Oracle® Cloud

Using Oracle Machine Learning User Interface on Autonomous Database

E78525-76
May 2025

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Preface

This document describes how to use Oracle Machine Learning and provides references to related documentation.

- Audience
  This document is intended for data scientists, developers, and business users.
- Conventions
- Documentation Accessibility
- Related Resources
  For more information, see these related resources.

Audience

This document is intended for data scientists, developers, and business users.

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

Documentation Accessibility

For information about Oracle's commitment to accessibility, visit the Oracle Accessibility Program website at `http://www.oracle.com/pls/topic/lookup?ctx=acc&id=docacc`.

Access to Oracle Support

Oracle customers that have purchased support have access to electronic support through My Oracle Support. For information, visit `http://www.oracle.com/pls/topic/lookup?ctx=acc&id=info` or visit `http://www.oracle.com/pls/topic/lookup?ctx=acc&id=trs` if you are hearing impaired.

Related Resources

For more information, see these related resources.

- *Getting Started with Oracle Cloud* Getting Started with Oracle Cloud
- *Accessibility Guide for Oracle Cloud Services* Accessibility Guide for Oracle Cloud Services

1

What's New

Provides a summary of the latest enhancements and features for Oracle Machine Learning User Interface on Oracle Autonomous Database.

Table 1-1 New Features

Features	Description
Support for email notifications	Oracle Machine Learning User Interface has been enhanced with the functionality to send email notifications for jobs. Jobs allow you to schedule the running of notebooks. You can now send email notifications to the specified users' email addresses about the selected events for the job. See Create Jobs to Schedule Notebooks for more information on how to send email notifications.
Support for NVIDIA GPU compute capabilities in OML Notebooks	Oracle Machine Learning Notebooks offers support for NVIDIA GPUs (Graphics Processing Unit) compute capabilities. With the new GPU capabilities in Oracle Machine Learning Notebooks, you can run advanced machine learning algorithms such as deep learning models, transformers (embedding models) for generating vectors, and small LLMs. The GPU feature is enabled for Oracle Autonomous Data Warehouse Serverless or Oracle Autonomous Transaction Processing Serverless instances with 16 or more ECPUs specified for the OML application. Both the Licensed and the Bring Your Own Licence (BYOL) versions are available. For cost details, refer to the *Oracle PaaS and IaaS Universal Credits Service Descriptions* document available on the Oracle Cloud Services contracts page. **Note:** GPU resources are available only on paid Oracle Autonomous Database Serverless instances. GPU resources are not available on Always Free Oracle Autonomous Database Serverless or Oracle Autonomous Database Serverless instances with fewer than 16 ECPUs allocated.
Oracle Machine Learning Notebooks Classic deprecated	Oracle Machine Learning Notebooks Classic has been deprecated since June 11, 2024. On October 29, 2024, you will no longer be able to create Classic notebooks, save them as templates, or select them for job scheduling. Existing Classic notebooks can be opened in read-only mode. You can continue to convert Classic notebooks to the new format using the **Copy to OML Notebooks** button on the Notebook Classic listing page. On December 31, 2024, Classic notebooks will no longer be available. The ADMIN user can access Classic notebooks in read-only mode and convert them to the new format. Jobs that still use Classic notebooks will show a status of `Disabled`. Associated job logs will not be accessible. On June 4, 2025, the ADMIN user will no longer have access to Classic notebooks, and any remaining notebooks will be deleted. If you have Classic notebooks or Classic template notebooks (personal or shared) that you wish to keep, you must convert these to the new format. If you have jobs that rely on Classic notebooks, these jobs must either be updated with a new notebook or recreated with a new notebook.

Table 1-1 (Cont.) New Features

Features	Description
Oracle Machine Learning Notebooks update	Oracle Machine Learning User Interface offers an enhanced notebook environment. Initially released as **Notebooks EA (Early Adopter)** in Oracle Autonomous Database Serverless, it is now accessed using **Notebooks** under the left navigation menu and home page. The enhanced notebook interface supports SQL, SQL Script, R, Python, Conda, and Markdown interpreters. You can write code, text, create rich visualizations, and perform data analytics including machine learning in the enhanced notebooks. **Note:** The original Zeppelin-based notebook interface is still available for a limited time under the left navigation menu item **Notebooks Classic**.
Support for model monitoring in Oracle Machine Learning User Interface	Oracle Machine Learning User Interface offers support for model monitoring. It allows you to create model monitors. The model monitors enable you to monitor the quality of model predictions over time, and provides you with insights on the underlying causes.
Support for data monitoring in Oracle Machine Learning User Interface	Oracle Machine Learning User Interface offers support for data monitoring. It allows you to monitor your data and evaluate how your data evolves over time. It helps you with insights on trends and multivariate dependencies in the data. It also provides you an early warning about data drift.

Table 1-1 (Cont.) New Features

Features	Description
Support for enhanced notebooks in Autonomous Database - Serverless	Oracle Machine Learning User Interface offers a new enhanced notebook environment *Notebooks EA (Early Adopter)* in Autonomous Database - Serverless. The enhanced notebook supports SQL, SQL Script, R, Python, Conda, and Markdown interpreters. You can write code, text, create rich visualizations, and perform data analytics including machine learning in the enhanced notebooks. **Note:** The enhanced notebook is available in the Oracle Machine Learning Notebook Early Adopter release. During the Early Adopter release period, both Zeppelin and the enhanced notebooks will be available, after which all notebooks will be converted to the new notebook environment. During the Early Adopter phase, you can use both the original Zeppelin and new Early Adopter notebook interfaces. Notebooks in the original interface can be copied to the Early Adopter release. The enhanced notebook interface in Oracle Autonomous Database Serverless provides the following enhanced features and user experiences: • **Rich and enhanced user experience:** The enhanced notebook offers modern look and feel, and richer visualization with many charting options. This will benefit users to better visualize and understand their data. In addition, it offers some useful features like side-by-side versions comparison, option to add comments to paragraphs, full screen size mode for paragraphs, option to define paragraph dependency, and so on. • **High availability:** The enhanced notebook, a multi-tenant application is deployed to the same middle-tier as Oracle Machine Learning server, and this requires no additional resources. Therefore, it is always running and readily available to render the new enhanced notebooks. • **High scalability:** The enhanced notebook assures high scalability in production. To scale up due to increased user demands, additional notebook instances can be easily added. There are tools to monitor system loads, and if a system is consistently overloaded, additional instance can be easily added to mitigate risks related to scalability.
Support for Python and R third-party libraries	Third-party libraries for Python and R are available on Oracle Machine Learning Notebooks. Oracle Machine Learning UI provides the Conda interpreter to install third-party Python and R libraries inside a notebook session. Conda is an open-source package and environment management system that enables the use of environments containing third-party Python and R libraries. • Users with `OML_SYS_ADMIN` role can install Python and R third-party libraries and upload them to object storage for persistence. The user with `OML_SYS_ADMIN` role is the administrator, also known as the admin. • Users with `OML_DEVELOPER` role can use the Conda interpreter to download and activate the third-party libraries using the Conda environment that are provisioned by the administrator. The user with `OML_DEVELOPER` role is the regular Oracle Machine Learning user.

Table 1-1 (Cont.) New Features

Features	Description
Support for R	Oracle Machine Learning for R is supported within Oracle Machine Learning Notebooks. By using Oracle Machine Learning for R, you can perform data exploration and machine learning modeling. OML4R is available through Oracle Machine Learning Notebooks on Oracle Autonomous Database Serverless, including Autonomous Data Warehouse , Autonomous Transaction Processing and Oracle Autonomous JSON Database services.
Support for cross-region Autonomous Data Guard	Oracle Machine Learning Notebooks provide cross-region Autonomous Data Guard support in newly provisioned and migrated databases.
Oracle Machine Learning repository migrated from Serverless database to each respective Oracle Autonomous Database instance	The Oracle Machine Learning (OML) repository has been migrated from Serverless database to each respective Oracle Autonomous Database instance. The migration of the Oracle Machine Learning repository ensures: • That all OML objects such as tables, jobs, stored procedures, and metadata are moved to the appropriate Oracle Autonomous Database instance. • Provides support for Refreshable Clones, which enables cloning of the Oracle Machine Learning metadata as well. **Note:** The migration of the Oracle Machine Learning (OML) repository is expected to be completed over a period of 30 days. The OML repository version is mentioned in **About** in the `<user>` drop-down list on the top right corner of your Oracle Machine Learning User Interface page. If the version is `1.0.0.0.0`, it indicates that the OML metadata is still in the Serverless database. If the version is `22.x`, it indicates that the OML repository has been migrated to your Oracle Autonomous Database instance.
Oracle Machine Learning Notebook supported on all Oracle Autonomous Database clones	Oracle Machine Learning Notebook is supported on all types of Oracle Autonomous Database - Serverless clones, including: • Full Clone: a new database is created with the data in the source database and metadata. • Refreshable Clone: a read-only full clone is created that can be easily refreshed with the data from the source database • Metadata Clone: a new database is created that includes all of the source database schema metadata, but not the source database data. **Note:** For a metadata clone, the Example Template notebooks are not supported.

2
Get Started

This section discusses how to get started with Oracle Machine Learning User Interface, and use Apache Zeppelin-based machine learning notebooks along with the OML Notebooks, where you can perform data exploration and data visualization, data preparation and machine learning.

- Get Started with Oracle Machine Learning User Interface
  Here is how you can get started with Oracle Machine Learning User Interface (UI).
- Access Oracle Machine Learning User Interface
  You can access Oracle Machine Learning **User Interface** from Autonomous Database.
- About Oracle Machine Learning Notebooks
  Oracle Machine Learning Notebooks is a collaborative web-based interface that supports notebook creation, scheduled run, and versioning. You can document work using Markdown and run SQL, R, and Python code for data exploration, visualization, and preparation, and machine learning model building, evaluation, and deployment. Oracle Machine Learning Notebooks also provide the Conda interpreter to create a custom conda environment that includes user-specified third-party Python and R libraries.
- Oracle Machine Learning User Interface Home Page
  The Oracle Machine Learning User Interface home page provides you quick links to important interfaces, help links, and the log of your high-level recent activities.

Related Topics

- About AutoML UI
- Jobs
  Jobs allow you to schedule the running of notebooks. On the Jobs page, you can create jobs, duplicate jobs, start and stop jobs, delete jobs, and monitor job status by viewing job logs, which are read-only notebooks.
- Templates
  By using the Oracle Machine Learning Notebooks templates, you can collaborate with other users by sharing your work, publishing your work as reports, and by creating notebooks from templates. You can store your notebooks as templates, share notebooks, and provide sample templates to other users.

2.1 Get Started with Oracle Machine Learning User Interface

Here is how you can get started with Oracle Machine Learning User Interface (UI).

1. Request access to Oracle Machine Learning UI. Contact your Service Administrator to create your OML user credentials and provide access to your Oracle Machine Learning UI account.
2. Access the Oracle Machine Learning UI account by using your credentials. In case you forget your password, then request the Administrator to reset it.

> **Note:**
>
> Once you receive your new password, you must change it immediately. Refer to the Oracle Machine Learning password policy for more information.

3. Once you log in for the first time, a workspace and project will be created for you. You can start creating your notebook. You can also create your additional projects in the default workspace or create new workspace with corresponding projects.

> **Note:**
>
> If you are using Oracle Cloud Free Tier, you have to provision an Oracle Autonomous Database. For more information, see Provision Autonomous Database

Related Topics

- OML Notebooks Interactive Tour
- About Oracle Machine Learning Password Policy
  All Oracle Machine Learning users must follow the password policy to create a strong and secure password.

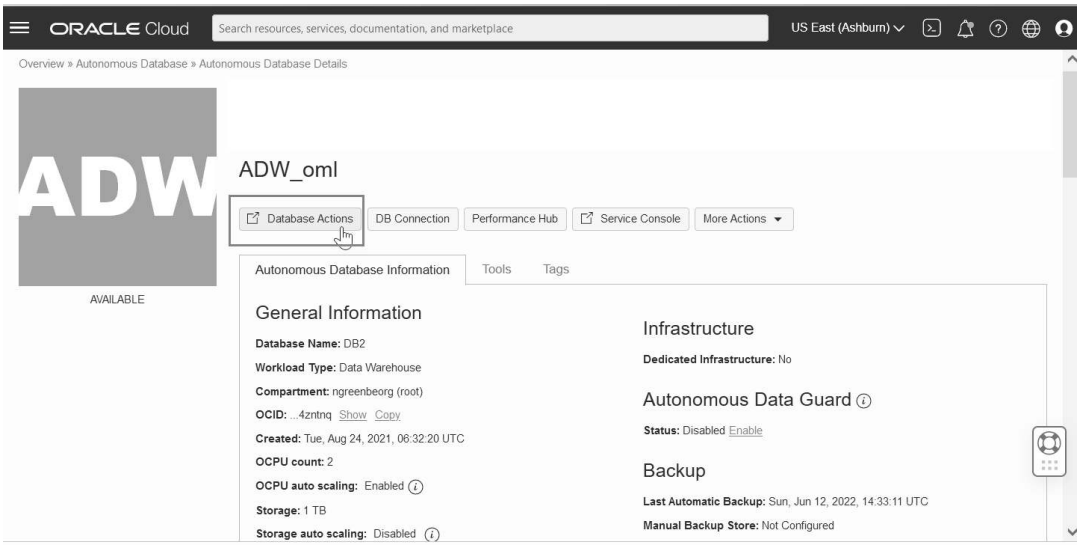
2.2 Access Oracle Machine Learning User Interface

You can access Oracle Machine Learning **User Interface** from Autonomous Database.

To access Oracle Machine Learning User Interface (UI) from Autonomous Database:

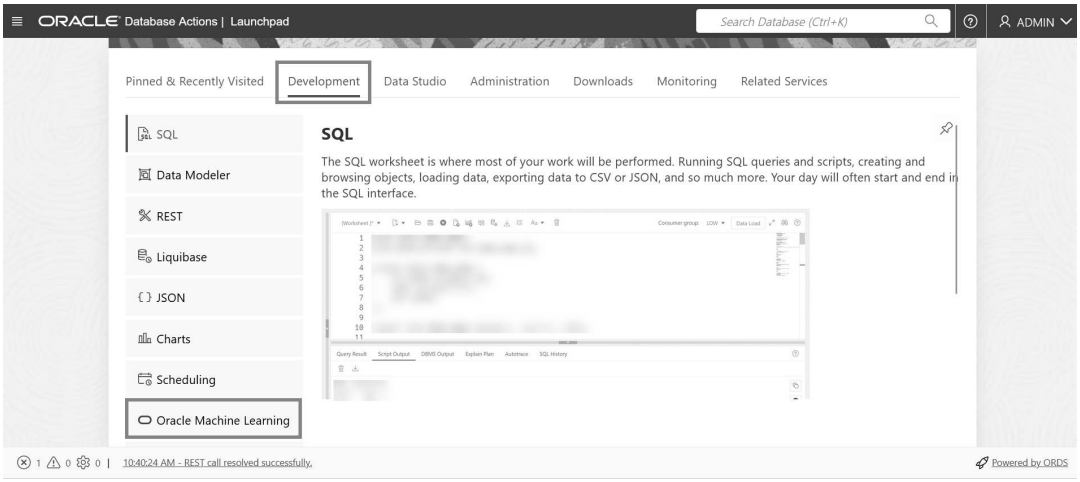
1. Select your Autonomous Database instance and on the Autonomous Database details page click **Database Actions**.

Figure 2-1 Database Actions



2. On the Database Actions page, go to the **Development** section and click **Oracle Machine Learning**. The Oracle Machine Learning sign in page opens.

Figure 2-2 Oracle Machine Learning option on Database Actions - Development tab



3. On the Oracle Machine Learning sign in page, enter your username and password.
4. Click **Sign In**.

This opens the Oracle Machine Learning user application.

- About Oracle Machine Learning Password Policy
  All Oracle Machine Learning users must follow the password policy to create a strong and secure password.

2.2.1 About Oracle Machine Learning Password Policy

All Oracle Machine Learning users must follow the password policy to create a strong and secure password.

When changing or modifying your Oracle Machine Learning password, ensure that you follow these conditions:

- The password must be between 12 and 30 characters long. It must include at least one uppercase letter, one lowercase letter, and one numeric character.
- The password cannot contain the username.
- The password cannot be one of the last 4 passwords used for the same username.
- The password cannot contain the double quote (") character.
- The password must not be the same password that is set less than 24 hours ago.

2.3 About Oracle Machine Learning Notebooks

Oracle Machine Learning Notebooks is a collaborative web-based interface that supports notebook creation, scheduled run, and versioning. You can document work using Markdown and run SQL, R, and Python code for data exploration, visualization, and preparation, and machine learning model building, evaluation, and deployment. Oracle Machine Learning Notebooks also provide the Conda interpreter to create a custom conda environment that includes user-specified third-party Python and R libraries.

Key features of Oracle Machine Learning Notebooks:

- Allows collaboration among data scientists, business and data analysts, application and dashboard developers, Database Administrators, and IT professionals

- Leverages the scalability and performance of Oracle Autonomous Database Platform
- Supports scheduling notebooks as jobs for one-off and recurring running of notebooks
- Enables versioning of notebooks
- Supports interpreters for SQL, PL/SQL, Python, R, Markdown, and Conda
- Typical Actions when Using Oracle Machine Learning Notebooks
  To begin with Oracle Machine Learning Notebooks, refer to the tasks listed in the table as a guide.

2.3.1 Typical Actions when Using Oracle Machine Learning Notebooks

To begin with Oracle Machine Learning Notebooks, refer to the tasks listed in the table as a guide.

Tasks	More Information
Access Oracle Machine Learning User Interface	Access Oracle Machine Learning User Interface (UI)
Create workspaces	Create Projects and Workspaces
Create projects	Create Projects and Workspaces
Access and create a notebook	Access and create a Notebook
Enable GPU Compute Capabilities in a Notebook	Enable GPU Compute Capabilities in a Notebook through the Python Interpreter
Create and Run an AutoML Experiment	Create AutoML UI Experiment
Run a Notebook using SQL Interpreter	Use the SQL Interpreter in a Notebook Paragraph
Run a Notebook using Python Interpreter	Use the Python Interpreter in a Notebook Paragraph
Run a Notebook using R Interpreter	Use the R Interpreter in a Notebook Paragraph
Run a Notebook using Conda Interpreter	Use the Conda Interpreter in a Notebook Paragraph
Use the Markdown Interpreter	Use the Markdown Interpreter and Generate Static html from Markdown Plain Text
Create a Data Monitor	Create a Data Monitor
Create a Model Monitor	Create a Model Monitor
Use the Scratchpad	Use the Scratchpad
Create jobs to schedule notebooks	Create Jobs to Schedule Notebook

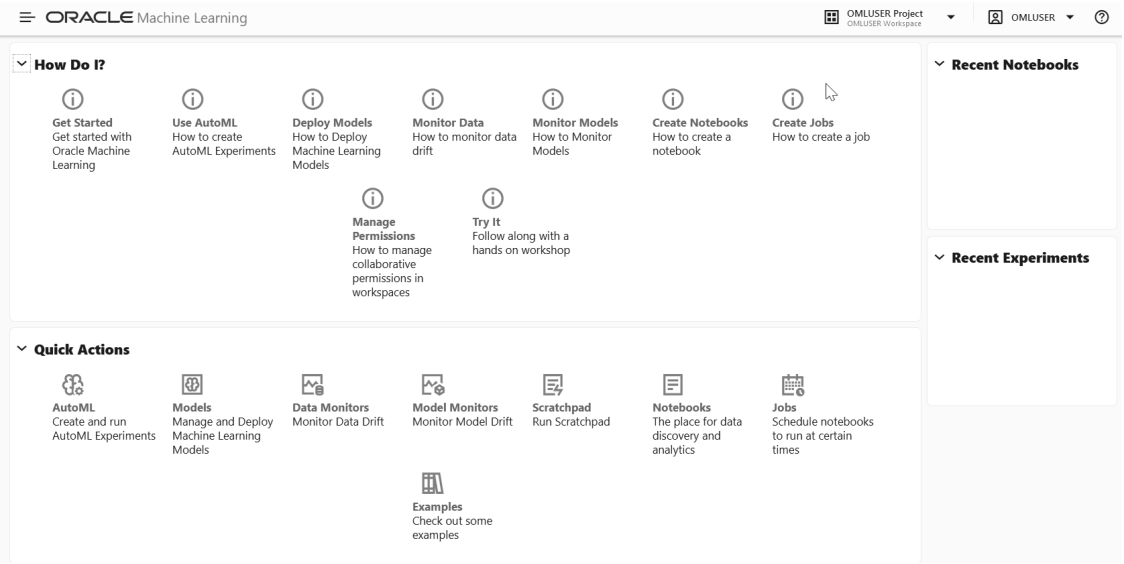
Related Topics

- Grant Workspace Permissions
  You can collaborate with other users in Oracle Machine Learning User Interface (UI) by granting permissions to access your workspace. A workspace consists of projects. Projects consist of notebooks and experiments.

2.4 Oracle Machine Learning User Interface Home Page

The Oracle Machine Learning User Interface home page provides you quick links to important interfaces, help links, and the log of your high-level recent activities.

Figure 2-3 Oracle Machine Learning UI Home Page



On the home page, you can access:

- The **How Do I** help links to:
  - **Get Started**
  - **Use AutoML**
  - **Deploy Models**
  - **Monitor Data**
  - **Create Notebooks**
  - **Create Jobs**
  - **Manage Permissions**
  - **Try It**
- The **Quick Actions** links to:
  - **AutoML**
  - **Models**
  - **Data Monitors**
  - **Model Monitors**
  - **Scratchpad**
  - **Notebooks**
  - **Jobs**
  - **Examples**
- The log of your **Recent Activities.**
- The application navigation by clicking  on the top left corner of the home page.

- The options to select and create new projects, access recent projects, manage workspace, and set workspace permissions by clicking  on the top right corner of the home page.
- The **Recent Notebooks** on the right pane of the home page.

Related Topics

- Notebooks
- Jobs
  Jobs allow you to schedule the running of notebooks. On the Jobs page, you can create jobs, duplicate jobs, start and stop jobs, delete jobs, and monitor job status by viewing job logs, which are read-only notebooks.
- Examples
  The Example Templates page lists the pre-populated Oracle Machine Learning notebook templates. You can view and use these templates to create your notebooks.

3
Project and Workspaces

A project is a logical grouping of notebooks and experiments within a workspace. A workspace is a virtual space where your projects reside, and multiple users can work on different projects. Permissions are granted on workspaces, and not on projects.

- Create Projects
  A project is a logical grouping of notebooks and experiments within a workspace. While you may own many projects, other workspaces and projects may be shared with you.
- Create and Manage Workspaces and Projects
  You can create and manage new projects and workspaces, provide access to your workspaces, manage permissions for users, and edit and delete workspaces.
- Grant Workspace Permissions
  You can collaborate with other users in Oracle Machine Learning User Interface (UI) by granting permissions to access your workspace. A workspace consists of projects. Projects consist of notebooks and experiments.

3.1 Create Projects

A project is a logical grouping of notebooks and experiments within a workspace. While you may own many projects, other workspaces and projects may be shared with you.

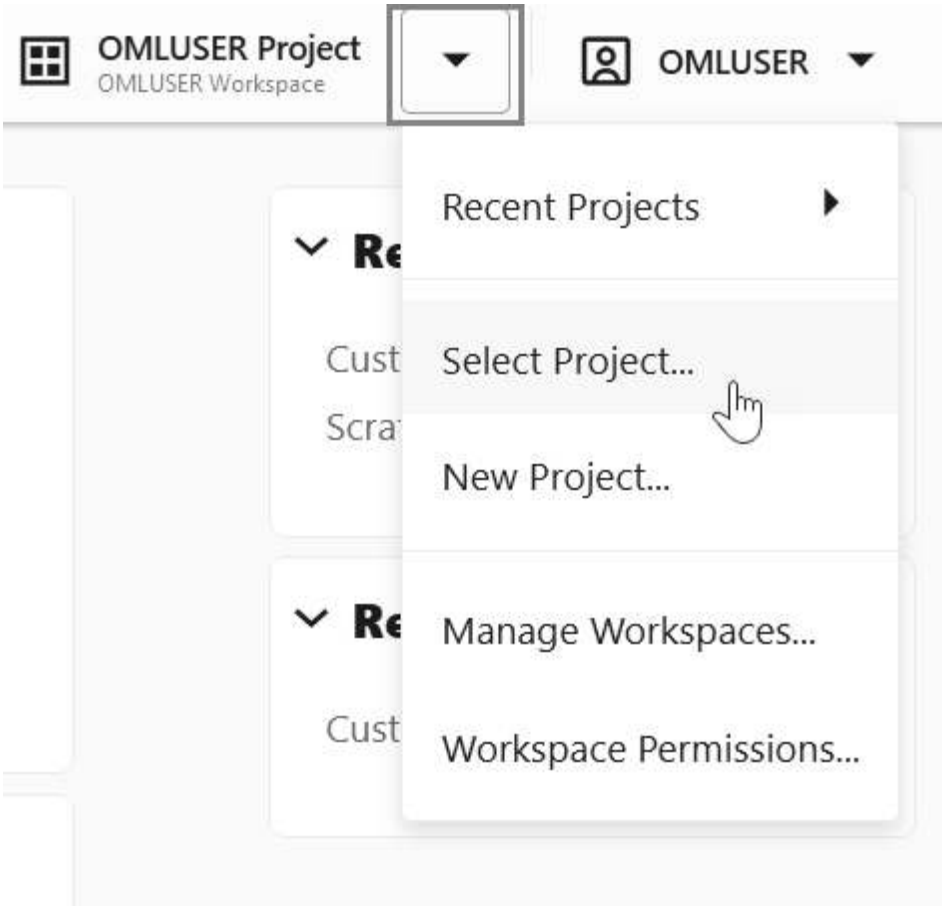
The initial workspace and the default project is created for you when you log in to Oracle Machine Learning User Interface (UI) for the first time. To create a new project:

1. On the top right corner of Oracle Machine Learning UI home page, click the project drop-down list. The project name and the workspace, in which the project resides, are displayed here. In this screenshot, the project name is `OMLUSER`, and the workspace name is also `OMLUSER`. If a default project exists, then the default project name is displayed here.

   > **Note:**
   >
   > The last project that you have worked on is stored in the browser cache and is the default project. If you clear the cache, then no default exists and you must select a project.

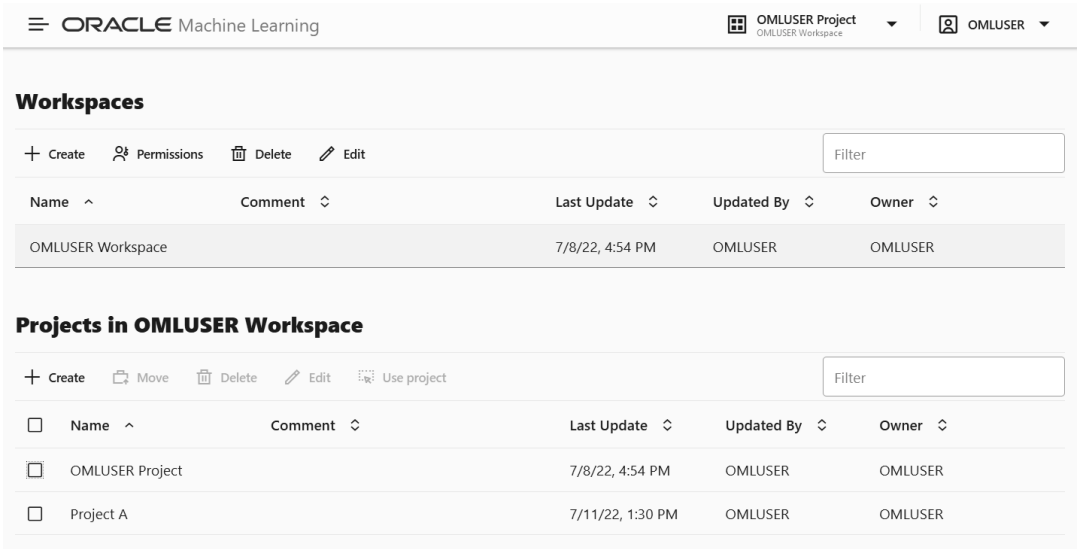
   You can create projects by using the **New Project** option: Click the down arrow next to the **Project** field and then click **New Project.** The Create Project dialog opens.

Figure 3-1 <OMLUSER> Project drop-down menu



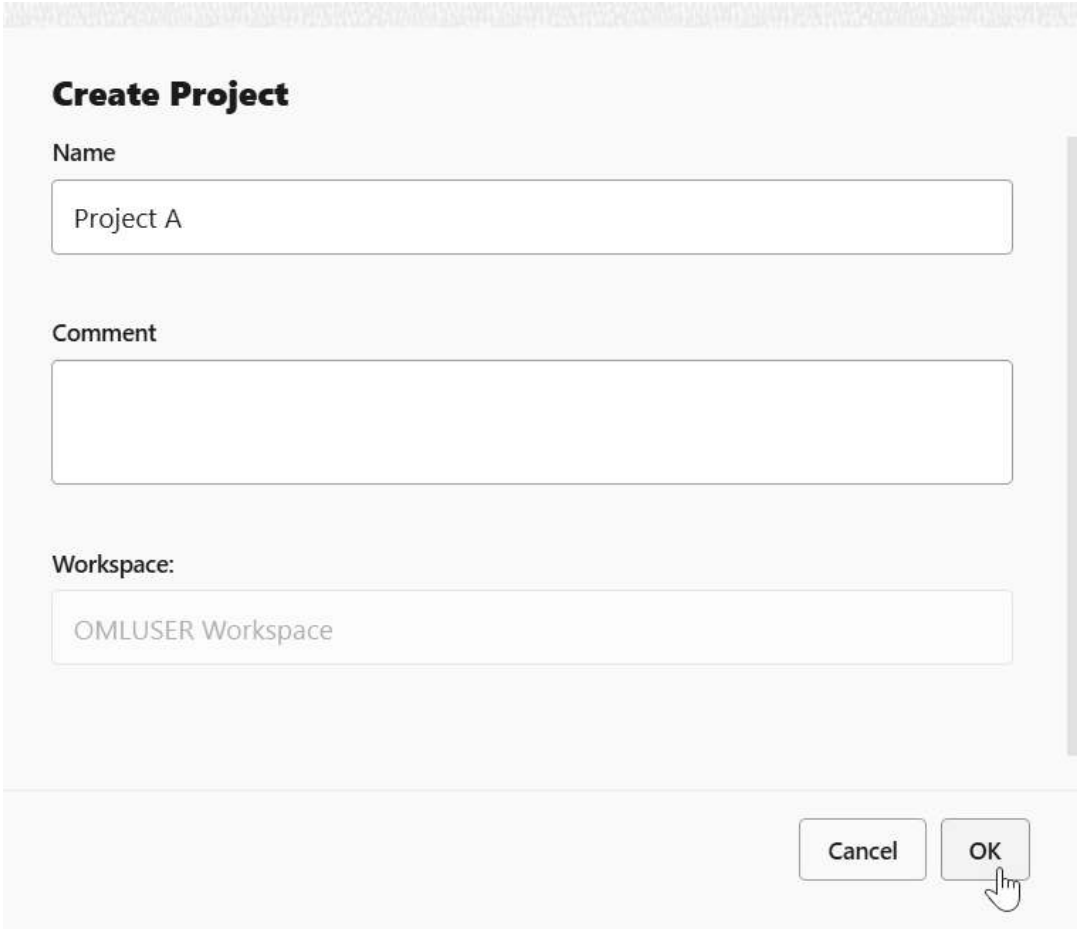
Use the **Create** option on the Workspaces page: Click the down arrow next to the **Project** field and click **Manage Workspace.** On the Manage Workspace page, under the *Projects in Workspace* section, click **Create.** The Create Project dialog opens.

Figure 3-2 Create Project in Manage Workspace page



2. In the **Create Project** dialog, enter the following:

Figure 3-3 Create Project dialog



   a. **Name:** Enter a name for your project.
   b. **Comments:** Enter comments, if any.
   c. **Workspace:** The default workspace is selected. This is a non-editable field. To select a different workspace or to create a new workspace, go to **Manage Workspace**.

3. Click **OK.**

The project `Project A` is created and is assigned to the default workspace. In this example, the default workspace is `OMLUSER`.

Related Topics

- Create and Manage Workspaces and Projects
  You can create and manage new projects and workspaces, provide access to your workspaces, manage permissions for users, and edit and delete workspaces.

3.2 Create and Manage Workspaces and Projects

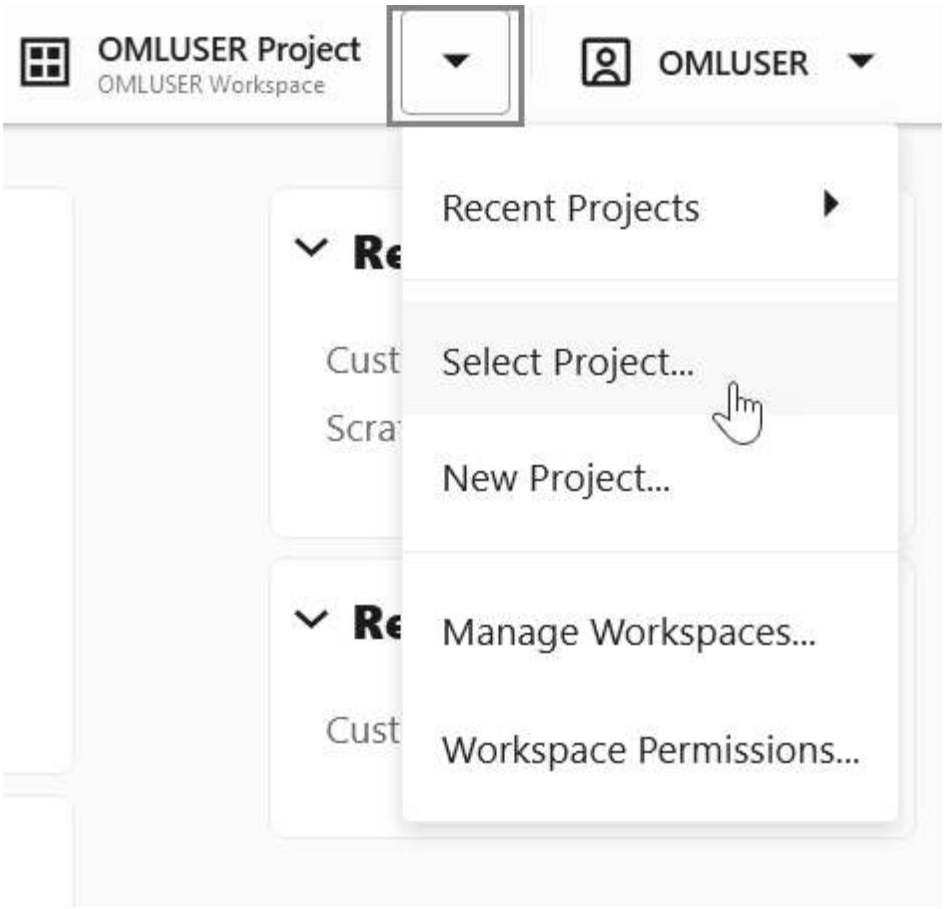
You can create and manage new projects and workspaces, provide access to your workspaces, manage permissions for users, and edit and delete workspaces.

The Workspaces page comprises two sections, one for workspaces and the other for projects.

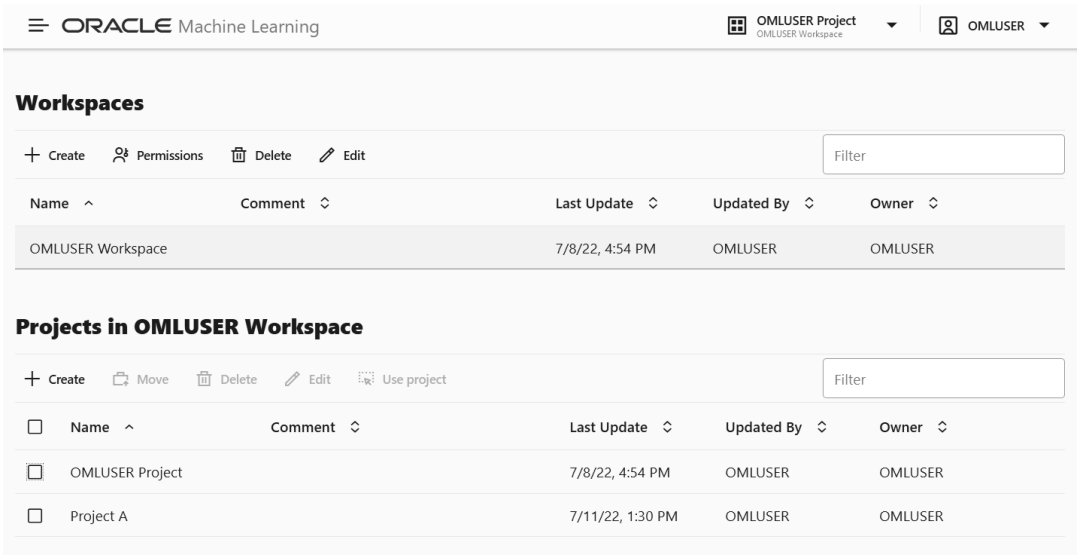
Create and Manage Workspace

To create and manage workspaces:

1. On the top right corner of your home page, click the down arrow next to the **Project** field, and click **Manage Workspaces.** The Workspaces page opens.



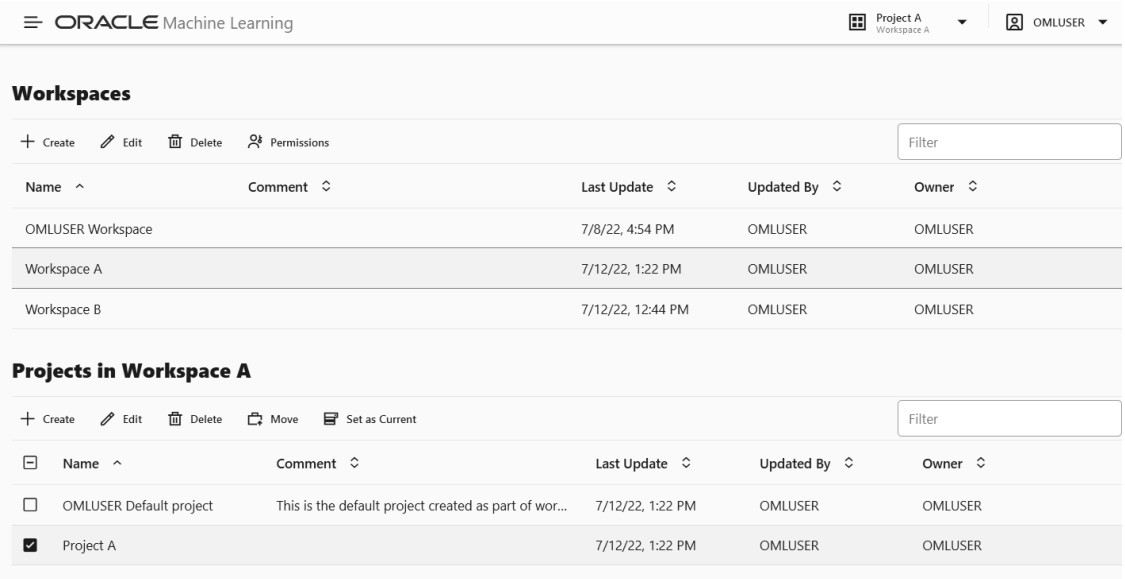
2. On the Workspaces page, you can create and manage workspaces and projects. To create and manage workspaces:



- On the upper section for workspace, click **Create** to create new workspace. In the Create Workspace dialog, enter a name for the workspace and click **OK.**
- Click **Edit** to edit the selected workspace. In the Edit Workspace dialog, you can edit the workspace name, and click **OK.**
- Click **Delete** to delete the selected workspace. Click **OK** to confirm the deletion of the selected workspace.
- Click **Permissions** to grant permissions to the selected users to access the workspace. In the Workspace Permission dialog, you can also delete users and modify their permissions.

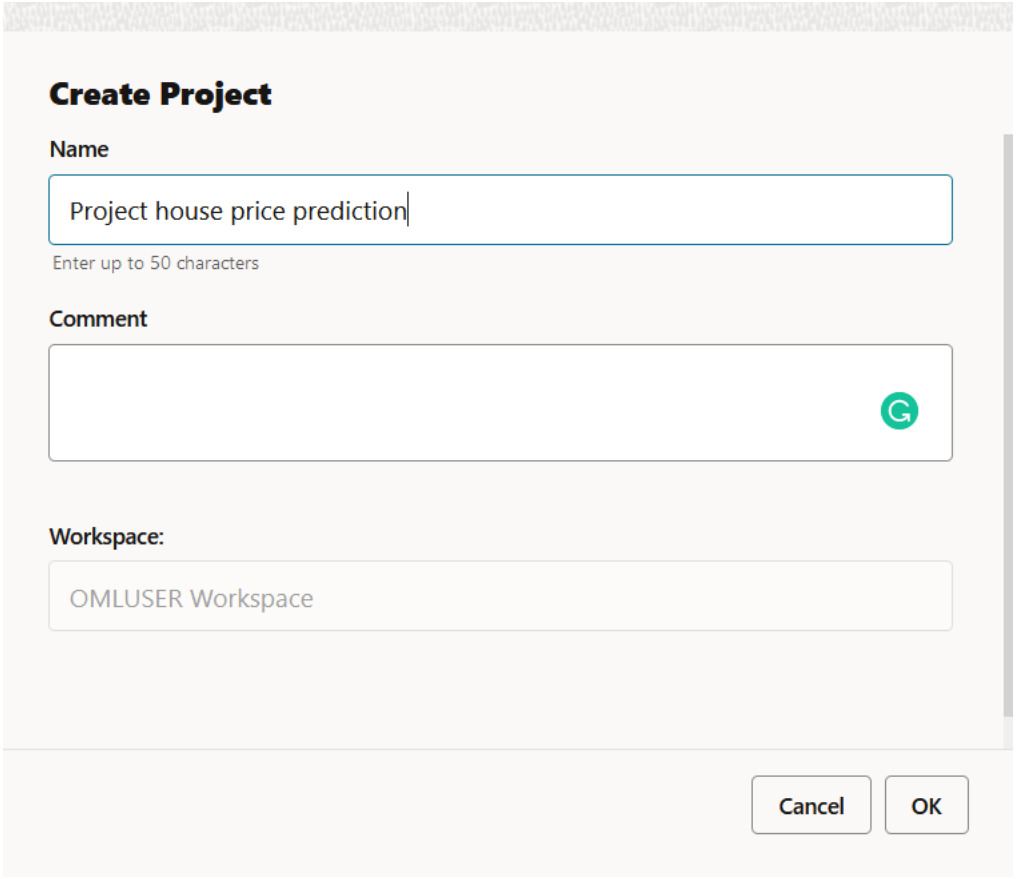
Create and Manage Projects

You can create and manage projects in the Projects in Workspaces section on the Workspaces page.



To create and manage projects:

1. On the upper section for workspace, click on the workspace in which you want to create the project.
2. On the lower section for projects, click **Create** to create a new project. The Create Project dialog opens. Enter a project name, enter comments if any, and click **OK.** Note that the Workspace field displays the workspace that you selected on the upper section.



3. Click on the project that you want to modify. The following options are enabled.
   - Click **Edit** to change the project name.
   - Click **Delete** to delete the selected project from the workspace.
   - Click **Move** to move the selected project to another workspace.
   - Click **Set as Current** to set the selected project as the default or current project.

3.3 Grant Workspace Permissions

You can collaborate with other users in Oracle Machine Learning User Interface (UI) by granting permissions to access your workspace. A workspace consists of projects. Projects consist of notebooks and experiments.

By granting different types of permissions such as **Manager, Developer,** and **Viewer,** you can allow another user to view your workspace and perform different tasks in your projects and notebooks such as edit, create, update, delete, run, view notebooks and so on. For more information about the permission types, see About Workspace Permission Types.

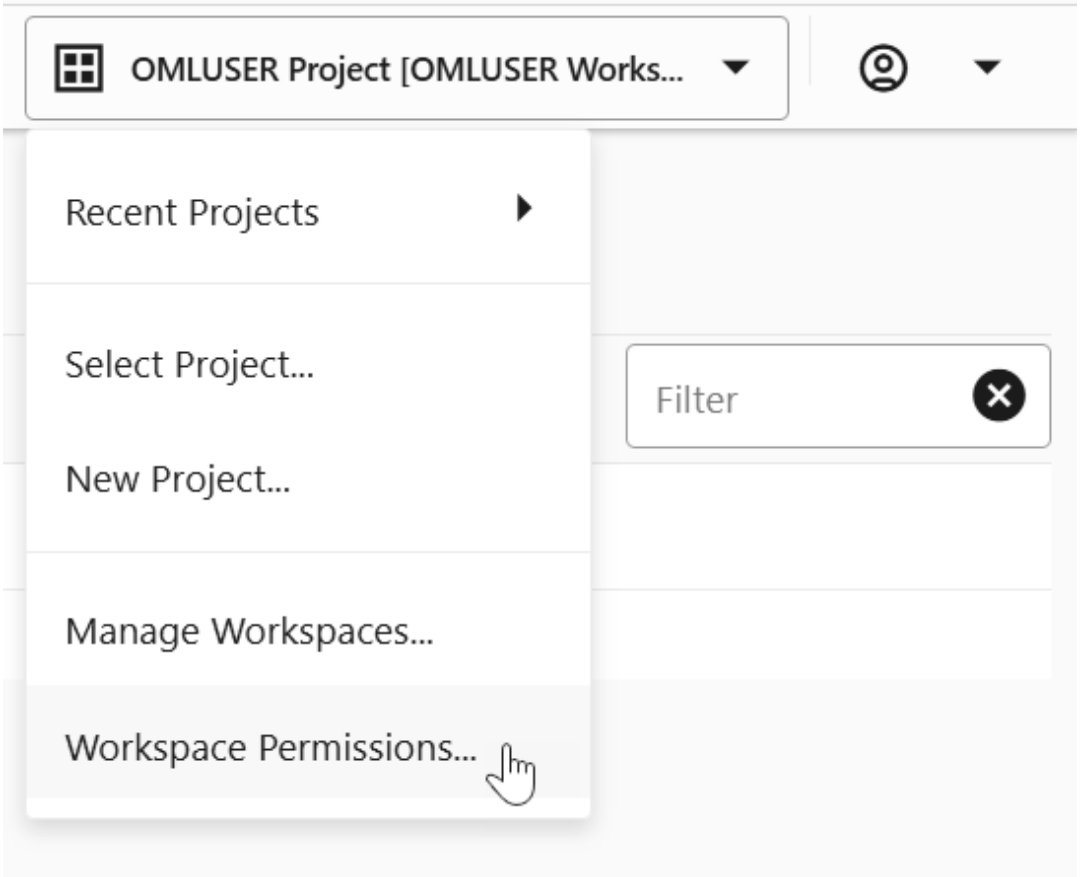
> **Caution:**
>
> If you grant the permission type **Manager** or **Developer,** the user can also drop tables, create tables, and run any scripts at any time on your account. The user with **Viewer** permission type can only view your notebooks and is not authorized to run or make any changes to your notebooks.

To grant permission to another user:

1. On the top right corner of Oracle Machine Learning UI home page, click the project and workspace drop-down list and select **Workspace Permission.**

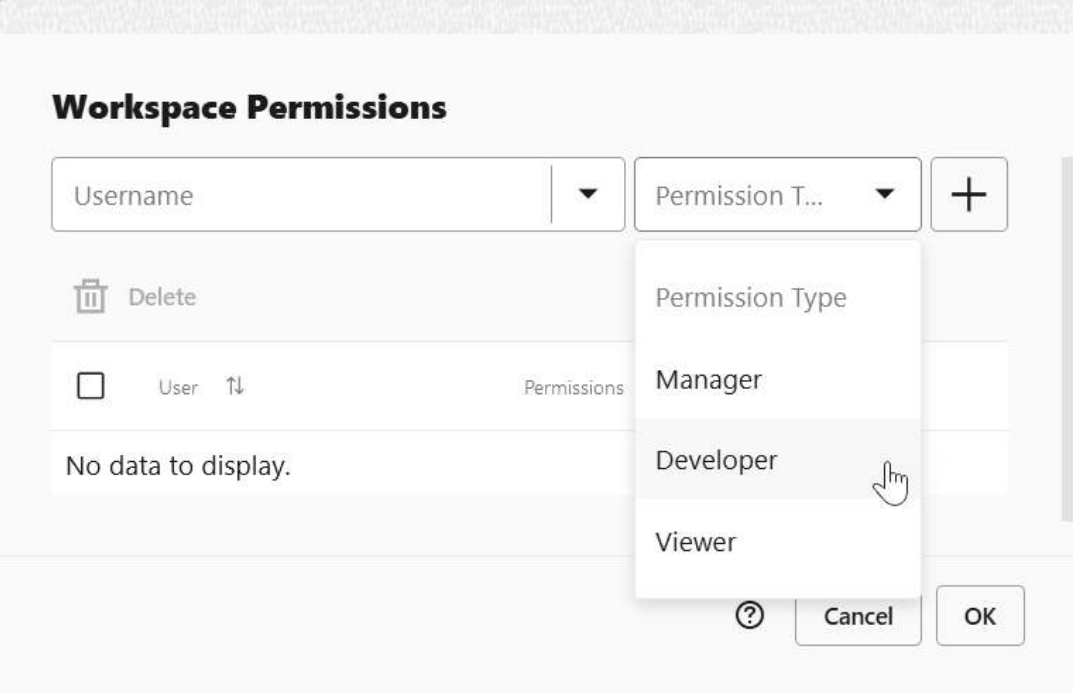
   The Permissions dialog box opens.
2. In the Permissions dialog box, select a user from the **Username** drop-down list.

Figure 3-4 OMLUSER Project drop-down menu



3. In the **Permissions** drop-down list, select the permission type you want to grant to the selected user.
   - **Manager**
   - **Developer**
   - **Viewer**

Figure 3-5 Workspace Permissions dialog



4. Click **Add.**

   The selected user is granted the assigned permission. The user name is displayed in the Permissions dialog box, along with the permission type.

5. Click **OK.** This completes the task of granting permission to a user. To delete a user and the associated permission, select the user and click **Delete.**

- About Workspace Permission Types
  Oracle Machine Learning UI allows three types of permissions. Depending on the permission type, you can allow the user to view or perform different tasks in your workspace, projects, and notebooks.

3.3.1 About Workspace Permission Types

Oracle Machine Learning UI allows three types of permissions. Depending on the permission type, you can allow the user to view or perform different tasks in your workspace, projects, and notebooks.

The permissions are privileges granted to shared objects in a given workspace. Here, operations that are allowed on shared objects, for example notebooks, are discussed. For instance, the user to whom the `Developer` permission is granted can only view scheduled jobs on shared notebooks; he cannot run these jobs. However, the user with `Developer` permission can always view and run scheduled jobs on notebooks that are created by him. The three types of permissions are listed in the following table along with the actions that are allowed.

> **Note:**
>
> Permissions are granted on workspaces, and not on projects.

Permission Types	Actions based on permission
Manager	• **Project:** Create, update, view and delete. • **Workspace:** View only. • **Notebooks:** Create, update, duplicate, run, export, import, and delete. **Jobs:** Schedule and run jobs.
Developer	• **Project:** View only. • **Workspace:** View only. • **Notebooks:** Create, update, run, duplicate, import, export, and delete notebooks. **Note:** A user with `Developer` permission can update, run, duplicate, import, export, and delete only those notebooks that were created by the user. • **Jobs:** View and run jobs of shared notebooks only. **Note:** A user with `Developer` permission cannot create jobs for notebooks that are shared.
Viewer	• **Project:** View only. • **Workspace:** View only. • **Notebooks:** View only. • **Jobs:** View jobs and job runs of shared notebooks only.

For tasks that can be performed by an Administrator, see: Oracle Machine Learning Administration Tasks

4
OML Notebooks

Oracle Machine Learning Notebooks is an enhanced web-based notebook platform for data analyst and data scientists. You can write code, text, create visualizations, and perform data analytics including machine learning. Notebooks work with interpreters in the back-end. In Oracle Machine Learning user interface, notebooks are available in a project, where you can create, edit, delete, copy, move, and even save notebooks as templates.

- About Oracle Machine Learning Notebooks
  Oracle Machine Learning Notebooks is an enhanced web-based notebook platform for data engineers, data analyst, R and Python users, and data scientists. You can write code, text, create visualizations, and perform data analytics including machine learning. Notebooks work with interpreters in the back-end.
- Access your Oracle Machine Learning Notebooks Page
  You can access the OML Notebooks page from the left navigation pane of Oracle Machine Learning Notebooks, or from the Notebooks page.
- Edit your Oracle Machine Learning Notebook
  Upon creating a notebook, it opens automatically, presenting you with a single paragraph using the default %sql interpreter. You can change the interpreter by explicitly specifying one of `%script`, `%python`, `%sql` , `%r` , `%md`, or `%conda`.
- Enable GPU Compute Capabilities in a Notebook through the Python Interpreter
  This topic demonstrates how to enable GPU compute capabilities in a notebook through the Python interpreter. It also shows how to get information about the current GPU on which the notebook is running, and other details.
- Visualize your Data in Oracle Machine Learning Notebooks
  Oracle Machine Learning Notebooks offer rich visualization capabilities of your data. The visualizations depend on the type of your dataset.
- Export a Notebook
  You can export a Notebook in Native format (`.dsnb`) file, Zeppelin format (`.json`) file, in Jupyter format (`.ipynb`), and later import them in to the same or a different environment.
- Import a Notebook
  You can import notebooks across Pluggable Databases (PDBs) into your workspace. Oracle Machine Learning UI supports the import of notebooks in the native format `(.dsnb)`, Zeppelin `(.json)` and Jupyter `(.ipynb)` notebooks.
- Use the SQL Interpreter in a Notebook Paragraph
  An Oracle Machine Learning notebook supports multiple languages. Each paragraph is associated with a specific interpreter. For example, to run SQL statements use the SQL interpreter. To run PL/SQL statements, use the `script` interpreter.
- Use the Python Interpreter in a Notebook Paragraph
  An Oracle Machine Learning notebook supports multiple languages. Each paragraph is associated with a specific interpreter. To run Python commands in a notebook, you must first connect to the Python interpreter. To use OML4Py, you must import the `oml` module.
- Use the R Interpreter in a Notebook Paragraph
  An Oracle Machine Learning notebook supports multiple languages. Each paragraph is associated with a specific interpreter. To run R functions in an Oracle Machine Learning notebook, you must first connect to the R interpreter.

- Use the Conda Interpreter in a Notebook Paragraph
  Oracle Machine Learning Notebooks provides a Conda interpreter to enable administrators to create conda environments with custom third-party Python and R libraries. Once created, you can download and activate Conda environments inside a notebook session also using the Conda interpreter.
- Use the Markdown Interpreter and Generate Static html from Markdown Plain Text
  Use the Markdown interpreter and generate static html from Markdown plain text.
- About Interpreters and Notebook Service Levels
  An interpreter is a plug-in that allows you to use a specific data processing language backend.
- Use the Scratchpad
  The Scratchpad provides you convenient one-click access to a notebook for running SQL statements, PL/SQL, R, and Python scripts that can be renamed. The Scratchpad is available on the Oracle Machine Learning User Interface (UI) home page.

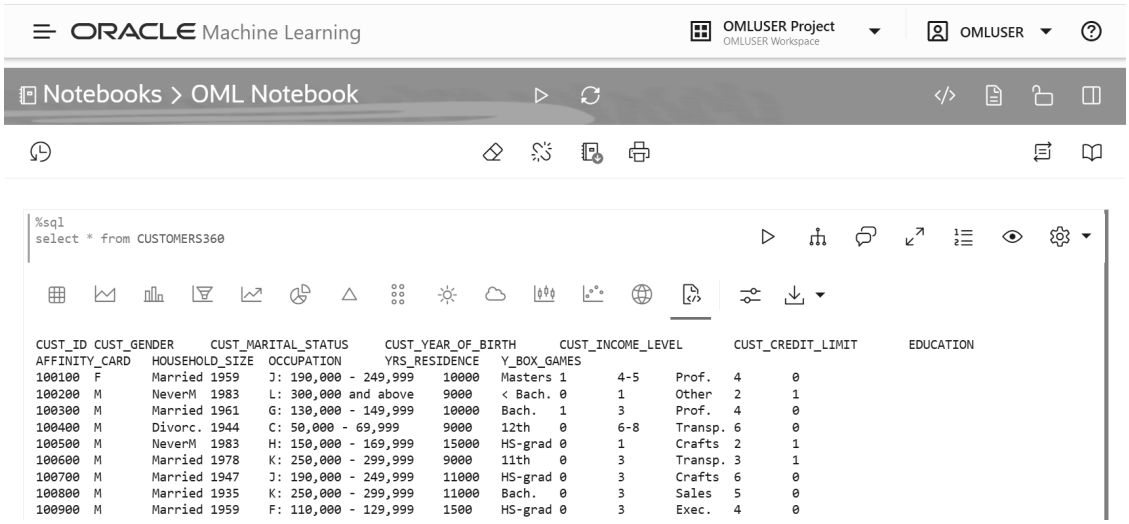
4.1 About Oracle Machine Learning Notebooks

Oracle Machine Learning Notebooks is an enhanced web-based notebook platform for data engineers, data analyst, R and Python users, and data scientists. You can write code, text, create visualizations, and perform data analytics including machine learning. Notebooks work with interpreters in the back-end.

In Oracle Machine Learning, notebooks are available in a project within a workspace, where you can create, edit, delete, copy, move, and even save notebooks as templates. A notebook can contain many paragraphs. A paragraph is a notebook component where you can write and run SQL statements, PL/SQL scripts, R and Python code, and conda instructions. You can run paragraphs individually or, run all the paragraphs in a notebook using a single button. A paragraph has an input section and an output section. In the input section, specify the interpreter to run along with the code or text. This information is sent to the interpreter to be run. In the output section, the results of the interpreter are provided.

> **Note:**
>
> There is a single namespace for both the original notebooks and the new notebooks. You cannot have a notebook with the same name in both notebook lists. A notebook copied from the original interface to the new will have `_new` appended to it.

Figure 4-1 OML Notebook



The Oracle Machine Learning Notebook provides:

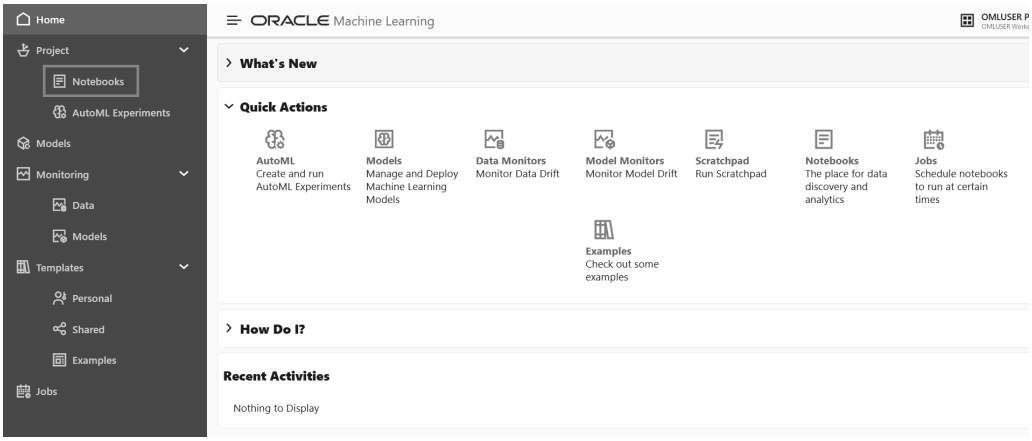
- Faster notebook loading time.
- The Oracle look and feel as it based on the Oracle Redwood theme.
- Enriched visualization in its Line chart, Area chart, Bar chart, Pyramid chart, Pie chart, Donut chart, Funnel chart, Tag Cloud, Treemap Diagram, Sunburst Diagram, Scatter Plot, Box Plot.
- Option to enter comments in notebook paragraphs.
- Option to create Paragraph Dependencies. The Paragraph Dependencies feature allows you to add dependencies between paragraphs. The dependents of a paragraph automatically run after the original paragraph is run.
- Simplified service level selection of High, Medium, Low, and GPU through drop-down menu.
- Layout of Zeppelin and Jupyter notebook.
- On-page versioning, viewing of version history, and version comparison.

4.2 Access your Oracle Machine Learning Notebooks Page

You can access the OML Notebooks page from the left navigation pane of Oracle Machine Learning Notebooks, or from the Notebooks page.

1. To access the Notebooks page:
   - Go to the Oracle Machine Learning left navigation pane, expand **Projects** and then click **Notebooks**.

Figure 4-2 Notebooks option on OML UI left navigation menu and home page



- Alternatively, you can click **Notebooks** under Quick Link on the home page to open the Notebooks page.

2. This opens the OML Notebooks page.
   - **Create:** Click **Create** to create a new notebook.
   - **Edit:** Click on a notebook row to select it and click **Edit.** You can edit the notebook name, and add comments in the Edit Notebook dialog box.
   - **Delete:** Click on a notebook row to select it and click **Delete.**
   - **Duplicate:** Click on a notebook row to select it , and click **Duplicate.** This creates a copy of a notebook, and the duplicate copy of the is listed on the Notebooks page with the suffix `_1` in the notebook name.
   - **Save as Template:** To save a notebook as a template, select the notebook and click **Save as Template.** In the Save as Template dialog, you can define the location of the template to save it in Personal or Shared under Templates.
   - **Import:** To import a notebook as .json files, click **Import**. Select the project and workspace in which to import the notebook.
   - **Export:** To export a notebook, click **Export.** You can export Notebooks in the `.dsnb` format, Zeppelin format `(.json )` file and in Jupyter format (`.ipynb)`, and later import them in to the same or a different environment.
   - **Version:** To create versions of a notebook, select it and click **Version**. The Versions page for that particular notebook opens. Here, you can create a new version of the notebook by clicking **+Version**. The Create Version dialog opens. Enter a name of the notebook version, a description, and click **OK.** The new version of the notebook gets created by the same name with a suffix `_2` for the second version. For subsequent versions, suffix (number) increments by one. To revert to an older version by clicking **Revert Version**. You also have the option to delete any version of the notebook. Click **Back to Notebooks** to go to the OML Notebooks page.

