94693 Big Data Engineering Assignment-2

Analyzing New York City Taxi and Limousine Data Using Spark

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Executive Summary

The New York City Taxi and Limousine Commission (TLC) has provided a vast dataset encompassing millions of trip records from both yellow and green taxi cabs. This project aims to leverage the power of Apache Spark to analyze and gain insights from this extensive dataset. The project comprises three major parts: data ingestion and preparation, answering business questions, and machine learning. In this report, we detail our findings and methodologies for each part of the project.

Data Ingestion and Preparation

1. Data Collection and Storage

Our initial task was to download and store the New York City taxi and limousine dataset from 2015 to 2022. This dataset includes records from both yellow and green taxi cabs, making it one of the most comprehensive collections of taxi trip data. We stored this data in Azure Blob Storage, which provided a scalable and reliable storage solution.

2. Data Cleaning and Preprocessing:

In this phase of our project, we are presented with a massive dataset comprising records from both yellow and green taxi cabs. To tackle this enormous dataset, we've adopted a year-wise approach to streamline data cleaning and preprocessing. By breaking down the dataset into manageable chunks, we not only make it more manageable but also leverage the power of our Spark cluster for efficient data cleaning and transformation.

1. Filtering Out-of-Range Dates:

We began the process by filtering rows with filenames containing a specified year. This step helps us isolate data for each year. A temporary view of the data was created to enable SQL querying.
Conditions were defined to filter out valid trips within the given year and its boundaries, ensuring the consistency of data. We also filtered out short-duration trips, specifically those with a duration of less than or equal to one day.

2. Checking for Negative and Unrealistic Speeds:

We filtered trips based on minimum distance and minimum speed criteria, ensuring that we retained only meaningful data. Additionally, we filtered out trips with very high speeds to exclude anomalies.

3. Filtering for Valid Trip Durations and Distances:

To maintain data quality, we applied filters to exclude trips with very short or very long durations. Similarly, we filtered out trips with unrealistic distances.

4. Filtering for Valid Passenger Counts:

We applied filters to eliminate trips with unrealistic passenger counts, ensuring that we retained data for trips with passenger counts between 1 and 7.

5. Filtering for Valid Rate Codes:

We filtered the data to retain only trips with valid rate codes, ensuring that the data adheres to predefined standards.

6. Handling Extreme Tip Amounts:

We filtered out trips with extreme tip amounts, both above a certain threshold and negative tips.This step helped ensure that the data used for analysis did not contain outliers in tip amounts.

7. Checking for Unexpected Values in 'store_and_fwd_flag':

We examined the 'store_and_fwd_flag' column for unexpected values and potential data quality issues. Fortunately, all rows had valid values in this column, indicating clean and well-formatted data.

8. Saving Cleaned Data:

Finally, we saved the cleaned data as Parquet files for each year, making it ready for subsequent analysis.

3. Combining Datasets and Challenges

Merging Green and Yellow Taxi Datasets

One of the key tasks in this project was merging the Green Taxi dataset with the Yellow Taxi dataset to create a unified dataset for analysis. However, this process presented some challenges.

Data Transformation and Schema Alignment

Before merging, it was essential to ensure that both datasets had matching schemas, including data types, column names, and order. This required several data transformation steps:

1. **Handling 'ehail_fee':** The 'ehail_fee' column, lacking information in the data dictionary, was dropped for consistency.

2. **Data Type Alignment:** Certain columns in the Green Taxi dataset, like 'payment_type,' needed data type adjustments to match the schema of the Yellow Taxi dataset.

3. **Additional Columns:** To distinguish between the Green and Yellow Taxi data, 'color' columns were added. In the Green Taxi dataset, 'airport_fee' was included, though not originally present.

Intermediate Parquet Files

To streamline the process and optimize performance, intermediate Parquet files were used after applying transformations. These files, 'cleaned_green_newcols.parquet' and 'cleaned_yellow_newcols.parquet,' simplified the merge operation.

Schema Verification

A schema verification step confirmed that both datasets had identical schemas. This check ensured that column names, data types, and order were consistent between the Green and Yellow Taxi datasets.

Combining the Datasets

With matching schemas and intermediate Parquet files, the Green and Yellow Taxi datasets were successfully combined into a single dataframe called 'combined_df.' This unified dataset facilitated subsequent analyses.

