ECS765P-Big Data Processing

Coursework: NYC Rideshare Analysis

Name: Addalin Lariena Rose Devasahaya Rajan

Student ID: 230187746

Common APIs:

- os: This module provides to interact with the Operating System. In all of the codes, this module
 is used to set up configurations to access the files stored in the Amazon S3 bucket which
 prevents from hardcoding the credentials directly in the python files.
- **SparkSession**: This class is part of the Apache Spark's core API that allows to work with structured data and execute data processing tasks in a distributed manner. In all of the codes, it is used to perform spark operations such as reading, processing and writing data to storage.
- **from_unixtime**: This function is provided by Spark SQL. It is used to convert Unix timestamp values to date-time format that makes sense to us. In all of the codes, this is used to convert the Unix timestamp value of the column 'date' of the joined DataFrame into date value.
- **Col**: This is a utility function provided by Spark SQL. It is used to reference or create columns in the DataFrames.
- Month: This function is a part of pyspark.sql.functions module. Where the module itself gives various built-in functions for manipulation and transformation of the DataFrames. In all of the codes, this function is used for extracting month or day component from the converted 'date' column.
- Concat: Like the month function, concat is also a part of the pyspark.sql.functions module. It is
 used to concat the strings from multiple columns to one string column. In most of the codes, it
 is used to concat newly created column 'month' and 'business' column.
- **FloatType**: This datatype is part of the pyspark.sql.types module. It represents floating point numbers. In most of the code, it is used to convert the string datatype to float datatype to perform numerical operations.

Explanation:

- 1. Loaded the csv files from the shared buckets using SparkSession.
- 2. Applied join on rideshare and taxi zone lookup tables firstly on pickup location, new columns were renamed according to the task. Then the intermediate result was joined with taxi zone lookup based on dropoff location and again columns were renamed.
- 3. The 'date' column was converted to date format using 'from_unixtime' function and 'col' was also used to reference the 'date' column.
- 4. Printed schema using printSchema function and printed number of rows using count function

Visualization:

```
2024-03-28 07:52:23,661 INFO scheduler.DAGScheduler: Job
  -- business: string (nullable = true)
    pickup_location: integer (nullable = true)
  -- dropoff location: integer (nullable = true)
  -- trip length: double (nullable = true)
  -- request_to_pickup: double (nullable = true)
  -- total_ride_time: double (nullable = true)
  -- on_scene_to_pickup: double (nullable = true)
  -- on scene to dropoff: double (nullable = true)
  -- time_of_day: string (nullable = true)
  -- date: string (nullable = true)
    passenger_fare: double (nullable = true)
  -- driver_total_pay: double (nullable = true)
  -- rideshare_profit: double (nullable = true)
  -- hourly_rate: string (nullable = true)
  -- dollars_per_mile: string (nullable = true)
  -- Pickup_Borough: string (nullable = true)
  -- Pickup_Zone: string (nullable = true)
 -- Pickup service zone : string (nullable = true)
 |-- Dropoff_Borough: string (nullable = true)
 |-- Dropoff_Zone: string (nullable = true)
 |-- Dropoff_service_zone: string (nullable = true)
2024-03-28 07:52:24,216 INFO storage.BlockManagerInfo: Rem
3 KiB. free: 2004.4 MiB)
```

```
2024-03-27 16:06:07,507 INFO
Number of rows: 69725864
2024-03-27 16:06:07,528 INFO
```

Challenges:

Learning curve of using spark operations on the dataframe was challenging. But by researching
on the spark operations and spark API, I was able to understand their operation and where to
use them.

- Understanding Spark operations and Spark API
- Knowing how to merge datasets

APIs Used Here:

- Lit: It is a function provided by pyspark.sql.functions. It is used to create new column with a constant value across.
- Count: It is an aggregate function provided by pyspark.sql.functions. It counts the non-null values in a dataframe or a within a group.
- StructType: It is a class provided by pyspark.sql.types. By specifying the names and datatypes of the columns, it is used to create a structure of the dataframe.
- StructField: It is a class provided by pyspark.sql.types. Used with StructType, it defines the column in the schema.
- StringType: It is a datatype provided by pyspark.sql.types. It is used to specify a column datatype as String.

