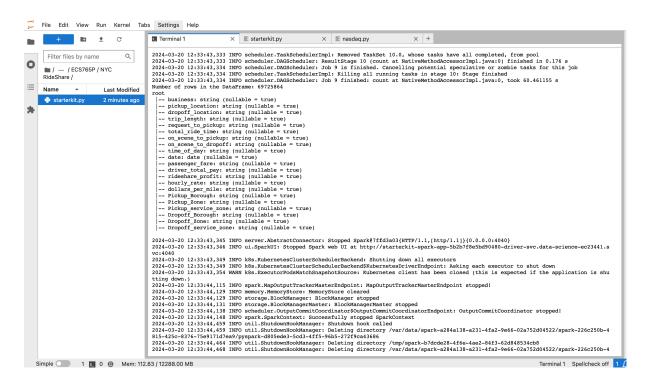
#### TASK 1:

#### **Explanation:**

- In this task, first we load the rideshare data and taxi zone data using load()
  function.
- 2. The rideshare data contains information about rides, like pickup and dropoff locations. The taxi zone data provides additional details about these locations such as borough and zone information.
- 3. The objective of this task is to add the rideshare data with additional location details.
- 4. I have merged rideshare data with taxi zone data using rideshare data's **pickup\_location** and taxi\_zone data's **LocationID**.
- 5. Similarly, for the dropoff location I have used rideshare data's **dropoff\_location** with taxi zone data's **LocationID**.

#### Result:



#### Challenges Faced:

1. One challenge was to correctly identify the type of join for the rideshare data with the taxi zone data based on location IDs. As we required all the data from rideshare and only the common data between rideshare and taxi zone.

- 2. Resolution- I have used Spark's join function with appropriate parameters to perform the left join between rideshare data and taxi zone data.
- 3. After joining the datasets, there was a need to rename columns to avoid conflicts.
- 4. Resolution- I have used spark's **alias()** function to rename the columns properly.
- 5. The rideshare data contained dates as timestamps, which were to be converted to a more readable format.
- 6. Resolution- I have used used Spark's **to\_date()** and **from\_unixtime()** functions to convert the timestamp column to a date format.

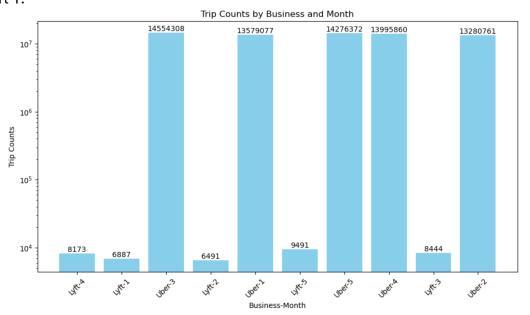
#### Knowledge Acquired:

- 1. Understanding of data joining techniques in Spark.
- 2. Data type conversion for improved data handling and analysis.

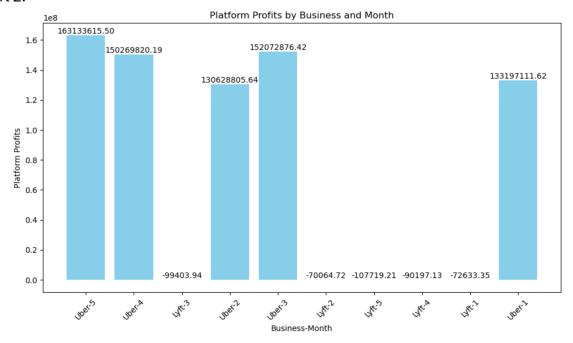
## TASK 2: Explanation:

- 1. This task involves conducting monthly analysis on rideshare data to get insights into trip counts, platform profits, and drivers' earnings.
- 2. The trip counts were calculated by aggregating data based on business, month col and using **count()** function.
- 3. To calculate the platform profits, first I had to convert rideshare\_profit into float and then aggregate business, month col and taking sum of rideshare\_profit using **sum()** function.
- 4. Similarly, to get the drivers earnings I have converted driver\_total\_pay into float and then using **sum()** function calculated the total driver's earnings for each business in each month.