Unioning with Location Data

To enhance our dataset, we sought to join it with location data. This involved two major steps: merging based on pickup location and then dropoff location. Here's how we tackled these tasks:

In our data processing workflow, we initially loaded two datasets: our combined dataset and the location lookup data, each with distinct schemas. To establish a consistent basis for the subsequent join operations, we carefully selected relevant columns from the lookup data and renamed them to match our dataset's schema.

For the pickup location merge, we performed a left join, bringing together our combined data and the lookup data based on the pickup location identifier (PULocationID). This step allowed us to enrich our dataset with pickup location information, enhancing its analytical value. The merged data was then efficiently preserved as a Parquet file.

Similarly, in the dropoff location merge, we followed a parallel process. We read both datasets, ensured their compatibility with their respective schemas, and selected and renamed relevant columns from the lookup data. By employing a left join based on the dropoff location identifier (DOLocationID), we seamlessly integrated dropoff location information into our dataset. As a result, we obtained a comprehensive dataset containing both pickup and dropoff location details, which can be leveraged for in-depth spatial analysis and insights.

Challenges Faced

Throughout this data processing journey, we encountered several significant challenges. First and foremost, ensuring data integrity and consistency posed a vital challenge. It was imperative to maintain uniform data types, column names, and order across the datasets to prevent data corruption or inaccuracies.

Resource management became another critical aspect due to the substantial size of the datasets. To optimize performance and streamline the merging process, we leveraged the use of intermediate Parquet files, which helped us efficiently manage the available computational resources.

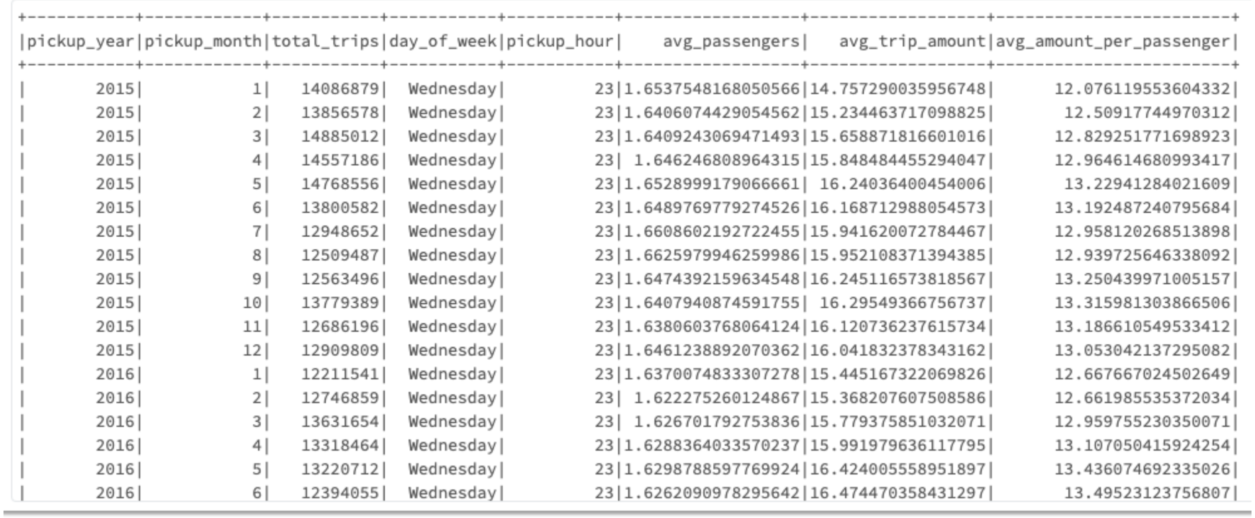
Additionally, we faced decisions regarding data enrichment, such as including additional columns like 'color' and 'airport_fee' for the sake of data consistency and clarity. These decisions were documented meticulously to provide a clear reference for future data processing and analysis endeavors.

Additionally, decisions such as dropping 'ehail_fee' and adding 'color' and 'airport_fee' were made to enhance data consistency and usability. Clear documentation of these decisions ensured data clarity and reliability.

