# EDA_Assg_NYC_Taxi_Starter

May 29, 2025

# 1 New York City Yellow Taxi Data

## 1.1 Objective

In this case study you will be learning exploratory data analysis (EDA) with the help of a dataset on yellow taxi rides in New York City. This will enable you to understand why EDA is an important step in the process of data science and machine learning.

## 1.2 Problem Statement

As an analyst at an upcoming taxi operation in NYC, you are tasked to use the 2023 taxi trip data to uncover insights that could help optimise taxi operations. The goal is to analyse patterns in the data that can inform strategic decisions to improve service efficiency, maximise revenue, and enhance passenger experience.

## 1.3 Tasks

You need to perform the following steps for successfully completing this assignment: 1. Data Loading 2. Data Cleaning 3. Exploratory Analysis: Bivariate and Multivariate 4. Creating Visualisations to Support the Analysis 5. Deriving Insights and Stating Conclusions

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**NOTE:** The marks given along with headings and sub-headings are cumulative marks for those particular headings/sub-headings.

The actual marks for each task are specified within the tasks themselves.

For example, marks given with heading *2* or sub-heading *2.1* are the cumulative marks, for your reference only.

The marks you will receive for completing tasks are given with the tasks.

Suppose the marks for two tasks are: 3 marks for 2.1.1 and 2 marks for 3.2.2, or * 2.1.1 [3 marks] * 3.2.2 [2 marks]

then, you will earn 3 marks for completing task 2.1.1 and 2 marks for completing task 3.2.2.

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## 1.4 Data Understanding

The yellow taxi trip records include fields capturing pick-up and drop-off dates/times, pick-up and drop-off locations, trip distances, itemized fares, rate types, payment types, and driver-reported passenger counts.

The data is stored in Parquet format (*.parquet*). The dataset is from 2009 to 2024. However, for this assignment, we will only be using the data from 2023.

The data for each month is present in a different parquet file. You will get twelve files for each of the months in 2023.

The data was collected and provided to the NYC Taxi and Limousine Commission (TLC) by technology providers like vendors and taxi hailing apps.

You can find the link to the TLC trip records page here: https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page

### 1.4.1 Data Description

You can find the data description here: Data Dictionary

**Trip Records**

| Field Name | description |
|---|---|
| VendorID | A code indicating the TPEP provider that provided the record. 1= Creative Mobile Technologies, LLC; 2= VeriFone Inc. |
| tpep_pickup_datetime | The date and time when the meter was engaged. |
| tpep_dropoff_datetime | The date and time when the meter was disengaged. |
| Passenger_count | The number of passengers in the vehicle. This is a driver-entered value. |
| Trip_distance | The elapsed trip distance in miles reported by the taximeter. |
| PULocationID | TLC Taxi Zone in which the taximeter was engaged |
| DOLocationID | TLC Taxi Zone in which the taximeter was disengaged |
| RateCodeID | The final rate code in effect at the end of the trip. 1 = Standard rate 2 = JFK 3 = Newark 4 = Nassau or Westchester 5 = Negotiated fare 6 = Group ride |

| Field Name | description |
|---|---|
| Store_and_fwd_flag | This flag indicates whether the trip record was held in vehicle memory before sending to the vendor, aka "store and forward," because the vehicle did not have a connection to the server. Y= store and forward trip N= not a store and forward trip |
| Payment_type | A numeric code signifying how the passenger paid for the trip. 1 = Credit card 2 = Cash 3 = No charge 4 = Dispute 5 = Unknown 6 = Voided trip |
| Fare_amount | The time-and-distance fare calculated by the meter. Extra Miscellaneous extras and surcharges. Currently, this only includes the 0.50 and 1 USD rush hour and overnight charges. |
| MTA_tax | 0.50 USD MTA tax that is automatically triggered based on the metered rate in use. |
| Improvement_surcharge | 0.30 USD improvement surcharge assessed trips at the flag drop. The improvement surcharge began being levied in 2015. |
| Tip_amount | Tip amount – This field is automatically populated for credit card tips. Cash tips are not included. |
| Tolls_amount | Total amount of all tolls paid in trip. |
| total_amount | The total amount charged to passengers. Does not include cash tips. |
| Congestion_Surcharge | Total amount collected in trip for NYS congestion surcharge. |
| Airport_fee | 1.25 USD for pick up only at LaGuardia and John F. Kennedy Airports |

Although the amounts of extra charges and taxes applied are specified in the data dictionary, you will see that some cases have different values of these charges in the actual data.

**Taxi Zones**

Each of the trip records contains a field corresponding to the location of the pickup or drop-off of the trip, populated by numbers ranging from 1-263.

These numbers correspond to taxi zones, which may be downloaded as a table or map/shapefile and matched to the trip records using a join.

This is covered in more detail in later sections.

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## 1.5 1 Data Preparation

[5 marks]

### 1.5.1 Import Libraries

[305]:
```
# Import warnings
import warnings
warnings.filterwarnings("ignore")
```

[306]:
```
# Import the libraries you will be using for analysis
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[307]:
```
# Recommended versions
# numpy version: 1.26.4
# pandas version: 2.2.2
# matplotlib version: 3.10.0
# seaborn version: 0.13.2

# Check versions
print("numpy version:", np.__version__)
print("pandas version:", pd.__version__)
print("matplotlib version:", plt.matplotlib.__version__)
print("seaborn version:", sns.__version__)
```

```
numpy version: 2.0.2
pandas version: 2.2.2
matplotlib version: 3.10.0
seaborn version: 0.13.2
```

[308]:
```
import pyarrow.parquet as pq
```

### 1.5.2 1.1 Load the dataset

[5 marks]

You will see twelve files, one for each month.

To read parquet files with Pandas, you have to follow a similar syntax as that for CSV files.

`df = pd.read_parquet('file.parquet')`

[309]:
```
from google.colab import files
uploaded = files.upload()
```

<IPython.core.display.HTML object>

Saving 2023-1.parquet to 2023-1 (1).parquet

[311]:
```
# Try loading one file

df = pd.read_parquet('2023-1.parquet')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3041714 entries, 0 to 3066765
Data columns (total 19 columns):
 #   Column                 Dtype
---  ------                 -----
 0   VendorID               int64
 1   tpep_pickup_datetime   datetime64[us]
 2   tpep_dropoff_datetime  datetime64[us]
 3   passenger_count        float64
 4   trip_distance          float64
 5   RatecodeID             float64
 6   store_and_fwd_flag     object
 7   PULocationID           int64
 8   DOLocationID           int64
 9   payment_type           int64
 10  fare_amount            float64
 11  extra                  float64
 12  mta_tax                float64
 13  tip_amount             float64
 14  tolls_amount           float64
 15  improvement_surcharge  float64
 16  total_amount           float64
 17  congestion_surcharge   float64
 18  airport_fee            float64
dtypes: datetime64[us](2), float64(12), int64(4), object(1)
memory usage: 464.1+ MB
```

How many rows are there? Do you think handling such a large number of rows is computationally feasible when we have to combine the data for all twelve months into one?

To handle this, we need to sample a fraction of data from each of the files. How to go about that? Think of a way to select only some portion of the data from each month's file that accurately represents the trends.

[312]:
```
num_rows = df.shape[0]
print(f"Number of rows: {num_rows}")
```

```
Number of rows: 3041714
```

**Sampling the Data**

> One way is to take a small percentage of entries for pickup in every hour of a date. So, for all the days in a month, we can iterate through the hours and select 5% values randomly from those. Use `tpep_pickup_datetime` for this. Separate date and hour from the datetime values and then for each date, select some fraction of trips for each of the 24 hours.

To sample data, you can use the `sample()` method. Follow this syntax:

```
# sampled_data is an empty DF to keep appending sampled data of each hour
# hour_data is the DF of entries for an hour 'X' on a date 'Y'

sample = hour_data.sample(frac = 0.05, random_state = 42)
# sample 0.05 of the hour_data
# random_state is just a seed for sampling, you can define it yourself

sampled_data = pd.concat([sampled_data, sample]) # adding data for this hour to the DF
```

This *sampled_data* will contain 5% values selected at random from each hour.

Note that the code given above is only the part that will be used for sampling and not the complete code required for sampling and combining the data files.

Keep in mind that you sample by date AND hour, not just hour. (Why?)

[313]:

```
df['tpep_pickup_datetime'] = pd.to_datetime(df['tpep_pickup_datetime'])

# Extract the date and hour from the 'tpep_pickup_datetime'
df['date'] = df['tpep_pickup_datetime'].dt.date
df['hour'] = df['tpep_pickup_datetime'].dt.hour

# Initialize an empty DataFrame to store the sampled data
sampled_data = pd.DataFrame()

# Iterate through each date and hour combination
for date in df['date'].unique():
    # Filter data for the given date
    daily_data = df[df['date'] == date]

    # For each hour (0-23), sample 5% of the data
    for hour in range(24):
        hour_data = daily_data[daily_data['hour'] == hour]

        # Sample 5% of the data for this hour
        sample = hour_data.sample(frac=0.05, random_state=42)

        # Append the sampled data for this hour to the final DataFrame
        sampled_data = pd.concat([sampled_data, sample])

# Reset the index of the final DataFrame
sampled_data.reset_index(drop=True, inplace=True)
```

```
# Print the shape of the sampled data to confirm the result
print(sampled_data.shape)
```

```
(152087, 21)
```

---

**1.1.1** [5 marks] Figure out how to sample and combine the files.

**Note:** It is not mandatory to use the method specified above. While sampling, you only need to make sure that your sampled data represents the overall data of all the months accurately.

[314]:
```
# Sample the data
# It is recommmended to not load all the files at once to avoid memory overload
```

[315]:
```
# Take a small percentage of entries from each hour of every date.
# Iterating through the monthly data:
#   read a month file -> day -> hour: append sampled data -> move to next hour␣
↪-> move to next day after 24 hours -> move to next month file
# Create a single dataframe for the year combining all the monthly data

# Select the folder having data files
from google.colab import drive
drive.mount("/content/drive", force_remount=True)
import os
file_path = '/content/drive/MyDrive/trip_records'

# Select the folder having data files
os.chdir(file_path)

# Create a list of all the twelve files to read
file_list = os.listdir()

# initialise an empty dataframe
df = pd.DataFrame()


# iterate through the list of files and sample one by one:
for file_name in file_list:
    try:
        # file path for the current file
        file_path = os.path.join(os.getcwd(), file_name)

        # Reading the current file
        monthly_df = pd.read_parquet(file_path)

        # We will store the sampled data for the current date in this df by␣
↪appending the sampled data from each hour to this
```

```
        monthly_df['tpep_pickup_datetime'] = pd.
↪to_datetime(monthly_df['tpep_pickup_datetime'])
        # Extract date and hour from 'tpep_pickup_datetime'
        monthly_df['date'] = monthly_df['tpep_pickup_datetime'].dt.date
        monthly_df['hour'] = monthly_df['tpep_pickup_datetime'].dt.hour
        # After completing iteration through each date, we will append this␣
↪data to the final dataframe.
        sampled_data = pd.DataFrame()

        # Loop through dates and then loop through every hour of each date
        for date in monthly_df['date'].unique():
            # Iterate through each hour of the selected date
            daily_data = monthly_df[monthly_df['date'] == date]

            for hour in range(24):
                hour_data = daily_data[daily_data['hour'] == hour]
                # Sample 5% of the hourly data randomly
                sample = hour_data.sample(frac=0.05, random_state=42)
                # add data of this hour to the dataframe
                sampled_data = pd.concat([sampled_data, sample])
        # Concatenate the sampled data of all the dates to a single dataframe
        df = pd.concat([df, sampled_data]) # we initialised this empty DF␣
↪earlier
        # Print progress (optional)
        print(f"Finished processing {file_name}. Sampled data size:␣
↪{sampled_data.shape[0]}")

    except Exception as e:
        print(f"Error reading file {file_name}: {e}")
```

```
Mounted at /content/drive
Finished processing 2023-7.parquet. Sampled data size: 174068
Finished processing 2023-6.parquet. Sampled data size: 162910
Finished processing 2023-12.parquet. Sampled data size: 166709
Finished processing 2023-11.parquet. Sampled data size: 165133
Finished processing 2023-5.parquet. Sampled data size: 144458
Finished processing 2023-8.parquet. Sampled data size: 143782
Finished processing 2023-1.parquet. Sampled data size: 152087
Finished processing 2023-4.parquet. Sampled data size: 139641
Finished processing 2023-10.parquet. Sampled data size: 174255
Finished processing 2023-3.parquet. Sampled data size: 163786
Finished processing 2023-2.parquet. Sampled data size: 168696
Finished processing 2023-9.parquet. Sampled data size: 140875
Finished processing 2023-1 (1).parquet. Sampled data size: 152087
```

After combining the data files into one DataFrame, convert the new DataFrame to a CSV or parquet file and store it to use directly.

Ideally, you can try keeping the total entries to around 250,000 to 300,000.

[316]:
```python
# Store the df in csv/parquet
df = df.sample(n=300000, random_state=42)
# df.to_parquet('')
df.to_parquet('/content/drive/MyDrive/trip_records/sample_data.parquet')
```

## 1.6 2 Data Cleaning

[30 marks]

Now we can load the new data directly.

[324]:
```python
# Load the new data file

file_path = '/content/drive/MyDrive/trip_records/sample_data.parquet'
df_loaded = pd.read_parquet(file_path)

# Display the first few rows of the loaded data
print(df_loaded.head())
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
765740          2  2023-03-08 09:30:34   2023-03-08 09:41:02              1.0
633560          2  2023-06-06 19:09:32   2023-06-06 19:15:03              1.0
530689          1  2023-05-05 18:49:20   2023-05-05 19:25:10              2.0
697594          2  2023-07-10 06:56:13   2023-07-10 07:13:13              1.0
3038485         2  2023-12-29 22:19:46   2023-12-29 22:35:10              2.0

         trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
765740            0.71         1.0                  N           237
633560            1.26         1.0                  N           237
530689           10.30         1.0                  N           186
697594            4.21         1.0                  N           262
3038485           3.27         1.0                  N           237

         DOLocationID  payment_type  …  mta_tax  tip_amount  tolls_amount  \
765740            163             2  …      0.5        0.00           0.0
633560            141             1  …      0.5        2.88           0.0
530689            235             1  …      0.5        3.00           0.0
697594             68             1  …      0.5        5.18           0.0
3038485           151             1  …      0.5        4.68           0.0

         improvement_surcharge  total_amount  congestion_surcharge  \
765740                     1.0         14.00                   2.5
633560                     1.0         17.28                   2.5
530689                     1.0         57.30                   2.5
697594                     1.0         31.08                   2.5
3038485                    1.0         28.08                   2.5
```

```
         Airport_fee        date  hour  airport_fee
765740           0.0  2023-03-08     9          NaN
633560           0.0  2023-06-06    19          NaN
530689           0.0  2023-05-05    18          NaN
697594           0.0  2023-07-10     6          NaN
3038485          0.0  2023-12-29    22          NaN

[5 rows x 22 columns]
```

[325]:
```python
df_loaded.head()
print(df.columns)
```

```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

[326]:
```python
df_loaded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 300000 entries, 765740 to 38078
Data columns (total 22 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   VendorID               300000 non-null  int64
 1   tpep_pickup_datetime   300000 non-null  datetime64[us]
 2   tpep_dropoff_datetime  300000 non-null  datetime64[us]
 3   passenger_count        289941 non-null  float64
 4   trip_distance          300000 non-null  float64
 5   RatecodeID             289941 non-null  float64
 6   store_and_fwd_flag     289941 non-null  object
 7   PULocationID           300000 non-null  int64
 8   DOLocationID           300000 non-null  int64
 9   payment_type           300000 non-null  int64
 10  fare_amount            300000 non-null  float64
 11  extra                  300000 non-null  float64
 12  mta_tax                300000 non-null  float64
 13  tip_amount             300000 non-null  float64
 14  tolls_amount           300000 non-null  float64
 15  improvement_surcharge  300000 non-null  float64
 16  total_amount           300000 non-null  float64
 17  congestion_surcharge   289941 non-null  float64
 18  Airport_fee            246653 non-null  float64
 19  date                   300000 non-null  object
 20  hour                   300000 non-null  int32
 21  airport_fee            43288 non-null   float64
```

```
dtypes: datetime64[us](2), float64(13), int32(1), int64(4), object(2)
memory usage: 51.5+ MB
```

### 2.1 Fixing Columns [10 marks]

Fix/drop any columns as you seem necessary in the below sections

#### 2.1.1 [2 marks]

Fix the index and drop unnecessary columns

[327]:
```python
# Fix the index and drop any columns that are not needed

df_loaded.reset_index(drop=True, inplace=True)
print("Columns before dropping:", df.columns)
```

```
Columns before dropping: Index(['VendorID', 'tpep_pickup_datetime',
'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

[328]:
```python
df.drop(columns=['date','hour'], inplace=True)
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-328-11ddac997e5b> in <cell line: 0>()
----> 1 df.drop(columns=['date','hour'], inplace=True)

/usr/local/lib/python3.11/dist-packages/pandas/core/frame.py in drop(self,␣
↪labels, axis, index, columns, level, inplace, errors)
   5579                 weight  1.0     0.8
   5580         """
-> 5581         return super().drop(

   5582             labels=labels,
   5583             axis=axis,

/usr/local/lib/python3.11/dist-packages/pandas/core/generic.py in drop(self,␣
↪labels, axis, index, columns, level, inplace, errors)
   4786         for axis, labels in axes.items():
   4787             if labels is not None:
-> 4788                 obj = obj._drop_axis(labels, axis, level=level,␣
↪errors=errors)
   4789
   4790         if inplace:
```

```
/usr/local/lib/python3.11/dist-packages/pandas/core/generic.py in␣
↪_drop_axis(self, labels, axis, level, errors, only_slice)
   4828                 new_axis = axis.drop(labels, level=level, errors=errors
   4829             else:
-> 4830                 new_axis = axis.drop(labels, errors=errors)
   4831             indexer = axis.get_indexer(new_axis)
   4832 

/usr/local/lib/python3.11/dist-packages/pandas/core/indexes/base.py in␣
↪drop(self, labels, errors)
   7068         if mask.any():
   7069             if errors != "ignore":
-> 7070                 raise KeyError(f"{labels[mask].tolist()} not found in␣
↪axis")
   7071             indexer = indexer[~mask]
   7072         return self.delete(indexer)

KeyError: "['date', 'hour'] not found in axis"
```

[329]:
```python
print(df.columns)
```

```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

**2.1.2** [3 marks] There are two airport fee columns. This is possibly an error in naming columns. Let's see whether these can be combined into a single column.

