NAME":"varchar2(7)","SCORE":"number","FINALGRADE":"number","DIFF":"number"}
'
);


NAME       SCORE      FINALGRADE DIFF
---------- ---------- ---------- ----------
Abbott     90         87          3
Branford   92         97         -5
Crandell   81         71         10
Dennison   85         72         13
Edgar      89         80          9
Faust      78         73          5
Greeley    82         91         -9
Hart       84         80          4
Isley      88         86          2
Jasper     91         83          8

10 rows selected.
```

7.5.3.4 Asynchronous Job Example

The following examples shows how to submit asynchronous jobs with non-XML output and with XML output.

Non-XML Output

When submitting asynchronous jobs, for JSON, PNG and relational outputs, set the `OUT_FMT` argument to `NULL` when submitting the job. When fetching the job result, specify `OUT_FMT` in the `pyqJobResult` call.

This example uses the IRIS table created in the example shown in the pyqTableEval Function (Autonomous Database) topic and the `linregrPredict` script created in the example shown in the pyqRowEval Function (Autonomous Database) topic.

Issue a `pyqGroupEval` function call to submit an asynchronous job. In the function, the `INP_NAM` argument specifies the data in the IRIS table to pass to the function.

The `PAR_LST` argument specifies submitting the job asynchronously with the special control argument `oml_async_flag`, capturing the images rendered in the script with the special control argument `oml_graphics_flag`, passing the input data as a `pandas.DataFrame` with the special control argument `oml_input_type`, along with values for the function arguments `modelName` and `datastoreName`.

The `OUT_FMT` argument is `NULL`.

The `GRP_COL` parameter specifies the column to group by.

The `SCR_NAME` parameter specifies the user-defined Python function stored with the name `linregrPredict` in the script repository.

The asynchronous call returns a job status URL in CLOB, you can call `set long [length]` to get the full URL.

```
set long 150
  select *
  from table(pyqGroupEval(
  inp_nam => 'IRIS',
  par_lst => '{"oml_input_type":"pandas.DataFrame",
  "oml_async_flag":true, "oml_graphics_flag":true,
              "modelName":"linregr", "datastoreName":"pymodel"}',
  out_fmt => NULL,
  grp_col => 'Species',
  ord_col => NULL,
  scr_name => 'linregrPredict',
  scr_owner => NULL
));
```

The output is the following:

```
NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--
```

```
https://<oml-cloud-service-location-url>/oml/api/py-scripts/v1/jobs/<job id>

1 row selected.
```

Run a `SELECT` statement that invokes the `pyqJobStatus` function, which returns a resource URL containing the job ID when the job result is ready.

```
select * from pyqJobStatus(
job_id => '<job id>');
```

The output is the following when the job is still pending.

```
NAME
--------------------------------------------------------------------------------
VALUE
--------------------------------------------------------------------------------
job is still running
1 row selected.
```

The output is the following when the job finishes.

```
NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--

https://<oml-cloud-service-location-url>/oml/api/py-scripts/v1/jobs/<job id>/
result

1 row selected.
```

Run a `SELECT` statement that invokes the `pyqJobResult` function.

In the `OUT_FMT` argument, the string `'PNG'` specifies to include both return value and images (titles and image bytes) in the result.

```
column name format a7
column value format a15
column title format a16
column image format a15
select * from pyqJobResult(
        job_id => '<job id>',
        out_fmt => 'PNG'
);
```

The output is the following.

