HOL Machine Learning – Credit Risk Analysis

Contents

Getting Started with Azure Machine Learning

In this detailed **lab**, we'll follow the process of **developing a predictive analytics** model in **Machine Learning Studio** and then deploying it as an Azure Machine Learning web service. We'll start with publicly available **credit risk data**, **develop** and **train** a predictive model based on that data, and then **deploy the model** as a **web service** that can be used by others for credit risk assessment.

Prerequisites

- **Client computer with Internet connectivity.**
- **Microsoft Account / Live Id**

Objectives

To create a credit risk assessment solution, we'll follow these steps through a series of tasks:

- Sign up for Machine Learning Workspace using a Microsoft Account
- Create a new experiment with Saved Dataset

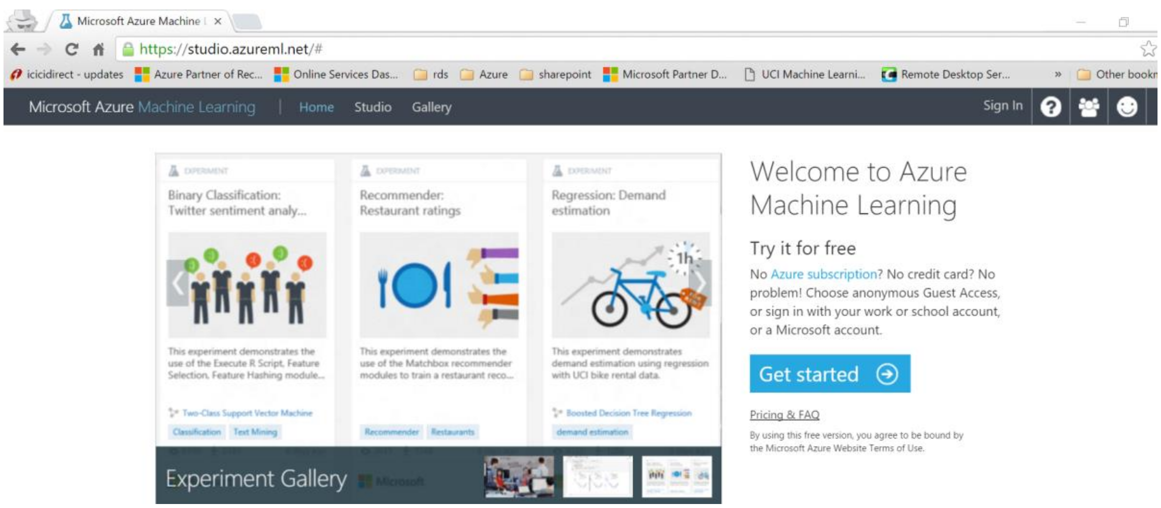
- Train and evaluate the models
- Deploy the web service