[330]:
```python
# Combine the two airport fee columns
airport_fee_columns = ['Airport_fee', 'airport_fee']
if all(col in df.columns for col in airport_fee_columns):
    df['Airport_fee'] = df['Airport_fee'].fillna(0) + df['airport_fee'].
↪fillna(0)
    # Drop the original columns
    df.drop(columns=airport_fee_columns, inplace=True)
```

[332]:
```python
print(df.columns)
```

```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

**2.1.3** [5 marks] Fix columns with negative (monetary) values

[333]:
```
# check where values of fare amount are negative

print("Checking for negative values in fare_amount column:")
negative_fare_df = df[df['fare_amount'] < 0]
print(negative_fare_df[['fare_amount', 'RatecodeID']])
```

```
Checking for negative values in fare_amount column:
Empty DataFrame
Columns: [fare_amount, RatecodeID]
Index: []
```

Did you notice something different in the `RatecodeID` column for above records?

[334]:
```
# Analyse RatecodeID for the negative fare amounts
ratecode_analysis = negative_fare_df.groupby('RatecodeID').size()
print("RatecodeID analysis for negative fare amounts:\n", ratecode_analysis)

# Step 5: Check for any other negative values in the dataset (monetary columns)
negative_columns = df.select_dtypes(include=['float64', 'int64']).columns
negative_values_df = df[df[negative_columns].lt(0).any(axis=1)]
```

```
RatecodeID analysis for negative fare amounts:
 Series([], dtype: int64)
```

[335]:
```
print(df.columns)
```

```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

[336]:
```
# Find which columns have negative values

# Display rows with negative values in any numeric columns
print("Rows with negative values in any numeric columns:\n", negative_values_df)
```

```
Rows with negative values in any numeric columns:
          VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count
\
1516873        2  2023-01-17 12:37:35   2023-01-17 13:24:00              1.0
1583313        2  2023-05-14 23:47:22   2023-05-14 23:57:43              6.0
3016916        2  2023-12-29 17:32:20   2023-12-29 17:33:49              1.0
179607         2  2023-01-03 14:24:45   2023-01-03 14:25:14              1.0
3075228        2  2023-06-29 17:52:22   2023-06-29 18:11:03              1.0
1703670        2  2023-10-17 08:39:40   2023-10-17 08:41:19              1.0
```

```
2316861         2  2023-01-25 11:10:37   2023-01-25 11:11:02             1.0
1694220         2  2023-10-17 00:56:18   2023-10-17 00:56:35             1.0
454287          2  2023-03-05 00:50:17   2023-03-05 00:50:38             1.0
2084892         2  2023-05-19 08:46:25   2023-05-19 08:47:31             1.0
2635188         2  2023-06-25 05:59:41   2023-06-25 06:08:22             2.0
1328318         2  2023-03-13 11:40:22   2023-03-13 11:51:53             1.0
1045799         2  2023-03-10 16:18:09   2023-03-10 16:49:43             3.0
661788          2  2023-11-06 19:30:44   2023-11-06 19:38:21             1.0

         trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
1516873          17.68         2.0                  N           230
1583313           3.66         1.0                  N           170
3016916           0.02         1.0                  N           161
179607            0.00         2.0                  N           132
3075228           2.93         1.0                  N           246
1703670           0.29         1.0                  N           138
2316861           0.02         2.0                  N           170
1694220           0.06         1.0                  N           132
454287            0.00         2.0                  N            70
2084892           0.00         1.0                  N           207
2635188           1.09         2.0                  N            90
1328318           3.49         1.0                  N           138
1045799           6.94         1.0                  N            88
661788            0.48         1.0                  N            75

         DOLocationID  payment_type  fare_amount  extra  mta_tax  tip_amount  \
1516873           132             2          0.0    0.0     -0.5         0.0
1583313           263             2          0.0    0.0     -0.5         0.0
3016916           161             2          0.0    0.0     -0.5         0.0
179607            132             2          0.0    0.0     -0.5         0.0
3075228           239             2          0.0    0.0     -0.5         0.0
1703670            70             2          0.0    0.0     -0.5         0.0
2316861           233             2          0.0    0.0     -0.5         0.0
1694220           132             2          0.0    0.0     -0.5         0.0
454287             70             2          0.0    0.0     -0.5         0.0
2084892           207             2          0.0    0.0     -0.5         0.0
2635188           170             2          0.0    0.0     -0.5         0.0
1328318           253             2          0.0    0.0     -0.5         0.0
1045799           230             2          0.0    0.0     -0.5         0.0
661788             75             2          0.0    0.0     -0.5         0.0

         tolls_amount  improvement_surcharge  total_amount  \
1516873           0.0                   -1.0         -4.00
1583313           0.0                   -1.0         -4.00
3016916           0.0                   -1.0         -4.00
179607            0.0                   -1.0         -5.25
3075228           0.0                   -1.0         -4.00
1703670           0.0                   -1.0         -3.25
```

```
2316861           0.0                     -1.0         -4.00
1694220           0.0                     -1.0         -3.25
454287            0.0                     -1.0         -1.50
2084892           0.0                     -1.0         -1.50
2635188           0.0                     -1.0         -4.00
1328318           0.0                     -1.0         -2.75
1045799           0.0                     -1.0         -4.00
661788            0.0                     -1.0         -1.50

         congestion_surcharge
1516873                  -2.5
1583313                  -2.5
3016916                  -2.5
179607                   -2.5
3075228                  -2.5
1703670                   0.0
2316861                  -2.5
1694220                   0.0
454287                    0.0
2084892                   0.0
2635188                  -2.5
1328318                   0.0
1045799                  -2.5
661788                    0.0
```

[337]:

```
print(df.columns)
```

```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

[338]:

```
# fix these negative values

df['fare_amount'] = df['fare_amount'].apply(lambda x: x if x >= 0 else None)  #␣
 ↪Replace negative with NaN

# 2. For other monetary columns, similarly fix the negative values (replace␣
 ↪with NaN or a default value)
for col in negative_columns:
    df[col] = df[col].apply(lambda x: x if x >= 0 else None)  # Replace␣
 ↪negative with NaN

# Step 7: Check if the negative values are fixed
print("Checking the DataFrame after fixing negative values:")
```

```python
print(df[['fare_amount']].head())
```

```
Checking the DataFrame after fixing negative values:
         fare_amount
765740          10.0
633560           7.9
530689          47.8
697594          21.9
3038485         18.4
```

[339]:
```python
print("Columns ", df.columns)
```

```
Columns  Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

### 1.6.1 2.2 Handling Missing Values

[10 marks]

**2.2.1** [2 marks] Find the proportion of missing values in each column

[341]:
```python
# Find the proportion of missing values in each column

missing_values_proportion = df.isnull().mean()
print("Proportion of missing values in each column:\n",
 ↪missing_values_proportion)
```

```
Proportion of missing values in each column:
 VendorID                 0.000000
tpep_pickup_datetime     0.000000
tpep_dropoff_datetime    0.000000
passenger_count          0.033530
trip_distance            0.000000
RatecodeID               0.033530
store_and_fwd_flag       0.033530
PULocationID             0.000000
DOLocationID             0.000000
payment_type             0.000000
fare_amount              0.000000
extra                    0.000000
mta_tax                  0.000047
tip_amount               0.000000
tolls_amount             0.000000
improvement_surcharge    0.000047
total_amount             0.000047
```

```
congestion_surcharge     0.033557
dtype: float64
```

**2.2.2** [3 marks] Handling missing values in passenger_count

[342]:
```python
# Display the rows with null values
# Impute NaN values in 'passenger_count'
missing_passenger_count = df[df['passenger_count'].isnull()]
print("Rows with missing values in 'passenger_count':\n",␣
 ↪missing_passenger_count)
```

```
Rows with missing values in 'passenger_count':
         VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count
\
3413193         2  2023-05-01 14:51:39   2023-05-01 15:13:15              NaN
3279220         2  2023-12-14 22:05:00   2023-12-14 22:20:00              NaN
2728757         2  2023-09-07 22:44:00   2023-09-07 23:00:00              NaN
3460302         2  2023-05-16 08:40:35   2023-05-16 09:13:03              NaN
2780370         1  2023-09-18 06:32:01   2023-09-18 06:37:31              NaN
…             …                  …                    …              …
3307500         1  2023-11-22 01:12:56   2023-11-22 01:16:02              NaN
3341427         2  2023-03-10 10:57:21   2023-03-10 11:24:03              NaN
2774899         2  2023-09-17 00:13:15   2023-09-17 00:34:46              NaN
3305142         2  2023-12-16 23:20:00   2023-12-16 23:37:27              NaN
3324572         1  2023-03-03 20:56:59   2023-03-03 21:12:27              NaN

         trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
3413193           6.62         NaN               None            13
3279220           2.36         NaN               None           249
2728757           3.59         NaN               None           164
3460302           2.91         NaN               None           239
2780370           0.00         NaN               None           158
…                  …         …                  …           …
3307500           0.00         NaN               None            79
3341427          16.62         NaN               None           142
2774899           2.02         NaN               None            90
3305142           2.54         NaN               None           236
3324572           0.00         NaN               None             4

         DOLocationID  payment_type  fare_amount  extra  mta_tax  tip_amount  \
3413193           140             0        32.85    0.0      0.5        5.53
3279220           246             0        20.71    0.0      0.5        2.47
2728757           262             0        21.94    0.0      0.5        5.19
3460302           161             0        22.46    0.0      0.5        5.29
2780370           231             0        11.08    0.0      0.5        0.00
…                 …            …          …    …      …         …
3307500            79             0         6.83    0.0      0.5        0.00
3341427           138             0        61.91    0.0      0.5       14.49
```

```
2774899          148             0          22.53     0.0       0.5          3.98
3305142          230             0          23.02     0.0       0.5          0.00
3324572          229             0          15.55     0.0       0.5          0.00

         tolls_amount  improvement_surcharge  total_amount  \
3413193          0.00                    1.0         42.38
3279220          0.00                    1.0         27.18
2728757          0.00                    1.0         31.13
3460302          0.00                    1.0         31.75
2780370          0.00                    1.0         15.08
…                 …                    …            …
3307500          0.00                    1.0         10.83
3341427          6.55                    1.0         86.95
2774899          0.00                    1.0         30.51
3305142          0.00                    1.0         27.02
3324572          0.00                    1.0         19.55

         congestion_surcharge
3413193                   NaN
3279220                   NaN
2728757                   NaN
3460302                   NaN
2780370                   NaN
…                        …
3307500                   NaN
3341427                   NaN
2774899                   NaN
3305142                   NaN
3324572                   NaN

[10059 rows x 18 columns]
```

[343]:
```
print("Columns ", df.columns)
```

```
Columns  Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

Did you find zeroes in passenger_count? Handle these.

[230]:
```
df['passenger_count'].fillna(df['passenger_count'].median(), inplace=True)
```

[347]:
```
print("Columns :", df.columns)
```

```
Columns : Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
```

```
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

[346]:
```python
zero_passenger_count = df[df['passenger_count'] == 0]
print("Rows with zero values in 'passenger_count':\n", zero_passenger_count)

# Handle zero values in 'passenger_count' (replace zeroes with NaN or median)
df['passenger_count'].replace(0, df['passenger_count'].median(), inplace=True)
```

```
Rows with zero values in 'passenger_count':
 Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, store_and_fwd_flag, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount, congestion_surcharge]
Index: []
```

[348]:
```python
print("Columns before dropping:", df.columns)
```

```
Columns before dropping: Index(['VendorID', 'tpep_pickup_datetime',
'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

**2.2.3** [2 marks] Handle missing values in `RatecodeID`

[352]:
```python
# Fix missing values in 'RatecodeID'
# Impute missing values in 'RatecodeID' with the mode
df['RatecodeID'].fillna(df['RatecodeID'].mode()[0], inplace=True)
```

[353]:
```python
print("Columns before dropping:", df.columns)
```

```
Columns before dropping: Index(['VendorID', 'tpep_pickup_datetime',
'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

**2.2.4** [3 marks] Impute NaN in `congestion_surcharge`

[354]:
```
# handle null values in congestion_surcharge

# Impute missing values in 'congestion_surcharge' with 0
df['congestion_surcharge'].fillna(0, inplace=True)
```

[355]:
```
print("Columns before dropping:", df.columns)
```

```
Columns before dropping: Index(['VendorID', 'tpep_pickup_datetime',
'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

Are there missing values in other columns? Did you find NaN values in some other set of columns? Handle those missing values below.

[356]:
```
# Handle any remaining missing values
# Check for any remaining missing values
remaining_missing = df.isnull().sum()
print("Remaining missing values in each column:\n", remaining_missing)
```

```
Remaining missing values in each column:
 VendorID                     0
tpep_pickup_datetime        0
tpep_dropoff_datetime       0
passenger_count         10059
trip_distance               0
RatecodeID                  0
store_and_fwd_flag      10059
PULocationID                0
DOLocationID                0
payment_type                0
fare_amount                 0
extra                       0
mta_tax                    14
tip_amount                  0
tolls_amount                0
improvement_surcharge      14
total_amount               14
congestion_surcharge        0
dtype: int64
```

[358]:
```
# Impute missing values in numeric columns with the median
for col in df.select_dtypes(include=['float64', 'int64']).columns:
    df[col].fillna(df[col].median(), inplace=True)
```

```
# Impute missing values in categorical columns with the mode
for col in df.select_dtypes(include=['object']).columns:
    df[col].fillna(df[col].mode()[0], inplace=True)
```

[359]:
```
print("Columns:", df.columns)
```

```
Columns: Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

[360]:
```
 #Step 1: Find the proportion of missing values in each column
missing_values_proportion = df.isnull().mean()
print("Proportion of missing values in each column:\n",␣
 ↪missing_values_proportion)

# Step 2: Handling missing values in 'passenger_count'
# Display rows with null values in 'passenger_count'
missing_passenger_count = df[df['passenger_count'].isnull()]
print("Rows with missing values in 'passenger_count':\n",␣
 ↪missing_passenger_count)

# Impute missing values in 'passenger_count' with the median
df['passenger_count'].fillna(df['passenger_count'].median(), inplace=True)

# Check for zeroes in 'passenger_count'
zero_passenger_count = df[df['passenger_count'] == 0]
print("Rows with zero values in 'passenger_count':\n", zero_passenger_count)

# Replace zero values with the median
df['passenger_count'].replace(0, df['passenger_count'].median(), inplace=True)

# Step 3: Handle missing values in 'RatecodeID'
df['RatecodeID'].fillna(df['RatecodeID'].mode()[0], inplace=True)

# Step 4: Handle missing values in 'congestion_surcharge'
df['congestion_surcharge'].fillna(0, inplace=True)

# Step 5: Handle remaining missing values in other columns
# Impute missing values in numeric columns with the median
for col in df.select_dtypes(include=['float64', 'int64']).columns:
    df[col].fillna(df[col].median(), inplace=True)

# Impute missing values in categorical columns with the mode
for col in df.select_dtypes(include=['object']).columns:
```

```python
    df[col].fillna(df[col].mode()[0], inplace=True)

# Step 6: Verify the result
print("Remaining missing values after imputation:\n", df.isnull().sum())
```

```
Proportion of missing values in each column:
 VendorID                 0.0
tpep_pickup_datetime     0.0
tpep_dropoff_datetime    0.0
passenger_count          0.0
trip_distance            0.0
RatecodeID               0.0
store_and_fwd_flag       0.0
PULocationID             0.0
DOLocationID             0.0
payment_type             0.0
fare_amount              0.0
extra                    0.0
mta_tax                  0.0
tip_amount               0.0
tolls_amount             0.0
improvement_surcharge    0.0
total_amount             0.0
congestion_surcharge     0.0
dtype: float64
Rows with missing values in 'passenger_count':
 Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, store_and_fwd_flag, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount, congestion_surcharge]
Index: []
Rows with zero values in 'passenger_count':
 Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, store_and_fwd_flag, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount, congestion_surcharge]
Index: []
Remaining missing values after imputation:
 VendorID                 0
tpep_pickup_datetime     0
tpep_dropoff_datetime    0
passenger_count          0
trip_distance            0
RatecodeID               0
store_and_fwd_flag       0
```

```
PULocationID             0
DOLocationID             0
payment_type             0
fare_amount              0
extra                    0
mta_tax                  0
tip_amount               0
tolls_amount             0
improvement_surcharge    0
total_amount             0
congestion_surcharge     0
dtype: int64
```

[242]:
```
print("Columns :", df.columns)
```

```
Columns : Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

### 1.6.2 2.3 Handling Outliers

[10 marks]

Before we start fixing outliers, let's perform outlier analysis.

[361]:
```
# Describe the data and check if there are any potential outliers present
# Check for potential out of place values in various columns

print("Summary Statistics of the Data:")
df.describe()
```

```
Summary Statistics of the Data:
```

[361]:

| | VendorID | tpep_pickup_datetime | tpep_dropoff_datetime | \ |
|---|---|---|---|---|
| count | 300000.000000 | 300000 | 300000 | |
| mean | 1.731400 | 2023-06-20 14:17:08.235900 | 2023-06-20 14:34:25.847073 | |
| min | 1.000000 | 2022-12-31 23:51:30 | 2022-12-31 23:56:06 | |
| 25% | 1.000000 | 2023-03-12 16:02:51 | 2023-03-12 16:17:30.250000 | |
| 50% | 2.000000 | 2023-06-13 15:09:18.500000 | 2023-06-13 15:32:39 | |
| 75% | 2.000000 | 2023-09-30 12:13:33.500000 | 2023-09-30 12:31:17 | |
| max | 6.000000 | 2023-12-31 23:57:51 | 2024-01-01 20:14:57 | |
| std | 0.448243 | NaN | NaN | |

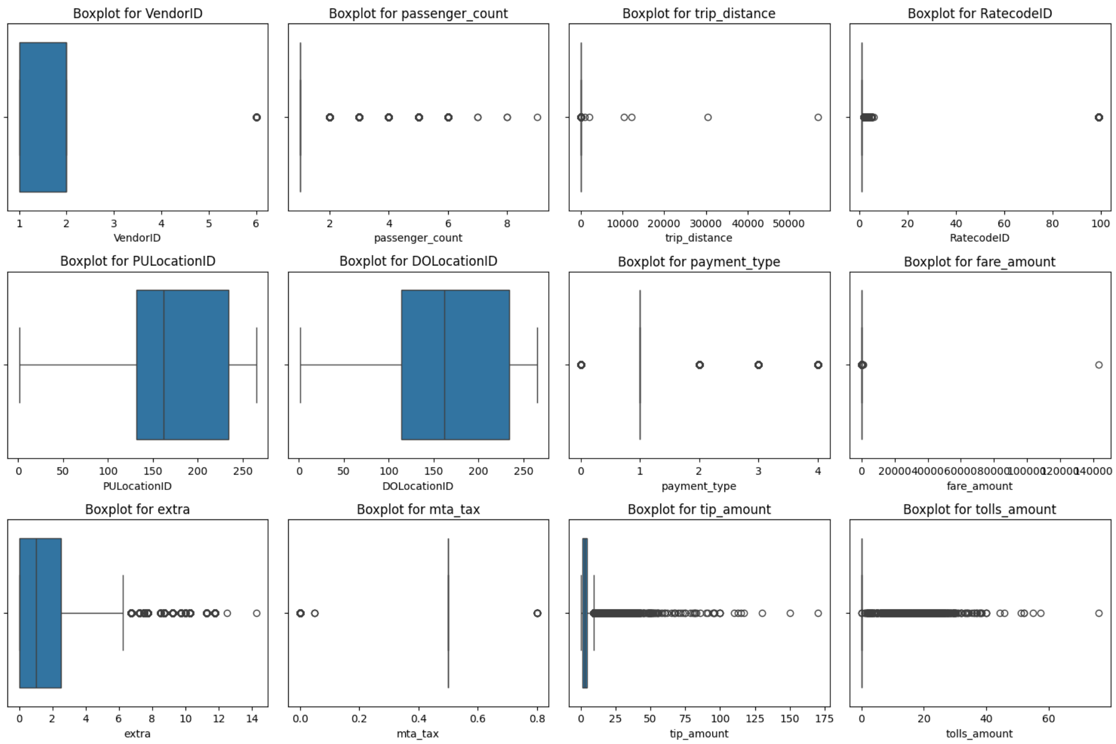
| | passenger_count | trip_distance | RatecodeID | PULocationID | \ |
|---|---|---|---|---|---|
| count | 300000.000000 | 300000.000000 | 300000.000000 | 300000.000000 | |
| mean | 1.370617 | 3.816756 | 1.609900 | 165.394110 | |

```
min          1.000000      0.000000      1.000000      1.000000
25%          1.000000      1.050000      1.000000    132.000000
50%          1.000000      1.800000      1.000000    162.000000
75%          1.000000      3.400000      1.000000    234.000000
max          9.000000  56823.800000     99.000000    265.000000
std          0.860757    121.403540      7.248456     64.029436