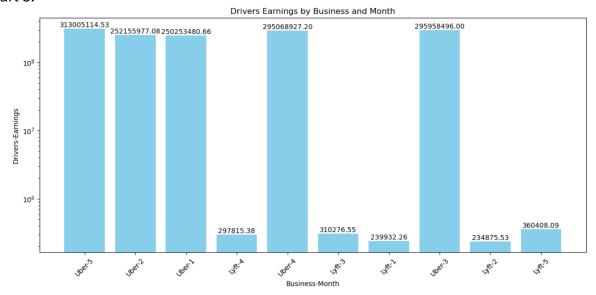
## Result: Part 1:



Part 2:



Part 3:



#### Challenges Faced:

- 1. Aggregating data by both business and month col to get insights of the data.
- Resolution- I have used Spark's groupBy() function with appropriate columns (groupBy("business", "month")) to aggregate the data before performing calculations.
- 3. Converting columns to required data types for numerical calculations was one of the challenge.
- 4. Resolution- I have utilized Spark's **withColumn()** function along with **cast()** to convert columns like rideshare\_profit and driver\_total\_pay to float to perform summation.

- 5. Writing the aggregated results to CSV files while ensuring proper formatting was a challenge.
- 6. Resolution- I have used Spark's **write()** function with suitable options (**option("header", "true"), mode("overwrite"))** to write the data to CSV files stored in the specified S3 bucket. Also, repartitioning the dataFrame to a single partition (**repartition(1)**) helped in generating a single CSV file.

#### Knowledge Acquired:

- 1. Understanding of data aggregation techniques in Spark, to generate insights from a huge dataset.
- 2. Proficiency in handling data type conversions for numerical calculations and analysis.
- 3. Familiarity with writing aggregated data to external storage systems, such as S3.

#### Insights:

#### For Drivers-

- 1. Uber seems to have a higher number of trips, which indicate more opportunities for drivers to get passengers and therefore earn more income.
- 2. Higher earnings on Uber could attract more drivers to the platform.
- 3. The data could give Lyft drivers a stronger position to negotiate better terms with Lyft for its further development.

#### For CEO-

- 1. Investigate why customers prefer one service over the other. It could be due to service quality, price or availability.
- 2. For Lyft, strategies might include marketing adv, promotions, or discounts. For Uber, it might be about expansion into new markets.
- 3. Lyft may need to innovate in pricing, quality of service, or driver benefits to differentiate itself from Uber.

#### TASK 3:

#### **Explanation:**

- 1. The task aims to analyze ride-sharing data to find out which boroughs are most popular for pickups and drop-offs for each month.
- 2. A Spark SQL query is executed to find the top 5 pickup boroughs for each month. The query selects the Pickup\_Borough, month, and trip\_count col from the pickup\_data dataframe. It calculates the trip count for each pickup borough within each month using the **COUNT(\*)** function and ranks them using the **ROW\_NUMBER()** window function.
- 3. Similarly, spark SQL query is executed to find the top 5 dropoff boroughs for each month. Similar to the previous query, it selects the Dropoff\_Borough, month, and trip\_count columns from the dropoff\_data dataframe.
- 4. Another objective of this task is to find top 30 most profitable routes.
- 5. For this a spark SQL query is executed to identify the top 30 routes based on the total profit earned. The query selects the Pickup\_Borough and Dropoff\_Borough

col and concatenated to form Route, and calculates the total profit earned by **sum(driver\_total\_pay)** for each route. The results are then ordered by total profit in descending order and limit of 30 is applied.

