Predicting Flights with Azure Databricks

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Agenda

- Introducing the flight prediction scenario
- What is Databricks?
- Exploring Databricks while getting to the solution

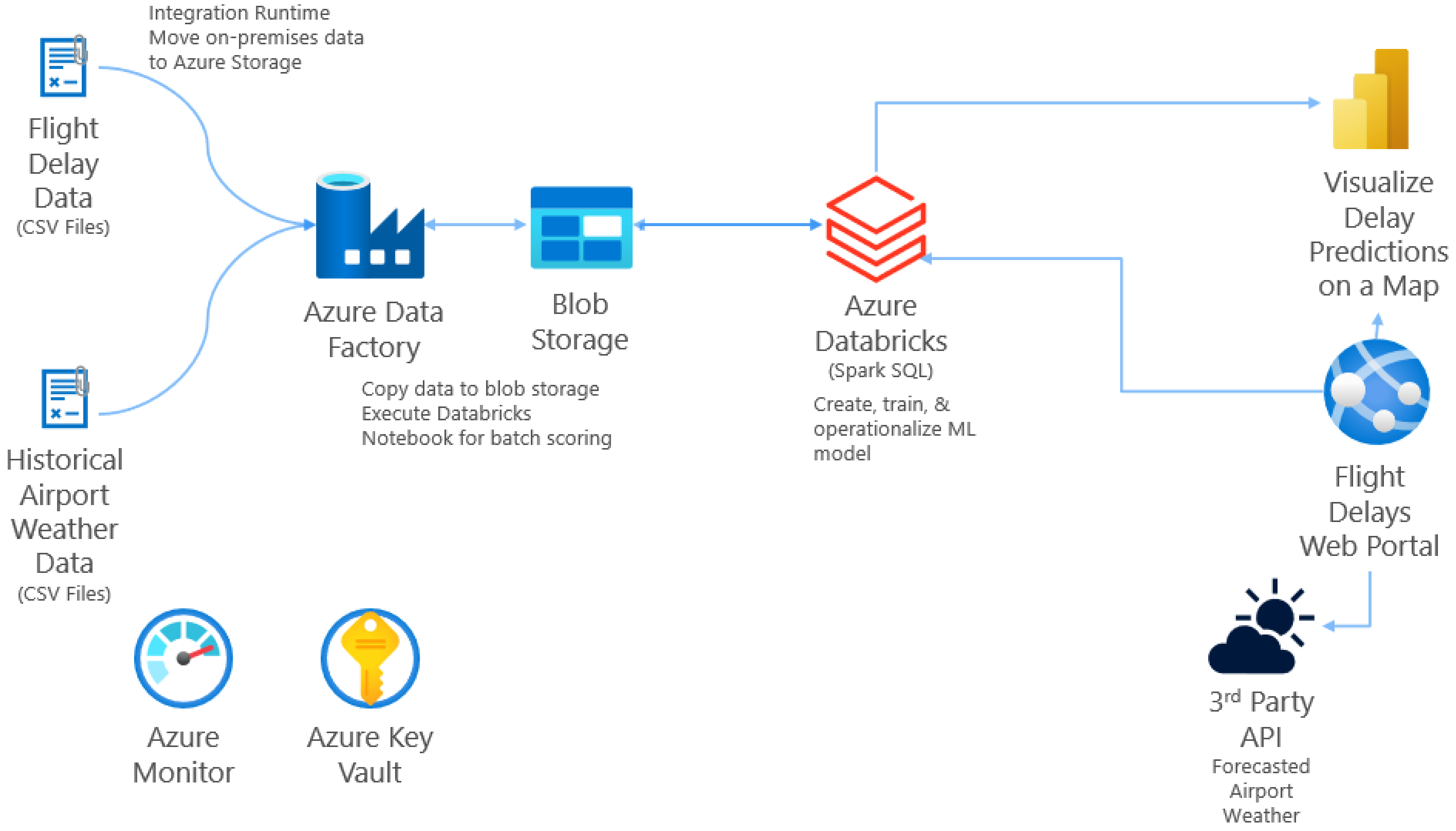
Scenario

- Margie's Travels – a *fictitious* concierge for business travelers - wants to enable their agents to **enter in the flight information** and **produce a prediction** as to **whether the departing flight will encounter a 15-minute or longer delay**, **considering the weather forecast** for the departure hour.

- Data details:
  - Sample data from 2013
  - 2.7 million flight delays with airport codes - **examples**
  - 20 columns – **features**

Training the model

- Using Decision Tree algorithm (**binary classification**) from Spark MLlib
- Part of the historical data (2013) is used for training and another part for test
- Flights are delayed have **DepDel15** value of 1
  - OST_R | BTS | Transtats – Departure Delay Indicator of 15 minutes or more
- Sample keeps all delayed and a downsample of 30% not delayed – **stratified sampling**
- One-Hot encoded categorical variables and use the Pipeline API
- 3-fold cross validation
- Save the model for use in other notebooks and saved in case cluster restarts



Source: Microsoft Cloud Workshop: Big Data Analytics and Visualization, Hands-on Lab

What is Databricks?

- Web-based analytics platform with 3 workloads:
  - **Databricks SQL** – for querying data lakes with SQL
  - **Databricks Data Science & Engineering** – for data engineers, data scientists, and ML engineers for data ingestion and analysis using the Apache Spark Ecosystem. This is the classic Databricks environment.
  - **Databricks Machine Learning** – experiment tracking, model training, feature development and management

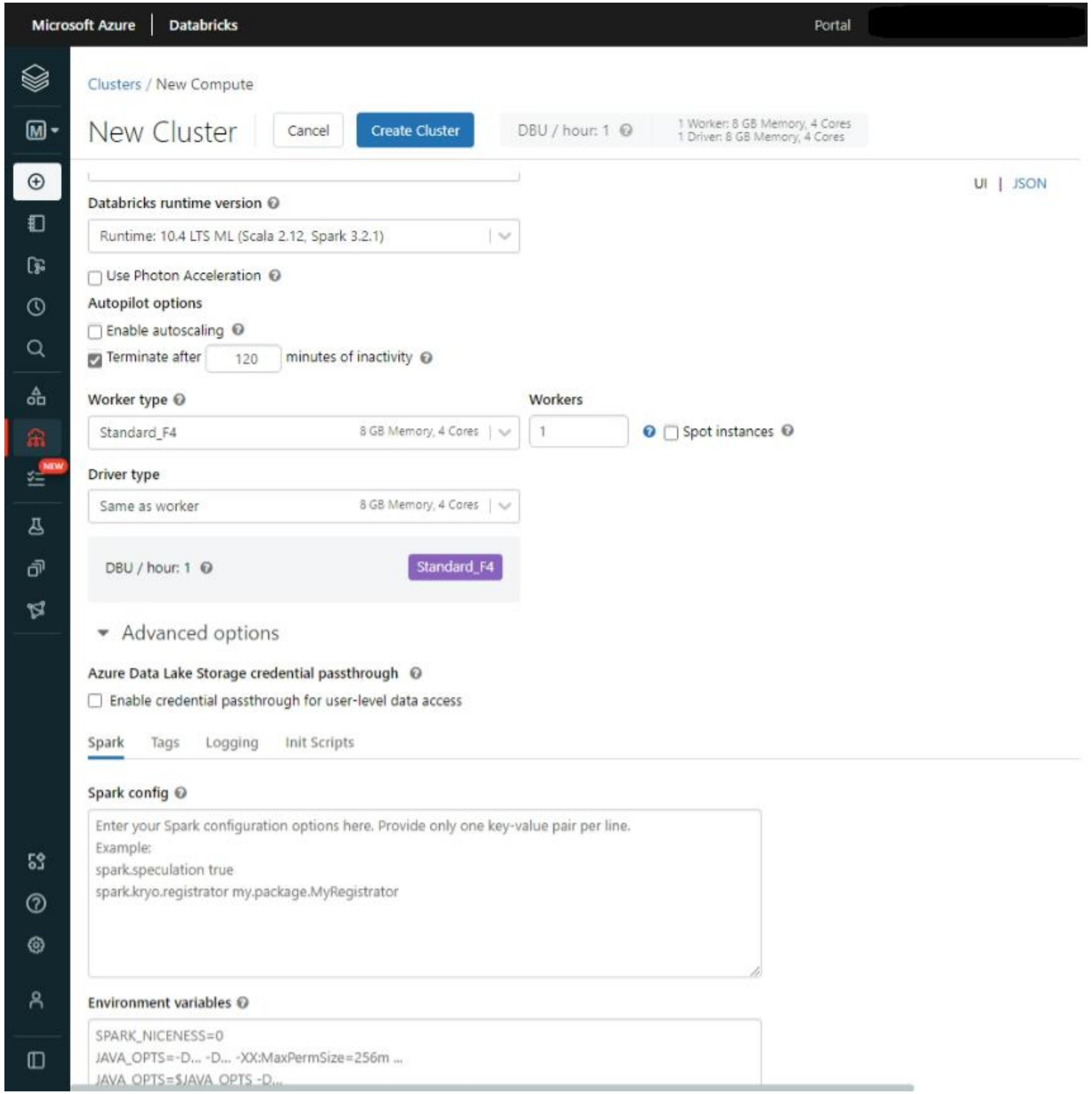
Loading the Data

Data to Load

Data	CSV Name	Databricks Table Name
Flight delays with airport codes	FlightDelaysWithAirportCodes.csv	flight_delays_with_airport_codes
Flight weather with airport code	FlightWeatherWithAirportCode.csv	flight_weather_with_airport_code
Airport code location lookup	AirportCodeLocationLookupClean.csv	airport_code_location_lookup_clean

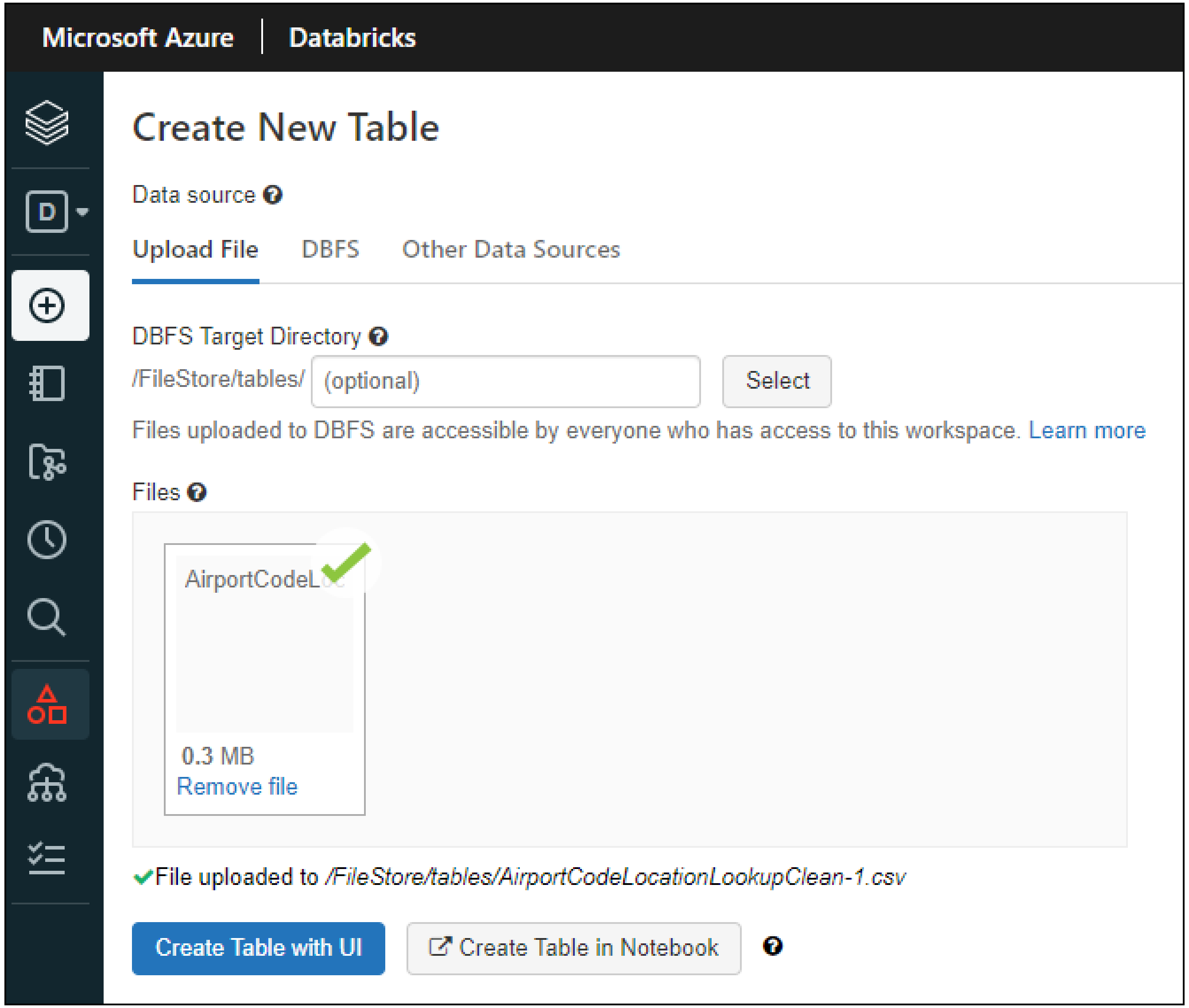
Creating a Cluster

- Clusters can be set for high concurrency, single node, or standard
- Runtimes include:
  - Standard or ML
  - ML runtimes include GPU or non-GPU
- Photon acceleration can be supported in cases
- Autoscaling is supported
- Terminate due to inactivity
- Workers and drivers support:
  - General usage
  - Compute optimized
  - Memory optimized
  - Storage optimized
  - GPU accelerated
- Integration with Azure Data Lake Storage
- Spark config and environment variables
- Init scripts
- … and more