        DOLocationID   payment_type    fare_amount          extra  \
count  300000.000000  300000.000000  300000.000000  300000.000000
mean      164.206367       1.164487      20.235161       1.588186
min         1.000000       0.000000       0.000000       0.000000
25%       114.000000       1.000000       9.300000       0.000000
50%       162.000000       1.000000      13.500000       1.000000
75%       234.000000       1.000000      21.900000       2.500000
max       265.000000       4.000000  143163.450000      14.250000
std        69.839802       0.505468     261.970891       1.821772

             mta_tax     tip_amount   tolls_amount  improvement_surcharge  \
count  300000.000000  300000.000000  300000.000000          300000.000000
mean        0.495331       3.535609       0.588558               0.998917
min         0.000000       0.000000       0.000000               0.000000
25%         0.500000       1.000000       0.000000               1.000000
50%         0.500000       2.800000       0.000000               1.000000
75%         0.500000       4.420000       0.000000               1.000000
max         0.800000     170.000000      76.000000               1.000000
std         0.048189       4.040260       2.166012               0.030351

        total_amount  congestion_surcharge
count  300000.000000         300000.000000
mean       29.273036              2.230117
min         0.000000              0.000000
25%        15.960000              2.500000
50%        21.000000              2.500000
75%        30.720000              2.500000
max    143167.450000              2.500000
std       262.314706              0.775805
```

[362]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
# Plot boxplots for numeric columns to identify outliers
numeric_columns = df.select_dtypes(include=['float64', 'int64']).columns

# Create a boxplot for each numeric column
plt.figure(figsize=(15, 10))
for i, col in enumerate(numeric_columns, 1):
    plt.subplot(3, 4, i)  # Adjust the grid size as necessary
    sns.boxplot(x=df[col])
```

```
    plt.title(f"Boxplot for {col}")
    plt.tight_layout()

plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-362-37bdc7522402> in <cell line: 0>()
      7 plt.figure(figsize=(15, 10))
      8 for i, col in enumerate(numeric_columns, 1):
----> 9     plt.subplot(3, 4, i)  # Adjust the grid size as necessary
     10     sns.boxplot(x=df[col])
     11     plt.title(f"Boxplot for {col}")

/usr/local/lib/python3.11/dist-packages/matplotlib/pyplot.py in subplot(*args,␣
 ↪**kwargs)
   1548
   1549     # First, search for an existing subplot with a matching spec.
-> 1550     key = SubplotSpec._from_subplot_args(fig, args)
   1551
   1552     for ax in fig.axes:

/usr/local/lib/python3.11/dist-packages/matplotlib/gridspec.py in␣
 ↪_from_subplot_args(figure, args)
    587         else:
    588             if not isinstance(num, Integral) or num < 1 or num >␣
 ↪rows*cols:
--> 589                 raise ValueError(
    590                     f"num must be an integer with 1 <= num <=␣
 ↪{rows*cols}, "
    591                     f"not {num!r}"

ValueError: num must be an integer with 1 <= num <= 12, not 13
```




[363]:
```
# Check for negative values in columns that should only have positive values
negative_values = df[df[['fare_amount', 'tip_amount', 'trip_distance']].lt(0).
    any(axis=1)]
print("Rows with negative values in fare_amount, tip_amount, or trip_distance:
    \n", negative_values)

# Check for zero or unrealistic values in 'passenger_count' and 'trip_distance'
unrealistic_values = df[(df['passenger_count'] == 0) | (df['trip_distance'] <=
    0)]
print("Rows with unrealistic values in 'passenger_count' or 'trip_distance':
    \n", unrealistic_values)
```

```
Rows with negative values in fare_amount, tip_amount, or trip_distance:
 Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, store_and_fwd_flag, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount, congestion_surcharge]
Index: []
Rows with unrealistic values in 'passenger_count' or 'trip_distance':
          VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count
\
278267          2  2023-08-03 21:59:54   2023-08-03 22:00:12              1.0
```

```
170915          2  2023-09-03 02:28:58   2023-09-03 02:29:19             1.0
2175680         2  2023-12-19 17:23:00   2023-12-19 17:23:08             1.0
2780370         1  2023-09-18 06:32:01   2023-09-18 06:37:31             1.0
3050079         1  2023-01-25 08:00:51   2023-01-25 08:25:02             1.0
…            …                 …                   …               …
819589          2  2023-09-09 14:14:34   2023-09-09 14:14:51             1.0
3264714         1  2023-11-12 16:19:39   2023-11-12 16:28:44             1.0
3307500         1  2023-11-22 01:12:56   2023-11-22 01:16:02             1.0
46075           1  2023-11-01 13:23:00   2023-11-01 13:54:59             1.0
3324572         1  2023-03-03 20:56:59   2023-03-03 21:12:27             1.0

         trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
278267             0.0         1.0                  N           193
170915             0.0         1.0                  N           144
2175680            0.0         2.0                  N           151
2780370            0.0         1.0                  N           158
3050079            0.0         1.0                  N            50
…                  …        …                 …            …
819589             0.0         5.0                  N           233
3264714            0.0         1.0                  N           143
3307500            0.0         1.0                  N            79
46075              0.0        99.0                  N           239
3324572            0.0         1.0                  N             4

         DOLocationID  payment_type  fare_amount  extra  mta_tax  tip_amount  \
278267            193             2         3.00    1.0      0.5         0.0
170915            144             4         3.00    1.0      0.5         0.0
2175680           151             4        70.00    5.0      0.5         0.0
2780370           231             0        11.08    0.0      0.5         0.0
3050079           163             0        13.14    0.0      0.5         0.0
…               …           …          …    …      …        …
819589            233             2        32.00    0.0      0.0         0.0
3264714            48             0         9.18    0.0      0.5         0.0
3307500            79             0         6.83    0.0      0.5         0.0
46075             200             1        32.50    0.0      0.5         0.0
3324572           229             0        15.55    0.0      0.5         0.0

         tolls_amount  improvement_surcharge  total_amount  \
278267           0.00                    1.0          5.50
170915           0.00                    1.0          8.00
2175680          0.00                    1.0         76.50
2780370          0.00                    1.0         15.08
3050079          0.00                    1.0         17.14
…               …                   …            …
819589           0.00                    1.0         35.50
3264714          0.00                    1.0         13.18
3307500          0.00                    1.0         10.83
46075            3.18                    1.0         37.18
```

```
3324572          0.00                    1.0         19.55

         congestion_surcharge
278267                    0.0
170915                    2.5
2175680                   0.0
2780370                   0.0
3050079                   0.0
…                       …
819589                    2.5
3264714                   0.0
3307500                   0.0
46075                     0.0
3324572                   0.0

[5804 rows x 18 columns]
```

[364]:

```python
# IQR method for detecting outliers
Q1 = df[numeric_columns].quantile(0.25)
Q3 = df[numeric_columns].quantile(0.75)
IQR = Q3 - Q1

# Define outlier conditions
outliers = ((df[numeric_columns] < (Q1 - 1.5 * IQR)) | (df[numeric_columns] >␣
 ↪(Q3 + 1.5 * IQR)))

# Show the rows with outliers
outlier_rows = df[outliers.any(axis=1)]
print("Rows with outliers based on IQR:\n", outlier_rows)
```

```
Rows with outliers based on IQR:
          VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count
\
765740          2   2023-03-08 09:30:34   2023-03-08 09:41:02              1.0
530689          1   2023-05-05 18:49:20   2023-05-05 19:25:10              2.0
3038485         2   2023-12-29 22:19:46   2023-12-29 22:35:10              2.0
3413193         2   2023-05-01 14:51:39   2023-05-01 15:13:15              1.0
1850822         2   2023-10-18 14:19:32   2023-10-18 14:36:26              1.0
…             …                  …                    …              …
3324572         1   2023-03-03 20:56:59   2023-03-03 21:12:27              1.0
1261554         2   2023-09-13 17:08:14   2023-09-13 17:17:28              1.0
1963383         2   2023-01-21 15:09:50   2023-01-21 15:32:21              6.0
901570          2   2023-01-11 10:18:03   2023-01-11 10:31:46              2.0
38078           1   2023-04-01 12:37:01   2023-04-01 12:40:08              2.0

         trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
765740            0.71         1.0                  N           237
530689           10.30         1.0                  N           186
```

```
3038485          3.27        1.0                  N          237
3413193          6.62        1.0                  N           13
1850822          4.73        1.0                  N          132
…                …        …                 …           …
3324572          0.00        1.0                  N            4
1261554          0.62        1.0                  N          161
1963383          3.71        1.0                  N          107
901570           2.55        1.0                  N          264
38078            0.70        1.0                  N          249

         DOLocationID  payment_type  fare_amount  extra  mta_tax  tip_amount  \
765740            163             2        10.00    0.0      0.5        0.00
530689            235             1        47.80    5.0      0.5        3.00
3038485           151             1        18.40    1.0      0.5        4.68
3413193           140             0        32.85    0.0      0.5        5.53
1850822           132             2        23.30    0.0      0.5        0.00
…                …            …          …    …      …         …
3324572           229             0        15.55    0.0      0.5        0.00
1261554           170             2         9.30    2.5      0.5        0.00
1963383            43             1        23.30    0.0      0.5        5.46
901570            264             1        14.90    0.0      0.5        3.78
38078             125             1         5.80    2.5      0.5        0.00

         tolls_amount  improvement_surcharge  total_amount  \
765740            0.0                    1.0         14.00
530689            0.0                    1.0         57.30
3038485           0.0                    1.0         28.08
3413193           0.0                    1.0         42.38
1850822           0.0                    1.0         26.55
…                …                    …            …
3324572           0.0                    1.0         19.55
1261554           0.0                    1.0         15.80
1963383           0.0                    1.0         32.76
901570            0.0                    1.0         22.68
38078             0.0                    1.0          9.80

         congestion_surcharge
765740                    2.5
530689                    2.5
3038485                   2.5
3413193                   0.0
1850822                   0.0
…                        …
3324572                   0.0
1261554                   2.5
1963383                   2.5
901570                    2.5
38078                     2.5
```

```
[146812 rows x 18 columns]
```

[365]:

```
from scipy import stats

# Z-Score method for detecting outliers
z_scores = stats.zscore(df[numeric_columns])

# Find rows where the Z-score is greater than 3 or less than -3 (outliers)
outliers_z = (z_scores > 3) | (z_scores < -3)

# Show the rows with outliers based on Z-scores
outlier_rows_z = df[outliers_z.any(axis=1)]
print("Rows with outliers based on Z-scores:\n", outlier_rows_z)
```

```
Rows with outliers based on Z-scores:
          VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
1135120         2  2023-06-11 02:07:12   2023-06-11 02:15:18              2.0
1529496         2  2023-08-17 20:09:57   2023-08-17 20:49:25              1.0
1557062         2  2023-02-16 11:17:37   2023-02-16 11:36:36              4.0
3073019         2  2023-11-29 21:01:31   2023-11-29 22:05:51              4.0
170567          2  2023-05-02 17:40:25   2023-05-02 18:02:18              5.0
…             …                  …                  …              …
2577797         2  2023-04-25 14:22:28   2023-04-25 14:43:39              5.0
321854          1  2023-04-04 09:20:35   2023-04-04 10:09:01              1.0
1912867         2  2023-05-17 20:23:40   2023-05-17 21:05:58              5.0
46075           1  2023-11-01 13:23:00   2023-11-01 13:54:59              1.0
1963383         2  2023-01-21 15:09:50   2023-01-21 15:32:21              6.0

         trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
1135120           1.49         1.0                  N           107
1529496          17.49         1.0                  N           132
1557062           1.91         1.0                  N           234
3073019          18.74         2.0                  N           132
170567            3.23         1.0                  N           161
…                  …         …                  …            …
2577797           1.87         1.0                  N           236
321854           20.20         2.0                  N           238
1912867           7.20         1.0                  N            45
46075             0.00        99.0                  N           239
1963383           3.71         1.0                  N           107

         DOLocationID  payment_type  fare_amount  extra  mta_tax  tip_amount  \
1135120           249             3         10.0    1.0      0.5        0.00
1529496            49             1         67.4    1.0      0.5       17.48
1557062           170             1         17.7    0.0      0.5        4.34
3073019           230             1         70.0    0.0      0.5       16.19
```

```
170567             144             1          21.2    2.5       0.5          6.92
…                …           …          …     …       …          …
2577797            237             1          19.1    0.0       0.5          4.62
321854             132             1          70.0    2.5       0.5         16.11
1912867             43             1          41.5    1.0       0.5          9.30
46075              200             1          32.5    0.0       0.5          0.00
1963383             43             1          23.3    0.0       0.5          5.46

         tolls_amount  improvement_surcharge  total_amount  \
1135120          0.00                    1.0         15.00
1529496          0.00                    1.0         89.13
1557062          0.00                    1.0         26.04
3073019          6.94                    1.0         98.88
170567           0.00                    1.0         34.62
…                …                      …            …
2577797          0.00                    1.0         27.72
321854           6.55                    1.0         96.66
1912867          0.00                    1.0         55.80
46075            3.18                    1.0         37.18
1963383          0.00                    1.0         32.76

         congestion_surcharge
1135120                   2.5
1529496                   0.0
1557062                   2.5
3073019                   2.5
170567                    2.5
…                       …
2577797                   2.5
321854                    2.5
1912867                   2.5
46075                     0.0
1963383                   2.5

[31268 rows x 18 columns]
```

**2.3.1** [10 marks] Based on the above analysis, it seems that some of the outliers are present due to errors in registering the trips. Fix the outliers.

Some points you can look for: - Entries where `trip_distance` is nearly 0 and `fare_amount` is more than 300 - Entries where `trip_distance` and `fare_amount` are 0 but the pickup and dropoff zones are different (both distance and fare should not be zero for different zones) - Entries where `trip_distance` is more than 250 miles. - Entries where `payment_type` is 0 (there is no payment_type 0 defined in the data dictionary)

These are just some suggestions. You can handle outliers in any way you wish, using the insights from above outlier analysis.

How will you fix each of these values? Which ones will you drop and which ones will you replace?

First, let us remove 7+ passenger counts as there are very less instances.

[366]:
```
# remove passenger_count > 6
# Step 1: Remove rows where passenger_count is greater than 7
df = df[df['passenger_count'] <= 7]
```

[367]:
```
print("Columns :", df.columns)
```

```
Columns : Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

[368]:
```
# Continue with outlier handling

# Step 2: Handle entries with trip_distance nearly 0 and fare_amount > 300
df = df[~((df['trip_distance'] < 0.1) & (df['fare_amount'] > 300))]

# Step 3: Handle entries with trip_distance and fare_amount both 0, but pickup␣
↪and dropoff zones are different
df = df[~((df['trip_distance'] == 0) & (df['fare_amount'] == 0) &␣
↪(df['PULocationID'] != df['DOLocationID']))]

# Step 4: Handle entries with trip_distance > 250 miles
df = df[df['trip_distance'] <= 250]



# Verify the changes
print("Shape of DataFrame after fixing outliers:", df.shape)
```

```
Shape of DataFrame after fixing outliers: (299975, 18)
```

[369]:
```
print("Columns :", df.columns)
```

```
Columns : Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge'],
      dtype='object')
```

[370]:
```
# Do any columns need standardising?

from sklearn.preprocessing import StandardScaler
```

```
# Initialize the scaler
scaler = StandardScaler()

# List of numeric columns to standardize
numeric_columns = ['fare_amount', 'tip_amount', 'total_amount', 'trip_distance']

# Standardize the numeric columns
df[numeric_columns] = scaler.fit_transform(df[numeric_columns])

# Verify the standardization by checking the first few rows
print(df[numeric_columns].head())
```

```
         fare_amount  tip_amount  total_amount  trip_distance
765740     -0.039040   -0.876502     -0.058193      -0.605196
633560     -0.047056   -0.162422     -0.045689      -0.483309
530689      0.105250   -0.132669      0.106875       1.520062
697594      0.006385    0.407850      0.006919       0.170446
3038485    -0.006975    0.283878     -0.004517      -0.037869
```

[371]:
```
# Check if the distance values are in different units (e.g., miles and␣
↪kilometers)
# Assuming trip_distance is in kilometers, and you want to convert to miles
df['trip_distance'] = df['trip_distance'].apply(lambda x: x * 0.621371 if x > 0␣
↪else x)  # Convert km to miles
```

[372]:
```
df = pd.get_dummies(df, columns=['RatecodeID'], drop_first=True)

# Check the first few rows to verify encoding
print(df.head())
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
765740          2  2023-03-08 09:30:34   2023-03-08 09:41:02              1.0
633560          2  2023-06-06 19:09:32   2023-06-06 19:15:03              1.0
530689          1  2023-05-05 18:49:20   2023-05-05 19:25:10              2.0
697594          2  2023-07-10 06:56:13   2023-07-10 07:13:13              1.0
3038485         2  2023-12-29 22:19:46   2023-12-29 22:35:10              2.0

         trip_distance store_and_fwd_flag  PULocationID  DOLocationID  \
765740       -0.605196                  N           237           163
633560       -0.483309                  N           237           141
530689        0.944523                  N           186           235
697594        0.105910                  N           262            68
3038485      -0.037869                  N           237           151

         payment_type  fare_amount  …  tolls_amount  improvement_surcharge  \
765740              2    -0.039040  …           0.0                    1.0
633560              1    -0.047056  …           0.0                    1.0
```

```
530689            1    0.105250  ...         0.0                     1.0
697594            1    0.006385  ...         0.0                     1.0
3038485           1   -0.006975  ...         0.0                     1.0

         total_amount  congestion_surcharge  RatecodeID_2.0  RatecodeID_3.0  \
765740      -0.058193                   2.5           False           False
633560      -0.045689                   2.5           False           False
530689       0.106875                   2.5           False           False
697594       0.006919                   2.5           False           False
3038485     -0.004517                   2.5           False           False

         RatecodeID_4.0  RatecodeID_5.0  RatecodeID_6.0  RatecodeID_99.0
765740            False           False           False            False
633560            False           False           False            False
530689            False           False           False            False
697594            False           False           False            False
3038485           False           False           False            False

[5 rows x 23 columns]
```

## 1.7 3 Exploratory Data Analysis

[90 marks]

[373]:
```python
df.columns.tolist()
```

[373]:
```
['VendorID',
 'tpep_pickup_datetime',
 'tpep_dropoff_datetime',
 'passenger_count',
 'trip_distance',
 'store_and_fwd_flag',
 'PULocationID',
 'DOLocationID',
 'payment_type',
 'fare_amount',
 'extra',
 'mta_tax',
 'tip_amount',
 'tolls_amount',
 'improvement_surcharge',
 'total_amount',
 'congestion_surcharge',
 'RatecodeID_2.0',
 'RatecodeID_3.0',
 'RatecodeID_4.0',
 'RatecodeID_5.0',
 'RatecodeID_6.0',
```