```
NAME            ID VALUE           TITLE            IMAGE
------- ---------- --------------- ---------------- ---------------
GROUP_s          1 [{"Species":"se Prediction of Pe 6956424F5277304
etosa              tosa","Sepal_Le tal Width        B47676F41414141
```

		ngth":4.6,"Sepa l_Width":3.6,"P etal_Length":1. 0,"Petal_Width" :0.2,"Pred_Peta l_Width":0.1325 345443},{"Speci es":"setosa","S	4E5355684555674 141416F41414141 486743415941414 1413130647A6B41 41414142484E435 356514943416749 6641686B6941414 141416C7753466C 7A4141415059514 141443245427144 2B6E61514141414 468305256683055 32396D644864686 36D554162574630 634778766447787 0596942325A584A 7A615739754D793 4784C6A49734947
GROUP_versicolor	1	[{"Species":"ve rsicolor","Sepa l_Length":5.1," Sepal_Width":2. 5,"Petal_Length ":3.0,"Petal_Wi dth":1.1,"Pred_ Petal_Width":0. 8319563387},{"S pecies":"versic	Prediction of Petal Width	6956424F5277304 B47676F41414141 4E5355684555674 141416F41414141 486743415941414 1413130647A6B41 41414142484E435 356514943416749 6641686B6941414 141416C7753466C 7A4141415059514 141443245427144 2B6E61514141414 468305256683055 32396D644864686 36D554162574630 634778766447787 0596942325A584A 7A615739754D793 4784C6A49734947
GROUP_virginica	1	[{"Species":"vi rginica","Sepal _Length":5.7,"S epal_Width":2.5 ,"Petal_Length" :5.0,"Petal_Wid th":2.0,"Pred_P etal_Width":1.7 55762924},{"Spe cies":"virginic	Prediction of Petal Width	6956424F5277304 B47676F41414141 4E5355684555674 141416F41414141 486743415941414 1413130647A6B41 41414142484E435 356514943416749 6641686B6941414 141416C7753466C 7A4141415059514 141443245427144 2B6E61514141414 468305256683055 32396D644864686 36D554162574630

```
                                                    634778766447787
                                                    0596942325A584A
                                                    7A615739754D793
                                                    4784C6A49734947

3 rows selected.
```

XML Ouput

If XML output is expected from the asynchronous job, set the `OUT_FMT` argument to `'XML'` when submitting the job and fetching the job result.

This example uses the script `myFitMultiple` created in the example shown in the pyqIndexEval Function (Autonomous Database) topic.

Issue a `pyqIndexEval` function call to submit an asynchronous job. In the function, the `PAR_LST` argument specifies submitting the job asynchronously with the special control argument `oml_async_flag`, along with values for the function arguments `sample_size`.

The asynchronous call returns a job status URL in CLOB, you can call `set long [length]` to get the full URL.

```
set long 150 select *
  from table(pyqIndexEval(
        par_lst => '{"sample_size":80,"oml_async_flag":true}',
        out_fmt => 'XML',
        times_num => 3,
        scr_name => 'myFitMultiple',
        scr_owner => NULL
));
```

The output is the following.

```
NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--
https://<oml-cloud-service-location-url>/oml/api/py-scripts/v1/jobs/<job id>

1 row selected.
```

Run a `SELECT` statement that invokes the `pyqJobStatus` function, which returns a resource URL containing the job id when the job result is ready.

```
select * from pyqJobStatus(
job_id => '<job id>'
);
```

The output is the following when the job is still pending.

```
NAME
--------------------------------------------------------------------------------
VALUE
--------------------------------------------------------------------------------
job is still running
1 row selected.
```

The output is the following when the job result is ready.

```
NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--
https://<oml-cloud-service-location-url>/oml/api/py-scripts/v1/jobs/<job id>/
result

1 row selected.
```

Run a `SELECT` statement that invokes the `pyqJobResult` function.

In the `OUT_FMT` argument, the string `'XML'` specifies that the table returned contains a CLOB that is an XML string.

```
select * from pyqJobResult(
         job_id => '<job id>',
         out_fmt => 'XML'
);
```

The output is the following.

```
NAME
--------------------------------------------------------------------------------
VALUE
--------------------------------------------------------------------------------
1
<root><pandas_dataFrame><ROW-pandas_dataFrame><id>1</id><score>0.94355
0631313753</score></ROW-pandas_dataFrame></pandas_dataFrame></root>

2
<root><pandas_dataFrame><ROW-pandas_dataFrame><id>2</id><score>0.92783
6941437123</score></ROW-pandas_dataFrame></pandas_dataFrame></root>

3
<root><pandas_dataFrame><ROW-pandas_dataFrame><id>3</id><score>0.93719
6049031545</score></ROW-pandas_dataFrame></pandas_dataFrame></root>


