AutoAI Lab

Introduction

This lab will demonstrate the award-winning AutoAI capability to build and deploy an optimized model based on the Titanic data set.

AutoAI in Cloud Pak for Data automatically analyzes your data and generates candidate model pipelines customized for your predictive modeling problem. AutoAI algorithms analyze your dataset to discover data transformations, estimator algorithms, and parameter settings that work best for your problem setting. Results are displayed on a leaderboard, showing the automatically generated model pipelines ranked according to your optimization objective.

Using AutoAI, you can build and deploy a machine learning model with sophisticated training features and no coding. The tool does most of the work for you.

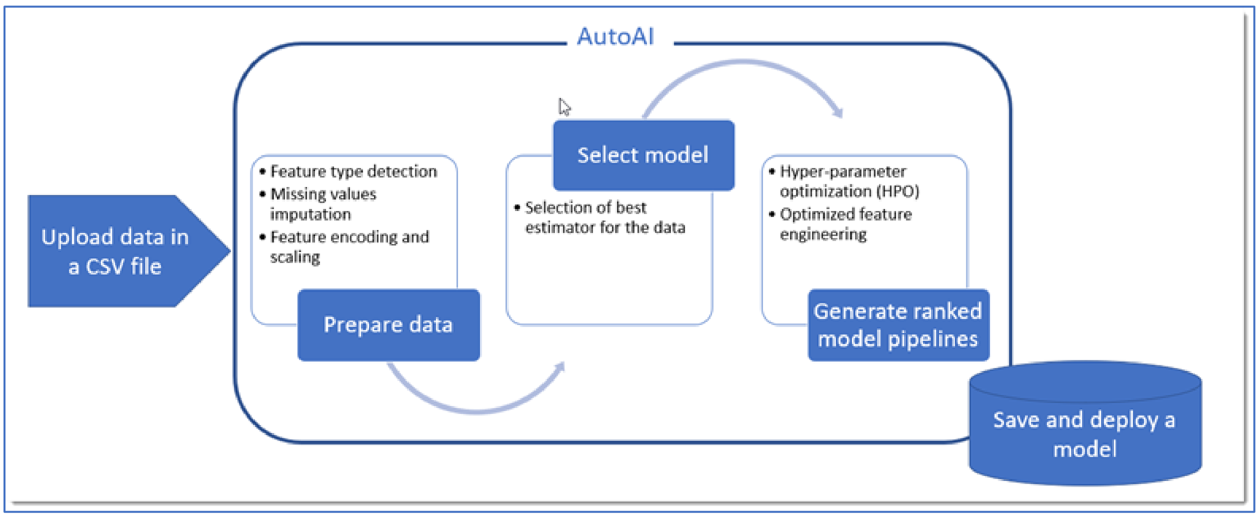


Figure 1- Auto AI Flow

The AutoAI process follows this sequence to build candidate pipelines:

- **Data pre-processing** - Most data sets contain different data formats and missing values, but standard machine learning algorithms work with numbers and no missing values. AutoAI applies various algorithms, or estimators, to analyze, clean, and prepare your raw data for machine learning. It automatically detects and categorizes features based on data type, such as categorical or numerical. Depending on the categorization, it uses hyper-parameter optimization to determine the best combination of strategies for missing value imputation, feature encoding, and feature scaling for your data.

- **Automated model selection -** The next step is automated model selection that matches your data. AutoAI uses a novel approach that enables testing and ranking candidate algorithms against small subsets of the data, gradually increasing the size of the subset for the most promising algorithms to arrive at the best match. This approach saves time without sacrificing performance. It enables ranking a large number of candidate algorithms and selecting the best match for the data.

- **Hyperparameter optimization -** Hyper-parameter optimization refines the best performing model pipelines. AutoAI uses a novel hyper-parameter optimization algorithm optimized for costly function evaluations such as model training and scoring that are typical in machine learning. This approach enables fast convergence to a good solution despite long evaluation times of each iteration.

- **Automated feature engineering -** Feature engineering attempts to transform the raw data into the combination of features that best represents the problem to achieve the most accurate prediction. AutoAI uses a unique approach that explores various feature construction choices in a structured, non-exhaustive manner, while progressively maximizing model accuracy using reinforcement learning. This results in an optimized sequence of transformations for the data that best match the algorithms of the model selection step.

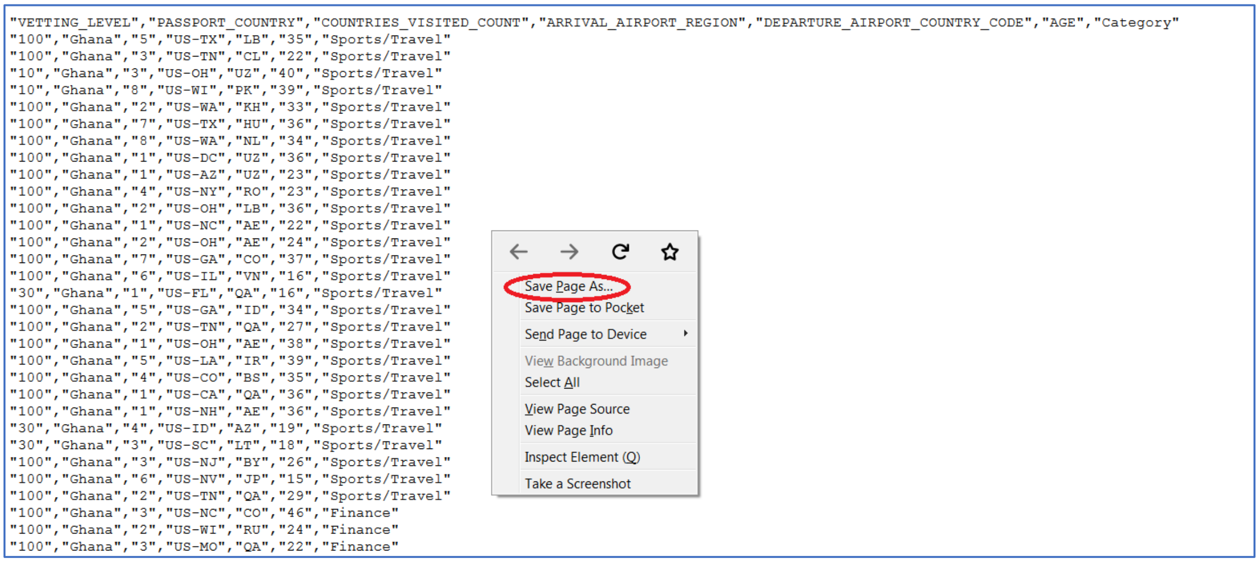
- **Repeat Hyperparameter optimization –** The Hyperparameter optimization step is repeated including the derived features from the feature engineering step.

We will perform the following steps in this lab:

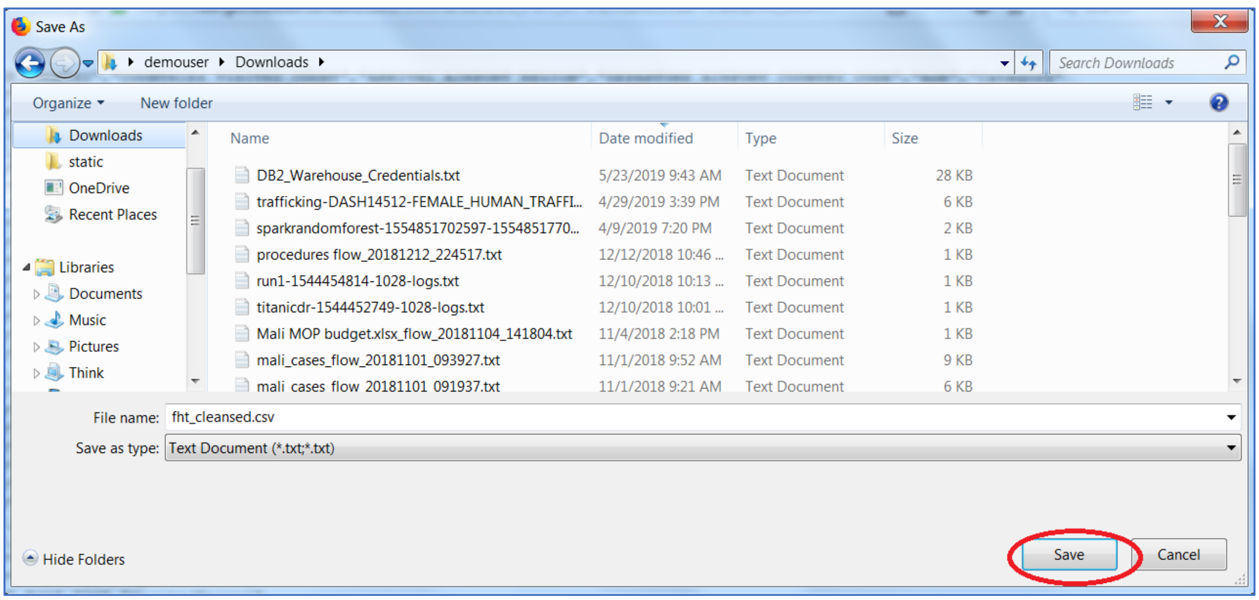
1. Download a female human trafficking cleansed dataset from the github repo
2. Add an Auto AI Experiment to create a model to predict the trafficking risk
3. Save and Deploy the model
4. Test the model

Step 1: Download a female human trafficking cleansed dataset

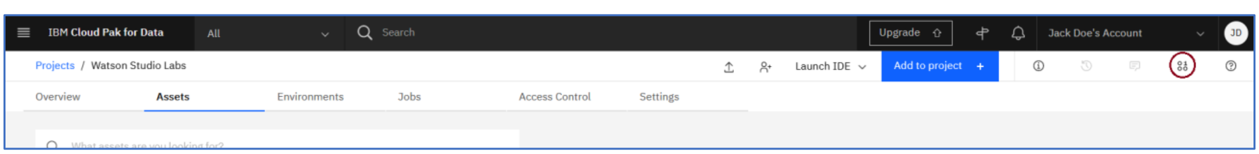
1. Download the fht_cleansed.csv data file from the following location by clicking here
2. Right-click on the window, and click **Save Page As…**



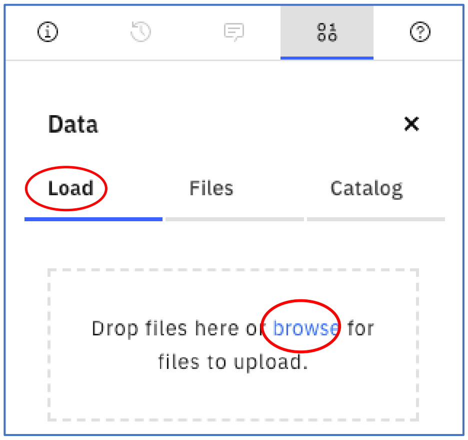
3. Click on **Save**.