#### Result:

#### Part 1:

2024-04-01 10:59:53,191 INFO scheduler.DAGScheduler: Job 8 is finished. Cancelling potential speculative or zombie tasks for this job 2024-04-01 10:59:53,192 INFO scheduler.TaskSchedulerImpl: Killing all running tasks in stage l1: Stage finished 2024-04-01 10:59:53,192 INFO scheduler.DAGScheduler: Job 8 finished: showString at NativeMethodAccessorImpl.java:0, took 194.755044 s 2024-04-01 10:59:53,217 INFO codegen.CodeGenerator: Code generated in 17.405446 ms 2024-04-01 10:59:53,237 INFO codegen.CodeGenerator: Code generated in 14.581417 ms

+	<del>-</del>
Month	trip_count
1	5854818
1	3360373
1	2589034
1	1607789
1	173354
2	5808244
2	3283003
2	2447213
2	1581889
2	166328
3	6194298
3	3632776
3	2757895
3	1785166
3	191935
4	6002714
4	3481220
4	2666671
4	1677435
4	175356
	1 1 1 1 1 2 2 2 2 2 3 3 3 3 3 4 4 4

only showing top 20 rows

#### Part 2:

2024-04-01 11:02:54,141 INFO scheduler.TaskSchedulerImpl: Removed TaskSet 16.0, whose tasks have all completed, from pool 2024-04-01 11:02:54,142 INFO scheduler.DAGScheduler: ResultStage 16 (showString at NativeMethodAccessorImpl.java:0) finished in 0.904 s 2024-04-01 11:02:54,142 INFO scheduler.DAGScheduler: Job 11 is finished. Cancelling potential speculative or zombie tasks for this job 2024-04-01 11:02:54,142 INFO scheduler.TaskSchedulerImpl: Killing all running tasks in stage 16: Stage finished 2024-04-01 11:02:54,143 INFO scheduler.DAGScheduler: Job 11 finished: showString at NativeMethodAccessorImpl.java:0, took 180.266814 s

Dropoff_Borough	Month	trip_count
Manhattan	1	5444345
Brooklyn	1	3337415
Queens	1	2480080
Bronx	1	1525137
Unknown	1	535610
Manhattan	2	5381696
Brooklyn	2	3251795
Queens	2	2390783
Bronx	2	1511014
Unknown	2	497525
Manhattan	3	5671301
Brooklyn	3	3608960
Queens	3	2713748
Bronx	3	1706802
Unknown	3	566798
Manhattan	4	5530417
Brooklyn	4	3448225
Queens	4	2605086
Bronx	4	1596505
Unknown	4	551857
±	h	L

only showing top 20 rows

#### Part 3:

```
2024-04-01 11:11:50,471 INFO scheduler.TaskSchedulerImpl: Removed TaskSet 20.0, whose tasks have all completed, from pool
2024-04-01 11:11:50,471 INFO scheduler.TRBKScheduler.ResultStage 20 (showString at NativeMethodAccessorImpl.java:0) finished in 0.065 s 2024-04-01 11:11:50,473 INFO scheduler.DAGScheduler: BesultStage 20 (showString at NativeMethodAccessorImpl.java:0) finished in 0.065 s 2024-04-01 11:11:50,473 INFO scheduler.DAGSchedulerImpl: Killing all running tasks in stage 20: Stage finished 2024-04-01 11:11:50,473 INFO scheduler.DAGSchedulerImpl: Killing all running tasks in stage 20: Stage finished 2024-04-01 11:11:50,503 INFO codegen.CodeGenerator: Code generated in 22.948474 ms
                                                             total profit
                                                             3.338577255500229E8
 Manhattan to Manhattan
  Brooklyn to Brooklyn
Queens to Queens
Manhattan to Queens
                                                              1.7394472147999212E8
                                                             |1.1470684719998907E8
|1.0173842820999995E8
  Queens to Manhattan
                                                             8.603540026000004E7
                                                             | 8.010710241999993E7
| 7.414622575999324E7
| 6.799047559E7
  Manhattan to Unknown
  Bronx to Bronx
Manhattan to Brooklyn
                                                              6.317616104999998E7
 Brooklyn to Manhattan
Brooklyn to Queens
Queens to Brooklyn
Queens to Unknown
                                                              5.045416243000008E7
                                                              |4.729286536000015E7
|4.629299990000003E7
  Bronx to Manhattan
                                                              3.2486325170000087E7
  Manhattan to Bronx
                                                              3.197876345000006E7
                                                             | 3.197876345000006E7
| 2.375088861999999E7
| 1.084882757E7
| 1.0464800209999997E7
 |Manhattan to EWR
|Brooklyn to Unknown
  Bronx to Unknown
  Bronx to Queens
                                                              1.0292266499999998E7
Queens to Bronx | 1.01828987299999 | Staten Island to Staten Island | 9686862.450000014
only showing top 20 rows
```

