

NYC Yellow Taxi Data Analysis using Azure and PySpark

1. Created Azure Resources:

- Resource Group

The screenshot shows the Microsoft Azure portal interface. The top navigation bar includes the 'Microsoft Azure' logo, an 'Upgrade' button, a search bar, and a 'Copilot' button. The user's profile 'grahul2910@gmail.com' is visible in the top right. The main content area is titled 'TaxiDataGroup' and shows the 'Overview' tab. On the left, a list of resource groups is displayed, with 'TaxiDataGroup' selected. The right pane shows the 'Essentials' section with a 'Resources' tab. A table lists the resources within the group:

Name	Type	Location
TaxiDataBricks	Azure Databricks Service	Central India

- Storage Account with ADLS Gen2 enabled

The screenshot shows the Microsoft Azure portal interface for the 'taxidatalake2025' storage account. The left sidebar shows the 'Containers' tab selected. The main content area displays a list of containers:

Name	Last modified	Anonymous access level	Lease state
\$logs	23/7/2025, 12:24:17 pm	Private	Available
taxidata	23/7/2025, 12:25:04 pm	Private	Available

- Container named taxidata

Home > taxidatalake2025 | Containers >

taxidata Container

Search

+ Add Directory ↑ Upload ↻ Refresh 🗑 Delete 📄 Copy 📄 Paste 🔄 Rename 🔑 Acquire lease 🔑 Break lease 🛠 Edit columns

taxidata

Authentication method: Access key ([Switch to Microsoft Entra user account](#))

Search blobs by prefix (case-sensitive) Only show active objects

Showing all 1 items

<input type="checkbox"/>	Name	Last modified	Access tier	Blob type	Size	Lease state
<input type="checkbox"/>	yellow-tripdata-2018-01.csv	23/7/2025, 12:27:10 pm	Hot (Inferred)	Block blob	942.46 MiB	Available ...

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- Azure Databricks workspace and cluster

Microsoft Azure Upgrade Search resources, services, and docs (G+)

Home > Resource groups > TaxiDataGroup >

TaxiDataGroup Azure Databricks Service

Search Delete

Overview

Activity log Access control (IAM) Tags Diagnose and solve problems Resource visualizer Settings Automation Help