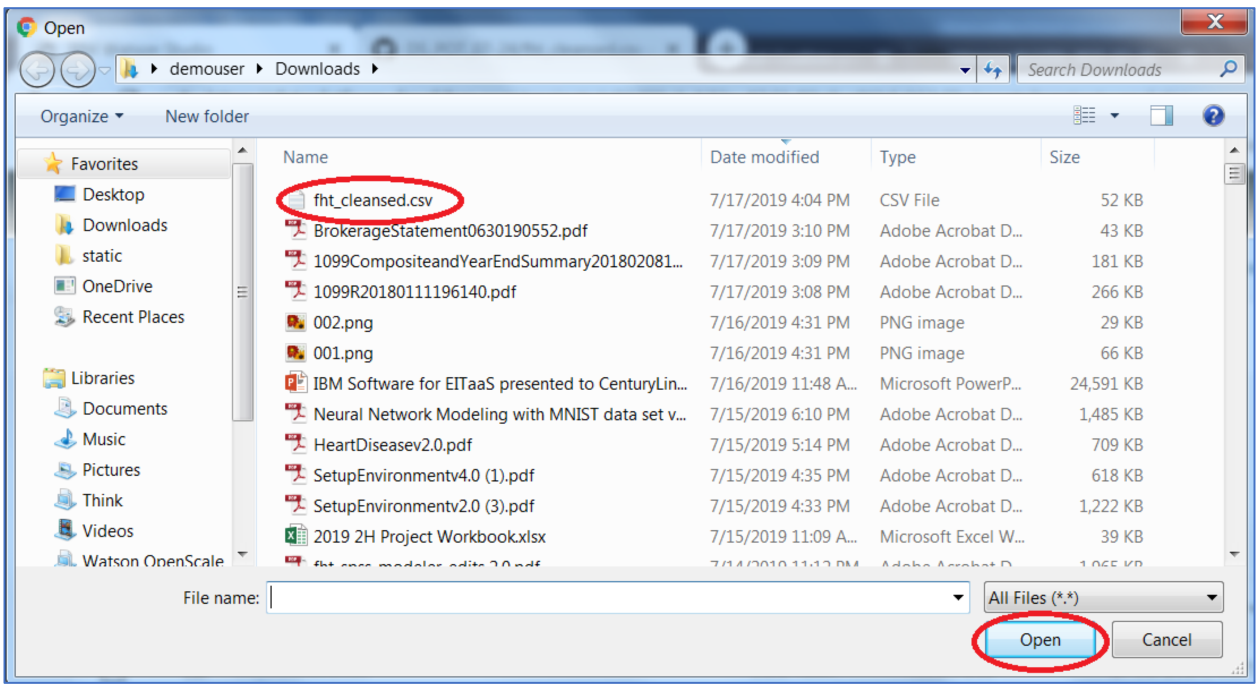
4. Go back to your Watson Studio Labs project. Click on the  icon.



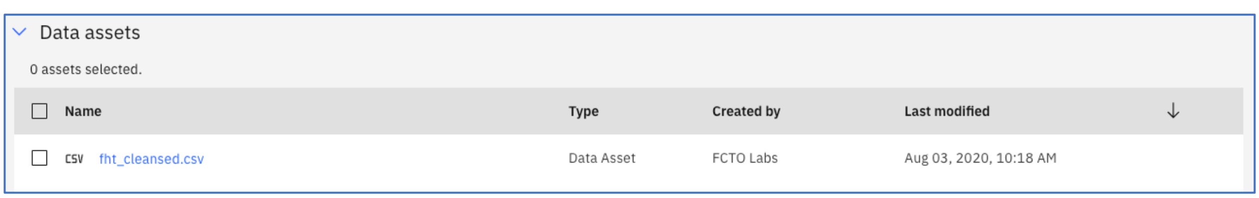
5. Click on the **Load** tab and then click on **browse**. If you don't see the **Load** tab, click on the icon again.



6. Go to the folder where the fht_cleansed.csv file is stored. Select the fht_cleansed.csv file and then click **Open**.

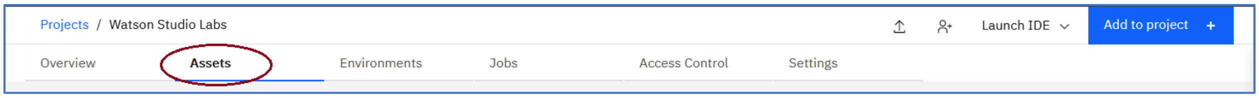


7. The fht_cleansed.csv file is now added as a Data Asset.

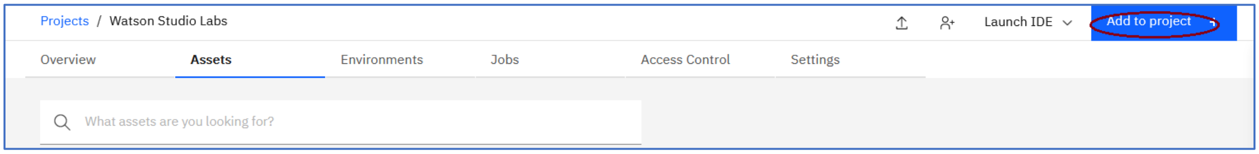


Step 2: Add an AutoAI Experiment.

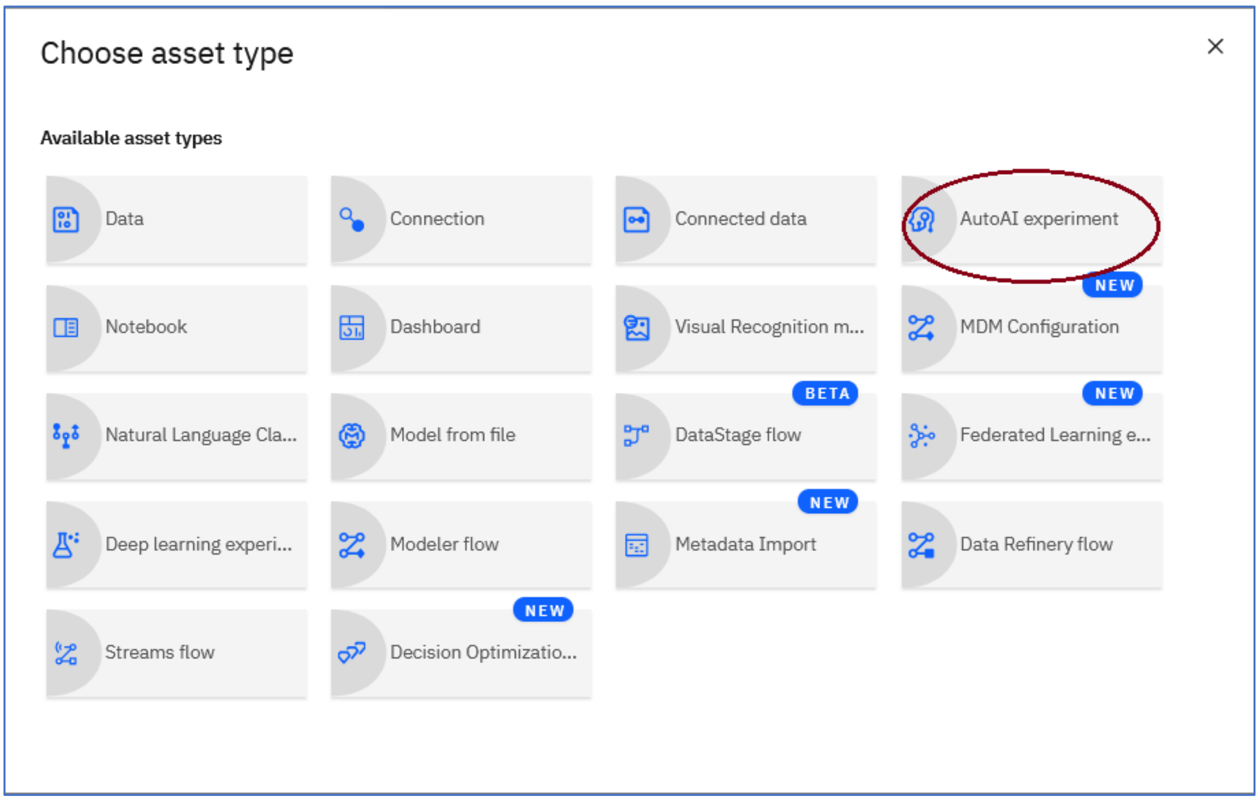
1. If not on the **Assets** page, click on the **Assets** Tab



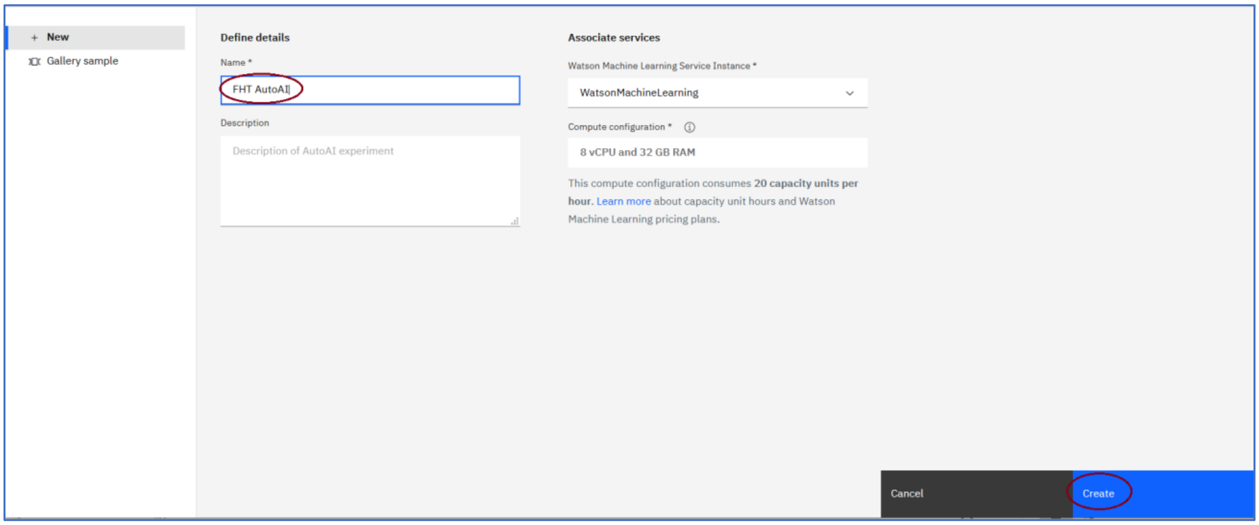
2. Click on **Add to project**.