3 rows selected.
```

7.5.4 Special Control Arguments (Autonomous Database)

Use the `PAR_LST` parameter to specify special control arguments and additional arguments to be passed into the Python script.

Argument	Syntax and Description
`oml_input_type`	**Syntax** **`oml_input_type`** : **`'pandas.DataFrame'`**, **`'numpy.recarray'`**, or **`'default'`** (default) **Description** Specifies the type of object to construct from data in the Autonomous Database. By default, a two-dimensional `numpy.ndarray` of type `numpy.float64` is constructed if all columns are numeric. Otherwise, a `pandas.DataFrame` is constructed.
`oml_na_omit`	**Syntax** **`oml_na_omit : bool, false`** (default) **Description** Determines if rows with any missing values will be omitted from the table to be evaluated. If `true`, omit all rows with missing values from the table. If `false`, do not omit rows with missing values from the table.
`oml_async_flag`	**Syntax** **`oml_async_flag`**: **`bool`**, **`false`** (default) **Description** If `true`, the job will be submitted asynchronously. If `false`, the job will be executed in synchronous mode.
`oml_graphics_flag`	**Syntax** **`oml_graphics_flag`**: **`bool`**, **`false`** (default) **Description** If `true`, the server will capture images rendered in the Python script. If `false`, the server will not capture images rendered in the Python script.
`oml_parallel_flag`	**Syntax** **`oml_parallel_flag`**: **`bool`**, **`false`** (default) **Description** If `true`, the Python script will be run with data parallelism. Data parallelism is only applicable to `pyqRowEval`, `pyqGroupEval`, and `pyqIndexEval`. If `false`, the Python script will not be run with data parallelism.
`oml_service_level`	**Syntax** **`oml_service_level`** : **`string`**, allowed values: **`'LOW'`**(default), **`'MEDIUM'`**, **`'HIGH'`** **Description** Controls the different levels of performance and concurrency in Autonomous Database.

Examples

- Input data is `pandas.DataFrame`:

```
par_lst => '{"oml_input_type":"pandas.DataFrame"}'
```

- Drop rows with missing values from input data:

  ```
  par_lst => '{"oml_na_omit":true}'
  ```

- Submit a job in asynchronous mode:

  ```
  par_lst => '{"oml_async_flag":true}'
  ```

- Use `MEDIUM` service level:

  ```
  par_lst => '{"oml_service_level":"MEDIUM"}'
  ```

7.5.5 Output Formats (Autonomous Database)

The `OUT_FMT` parameter controls the format of output returned by the table functions `pyqEval`, `pyqGroupEval`, `pyqIndexEval`, `pyqRowEval`, `pyqTableEval`, and `pyqJobResult`.

The output formats are:

- JSON
- Relational
- XML
- PNG
- Asynchronous Mode Output

JSON

When `OUT_FMT` is set to `JSON`, the table functions return a table containing a CLOB that is a JSON string.

The following example invokes the `pyqEval` function on the `'pyqFun1'` created in the `pyqEval` function section.

```
SQL> select *
    from table(pyqEval(
        par_lst => '{"oml_service_level":"MEDIUM"}',
        out_fmt => 'JSON',
        scr_name => 'pyqFun1'));


NAME
--------------------------------------------------------------------------------
VALUE
--------------------------------------------------------------------------------
[{"FLOAT":0,"ID":0,"NAME":"demo_0"},{"FLOAT":0.1,"ID":1,"NAME":"demo_1
"},{"FLOAT":0.2,"ID":2,"NAME":"demo_2"},{"FLOAT":0.3,"ID":3,"NAME":"de
mo_3"},{"FLOAT":0.4,"ID":4,"NAME":"demo_4"},{"FLOAT":0.5,"ID":5,"NAME"
:"demo_5"},{"FLOAT":0.6,"ID":6,"NAME":"demo_6"},{"FLOAT":0.7,"ID":7,"N
AME":"demo_7"},{"FLOAT":0.8,"ID":8,"NAME":"demo_8"},{"FLOAT":0.9,"ID":
9,"NAME":"demo_9"}]

