



CP 422 – Programming for Big Data

Fall 2024

Group 23

Assignment #2

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Submission Date: November 11, 2024

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Group-ID-23-CP422-A2.pdf (6)

November 11, 2024

#CP422 Assignment 2

0.1 Loading Data

```
[ ]: from pyspark.sql import SparkSession

# Initialize SparkSession
spark = SparkSession.builder \
    .appName("TaxiDataAnalysis") \
    .getOrCreate()

# Read the CSV file into a Spark DataFrame
df = spark.read.format("csv") \
    .option("header", "true") \
    .option("inferSchema", "true") \
    .load("dbfs:/FileStore/tables/yellow_tripdata_2015_01.csv")

# Create a temporary view for SQL queries
df.createOrReplaceTempView("yellow_taxi_data")
```

0.2 Q1: Outlier Detection

0.2.1 Task 1: Write a SQL query to find trips with fare amounts over \$1000.

```
[ ]: # SQL query to find trips with fare amounts over $1000
query = """
SELECT *
FROM yellow_taxi_data
WHERE fare_amount > 1000
"""

# Run the query
result_df = spark.sql(query)

# Show the results
result_df.show()
```

[Stage 136:=====> (9 + 1) / 10]

```

+-----+-----+-----+-----+-----+
--+-----+-----+-----+-----+-----+
-----+-----+-----+-----+-----+
-----+-----+-----+
|VendorID|tpep_pickup_datetime|tpep_dropoff_datetime|passenger_count|trip_distance|
pickup_longitude|pickup_latitude|RateCodeID|store_and_fwd_flag|
dropoff_longitude|dropoff_latitude|payment_type|fare_amount|extra|mta_tax|tip_
amount|tolls_amount|improvement_surcharge|total_amount|
+-----+-----+-----+-----+-----+
--+-----+-----+-----+-----+-----+
-----+-----+-----+-----+-----+
-----+-----+-----+
|      2| 2015-01-02 20:06:34| 2015-01-02 20:23:33|      1|
0.4|-74.01433563232422|40.711856842041016|      1|
N|-73.98519134521484| 40.76046371459961|      2|      3005.5| 0.05|      0.5|
0.0|      0.0|      0.3|      3006.35|
|      1| 2015-01-22 21:12:26| 2015-01-22 21:20:36|      1|
1.7|-73.96153259277344| 40.77063751220703|      1|
N|-73.97850799560547|40.749515533447266|      2|      4008.0| 0.5|      0.5|
0.0|      0.0|      0.3|      4009.3|
+-----+-----+-----+-----+-----+
--+-----+-----+-----+-----+-----+
-----+-----+-----+-----+-----+
-----+-----+-----+

```

0.2.2 Task 2: Write another query to find trips with zero or negative fare amounts.

```

[ ]: # SQL query to find trips with zero or negative fare amounts
query = """
SELECT *
FROM yellow_taxi_data
WHERE fare_amount <= 0
"""

# Run the query
result_df = spark.sql(query)

# Show the results
result_df.show()

```

```

+-----+-----+-----+-----+-----+
--+-----+-----+-----+-----+-----+
-----+-----+-----+-----+-----+
-----+-----+-----+
|VendorID|tpep_pickup_datetime|tpep_dropoff_datetime|passenger_count|trip_distance|

```

ce	pickup_longitude	pickup_latitude	RateCodeID	store_and_fwd_flag	dropoff_longitude	dropoff_latitude	payment_type	fare_amount	extra	mta_tax	tip_amount	tolls_amount	improvement_surcharge	total_amount
1	2015-01-28 20:22:19	2015-01-28 20:23:19												
4.8	-74.03569030761719	40.743648529052734	5											
N	-74.03571319580078	40.74365997314453	3		0.0	0.0	0.0							
0.0	0.0	0.3	0.3											
2	2015-01-17 22:40:27	2015-01-17 22:43:04												
0.11	-74.00235748291016	40.73982620239258	1											
N	-74.00111389160156	40.74110794067383	4		-3.5	-0.5	-0.5							
0.0	0.0	0.3	-4.8											
2	2015-01-15 17:33:24	2015-01-15 17:33:31												
0.0	-73.9825668334961	40.73979949951172	1											
-73.9825668334961	40.73979949951172	3		-2.5	-1.0	-0.5								
-0.7	0.0	0.3	-5.0											
1	2015-01-21 10:16:35	2015-01-21 10:16:54												
0.0	-73.9929428100586	40.76789855957031	5											
-73.9929428100586	40.767887115478516	1		0.0	0.0	0.0								
11.0	0.0	0.3	11.3											
2	2015-01-06 12:43:31	2015-01-06 12:46:07												
0.23	-73.9603271484375	40.76001739501953	2											
N	-73.96344757080078	40.76166534423828	2		0.0	0.0	0.5							
0.0	0.0	0.3	0.0											
1	2015-01-23 23:57:43	2015-01-24 00:35:26												
13.4	-73.97903442382812	40.7663688659668	5											
N	-74.15727996826172	40.73886489868164	4		0.0	0.0	0.0							
0.0	0.0	0.3	0.3											
2	2015-01-16 16:00:45	2015-01-16 16:00:53												
0.0	-73.9377212524414	40.75819396972656	1											
-73.9377212524414	40.75819396972656	3		-2.5	-1.0	-0.5								
0.0	0.0	0.3	-4.3											
1	2015-01-08 22:26:34	2015-01-08 22:26:34												
0.0	0.0	0.0	5											
0.0	0.0	2	0.0	0.0	0.0	0.0								
0.0	0.3	0.3												
2	2015-01-31 23:38:52	2015-01-31 23:38:54												
0.0	0.0	0.0	2											
0.0	0.0	2	-52.0	0.0	-0.5	0.0								
0.0	0.3	-52.8												
1	2015-01-22 09:32:57	2015-01-22 09:54:39												
2.4	-73.95448303222656	40.74155807495117	5											
N	-73.99308013916016	40.74636459350586	1		0.0	0.0	0.0							
10.0	0.0	0.3	10.3											
1	2015-01-05 02:27:56	2015-01-05 02:32:51												

2.9	0.0	0.0	5						
N -73.97557067871094	40.74790573120117		3		0.0	0.0	0.0		
0.0	5.33	0.3	5.63						
	2	2015-01-10 02:23:53	2015-01-10 02:23:58			2			
0.0	0.0	0.0	5			N			
0.0	0.0	1	-6.8	0.0	0.0	-1.0			
0.0	0.3	-8.1							
	2	2015-01-13 08:45:10	2015-01-13 08:46:32			5			
0.0 -73.90199279785156	40.76407241821289		1						
N -73.90202331542969	40.764068603515625		2		0.0	0.0	0.0		
0.0	0.0	0.3	0.0						
	2	2015-01-14 11:52:09	2015-01-14 11:52:20			1			
0.0 -73.78995513916016	40.64694595336914		2			N			
0.0	0.0	3	-52.0	0.0	-0.5	-14.33			
-5.33	0.3	-72.46							
	2	2015-01-03 02:01:25	2015-01-03 02:01:54			1			
0.03 -73.95340728759766	40.81114959716797		1						
N -73.95375061035156	40.811302185058594		2		-2.5	-0.5	-0.5		
0.0	0.0	0.3	-3.8						
	2	2015-01-20 20:44:47	2015-01-20 20:44:48			1			
0.0	0.0	0.0	1			N			
-73.9373779296875	40.758209228515625		1		0.0	0.0	0.0		
0.0	0.0	0.3	0.0						
	2	2015-01-17 11:12:35	2015-01-17 11:14:52			1			
0.0 -73.93765258789062	40.758121490478516		1						
N -73.93766021728516	40.75809097290039		1		0.0	0.0	0.0		
0.0	0.0	0.3	0.0						
	2	2015-01-12 15:07:29	2015-01-12 15:07:35			1			
0.0	0.0	0.0	2			N			
0.0	0.0	2	-52.0	0.0	-0.5	0.0			
0.0	0.3	-52.8							
	2	2015-01-06 14:07:25	2015-01-06 14:08:27			1			
0.03 -73.99456024169922	40.740318298339844		1						
N -73.99533081054688	40.74095153808594		4		-2.5	0.0	-0.5		
0.0	0.0	0.3	-3.3						
	2	2015-01-10 21:10:20	2015-01-10 21:12:39			1			
0.03 -73.986328125	40.755279541015625		1						
N -73.98542022705078	40.755088806152344		4		-3.5	-0.5	-0.5		
0.0	0.0	0.3	-4.8						
+	+	+	+	+	+	+	+	+	+
-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-

only showing top 20 rows

0.3 Q2: Correlation Analysis

###Task 1.1: Write SQL queries to calculate the correlation between fare_amount and trip_distance.

```
[ ]: query = """
SELECT corr(fare_amount, trip_distance) AS fare_trip_distance_corr
FROM yellow_taxi_data
"""

# Run the query
result_df = spark.sql(query)

# Show the results
result_df.show()
```

[Stage 138:=====> (8 + 7) / 15]

```
+-----+
|fare_trip_distance_corr|
+-----+
| 4.422117955836895E-4|
+-----+
```

0.3.1 Task 1.2: Write SQL queries to calculate the correlation between total_amount and trip_distance.

```
[ ]: query="""
SELECT corr(total_amount, trip_distance) AS total_trip_distance_corr
FROM yellow_taxi_data
"""

# Run the query
result_df = spark.sql(query)

# Show the results
result_df.show()
```

[Stage 141:=====> (8 + 7) / 15]

```
+-----+
|total_trip_distance_corr|
+-----+
| 3.339064563073854...|
+-----+
```

0.4 Task 2: Analysis of Correlations

Correlation between fare_amount and trip_distance: - A positive correlation coefficient close to 1 indicates a strong positive linear relationship, suggesting that as the trip distance increases, the fare amount also increases proportionally.

Correlation between total_amount and trip_distance: - This correlation measures how the total amount (including fare and additional charges) relates to trip distance. A strong positive correlation implies that longer trips tend to have higher total charges.

