Adobe Experience Platform

Data Science Workspace Overview – Nov 2019

Adobe

Agenda

- What is Data Science
- DSW Features
- DSW Terminologies
- How it works - Demo
- Use Cases
- Q&A

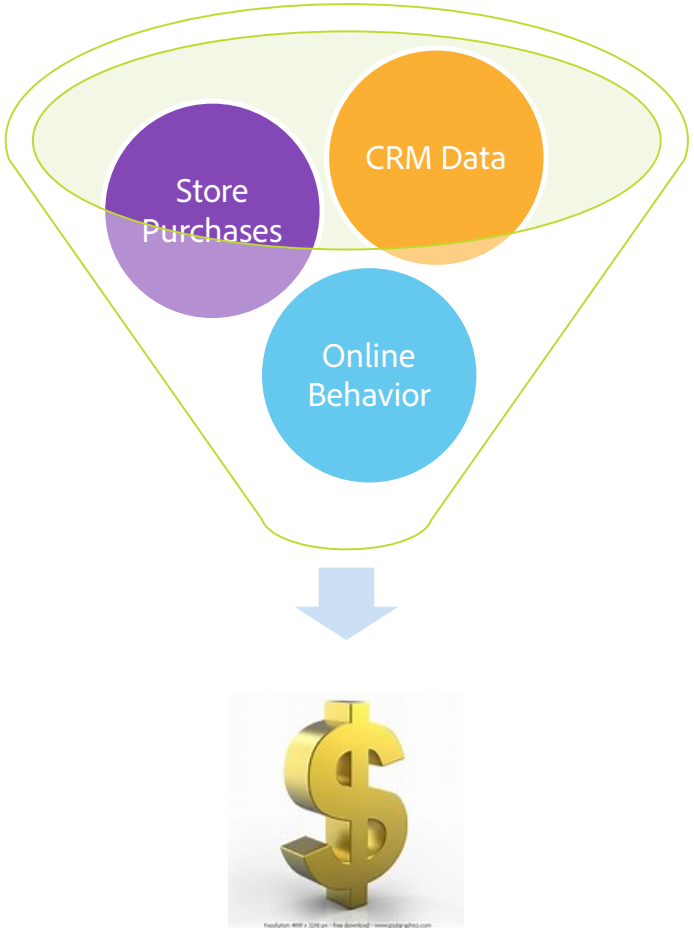
© 2019 Adobe. All Rights Reserved.

Adobe

What is Data Science?

"almost ***everything*** that has something to do with ***data***"*

"Data science is the study of ***where*** information comes from, ***what*** it represents and ***how*** it can be turned into a ***valuable*** resource in the creation of business and IT ***strategies***."**

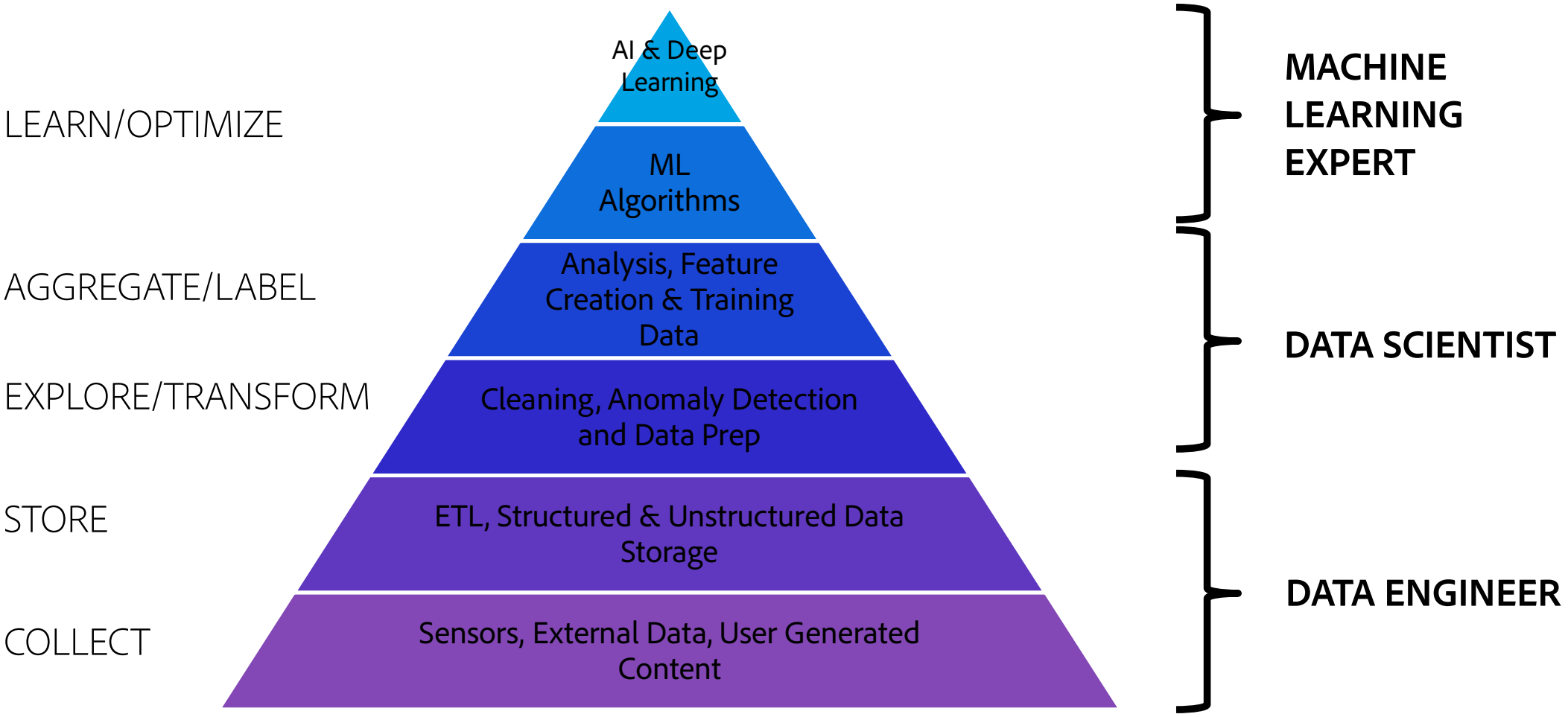


* Journal of Data Science
** https://searchenterpriseai.techtarget.com

© 2019 Adobe. All Rights Reserved.

Adobe

Data Science Hierarchy of Needs

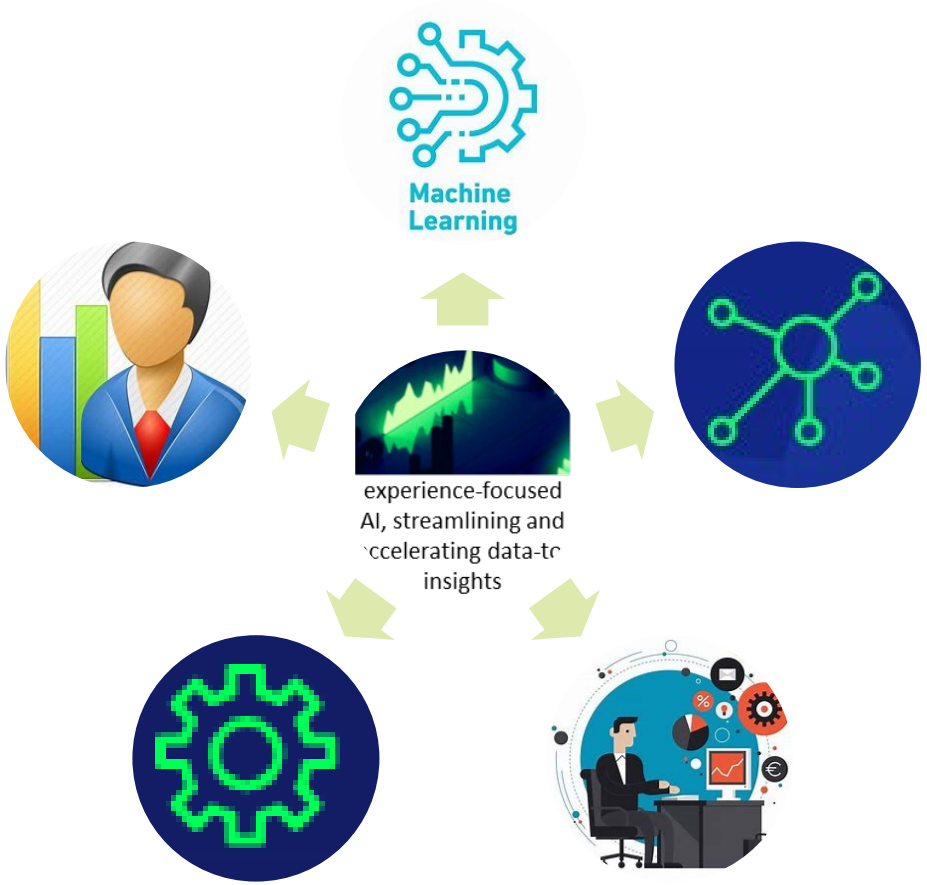


© 2019 Adobe. All Rights Reserved.

Adobe

Data Science Workspace

Building Intelligent Services on Adobe Experience Platform



With DSW, AEP allows you to streamline and accelerate data-to-insights with

- ✓ Integrated access to data stored in Platform
- ✓ The computing power essential for machine learning/AI & managing big datasets
- ✓ Prebuilt ML recipes to accelerate into AI-driven experiences
- ✓ Simplified authoring, reuse, and modification of recipes for data scientists of varied skill levels
- ✓ Intelligent service publishing and sharing in just a few clicks - and monitoring & retraining for continuous optimization of personalized experiences

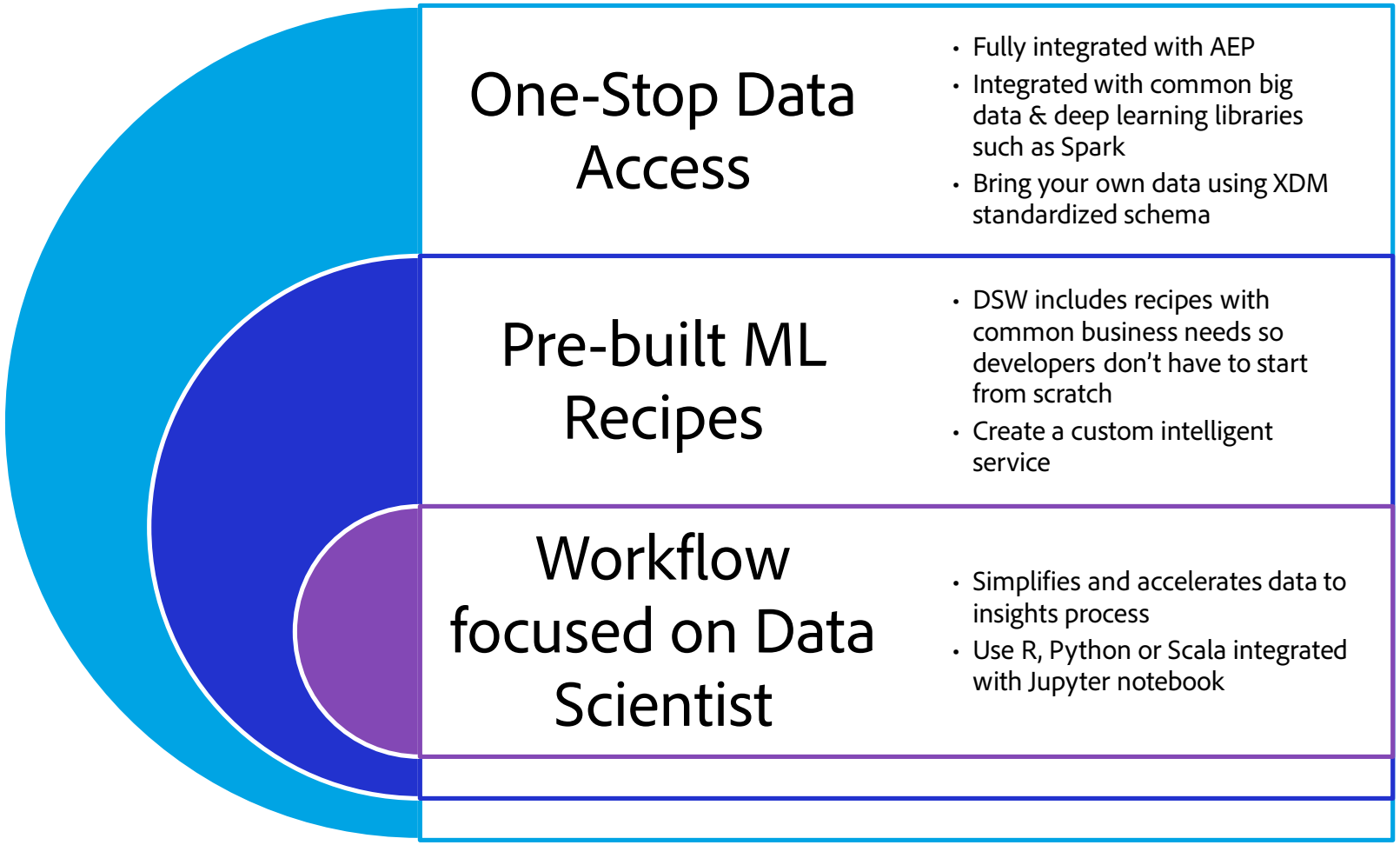
Data scientists of all skill levels will achieve insights faster and more effective digital experiences sooner.

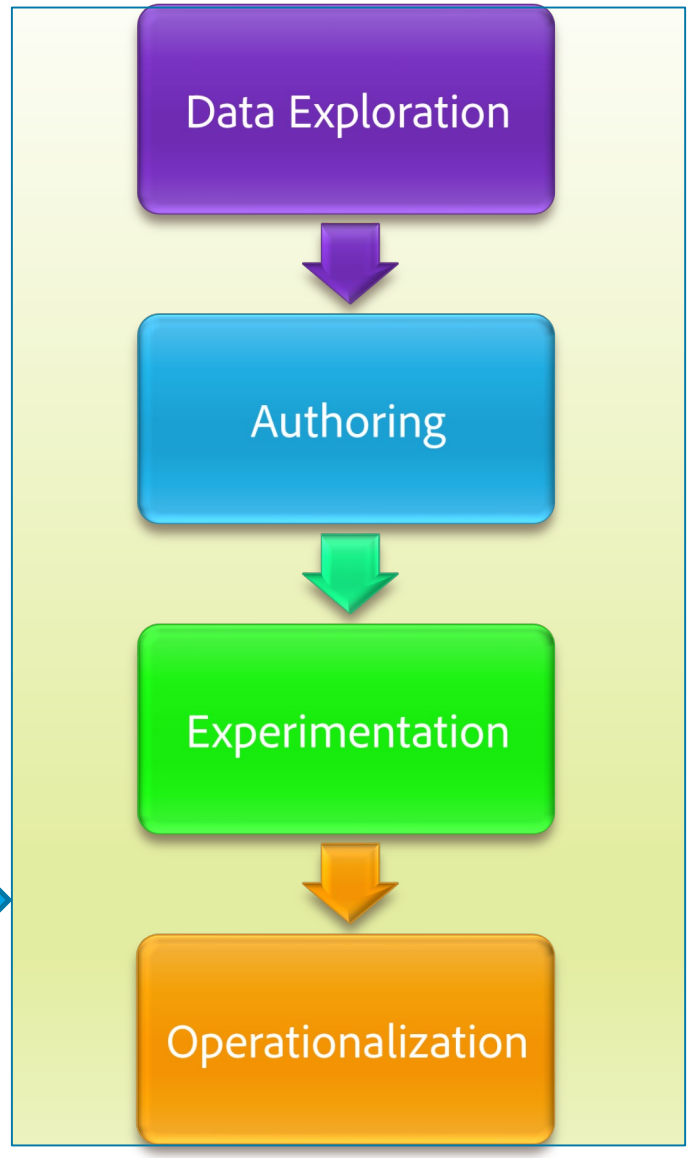
© 2019 Adobe. All Rights Reserved.

Adobe

Why Data Science Workspace?

Data to insights





© 2019 Adobe. All Rights Reserved.

Adobe

DSW Terminologies?

Lets look at some terminologies used in Data Science Workspace

Algorithm

Standard DS techniques such as classification, regression, k-means clustering, etc.

Feature

An individual measurable property or characteristics of a phenomenon being observed

Feature Engineering

Process of converting raw data into usable form for analysis using domain knowledge

Recipe

A propriety algorithm or an ensemble of algorithms to help solve specific business problems

Instance

An occurrence of the recipe configured with the right data definition to help solve specific biz problems – one recipe can create many instances

Trained Model

An instance of the recipe that is trained using historical data to learn from. The trained model finds patterns in the training data to predict the target

Service

Service that is created from a "trained model" to be used in building experiments

Jupyter Notebook

An open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text

Hyperparameters

High level properties of a model, different from standard model parameters that are usually fixed.

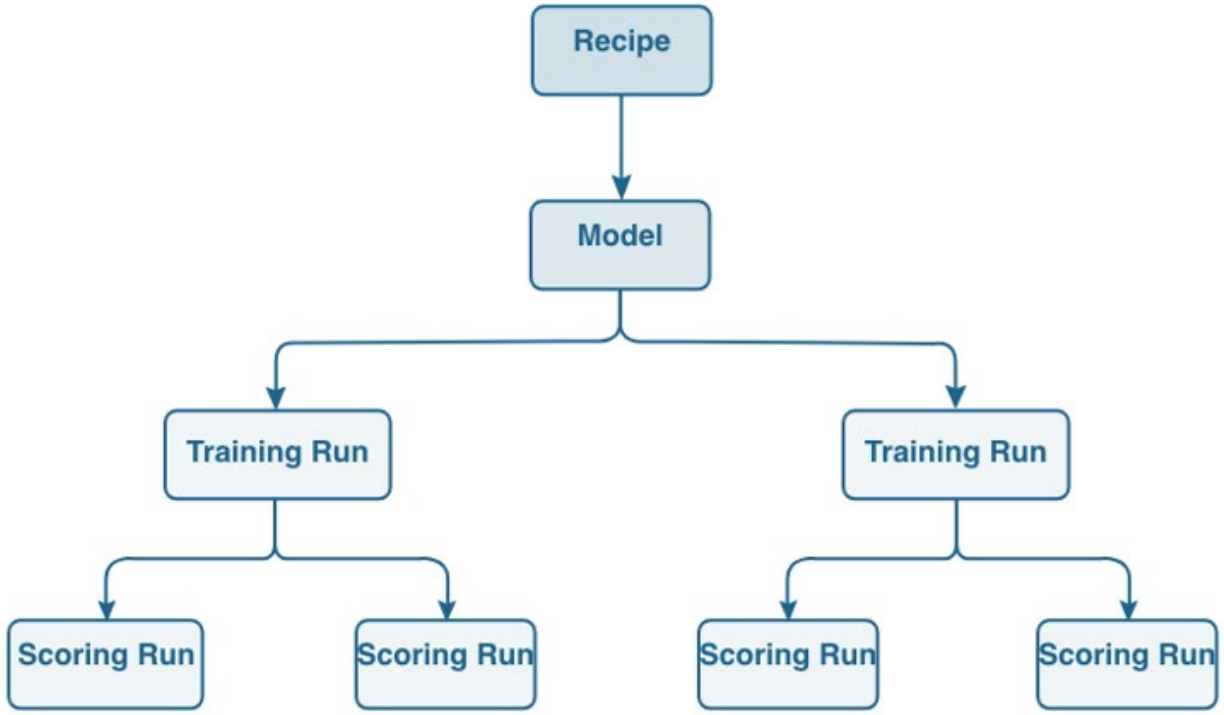
Ex: depth of decision tree, number of hidden layers, learning rate, etc.

© 2019 Adobe. All Rights Reserved.

Adobe

Relationship between Model, Recipe and Experiments

The following chart outlines the hierarchical relationship between Recipes, Models, Training Runs, and Scoring Runs.



© 2019 Adobe. All Rights Reserved.

How does it work?

Define the Problem

It all starts with a business problem. Lets look at some of the business problems faced by companies today:

- ✓ A retailer might want to predict what products to recommend to a customer
- ✓ A brand might want to predict who would purchase of their products
- ✓ A telecom company might want to predict who would churn and build effective strategies to stop churn
- ✓ A retailer might want to understand their customer better and would like to build customer segments for effective marketing strategies

For today's session, lets consider the business problem of - **"A retailer might want to predict who would stop making a purchase and churn"**

© 2019 Adobe. All Rights Reserved.