Estimated time to complete this lab: **1-2 Hours**

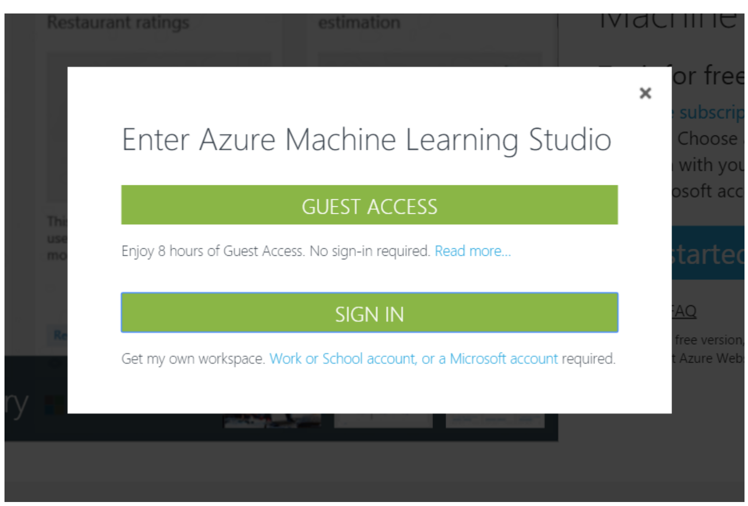
Exercise 1: Machine Learning

Task 1: Login

1. Launch an **In-Private Browser Window** and navigate to https://studio.azureml.net/ . The following page should load.

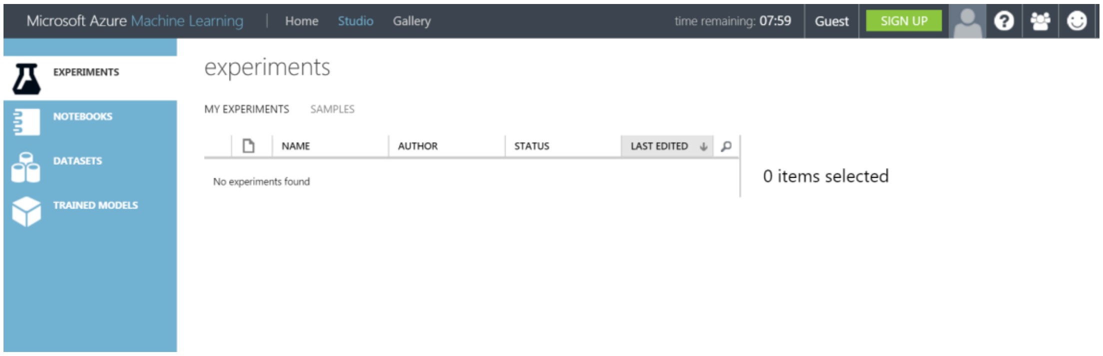


2. Click on the **Get Started** link, which should pop up a dialog box as shown below



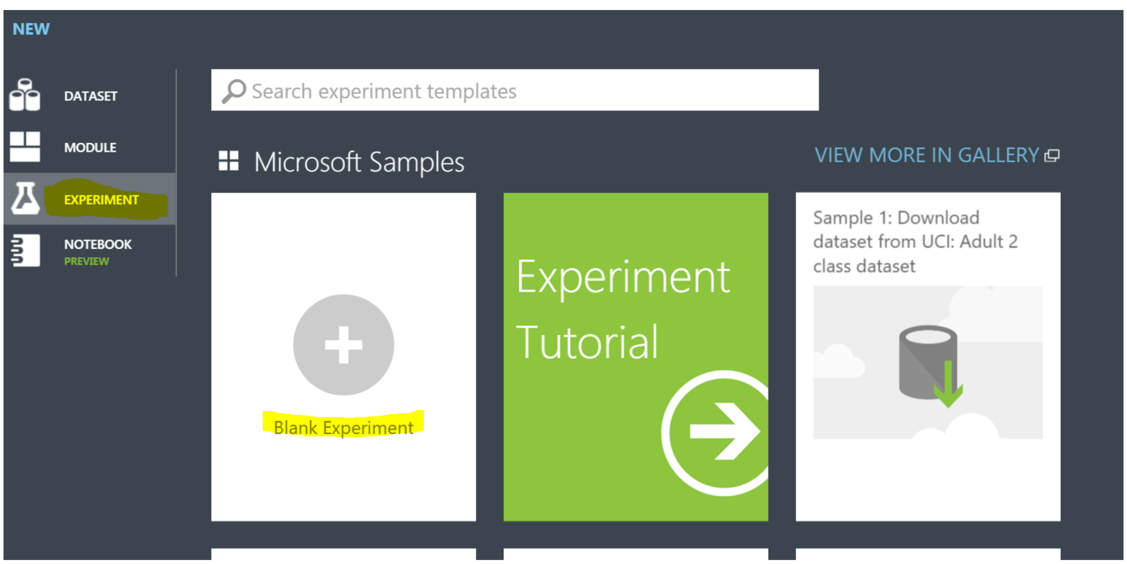
3. We will use the Sign in through a Microsoft Account for access to a free Azure ML studio access.

4. Close the Take a tour window.

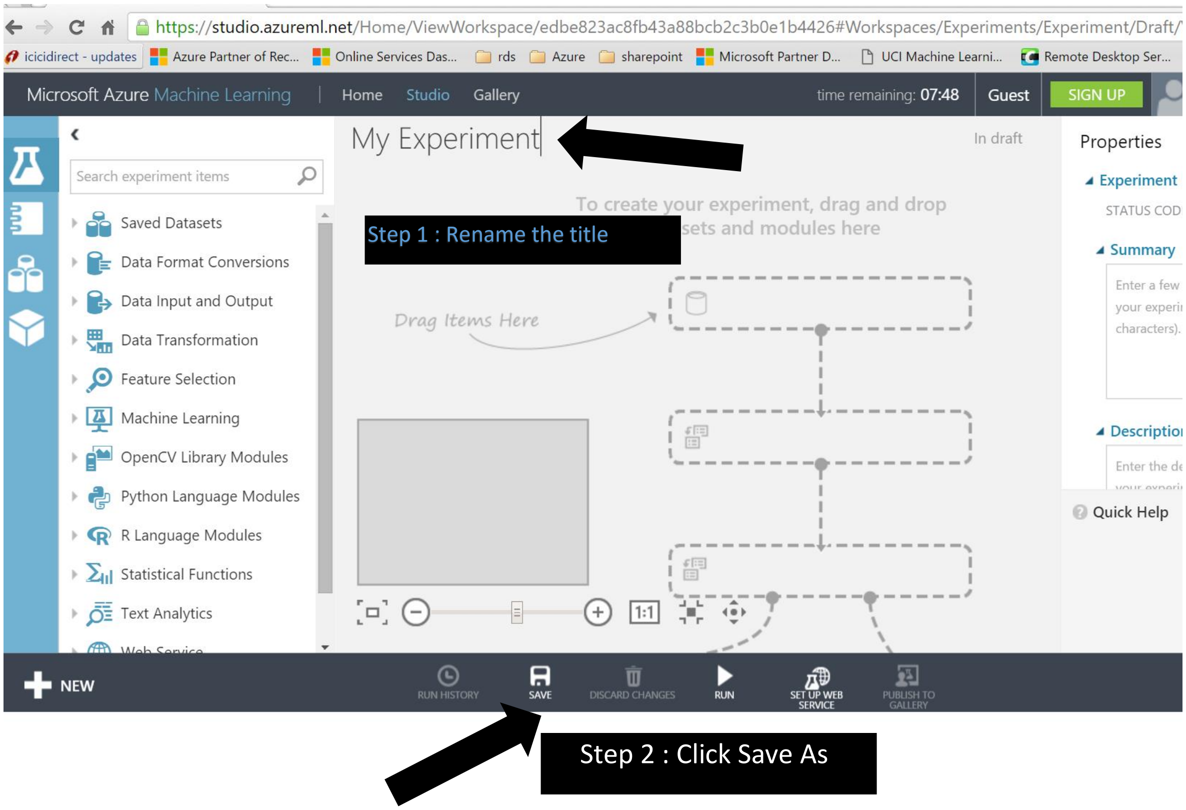


Task 2: Create a Blank Experiment and use Existing Credit Data

1. Click on the **+NEW** link at the bottom of the page, then Select **Experiment** and click on creating a **Blank Experiment**.



