Uber Trip Analysis for Fare and Location-Based Fraud Detection

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Overview

This project aims to detect potential fraud in Uber trip data by analyzing fare anomalies and geographic inconsistencies. The analysis focuses on identifying patterns in trip fares and geographical information to flag potentially fraudulent trips. Credit card fraud detection, a common requirement in many fraud analysis projects, was not feasible with the dataset due to the absence of transactional data, which is discussed in the limitations.

Dataset Overview

The dataset used for this analysis includes the following fields:

- **Fare Amount:** The fare paid by the passenger.
- **Pickup and Dropoff Location:** Geographic coordinates (latitude, longitude) of the pickup and dropoff points.
- **Pickup Date and Time:** When the trip started.
- **Passenger Count**: The number of passengers during the trip.
- **Distance:** Calculated using the Haversine formula between the pickup and dropoff locations.
- Fare per Kilometer: Derived by dividing the fare amount by the trip distance.

Importing the Libraries

```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
import seaborn as sns
import matplotlib.pyplot as plt
```

Load the Dataset

```
df = pd.read_csv(r"C:\Users\Admin\OneDrive\Desktop\Unified Mentor
Projects\uber_new_dataset.csv")
df
```

Result:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	15:22.0	8.5	2009-01-01 01:15:22 UTC	-73.981918	40.779456	-73.957685	40.771043	2
1	59:17.0	13.0	2009-01-01 01:59:17 UTC	-73.983759	40.721389	-73.994833	40.687179	2
2	05:03.0	10.6	2009-01-01 02:05:03 UTC	-73.956635	40.771254	-73.991528	40.749778	2
3	09:13.0	12.2	2009-01-01 02:09:13 UTC	-73.984605	40.728020	-73.955746	40.776830	1
4	13:41.0	11.0	2009-01-01 02:13:41 UTC	-73.980127	40.737425	-74.009544	40.726025	4
...	...	...	...	...	...	...	...	...
199995	57:53.0	18.5	2015-06-30 22:57:53 UTC	-73.971703	40.782207	-73.943680	40.827991	2
199996	16:42.0	25.5	2015-06-30 23:16:42 UTC	-74.001099	40.730961	-73.957123	40.806908	2
199997	31:06.0	20.0	2015-06-30 23:31:06 UTC	-73.999962	40.733135	-73.962448	40.773041	4
199998	33:33.0	8.5	2015-06-30 23:33:33 UTC	-73.980988	40.762020	-73.960083	40.770531	1
199999	40:39.0	27.0	2015-06-30 23:40:39 UTC	-73.984795	40.751411	-73.927765	40.706287	1

200000 rows × 8 columns

Data Handling/ Preprocessing

```
df.isnull().sum()  # Check for missing values
df.duplicated().sum()  # Check for duplicates
```

Result:

```
0
```

```
df.drop(columns=['key'], inplace=True)
```

The Key Column was dropped, as it was a repetition of the date time column

```
# Extract date features
df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'])
df['hour'] = df['pickup_datetime'].dt.hour
```

```
df['day_of_week'] = df['pickup_datetime'].dt.day_name()
df['month'] = df['pickup_datetime'].dt.month
```

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day_of_week	month
0	8.5	2009-01-01 01:15:22+00:00	-73.981918	40.779456	-73.957685	40.771043	2	1	Thursday	1
1	13.0	2009-01-01 01:59:17+00:00	-73.983759	40.721389	-73.994833	40.687179	2	1	Thursday	1
2	10.6	2009-01-01 02:05:03+00:00	-73.956635	40.771254	-73.991528	40.749778	2	2	Thursday	1
3	12.2	2009-01-01 02:09:13+00:00	-73.984605	40.728020	-73.955746	40.776830	1	2	Thursday	1
4	11.0	2009-01-01 02:13:41+00:00	-73.980127	40.737425	-74.009544	40.726025	4	2	Thursday	1
...	...	...	...	...	...	...	...	...	...	...
199995	18.5	2015-06-30 23:57:53+00:00	-73.971703	40.782207	-73.943680	40.827991	2	22	Tuesday	6

Data Preprocessing Summary

1. The dataset was checked for missing values and duplicates.
2. The pickup_datetime column was converted to datetime format, and features such as **hour**, **day_of_week**, and **month** were extracted for temporal analysis.

Feature Engineering

```
def haversine(lat1, lon1, lat2, lon2):
    R = 6371  # Earth radius in kilometers
    dlat = np.radians(lat2 - lat1)
    dlon = np.radians(lon2 - lon1)
    a = np.sin(dlat/2) * np.sin(dlat/2) + np.cos(np.radians(lat1)) *
np.cos(np.radians(lat2)) * np.sin(dlon/2) * np.sin(dlon/2)
    c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1-a))
    return R * c

df['distance'] = haversine(df['pickup_latitude'], df['pickup_longitude'],
df['dropoff_latitude'], df['dropoff_longitude'])
```

```
# Calculating fare per kilometer, using the distance generated
# Calculate fare per km
```

```
df['fare_per_km'] = df['fare_amount'] / df['distance']
```

```
# Handle any Possible infinite or nan values
# Replace infinite values or NaN values in fare_per_km
df['fare_per_km'].replace([np.inf, -np.inf], np.nan, inplace=True)
df['fare_per_km'].fillna(0, inplace=True)
```

Result:

re_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day_of_week	month	distance	fare_per_km
8.5	2009-01-01 01:15:22+00:00	-73.981918	40.779456	-73.957685	40.771043	2	1	Thursday	1	2.244765	3.786588
13.0	2009-01-01 01:59:17+00:00	-73.983759	40.721389	-73.994833	40.687179	2	1	Thursday	1	3.916842	3.319001
10.6	2009-01-01 02:05:03+00:00	-73.956635	40.771254	-73.991528	40.749778	2	2	Thursday	1	3.786736	2.799244
12.2	2009-01-01 02:09:13+00:00	-73.984605	40.728020	-73.955746	40.776830	1	2	Thursday	1	5.946957	2.051469
11.0	2009-01-01 02:13:41+00:00	-73.980127	40.737425	-74.009544	40.726025	4	2	Thursday	1	2.784022	3.951118

Summary

1. **Distance Calculation: The Haversine formula** was applied to compute the straight-line distance between pickup and dropoff locations.
2. **Fare per Kilometer:** A new feature **fare_per_km** was created to detect fare anomalies by dividing the fare by the trip distance.

