

Conclusion/Remarks:

1.1 After loading data rows 3041714 , columns 19

Conclusion/Remarks:

1.1 Sample Data created with 5% data from each hour from 12 months file

Conclusion/Remarks:

2.1 Checking missing value percentage

Conclusion/Remarks:

2.1.1 Fix the index and drop unnecessary columns: Index reset done, but will drop column later after analysis

Conclusion/Remarks:

2.1.2 So as there are 1747917 rows missing in airport_fee and 213357 rows in Airport_fee, so we can combine

Conclusion/Remarks:

2.1.2 For After combining , Airport_fee missing value percentage reduced from 11.25% to 3.42%

Conclusion/Remarks:

2.1.2 Dropped column airport_fee

Conclusion/Remarks:

2.1.3 Checking the distribution of RatecodeID of the negative amount value sets., Mainly it is 1 and 2

Conclusion/Remarks:

2.1.3 Detail checking the distribution of RatecodeID of the negative amount value sets., Mainly it is 1 and 2

Conclusion/Remarks:

2.2.2 Handling missing values in passenger count: Here from the distribution we can see around 75% is for passenger count 1. So taking the mode to impute NaN values here

Conclusion/Remarks:

2.2.3 Handle missing values in RatecodeID: As the mode of RatecodeID is 1 so imputing with it

Conclusion/Remarks:

2.2.4 Impute NaN in congestion_surcharge: As there are 3 discrete values and mode is 2.5, so imputing with it

Conclusion/Remarks:

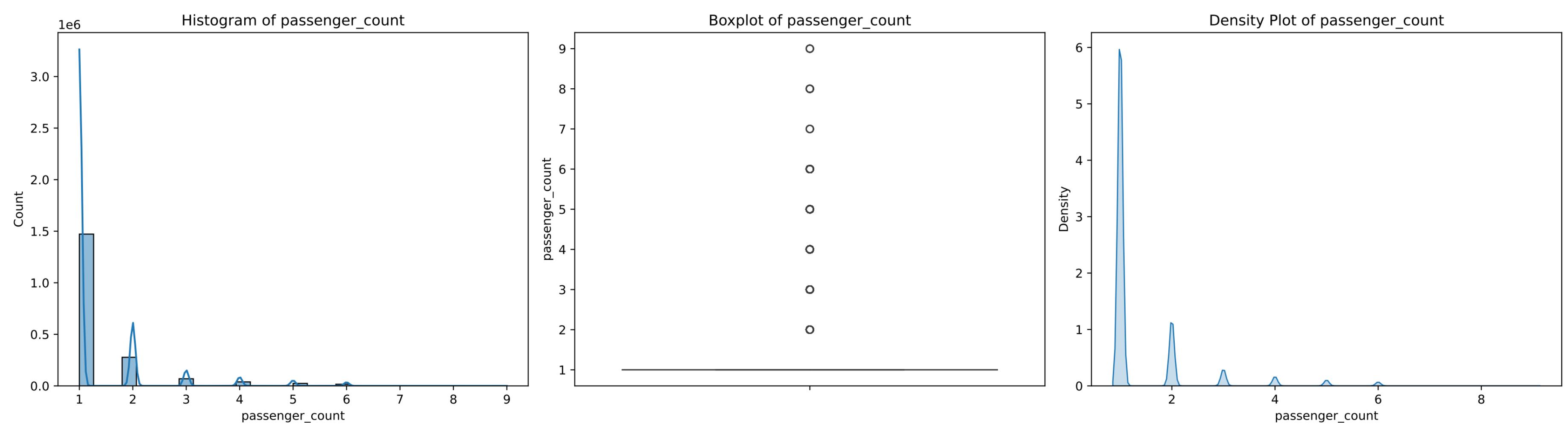
2.2.4 Impute NaN in store_and_fwd_flag: As there are 2 discrete values and mode is N, so imputing with it

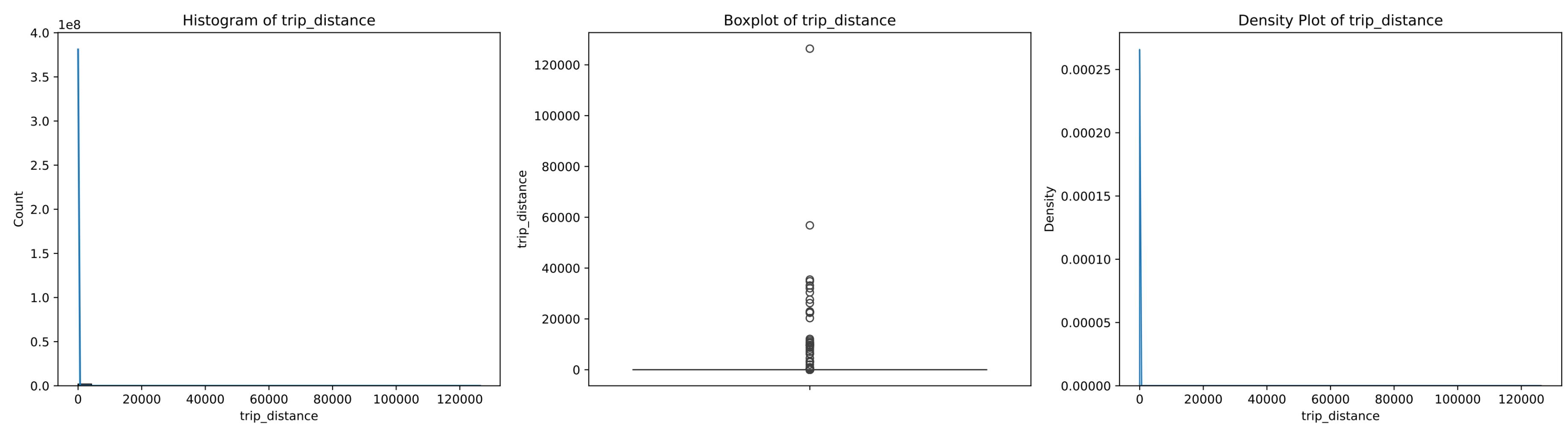
Conclusion/Remarks:

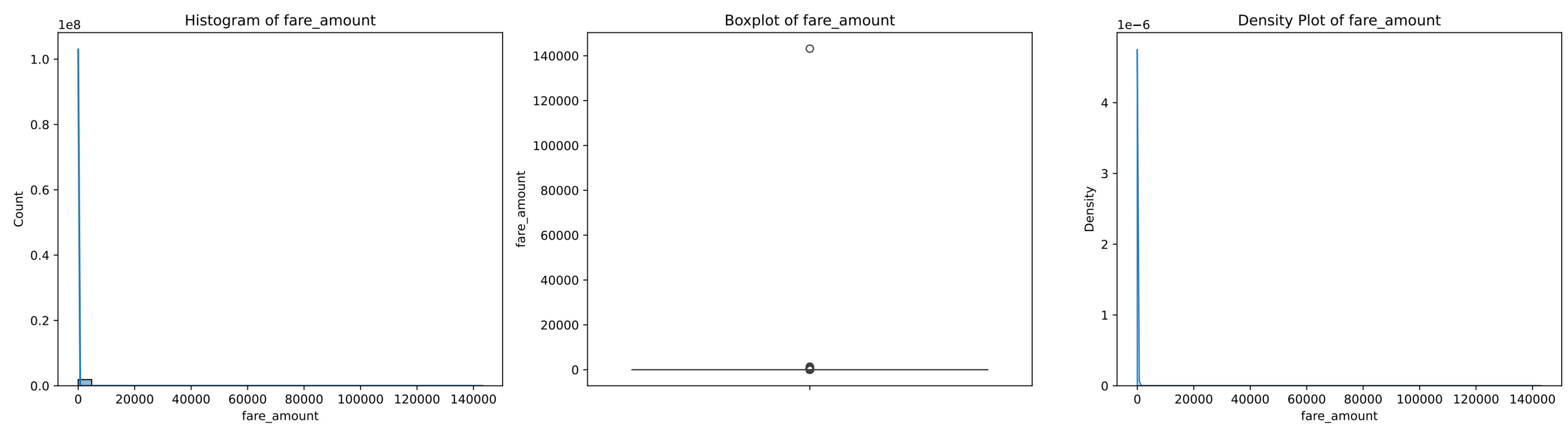
2.2.4 Impute NaN in airport_fe: As there are 4 discrete values and mode is 0, so imputing with it

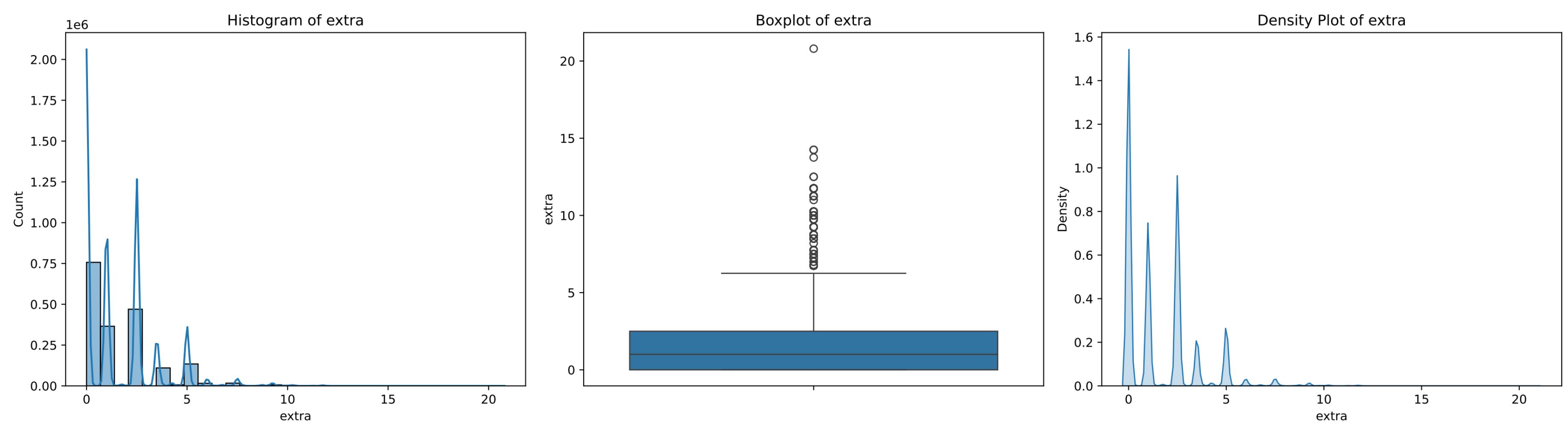
Conclusion/Remarks:

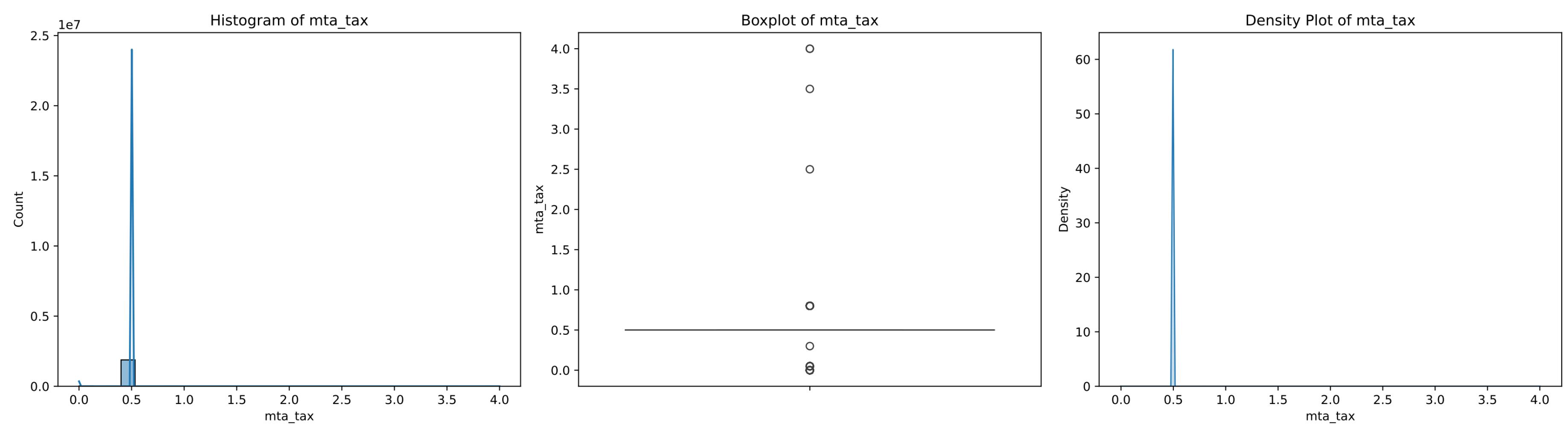
2.3 Checking the Outlier count, percentage and Skewness

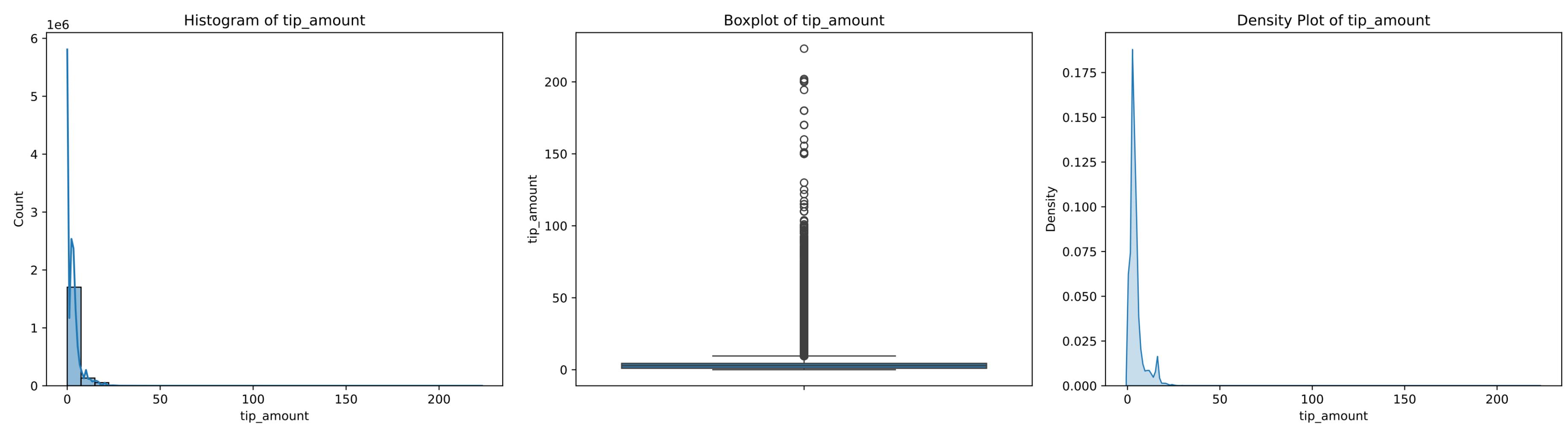


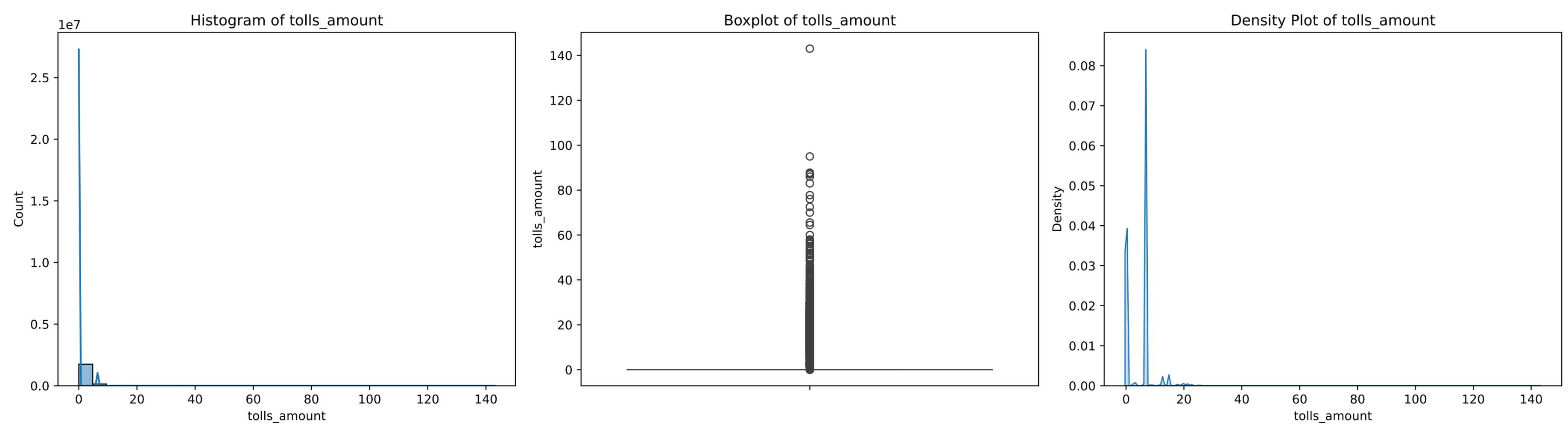


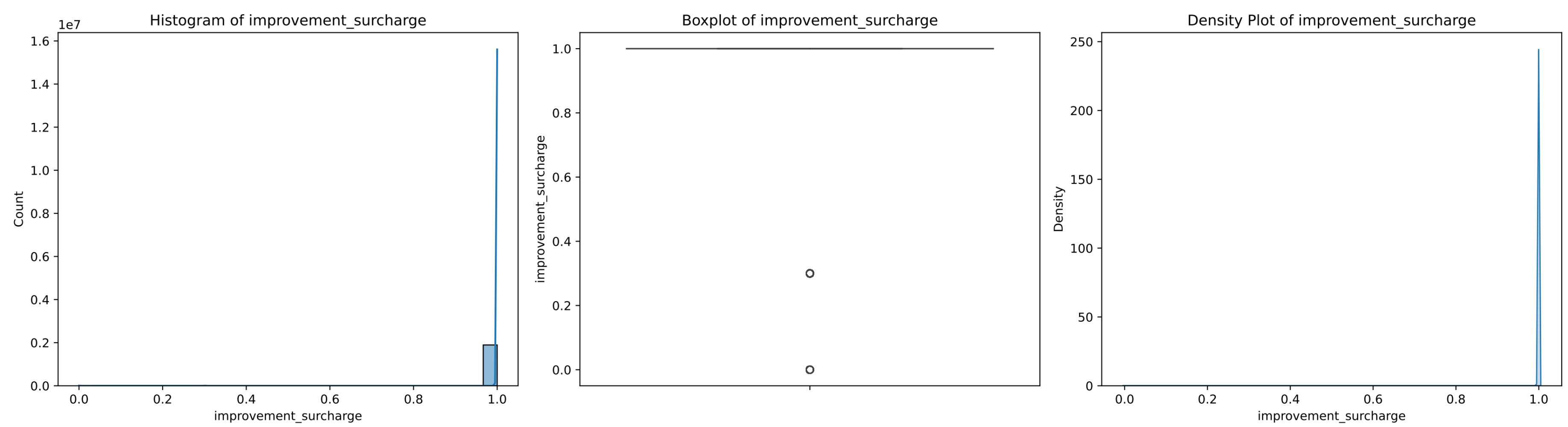


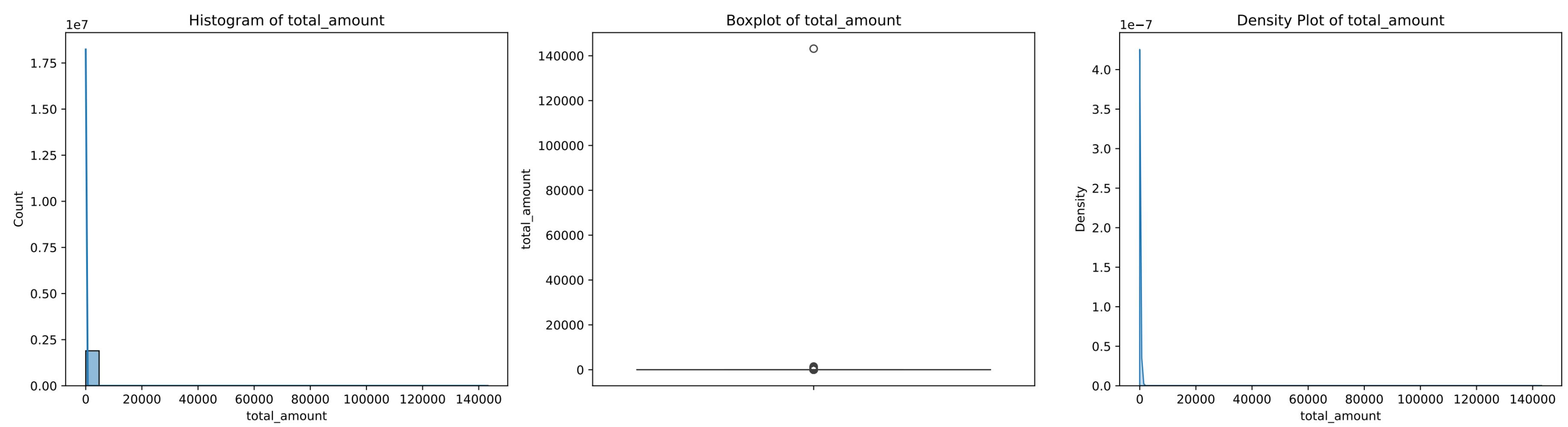


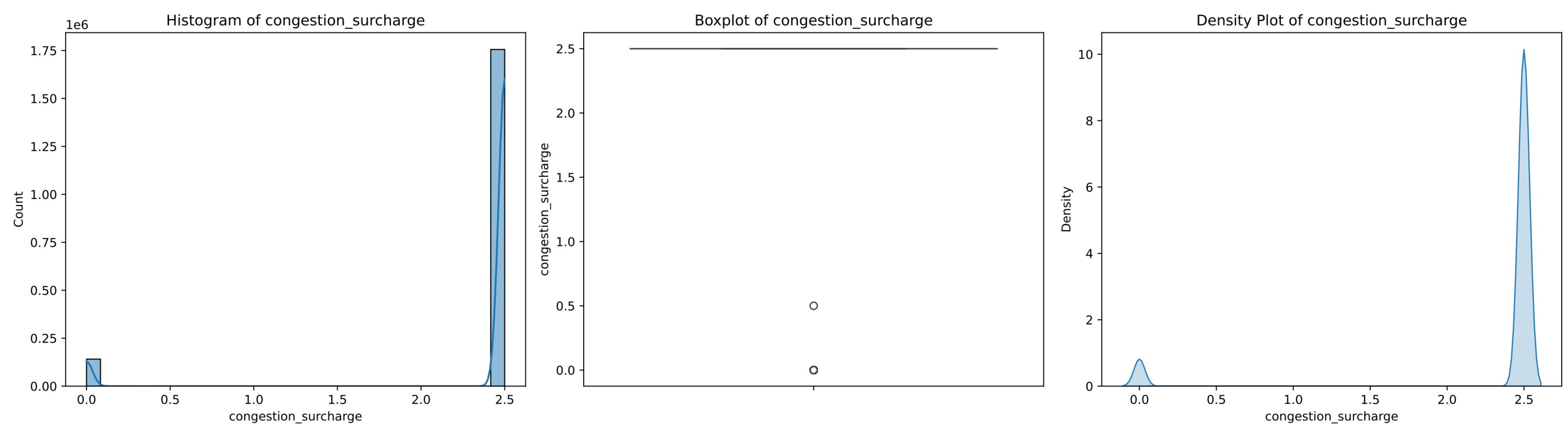


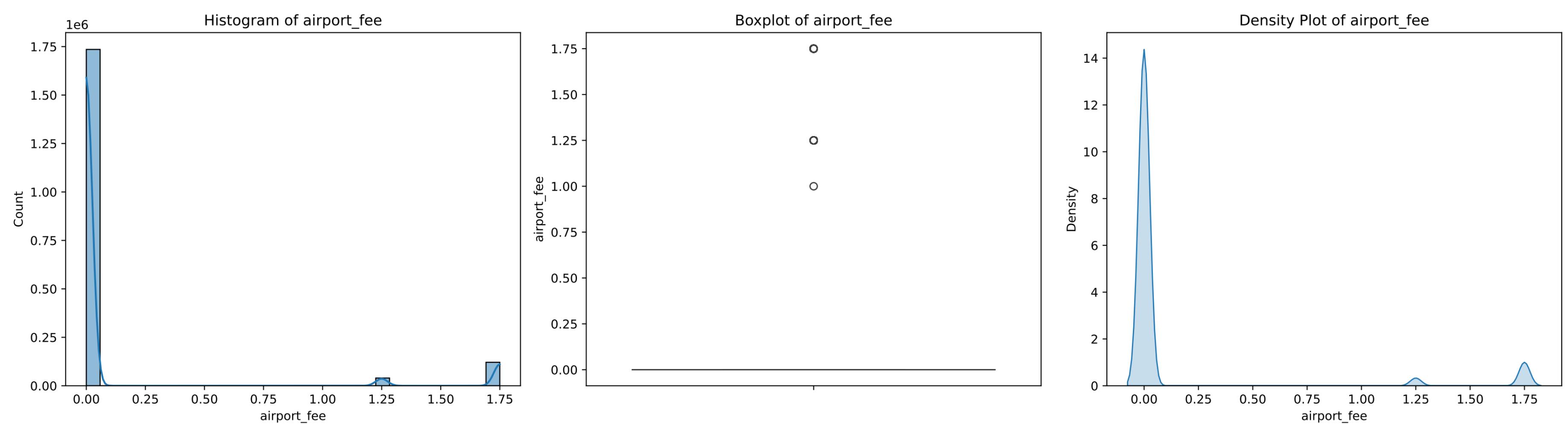












Conclusion/Remarks:

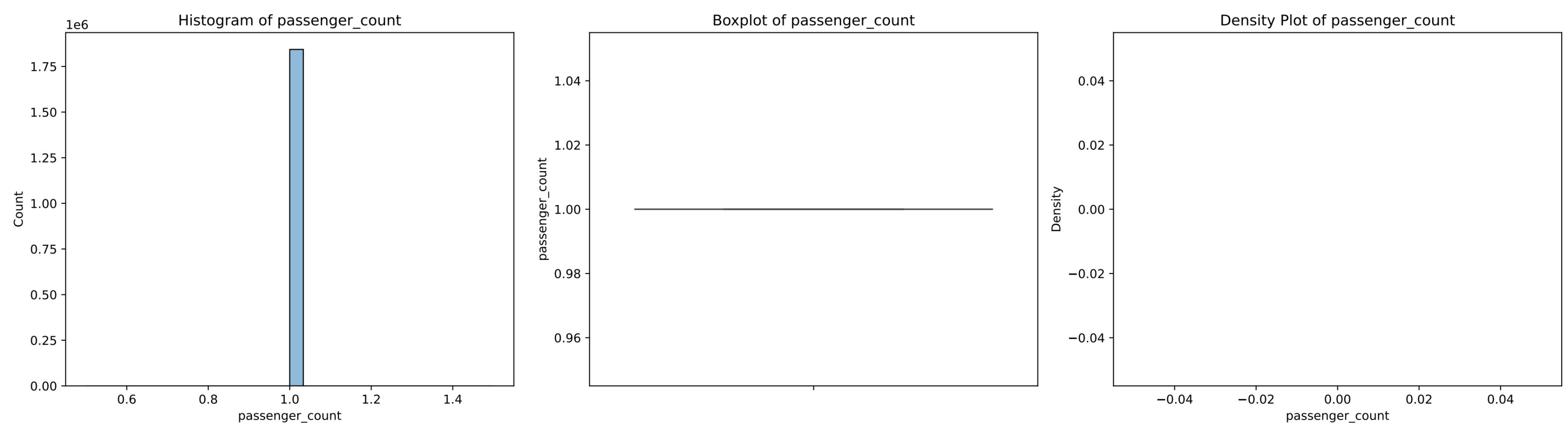
2.3 Analysing outliers for numerical values Only in Histogram,Box and KDE Plot. And there are lot of outliers in long skew. So dropping of 5% extreme data

Conclusion/Remarks:

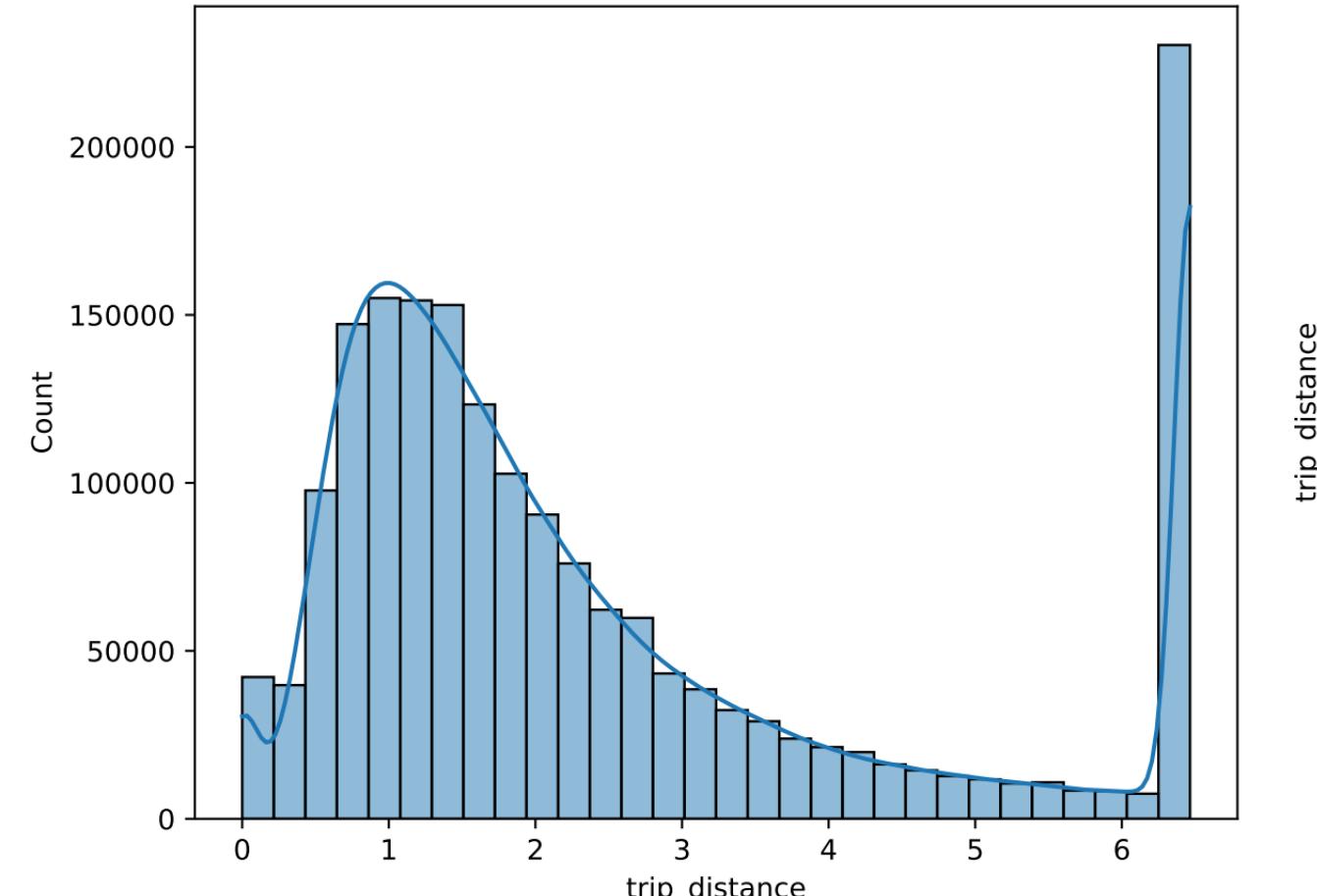
2.3 Removes entire rows where certain columns have outliers. Drops rows only if the percentage of outliers in a column is below a given threshold (5%). Keeps track of outlier percentages before and after removal

Conclusion/Remarks:

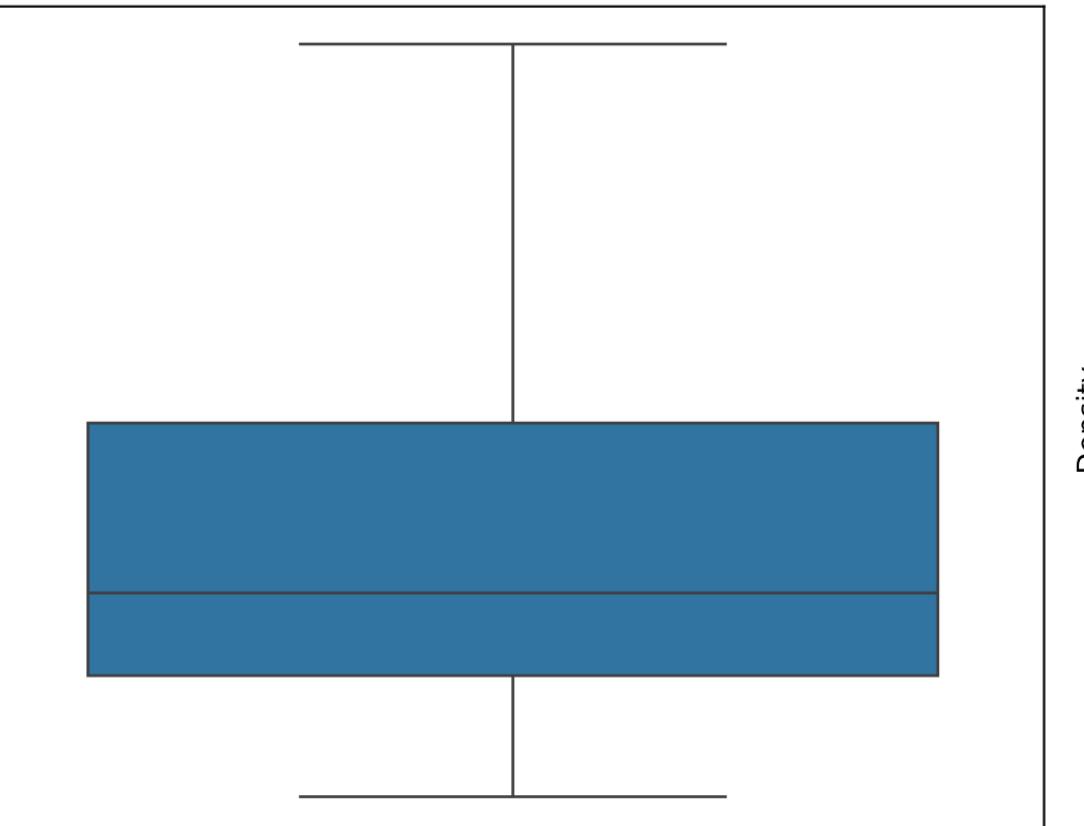
2.3 Analysing the Skewness by Clipping data outside
 $\text{lower_bound} = Q1 - 1.5 * \text{IQR}$,
 $\text{upper_bound} = Q3 + 1.5 * \text{IQR}$



