



Sensible Machine Learning Guide

PV 840 SV340

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Overview

Sensible Machine Learning lets businesses build, manage, and deploy highly accurate time-series forecast models that power downstream planning processes. With Sensible Machine Learning you can perform tasks such as:

- Create thousands of daily or weekly demand planning in forecasts across products and locations.
- Capture business intuition such as promotions, events and external factors in forecasts.
- Unify and align demand plans with driver-based sales, material costs, inventory, and labor plans across Profit and Loss, Balance Sheet and Cash Flow.
- Manage the data quality and pipelines required for modeling.
- Monitor model health and performance over time.
- Increase budget, plan and forecast confidence using drill-back and testing capabilities.

Setup and Installation

This section contains important details related to the planning, configuring, and installation of your solution. Before you install the solution, familiarize yourself with these details.

See also: [MarketPlace Solution Modification Considerations](#)

Dependencies

Component	Description
OneStream 8.2.2 or later	Minimum OneStream Platform version required to install this version of Sensible Machine Learning.
Xperiflow Business Rules V140 (XBR)	External API client library to allow SML to interface with the Xperiflow Engine. The required version of XBR is packaged with all SML versions.

Set Up Sensible Machine Learning

Setting up Sensible Machine Learning is a multi-step process. You must complete a separate contract outside of the standard OneStream application environment. Contact your OneStream account representative before proceeding with the next steps.

1. Enter a support ticket to have Sensible Machine Learning installed in your OneStream environment.
2. After the OneStream support team ensures that the proper contract is in place, they send a link to download the Sensible Machine Learning solution and a meeting request to complete the setup.
3. The OneStream support team installs the Sensible Machine Learning data science engine in your OneStream environment and then walks you through the process of installing the Sensible Machine Learning solution.

Setup and Installation

4. After both components are installed, the OneStream support team helps you test that Sensible Machine Learning is set up correctly and functioning properly.

NOTE: Upon completion of the initial onboarding and set up process, additional upgrades and releases can be found on the OneStream Solution Exchange. Limited availability to OneStream environments enabled with AI Services.

Settings

To access the global options page, click **Settings**  on the bottom of the side navigation bar.

NOTE: Only power users can open the **Settings** page.

Global options include:

- [Solution Information](#)
- [Engine Information](#)
- [Global Settings](#)
- [Thresholds](#)
- [Solution Setup](#)
- [Uninstall](#)

Solution Information

Provides the following information for the Sensible Machine Learning solution:

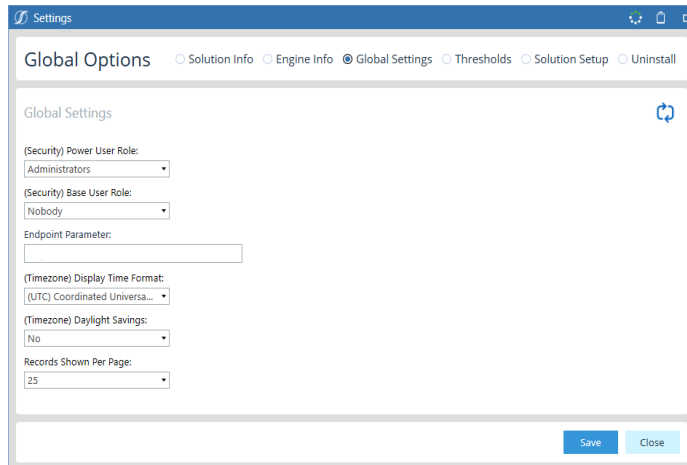
- Solution version
- Installed engine version
- Base engine version

Engine Information

Provides the following information about the Xperiflow Engine:

- **Engine Configurations** show current limits set on the Xperiflow Engine

Global Settings



(Security) Power User Role: Select users who can build and deploy models and access the global settings content. Default is Administrators.

(Security) Base User Role: Select users for this role. Default is Administrators. These users can look at models already created.

Endpoint Parameter: Predefined endpoint to access application. Do not make changes to this value unless instructed to do so.

(Timezone) Display Time Format: The time zone of the times shown in Sensible Machine Learning. The Display Time Format does not modify times for or relating to source and predicted data.

NOTE: This time is not the time that is used for entries in the various log files.

(Timezone) Daylight Savings: Indicates whether the selected time zone includes daylight saving time.

Records Show Per Page: Default amount of records shown in grids that are paged throughout SML.

Thresholds

Provides the following information about the configured Build and Model Thresholds:

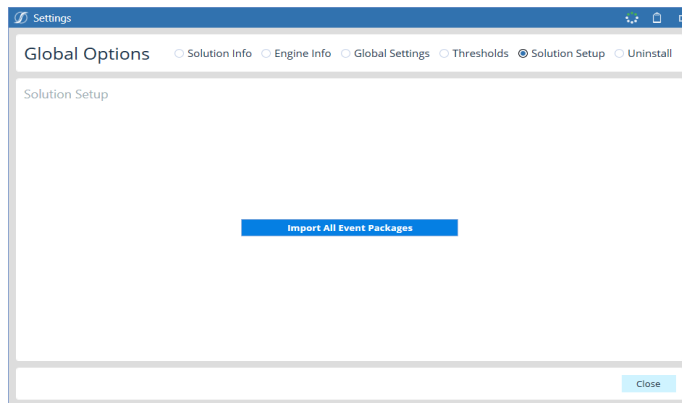
Settings

- **Project Thresholds** allow the user to pick a project and see the required thresholds for Feature Selection, Generation, Transformation, Grouping, and Models.
- **Default Thresholds** allow the user to configure the default required thresholds that will be used within all projects for Feature Selection, Generation, Transformation, Grouping, and Models.

Solution Setup

Import All Event Packages: Import the predefined event and location packages. See [Configure Library - Events](#).

When you upgrade releases of Sensible Machine Learning, you can re-import the predefined event packages. When this happens, Solution Setup in the Settings displays the following:



Click **Import All Event Packages** to run the job to re-import the Sensible Machine Learning event packages.

Uninstall

You can uninstall the Sensible Machine Learning User Interface or the entire solution. If performed as part of an upgrade, any modifications performed on standard Sensible Machine Learning objects are removed. There are two uninstall options:

- **Uninstall UI** removes Sensible Machine Learning, including related dashboards and business rules but leaves the database and related tables in place.

Settings

Choose this option if you want to accept a Sensible Machine Learning update without removing data tables.

The Sensible Machine Learning Release Notes indicate if an over install is supported.

- **Uninstall Full** removes all related data tables, data, Sensible Machine Learning Dashboards, and Business Rules.

Choose this option to completely remove Sensible Machine Learning or to perform an upgrade that is so significant in its changes to the data tables that this method is required.

NOTE: Neither an Uninstall UI or Uninstall Full removes your Sensible Machine learning projects. Uninstall Full only removes the stored Global Settings (Endpoint, Security, Time Format). Projects are not lost during either Uninstall.

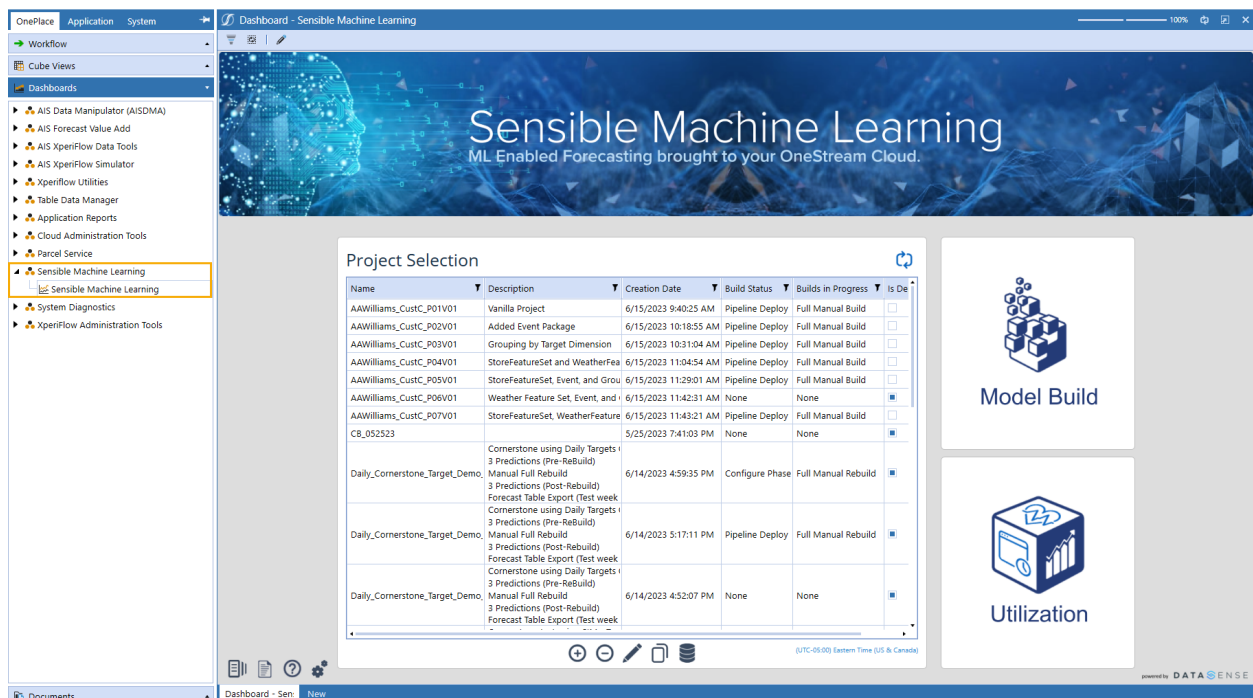
CAUTION: Uninstall procedures are irreversible.

Navigate in Sensible Machine Learning

The following sections describe the different ways to navigate in Sensible Machine Learning.











Sensible Machine Learning Home Page

The Home page displays when you click on the Sensible Machine Learning dashboard in OnePlace. This is the starting point to creating and managing your Sensible Machine Learning projects.



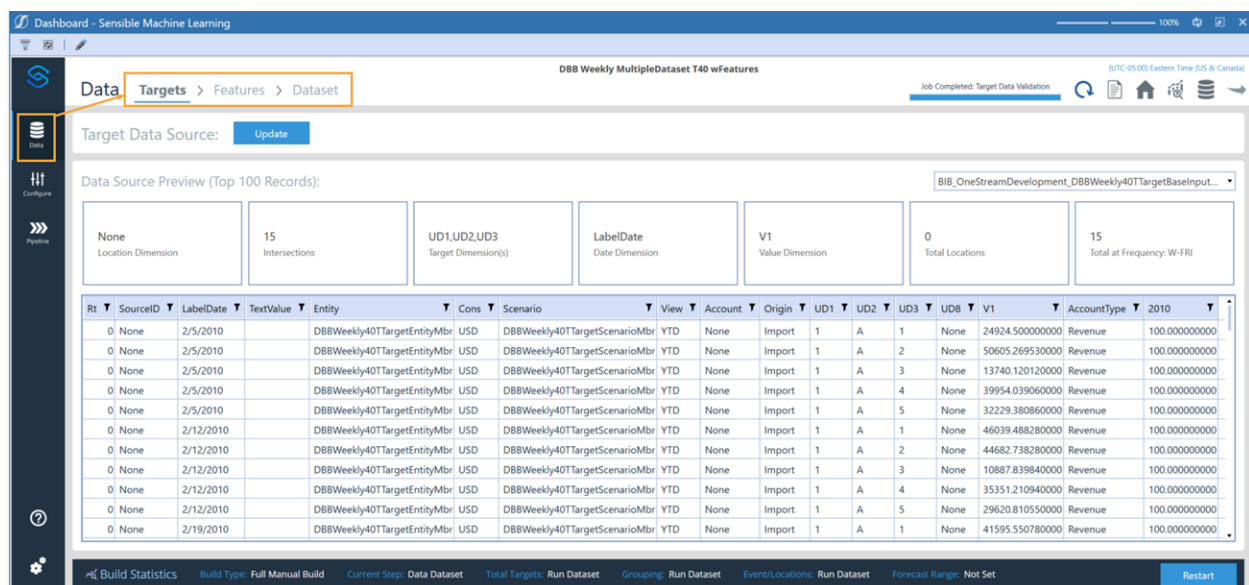
Use the Home page to:

Navigate in Sensible Machine Learning

- View project and build status. See [Create a Model Build Project](#).
- Add , delete , update , and copy  projects, and refresh  the list of available projects.
- Update your data source  for existing projects. See [Update a Target or Feature Data Source](#).
- Manage existing projects through the Model Build and Utilization phases. See [Model Build Phase](#) and [Utilization Phase](#).
- View and extract System Logging Tables . See [View System Logging Tables](#).
- View the AI Services log . See [View AI Services Activity](#).
- Access this User Guide .
- Configure global settings . See [Settings](#).

Navigate Sensible Machine Learning Pages

When you are in Model Build or Utilization, the left side navigation includes different sections and the top left navigation shows the pages available in the selected section.



The screenshot shows the 'Dashboard - Sensible Machine Learning' interface. The top navigation bar includes 'Data', 'Targets', 'Features', and 'Dataset'. The 'Data' section is active, showing a 'Target Data Source' and a 'Data Source Preview (Top 100 Records)'. The preview includes a table with columns: Rt, SourceID, LabelDate, TextValue, Entity, Cons, Scenario, View, Account, Origin, UD1, UD2, UD3, UD8, V1, AccountType, and 2010. The table contains 10 rows of data.

Rt	SourceID	LabelDate	TextValue	Entity	Cons	Scenario	View	Account	Origin	UD1	UD2	UD3	UD8	V1	AccountType	2010
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	1	None	24924.500000000	Revenue	100.000000000
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	2	None	50605.269530000	Revenue	100.000000000
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	3	None	13740.120120000	Revenue	100.000000000
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	4	None	39954.039060000	Revenue	100.000000000
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	5	None	32229.380860000	Revenue	100.000000000
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	1	None	46039.488280000	Revenue	100.000000000
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	2	None	44682.738280000	Revenue	100.000000000
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	3	None	10887.839840000	Revenue	100.000000000
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	4	None	35351.210940000	Revenue	100.000000000
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	5	None	29620.810550000	Revenue	100.000000000
0	None	2/19/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None	Import	1	A	1	None	41595.550780000	Revenue	100.000000000

Toolbar Icons

Each page in the Model Build and Utilization phases includes a set of buttons at the top right of the page that provide additional navigation, project update, settings, or analysis functions.

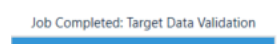










Icon	Description
	Shows status of most recently started non-queued or scheduled job for the current SML project. Click to see additional execution details of the current job in the Job Progress dialog box. See View Job Progress .
 Refresh	Refresh and update the current Sensible Machine Learning page.
 AI Services Log	Opens the AI Services log where you can review job errors, job activity, and tasks that have run or are currently running for specific jobs. See View AI Services Activity .
 Home	Navigate to the project Home page.
 Explore Targets and Features	View and run exploratory data to analyze each target and feature in the data set. Only available in the Model Build phase after completing the Dataset step of the Model Build. See Explore Target and Feature Data .
 Show Data Update	Opens a page where you can update target and feature data sets. This is only available after completing the Dataset step of the Model Build. See Update a Target or Feature Data Source .
 Consumption Groups	Opens the Consumption Groups Dialog box, which lets you create, delete, and export consumption groups. Only available after completing the Dataset step of the Model Build. See Manage Consumption Groups .

Chart and Table Toolbar Buttons

Charts and tables in the Model Build and Utilization phases include toolbar buttons for inspecting and exporting data and maximizing and minimizing the table or chart.

Icon	Description
 Inspect	Drills into the data to view it in aggregated or raw form. All data inspect windows provide a Print Preview option from which you can save or print the data.

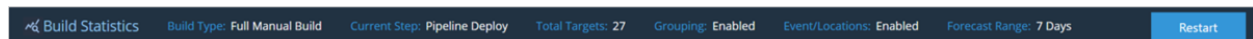
Icon	Description
 Export to	Exports data in the chart or table to Print Preview, PDF, Image, or Excel
 Maximize	Maximizes the chart or table in the workspace.
 Minimize	Minimizes the chart or table.

Review Build Statistics and Restart a Project Build

Build Statistics display at the bottom of each Sensible Machine Learning page and provide the project status and other details specific to the current page.

Model Build Phase Build Statistics

Build statistics provide you with a quick summary of information about the model in the Model Build phase.



The Build Statistics in the Model Build phase include:

Build Type: The type of build, such as Full Manual Build.

Current Step: The project build's current model build section, such as Configure Phase.

Total Targets: Total number of targets for the current project build.

Grouping: Indicates if grouping is being used in the project build.

Event/Locations: Indicates if events and locations can be used in the project build.

Forecast Range: The number of days, weeks or months to forecast forward. The default is seven days, or three months, or four weeks. Changes made on the [Forecast page](#) in the Model Build section are reflected here.

Restart a Project Build

You can restart a Sensible Machine Learning project using the **Build Statistics** pane. You should only restart a project if a mistake is made during the Model Build phase that would require too much effort to fix or to create another project.

When running a restart, you can redo these model building steps:

- Change the data sets used for the modeling project.
- Modify target and feature data set configurations, and groupings.
- Add new locations and events or reconfigure existing location and event data, reinstall event packages.
- Remap events and locations to targets.
- Reset the project's forecast range.
- Rerun a pipeline.

IMPORTANT: A restart project job cannot be canceled once it starts.

To restart a project build for the current project:

1. Click **Restart** in the **Build Statistics** pane.
2. In the **Restart** dialog box, select a restart option:

Restart: This reverts the project back to the Data section of the Model Build phase, prior to the **Dataset** page.

Restart Job: Lets you begin a job based on a specified checkpoint in the project. Select the job from the list, then enter the ID of the selected job in the text box that displays. Selecting this option navigates you to the **Home** page

NOTE: Restarting using the Restart Job option can cause a loss of data such as predictions and configurations collected after the specified checkpoint.

3. Click **Confirm** to begin the restart job, then click **OK** in the message box that displays to close the **Restart** dialog box. For the **Restart Job** option, this navigates you to the **Home** page. For the **Restart** job option, this navigates you to the Data section, prior to the **Dataset** page.

Delete a Project Build

You can delete a project build using the **Build Statistics** pane. This functionality is available if the build is a rebuild. You should only delete a project build if a mistake has been made or if the rebuild is no longer required.

NOTE: This only deletes the project build that is being rebuilt. The project's deployed builds and the project itself are not deleted.

To delete a project build:

1. Click **Restart** in the **Build Statistics** pane.
2. In the **Restart** dialog box, select **Delete** as the option.
3. Click **Confirm**.

Sensible Machine Learning deletes the project and returns to the **Home** page.

Restart a Job

You can also restart a job from a Job Checkpoint using the **Build Statistics** pane. This lets you select a recent checkpoint of a job (such as Data, Configuration, Pipeline, or Auto-Rebuild) and revert to that point in the model build.

IMPORTANT: This capability is an advanced feature and should be used only under known circumstances. Restarting a Job can result in the loss of historic job information including but not limited to task, job, and prediction information and records. For this reason, this functionality should be reserved for known circumstances.

To restart a job:

1. Click **Restart** in the Build Statistics pane.
2. Select **Restart Job** as the restart option.

3. Select the job checkpoint you would like to restart. Click **Confirm**.

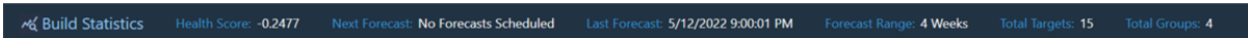
The full project now has the exact settings, configurations, and statuses that were present at the time of the selected checkpoint.

NOTE: You are not able to re-enter the project in either Model Build or Utilization until the restart job is complete. The Restart job cannot be reverted or canceled.

IMPORTANT: Once the job has been reverted, all previously available checkpoints no longer exist.

Utilization Phase Build Statistics

Build statistics provide you with a quick summary of information about the model in Utilization phase.



The Build Statistics in the Utilization phase include:

Health Score: Ranges from -1 to 1 indicating improvement or degradation in the model's predictive accuracy. The Health Score shows the change of Evaluation Metric Scores with each new prediction run, averaged.

Next Forecast: Date and time of next forecast. If no forecasts are scheduled, this shows **No Forecasts Scheduled**.

Last Forecast: Date and time of the last forecast.

Forecast Range: The number of days, weeks or months to forecast forward.

Total Targets: Total number of targets.

Total Groups: Total number of groups.

Sort Data in Tables

Tables for targets and features may contain a lot of entries. You can filter the displayed entries by changing the sort options and series type. You can also move through specific pages to locate entries.

Data Elements

The screenshot shows a 'Data Elements' section with a list of categories: [Categories]Call, [Categories]Pints, [Categories]Appetizers, [Categories]Entrees, [Categories]Specials, [Categories]Tallboys, [Categories]Sandwiches, [Categories]Specialty_Cocktails, and [Categories]Bottled_Beer. Below the list is a 'Filter' button. To the right is a configuration panel with the following settings: Sort Option: Summation (dropdown), DESC (dropdown); Series Type: Targets (dropdown); Data Type: Numeric (dropdown); (+) Filter: Name (dropdown); Filter Type: Contains (dropdown); Input Text Box: Burger; Page Number: 1 of 3 (with navigation arrows and a search icon).

TIP: Sort options are specific to the current page. The sort options displayed in the previous graphic are an example from the [Data Explore](#) page.

Sort Option: Sort by specific column in ascending (ASC) or descending (DESC) order.

Series Type: Options are targets or source features. Only available on the [Data Explore](#) page.

Data Type: Numeric. Only available on the [Data Explore](#) page.

(+) Filter: Optional. Use to filter results based on a specific column.

Filter Type: Available if **Filter** is selected. Method of filtering (equals, not equals, or contains).

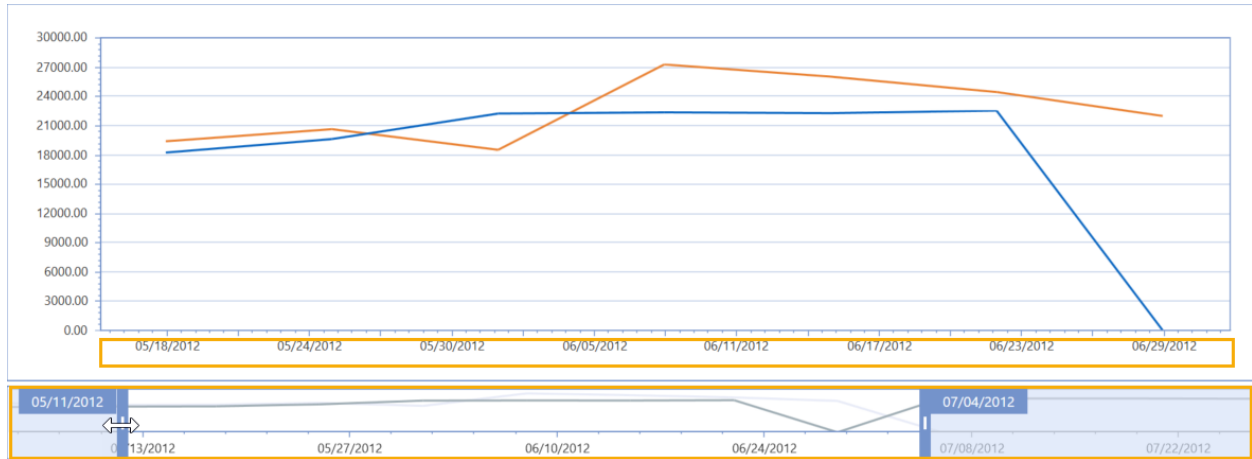
Input Text Box: Available if **Filter** is selected. Select the value to apply for the filter type.

Page Number: Click a page number to go to that page.

Date Range Sliders for Line Charts

Line charts provide a date range slider that lets you drag and drop to adjust the start and end dates for the content visualized in the chart.

Navigate in Sensible Machine Learning




View AI Services Activity

The AI Services Activity Log provides critical insight into:

- Job traffic and activity.
- All tasks run for a job.
- The completion status of all Sensible Machine Learning jobs.
- Why a job may not have completed successfully.

You can review this information at any time in the project creation process or during model build or utilization phases.

Access the Activity Logs

To open the **AI Services Log**, click  at the top of any Sensible Machine Learning page. This button is also available on the Sensible Machine Learning [Home page](#).

The log displays the job activity and error log for Sensible Machine Learning. You can order, sort, and filter records for both views. To filter the logs, select a search type from the drop-down menu. After selecting a search type, a Search Method and Filter Value display for both jobs and tasks. Edit the Search method if needed and input a filter value. Click **Filter** once these settings have been selected. Select a job and click **Progress** to see the selected job's progress in the [Job Progress dialog box](#), which shows the job's current activity status.

View AI Services Activity

AI Services Log

AI Services Activity Log Job Activity Error Log

Job Activity Table

Drag a column header and drop it here to group by that column

Job Activity ID	Activity Type	Activity Status	Percent Complete	Creation Time	Queued Time	Start Time	End Time	Last Activity Time	Is Scheduled	Project Name	App Name
07580EE1-67EC-77DB-0657-B100311A6550	Pipeline	completed	1	6/19/2023 10:19:19 AM	6/19/2023 10:19:19 AM	6/19/2023 10:19:20 AM	6/19/2023 10:43:04 AM	6/19/2023 10:43:04 AM	<input type="checkbox"/>	DH_SpecialCharactersTest_06152023	SML
A9438873-665E-B635-00F6-9320311688F2	Pipeline	completed	1	6/13/2023 11:15:14 AM	6/19/2023 10:21:22 AM	6/19/2023 10:25:14 AM	6/19/2023 10:28:27 AM	6/19/2023 10:28:27 AM	<input type="checkbox"/>	DH_TB01_Order Column Name Combo_06062023	SML
1E6E4F8-FC06-5338-0653-01C0311A6480	Restore	completed	1	6/19/2023 10:13:51 AM	6/19/2023 10:13:51 AM	6/19/2023 10:13:52 AM	6/19/2023 10:25:13 AM	6/19/2023 10:25:13 AM	<input type="checkbox"/>	DH_TB01_Order Column Name Combo_06062023	SML
51D023A0-037E-A885-00FD-3860311A648A	DataLoad	completed	1	6/19/2023 10:14:11 AM	6/19/2023 10:14:11 AM	6/19/2023 10:14:12 AM	6/19/2023 10:25:13 AM	6/19/2023 10:25:13 AM	<input type="checkbox"/>	DH_SpecialCharactersTest_06152023	SML
02DA0DD7-7083-1490-075A-7740311A646A	TargetDataValidation	completed	1	6/19/2023 10:11:28 AM	6/19/2023 10:11:28 AM	6/19/2023 10:11:30 AM	6/19/2023 10:11:48 AM	6/19/2023 10:11:48 AM	<input type="checkbox"/>	DH_SpecialCharactersTest_06152023	SML
35F15C54-56DC-8485-0393-F460311A0928	ProjectDeletion	completed	1	6/18/2023 8:54:02 PM	6/18/2023 8:54:02 PM	6/18/2023 8:54:03 PM	6/18/2023 8:54:22 PM	6/18/2023 8:54:22 PM	<input type="checkbox"/>	<Deleted Project>	None
3C6928C1-7E0E-EC6D-0517-78C0311A0764	ProjectCreation	completed	1	6/18/2023 8:38:37 PM	6/18/2023 8:38:37 PM	6/18/2023 8:38:38 PM	6/18/2023 8:41:21 PM	6/18/2023 8:41:21 PM	<input type="checkbox"/>	<Deleted Project>	SML
DABC742D-A4CF-F9EB-00AA-EDC0311888E8	ModelForecastExport	completed	1	6/16/2023 12:56:32 PM	6/16/2023 12:56:32 PM	6/16/2023 12:56:32 PM	6/16/2023 12:57:19 PM	6/16/2023 12:57:19 PM	<input type="checkbox"/>	SR_CustC_P04V01	SML
2F98D838-167B-3338-0209-464031188376	Prediction	completed	1	6/16/2023 12:08:49 PM	6/16/2023 12:08:49 PM	6/16/2023 12:08:49 PM	6/16/2023 12:15:59 PM	6/16/2023 12:15:59 PM	<input type="checkbox"/>	DH_OverlappingDates_Predictions_06162023	SML
38D373DB-8CBB-F5C6-0236-F18031188345	DataSourceUpdate	completed	1	6/16/2023 12:07:09 PM	6/16/2023 12:07:09 PM	6/16/2023 12:07:10 PM	6/16/2023 12:07:58 PM	6/16/2023 12:07:58 PM	<input type="checkbox"/>	DH_OverlappingDates_Predictions_06162023	SML
57C1F1D5-A60A-0371-032A-887031188376	Dwellition	error	0	6/16/2023 12:03:58 PM	6/16/2023 12:03:58 PM	6/16/2023 12:04:00 PM	6/16/2023 12:04:07 PM	6/16/2023 12:04:07 PM	<input type="checkbox"/>	DH_OverlappingDates_Predictions_06162023	SML

1 of 40 | Search Type: None | Status: [queued, running, r...] | Projects: All | Order By: Last Activity Time | DESC | Filter | Progress

Tasks for Job: 07580EE1-67EC-77DB-0657-B100311A6550

Drag a column header and drop it here to group by that column

Task Activity ID	Task Type	Activity Status	Percent Complete	Queued Time	Start Time	End Time	Last Activity Time	Task Execution Type	Task Level	Task Order	Task Path
6475A26D-E8EC-0882-074E-6580311A6553	ExportOrchestrator	completed	1	6/19/2023 10:19:25 AM	6/19/2023 10:43:00 AM	6/19/2023 10:43:00 AM	6/19/2023 10:43:02 AM	parallel	1	7	PipelineOrchestrator.ExportOrchestrator
2F172701-4256-E855-06C3-14A0311A6553	PipelineOrchestrator	completed	1	6/19/2023 10:19:25 AM	6/19/2023 10:19:25 AM	6/19/2023 10:43:02 AM	6/19/2023 10:43:02 AM	sequential	0	0	PipelineOrchestrator
DF3886C0-F849-631F-074E-9360311A6553	PostPipelineCheckpoint	completed	1	6/19/2023 10:19:25 AM	6/19/2023 10:39:58 AM	6/19/2023 10:42:59 AM	6/19/2023 10:43:00 AM	atomic	1	6	PipelineOrchestrator.PostPipelineCheckpoint
22138A60-3780-8B55-074E-07C0311A6553	PipelineStatsOrchestrator	completed	1	6/19/2023 10:19:25 AM	6/19/2023 10:36:15 AM	6/19/2023 10:39:54 AM	6/19/2023 10:39:54 AM	parallel	1	5	PipelineOrchestrator.PipelineStatsOrchestrator
125F128-87C9-33A5-0298-F320311A6741	FeatureImpact	completed	1	6/19/2023 10:36:16 AM	6/19/2023 10:36:25 AM	6/19/2023 10:39:52 AM	6/19/2023 10:39:54 AM	atomic	2	24	PipelineOrchestrator.PipelineStatsOrchestrator.Fe...
933F8349-8DBA-E275-01AE-2E80311A6741	FeatureImpact	completed	1	6/19/2023 10:36:16 AM	6/19/2023 10:36:25 AM	6/19/2023 10:39:44 AM	6/19/2023 10:39:46 AM	atomic	2	14	PipelineOrchestrator.PipelineStatsOrchestrator.Fe...
0E9E984-F590-31A3-0228-2860311A6741	FeatureImpact	completed	1	6/19/2023 10:36:16 AM	6/19/2023 10:36:25 AM	6/19/2023 10:39:19 AM	6/19/2023 10:39:19 AM	atomic	2	19	PipelineOrchestrator.PipelineStatsOrchestrator.Fe...
4F81C4D2-8FF1-8F85-023A-5560311A6741	FeatureImpact	completed	1	6/19/2023 10:36:16 AM	6/19/2023 10:36:22 AM	6/19/2023 10:39:18 AM	6/19/2023 10:39:19 AM	atomic	2	20	PipelineOrchestrator.PipelineStatsOrchestrator.Fe...
16173185-0D3F-2A8C-0287-ACC0311A6741	FeatureImpact	completed	1	6/19/2023 10:36:16 AM	6/19/2023 10:36:24 AM	6/19/2023 10:39:15 AM	6/19/2023 10:39:15 AM	atomic	2	25	PipelineOrchestrator.PipelineStatsOrchestrator.Fe...
EA1DC97C-5075-4883-025A-F580311A6741	FeatureImpact	completed	1	6/19/2023 10:36:16 AM	6/19/2023 10:36:22 AM	6/19/2023 10:38:44 AM	6/19/2023 10:38:44 AM	atomic	2	21	PipelineOrchestrator.PipelineStatsOrchestrator.Fe...
6118315A-7558-06FF-0185-07A0311A6741	FeatureImpact	completed	1	6/19/2023 10:36:16 AM	6/19/2023 10:36:22 AM	6/19/2023 10:38:55 AM	6/19/2023 10:38:56 AM	atomic	?	13	PipelineOrchestrator.PipelineStatsOrchestrator.Fe...

1 of 45 | Search Type: None | Status: [queued, running, r...] | Order By: Last Activity Time | DESC | Filter

Monitor Job Activity

Sensible Machine Learning tracks all jobs and each job's tasks. Use the Job Activity Table in the AI Services Activity log to see general job traffic and job details, completion status, queue order of jobs set to run immediately or on a schedule, and other job and task details.

View AI Services Activity

The screenshot displays the 'AI Services Activity Log' interface. At the top, there's a header 'AI Services Activity Log' with navigation options for 'Job Activity' and 'Error Log'. Below this is the 'Job Activity Table' pane, which contains a table with columns: Job Activity ID, Activity Type, Activity Status, Percent Complete, Creation Time, Queued Time, Start Time, End Time, Last Activity Time, Is Scheduled, Project Name, App Name, Total Tasks, and Completion. The table lists several jobs, all with a status of 'completed'. Below the table is a search and filter section with dropdowns for 'Search Type', 'Status', 'Projects', and 'Order By', along with 'Filter' and 'Progress' buttons. Below the Job Activity Table is the 'Tasks for Job: a56ec261-5f62-65a7-028a-c58031181705' pane. It has a similar search and filter section and a table with columns: Task Activity ID, Task Type, Activity Status, Percent Complete, Queued Time, Start Time, End Time, Last Activity Time, Task Execution Type, Task Level, Task Order, and Task Path. This table shows tasks for the selected job, including 'DataSourceSnapshot', 'DataSourceUpdateOrchestrator', and 'DataSourceValidation', all with a status of 'completed'. At the bottom right of the interface is a 'Close' button.

The **Job Activity** page has a **Job Activity Table** pane and a **Tasks** pane. Both panes list activity in the OneStream grid, so items in the grid can be ordered, sorted by any column, and filtered. All items in a grid can be sorted using the sort functionality.

TIP: Use the scroll bars in either pane to see all columns.

Each item in the Job Activity Table represents a job that has run in Sensible Machine Learning. Select a job to see the job's tasks in the **Tasks** pane. Each job includes the following:

Job Activity ID: Unique GUID given to the job when first queued.

Activity Type: Part of the project or page in Sensible Machine Learning where the job was generated.

Activity Status: The current status of the job.

- **queued:** Indicates if the job or task is queued to run. If a job is scheduled, it is queued with a QueuedTime when the job is scheduled to run.
- **running:** The job or task is currently running.
- **running_subtasks:** An orchestrator task is currently running subtasks.

View AI Services Activity

- **completed:** The job or task completed successfully.
- **syserror/syscancelled:** The job or task failed due to a system failure or the system canceling the job or task.
- **usercancelled:** The job or task was cancelled by a user.
- **syserror_re-runnable:** The job or task failed due to a data validation error and can be re-run once the issue has been resolved.
- **worker_queued:** The task is currently in the queue to be picked up by a worker. This is only an activity status for atomic tasks and not jobs.

Percent Complete: Completion percentage of all the job's tasks.

Creation Time, Queued Time: Time that the job was created and moved to the job execution queue.

Start Time, End Time: Job's start and end dates and times.

Last Activity Time: Time that the most recent job activity completed. When a job successfully completes, this is the same as the End Time.

Is Scheduled: Selected indicates that the job was originally scheduled or scheduled to run at a future date and time.

Project Name: Name given to the project when it was created. <No Project> displays if the job did not execute for a specific Sensible Machine Learning project. <Deleted Project> displays if the job run for a specific Sensible Machine Learning project has been deleted.

App Name: Application responsible for running the job.

Total Tasks, Completed Tasks: Number of tasks run by the job and the number of tasks that ran successfully.

Server Name: The name of the server where the job completed.

Project ID: GUID given to the Sensible Machine Learning project when it was created.

Information displayed for tasks include:

Task Activity ID: Unique identifier assigned to the task when it is created.

Activity Status: The current status of the job.

View AI Services Activity

- **queued**: Indicates if the job or task is queued to run. If a job is scheduled, it is queued with a QueuedTime when the job is scheduled to run.
- **running**: The job or task is currently running.
- **running_subtasks**: An orchestrator task is currently running subtasks.
- **completed**: The job or task completed successfully.
- **syserror/syscancelled**: The job or task failed due to a system failure or the system canceling the job or task.
- **syserror_re-runnable**: The job or task failed due to a data validation error and can be re-run once the issue is resolved.
- **data_validation_error**: The job or task failed due to a data validation error.
- **worker_queued**: The task is currently in the queue to be picked up by a worker. This is only an activity status for atomic tasks and not jobs.

Percent Complete: Completion percentage of all the job's tasks.

Queued Time, Start Time, End Time, Last Activity Time, Percent Complete: These columns have the same type of information as they do for jobs, but these are for a selected job's tasks.

Task Execution Type: Indicates whether the task is synthetic, atomic, sequential, or parallel.

Task Level, Task Order: Order of a job within the displayed task level.

Task Path: The routine within the job where the task runs.

- **Synthetic**: A task that runs within an atomic task. It is only included in the AI Services Task Activity log if the task fails.
- **Atomic**: One which has a simple, self-contained definition (for example, one that is not described in terms of other workflow tasks) and only one instance of the task runs when it is initiated.
- **Sequential**: Tasks are distributed across different processors and run in a specific order.
- **Parallel**: Task is distributed with other tasks across different processors and concurrently run by processes.

Process ID: Unique identifier assigned to the process in which the job was run.

Server Name: The name of the server that completed the job.

View AI Services Activity

Parent Task Activity ID: Unique identifier assigned to the task's parent when it is created.

Job Activity ID: Unique identifier assigned to the task's job when it is created.

Review Job Errors

Use the Error Log for information on why a job did not run properly or run to completion, and to aid in error diagnosis and resolution. Types of errors include job execution errors for a specific project, Sensible Machine Learning updates, and login and other connection failures.

Message	Captured Time	Log Level	Log Source	Project Name	Error Category	Error Info
Task 118fd97-92d2-35fe-0671-83e031177a59 was exiting timeout thread at 2023-06-14 23:10:39.601944.	6/14/2023 11:10:39 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:10:39.601] [xperiflow.server.warning.conduit][INFO
Task 118fd97-92d2-35fe-0671-83e031177a59 was started in task timeout thread at 2023-06-14 23:10:39.445699.	6/14/2023 11:10:39 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:10:39.445] [xperiflow.server.warning.conduit][INFO
Task 118fd97-92d2-35fe-0671-83e031177a59 entered task timeout at 2023-06-14 23:10:39.383195.	6/14/2023 11:10:39 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:10:39.383] [xperiflow.server.warning.conduit][INFO
Task 5c12fb87-4c91-d9c7-03eb-4100311784f8 was exiting timeout thread at 2023-06-14 23:05:05.183501.	6/14/2023 11:05:05 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:05:05.183] [xperiflow.server.warning.conduit][INFO
Task 5c12fb87-4c91-d9c7-03eb-4100311784f8 was started in task timeout thread at 2023-06-14 23:05:05.027238.	6/14/2023 11:05:05 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:05:05.027] [xperiflow.server.warning.conduit][INFO
Task 5c12fb87-4c91-d9c7-03eb-4100311784f8 entered task timeout at 2023-06-14 23:05:04.964735.	6/14/2023 11:05:04 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:05:04.964] [xperiflow.server.warning.conduit][INFO
Task 306b81aa-14da-d4f9-0671-c4c031177a59 was exiting timeout thread at 2023-06-14 23:05:02.714652.	6/14/2023 11:05:02 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:05:02.714] [xperiflow.server.warning.conduit][INFO
Task 306b81aa-14da-d4f9-0671-c4c031177a59 was started in task timeout thread at 2023-06-14 23:05:01.558354.	6/14/2023 11:05:01 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:05:01.558] [xperiflow.server.warning.conduit][INFO
Task 306b81aa-14da-d4f9-0671-c4c031177a59 entered task timeout at 2023-06-14 23:05:01.480232.	6/14/2023 11:05:01 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:05:01.480] [xperiflow.server.warning.conduit][INFO
Task 7da48600-4d9e-ee32-0127-a1e031177d1f was exiting timeout thread at 2023-06-14 23:01:21.979936.	6/14/2023 11:01:21 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:01:21.979] [xperiflow.server.warning.conduit][INFO
Task 7da48600-4d9e-ee32-0127-a1e031177d1f was started in task timeout thread at 2023-06-14 23:01:21.808033.	6/14/2023 11:01:21 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:01:21.808] [xperiflow.server.warning.conduit][INFO
Task 7da48600-4d9e-ee32-0127-a1e031177d1f entered task timeout at 2023-06-14 23:01:21.761156.	6/14/2023 11:01:21 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 23:01:21.761] [xperiflow.server.warning.conduit][INFO
Task d9af0b3b-3b21-cf54-03b8-f52031177f17 was exiting timeout thread at 2023-06-14 22:19:29.181761.	6/14/2023 10:19:29 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:19:29.181] [xperiflow.server.warning.conduit][INFO
Task d9af0b3b-3b21-cf54-03b8-f52031177f17 was started in task timeout thread at 2023-06-14 22:19:29.009878.	6/14/2023 10:19:29 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:19:29.009] [xperiflow.server.warning.conduit][INFO
Task d9af0b3b-3b21-cf54-03b8-f52031177f17 entered task timeout at 2023-06-14 22:19:28.947390.	6/14/2023 10:19:28 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:19:28.947] [xperiflow.server.warning.conduit][INFO
Task a04be540-8a48-082c-0159-776031177f33 was exiting timeout thread at 2023-06-14 22:17:56.487453.	6/14/2023 10:17:56 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:17:56.487] [xperiflow.server.warning.conduit][INFO
Task a04be540-8a48-082c-0159-776031177f33 was started in task timeout thread at 2023-06-14 22:17:56.346802.	6/14/2023 10:17:56 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:17:56.346] [xperiflow.server.warning.conduit][INFO
Task a04be540-8a48-082c-0159-776031177f33 entered task timeout at 2023-06-14 22:17:56.284300.	6/14/2023 10:17:56 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:17:56.284] [xperiflow.server.warning.conduit][INFO
Task a32c26a3-ba06-fd7c-0144-848031177f58 was exiting timeout thread at 2023-06-14 22:17:37.515929.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:17:37.515] [xperiflow.server.warning.conduit][INFO
Task a32c26a3-ba06-fd7c-0144-848031177f58 was started in task timeout thread at 2023-06-14 22:17:37.344048.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:17:37.344] [xperiflow.server.warning.conduit][INFO
Task a32c26a3-ba06-fd7c-0144-848031177f58 entered task timeout at 2023-06-14 22:17:37.281546.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:17:37.281] [xperiflow.server.warning.conduit][INFO
Task 894d60de-324b-529d-03a5-750031177f1b was exiting timeout thread at 2023-06-14 22:17:37.234670.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:17:37.234] [xperiflow.server.warning.conduit][INFO
Task 894d60de-324b-529d-03a5-750031177f1b was started in task timeout thread at 2023-06-14 22:17:37.062788.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:17:37.062] [xperiflow.server.warning.conduit][INFO
Task 894d60de-324b-529d-03a5-750031177f1b entered task timeout at 2023-06-14 22:17:37.000286.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:17:37.000] [xperiflow.server.warning.conduit][INFO
Task a0a8fedb-70b9-8eb6-04be-66e031177f39 was exiting timeout thread at 2023-06-14 22:16:14.391644.	6/14/2023 10:16:14 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	[2023-06-14 22:16:14.391] [xperiflow.server.warning.conduit][INFO

Each entry includes the following information:

Message: Message associated with the error.

Captured Time: The time that the error occurred.

Log Level: Categorizes the severity of the error. Though warnings are logged, they do not necessarily stop a job from running.

Log Source: XperiFlow module where the error occurred.

View AI Services Activity

Project Name: The name of the project that caused the error. <No Project> displays if the error did not occur for a specific Sensible Machine Learning project.

Error Category: General type of error that occurred. NA displays for errors not associated with a specific category.

Error Info: Similar to the information in the Message column, this is detailed information about what occurred to cause the error. For SQL statements that cause an error, this can include details about where in the statement the failure occurred. This information can help technical support with error diagnosis and resolution.

Server Name: The name of the server where the error occurred. Useful when a job is parallelized with multiple servers.

Process Name, Process ID: Unique identifiers that point to the specific process within a server where the error occurred.

Thread Name, Thread ID: Unique identifiers that point to the thread in which the error occurred.

Project ID: Unique identifier given to the project when the project was created. Zeros in this column indicate the error is not associated with a specific project.

Job Activity ID, Task Activity ID: Unique identifiers for the job and task within the job that encountered the error. Zeros in this column indicate the error was not associated with a specific Sensible Machine Learning task or job.

Log Level Number: The number assigned to the type of error. For example, a warning is level 30, an error is level 40.

NOTE: Jobs that are not associated with a specific project show zeros for the Job ID, Task ID, and Project ID.

Find Specific Jobs, Tasks, or Errors

The AI Services Log also lets you search for specific jobs, tasks within jobs, and errors. This is useful when you want to find a specific item or items (jobs, tasks, or errors) within a large number of items, or your Job Activity or Error log has multiple pages. Use the search along with table [sorting](#) to speed your search of items in the AI Services Activity Log.

Select a search type, then type an ID for the item you want to search for and click **Filter**. In the Job Activity, you can find Jobs by the Job Activity ID or Project ID to find all jobs in a project. Search by Task Activity ID to find specific tasks.

View AI Services Activity

The Error log lets you find specific errors by Job Activity ID or Task Activity ID, or Project ID. The ID you enter must match the ID exactly, though lowercase letters in the search will match. The following graphic shows the search in the Error Log.

The screenshot displays the 'AI Services Activity Log' interface with the 'Error Log' tab selected. A search filter is applied to the 'Job Activity ID' column, showing results for the ID '9085C582-0526-BBF1-02DC-978031177A56'. The table lists various tasks with their captured times, log levels, sources, project names, error categories, and error info.

Message	Captured Time	Log Level	Log Source	Project Name	Error Category	Job Activity ID	Error Info
Task 118fa997-92d2-35fe-0671-83e031177a59 was exiting timeout thread at 2023-06-14 23:10:39.601944.	6/14/2023 11:10:39 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:10:39.601944]
Task 118fa997-92d2-35fe-0671-83e031177a59 was started in task timeout thread at 2023-06-14 23:10:39.445699.	6/14/2023 11:10:39 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:10:39.445699]
Task 118fa997-92d2-35fe-0671-83e031177a59 entered task timeout at 2023-06-14 23:10:39.383195.	6/14/2023 11:10:39 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:10:39.383195]
Task 5c12fb87-4c91-d9c7-03eb-4100311784f8 was exiting timeout thread at 2023-06-14 23:05:05.183501.	6/14/2023 11:05:05 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:05:05.183501]
Task 5c12fb87-4c91-d9c7-03eb-4100311784f8 was started in task timeout thread at 2023-06-14 23:05:05.027238.	6/14/2023 11:05:05 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:05:05.027238]
Task 5c12fb87-4c91-d9c7-03eb-4100311784f8 entered task timeout at 2023-06-14 23:05:04.964735.	6/14/2023 11:05:04 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:05:04.964735]
Task 306b81aa-f4da-d4f9-0671-c4c031177a59 was exiting timeout thread at 2023-06-14 23:05:02.714652.	6/14/2023 11:05:02 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:05:02.714652]
Task 306b81aa-f4da-d4f9-0671-c4c031177a59 was started in task timeout thread at 2023-06-14 23:05:01.558354.	6/14/2023 11:05:01 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:05:01.558354]
Task 306b81aa-f4da-d4f9-0671-c4c031177a59 entered task timeout at 2023-06-14 23:05:01.480232.	6/14/2023 11:05:01 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:05:01.480232]
Task 7da48600-4d9e-ee32-0127-a1e031177d1f was exiting timeout thread at 2023-06-14 23:01:21.979936.	6/14/2023 11:01:21 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:01:21.979936]
Task 7da48600-4d9e-ee32-0127-a1e031177d1f was started in task timeout thread at 2023-06-14 23:01:21.808033.	6/14/2023 11:01:21 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:01:21.808033]
Task 7da48600-4d9e-ee32-0127-a1e031177d1f entered task timeout at 2023-06-14 23:01:21.761156.	6/14/2023 11:01:21 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 23:01:21.761156]
Task d9af0b3b-3b21-cf54-03b8-f52031177f17 was exiting timeout thread at 2023-06-14 22:19:29.181761.	6/14/2023 10:19:29 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:19:29.181761]
Task d9af0b3b-3b21-cf54-03b8-f52031177f17 was started in task timeout thread at 2023-06-14 22:19:29.009878.	6/14/2023 10:19:29 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:19:29.009878]
Task d9af0b3b-3b21-cf54-03b8-f52031177f17 entered task timeout at 2023-06-14 22:19:28.947390.	6/14/2023 10:19:28 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:19:28.947390]
Task a04be540-8a48-082c-0159-776031177f33 was exiting timeout thread at 2023-06-14 22:17:56.487453.	6/14/2023 10:17:56 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:17:56.487453]
Task a04be540-8a48-082c-0159-776031177f33 was started in task timeout thread at 2023-06-14 22:17:56.346802.	6/14/2023 10:17:56 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:17:56.346802]
Task a04be540-8a48-082c-0159-776031177f33 entered task timeout at 2023-06-14 22:17:56.284300.	6/14/2023 10:17:56 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:17:56.284300]
Task a32c26a3-ba06-fd7c-0144-848031177f38 was exiting timeout thread at 2023-06-14 22:17:37.515929.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:17:37.515929]
Task a32c26a3-ba06-fd7c-0144-848031177f38 was started in task timeout thread at 2023-06-14 22:17:37.344048.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:17:37.344048]
Task a32c26a3-ba06-fd7c-0144-848031177f38 entered task timeout at 2023-06-14 22:17:37.281546.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:17:37.281546]
Task 894660de-324b-529d-03a5-750031177f1b was exiting timeout thread at 2023-06-14 22:17:37.234670.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:17:37.234670]
Task 894660de-324b-529d-03a5-750031177f1b was started in task timeout thread at 2023-06-14 22:17:37.062788.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:17:37.062788]
Task 894660de-324b-529d-03a5-750031177f1b entered task timeout at 2023-06-14 22:17:37.000286.	6/14/2023 10:17:37 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:17:37.000286]
Task a0af8ebc-70b9-8eb6-04be-66e031177f39 was exiting timeout thread at 2023-06-14 22:16:14.391644.	6/14/2023 10:16:14 PM	INFO	xperiflow.server.warning.conduit	Daily_Cornerstone_Target_Demo_2	NA	9085C582-0526-BBF1-02DC-978031177A56	[2023-06-14 22:16:14.391644]

Search filters at the bottom: Search Type: Job Activity ID, Search Method: Equals, Filter Value: 9085C582-0526-BBF1-0, Projects: Daily_Cornerstone..., Order By: Captured Time, DESC. Filter button is present.