Essentials

Status : Active

Resource group : TaxiDataGroup

Location : Central India

Subscription : Azure subscription 1

Subscription ID : 4b697afd-e4c5-4b02-a867-3c947bb49a87

Tags (edit) : Add tags

Managed Resource Group : databricks-rg-TaxiDataGroup-e6di6ccm1j1n4

URL : https://adb-613387513590477.17.azuredatabricks.net

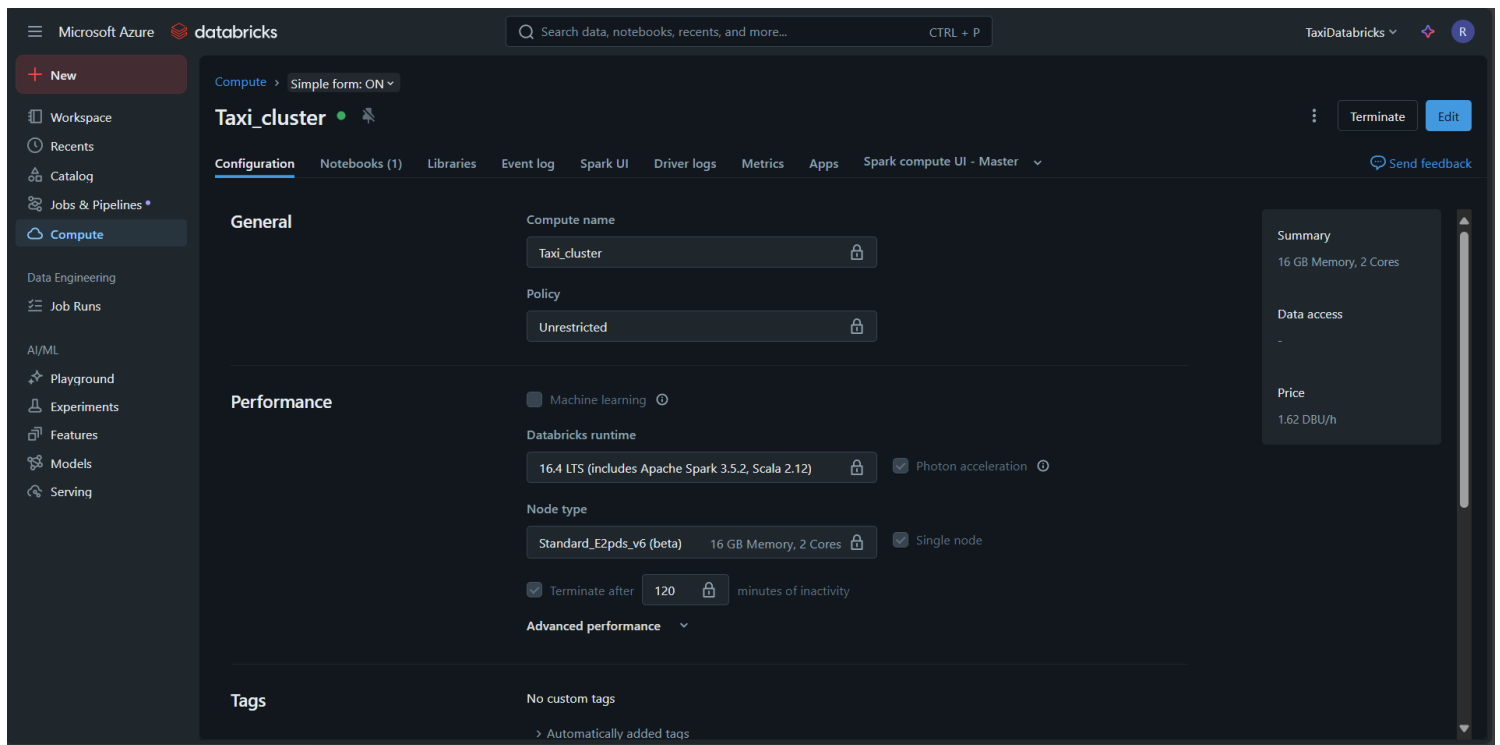
Pricing Tier : Standard (Apache Spark, Secure with Microsoft Entra ID) (Click to ...)

Enable No Public IP : Yes

Launch Workspace Upgrade to Premium

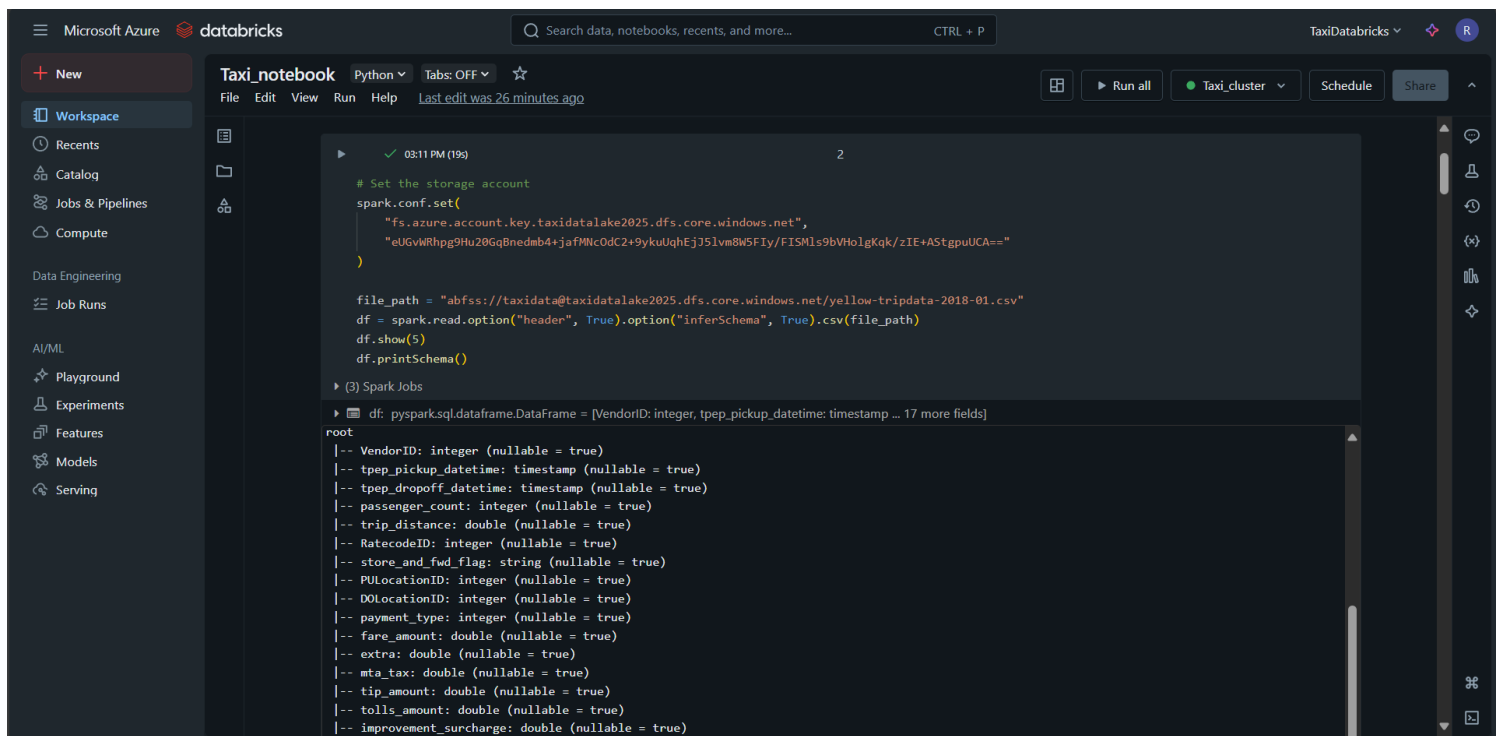
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2. Data Upload:

- Uploaded the dataset `yellow_tripdata_2018-01.csv` into the `taxidata` container in the storage account.



3. Databricks Notebook Setup:

- Connected Databricks to the storage using ABFSS protocol and OAuth credentials.

- Read the CSV file using an explicitly defined schema and converted date columns (tpep_pickup_datetime, tpep_dropoff_datetime) to timestamps.

Query 1: Top Pickup Locations

- Grouped data by PULocationID.
- Summed the number of passengers per pickup location.

The screenshot shows the Databricks interface for a notebook named 'Taxi_notebook'. The code cell contains the following Python code:

```
df = df.withColumn(
    "Revenue",
    (col("fare_amount") + col("extra") + col("mta_tax") +
     col("improvement_surcharge") + col("tip_amount") +
     col("tolls_amount") + col("total_amount"))
)
df.select("VendorID", "fare_amount", "extra", "mta_tax", "tip_amount", "tolls_amount", "improvement_surcharge", "total_amount", "Revenue").
show(100)
```

The output shows a Spark job with 18 fields. The resulting table has columns: VendorID, fare_amount, extra, mta_tax, tip_amount, tolls_amount, improvement_surcharge, total_amount, and Revenue. The data is sorted by total_amount in descending order.

VendorID	fare_amount	extra	mta_tax	tip_amount	tolls_amount	improvement_surcharge	total_amount	Revenue
1	4.5	0.5	0.5	0.0	0.0	0.3	5.8	11.6
1	14.0	0.5	0.5	0.0	0.0	0.3	15.3	30.6
1	6.0	0.5	0.5	1.0	0.0	0.3	8.3	16.6
1	33.5	0.5	0.5	0.0	0.0	0.3	34.8	69.6
1	12.5	0.5	0.5	2.75	0.0	0.3	16.55	33.1
1	4.5	0.5	0.5	0.0	0.0	0.3	5.8	11.6
1	9.0	0.5	0.5	2.05	0.0	0.3	12.35	24.700000000000003
1	4.0	0.5	0.5	1.0	0.0	0.3	6.3	12.6
1	5.5	0.5	0.5	1.7	0.0	0.3	8.5	17.0
1	5.5	0.5	0.5	0.0	0.0	0.3	6.8	13.6
1	5.5	0.5	0.5	1.35	0.0	0.3	8.15	16.3
1	16.5	0.5	0.5	0.0	0.0	0.3	17.8	35.6
2	5.5	0.5	0.5	0.0	0.0	0.3	6.8	13.6
2	7.5	0.5	0.5	0.0	0.0	0.3	8.8	17.6
2	10.0	0.5	0.5	0.0	0.0	0.3	11.3	22.6
1	19.0	0.5	0.5	4.05	0.0	0.3	24.35	48.7
2	25.5	0.5	0.5	6.7	0.0	0.3	33.5	67.0

Query 2: Top Dropoff Locations

- Grouped data by DOLocationID.
- Aggregated the number of passengers per dropoff location.
- Sorted to identify most common drop-off zones.