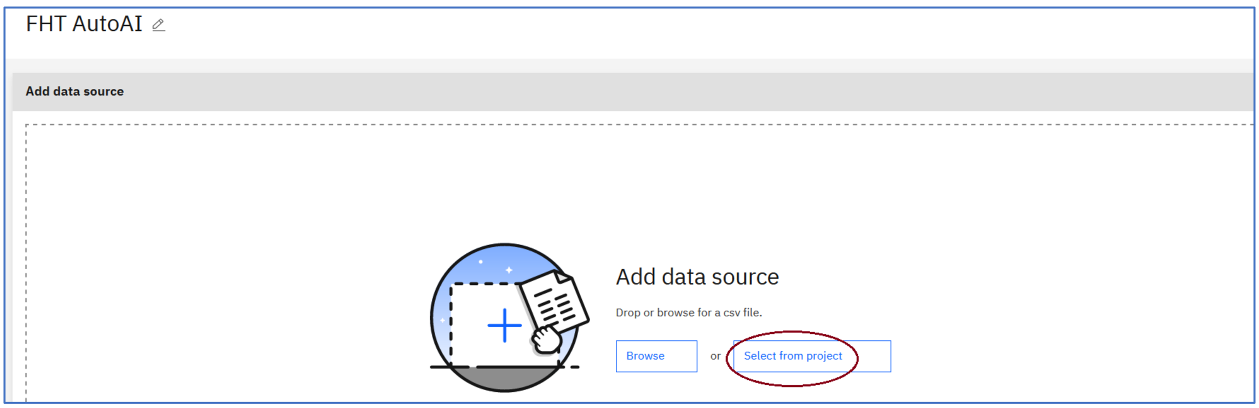
3. Click on **AutoAI Experiment.**



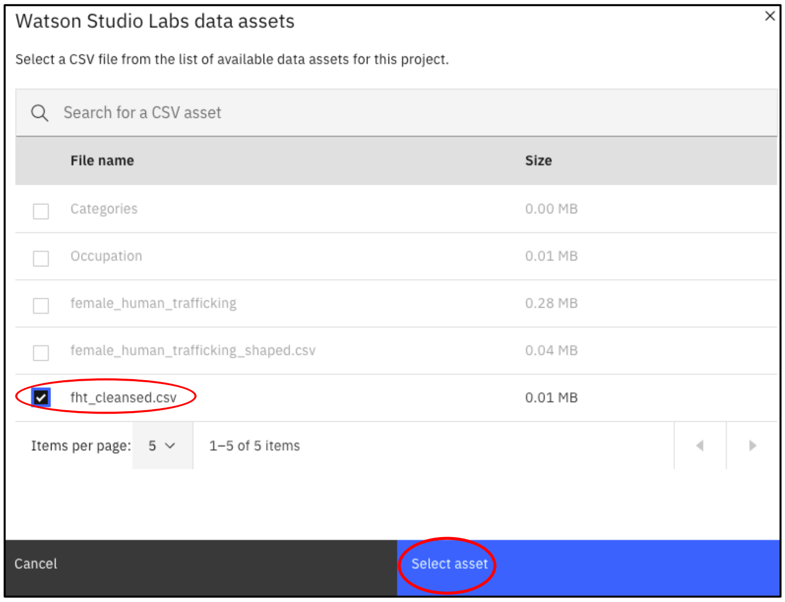
4. Enter an **Asset name**, leave the defaults for the **Watson Machine Learning** and **Compute configuration** and click on **Create**.



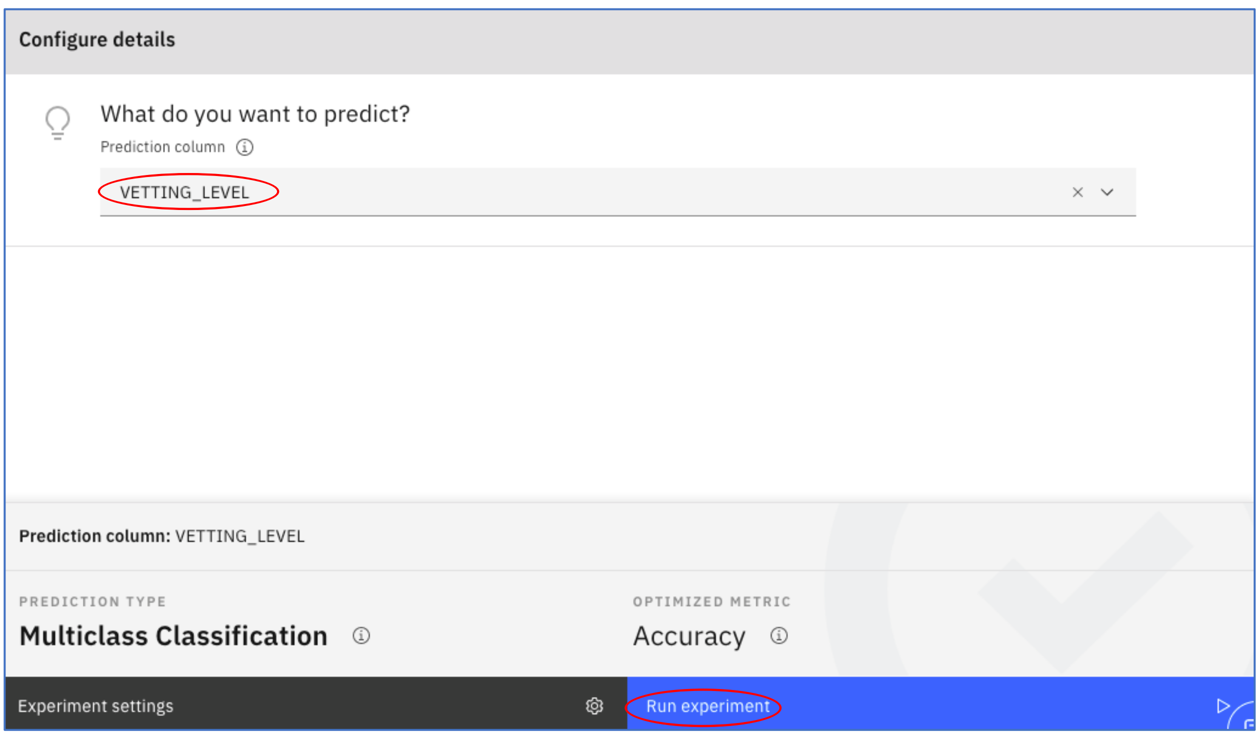
5. Click on **Select from project**.



6. Select the **fht_cleansed.csv** dataset and click on **Select asset**.



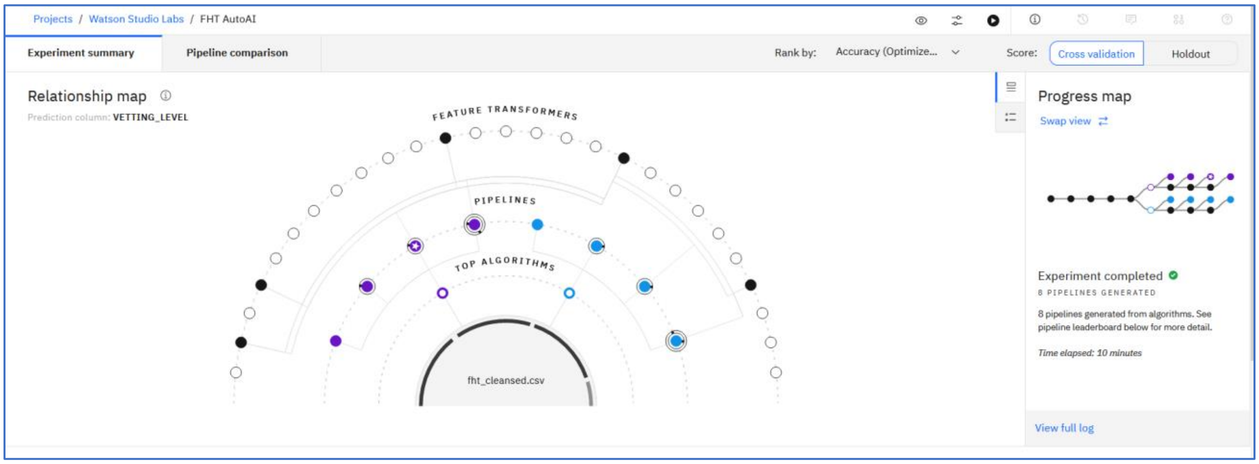
7. Select **VETTING_LEVEL** as the column to predict, leave the default for **OPTIMIZED METRIC** and click on **Run Experiment**. Note the system scanned the VETTING_LEVEL values to determine that a **Multiclass Classification** was the **PREDICTION TYPE**.



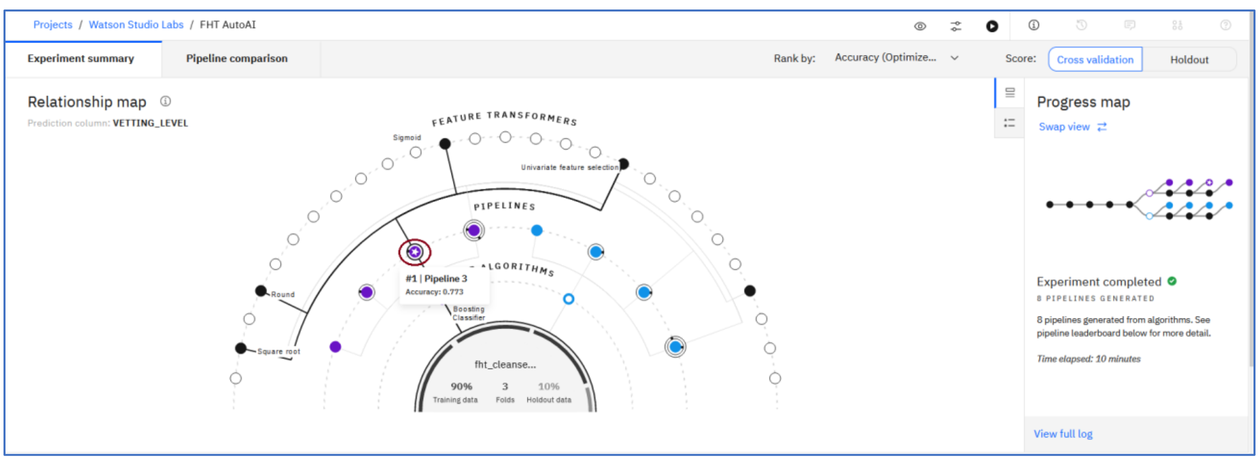
8. It will take several minutes for the eight alternative pipelines to be analyzed. The first pipeline picks the best algorithm. In this case, it is a **Gradient Boosting** classifier. The second pipeline performs a hyperparameter optimization to see if tuning the algorithm parameters will improve the performance metric. The third pipeline will derive new

features (i.e. feature engineering) to try to improve the performance metric. The fourth pipeline will do another hyperparameter optimization including the newly derived features. The next 4 pipelines do the same thing for the second-best algorithm. Note, you can move ahead at any point after the first pipeline has been created. We are going to proceed as if Pipeline 3 is the best ranked pipeline. Yours could be different.