View Job Progress

You can view job progress after you have started at least one job in a Sensible Machine Learning project. Click the **Job Progress Bar** Job Completed: Target Data Validation in the Sensible Machine Learning toolbar to access the **Job Progress** dialog box.

The screenshot shows a dialog box titled "Data Dataset Load" with a "Last Refresh" of "1/26/2023 4:17:56 PM". The job is in a "Running" state, indicated by a blue progress bar at 73.00% completion and a timer showing "00:01:25". Below the progress bar are six summary boxes: "Queued Time" (1/26/2023 4:16:30 PM), "Start Time" (1/26/2023 4:16:31 PM), "End Time" (None), "Last Activity Time" (1/26/2023 4:17:57 PM), "Tasks Completed" (11 / 14), and "Tasks Running" (2). At the bottom, there are buttons for "Job Activity", "Error Log", and "Close".

Captured Time	Log Level	Message
01/26/2023 9:16:37...	INFO	Task f41e8434-b094-8d4b-0549-e02030bdfe0e entered task timeout at 2023-01-26 21:16:37.574425.
01/26/2023 9:16:37...	INFO	Task f41e8434-b094-8d4b-0549-e02030bdfe0e was exiting timeout thread at 2023-01-26 21:16:37.934461.
01/26/2023 9:16:37...	INFO	Task f41e8434-b094-8d4b-0549-e02030bdfe0e was started in task timeout thread at 2023-01-26 21:16:3...
01/26/2023 9:16:40...	INFO	Task 06ef179d-1ed6-0df9-05c3-9bc030bdfe11 entered task timeout at 2023-01-26 21:16:40.129971.
01/26/2023 9:16:40...	INFO	Task 06ef179d-1ed6-0df9-05c3-9bc030bdfe11 was exiting timeout thread at 2023-01-26 21:16:40.442476.
01/26/2023 9:16:40...	INFO	Task 06ef179d-1ed6-0df9-05c3-9bc030bdfe11 was started in task timeout thread at 2023-01-26 21:16:40...
01/26/2023 9:17:03...	INFO	Task 56eab422-4cf7-525c-0660-bee030bdfe11 entered task timeout at 2023-01-26 21:17:03.558779.
01/26/2023 9:17:03...	INFO	Task 56eab422-4cf7-525c-0660-bee030bdfe11 was started in task timeout thread at 2023-01-26 21:17:03...

This dialog box shows the most recently active job that is not in a queued state for the current Sensible Machine Learning project. It shows a condensed view of the AI Services Log. Links are also included to the **Job Activity Log** and **Error Log** pages that automatically filter to the job shown in the **Job Progress** dialog box.

The following information is included in the **Job Progress** dialog box.

- **Queued Time:** Time that the job is moved to the job execution queue.
- **Start Time:** Time that the job started.

View Job Progress

- **End Time:** Time that the job ended.
- **Last Activity Time:** Time of last activity performed by the job.
- **Tasks Completed:** The number of tasks that have been completed for the given job.
- **Tasks Running:** The number of tasks that are currently running for the job.
- **Progress Bar:** How close the job is to completion and how long it has been running.
- **Logging Grid:** Error log entries for the job. These may be errors, warnings, or other relevant information.

Explore Target and Feature Data Sources

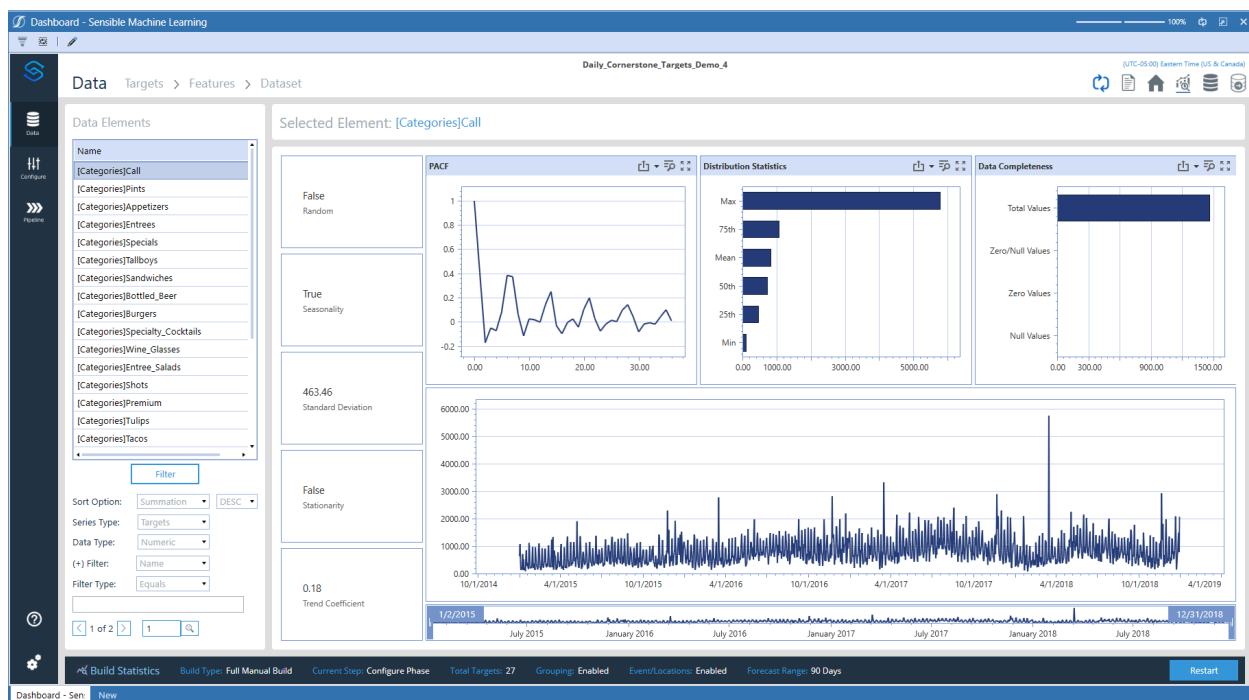
After you have processed and merged the data sets for your Sensible Machine Learning project, data analysis for each target becomes available. Click the **Explore Targets and Features** icon in the [Sensible Machine Learning toolbar](#) to access the page.

TIP: The **Explore Targets and Features** page is only available during the Model Build phase.

The Data Elements pane on the **Explore Targets and Features** page shows the data elements represented in the information on the page. The information on the page changes depending on whether you are viewing targets or features. Target information displays by default.

To change the data elements represented on the page, select **Features** or **Targets** in the Series Type field click **Filter**.

Target Data

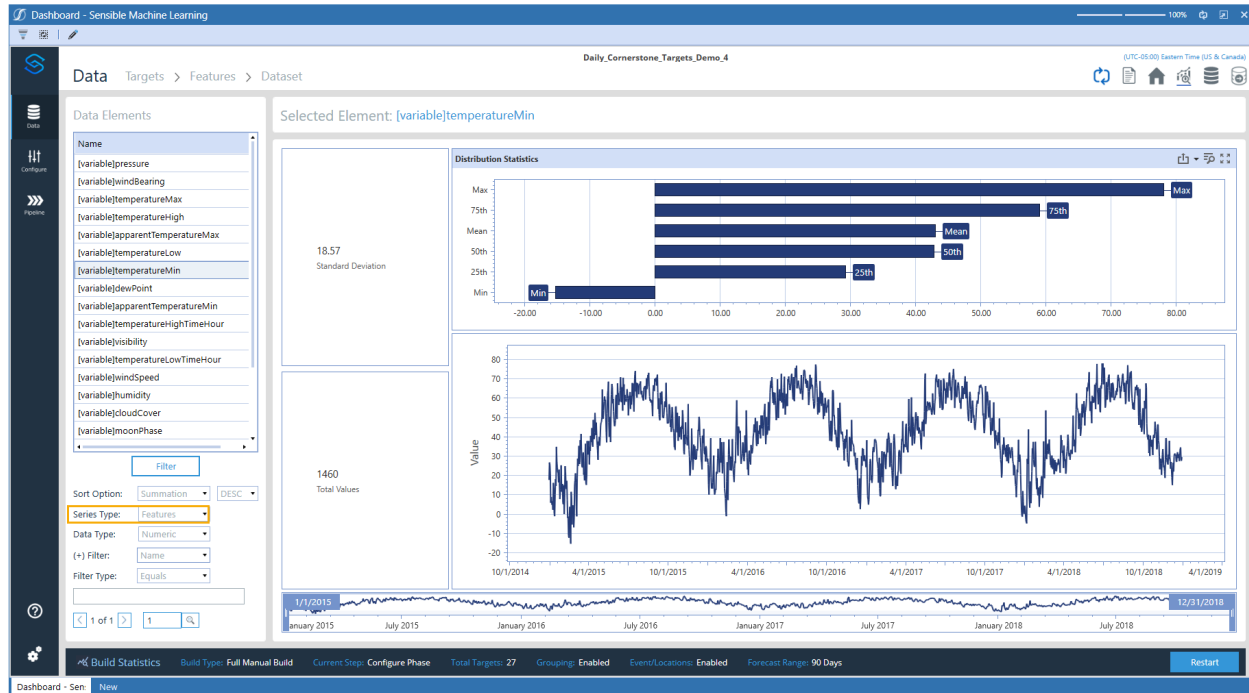


Explore Target and Feature Data Sources

Each target in the data source displays with the following information:

- **Random:** Indicates if a data set does not contain any recognizable patterns. This signifies that it may be difficult for models to learn from historical data.
- **Seasonality:** Indicates if a data set contains any seasonal patterns or cycles that repeat over a period of time. If a data set has seasonality, models can use it to increase predictive accuracy.
- **Standard Deviation:** Indicates the standard deviation of the target.
- **Stationarity:** Indicates if the statistical properties of the data set do not change over time.
- **Trend Coefficient:** This is the result of a Mann Kendall test which produces a value between -1 and 1. A coefficient greater than zero indicates the statistical significance of a positive trend. A coefficient less than zero indicates the statistical significance of a negative trend.
- **Partial Autocorrelation Function (PACF) Plot:** Demonstrates correlation (-1 to 1) of values based on the time increment between them. For example, a daily-level data set with a PACF score of 0.5 at an x-axis point of 7 signals that, on average, today's value has a correlation coefficient of 0.5 with the value of 7 days prior.
- **Distribution Statistics:** Bar chart representing these values: Maximum, 75th percentile, Mean, 50th percentile, 25th percentile, and Minimum.
- **Data Completeness:** Bar chart representing how many zero or null values are found for each target of the data set.
- **Historical Actuals Plot:** Plots all the historical actuals from the data.

Feature Data



Each feature in the data source displays with the following information:

- **Standard Deviation:** Indicates the standard deviation of the feature.
- **Total Values:** The number of unique values created by feature data.
- **Distribution Statistics:** Bar chart representing these values: Maximum, 75th percentile, Mean, 50th percentile, 25th percentile, and Minimum.
- **Historical Actuals Plot:** Plots all the historical actuals from the data.


Update a Target or Feature Data Source

Use the **Data Source Update** page to update data tables or change the data source connection for a target or feature data source. This can be done at any time after specifying data targets and verifying your data source using the **Data > Dataset** page. However, it is especially useful during the Utilization phase when new data may be available in a new table that must be added to the data source. The **Data Source Update Utility** page also displays statistics about each data source.

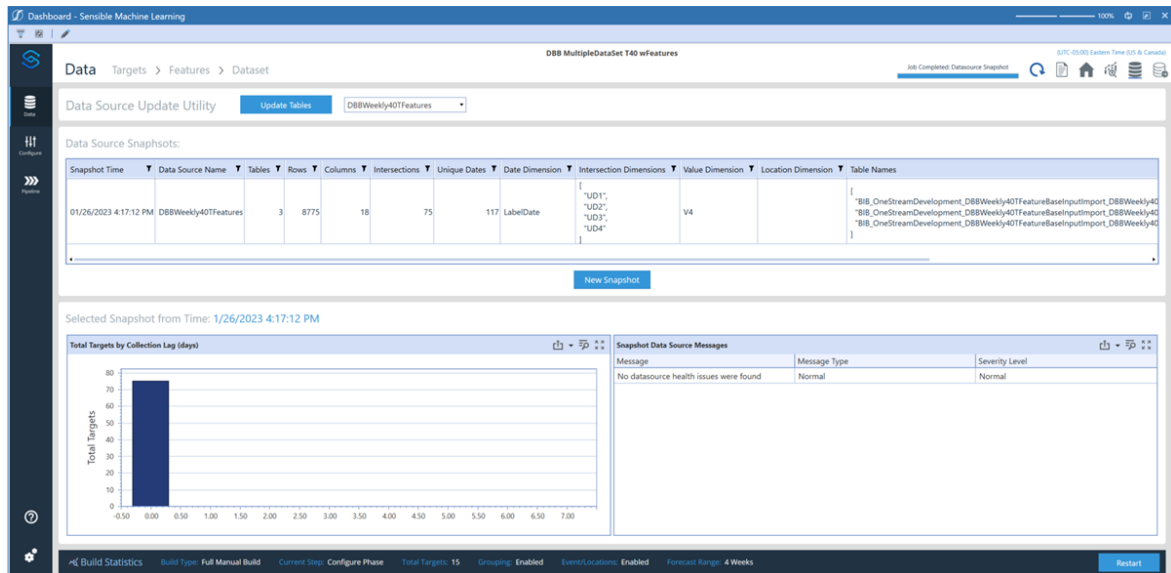
TIP: The process of updating a data source is similar to the processes used [to specify targets and define the data set](#) and to [specify data features](#) and is only available after you specify targets and features. However, instead of selecting data tables for the first time in the modeling process, you are changing the tables used.

NOTE: The dimensions of a data source cannot be changed. Also, you must [specify targets and define the data set](#) and [verify your data sets](#) before you can use the Data Update utility.

Update a Data Source

1. At any time after specifying data targets and features and verifying your data source, click **Show Data Update**  on the current page toolbar. The **Data Source Update Utility** page displays.

Update a Target or Feature Data Source



2. Use the drop-down menu at the top of the page to select the target or feature data source to update.
3. Click **Update Tables** at the top of the **Data Source Utility** page. The **Update Dataset Connection** dialog box displays, based on whether you select a target or feature data source to update. The following graphic shows the dialog box to update the target data set.

Update a Target or Feature Data Source

Source Connection:* PRD1_smlqa_BIBlend

Table/View Name:* BIB_OneStreamDevelopm ...

Data Source Name:* Target Dataset

Preview:

Rt	SourceID	LabelDate	TextValue	Entity	Cons	Scenario	View	Account
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/12/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TargetEntityMbr	USD	DBBWeekly40TargetScenarioMbr	YTD	None

Target Dimension(s):* UD1,UD2,UD3

Value Dimension:* V1

Date Dimension:* LabelDate

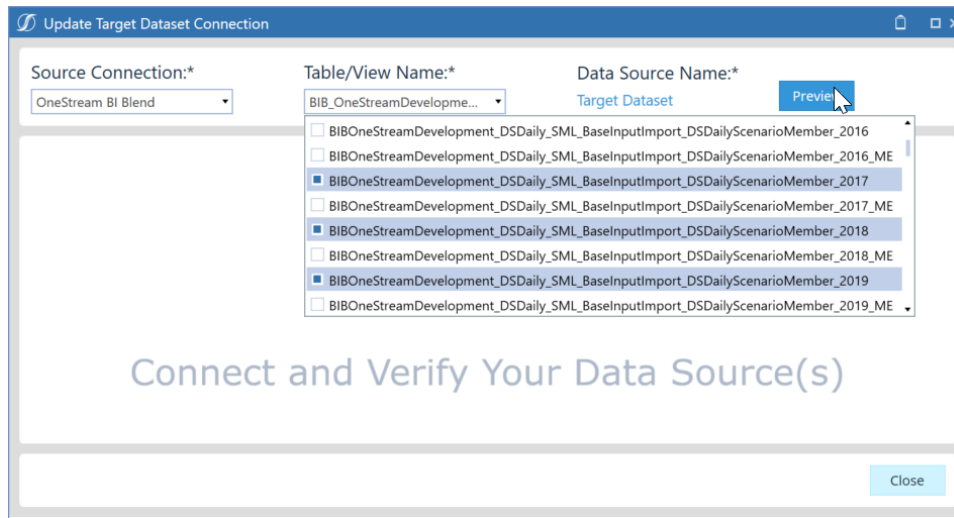
Location Dimension: None

4. Click **Update** in the upper right corner of the dialog box. This lets you change the Table Name and Source Connection.
5. In the Source Connection field, select the type of connection from the list.
6. In the Table Name field, select the names of target or feature tables to use for the project, and deselect the names of target or feature tables you do not want to be in the data set update.

TIP: Only the first selected table name displays in the list. You can click the field to see all the selected import data files.

7. Once the table and Source Connection are updated, click **Preview**.

Update a Target or Feature Data Source



8. If the tables and data are correct, click **Update** at the bottom of the dialog box. This starts the Data Update job, which validates and updates the data source and creates statistics for the updated data.

Data Source Statistics

The **Data Source Update Utility** page shows numerous statistics from the selected target or feature data source.

Data Source Snapshots: These are snapshots of the data source that are taken by clicking **New Snapshot** to run the Data Source Snapshot job. Snapshots can also be taken during the data set job, data update job, and prediction jobs. A snapshot can be selected to populate the Total Targets by Collection Lag (days) and the Snapshot Data Source Messages at the bottom of the page.

Total Targets by Collection Lag (days): This chart visualizes the latest view of the collection lag for the target data set. It shows the number of targets that have a given collection lag by the number of days. Click **New Snapshot** to create a new snapshot for the data source. This chart updates when you run a new [prediction](#) or snapshot. The chart also updates with each data set job and an update of target data source.

Snapshot Data Source Messages: This shows any messages from the data source snapshot. For example, warnings for missing intersections or intersections that have been added since the last snapshot.

Manage Consumption Groups



Consumption groups are the connections to a data table in OneStream. Use the Consumption Groups page to manage consumption groups that are used to load model predictions and insights into tables within OneStream.

NOTE: The destination Data Connection will be the same as the specified Data Source Connection for the Target Data Source

Consumption groups can be created after you have specified targets and features and verified your data sets using the [Data > Dataset](#) page.

Create Consumption Groups

The consumption groups you create are available when you run a new prediction.

1. Click the **Consumption Groups**  icon in the Sensible Machine learning toolbar. The **Consumption Groups** dialog box displays.
2. Click **Add a New Consumption Group** .
3. In the **Add Consumption Group** dialog box, select the type of consumption to add in the Consumption Type field. This determines the other settings. See the Consumption Group types [here](#).
4. Type a name for your consumption group in the Consumption Group field.
5. Type a name for the Output name in the Output Name field.
6. Make selections from these options (or subset of options based on consumption type). The options you can select include the following values:

Export Action: The type of action this consumption group should be auto-attached to. If auto-attached, it automatically runs and exports as a part of that type of action. Examples include prediction and pipeline jobs.

Actuals Types: The type of actuals (engine cleaned, engine uncleaned, source) to include in the consumption group.

Target Frequency: The frequency to export data in.

Manage Consumption Groups

Merge Method: The type of merge to perform on data if there are multiple data points for a date.

Models to Return: The models to return in the consumption group.

Prediction Intervals: Indicates if prediction intervals should be included in the export.

Extraction Type: Select **Batch** to export only the latest prediction run. Select **Time** to use Start Date Type and End Date Type fields for the earliest prediction to the latest prediction or custom time frames.

Start Date Type: If the earliest start date or a custom beginning date should be used.

Start Date Time, Start Date Hour: The beginning date and hour of the day of the consumption group (inclusive). Available if the If Start Date Type is set to **Custom**.

End Date Type: If the latest end date or a custom end date should be used.

End Date Time, End Date Hour: The end date and end hour of the day of the consumption group (inclusive). Available if the If End Date Type is set to **Custom**.

Group Name: Type a name for the consumption group to be exported.

Output Table Name: The name of the outputted table. This is in the same database as the target data set.

The screenshot shows a dialog box titled "Add Consumption Group". It contains the following fields and values:

- Consumption Type: Model Forecast Deployed
- Group Name: Weekly_Targets
- Output Table Name: Weekly_Featured
- Export Action: Prediction Cluster Orchestr...
- Actuals Types: Engine Cleaned
- Target Frequency: Project Frequency
- Start Date Type: Earliest Start
- Start Date Time: 2/5/2010 12:00:00 AM
- End Date Type: Latest End
- End Date Time: 7/27/2012 12:00:00 AM
- Merge Method: Latest
- Models to Return: All
- Prediction Intervals: Included
- Extraction Type: Time

Buttons: Save, Close

7. Click **Save**.

Export Consumption Group Data

You can manually export all data defined in a consumption group to the associated new or existing OneStream table. If the table already exists, it must have the correct schema; otherwise, it does not populate the prediction data.

NOTE: Groups can also be automatically exported by setting the Export Action option of a given consumption group.

To export a consumption group:

1. Select a group and then click **Export Group**

NOTE: Some consumption types may require you to select what to export data for (all deployed builds or a given build based on build time).

2. Confirm that you want to export the group by clicking **Export**.

Consumption Group Types

There are multiple types of consumption groups that can be configured to export a variety of information from Sensible Machine Learning. These exports can be used in downstream processes for a variety of applications.

The following list describes the consumption group types and shows the schema for each.

Feature Effect

Description: The feature effect consumption type contains data informing how a given feature and its values compare to a given target's actual values and prediction values. This provides insight into whether a correlation exists between certain feature values and predictions or actuals. See [Appendix 4: Interpretability](#) for details.

Schema: Model, FeatureLowerBound, FeatureUpperBound, FeatureAvgValue, PredictionAvgValue, TargetAvgValue, FeatureName, FeatureShortName, TargetName, ConsumptionID, ProjectID, ConsumptionRunID, ConsumptionRunTime, XperimentKernelID, XperimentBuildID, XperimentSetID, BuildInfoID, [TargetDimensions]

Feature Impact

Description: The feature impact consumption type contains data informing how much a given feature influences the model for a given target. A large FeatureImpactValue means that the feature is an important driver for the model predictions for that target. See [Appendix 4: Interpretability](#) for details.

Schema: FeatureName, FeatureShortName, FeatureImpactValue, FeatureImpactType, TargetName, ModelName, Category, ConsumptionID, ProjectID, ConsumptionRunID, ConsumptionRunTime, XperimentKernelID, XperimentBuildID, XperimentSetID, BuildInfoID, [TargetDimensions]

Model Forecast Backtest

Description: The model forecast backtest consumption type contains the backtest results (and possibly prediction intervals) made by models for each target from the model build phase of the application.

NOTE: Not all model builds contain a backtest portion. It is dependent on the number of [data points](#).

Schema: Model, ModelCategory, TargetName, Value, LowerPI, UpperPI, Date, ModelRank, ConsumptionID, ProjectID, SplitID, ConsumptionRunID, ConsumptionRunTime, XperimentKernelID, XperimentBuildID, XperimentSetID, BuildInfoID, [TargetDimensions]

Model Forecast Deployed

Description: The model forecast deployed consumption type contains the predictions (and possibly prediction intervals) made by models for each target from the utilization phase of the application.

Schema: Model, ModelCategory, TargetName, Value, LowerPI, UpperPI, Date, ModelRank, PredictionCallID, PredictionScheduledTime, ConsumptionID, ProjectID, ConsumptionRunID, ConsumptionRunTime, ForecastStartDate, ForecastNumber, ForecastName, XperimentKernelID, XperimentBuildID, XperimentSetID, BuildInfoID, [TargetDimensions]

Model Forecast V1

Description: The model forecast v1 consumption type is the same as the model forecast deployed consumption type but keeps the same table schema as Sensible Machine Learning versions SV103 and earlier. This consumption type is deprecated Sensible Machine Learning versions SV200 and later, and should not be used except for maintaining backwards compatibility for existing processes while they are transferred to newer consumption types

Schema: Model, ModelCategory, TargetName, Value, Date, ModelRank, FKPredictionCallID, PredictionScheduledTime, FKConsumptionID, FKProjectID, ConsumptionRunID, ConsumptionRunTime, [TargetDimensions]

Prediction Explanations Backtest

Description: The prediction explanations backtest consumption type contains the amount that the feature influenced (positive or negative) the prediction of a given model for a given target for a given date during the backtest in the model build section of the application. See [Appendix 4: Interpretability](#) for details.

Schema: Date, FeatureName, FeatureShortName, PredictionExplanationValue, FeatureValue, PredictionExplanationType, TargetName, Model, ModelStage, ModelCategory, ModelIterationID, ConsumptionID, ProjectID, ConsumptionRunID, ConsumptionRunTime, XperimentKernelID, XperimentBuildID, XperimentSetID, BuildInfoID, [TargetDimensions]

Prediction Explanations Deployed

Description: The prediction explanations deployed consumption type contains the amount that the feature influenced (positive or negative) the prediction of a given model for a given target for a given date during the forecasts in the utilization section of the application. See [Appendix 4: Interpretability](#) or details.

Schema: Date, FeatureName, FeatureShortName, PredictionExplanationValue, FeatureValue, PredictionExplanationType, TargetName, Model, ModelStage, ModelCategory, ModelIterationID, ConsumptionID, ProjectID, ConsumptionRunID, ConsumptionRunTime, PredictionCallID, PredictionScheduledTime, ForecastStartDate, ForecastNumber, ForecastName, XperimentKernelID, XperimentBuildID, XperimentSetID, BuildInfoID, [TargetDimensions]

View System Logging Tables


Use system logging tables to help debug any issues with a Sensible Machine Learning initial environment installation or an environment upgrade. The logging tables are meant to be used by advanced or power users.

Each table contains records ordered by a given column for each table.

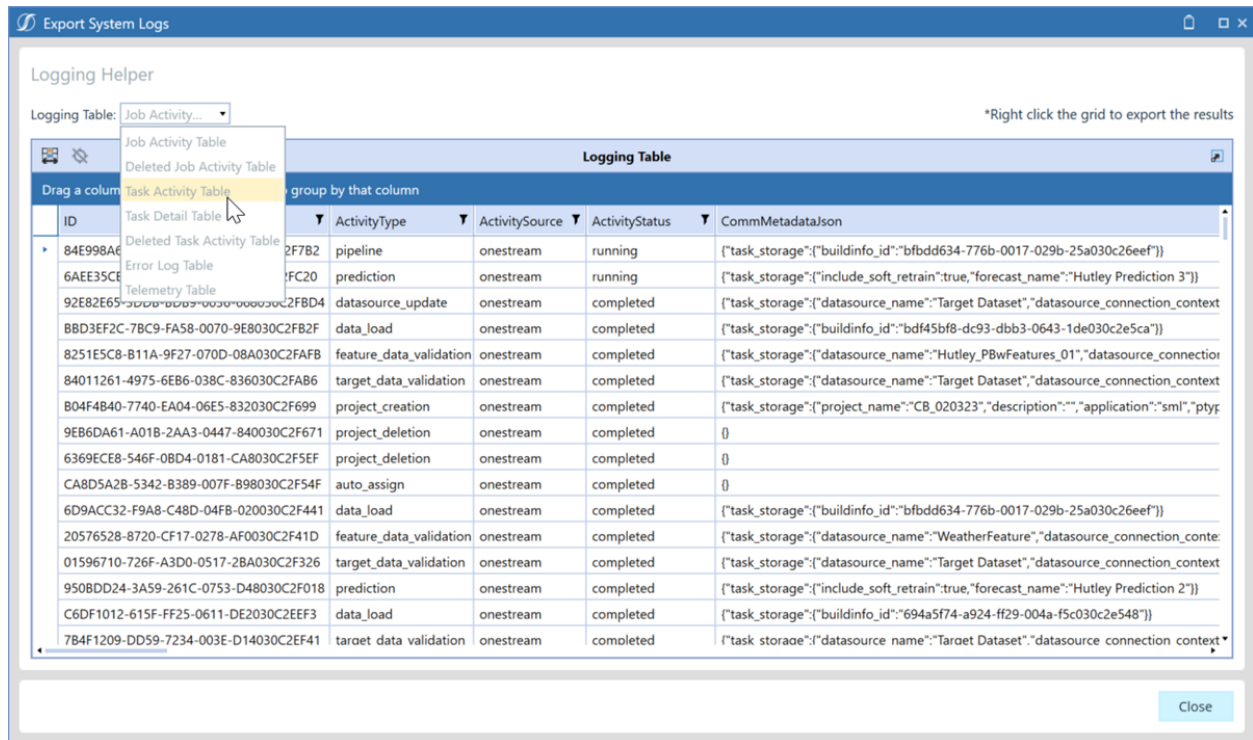
These tables are not paged, so some data may be inaccessible. You can export Logging information, which retrieves all data in the selected table. To do this, select the table to display it, right-click in the table and select **Export**, then select the output type.

To quickly find a specific logging record, press **CTRL + F** to open a full text search on the selected table, then enter a string in the record.

The system logging tables are only accessible from the [Sensible Machine Learning Home Page](#).

Click  on the **Home** page to view and extract system logging tables.

View System Logging Tables



System Logging Tables

The following list describes each of the available logging tables.

Job Activity Table: Includes information related to jobs that have been run. Similar to the AI-services log.

Deleted Job Activity Table: Similar to the Job Activity table, but contains jobs that have been deleted from a restart job run.

Task Activity Table: Includes information related to tasks that have been run. Similar to the AI-services log.

Task Detail Table: Includes intermediate updates of what is occurring within each task.

Deleted Task Activity Table: Similar to the Task Activity table, but contains tasks that have been deleted from running a restart job.

Error Log Table: Includes information about errors or logging information that has occurred. Similar to the AI-services error log.

View System Logging Tables

Telemetry Table: Contains information regarding the environment status on each machine in the environment. This includes CPU percentage, number of processes, and database connections.

Model Build Phase

The Model Build phase walks you through building a highly accurate machine learning models that are specific to the forecasting problem you are trying to solve.

NOTE: You must have a business administrator or higher security role to access pages in the Model Build phase.

TIP: The Consumption Groups page cannot be accessed until the **Data > Dataset** page has run the job to merge the data sets. The page can always be accessed in the Utilization phase.

Model building in Sensible Machine Learning is a three-section phase where you configure, build, and deploy machine learning or statistical models for time series forecasting in a Sensible Machine Learning project. It begins with sourcing data into Sensible Machine Learning. The data is typically sourced from an external database connection.

From there, you can add various machine learning parameters to your project. This includes parameters such as locations, events, forecast ranges, and model configurations. Most of these are defined in the [Configure section](#).

After specifying the data and the configurations to generate, engineer, and transform the data, use the Model Build phase **Pipeline** page to [run a model pipeline](#).

IMPORTANT: You should have a thorough understanding of the data in any target or feature data source used in the machine learning or statistical model you are working with. Various steps in the Model Build and Utilization phases let you review and verify the data being used and how the data is configured for Sensible Machine Learning.

NOTE: Times shown are in the specified time zone. However, custom time frames use the actual prediction data generated dates.

See [Appendix 2: Use Case Example](#) for information about models used by Sensible Machine Learning.

Create a Model Build Project

The Sensible Machine Learning Home page displays when you [start the Sensible Machine Learning Solution](#). The Project Selection grid shows each existing Sensible Machine Learning project and includes the following information for each:

Name: Name of the project.

Description: Optional description of the project. Can be added when creating or editing a project.

Creation Date: Date the project was created.

Build Status: Indicates the current model build section for each project. A value of **NONE** means the project is in the Utilization phase.

Buils in Progress: Indicates if there are builds in progress for each project. A value of **NONE** means the project is in the Utilization phase.

Is Deployed: Select to indicate that the project is deployed.

You can sort each column in the grid.


The screenshot shows the Sensible Machine Learning dashboard. At the top, there's a header with the text 'Sensible Machine Learning ML Enabled Forecasting brought to your OneStream Cloud.' Below this is a 'Project Selection' table with the following data:

Name	Description	Creation Date	Build Status	Buils in Progress	Is Deployed
AAWilliams_CutC_P01V01	Vanilla Project	6/15/2023 9:40:23 AM	Pipeline Deploy	Full Manual Build	<input type="checkbox"/>
AAWilliams_CutC_P02V01	Added Event Package	6/15/2023 10:18:55 AM	Pipeline Deploy	Full Manual Build	<input type="checkbox"/>
AAWilliams_CutC_P03V01	Grouping by Target Dimension	6/15/2023 10:31:04 AM	Pipeline Deploy	Full Manual Build	<input type="checkbox"/>
AAWilliams_CutC_P04V01	StoreFeatureSet and WeatherFea	6/15/2023 11:04:54 AM	Pipeline Deploy	Full Manual Build	<input type="checkbox"/>
AAWilliams_CutC_P05V01	StoreFeatureSet, Event, and Grou	6/15/2023 11:29:01 AM	Pipeline Deploy	Full Manual Build	<input type="checkbox"/>
AAWilliams_CutC_P06V01	Weather Feature Set, Event, and	6/15/2023 11:42:31 AM	None	None	<input checked="" type="checkbox"/>
AAWilliams_CutC_P07V01	StoreFeatureSet, WeatherFeature	6/15/2023 11:43:21 AM	Pipeline Deploy	Full Manual Build	<input type="checkbox"/>
CL_052523		5/25/2023 7:41:03 PM	None	None	<input checked="" type="checkbox"/>
Daily_Cornerstone_Target_Demo	Cornerstone using Daily Targets 3 Predictions (Pre-ReBuild) Manual Full ReBuild	6/14/2023 4:59:35 PM	Configure Phase	Full Manual ReBuild	<input checked="" type="checkbox"/>
Daily_Cornerstone_Target_Demo	3 Predictions (Post-ReBuild) Forecast Table Export (Test week Cornerstone using Daily Targets 3 Predictions (Pre-ReBuild)	6/14/2023 5:17:11 PM	Pipeline Deploy	Full Manual ReBuild	<input checked="" type="checkbox"/>
Daily_Cornerstone_Target_Demo	Manual Full ReBuild Forecast Table Export (Test week Cornerstone using Daily targets 3 Predictions (Pre-ReBuild)	6/14/2023 4:52:07 PM	None	None	<input checked="" type="checkbox"/>
Daily_Cornerstone_Target_Demo	Manual Full ReBuild				<input checked="" type="checkbox"/>

Below the table are two large buttons: 'Model Build' (with a cube icon) and 'Utilization' (with a cube icon containing a bar chart). The dashboard footer includes 'powered by DATA SENSE'.

Start a New Project

The first step to create a model build project is to start a new project. To do this:

1. In the Project Selection grid, click the **Add a New Project**  button. The **Add Project** dialog box displays.
2. Type a name for your project in the Project Name field. The name should be descriptive enough so you can recognize the project in the list.
3. Optionally type a description for the project in the Project Description field. Descriptions are useful to differentiate multiple Sensible Machine Learning projects with similar project names.
4. Security Access (Admins Only):
 - Assign different users or groups to any of the following levels of security access:
 - **Viewer**: Read-only access. Cannot modify anything within a Model Build or run any jobs.
 - **Editor**: Read/Write access. Can modify anything within a Model Build, but does not have access to higher administrative level privileges (Example: Deleting a project)
 - **Manager**: Read/Write/Delete access. Full capabilities to modify anything within a project and higher level project settings.

NOTE: When assigning security roles to a project, the creator of the project will automatically be assigned a Manager role.


5. Click **Add**. A message displays in the dialog box asking you to verify running the job to create the project. To verify, click **Save** to start the project creation and [view job progress](#).
6. When the job completes, click **Close** to close the **Project Creation** dialog box.

Sensible Machine Learning stores the project and assigns it a project ID, which you can see in the [AI Services Job Activity log](#). All project status details are associated with the project ID.

When complete, the project displays in the Project Selection list.


Model Build Phase

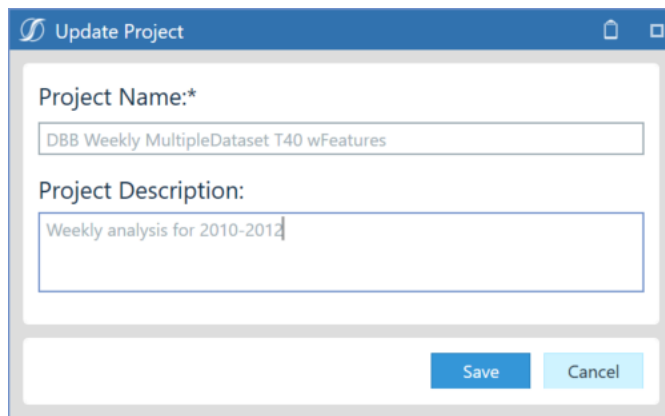
- To work with any project, click to select it, and then click the **Model Build** or **Utilization** icon.
- For a new project, click the project in the list, click **Model Build**, and then continue by [specifying targets and features using the correct data sets](#).

TIP: While working on any project, you can return to the Sensible Machine Learning Home page by clicking the **Home**  button at the top of the current page.

Update Information for an Existing Project

You can change or update information for a project after it is created. To do this:

1. In the Project Selection grid, click the project you want to edit, and then click the **Update the selected Project**  button. The **Update Project** dialog box displays.




The screenshot shows a dialog box titled "Update Project". It has a blue header bar with a refresh icon on the left and window control icons on the right. The main area contains two text input fields. The first is labeled "Project Name:*" and contains the text "DBB Weekly MultipleDataset T40 wFeatures". The second is labeled "Project Description:" and contains the text "Weekly analysis for 2010-2012". At the bottom right of the dialog are two buttons: "Save" and "Cancel".

2. Update the Project Name or Project Description as needed.
3. Click **Save** to update the project information.

Copy an Existing Project

You can copy a project in its entirety to add redundancy and apply different scenarios or configurations.

NOTE: When copying a project with one or more predictions run or scheduled, prediction results at the time the copy is made are copied to the new project. However, the job records of any predictions running are not copied to the resulting project. These are the records that are on the **Manage > Predict** page of the original project.


1. In the Project Selection grid, click the project you want to copy, then click the **Copy the selected Project**  button.
2. A message displays in the **Copy Project** dialog box to confirm running the copy project job. Verify that the project to copy is correct and type the desired name of the project that will be created as a copy. Click **Copy**.
3. A message displays to show you that the project is marked to copy. The project copy job queues and runs in a background job. You can check the status of the job in the [AI Services Log](#).

Once the job completes, the copied project shows in the Project Selection grid, as an exact replica of the copied project with the specified project name.

Delete an Existing Project

NOTE: You must be a OneStream administrator. Power users cannot delete a project.

You can delete a project after it is created. To do this:

1. In the Project Selection grid, click the project you want to delete, then click **Delete the selected Project** .
2. A message displays in the **Delete Project** dialog box to confirm the deletion. Type the project name in the text box to verify the deletion. Click **Delete**. You must enter the project name exactly as it is to confirm deletion.
3. A message displays to show you that the project is marked for deletion and deleted in a background job. Click **OK**.
4. After the delete project job completes, the project is removed from the Project Selection grid.

Update Project Data Sources

From the Project Selection grid, select a project and click  to update its target or feature data source. See [Update a Target or Feature Data Source](#) for details.

Model Build Phase Data Section

The Data section is where you start putting together the data from imported data tables to build data models. Pages in the Data section let you:

- Import target data tables to form the target data set.
- Optionally import feature tables from different feature data sets.
- Select dimensions to be used by Sensible Machine Learning for each data table.
- Group or cluster targets together to optimize downstream Sensible Machine Learning job run times, or to gain predictive accuracy.

When working through the Data section pages, the first thing to know which data set is being used to build a model. The data set can be from any relational table from a OneStream external database.

Specify Targets and Define the Data Set

After configuring your source data in OneStream and creating your Sensible Machine Learning project, you can use the **Targets** page (**Data > Targets**) to configure your target source data to use in your model. This is a two-step process.

- Define the database connection and data tables to use.
- Specify target data source dimensions by selecting fields that contain the desired target dimensions, value dimension, date dimension, and location dimension (optional). You can specify multiple target data tables to be used during this step.

NOTE: A location can be selected as both a target dimension and a location dimension. Selecting a column as a location dimension ensures that, when [configuring locations for your project](#), all the locations within that source column are pre-populated and pre-mapped to the respective target. Selecting a location as a target dimension adds further uniqueness and more granularity to the target intersection.

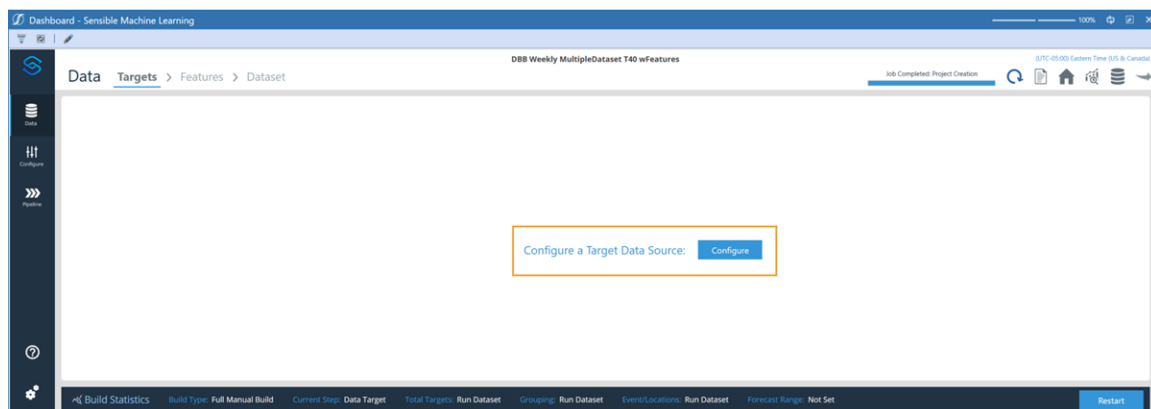
It is recommended to have a clustered column store index on data sources when able to avoid possible timeout issues.

IMPORTANT: You should have detailed knowledge of your target data sources and how the sourced data in the data columns match to dimensions used to store that data. See [Appendix 1: Data Quality Guide](#) for information on data planning for your project.

Define Your Target Data Source Connection

The first part to specifying targets and defining your data set for Sensible Machine Learning is to define the source connection for your data set.

1. Click **Data > Targets**.
2. The first time you access this page for a project, you must configure the data in your target data source.



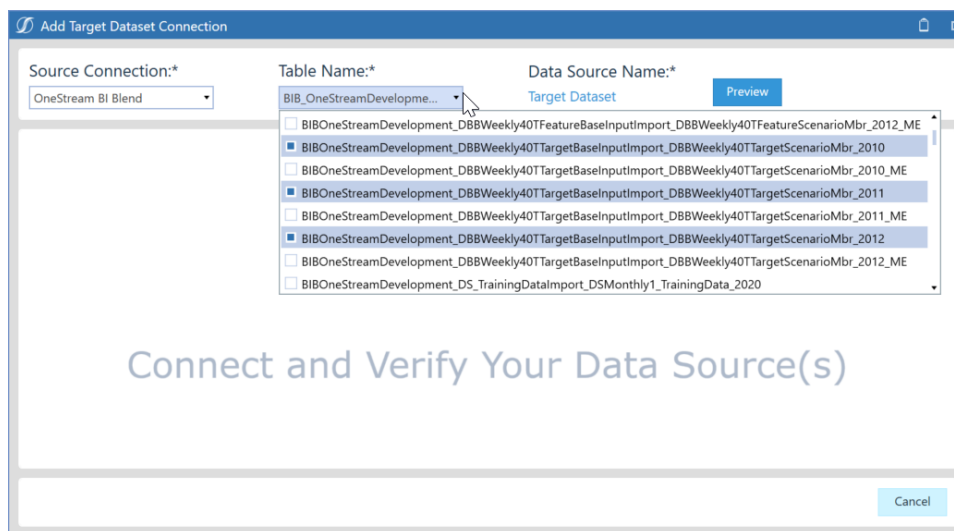
3. Click **Configure**. The **Add Target Data Set Connection** dialog box displays.
4. In the Source Connection field, select the connection of your Target Data Set.

Model Build Phase

NOTE: This will be the same destination Connection for any Consumption Groups created in this project.

5. In the Table Name field, select the names of the initial set of target tables you created for importing into your Sensible Machine Learning project. If you imported multiple target data sources to use for the first model prediction, select the import table name for each. Select the check box next to each target table you are using for the first model prediction.

TIP: Only the first selected table name displays in the list after selecting. You can click the field to see all the selected import data files.

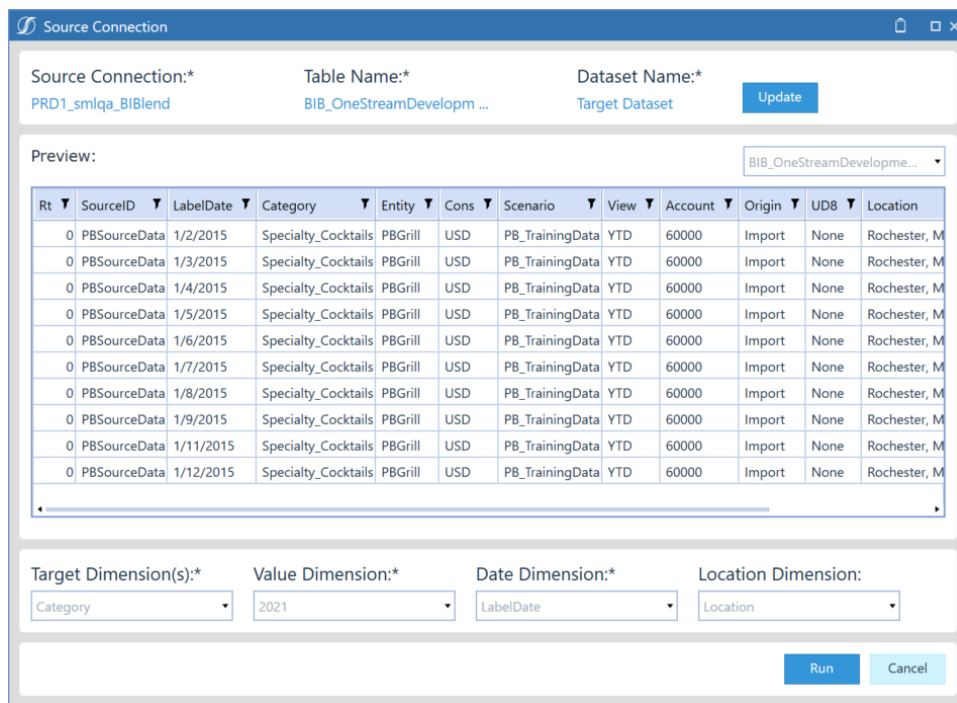


NOTE: The Data Source Name is required but is set to **Target Data Set** by default.

6. Click **Preview**.

A default Source Connection Name, the first imported Table Name and a default Data Source Name at the top of the **Add Target Data Set Connection** dialog box.

Model Build Phase



The **Preview** pane shows data from the first imported target data set. Each row of data in the **Preview** pane corresponds to a unique combination of data in the user-defined dimensions in the target source data set.

Use the information in the **Preview** pane to verify that the data in the correct target data source is being used. This includes data from the source shown in the Preview table and the target data source tables shown in the upper-right list in the **Preview** pane.

If the data in the Preview pane does not appear to be the correct source data, or the source tables are incorrect, you can click **Update** to change the selected source connection or target data source tables.

Once you are sure the correct source connection and data tables are being used and the source data shown in the Preview pane are verified, you can select the dimensions being used for the target data source connection.

Select Target Data Source Dimensions

Continue defining the data set by specifying the target dimensions, value dimension, date dimension and location dimension (optional) to use in your Sensible Machine Learning model. This consists of matching the dimensions to be used for the target data in your Sensible Learning Machine model to the dimensions reserved while creating a cube for the target data source.

NOTE: Only the specific dimensions reserved for Sensible Machine Learning should be selected for each of the dimension types. If a dimension type does not correlate to data in the target data set, leave the field blank. If the location dimension is not being used, select **None**.

1. In the Target Dimensions field, select the target dimensions that have been defined to store data from your target data sources.

These columns in the source data set define all the target variables that are used for predictions. The distinct combination of values across the target dimensions defines a target.

Select the check box next to each applicable dimension. For example, if the user-defined dimensions UD1, UD2, and UD3 were reserved for source data and mapped to specific data columns in the data source, select **UD1**, **UD2**, and **UD3** from the list.

NOTE: Selecting more target dimensions leads to a higher number of unique intersections (or targets) for which to forecast.

2. In the Value Dimension field, select the dimension used for the value data coming from the target data source. Typically, this dimension is used to store source data values such as sales numbers.
3. In the Date Dimension field, select the dimension reserved for date data coming from the target data source. Typically, this dimension is used to store the date data from the target data source.
4. In the Location Dimension field, optionally select the dimension reserved for location data coming from the target data source. Select **None** if your data source does not include location information. The Location Dimension is used for mapping event and feature information to relevant targets in the [Configure](#) section.

For example, the following data table contains weekly sales dollars by location, store, store type, department, and date. The potential target dimensions include Location, Store, Store_Type, and Dept, with Dept having the highest granularity. One or more of these can be selected, depending on the desired forecast level. The value dimension, in this case, would be weekly sales dollars, and the date dimension would be Date. Location can be selected as both a target dimension and the location dimension.

Model Build Phase

	A	B	C	D	E	F
1	Location	Store	Store_Typ	Dept	Date	Weekly_Sales
2	Texas	1	A	Food	2/5/2018	24924.5
3	Texas	1	A	Hobbies	2/5/2018	50605.26953
4	Texas	1	B	Food	2/5/2018	13740.12012
5	Texas	1	B	Hobbies	2/5/2018	39954.03906
6	Texas	2	A	Food	2/5/2018	32229.38086
7	Texas	2	A	Hobbies	2/5/2018	5749.029785
8	Texas	2	B	Food	2/5/2018	21084.08008
9	Texas	2	B	Hobbies	2/5/2018	40129.01172
10	California	1	A	Food	2/5/2018	16930.99023
11	California	1	A	Hobbies	2/5/2018	30721.5
12	California	1	B	Food	2/5/2018	24213.17969
13	California	1	B	Hobbies	2/5/2018	8449.540039
14	California	2	A	Food	2/5/2018	41969.28906
15	California	2	A	Hobbies	2/5/2018	19466.91016
16	California	2	B	Food	2/5/2018	10217.5498
17	California	2	B	Hobbies	2/5/2018	13223.75977

Add Target Dataset Connection

Source Connection:* PRD1_smlqa_BIBlend Table Name:* BIB_OneStreamDevelopm ... Data Source Name:* Target Dataset Update


Preview: BIB_OneStreamDevelopme...