Adobe

How does it work?

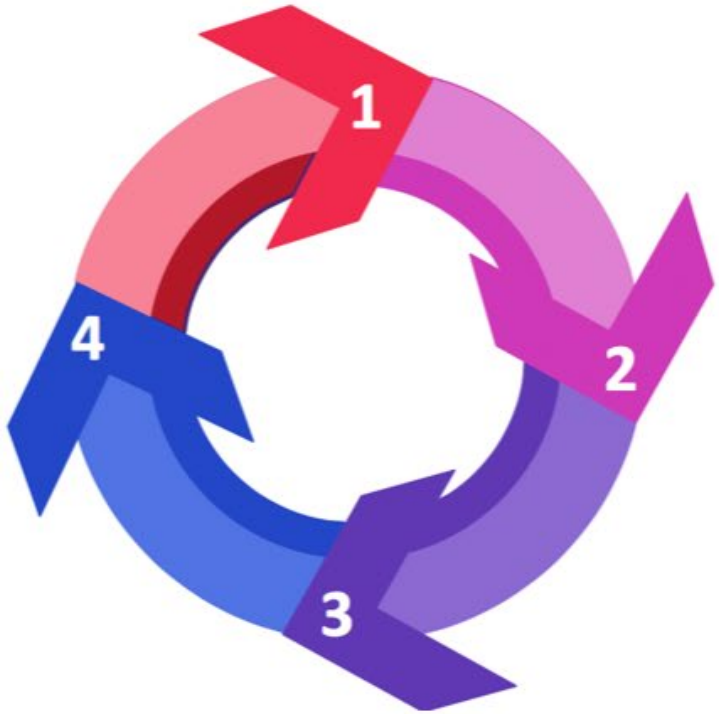
***Objective**: Consider a fitness retailer, Luma. When customers shop at the website and click on a product, they are presented with personalized product recommendations.*

Data Preparation

Access omni-channel data and easily prep it for insights

Model Development

Author your model and package it with one click to test at scale



Consumption

Score and Consume Insights
Bonus: Enrich & Segment Unified Profile with Scored Insights

Experimentation

Train and tune your model to optimize it

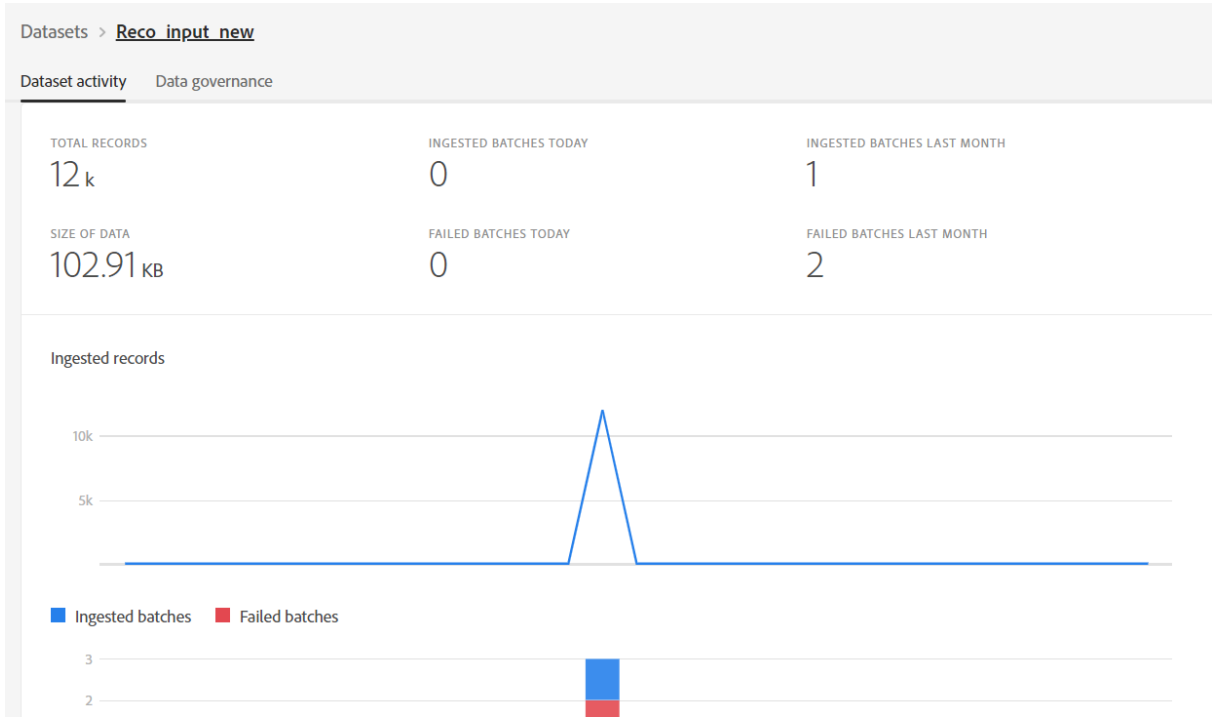
© 2019 Adobe. All Rights Reserved.

Adobe

Data Preparation

First step in a model building is data preparation

Lets see how the input data looks like



RECOMMENDATIONS INPUT SCHEMA

	_aepgdcdevenablement1.itemId	_aepgdcdevenablement1.interactionType	_aepgdcdevenablement1.userId	_id
0	LLWH10	Purchase	matab@adobe.com	matab@adobe.com
1	LLWS01	Purchase	matab@adobe.com	matab@adobe.com
2	LLWP09	Purchase	matab@adobe.com	matab@adobe.com
3	LLMH09	Purchase	punyakot@adobe.com	pbhatt@adobe.com
4	LLMP09	Purchase	punyakot@adobe.com	pbhatt@adobe.com

© 2019 Adobe. All Rights Reserved.

Adobe

Data Preparation

First step in a model building is data preparation

Lets look at the Jupyter Notebook and read the data and perform some exploratory data analysis

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

```
from platform_sdk.dataset_reader import DatasetReader
from datetime import date
dataset_reader = DatasetReader(PLATFORM_SDK_CLIENT_CONTEXT, dataset_id="5d96f6bca74eb91656574254")
# If you do not see any data or would like to expand the default date range, change the following query
data = dataset_reader.read()
data.head()
```

Summary Stats

[3]:
```
data.describe()
```

[3]:

	_aepgdcdevenablement1.interactionType	_aepgdcdevenablement1.itemId	_aepgdcdevenablement1.userId	_id	timestamp
count	11989	11989	11989	11989	11989
unique	2	99	865	864	26
top	Purchase	LLMP11	clanchesterel@prweb.com	clanchesterel@prweb.com	1970-01-01T00:00:43.685000
freq	11803	467	47	47	11780

© 2019 Adobe. All Rights Reserved.

Adobe

Model Development

After data exploration and preparing the data in the right format, the next step is to build a model

A recommendations model based on Collaborative filtering is created

```
Users = data['_aepgdcdevenablement1.userId'].unique()

Reco = pd.DataFrame()

for i in Users:
    Users_a = data[(data['_aepgdcdevenablement1.userId'] == i)]
    Users_a = Users_a.sort_values(['_aepgdcdevenablement1.userId', 'Score'], ascending=[True, True])
    Users_a = Users_a[~Users_a['Item'].isin(data1['_aepgdcdevenablement1.itemId'][(data1['_aepgdcdevenablement1.userId']==i)])]
    Users_a = Users_a[Users_a.Item != 0]
    Top5 = Users_a.iloc[0:4,:2]
    Reco = Reco.append(Top5)

data = pd.DataFrame(Reco.groupby('_aepgdcdevenablement1.userId')['Item'].apply('#'.join)).reset_index()
data.columns = ['_aepgdcdevenablement1.userId', '_aepgdcdevenablement1.recommendations']
data.head(5)
```

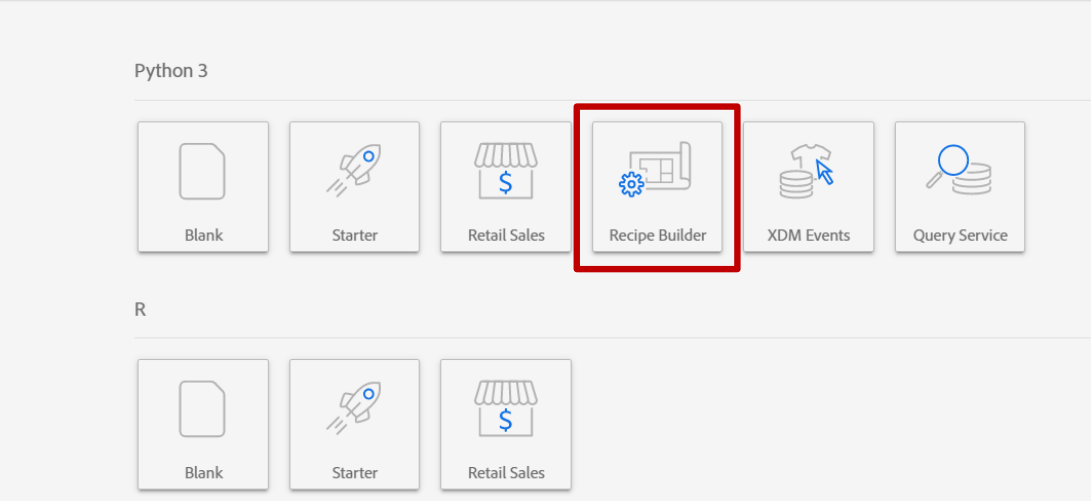
© 2019 Adobe. All Rights Reserved.

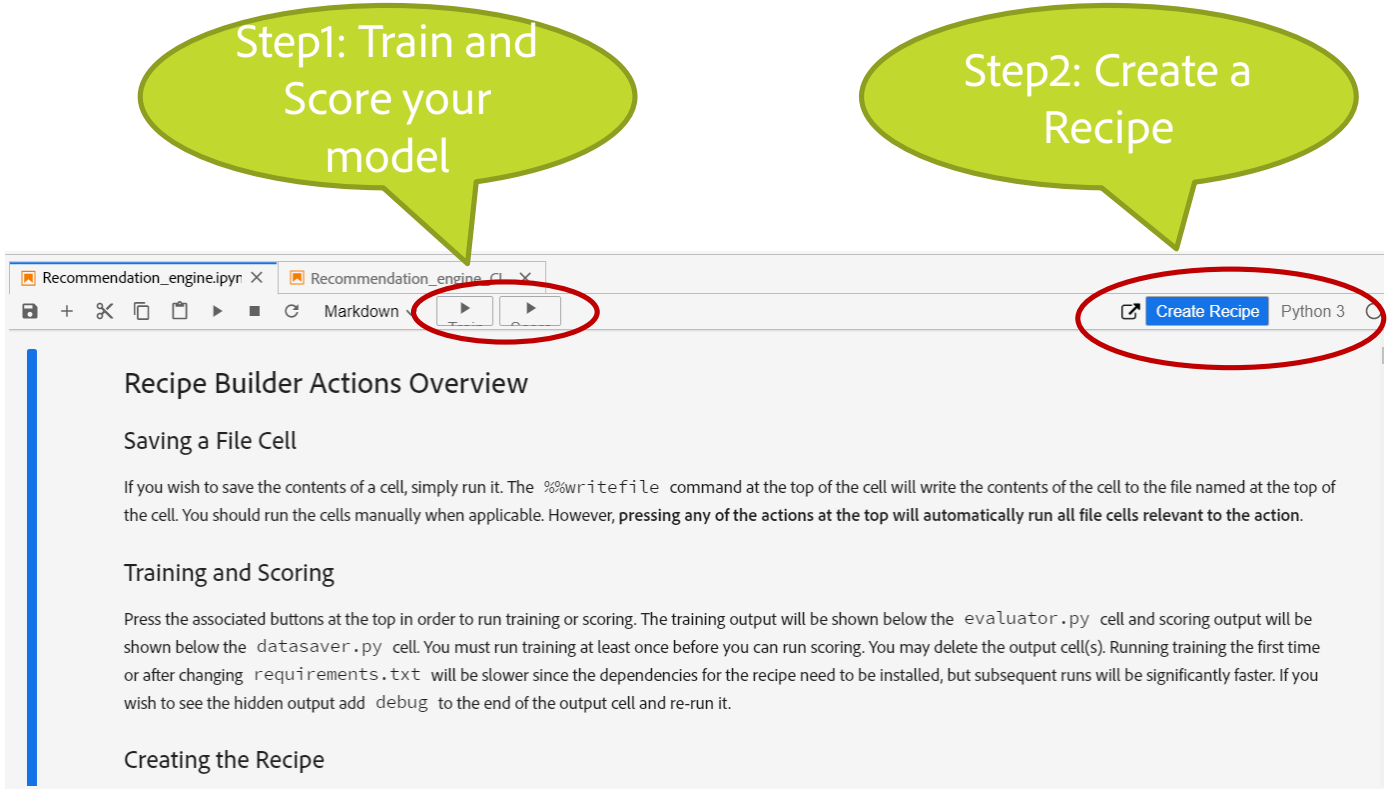
Adobe

Experimentation

Once you are satisfied with the model you have built, you can create a recipe out of it and perform experiments

Lets look at how a recipe is built





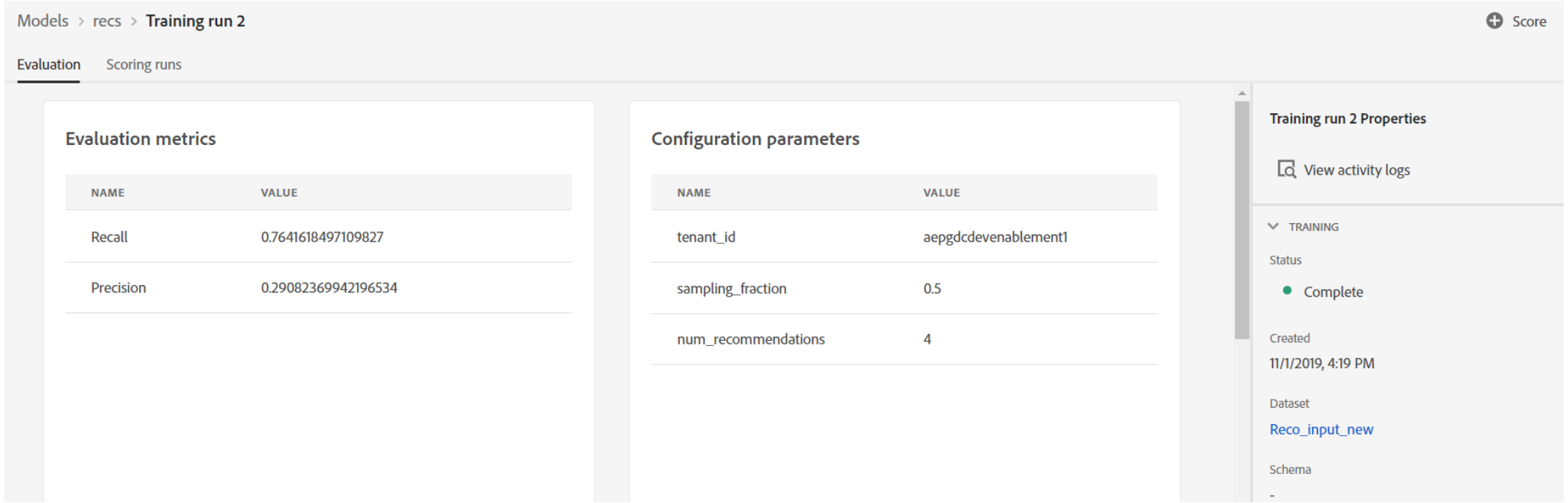
© 2019 Adobe. All Rights Reserved.

Adobe

Experimentation

Training and scoring

Create experiments by changing the hyper-tuning parameters



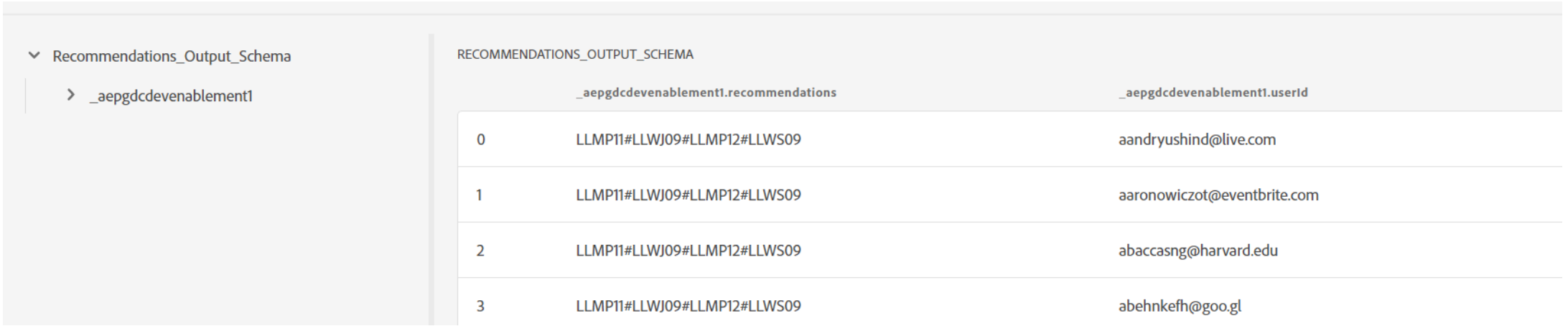
© 2019 Adobe. All Rights Reserved.

Adobe

Consumption

Score the data and create Segments with Segment Unified Profile

Score and Preview the scored dataset



	_aepgdcdevenablement1.recommendations	_aepgdcdevenablement1.userId
0	LLMP11#LLWJ09#LLMP12#LLWS09	aandryushind@live.com
1	LLMP11#LLWJ09#LLMP12#LLWS09	aaronowiczot@eventbrite.com
2	LLMP11#LLWJ09#LLMP12#LLWS09	abaccasng@harvard.edu
3	LLMP11#LLWJ09#LLMP12#LLWS09	abehnkefh@goo.gl

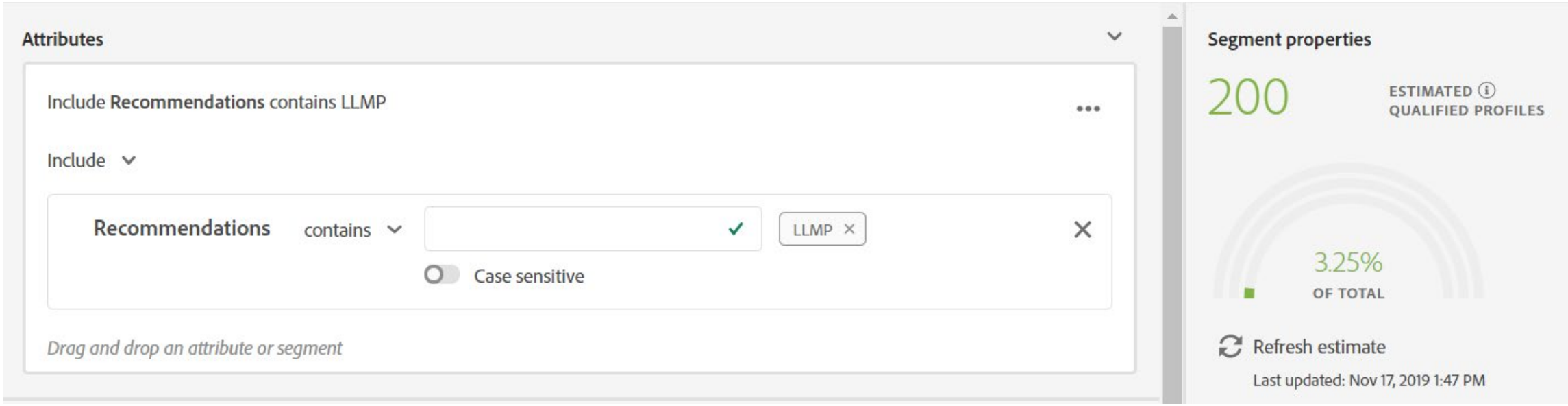
© 2019 Adobe. All Rights Reserved.