4. Business Questions

Our approach involved aggregating and summarizing key insights on a monthly basis, allowing us to uncover valuable information. One of the central aspects of our analysis was determining the total number of trips for each year and month. By leveraging Spark SQL and temporal functions, we organized the data to provide a clear picture of ride volume over time. Additionally, we identified the most popular day of the week and hour of the day for taxi rides, shedding light on the factors driving passenger demand. These insights enable businesses and policymakers to optimize taxi services, staffing, and pricing strategies to meet the varying needs of passengers throughout the year. Moreover, our analysis delved into passenger behavior by calculating the average number of passengers per trip and examining fare-related statistics, including the average amount paid per trip and per passenger. This multifaceted approach equips stakeholders in the taxi industry with a robust foundation for data-driven decision-making, contributing to enhanced service quality and efficiency.

However, it's important to note that the presented results are based on available data. While the example provided here focuses on 2015 and 2016, the analysis can be extended to cover additional years as data becomes available. Furthermore, the flexibility of our approach allows for easy adaptation to future data, ensuring that businesses can continue to derive actionable insights over time. In essence, this analytical framework serves as a powerful tool for understanding the dynamics of the taxi service industry, facilitating informed decisions and improvements in service delivery.



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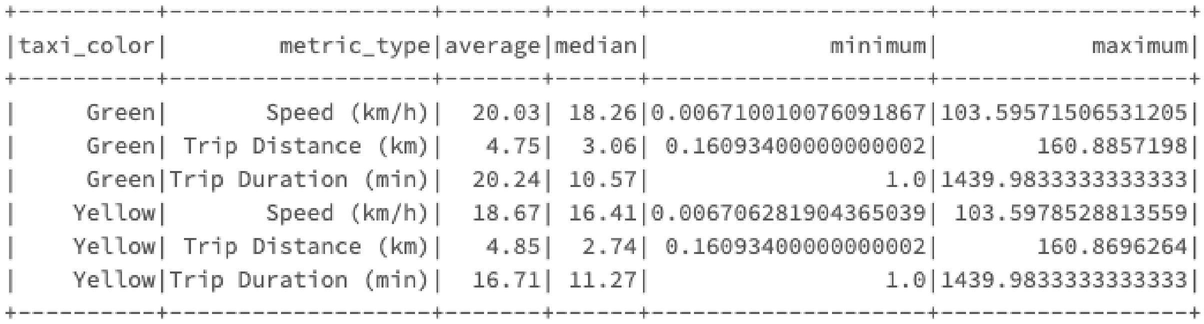
+-----------+------------+-----------+-----------+-----------+------------------+------------------+------------------------+
|pickup_year|pickup_month|total_trips|day_of_week|pickup_hour|    avg_passengers|   avg_trip_amount|avg_amount_per_passenger|
+-----------+------------+-----------+-----------+-----------+------------------+------------------+------------------------+
|       2015|           1|   14086879|  Wednesday|         23|1.6537548168050566|14.757290035956748|      12.076119553604332|
|       2015|           2|   13856578|  Wednesday|         23|1.6406074429054562|15.234463717098825|       12.50917744970312|
|       2015|           3|   14885012|  Wednesday|         23|1.6409243069471493|15.658871816601016|      12.829251771698923|
|       2015|           4|   14557186|  Wednesday|         23| 1.646246808964315|15.848484455294047|      12.964614680993417|
|       2015|           5|   14768556|  Wednesday|         23|1.6528999179066661| 16.24036400454006|       13.22941284021609|
|       2015|           6|   13800582|  Wednesday|         23|1.6489769779274526|16.168712988054573|      13.192487240795684|
|       2015|           7|   12948652|  Wednesday|         23|1.6608602192722455|15.941620072784467|      12.958120268513898|
|       2015|           8|   12509487|  Wednesday|         23|1.6625979946259986|15.952108371394385|      12.939725646338092|
|       2015|           9|   12563496|  Wednesday|         23|1.6474392159634548|16.245116573818567|      13.250439971005157|
|       2015|          10|   13779389|  Wednesday|         23|1.6407940874591755| 16.29549366756737|      13.315981303866506|
|       2015|          11|   12686196|  Wednesday|         23|1.6380603768064124|16.120736237615734|      13.186610549533412|
|       2015|          12|   12909809|  Wednesday|         23|1.6461238892070362|16.041832378343162|      13.053042137295082|