0.5 Q3: Trip Duration Prediction

0.5.1 Task 1: Calculate the trip duration in minutes for each trip.

```
[ ]: from pyspark.sql.functions import unix_timestamp

# Add a new column 'trip_duration_minutes' to the DataFrame
df_with_duration = df.withColumn(
    "trip_duration_minutes",
    (unix_timestamp("tpep_dropoff_datetime") -
     unix_timestamp("tpep_pickup_datetime")) / 60
)

# Create a temporary view with the new column
df_with_duration.createOrReplaceTempView("yellow_taxi_with_duration")
```

0.5.2 Task 2: Write a SQL query to find the average trip duration for trips with different passenger counts.

```
[ ]: query = """
SELECT passenger_count, AVG(trip_duration_minutes) AS average_trip_duration
FROM yellow_taxi_with_duration
GROUP BY passenger_count
ORDER BY passenger_count
"""

# Run the query
result_df = spark.sql(query)

# Show the results
result_df.show()
```

[Stage 144:=====>

(9 + 6) / 15]

```
+-----+-----+
|passenger_count|average_trip_duration|
+-----+-----+
|              0|  12.558855039350089|
|              1|  14.246676076779718|
|              2|  13.842955421433144|
```


N -73.97478485107422	40.75061798095703	1	12.0	1.0	0.5
3.25	0.0	0.3	17.05	1-2 miles	
	1 2015-01-10 20:33:38	2015-01-10 20:53:28		1	
3.3 -74.00164794921875	40.7242431640625	1			
N -73.99441528320312	40.75910949707031	1	14.5	0.5	0.5
2.0	0.0	0.3	17.8	2-5 miles	
	1 2015-01-10 20:33:38	2015-01-10 20:43:41		1	
1.8 -73.96334075927734	40.80278778076172	1			
N -73.95182037353516	40.82441329956055	2	9.5	0.5	0.5
0.0	0.0	0.3	10.8	1-2 miles	
	1 2015-01-10 20:33:39	2015-01-10 20:35:31		1	
0.5 -74.00908660888672	40.71381759643555	1			
N -74.00432586669922	40.71998596191406	2	3.5	0.5	0.5
0.0	0.0	0.3	4.8	<1 mile	
	1 2015-01-10 20:33:39	2015-01-10 20:52:58		1	
3.0 -73.97117614746094	40.762428283691406	1			
N -74.00418090820312	40.742652893066406	2	15.0	0.5	0.5
0.0	0.0	0.3	16.3	2-5 miles	
	1 2015-01-10 20:33:39	2015-01-10 20:53:52		1	
9.0 -73.87437438964844	40.7740478515625	1			
N -73.98697662353516	40.75819396972656	1	27.0	0.5	0.5
6.7	5.33	0.3	40.33	>5 miles	
	1 2015-01-10 20:33:39	2015-01-10 20:58:31		1	
2.2 -73.9832763671875	40.726009368896484	1			
N -73.99246978759766	40.7496337890625	2	14.0	0.5	0.5
0.0	0.0	0.3	15.3	2-5 miles	
	1 2015-01-10 20:33:39	2015-01-10 20:42:20		3	
0.8 -74.0026626586914	40.7341423034668	1			
N -73.99501037597656	40.72632598876953	1	7.0	0.5	0.5
1.66	0.0	0.3	9.96	<1 mile	
	1 2015-01-10 20:33:39	2015-01-10 21:11:35		3	
18.2 -73.78304290771484	40.64435577392578	2			
N -73.98759460449219	40.75935745239258	2	52.0	0.0	0.5
0.0	5.33	0.3	58.13	>5 miles	
	1 2015-01-10 20:33:40	2015-01-10 20:40:44		2	
0.9 -73.98558807373047	40.767948150634766	1			
N -73.98591613769531	40.75936508178711	1	6.5	0.5	0.5
1.55	0.0	0.3	9.35	<1 mile	
	1 2015-01-10 20:33:40	2015-01-10 20:41:39		1	
0.9 -73.98861694335938	40.72310256958008	1		N	
-74.00439453125	40.72858428955078	1	7.0	0.5	0.5
1.66	0.0	0.3	9.96	<1 mile	
	1 2015-01-10 20:33:41	2015-01-10 20:43:26		1	
1.1 -73.99378204345703	40.75141906738281	1		N	
-73.9674072265625	40.75721740722656	1	7.5	0.5	0.5
1.0	0.0	0.3	9.8	1-2 miles	
	1 2015-01-10 20:33:41	2015-01-10 20:35:23		1	
0.3 -74.00836181640625	40.704376220703125	1			

N -74.00977325439453 40.707725524902344	2	3.0	0.5	0.5
0.0 0.0 0.3 4.3	<1 mile			
1 2015-01-10 20:33:41 2015-01-10 21:03:04		1		
3.1 -73.97394561767578 40.76044845581055	1			
N -73.99734497070312 40.73521041870117	1	19.0	0.5	0.5
3.0 0.0 0.3 23.3	2-5 miles			
1 2015-01-10 20:33:41 2015-01-10 20:39:23		1		
1.1 -74.00672149658203 40.73177719116211	1		N	
-73.9952163696289 40.73989486694336	2	6.0	0.5	0.5
0.0 0.0 0.3 7.3	1-2 miles			
2 2015-01-15 19:05:39 2015-01-15 19:32:00		1		
2.38 -73.97642517089844 40.739810943603516	1			
N -73.98397827148438 40.75788879394531	1	16.5	1.0	0.5
4.38 0.0 0.3 22.68	2-5 miles			
2 2015-01-15 19:05:40 2015-01-15 19:21:00		5		
2.83 -73.96870422363281 40.75424575805664	1			
N -73.95512390136719 40.78685760498047	2	12.5	1.0	0.5
0.0 0.0 0.3 14.3	2-5 miles			
2 2015-01-15 19:05:40 2015-01-15 19:28:18		5		
8.33 -73.8630599975586 40.76958084106445	1			
N -73.95271301269531 40.78578186035156	1	26.0	1.0	0.5
8.08 5.33 0.3 41.21	>5 miles			
2 2015-01-15 19:05:41 2015-01-15 19:20:36		1		
2.37 -73.94554138183594 40.779422760009766	1			
N -73.98085021972656 40.78608322143555	1	11.5	1.0	0.5
0.0 0.0 0.3 13.3	2-5 miles			
2 2015-01-15 19:05:41 2015-01-15 19:20:22		2		
7.13 -73.87445831298828 40.774009704589844	1			
N -73.95237731933594 40.718589782714844	1	21.5	1.0	0.5
4.5 0.0 0.3 27.8	>5 miles			

+-----+-----+-----+-----+-----+-----+
 --+-----+-----+-----+-----+-----+-----+
 -----+-----+-----+-----+-----+-----+-----+
 -----+-----+-----+-----+-----+-----+-----+

only showing top 20 rows

0.8 Task 2: Write a SQL query to calculate the average fare amount for each distance bin.

```
[ ]: from pyspark.sql.functions import when

# Create the distance_bin column based on the conditions
df_with_bins = df.withColumn(
    "distance_bin",
    when(df.distance <= 1, "<1 mile")
    .when((df.distance > 1) & (df.distance <= 2), "1-2 miles")
```

```

        .when((df.distance > 2) & (df.distance <= 5), "2-5 miles")
        .when(df.distance > 5, ">5 miles")
        .otherwise("Unknown")
    )

    # Create a temporary view with the new column
    df_with_bins.createOrReplaceTempView("yellow_taxi_with_bins")

    # Now run the SQL query without the CASE expression in the ORDER BY clause
    query = """
    SELECT distance_bin, AVG(fare_amount) AS average_fare_amount
    FROM yellow_taxi_with_bins
    GROUP BY distance_bin
    ORDER BY distance_bin
    """

    # Run the query
    result_df = spark.sql(query)

    # Show the results
    result_df.show()

```

```

-----
AttributeError                                Traceback (most recent call last)
File <command-1915345996946306>:6
      1 from pyspark.sql.functions import when
      3 # Create the distance_bin column based on the conditions
      4 df_with_bins = df.withColumn(
      5     "distance_bin",
----> 6     when(df.distance <= 1, "<1 mile")
      7     .when((df.distance > 1) & (df.distance <= 2), "1-2 miles")
      8     .when((df.distance > 2) & (df.distance <= 5), "2-5 miles")
      9     .when(df.distance > 5, ">5 miles")
     10     .otherwise("Unknown")
     11 )
     13 # Create a temporary view with the new column
     14 df_with_bins.createOrReplaceTempView("yellow_taxi_with_bins")

File /databricks/spark/python/pyspark/instrumentation_utils.py:48, in _
    _wrap_function.<locals>.wrapper(*args, **kwargs)
     46 start = time.perf_counter()
     47 try:
--> 48     res = func(*args, **kwargs)
     49     logger.log_success(
     50         module_name, class_name, function_name, time.perf_counter() -
    _start, signature
     51     )

```

```
52     return res
```

File /databricks/spark/python/pyspark/sql/dataframe.py:2964, in DataFrame.

```
↪ __getattr__(self, name)
    2934 """Returns the :class:`Column` denoted by ``name``.
    2935
    2936 .. versionadded:: 1.3.0
    (...)
    2961 +----+
    2962 """
    2963 if name not in self.columns:
-> 2964     raise AttributeError(
    2965         "%s' object has no attribute '%s'" % (self.__class__.__name__,
↪ name)
    2966     )
    2967 jc = self._jdf.apply(name)
    2968 return Column(jc)
```

AttributeError: 'DataFrame' object has no attribute 'distance'

0.9 Visualization:

We can visualize the average fare amount per distance bin using a bar chart.