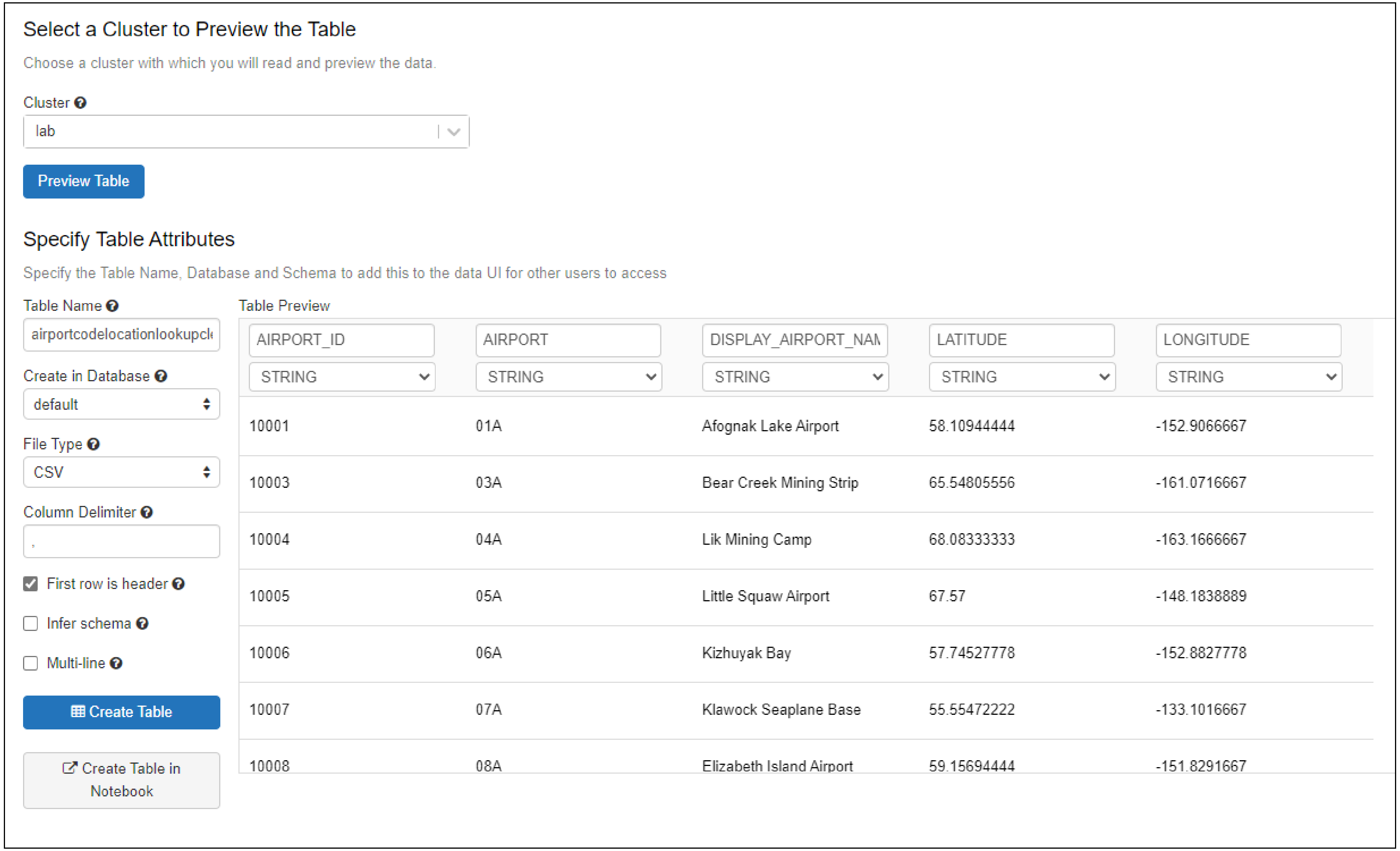


Loading the Data into Azure Databricks

- Done in the Data Science and Engineering load
- Uses a cluster for loading data into Azure Databricks
- Tables have 2 different types:
  - Global tables - accessible across all clusters
  - Local tables - available only within one cluster



Creating a Table

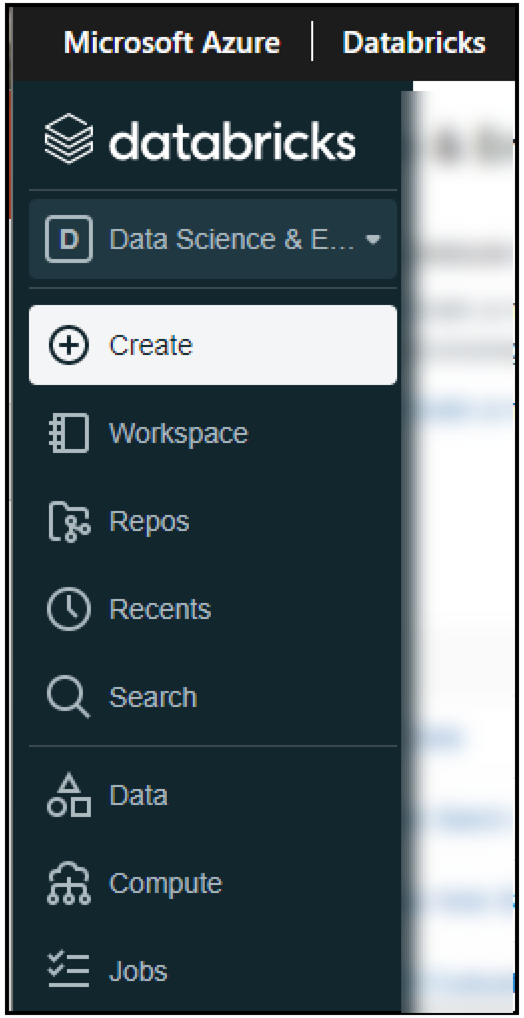


Databricks
Data Science & Engineering

Classic Databricks

Databricks Data Science & Engineering

- Classic Databricks environment
- Backbone for the ML environment
- Key components:
  - Workspaces
  - Runtimes
  - Clusters
  - Notebooks
  - Jobs

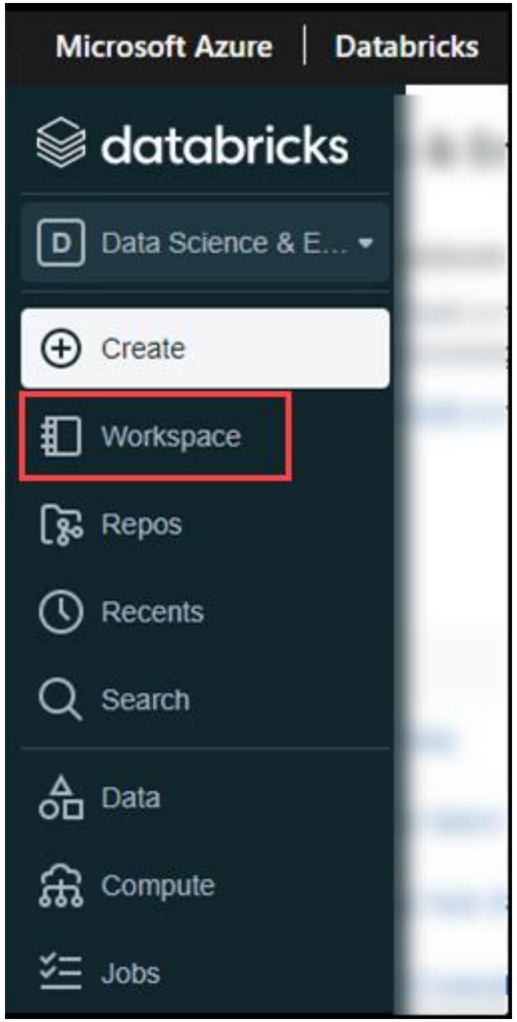


Preparing our data

- This is all in a **notebook** labeled *01 Data Preparation*.
- Preparation steps:
  1. Explore the data.
  2. Munge the data for flight delays with airport codes with R.
  3. Export the prepared data to a **global table**.
  4. Prepare the weather data with Python.
  5. Join the flight and weather datasets using Spark SQL.
  6. Store the flight delays with weather in a **global table**.