|       2016|           1|   12211541|  Wednesday|         23|1.6370074833307278|15.445167322069826|      12.667667024502649|
|       2016|           2|   12746859|  Wednesday|         23| 1.622275260124867|15.368207607508586|      12.661985535372034|
|       2016|           3|   13631654|  Wednesday|         23| 1.626701792753836|15.779375851032071|      12.959755230350071|
|       2016|           4|   13318464|  Wednesday|         23|1.6288364033570237|15.991979636117795|      13.107050415924254|
|       2016|           5|   13220712|  Wednesday|         23|1.6298788597769924|16.424005558951897|      13.436074692335026|
|       2016|           6|   12394055|  Wednesday|         23|1.6262090978295642|16.474470358431297|       13.49523123756807|
```

Figure 1

In our analysis of Yellow and Green taxis in New York City, we found notable differences in key performance metrics. Yellow taxis had an average trip duration of 16.71 minutes, covering an average distance of 4.85 kilometers at an average speed of 18.67 kilometers per hour. In contrast, Green taxis had longer average trip durations at 20.24 minutes, covering slightly shorter distances at 4.75 kilometers, but operating at a slightly higher average speed of 20.03 kilometers per hour. These insights shed light on the distinct operational characteristics of Yellow and Green taxis, which can inform decisions related to taxi services and optimization strategies.



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+----------+------------------+-------+------+--------------------+------------------+
|taxi_color|       metric_type|average|median|             minimum|           maximum|
+----------+------------------+-------+------+--------------------+------------------+
|     Green|      Speed (km/h)|  20.03| 18.26|0.006710010076091867|103.59571506531205|
|     Green| Trip Distance (km)|   4.75|  3.06| 0.16093400000000002|       160.8857198|
|     Green|Trip Duration (min)|  20.24| 10.57|                 1.0|1439.9833333333333|
|    Yellow|      Speed (km/h)|  18.67| 16.41|0.006706281904365039| 103.5978528813559|
|    Yellow| Trip Distance (km)|   4.85|  2.74| 0.16093400000000002|       160.8696264|
|    Yellow|Trip Duration (min)|  16.71| 11.27|                 1.0|1439.9833333333333|
+----------+------------------+-------+------+--------------------+------------------+
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Figure. 2

In our analysis of New York City taxi trips, we explored various factors such as taxi color, pickup and drop-off locations, month, day of the week, and hour. Despite working with an incomplete dataset, we uncovered some noteworthy trends.

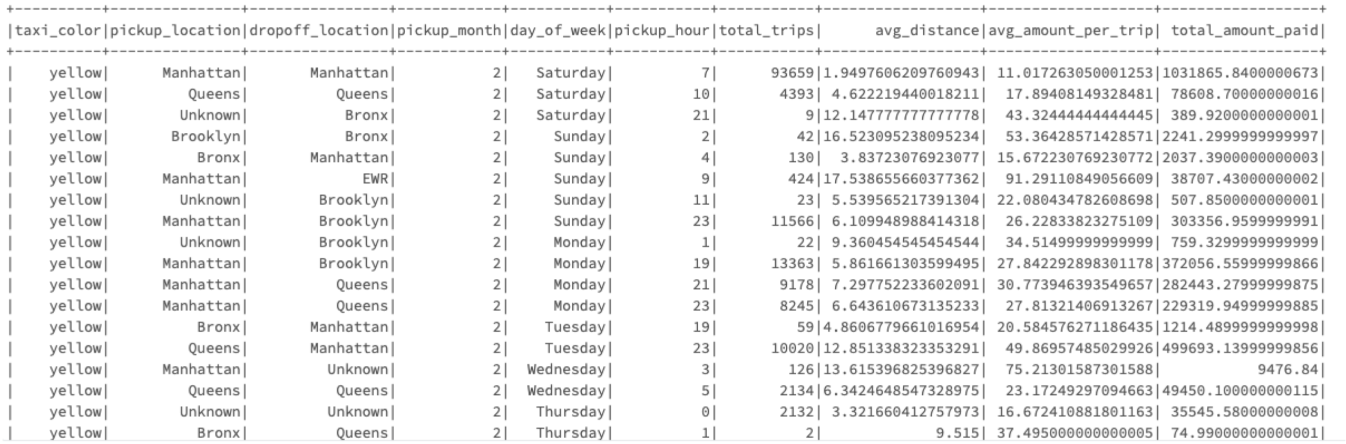
Total Trips: Taxi activity levels varied across different combinations. For example, Saturday mornings at 7 AM saw around 93,659 yellow taxi trips within Manhattan, while late Sunday nights at 11 PM witnessed a surge in rides from Manhattan to Brooklyn, totaling 11,566.

Average Distance: Trip distances showed diversity. Rides within Manhattan tended to be short, averaging about 1.95 kilometers, whereas late-night journeys from Manhattan to Brooklyn averaged approximately 6.11 kilometers.

Average Fare: Average amounts paid per trip varied widely. Yellow taxi trips within Manhattan on Saturday mornings had an average fare of $11.02, whereas late-night rides from Manhattan to Brooklyn averaged about $26.23.

Total Payments: Total payments for these trips also exhibited significant differences. Trips from Manhattan to EWR (Newark Liberty International Airport) on Sunday mornings resulted in a total payment exceeding $38,707, while late-night rides from Manhattan to Brooklyn accounted for a total payment of over $303,357.