1 row selected.
```

Relational

When `OUT_FMT` is specified with a JSON string where column names are mapped to column types, the table functions return the response by reshaping it into table columns.

For example, if `OUT_FMT` is specified with `{"NAME":"varchar2(7)", "DIFF":"number"}`, the output should contain a `NAME` column of type `VARCHAR2(7)` and a `DIFF` column of type `NUMBER`. The following example uses the table `GRADE` and the script `'computeGradeDiff'` (created in Asynchronous Jobs (Autonomous Database)) and invokes the `computeGradeDiff` function:

```
SQL> select *
  from table(pyqTableEval(
        inp_nam => 'GRADE',
        par_lst => '{"oml_input_type":"pandas.DataFrame"}',
        out_fmt => '{"NAME":"varchar2(7)","DIFF":"number"}',
        scr_name => 'computeGradeDiff'));


NAME DIFF
------- ----------
Abbott   3
Branfor -5
Crandel 10
Denniso 13
Edgar    9
Faust    5
Greeley -9
Hart     4
Isley    2
Jasper   8

10 rows selected.
```

XML

When `OUT_FMT` is specified with `XML`, the table functions return the response in a table with fixed columns. The output consists of two columns. The `NAME` column contains the name of the row. The `NAME` column value is `NULL` for `pyqEval`, `pyqTableEval`,`pyqRowEval` function returns. For `pyqGroupEval`, `pyqIndexEval`, the `NAME` column value is the group/index name. The `VALUE` column contains the XML string.

The XML can contain both structured data and images, with structured or semi-structured Python objects first, followed by the image or images generated by the Python function. Images are returned as a base 64 encoding of the PNG representation. To include images in the XML string, the special control argument `oml_graphics_flag` must be set to true.

In the following code, the python function `gen_two_images` is defined and stored with name `plotTwoImages` in the script repository. The function renders two subplots with random dots in red and blue color and returns the number of columns of the input data.

```
begin
         sys.pyqScriptCreate('plotTwoImages','def gen_two_images (dat):
               import numpy as np
               import matplotlib.pyplot as plt
               np.random.seed(22)
```

```
                  fig = plt.figure(1);
                  fig2 = plt.figure(2);
                  ax = fig.add_subplot(111);
                  ax.set_title("Random red dots")
                  ax2 = fig2.add_subplot(111);
                  ax2.set_title("Random blue dots")
                  ax.plot(range(100), np.random.normal(size=100), marker = "o",
                          color = "red", markersize = 2)
                  ax2.plot(range(100,0,-1), marker = "o", color = "blue",
markersize = 2)
                  return dat.shape[1]
       ',FALSE,TRUE);
end;
/
```

The following example shows the XML output of a `pyqRowEval` function call where both structured data and images are included in the result:

```
SQL> select *
    from table(pyqRowEval(
         inp_nam => 'GRADE',
         par_lst => '{"oml_graphics_flag":true}',
         out_fmt => 'XML',
         row_num => 5,
         scr_name => 'plotTwoImages'
));


NAME
------------------------------------------------------------------------------
--
VALUE
----------------------------------------------------------------------
1
<root><Py-data><int>7</int></Py-data><images><image><img src="data:ima
ge/pngbase64"><![CDATA[iVBORw0KGgoAAAANSUhEUgAAAoAAAAHgCAYAAAA10dzkAAA
ABHNCSVQICAgIfAhkiAAAAAlwSFlzAAAPYQAAD2EBqD+naQAAADh0RVh0U29mdHdhcmUAb
WF0cGxvdGxpYiB2ZXJzaW9uMy4xLjIsIGh0dHA6Ly9tYXRwbG90bGliLm9yZy8li6FKAAA
gAElEQVR4nOydeZwcVb32n549k0xCSMhGEohhEZFNUAEBE0UUIYOACG4gFxWvgGzqldf3s
lz1xYuKLBe3i7LcNyhctoxsviCJoAQFNAKCCLITQYbZqb