Adobe

Consumption

Score the data and create Segments with Segment Unified Profile

Create segments with the recommendations using Segment UI



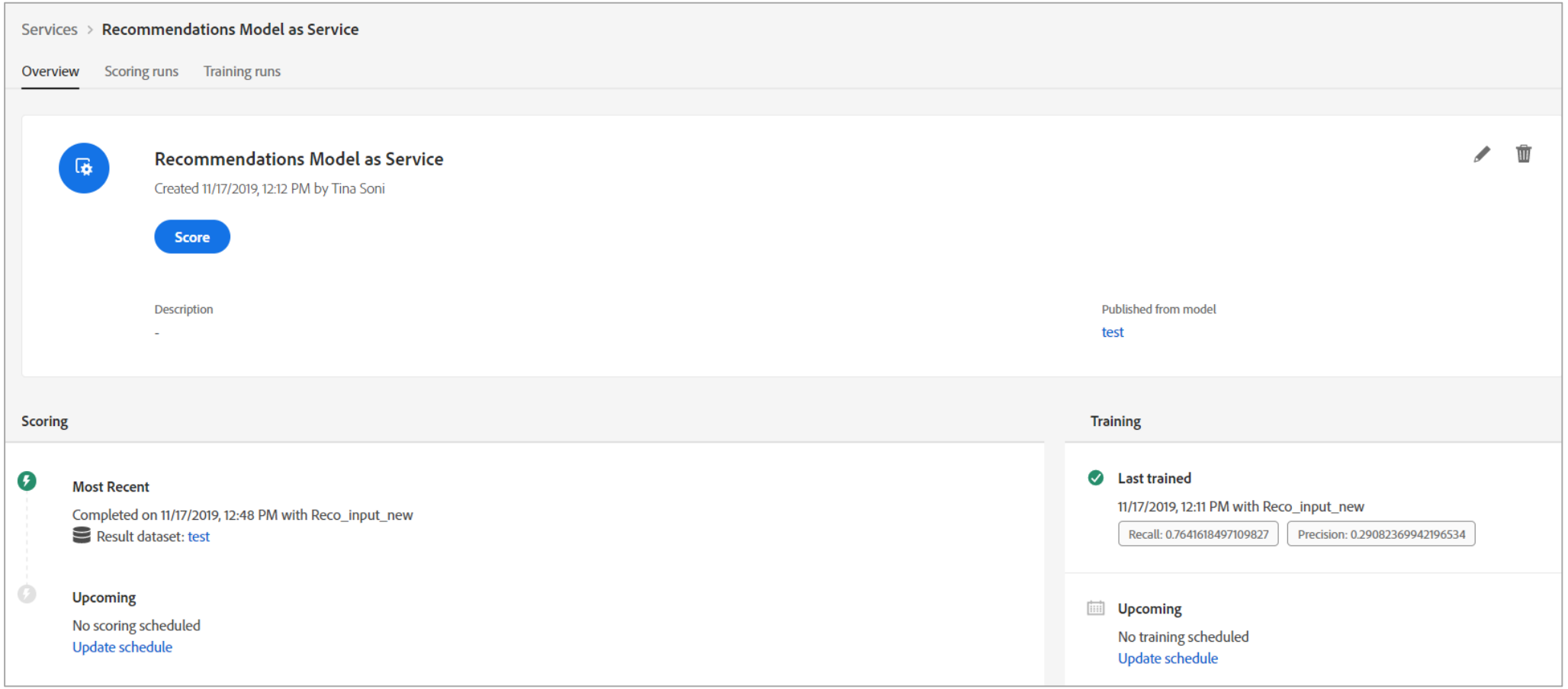
© 2019 Adobe. All Rights Reserved.

Adobe

Consumption

Publish the model as a service

Publish the model as a service and schedule it to run at frequent intervals



© 2019 Adobe. All Rights Reserved.

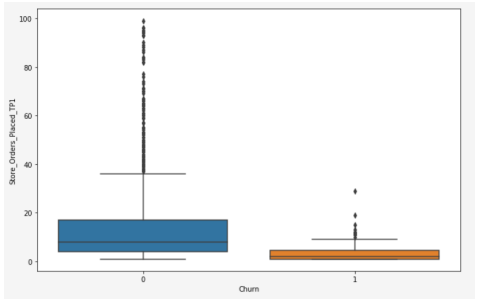
Adobe

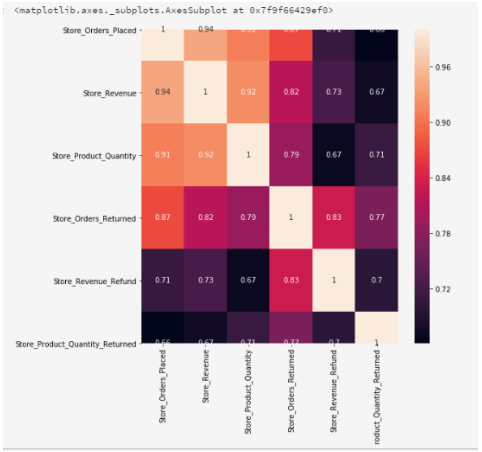
Churn Prediction Model for an American Office Products dealer

Objective: Based on prior customer history and purchase behaviour, build a churn prediction model to predict customers likelihood to churn based on a purchase rhythm

Approach

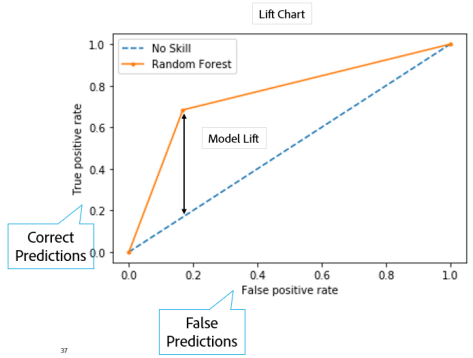
- Used **invoice** data to build a churn prediction machine learning model, build a recipe and publish it as a service for future scoring
  - propensity to Churn model
- **Data Cleaning and Exploration done in DSW**





Outcome

- Insights into attributes that drive Churn
- A significant lift was achieved in the model



- **Recipe** was built to package the model for future training and scoring runs
- Model was published as a service and scheduled for scoring new data
- Model was tested to train and score on large datasets using **Pyspark**

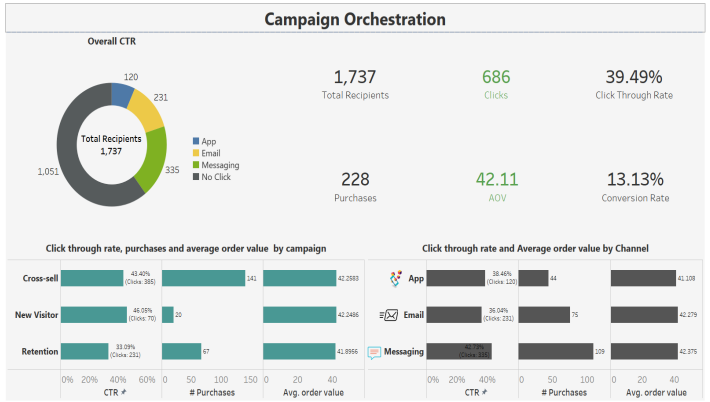
© 2019 Adobe. All Rights Reserved.

Recommendation engine & propensity to buy model - AEP POC

Objective: Based on customers' purchase behavior, Luma, an online retail store wants to send ***triggered campaigns*** to their customers based on their online and offline activity. We leverage DSW for building an engine for product recommendation.

Approach

- Used **online and offline** data to build two machine learning models using **templatized recipe builder available in DSW**:
  - propensity to buy model
  - recommendations engine to predict products that can be recommended to a customer
- **Connected AEP and Tableau** for **Campaign Orchestration Dashboard** for customer journeys (recommendations from DSW to conversion and AOV)



Outcome

- Used the scores and recommendations from this model to **create segments** that were shared with **Adobe Campaign**
- Created **personas** for customized targeting such as :

  Janet -- "High propensity to buy, prefers email and recommended products are yoga pants"

- Improved efficiency with integration of feedback into system -- Analyzed the campaign effectiveness, user's purchase behavior, lifetime value and loyalty in **near real-time** so that **marketer can re-strategize, cross-sell and retarget their customers**.

© 2019 Adobe. All Rights Reserved.

Adobe

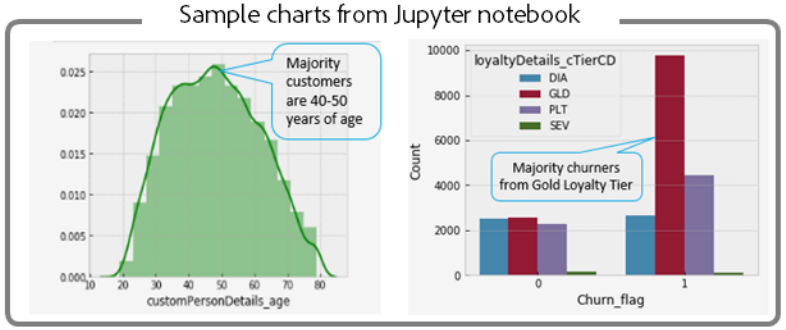
Churn prediction for an American gaming hotel and casino corporation

Objective: Predict users' likelihood to churn using AEP, DSW capabilities. Churn scores further used to make segments and target users at high risk.

Approach

1. Leverage the **data sets in AEP in the XDM format** – Analytics and client-specific datasets ingested in AEP
2. **Query services** used for **data aggregation** from event level data to profile one-view
3. **Data cleaning and exploration in DSW**

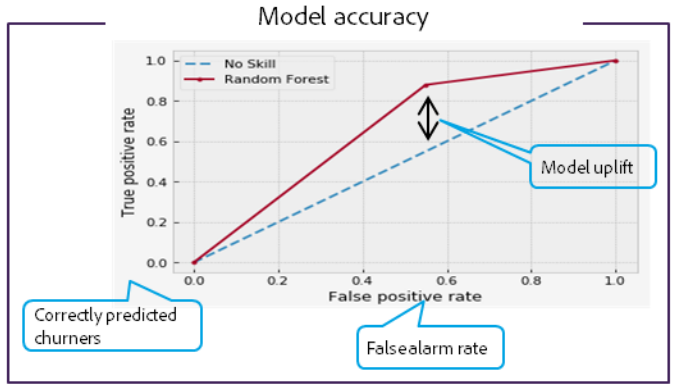
Sample charts from Jupyter notebook



4. Insights generation for quick action
5. **Model building** using jupyter notebook within DSW and **pre-built recipe notebook**
6. Algorithm for most robust model – Random Forest

Outcome

1. Insights on attributes that drive churn behaviour for actioning.
2. Model gave a significant lift in accuracy of prediction.



3. **Recipe within DSW can be leveraged to train and score model**, for each scoring run, we can view the accuracy parameters
4. Model can be **deployed as a service for scheduled scoring** for hourly, daily, weekly runs, on new datasets.

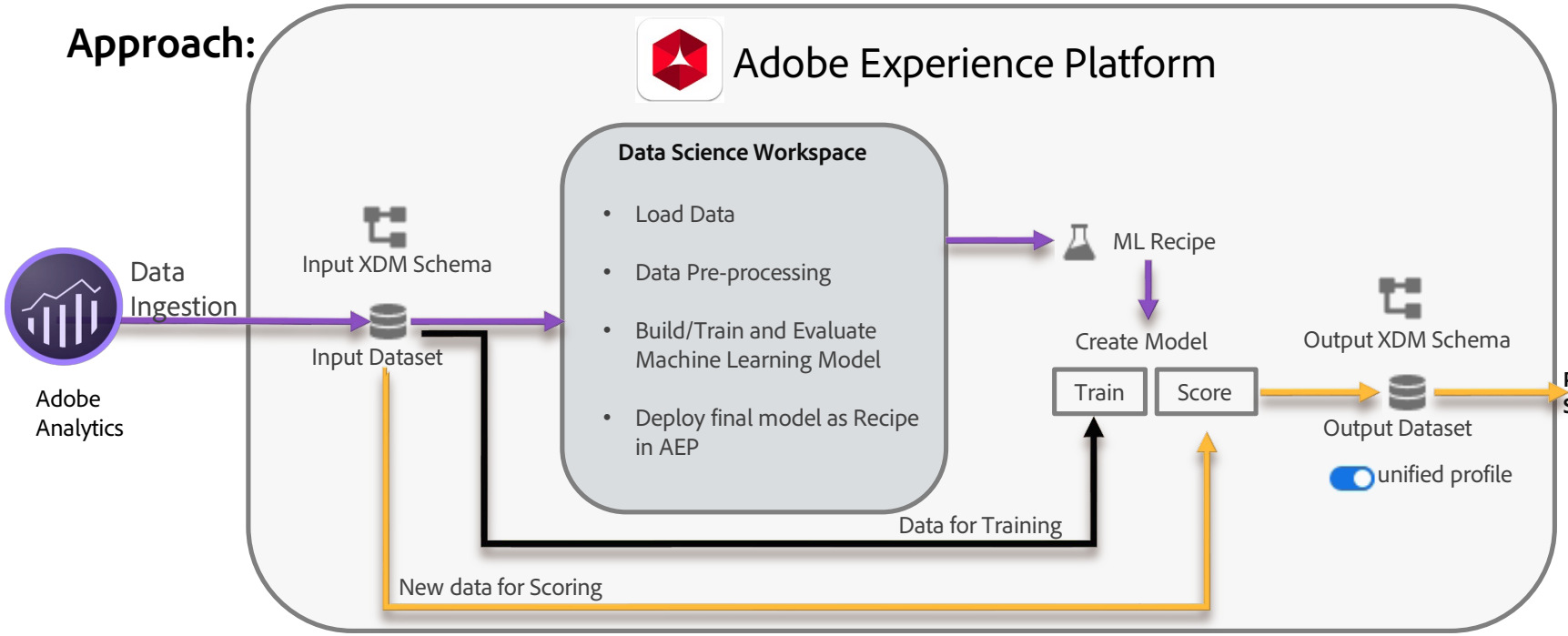
© 2019 Adobe. All Rights Reserved.

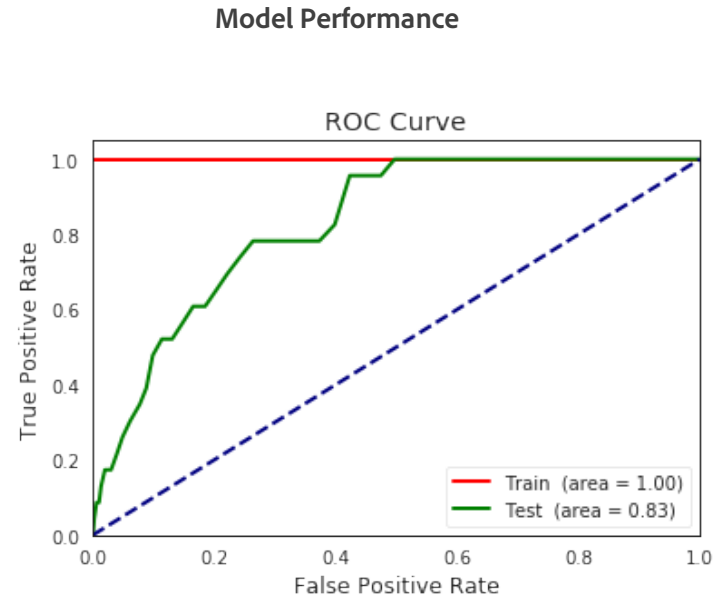
Adobe

Customer POC – Propensity to purchase modeling

Objective: Predict users' propensity to purchase the insurance product using AEP, DSW. Predicted propensity scores will be used further to make segments and target users that can be persuadable.

Approach:





Outcome: Propensity sores of new users are at disposal to the customer.

Output dataset activated to unified profile to make the scores of the users available across all platforms.

© 2019 Adobe. All Rights Reserved.

Adobe

Key Takeaways

1. Platform has been architected from the ground up to deliver better personalized experiences at scale.

2. Incremental value with Real-Time Customer Profiles, Data Science Intelligence and External API Activation.

3. Data Science Workspace gives power to companies to deliver real-time, personalized and relevant experiences to their customers

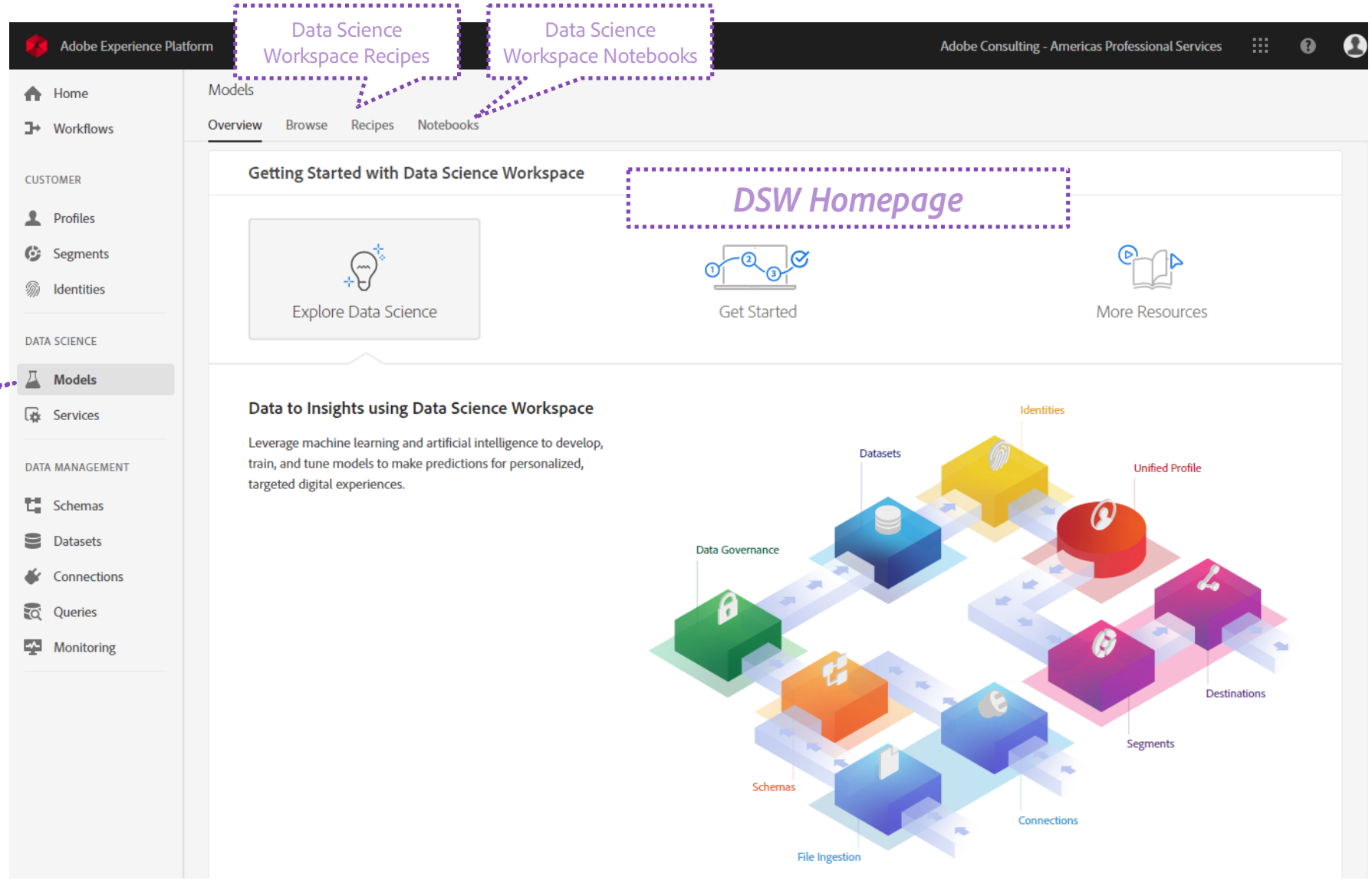
© 2019 Adobe Inc. All Rights Reserved.