Explanation:

- Part 1:

- Selected the columns only needed for this part to simplify processing and reduce memory usage
- Created a new dataframe by building a new schema using StructType class
- Processing trip count by looping into each month, grouping by business and counting by using count function, and finally storing them in the new dataframe
- Ordering the results by month, repartitioning it to a single file and writing it as csv file to the shared bucket
- Using Pandas, matplotlib, numpy and seaborn libraries the results were plotted into histogram

- Part 2:

- Selected the columns only needed for this part to simplify processing and reduce memory usage
- o Extracting month values from 'date' column to a new column called 'month'
- o 'rideshare profit' field is casted to FloatType for further processing
- Concating 'business' and 'month' column values to a new column called 'business_month'
- Adding the platform profits ('rideshare_profit' values) grouped by 'business_month' column using count function
- Repartitioning the resulting dataframe to a single file and writing it as csv file to the shared bucket
- Using Pandas, matplotlib, numpy and seaborn libraries the results were plotted into histogram

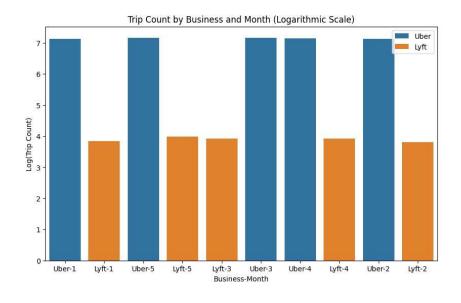
- Part 3:

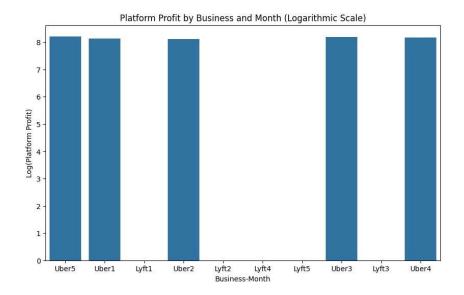
- Selected the columns only needed for this part to simplify processing and reduce memory usage
- o Extracting month values from 'date' column to a new column called 'month'
- 'driver_total_pay' field is casted to FloatType for further processing
- Concating 'business' and 'month' column values to a new column called 'business month'
- Adding the drivers earnings ('driver_total_pay' values) grouped by 'business_month' column

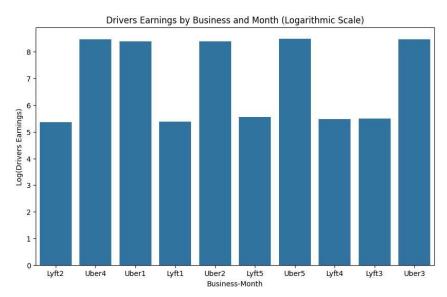
- Repartitioning the resulting dataframe to a single file and writing it as csv file to the shared bucket
- Using Pandas, matplotlib, numpy and seaborn libraries the results were plotted into histogram

- Part 4:

- From the trip count:
 - It is noticeable that Uber has higher trip counts than Lyft in general
 - For both business the trend of trip count increases overall
 - The highest trip count value is for the month of May
 - From the results, as a driver I will try to maximise my earnings in month of May and as the CEO I can do more marketing or make informed decisions on the resource allocation problems.
- From platform profits:
 - Uber has higher platform profits overall compared to Lyft
 - For both the businesses the platform profit increases towards May
 - Lyft shows negative profit in all months except May
 - From the results, as a stockbroker I can use this to guide my investment decisions by investing into Uber and as a CEO by looking into the company's finance I can make decisions for better cost management and better strategies in pricing
- From drivers earnings:
 - Uber drivers earn higher compared to Lyft drivers overall
 - There is an increase of earnings towards May for both the businesses
 - The most profitable month for the drivers is in May
 - From the results, as a driver I can apply in Uber due to higher earnings compared to Lyft and as a CEO monitoring the drivers earnings can provide insights on the drivers satisfaction and retention rates







Challenges:

Visualizing values with large variations between them in the histogram. Due to the large
variation in the big and small values, the histogram did not showcase all the values properly. To
rectify this I used logarithmic scaling to compress the large values for better visualization for
better analysation and interpretation of the graph.