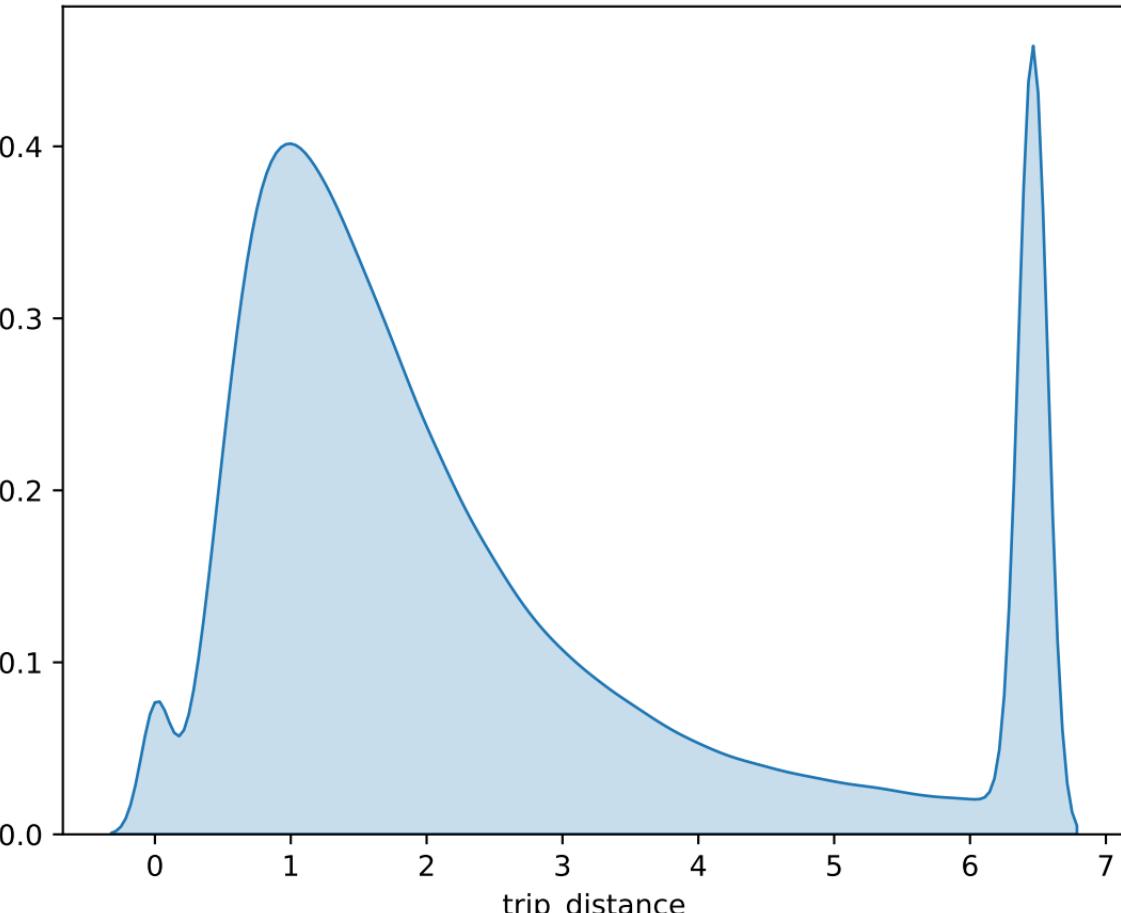
Histogram of trip_distance



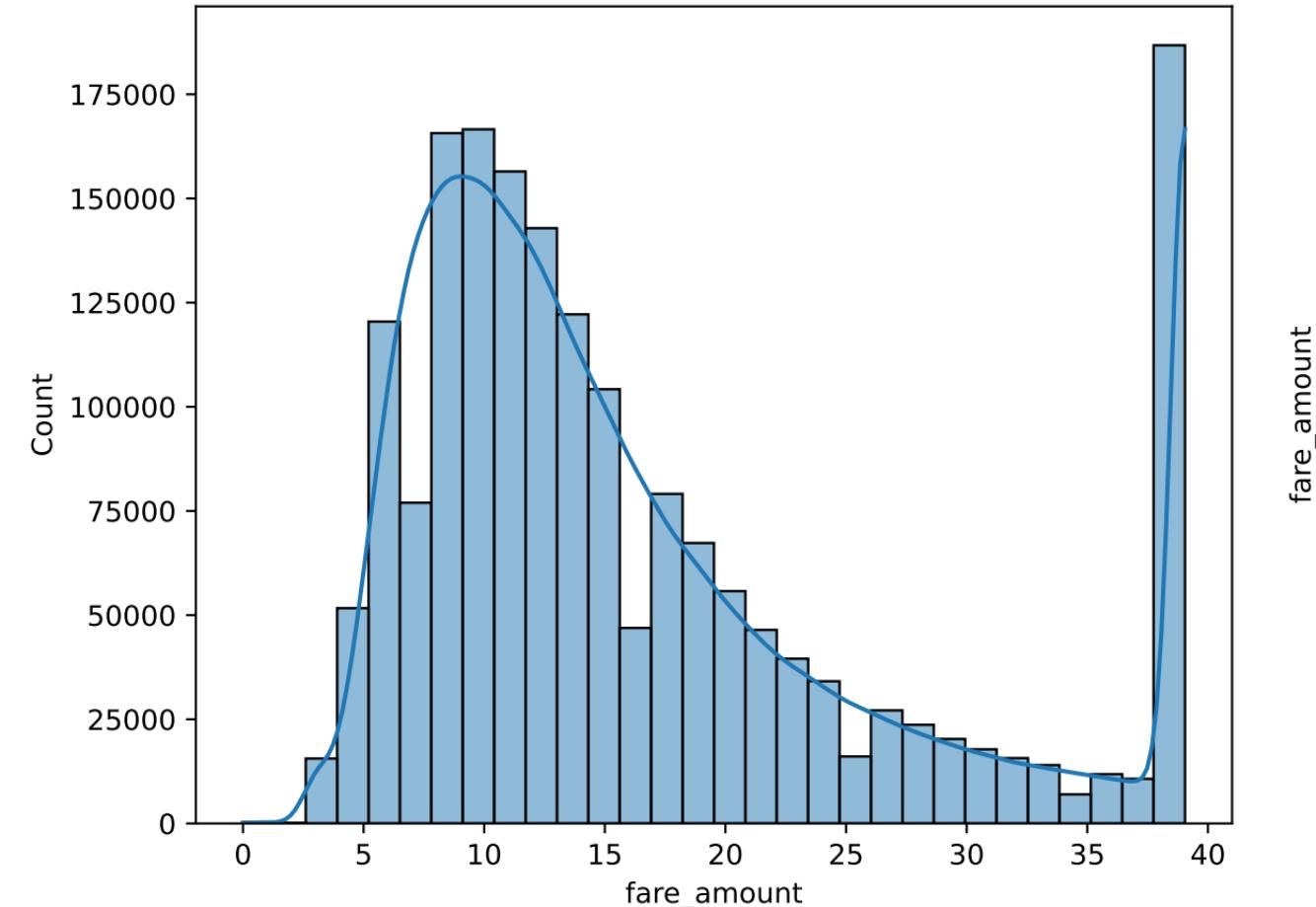
Boxplot of trip_distance



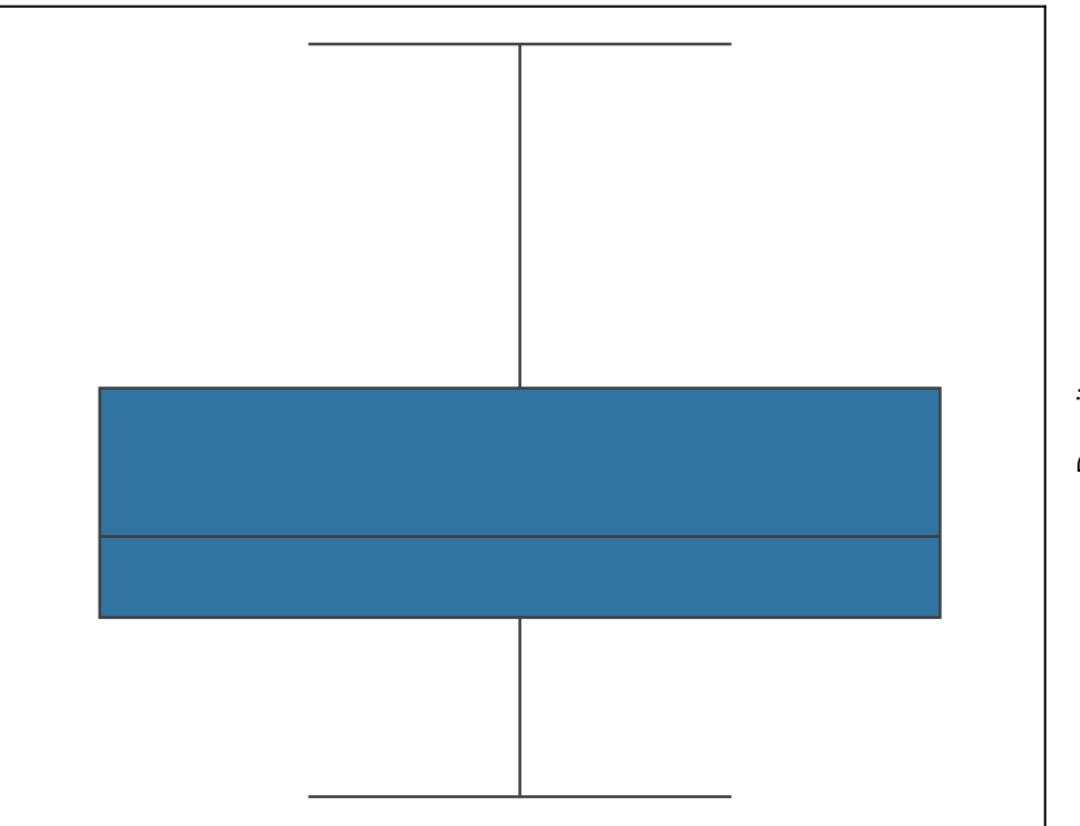
Density Plot of trip_distance



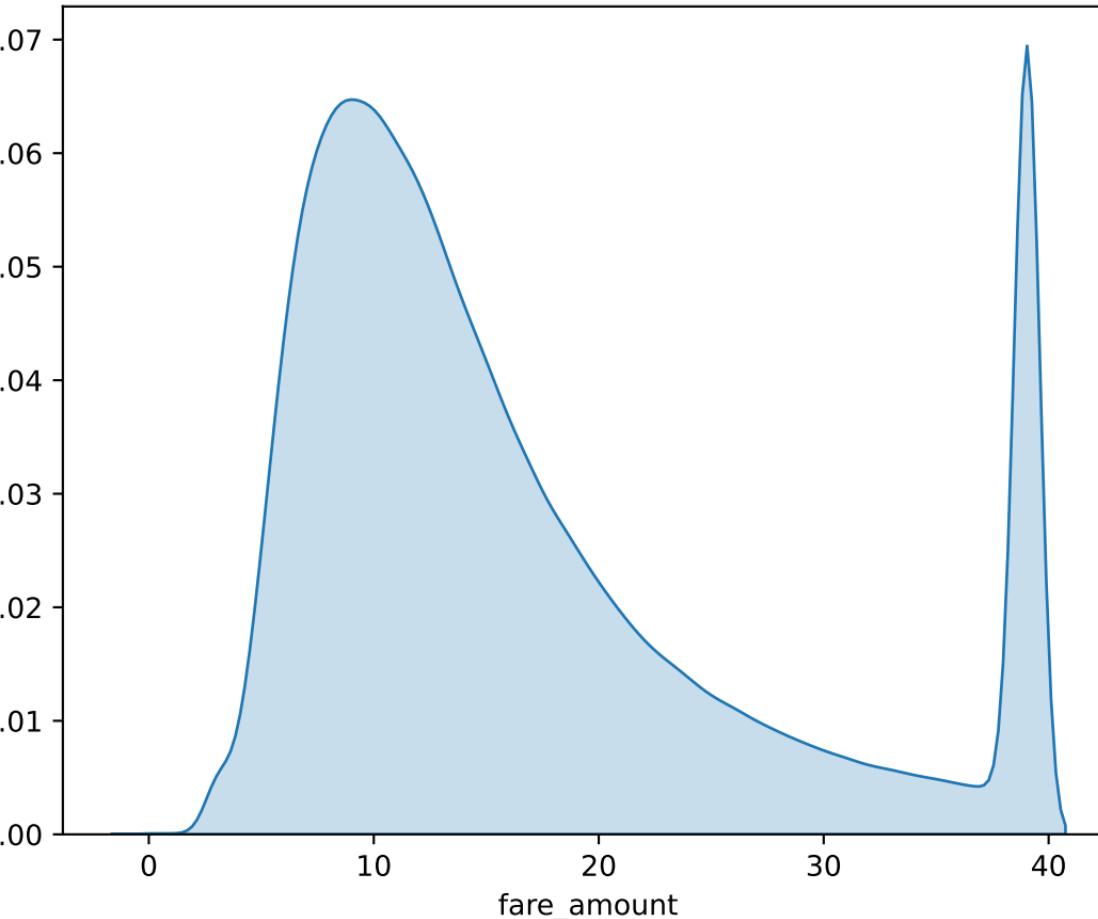
Histogram of fare_amount



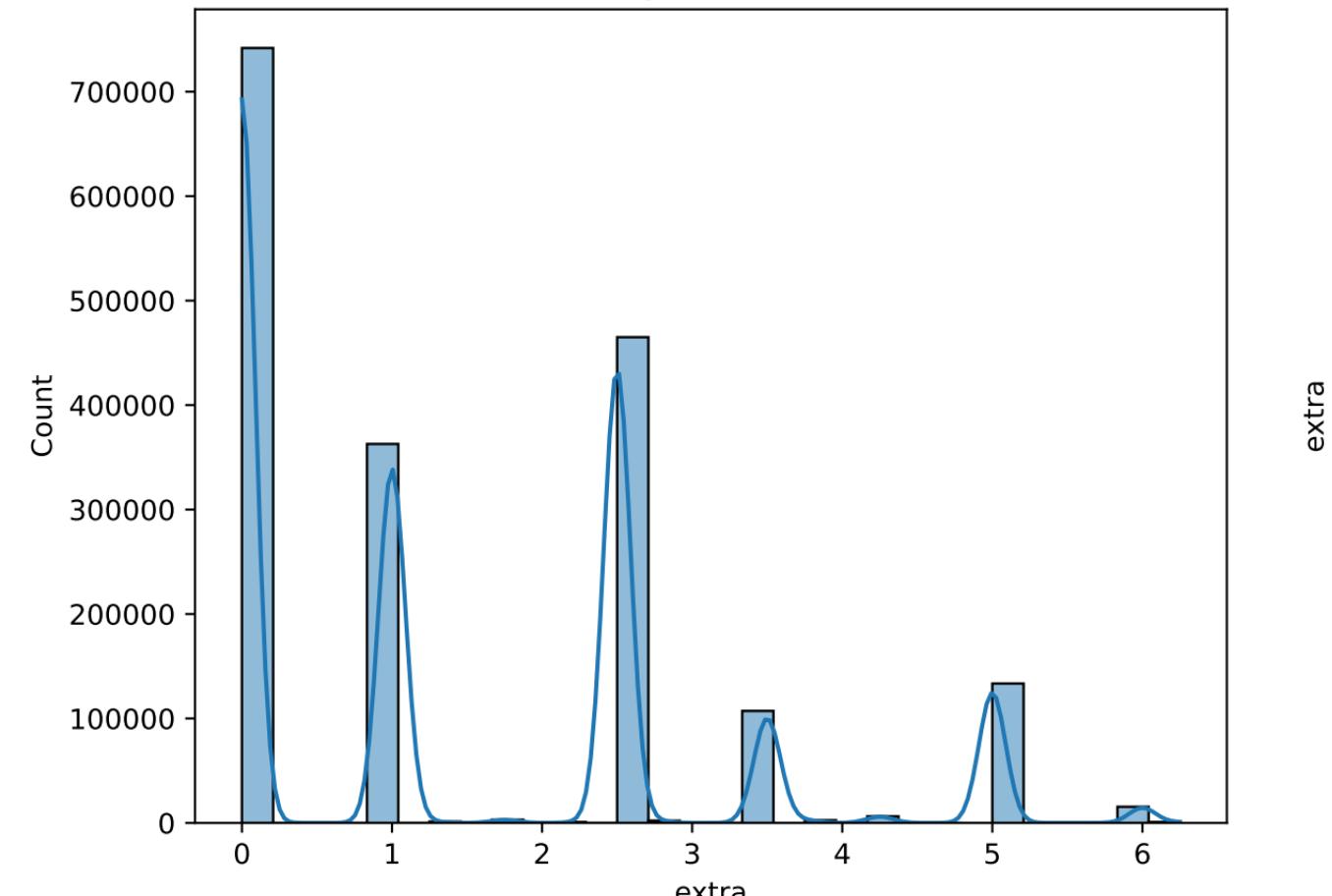
Boxplot of fare_amount



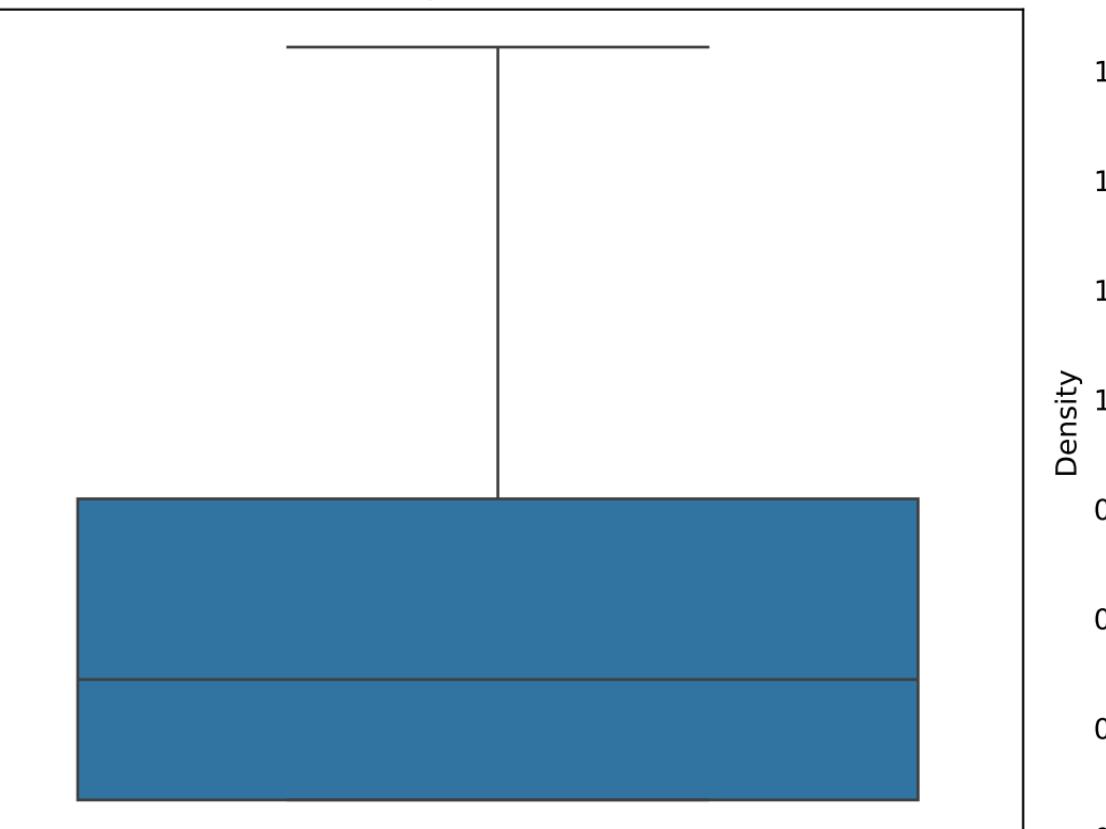
Density Plot of fare_amount



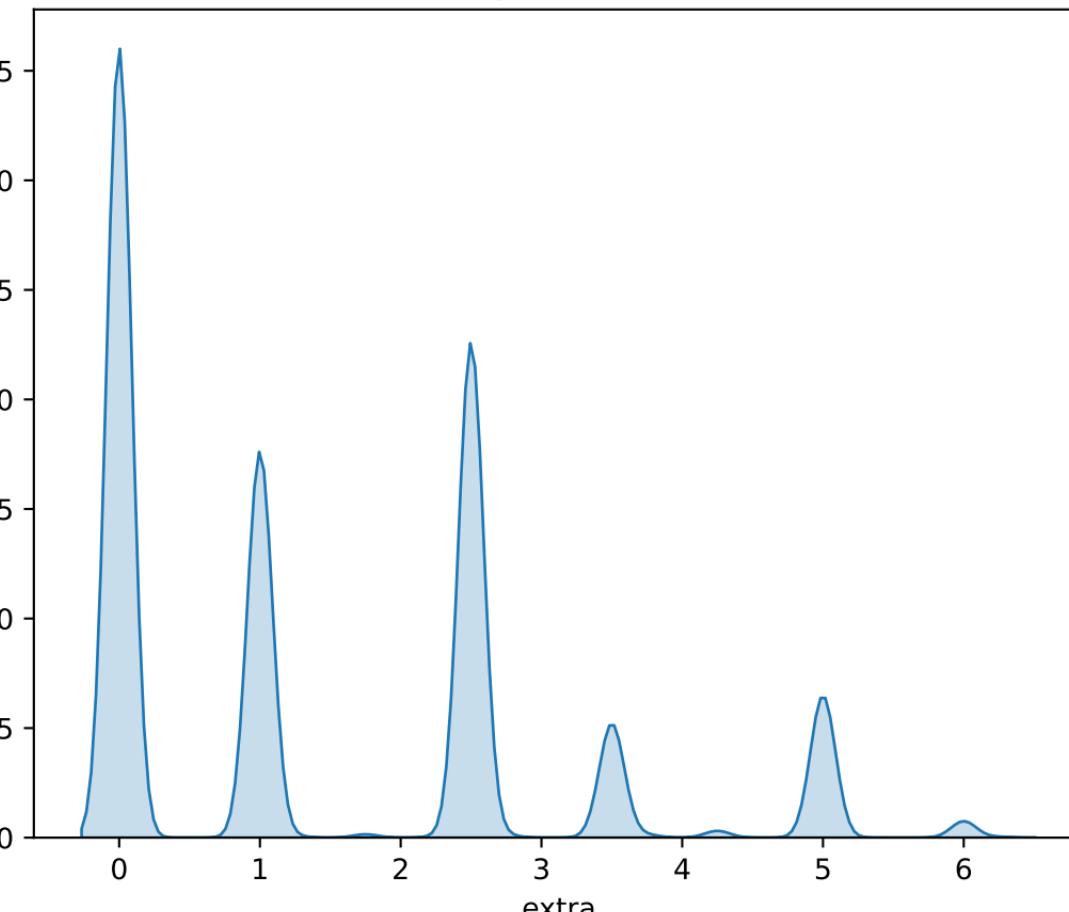
Histogram of extra

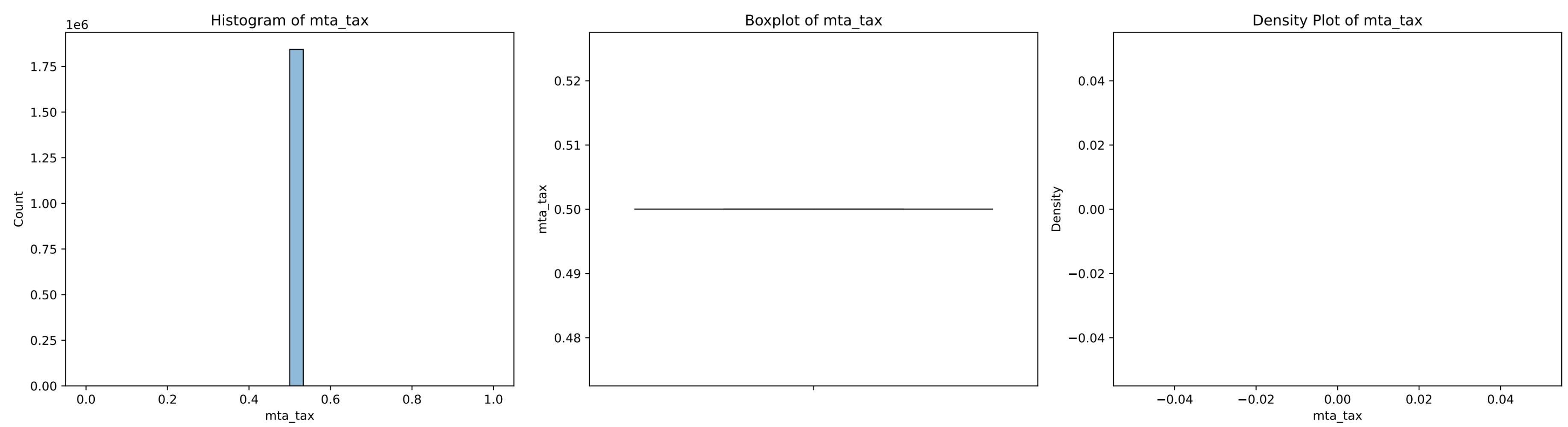


Boxplot of extra

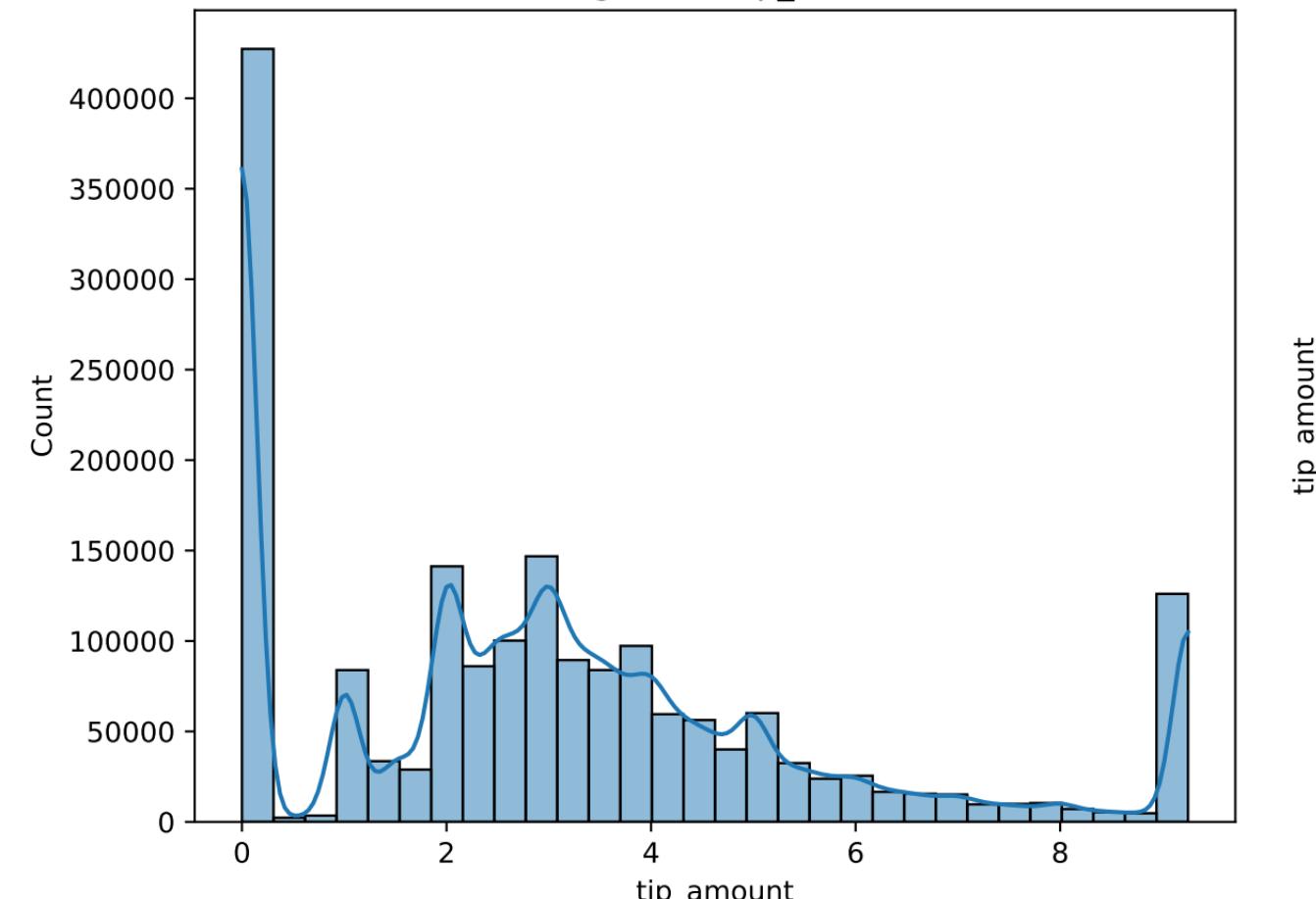


Density Plot of extra

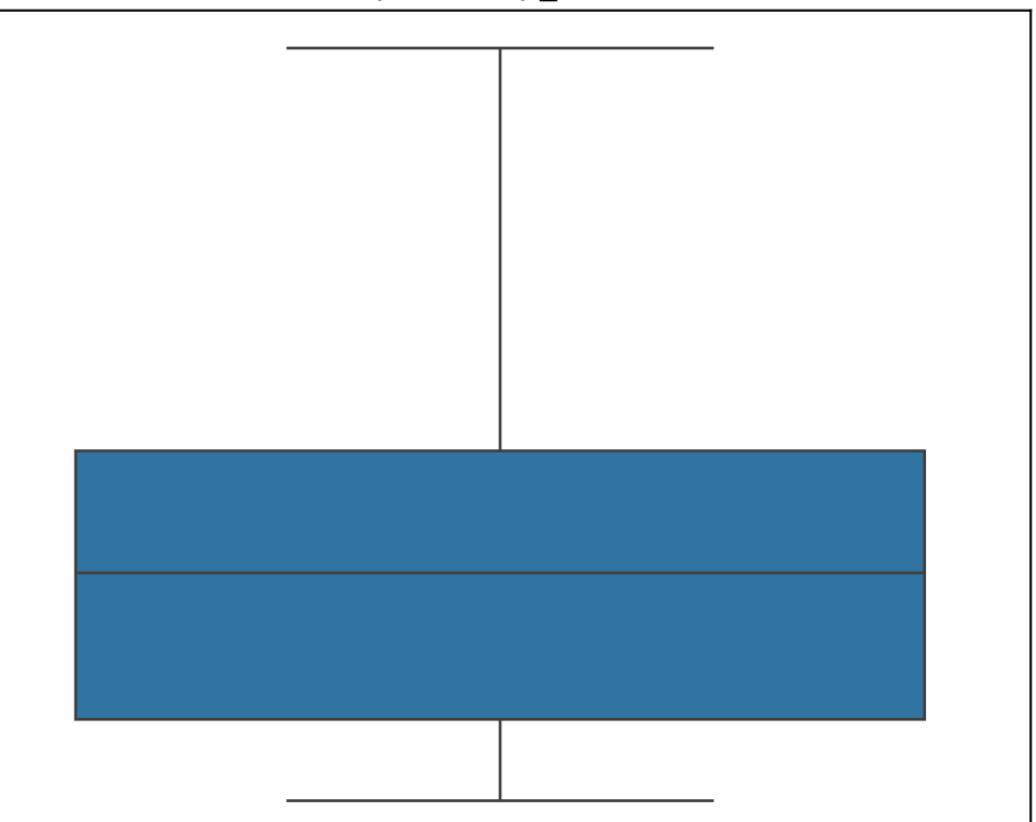




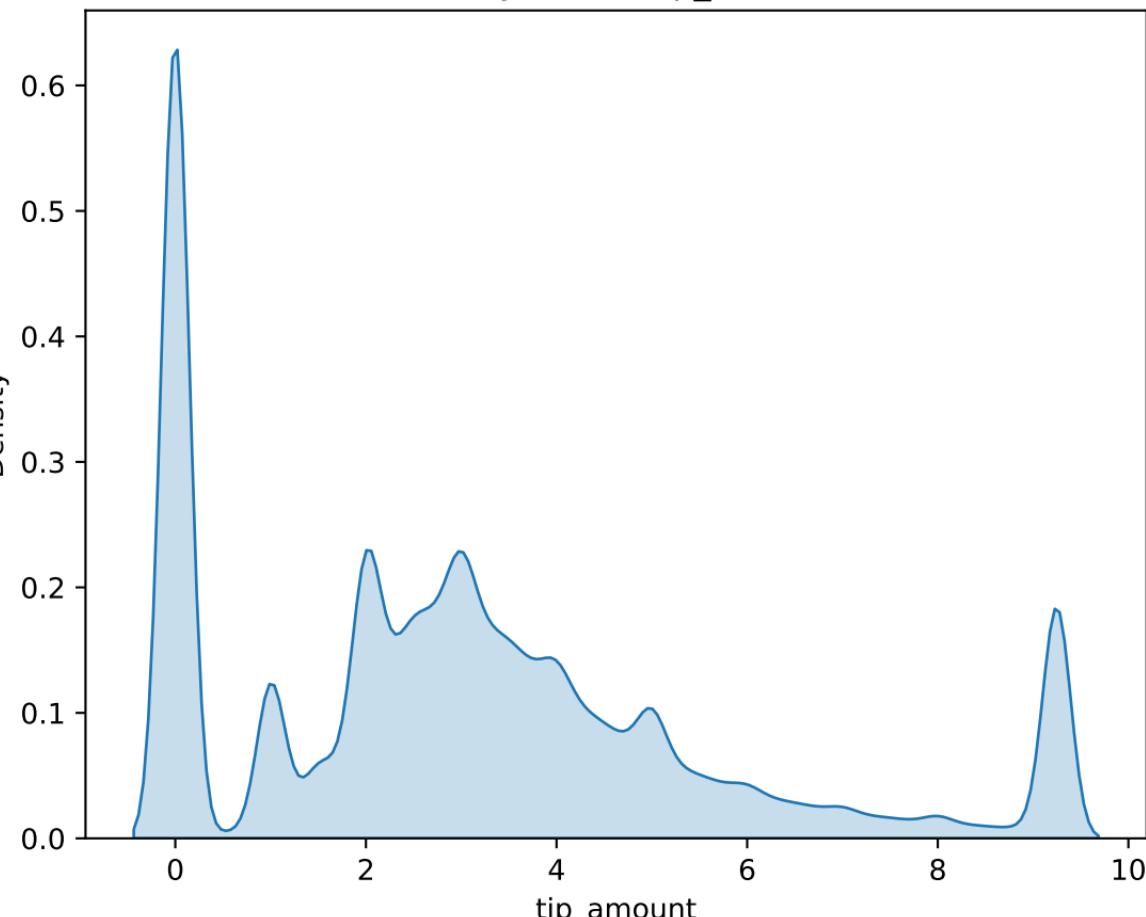
Histogram of tip_amount

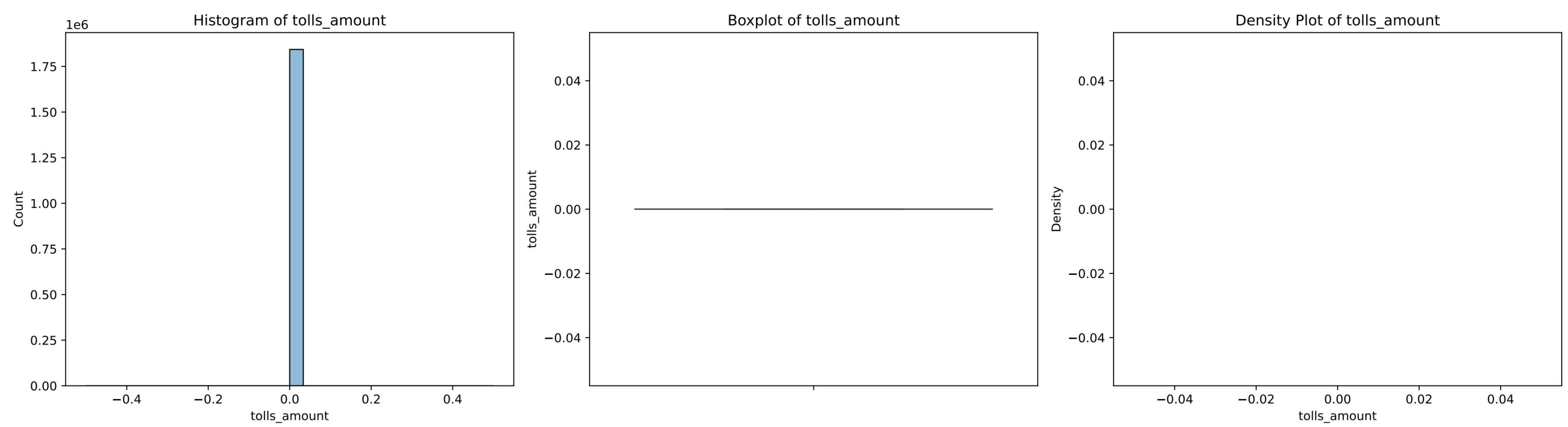


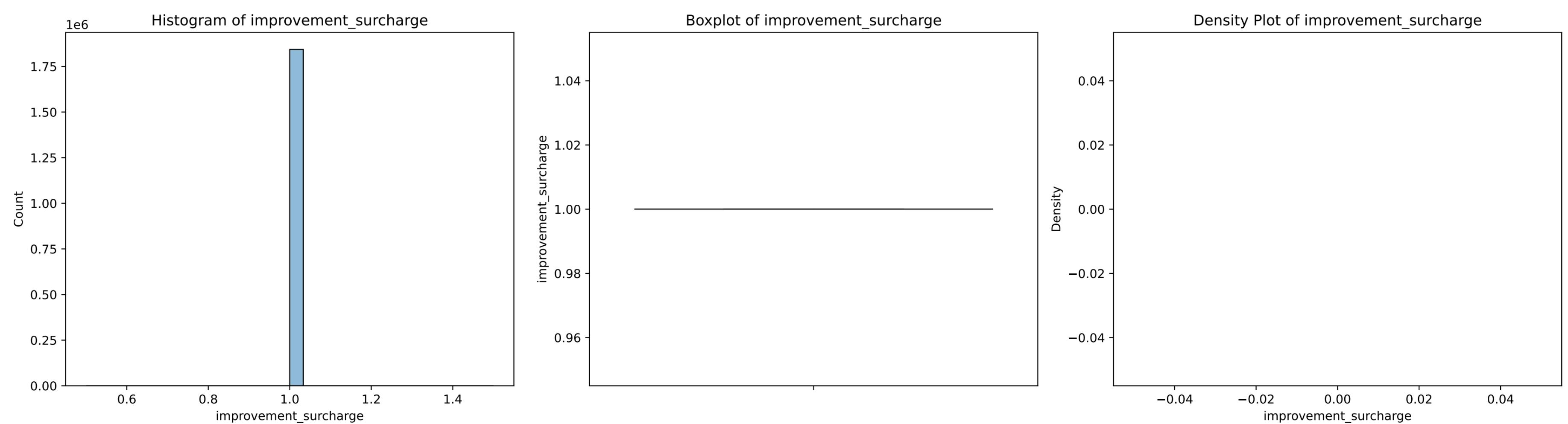
Boxplot of tip_amount



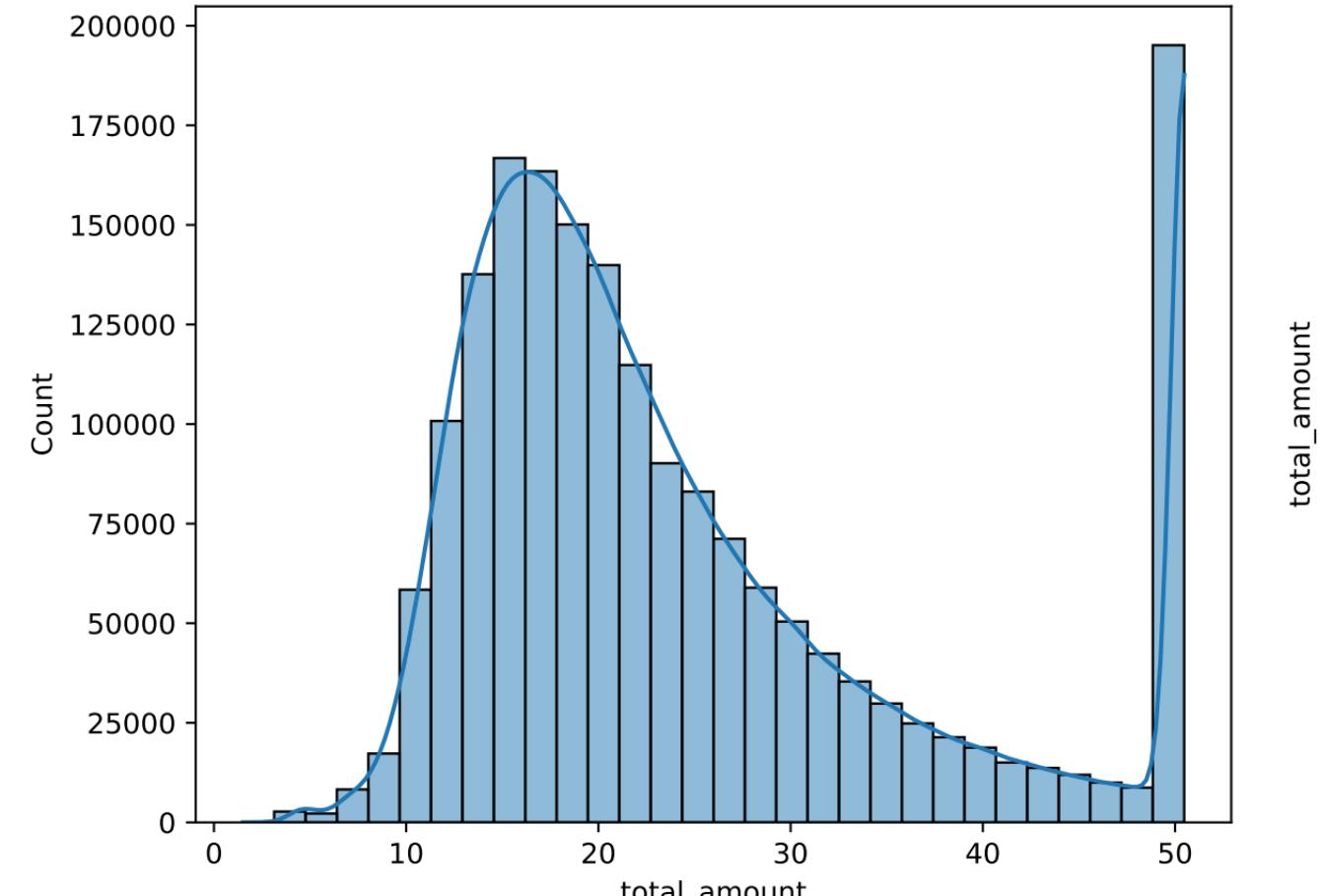
Density Plot of tip_amount



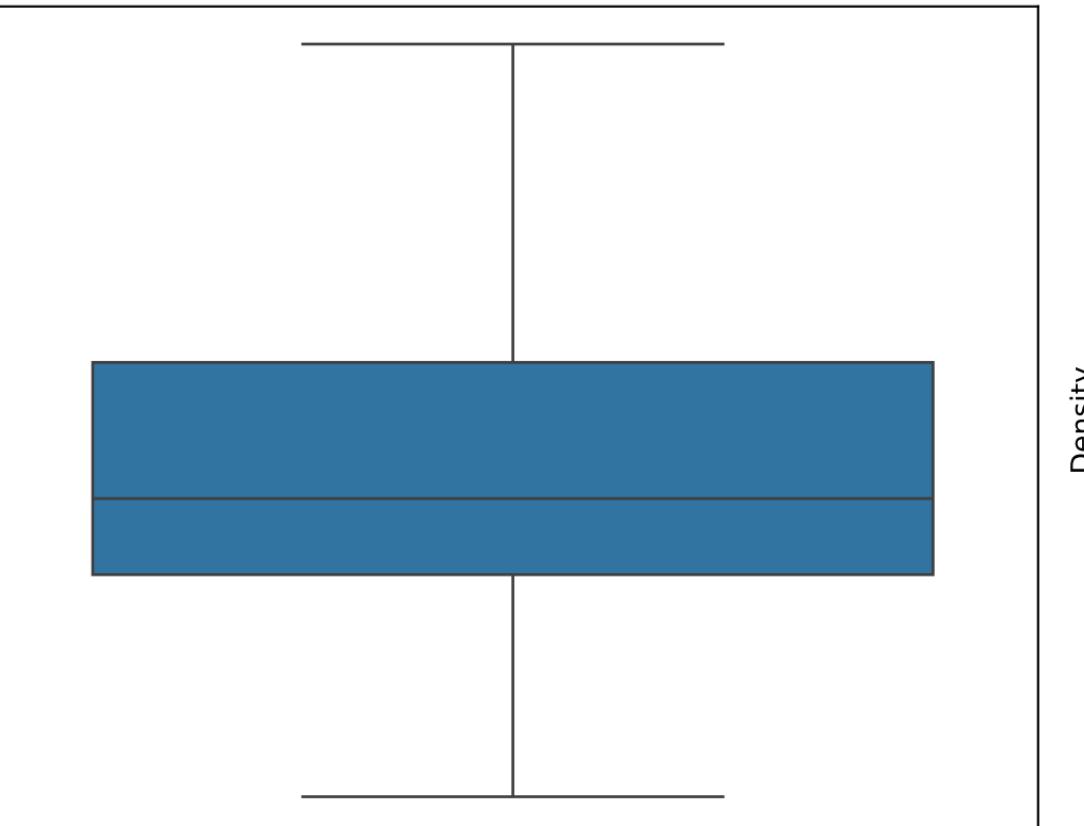




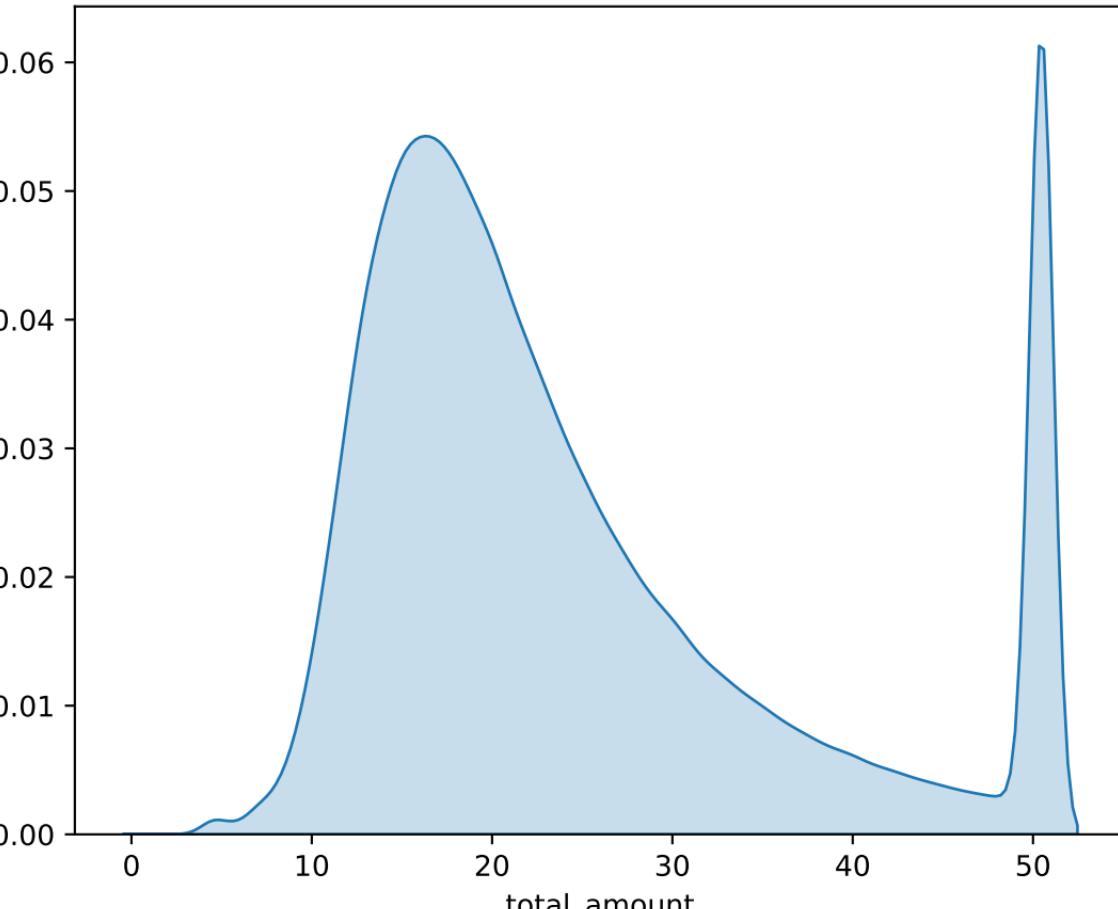
Histogram of total_amount

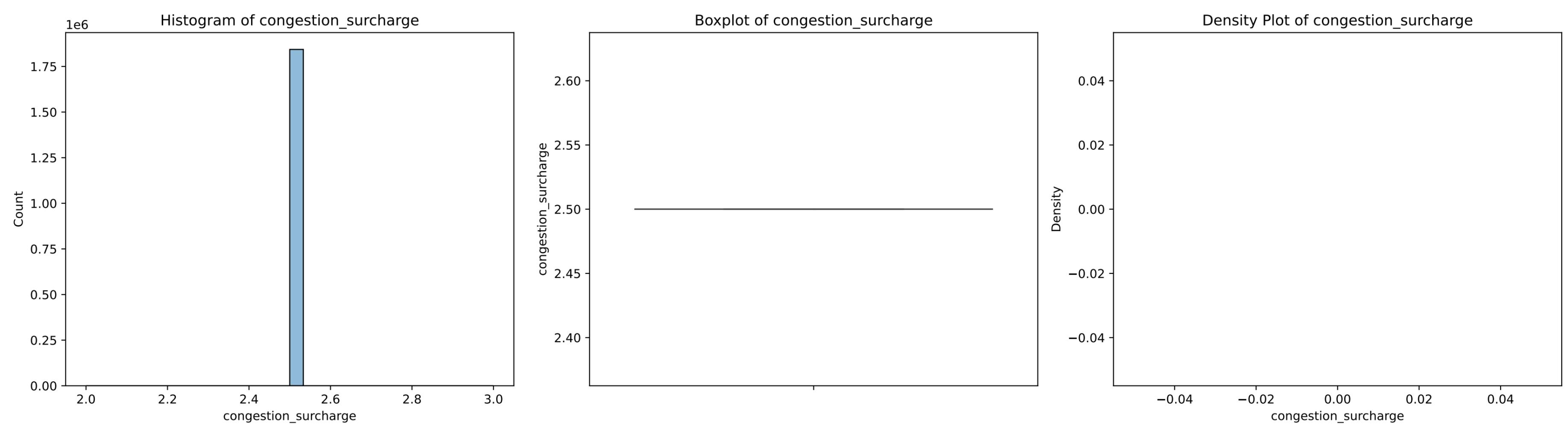


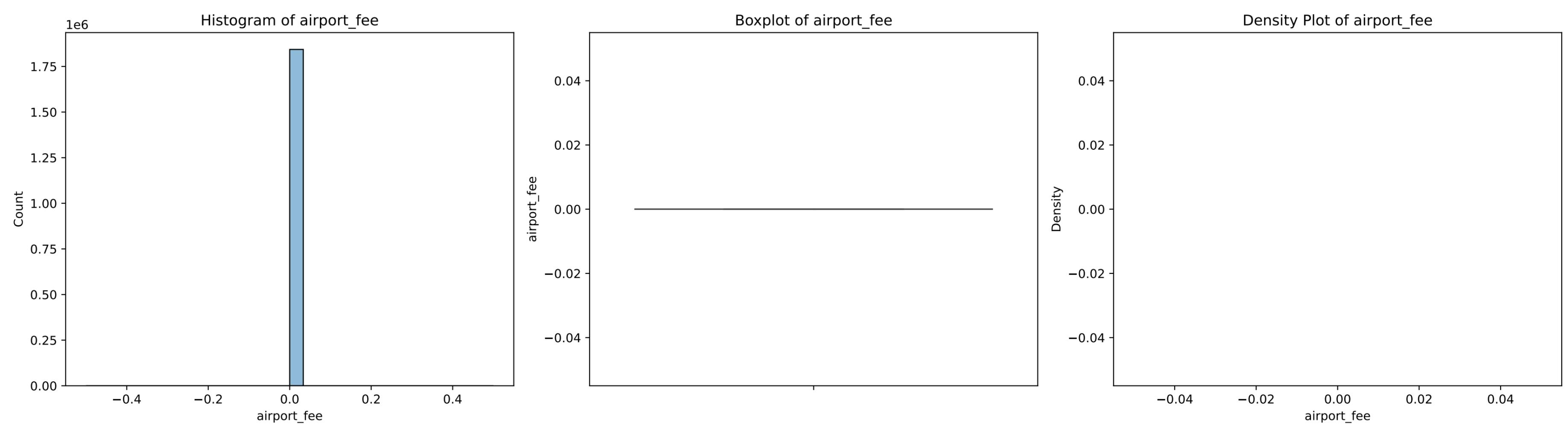
Boxplot of total_amount



Density Plot of total_amount

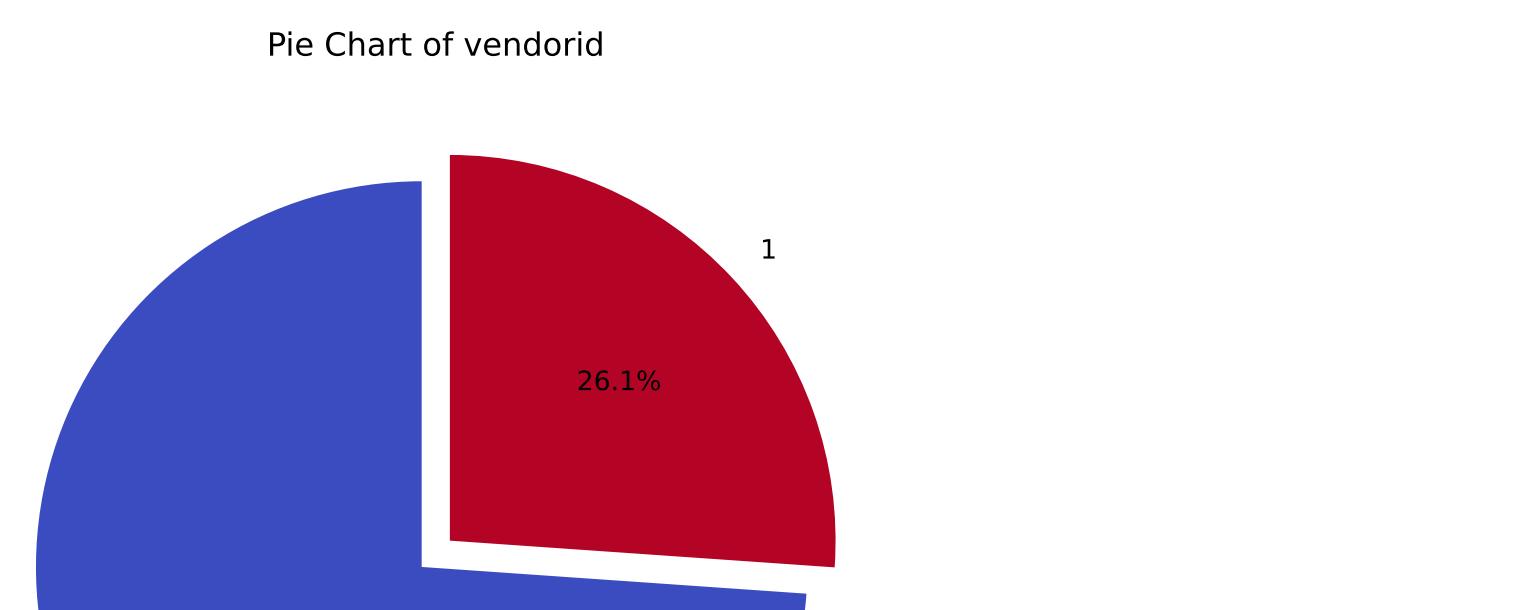
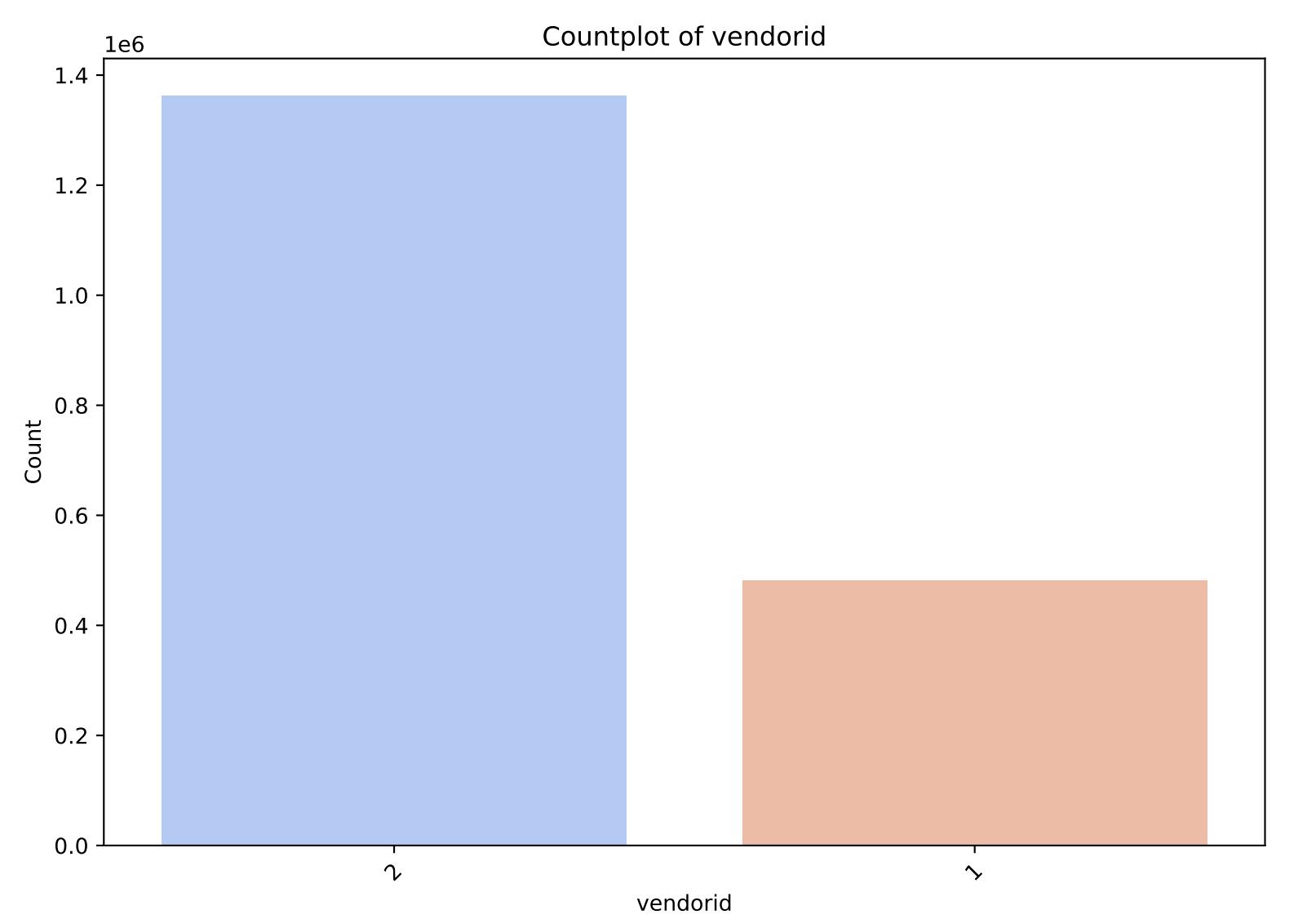


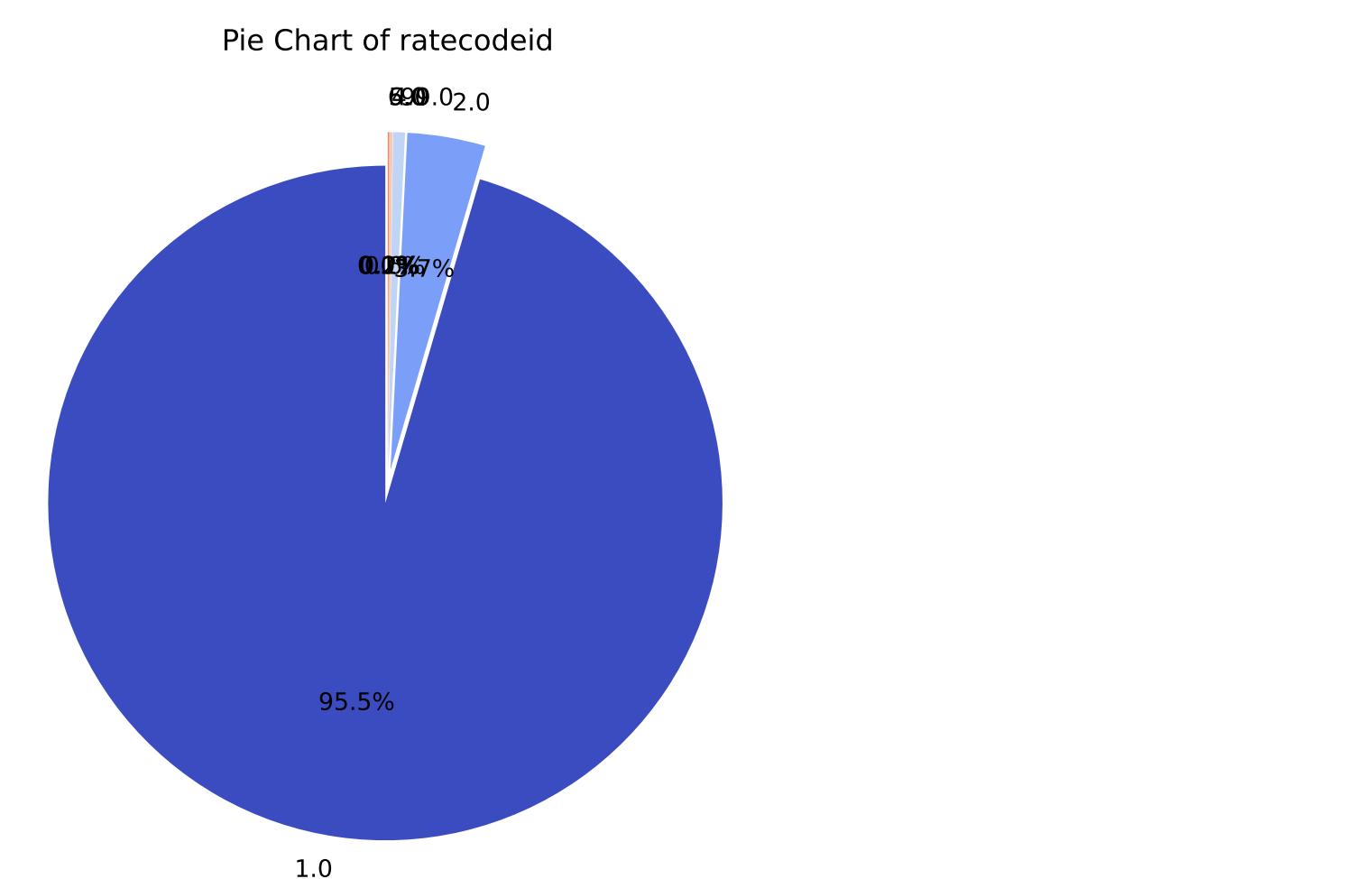
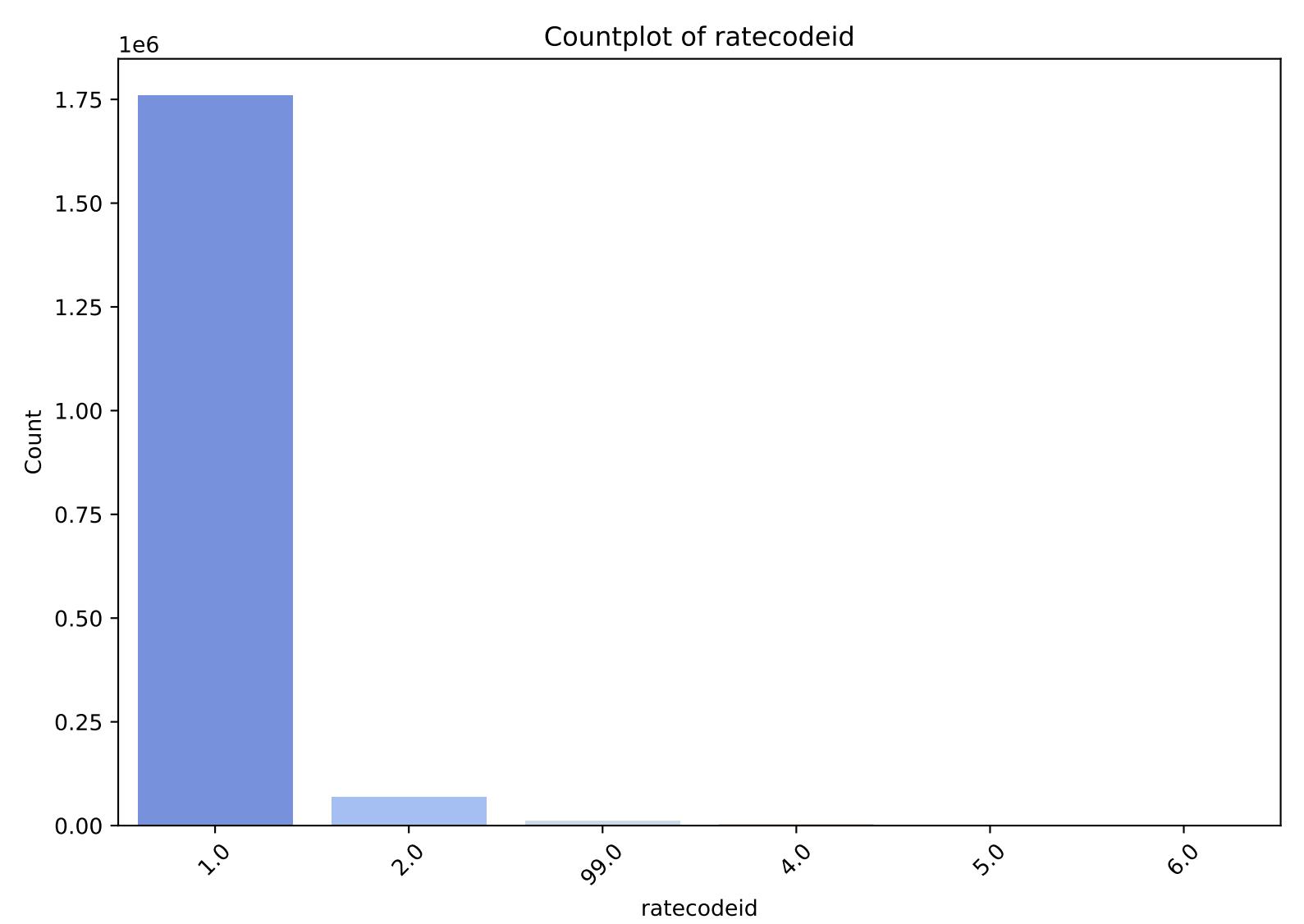


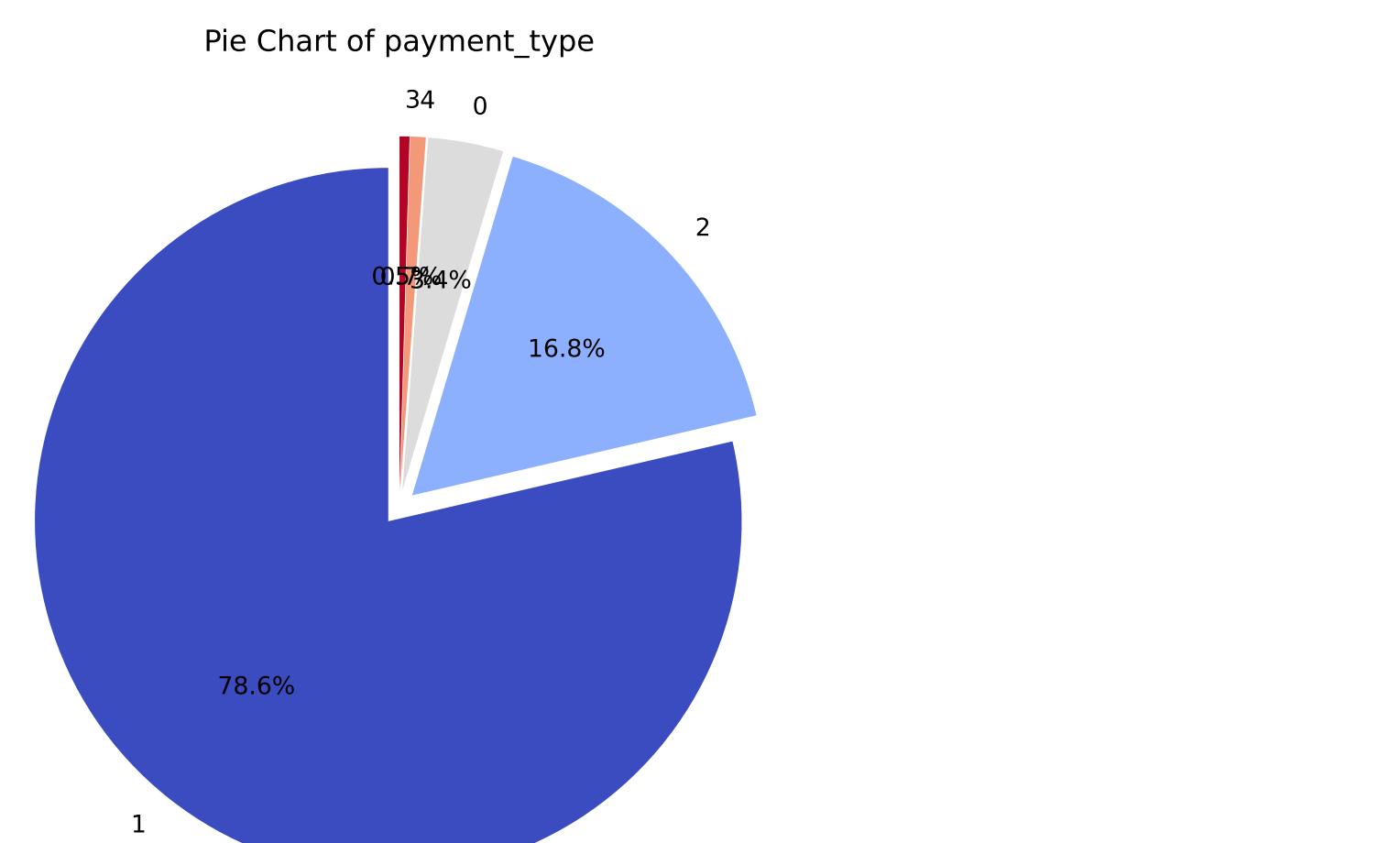
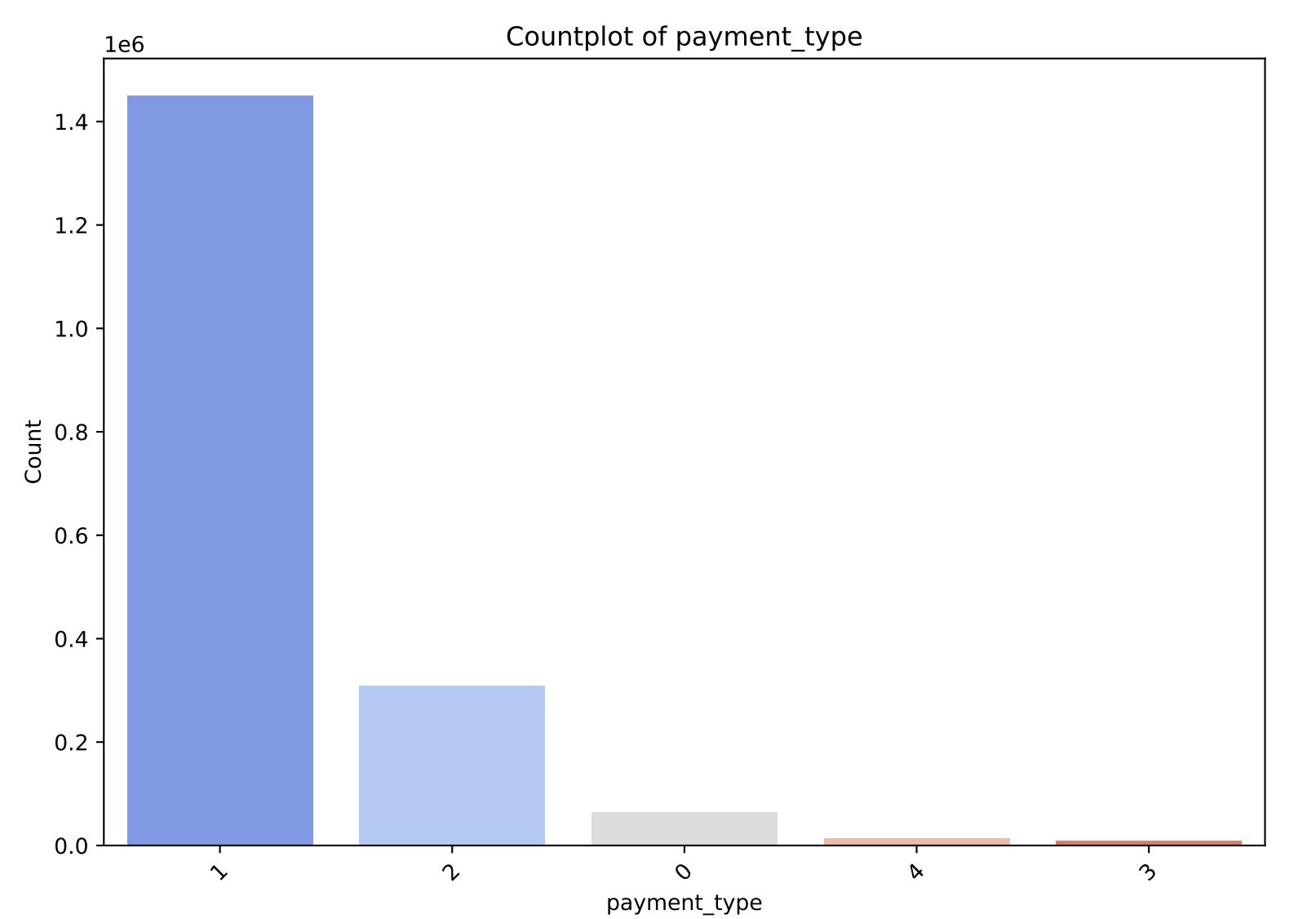


Conclusion/Remarks:

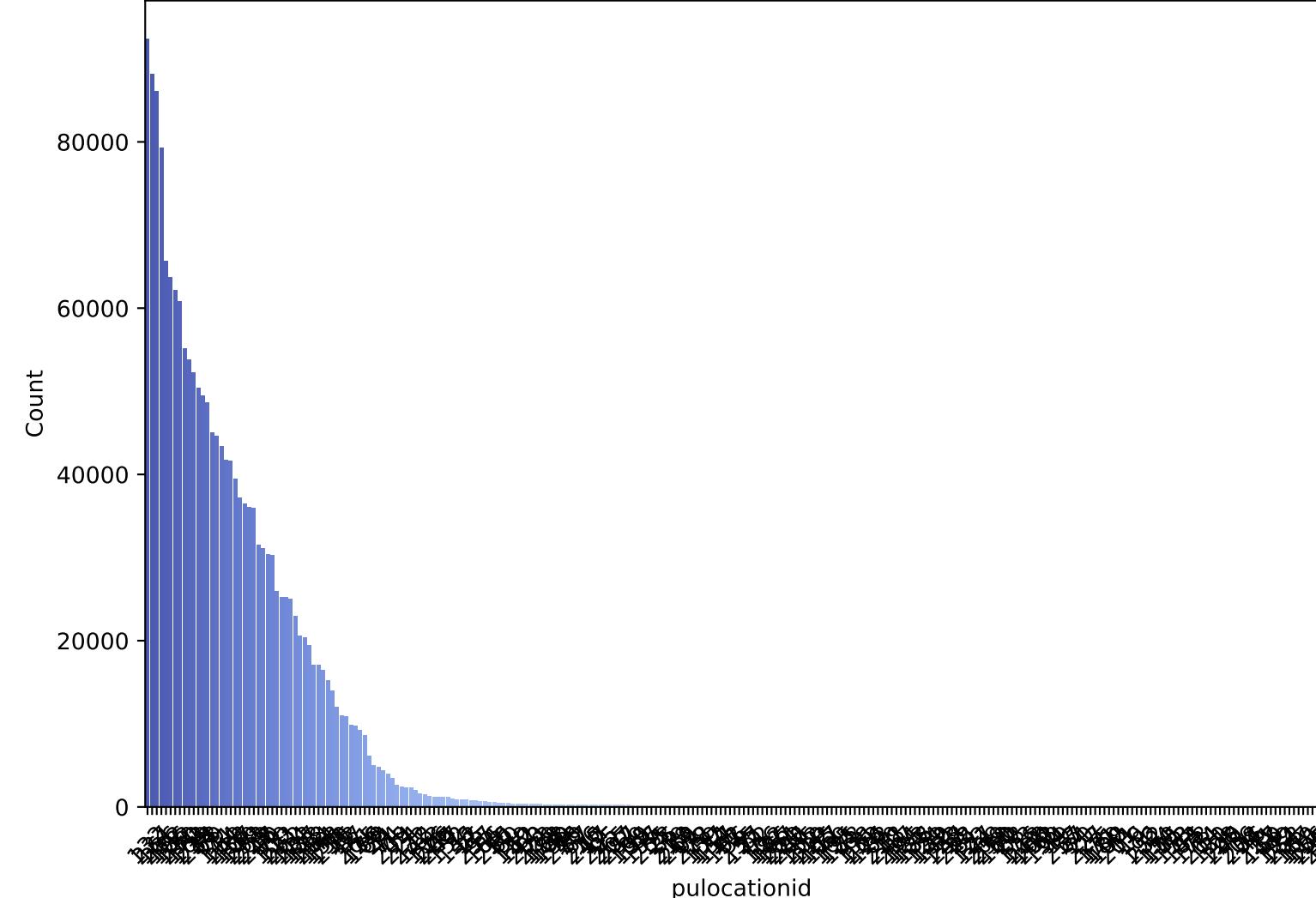
2.3 Analysing the Outlier and Skewness After Clipping data



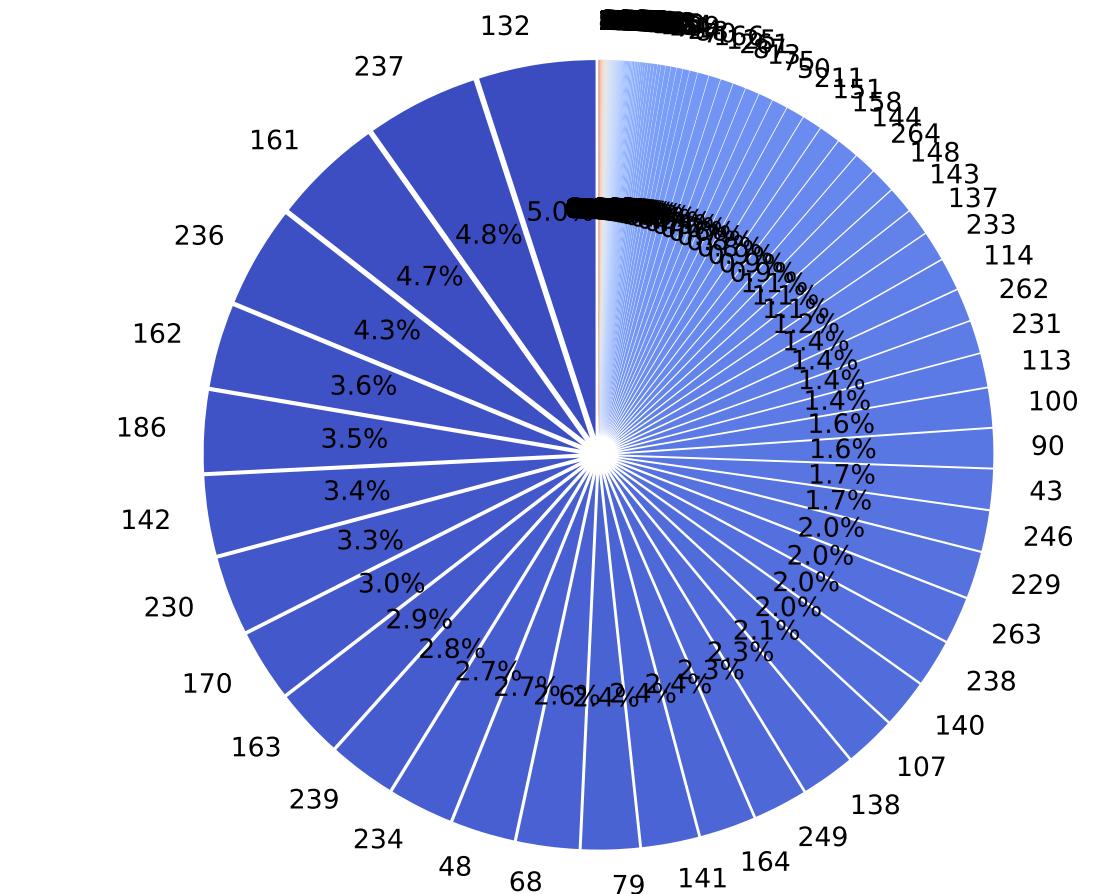




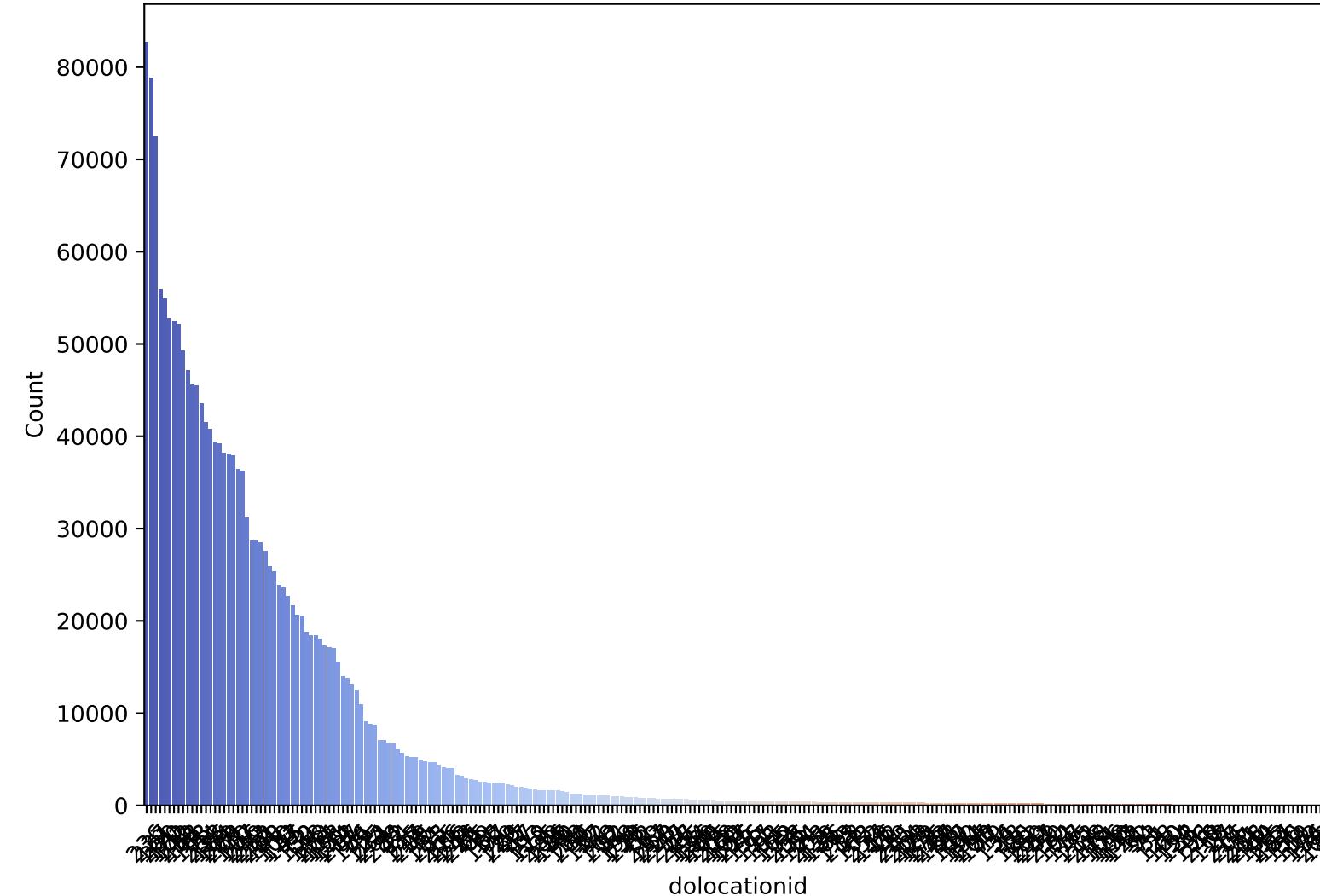
Countplot of pulocationid



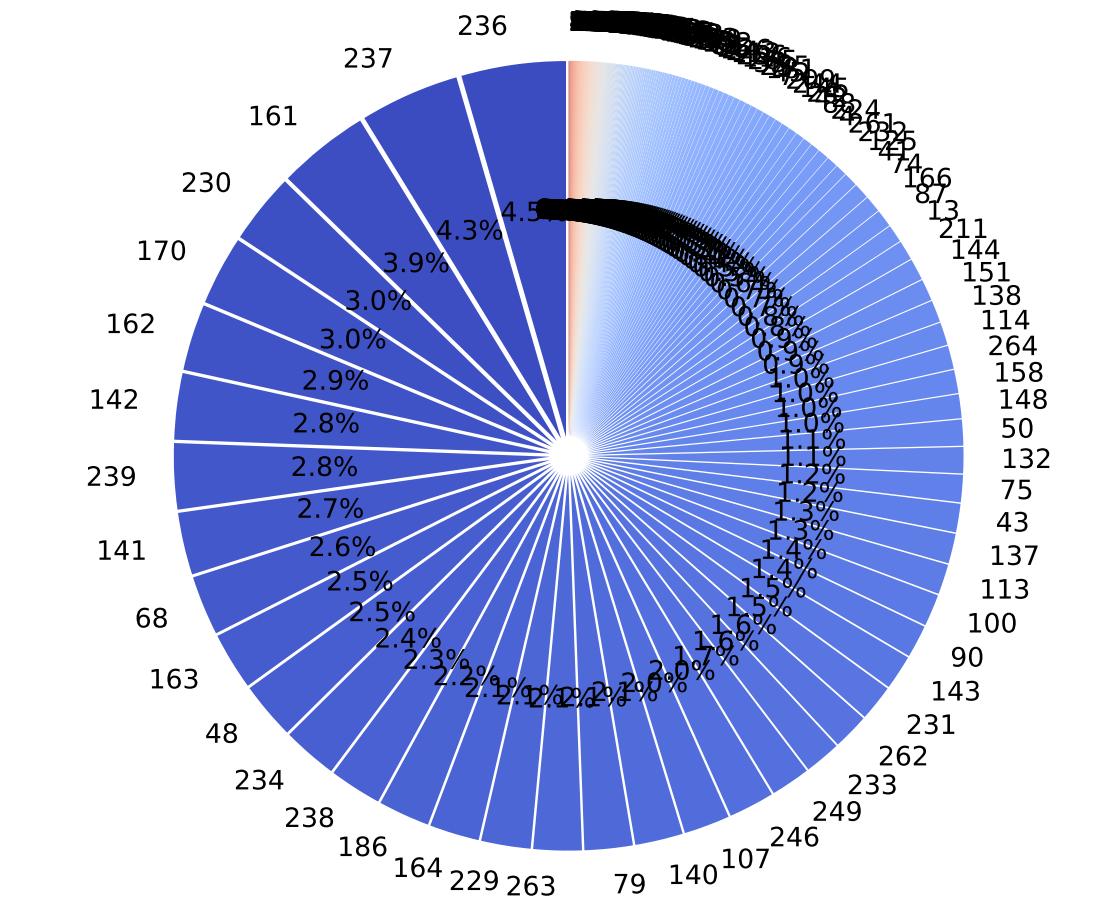
Pie Chart of pulocationion



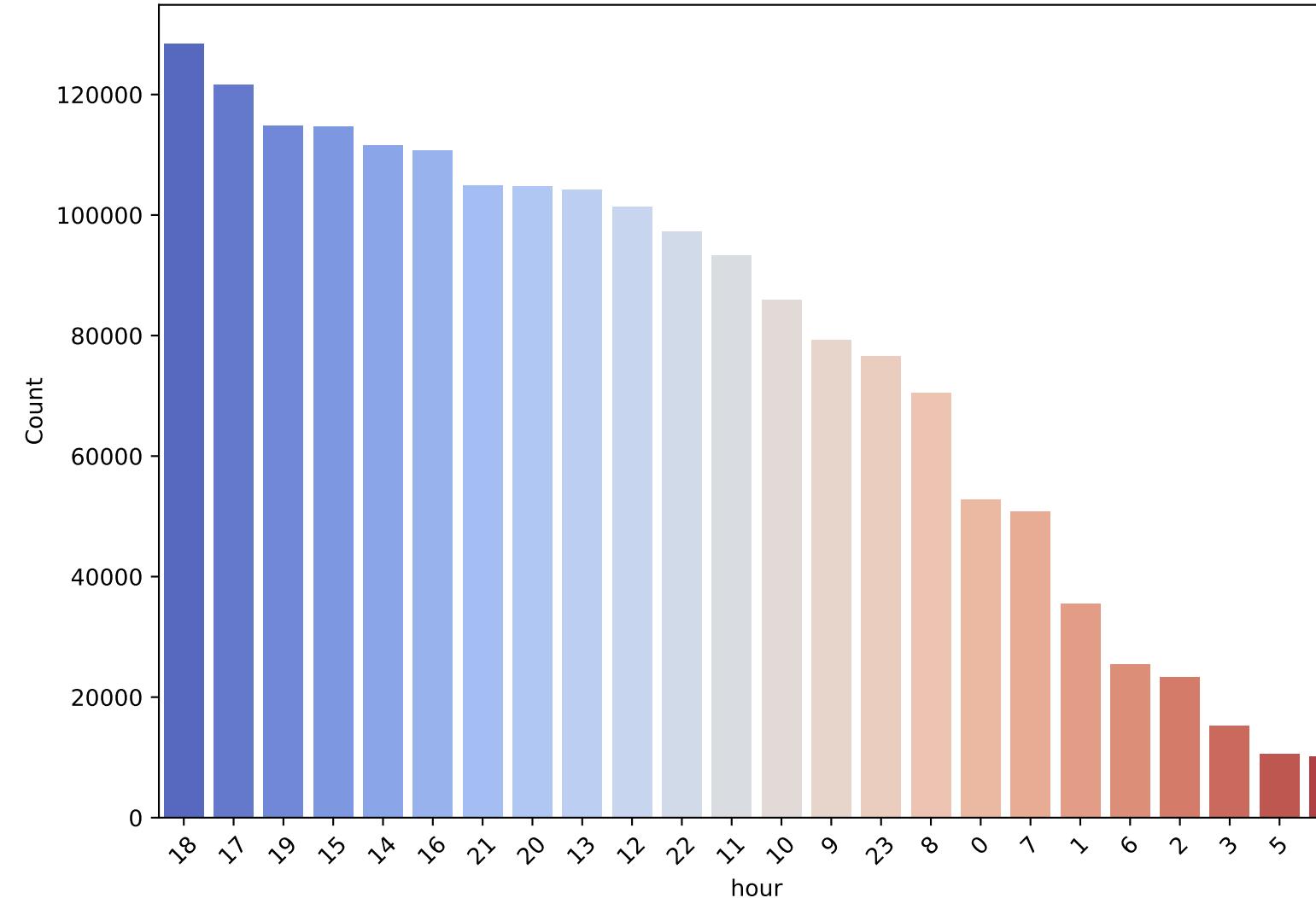
Countplot of dolocationid



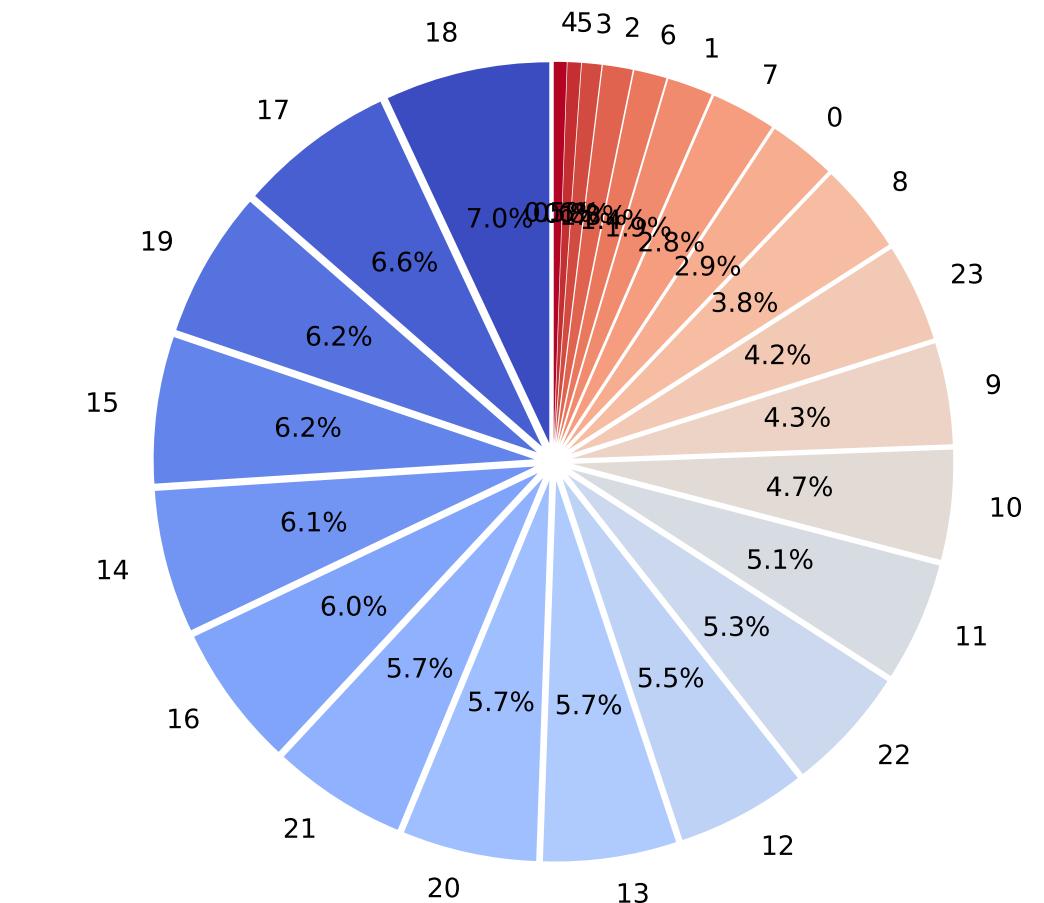
Pie Chart of dolocationid



Countplot of hour

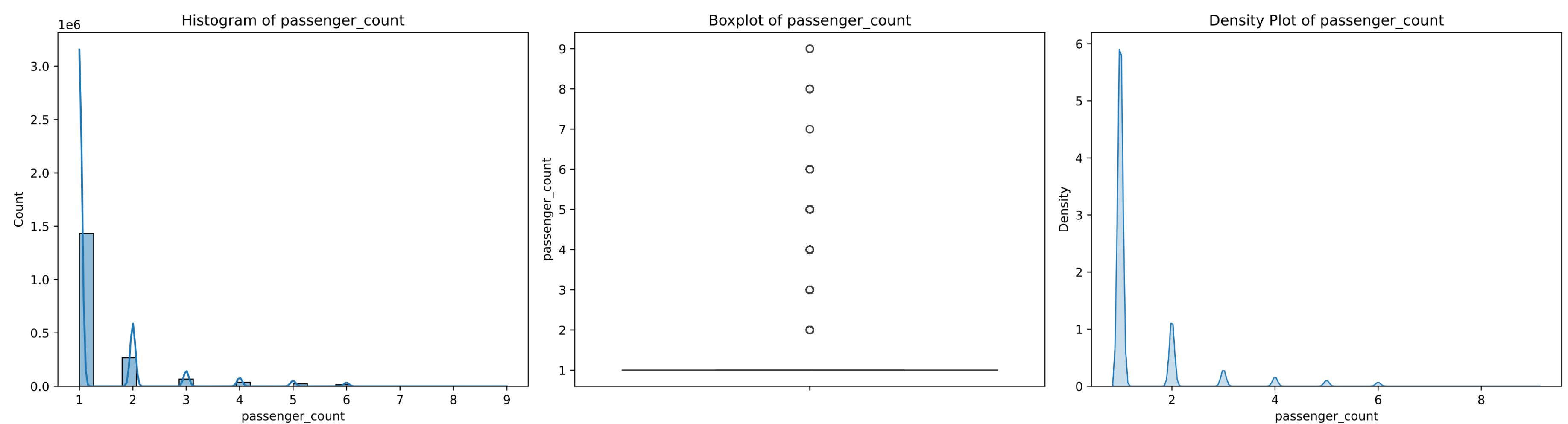


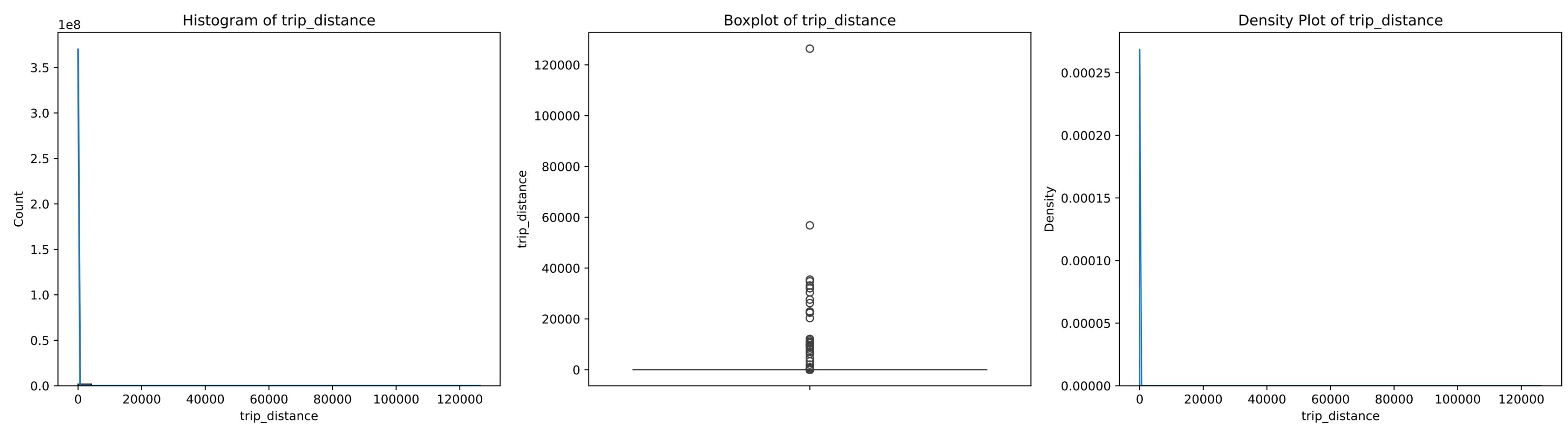
Pie Chart of hour

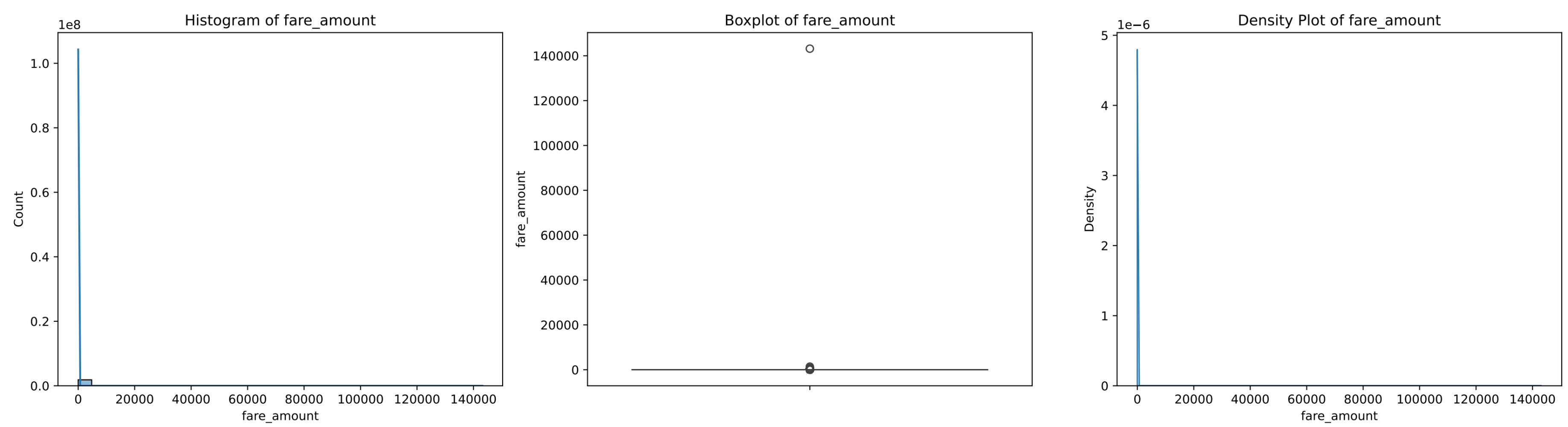


Conclusion/Remarks:

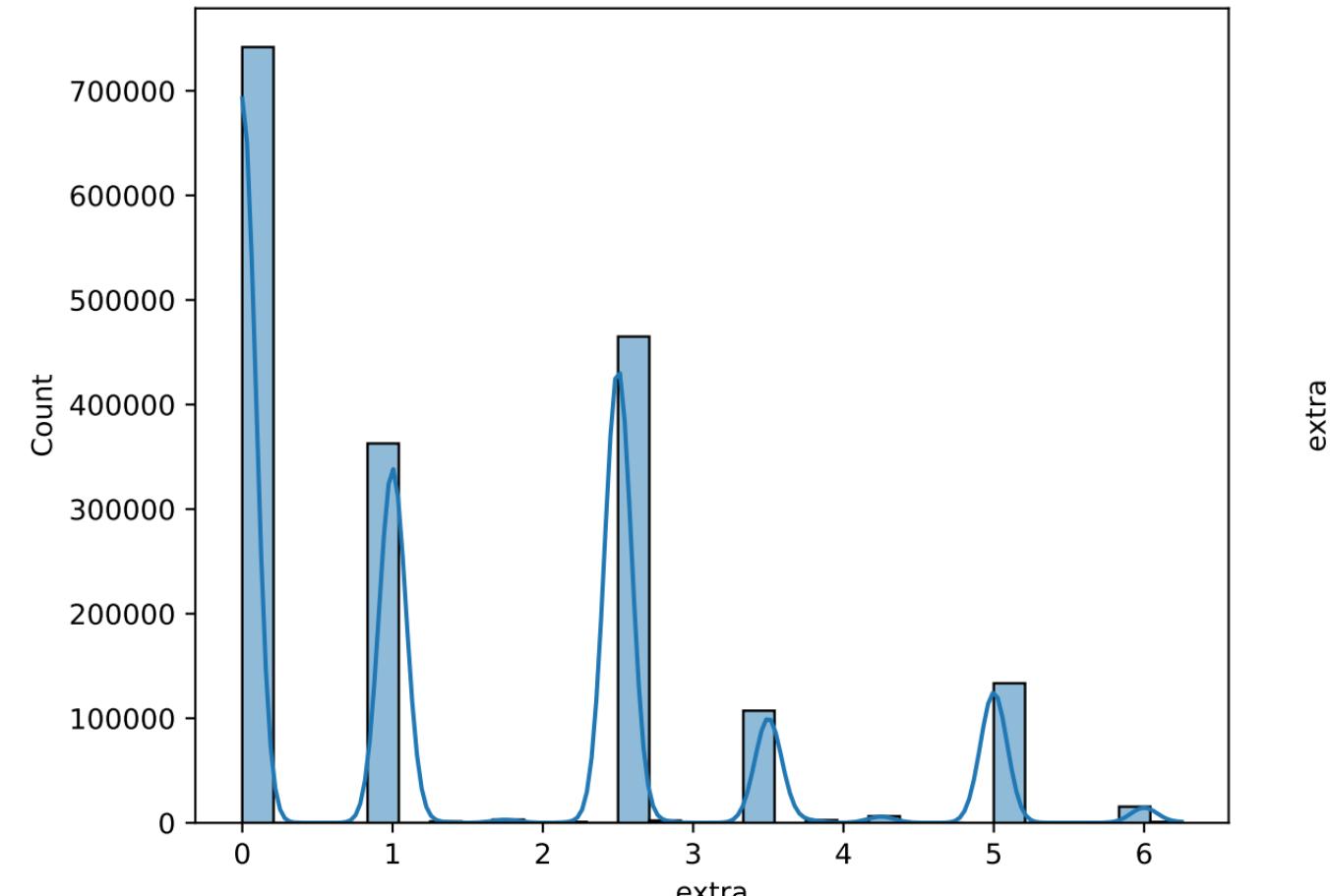
2.3 Analysing the cardinal type data like vendor, ratecode,payment type, picup location, drop location, hourly pick up etc.



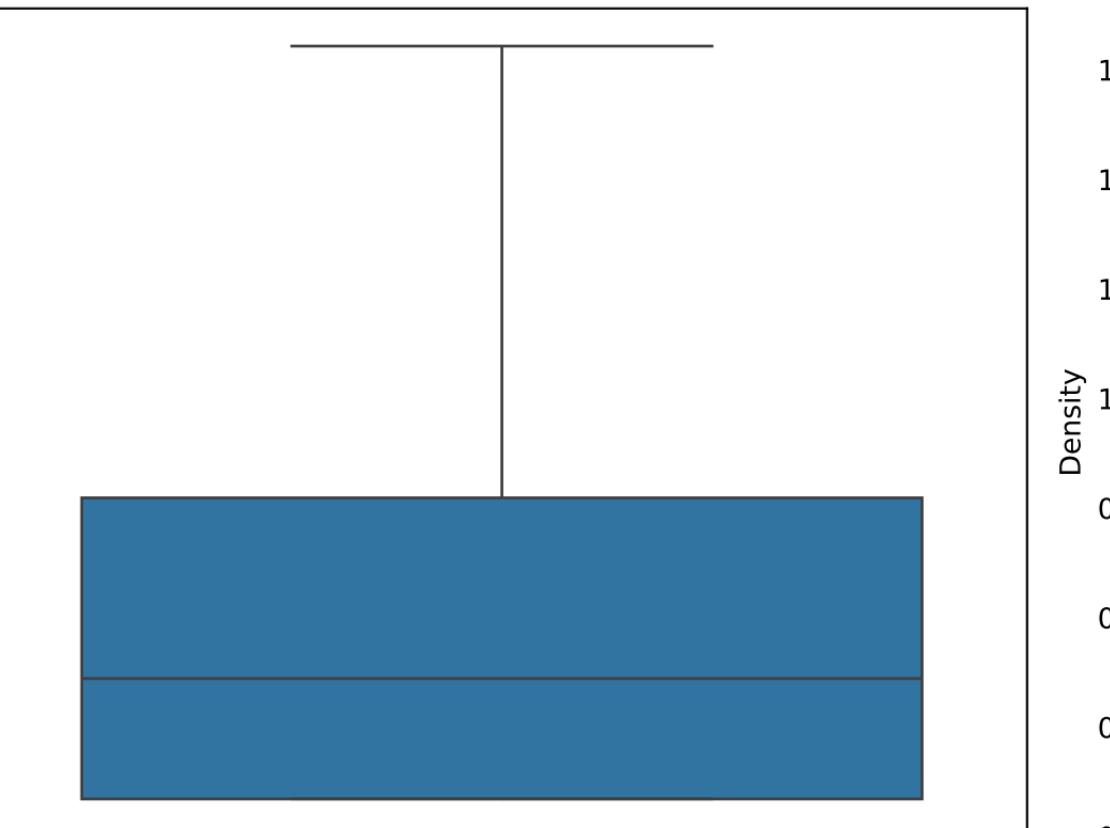




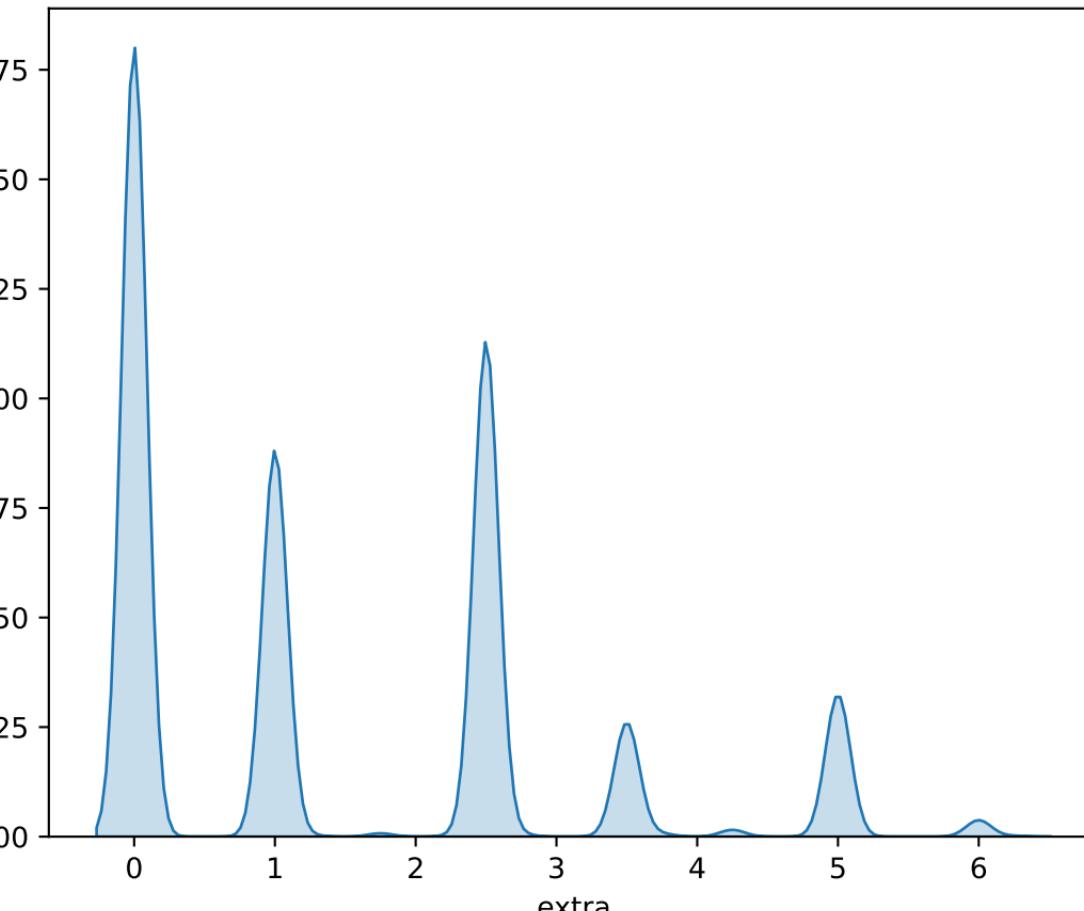
Histogram of extra

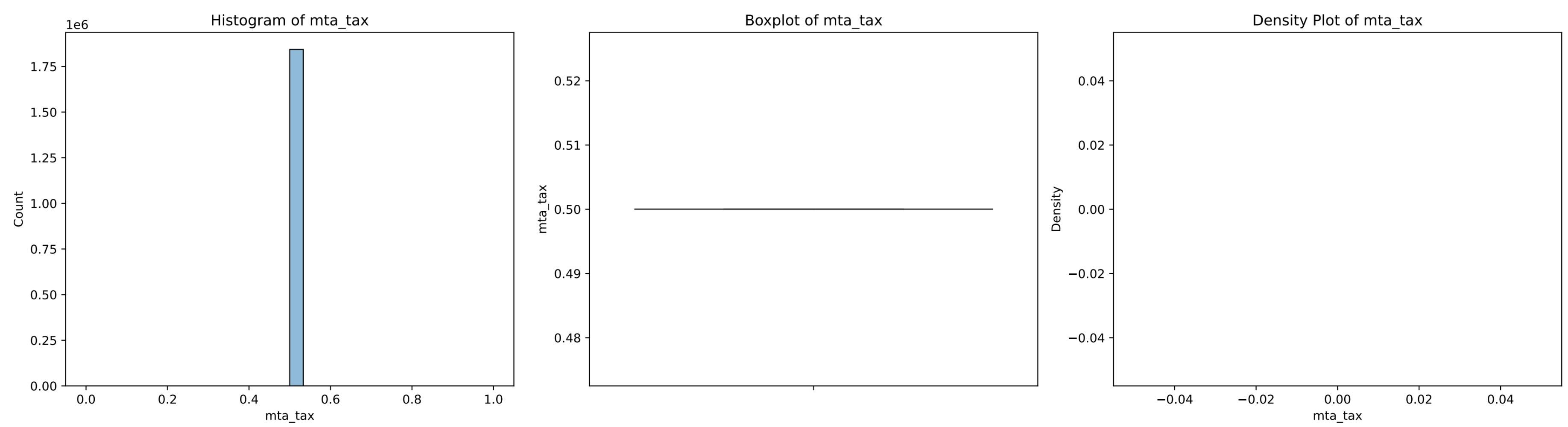


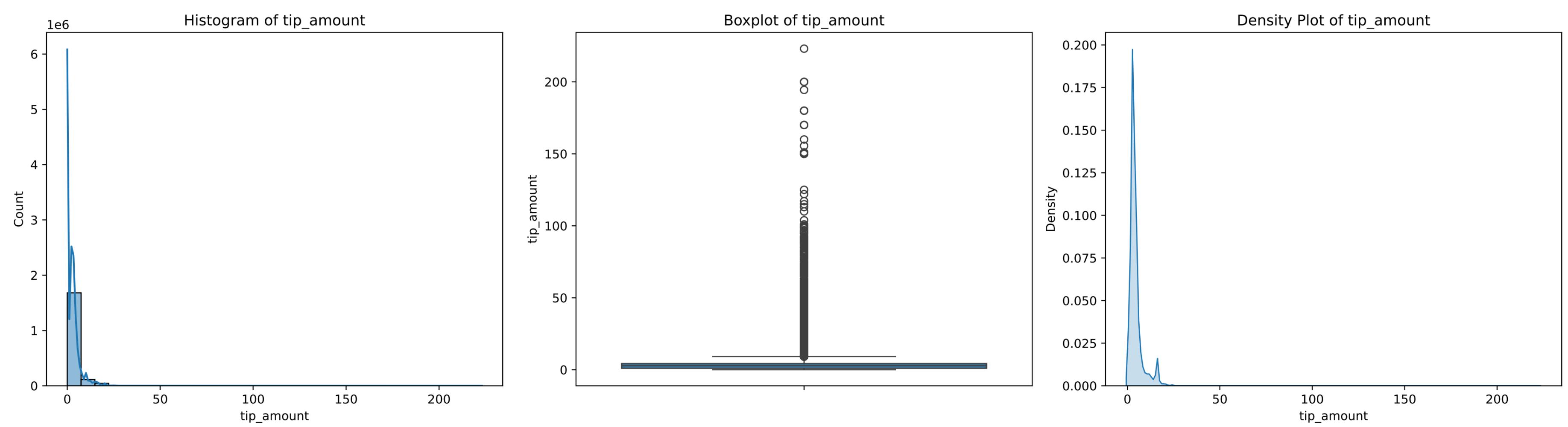
Boxplot of extra

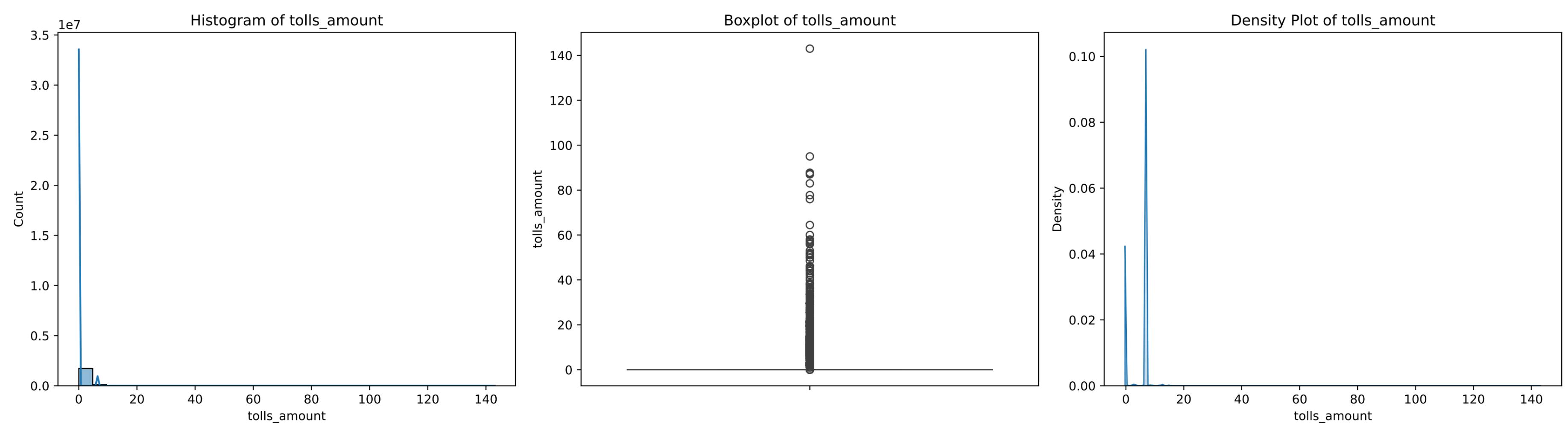


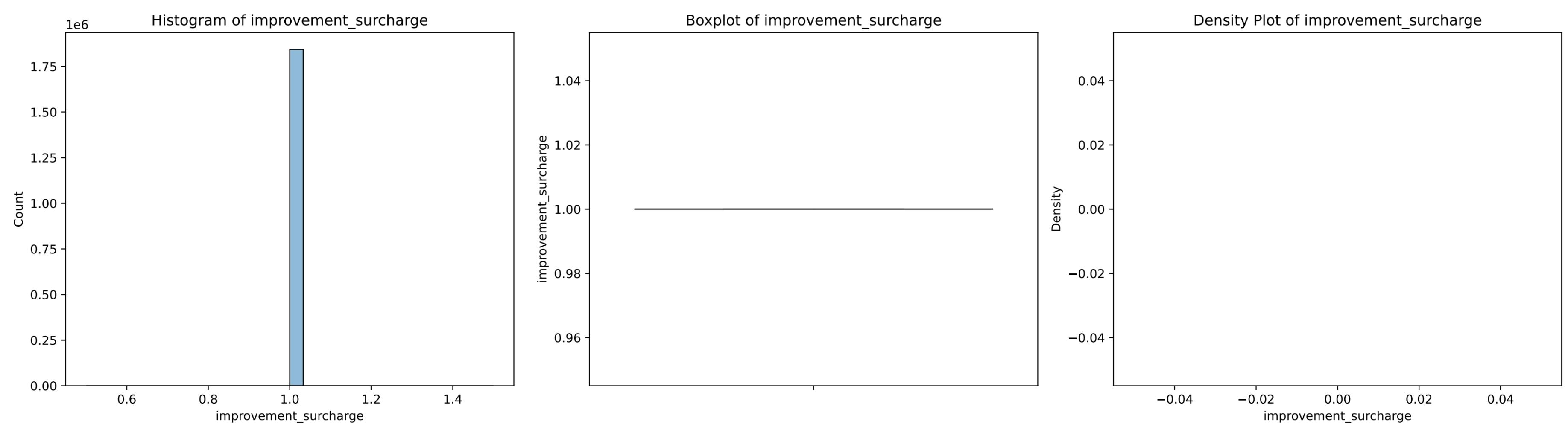
Density Plot of extra

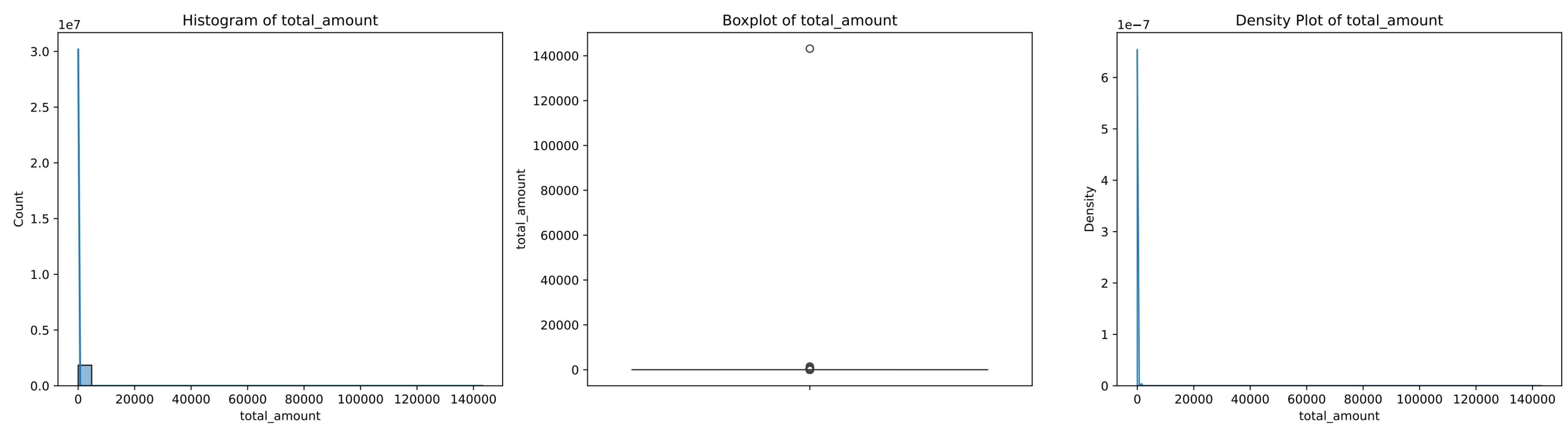


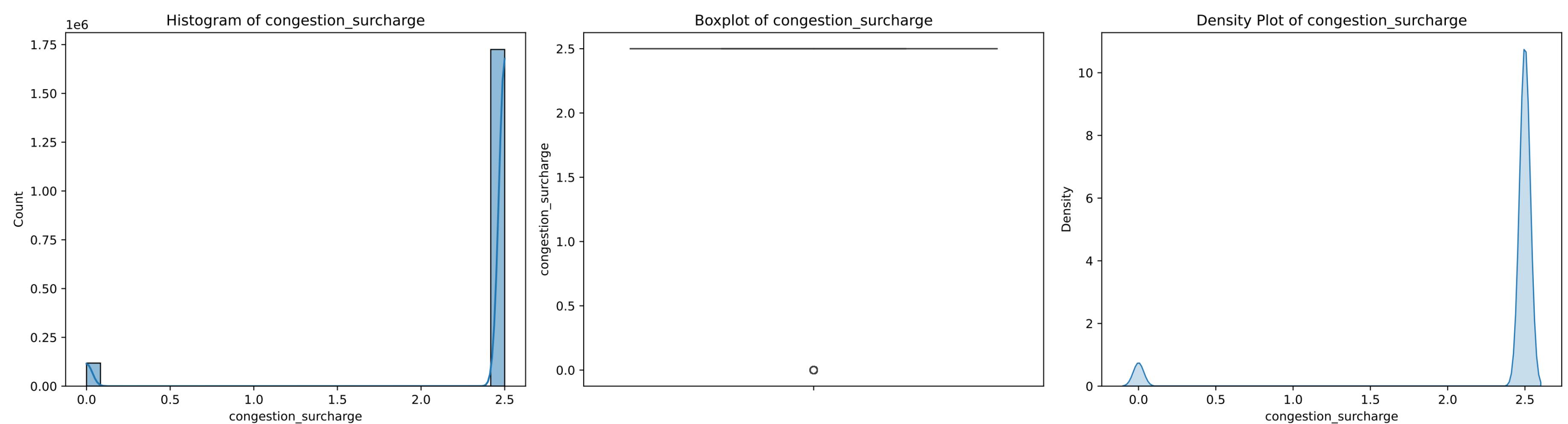


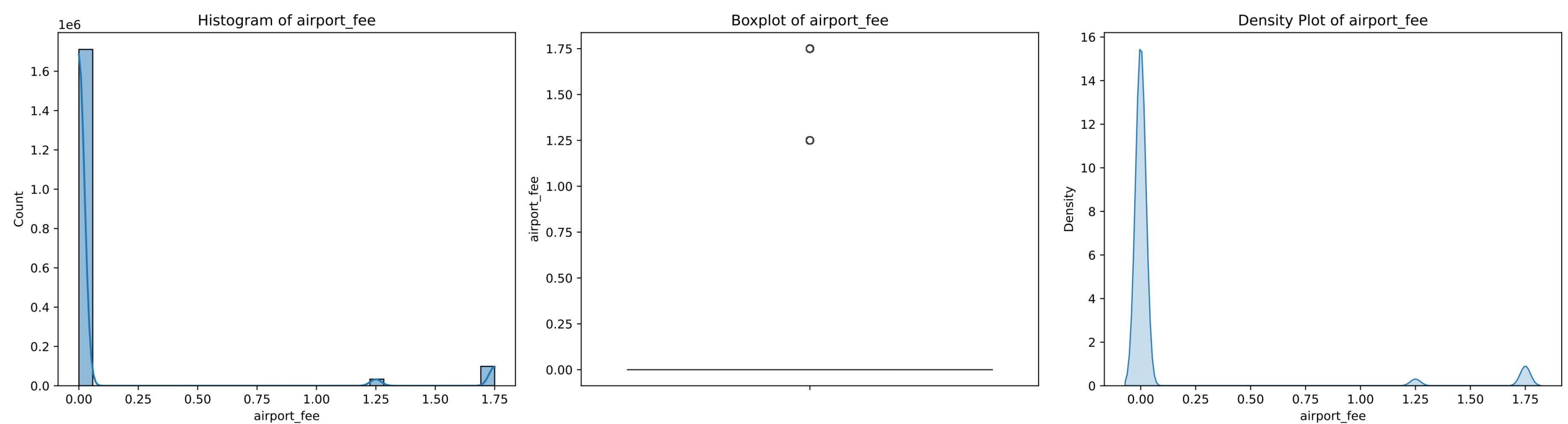












Conclusion/Remarks:

2.3 Analysing the data in Hystogram, Box plot and KDE plot. It looks much better

Conclusion/Remarks:

2.3.1 Remoded records with trip distance 0 or greater than 300. Also if fare amount is 0 but pick up and drop location is different, then it is problematic data

Conclusion/Remarks:

2.3.1 Analysing trip_distance for rows where Payment type =0 (not defined) or 3 (no charge)
1> trip_distance=0 and total_amount<> 0 then no meaning of payment_type.Impute
payment_type = 4 (Dispute) 2> trip_distance<> 0 and total_amount<> 0 and tip_amount = 0
then Impute payment_type = 2 (Cash) 3> trip_distance<> 0 and total_amount<> 0 and
tip_amount <> 0 then Impute payment_type = 1 (Credit card) from Mode) - drop these records

Conclusion/Remarks:

2.3.1 Marking the trips as disputed(4) where trip_distance = 0 and total_amount != 0

Conclusion/Remarks:

2.3.1 Imputing the payment_type as Cash(2) where tip_amount = 0 and total_amount != 0, as trip_amount is not applicable in Cash Payment

Conclusion/Remarks:

2.3.1 Imputing the payment_type as Credit Card(1) where tip_amount != 0 and total_amount != 0

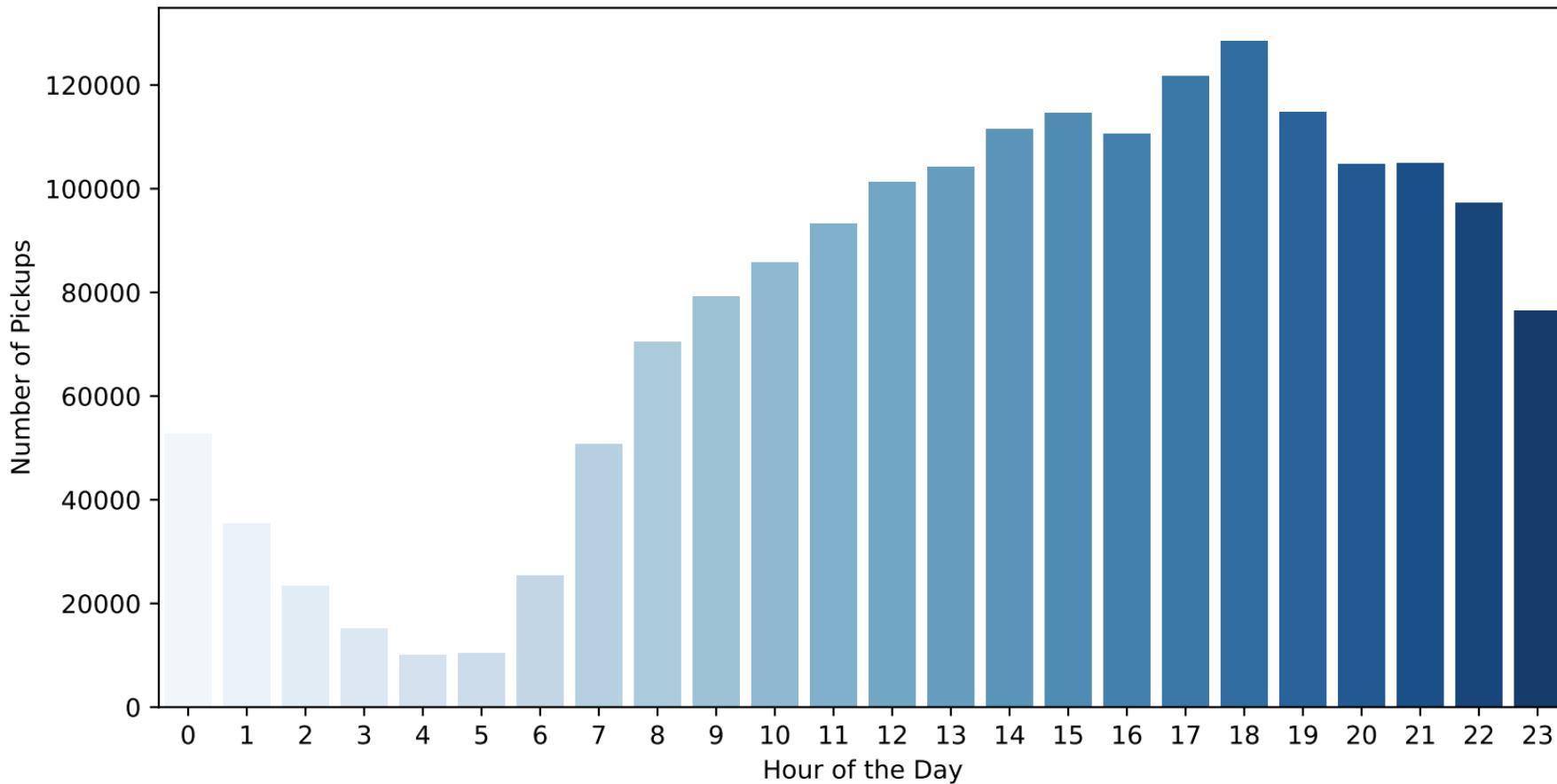
Conclusion/Remarks:

2.3.1 Dropping some records based on above 3 conditions, passenger count > 6 and

Conclusion/Remarks:

3.1.2 Analysing pickup count by month, day and year wise. in 2nd June 18:00 PM was the maximum pickup

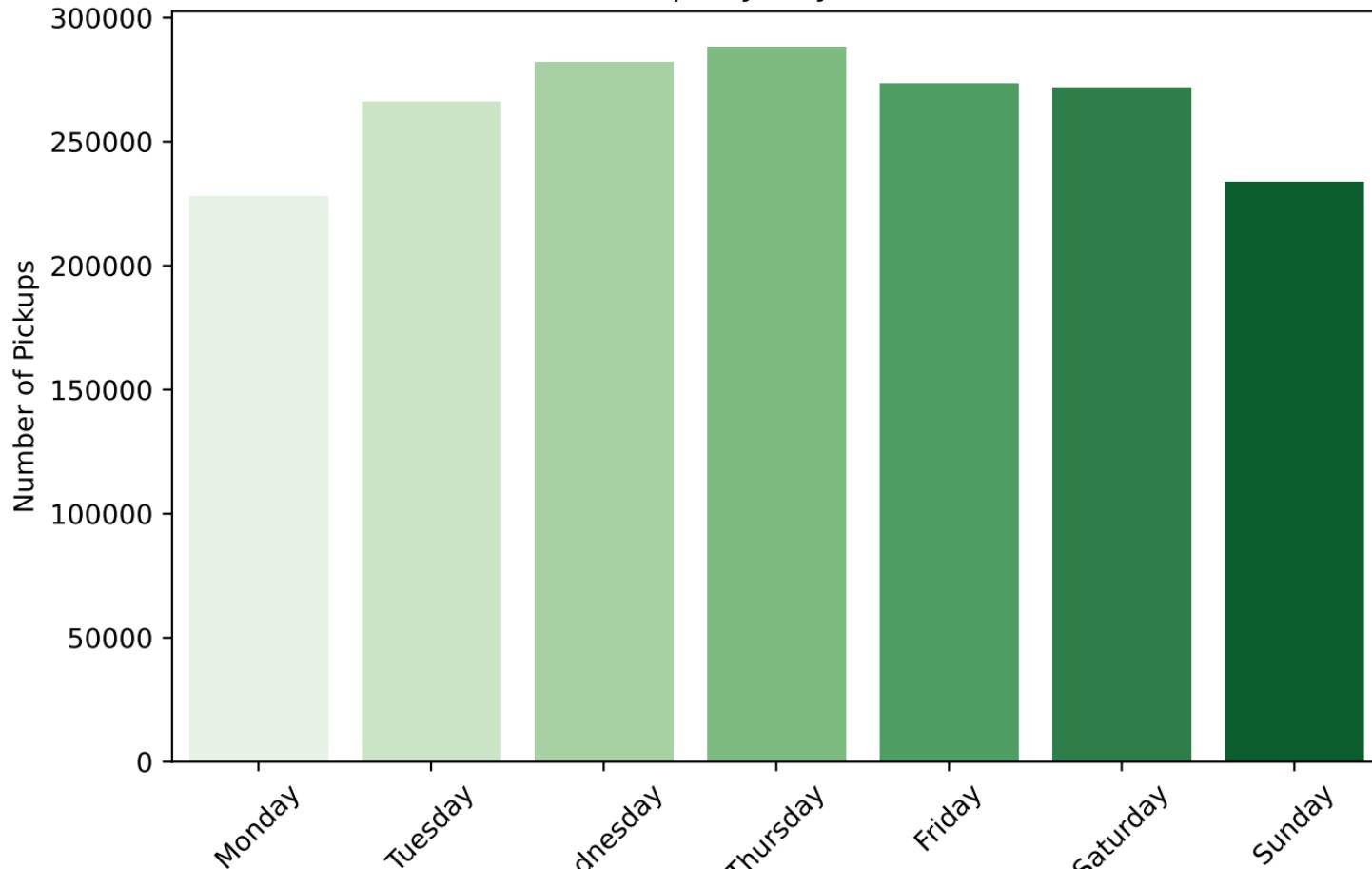
Taxi Pickups by Hour



Conclusion/Remarks:

3.1.2 Analysing pickup Hour Wise. Around 18:00 PM is maximum pickup

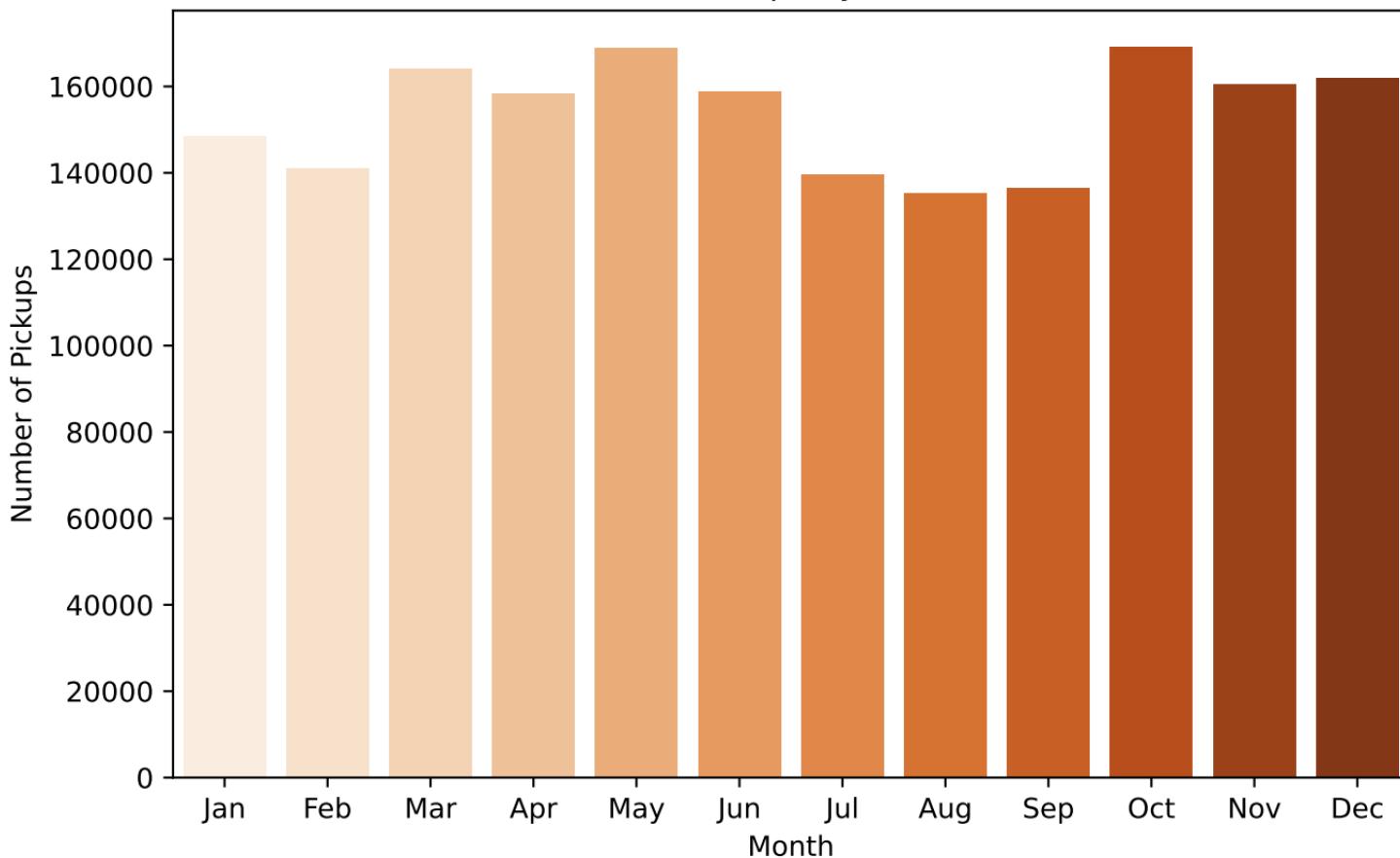
Taxi Pickups by Day of the Week



Conclusion/Remarks:

3.1.2 Analysing pickup Day Wise. Around Thursday is maximum pickup

Taxi Pickups by Month



Conclusion/Remarks:

3.1.2 Analysing pickup Month Wise. In the month of October is maximum pickup

Conclusion/Remarks:

3.1.3 Analysing Negative value count for fare_amount(1284311), tip_amount(1143079), total_amount(1304872), trip_distance(1447231)

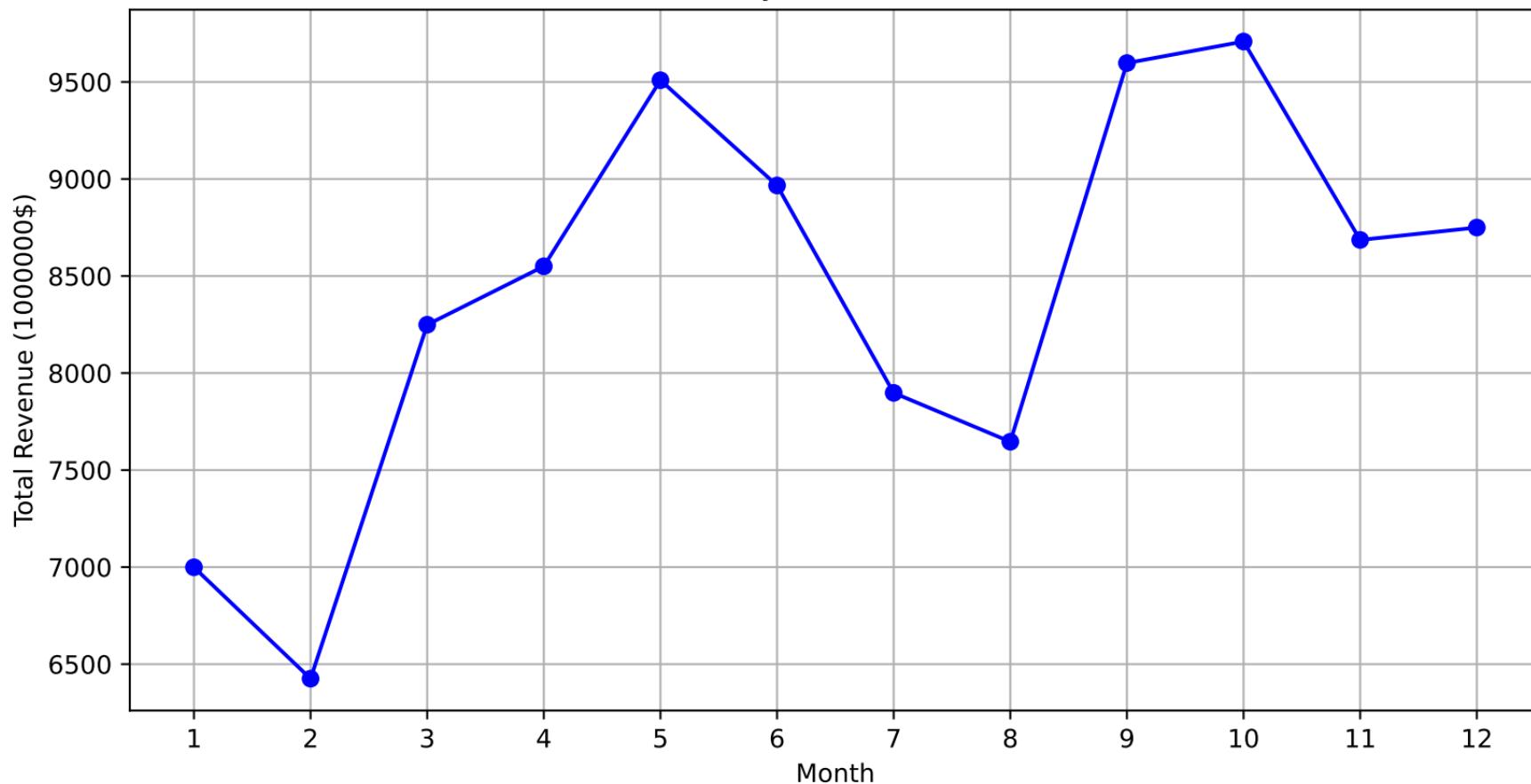
Conclusion/Remarks:

3.1.3 First checking the record counts for the amount ≥ 0

Conclusion/Remarks:

3.1.3 Cleaned the data, Only for the amount > 0 retained

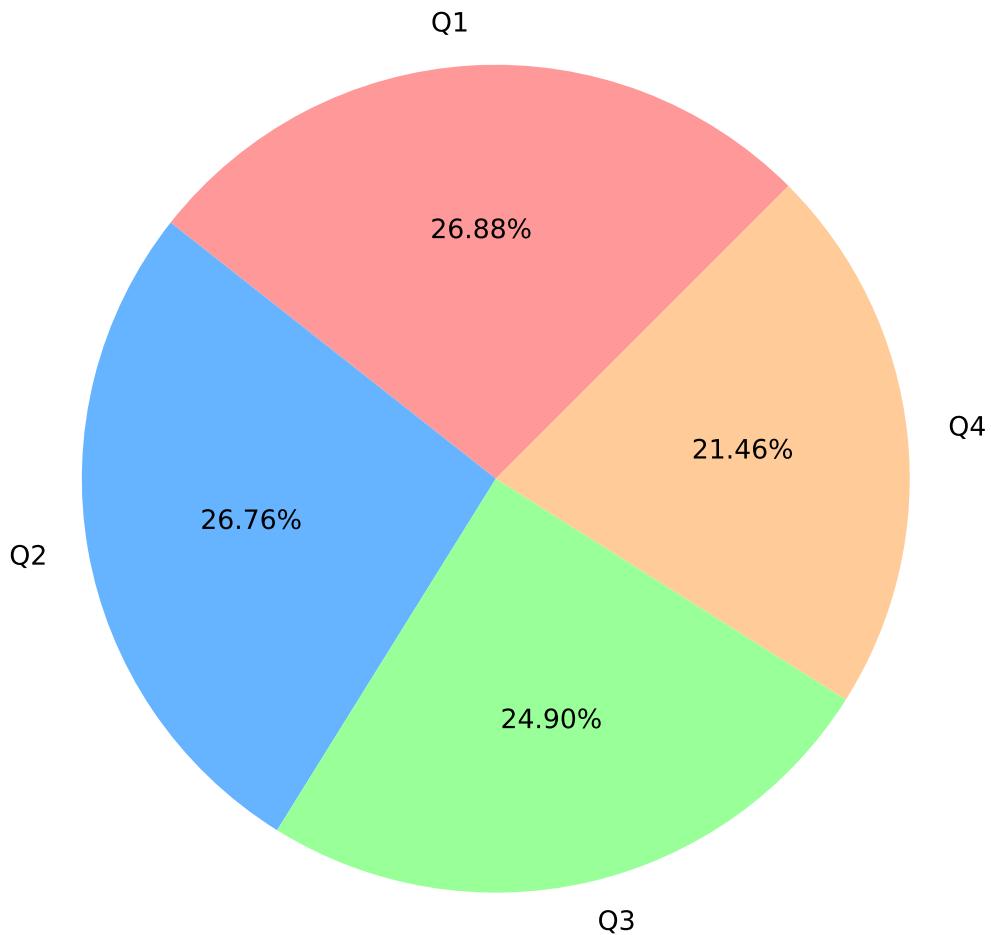
Monthly Revenue Trend



Conclusion/Remarks:

3.1.4 Analysing monthly revenue. October is the highest with count 4765013

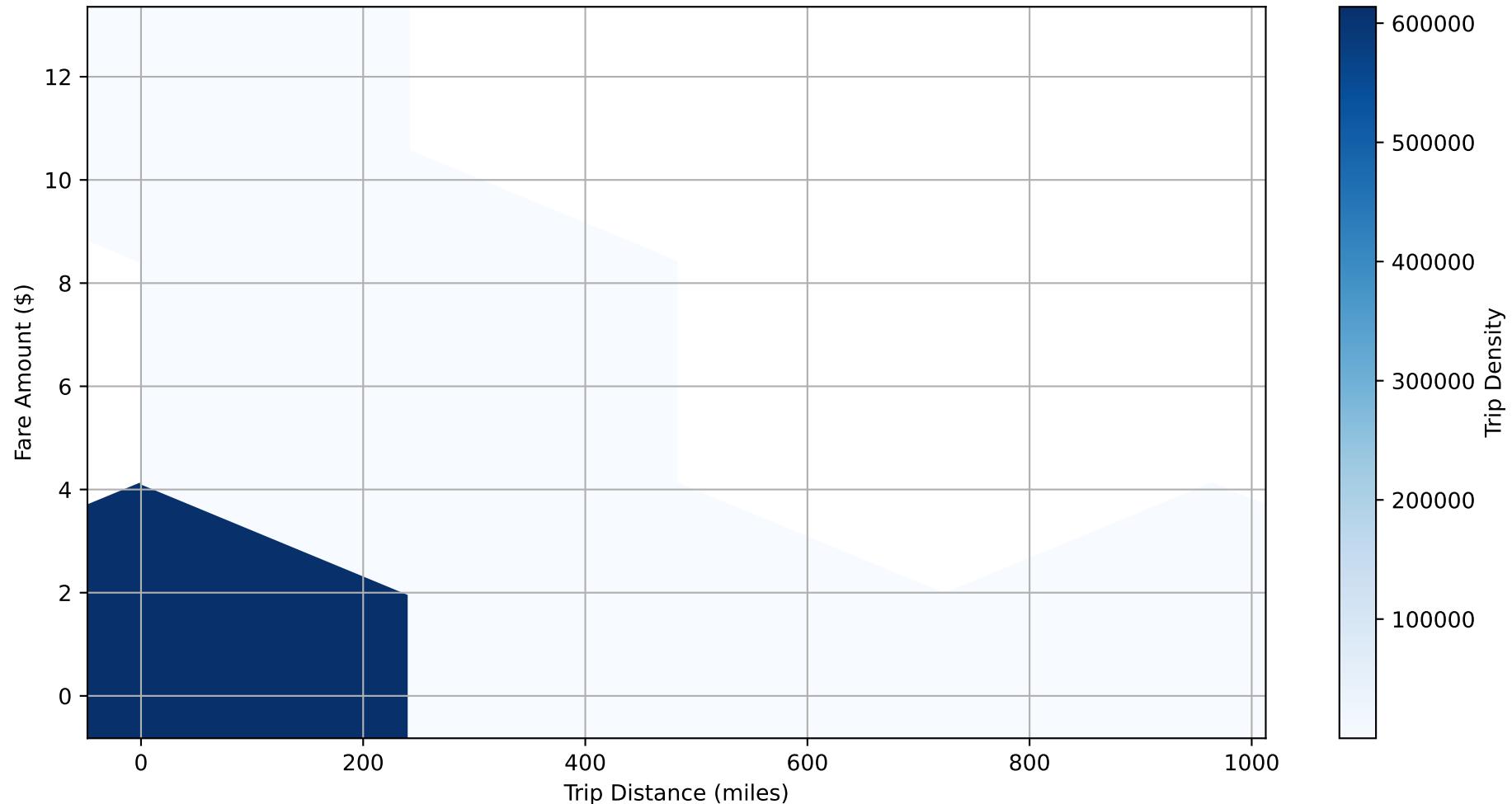
Proportion of Revenue by Quarter



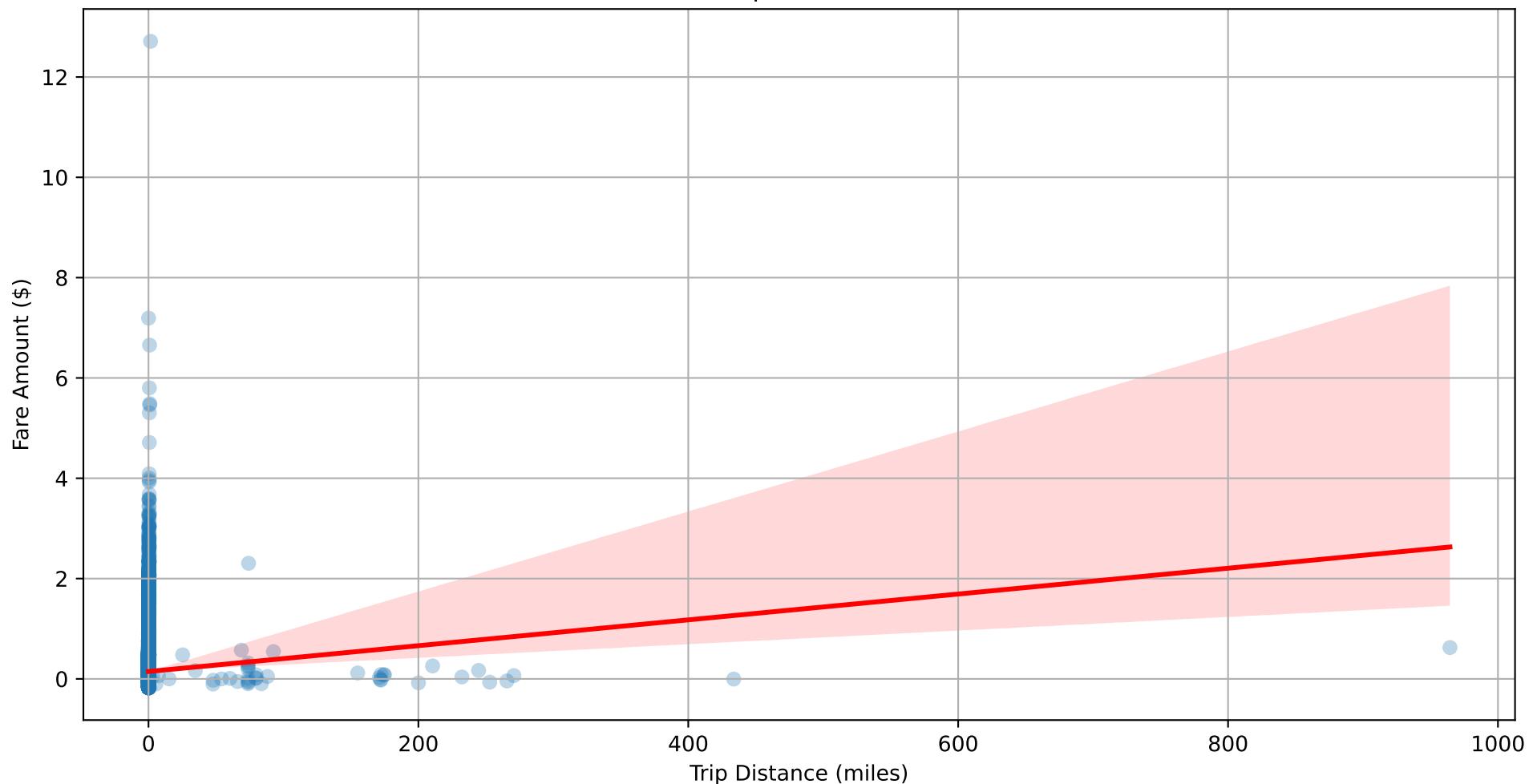
Conclusion/Remarks:

3.1.5 Analysing Quarterly revenue. Q2 is the highest with 26.960258% of yearly revenue

Trip Fare vs. Distance (Hexbin Density Plot)



Effect of Trip Distance on Fare



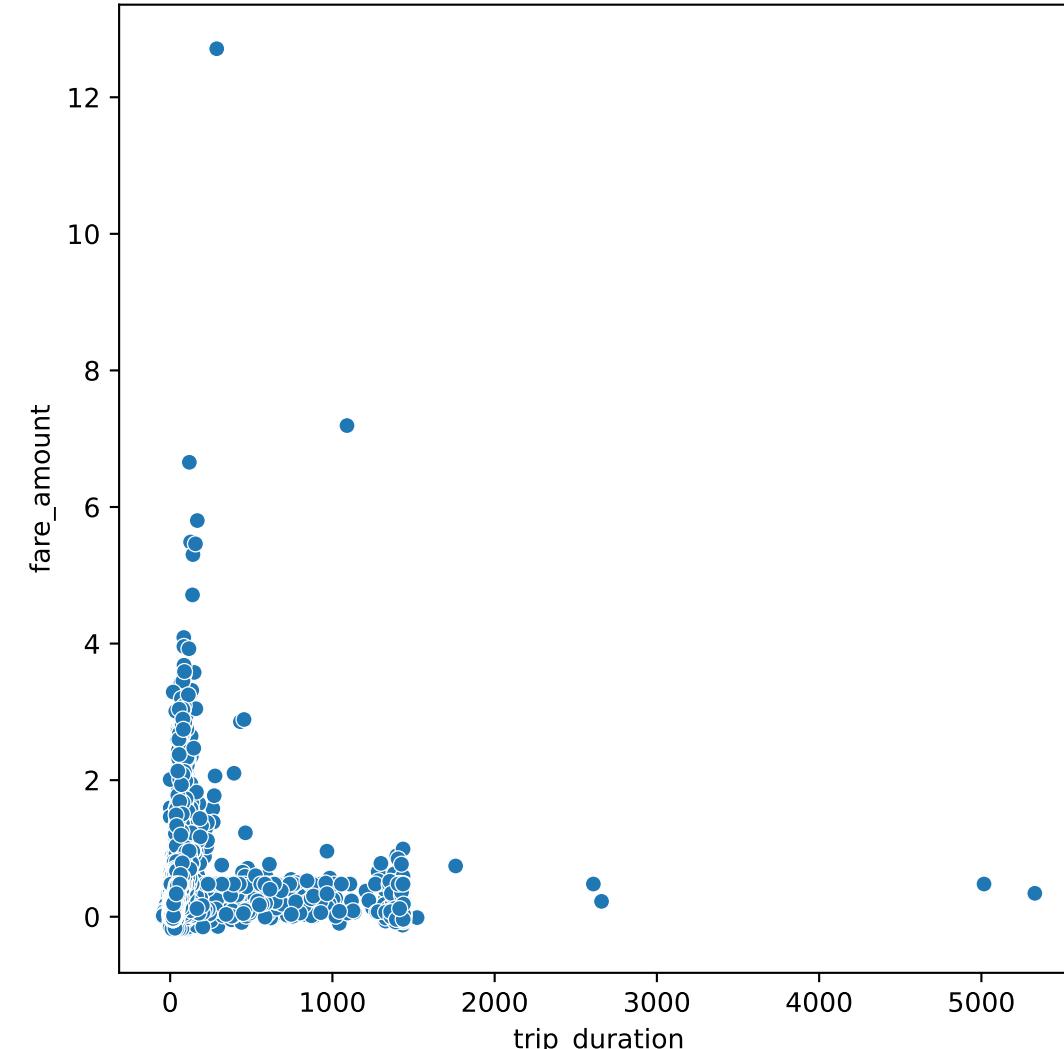
Conclusion/Remarks:

3.1.6 Analysing Showing Trip Distance Vs. Fare Amount. It is a line with small slope

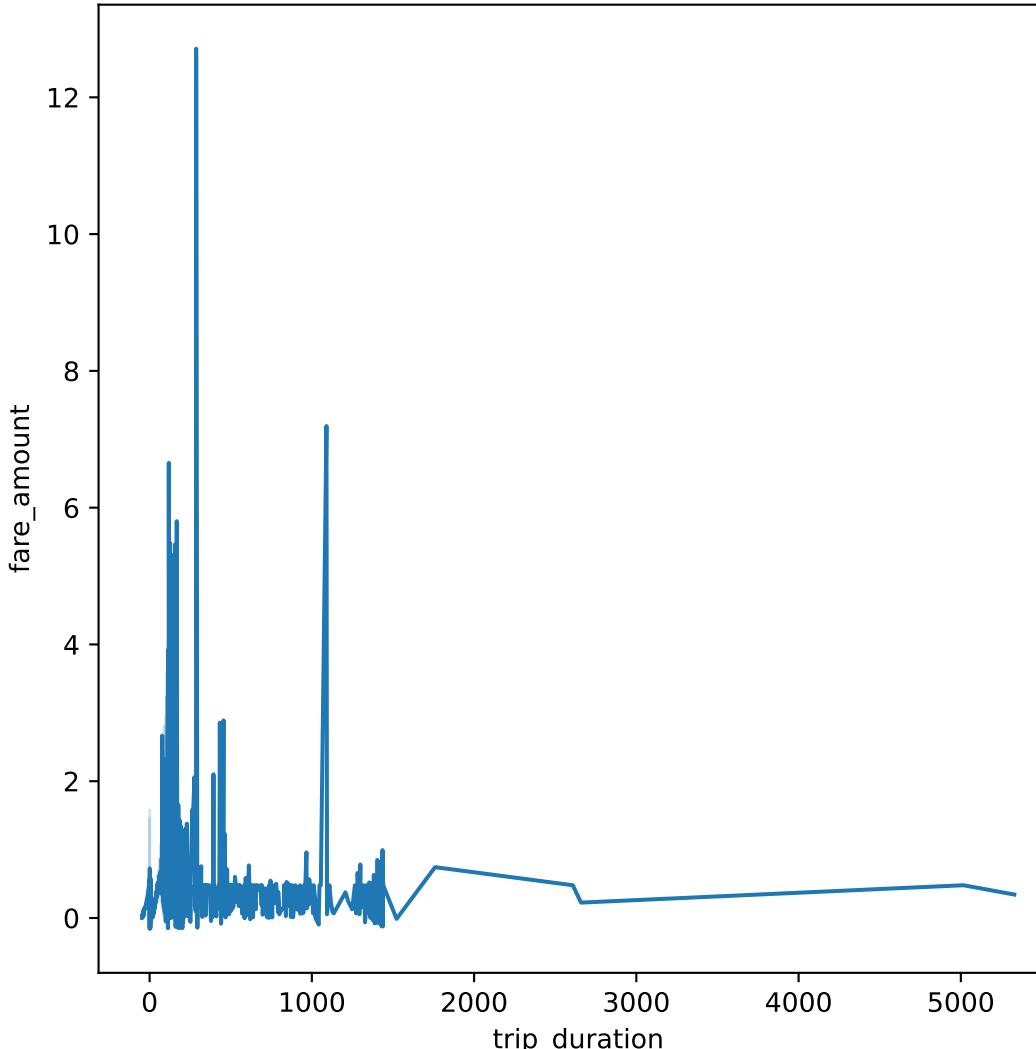
Conclusion/Remarks:

3.1.7 Added new column trip_duration = (drop time - pick time)/60

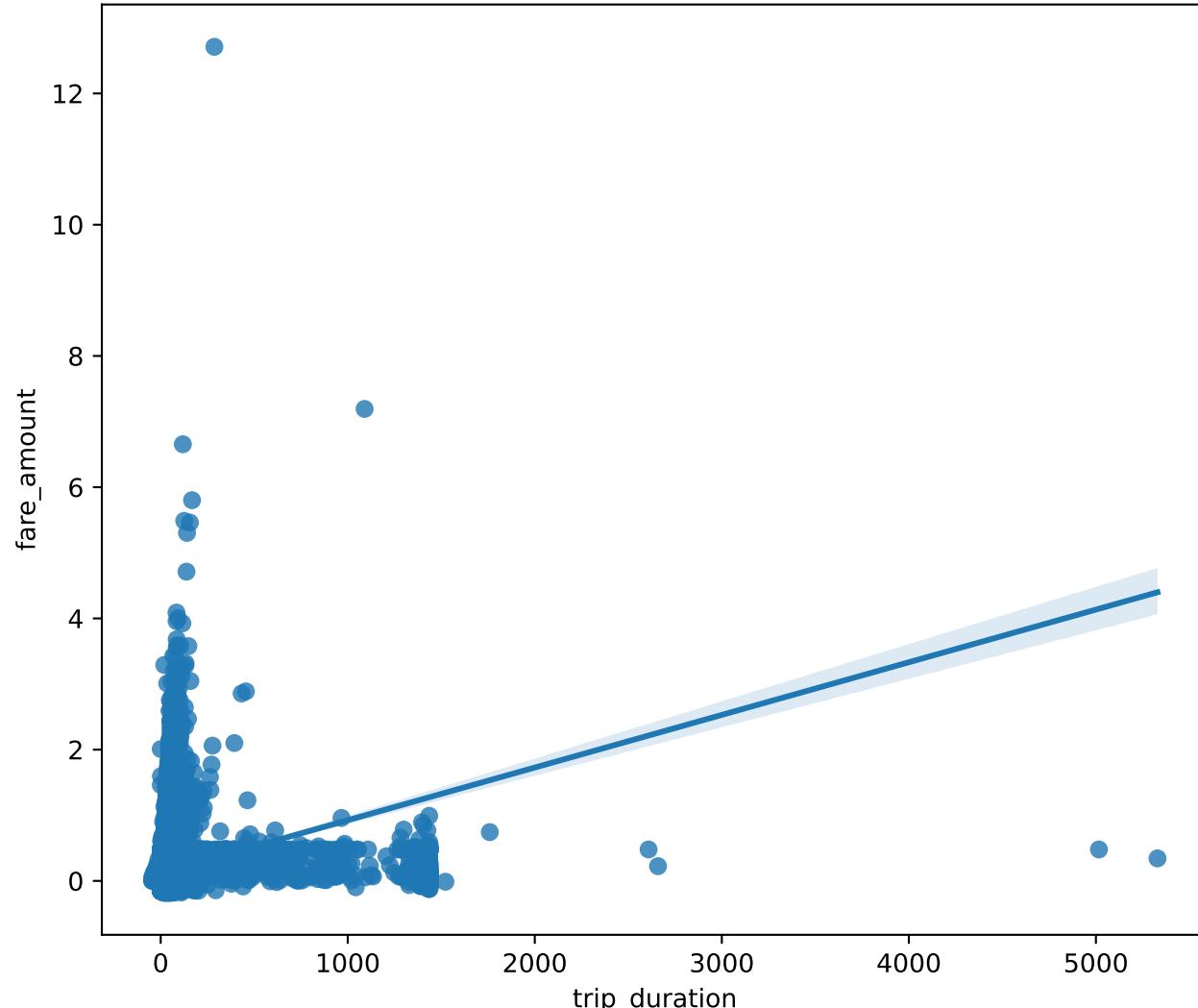
Scatter: trip_duration vs fare_amount



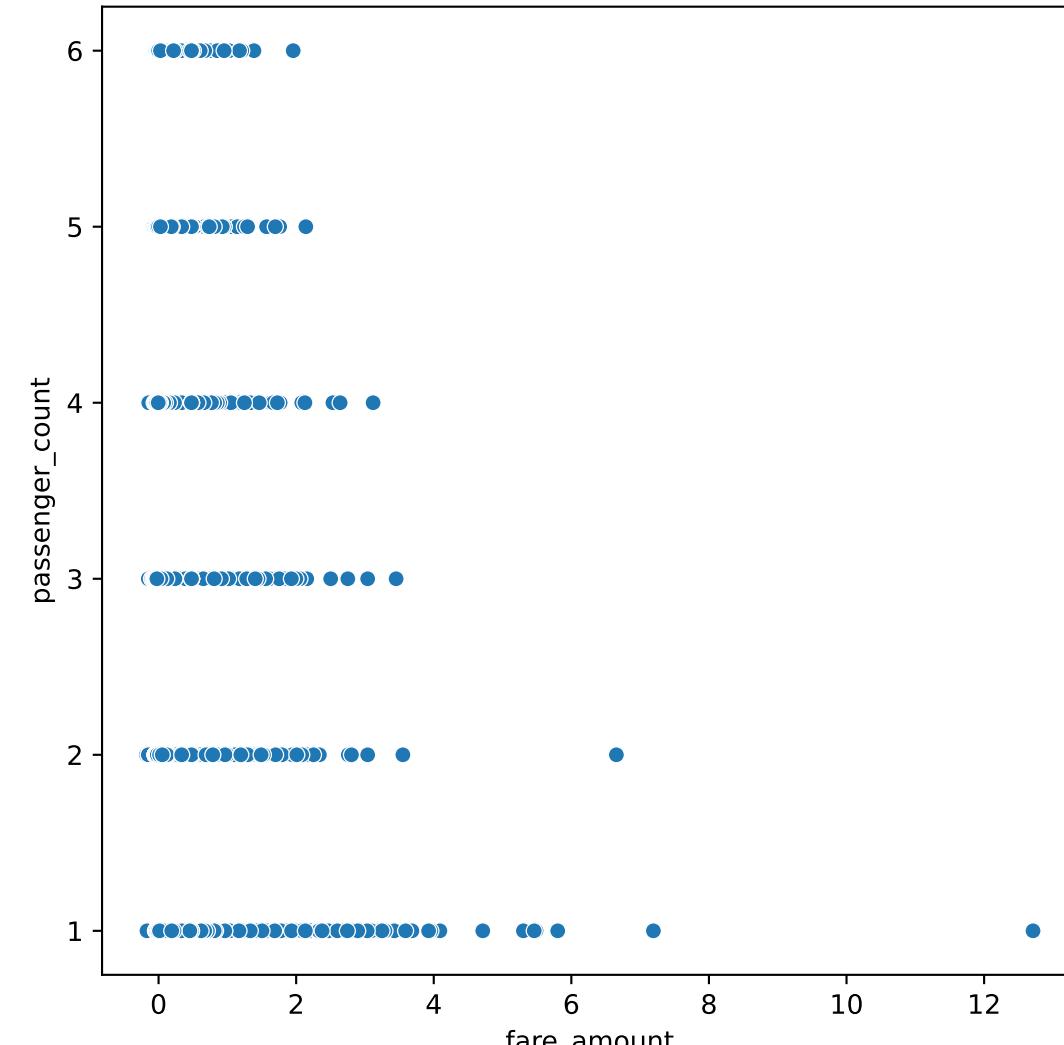
Trend of fare_amount by trip_duration



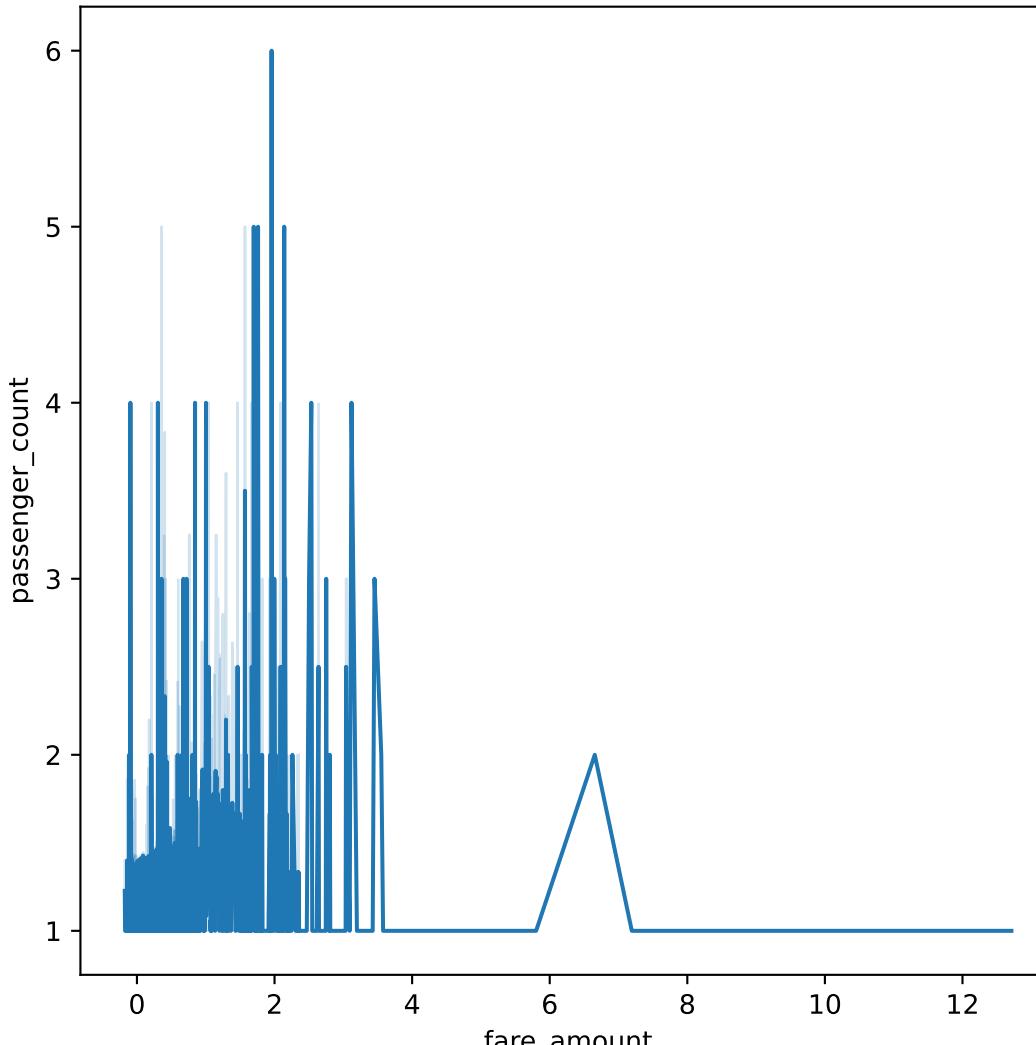
Regression: trip_duration vs fare_amount



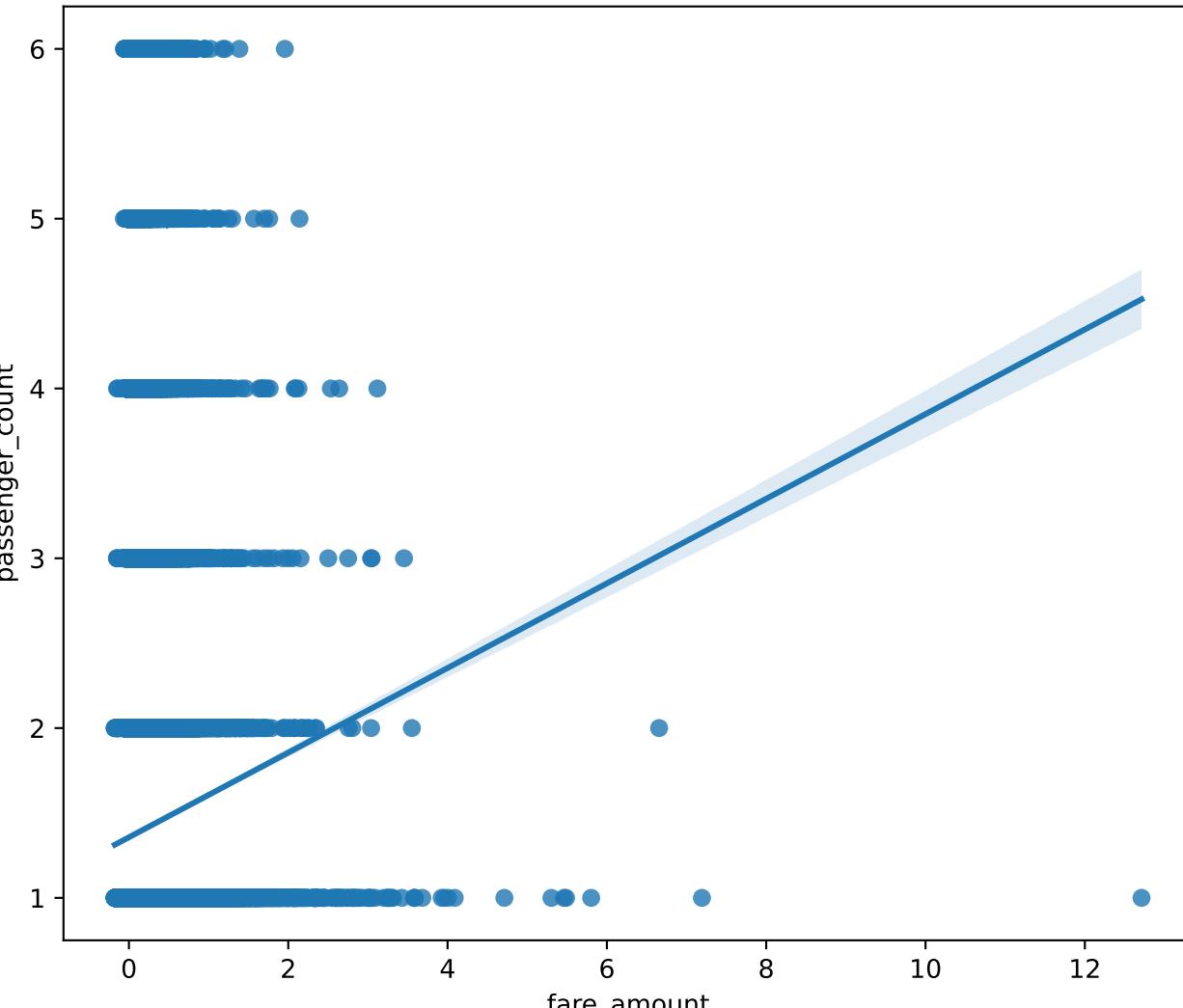
Scatter: fare_amount vs passenger_count



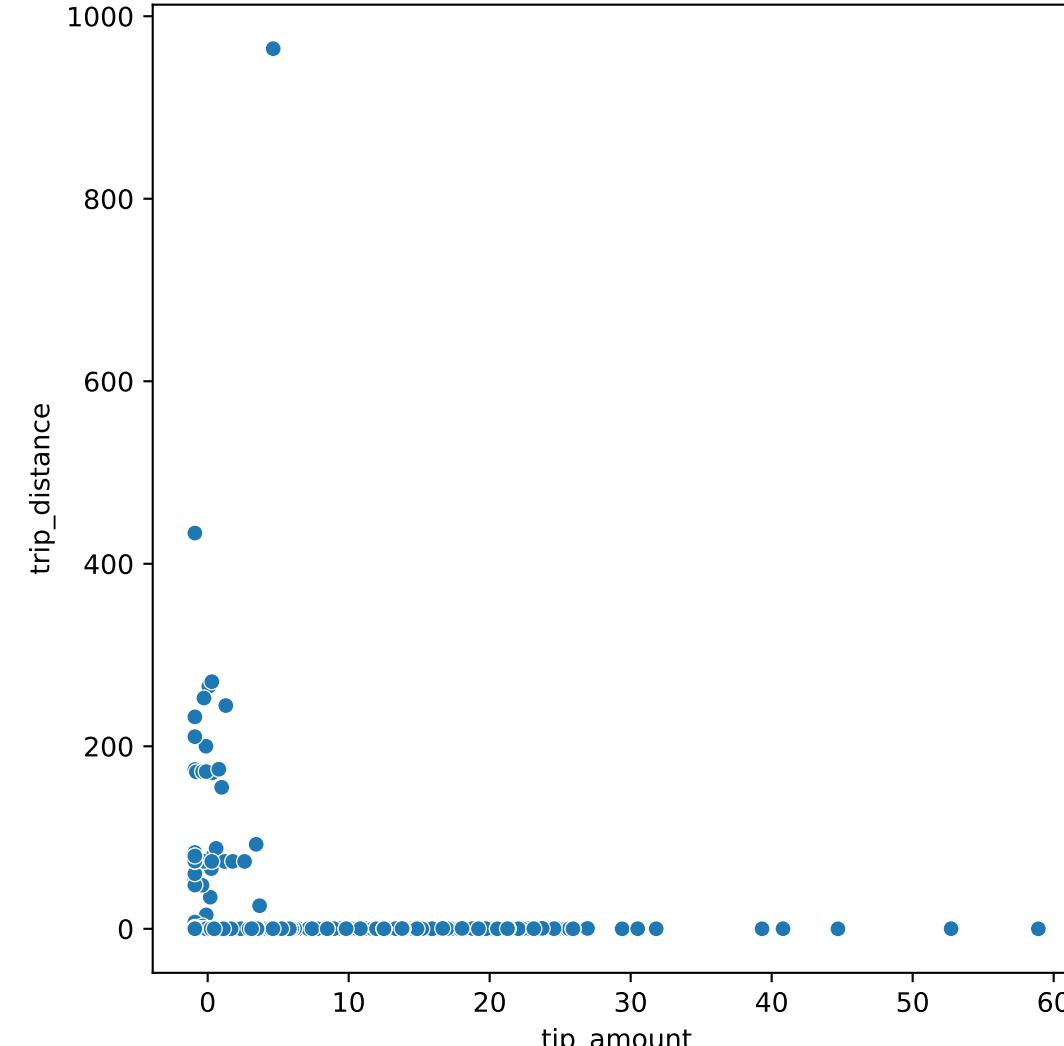
Trend of passenger_count by fare_amount



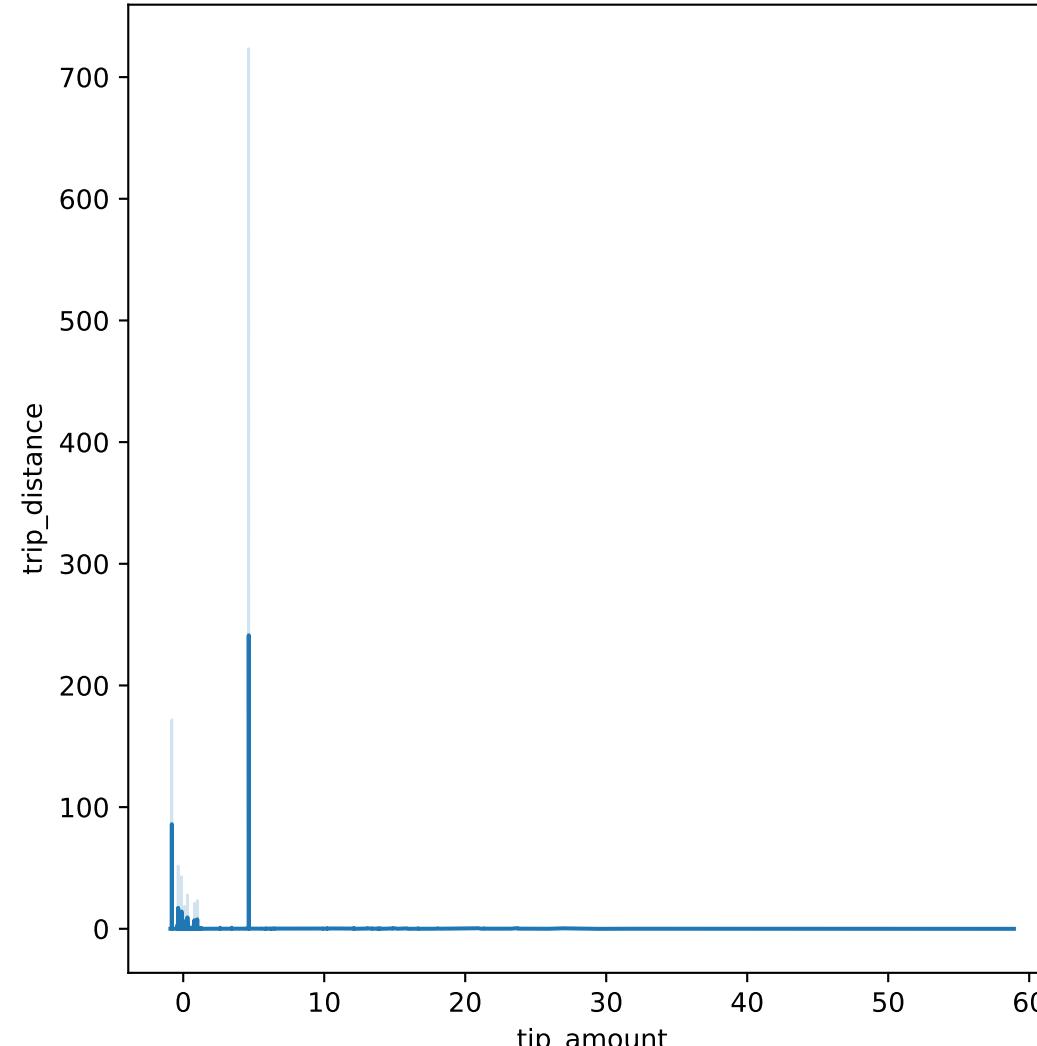
Regression: fare_amount vs passenger_count



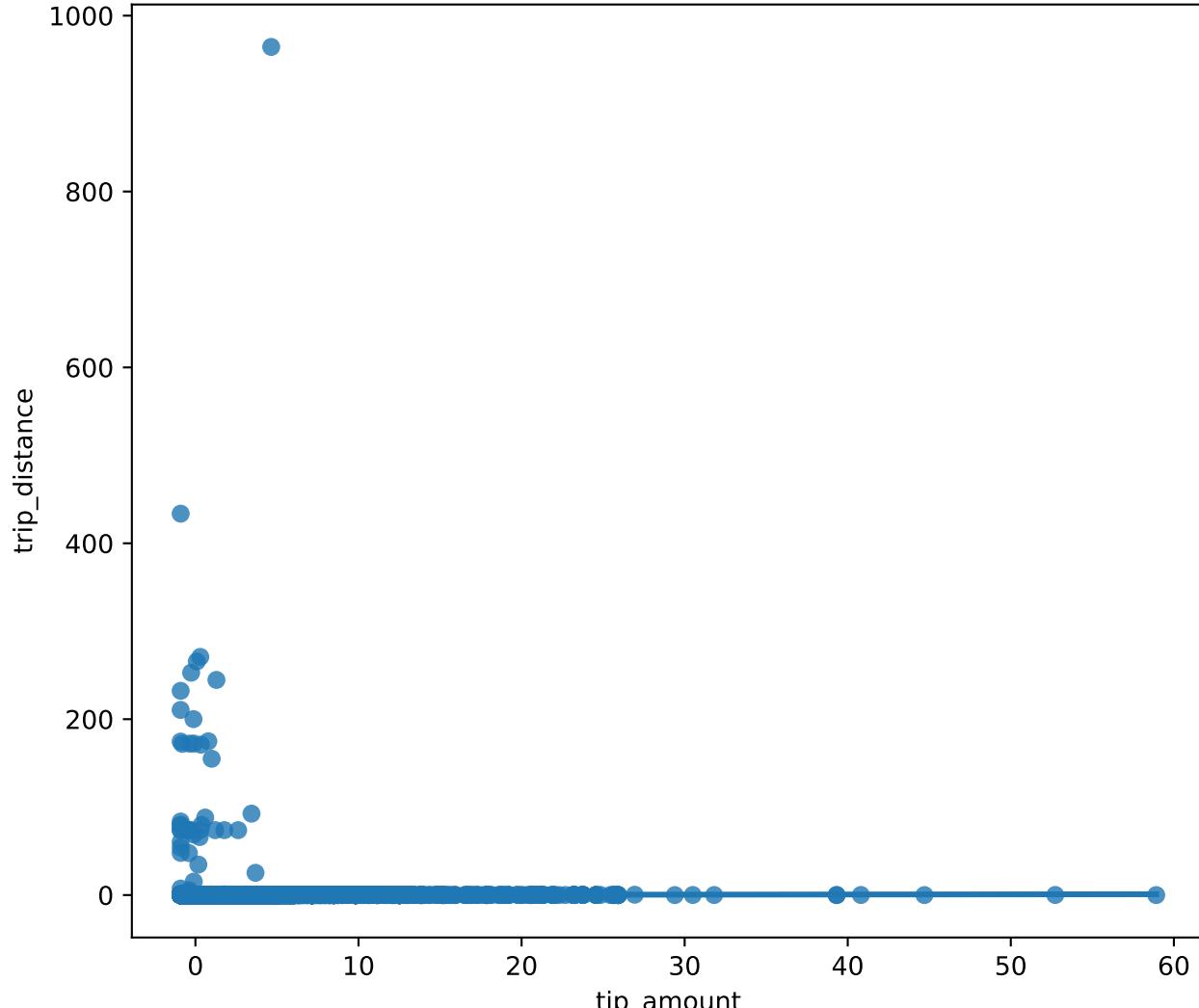
Scatter: tip_amount vs trip_distance



Trend of trip_distance by tip_amount



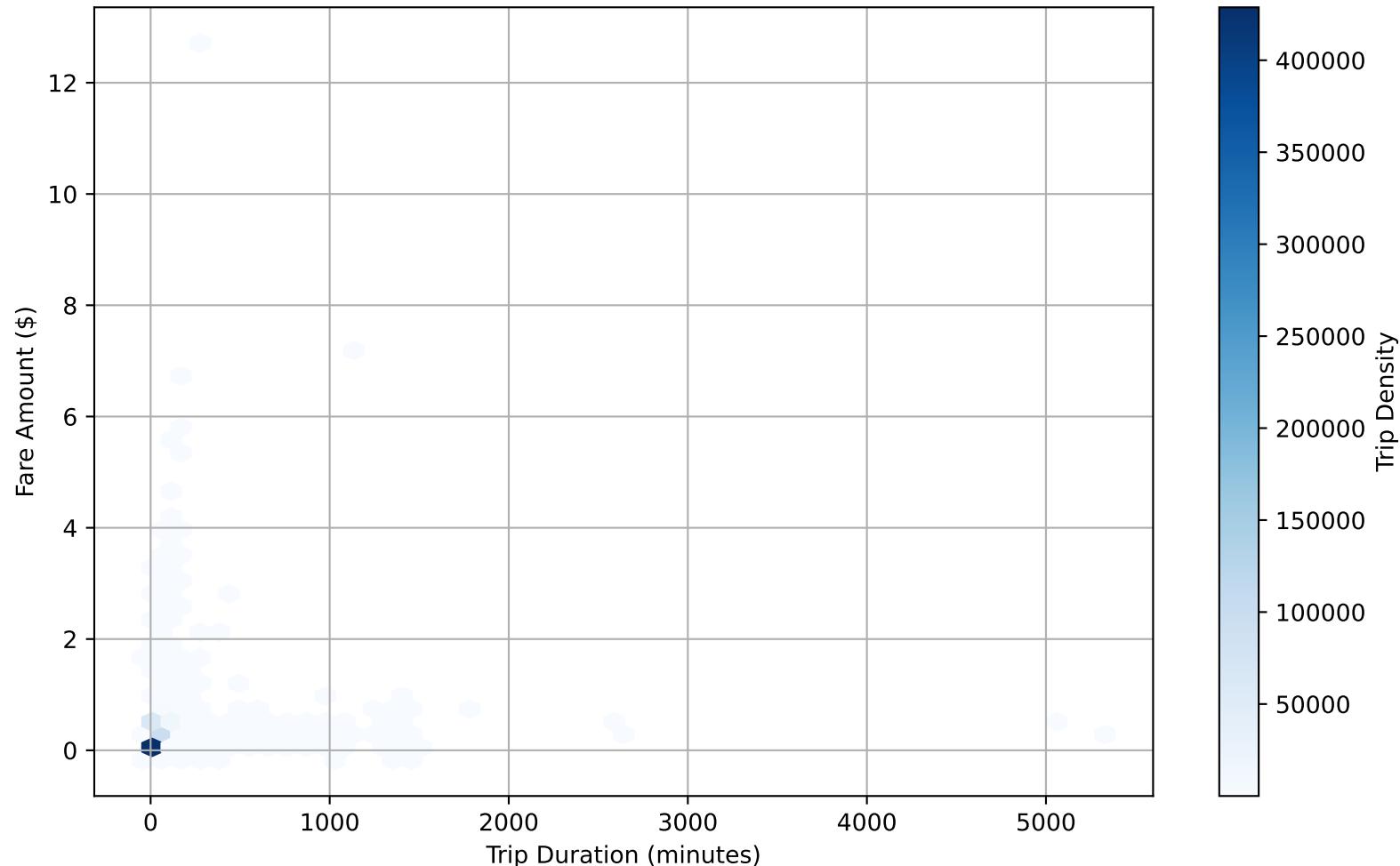
Regression: tip_amount vs trip_distance



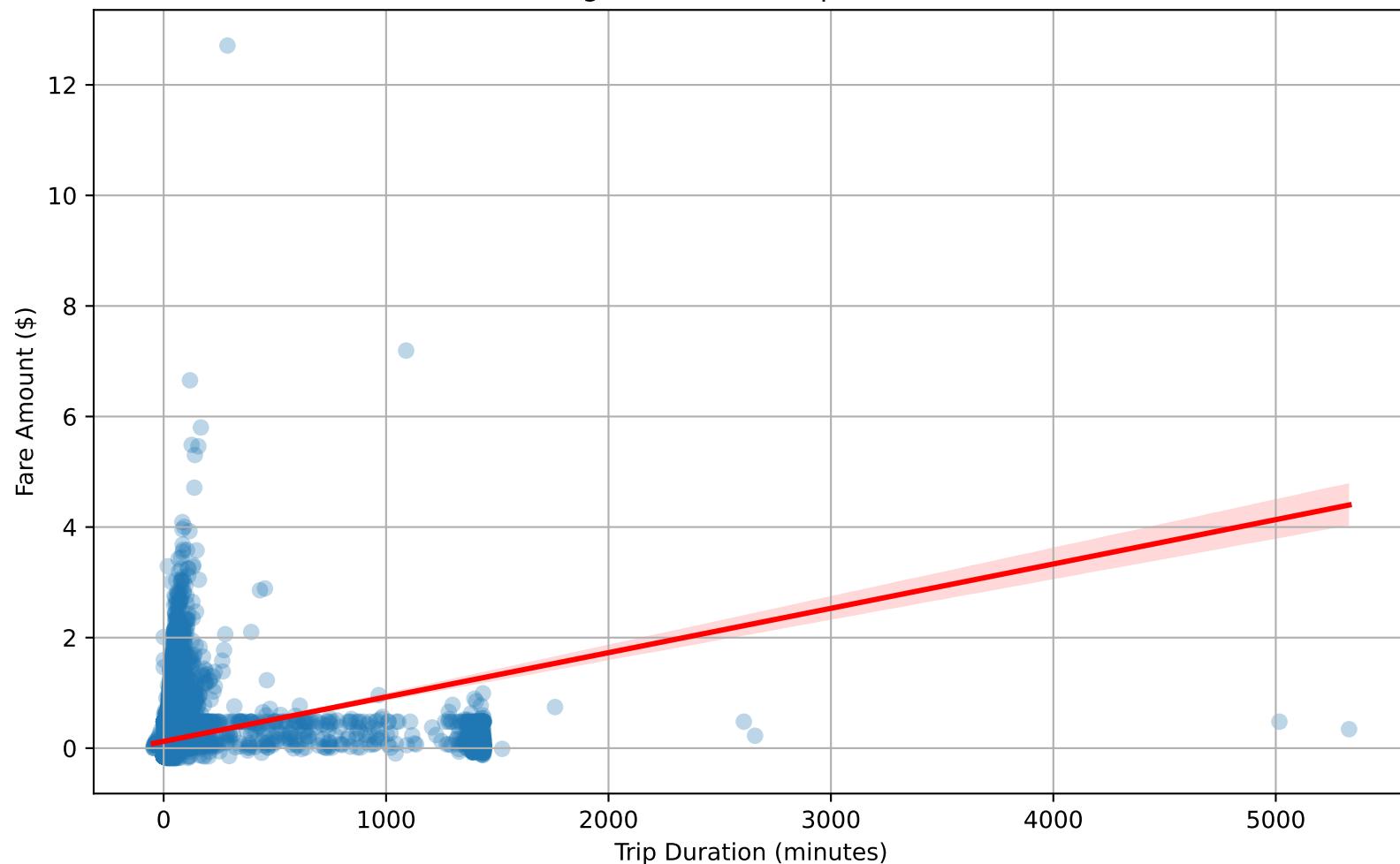
Conclusion/Remarks:

3.1.7 Visualization 1> fare_amount and trip duration 2> fare_amount and passenger_count 3> tip_amount and trip_distance By Scatter, Line and Regression Plot

Hexbin Plot: Trip Duration vs Fare Amount



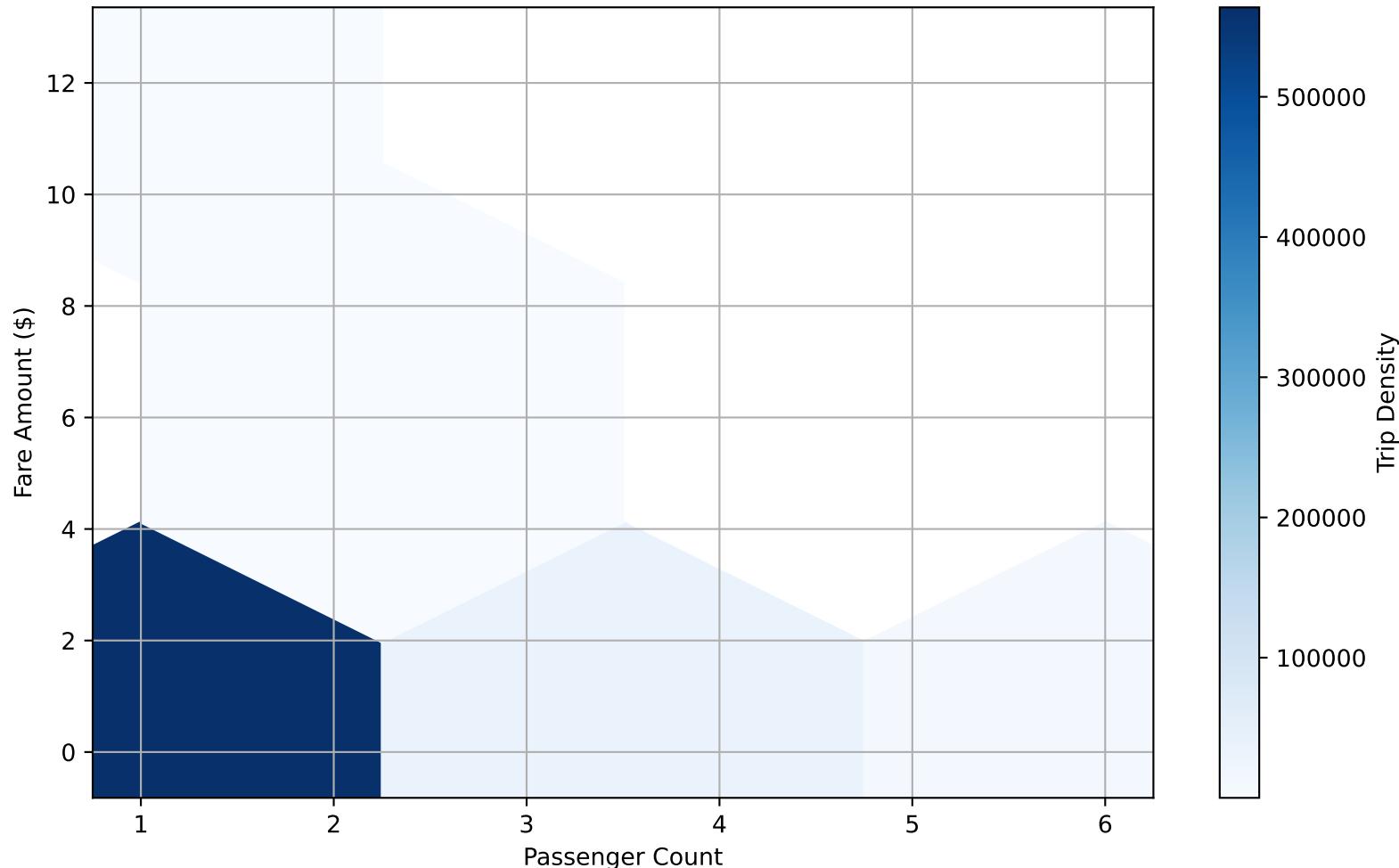
Scatter Plot with Regression Line: Trip Duration vs Fare Amount



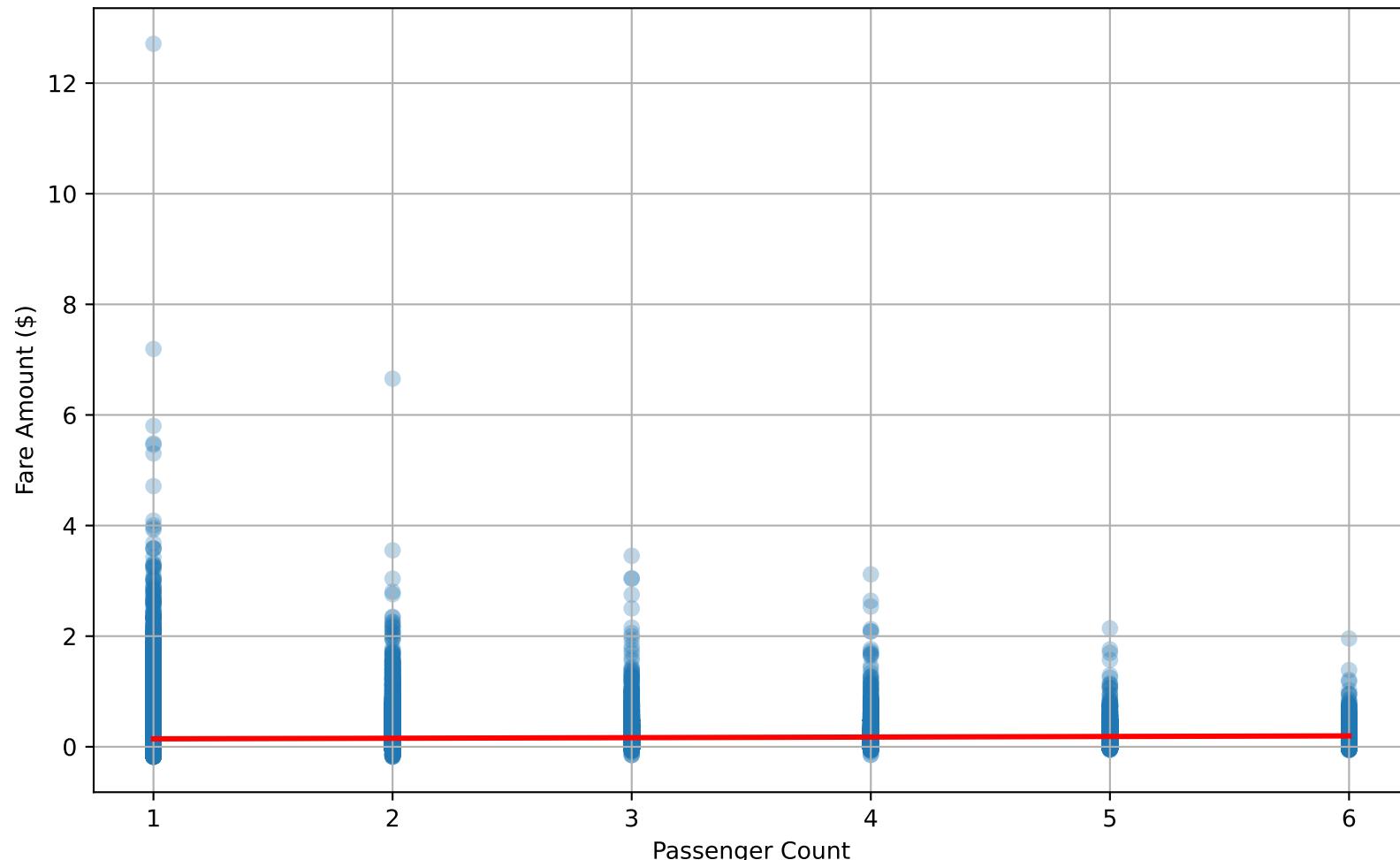
Conclusion/Remarks:

3.1.6 Visualization 1> trip_duration and fare_amount. It is interestingly fare_amount does not increase with trip_duration

Hexbin Plot: Fare Amount vs. Passenger Count



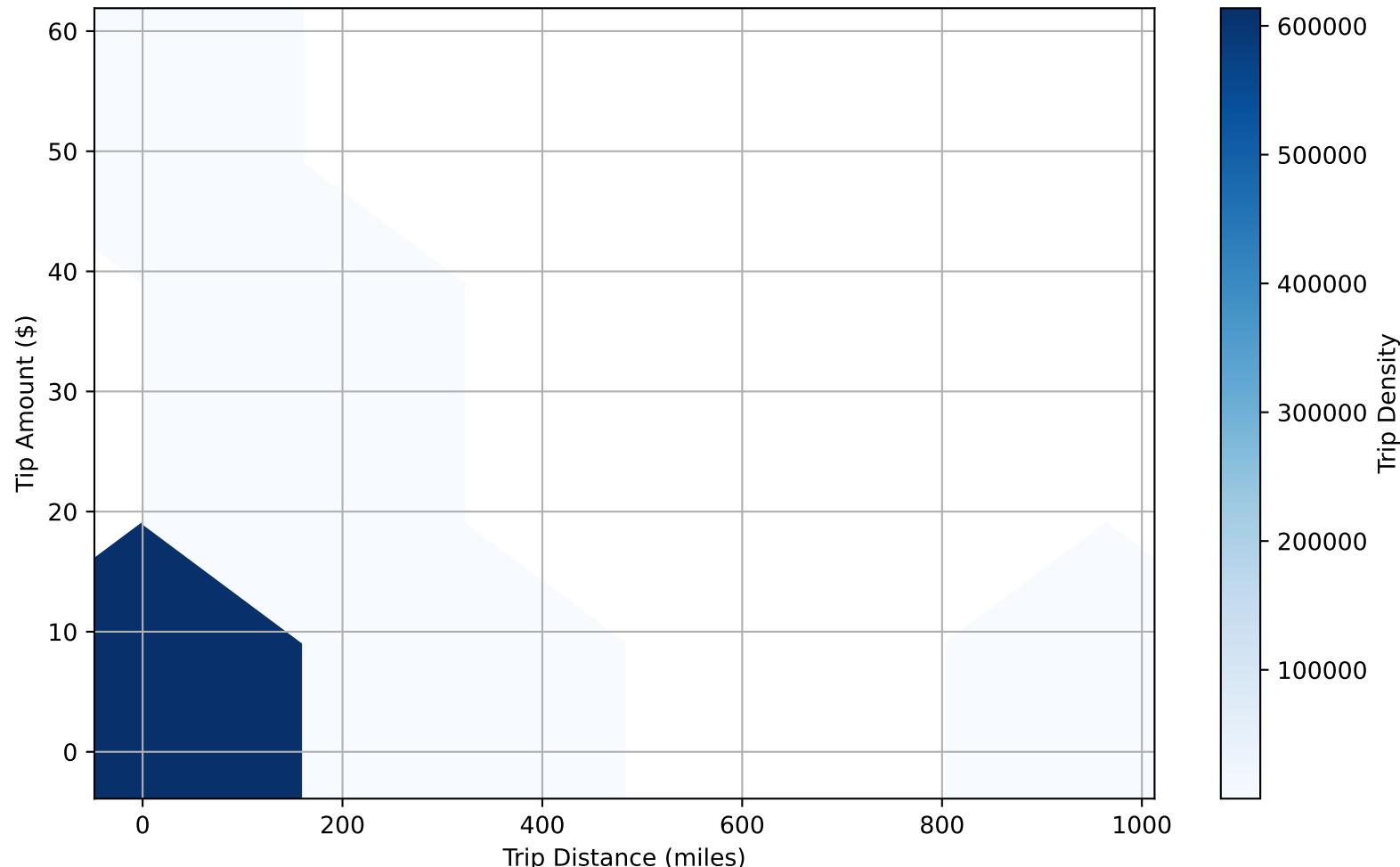
Scatter Plot with Regression Line: Fare Amount vs. Passenger Count



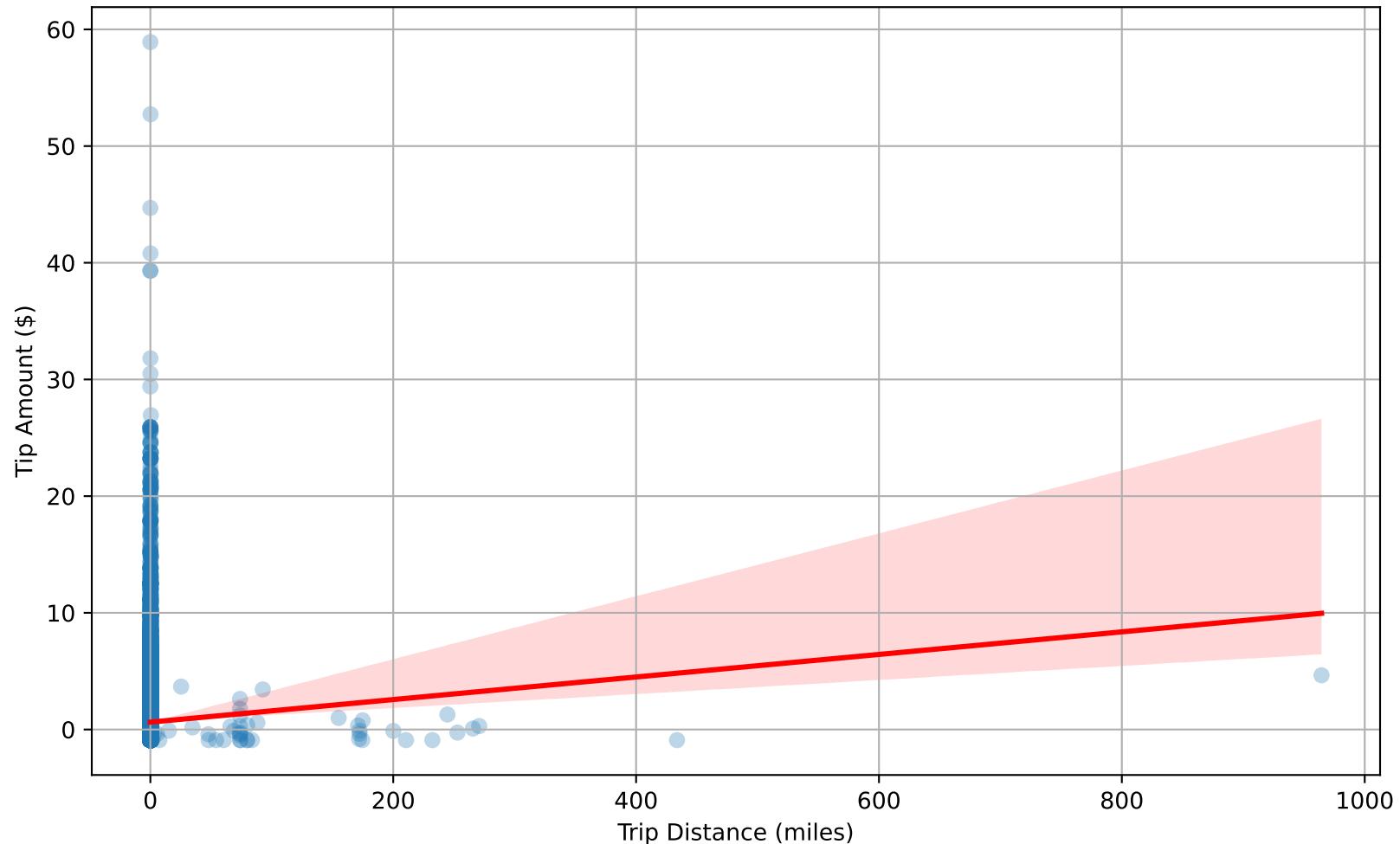
Conclusion/Remarks:

3.1.6 Visualization 2> fare_amount and passenger_count. It is interestingly does not increase with passenger count

Hexbin Plot: Tip Amount vs. Trip Distance



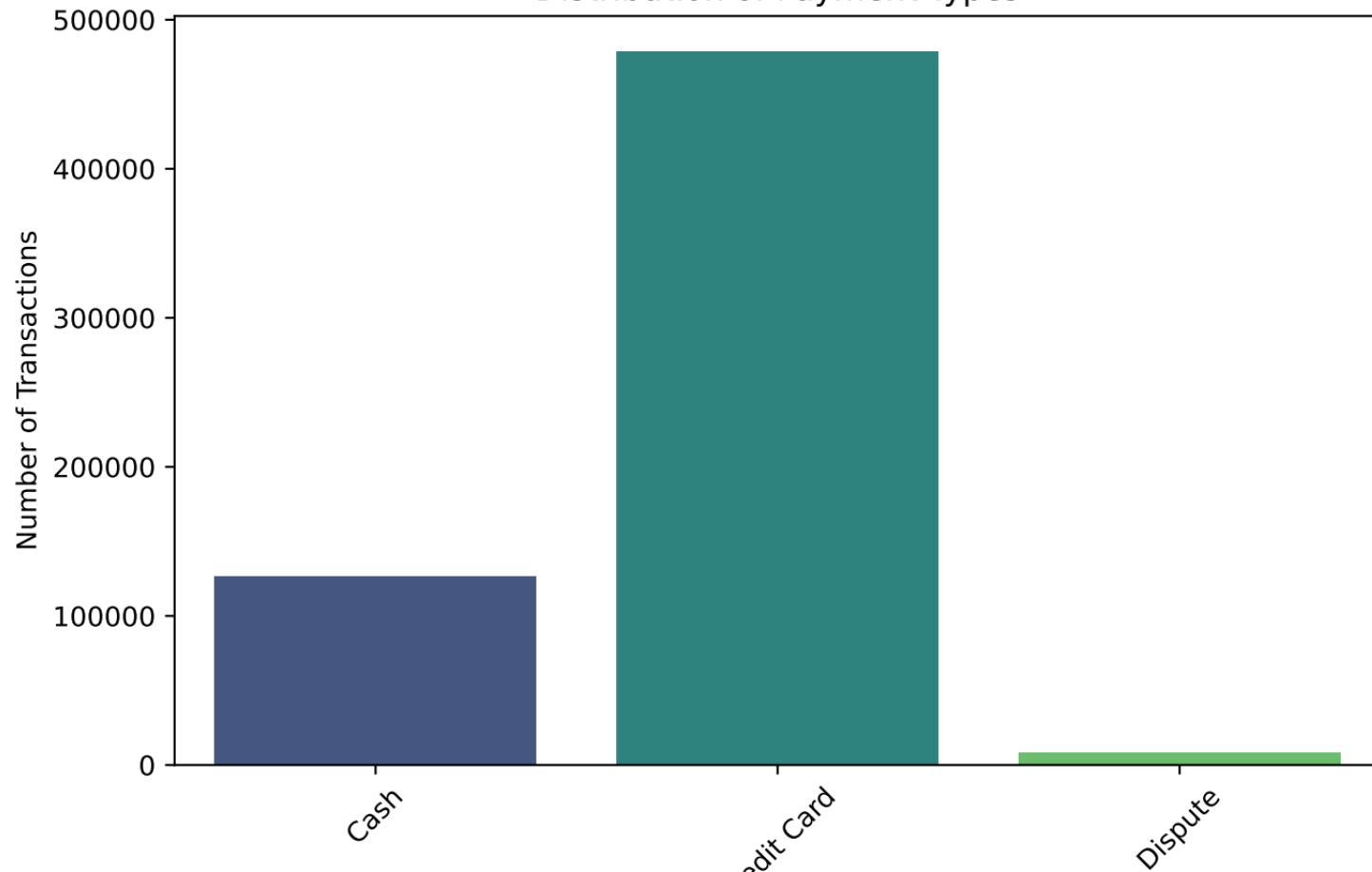
Scatter Plot with Regression Line: Tip Amount vs. Trip Distance



Conclusion/Remarks:

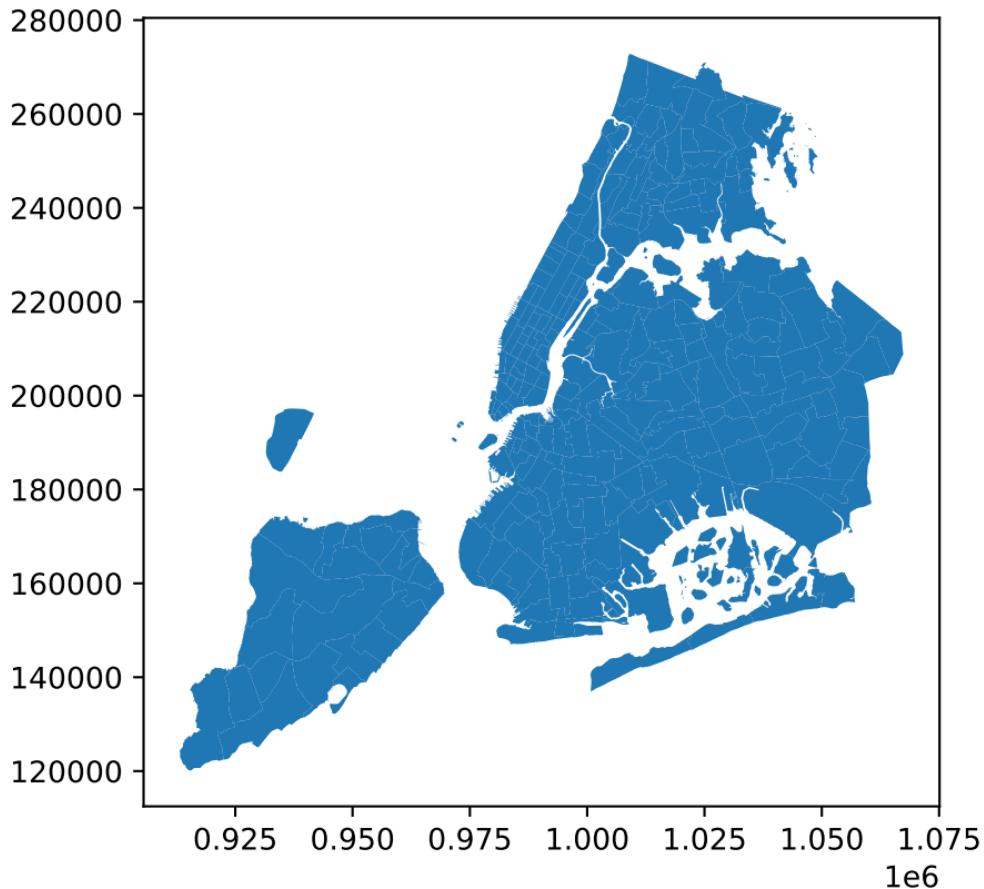
3.1.6 Visualization 3> tip_amount and trip_distance. Interestingly the top fares for very close distance

Distribution of Payment Types



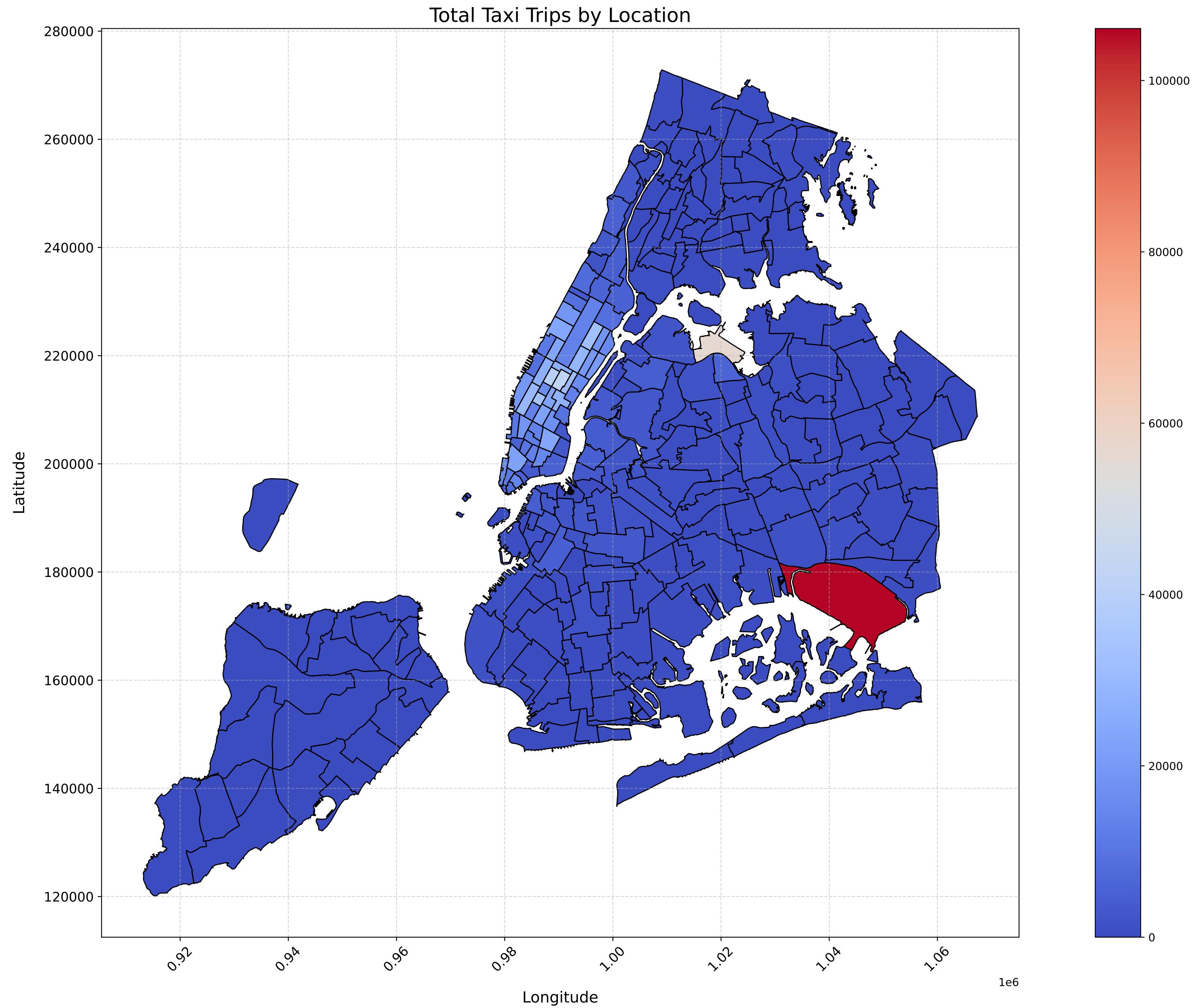
Conclusion/Remarks:

3.1.6 Visualization: Bar Plot of Payment Type Distribution -> Credit Card is of Most use



Conclusion/Remarks:

3.1.11 Group data by location IDs to find the total number of trips per location ID. It is showing top 10 in total trip count



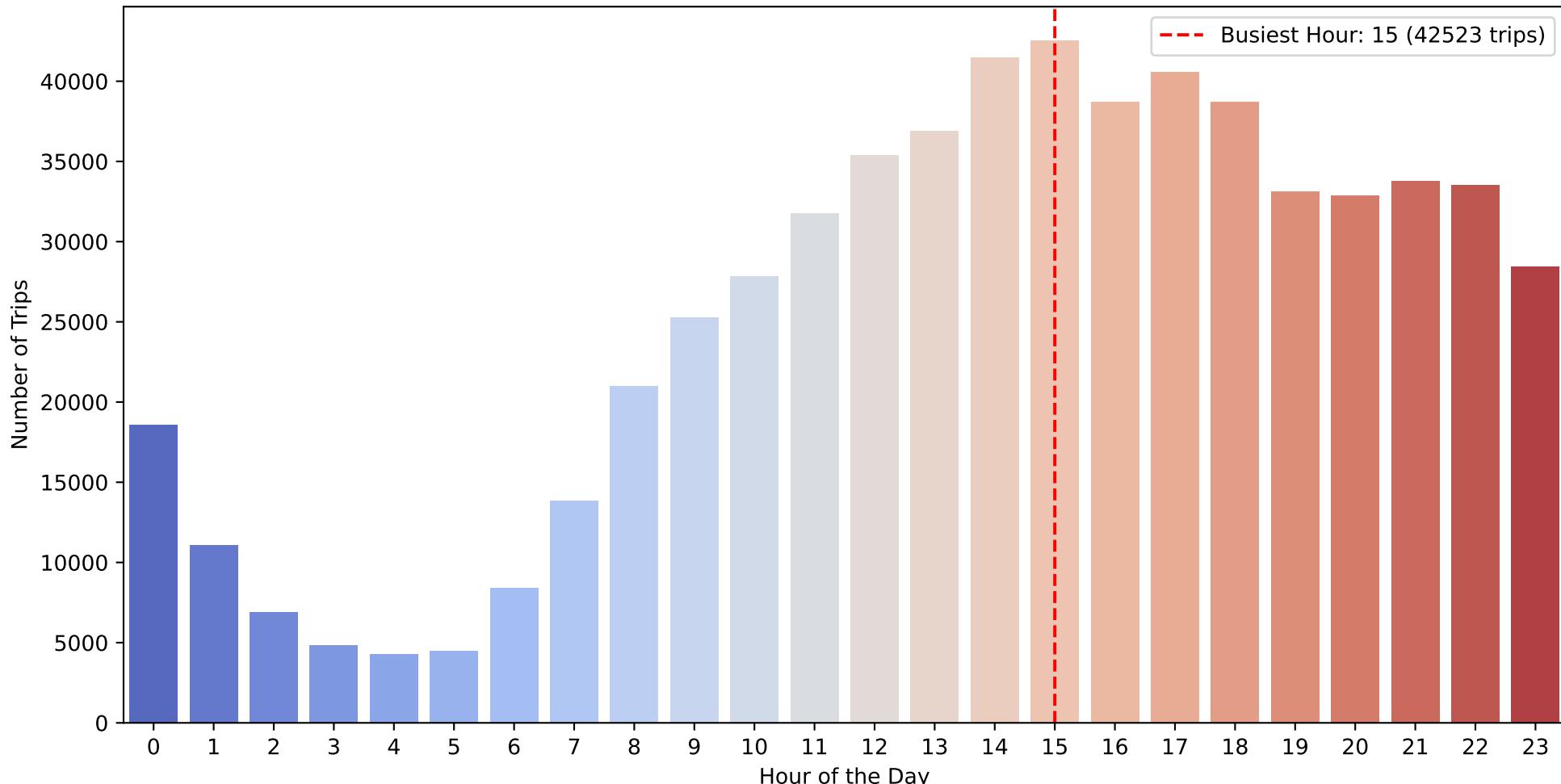
Conclusion/Remarks:

3.1.13 Plot a color-coded map showing zone-wise trips

Conclusion/Remarks:

3.2.1 Showing slow routes overall and hour basis. We can increase the surcharge in those routes and hours to make more revenue.