Rt	SourceID	LabelDate	TextValue	Entity	Cons	Scenario	View	Account
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None

Target Dimension(s):* UD1, UD2, UD3 Value Dimension:* V1 Date Dimension:* LabelDate Location Dimension: None

Run Cancel

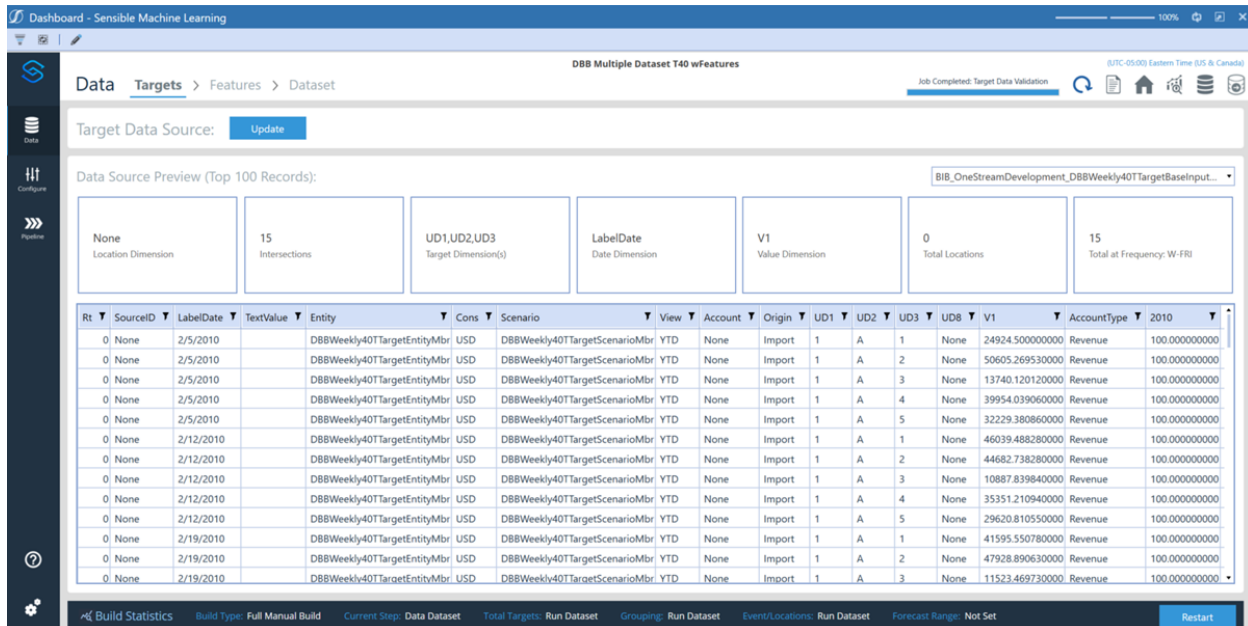
Model Build Phase

5. Click **Run** after making your target dimension selections. This [adds a job to the job queue](#) to validate the data and add the target data set to the model.
6. When the task completes, click **Refresh Current Page** .

The **Data Source Preview** pane displays.

NOTE: Once the **Data Source Preview** pane displays in the **Targets** page, the **Configure** button no longer displays on the page. that is the default view for the page.

The data in the **Data Source Preview** pane displays information on the dimensions used to run the preview, as well as the number of data intersections in the Sensible Machine Learning data sources. Location and frequency information also displays.



The screenshot shows the 'Data Source Preview' pane in the Sensible Machine Learning interface. The pane is titled 'Data Source Preview (Top 100 Records):' and displays a summary of target data source information. The summary includes:

- Location Dimension: None
- Intersections: 15
- Target Dimension(s): UD1,UD2,UD3
- Date Dimension: LabelDate
- Value Dimension: V1
- Total Locations: 0
- Total at Frequency: W-FRI: 15

Below the summary is a table of top 100 records. The table has the following columns: Rt, SourceID, LabelDate, TextValue, Entity, Cons, Scenario, View, Account, Origin, UD1, UD2, UD3, UD8, V1, AccountType, and 2010. The table contains 10 rows of data, each representing a record from the target data source.

Review the information in the **Data Source Preview** pane to verify the data targets are correctly defined for the model.

The list on the right side of the **Data Source Preview** pane lists any data files imported. Click it to see the fill list of all target target data files selected for this Sensible Machine Learning project. This is useful for verifying that the correct files were imported.

If any data in the **Data Source Preview** pane is not as expected, you can click **Update** to open the **Update Target Database Connection** dialog box and reselect target data source dimensions, or click **Update** in the dialog box to [change target data set connection information](#).

NOTE: The **Update** button is visible after the initial source connection is saved but is no longer visible after running the data set job in the **Data > Dataset** page.

Once you verify the data in the **Data Source Preview** pane, you can continue by [specifying data features](#). If features are not included in your data sources, continue by [verifying your data sets in Sensible Machine Learning](#).

Specify Data Features

Data Sources containing features can be added on the **Data > Features** page. You can use features during modeling to help enhance prediction accuracy.

The **Features** page lets you specify multiple feature data sources. You can see previews of the features contained in each feature data source. Users can also commit or uncommit the features from the project build, as well as modify settings for each individual feature.

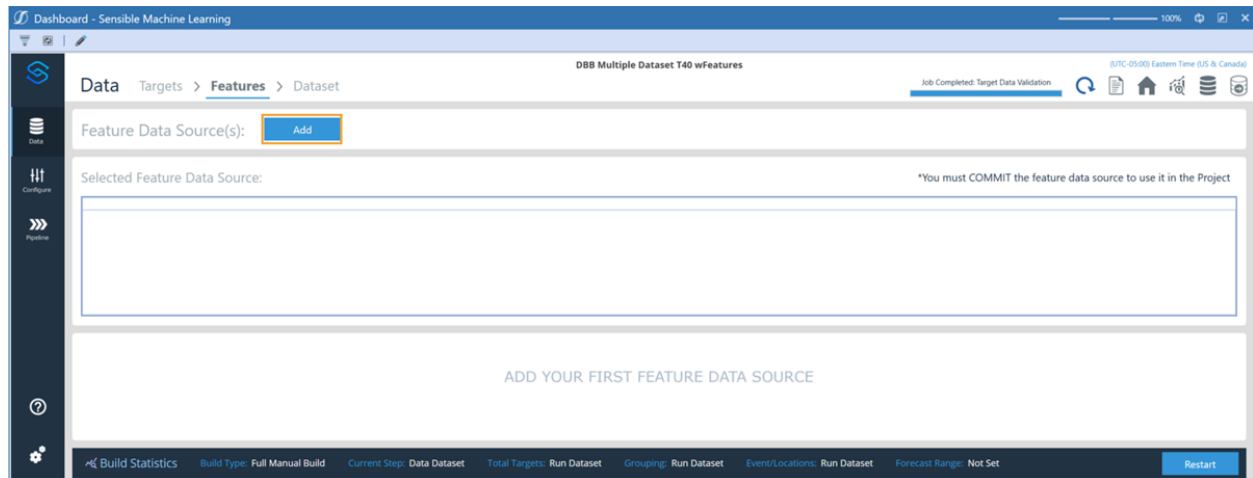
NOTE: If you are not using a features data source in your project, you can skip this page and continue by [verifying your data sets](#).

Define Your Feature Data Source Connection

This page shows what your data definition looks like before configuring the definitions. Panel on the right changes after you configure it.

Click **Data > Features** to open the **Features** page. This first time you access this page, the Feature Data Source pane shows no feature data set information.

Model Build Phase



You can use the **Features** page (**Data > Features**) to configure your feature source data to use in your model. Like [specifying targets and defining your target data set](#), this is a two-step process.

- Define the database connection and data tables to use.
- Specify feature data source dimensions by selecting fields that contain the desired feature dimension(s), value dimension, date dimension, and location dimension (optional). You can specify multiple feature data tables to be used during this step.

IMPORTANT: You should have detailed knowledge of your feature data sources and how the sourced data in the data columns match to dimensions used to store that data. See the [Sensible Machine Learning Data Quality Guide](#) for information on data planning for your project.

Specify the Data Source Connection

The first part to specifying features and defining your feature data set for Sensible Machine Learning is to define the source connection for your data set.

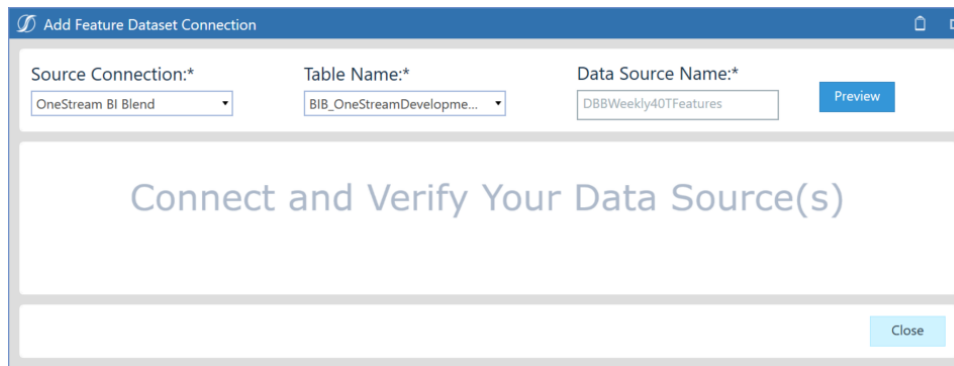
1. In the **Feature Data Sources** pane, click **Add** to add a feature data source to your Sensible Machine Learning model. The **Add Feature Data Set Connection** dialog box displays.
2. In the Source Connection field, select the connection of your Feature Data Set.

Model Build Phase

3. In the Table Name field, select the names of the initial set of feature tables you created for importing into your Sensible Machine Learning project. If you imported multiple feature data sources for the first model prediction, select the import table name for each. Select the check box next to each feature table you are using for the first model prediction.

TIP: Only the first selected table name displays in the list after selecting. You can click the field to see all the selected import data files.

4. In the Data Source Name field, type a name for the feature data source you are creating.



5. Click **Preview**.

A default Source Connection Name, the first imported Table Name and the Data Source Name display at the top of the **Add Feature Data Set Connection** dialog box.

IMPORTANT: Use the information in the **Preview** pane to verify that the data in the correct feature data source is being used. This includes data from the source shown in the Preview table and the target data source tables shown in the upper-right list in the **Preview** pane.

If you cannot verify the data in the **Preview** pane is the correct source data, or the source tables are incorrect, you can click **Update** to change the selected source connection or target data source tables.

Once you are sure the correct source connection and data tables are being used and the source data shown in the **Preview** pane are verified, you can select the dimensions being used for the target data source connection.

Select Feature Data Source Dimensions

Continue specifying features and defining the data set by specifying any feature dimensions, value dimension, date dimension or location dimension for the data set to use in your Sensible Machine Learning model. This is basically matching the dimensions to be used for the feature data in your Sensible Learning Machine model to the dimensions reserved while creating a cube for the feature data source.

NOTE: Only the specific dimensions reserved for Sensible Machine Learning should be selected for each of the dimension types. If a dimension type does not correlate to data in the feature data set, leave the field blank. If the location dimension is not being used, select **None**.

1. In the Feature Dimensions field, select the feature dimensions that have been defined to store data from your feature data sources.

The columns in the source feature data set define all the feature variables that are used for predictions. The distinct combination of values across the feature dimensions define a feature.

Select the check box next to each applicable dimension. For example, if the user-defined dimensions UD1, UD2, UD3 and UD4 were reserved for source data and mapped to specific data columns in the data source, select **UD1**, **UD2**, **UD3**, and **UD4** from the list.

If dimensions are selected for the feature data source that have the same name as a dimension in the target data source, then those dimensions are used to map features to targets. For example, UD1 is in the feature dimensions and the target dimensions, features with a value in the UD1 dimension are only mapped to targets with that same value in the UD1 dimension.

NOTE: Setting the feature dimensions to the exact same dimensions specified for the target data set causes an error when running the job to validate the data and add the feature data set to the model.

TIP: Selecting more feature dimensions leads to a higher number of unique intersections (or features) you can use in forecasting.

2. In the Value Dimension field, select the dimension used for the value data coming from the feature data source. Typically, this dimension is used to store source data values such as sales numbers.

NOTE: Only numeric values can be used to aid in predictions. Other types of values such as text are ignored.

3. In the Date Dimension field, select the dimension reserved for date data coming from the feature data source.
4. In the Location Dimension field, select the dimension reserved for location data coming from the feature data source (optional).

Select **None** if your feature data source does not include location information. The Location dimension is used during modeling to automatically map features to targets that have a location that is geographically inside of or equivalent to a given feature's location. For example, a feature with the location **Michigan** is mapped to a target with the location **Rochester, Michigan**, but is not mapped to a target with the location **USA**.

TIP: The location dimension can also be a feature dimension that adds uniqueness.

NOTE: A location can be selected as both a feature dimension and a location dimension. Selecting a column as a location dimension ensures that, when [configuring locations for your project](#), all the locations within that source column are pre-populated. Selecting a location as a feature dimension adds further uniqueness and more granularity to the feature intersection.

Model Build Phase


Source Connection:* PRD1_smlqa_BIBlend Table Name:* BIB_OneStreamDevelopm ... Data Source Name:* DBBWeekly40TFeatures Update

Preview: BIB_OneStreamDevelopme...

Rt	SourceID	LabelDate	TextValue	Entity	Cons	Scenario	View	Account
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/5/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None
0	None	2/19/2010		DBBWeekly40TFeatureEntityMbr	USD	DBBWeekly40TFeatureScenarioMbr	YTD	None

Feature Dimension(s): UD1, UD2, UD3, UD4 Value Dimension:* V4 Date Dimension:* LabelDate Location Dimension: None

Run Close

5. Click **Run** after making your feature dimension selections. This adds a job to the job queue to validate the data and add the feature data set to the model. The job runs tasks to complete the data definitions. A progress bar shows task progress. You can click **Cancel Task** at any time while the task is running to stop running the data definitions.
6. When the task completes, click **Refresh Current Page** .

The **Features** page displays the added feature data source listed in the **Selected Feature Data Source** pane. The **Feature Data Source Preview** pane displays below the **Selected Feature Data Source** pane, showing information for the top 100 feature records.

NOTE: Once the **Data Source Preview** pane displays in the **Features** page, the **Configure** button no longer shows on the page, as it is the default view for the page.

Model Build Phase

Name	Committed	Allow Feature Selection	Allow Feature Engineering	Known in Advance	Scenario Modeling Feature
Weather	<input checked="" type="checkbox"/>	34	34	0	0

time	variable	value	location	Dummy/Value
1/1/2015 12:00:00 AM	summary	Mostly cloudy throughout the day.	Rochester, Michigan	100
1/1/2015 12:00:00 AM	icon	partly-cloudy-day	Rochester, Michigan	100
1/1/2015 12:00:00 AM	sunriseTimeHour	13	Rochester, Michigan	100
1/1/2015 12:00:00 AM	sunsetTimeHour	22	Rochester, Michigan	100
1/1/2015 12:00:00 AM	moonPhase	0.4	Rochester, Michigan	100
1/1/2015 12:00:00 AM	precipIntensity	0	Rochester, Michigan	100
1/1/2015 12:00:00 AM	precipIntensityMax	0	Rochester, Michigan	100
1/1/2015 12:00:00 AM	precipIntensityMaxTimeHour	25	Rochester, Michigan	100
1/1/2015 12:00:00 AM	precipProbability	0	Rochester, Michigan	100
1/1/2015 12:00:00 AM	precipType	0	Rochester, Michigan	100

You can also edit, delete, commit, or add a new feature set.

Edit Feature Data Source Attributes


Once a feature data source has been added to the project, the Selected Feature Data Source pane displays it at the top of the **Features** page. Sensible Machine Learning lets you set specific attributes for each feature in the data set.

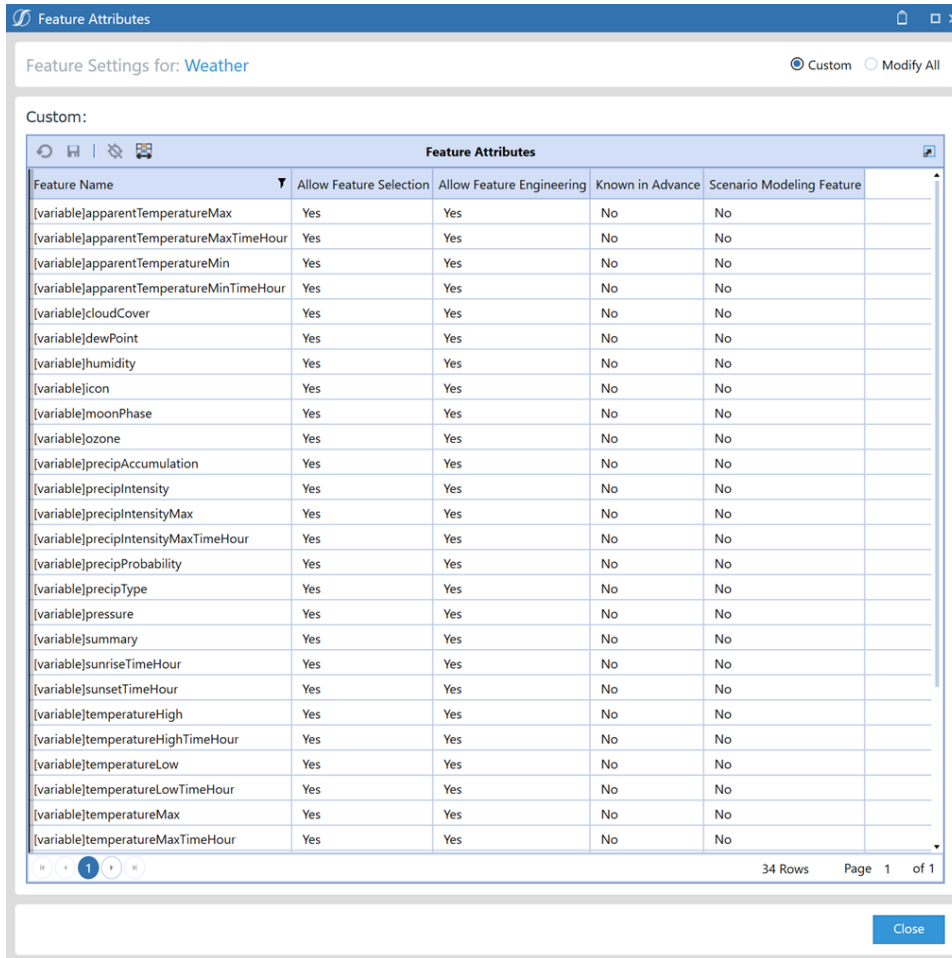
Editing feature data source attributes is optional. Each feature's attributes have a default setting. Review the selections for each attribute. If you are satisfied with the defaults, click **Cancel** in the **Feature Attributes** dialog box without making changes, then [commit the feature data source](#).

1. Click to select the data source whose attributes you want to edit.

TIP: Data information for the selected feature data set displays in the Data Source Preview pane.

Model Build Phase

- Click the **Edit the Selected Feature Data Source's Attributes**  button at the bottom of the pane. The **Feature Attributes** dialog box defaults to Custom view, which lists all the selected data source's feature attributes, and shows whether each attribute is selected (**Yes**) or not selected (**No**).



Feature Name	Allow Feature Selection	Allow Feature Engineering	Known in Advance	Scenario Modeling Feature
[variable]apparentTemperatureMax	Yes	Yes	No	No
[variable]apparentTemperatureMaxTimeHour	Yes	Yes	No	No
[variable]apparentTemperatureMin	Yes	Yes	No	No
[variable]apparentTemperatureMinTimeHour	Yes	Yes	No	No
[variable]cloudCover	Yes	Yes	No	No
[variable]dewPoint	Yes	Yes	No	No
[variable]humidity	Yes	Yes	No	No
[variable]icon	Yes	Yes	No	No
[variable]moonPhase	Yes	Yes	No	No
[variable]ozone	Yes	Yes	No	No
[variable]precipAccumulation	Yes	Yes	No	No
[variable]precipIntensity	Yes	Yes	No	No
[variable]precipIntensityMax	Yes	Yes	No	No
[variable]precipIntensityMaxTimeHour	Yes	Yes	No	No
[variable]precipProbability	Yes	Yes	No	No
[variable]precipType	Yes	Yes	No	No
[variable]pressure	Yes	Yes	No	No
[variable]summary	Yes	Yes	No	No
[variable]sunriseTimeHour	Yes	Yes	No	No
[variable]sunsetTimeHour	Yes	Yes	No	No
[variable]temperatureHigh	Yes	Yes	No	No
[variable]temperatureHighTimeHour	Yes	Yes	No	No
[variable]temperatureLow	Yes	Yes	No	No
[variable]temperatureLowTimeHour	Yes	Yes	No	No
[variable]temperatureMax	Yes	Yes	No	No
[variable]temperatureMaxTimeHour	Yes	Yes	No	No

Each feature data set listed includes the following attributes:

Allow Feature Selection: The default value **Yes** allows the attribute to be filtered out during the feature selection process. Select **No** to ensure the feature is not filtered out during the feature selection process.

If too many features for a given target are set to **No**, then they still go through the feature selection process. This is to prevent too many features from being fed into any one model. This limit depends on which models are being run.

Known In Advance: The default value **No** indicates that this feature does not have data that extends past the last actual data point (such as weather forecast for the next two weeks). Known-in-advance features cannot have any missing data past the forecast range (for example, five weeks for a five week forecast). Select **Yes** for the attributes that you know have data that extends beyond the forecast range.

IMPORTANT: The prediction job cannot run if this setting is set to **Yes** and the feature is not available through the forecast when trying to run predictions.

Allow Feature Engineering: The default value **Yes** indicates the feature can be engineered. Selecting **No** ensures that a feature cannot be engineered, such as lagging temperature by two weeks.


Scenario Modeling Feature: Select **Yes** if the feature should be included when defining custom Scenarios in Utilization and the intention of the project is to run predictions on different Scenarios. Otherwise, select **No**.

NOTE: When selecting **Yes** for any event:

- The project will be considered a Scenario Modeling project by the Xperiflow Engine.
- Altering a Scenario Modeling project after the job has run requires a Restart or Manual Rebuild.
- **Known In Advance** automatically changes to **Yes**.

3. In the **Feature Attributes** dialog box, edit the feature's attributes in one of the following ways:


Custom: Allows you to modify individual attribute values for features as desired.

- Select a feature, then select the attributes values for that feature by clicking in each of the attribute selection fields and selecting **Yes** or **No** depending on the desired value.
- Click the **Save** button  in the button bar to save your feature attribute changes.

Modify All: Allows you to apply an individual attribute value to all features in a given feature data set.

- Select the attribute option to apply the value.

Model Build Phase

- Select the value of the attribute to apply.
- Click the **Save** button  at the bottom of the Feature Attributes dialog box, to save your feature attribute change and apply the selected value to the selected attribute for all features.

The data in the Data Source Preview pane displays information on the dimensions used to run the preview, as well as the number of data intersections in the Sensible Machine Learning data sources to be used for the model.

Verify Data Source Information

Review the information in the Data Source Preview pane to verify the data features are correctly defined for the model.

The list on the right side of the Data Source Preview pane lists the imported feature data files. Click it to see the full list of all feature data files imported for the data source that is currently selected in the Data Source Preview pane. This is useful for verifying that the correct files were imported.

If any data in the Data Source Preview pane is not as expected, you can select the feature data source in the **Selected Feature Data Source** pane and do the following:


- Click the **Update the Selected Feature Data Source** button. This opens the **Update Feature Database Connection** dialog box so you can [reselect feature data source dimensions](#).
- Select the feature data source in the **Selected Feature Data Source** pane and click the **Delete** button, then click **Delete** again to remove the selected feature data source from the list.

Once you verify the data in the **Data Source Preview** pane, you can continue by [specifying data features](#). If features are not included in your data sources, continue by [verifying your data sets in Sensible Machine Learning](#).

Commit or Decommmit a Feature Data Source

You must commit any feature data sources to use in the Sensible Machine Learning project. You can also decommit any committed feature data source.

Model Build Phase

1. In the **Selected Feature Data Source** pane, select the feature data source and click the **Commit**  button.
2. A message box informs you that the selected data source's commit status has changed. Click **OK** to close the message box.
3. Commit any other feature data sources as needed by repeating the previous steps.

Once you have committed your data sets, continue by [verifying the data sets](#) to be used with your Sensible Machine Learning project.

NOTE: Feature data sources can only be committed for a full build and not for a partial build.

Verify Your Data Sets

Once you have specified the targets and features to be used in your Sensible Machine Learning project, you can merge the target data set and any additional feature data sets.

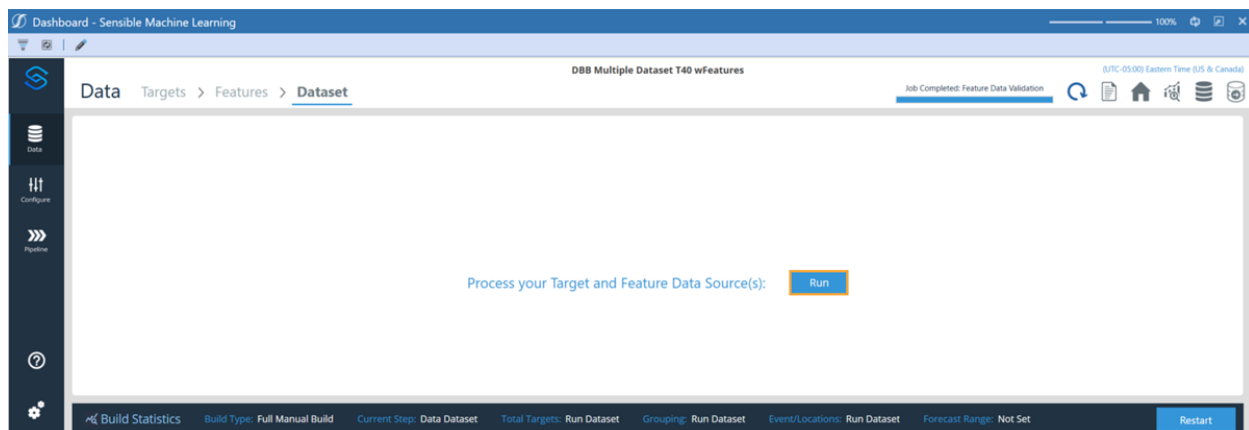
Use the **Data Set** page to:

- Run the job to merge your data sets.
- Review the project-level and advanced views of the merged data. Both views provide statistics on the merged data set and provide insight into how well your target data set is suited for your project.

Merge Your Target and Feature Data Sources

The first time you access the **Dataset** page, you must run the job that groups target data sources and processes and merges your target and feature data sets.

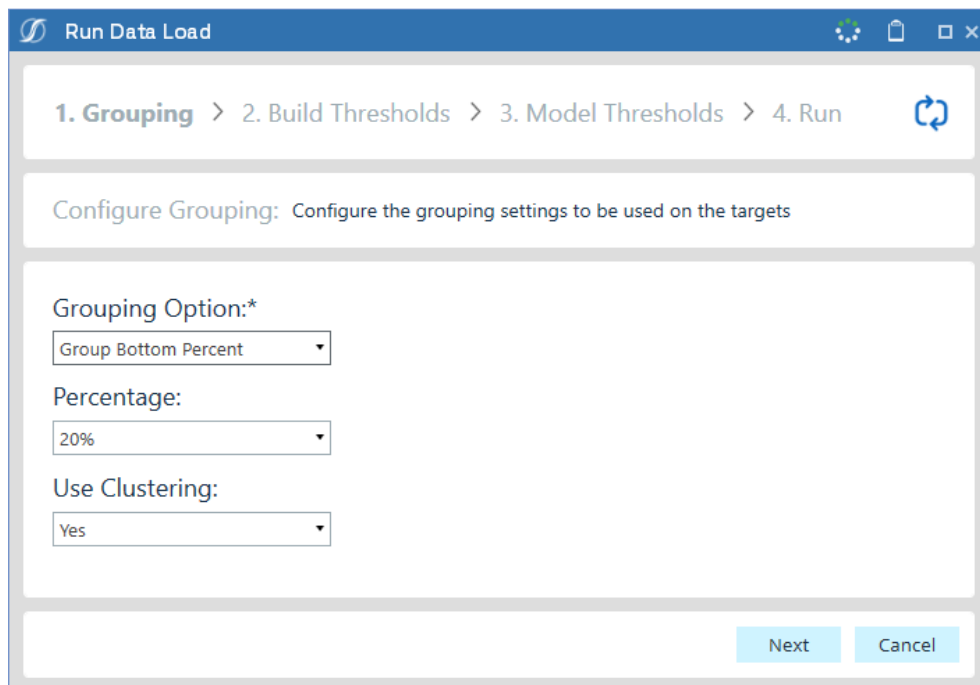
Model Build Phase



Run Data Dataset

Use settings in the **Run Data Dataset** dialog box to determine how your data is grouped for your project, as well as configure the thresholds required to run feature engineering, grouping, and each model. Click **Run** on the **Dataset** page. The **Run Data Dataset** dialog box displays, which is broken up into the following steps:

Step 1: Grouping



Model Build Phase

In the Grouping Option field, select how you want to group targets for the model:

No Groups: Targets are not grouped for this model.

Group Bottom Percent: Groups together all targets that fall below a given percent of total significance. Use the Significance by Target charts and the Grouping Percentage (Bottom X Percent) drop-down option to understand how many targets fall below a given percent of total significance. In a situation where 50 targets out of 1,000 make up 90% of the total significance, it can be beneficial to group the lowest 10% to spend the majority of the model build resource on training the most significant targets.

If selecting Group Bottom Percent as the grouping option, you must also set the following options that display in the dialog box based on these selections:

- **Percentage:** Select the appropriate bottom percentage from the list.
- **Use Clustering:** Set to **Yes** take the targets grouped together that fall below a given percent of total significance and group further based on data similarities recognized by the XperiFlow engine.
- **Group By Target Dimensions:** Groups targets together based on the selected target dimensions. Grouping similar targets can lead to accuracy improvements by running group models against them. Some examples for target dimensions to group by can be region, entity, or store.

If selecting Group By Target Dimensions as the grouping option, you must also set the following options that display in the dialog box based on these selections:

- **Target Dimensions:** Shows dimensions selected when you [select targets and define the data set](#). Select the dimensions you want to be grouped

TIP: Two or more target dimensions must exist to select the dimensions to be grouped.

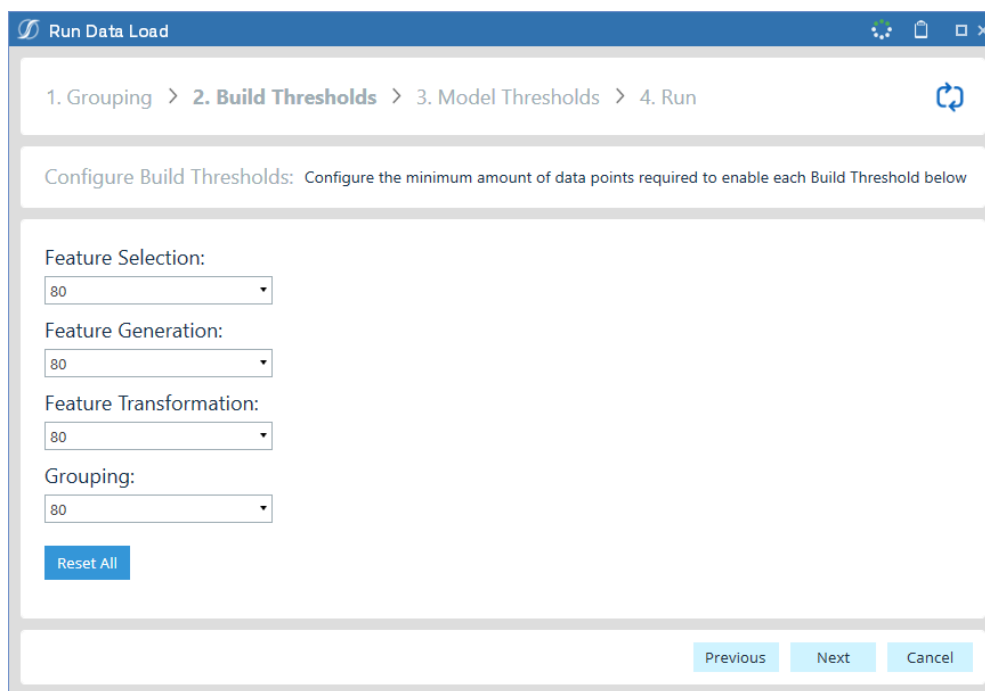
- **Group by Clustering:** This selection groups targets together based on data similarities recognized by the XperiFlow engine. The primary reason for grouping by clustering is to improve predictive accuracy.

Clustering involves grouping targets. A clustering algorithm classifies each target into a specific group, since targets in the same group typically have similar properties or features. Targets in different groups typically have highly dissimilar properties or features. Clustering provides valuable insights into data by showing what groups the targets fall into when clustering is applied.

Model Build Phase

Providing inverted views, both charts on this page illustrate the percent of total significance of targets along with the percentage within which they would be included for grouping.

Step 2: Build Thresholds



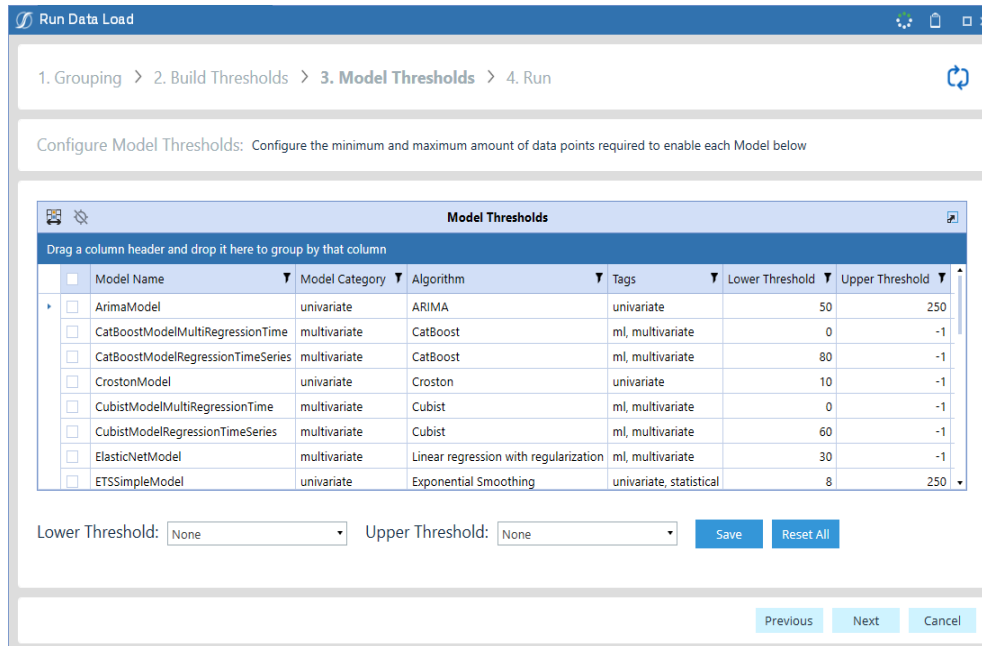
The screenshot shows a window titled "Run Data Load" with a breadcrumb trail: "1. Grouping > 2. Build Thresholds > 3. Model Thresholds > 4. Run". Below the breadcrumb is a refresh icon. The main content area is titled "Configure Build Thresholds: Configure the minimum amount of data points required to enable each Build Threshold below". It contains four dropdown menus, each labeled with a configuration type and set to the value "80": "Feature Selection", "Feature Generation", "Feature Transformation", and "Grouping". A blue "Reset All" button is located below these menus. At the bottom right of the dialog are three buttons: "Previous", "Next", and "Cancel".

The Build Thresholds section of the dialog allows the user to configure how many data points are required to enable the following:

- **Feature Selection**
- **Feature Generation**
- **Feature Transformation**
- **Grouping**

The **Reset All** button will reset any changes made into these configurations to the defaults set in the Global Settings Dialog.

Step 3: Model Thresholds



The Model Thresholds section of the dialog allows the user to configure how many data points are required to enable each model:


- **Lower Threshold Combo Box:** The minimum required data points for the model to be used.
- **Upper Threshold Combo Box:** The maximum required data points for the model to be used.
- **Save Button:** Updates the selected models to the new thresholds configured in the Lower and Upper Threshold combo boxes.
- **Reset All Button:** Resets any changes made to these configurations to the defaults set in the Global Settings Dialog.

Step 4: Run

Click **Run** to start the data load job and monitor job progress. Click **Close** to close the **Job Progress** dialog box at any time while the job is running or after it has completed.

Model Build Phase

The XperiFlow engine merges the target and feature data sets together, analyzes the targets, and creates target groupings if grouping is selected. It also gathers descriptive statistics on the results.

When the job successfully completes, click **Refresh Current Page** . The **Dataset** page updates and displays an overview, aggregate, and advanced pages that show statistics on the merged data set.

The **Run** button no longer displays once the data set job successfully completes. The Data Set Overview pane displays key statistics for your project, including the number of features and targets, the frequency of the data, and the number of unique dates.

Build Statistics at the bottom of the **Dataset** page update to show the number of total targets, and indicate whether Grouping, Events, and Locations are enabled. Also, the **Explore Targets and Features**, **Data Source Update** (for initial rebuild) and **Consumption Groups** pages are now enabled, and shows target and feature (if used in the data set) statistics for each unique data element in the data set.

Review Dataset Overview Statistics

The following graphic shows the **Dataset** page overview statistics:

Model Build Phase

The screenshot shows the 'Dataset Overview' page in the Sensible Machine Learning dashboard. The page title is 'DBB MultipleDataSet T40 wFeatures'. The 'Dataset Overview' section has three tabs: 'Overview' (selected), 'Aggregate', and 'Advanced'. The statistics shown are: 75 Features, Weekly Frequency, 15 Targets, 126 Total Dates, and 126 Unique Dates. Below these are two tables: 'Target Volatility Decomposition' and 'Target Group Information'. The 'Target Volatility Decomposition' table has columns for Calculation, Significance, Low Volatility, Medium Volatility, High Volatility, No History, and Total. The 'Target Group Information' table has columns for Group Name, Targets, and % of Targets. At the bottom, there is a status bar with 'Build Statistics', 'Build Type: Full Manual Build', 'Current Step: Pipeline Deploy', 'Total Targets: 15', 'Grouping: Enabled', 'Event/Locations: Enabled', 'Forecast Range: 4 Weeks', and a 'Restart' button.

Calculation	Significance	Low Volatility	Medium Volatility	High Volatility	No History	Total
% Quantity Of Tar...	Low Significance	6.67%	33.33%	0.00%	0.00%	40.00%
% Quantity Of Tar...	Medium Significa...	13.33%	26.67%	0.00%	0.00%	40.00%
% Quantity Of Tar...	High Significance	20.00%	0.00%	0.00%	0.00%	20.00%
% Quantity Of Tar...	Total	40.00%	60.00%	0.00%	0.00%	100.00%
% Volume Signific...	Low Significance	2.17%	13.66%	0.00%	0.00%	15.83%
% Volume Signific...	Medium Significa...	13.98%	28.94%	0.00%	0.00%	42.92%
% Volume Signific...	High Significance	41.25%	0.00%	0.00%	0.00%	41.25%
% Volume Signific...	Total	57.40%	42.60%	0.00%	0.00%	100.00%

Group Name	Targets	% of Targets
cluster_0	3	20.00%
cluster_1	3	20.00%
SingleTargets	9	60.00%

Low Volatility = $(StDev / Avg Significance) < 0.3$
Medium Volatility = $(StDev / Avg Significance)$ between 0.3 and 1.0
High Volatility = $(StDev / Avg Significance) > 1.0$
No History = < 5 historical datapoints
Note: Negative target significance is treated as positive significance within the calculations

The top of the Dataset Overview statistics view includes:

Features: The number of unique features produced by the data set job.

Frequency: Shows the time frequency of the overall data set. The time frequency is set based on the target that has the most granular level data. Frequency can be one of the following values:

- Daily
- Weekly
- Monthly
- Yearly

NOTE: The frequency of an entire data set remains constant across all targets. If a data set frequency is not constant across all targets, it is recommended that the data set is split into multiple projects (one for each frequency). If kept in the same project, the most granular frequency target determines the overall data set frequency. The targets that are a less granular frequency have non-matching dates treated as missing values and are cleaned to get a complete series of the same frequency as the most granular data.

Model Build Phase

Targets: The number of unique targets in the merged data set.

Unique Dates: The number of unique dates in the merged data set.

Total Dates: The total number of unique dates in the merged data set. This may be greater than the unique dates because the data set may be missing dates based on frequency. The Total Dates statistic includes these missing dates.

Project statistics at the bottom of the Overview include:

Target Volatility Decomposition Chart: Shows the number of different volatile targets (low, medium, high). This is based on the standard deviation of the target versus the mean. It also shows how many of those targets are determined to be low, medium, or high significance.

Grouping Method: The grouping method chosen for this model build.

Target Group Information: The number and percentage of target in each group (and single targets).

Review Dataset Aggregate Statistics

The Dataset Aggregate statistics include the same statistics as the top of the data set overview (Features, Frequency, Targets, Total Dates, Unique Dates).



It also includes the following information:

Model Build Phase

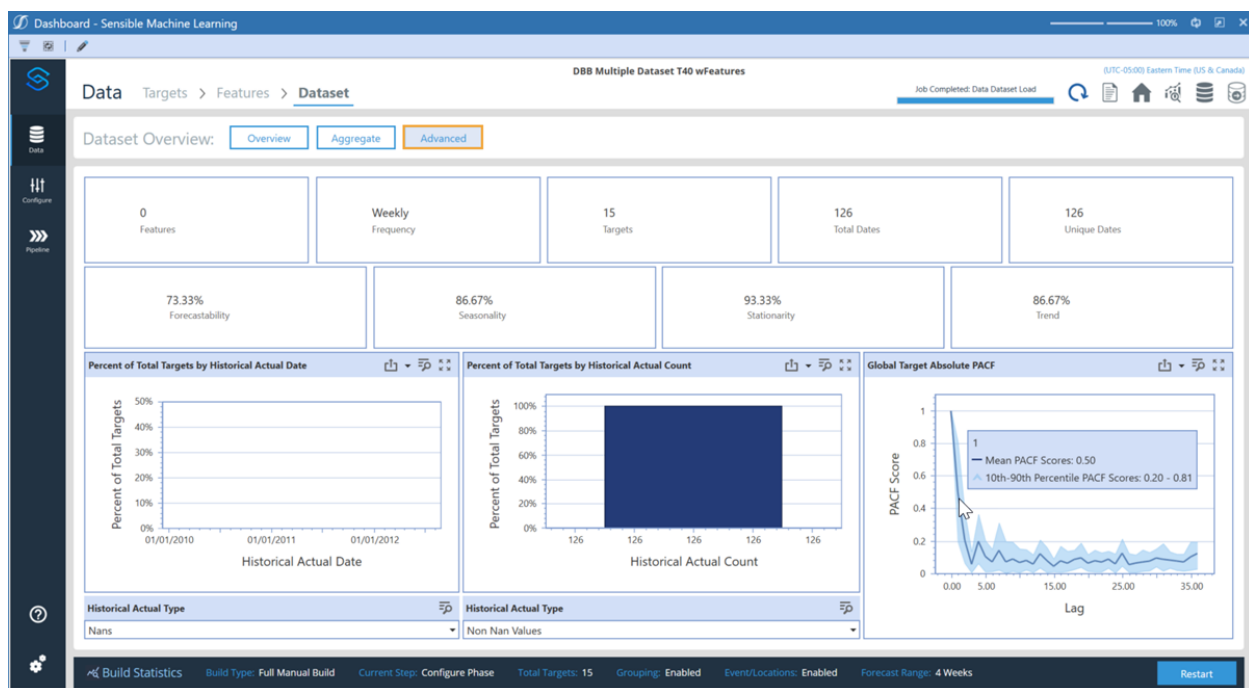
Aggregate Target Time Series: The aggregation of all targets on each given date in the data set. This helps to identify data set seasonality as a whole, on given time periods, or large trends over time.

TIP: Use the [date range sliders](#) at the bottom of the page to change the time range on the Aggregate Target Time Series chart.

% Missing: The percent of targets that are missing data on each given date.

Review Advanced Data Set Statistics

The Advanced view of the data set statistics shows the statistics in the Project view along with additional charts. Click **Advanced** in the Data Set Project view to display the advanced statistics.



The Dataset Aggregate statistics include:

Forecastability: A percentage grade that is specific to Sensible Machine Learning that indicates how forecastable the target data set is. This metric is calculated as a percent of total targets (0-100%) within the data set that are synonymous with random noise (which means no reasonable patterns can be detected). A score closer to 100% is desired.

Model Build Phase

Seasonality: A calculation of the percent of total targets (0-100%) in the target data set that have identifiable seasonality. A score closer to 100% is desired.

Stationarity: Indicates the percent of total targets (0-100%) in the target data set that are stationary, which means they do not experience a noticeable value level-shift. For example, a target whose mean value changes by 20% year-over-year would not be considered stationary. For certain time series models, it is easier to predict for stationary targets.

Trend: A calculation of the percent of total targets (0-100%) in the target data set that have an identifiable trend.

Percent of Total Targets by Historical Actual Date: This chart visualizes the percent of total targets with either non-zero and non-missing values, zero (Zeros) values, or missing (Nans) values (depending on the drop-down selection) over the data set's historical time frame. This provides the essential view on data sparsity over time.

Percent of Total Targets by Historical Actual Count: This distribution chart visualizes the percent of total targets with a given number of non-zero, non-missing, or non-zero or non-missing data points (x-axis), providing another view of data sparsity. Ideally, there should be as many targets as possible approaching the maximum number of available data points.

Global Target Absolute PACF (Partial Autocorrelation Function): A PACF chart demonstrates correlation (-1 to 1) of values based on the time increment between them. For example, a daily-level data set with a PACF score of 0.5 at an x-axis point of 7 signals that, on average, today's value has a correlation coefficient of 0.5 with the value of 7 days prior. This chart visualizes the mean, 90th percentile, and 10th percentile PACF score.

Use the information shown in the updated **Dataset** page to verify that target and grouping results are as expected. If you are satisfied with the grouping results, continue in the Model Build phase to the [Configure section](#).

Model Build Phase Configure Section

The Configuration section of the Model Build phase is where you can:

- Import, configure, and map locations and events to targets.
- Set forecast and modeling parameters.


Use the individual pages in the Configuration section of the Modeling phase to:

- [Analyze Forecasts and Set a Forecast Range](#)
- [Configure Locations](#)
- [Configure Library - Features](#)
- [Configure Library - Events](#)
- [Assign Generators and Locations](#)
- [Set Modeling Options](#)

Analyze Forecasts and Set a Forecast Range

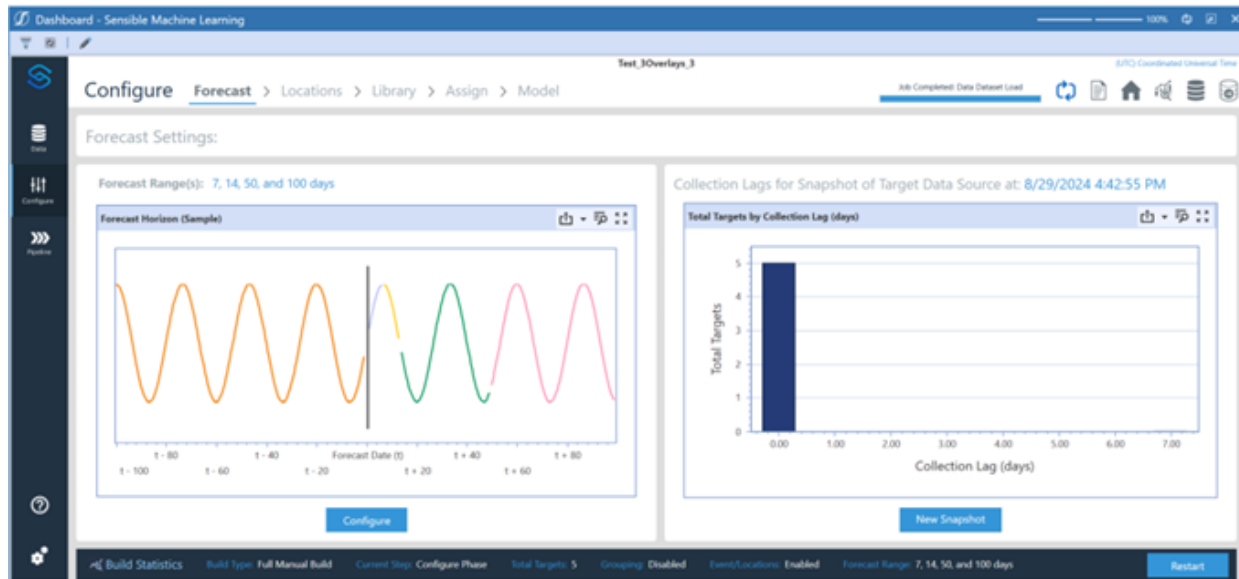
The **Forecast** page provides an easy-to-navigate step to set the desired forecast range. The forecast range is how far forward into the future the model is to forecast. The forecast range is dynamic based on the data set frequency (Days, Weeks, Months). Use the Forecast Range field in the Settings pane to set the forecast range.

The Forecast Horizon chart in the Settings pane displays an example of the configured forecast range. The line plot represents a pseudo-data set with the Actuals line representing the data set, the vertical line (Forecast Start Marker) representing the first data point of the forecast, and the Forecast line representing the additional forecasted data points. This representation shows what dates a forecast for your data would be over but is not your actual data nor your forecasted data.

Collection lag is the length of time between when a data point occurs and when that data point is collected. Click **New Snapshot** to take a snapshot of the collection lags for the target data source, then click **Refresh**  to refresh the page.

Use the **Forecast** page to select the desired forecast range for your prediction runs. You can also run new data snapshots from this page.

Model Build Phase



Set the Forecast Range

Use the **Forecast** page to set one or multiple **Forecast Ranges**, which determine how far forward from the latest date in the data set you want predictions generated for each forecast run. To configure the forecast ranges, follow these steps:

Model Build Phase

Configure Forecast Range(s): Configure the forecast ranges below. This project is able to have up to 5 ranges.

Forecast Range(s):

Forecast Range #1
7
Must be an integer greater than 0 and less than 1,000.

Forecast Range #2
14
Must be an integer greater than 0 and less than 1,000.

Forecast Range #3
50
Must be an integer greater than 0 and less than 1,000.

Forecast Range #4
100
Must be an integer greater than 0 and less than 1,000.

+ -

Save Close

1. Click the **Configure** button to launch the dialog.
2. Input the desired forecast ranges for the Model build.
 - a. Use the add (+) and remove (-) buttons to adjust the quantity of desired forecast ranges to be run.
3. Once the forecast ranges are configured, click the **Save** button to commit them to the Model Build.

Once the forecast ranges have been configured, the **Forecast Horizon** chart will update to give a visualization of the varying lengths of the forecasts.

Configure Locations

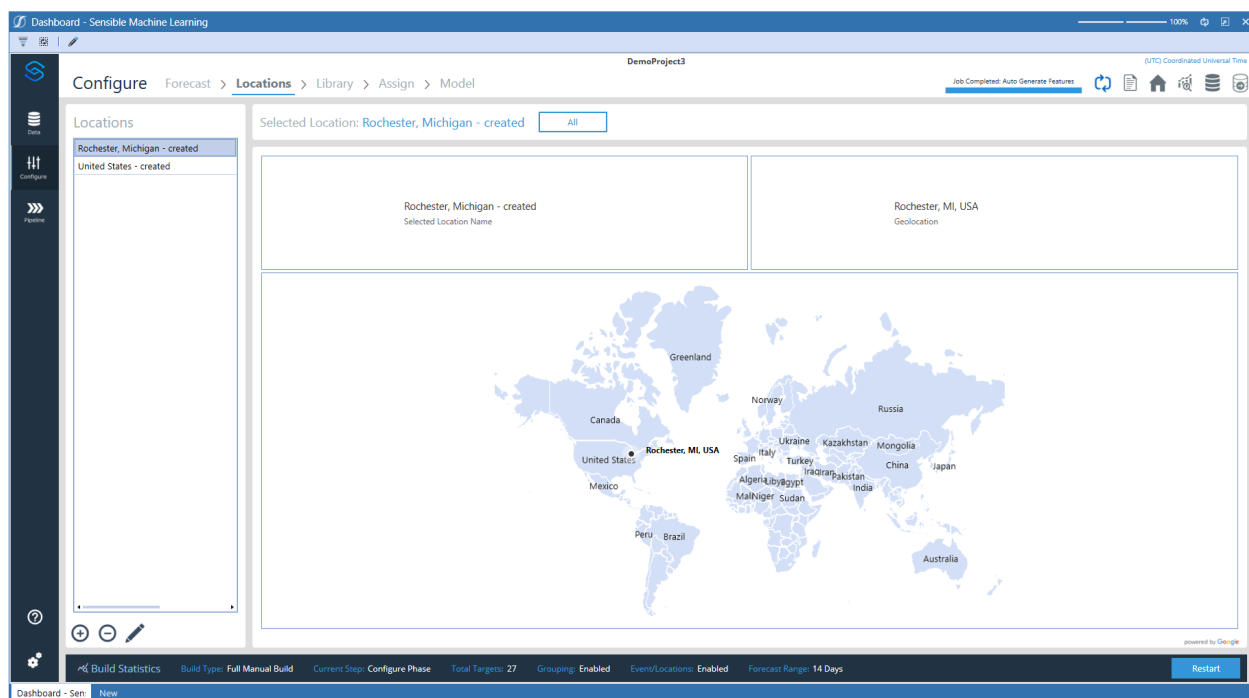
Once you have grouped source data using the **Dataset** page, you can use the **Locations** page to manage locations to be used in your target data sets. You can add, delete, or edit locations using this page.