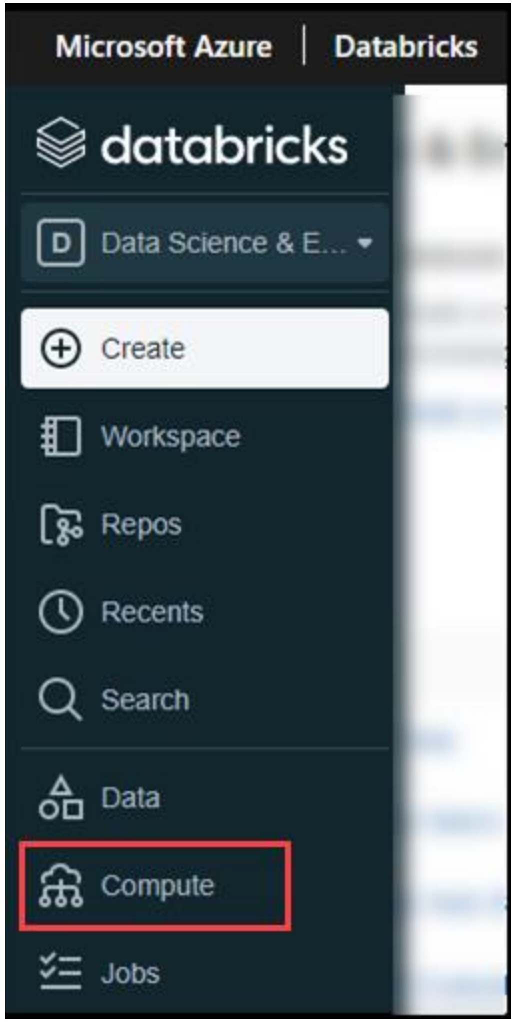
Workspaces

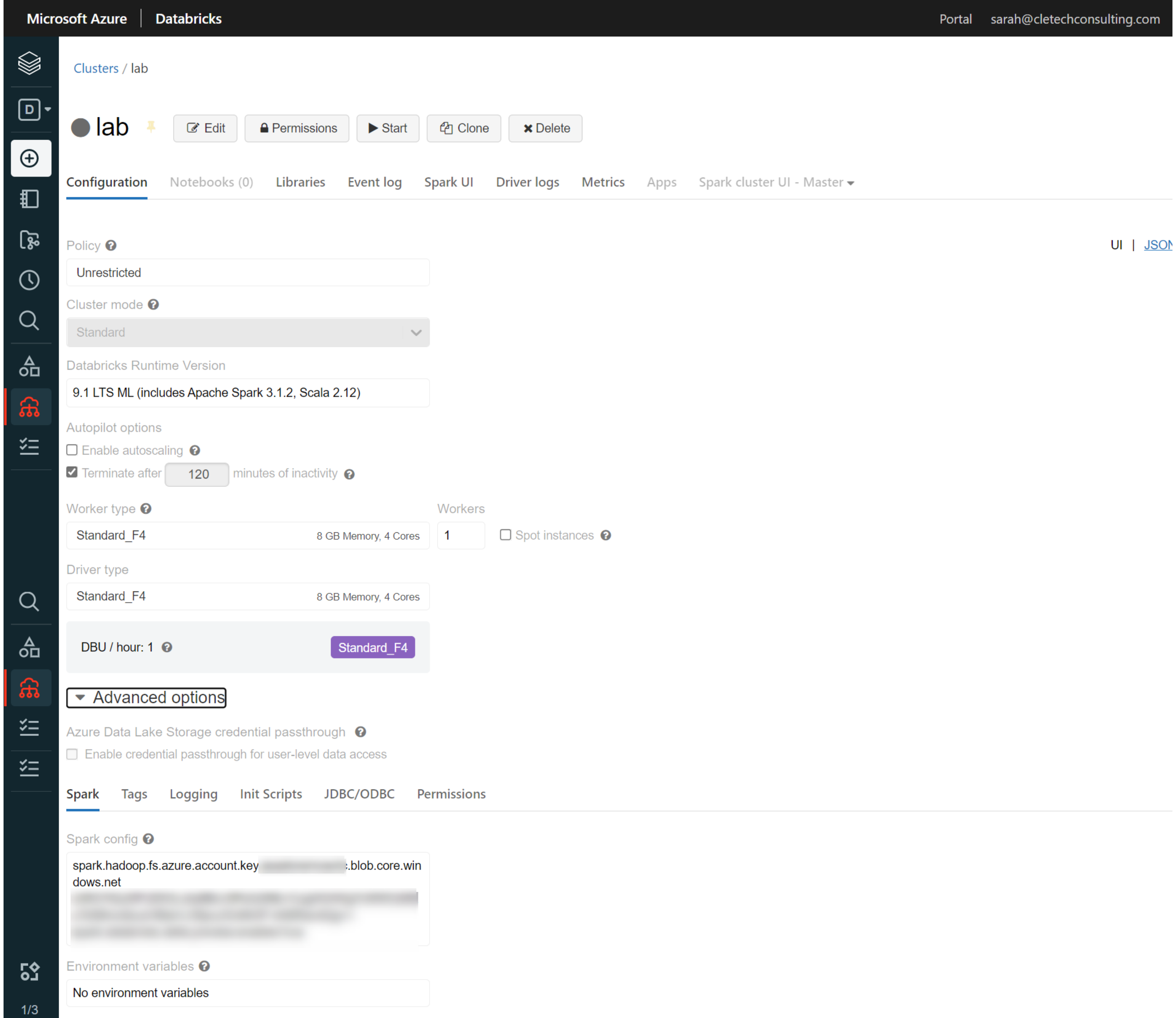
- Environment for all Azure Databricks assets
- Organizes notebooks, libraries, and experiments into folders
  - **Notebooks** – runnable code + markdown
  - **Libraries** – third party resources or locally built code accessible to clusters
  - **Experiments** – MLflow machine learning model activities
- Provides access to clusters and jobs
- Integrates with Git through Repos



Clusters

- Powerhouse for Azure Databricks
  - Compute and configuration
  - Supports workloads for:
    - Data engineering
    - Data science
    - Data analytics
  - Takes time to start
- Two types
  - **All-purpose** – can be shared for collaborative works; manually managed
  - **Job clusters** – used for jobs, created and terminated by the Azure Databricks job scheduler; cannot be restarted




Microsoft Azure
Databricks
Portal
sarah@cletechconsulting.com
Clusters / lab
lab
Edit
Permissions
Start
Clone
Delete
Configuration
Notebooks (0)
Libraries
Event log
Spark UI
Driver logs
Metrics
Apps
Spark cluster UI - Master
Policy
UI | JSON
Unrestricted
Cluster mode
Standard
Databricks Runtime Version
9.1 LTS ML (includes Apache Spark 3.1.2, Scala 2.12)
Autopilot options
Enable autoscaling
Terminate after
120
minutes of inactivity
Worker type
Standard_F4
8 GB Memory, 4 Cores
Workers
1
Spot instances
Driver type
Standard_F4
8 GB Memory, 4 Cores
DBU / hour: 1
Standard_F4
Advanced options
Azure Data Lake Storage credential passthrough
Enable credential passthrough for user-level data access
Spark
Tags
Logging
Init Scripts
JDBC/ODBC
Permissions
Spark config
spark.hadoop.fs.azure.account.key
.blob.core.windows.net
Environment variables
No environment variables
1/3

Runtimes

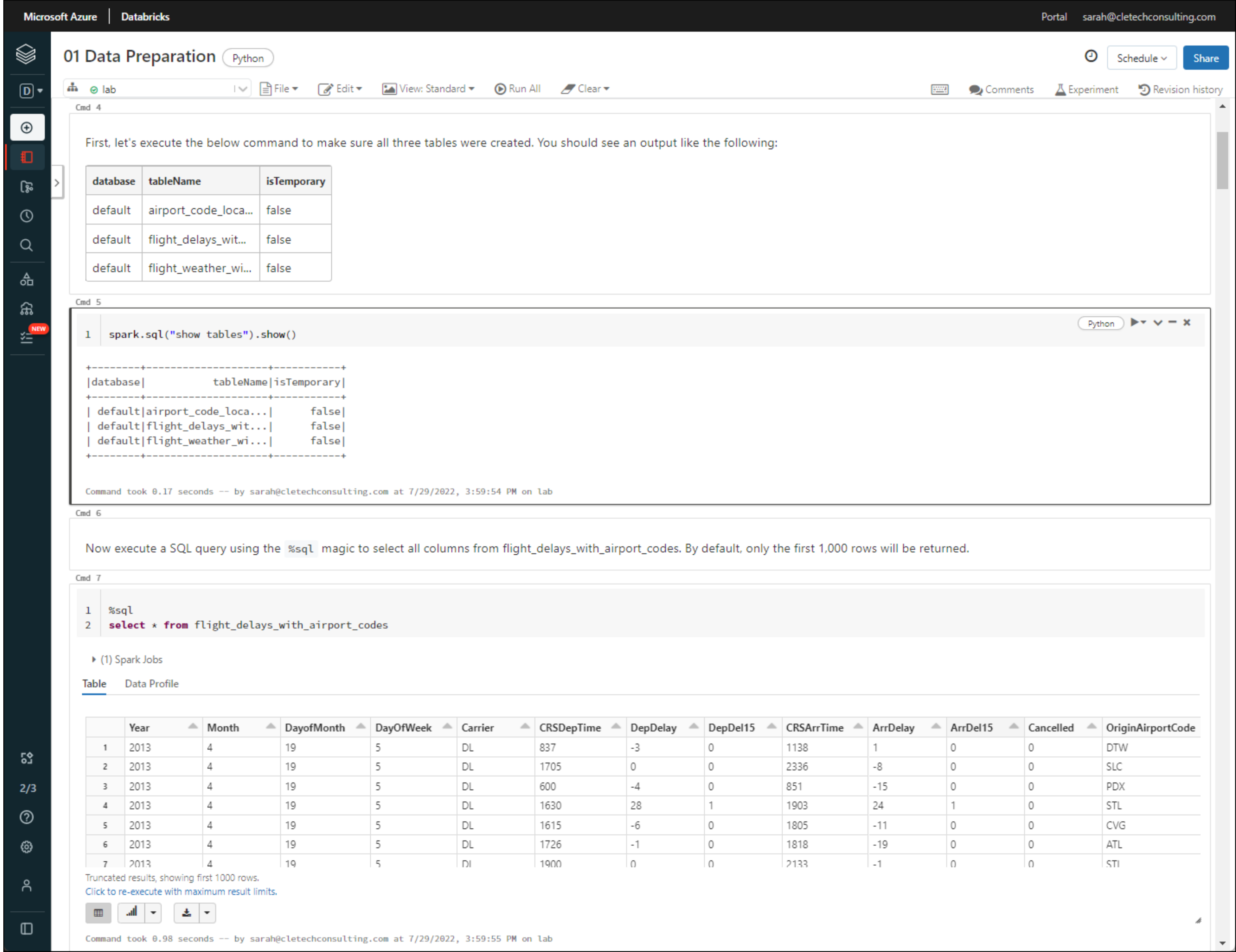
- Assigned at the cluster-level
- Provides the engine for the platform, based on Apache Spark
- Includes Delta Lake for storage
- GPU-enabled support available
- Ubuntu and system libraries
- Supports the following languages:
  - Python
  - R
  - Java
  - Scala

Special Runtimes

- Databricks Runtime for Machine Learning
- Databricks Light
- Photon-enabled runtimes
  - Uses a native vectorized query engine
  - Currently in Public Preview
  - Works in both Azure Databricks clusters and Databricks SQL endpoints

Notebooks

- Can mix Markdown and languages to present data
- Example: Data Preparation notebook with:
    - Markdown
    - SQL
    - Python
    - R



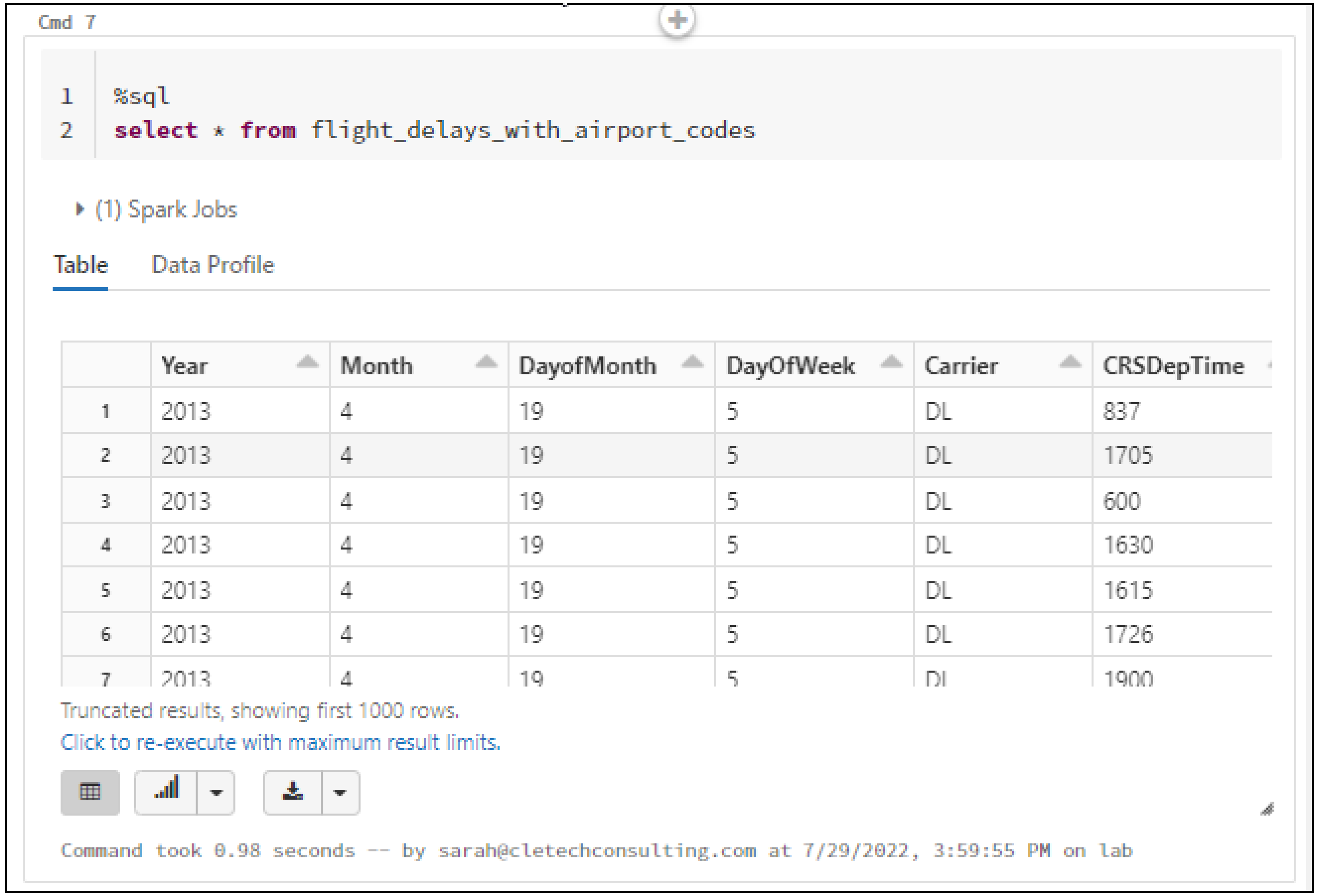
Notebook cells

- Command number helps for execution and navigation
- Execution details include:
  - Duration
  - User
  - Timestamp
  - Cluster name
- Example shows Python command and output

```
Cmd 5

1   spark.sql("show tables").show()

+--------+--------------------+-----------+
|database|           tableName|isTemporary|
+--------+--------------------+-----------+
| default|airport_code_loca...|      false|
| default|flight_delays_wit...|      false|
| default|flight_weather_wi...|      false|
+--------+--------------------+-----------+

Command took 0.17 seconds -- by sarah@cletechconsulting.com at 7/29/2022, 3:59:54 PM on lab
```