Number of Trips Per Hour



Conclusion/Remarks:

3.2.2 Inference from the Hourly Traffic Patterns

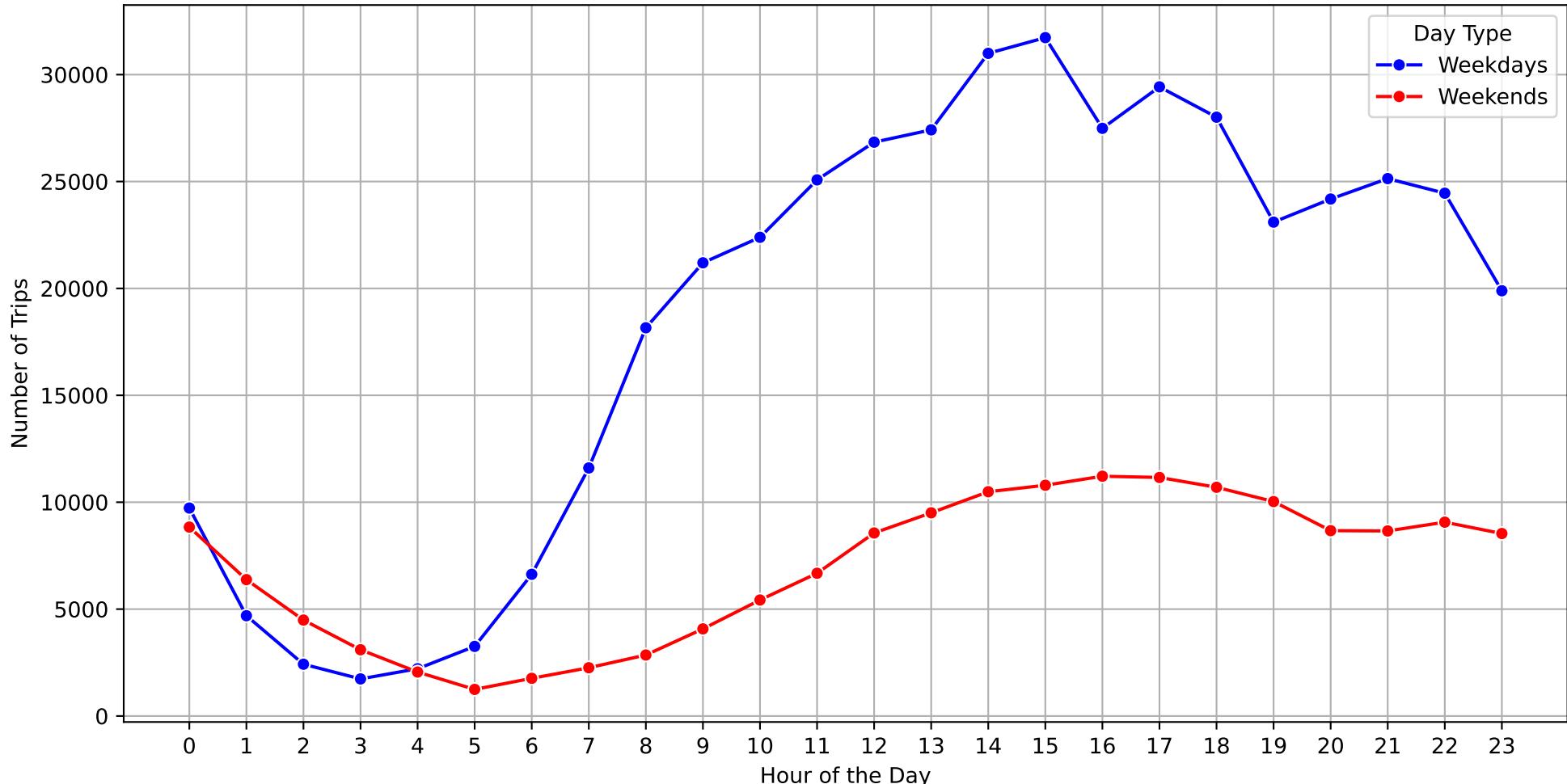
Weekday Trends (Blue Line):

- Morning rush between 7 AM - 10 AM due to office commuters.
- Increase in trips from noon to evening suggests people heading for lunch, meetings, or errands.
- Peak from 5 PM - 9 PM aligns with office closure and evening social activities.
- Drop after 10 PM as fewer people travel late at night.

Weekend Trends (Red Line):

- Fewer trips overall compared to weekdays.

Hourly Traffic Pattern: Weekdays vs. Weekends



Conclusion/Remarks:

Inference from the Hourly Traffic Patterns

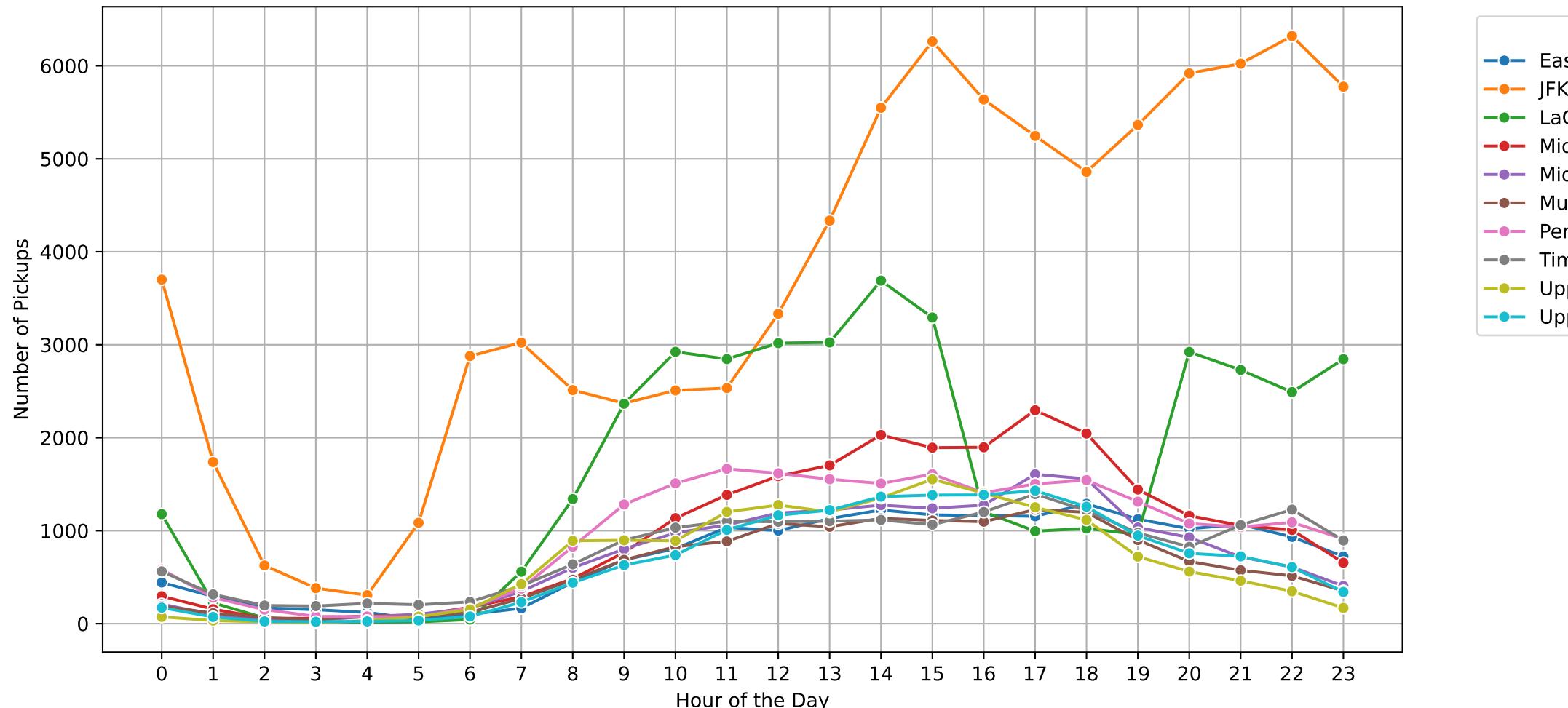
Weekday Trends (Blue Line)

There's a morning rush between 7 AM - 10 AM, likely due to office commuters.
A steady increase in trips from noon to evening suggests people heading for lunch, meetings, or errands.

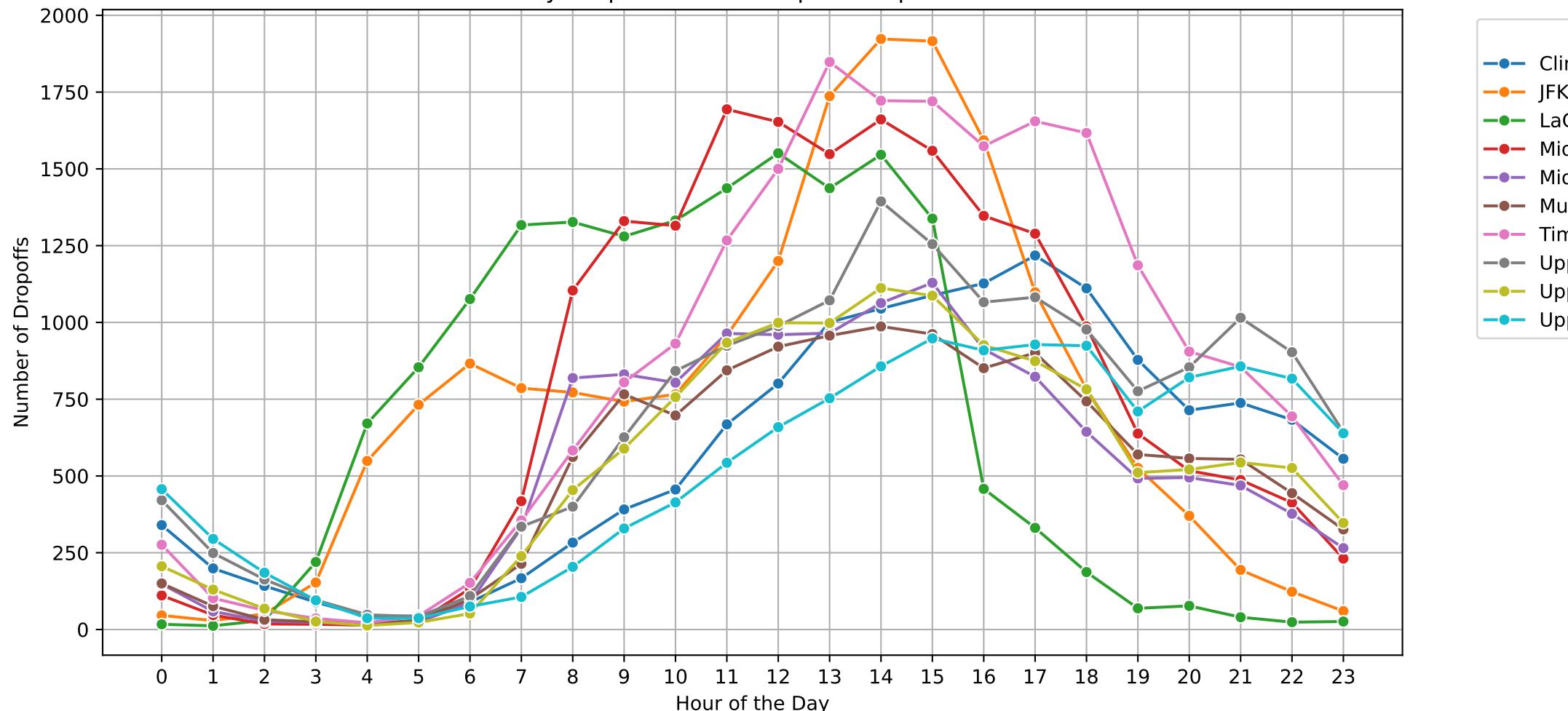
The peak occurs around 5 PM - 9 PM, which aligns with office closure and evening social activities.

A drop after 10 PM as fewer people travel late at night.

Hourly Pickup Trends in Top 10 Pickup Zones



Hourly Dropoff Trends in Top 10 Dropoff Zones

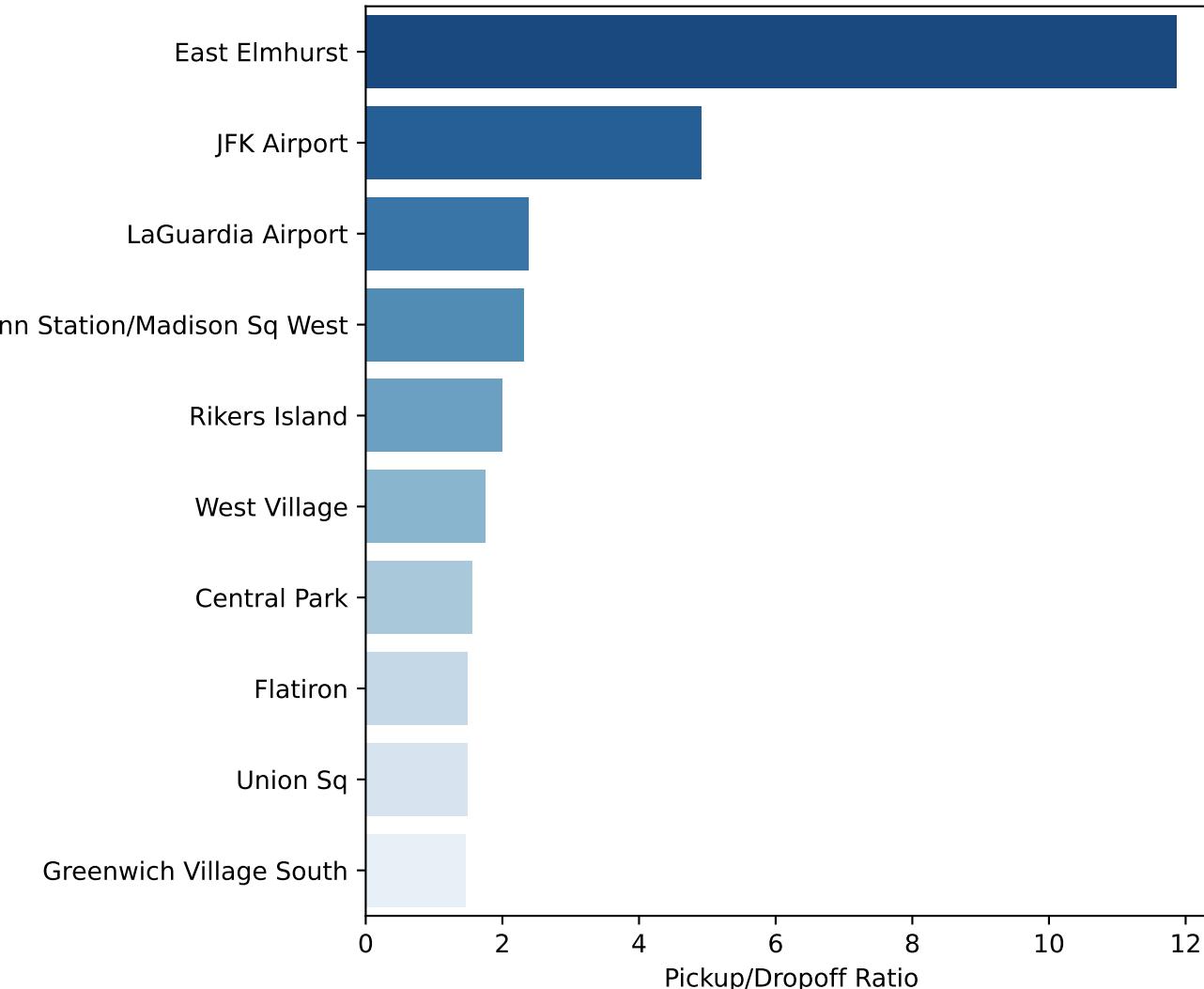


Conclusion/Remarks:

3.2.5 Showing Top 10 Pickup and Dropoff Zones, Throughout the Day, Hour Wise in Line plot.
Aroung 15:00 PM both are high

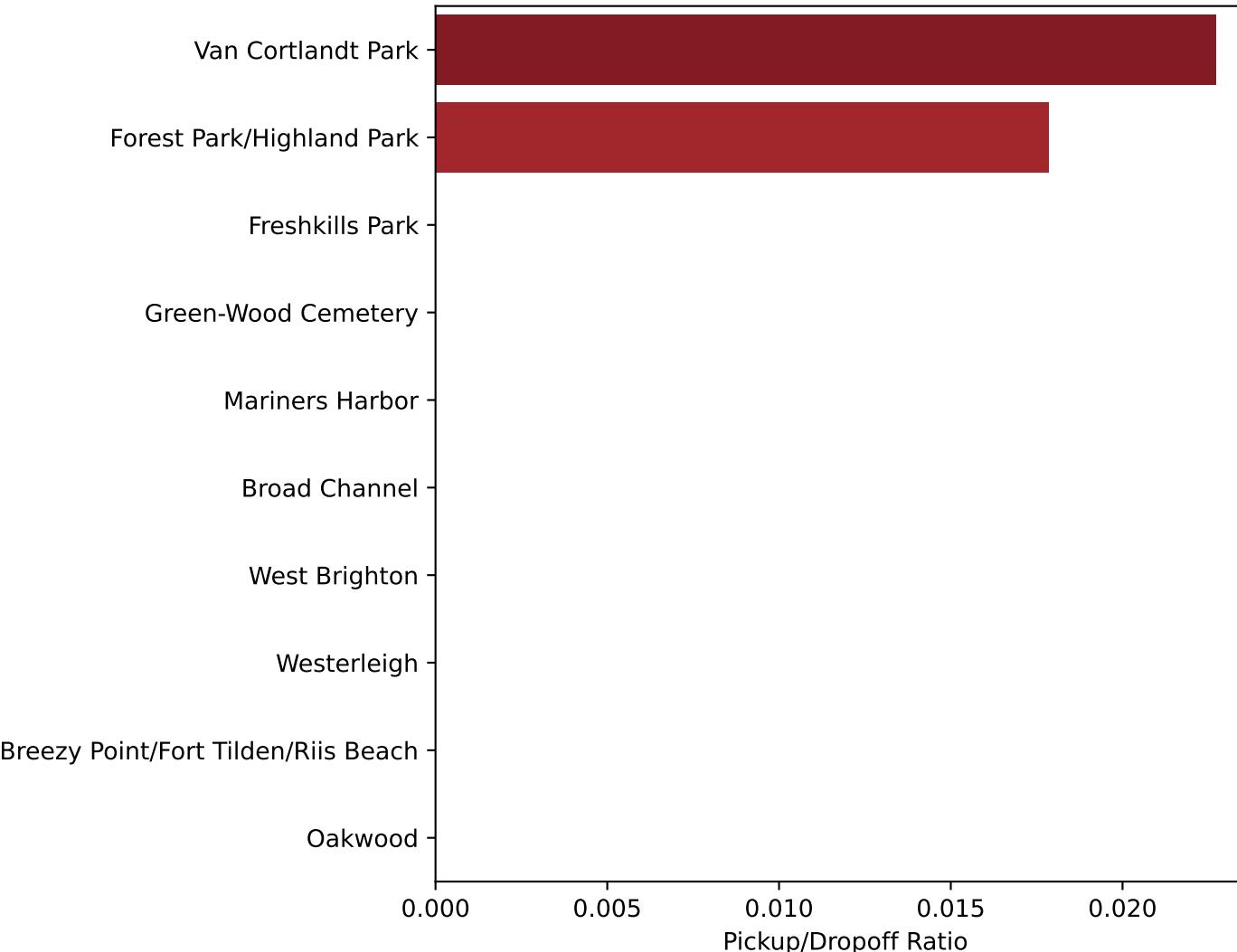
Top 10 Zones with Highest Pickup/Dropoff Ratio

Zone



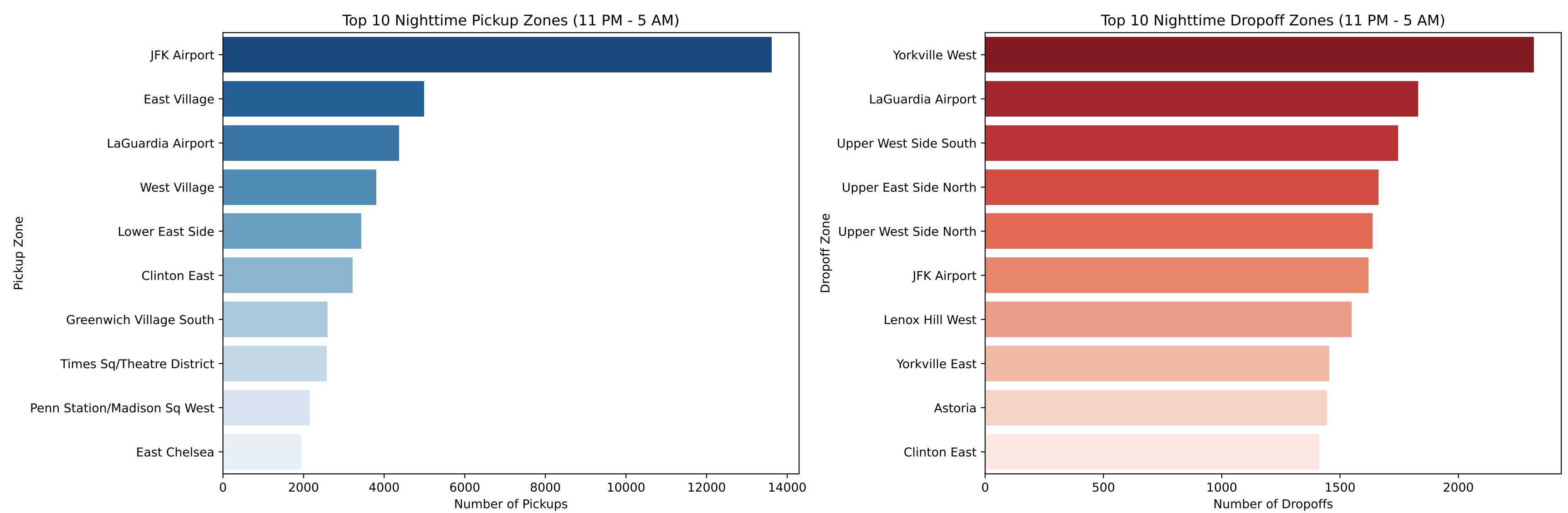
Bottom 10 Zones with Lowest Pickup/Dropoff Ratio

Zone



Conclusion/Remarks:

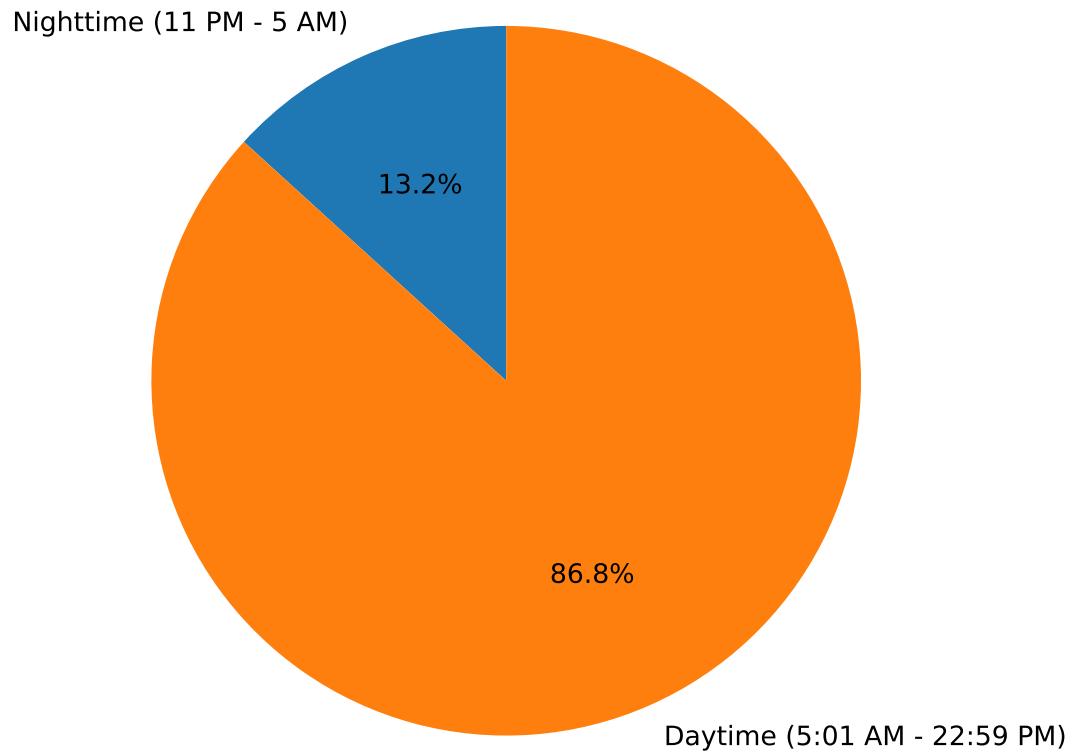
3.2.6 Showing Top & Botth 10 Pickup and Dropoff Ratio. East Elmhurstis the heighest and Forest Park/Highland Park is the lowest



Conclusion/Remarks:

3.2.7 Showing Zones with high Pickup and Dropoff Between 11:00-17:00. JFK Airport the highest Pickup and Yorkville West is the highest Dropoff

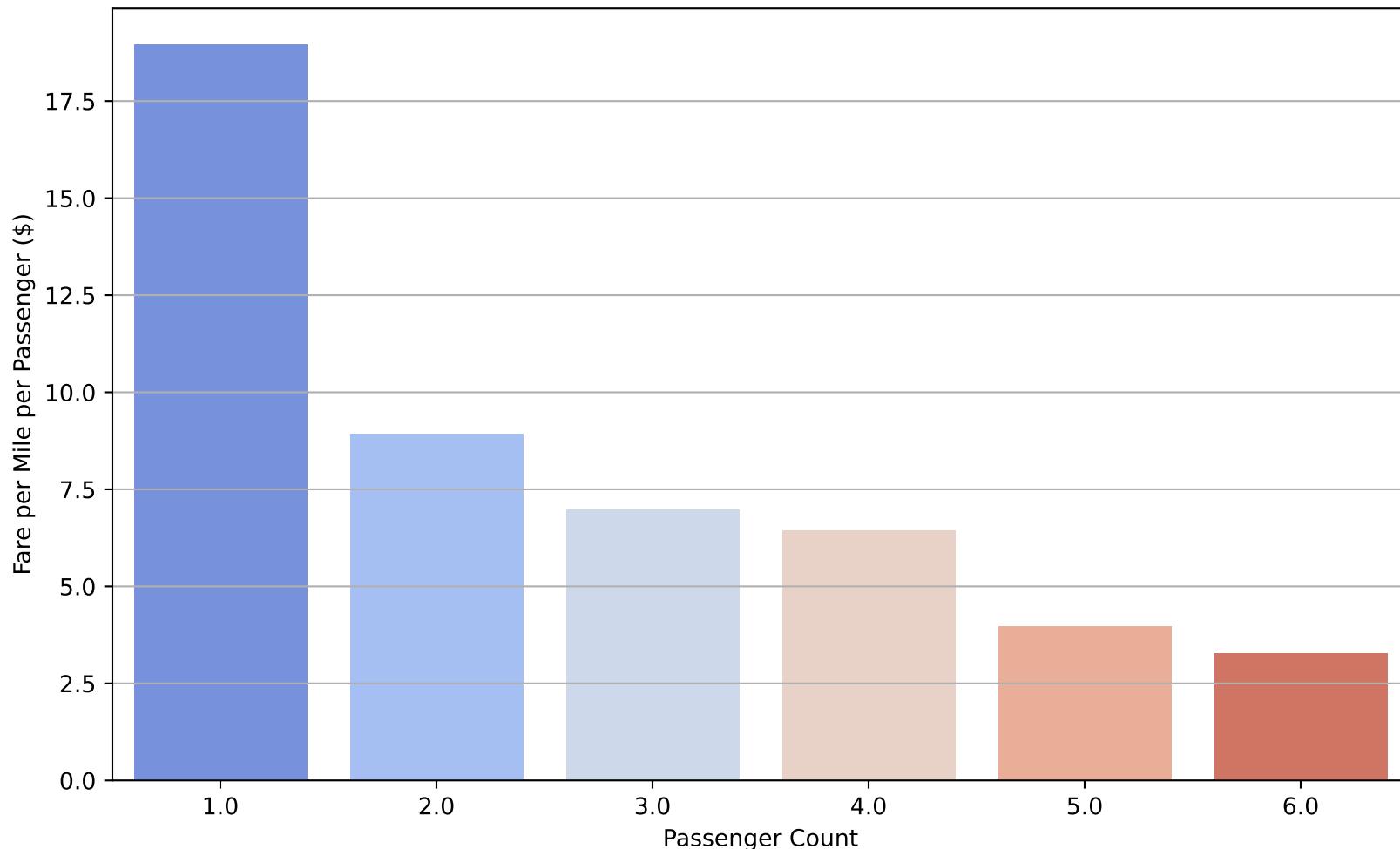
Revenue Share: Nighttime vs. Daytime



Conclusion/Remarks:

3.2.8 Showing the revenue share for nighttime and daytime hours. 86.8% in day time

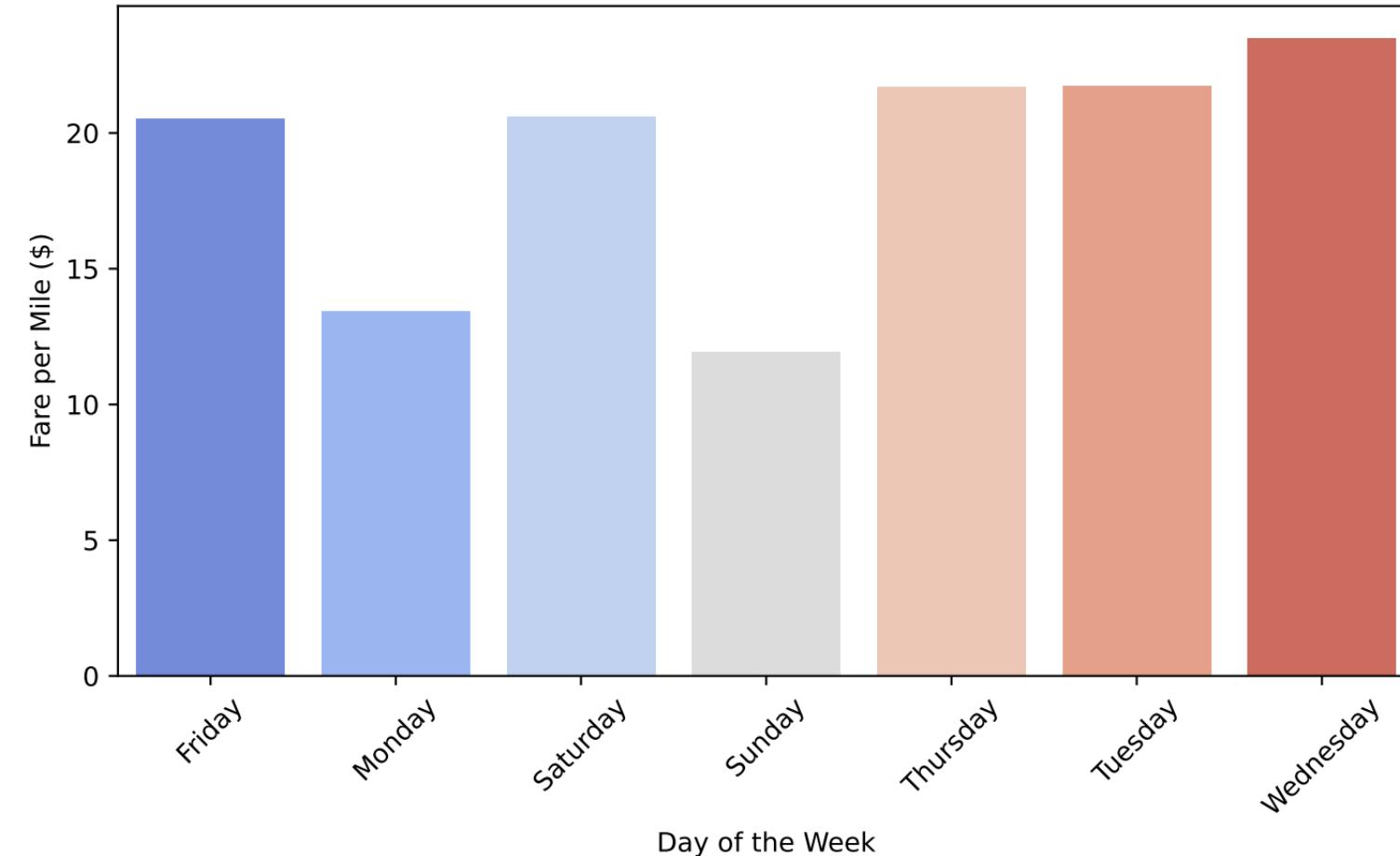
Average Fare per Mile per Passenger



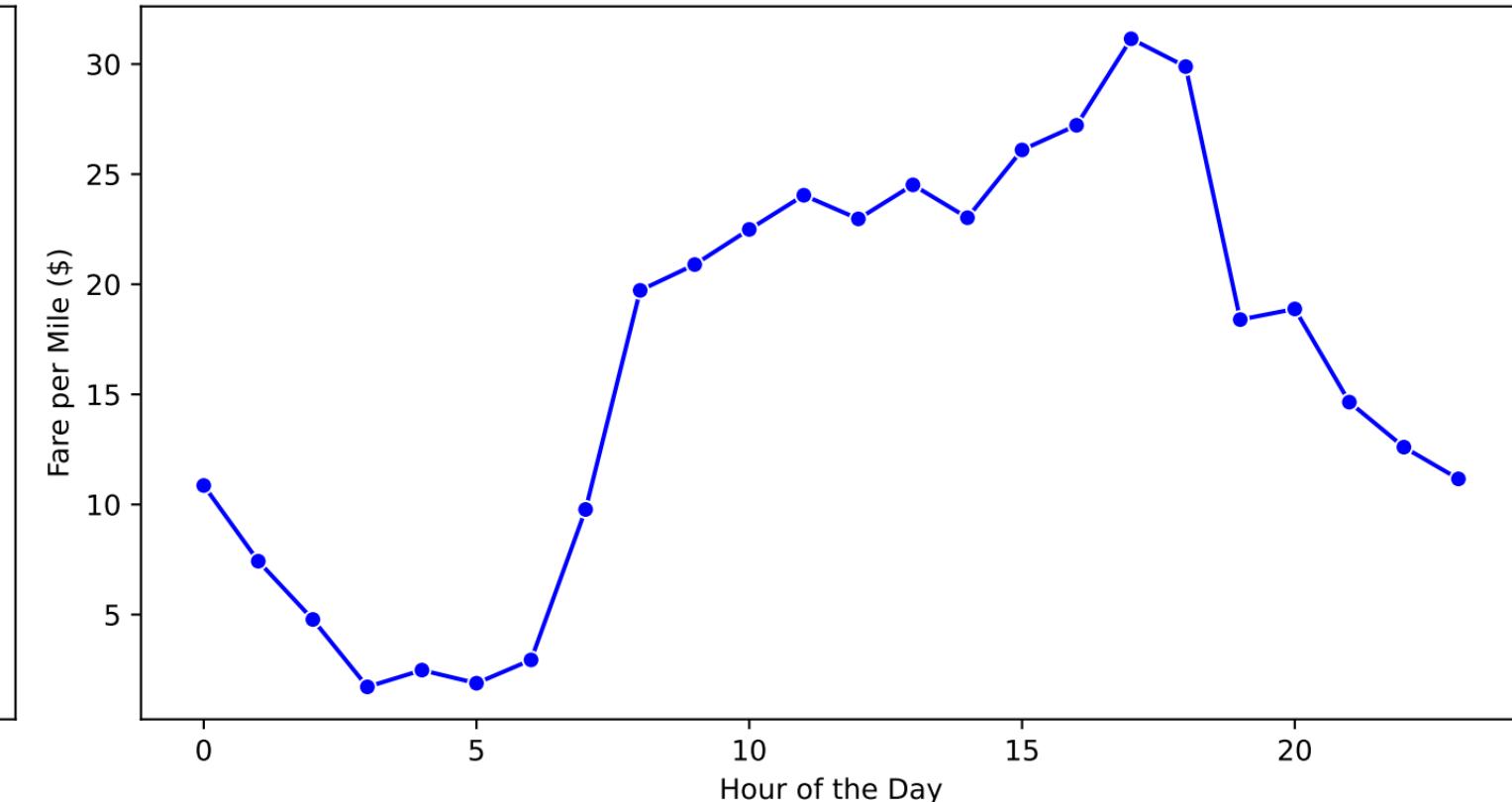
Conclusion/Remarks:

3.2.9 Showing the different passengercount and fare per mile

Average Fare per Mile by Day of the Week



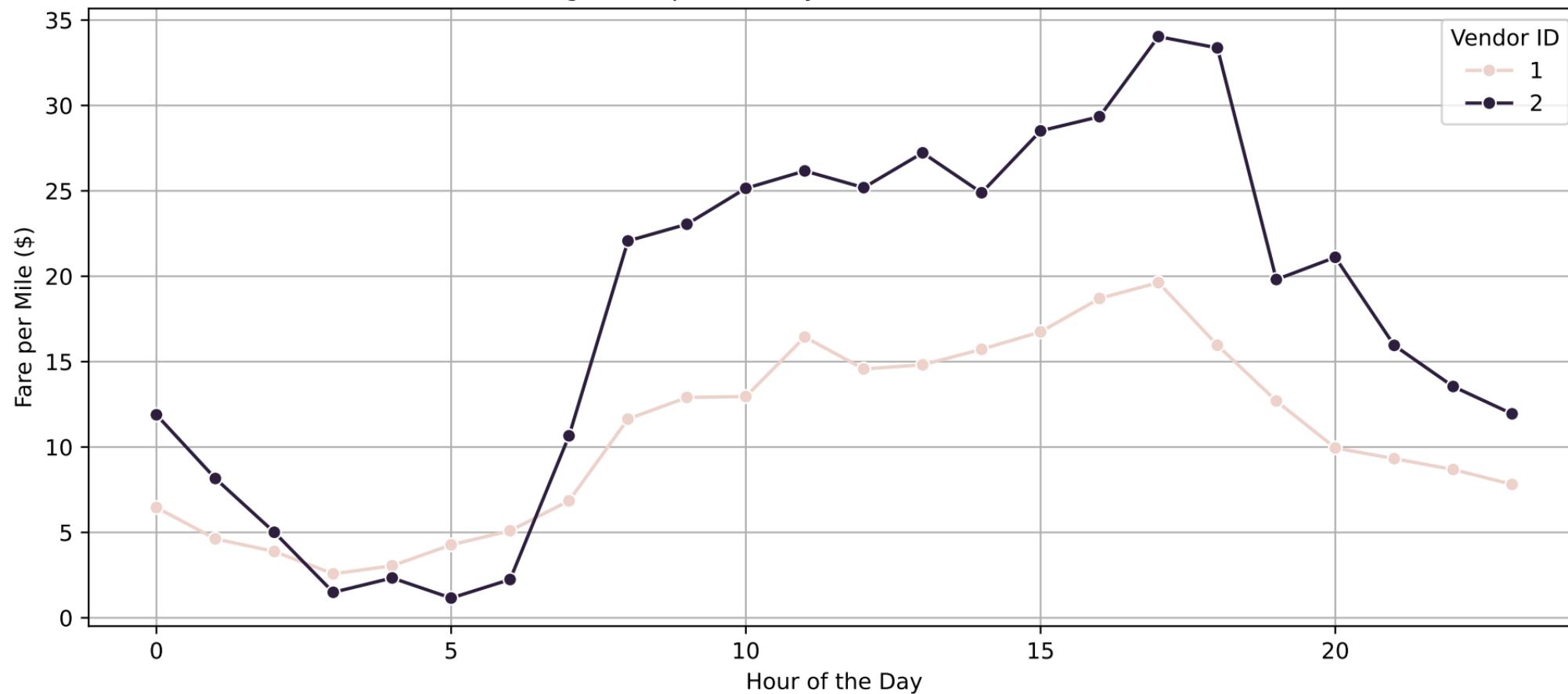
Average Fare per Mile by Hour of the Day



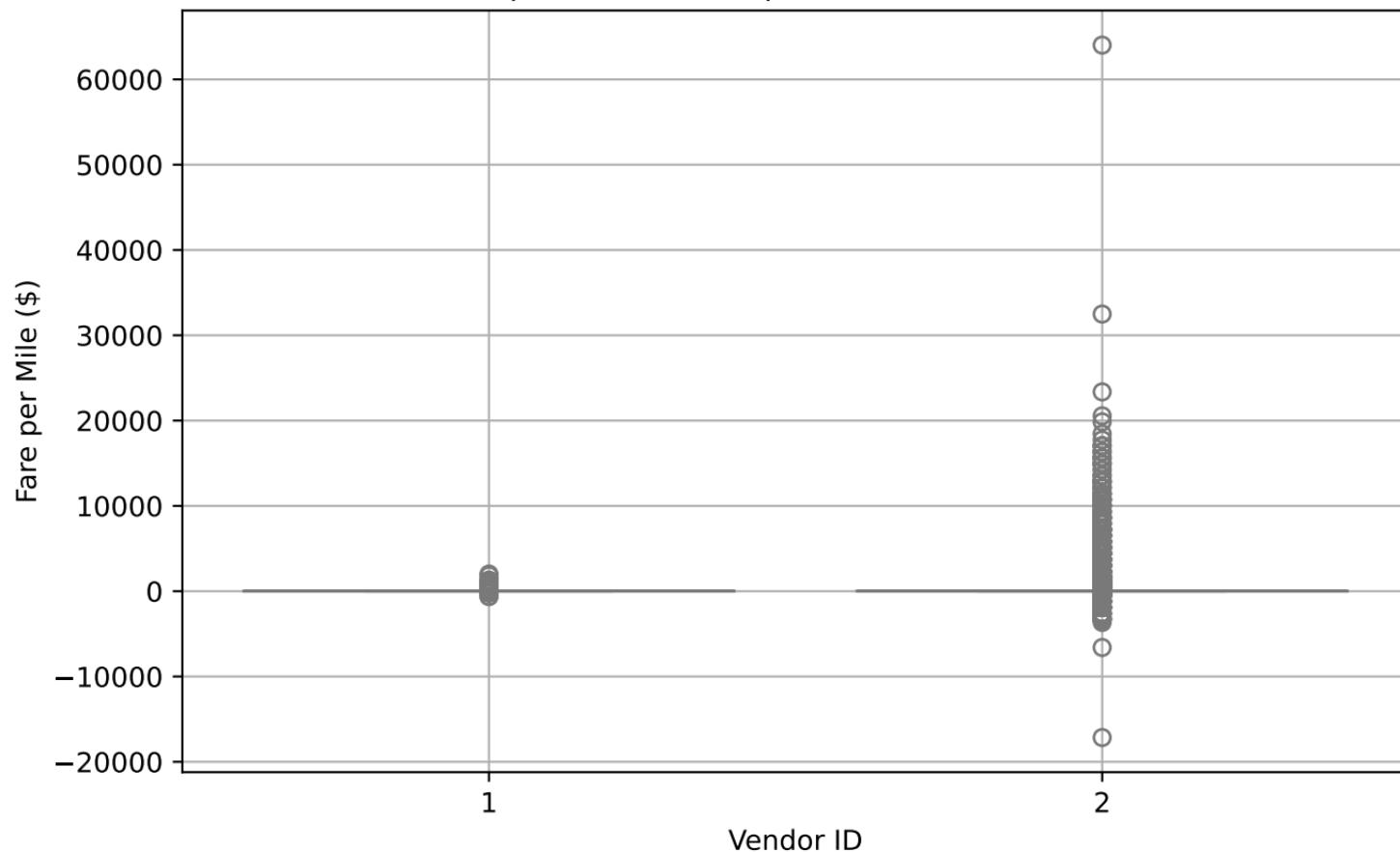
Conclusion/Remarks:

3.2.10 Showing the average fare per mile by hours of the day and by days of the week

Average Fare per Mile by Hour for Different Vendors



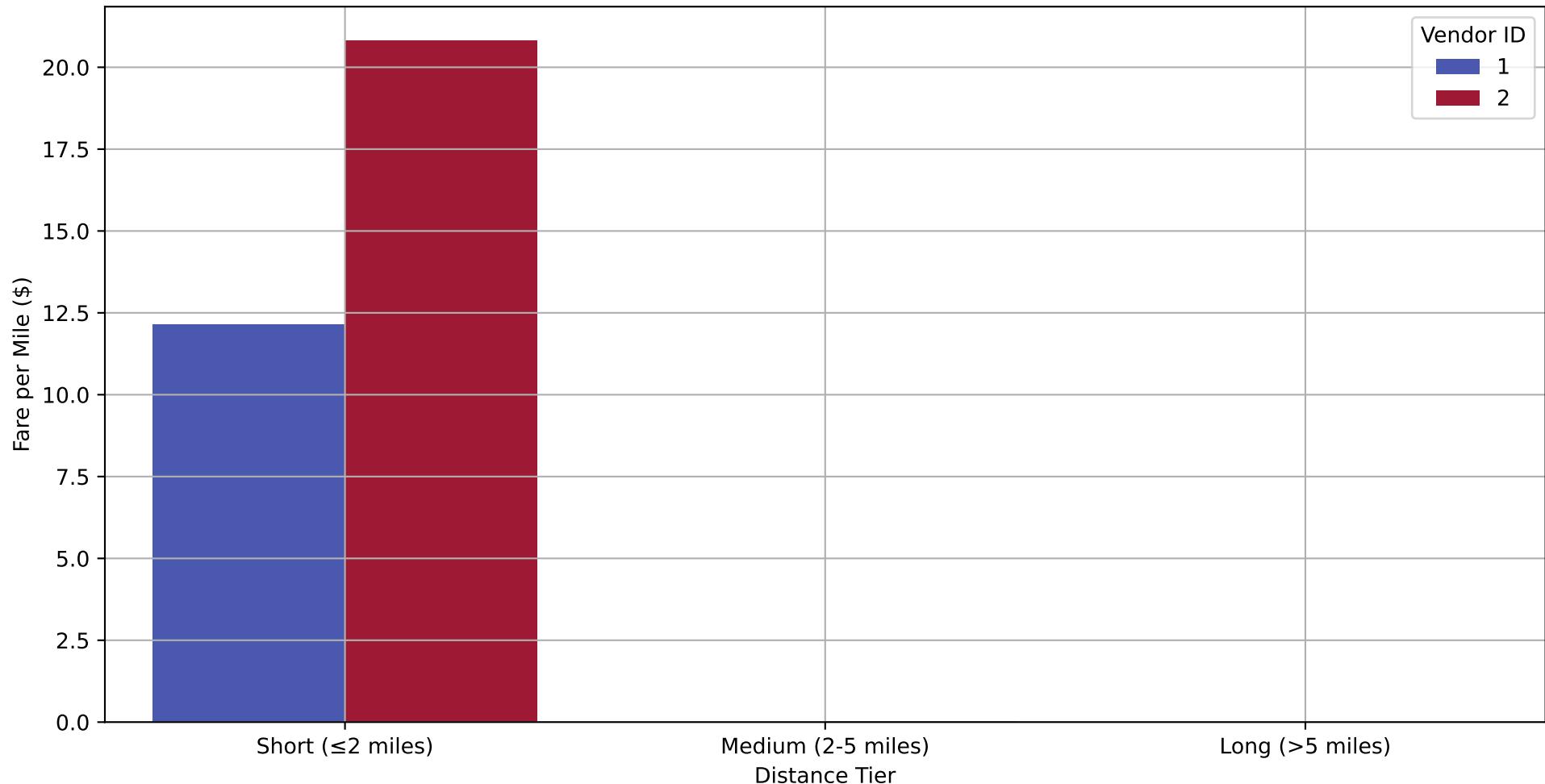
Comparison of Fare per Mile Across Vendors



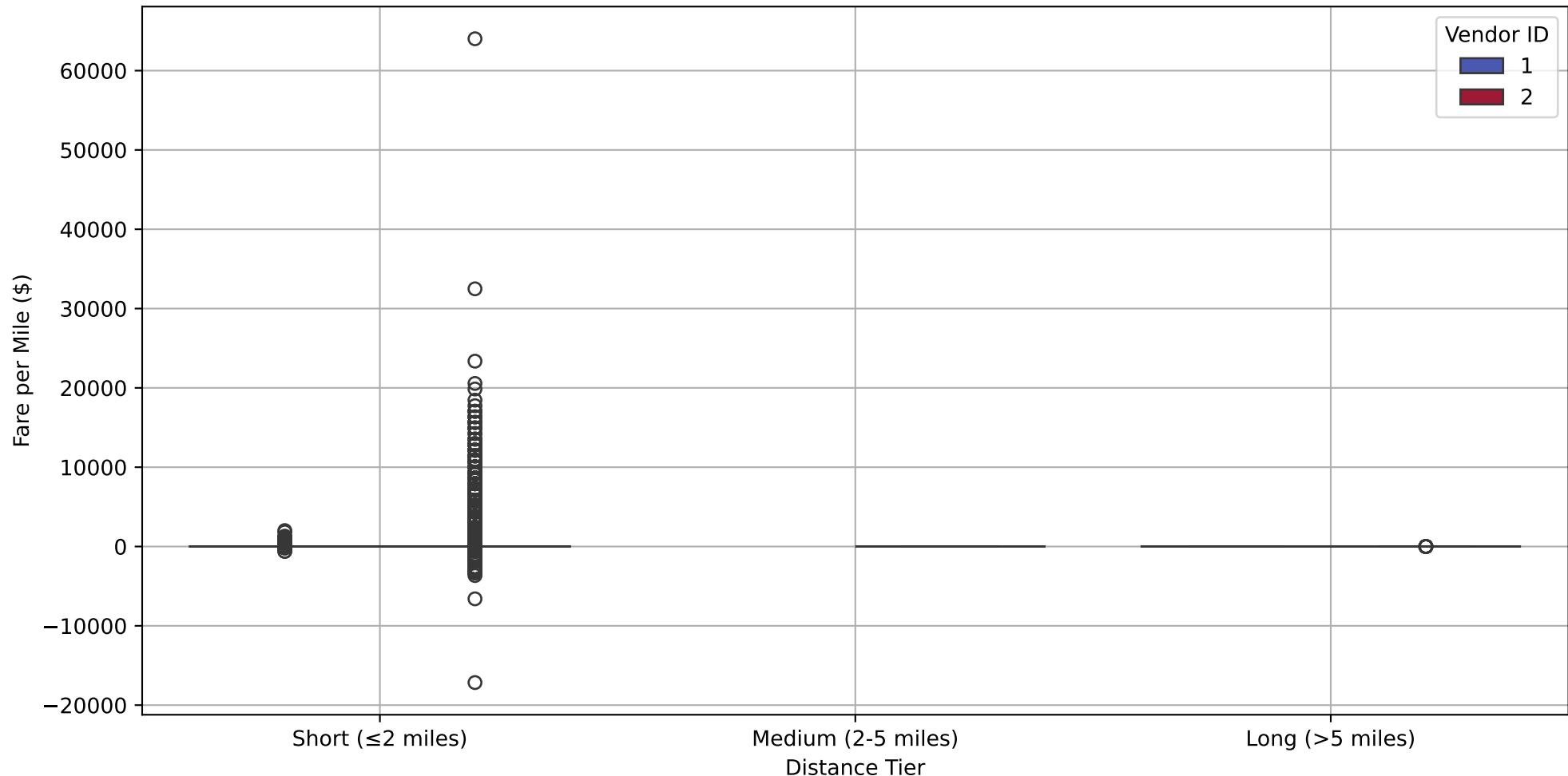
Conclusion/Remarks:

3.2.11 Showing Fare per mile rate for different vendors, throughout the day. Vendor 1 is cheaper.

Average Fare per Mile by Vendor Across Distance Tiers



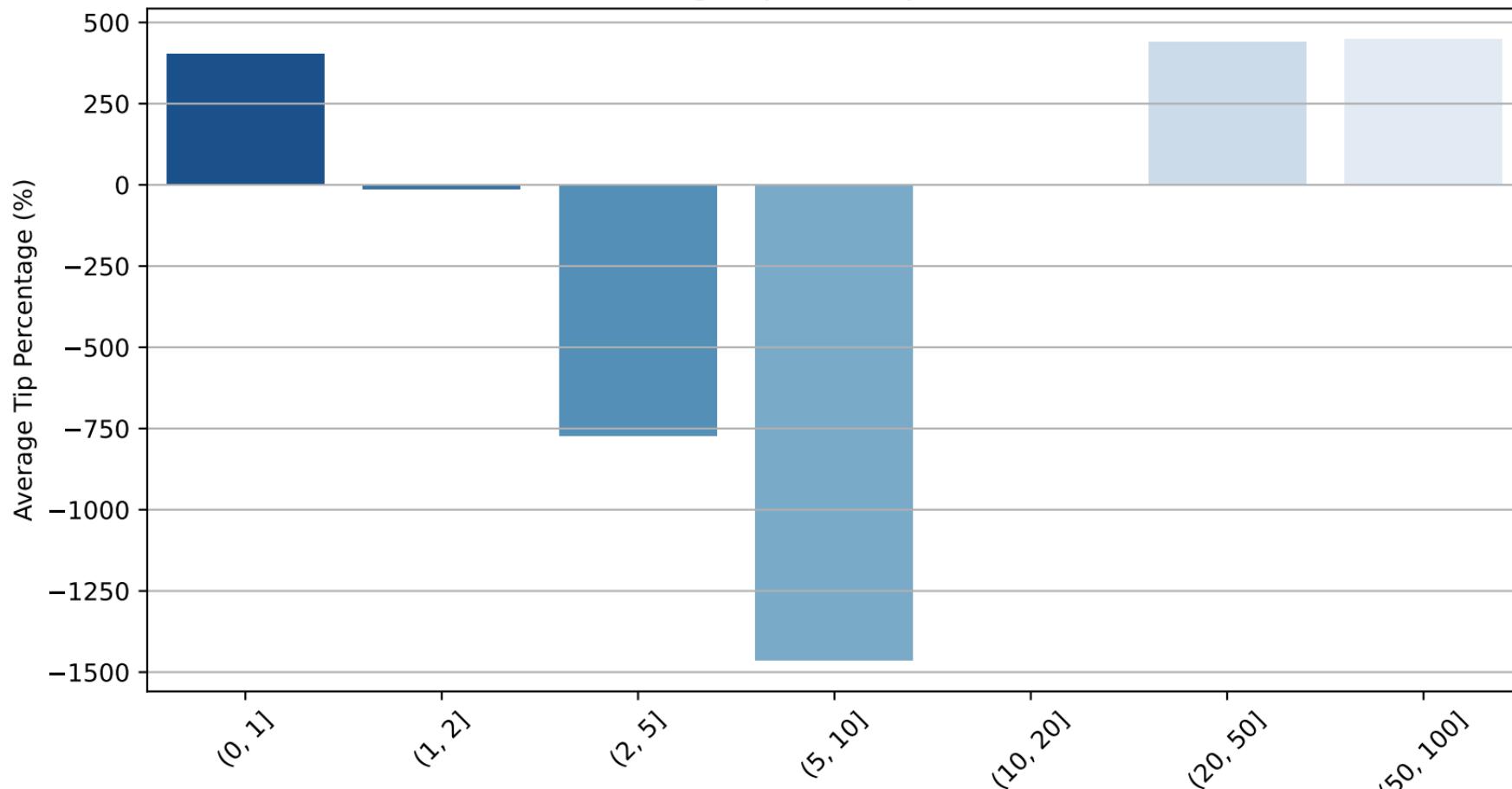
Distribution of Fare per Mile Across Vendors in Different Distance Tiers



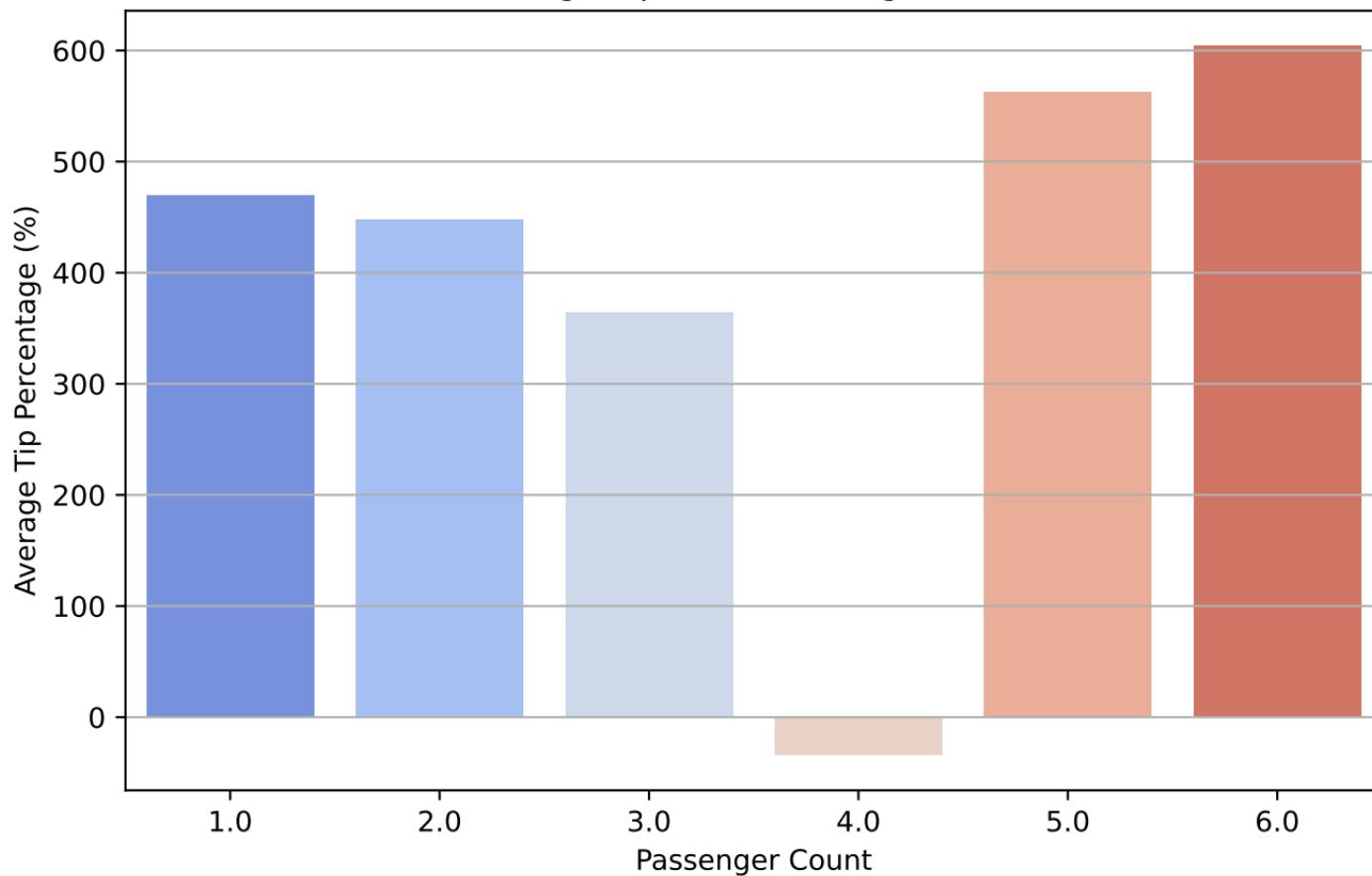
Conclusion/Remarks:

3.2.12 Showing the comparison of fare rates of the different vendors in a tiered fashion. Here is also vendor 1 is cheaper