- Computing sum and total count by using Spark
- Writing results in a csv file
- Scaling extremely large values for better visualization
- Creating new dataframe from schema
- Knowing how to aggregate data

APIs Used Here:

- Lit: It is a function provided by pyspark.sql.functions. It is used to create new column with a constant value across.
- Count: It is an aggregate function provided by pyspark.sql.functions. It counts the non-null values in a dataframe or a within a group.
- Sum: It is an aggregate function provided by pyspark.sql.functions. It aggregates values in a dataframe column or a within a group.
- StructType: It is a class provided by pyspark.sql.types. By specifying the names and datatypes of the columns, it is used to create a structure of the dataframe. StructField: It is a class provided by pyspark.sql.types. Used with StructType, it defines the column in the schema.
- StringType: It is a datatype provided by pyspark.sql.types. It is used to specify a column datatype as String.

Explanation:

Part 1:

- Selected the columns only needed for this part to simplify processing and reduce memory usage
- Created a new dataframe by building a new schema using StructType class
- Processing trip count by looping into each month, grouping by pickup borough, counting by using count function and taking only top 5 by descending order, and finally storing them in the new dataframe
- o Ordering the dataframe by month and printing it

- Part 2:

- Selected the columns only needed for this part to simplify processing and reduce memory usage
- Created a new dataframe by building a new schema using StructType class
- Processing trip count by looping into each month, grouping by dropoff borough, counting by using count function and taking only top 5 by descending order, and finally storing them in the new dataframe
- Ordering the dataframe by month and printing it

- Part 3:

- Selected the columns only needed for this part to simplify processing and reduce memory usage
- Adding the total_profit ('driver_total_pay' values) grouped by 'Pickup_Borough' and 'Dropoff Borough' columns
- Creating new column 'Route' by concatenating Pickup_Borough and Dropoff_Borough columns
- Dropped Pickup_Borough and Dropoff_Borough columns
- o Ordering dataframe by total_profit in descending order and taking only top 30
- o Printing the resulting dataframe

- Part 4:

- Manhattan has the highest trip count for pickup and dropoff borough overall
- Manhattan to Manhattan route has the highest total profit
- As a driver, since there is more demand and profit for the Manhattan route I will
 reschedule to align most of my trips this route.

 As CEO, by looking into this resources can be allocated to Manhattan route to meet the demands and also amp up the marketing efforts into this route

Pickup_Borough Mo	nth t	rip_count
	+-	
Manhattan	1	5854818
Brooklyn	1	3360373
Queens	1	2589034
Bronx	1	1607789
Staten Island	1	173354
Bronx	2	1581889
Manhattan	2	5808244
Queens	2	2447213
Brooklyn	2	3283003
Staten Island	2	166328
Queens	3	2757895
Manhattan	3	6194298
Bronx	3	1785166
Brooklyn	3	3632776
Staten Island	3	191935
Manhattan	4	6002714
Brooklyn	4	3481220
Bronx	4	1677435
Queens	4	2666671
Staten Island	4	175356