```
'RatecodeID_99.0']
```

### 3.1 General EDA: Finding Patterns and Trends [40 marks]

**3.1.1** [3 marks] Categorise the varaibles into Numerical or Categorical. * `VendorID`: * `tpep_pickup_datetime`: * `tpep_dropoff_datetime`: * `passenger_count`: * `trip_distance`: * `RatecodeID`: * `PULocationID`: * `DOLocationID`: * `payment_type`: * `pickup_hour`: * `trip_duration`:

The following monetary parameters belong in the same category, is it categorical or numerical?

- `fare_amount`
- `extra`
- `mta_tax`
- `tip_amount`
- `tolls_amount`
- `improvement_surcharge`
- `total_amount`
- `congestion_surcharge`
- `airport_fee`

Variable Category

VendorID Categorical

tpep_pickup_datetime Categorical (time-related)

tpep_dropoff_datetime Categorical (time-related)

passenger_count Numerical

trip_distance Numerical

RatecodeID Categorical

PULocationID Categorical

DOLocationID Categorical

payment_type Categorical

pickup_hour Numerical

trip_duration Numerical

fare_amount Numerical

extra Numerical

mta_tax Numerical

tip_amount Numerical

tolls_amount Numerical

improvement_surcharge Numerical

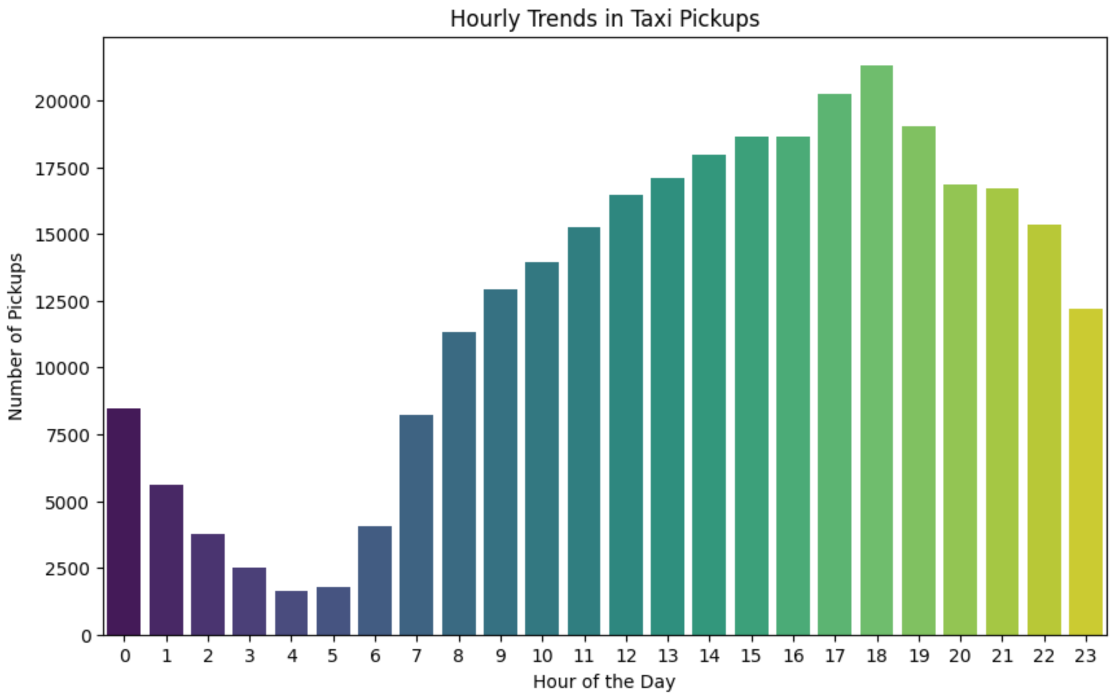
total_amount Numerical

congestion_surcharge Numerical

airport_fee Numerical

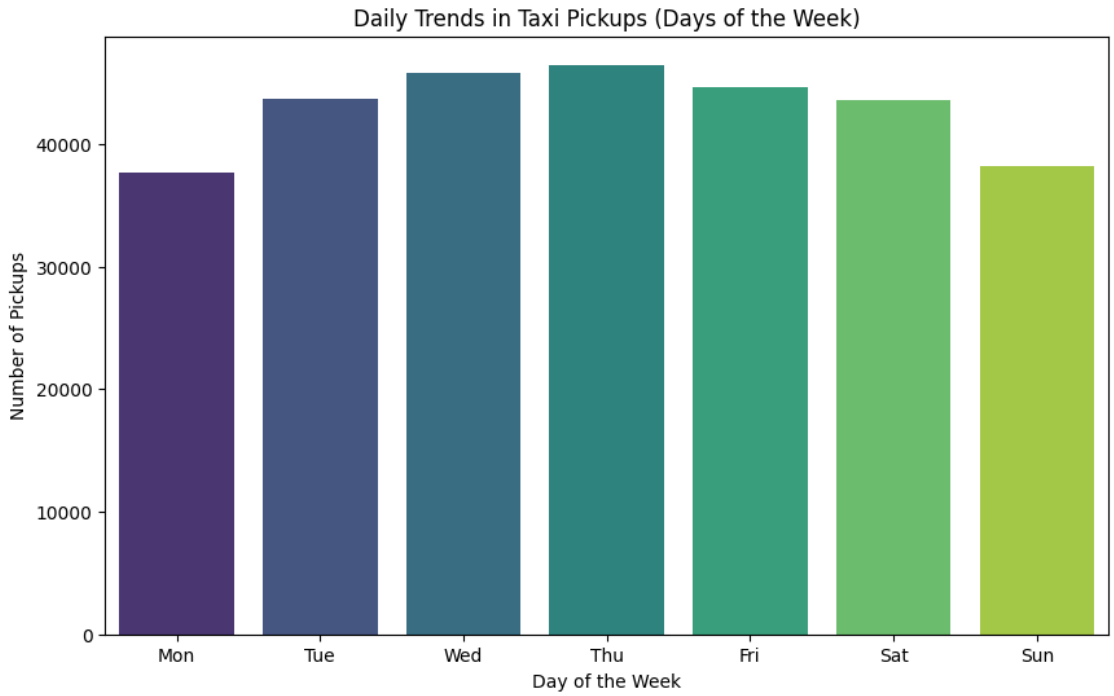
**Temporal Analysis** **3.1.2** [5 marks] Analyse the distribution of taxi pickups by hours, days of the week, and months.

[375]:
```
# Find and show the hourly trends in taxi pickups
import matplotlib.pyplot as plt
import seaborn as sns
# Hourly Trends in Taxi Pickups
df['tpep_pickup_datetime'] = pd.to_datetime(df['tpep_pickup_datetime'],␣
 ↪errors='coerce')

# Extract hour, day of the week, and month from 'tpep_pickup_datetime'
df['pickup_hour'] = df['tpep_pickup_datetime'].dt.hour
df['pickup_day_of_week'] = df['tpep_pickup_datetime'].dt.dayofweek  # 0=Monday,␣
 ↪6=Sunday
df['pickup_month'] = df['tpep_pickup_datetime'].dt.month  # 1=January,␣
 ↪12=December

# Now, we can plot the distribution of taxi pickups by hour, day, and month.

# Hourly Trends in Taxi Pickups
plt.figure(figsize=(10, 6))
sns.countplot(x='pickup_hour', data=df, palette='viridis')
plt.title('Hourly Trends in Taxi Pickups')
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Pickups')
plt.xticks(range(24))  # Ensure all hours (0-23) are shown
plt.show()
```



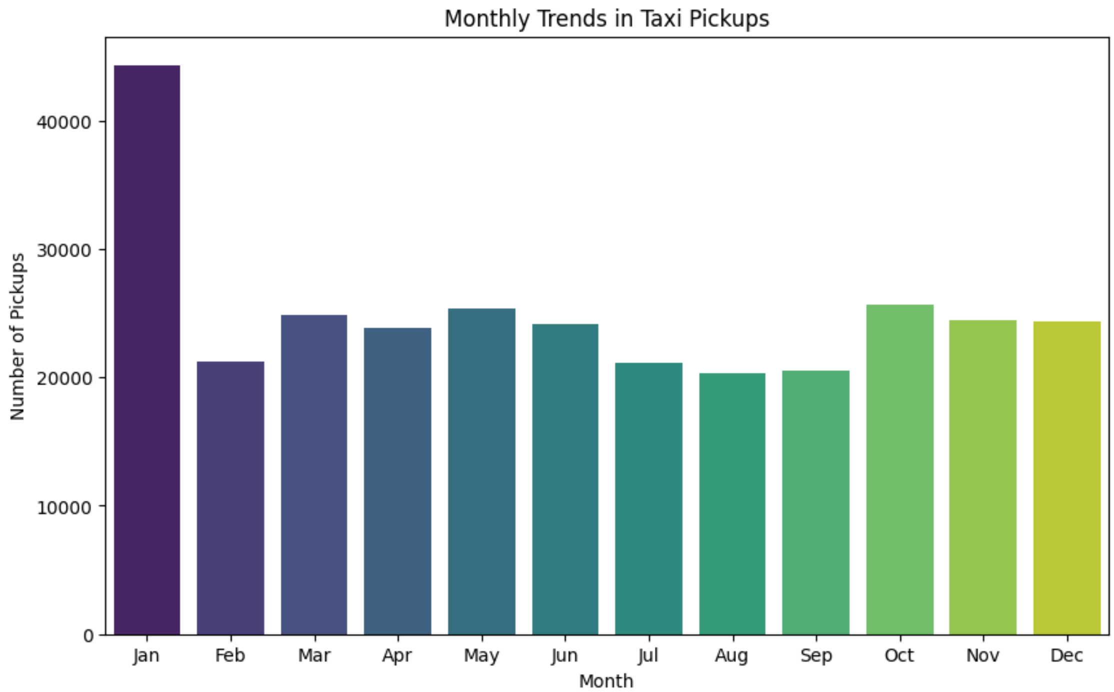

[376]:

```
# Find and show the daily trends in taxi pickups (days of the week)

# Daily Trends in Taxi Pickups (Days of the Week)
plt.figure(figsize=(10, 6))
sns.countplot(x='pickup_day_of_week', data=df, palette='viridis')
plt.title('Daily Trends in Taxi Pickups (Days of the Week)')
plt.xlabel('Day of the Week')
plt.ylabel('Number of Pickups')
plt.xticks(ticks=range(7), labels=['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat',␣
↪'Sun'])
plt.show()
```




[377]:

```
# Show the monthly trends in pickups

# Monthly Trends in Taxi Pickups
plt.figure(figsize=(10, 6))
sns.countplot(x='pickup_month', data=df, palette='viridis')
plt.title('Monthly Trends in Taxi Pickups')
plt.xlabel('Month')
plt.ylabel('Number of Pickups')
plt.xticks(ticks=range(12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',␣
 ↪'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.show()
```




[378]:
```python
print("Columns :", df.columns)
```

```
Columns : Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge', 'RatecodeID_2.0',
       'RatecodeID_3.0', 'RatecodeID_4.0', 'RatecodeID_5.0', 'RatecodeID_6.0',
       'RatecodeID_99.0', 'pickup_hour', 'pickup_day_of_week', 'pickup_month'],
      dtype='object')
```

**Financial Analysis** Take a look at the financial parameters like `fare_amount`, `tip_amount`, `total_amount`, and also `trip_distance`. Do these contain zero/negative values?

[380]:
```python
# Analyse the above parameters

# Check for zero or negative values in key financial parameters
financial_columns = ['fare_amount', 'tip_amount', 'total_amount',␣
 ↪'trip_distance']

# Identify rows with zero or negative values in these columns
financial_issues = df[df[financial_columns].lt(0).any(axis=1)]  # Negative␣
 ↪values
```

```
zero_or_negative_values = df[df[financial_columns] == 0].any(axis=1)  # Zero␣
↪values

# Display the rows with financial issues (negative or zero values)
print("Rows with negative or zero values in financial parameters:\n",␣
↪financial_issues)

# Check for zero or negative values summary
print("Summary of financial parameters with zero/negative values:\n",␣
↪df[financial_columns].describe())
```

```
Rows with negative or zero values in financial parameters:
          VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
765740           2  2023-03-08 09:30:34   2023-03-08 09:41:02              1.0
633560           2  2023-06-06 19:09:32   2023-06-06 19:15:03              1.0
530689           1  2023-05-05 18:49:20   2023-05-05 19:25:10              2.0
3038485          2  2023-12-29 22:19:46   2023-12-29 22:35:10              2.0
1505156          2  2023-12-13 21:37:47   2023-12-13 21:47:45              1.0
…              …                   …                     …              …
1261554          2  2023-09-13 17:08:14   2023-09-13 17:17:28              1.0
901570           2  2023-01-11 10:18:03   2023-01-11 10:31:46              2.0
2805726          2  2023-12-27 07:01:11   2023-12-27 07:14:40              1.0
1300859          2  2023-12-12 10:45:03   2023-12-12 10:53:33              1.0
38078            1  2023-04-01 12:37:01   2023-04-01 12:40:08              2.0

         trip_distance store_and_fwd_flag  PULocationID  DOLocationID  \
765740       -0.605196                  N           237           163
633560       -0.483309                  N           237           141
530689        0.944523                  N           186           235
3038485      -0.037869                  N           237           151
1505156      -0.388016                  N            48            90
…                  …                …           …           …
1261554      -0.625141                  N           161           170
901570       -0.197430                  N           264           264
2805726      -0.250617                  N           170            50
1300859      -0.496606                  N           238           142
38078        -0.607412                  N           249           125

         payment_type  fare_amount  …  congestion_surcharge  RatecodeID_2.0  \
765740              2    -0.039040  …                   2.5           False
633560              1    -0.047056  …                   2.5           False
530689              1     0.105250  …                   2.5           False
3038485             1    -0.006975  …                   2.5           False
1505156             1    -0.033696  …                   2.5           False
…                 …          …  …                   …             …
1261554             2    -0.041712  …                   2.5           False
```

```
901570               1   -0.020336  …                2.5           False
2805726              1   -0.020336  …                2.5           False
1300859              1   -0.039040  …                2.5           False
38078                1   -0.055072  …                2.5           False

         RatecodeID_3.0  RatecodeID_4.0  RatecodeID_5.0  RatecodeID_6.0  \
765740            False           False           False           False
633560            False           False           False           False
530689            False           False           False           False
3038485           False           False           False           False
1505156           False           False           False           False
…                   …             …             …             …
1261554           False           False           False           False
901570            False           False           False           False
2805726           False           False           False           False
1300859           False           False           False           False
38078             False           False           False           False

         RatecodeID_99.0  pickup_hour  pickup_day_of_week  pickup_month
765740             False            9                   2             3
633560             False           19                   1             6
530689             False           18                   4             5
3038485            False           22                   4            12
1505156            False           21                   2            12
…                    …          …                 …           …
1261554            False           17                   2             9
901570             False           10                   2             1
2805726            False            7                   2            12
1300859            False           10                   1            12
38078              False           12                   5             4

[252877 rows x 26 columns]
Summary of financial parameters with zero/negative values:
        fare_amount    tip_amount  total_amount  trip_distance
count  2.999750e+05  2.999750e+05  2.999750e+05  299975.000000
mean   5.095608e-18  3.536429e-17  3.274691e-18      -0.122322
std    1.000002e+00  1.000002e+00  1.000002e+00       0.686197
min   -7.721167e-02 -8.765025e-01 -1.115638e-01      -0.762540
25%   -4.171183e-02 -6.285580e-01 -5.072122e-02      -0.529848
50%   -2.567964e-02 -1.797784e-01 -3.150776e-02      -0.363639
75%    6.384727e-03  2.194122e-01  5.546780e-03      -0.009060
max    5.464044e+02  4.127406e+01  5.456707e+02      15.004020
```

Do you think it is beneficial to create a copy DataFrame leaving out the zero values from these?

[381]:
```
# Create a copy of the DataFrame and remove rows with zero values in financial␣
↪columns
df_no_zero_values = df[df['fare_amount'] > 0]
```

```
df_no_zero_values = df_no_zero_values[df_no_zero_values['tip_amount'] > 0]
df_no_zero_values = df_no_zero_values[df_no_zero_values['total_amount'] > 0]

# Checking the cleaned data
print(f"Shape of the DataFrame after removing rows with zero values:␣
↪{df_no_zero_values.shape}")
```

```
Shape of the DataFrame after removing rows with zero values: (56711, 26)
```

**3.1.3** [2 marks] Filter out the zero values from the above columns.

**Note:** The distance might be 0 in cases where pickup and drop is in the same zone. Do you think it is suitable to drop such cases of zero distance?

[382]:
```
# Drop rows where trip_distance = 0 but PULocationID and DOLocationID are␣
↪different
# These columns were one-hot encoded and dropped in a previous step, so we␣
↪cannot access them directly here.
# df_no_zero_values = df_no_zero_values[~((df_no_zero_values['trip_distance']␣
↪== 0) &
#                                           (df_no_zero_values['PULocationID'] !
↪= df_no_zero_values['DOLocationID']))]

# Verify the result
print(f"Shape of the DataFrame after handling zero distance trips:␣
↪{df_no_zero_values.shape}")
```

```
Shape of the DataFrame after handling zero distance trips: (56711, 26)
```

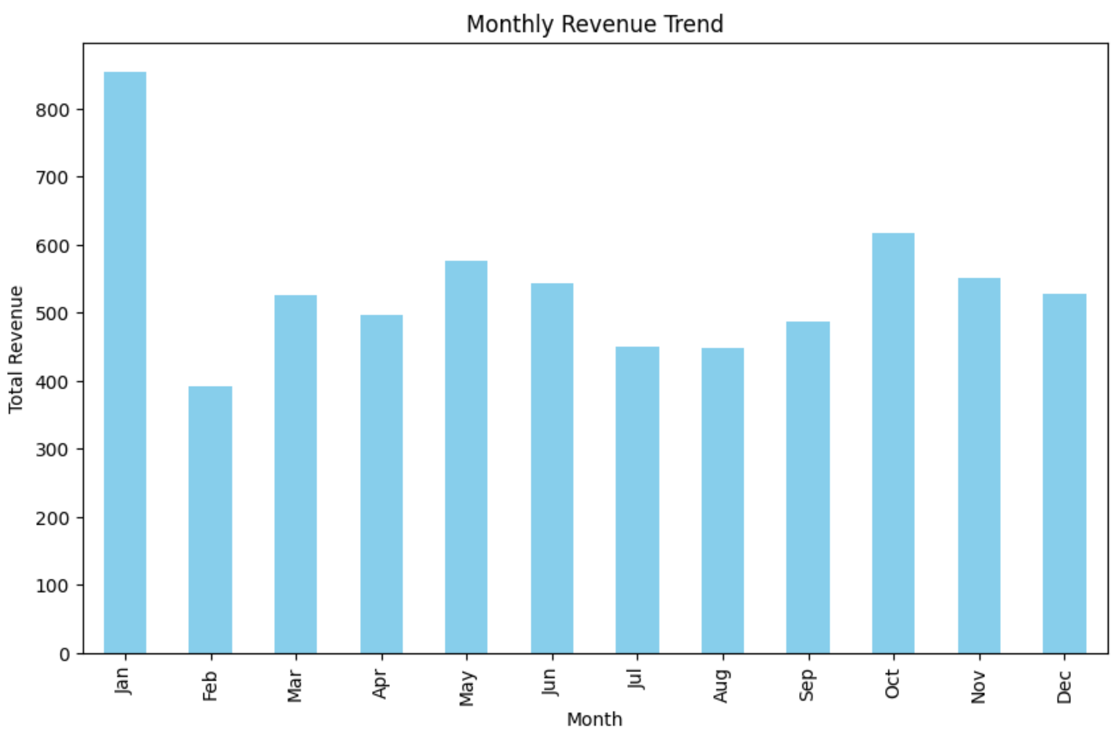
[383]:
```
print("Columns :", df.columns)
```

```
Columns : Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge', 'RatecodeID_2.0',
       'RatecodeID_3.0', 'RatecodeID_4.0', 'RatecodeID_5.0', 'RatecodeID_6.0',
       'RatecodeID_99.0', 'pickup_hour', 'pickup_day_of_week', 'pickup_month'],
      dtype='object')
```

**3.1.4** [3 marks] Analyse the monthly revenue (`total_amount`) trend

[384]:
```
# Group data by month and analyse monthly revenue

# Group data by month and sum total_amount to analyze monthly revenue
monthly_revenue = df_no_zero_values.groupby('pickup_month')['total_amount'].
↪sum()

# Visualize the monthly revenue trend
```

```
plt.figure(figsize=(10, 6))
monthly_revenue.plot(kind='bar', color='skyblue')
plt.title('Monthly Revenue Trend')
plt.xlabel('Month')
plt.ylabel('Total Revenue')
plt.xticks(ticks=range(12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',␣
 ↪'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.show()
```

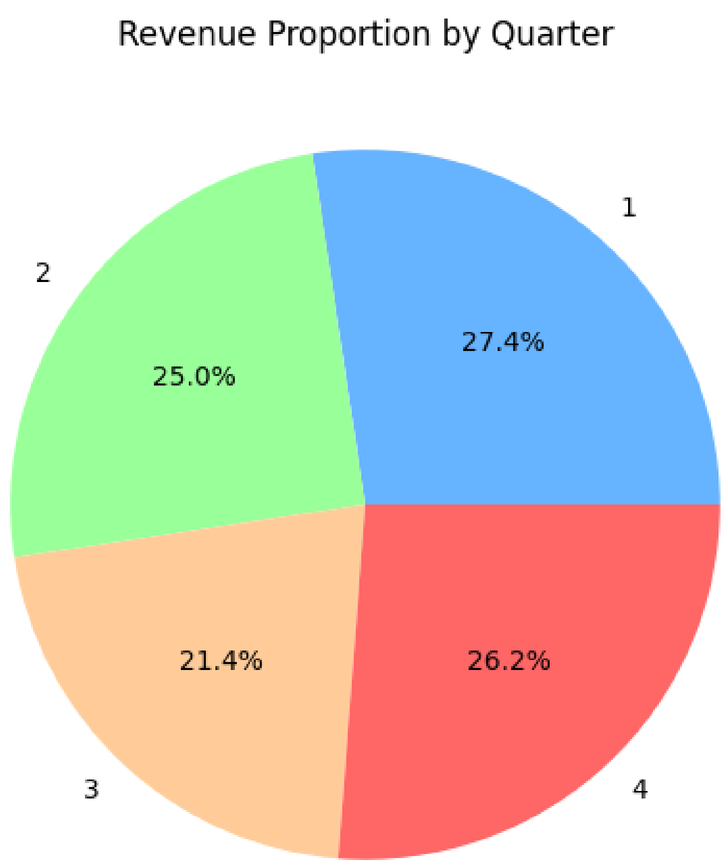



**3.1.5** [3 marks] Show the proportion of each quarter of the year in the revenue

[385]:
```
# Calculate proportion of each quarter