Adobe

Questions


Adobe

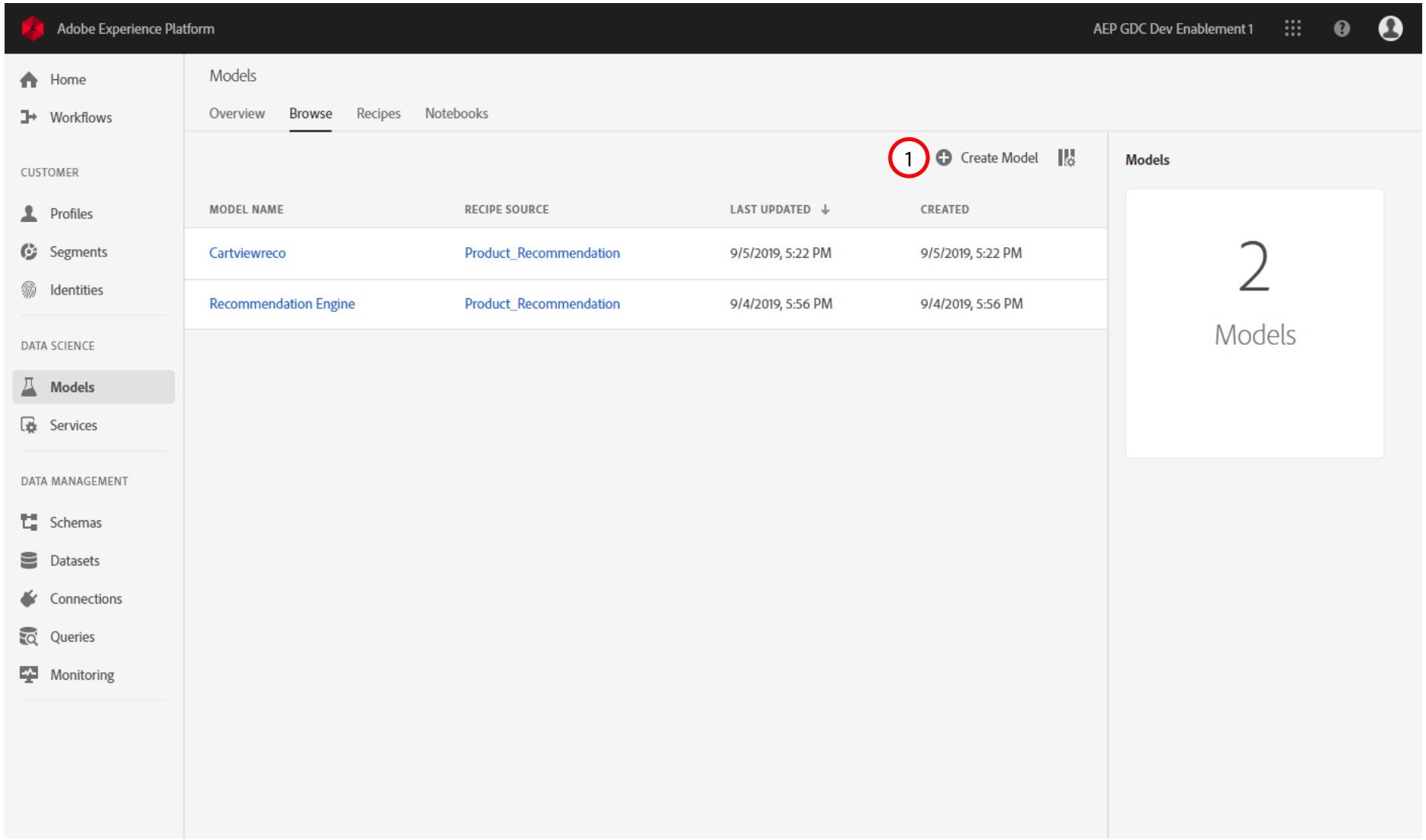
Overview of Data Science Workspace in Adobe Experience Platform



Data Science Workspace

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Overview of Data Science Workspace in Adobe Experience Platform

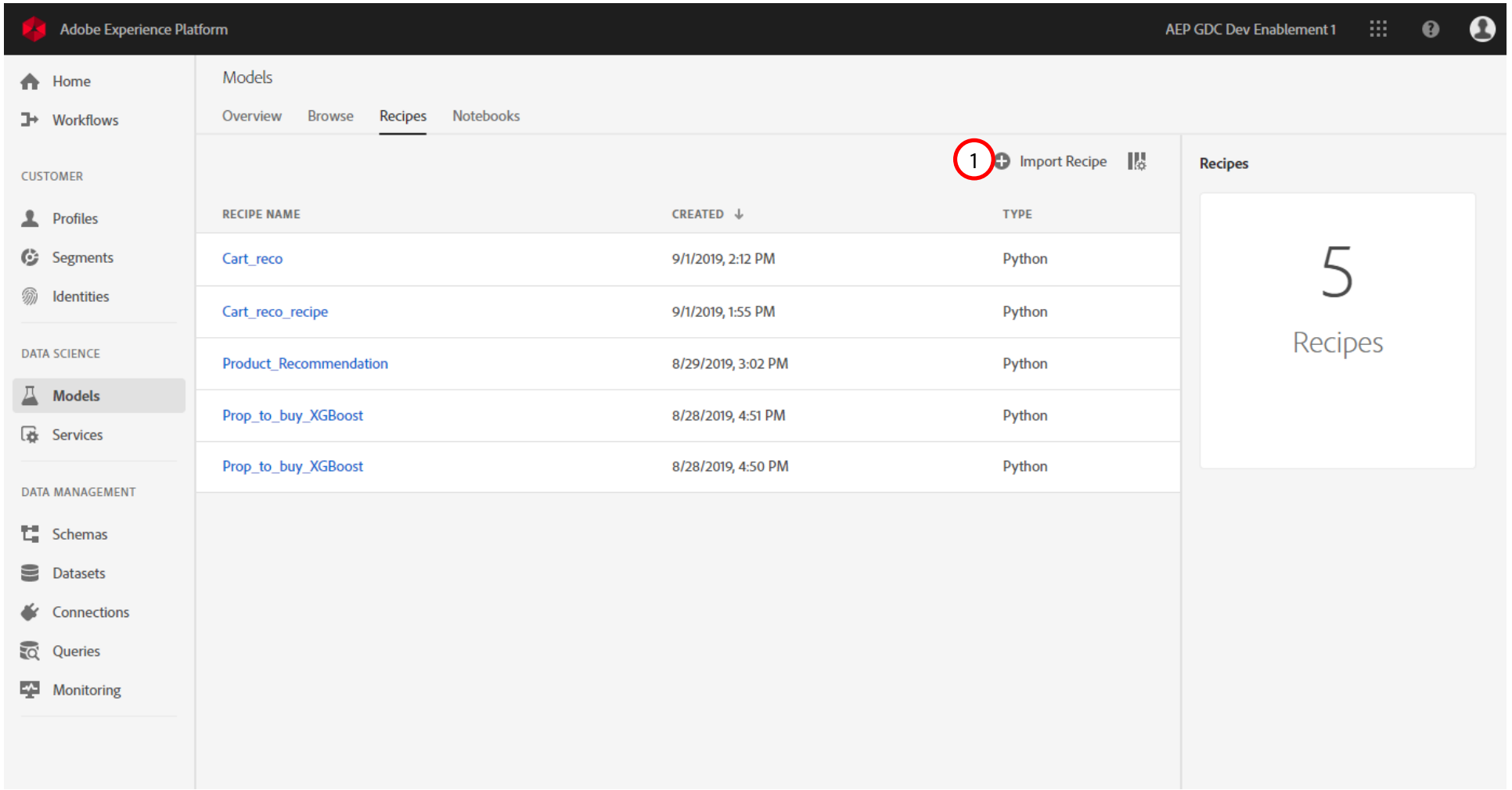


"Browse" shows all the models that are created

There is also an option to create a new model[1]

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Overview of Data Science Workspace in Adobe Experience Platform

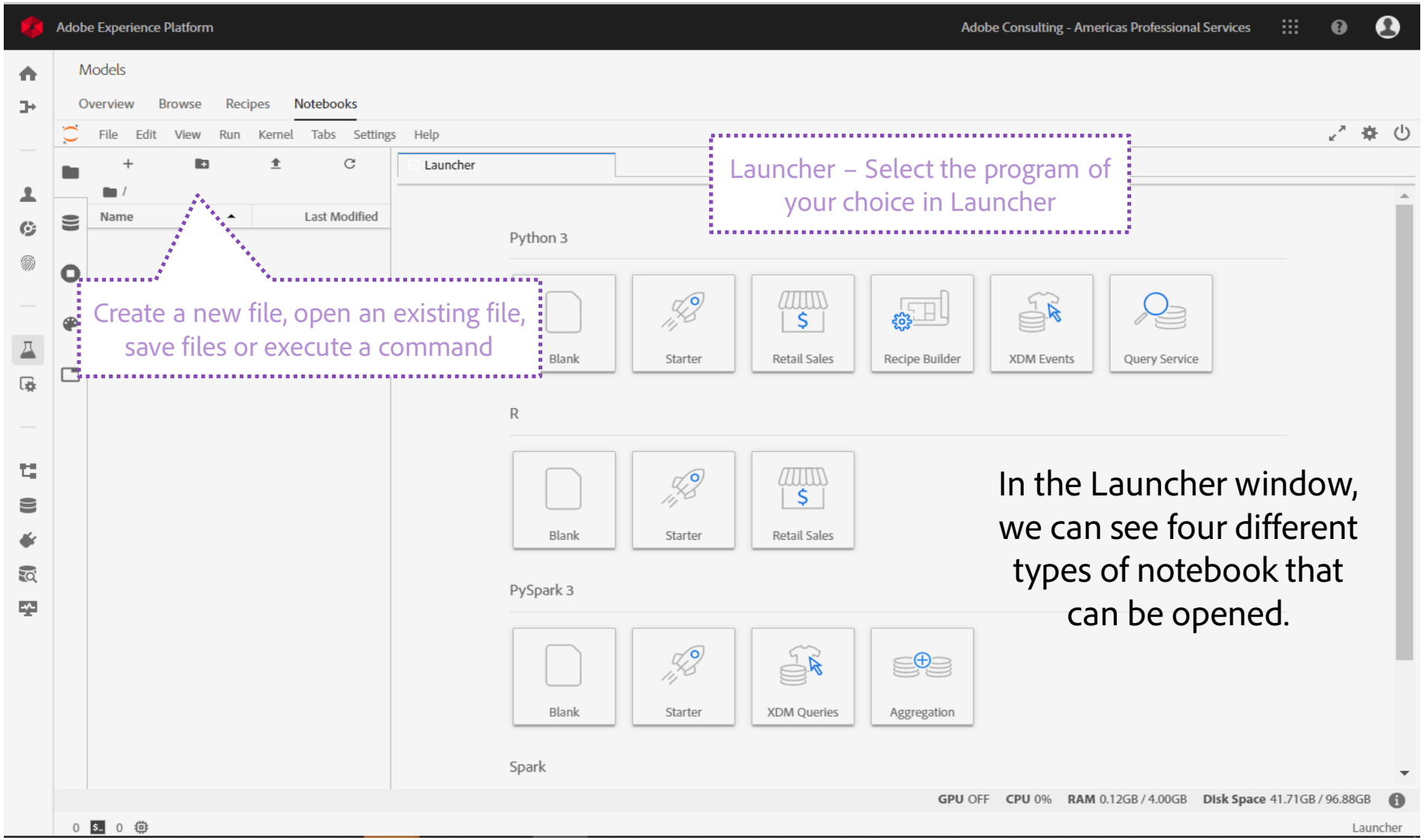


A “Recipe” is a reusable component of a model which can be deployed for different datasets.

Any existing Recipe[1] can also be imported using the “Import Recipe” Option

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Overview of Data Science Workspace in Adobe Experience Platform

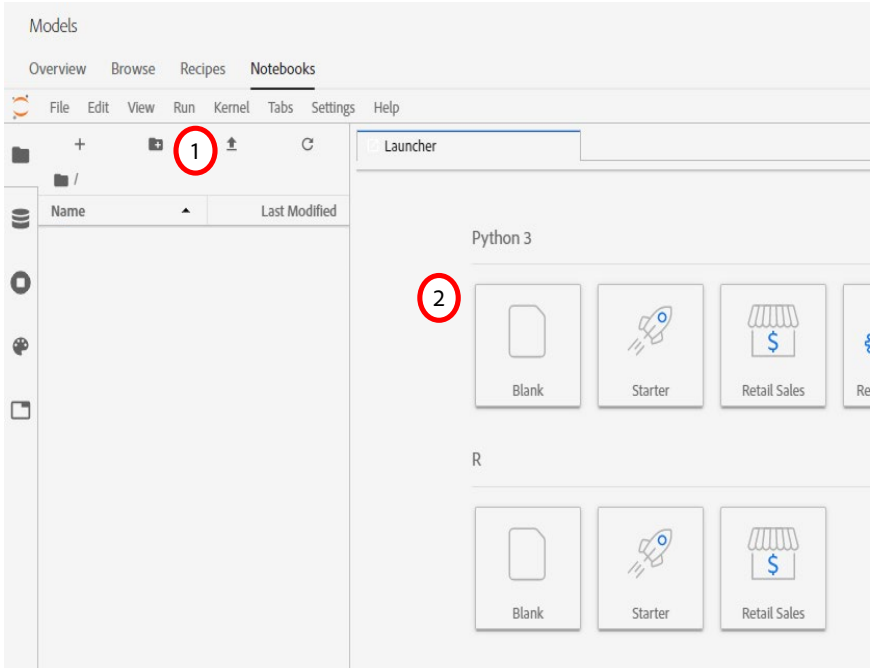


© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Overview of Data Science Workspace in Adobe Experience Platform

Adding Notebooks

- To add your notebooks to Data Science Workspace, you can manually drag-drop them at the windows pane to your left.
- Else, you could click on the upload[1] symbol and locate your files through explorer.
- You can also start a blank notebook[2] and start exploring datasets and trying basic commands.

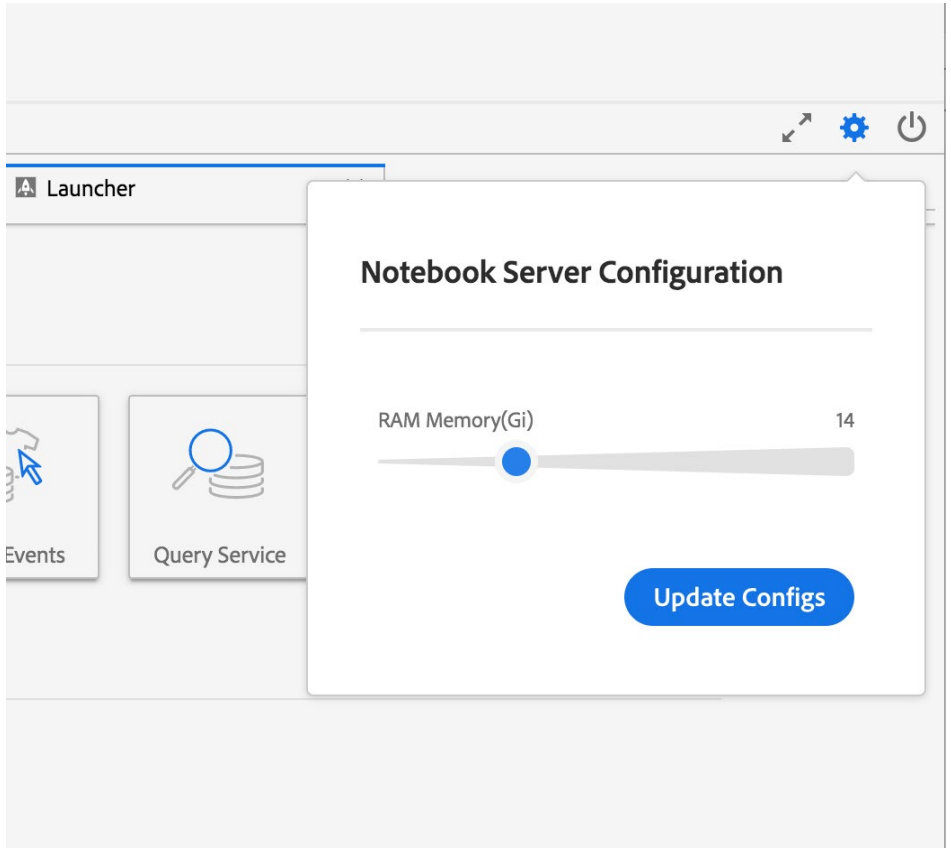


© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Overview of Data Science Workspace in Adobe Experience Platform

Increasing RAM

While performing powerful computations or executing a model that requires more computing resources, there is an option in AEP to increase RAM memory



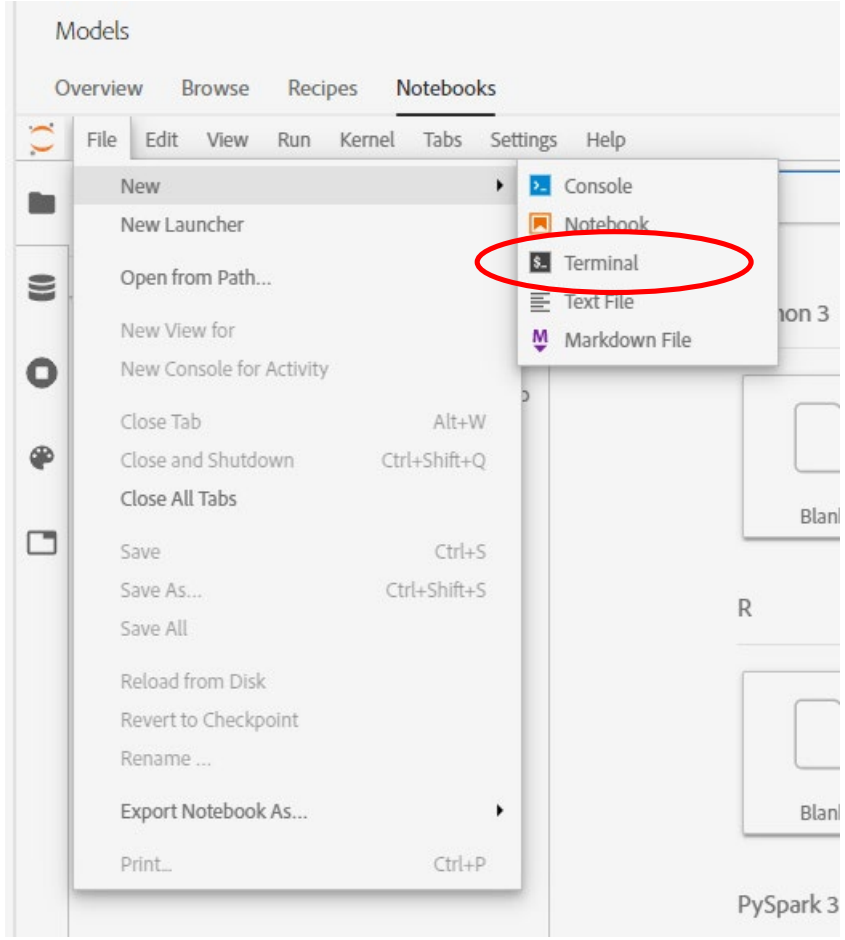
© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Overview of Data Science Workspace in Adobe Experience Platform

Installing New Libraries

If you want to install new libraries that are not already present, it can be done through the terminal window

File -> New -> Terminal



© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Overview of Data Science Workspace in Adobe Experience Platform

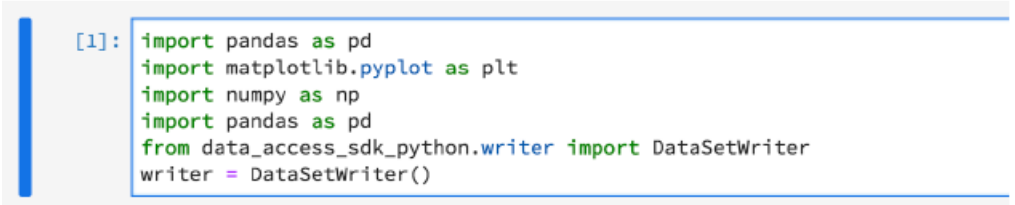
Executing a Command

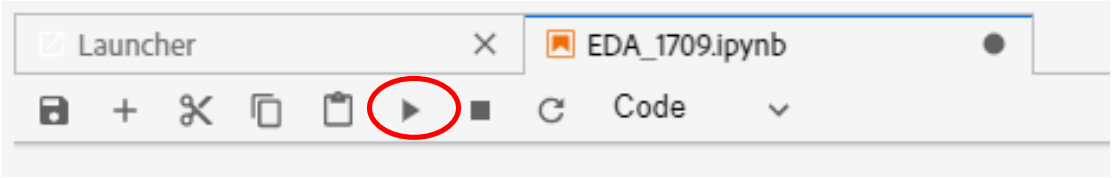
Select the cell you want to execute

Press “Shift+Enter”