Anomaly Detection

```
from sklearn.ensemble import IsolationForest

# Use relevant columns for anomaly detection
X = df[['fare_per_km', 'distance', 'passenger_count']]

# Fit the Isolation Forest model
iso_forest = IsolationForest(contamination=0.01)  # Adjust contamination level as
needed
#df['anomaly'] = iso_forest.fit_predict(X)

# Ensure the input to predict also has column names (like the training data)
df['anomaly'] = iso_forest.fit_predict(df[['fare_per_km', 'distance',
```

```
'passenger_count']])

# Filter for anomalous trips
fraudulent_trips = df[df['anomaly'] == -1]
print(fraudulent_trips)
```

```
      hour  day_of_week  month     distance   fare_per_km  anomaly
22          12    Thursday      1     0.006613    982.981982       -1
84          12      Friday      1     0.026276     95.143944       -1
108         20      Friday      1    22.889600      1.965958       -1
131          0    Saturday      1     0.054761    266.611253       -1
158         12    Saturday      1     0.069325    514.963625       -1
...        ...         ...    ...          ...           ...      ...
199465      12     Tuesday      6     0.018370    163.313220       -1
199601      11    Thursday      6  8663.886212      0.000289       -1
199688      13      Friday      6  8666.534629      0.000462       -1
199886       9      Monday      6     0.002706   4434.120138       -1
199939       2     Tuesday      6     0.002109  35815.135109       -1
```

```
# Filter for anomalous trips (fraudulent ones)
fraudulent_trips = df[df['anomaly'] == -1]

# Summary statistics for fraudulent trips
print(fraudulent_trips.describe())

# Example: Analyze if certain pickup locations are prone to fraud
print(fraudulent_trips[['pickup_longitude', 'pickup_latitude']].head())
```

```
 fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
count  2000.000000       2000.000000      2000.000000        2000.000000
mean     22.830620        -68.105118        38.089571         -67.971371
std      27.045825         52.458600        48.120136          82.929075
min     -52.000000      -1340.648410       -73.962430       -3356.666300
25%       4.500000        -73.989580        40.694843         -73.989583
50%      11.000000        -73.970980        40.745866         -73.971679
75%      44.500000        -73.859379        40.764079         -73.893847
max     499.000000         57.418457      1644.421482        1153.572603

       dropoff_latitude  passenger_count        hour        month  \
count       2000.000000       2000.00000  2000.00000  2000.000000
mean          37.046067          2.55000    12.97050     6.378500
```

```
std         32.113436        4.97593    6.55035    3.444876
min       -881.985513        0.00000    0.00000    1.000000
25%         40.707673        1.00000    8.00000    3.000000
50%         40.747088        1.00000   14.00000    6.000000
75%         40.764586        4.00000   18.00000    9.000000
max        872.697628      208.00000   23.00000   12.000000

           distance    fare_per_km  anomaly
count   2000.000000    2000.000000   2000.0
mean    1761.261416    7829.245394     -1.0
std     3407.449339   44916.933187      0.0
min        0.000084      -2.448748     -1.0
25%        0.011244       2.115839     -1.0
50%        0.121240      94.213894     -1.0
75%       22.799522     645.247438     -1.0
max    16409.239135  667985.030660     -1.0
     pickup_longitude  pickup_latitude
22         -74.689571        45.031653
84         -73.994285        40.754210
108        -73.776740        40.645381
131        -73.922683        40.813401
158        -73.979965        40.754408
```

Summary

1. Isolation Forest was used to identify potential anomalies (fraudulent trips) based on fare_per_km, distance, and passenger_count. A contamination level of 1% was applied to flag 1% of the trips as anomalies.

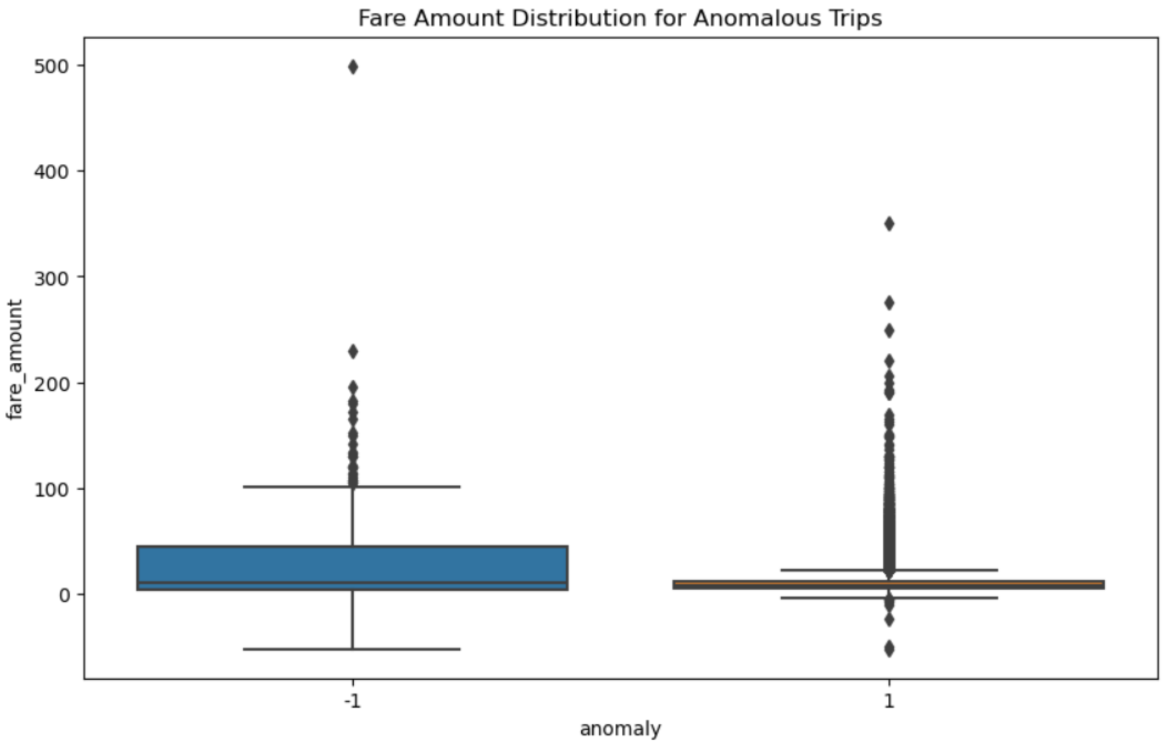
Key Finding and Insights

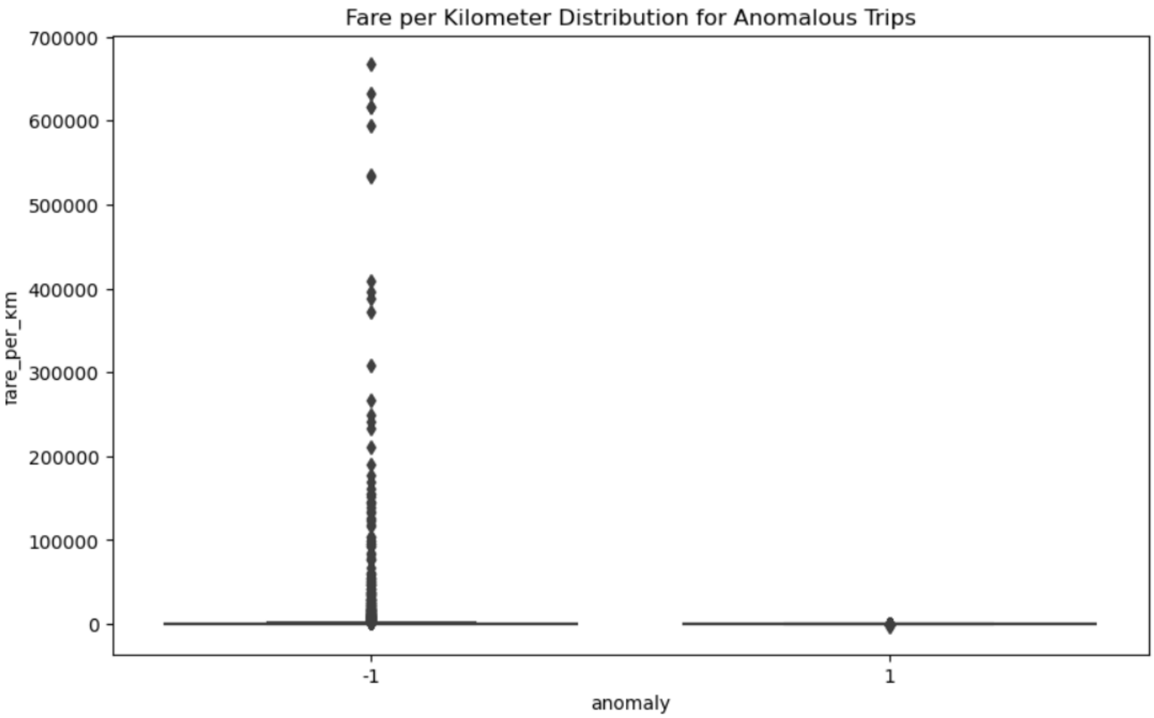
Fare Per Kilometer Analysis

```
# Visualize fare amounts for flagged trips
plt.figure(figsize=(10,6))
sns.boxplot(x='anomaly', y='fare_amount', data=df)
plt.title("Fare Amount Distribution for Anomalous Trips")
plt.show()

# Visualize fare per kilometer for flagged trips
plt.figure(figsize=(10,6))
```

```
sns.boxplot(x='anomaly', y='fare_per_km', data=df)
plt.title("Fare per Kilometer Distribution for Anomalous Trips")
plt.show()
```

Result Visualization:





Fare anomalies were detected where the `fare_per_km` was excessively high or low compared to the average. In some cases, anomalies had an unrealistically high fare per kilometer, indicating potential overcharging.