The screenshot shows the Databricks interface for the same 'Taxi_notebook'. The code cell contains the following Python code:

```
df = df.withColumn("pickup_time", to_timestamp("tpep_pickup_datetime", "yyyy-MM-dd HH:mm:ss"))
df = df.withColumn("passenger_count", when(col("passenger_count").isNull(), 0).otherwise(col("passenger_count").cast("int")))
window_spec = Window.partitionBy("PULocationID").orderBy("pickup_time").rowsBetween(Window.unboundedPreceding, Window.currentRow)
df = df.withColumn("cumulative_passenger_count", _sum("passenger_count").over(window_spec))
df.select("pickup_time", "PULocationID", "passenger_count", "cumulative_passenger_count").orderBy("pickup_time").show(100)
```

The output shows a Spark job with 22 fields. The resulting table has columns: pickup_time, PULocationID, passenger_count, and cumulative_passenger_count. The data is sorted by pickup_time.

pickup_time	PULocationID	passenger_count	cumulative_passenger_count
2018-01-01 00:00:00	229	1	1
2018-01-01 00:00:02	68	1	1
2018-01-01 00:00:03	255	1	1
2018-01-01 00:00:03	236	3	3
2018-01-01 00:00:04	37	1	1
2018-01-01 00:00:04	141	1	1
2018-01-01 00:00:06	162	1	1
2018-01-01 00:00:11	238	1	1
2018-01-01 00:00:13	144	1	1
2018-01-01 00:00:14	170	1	1
2018-01-01 00:00:14	141	1	2
2018-01-01 00:00:15	232	2	2
2018-01-01 00:00:15	90	1	1
2018-01-01 00:00:16	265	1	1
2018-01-01 00:00:17	229	1	2
2018-01-01 00:00:18	138	4	4
2018-01-01 00:00:19	161	1	1
2018-01-01 00:00:20	164	2	2

Query 3: Revenue Generated by Each Vendor

- Created a derived column Revenue by summing:
 - fare_amount + extra + mta_tax + tip_amount + tolls_amount + improvement_surcharge + congestion_surcharge
- Grouped the dataset by VendorID.
- Aggregated total revenue per vendor.

The screenshot shows a Databricks workspace with a notebook named 'Tax_i_notebook'. The notebook contains a Python script that uses Spark SQL functions to calculate cumulative revenue by vendor. The script defines a window specification partitioned by VendorID and ordered by pickup_time, then uses the avg function to calculate the cumulative average fare and total amount. The result is displayed as a table with columns: pickup_time, VendorID, fare_amount, total_amount, cumulative_avg_fare, and cumulative_avg_total. The table shows data for various pickup times and vendors, with the cumulative values increasing over time.

```
from pyspark.sql.functions import col, avg, to_timestamp, year
from pyspark.sql.window import Window

df = df.withColumn("pickup_time", to_timestamp("tpep_pickup_datetime", "yyyy-MM-dd HH:mm:ss"))
window_spec = Window.partitionBy("VendorID").orderBy("pickup_time").rowsBetween(Window.unboundedPreceding, Window.currentRow)
df = df.withColumn("cumulative_avg_fare", avg("fare_amount").over(window_spec))
df = df.withColumn("cumulative_avg_total", avg("total_amount").over(window_spec))
df.select("pickup_time", "VendorID", "fare_amount", "total_amount", "cumulative_avg_fare", "cumulative_avg_total").show(10)
```

pickup_time	VendorID	fare_amount	total_amount	cumulative_avg_fare	cumulative_avg_total
2018-01-01 00:00:00	2	27.0	27.8	27.0	27.8
2018-01-01 00:00:02	2	7.5	8.8	17.25	18.3
2018-01-01 00:00:03	2	5.5	6.8	13.333333333333334	14.466666666666667
2018-01-01 00:00:03	1	20.5	21.8	20.5	21.8
2018-01-01 00:00:04	1	13.5	14.8	17.0	18.3
2018-01-01 00:00:04	2	8.0	9.3	12.0	13.175
2018-01-01 00:00:06	1	23.5	29.75	19.166666666666668	22.116666666666664
2018-01-01 00:00:11	1	7.0	9.95	16.125	19.075
2018-01-01 00:00:13	1	6.0	9.1	14.1	17.08
2018-01-01 00:00:14	1	5.0	7.3	12.583333333333334	15.449999999999998

Query 4: Moving Count of Payments by Payment Mode

- Used a Window function to calculate a rolling count of rides per payment_type, ordered by pickup timestamp.
- Enabled tracking of trends in payment methods over time.