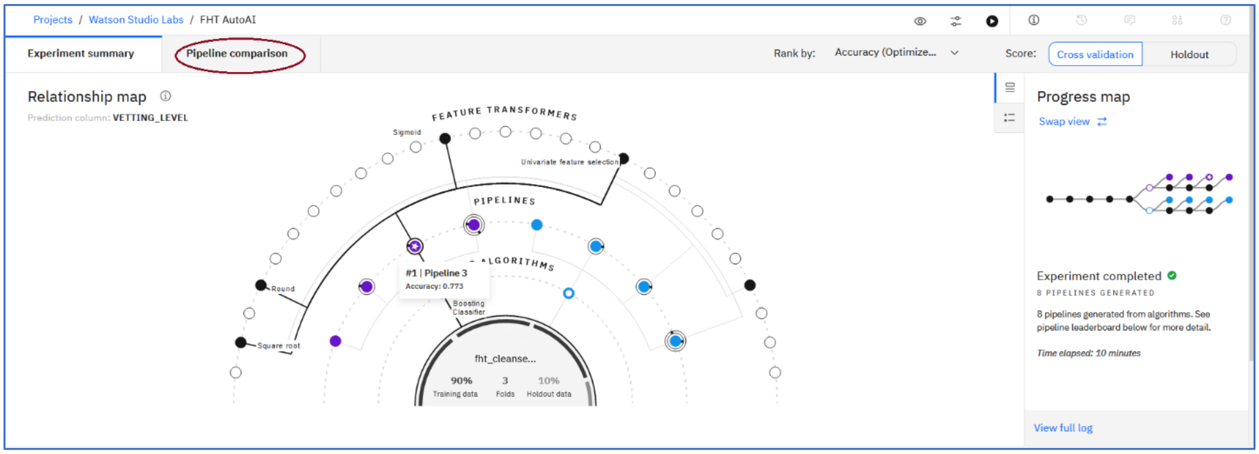
9. When the AutoAI run is completed you will see a display similar to below.



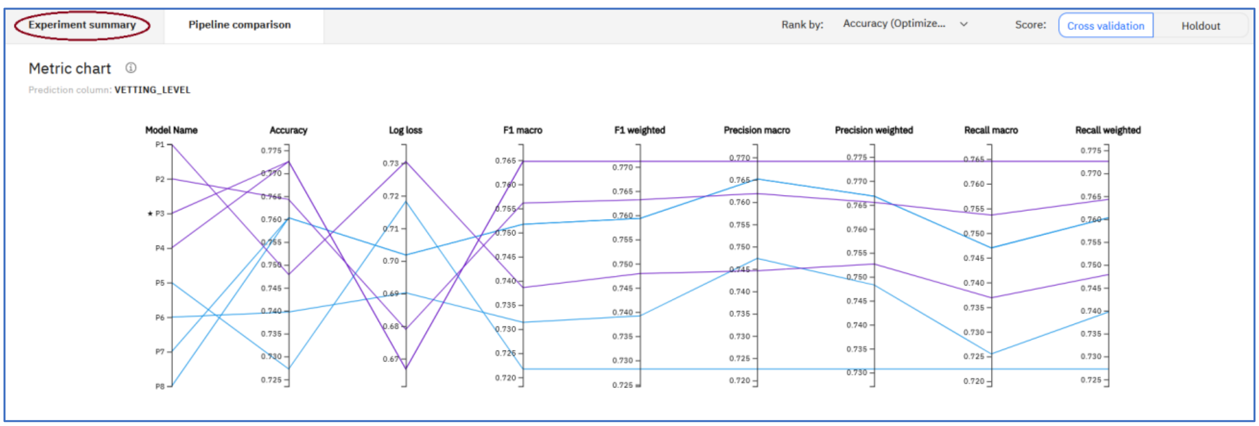
10. Hover over the  icon in the Pipelines semi-circle. This is the top ranked pipeline based on the accuracy metric. It is shown to be Pipeline 3 with a Gradient Boosted classifier and an accuracy of .77. Note, if you click on the  icon, you will be taken to the metrics for Pipeline 3 (don't do this yet).



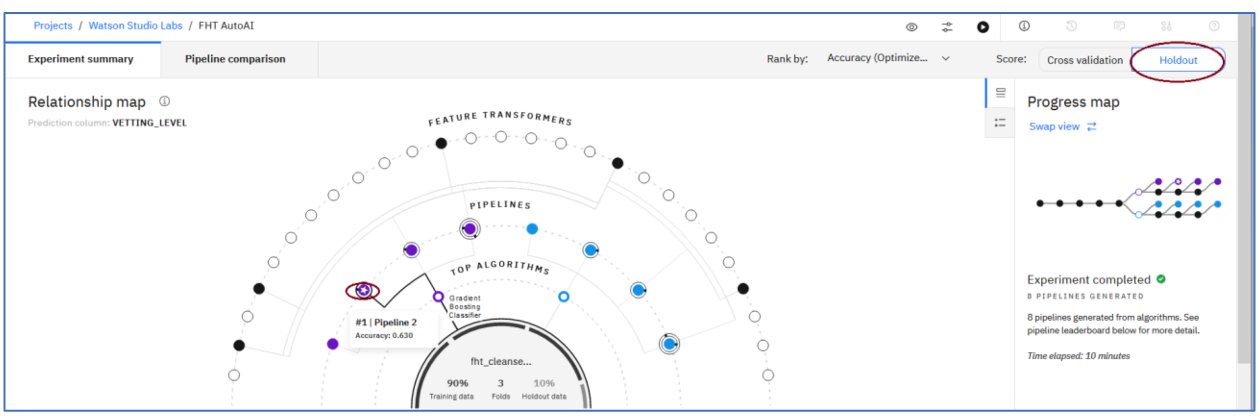
11. Click on the **Pipeline comparison**.



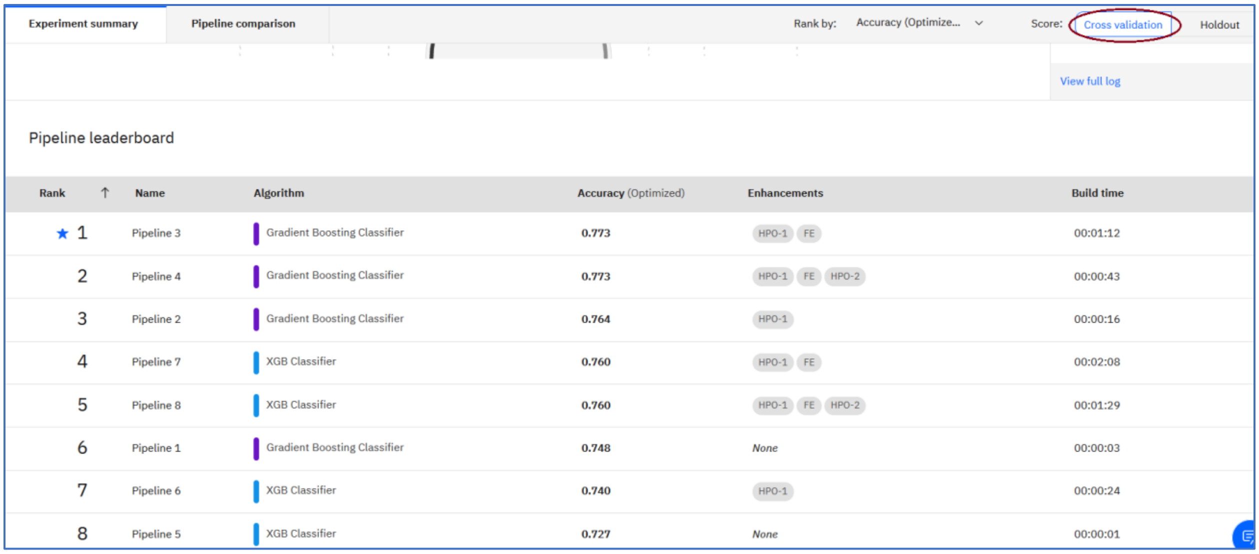
12. This will display a diagram showing the metrics associated with each pipeline on a single chart. Click on **Experiment summary** to return to the prior panel.



13. Click on **Holdout**. Note that the  icon has shifted. Hover over the  and we see that now Pipeline 2 is the highest ranked pipeline with accuracy reduced to .63 on the holdout sample.



14. Click on the **Cross validation** tab and then scroll down. The Pipeline leaderboard is displayed with the pipelines ranked by accuracy.



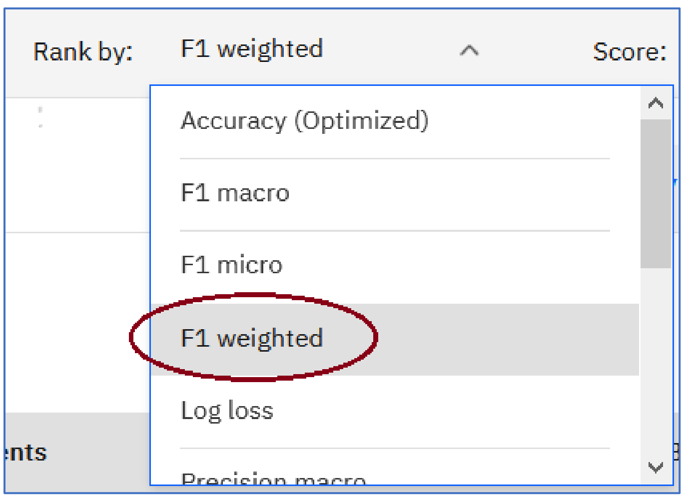
Experiment summary | Pipeline comparison | Rank by: Accuracy (Optimize... | Score: Cross validation | Holdout

View full log

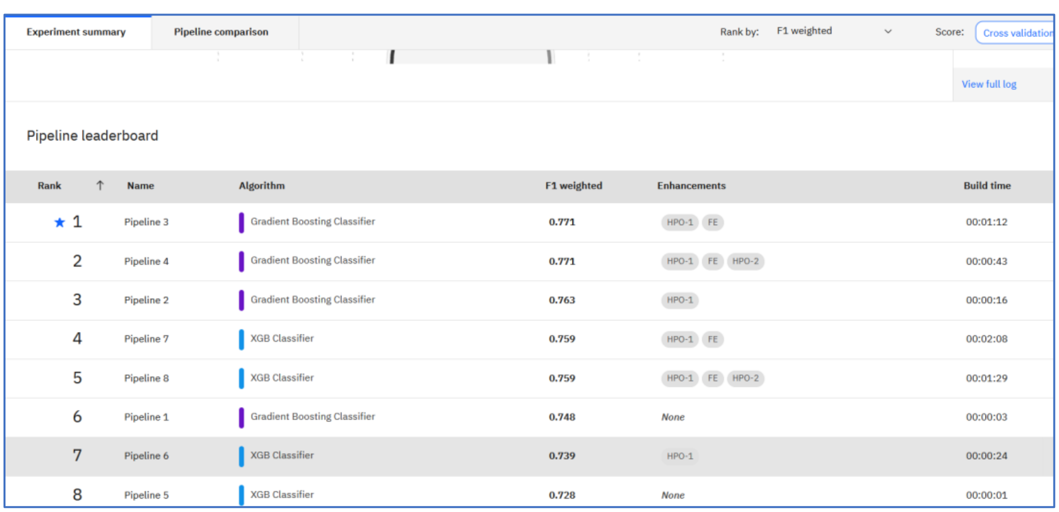
Pipeline leaderboard

Rank	Name	Algorithm	Accuracy (Optimized)	Enhancements	Build time
★ 1	Pipeline 3	Gradient Boosting Classifier	0.773	HPO-1 FE	00:01:12
2	Pipeline 4	Gradient Boosting Classifier	0.773	HPO-1 FE HPO-2	00:00:43
3	Pipeline 2	Gradient Boosting Classifier	0.764	HPO-1	00:00:16
4	Pipeline 7	XGB Classifier	0.760	HPO-1 FE	00:02:08
5	Pipeline 8	XGB Classifier	0.760	HPO-1 FE HPO-2	00:01:29
6	Pipeline 1	Gradient Boosting Classifier	0.748	None	00:00:03
7	Pipeline 6	XGB Classifier	0.740	HPO-1	00:00:24
8	Pipeline 5	XGB Classifier	0.727	None	00:00:01