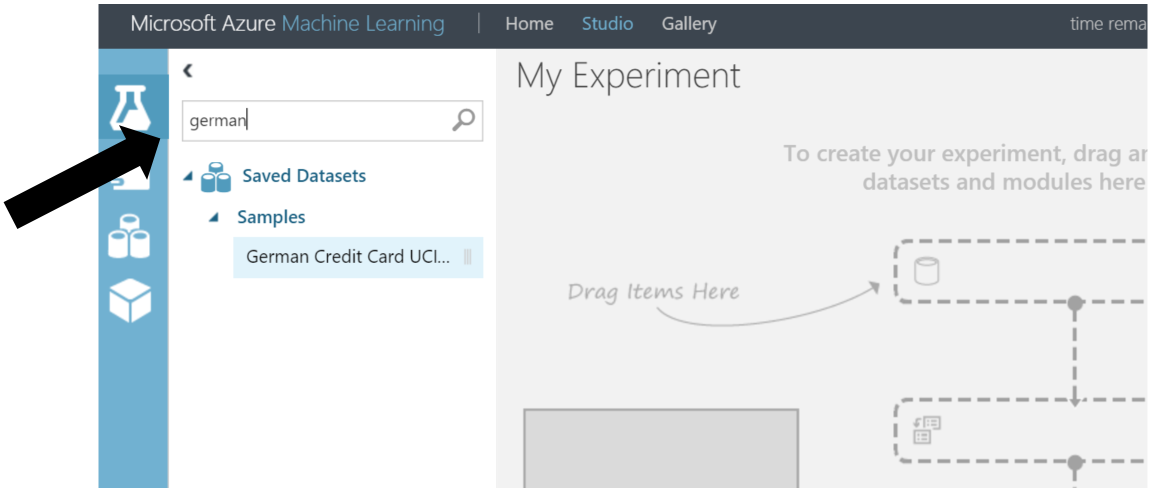
2. Name the Experiment accordingly, the current title shows up as ***Experiment created on <Today's Date>***'. You can edit that text by simply selecting and updating it. Once the name is changed, click on the **Save → Save As** button at the bottom of the page



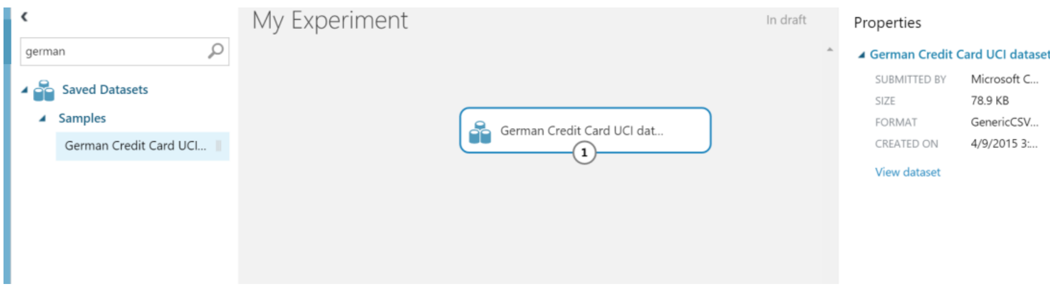
TIP:

*It's a good practice to fill in **Summary** and **Description** for the experiment in the **Properties** pane. These properties give you the chance to document the experiment so that anyone who looks at it later will understand your goals and methodology.*

3. In the Search experiment text box, type the keyword **German,** and it should show **German Credit Card Data** under **Saved Datasets.**

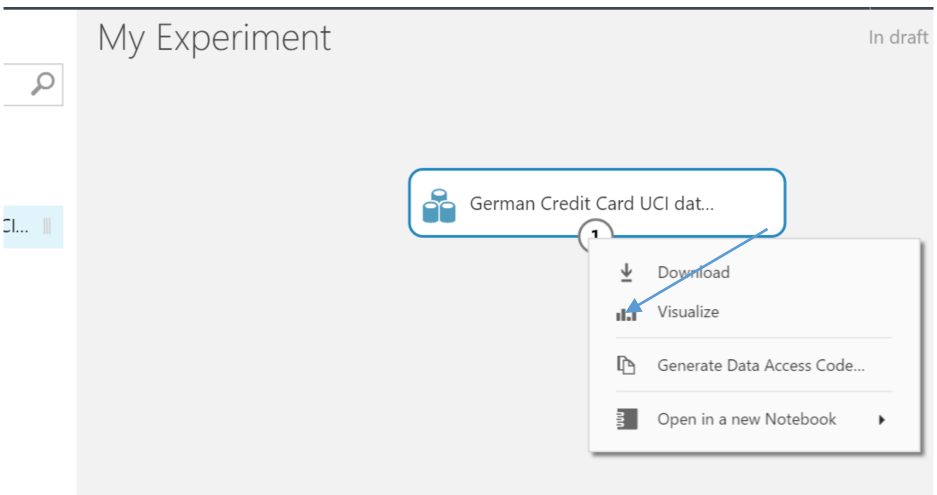


4. Drag the German Credit Card UCI Dataset on to the **Canvas** on the right.



Task 3: Preparing the Data

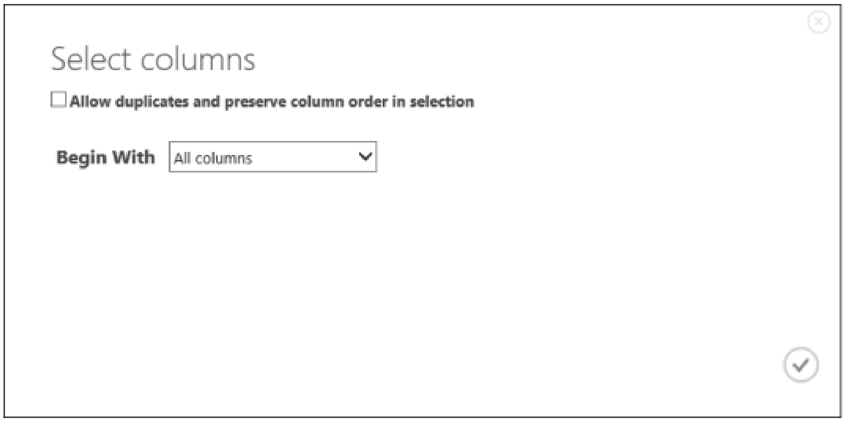
1. You can view the first 100 rows of the data and some statistical information for the whole dataset by clicking the **output port** of the dataset and selecting **Visualize**. Notice that ML Studio has already identified the data type for each column. It has also given generic headings to the columns because the data file did not come with column headings.