queries.

# Challenges Faced: 1. The main challenge was understand the need to create temporary views for each dataframe and check whether they are correctly registered for Spark SQL

- 2. Resolution: I have used the **createOrReplaceTempView()** function to create temporary views for each dataframe.
- 3. Another challenge was to correctly rank the top pickup and dropoff boroughs for each month.
- 4. Resolution- This is achieved by using the **ROW\_NUMBER()** window function with appropriate partitioning and ordering within the Spark SQL queries.
- 5. Concatenating pickup and dropoff boroughs to form routes for the top 30 routes posed a challenge due to string manipulation.
- 6. Resolution- Used **CONCAT()** function within the Spark SQL query to concatenate the boroughs into routes.

#### Knowledge Acquired:

- 1. Understood the importance of creating temporary views for dataframes to enable Spark SQL operations.
- 2. Learned how to utilize window functions like ROW\_NUMBER() for ranking data.

#### Insights:

#### For Driver -

- 1. Trip counts are highest in Manhattan, which indicates that a driver will find more customers and potentially make more money working in this borough.
- 2. Depending on demand and trip counts in each borough, a driver could manage its schedule to get higher trip counts.
- 3. Based on the most profitable routes, drivers can position themselves in certain areas to increase the chance of picking up higher-paying fares.

#### For CEO –

1. For Uber, add more cars in high-demand areas (like Manhattan) to increase the revenue and maintain market dominance.

2. Despite lower numbers, Lyft has the opportunity to capture market share from Uber by targeting less-served boroughs or improving services.

#### TASK 4:

#### Explanation:

- In this task we calculate the average driver total pay for each time of day. The
  query selects the time\_of\_day column and calculates the average driver total
  pay using the AVG() aggregation function. The results are grouped by
  time\_of\_day and ordered by average\_drive\_total\_pay in descending order.
- 2. In the next part of the task we find the average trip length for each time of day.
- 3. First the trip\_length column in the rideshare\_with\_month dataframe was converted to float data type using the **withColumn**() and **cast()** function.
- 4. Spark SQL query was executed to calculate the average trip length for each time of day. Similar to the previous query, it selects the time\_of\_day column and calculates the average trip length using the AVG() aggregation function. The results were grouped by time\_of\_day and ordered by average\_trip\_length in descending order.
- 5. The avg\_driver\_total\_pay and average\_trip\_length dataframes are joined on the time\_of\_day column to calculate the average earning per mile. The result is obtained by dividing the average driver total pay by average trip length. The orderBy() function is used to sort the results by average\_earning\_per\_mile