15. Click on the icon adjacent to Accuracy and click F1 Weighted



16. The list is now ranked by the F1 Weighted metric.



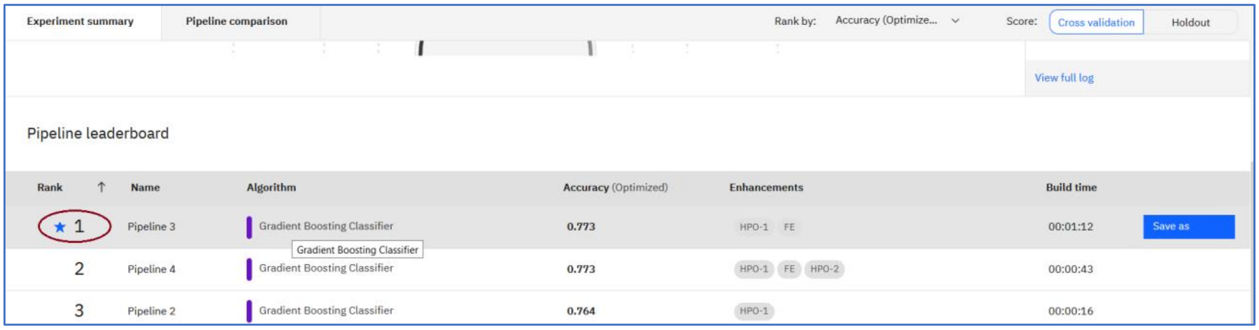
Experiment summary | Pipeline comparison | Rank by: F1 weighted | Score: Cross validation

View full log

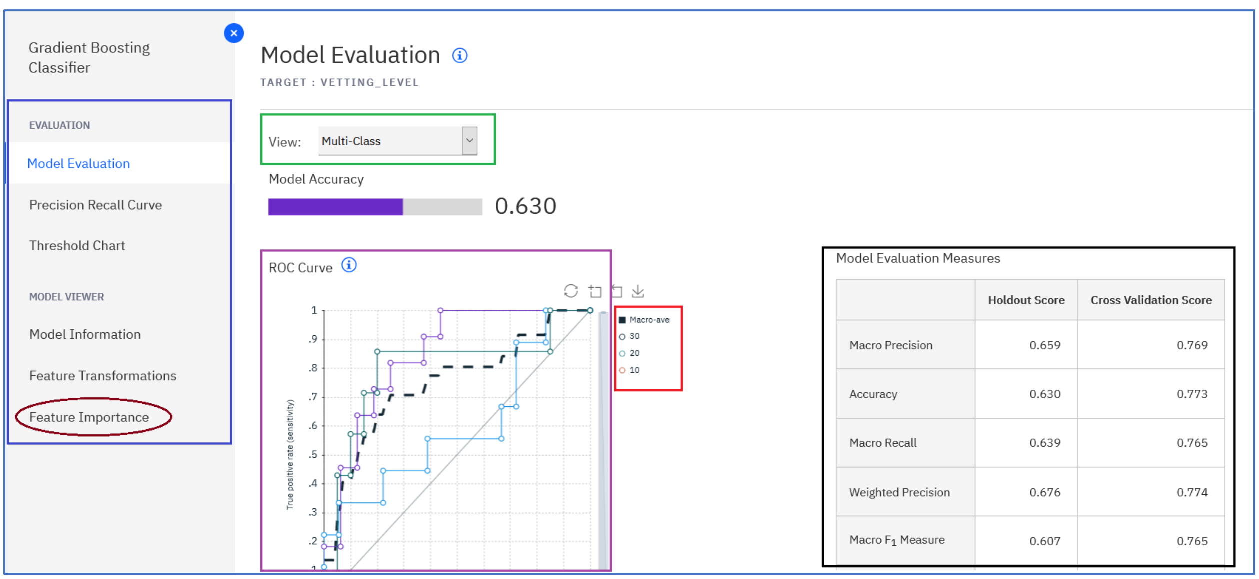
Pipeline leaderboard

Rank	Name	Algorithm	F1 weighted	Enhancements	Build time
★ 1	Pipeline 3	Gradient Boosting Classifier	0.771	HPO-1 FE	00:01:12
2	Pipeline 4	Gradient Boosting Classifier	0.771	HPO-1 FE HPO-2	00:00:43
3	Pipeline 2	Gradient Boosting Classifier	0.763	HPO-1	00:00:16
4	Pipeline 7	XGB Classifier	0.759	HPO-1 FE	00:02:08
5	Pipeline 8	XGB Classifier	0.759	HPO-1 FE HPO-2	00:01:29
6	Pipeline 1	Gradient Boosting Classifier	0.748	None	00:00:03
7	Pipeline 6	XGB Classifier	0.739	HPO-1	00:00:24
8	Pipeline 5	XGB Classifier	0.728	None	00:00:01

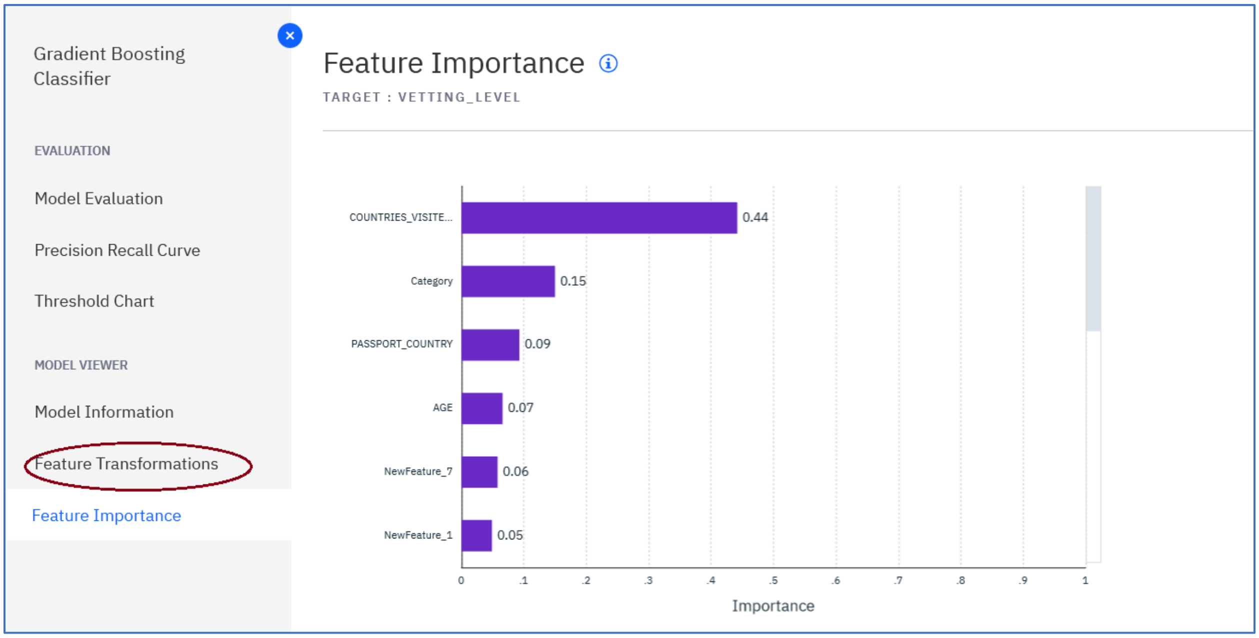
17. Return to the Accuracy ranked list by clicking on the and selecting **Accuracy** (**Optimized**). Click on **Pipeline 3**.



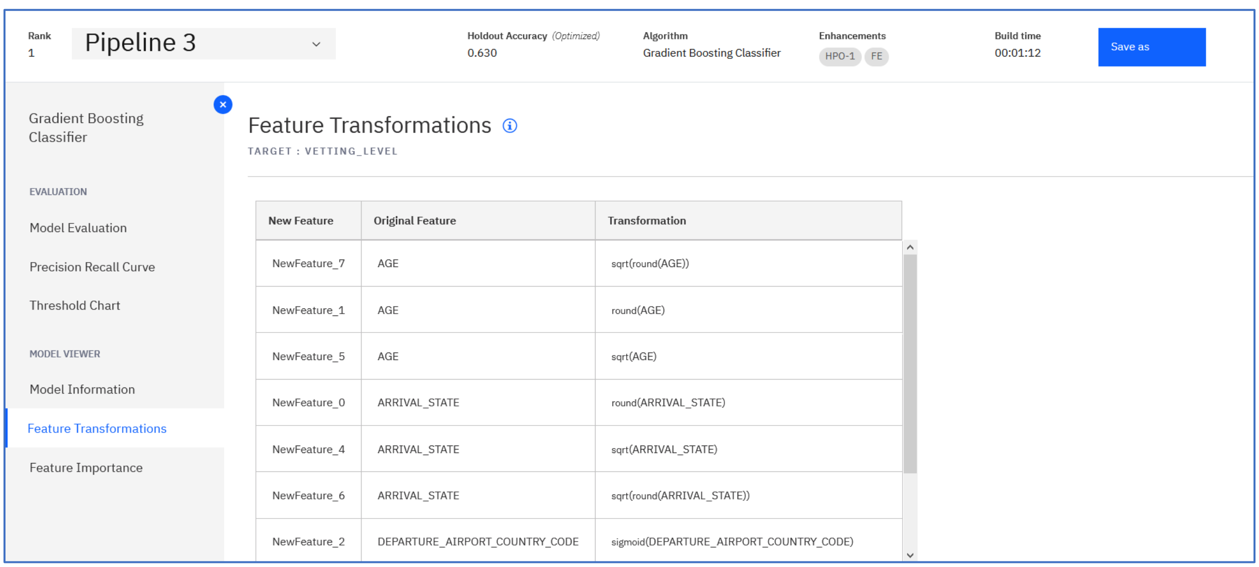
18. The **Model Evaluation** panel is displayed. The model evaluation metric for the holdout sample is displayed. Highlighted in blue rectangle below are links to additional model information and metrics. Highlighted in the green rectangle is a drop down containing the options multi-class, and then options for 3 binary metrics (30 versus rest, 20 versus rest, and 10 versus rest). Highlighted in the purple rectangle is the Receiver Operating Characteristic (ROC) curve. This plots the true positive rate versus the false positive rate at varying thresholds. Highlighted in the red rectangle is a clickable legend. Clicking on the circles will toggle the corresponding display on/off. Finally, highlighted in the black rectangle are model metrics for both the holdout sample, and the cross validation sample. Click on **Feature Importance.**



19. According to the **Feature Importance**, the **COUNTRIES_VISITED_COUNT** feature is the most important, followed by the **Category** feature, the **Passport Country** feature and the **Age** feature. Two derived features are also listed, NewFeature_7, and NewFeature_1). We can examine the derived features by clicking on **Feature Transformation**.