Column headings *are not essential, but they will make it easier to work with the data in the model. Also, when we eventually publish this model in a web service, the headings will help identify the columns to the user of the service. We can add column headings using the [Metadata Editor]module. The [Metadata Editor]module is used to change the metadata associated with a dataset. In this case, it can provide more friendly names for column headings. To do this, we'll direct [Metadata Editor]to act on all columns and then provide a list of names to be added to the columns.*

2. In the module palette **(one used before to find German Dataset)**, type "**metadata**" in the Search box. You'll see **Metadata Editor** in the module list.
3. Click and drag the Metadata Editor module onto the canvas and drop it below the dataset.
4. Connect the dataset to the Metadata Editor: click the output port of the dataset, drag to the input port of Metadata Editor, then release the mouse button. The dataset and module will remain connected even if you move either around on the canvas.
5. With the Metadata Editor still selected, in the **Properties** pane to the right of the canvas, click Launch column selector.
6. In the **Select columns** dialog, set the **Begin with** field to "**All columns**".

7. The row beneath Begin with allows you to include or exclude specific columns for the Metadata Editor to modify. Since we want to modify all columns, delete this row by clicking the minus sign ("-") to the right of the row. The dialog should look like this:

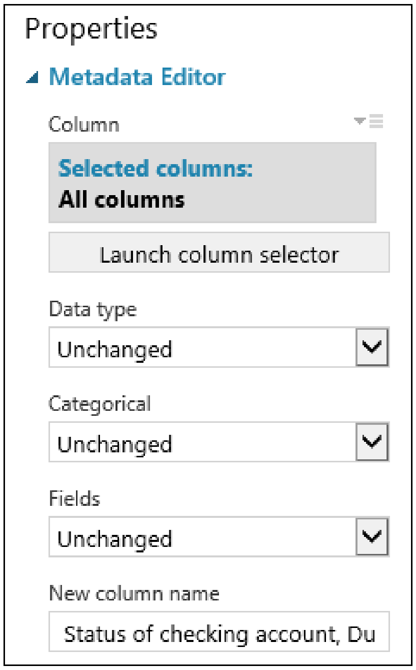


8. Click the OK checkmark.

9. Back in the **Properties** pane, look for the New column names parameter. In this field, enter a list of names for the 21 columns in the dataset, separated by commas and in column order. You can obtain the columns names from the dataset documentation on the UCI website, or for convenience you can copy and paste the following:

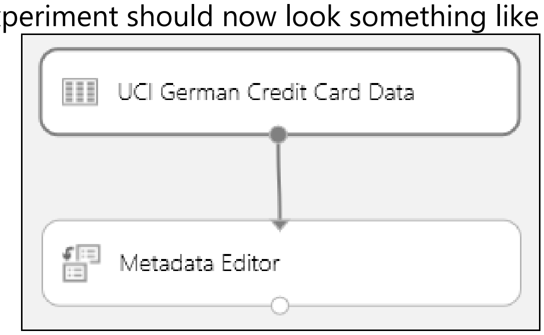
status of checking account, duration in months, credit history, purpose, credit amount, savings account/bond, present employment since, installment rate in percentage of disposable income, personal status and sex, other debtors, present residence since, property, age in years, other installment plans, housing, number of existing credits, job, number of people providing maintenance for, telephone, foreign worker, credit risk

10. The **Properties** pane will look like this:



TIP:
If you want to verify the column headings, run the experiment (click RUN below the experiment canvas), click the output port of the Metadata Editor module, and select View Results. You can view the output of any module in the same way to view the progress of the data through the experiment.

11. The experiment should now look something like this:



Task 4: Create Training and Test DataSets

The next step of the experiment is to generate separate datasets that will be used for training and testing our model. To do this, we use the Split module.

1. Find the **Split** module, drag it onto the canvas, and connect it to the last Metadata Editor module.

2. By default, the split ratio is 0.5 and the Randomized split parameter is set. This means that a random half of the data will be output through one port of the Split module, and half out the other. You can adjust these, as well as the Random seed parameter, to change the split between training and scoring data. For this lab, we'll leave them as-is.

   TIP:

   The split ratio essentially determines how much of the data is output through the left output port. For instance, if you set the ratio to 0.7, then 70% of the data is output through the left port and 30% through the right port.

3. We can use the outputs of the Split module however we like, but let's choose to use the **left output as training data** and the **right output as scoring data**.

4. The cost of misclassifying a high credit risk as low is 5 times larger than the cost of misclassifying a low credit risk as high. To account for this, we'll generate a new dataset that reflects this cost function. In the new dataset, each high example is replicated 5 times, while each low example is not replicated.

5. We can do this replication using **R code**. Find and drag the **Execute R Script** module onto the experiment canvas and connect the **left output port** of the Split module to the **first input** port ("Dataset1") of the **Execute R Script** module.

6. In the Properties pane, delete the default text in the R Script parameter and enter this script:

```
dataset1 <- maml.mapInputPort(1)
data.set<-dataset1[dataset1[,21]==1,]
pos<-dataset1[dataset1[,21]==2,]
for (i in 1:5) data.set<-rbind(data.set,pos)
maml.mapOutputPort("data.set")
```

We need to do this same replication operation for each output of the Split module so that the training and scoring data have the same cost adjustment.