The screenshot shows a Databricks workspace with a notebook named 'Tax_i_notebook'. The notebook contains a Python script that uses Spark SQL functions to calculate a moving count of payments by payment type. The script defines a window specification partitioned by payment_type and ordered by tpep_pickup_datetime, then uses the count function to calculate the moving count. The result is displayed as a table with columns: tpep_pickup_datetime, payment_type, and payment_type_moving_count. The table shows data for various pickup times and payment types, with the moving count increasing over time.

```
from pyspark.sql.window import Window
from pyspark.sql.functions import count

window_spec = Window.partitionBy("payment_type").orderBy("tpep_pickup_datetime") \
    .rowsBetween(Window.unboundedPreceding, Window.currentRow)

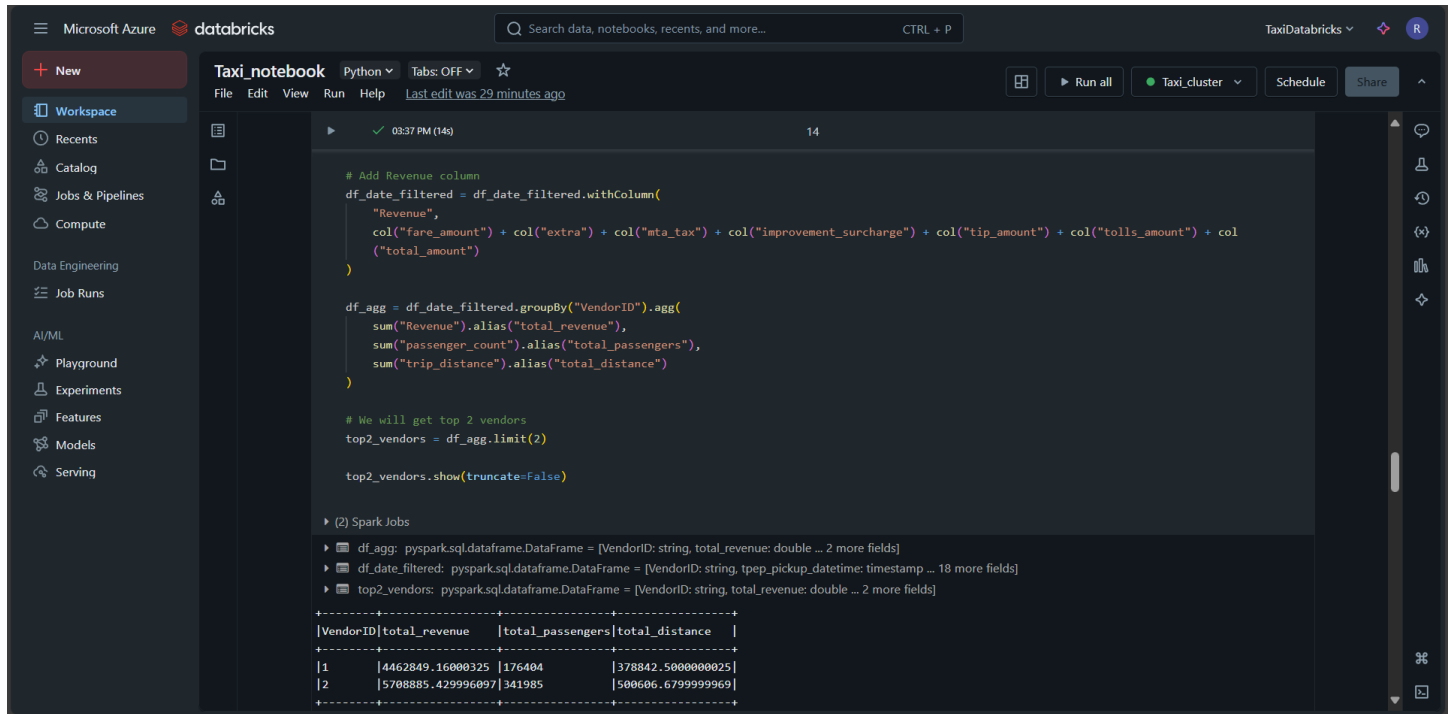
df_moving_count = df.withColumn(
    "payment_type_moving_count",
    count("*").over(window_spec)
).select(
    "tpep_pickup_datetime", "payment_type", "payment_type_moving_count"
).orderBy("tpep_pickup_datetime")

df_moving_count.show(100, truncate=False)
```