SQL notebook cell

- Using the magic commands – start with % - to indicate using SQL
- Other magic commands include:
  - %fs
  - %python
  - %md
  - %r
  - %scala
  - %sh



DataFrame schema

- dfFlightDelays is a DataFrame
- Python code, using pretty print `pprint` library

Cmd 19

```
pprint.pprint(dfFlightDelays.dtypes)
```

```
[('Year', 'string'),
 ('Month', 'string'),
 ('DayofMonth', 'string'),
 ('DayOfWeek', 'string'),
 ('Carrier', 'string'),
 ('CRSDepTime', 'string'),
 ('DepDelay', 'string'),
 ('DepDel15', 'string'),
 ('CRSArrTime', 'string'),
 ('ArrDelay', 'string'),
 ('ArrDel15', 'string'),
 ('Cancelled', 'string'),
 ('OriginAirportCode', 'string'),
 ('OriginAirportName', 'string'),
 ('OriginLatitude', 'string'),
 ('OriginLongitude', 'string'),
 ('DestAirportCode', 'string'),
 ('DestAirportName', 'string'),
 ('DestLatitude', 'string'),
 ('DestLongitude', 'string')]
```

Command took 0.04 seconds -- by sarah@cletechconsulting.com at 7/29/2022, 3:59:55 PM on lab

Data munging

- Using SparkR to clean
- Yes… R in the same notebook as SQL… labeled as a Python notebook

Cmd 24

```
%r
library(SparkR)

# Select only the columns we need, casting CRSDepTime as long and DepDel15 as int, into a new DataFrame
dfflights <- sql("SELECT OriginAirportCode, OriginLatitude, OriginLongitude, Month, DayofMonth,
cast(CRSDepTime as long) CRSDepTime, DayOfWeek, Carrier, DestAirportCode, DestLatitude, DestLongitude,
cast(DepDel15 as int) DepDel15 from flight_delays_with_airport_codes")

# Delete rows containing missing values
dfflights <- na.omit(dfflights)

# Round departure times down to the nearest hour, and export the result as a new column named
"CRSDepHour"
dfflights$CRSDepHour <- floor(dfflights$CRSDepTime / 100)

# Trim the columns to only those we will use for the predictive model
dfflightsClean = dfflights[, c("OriginAirportCode","OriginLatitude", "OriginLongitude", "Month",
"DayofMonth", "CRSDepHour", "DayOfWeek", "Carrier", "DestAirportCode", "DestLatitude", "DestLongitude",
"DepDel15")]

createOrReplaceTempView(dfflightsClean, "flight_delays_view")
```

```
Attaching package: ‘SparkR’

The following object is masked _by_ ‘.GlobalEnv’:

    setLocalProperty

The following objects are masked from ‘package:stats’:

    cov, filter, lag, na.omit, predict, sd, var, window

The following objects are masked from ‘package:base’:

    as.data.frame, colnames, colnames<-, drop, endsWith, intersect,
    rank, rbind, sample, startsWith, subset, summary, transform, union
```

Command took 1.29 seconds -- by sarah@cletechconsulting.com at 7/29/2022, 3:59:55 PM on lab

Export to a Databricks table

- Storing munged data into another table
- `saveAsTable()` – creates **global** table
- `createOrReplaceTempView()` and `registerTempTable()` create **local** tables

```
Cmd 33
1  dfFlightDelays_Clean.write.mode("overwrite").saveAsTable("flight_delays_clean")
```

Python

▸ (4) Spark Jobs

Command took 11.38 seconds -- by sarah@cletechconsulting.com at 7/29/2022, 3:59:55 PM on lab

Cleaning weather data with Python

- WindSpeed: Replace missing values with 0.0, and “M” values with 0.005
- HourlyPrecip: Replace missing values with 0.0, and “T” values with 0.005
- SeaLevelPressure: Replace “M” values with 29.92 (the average pressure)
- Convert WindSpeed, HourlyPrecip, and SeaLevelPressure to numeric columns
- Round “Time” column down to the nearest hour, and add value to a new column named “Hour”
- Eliminate unneeded columns from the dataset

Cmd 56

```
# Round Time down to the next hour, since that is the hour for which we want to use flight data. Then, add the rounded Time to a new column named "Hour", and append that column to the dfWeather DataFrame.
df = dfWeather.withColumn('Hour', F.floor(dfWeather['Time']/100))

# Replace any missing HourlyPrecip and WindSpeed values with 0.0
df = df.fillna('0.0', subset=['HourlyPrecip', 'WindSpeed'])

# Replace any WindSpeed values of "M" with 0.005
df = df.replace('M', '0.005', 'WindSpeed')

# Replace any SeaLevelPressure values of "M" with 29.92 (the average pressure)
df = df.replace('M', '29.92', 'SeaLevelPressure')

# Replace any HourlyPrecip values of "T" (trace) with 0.005
df = df.replace('T', '0.005', 'HourlyPrecip')

# Be sure to convert WindSpeed, SeaLevelPressure, and HourlyPrecip columns to float
# Define a new DataFrame that includes just the columns being used by the model, including the new Hour feature
dfWeather_Clean = df.select('AirportCode', 'Month', 'Day', 'Hour', df['WindSpeed'].cast('float'), df['SeaLevelPressure'].cast('float'), df['HourlyPrecip'].cast('float'))
```

df: pyspark.sql.dataframe.DataFrame = [AirportCode: string, Month: integer ... 6 more fields]

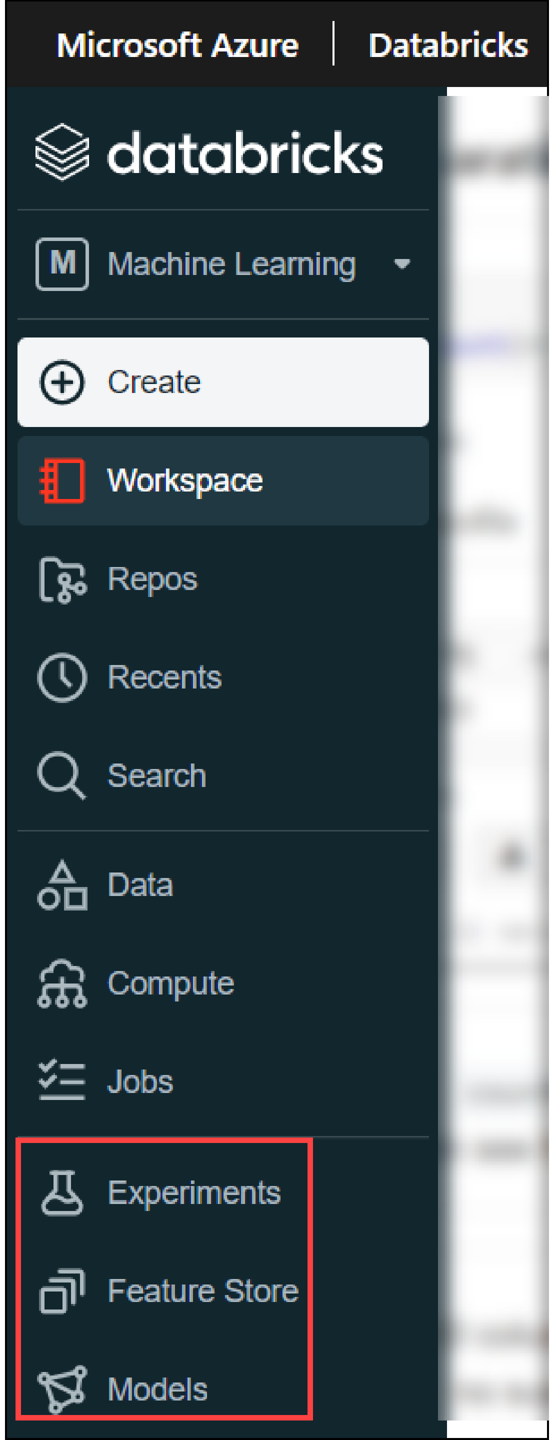
dfWeather_Clean: pyspark.sql.dataframe.DataFrame = [AirportCode: string, Month: integer ... 5 more fields]

Command took 0.14 seconds -- by sarah@cletechconsulting.com at 7/29/2022, 3:59:56 PM on lab

Databricks Machine Learning

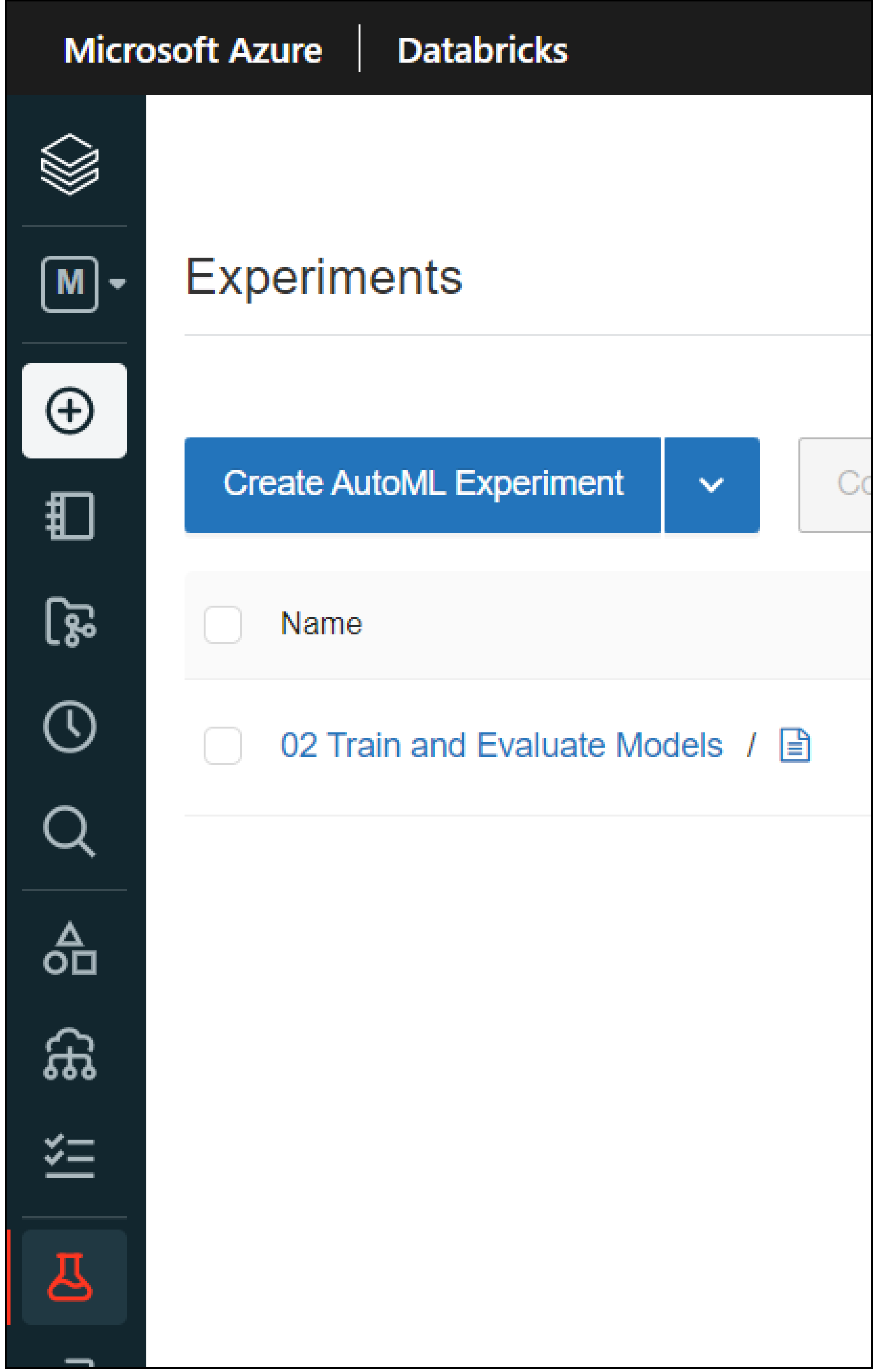
Databricks Machine Learning

- Builds on top of Data Science & Engineering
- Same workspace components
- ML components:
  - Experiments
  - Feature Stores
  - Models