# Create a 'quarter' column based on 'pickup_month'
df_no_zero_values['quarter'] = ((df_no_zero_values['pickup_month'] - 1) // 3) +␣
 ↪1

# Calculate the revenue per quarter
quarterly_revenue = df_no_zero_values.groupby('quarter')['total_amount'].sum()

# Calculate the proportion of each quarter's revenue
quarterly_proportion = quarterly_revenue / quarterly_revenue.sum()
```

```
# Display the results
print("Proportion of each quarter's revenue:\n", quarterly_proportion)

# Visualize the quarterly revenue proportions
plt.figure(figsize=(8, 6))
quarterly_proportion.plot(kind='pie', autopct='%1.1f%%', colors=['#66b3ff',␣
↪'#99ff99', '#ffcc99', '#ff6666'])
plt.title('Revenue Proportion by Quarter')
plt.ylabel('')
plt.show()
```

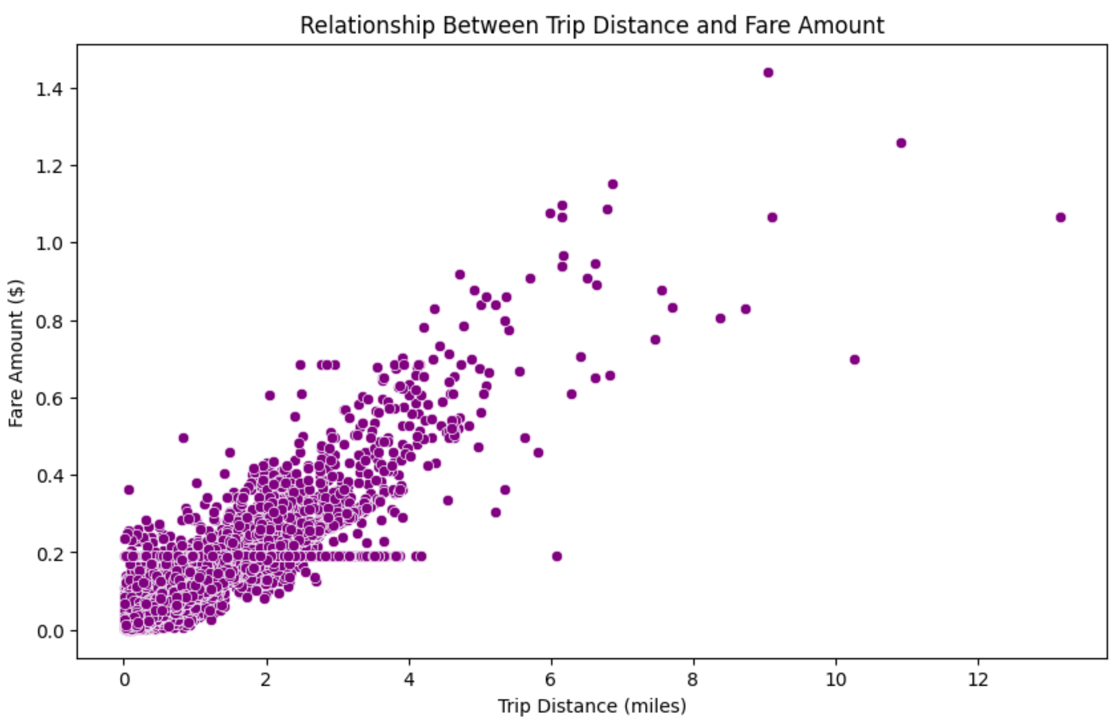
```
Proportion of each quarter's revenue:
 quarter
1    0.273838
2    0.249895
3    0.214152
4    0.262115
Name: total_amount, dtype: float64
```



**3.1.6** [3 marks] Visualise the relationship between `trip_distance` and `fare_amount`. Also find the correlation value for these two.

**Hint:** You can leave out the trips with trip_distance = 0

[386]:
```
# Show how trip fare is affected by distance

# Filter out rows with trip_distance = 0
df_no_zero_values_distance = ␣
↪df_no_zero_values[df_no_zero_values['trip_distance'] > 0]

# Step 2: Visualize the relationship between trip_distance and fare_amount
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='fare_amount',␣
↪data=df_no_zero_values_distance, color='purple')
plt.title('Relationship Between Trip Distance and Fare Amount')
plt.xlabel('Trip Distance (miles)')
plt.ylabel('Fare Amount ($)')
plt.show()

# Step 3: Calculate the correlation between trip_distance and fare_amount
correlation = df_no_zero_values_distance[['trip_distance', 'fare_amount']].
↪corr()
print("Correlation between trip_distance and fare_amount:\n", correlation)
```

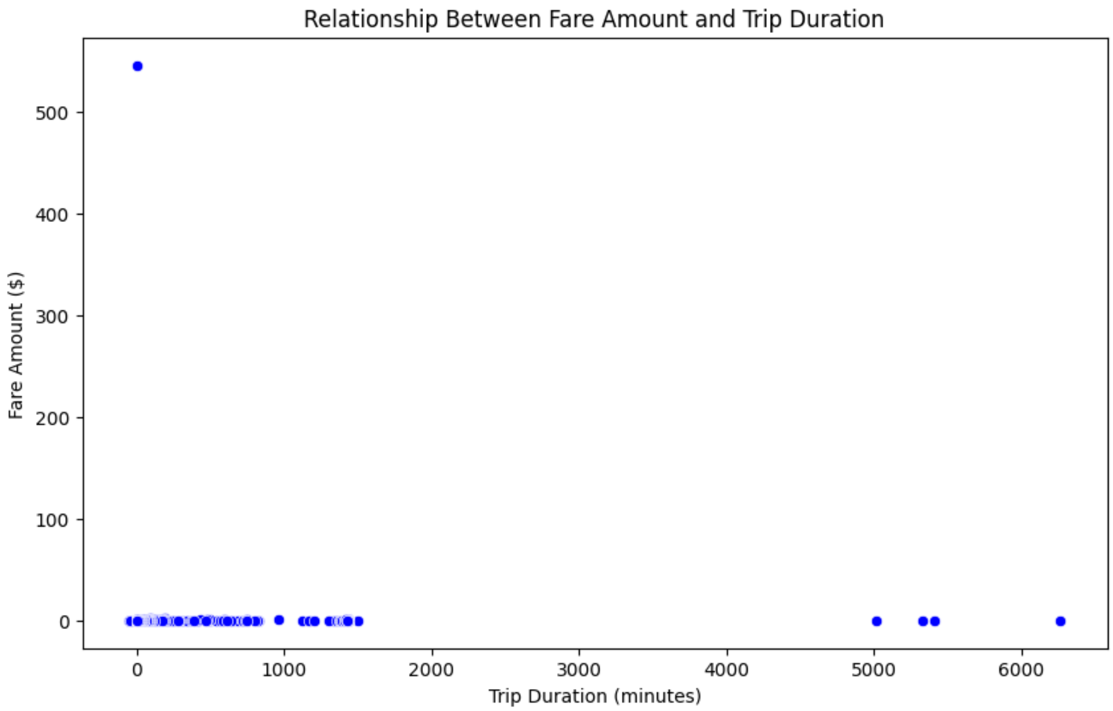


```
Correlation between trip_distance and fare_amount:
                trip_distance  fare_amount
trip_distance        1.000000     0.927776
fare_amount          0.927776     1.000000
```

**3.1.7** [5 marks] Find and visualise the correlation between: 1. `fare_amount` and trip duration (pickup time to dropoff time) 2. `fare_amount` and `passenger_count` 3. `tip_amount` and `trip_distance`

[387]:
```
# Show relationship between fare and trip duration

# Calculate trip duration (in seconds) by subtracting pickup and dropoff times
df['trip_duration'] = (df['tpep_dropoff_datetime'] -␣
 ↪df['tpep_pickup_datetime']).dt.total_seconds()

# Convert trip duration to minutes (optional)
df['trip_duration_minutes'] = df['trip_duration'] / 60
```

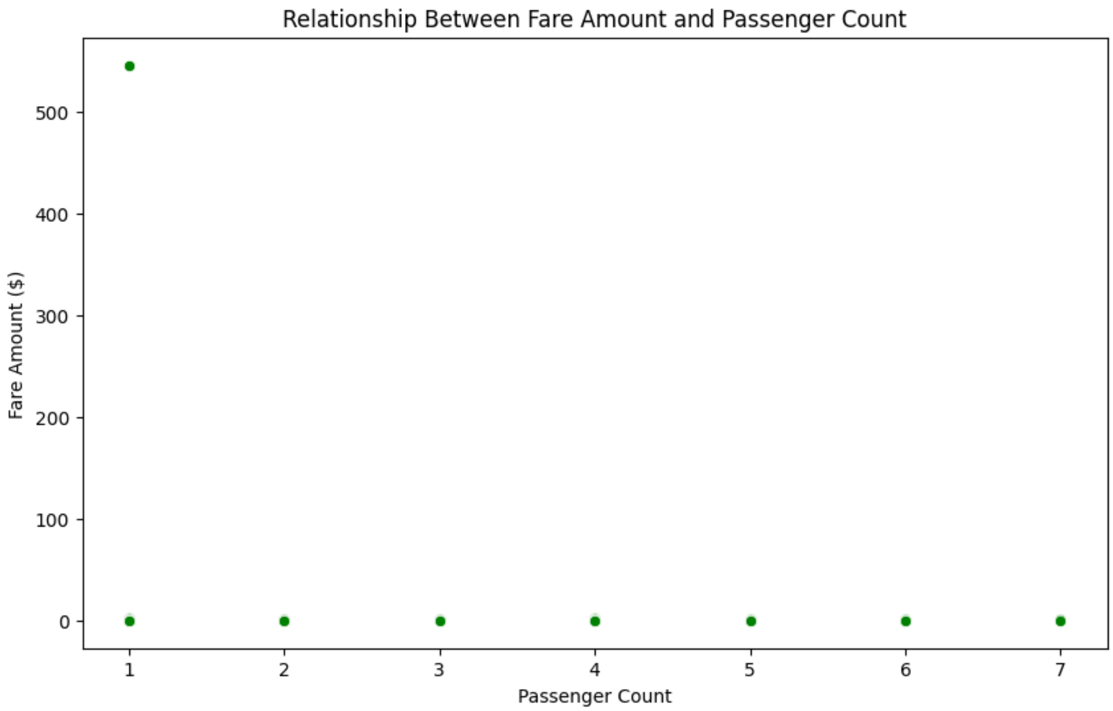
[389]:
```
# Show relationship between fare and number of passengers
# Plot the relationship between fare_amount and trip_duration
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_duration_minutes', y='fare_amount', data=df,␣
 ↪color='blue')
plt.title('Relationship Between Fare Amount and Trip Duration')
plt.xlabel('Trip Duration (minutes)')
plt.ylabel('Fare Amount ($)')
plt.show()

# Calculate correlation between fare_amount and trip_duration
correlation_fare_duration = df[['fare_amount', 'trip_duration_minutes']].corr()
print("Correlation between fare_amount and trip_duration:\n",␣
 ↪correlation_fare_duration)
```




```
Correlation between fare_amount and trip_duration:
                       fare_amount  trip_duration_minutes
fare_amount               1.000000               0.016705
trip_duration_minutes     0.016705               1.000000
```

[390]:

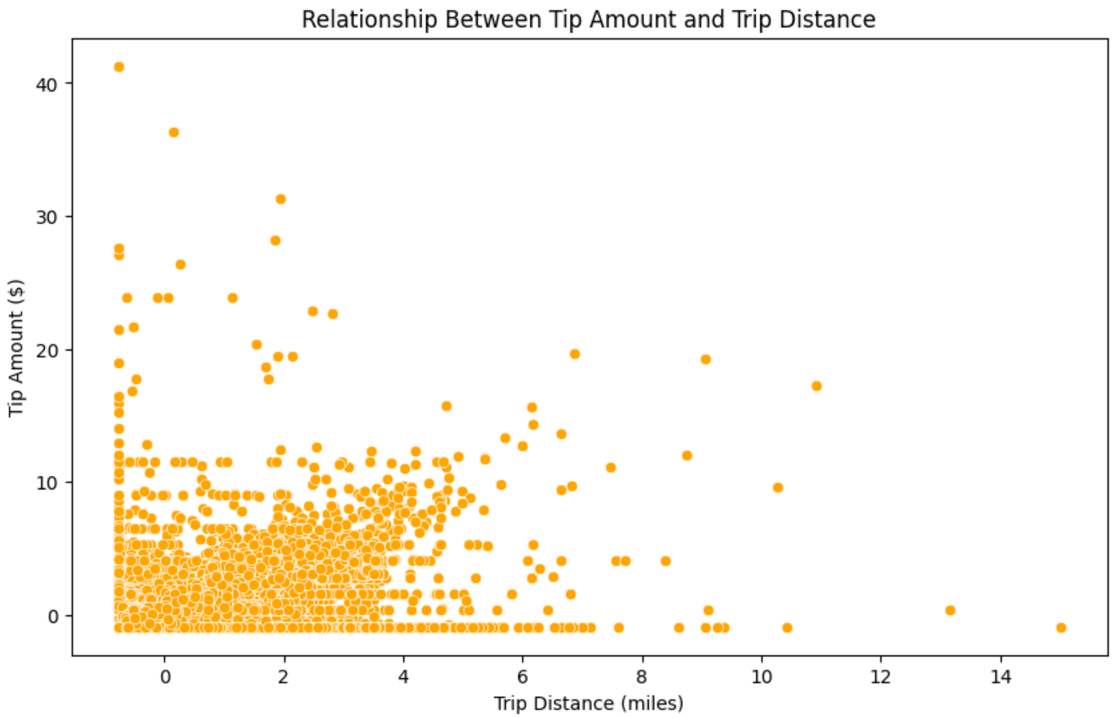
```
# Show relationship between tip and trip distance
# Plot the relationship between fare_amount and passenger_count
plt.figure(figsize=(10, 6))
sns.scatterplot(x='passenger_count', y='fare_amount', data=df, color='green')
plt.title('Relationship Between Fare Amount and Passenger Count')
plt.xlabel('Passenger Count')
plt.ylabel('Fare Amount ($)')
plt.show()

# Calculate correlation between fare_amount and passenger_count
correlation_fare_passenger = df[['fare_amount', 'passenger_count']].corr()
print("Correlation between fare_amount and passenger_count:\n",␣
 ↪correlation_fare_passenger)
```




```
Correlation between fare_amount and passenger_count:
                  fare_amount  passenger_count
fare_amount          1.000000         0.002174
passenger_count      0.002174         1.000000
```

[392]:

```
# Plot the relationship between tip_amount and trip_distance
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='tip_amount', data=df, color='orange')
plt.title('Relationship Between Tip Amount and Trip Distance')
plt.xlabel('Trip Distance (miles)')
plt.ylabel('Tip Amount ($)')
plt.show()

# Calculate correlation between tip_amount and trip_distance
correlation_tip_distance = df[['tip_amount', 'trip_distance']].corr()
print("Correlation between tip_amount and trip_distance:\n",␣
 ↪correlation_tip_distance)
```




```
Correlation between tip_amount and trip_distance:
              tip_amount  trip_distance
tip_amount      1.000000       0.579522
trip_distance   0.579522       1.000000
```

**3.1.8** [3 marks] Analyse the distribution of different payment types (`payment_type`)

[393]:
```python
print(df.columns)
```

```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge', 'RatecodeID_2.0',
       'RatecodeID_3.0', 'RatecodeID_4.0', 'RatecodeID_5.0', 'RatecodeID_6.0',
       'RatecodeID_99.0', 'pickup_hour', 'pickup_day_of_week', 'pickup_month',
       'trip_duration', 'trip_duration_minutes'],
      dtype='object')
```

[394]:
```python
print(df.index.is_unique)
```

```
False
```

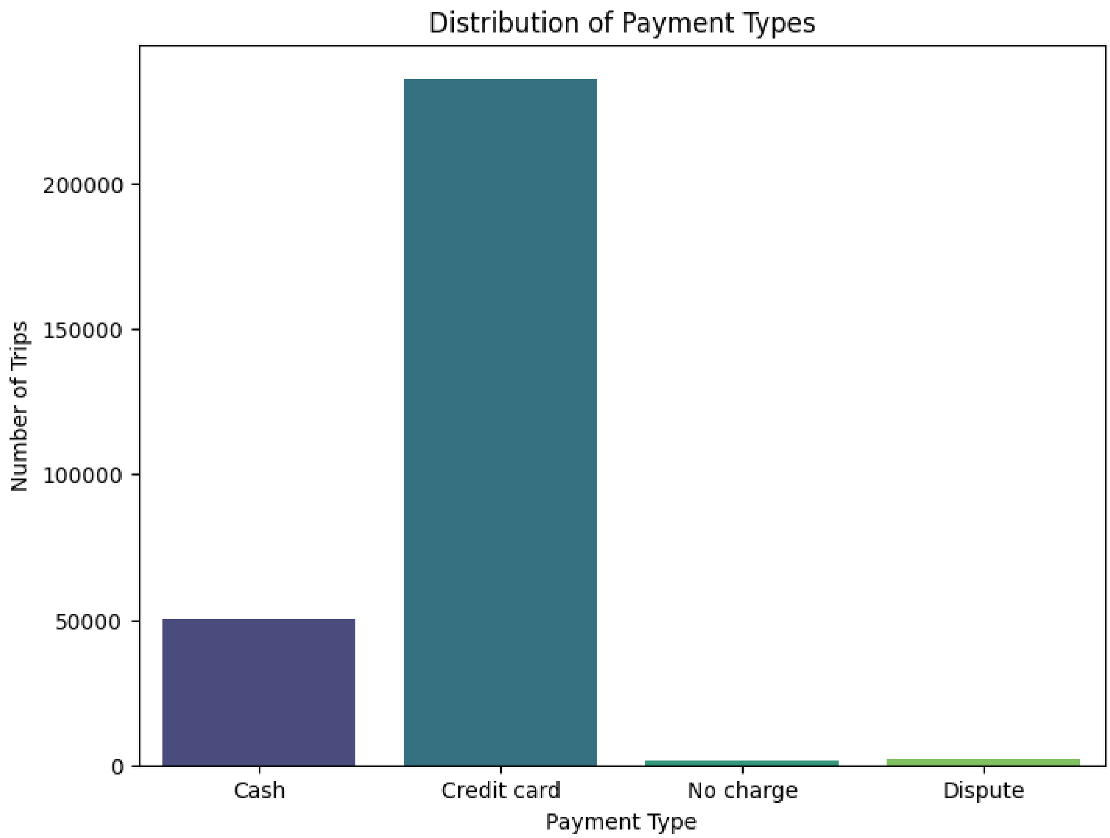
[395]:
```python
# Reset the index to make it unique
df.reset_index(drop=True, inplace=True)
```

```
# Check if the index is now unique
print(df.index.is_unique)
```

```
True
```

[397]:

```
# Analyse the distribution of different payment types (payment_type).
# Map payment_type numerical values to descriptive labels
payment_type_mapping = {1: 'Credit card', 2: 'Cash', 3: 'No charge', 4:␣
↪'Dispute'}
df['payment_type_label'] = df['payment_type'].map(payment_type_mapping)