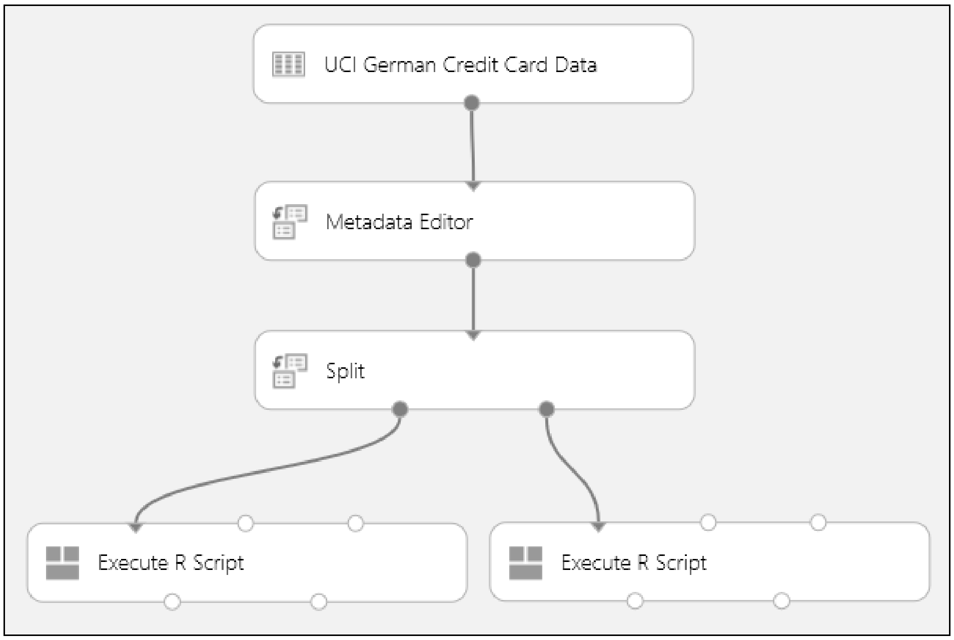
7. Right-click the Execute R Script module and select **Copy**.

8. Right-click the experiment canvas and select **Paste**.
9. Connect the first input port of this [Execute R Script] module to the right output port of the [Split] module.

TIP:

The copy of the Execute R Script module contains the same script as the original module. When you copy and paste a module on the canvas, the copy retains all the properties of the original.

Our experiment now looks something like this:



Task 5: Train, Score and Evaluate

In this experiment we want to try different algorithms for our predictive model. We'll create two different types of models and then compare their scoring results to decide which algorithm we want to use in our final experiment.

There are a number of models we could choose from. To see the models available, expand the **Machine Learning** node in the module palette, and then expand **Initialize Model** and the nodes beneath it. For the purposes of this experiment, we'll select the **Two-Class Boosted Decision** Trees module. We'll use the appropriate modules to initialize the learning algorithms and use [Train Model] modules to train the model.

Train the model

Let's set up the boosted decision tree model:

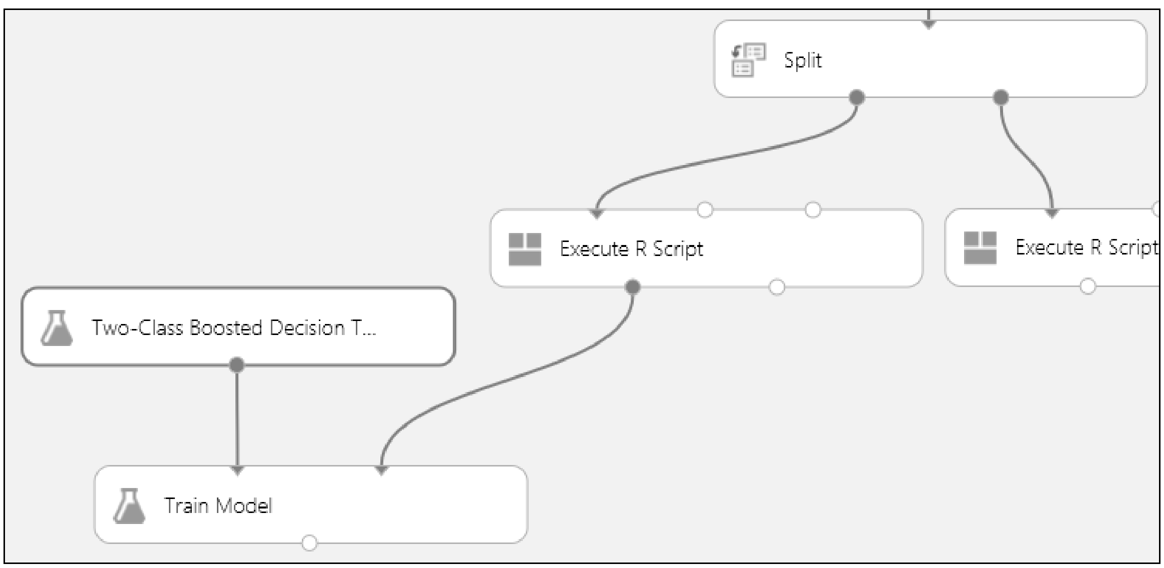
1. Find the Two-Class Boosted Decision Tree module in the module palette and drag it onto the canvas.
2. Find the Train Model module, drag it onto the canvas, and then connect the output of the boosted decision tree module to the left input port ("Untrained model") of the Train Model module.
3. Connect the left output ("Result Dataset") of the left Execute R Script module to the right input port ("Dataset") of the Train Model module.

   TIP:

   We don't need two of the inputs and one of the outputs of the Execute R Script module for this experiment, so we'll just leave them unattached. This is not uncommon for some modules.

4. Select the Train Model module. In the **Properties** pane, click **Launch column selector**, select **Include** in the first dropdown, select **column indices** in the second dropdown, and enter "21" in the text field (you can also select **column names** and enter "Credit Risk"). This identifies column 21, the credit risk value, as the column for the model to predict.

   This portion of the experiment now looks something like this:



Score and evaluate the models

We'll use the scoring data that was separated out by the **Split** module to score our trained models. We can then compare the results of the two models to see which generated better results.