Experiments

- In the 02 Train and Evaluate Models notebook, Cmd27
- Uses `mlflow` to trigger experiment via code
- Experiments can show `MLflow` experiments across an organization that you have access to

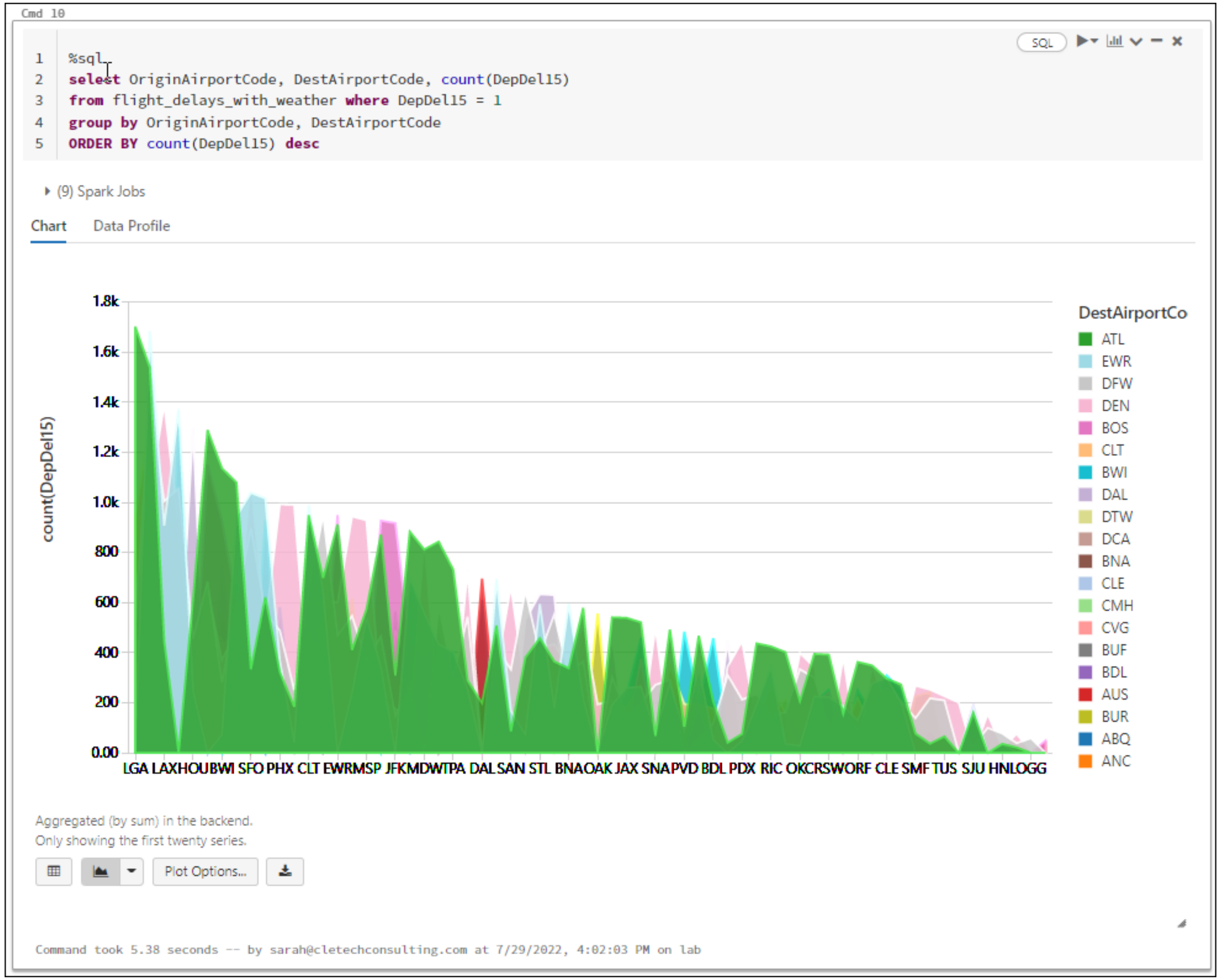


Creating your own AutoML experiment

- Select a compute cluster
- ML Problem Type:
  - Classification
  - Regression
  - Forecasting – ML Runtimes 10.x and higher
- Evaluation metric (advanced configuration):
  - Classification
    - F1 score
    - Accuracy
    - Log loss
    - Precision
    - ROC/AUC
  - Regression
    - R-squared
    - Mean absolute error
    - Mean squared error
    - Root mean squared error

Train and Evaluate Models

- Working with PySpark in Python
- Using stratified sampling with sampleBy() function
- Using **binary classification** – flight is either delayed or it is not
- Using the Decision Tree classifier from Spark MLib
- Models will be saved for **batch scoring**



Training and Evaluating Models

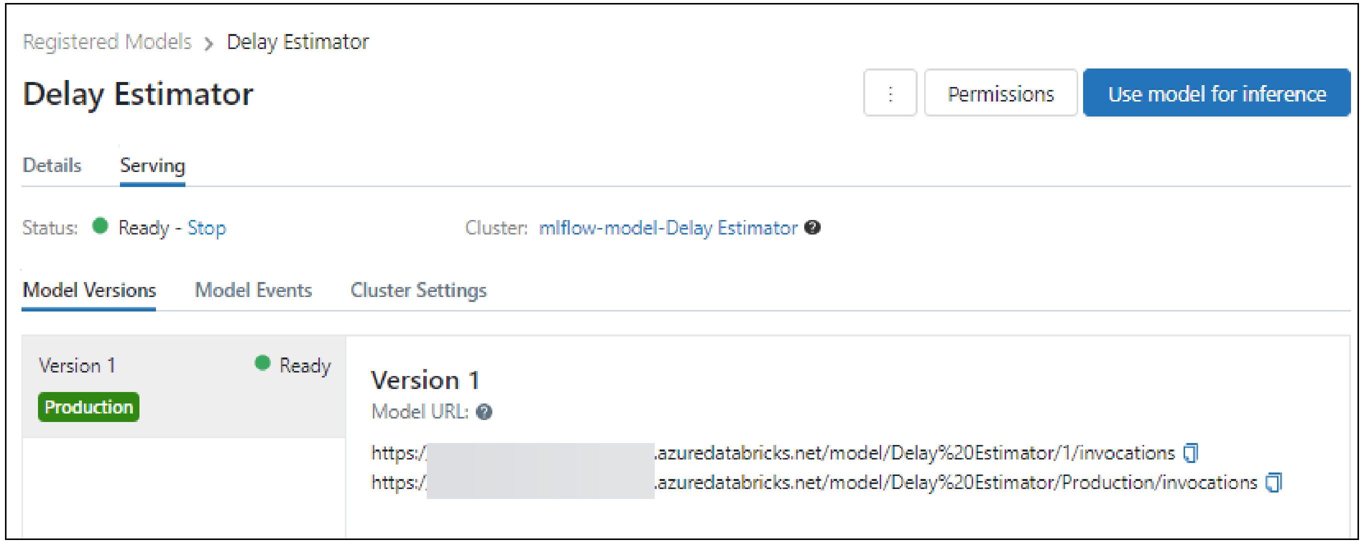
1. Load the cleaned flight delays with weather data.
2. Sample the data by the **DepDel15** field using `sampleBy()`.
   - We will pass a fraction for **stratified sampling**.
3. Select an algorithm and transform the features.
   - Flight delayed or not – binary classification => Decision Tree classifier from Spark MLib.
   - Using `StringIndexer` and `OneHotEncoderEstimator` for categorical conversion
   - Using the Pipeline API for tying multiple stages together
4. Save the model for batch scoring.

Batch Scoring

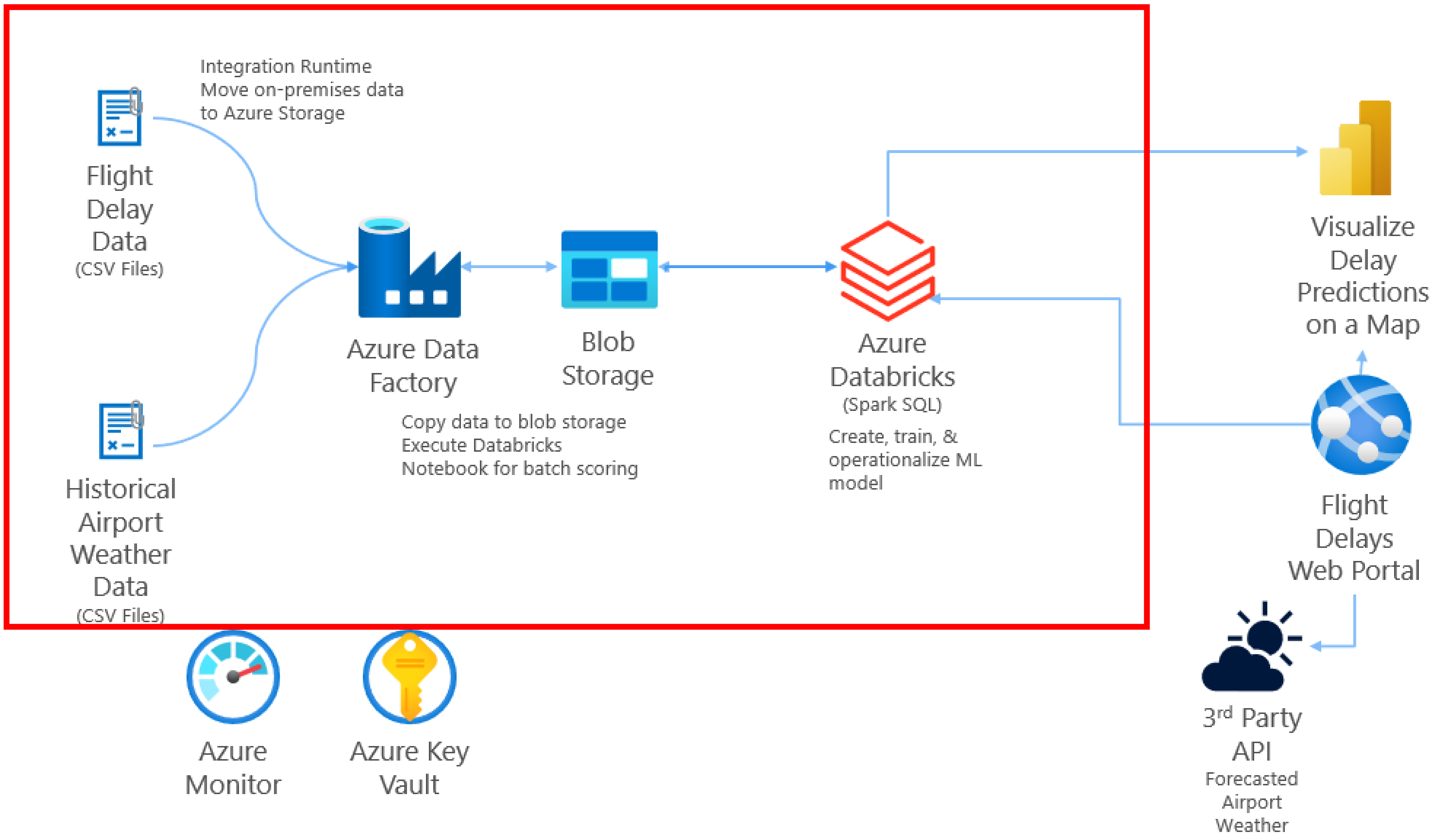
- Reads from Azure Data Storage
- Creates DataFrames for the CSVs
- Load the trained model
- Make predictions against the set
- Save the scored data in a global table **scoredflights**

Deploy model for batch scoring

1. Register the model with MLflow.
2. Move the model to Production.
3. Set up the service for the model.
4. Test the service.
5. Once all is confirmed, set up the pipeline for batch scoring.