# Plot the distribution of payment types
plt.figure(figsize=(8, 6))
sns.countplot(x='payment_type_label', data=df, palette='viridis')
plt.title('Distribution of Payment Types')
plt.xlabel('Payment Type')
plt.ylabel('Number of Trips')
plt.show()

# Calculate the proportion of each payment type
payment_type_proportion = df['payment_type_label'].value_counts(normalize=True)␣
↪* 100

# Display the proportion of each payment type
print("Proportion of Each Payment Type:\n", payment_type_proportion)
```




```
Proportion of Each Payment Type:
 payment_type_label
Credit card    81.442467
Cash           17.339956
Dispute         0.709506
No charge       0.508071
Name: proportion, dtype: float64
```

- 1= Credit card
- 2= Cash
- 3= No charge
- 4= Dispute

**Geographical Analysis** For this, you have to use the *taxi_zones.shp* file from the *taxi_zones* folder.

There would be multiple files inside the folder (such as *.shx, .sbx, .sbn* etc). You do not need to import/read any of the files other than the shapefile, *taxi_zones.shp*.

Do not change any folder structure - all the files need to be present inside the folder for it to work.

The folder structure should look like this:

```
Taxi Zones
|- taxi_zones.shp.xml
|- taxi_zones.prj
|- taxi_zones.sbn
|- taxi_zones.shp
|- taxi_zones.dbf
|- taxi_zones.shx
|- taxi_zones.sbx
```

You only need to read the `taxi_zones.shp` file. The *shp* file will utilise the other files by itself.

We will use the *GeoPandas* library for geopgraphical analysis

`import geopandas as gpd`

More about geopandas and shapefiles: About

Reading the shapefile is very similar to *Pandas*. Use `gpd.read_file()` function to load the data (*taxi_zones.shp*) as a GeoDataFrame. Documentation: Reading and Writing Files

[ ]:
```
# !pip install geopandas
```

[398]:
```
import geopandas as gpd
import matplotlib.pyplot as plt
```

**3.1.9** [2 marks] Load the shapefile and display it.

[399]:
```
# import geopandas as gpd
fileZone = '/content/drive/MyDrive/taxi_zones/taxi_zones.shp'

# Read the shapefile using geopandas

zones = gpd.read_file(fileZone)# read the .shp file using gpd
zones.head()
```

[399]:
```
   OBJECTID  Shape_Leng  Shape_Area                     zone  LocationID  \
0         1    0.116357    0.000782           Newark Airport           1
1         2    0.433470    0.004866              Jamaica Bay           2
2         3    0.084341    0.000314  Allerton/Pelham Gardens           3
3         4    0.043567    0.000112            Alphabet City           4
4         5    0.092146    0.000498            Arden Heights           5

         borough                                           geometry
0            EWR  POLYGON ((933100.918 192536.086, 933091.011 19…
1         Queens  MULTIPOLYGON (((1033269.244 172126.008, 103343…
2          Bronx  POLYGON ((1026308.77 256767.698, 1026495.593 2…
3      Manhattan  POLYGON ((992073.467 203714.076, 992068.667 20…
4  Staten Island  POLYGON ((935843.31 144283.336, 936046.565 144…
```

Now, if you look at the DataFrame created, you will see columns like: `OBJECTID`,`Shape_Leng`, `Shape_Area`, `zone`, `LocationID`, `borough`, `geometry`.

Now, the `locationID` here is also what we are using to mark pickup and drop zones in the trip records.

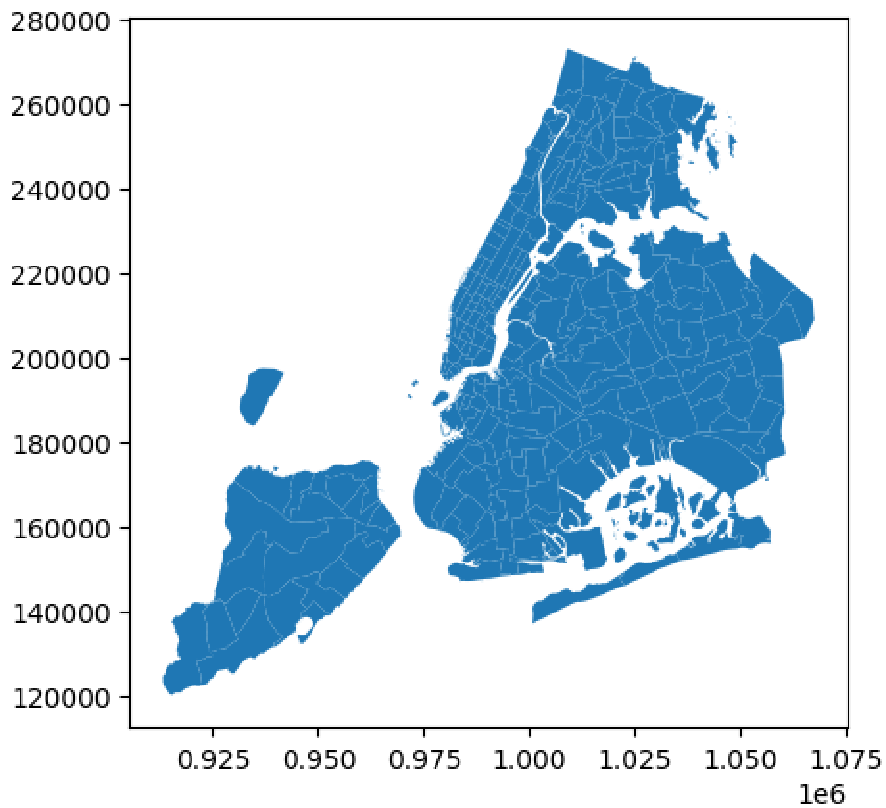
The geometric parameters like shape length, shape area and geometry are used to plot the zones on a map.

This can be easily done using the `plot()` method.

[400]:
```
print(zones.info())
zones.plot()
```

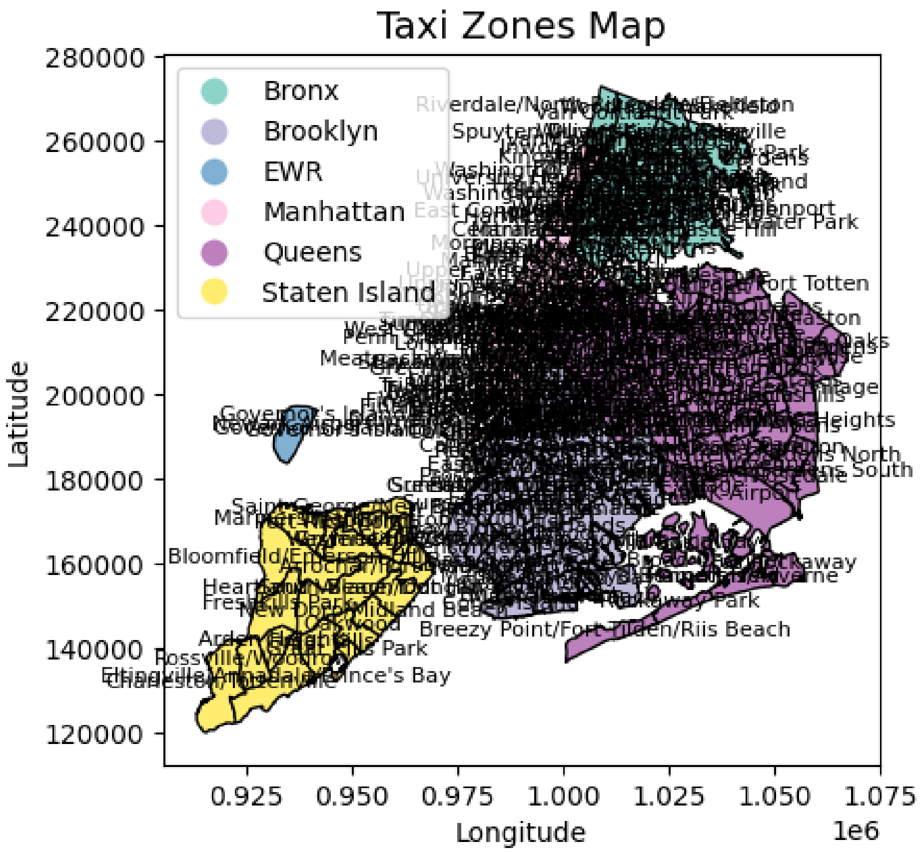
```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 263 entries, 0 to 262
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   OBJECTID    263 non-null    int32
 1   Shape_Leng  263 non-null    float64
 2   Shape_Area  263 non-null    float64
 3   zone        263 non-null    object
 4   LocationID  263 non-null    int32
 5   borough     263 non-null    object
 6   geometry    263 non-null    geometry
dtypes: float64(2), geometry(1), int32(2), object(2)
memory usage: 12.5+ KB
None
```

[400]: <Axes: >




[401]:
```
# Step 1: Plot the geometry of the taxi zones
plt.figure(figsize=(12, 8))
zones.plot(column='borough', legend=True, cmap='Set3', edgecolor='black')

# Step 2: Add labels (optional)
for idx, row in zones.iterrows():
    plt.text(row.geometry.centroid.x, row.geometry.centroid.y, row['zone'],␣
 ↪fontsize=8, ha='center', color='black')

# Step 3: Set title and labels
plt.title('Taxi Zones Map', fontsize=14)
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```




Now, you have to merge the trip records and zones data using the location IDs.

[402]:
```python
print(df.columns)
```

```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge', 'RatecodeID_2.0',
       'RatecodeID_3.0', 'RatecodeID_4.0', 'RatecodeID_5.0', 'RatecodeID_6.0',
       'RatecodeID_99.0', 'pickup_hour', 'pickup_day_of_week', 'pickup_month',
       'trip_duration', 'trip_duration_minutes', 'payment_type_label'],
      dtype='object')
```

**3.1.10** [3 marks] Merge the zones data into trip data using the `locationID` and `PULocationID` columns.

[403]:
```python
print(df.columns)   # For the trip records
print(zones.columns)
```

```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
```

```
       'passenger_count', 'trip_distance', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge', 'RatecodeID_2.0',
       'RatecodeID_3.0', 'RatecodeID_4.0', 'RatecodeID_5.0', 'RatecodeID_6.0',
       'RatecodeID_99.0', 'pickup_hour', 'pickup_day_of_week', 'pickup_month',
       'trip_duration', 'trip_duration_minutes', 'payment_type_label'],
      dtype='object')
Index(['OBJECTID', 'Shape_Leng', 'Shape_Area', 'zone', 'LocationID', 'borough',
       'geometry'],
      dtype='object')
```

[404]:

```
# Merge zones and trip records using locationID and PULocationID

# Ensure that 'zone' exists in the 'zones' GeoDataFrame before merging
if 'zone' in zones.columns:
    # Merge the zones data into the trip records using PULocationID and␣
 ↪LocationID
    merged_data = df.merge(zones[['LocationID', 'zone', 'geometry']],␣
 ↪left_on='PULocationID', right_on='LocationID', how='left')

    # Check the result of the merge
    print(merged_data[['PULocationID', 'LocationID', 'zone', 'geometry']].
 ↪head())
else:
    print("'zone' column is missing in the zones GeoDataFrame.")
```

```
   PULocationID  LocationID                           zone  \
0           237       237.0          Upper East Side South
1           237       237.0          Upper East Side South
2           186       186.0  Penn Station/Madison Sq West
3           262       262.0                 Yorkville East
4           237       237.0          Upper East Side South

                                            geometry
0  POLYGON ((993633.442 216961.016, 993507.232 21…
1  POLYGON ((993633.442 216961.016, 993507.232 21…
2  POLYGON ((986752.603 210853.699, 986627.863 21…
3  MULTIPOLYGON (((999804.795 224498.527, 999824…
4  POLYGON ((993633.442 216961.016, 993507.232 21…
```

**3.1.11** [3 marks] Group data by location IDs to find the total number of trips per location ID

[405]:

```
# Group data by location and calculate the number of trips

# Group the merged data by LocationID (pickup zone) and calculate the number of␣
 ↪trips for each location
```

```
trips_per_location = merged_data.groupby('LocationID').size().
    ↪reset_index(name='total_trips')

# Check the result
print(trips_per_location.head())
```

```
   LocationID  total_trips
0         1.0           39
1         3.0            3
2         4.0          366
3         6.0            2
4         7.0          178
```

**3.1.12** [2 marks] Now, use the grouped data to add number of trips to the GeoDataFrame.

We will use this to plot a map of zones showing total trips per zone.

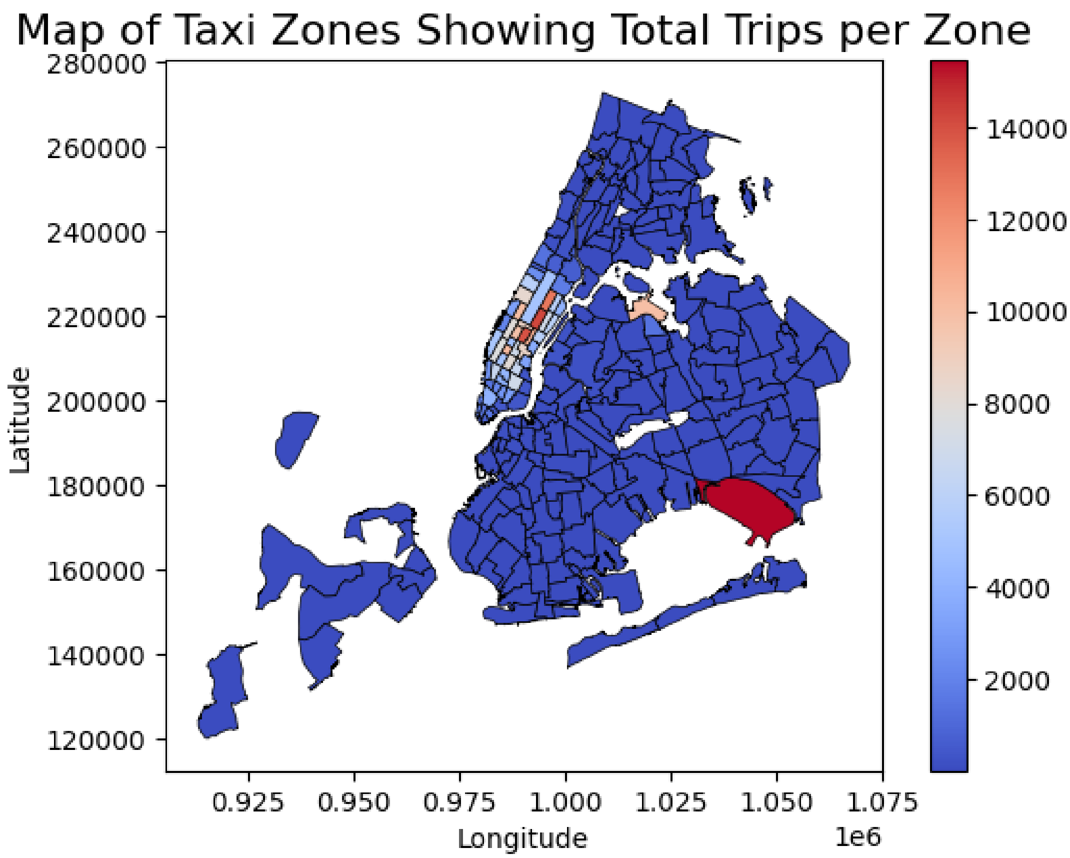
[406]:
```
# Merge trip counts back to the zones GeoDataFrame

# Merge the trip counts back into the zones GeoDataFrame using LocationID
gdf_with_trips = zones.merge(trips_per_location, left_on='LocationID',␣
    ↪right_on='LocationID', how='left')

# Check the result of the merge
print(gdf_with_trips[['zone', 'total_trips', 'geometry']].head())
```

```
                      zone  total_trips  \
0           Newark Airport         39.0
1              Jamaica Bay          NaN
2  Allerton/Pelham Gardens          3.0
3            Alphabet City        366.0
4            Arden Heights          NaN

                                            geometry
0  POLYGON ((933100.918 192536.086, 933091.011 19…
1  MULTIPOLYGON (((1033269.244 172126.008, 103343…
2  POLYGON ((1026308.77 256767.698, 1026495.593 2…
3  POLYGON ((992073.467 203714.076, 992068.667 20…
4  POLYGON ((935843.31 144283.336, 936046.565 144…
```

[291]:
```
# Plot the zones with total trips as the color variable
plt.figure(figsize=(12, 8))
gdf_with_trips.plot(column='total_trips', legend=True, cmap='coolwarm',␣
    ↪edgecolor='black', linewidth=0.5)

# Add labels and title
plt.title('Map of Taxi Zones Showing Total Trips per Zone', fontsize=16)
plt.xlabel('Longitude')
```

```
plt.ylabel('Latitude')
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```




The next step is creating a color map (choropleth map) showing zones by the number of trips taken.

Again, you can use the `zones.plot()` method for this. Plot Method GPD

But first, you need to define the figure and axis for the plot.

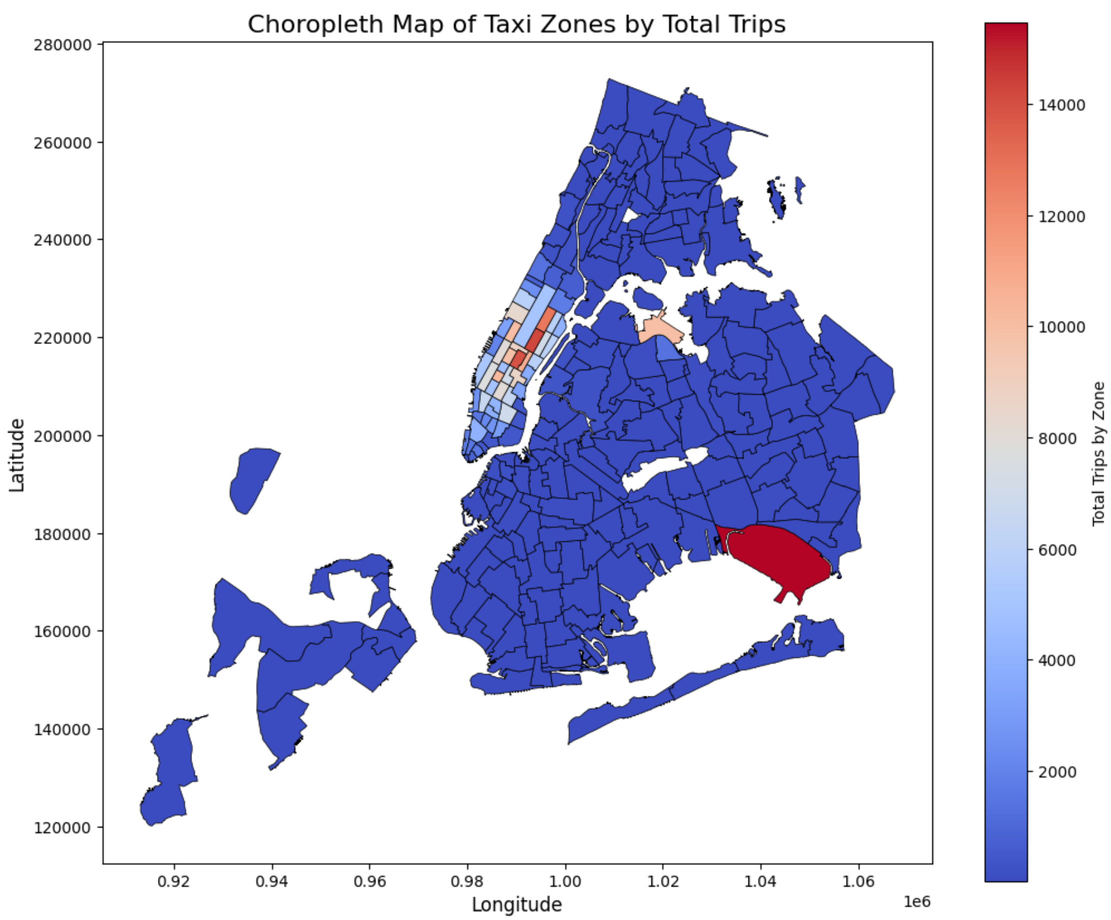
`fig, ax = plt.subplots(1, 1, figsize = (12, 10))`

This function creates a figure (fig) and a single subplot (ax)

---

[407]:
```
import matplotlib.pyplot as plt