> **Note:**
>
> You can also version a notebook by opening it, and then clicking on the  option. By using this option, you can create new versions, view version history, restore older versions, and delete any older versions of the notebook that you have opened.

- Work with Notebook Versions on the Notebooks Page
  By creating versions of your notebook, you can archive your work in a notebook.

4.2.1 Work with Notebook Versions on the Notebooks Page

By creating versions of your notebook, you can archive your work in a notebook.

You can create versions of notebooks on the Notebooks page, as well as in the Notebook editor. In this example, the **Notebook Versioning Demo** notebook is created and versioned as **Version 1**.

> **Note:**
>
> A versioned notebook is non-editable. If you want to make any changes to a particular version of a notebook, you must restore that version to edit it.

Prerequisites: The *Notebook Versioning Demo* notebook. This notebook is created as part of the example here.

To create a new notebook version and view version history:

1. On the Notebooks page, click **Create Notebooks**.
2. In the Create Notebooks dialog, enter the name `Notebook Versioning Demo` in the **Name** field and click **OK**. The notebook is created and it opens in the notebook editor.
3. On the notebook, hover your cursor over the lower border of the paragraph and click the + icon to add a paragraph. Add two more paragraphs to this notebook, and paste the following PL/SQL script in the paragraphs:

   a. In the first paragraph, copy and paste the following PL/SQL script. This script creates the view `ESM_SH_DATA` from the `SALES` table present in the `SH` schema.

```
%script

CREATE OR REPLACE VIEW ESM_SH_DATA AS
  SELECT TIME_ID, AMOUNT_SOLD FROM SH.SALES;
```

b. In the second paragraph, copy and paste the following SQL script. This script gives a count of the record present in the view `ESM_SH_DATA`.

```
%script
SELECT count(*) from ESM_SH_DATA;
```

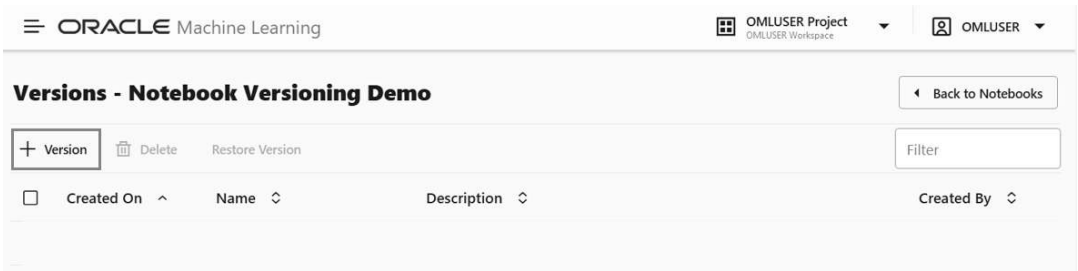
c. In the third paragraph, copy and paste the following SQL script to review the data in a tabular format.

```
SELECT * FROM ESM_SH_DATA
FETCH FIRST 10 ROWS ONLY;
```

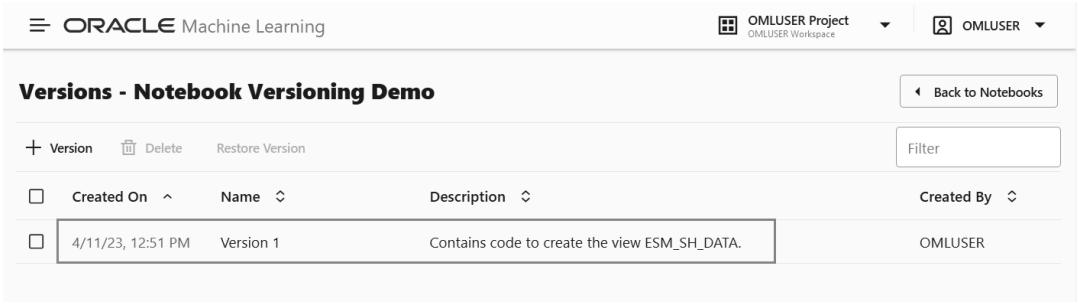
4. Run all the paragraphs, and go back to the Notebooks page after all the paragraphs run successfully.
5. On the Notebooks page, select the **Notebook Versioning Demo** notebook to enable all the edit options, and click **Versions** to go to the versions page for this notebook.

   The *Versions - Notebook Versioning Demo* page opens.
6. On the *Versions - Notebook Versioning Demo* page, click **Version** to create a new version of the notebook. This opens the Create Version dialog.

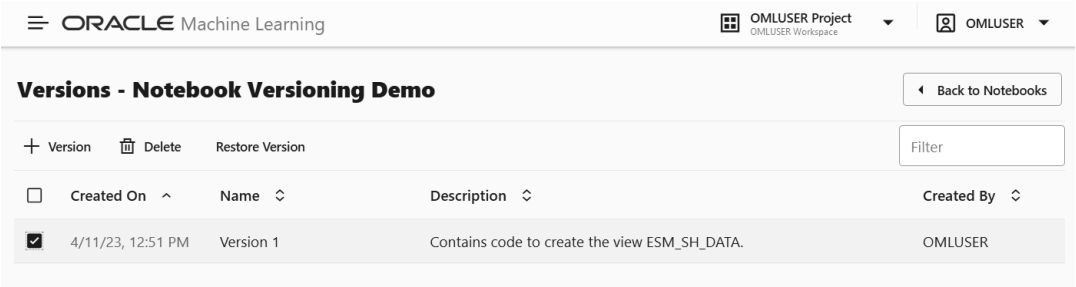
Figure 4-3 Versions page



7. In the Create Versions dialog:
   a. **Name:** Enter `Version 1` for the new version of this notebook
   b. **Comments:** Enter comments, if any.
   c. Click **OK.** Once the notebook version is created, it is listed on the *Versions - Notebook Versioning Demo* page.



8. On the *Versions - Notebook Versioning Demo* page, select **Version 1** of the notebook version that you just created to enable all the available options.



- Click **Delete** to delete the selected version of the notebook.
- Click **Restore** to restore the selected version of the notebook.

> **Note:**
>
> Restoring a selected version of the notebook will discard all the unversioned changes, if any.

- Click **Back to Notebooks** to go back to the Notebooks page.

4.3 Edit your Oracle Machine Learning Notebook

Upon creating a notebook, it opens automatically, presenting you with a single paragraph using the default %sql interpreter. You can change the interpreter by explicitly specifying one of `%script`, `%python`, `%sql` , `%r` , `%md`, or `%conda`.

Set the context with a project with which your notebook is associated. You can edit an existing notebook in your project. To edit an existing notebook:

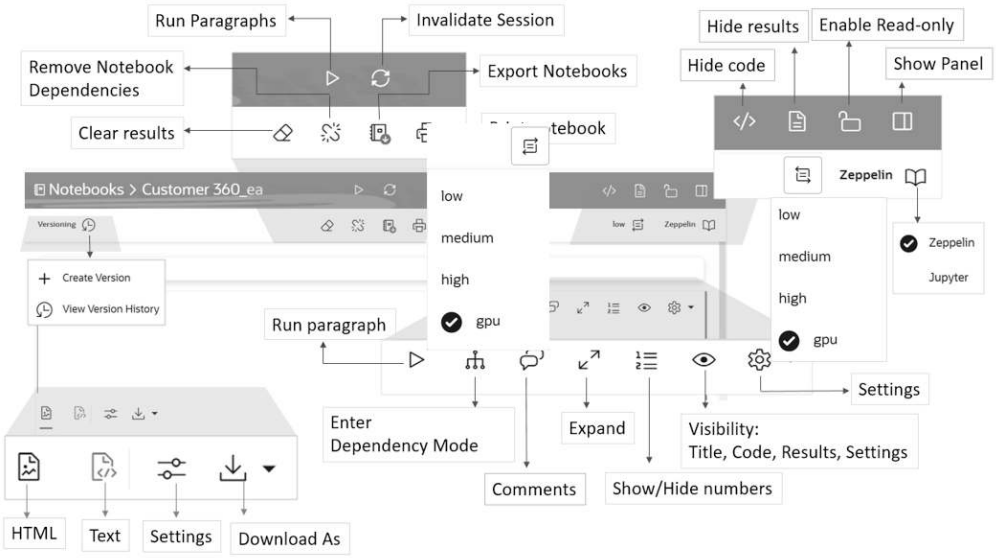
1. On the Oracle Machine Learning home page, select the project in which your notebook is available.

   > **Note:**
   >
   > A project is a logical grouping of notebooks and experiments within a workspace. While you may own many projects, other workspaces and projects may be shared with you.

2. Click the notebook that you want to open and edit.

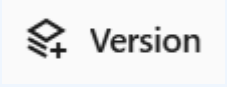
   The selected notebook opens in edit mode.

3. In the edit mode, you can use the following Oracle Machine Learning Notebook toolbar options:



Notebook level edit options:

- Click  to run all paragraphs in the notebook
- Click  to invalidate and reset the notebook session.
- Click  to create a new version this notebook, or to view the earlier versions of the notebook.
  - **Create Version:** Click this option to create a new version of this notebook. You have the option to provide a new name for the version, and a description about it. When you create a new notebook version, the paragraph results of each run session are stored in the versioned notebook. When you restore a notebook, the paragraph results of each run session are also restored. You can also create notebook versions from the editor. For more information, see Work with Notebook Versions in the Notebook Editor
  - **View Version History:** Click this option to view the earlier versions of the notebook. You have the option to restore any earlier version, compare versions, and delete any earlier version that you created.

> **Note:**
>
> You can also create notebook versions, view version history, and delete older versions from the 
>
> option on the Notebooks page.

- Click  to clear paragraph results.
- Click  to clear paragraph dependencies.
- Click  to export the notebook. You can export the notebook as a `.dsnb` file, `.zpln` file (Zeppelin notebook) and `.ipynb` file (Jupyter notebook). You have these settings while exporting a notebook:
  - Export All
  - Exclude code
  - Exclude results
  - Exclude Timestamp
- Click  to print the notebook
- Click  to hide the code of all paragraphs in the notebook
- Click  to hide the results of all the paragraph in the notebook
- Click  to enable read-only mode for this notebook.

  > **Note:**
  >
  > The read-only mode is available only for the Oracle Machine Learning Notebook.

- Click  to show the edit panel. The edit options in the panel are the same edit options available for the paragraph. Clicking the panel icon opens the edit pane on the right, and the edit tool bar in the paragraph is hidden.
- Click  to change the notebook service level to either low, medium, high, or GPU.

- Click  to switch the OML notebook to either Zeppelin or Jupyter notebook

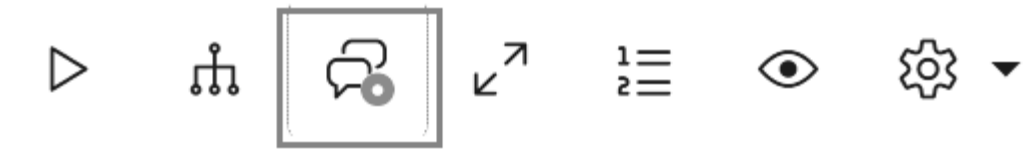
Paragraph level edit options:

- Click  to run the selected paragraph

- Click  to enter into Dependency Mode. In Dependency Mode, you must select and deselect paragraphs in order to add or remove them as dependents.

> **Note:**
>
> The Paragraph Dependencies feature allows you to add dependencies between paragraphs. The dependents of a paragraph automatically run after the original paragraph is run.

- Click  to open the Comments dialog. Type in your comments here, and press **Enter** to add the comment. You can also delete any comments by clicking the corresponding **Delete** icon. Click the comments icon to close the dialog. You can provide comments for each paragraph in a notebook. Paragraphs with comments are indicated by a green dot on the comments icon.



- Click  to view the notebook paragraph in full screen mode. To view the paragraph in the normal mode, click the collapse icon.

- Click  to show line numbers in the notebook paragraph.

- Click  to view the paragraph title, code, results, and the paragraph settings.

- Click  to :
  - **Move up:** Click to move the paragraph up in the notebook.

  - **Move down:** Click to move the paragraph down in the notebook.
  - **Clear results:** Click to clear the results of the commands that you ran in the paragraph.
  - **Open as Embedded Window:** Click to view the current paragraph separately in your browser.
  - **Clone Paragraph:** Click to clone the paragraph. The paragraph is cloned in the same notebook.
  - **Disable Run:** Click to disable running of the paragraph. To enable run, go to **Settings** and click **Enable Run**.
  - **Delete Paragraph:** Click to delete the paragraph.

- Click  to view the paragraph in HTML format
- Click  to view the paragraph in text format
- Click  to adjust settings of the notebook paragraph output. This setting is specifically applicable to visualizations in graphs, charts etc.
- Click  to download the paragraph as a text file, or as .png or .svg files, as applicable, for paragraphs that contains graphs or charts as output.

- Work with Notebook Versions in the Notebook Editor
  By creating versions of your notebook, you can archive your work in a notebook.
- Create Paragraph Dependencies
  Paragraph Dependencies allow you to add dependencies between paragraphs. The dependent paragraphs automatically run after the original paragraph is run, according to the order of dependency.

4.3.1 Work with Notebook Versions in the Notebook Editor

By creating versions of your notebook, you can archive your work in a notebook.

You can create versions of notebooks in the Notebooks editor, as well as on the Notebooks page. In this example:

- The original notebook *Notebook Versioning Demo*, is edited to add a script to build a machine learning model.
- The *Notebook Versioning Demo* notebook is then versioned as **Version 2** to archive the code to build the machine learning model.
- The **Version 2** and **Version 1** of the **Notebook Versioning Demo** notebook are compared using the **Compare Versions** feature.

> **Note:**
>
> A versioned notebook is non-editable. If you want to make any changes to a particular version of a notebook, you must restore that version to edit it.

To create a new notebook version and view version history:

1. On the Notebooks EA page, click on the **Notebook Versioning Demo** notebook to open it in the notebook editor.

   > **Note:**
   >
   > Version 1 of this notebook is already created as part of the example in Work with Notebook Versions on the Notebooks Page. It contains the archived code to create the view `ESM_SH_DATA`, count the record, and view the data. Clicking on the notebook opens the original version which is editable.

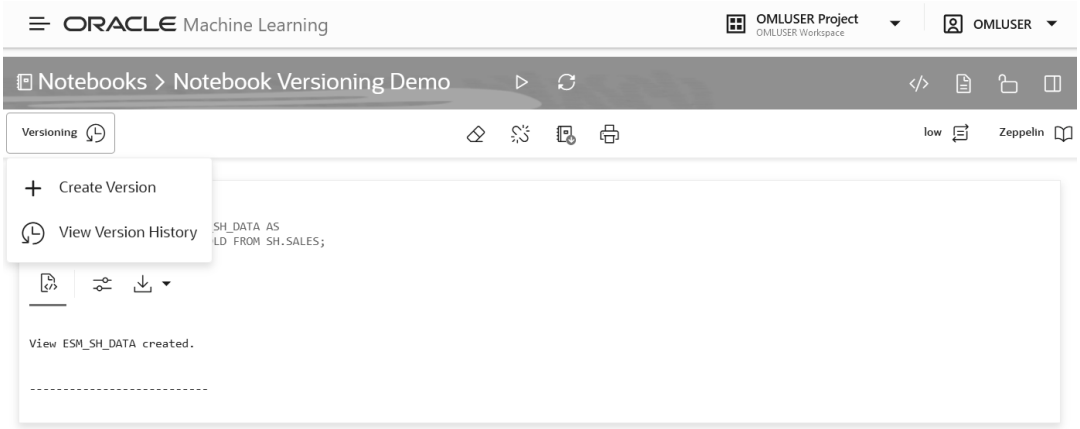
2. Now, edit the notebook to add a script to build a machine learning model. On the notebook, hover your cursor over the lower border of the third paragraph, and click the + icon to add a new paragraph.

3. Copy and paste the following script to the new paragraph. This script builds a machine learning model using the ESM algorithm.

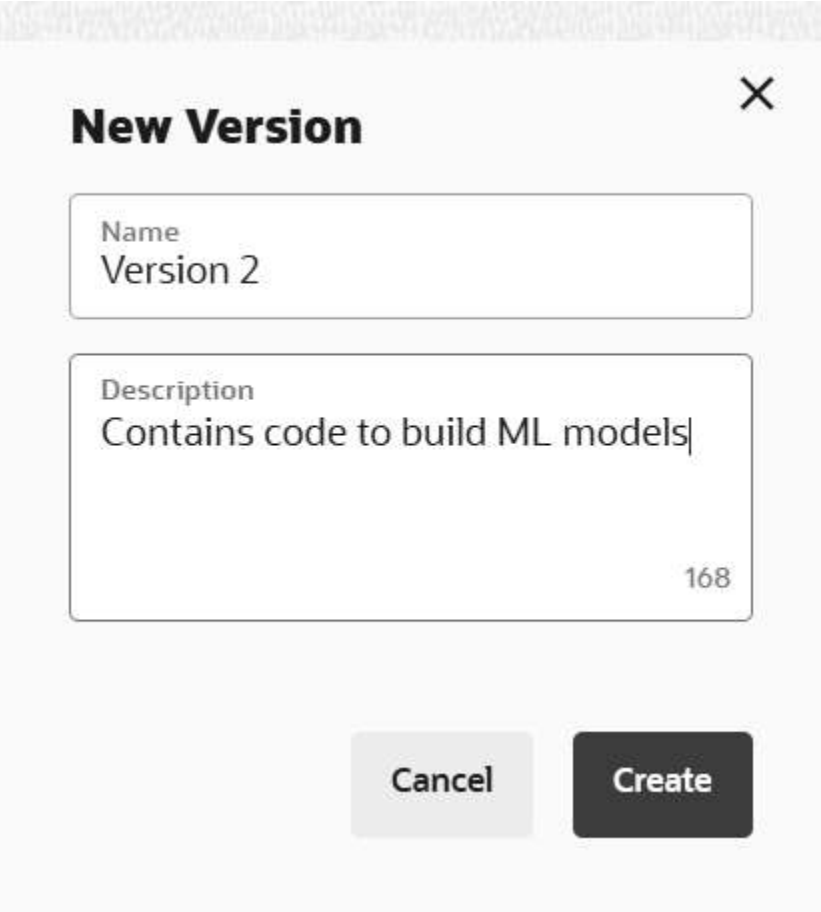
```
%script

BEGIN DBMS_DATA_MINING.DROP_MODEL('ESM_SALES_FORECAST_1');
EXCEPTION WHEN OTHERS THEN NULL; END;
/
DECLARE
    v_setlst DBMS_DATA_MINING.SETTING_LIST;
BEGIN

    v_setlst('ALGO_NAME')            := 'ALGO_EXPONENTIAL_SMOOTHING';
    v_setlst('EXSM_INTERVAL')        := 'EXSM_INTERVAL_QTR'; --
accumulation int'l = quarter
    v_setlst('EXSM_PREDICTION_STEP') := '4';                 -- prediction
step = 4 quarters
    v_setlst('EXSM_MODEL')           := 'EXSM_WINTERS';      -- ESM model
= Holt-Winters
    v_setlst('EXSM_SEASONALITY')     := '4';                 -- seasonal
cycle = 4 quarters

    DBMS_DATA_MINING.CREATE_MODEL2(
        MODEL_NAME          => 'ESM_SALES_FORECAST_1',
        MINING_FUNCTION     => 'TIME_SERIES',
```

```
        DATA_QUERY          => 'select * from ESM_SH_DATA',
        SET_LIST            => v_setlst,
        CASE_ID_COLUMN_NAME => 'TIME_ID',
        TARGET_COLUMN_NAME  =>'AMOUNT_SOLD');
END;
```

4. Now, archive this notebook along with the code to build the machine learning model by versioning it. On the top left corner of the notebook editor, click **Versioning** 
5. The options to **Create Version** and **View Version History** opens.

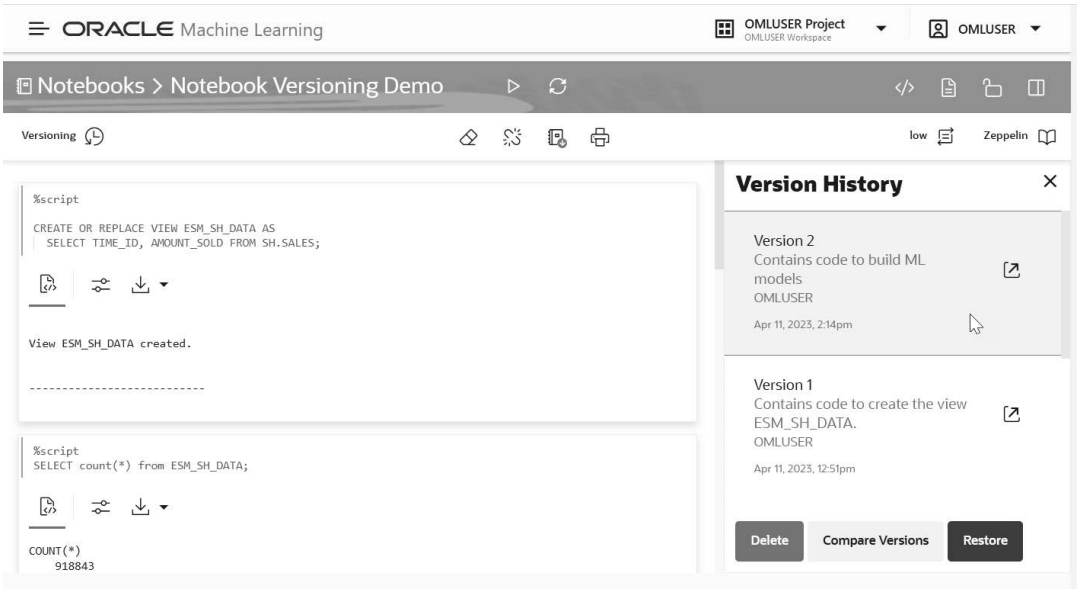


6. Click **Create Version**. The New Version dialog opens.
7. In the **New Version** dialog:
   a. **Name:** Here, the name `Version 2` is taken by default. Let's retain this name.
   b. **Comments:** Enter comments, if any.
   c. Click **Create.** A message is displayed confirming the creation of the new version.

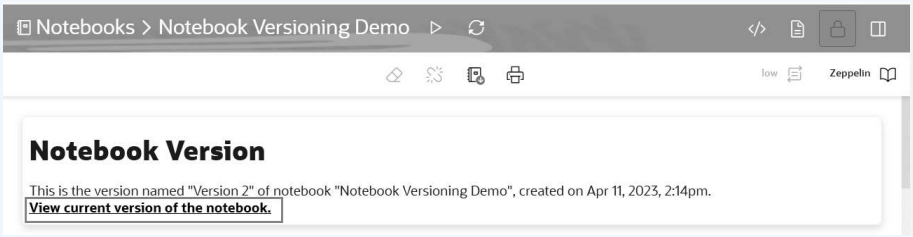


Version 2 of this notebook now contains the archived code to create the machine learning model.

8. To view the version that you just created, click **Versioning** , and then click **View Version History**.
9. On the right pane of the notebook editor, the **Version History** pane opens. Hover your cursor over any notebook version and click on it to enable the available options.
10. You can perform the following tasks in the Version History pane:



- Click  to open the selected version.

> **Note:**
>
> Clicking on any versioned notebook opens the notebook in read-only mode, as versioned notebooks are non-editable. To view the current editable version, click **View current version of the notebook**.
>
> 
>

- Click **Delete** to delete the selected version.
- Click **Compare Versions** to compare the selected and current version of the notebook. You can select other available versions from the drop-down list. In this example, Version 2 of the notebook (under Current State) is compared with Version 1. New additions are highlighted in green, as shown in the screenshot here, and deletions are highlighted in red.

- Click **Restore** to restore the selected version.

> **Note:**
>
> Restoring a selected version of the notebook will discard all the unversioned changes, if any.

4.3.2 Create Paragraph Dependencies

Paragraph Dependencies allow you to add dependencies between paragraphs. The dependent paragraphs automatically run after the original paragraph is run, according to the order of dependency.

To create paragraph dependencies:

1. On the Notebooks page, click **Create Notebooks**.
2. In the Create Notebooks dialog, enter the name `Paragraph Dependencies Demo` in the **Name** field and click **OK**.

   The notebook is created and it opens in the notebook editor.
3. On the notebook, hover your cursor over the lower border of the paragraph and click the + icon to add a paragraph. Add two more paragraphs to this notebook, and paste the following PL/SQL script in the paragraphs:

   a. In the first paragraph, copy and paste the following PL/SQL script. This script creates the view `ESM_SH_DATA` from the `SALES` table present in the `SH` schema.

```
%script
```

```
CREATE OR REPLACE VIEW ESM_SH_DATA AS
  SELECT TIME_ID, AMOUNT_SOLD FROM SH.SALES;
```

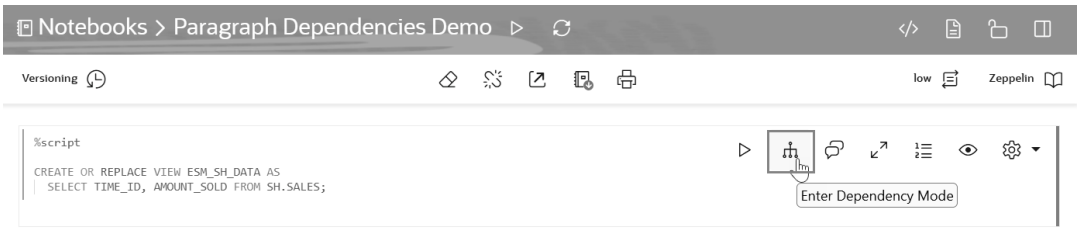
b. In the second paragraph, copy and paste the following SQL script. This script gives a count of the record present in the view `ESM_SH_DATA`.

```
%script
SELECT COUNT(*) FROM ESM_SH_DATA;
```

c. In the third paragraph, copy and paste the following SQL script to review the data in a tabular format.

```
%sql
SELECT * FROM ESM_SH_DATA
FETCH FIRST 10 ROWS ONLY;
```

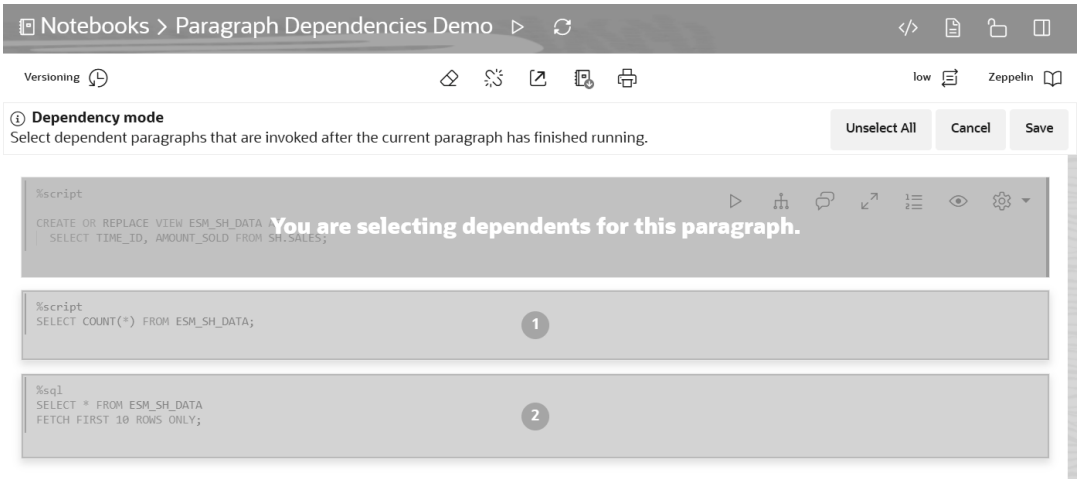
4. Go to the first paragraph and click on the **Enter Dependency Mode** icon.



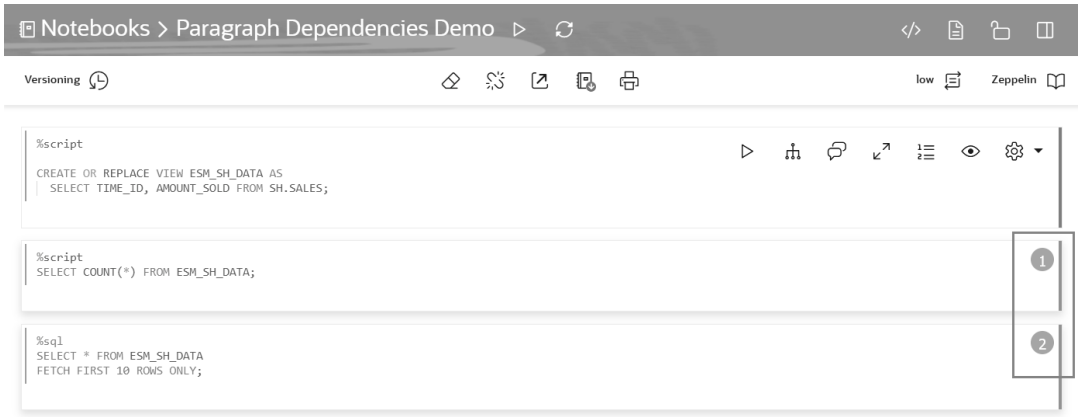
The message appears: *You are selecting dependents for this paragraph*

5. Click on the second and third paragraph to add them as dependents of paragraph one.

> **Note:**
>
> The order of paragraph dependency is based on the order of your click.



6. Click **Save.** Once the dependent paragraphs are defined and saved, it is indicated by the numbers as shown in the screenshot here:



7. Now, go to the first paragraph and click **Run**. After the first paragraph starts successfully, the subsequent dependent paragraphs start to run according to the order of dependency.

4.4 Enable GPU Compute Capabilities in a Notebook through the Python Interpreter

This topic demonstrates how to enable GPU compute capabilities in a notebook through the Python interpreter. It also shows how to get information about the current GPU on which the notebook is running, and other details.

Prerequisites:

- Paid Autonomous Database Serverless database instances.
- The GPU feature is enabled for Oracle Autonomous Data Warehouse Serverless or Oracle Autonomous Transaction Processing Serverless instances with 16 or more ECPUs specified for the OML application. For cost details, refer to the *Oracle PaaS and IaaS Universal Credits Service Descriptions* document available on the Oracle Cloud Services contracts page.

> **Note:**
>
> The GPU feature is not supported for Notebooks Classic.

- While basic NVIDIA libraries are included with the base environment, you are expected to create a custom Conda environment with the GPU-enabled 3rd party libraries required for your project. Only GPU-enabled packages will benefit from GPUs in Python paragraphs.

> **Note:**
>
> By default, pre-installed and pre-configured NVIDIA libraries are provided to the GPU interpreter container in the host VM. However, third-party Python packages that use GPUs typically require specific versions of NVIDIA CUDA libraries as dependencies, which may override the included libraries.

- Third-party GPU-enabled Python packages. In this example, we use `pytorch`.

> **Note:**
>
> There is an expected delay in starting a notebook with GPU compute capabilities due to reserving and starting the GPU resources, which may take a few minutes.

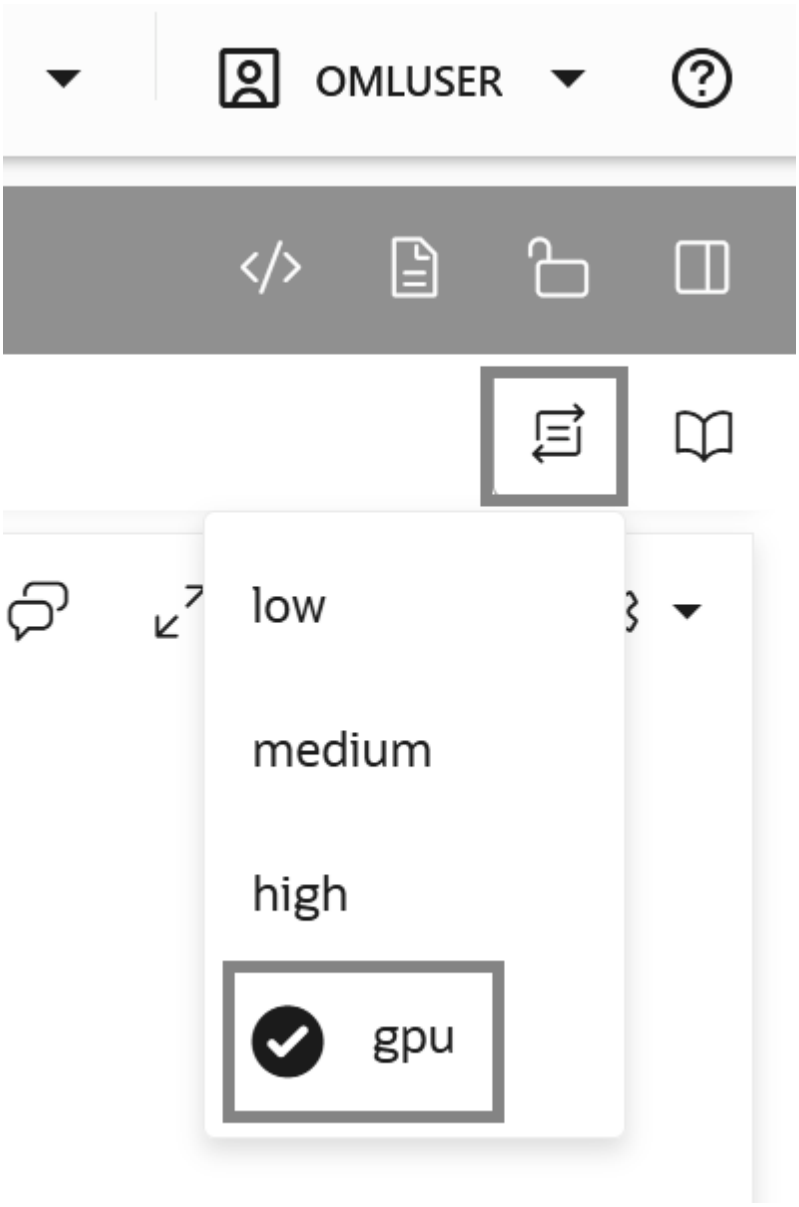
Generating embeddings using transformer models can be done in Python memory using OML Notebooks' Python interpreter. Using GPUs, transformer models, e.g., for generating sentence and image embeddings, can process larger volume data more quickly and efficiently.

To use the GPU compute capability in OML Notebooks:

- Create a Conda environment with the desired third-party GPU-enabled Python packages (ADMIN role required).
- Download and activate the Conda environment in OML Notebooks to use the GPU compute capabilities (OML_DEVELOPER role required).
- In OML Notebooks, select the notebook type **gpu** from the **Update Notebook Type** drop-down menu in the notebook editor (OML_DEVELOPER role required). This setting is persisted in the notebook until you change it to another type.

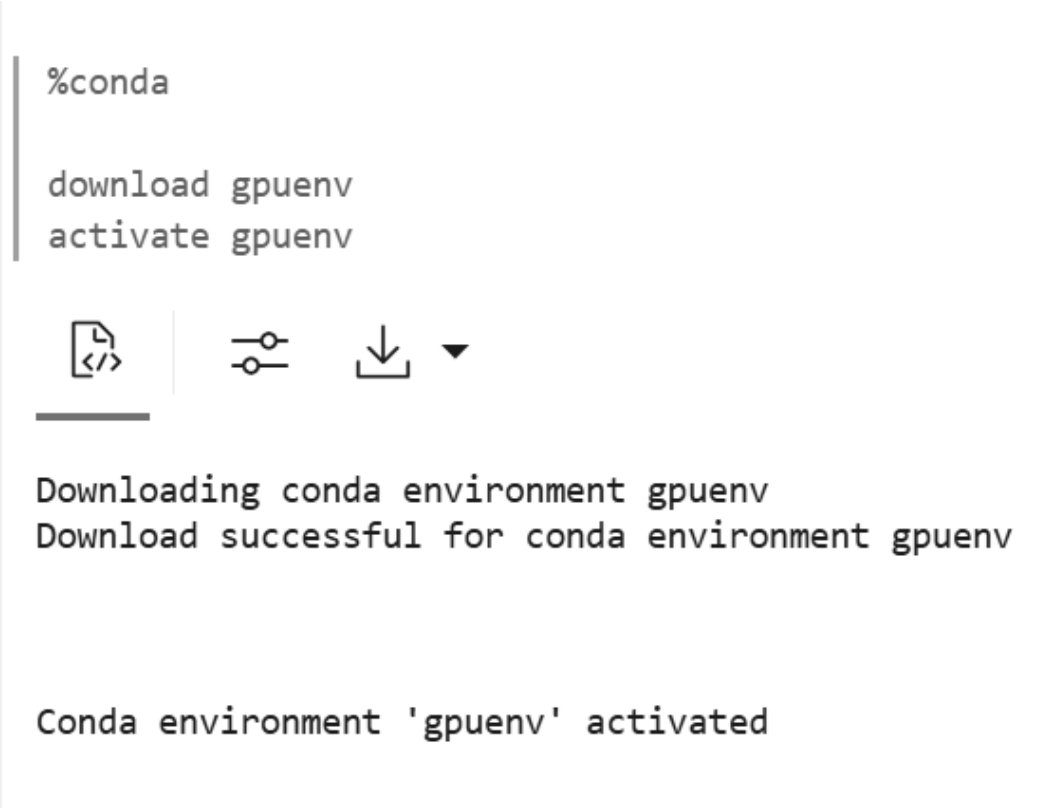
To enable GPU compute capabilities in a notebook, and to view information on GPU:

1. Create a notebook and open it in the notebook editor. Click on the **Update Notebook Type** icon and select **gpu**. By selecting **gpu**, you enable the notebook with GPU compute capabilities.



2. Run the following command to download and activate a Conda environment. To know more about how to create Conda environments for Python and R, see the Related Links section below.

```
%conda

download gpuenv
activate gpuenv
```



3. In this Conda environment, you will import the third-party GPU-enabled Python library Torch. Add a Python paragraph in the notebook to import the Python library `torch`. Type the directive `%python` and run the following command:

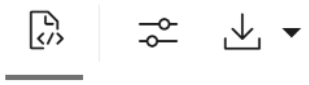
```
%python
import torch
import torch.nn as nn
import torch.optim as optim
import time
```

4. In another Python paragraph in the notebook and run the following command to check if GPU is available and use it:

```
%python
        device = torch.device('cuda' if torch.cuda.is_available()else
'cpu')
        print(f"Device in use is: {device}")
```

The command returns the following information:

```
%python

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Device in use is: {device}")
```



```
Device in use is: cuda
```

5. In this step, we will create another Python paragraph and run the following to:
   - Set the device to CPU or GPU if available
   - Create tensors on the specified device
   - Measure time for basic operations, and
   - Print the operations and results

```
%python

import torch
import time
import matplotlib.pyplot as plt

# Set the device to CPU or GPU if available
device = 'cuda' if torch.cuda.is_available() else 'cpu'
print(f"Running on device: {device}")

# Create tensors on the specified device
x = torch.randn(2, 3, device=device)
y = torch.tensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]], device=device)

# Measure time for basic operations
start_time = time.time()
z = x + y  # Element-wise addition
w = torch.mm(x, y.T)  # Matrix multiplication
v = torch.matmul(x, y.T)  # Another way to perform matrix multiplication
end_time = time.time()

# Print the operations and results
print(f"x:\n{x}")
print(f"y:\n{y}")
print(f"Element-wise addition (z = x + y):\n{z}")
print(f"Matrix multiplication (w = x * y^T):\n{w}")
print(f"Matrix multiplication using matmul (v = x @ y^T):\n{v}")
print(f"Tensor operations time: {end_time - start_time:.6f} seconds\n")
```

The command returns the following information:

```
Running on device: cuda
x:
tensor([[ 0.2912, -0.2930, -0.9653],
        [-1.2589, -0.1367, -0.2080]], device='cuda:0')
y:
tensor([[1., 2., 3.],
        [4., 5., 6.]], device='cuda:0')
Element-wise addition (z = x + y):
tensor([[1.2912, 1.7070, 2.0347],
        [2.7411, 4.8633, 5.7920]], device='cuda:0')
Matrix multiplication (w = x * y^T):
tensor([[-3.1905, -6.0915],
        [-2.1563, -6.9672]], device='cuda:0')
Matrix multiplication using matmul (v = x @ y^T):
tensor([[-3.1905, -6.0915],
        [-2.1563, -6.9672]], device='cuda:0')
Tensor operations time: 0.000240 seconds
```

Related Topics

- Resource Services and Notebooks
  This topic lists the number of notebooks that you can run concurrently per Autonomous Database instance for each Resource service.
- Use the Conda Interpreter in a Notebook Paragraph
  Oracle Machine Learning Notebooks provides a Conda interpreter to enable administrators to create conda environments with custom third-party Python and R libraries. Once created, you can download and activate Conda environments inside a notebook session also using the Conda interpreter.
- Create a Conda Environment for Python and Install Python Packages
  This topic demonstates how to create a Conda environment for Python packages, with Python 3.12.3 that is compatible with OML4Py. Here, you will also install the Python packages—tensorflow and seaborn from the `conda-forge` channel.
- Create a Conda Environment for R and Install R Packages
  This topic shows how to create a Conda environment for R packages, with R-4.0.5 for OML4R compatibility, and install the `forecast` and `ggplot2` packages.

4.5 Visualize your Data in Oracle Machine Learning Notebooks

Oracle Machine Learning Notebooks offer rich visualization capabilities of your data. The visualizations depend on the type of your dataset.

The following visualization options are available:

- Visualize Data in a Table
  A table is an arrangement of information or data in rows and columns. Using the Oracle Machine Learning Notebooks, you can create database tables, and also view the information in a tabular format.
- Visualize Data in a Bar Chart
  A bar chart is a graphical representation of data in rectangular bars. The length or height of the bars, depending on the horizontal or vertical orientation, depict the dataset distribution. One axis represents a category, while the other represents values or counts.
- Visualize Data in a Funnel Chart
  A funnel chart is a graphical representation that resembles the shape of a funnel where each segment gets progressively narrower. The segments are arranged vertically and depict a hierarchy. Within the funnel chart, each segment corresponds to a step or stage in a sequential process.
- Visualize Data in a Pyramid Chart
  Pyramid charts present your data in a distinctive triangular configuration, horizontally segmented into partitions. Each segment in the pyramid charts represents points or steps in ascending or descending order.
- Visualize Data in a Scatter Plot
  Scatter plots represent the relationship between two numeric variables in a data set. It represents data points on a two-dimensional plane and show how much one variable is affected by another. The independent variable is plotted on the X-axis, while the dependent variable is plotted on the Y-axis. You can display points by one or more grouping variables such that each group has a distinct color and shape.
- Visualize Data in a Line Chart
  A line chart is a graphical representation used to display data points connected by straight lines.
- Visualize Data in an Area Chart
  An area chart uses lines to connect the data points and fills the area below these lines to the x-axis. Each data series contributes to the formation of a distinct shaded region. This emphasizes its contribution to the overall trend. As the data points fluctuate, the shaded areas expand or contract.
- Visualize Data in a Pie Chart
  A pie chart is a graphical representation of data in a circular form, with each slice of the circle representing a fraction that is a proportionate part of the whole.
- Visualize Data in a Box Plot
  A box plot provides an overview of data distributions in numeric data. It provides general information about the symmetry, skewness, variance, and outliers in a dataset. The box plot uses boxes and lines to depict the data distribution.

4.5.1 Visualize Data in a Table

A table is an arrangement of information or data in rows and columns. Using the Oracle Machine Learning Notebooks, you can create database tables, and also view the information in a tabular format.

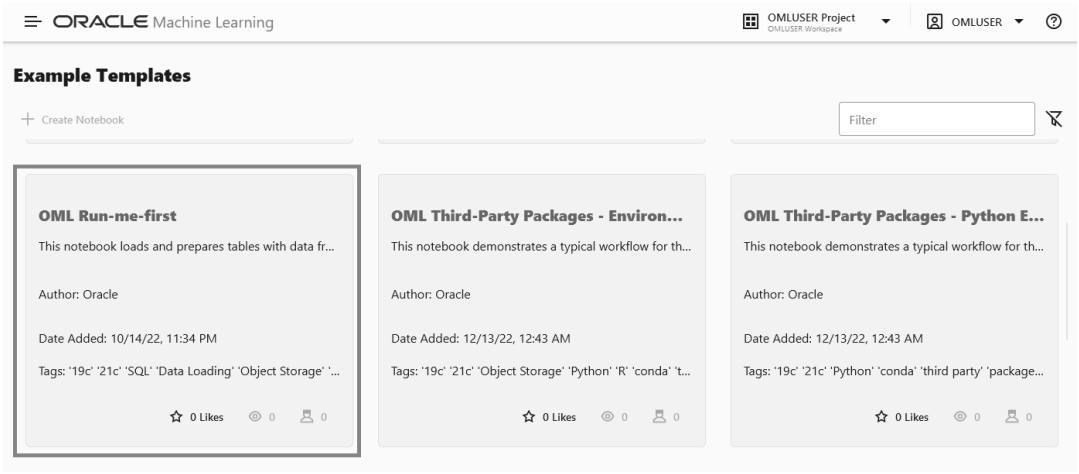
Dataset: `CUSTOMER_INSURANCE_LTV`. In this example, we will use the example template notebook *OML-Run-me-first*.

To visualize data in a table:

1. On the Oracle Machine Learning UI home page, click **Examples**. Or, open the left navigation menu by clicking the Cloud menu icon click Cloud menu icon on the top left corner of the page. Click **Templates** and then click **Examples.**

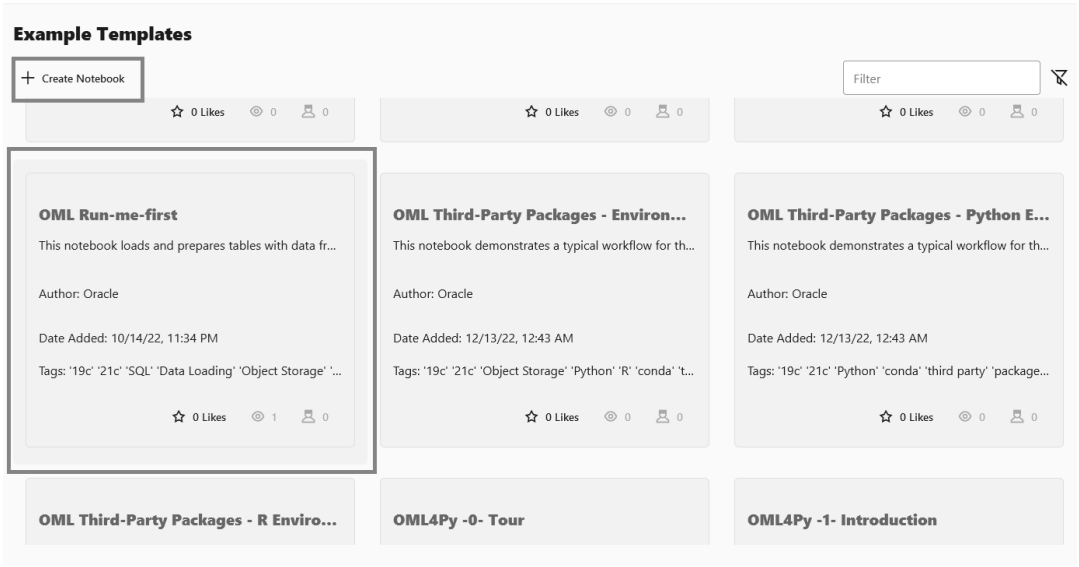
2. The *OML-Run-Me-First* example template is listed. If you are unable to view it, type the name in the Filter field.

Figure 4-4 OML Run-me-first Example Template



3. Click on the *OML Run-me-first* tile (and not on the name) to highlight it in blue. Then click the **Create Notebook** icon.

Figure 4-5 Create option on the Example Template page

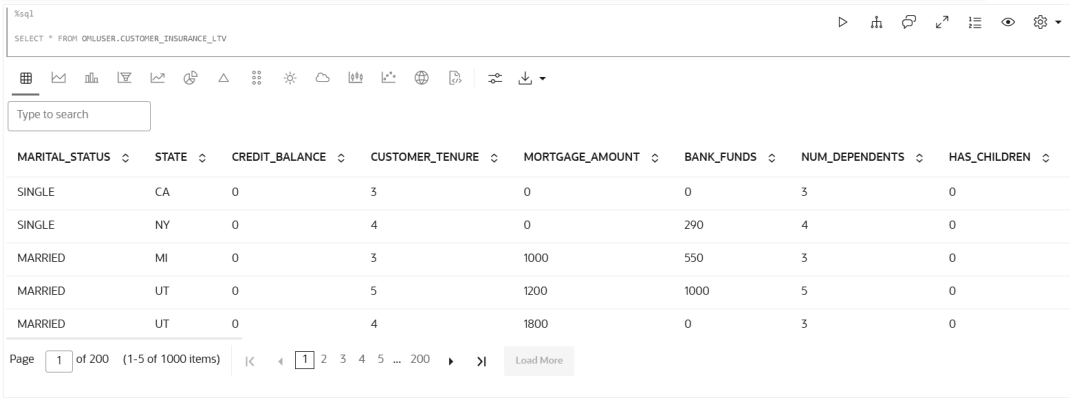


4. In the Create Notebook Dialog, click **OK.**
5. Click **Open Notebook** in the confirmation dialog to open the notebook.
6. Click the **Run Paragraphs** icon in the notebook to run all the paragraphs. This will also create the `CUSTOMER_INSURANCE_LTV` table. Click **Confirm** in the Confirmation dialog.
7. To view the data in a table format, run the following script in a SQL paragraph:

```
%sql

SELECT * FROM OMLUSER.CUSTOMER_INSURANCE_LTV
```

The script presents the data in a tabular format as shown in the screenshot:

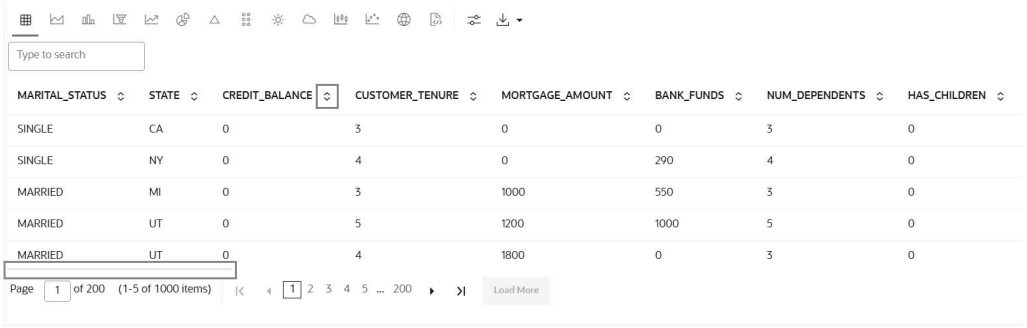
Figure 4-6 View the CUSTOMER_INSURANCE_LTV table



8. In this table, you can customize your views and settings.

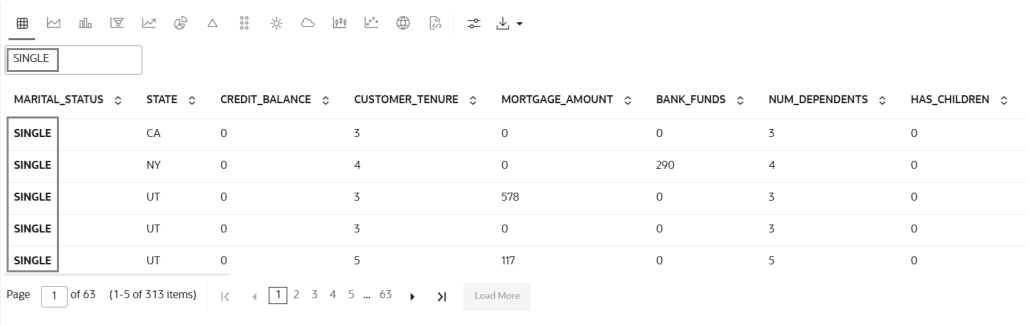
- Sort the columns in ascending or descending order: Click on the down arrow or up arrow against the columns to sort the data in ascending or descending order.

Figure 4-7 Sort Table Columns



- Use the horizontal scroll bar to scroll horizontally to view the columns on the right.
- Filter specific search terms. In the **Search** field, type the entry or term that you are looking for. In this example, the term `Single` is entered. All the rows that contain the term SINGLE in the column `MARITAL_STATUS` are filtered for display.

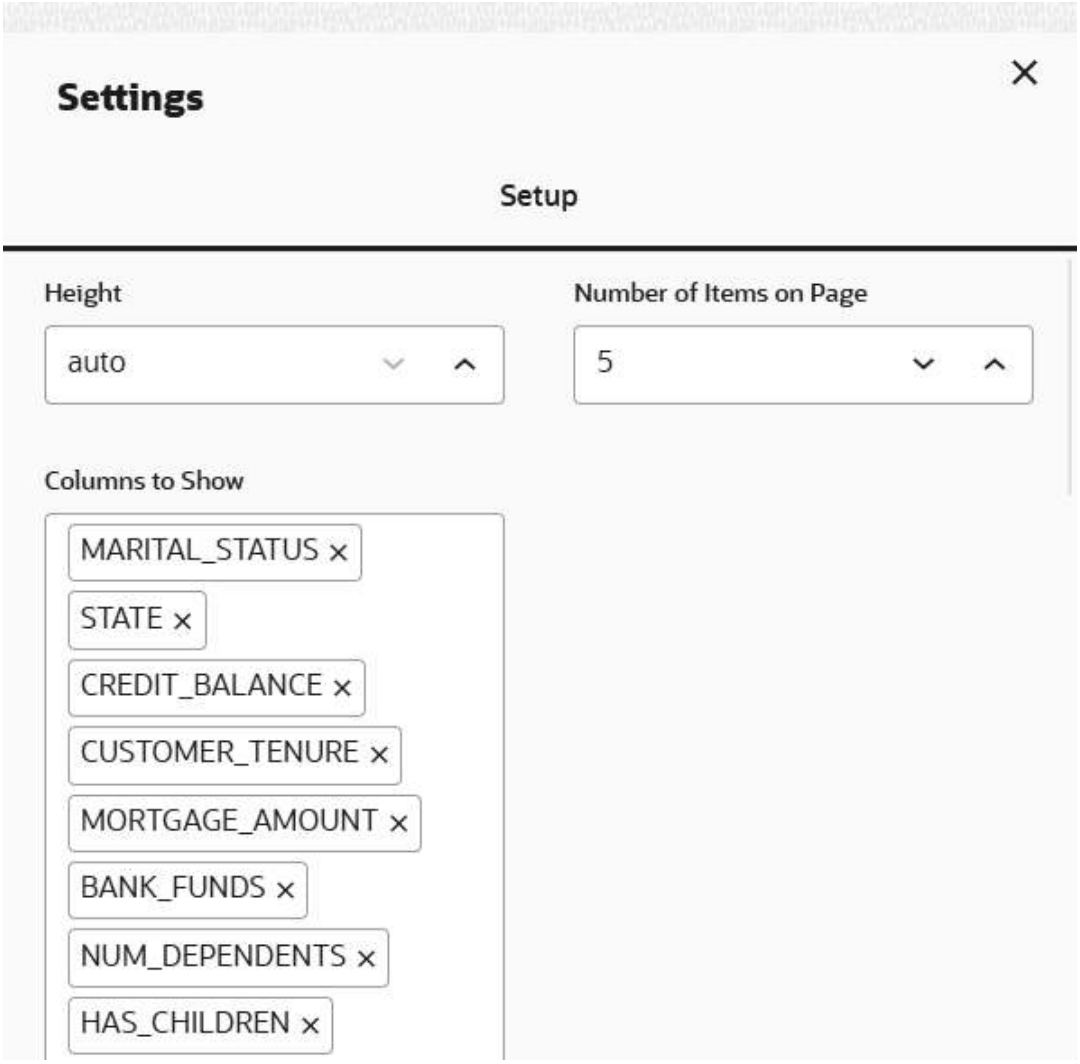
Figure 4-8 Filtering table columns by keywords



> **Note:**
>
> Rows that do not contain this term are hidden from the view and the remaining rows highlight the location of the search term within the row.

9. By default, 5 rows are displayed. If you want to view more rows or customize the table settings, click on the **Settings** icon to open the Settings dialog. Here, you can edit the following:

Figure 4-9 Settings dialog



- **Height:** This parameter changes the height of the visualization. Click on the up or down arrow to increase or decrease the visualization height.
- **Number of Items on Page:** Click on the up or down arrow, as applicable, to set the number of rows to be displayed on the page. By default, 5 rows are displayed.

Columns to Display: By default, all the columns are listed. If you want to remove any column from displaying, click on the X in the column name. To view the column again, click inside the **Columns to Show** field. The hidden columns are displayed. Click on the column

that you want to view again. In this example the column MARITAL_STATUS was removed. Clicking on the **Columns to Show** field displays it. Click on it to include in the display.

This completes the task of creating a table, and visualizing the data in it.

4.5.2 Visualize Data in a Bar Chart

A bar chart is a graphical representation of data in rectangular bars. The length or height of the bars, depending on the horizontal or vertical orientation, depict the dataset distribution. One axis represents a category, while the other represents values or counts.

When to use this chart: Use bar charts to show a distribution of data points, and perform a comparison of metric values across different subgroups of your data.

Dataset: CUSTOMER_INSURANCE_LTV. In this example, we will use the example template notebook OML-Run-me-first.

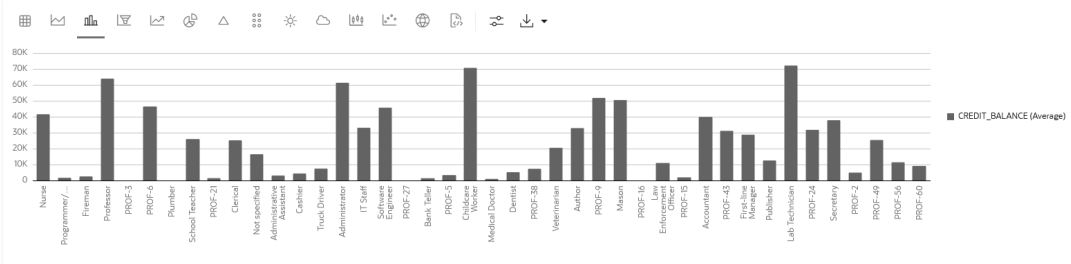
To visualize data in a bar chart:

1. In the OML-Run-Me-First notebook, go to the paragraph where you viewed the CUSTOMER_INSURANCE_LTV. Click on the bar chart icon.

Figure 4-10 Tool bar showing the bar chart icon

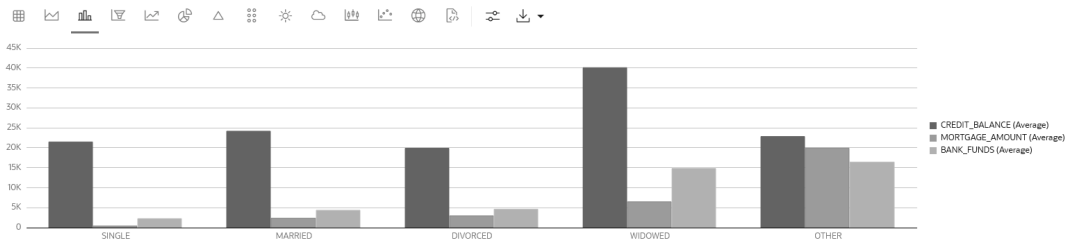
2. By default, it shows CREDIT_BALANCE along the Y-axis and the data is grouped by MARITAL_STATUS along the X-axis.

Figure 4-11 Default Bar Chart



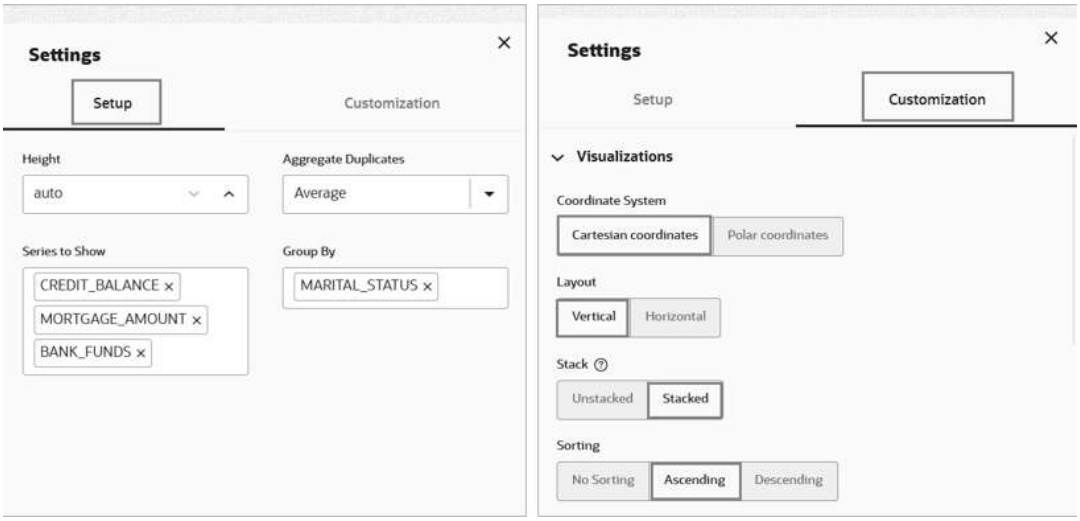
3. Click on the **Settings** icon to get a different view of this data. Under **Setup:**
   - **Series to Show:** Select CREDIT_BALANCE, MORTGAGE_AMOUNT, and BANK_FUNDS.
   - In **Group By:** Select MARITAL_STATUS.
4. The average of CREDIT_BALANCE, MORTGAGE_AMOUNT, and BANK_FUNDS are each represented by adjacent bar charts, and the bar charts are grouped by MARITAL_STATUS—single, married, divorced, widowed, and others. The bar chart now looks like this, as shown in the screenshot below:

Figure 4-12 Bar Chart



5. Once again, click on the Settings icon and click **Customization**:

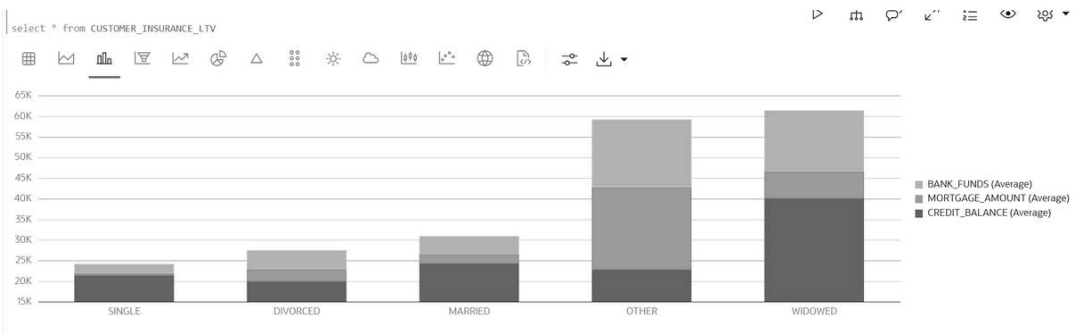
Figure 4-13 Settings - Bar Chart



- **Coordinate System**—The coordinate system of the chart. Supported Values—Polar Coordinates, Cartesian Coordinates. Click **Cartesian Coordinates.**
- **Layout**—The chart orientation. Either horizontal or vertical.
- **Stack**—Defines whether the data items are stacked or not. Click **Stacked.**
- **Sorting**—Specifies the sorting of the data. It should only be used for pie charts, bar/line/area charts with one series, or stacked bar/area charts. Sorting will not apply when using a hierarchical group axis. Click **Ascending.**
- **Zoom**—Specifies the zoom and scroll behavior of the chart. Live behavior means that the chart will be updated continuously as it is being manipulated, while "delayed" means that the update will wait until the zoom/scroll action is done. While "live" zoom and scroll provides the best end user experience, no guarantees are made about the rendering performance or usability for large data sets or slow client environments. If performance is an issue, "delayed" zoom and scroll should be used instead.