2
<root><Py-data><int>7</int></Py-data><images><image><img src="data:ima
ge/pngbase64"><![CDATA[iVBORw0KGgoAAAANSUhEUgAAAoAAAAHgCAYAAAA10dzkAAA
ABHNCSVQICAgIfAhkiAAAAAlwSFlzAAAPYQAAD2EBqD+naQAAADh0RVh0U29mdHdhcmUAb
WF0cGxvdGxpYiB2ZXJzaW9uMy4xLjIsIGh0dHA6Ly9tYXRwbG90bGliLm9yZy8li6FKAAA
gAElEQVR4nOydeZwcVb32n549k0xCSMhGEohhEZFNUAEBE0UUIYOACG4gFxWvgGzqldf3s
lz1xYuKLBe3i7LcNyhctoxsviCJoAQFNAKCCLITQYbZqb
2 rows selected
```

PNG

When `OUT_FMT` is specified with `PNG`, the table functions return the response in a table with fixed columns (including an image bytes column). When calling the SQL API, you must set the

special control argument `oml_graphics_flag` to `true` so that the web server can capture images rendered in the executed script.

The PNG output consists of four columns. The `NAME` column contains the name of the row. The `NAME` column value is `NULL` for `pyqEval` and `pyqTableEval` function returns. For `pyqRowEval`, `pyqGroupEval`, `pyqIndexEval`, the `NAME` column value is the chunk/group/index name. The `ID` column indicates the ID of the image. The `VALUE` column contains the return value of the executed script. The `TITLE` column contains the titles of the rendered PNG images. The `IMAGE` column is a BLOB column containing the bytes of the `PNG` images rendered by the executed script.

The following example shows the PNG output of a `pyqRowEval` function call.

```
SQL> column name format a7
column valueformat a5
column title format a16
column image format a15
select *
from table(pyqRowEval(
    inp_nam => 'GRADE',
    par_lst => '{"oml_graphics_flag":true}',
    out_fmt => 'PNG',row_num => 5,
    scr_name => 'plotTwoImages',
    scr_owner =>NULL
));


NAME            ID VALUE TITLE            IMAGE
------- --------- ----- ---------------- ---------------
CHUNK_1          1 7     Random red dots  6956424F5277304
                                          B47676F41414141
                                          4E5355684555674
                                          141416F41414141
                                          486743415941414
                                          1413130647A6B41
                                          41414142484E435
                                          356514943416749
                                          6641686B6941414
                                          141416C7753466C
                                          7A41414150

CHUNK_1          2 7     Random blue dots 6956424F5277304
                                          B47676F41414141
                                          4E5355684555674
                                          141416F41414141
                                          486743415941414
                                          1413130647A6B41
                                          41414142484E435
                                          356514943416749
                                          6641686B6941414
                                          141416C7753466C
                                          7A41414150

CHUNK_2          1 7     Random red dots  6956424F5277304
                                          B47676F41414141
                                          4E5355684555674
```

```
                                        141416F41414141
                                        486743415941414
                                        1413130647A6B41
                                        41414142484E435
                                        356514943416749
                                        6641686B6941414
                                        141416C7753466C
                                        7A41414150

CHUNK_2          2 7     Random blue dots 6956424F5277304
                                        B47676F41414141
                                        4E5355684555674
                                        141416F41414141
                                        486743415941414
                                        1413130647A6B41
                                        41414142484E435
                                        356514943416749
                                        6641686B6941414
                                        141416C7753466C
                                        7A41414150

4 rows selected.
```

Asynchronous Mode Output

When you set `oml_async_flag` to `true` to run an asynchronous job, set `OUT_FMT` to `NULL` for jobs that return non-XML results, or set it to XML for jobs that return XML results, as described below.

See also oml_async_flag Argument.

Asynchronous Mode: Non-XML Output

When submitting asynchronous jobs, for JSON, PNG, and relational outputs, set `OUT_FMT` to `NULL` when submitting the job. When fetching the job result, specify `OUT_FMT` in the `pyqJobResult` call.

The following example shows how to get the JSON output from an asynchronous `pyqIndexEval` function call:

```
SQL> select *
    from table(pyqGroupEval(
        inp_nam => 'GRADE',
        par_lst => '{"oml_async_flag":true, "oml_graphics_flag":true}',
        out_fmt => NULL,
        grp_col => 'GENDER',
        ord_col => NULL,
        scr_name => 'inp_twoimgs',
        scr_owner => NULL
    ));


NAME
--------------------------------------------------------------------------------
VALUE
--------------------------------------------------------------------------------
```

```
https://<host name>/oml/tenants/<tenant name>/databases/<database
name>/api/py-scripts/v1/jobs/<job id>

1 row selected.