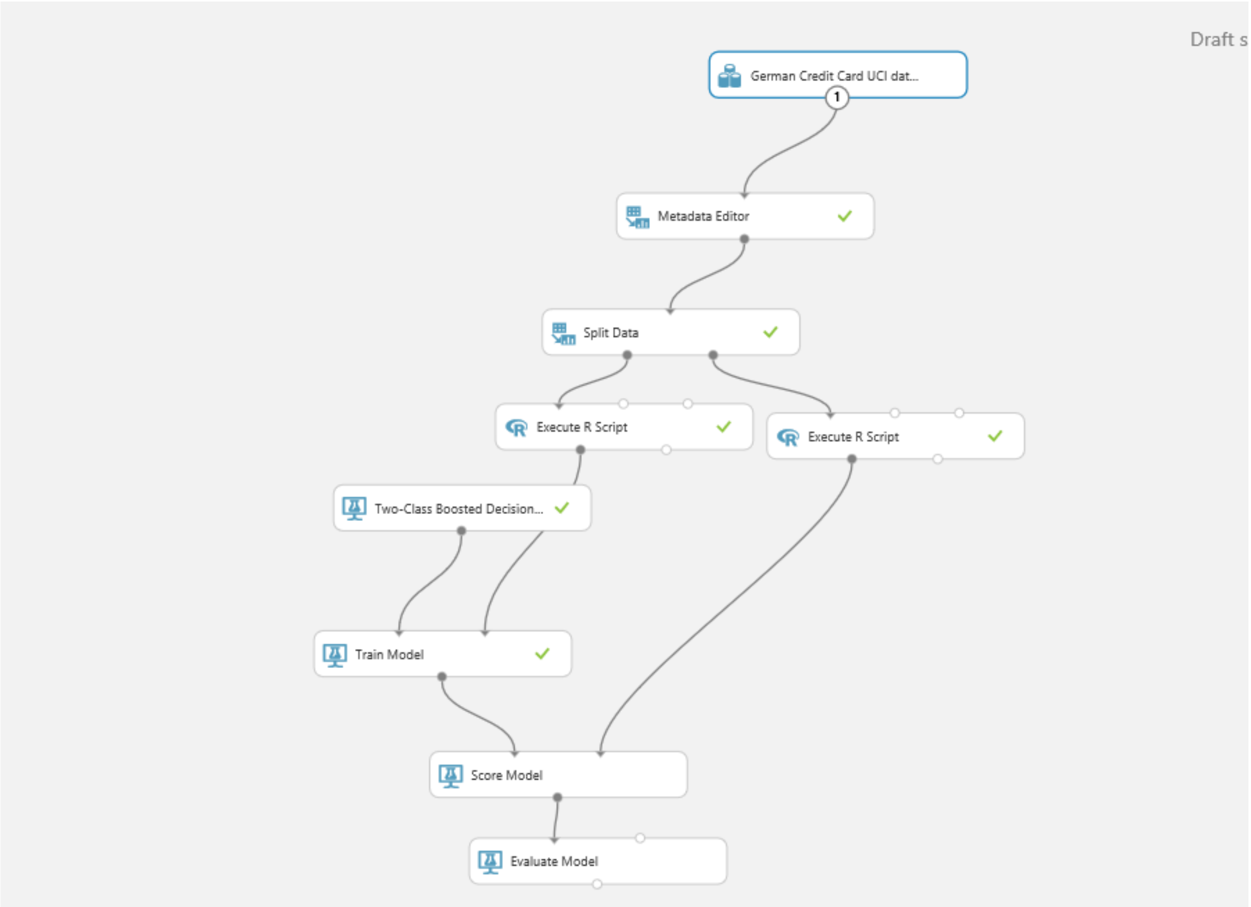
1. Find the Score Model module and drag it onto the canvas.

2. Connect the left input port of this module to the boosted decision tree model (that is, connect it to the output port of the Train Model module that's connected to the Two-Class Boosted Decision Tree module).
3. Connect the right input port of the Score Model module to the output of the right Execute R Script module.

   To evaluate the scoring results, we'll use the Evaluate Model module.

1. Find the Evaluate Model module and drag it onto the canvas.
2. Connect the left input port to the output port of the Score Model module associated with the boosted decision tree model.