#### Result:

#### Part 1:

```
2024-03-25 11:48:52,641 INFO scheduler.TaskSetManager: Finished task 194.0 in stage 23.0 (TID 1437) in 14 ms on 10.132.69.132 (executor 2) (197 / 200)
2024-03-25 11:48:52,641 INFO scheduler.TaskSetManager: Starting task 199.0 in stage 23.0 (TID 1442, 10.135.39.24, executor 1, partition 199, PR OCESS_LOCAL, 7344 bytes)
2024-03-25 11:48:52,642 INFO scheduler.TaskSetManager: Finished task 197.0 in stage 23.0 (TID 1440) in 7 ms on 10.135.39.24 (executor 1) (198/2 00)
2024-03-25 11:48:52,646 INFO scheduler.TaskSetManager: Finished task 199.0 in stage 23.0 (TID 1442) in 5 ms on 10.135.39.24 (executor 1) (199/2 00)
2024-03-25 11:48:52,648 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 23.0 (TID 1441) in 11 ms on 10.132.69.132 (executor 2) (200 / 2024-03-25 11:48:52,648 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 23.0 (TID 1441) in 11 ms on 10.132.69.132 (executor 2) (200 / 2024-03-25 11:48:52,648 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 23.0 (TID 1441) in 11 ms on 10.132.69.132 (executor 2) (200 / 2024-03-25 11:48:52,648 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 23.0 (TID 1441) in 11 ms on 10.132.69.132 (executor 2) (200 / 2024-03-25 11:48:52,648 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 23.0 (TID 1441) in 11 ms on 10.132.69.132 (executor 2) (200 / 2024-03-25 11:48:52,648 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 23.0 (TID 1441) in 11 ms on 10.132.69.132 (executor 2) (200 / 2024-03-25 11:48:52,648 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 23.0 (TID 1442) in 5 ms on 10.135.39.24 (executor 1) (199/2 / 200 / 2024-03-25 11:48:52,650 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 23.0 (TID 1442) in 5 ms on 10.135.39.24 (executor 1) (199/2 / 2024-03-25 11:48:52,650 INFO scheduler.TaskSetManager: Finished task 199.0 in stage 23.0 (TID 1441) in 11 ms on 10.135.39.24 (executor 1) (199/2 / 2024-03-25 11:48:52,650 INFO scheduler.TaskSetManager: Finished task 199.0 in stage 23.0 (TID 1441) in 11 ms
```