The bar chart now presents the data in a stacked manner, and in ascending order, as shown in the screenshot below:

Figure 4-14 Stacked Bar Chart



This completes the task of visualizing your data in a bar chart, and customizing its output.

4.5.3 Visualize Data in a Funnel Chart

A funnel chart is a graphical representation that resembles the shape of a funnel where each segment gets progressively narrower. The segments are arranged vertically and depict a hierarchy. Within the funnel chart, each segment corresponds to a step or stage in a sequential process.

When to use this chart: Use this chart to visualize a linear sequential process, mostly in business and sales contexts. For example, you can use a funnel chart to track the sales process, order fulfillment, website visitor trends, and so on.

Dataset: `CUSTOMER_INSURANCE_LTV`. In this example, we will use the example template notebook *OML-Run-me-first*.

To visualize the data in a funnel chart:

1. In the OML-Run-Me-First notebook, go to the paragraph where you viewed the `CUSTOMER_INSURANCE_LTV`. Click on the Funnel chart icon.

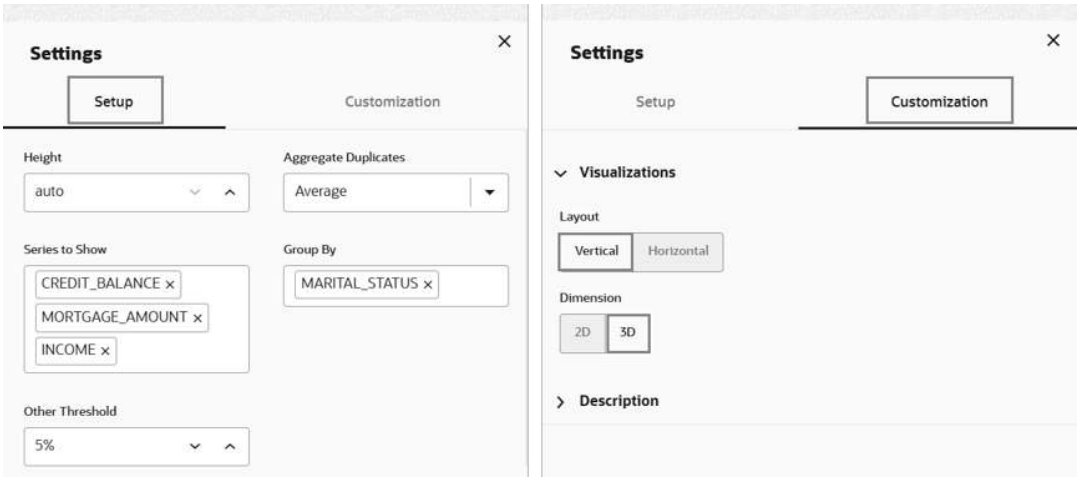
Figure 4-15 Tool bar showing the funnel chart icon

2. The data is displayed as below. Hover your cursor to view the series that is plotted in the funnel chart for each of the 5 groups.

Figure 4-16 Funnel Chart

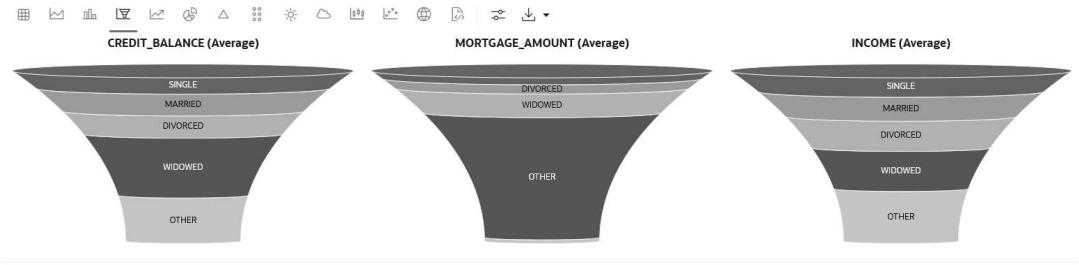
3. Let's compare a few attributes `CREDIT_BALANCE`, `MORTGAGE_AMOUNT` and `INCOME` of the same groups. Click **Settings** and edit the following:

Figure 4-17 Settings - Funnel Chart



4. These attributes `CREDIT_BALANCE`, `MORTGAGE_AMOUNT` and `INCOME` are now displayed in three funnel charts, as shown in the screenshot below:

Figure 4-18 Funnel Chart after Customization



This completes the task of visualizing your data in a funnel chart.

4.5.4 Visualize Data in a Pyramid Chart

Pyramid charts present your data in a distinctive triangular configuration, horizontally segmented into partitions. Each segment in the pyramid charts represents points or steps in ascending or descending order.

When to use this chart: Use this chart to depict hierarchical structures and the relative proportions of different values. They are typically used for displaying demographic data, market segmentation, or organizational structures. In any case, the data must have a progressive order.

Dataset: `CUSTOMER_INSURANCE_LTV`. In this example, we will use the example template notebook OML-Run-me-first.

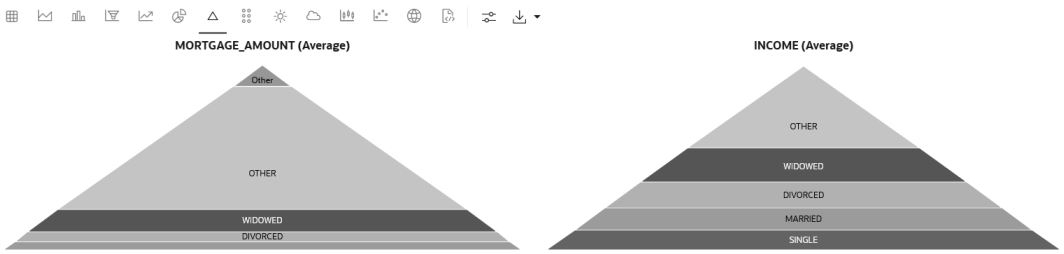
To visualize data in a pyramid chart:

1. In the OML-Run-Me-First notebook, go to the paragraph where you viewed the `CUSTOMER_INSURANCE_LTV`.
2. Click on the pyramid chart icon.

Figure 4-19 Pyramid icon on the toolbar

3. Click the **Settings** icon . Under **Setup:**
   - **Aggregate Duplicates:** Select **Average.**
   - **Series to Show:** Select `INCOME` and `MORTGAGE_AMOUNT`.
   - **Group By:** Select `MARITAL_STATUS`.

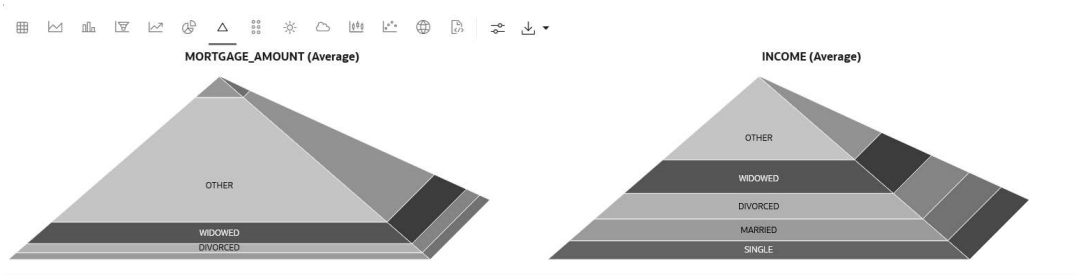
Figure 4-20 Pyramid Chart showing two series



The Pyramid chart is now shows the average for the two series `INCOME` and `MORTGAGE_AMOUNT`, grouped by `MARITAL_STATUS`.

4. On the Settings dialog, click **Customization:**
   - Click **Customization** expand **Visualization.**
   - Click **3D** under **Dimension**

Figure 4-21 Pyramid Chart rendered in three dimension



5. Click the **Setup** tab again, and change **Group By** to `GENDER`.

Figure 4-22 Pyramid Chart - Depicting the two series grouped by Gender

This completes the task of visualizing your data in a pyramid chart. The pyramid chart shows a clear correlation between the two genders, and their income level and mortgage amount. For both the categories, the average income and mortgage amount taken is higher for Females.

4.5.5 Visualize Data in a Scatter Plot

Scatter plots represent the relationship between two numeric variables in a data set. It represents data points on a two-dimensional plane and show how much one variable is affected by another. The independent variable is plotted on the X-axis, while the dependent variable is plotted on the Y-axis. You can display points by one or more grouping variables such that each group has a distinct color and shape.

When to use this chart: Use the scatter plot when you have paired numerical data, and you want to determine the relationship between the related variables in certain scenarios, identifying correlations and trends (linear and non-linear relationships), detecting outliers, understanding data distribution, identifying groupings or clusters of data. Scatter plots can also be useful when comparing multiple datasets where each datasets values are represented as a different group. Scatter plots are also useful for evaluating regression models by plotting, e.g., actual versus predicted values.

Dataset: `CUSTOMER_INSURANCE_LTV`. In this example, we will use the example template notebook OML-Run-me-first.

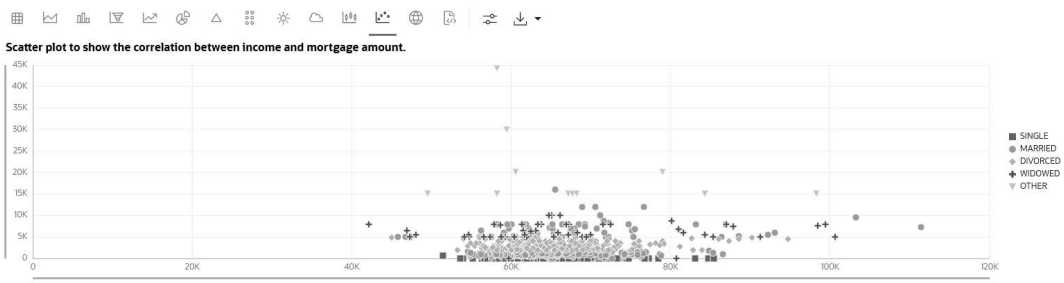
To visualize data in a scatter plot:

1. In the OML-Run-Me-First notebook, go to the paragraph where you viewed the `CUSTOMER_INSURANCE_LTV`. Click on the Scatter plot icon. A default scatter plot is shown that you will customize in the next step.

Figure 4-23 Toolbar highlighting the Scatter Plot icon

2. Click the **Settings** icon. In the Settings dialog, under **Setup**:
   - **Series to show on X-axis:** Click and select `INCOME`.
   - **Series to show on Y-axis:** Click and select `MORTGAGE_AMOUNT`.
   - **Group By:** Select `MARITAL_STATUS`.
3. Click **Customization:**
   - **Visualization:** Retain the default settings.
   - **Description:** Under **Title**, enter `Scatter plot to show the correlation between income and mortgage amount.`

Figure 4-24 Scatter Plot



This completes the task of visualizing your data in a scatter plot. The scatter plot shows a strong correlation between Income and Mortgage amount in the income range 50k to 80k.

4.5.6 Visualize Data in a Line Chart

A line chart is a graphical representation used to display data points connected by straight lines.

When to use this chart: Use this chart to visualize trends, changes, and relationships in data over a continuous period.

Dataset: `SH.SALES` table in the `SH` schema.

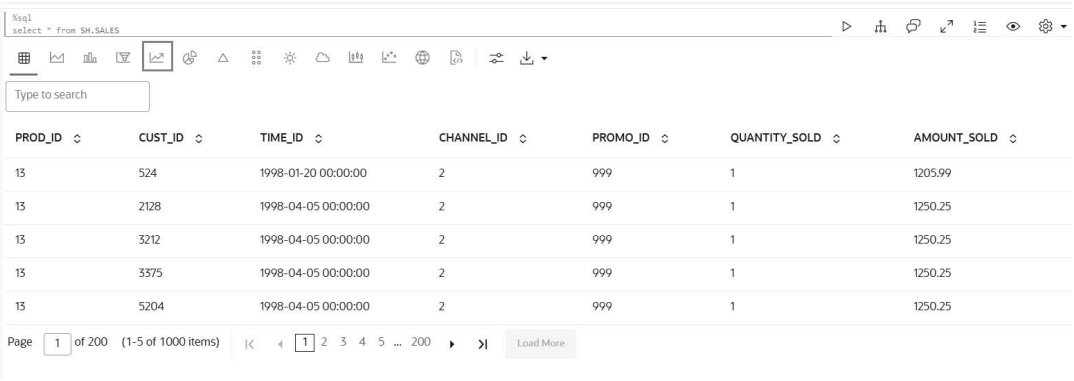
To visualize data in a line chart:

1. Enter the text of the first step here.

```
%sql
select * from SH.SALES
```

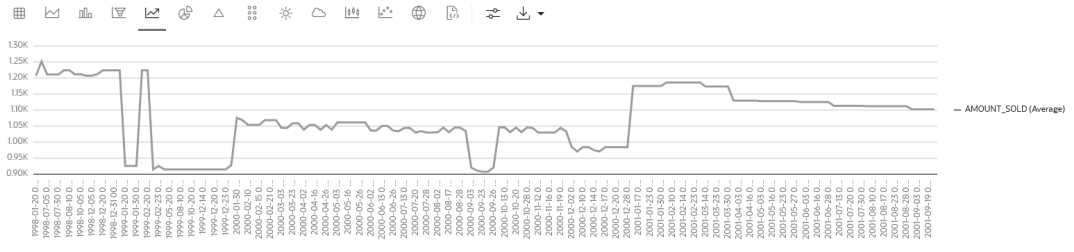
2. By default, the dataset is displayed in a table. Click on the line chart icon.

Figure 4-25 Sales Table with the Line Chart icon highlighted



3. By default, the line chart shows the average amount sold from the year 1998 till 2001, as shown in the screenshot below.

Figure 4-26 Line Chart - Depicting the average of amount sold from 1998 - 2001



Click on the Settings icon to view the attributes that are plotted along the X and Y axis. The dates on which the product was sold from the year 1998 till 2001 are plotted along the X-axis. Corresponding to each sale date, the average of the amount sold is plotted along the Y-axis.

4. Click on the Settings icon. Under **Setup,** edit the following:

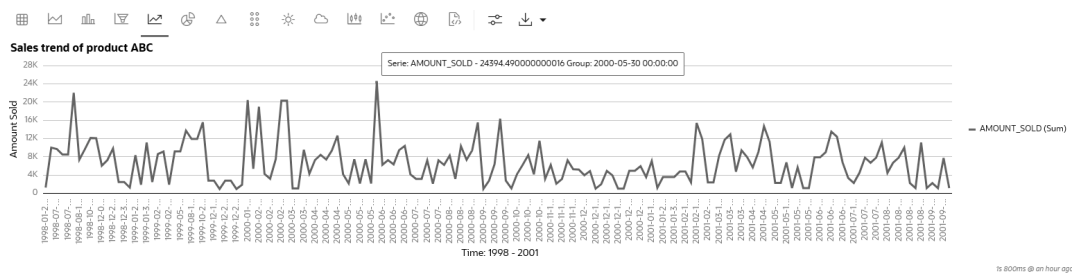
   - **Aggregate Duplicate:** Decides what should happen with values that are within the same group. Select **Sum.** This will show the sum of the amount sold for the product with `PROD_ID` 13, from 1998 to 2001.
   - **Series to Show:** All fields in the result-set that are of type number can be selected. Selecting multiple fields will add additional diagrams to the visualization. Select `AMOUNT SOLD`.
   - **Group By:** All fields in the result-set can be selected. The more groups exist, the more the dataset shrinks since it collects all fields and concatenates same values. Select `TIME_ID`.

5. Click **Customization** and edit the following:

   - **X-axis:** Enter Time: `1998 - 2001`. The dates on which the product was sold from the year 1998 till 2001 are plotted along the X-axis.
   - **Y-axis:** Enter `Amount Sold`. Corresponding to each sale date, the sum of the amount sold is plotted along the Y-axis.
   - **Description:** Enter `Sales trend of product ABC`

   The line chart now displays the sum of the amount sold from the year 1998 to 2001, as shown below. Hover your cursor over the highest point in the line chart to view the values. You can see that on 5/30/2000, the product recorded the highest sale in terms of the sum of the amount sold.

Figure 4-27 Line chart Line chart - Depicting the sum of amount sold from 1998 - 2001



This completes the task of visualizing your data in a line chart.

4.5.7 Visualize Data in an Area Chart

An area chart uses lines to connect the data points and fills the area below these lines to the x-axis. Each data series contributes to the formation of a distinct shaded region. This emphasizes its contribution to the overall trend. As the data points fluctuate, the shaded areas expand or contract.

When to use this chart: Use this chart to visualize trends, changes, and relationships in data over a continuous period.

Dataset: `SH.SALES` table in the `SH` schema.

To visualize data in an area chart:

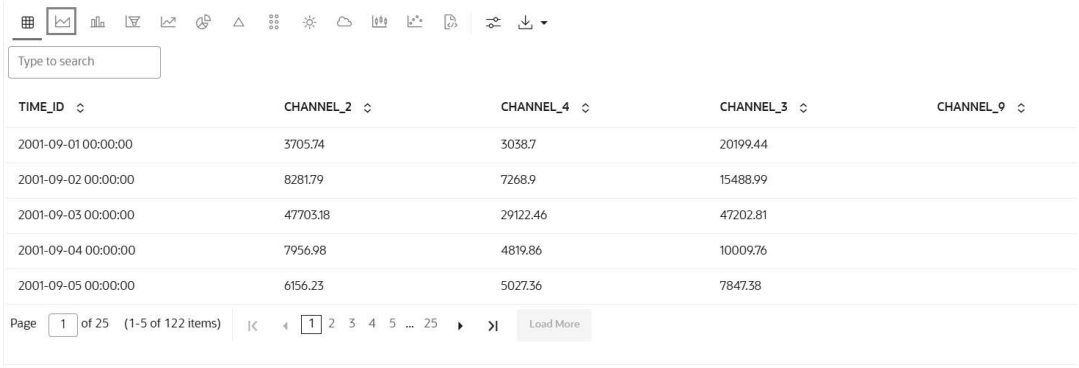
1. In another `%sql` paragraph, run the following script:

```
SELECT
      TIME_ID,
```

```
      -- Use MAX(TOTAL_SOLD) to handle cases with duplicate TIME_ID and
CHANNEL_ID
      MAX(CASE WHEN CHANNEL_ID = 2 THEN TOTAL_SOLD ELSE NULL END) AS
Channel_2,
      MAX(CASE WHEN CHANNEL_ID = 4 THEN TOTAL_SOLD ELSE NULL END) AS
Channel_4,
      MAX(CASE WHEN CHANNEL_ID = 3 THEN TOTAL_SOLD ELSE NULL END) AS
Channel_3,
      MAX(CASE WHEN CHANNEL_ID = 9 THEN TOTAL_SOLD ELSE NULL END) AS
Channel_9
FROM (SELECT TIME_ID, CHANNEL_ID, sum(AMOUNT_SOLD) TOTAL_SOLD
  FROM SH.SALES
      WHERE TIME_ID >= TO_DATE('2001-09-01', 'YYYY-MM-DD')
      GROUP BY TIME_ID, CHANNEL_ID
      ORDER BY TIME_ID)
GROUP BY TIME_ID
ORDER BY TIME_ID
```

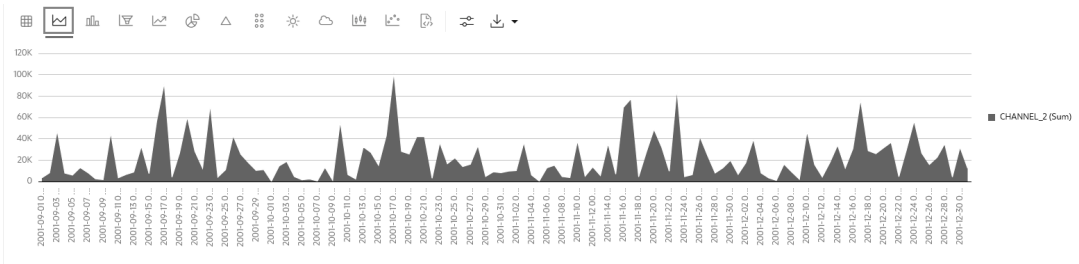
This script groups the data by `TIME_ID` and `CHANNEL_ID`. It presents the data from 2001-09-01 and later. It shows the value for `TOTAL_SOLD` for each of the four channels grouped by `CHANNEL_2`, `CHANNEL_3`, `CHANNEL_4` and `CHANNEL_9`.

2. The data from the `SALES` table is now presented for the following columns—`TIME_ID`, `CHANNEL_2`, `CHANNEL_3`, `CHANNEL_4` and `CHANNEL_9`.



3. Now, click on the the area chart icon Area chart icon in the tool bar to visualize the data in an area chart.

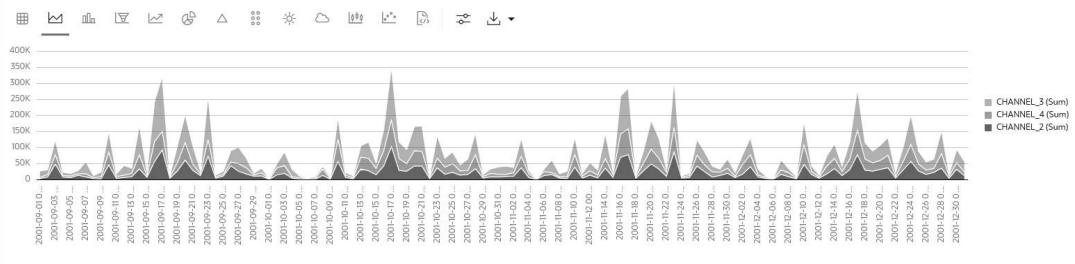
Figure 4-28 Area Chart showing the sum for CHANNEL_2



4. Click on the **Settings** icon to open the Settings dialog. Under **Setup:**
   - **Series to Show:** Click to add `CHANNEL_3`, `CHANNEL_4` and `CHANNEL_9`.

- **Group By:** Retain the default, that is, `TIME_ID`.
- **Aggregate Duplicates:** Retain the default, that is, `SUM`.

5. Click **Customization** and under **Visualization**, click **Stacked.** The area chart is now presented as shown in the screenshot.



This completes the task of visualizaing your data in an area chart.

4.5.8 Visualize Data in a Pie Chart

A pie chart is a graphical representation of data in a circular form, with each slice of the circle representing a fraction that is a proportionate part of the whole.

When to use this chart: Use this chart to visualize the numerical proportion of the parts to the whole.

Dataset: The `IRIS` dataset. The `IRIS` dataset contains 3 classes. These classes are the three different Iris species—Setosa, Versicolor, and Virginica. The dataset has 50 samples each, and four numeric properties about those classes—Sepal Length, Sepal Width, Petal Length, and Petal Width.

To visualize data in a pie chart:

1. Run the following script in an R paragraph to create the IRIS dataset:

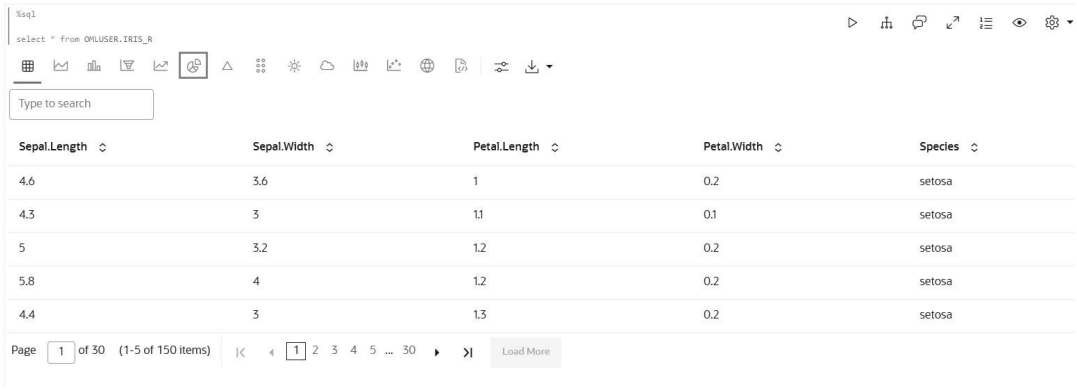
```
%r
library(ORE)

if (ore.exists("IRIS_R")) ore.drop(table="IRIS_R")

ore.create(iris, table = "IRIS_R", overwrite=TRUE)

ore.exec("ANALYZE TABLE IRIS_R COMPUTE STATISTICS")

z.show(cat("Shape:", dim(IRIS_R)))
```

   This creates the table `IRIS_R`.

2. Now, run the following SQL command to view the dataset.

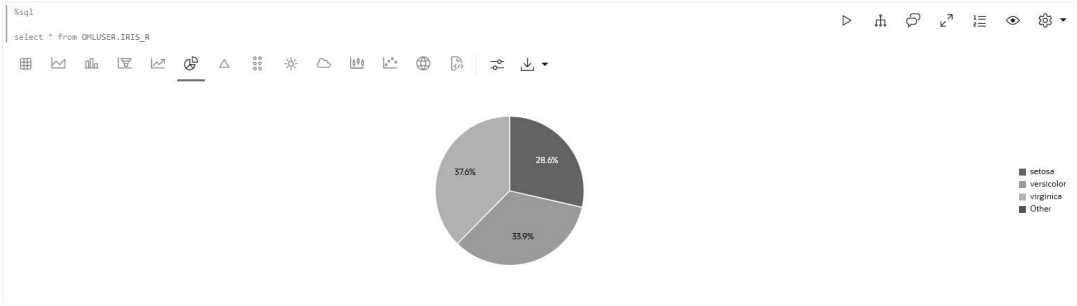
```
%sql
select * from OMLUSER.IRIS_R
```

3. By default, the dataset is displayed in a table. Click on the pie chart icon.



4. The data is now displayed in a pie chart. By default, the pie chart shows the average sepal length for each of the three species of iris. It also shows a 5% threshold for others.

Figure 4-29 Pie Chart - Depicts the average sepal length for the three classes



5. Click on the **Settings** icon to open the Settings dialog. Click **Customization.**
   - **Variant:** Click **Donut.**
   - **Inner Radius:** Click the up arrow and set it to `40`.
   - **Label:** Type `Sepal Length of the 3 Iris species.`
   - Close the dialog. The data is now rendered in a donut chart, as shown below:

6. Once again, click on the Settings icon. Under **Setup**, click **Series to Show** and then select **Petal Length** while retaining **Sepal Length.**

7. Click Customization:
   - **Variant:** Click **Pie.**
   - **Dimension:** Click **3D.**
   - **Sorting:** Click **Ascending.**

   The data is now displayed in two 3 dimensional pie charts, one showing the average sepal length, and the other showing the average petal length for each of the three species of the iris flower.

This completes the task of visualizing your data in a piee chart.

4.5.9 Visualize Data in a Box Plot

A box plot provides an overview of data distributions in numeric data. It provides general information about the symmetry, skewness, variance, and outliers in a dataset. The box plot uses boxes and lines to depict the data distribution.

The box plot has the following components:

- **Central Box**—Inter-quartile range and quartiles:
  - **Q1 (First Quartile)**—This is the value below which 25% of the data falls. It represents the boundary between the lowest 25% and highest 75% of values.
  - **Q3 (Third Quartile)**—This represents the value below which 75% of the data falls, serving as a border between the lowest 75% and highest 25% of values.
  - **Interquartile Range (IQR)**—The IQR is the range in which the central 50% of the values fall. IQR = Q3 - Q1
- **Whiskers**—The whiskers of the box plot extend from the central box to the minimum and maximum data values that are not considered outliers. They provide a graphical representation of the majority of the data's distribution.
- **Outliers**—Outliers are data points that deviate significantly from other data points, typically due to data variability or errors. An outlier is plotted as a dot beyond the ends of the whiskers of a box plot.
- **Median**—The median is the value that divides the dataset into two halves, with 50% of the values falling below it and 50% falling above it. In the box plot, a line or a mark inside the central frame represents the median.

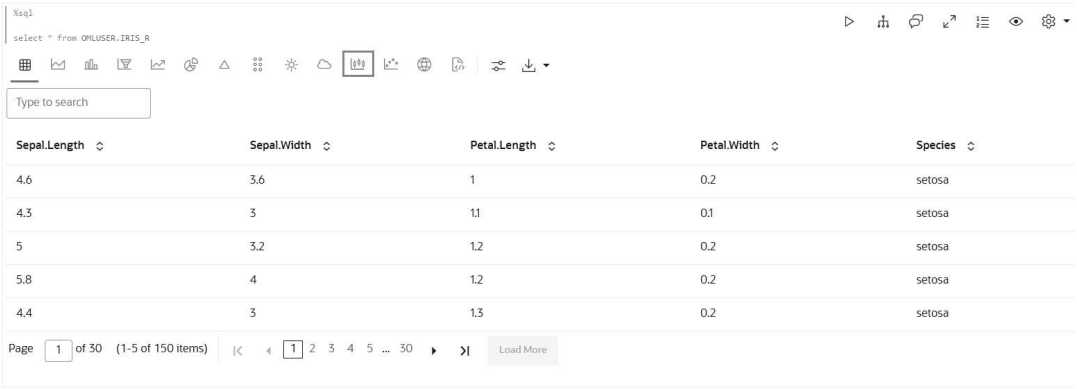
When to use this chart: Use this chart to show distributions of numeric data, especially if you want to compare them between multiple groups.

Dataset: `IRIS` dataset. The `IRIS` dataset contains 3 classes (three different Iris species - Setosa, Versicolor, and Virginica) along with 50 samples each, and four numeric properties about those classes: Sepal Length, Sepal Width, Petal Length, and Petal Width.

To visualize data in a box plot:

1. We have already created the `IRIS` dataset in the topic *Visulize your data in a pie chart*. We will use the same table `IRIS_R` to visualize the data in a box plot. Open the notebook and go to the paragraph where the `IRIS_R` table is populated.

Figure 4-30 IRIS dataset in a table with boxplot icon highlighted



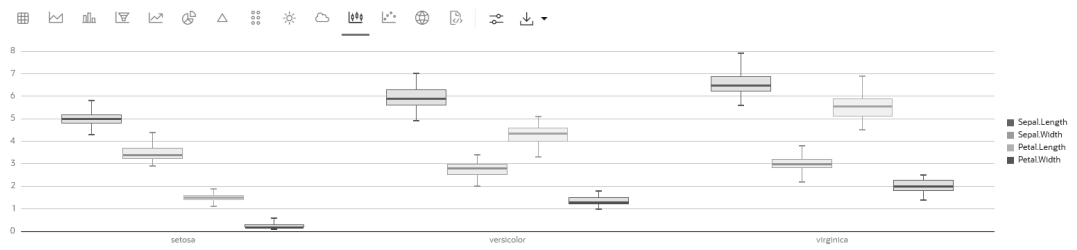
2. Click the box plot icon. The dataset is now displayed in a box plot.

Figure 4-31 Boxplot 1 Depicts the data grouped by the 3 species Setosa, Versicolor, and Virginca

As you can see, by default the data is grouped by the 3 species (classes) - Setosa, Versicolor, and Virginca along the X-axis, and the sepal length along the Y axis. Hover your cursor over each box plot to view the count.

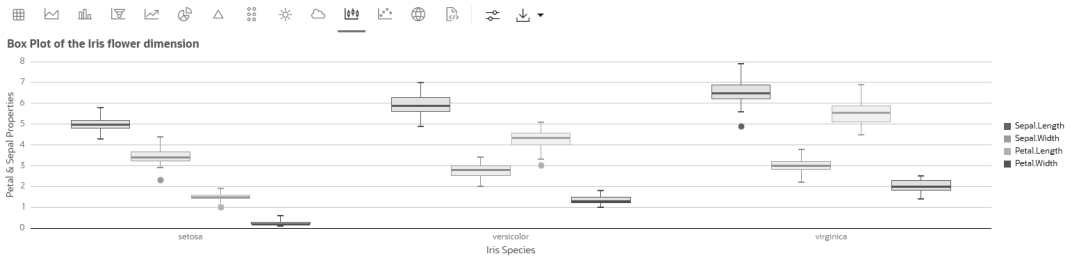
3. Click on Settings to view how the data is plotted. Under **Setup**, go to **Series to Show**, and click to add the other three numeric properties—`Sepal Width`, `Petal Length`, and `Petal Width`.

Figure 4-32 Box Plot 2 - Depicts the Iris 3 species and their properties Sepal Width, Sepal Length, Petal Width, and Petal Length



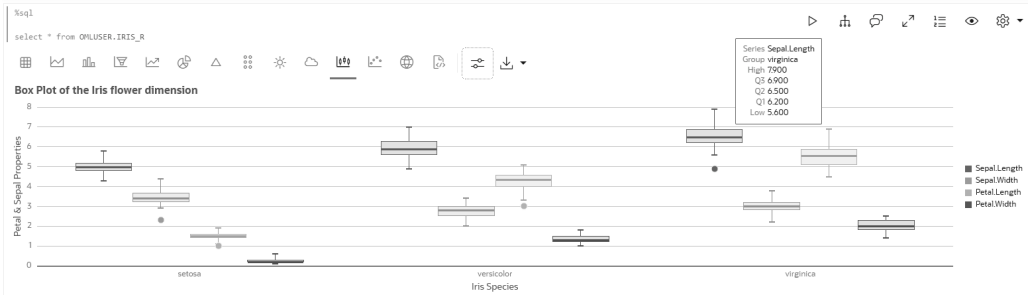
4. Under Settings, click **Customizations**, edit the following settings:
   - **Visualization:** Click **Show Outliers.**
   - In the **Text** field, enter `Iris Species`. **Color:** Enter `rgb(7, 17, 215, 0.88)`
   - **Y-Axis:** In the **Text** field, enter `Petal & Sepal Properties`. **Color:** Enter `rgb(7, 17, 215, 0.88)`
   - **Description:** Enter the following - `Box Plot of the Iris flower dimension.`
   - **Color:** Enter `rgb(241, 8, 24)`
   - Once done, close the dialog.

Figure 4-33 Box Plot 3 - Shows the Outlier, Box Plot description, and descriptions for X-Axis and Y-Axis



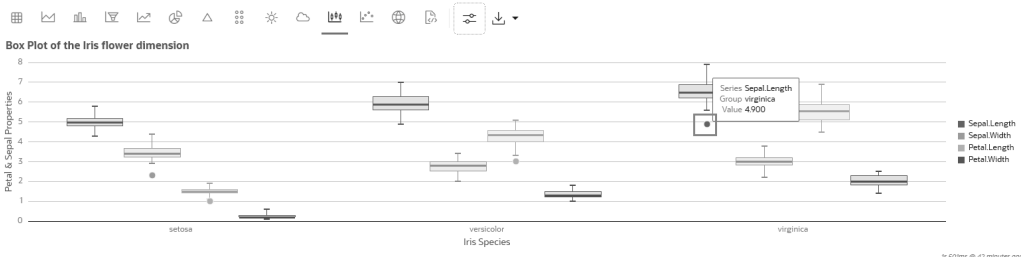
5. The box plot now displays the dataset as below:
   - Hover your cursor over each box plot to view the values. In the screenshot here, the cursor is over the Sepal Length series for the species Virginica. The length ranges from 5.6 to 7.9. There is also an outlier for this, and it is indicated by the dot below the box plot whisker.

Figure 4-34 Box Plot 4 - Shows the value for the class Virginica and property Sepal Length



   - Hover your cursor over the dot that indicates the outlier for the group virginica. It shows the outlier value at 4.9 for Virginica sepal length. This means that in the species Virginica, there are sepals whose length is significantly below the lower count (5.6).

Figure 4-35 Box Plot 5 - Shows the Outlier value for Virginica (Class) Sepal Length (Property)



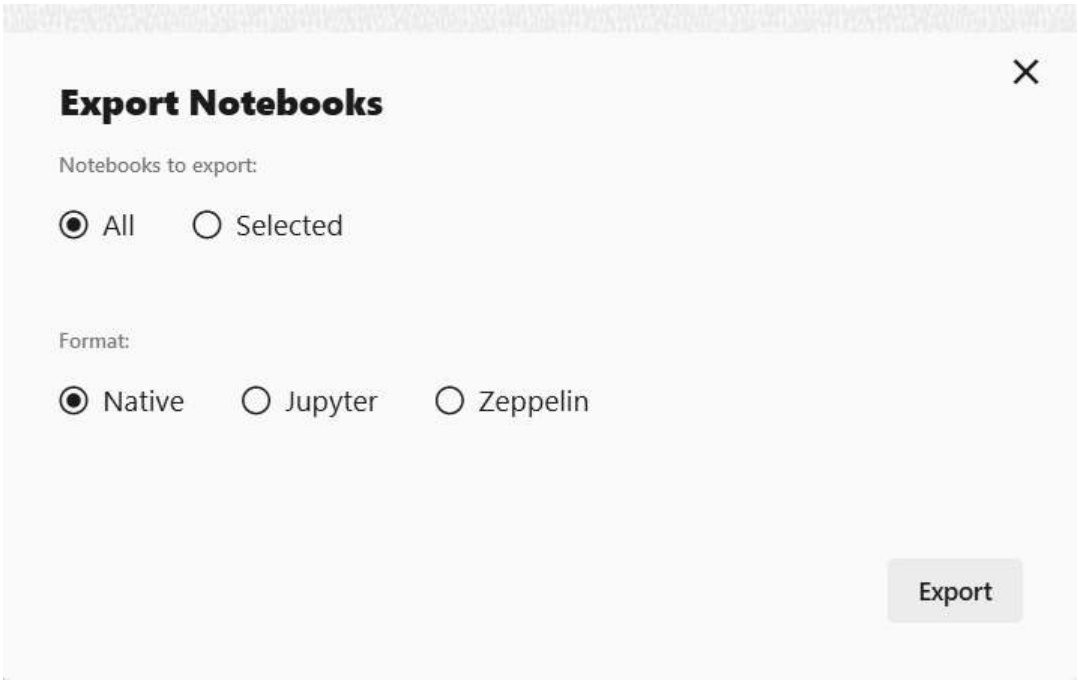
This completes the task of visualizing your data in a box plot.

4.6 Export a Notebook

You can export a Notebook in Native format (`.dsnb`) file, Zeppelin format (`.json`) file, in Jupyter format (`.ipynb`), and later import them in to the same or a different environment.

To export a Notebook:

1. On the Notebooks page, select the notebooks that you want to export. You have the option to export one or more or all the notebooks.
2. On the top panel of the notebook editor, click **Export** and then click any one of the following options:



- **Notebooks to Export** — To export notebooks, click:
  - **All** — To export all the notebooks listed on the Notebooks page.
  - **Selected** — To export the selected notebooks.
- **Format** — Click the format in which you want to export your notebook:

- **Native**— Exports the notebook as a `.dsnb` (Data Studio Notebook) file.
- **Jupyter** — Exports the notebook as a `.ipynb` file.
- **Zeppelin** — Exports the notebook as a `.json` (JavaScript Object Notation) file.

The exported notebooks are saved either as `.dsnb` files, `.json` files or `.ipynb` files in a zipped folder.

Related Topics

- About Interpreters and Notebook Service Levels
  An interpreter is a plug-in that allows you to use a specific data processing language backend.

4.7 Import a Notebook

You can import notebooks across Pluggable Databases (PDBs) into your workspace. Oracle Machine Learning UI supports the import of notebooks in the native format `(.dsnb)`, Zeppelin `(.json)` and Jupyter `(.ipynb)` notebooks.

Oracle Machine Learning UI supports the import of both Zeppelin (.json) and Jupyter (.ipynb) notebooks.

> **Note:**
>
> Starting in Oracle Database 20c,"database" refers specifically to the data files of a multitenant container database (CDB), pluggable database (PDB), or application container.

To import a notebook:

1. On Oracle Machine Learning UI home page, click **Notebooks.**
2. On the Notebooks page, click **Import.**

   This opens the **File Upload** dialog. Browse and select the notebook that you want to import.

   > **Note:**
   >
   > You must have the notebook saved as a `.json` file or `.dsnb` file to import it. You can import notebooks exported from non-Oracle Apache Zeppelin environments, but only paragraphs types that are supported may be run.

3. In the File Upload dialog, browse and select the notebook and click **Open.**

   This imports the notebook file into your workspace.

4. Click the imported notebook to open it. On the Notebooks page, click the gear icon to view the interpreter bindings.

Related Topics

- About Interpreters and Notebook Service Levels
  An interpreter is a plug-in that allows you to use a specific data processing language backend.

- Database and Instance

4.8 Use the SQL Interpreter in a Notebook Paragraph

An Oracle Machine Learning notebook supports multiple languages. Each paragraph is associated with a specific interpreter. For example, to run SQL statements use the SQL interpreter. To run PL/SQL statements, use the `script` interpreter.

In an Oracle Machine Learning UI notebook, you can add multiple paragraphs, and each paragraph can be connected to different interpreters such as SQL or Python. You identify which interpreter to use by specifying `%` followed by the interpreter to use: `sql`, `script`, `r`, `python`, `conda`, `markdown`.

A paragraph has an input section and an output section. In the input section, specify the interpreter to run along with the text. This information is sent to the interpreter to be run. In the output section, the results of the interpreter are provided.
You can use the following directives in a notebook paragraph:

- `%sql` — Supports standard SQL statements. In `%sql` the results of a `SELECT` statement are directly displayed in a table viewer, with access to other visualization options. Use the options in the chart settings to perform groupings, summation, and other operations.
- `%script` — Supports both SQL statements and PL/SQL. In `%script`, the results of a `SELECT` statement are provided as text string output.
- `%conda` — Supports the Conda environment. Type `%conda` at the beginning of the paragraph to connect to the Conda environment and work with third-party libraries for Python.
- `%r` — Supports R scripts. Type `%r` at the beginning of the paragraph to connect to the R interpreter.
- `%python` — Supports Python scripts. Type `%python` at the beginning of the paragraph to connect to the Python interpreter.
- `%md` — Supports Markdown markup language.

> **Note:**
>
> To run a **Group By** on all your data, then it is recommended to use SQL scripts to do the grouping in the database, and return the summary information for charting in the notebook. Grouping at the notebook level works well for small sets of data. If you pull too much data to the notebook, you may encounter issues due to insufficient memory. You can set the row limit for your notebook by using the option **Render Row Limit** on the Connections Group page.

To fetch and visualize data in a notebook:

1. On the Notebook page, click the notebook that you want to run.

   The notebook opens in edit mode.

2. Type `%SQL` to call the SQL interpreter, and press Enter. Your notebook is now ready to run SQL statements.

3. Type the SQL statement to fetch data from an Oracle Database. For example, type `SELECT * FROM TABLENAME` and click ▷. Alternatively, press Shift+Enter keys to run the notebook.

> **Note:**
>
> Notebooks must be opened as a regular user, that is, a non-administrator user. The **Run** notebook option is not available to the Administrator.

This fetches the data in the notebook.

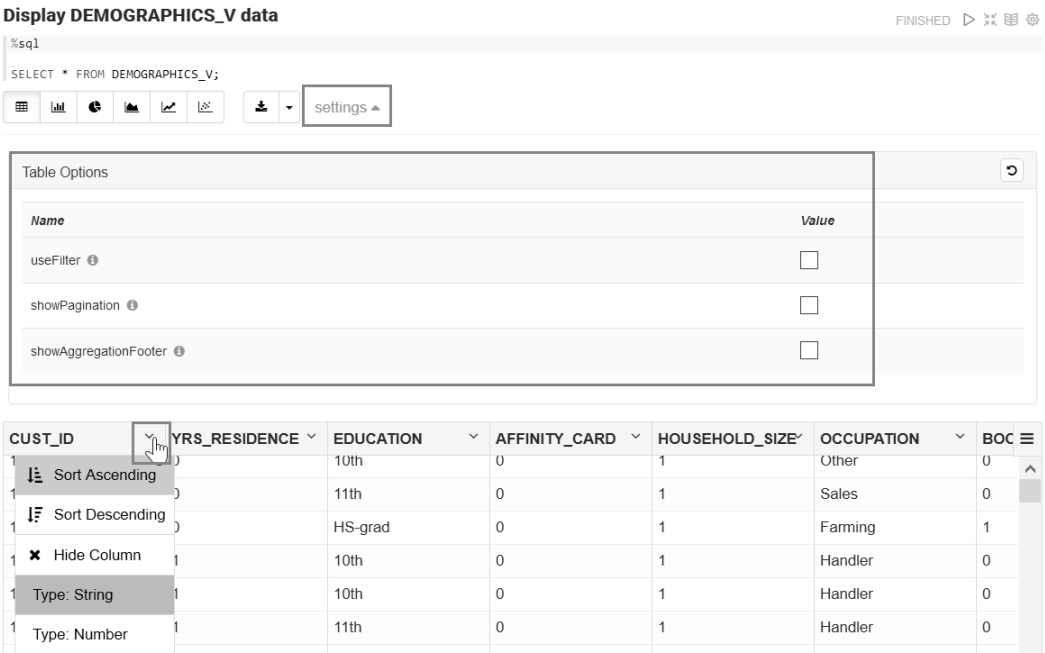
4. The data is displayed in the output of the paragraph.

The results of the interpreter appear in the output section. The output section of the paragraph comprises a charting component that displays the results in graphical output. The chart interface allows you to interact with the output in the notebook paragraph. You have the option to run and edit single a paragraph or all paragraphs in a notebook.

For Table Options, click **settings** and select:

- **useFilter:** To enable filter for columns.
- **showPagination:** To enable pagination for enhanced navigation.
- **showAggregationFooter:** To enable a footer to display aggregated values.

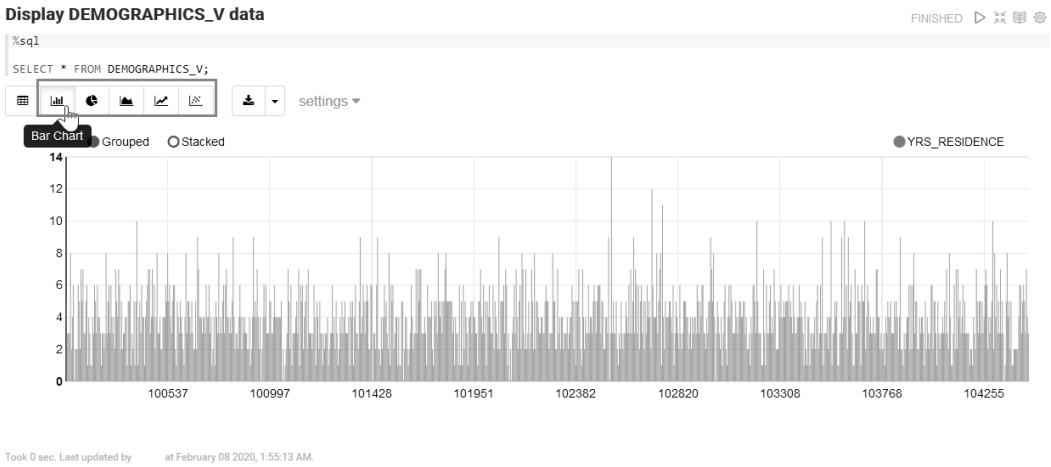
You can also sort the columns by clicking the down arrow next to the column name.



To visualize the tabular data, click the respective icons for each of the each graphical representation, as shown here:

- Click to represent the data in a Bar Chart.
- Click  to represent the data in a Pie Chart.

- Click to represent the data in an Area Chart.
- Click to represent the data in a Line Chart.
- Click to represent the data in a Scatter Chart.



- About Oracle Machine Learning for SQL
  Oracle Machine Learning for SQL (OML4SQL) provides a powerful, state-of-the-art machine learning capability within Oracle Database. You can use Oracle Machine Learning for SQL to build and deploy predictive and descriptive machine learning models, add intelligent capabilities to existing and new applications.
- Set Output Format in Notebooks
  Oracle Machine Learning Notebooks allow you to preformat query output in notebooks.
- Output Formats Supported by SET SQLFORMAT Command
  By using the `SET SQLFORMAT` command, you can generate the query output in a variety for formats.

Related Topics

- Edit Oracle Database Interpreter Connection
  When defining an Oracle Database interpreter connection, a reference to a compute resource is created. This reference contains all connection-related information about the interpreter.
- Edit Oracle Database Interpreter Connection
  When defining an Oracle Database interpreter connection, a reference to a compute resource is created. This reference contains all connection-related information about the interpreter.

4.8.1 About Oracle Machine Learning for SQL

Oracle Machine Learning for SQL (OML4SQL) provides a powerful, state-of-the-art machine learning capability within Oracle Database. You can use Oracle Machine Learning for SQL to build and deploy predictive and descriptive machine learning models, add intelligent capabilities to existing and new applications.

Oracle Machine Learning for SQL offers an extensive set of in-database algorithms for performing a variety of machine learning tasks, such as classification, regression, anomaly

detection, feature extraction, clustering, and market basket analysis, among others. The programmatic interfaces to OML4SQL are PL/SQL for building and maintaining models and a family of SQL functions for scoring.

Use Oracle Machine Learning Notebook with the SQL and PL/SQL interpreters to run SQL statements (`%sql`) and PL/SQL scripts (`%script`) respectively. Use Oracle Machine Learning for SQL to:

- Perform data exploration and data analysis
- Build, evaluate and deploy machine learning models, and
- Score data using those models

4.8.2 Set Output Format in Notebooks

Oracle Machine Learning Notebooks allow you to preformat query output in notebooks.

To preformat query output, you must use the command `SET SQLFORMAT` as follows:

1. Open a notebook in Oracle Machine Learning.
2. Type the command:

   ```
   %script

   SET SQLFORMAT format_option
   ```

   For example, if you want the output in ansiconsole format, then type the command followed by the SQL query as:

   ```
   SET SQLFORMAT ansiconsole;

   SELECT * FROM HR.EMPLOYEES;
   ```

   Here, the output format is `ansiconsole`, and the table name is `HR.EMPLOYEES`.

> **Note:**
>
> This formatting is available for the Script interpreter. Therefore, you must add the prefix `%script` as shown in this example.

4.8.3 Output Formats Supported by SET SQLFORMAT Command

By using the `SET SQLFORMAT` command, you can generate the query output in a variety for formats.

> **Note:**
>
> These output formats are available for the Script interpreter. Therefore, you must include the prefix `%script`.

The available output formats are:

- CSV — The CSV format produces standard comma-separated variable output, with string values enclosed in double quotes. The syntax is:

  ```
  %script
  ```

```
SET SQLFORMAT CSV
```

- HTML — The HTML format produces the HTML for a responsive table. The content of the table changes dynamically to match the search string entered in the text field. The syntax is:

  ```
  %script

  SET SQLFORMAT HTML
  ```

- XML — The XML format produces a tag based XML document. All data is presented as `CDATA` tags. The syntax is:

  ```
  %script

  SET SQLFORMAT XML
  ```

- JSON — The JSON format produces a JSON document containing the definitions of the columns along with the data that it contains. The syntax is:

  ```
  %script

  SET SQLFORMAT JSON
  ```

- ANSICONSOLE — The ANSICONSOLE format resizes the columns to the width of the data to save space. It also underlines the columns, instead of separate line of output. The syntax is:

  ```
  %script

  SET SQLFORMAT ANSICONSOLE
  ```

- INSERT — The INSERT format produces the INSERT statements that could be used to recreate the rows in a table. The syntax is:

  ```
  %script

  SET SQLFORMAT INSERT
  ```

- LOADER — The LOADER format produces pipe delimited output with string values enclosed in double quotes. The column names are not included in the output. The syntax is:

  ```
  %script

  SET SQLFORMAT LOADER
  ```

- FIXED — The FIXED format produces fixed width columns with all data enclosed in double-quotes. The syntax is:

  ```
  %script

  SET SQLFORMAT FIXED
  ```

- DEFAULT — The DEFAULT option clears all previous `SQLFORMAT` settings, and returns to the default output. The syntax is:

  ```
  %script

  SET SQLFORMAT DEFAULT
  ```

> **Note:**
>
> You can also run this command without the format name `DEFAULT` by simply typing `SET SQLFORMAT`.

- DELIMITED — The DELIMITED format allows you to manually define the delimiter string, and the characters that are enclosed in the string values. The syntax is:

  ```
  %script

  SQLFORMAT DELIMITED delimiter left_enclosure right_enclosure
  ```

  For example,

  ```
  %script

  SET SQLFORMAT DELIMITED ~del~ " "

  SELECT * FROM emp WHERE deptno = 20;
  ```

  Output:

  ```
  "EMPNO"~del~"ENAME"~del~"JOB"~del~"MGR"~del~"HIREDATE"~del~"SAL"~del~"COMM"~de
  l~"DEPTNO"
  ```

  In this example, the delimiter string is `~del~` and string values such as `EMPNO, ENAME, JOB` and so on, are enclosed in double quotes.

4.9 Use the Python Interpreter in a Notebook Paragraph

An Oracle Machine Learning notebook supports multiple languages. Each paragraph is associated with a specific interpreter. To run Python commands in a notebook, you must first connect to the Python interpreter. To use OML4Py, you must import the `oml` module.

In an Oracle Machine Learning UI notebook, you can add multiple paragraphs, and each paragraph can be connected to different interpreters such as SQL or Python. You identify which interpreter to use by specifying `%` followed by the interpreter to use: `sql`, `script`, `r`, `python`, `conda`, `markdown`.

This example shows you how to:

- Connect to a Python interpreter to run Python commands in a notebook
- Import the Python modules - `oml`, `matplotlib`, and `numpy`
- Check if the `oml` module is connected to the Oracle Database

> **Note:**
>
> `z` is a reserved keyword and must not be used as a variable in `%python` paragraphs in Oracle Machine Learning UI notebooks.

Assumption: The example assumes that you have created a new notebook named **Py Note.**

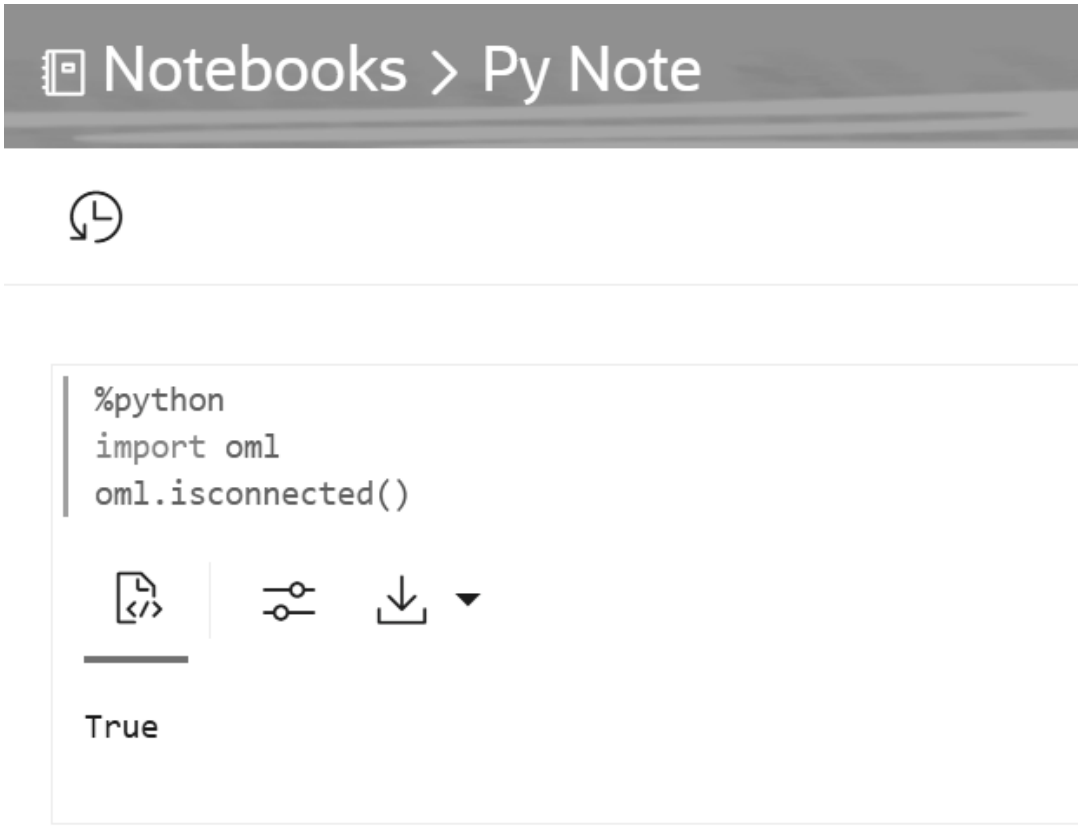
1. Open the Py Note notebook and click the interpreter bindings icon. View the available interpreter bindings.
2. To connect to the Python interpreter, type `%python`

   You are now ready to run Python scripts in your notebook.
3. To use OML4Py module, you must import the `oml` module. Type the following Python command to import the `oml` module, and the click run icon. Alternatively, you can press Shift+Enter keys to run the notebook.

   ```
   import oml
   ```

4. To verify if the `oml` module is connected to the Database, type:

```
oml.isconnected()
```



Once your notebook is connected, the command returns `TRUE`. The notebook is now connected to the Python interpreter, and you are ready to run python commands in your notebook.

Example to demonstrate the use of the Python modules - `matplotlib` and `numpy` , and use random data to plot two histograms.

5. Type the following commands to import the modules:

```
%python
import matplotlib.pyplot as plt
import numpy as np
```

- `Matplotlib` - Python module to render graphs
- `Numpy` - Python module for computations

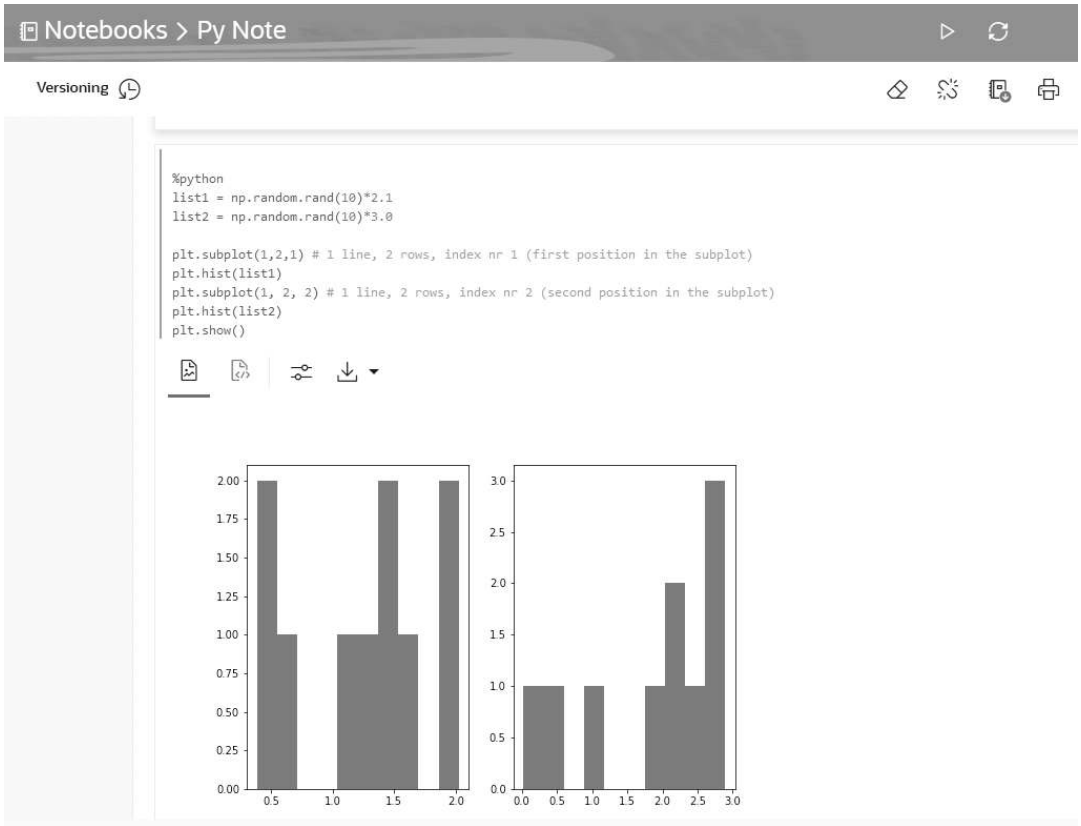
6. Type the following commands to compute and render the data in two histograms.

```
list1 = np.random.rand(10)*2.1
list2 = np.random.rand(10)*3.0

plt.subplot(1,2,1) # 1 line, 2 rows, index nr 1 (first position in the
subplot)
```

```
plt.hist(list1)
plt.subplot(1, 2, 2) # 1 line, 2 rows, index nr 2 (second position in the
subplot)
plt.hist(list2)
plt.show()
```

In this example, the commands import two Python module to compute and render the data in two histograms list1 and list2.