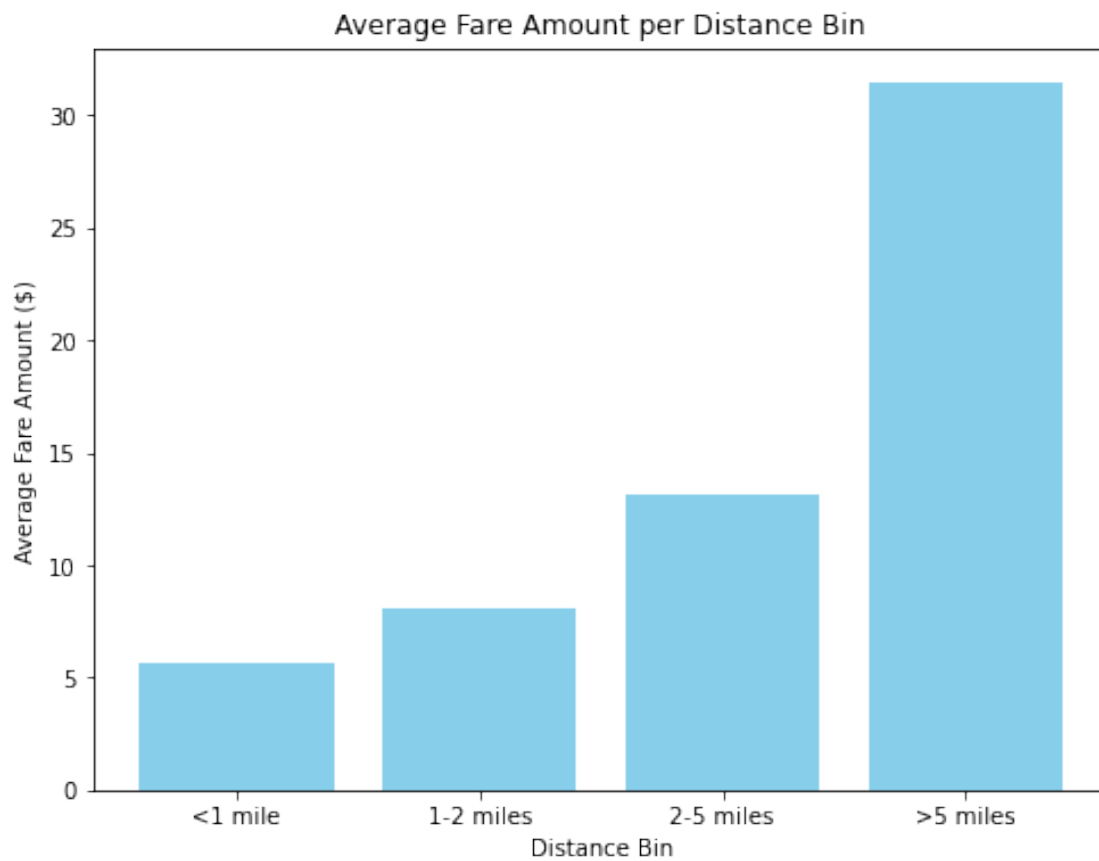
```
[ ]: # Convert the query result to a Pandas DataFrame for plotting
average_fare_by_bin = spark.sql("""
    SELECT distance_bin, AVG(fare_amount) AS average_fare_amount
    FROM yellow_taxi_with_bins
    GROUP BY distance_bin
""").toPandas()

import pandas as pd
import matplotlib.pyplot as plt

# Ensure the bins are in the correct order
bin_order = ['<1 mile', '1-2 miles', '2-5 miles', '>5 miles']
average_fare_by_bin['distance_bin'] = pd.
    ↪ Categorical(average_fare_by_bin['distance_bin'], categories=bin_order,
    ↪ ordered=True)
average_fare_by_bin = average_fare_by_bin.sort_values('distance_bin')

# Plot the average fare amount per distance bin
plt.figure(figsize=(8,6))
plt.bar(average_fare_by_bin['distance_bin'],
    ↪ average_fare_by_bin['average_fare_amount'], color='skyblue')
plt.xlabel('Distance Bin')
plt.ylabel('Average Fare Amount ($)')
```

```
plt.title('Average Fare Amount per Distance Bin')
plt.show()
```



0.10 Q5:

```
[ ]: # SQL query to create distance bins and calculate average fare for each bin
query = """
SELECT
    CASE
        WHEN trip_distance < 1 THEN '<1 mile'
        WHEN trip_distance >= 1 AND trip_distance < 2 THEN '1-2 miles'
        WHEN trip_distance >= 2 AND trip_distance < 5 THEN '2-5 miles'
        WHEN trip_distance >= 5 AND trip_distance < 10 THEN '5-10 miles'
        ELSE '>10 miles'
    END AS distance_bin,
    AVG(fare_amount) AS average_fare
FROM yellow_taxi_data
GROUP BY distance_bin
ORDER BY
```

```

CASE
  WHEN distance_bin = '<1 mile' THEN 1
  WHEN distance_bin = '1-2 miles' THEN 2
  WHEN distance_bin = '2-5 miles' THEN 3
  WHEN distance_bin = '5-10 miles' THEN 4
  WHEN distance_bin = '>10 miles' THEN 5
END
"""

# Execute the query
distance_fare_bins = spark.sql(query)

# Show the result
distance_fare_bins.show()

```

[Stage 148:=====>

(9 + 6) / 15]

```

+-----+-----+
|distance_bin|    average_fare|
+-----+-----+
|    <1 mile| 5.672120578999713|
|   1-2 miles| 8.04041196316821|
|   2-5 miles|13.087495501926742|
|  5-10 miles|23.568011860162635|
|   >10 miles| 44.72180584584484|
+-----+-----+

```

0.11 Visualization

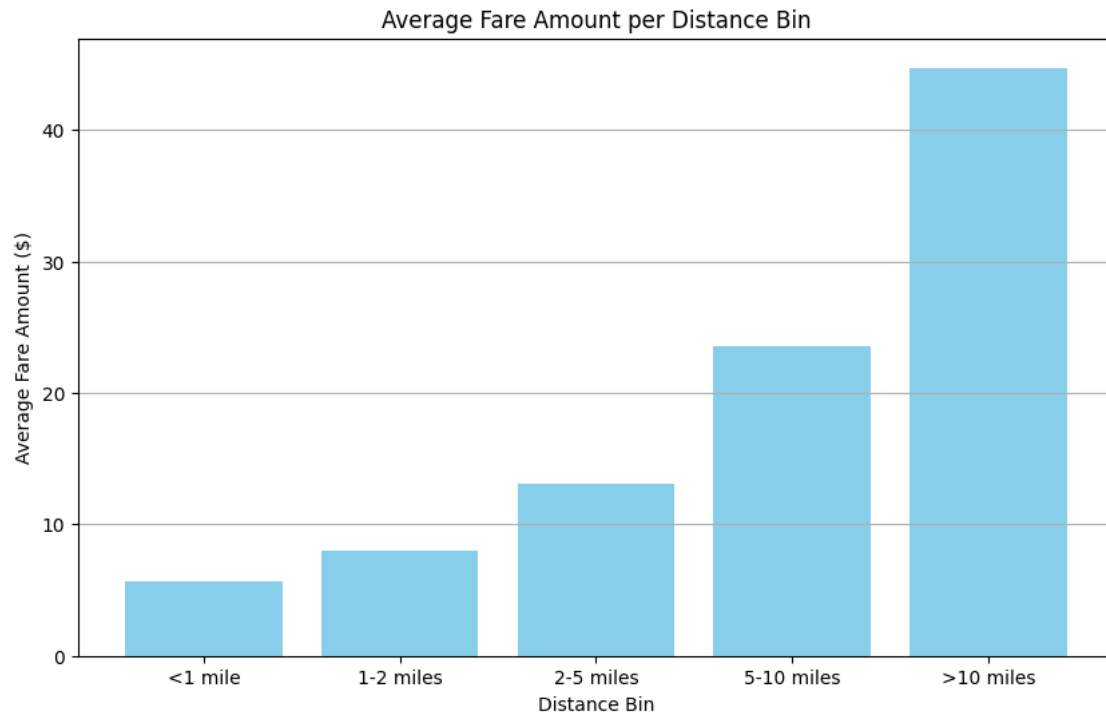
```

[ ]: # Convert the Spark DataFrame to Pandas for plotting
distance_fare_bins_df = distance_fare_bins.toPandas()

# Import necessary libraries for plotting
import matplotlib.pyplot as plt

# Plot the average fare per distance bin
plt.figure(figsize=(10, 6))
plt.bar(distance_fare_bins_df['distance_bin'],
        distance_fare_bins_df['average_fare'], color='skyblue')
plt.xlabel('Distance Bin')
plt.ylabel('Average Fare Amount ($)')
plt.title('Average Fare Amount per Distance Bin')
plt.grid(axis='y')
plt.show()

```



```
[ ]: # Convert the Spark DataFrame to Pandas for plotting
distance_fare_bins_df = distance_fare_bins.toPandas()

# Import necessary libraries for plotting
import matplotlib.pyplot as plt

# Plot the average fare per distance bin
plt.figure(figsize=(10, 6))
plt.bar(distance_fare_bins_df['distance_bin'],
        ↪distance_fare_bins_df['average_fare'], color='skyblue')
plt.xlabel('Distance Bin')
plt.ylabel('Average Fare Amount ($)')
plt.title('Average Fare Amount per Distance Bin')
plt.grid(axis='y')
plt.show()
```


1 Q6: Passenger Count Distribution

1.1 Task 1 & 2:

1.1.1 Write a SQL query to count the number of trips by passenger count and calculate the average fare amount for each passenger count group

```
[ ]: # SQL query to count number of trips by passanger count
trip_per_passanger = spark.sql("""
SELECT passenger_count, count(*) AS trips, avg(fare_amount) AS avg_fare --
    ↳trips counts total number of trips per passanger count, avg_fare take avg
    ↳fare amount for each group
FROM yellow_taxi_data
GROUP BY passenger_count -- groups by disting passanger count
ORDER BY passenger_count ASC;
""")

trip_per_passanger.show()
```

passenger_count	trips	avg_fare
0	6565	11.205294744859103
1	8993870	11.78195472471847
2	1814594	12.420621907710354
3	528486	12.124618192345713
4	253228	12.202182618035936
5	697645	11.963545757512774
6	454568	11.797696494253884
7	9	11.255555555555555
8	10	29.580000000000002
9	11	52.900000000000006