SQL> select * from pyqJobStatus(
        job_id => '<job id>');


NAME
--------------------------------------------------------------------------------
VALUE
--------------------------------------------------------------------------------

https://<host name>/oml/tenants/<tenant name>/databases/<database
 name>/api/py-scripts/v1/jobs/<job id>/result

1 row selected.


SQL> column name format a7
column value format a5
column title format a16
column image format a15
select * from pyqJobResult(
     job_id => '<job id>',
     out_fmt => 'PNG'
     );


NAME            ID VALUE TITLE            IMAGE
------- ---------- ----- ---------------- ---------------
GROUP_F          1 7     Random red dots  6956424F5277304
                                          B47676F41414141
                                          4E5355684555674
                                          141416F41414141
                                          486743415941414
                                          1413130647A6B41
                                          41414142484E435
                                          356514943416749
                                          6641686B6941414
                                          141416C7753466C
                                          7A4141415059514
                                          141443245427144
                                          2B6E61514141414
                                          468305256683055
                                          32396D644864686
                                          36D554162574630
                                          634778766447787
                                          0596942325A584A
                                          7A615739754D793
                                          4784C6A49734947

GROUP_F          2 7     Random blue dots 6956424F5277304
                                          B47676F41414141
```

```
                                                4E5355684555674
                                                141416F41414141
                                                486743415941414
                                                1413130647A6B41
                                                41414142484E435
                                                356514943416749
                                                6641686B6941414
                                                141416C7753466C
                                                7A4141415059514
                                                141443245427144
                                                2B6E61514141414
                                                468305256683055
                                                32396D644864686
                                                36D554162574630
                                                634778766447787
                                                0596942325A584A
                                                7A615739754D793
                                                4784C6A49734947

GROUP_M          1 7     Random red dots       6956424F5277304
                                                B47676F41414141
                                                4E5355684555674
                                                141416F41414141
                                                486743415941414
                                                1413130647A6B41
                                                41414142484E435
                                                356514943416749
                                                6641686B6941414
                                                141416C7753466C
                                                7A4141415059514
                                                141443245427144
                                                2B6E61514141414
                                                468305256683855
                                                32396D644864686
                                                36D554162574630
                                                634778766447787
                                                0596942325A584A
                                                7A615739754D793
                                                4784C6A49734947

GROUP_M          2 7     Random blue dots      6956424F5277304
                                                B47676F41414141
                                                4E5355684555674
                                                141416F41414141
                                                486743415941414
                                                1413130647A6B41
                                                41414142484E435
                                                356514943416749
                                                6641686B6941414
                                                141416C7753466C
                                                7A4141415059514
                                                141443245427144
                                                2B6E61514141414
                                                468305256683055
                                                32396D644864686
                                                36D554162574630
```

```
                                                634778766447787
                                                0596942325A584A
                                                7A615739754D793
                                                4784C6A49734947

4 rows selected
```

Asynchronous Mode: XML Output

If XML output is expected from the asynchronous job, you must set `OUT_FMT` to `XML` when submitting the job and fetching the job result.

The following example shows how to get the XML output from an asynchronous `pyqIndexEval` function call.

```
SQL> select *
    from table(pyqIndexEval(
        par_lst => '{"oml_async_flag":true}',
        out_fmt => 'XML',
        times_num => 3,
        scr_name => 'idx_ret_df',
        scr_owner => NULL
));


NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--
https://<host name>/oml/tenants/<tenant name>/databases/<database
name>/api/py-scripts/v1/jobs/<job id>

1 row selected.


SQL> select * from pyqJobStatus(
    job_id => '<job id>'
);


  2
NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--

https://<host name>/oml/tenants/<tenant name>/databases/<database
name>/api/py-scripts/v1/jobs/<job id>/result
```

```
1 row selected.