#### Part 2:

```
2024-03-25 13:16:01,265 INFO scheduler.TaskSetManager: Finished task 197.0 in stage 26.0 (TID 1687) in 8 ms on 10.135.82.160 (executor 2) (197/
200)
2024-03-25 13:16:01,267 INFO scheduler.TaskSetManager: Starting task 199.0 in stage 26.0 (TID 1689, 10.132.70.13, executor 1, partition 199, PR
OCESS_LOCAL, 7344 bytes)
2024-03-25 13:16:01,268 INFO scheduler.TaskSetManager: Finished task 196.0 in stage 26.0 (TID 1686) in 14 ms on 10.132.70.13 (executor 1) (198/
2024-03-25 13:16:01,270 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 26.0 (TID 1688) in 7 ms on 10.135.82.160 (executor 2) (199/
2024-03-25 13:16:01,278 INFO scheduler.TaskSetManager: Finished task 199.0 in stage 26.0 (TID 1689) in 11 ms on 10.132.70.13 (executor 1) (200/
2024-03-25 13:16:01,278 INFO scheduler.TaskSchedulerImpl: Removed TaskSet 26.0, whose tasks have all completed, from pool
2024-03-25 13:16:01,279 INFO scheduler.DAGScheduler: ResultStage 26 (showString at NativeMethodAccessorImpl.java:0) finished in 0.703 s 2024-03-25 13:16:01,279 INFO scheduler.DAGScheduler: Job 17 is finished. Cancelling potential speculative or zombie tasks for this job 2024-03-25 13:16:01,279 INFO scheduler.TaskSchedulerImpl: Killing all running tasks in stage 26: Stage finished 2024-03-25 13:16:01,279 INFO scheduler.DAGScheduler: Job 17 finished: showString at NativeMethodAccessorImpl.java:0, took 92.925872 s
|time of day|average trip length|
    night 5.323984802300156
morning 4.9273718666272845
afternoon 4.861410525884581
evening 4.484750367647451
2024-03-25 13:16:01,301 INFO server.AbstractConnector: Stopped Spark@6e9ea780{HTTP/1.1,[http/1.1]}{0.0.0.0:4040}
2024-03-25 13:16:01,302 INFO ui.SparkUI: Stopped Spark web UI at http://starterkit-spark-app-e697848e75b772fe-driver-svc.data-science-ec23441.s
2024-03-25 13:16:01,306 INFO k8s.KubernetesClusterSchedulerBackend: Shutting down all executors
2024-03-25 13:16:01,307 INFO k8s.KubernetesClusterSchedulerBackend$KubernetesDriverEndpoint: Asking each executor to shut down 2024-03-25 13:16:01,314 WARN k8s.ExecutorPodsWatchSnapshotSource: Kubernetes client has been closed (this is expected if the application is shu
2024-03-25 13:16:02,367 INFO spark.MapOutputTrackerMasterEndpoint: MapOutputTrackerMasterEndpoint stopped! 2024-03-25 13:16:02,387 INFO memory.MemoryStore: MemoryStore cleared 2024-03-25 13:16:02,388 INFO storage.BlockManager: BlockManager stopped
2024-03-25 13:16:02,300 INFO Storage.BlockManagerEstopped
2024-03-25 13:16:02,300 INFO storage.BlockManagerMaster: BlockManagerMaster stopped
2024-03-25 13:16:02,400 INFO scheduler.OutputCommitCoordinator$OutputCommitCoordinatorEndpoint: OutputCommitCoordinator stopped!
2024-03-25 13:16:02,412 INFO spark.SparkContext: Successfully stopped SparkContext
2024-03-25 13:16:02,797 INFO util.ShutdownHookManager: Shutdown hook called
2024-03-25 13:16:02,797 INFO util.ShutdownHookManager: Deleting directory /var/data/spark-ae990723-8cbl-4096-a3al-59clecd74831/spark-4a0378d8-6
994-4e0f-8d97-d97748c9ef96/pyspark-f44c6ae5-5cf8-4a3a-aaad-9b7e19b9b3a
2024-03-25 13:16:02,809 INFO util.ShutdownHookManager: Deleting directory /tmp/spark-7b8f970a-f1bb-490b-a0a4-db3e9c2cb1cd 2024-03-25 13:16:02,802 INFO util.ShutdownHookManager: Deleting directory /var/data/spark-ae990723-8cb1-4096-a3a1-59clecd74831/spark-4a0378d8-6
994-4e0f-8d97-d97748c9ef96
```

#### Part 3:

```
2024-03-25 14:15:25,179 INFO scheduler.TaskSetManager: Finished task 196.0 in stage 30.0 (TID 1979) in 11 ms on 10.134.57.84 (executor 1) (197/200)
2024-03-25 14:15:25,181 INFO scheduler.TaskSetManager: Starting task 199.0 in stage 30.0 (TID 1982, 10.134.24.221, executor 2, partition 199, PROCESS LOCAL, 7626 bytes)
2024-03-25 14:15:25,183 INFO scheduler.TaskSetManager: Finished task 197.0 in stage 30.0 (TID 1980) in 10 ms on 10.134.24.221 (executor 2) (198/200)
2024-03-25 14:15:25,187 INFO scheduler.TaskSetManager: Finished task 198.0 in stage 30.0 (TID 1981) in 9 ms on 10.134.57.84 (executor 1) (199/2 00)
2024-03-25 14:15:25,192 INFO scheduler.TaskSetManager: Finished task 199.0 in stage 30.0 (TID 1981) in 9 ms on 10.134.24.221 (executor 2) (200/200)
2024-03-25 14:15:25,192 INFO scheduler.TaskSetManager: Finished task 199.0 in stage 30.0 (TID 1982) in 11 ms on 10.134.24.221 (executor 2) (200/200)
2024-03-25 14:15:25,193 INFO scheduler.TaskScheduler.MaskSet 30.0, whose tasks have all completed, from pool 2024-03-25 14:15:25,193 INFO scheduler.DAGScheduler: ResultStage 30 (showString at NativeMethodAccessorImpl.java:0) finished in 1.122 s 2024-03-25 14:15:25,194 INFO scheduler.DAGScheduler: Job 19 is finished. Cancelling potential speculative or zombie tasks for this job 2024-03-25 14:15:25,194 INFO scheduler.DAGScheduler: Job 19 finished: showString at NativeMethodAccessorImpl.java:0, took 174.801553 s 1.1. (a) 1.1. (b) 1.1. (b) 1.1. (b) 1.1. (c) 1.1. (c)
```