		rip_count
00.4407.000000		2480080
Manhattan		
		1525137
Brooklyn		
Unknown		
Bronx	2	1511014
Queens	2	2390783
Manhattan	2	5381696
Brooklyn	2	3251795
Unknown	2	497525
Manhattan	3	5671301
Queens	3	2713748
Unknown	3	566798
Brooklyn	3	3608960
Bronx	3	1706802
Manhattan		
Brooklyn	4	3448225
		1596505
Queens		
		551857

```
2024-04-04 08:38:26,850 INFO codegen.CodeGene
               total_profit|
                                                               Route
 3.3385772555002296E8 | Manhattan to Manh...
 1.7394472147999206E8 Brooklyn to Brooklyn
 1.1470684719998911E8 | Queens to Queens
1.0173842820999993E8 | Manhattan to Queens
8.603540026E7 | Queens to Manhattan
8.010710241999993E7 | Manhattan to Unknown
   7.414622575999323E7
                                               Bronx to Bronx
  6.799047558999999E7 | Manhattan to Broo...
6.317616104999997E7 | Brooklyn to Manha...
5.045416243000008E7 | Brooklyn to Queens
4.7292865360000156E7 | Queens to Brooklyn
4.629299990000004E7 | Queens to Unknown
 5.045416243000008E7
4.7292865360000156E7
   3.248632517000009E7
                                        Bronx to Manhattan
  3.1978763450000055E7
                                        Manhattan to Bronx
                                      Manhattan to EWR
Brooklyn to Unknown
Bronx to Unknown
Bronx to Queens
Queens to Bronx
 2.3750888619999994E7
             1.084882757E7
   1.046480020999999E7
              1.02922665E7
 1.0182898729999997E7 Queens to Bronx
9686862.45000001 Staten Island to ...
only showing top 20 rows
 2024-04-04 08:38:26,866 INFO server.AbstractC
```

Challenges:

No challenges were faced here

- Able to concatenate values of 2 columns into a new column
- Using spark to find the top-k data from the dataframe

APIs Used Here:

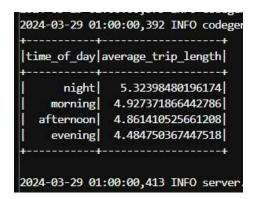
- avg: It is a function provided by pyspark.sql.functions. It calculates the mean of the values in a dataframe column.

Explanation:

- Part 1:
 - Selected the columns only needed for this part to simplify processing and reduce memory usage
 - Filtering dataframe according to time of day into 4 new dataframes
 - List of tuples is made where each element has the time of day and the average of the total driver pay for that time of day from the filtered dataframes
 - A new dataframe is made with the list of tuples and is ordered by the average total driver pay
 - o The resulting dataframe is printed
- Part 2:
 - Selected the columns only needed for this part to simplify processing and reduce memory usage
 - Filtering dataframe according to time of day into 4 new dataframes
 - List of tuples is made where each element has the time of day and the average of the trip length for that time of day from the filtered dataframes
 - A new dataframe is made with the list of tuples and is ordered by the average trip length
 - o The resulting dataframe is printed
- Part 3:
 - Selected the columns only needed for this part to simplify processing and reduce memory usage
 - o Filtering dataframe according to time of day into 4 new dataframes
 - List of tuples is made where each element has the time of day and the average of the trip length for that time of day from the filtered dataframes
 - A new dataframe is made with the list of tuples and is ordered by the average trip length
 - List of tuples is made where each element has the time of day and the average of the total driver pay for that time of day from the filtered dataframes
 - A new dataframe is made with the list of tuples and is ordered by the average total driver pay
 - The dataframes made for average of trip length and average of driver total pay is joined using inner join on the column time of day and a new column 'average_earning_per_mile' is created where the average driver total pay is divided by the average trip length
 - Unnecessary columns are dropped and the resulting dataframe is printed
- Part 4:
 - o For average earnings and trip length:
 - Afternoon trips have the highest average earning per mile
 - Night trips have the longest trip length
 - o For time of day and driver earnings

- Drivers earn more per mile in afternoon trips
- As a driver, I would align my schedule to more afternoon trips as it has more earnings and demand
- As a CEO, I would ensure resources are allocated to afternoon trips and pricing strategies can be made to maximize night trips

Visualization:



```
2024-03-29 01:42:43,811 INFO codegen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.CodeGen.C
```

Challenges:

No challenges were faced here

- Able to create dataframe from a list of tuples
- Using spark to join 2 dataframes and create a new column in the same line
- Able to provide average summaries on conditions