Model Build Phase

Locations provide a means to map events and features to specific targets. To do this, a location must also be mapped to one or several targets. This can either happen automatically by specifying a location dimension using the [Targets](#) page, or you can manually map locations to targets using the [Assign](#) page.

Other ways to add locations include:


- Using the location dimension of a data set job.
- Configuring generators that include locations in its features. See [Configure Library Features](#).
- [Importing event packages](#). See [Configure Library Events](#).
- Uploading a locations file containing location names and addresses. This is similar to uploading an events file. See [Configure Library Events](#) for instructions.

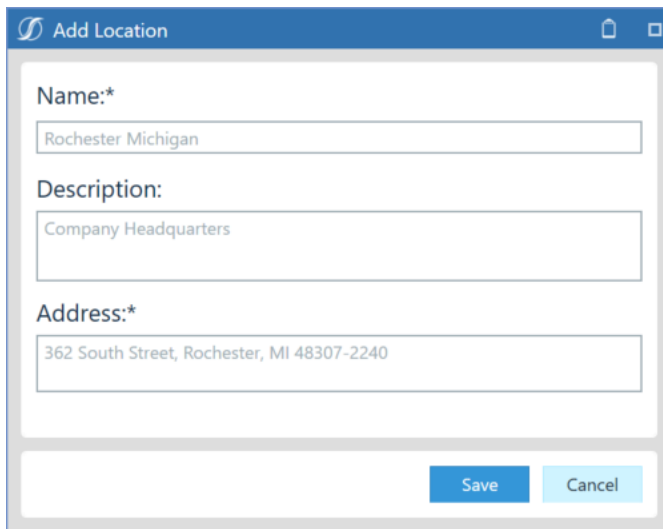


IMPORTANT: Be aware of the geolocation assigned to a location name. For example, if a location name of **Rochester** is imported through a location dimension of the target data set, it may map to Rochester, New York by default, regardless of whether that location was meant for Rochester, Michigan. In a situation like this, the Rochester location should be edited with an address of "Rochester, Michigan."

Duplicate geolocation or location names are not allowed.

Add a Location

1. Click the **Add New Location**  button at the bottom of the Locations pane. The **Add Location** dialog box displays.




2. Type a name for the location. This is the location name that displays in the location options when you [assign generators and locations to targets](#).


NOTE: The location name cannot include the keyword created, but any locations created through the location dimension or Generator Configuration include this keyword. If anything other than the description is updated for these locations, then the name must also change to not include the created keyword.

Model Build Phase

3. Optionally type a description for the location. The description also displays in the location options when you assign locations to targets.
4. Type an address for the location you are adding. The address cannot contain any special characters. The correct street address is not required.
5. Click **Save**. A message box notifies you that the location has been added.
6. Click **OK** to add the location and close the **Add Location** dialog box.

The location is added to the Locations pane and is selected as the current location. The interactive map also displays the location. **Delete** and **Update** buttons display at the bottom of the Locations pane so you can delete or edit the location.

To update a location, select it in the Locations pane and click the **Update**  button, then use the **Update Location** dialog box to edit the name, description or address information for the selected location.

To delete a location, select it in the Locations pane and click the **Delete**  button. A message box displays the location name and asks to confirm the deletion. Click **Delete** to delete the location from your locations list.

Find Locations on the Interactive Map

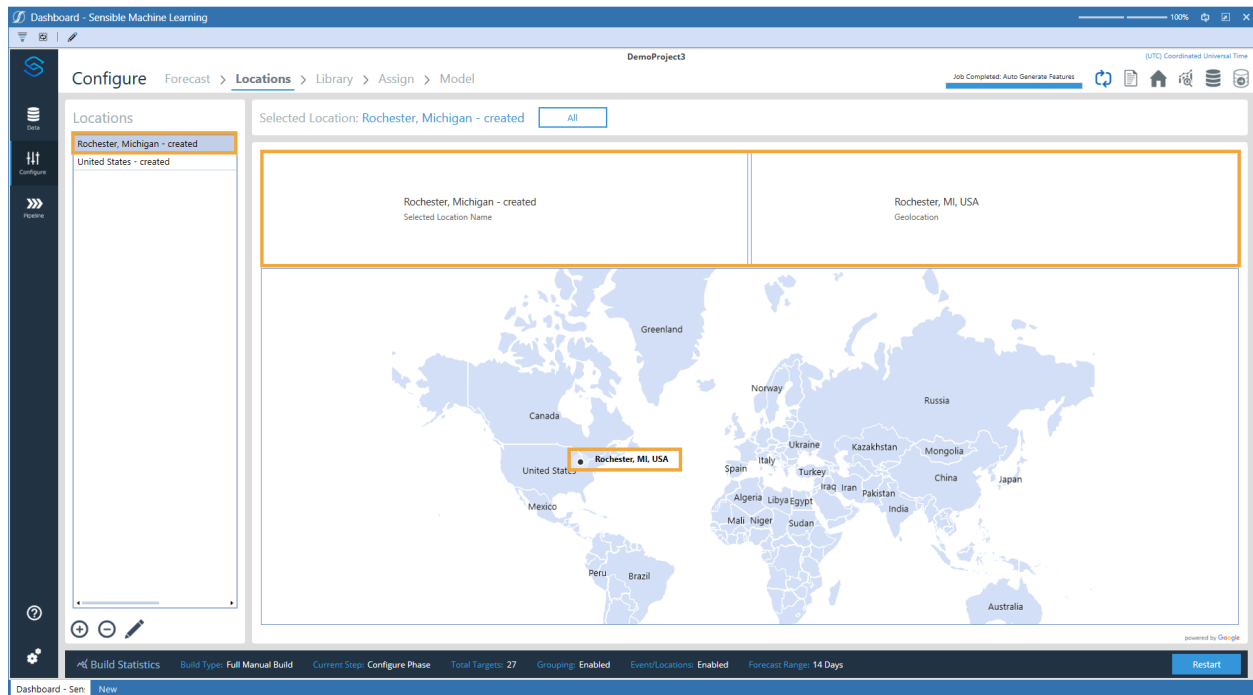
Use the interactive map on the **Locations** page to zoom in on specific locations anywhere on the globe. You can also move the map's center by clicking and holding down the mouse button to move the map.

There are two views you can use to view added locations: a single location view and an all locations view. Both views list all added locations in the Locations pane and the interactive map. Click the **Change view option** button at the top of the Selected Location pane to toggle between the two views.

Find a Single Location

Click a location in the Locations pane to switch to the Single Location view. The Single Location view displays the selected location's name and geolocation at the top of the interactive map, and highlights the location in the interactive map.

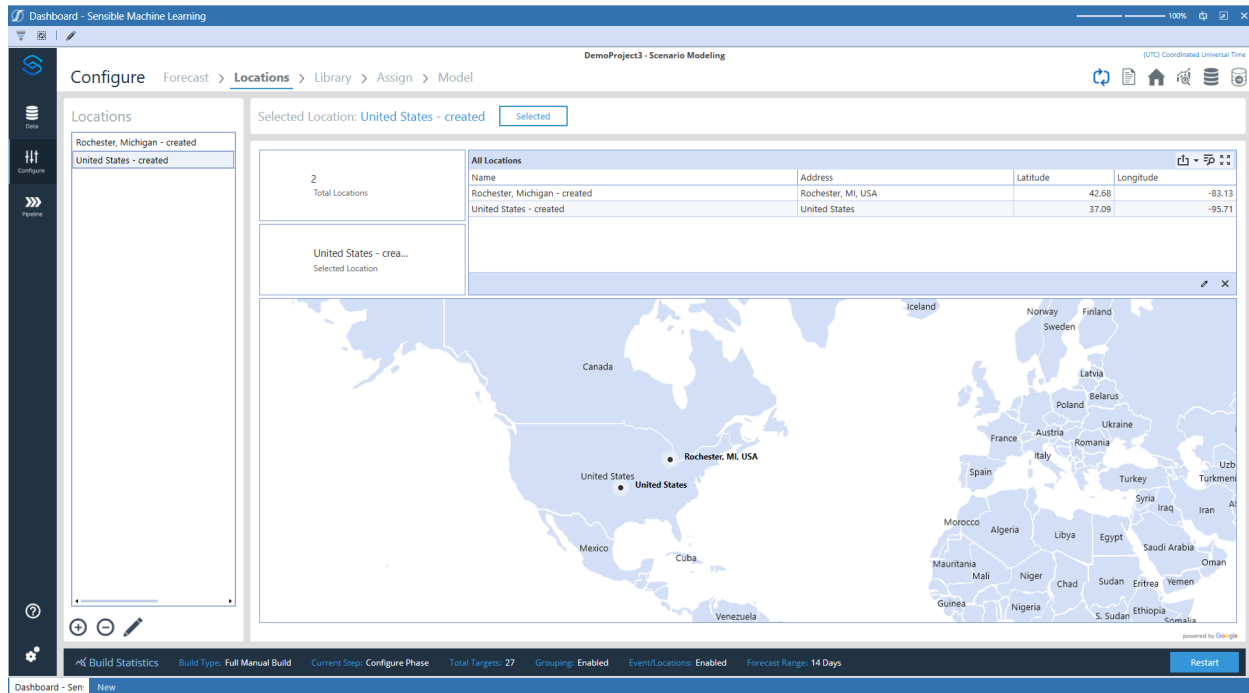
Model Build Phase



Find All Locations

The All Locations view displays the last selected location's address and the total number of locations at the top of the interactive map. The All Locations pane lists each location, which includes the name, address, and longitude and latitude of each location. All added locations display on the interactive map.

Model Build Phase



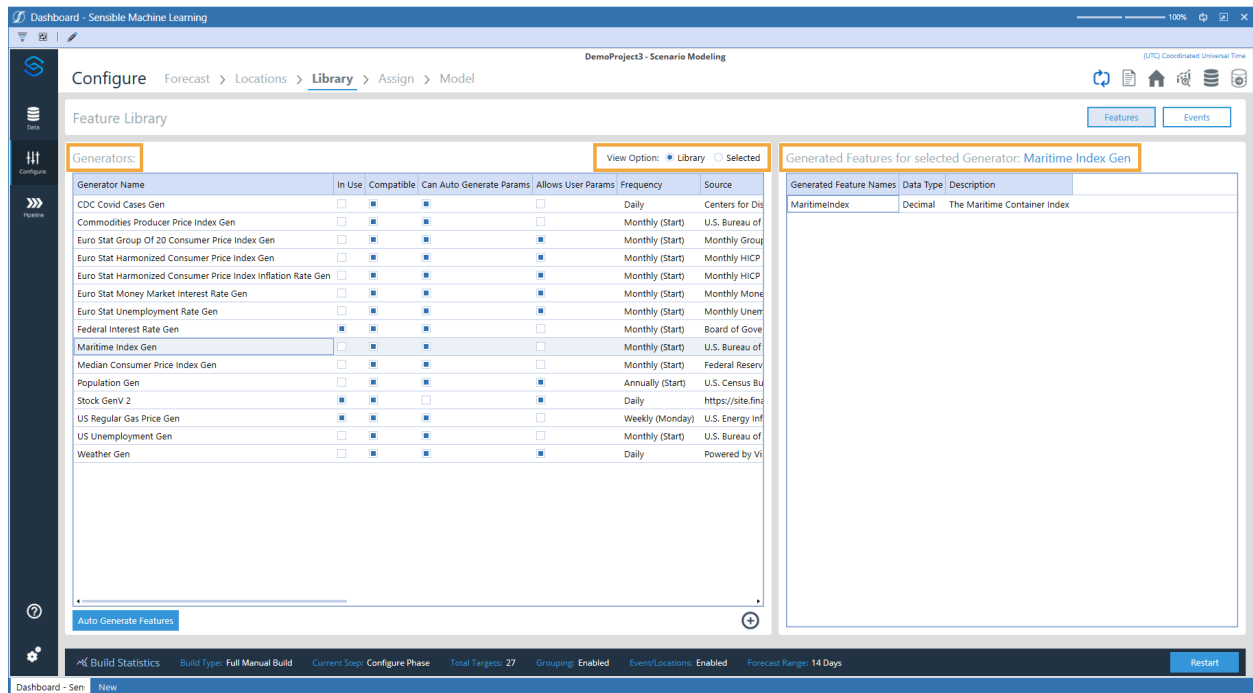
Once you have added all the locations to be used in your project, you can continue by [configuring events](#).

Configure Library - Features

The **Features** view of the **Library** page in the Configure section lets you select the generators used to add external features to the data set. External features can increase the predictive accuracy of the Machine Learning models. You can create multiple data sets containing features (also known as generator instances) from the library of generators that Sensible Machine Learning provides.

The Generators pane has a Library view that lists all generators currently available in the Generator library, and a Selected view that lists the generators specifically selected to add external features to the data set.

Model Build Phase



The following information displays for each generator.

In Use: A checked box means the generator is used in the current model build.

Compatible: A checked box means the generator is compatible with the current model build. This is based on number of data points, frequency, and the data set's earliest start date.

Can Auto Generate Params: A checked box means the generator can generate the necessary initial parameters required to gather external data.

Allows User Params: A checked box means you can add additional parameters to the generator. See [Add Generator Configurations](#) for instructions.

Frequency: The frequency of the external data (Daily, Weekly, Monthly). This is merged into the target data frequency.

Source: The data source and citation for the external information.

Select a generator from the Generators pane to show its generated features in the Generated Features pane. This can be one to many features, depending on the type of generator. The Generated Features pane also displays the following information for each selected generator.

Generated Feature Names: The name of each feature being generated.

Data Type: The type of data (such as integer, boolean, or decimal) that the feature contains.


Model Build Phase

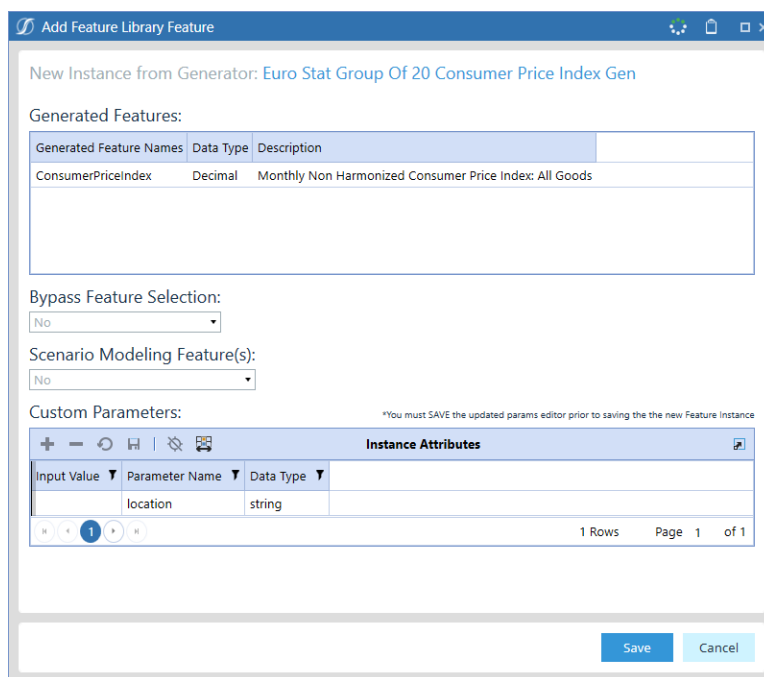
Description: A brief description of the information the feature contains.

You can add any of the compatible generators to use in the pipeline as external features.

Add a Generator Configuration

To add generator configurations:

1. Select desired generator and click **Add a new Feature Library Feature** . The **Add Feature Library Feature** dialog box displays.



New Instance from Generator: Euro Stat Group Of 20 Consumer Price Index Gen

Generated Features:

Generated Feature Names	Data Type	Description
ConsumerPriceIndex	Decimal	Monthly Non Harmonized Consumer Price Index: All Goods

Bypass Feature Selection:
No

Scenario Modeling Feature(s):
No

Custom Parameters: **You must SAVE the updated params editor prior to saving the the new Feature Instance

Input Value	Parameter Name	Data Type
	location	string

1 Rows Page 1 of 1

Save Cancel

2. In the Bypass Feature Selection field, select **Yes** if the feature should bypass feature selection. Otherwise, select **No**.

NOTE: Only select **Yes** for Bypass Feature Selection if it is certain that the listed generated features benefit your models. Sensible Machine Learning runs all generated features through a feature selection process to determine if the feature is important to the models.

Model Build Phase

3. In the Scenario Modeling Feature field, select **Yes** if the feature should be included when defining custom Scenarios in Utilization and the intention of the project is to run predictions on different Scenarios. Otherwise, select **No**.

NOTE: When selecting **Yes** for any event:

- The project will be considered a Scenario Modeling project by the Xperiflow Engine.
- Altering a Scenario Modeling project after the job has run requires a Restart or Full Manual Rebuild.
- **Known In Advance** automatically changes to **Yes**.

4. If a generator allows for custom parameters, they must be input into the table editor labeled **Custom Parameters**:

Add Feature Library Feature

New Instance from Generator: Weather Gen

Generated Features:

Generated Feature Names	Data Type	Description
feelslike	Decimal	The temperature it feels like outside
feelslikemax	Decimal	The max temperature it felt like on a given day
feelslikemin	Decimal	The min temperature it felt like on a given day
humidity	Decimal	A given day's humidity

Bypass Feature Selection:
No

Scenario Modeling Feature(s):
Yes


Custom Parameters: *You must SAVE the updated params editor prior to saving the the new Feature Instance

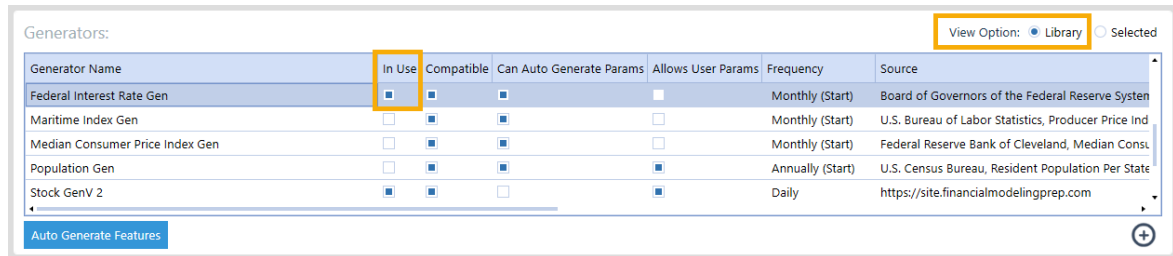
Input Value	Parameter Name	Data Type
362 South Street, Rochester, MI 48307	location	string

1 Rows Page 1 of 1

Save Cancel

Model Build Phase

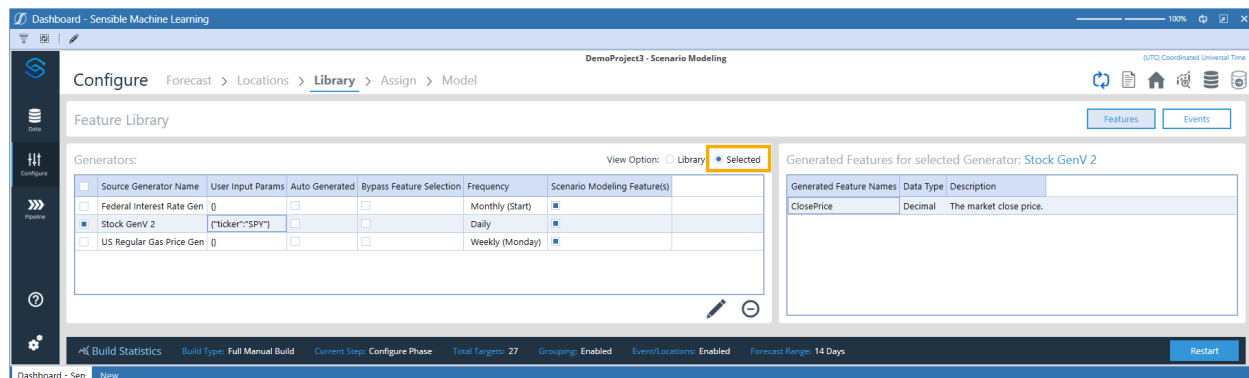
- After you enter input values for all the listed custom parameters, click the **Save** icon  on the table editor to save the values.
5. Click **Save** to close the **Add Feature Library Feature** dialog box. The generator configuration is validated and added to the Selected list if valid. This also checks the **In Use** option in the Generator Pane Library list so you can see the selected generators from the Library view.



Generator Name	In Use	Compatible	Can Auto Generate Params	Allows User Params	Frequency	Source
Federal Interest Rate Gen	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)	Board of Governors of the Federal Reserve System
Maritime Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)	U.S. Bureau of Labor Statistics, Producer Price Ind
Median Consumer Price Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)	Federal Reserve Bank of Cleveland, Median Cons
Population Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Annually (Start)	U.S. Census Bureau, Resident Population Per State
Stock GenV 2	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Daily	https://site.financialmodelingprep.com

TIP: You can use custom parameters to further customize generated features. For example, when creating an instance using the WeatherGen Generator, you can enter a location parameter to get the WeatherGen Features for a specific location.

Once you select a generator and add it to the list of selected generators, you can click the **Selected** radio button at the top of the Generators pane to see the generators selected for your models.




Source Generator Name	User Input Params	Auto Generated	Bypass Feature Selection	Frequency	Scenario Modeling Feature(s)
<input type="checkbox"/> Federal Interest Rate Gen	0	<input type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)	<input checked="" type="checkbox"/>
<input checked="" type="checkbox"/> Stock GenV 2	["ticker":"SPY"]	<input type="checkbox"/>	<input type="checkbox"/>	Daily	<input checked="" type="checkbox"/>
<input type="checkbox"/> US Regular Gas Price Gen	0	<input type="checkbox"/>	<input type="checkbox"/>	Weekly (Monday)	<input checked="" type="checkbox"/>

Generated Feature Names	Data Type	Description
ClosePrice	Decimal	The market close price.


Delete a Generator Configuration

To delete a generator configuration:

1. In the Selected view of the Generators pane, select the generator to delete and click **Delete the Selected Configuration** .
2. In the **Delete Feature Library Feature** dialog box, click **Delete**, then click **OK**. The generator is removed from the list.

Update a Generator Configuration

To update a generator configuration:

1. In the Selected view of the Generators pane, select the generator to edit and click **Update** . The **Update Feature Library Feature** dialog box displays.
2. Use the **Update Feature Library Feature** dialog box to update the generator's configuration. This dialog box works the same way as the **Add Feature Library Feature** dialog box. See instructions in [Add a Generator Configuration](#) for information on using the dialog box.

Generator Configurations Information

The Generators pane lists generator configurations currently set for the model build. The following information displays for each generator configuration:

Source Generator Name: The name of the generator to be used in the configuration.

User Input Params: The input parameters provided by the user (if any).

Use Automatic Params: Indicates if the generator configuration is set to use the automatic parameters.



Bypass Feature Selection: Indicates if the features generated by this configuration bypass feature selection.

Frequency: The frequency of the external data. This merges into the target data frequency.

Model Build Phase

Generators: View Option: Library Selected

<input type="checkbox"/>	Source Generator Name	User Input Params	Auto Generated	Bypass Feature Selection	Frequency	Scenario Modeling Feature(s)
<input type="checkbox"/>	Federal Interest Rate Gen	{}	<input type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)	<input checked="" type="checkbox"/>
<input checked="" type="checkbox"/>	Stock GenV 2	{"ticker": "SPY"}	<input type="checkbox"/>	<input type="checkbox"/>	Daily	<input checked="" type="checkbox"/>
<input type="checkbox"/>	US Regular Gas Price Gen	{}	<input type="checkbox"/>	<input type="checkbox"/>	Weekly (Monday)	<input checked="" type="checkbox"/>

When you select a generator configuration, the right pane shows the features generated by the generator. This may be a single feature or many features, depending on the type of generator. The following information displays:

Generated Feature Names: The name of the feature being generated.

Data Type: The type of data, such as integer, Boolean, or decimal, that the feature contains.

Description: A brief explanation of the information the feature contains.

Generated Features for selected Generator: **StockGen**

Generated Feature Names	Data Type	Description
ClosePrice	Decimal	The market close price.

After auto-assigning events and locations or assigning events and locations to specific targets, you can move to the [Model](#) page.

Generator Custom Parameters

Some generators can take in custom parameters to fetch specific data from external sources. While certain generators can take in a location address, they do not support all locations. Below are details on what options can be provided for the custom parameters for generators that have these limitations.

Model Build Phase

- EuroStatHarmonizedConsumerPriceIndexGen
 - Supported Locations:
 - Luxembourg, Iceland, Czechia, European Union, Malta, Latvia, Romania, Finland, Portugal, Germany, Belgium, Denmark, Poland, Cyprus, Europe, Hungary, France, Spain, Bulgaria, Albania, Sweden, Norway, Croatia, North Macedonia, Serbia, Slovenia, Slovakia, Austria, Netherlands, Italy, Lithuania, Estonia, Switzerland, Montenegro
- EuroStatGroupOf20ConsumerPriceIndexGen
 - Supported Locations:
 - Italy, France, Germany
- EuroStatHarmonizedConsumerPriceIndexInflationRateGen
 - Supported Locations:
 - Romania, Estonia, Bulgaria, Spain, Latvia, Iceland, Norway, Europe, Croatia, Sweden, Albania, Montenegro, Belgium, Portugal, Cyprus, Serbia, Luxembourg, Italy, North Macedonia, European Union, Czechia, Switzerland, Hungary, Poland, Lithuania, Malta, Slovakia, Finland, Slovenia, France, Austria, Germany, Netherlands, Denmark
- EuroStatUnemploymentRateGen
 - Supported Locations:
 - Malta, Switzerland, Norway, France, Lithuania, Latvia, Luxembourg, Netherlands, Slovakia, Bulgaria, Spain, Iceland, Italy, Estonia, Croatia, Belgium, Poland, Slovenia, Finland, Czechia, Sweden, Cyprus, Germany, Austria, Denmark, Hungary, Romania, Portugal
- EuroStatMoneyMarketInterestRateGen
 - Supported Locations:
 - Poland, Sweden, Denmark, Bulgaria, Hungary, Romania, Czechia
- EuroStatHouseholdSavingsRateGen

Model Build Phase

- Supported Locations:
 - Poland, Slovenia, Sweden, Spain, Finland, Portugal, Austria, Belgium, France, Denmark, Italy, Germany, Norway, Czechia, Hungary, Netherlands
- Harmonized Consumer Price Index
 - Supported Locations:
 - United States
- Harmonized Consumer Price Index Inflation Rate
 - Supported Locations:
 - United States
- Unemployment
 - Supported Locations:
 - Japan, United States
- Canada Population
 - Supported Locations:
 - Canada
 - Newfoundland and Labrador, Canada
 - Prince Edward Island, Canada
 - Nova Scotia, Canada
 - Quebec, Canada
 - Ontario, Canada
 - Manitoba, Canada
 - Saskatchewan, Canada

Model Build Phase

- Alberta, Canada
- British Columbia, Canada
- Yukon, Canada
- Northwest Territories, Canada
- Nunavit, Canada
- Canada Consumer Price Index
 - Supported Locations:
 - Canada
 - Newfoundland and Labrador, Canada
 - Prince Edward Island, Canada
 - Nova Scotia, Canada
 - New Brunswick, Canada
 - Quebec, Canada
 - Ontario, Canada
 - Manitoba, Canada
 - Saskatchewan, Canada
 - Alberta, Canada
 - British Columbia, Canada
 - Whitehorse, Yukon, Canada
 - Yellowknife, Northwest Territories, Canada
 - Iqaluit, Nunavit, Canada
 - Calgary, Alberta, Canada

- Charlottetown and Summerside, Prince Edward Island, Canada
- Edmonton, Alberta, Canada
- Halifax, Nova Scotia, Canada
- Montreal, Quebec, Canada
- Regina, Saskatchewan, Canada
- Saint John, New Brunswick, Canada
- Saskatoon, Saskatchewan, Canada
- St. John's, New Brunswick, Canada
- Thunder Bay, Ontario, Canada
- Toronto, Ontario, Canada
- Vancouver, British Columbia, Canada
- Victoria, British Columbia, Canada
- Winnipeg, Manitoba, Canada

Configure Library - Events


Use the **Events** view of the **Library** page to add, edit, and delete events along with their occurrences. Events can be created manually, through an event file upload, or by selecting a pre-established event package.

The modeling process uses calendar-based events to increase the model accuracy.

Add events that you know are related to the targets being predicted. When created, an event is initially be empty with no dates (occurrences) assigned to the event. You must define one or more occurrences that define what days that particular event falls on. You can add locations to the event to map events to targets using the assigned location dimension.

NOTE: This capability also exists in the **Manage Events** page in the Utilization phase. However, you cannot add or delete events from the **Manage Events** page.

Add Events

To add events, click the **Add** button  at the bottom of the Events pane. Then use the **Add Event** dialog box to add a single event, or to add an events package.

NOTE: Events are validated, and all event details and mappings are stored for later use. You cannot have two separate events with the same name. However, two separate events can have different names with the same occurrences.

Add a Single Event

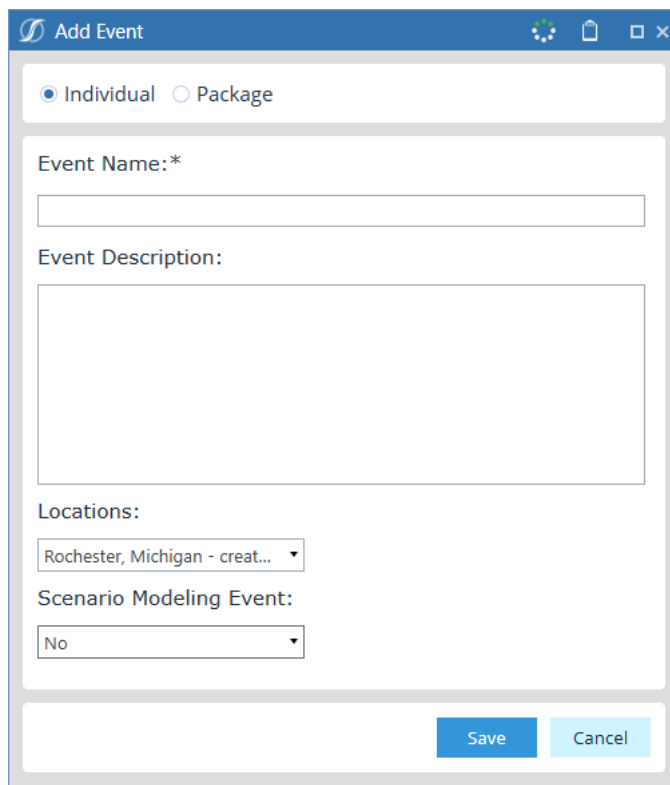
When creating a single event, you can also add locations to the event. Locations are used to map events to targets using assigned locations. This simplifies the assignment of the event to targets.

1. In the **Add Event** dialog box, select **Individual**.
2. Type a unique name for the event you want to add in the Event Name field.

NOTE: Each event in your project must have a unique Event name.

3. Optionally type a description for the event.
4. If adding one or more locations, click the **Locations** drop-down and select the check boxes next to the locations you want to add to the event. The locations in the list are created when you [configure locations](#).

Model Build Phase



Add Event

Individual Package

Event Name:*

Event Description:

Locations:

Rochester, Michigan - creat...

Scenario Modeling Event:

No

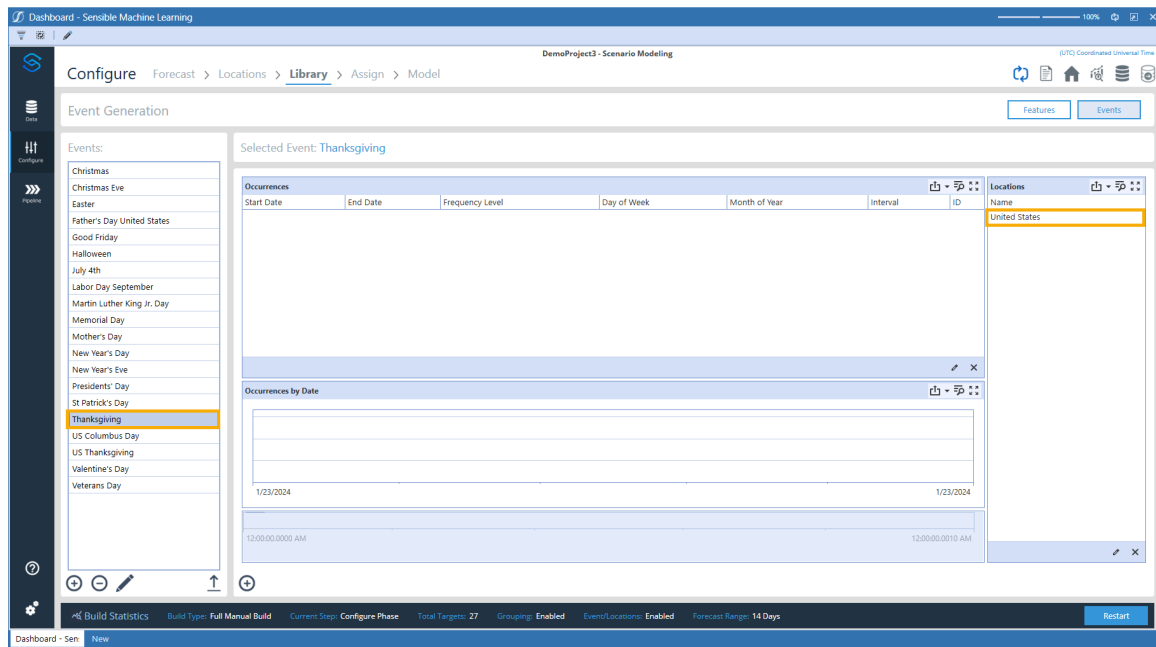
Save Cancel

5. In the Scenario Modeling Event field, select **Yes** if the event should be included when defining custom Scenarios in Utilization. Otherwise, select **No**.

NOTE: Only select **Yes** for Scenario Modeling Feature if the intention of the project is to run predictions on different Scenarios. If **Yes** is selected for any event, the project will be considered a Scenario Modeling project by the Xperiflow Engine.

6. Click **Save**. A message box informs you that the event has been added.
7. Click **OK** to add the event to the Events pane. Any locations you added to the event display in the Locations pane.

Model Build Phase



Add Events Using an Events Package

Event packages are a useful time saver when defining the events you want to assign to targets. Each event added from event packages includes an event occurrence rule.

Events that fall on the same date in a year include the appropriate specific occurrence rule. Events that fall on relative day in a year include a relative date occurrence rule (for example, the Thanksgiving U.S. holiday falls on the fourth Thursday in November).

You can add multiple events at once this way, then delete or edit individual events from the package.

To add an event package:

1. In the **Add Event** dialog box, select **Package**. A list of pre-configured event packages displays.
2. Click the check boxes for each event package whose events you want to add to your events list.

Model Build Phase

Individual Package

Select Packages to Add:

<input type="checkbox"/>	Name	Description
<input type="checkbox"/>	Canada Holidays	Standard Canadian holidays.
<input type="checkbox"/>	China Holidays	Standard Chinese holidays.
<input type="checkbox"/>	Covid Stay At Home State Events	Covid stay at home orders for each state in the Uni
<input type="checkbox"/>	Denmark Holidays	Standard Denmark holidays.
<input type="checkbox"/>	Finland Holidays	Standard Finland holidays.
<input type="checkbox"/>	France Holidays	Standard French holidays.
<input type="checkbox"/>	German Holidays	Standard German holidays.
<input type="checkbox"/>	Italy Holidays	Standard Italian holidays.
<input type="checkbox"/>	Mexico Holidays	Standard Mexican holidays.
<input type="checkbox"/>	Religious Holiday Events	Religious holidays around the world.
<input checked="" type="checkbox"/>	Sporting Events	Major sporting events around the world.
<input type="checkbox"/>	Sweden Holidays	Standard Sweden holidays.
<input type="checkbox"/>	United Kingdom Holidays	Standard United Kingdom holidays.
<input type="checkbox"/>	United States Holidays	Standard American holidays.

Scenario Modeling Event:

3. In the Scenario Modeling Event field, select **Yes** if the event should be included when defining custom Scenarios in Utilization. Otherwise, select **No**.

NOTE: Only select **Yes** for Scenario Modeling Event if the intention of the project to run predictions on different Scenarios. If **Yes** is selected for any event, the project will be considered a Scenario Modeling project by the Xperiflow Engine.

4. Click **Add**.
5. A message box informs you that the events package has been added. Click **OK** to close the message box and add the events from the selected packages to the events list.

NOTE: If an event already exists and an event package is added with the same name, the two events will be merged. The merging functionality makes a super set of all occurrences and locations between the two versions of events.

Adding an event package may also add locations associated with the event package if they don't exist in the project. They are added with the special engine suffix created. See [Add Locations](#) for more information.

Upload an Event or Location File

You can upload an existing event or location file in CSV format that contains your company's events or location information. This saves time over having to manually enter events in the **Events** page.

TIP: This functionality also exists in the **Events** page (Manage section) in the Utilization phase.

NOTE: Sensible Machine Learning also lets you upload a locations file or a mapper file for events or locations. Use this procedure to upload files of those types as well. Uploading a locations file saves time over having to use the [Locations](#) page to manually [add the locations](#) that you want to assign to targets. Uploading a events or locations mapper file saves time over having to manually assign events or locations to targets on the [Assign](#) page.

Upload Types

You upload various types of data and event or location data mappings in a .csv file. The following describes the different types of uploads that can be done.

Event Upload

This upload lets you add various events and occurrences using a .csv file upload. If an event from the file already exists in the project, the occurrences in the file are added to the already existing event.

NOTE: Occurrences uploaded through an event upload are created as single day occurrences with no occurrence rules. Occurrences are expected to be in Month/Day/Year format.

Column Definitions:

Model Build Phase

EventName: Name of event to create or add occurrences to.

Occurrence: A single date the event occurred.

Example:

	A	B	C
1	EventName	Occurrence	
2	Happy Hour	1/5/2023	
3	Happy Hour	1/6/2023	
4	Happy Hour	1/7/2023	
5	Closed	12/25/2022	
6	Closed	12/25/2021	
7	Closed	12/25/2023	

If no **Happy Hour** or **Closed** events exist in the project, their three occurrences are added to the existing events. Otherwise the events are created with their three occurrences listed in the file.

Location Upload

This upload lets you create various locations through a .csv file upload. The job fails if any of the below cases are encountered:

- LocationName already exists in the project.
- LocationAddress maps to a well-formatted address already in the project.

NOTE: Use as specific an address as possible. For example, an address such as **Rochester** may lead to unexpected results because the state is not specified, (Rochester could mean Rochester, New York, Rochester, Michigan, Rochester, Minnesota).

Column Definitions:

LocationName: Name of the location to create.

LocationAddress: Address of location to create.

Example:

LocationName	LocationAddress
Little Caesars Arena	2645 Woodward Ave, Detroit, MI 48201
White House	1600 Pennsylvania Avenue NW Washington, D.C. 20500
The Big House	1201 S Main St, Ann Arbor, MI 48104

Model Build Phase

This creates three locations (Little Caesars Arena, White House, The Big House) with the associated location addresses.

Event Target Mapper Upload

This upload lets you assign various events to targets using a .csv file upload. Any prior event assignments are preserved. Only new assignments are created.

NOTE: If an EventName column does not exist in the project, a warning message is written to the AI Services log, but the job continues. If a TargetName column does not correspond to an existing target in a train state (in model build) a warning message is written to the AI Services log, but the job continues.

Column Definitions:

EventName: Name of the event to assign to the associated target.

TargetName: The full target name to map to assign an event to.

Example:

EventName	TargetName
Happy Hour	[UD1]Lunch~[UD2]Alcohol
Happy Hour	[UD1]Dinner~[UD2]Alcohol
Closed	[UD1]Lunch~[UD2]Burgers

This creates three new event assignments. You can see these assignments on the Model Build phase **Assign** page. The **Happy Hour** event is assigned to two targets ([UD1]Lunch~[UD2]Alcohol and [UD1]Dinner~[UD2]Alcohol) and the **Closed** event is assigned to one target ([UD1]Lunch~[UD2]Burgers). Any prior event assignments are preserved. Only new assignments are created.

Event Target Dimension Mapper Upload

This upload lets you assign events to targets based on dimensions using a .csv file upload. Any prior event assignments are preserved. Only new assignments are created.

NOTE: If an EventName column does not exist in the project, a warning message is written to the AI Services log, but the job continues. All target dimensions must be included in columns. Leave values in the column blank if not mapping to the dimension.

Column Definitions:

EventName: Name of the event to assign to the associated target.

Model Build Phase

TargetDim1*: Targets with this value in TargetDim1* along with other dimension values are assigned this event. Values can be left blank to assign to targets regardless of this dimension.

TargetDim2*: Targets with this value in TargetDim2* along with other dimension values are assigned this event. Values can be left blank to assign to targets regardless of this dimension.

Replace TargetDim1, 2 through n with the actual target dimension name, such as UD1, UD2, Scenario, or Category.

Example:

EventName	UD1	UD2
Happy Hour		Alcohol
Closed	Lunch	Burgers
Christmas		

This example assumes the below image is the target data set with only two target dimensions (UD1 and UD2). The target data set has four targets.

Date	UD1	UD2	Value
1/1/2020	Lunch	Alcohol	100
1/1/2020	Dinner	Alcohol	50
1/1/2020	Lunch	Burgers	200
1/1/2020	Dinner	Burgers	88

The upload file assigns the **Happy Hour** event to all targets with the UD2 dimension as Alcohol ([UD1]Lunch~[UD2]Alcohol and [UD1]Dinner~[UD2]Alcohol). It assigns the **Closed** event to all targets with UD1 as Lunch and UD2 as Burgers ([UD1]Lunch~[UD2]Burgers), and assigns **Christmas** to all targets since all target dimensions are blank.

These new event assignments can be seen on the configure assign page of the model build section of Sensible Machine Learning. Any prior event assignments are preserved. Only new assignments are created.

Event Location Mapper Upload

This upload lets you assign various locations to events using a .csv file upload. Any prior event-location assignments are preserved. Only new assignments are created. Event location assignments are useful when running the Auto Assign job to assign events to targets.

NOTE: Use as specific an address as possible. For example, an address such as **Rochester** may lead to unexpected results because the state is not specified, (Rochester could mean Rochester, New York, Rochester, Michigan, Rochester, Minnesota). If an EventName column does not exist in the project, a warning message is written to the AI Services log, but the job continues. If a LocationAddress column does not correspond to an existing target in a train state (in model build) a warning message is written to the AI Services log, but the job continues.

Column Definitions:

EventName: Name of the event to assign LocationAddress to.


LocationAddress: Address of the location to assign to the event.

Example:

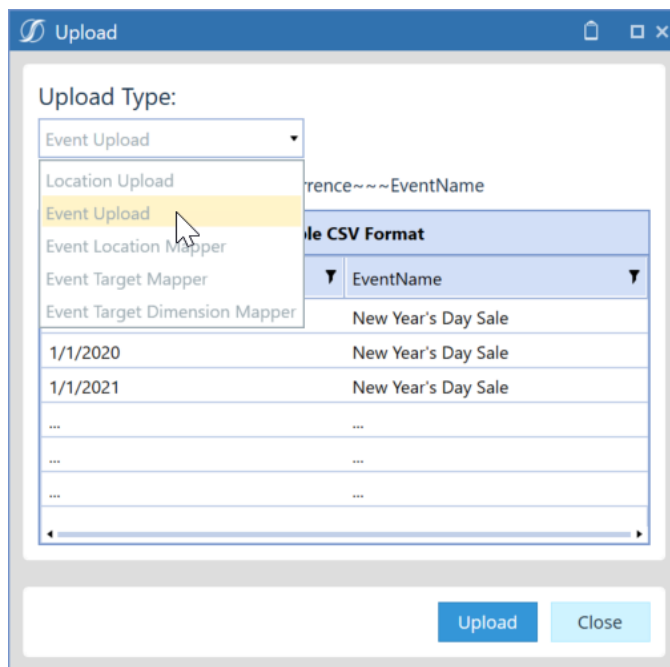
EventName	LocationAddress
Happy Hour	2645 Woodward Ave, Detroit, MI 48201
Closed	1600 Pennsylvania Avenue NW Washington, D.C. 20500
Christmas	1201 S Main St, Ann Arbor, MI 48104

This adds new locations to the specified events. You can see this on the **Events** page. The Happy Hour event has the 2645 Woodward location. The Closed event has the 1600 Pennsylvania Ave location. The Christmas event has the 1201 S Main St. location. Any prior locations added to these events are preserved, only new locations are added to the events.

Upload an Event File

1. Click the **Upload** button  at the bottom of the Events pane. The **Upload** dialog box displays.
2. In the Upload Type field, select the type of file you want to upload, or use the default **Event** upload type.

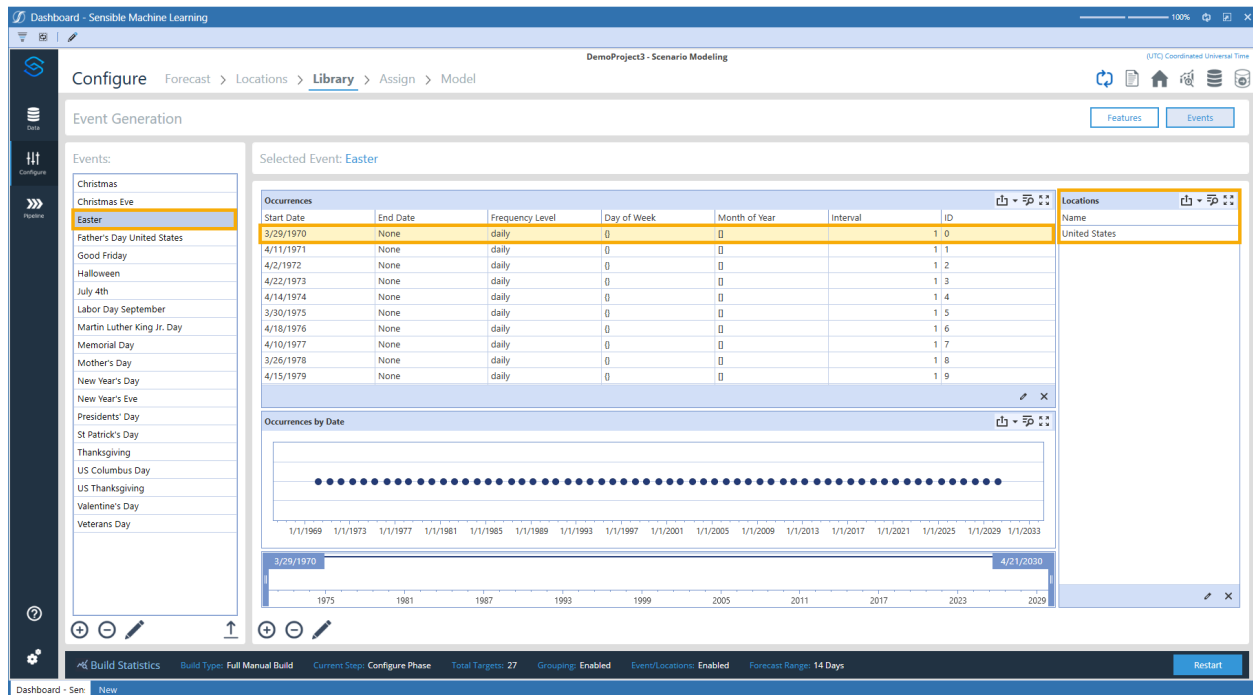
Model Build Phase



3. Click **Upload**, then use the Windows **Open** dialog box to navigate to and select the file you want to upload.
4. Click **OK**. Sensible Machine Learning queues the job to upload the selected file. The Windows **Open** dialog box closes when the job completes.
5. Click **Update** to add the information from the file to the appropriate page.

The events defined in the events file display in the Events pane. Information for the event selected in the Events pane displays in the Occurrences pane and the Occurrences by Date pane maps the event occurrences for the selected event. Any locations for the selected event that were in the uploaded events file display in the Locations pane.

Model Build Phase




Delete an Event

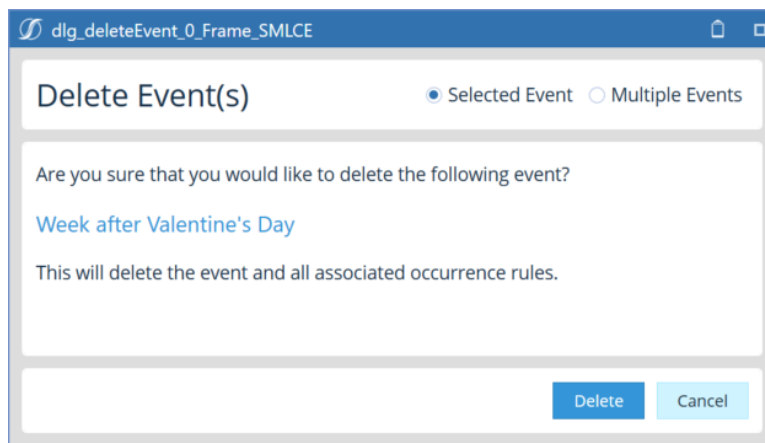
You can delete any event that is not assigned to a target that has started or completed the pipeline job. If unsure that an event can be useful, the machine learning engine can determine if the event is useful for the model.

When you delete an event, any associated occurrence rules for the event are also deleted. If the event is currently assigned to a target that has not been through the pipeline job, then the associated assignment is also deleted. This applies to any event, whether it was added manually, from an events package, or as part of an events file.

To delete a single event:

1. Select the event from the Events pane and click **Delete** .
2. A message box lists the selected event and asks to confirm the deletion. Click **Delete**.

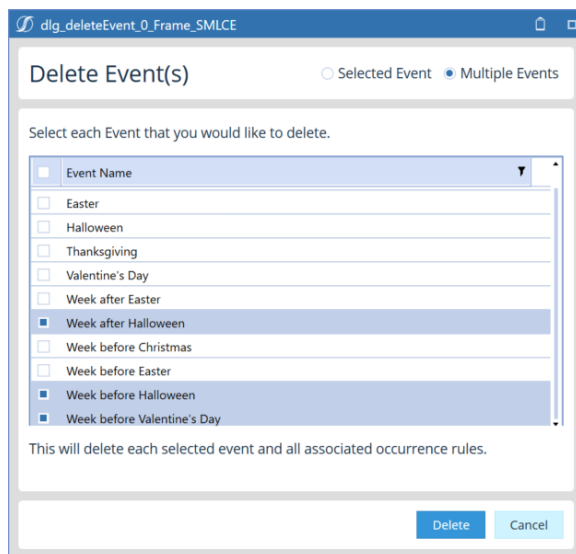
Model Build Phase



3. Click **OK** to close the message box and delete the event.

To delete multiple events:


1. Click **Delete** on the **Events** pane.
2. In the **Delete Events** dialog box, select the **Multiple Events** option.
3. Select check boxes for all events that are to be deleted. Click **Delete**.