20. Eight derived features are listed in the Feature Transformation panel. The derived features operate on 3 of the input features, AGE, ARRIVAL_STATE, and DEPARTURE_AIRPORT_COUNTRY_CODE. Univariate transformations include, sqrt, round, and sigmoid functions.



21. Optionally, click on the other links on the left hand side menu to explore the **Precision Recall** curve, the **Threshold** Chart, and **Model Information** panels.

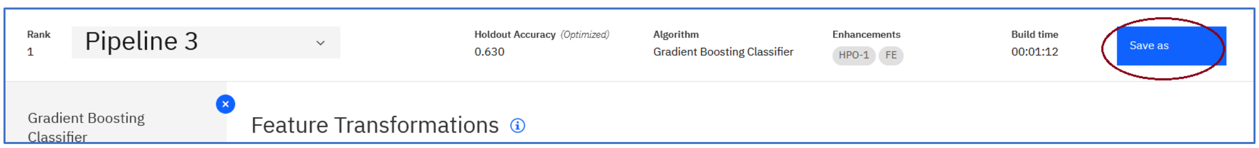
Step 3: Save and Deploy the Model

In this section, we will save and then deploy the model. You create a deployment for a machine learning model so you can submit new data to a model and get a score, or prediction back. To deploy the model, you must have a *deployment space* where you can organize the assets you need to create and monitor deployments. A space contains an overview of deployment status, the deployable assets, deployments, associated input and output data, and the associated environments.

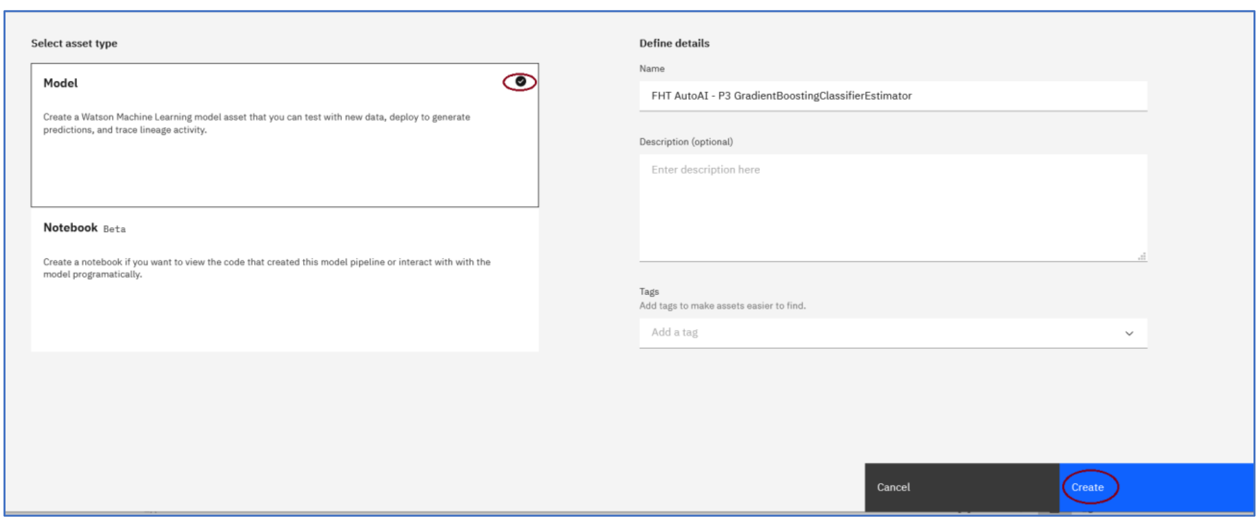
To deploy a model, we first **promote** the model to a deployment space. When you promote a model to a space, components required for a successful deployment, such as a training library, model definition, other dependent assets, or environment definition are automatically promoted as well. After promoting a model and the data assets needed to a deployment space, you can create a deployment in the space.

You can create a deployment space, promote the model, and create a deployment through the user interface or programmatically.

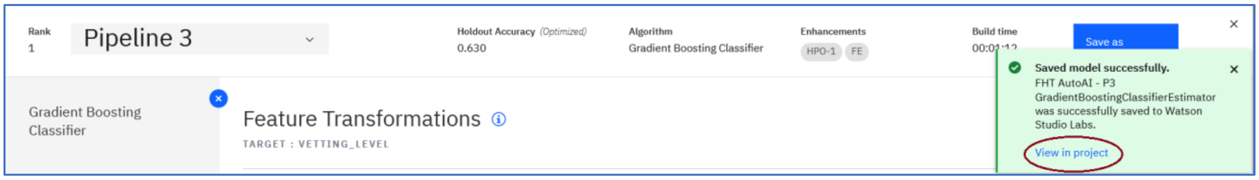
1. **Click on Save as.**



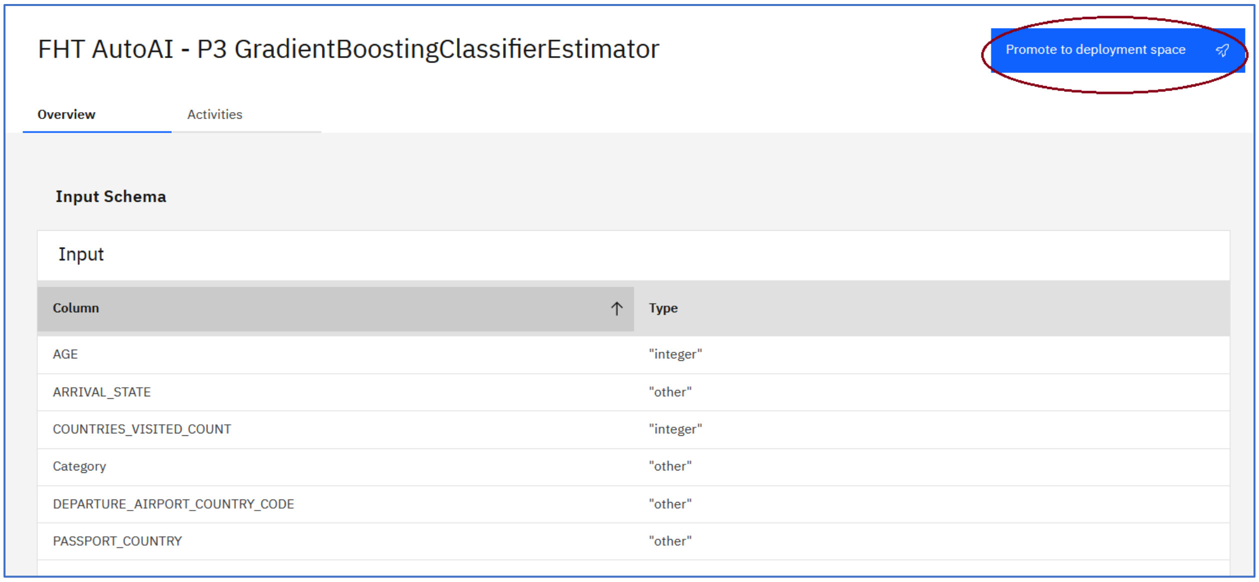
2. AutoAI can generate both a machine learning model as well as a Jupyter notebook. The Jupyter notebook can contain the source code to build the model, or the source code plus the deployment code. Feel free to experiment with saving the notebooks. For this lab, we will save the model. Make sure the Model is checked, optionally change the **Name**, and click **Create**.



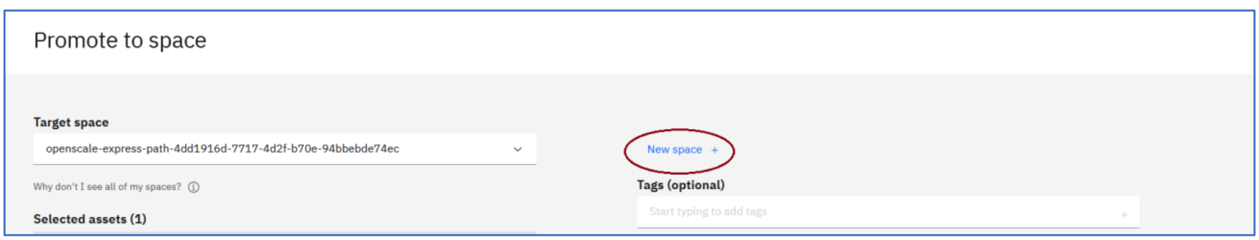
3. A message is displayed showing the model was successfully saved. Click on **View in project.**



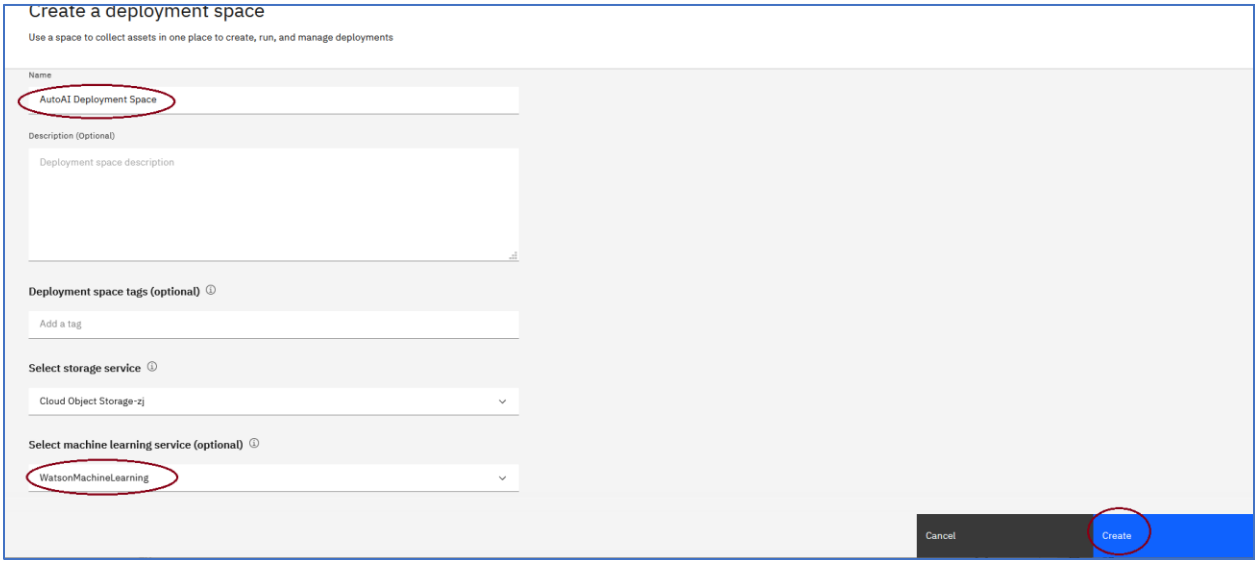
4. As mentioned above, we will need to promote the model to a deployment space. Click on **Promote to deployment space**.