SQL> select * from pyqJobResult(
        job_id => '<job id>',
        out_fmt => 'XML'
);


  2    3    4
NAME
--------------------------------------------------------------------------------
--
VALUE
--------------------------------------------------------------------------------
--
1
<root><pandas_dataFrame><ROW-
pandas_dataFrame><ID>1</ID><RES>a</RES></ROW-pandas
_dataFrame></pandas_dataFrame></root>

2
<root><pandas_dataFrame><ROW-
pandas_dataFrame><ID>2</ID><RES>b</RES></ROW-pandas
_dataFrame></pandas_dataFrame></ro

3
<root><pandas_dataFrame><ROW-
pandas_dataFrame><ID>3</ID><RES>c</RES></ROW-pandas
_dataFrame></pandas_dataFrame></root>

3 rows selected
```

8

Administrative Tasks for Oracle Machine Learning for Python

If you find that your Python process is consuming too many of your machine's resources, or causing your machine to crash, you can get information about, or set limits for, the resources Python is using.

The Python system and process utilities library `psutil` is a cross-platform library for retrieving information on running processes and system utilization, such as CPU, memory, disks, network, and sensors, in Python. It is useful for system monitoring, profiling, limiting process resources, and the management of running processes.

The function `psutil.Process.rlimit` gets or sets process resource limits. In `psutil`, process resource limits are constants with names beginning with `psutil.RLIMIT_`. Each resource is controlled by a soft limit and hard limit tuple.

For example, `psutil.RLIMIT_AS` represents the maximum size (in bytes) of the virtual memory (address space) used by the process. The default limit of `psutil.RLIMIT_AS` can be -1 (`psutil.RLIM_INFINITY`). You can lower the resource limit of `psutil.RLIMIT_AS` to prevent your Python program from loading too much data into memory, as shown in the following example.

Example 8-1 Resource Control with psutil.RLIMIT_AS

```
import psutil
import numpy as np

# Get the current OS process.
p = psutil.Process()

# Get a list of available resources.
[attr for attr in dir(psutil) if attr[:7] == 'RLIMIT_']

# Display the Virtual Memory Size of the current process.
p.memory_info().vms

# Get the process resource limit RLIMIT_AS.
soft, hard = p.rlimit(psutil.RLIMIT_AS)
print('Original resource limits of RLIMIT_AS (soft/hard): {}/{}'.format(soft,
hard))

# Check the constant used to represent the limit for an unlimited resource.
psutil.RLIM_INFINITY

# Set resource RLIMIT_AS (soft, hard) limit to (1GB, 2GB).
p.rlimit(psutil.RLIMIT_AS, (pow(1024,3)*1, pow(1024,3)*2))

# Get the current resource limit of RLIMIT_AS.
cur_soft, cur_hard = p.rlimit(psutil.RLIMIT_AS)
print('Current resource limits of RLIMIT_AS (soft/hard): {}/
```

```
{}'.format(cur_soft, cur_hard))

# Define a list of sizes to be allocated in MB (megabytes).
sz = [5, 10, 20]

# Define a megabyte variable in bytes.
MB = 1024*1024

# Allocate an increasing amount of data.
for val in sz:
    stmt = "Allocate %s MB " % val
    try:
        print("virtual memory: %d MB" % int(p.memory_info().vms/MB))
        m = np.arange(val*MB/8, dtype="u8")
        print(stmt + " Success.")
    except:
        print(stmt + " Fail.")
        raise

# Delete the allocated variable.
del m

# Raise the soft limit of RLIMIT_AS to 2GB.
p.rlimit(psutil.RLIMIT_AS, (pow(1024,3)*2, pow(1024,3)*2))

# Get the current resource limit of RLIMIT_AS.
cur_soft, cur_hard = p.rlimit(psutil.RLIMIT_AS)
print('Current resource limits of RLIMIT_AS (soft/hard): {}/
{}'.format(cur_soft, cur_hard))

# Retry: allocate an increasing amount of data.
for val in sz:
    stmt = "Allocate %s MB " % val
    try:
        print("virtual memory: %d MB" % int(p.memory_info().vms/MB))
        m = np.arange(val*MB/8, dtype="u8")
        print(stmt + " Success.")
    except:
        print(stmt + " Fail.")
        raise
```

Listing for This Example