4. Click **OK** to close the message box and delete the selected events.

NOTE: You can delete all events if the pipeline job has not run yet.

Add an Occurrence Rule to an Event

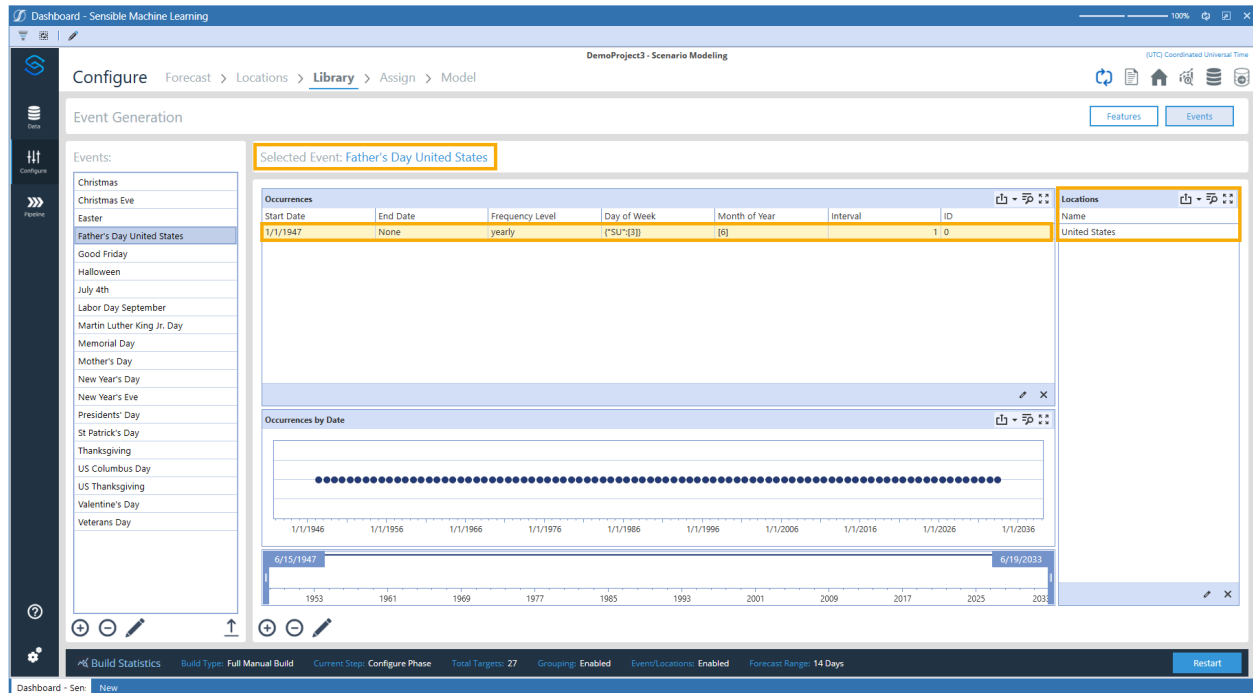
To add an occurrence rule, in the **Events** pane, select the event you want to add the occurrence to and click **Add a New Occurrence** . Then use the **Add Occurrence Rule** dialog box to add a specific occurrence rule or a relative occurrence rule.

Add a Specific Occurrence Rule

1. In the **Add Occurrence Rule** dialog box, click **Specific**.
2. Select values in the Date Start fields to specify the Month, Date and Year of the event.
3. In the Date End field, do one of the following:
 - Select **None** to have the occurrence fall on the same day of each year.
 - Select **Custom**, then use the Month, Date, and Year fields to set the last date you want the occurrence rule to apply to.
4. In the Interval field, select the rule's interval. The interval is how many steps of the frequency are between the occurrences. For example, an interval of 2 with a frequency of yearly will be once every other year.
5. In the Frequency field, select the rule's frequency from the list (Yearly, Monthly, Weekly or Daily).
6. Click **Save**. A message box informs you that the events package has been added.
7. Click **OK** to close the message box and the **Add Occurrence Rule** dialog box, and add the occurrence rule to the events list.

The occurrence rule displays in the selected event's list of occurrences, and the **Occurrences by Date** chart updates to include the added occurrence.

Model Build Phase



Add a Relative Occurrence Rule

1. In the **Add Occurrence Rule** dialog box, click **Relative**.
2. Select values in the Date Start fields to specify the Month, Date and Year of the event.
3. In the Date End field, do one of the following:
 - Select **None** to have the occurrence fall on the same day of each year.
 - Select **Custom**, then use the Month, Date, and Year fields to set the last date you want the occurrence rule to apply to.

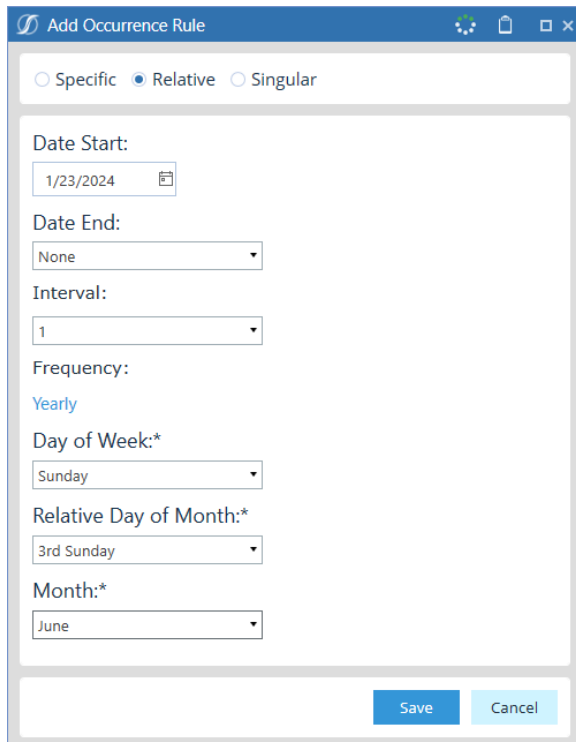
For example, if the occurrence rule is for a multiple-day event that lasts from October 1st to October 4th each year, set the date start to Month=10, Day=1, and year to the specific year for the occurrence. Then set the date end to Month=10, Day=4, and year to the specific year for the occurrence.

4. In the Interval field, select the rule's interval.
5. In the Day of Week field, select the day of the week on which the event falls.

Model Build Phase

6. In the Relative Day of Month field, select the month in which the event falls.
7. Click **Save**. A message box informs you that the events package has been added.
8. Click **OK** to close the message box and the **Add Occurrence Rule** dialog box, and add the occurrence rule to the events list.

The following graphic shows a relative occurrence rule set up for Father's day in the U.S., which occurs on the third Sunday in June of each year.



The screenshot shows a dialog box titled "Add Occurrence Rule". At the top, there are three radio buttons: "Specific", "Relative" (which is selected), and "Singular". Below this, there are several fields:

- "Date Start:" with a text box containing "1/23/2024" and a calendar icon.
- "Date End:" with a dropdown menu set to "None".
- "Interval:" with a dropdown menu set to "1".
- "Frequency:" with a blue link labeled "Yearly".
- "Day of Week:*" with a dropdown menu set to "Sunday".
- "Relative Day of Month:*" with a dropdown menu set to "3rd Sunday".
- "Month:*" with a dropdown menu set to "June".

At the bottom right, there are two buttons: "Save" (in blue) and "Cancel" (in light blue).

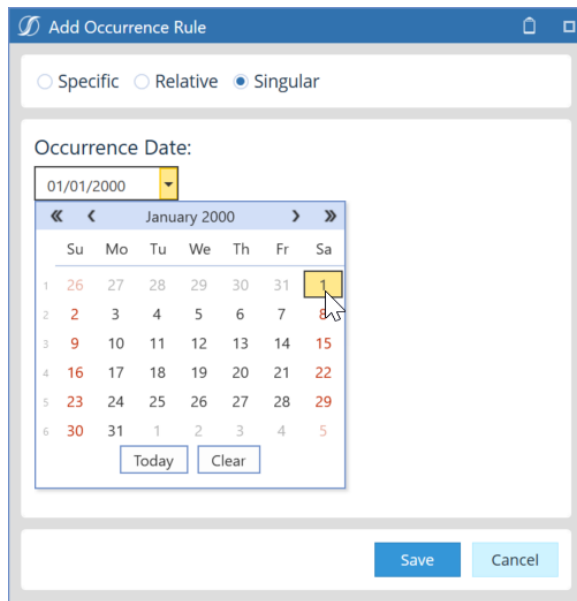
Add a Single Occurrence Rule

1. In the **Add Occurrence Rule** dialog box, click **Single**.
2. Select the single date of occurrence for the event.
3. Click **Save**. A message box informs you that the events package has been added.

Model Build Phase

4. Click **OK** to close the message box and the **Add Occurrence Rule** dialog box, and add the occurrence rule to the events list.

The following graphic shows a single occurrence rule set up for New Year's Day for 2000.



Once you have created and configured all the events for your project, you can [assign the generators and locations](#) you have configured for your project.

Auto Generate Features

Some generators support the automatic creation of configurations based on the user's project configuration and dataset. Features that are available for auto-generation are flagged in the **Can Auto Generate Params** field in the Library view of the Generators pane.

Model Build Phase

Generators: View Option: Library Selected

Generator Name	In Use	Compatible	Can Auto Generate Params	Allows User Params	Frequency
CDC Covid Cases Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)
Commodities Producer Price Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)
Euro Stat Group Of 20 Consumer Price Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)
Euro Stat Harmonized Consumer Price Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)
Euro Stat Harmonized Consumer Price Index Inflation Rate Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)
Euro Stat Money Market Interest Rate Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)
Euro Stat Unemployment Rate Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)
Federal Interest Rate Gen	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)
Maritime Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)
Median Consumer Price Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)
Population Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Annually (Start)
Stock GenV 2	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)

To use **Auto Generate Features**:

1. Click the **Auto Generate Features** button.
2. Select which generators to auto-generate.

Select from the available Auto-Generation Options:

Generator Name	In Use	Compatible	Frequency	Source
<input type="checkbox"/> CDC Covid Cases Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Daily	Centers for Disease Control and Prevention, COVID-
<input type="checkbox"/> Commodities Producer Price Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)	U.S. Bureau of Labor Statistics, Producer Price Index
<input type="checkbox"/> Euro Stat Group Of 20 Consumer Price Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)	Monthly Group of 20 Consumer Price Index. https://
<input type="checkbox"/> Euro Stat Harmonized Consumer Price Index Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)	Monthly HICP Index - All goods. https://ec.europa.e
<input type="checkbox"/> Euro Stat Harmonized Consumer Price Index Inflation Rate Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)	Monthly HICP Inflation Index - All goods. https://ec
<input type="checkbox"/> Euro Stat Money Market Interest Rate Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)	Monthly Money Market Interest Rate. https://ec.eur
<input type="checkbox"/> Euro Stat Unemployment Rate Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)	Monthly Unemployment Rates Ages 24-75. https://
<input checked="" type="checkbox"/> Maritime Index Gen	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)	U.S. Bureau of Labor Statistics, Producer Price Index
<input checked="" type="checkbox"/> Median Consumer Price Index Gen	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)	Federal Reserve Bank of Cleveland, Median Consum
<input checked="" type="checkbox"/> Population Gen	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Annually (Start)	U.S. Census Bureau, Resident Population Per State, r
<input checked="" type="checkbox"/> US Unemployment Gen	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	Monthly (Start)	U.S. Bureau of Labor Statistics, Unemployment Rate
<input type="checkbox"/> Weather Gen	<input type="checkbox"/>	<input checked="" type="checkbox"/>	Daily	Powered by Visual Crossing Weather



3. Click the **Auto Generate** button.
4. The **Job Progress** dialog box appears and can be closed at any time.
5. Once the **Auto Generate Feature** job is completed, the selected generators can be seen in

Model Build Phase

the **Selected** pane.

Generators: View Option: Library Selected

<input type="checkbox"/>	Source Generator Name	User Input Params	Auto Generated	Bypass Feature Selection	Frequency	Scenario
<input type="checkbox"/>	Maritime Index Gen	{}	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)	<input type="checkbox"/>
<input type="checkbox"/>	Median Consumer Price Index Gen	{}	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)	<input type="checkbox"/>
<input type="checkbox"/>	Population Gen	{"location": "Michigan"}	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Annually (Start)	<input type="checkbox"/>
<input type="checkbox"/>	US Unemployment Gen	{}	<input checked="" type="checkbox"/>	<input type="checkbox"/>	Monthly (Start)	<input type="checkbox"/>

Assign Generators and Locations

Use the **Assign** page to map events and locations to targets. This page has a Project view and Target view.

Any location dimension specified on the [Targets](#) are automatically assigned locations to your targets. Use the Assign page to map events and locations to targets for use during [Pipeline](#), where these events and locations can generate predictive features or serve as predictive features themselves.

NOTE: There is a limited number of locations and events that can be assigned to any individual target.

You can map locations and events to targets in these ways:

Auto Assign: All events are assigned to targets based on their locations. If any of the target's locations are geographically within any of the event's locations, the event is assigned to the target. A target without a location, whether removed on the Target view or not present, cannot have events assigned to it through a shared location. Click **Auto Assign** to assign events based on the currently applied locations for all targets. See [Auto-Assign Generators and Locations](#).

NOTE: You must have at least one location in the Target view mapped (selected and applied) to use Auto Assign. The Auto Assign job uses the selected locations in order to automatically map Generators which contain the selected location(s).

Manual Assignments: In the Target view, you can assign events and locations to a target using arrow buttons and clicking **Apply**. Selecting **Apply to All** applies whatever mappings are present for the currently selected target to all other targets in the data set. See [Assign Generators and Locations to a Specific Target](#).

Event Target Mapper File Upload: Upload a file that maps events to target names. See [Upload an Event File](#).

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Event Target Dimension Mapper File Upload: Upload a file that maps events to targets based on dimensionality. See [Upload an Event File](#).

View Project Location and Generator Information

Use the Project view to see the number of:

- Generators and locations currently being used by your model.
 - Generators/Locations mapped to at least one target.
 - Total Generators/Locations Mapped
 - Total Target-Generators/Location Mappings
- Locations mapped to at least one target.
- A list of all events defined in your project. See [Configure Library - Features](#).
- The interactive map showing all locations defined in your project. This is the same interactive map on the [Locations](#) page.

The screenshot displays the 'Configure' phase of a project in the Sensible Machine Learning dashboard. The breadcrumb navigation is 'Configure > Forecast > Locations > Library > Assign > Model'. The main content area is titled 'Event/Location Assignments' and features two tabs: 'Auto Assign' and 'Target View'. Below the tabs are eight summary cards:

- Total Generators: 23
- Total Targets Mapped To At Least One Generator: 27
- Total Locations: 2
- Total Targets Mapped To At Least One Location: 27
- Total Generators Mapped: 5
- Total Target Generator Mappings: 135
- Total Locations Mapped: 1
- Total Target Location Mappings: 27

Below the summary cards are two tables:

All Events	
Name	Locations
Christmas	United States
Christmas Eve	United States
Easter	United States
Father's Day United States	United States
Good Friday	United States
Halloween	United States
July 4th	United States
Labor Day September	United States
Martin Luther King Jr. Day	United States
Memorial Day	United States
Mother's Day	United States
New Year's Day	United States
New Year's Eve	United States
Presidents' Day	United States
St Patrick's Day	United States

All Locations	
United States	
Rochester, MI, USA	

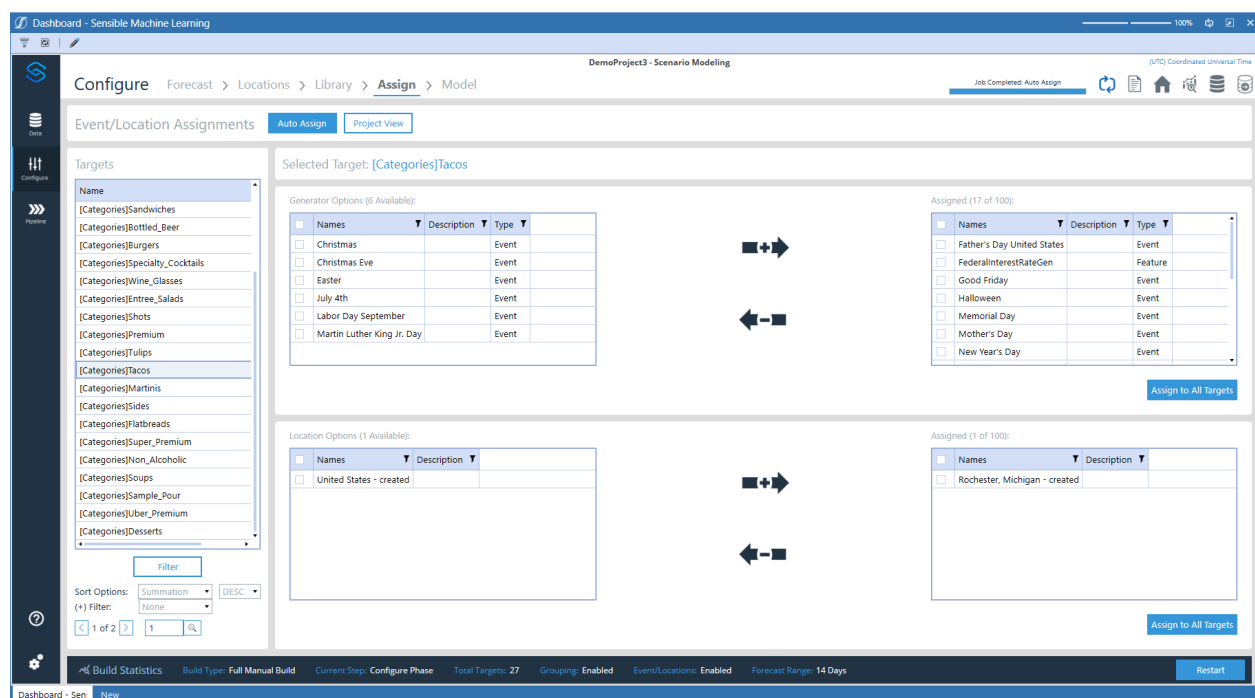
The 'All Locations' table is accompanied by an interactive map of the United States with markers for 'United States' and 'Rochester, MI, USA'. At the bottom of the dashboard, a status bar shows: 'Build Statistics', 'Build Type: Full Manual Build', 'Current Step: Configure Phase', 'Total Targets: 27', 'Grouping: Enabled', 'Event/Locations: Enabled', 'Forecast Range: 14 Days', and a 'Restart' button.

View Generator and Location Assignments by Target

For the target selected in a list on the left, you can add all the events and locations added in the previous pages to be associated with the target. To do this, click the plus arrow to add them. Click the minus arrow to remove them.

In Target view, you can see the events and locations assigned to each target.



TIP: When a location dimension is selected for the target data set, the respective location for each target displays in the selected locations pane.



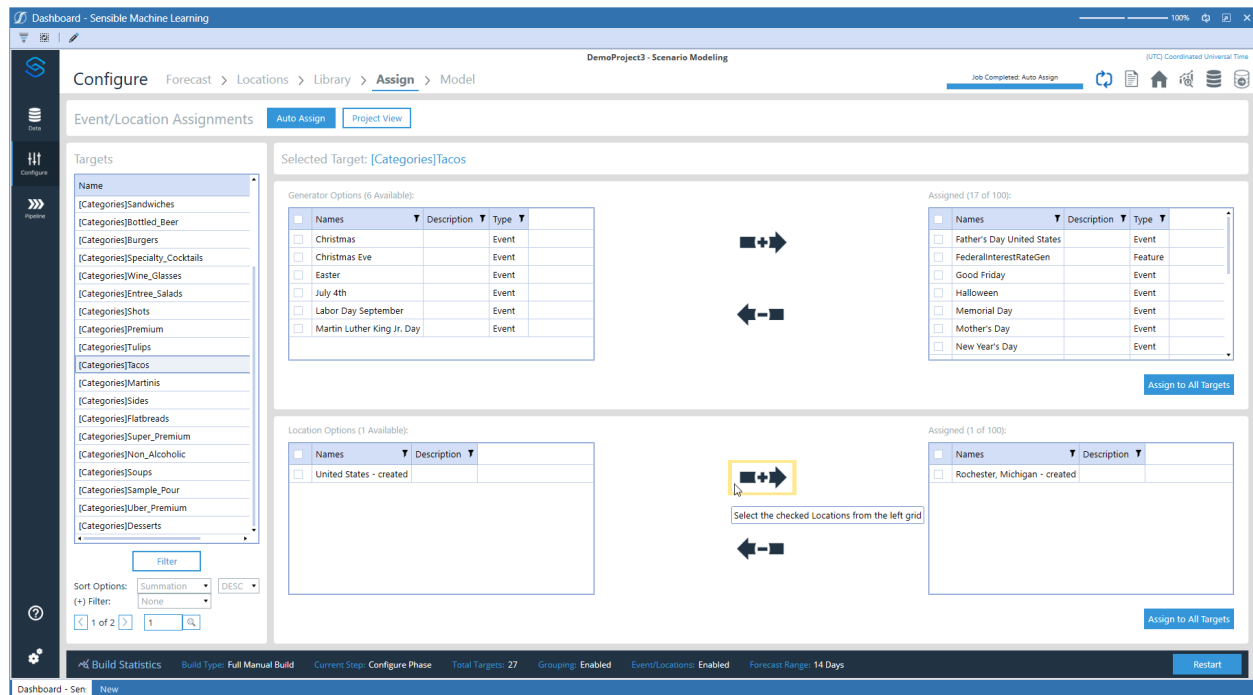
Assign Generators and Locations to a Specific Target

Assigning events and locations to a target allows you to use inputted information in the modeling process. Generators and locations can be assigned to a single target or to all targets in the model build.

Model Build Phase

1. If in Project view, click **Target View** to switch to the **Assign** page Target view.
2. In the Targets pane, select a target to which you want to assign events and locations. The Selected Target pane shows the target name and all available events and locations that can be assigned.
3. In the Generator Options table, select check boxes next to the generators you want to assign to the target, or select the check box in the table header row to select all available events.
4. Click the **Select the Checked Generators**  button to move the selected generators from the Event Options table to the Selected table.
5. In the Location Options table, select check boxes next to the locations you want to assign to the target, or select the check box in the table header row to select all available locations.
6. Click the **Select the Checked Locations**  button to move the selected locations from the Location Options table to the Selected table.
7. The add and remove buttons will only apply the events and locations to the currently selected target. To apply these changes to all targets:
 - Click **Apply to All** to apply the current event and location assignments to the selected target.
8. Select another target in the Targets and repeat steps 3 through 7 to make assignments for that target. Repeat until you have assigned generators and locations for all targets in the project.

Model Build Phase



TIP: To deselect events or locations, select them from the respective Selected table and click Remove to remove the selected events or locations from the selected lists.

Auto-assign Generators and Locations to Targets

Auto Assign uses the selected locations to automatically map Generators that contain the selected locations.

1. Click **Target View** to assign one or more locations from the Locations Options list to the Selected list.

NOTE: To run Auto Assign, you must have at least one location under Selected Locations (both selected and applied) on the Target View page.

1. Click **Auto Assign**. A message box asks you to confirm that you want to run Auto Assign to assign events to targets based on their locations.
2. Click **Run**. The auto assign job posts to the job queue.

3. Click **OK** to close the jobs message box. The **Job Progress** dialog box displays.
4. Click **Close** at any time to close the **Job Progress** dialog box. The number of total mapped events and locations updates in the **Assign** page Project view.

After auto-assigning events and locations or assigning events and locations to specific targets, you can move to the [Forecast](#) page to set forecast ranges.

Set Modeling Options

The **Model** page in the Configure section lets you set various options that manage how the Sensible Machine Learning engine runs your modeling pipeline. These parameters tweak processes related to feature transformation and modeling.

Use this page to configure the model settings that run in the model pipeline. Adjusting these settings for your modeling project is optional. You can accept the default settings and [run the pipeline](#).

View Options

View options on the **Model** page let you set options for the entire project or create different options for each target in the model build.

Set Project-wide Model Options

The Project View lets you set options that apply to all targets.

1. Set a value for **Train Intensity**. This parameter varies between 1 and 5. It is a scale of how many hyperparameter tuning iterations you want to occur during training. The higher the training intensity number, the more iterations are performed to find the optimal hyperparameters, which potentially leads to increased accuracy. However the run time for the modeling job increases with a higher intensity.

Typically, training intensities between 3 and 5 prove to achieve both high-quality accuracy and reasonable computing run times.

2. Set a value for **Deployment Strategy**. This specifies which models to deploy after the model training phase. Select Auto if you want Sensible Machine Learning to determine the most effective deployment strategy for your project.

NOTE: Selecting Top Model or Best 3 Models for the deployment strategy treats targets in groups as a whole, not as individual targets.

3. Set a value for **Allow Negative Targets**. The default setting of **False** ensures that Sensible Machine Learning does not predict values below zero for the project.
4. Set a value for **Evaluation Metric**. Specify the error metric that evaluates model accuracy during training and testing. See [Appendix 3: Error Metrics](#) for an error metric list and details.
5. Set a value for **Clean Missing Method**. This setting determines the method used to handle missing data values during data cleaning. Values are:

Interpolate: Fills in missing data using linear interpolation between the surrounding non-missing data points. For example [1.0, nan, 3.0, nan, -5.0] becomes [1.0, 2.0, 3.0, -1.0, -5.0]

Kalman: Fills in missing data using a [Kalman filter](#).

Local Median: Fills in missing data using the median of the past n and future n days from the missing data point where n depends on the frequency. For example, ($n=2$) [1.0, nan, 2.0, 3.0, nan, 6.0] becomes [1.0, 2.0, 3.0, 3.0, 6.0]

Mean: Fills in missing data using the mean value of the non-missing data. For example [1.0, nan, 3.0, nan, 5.0] becomes [1.0, 3.0, 3.0, 3.0, 5.0]

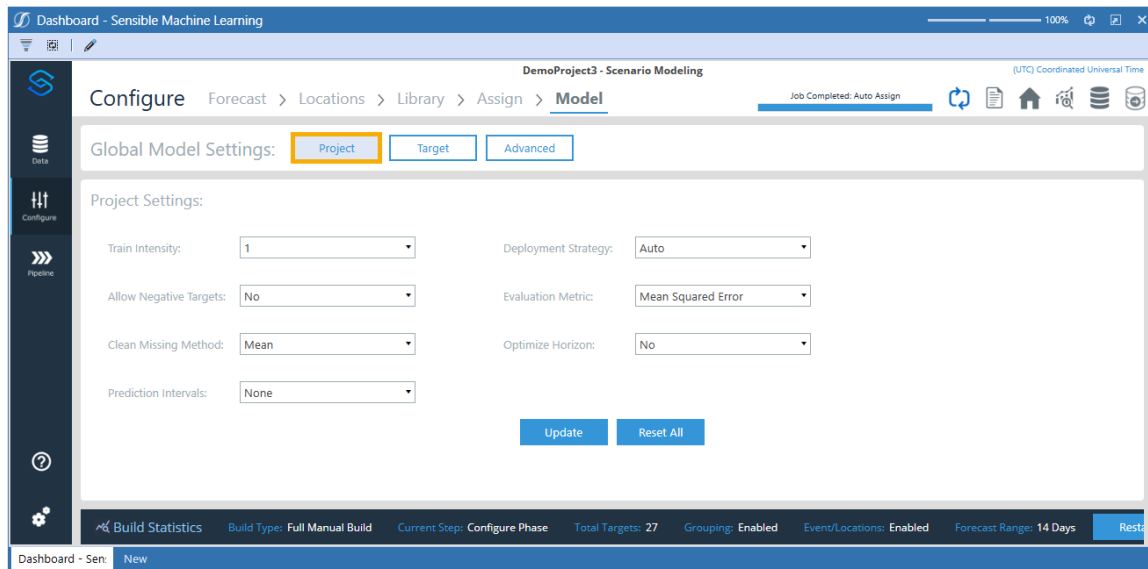
Zero: Fills in missing data with 0. For example [1.2, nan, 3.0, nan, nan] becomes [1.2, 0, 3.0, 0, 0]

6. Set a value for **Optimize Horizon**. Set to **Yes** to split the test portion of the largest split into smaller chunks equal to the forecast range (or only 10 chunks, if the amount of chunks created by separating the split into forecast range sized chunks is more than 10).

These chunks are used in the model selection stage to perform individual predictions on each chunk. This results in a better test of which model performs best on the given forecast range, but also results in longer run times.

7. Set a value for **Prediction Intervals**. If set to a percentage, prediction intervals run for models and give a confidence band for predictions and back tests of the selected percentage.
8. Set a value for **Compute Intervals for**. This setting only displays if the prediction interval value is set to something other than **None**. It specifies which models' prediction intervals are calculated in the prediction. Back tests compute prediction intervals for all models (if prediction interval value is set to something other than **None**).

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9. Set a value for **Model Ranking**. This setting is only for projects that have a grouping strategy configured. Select from the following options:
 - **Targets**: Calculates the model ranking for each individual target in a project.
 - **Groups**: Calculates the model ranking for each group of targets in a project.
10. When you have made your settings, click **Update** at the bottom of the Project Settings pane.
11. A message box informs you that project level settings have been updated. Click **OK** to close the message box.

NOTE: Targets set to **Project** use these setting. Targets set to **Advanced** do not use these settings unless reset to **Project**.

TIP: Click **Reset All** to reset all targets to use the project level settings.

Set Model Options for Each Target

The Targets view lets you select advanced settings on a target-by-target basis. This provides finer-grained modeling during the pipeline run, but can increase the run time of the pipeline job.

To use the advanced settings:

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1. In the Targets pane, select a target, then use the drop-downs to change setting values for the selected target or group. Settings are as follows:

Models: Specify the models offered by Sensible Machine Learning to be trained for a selected target.

Evaluation Metric: This is the same as the [Project view](#).

Tuning Strategy: Select the strategy by which to tune hyperparameters during training.

Tuning Iterations: This is the same as Training Intensity on the Project view.

Clean Missing Method. This setting determines the method used to handle missing data values during data cleaning. Values are:

- **Interpolate:** Fills in missing data using linear interpolation between the surrounding non-missing data points. For example [1.0, nan, 3.0, nan, -5.0] becomes [1.0, 2.0, 3.0, -1.0, -5.0]
- **Kalman:** Fills in missing data using a [Kalman filter](#).
- **Local Median:** Fills in missing data using the median of the past n and future n days from the missing data point where n depends on the frequency. For example, ($n=2$) [1.0, nan, 2.0, 3.0, nan, 6.0] becomes [1.0, 2.0, 3.0, 3.0, 6.0]
- **Mean:** Fills in missing data using the mean value of the non-missing data. For example [1.0, nan, 3.0, nan, 5.0] becomes [1.0, 3.0, 3.0, 3.0, 5.0]
- **Zero:** Fills in missing data with 0. For example [1.2, nan, 3.0, nan, nan] becomes [1.2, 0, 3.0, 0, 0]

Allow Negative Targets: This is the same as the [Project view](#).

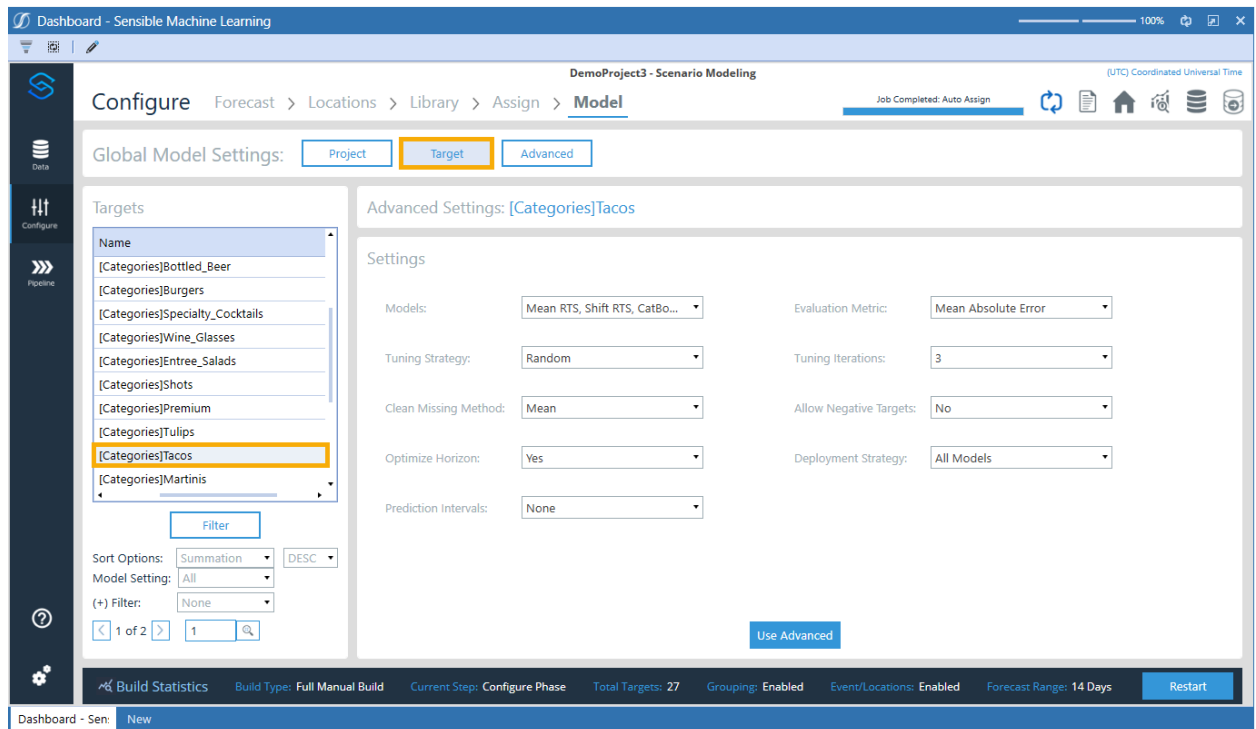
Optimize Horizon: This is the same as the [Project view](#).

Deployment Strategy: This is the same as the [Project view](#).


Prediction Intervals: This is the same as the [Project view](#).

Compute Intervals for: This is the same as the [Project view](#).

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2. Click **Use Advanced** at the bottom of the Settings pane. A message box notifies you that the selected advanced settings will be used for the selected target.
3. Click **OK** to close the message box. Sensible Machine learning then uses your advanced settings for that target when running the pipeline job.
4. Repeat the previous steps for any other targets in your project.
5. Once advanced settings are made for a target, if you want to change those advanced settings, use the previous steps to select the target and change values for each setting, then click **Update** at the bottom of the Settings pane.

TIP: Click **Use Project** at the bottom of the Settings pane to use the values set in the Project view for the selected target. Click **Refresh**  to see the targets with the Advanced model settings in the Targets pane.

Set Advanced Settings

The Advanced view lets you select advanced settings for the project.

IMPORTANT: This is an advanced page and should only be used by users with a deeper understanding of cross-validation and modeling techniques.

Configure Cross Validation

The Cross Validation Settings pane sets the desired cross-validation configuration for the model build.

The first selection must be the cross-validation type which is one of the following:

Total Splits: Set the total number of splits to be used in the model build.

Custom Dates: Add rows to the table editor using the **Add +** button. Each split number must have every data set type listed as **True** on the Saved settings pane on the right. Data set types for a given split cannot overlap and must be contiguous. Each row must contain the following information:

- **Split Number:** The split to which the row's information corresponds.
- **Dataset Type:** The data set type for which the row belongs.
- **Start (Datetime):** The start date of the split portion. The range of valid dates is displayed at the top of the table.
- **End (Datetime):** The end date of the split portion. The range of valid dates is displayed at the top of the table.

Custom Percentiles: The same as the Custom Dates settings but using start and end percentages for the data set portions instead of dates. The percentages are decimals that can be on or after zero and before or on one. For example 0.1 thru 0.8 for each split number.

NOTE: For custom dates and custom percentiles, the data set type column values should be in this order for each split number: **Train, Validation, Test, Holdout.**


Default: The default settings recommended by Sensible Machine Learning based on the data set.

Configure Avoidance Periods

The Avoidance Periods table contains portions of the data set that should not be used when evaluating metrics for model performance.

To add avoidance periods:

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1. Click the **Add +** button.
2. Enter a start and end date.
3. Click **Save**  on table editor.
4. Click **Save** after configuring cross-validation settings and avoidance periods.

Settings are validated. If settings are determined to be valid, they are saved and the page refreshes with newly saved settings on right pane. If settings are invalid, a message displays with the validation errors of the configured settings and avoidance periods.

View Saved Settings

The Saved Settings pane shows what the current cross-validation settings are for the model build. It includes the following:

Current Splits: This chart shows the different test, train, validation, and holdout portions and which dates from the data set belong to each portion.

Has Holdout Set: Indicates if the cross-validation strategy has a holdout set (True, False). This is dependent on the number of dates in the data set.

Has Test Set: Indicates if the cross-validation strategy has a test set (True, False). This is dependent on the number of dates in the data set.

Has Training Set: Indicates if the cross-validation strategy has a training set (True, False).

Has Validation Set: Indicates if the cross-validation strategy has a validation set (True, False). This is dependent on the number of dates in the data set.

Strategy Name: The name of the cross-validation strategy.

Total Splits: The total number of splits in the cross-validation strategy.

If you are satisfied with the cross-validation and avoidance period settings, continue in the Model Build phase [Pipeline section](#) by [running the pipeline](#).

Model Build Phase Pipeline Section

The Pipeline section of the Model Build phase is where you run the Sensible Machine Learning pipeline. This brings all prior configurations and parameter selections together. The pipeline:

Model Build Phase

- Generates, transforms, and selects features based on predictive capability.
- Selects optimal hyperparameter sets for each model of each target.
- Trains models and tests them on historical data.

Running a pipeline produces the best model for each given target. After running a pipeline, you can view various statistics and metrics before deploying the models for utilization.

In the Pipeline section, the XperiFlow engine uses all the information and configurations gathered from the pages in the Data and Configuration sections to run feature engineering for each target.

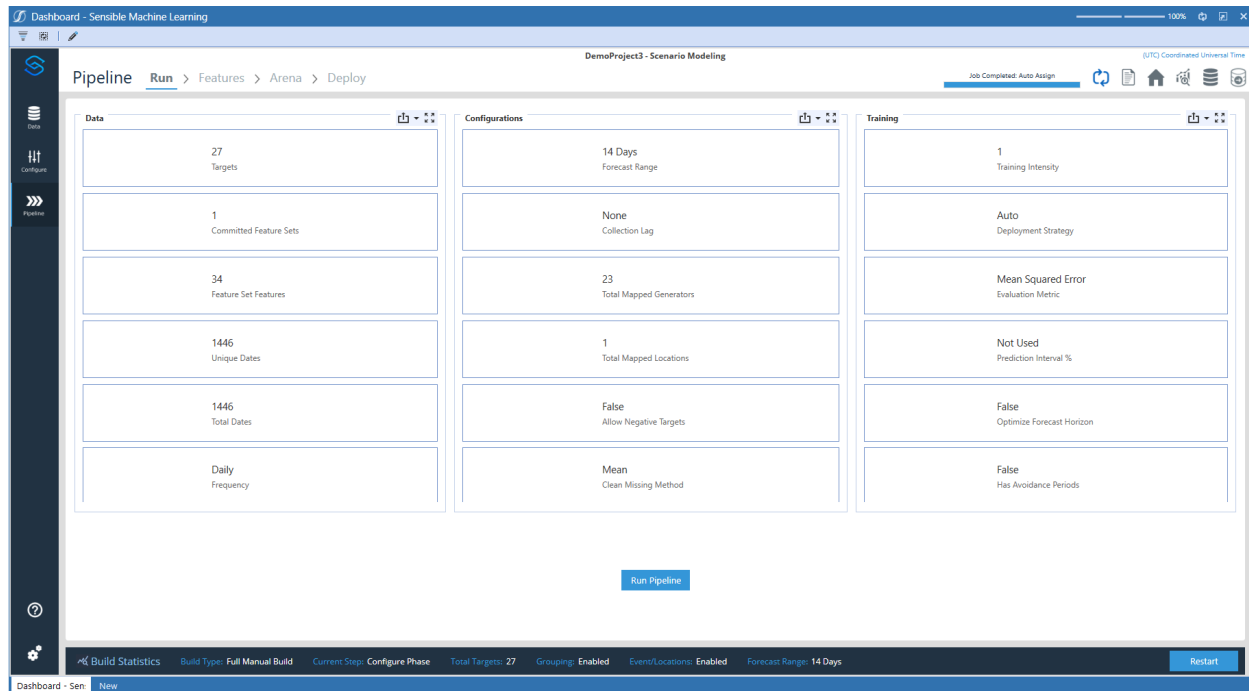
While creating numerous new features, the engine also iteratively selects the best features to keep for each target. These are later used for all the models run for each specific target.

Run the Pipeline

When running a pipeline, all specified data configurations are brought together to generate and transform the data. It then selects the most predictive features and iteratively trains and tests models against historical data. This is the longest run of the solution because it is where the most data science work completes.

When you first navigate to the **Run** page in the Pipeline section, a **Run Pipeline** button displays in the center of the page with a variety of statistics and settings showing some of the project's currently configured settings. This indicates your data is ready for modeling.

Model Build Phase




Click **Run Pipeline** to run the pipeline job.

NOTE: The pipeline job must run to successful completion before you can access other pages in the Pipeline section.

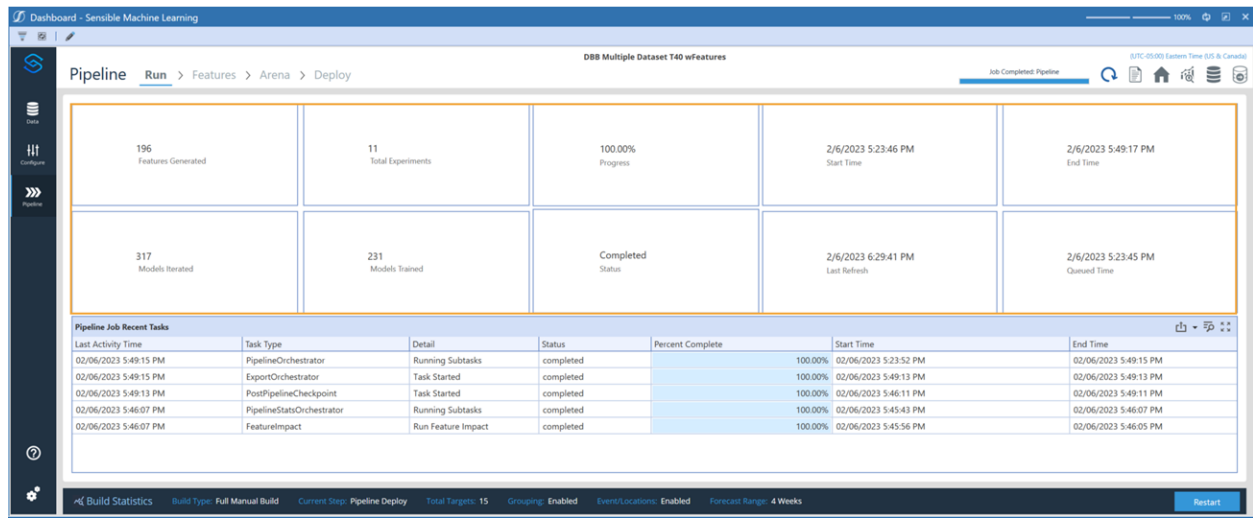
During the pipeline run, the XperiFlow engine does the following:

Feature Generation, Transformation, and Selection: The engine takes in all the data and information that is added to the project in the Data and Configure sections and begins the process of running feature engineering for each target. While creating numerous new features, the engine also selects the best features to keep for each target. These are used later for all the models that run for a target to increase the predictive accuracy.

Hyperparameter Tuning, Model Training, and Model Selection: With all the configurations and the newly found important features, the engine runs multiple models for each configuration to find the best ones. This process involves hyperparameter tuning each model on multiple splits of the data and then saving the accuracy metrics of each model.

When the pipeline run completes, click **Refresh**  to view a summary page that displays pipeline job results. Run statistics for the most recently completed pipeline job display, as shown in the following graphic:

Model Build Phase



After the pipeline run job completes, the top half **Run** page shows:

Features Generated: Total number of features generated by the pipeline job.

Total Experiments: Total number of groups plus single targets being run in the model build. The AI Services engine is running an experiment for each of these targets or groups to find the best model possible.

Progress: The current completion percentage of the pipeline job.

Models Iterated: Number of times models were iterated with different hyperparameter settings during the pipeline job.

Models Trained: Number of unique models that were trained.

Status: The completion status of the most recently started pipeline job.

Start Time, End Time: Start and end time of the most recently completed pipeline job.

Last Refresh, Queued Time: Date and time the pipeline run page was last refreshed.

The bottom half of the **Run** page shows:

Pipeline Job Recent Tasks: Table that displays details of the most recent tasks run in the pipeline job. This table shows running tasks while the pipeline job is running and completed tasks after the pipeline job successfully completes.

Analyze Features

The **Features** page in the Pipeline section is an exploratory page that visualizes the feature generation, transformation, and selection that occur during the [Pipeline](#) run.

You can get valuable insights by analyzing the types of features selected for given targets. This helps to better understand what influences predictive accuracy.

This page includes an Overview, Generalization, and a Targets view. Click the buttons at the top of the page to switch between the views.

View Predictive Features

The Overview view provides insights into the predictive features generated and selected during Pipeline across all targets. Metrics for how long feature engineering ran during the pipeline are also provided.

Feature Engineering Duration: The number of seconds feature engineering ran.

Feature Transformation Rounds: The number of rounds that occurred during feature engineering.

Max Feature Selection Rounds: The maximum number of rounds of feature selection run across all targets.

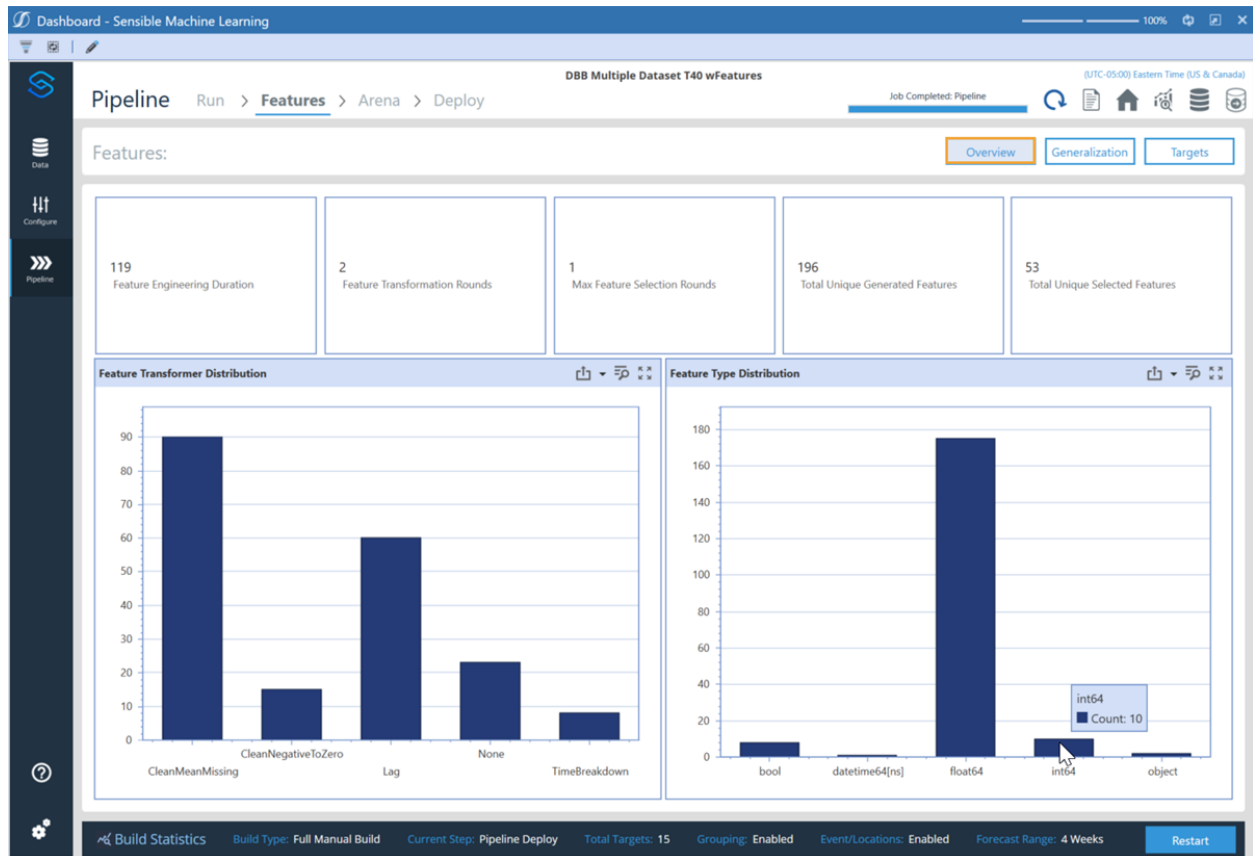
Total Unique Generated Features: The number of features generated or transformed by the XperiFlow engine.

Total Unique Selected Features: The number of features used by at least one model.

Feature Transformer Distribution Chart: A bar chart showing how many features were created using each type of transformer.

Feature Type Distribution: A bar chart showing the number of features for each data type.

Model Build Phase



The naming convention for features signals the order in which transformations to them occurred during Pipeline and can include the following terms:

CleanNegativeToZero: If you chose to not allow negative targets, all negative target values are cleaned by assigning them as zeros.

CleanMissing: This is a standard job by XperiFlow to impute for missing values.

From Source: Shows how many features and events are from the data source.

Lag(frequency=[X],lag_step=[Y]): A feature like this is a lag of Y periods with X frequency.

TimeBreakdown-[X]: This feature analyzes the minute, hour, day, week, or month that a data point occurred.

View Generalization Pipeline Features

The Generalization view provides insights into the how generalized different features were across targets. The grid shows the following information:

Feature Name: The shorter common feature name for features. For example, “SalesLunch-Lag7” and “SalesDinner-Lag7” would both be “Lag7” (assuming SalesLunch and SalesDinner are targets).

Feature Trail: The full common feature name for features. Similar to Feature Name, but the full name instead of the short name.

Utilization Percentage: The percentage of eligible targets that used the feature in at least one model.

Target Candidate Count: The number of targets that were eligible to use the feature.

Target Utilization Count: The number of targets that used the feature in at least one model.

Data Type: The data type of the given feature.