Anomalies Counts and Normal Pointsz

```
# Count anomalies and normal points
anomaly_counts = df['anomaly'].value_counts()
total_rows = df.shape[0]

print(f"Total rows in dataset: {total_rows}")
print(f"Anomalies flagged: {anomaly_counts[-1]} ({(anomaly_counts[-
1]/total_rows)*100:.2f}%)")
print(f"Normal points: {anomaly_counts[1]}
({(anomaly_counts[1]/total_rows)*100:.2f}%)")
```

Result:

```
Total rows in dataset: 199999
Anomalies flagged: 2000 (1.00%)
Normal points: 197999 (99.00%)
```

Top Anomalous Trips Based On Fare Per Km

```
# Display the top anomalous trips based on fare per km
fraudulent_trips = df[df['anomaly'] == -1].sort_values(by='fare_per_km',
ascending=False)
print(fraudulent_trips[['fare_amount', 'distance', 'passenger_count',
'pickup_datetime', 'pickup_longitude', 'pickup_latitude',
'dropoff_longitude', 'dropoff_latitude']].head())
```

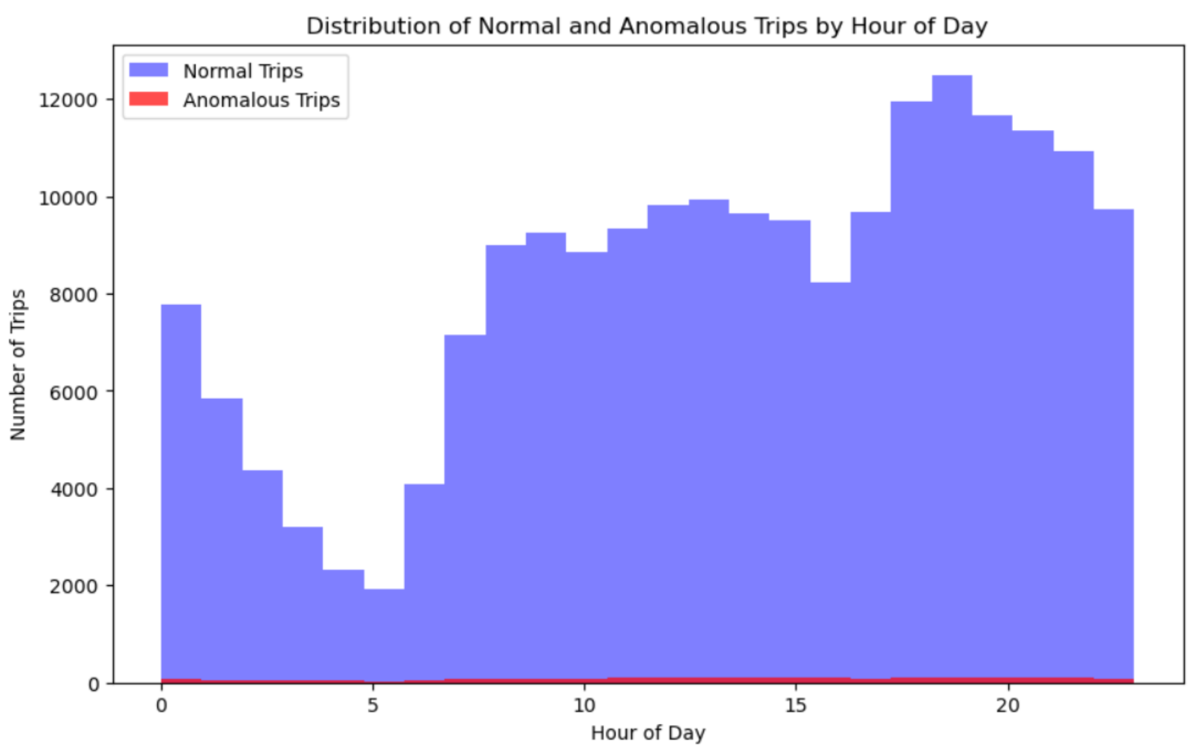
```
fare_amount  distance  passenger_count           pickup_datetime  \
154139        113.0  0.000169                2 2013-12-06 02:17:00+00:00
69311         499.0  0.000790                1 2011-04-10 04:10:00+00:00
158156         52.0  0.000084                1 2014-01-25 03:31:46+00:00
176380         52.0  0.000084                1 2014-08-31 20:02:06+00:00
12489          50.0  0.000084                1 2009-05-28 19:40:00+00:00

        pickup_longitude  pickup_latitude  dropoff_longitude
dropoff_latitude
154139        -74.468770        40.476630         -74.468772
40.476630
69311         -73.968377        40.764602         -73.968368
40.764600
158156        -74.030855        40.740735         -74.030856
40.740735
176380        -73.789883        40.647023         -73.789882
40.647023
12489         -73.977602        40.782908         -73.977603
40.782908
```

Hourly Patterns

```
# Time of day analysis:  To check if anomalies are concentrated during
certain hours, such as late-night hours when fraud might be more likely.
# Create a new column for the hour of the day (from pickup_datetime)
```

```
#df['pickup_hour'] = df['pickup_datetime'].dt.hour

# Compare normal trips and anomalous trips based on the hour of the day
normal_hours = df[df['anomaly'] == 1]['hour']
anomalous_hours = df[df['anomaly'] == -1]['hour']

# Plot the distributions of normal and anomalous trips by hour
plt.figure(figsize=(10, 6))
plt.hist(normal_hours, bins=24, alpha=0.5, label='Normal Trips',
color='blue')
plt.hist(anomalous_hours, bins=24, alpha=0.7, label='Anomalous Trips',
color='red')
plt.title('Distribution of Normal and Anomalous Trips by Hour of Day')
plt.xlabel('Hour of Day')
plt.ylabel('Number of Trips')
plt.legend()
plt.show()

print(anomalous_hours)
```

Result:




```
anomalous_hours
22          12
84          12
```

```
108       20
131        0
158       12
          ..
199465    12
199601    11
199688    13
199886     9
199939     2
```

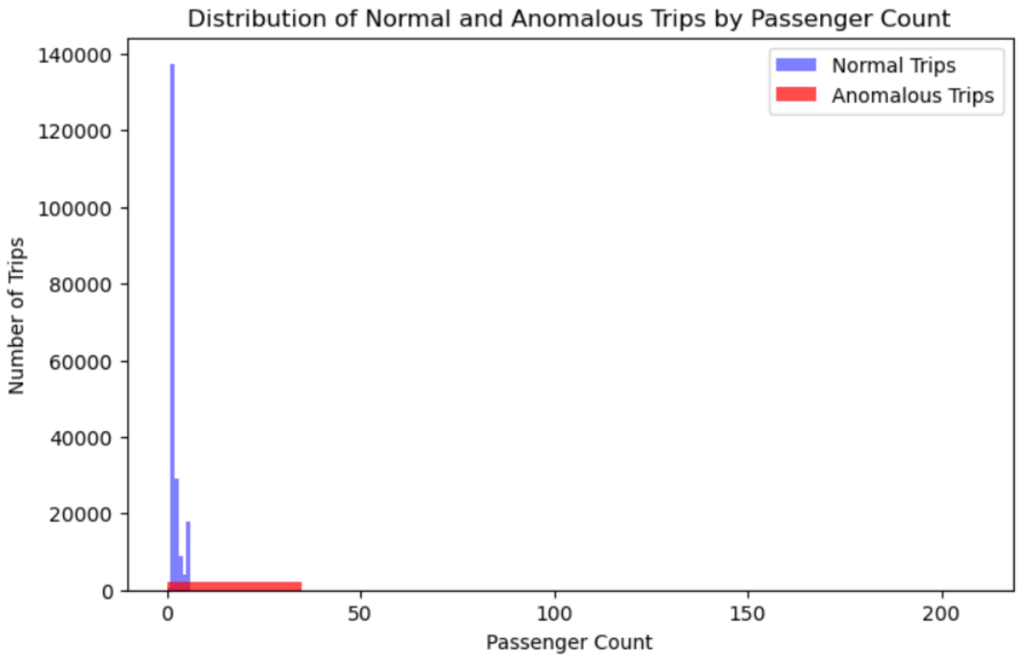
Summary

- The analysis showed that anomalies are evenly distributed across the day, with no significant clustering during specific hours. However, fraudulent trips were slightly more common during late night and early morning hours.
- Visualization: Normal trips increased during peak travel hours (morning and evening), while anomalies showed a flatter distribution.