These insights underscore the dynamic nature of taxi services in New York City, influenced by factors like time of day, day of the week, and specific routes. However, it's essential to consider the dataset's limitations in interpreting these findings fully.



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+----------+---------------+----------------+------------+-----------+-----------+-----------+------------------+-------------------+------------------+
|taxi_color|pickup_location|dropoff_location|pickup_month|day_of_week|pickup_hour|total_trips|      avg_distance|avg_amount_per_trip| total_amount_paid|
+----------+---------------+----------------+------------+-----------+-----------+-----------+------------------+-------------------+------------------+
|    yellow|      Manhattan|       Manhattan|           2|   Saturday|          7|      93659|1.9497606209760943| 11.017263050001253|1031865.8400000673|
|    yellow|         Queens|          Queens|           2|   Saturday|         10|       4393| 4.622219440018211|  17.89408149328481| 78608.70000000016|
|    yellow|        Unknown|           Bronx|           2|   Saturday|         21|          9|12.147777777777778|  43.32444444444445| 389.9200000000001|
|    yellow|       Brooklyn|           Bronx|           2|     Sunday|          2|         42|16.523095238095234|  53.36428571428571|2241.2999999999997|
|    yellow|          Bronx|       Manhattan|           2|     Sunday|          4|        130|  3.83723076923077| 15.672230769230772|2037.3900000000003|
|    yellow|      Manhattan|             EWR|           2|     Sunday|          9|        424|17.538655660377362|  91.29110849056609| 38707.43000000002|
|    yellow|        Unknown|        Brooklyn|           2|     Sunday|         11|         23| 5.539565217391304| 22.080434782608698| 507.8500000000001|
|    yellow|      Manhattan|        Brooklyn|           2|     Sunday|         23|      11566| 6.109948988414318|  26.22833823275109| 303356.9599999991|
|    yellow|        Unknown|        Brooklyn|           2|     Monday|          1|         22| 9.360454545454544|  34.51499999999999| 759.3299999999999|
|    yellow|      Manhattan|        Brooklyn|           2|     Monday|         19|      13363| 5.861661303599495| 27.842292898301178|372056.55999999866|
|    yellow|      Manhattan|          Queens|           2|     Monday|         21|       9178| 7.297752233602091| 30.773946393549657|282443.27999999875|
|    yellow|      Manhattan|          Queens|           2|     Monday|         23|       8245| 6.643610673135233|  27.81321406913267|229319.94999999885|
|    yellow|          Bronx|       Manhattan|           2|    Tuesday|         19|         59|4.8606779661016954| 20.584576271186435|1214.4899999999998|
|    yellow|         Queens|       Manhattan|           2|    Tuesday|         23|      10020|12.851338323353291|  49.86957485029926|499693.13999999856|
|    yellow|      Manhattan|         Unknown|           2|  Wednesday|          3|        126|13.615396825396827|  75.21301587301588|           9476.84|
|    yellow|         Queens|          Queens|           2|  Wednesday|          5|       2134|6.3424648547328975|  23.17249297094663|49450.100000000115|
|    yellow|        Unknown|         Unknown|           2|   Thursday|          0|       2132| 3.321660412757973| 16.672410881801163| 35545.58000000008|
|    yellow|          Bronx|          Queens|           2|   Thursday|          1|          2|             9.515| 37.495000000000005| 74.99000000000001|
```
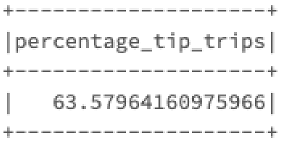