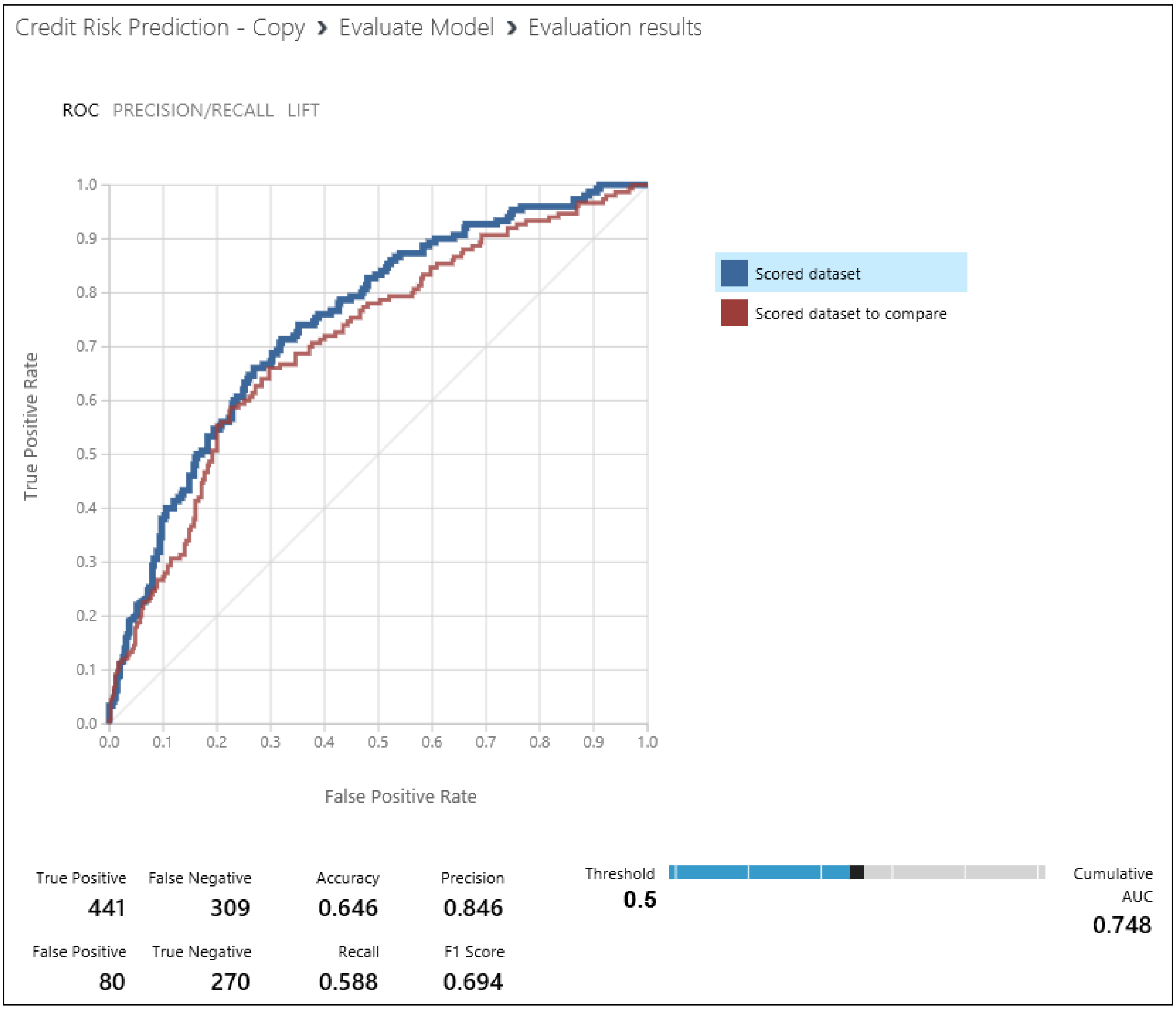
   The experiment should now look something like this:



3. Click the **RUN** button below the canvas to run the experiment. It may take a few minutes. You'll see a spinning indicator on each module to indicate that it's running, and then a green check mark when the module is finished.
4. When all the modules have a check mark, the experiment has finished running. To check the results, click the output port of the Evaluate Model module and select **Visualize**.

The [Evaluate Model]() module produces curves and metrics that allow you to compare the results of the two scored models or a single model. You can view the results as Receiver Operator Characteristic (ROC) curves, Precision/Recall curves, or Lift curves. Additional data displayed includes a confusion matrix, cumulative values for the area under the curve (AUC), and other metrics. You can change the threshold value by moving the slider left or right and see how it affects the set of metrics.

5. Click **Scored dataset** to highlight the associated curve and to display the associated metrics below. In the legend for the curves, "Scored dataset" corresponds to the left input port of the [Evaluate Model]() module - in our case, this is the boosted decision tree model.



TIP:

*Each time you run the experiment a record of that iteration is kept in the Run History. You can view these iterations, and return to any of them, by clicking **VIEW RUN HISTORY** below the canvas. You can also click **Prior Run** in the **Properties** pane to return to the iteration immediately preceding the one you have open. For more information, see [Manage experiment iterations in Azure Machine Learning Studio](#).*

Task 6: Deploy as a Web Service

To make this predictive model useful to others, we'll deploy it as a web service on Azure.

Up to this point we've been experimenting with training our model. But the deployed service is no longer going to do training - it will be generating predictions based on the user's input. So we're going to do some preparation and then deploy this experiment as a working web service that users can access. A user will be able to send a set of credit application data to the service, and the service will return the prediction of credit risk.

To do this, we need to:

- Convert the *training experiment* we've created into a *predictive experiment*
- Deploy the predictive experiment as a web service

Convert the training experiment to a predictive experiment

Converting to a predictive experiment involves three steps:

- *Save the model we've trained and replace our training modules with it*
- *Trim the experiment to remove modules that were only needed for training*
- *Define where the web service input and output nodes should be*

1. All three steps can be accomplished by just clicking **Setup Web Service** at the bottom of the experiment canvas (select the **Predictive Web Service** option). Click **Setup Web Service.**

When you click **Setup Web Service**, several things happen:

- The model we trained is saved as a **Trained Model** module in the module palette to the left of the experiment canvas (you can find it in the palette under **Trained Models**).

Modules that were used for training are **removed**. Specifically:

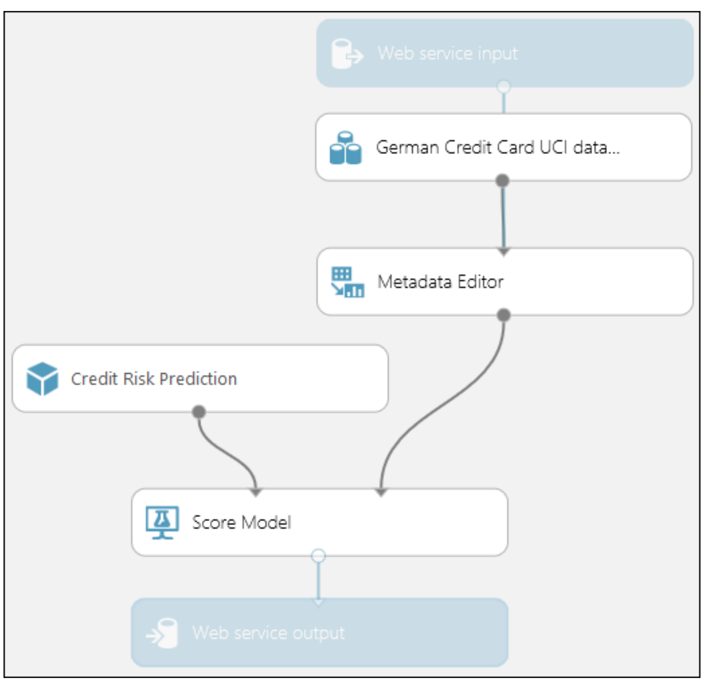
- *Two-Class Boosted Decision Tree*
- *Train Model*
- *Split*
- *The second Execute R Script module that was used for test data*
- *The saved trained model is added to the experiment.*
- ***Web service input** and **Web service output** modules are added.*

NOTE:

The experiment has been saved in two parts: the original training experiment, and the new predictive experiment. You can access either one using the tabs at the top of the experiment canvas.