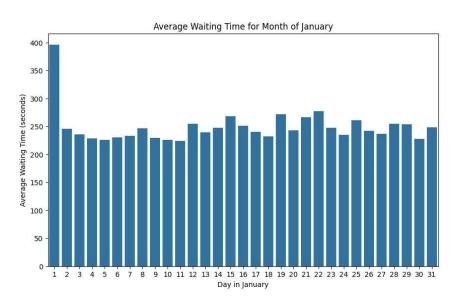
APIs Used Here:

- avg: It is a function provided by pyspark.sql.functions. It calculates the mean of the values in a dataframe column.
- Dayofmonth: It is a function provided by pyspark.sql.functions. It is used to extract the day of the month from columns that have DateType or TimestampType

Explanation:

- Part 1:
 - Selected the columns only needed for this part to simplify processing and reduce memory usage
 - Filtering dataframe according to month of January
 - Renamed 'date' column as 'day'
 - Average waiting time is calculated by averaging the 'request_to_pickup' column grouped by day into a new column 'average_waiting_time'
 - Dataframe is then ordered by day, repartitioned into a single file and written as csv file in the shared bucket
 - Using Pandas, matplotlib, numpy and seaborn libraries the results were plotted into histogram
- Part 2:
 - The average exceeds 300 seconds on the day 1
- Part 3:
 - o It is noticeable that for day 1 it could be due to New Year's celebration

Visualization:



Challenges:

No challenges faced here

Knowledge Gained:

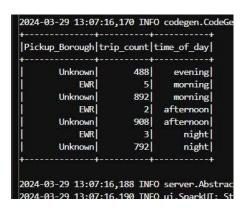
- Finding anomalies in a dataset using spark and visualization

APIs Used Here:

- Lit: It is a function provided by pyspark.sql.functions. It is used to create new column with a constant value across.
- Count: It is an aggregate function provided by pyspark.sql.functions. It counts the non-null values in a dataframe or a within a group.

Explanation:

- Part 1:
 - Selected the columns only needed for this part to simplify processing and reduce memory usage
 - o Filtering dataframe according to time of day into 4 new dataframes
 - o counting trip count grouped by pickup borough for all 4 time of day in separate dataframes
 - o joining all dataframes and filtering by trip count for more than 0 and less than 1000
 - o printing the resulting dataframe
- Part 2:
 - Selected the columns only needed for this part to simplify processing and reduce memory usage
 - o Filtering dataframe according to evening time of day
 - o counting trip count grouped by pickup borough
 - o printing the resulting dataframe
- Part 3:
 - Selected the columns only needed for this part to simplify processing and reduce memory usage
 - Filtering dataframe where Pickup_Borough is Brooklyn and Dropoff_Borough is Staten Island
 - o printing the number of trips from Brooklyn to Staten Island and 10 rows of data from resulting dataframe



```
2024-03-29 12:38:18,266 INFO scheduler.DAGSo
2024-03-29 12:38:18,295 INFO codegen.CodeGer
|Pickup_Borough|trip_count|time_of_day|
        Queens 2223003
                              evening
                     488
       Unknown
                                evening
                 3075616
151276
      Brooklyn
                                evening
 Staten Island
                                evening
     Manhattan 5724796
                                 evening
         Bronx 1380355
                                evening
2024-03-29 12:38:18,312 INFO server.Abstrac
2024-03-29 12:38:18,313 INFO ui.SparkUI: St
```

The number of trips from Brooklyn to Staten Island is 69437

```
2024-03-29 13:16:55,869 INFO codegen.CodeGenerator: Code generator: Code gener
```

Challenges:

No challenges faced here

Knowledge Gained:

To filter dataframe using one or more conditions

APIs Used Here:

- Lit: It is a function provided by pyspark.sql.functions. It is used to create new column with a constant value across.
- Count: It is an aggregate function provided by pyspark.sql.functions. It counts the non-null values in a dataframe or a within a group.