2 Q7: Heatmap of Trip Frequencies

2.1 Task 1: Write SQL queries to find the most frequent pickup and drop-off locations rounded to three decimal places of latitude and longitude

```
[ ]: #sql to find frequent pickup long and lat rounded by 3 grouped by long and lat
Frequent_pickup_locations = spark.sql("""
SELECT round(pickup_longitude, 3) AS longitude, round(pickup_latitude, 3) AS
    ↳latitude, count(*) AS frequency
FROM yellow_taxi_data
GROUP BY longitude, latitude
""")
```

```
Frequent_pickup_locations.show()
```

```
#sql to find frequent dropofflong and lat rounded by 3 grouped by long and lat
Frequent_dropoff_locations = spark.sql("""
SELECT round(dropoff_longitude, 3) AS longitude, round(dropoff_latitude, 3) AS_
    ↪latitude, count(*) AS frequency
FROM yellow_taxi_data
GROUP BY longitude, latitude
""")
```

```
Frequent_dropoff_locations.show()
```

longitude	latitude	frequency
-74.004	40.748	14040
-73.984	40.762	8200
-73.98	40.786	5622
-73.979	40.762	22089
-73.991	40.724	6126
-73.997	40.719	2627
-73.963	40.777	2433
-73.961	40.779	864
-73.995	40.742	1019
-73.985	40.756	2336
-73.944	40.835	539
-73.97	40.749	1817
-73.98	40.78	2244
-74.0	40.711	240
-74.008	40.724	2186
-73.991	40.714	265
-73.911	40.7	100
-73.968	40.761	3584
-73.9	40.746	175
-73.98	40.757	722

only showing top 20 rows

longitude	latitude	frequency
-73.979	40.762	23961
-73.959	40.776	1920
-73.984	40.762	7583
-74.004	40.748	9561
-74.008	40.724	1273
-73.98	40.786	4445
-73.985	40.756	4172

	-73.995	40.742	2258
	-73.991	40.714	694
	-73.951	40.669	136
	-73.944	40.835	505
	-73.999	40.762	471
	-73.98	40.78	3119
	-73.991	40.724	5543
	-73.943	40.802	685
	-73.985	40.692	720
	-73.961	40.779	3675
	-73.97	40.749	3103
	-73.943	40.707	555
	-73.98	40.757	1825

+-----+-----+-----+

only showing top 20 rows

2.2 Task 2: Visualize the frequencies using a heatmap.

```
[ ]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

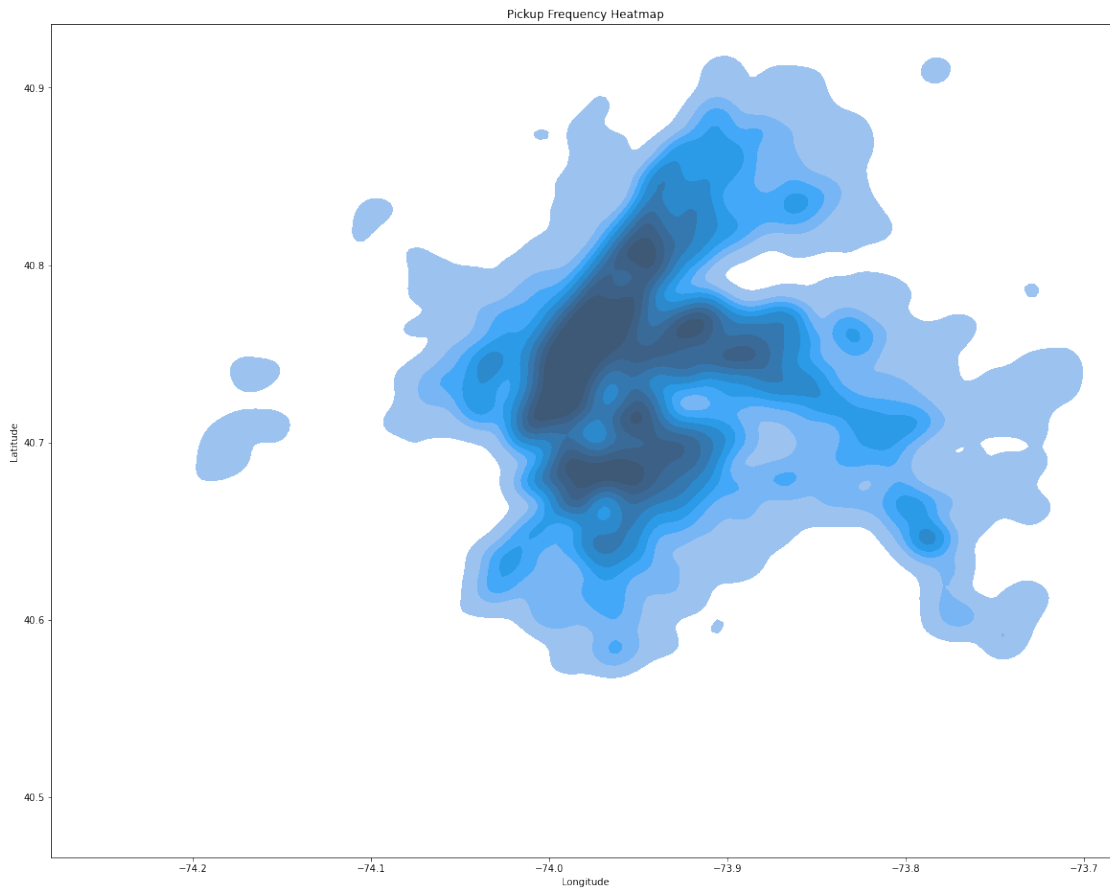
data = Frequent_pickup_locations.toPandas()

#nyc bound
lat_min, lat_max = 40.4774, 40.9176
lon_min, lon_max = -74.2591, -73.7004

# Filter points within nyc bound only
cleaned = data[(data['latitude'] >= lat_min) & (data['latitude'] <= lat_max) &
               (data['longitude'] >= lon_min) & (data['longitude'] <= lon_max)]

plt.figure(figsize=(20, 16))

#plot
sns.kdeplot(x=cleaned['longitude'], y=cleaned['latitude'], fill=True,
            shade=True, bw_adjust=0.5)
plt.title('Pickup Frequency Heatmap')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```



```
[ ]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

data = Frequent_dropoff_locations.toPandas()

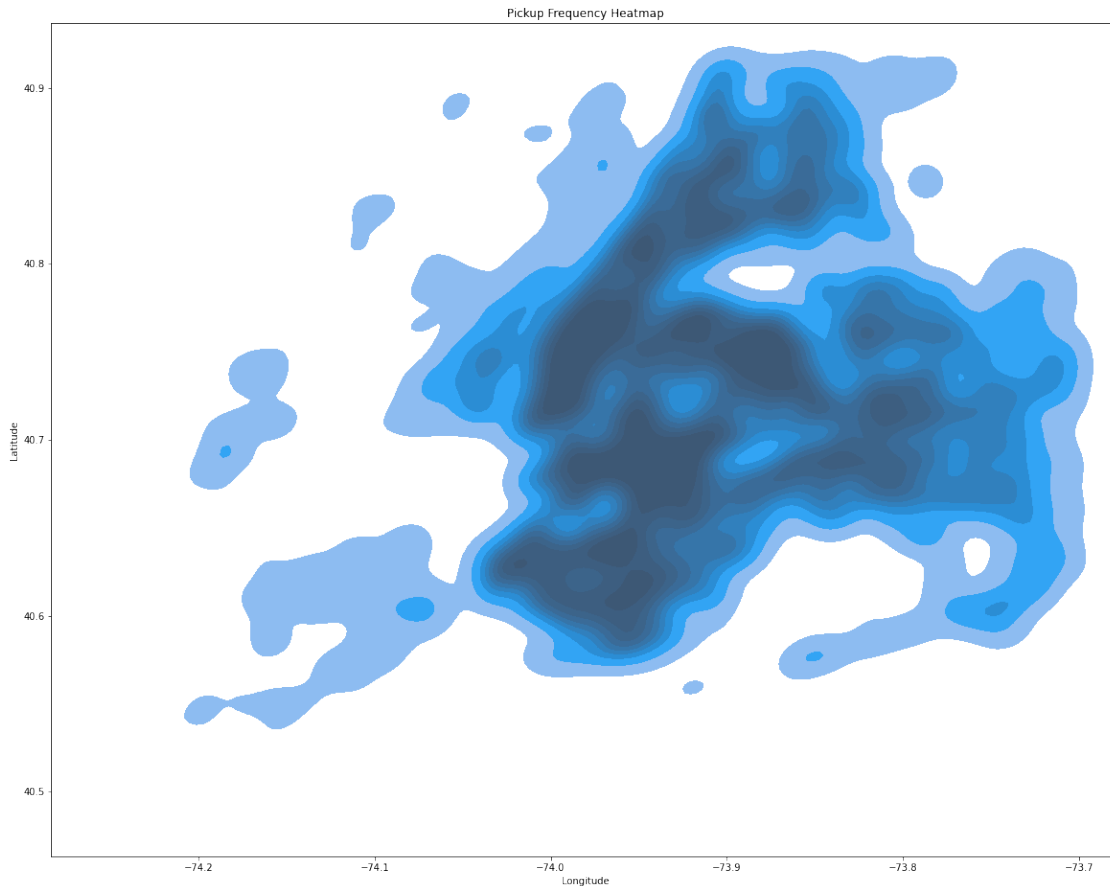
#nyc bound
lat_min, lat_max = 40.4774, 40.9176
lon_min, lon_max = -74.2591, -73.7004