7. Click **Run.**



The output section of the paragraph which contains a charting component displays the results in two histograms - list1 and list2, as shown in the screenshot.

- About Oracle Machine Learning for Python
  Oracle Machine Learning for Python (OML4Py) is a component of Oracle Autonomous Database, which includes Oracle Autonomous Data Warehouse (ADW), Oracle Autonomous Transaction Processing (ATP), and Oracle Autonomous JSON Database (AJD). By using Oracle Machine Learning UI notebooks, you can run Python functions on data for data exploration and preparation while leveraging Oracle Database as a high-performance computing environment. Oracle Machine Learning User Interface (UI) is available through Autonomous Data Warehouse (ADW) , Autonomous Transaction Processing (ATP) and Autonomous JSON Database (AJD) services.

4.9.1 About Oracle Machine Learning for Python

Oracle Machine Learning for Python (OML4Py) is a component of Oracle Autonomous Database, which includes Oracle Autonomous Data Warehouse (ADW), Oracle Autonomous

Transaction Processing (ATP), and Oracle Autonomous JSON Database (AJD). By using Oracle Machine Learning UI notebooks, you can run Python functions on data for data exploration and preparation while leveraging Oracle Database as a high-performance computing environment. Oracle Machine Learning User Interface (UI) is available through Autonomous Data Warehouse (ADW) , Autonomous Transaction Processing (ATP) and Autonomous JSON Database (AJD) services.

Oracle Machine Learning for Python (OML4Py) makes the open source Python scripting language and environment ready for the enterprise and big data. Designed for problems involving both large and small volumes of data, Oracle Machine Learning for Python integrates Python with Oracle Autonomous Database, including its powerful in-database machine learning algorithms, and enables deployment of Python code.

Use Oracle Machine Learning for Python to:

- Perform data exploration, data analysis, and machine learning using Python leveraging Oracle Database as a high performance compute engine
- Build and evaluate machine learning models and score data using those models from an integrated Python API using in-database algorithms
- Deploy user-defined Python functions through a REST interface with data-parallel and task-parallel processing

The Python interpreter uses Python 3.8.5 to process Python scripts in Oracle Machine Learning UI notebooks. To use the interpreter, specify the `%python` directive at the beginning of the paragraph. The Python interpreter supports the following Python modules:

- `cx_Oracle 7.3.0`
- `cycler 0.10.0`
- `joblib 0.14.0`
- `kiwisolver 1.1.0`
- `matplotlib 3.1.2`
- `numpy 1.18.1`
- `pandas 0.25.3`
- `pyparsing 2.4.0`
- `python-dateutil 2.8.1`
- `pytz 2019.3`
- `scikit_learn 0.22.1`
- `scipy 1.4.1`
- `six 1.13.0`

Related Topics

- About Oracle Machine Learning for Python

4.10 Use the R Interpreter in a Notebook Paragraph

An Oracle Machine Learning notebook supports multiple languages. Each paragraph is associated with a specific interpreter. To run R functions in an Oracle Machine Learning notebook, you must first connect to the R interpreter.

In an Oracle Machine Learning UI notebook, you can add multiple paragraphs, and each paragraph can be connected to different interpreters such as R or SQL or Python. You identify which interpreter to use by specifying `%` followed by the interpreter to use: `sql`, `script`, `r`, `python`, `conda`, `markdown`.

This example shows how to:

- Connect to the R interpreter to run R commands in a notebook.
- Verify the connection to Oracle Autonomous Database, and
- Load the ORE libraries

1. To connect to the R interpreter, type the following directive at the beginning of the notebook paragraph, and press Enter:

   ```
   %r
   ```

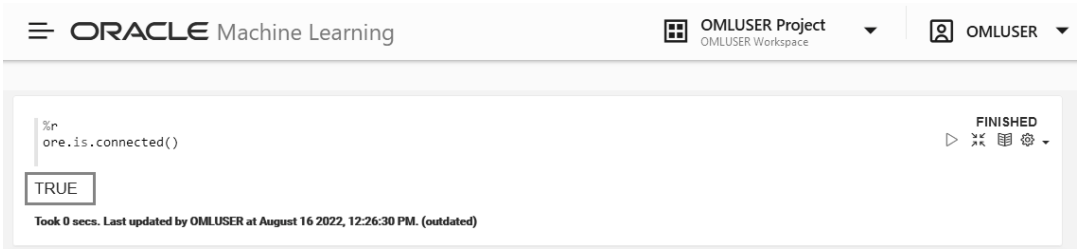
   To know more about interpreters, see About Interpreters and Notebook Service Levels and Change Notebook Service Level.

2. To verify the database connection, type the following command and press Enter:

   ```
   ore.is.connected()
   ```

   Once your notebook is connected, the command returns `TRUE`, as shown in the screenshot here. The notebook is now connected to the R interpreter, and you are ready to run R commands in your notebook.

Figure 4-36 Command to Test Database Connection

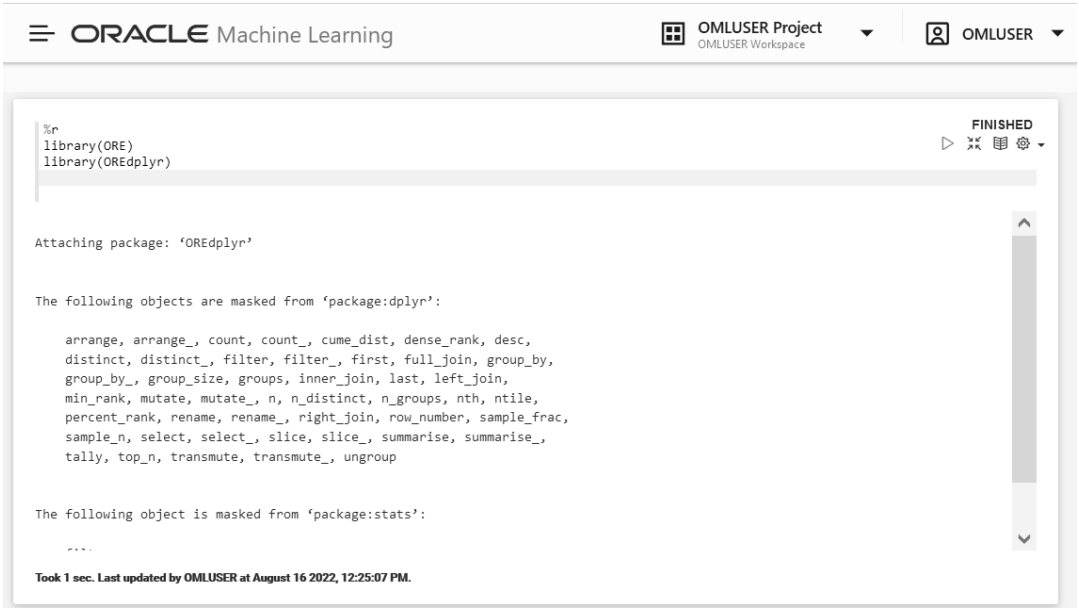


3. To import R Libraries, run the following commands:

   ```
   library(ORE)
   library(OREdplyr)
   ```

   Once the packages are loaded successfully, the list of ORE packages are displayed as shown in the screenshot here. Scroll down to view the entire list.

Figure 4-37 Command to Import R packages



- About Oracle Machine Learning for R
  Oracle Machine Learning for R (OML4R) is a component of the Oracle Machine Learning family of products, which integrates R with Oracle Autonomous Database.

4.10.1 About Oracle Machine Learning for R

Oracle Machine Learning for R (OML4R) is a component of the Oracle Machine Learning family of products, which integrates R with Oracle Autonomous Database.

Oracle Machine Learning for R makes the open source R scripting language and environment ready for enterprise and big data. It is designed for problems involving for both large and small data volumes. OML4R allows users to run R commands and scripts for statistical, machine learning, and perform visualization analyses on database tables and views using R syntax.

Oracle Machine Learning for R is available in Oracle Machine Learning UI, currently available through Oracle Autonomous Database, including Autonomous Data Warehouse, Autonomous Transaction Processing, and Autonomous JSON Database. Oracle Machine Learning for R Embedded R Execution functionality can be deployed through SQL and REST APIs on Autonomous Database.

Use Oracle Machine Learning for R to:

- Perform data exploration and data preparation while seamlessly leveraging Oracle Database as a high-performance computing environment.
- Run user-defined R functions on database spawned and controlled R engines, with system-supported data-parallel and task-parallel capabilities.
- Access and use powerful in-database machine learning algorithms from R language.

To use the R interpreter, specify the `%r` directive at the beginning of the paragraph. The following R packages are installed to support Oracle Machine Learning for R.

Supported Oracle Machine Learning for R Proprietary R Packages

The supported Oracle Machine Learning for R proprietary R packages are:

- ORE_1.5.1
- OREbase_1.5.1
- OREcommon_1.5.1
- OREdm_1.5.1
- OREdplyr_1.5.1
- OREeda_1.5.1
- OREembed_1.5.1
- OREgraphics_1.5.1
- OREmodels_1.5.1
- OREpredict_1.5.1
- OREstats_1.5.1
- ORExml_1.5.1

Supported Open Source R Modules

The following open source R packages are supported by Oracle Machine Learning for R:

- R-4.0.5
- Cairo_1.5-15
- ROracle_1.4-1: DBI_1.1-2
- arules_1.7-3
- png_0.1-7
- randomForest_4.6-14
- statmod_1.4-36
- dplyr_1.0-9:
- R6_2.5.1
- assertthat_0.2.1
- cli_3.3.0
- crayon_1.5.1
- ellipsis_0.3.2
- fansi_1.0.3
- generics_0.1.2
- glue_1.6.2
- lazyeval_0.2.2
- lifecycle_1.0.1
- magrittr_2.0.3
- pillar_1.7.0
- pkgconfig_2.0.3
- purrr_0.3.4

- rlang_1.0.2
- tibble_3.1.7
- tidyselect_1.1.2
- utf8_1.2.2
- vctrs_0.4.1

Oracle Machine Learning for R Interpreter Requirements

The R interpreter requires the following open source R packages:

- Rkernel 1.3:
  - base64enc 0.1-3
  - cli 3.3.0
  - crayon 1.5.1
  - digest 0.6.29
  - ellipsis 0.3.2
  - evaluate 0.15
  - fansi 1.0.3
  - fastmap 1.1.0
  - glue 1.6.2
  - htmltools 0.5.2
  - IRdisplay 1.1
  - jsonlite 1.8.0
  - lifecycle 1.0.1
  - pbdZMQ 0.3-7
  - pillar 1.7.0
  - repr 1.1.4
  - rlang 1.0.2
  - utf8 1.2.2
  - uuid 1.1-0
  - vctrs 0.4.1
- knitr 1.39:
  - evaluate_0.15
  - glue_1.6.2
  - highr_0.9
  - magrittr_2.0.3
  - stringi_1.7.6
  - stringr_1.4.0
  - xfun_0.31

- `yaml_2.3.5`

4.11 Use the Conda Interpreter in a Notebook Paragraph

Oracle Machine Learning Notebooks provides a Conda interpreter to enable administrators to create conda environments with custom third-party Python and R libraries. Once created, you can download and activate Conda environments inside a notebook session also using the Conda interpreter.

An Oracle Machine Learning notebook supports multiple languages. For this, you must create a notebook with some paragraphs to run SQL queries, and other paragraphs to run PL/SQL scripts. To run a notebook in different scripting languages, you must first connect the notebook paragraphs with the respective interpreters such as SQL, PL/SQL, R, Python, or Conda.

This topic shows how to start working in the Conda environment:

- Connect to the Conda interpreter
- Download and activate the Conda environment
- View the list of packages in the Conda environment
- Run a Python function to import the Iris dataset, and use the seaborn package for visualization

1. Type `%conda` at the beginning of the paragraph to connect to the Conda interpreter, and press Enter.

   ```
   %conda
   ```

2. Next, download and activate the Conda environment. Type:

   ```
   download sbenv
   activate sbenv
   ```

In this example, the Conda environment is downloaded and activated. The name of the Conda environment in this example is `sbenv`.

Download and activate the environment

```
%conda

download sbenv

activate sbenv
```

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


usage: conda [-h] [-V] command ...

conda is a tool for managing and deploying applications, environments and packages.

Options:

positional arguments:
  command
    clean        Remove unused packages and caches.
    config       Modify configuration values in .condarc. This is modeled
                 after the git config command. Writes to the user .condarc
                 file (/u01/.condarc) by default.
    create       Create a new conda environment from a list of specified
```

Took 53 secs. Last updated by OMLUSER

3. You can view all the packages that are present in the Conda environment. To view the list of packages, type `list`.

List the packages available in the environment

```
%conda

list
```

```
# 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
```

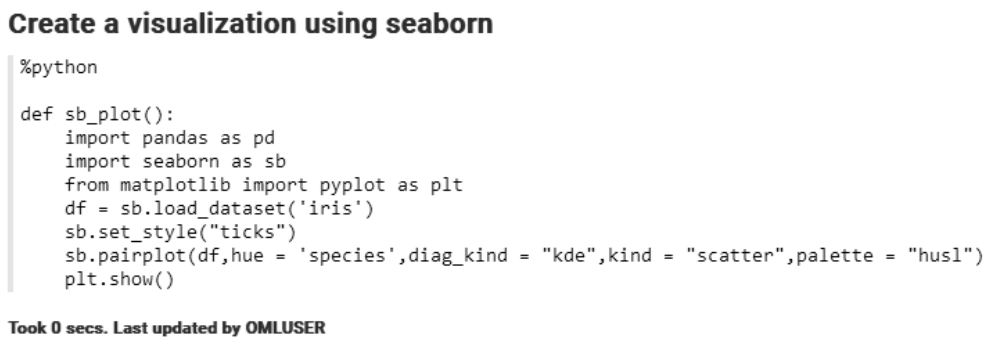
Took 2 secs. Last updated by OMLUSER

4. Here's an example that demonstrates how to use the seaborn library package for visualization. Seaborn is a Python visualization library based on matplotlib. It provides a high-level interface for drawing attractive statistical graphics. This example

- Imports Pandas and seaborn
- Loads the Iris dataset
- Plots the datapoints, that is, the three different species of the Iris flower - Setosa, Virginica, and Versicolor based on its dimensions. It creates a scatter plot

Type:

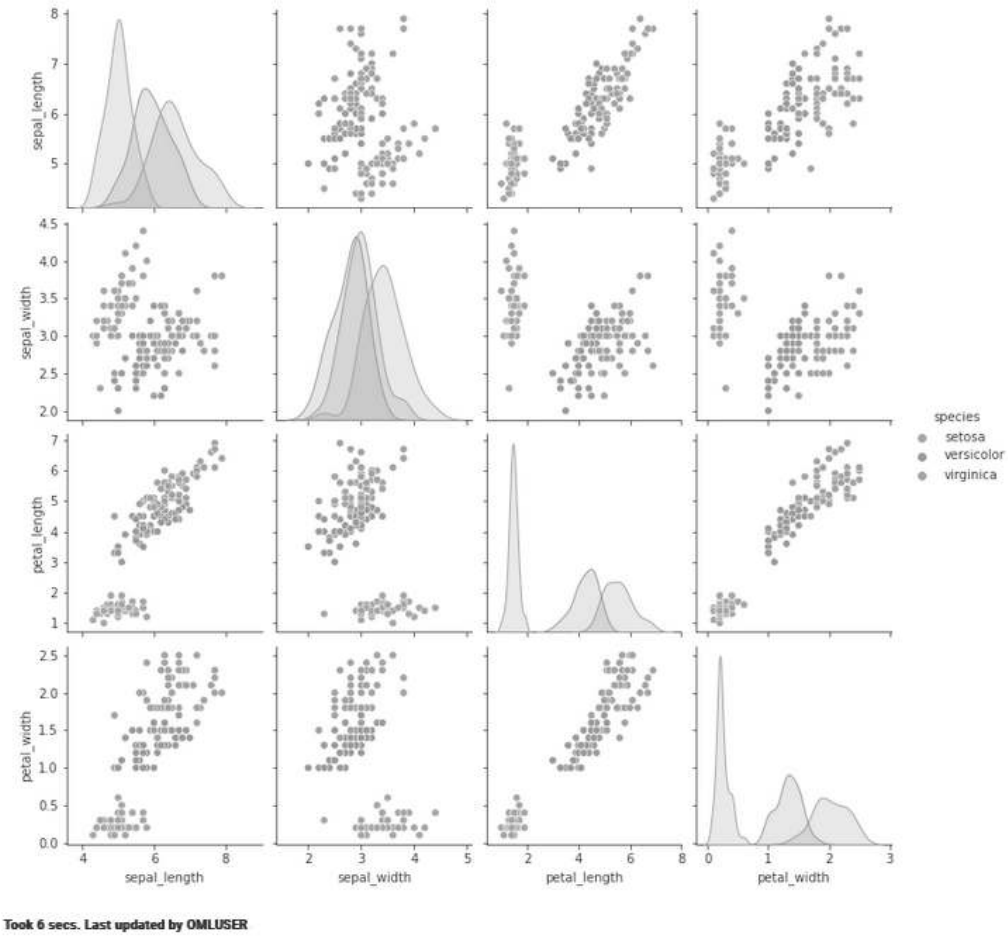
```
%python

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()
```



5. Run the function in a Python paragraph.

   Type:

```
%python
sb_plot()
```



- About the Conda Environment and Conda Interpreter
  Conda is an open-source package and environment management system that allows the use of environments containing third-party Python and R libraries. Oracle Machine Learning User Interface (UI) provide the conda interpreter to install third-party Python and R libraries inside a notebook session.
- Conda Interpreter Commands
  This table lists the commands for the Conda interpreter.
- Create a Conda Environment for Python and Install Python Packages
  This topic demonstates how to create a Conda environment for Python packages, with Python 3.12.3 that is compatible with OML4Py. Here, you will also install the Python packages—tensorflow and seaborn from the `conda-forge` channel.
- Create a Conda Environment for R and Install R Packages
  This topic shows how to create a Conda environment for R packages, with R-4.0.5 for OML4R compatibility, and install the `forecast` and `ggplot2` packages.
- Upload the Conda environments to an Object Storage bucket associated with the Autonomous Database
  There is one Object Storage bucket for each data center region. The Conda environment is saved to a folder in Object Storage corresponding to the tenancy and database. The folder is managed by Autonomous Database and is 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.

4.11.1 About the Conda Environment and Conda Interpreter

Conda is an open-source package and environment management system that allows the use of environments containing third-party Python and R libraries. Oracle Machine Learning User Interface (UI) provide the conda interpreter to install third-party Python and R libraries inside a notebook session.

Third-party libraries installed in Oracle Machine Learning Notebooks can be used in:

- Standard Python
- Standard R
- Oracle Machine Learning for Python embedded Python execution from the Python, SQL and REST APIs
- Oracle Machine Learning for R embedded R execution from the R, SQL, and REST APIs

To start working in the Conda environment:

1. Ensure that a Conda environment is saved to Object Storage, or update an existing package by installing a new version.

   > **Note:**
   >
   > You must be signed in as ADMIN user to create the Conda environment. The administrator manages the lifecycle of an environment, including adding or deleting packages from it, and removing environments. The Conda environments are stored in an Object Storage bucket associated with the Autonomous Database.

2. Sign into Oracle Machine Learning UI and download the Conda environment. To download the Conda environment, type:

   ```
   %conda


   download myenv
   ```

3. Activate the Conda environment. To activate the Conda environment, type:

   ```
   activate myenv
   ```

   > **Note:**
   >
   > There is only one active Conda environment at a given point in time.

4. Create a notebook, use the Conda interpreter to use third-party libraries in the Object Storage. To use the Conda interpreter, type `%conda` at the beginning of the paragraph to connect to the Conda environment, and work with third-party libraries for Python. You can switch between the preinstalled Conda environments. For example, you can have an environment for working with Graph analysis, and another environment for Oracle Machine Learning analysis.

5. Deactivate the Conda environment. As a best practice, deactivate the Conda environment after you have finished working on your machine learning analysis. To deactivate the environment, type:

```
deactivate
```

4.11.2 Conda Interpreter Commands

This table lists the commands for the Conda interpreter.

Conda Interpreter Commands

Table 4-1 Conda Interpreter Commands

Tasks	Commands	Role
Create a Conda environment.	`create -n <env_name> <python_version>`	• ADMIN
Remove a list of packages from a specified conda environment. It is also an alias for conda `uninstall`.	`remove -n <env_name> --all` **Note:** The Conda environment is deleted from the user session.	• ADMIN • OML user
List user-created local environment.	`env list`	• ADMIN • OML user
Remove user-created local environment.	`env remove -n <env_name>`	• ADMIN • OML user
List all packages and versions installed in active environment.	`list`	• ADMIN • OML user
Activate a user-created local environment.	`activate -n <env_name>`	• ADMIN • OML user
Deactivate the current environment.	`deactivate`	• ADMIN • OML user
Install an external package from a public Conda channel.	`install -n <env_name> <package_name>`	• ADMIN
Uninstall a specific package from a Conda environment. It is also an alias for `remove`.	`uninstall -n <env_name> <package_name>`	• ADMIN
Display information about current conda install.	`info`	• ADMIN • OML user
View the command line help.	`COMMANDNAME --help`	• ADMIN • OML user

Table 4-1 (Cont.) Conda Interpreter Commands

Tasks	Commands	Role
Upload a Conda environment to object storage. **Note:** This is an Autonomous Database specific command.	`upload --overwrite <env_name> --description 'some description' -t <name> <value>` **Note:** You can provide many tags. For example: `-t <name1> <value1> -t <name2> <value2> ..`	• ADMIN
Download and unpack a specific Conda environment from the object storage. **Note:** This is an Autonomous Database specific command.	`download --overwrite <env_name>`	• ADMIN • OML user
List local environments available to the user.	`list-local-envs`	• ADMIN • OML user
List all Conda environments in the object storage. **Note:** This is an Autonomous Database specific command.	`list-saved-envs --installed-packages -e <env_name>`	• ADMIN • OML user

Table 4-1 (Cont.) Conda Interpreter Commands

Tasks	Commands	Role
Delete a Conda environment. **Note:** This is an Autonomous Database specific command. **Note:** The Conda environment is deleted from the Object Storage.	`delete <env_name>`	• ADMIN
Update conda packages to the latest compatible version.	`update`	• ADMIN
Upgrade the current conda package. It is also an alias for conda `update`.	`upgrade`	• ADMIN
Search for packages and display associated information. The input is a `MatchSpec`, a query language for conda packages.	`search`	• ADMIN • OML user

4.11.3 Create a Conda Environment for Python and Install Python Packages

This topic demonstates how to create a Conda environment for Python packages, with Python 3.12.3 that is compatible with OML4Py. Here, you will also install the Python packages—tensorflow and seaborn 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 a community channel made up of thousands of contributors, and 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.

Note:

You must be signed in as ADMIN user to create the Conda environment.

Note:

To avoid version conflicts, please do not install packages that are already included in OML4Py. For a complete list of pre-installed packages and their versions, see Python Libraries in OML4Py.

To create a Conda environment:

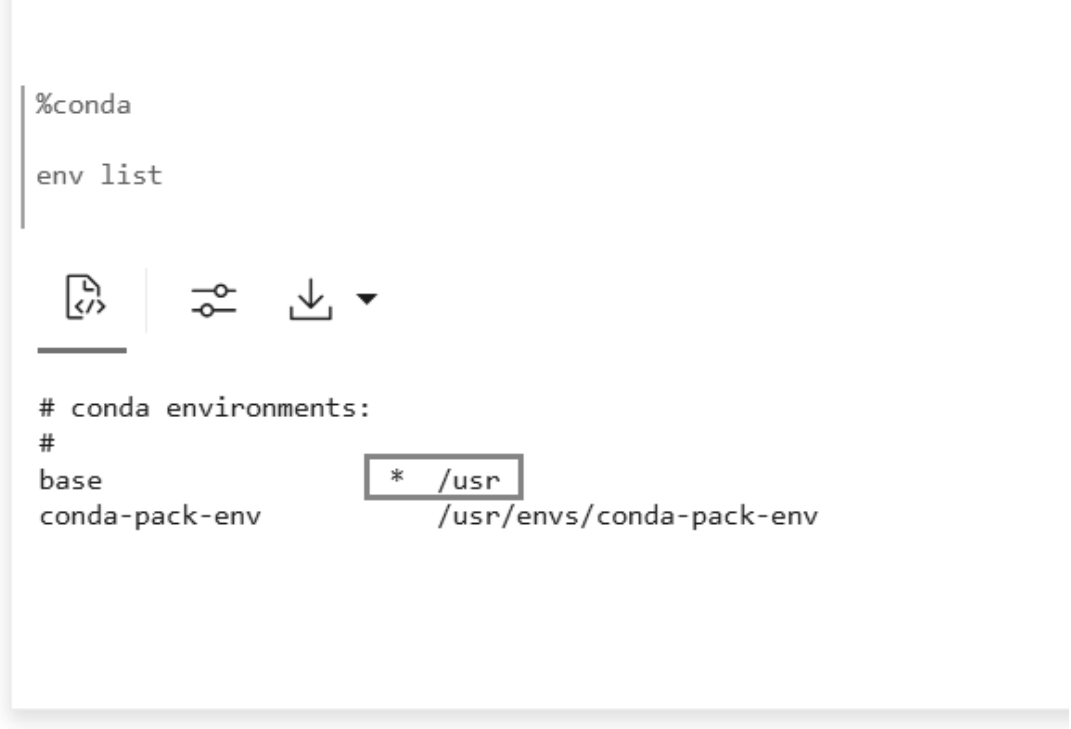
1. Run the following command to list the environments that are available by default. Conda contains default environments with some core system libraries and conda dependencies. Run the following command to list the available environments.

```
%conda

env list
```

> **Note:**
>
> The active environment is marked with an asterisk (*).

The command returns the list of following environments:

Figure 4-38 Command to list Conda environments



2. Now, run the following command to create an environment by the name `mypyenv` from the `conda-forge` channel and also install the Python packages tensorflow and seaborn:

```
%conda

create -n mypyenv -c conda-forge --override-channels --strict-channel-
priority python=3.12.3 tensorflow seaborn
```

> **Note:**
>
> In this example, we are using the `conda-forge` channel to install the Python packages.

In this command:

- `-n`: This is the name of the environment. In this example, it is `mypyenv`.
- `-c`: This is the channel name. In this example, it is `conda-forge`
- `--override-channels`: This argument ensures that the system does not search default, and requires a channel to be mentioned.
- `--strict-channel-priority`: This argument ensures that packages in lower priority channels are not considered if a package with the same name appears in a higher priority channel. In this example, the priority is given to Python 3.12.3, tensorflow, and seaborn

The command returns the following message once it creates the environment and installs the listed package. Scroll down the paragraph to view the complete details.

Figure 4-39 Command to create a Conda environment

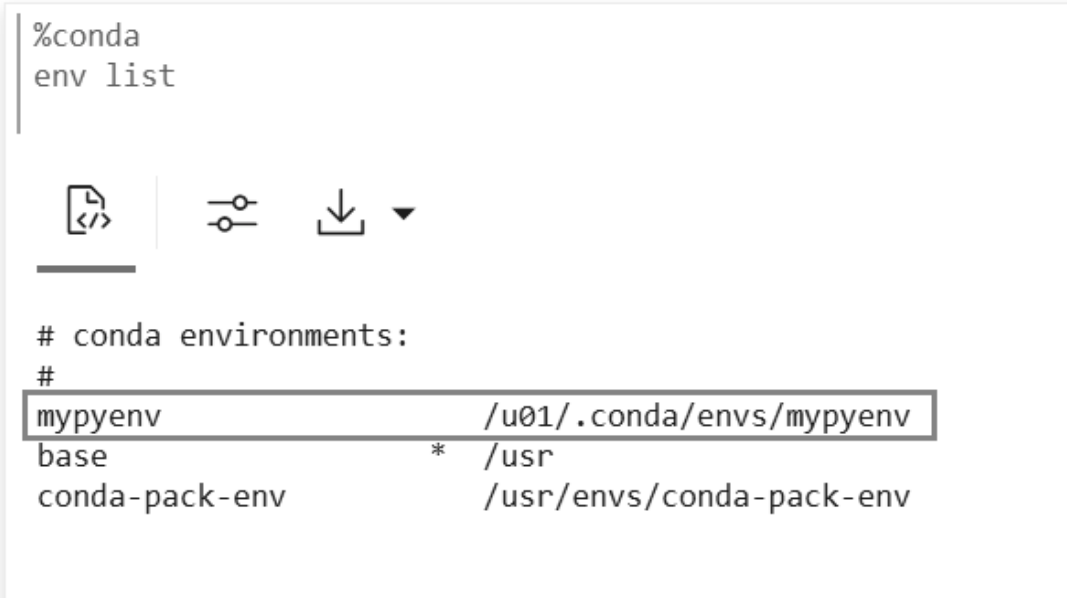
3. Now, verify the environment that you created. Run the following command once again to view the list of environments.

```
%conda

env list
```

> **Note:**
>
> The `mypyenv` environment is not yet active. The active environment is marked with an asterisk (*), and in this list, it is present against the base environment usr.

Note that the environment `mypyenv` is listed in the output.

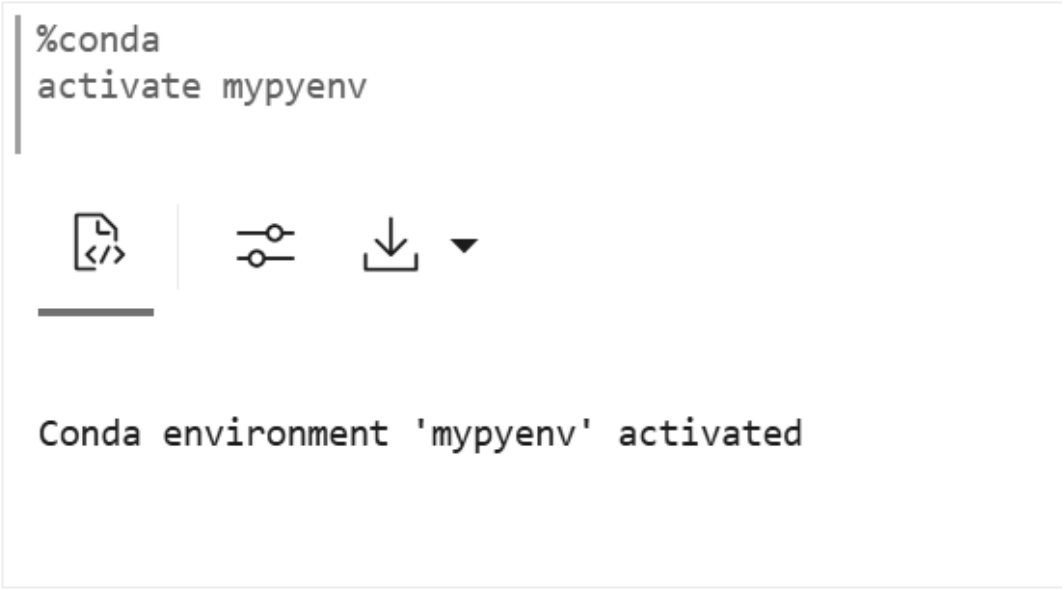
Figure 4-40 mypyenv environment created



4. To activate the environment `mypyenv`, run the following command:

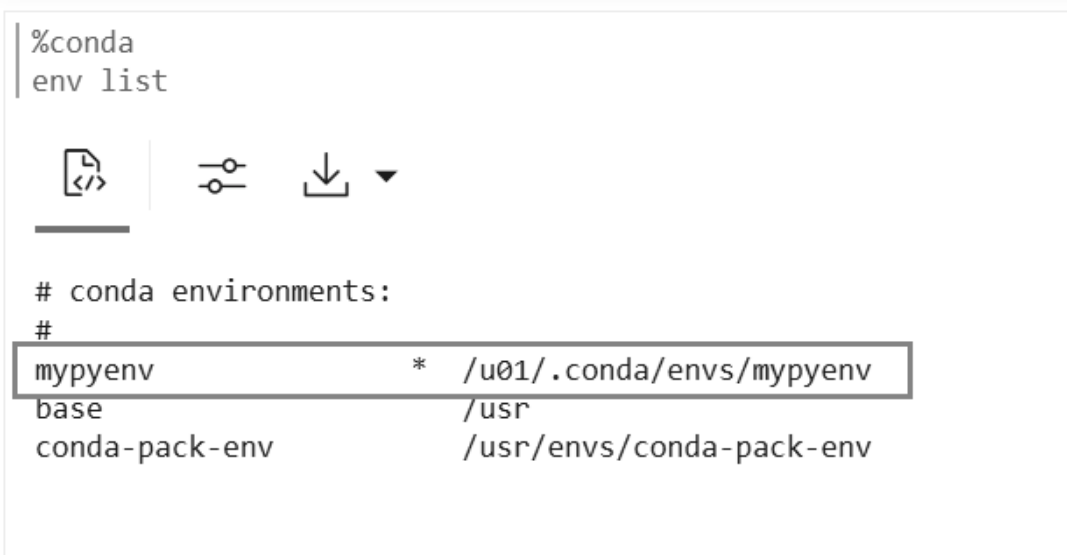
```
%conda

activate mypyenv
```

Figure 4-41 Command to activate Conda environment



5. Now, run the command to list the environment once again to view the list of active environments. Note that the asterisk (*) is now present against the `mypyenv` environment.

Figure 4-42 Activated environment mypyenv listed



The asterisk (*) next to the environment name confirms the activation. This completes the task of creating, activating and verifying a Conda environment.

4.11.4 Create a Conda Environment for R and Install R Packages

This topic shows how to create a Conda environment for R packages, with R-4.0.5 for OML4R compatibility, and install the `forecast` and `ggplot2` packages.

> **Note:**
>
> You must be signed in as ADMIN user to create the Conda environment.

> **Note:**
>
> To avoid version conflicts, please do not install packages that are already included in OML4R. For a complete list of pre-installed packages and their versions, see About the OML4R Supporting Packages

To create a Conda environment named `myrenv` with R-4.0.5 for OML4R compatibility and install the packages `forecast` and `ggplot2`:

1. Run the following command to create the environment for R by the name `myrenv` and also install the packages `forecast` and `ggplot2`:

   ```
   %conda

   create -n myrenv -c conda-forge --override-channels --strict-channel-
   priority r-base=4 r-forecast r-ggplot2
   ```

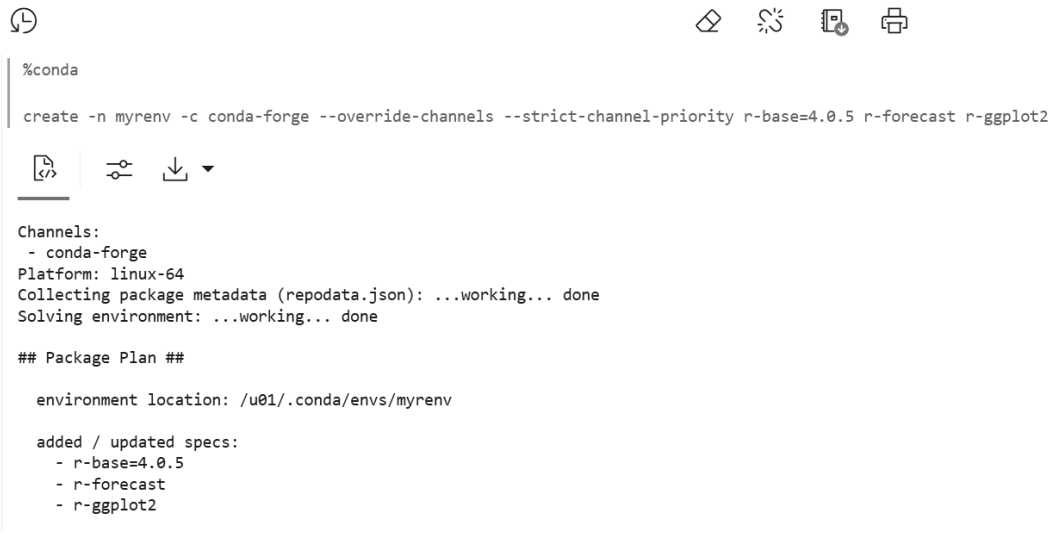
   In this example, we are using the `conda-forge` channel to install the R packages.

   In this command:

- `-n`: This is the name of the environment. In this example, it is `myrenv`.
- `-c`: This is the channel name. In this example, it is `conda-forge`.
- `--override-channels`: This argument ensures that the system does not search default, and requires a channel to be mentioned.
- `--strict-channel-priority`: This argument ensures that packages in lower priority channels are not considered if a package with the same name appears in a higher priority channel. In this example, the priority is given to `R-4.0.5`, `forecast`, and `ggplot2`.

The command returns the following:

Figure 4-43 Command to create Conda environment for R and install R Packages

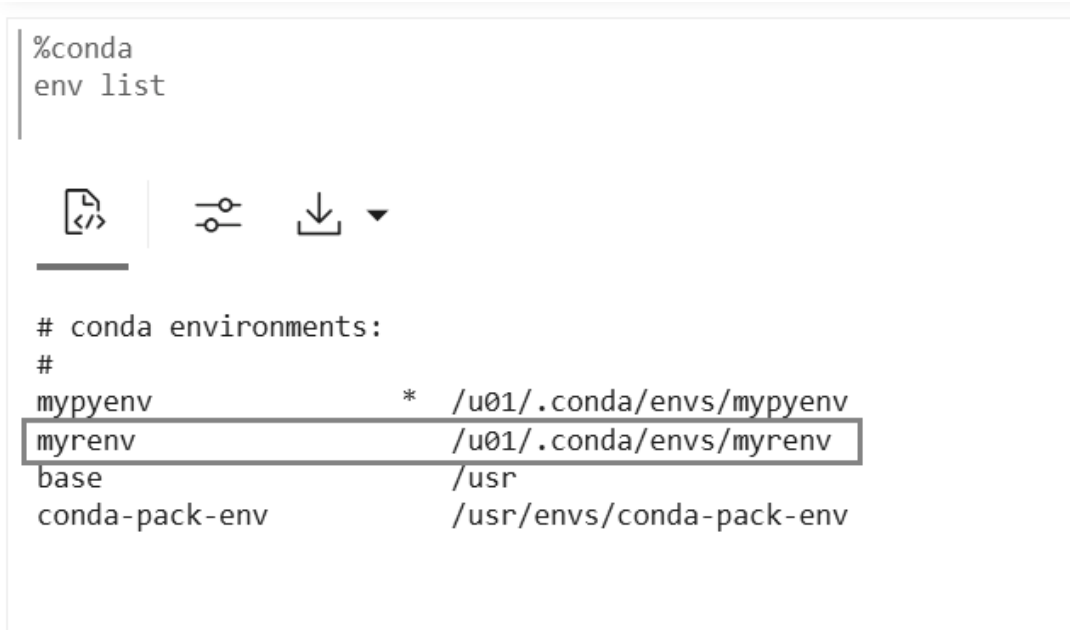


2. You may now verify the Conda environment for R that you just created. Run the following command in a `%conda` paragraph to view the list of environments.

```
env list
```

Note that the `myrenv` environment is now listed along with the `mypyenv` in the output.

Figure 4-44 myrenv environment created and listed



Note that the asterisk (*) is against the `mypyenv`, indicating that this environment is active currently.

4.11.5 Upload the Conda environments to an Object Storage bucket associated with the Autonomous Database

There is one Object Storage bucket for each data center region. The Conda environment is saved to a folder in Object Storage corresponding to the tenancy and database. The folder is managed by Autonomous Database and is 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.

This topic shows how to upload a Conda environment to the Object Storage bucket associated with the Autonomous Database instance using the `upload` command. You will provide environment descriptions and tags, one for the user name and one for the application name. You will also overwrite any environment with the same name if it exists. The application tag is required for use with embedded execution. For example, OML4Py embedded Python execution works with Conda environments containing the OML4PY tag.

To upload a Conda environment to the Object Storage bucket:

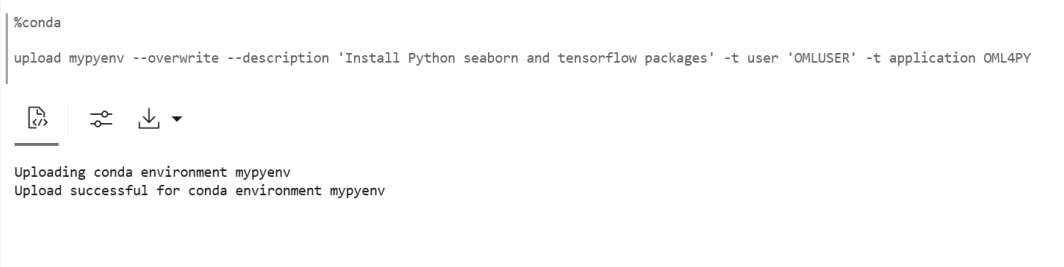
1. In a Conda paragraph in your notebook, run the following command to upload the `mypyenv` to the Object Storage bucket associated with the ADB.

   ```
   upload mypyenv --overwrite --description 'Install Python seaborn and
   tensorflow packages' -t user 'OMLUSER' -t application OML4PY
   ```

   In this command, you use the upload command and provide the following:

   - `--description`: a description of your task.
   - `-t`: A tag for the user `OMLUSER` and for the application `OML4PY`.

Figure 4-45 Command to load the Conda environment for Py

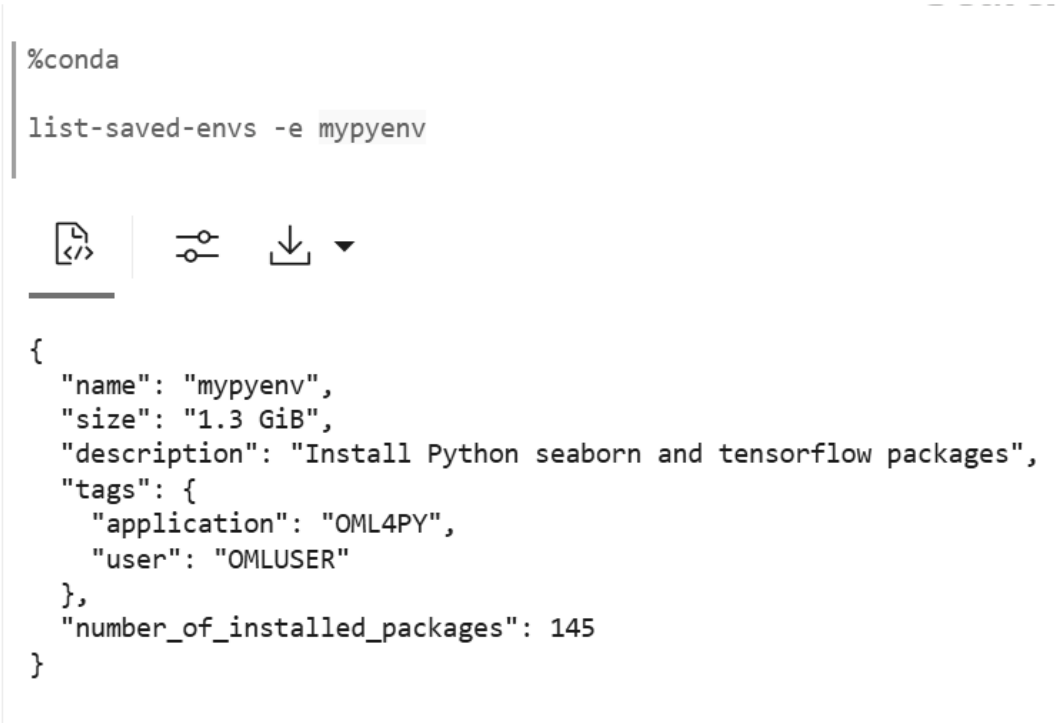


2. Now, run the following command to view the list of saved environments in mypyenv:

```
list-saved-envs -e mypyenv
```

The command returns the following:

Figure 4-46 View saved environment mypyenv

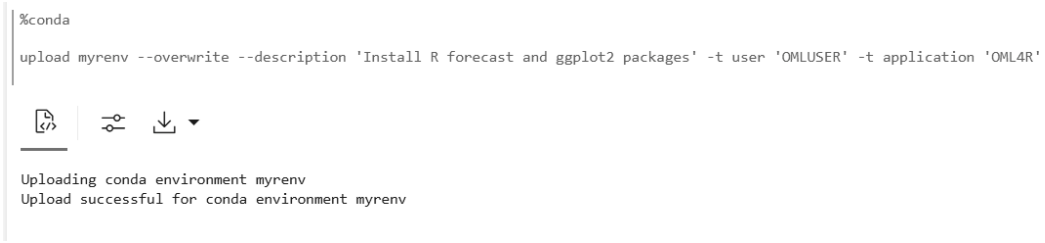


3. Now upload the `myrenv` to the object storage by running the following command in a Conda paragraph:

```
%conda

upload myrenv --overwrite --description 'Install R forecast and ggplot2
packages' -t user 'OMLUSER' -t application 'OML4R
```

The command returns the following:

Figure 4-47 Command to upload Conda environment for R

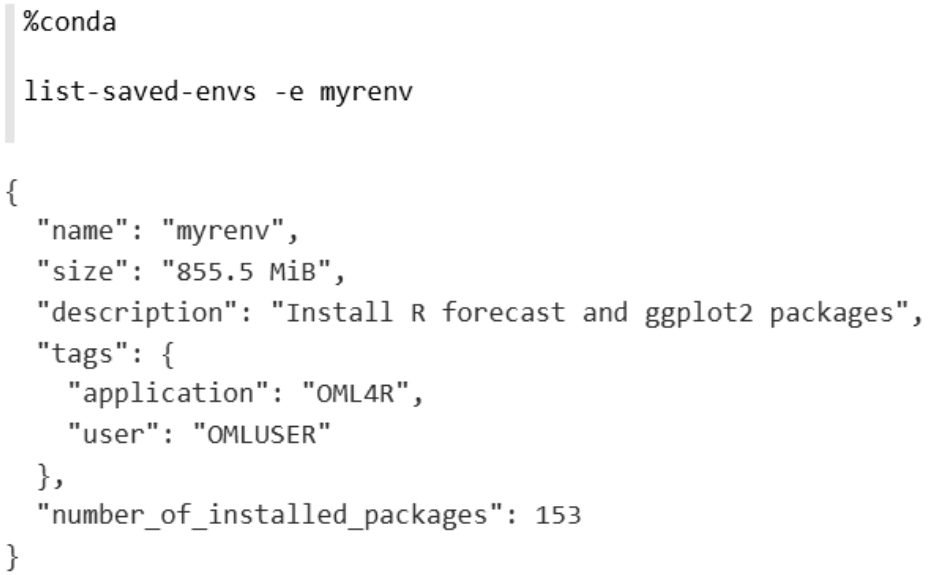


4. Again, run the following command to view the list of saved environments in `myrenv`:

```
%conda

list-saved-envs -e myrenv
```

The command returns the following:

Figure 4-48 View saved environment myrenv



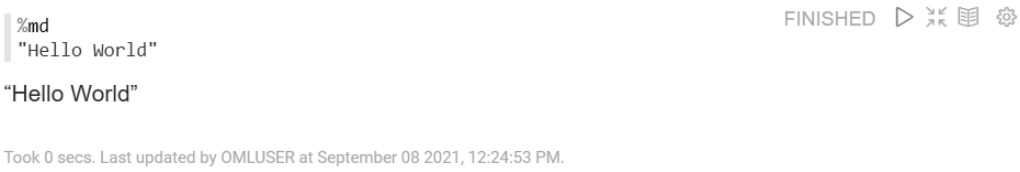
This completes the task of uploading the Python and R environments `mypyenv` and `myrenv` to the Object Storage associated with the ADB. The environments are now available for you to download and use. The environments will remain in the Object Storage until it is deleted.

4.12 Use the Markdown Interpreter and Generate Static html from Markdown Plain Text

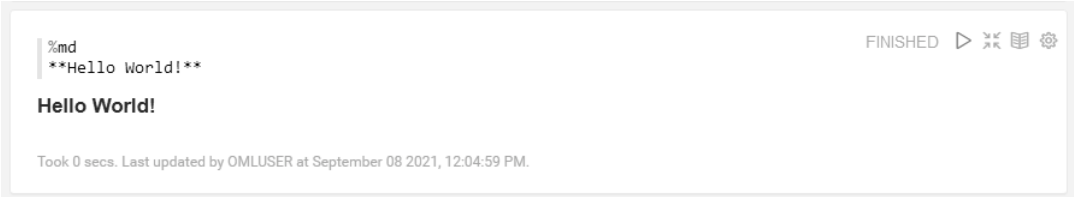
Use the Markdown interpreter and generate static html from Markdown plain text.

To call the Markdown interpreter and generate static html from Markdown plain text:

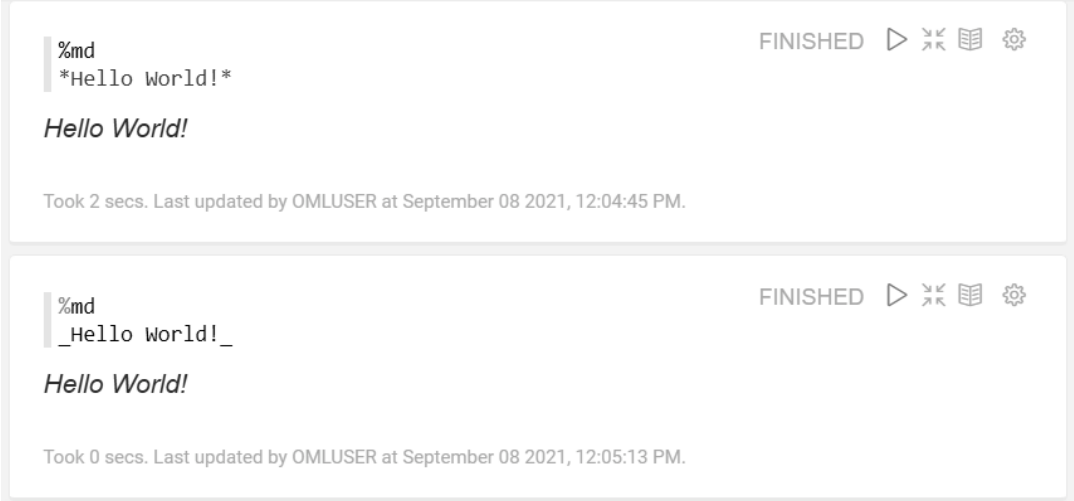
1. In your notebook, type `%md` and press Enter.
2. Type `"Hello World!"` and click Run. The static html text is generated, as seen in the screenshot below.



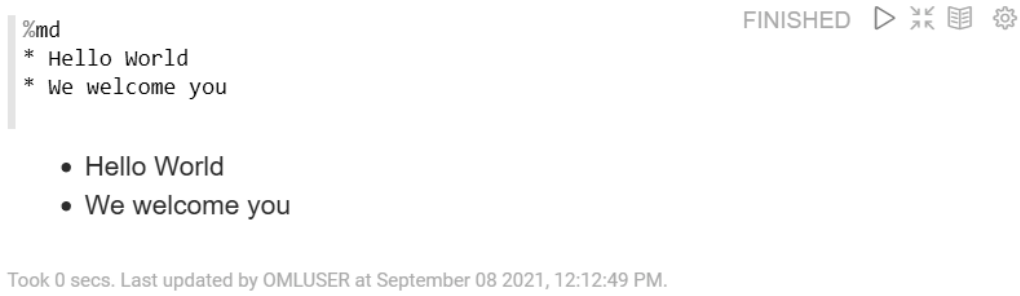
3. You can format the text in bold. To display the text in bold, write the same text inside two asterisks pair and click Run.



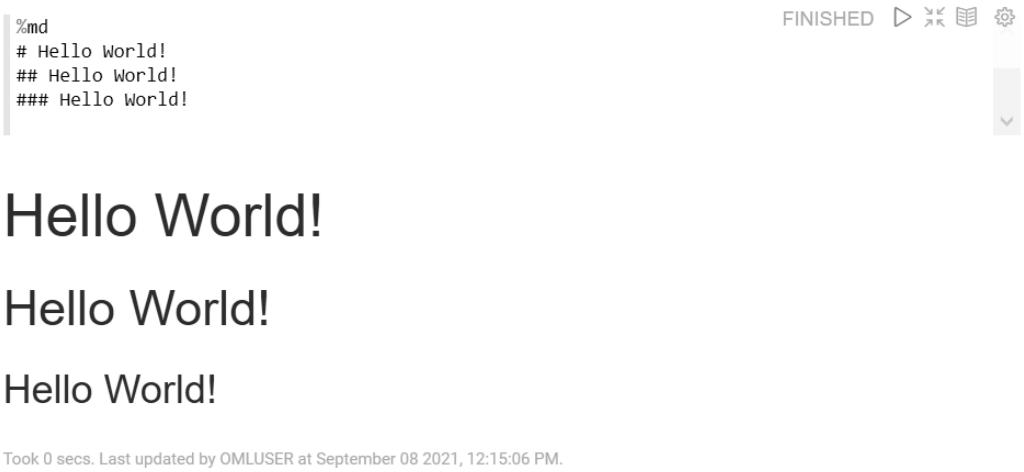
4. To display the text in italics, write the same text inside an asterisk pair or underscore pair as shown in the screenshot, and click Run.



5. To display the text in a bulleted list, prefix `*`(asterisk) to the text, as shown in the screenshot below:



6. To display the text in heading1, heading 2 and heading 2, prefix `#` (hash) to the text and click Run. For H1, H2, and H3, you must prefix one, two, and three hashes respectively.



4.13 About Interpreters and Notebook Service Levels

An interpreter is a plug-in that allows you to use a specific data processing language backend.

For the Zeppelin Notebooks in Oracle Machine Learning UI, you use the SQL, PL/SQL, Python and R interpreters within an Oracle Database interpreter group, and the Markdown interpreter for plain text formatting syntax so that it can be converted to HTML. You use the Conda interpreter to connect to the Conda environment and work with Python third-party library packages.

To use the interpreters, you must use these directives at the beginning of the paragraph in a notebook

- SQL — `%sql`
- PL/SQL — `%script`
- Python — `%python`
- R - `%r`
- Markdown — `%md`
- Conda — `%conda`

Notebooks contain an internal list of service levels that define the order of the interpreters in an interpreter group. The default order of interpreter bindings in the Oracle Database interpreter group is:

- **low** — Provides the least level of resources for in-database operations, typically serial (non-parallel) execution. It supports the maximum number of concurrent in-database operations by multiple users. The interpreter with low priority is listed at the top of the interpreter list, and hence, is the default.
- **medium** — Provides a fixed number of CPUs to run in-database operations in parallel, where possible. It supports a limited number of concurrent users, typically 1.25 times the number of CPUs allocated to the pluggable database.
- **high** — Provides the highest level of CPUs to run in-database operations in parallel, up to the number of CPUs allocated to the pluggable database. It offers the highest performance, but supports the minimum number of concurrent in-database operations, typically 3.

- **gpu** — Provides GPU compute capabilities in a notebook through the Python interpreter with the database service level set to **high**. The memory settings is 8 GB (DDR4), by default. It is extensible up to 200 GB.

With respect to interpreter bindings, you can perform the following tasks:

- Bind and unbind interpreters: If you do not bind any specific interpreter to your notebook, then you get the error message:

  ```
  Not supported interpreter <name of interpreter>
  ```

- Set and re-order interpreter bindings. You may want to set and re-order interpreter bindings if you want to use a specific interpreter for a specific paragraph in a notebook. In that case, you have to select the specific interpreter for that paragraph.
- Change the interpreter binding for any specific paragraph in a notebook

You must note the interpreter binding order in the following scenarios:

- Notebook creation — When you create a notebook, the notebook inherits the initial interpreter binding order, which is low (default), medium, high.
- Notebook import — When importing a notebook, the notebook inherits the defined interpreter bindings. However, after you import a notebook, ensure to check the order of the interpreter bindings and that the required interpreters are selected.
- Notebook export — When exporting a notebook, the notebook inherits the defined interpreter bindings.
- Notebook creation from templates — When you create a notebook from templates, the notebook inherits the default order of interpreter bindings.
- Change Notebook Service Level
  Notebook type corresponds to the ADB service levels — low, medium, high and gpu. These service levels affect parallelism in the database. The notebook type that is set for a notebook applies to all the paragraphs in that notebook.
- Verify Notebook Service Level
  After changing the Notebook service level, you can use a SQL statement to view and verify the information. Notebook type, referred to as interpreter bindings in Notebooks Classic, corresponds to the ADB service levels — low, medium, high and gpu. These service levels affect parallelism in the database.

4.13.1 Change Notebook Service Level

Notebook type corresponds to the ADB service levels — low, medium, high and gpu. These service levels affect parallelism in the database. The notebook type that is set for a notebook applies to all the paragraphs in that notebook.

> **Note:**
>
> In Notebooks Classic, the notebook type is referred to as the interpreter bindings. The notebook type **gpu** is not available in Notebooks Classic.

To use the interpreters, you must use these directives at the beginning of a paragraph in a notebook

- SQL — `%sql`
- PL/SQL — `%script`

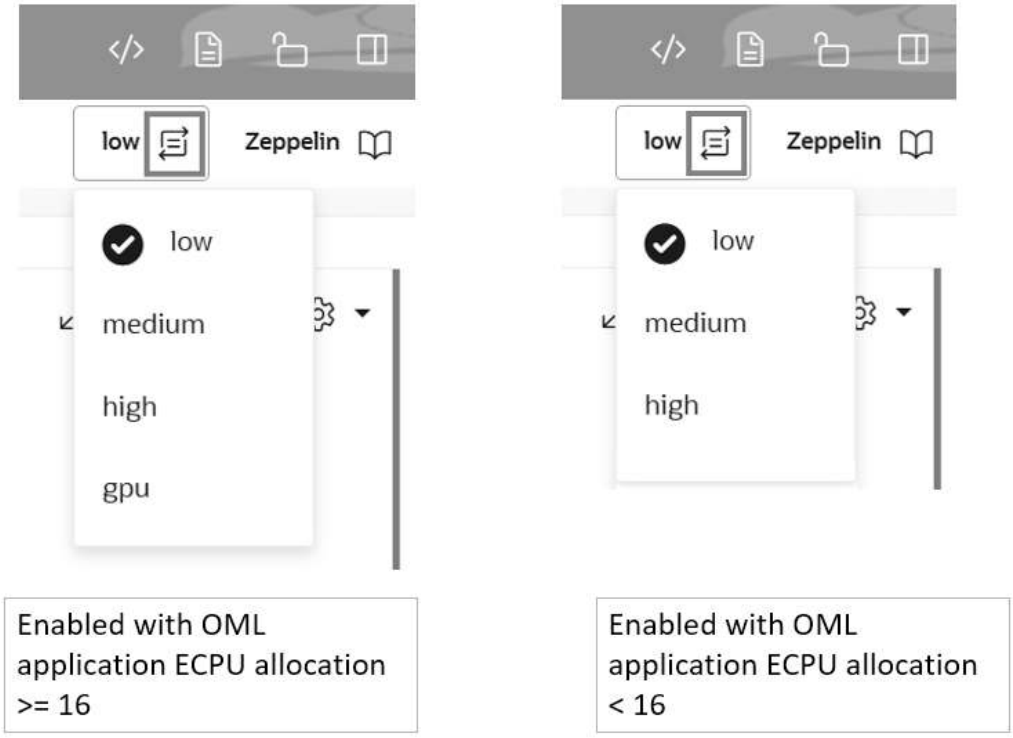
- Python — `%python`
- R — `%r`
- Markdown — `%md`
- Conda — `%conda`

You can change notebook service levels in both the new Notebook and Notebooks Classic.

Change Notebook Service Levels in the new Notebook

1. Open your notebook in the notebook editor.
2. Click on the **Update Notebook Type** icon on the top right corner. The available notebook types are displayed. The current notebook type is indicated by a tick mark, and is also displayed next to the **Update Notebook Type** icon.

Figure 4-49 ADB service levels as displayed in a notebook



The Notebook Types (ADB service levels) are:

- **low** —Provides the least level of resources for in-database operations, typically serial (non-parallel) execution. It supports the maximum number of concurrent in-database operations by multiple users. The interpreter with low priority is listed at the top of the interpreter list, and hence, is the default.
- **medium**—Provides a fixed number of CPUs to run in-database operations in parallel, where possible. It supports a limited number of concurrent users, typically 1.25 times the number of CPUs allocated to the pluggable database.
- **high**—Provides the highest level of CPUs to run in-database operations in parallel, up to the number of CPUs allocated to the pluggable database. It offers the highest

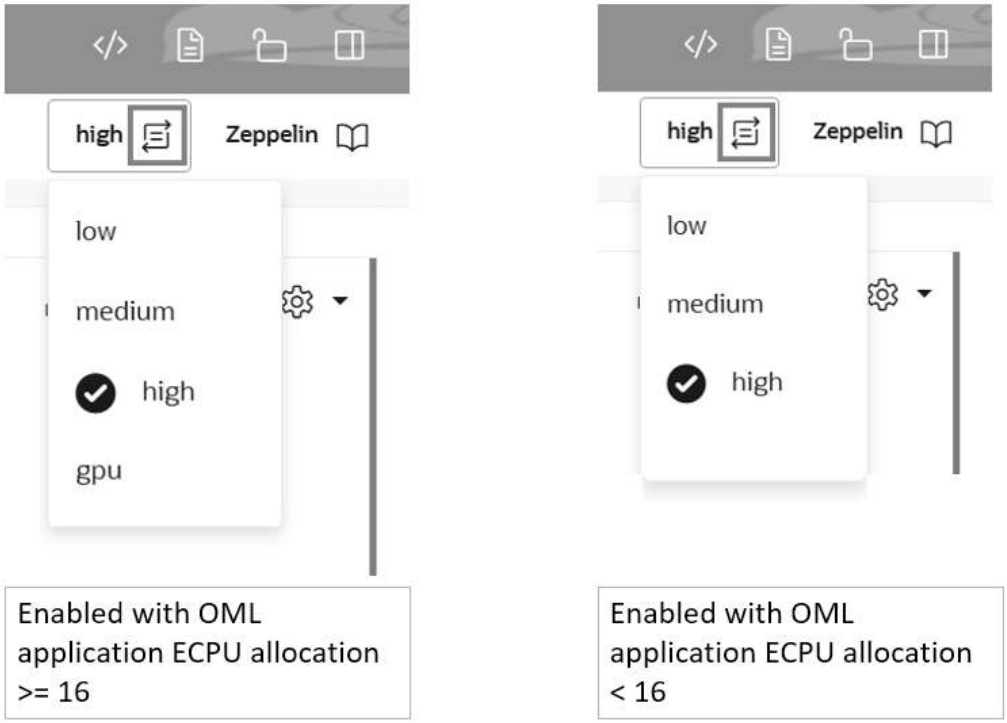
performance, but supports the minimum number of concurrent in-database operations, typically 3.

- **gpu**—Provides GPU compute capabilities in a notebook through the Python interpreter with the database service level set to **high**. The notebook memory setting is 32 GB (DDR4), by default. It is extensible up to 200 GB.

3. To change the notebook type, click on the type that you want to select. In this example, let's click **high.** A confirmation message is displayed stating: `Notebook Type is updated to "high".`

> **Note:**
>
> The updated notebook type is applicable to all the paragraphs in the notebook. You cannot change the notebook type at the paragraph level.

Figure 4-50 ADB service level - high



4.13.2 Verify Notebook Service Level

After changing the Notebook service level, you can use a SQL statement to view and verify the information. Notebook type, referred to as interpreter bindings in Notebooks Classic, corresponds to the ADB service levels — low, medium, high and gpu. These service levels affect parallelism in the database.

For Python notebooks, the interpreter binding is used for all python paragraphs.

> **Note:**
>
> For Python notebooks, do not override the interpreter binding at the paragraph level.

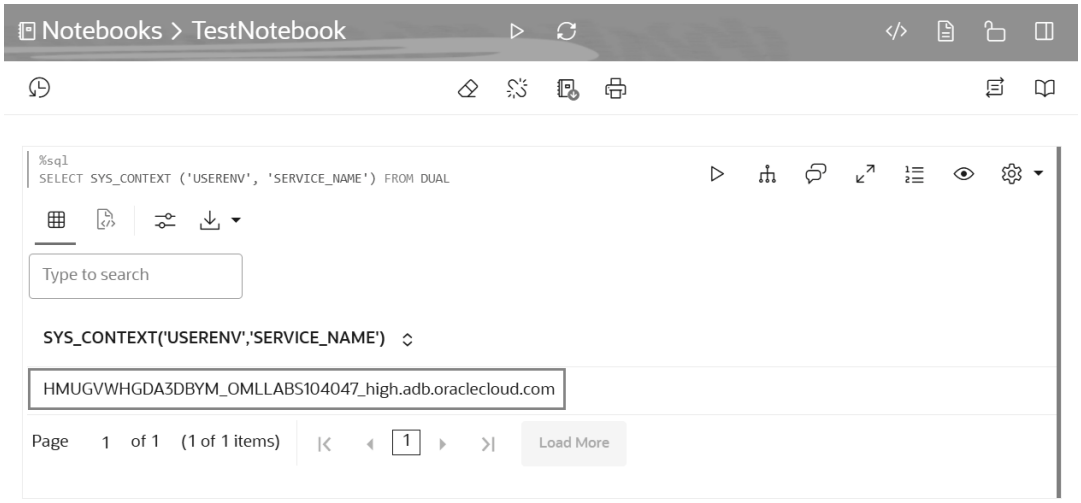
Verify Notebook Service Level in a Notebook

1. Open the notebook for which you want to verify the updated notebook type.
2. Run the following SQL statement:

```
%sql
SELECT SYS_CONTEXT ('USERENV', 'SERVICE_NAME') FROM DUAL;
```

3. Click **Run.** The SQL statement returns the following information about the updated notebook type, as shown in the screenshot below:

Figure 4-51 ADB service level information as displayed in a notebook



You can see that the service level is now displayed as **high**. In this example:

- `HMUGVWHGDA3DBYM` is the tenant name
- `OMLLABS104047` is the database name
- `high` is the ADB service name
- `adb.oraclecloud.com` is the domain

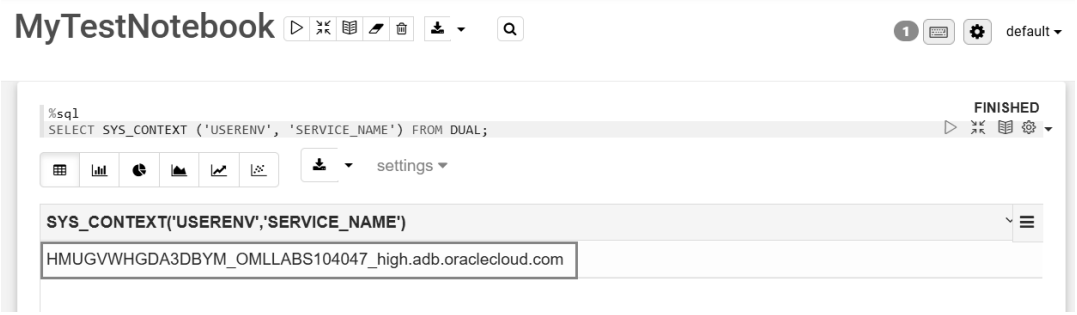
Verify Interpreter Bindings in Notebooks Classic

1. Open the Notebooks Classic for which you want to validate the updated interpreter bindings.
2. Run the following SQL statement:

```
%sql
SELECT SYS_CONTEXT ('USERENV', 'SERVICE_NAME') FROM DUAL;
```

3. The SQL statement returns the following information about the updated interpreter bindings, as shown in the screenshot below:

Figure 4-52 ADB service level information as displayed in Notebooks Classic



You can see that the service level is now displayed as **high**. In this example:

- `HMUGVWHGDA3DBYM` is the tenant name
- `OMLLABS104047` is the database name
- `high` is the ADB service name
- `adb.oraclecloud.com` is the domain

4.14 Use the Scratchpad

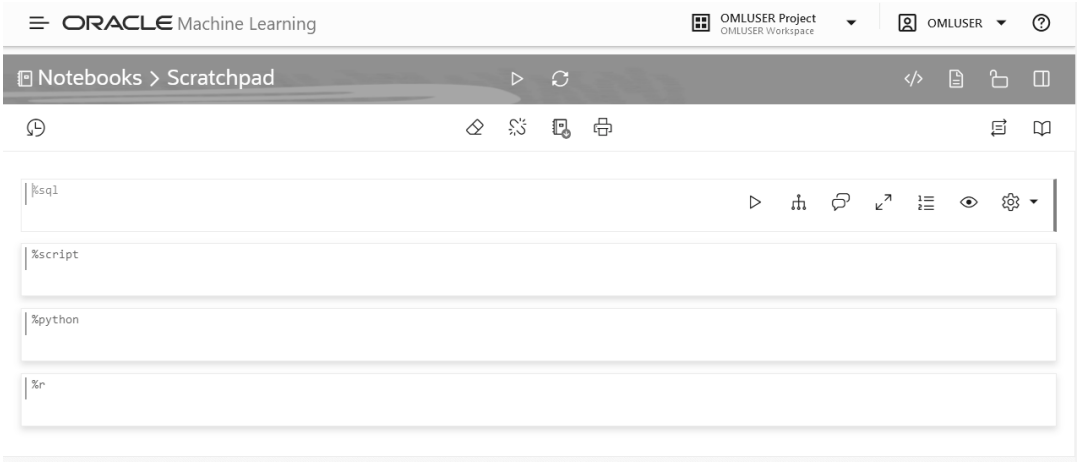
The Scratchpad provides you convenient one-click access to a notebook for running SQL statements, PL/SQL, R, and Python scripts that can be renamed. The Scratchpad is available on the Oracle Machine Learning User Interface (UI) home page.

> **Note:**
>
> The Scratchpad is a regular notebook that is prepopulated with four paragraphs - `%sql, %script, , %python` and `%r`.

After you run your scripts, the Scratchpad is automatically saved as a notebook by the default name **Scratchpad** on the Notebooks page. You can access it later on the Notebooks page. You can run all the paragraphs together or one paragraph at a time.

1. To open and use the scratchpad, click **Scratchpad** on the Oracle Machine Learning UI home page under **Quick Actions.** The Scratchpad opens. The Scratchpad has four paragraphs each with the following directives:
   - `%sql` — Allows you to run SQL statements.
   - `%script` — Allows you to run PL/SQL scripts.
   - `%python` — Allows you to run Python scripts.
   - `%r` — Allows you to run R scripts.

Figure 4-53 Scratchpad

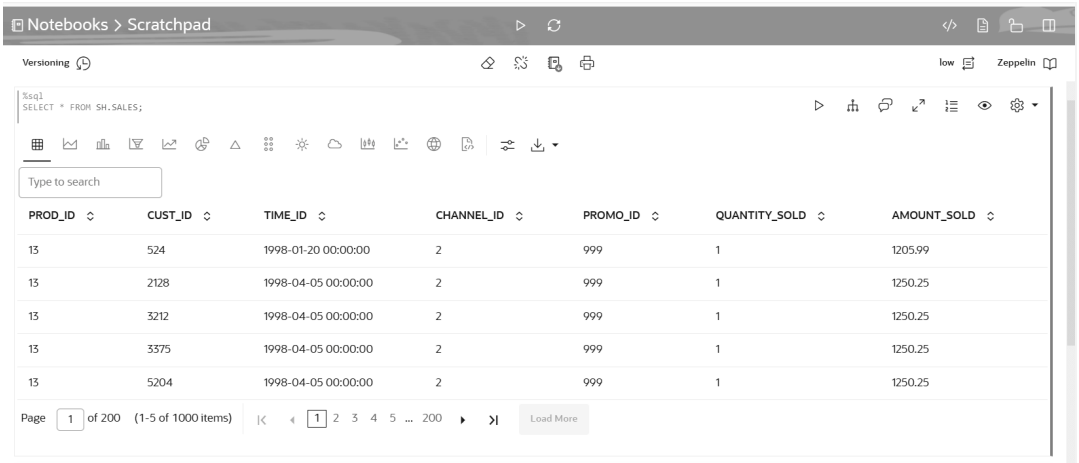


2. To run SQL script:
   a. Go to the paragraph with the `%sql` directive.
   b. Type the following command and click the Run icon. Alternatively, you can press Shift+Enter keys to run the paragraph.

```
SELECT * FROM SH.SALES;
```

In this example, the SQL statement fetches all of the data about product sales from the table SALES. Here, SH is the schema name, and SALES is the table name. Oracle Machine Learning UI fetches the relevant data from the database and displays it in a tabular format.

Figure 4-54 SQL Statement in Scratchpad



3. To run PL/SQL script:
   a. Go to the paragraph with the `%script` directive.
   b. Enter the following PL/SQL script and click the Run icon. Alternatively, you can press Shift+Enter keys to run the paragraph.

```
CREATE TABLE small_table
    (
```

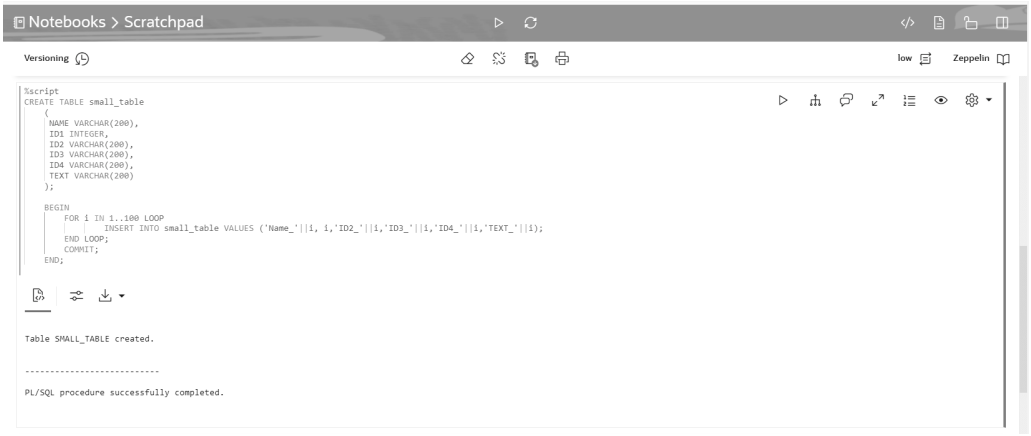
```
    NAME VARCHAR(200),
    ID1 INTEGER,
    ID2 VARCHAR(200),
    ID3 VARCHAR(200),
    ID4 VARCHAR(200),
    TEXT VARCHAR(200)
   );

   BEGIN
       FOR i IN 1..100 LOOP
               INSERT INTO small_table VALUES ('Name_'||i, i,'ID2_'||
i,'ID3_'||i,'ID4_'||i,'TEXT_'||i);
       END LOOP;
       COMMIT;
   END;
```

The PL/SQL script successfully creates the table SMALL_TABLE. The PL/SQL script in this example contains two parts:

- The first part of the script contains the SQL statement `CREATE TABLE` to create a table named `small_table`. It defines the table name, table column, data types, and size. In this example, the column names are `NAME`, `ID1`, `ID2`, `ID3`, `ID4`, and `TEXT`.
- The second part of the script begins with the keyword `BEGIN`. It inserts 100 rows in to the table `small_table`.

> **Note:**
>
> When using the `CREATE` statement with a primary key, it fails and displays the error message Insufficient privileges. This error occurs due to lockdown profiles in the database. If you encounter this error, contact your database administrator or the designated security administrator to grant the required privileges.

Figure 4-55 PL/SQL Script in Scratchpad



4. To run python script:

a. To use OML4Py, you must first import the `oml` module. `oml` is the OML4Py module that allows you to manipulate Oracle Database objects such as tables and views, call user-defined Python functions using embedded execution, and use the database machine learning algorithms. Go to the paragraph with `%python` directive. To import the `oml` module, type the following command and click the Run icon. Alternatively, you can press Shift+Enter keys to run the paragraph.

```
import oml
```

b. To check if the `oml` module is connected to Oracle Database, type `oml.isconnected()` and click the Run icon. Alternatively, you can press Shift+Enter keys to run the paragraph.

```
oml.isconnected()
```

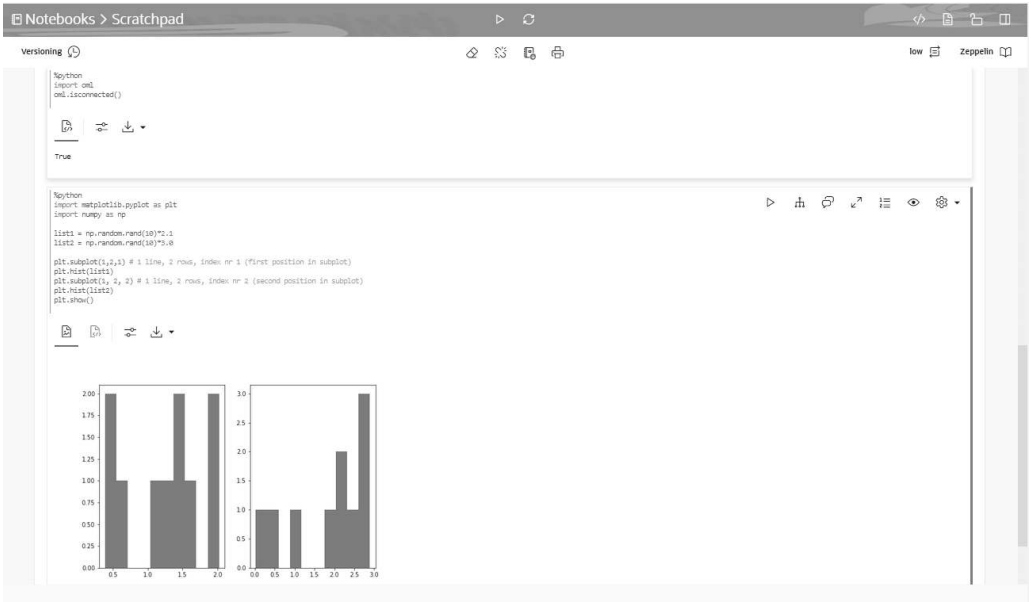
c. You are now ready to run your Python script. Type the following Python code and click the run icon. Alternatively, you can press Shift+Enter keys to run the paragraph.