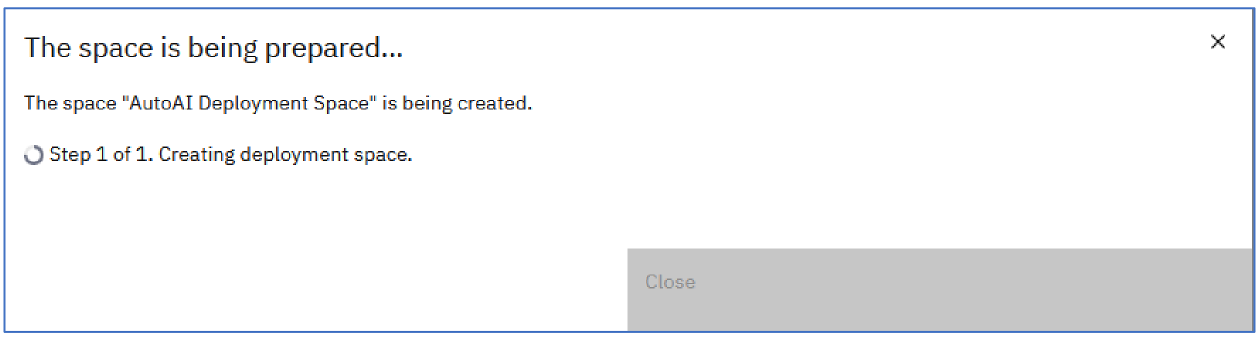
5. A deployment space already exists due to the Watson OpenScale set up in Lab-1. We will create a new space for our model deployment. Click on **New space**.

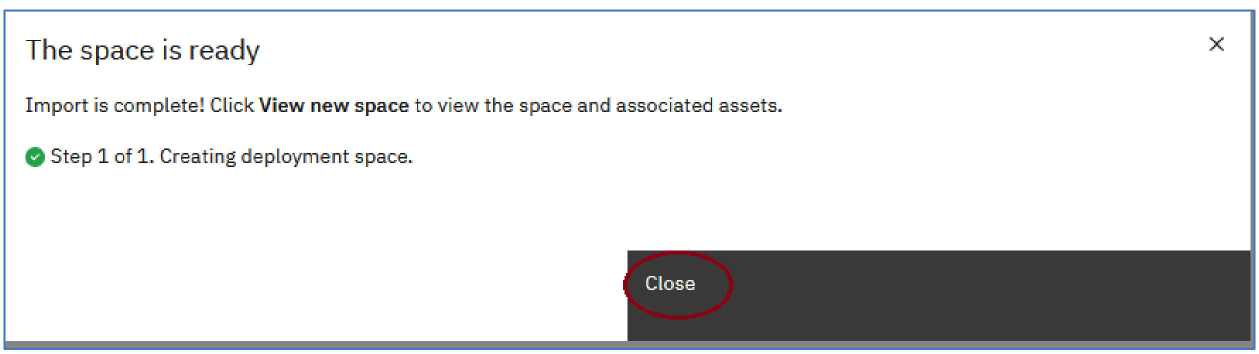


6. Enter **AutoAI Deployment Space** for the Name, scroll down and select **WatsonMachineLearning** for the **Select machine learning service**, and click **Create**.

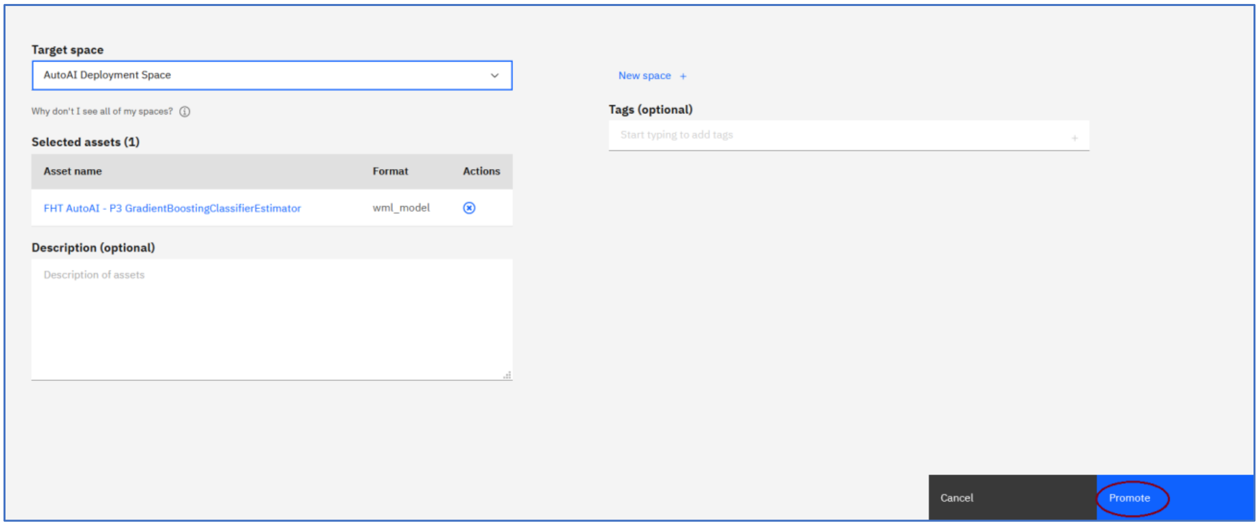


7. Two message boxes are displayed. Click **Close** in the second message box.

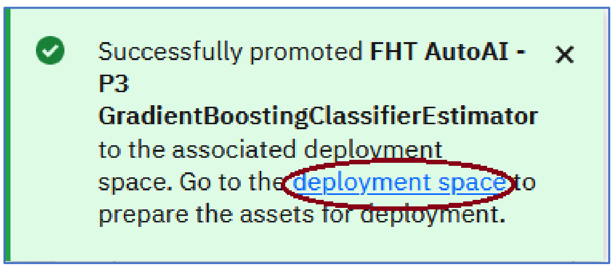




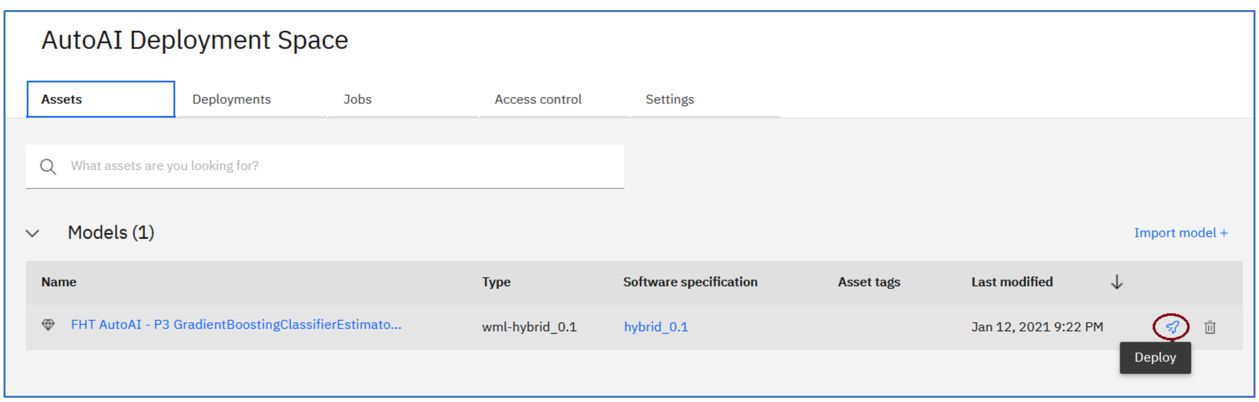
8. Click **Promote**.



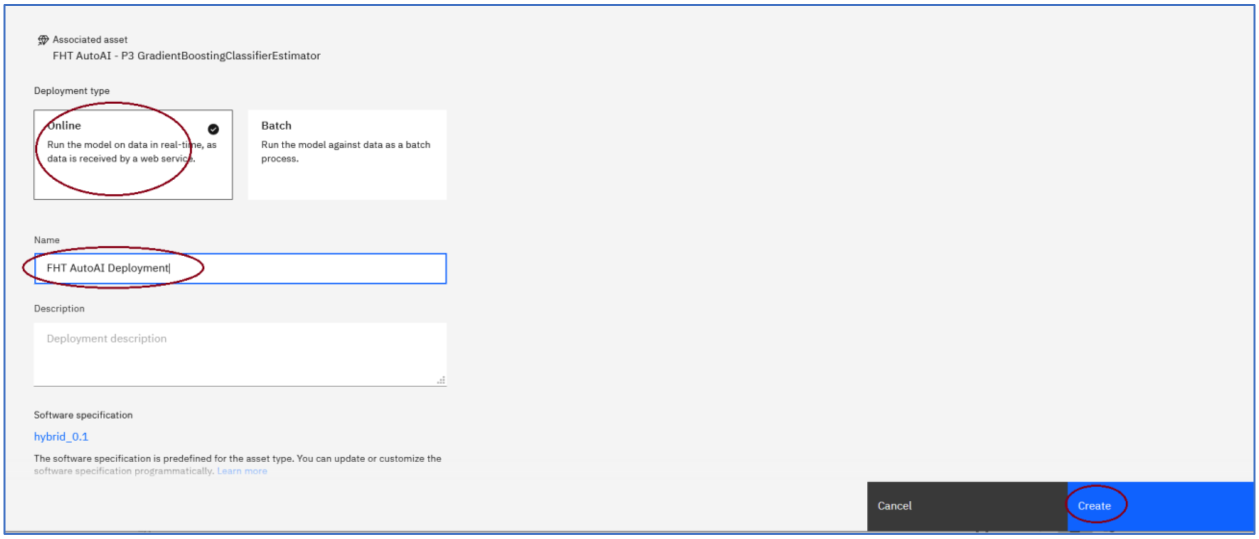
9. A message is displayed. Click **Deployment Space** in the message.