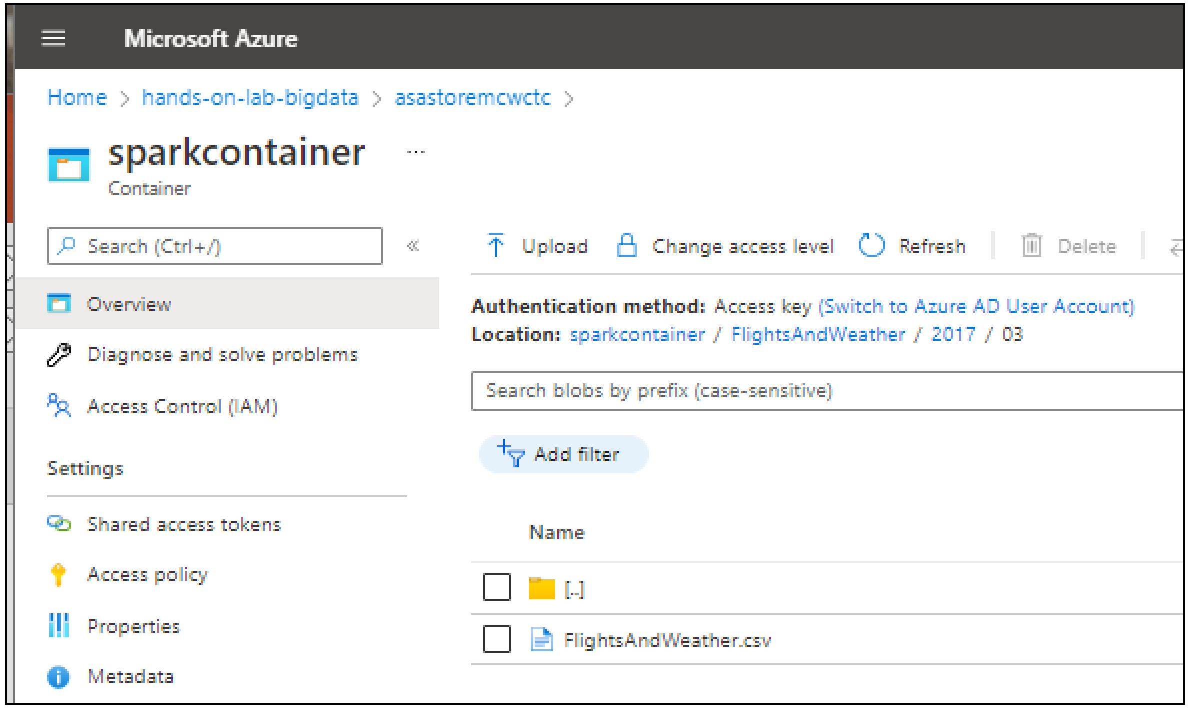
Setting up the Azure Data Factory Pipeline with the Azure Databricks Notebook



Source: [Microsoft Cloud Workshop: Big Data Analytics and Visualization](), Hands-on Lab

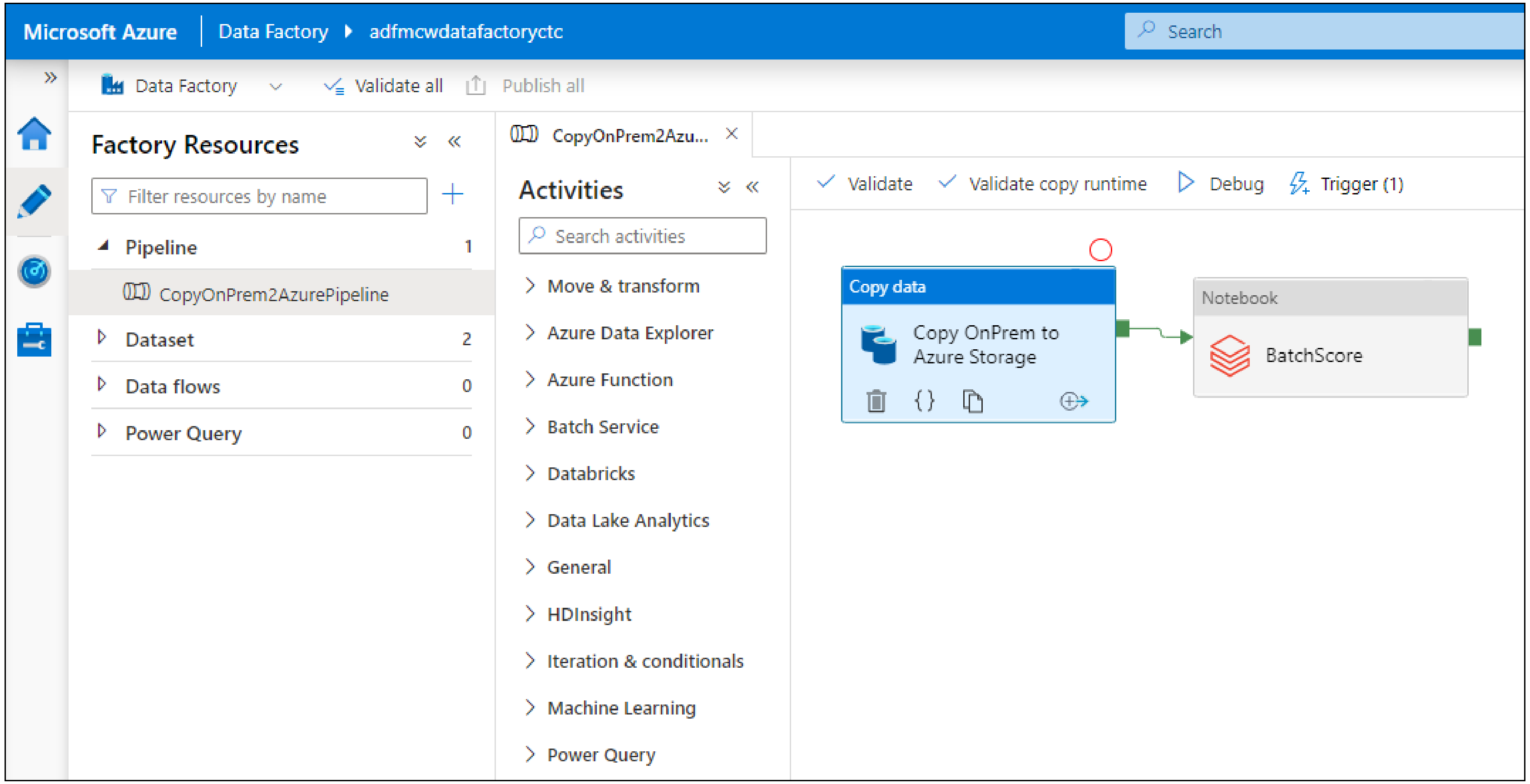
Data Source: Data Lake

- Using Azure Storage
- CSVs will get migrated from an on-premises environment to Azure Storage using Azure Data Factory



Azure Data Factory

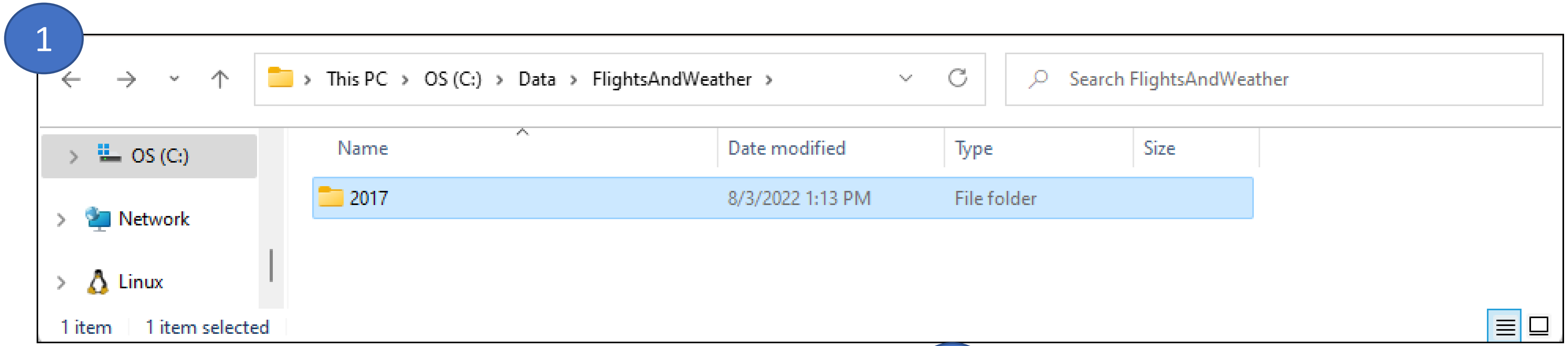
- Azure Data Factory can migrate data from on-premises to Azure Storage.
- Once migrated, we can run a Databricks notebook to score the data.

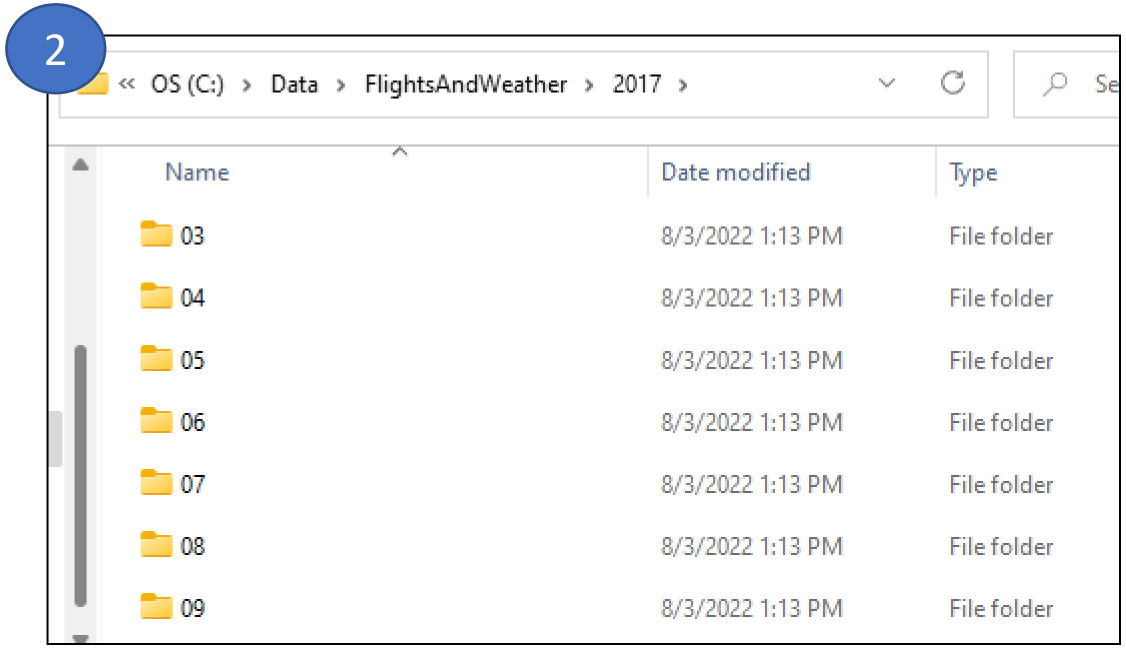


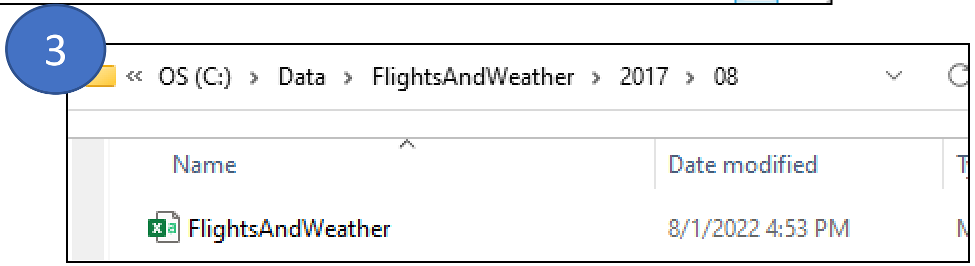
Setting Up Azure Data Factory

1. Set up the integration runtime.
2. Create a pipeline that uses the integration runtime to move from local to Azure.
3. Add Azure Databricks notebook for batch scoring
4. Publish changes.
5. Trigger the pipeline.