tpep_pickup_datetime	payment_type	payment_type_moving_count
2018-01-01 00:01:19	1	137
2018-01-01 00:01:20	2	145
2018-01-01 00:01:22	2	147
2018-01-01 00:01:22	2	146
2018-01-01 00:01:22	1	138
2018-01-01 00:01:24	1	139
2018-01-01 00:01:24	1	140
2018-01-01 00:01:25	2	148
2018-01-01 00:01:25	1	141
2018-01-01 00:01:26	2	149
2018-01-01 00:01:26	1	142
2018-01-01 00:01:28	2	150
2018-01-01 00:01:29	1	143

Query 5: Top 2 Highest Earning Vendors on a Particular Date

- Filtered rides from January 15, 2018.
- Computed Revenue per row as in Query 3.
- Aggregated total revenue, passenger count, and trip distance by vendor.
- Sorted and selected the top 2 vendors by revenue.



```
# Add Revenue column
df_date_filtered = df_date_filtered.withColumn(
    "Revenue",
    col("fare_amount") + col("extra") + col("mta_tax") + col("improvement_surcharge") + col("tip_amount") + col("tolls_amount") + col("total_amount")
)

df_agg = df_date_filtered.groupBy("VendorID").agg(
    sum("Revenue").alias("total_revenue"),
    sum("passenger_count").alias("total_passengers"),
    sum("trip_distance").alias("total_distance")
)

# We will get top 2 vendors
top2_vendors = df_agg.limit(2)

top2_vendors.show(truncate=False)
```