OR

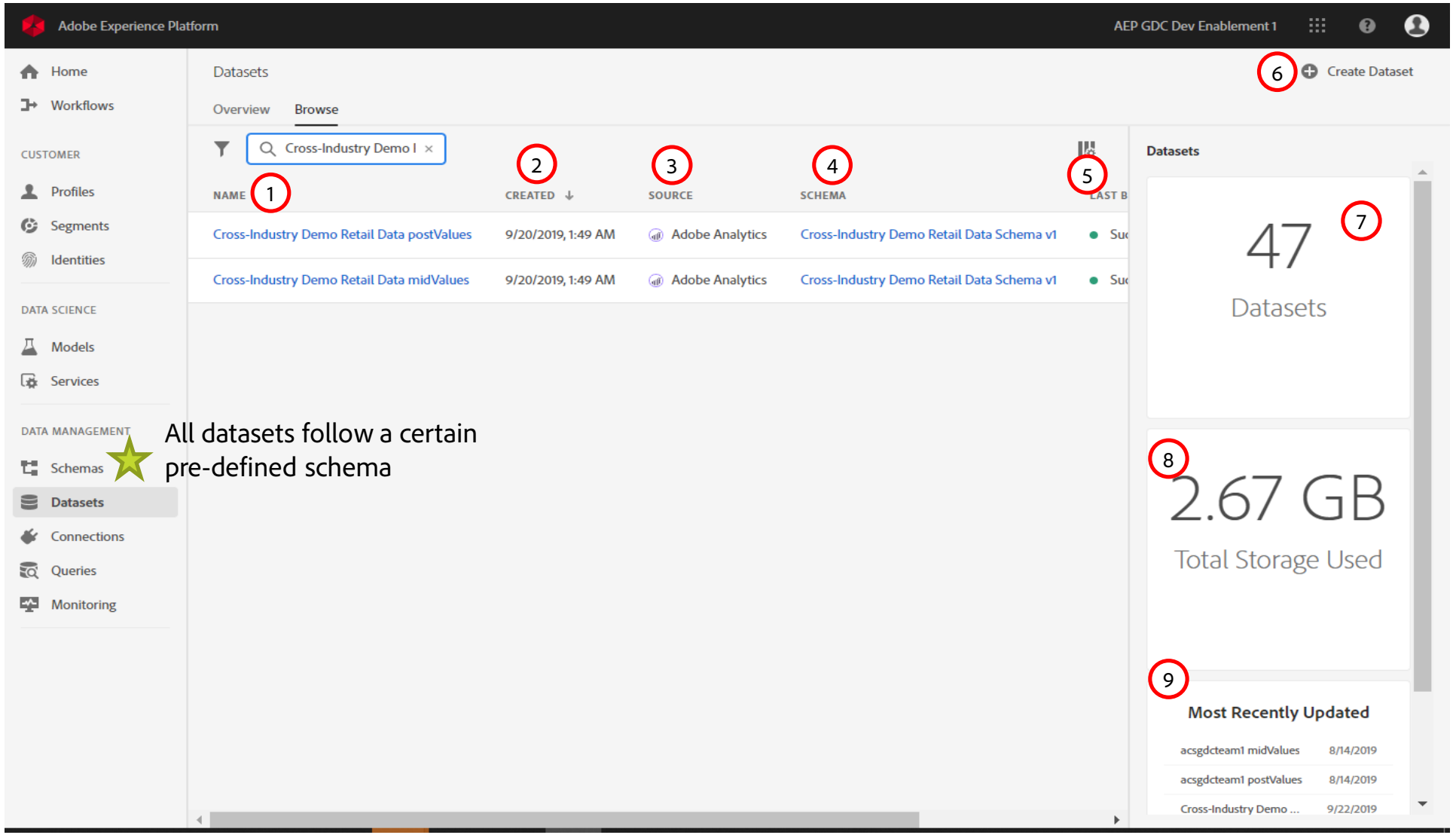
Click on the “Play” button on top left hand side





© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

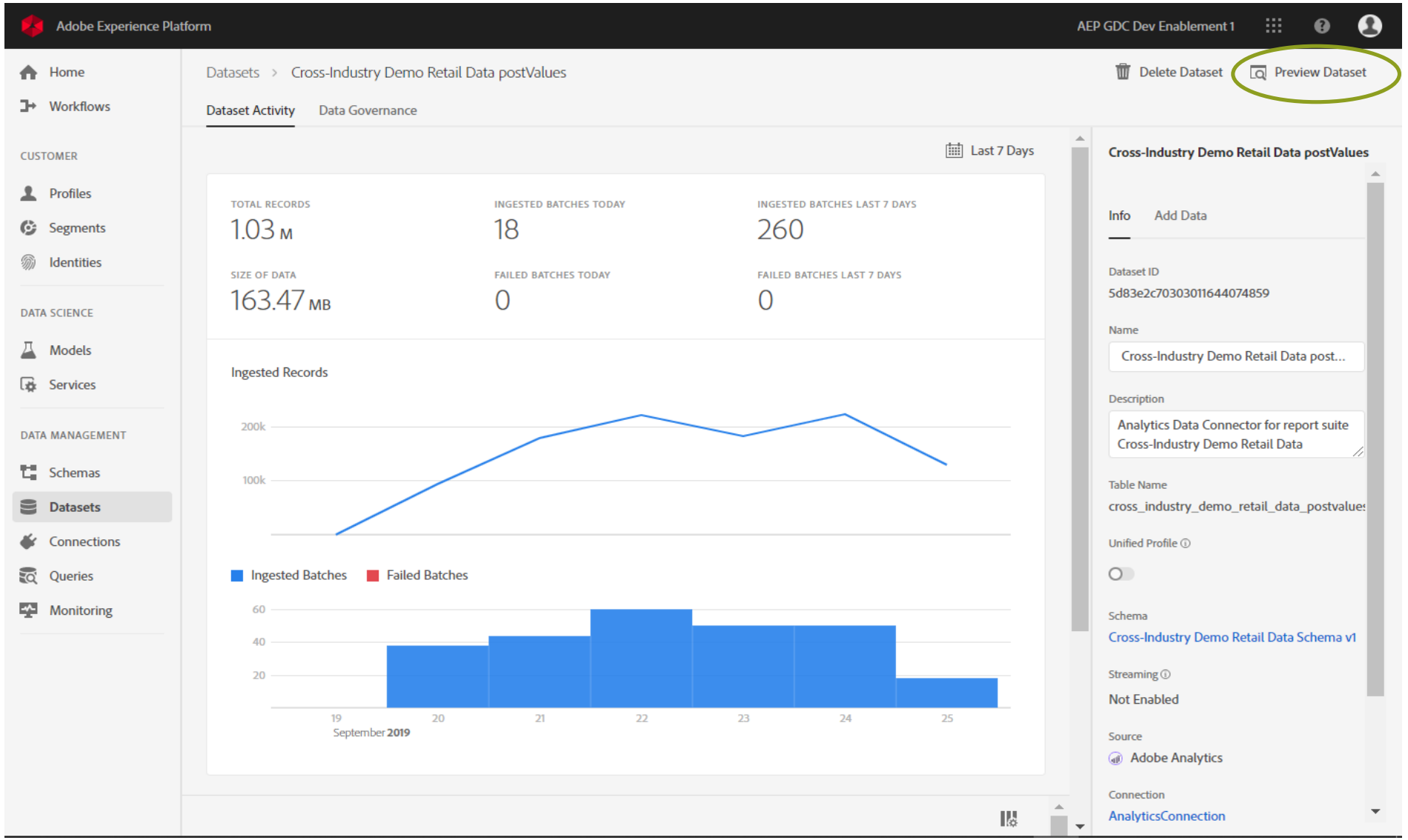
Overview of Adobe Experience Platform - Datasets



Datasets lists down all the data that is ingested in AEP[1], the date of creation[2], Source[3], Schema[4] and Last Modified[5] There is an option to create a dataset[6] and the window also provides a view of the number of datasets[7], storage[8] and most recently updated[9]

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Overview of Adobe Experience Platform – Dataset characteristics

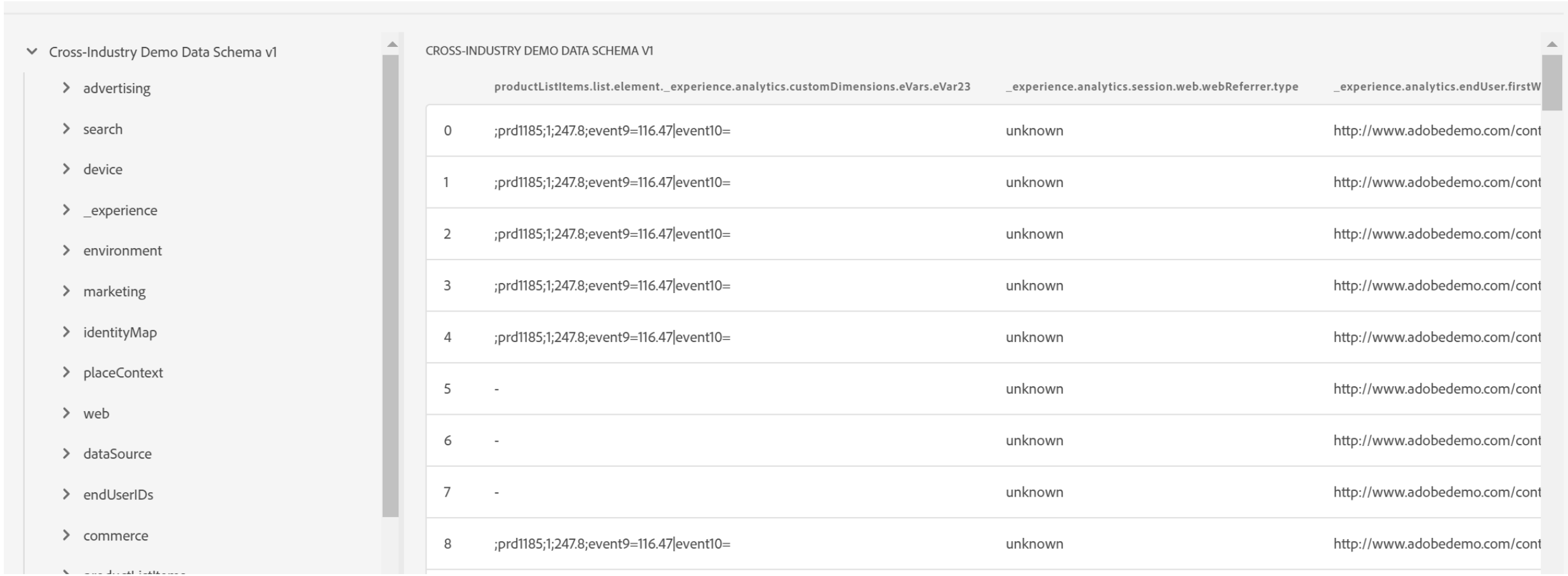


Click on the name of the dataset to open a window with dataset characteristics including number of records, batches ingested, failed batches, Dataset ID, Schema, etc.

Click Preview Dataset to view the actual data

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Overview of Adobe Experience Platform – Dataset Preview



© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

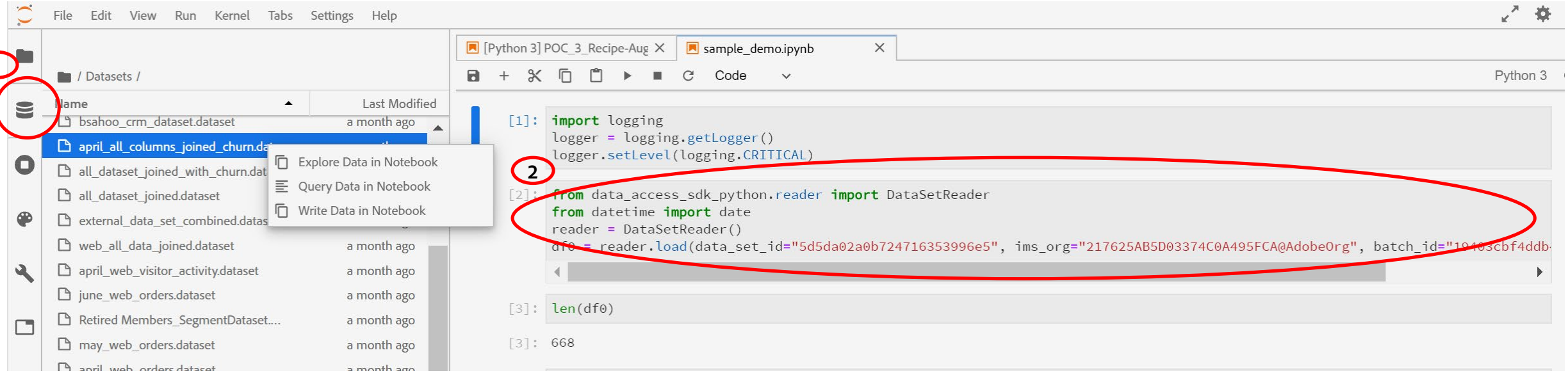
Data Exploration

Explore Dataset in AEP Data Science Workspace Jupyter Notebook

There are 2 ways to read a dataset in AEP Jupyter Notebook

1. Select “Datasets” in Notebooks and select “Explore Data in Notebook”

2. Write the code, change the dataset ID and Batch ID. Execute the command



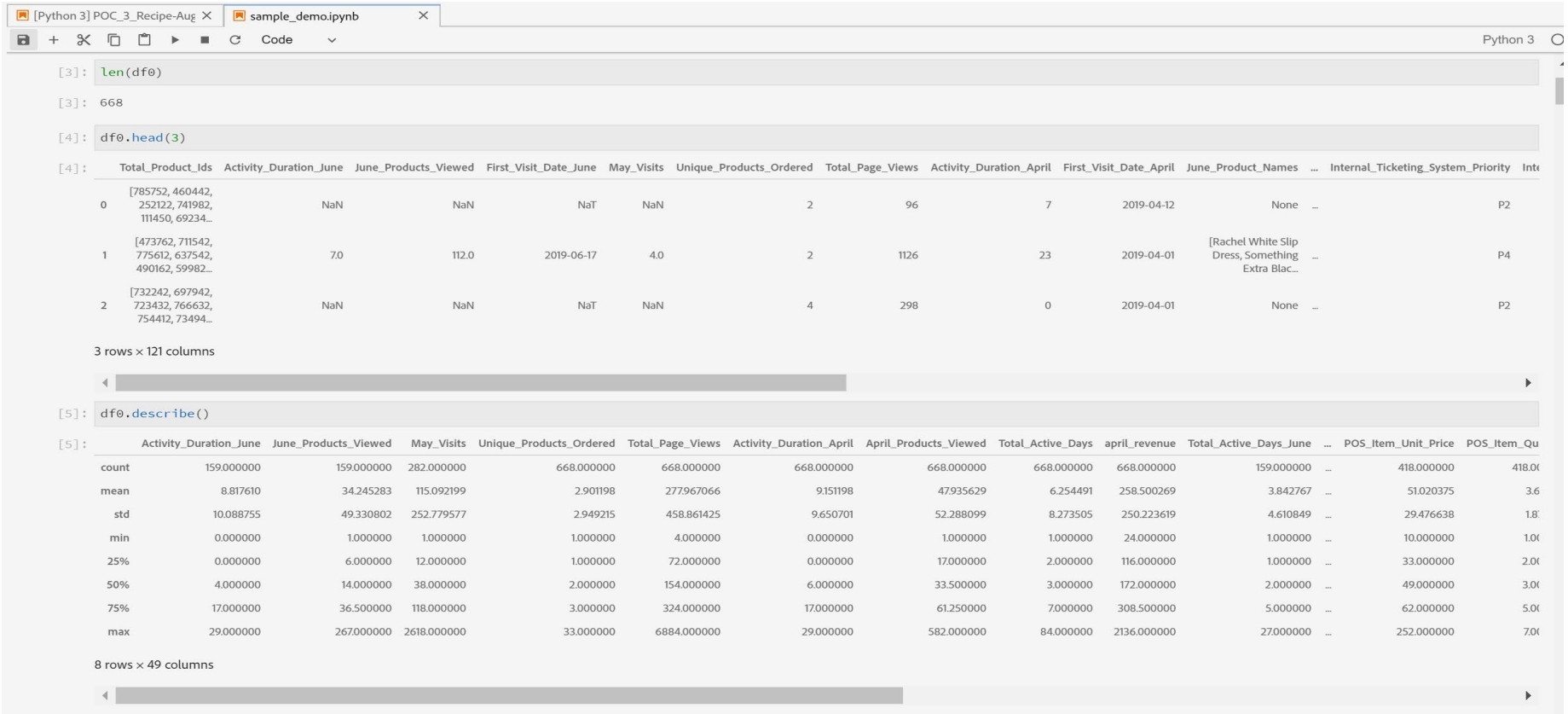
© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Data Science Workspace

Quick Summary statistics to understand the distribution of different attributes in data.

Use <dataset>.head(10) to view 10 records of the data

<dataset>.describe() gives a summary statistics of the data

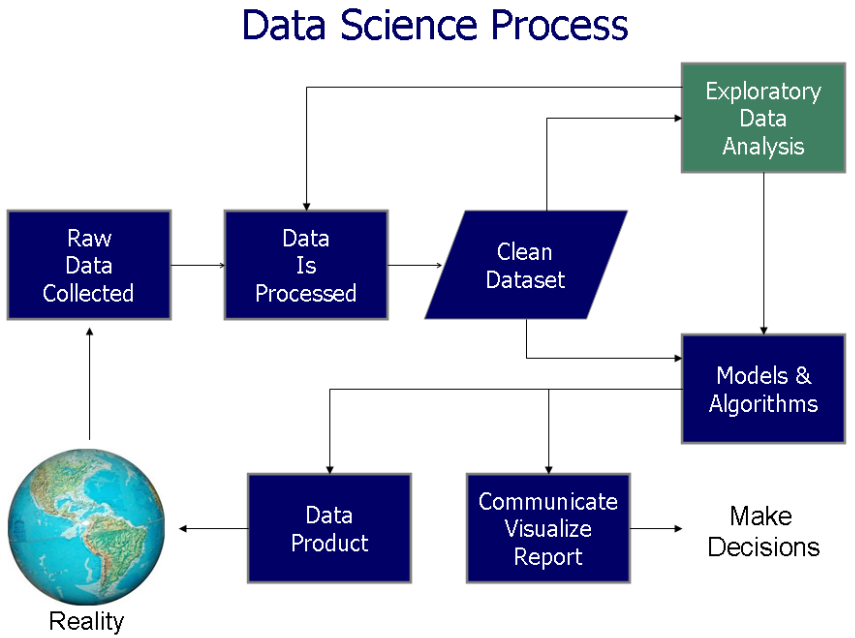


© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Exploratory Data Analysis

What is it and why is it important

- ✓ Exploratory data analysis is an approach to analyze and understand the data, discover patterns, anomalies and existing relationships with features present in the data
- ✓ It is often performed through visual methods incorporating techniques like density plots, scatter plots, box plots and correlation analysis
- ✓ This is an important step in building an advanced ML model because every ML algorithm follows a GIGO principle, i.e., Garbage In Garbage Out.



© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Exploratory Data Analysis
Different types of Visualizations

- ✓ Few types of data visualizations are:
  - ✓ Box Plots
  - ✓ Scatter Plots
  - ✓ Histograms
  - ✓ Correlation Matrix

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Data Science Workspace

Data Exploration – Box Plots

A Box plot is a visualization which can help data scientists detect outliers. Outliers tend to skew the model results and it is important to treat the outliers appropriately

In Python, the code used to generate Box plots is as below

```
plt.figure(figsize=(12,6))
sns.boxplot(x='Person_Gender', y='Total_Orders_Placed' , data=df0)
```

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

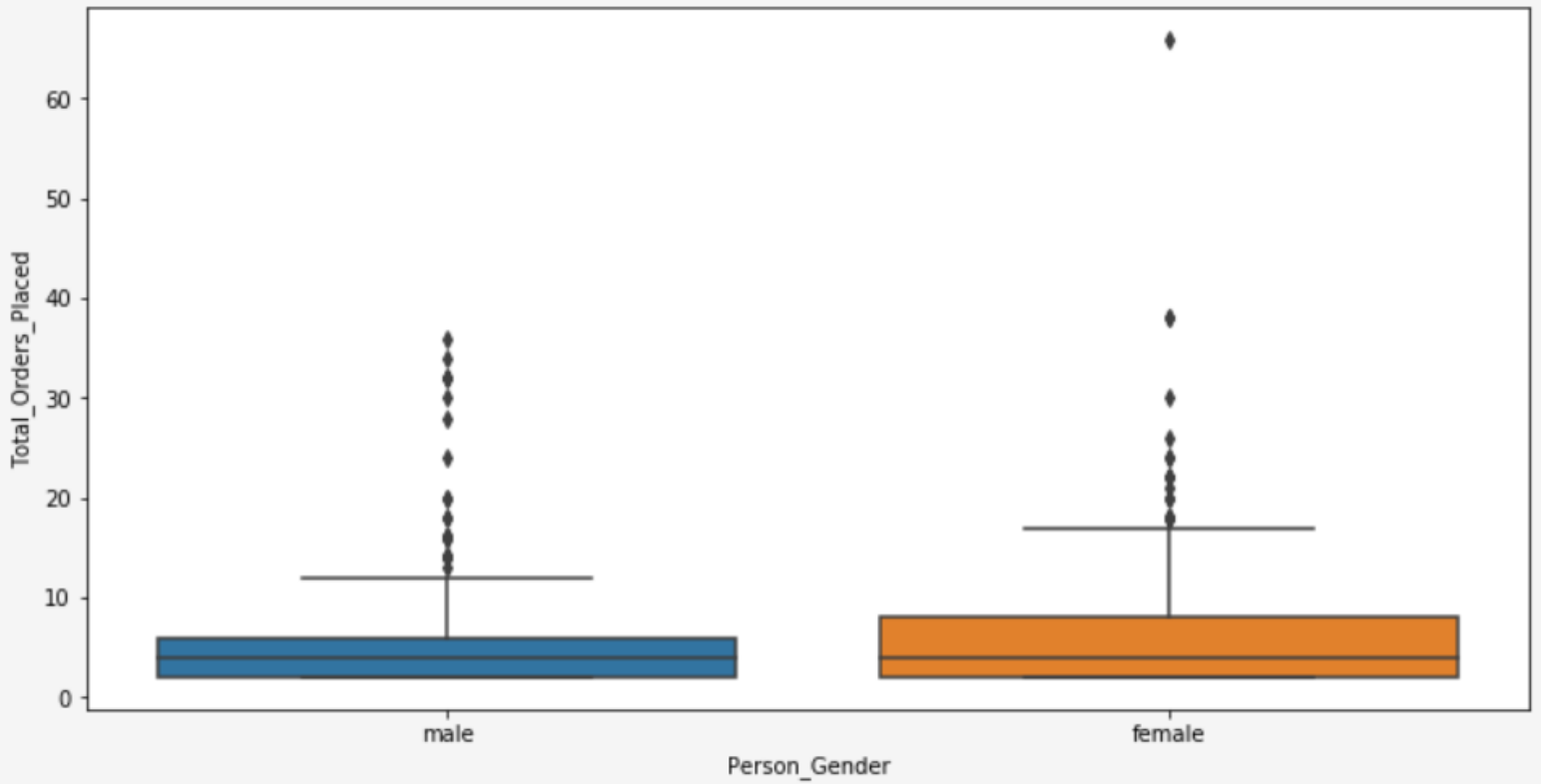
Data Science Workspace

Data Exploration – Box Plots

The below plots show presence of outliers

```
plt.figure(figsize=(12,6))
sns.boxplot(x='Person_Gender', y='Total_Orders_Placed' , data=df0)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe39247d470>
```



© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Data Science Workspace

Data Exploration – Scatter Plots

Scatter Plots are 2-dimensional plots that can help a data scientist evaluate relationships between 2 dimensions

In Python, the code used to generate scatter plots is as below

```
plt.figure(figsize=(12,6))
ax = sns.scatterplot(x="Total_Active_Days", y="Total_Products_Viewed", hue="Person_Gender", data=df0)
```

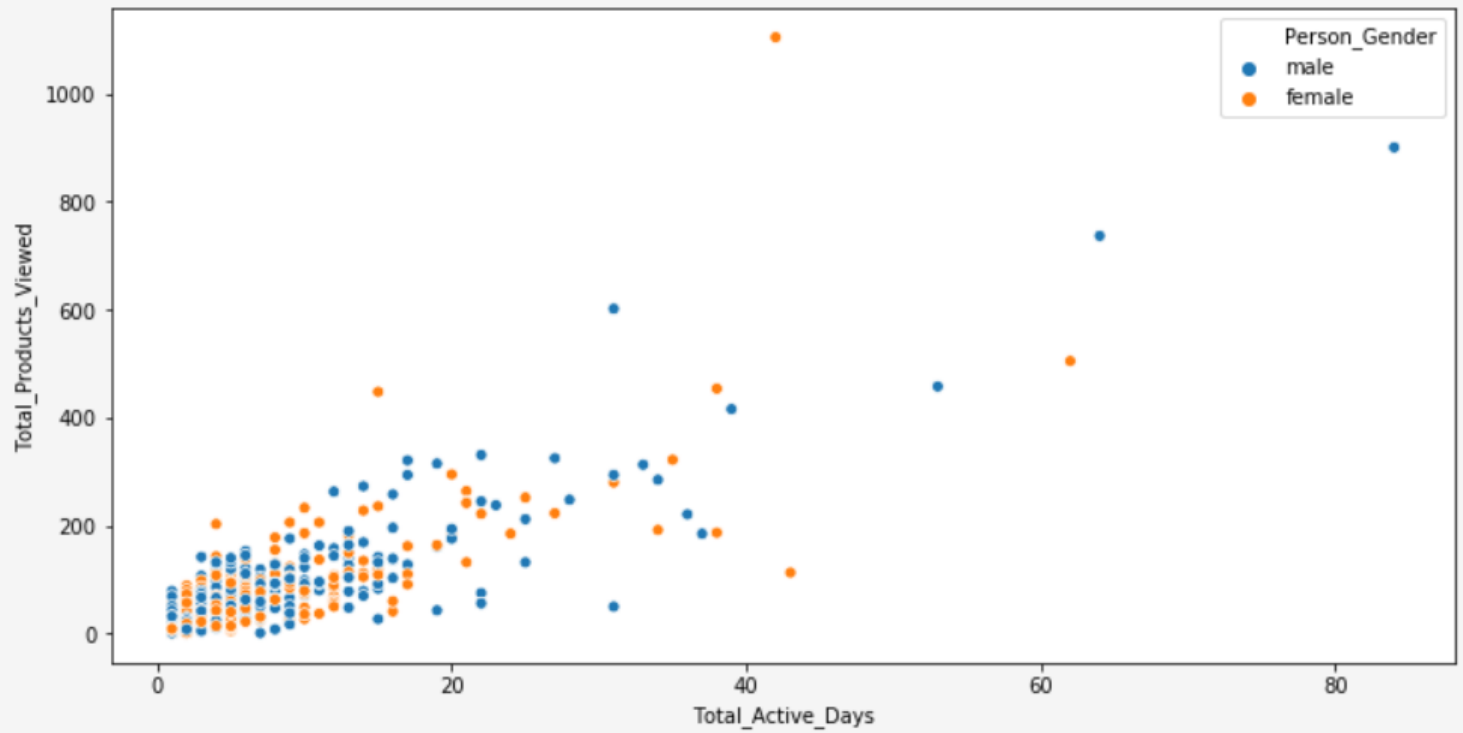
© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Data Science Workspace

Data Exploration – Scatter Plots

The below plots show presence of outliers

```
plt.figure(figsize=(12,6))
ax = sns.scatterplot(x="Total_Active_Days", y="Total_Products_Viewed", hue="Person_Gender", data=df0)
```



© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Data Science Workspace

Data Exploration – Histograms

A histogram is a plot that is used to discover the underlying frequency distribution (shape) of a set of continuous numerical data like number of orders, age, etc.

In Python, the code used to generate Box plots and scatter plots is as below

```
import matplotlib.pyplot as plt
%matplotlib inline
plt.figure(figsize=(12,6))
plt.title('Total_Orders_Placed')
df0['Total_Orders_Placed'].hist(bins=[0,5,10,15,20,25,30,35])
```

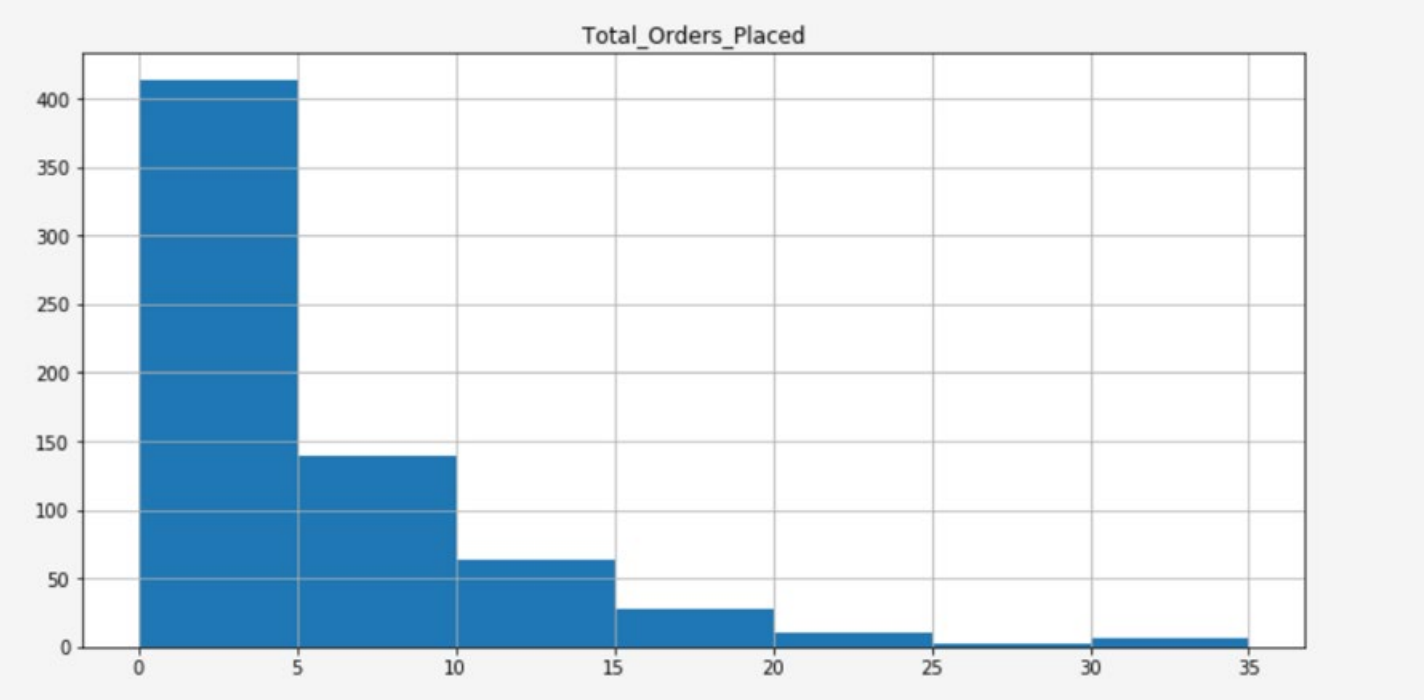
© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Data Science Workspace

Data Exploration – Histograms

The output of the code is below

Interpretation: This histogram is done on Total orders placed and the plot shows that maximum customer place <5 orders



© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Data Science Workspace

Data Exploration – Correlation matrix

A Correlation Matrix is a table that gives correlation coefficients between variables. This matrix is used to summarize data and provide insights into relationships between different variables. It is also used as inputs to advanced analytics

In Python, the code used to generate a correlation matrix is as below

```
import seaborn as sns
plt.figure(figsize=(5,5))
sns.heatmap(df1.corr(), annot = True)
```

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Data Science Workspace

Data Exploration – Correlation matrix

Interpretation: Correlation coefficients range from -1 to +1, signs indicating the direction of the relation

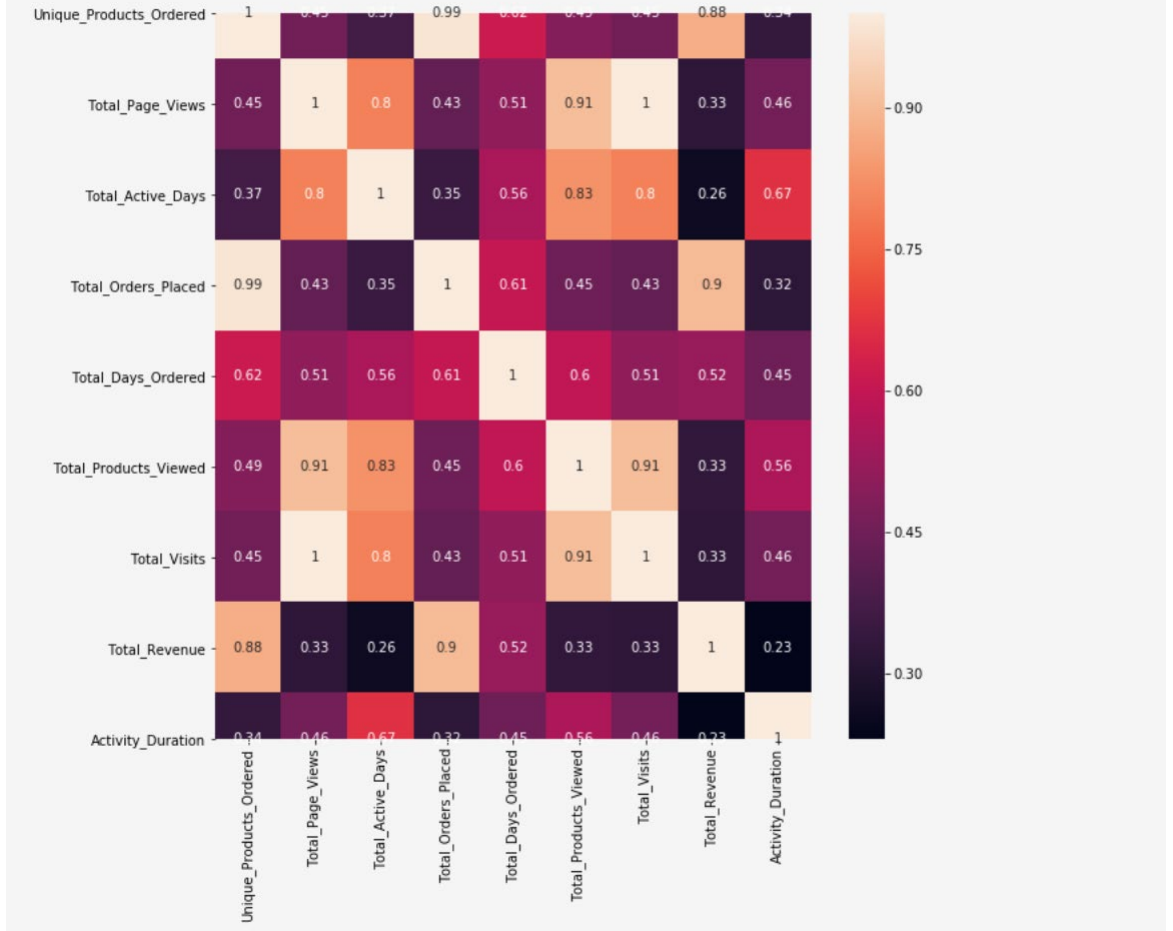
Below are thumb rules to interpret a correlation matrix

Absolute Correlation coefficients that are

- 0.8 – 1 – Very Strong correlation
- 0.6 – 0.8 – Strong correlation
- 0.4 – 0.6 – moderate correlation
- <0.4 – No correlation

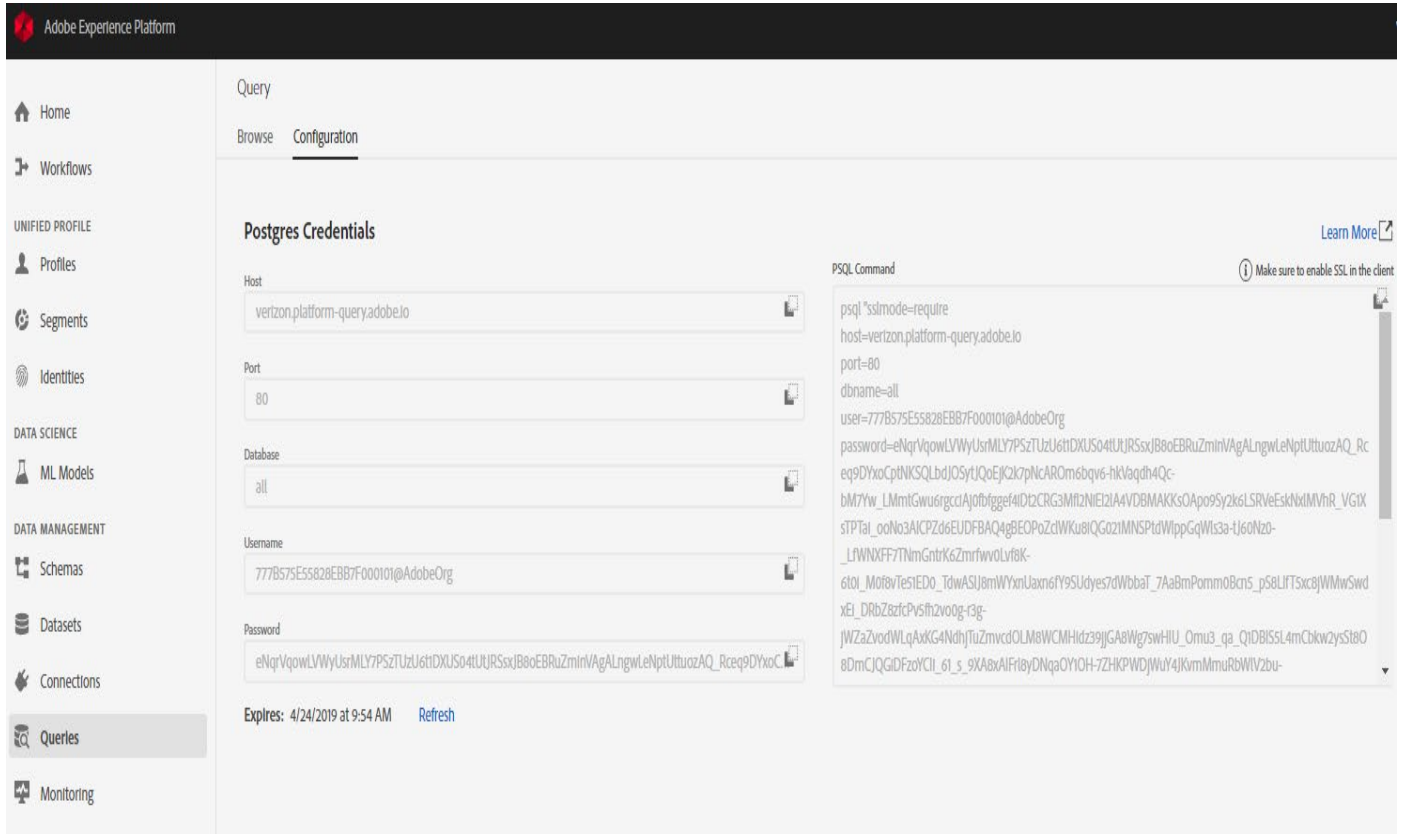
```
import seaborn as sns
plt.figure(figsize=(10,10))
sns.heatmap(df1.corr(), annot = True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe391ebd4e0>
```



© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Interacting with 3rd party tools
Tableau and PowerBI