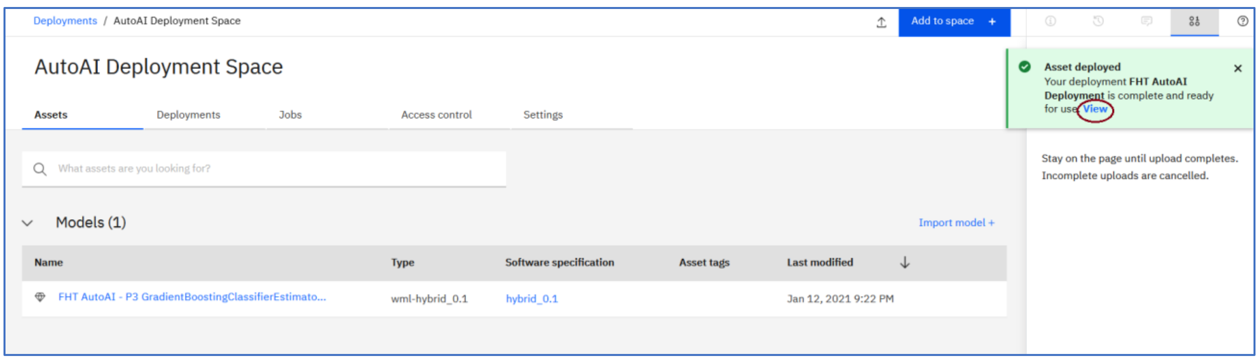
10. Hover over the promoted model until you see the deploy icon  appear on the right. Click on the  icon.



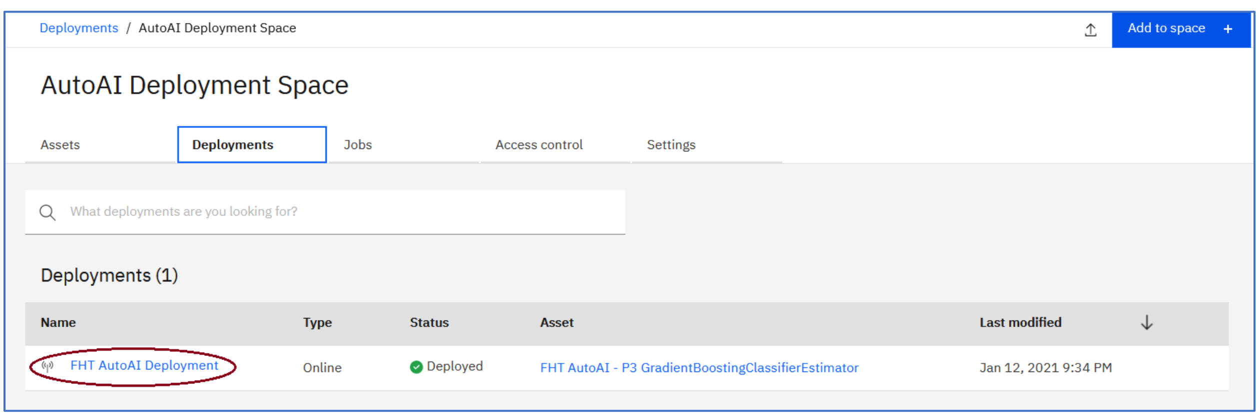
11. Click **Online** for an **Deployment type**, enter **FHT AutoAI Deployment** for the **Name**, and click **Create**.



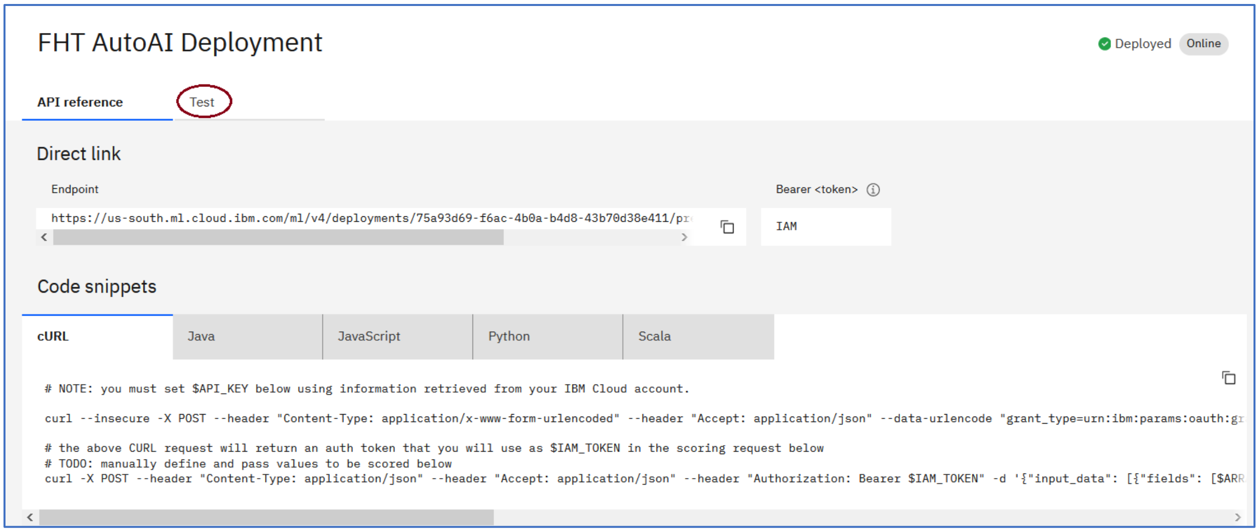
12. Wait for a message to be displayed. Click **View** in the message, or click the **Deployment** tab.



13. The asset is successfully deployed. Click on the deployed asset.



14. The **API Reference** panel provides information for the application developers to invoke the deployed model. It includes sample code in various programming languages and the scoring endpoint to be used when invoking the web service.



15. Enter the following values:

PASSPORT_COUNTRY – **Ghana**

COUNTRIES_VISITED_COUNT – **3**

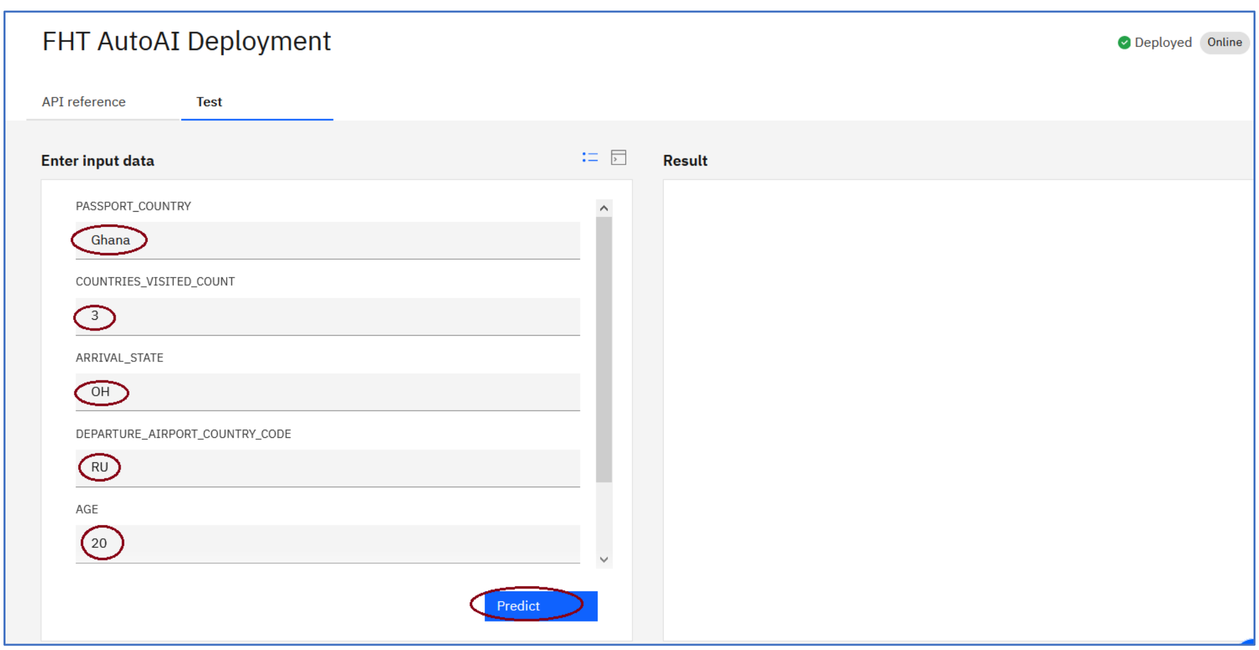
ARRIVAL_STATE – **OH**

DEPARTURE_AIRPORT_COUNTRY_CODE – **RU**

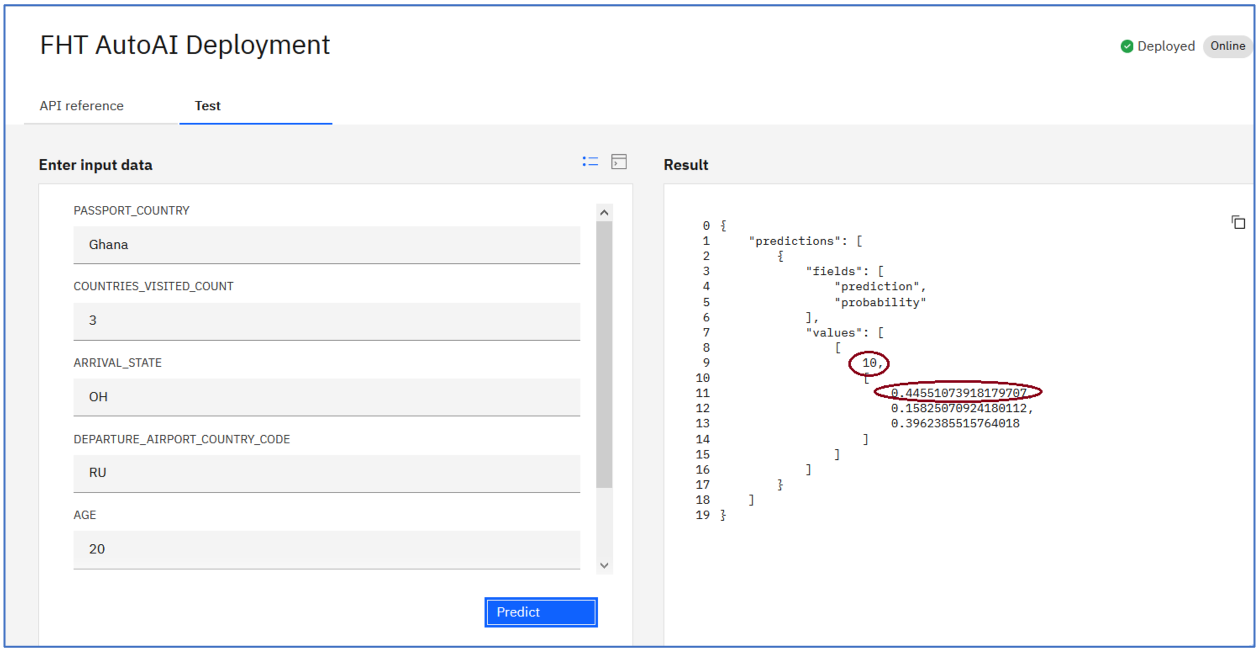
AGE – **20**

Category – **Sports/Travel**

Click **Predict**.



16. The prediction is **10** (high risk) of trafficking with 44.6 % confidence.



You have successfully completed the Lab!!!

- ✓ Downloaded a female human trafficking cleansed dataset from the github repo
- ✓ Added an Auto AI Experiment to create a model to predict the trafficking risk
- ✓ Saved and Deployed the model
- ✓ Tested the model