Local Folder Setup

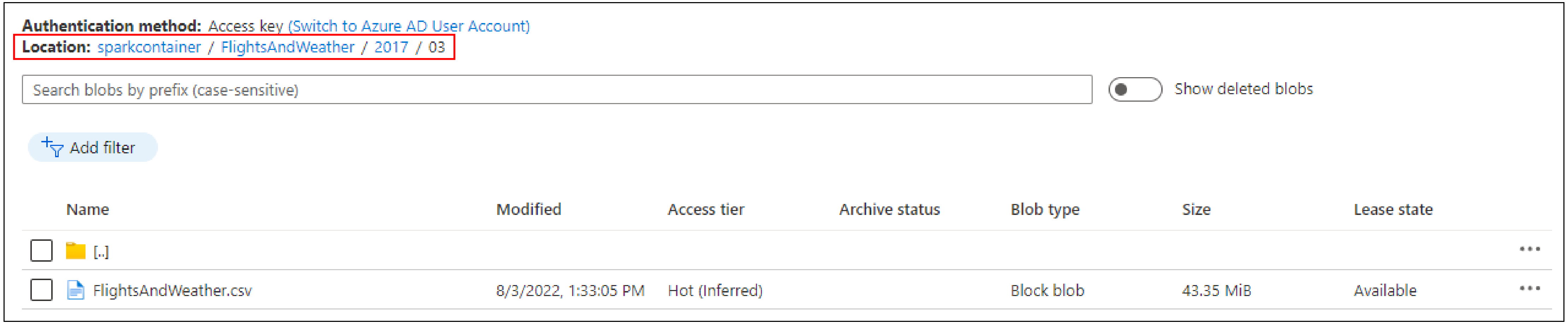




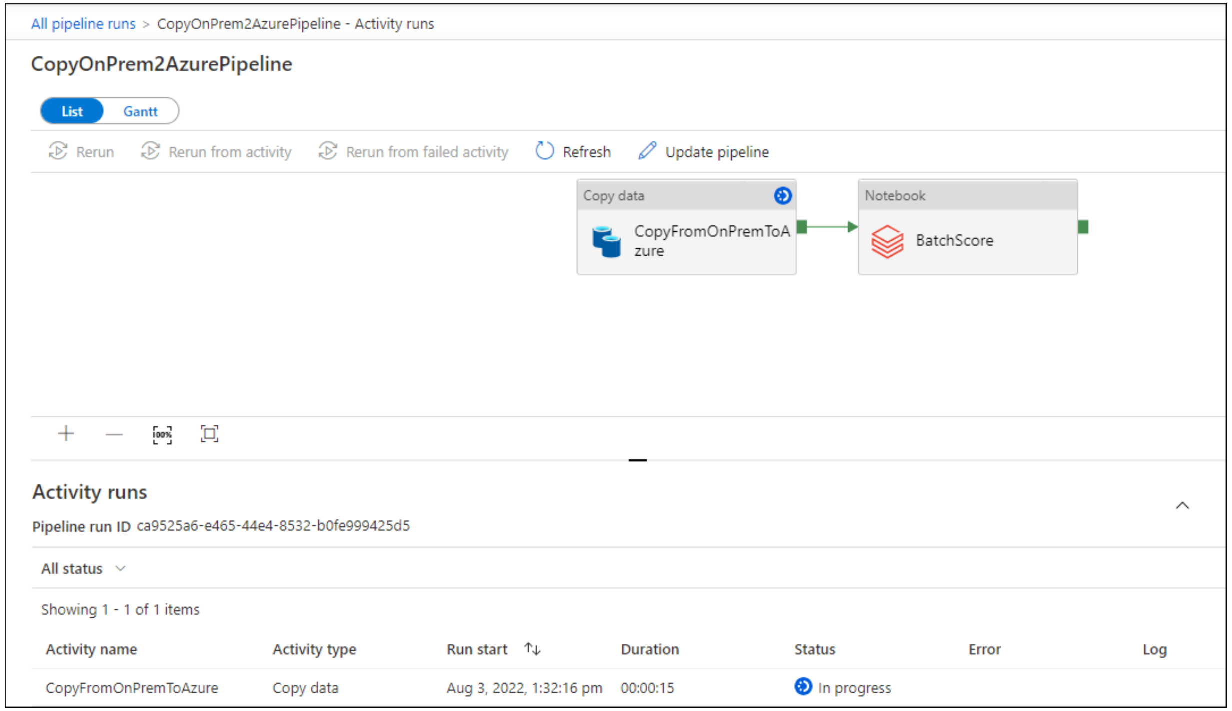


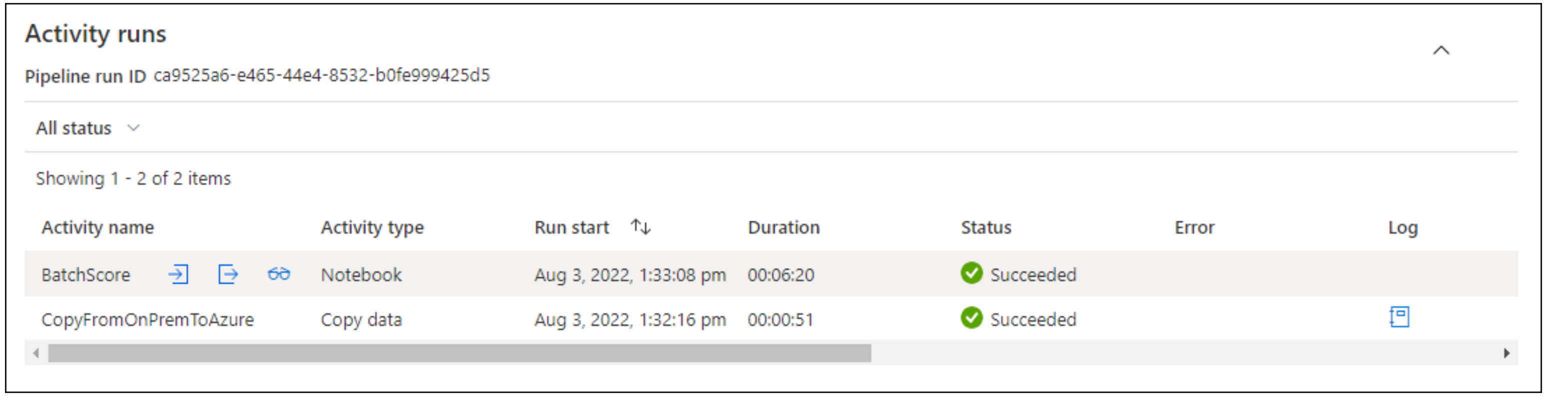
Put the files in a location where the integration runtime will have permission to access them.

Azure Storage Setup



Monitoring Pipeline Runs





Batch Scoring Notebook

- Defines schema for expected CSV file
- Read in the CSV from the Azure Storage
- Use the saved pipeline model
- Make a prediction for the data within the CSV
- Write the prediction to a **global table** named `scoredflights`

Review results

- Databricks SQL
- Databricks Notebook

Cmd 6

```
%sql
SELECT  OriginAirportCode, Month, DayofMonth, CRSDepHour, Sum(prediction) NumDelays,
    CONCAT(Latitude, ',', Longitude) OriginLatLong
    FROM scoredflights s
    INNER JOIN airport_code_location_lookup_clean a
    ON s.OriginAirportCode = a.Airport
    WHERE Month = 4
    GROUP BY OriginAirportCode, OriginLatLong, Month, DayofMonth, CRSDepHour
    Having Sum(prediction) > 1
    ORDER BY NumDelays DESC
```

(2) Spark Jobs

Table | Data Profile

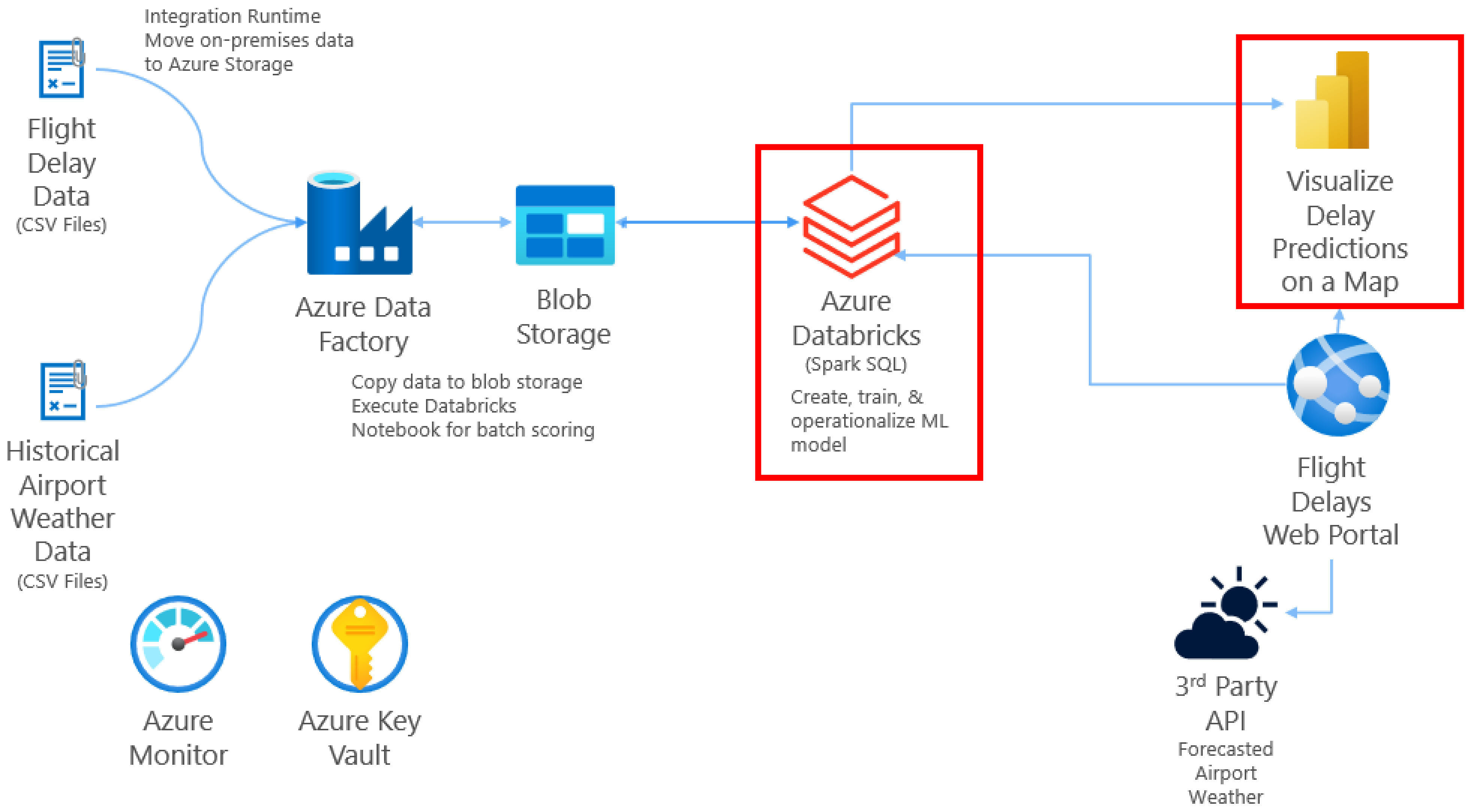
	OriginAirportCode	Month	DayofMonth	CRSDepHour	NumDelays	OriginLatLong
1	ATL	4	28	16	120	33.63666667,-84.42777778
2	MSP	4	12	19	88	44.88194444,-93.22166667
3	MSP	4	11	19	72	44.88194444,-93.22166667
4	MSP	4	21	19	72	44.88194444,-93.22166667
5	ATL	4	14	16	72	33.63666667,-84.42777778
6	ORD	4	17	12	66	41.97944444,-87.9075
7	MSP	4	5	17	64	44.88194444,-93.22166667

Truncated results, showing first 1000 rows.