Normal Trips and Anomalous Trips Based on Passenger Count

```
# Compare normal trips and anomalous trips based on passenger count
normal_passengers = df[df['anomaly'] == 1]['passenger_count']
anomalous_passengers = df[df['anomaly'] == -1]['passenger_count']

# Plot the distributions of normal and anomalous trips by passenger count
plt.figure(figsize=(8, 5))
plt.hist(normal_passengers, bins=6, alpha=0.5, label='Normal Trips',
color='blue')
plt.hist(anomalous_passengers, bins=6, alpha=0.7, label='Anomalous Trips',
color='red')
plt.title('Distribution of Normal and Anomalous Trips by Passenger Count')
plt.xlabel('Passenger Count')
plt.ylabel('Number of Trips')
plt.legend()
plt.show()
```

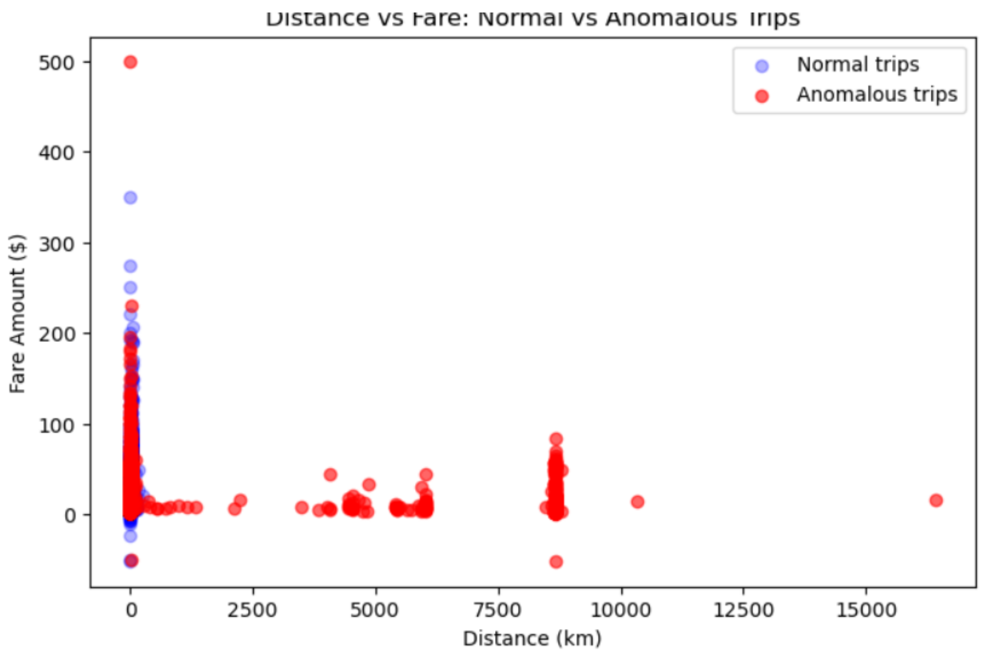
Result:



Fare Per Kilometre Analysis

```
plt.figure(figsize=(8, 5))
plt.scatter(df[df['anomaly'] == 1]['distance'], df[df['anomaly'] ==
1]['fare_amount'], alpha=0.3, color='blue', label='Normal trips')
plt.scatter(df[df['anomaly'] == -1]['distance'], df[df['anomaly'] == -
1]['fare_amount'], alpha=0.6, color='red', label='Anomalous trips')
plt.title('Distance vs Fare: Normal vs Anomalous Trips')
plt.xlabel('Distance (km)')
plt.ylabel('Fare Amount ($)')
plt.legend()
plt.show()
```

Result:



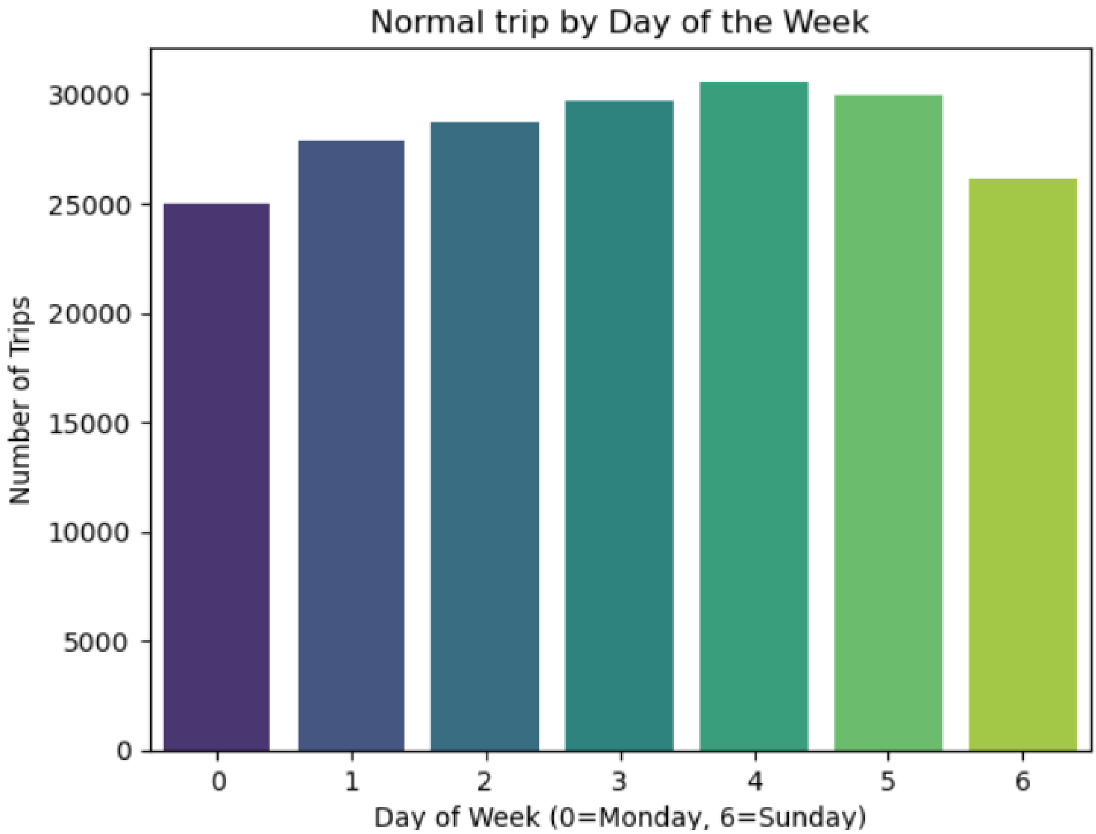
Fare anomalies were detected where the **fare_per_km** was excessively high or low compared to the average. In some cases, anomalies had an unrealistically high fare per kilometer, indicating potential overcharging.