Explanation:

- Selected the columns only needed for this part to simplify processing and reduce memory usage
- Aggregating the count of routes by 'Pickup_Zone', 'Dropoff_Zone', and business and Grouping the aggregated route counts by 'Pickup_Zone' and 'Dropoff_Zone'
- Adding a new column 'total_count' that has the sum of counts for Uber and Lyft, ordering them in descending order and getting the top 10
- Adding new column 'route' by concatenating 'Pickup Zone' and 'Dropoff Zone' columns
- Unnecessary columns are dropped and resulting dataframe is printed

Visualization:

```
2024-04-04 14:05:27,158 INFO codegen.CodeGenerator: Code generated in 15
Lyft | Uber
           |total count |Route
                        JFK Airport to NA
46
     253211 253257
184
     202719 202903
                        East New York to East New York
     155803 155881
                        Borough Park to Borough Park
     151521 151562
                        LaGuardia Airport to NA
     126253 126279
                        Canarsie to Canarsie
 1770 107392 109162
                        South Ozone Park to JFK Airport
                        Crown Heights North to Crown Heights North
    98591 98691
 100
 300
     98274 98574
                        |Bay Ridge to Bay Ridge
     90692
            90767
                        Astoria to Astoria
     89652 89671
                        |Jackson Heights to Jackson Heights
2024-04-04 14:05:27,174 INFO server.AbstractConnector: Stopped Spark@6f0
```

Challenges:

- Using Pivot to create columns for Uber and Lyft, I wanted to find a way to create columns for the businesses without extra step. So I had to learn and see what pivot does here.

Knowledge Gained:

- Usage of pivot for creating columns

APIs Used Here:

- StructType: It is a class provided by pyspark.sql.types. By specifying the names and datatypes of the columns, it is used to create a structure of the dataframe.
- StructField: It is a class provided by pyspark.sql.types. Used with StructType, it defines the column in the schema.
- StringType: It is a datatype provided by pyspark.sql.types. It is used to specify a column datatype as String.
- Graph: It is provided by the graphframes. It allows for representing, manipulating and analysing graphs that are made from dataframes
- SQLContext: It is from pyspark.sql. It is used for working with structured data and executing SQL queries in Spark

Explanation:

- Define the schema for vertices and edges in the graph
- Creating vertices and edges dataframes
- Creating graph using the vertices and edges dataframes
- Finding the vertices in the graph where the pickup and dropoff locations are in the same borough and service zone and printing the count of it
- Specific columns are selected from the vertices and 10 rows of data are printed

```
2024-03-30 19:27:37,606 INFO codegen.CodeGenerator: Code
|id |Borough
                                               service zone
                    Zone
     EWR
                    Newark Airport
                                               EWR
                    Jamaica Bay Boro Zone
|Allerton/Pelham Gardens Boro Zone
|Alphabet City Yellow Zon
     Queens
     Bronx
     Manhattan
                                                Yellow Zone
     Staten Island Arden Heights
                                                Boro Zone
     Staten Island Arrochar/Fort Wadsworth Boro Zone
                    Astoria
     Queens
                                               Boro Zone
                    Astoria Park
     Queens
                                               Boro Zone
                     Auburndale
                                                Boro Zone
                    Baisley Park
                                               Boro Zone
only showing top 10 rows
 ample of Edges DataFrame:
2024-03-30 19:27:37,853 INFO datasources.FileSourceStrategy
```

```
2024-04-01 11:00:45,214 INFO codeger
|id |id |Borough |service_zone|
182 242 Bronx
                  Boro Zone
248 242 Bronx
                  Boro Zone
242 20 Bronx
                  Boro Zone
20 | 20 | Bronx
                  Boro Zone
236 262 Manhattan Yellow Zone
262 170 Manhattan Yellow Zone
239 239 Manhattan Yellow Zone
94 | 69 | Bronx
                  Boro Zone
47 | 247 | Bronx
                  Boro Zone
76 76 Brooklyn Boro Zone
only showing top 10 rows
2024-04-01 11:00:45,275 INFO spark.
```

```
2024-04-01 11:1/:38,725 INFO of the control of the
```

2024-04-01 11:00:43,943 INFO scheduler.DAGSchedule countof same borough and service zone: 46886992 2024-04-01 11:00:44,188 INFO datasources.FileSources

Challenges:

No challenges were faced here

Knowledge Gained:

Creating graph and traversing it