```
import matplotlib.pyplot as plt
import numpy as np

list1 = np.random.rand(10)*2.1
list2 = np.random.rand(10)*3.0

plt.subplot(1,2,1) # 1 line, 2 rows, index nr 1 (first position in
subplot)
plt.hist(list1)
plt.subplot(1, 2, 2) # 1 line, 2 rows, index nr 2 (second position in
subplot)
plt.hist(list2)
plt.show()
```

In this example, the commands import two python packages to compute and render the data in two histograms for `list1` and `list2`. The Python packages are:

- Matplotlib — Python package to render graphs.
- Numpy — Python package for computations.

Figure 4-56 Python script in Scratchpad



The two graphs for `list1` and `list 2` are generated by the python engine, as shown in the screenshot here.

5. After you have created and run your scripts in the Scratchpad, the Scratchpad is automatically saved as a notebook by the name default name **Scratchpad** on the Notebooks page. You can edit the name of the notebook and save it with the new name by clicking **Edit.**

5
AutoML UI

AutoML User Interface (AutoML UI) is an Oracle Machine Learning interface that provides you no-code automated machine learning modeling. When you create and run an experiment in AutoML UI, it performs automated algorithm selection, feature selection, and model tuning, thereby enhancing productivity as well as potentially increasing model accuracy and performance.

The following steps comprise a machine learning modeling workflow and are automated by the AutoML user interface:

1. Algorithm Selection: Ranks algorithms likely to produce a more accurate model based on the dataset and its characteristics, and some predictive features of the dataset for each algorithm.
2. Adaptive Sampling: Finds an appropriate data sample. The goal of this stage is to speed up Feature Selection and Model Tuning stages without degrading the model quality.
3. Feature Selection: Selects a subset of features that are most predictive of the target. The goal of this stage is to reduce the number of features used in the later pipeline stages, especially during the model tuning stage to speed up the pipeline without degrading predictive accuracy.
4. Model Tuning: Aims at increasing individual algorithm model quality based on the selected metric for each of the shortlisted algorithms.
5. Feature Prediction Impact: This is the final stage in the AutoML UI pipeline. Here, the impact of each input column on the predictions of the final tuned model is computed. The computed prediction impact provides insights into the behavior of the tuned AutoML model.

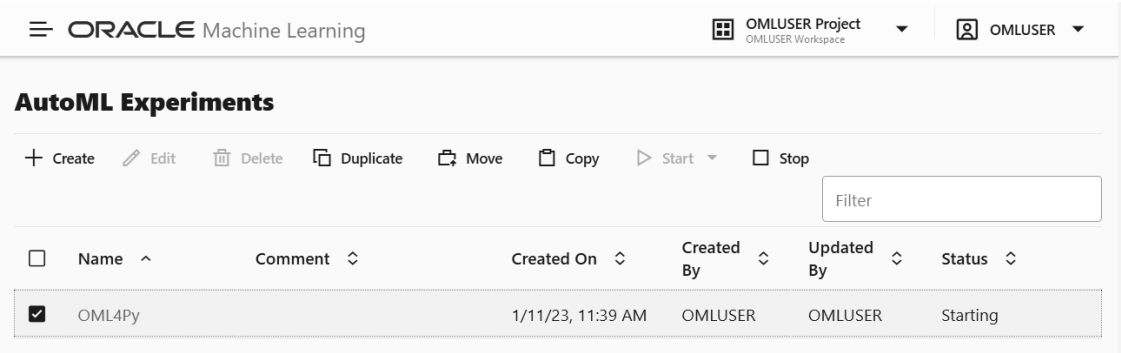
Business users without extensive data science background can use AutoML UI to create and deploy machine learning models. Oracle Machine Learning AutoML UI provides two functional features:

- Create machine learning models
- Deploy machine learning models

AutoML UI Experiments

When you create an experiment in AutoML UI, it automatically runs all the steps involved in the machine learning workflow. In the Experiments page, all the experiments that you have created are listed. To view any experiment details, click an experiment. Additionally, you can perform the following tasks:

Figure 5-1 AutoML Experiments page



- **Create:** Click **Create** to create a new AutoML UI experiment. The AutoML UI experiment that you create resides inside the project that you selected in the Project under the Workspace.
- **Edit:** Select any experiment that is listed here, and click **Edit** to edit the experiment definition.
- **Delete:** Select any experiment listed here, and click **Delete** to delete it. You cannot delete an experiment which is running. You must first stop the experiment to delete it.
- **Duplicate:** Select an experiment and click **Duplicate** to create a copy of it. The experiment is duplicated instantly and is in Ready status.
- **Move:** Select an experiment and click **Move** to move the experiment to a different project in the same or a different workspace. You must have either the `Administrator` or `Developer` privilege to move experiments across projects and workspaces.

  > **Note:**
  >
  > An experiment cannot be moved if it is in RUNNING, STOPPING or STARTING states, or if an experiment already exists in the target project by the same name.

- **Copy:** Select an experiment and click **Copy** to copy the experiment to another project in the same or different workspace.
- **Start:** If you have created an experiment but have not run it, then click **Start** to run the experiment.
- **Stop:** Select an experiment that is running, and click **Stop** to stop the running of the experiment.
- Access AutoML UI
  You can access AutoML UI from Oracle Machine Learning UI home page.
- Create AutoML UI Experiment
  To use the Oracle Machine Learning AutoML UI, you start by creating an experiment. An experiment is a unit of work that minimally specifies the data source, prediction target, and prediction type. After an experiment runs successfully, it presents you a list of machine learning models in order of model quality according to the metric selected. You can select any of these models for deployment or to generate a notebook. The generated notebook contains Python code using OML4Py and the specific settings AutoML used to produce the model.

- View an Experiment
  In the AutoML UI Experiments page, all the experiments that you have created are listed. Each experiment will be in one of the following stages: Completed, Running, and Ready.

Related Topics

- Automatic Machine Learning

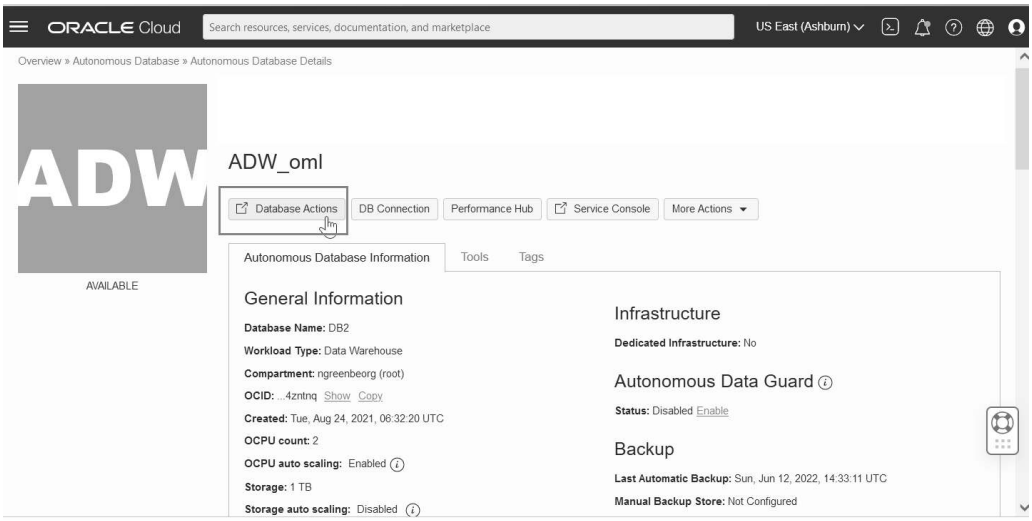
5.1 Access AutoML UI

You can access AutoML UI from Oracle Machine Learning UI home page.

To access AutoML UI, you must first sign in to Oracle Machine Learning from Autonomous Database:

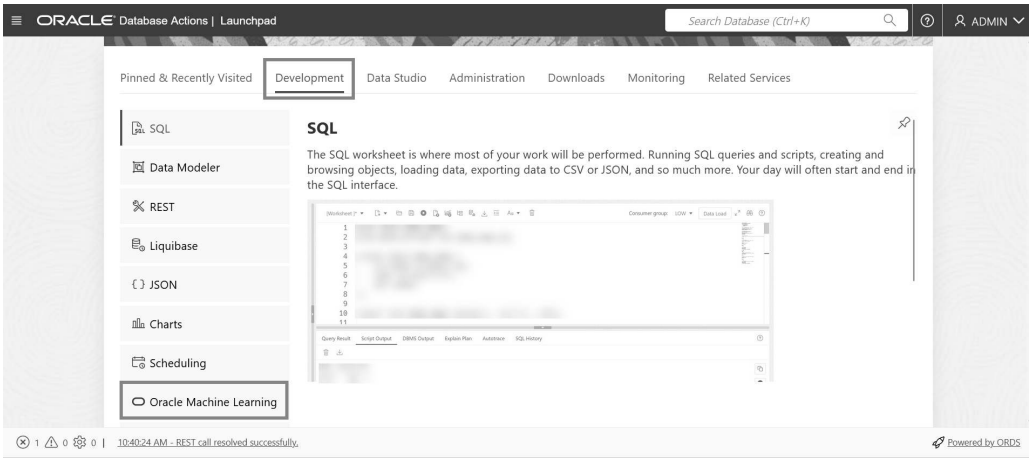
1. To sign in to Oracle Machine Learning from an Autonomous Database instance:
   a. Select an Autonomous Database instance and on the Autonomous Database details page click **Database Actions.**

Figure 5-2 Database Actions



   b. On the Database Actions page, go to the Development section and click **Oracle Machine Learning**.

Figure 5-3 Oracle Machine Learning option in Database Actions Launchpad



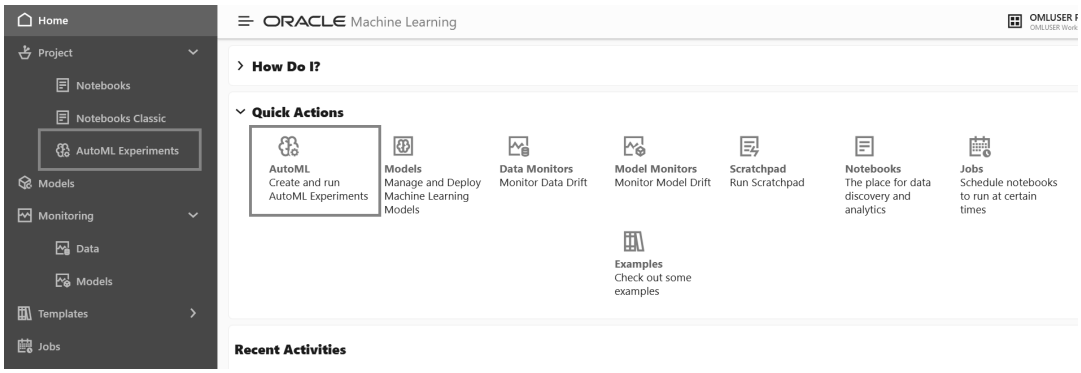
The Oracle Machine Learning sign in page opens.

c. Enter your username and password, and click **Sign in.**

This opens the Oracle Machine Learning Notebooks home page.

2. On your Oracle Machine Learning Notebooks home page, click **AutoML.**.

Figure 5-4 AutoML options on Oracle Machine Learning home page and Left Navigation menu



Alternatively, you can click the Cloud menu and click **AutoML** under Projects.

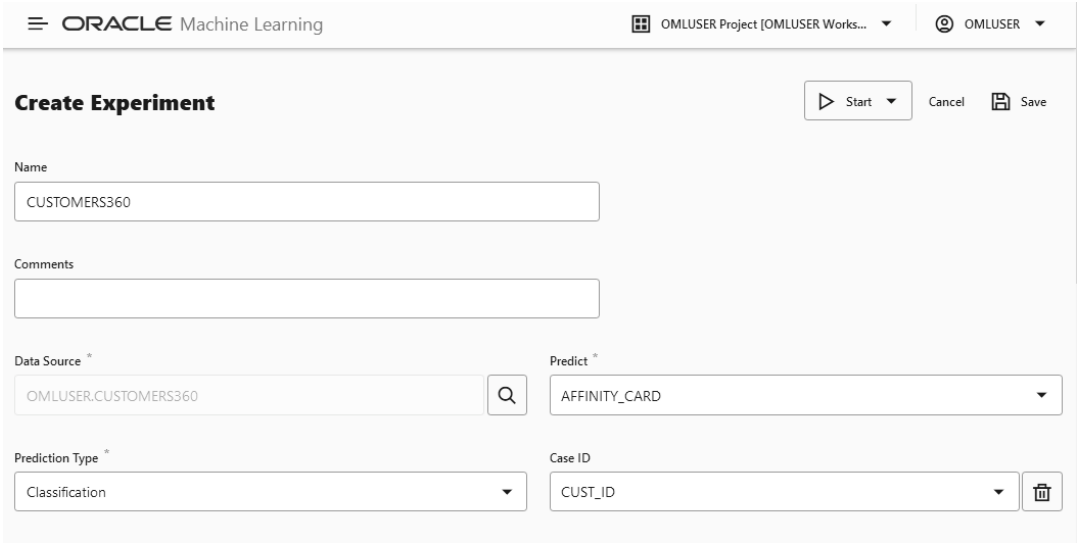
5.2 Create AutoML UI Experiment

To use the Oracle Machine Learning AutoML UI, you start by creating an experiment. An experiment is a unit of work that minimally specifies the data source, prediction target, and prediction type. After an experiment runs successfully, it presents you a list of machine learning models in order of model quality according to the metric selected. You can select any of these models for deployment or to generate a notebook. The generated notebook contains Python code using OML4Py and the specific settings AutoML used to produce the model.

To create an experiment, specify the following:

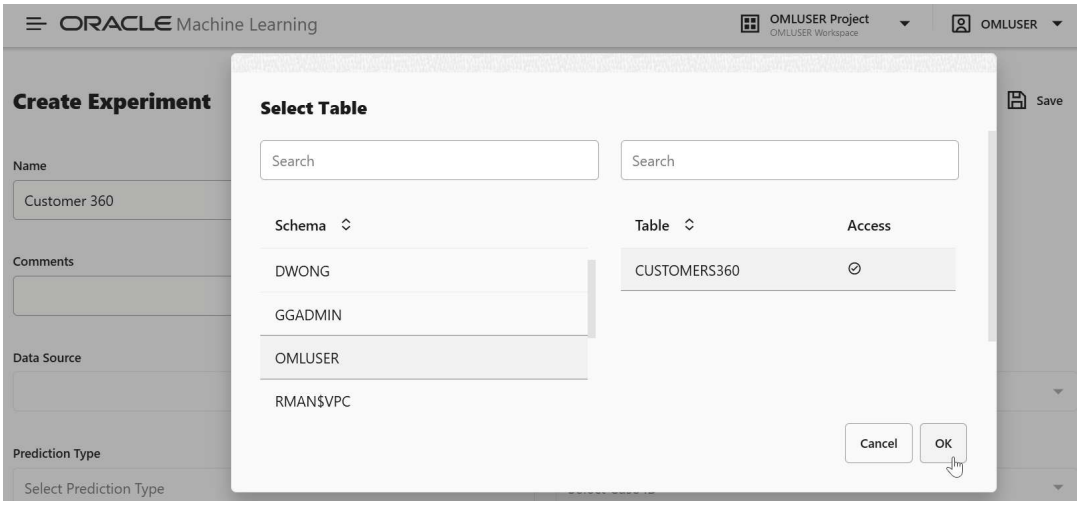
1. In the **Name** field, enter a name for the experiment.

Figure 5-5 Create an AutoML Experiment



2. In the **Comments** field, enter comments, if any.
3. In the **Data Source** field, select the schema and a table or view in that schema. Click the search icon to open the Select Table dialog box. Browse and select a schema, and then select a table from the schema list, which is the data source of your AutoML UI experiment.

Figure 5-6 Select Table dialog



a. In the Schema column, select a schema.

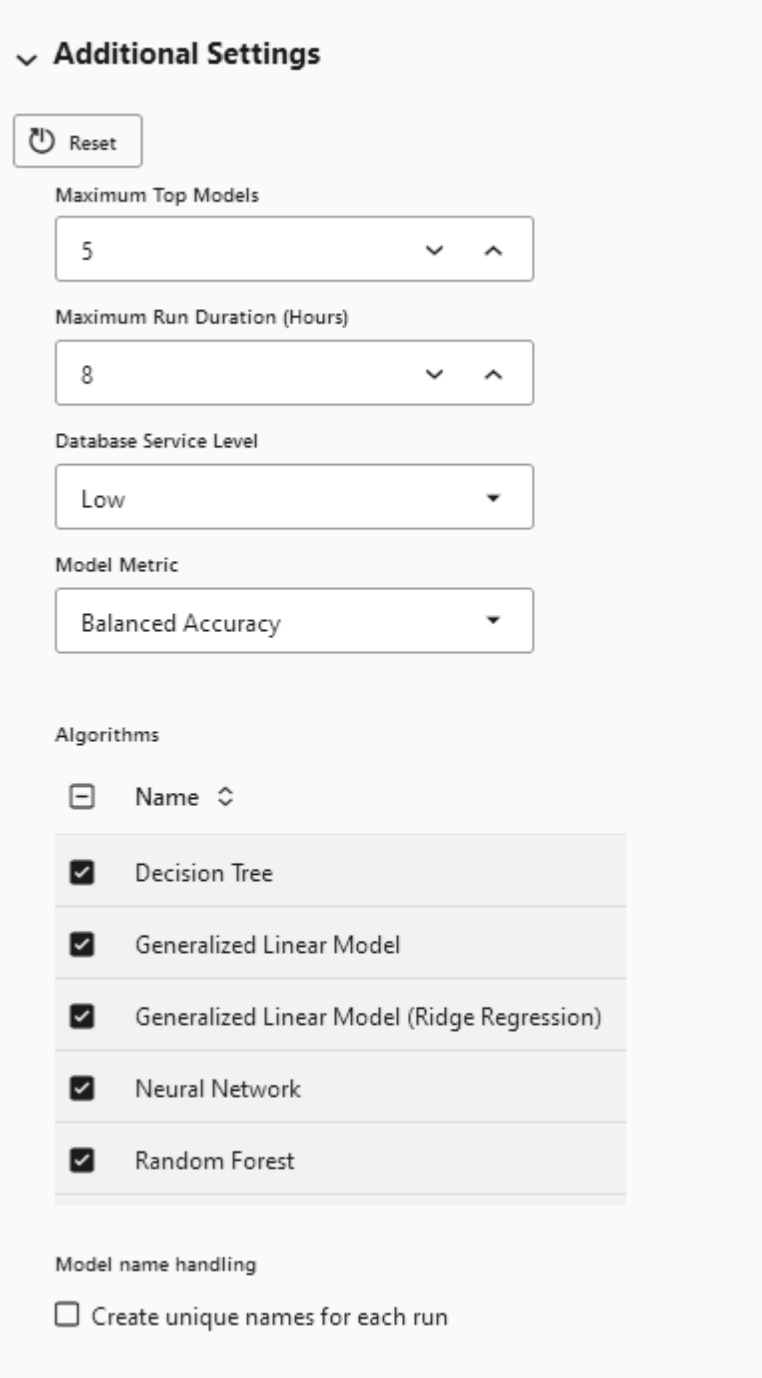
> **Note:**
>
> While you select the data source, statistics are displayed in the Features grid at the bottom of the experiment page. Busy status is indicated until the computation is complete. The target column that you select in Predict is highlighted in the Features grid.

b. Depending on the selected schema, the available tables are listed in the Table column. Select the table and click **OK.**

> **Note:**
>
> To create an AutoML experiment for a table or view present in the schema of another user, ensure that you have explicit privileges to access that table or view in the schema. Request the Database Administrator or the owner of the schema to provide you with the privileges to access the table or view. For example:
>
> ```
> grant select on <table> to <user>
> ```

4. In the **Predict** drop-down list, select the column from the selected table. This is the target for your prediction.
5. In the **Prediction Type** field, the prediction type is automatically selected based on your data definition. However, you can override the prediction type from the drop-down list, if data type permits. Supported Prediction Types are:
   - **Classification:** For non-numeric data type, Classification is selected by default.
   - **Regression:** For numeric data type, Regression is selected by default.
6. The **Case ID** helps in data sampling and dataset split to make the results reproducible between experiments. It also aids in reducing randomness in the results. This is an optional field.
7. In the **Additional Settings** section, you can define the following:

Figure 5-7 Additional Settings for AutoML Experiments



a. **Reset:** Click **Reset** to reset the settings to the default values.

b. **Maximum Top Models:** Select the maximum number of top models to create. The default is `5` models. You can reduce the number of top models to 2 or 3 since tuning models to get the top one for each algorithm requires additional time. If you want to get the initial results even faster, consider the top recommended algorithm. For this, set the **Maximum Top Models** to `1`. This will tune the model for that algorithm.

c. **Maximum Run Duration:** This is the maximum time for which the experiment will be allowed to run. If you do not enter a time, then the experiment will be allowed to run for up to the default, which is `8` hours.

d. **Database Service Level:** This is database connection service level and query parallelism level. Default is `Low`. This results in no parallelism and sets a high runtime limit. You can create many connections with `Low` database service level. You can also change your database service level to `Medium` or `High`.

- `High` level gives the greatest parallelism but significantly limits the number of concurrent jobs.
- `Medium` level enables some parallelism but allows greater concurrency for job processing.

> **Note:**
>
> Changing the database service level setting on the *Always Free Tier* will have no effect since there is a 1 OCPU limit. However, if you increase the OCPUs allocated to your autonomous database instance, you can increase the **Database Service Level** to `Medium` or `High`.

> **Note:**
>
> The **Database Service Level** setting has no effect on AutoML container level resources.

e. **Model Metric:** Select a metric to choose the winning models. The following metrics are supported by AutoML UI:

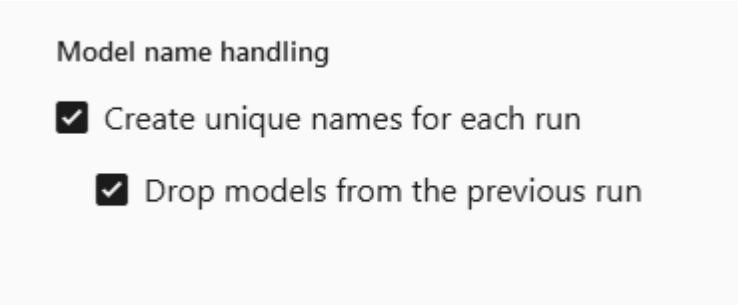
- For Classification, the supported metrics are:
  - Balanced Accuracy
  - ROC AUC
  - F1 (with weighted options). The weighted options are weighted, binary, micro and macro.
    - Micro-averaged: Here, all samples equally contribute to the final averaged metric
    - Macro-averaged: Here, all classes equally contribute to the final averaged metric
    - Weighted-averaged: Here, each class' contribution to the average is weighted by its size
  - Precision (with weighted options)
  - Recall (with weighted options)
- For Regression, the supported metrics are:
  - R2 (default)
  - Negative mean squared error
  - Negative mean absolute error
  - Negative median absolute error

f. **Algorithm:** The supported algorithms depend on **Prediction Type** that you have selected. Click the corresponding checkbox against the algorithms to select it. By default, all the candidate algorithms are selected for consideration as the experiment runs. The supported algorithms for the two Prediction Types:

- For Classification, the supported algorithms are:
  - Decision Tree
  - Generalized Linear Model
  - Generalized Linear Model (Ridge Regression)
  - Neural Network
  - Random Forest
  - Support Vector Machine (Gaussian)
  - Support Vector Machine (Linear)
- For Regression, the supported algorithms are:
  - Generalized Linear Model
  - Generalized Linear Model (Ridge Regression)
  - Neural Network
  - Support Vector Machine (Gaussian)
  - Support Vector Machine (Linear)

> **Note:**
>
> You can remove algorithms from being considered if you have preferences for particular algorithms, or have specific requirements. For example, if model transparency is essential, then excluding models such as Neural Network would make sense. Note that some algorithms are more compute intensive than others. For example, Naïve Bayes and Decision Tree are normally faster than Support Vector Machine or Neural Network.

g. **Model Name Handling:** Here, you have the option to retain the original model name or generate unique model names everytime you run an experiment. By default, this option is deselected.

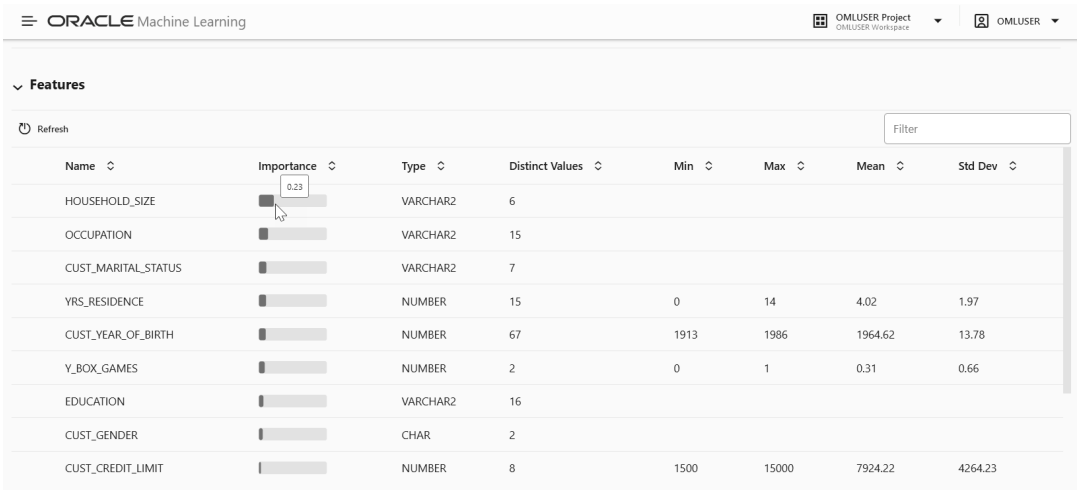


- **Create unique names for each run:** Select this option to generate model names that are unique. Selecting this option also gives you the choice to select or deselect the option **Drop models from the previous run.**

- **Drop models from the previous run:** Select this option to drop the models that were generated in the prior experiment runs. Deselect this option to retain the models that were generated in the prior runs. These models are available in the user schema.

8. Expand the **Features** grid to view the statistics of the selected table. The supported statistics are Distinct Values, Minimum, Maximum, Mean, and Standard Deviation. The supported data sources for Features are tables, views and analytic views. The target column that you selected in Predict is highlighted here. After an experiment run is completed, the Features grid displays an additional column **Importance**. Feature Importance indicates the overall level of sensitivity of prediction to a particular feature.

Figure 5-8 Features

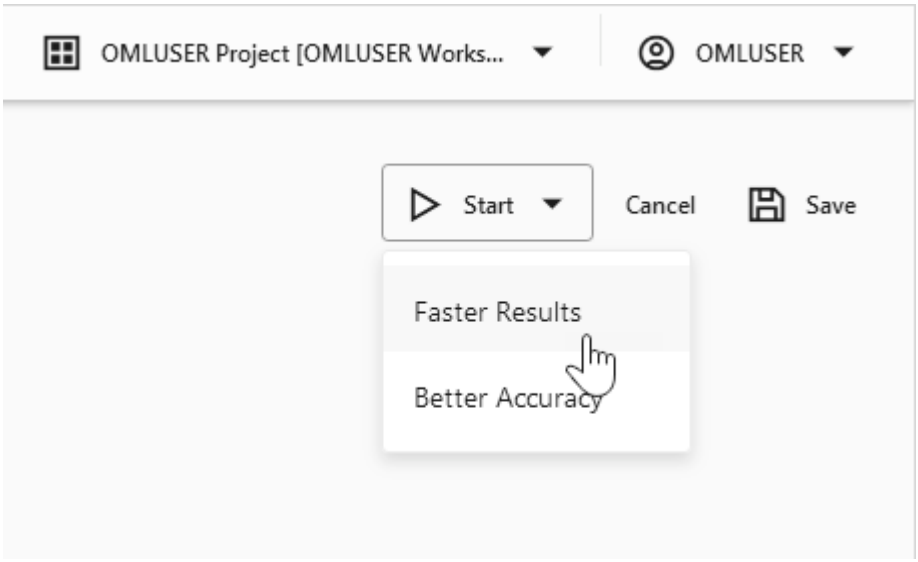


You can perform the following tasks:

- **Refresh:** Click Refresh to fetch all columns and statistics for selected data source.
- **View Importance:** Hover your cursor over the horizontal bar under Importance to view the value of Feature Importance for the variables. The value is always depicted in the range `0` to `1`, with values closer to 1 being more important.

9. When you complete defining the experiment, the **Start** and **Save** buttons are enabled.

Figure 5-9 Start Experiment options



- Click **Start** to run the experiment and start the AutoML UI workflow, which is displayed in the progress bar. Here, you have the option to select:
  a. **Faster Results:** Select this option if you want to get candidate models sooner, possibly at the expense of accuracy. This option works with a smaller set of the hyperparamter combinations, and hence yields faster result.
  b. **Better Accuracy:** Select this option if you want more pipeline combinations to be tried for possibly more accurate models. A pipeline is defined as an algorithm, selected data feature set, and set of algorithm hyperparameters.

  > **Note:**
  >
  > This option works with the broader set of hyperparameter options recommended by the internal meta-learning model. Selecting **Better Accuracy** will take longer to run your experiment, but may provide models with more accuracy.

  Once you start an experiment, the progress bar appears displaying different icons to indicate the status of each stage of the machine learning workflow in the AutoML experiment. The progress bar also displays the time taken to complete the experiment run. To view the message details, click on the respective message icons.
- Click **Save** to save the experiment, and run it later.
- Click **Cancel** to cancel the experiment creation.

- Supported Data Types for AutoML UI Experiments
  When creating an AutoML experiment, you must specify the data source and the target of the experiment. This topic lists the data types for Python and SQL that are supported by AutoML experiments.

5.2.1 Supported Data Types for AutoML UI Experiments

When creating an AutoML experiment, you must specify the data source and the target of the experiment. This topic lists the data types for Python and SQL that are supported by AutoML experiments.

Table 5-1 Supported Data Types by AutoML Experiments

Data Types	SQL Data Types	Python Data Types
Numerical	• NUMBER • INTEGER • FLOAT • NUMERICALS • BINARY_DOUBLE • BINARY_FLOAT	• INTEGER • FLOAT(NUMBER) • FLOAT(BINARY_DOUBLE) • FLOAT(BINARY_FLOAT)
Categorical	• CHAR • VARCHAR2 • CATEGORICALS	• STRING(VARCHAR2) • STRING(CHAR) • STRING(CLOB)
Unstructured Text	• CHAR • VARCHAR2 • CLOB • BLOB • BFILE	• BYTES(RAW, BLOB)

5.3 View an Experiment

In the AutoML UI Experiments page, all the experiments that you have created are listed. Each experiment will be in one of the following stages: Completed, Running, and Ready.

To view an experiment, click the experiment name. The Experiment page displays the details of the selected experiment. It contains the following sections:

Edit Experiment

In this section, you can edit the selected experiment. Click **Edit** to make edits to your experiment.

> **Note:**
>
> You cannot edit an experiment that is running.

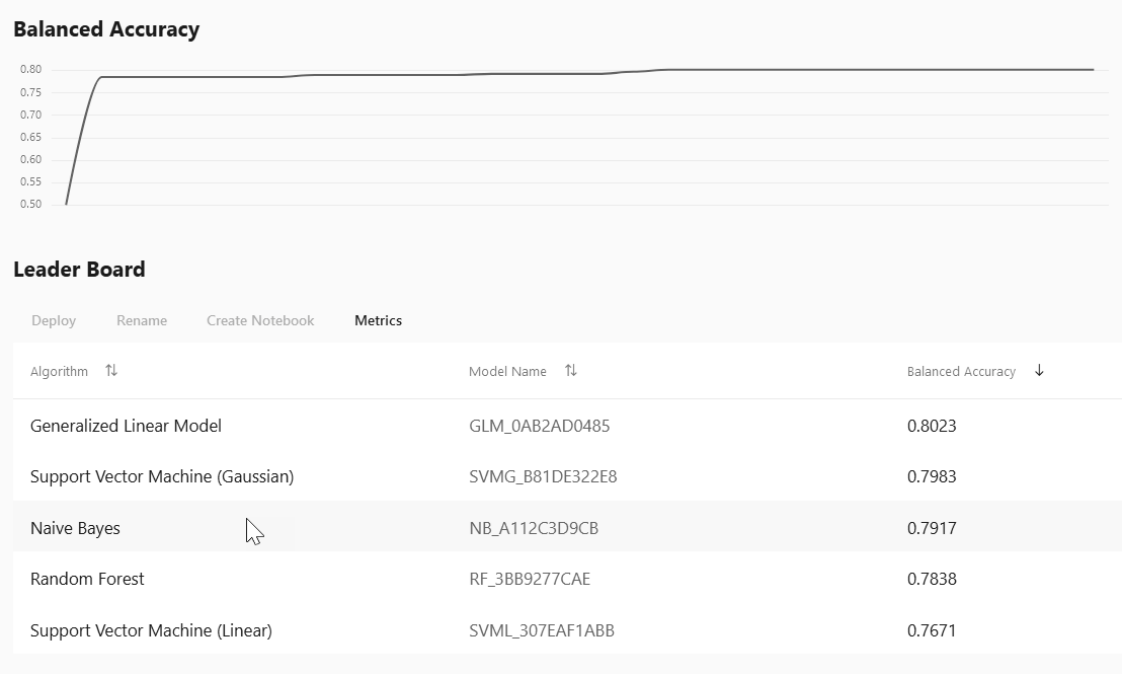
Metric Chart

The Model Metric Chart depicts the best metric value over time as the experiment runs. It shows improvement in accuracy as the running of the experiment progresses. The display name depends on the selected model metric when you create the experiment.

Leader Board

When an experiment runs, it starts to show the results in the Leader Board. The Leader Board displays the top performing models relative to the model metric selected along with the algorithm and accuracy. You can view the model details and perform the following tasks:

Figure 5-10 Leader Board



- View Model Details: Click on the **Model Name** to view the details. The model details are displayed in the Model Details dialog box. You can click multiple models on the Leader Board, and view the model details simultaneously. The Model Details window depicts the following:
  - Prediction Impact: Displays the importance of the attributes in terms of the target prediction of the models.
  - Confusion Matrix: Displays the different combination of actual and predicted values by the algorithm in a table. Confusion Matrix serves as a performance measurement of the machine learning algorithm.
- **Deploy:** Select any model on the Leader Board and click **Deploy** to deploy the selected model. Deploy Model.
- **Rename:** Click **Rename** to change the name of the system generated model name. The name must be alphanumeric (not exceeding 123 characters) and must not contain any blank spaces.
- **Create Notebook:** Select any model on the Leader Board and click Create Notebooks from AutoML UI Models to recreate the selected model from code.
- **Metrics:** Click **Metrics** to select additional metrics to display in the Leader Board. The additional metrics are:
  - For Classification

- Accuracy: Calculates the proportion of correctly classifies cases - both Positive and Negative. For example, if there are a total of TP (True Positives)+TN (True Negatives) correctly classified cases out of TP+TN+FP+FN (True Positives+True Negatives+False Positives+False Negatives) cases, then the formula is: `Accuracy = (TP+TN)/(TP+TN+FP+FN)`
- Balanced Accuracy: Evaluates how good a binary classifier is. It is especially useful when the classes are imbalanced, that is, when one of the two classes appears a lot more often than the other. This often happens in many settings such as Anomaly Detection etc.
- Recall: Calculates the proportion of actual Positives that is correctly classified.
- Precision: Calculates the proportion of predicted Positives that is True Positive.
- F1 Score: Combines precision and recall into a single number. F1-score is computed using harmonic mean which is calculated by the formula: `F1-score = 2 × (precision × recall)/(precision + recall)`

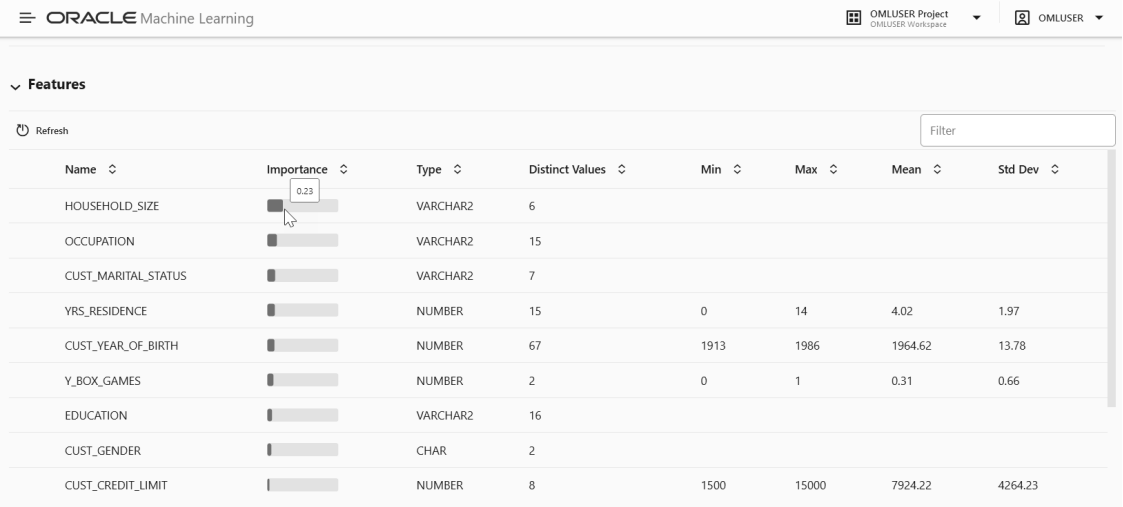
– For Regression:

- R2 (Default): A statistical measure that calculates how close the data are to the fitted regression line. In general, the higher the value of R-squared, the better the model fits your data. The value of R2 is always between 0 to 1, where:
  - `0` indicates that the model explains none of the variability of the response data around its mean.
  - `1` indicates that the model explains all the variability of the response data around its mean.
- Negative Mean Squared Error: This is the mean of the squared difference of predicted and true targets.
- Negative Mean Absolute Error: This is the mean of the absolute difference of predicted and true targets.
- Negative Median Absolute Error: This is the median of the absolute difference between predicted and true targets.

Features

The **Features** grid displays the statistics of the selected table for the experiment.The supported statistics are Distinct Values, Minimum, Maximum, Mean, and Standard Deviation. The supported data sources for Features are tables, views and analytic views. The target column that you selected in Predict is highlighted here. After an experiment run is completed, the Features grid displays an additional column **Importance**. Feature Importance indicates the overall level of sensitivity of prediction to a particular feature. Hover your cursor over the graph to view the value of **Importance.** The value is always depicted in the range `0` to `1`, with values closer to `1` being more important.

Figure 5-11 Features



- Create Notebooks from AutoML UI Models
  You can create notebooks using OML4Py code that will recreate the selected model using the same settings. It also illustrates how to score data using the model. This option is helpful if you want to use the code to re-create a similar machine learning model.

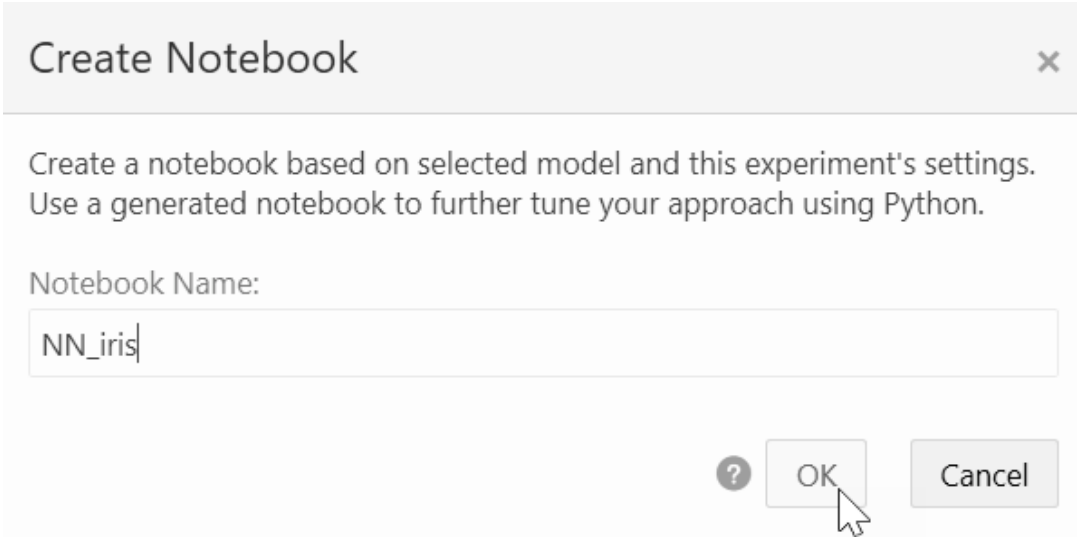
5.3.1 Create Notebooks from AutoML UI Models

You can create notebooks using OML4Py code that will recreate the selected model using the same settings. It also illustrates how to score data using the model. This option is helpful if you want to use the code to re-create a similar machine learning model.

To create a notebook from an AutoML UI model:

1. Select the model on the Leader Board based on which you want to create your notebook, and click **Create Notebook.** The Create Notebook dialog opens.

Figure 5-12 Create Notebook dialog



2. In the **Notebook Name** field, enter a name for your notebook.

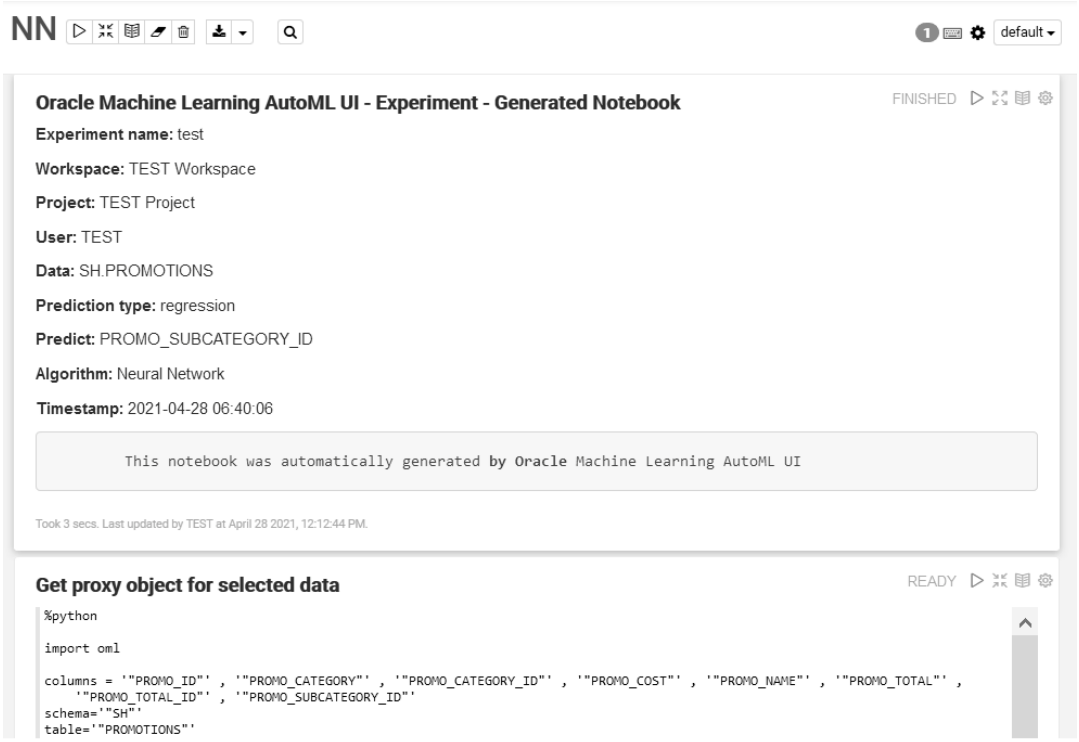
   The REST API endpoint derives the experiment metadata, and determines the following settings as applicable:

   - Data Source of the experiment (schema.table)
   - Case ID. If the Case ID for the experiment is not available, then the appropriate message is displayed.
   - A unique model name based on the current model name is generated
   - Information related to scoring paragraph:
     - Case ID: If available, then it merges the Case ID column into the scoring output table
     - Generate unique predict output table name based on build data source and unique suffix
     - Prediction column name: PREDICTION
     - Prediction probability column name: PROBABILITY (applicable only for Classification)

3. Click **OK.** The generated notebook is listed in the Notebook page. Click to open the notebook

   The generated notebook displays paragraph titles for each paragraph along with the python codes. Once you run the notebook, it displays information related to the notebook as well as the AutoML experiment such as the experiment name, workspace and project in which the notebook is present, the user, data, prediction type and prediction target, algorithm, and the time stamp when the notebook is generated.

Figure 5-13 AutoML UI Generated notebook



6
Data Monitoring

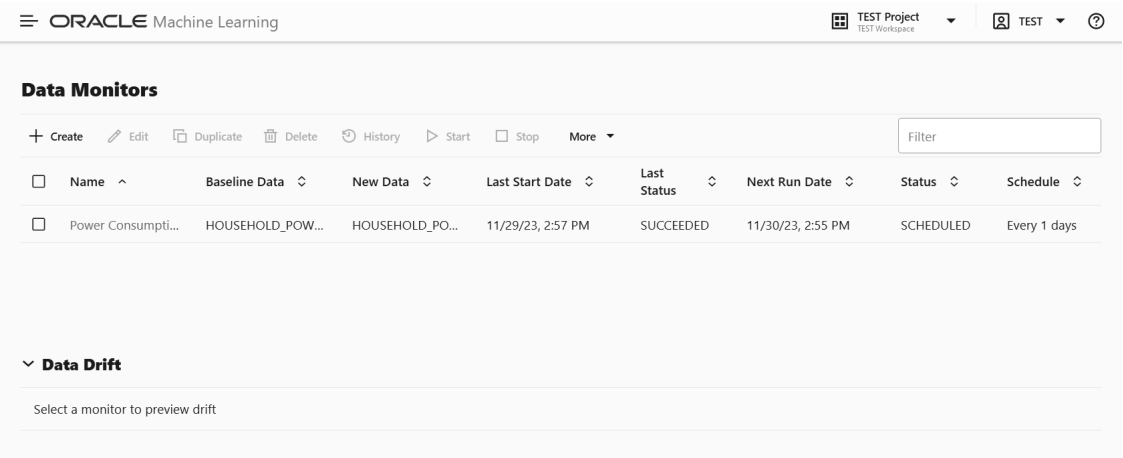
Data Monitoring evaluates how your data evolves over time. It helps you with insights on trends and multivariate dependencies in the data. It also gives you an early warning about data drift.

Data drift occurs when data diverges from the original baseline data over time. Data drift can happen for a variety of reasons, such as a changing business environment, evolving user behavior and interest, data modifications from third-party sources, data quality issues, or issues with upstream data processing pipelines.

The key to accurately interpret your models and to ensure that the models are able to solve business problems is to understand how data evolves over time. Data monitoring is complementary to successful model monitoring, as understanding the changes in data is critical in understanding the changes in the efficacy of the models. The ability to quickly and reliably detect changes in the statistical properties of your data ensures that your machine learning models are able to meet business objectives.

You can monitor your data using the data monitoring functionality of Oracle Machine Learning User Interface. To monitor your data, click on the Cloud menu on the Oracle Machine Learning UI home page, click **Monitoring** and then click **Data** to open the Data Monitors page. On the Data Monitors page, you can perform the following tasks:

Figure 6-1 Data Monitors page

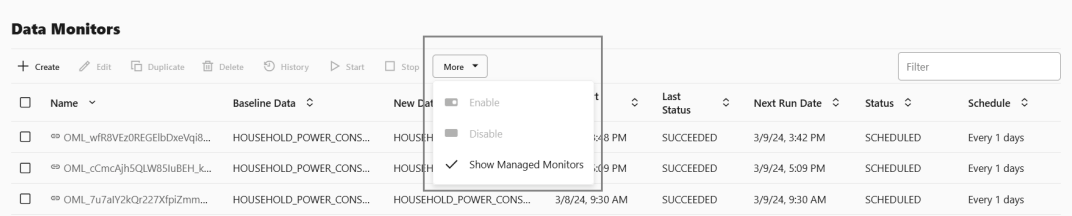


- **Create:** Create a data monitor.

> **Note:**
>
> The supported data types for data monitoring are NUMERIC and CATEGORICAL.

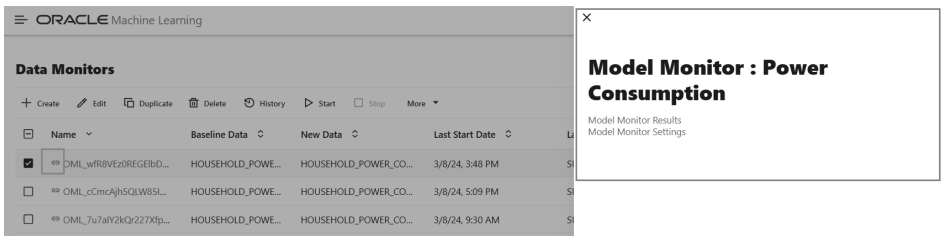
- **Edit:** Select a data monitor and click **Edit** to edit a data monitor.
- **Duplicate:** Select a data monitor and click **Duplicate** to create a copy of the monitor.
- **Delete:** Select a data monitor and click **Delete** to delete a data monitor.
- **History:** Select a data monitor and click **History** to view the runtime details. Click **Back to Monitors** to go back to the Data Monitoring page.
- **Start:** Start a data monitor.
- **Stop:** Stop a data monitor that is running.
- **More:** Click **More** for additional options to:

Figure 6-2 More option under Data Monitors



  - **Enable:** Select a data monitor and click **Enable** to enable a monitor that is disabled. By default, a data monitor is enabled. The status is displayed as `SCHEDULED`.
  - **Disable:** Select a data monitor and click **Disable** to disable a data monitor. The status is displayed as `DISABLED`.
  - **Show Managed Monitors:** Click this option to view the data monitors that are created and managed by OML Services REST API and Model Monitors in Oracle Machine Learning UI. The data monitors that are managed by these two components have a system generated name, and are indicated by specific icons against its name.
    * Click on the link icon against a managed data monitor name to view the details of the associated model monitor. The associated model monitor details are displayed on a separate pane that slides in. The slide-in pane displays the model monitor name with links to view the model monitor results and settings. Clicking on the link icon also displays the data drift details on the lower pane of the Data Monitors page. Click on the X on the top left corner to close the pane.

Figure 6-3 Data Monitors page displaying the associated model monitor results and settings

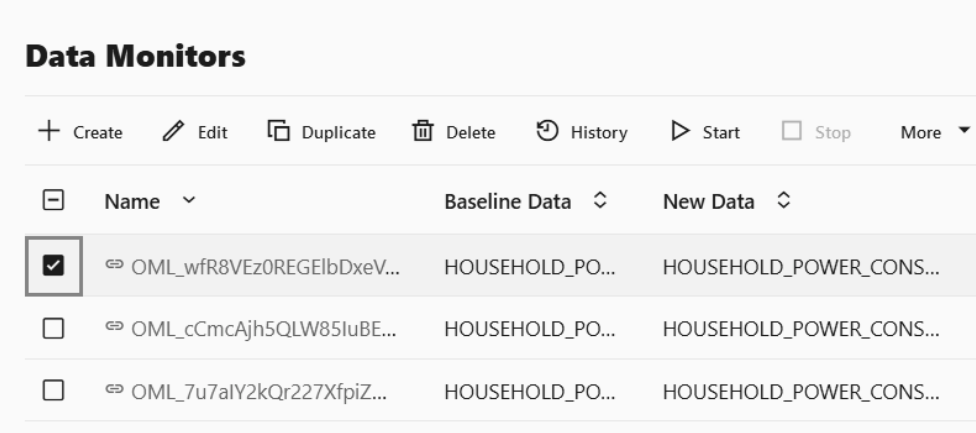


In this example, the slide-in pane displays the details of the model monitor Power Consumption. On the slide-in pane:

- Click **Model Monitor Results** to view the results computed by the model monitor — settings, models, model drift, metric, and prediction statistics. Click **Monitors** to return to the Data Monitors page. See View Model Monitor Results.
- Click **Model Monitor Settings** to view and edit the settings, details, and models monitored by the model monitor on the Edit Model Monitor page. Click **Cancel** to return to the Data Monitors page. Click **Save** to save any changes.

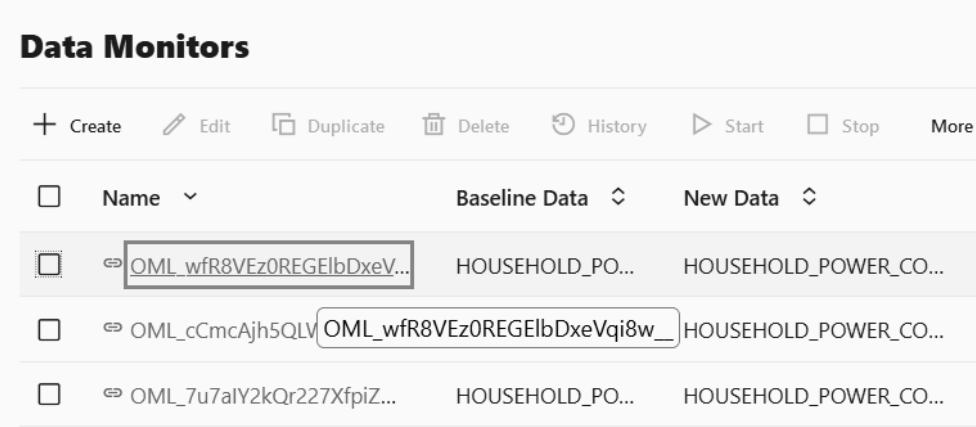
* Click on the check box against the data monitor name to view the data drift values on the lower pane.

Figure 6-4 Select a managed data monitor



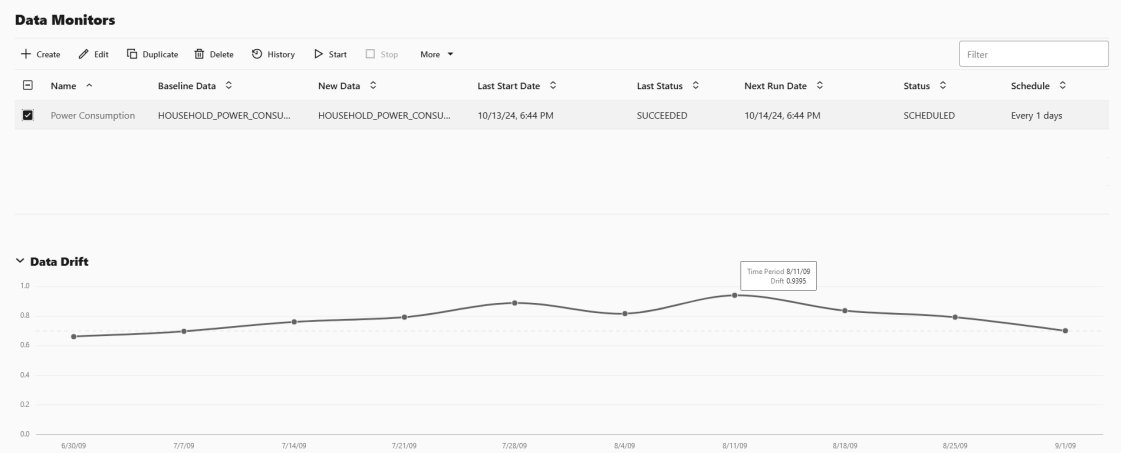
* Click on the data monitor name to view the details of the data monitor — settings, data drift values and monitored features.

Figure 6-5 Data monitor click



The Data Monitors page displays the information about the selected monitor: Monitor name, Baseline Data, New Data, Last Start Date, Last Status, Next Run Data, Status, and Schedule. The page also displays the data drift, if the data monitor has run successfully. To view data drift:

Figure 6-6 Data Drift preview on Data Monitors page



Select a data monitor that has run successfully, as shown in the screenshot. On the lower pane, the data drift of the selected monitor is displayed. The X axis depicts the analysis period, and the Y axis depicts the data drift values. The horizontal dotted line is the threshold value, and the line depicts the drift value for each point in time for the analysis period. Hover your mouse over the line to view the drift values. For more information on this example, see View Data Monitor Results.

- Create a Data Monitor
  Data Monitoring allows you to detect data drift over time and the potentially negative impact on the performance of your machine learning models. On the Data Monitor page, you can create, run, and track data monitors and the results.
- View Data Monitor Results
  The Data Monitor Results page displays the information on the selected data monitor that have run successfully, along with data drift details for each monitored feature.
- View History
  The History page displays the runtime details of data monitors.

Related Topics

- View History
  The History page displays the runtime details of data monitors.

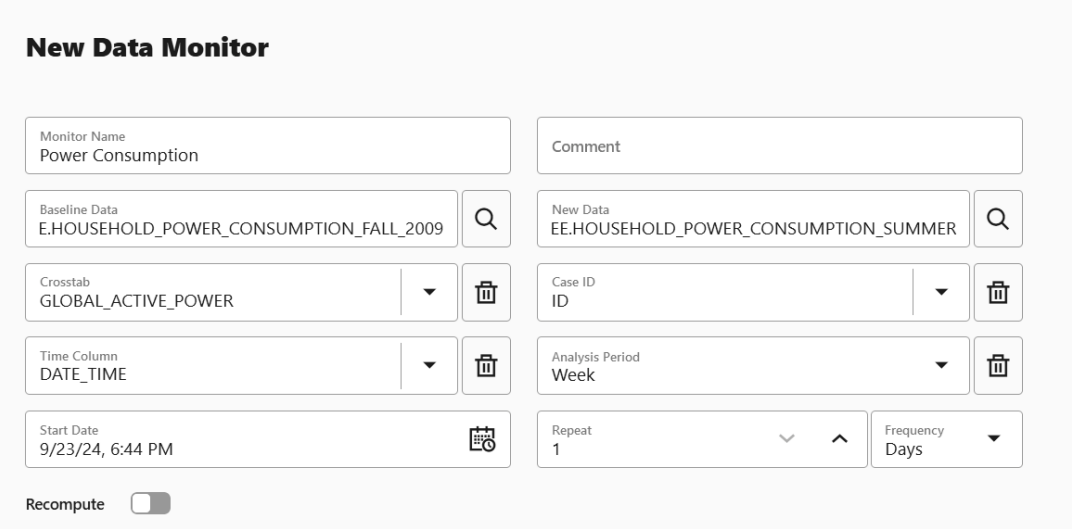
6.1 Create a Data Monitor

Data Monitoring allows you to detect data drift over time and the potentially negative impact on the performance of your machine learning models. On the Data Monitor page, you can create, run, and track data monitors and the results.

To create a data monitor:

1. On the Oracle Machine Learning UI left navigation menu, expand **Monitoring** and then click **Data** to open the Data Monitoring page.
2. On the Data Monitoring page, click **Create** to open the New Data Monitor page.
3. On the New Data Monitor page, enter the following details:

Figure 6-7 New Data Monitor



a. **Monitor Name:** Enter a name for the data monitor.

b. **Comments:** Enter comments. This is an optional field.

c. **Baseline Data:** This is a table or view that contains baseline data to monitor. Click the search icon to open the **Select Table** dialog. Here, select a schema, and then a table.

> **Note:**
>
> The supported data types for data monitoring are `NUMBER`, `BINARY_DOUBLE`, `FLOAT`, `BINARY_FLOAT`, `VARCHAR2`, `CHAR`, `NCHAR`, and `NVARCHAR2` with length `<=4000`.

d. **New Data:** This is a table or view with new data to be compared against the baseline data. Click the search icon to open the **Select Table** dialog. Select a schema, and then a table.

> **Note:**
>
> The supported data types for data monitoring are `NUMBER`, `BINARY_DOUBLE`, `FLOAT`, `BINARY_FLOAT`, `VARCHAR2`, `CHAR`, `NCHAR`, and `NVARCHAR2` with length `<=4000`.

e. **Crosstab:** Select an attribute from the drop-down list. This attribute in the baseline and new data acts as an anchor or target for bi-variate analysis of your data.

> **Note:**
>
> The target column in supervised problems can be passed as an anchor column in this field. For unsupervised problems, it can be any column of interest. However, it will be application specific.

f. **Case ID:** This is an optional field. Enter a case identifier for the baseline and new data to improve the repeatability of the results.

g. **Time Column:** This is the name of a column storing time information in the New Data table or view. Select the time column from the drop-down list.

> **Note:**
>
> If the Time Column is blank, the entire New Data is treated as one period.

h. **Analysis Period:** This is the length of time for which data monitoring is performed on the New Data. Select the analysis period for data monitoring. The options are `Day`, `Week`, `Month`, `Year`.

i. **Start Date:** This is the start date of your data monitor schedule. If you do not provide a start date, the current date will be used as the start date.

j. **Repeat:** This value defines the number of times the data monitor run will be repeated for the frequency defined. Enter a number between 1 and 99. For example, if you enter `2` in the **Repeat** field here, and `Minutes` in the **Frequency** field, then the data monitor will run every 2 minutes.

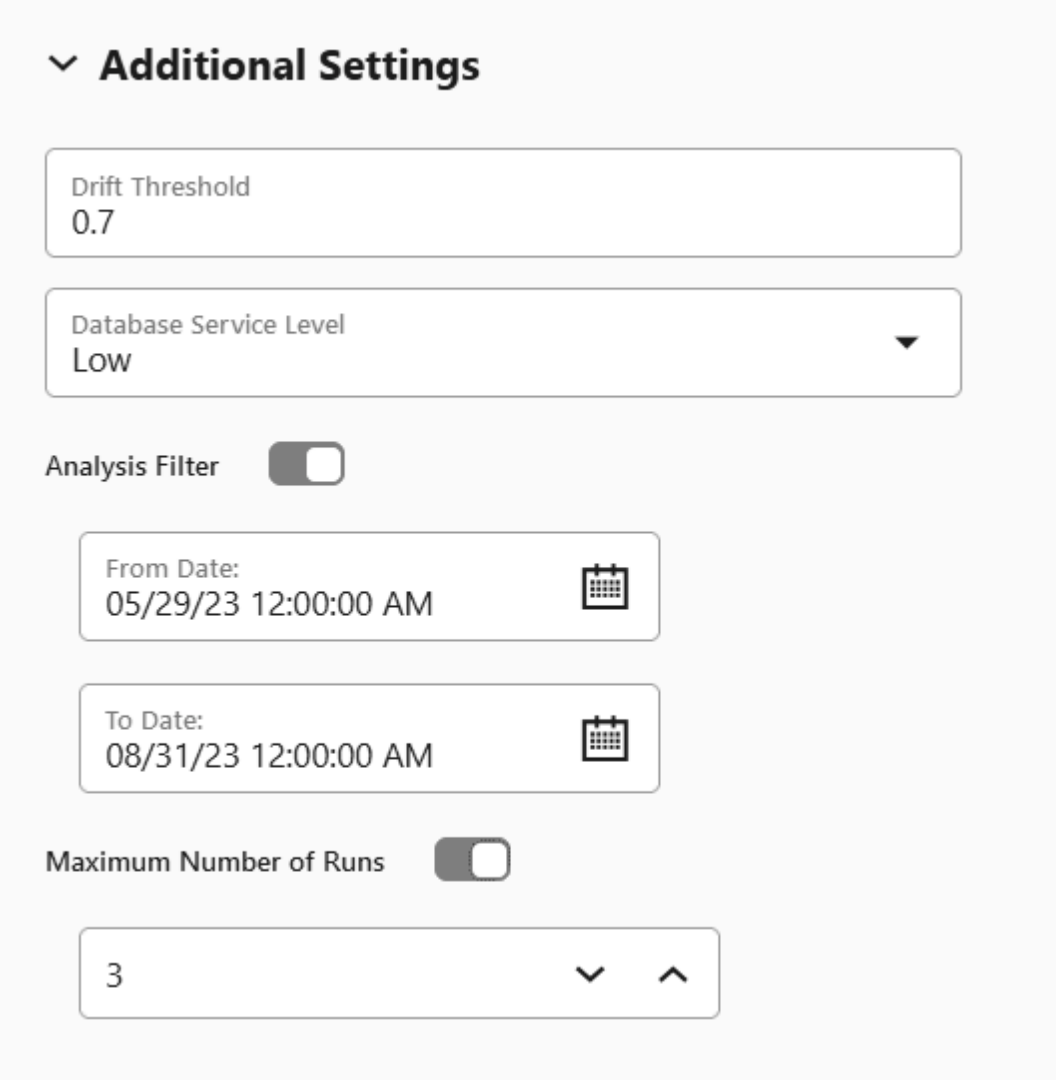
k. **Frequency:** This value determines how frequently the data monitor run will be performed on the New Data. Select a frequency for data monitoring. The options are Minutes, Hours, Days, Weeks, Months. For example, if you select `Minutes` in the **Frequency** field, `2` in the **Repeat** field, and `5/30/23` in the **Start Date** field, then as per the schedule, the data monitor will run from 5/30/23 every 2 minutes.

4. Click **Recompute:** Select this option to recompute the analysis for the already computed time period. By default, Recompute is disabled.

   - When enabled, the data drift analysis is performed for the time period specified in the Start Date field and the end time. The analysis will overwrite the already existing results for the specified time period. This means that the analysis will be computed for the time period with new data other than the current data. New analysis results may overlap with the existing results depending on the selected frequency.
   - When disabled, the data for the time period that is present in the results table will be retained as is. Only the new data for the most recent time period will be considered for analysis, and the results will be added to the results table.

5. Click **Additional Settings** to expand this section and provide advanced settings for your data monitor:

Figure 6-8 Data Monitoring Additional Settings



a. **Drift Threshold:** Drift captures the relative change in performance between the baseline data and the new data period. Based on your specific machine learning problem, set the threshold value for your data drift detection. The default is `0.7`.

> **Note:**
>
> You may adjust the threshold value depending on your use case. Increasing the value will generate fewer alerts, while decreasing the value will generate more alerts.

- A drift above this threshold indicates a significant change in your data. Exceeding the threshold indicates that rebuilding and redeploying your model may be necessary.
- A drift below this threshold indicates that there are insufficient changes in the data to warrant further investigation or action.

b. **Database Service Level:** This is the Autonomous Database service levels - `Low`, `Medium`, `High` and `GPU`. The default is `Low`.

- Service level `Medium` provides more resources to the data monitor run compared to `Low`.
- Service level `High` provides more resources to the data monitor run compared to `Medium`.

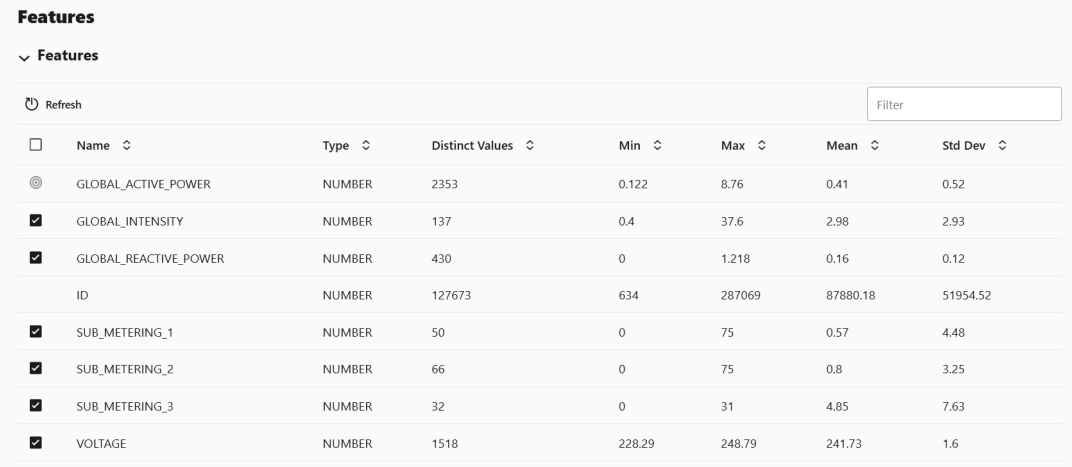
c. **Analysis Filter:** Enable this option if you want the data monitoring analysis for a specific time period. Move the slider to the right to enable it, and then select a date in **From Date** and **To Date** fields respectively. By default, this field is disabled.

- **From Date:** This is the start date or timestamp of monitoring in New Data. It assumes the existence of a time column in the table. This is a mandatory field if you use the Analysis Filter option.
- **To Date:** This is the end date or timestamp of monitoring in the New Data. It assumes the existence of a time column in the table. This is a mandatory field if you use the Analysis Filter option.

d. **Maximum Number of Runs:** This is the maximum number of times the data monitor can be run according to this schedule. The default is `3`.

6. The Features grid displays the list of features to monitor. Here, you can select or deselect features to include or exclude from monitoring. By default, all features are selected. Feature statistics are provided if the selected data is a table and has RDBMS statistics automatically gathered by Autonomous Database. Oracle Machine Learning Services calculates the statistics on the first run for both, tables and views, and the computations are displayed here after the first run. The statistics are updated by subsequent runs.

Figure 6-9 Features grid in Data Monitor



Name	Type	Distinct Values	Min	Max	Mean	Std Dev
GLOBAL_ACTIVE_POWER	NUMBER	2353	0.122	8.76	0.41	0.52
GLOBAL_INTENSITY	NUMBER	137	0.4	37.6	2.98	2.93
GLOBAL_REACTIVE_POWER	NUMBER	430	0	1.218	0.16	0.12
ID	NUMBER	127673	634	287069	87880.18	51954.52
SUB_METERING_1	NUMBER	50	0	75	0.57	4.48
SUB_METERING_2	NUMBER	66	0	75	0.8	3.25
SUB_METERING_3	NUMBER	32	0	31	4.85	7.63
VOLTAGE	NUMBER	1518	228.29	248.79	241.73	1.6

> **Note:**
>
> The **Case ID** and **Cross-Tab** columns cannot be selected.

7. Click **Save.** This completes the task of creating your data monitor.

> **Note:**
>
> You must now go to the Data Monitoring page, select the data monitor and click **Start** to begin data monitoring.

After the data monitor runs successfully, select the monitor on the **Data Monitoring** page to view the data drift and other details of the data monitor. See Data Monitoring for more information.

6.2 View Data Monitor Results

The Data Monitor Results page displays the information on the selected data monitor that have run successfully, along with data drift details for each monitored feature.

On the Data Monitors page, click on a data monitor that has run successfully. In this example, the data monitor **Power Consumption** is selected. The results of the data monitor is displayed on the Data Monitor Results page which comprises these sections:

- **Settings** — The Settings section displays the data monitor settings. Click on the arrow against **Settings** to expand this section. You have the option to edit the data monitor settings by clicking **Edit** on the top right corner of the page. In this screenshot, the settings for the data monitor **Power Consumption** is seen.

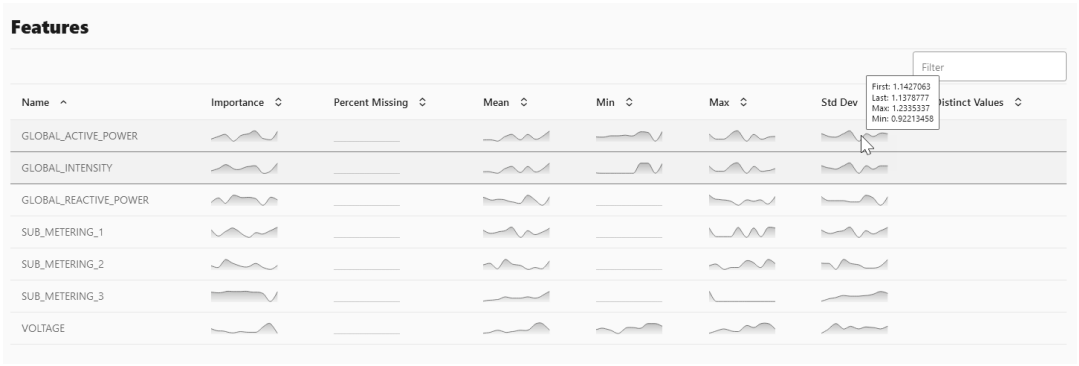
Figure 6-10 Settings section on the Data Monitor Results page

- **Drift** — The Drift section displays the details of data drift for each monitored feature. In this example, the data monitor **Power consumption** data monitor is selected. The X axis depicts the analysis period, and the Y axis depicts the data drift values. The horizontal dotted line is the threshold value, and the line depicts the drift value for each point in time for the analysis period. Hover your mouse over the line to view the drift values.

Figure 6-11 Data Drift section on the Data Monitor Results page

- **Features** — The Features section displays the monitored features along with the computed statistics.

Figure 6-12 Features section on the Data Monitor Results page



The value in the **Importance** column indicates how impactful the feature has been on data drift over a specified time period.

For numerical data, the following statistics are computed:

- Mean
- Standard Deviation
- Range (Minimum, Maximum)
- Number of nulls

For categorical data, the following statistics are computed:

- Number of unique values
- Number of nulls

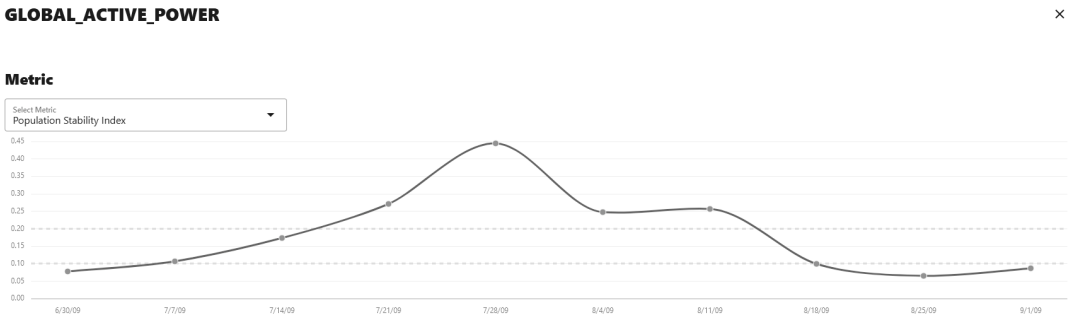
For each monitored feature, hover your mouse to view the following additional details, as shown in the screenshot here.

- First: This is the first value of the computed statistics for the analysis period.
- Last: This is the last value of the computed statistics for the analysis period.

- Max: This is the highest value of the computed statistics for the analysis period.
- Min: This is the lowest value of the computed statistics for the analysis period.

- Click on any monitored feature in the **Features** section to view the Metric, Statistics, Distribution, and Distribution with Crosstab Column, as shown in the screenshot here. In the screenshot here, the Population Stability Index is shown for the feature GLOBAL_REACTIVE_POWER.

Figure 6-13 Population Stability Index



The computations include:

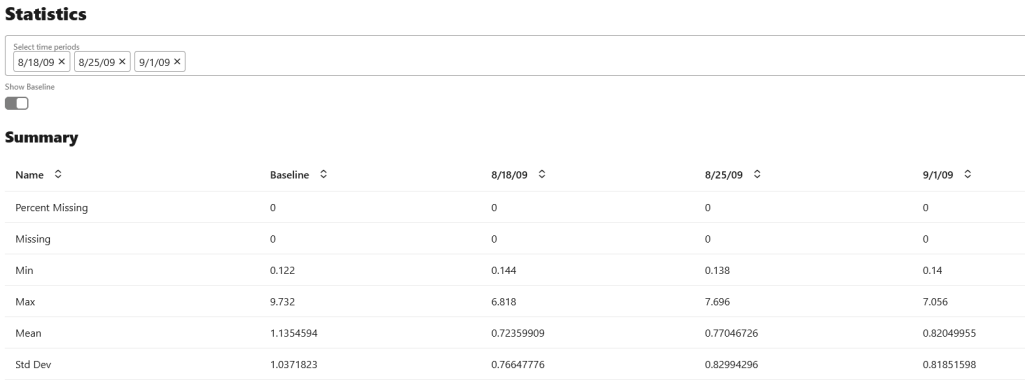
- **Metric:** The following metrics are computed:
  - Population Stability Index (PSI): This is a measure of how much a population has shifted over time or between two different samples of a population in a single number. The two distributions are binned into buckets, and PSI compares the percents of items in each of the buckets. PSI is computed as
    `PSI = sum((Actual_% - Expected_%) x ln (Actual_% / Expected_%))`

    The interpretation of PSI value is:
    - `PSI < 0.1` implies no significant population change
    - `0.1 <= PSI < 0.2` implies moderate population change
    - `PSI >= 0.2` implies significant population change
  - Jenson Shannon Distance (JSD): This is a measure of the similarity between two probability distributions. JSD is the square root of the Jensen-Shannon Divergence which is related to the Kullbach-Leibler Divergence (KLD). JSD is computed as:
    `SD(P || Q)= sqrt(0.5 x KLD(P || M) + 0.5 x KLD(Q || M))`

    Where, P and Q are the 2 distributions, `M = 0.5 x (P + Q), KLD(P || M) = sum(Pi x ln(Pi / Mi)), and KLD(Q || M) = sum(Qi x ln(Qi / Mi))`

    The value of JSD ranges between 0 and 1.
  - Crosstab Population Stability Index: This is the PSI for two variables.
  - Crosstab Jenson Shannon Distance: This is the JSD for two variables.
- **Statistics:** You can view statistics for up to 3 selected periods. Data drift is quantified using these statistical computations.

Figure 6-14 Statistics



Name	Baseline	8/18/09	8/25/09	9/1/09
Percent Missing	0	0	0	0
Missing	0	0	0	0
Min	0.122	0.144	0.138	0.14
Max	9.732	6.818	7.696	7.056
Mean	1.1354594	0.72359909	0.77046726	0.82049955
Std Dev	1.0371823	0.76647776	0.82994296	0.81851598

For numerical data, the following statistics are computed:

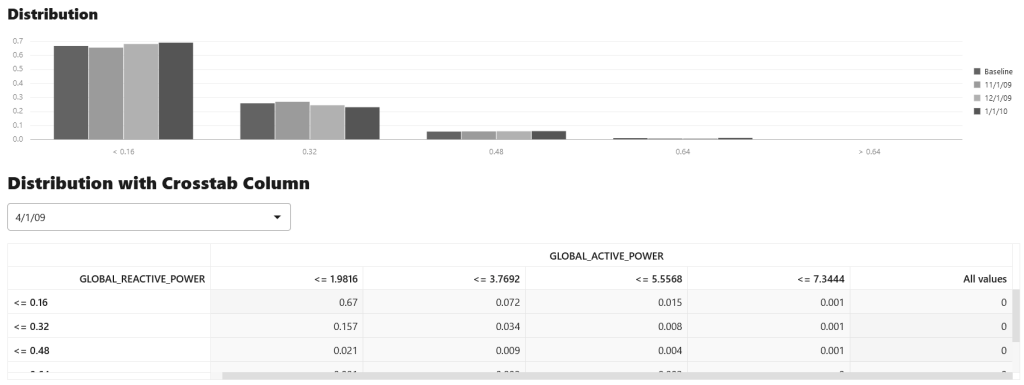
* Mean
* Standard Deviation
* Range (Minimum, Maximum)
* Number of nulls

For categorical data, the following statistics are computed:

* Number of unique values
* Number of nulls

– **Distribution:** The feature distribution chart with legend displays bins of feature for selected periods and the baseline (optional).

Figure 6-15 Distribution Chart and Distribution with Crosstab column



GLOBAL_REACTIVE_POWER	GLOBAL_ACTIVE_POWER				
	<= 1.9816	<= 3.7692	<= 5.5568	<= 7.3444	All values
<= 0.16	0.67	0.072	0.015	0.001	0
<= 0.32	0.157	0.034	0.008	0.001	0
<= 0.48	0.021	0.009	0.004	0.001	0

– **Distribution with Crosstab Column:** The heat map indicates the density of distribution for the selected crosstab and the feature column. Red denotes highest density.

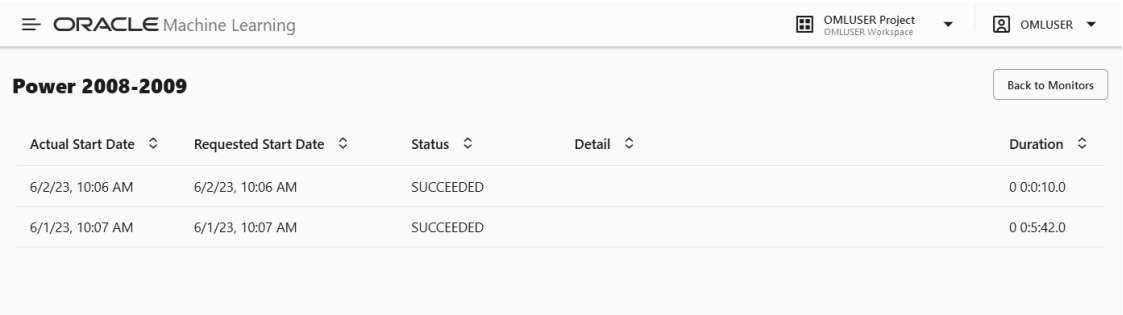
> **Note:**
>
> In data drift monitoring, `nulls` are are tracked separately as `number_of_missing_values`.

6.3 View History

The History page displays the runtime details of data monitors.

Select a data monitor and click **History** to view the runtime details. The history page displays the following information about the data monitor runtime:

Figure 6-16 Data Monitor History page



- **Actual Start Date:** This is the date when the data monitor actually started.
- **Requested Start Date:** This is the date entered in the `Start Date` field while creating the data monitor.
- **Status:** The statuses are `SUCCEEDED` and `FAILED`.
- **Detail:** If a data monitor fails, the details are listed here.
- **Duration:** This is the time taken to run the data monitor.

Click **Back to Monitors** to go back to the Data Monitoring page.

7

Model Monitoring

Model monitoring allows you to monitor the quality of model predictions over time and helps you with insights on the causes of model quality issues.

The Model Monitor page allows you to create, run, and track model monitors and results. This page lists the model monitors. You can preview the model drift by selecting a single model monitor of interest, as shown in the screenshot below. In this screenshot, the monitor **Power Consumption** is selected. On the lower pane of the Model Monitors page, the **Model Drift** for the selected monitor is displayed. The X axis depicts the analysis period, and the Y axis depicts the model drift values. The horizontal red dotted line is the threshold value. The line depicts the drift value for each point in time for the analysis period. Hover your mouse over the line to view the drift values.

Figure 7-1 Model Monitors page

You can perform the following tasks on the Model Monitors page:

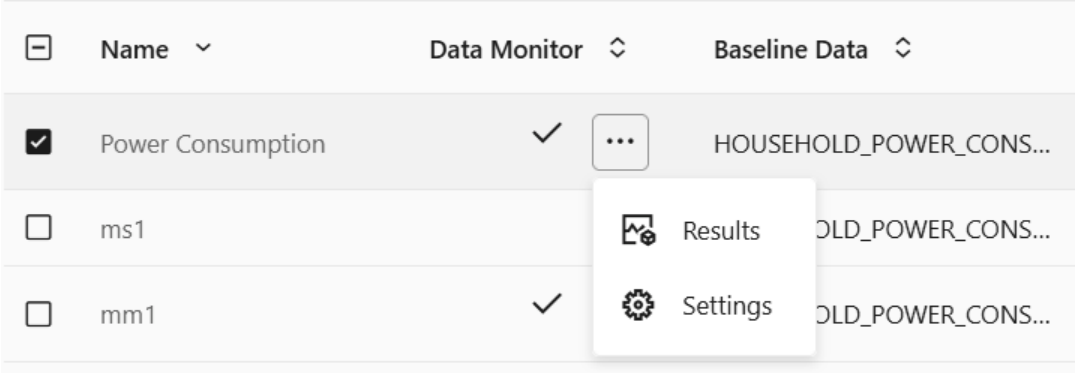
- **Create:** Create a model monitor.
- **Edit:** Select a model monitor and click **Edit** to edit the monitor.
- **Duplicate:** Select a model monitor and click **Duplicate** to create a copy of the monitor.
- **Delete:** Select a model monitor and click **Delete** to delete the model monitor.
- **History:** Select a model monitor and click **History** to view the runtime details of the model monitor. If there is a data monitor job associated with the model monitor, the data monitor runtime details are displayed on the lower pane. Click **Back to Monitors** to go back to the **Model Monitoring** page.
- **Start:** Start a model monitor.
- **Stop:** Stop a model monitor that is running.
- **More:** Select a model monitor, click **More** and then click:

- **Enable:** Enable a model monitor schedule. By default, the model monitor is enabled. The status is displayed as `SCHEDULED`.
- **Disable:** Disable a model monitor schedule. The status is displayed as `DISABLED`.
- **Show Managed Monitors:** Click this option to view the models created and managed by OML Services REST API.

The Model Monitors page displays the following information about the model monitors:

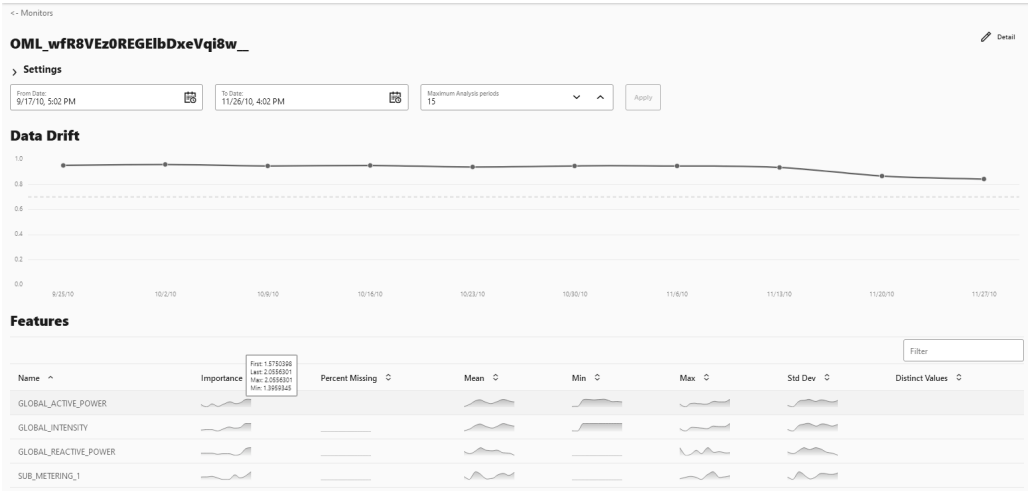
- **Name:** This is the name of the model monitor.
- **Data Monitor:** The check mark in this column indicates that there is a data monitor job associated with the model monitor. Click on the three dots to view:

Figure 7-2 View Results and Settings of Data Monitor



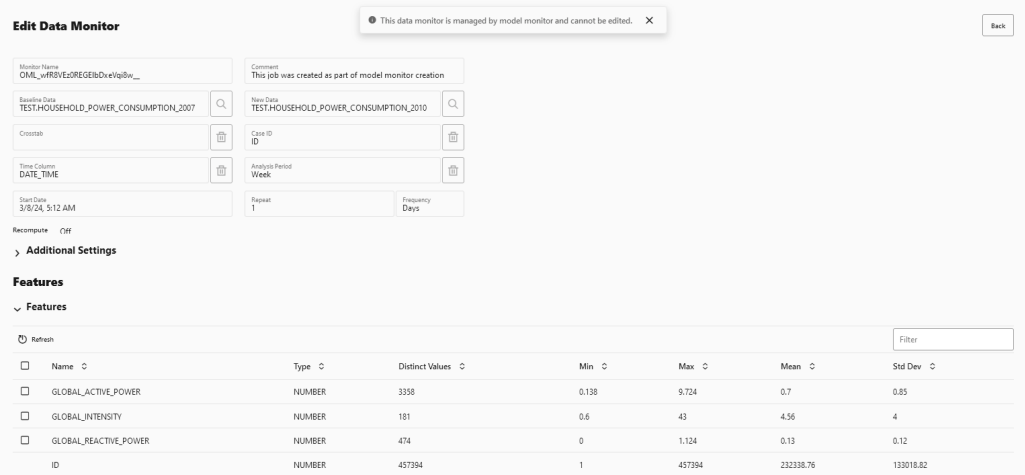
- **Results:** Displays the data monitoring results computed by the data monitor job. The data monitor name is auto-generated along with the prefix OML. The data drift and monitored features along with the computed statistics are displayed in view-only mode on a separate page. Click **Monitors** on the top left corner to return to the Model Monitors page. Click **Details** on the top right corner to view the settings of the data monitor.

Figure 7-3 Data Monitor Results



– **Settings:** Displays the data monitor settings, additional settings, and the monitored features in view-only mode. Click **Back** on the top right corner of the page to return to the Model Monitors page.

Figure 7-4 Data Monitor Settings



- **Baseline Data:** This is a table or view that contains baseline data to monitor.
- **New Data:** This is a table or view with new data to be compared against the baseline data.
- **Last Start Date:** This is the date on which the model monitor was last started.
- **Last Status:** This is the latest status of the model monitor. The statuses are SUCCEEDED, FAILED, RUNNING, SCHEDULED.
- **Next Run Date:** This is the date on which the next run is scheduled.
- **Status:** This is the current status of the model monitor.
- **Schedule:** This is the frequency of the monitoring job, that is, how frequently the model monitor is set to run on the New Data.
- Create a Model Monitor
  A model monitor helps you monitor several compatible models, and compute the model drift chart. Compatible models refer to those models that are trained on the same target and mining function. The model drift chart consists of multiple series of data drift points, one for each monitored model.
- View Model Monitor Results
  The Model Monitor Results page displays the monitoring results of each model that are being monitored. By clicking on any model that has run successfully, you can view the detailed analysis of each model such as model drift, model metrics, prediction statistics, feature impact, prediction distribution and predictive versus drift importance for each feature. The predictive impact versus drift importance for each monitored feature is computed only if data monitoring is enabled.
- View Model History
  The History page displays the runtime details of the model monitors.

7.1 Create a Model Monitor

A model monitor helps you monitor several compatible models, and compute the model drift chart. Compatible models refer to those models that are trained on the same target and mining

function. The model drift chart consists of multiple series of data drift points, one for each monitored model.

A model monitor can optionally monitor data to provide additional insight. This additional insight is the Drift Feature Importance versus Predictive Feature Impact chart which is generated when you select the Monitor Data option while creating the model monitor.

This topic discusses hows how to create a model monitor. The example uses the *Individual household electricity consumption* dataset which includes various consumption metrics of a household for the year 2009. The data is split into seasons - SPRING, SUMMER, FALL, and WINTER. The goal is to understand if and how household consumption has changed over the seasons. The example shows how to track the effects of data drifts on model predictive accuracy.

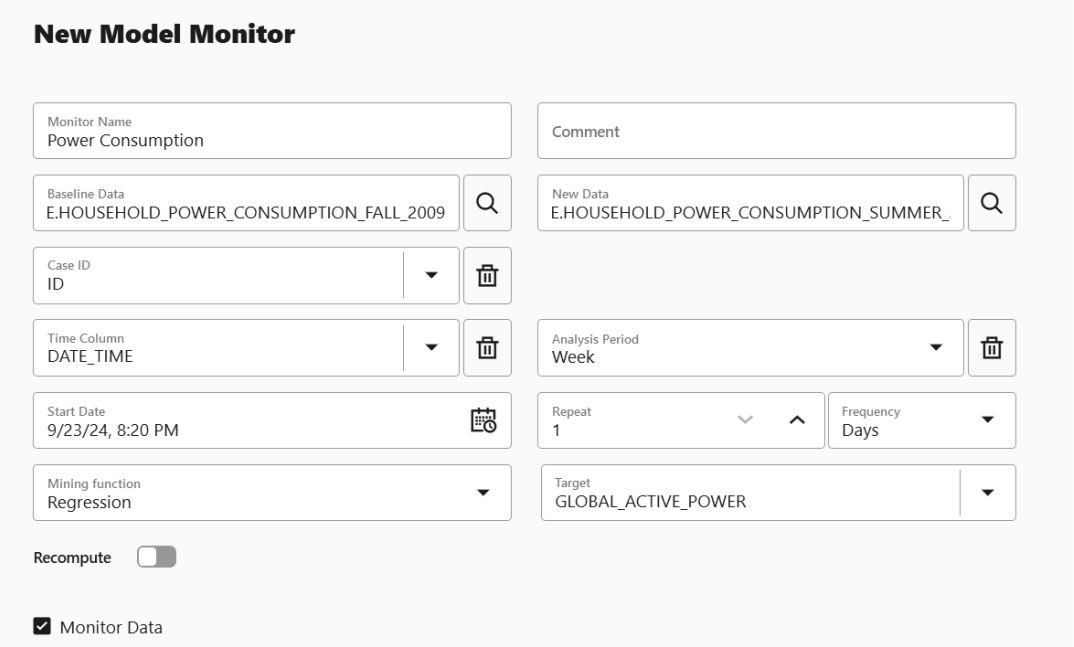
The dataset comprises the following columns:

- `DATE_TIME` — Contains the date and time related information in `dd:mm:yyyy:hh:mm:ss` format.
- `GLOBAL_ACTIVE_POWER` — This is the household global minute-averaged active power (in kilowatt).
- `GLOBAL_REACTIVE_POWER` — This is the household global minute-averaged reactive power (in kilowatt).
- `VOLTAGE` — This is the Minute-averaged voltage (in volt).
- `GLOBAL_INTENSITY` — This is the household global minute-averaged current intensity (in ampere).
- `SUB_METERING_1` — This is the energy sub-metering No. 1 (in watt-hour of active energy). It corresponds to the kitchen.
- `SUB_METERING_2` — This is the energy sub-metering No. 2 (in watt-hour of active energy). It corresponds to the laundry room.
- `SUB_METERING_3` — This is the energy sub-metering No. 2 (in watt-hour of active energy). It corresponds to an electric water heater and air conditioner.

To create a model monitor:

1. On the Oracle Machine Learning UI left navigation menu, expand **Monitoring** and then click **Models** to open the Model Monitoring page. Alternatively, you can click on the Model Monitoring icon to open the Model Monitoring page.
2. On the Model Monitoring page, click **Create** to open the New Model Monitor page.
3. On the New Model Monitor page, enter the following details:

Figure 7-5 New Model Monitor page



a. **Monitor Name:** Enter a name for the model monitor. Here, the name Power Consumption is used.

b. **Comment:** Enter comments. This is an optional field.

c. **Baseline Data:** This is a table or view that contains baseline data to monitor. Click the search icon to open the **Select Table** dialog. Select a schema, and then a table. Here, the table containing the data for the year 2007 is selected.

d. **New Data:** This is a table or view with new data to be compared against the baseline data. Click the search icon to open the **Select Table** dialog. Select a schema, and then a table. Here, the table containing the data for the year 2009 is selected.

e. **Case ID:** This is an optional field. Enter a case identifier for the baseline and new data to improve the repeatability of the results.

f. **Time Column:** This is the name of a column storing time information in the New Data table or view. The `DATE_TIME` column is selected from the drop-down list.

> **Note:**
>
> If the Time Column is blank, the entire New Data is treated as one period.

g. **Analysis Period:** This is the length of time for which model monitoring is performed on the New Data. Select the analysis period for model monitoring. The options are `Day`, `Week`, `Month`, `Year`.

h. **Start Date:** This is the start date of your model monitor schedule. If you do not provide a start date, the current date will be used as the start date.

i. **Repeat:** This value defines the number of times the model monitor run will be repeated for the frequency defined. Enter a number between 1 and 99. For example, if you enter

2 in the **Repeat** field here, and Minutes in the **Frequency** field, then the model monitor will run every 2 minutes.

j. **Frequency:** This value determines how frequently the model monitor run will be performed on the New Data. Select a frequency for model monitoring. The options are Minutes, Hours, Days, Weeks, Months. For example, if you select `Minutes` in the **Frequency** field, `2` in the **Repeat** field, and `5/30/23` in the **Start Date** field, then as per the schedule, the model monitor will run from `5/30/23` every `2` minutes.

k. **Mining Function:** The available mining functions are `Regression` and `Classification`. Select a function as applicable. In this example, `Regression` is selected.

l. **Target:** Select an attribute from the drop-down list. In this example, `GLOBAL_ACTIVE_POWER` is used as the target for regression models.

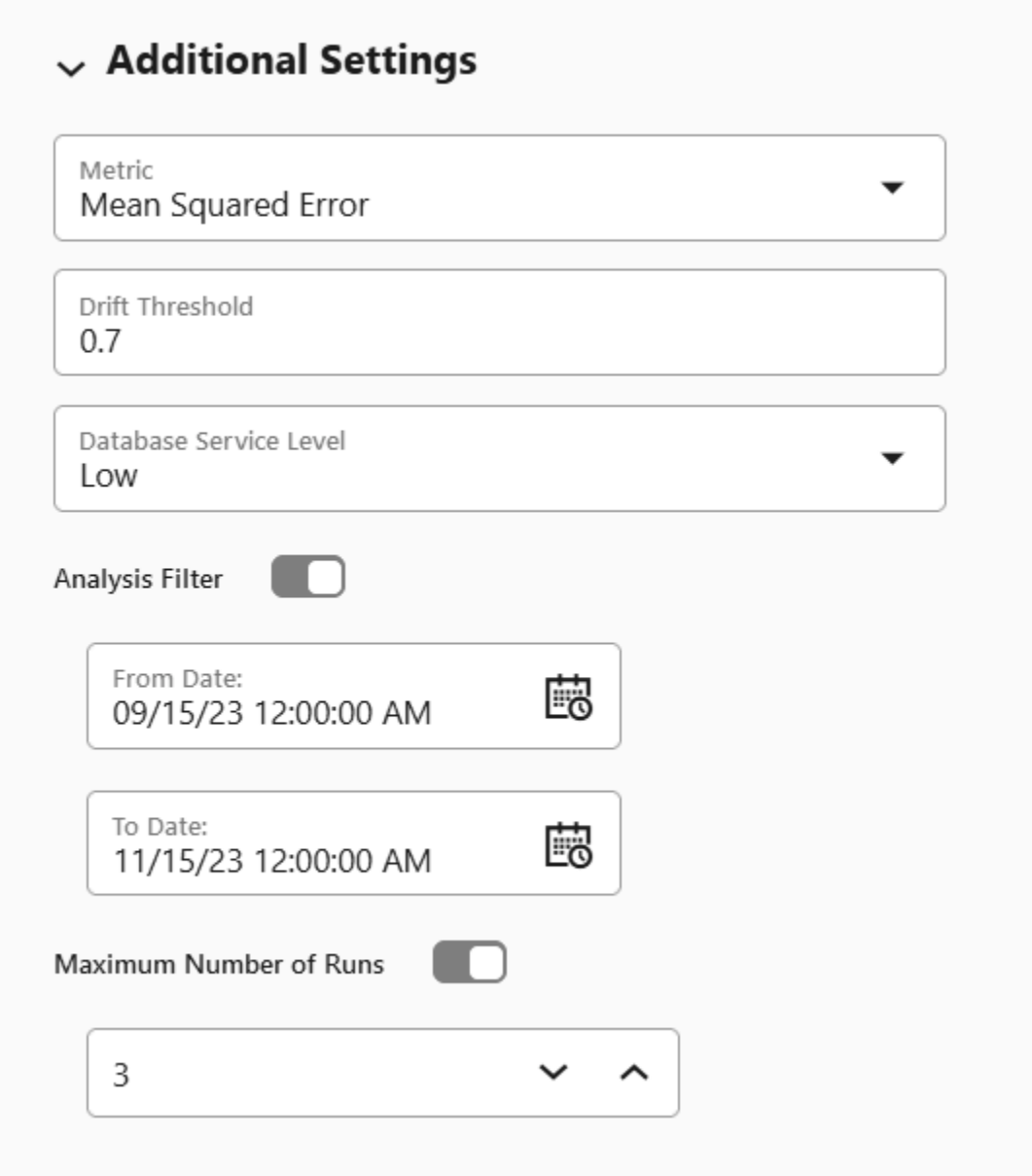
m. **Recompute:** Select this option to update the already computed periods. This means that only time periods not present in the output result table will be computed. By default, Recompute is disabled.

- When enabled, the drift analysis is performed for the time period specified in the Start Date field and the end time. The analysis will overwrite the already existing results for the specified time period. This means that the analysis will be computed for the time period with new data other than the current data.
- When disabled, the data for the time period that is present in the results table will be retained as is. Only the new data for the most recent time period will be considered for analysis, and the results will be added to the results table.

n. **Monitor Data:** Select this option to enable data monitoring for the specified data. When enabled, a data monitor is also created along with the model monitor to compute the Predictive Feature Impact versus Drift Feature Impact in the model specific results.

4. Click **Additional Settings** to expand this section and provide advanced settings for your model monitor:

Figure 7-6 Additional Settings section on the New Model Monitor page



a. **Metric:** Depending on the mining function selected in the **Mining Function** field in the Create Model Monitor page, the applicable metrics are listed. Click on the drop-down list to select a metric.

   For the mining function Classification, the metrics are:

   - Accuracy — Calculates the proportion of correctly classifies cases - both Positive and Negative. For example, if there are a total of TP (True Positives)+TN (True Negatives) correctly classified cases out of TP+TN+FP+FN (True Positives+True Negatives+False Positives+False Negatives) cases, then the formula is:
     `Accuracy = (TP+TN)/(TP+TN+FP+FN)`
   - Balanced Accuracy — Evaluates how good a binary classifier is. It is especially useful when the classes are imbalanced, that is, when one of the two classes

appears a lot more often than the other. This often happens in many settings such as Anomaly Detection etc.

- ROC AUC (Area under the ROC Curve) — Provides an aggregate measure of discrimination regardless of the decision threshold. AUC - ROC curve is a performance measurement for the classification problems at various threshold settings.
- Recall — Calculates the proportion of actual Positives that is correctly classified.
- Precision — Calculates the proportion of predicted Positives that is True Positive.
- F1 Score — Combines precision and recall into a single number. F1-score is computed using harmonic mean which is calculated by the formula:
  `F1-score = 2 × (precision × recall)/(precision + recall)`

For multi-class classification, the metrics are:

- Accuracy
- Balanced Accuracy
- Macro_F1
- Macro_Precision
- Macro_Recall
- Weighted_F1
- Weighted_Precision
- Weighted_Recall

For Regression, the metrics are:

- R2 — A statistical measure that calculates how close the data are to the fitted regression line. In general, the higher the value of R-squared, the better the model fits your data. The value of R2 is always between 0 to 1, where:
  - `0` indicates that the model explains none of the variability of the response data around its mean.
  - `1` indicates that the model explains all the variability of the response data around its mean.
- Mean Squared Error — This is the mean of the squared difference of predicted and true targets.
- Mean Absolute Error — This is the mean of the absolute difference of predicted and true targets.
- Median Absolute Error — This is the median of the absolute difference between predicted and true targets.

b. **Drift Threshold:** Drift captures the relative change in performance between the baseline data and the new data period. Based on your specific machine learning problem, set the threshold value for your model drift detection. The default is `0.7`.

- A drift above this threshold indicates a significant change in model predictions. Exceeding the threshold indicates that rebuilding and redeploying your model may be necessary.
- A drift below this threshold indicates that there are insufficient changes in the data to warrant further investigation or action.

c. **Database Service Level:** This is the service level for the job, which can be LOW, MEDIUM, HIGH, or GPU.

d. **Analysis Filter:** Enable this option if you want the model monitoring analysis for a specific time period. Move the slider to the right to enable it, and then select a date in **From Date** and **To Date** fields respectively. By default, this field is disabled.

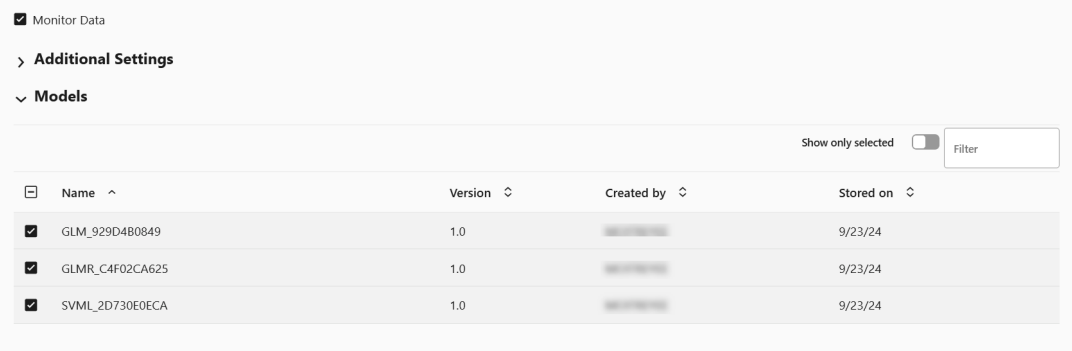
   - **From Date:** This is the start date or timestamp of monitoring in New Data. It assumes the existence of a time column in the table. This is a mandatory field if you use the Analysis Filter option.
   - **To Date:** This is the end date or timestamp of monitoring in the New Data. It assumes the existence of a time column in the table. This is a mandatory field if you use the Analysis Filter option.

e. **Maximum Number of Runs:** This is the maximum number of times the model monitor can be run according to this schedule. The default is `3`.

5. In the **Models** section, select the model that you want to monitor and then click **Save** on the top right corner of the page. Once you provide a value in the **Mining Function** and **Target** fields, the list of models that have been deployed are obtained and is displayed here in the Models section. Models are deployed from the Models page, or from the AutoML Leaderboard. You can view the complete list of deployed models in the Deployments tab on the Models page. The deployed models are managed by OML Services.

> **Note:**
>
> If you drop any models, you have to redeploy the models. Models are not schema based models, but models deployed to OML Services.

Figure 7-7 Models section on the New Model Monitor page



Once the model monitor is successfully created, it displays the message: `Model monitor has been created successfully.`

> **Note:**
>
> You must now go to the Model Monitoring page, select the model monitor and click **Start** to begin model monitoring.

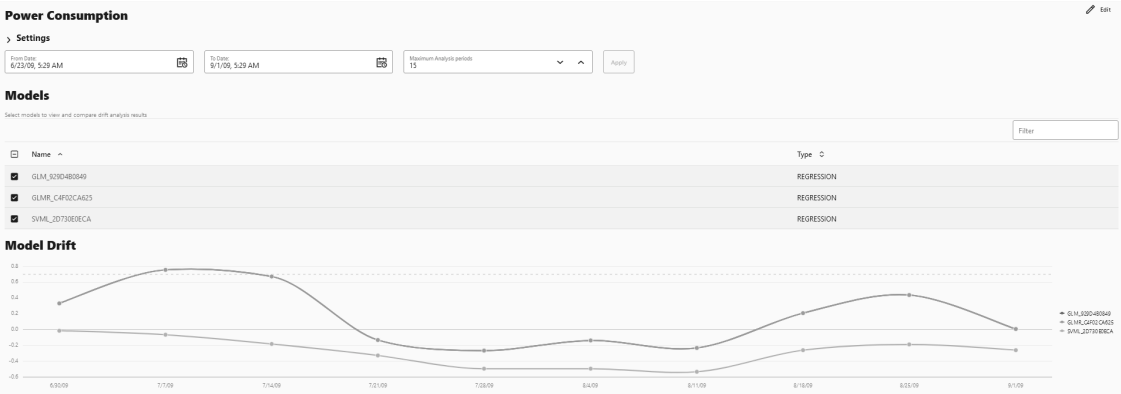
7.2 View Model Monitor Results

The Model Monitor Results page displays the monitoring results of each model that are being monitored. By clicking on any model that has run successfully, you can view the detailed analysis of each model such as model drift, model metrics, prediction statistics, feature impact, prediction distribution and predictive versus drift importance for each feature. The predictive impact versus drift importance for each monitored feature is computed only if data monitoring is enabled.

1. Model Monitor Results page

The Model Monitor Results page lists all the models that are monitored by the monitor. The name of the monitor is displayed at the top of the page. As seen in this screenshot, the monitor name **Power Consumption** is displayed at the top. The models GLM_929D4B0849, GLMR_C4F02CA625 and SVML_2D730E0ECA monitored by the **Power Consumption** monitor are listed in the Models section. By default, the details of all the monitored models are displayed. You can choose to view the details of one monitor at a time by deselecting the other monitors.

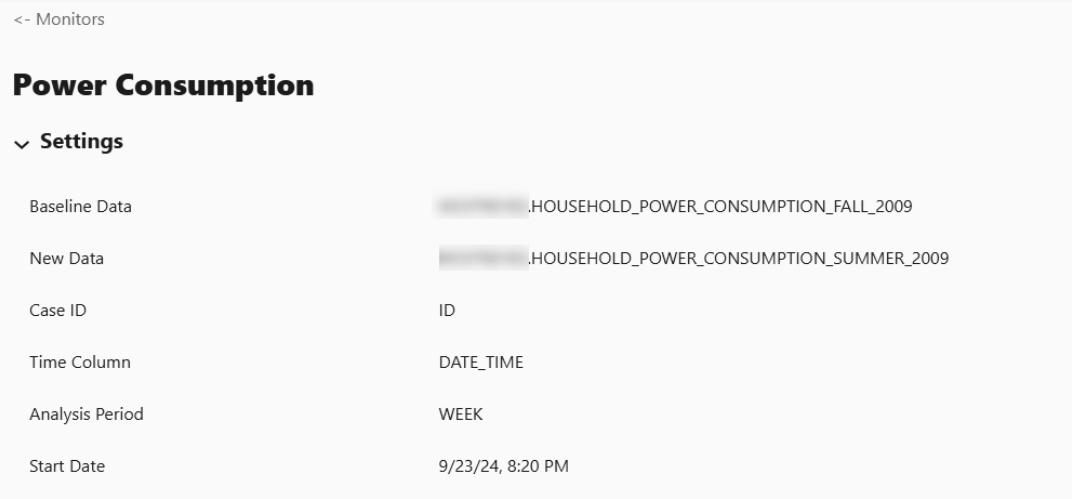
Figure 7-8 Model Monitor Results page



The Model Monitor Results page comprises these sections:

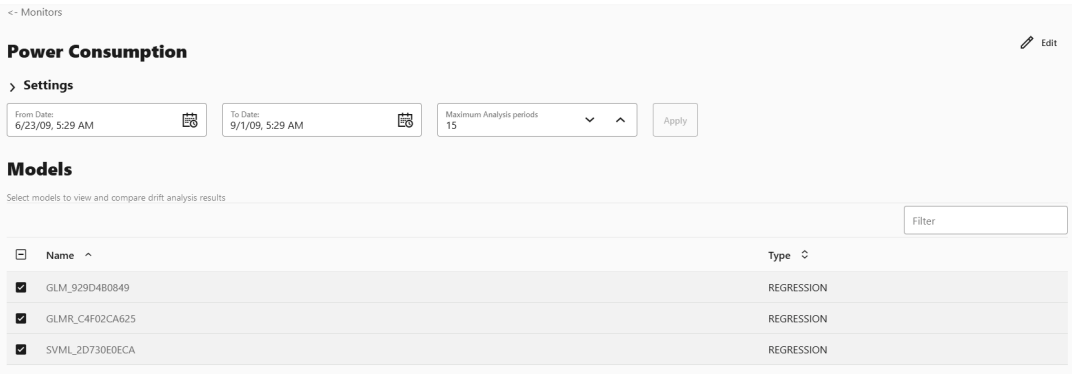
- **Settings** — The Settings section displays the model monitor settings. Click on the arrow against **Settings** to expand this section. You have the option to edit the model monitor settings by clicking **Edit** on the top right corner of the page.

Figure 7-9 Model Monitor Settings



- **Models** — The Models section lists all the models that are monitored by the monitor. In this example, the models GLM_929D4B0849, GLMR_C4F02CA625 and SVML_2D730E0ECA monitored by the **Power Consumption** monitor are listed.

Figure 7-10 Models on the Model Monitor Results page

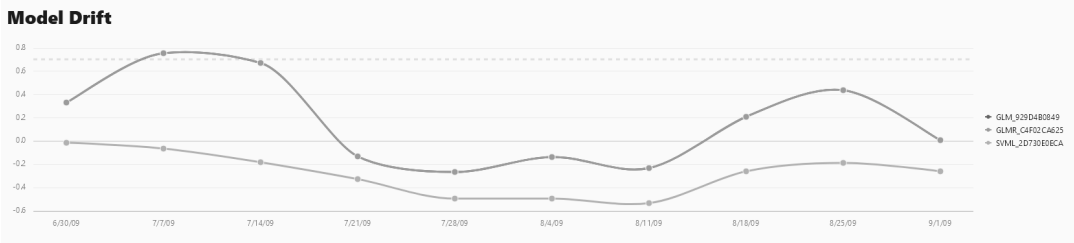


You can choose to view and compare the results of one or more monitored models by deselecting the ones that you want to exclude. You can also view the results of each feature of the model by clicking on the model. These results — Feature Impact chart, Prediction Distribution, and Predictive Impact versus Drift Importance chart are displayed on a separate pane that slides in. The Predictive Impact versus Drift Importance chart is computed only if the **Monitor Data** option is selected while creating the model monitor.

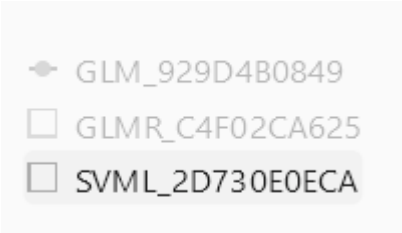
- **Model Drift** — The Model Drift section is displayed just below the Models section. Model drift is the percentage change in the performance metric between the baseline period and the new period. A negative value indicates that the new period has a better performance metric which could happen due to noise.
The X axis depicts the analysis period, and the Y axis depicts the drift values. The horizontal dotted line represents the drift threshold settings that each monitor gets by default. The default covers the typical use case. However, you can choose to customize it based on specific use case. The line depicts the drift value for each point in time for the analysis period. Hover your mouse over the line to view the drift values. A drift above the threshold indicates significant change in model predictions. Exceeding the threshold suggests rebuilding and redeploying your model may be necessary. If the drift is below the

threshold, it indicates that there are insufficient changes in the data to warrant further investigation or action. That is, possibly rebuilding a machine learning model using this data.

Figure 7-11 Model Drift on the Models Monitor Results page

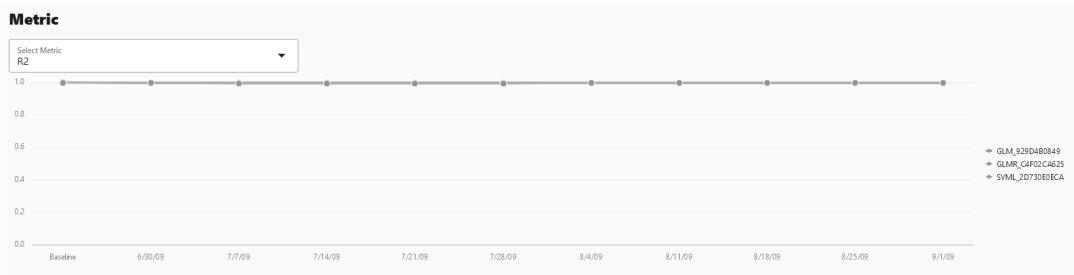


If you want to view the drift details of one model at a time, click on the model name on the right to select or deselect it, as shown here.



- **Metric** — This Metric section displays the computed metrics for the selected models. The computed metric is plotted along the y axis, and the time period is plotted along the x axis. In this example, the metric R2 or R-squared is displayed for all the three models. Hover your cursor on other points on the line to view the details of the computed metric. The value of R2 for all the models is equal to 1. Here, the value of R2 for all the three monitored models is 1. This indicates that all the three models are good fit for the data.

Figure 7-12 Metric



The computed metrics for **Regression** are:

– R2 — A statistical measure that calculates how close the data are to the fitted regression line. In general, the higher the value of R-squared, the better the model fits your data. The value of R2 is always between 0 to 1, where:

  * 0 indicates that the model explains none of the variability of the response data around its mean.

    - `1` indicates that the model explains all the variability of the response data around its mean.
  - Mean Squared Error — This is the mean of the squared difference of predicted and true targets.
  - Mean Absolute Error — This is the mean of the absolute difference of predicted and true targets.
  - Median Absolute Error — This is the median of the absolute difference between predicted and true targets.

  The computed metrics for **Binary Classification** are:

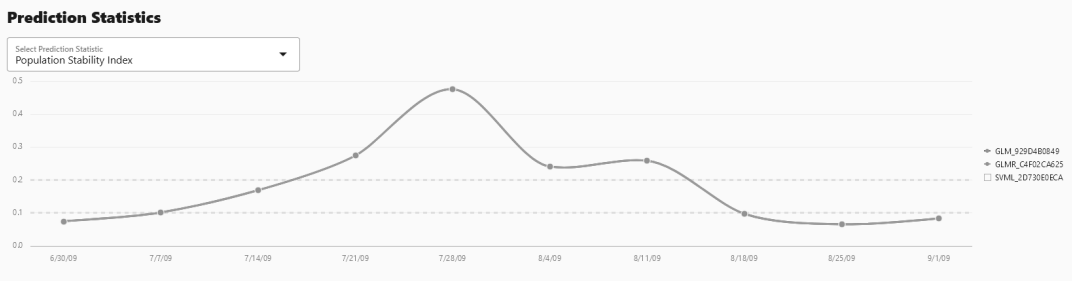
  - Accuracy — Calculates the proportion of correctly classifies cases - both Positive and Negative. For example, if there are a total of TP (True Positives)+TN (True Negatives) correctly classified cases out of TP+TN+FP+FN (True Positives+True Negatives+False Positives+False Negatives) cases, then the formula is:
    `Accuracy = (TP+TN)/(TP+TN+FP+FN)`
  - Balanced Accuracy — Evaluates how good a binary classifier is. It is especially useful when the classes are imbalanced, that is, when one of the two classes appears a lot more often than the other. This often happens in many settings such as Anomaly Detection etc.
  - ROC AUC (Area under the ROC Curve) — Provides an aggregate measure of discrimination regardless of the decision threshold. AUC - ROC curve is a performance measurement for the classification problems at various threshold settings.
  - Recall — Calculates the proportion of actual Positives that is correctly classified.
  - Precision — Calculates the proportion of predicted Positives that is True Positive.
  - F1 Score — Combines precision and recall into a single number. F1-score is computed using harmonic mean which is calculated by the formula:
    `F1-score = 2 × (precision × recall)/(precision + recall)`

  The computed metrics for **Multi-class Classification** are:

  - Accuracy
  - Balanced Accuracy
  - Macro_F1
  - Macro_Precision
  - Macro_Recall
  - Weighted_F1
  - Weighted_Precision
  - Weighted_Recall

- **Prediction Statistics** — Scroll further down to view the **Prediction Statistics** section. The computed prediction statistic is plotted along the y axis, and the time period is plotted along the x axis. In this screenshot, the Population Stability Index for the Generalized Linear Model — Regression model GLMR_C4F02CA625 for 10/30/10 is displayed. Hover your cursor on other points on the line to view the computed metric.

Figure 7-13 Prediction Statistics



Click on the drop-down list to view all the prediction statistics. The statistics of the predictions of the model vary according to the type of model.

For **Regression**, the computed prediction statistics are:

- Population Stability Index — This is a measure of how much a population has shifted over time or between two different samples of a population in a single number. The two distributions are binned into buckets, and PSI compares the percents of items in each of the buckets. PSI is computed as