```
>>> import psutil
>>> import numpy as np
>>>
>>> # Get the current OS process.
... p = psutil.Process()
>>>
>>> # Get a list of available resources.
... [attr for attr in dir(psutil) if attr[:7] == 'RLIMIT_']
['RLIMIT_AS', 'RLIMIT_CORE', 'RLIMIT_CPU', 'RLIMIT_DATA',
 'RLIMIT_FSIZE', 'RLIMIT_LOCKS', 'RLIMIT_MEMLOCK', 'RLIMIT_MSGQUEUE',
 'RLIMIT_NICE', 'RLIMIT_NOFILE', 'RLIMIT_NPROC', 'RLIMIT_RSS',
 'RLIMIT_RTPRIO', 'RLIMIT_RTTIME', 'RLIMIT_SIGPENDING', 'RLIMIT_STACK']
```

```
>>>
>>> # Display the Virtual Memory Size of the current process.
... p.memory_info().vms
413175808
>>>
>>> # Get the process resource limit RLIMIT_AS.
... soft, hard = p.rlimit(psutil.RLIMIT_AS)
>>> print('Original resource limits of RLIMIT_AS (soft/hard): {}/
{}'.format(soft, hard))
Original resource limits of RLIMIT_AS (soft/hard): -1/-1
>>>
>>> # Check the constant used to represent the limit for an unlimited
resource.
... psutil.RLIM_INFINITY
-1
>>>
>>> # Set the resource RLIMIT_AS (soft, hard) limit to (1GB, 2GB).
... p.rlimit(psutil.RLIMIT_AS, (pow(1024,3)*1, pow(1024,3)*2))
>>>
>>> # Get the current resource limit of RLIMIT_AS.
... cur_soft, cur_hard = p.rlimit(psutil.RLIMIT_AS)
>>> print('Current resource limits of RLIMIT_AS (soft/hard): {}/
{}'.format(cur_soft, cur_hard))
Current resource limits of RLIMIT_AS (soft/hard): 1073741824/2147483648
>>>
>>> # Define a list of sizes to be allocated in MB (megabytes).
... sz = [100, 200, 500, 1000]
>>>
>>> # Define a megabyte variable in bytes.
... MB = 1024*1024
>>>
>>> # Allocate an increasing amount of data.
... for val in sz:
...     stmt = "Allocate %s MB " % val
...     try:
...         print("virtual memory: %d MB" % int(p.memory_info().vms/MB))
...         m = np.arange(val*MB/8, dtype="u8")
...         print(stmt + " Success.")
...     except:
...         print(stmt + " Fail.")
...         raise
...
virtual memory: 394 MB
Allocate 100 MB Success.
virtual memory: 494 MB
Allocate 200 MB Success.
virtual memory: 594 MB
Allocate 500 MB Fail.
Traceback (most recent call last):
  File "<stdin>", line 6, in <module>
MemoryError
>>>
>>> # Delete the allocated variable.
... del m
>>>
>>> # Raise the soft limit of RLIMIT_AS to 2GB.
```

```
... p.rlimit(psutil.RLIMIT_AS, (pow(1024,3)*2, pow(1024,3)*2))
>>>
>>> # Get the current resource limit of RLIMIT_AS.
... cur_soft, cur_hard = p.rlimit(psutil.RLIMIT_AS)
>>> print('Current resource limits of RLIMIT_AS (soft/hard): {}/
{}'.format(cur_soft, cur_hard))
Current resource limits of RLIMIT_AS (soft/hard): 2147483648/2147483648
>>>
>>> # Retry: allocate an increasing amount of data.
... for val in sz:
...     stmt = "Allocate %s MB " % val
...     try:
...         print("virtual memory: %d MB" % int(p.memory_info().vms/MB))
...         m = np.arange(val*MB/8, dtype="u8")
...         print(stmt + " Success.")
...     except:
...         print(stmt + " Fail.")
...         raise
...
virtual memory: 458 MB
Allocate 100 MB Success.
virtual memory: 558 MB
Allocate 200 MB Success.
virtual memory: 658 MB
Allocate 500 MB Success.
virtual memory: 958 MB
Allocate 1000 MB Success.
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