# Filter points within nyc bound only
cleaned = data[(data['latitude'] >= lat_min) & (data['latitude'] <= lat_max) &
               (data['longitude'] >= lon_min) & (data['longitude'] <= lon_max)]

plt.figure(figsize=(20, 16))

#plot
```

```
sns.kdeplot(x=cleaned['longitude'], y=cleaned['latitude'], fill=True,
            shade=True, bw_adjust=0.5)
plt.title('Pickup Frequency Heatmap')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```



3 Q8: Busiest Days and Times Analysis

3.1 Task 1: Write a SQL query to determine which day of the week generated the most revenue.

```
[ ]: revenue_per_day = spark.sql("""
--> since yellow taxi payment is determined at the end of the trip the day of
    ↳ the revenue generated will be based upon day at drop off
--> in cases where the pickup date is thursday and drop off is friday the fare
    ↳ amount will be according to the drop off date of friday.
SELECT
CASE dayofweek(tpep_dropoff_datetime)
```

```

    WHEN 1 THEN 'Sunday'
    WHEN 2 THEN 'Monday'
    WHEN 3 THEN 'Tuesday'
    WHEN 4 THEN 'Wednesday'
    WHEN 5 THEN 'Thursday'
    WHEN 6 THEN 'Friday'
    WHEN 7 THEN 'Saturday'
END AS daysWeek, sum(fare_amount) AS Revenue
FROM yellow_taxi_data
GROUP BY daysWeek
ORDER BY Revenue DESC
""")

revenue_per_day.show()

```

```

+-----+-----+
| daysWeek|          Revenue|
+-----+-----+
| Saturday|2.7051229790000014E7|
|   Friday|2.6806555599999305E7|
| Thursday|2.6465400489999287E7|
|Wednesday|1.9920160110000014E7|
|   Sunday|1.9383329830000013E7|
|   Monday|1.6159452960000008E7|
|   Tuesday|1.5998956560000008E7|
+-----+-----+

```

3.2 Task 2: Write another query to find the busiest hour of the day based on the count of pickups

```

[ ]: busiest_hour = spark.sql("""
SELECT hour(tpcp_pickup_datetime) AS hour_of_the_day, Count(*) AS pickups
FROM yellow_taxi_data
GROUP BY hour_of_the_day
ORDER BY pickups DESC
""")

busiest_hour.show(24)

```

```

+-----+-----+
|hour_of_the_day|pickups|
+-----+-----+
|                19| 805230|
|                18| 799587|
|                20| 733952|
|                21| 711579|
|                22| 686959|

```

	17	668790
	14	658887
	15	648688
	12	637479
	13	635587
	11	596504
	23	592429
	9	580034
	16	576598
	10	567818
	8	561802
	0	469971
	7	456127
	1	355145
	6	268455
	2	268133
	3	198524
	4	143271
	5	127437
+-----+-----+		

#Q9: Trip Duration and Time of Day Analysis

3.3 Task 1: Calculate the average trip duration for each hour of the day

```
[ ]: #the yellow_taxi_with_duration was created earlier in question3 task 1 with a
      ↳column called trip_duration_minutes calculating the time for each trip.
      #we can use this dataframe and group data by hour of the day at pickup and
      ↳average each trip duration for each hour of a day
avg_trip_dration_per_hour = spark.sql("""
SELECT HOUR(tppep_pickup_datetime) AS pickup_hour, avg(trip_duration_minutes) AS
      ↳avg_trip_minutes
FROM yellow_taxi_with_duration
GROUP BY pickup_hour
ORDER BY pickup_hour;
""")

avg_trip_dration_per_hour.show(24)
```

+-----+-----+	
pickup_hour	avg_trip_minutes
+-----+-----+	
	0 13.313322275913483
	1 13.054973602331446
	2 13.145008571616827
	3 13.435592589980732
	4 13.242055614883688

	5	13.76538367977902
	6	11.877530064008267
	7	12.796801292914775
	8	13.587299440016215
	9	13.489896511813681
	10	13.228424923713806
	11	13.17238671771968
	12	13.280298749710424
	13	13.579905845567446
	14	14.454319127053141
	15	32.09129095959835
	16	14.041422302308805
	17	13.826888584857201
	18	13.33810871529094
	19	12.883962532444134
	20	12.333422598934755
	21	12.416918945987238
	22	12.678930717359632
	23	13.098988655180626
+-----+		

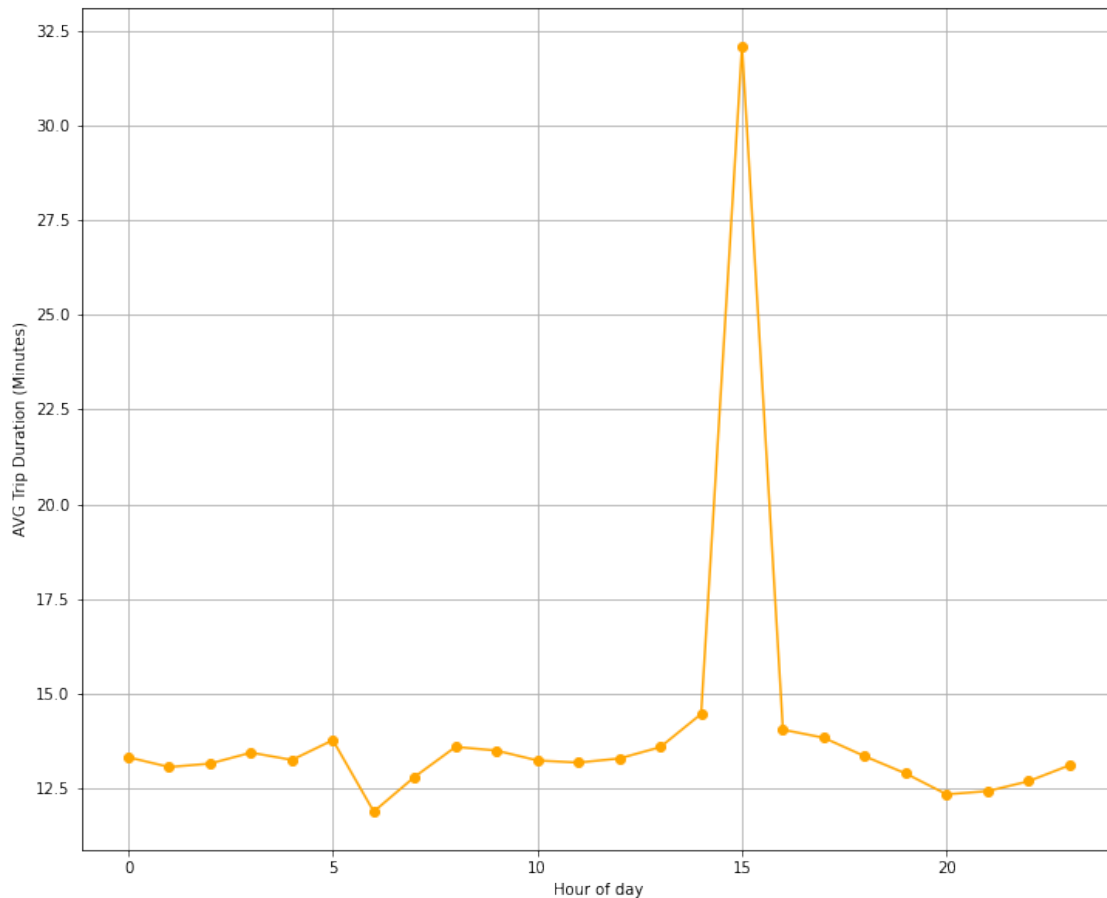
3.4 Visualization

```
[ ]: import pandas as pd
import matplotlib.pyplot as plt

data = avg_trip_dration_per_hour.toPandas()

plt.figure(figsize=(12, 10))
plt.plot(data['pickup_hour'], data['avg_trip_minutes'], marker='o',
         color='orange')
plt.grid(True)
plt.xlabel('Hour of day')
plt.ylabel('AVG Trip Duration (Minutes)')

plt.show()
```

3.5 Q10: Payment Type Fare Comparison

```
[ ]: # SQL query to calculate average fare amount for each payment type
query = """
SELECT payment_type, AVG(fare_amount) AS average_fare_amount
FROM yellow_taxi_data
GROUP BY payment_type
"""

# Execute the query
result_df = spark.sql(query)

# Show the result
result_df.show()
```

[Stage 49:=====>

(9 + 6) / 15]

```
+-----+-----+
|payment_type|average_fare_amount|
+-----+-----+
```