#### Challenges Faced:

- Converting the trip\_length column to float data type required handling data type errors.
- 2. Resolution- The resolution involved using the **cast()** method along with the **withColumn()** function to ensure accurate data type conversion.
- 3. Joining the avg\_driver\_total\_pay and average\_trip\_length dataframes using the **join()** function with the appropriate join condition.

#### Knowledge Acquired:

Need to maintain data type consistency for accurate calculations.

#### Insights:

For Drivers-

- 1. Drivers earn the most in the afternoon, which may suggest a higher volume of rides or may be higher rates during these hours.
- 2. The morning and evening times also show substantial earnings, likely due to commuter traffic.
- 3. The longest trips occur at night, which may be due to a higher number of longdistance fares, like travelling to airport or railway stations.

#### For CEO-

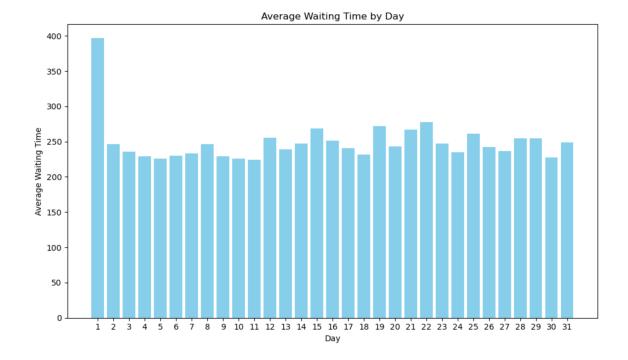
1. We can provide some discounts to boost number of rides during profitable times or encourage longer trips during off-peak hours. For example, we can provide discounts on rental cars during summer vacations.

#### TASK 5:

#### **Explanation:**

- 1. In this task we are calculating the average waiting time of each day for the month of January.
- 2. First I have converted the "request\_to\_pickup" column in the rideshare\_with\_month dataframe to integer data type using the **withColumn()** and **cast()** function.
- 3. A new dataframe named january\_data is created by filtering the rideshare\_with\_month dataframe to include only the data for the month of January. This is achieved by using the filter() function with the condition col("month") == 1.
- 4. The **dayofmonth()** function from the pyspark.sql.functions module is applied to the "date" column of the january\_data dataframe to extract the day component from the date.
- 5. The **groupBy()** function is applied to the "day" column of the january\_data dataframe to group the records by day. Then, the **avg()** function is used to calculate the average value of the "request\_to\_pickup" column for each day.
- 6. The **repartition()** function is used to ensure that the data is written to a single partition before writing to a CSV file. The data is then written to a CSV file in the specified S3 bucket location using the **write()** function.

Result:



#### Challenges Faced:

- 1. Ensuring that the data is repartitioned to a single partition before writing to a CSV file can improve performance and avoid issues related to multiple small output files.
- 2. The resolution involved using the **repartition()** function.

#### Knowledge Acquired:

1. Understanding the options involved in writing dataframes to external storage like s3 bucket.

#### Insights:

- 1. We can observe from the visualization that **January 1**<sup>st</sup> has the most average waiting time.
- 2. Increased travel and celebrations around New Year's Day can lead to more ride requests, causing longer wait times for drivers.
- 3. We can see that every 7-8<sup>th</sup> day has a higher waiting time. Weekends tend to be busier for rideshare services in general as more people travel and go out. This naturally leads to higher wait times for riders and less availability for drivers.
- 4. There could be times when there simply aren't enough drivers on the road. This could be due to factors like bad weather or any festival.
- 5. Big concerts, sporting events, or conferences can create temporary spikes in demand for rides. This can lead to longer wait times for drivers.