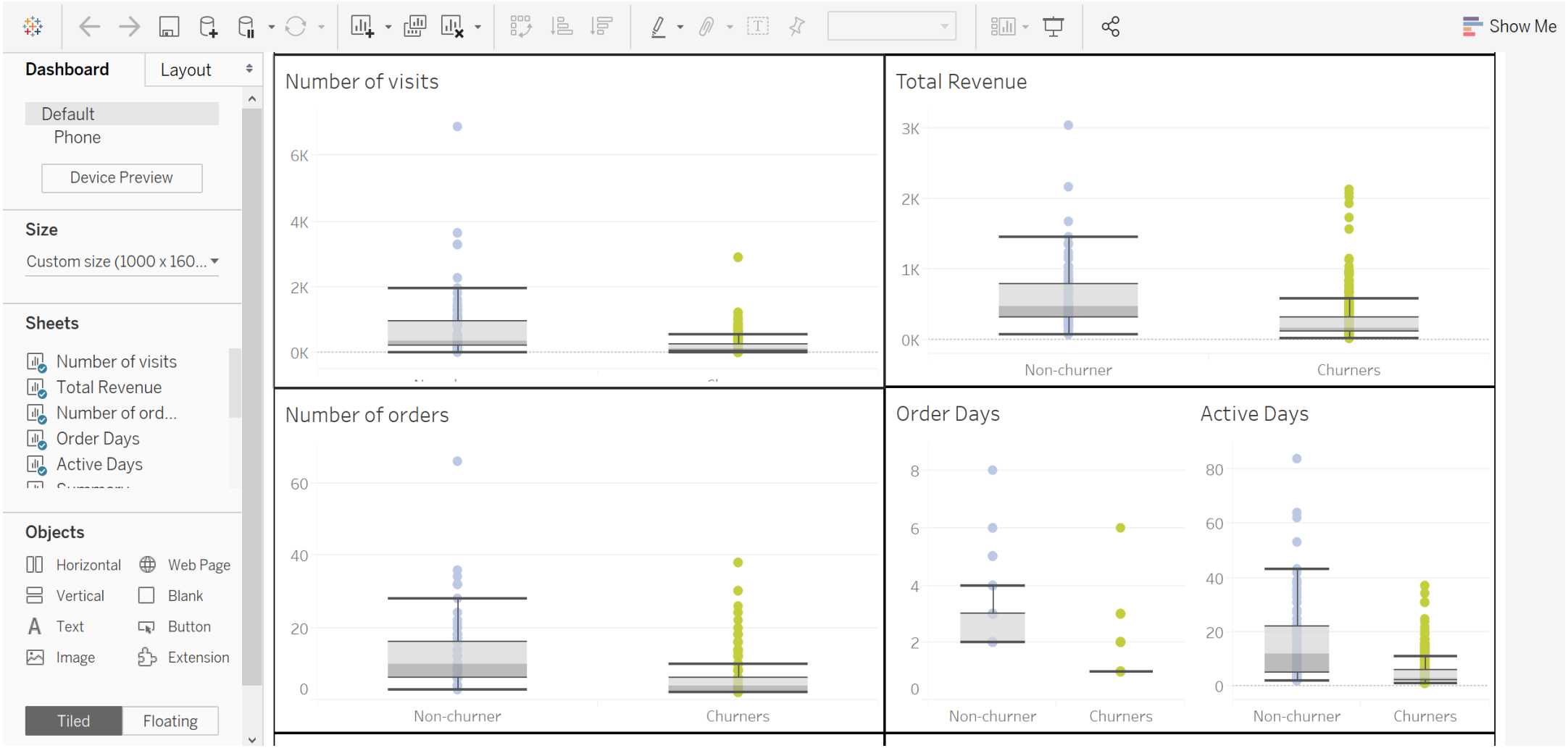


- BI Tools
  - Tableau, PowerBI
  - Provides credentials and instructions for connecting supported clients
  - Connectivity achieved using existing PostgreSQL drivers

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Interacting with 3rd party tools

Build Dashboards in third party data visualization tools such as tableau



AEP data accessed and read in Tableau

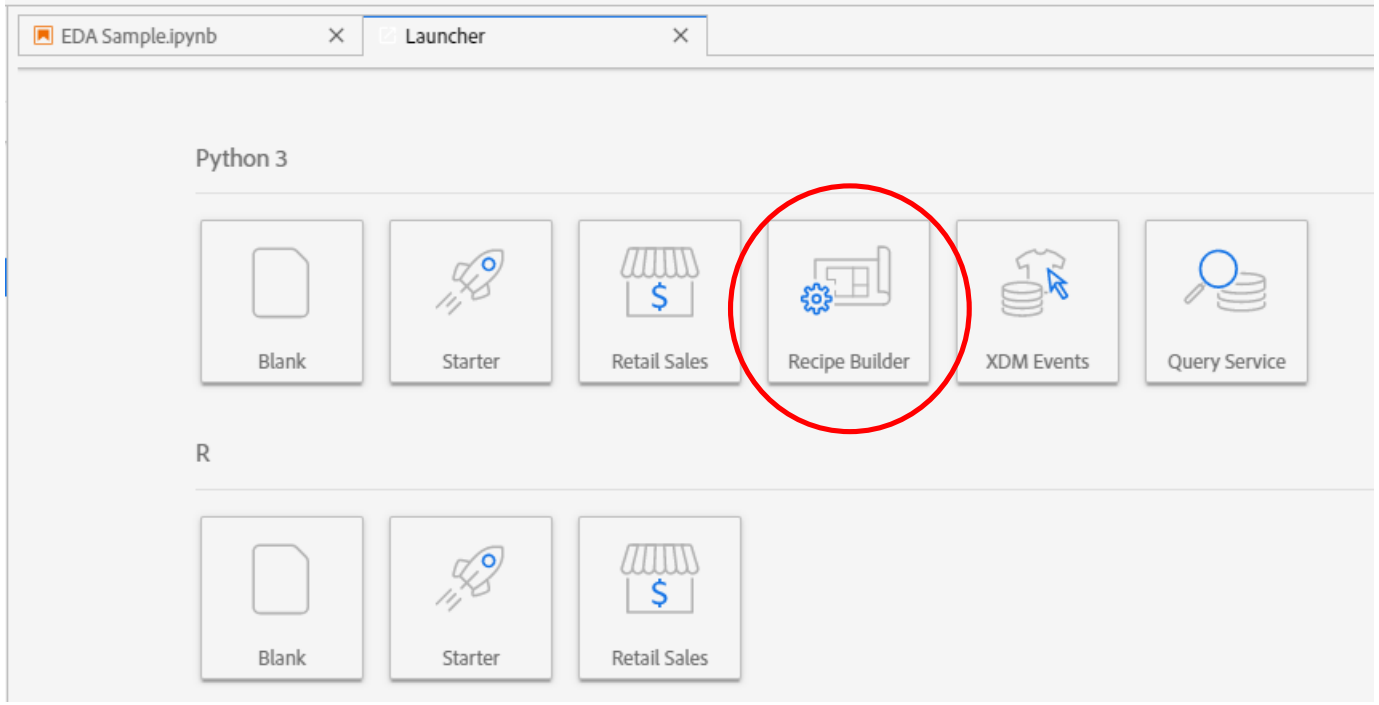
© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Recipe Building

Build a recipe out of the trained model to be used as a reusable component to score multiple populations

A recipe is a reusable component that is built out of a pre-trained and validated model which can be used to

score multiple other populations



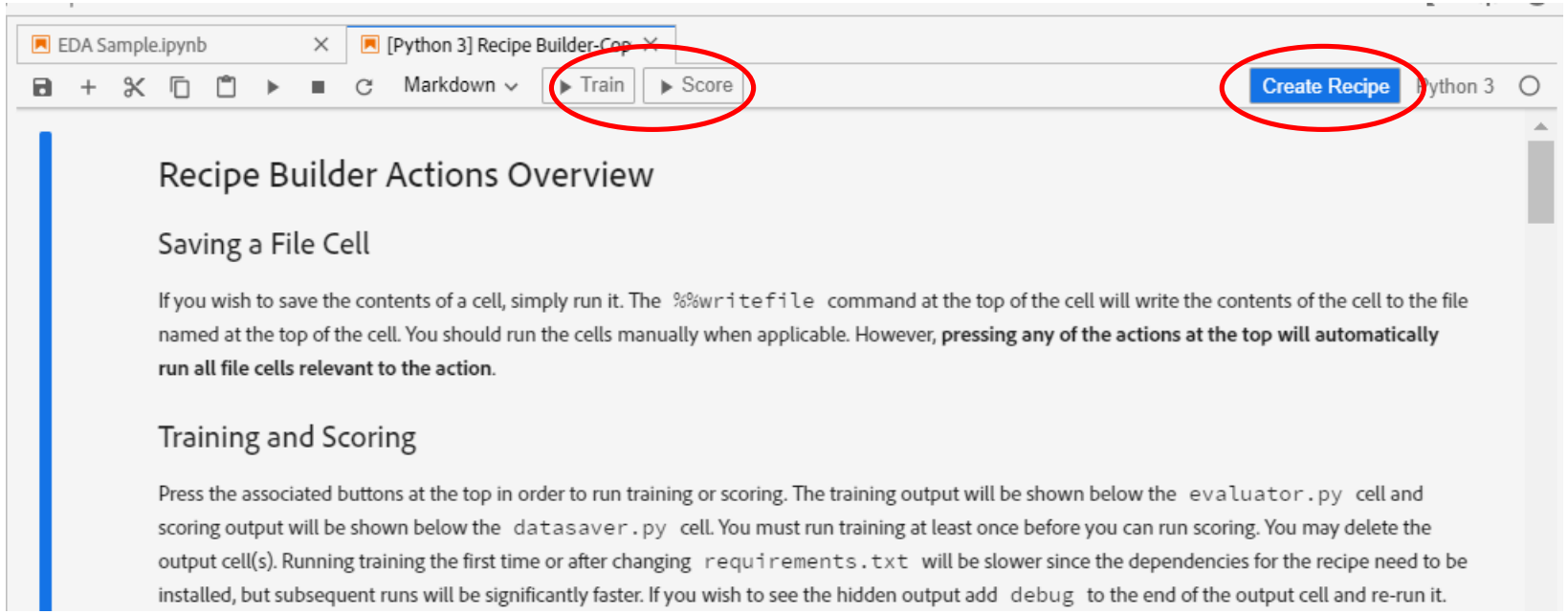
Select Recipe Builder

from Launcher

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Recipe Building

Build a recipe out of the trained model to be used as a reusable component to score multiple populations



Step 1 – Train your model

Step 2 – Score the model

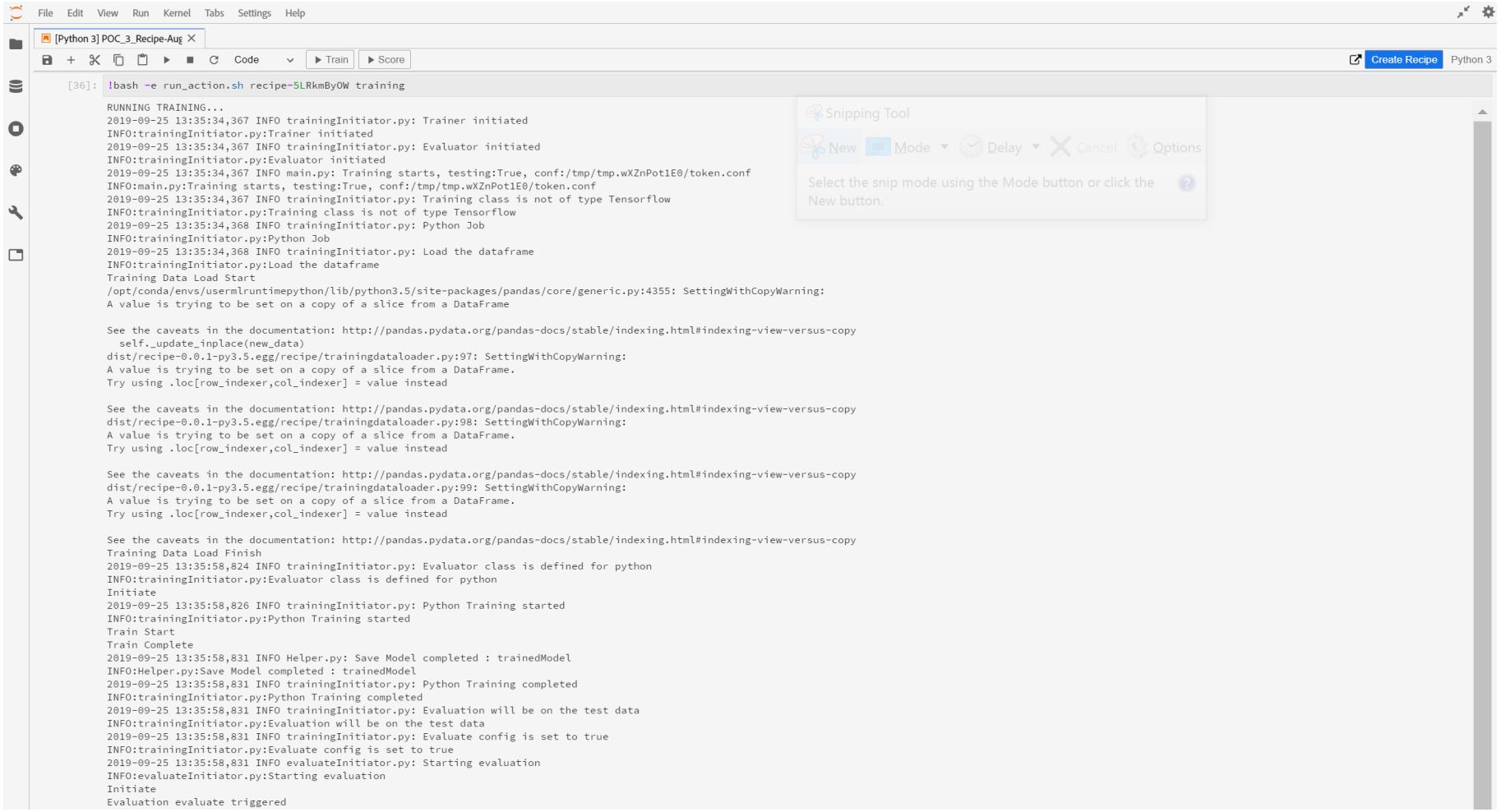
Step 3 – Select “Create Recipe” to create a new recipe

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Recipe Building

Build a recipe out of the trained model to be used as a reusable component to score multiple populations

Step 1 – Train the model

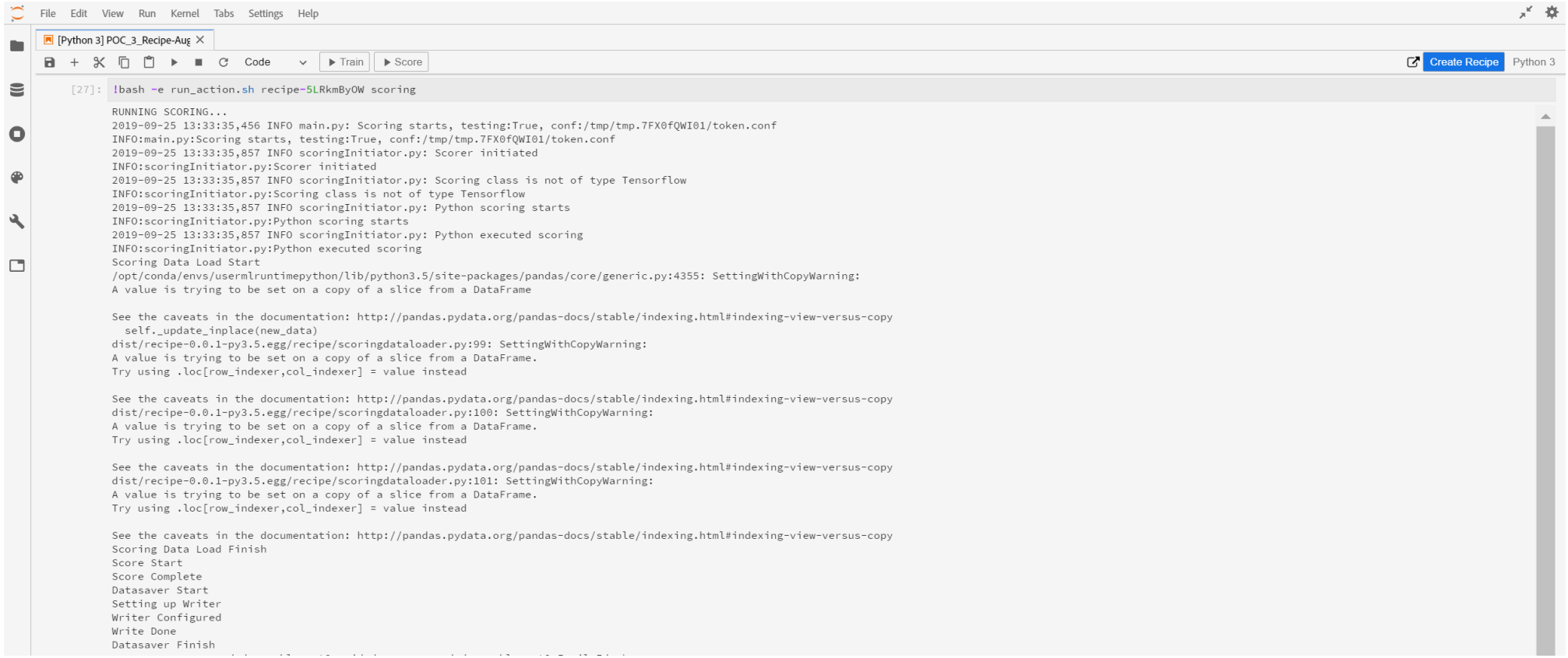


© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Recipe Building

Build a recipe out of the trained model to be used as a reusable component to score multiple populations

Step 2 –Score the model

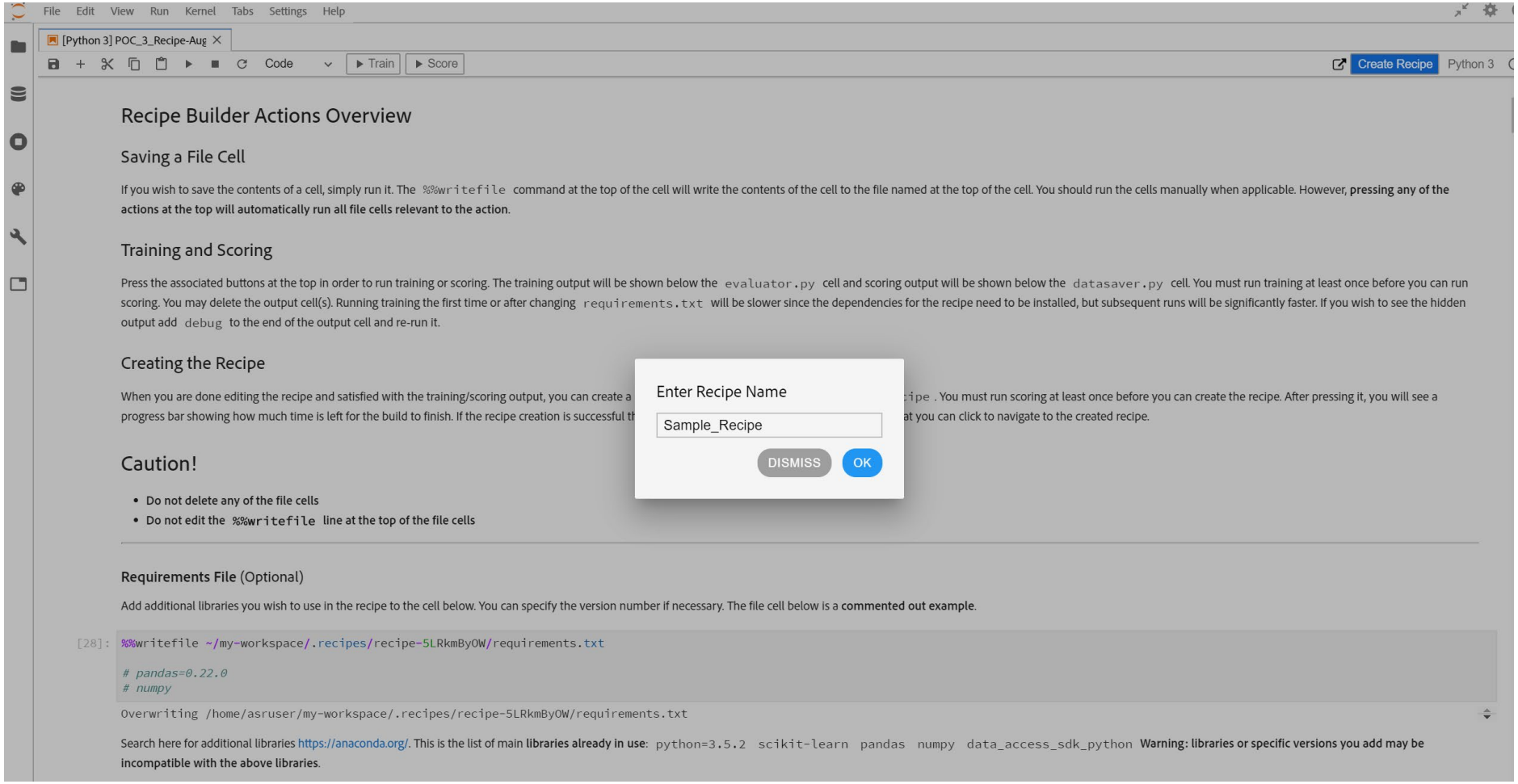


© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Recipe Building

Build a recipe out of the trained model to be used as a reusable component to score multiple populations