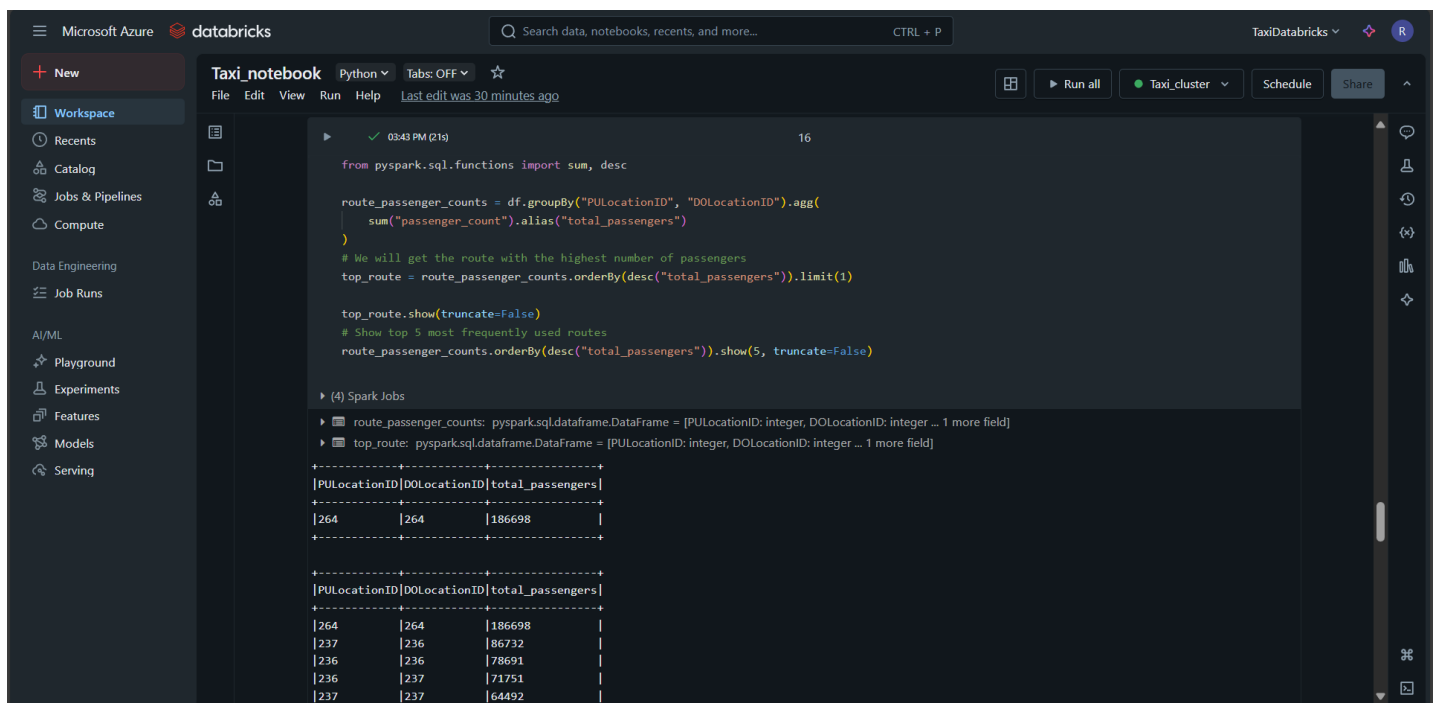
▶ (2) Spark Jobs

- ▶ df_agg: pyspark.sql.dataframe.DataFrame = [VendorID: string, total_revenue: double ... 2 more fields]
- ▶ df_date_filtered: pyspark.sql.dataframe.DataFrame = [VendorID: string, tpep_pickup_datetime: timestamp ... 18 more fields]
- ▶ top2_vendors: pyspark.sql.dataframe.DataFrame = [VendorID: string, total_revenue: double ... 2 more fields]

VendorID	total_revenue	total_passengers	total_distance
1	4462849.16000325	176404	378842.5000000025
2	5708885.429996097	341985	500606.6799999969

Query 6: Route with Most Passengers

- Grouped by both PULocationID and DOLocationID to define a "route."
- Summed passenger_count for each route.
- Identified the route with the highest total passengers.



```
from pyspark.sql.functions import sum, desc

route_passenger_counts = df.groupBy("PULocationID", "DOLocationID").agg(
    sum("passenger_count").alias("total_passengers")
)

# We will get the route with the highest number of passengers
top_route = route_passenger_counts.orderBy(desc("total_passengers")).limit(1)

top_route.show(truncate=False)

# Show top 5 most frequently used routes
route_passenger_counts.orderBy(desc("total_passengers")).show(5, truncate=False)
```

▶ (4) Spark Jobs

- ▶ route_passenger_counts: pyspark.sql.dataframe.DataFrame = [PULocationID: integer, DOLocationID: integer ... 1 more field]
- ▶ top_route: pyspark.sql.dataframe.DataFrame = [PULocationID: integer, DOLocationID: integer ... 1 more field]

PULocationID	DOLocationID	total_passengers
264	264	186698

PULocationID	DOLocationID	total_passengers
264	264	186698
237	236	86732
236	236	78691
236	237	71751
237	237	64492

Query 7: Top Pickup Locations in the Last N Seconds

- Retrieved the maximum pickup timestamp from the dataset.
- Defined a time window (last 5 or 10 seconds).
- Filtered data to include only trips within that time frame.
- Aggregated and sorted pickup locations by passenger count to detect demand surges.

The screenshot shows the Databricks interface with a notebook titled 'Taxi_notebook'. The code in the notebook is as follows:

```
from pyspark.sql.functions import max as _max, sum as _sum, col, expr, desc

df_input = df
latest_ts = df_input.agg(_max("tpep_pickup_datetime")).first()[0]

window_seconds = 10
window_start = expr(f"timestamp('{latest_ts}') - INTERVAL {window_seconds} seconds")

recent_rides = df_input.filter(
    (col("tpep_pickup_datetime") > window_start) &
    (col("tpep_pickup_datetime") <= latest_ts)
)

top_pickup_locations = recent_rides.groupBy("PULocationID").agg(
    _sum("passenger_count").alias("total_passengers")
).orderBy(desc("total_passengers"))

top_pickup_locations.show(truncate=False)
```

The output of the query is displayed below the code:

```
┌(4) Spark Jobs┐
┌ df_input: pyspark.sql.dataframe.DataFrame = [VendorID: string, tpep_pickup_datetime: timestamp ... 17 more fields]
┌ recent_rides: pyspark.sql.dataframe.DataFrame = [VendorID: string, tpep_pickup_datetime: timestamp ... 17 more fields]
┌ top_pickup_locations: pyspark.sql.dataframe.DataFrame = [PULocationID: integer, total_passengers: long]
+-----+-----+
|PULocationID|total_passengers|
+-----+-----+
|48          |2              |
+-----+-----+
```