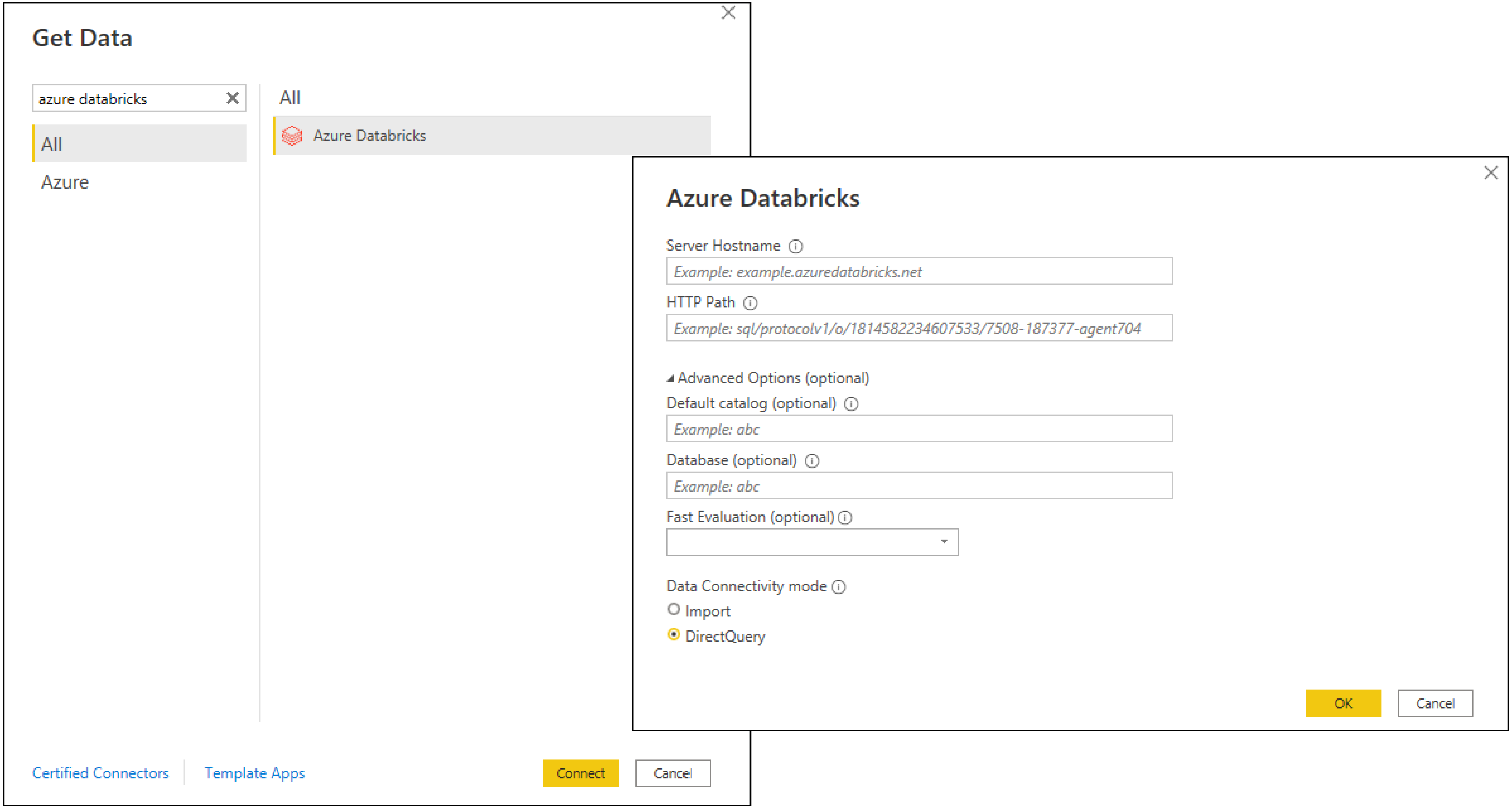
Click to re-execute with maximum result limits.

Command took 3.43 seconds -- by sarah@cletechconsulting.com at 8/3/2022, 2:35:08 PM on lab

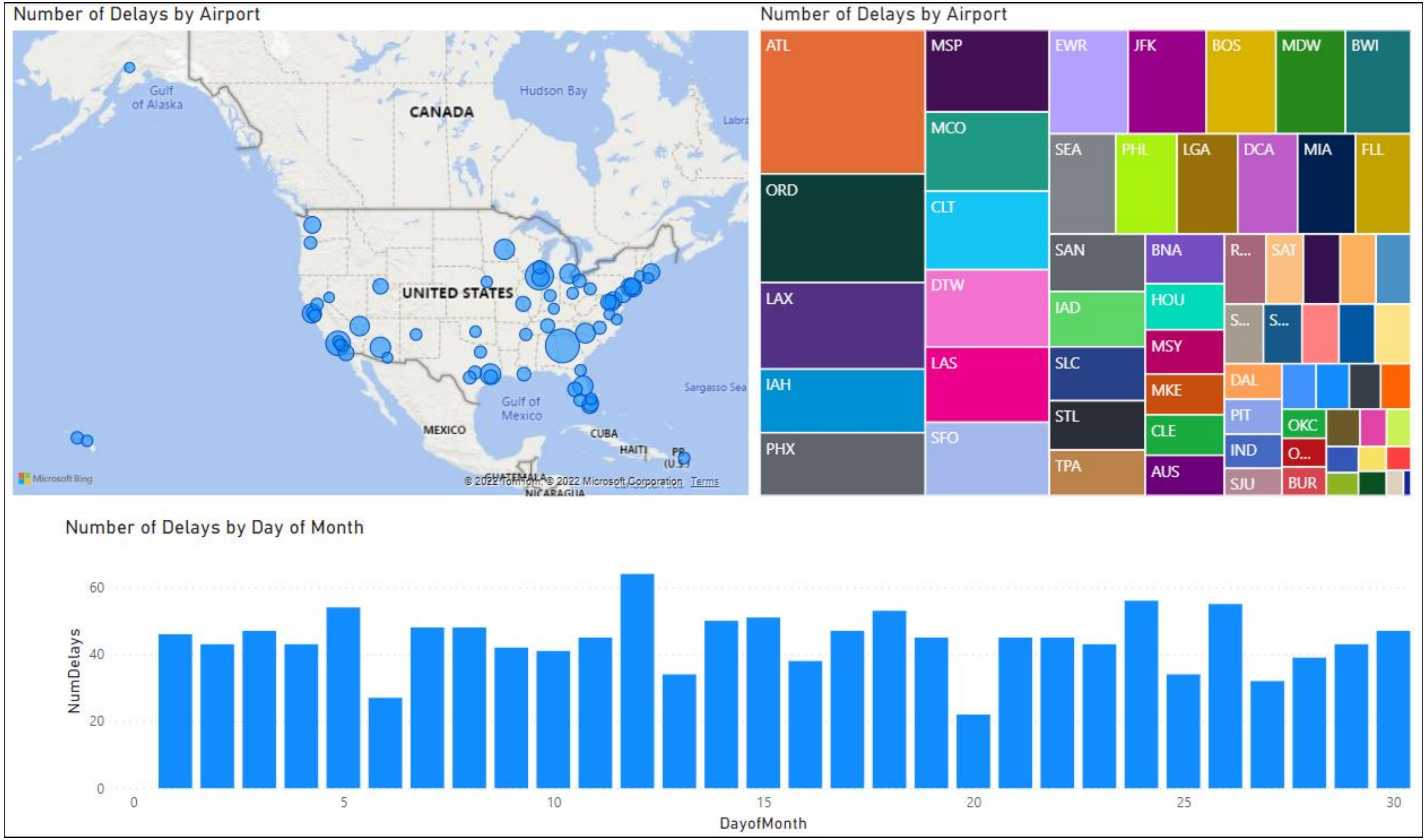
Databricks as a Data Source



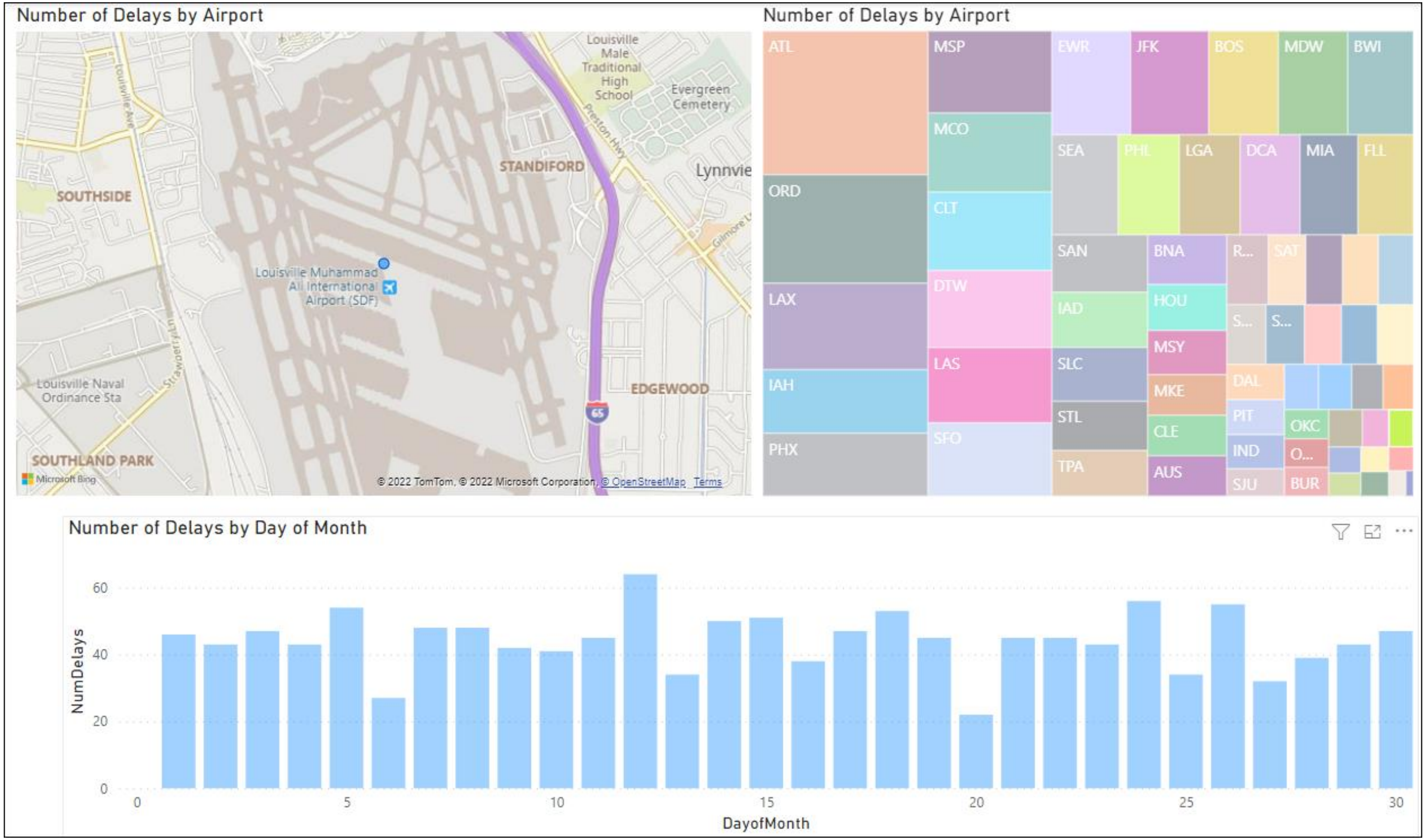
Source: Microsoft Cloud Workshop: Big Data Analytics and Visualization, Hands-on Lab


Get Data
azure databricks
All
Azure
All
Azure Databricks
Certified Connectors
Template Apps
Connect
Cancel
Azure Databricks
Server Hostname
Example: example.azuredatabricks.net
HTTP Path
Example: sql/protocolv1/o/1814582234607533/7508-187377-agent704
Advanced Options (optional)
Default catalog (optional)
Example: abc
Database (optional)
Example: abc
Fast Evaluation (optional)
Data Connectivity mode
Import
DirectQuery
OK
Cancel

Summary data in Power BI



Looking at SDF's track record



Additional Resources

- User guides
  - Databricks SQL user guide - Azure Databricks - Databricks SQL | Microsoft Docs
  - Databricks Data Science & Engineering guide - Azure Databricks | Microsoft Docs
  - Databricks Machine Learning guide - Azure Databricks | Microsoft Docs
- Microsoft Learn pathways
  - Build and operate machine learning solutions with Azure Databricks - Learn | Microsoft Docs
  - Data engineering with Azure Databricks - Learn | Microsoft Docs
  - Perform data science with Azure Databricks - Learn | Microsoft Docs

Any Questions?

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