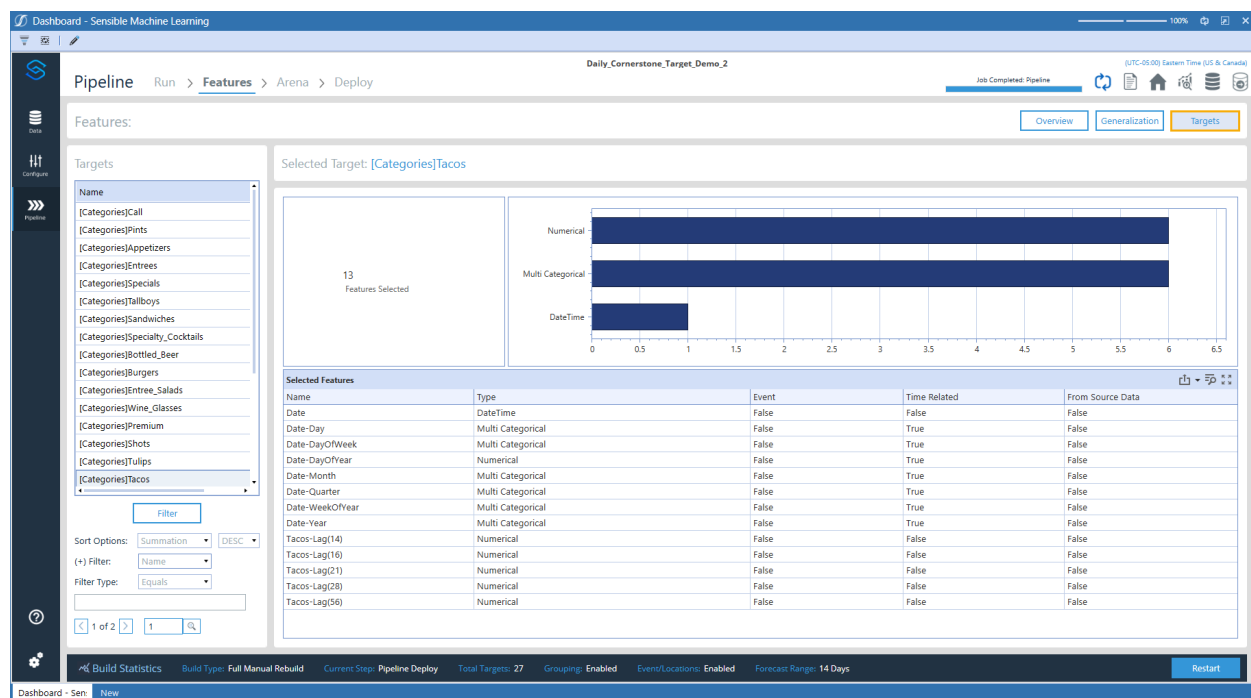
The screenshot shows the 'Generalization' view of a pipeline. The table below represents the data shown in the 'Feature Generalization' section of the dashboard.

Feature Name	Feature Trail	Utilization Percentage	Target Candidate Count	Target Utilization Count	Data Type
LabelDate-Year	{{(LabelDate)CleanMeanMissing}TimeBreakdown-Ye...	100.00%	15	15	int64
LabelDate-WeekOfYear	{{(LabelDate)CleanMeanMissing}TimeBreakdown-W...	100.00%	15	15	int64
LabelDate-Quarter	{{(LabelDate)CleanMeanMissing}TimeBreakdown-Q...	100.00%	15	15	int64
LabelDate-Month	{{(LabelDate)CleanMeanMissing}TimeBreakdown-M...	100.00%	15	15	int64
LabelDate	{(LabelDate)CleanMeanMissing}	100.00%	15	15	datetime64...
Lag(8)	{{{([UD1]-[UD2]-[UD3])CleanMeanMissing}CleanN...	86.67%	15	13	float64
Lag(4)	{{{([UD1]-[UD2]-[UD3])CleanMeanMissing}CleanN...	86.67%	15	13	float64
Lag(5)	{{{([UD1]-[UD2]-[UD3])CleanMeanMissing}CleanN...	66.67%	15	10	float64
Easter	{Easter(lag_range=0:00:00,event_id=2cd808c6-f06d...	60.00%	15	9	float64
Lag(6)	{{{([UD1]-[UD2]-[UD3])CleanMeanMissing}CleanN...	53.33%	15	8	float64
FederalInterestRate	{FederalInterestRate(lag_range=-77 days, 0:00:00){[...	53.33%	15	8	float64
ConfirmedUSCases	{ConfirmedUSCases(lag_range=-35 days, 0:00:00){[...	53.33%	15	8	int64
CommoditiesProducerPriceIndex	{CommoditiesProducerPriceIndex(lag_range=-77 d...	40.00%	15	6	float64
Father's Day	{Father's Day(lag_range=0:00:00,event_id=4e22b85...	13.33%	15	2	float64
Thanksgiving	{Thanksgiving(lag_range=0:00:00,event_id=5353e2...	0.00%	15	0	float64

View Predictive Features for Targets

The Targets view provides insights into the different predictive features that were selected for each given target and used by models during Pipeline.

Click a target in the Targets pane to see how many features were selected for it and used by models during the pipeline run and how many of those selected features are in each feature category. The table lists each selected feature for the current target, with its type and name, and whether the feature is an event feature, time-related feature, or if it originated from source data.



Selected features are broken down by types and represented visually on this page. Types include:

Numerical: Examples of this include temperature (67 degrees) or a 7-day lagged value (a feature for avocado sales today is the avocado sales from 7 days ago).

Multi Categorical: An example of this would be day of the week (1-7).

DateTime: The date dimension is always included in this.

Binary Categorical For example: “For the given date (row of data), did the event St. Patrick’s Day occur (0 or 1)?”

Analyze the Arena Summary

The **Arena** page is an exploratory page that does not require any specific action. It provides valuable insight by analyzing evaluation metrics and features across models and targets gathered during the model arena.

The **Arena** page consists of different views (Accuracy, Impact, Explanation, and CV Strategy). To select a view, click on its button at the top of the page.

For all views available for the **Arena** page, use the Top Models Visible next to the different view buttons to filter the models available in the **Leaderboard** pane. This displays the training results for the number that is selected. Ranked models outside the selected number of models visible include (Not Visible) in the Rank.

NOTE: For Impact and Explanation views, the message "No impact data exists for this selection" when there is no impact data available for the project.

Arena Accuracy View

The Accuracy view shows the model metrics, predictions, and prediction intervals (if configured) in different model stages. Any target that is a part of the model build can have its models examined in this view.

This helps to answer questions such as:

- Which type of model has the best accuracy for a given target?
- By how much did the model win?

It also helps you understand how closely the forecasted values overlay the actuals in the line chart, which can provide answers to questions such as:

- Are there spikes that aren't being caught by the forecasts?
- If so, could adding any events help catch these spikes?

NOTE: Error metric scores do not dynamically adjust based on the time period specified by the range slider at the bottom of the page.

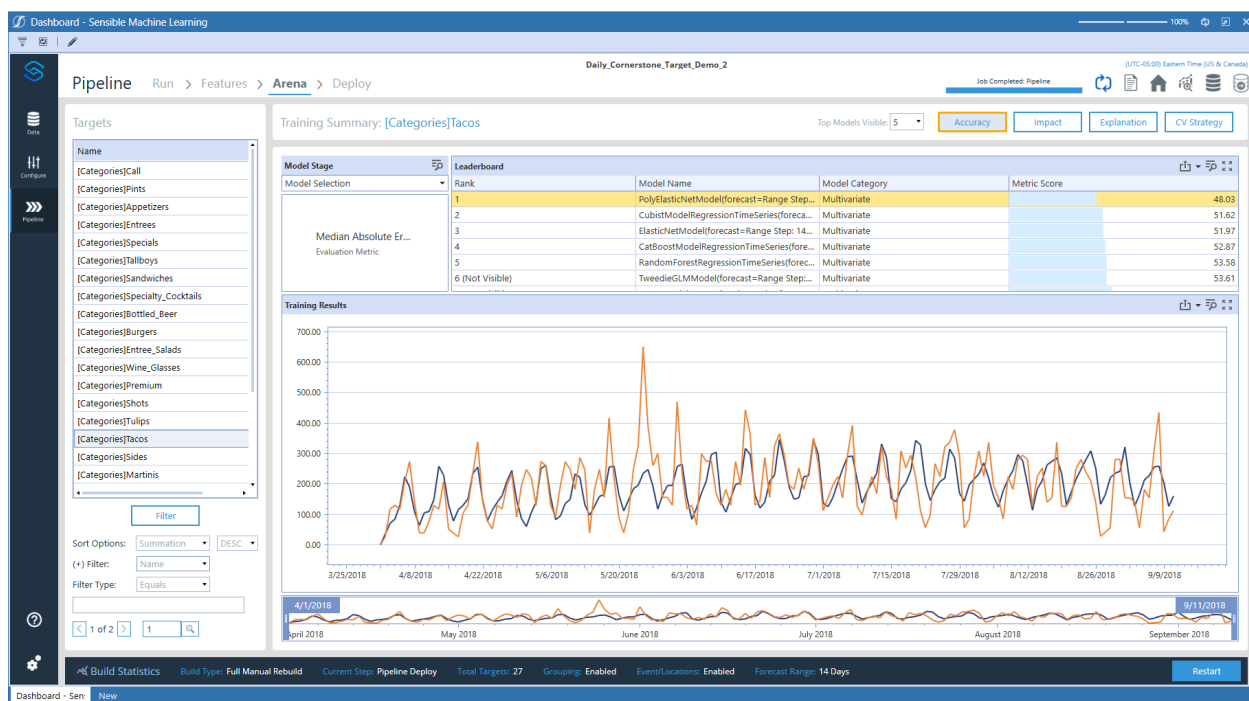
The table on this page displays:

Model Build Phase

- The model algorithms run for a given target (such as XGBoost, CatBoost, or Shift).
- The type of model algorithm (ML, Statistical, or Baseline).
- The evaluation metric (such as Mean Squared Error, Mean Absolute Error, and Mean Absolute Percentage Error) and the associated score.
- The train time (How long did it take to train the given model during Pipeline?).

With all the configurations and the newly found important features, the engine runs multiple models per configuration to find the best. This process involves hyperparameter tuning each model on multiple splits of the data and then saving the accuracy metrics of each model.

To analyze the training results, click a target in the Targets pane to see the accuracy metrics of each of its deployed models if implemented over the course of its past data. Each model listed shows its name and category, along with the type of evaluation metric used and the evaluation metric score. Select a model name in the models list to view a line chart that shows how close the forecasted values are to the actuals.



Model Build Phase

The line chart corresponds to the highlighted model in the table. It visualizes both the predictions made for the historical actual test period (blue) and the historical actuals (orange). The time frame in this chart is only a subset of the total time frame for the historical data, as this time frame is for a specific portion of a split.

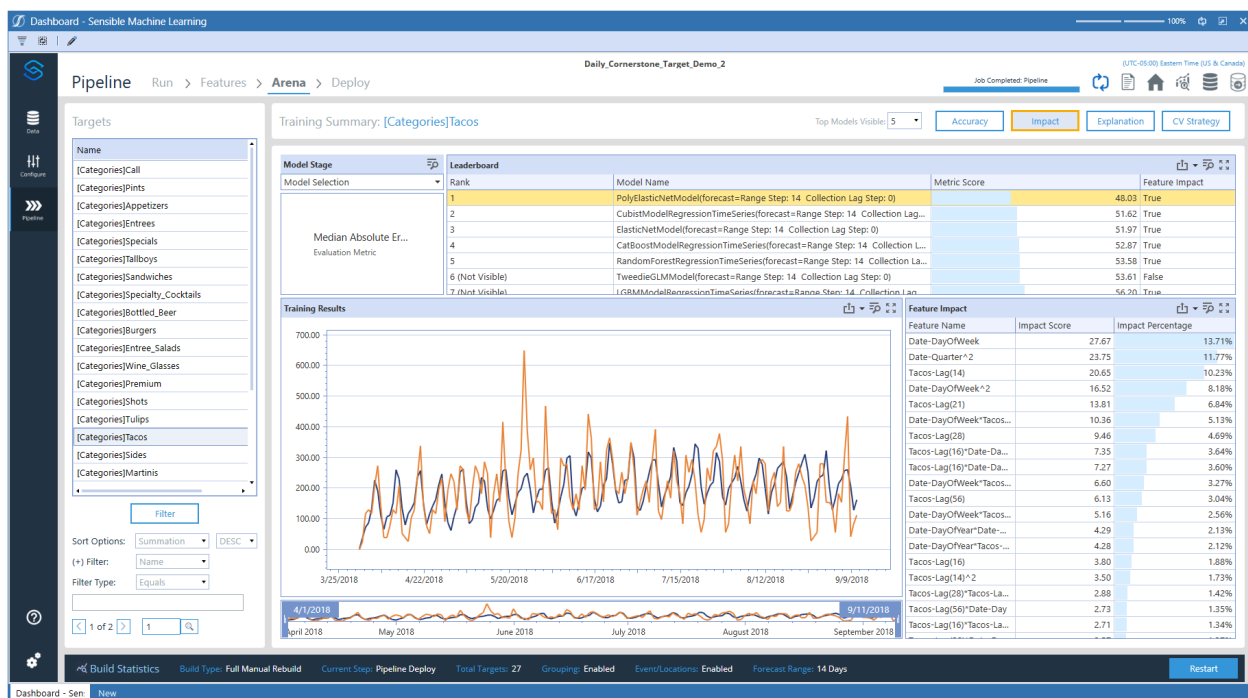
At a high level, this page provides the view of how the best version of each model (such as XGBoost, CatBoost, ExponentialSmoothing, Shift, and Mean) has performed against unseen historical data for each target and more specifically, on the test set of the historical data.

The optimal error metric score can be the lowest score, the highest score, or the closest to zero. It is dependent on the type of metric. See [Appendix 3: Error Metrics](#) for more information about the error metrics Sensible Machine Learning uses.

Arena Impact View

The Impact view shows the same information as the Accuracy view but also includes the feature impact scores for different models. Any target that is a part of the model build can have its models examined in this view. The feature impact score shows how much influence the feature had for a given model.

NOTE: Feature impact data is dependent on the type of model. Not all models have [feature impact data](#).

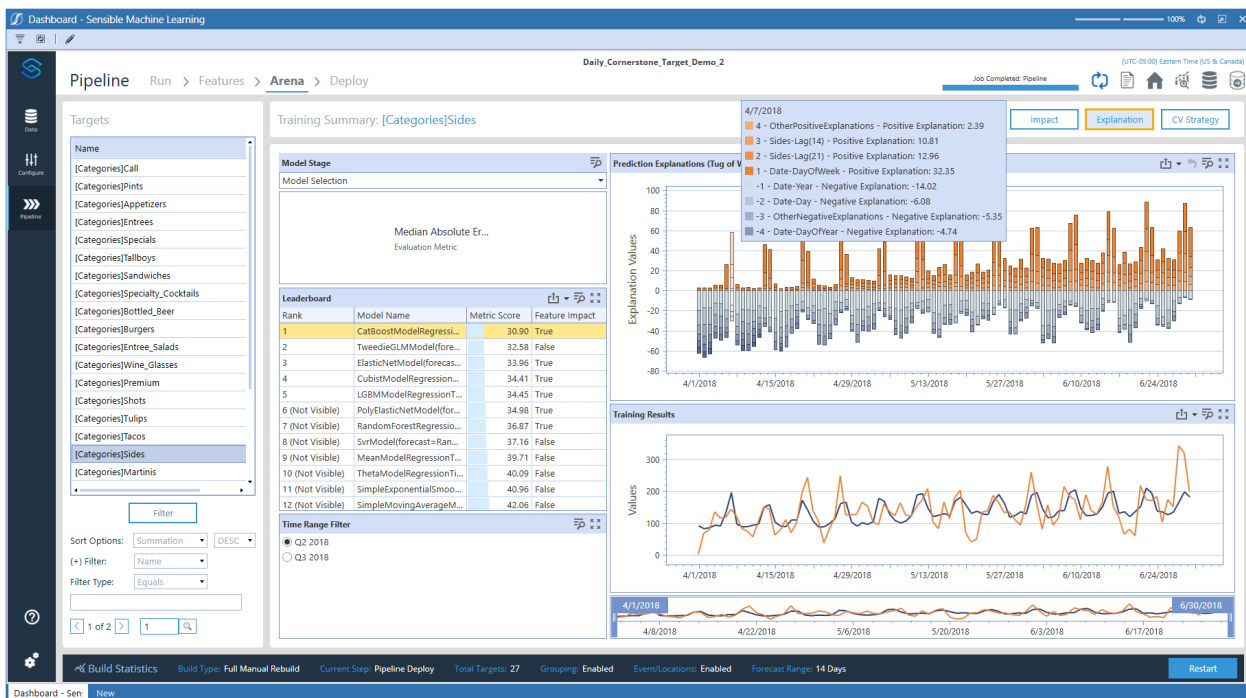


Arena Explanation View

The Explanation view shows the model metrics, predictions, and prediction intervals (if configured) in different model stages similar to the Accuracy view. The Explanation view also includes the prediction explanations of the models. Select a model from the Leaderboard grid to see its prediction explanations in a Tug of War plot on the right side. For each data point, this plot shows the features that had the largest magnitude effect (negative or positive) on the prediction for the displayed date. Any target that is a part of the model build can have its models examined in this view.

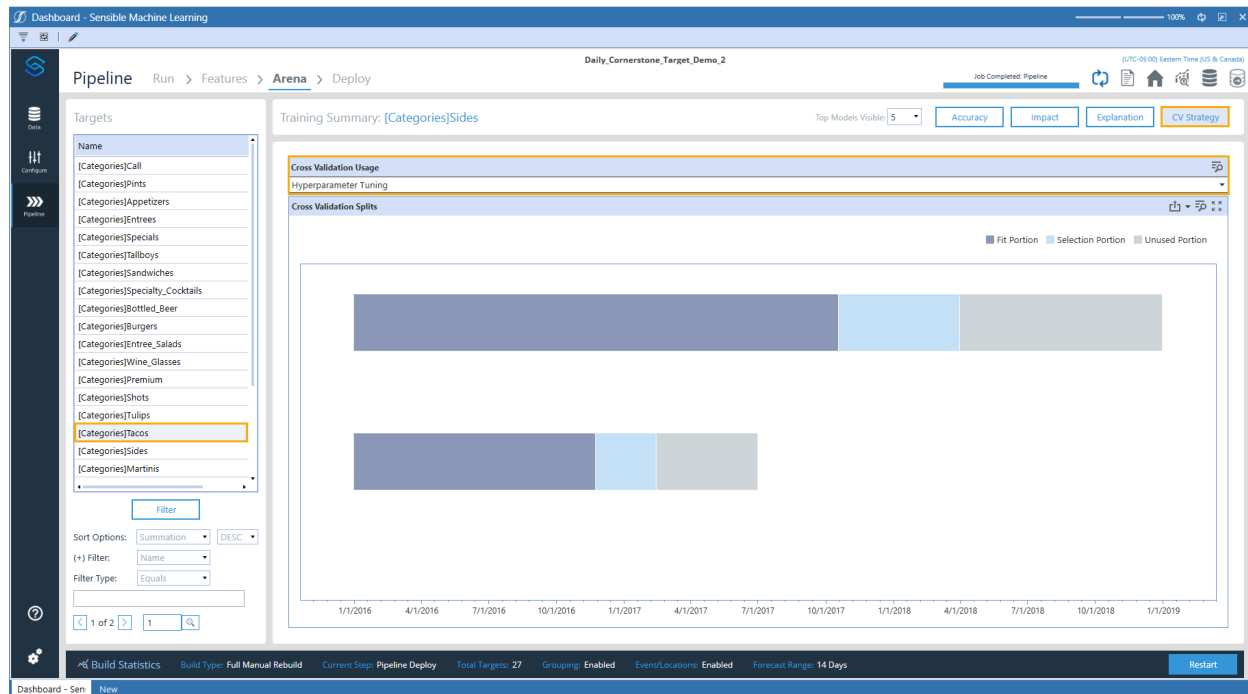
TIP: To drill down into a specific date, double-click the date in the tug-of-war plot to see a feature-by-feature view of prediction explanations for that date.

NOTE: Only models that use features have feature explanation data.



Arena CV Strategy View

The CV Strategy view shows how the splits were used in each model stage and the portion of the splits. Select the Model stage using the Cross Validation Usage drop-down. Split usage can then display in the Cross Validation Splits Chart.



The number of splits and size of each portion of the splits can be configured when you [Set Modeling Options](#). A description of how each portion of the split is used follows.

Train Set: The split of historical data on which the models initially train and learn patterns, seasonality, and trends.

Validation Set: The split of historical data on which the optimal hyperparameter set is selected for each model, if applicable. A model makes predictions on the validation set time period for each hyperparameter iteration. The hyperparameter set with the best error metric when comparing predictions to the actuals in the validation set time period is selected. This split does not occur when the historical data set does not have enough data points.

Test Set: The split of historical data used to select the best model algorithm compared to the others. For example, an XGBoost model gets ranked higher than a baseline model based on evaluation metric score. This split does not occur when the historical data set does not have enough data points.

Holdout Set: The split of historical data used to simulate live performance for the model algorithms. This is the truest test of model accuracy. This set can also serve as a check for overfit models. This split does not occur when the historical data set does not have enough data points.

Deploy Your Model

The **Deploy** page provides information that lets you fully analyze and understand the effectiveness of your model before deploying it to production. Once satisfied, you deploy your model using this page, which collects necessary information from the pipeline job to be able to run the deployed models in utilization. This information includes:

- The most optimal hyperparameters for deployed models.
- How to generate and transform features selected for the deployed models.

Analyze Pipeline Performance Overview Statistics

General statistics shown here include:

Features Generated: Number of features generated for the entire data set.

Features Selected: Number of features selected for the data set based on being able to positively contribute to predictive accuracy.

Models Iterated: Number of times models were iterated with different hyperparameter settings during the pipeline job.

Train Time: Total train time across all targets and target groups during Pipeline. This total time is not sequential however, as much of the Pipeline is run in parallel through the XperiFlow Conduit Orchestration.

The charts on this page include:

“Best” Models: Descending bar chart that visualizes the breakdown of best models selected across all targets, so you can understand how frequently different models and model types are winning.

Baseline Win Margin by Group Significance: Each bar in this chart represents an even-sized bin of targets. Bar heights indicate the percent by which the best statistical or machine learning model beat or lost to the best baseline model based on the selected [error metric](#), summed across all targets within the bin.

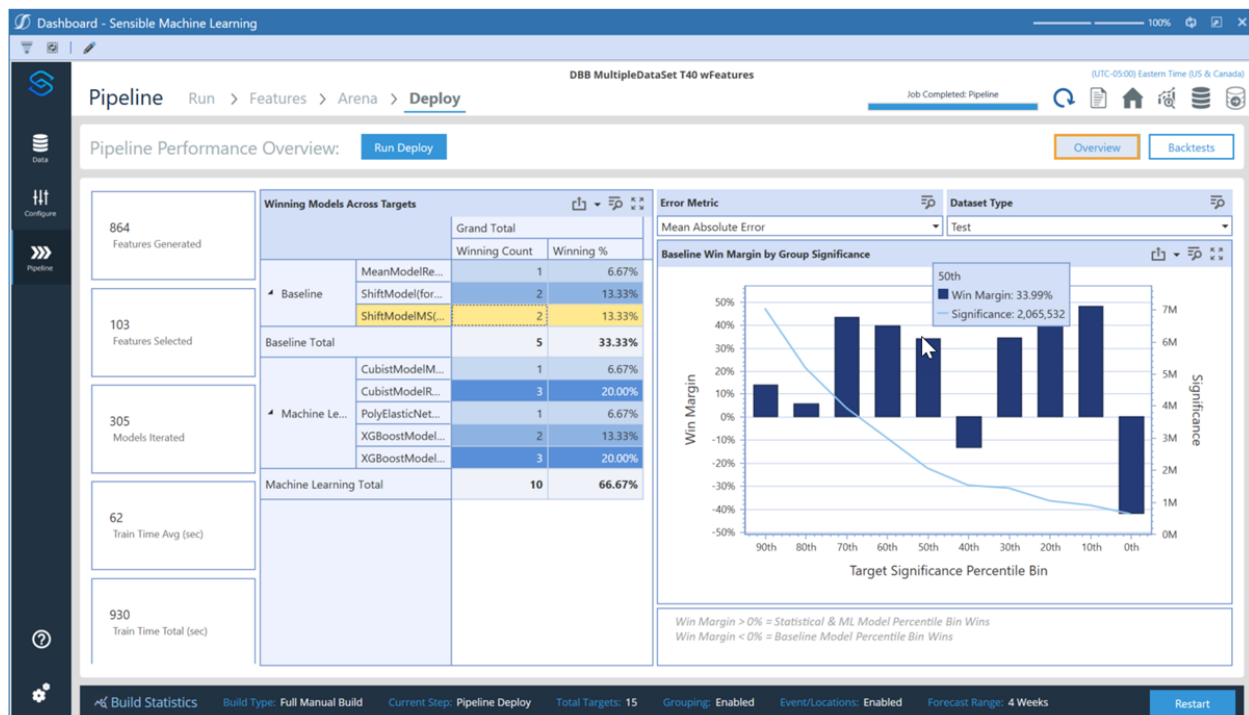
Model Build Phase

The light blue line in the chart represents the bin's total significance. Bin refers to the value amount selected during the Data section, such as total units or dollars. Positive win margins are ideal. This means that machine learning and statistical models are beating the simplistic models on average.

It is possible however, for a bar to be negative due to an instance where the best baseline model beats the best machine learning or statistical model. For example, in a ten-target bin, nine machine learning and statistical models can beat the best baseline by 10 percent each, but one baseline model that wins by 120 percent can swing the bar to be negative.

Use the Overview view to get valuable insight by analyzing the Best Models and Baseline Win Margin by Group Significance charts. This can help answer questions such as:

- How often are my machine learning and statistical models beating the best baseline model?
- By how much are my best machine learning and statistical models beating the best baseline model?
- Are the best baseline models being beaten for my most significant targets? This is specific to non-units-based value dimensions, such as sales dollars.



Analyze Backtest Results

The Backtests view provides an aggregated view of how well the models selected during [Pipeline](#) performed for the whole data set. It provides a similar view to the **Train** page, but does so in relation to the holdout set of data.

Use information in the Backtest view to get valuable insights by analyzing evaluation metrics across models and targets. This can help answer questions such as:

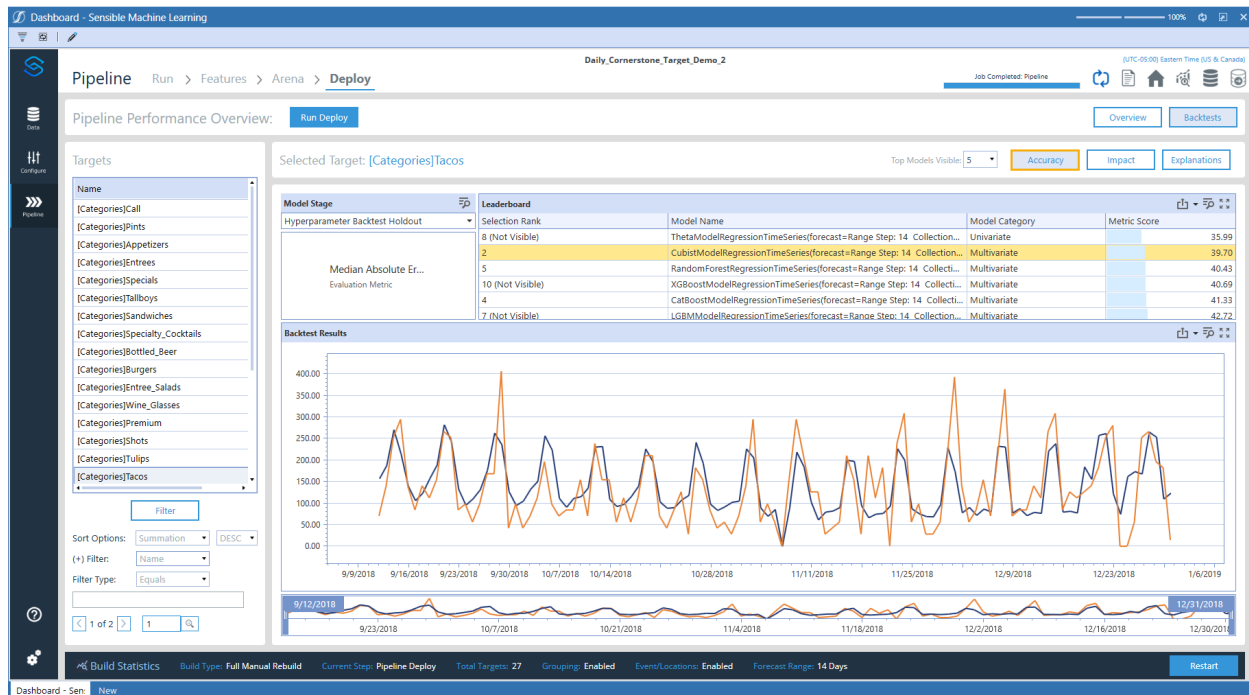
- Which type of model has the best accuracy for a given target?
- Did actuals often fall within the prediction interval bounds?
- Which features are important to predictions of different models for different targets?
- By how much did the model win?
- How close are the forecasted values to the actuals in the line chart?
- Are there spikes that aren't being caught by the forecasts? If so, could adding any events help catch these spikes?

Deploy Backtest Accuracy View

To analyze the training results in the Backtests view, click a target in the Targets pane to see the accuracy of each of its deployed models compared to its past data. Each model displays its name and category, type of evaluation metric used, and the evaluation metric score. Select a model in the models list to view a line chart that shows how close the forecasted values are to the actuals.

You can review the available statistics and visualizations for each target before deploying the models for utilization.

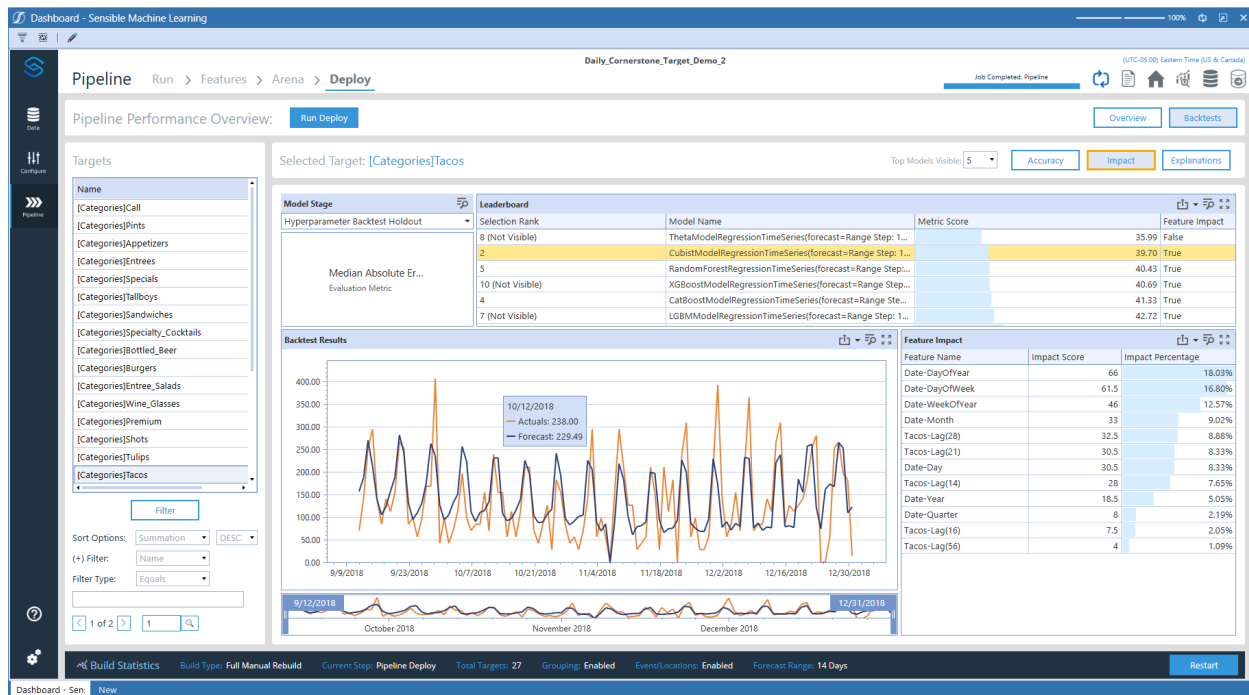
Model Build Phase



Deploy Backtest Impact View

The Impact view shows the same information as the Accuracy view, but also includes the feature impact scores for different models. Any target that is a part of the model build can have its models examined in this view. The feature impact score shows how much influence the feature had for a given model. It is the same as the Arena Backtest Accuracy View but is on the holdout set of the split. Only models with features have feature impact data.

Model Build Phase

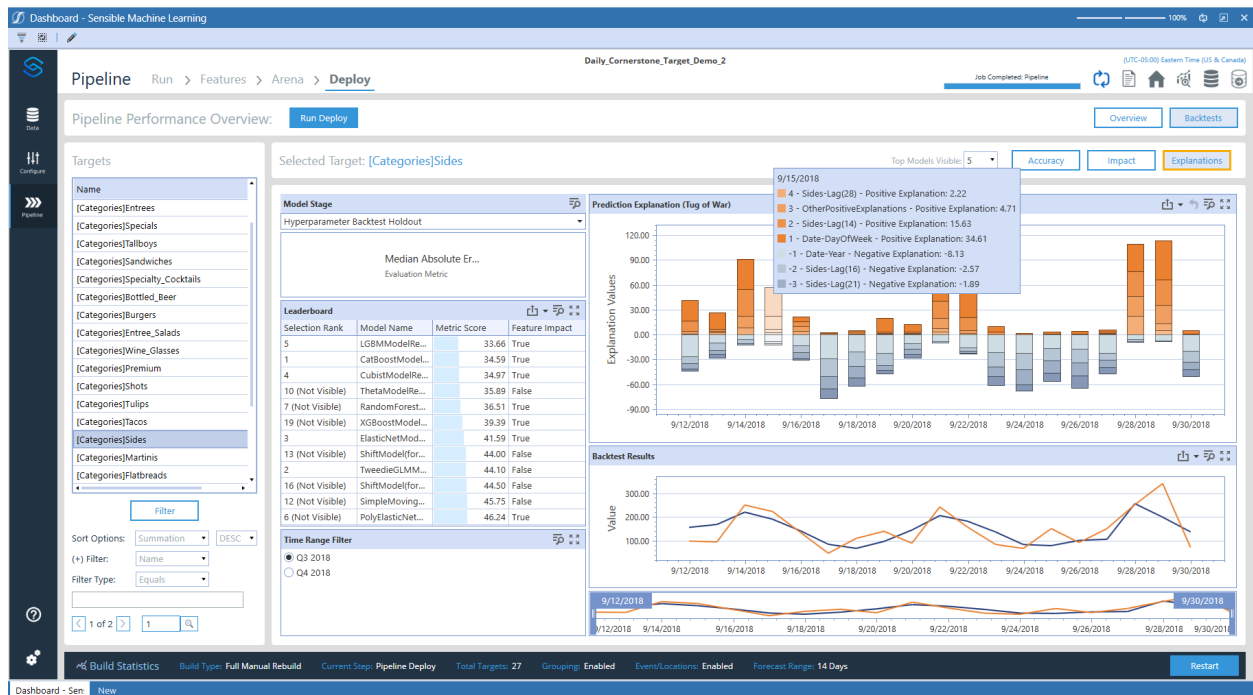


Deploy Backtest Explanation View

The Explanation view shows the model metrics, predictions, and prediction intervals (if configured) in different model stages similar to the Accuracy View. The Explanation view also includes the prediction explanations of the models. Select a model from the Leaderboard grid to see its prediction explanations in a Tug of War plot on right side. This plot shows for each data point the features that had the largest magnitude effect (negative or positive) on the prediction for that date. Any target that is a part of the model build can have its models examined in this view. It is the same as the Arena Explanation view but is on the holdout set of the split. Only models with features have feature explanation data.

TIP: To drill down into a specific date, double-click the date in the tug-of-war plot to see a feature-by-feature view of prediction explanations for that date.

Model Build Phase



Deploy Your Model

After reviewing the available statistics and visualizations for each target, click the **Run Deploy** button. This creates the deployment job, which upon completion changes the project's status and moves the project from the Model Build phase to the Utilization phase.

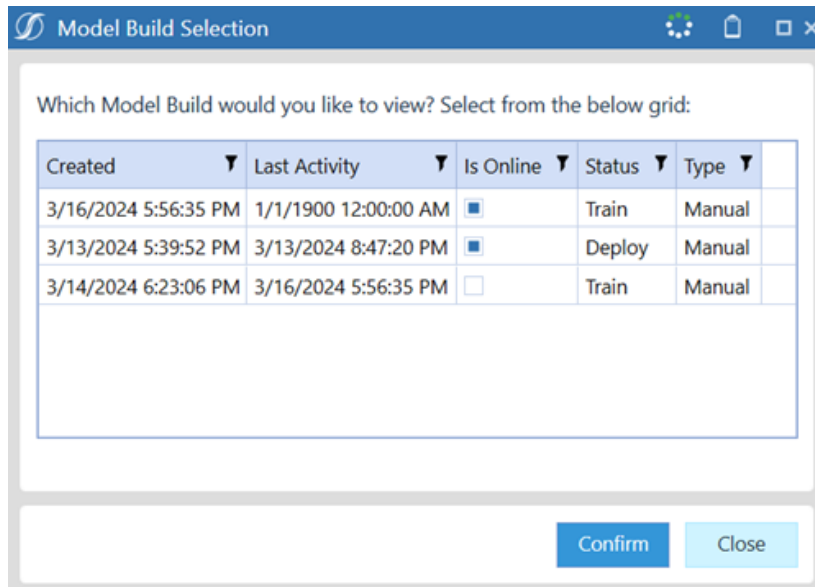
The deployment job takes the best models selected during [pipeline](#) and deploys them for generating forecasts.

Additionally, after the models have been chosen for deployment, Sensible Machine Learning creates the feature schemas and pre-trained models needed to run predictions against the models in the [Utilization](#) phase.

Viewing Historical Model Builds

In the event of a Restart or Rebuild being run on a Model Build, a project may contain several historical Model Builds. If this is the case, when entering the Model Build Phase of SML, a dialog to select from the historical Model Builds will be provided.

Model Build Phase



Model Build Information

In the provided dialog, the following information displays for each model build available:

Created: The date and time the Model Build was created.

Last Activity: The date and time of the last activity.

Is Online: Indicates if the Model Build is still active.

NOTE: A build will be offline after a Restart or a new build is deployed to Utilization.

Status: Indicates if the Model Build is being configured (Train) or is used in Utilization (Deploy).

Type: Indicates if the Model Build is configured and deployed by the user (Manual) or an Auto Rebuild was run on the Model Build (Auto).

Utilization Phase

The Utilization phase consists of these sections:

[Manage](#): Run predictions, monitor model health, audit model builds, and update event occurrences.

[Analysis](#): Analyze results from model forecasts, view statistics on how well the deployed models are performing.

[Insights](#): Visualize how features, events, and time affect model results.

Utilization Phase Manage Section

The Manage section consists of these pages:

- **[Predict](#)**: Run, schedule, and delete scheduled predictions.
- **[Health](#)**: Monitor model health by project and target and run full or partial rebuilds to restore model health.
- **[Audit](#)**: View detailed audit information for all model builds for the project.
- **[Events](#)**: Review and modify event occurrences that are defined in the [Events](#) page of the Model Build phase.
- **[Scenarios](#)**: Review and modify event occurrences that are defined in the [Events](#) page of the Model Build phase.

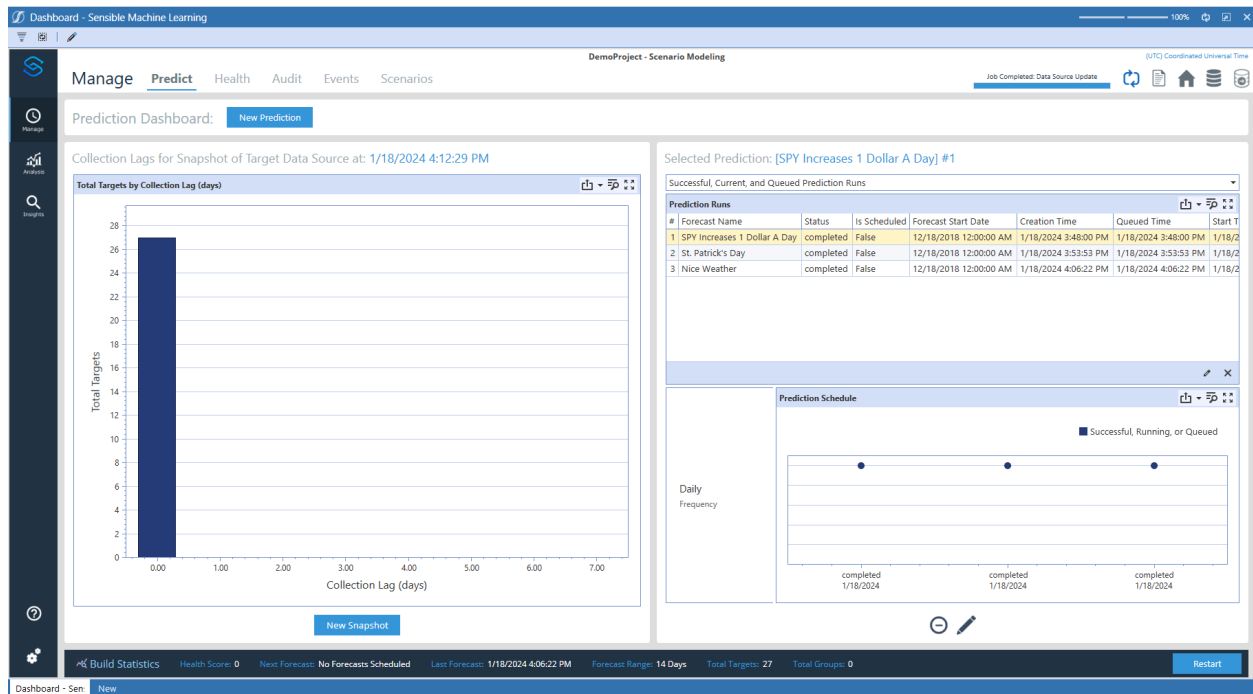
Run or Schedule a Prediction

From the **Predict** page, you can:

- Run and schedule predictions.
- Delete scheduled prediction runs.
- View prediction status.

Utilization Phase

- View the collection lag for the target data set.
- Create a new snapshot.

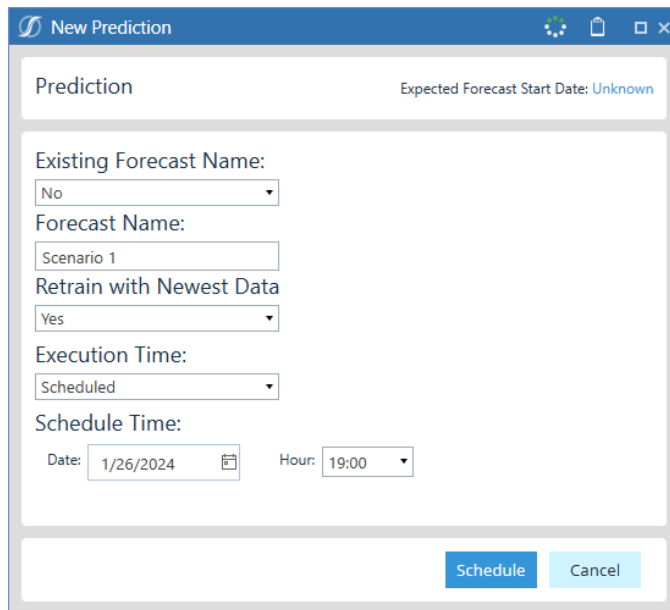


When you run a new prediction, the XperiFlow engine uses the forecast range established on the **Forecast** page of the Configure section to generate a forecast for each target using the deployed models. This prediction is made from the date of the last data point in the loaded data and extends to the forecast range. The XperiFlow engine also recognizes and collects any actual data points following the date of deployment, bringing it in as actual values on the **Prediction** page of the Analysis section.

IMPORTANT: Before running a new prediction, you must load and transform any additional data sets being used for your model. Perform the steps in Upload and Associate Data Sets for the next data set. Verify rows in the transformation table are approximately the same as in the actual data file.

To run a new prediction:

1. Click **New Prediction**. The **New Prediction** dialog box displays.



2. Make selections from these options:

- **Retrain with Newest Data:** Select **Yes** to retrain all models on any new data that has been uploaded to the project before making a prediction. For example, if the model learned from three years of historical data during the [Pipeline](#) section, and three months of new data has been uploaded during the Utilization phase, the model can now learn from three years and three months of data.
- **Existing Forecast Name:** If a forecast name should be included and used to label the prediction run.
- **Forecast Name:** Enter a name to label the prediction. This name displays in different [consumption group export tables](#). This name must be unique for a given forecast start date. For example, you can't have 2 editions of "Scenario 1" for the forecast start date of 1/1/2020, but you can have "Scenario 1" and "Scenario 2" for the forecast start date of 1/1/2020.

TIP: Forecast names are a great way to link forecasts across multiple prediction runs. Prediction runs with the same forecast name are linked and can be visualized on the **Prediction** page.

- **Execution Time:** Select **Immediately** to move the prediction job to the Job queue. Otherwise, select **Schedule** and use the date/time fields that display to set the hour, day, month, and year when you want the prediction job to run.


NOTE: Scheduled time is based on local time specified in the [Global Settings](#).


3. Click **Schedule**.

Analyze Predictions

After running an initial prediction, the **Predict** page displays the following information.


Total Targets by Collection Lag: This chart in the Collection Lags pane visualizes the latest view of the collection lag for the target data set. Click **New Snapshot** to create a new snapshot for

the data source, then click **Refresh**  to refresh the page. This chart updates when you run a new prediction, snapshot, target data source update, or data set job.


Prediction Runs: This table in the Selected Predictions pane displays information about predictions that have been run or are scheduled to run, including status, queued time, creation time, start time, end time, and job ID. To delete a queued or scheduled prediction, select it and click .

NOTE: At least three prediction jobs must run to completion for Sensible Machine Learning to have enough data to produce a health score for the model. See [Manage Model Health](#) for more information.

Prediction Schedule: This chart in the Selected Predictions pane shows completed and scheduled predictions.

Click **New Snapshot** to take a snapshot of the collection lags for the target data source, then click **Refresh**  to refresh the page.

Update a Scheduled Prediction

1. Click **Update**  below the Prediction Schedule pane.
2. In the **Update Prediction** dialog box, use the Existing Forecast Name field to indicate whether you want to update the schedule for an existing forecast. If selecting Yes, select the name of the forecast to update from the Forecast Name drop-down. If selecting No, type the name of the forecast to update.
3. Click **Save**. A message box informs you that the Prediction Call forecast name is modified.
4. Click **OK** to close the message box and the **Update Prediction** dialog box.

Manage Model Health

The **Health** page has two views into the health of your model: Project Overview and Targets. It's also where you can run a rebuild of the project.

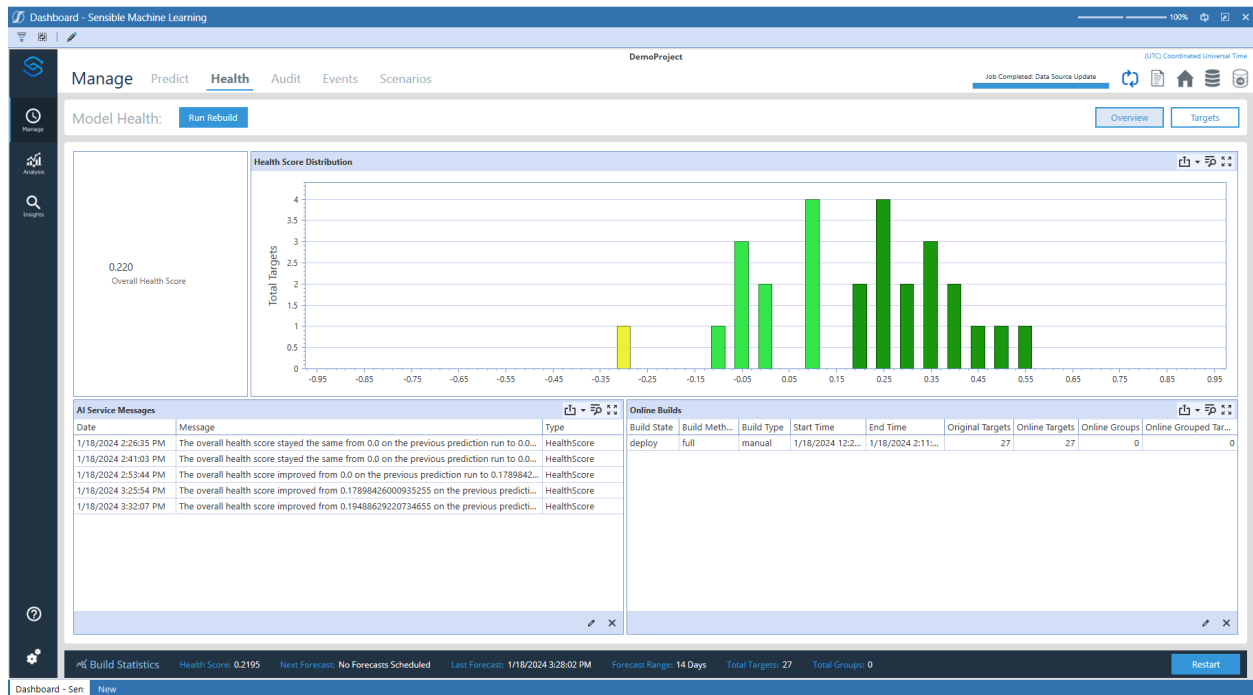
Analyze Model Health by Project

The Project Overview view shows a color-coded distribution chart visualizing the health of the best models. The Overall Health Score is a scaled metric ranging between -1 and 1, which indicates improvement or degradation in a model's predictive accuracy.

A positive (green) health score signals that a model's predictive accuracy has improved since it was deployed. A negative (red) health score signals a decrease in predictive accuracy since initial deployment.

The AI Service Messages provides information on how the overall health score has changed with each prediction. The Online Builds pane lists details of all builds for the project.

Utilization Phase



Analyze Model Health by Target

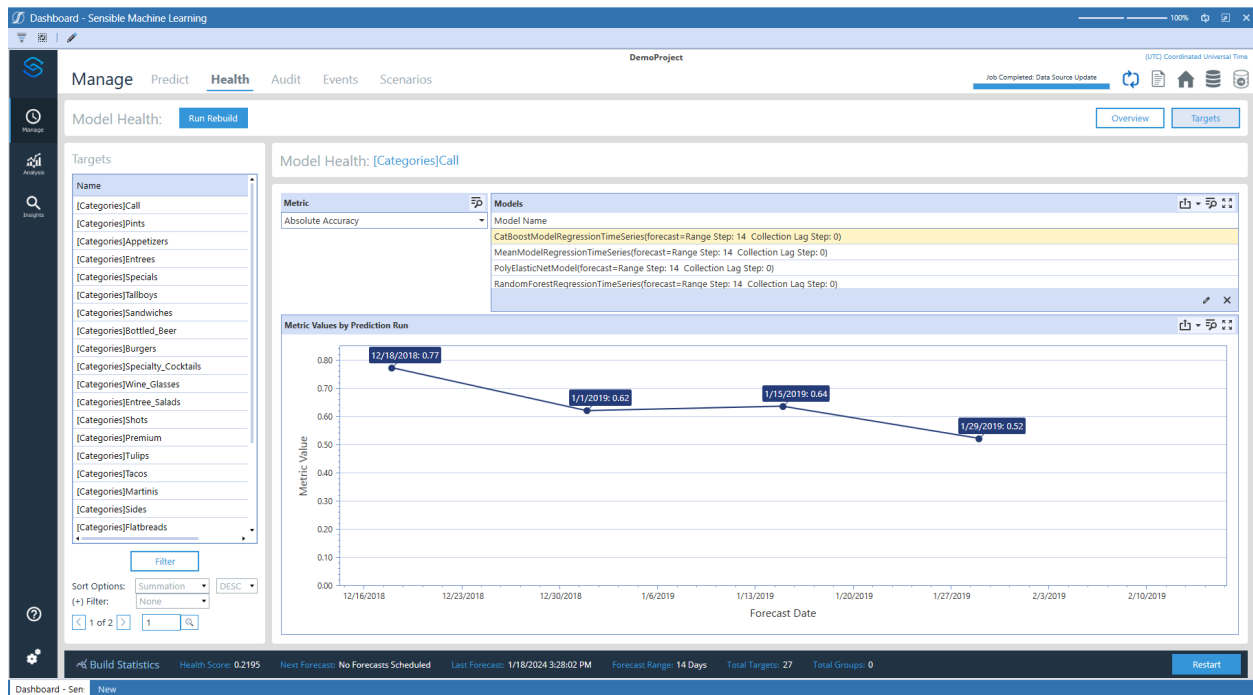
In the Targets view, you can see how the evaluation metric score for a given target/model/metric score combination changed over time.