2. We need to take an additional step with our experiment. Machine Learning Studio removed one Execute R Script module when it removed the Split module, but it left the other Execute R Script module. Since that module was only used for training and testing (it provided a weighting function on the sample data), we can now remove it and connect Metadata Editor to Score Model.

Our experiment should now look like this:



You may be wondering why we left the UCI German Credit Card Data dataset in the predictive experiment. The service is going to use the user's data, not the original dataset, so why leave them connected?

It's true that the service doesn't need the original credit card data. But it does need the schema for that data, which includes information such as how many columns there are and which columns are numeric. This schema information is necessary in order to interpret the user's data. We leave these components connected so that the scoring module will have the dataset schema when the service is running. The data isn't used, just the schema.

3. Run the experiment one last time (click **Run**). If you want to verify that the model is still working, click the output of the [Score Model](#) module and select **View Results**. You'll see that the original data is displayed, along with the credit risk value ("Scored Labels") and the scoring probability value ("Scored Probabilities").

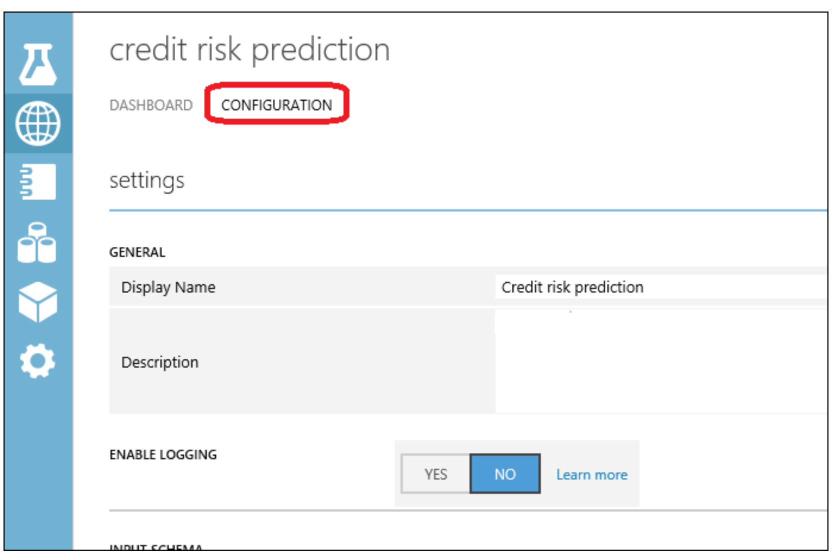
Deploy the web service

4. To deploy a web service derived from our experiment, click **Deploy Web Service** below the canvas. Machine Learning Studio deploys the experiment as a web service and takes you to the service dashboard.

TIP:

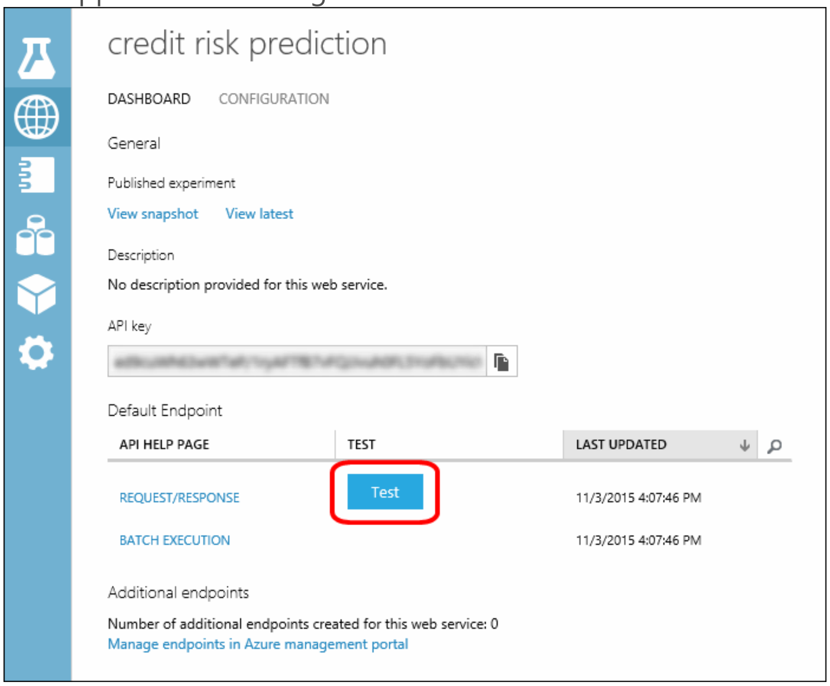
*You can update the web service after you've deployed it. For example, if you want to change your model, just edit the training experiment, tweak the model parameters, and click **Deploy Web Service**. When you deploy the experiment again, it will replace the web service, now using your updated model.*

You can configure the service by clicking the **CONFIGURATION** tab. Here you can modify the service name (it's given the experiment name by default) and give it a description. You can also give more friendly labels for the input and output columns.



Test the web service

1. On the **DASHBOARD** page, click the **Test** link under **Default Endpoint**. A dialog will pop up and ask you for the input data for the service. These are the same columns that appeared in the original German credit risk dataset.



2. Enter a set of data and then click **OK**.

The results generated by the web service are displayed at the bottom of the dashboard. The way we have the service configured, the results you see are generated by the scoring module.

Summary

In this lab you learned how to provision and use a Machine Learning experiment from the Azure ML studio.