  ```
  PSI = sum((Actual_% - Expected_%) x ln (Actual_% / Expected_%))
  ```

  The interpretation of PSI value is:

  * `PSI < 0.1` implies no significant population change
  * `0.1 <= PSI < 0.2` implies moderate population change
  * `PSI >= 0.2` implies significant population change

- Min — This is the lowest value of the computed statistics for the analysis period.
- Mean — This is the average value of the computed statistics for the analysis period.
- Max — This is the highest value of the computed statistics for the analysis period.
- Standard Deviation — This is the value that shows how much variation from the mean exists.

For **Binary Classification**, the computed prediction statistics are:

- Population Stability Index
- Mean
- Min
- Max
- Standard Deviation
- Bin Distribution of prediction probabilities
- Class distribution

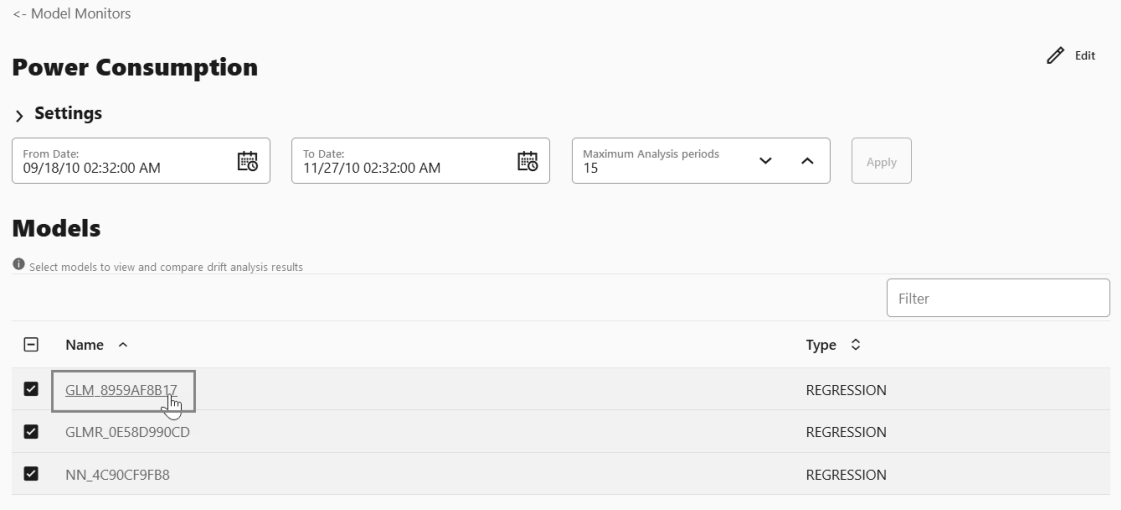
For **Multi-class Classification**, the computed prediction statistics are:

- Population Stability Index
- Class Distribution

2. Model Monitor Details

You can view the details of each feature of the model by clicking on the model name. These details include the Feature Impact chart, Prediction Distribution and the Predictive Impact versus Drift Importance chart. In this example, the model GLM_8959AF817 is selected.

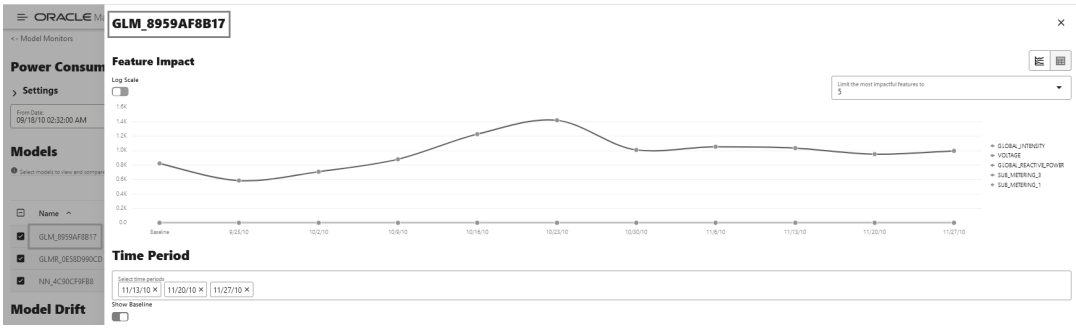
Figure 7-14 Model selection for details



The computed results are displayed on a separate pane that slides in. You can select up to 3 analysis periods comparison. You also have the option to hide or show the baseline details. The computed details of the model features are:

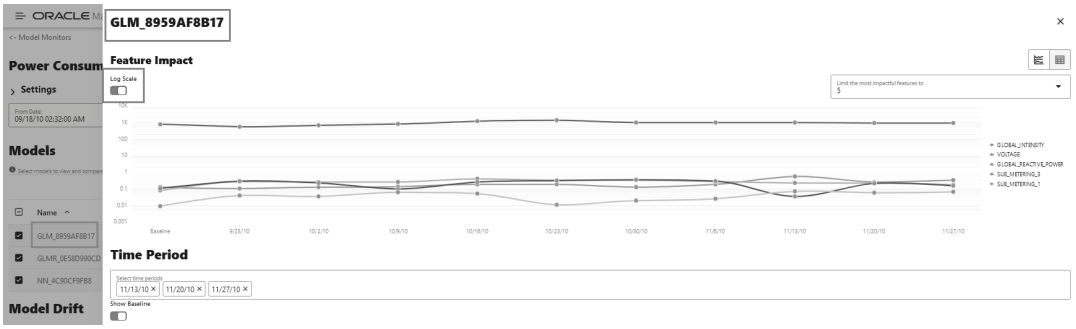
- **Feature Impact** — The Feature Impact chart computes the impact of each feature in the model for the specified time. The chart also the gives you the option to view the feature impact on a linear scale as well as on a logarithmic scale. Hover your mouse over the chart to view the details - Feature Name, Date, and Feature Impact.
  - Click **Log Scale** to view the feature impact computation on a logarithmic scale.
  - Click  to view the feature impact computation in a line graph.
  - Click  to view the feature impact computation in a table.
  - Click **Limit the most impactful features to** drop down list to select a value.

Figure 7-15 Viewing Feature Impact on a liner scale



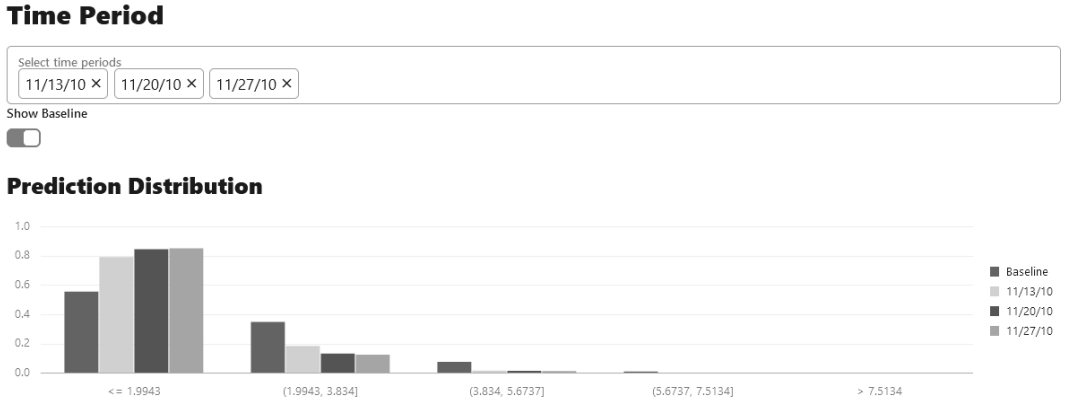
In this screenshot, the feature GLOBAL_INTENSITY, that is, the global minute-averaged current intensity of the household electric consumption is seen to have the maximum impact on the model GLM_8959AF817 as compared to the other features. Click on **Log Scale** to view feature impact computation on a logarithmic scale, as shown in the screenshot below. Click X on the top right corner of the pane to exit.

Figure 7-16 Viewing Feature Impact on a Logarithmic Scale



- **Prediction Distribution** — Scroll down to view the Prediction Distribution. Prediction Distribution is plotted for each analysis period. The Baseline data is displayed, if selected. The bins are plotted along X-axis, and the values are plotted along the Y-axis. Hover your mouse over each histogram to view the computed details. Click X on the top right corner of the pane to exit.

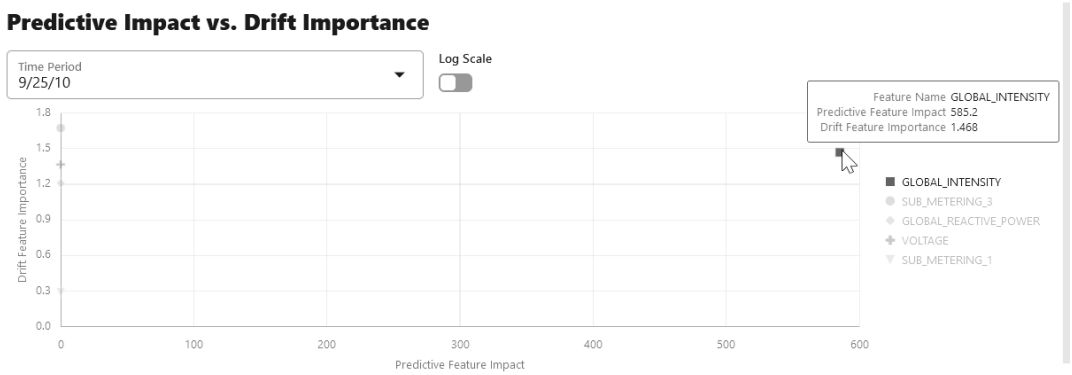
Figure 7-17 Prediction Distribution



- **Predictive Impact vs Drift Importance** — Scroll further down the pane to view the Prediction Impact versus Drift Importance chart. This chart helps in understanding how the most impactful features drift over time. Drift Feature Importance is plotted along the Y-axis and Prediction Feature Impact is plotted along the X-axis. Click X on the top right corner of the pane to exit.

> **Note:**
>
> The Prediction Impact vs Drift Importance chart is computed only if you select the **Monitor Data** option while creating the model monitor.

Figure 7-18 Predictive Feature Impact versus Drift Importance



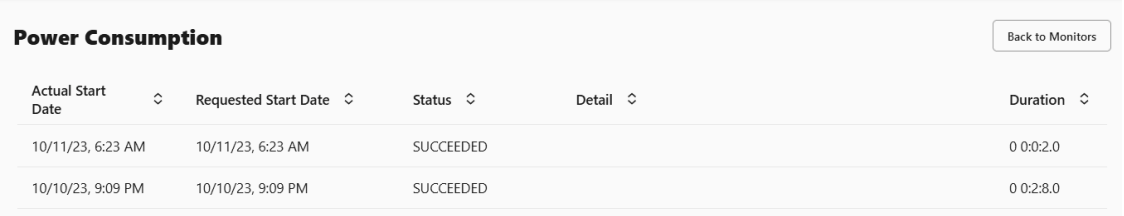
In this screenshot, you can see that the feature GLOBAL_INTENSITY has the maximum impact on the selected predictive model GLM_8959AF817 as compared to the other features - SUB_METERING_3, GLOBAL_REACTIVE_POWER, VOLTAGE, and SUB-METERING_1.

7.3 View Model History

The History page displays the runtime details of the model monitors.

Select a model monitor and click **History** to view the runtime details. The history page displays the following information about the model monitor runtime:

Figure 7-19 View Model History



- **Actual Start Date:** This is the date when the model monitor actually started.

- **Requested Start Date:** This is the date entered in the **Start Date** field while creating the model monitor.
- **Status:** The statuses are SUCCEEDED and FAILED.
- **Detail:** If a model monitor fails, the details are listed here.
- **Duration:** This is the time taken to run the model monitor.

Click **Back to Monitors** to go back to the Model Monitoring page.

8
Models

The Models page displays the user models and the list of deployed models. User Model lists the models in a user's schema, and Deployments lists the models deployed to Oracle Machine Learning Services.

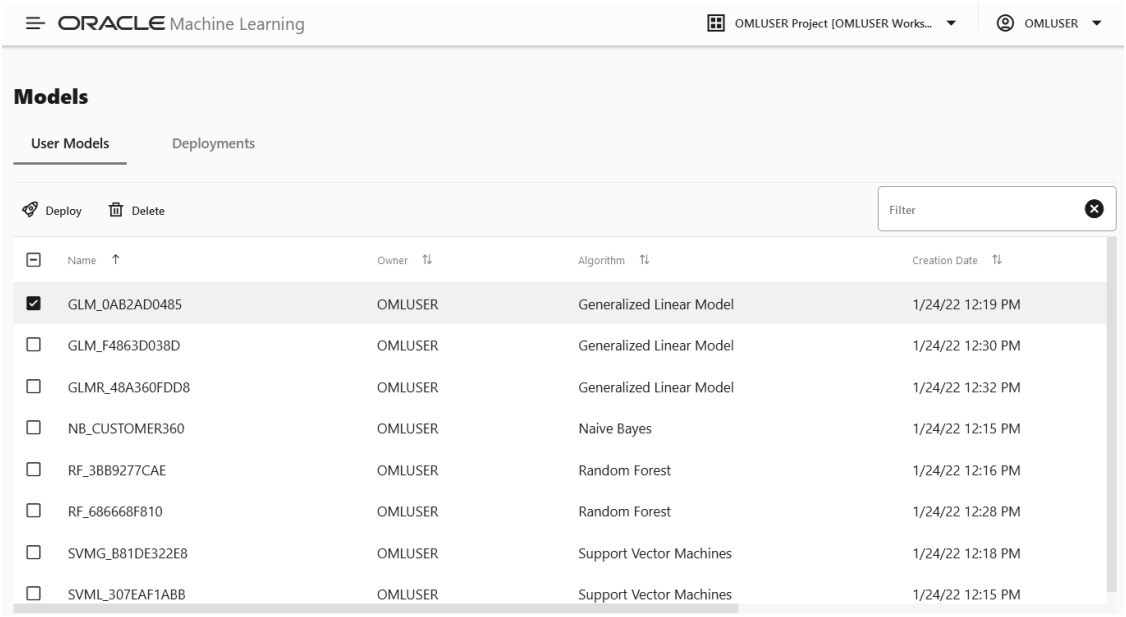
Under Models, the model information and model deployment are available under:

- **User Models:** Lists all the models that are created in a database schema. In the Models view, you can browse, view, deploy and delete models.
- **Deployments:** Lists all the deployed models. In the Deployments view, you can view the model metadata and the REST API URI of the deployed models.

User Models

In the User Models view, you can browse, view, and deploy models. The User Models view lists the models that are available in the database schema:

Figure 8-1 User Models



- Name: Displays the model name. Model names can be any valid database object name.
- Owner: Displays the user who built the model.
- Algorithm: Displays the name of the algorithm used.
- Creation Date: Displays the date on which the model is built.
- Target: Displays the prediction target selected when the experiment is created.

You can perform the following tasks:

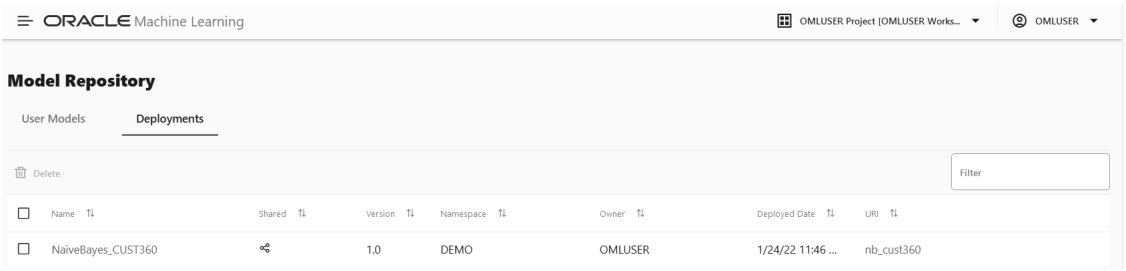
- **Deploy:** To deploy a model, select the model and click **Deploy.**
- **Delete:** To delete a model, select the model and click **Delete.**

Deployments

In the Deployments view, you can view the list of all the deployed models. Here, you can view the model metadata, view the REST API URI of the deployed models, and also delete any deployed model.

To delete a deployed model, select the model and click **Delete.**

Figure 8-2 Deployed Models



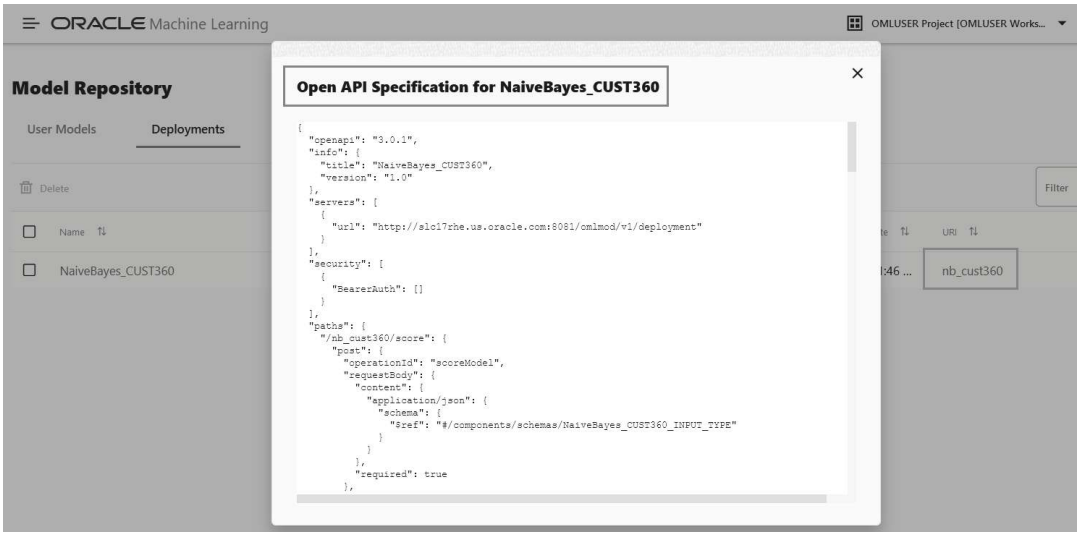
The following information are displayed for each deployed model:

- **Name:** The name of the deployed model.
- **Shared:** Allows users in the same PDB to use the model.
- **Version:** Displays the model version.
- **Namespace:** Displays the model namespace.
- **Owner:** The name of the user who deployed the model.
- **Deployed Date:** Displays the date of model deployment.

> **Note:**
>
> You cannot re-deploy the same model. However, you can create a new version of the model and deploy it. You can then track the model based on the version.

- **URI:** Displays the URI name. Click on the URI link to view the REST API URI of the model.

Figure 8-3 REST API Specification of a Deployed Model



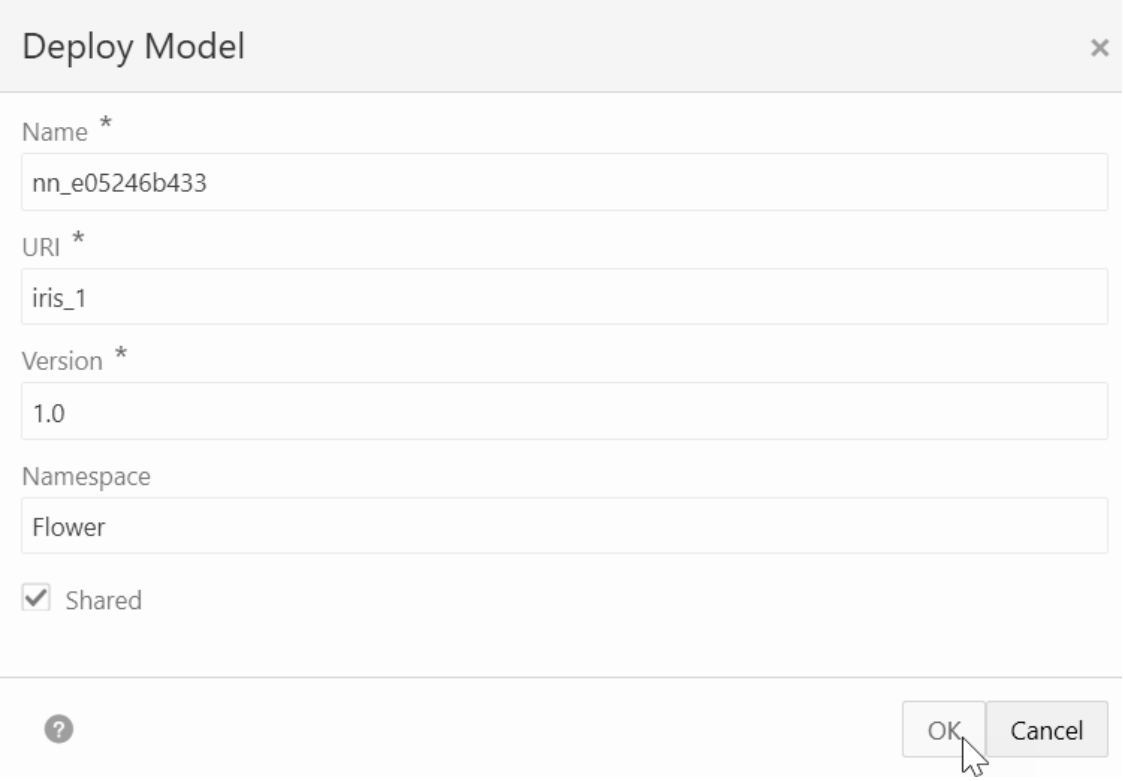
- Deploy Model
  When you deploy a model, you create an Oracle Machine Learning Services endpoint for scoring.

8.1 Deploy Model

When you deploy a model, you create an Oracle Machine Learning Services endpoint for scoring.

In the Deploy Model dialog, you can define the model deployment in the context of your AutoML UI experiment. To deploy a model, define the following:

Figure 8-4 Deploy Model dialog



1. In the **Name** field, the system generated model name is displayed here by default. You can edit this name. The model name must be a unique alphanumeric name with maximum 50 characters.
2. In the **URI** field, enter a name for the model URI. The URI must be alphanumeric, and the length must be max 200 characters.
3. In the **Version** field, enter a version of the model. The version must be in the format `xx.xx` where `x` is a number.
4. In the **Namespace** field, enter a name for the model namespace.
5. Click **Shared** to allow users with access to the database schema to view and deploy the model.
6. Click **OK.** After a model is successfully deployed, it is listed in the Deployments page.
7. You can view the following details:
   - Model Metadata - Select a deployed model and click the model name to view model metadata such as the model name, mining function, algorithm, attributes and so on.
   - REST API - Select a deployed model and click the link under URI to view the REST API URI of the model.

9 Templates

By using the Oracle Machine Learning Notebooks templates, you can collaborate with other users by sharing your work, publishing your work as reports, and by creating notebooks from templates. You can store your notebooks as templates, share notebooks, and provide sample templates to other users.

> **Note:**
>
> You can also collaborate with other Oracle Machine Learning Notebooks users by providing access to your workspace. The authenticated user can then access the projects in your workspace, and access your notebooks. The access level depends on the permission type granted - Manager, Developer, or Viewer. For more information about collaboration among users, see How to collaborate in Oracle Machine Learning Notebooks

- Use the Personal Templates
  Personal Templates lists the notebook templates that you have created.
- Use the Shared Templates
  In the Shared Templates, you can share notebook templates with all authenticated users the notebook templates you create from existing notebooks available in Templates.
- Use the Example Templates
  The Example Templates page lists the pre-populated Oracle Machine Learning notebook templates. You can view and use these templates to create your notebooks.

9.1 Use the Personal Templates

Personal Templates lists the notebook templates that you have created.

You can perform the following tasks:

- View selected templates in read-only mode.
- Create new notebooks from selected templates.
- Edit selected templates.
- Share selected notebook templates in Shared Templates.
- Delete selected notebook templates.
- Create Notebooks from Templates
  You can create new notebooks from an existing template, and store them in Personal Templates for later use.
- Share Notebook Templates
  You can share templates from Personal Templates. You can also share templates for editing.
- Edit Notebook Templates Settings
  You can modify the settings of an existing notebook template in Personal Templates.

9.1.1 Create Notebooks from Templates

You can create new notebooks from an existing template, and store them in Personal Templates for later use.

You must select a notebook template.

To create a new notebook from a template:

1. On the Personal Templates page, select the template based on which you want to create the notebook, and click **New Notebook.**

   The Create Notebook dialog box opens.
2. In the **Name** field, provide a name for the notebook.
3. In the **Comments** field, enter comments, if any.
4. In the **Project** field, select the project in which you want to save your notebook.
5. In the **Connection** field, the default connection is selected.
6. Click **OK.**

The notebook is created, and is available on the Notebooks page.

9.1.2 Share Notebook Templates

You can share templates from Personal Templates. You can also share templates for editing.

To share a template:

1. Select the notebook template in Personal Templates and click **Share.**

   The Save to Shared Templates dialog box opens.
2. In the **Name** field, enter a new name for the template.
3. In the **Comments** field, provide comments, if any.
4. In the **Tags** field, enter tags separated by commas. To enable easy searching, use descriptive tags.
5. Click **OK.**

Once the template is successfully created and shared, a message appears stating that the template is created in Shared.

9.1.3 Edit Notebook Templates Settings

You can modify the settings of an existing notebook template in Personal Templates.

To edit notebook template settings:

1. Select the notebook template in Personal Templates and click **Edit Settings.**

   The Edit Template dialog box opens.
2. In the **Name** field, edit the name, as applicable.
3. In the **Comments** field, edit the comments, if any.
4. In the **Tags** field, edit the tags, as applicable.
5. Click **OK.**

9.2 Use the Shared Templates

In the Shared Templates, you can share notebook templates with all authenticated users the notebook templates you create from existing notebooks available in Templates.

The Shared Templates page tracks notebook templates when you perform the following:

- Like templates
- Create notebooks from templates
- View templates

The Shared Templates page displays the following information about the templates:

- Template name
- Description
- Number of likes
- Number of creations
- Number of static views

You can perform the following tasks:

- Create templates by clicking **New Notebook**
- Edit template settings by clicking **Edit Settings**
- Delete any selected template by clicking **Delete**
- Search templates by Name, Tag, Author
- Sort templates by Name, Date, Author, Liked, Viewed, Used
- View templates by clicking **Show Liked Only** or **Show My Items Only**
- Create Notebooks from Templates
  You can create new notebooks from an existing template, and store them in Personal Templates for later use.
- Edit Notebook Templates Settings
  You can modify the settings of an existing notebook template in Personal Templates.

9.2.1 Create Notebooks from Templates

You can create new notebooks from an existing template, and store them in Personal Templates for later use.

You must select a notebook template.

To create a new notebook from a template:

1. On the Personal Templates page, select the template based on which you want to create the notebook, and click **New Notebook.**

   The Create Notebook dialog box opens.
2. In the **Name** field, provide a name for the notebook.
3. In the **Comments** field, enter comments, if any.
4. In the **Project** field, select the project in which you want to save your notebook.
5. In the **Connection** field, the default connection is selected.

6. Click **OK.**

The notebook is created, and is available on the Notebooks page.

9.2.2 Edit Notebook Templates Settings

You can modify the settings of an existing notebook template in Personal Templates.

To edit notebook template settings:

1. Select the notebook template in Personal Templates and click **Edit Settings.**

   The Edit Template dialog box opens.
2. In the **Name** field, edit the name, as applicable.
3. In the **Comments** field, edit the comments, if any.
4. In the **Tags** field, edit the tags, as applicable.
5. Click **OK.**

9.3 Use the Example Templates

The Example Templates page lists the pre-populated Oracle Machine Learning notebook templates. You can view and use these templates to create your notebooks.

The Example Templates page displays the following information about the templates:

- Template name
- Description
- Number of likes. Click **Likes** to mark it as liked.
- Number of static views
- Number of uses

You cannot alter any templates in the Example Templates page. The search options are:

- Search templates by Name, Tag, Author
- Sort templates by Name, Date, Author, Liked, Viewed, Used
- View templates that are liked by clicking **Show Liked only**
- Create a Notebook from the Example Templates
  Using the Oracle Machine Learning Example Templates, you can create a notebook from the available templates.
- Example Templates
  Oracle Machine Learning Notebooks provide you notebook example templates that are based on different machine learning algorithms and languages such as Python, R, and SQL. The example templates are processed in Oracle Autonomous Database.

9.3.1 Create a Notebook from the Example Templates

Using the Oracle Machine Learning Example Templates, you can create a notebook from the available templates.

To create a notebook:

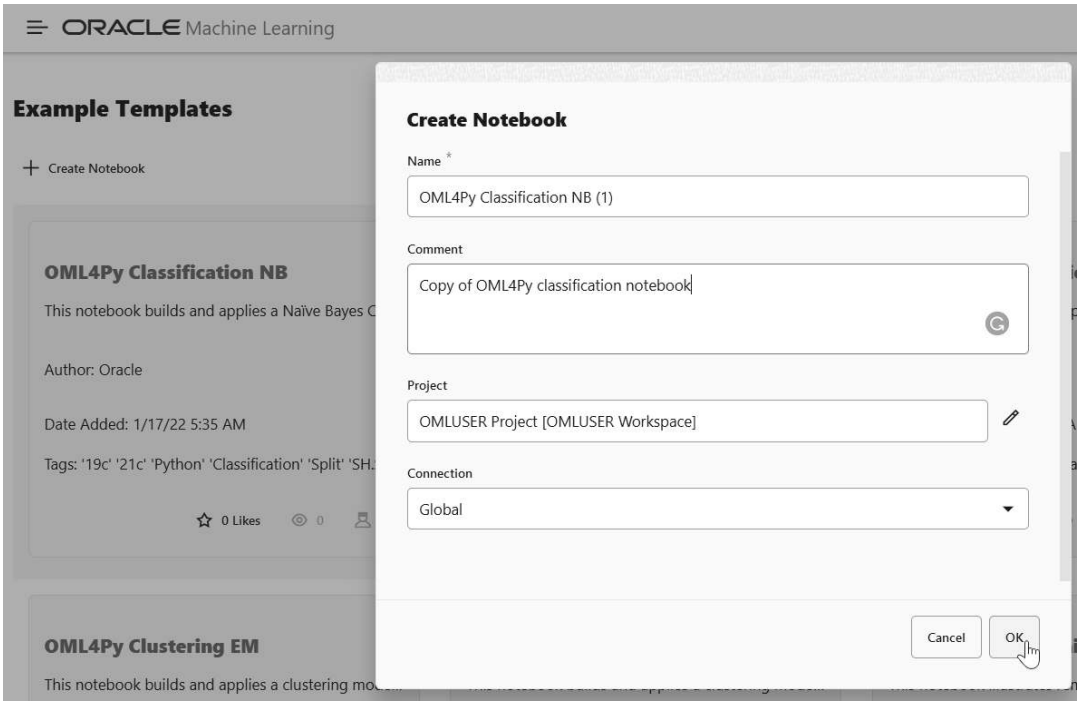
1. On the Example Templates page, select the template based on which you want to create a notebook.

2. Click **New Notebook.**

   The Create Notebook dialog box opens.

3. In the **Create Notebook** dialog, the name of the selected template appears. In the **Name** field, you can change the notebook name.

Figure 9-1 Create Notebook dialog



4. In the **Comment** field, if any comment is available for the template, then it is displayed. You can edit the comment.

5. In the **Project** field, click the edit icon .

6. Select the project in which you want to save the notebook.

7. In the **Connection** field, the default connection is selected.

8. Click **OK.**

The notebook is created and is available on the Notebooks page.

9.3.2 Example Templates

Oracle Machine Learning Notebooks provide you notebook example templates that are based on different machine learning algorithms and languages such as Python, R, and SQL. The example templates are processed in Oracle Autonomous Database.

You can create your own editable and runnable Oracle Machine Learning notebooks based on any of these Oracle Machine Learning for R example template notebooks:

- **OML Export and Import Serialized Models:** Use this notebook to export and import native serialized models using the `DBMS_DATA_MINING.EXPORT_SERMODEL` and `DBMS_DATA_MINING.IMPORT_SERMODEL` procedures. Oracle Machine Learning provides APIs to streamline the process of migrating models across databases and platforms.

- **OML Wiki ESA Model:** Use this notebook for text document categorization by calculating semantic relatedness (how similar in meaning two words or pieces of text are to each other) between the documents and a set of topics that are explicitly defined and described by humans. The Oracle Machine Learning for SQL function `ESA`, Oracle Machine Learning for Python function `oml.esa` and Oracle Machine Learning for R function `ore.odmESA` extract text-based features from a corpus of documents and performs document similarity comparisons. In this notebook, the wiki ESA model is imported to Autonomous Database for use with the following OML template notebook examples:
  - OML4SQL Feature Extraction ESA Wiki Model
  - OML4Py Feature Extraction ESA Wiki Model
  - OML4R Feature Extraction ESA Wiki Model
- **OML Services Batch Scoring:** Use this notebook to run batch scoring jobs through a REST interface via OML Services. OML Services supports batch scoring for regression, classification, clustering, and feature extraction.
  - Authenticate the database user and obtain a token
  - Create a batch scoring job
  - View the details and output of the batch scoring job
  - Update, disable, and delete a batch scoring job
- **OML Services Data Monitoring:** Use this notebook to perform data monitoring. This notebook runs provides you with the data monitoring workflow steps through the REST interface that includes:
  - Authenticate the database user and obtain a token
  - Create a data monitoring job
  - View the details and output of the data monitoring job
  - Update, disable, and delete a data monitoring job
- **OML Services Model Monitoring:** Use this notebook to understand and perform model monitoring. This notebook runs provides you with the model monitoring workflow steps through the REST interface that includes:
  - Authenticate the database user and obtain a token
  - Create a model monitoring job
  - View the details and output of the model monitoring job
  - Update, disable, and delete a model monitoring job
- **OML Third-Party Packages - Environment Creation:** Use this notebook to download and activate the Conda environment, and to use the libraries in your notebook sessions. Oracle Machine Learning Notebooks provide a Conda interpreter to install third-party Python and R libraries in a Conda environment for use within Oracle Machine Learning Notebooks sessions, as well as within Oracle Machine Learning for Python and Oracle Machine Learning for R embedded execution calls.
  The third-party libraries installed in Oracle Machine Learning Notebooks can be used in:
  - Standard Python
  - Standard R
  - Oracle Machine Learning for Python embedded Python execution from the Python, SQL and REST APIs

– Oracle Machine Learning for R embedded R execution from the R, SQL, and REST APIs

> **Note:**
>
> The Conda environment is installed and managed by the ADMIN user with `OML_SYS_ADMIN` role. The administrator can create a shared environment, and add or delete packages from it. The Conda environments are stored in the Object Storage bucket associated with the Autonomous Database.

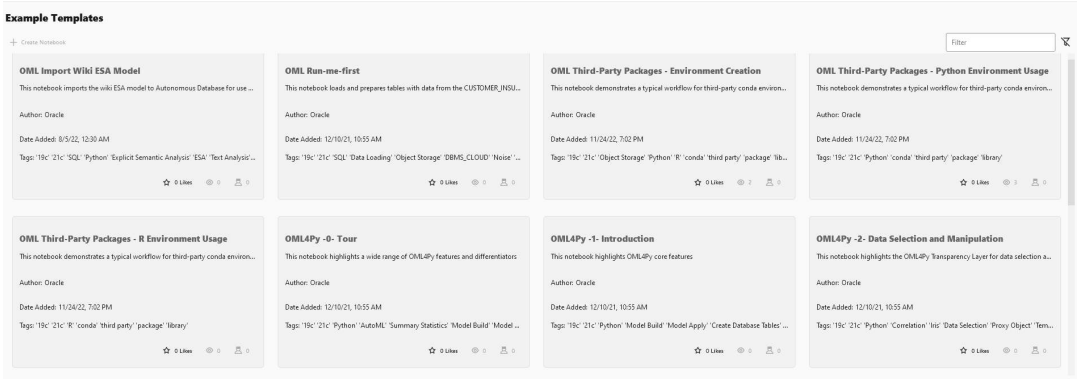
Conda is an open source package and environment management system that enables the use of virtual environments containing third-party R and Python packages. With conda environments, you can install and update packages and their dependencies, and switch between environments to use project-specific packages.

This template notebook *OML Third-Party Packages - Environment Creation* contains a typical workflow for third-party environment creation and package installation in Oracle Machine Learning Notebooks.

– Section 1 contains commands to create and test Conda environments.

– Section 2 contains commands to create a Conda environment, install packages, and commands to upload the conda environment to an Object Storage bucket associated with the Oracle Autonomous Database.

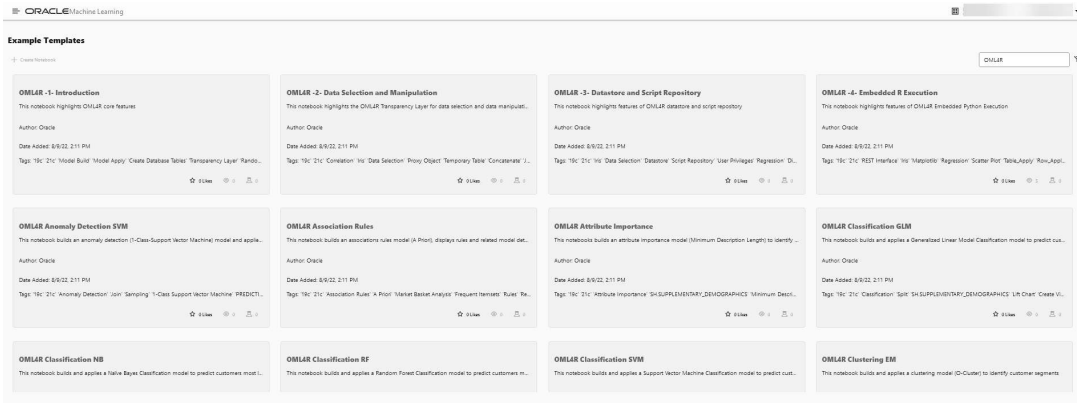
Figure 9-2 Conda Example Templates



- **OML Third-Party Packages - Python Environment Usage:** Use this template notebook to understand the typical workflow for third-party environment usage in Oracle Machine Learning Notebooks using Python and Oracle Machine Learning for Python. You download and use the libraries in Conda environments that were previously created and saved to an Object Storage bucket folder associated with the Autonomous Database.
  This notebook contains commands to:
  – List all environments stored in Object Storage
  – List a named environment stored in Object Storage
  – Download and activate the `mypyenv` environment
  – List the packages available in the Conda environment
  – Import Python libraries
  – Load datasets

  - Build models
  - Score models
  - Create Python user defined functions (UDFs)
  - Run the user defined functions (UDFs) in Python
  - Create and run user defined functions in the SQL and REST APIs for embedded Python execution
  - Create and run Python user defined functions using the SQL API for embedded Python execution - asynchronous mode
- **OML Third-Party Packages - R Environment Usage:** Use this template notebook to understand the typical workflow for third-party environment usage in Oracle Machine Learning for R.
  This notebook contains commands to:
  - List all environments stored in Object Storage
  - List a named environment stored in Object Storage
  - Download and activate the `myrenv` environment
  - Show the list of available OML4R Conda environments
  - Import R libraries
  - Load and prepare data
  - Build models
  - Score models
  - Create R user defined functions (UDFs)
  - Run user defined functions (UDFs) in R
  - Save the user defined functions (UDFs) to the script repository
  - Run the R user defined function in SQL and REST APIs for embedded R execution
  - Add the OML user to the Access Control List
  - Run the R user defined functions using the REST API for embedded R execution in synchronous mode
- **OML4R-1: Introduction:** Use this notebook to understand how to:
  - Load the ORE Library
  - Create database tables
  - Use the transparency layer
  - Rank attributes for predictive value using the in-database attribute importance algorithm
  - Build predictive models, and
  - Score data using these models

Figure 9-3 Oracle Machine Learning for R Example Templates



- **OML4R-2: Data Selection and Manipulation:** Use this notebook to understand the features of the transparency layer involving data selection and manipulation.
- **OML4R-3: Datastore and Script Repository:** Use this notebook to understand the datastore and script repository features of OML4R.
- **OML4R-4: Embedded R Execution:** Use this notebook to understand OML4R embedded R execution. First, a linear model is built in R directly, then a user-define R function is created to build the linear model, the function is then saved to the script repository, and the data is scored in parallel using R engines spawned by the Oracle Autonomous Database environment. The notebook also demonstrates how to call these scripts using the SQL interface and REST API for R with embedded R execution.

> **Note:**
>
> To use the SQL API for embedded R execution, a user-defined R function must reside in the OML4R script repository, and an Oracle Machine Learning (OML) cloud account USERNAME, PASSWORD, and URL must be provided to obtain an authentication token.

- **OML4R Anomaly Detection Support Vector Machine (SVM):** Use this notebook to build a One-Class SVM model and then use it to flag unusual or suspicious records.
- **OML4R Association Rules Apriori:** Use this notebook to build association rules models using the A Priori algorithm with data from the SH schema (SH.SALES). All computation occurs inside Oracle Autonomous Database.
- **OML4R Attribute Importance Minimum Description Length (MDL):** Use this notebook to compute Attribute Importance, which uses the Minimum Description Length algorithm, on the SH schema data. All functionality runs inside Oracle Autonomous Database. Oracle Machine Learning supports Attribute Importance to identify key factors such as attributes, predictors, variables that have the most influence on a target attribute.
- **OML4R Classification Generalized Linear Model (GLM):** Use this notebook to predict customers most likely to be positive responders to an Affinity Card loyalty program. This notebook builds and applies a classification generalized linear model using the Sales History (SH) schema data. All processing occurs inside Oracle Autonomous Database.
- **OML4R Classification Naive Bayes (NB):** Use this notebook to predict customers most likely to be positive responders to an Affinity Card loyalty program. This notebook builds and applies a classification decision tree model using the Sales History (SH) schema data. All processing occurs inside Oracle Autonomous Database.

- **OML4R Classification Random Forest (RF):** Use this notebook to use the Random Forest algorithm for classification in OML4R, and predict customers most likely to be positive responders to an Affinity Card loyalty program.
- **OML4R Classification Modeling to Predict Target Customers using Support Vector Machine (SVM):** Use this notebook to use the Classification modeling to predict Target Customers using Support Vector Machine Model.
- **OML4R Clustering - Identifying Customer Segments using Expectation Maximization Clustering:** Use this notebook to understand how to identify natural clusters of customers using the CUSTOMERS data set from the SH schema using the unsupervised learning Expectation Maximization (EM) algorithm. The data exploration, preparation, and machine learning run inside Oracle Autonomous Database.
- **OML4R Clustering - Identifying Customer Segments using K-Means Clustering:** Use this notebook to understand how to identify natural clusters of customers using the `CUSTOMERS` data set from the SH schema using the unsupervised learning K-Means (KM) algorithm. The data exploration, preparation, and machine learning run inside Oracle Autonomous Database.
- **OML4R Clustering - Orthogonal Partitioning Clustering (OC):** Use this notebook to understand how to identify natural clusters of customers using the CUSTOMERS data set from the SH schema using the unsupervised learning k-Means algorithm. The data exploration, preparation, and machine learning runs inside Oracle Autonomous Database.
- **OML4R Data Cleaning Outlier:** Use this notebook understand and to exclude records with outliers using OML4R.
- **OML4R Data Cleaning - Recode Synonymous Values:** Use this notebook to recode synonymous value using OML4R.
- **OML4R Data set Creation:** Use this notebook to load the sample data sets `MTCARS` and `IRIS` and to import them into your Oracle Autonomous Database instance using the `ore.create()` function.

> **Note:**
>
> The following example template notebooks prefixed with an asterisk (*), use the `CUSTOMER_INSURANCE_LTV` data set. This data set is generated by the `OML Run-me-first` notebook. Hence, you must run the `OML Run-me-first` notebook that is available under the Examples Templates.

- ***** **OML4R Data Cleaning Missing Data:** Use this notebook to perform missing value replacement using OML4R.
- ***** **OML4R Data Cleaning Duplicate Removal:** Use this notebook to remove duplicate records using OML4R.
- ***** **OML4R Data Transformation Binning:** Use this notebook to bin numerical columns using OML4R.
- ***** **OML4R Data Transformation Categorical Record:** Use this notebook to recode a categorical string variable to a numeric variable and string-to-string recoding using OML4R.
- ***** **OML4R Data Transformation: Normalization and Scaling:** Use this notebook to normalize and scale data using OML4R.
- ***** **OML4R Data Transformation: One-Hot Encoding:** Use this notebook to perform one-hot encoding using OML4R.

- *** OML4R Feature Selection - Supervised Algorithm:** Use this notebook to perform feature selection using in-database supervised algorithms using OML4R. This notebook demonstrates how to build a Random Forest model to predict whether the customer would buy insurance or not, and then use Feature Importance to perform feature selection.
- *** OML4R Feature Selection Using Summary Statistics:** Use this notebook to perform feature selection using summary statistics using OML4R. This notebook demonstrates how to use OML4R to select features based on number of distinct values, null values, proportion of constant values.
- **OML4R Feature Engineering Aggregation:** Use this notebook to perform aggregation for min, max, mean, and count using OML4R. This template uses the `SALES` table present in the `SH` schema, and shows how to create features by aggregating the amount sold for each customer and product pair.
- **OML4R Feature Extraction Explicit Semantic Analysis (ESA) Wiki Model:** This notebook uses the use the Wikipedia Model as an example. Use this notebook to use the Oracle Machine Learning for R function `ore.odmESA` to extract text-based features from a corpus of documents and performs document similarity comparisons. All processing occurs inside Oracle Autonomous Database.

  > **Note:**
  >
  > The pre-built Wikipedia model must be installed in your Autonomous Database instance to run this notebook.

- **OML4R Data Transformation Date Data types:** Use this notebook to perform various operations on date and time data using database table proxy objects using Oracle Machine Learning for R.
- **OML4R Feature Extraction Singular Value Decomposition (SVD):** Use this notebook to use the in-database SVD for feature extraction. This notebook uses the Oracle Machine Learning for R function `ore.odmSVD` to create a model that uses the Singular Value Decomposition (SVD) algorithm for feature extraction.
- **OML4R Partitioned Model Support Vector Machine (SVM):** Use this notebook to build an SVM model to predict the number of years a customer resides at their residence but partitioned on customer gender. The model is then used to predict the target, then predict the target with prediction details.
- **OML4R Regression Generalized Linear Model (GLM):** Use this notebook to understand how to predict numerical values using multiple regression. This notebook uses the Generalized Linear Model algorithm.
- **OML4R Regression Neural Network (NN):** Use this notebook to understand how to predict numerical values using multiple regression. This notebook uses the Neural Network algorithm.
- **OML4R Regression Support Vector Machine (SVM):** Use this notebook to understand how to predict numerical values using multiple regression. This notebook uses the Support Vector Machine algorithm.
- **OML4R REST API:** Use this notebook to understand how to use the OML4R REST API to call user-defined R functions, and to list those available in the R script repository.

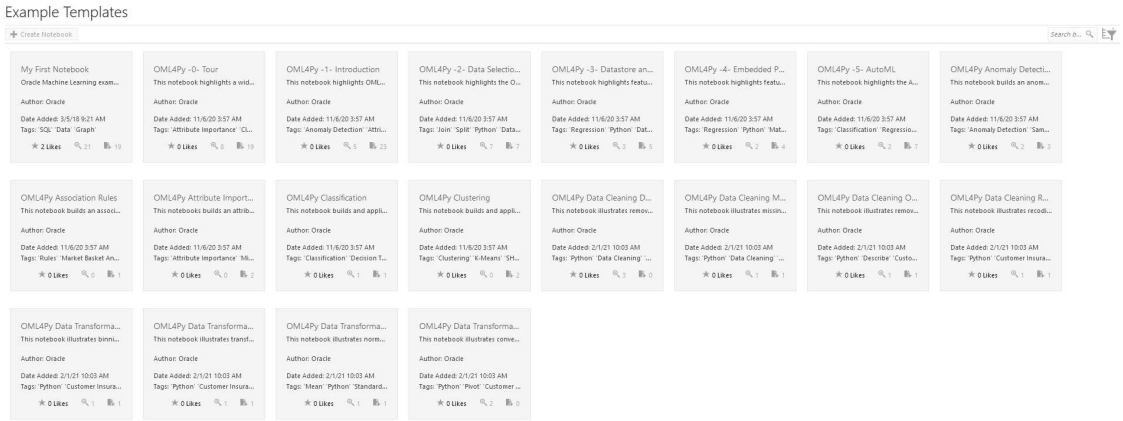
> **Note:**
>
> To run a script, it must reside in the R script repository. An Oracle Machine Learning cloud service account user name and password must be provided for authentication.

- **OML4R Statistical Function:** Use this notebook to understand and use various statistical functions. The notebook uses data from the SH schema through the OML4R transparency layer.
- **OML4R Text Mining Support Vector Machine (SVM):** Use this notebook to understand how to use unstructured text data to build machine learning models, leverage Oracle Text, use Oracle Machine Learning in-database algorithms predictive features, and extract features from text columns.
  This notebook builds a Support Vector Machine (SVM) model to predict customers that are most likely to be positive responders to an Affinity Card loyalty program. The data comes from a text column that contains user generated comments.

Oracle Machine Learning for Python Example Templates

You can create your Oracle Machine Learning notebooks based on any of these Oracle Machine Learning for Python example templates:

Figure 9-4 Oracle Machine Learning for Python Example Templates



- **My First Notebook:** Use the My First Notebook notebook for basic machine learning functions, data selection and data viewing. This template uses the `SH` schema data.
- **OML4Py -0- Tour:** This notebook is the first of a series 0 through 5 that is intended to introduce you to the range of OML4Py functionality through short examples.
- **OML4Py -1- Introduction:** This notebook provides an overview on how to load OML library, create database tables, use the transparency layer, rank attributes for predictive value using the in-database attribute importance algorithm, build predictive models, and score data using these models.
- **OML4Py -2- Data Selection and Manipulation:** Use this notebook to learn how to work with the transparency layer which involves data selection and manipulation.
- **OML4Py -3- Datastores:** Use this notebook to learn how to work with datastores, move objects between datastore and a Python sessions, manage datastore privileges, save model objects and Python objects in a datastore, delete datastores and so on.

- **OML4Py -4- Embedded Python Execution:** Use this notebook to understand embedded Python Execution. In this notebook, a linear model is build in Python directly, and then a function is created that uses Python engines spawned by the Autonomous Database environment.
- **OML4Py -5- AutoML:** Use this notebook to understand the AutoML workflow in OML4Py. In this notebook, the `WINE` data set from scikit-learn is used. Here, AutoML is used for classification on the `target` column, and for regression on the `alcohol` column.

> **Note:**
>
> The following example template notebooks prefixed with an asterisk (*), use the `CUSTOMER_INSURANCE_LTV_PY` data set. This data set has duplicated values artificially generated by **OML4SQL Noise** notebook. Hence, you must run the **OML4SQL Noise** first before running the notebook.

- ***** **OML4Py Data Cleaning Duplicates Removal:** Use this notebook to understand how to remove duplicate records using OML4Py. This notebook uses the customer insurance lifetime value data set which contains customer financial information, lifetime value, and whether or not the customer bought insurance.
- ***** **OML4Py Data Cleaning Missing Data:** Use this notebook to understand how to fill in missing values using OML4Py. This notebook uses the customer insurance lifetime value data set which contains customer financial information, lifetime value, and whether or not the customer bought insurance.
- ***** **OML4Py Data Cleaning Recode Synonymous Values:** Use this notebook to understand how to recode synonymous value using OML4Py. This notebook uses the customer insurance lifetime value data set which contains customer financial information, lifetime value, and whether or not the customer bought insurance.
- **OML4Py Data Cleaning Outlier Removal:** Use this notebook to understand how to clean data to remove outliers. This notebook uses the `CUSTOMER_INSURANCE_LTV` data set which contains customer financial information, lifetime value, and whether or not the customer bought insurance. In the data set `CUSTOMER_INSURANCE_LTV`, the focus is on numerical values and removal of records with values in the top and bottom 5%.
- **OML4Py Data Transformation Binning:** Use this notebook to understand how to bin a numerical column and visualize the distribution.
- **OML4Py Data Transformation Categorical - Convert Categorical Variables to Numeric Variables:** Use this notebook to understand how to convert categorical variables to numeric variables using OML4Py. The notebooks demonstrates how to convert a categorical variable with each distinct level/value coded to an integer data type.
- **OML4Py Data Transformation Normalization and Scaling:** Use this notebook to understand how to normalize and scale data using z-score (mean and standard deviation), min max scaling, and log scaling.

> **Note:**
>
> When building or applying a model using in-database Oracle Machine Learning algorithms, automatic data preparation will normalize data automatically as needed, by specific algorithms.

- **OML4Py Data Transformation One Hot Encoding:** Use this notebook to understand how to perform one hot encoding using OML4Py. Machine learning algorithms cannot work with categorical data directly. Categorical data must be converted to numbers. This notebook uses the customer insurance lifetime value data set which contains customer financial information, lifetime value, and whether or not the customer bought insurance.

  > **Note:**
  >
  > If you plan to use the in-database algorithms, one hot encoding is automatically applied for those algorithms requiring it. The in-databae algorithms automatically explode the categorical columns and fit the model on the prepared data internally.

- **OML4Py Anomaly Detection:** Use this notebook to detect anomalous records, customers or transactions in your data. This template uses the unsupervised learning algorithm 1-Class Support Vector Machine. The notebook template builds a 1-Class Support Vector Machine (SVM) model.
- **OML4Py Association Rules:** Use this notebook for market basket analysis of your data, or to detect co-occurring items, failures or events in your data. This template uses the apriori Association Rules model using the `SH` schema data (`SH.SALES`).
- **OML4Py Attribute Importance:** Use this notebook to identify key attributes that have maximum influence over the target attribute. The target attribute in the build data of a supervised model is the attribute that you want to predict. The template builds an Attribute Importance model using the `SH` schema data.
- **OML4Py Classification:** Use this notebook for predicting customer behavior and similar predictions. The template builds and applies the classification algorithm Decision Tree to build a Classification model based on the relationships between the predictor values and the target values. The template uses the `SH` schema data.
- **OML4Py Clustering:** Use this notebook to identify natural clusters in your data. The notebook template uses the unsupervised learning *k*-Means algorithm on the `SH` schema data.
- **OML4Py Data Transformation :** Use this notebook to convert categorical variables to numeric variables using OML4Py. This template shows how to convert a categorical variable with each distinct level/value coded to an integer data type.
- **OML4Py Data Set Creation:** Use this notebook to create data set from sklearn package to OML data frame using OML4Py.
- **OML4Py Feature Engineering Aggregation:** Use this notebook template to fill in missing values using OML4Py. This notebook uses the `SH` schema SALES table, which contains transaction records for each customer and products purchased. Features are created by aggregating the amount sold for each customer and product pair.
- **OML4Py Feature Selection Supervised Algorithm Based:** Use this notebook to perform feature selection using in-database supervised algorithms using OML4Py.
- **OML4Py Feature Selection Summary Statistics:** Use this notebook template to perform feature selection using summary statistics using OML4Py. The notebook shows how to use OML4Py to select features based on number of distinct values, null values, proportion of constant values. The data set used here `CUSTOMER_INSURANCE_LTV_PY` has null values generated by the OML4SQL Noise notebook artificially. You must first run the OML4SQL Noise notebook before running the OML4Py Feature Selection Summary Statistics notebook.

- **OML4Py Partitioned Model:** Use this notebook to build partitioned models. This notebook builds an SVM model to predict the number of years a customer resides at their residence but partitioned on customer gender. It uses the model to predict the target, and then predict the target with prediction details.
  Oracle Machine Learning enables automatically building of an ensemble model comprised of multiple sub-models, one for each data partition. Sub-models exist and are used as one model, which results in simplified scoring using the top-level model only. The proper sub-model is chosen by the system based on partition values in the row of data to be scored. Partitioned models achieve potentially better accuracy through multiple targeted models.
- **OMP4Py REST API:** Use this notebook to call embedded Python execution. OML4Py contains a REST API to run user-defined Python functions saved in the script repository. The REST API is used when separation between the client and the Database server is beneficial. Use the OML4Py REST API to build, train, deploy, and manage scripts.

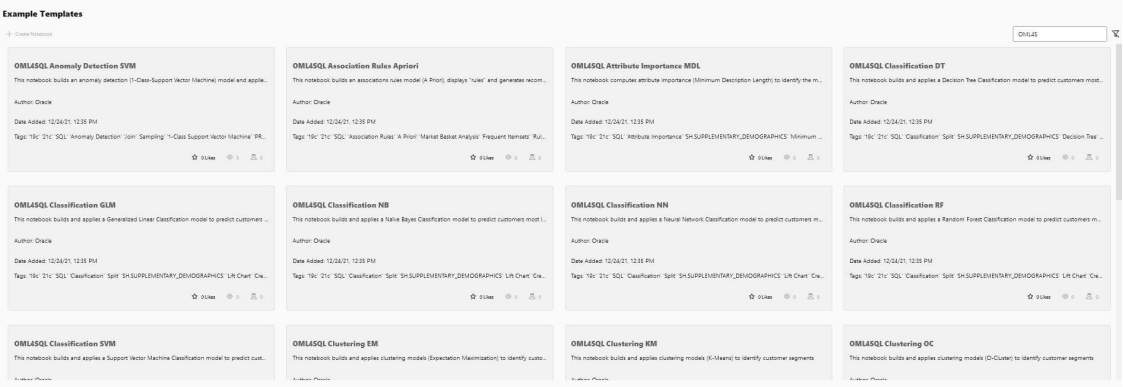
> **Note:**
>
> To run a script, it must reside in the OML4Py script repository. An Oracle Machine Learning cloud service account user name and password must be provided for authentication.

- **OML4Py Regression Modeling to Predict Numerical Values:** Use this notebook to predict numerical values using multiple regression.
- **OML4Py Statistical Functions:** Use this notebook to use various statistical functions. The statistical functions use data from the `SH` schema through the OML4Py transparency layer.
- **OML4Py Text Mining:** Use this notebook to build models using Text Mining capability in Oracle Machine Learning.
  In this notebook, an SVM model is built to predict customers most likely to be positive responders to an Affinity Card loyalty program. The data comes with a text column that contains user generated comments. With a few additional specifications, the algorithm automatically uses the text column and builds the model on both the structured data and unstructured text.

Oracle Machine Learning for SQL Example Templates

You can create your Oracle Machine Learning notebooks based on any of these Oracle Machine Learning for SQL example templates:

Figure 9-5 Oracle Machine Learning for SQL Example Templates



- **OML4SQL Anomaly Detection:** Use this notebook to detect unusual or rare occurrences. Oracle Machine Learning supports anomaly detection to identify rare or unusual records (customers, transactions, etc.) in the data using the semi-supervised learning algorithm One-Class Support Vector Machine. This notebook builds a 1Class-SVM model and then uses it to flag unusual or suspicious records. The entire machine learning methodology runs inside Oracle Autonomous Database.
- **OML4SQL Association Rules:** Use this notebook to apply Association Rules machine learning technique, also known as Market Basket Analysis to discover co-occurring items, states that lead to failures, or non-obvious events. This notebook builds associations rules models using the A Priori algorithm with the `SH.SALES` data from the `SH` schema. All computation occurs inside Oracle Autonomous Database.
- **OML4SQL Attribute Importance - Identify Key Factors:** Use this notebook to identify key factors, also known as attributes, predictors, variables that have the most influence on a target attribute. This notebook builds an Attribute Importance model, which uses the Minimum Description Length algorithm, using the `SH` schema data. All functionality runs inside Oracle Autonomous Database.
- **OML4SQL Classification - Predicting Target Customers:** Use this notebook to predict customers that are most likely to be positive responders to an Affinity Card loyalty program. This notebook builds and applies classification decision tree models using the `SH` schema data. All processing occurs inside Oracle Autonomous Database.
- **OML4SQL Clustering - Identifying Customer Segments:** Use this notebook to identify natural clusters of customers. Oracle Machine Learning supports clustering using several algorithms, including k-Means, O-Cluster, and Expectation Maximization. This notebook uses the CUSTOMERS data set from the `SH` schema using the unsupervised learning k-Means algorithm. The data exploration, preparation, and machine learning runs inside Oracle Autonomous Database.
- **OML4SQL Data Cleaning - Removing Duplicates:** Use this notebook to remove duplicate records using Oracle SQL. The notebook uses the customer insurance lifetime value data set which contains customer financial information, lifetime value, and whether or not the customer bought insurance. The data set `CUSTOMER_INSURANCE_LTV_SQL` has duplicate values generated by the OML4SQL Noise notebook.

  > **Note:**
  >
  > You must first run the OML4SQL Noise notebook before running the OML4SQL Data Cleaning notebook.

- **OML4SQL Data Cleaning - Missing Data:** Use this template to replace missing values using Oracle SQL and the DBMS_DATA_MINING_TRANSFORM package. The data set `CUSTOMER_INSURANCE_LTV_SQL` has missing values artificially generated by the OML4SQL Noise notebook. You must first run the OML4SQL Noise notebook before running the OML4SQL Data Cleaning notebook.

  > **Note:**
  >
  > When building or applying a model using in-database Oracle Machine Learning algorithms, this operation may not be needed separately if automatic data preparation is enabled. Automatic data preparation automatically replaces missing values of numerical attributes with the mean and missing values of categorical attributes with the mode.

- **OML4SQL Data Cleaning Outlier Removal:** Use this notebook to remove outliers using Oracle SQL and the DBMS_DATA_MINING_TRANSFORM package. The notebook uses the customer insurance lifetime value data set, which contains customer financial information, lifetime value, and whether or not the customer bought insurance. In the data set `CUSTOMER_INSURANCE_LTV`, it focuses on numeric values and removes records with values in the top and bottom 5%.
- **OML4SQL Data Cleaning Recode Synonymous Values:** Use this notebook to recode synonymous value of a column using Oracle SQL. The notebook uses the customer insurance lifetime value data set, which contains customer financial information, lifetime value, and whether or not the customer bought insurance. The data set `CUSTOMER_INSURANCE_LTV_SQL` has recoded values generated by the OML4SQL Noise notebook. You must first run the OML4SQL Noise notebook before running the OML4SQL Data Cleaning - Recode Synonymous Values notebook.
- **OML4SQL Data Transformation Binning:** Use this notebook to bin numeric columns using Oracle SQL and the DBMS_DATA_MINING_TRANSFORM package. This notebook shows how to bin a numerical column and visualize the distribution.
- **OML4SQL Data Transformation Categorical:** Use this notebook to convert a categorical variable to a numeric variable using Oracle SQL. The notebook shows how to convert a categorical variable with each distinct level/value coded to an integer, and how to create an indicator variable based on a simple predicate.
- **OML4SQL Data Transformation Normalization and Scale:** Use this notebook to normalize and scale data using Oracle SQL and the DBMS_DATA_MINING_TRANSFORM package. The notebook shows how to normalize data using using z-score (mean and standard deviation), min max scaling, and log scaling. When building or applying a model using in-database Oracle Machine Learning algorithms, automatic data preparation normalizes data automatically, as needed, by specific algorithms.
- **OML4SQL Dimensionality Reduction - Non-negative Matrix Factorization:** Use this notebook to perform dimensionality reduction using the in-database non-negative matrix factorization algorithm. This notebook shows how to convert a table with many columns to a reduced feature set. Non-negative Matrix Factorization produces non-negative coefficients.
- **OML4SQL Dimensionality Reduction - Singular Value Decomposition:** Use this notebook to perform dimensionality reduction using the in-database singular value decomposition (SVD) algorithm.
- **OML4SQL: Exporting Serialized Models:** Use this notebook to export serialized models to Oracle Cloud Object Storage. This notebook creates Oracle Machine Learning regression and classification models and exports the models in a serialized format so that they can be scored using the Oracle Machine Learning (OML) Services REST API. OML Services provides REST API endpoints hosted on Oracle Autonomous Database. These endpoints enable the storing of Oracle Machine Learning models along with its metadata and create scoring endpoints for the model. The REST API for OML Services supports both Oracle Machine Learning models and ONNX format models, and enables cognitive text functionality.
- **OML4SQL Feature Engineering Aggregation and Time:** Use this notebook to generate aggregated features and also extract date and time features using Oracle SQL. The notebook also shows how to extract date and time features from the field `TIME_ID`.
- **OML4SQL Feature Selection Algorithm Based:** Use this notebook to perform feature selection using in-database supervised algorithms. The notebook first builds a random forest model to predict if the customer will buy insurance, then it uses Feature Importance values for feature selection. It then build a decision tree model for the same classification

task, and obtains split nodes. For the top splitting nodes with highest support, features associated with those nodes are selected.

- **OML4SQL Feature Selection Unsupervised Attribute Importance:** Use this notebook to perform feature selection using the in-database unsupervised algorithm Expectation Maximization (EM). This notebook illustrates using the `CREATE_MODEL` function, which leverages the settings table in contrast to the `CREATE_MODEL2` function used in other notebooks.
- **OML4SQL Feature Selection Using Summary Statistics:** Use this notebook to perform feature selection using summary statistics using Oracle SQL. The data set `CUSTOMER_INSURANCE_LTV_SQL` has null values generated by OML4SQL Noise notebook artificially. You must first run the OML4SQL Noise notebook before running the OML4SQL Feature Selection Using Summary Statistics.
- **OML4SQL Noise:** Use this notebook to replace normal values by null values, and to add duplicated rows. In this notebook, the data set used by the Data Preparation notebooks is prepared, in particular those for data cleaning and feature selection. It uses the customer insurance lifetime value data set which contains customer financial information, lifetime value, and whether or not the customer bought insurance.

> **Note:**
>
> Run the OML4SQL Noise notebook before the Data Preparation notebooks.

- **OML4SQL Partitioned Model:** Use this notebook to build partitioned models. Partitioned models achieve potentially better accuracy through multiple targeted models. The notebook builds an SVM model to predict the number of years a customer resides at their residence but partitioned on customer gender. The model is then used to predict the target first, and then to predict the target with prediction details.
- **OML4SQL Text Mining:** Use this notebook to build models using text mining capability. Oracle Machine Learning handles both structured data and unstructured text data. By leveraging Oracle Text, Oracle Machine Learning in-database algorithms automatically extracts predictive features from the text column.
  This notebook builds an SVM model to predict customers most likely to be positive responders to an Affinity Card loyalty program. The data comes with a text column that contains user generated comments. With a few additional specifications, the algorithm automatically uses the text column and builds the model on both the structured data and unstructured text.
- **OML4SQL Regression:** Use this notebook to predict numerical values. This template uses multiple regression algorithms such as Generalized Linear Models (GLM).
- **OML4SQL Statistical Function:** Use this notebook for descriptive and comparative statistical functions. The notebook template uses `SH` schema data.
- **OML4SQL Time Series:** Use this notebook to build time series models on your time series data for forecasting. This notebook is based on the Exponential Smoothing Algorithm. The sales forecasting example in this notebook is based on the `SH.SALES` data. All computations are done inside Oracle Autonomous Database.

10
Jobs

Jobs allow you to schedule the running of notebooks. On the Jobs page, you can create jobs, duplicate jobs, start and stop jobs, delete jobs, and monitor job status by viewing job logs, which are read-only notebooks.

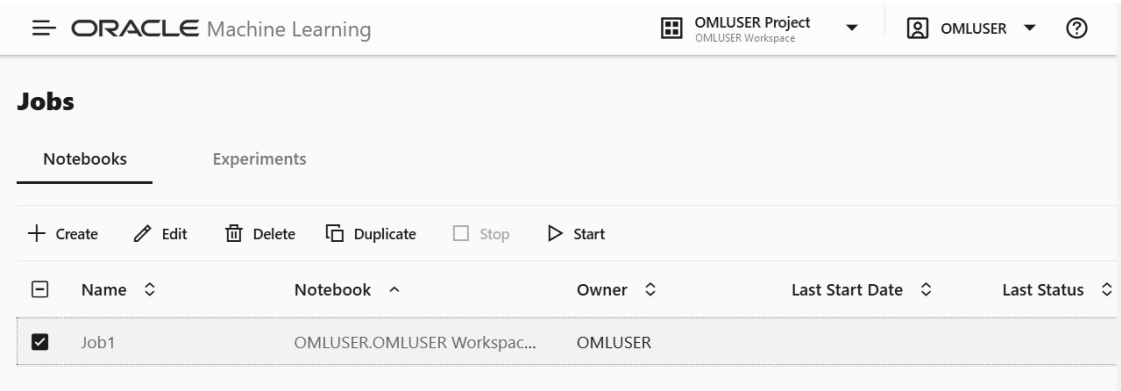
- About Jobs
  The Jobs page lists all the jobs created, along with the job name, notebook, owner of the job, last start date, next run date, status, and schedule.
- Create Jobs to Schedule Notebooks
  You can create jobs to schedule your notebook with the notebook scheduling settings.
- View Job Logs
  You can view the historical logs of any particular job in the Job Log interface.

10.1 About Jobs

The Jobs page lists all the jobs created, along with the job name, notebook, owner of the job, last start date, next run date, status, and schedule.

You can perform the following tasks:

Figure 10-1 Jobs page



- Edit jobs: You can edit the metadata of any job listed on the Jobs page. Click **Edit** to edit the selected job.
- Create jobs. Click **Create** to create a new job to schedule your notebook.
- Duplicate jobs: You can create a copy of an existing job listed on the Jobs page. Click **Duplicate** to make a copy of the selected job.
- Stop jobs: Click **Stop** to terminate a job that is currently running.
- Start jobs: The **Start** button is enabled only for jobs that are in *Scheduled* status. Click **Start** to start a scheduled job. The **Start** option is not applicable for the following conditions:

  - Jobs that have already completed its scheduled run cannot be re-started.
  - Jobs that have failed more than the allowed number of times, and are currently in *Broken* status, cannot be re-started.
- Delete jobs: Click **Delete** to delete any job listed on the Jobs page.

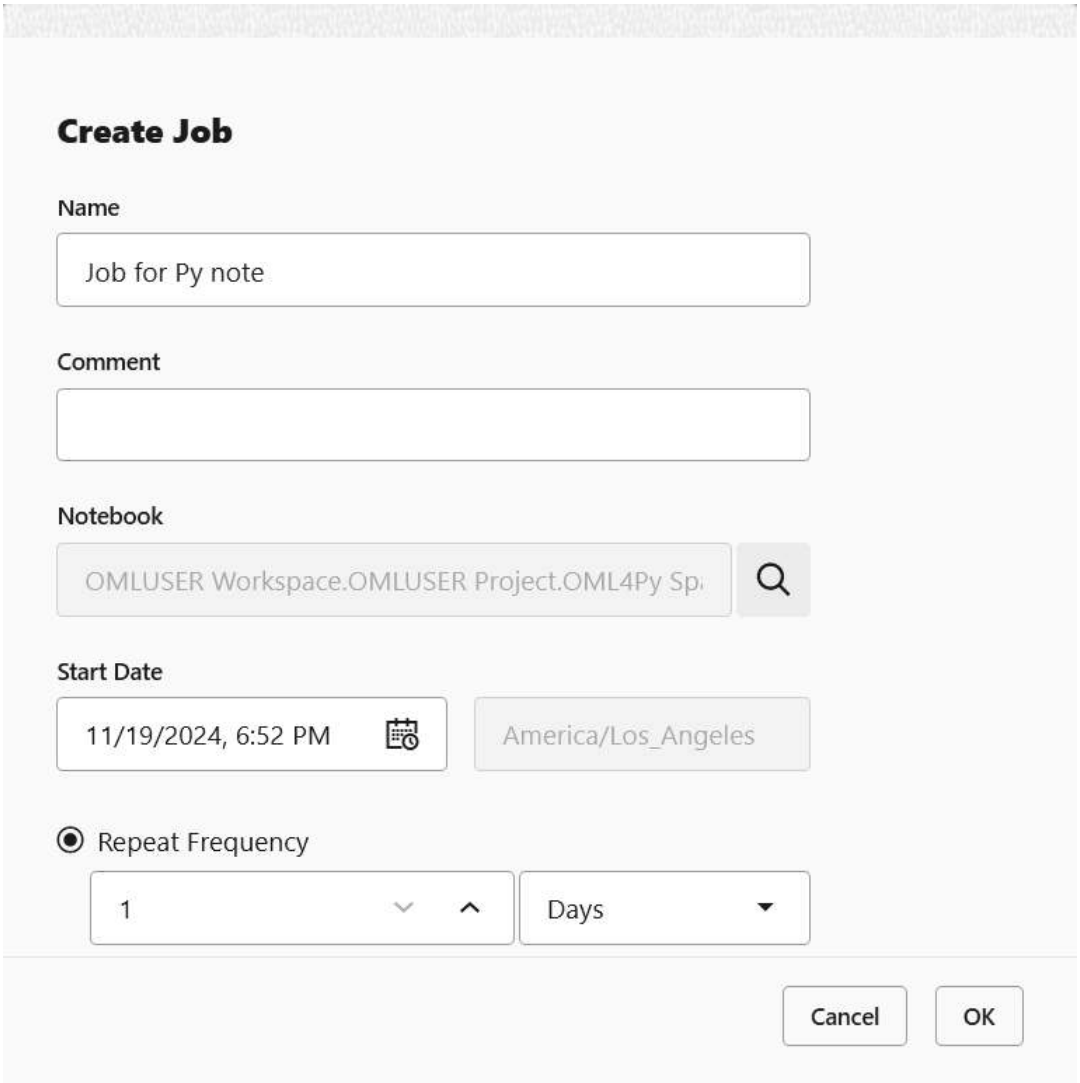
10.2 Create Jobs to Schedule Notebooks

You can create jobs to schedule your notebook with the notebook scheduling settings.

To create jobs, enter the following details in the Create Jobs dialog box:

1. On the Jobs page, click **Create.** The Create Jobs dialog opens.

Figure 10-2 Create Jobs dialog

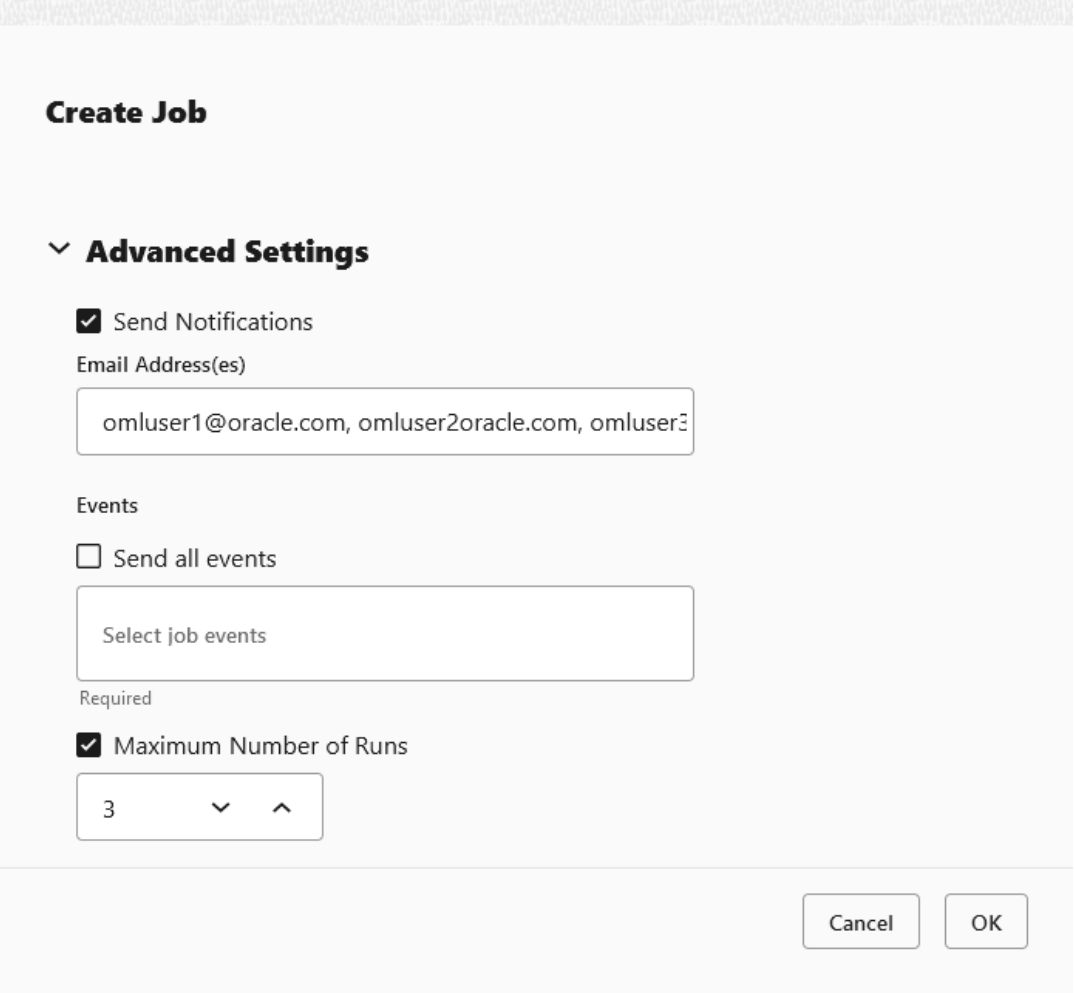


2. In the **Name** field, enter a name for the job. The number of characters in the job name must not exceed 128 bytes.
3. In the **Notebook** field, click the search icon to select a notebook to create a job.

> **Note:**
>
> Only notebooks that are owned by the user or shared are available for selection.

4. In the **Start Date** field, click the date-time editor to set the date and time for your job to commence. Based on the selected date and time, the next run date is computed.
5. Optionally, in the **Repeat** section, select:
   - **Frequency:** To set the repeat settings and frequency. You can set the frequency in minutes, hours, days, week, and month.
   - **Custom:** To customize the job settings.
6. Expand the **Advanced Settings** section, select one or more of the following options:

Figure 10-3 Advanced Settings in Create Jobs dialog



   - **Send Notifications:** Select this option to send email notifications to the specified users' email addresses about the selected events for the job.

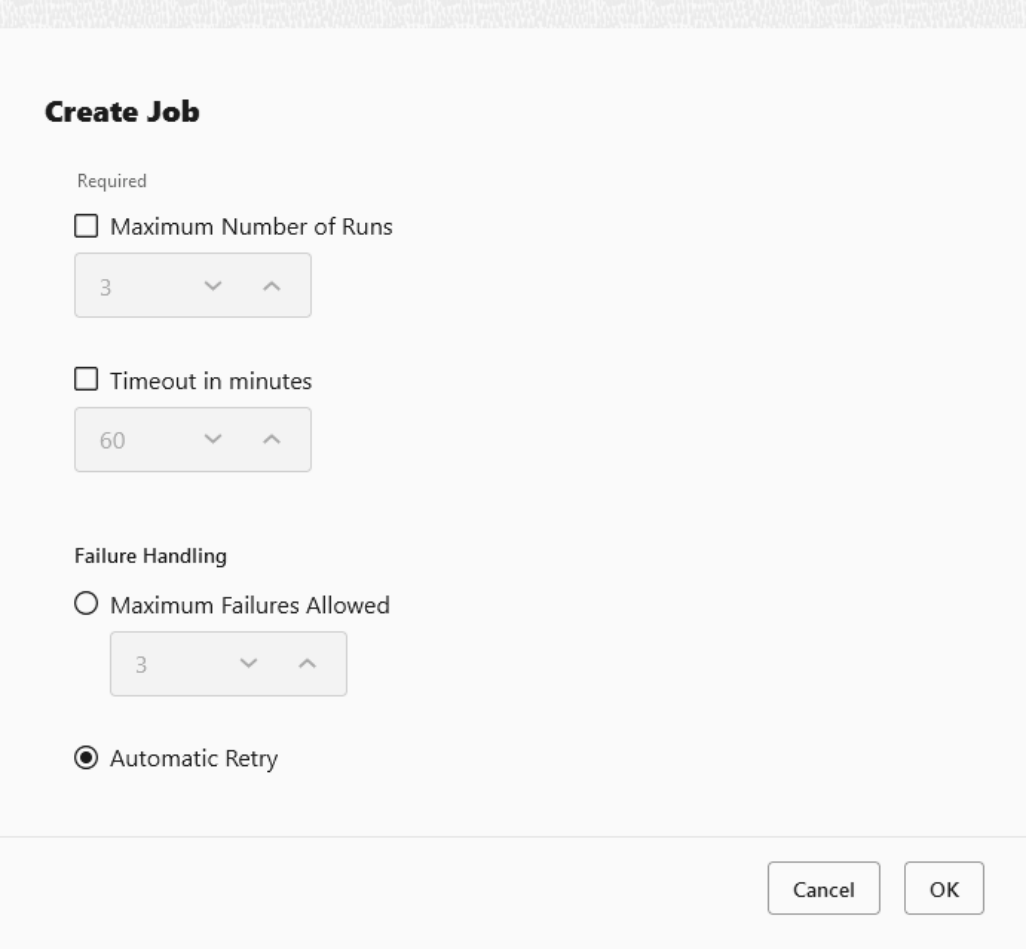
> **Note:**
>
> Email server must be set up for notifications to work.

- **Email Address:** Enter the email ID of the users. By default, you can enter three email IDs, separated by comma. To send emails to more users, contact your Administrator.

> **Note:**
>
> The email notification feature is only available to the paid customer. This feature is not available in the free trial account.

- **Events:** Select the event for which you want to send the notification. The supported job events are:
  - `JOB_START`: Indicates that the job has started for the first time, or a job was started on a retry attempt.
  - `JOB_SUCCEEDED`: Indicates that the job has completed successfully.
  - `JOB_FAILED`: Indicates that the job resulted in an error, or was not able to run due to process death or database shutdown.
  - `JOB_BROKEN`: Indicates that the job is marked broken after retrying unsuccessfully. It also indicates failed job run after 16 attempts.
  - `JOB_COMPLETED`: Indicates that the job has a status of `COMPLETED` after it has reached its maximum number of runs or its end date.
  - `JOB_STOPPED`: Indicates that the job has terminated normally after a soft stop or hard stop was issued.
- **Maximum Number of Runs:** To specify the maximum number of times the job must run before it is stopped. When the job reaches the maximum run limit, it will stop.

Figure 10-4 Advanced Settings-2 in Create Jobs dialog



- **Timeout in Minutes:** To specify the maximum amount of time a job should be allowed to run.
- **Maximum Failures Allowed:** To specify the maximum number of times a job can fail on consecutive scheduled runs. When the maximum number of failures is reached, the next run date column in the Jobs UI will show an empty value to indicate the job is no longer scheduled to run. The Status column may show the status as `Failed`.
- **Automatic Retry:** Select this option if you want the job to restart in case the job fails.

7. Click **OK.**

10.3 View Job Logs

You can view the historical logs of any particular job in the Job Log interface.

You can view a log in the read-only Notebook. To view job logs:

1. To view the history of a job, select the job and click View.
2. To delete a particular job log, select it and click Delete.

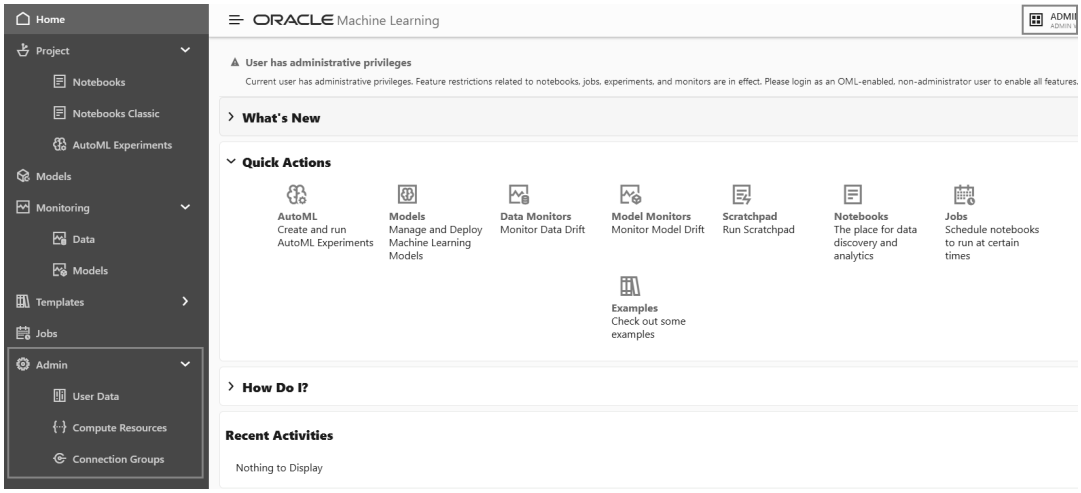
11
Admin

Oracle Machine Learning is managed at the system level and at the application level by an administrator.

- Administrator — Creates and manages Oracle Machine Learning user accounts, manages compute resourses, connection groups, and notebook sessions. The Administrator also reassigns user workspace.

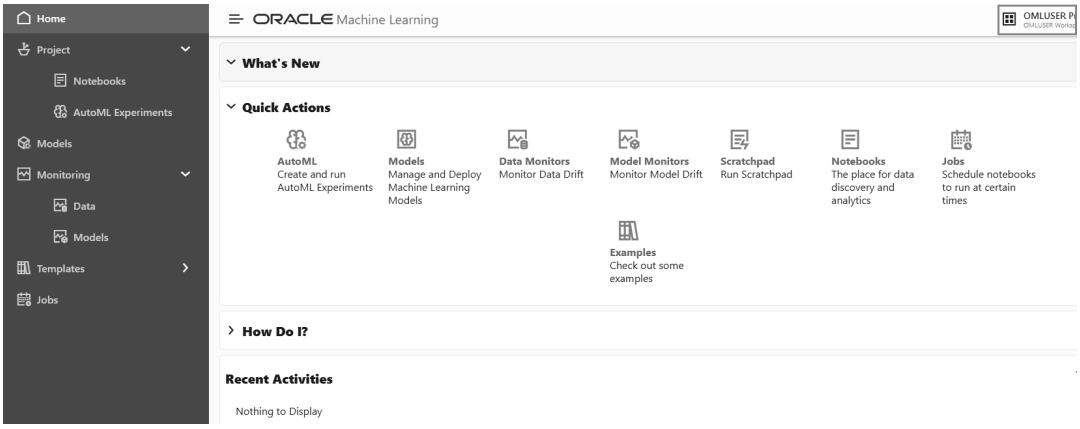
> **Note:**
>
> The Administrator is not authorized to run notebooks. The Administrator can only read notebooks.

Figure 11-1 OML UI Admin home page and left navigation menu



- Developer — This is the default user role that allows you to create and run notebooks, run SQL Statements, create SQL scripts, run Python scripts, create jobs to schedule and run notebooks, use example template notebooks, create and run AutoML experiments, and deploy models.

Figure 11-2 OML UI Developer home page and left navigation menu



- Typical Workflow for Managing Oracle Machine Learning
  To manage Oracle Machine Learning User Interface and other administrative tasks, refer to the tasks listed in the table as a guide.
- Access OML User Management from Command Line
  You can obtain the Oracle Machine Learning User Management URL for a specific tenancy from the Oracle Cloud Infrastructure (OCI) command line.
- Manage OML Users and User Accounts
  An administrator manages new user account and user credentials creation for Oracle Machine Learning.
- About User Data
  On the User Data page in Oracle Machine Learning, you can view existing user data, reassign, and delete it.
- About Compute Resource
  The term Compute Resource refers to services such as a database, or any other backend service to which an interpreter connects.
- Get Started with Connection Groups
  A connection group, also known as a Zeppelin interpreter set, is a collection of database connections.
- Get Started with Notebook Sessions
  The Notebook Sessions page provides you an overview of your notebooks, and allows you to manage notebook sessions from your workspace or in workspaces where you have collaboration rights.

11.1 Typical Workflow for Managing Oracle Machine Learning

To manage Oracle Machine Learning User Interface and other administrative tasks, refer to the tasks listed in the table as a guide.

Tasks	Oracle Machine Learning Interface/OCI CLI Interface	More Information
Obtain Oracle Machine Learning User Management URL from OCI command line	Oracle Cloud Infrastructure (OCI) Command Line Interface (CLI)	Access OML User Management from Command Line
User account and password creation	Oracle Machine Learning User Management interface	Create Users for Oracle Machine Learning

Tasks	Oracle Machine Learning Interface/OCI CLI Interface	More Information
Connection Groups — View and Reset	Oracle Machine Learning User Interface	Work with Connection Groups
Compute Resource — View	Oracle Machine Learning User Interface	About Compute Resource
User Data administration — Delete all users, all user related objects such as workspace, projects, and notebooks, and workspace reassignment	Oracle Machine Learning User Interface	About User Data
Notebook session — Loading and stopping of notebook sessions	Oracle Machine Learning User Interface	Get Started with Notebook Sessions
Conda environment — Installation and management of the Conda environment, add and delete of packages from the environment.	Oracle Autonomous Database	About the Conda Environment and Conda Interpreter
Change the default number of email recipients for job notifications.	Create Jobs in Oracle Machine Learning User Interface	Change the variable `oml.emails.maxRecipients` in the `oml.conf` file. By default, a user can send email notification to 3 email addresses.

> **Note:**
>
> The tasks listed here can be performed by an administrator only.

11.2 Access OML User Management from Command Line

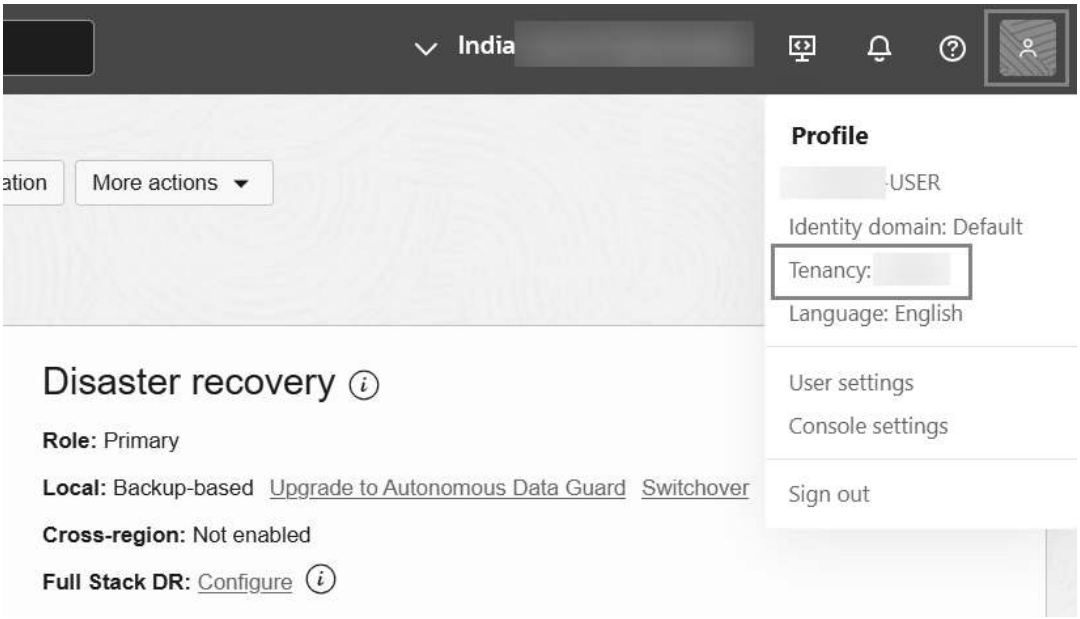
You can obtain the Oracle Machine Learning User Management URL for a specific tenancy from the Oracle Cloud Infrastructure (OCI) command line.

Prerequisite: Tenancy ID

To obtain the Oracle Machine Learning User Management URL for a specific tenancy from the OCI command line, you must first obtain the tenancy ID.

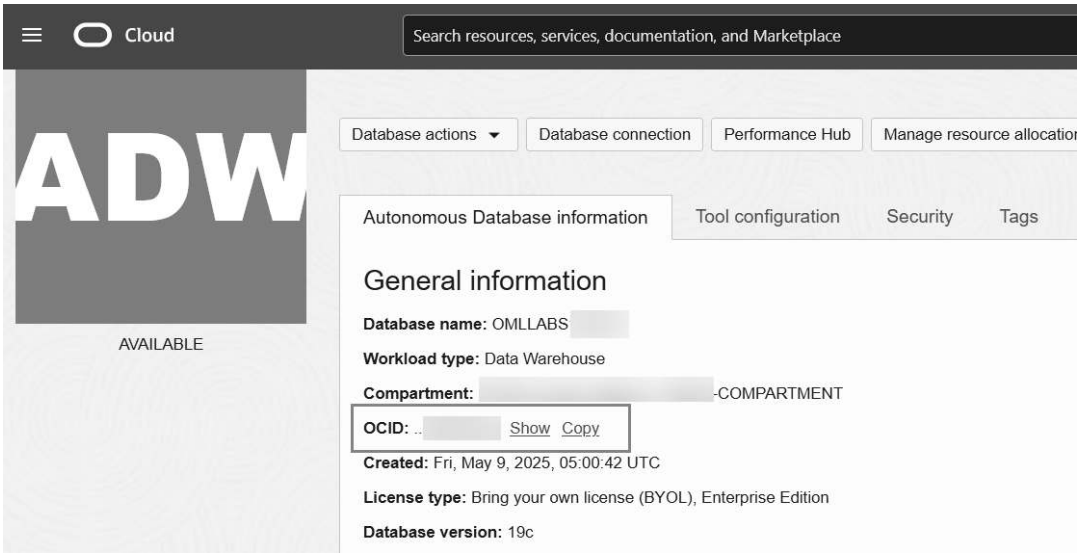
1. To obtain the tenancy ID, go to your OCI **Profile** on the top right corner of the Oracle Cloud page and click **Tenancy**.

Figure 11-3 Tenancy information in PCI Profile



2. On the Tenancy details page, click **Copy** to obtain the tenancy URL.

Figure 11-4 OCID



3. Type the following command in your OCI command line interface:

```
oci db database list  --compartment-id  <tenancy OCID>
```

Here,

- `compartment-id`: This is the unique ID assigned to your compartment.
- `OCID`: This is the Oracle Cloud Identifier (OCID) for your tenancy.

This command returns the following:

```
"connection-urls": {
        "apex-url": https://<tenancy ID>-<database
name>.<region>.oraclecloudapps.com/ords/apex,
        "graph-studio-url": https://<tenancy ID>-<database
name>.<region>.oraclecloudapps.com/graphstudio/,
        "machine-learning-user-management-url": https://<tenancy ID>-
<database name>.<region>-1.oraclecloudapps.com/omlusers/,
        "sql-dev-web-url": https://<tenancy ID>-<database
name>.<region>-1.oraclecloudapps.com/ords/sql-developer
      },
```

This completes the task of obtaining the Oracle Machine Learning User Management URL from OCI command line interface.

11.3 Manage OML Users and User Accounts

An administrator manages new user account and user credentials creation for Oracle Machine Learning.

Table 11-1 Administrative Tasks for OML Users and User Accounts

Tasks	Links
Create User Accounts for Oracle Machine Learning Components	Creating User Accounts for Oracle Machine Components
Create Users on Autonomous Database with Database Actions	Creating Users on Autonomous Database with Database Actions
Create Users on Autonomous Database - Connecting with a Client Tool	Creating Users with Autonomous Database with Client-Side Tools
Create Users on Autonomous Database	Create Users on Autonomous Database
Add Existing Database User Account to Oracle Machine Learning Components	Add Existing Database User Account to Oracle Machine Learning Components
Unlock User Accounts on Autonomous Database	Unlock User Accounts with Autonomous Database
About User Passwords on Autonomous Database	About User Passwords on Autonomous Database

- Add Existing Database User Account to Oracle Machine Learning Components
  As the ADMIN user you can add an existing database user account to provide access to Oracle Machine Learning components.

Related Topics

- Manage Users

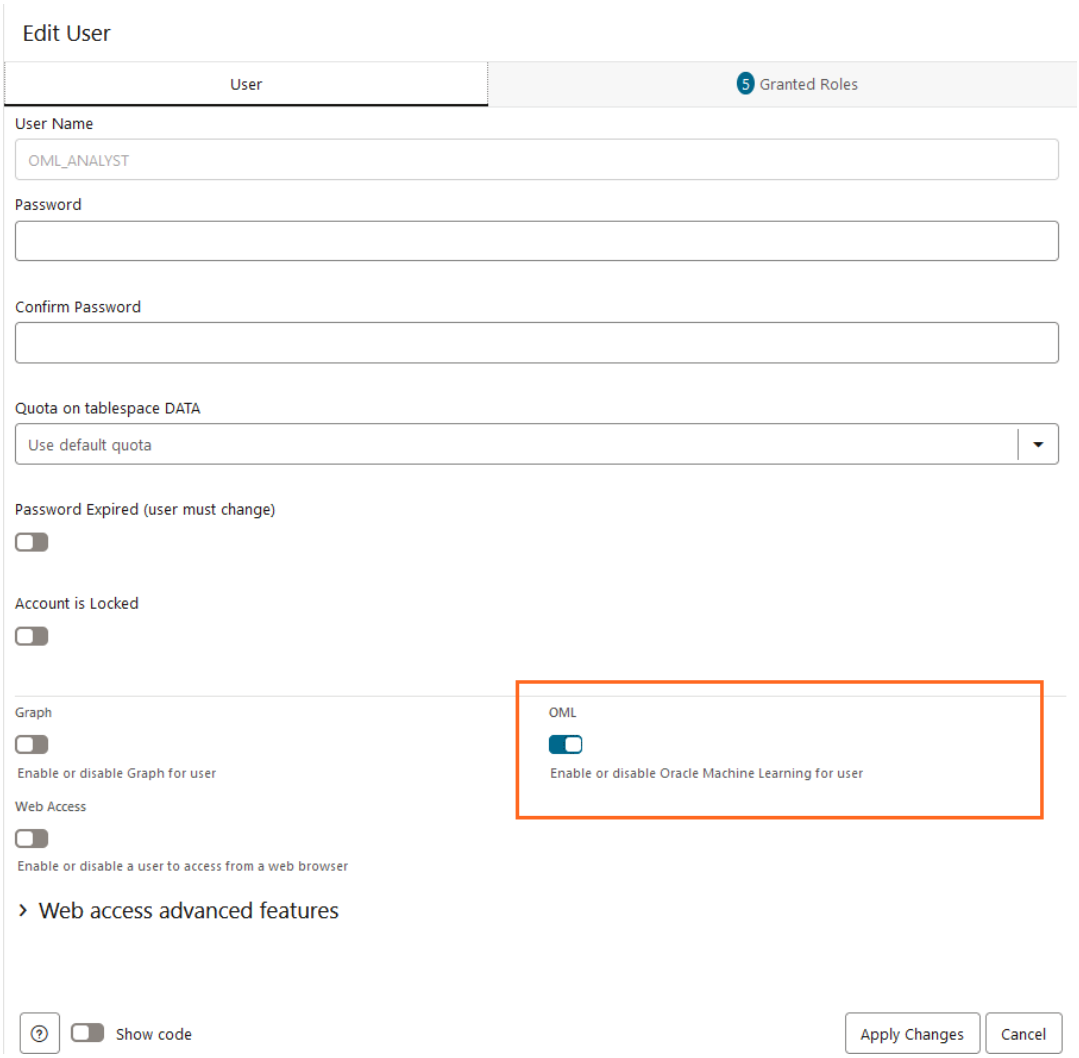
11.3.1 Add Existing Database User Account to Oracle Machine Learning Components

As the ADMIN user you can add an existing database user account to provide access to Oracle Machine Learning components.

To add an existing database user account:

1. On the Autonomous Databases page, under the **Display Name** column, select an Autonomous Database.
2. On the Autonomous Database Details page, select **Database Actions** and click **Database Users**.
3. In the All Users, search for the user of interest or select the user. For example, search the user **OML_ANALYST**.
4. In the user's card, click  and select **Edit**
5. In the Edit User panel, select **OML**.

   For example:



6. Click **Apply Changes**.

This grants the required privileges to use the Oracle Machine Learning application. In Oracle Machine Learning this user can then access any tables the user has privileges to access in the database.

11.4 About User Data

On the User Data page in Oracle Machine Learning, you can view existing user data, reassign, and delete it.

The User Data page lists details of the Oracle Machine Learning user such as the name, role, comments, last updated date. You can perform the following tasks:

- **Delete User Data:** To delete a user, select the user to delete and click **Delete User Data.**
- **Reassign:** To reassign workspace and templates from one user to another.
- Reassign
  The **Reassign** option allows you to reassign workspaces, along with templates, from one user to another.

11.4.1 Reassign

The **Reassign** option allows you to reassign workspaces, along with templates, from one user to another.

To reassign workspaces:

1. On the User Data page, select the user from whom you want to reassign workspace and click **Reassign.**

   The Reassign page opens.
2. In the **Target User** field, select the user to whom you want to reassign workspace.
3. Select **All Templates** if you want to reassign all the templates associated with the user selected in the User Data page.
4. Select:
   - **Reassign all workspaces:** To reassign all the workspaces associated with the selected user.
   - **Select workspaces to reassign:** To reassign particular workspaces associated with the selected user.
5. Click **Reassign.**

After the templates and workspaces are reassigned successfully, a notification message is displayed on the User Data page with the number of templates and workspaces reassigned.

11.5 About Compute Resource

The term Compute Resource refers to services such as a database, or any other backend service to which an interpreter connects.

> **Note:**
>
> You must have the Administrator role to access the Compute Resources page.

The Compute Resources page displays the list of compute resources along with the name of each resource, its type, comments, and last updated details. To view details of each Compute

Resource, click the Compute Resource name. The connection details are displayed on the **Oracle Resources** page.

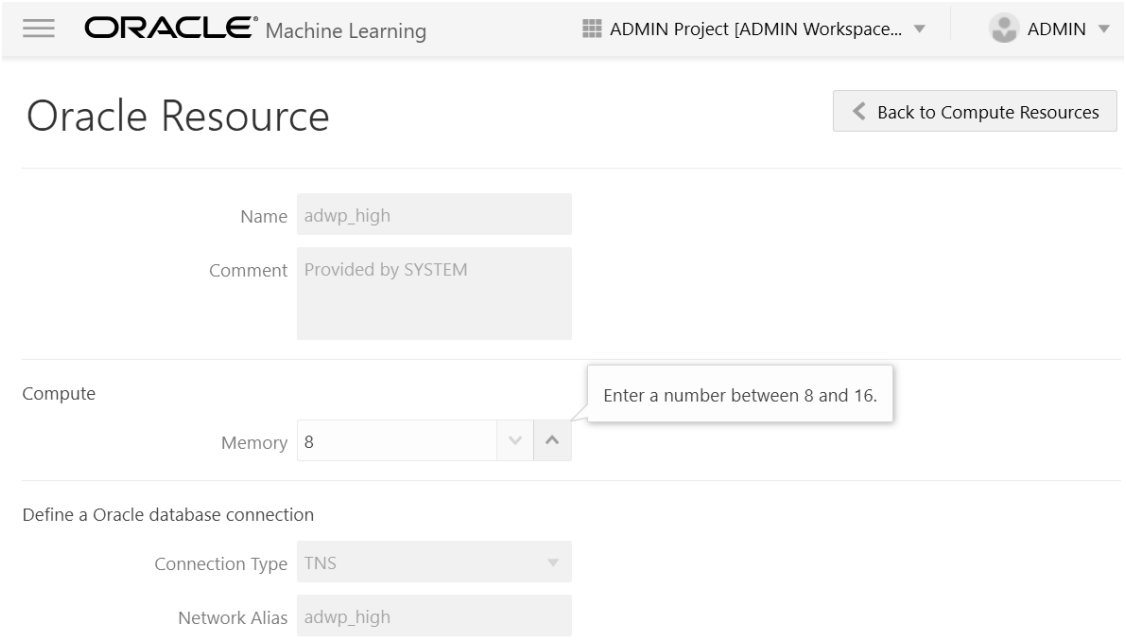
- Oracle Resource
  The Oracle Resource page displays the details of the selected compute resource on the Compute Resources page. You can configure the memory settings (in Gigabytes) for the Python interpreter for the selected compute resource.

11.5.1 Oracle Resource

The Oracle Resource page displays the details of the selected compute resource on the Compute Resources page. You can configure the memory settings (in Gigabytes) for the Python interpreter for the selected compute resource.

> **Note:**
>
> You must have Administrator privilege to configure the memory settings.

Figure 11-5 Oracle Resource



To manage memory settings for the interpreter:

1. **Name**—Displays the name of the selected resource.
2. **Comment**—Displays comment, if any.
3. **Memory**—You can configure memory settings (in Gigabytes) for the interpreter in this field. The interpreter supports Markdown, Python, SQL, Script, and R languages.
   - For the resource `databasename_gpu`, the memory settings (in Gigabytes) must be between 8 and 200. The memory setting for `gpu` configures the amount of host RAM that the interpreter container can use. The GPU VRAM is not configurable and the

container has access to all GPU memory available. For NVIDIA A10 Tensor Core GPUs, it is 24GB.

- For the resource `databasename_high`, the memory settings (in Gigabytes) must be between 8 and 96.
- For the resource `databasename_medium`, the memory settings (in Gigabytes) must be between 4 and 8.
- For the resource `databasename_low`, the memory settings (in Gigabytes) must be between 2 and 4.

> **Note:**
>
> The Memory setting is applicable only for the Python interpreter.

4. **Connection Type**—Displays the database connection of the resource.
5. **Network Alias**—Displays the alias of the network connection.

- Resource Services and Notebooks
  This topic lists the number of notebooks that you can run concurrently per Autonomous Database instance for each Resource service.

11.5.1.1 Resource Services and Notebooks

This topic lists the number of notebooks that you can run concurrently per Autonomous Database instance for each Resource service.

The Resource Services and Number of Notebooks table lists the Compute Resources assigned for running at different Resource Service levels - GPU, High, Medium and Low. The GPU compute capability applies only to the Python interpreter.

Table 11-2 Resource Services and Number of Notebooks

Resource Service	OCPUs (Oracle CPUs), ECPUs and GPUs	Memory	Number of Concurrent Notebooks, UDFs
GPU	1 NVIDIA A10 Tensor Core **Note:** The GPU setting includes a HIGH setting with	8 GB (DDR4), by default. Extensible up to 200 GB	The number of concurrent notebooks you can run is determined by: • The GPU resources of the region where your ADB instance is deployed, and • The number of GPU resources available at the time you run the notebooks If GPU resources are not available when requested, you will receive an error message. You should try again later. **Note:** GPU resources are available only on paid Oracle Autonomous Database Serverless. GPU resources are not available if less than 16 ECPUs are allocated for OML.

Table 11-2 (Cont.) Resource Services and Number of Notebooks

Resource Service	OCPUs (Oracle CPUs), ECPUs and GPUs	Memory	Number of Concurrent Notebooks, UDFs
	edatabaseserverside.		
High	Up to 8 OCPUs	8 GB (up to 16 GB)	Up to 3
Medium	Up to 4 (OCPUs)	4 GB (up to 8 GB)	Up to max (1.25 × number of OCPUs)
Low	1	2 GB (up to 4 GB)	Up to 100

Note:

The number of current notebooks run is calculated by the formula `1.25 x (number of OCPUs)` provisioned for the corresponding Autonomous Database instance. OCPU stands for Oracle CPU.
For example, if a database is provisioned with 4 OCPUs, then the maximum number of notebooks run would be 5 (1.25 x 4) in Medium level.

Table 11-2 (Cont.) Resource Services and Number of Notebooks

Resource Service	OCPUs (Oracle CPUs), ECPUs and GPUs	Memory	Number of Concurrent Notebooks, UDFs
TP This service is available for Oracle Autonomous Transaction Processing (ATP) database.	User specified	2 GB	Up to 60
TPURGENT This service is available for Oracle Autonomous Transaction Processing (ATP) database.	User specified	2 GB.	Up to 60

Table 11-2 (Cont.) Resource Services and Number of Notebooks

Resource Service	OCPUs (Oracle CPUs), ECPUs and GPUs	Memory	Number of Concurrent Notebooks, UDFs
ECPU setting. OML apps on ADB-Serverless have ECPU specifications separate from the database.	User specified	• Low — 2GB • Medium — 4GB • High — 8GB • GPU — 8GB (default). Can be extended upto 200 GB by the Admin. This allocation is based on the assumption that one VM is allocated for the PDB.	All processes share the CPU resources. Running of UDFs is situation-specific. • If you are performing data processing at the compute level, you may require more memory depending on your data size. **Note:** The Admin can allocate more memory in Oracle Resource. • If Low resource level is sufficient, you may be able to run approximately 60 UDFs concurrently. • If High resource level is required, you may be able to run approximately 16 UDFs concurrently.

For more information on Database service and concurrency, see Database Service Names for Autonomous Database

11.6 Get Started with Connection Groups

A connection group, also known as a Zeppelin interpreter set, is a collection of database connections.

- About Connection Groups
  On the Connection Group page, a user with Administrator role can manage your connections that constitute the connection group.
- About Global Connection Group
  The Global Connection Group is created automatically when a new database is provisioned.
- Edit Oracle Database Interpreter Connection
  When defining an Oracle Database interpreter connection, a reference to a compute resource is created. This reference contains all connection-related information about the interpreter.

11.6.1 About Connection Groups

On the Connection Group page, a user with Administrator role can manage your connections that constitute the connection group.

You can **Edit,** and **Stop** one or more connections that are listed under a connection group on this page.

> **Note:**
>
> Only an Administrator user can manage connection groups.

The following information about the connections are available:

- **Name:** This is the name of the interpreter.
- **Default:** A check mark indicates whether the connection is the default connection or not.
- **Scope:** Indicates the scope of the connection.
- **Comment:** Displays any comment related to the interpreter.
- **Owner:** Displays the name of the user who created the connection.
- **Last Updated:** Indicates the date and time when the connection was last updated.

You can perform the following tasks:

- **Edit:** To edit the interpreter connection, select the connection and click **Edit.**
- **Stop:** To stop the interpreter connection, select the connection and click **Stop.**
- **Refresh:** Click the **Refresh** button in the following conditions:
  - If you rename the Pluggable Database (PDB).
  - If you do a Wallet rotation. Wallet rotation invalidates the current wallet. Hence, a new Wallet is needed for the database connection.

11.6.2 About Global Connection Group

The Global Connection Group is created automatically when a new database is provisioned.

The Global Connection Group comprises the following:

- Compute Resource definition — A Compute Resource is associated with the Pluggable Database (PDB). After a new PDB is provisioned, a Compute Resource is added for the PDB. A tenant may provision more than one PDB, and for each PDB a Compute Resource

is added. The settings in the Compute Resource are relevant to its own PDB. The Compute Resource is associated to an Oracle Wallet. The Oracle wallet contains the credentials to connect to the user PDB.

> **Note:**
>
> The Compute Resource definition can be edited by the Administrator only.

- Connection Group definition — The Global Connection Group comprises a single connection of type `Global`. Only one Global Connection Group for each Compute Resource is allowed per PDB. No password is required for this connection as it uses the Wallet containing the credentials for the PDB. The Wallet is associated to the Compute Resource.

> **Note:**
>
> A Global Connection Group can be edited by the Administrator only.

Reset: To reset the interpreter connection, click the connection group name. The connection group opens on a separate page, listing all the interpreter connections in the group. Select the connection you want to reset and click **Reset.** When you click **Reset,** then all connections supported by the interpreter are closed, and all notebooks using that connection are cancelled.

> **Note:**
>
> The **Reset** option is available only to the Administrator.

11.6.3 Edit Oracle Database Interpreter Connection

When defining an Oracle Database interpreter connection, a reference to a compute resource is created. This reference contains all connection-related information about the interpreter.

Compute Resources for an Oracle Database interpreter is defined by your service. You can edit the following:

> **Note:**
>
> You must have the Administrator role to edit these fields.

1. **Name:** You can edit the name of the interpreter editor here. This is useful if you have several definitions of the same interpreter type in the same interpreter set. By specifying a name, you can turn on or turn off the specific binding to a notebook.
2. **Type:** This is a non-editable field. It indicates the connection type
3. **Binding Mode:** This is a non-editable field. It defines the behavior of the interpreter instance in memory, and how the resources are shared. By default, the Binding Mode of the Global Connection Group is set to Scoped. It ensures that each notebook creates a new interpreter instance in the same interpreter process.

4. **Row Render Limit:** This determines the number of rows to be displayed in the paragraph results when fetching a data structure that can be presented as a table or graph using the Zeppelin built-in plotting service. You must consider the browser capabilities when modifying this setting. The default limit is `1000`.

   > **Note:**
   >
   > Zeppelin plotting service works with data that is fetched previously to the client-side for a snapper UI.

5. **Comments:** Enter any information related to the interpreter not exceeding `1000` characters.

   > **Note:**
   >
   > You must have Administrator role to edit this field.

6. In the Compute Resource section, the **Resources** field indicates the priority of the compute resource. This is a non-editable field.

7. In the Database section, you can specify additional settings related to PL/SQL DBMS output. Select **Enabled** to allow the PL/SQL interpreter to display the messages sent to the DBMS_OUTPUT in the paragraph results.

8. Click **Save.**

11.7 Get Started with Notebook Sessions

The Notebook Sessions page provides you an overview of your notebooks, and allows you to manage notebook sessions from your workspace or in workspaces where you have collaboration rights.

On the Notebook Sessions page, you unload and cancel notebook sessions. You can perform the following tasks:

- **Stop:** Select the notebook that is running, and click **Stop.** This stops the selected notebook in the server.
- **Unload:** Select the notebook that is loaded, and click **Unload.** This removes the selected notebook from memory on the server.

The Notebook Sessions page displays the following information about your notebooks:

- Notebook: The name of the notebook.
- Project: The project in which the notebook resides.
- Workspace: The workspace in which the project is available.
- Connection: The connection name.
- Owner: The owner of the notebook.
- Status: The statuses of a notebook are:
  - **Loaded:** Indicates that the notebook is loaded but not tied to the websocket or running.
  - **Active:** Indicates that the notebook is tied to the websocket but is not running.

- **Running:** Indicates that the notebook paragraph is queued to run or is running.