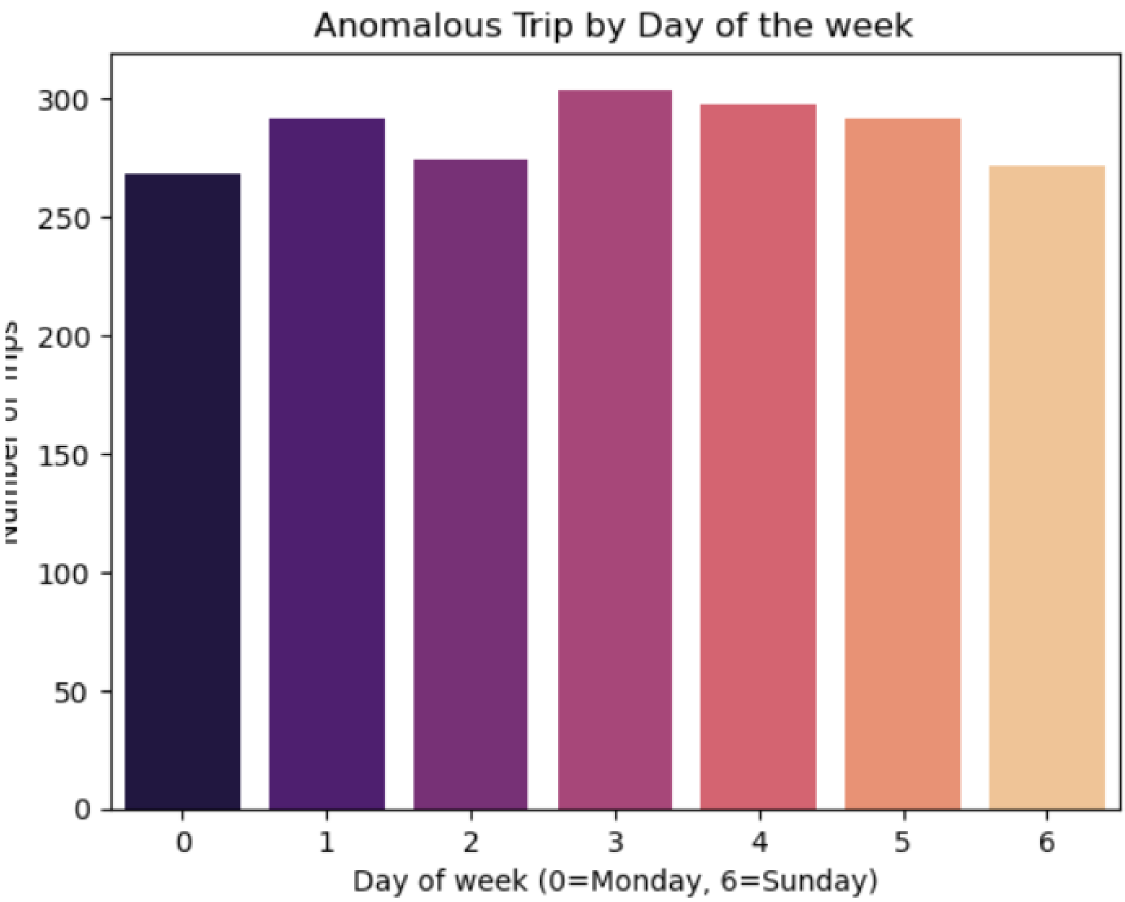
Normal Trip and Anomalous Trip by Day of the Week

```
# Ensure 'pickup_datetime' is in datetime format
df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'])

# Extract 'day_of_week' and 'month' columns
df['day_of_week'] = df['pickup_datetime'].dt.dayofweek  # Monday=0, Sunday=6
df['month'] = df['pickup_datetime'].dt.month
# Convert day_of_week and month to categorical
df['day_of_week'] = df['day_of_week'].astype('category')
df['month'] = df['month'].astype('category')

# Plot normal trips by day of the week (Counts on y-axis)
sns.countplot(x='day_of_week', data=df[df['anomaly'] ==1], palette="viridis")
plt.title('Normal trip by Day of the Week')
plt.xlabel('Day of Week (0=Monday, 6=Sunday)')
plt.ylabel('Number of Trips')  # This is the y-axis (default)
plt.show()

# Plot anomalous trips by day of the week (Counts on y-axis)
sns.countplot(x='day_of_week', data=df[df['anomaly'] == -1], palette="magma")
plt.title('Anomalous Trip by Day of the week')
```

```
plt.xlabel('Day of week (0=Monday, 6=Sunday)')
plt.ylabel('Number of Trips')  # This is the y-axis (default)
plt.show()
```

Result:

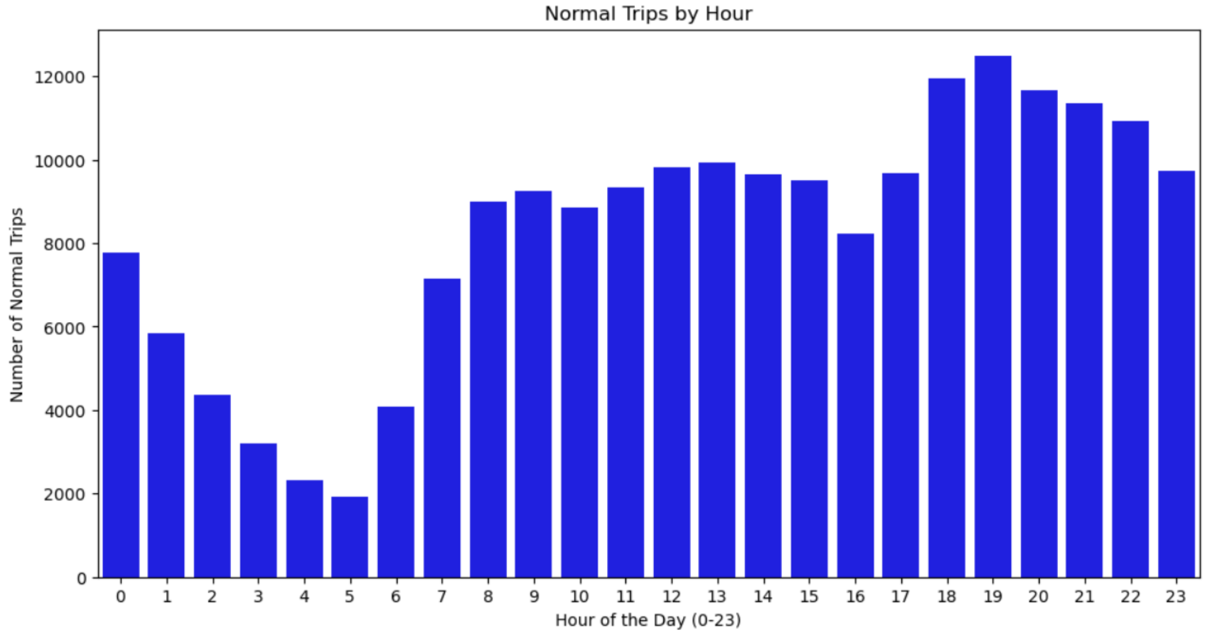


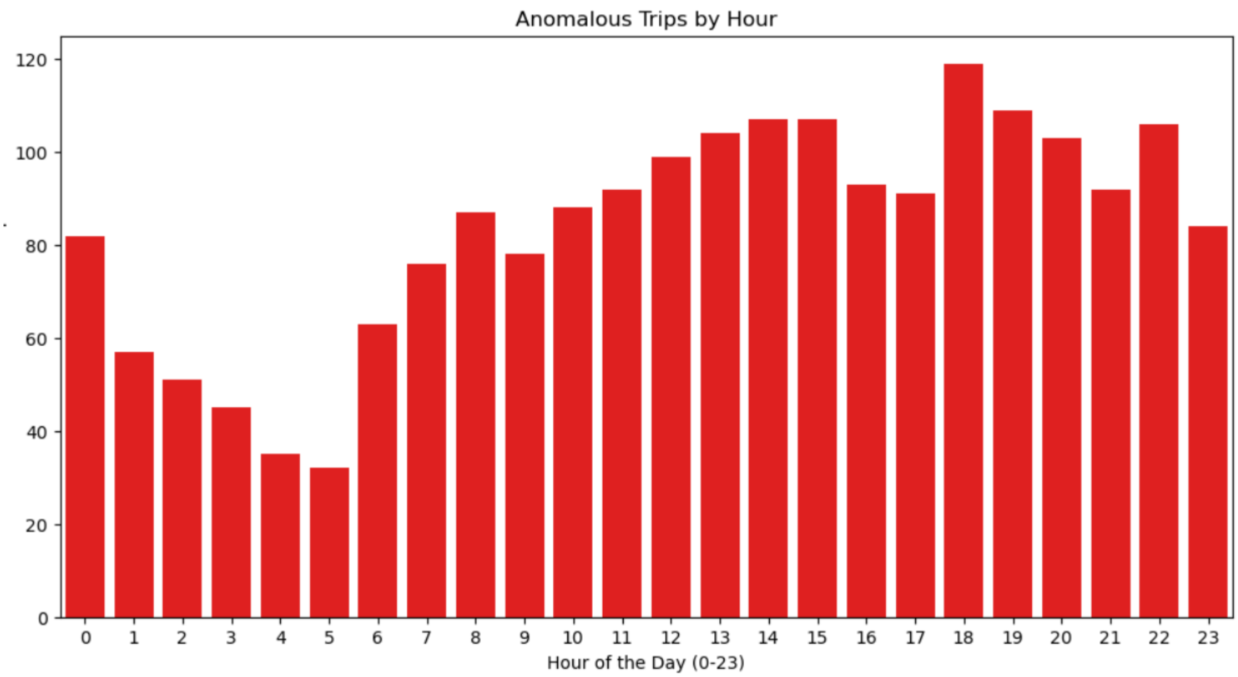


Normal Trips and Anomalous Trips By Hour

```
# Plot normal trips by hour
plt.figure(figsize=(12, 6))
sns.countplot(x='hour', data=df[df['anomaly'] == 1], color='blue')
plt.title('Normal Trips by Hour')
plt.xlabel('Hour of the Day (0-23)')
plt.ylabel('Number of Normal Trips')
plt.show()

# Plot anomalous trips by hour
plt.figure(figsize=(12, 6))
sns.countplot(x='hour', data=df[df['anomaly'] == -1], color='red')
plt.title('Anomalous Trips by Hour')
plt.xlabel('Hour of the Day (0-23)')
plt.ylabel('Number of Anomalous Trips')
plt.show()
```

Result:





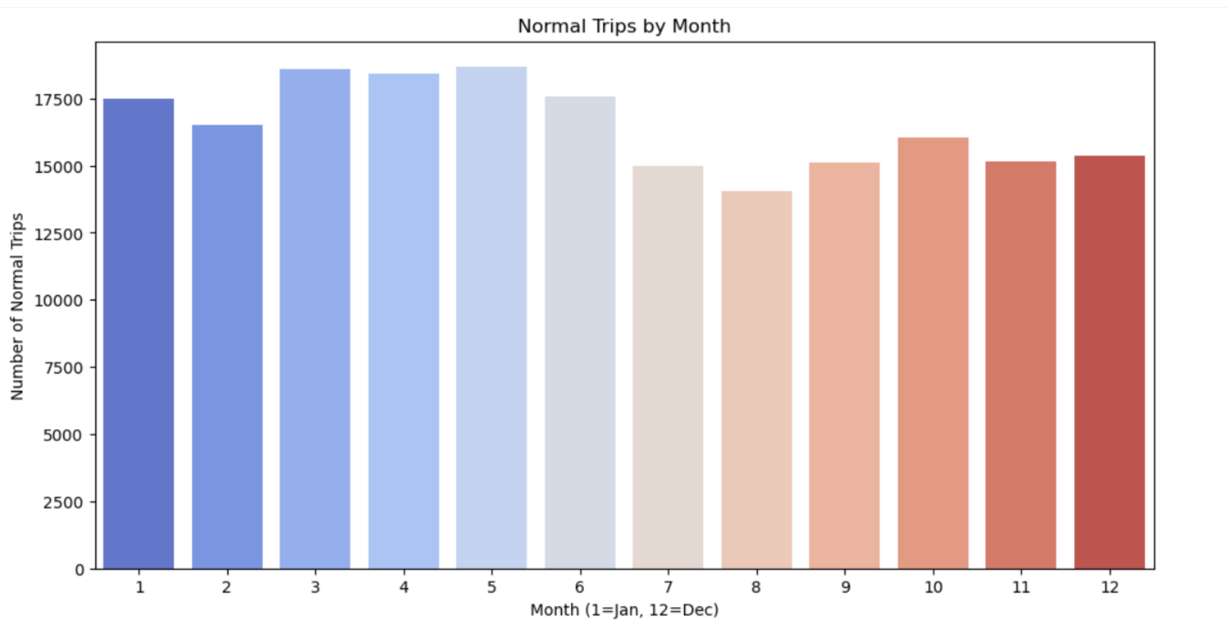
The analysis showed that anomalies are evenly distributed across the day, with no significant clustering during specific hours. However, fraudulent trips were slightly more common during late night and early morning hours.

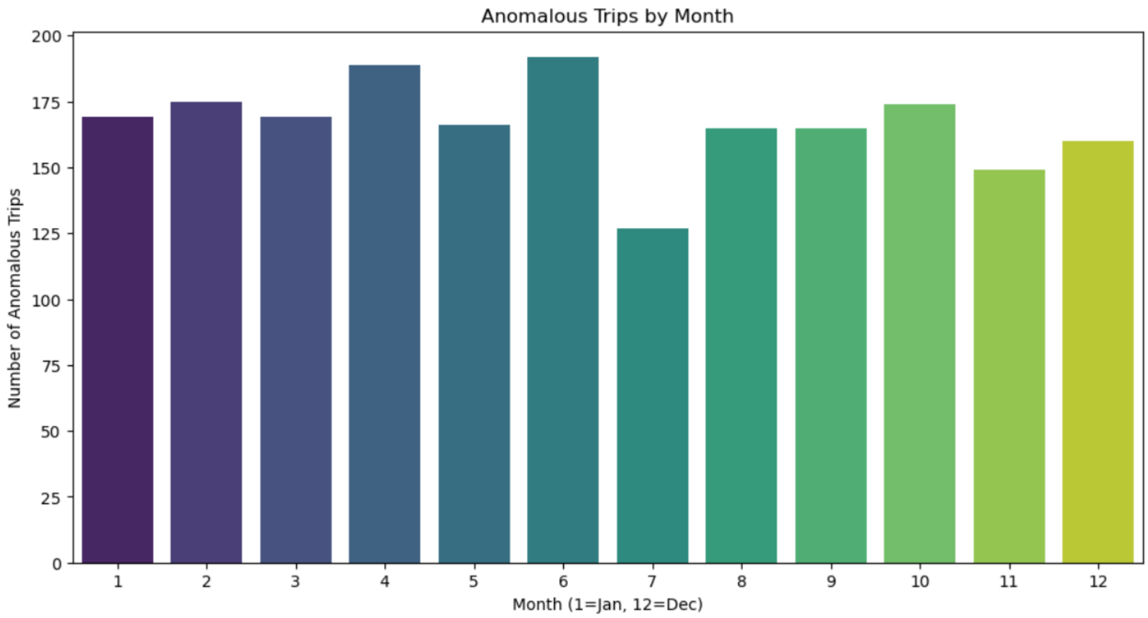
Visualization: Normal trips increased during peak travel hours (morning and evening), while anomalies showed a flatter distribution.