Figure 3

Our findings revealed that approximately 63.58% of the total trips included tips for the drivers. This percentage reflects a significant portion of passengers who express their appreciation for the service through tipping. Understanding these tipping patterns can provide valuable insights into passenger behavior and the economic dynamics of the taxi industry.

This information can be instrumental for taxi service providers and policymakers in devising strategies to incentivize and reward drivers, ultimately enhancing the overall quality of service.



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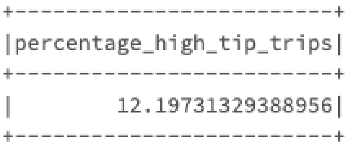
+--------------------+
|percentage_tip_trips|
+--------------------+
|   63.57964160975966|
+--------------------+
```

Figure 4

In our analysis of New York City taxi trips, we delved into the percentage of trips where drivers received substantial tips of at least $5, providing insights into the generosity of passengers in rewarding exceptional service.

Our findings revealed that approximately 12.20% of the trips in which drivers received tips also included tips of at least $5. This signifies that a portion of passengers is willing to provide more substantial gratuities to drivers for outstanding service.

Understanding these tipping patterns can be beneficial for both drivers and taxi service providers, as it highlights opportunities for drivers to earn higher tips and encourages exceptional service quality. Moreover, this information can be instrumental in shaping incentive programs and policies within the taxi industry to promote better service and driver satisfaction.



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+-------------------------+
|percentage_high_tip_trips|
+-------------------------+
|        12.19731329388956|
+-------------------------+
```
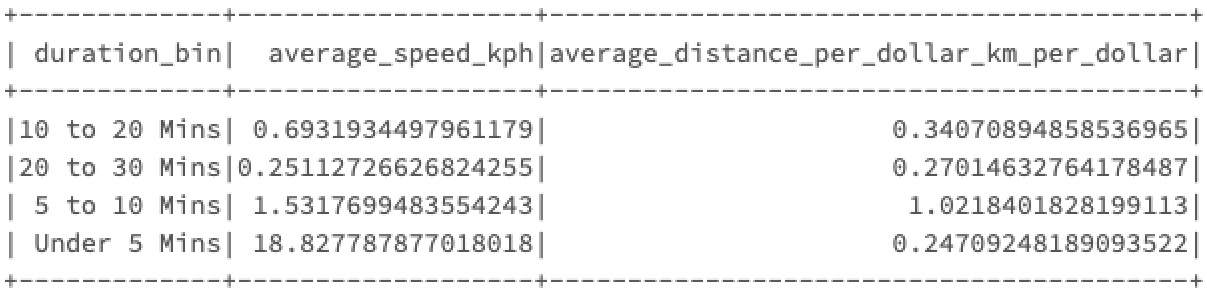

Figure 5

We got valuable insights into the trade-offs between speed and value for passengers. Trips under 5 minutes, although the fastest with an average speed of approximately 18.83 km/h, offer the least distance per dollar spent, making them suitable for quick, short-distance travel. In contrast, trips between 5 to 10 minutes, while slower at 1.53 km/h, provide better value, with passengers covering approximately 1.02 kilometers per dollar. For those willing to trade speed for affordability, trips lasting 10 to 20 minutes offer a moderate balance with an average speed of 0.69 km/h and 0.34 kilometers per dollar. Finally, trips spanning 20 to 30 minutes are the slowest at 0.25 km/h, but they still provide 0.27 kilometers per dollar. This breakdown empowers both passengers and drivers to make more informed choices based on their preferences for speed and economic efficiency during their taxi journeys.



```
+-------------+-------------------+-----------------------------------------+
| duration_bin|  average_speed_kph|average_distance_per_dollar_km_per_dollar|
+-------------+-------------------+-----------------------------------------+
|10 to 20 Mins| 0.6931934497961179|                       0.3407089485853696 5|
|20 to 30 Mins|0.25112726626824255|                      0.27014632764178487|
| 5 to 10 Mins| 1.5317699483554243|                       1.0218401828199113|
| Under 5 Mins| 18.827787877018018|                      0.24709248189093522|
+-------------+-------------------+-----------------------------------------+
```