#### TASK 6:

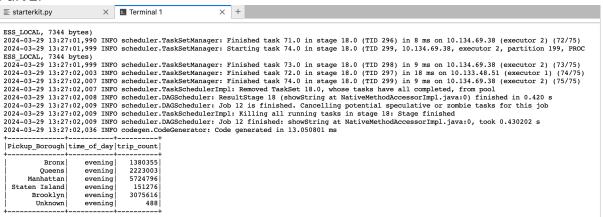
#### Explanation:

- In this task, we retrieve the trip count data for different pickup boroughs at different times of the day. It calculates the count of trips for each combination of pickup borough and time of day using the COUNT(\*) function. The GROUP BY clause is used to group the data based on pickup borough and time of day. The HAVING clause filters the results to include only trip counts greater than 0 and less than 1000.
- Next part focuses on trips occurring in the evening. We filter the data to include only trips where the time of day is 'evening' by using time\_of\_day = 'evening' condition.
- 3. In the third part of the task we retrieve data for trips that started in Brooklyn and ended in Staten Island. It selects the pickup borough, dropoff borough, and pickup zone (Pickup\_Zone) columns from the rideshare\_with\_month DataFrame where the pickup borough is 'Brooklyn' and the dropoff borough is 'Staten Island'. It limits the output to the first 10 records using the LIMIT clause.
- 4. The total number of trips between Brookly and Staten Island is 69437.

#### Result:

#### Part 1:

#### Part 2:



#### Part 3:

```
2024-03-29 14:12:48,319 INFO storage.BlockManagerInfo: Added broadcast_22_piece0 in memory on 10.134.102.47:39403 (size: 53.1 KiB, free: 2.1 Gi
B)
2024-03-29 14:12:48,451 INFO scheduler.TaskSetManager: Finished task 0.0 in stage 9.0 (TID 54) in 340 ms on 10.134.102.47 (executor 2) (1/1)
2024-03-29 14:12:48,452 INFO scheduler.TaskScheduler.Impl: Removed TaskSet 9.0, whose tasks have all completed, from pool
2024-03-29 14:12:48,453 INFO scheduler.DAGScheduler: ResultStage 9 (showString at NativeMethodAccessorImpl.java:0) finished in 0.351 s
2024-03-29 14:12:48,453 INFO scheduler.DAGScheduler: Job 8 is finished. Cancelling potential speculative or zombie tasks for this job
2024-03-29 14:12:48,453 INFO scheduler.TaskSchedulerImpl: Killing all running tasks in stage 9: Stage finished
2024-03-29 14:12:48,454 INFO scheduler.DAGScheduler: Job 8 finished: showString at NativeMethodAccessorImpl.java:0, took 0.355446 s
2024-03-29 14:12:48,479 INFO codegen.CodeGenerator: Code generated in 15.457079 ms
  |Pickup_Borough|Dropoff_Borough|
                                                                                                                                         Pickup Zone
                                                         Staten Island DUMBO/Vinegar Hill
Staten Island Dyker Heights
Staten Island Bensonhurst East
Staten Island Williamsburg (Sou...
Staten Island Bay Ridge
Staten Island Bay Ridge
                       Brooklyn
Brooklyn
Brooklyn
Brooklyn
```

### Challenges Faced:

Brooklyn

Brooklyn Brooklyn Brooklyn Brooklyn Brooklyn

Staten Island Bay Ridge
Staten Island Flatbush/Ditmas Park
Staten Island Bay Ridge
Staten Island Bath Beach
Staten Island Bay Ridge

1. Executing SQL queries on large datasets have impact on performance, especially if the queries involve complex aggregations or filters. It was essential to optimize queries and consider indexing columns for faster execution.

#### Knowledge Acquired:

1. Understanding how to apply filters in SQL queries using the WHERE clause to retrieve data that meets specific conditions.