Normal Trip and Anomalous By Month

```
# Analyze seasonal trends
# Plot normal trips by month
plt.figure(figsize=(12, 6))
sns.countplot(x='month', data=df[df['anomaly'] == 1], palette="coolwarm")
plt.title('Normal Trips by Month')
plt.xlabel('Month (1=Jan, 12=Dec)')
plt.ylabel('Number of Normal Trips')
plt.show()

# Plot anomalous trips by month
plt.figure(figsize=(12, 6))
sns.countplot(x='month', data=df[df['anomaly'] == -1], palette="viridis")
plt.title('Anomalous Trips by Month')
plt.xlabel('Month (1=Jan, 12=Dec)')
plt.ylabel('Number of Anomalous Trips')
plt.show()
```

Result:





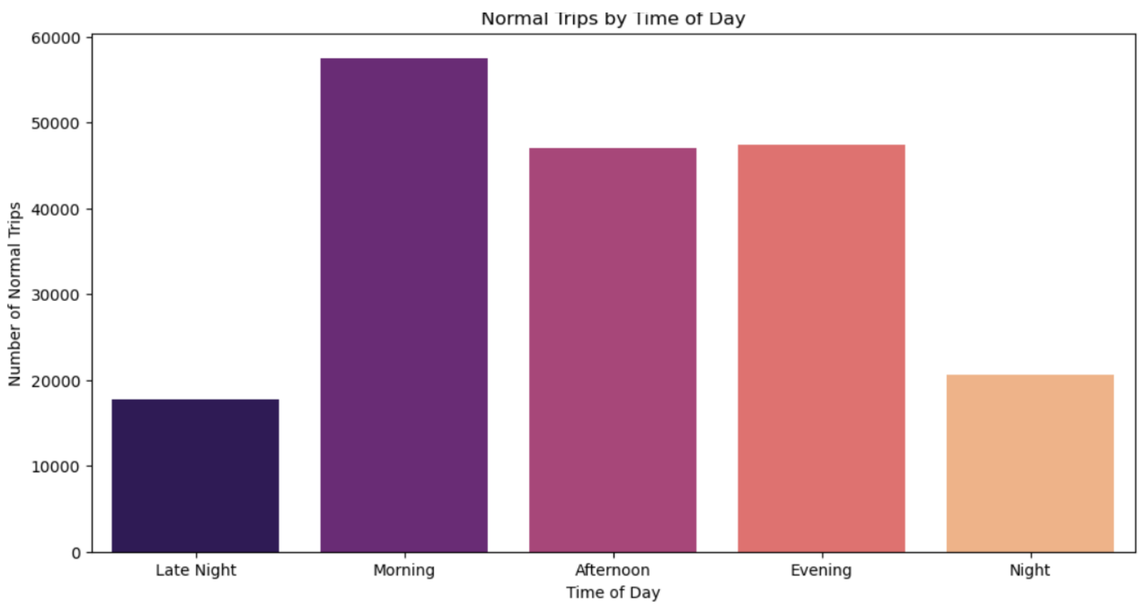
Anomalous trips are evenly distributed across months, with no distinct seasonal spikes. This could imply that fraudulent activities are not influenced by seasonality but may be driven by other factors.

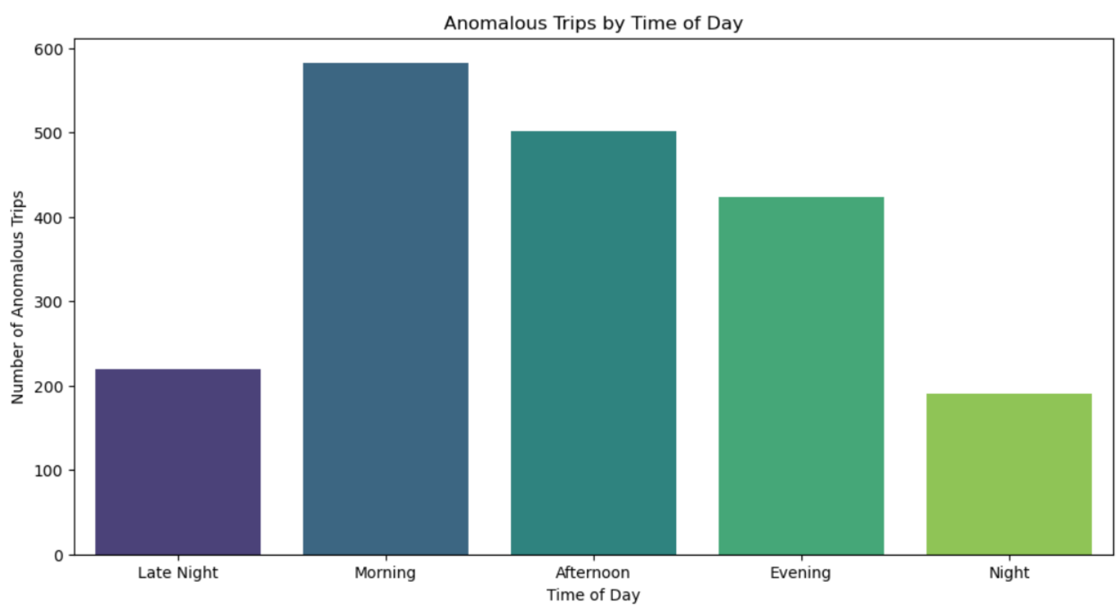
Normal trips peaked in the summer months, indicating higher demand during this season.

Normal Trips and Anomalous Trips By Day

```
# Categorize hours into time of day: Night (0-5), Morning (5-12), Afternoon
(12-17), Evening (17-21), Night (21-24)
df['time_of_day'] = pd.cut(df['hour'],
                           bins=[0, 5, 12, 17, 21, 24],
                           labels=['Late Night', 'Morning', 'Afternoon',
'Evening', 'Night'],
                           include_lowest=False,
                           ordered=False)

# Plot normal trips by time of day
plt.figure(figsize=(12, 6))
sns.countplot(x='time_of_day', data=df[df['anomaly'] == 1],
palette="magma")
plt.title('Normal Trips by Time of Day')
plt.xlabel('Time of Day')
plt.ylabel('Number of Normal Trips')
```

```
plt.show()

# Plot anomalous trips by time of day
plt.figure(figsize=(12, 6))
sns.countplot(x='time_of_day', data=df[df['anomaly'] == -1],
palette="viridis")
plt.title('Anomalous Trips by Time of Day')
plt.xlabel('Time of Day')
plt.ylabel('Number of Anomalous Trips')
plt.show()
```





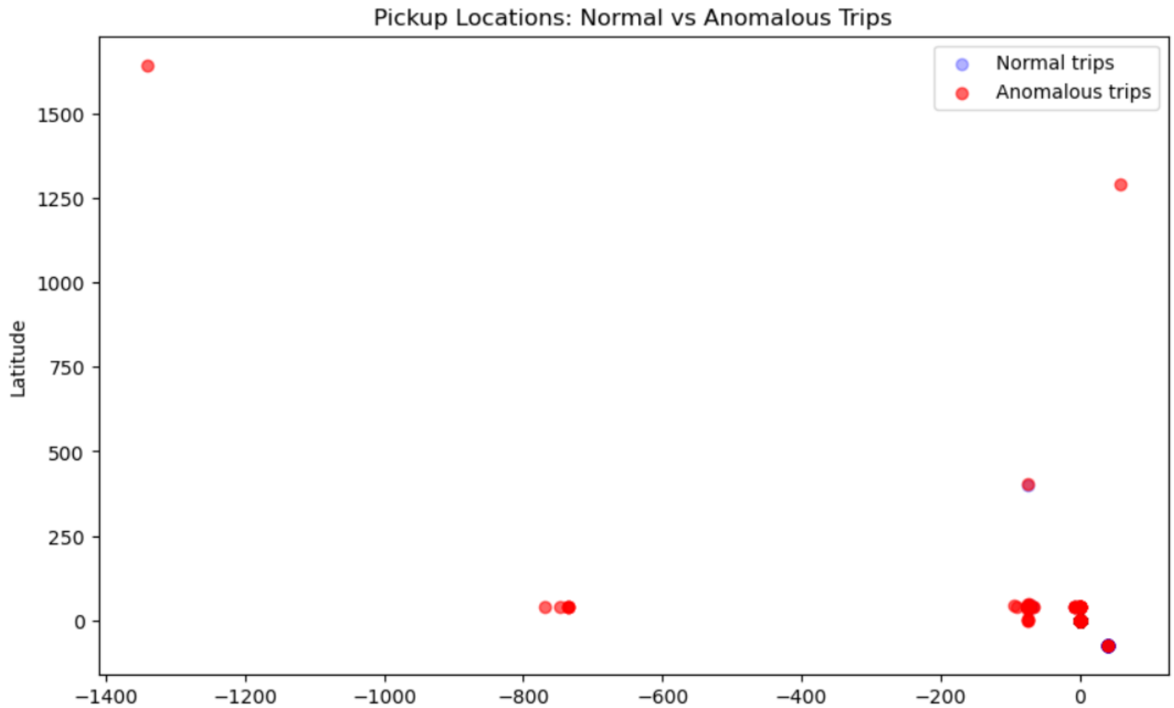
Evening and late-night trips showed a slightly higher concentration of anomalies. These hours could be more susceptible to fraud, as passengers may be less vigilant or systems more lenient during off-peak times.