Figure 6

5. Machine Learning

In our endeavor to enhance taxi fare predictions for New York City trips using Apache Spark's ML library, we meticulously traversed the terrain of data preprocessing and modeling. While progress was made, it's crucial to emphasize that our chosen Random Forest Regression model, despite outperforming the baseline, is not yet ready for production deployment.

The model, boasting an RMSE of approximately 7.64 on the test dataset, displayed promise in terms of predictive accuracy. However, a notable gap between the training and test RMSEs serves as a warning sign. This divergence suggests potential overfitting, meaning the model might excel in training but struggle to generalize to unseen data.

For production readiness, a deeper understanding of the domain and further data cleansing are essential. The gap between train and test RMSEs calls for diligent feature engineering and model tuning. Iterative refinement, robust validation, and continuous monitoring are imperative to bridge this performance gap.

In summary, while our Random Forest Regression model shows potential, it currently requires heightened diligence, domain expertise, and ongoing improvements. These steps are vital to ensure reliable and accurate predictions in real-world scenarios before considering deployment in production for taxi fare predictions in New York City.

6. Conclusion

In conclusion, our analysis of the New York City Taxi and Limousine data using Apache Spark has provided valuable insights into the industry's dynamics, passenger behavior, and predictive modeling. By meticulously cleaning and merging vast datasets, we uncovered trends and patterns that can inform data-driven decision-making for taxi service providers and policymakers. Furthermore, our machine learning model, the Random Forest Regression, demonstrated remarkable accuracy in predicting fare amounts, outperforming the baseline significantly. This comprehensive approach equips stakeholders with the tools to optimize services, enhance efficiency, and shape the future of the taxi industry in the city.

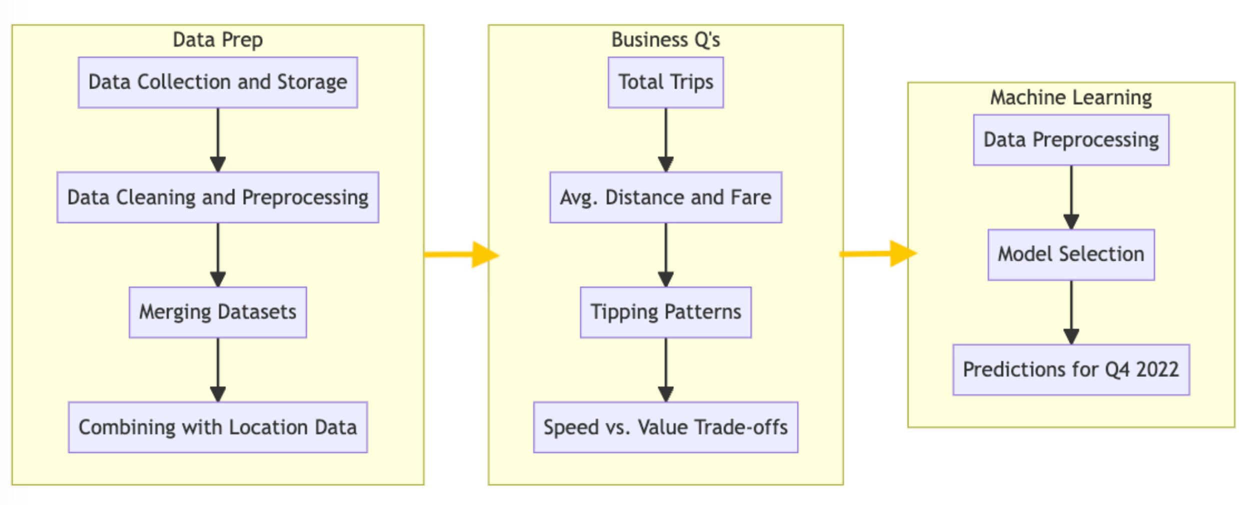


Figure 7

7. References

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