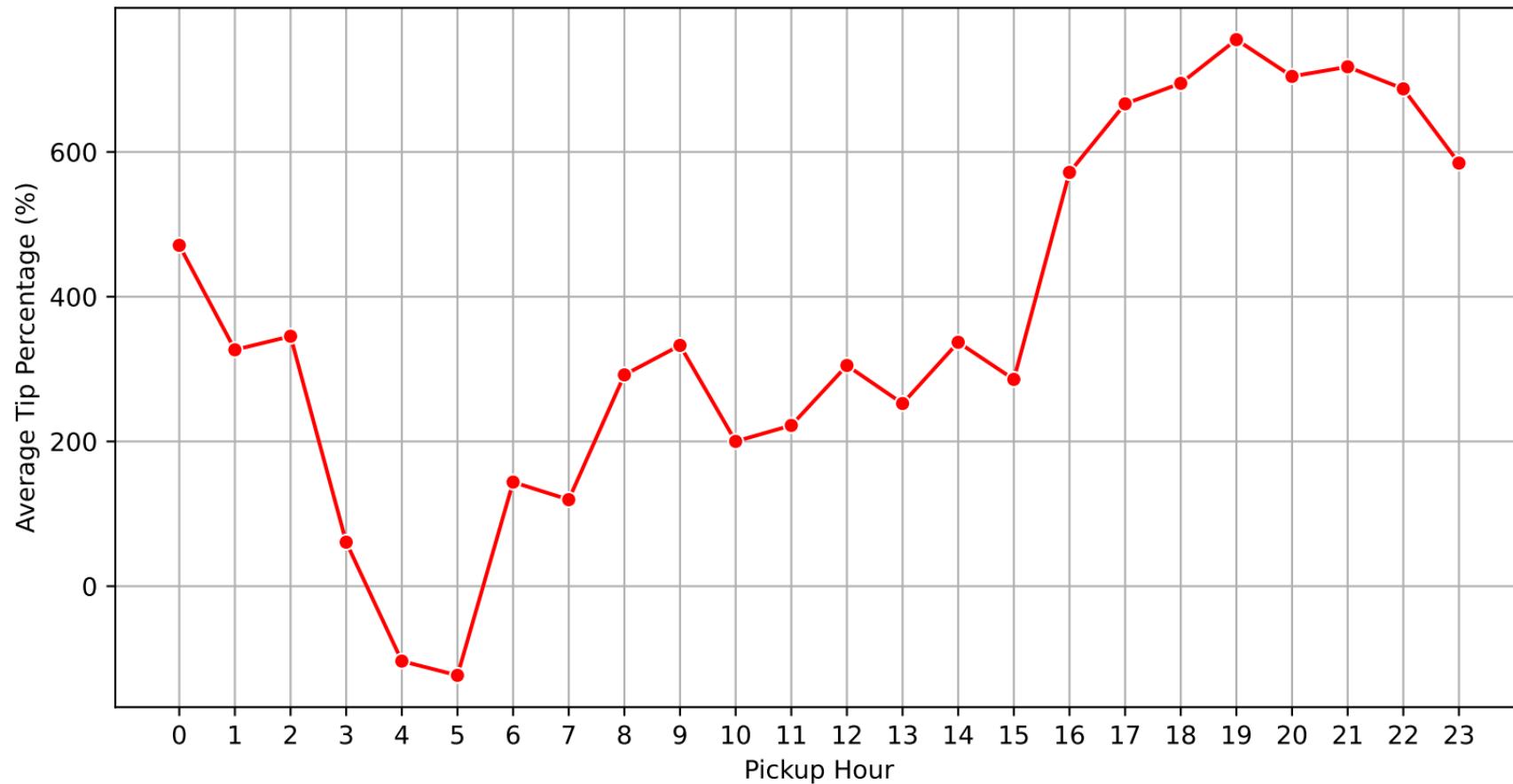
Average Tip % vs Trip Distance



Average Tip % vs Passenger Count



Average Tip % vs Pickup Time

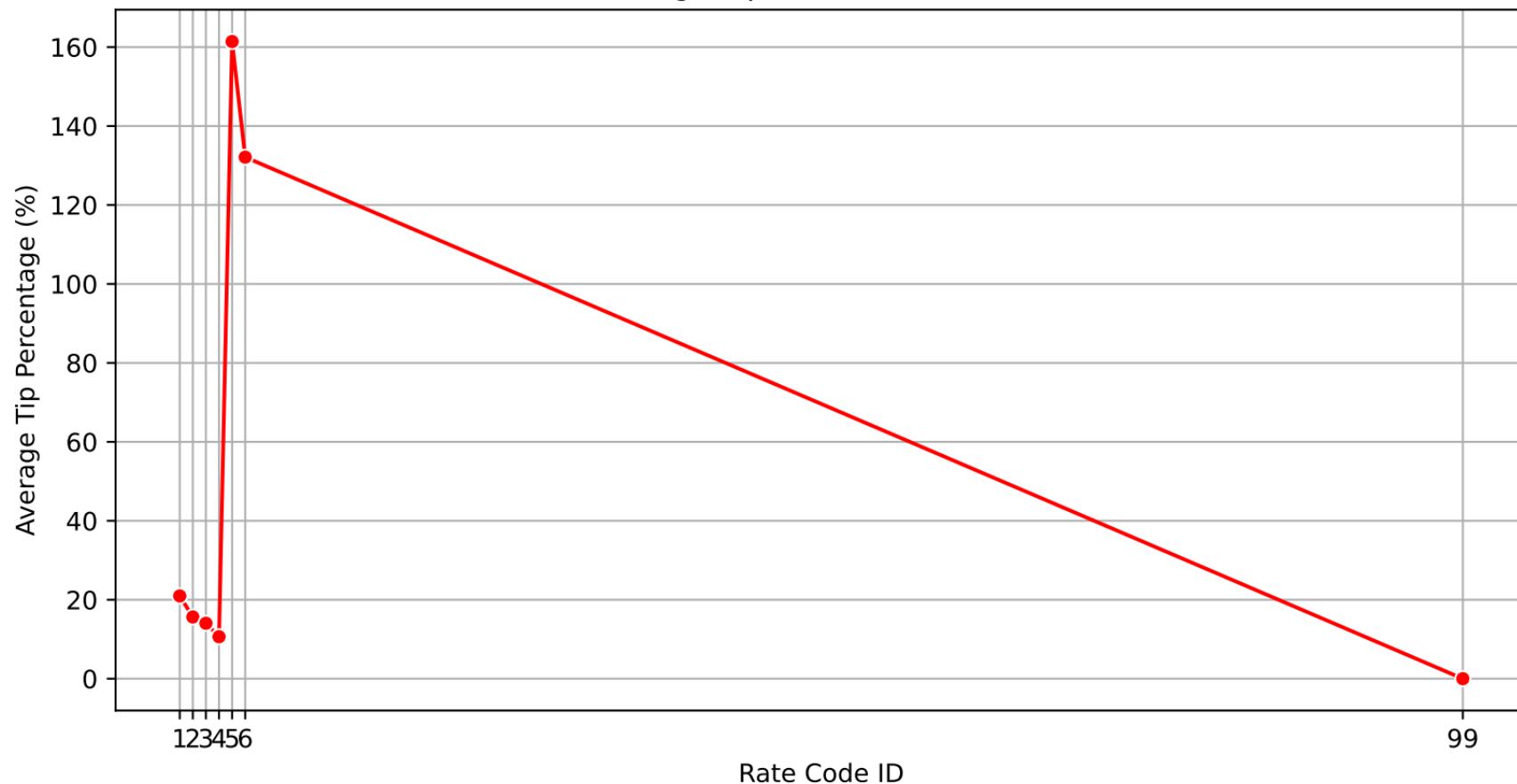


Conclusion/Remarks:

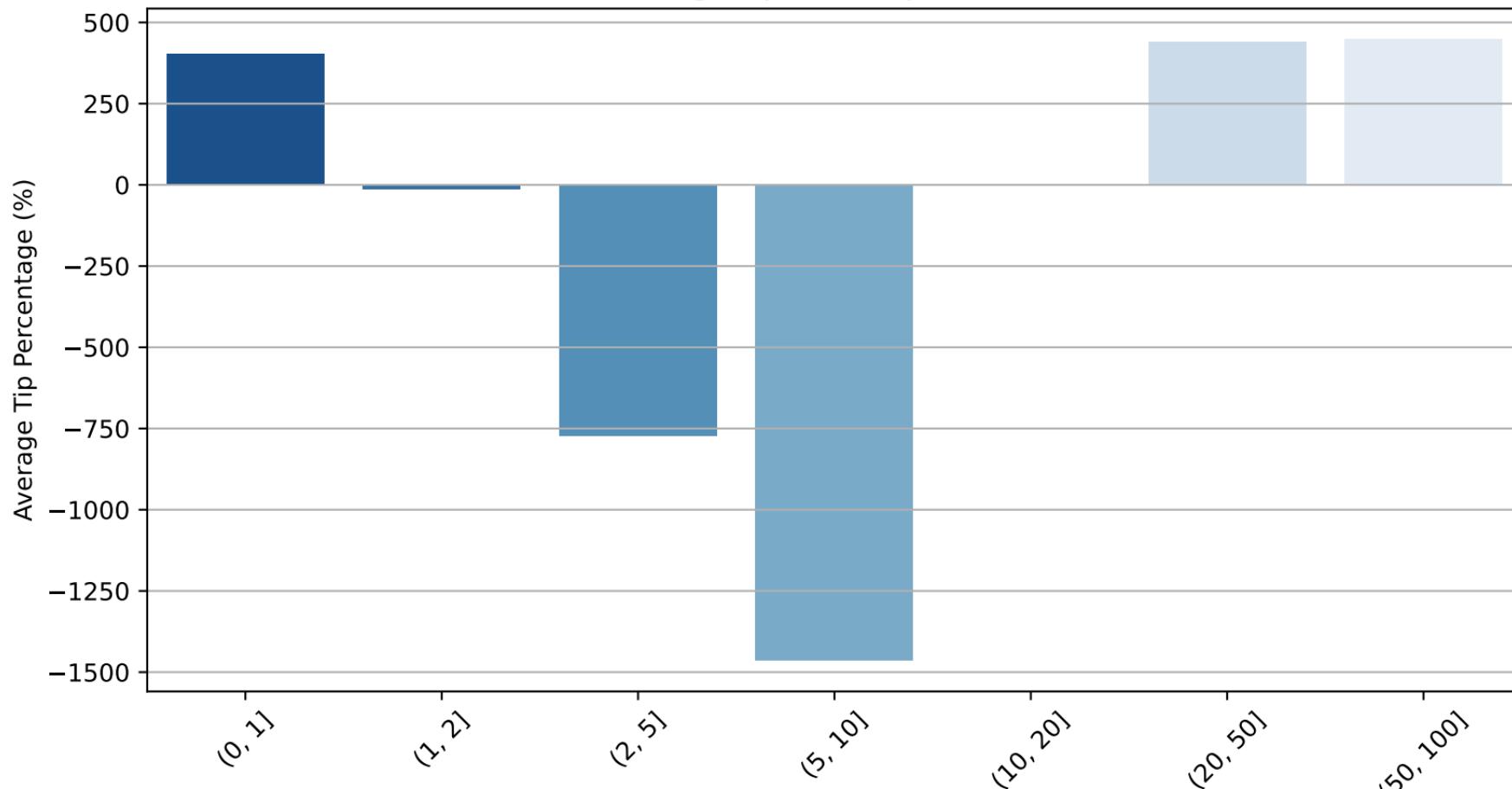
3.2.13 Showing analysis average tip percentages based on trip distances, passenger counts and time of pickup. Tips depends on factors like, Trip distance- between 2 to 20 mile very few tips, Hours - Between 3:30 to 5:00 AM no trips almostn

But I think there should be another factor which is ratecode

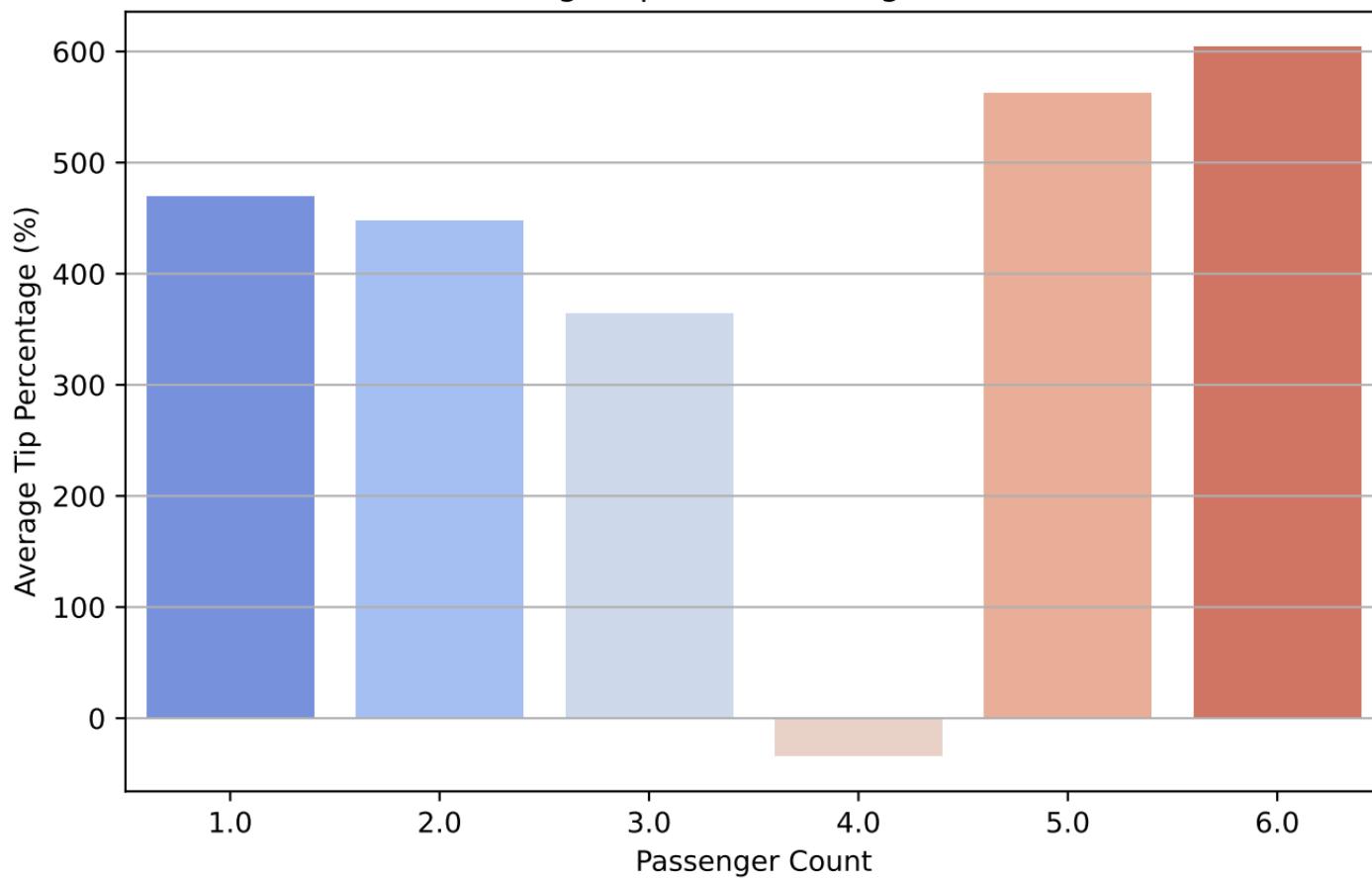
Average Tip % vs Rate Code ID



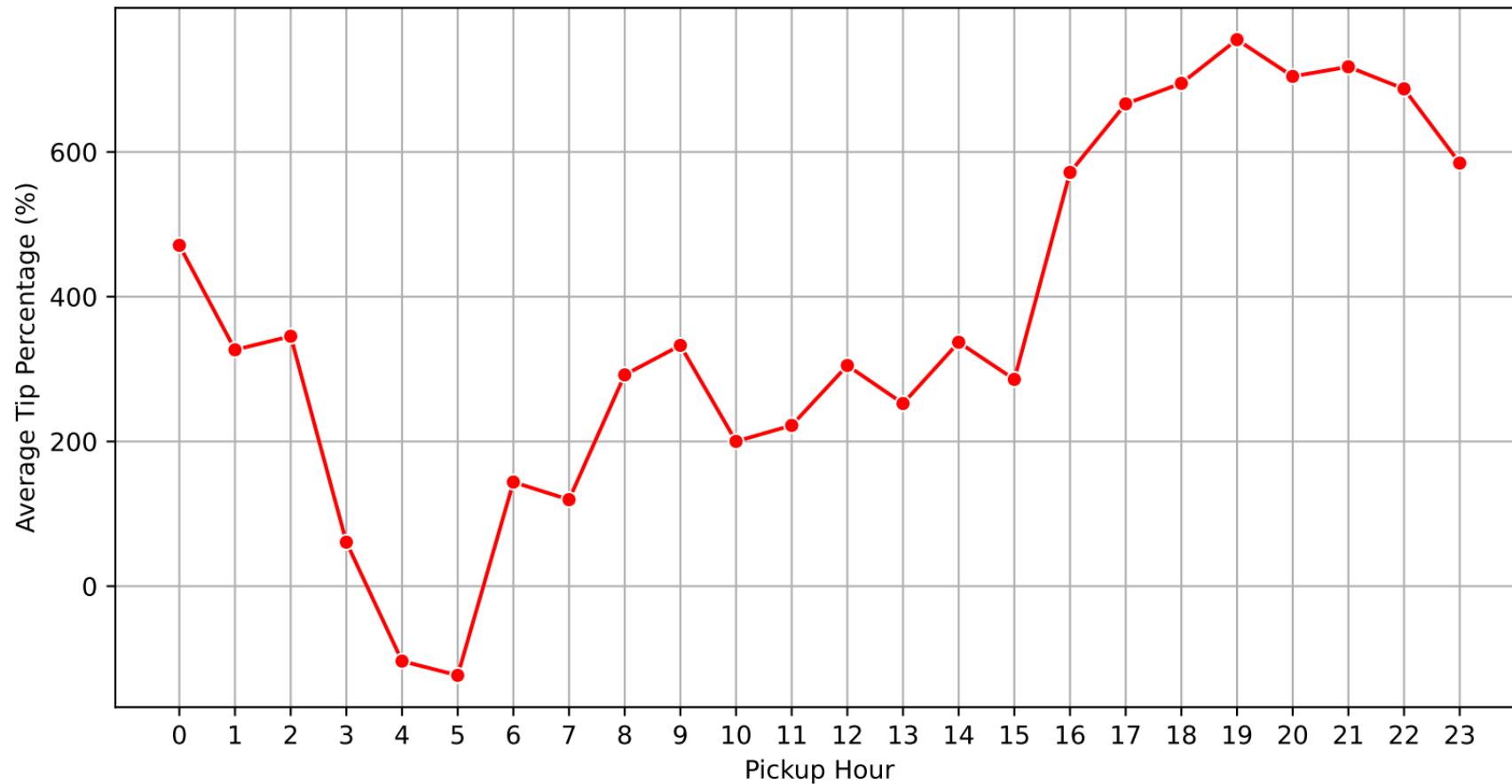
Average Tip % vs Trip Distance



Average Tip % vs Passenger Count



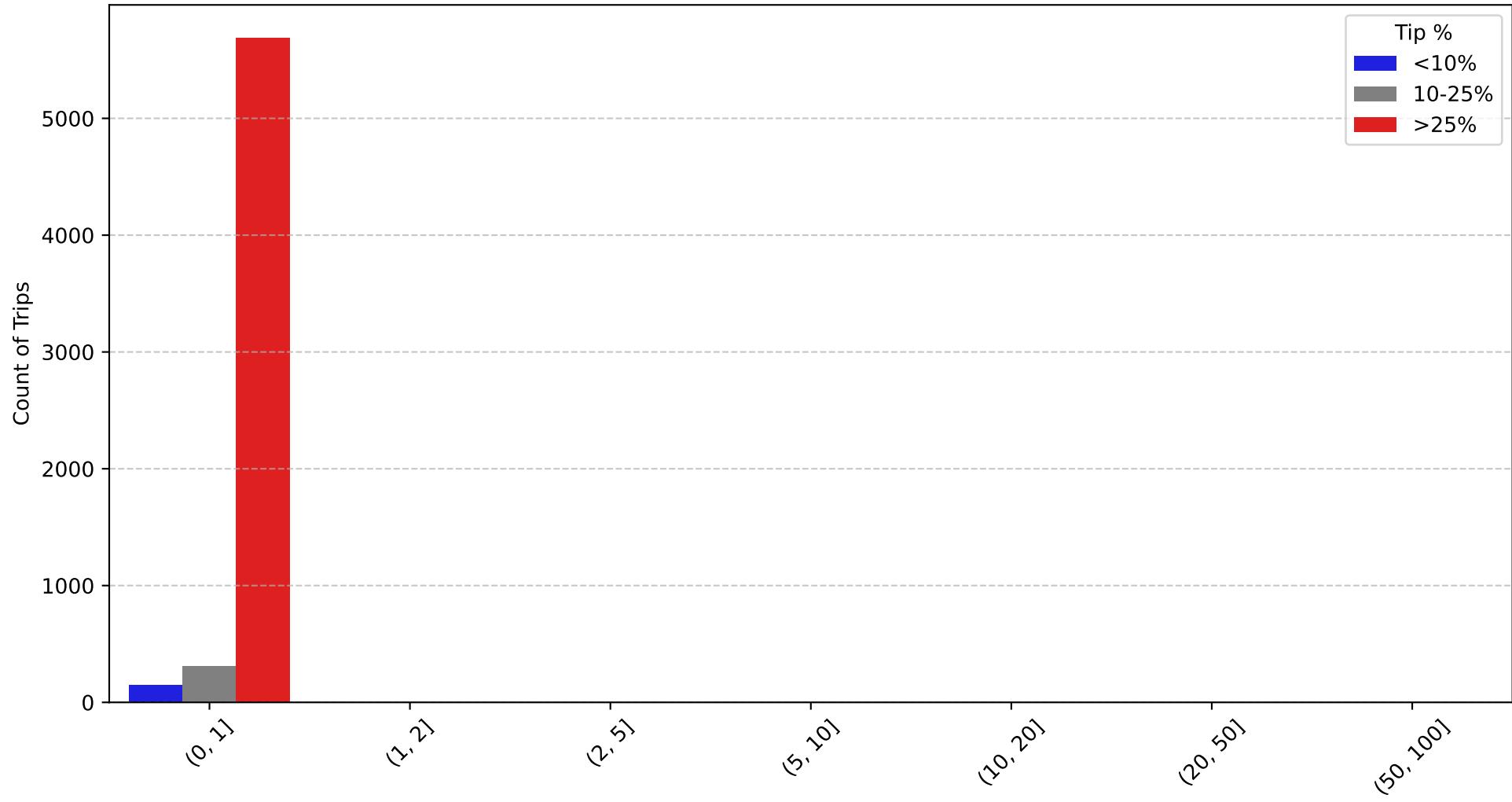
Average Tip % vs Pickup Time



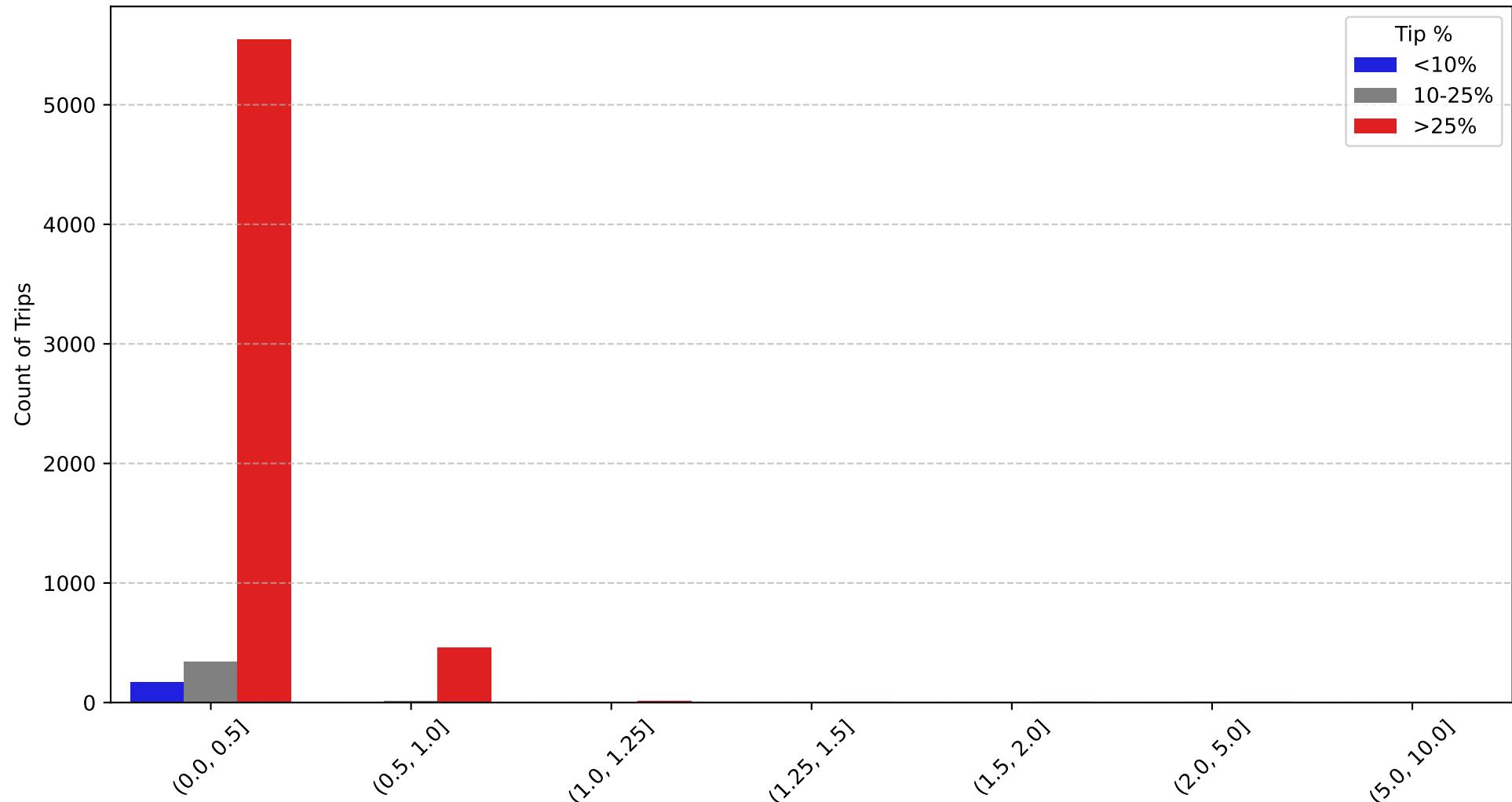
Conclusion/Remarks:

3.2.13 After analysing, it is clear that average tip is maximum for retecode 5, which is Negotiated fare

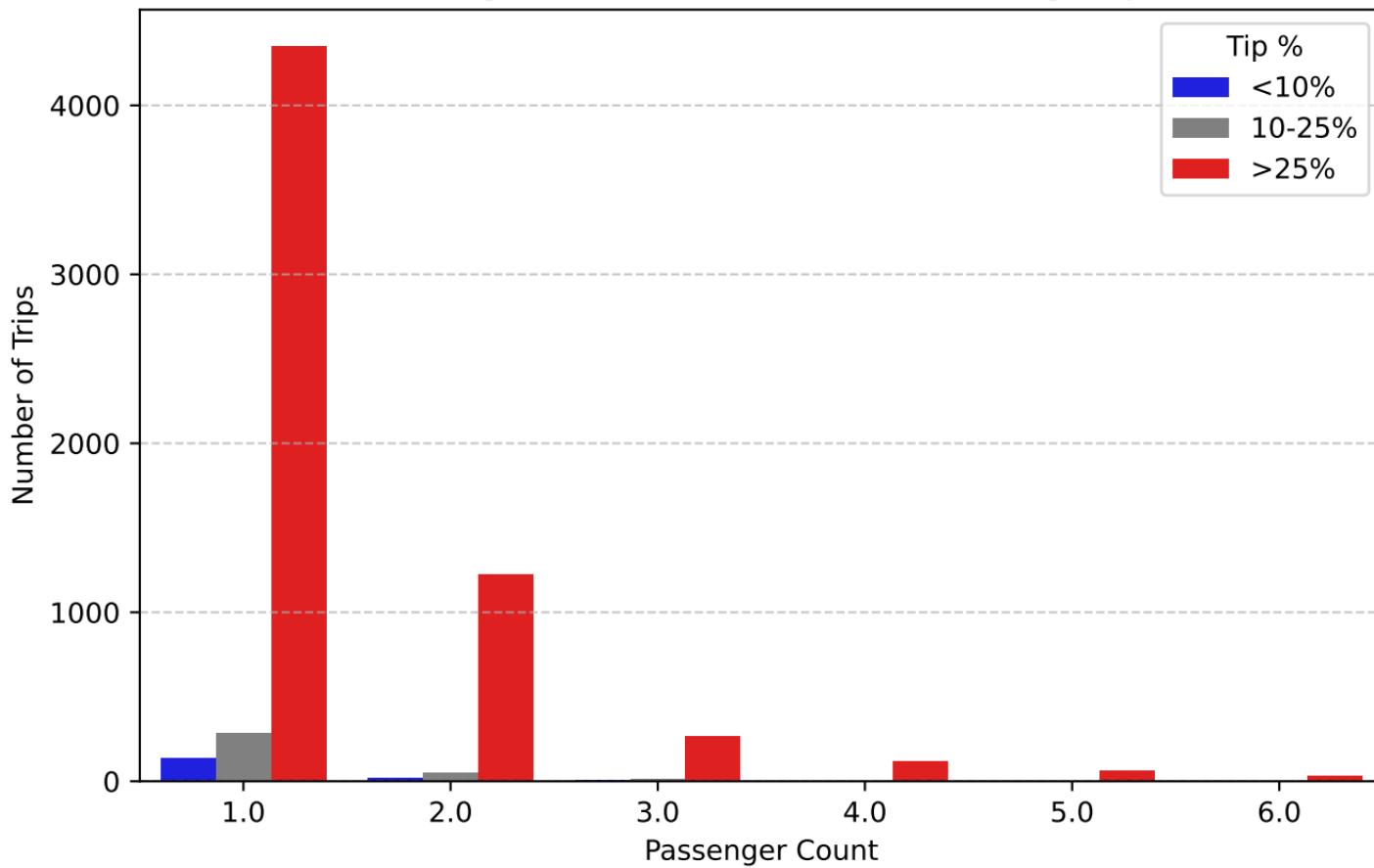
Trip Distance vs. Count of Trips (Colored by Tip Category)



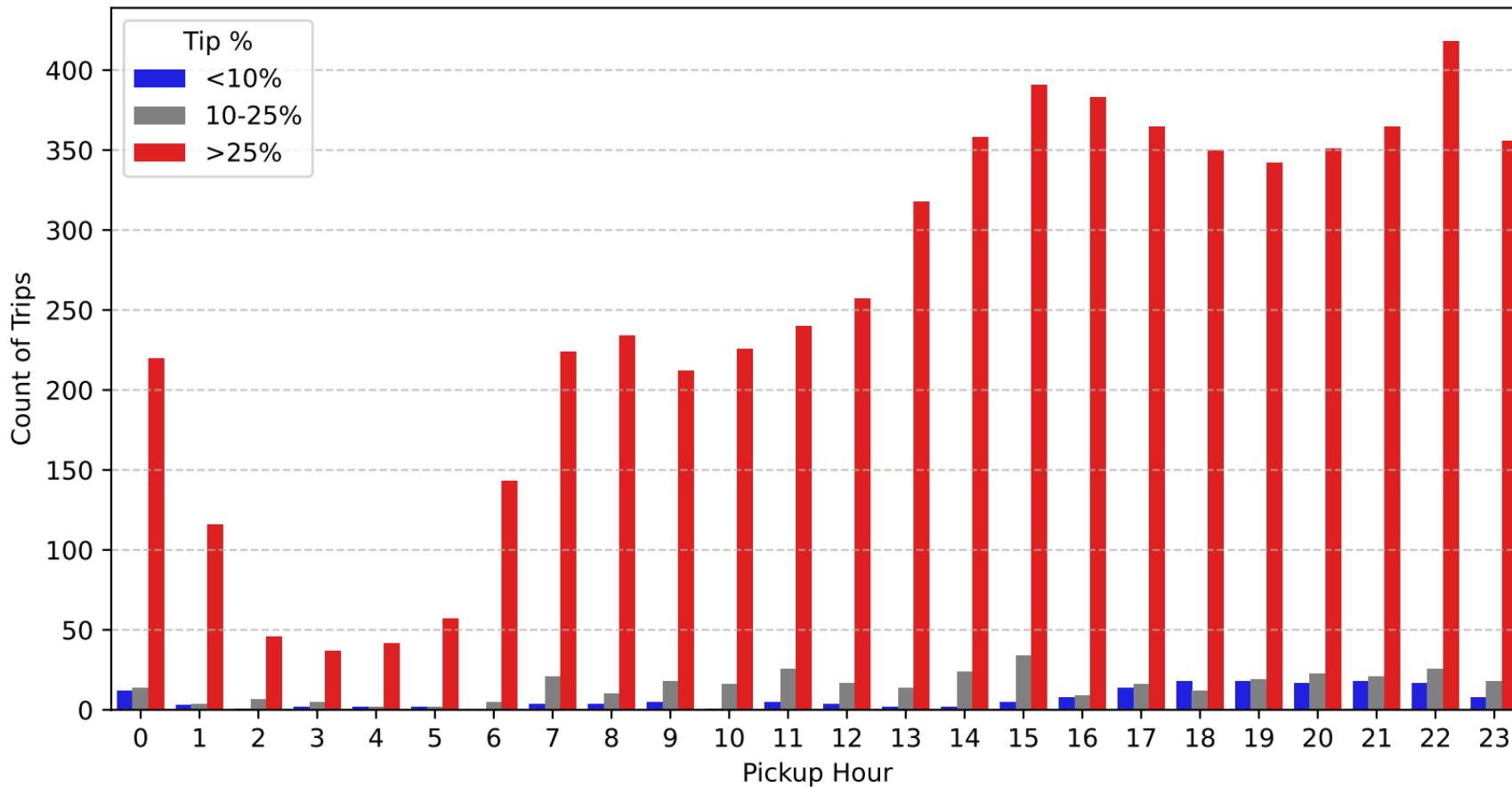
Fare Amount vs. Count of Trips (Colored by Tip Category)



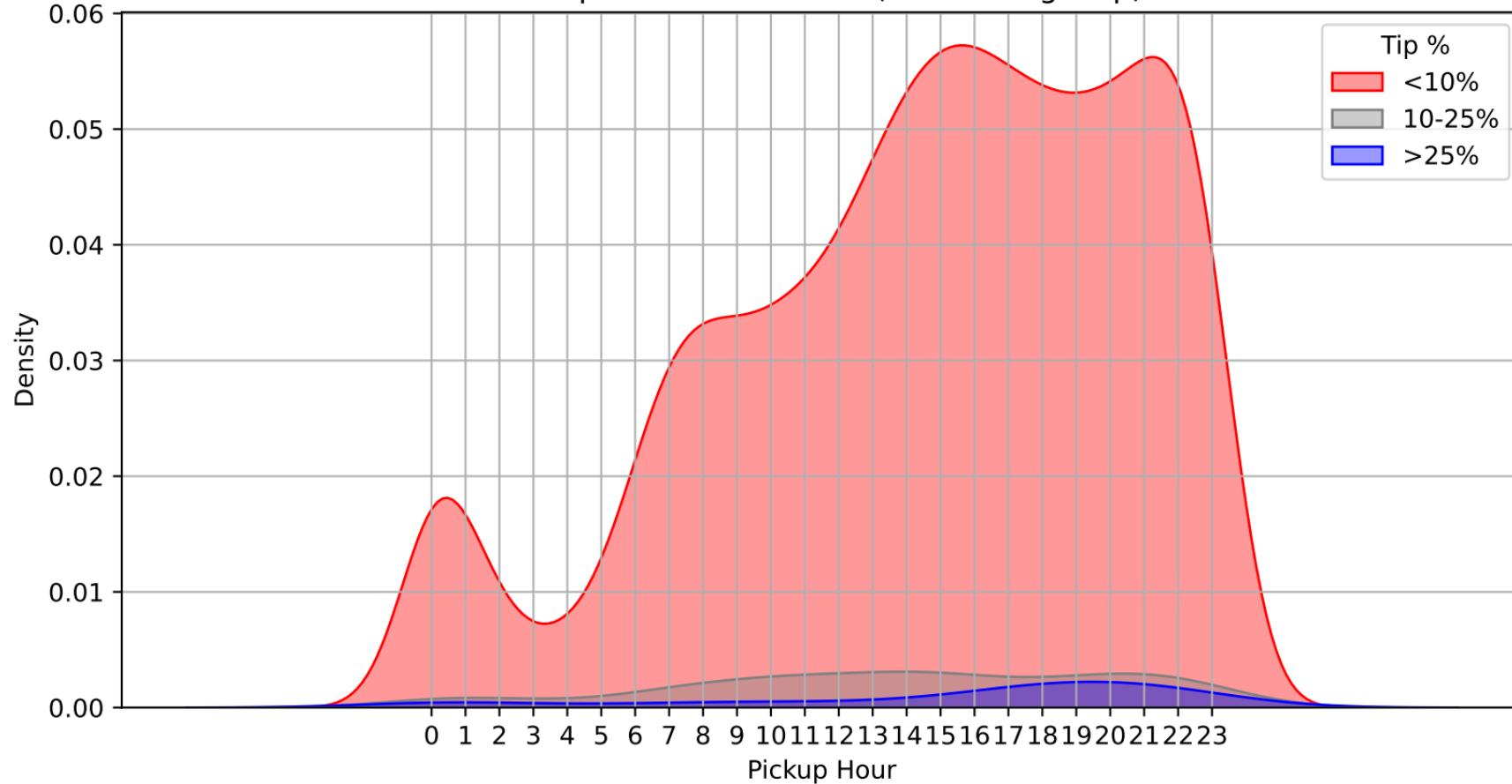
Passenger Count Distribution (Low vs. High Tip)



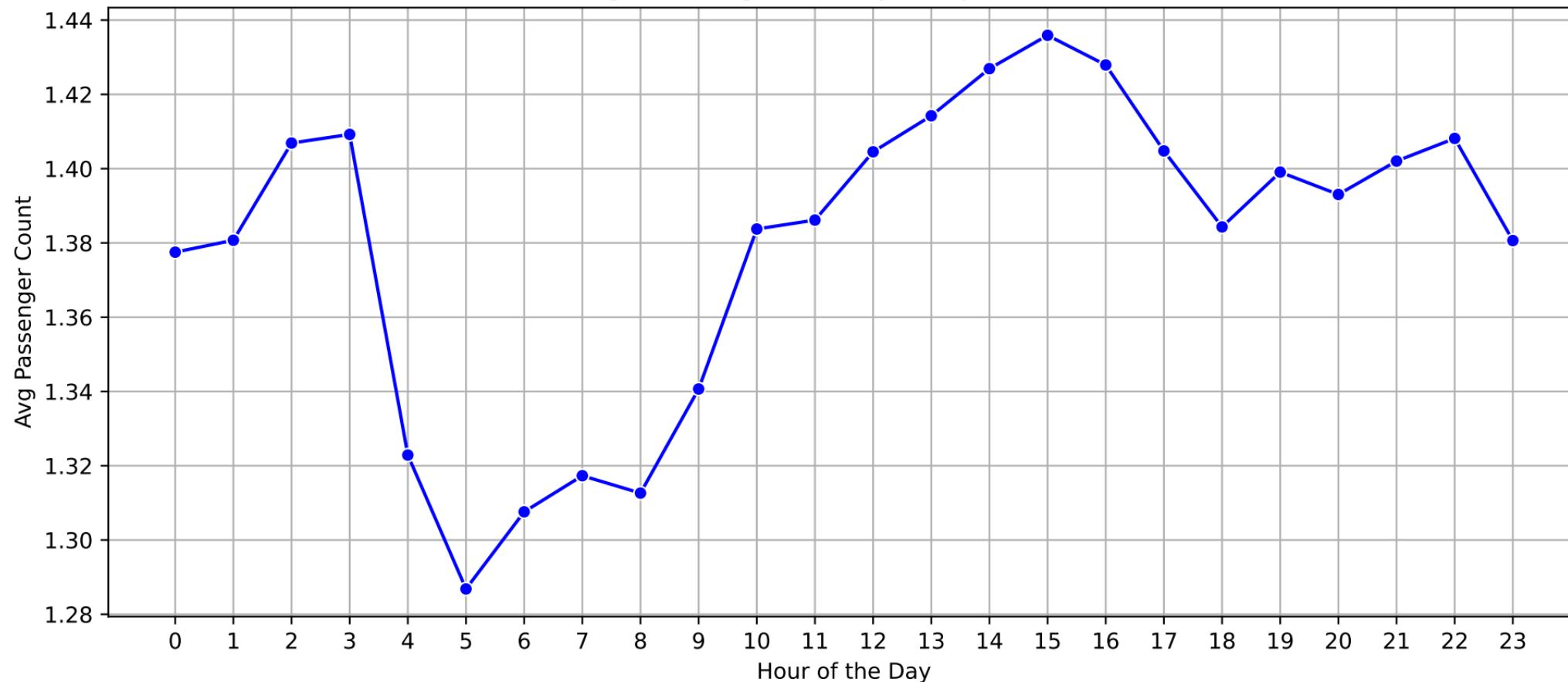
Pickup Hour Distribution (Low vs. High Tip)



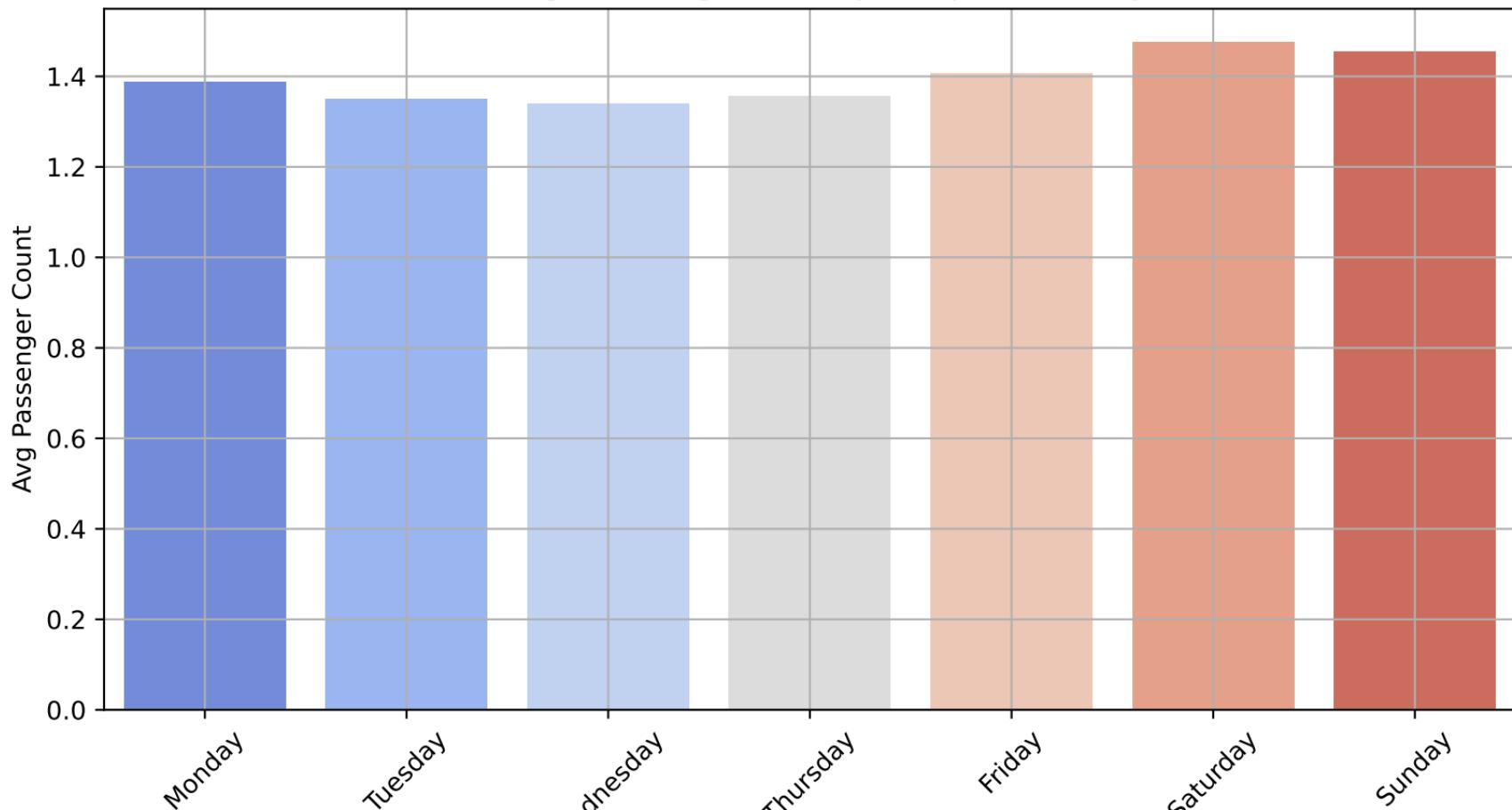
Pickup Hour Distribution (Low vs. High Tip)

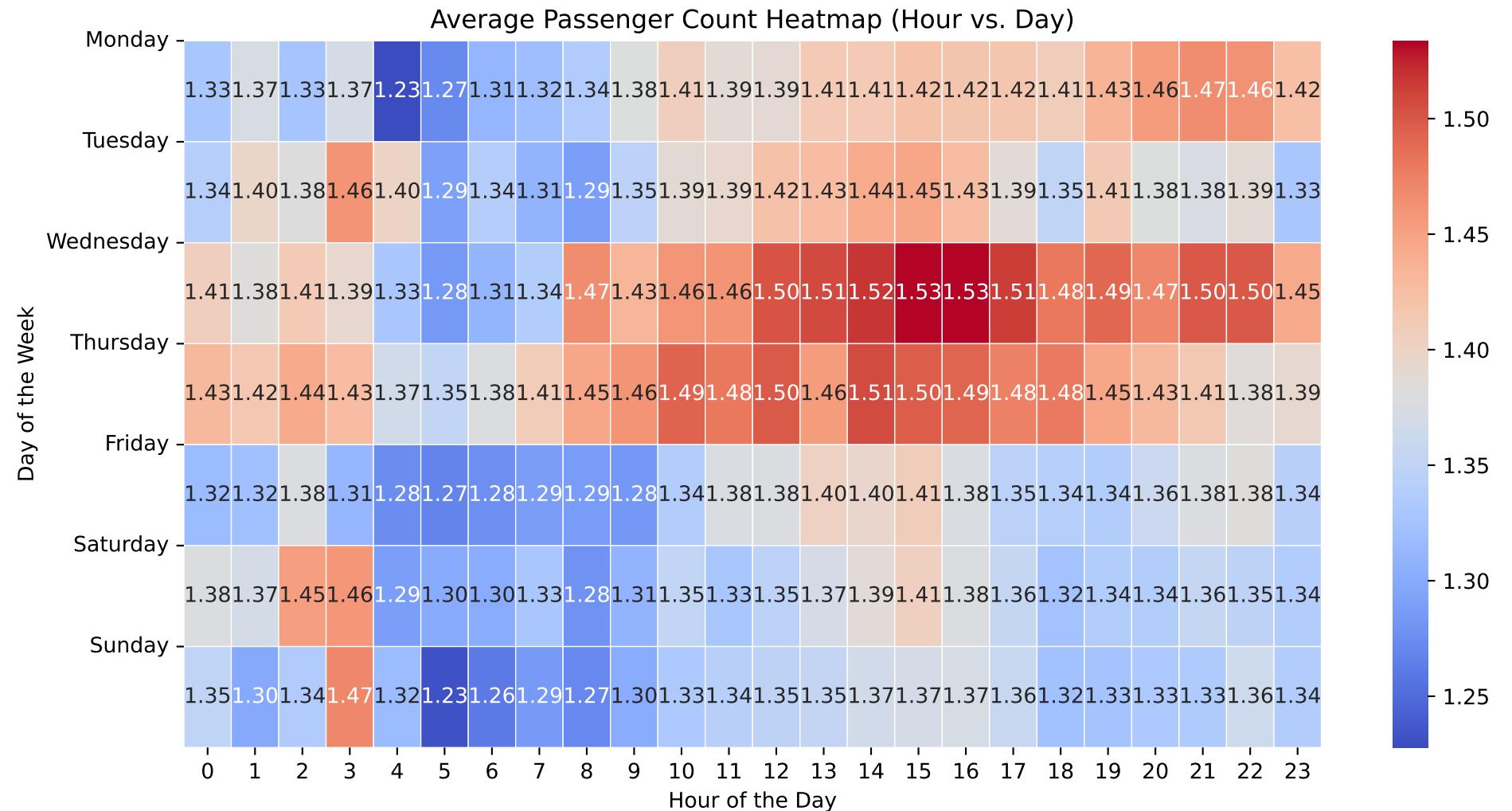


Average Passenger Count per Trip Across Hours



Average Passenger Count per Trip Across Days





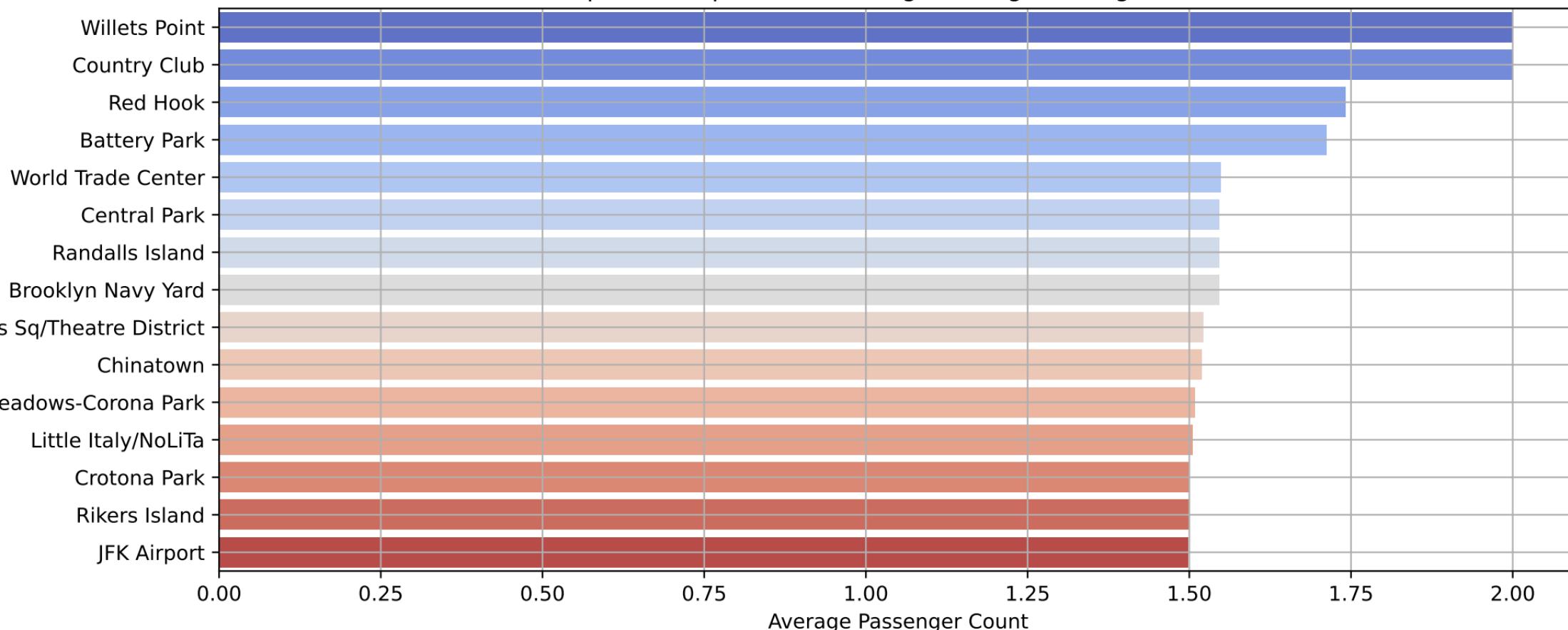
Conclusion/Remarks:

3.2.14 Showing the analysis the variation of passenger count across hours and days of the week

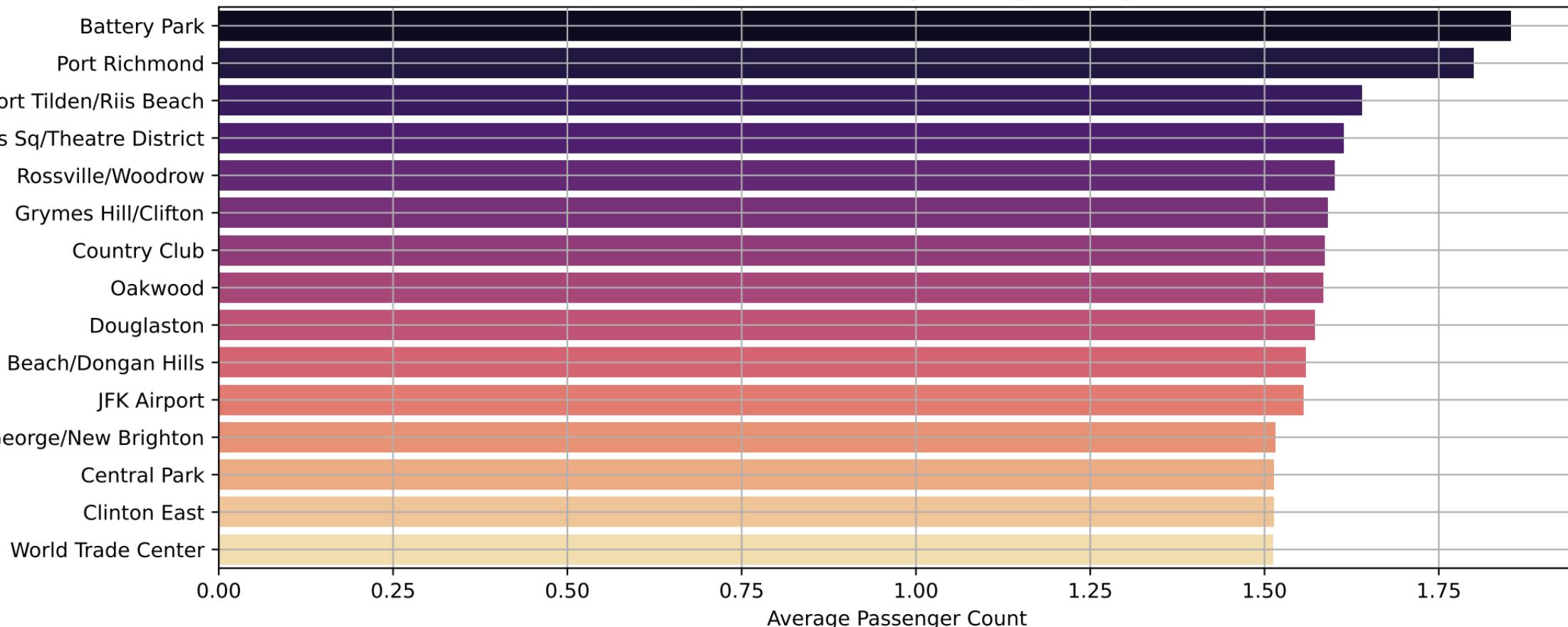
Average passenger count is highest at 15:00 & 16:00 with value 1.53 PM

Average passenger count is highest on Weekends

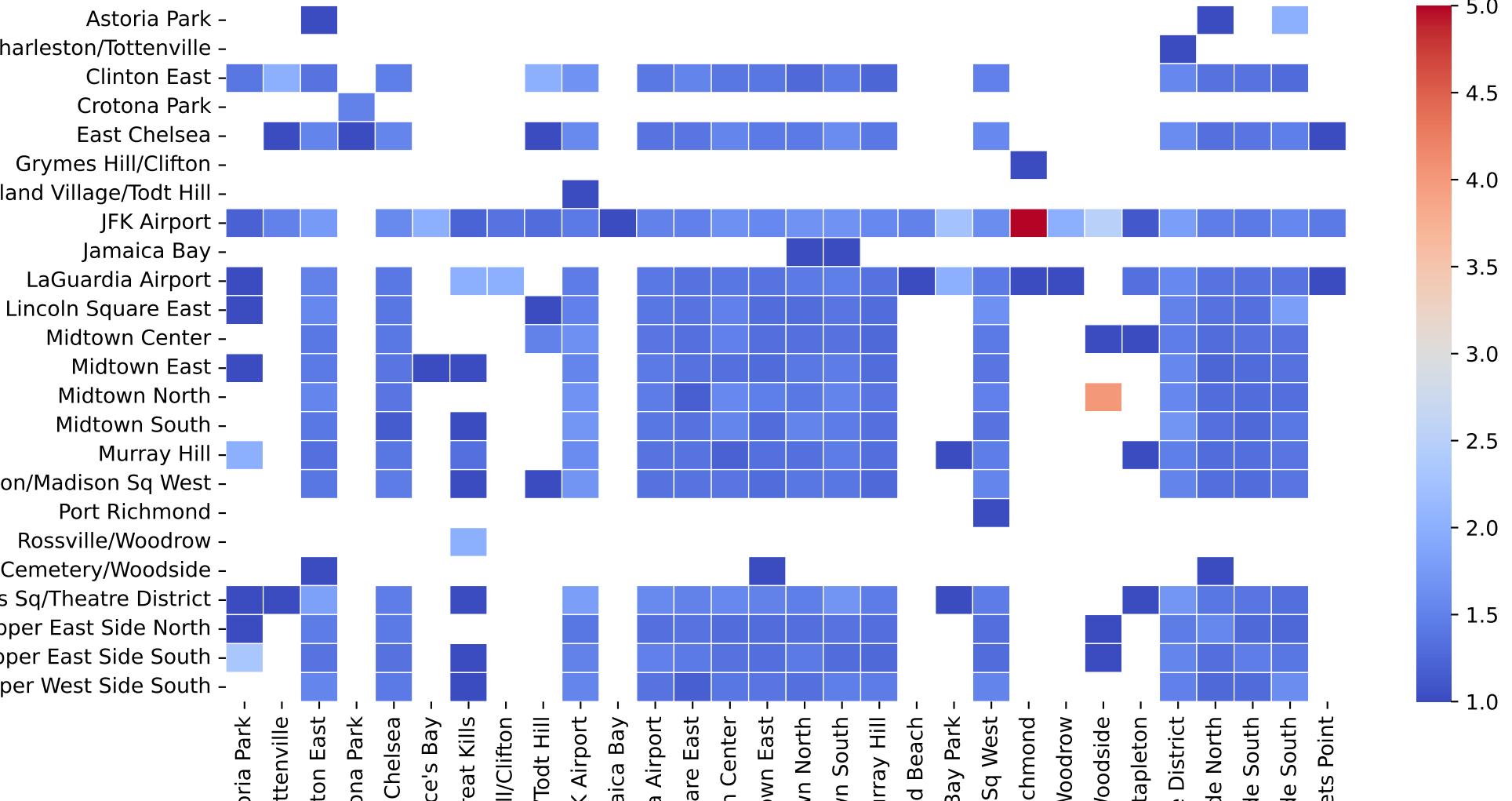
Top 15 Pickup Zones with Highest Avg Passenger Count



Top 15 Dropoff Zones with Highest Avg Passenger Count



Passenger Count Heatmap (Top & Bottom 15 Pickup vs. Dropoff Zones)



Conclusion/Remarks:

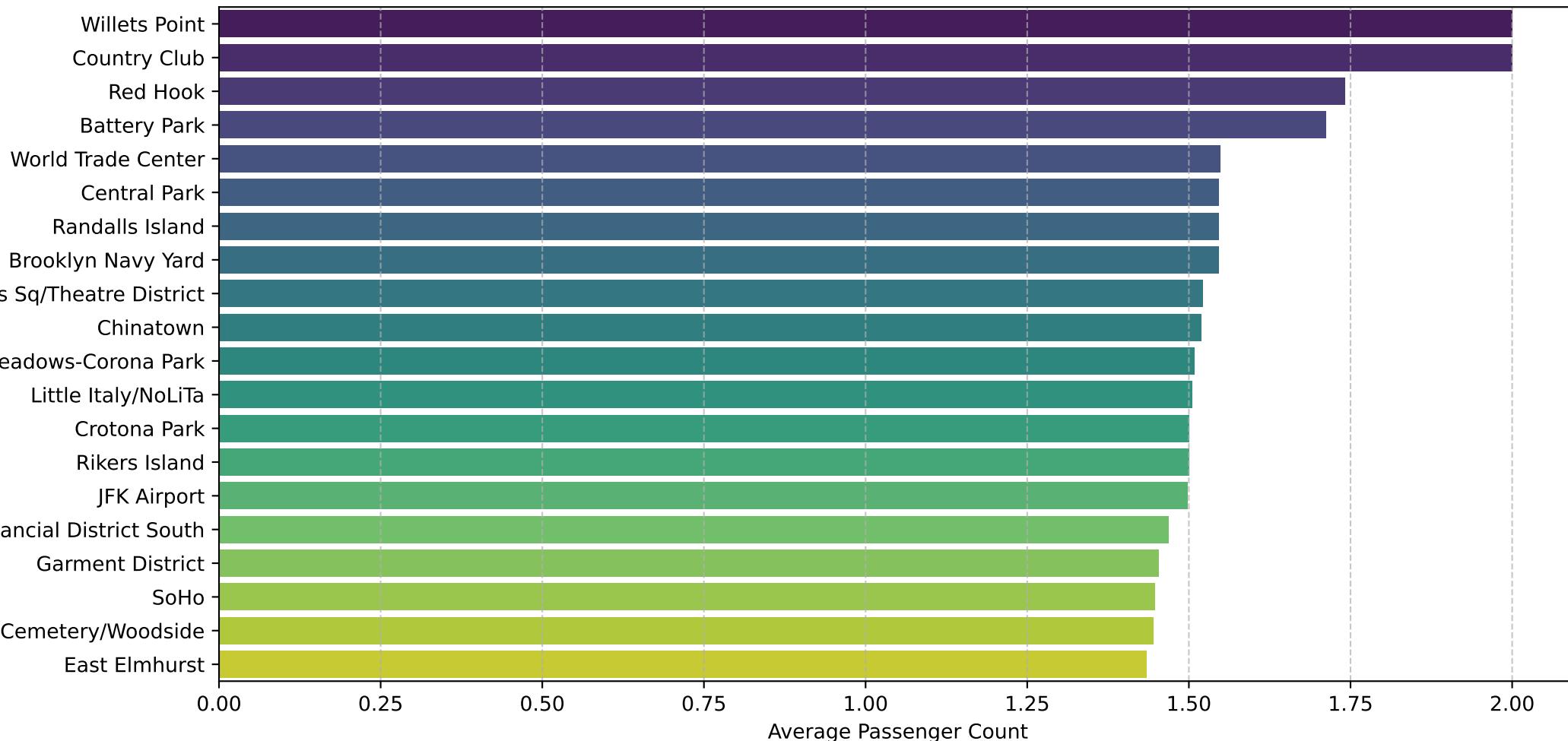
3.2.15 Showing the analysis the variation of passenger counts across zones

Willets Point and Country Club has the highest pickups

Battery park has the highest Dropoff

Point Richmond has the highest in total Pickup and Dropoff together

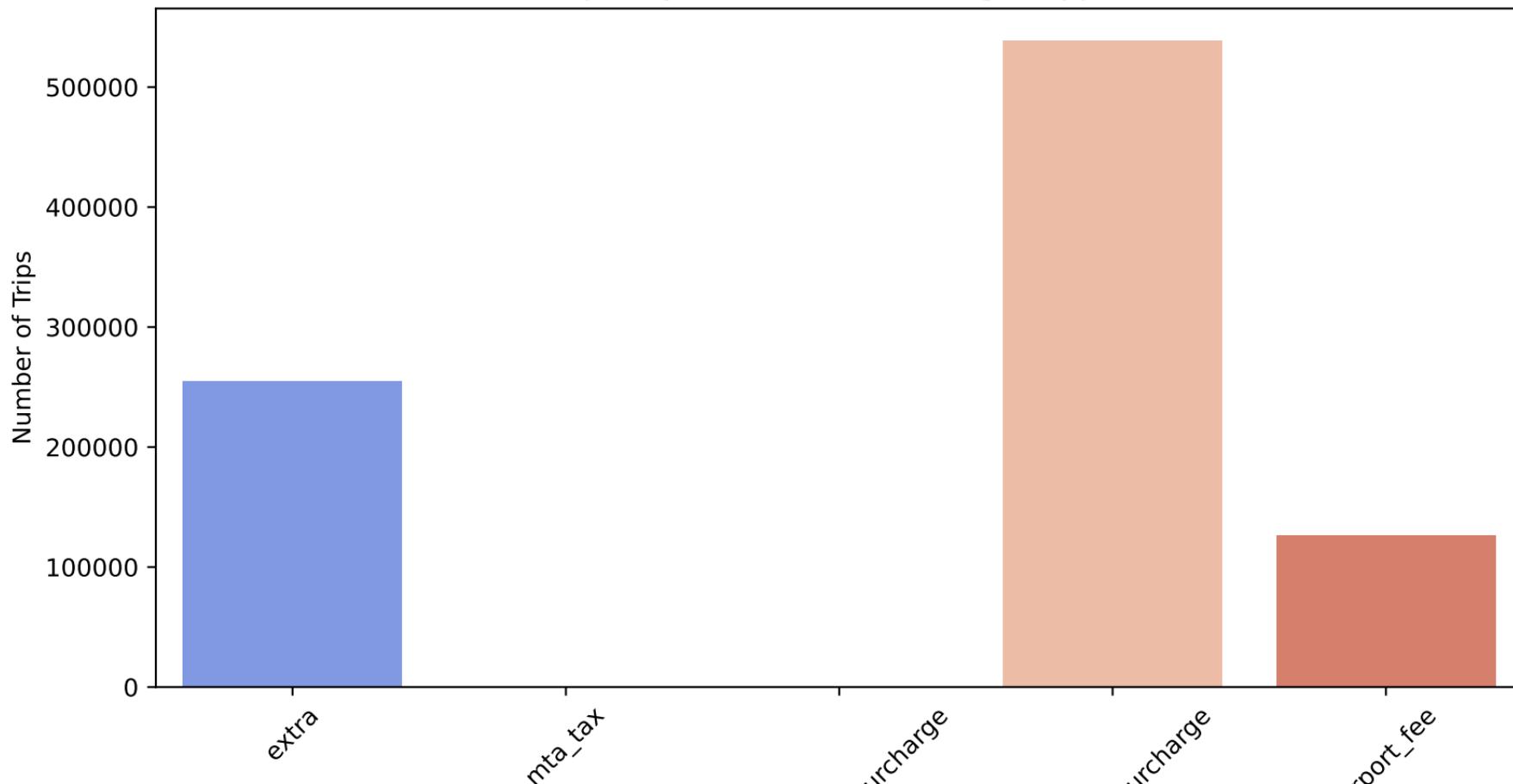
Top 20 Zones with Highest Average Passenger Count



Conclusion/Remarks:

3.2.15 Showing the analysis the average passenger counts per trip across pickup zones
Willets Point is the highest with value 2