Click a target in the **Targets** pane to see the average metric score for each of its models, based on the error metric selected in the Metric Name field. Use the Metric Name drop-down to select the type of error metric. See [Appendix 3: Error Metrics](#) for more information on the error metrics Sensible Machine Learning uses.

For each model of the selected target, you can view a line graph that shows the metric scores for each of its prediction runs. Click a model name in the top pane to view the model's prediction run information in the line chart. This includes the date of each of the model's prediction runs and the average metric score for each.

TIP: A forecast is not included in the line chart if no actuals are present for the metrics to be calculated. The date displays on the x-axis, but no corresponding value displays.

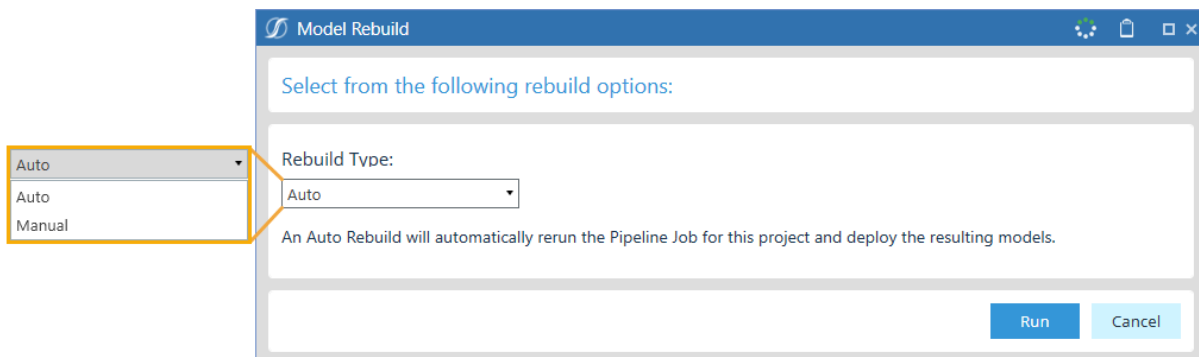
Utilization Phase



Rebuild the Model

You can rebuild the model when needed. The rebuild process can be automated to run as a data management job in the background, or you can click **Run Rebuild** on the **Health** page to run it manually. There are two rebuild methods:

- **Auto Rebuild:** Automatically rebuilds and deploys the entire project using the same configurations from the latest build. The new build's models are trained on more historical data than in the initial build when additional data is being used since the latest build.



Utilization Phase

- **Manual Rebuild:** Returns you to the **Dataset** page of the Data Section in the Model Build phase. You can walk through the Model Build phase, setting different configurations as needed.

Audit Project Model Builds

The **Audit** page lets you view details of builds that have been run on the project and the target configurations. The page provides a full audit of what has been run.

Build Type	Build State	Build Fill	Is Online	Start Time	End Time	Total Targets	Total Groups	Total Single Targets	Forecast Range	Feature Generation Enabled	Feature Transformation Enabled	Feature Selection Enabled
manual	deploy	full	<input checked="" type="checkbox"/>	1/18/2024 12:27:59 PM	1/18/2024 2:11:32 PM	27	0	27	14	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>

Name	Series Type	Build State	Build Time	Significance	Use Auto Modeling	Allow Negative Targets	Deploy Strategy	Current Best Model	Total Models
[Categories]Appetizers	single	deploy	1/18/2024 12:27:59 PM	782655.25	<input checked="" type="checkbox"/>	<input type="checkbox"/>	best_three	XGBoostModelRegressionTimeSeries(forecast=Range Step: 14 Collection Lag Step: 0)	18
[Categories]Bottled_Beer	single	deploy	1/18/2024 12:27:59 PM	447965.95	<input checked="" type="checkbox"/>	<input type="checkbox"/>	best_three	RandomForestRegressionTimeSeries(forecast=Range Step: 14 Collection Lag Step: 0)	18
[Categories]Burgers	single	deploy	1/18/2024 12:27:59 PM	425628.5	<input checked="" type="checkbox"/>	<input type="checkbox"/>	best_three	XGBoostModelRegressionTimeSeries(forecast=Range Step: 14 Collection Lag Step: 0)	18
[Categories]Call	single	deploy	1/18/2024 12:27:59 PM	1174219.25	<input checked="" type="checkbox"/>	<input type="checkbox"/>	best_three	CatBoostModelRegressionTimeSeries(forecast=Range Step: 14 Collection Lag Step: 0)	18
[Categories]Specialty_Cocktails	single	deploy	1/18/2024 12:27:59 PM	412609.5	<input checked="" type="checkbox"/>	<input type="checkbox"/>	best_three	XGBoostModelRegressionTimeSeries(forecast=Range Step: 14 Collection Lag Step: 0)	18
[Categories]Super_Premium	single	deploy	1/18/2024 12:27:59 PM	161882	<input checked="" type="checkbox"/>	<input type="checkbox"/>	best_three	PolyElasticNetModel(forecast=Range Step: 14 Collection Lag Step: 0)	18
[Categories]Tacos	single	deploy	1/18/2024 12:27:59 PM	218824.65	<input checked="" type="checkbox"/>	<input type="checkbox"/>	best_three	XGBoostModelRegressionTimeSeries(forecast=Range Step: 14 Collection Lag Step: 0)	18

Manage Configured Events

The **Events** page in the Utilization phase lets you manage and modify events defined in your project during the Events step in the Modeling phase.

The Utilization phase **Events** page in the works the same way as the **Events** page in the Modeling phase. See [Configure Events](#) for information on how to modify the events defined during modeling.

Manage Scenarios

The **Scenarios** page in the Utilization phase is where **Scenario Modeling** configurations can be made. This feature is designed to empower users with the ability to simulate various future scenarios. This functionality enables the configuration of hypothetical sets of feature values or potential events.

Overview

- **Configure Scenarios:** Users can define and customize scenarios by specifying future feature values or predicting the occurrence of certain events.
- **Run Predictions:** After scenarios are configured, predictions can be run for each Scenario. The Xperiflow Engine will factor the user submitted values for feature values and event occurrences in the prediction.
- **Forecasting Impacts:** By leveraging this feature, users can explore how different features and events might influence their forecasts. This predictive capability enables strategic planning and preparing for a range of potential outcomes.

Key Benefits:

- **Enhanced Preparedness:** Scenario Modeling equips users with the tools to anticipate and plan for various future conditions, thereby improving decision-making processes.
- **Customizable Simulations:** The feature offers flexibility, enabling users to tailor Scenarios according to their specific forecasting needs.
- **Predictive Insights:** Through precise modeling, users gain insights into how different variables and events could potentially impact their forecasts.

Scenarios Table

The following information is displayed for each Scenario in the left pane of the page.

Scenario Name: The name of the Scenario.

Description: The description of the Scenario.

Forecast Start Date: The expected start date of the forecast when the Scenario is run.


IMPORTANT: Only Scenarios for the current forecast period will be shown on the **Scenarios** page. Please ensure that all target and feature data sources are up-to-date and a **Date Source Update** job has been run for all data sources. This allows Xperiflow to generate an accurate Forecast Start Date.

Status: The current status of the Scenario showing if it is ready to be used in a prediction. The available statuses are:

- **Not Ready:** Scenario has not received Feature/Event values and a prediction cannot be run for this scenario.
- **Ready:** Scenario has received Feature/Event values and can be used to run a prediction.
- **Complete:** A prediction was run using this Scenario.

Create a Scenario


To create a Scenario:

1. Click the **Add** button  at the bottom left of the pane.
2. Type a unique name for the scenario.

NOTE: Each scenario in the project must have a unique name and cannot include special characters, excluding underscores.

3. Type a description for the scenario. This is optional.
4. Click the **Create** button .

Edit a Scenario

1. Click the **Edit** button  at the bottom left of the pane.
2. Change the scenario name.

NOTE: Each scenario in the project must have a unique name and cannot include special characters, except underscores.

3. Update or add a description for the scenario. This is optional.
4. Click the **Save** button.

NOTE: If a prediction has already been run on the Scenario being edited, the Forecast Name for the prediction will be updated on all other pages in Utilization that it appears.

Edit Feature Values and Event Occurrences

To edit the Feature Values and Event Occurrences, click the **Edit Feature Values** button at the top right of the page.

1. On the first entry of the Edit Feature Values dialog box for each Scenario, an Excel file will be generated by Xperiflow. A status bar for the Excel Creation job is shown and will be replaced with the Excel file once fully generated.

NOTE: This file will contain historical values for every Feature and Event set to Scenario Modeling Feature or Scenario Modeling Event during Model Build.

2. Once the Excel file is displayed, the Features and Events required to run a Scenario will appear in each column. The following rules should be followed when providing values:
 - **All required cells must be completed before submitting to Xperiflow.** Cells that require a value from the user are highlighted yellow. The frequency of the Feature or Event will determine how much data is necessary.
 - **The Save button must be clicked in the Excel sheet.** If the Excel is not saved before submission, the last saved version of the sheet will be submitted to Xperiflow.
 - **Data Type Guidelines:**
 - **Events:**
 - **0** – No Occurrence on that date
 - **1** – Event Occurrence on that date

- **Features:**
 - Reference historical data to match the proper data type of that Feature.
- 3. After inputting the Scenario data into the Excel sheet, press the **Submit** button. Xperiflow will validate the data in the Excel sheet and give feedback on any changes that need to be made.
- 4. Upon successful submission to Xperiflow, the status of the Scenario will update to **Ready**, and it is ready to be used in a prediction.

Scenario Feature Table

The following information displays for each Scenario in the pane of the page.

Feature Name: The name of the Feature/Event.

Detailed Name: The detailed version of the name used to generate the Feature/Event. This includes any Custom Parameters or Location configurations.

Source: The name of the generator used to generate the Feature/Event.

Required: Indicates whether or not the Feature/Event is required for completing a Scenario.

Creation Method: The method that provided data for the Feature/Event.

Status: The current status of the Feature/Event showing if it is ready to be used in a prediction. The available statuses are:

- **Not Ready:** Feature/Event value has not been provided, and a prediction cannot be run for this scenario.
- **Ready:** Feature/Event value has been provided and can be used to run a prediction.

Explore Scenario Data

To view the historical and user input values of a Scenario, select different Features or Events from the **Scenario Features** table. With each selection change, the bottom pane will update with a time series view of Feature data and occurrence view of Event data:

Feature Time Series Data

Utilization Phase

Feature Name	Detailed Name	Source	Fr
USUnemploymentRate	USUnemploymentRate(lag_range=0:00:00){(USUnemploymentGen)}	USUnemploymentGen	M
Christmas Eve	Christmas Eve(lag_range=0:00:00,event_name=Christmas Eve,locations=['United States']){(EventGenV2)}	EventGenV2	D
Christmas	Christmas(lag_range=0:00:00,event_name=Christmas,locations=['United States']){(EventGenV2)}	EventGenV2	D
ClosePrice_StockGenV2(SPY)	ClosePrice(lag_range=0:00:00,ticker=SPY){(StockGenV2)}	StockGenV2	D
Winter Sales Promotion	Winter Sales Promotion(lag_range=0:00:00,event_name=Winter Sales Promotion,locations=[]){(EventGenV2)}	EventGenV2	D



Event Occurance Data

Feature Name	Detailed Name	Source	Fr
USUnemploymentRate	USUnemploymentRate(lag_range=0:00:00){(USUnemploymentGen)}	USUnemploymentGen	M
Christmas Eve	Christmas Eve(lag_range=0:00:00,event_name=Christmas Eve,locations=['United States']){(EventGenV2)}	EventGenV2	D
Christmas	Christmas(lag_range=0:00:00,event_name=Christmas,locations=['United States']){(EventGenV2)}	EventGenV2	D
ClosePrice_StockGenV2(SPY)	ClosePrice(lag_range=0:00:00,ticker=SPY){(StockGenV2)}	StockGenV2	D
Winter Sales Promotion	Winter Sales Promotion(lag_range=0:00:00,event_name=Winter Sales Promotion,locations=[]){(EventGenV2)}	EventGenV2	D



Run Predictions

Once at least one Scenario has a status of **Ready**, a prediction can be run using any Ready Scenarios. Reference the Manage Predict page section of the documentation for more detailed instructions on how to run predictions.

Scenario Analysis

Once at least one Scenario has been used to run a prediction, the results of that prediction run can be found in the Analysis section of Utilization. Please reference the Analysis section of the documentation, for more detailed instructions on viewing prediction results.

Local Excel Storage and Upload

While using Scenario Modeling, the Excel files generated by Xperiflow are available to be used locally and re-uploaded. Here is some information on how to use this capability:

- The upload functionality in the **Edit Feature Values** dialog box is intended for uploading a local version of the Xperiflow generated Excel file. This will not accept any custom .csv or .xlsx files.
- To get a local copy of the generated Excel file, use the **Save As** option in the Excel toolbar and select **Save As File on Local Folder**.

Utilization Phase Analysis Section

The Analysis section consists of these pages:

- [Prediction](#): Analyze results from model forecasts, different builds, and different stages of the project.
- [Overview](#): Provides general statistics on how well the deployed models are performing in utilization across all targets.

Analyze Prediction Results for Targets

Use the **Prediction** page in the Analysis section to analyze results from model forecasts, different builds, and different stages of the project. This page visualizes the forecasted values for each model (blue) and back filled actuals for each target (orange). It is similar to the **Train** page and Backtest view of the Model Build phase Pipeline section, but this page displays in-production results.

This page includes an Accuracy view (default), an Impact view, and an Explanation view. Use the fields at the top of the page to filter the information displayed on any of the views. These fields include:

Utilization Phase

Top Models Visible: Select the number of models you want reflect in the information on the page. The Leaderboard - Latest Build list in each view displays (not Visible) in the Selection Rank column for models not selected in the top models.

Actuals View: The actuals to include in the line chart. Select **All** to see prior actuals to determine why a model made a prediction.

Forecast View: Determines how overlapping forecasts should be shown (blended or each forecasted version).

NOTE: Feature impact data is dependent on the type of model. Not all models have [feature impact](#) data.

Analyze Prediction Accuracy View Information

Click the **Accuracy** button at the top left of the **Prediction** page to view prediction accuracy information.

Click a target in the **Targets** pane to see the average metric score for each of its models, based on the error metric selected in the Metric drop-down. You can further filter the Leaderboard - Latest Build table by model stage build status.

The Accuracy view includes the following:

Metric: Use the Metric drop-down to select the type of error metric. See [Appendix 3: Error Metrics](#) for more information on the error metrics Sensible Machine Learning uses.

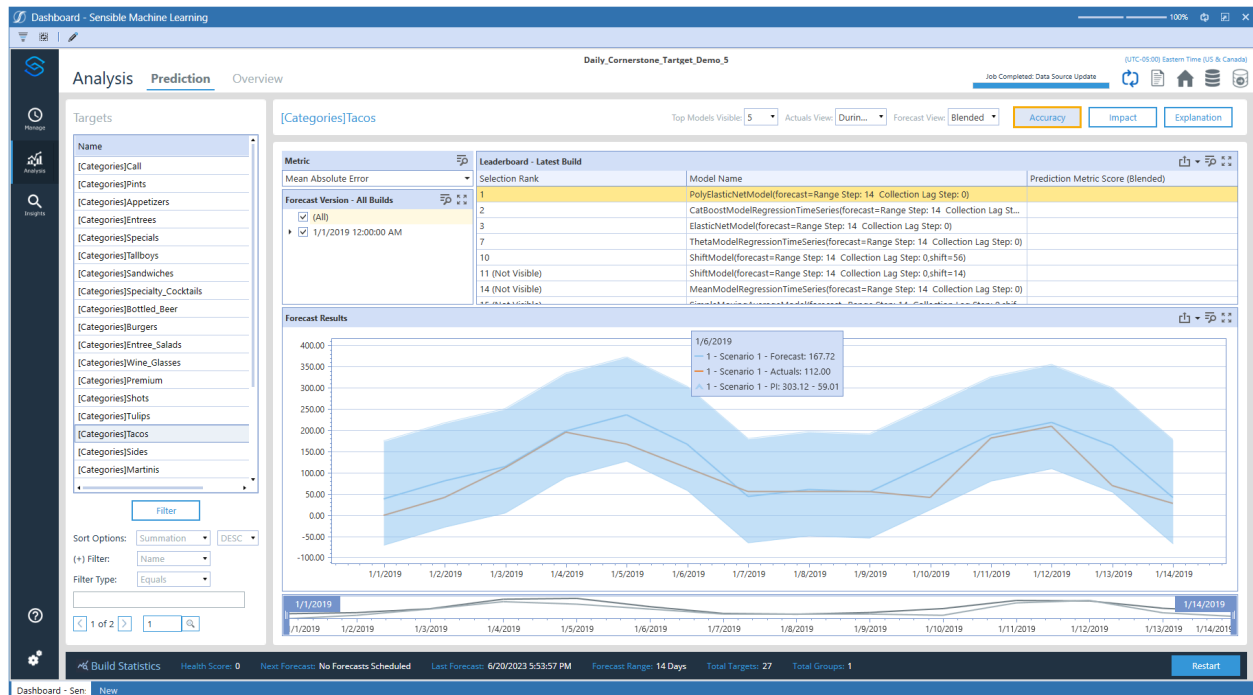
For each model of the selected target, you can view a line graph that shows the metric scores for each of its prediction runs. Click a model name in the top pane to view the model's forecast result information in the line chart. This includes the date of each of the model's prediction runs and the actuals score for each.

Leaderboard - Latest Build: Shows the selection rank for each model, the name of the model, and its prediction metric scores.

NOTE: If multiple Forecast Ranges were configured on the Configure Forecast page, each forecast range will be overlaid on top of each other. There are custom overlay models generated and included in this leaderboard.

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Forecast Results: Visualizes the predictions made over time in comparison to actual values that were brought in during production. Any data or forecasts before initial deployment cannot be viewed. The chart dynamically updates when you change options in the Model Stage, Metric, and Build Status drop downs or when you select a different target. Hover over different areas of the lines in the chart for detailed information. Use the date sliders at the bottom of the graph to change the results to a different date range.

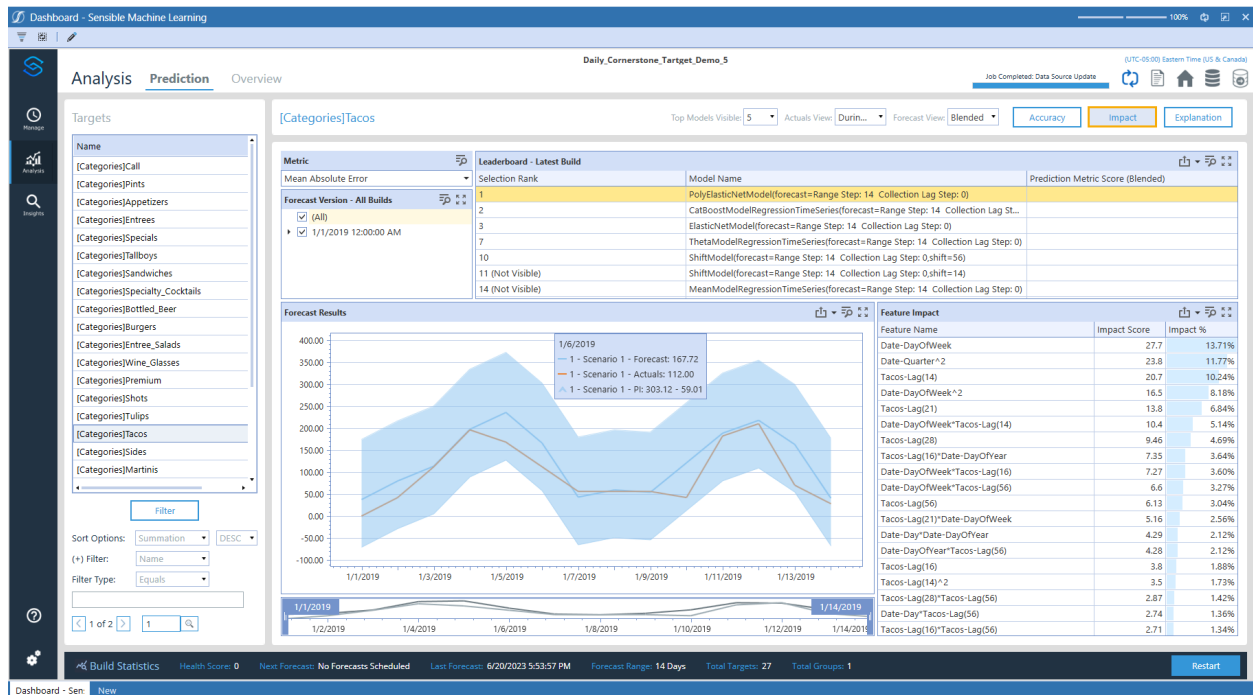


Analyze Prediction Impact

The Impact view shows the same information as the Accuracy view but also includes the feature impact scores for different models. The feature impact score shows how much influence a feature has for a given model.

NOTE: Feature impact data is dependent on the type of model. Not all models have [feature impact](#) data.

Utilization Phase

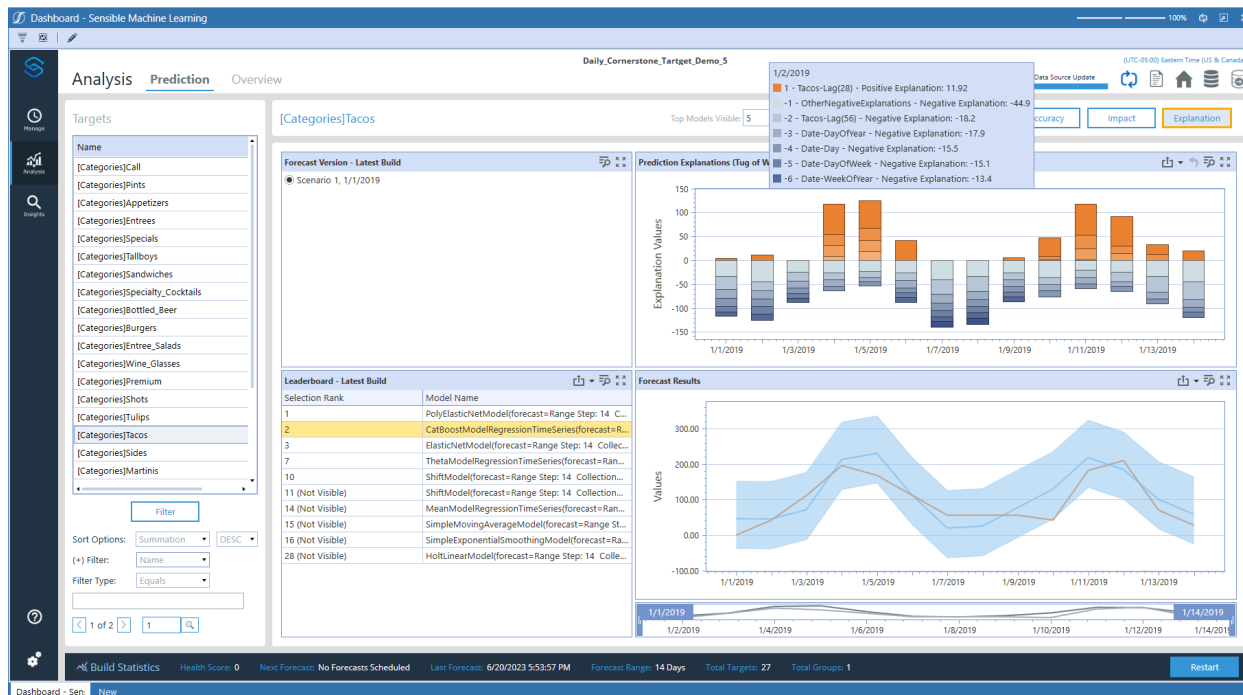


Analyze Prediction Explanations

The Explanation view shows the model metrics, predictions, and prediction intervals (if configured). The Explanation view also includes the feature values for the features used for a given model. Select a model from the Leaderboard grid to see its features and feature values for different dates over the course of the prediction. The top grid can be visually compared to the bottom grid to see which features had a large impact on the prediction.

TIP: To zoom in on a specific date, double-click the date in the Tug-of-War plot to see a feature-by-feature view of prediction explanations for that date.

NOTE: Feature impact data is dependent on the type of model. Not all models have [feature impact](#) data.



Analyze Deployed Model Performance

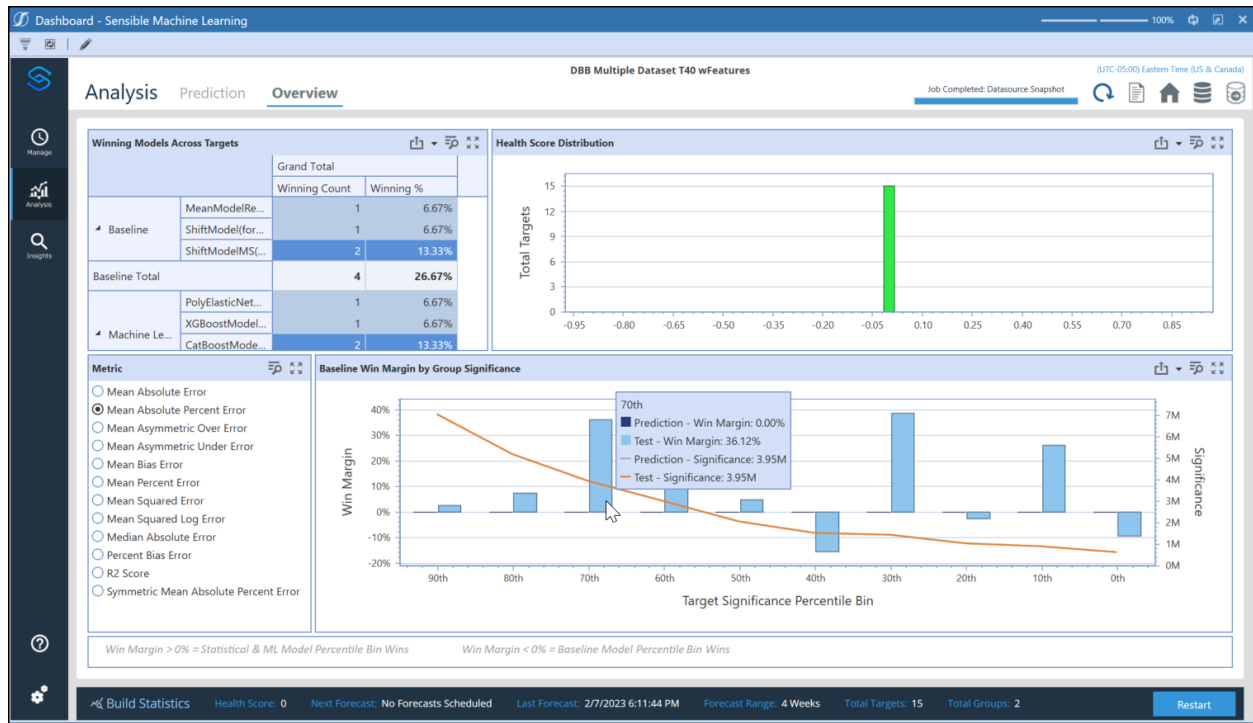
The **Overview** page in the Analysis section provides general statistics on how well the deployed models are performing in utilization across all targets. Hover over individual bars in a chart for detailed information.

From **Metric** select an error metric on which to display.

When you make changes to the **Metric** radio buttons, the **Health Score Distribution** and **Baseline Win Margins by Grouped Significance** charts dynamically update.

For information on other types of navigation, see [Chart and Table Toolbar Buttons](#).

Utilization Phase



The panes on this page are as follows.

Health Score Distribution: A color-coded distribution chart visualizing the health the best models. Health score is a scaled metric ranging between -1 and 1, informing of improvement or degradation in a model's predictive accuracy. A positive (green) health score signals that, since initial deployment, a model's predictive accuracy has improved. A negative (red) health score signals a decrease in predictive accuracy since initial deployment.

Baseline Win Margin by Group Significance: Each bar in this chart represents an even-sized bin of targets. The height of the bars refers to the percent by which the best statistical or machine learning model beat or lost to the best baseline model with regards to the specified evaluation metric, across all targets within the bin.

The light blue line in the chart represents the total significance of a bin, which refers to the value amount selected during the [Model Build Data section](#), such as total units or dollars. Positive win margins are ideal, indicating that machine learning and statistical models are beating the simplistic models on average. This chart is based on accuracy in Utilization. Like the Metric Values charts, displayed charts are based on Type and Metric Option selections.

Utilization Phase Insights Section

The Insights section consists of the following pages:

Utilization Phase

- **Features**: Explore project insights from both pre- and post-deployment for the features selected for specific targets, and explore how time and events deviate from the average.
- **Interpretability**: Gain insight and understanding on how different features have influenced a particular model's predictions.

Analyze Features for Predicted Targets

The **Features** page lets you explore project and target insights for the features selected for specific targets. This page is split into the Generalization view and the Target view.

Insights Features Generalization View

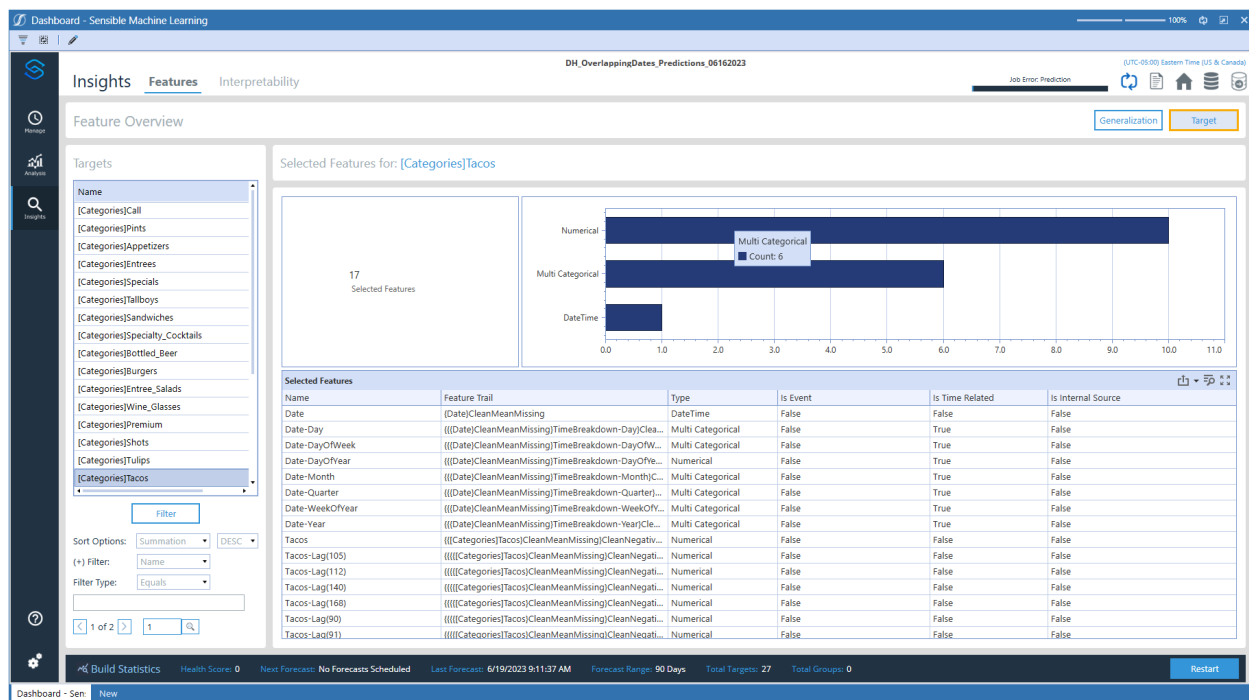
The Generalization view gives insight into how widely used the features were across deployed targets. The Features Generalization grid in this view is a similar view to the [Pipeline Features Generalization view](#). The use of different features displays as a percentage of total targets for which they are eligible.

The screenshot shows the 'Features' tab in the 'Insights' section of the Sensible Machine Learning dashboard. The 'Generalization' view is active, displaying a table of feature utilization across targets. The table has columns for Feature Name, Feature Trail, Utilization Percentage, Target Candidate Count, Target Utilization Count, and Data Type. The data is as follows:

Feature Name	Feature Trail	Utilization Percentage	Target Candidate Count	Target Utilization Count	Data Type
LabelDate-Year	{{(LabelDate)CleanMeanMissing}TimeBreakdown-Year C...	100.00%	15	15	int64
LabelDate-WeekOfYear	{{(LabelDate)CleanMeanMissing}TimeBreakdown-Week...	100.00%	15	15	int64
LabelDate-Quarter	{{(LabelDate)CleanMeanMissing}TimeBreakdown-Quart...	100.00%	15	15	int64
LabelDate-Month	{{(LabelDate)CleanMeanMissing}TimeBreakdown-Mont...	100.00%	15	15	int64
LabelDate	{LabelDate}CleanMeanMissing	100.00%	15	15	datetime64[ns]
Lag(8)	{{(Lag(8))CleanMeanMissing}CleanNegati...	86.67%	15	13	float64
Lag(4)	{{(Lag(4))CleanMeanMissing}CleanNegati...	86.67%	15	13	float64
Lag(5)	{{(Lag(5))CleanMeanMissing}CleanNegati...	66.67%	15	10	float64
Easter	{Easter(lag_range=0:00:00,event_id=2cd808c6-f06d-224...	60.00%	15	9	float64
Lag(6)	{{(Lag(6))CleanMeanMissing}CleanNegati...	53.33%	15	8	float64
FederalInterestRate	{FederalInterestRate(lag_range=-77 days, 0:00:00)}{Fed...	53.33%	15	8	float64
ConfirmedUSCases	{ConfirmedUSCases(lag_range=-35 days, 0:00:00)}{Covi...	53.33%	15	8	int64
CommoditiesProducerPriceIndex	{CommoditiesProducerPriceIndex(lag_range=-77 days, ...	40.00%	15	6	float64
Father's Day	{Father's Day(lag_range=0:00:00,event_id=4e22b852-8a...	13.33%	15	2	float64
Thanksgiving	{Thanksgiving(lag_range=0:00:00,event_id=5353e2e9-6...	0.00%	15	0	float64

Insights Features Targets View

The Targets view shows the selected features for a given target and the breakdown of the different data types of the selected features. This is the same as the [Pipeline Features Target View](#). The use of different features displays as a percentage of total targets for which they are eligible.



Build Confidence in Your Deployed Models

Model interpretability is a critical component to building confidence and trust in deployed models. The **Interpretability** page offers the ability to understand how different features have influenced a particular model's predictions. Sensible Machine Learning offers this interpretability in the form of Feature Impact and Feature Effects.

Features: [Features](#) measures the impact or influence that a particular feature has on a model's predictions. The larger the impact number is, the more influential that feature is on the model's predictions. Visualizing feature impact for all features that are powering a model is a great way to understand how influential features are in comparison to one and other. The range of feature impact values is relative to the model and will not be standardized across model to model.

Utilization Phase

Feature Effects: [Feature Effects](#) measures how a model's average prediction and actuals values compares to a feature's value in order to showcase how a feature value influences a model's prediction. Feature effects are commonly displayed through scatter plots to visualize how a model's average prediction value changes when a feature takes on different values.



NOTE: Features and Feature Effects are only calculated for certain Machine Learning models.

Help and Miscellaneous Information

Display Settings

OneStream and MarketPlace solutions frequently require the display of multiple data elements for proper data entry and analysis. Therefore, the recommended screen resolution is a minimum of 1920 x 1080 for optimal rendering of forms and reports.

Additionally, OneStream recommends that you adjust the Windows System Display text setting to 100% and do not apply any Custom Scaling options.

Package Contents and Naming Conventions

The package file name contains multiple identifiers that correspond with the platform. Renaming any of the elements contained in a package is discouraged in order to preserve the integrity of the naming conventions.

Example Package Name: SML_PV8.4.0_SV340_PackageContents.zip

Identifier	Description
SML	Solution ID
PV8.4.0	Minimum Platform version required to run solution
SV340	Solution version
PackageContents	File name

MarketPlace Solution Modification Considerations

A few cautions and considerations regarding the modification of MarketPlace solutions:

- Major changes to business rules or custom tables within a MarketPlace solution will not be supported through normal channels as the resulting solution is significantly different from the core solution.
- If changes are made to any dashboard object or business rule, consider renaming it or copying it to a new object first. This is important because if there is an upgrade to the MarketPlace solution in the future and the customer applies the upgrade, this will overlay and wipe out the changes. This also applies when updating any of the standard reports and dashboards.
- If modifications are made to a MarketPlace solution, upgrading to later versions will be more complex depending on the degree of customization. Simple changes such as changing a logo or colors on a dashboard do not impact upgrades significantly. Making changes to the custom database tables and business rules, which should be avoided, will make an upgrade even more complicated.

Appendix 1: Data Quality Guide

This section describes the importance and different aspects of data quality, how Sensible Machine Learning perceives the data based on varying levels of data quality, and how data volume affects the XperiFlow engine and Sensible Machine Learning functionality.

Why Data Quality Matters

The single biggest indicator of effective forecasting produced by Sensible Machine Learning is the quality of the source data. The following sections describe the components and best practices.

Collection Lag

Collection lag is the time between the most recent date in the data set (across all targets) and the latest received data for a single target.

The following image is a daily level data set containing a date column and two target columns named Apples and Bananas. As seen in the data set, the most recent date in the data set is 10/17/2021 (provided by Bananas). In this example, Apples has a collection lag of two days, which implies Apple's data is received two days after the most recent date in the data set.

A two-day collection lag is considered normal.

Date	Apples	Bananas
10/9/2021	100	82
10/10/2021	95	22
10/11/2021	64	14
10/12/2021	62	97
10/13/2021	29	89
10/14/2021	99	93
10/15/2021	43	73
10/16/2021		46
10/17/2021		(Most Recent Date) 60

Target Collection Lag: The time between the most recent date of the data set and when you receive the corresponding data for a specific target variable for that moment in time. In the following image, the target collections are: Apples – 2 days, Bananas – 0 days, Carrots – 4 days.

Date	Apples	Bananas	Carrots
10/9/2021	100	82	24
10/10/2021	95	22	73
10/11/2021	64	14	40
10/12/2021	62	97	10
10/13/2021	29	89	39
10/14/2021	99	93	
10/15/2021	43	73	
10/16/2021		46	
10/17/2021	(Most Recent Date)	60	

Data Collection Process

Having a good understanding of how your data is collected is extremely important. The quality of the data collection process determines the amount of effort needed to pre-process data prior to using Sensible Machine Learning.

The following sections describe what defines a good source data collection process.

Uniform Data Collection

Uniform Data Collection is defined as having a consistent data collection procedure for building the source data set.

Important questions to consider are:

- Is there a consistent data collection procedure across all business units or do business units implement their own practices?
- Do all business units report the same information, on the same frequency, and at the same time?

Ensuring that data is sourced using the same procedure and practices across all sources minimizes the effort to identify and correct any discovered inconsistencies. Overall, a highly fragmented and disjointed data collection process should be addressed and fixed before using a data source in Sensible Machine Learning.

Uniform Intra-Target Collection

Uniform intra-target collection is defined as a particular target maintaining the same data collection practices and procedures over time. Important questions to consider are:

Appendix 1: Data Quality Guide

- Does the frequency and the collection lag of the target remain consistent over time?
- Do the number of sources feeding a target remain consistent over the course of time?

Intra-target collection process integrity is important to maintain over the course of time. Otherwise, you risk the statistical and ML models mistaking a data collection inconsistency for changes in the underlying data pattern for that target.

The following example illustrates the difference between a non-uniform intra-target collection procedure versus a uniform procedure.

A clothing company that owns a variety of clothing brands wants to predict the unit sales of shirts and pants. They have historical retail sales data dating back to 2014. In 2017, this clothing company merged Brand B that they own with Brand A (having Brand B be absorbed by Brand A).

Consolidate Data at Merger (Non-Uniform)

The following table shows a non-uniform intra-target collection pattern. It is non-uniform because from 01/01/2017 onward there are two sources feeding BrandA-Shirts and BrandA-Pants. Before 01/01/2017 there was only one source. This fundamentally changes the collection process for these targets.

Date	BrandA-Shirts	BrandA-Pants	BrandB-Shirts	BrandB-Pants
10/1/2014	30	14	17	13
10/2/2014	35	15	21	16
...
12/30/2016	34	18	20	15
12/31/2016	36	20	22	17
1/1/2017	60	38	DNE	DNE
1/2/2017	59	35	DNE	DNE
1/3/2017	58	37	DNE	DNE

The problem with this method is that the models that run against BrandA-Shirts and BrandA-Pants are not aware that this merger happened. The models assume that BrandA targets magically and organically doubled their sales at the start of the year. In future projections, the models may see this doubling as a common occurrence and predict this to happen at the start of every year which would be wrong.

The Correct Way: Backdate the Consolidation of Brands to the Beginning of the Data (Uniform)

This is the correct way to handle this merger from a machine learning data perspective because it maintains uniformity of target data collection over time. With the uniform option, even though the merger officially occurred on 01/01/2017, the values of Brand A and Brand B are aggregated back to the beginning of the data set.

Date	BrandAB-Shirts	BrandAB-Pants
10/1/2014	47	27
10/2/2014	56	31
...
12/30/2016	54	33
12/31/2016	58	37
1/1/2017	60	38
1/2/2017	59	35
1/3/2017	58	37

This has two benefits over a non-uniform intra-target collection.

- The models are trained off the combined Brand A and B which is the case moving forward.
- This removes the Shutdown Brand B from the data set that serves no purpose moving forward and should not be receiving predictions.

Data Set Frequency

Data Set Frequency refers to the time frequency of the overall data set. The time frequency is set based on the target that has the most granular level data.

It is expected that the frequency of an entire data set remains constant across all targets. If a data set frequency is not constant across all targets, the most granular frequency target determines the overall data set frequency. The targets that are of a less granular frequency are based on the configured cleaning method selected in the [Configure > Model page](#) in the Model Build phase to get a complete series of the same frequency as the most granular data.

This is illustrated by the following two data sets.

Appendix 1: Data Quality Guide

(Left Dataset)

Date	DayOfWeek	Target A	Target B
1/4/2021	Mon	7	32
1/5/2021	Tue	4	
1/6/2021	Wed	7	
1/7/2021	Thu	10	
1/8/2021	Fri	11	
1/9/2021	Sat	5	
1/10/2021	Sun	7	
1/11/2021	Mon	6	49
1/12/2021	Tue	2	
1/13/2021	Wed	4	

(Right Dataset)

Date	DayOfWeek	Target A	Target B
1/4/2021	Mon	7	32
1/5/2021	Tue	4	40
1/6/2021	Wed	7	40
1/7/2021	Thu	10	40
1/8/2021	Fri	11	40
1/9/2021	Sat	5	40
1/10/2021	Sun	7	40
1/11/2021	Mon	6	49
1/12/2021	Tue	2	40
1/13/2021	Wed	4	40

Mean Imputation

The Left Dataset is the raw data given to Sensible Machine Learning. The Right Dataset is the data set processed by Sensible Machine Learning after the initial data load. In this scenario, Target A is a daily frequency and determines the underlying frequency of the entire data set. This means all other targets are expected to also be daily frequency. If any additional targets are not of the same frequency, Sensible Machine Learning fills their missing values based on the configured cleaning method selected in the [Configure > Model](#) page in the Model Build phase. Target B illustrates this as a weekly granularity in the Left data set and being filled with the mean value of the entire column in the Right Dataset.

Data Collection Best Practices

The most concise way to describe the best practices is to avoid all the data quality problems shown in [Data Quality](#), [Data Collection Process](#), and [Data Set Frequency](#).

Additional best practices include:

Use the Same Target Collection Lags for all Targets

All targets should have close to the same target collection lags. If there are large differences in collection lags across targets, break up the data into two or more separate projects where you can separate the project based on similar target collection lags across the data.

Ensure the Target Collection Lag Remains Constant Over Time

The source data should be routinely updated at a consistent interval. This minimizes the need to interpolate the most recent dates. If the actual collection lag changes, then you must reconfigure the models by doing a full model rebuild.

Provide Complete Data

It's okay to fill a few missing values or a few partial sections of target data if they can be reasonably interpolated. If greater than five percent of data is missing, performance can become unstable for targets. This is because models are learning from fake interpolated patterns found in the data that may not match. The more complete the data is, the better the forecast results.

Do Not Use Fake Data

No reasonable model accuracy can be assumed if source data is manufactured to represent real data.

For example, take a target that is only available at a yearly frequency and guess its allocation at a monthly frequency, then provide this to Sensible Machine Learning as a monthly frequency target. The model would learn from a fake monthly variation that most likely does not match the monthly reality. Therefore, you cannot reasonably assume that the model accuracy for that target at the monthly level produces accurate forecasts.

In general, if the data provided to Sensible Machine Learning (or any model) does not match the reality of the historical data patterns, then no reasonable forecasts should be expected from Sensible Machine Learning for those targets. Learning from fake data can lead to inaccurate results.

Ensure Uniform Data Collection Practices

Ensure that all data collection practices remain consistent across the entire history and future of the source data. This ensures that models have consistent data patterns to learn from. A model can mistake a change in the data collection pattern as a new trend or seasonal data pattern which can cause inaccurate results.

Ensure a Constant Frequency Across All Targets

Ensure that all targets included in the source data are of the same frequency. Any targets that are less granular than the data set frequency produce inaccurate results.

Do Not Change Source Data While Sensible Machine Learning is Running

Changing the data source targets while a Sensible Machine Learning job is running may cause Sensible Machine Learning to stop responding. This is because Sensible Machine Learning avoids making a copy of the data source used to power the solution.

Align the Target Units to the Business Problem

It is important to align the target units to the business problem that Sensible Machine Learning is being used to solve.

For example, if the downstream use case is supply chain demand planning, it is best to have the targets' units be unit sales rather than dollar sales. This is because the raw units sold more closely align to the downstream use case when estimating how much product to move to certain retail locations.

Using dollar sales does not effectively align to this use case and creates these challenges:

- Models are expected to learn price appreciation or changes in the price per unit. Price-per-unit changes are a form of non-uniform target collection which should be avoided.

- The forecast dollar sales must be converted back into unit sales to align to the demand planning use case. This can lead to conversion errors, which complicates the inherent error that exists in any forecast.

Data Volume

This section explores all aspects of data volume, from an educational perspective, to show how data volume components influence performance and use case alignment.

The size and shape of the source data set determines:

- Data patterns that can be learned.
- Model algorithms that can be leveraged.
- How far forward you can accurately forecast data.
- Effectiveness of features (external variables).
- Model train and build time.
- Overall model accuracy and use case performance.

Data Granularity and Learnable Data Patterns

Before understanding the influence of data volumes, it is important to understand how data granularity determines what data patterns can be learned by models. A *data pattern* is an underlying structure of a time series.

Common data patterns include:

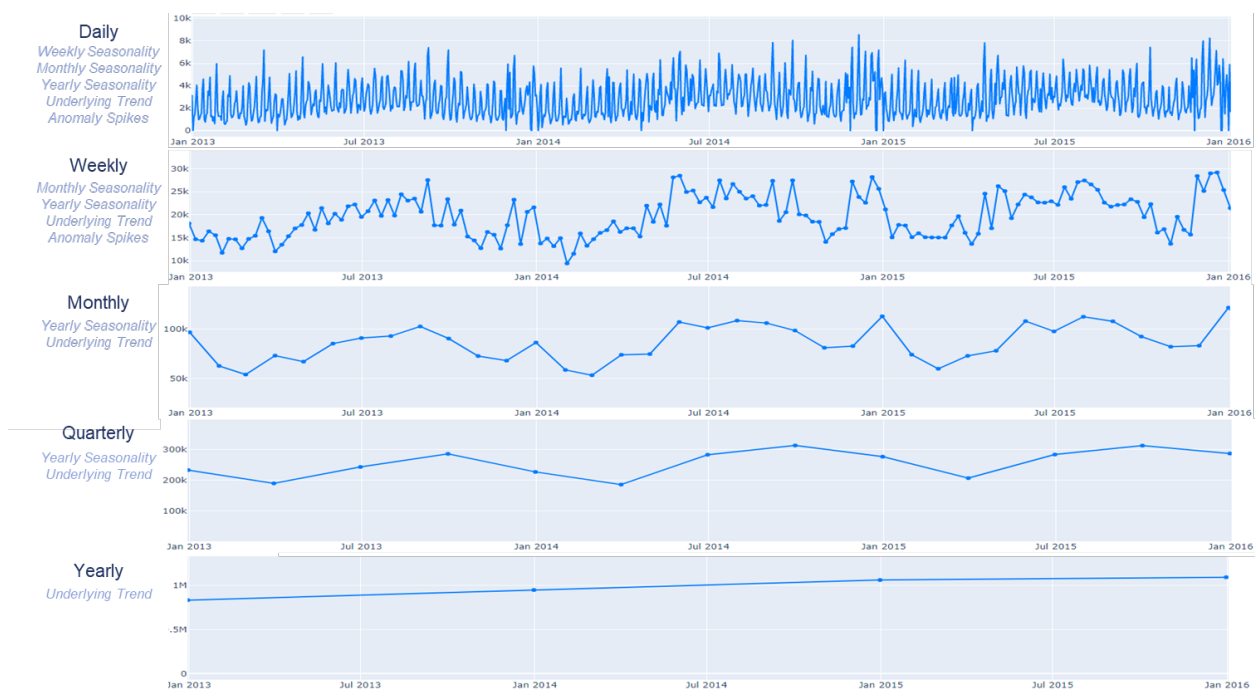
- **Seasonality:** A repeated pattern occurring on a constant frequency, for example weekly seasonality where the same sort of high and low point would occur on the same day of the week. There can be many forms of seasonality occurring within the same time series.
- **Trend:** An underlying slope (linear or non-linear) that increases or decreases the time series average over time.

Appendix 1: Data Quality Guide

- **Anomalies** (also known as outliers): An explainable or unexplainable data pattern that deviates from the normal seasonality or trend. These are typically one-off high or low points. In more extreme cases, these can surface as longer-term data shifts lasting weeks, months, or years.

It is best to address anomalies either by removing them or using features and events to inform models of their occurrence.

The following graphic overlays the same sales data at varying levels of aggregation (daily, weekly, monthly, quarterly, yearly). As aggregations continue up to yearly, different forms of seasonal variation and anomalies become hidden.



It is important to use the right tools for the forecasting job. Sophisticated machine learning models perform best when multiple seasonal variations and an underlying trend exist. Machine learning models leverage features to learn intricate seasonal patterns that exist within a time series to get the best line following result. Machine learning models are better suited for short range demand planning scenarios, where high daily forecast accuracy is needed, compared to more statistical based models.

Statistical based models are better suited for monthly, quarterly, or yearly data sets with fewer data patterns. This makes statistical models better at solving long range or growth-based use cases, since the business cares more about the underlying trend.



Impact of Data Points and Data Granularity

The number of data points determines the functionality that can be used during the model build process. For data sets of coarser data granularity, Sensible Machine Learning adjusts to not waste resources on functionality that does not contribute to model performance. For example, Sensible Machine Learning does not run machine learning models on a monthly data set because there are too few seasonal data patterns to learn from monthly level data. Sensible Machine Learning is optimized to produce the best performance out of any level of data set provided.