Step 3 –Build Recipe – Give a name

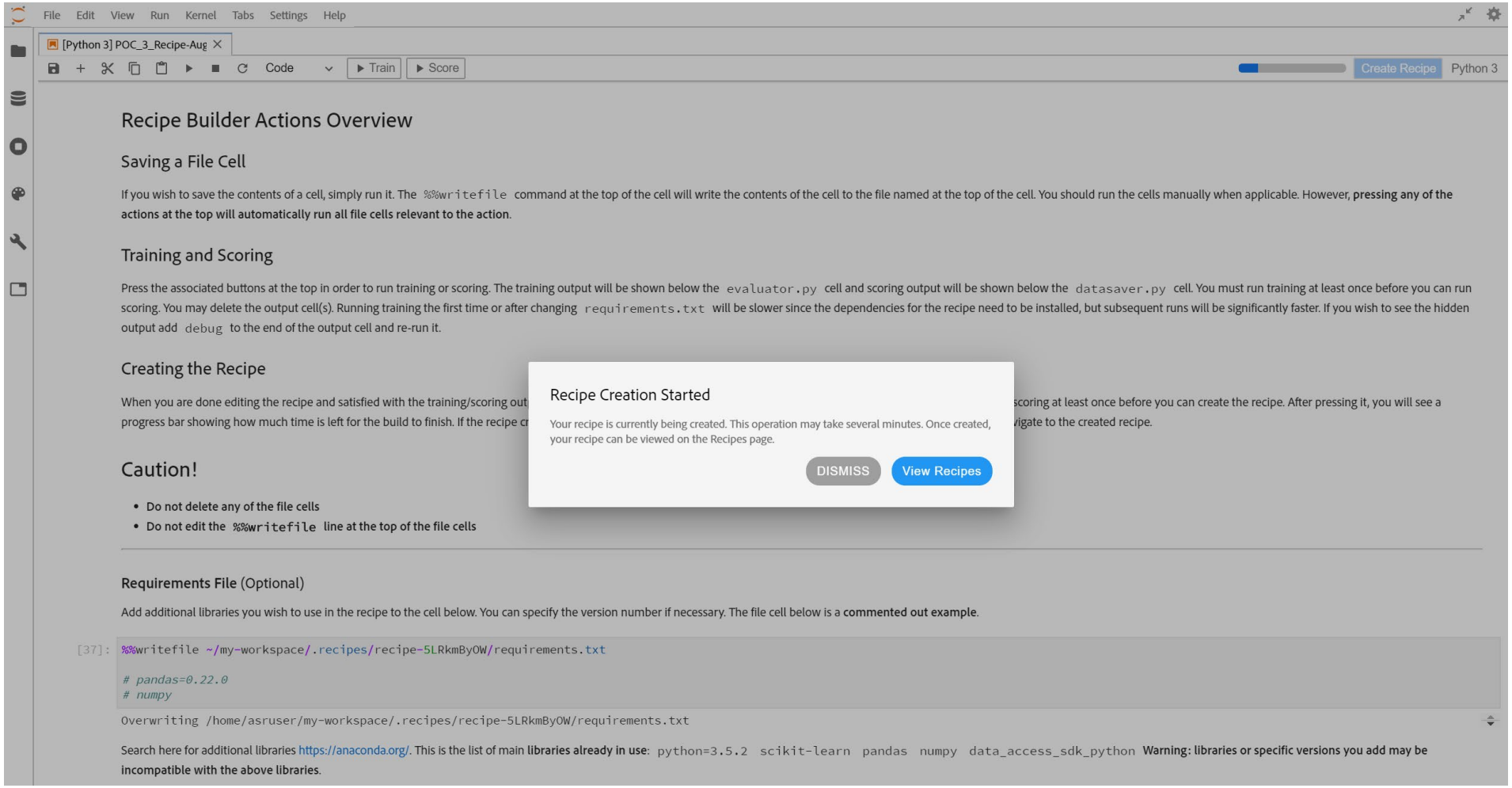


© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Recipe Building

Build a recipe out of the trained model to be used as a reusable component to score multiple populations

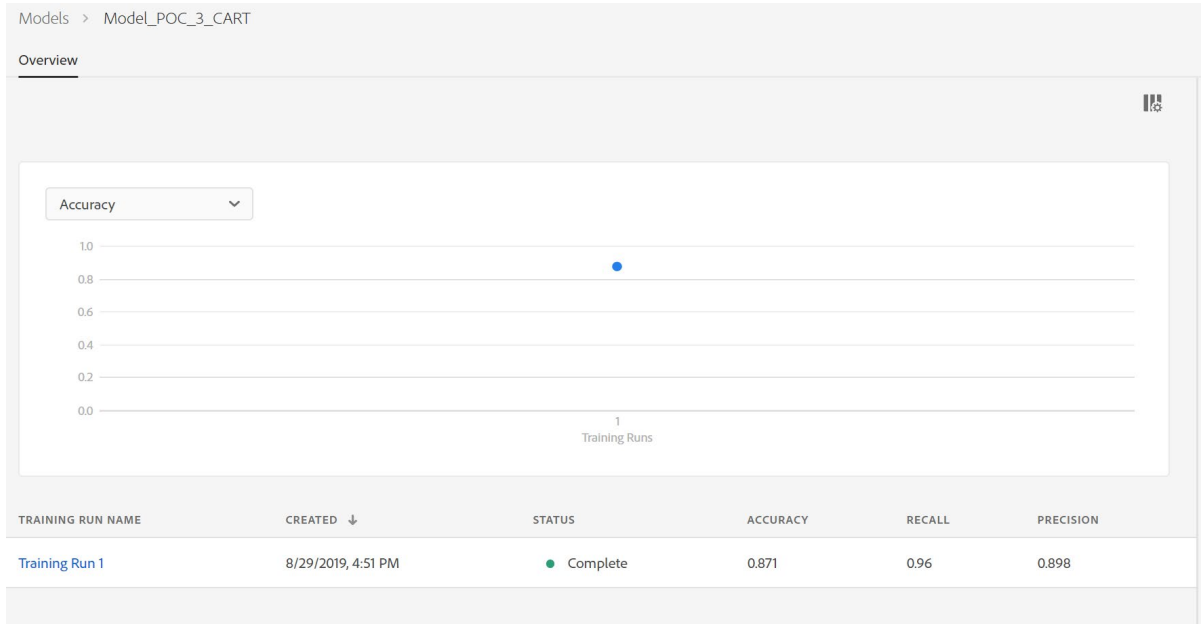
Step 3 –Build Recipe

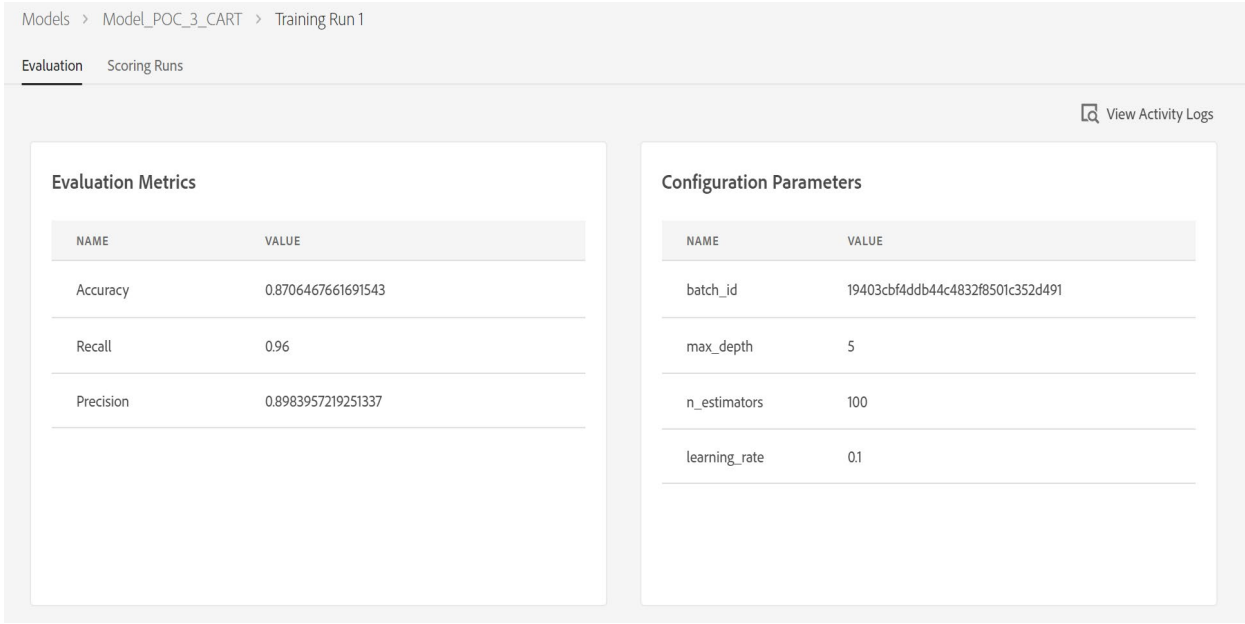


© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Train and **Evaluate** ML Model

Train the model on a subset of the data and evaluate on other subset to check the performance.

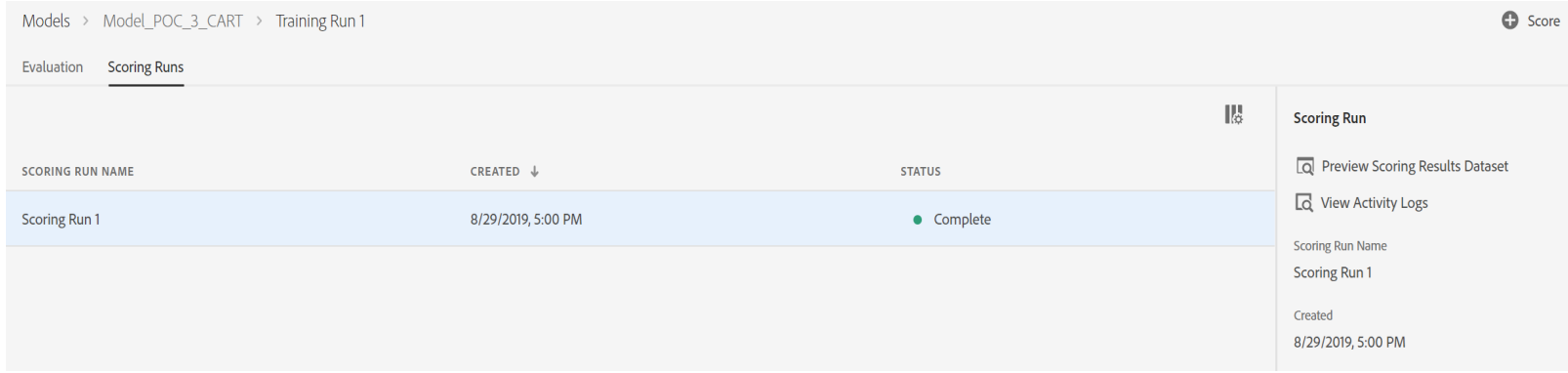




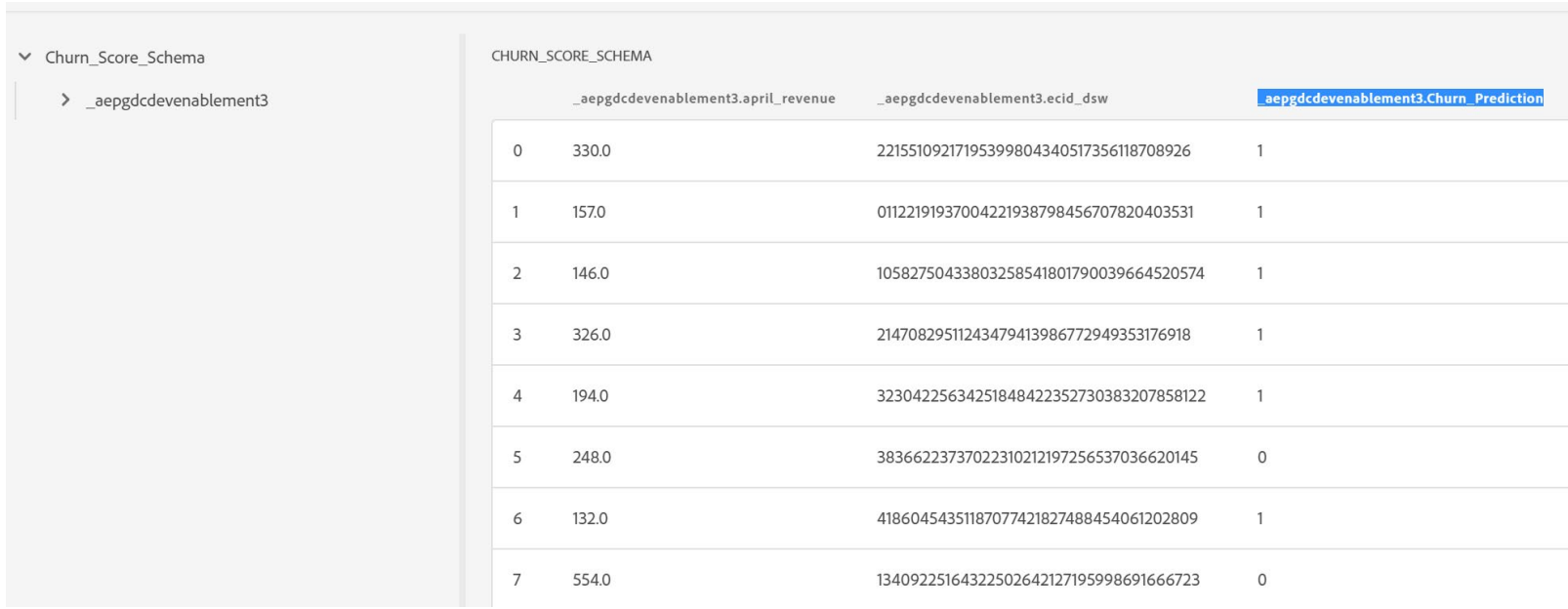
© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Score New Data

Use the trained model to score new data coming into the platform and record model predictions in the output dataset.



Scoring Run



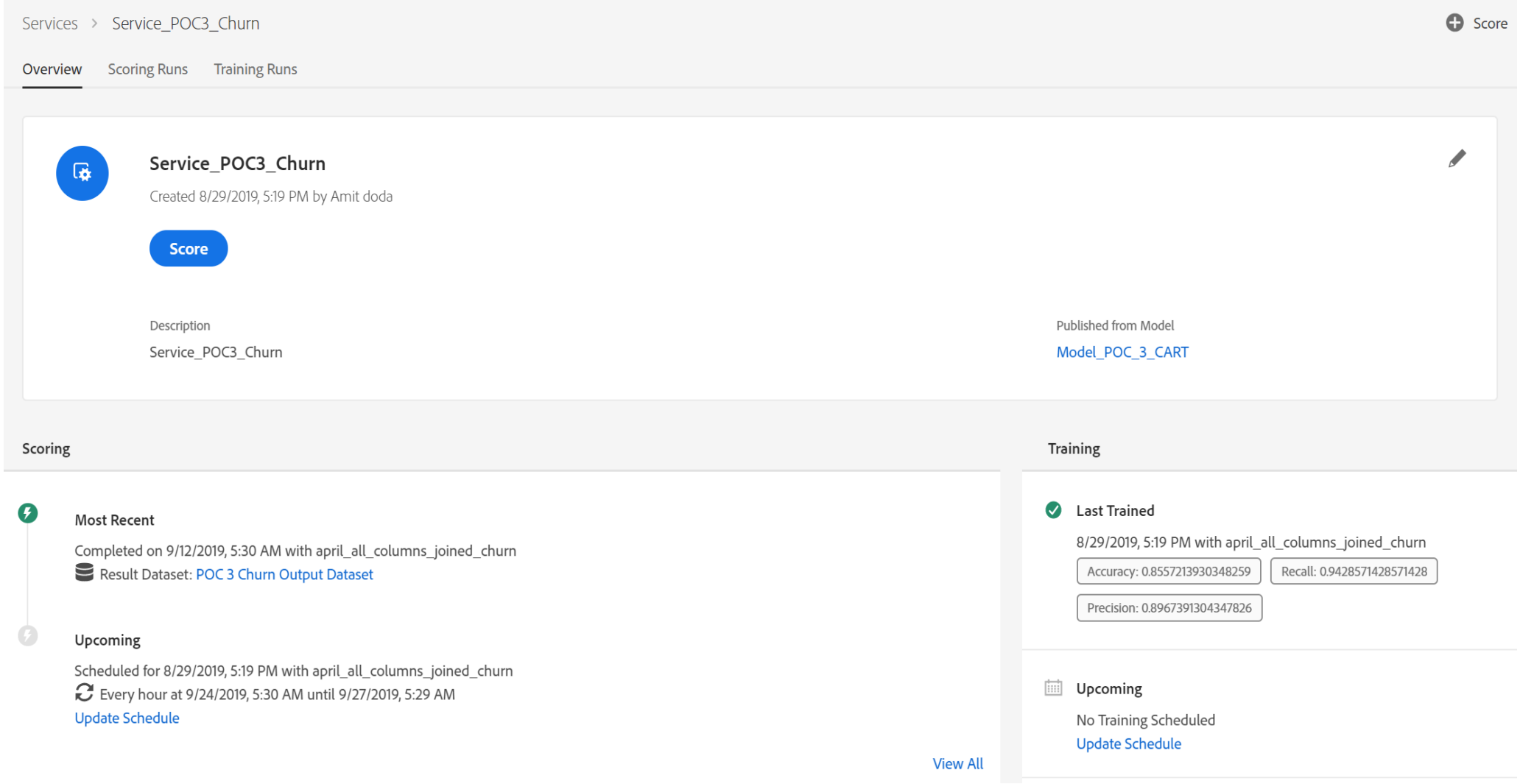
	_aepgdcdevenablement3.april_revenue	_aepgdcdevenablement3.ecid_dsw	_aepgdcdevenablement3.Churn_Prediction
0	330.0	221551092171953998043405173561187089 26	1
1	157.0	011221919370042219387984567078204035 31	1
2	146.0	105827504338032585418017900396645205 74	1
3	326.0	214708295112434794139867729493531769 18	1
4	194.0	323042256342518484223527303832078581 22	1
5	248.0	383662237370223102121972565370366201 45	0
6	132.0	418604543511870774218274884540612028 09	1
7	554.0	134092251643225026421271959986916667 23	0

Output Dataset with predictions

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Model as a **Service :** Publish & Schedule

Publish the model as a service and schedule it to run (both train and score) hourly, daily, weekly etc. on the new set of data.



© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.

Scoring **Runs**

Hourly scheduled scoring runs of a sample ML Service.

Overview | Scoring Runs | Training Runs

SCORING RUN NAME	CREATED ↓	STATUS
Scoring Run 25	9/12/2019, 5:30 AM	Complete
Scoring Run 24	9/12/2019, 4:32 AM	Complete
Scoring Run 23	9/12/2019, 3:31 AM	Complete
Scoring Run 22	9/12/2019, 2:30 AM	Complete
Scoring Run 21	9/12/2019, 1:33 AM	Complete
Scoring Run 20	9/12/2019, 12:32 AM	Complete
Scoring Run 19	9/11/2019, 11:31 PM	Complete
Scoring Run 18	9/11/2019, 10:31 PM	Complete
Scoring Run 17	9/11/2019, 9:30 PM	Complete
Scoring Run 16	9/11/2019, 8:30 PM	Complete

© 2016 Adobe Systems Incorporated. All Rights Reserved. Adobe Confidential.


Adobe