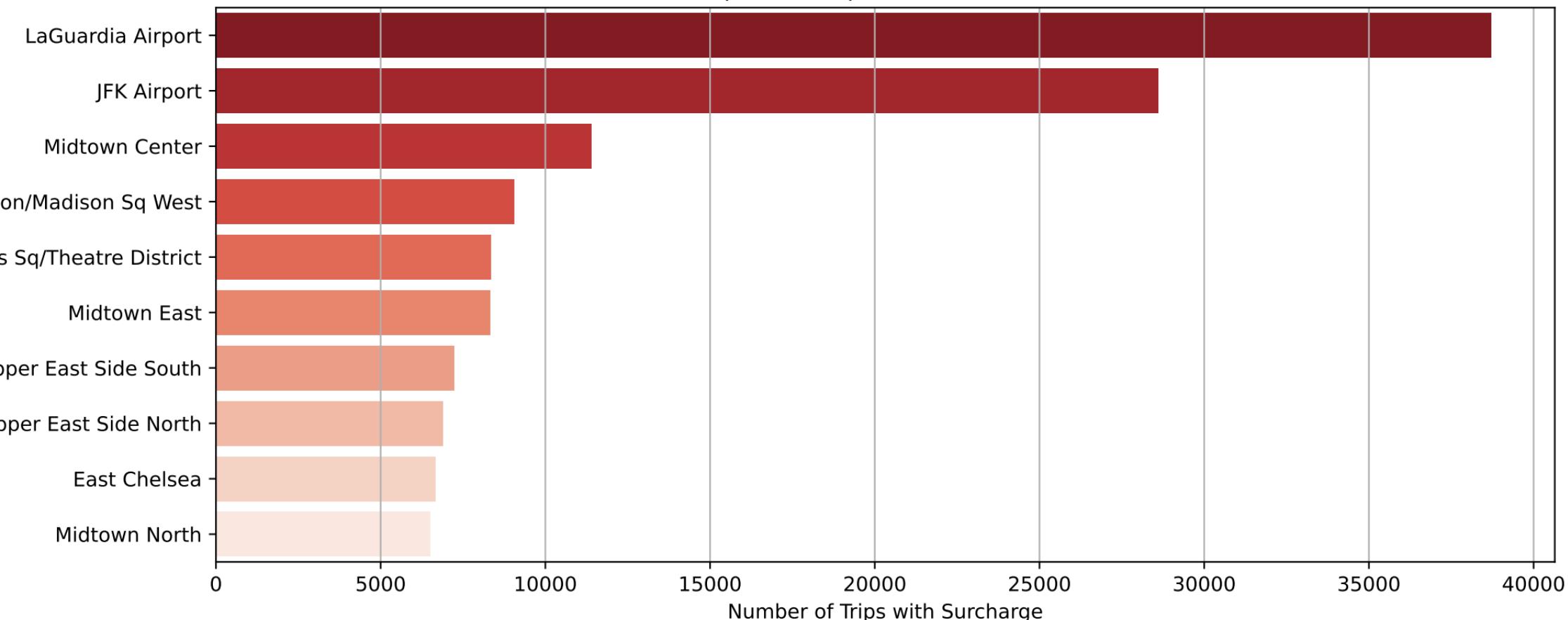
Frequency of Different Surcharges Applied



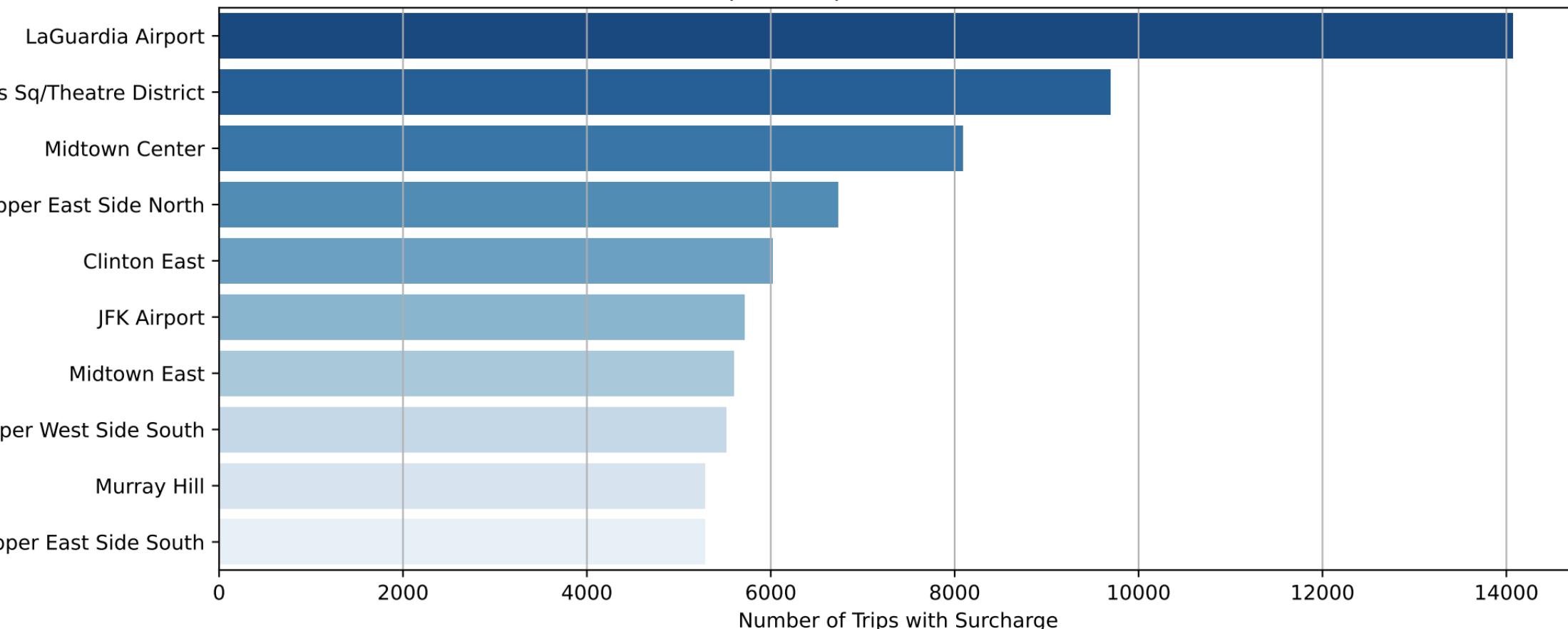
Conclusion/Remarks:

3.2.16 Showing the analysis of surcharges applied more frequently
congestion_surcharge is applied maximum

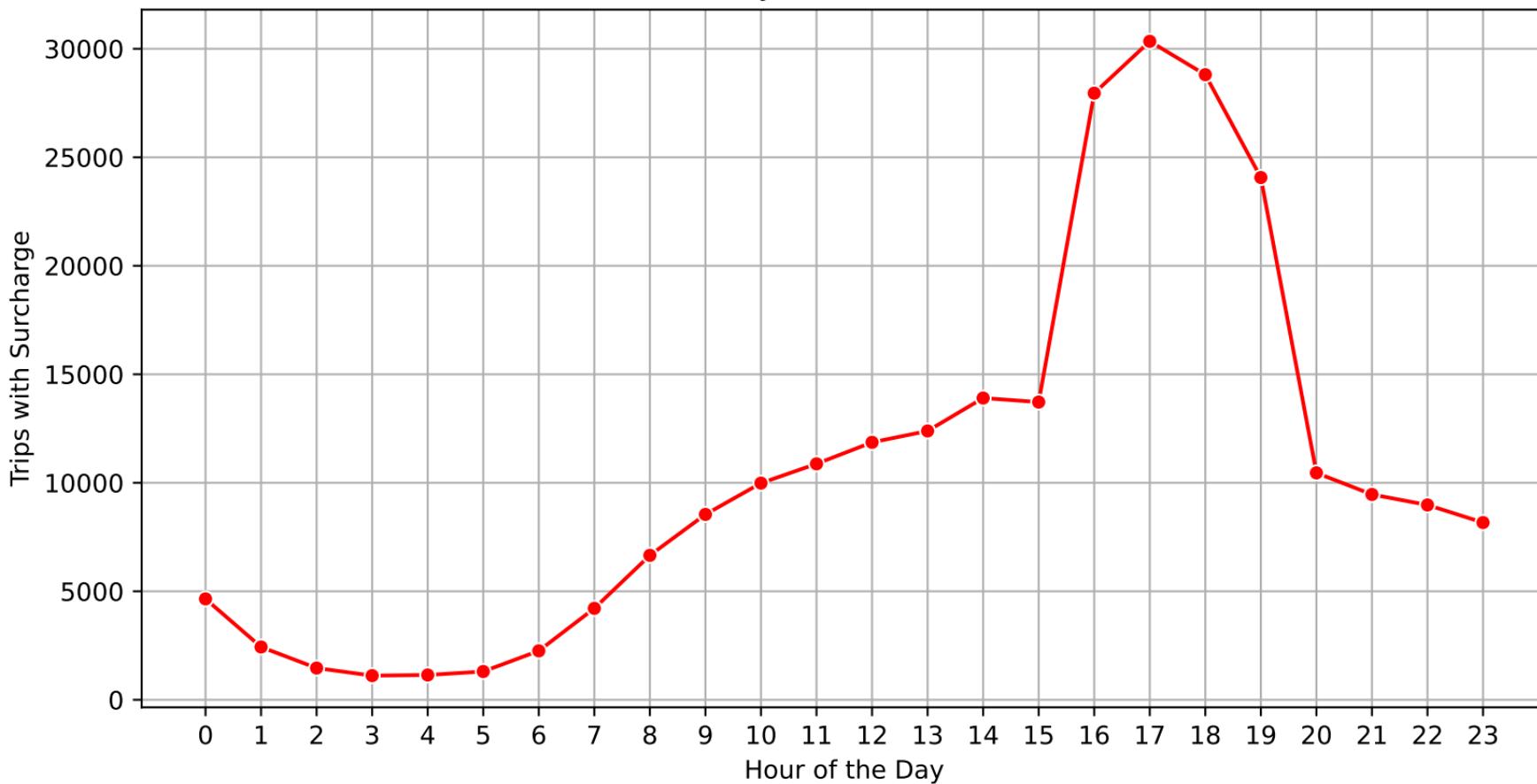
Top 10 Pickup Zones with extra



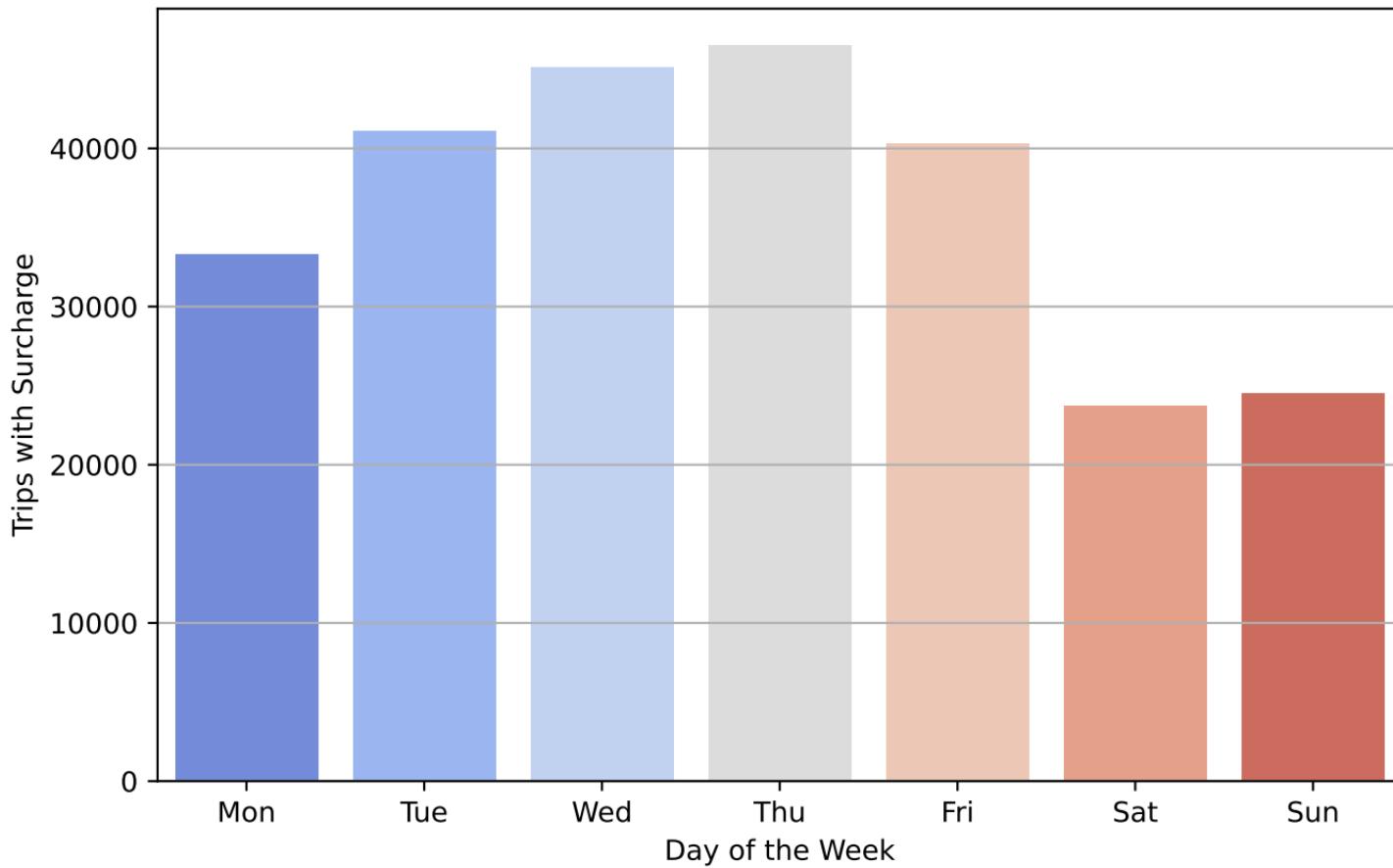
Top 10 Dropoff Zones with extra



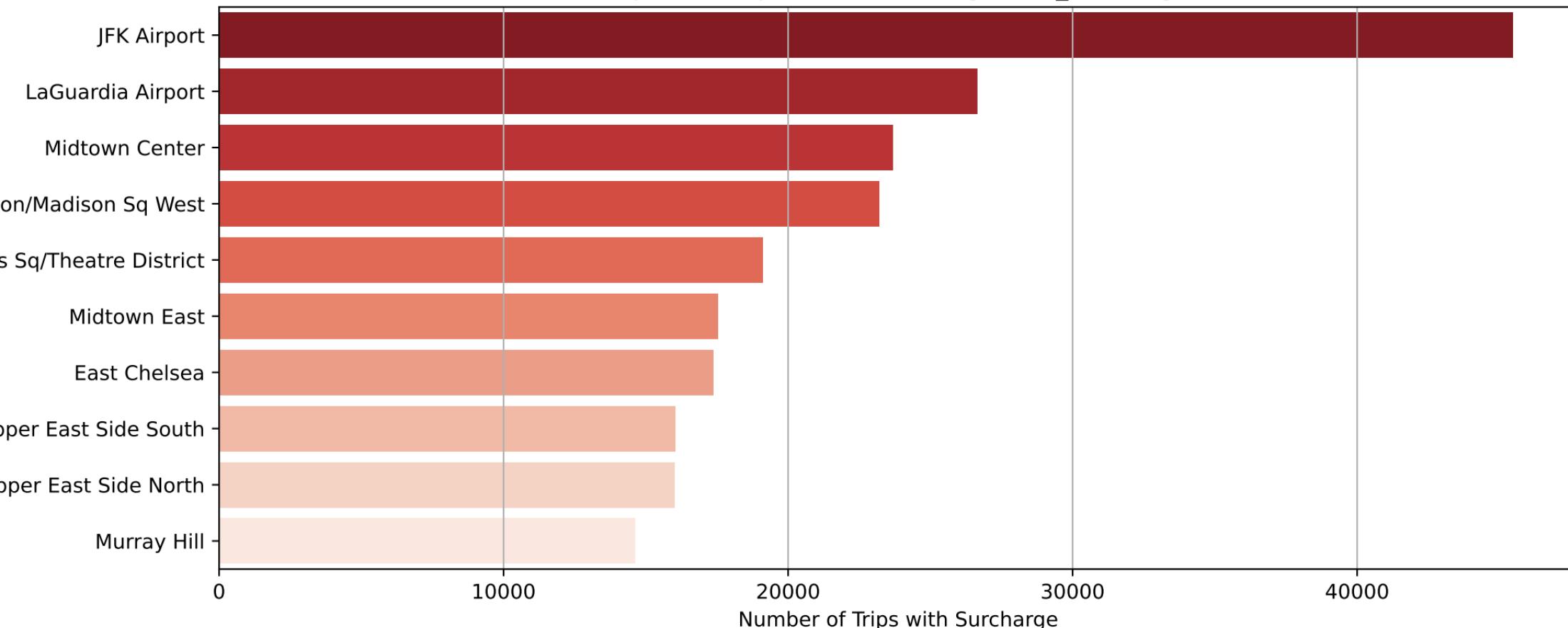
Hourly Trends of extra



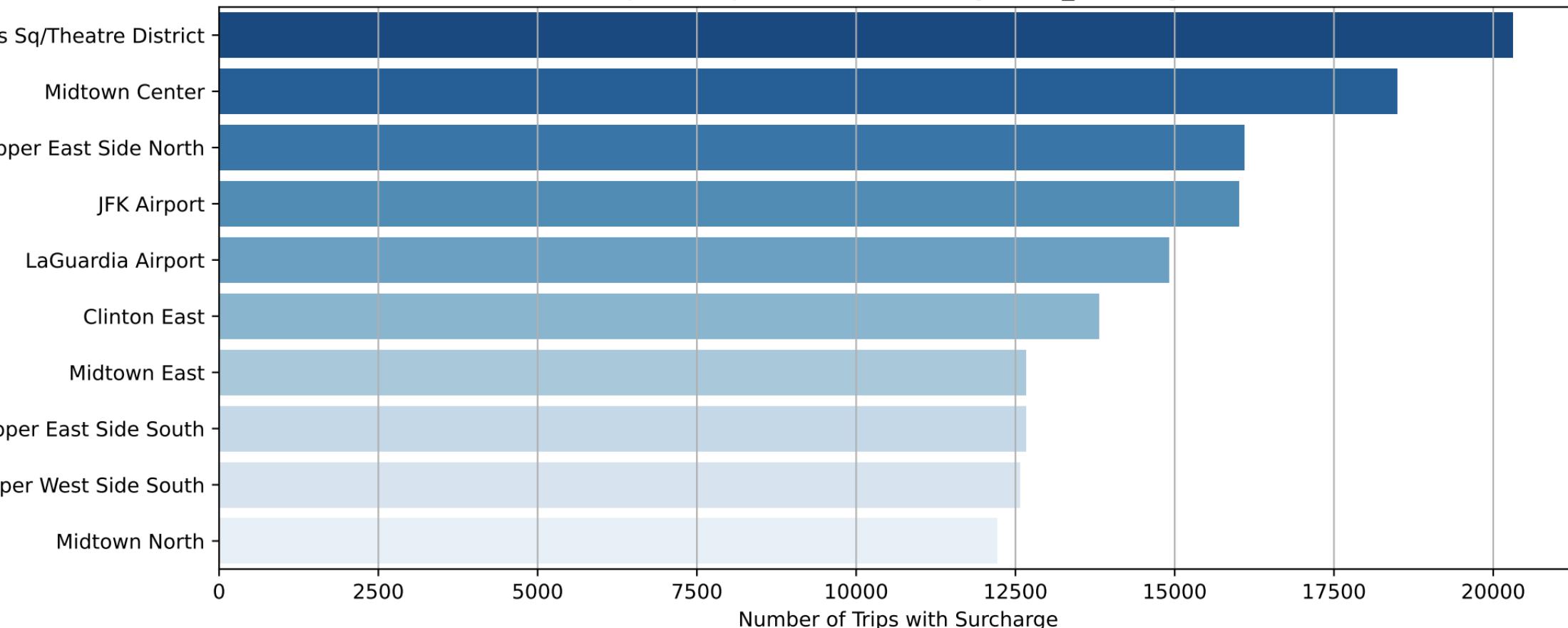
Weekly Trends of extra



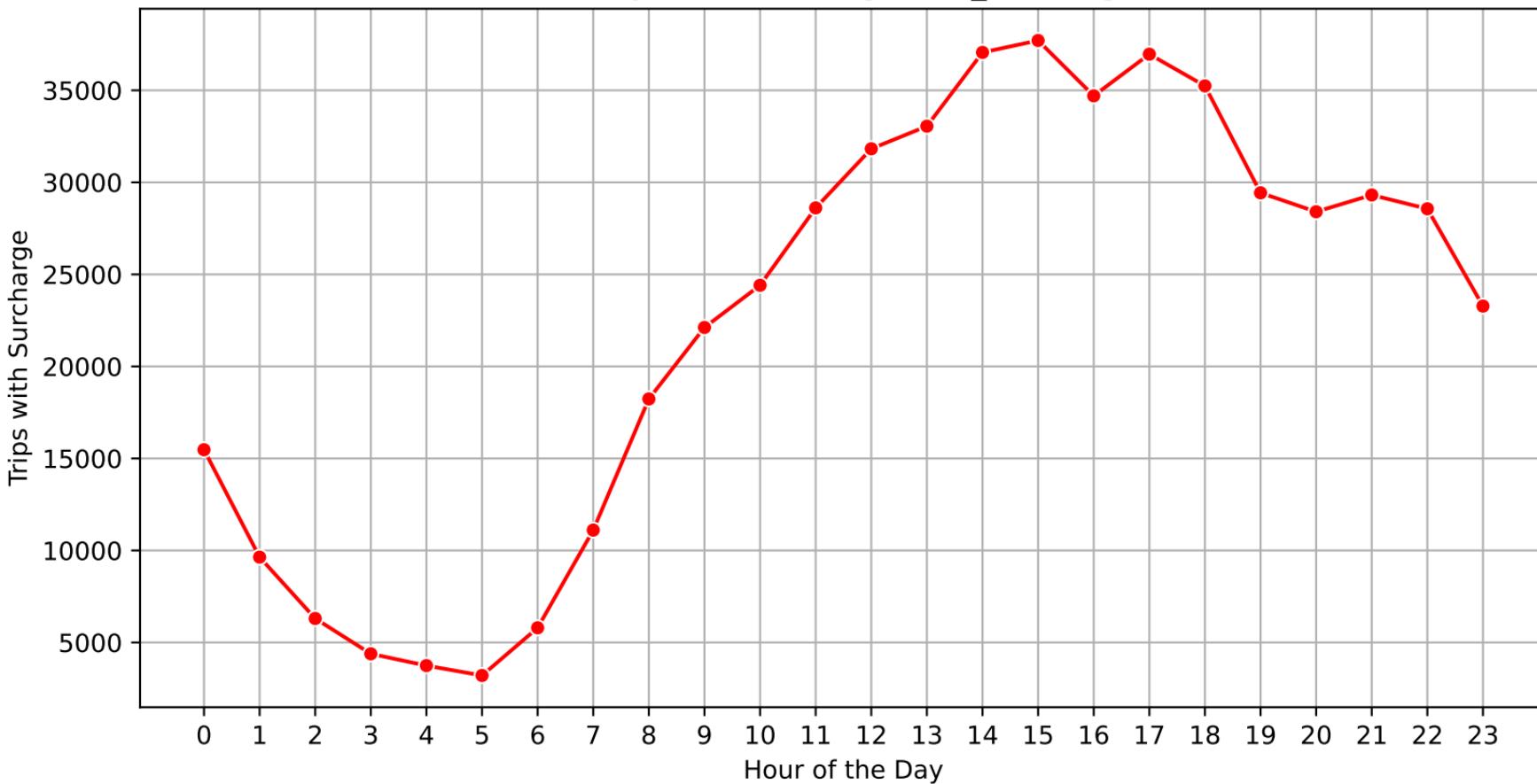
Top 10 Pickup Zones with congestion_surcharge



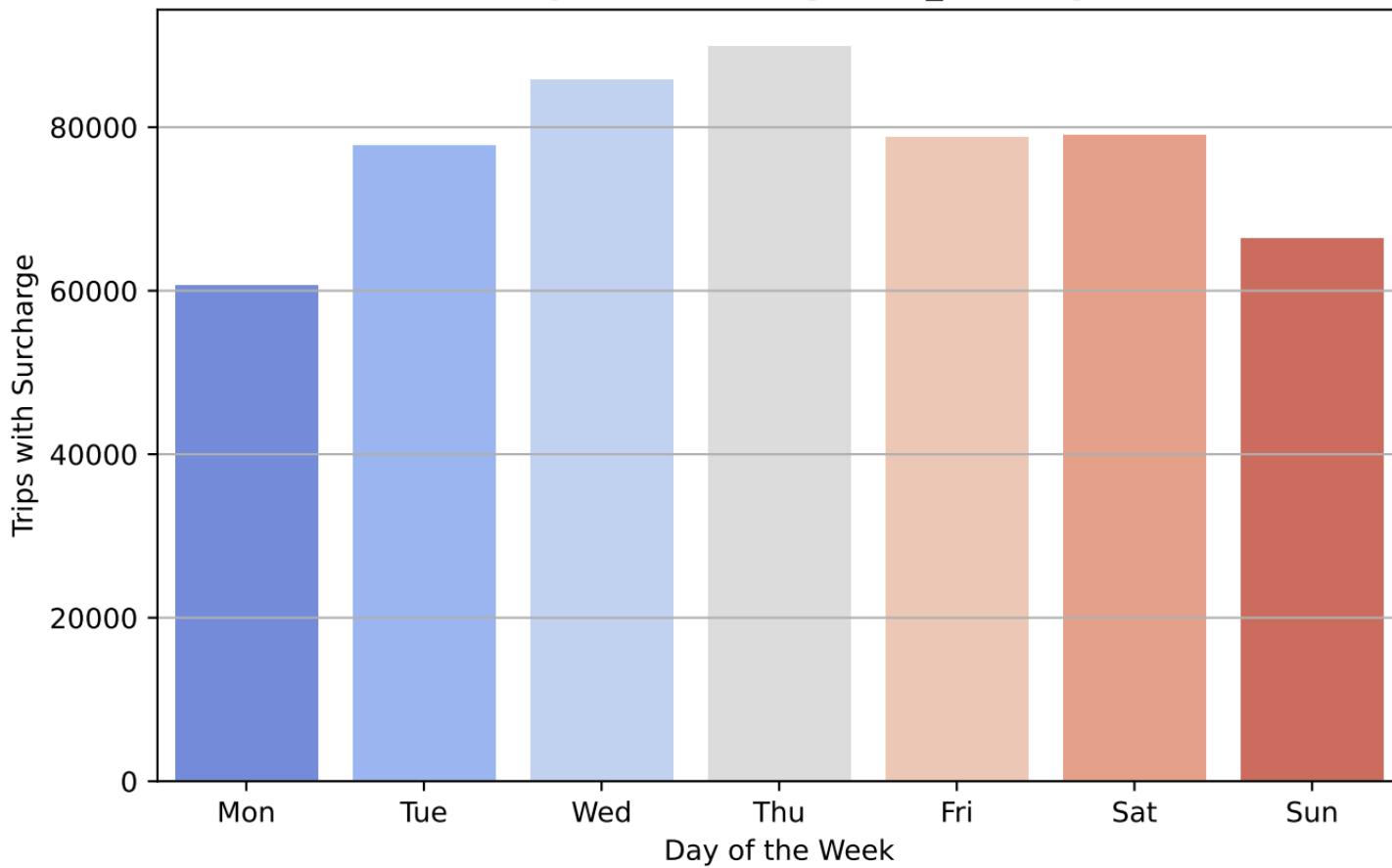
Top 10 Dropoff Zones with congestion_surcharge



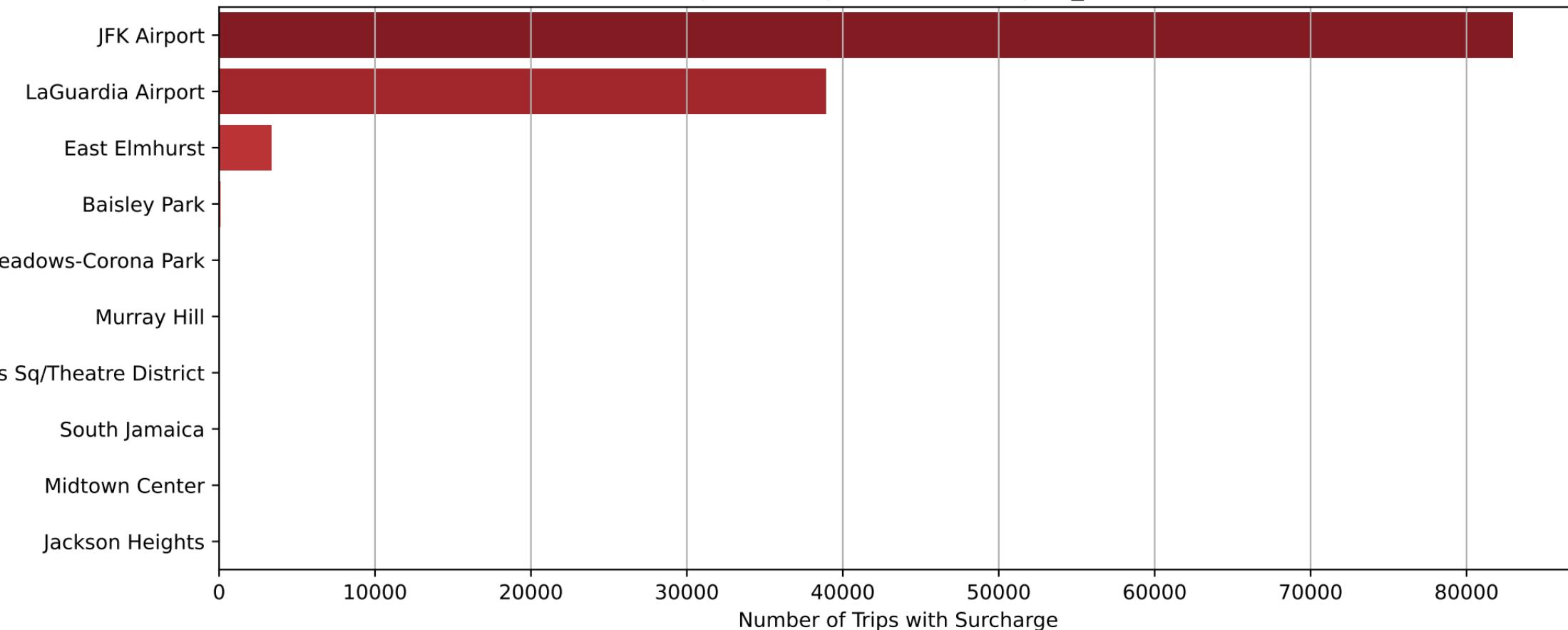
Hourly Trends of congestion_surcharge



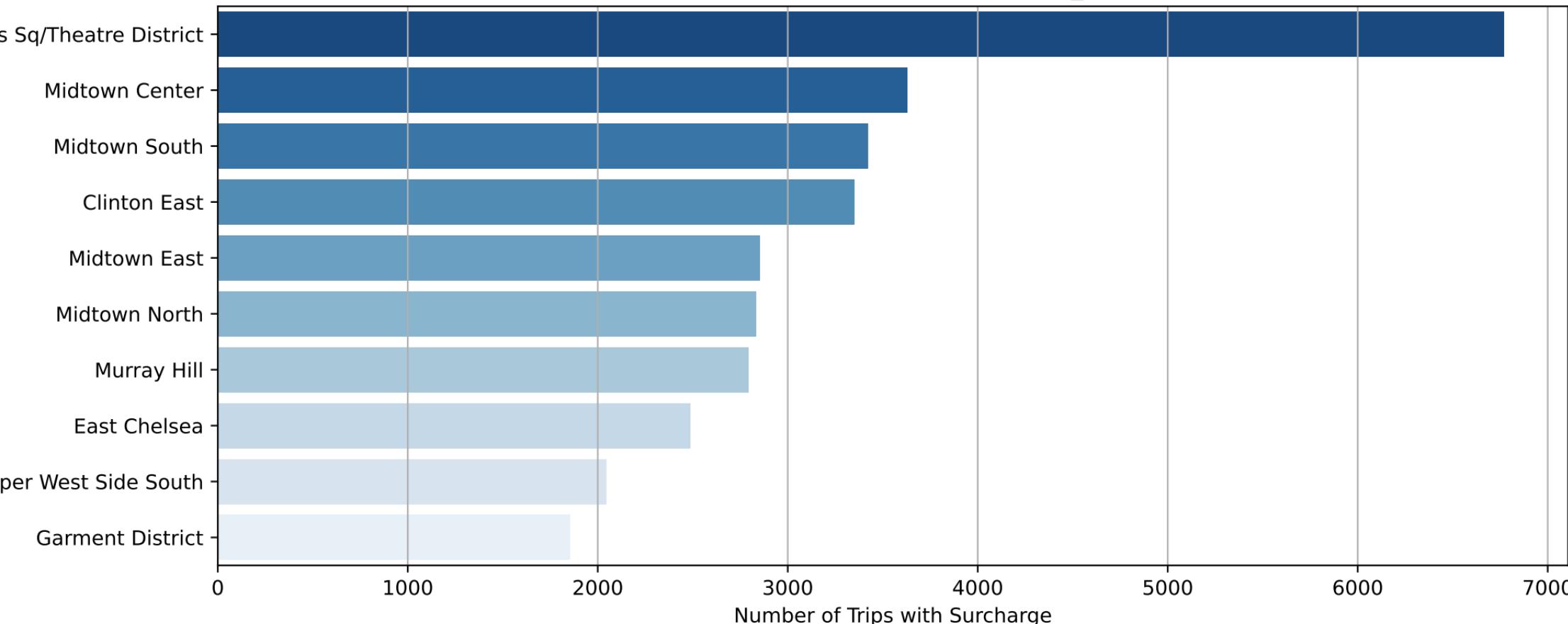
Weekly Trends of congestion_surcharge



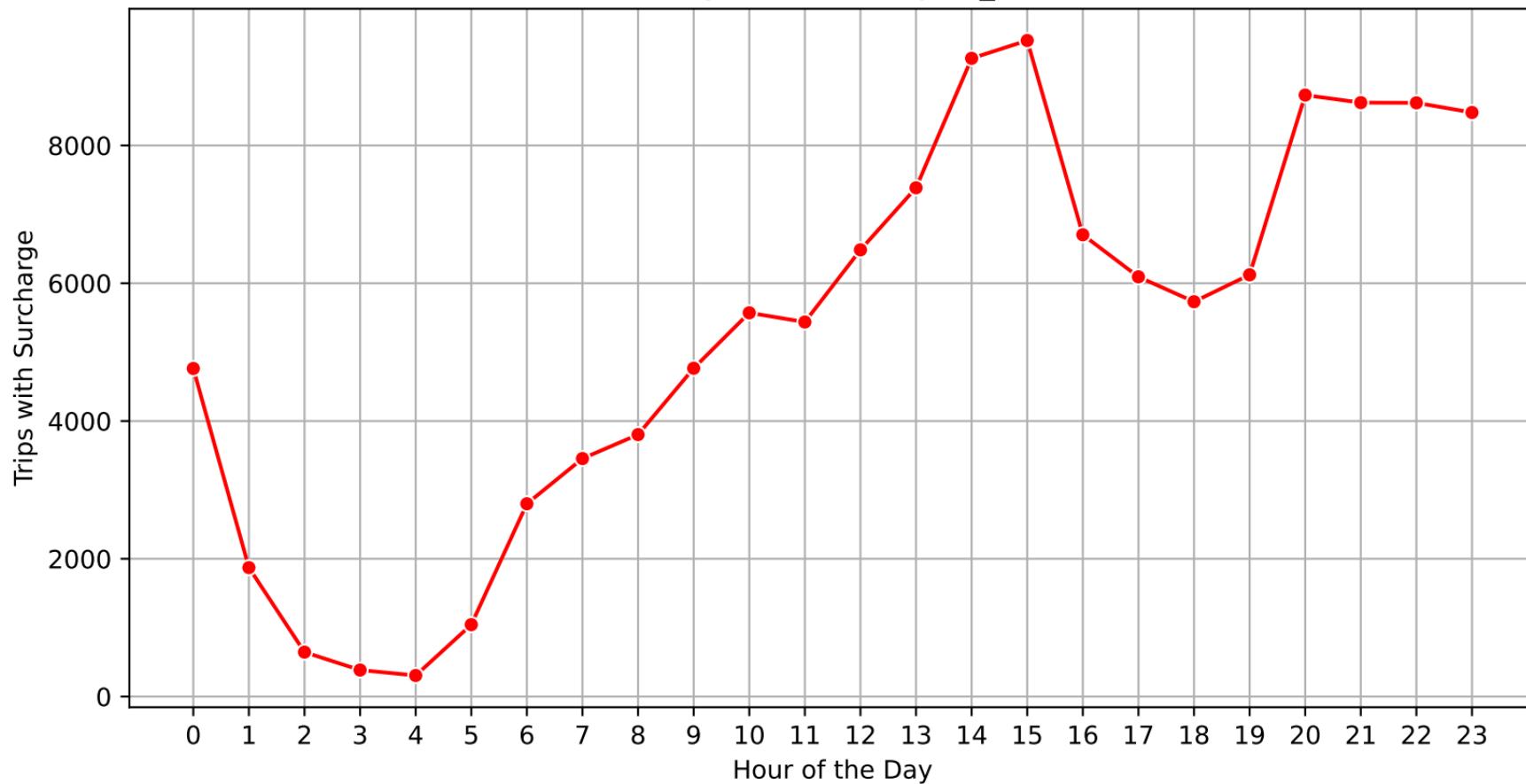
Top 10 Pickup Zones with airport_fee



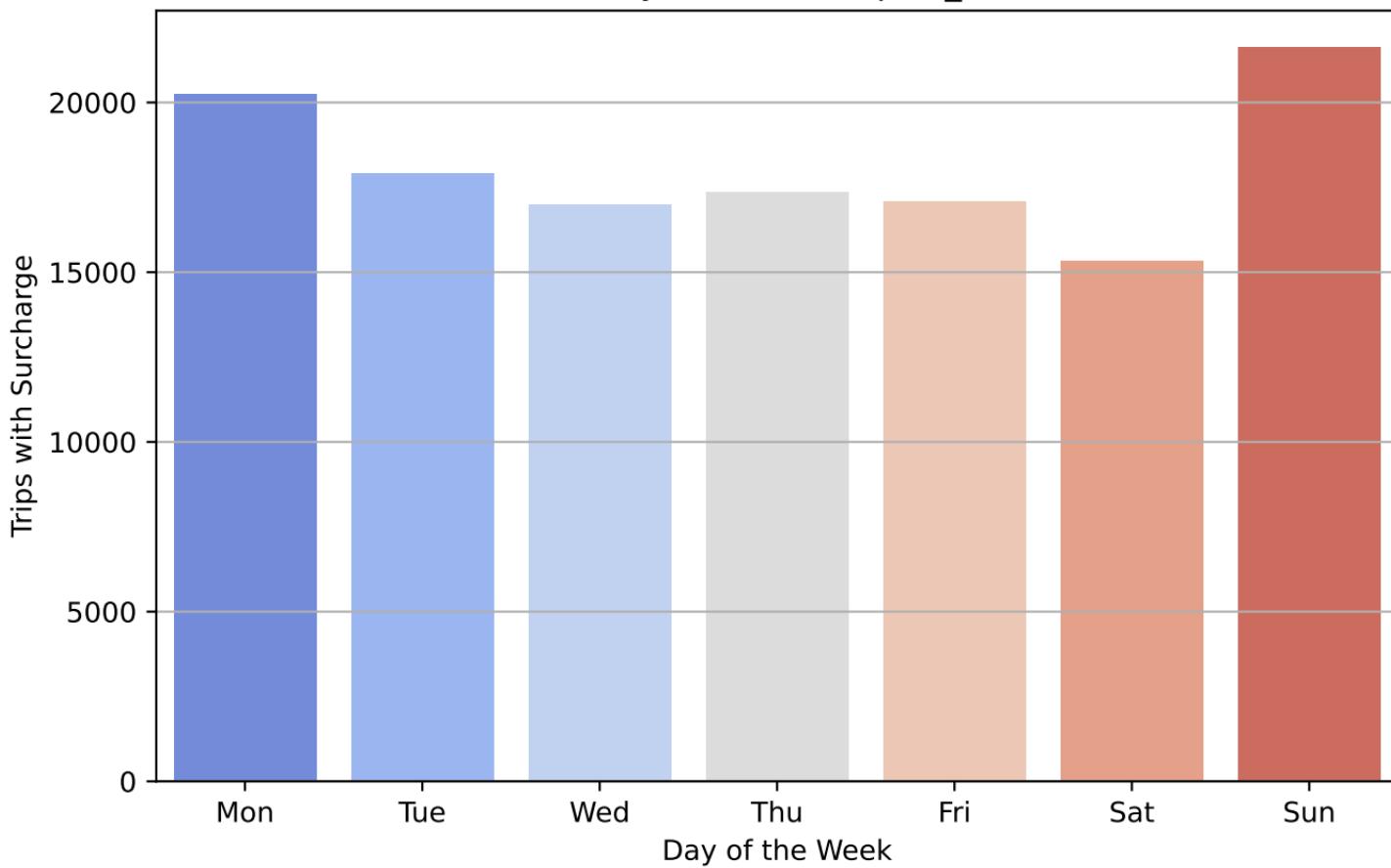
Top 10 Dropoff Zones with airport_fee



Hourly Trends of airport_fee



Weekly Trends of airport_fee



Conclusion/Remarks:

3.2.16 Showing the analysis of Zone wise surcharges applied more frequently

LaGuardia Airport is Pickup Zone where maximum surcharge type extra applied

LaGuardia Airport is Dropoff Zone where maximum surcharge type extra applied

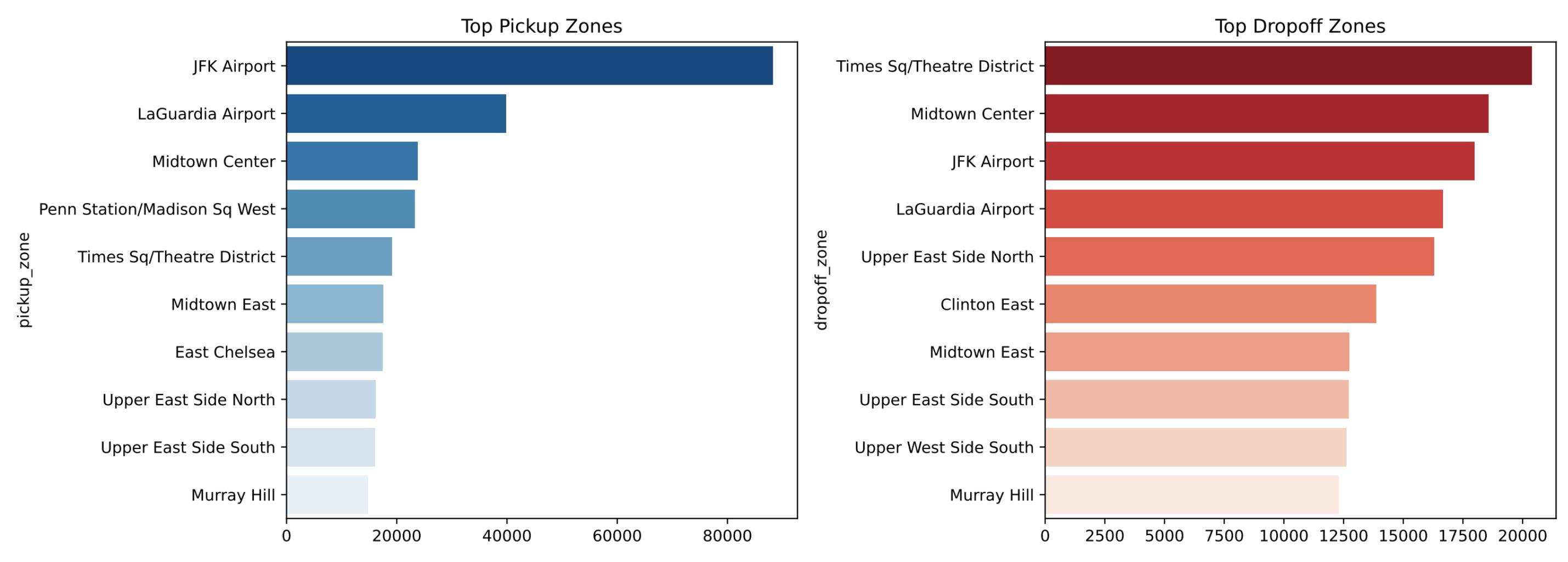
The maximum surcharge type extra applied at around 17:00 PM

The maximum surcharge type extra applied at on Thursday

JFK Airport is Pickup Zone where maximum surcharge type congestion_surcharge applied

Times Sq/Theatre District is Dropoff Zone where maximum surcharge type
congestion_surcharge applied

The maximum surcharge type congestion_surcharge applied at around 15:00 PM



Conclusion/Remarks:

4.1.1 Identify and Optimize Routes with High Demand

Insights from df_merged:

Analyze the busiest pickup/dropoff zones by hour, day, and season.

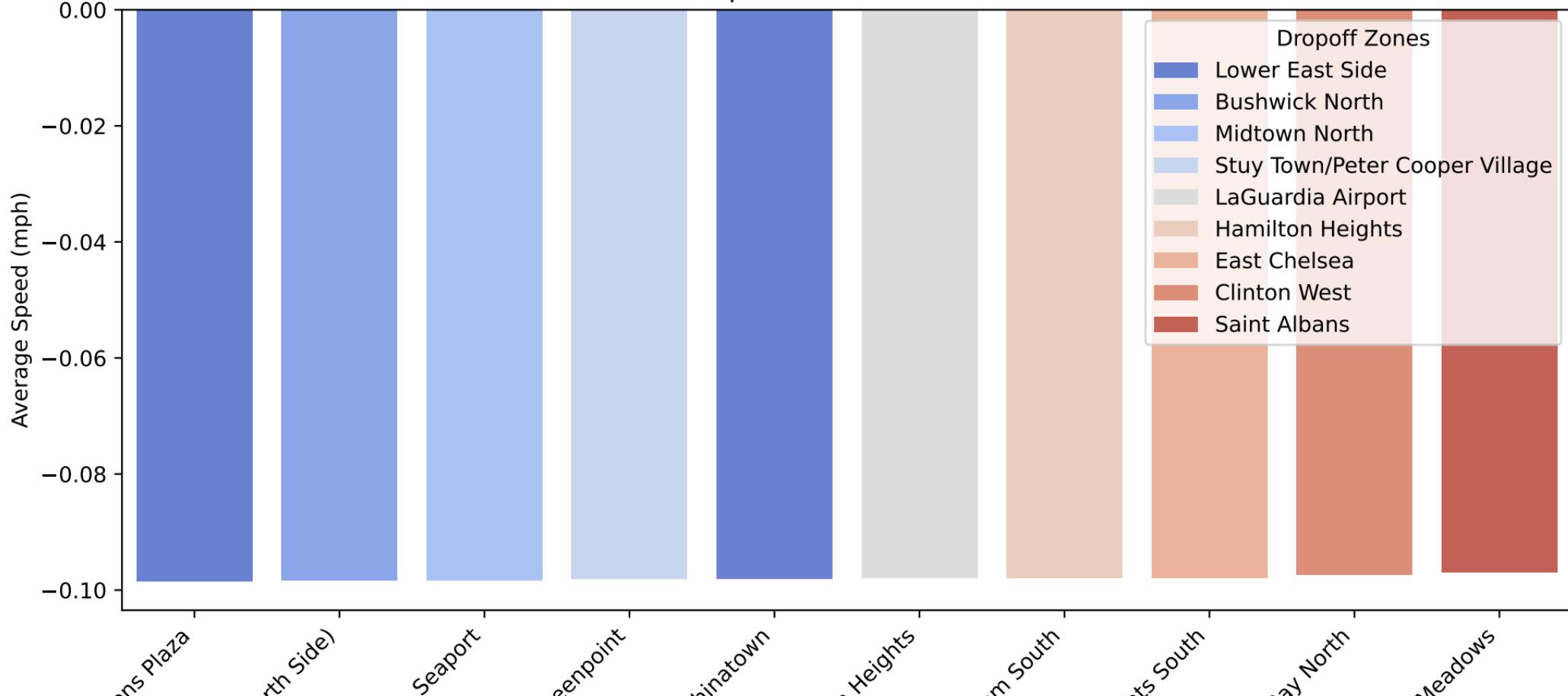
Identify peak demand locations (e.g., airports, entertainment districts, business hubs).

Optimization Strategy:

Dynamic Routing System: Implement real-time route optimization to direct available cabs to high-demand zones.

Pre-positioning Strategy: During peak hours, dispatch cabs ahead of demand to hot zones to reduce wait times.

Top 10 Slowest Routes



Conclusion/Remarks:

4.1.1 Reduce Idle Time by Identifying Low-Demand Areas

Insights from df_merged:

Identify zones with low trip frequency but high supply.

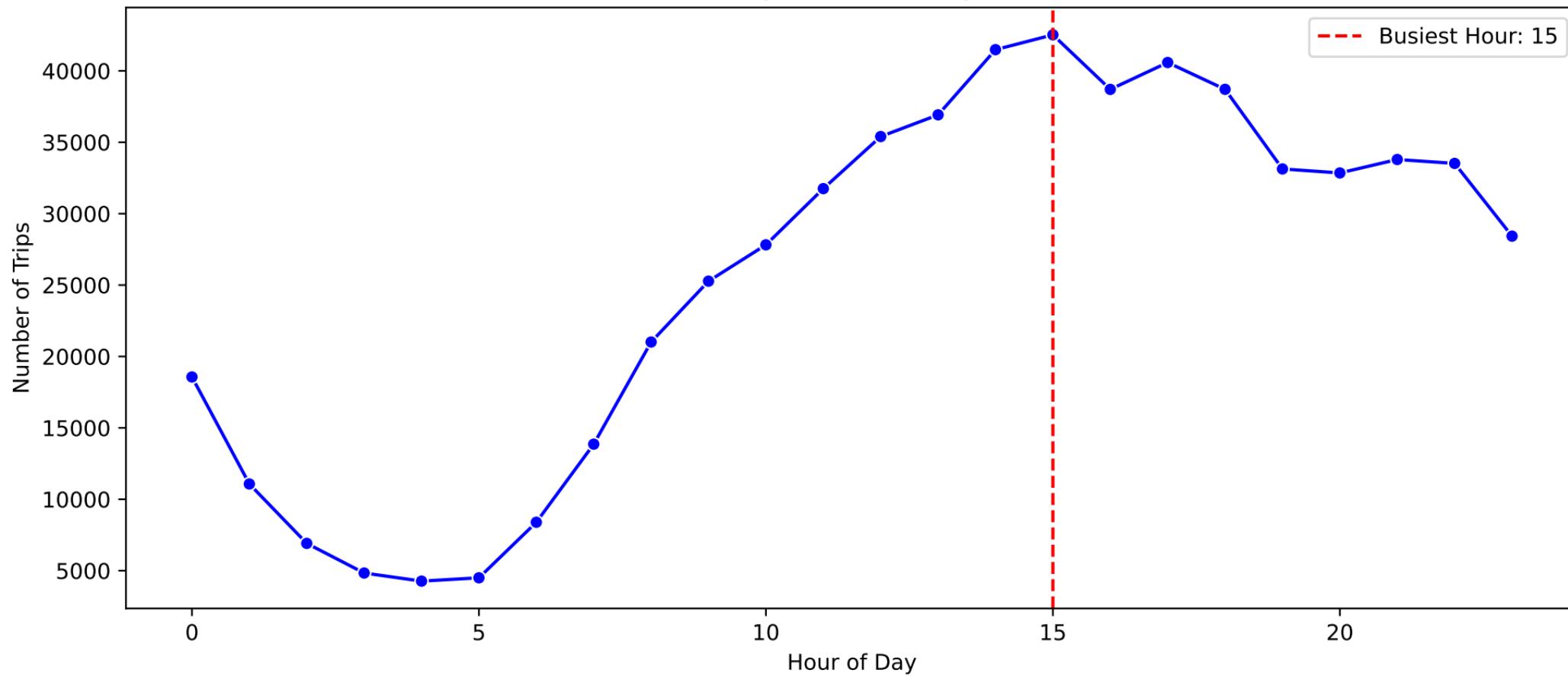
Detect times when cabs wait too long for trips in specific zones.

Optimization Strategy:

Reallocate Vehicles Dynamically: Move cabs from low-demand to high-demand areas.

Surge Pricing Awareness: If demand is low in an area, reduce prices or offer discounts to encourage trips.

Hourly Demand Analysis



Conclusion/Remarks:

4.1.1 Optimize Dispatching for Night vs. Daytime Hours

Insights from df_merged:

Night hours (11 PM - 5 AM) may have fewer but longer trips (e.g., airport rides).

Daytime hours may have shorter, frequent rides (e.g., commuters).

Optimization Strategy:

Adjust Fleet Size Based on Hourly Trends:

- Night: Allocate more cars near airports, railway stations, or nightlife hubs.
- Day: Focus on business districts and commuter-heavy zones.

Offer Nighttime Incentives: Encourage drivers to operate during low-driver hours with

Conclusion/Remarks:

4.1.1 Improve Route Efficiency for Slow Routes

Insights from df_merged:

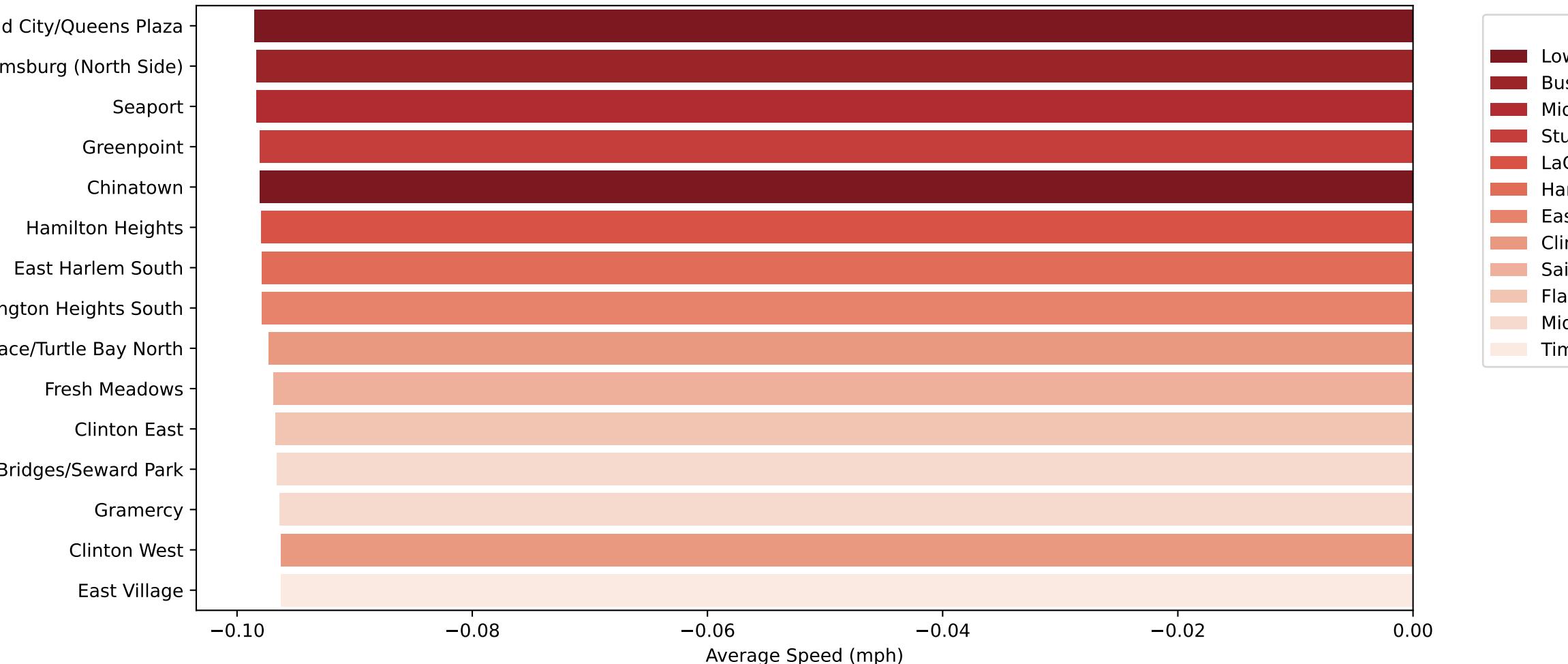
- Calculate average speed per route and hour to find slow zones.
- Identify roads with frequent congestion or delays.

Optimization Strategy:

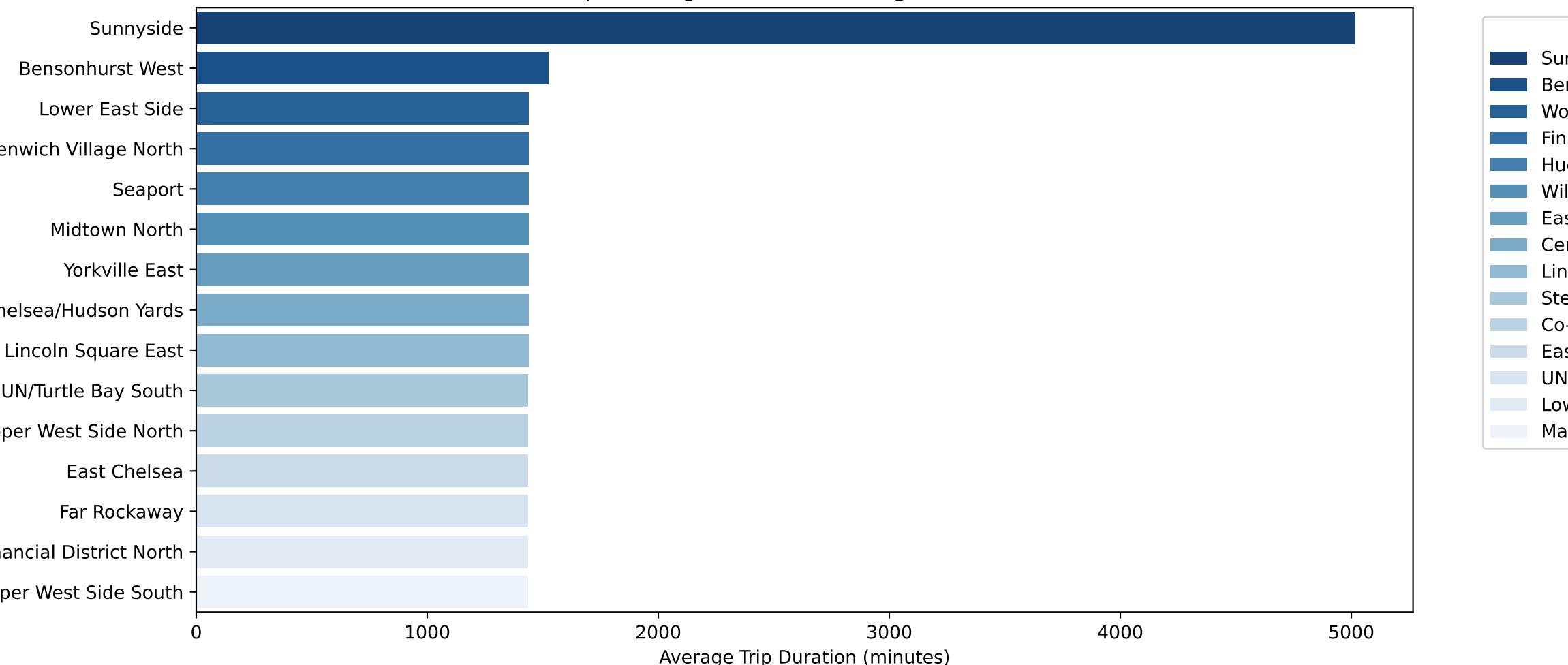
Navigation & Traffic Data Integration:

- Use real-time traffic data to reroute cabs away from slow zones.
- Implement AI-based predictive routing based on historical traffic trends.

Top 15 Slowest Routes (Low Speed)



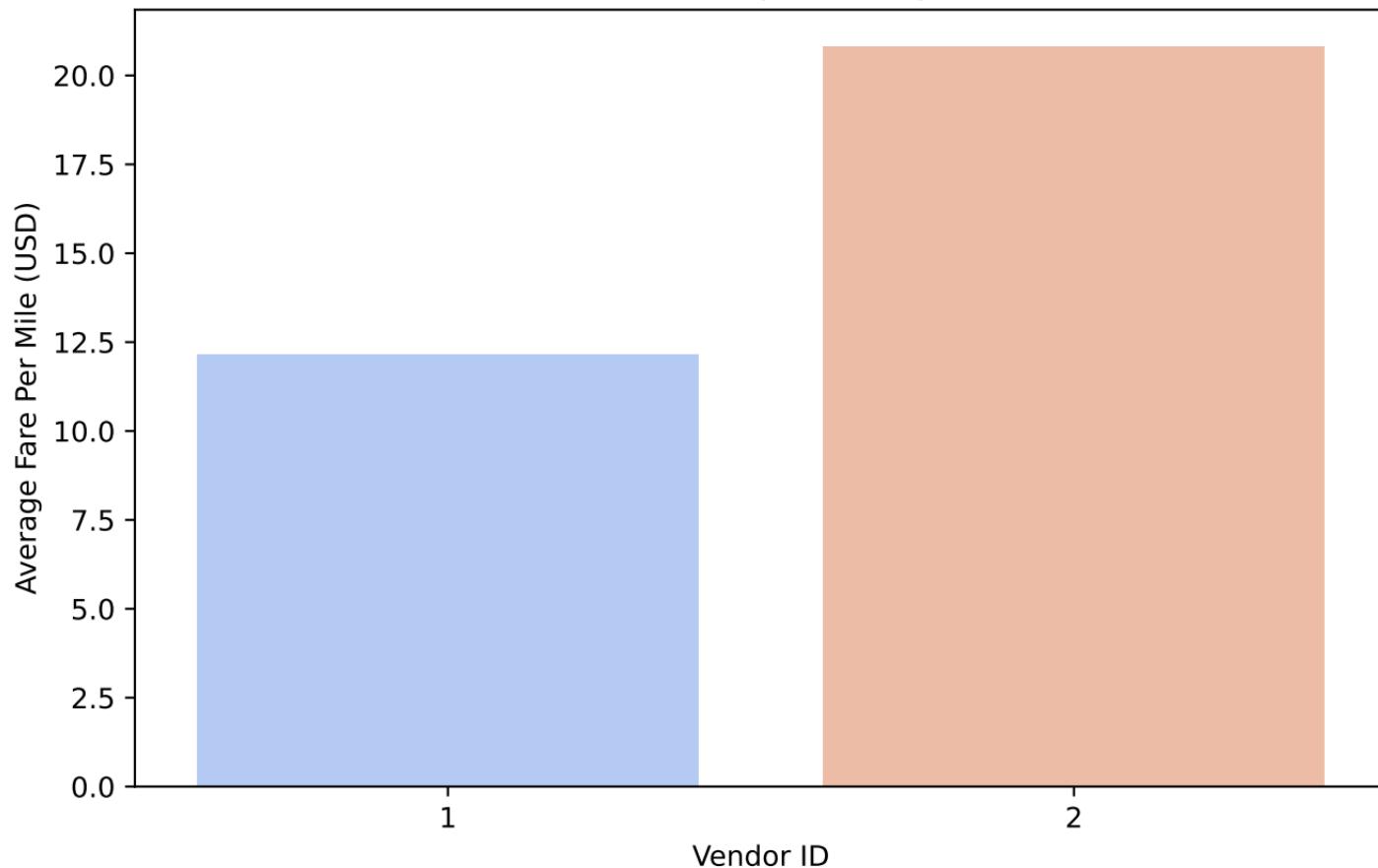
Top 15 Congested Routes (Long Travel Time)



Conclusion/Remarks:

4.1.1 Showing Top 15 Slowest Routes and Congested Routes to implement strategy to generate more revenue

Fare Per Mile Comparison by Vendor



Conclusion/Remarks:

4.1.1 Increase Revenue Per Trip by Optimizing Fare & Tip Collection

Insights from df_merged:

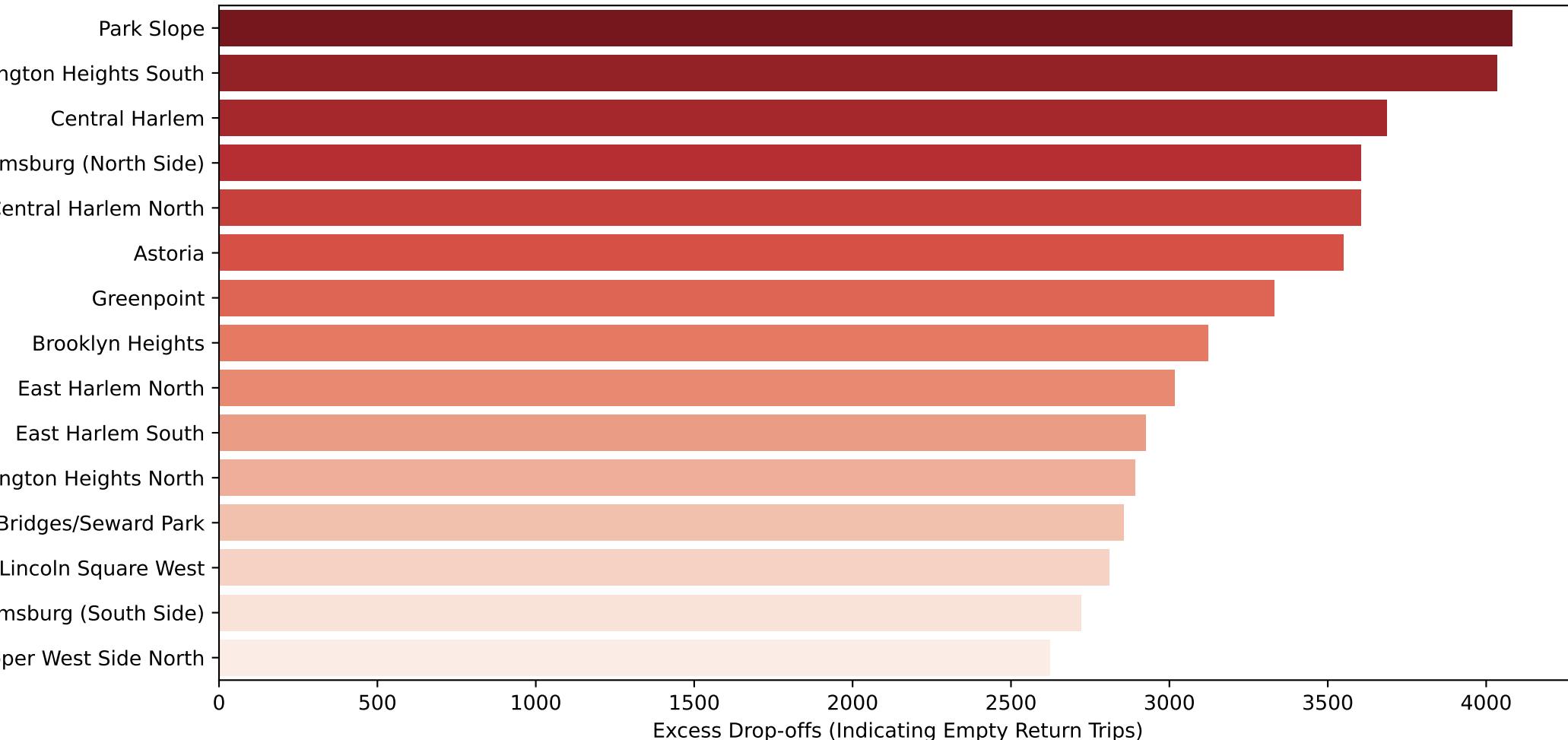
- Long-distance trips → Lower fare per mile.
- Short trips → Higher fare per mile, but more frequent.
- Tips depend on passenger count, trip distance, and pickup time.