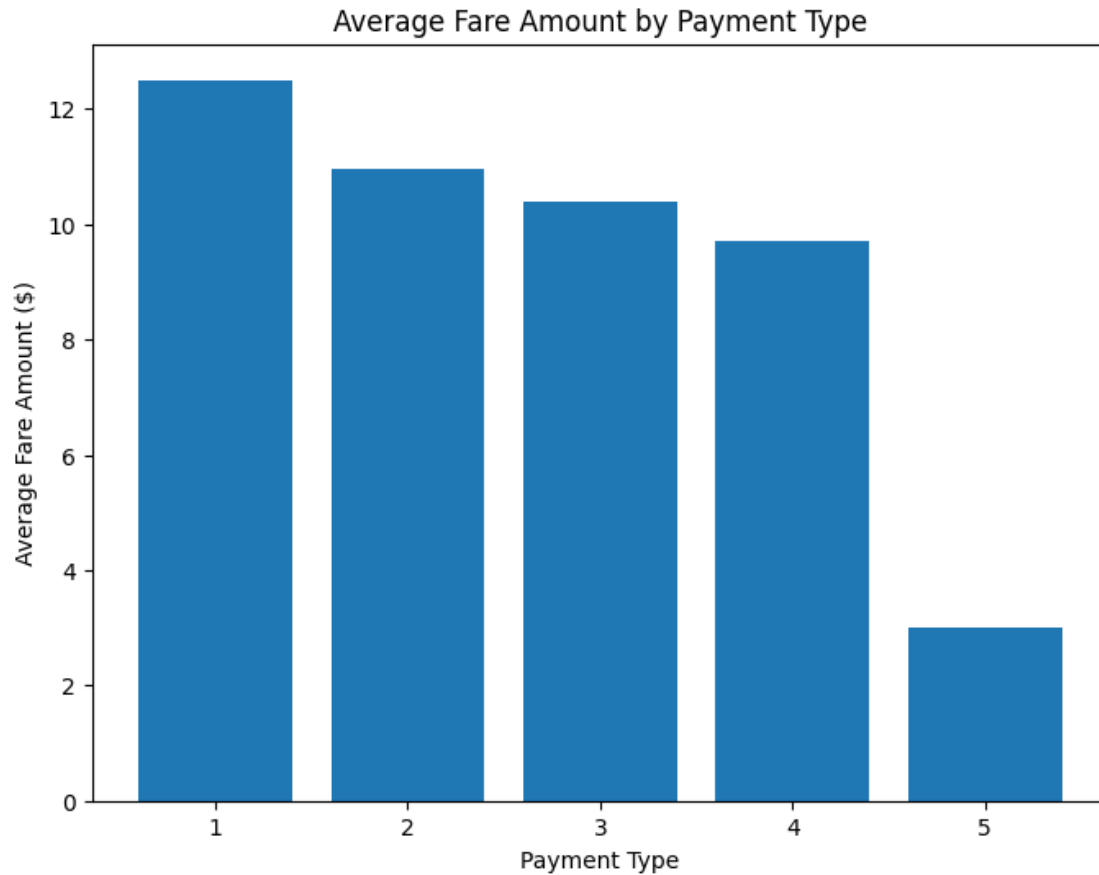
	1	12.50128976774208
	3	10.396839148892102
	4	9.71586034079519
	2	10.948657421477954
	5	3.0
+-----+-----+		

3.6 Visualization:

```
[ ]: # Convert the Spark DataFrame to a Pandas DataFrame for plotting
average_fare_by_payment_type = result_df.toPandas()

# Import necessary libraries for plotting
import matplotlib.pyplot as plt

# Plot the average fare by payment type
plt.figure(figsize=(8, 6))
plt.bar(average_fare_by_payment_type['payment_type'],
        ↪average_fare_by_payment_type['average_fare_amount'])
plt.xlabel('Payment Type')
plt.ylabel('Average Fare Amount ($)')
plt.title('Average Fare Amount by Payment Type')
plt.show()
```



3.7 Q11: : Time Series Analysis of Trips

```
[ ]: # SQL query to count trips per day
query = """
SELECT DATE(tpep_pickup_datetime) AS trip_date, COUNT(*) AS trip_count
FROM yellow_taxi_data
GROUP BY trip_date
ORDER BY trip_date
"""

# Execute the query
daily_trip_counts = spark.sql(query)

# Show the result
daily_trip_counts.show()
```

[Stage 55:=====>

(9 + 6) / 15]

```
+-----+-----+
| trip_date|trip_count|
```

```

+-----+-----+
|2015-01-01|    382014|
|2015-01-02|    345296|
|2015-01-03|    406769|
|2015-01-04|    328848|
|2015-01-05|    363454|
|2015-01-06|    384324|
|2015-01-07|    429653|
|2015-01-08|    450920|
|2015-01-09|    447947|
|2015-01-10|    515540|
|2015-01-11|    419629|
|2015-01-12|    396367|
|2015-01-13|    448517|
|2015-01-14|    442656|
|2015-01-15|    451186|
|2015-01-16|    478124|
|2015-01-17|    476827|
|2015-01-18|    427042|
|2015-01-19|    342795|
|2015-01-20|    405581|
+-----+-----+
only showing top 20 rows

```

3.8 Visualization:

```

[ ]: # Convert the result to a Pandas DataFrame
import pandas as pd
daily_trip_counts_df = daily_trip_counts.toPandas()

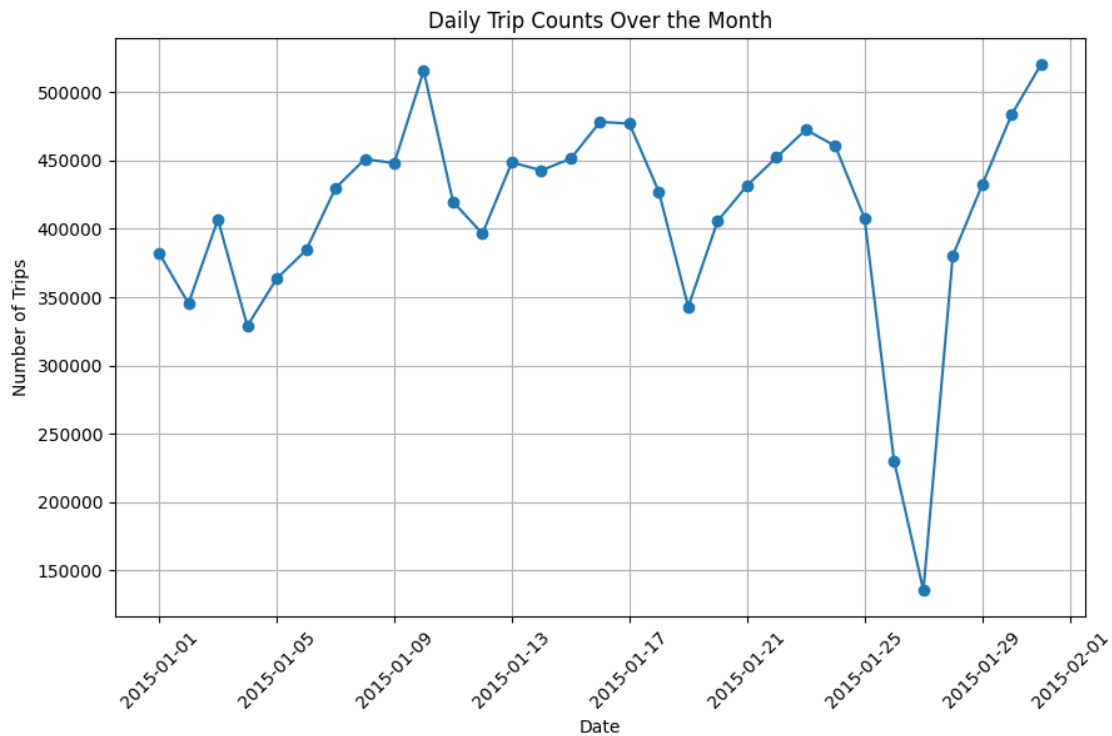
# Import necessary libraries for plotting
import matplotlib.pyplot as plt

# Convert 'trip_date' to datetime format for accurate plotting
daily_trip_counts_df['trip_date'] = pd.
↳to_datetime(daily_trip_counts_df['trip_date'])

# Plot the daily trip counts
plt.figure(figsize=(10, 6))
plt.plot(daily_trip_counts_df['trip_date'], daily_trip_counts_df['trip_count'],
↳marker='o')
plt.xlabel('Date')
plt.ylabel('Number of Trips')
plt.title('Daily Trip Counts Over the Month')
plt.xticks(rotation=45)

```

```
plt.grid(True)
plt.show()
```



```
[ ]:
```

3.9 Q12: Location Analysis

```
[ ]: # SQL query to find the top 10 pickup locations
pickup_query = """
SELECT pickup_longitude, pickup_latitude, COUNT(*) AS trip_count
FROM yellow_taxi_data
GROUP BY pickup_longitude, pickup_latitude
ORDER BY trip_count DESC
LIMIT 10
"""

# Execute the query
top_pickup_locations = spark.sql(pickup_query)

# Show the result
top_pickup_locations.show()
```

24/11/07 13:53:01 WARN RowBasedKeyValueBatch: Calling spill() on

RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:01 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
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 24/11/07 13:53:05 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:05 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.

```
+-----+-----+-----+
| pickup_longitude| pickup_latitude|trip_count|
+-----+-----+-----+
|                0.0|                0.0|    243478|
|-73.94863891601562| 40.74489974975586|    1043|
| -74.1863021850586| 40.69314193725586|     729|
| -73.9867172241211| 40.7222900390625|     429|
|-73.91512298583984| 40.74357604980469|     306|
|-74.00314331054688| 40.72767639160156|     233|
|-73.92151641845703|40.691463470458984|     153|
|-73.98845672607422|40.731502532958984|     147|
|-73.97827911376953| 40.6429443359375|     121|
|-73.94208526611328|40.754417419433594|     108|
+-----+-----+-----+
```

24/11/07 13:53:10 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:10 WARN RowBasedKeyValueBatch: Calling spill() on

RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:10 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:10 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:10 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:10 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:10 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:15 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:15 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:15 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:15 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:15 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.
 24/11/07 13:53:15 WARN RowBasedKeyValueBatch: Calling spill() on
 RowBasedKeyValueBatch. Will not spill but return 0.