Functional Overview by Data Granularity



XperiFlow Engine Functionality by Data Point Range

Total Data Points	16 – 36 Data Points	36 – 80 Data Points		80 – 300 Data Points		300+ Data Points	
Data Granularity	Quarterly/Monthly	Monthly/Weekly		Weekly/Daily		Daily	
Train Data Points	< 80 Train Data Points	< 80 Train Data Points	>= 80 Train Data Points	< 80 Train Data Points	>= 80 Train Data Points	< 80 Train Data Points	>= 80 Train Data Points
Auto ML	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Data Cleansing	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Event Builder	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Auto External Data Collection	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Auto Feature Engineering	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Univariate Models (Statistical Models)	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Multivariate Models (ML Models)	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Multi-Series Models (Target Grouping)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Allows External Features	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Baseline Comparisons	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Backtest Performance	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>

16 to 36 Data Points (Quarterly to Monthly)

This is the most restrictive model build pipeline offered. The data is most likely monthly data with only one to three seasonal cycles. All models offered for this data point range are univariate, simple models, meaning they are trend-based models with no features to enhance predictive capability.

Data: Most likely monthly data with little to no seasonality. Typically, only one to three seasonal cycles exist within the number of historical data points. Limited seasonality implies that models trained against this data rely exclusively on learning the underlying trend.

Functionality: The functionality for this data point range is the most restrictive offered. Functionality is restricted due to low data volumes. Models that can be used with low data volumes do not accept features. Therefore, events, locations, external data, external features, feature engineering, and feature selection cannot be provided or run in Sensible Machine Learning for these data volumes.

With the 16 to 36 data points range, there may be enough data for a validation set for training to compare model accuracy. This is not a perfect situation, since this validation set is being used for model hyperparameter tuning and selecting the best model, during training.

Since there is not enough data that can be held out during training to compare model accuracy, backtest accuracy comparisons are deactivated on the **Deploy** page. Grouping functionality is also not available since there are no grouping models that can be run.

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Features: Features cannot be used for this data point range. This is because there is not enough data to learn any meaningful relationships between any feature and target variable.

Models: Models in this data point range are basic statistical models that extract an underlying trend or basic seasonality. Given the limited amount of data to train on, these models typically forecast conservatively and do not project aggressive increases or decreases in the underlying trend. With only one to three yearly seasonal cycles typically existing with this amount of data, the models struggle to find the seasonality with accuracy. The models typically catch only apparent seasonality patterns spotted over at least three seasonal cycles.

Models running against this amount of data can train much faster than larger data point ranges and more complex models.

Model Selection: Model selection can be difficult for models with a low number of data points. There is no back-test procedure or train-test procedure that can validate which models will perform the best in production outside of using the validation set once there are 20 data points.

The best performing model is chosen based on the best fit for the validation data if available. This implies that models could be overfit to the training data. To deal with this, Sensible Machine Learning selects models from the Model Arena of the model build phase based on some of the structural integrity of a particular target. For example, if the historical data offers little to no repeated seasonality, the seasonal statistical models do not run against that target in the Model Arena.

Selecting the Models to Train: Sensible Machine Learning inspects a target's data patterns to determine which models should be allowed to train. Inspecting the data patterns includes determining whether there is seasonality in the existing underlying data. Sensible Machine Learning only trains models that match the structural data patterns of the data.

Selecting the Best Trained Model: The best trained model is chosen by whatever model best overfits the training data or validation data, if applicable. The effectiveness of the Selecting the Model to Train process is very important.

Use Cases: This data point range is best associated with long term growth, high-level or long-range planning, or strategic growth use cases, since there are only underlying trends and slight seasonality.

It is recommended to leverage all the models for your targets. This gives downstream users from Sensible Machine Learning the flexibility to choose the model forecasts to use.

36 to 80 Data Points (Monthly to Weekly)

This is the second most restrictive model build pipeline offered. The data is typically monthly or weekly with three or more seasonal cycles. All models offered for this data point range are univariate simple trend and seasonal models. This means these models can detect a single seasonality with an underlying trend. However, there are still not enough underlying data patterns to warrant the use of features.

Data: Most likely monthly or weekly level data with a single seasonality and trend.

Functionality: The same limitations for the 16 to 36 data point range exist with a few exceptions.

With the 36 to 80 data points range, there is enough data for a validation set for training to compare model accuracy. This is not a perfect situation, since this validation set is being used for model hyperparameter tuning and selecting the best model during training. Backtest accuracy comparisons are deactivated on the **Deploy** page. Grouping functionality is not available since there are no grouping models for this data point range.

Features: Features are not allowed for this data point range. This is because there is not enough data to learn meaningful relationships between any feature and the target variable, since there are minimal data patterns to learn.

Models: Models for this data point range are statistical models that extract underlying trends and some seasonality. With limited data to train on, these models typically forecast conservatively and do not project aggressive increases or decreases in the underlying trend. These models typically only catch seasonal patterns spotted over at least three seasonal cycles.

Models running against this amount of data can train very fast, compared to larger data point ranges and more complex models.

Model Selection: As mentioned in the [16 to 36 Data Points \(Quarterly to Monthly\)](#) section, the same difficulties apply to model selection and Selecting the Best Trained Model in most situations. However, as the data points approach 20 or more, Sensible Machine Learning uses a validation data set for hyperparameter tuning.

Selecting the Models to Train: Sensible Machine Learning inspects the target's data patterns to determine which models should be allowed to train. This includes determining whether there is seasonality or an underlying trend that exists in the data. Sensible Machine Learning only trains models that match the structural data patterns.

Selecting the Best Trained Model: The best trained model can be chosen by whatever model overfit the most to the training data for 20 or less data points. If there are more than 20 data points, a validation set is used for hyperparameter tuning and choosing the model that had the lowest error on this section.

Use Cases: This data point range is best associated with long term growth, or high-level or long-range planning use cases given that there exists an underlying trend and single seasonality. This provides some understanding of the months or time periods within a given year that are spiking or dipping.

80 to 300 Data Points (Weekly to Daily)

A data set with 80 to 300 data points can leverage almost all capabilities of Sensible Machine Learning.

Data: The data will most likely be daily level data with multiple data patterns that can be learned.

These data patterns consist of:

- **Seasonality:** Multiple seasonalities may exist within the data. This may be overlaid seasonality of weekly, monthly, quarterly, or yearly.
- **Trend:** An underlying change in the mean value over time.
- **Anomalies:** Spikes or dips in the data that can be explained by re-occurring events and holidays.

These data patterns may be difficult to learn since there are likely not enough data pattern repetitions. For example, a daily level data set with only 300 data points does not have a complete picture of yearly seasonality. Therefore, a model running against this data set most likely cannot assume any yearly seasonality exists, even if it does exist.

Functionality: Almost all the functionality available in Sensible Machine Learning may be leveraged. The cross-validation strategy used improves the closer you get to 300 data points.

Features: Sensible Machine Learning uses all possible feature types to get the most highly performing models. However, weekly level data sets may not see an effective benefit from event-based features since events occur daily.

Models: All different model types can be leveraged with at least 80 data points in the train set of the largest split. Models that run against these 80-300 data points are typically a mix of machine learning and statistical models. This data point range blends the usage of models that leverage features and pit them against models that do not use features.

Model Selection: The models that perform best are typically ML models or more advanced statistical models, since there is a decent amount of data patterns to learn from.

Selecting the Models to Train: Sensible Machine Learning gets a list of candidate models to run in the Model Arena. It defaults to running a recommended set of machine learning models. Two of these are XGBoostTimeSeries and CatBoostTimeSeries. After the models have been selected, the Model Arena then trains these models and compares them against each other. Sensible Machine Learning also includes common baseline models (shift and mean models).

Selecting the Best Trained Model: In the Model Arena, the cross-validation strategy used improves the closer you get to 500 data points.

Use Case: This data point range is best associated with an annual demand plan. This is because Sensible Machine Learning can learn a fair amount of seasonal data patterns which provide accurate forecasts on any given day or weekly interval.

Daily granular data sets within this data point range may struggle to produce accurate forecasts longer than six months given that there may not have been enough daily history to learn yearly seasonal data patterns.

300+ Data Points (Daily)

All capabilities of Sensible Machine Learning are unlocked for data sets with more than 300 data points.

Data: The data is most likely daily level data with multiple data patterns that can be learned.

These data patterns consist of:

- **Seasonality:** Multiple seasonality may exist within the data. This may be overlaid seasonality of weekly, monthly, quarterly, or yearly.
- **Trend:** An underlying change in the mean value over time.
- **Anomalies:** Spikes or dips in the data that can be explained by re-occurring events and holidays.

Functionality: All functionality of Sensible Machine Learning is available for data sets with more than 500 data points.

Features: Sensible Machine Learning leverages all possible feature types to get the most performing models.

Models: All different model types can be leveraged with at least 80 data points in the train set of the largest split. Models that run against data with more than 300 data points take the longest to train. This is because the models running against larger data sets have more parameters to tune, more data for models to consume, and more data patterns to learn. The train time duration per target is higher than other data point ranges.

The models that perform best here are typically machine learning models due to high volume of data patterns to learn from.

Model Selection

Selecting the Models to Train: Before running the Model Arena with 300+ data points, Sensible Machine Learning gets a list of candidate models to run in the Model Arena. It defaults to running a recommended set of machine learning models. Two of these models are XGBoostTimeSeries, and CatBoostTimeSeries. After the models have been selected, the Model Arena trains these models and compares them against each other. Sensible Machine Learning also includes common baseline models (shift and mean models).

Selecting the Best Trained Model: In the Model Arena, a comprehensive cross-validation strategy is leveraged for hyperparameter tuning and model validation to determine which models are the most likely to perform best in production. A nested time series cross-validation strategy is leveraged.

Use Cases: This data point range is best associated with annual demand planning or operational level demand planning use cases. This is because Sensible Machine Learning can learn from multiple seasonal data patterns which provide highly accurate forecasts on any given day. These granular forecasts can be used to drive operational level decisions.

Grouping: Modeling Targets Together

By default, Sensible Machine Learning builds at least one model per target. It allows grouping on the **Dataset** page of the Model Build phase which is advanced functionality that allows targets to be grouped and treated as if they are a single target. Grouped targets are trained using multi-series models which work by treating the target name as a feature and collective target values as the target column.

The following graphic illustrates what a grouped data set looks like:

TargetA	TargetB	TargetC	Date		TargetName	TargetValue	Date
7	14	20	1/1/2019		TargetA	7	1/1/2019
5	8	18	1/2/2019		TargetA	5	1/2/2019
3	4	15	1/3/2019		TargetA	3	1/3/2019
...			TargetA
					TargetB	14	1/1/2019
					TargetB	8	1/2/2019
					TargetB	4	1/3/2019
					TargetB
					TargetC	20	1/1/2019
					TargetC	18	1/2/2019
					TargetC	15	1/3/2019
					TargetC

On the left is what a single target machine learning data set looks like. On the right, is the data format that a multi-series model expects.

Single Targets vs. Grouped Targets

Single targets run with single series models and grouped targets run with multi-series models. Each approach comes with pros and cons depending on the data and the business problem.

With grouped targets, a multi-series model can establish relationships between the targets that are being grouped. If the targets are highly correlated and exhibit similar data patterns, it is likely that this can lead to better target accuracy than if the targets were only treated as single targets with single series models. However, if the targets are not correlated or exhibit little to no common historical data patterns, it is equally likely that the target accuracy would be worse than if the targets were only treated as single target with single series models.

Additionally, with grouped targets and multi-series models, it is more difficult for XperiFlow to choose features that will provide benefit to all targets involved in the group. This is because there are limits on the total number of features that can be used for a given model. This can potentially lead to important features that would typically only benefit a single or few targets that a part of a group from being included in the multi-series model. Therefore, it is possible to see target accuracy suffer for certain targets in a group.

Group Targets

There are circumstances where it may be beneficial to group targets.

Highly Correlated Targets

Grouping targets that are highly correlated or related can lead to better individual target accuracy. This happens because the multi-series model can establish non-linear relationships between the different target values.

For example, consider two targets, Dinner Sales and Alcohol Sales, for a restaurant where we want to forecast the daily sales for the next 14 days. It is likely that people will order alcoholic beverages around dinner time. As a result, it will likely be beneficial to group these two targets and allow the multi-series model to establish relationships between Dinner Sales and Alcohol Sales to positively influence the accuracy of both targets.

New Targets with Little Historical Data

Grouping targets that have little historical data with well established targets that have a healthy amount of historical data can yield better accuracy for those targets.

For example, a new suite of high-top sneakers is introduced to the market by a shoe company and have only been sold for the past six months. The shoe company has never sold high-top sneakers before but has been selling a suite of standard sneakers for over four years. For this shoe company, it may be beneficial to group the high-top sneaker targets with the standard sneaker products. This is because the high-top sneaker may exhibit similar sales patterns to the standard sneakers, therefore, a multi-series model may be able to establish relationships between the high-top sneakers and the standard sneaker, allowing the high-top sneakers to rely on the standard sneakers' historical patterns as its own. If grouping was not used in this scenario, then the new high-top sneakers would only have six months of historical data to try and establish a meaningful forecast.

Understanding Accuracy

Interpreting model accuracy can be difficult in data science, since there are many ways to quantify accuracy. Sensible Machine Learning uses multiple viewpoints of model performance to provide a complete picture.

Accuracy Degradation Over Time

It is normal and expected that model accuracy degrades over time. This is a symptom of the underlying data patterns changing since the model was initially deployed.

The Importance of Model Refits

Model Refit: Taking a deployed model and refitting the same model configuration on the latest data.

Sensible Machine Learning attempts to automatically protect against model accuracy degradation by giving the option to **Refit with Latest Data** before running its next prediction. This functionality defaults to **True**, and the prediction takes longer because every model is refit. This functionality refits the production model with the latest refreshed source data. Often, this functionality is enough to keep a model healthy. In some cases, this may even increase model accuracy over time leading to a positive health score.

OneStream recommends leaving **Refit with Latest Data** set to **True** unless the project needs quick and frequent predictions.

The Importance of Model Rebuilds

Rebuild: A rebuild consists of creating new models, data sources, and configurations for a set of targets.

The underlying data patterns are expected to change over the course of time which will cause model accuracy degradation. This implies that:

- Some of the features that were once important may no longer be useful.
- There may be new events that can positively influence accuracy.
- A different intelligent model may better represent the data.

The Purpose of a Partial Rebuild

In large projects, there may be some targets that degrade to unacceptable levels faster than others. Instead of rebuilding all targets and spending time retraining, the partial rebuild option allows you to rebuild only the poorly performing targets.

Know When to Rebuild

Sensible Machine Learning provides indicators throughout the Model Utilization section.

Model Health Distribution Chart: The chart is available on the **Manage Health** page and the **Analysis Overview** page. It plots and color codes the health score for all targets; green = healthy, yellow = warning, and red = unhealthy. If a cluster of red is found with mostly green, this may be an indicator to execute a Partial Rebuild to get the red targets back into the green. If there is mostly yellow and red, this may be an indicator to execute a Full Rebuild.

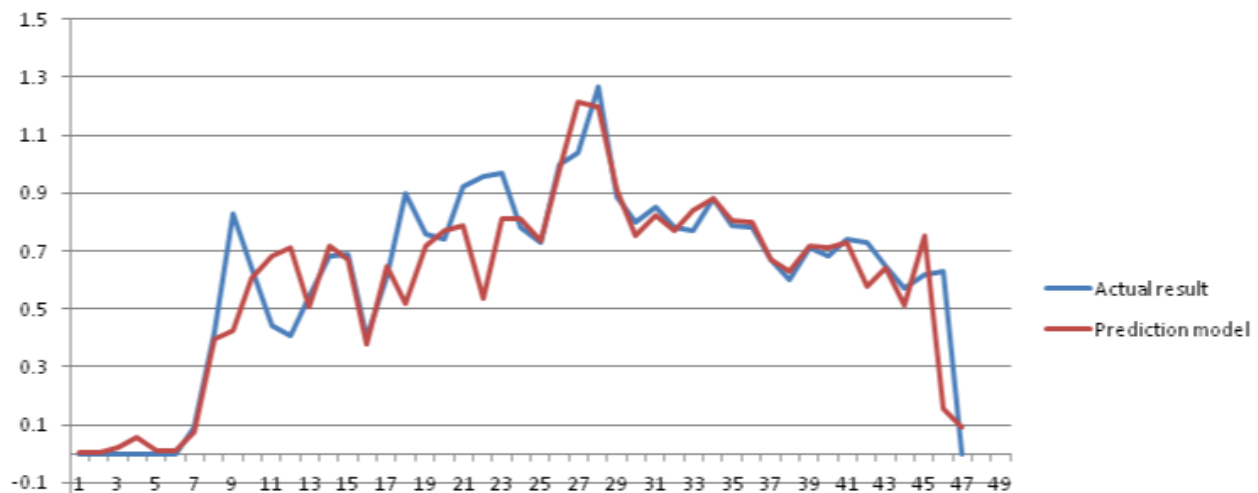
XperiFlow Suggestions: A message grid view that lets you know if a rebuild is suggested.

Quantifying Model Accuracy

Error Metrics

Error metrics evaluate a model's accuracy and quantify how far off predictions are from actuals. All error metrics typically work with two inputs: actual data and associated model predictions that line up against those actuals. An arbitrary error metric output is a single number that can be compared relative to predictions made on the same data.

The following graphic shows an arbitrary set of actuals and predictions:



All error metrics work by quantifying the difference between a set of predictions and actuals. The further away a prediction from its associated actual, the higher the respective error is for that given data point pair.

Variations in quantifying this difference between actuals and predictions produce several different types of error metrics.

For example, Mean Squared Error (MSE) works by squaring the absolute difference between each actual-prediction pair while Mean Absolute Error (MAE) takes the absolute difference between each actual-prediction pair.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i|$$

A smaller number for most error metrics is better than a higher number (minimizing error). However, there are certain error metrics such as R2 Score that look to maximize its value to **1**. R2 Score is the variance proportion in the dependent variable that can be predicted from independent variables and is closely related to Mean Square Error (MSE).

Evaluation Metrics

An evaluation metric is the error metric that evaluates model accuracy.

You can specify the evaluation metric on the **Modeling Configuration** page of the Model Build section. You can select the evaluation metric or let Sensible Machine Learning set the evaluation metric to what it thinks is the best metric to use for the modeling task.

The selected evaluation metric is used to:

- Choose the best model parameters for a model on a target.
- Compare accuracy across models for a target.
- Select the best performing model for a target in training that is then put into production.
- Compare statistical or machine learning models to baseline models.
- Calculate the health scores. The health score is a mathematical equation that quantifies how evaluation metric changes over time.

Comparisons to Baseline Models

Sensible Machine Learning compares statistical or machine learning models to baseline models to quantify the benefit of using Sensible Machine Learning versus traditional forecasting methodologies. This comparison provides an understanding of the benefit of using intelligent models over more traditional forecasting methodologies.

Sensible Machine Learning creates these comparisons by comparing the evaluation metric of an intelligent model and the evaluation metric of a baseline model. The **Pipeline Deploy** page of the Model Build section shows the comparison between baselines and machine learning models in different ways. This provides a quality assurance check that intelligent models can learn more than traditional baseline forecasting methodologies for this forecasting problem.

When Baseline Models Outperform Machine Learning Models

You may experience a situation where baseline models, like shift and mean models, outperform their machine learning counterparts because:

- There is not enough meaningful training data that the machine learning models can learn. Providing machine learning models with more features and data instances to learn from (seasonal, event, weather) typically leads to improved predictive capability. If the time on a machine learning model is trained is too short, the model could perform poorly. If making the training time frame longer is not possible, consider adding additional features and events that could help capture some important data relationships.
- The level of target dimension aggregation selected within the data may not be ideal. Depending on the data set, sparse data can originate from creating too deep, or specific, a target dimension. Typically, it is difficult for machine learning or statistical models to learn anything meaningful from a highly sparse target (many values are 0).

Rolling up to a high-level, or generic, target dimension could hide underlying trends and insights. In the case of a generic target dimension, it is best to use dollar sales over unit sales to ensure that quantified products and services sold are weighted by their dollar amount. This can make it easier for the models to understand value. Intuitively, this makes sense when you consider a situation where the selected target dimension and value are too generic, such as unit sales of clothing.

In this scenario, unit sales could be dominated by high-quantity products with low-value sales compared to low-quantity products with high-value dollar amounts (for example, socks versus Cashmere sweaters). Given unit sales with an overly generic target dimension, a model will struggle to learn seasonality and trend. Keep in mind that this case will align more closely to a sales planning use case than a supply chain use case.

Appendix 1: Data Quality Guide

The following provides a conceptual example of target dimension aggregation level. This is not the same across all data sets. Methods for target dimension aggregation should always be assessed to ensure optimized machine learning model learning capabilities.



NOTE: OneStream recommends that you create small project experiments to test varying levels of target dimension aggregation, different amounts of data instances, and different events and features on a small subset of the entire data set. This allows you to determine the best data set format for your project. Do this experimentation until you have Statistical and Machine Learning Models winning consistently over baselines for the most important 60-80% of targets.

XperiFlow Health Score

The XperiFlow Health Score indicates how a deployed model's performance changes over time. The health score range is between -1 and 1. A health score value of zero means that the model performance has remained constant while the model has been in production. A negative health score implies that the model performance has degraded while the model has been in production. A positive health score implies that the model performance has improved since it has been deployed.

The health score is a calculated, weighted rate of change of the evaluation metric at discrete time intervals over the course of the model being in production.

Other Model Performance Considerations

Fundamental Changes to Business Over Time

In almost every data science problem, *the more data, the better*. Time series forecasting is one of the few data science problems that has an exception to that statement. To properly adjust this statement for time series, it should be phrased as: *the more data, the better... as long as the data patterns remain largely consistent from the beginning of the data history to now*.

This means that if the data patterns change wildly over the course of time, the old and outdated data patterns have little to no importance to the data patterns that exist and need to be forecasted now. From a model point of view, blending old and outdated data patterns with new patterns may only lead to confuse the models and lead to bad performance. Examples of this include data sets or businesses that have been heavily affected by the COVID-19 pandemic in 2020, and completely changes the underlying sales patterns and consumer behavior to look nothing like pre-COVID-19.

Long Forecast Ranges Using Daily Data

Long forecast ranges will typically yield lower performance to shorter forecast ranges. This is because there will be more meaningful features able to aid in the prediction when the forecast range is shorter.

Explaining with Lags

In time series forecasting, a target variable is usually heavily correlated with its most recent prior values.

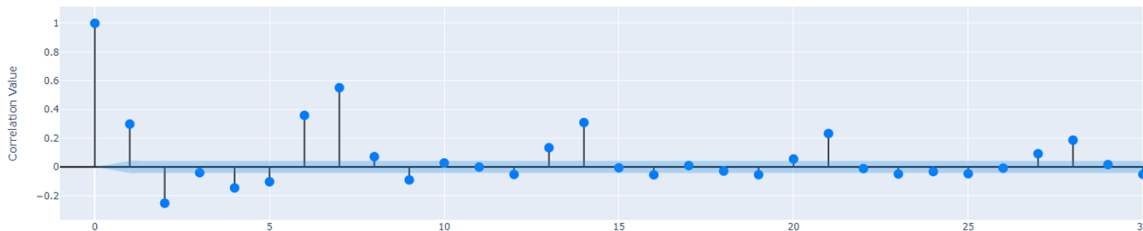
In a daily granularity restaurant sales forecasting example, the sales value today will be heavily correlated with the sales value from 7 days ago. This is because a strong weekly seasonal data pattern found in the data in a daily level data set, today's (Monday's) sales value will be correlated with prior values.

The following graphic shows the daily sales data. There are routine spikes near the weekend. This is weekly seasonality which makes intuitive sense given that this is a restaurant bar that will experience higher sales on the weekend.



Appendix 1: Data Quality Guide

The following auto-correlation plots how correlated each lag of the target variable is with the actual target variable. The 6th and 7th day target lags are highly correlated (.35, .55 respectively) with the target. Additionally, as you move further out, 14, 21, and 28 day target lags are the next highly correlated with the target. The key takeaway is that the further away you get from the actual day (lag days), the less correlated that value is. The smaller the lag number, the more likely the correlation value is high, the more important the lag is in aiding in the prediction of the target.



What do lags have to do with a Long Forecast Range?

In time series, lags of the target variable are powerful features that ultimately lead to a big performance boost. Like the correlation plot shows, a lag feature will typically become less impactful to the model performance the further away you get from the current day.

In time series forecasting, you are forced to lag any features values that you do not know in advance by the length of the forecast range. That means if we want to forecast 21 days ahead on this data set, we can only leverage lags greater than 21 days. Lags of 1, 6, 7, 13, 14, and 20 days will not be able to be used as features in this case. If we were to attempt to produce a 21-day forecast with the previous lags, all of those lags would be missing data necessary to make a prediction.

To summarize:

- The smaller the lag number, the more likely the correlation value is high, the more important the lag is when aiding in the prediction of the target.
- You are forced to lag any features values that you do not know in advance by the length of the forecast range.

Having a large forecast range leads to having less impactful lag features that give lower model performance compared to a short forecast range.

NOTE: Features that are known in advance are features such as events since they happen on a repeated basis. There is no need to lag events.

Appendix 2: Use Case Example

A grocery store company has ten store locations across Florida. This parent company wants to accurately forecast daily sales for 100 different products such as bread, hamburgers, and soda at each location. Provided with daily historical sales over the last three years, Sensible Machine Learning generates hundreds to thousands of performance-enhancing features to train and select the most accurate forecasting model possible to optimize downstream business processes.

There are four main feature types recognized by Sensible Machine Learning. The feature types are largely categorized by how they are created or gathered.

Common Definitions

Time Series Forecasting: *Time series forecasting* uses a model to predict future values based on previously observed values. A simple example of this predicting future grocery store hamburger sales based on historical sales over time.

Other features (see below) could be incorporated to improve the predictive capability of a model.

Sensible Machine Learning Project: A Sensible Machine Learning project is a collection of targets, data sources, and model configurations.

Targets and Features: A *target* is a subject that is to be forecasted and is represented by a single series of historical data (such as beer, martini, and sandwich sales).

A *feature* is a measurable characteristic of a phenomenon that can be represented as a data series that can be leveraged to improve the predictive accuracy of a model. Multivariate models can learn complex non-linear relationships between a target variable and multiple feature variables.



Appendix 2: Use Case Example

In this example, machine and statistical models produce forecasts for each target such as beer, martini, and sandwiches. Models that produce the forecasts can use feature variables such as New Year's or Gas Price to enhance forecast accuracy.

Model Training: In machine learning context, model training is the process of providing machine learning algorithms with data used to learn trends and patterns.

Iterations (Machine Learning): In machine learning, iterations are the number of times an algorithm's parameters are updated. Iterations are done to achieve optimal algorithm performance.

Hyperparameters:

- Cannot be learned from the data.
- Are tunable (hyperparameter tuning). Different hyperparameter tunings result in different model parameter optimizations. This leads to different levels of accuracy.
- Directly control the behavior of the training algorithm.
- Have significant impact on the performance of the model being trained.
- Express high-level structural settings for algorithms.

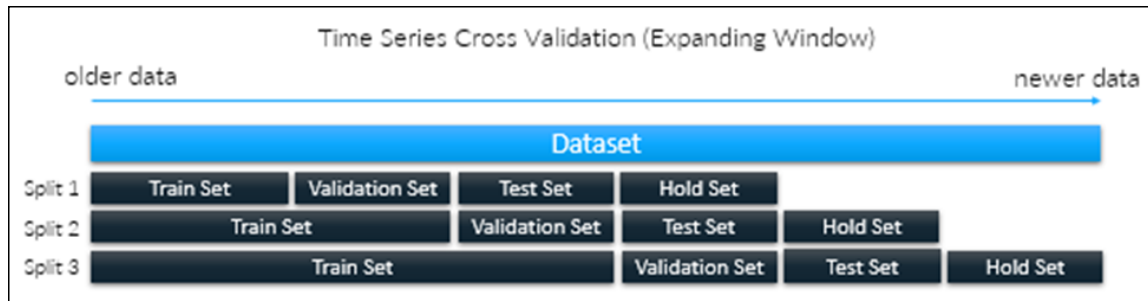
Cross-Validation: A technique that tests statistical or machine learning model performance prior to putting the model into production. Cross-validation works by reserving specific data set samples on which the model is not trained. The model makes predictions on these untrained samples to evaluate its accuracy. Cross-validation provides understanding of how well a model performs before putting the model into production.

Cross-validation is used to :

- Choose the best hyperparameters (the best variation) of a model.
- Compare different models to determine the best model to deploy.

A cross-validation for a time series uses methods such as walk-forward cross-validation (or sliding-window) and expanding-window cross-validation (or forward-chaining). The following images illustrate these methods.

Appendix 2: Use Case Example



Meta-Learning: Machine learning algorithms that learn from the output of other machine learning algorithms. Rather than increasing the performance of a single model, several complementary models can be combined to increase model performance.

Ensembles: A meta-learning approach that uses the principle of creating a varied team of experts. Ensemble methods are based on the idea that, by combining multiple weaker learners, a stronger learner is created.

Boosting: An ensemble technique that sequentially boosts the performance of weak learners to construct a stronger algorithmic ensemble as a linear combination of simple weak algorithms. Each weak learner in the sequence tries to improve or correct mistakes made by the previous learner. At each iteration of the Boosting process:

- Re-sampled data sets are constructed specifically to generate complementary learners.
- Each learner's vote is weighted based on its past performance and errors.

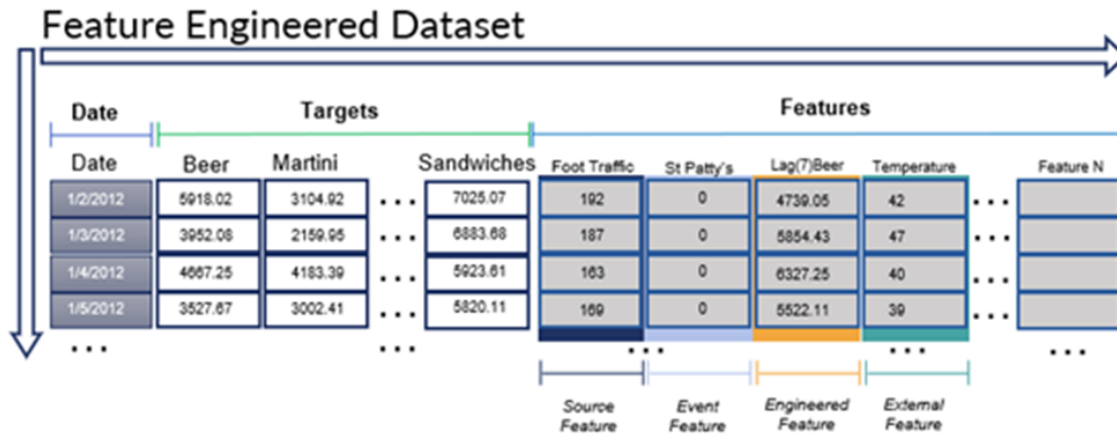
Some of the most popular boosting techniques include:

- AdaBoost (Adaptive Boosting)
- Gradient Boosting
- XGBoost (Extreme Gradient Boosting)

Feature Types

There are four main feature types recognized by Sensible ML. Feature types are largely categorized by how they are created or gathered.

Appendix 2: Use Case Example



Source Feature: A data column in the source data set that enters Sensible Machine Learning. Specify source features in the **Data Features** page of Sensible Machine Learning.

You can create additional features if you have already collected features outside of Sensible Machine Learning and you know these features help the modeling process. However, creating additional features in Sensible Machine Learning is not necessary and not heavily used since so much of Sensible Machine Learning is geared towards generating external features, event features, and engineered features for you. Source features are largely considered a Data Science function of Sensible Machine Learning.

External Feature: A data column that is grafted onto the source data and not originally included in the source data. External features are largely found through external data APIs such as weather or macro-economic data. The most common ways to graft an external feature to the source data is by leveraging the Location capability in Sensible Machine Learning that fetches [features such as weather data](#).

Event Feature: A special subset of an external feature generated using the Event Builder in Sensible Machine Learning. An event feature is always a binary categorical data column generated from the events included in the Sensible Machine Learning Model Build phase.

Event Features have a profound positive effect on model performance.

Engineered Feature: A data column built by augmenting and transforming existing columns in the source data as well as other previously engineered features. Examples of this transformation process include cleaning missing values, lagging, moving averages, time breakdowns, and scaling values in an existing feature to create new engineered features.

Typically, a huge part of a data scientist's time goes toward manufacturing engineered features to improve overall model performance. Sensible Machine Learning creates engineered features by autonomously running statistical column transformations against each column in the source data set. This genetic algorithm style creation of engineered features leads to creating thousands of unique engineered features that Sensible Machine Learning can choose from and leverage in the modeling process.

Model Types

Univariate (statistical) models: A model that does not accept external variables to make predictions. Univariate models are used when there are not many data patterns to learn from, such as with one or two seasons.

Multivariate (machine learning) model: A model that leverages external variables in its predictions. These models are used when there are many data patterns to learn from, such as multiple seasons, anomalies, and a trend.

Multi-series model: A type of multivariate model that is trained to make predictions on a group of targets. A multi-series model requires data to be pivoted in a special long-form data format.

Single series model: A model that is trained to make predictions on a single target. A single series model can be a multivariate model or univariate model.

Baseline model: A type of naïve model that emulates what traditional forecasting methodologies may look like. A baseline model acts as an initial comparison benchmark for more intelligent models.

Appendix 3: Error Metrics

NOTE: Only some of these Error Metrics can be used as evaluation metrics. The rest are computed metrics (not used for evaluating which model is better than another).

Mean Absolute Error (MAE)

An error measurement between paired observations expressing the same phenomenon. Examples of **Y** versus **X** include predicted versus observed comparisons, subsequent time versus initial time, and one measurement technique versus an alternative measurement technique.

Formula:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_{actual} - \hat{y}_{forecast}|$$

Interpretation: Lower is better.

Benefits:

- Easily interpretable.
- No favoritism towards over- or under-predictions.

Shortcomings:

- Relative size of the error is not obvious as with percentages.

Mean Absolute Percent Error (MAPE)

A prediction accuracy measurement of a forecasting method. Also known as mean absolute percentage deviation.

Formula:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|$$

where A_t is the actual value and F_t is the forecast value. Their difference is divided by the actual value A_t . The absolute value in this ratio is summed for every forecasted point in time and divided by the number of fitted points n .

Interpretation: Lower is better.

Benefits:

- Easily explainable.
- Scale-independent / expressed as a percentage.

Shortcomings:

- Returns undefined values when forecasting for actual values of zero.
- Favors models that under-forecast due to heavier penalty on forecasts higher than actuals. Forecasts below actuals cannot be worse than 100% Mean Absolute Percent Error (MAPE).

Mean Absolute Scaled Error (MASE)

A measure that determines how effective forecasts generated through an algorithm are by comparing the forecast predictions with the output of a naïve forecasting approach.

Formula:

$$MASE = \frac{MAE}{(1/n - 1) \sum_{i=2}^n |a_i - a_{i-1}|}$$

Interpretation: Lower is better

Benefit: Independent of the data's scale, so it can be used to compare forecasts across data sets with different scales.

Mean Asymmetric Over Error (MAOE)

A combination of both Mean Squared Error (MSE) and Mean Absolute Error (MAE) depending on whether the predicted value is over or under the actual value. If the predicted value is over the actual value, then the error metric applied is MSE (squared difference). If the predicted value is under the actual value, then the error metric applied is MAE (absolute difference).

Formula:

$$MAOE = \frac{1}{n} \sum_{t=1}^n \begin{cases} (A_t - F_t)^2 & \text{for } A_t \leq F_t \\ |A_t - F_t| & \text{for } A_t > F_t \end{cases}$$

Interpretation: Lower is better.

Benefit: Favors models that under predict. May be useful if there is a difference in penalty in real world application for over predictions.

Shortcomings: Can over penalize a model for over predicting just once or twice way more than under predicting consistently.

Mean Asymmetric Under Error (MAUE)

Similar to Mean Asymmetric Over Error (MAOE), but applies Mean Squared Error (MSE) to predictions below the actual value and Mean Absolute Error (MAE) to predictions above the actual value.

Formula:

$$MAUE = \frac{1}{n} \sum_{t=1}^n \begin{cases} |A_t - F_t| & \text{for } A_t \leq F_t \\ (A_t - F_t)^2 & \text{for } A_t > F_t \end{cases}$$

Interpretation: Lower is better.

Benefit: Favors models that over predict. May be useful if there is a penalty differences in real world application for under predictions.

Shortcomings: Can over penalize a model for under predicting just once or twice way more than over predicting consistently.

Mean Bias Error (MBE)

Mean Bias Error (MBE) is primarily used to estimate the average bias in a model and determine what is needed to correct the model bias. MBE captures the average bias in the prediction.

Formula:

$$MBE = \frac{1}{n} \sum_{i=1}^n (P_i - O_i)$$

where O_i is the observation value and P_i is the forecast value.

Interpretation: Typically not used as a measure of model error, as high individual errors in prediction can also produce a low MBE. MBE reflects a prediction's average bias. A positive value represents overestimating bias and a negative value represents an underestimating bias.

Shortcomings: This is typically not used to measure model error.

Mean Percent Error (MPE)

The computed average of percentage errors by which a model's forecasts differ from actual values of the forecasted quantity.

Formula:

Interpretation: Closer to zero is better.

Benefits: Can be used as a measure of the bias in the forecasts

Shortcomings:

- Measure is undefined when a single actual value is zero.
- Positive and negative forecast errors can offset each other.

Mean Squared Error (MSE)

The average squared difference between the estimated values and the actual value. MSE is a risk function, corresponding to the expected value of the squared error loss.

$$MSE = \frac{1}{N} \sum_{i=1}^N (f_i - y_i)^2$$

where N is the number of data points, f_i the value returned by the model and y_i the actual value for data point i .

Interpretation: Lower is better.

Benefits:

- Increased penalty for larger errors.
- Ensures positive values for easy interpretation.

Shortcomings:

- Less intuitive than MAE.

Mean Squared Logarithmic Error (MSLE)

A measure of the ratio between the true and predicted values. MSLE is a variation of Mean Squared Error (MSE).

Formula:

$$MSLE = \frac{1}{n} \sum_{i=1}^n (\log(Y_i) - \log(\hat{Y}_i))^2$$

Interpretation: The loss is the mean over the seen data of the squared differences between the log-transformed true and predicted values.

Benefit: Treats small differences between small true and predicted values approximately the same as large differences between large true and predicted values.

Shortcomings: Penalizes underestimates more than overestimates.

Median Absolute Error (MedAE)

The loss is calculated by taking the median of all absolute differences between the target and the prediction. If \hat{y} is the predicted value of the sample and y_1 is the corresponding true value, then the median absolute error estimated over n samples is defined as follows:

Formula:

$$MedAE(y, \hat{y}) = \text{median}(|y_1 - \hat{y}_1|, \dots, |y_n - \hat{y}_n|)$$

Interpretation: Lower is better

Benefit: Robust to outliers

Symmetric Mean Absolute Percent Error (SMAPE)

An accuracy measure based on percentage (or relative) errors.

Formula:

$$\text{SMAPE} = \frac{100\%}{n} \sum_{t=1}^n \frac{|F_t - A_t|}{(|A_t| + |F_t|)/2}$$

where A_t is the actual value and F_t is the forecast value.

The absolute difference between A_t and F_t is divided by half the sum of absolute values of the actual value A_t and the forecast value F_t . The value of this calculation is summed for every fitted point t and divided again by the number of fitted points n .

Interpretation: Lower is better

Benefits:

- Expressed as a percentage.
- Lower and upper bounds (0% - 200%).

Shortcomings:

- Unstable when both the true value and the forecast value are close to zero.
- Not as intuitive as MAPE (Mean Absolute Percent Error).
- Can return a negative value.

R² (R-Squared)

A statistical measure of fit that indicates how much variation of a dependent variable is explained by the independent variables in a regression model.

Formula:

Appendix 3: Error Metrics

X	Y	X ²	Y ²	XY
4	5	16	25	20
8	10	64	100	80
12	15	144	225	180
16	20	256	400	320
$\sum X = 40$	$\sum Y = 50$	$\sum X^2 = 480$	$\sum Y^2 = 750$	$\sum XY = 600$

Now,

$$R^2 = \frac{N \times \sum XY - (\sum X \sum Y)}{\sqrt{[N \sum x^2 - (\sum x)^2][N \sum y^2 - (\sum y)^2]}}$$

Putting all the values,

$$R^2 = \frac{4 \times 600 - (40 \times 50)}{\sqrt{[4 \times 480 - (40)^2][4 \times 750 - (50)^2]}}$$

Solving we get

$$R^2 = \frac{400}{17.89 \times 22.36}$$

$$= \frac{400}{400}$$

$$= 1$$

Therefore correlation coefficient is 1.

Interpretation: Higher is usually better; Measures the strength of the relationship between independent and dependent variables in a regression model; Ranges between 0 (No Correlation) and 1 (Perfect Correlation)

Benefits: Commonly used as a measurement technique

Shortcomings:

- Sometimes, a high R-Squared value can indicate problems with the regression model.
- Does not reveal the causation relationship between the independent and dependent variables.

Symmetric Mean Absolute Percent Error (SMAPE)

A measure to compare true observed response with predicted response in regression tasks.

Formula:

Appendix 3: Error Metrics

$$\text{SMAPE} = \frac{100\%}{n} \sum_{t=1}^n \frac{|F_t - A_t|}{(|A_t| + |F_t|)/2}$$

where A_t is the actual value and F_t is the forecast value.

Interpretation: The value of this calculation is summed for every fitted point t and divided again by the number of fitted points n .

Benefits: Has both a lower bound and an upper bound.

Shortcomings: If the actual value or forecast value is 0, the value of error goes to the error upper limit.

Appendix 4: Interpretability

Feature Effects

For a specific trained model, a specific feature of that model and its value, the feature effects shows the average prediction of that model versus the average value of the actuals. The average is taken across all dates where that feature was equal to the specific feature value. Use this information to see how accurate a model is on average for a specific feature. Used with the feature impact score of the feature, this is a useful diagnostic for decomposing the model performance and identifying potential areas for improvement. This could mean adding different impactful features so a model is less reliant on a feature that shows large deviances between average predictions and average actuals, or removing a poorly performing feature.

Take for example, given model A, a daily data set between 1/1/2020 and 1/1/2021, binary feature B that takes on values 0 and 1 and is used by model A:

- The feature effects graph for feature B would have on the X axis 0 and 1.
- The Y axis over 0 would be the average value of the actuals on all days the feature took on 0, as well as the average prediction on all days the feature took on value 0. The same applies for a feature value of 1.

The following example looks at the feature effects of the Cubist Model for the feature Date-Quarter and a specific target. The average prediction on all the days the Date-Quarter takes on a value of 2 is roughly 20, and the average actuals is roughly 40. This same logic can be applied to all the feature values Date-Quarter takes on, namely, 1, 2, 3, and 4.

Appendix 4: Interpretability

ModelName	Feature Impact
CatBoostModelRegressionTimeSeries(forecast=Range Step: 7 Collection Lag Step: 0)	False
CubistModelRegressionTimeSeries(forecast=Range Step: 7 Collection Lag Step: 0)	False
MeanModelRegressionTimeSeries(forecast=Range Step: 7 Collection Lag Step: 0)	False
PolyElasticNetModel(forecast=Range Step: 7 Collection Lag Step: 0)	False
ShiftModel(forecast=Range Step: 7 Collection Lag Step: 0,shift=10)	False
ShiftModel(forecast=Range Step: 7 Collection Lag Step: 0,shift=14)	False

Features		Feature Impact
FeatureShortName		
Date-Day		36.00
Date-Month		12.50
Date-WeekOfYear		5.50
Date-DayOfWeek		2.00
Date-Quarter		0.00



Feature Impact

Feature impact is a way to understand the overall importance a feature has to a model's predictions. The higher a feature's impact score, the more significant that feature is to the model's outputs.

For example, the following chart shows the Date-Year feature has the most significant impact on the model's predictions, where Date-Month was rather trivial in comparison. Specifically, changes in the Date-Year feature cause large changes in the model's output, whereas changes in the Date-Month feature cause much smaller changes in the model output.

Feature Impact		Feature Impact (Average)
FeatureShortName		
Date-Year		21.91
Date-DayOfYear		12.36
Date-WeekOfYear		4.86
Date-Day		4.32
Date-DayOfWeek		2.37
Date-Quarter		2.29
Date-Month		1.28

There are various and evolving mathematical methods for calculating feature's impact on a model. The two methods implemented by the engine are Permutation Importance and Shapley Additive Explanations (SHAP).

The permutation importance of a feature is the decrease in the model's prediction quality when that feature is randomly shuffled. This removes the model's ability to use that feature, but not its reliance since the model is already trained on the unshuffled version of the feature. The performance decrease's magnitude is the feature's relative importance for the model. If shuffling the feature has little effect on the model's error, that feature is not important since the model did not rely heavily on the feature. If shuffling a feature causes a large performance decrease, the model relies heavily on that feature, meaning the feature is important.

The SHAP feature impact value indicates the average magnitude this feature moved the model's prediction from the model's average prediction across all data points. SHAP is an algorithm for calculating Shapley values, where the Shapley values are the feature's fair attribution contributions to the model output for a specific data point.

If a model's average prediction across all data points is x , the Shapley values of the features for a specific data point x' tells how the model got from its average prediction x to the specific prediction for x' , where $x' = x + \text{sum}(\text{Shapley values})$ and the sum is taken across all features the model uses. The average magnitude of a specific feature's Shapley value for across all data points predicted can go from specific data point explanations to an overall feature impact.

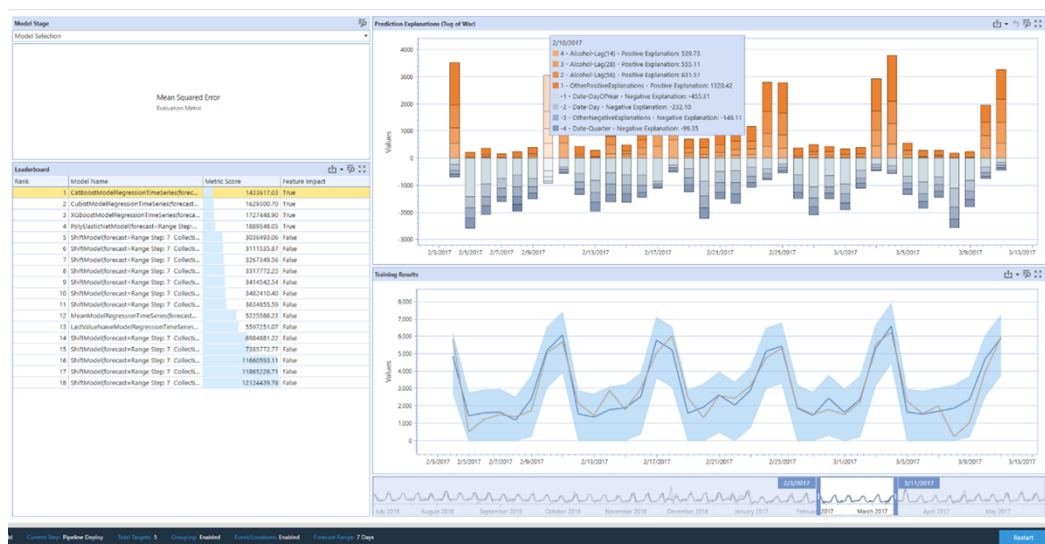
For more information on the specific math behind the SHAP implementation, see: <https://christophm.github.io/interpretable-ml-book/shap.html>

Prediction Explanations

For a specific predicted data point, prediction explanations show how the model uses the features to form that prediction. XperiFlow uses Shapley Additive Explanations (SHAP) as its prediction explanation method. SHAP for prediction explanations and for feature impact is the same algorithm. The only difference in prediction explanations, the Shapley magnitude average values of the Shapley are not taken. Instead, the Shapley values at each data point are shown to explain how the model got from its average prediction to the actual prediction.

Appendix 4: Interpretability

This can be seen in the following graphic. Zooming in on the first predicted point, the model's prediction is higher than average, and the Shapley values represent this. The orange boxes show positive Shapley values, driving the prediction upward from the average. The blue boxes show negative Shapley values, driving the prediction downwards. For the first data point, the positive Shapley values far outweigh the negative Shapley values, leading to a higher prediction. Each box is associated with a specific feature, and shows for the feature and data point how the feature affects the prediction output; either by driving it down, driving it up, or being insignificant. The sum of the Shapley values plus the average model prediction gives the model prediction for a specific data point.



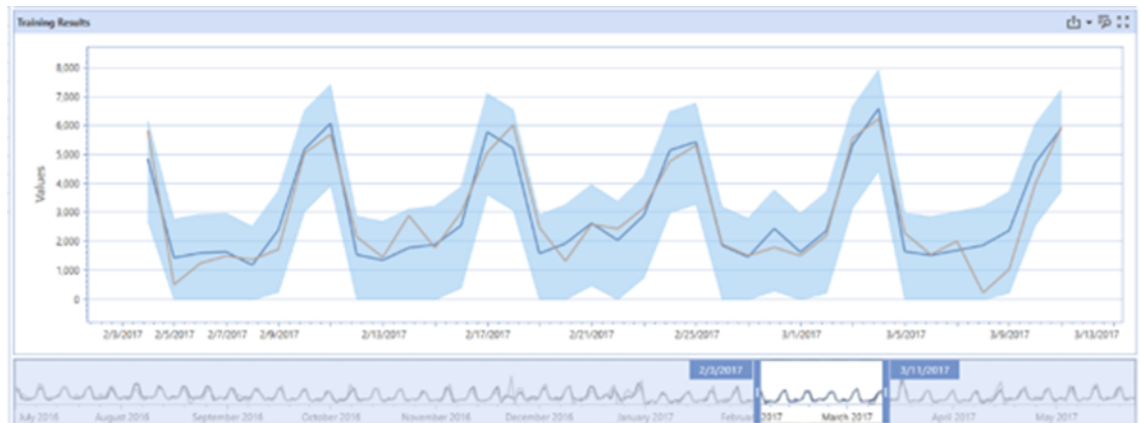
Prediction Intervals

A prediction interval is a value range for a data point prediction that likely contains the true actual future value of the data point. Prediction intervals are useful since time series data is a stochastic process, which means an underlying process generates the actual data has randomness involved. The prediction interval can help account for this randomness.

Prediction intervals instantiate using an alpha value. For example, an alpha of .05 gives a 95% prediction interval. This means if the stochastic process generating the data is sampled an infinite number of times, you could expect 95% of the actual values to fall within this interval. These intervals move the models from simply predicting a point forecast, which can be interpreted as the mean of all the potential futures, to forecasting the distribution of the potential futures.

In the following example, the orange line is the point forecast and the shaded blue region around the orange line is the prediction interval.

Appendix 4: Interpretability



There are various and evolving methods to calculate prediction intervals. The XperiFlow engine uses conformal prediction intervals, parametric prediction intervals, and non-parametric prediction intervals.

Parametric prediction intervals assume the error of the data follows a specific distribution (where the error is the difference between the actual value and the predicted value). The error metrics statistics are used to fit this distribution. Then, depending on the alpha level that instantiates the prediction interval, the proper values can be extracted from the distribution to surround the point forecast and form the prediction interval.

The non-parametric approach works similarly without assuming the error metrics. The non-parametric approach orders errors by size and uses the $(1-\alpha)\%$ error as the top of the interval, and the $(\alpha)\%$ error as the bottom. Specifically, if alpha is .05, the 95% percent largest error forms the top of the interval, and the 95% smallest error (which is either negative or zero) forms the bottom of the interval.