Output-

The screenshot shows the Databricks interface with the same 'Taxi_notebook'. The code in the notebook is as follows:

```
from pyspark.sql.functions import sum as _sum
from pyspark.sql.functions import col

df = df.withColumn("Revenue", col("fare_amount") + col("extra") + col("mta_tax") + col("tip_amount") + col("tolls_amount") + col("improvement_surcharge") + col("congestion_surcharge"))

vendor_revenue = df.groupBy("VendorID") \
    .agg(_sum("Revenue").alias("total_revenue")) \
    .orderBy("total_revenue", ascending=False)
```

The output of the query is displayed below the code:

```
┌ df: pyspark.sql.dataframe.DataFrame = [VendorID: string, tpep_pickup_datetime: timestamp ... 18 more fields]
┌ vendor_revenue: pyspark.sql.dataframe.DataFrame = [VendorID: string, total_revenue: double]
+-----+-----+
|VendorID|total_revenue|
+-----+-----+
|48      |2.0          |
+-----+-----+
```

Below this, there is another code block that writes data to storage:

```
storage_account_name = "taxidatalake2025"
container_name = "taxidata"
abfss_path = f"abfss://{container_name}@taxidatalake2025.dfs.core.windows.net"

top_pickup_locations.write.mode("overwrite").parquet(f"{abfss_path}/query1_top_pickup_locations")
top_dropoff_locations.write.mode("overwrite").parquet(f"{abfss_path}/query2_top_dropoff_locations")
vendor_revenue.write.mode("overwrite").parquet(f"{abfss_path}/query3_vendor_revenue")
df_moving_count.write.mode("overwrite").parquet(f"{abfss_path}/query4_moving_count")
top2_vendors.write.mode("overwrite").parquet(f"{abfss_path}/query5_top2_vendors")
top_route.write.mode("overwrite").parquet(f"{abfss_path}/query6_top_route")
top_pickup_locations.write.mode("overwrite").parquet(f"{abfss_path}/query7_top_pickup_locations")
```

The output of this code block is displayed below:

```
┌(20) Spark Jobs┐
┌ df: pyspark.sql.dataframe.DataFrame = [VendorID: string, tpep_pickup_datetime: timestamp ... 18 more fields]
┌ vendor_revenue: pyspark.sql.dataframe.DataFrame = [VendorID: string, total_revenue: double]
+-----+-----+
|VendorID|total_revenue|
+-----+-----+
|48      |2.0          |
+-----+-----+
```

Microsoft Azure

Upgrade

Search resources, services, and docs (G+I)

Copilot

grahul2910@gmail.com

DEFAULT DIRECTORY

Home > Storage accounts > taxidatalake2025 | Containers >

taxidata

Container

Search

«

+ Add Directory

↑ Upload

↻ Refresh

🗑 Delete

📄 Copy

📄 Paste

🔄 Rename

🔒 Acquire lease

🔓 Break lease

🔗 Edit columns

Overview

Diagnose and solve problems

Access Control (IAM)

Settings

taxidata

Authentication method: Access key (Switch to Microsoft Entra user account)

Search blobs by prefix (case-sensitive)

Only show active objects

Showing all 8 items

<input type="checkbox"/>	Name	Last modified	Access tier	Blob type	Size	Lease state
<input type="checkbox"/>	📁 query1_top_pickup_locations	25/7/2025, 5:20:14 pm				...
<input type="checkbox"/>	📁 query2_top_dropoff_locations	25/7/2025, 5:20:25 pm				...
<input type="checkbox"/>	📁 query3_vendor_revenue	25/7/2025, 5:20:38 pm				...
<input type="checkbox"/>	📁 query4_moving_count	25/7/2025, 5:33:17 pm				...
<input type="checkbox"/>	📁 query5_top2_vendors	25/7/2025, 5:33:32 pm				...
<input type="checkbox"/>	📁 query6_top_route	25/7/2025, 5:33:43 pm				...
<input type="checkbox"/>	📁 query7_top_pickup_locations	25/7/2025, 5:33:53 pm				...
<input type="checkbox"/>	📄 yellow-tripdata-2018-01.csv	23/7/2025, 12:27:10 pm	Hot (Inferred)	Block blob	942.46 MiB	Available

Add or remove favorites by pressing Ctrl+Shift+F