[Stage 83:>

(0 + 8) / 9]

```
+-----+-----+-----+
| dropoff_longitude| dropoff_latitude|trip_count|
+-----+-----+-----+
|                0.0|                0.0|    235318|
|-73.94863891601562| 40.74489974975586|    1043|
| -74.1863021850586| 40.69314193725586|     729|
| -73.9867172241211| 40.7222900390625|     428|
|-73.91512298583984| 40.74357604980469|     322|
|-74.00314331054688| 40.72767639160156|     233|
|-73.98845672607422|40.731502532958984|     155|
|-73.92151641845703|40.691463470458984|     153|
|-73.97827911376953| 40.6429443359375|     121|
|-73.94208526611328|40.754417419433594|     108|
+-----+-----+-----+
```

```
[ ]: dropoff_query = """
SELECT dropoff_longitude, dropoff_latitude, COUNT(*) AS trip_count
FROM yellow_taxi_data
GROUP BY dropoff_longitude, dropoff_latitude
ORDER BY trip_count DESC
LIMIT 10
"""

# Execute the query
top_dropoff_locations = spark.sql(dropoff_query)

# Show the result
top_dropoff_locations.show()
```

```
[ ]:
```

3.10 Visualization

```
[ ]:
```

```
[ ]: import matplotlib.pyplot as plt

# Convert the Spark DataFrames to Pandas DataFrames
pickup_df = top_pickup_locations.toPandas()
dropoff_df = top_dropoff_locations.toPandas()

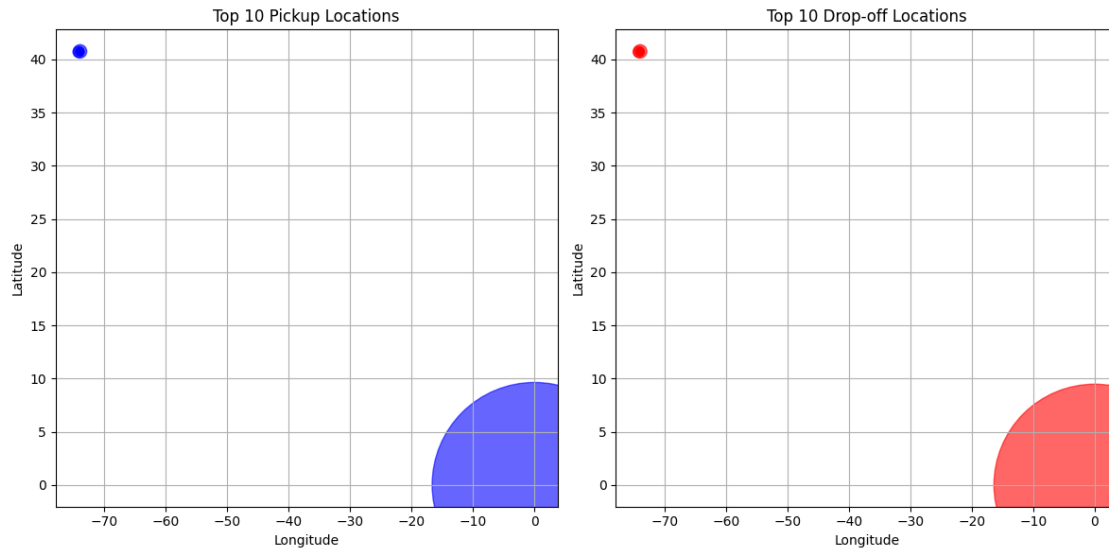
# Plot settings
plt.figure(figsize=(12, 6))

# Scatter plot for top pickup locations
plt.subplot(1, 2, 1)
plt.scatter(pickup_df['pickup_longitude'], pickup_df['pickup_latitude'],
            s=pickup_df['trip_count'] * 0.1, c='blue', alpha=0.6)
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Top 10 Pickup Locations')
plt.grid(True)

# Scatter plot for top drop-off locations
plt.subplot(1, 2, 2)
plt.scatter(dropoff_df['dropoff_longitude'], dropoff_df['dropoff_latitude'],
            s=dropoff_df['trip_count'] * 0.1, c='red', alpha=0.6)
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Top 10 Drop-off Locations')
plt.grid(True)
```



```
# Show the plots
plt.tight_layout()
plt.show()
```



3.11 Q13: Fare Amount Distribution Analysis

```
[ ]: # SQL query to get summary statistics for fare amounts
summary_query = """
SELECT
    MIN(fare_amount) AS min_fare,
    MAX(fare_amount) AS max_fare,
    AVG(fare_amount) AS avg_fare,
    PERCENTILE_APPROX(fare_amount, 0.5) AS median_fare,
    STDDEV(fare_amount) AS stddev_fare
FROM yellow_taxi_data
"""

# Execute the query
summary_stats = spark.sql(summary_query)

# Show the result
summary_stats.show()
```

[Stage 110:=====> (11 + 4) / 15]

```
+-----+-----+-----+-----+
|min_fare|max_fare|      avg_fare|median_fare|      stddev_fare|
+-----+-----+-----+-----+-----+
```

	-450.0	4008.0	11.905659425776989	9.0	10.302537135952232
+	-----+	-----+	-----+	-----+	-----+

3.12 Visualization:

```
[ ]: from pyspark.sql import SparkSession

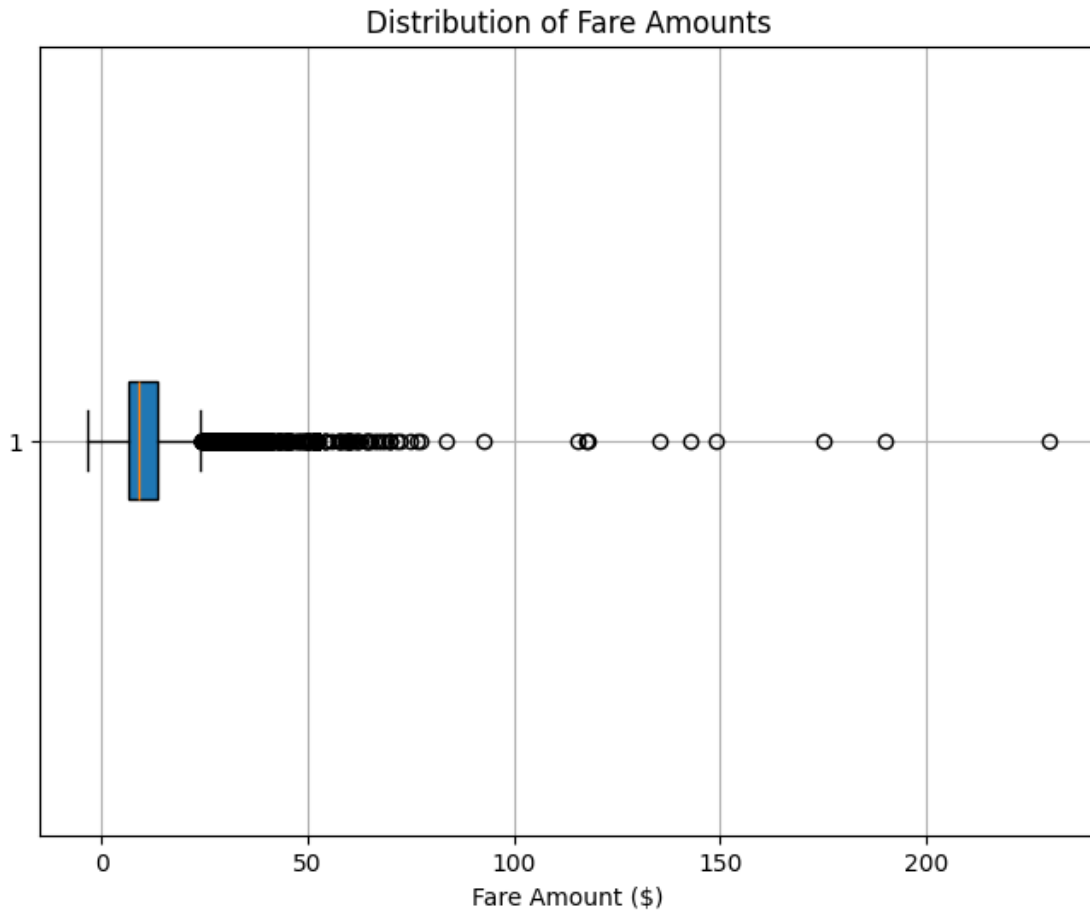
# Initialize Spark session (if not already initialized)
spark = SparkSession.builder \
    .appName("FareAmountAnalysis") \
    .getOrCreate()

# Execute the query with a LIMIT to reduce data size for testing
limited_fare_amount_df = spark.sql("SELECT fare_amount FROM yellow_taxi_data_
    ↳LIMIT 10000").toPandas()

# Import necessary libraries for plotting
import matplotlib.pyplot as plt

# Plot a box plot for fare amounts
plt.figure(figsize=(8, 6))
plt.boxplot(limited_fare_amount_df['fare_amount'], vert=False,
    ↳patch_artist=True)
plt.xlabel('Fare Amount ($)')
plt.title('Distribution of Fare Amounts')
plt.grid(True)
plt.show()
```

24/11/07 14:03:04 WARN SparkSession: Using an existing Spark session; only runtime SQL configurations will take effect.



3.13 Question 14

```
[ ]: %sql
SELECT
  CASE
    WHEN trip_distance BETWEEN 0 AND 1 THEN '0-1 mile'
    WHEN trip_distance > 1 AND trip_distance <= 3 THEN '1-3 miles'
    WHEN trip_distance > 3 AND trip_distance <= 5 THEN '3-5 miles'
    WHEN trip_distance > 5 THEN '>5 miles'
  END AS distance_range,
  AVG(trip_duration) AS avg_duration
FROM (
  SELECT
    trip_distance,
    (unix_timestamp(tpep_dropoff_datetime) -
    ↪ unix_timestamp(tpep_pickup_datetime)) / 60 AS trip_duration
    FROM yellow_taxi_data
) trips
```

```
GROUP BY distance_range;
```