Geographical Analysis

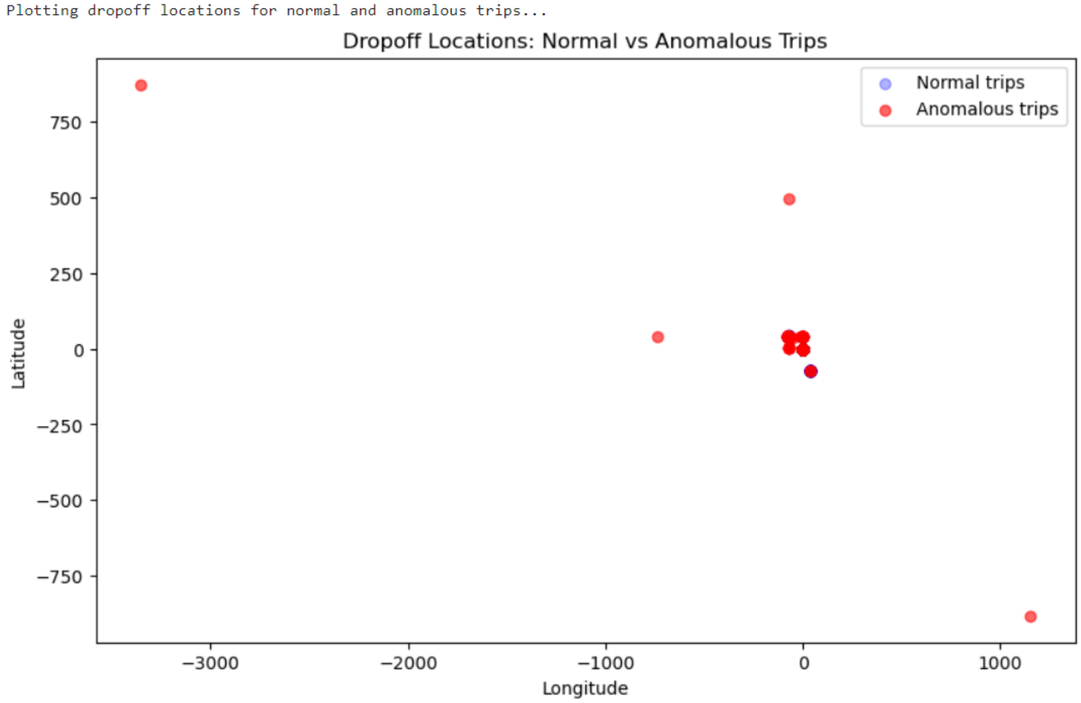
```
# Log the number of normal and anomalous trips
print(f"Number of normal trips: {len(df[df['anomaly'] == 1])}")
print(f"Number of anomalous trips: {len(df[df['anomaly'] == -1])}")

# Pickup locations plot with logging
plt.figure(figsize=(10, 6))
print("Plotting pickup locations for normal and anomalous trips...")
plt.scatter(df[df['anomaly'] == 1]['pickup_longitude'],
            df[df['anomaly'] == 1]['pickup_latitude'],
            color='blue', alpha=0.3, label='Normal trips')
plt.scatter(df[df['anomaly'] == -1]['pickup_longitude'],
            df[df['anomaly'] == -1]['pickup_latitude'],
            color='red', alpha=0.6, label='Anomalous trips')
plt.title('Pickup Locations: Normal vs Anomalous Trips')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.legend()
plt.show()

# Dropoff locations plot with logging
plt.figure(figsize=(10, 6))
print("Plotting dropoff locations for normal and anomalous trips...")
plt.scatter(df[df['anomaly'] == 1]['dropoff_longitude'],
            df[df['anomaly'] == 1]['dropoff_latitude'],
            color='blue', alpha=0.3, label='Normal trips')
plt.scatter(df[df['anomaly'] == -1]['dropoff_longitude'],
            df[df['anomaly'] == -1]['dropoff_latitude'],
            color='red', alpha=0.6, label='Anomalous trips')
plt.title('Dropoff Locations: Normal vs Anomalous Trips')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.legend()
plt.show()

print("Geographical analysis completed.")
```

Results:

```
Number of normal trips: 197999
Number of anomalous trips: 2000
Plotting pickup locations for normal and anomalous trips...
```




```
Plotting dropoff locations for normal and anomalous trips...
```




```
Geographical analysis completed.
```

1. Pickup and Dropoff Locations: Anomalous trips often involved extremely short distances or locations that were nearly identical, suggesting potential fare

manipulation or system errors. For example, several trips had almost identical pickup and dropoff coordinates but charged high fares.

2. Visual Representation: The scatter plots of pickup and dropoff locations highlighted geographical outliers, especially where trips had high fares for negligible travel.

Interpretations

- **Overpriced Short Trips:** A significant number of flagged trips had unusually high fares for very short distances, indicating potential fare manipulation.
- **Location-Based Patterns:** Geographically, some anomalies were clustered around areas with nearly identical pickup and dropoff locations, suggesting the possibility of fraudulent data entry or trip overcharging.
- **Time-Based Anomalies:** The relatively flat distribution of anomalies across hours and months suggests that fraudulent activity is consistent and not influenced by external factors like time or seasonality.

Recommendation

- **Enhanced Fare Monitoring**: Implement more stringent checks on fare amounts relative to the distance traveled. Trips with high fare_per_km ratios should be flagged for review.
- **Geographic Validation:** Consider applying geospatial validation to detect cases where pickup and dropoff coordinates are nearly identical, and compare them to the fare charged. Flagging short-distance, high-fare trips can help reduce overcharging incidents.
- **Time-Based Fraud Detection:** Increase monitoring during late-night and early-morning hours when anomalies are slightly more frequent. Special fare policies during off-peak hours could also help deter fraud.
- **Real-Time Anomaly Detection:** Deploy real-time anomaly detection using machine learning models like Isolation Forest to flag suspicious trips as they occur, reducing the potential for repeated fraud.

Limitations and Challenges

- **Absence of Credit Card Data:**
    - The dataset did not contain any transactional information related to credit card payments, cardholder details, or transaction IDs, which are essential for conducting credit card fraud detection. Without these fields, analyzing fraud from a financial transaction perspective was impossible, limiting the project to fare and location-based fraud detection.
    - **Why We Couldn't Do Credit Card Fraud Detection:** Credit card fraud detection typically requires features like transaction amounts, cardholder information, and fraud labels to detect suspicious transactions. Since this dataset focuses on trip data without any financial transaction details, we could only analyze fare-related anomalies.

- **Limited Ground Truth:**
    - The dataset did not contain any explicit labels for whether a trip was fraudulent or not, which limited the evaluation of the model's performance. The anomalies flagged by the Isolation Forest are based purely on data patterns, but further validation with actual fraudulent trip data would be needed to confirm the model's effectiveness.

Conclusion

The Uber Trip Analysis successfully identified fare and location-based anomalies that could indicate fraudulent activity. By leveraging features like f**are_per_km, distance,** and **passenger_count,** we could detect suspicious trips where fares were disproportionately high for the distance traveled or where pickup and dropoff locations were nearly identical.

While the lack of credit card transaction data limited the scope of the analysis, the methods applied here could be valuable for fare-based fraud detection and can be extended with additional financial data in the future.