Optimization Strategy:

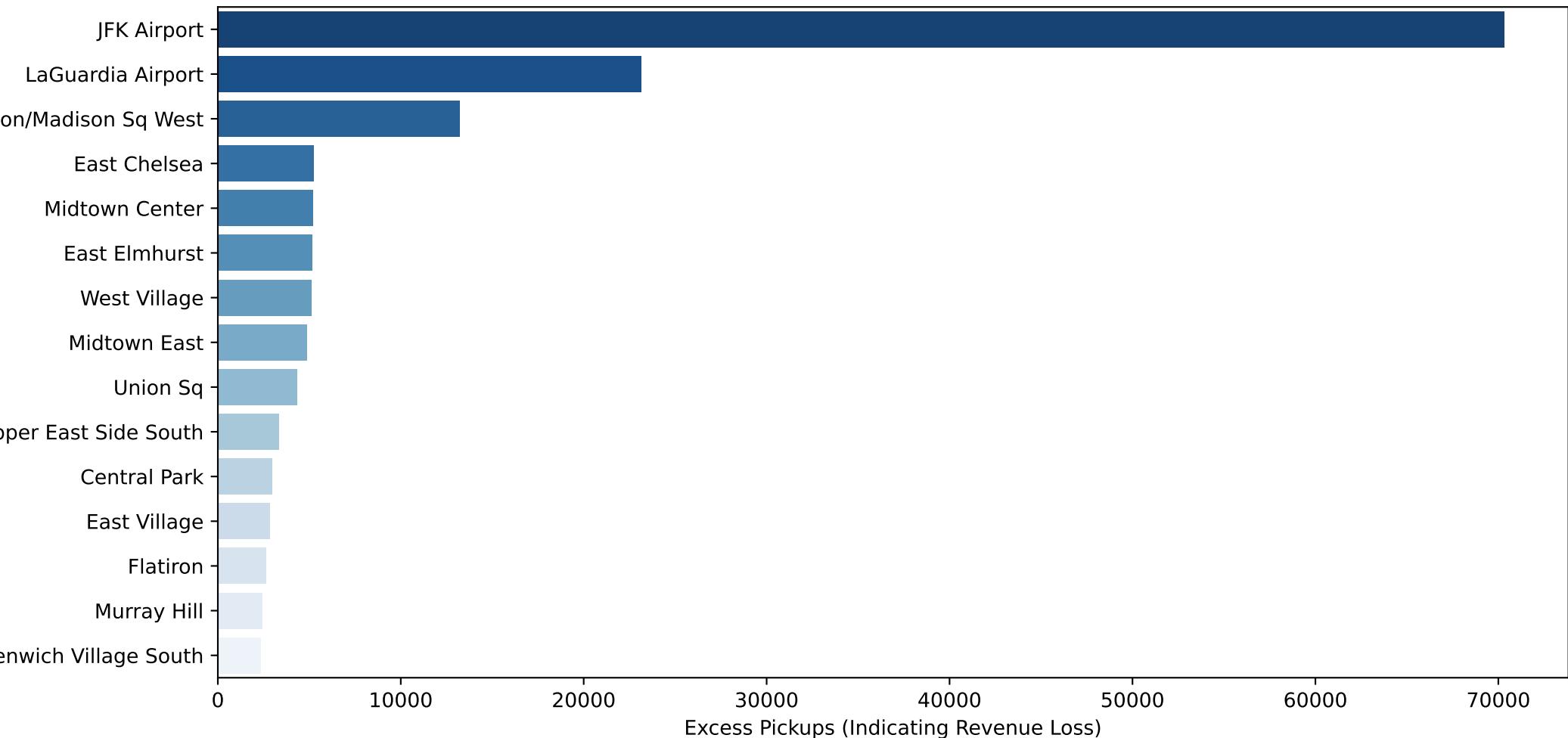
Dynamic Pricing Based on Demand:

- Lower fares in high-competition areas.
- Increase fares for peak hours and low-supply areas.

Top 15 Zones with Empty Return Trips



Top 15 Revenue Loss Zones (More Pickups than Drop-offs)



Conclusion/Remarks:

4.1.1 Balance Supply and Demand to Reduce Empty Trips

Insights from df_merged:

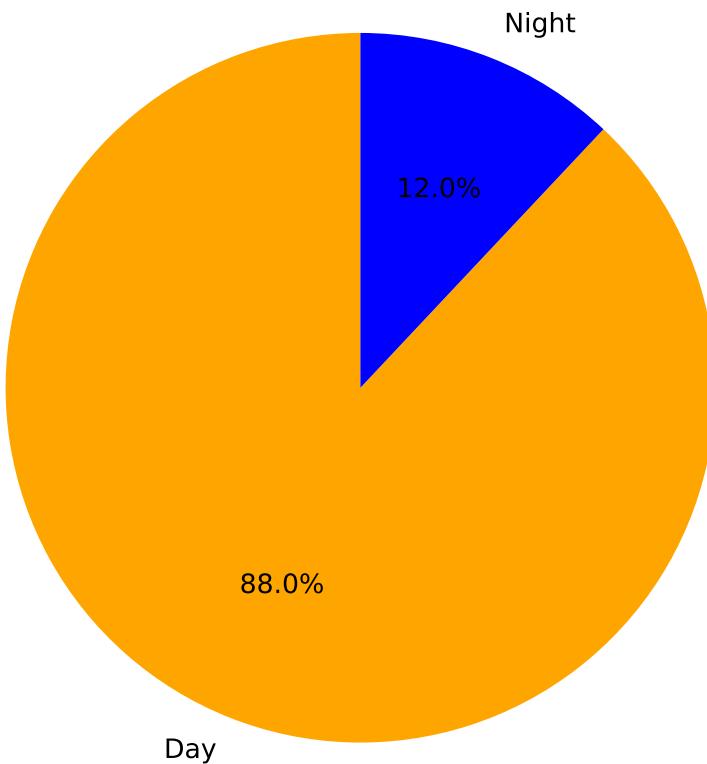
- Identify times and areas where drop-offs happen, but pickups are low → leads to empty trips.
- Zones with many outgoing trips but fewer incoming trips cause revenue loss.

Optimization Strategy:

Backhaul Optimization:

- Encourage drivers to pick up passengers from low-demand return zones.

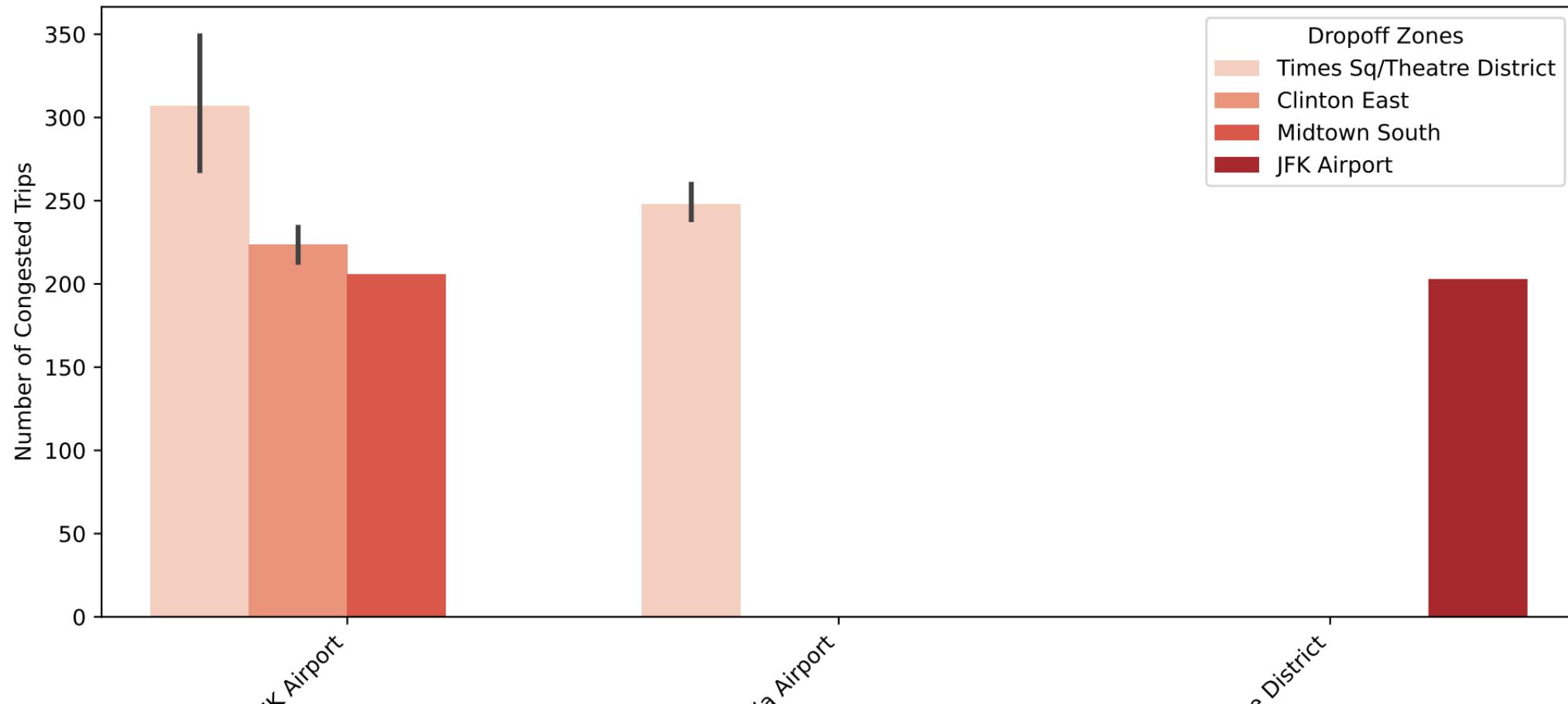
Revenue Share: Night vs Day



Conclusion/Remarks:

4.1.1 Compare nigh vs Day time Revenue share

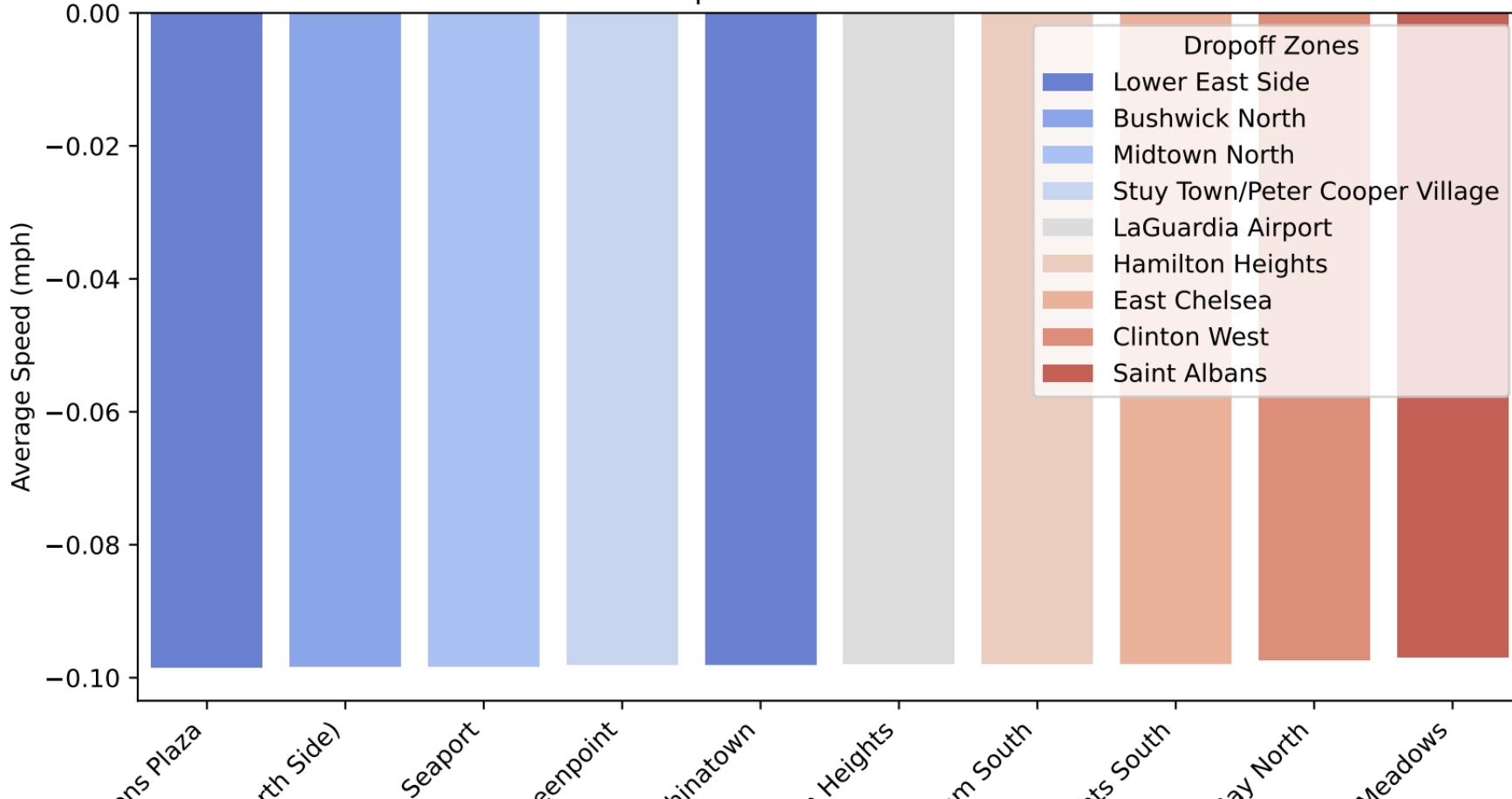
Top 20 Most Congested Routes



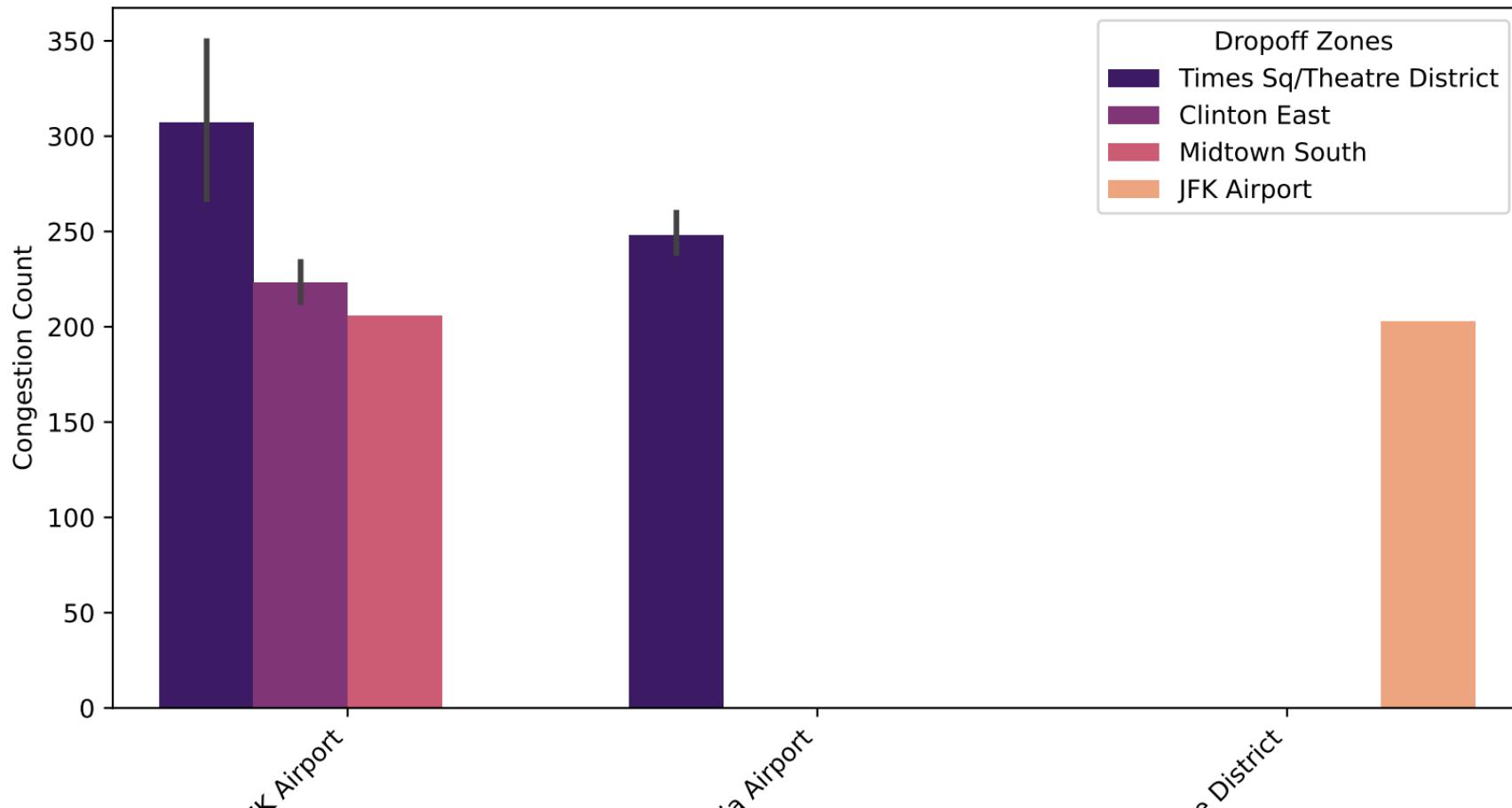
Conclusion/Remarks:

4.1.1 Compare Routes with High Congestion Pickup Zone and corresponding Dropoff Zones. JFK Airport is the most congested

Top 10 Slowest Routes



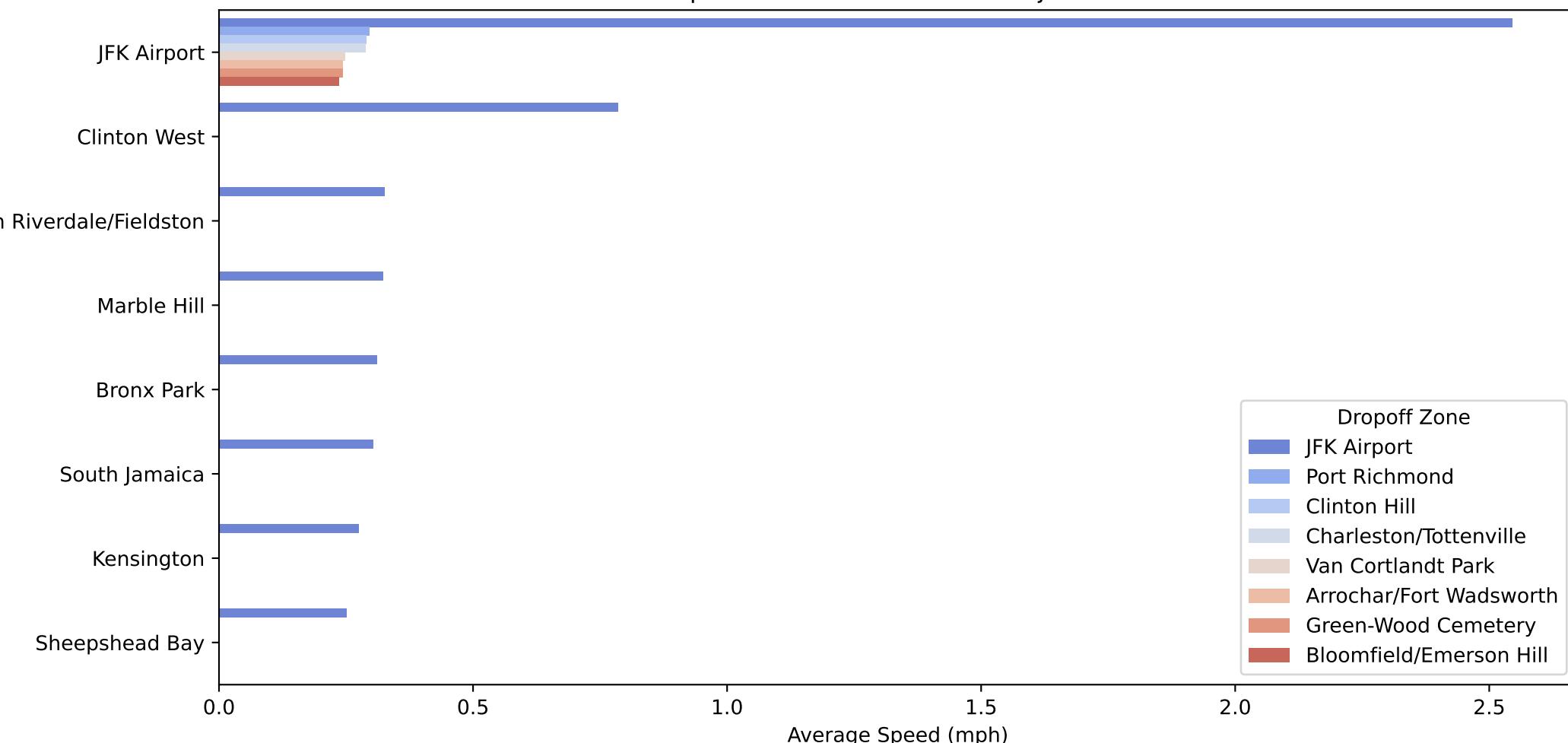
Top 10 Most Congested Routes



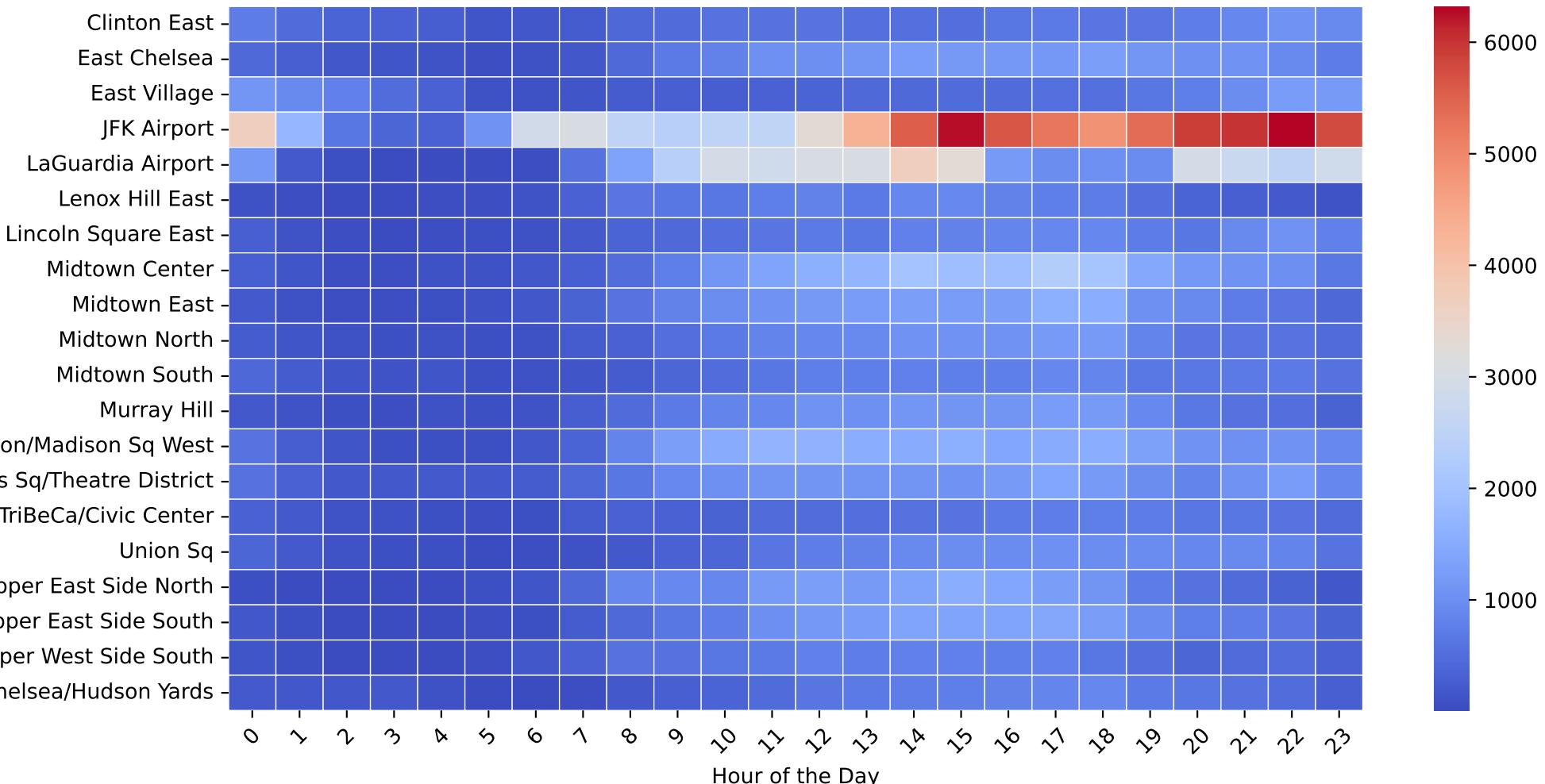
Conclusion/Remarks:

4.1.1 Compare the Top 10 slowest route with corresponding Dropoff

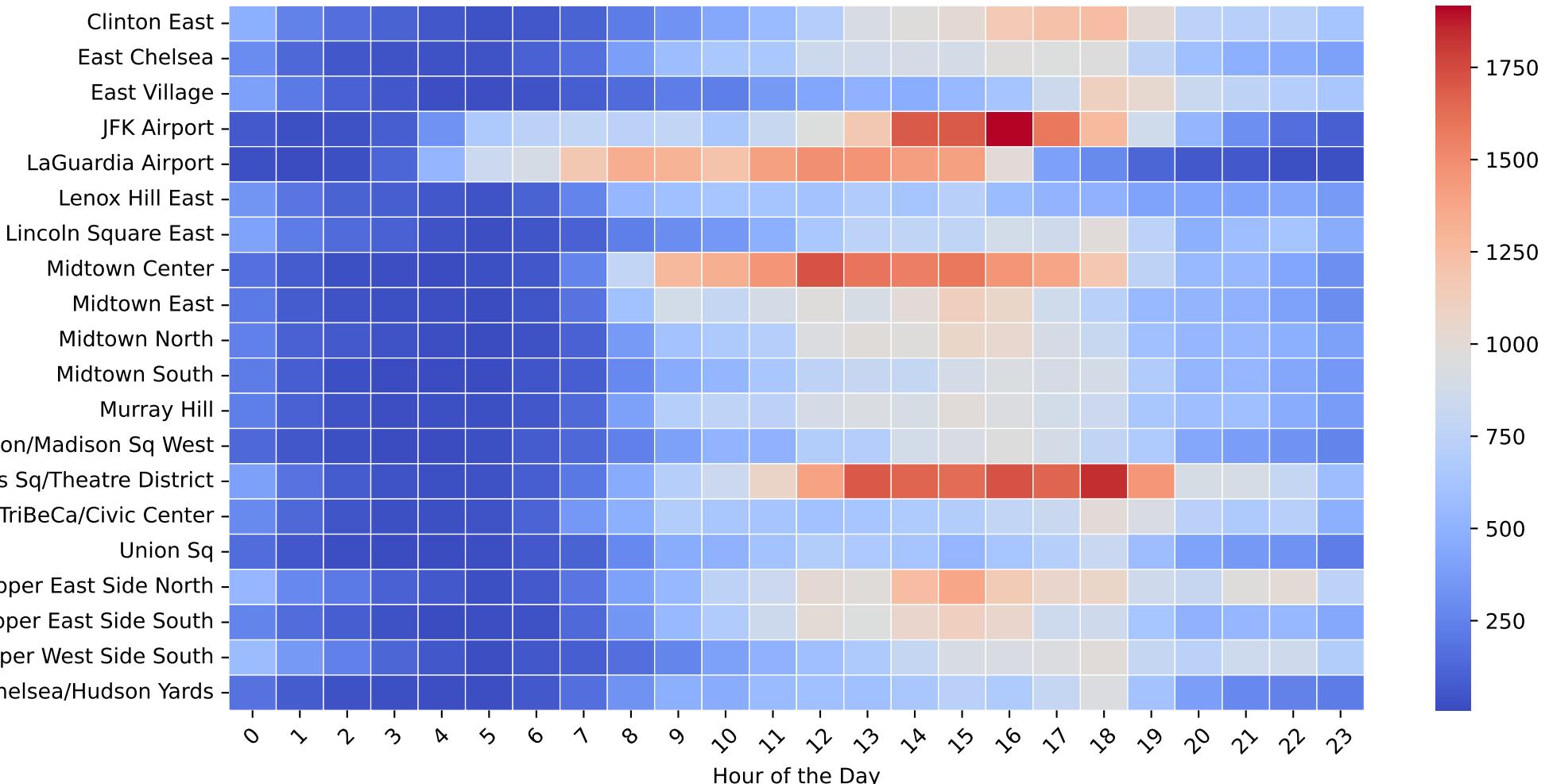
Top 15 Fastest Routes Near Major Hubs



Pickup Count Heatmap (Zone vs. Hour)



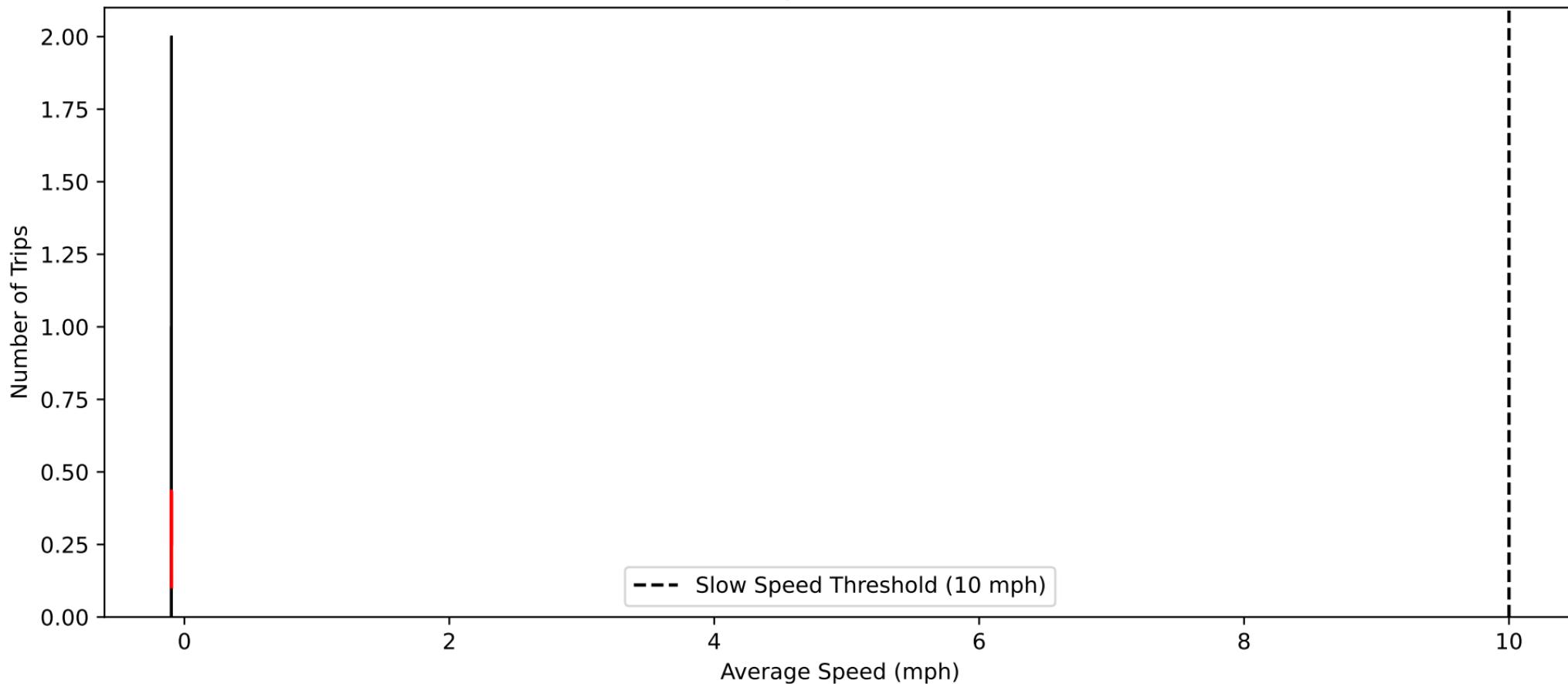
Dropoff Count Heatmap (Zone vs. Hour)



Conclusion/Remarks:

4.1.1 Compare Pickup vs Dropoff vs Hour in Heatmap. JFK airport Pickup 15:00 and 22:00 and Dropoff at 16:00

Distribution of Speeds in Different Zones



Conclusion/Remarks:

4.1.1 Showing Slow Route Speeds

Conclusion/Remarks:

4.1.2 Strategic Cab Positioning to Maximize Revenue & Reduce Empty Trips

By analyzing trip data across time, days, and months, we can strategically position cabs:

1 Busiest Zones & Peak Demand:

- Deploy more cabs where demand is high.

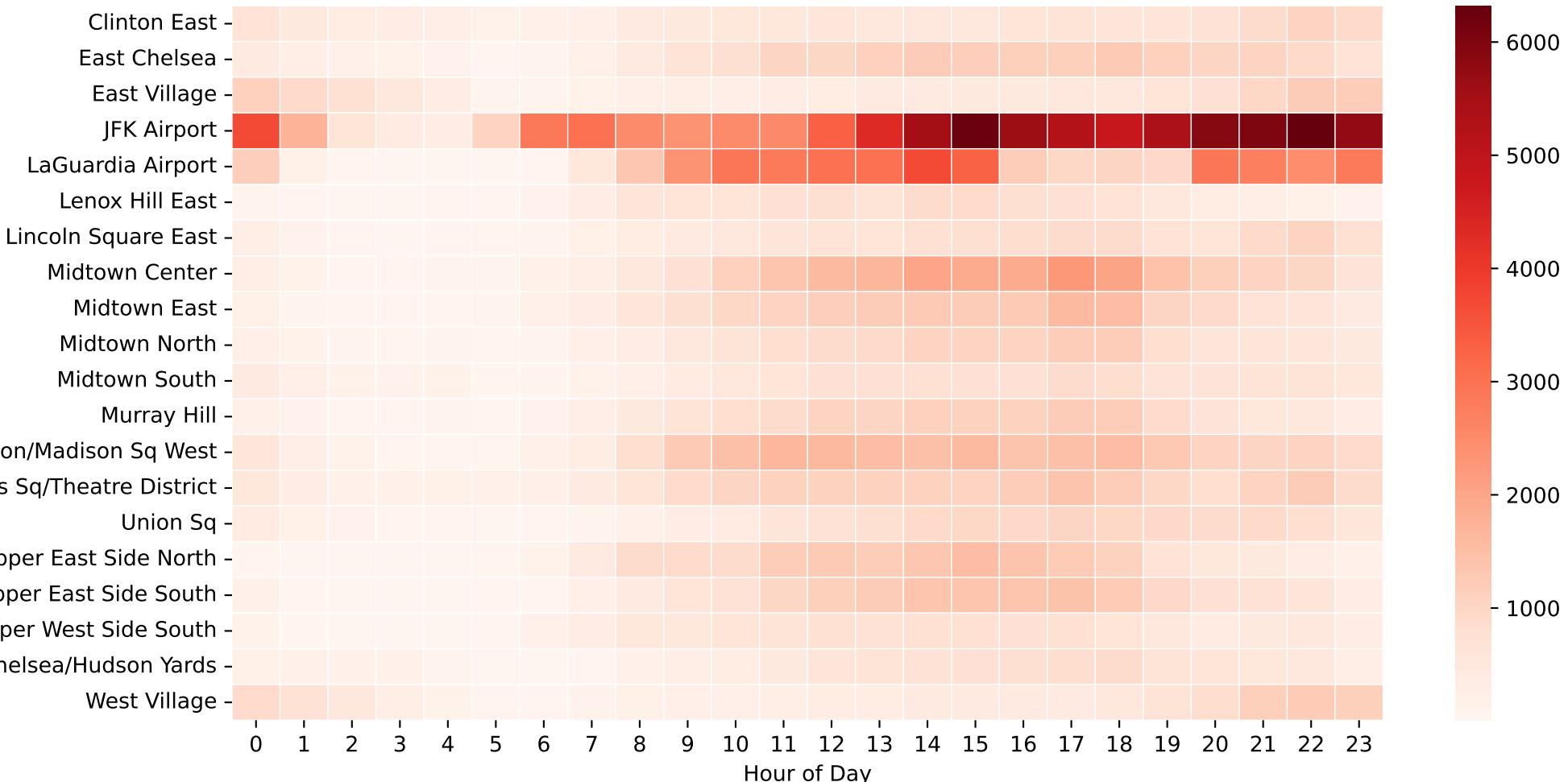
2 Imbalanced Zones (High Drop-offs, Low Pickups):

- Prevent empty trips by repositioning cabs.

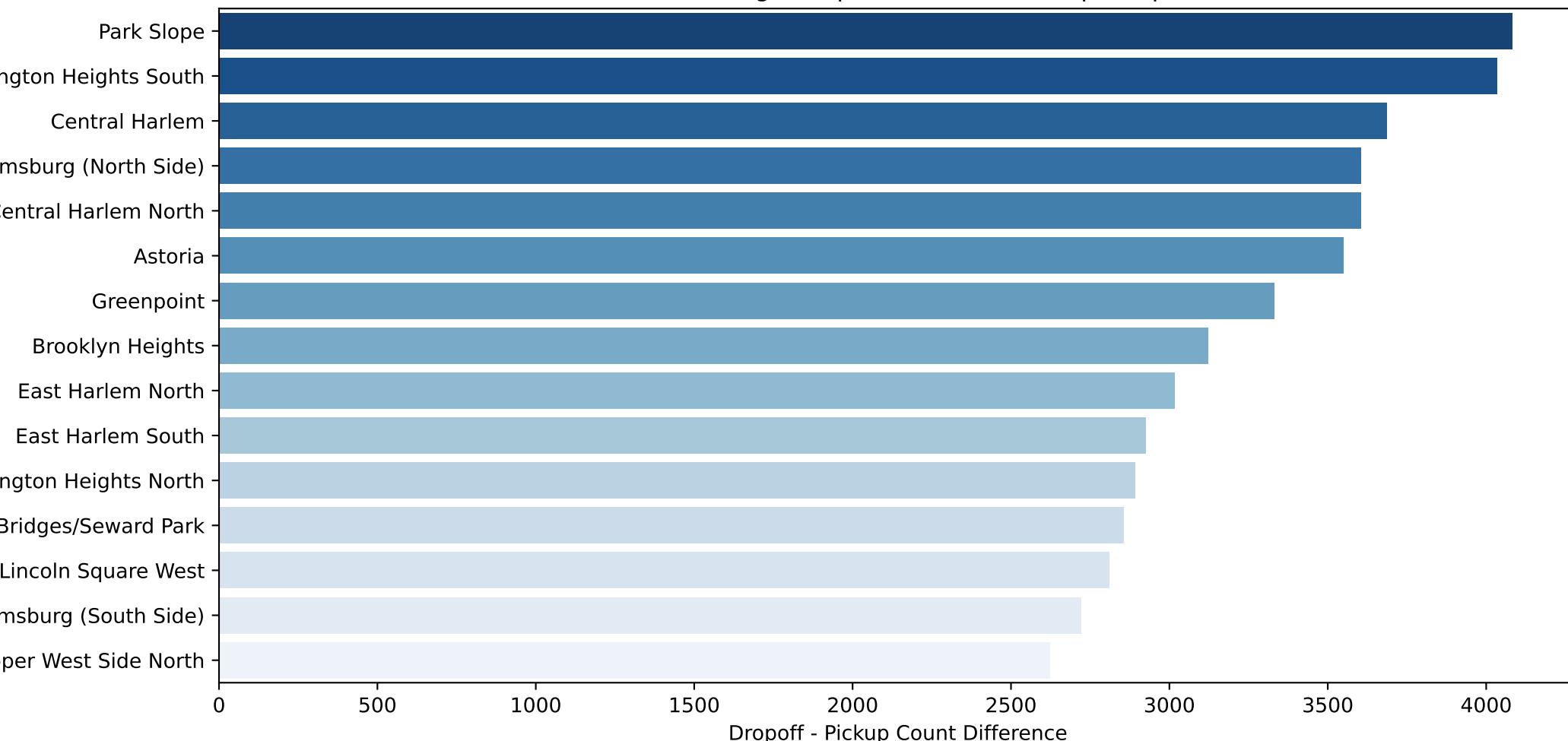
3 Time-Based Demand Shifts:

- Utilize machine learning models to predict future demand and adjust cab deployment accordingly.

Heatmap of Busiest Pickup Zones by Hour



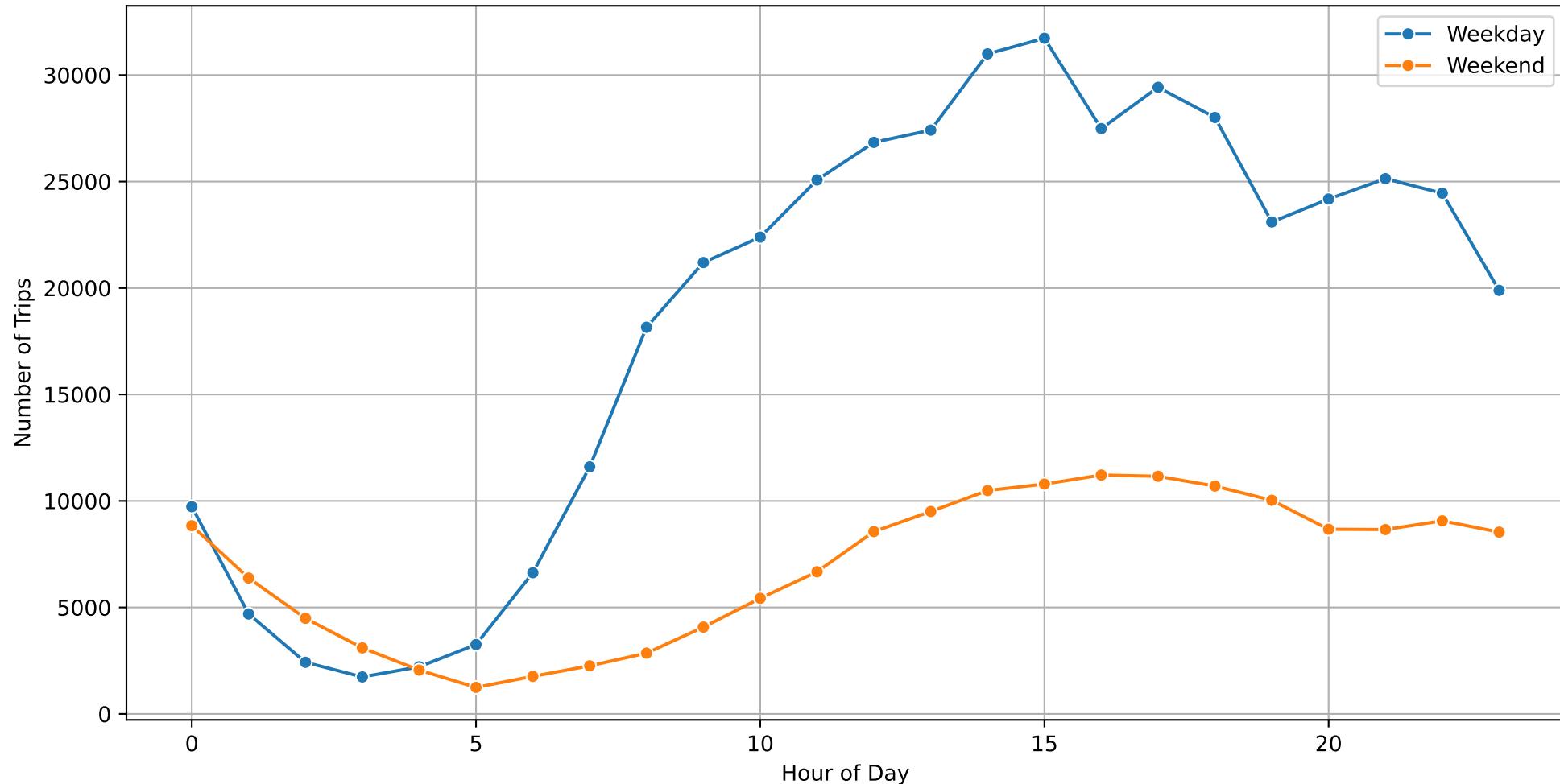
Zones with High Drop-offs but Low Pickups (Top 15)



Conclusion/Remarks:

4.1.2 Showing Zones where Low Pickup but High Dropoff. From this we can plan strategically

Weekday vs. Weekend Hourly Traffic Patterns



Conclusion/Remarks:

4.1.2 Showing Weekend vs. Weekday Demand Distribution

Conclusion/Remarks:

4.1.3 To Optimize Pricing While Staying Competitive

We analyze fare trends, demand patterns, and vendor competition:

1 Demand-Based Surge Pricing:

- Adjust fares based on peak vs. off-peak hours.

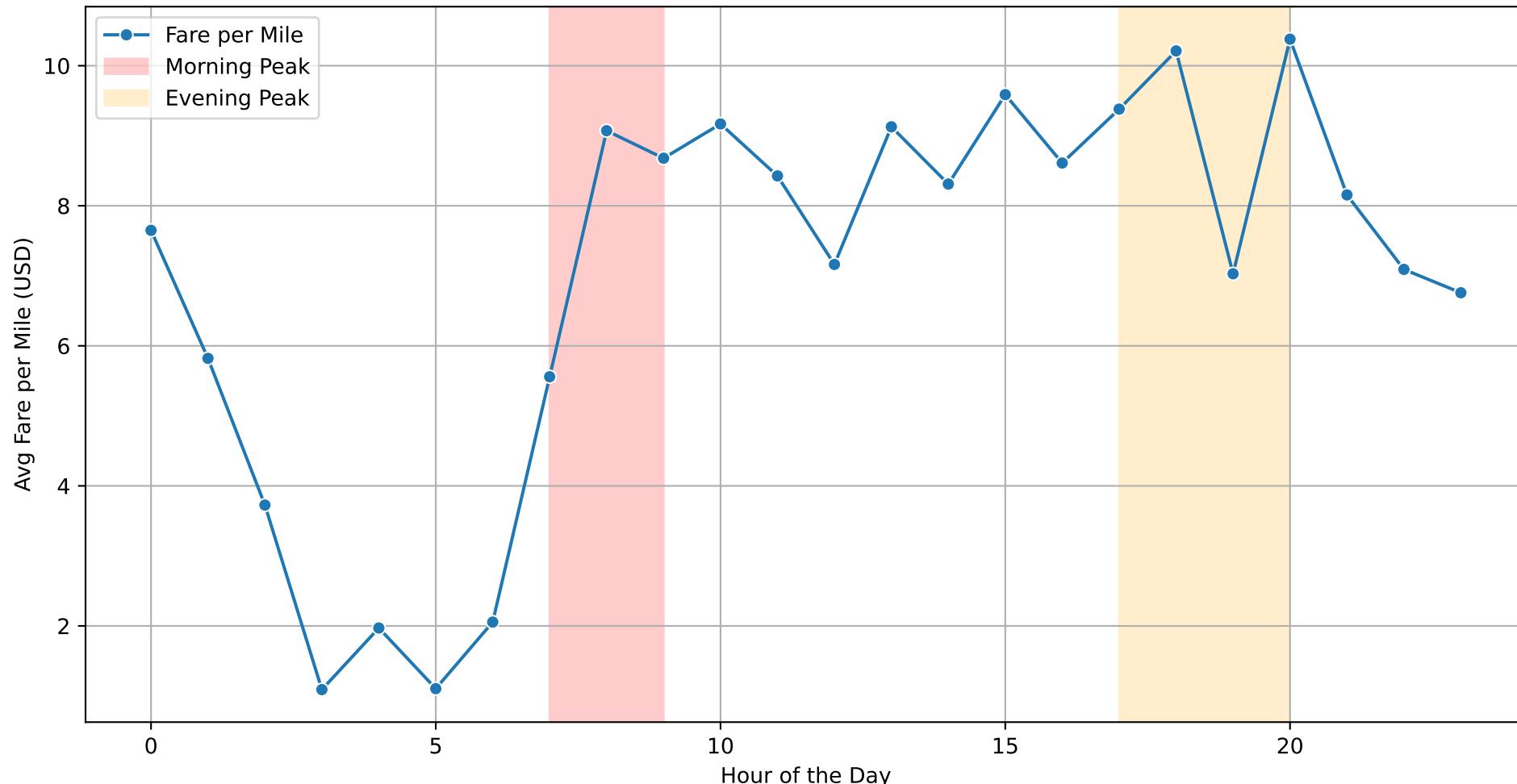
2 Distance-Based Tiered Pricing:

- Optimize fare per mile based on trip length.

3 Competitive Vendor Pricing:

- Monitor and respond to competitor pricing.

Dynamic Pricing Strategy: Peak vs. Off-Peak Hours



Conclusion/Remarks:

4.1.3 Showing plot to Identify peak demand hours where higher fares can be applied

Conclusion/Remarks:

4.1.3 Distance-Based Tiered Pricing Strategy

Adjust fares based on trip length to optimize revenue:

Short trips (<2 miles):

- Slightly higher fare per mile to compensate for short distances.

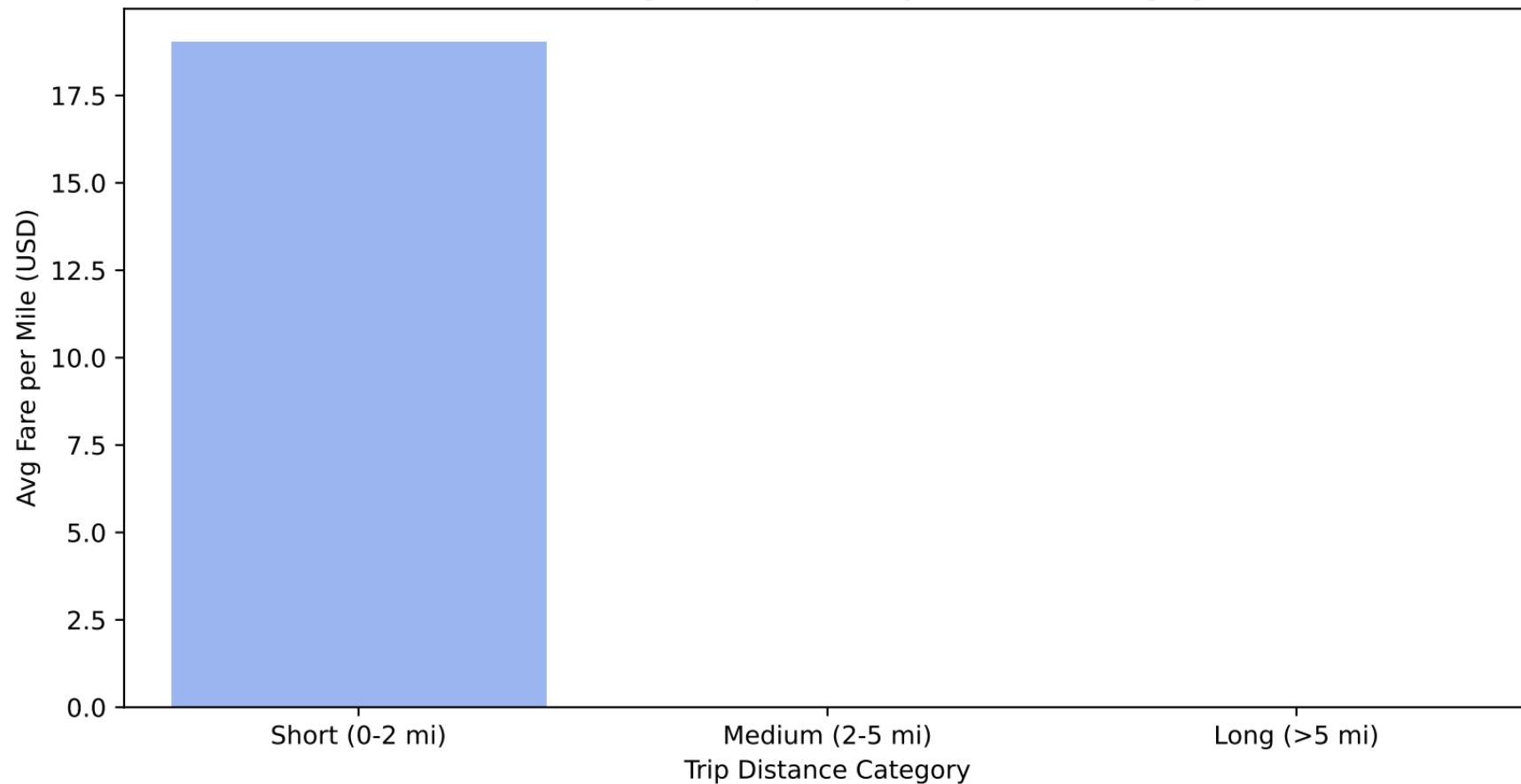
Mid-range trips (2-5 miles):

- Standard fare per mile for balanced pricing.

Long trips (>5 miles):

- Lower fare per mile to encourage long-distance travel.

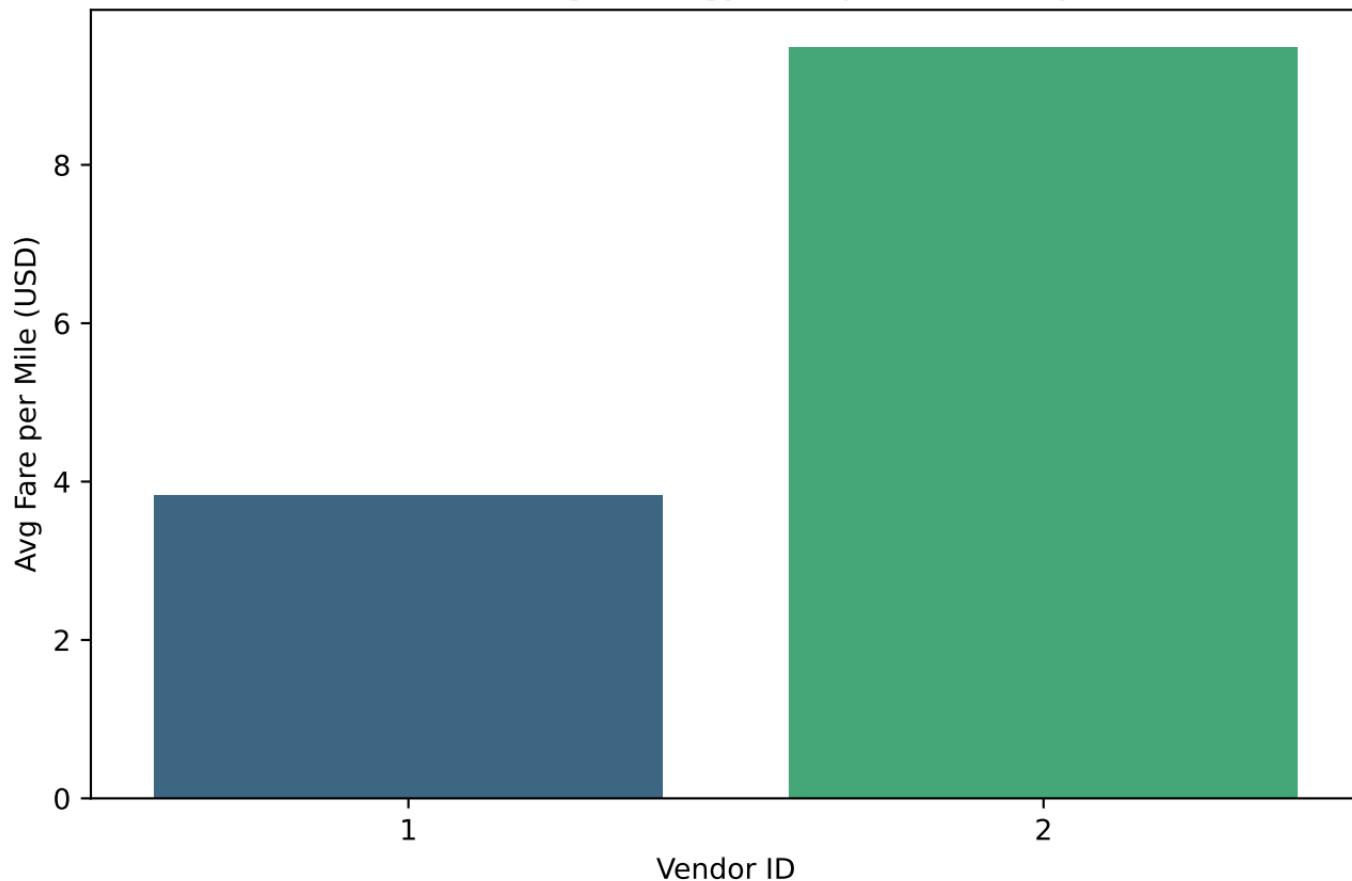
Tiered Pricing: Fare per Mile by Distance Category



Conclusion/Remarks:

4.1.3 Showing Tiered Pricing: Fare per Mile by Distance Category

Vendor Pricing Strategy: Competitive Analysis



Conclusion/Remarks:

4.1.3 Showing the comparison fare per mile for different vendors and adjust pricing to stay competitive

Conclusion/Remarks:

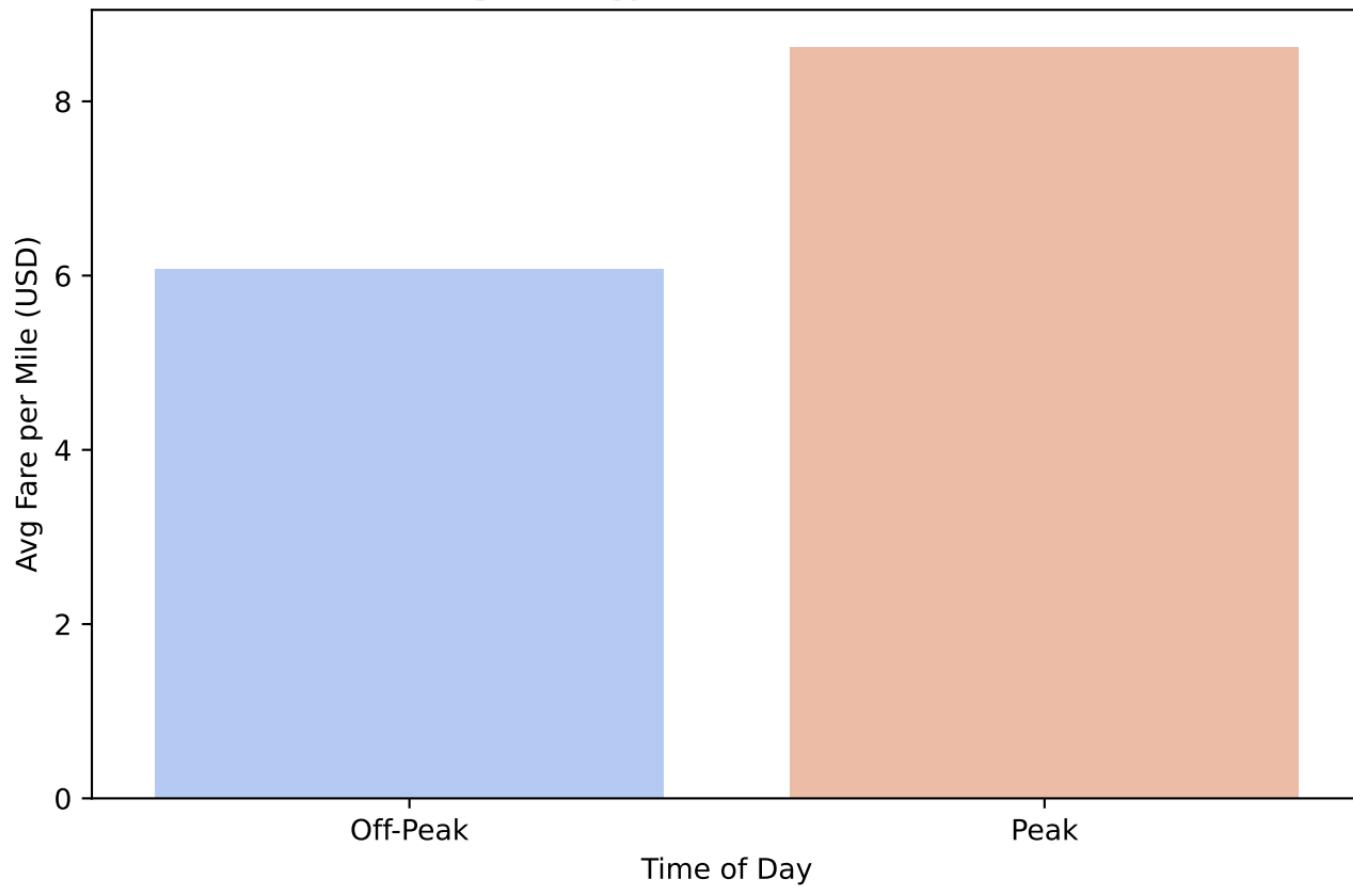
Time-Based Discounts for Off-Peak Hours

Offer discounts between 10 PM - 5 AM to boost nighttime rides.

Justification:

- Encourages more passengers to travel during low-demand hours.
- Helps drivers fill empty rides, reducing idle time.
- Improves overall revenue by maintaining a steady stream of trips.

Off-Peak Pricing Strategy: Discounts for Low-Demand Hours



Conclusion/Remarks:

4.1.3 Showing the Off-Peak Pricing Strategy: Discounts for Low-Demand Hours