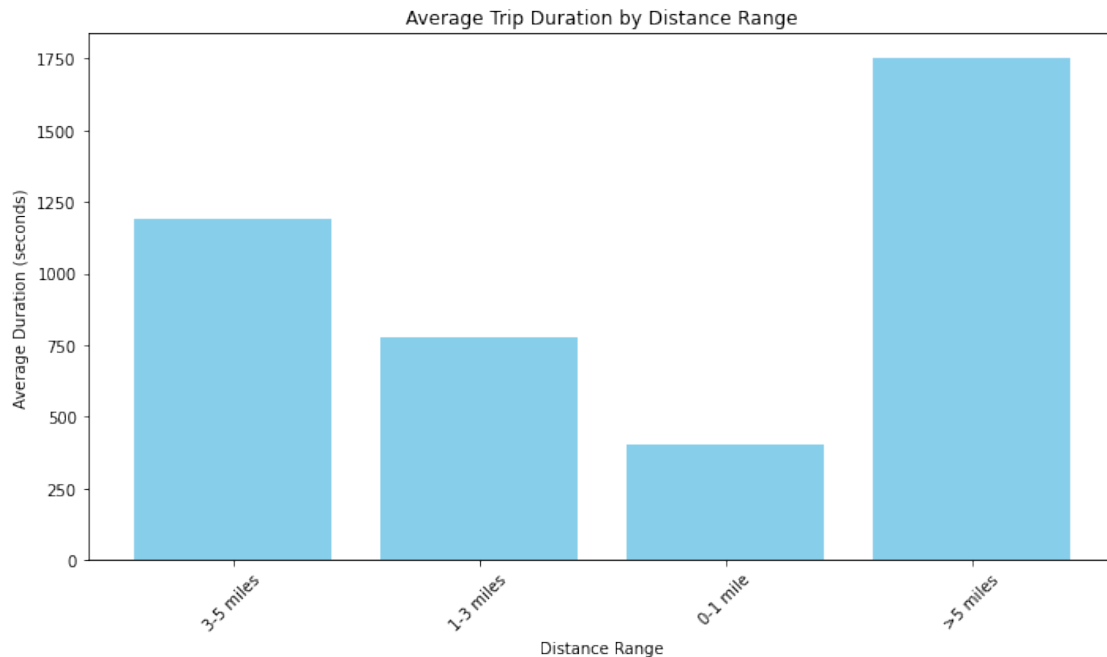
3.14 Visualization

```
[ ]: query = """
SELECT
    CASE
        WHEN trip_distance BETWEEN 0 AND 1 THEN '0-1 mile'
        WHEN trip_distance > 1 AND trip_distance <= 3 THEN '1-3 miles'
        WHEN trip_distance > 3 AND trip_distance <= 5 THEN '3-5 miles'
        WHEN trip_distance > 5 THEN '>5 miles'
    END AS distance_range,
    AVG(trip_duration) AS avg_duration
FROM (
    SELECT
        trip_distance,
        (unix_timestamp(tpep_dropoff_datetime) -
         unix_timestamp(tpep_pickup_datetime)) AS trip_duration
    FROM yellow_taxi_data
) trips
GROUP BY distance_range
"""

df = spark.sql(query).toPandas() # Convert the Spark DataFrame to Pandas

# Plot the data
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.bar(df['distance_range'], df['avg_duration'], color='skyblue')
plt.xlabel('Distance Range')
plt.ylabel('Average Duration (seconds)')
plt.title('Average Trip Duration by Distance Range')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



3.15 Question 15

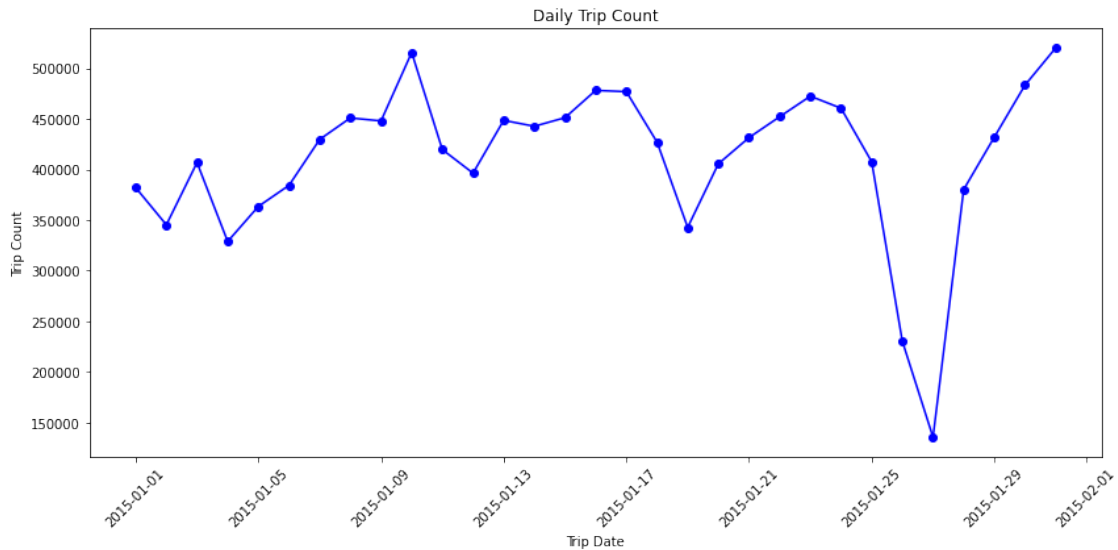
```
[ ]: %sql
SELECT
    DATE(tpcp_pickup_datetime) AS trip_date,
    COUNT(*) AS trip_count
FROM yellow_taxi_data
GROUP BY trip_date
ORDER BY trip_date;
```

3.16 Question 15 Visualization

```
[ ]: query = """
SELECT
    DATE(tpcp_pickup_datetime) AS trip_date,
    COUNT(*) AS trip_count
FROM yellow_taxi_data
GROUP BY trip_date
ORDER BY trip_date
"""
df = spark.sql(query).toPandas()

# Plotting the data
import matplotlib.pyplot as plt
```

```
plt.figure(figsize=(12, 6))
plt.plot(df['trip_date'], df['trip_count'], marker='o', linestyle='-', color='b')
plt.xlabel('Trip Date')
plt.ylabel('Trip Count')
plt.title('Daily Trip Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



3.17 Question 17

```
[ ]: %sql
SELECT
    HOUR(tpep_pickup_datetime) AS hour_of_day,
    AVG(passenger_count) AS avg_passenger_count
FROM yellow_taxi_data
GROUP BY hour_of_day
ORDER BY hour_of_day;
```

3.18 Question 17 Visualization

```
[ ]: query = """
SELECT
    HOUR(tpep_pickup_datetime) AS hour_of_day,
    AVG(passenger_count) AS avg_passenger_count
FROM yellow_taxi_data
GROUP BY hour_of_day
"""
```

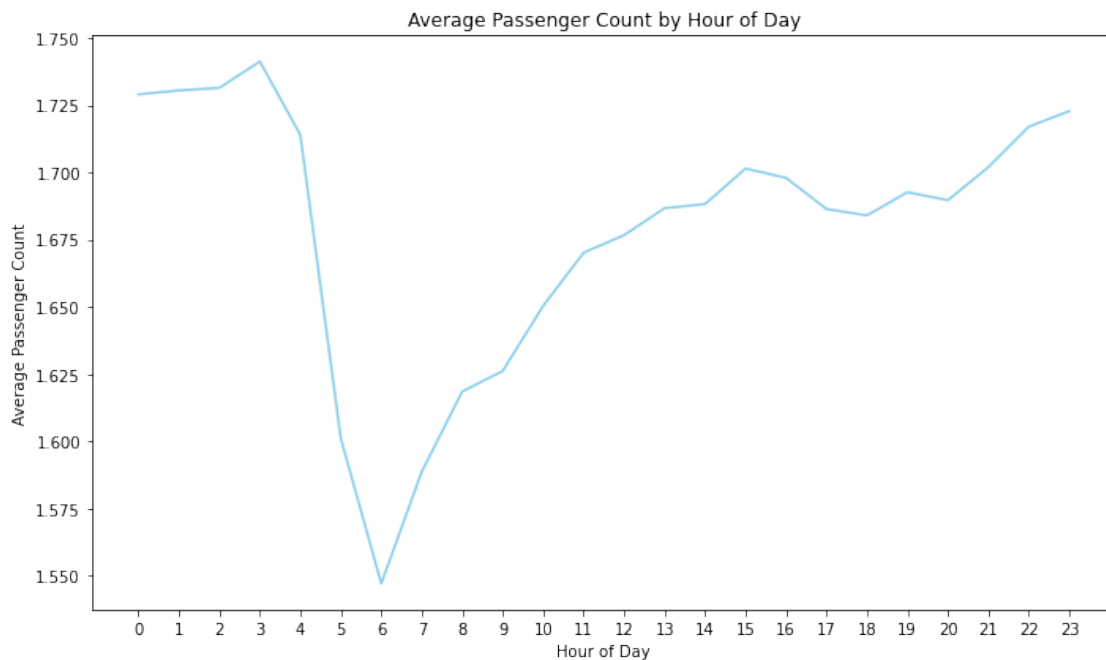
```

ORDER BY hour_of_day
"""
df = spark.sql(query).toPandas()

# Plotting the data
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.plot(df['hour_of_day'], df['avg_passenger_count'], color='skyblue')
plt.xlabel('Hour of Day')
plt.ylabel('Average Passenger Count')
plt.title('Average Passenger Count by Hour of Day')
plt.xticks(range(0, 24)) # Show each hour from 0 to 23
plt.tight_layout()
plt.show()

```



3.19 Question 18

```

[ ]: %sql
SELECT
    DAYOFWEEK(tpcp_pickup_datetime) AS day_of_week,
    SUM(total_amount) AS total_revenue
FROM yellow_taxi_data
GROUP BY day_of_week
ORDER BY day_of_week;

```

3.20 Question 18 Visualization

```
[ ]: query = """
SELECT
    DAYOFWEEK(tpep_pickup_datetime) AS day_of_week,
    SUM(total_amount) AS total_revenue
FROM yellow_taxi_data
GROUP BY day_of_week
ORDER BY day_of_week
"""

df = spark.sql(query).toPandas()

# Map day numbers to day names for better readability
day_names = {1: 'Sunday', 2: 'Monday', 3: 'Tuesday', 4: 'Wednesday',
             5: 'Thursday', 6: 'Friday', 7: 'Saturday'}
df['day_of_week'] = df['day_of_week'].map(day_names)

# Plotting the data
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.bar(df['day_of_week'], df['total_revenue'], color='skyblue')
plt.xlabel('Day of the Week')
plt.ylabel('Total Revenue')
plt.title('Total Revenue by Day of the Week')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