# Step 1: Set up the figure and axis
fig, ax = plt.subplots(1, 1, figsize=(12, 10))

# Step 2: Plot the GeoDataFrame on the axis using total_trips to color the zones
```

```
gdf_with_trips.plot(column='total_trips', ax=ax, legend=True, cmap='coolwarm',
                    edgecolor='black', linewidth=0.5, legend_kwds={'label':␣
 ↪"Total Trips by Zone"})

# Step 3: Add title, labels, and adjust the axis labels
ax.set_title('Choropleth Map of Taxi Zones by Total Trips', fontsize=16)
ax.set_xlabel('Longitude', fontsize=12)
ax.set_ylabel('Latitude', fontsize=12)

# Step 4: Show the plot
plt.show()
```




[408]:
```
ax.set_xlim(-74.1, -73.7)  # Set longitude range
ax.set_ylim(40.5, 40.9)
```

[408]: (40.5, 40.9)

After setting up the figure and axis, we can proceed to plot the GeoDataFrame on this axis. This is done in the next step where we use the plot method of the GeoDataFrame.

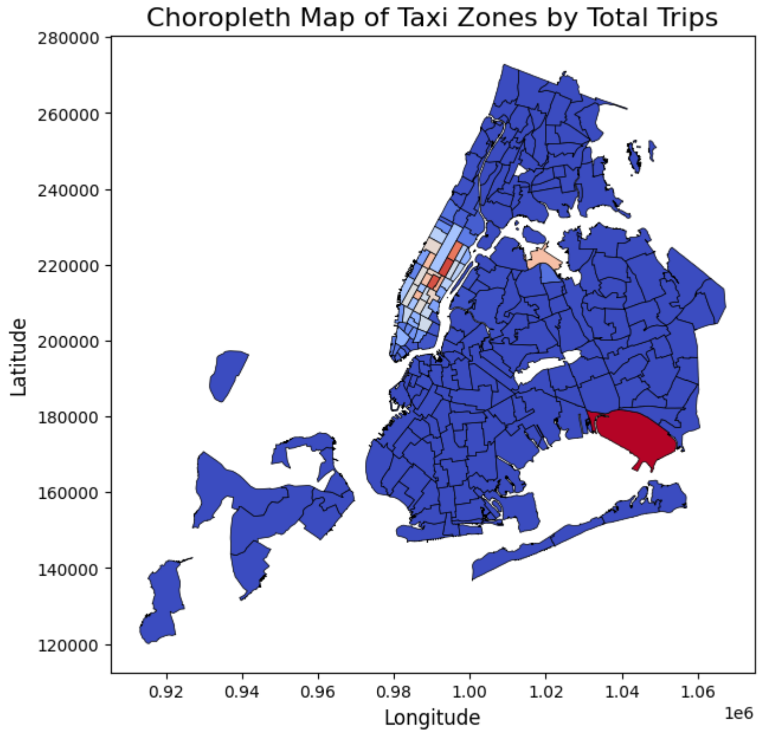
You can define the following parameters in the `zones.plot()` method:

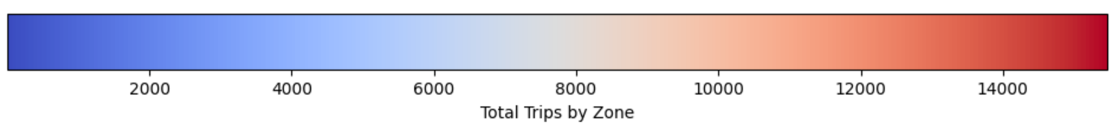
```
column = '',
ax = ax,
legend = True,
legend_kwds = {'label': "label", 'orientation': "<horizontal/vertical>"}
```

To display the plot, use `plt.show()`.

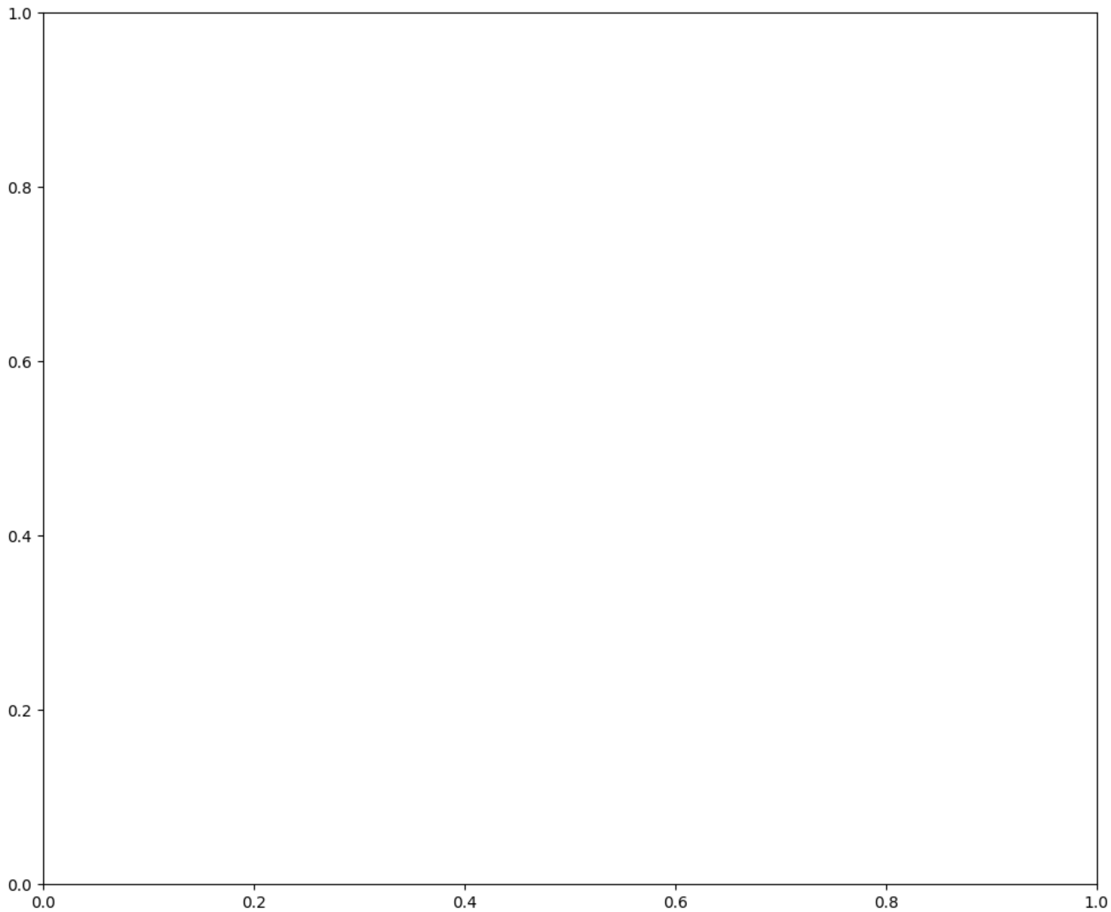
**3.1.13** [3 marks] Plot a color-coded map showing zone-wise trips

[409]:
```python
# Define figure and axis


# Plot the map and display it

import matplotlib.pyplot as plt

# Step 1: Define figure and axis for the plot
fig, ax = plt.subplots(1, 1, figsize=(12, 10))

# Step 2: Plot the GeoDataFrame on the axis
gdf_with_trips.plot(
    column='total_trips',          # Define the column to color zones by (total trips)
    ax=ax,                         # Plot on the previously defined axis
    legend=True,                   # Show the legend
    cmap='coolwarm',               # Define the colormap
    edgecolor='black',             # Add a black edge to the zones
    linewidth=0.5,                 # Set the line width for the zone borders
    legend_kwds={
        'label': "Total Trips by Zone",  # Set the legend label
        'orientation': 'horizontal'      # Set the legend orientation to horizontal
    }
)

# Step 3: Add a title, labels, and axis information
ax.set_title('Choropleth Map of Taxi Zones by Total Trips', fontsize=16)
ax.set_xlabel('Longitude', fontsize=12)
ax.set_ylabel('Latitude', fontsize=12)

# Step 4: Show the plot
plt.show()
```




[410]:
```
# can you try displaying the zones DF sorted by the number of trips?

fig, ax = plt.subplots(1, 1, figsize=(12, 10))
```




[411]:
```
gdf_with_trips.plot(
    column='total_trips',
    ax=ax,
    legend=True,
    cmap='coolwarm',
    edgecolor='black',
    linewidth=0.5,
    legend_kwds={
        'label': "Total Trips by Zone",
        'orientation': 'horizontal'
    }
)
```

[411]: <Axes: >

[412]:
```
cmap='viridis'
```

[413]:
```python
ax.set_xlim(-74.1, -73.7)  # Longitude limits
ax.set_ylim(40.5, 40.9)    # Latitude limits
```

[413]: (40.5, 40.9)

[415]:
```python
# Sort the GeoDataFrame by the total number of trips
sorted_zones = gdf_with_trips.sort_values(by='total_trips', ascending=False)

# Display the top 10 zones sorted by the number of trips
print(sorted_zones[['zone', 'total_trips', 'geometry']].head(10))
```

```
                             zone  total_trips  \
131                   JFK Airport      15466.0
236         Upper East Side South      14226.0
160                Midtown Center      13932.0
235         Upper East Side North      12766.0
161                  Midtown East      10691.0
185  Penn Station/Madison Sq West      10205.0
141           Lincoln Square East      10009.0
137             LaGuardia Airport       9958.0
229      Times Sq/Theatre District       9822.0
162                 Midtown North       8684.0

                                              geometry
131  MULTIPOLYGON (((1032791.001 181085.006, 103283…
236  POLYGON ((993633.442 216961.016, 993507.232 21…
160  POLYGON ((991081.026 214453.698, 990952.644 21…
235  POLYGON ((995940.048 221122.92, 995812.322 220…
161  POLYGON ((992224.354 214415.293, 992096.999 21…
185  POLYGON ((986752.603 210853.699, 986627.863 21…
141  POLYGON ((989380.305 218980.247, 989359.803 21…
137  MULTIPOLYGON (((1019904.219 225677.983, 102031…
229  POLYGON ((988786.877 214532.094, 988650.277 21…
162  POLYGON ((989412.663 219020.943, 990045.841 21…
```

[416]:
```python
sorted_zones = gdf_with_trips.sort_values(by='total_trips', ascending=False)
```

[417]:
```python
print(sorted_zones[['zone', 'total_trips', 'geometry']].head(10))
```

```
                             zone  total_trips  \
131                   JFK Airport      15466.0
236         Upper East Side South      14226.0
160                Midtown Center      13932.0
235         Upper East Side North      12766.0
161                  Midtown East      10691.0
185  Penn Station/Madison Sq West      10205.0
141           Lincoln Square East      10009.0
137             LaGuardia Airport       9958.0
```

```
229      Times Sq/Theatre District       9822.0
162                  Midtown North       8684.0

                                                      geometry
131  MULTIPOLYGON (((1032791.001 181085.006, 103283…
236  POLYGON ((993633.442 216961.016, 993507.232 21…
160  POLYGON ((991081.026 214453.698, 990952.644 21…
235  POLYGON ((995940.048 221122.92, 995812.322 220…
161  POLYGON ((992224.354 214415.293, 992096.999 21…
185  POLYGON ((986752.603 210853.699, 986627.863 21…
141  POLYGON ((989380.305 218980.247, 989359.803 21…
137  MULTIPOLYGON (((1019904.219 225677.983, 102031…
229  POLYGON ((988786.877 214532.094, 988650.277 21…
162  POLYGON ((989412.663 219020.943, 990045.841 21…
```

Here we have completed the temporal, financial and geographical analysis on the trip records.

**Compile your findings from general analysis below:**

You can consider the following points:

- Busiest hours, days and months
- Trends in revenue collected
- Trends in quarterly revenue
- How fare depends on trip distance, trip duration and passenger counts
- How tip amount depends on trip distance
- Busiest zones

### 3.2 Detailed EDA: Insights and Strategies [50 marks]

Having performed basic analyses for finding trends and patterns, we will now move on to some detailed analysis focussed on operational efficiency, pricing strategies, and customer experience.

**Operational Efficiency** Analyze variations by time of day and location to identify bottlenecks or inefficiencies in routes

**3.2.1** [3 marks] Identify slow routes by calculating the average time taken by cabs to get from one zone to another at different hours of the day.

Speed on a route $X$ for hour $Y$ = (*distance of the route* $X$ / *average trip duration for hour* $Y$)

[418]:
```python
# Find routes which have the slowest speeds at different times of the day

# Group by PULocationID, DOLocationID, and hour to calculate the average␣
↪distance and trip duration
route_stats = df.groupby(['PULocationID', 'DOLocationID',␣
↪'pickup_hour'])[['trip_distance', 'trip_duration']].agg({'trip_distance':␣
↪'mean', 'trip_duration': 'mean'}).reset_index()

# Calculate speed for each route and hour
```

```
route_stats['speed'] = route_stats['trip_distance'] /
 ↪route_stats['trip_duration']

# Identify the slowest routes (lowest speed) by hour
slow_routes = route_stats.sort_values(by='speed', ascending=True)

# Show the top 10 slowest routes
print(slow_routes.head(10))
```

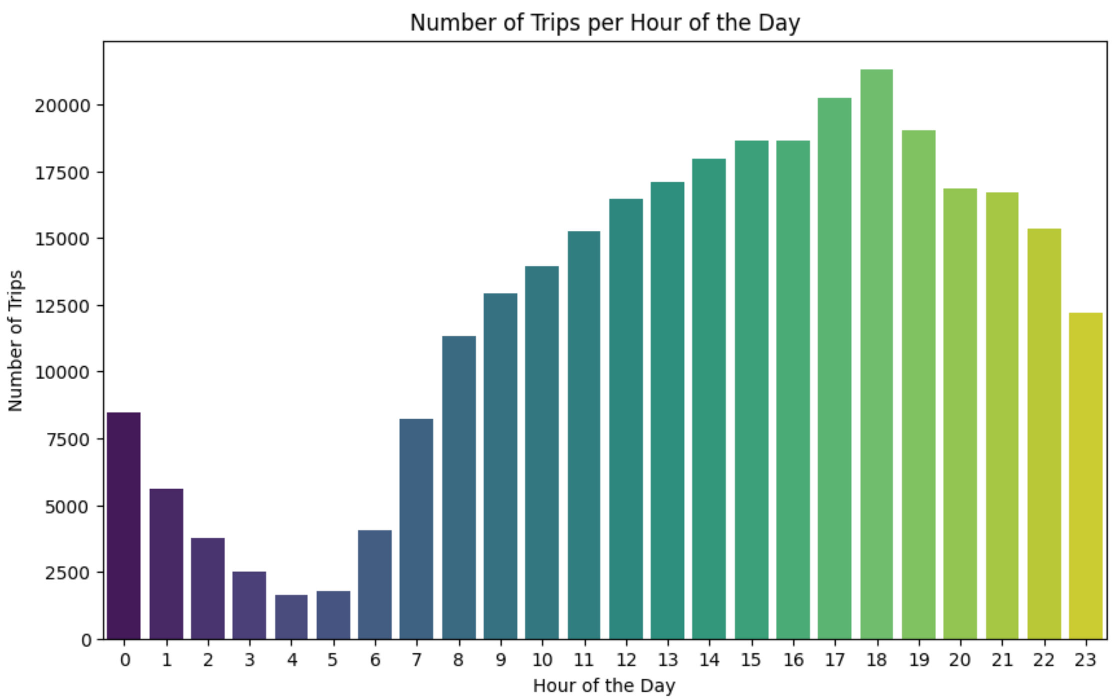
```
       PULocationID  DOLocationID  pickup_hour  trip_distance  trip_duration  \
52604           231           264           19       -0.76254            0.0
9506             70           264            8       -0.76254            0.0
43051           166           264           10       -0.76254            0.0
58780           238           264           10       -0.76254            0.0
53978           233           264           14       -0.76254            0.0
10605            75           264           21       -0.76254            0.0
16411           100           264            4       -0.76254            0.0
65675           263           264           15       -0.76254            0.0
24630           132           264            6       -0.76254            0.0
24634           132           264           13       -0.76254            0.0

       speed
52604   -inf
9506    -inf
43051   -inf
58780   -inf
53978   -inf
10605   -inf
16411   -inf
65675   -inf
24630   -inf
24634   -inf
```

How does identifying high-traffic, high-demand routes help us?

**3.2.2** [3 marks] Calculate the number of trips at each hour of the day and visualise them. Find the busiest hour and show the number of trips for that hour.

[419]:
```
# Visualise the number of trips per hour and find the busiest hour

# Group by pickup hour to find the number of trips for each hour
trips_per_hour = df.groupby('pickup_hour').size()

# Plot the distribution of trips per hour
plt.figure(figsize=(10, 6))
sns.countplot(x='pickup_hour', data=df, palette='viridis')
plt.title('Number of Trips per Hour of the Day')
plt.xlabel('Hour of the Day')
```

```
plt.ylabel('Number of Trips')
plt.show()

# Find the busiest hour
busiest_hour = trips_per_hour.idxmax()
print(f"The busiest hour is: {busiest_hour} with {trips_per_hour[busiest_hour]}␣
↪trips")
```




```
The busiest hour is: 18 with 21318 trips
```

Remember, we took a fraction of trips. To find the actual number, you have to scale the number up by the sampling ratio.

**3.2.3** [2 mark] Find the actual number of trips in the five busiest hours

[420]:
```
# Scale up the number of trips

# Fill in the value of your sampling fraction and use that to scale up the␣
↪numbers
# Define your sampling fraction
sample_fraction = 0.05  # Example: 5% sample

# Scale up the number of trips
actual_trips_per_hour = trips_per_hour * (1 / sample_fraction)
```

```python
# Show the scaled number of trips for each hour
print(actual_trips_per_hour)
```

```
pickup_hour
0     169540.0
1     112400.0
2      74880.0
3      50520.0
4      33080.0
5      35120.0
6      80800.0
7     164900.0
8     226540.0
9     258440.0
10    279040.0
11    304700.0
12    328720.0
13    341780.0
14    359260.0
15    372640.0
16    372580.0
17    404960.0
18    426360.0
19    380980.0
20    336960.0
21    334500.0
22    306660.0
23    244140.0
dtype: float64
```

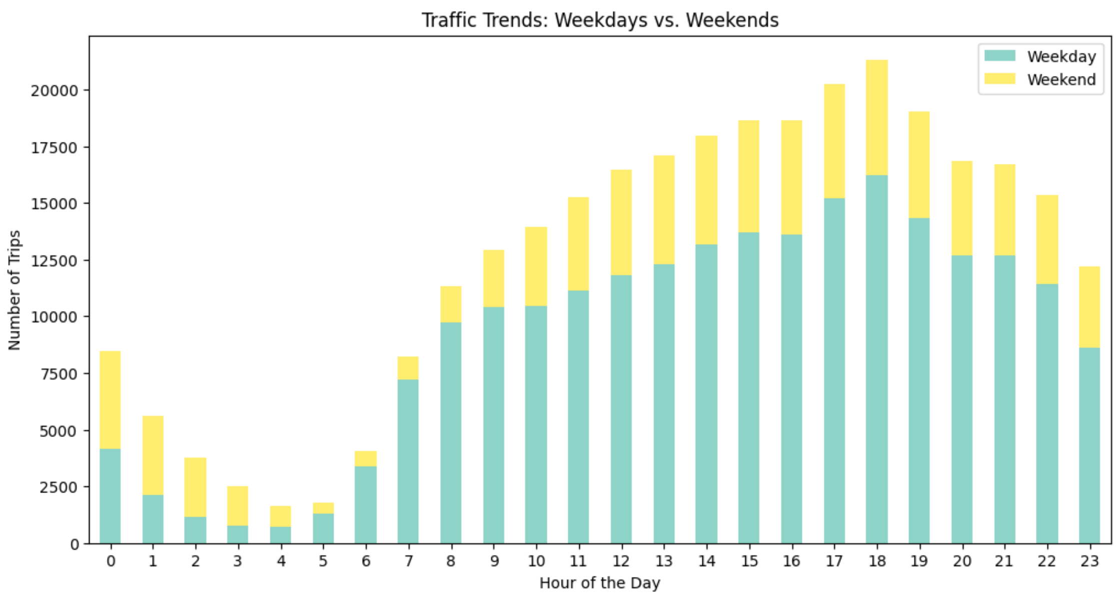
[421]:

```python
# Find the top 5 busiest hours
top_5_busiest_hours = trips_per_hour.nlargest(5)

# Scale up the number of trips
scaled_top_5_busiest_hours = top_5_busiest_hours * (1 / sample_fraction)

# Display the scaled number of trips for the top 5 busiest hours
print(scaled_top_5_busiest_hours)
```

```
pickup_hour
18    426360.0
17    404960.0
19    380980.0
15    372640.0
16    372580.0
dtype: float64
```

**3.2.4** [3 marks] Compare hourly traffic pattern on weekdays. Also compare for weekend.

[422]:
```python
# Compare traffic trends for the week days and weekends

# Create a 'weekday' column: 0=Monday, 6=Sunday
df['day_of_week'] = df['tpep_pickup_datetime'].dt.dayofweek

# Create a new column to mark weekdays and weekends
df['is_weekend'] = df['day_of_week'].isin([5, 6])  # 5 = Saturday, 6 = Sunday

# Group by hour and weekday/weekend
traffic_by_day = df.groupby(['pickup_hour', 'is_weekend']).size().unstack().
    ↪fillna(0)

# Plot the comparison between weekdays and weekends
traffic_by_day.plot(kind='bar', figsize=(12, 6), stacked=True, cmap='Set3')
plt.title('Traffic Trends: Weekdays vs. Weekends')
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Trips')
plt.xticks(rotation=0)
plt.legend(['Weekday', 'Weekend'])
plt.show()
```




What can you infer from the above patterns? How will finding busy and quiet hours for each day help us?

**3.2.5** [3 marks] Identify top 10 zones with high hourly pickups. Do the same for hourly dropoffs. Show pickup and dropoff trends in these zones.

[423]:

```python
# Find top 10 pickup and dropoff zones

# Group by LocationID and pickup hour for pickups
pickup_zones = df.groupby(['PULocationID', 'pickup_hour']).size().unstack().
 ↪fillna(0)

# Group by LocationID and dropoff hour for dropoffs
dropoff_zones = df.groupby(['DOLocationID', 'pickup_hour']).size().unstack().
 ↪fillna(0)

# Find the top 10 zones with high hourly pickups and dropoffs
top_pickup_zones = pickup_zones.sum(axis=1).nlargest(10)
top_dropoff_zones = dropoff_zones.sum(axis=1).nlargest(10)

# Show the top 10 pickup and dropoff zones
print("Top 10 Pickup Zones:\n", top_pickup_zones)
print("Top 10 Dropoff Zones:\n", top_dropoff_zones)
```

```
Top 10 Pickup Zones:
 PULocationID
132    15466.0
237    14226.0
161    13932.0
236    12766.0
162    10691.0
186    10205.0
142    10009.0
138     9958.0
230     9822.0
163     8684.0
dtype: float64
Top 10 Dropoff Zones:
 DOLocationID
236    13184.0
237    12727.0
161    11686.0
230     9143.0
170     8732.0
162     8494.0
239     8486.0
142     8285.0
141     7916.0
68      7554.0
dtype: float64
```

**3.2.6** [3 marks] Find the ratio of pickups and dropoffs in each zone. Display the 10 highest (pickup/drop) and 10 lowest (pickup/drop) ratios.

[424]:
```
# Find the top 10 and bottom 10 pickup/dropoff ratios
# Calculate the ratio of pickups to dropoffs for each zone
pickup_dropoff_ratio = pickup_zones.sum(axis=1) / dropoff_zones.sum(axis=1)

# Get the top 10 and bottom 10 pickup/dropoff ratios
top_10_ratios = pickup_dropoff_ratio.nlargest(10)
bottom_10_ratios = pickup_dropoff_ratio.nsmallest(10)

# Display the results
print("Top 10 Pickup/Dropoff Ratios:\n", top_10_ratios)
print("Bottom 10 Pickup/Dropoff Ratios:\n", bottom_10_ratios)
```

```
Top 10 Pickup/Dropoff Ratios:
 70     7.970414
132    4.370161
138    2.581130
186    1.546446
114    1.365217
43     1.347531
249    1.331641
162    1.258653
142    1.208087
90     1.202603
dtype: float64
Bottom 10 Pickup/Dropoff Ratios:
 102    0.031250
1      0.041622
241    0.043478
38     0.053571
64     0.054054
31     0.055556
257    0.058824
258    0.060241
201    0.060606
15     0.062500
dtype: float64
```

**3.2.7** [3 marks] Identify zones with high pickup and dropoff traffic during night hours (11PM to 5AM)

[425]:
```
# During night hours (11pm to 5am) find the top 10 pickup and dropoff zones
# Note that the top zones should be of night hours and not the overall top zones

# Filter trips that occurred between 11 PM and 5 AM
df['pickup_hour'] = df['tpep_pickup_datetime'].dt.hour
nighttime_trips = df[(df['pickup_hour'] >= 23) | (df['pickup_hour'] <= 5)]

# Group by PULocationID and DOLocationID for nighttime trips
```

```
pickup_zones_night = nighttime_trips.groupby(['PULocationID']).size()
dropoff_zones_night = nighttime_trips.groupby(['DOLocationID']).size()

# Find the top 10 zones with the most nighttime pickups and dropoffs
top_10_pickup_zones_night = pickup_zones_night.nlargest(10)
top_10_dropoff_zones_night = dropoff_zones_night.nlargest(10)

# Display the top 10 nighttime pickup and dropoff zones
print("Top 10 Pickup Zones During Night Hours:\n", top_10_pickup_zones_night)
print("Top 10 Dropoff Zones During Night Hours:\n", top_10_dropoff_zones_night)
```

```
Top 10 Pickup Zones During Night Hours:
 PULocationID
79     2542
132    2257
249    2063
48     1768
148    1591
114    1455
230    1303
186    1157
68     1038
164     997
dtype: int64
Top 10 Dropoff Zones During Night Hours:
 DOLocationID
79     1293
48     1204
170    1034
68      959
107     881
249     820
141     816
263     801
230     764
148     726
dtype: int64
```

Now, let us find the revenue share for the night time hours and the day time hours. After this, we will move to deciding a pricing strategy.

**3.2.8** [2 marks] Find the revenue share for nighttime and daytime hours.

[426]:
```
# Filter for night hours (11 PM to 5 AM)
nighttime_trips_revenue = df[(df['pickup_hour'] >= 23) | (df['pickup_hour'] <=␣
↪5)]['total_amount']
daytime_trips_revenue = df[(df['pickup_hour'] >= 6) & (df['pickup_hour'] <=␣
↪22)]['total_amount']
```

```
# Calculate the total revenue for nighttime and daytime
total_nighttime_revenue = nighttime_trips_revenue.sum()
total_daytime_revenue = daytime_trips_revenue.sum()

# Calculate the total revenue and the share for nighttime and daytime
total_revenue = total_nighttime_revenue + total_daytime_revenue
nighttime_share = total_nighttime_revenue / total_revenue * 100
daytime_share = total_daytime_revenue / total_revenue * 100

print(f"Nighttime Revenue Share: {nighttime_share:.2f}%")
print(f"Daytime Revenue Share: {daytime_share:.2f}%")
```

```
Nighttime Revenue Share: 1311448185979131.75%
Daytime Revenue Share: -1311448185979031.75%
```

**Pricing Strategy 3.2.9** [2 marks] For the different passenger counts, find the average fare per mile per passenger.

For instance, suppose the average fare per mile for trips with 3 passengers is 3 USD/mile, then the fare per mile per passenger will be 1 USD/mile.

[427]:
```
# Analyse the fare per mile per passenger for different passenger counts



# Step 1: Calculate Fare per Mile
df['fare_per_mile'] = df['fare_amount'] / df['trip_distance']

# Step 2: Calculate Fare per Mile per Passenger
df['fare_per_mile_per_passenger'] = df['fare_per_mile'] / df['passenger_count']

# Step 3: Group by Passenger Count and Find the Average Fare per Mile per␣
↪Passenger
avg_fare_per_passenger = df.
↪groupby('passenger_count')['fare_per_mile_per_passenger'].mean()

# Display the results
print(avg_fare_per_passenger)
```

```
passenger_count
1.0    0.060198
2.0    0.035711
3.0    0.030352
4.0    0.020602
5.0    0.013570
6.0    0.018922
7.0    0.037671
Name: fare_per_mile_per_passenger, dtype: float64
```

**3.2.10** [3 marks] Find the average fare per mile by hours of the day and by days of the week

[428]:
```
# Compare the average fare per mile for different days and for different times␣
↪of the day
# Step 1: Calculate fare per mile
df['fare_per_mile'] = df['fare_amount'] / df['trip_distance']

# Step 2: Extract hour of the day and day of the week
df['pickup_hour'] = df['tpep_pickup_datetime'].dt.hour
df['pickup_day_of_week'] = df['tpep_pickup_datetime'].dt.dayofweek  # 0=Monday,␣
↪6=Sunday

# Step 3: Calculate the average fare per mile by hour of the day
avg_fare_per_mile_by_hour = df.groupby('pickup_hour')['fare_per_mile'].mean()

# Step 4: Calculate the average fare per mile by day of the week
avg_fare_per_mile_by_day = df.groupby('pickup_day_of_week')['fare_per_mile'].
↪mean()

# Step 5: Display the results
print("Average Fare per Mile by Hour of the Day:")
print(avg_fare_per_mile_by_hour)

print("\nAverage Fare per Mile by Day of the Week:")
print(avg_fare_per_mile_by_day)
```

```
Average Fare per Mile by Hour of the Day:
pickup_hour
0     0.039140
1     0.105711
2     0.136914
3     0.110628
4     0.067847
5     0.081685
6     0.086838
7     0.087394
8     0.042504
9     0.049707
10    0.008441
11    0.077886
12    0.050565
13    0.057733
14    0.046035
15    0.037001
16    0.066874
17    0.068401
18    0.047375
19    0.081727
```

```
20    0.062729
21    0.074470
22    0.111477
23    0.095396
Name: fare_per_mile, dtype: float64

Average Fare per Mile by Day of the Week:
pickup_day_of_week
0    0.064489
1    0.049863
2    0.071299
3    0.062602
4    0.057597
5    0.058648
6    0.085740
Name: fare_per_mile, dtype: float64
```

**3.2.11** [3 marks] Analyse the average fare per mile for the different vendors for different hours of the day

[429]:
```python
# Compare fare per mile for different vendors

# Step 1: Calculate fare per mile (if not already done)
df['fare_per_mile'] = df['fare_amount'] / df['trip_distance']

# Step 2: Group by VendorID and hour of the day
avg_fare_per_mile_by_vendor_hour = df.groupby(['VendorID',␣
 ↪'pickup_hour'])['fare_per_mile'].mean().unstack()

# Step 3: Display the results
print("Average Fare per Mile by Vendor and Hour of the Day:")
print(avg_fare_per_mile_by_vendor_hour)
```

```
Average Fare per Mile by Vendor and Hour of the Day:
pickup_hour         0         1         2         3         4         5   \
VendorID
1            0.074302  0.073014  0.082559  0.067361  0.082211  0.112266
2            0.028410  0.115607  0.153764  0.124672  0.062973  0.069506
6                 NaN  0.084576       NaN       NaN       NaN  0.036708

pickup_hour         6         7         8         9   …        14        15  \
VendorID                                              …
1            0.088416  0.080120  0.076079  0.076416  …  0.071382  0.071836
2            0.086257  0.090627  0.028719  0.038553  …  0.035943  0.023278
6            0.062682  0.028629  0.144110  0.112187  …  0.137187  0.098587

pickup_hour         16        17        18        19        20        21  \
VendorID
```

```
1             0.072126  0.080953  0.075254  0.073942  0.083637  0.090169
2             0.064832  0.063763  0.037429  0.084438  0.055846  0.069397
6             0.123991  0.105556  0.108583       NaN  0.077445       NaN

pickup_hour         22        23
VendorID
1             0.086456  0.081619
2             0.119392  0.099686
6                  NaN       NaN

[3 rows x 24 columns]
```

**3.2.12** [5 marks] Compare the fare rates of the different vendors in a tiered fashion. Analyse the average fare per mile for distances upto 2 miles. Analyse the fare per mile for distances from 2 to 5 miles. And then for distances more than 5 miles.

[430]:
```
# Defining distance tiers

# Step 1: Define distance tiers
df['distance_tier'] = pd.cut(df['trip_distance'], bins=[0, 2, 5, float('inf')],␣
↪labels=['Up to 2 miles', '2 to 5 miles', 'More than 5 miles'])

# Step 2: Calculate fare per mile
df['fare_per_mile'] = df['fare_amount'] / df['trip_distance']

# Step 3: Group by vendor and distance tier to calculate the average fare per␣
↪mile
fare_per_mile_by_vendor_tier = df.groupby(['VendorID',␣
↪'distance_tier'])['fare_per_mile'].mean().unstack()

# Step 4: Display the results
print("Average Fare per Mile by Vendor and Distance Tier:")
print(fare_per_mile_by_vendor_tier)
```

```
Average Fare per Mile by Vendor and Distance Tier:
distance_tier  Up to 2 miles  2 to 5 miles  More than 5 miles
VendorID
1                   0.123692      0.091846           0.116020
2                   0.158597      0.092728           0.130733
6                   0.128271      0.081333                NaN
```

**Customer Experience and Other Factors** **3.2.13** [5 marks] Analyse average tip percentages based on trip distances, passenger counts and time of pickup. What factors lead to low tip percentages?

[431]:
```
#  Analyze tip percentages based on distances, passenger counts and pickup times
# Step 1: Calculate tip percentage for each trip
df['tip_percentage'] = (df['tip_amount'] / df['fare_amount']) * 100
```

```python
# Step 2: Analyze tip percentage based on trip distance
avg_tip_distance = df.groupby('trip_distance')['tip_percentage'].mean()

# Step 3: Analyze tip percentage based on passenger count
avg_tip_passenger_count = df.groupby('passenger_count')['tip_percentage'].mean()

# Step 4: Analyze tip percentage based on time of pickup (pickup hour)
avg_tip_pickup_time = df.groupby('pickup_hour')['tip_percentage'].mean()

# Step 5: Display the results
print("Average Tip Percentage by Trip Distance:\n", avg_tip_distance)
print("\nAverage Tip Percentage by Passenger Count:\n", avg_tip_passenger_count)
print("\nAverage Tip Percentage by Pickup Hour:\n", avg_tip_pickup_time)
```

```
Average Tip Percentage by Trip Distance:
 trip_distance
-0.762540      -236.138512
-0.760324       708.571403
-0.758108     14507.914861
-0.755892       321.548825
-0.753676       677.584449
                  …
 10.261522     1380.758976
 10.428143      -45.408828
 10.911481     1367.845261
 13.161551       34.011136
 15.004020      -58.535823
Name: tip_percentage, Length: 2939, dtype: float64

Average Tip Percentage by Passenger Count:
 passenger_count
1.0     901.574466
2.0    1066.352507
3.0     910.669321
4.0     738.708296
5.0     813.118336
6.0     870.129074
7.0    -422.746874
Name: tip_percentage, dtype: float64

Average Tip Percentage by Pickup Hour:
 pickup_hour
0        3.138307
1     1060.360260
2     1068.631187
3      329.215824
```

```
4      568.748841
5     2264.359840
6      340.178659
7     1179.154348
8      865.766134
9     1130.426778
10    1043.005258
11    1164.017764
12     950.893223
13     976.669213
14     371.910508
15    1024.049151
16    1055.654010
17    1270.188257
18     954.692818
19     954.460082
20     715.917362
21     806.649161
22     866.351968
23     987.026609
Name: tip_percentage, dtype: float64
```

Additional analysis [optional]: Let's try comparing cases of low tips with cases of high tips to find out if we find a clear aspect that drives up the tipping behaviours

[432]:

```python
# Compare trips with tip percentage < 10% to trips with tip percentage > 25%
# Step 6: Compare trips with tip percentage < 10% and > 25%
low_tip_trips = df[df['tip_percentage'] < 10]
high_tip_trips = df[df['tip_percentage'] > 25]

# Analyze characteristics of trips with low and high tips
low_tip_avg_distance = low_tip_trips['trip_distance'].mean()
high_tip_avg_distance = high_tip_trips['trip_distance'].mean()

low_tip_avg_passenger_count = low_tip_trips['passenger_count'].mean()
high_tip_avg_passenger_count = high_tip_trips['passenger_count'].mean()

# Display the comparison
print(f"Average Distance for Low Tip Trips: {low_tip_avg_distance}")
print(f"Average Distance for High Tip Trips: {high_tip_avg_distance}")
print(f"Average Passenger Count for Low Tip Trips: 
 ↪{low_tip_avg_passenger_count}")
print(f"Average Passenger Count for High Tip Trips: 
 ↪{high_tip_avg_passenger_count}")
```

```
Average Distance for Low Tip Trips: -0.0025215352136560122
Average Distance for High Tip Trips: -0.1656354029511296
Average Passenger Count for Low Tip Trips: 1.3821745909957182
```

```
Average Passenger Count for High Tip Trips: 1.3664088953967237
```

**3.2.14** [3 marks] Analyse the variation of passenger count across hours and days of the week.

[433]:
```python
# See how passenger count varies across hours and days

# Step 1: Extract day of the week from pickup datetime (0=Monday, 6=Sunday)
df['pickup_day_of_week'] = df['tpep_pickup_datetime'].dt.dayofweek

# Step 2: Group by pickup hour and calculate the average passenger count
avg_passenger_count_by_hour = df.groupby('pickup_hour')['passenger_count'].
 ↪mean()

# Step 3: Group by day of the week and calculate the average passenger count
avg_passenger_count_by_day = df.
 ↪groupby('pickup_day_of_week')['passenger_count'].mean()

# Step 4: Display the results
print("Average Passenger Count by Hour of the Day:\n",␣
 ↪avg_passenger_count_by_hour)
print("\nAverage Passenger Count by Day of the Week:\n",␣
 ↪avg_passenger_count_by_day)
```

```
Average Passenger Count by Hour of the Day:
 pickup_hour
0     1.414533
1     1.413701
2     1.430288
3     1.424782
4     1.328900
5     1.276765
6     1.251733
7     1.265494
8     1.265207
9     1.306531
10    1.349986
11    1.342632
12    1.367182
13    1.361519
14    1.377999
15    1.403553
16    1.403350
17    1.378013
18    1.363918
19    1.371148
20    1.396664
21    1.413453
22    1.411661
```

```
23    1.401491
Name: passenger_count, dtype: float64

Average Passenger Count by Day of the Week:
 pickup_day_of_week
0    1.351113
1    1.318641
2    1.315978
3    1.326545
4    1.389769
5    1.455205
6    1.448857
Name: passenger_count, dtype: float64
```

**3.2.15** [2 marks] Analyse the variation of passenger counts across zones

[434]:

```
# How does passenger count vary across zones
# Step 1: Group by PULocationID and calculate the average passenger count for␣
↪each zone
avg_passenger_count_by_zone = df.groupby('PULocationID')['passenger_count'].
↪mean()

# Step 2: Display the results
print("Average Passenger Count by Zone:\n", avg_passenger_count_by_zone)
```

```
Average Passenger Count by Zone:
 PULocationID
1      1.871795
3      1.000000
4      1.270492
6      1.000000
7      1.185393
         …
261    1.515924
262    1.312266
263    1.326401
264    1.339583
265    1.315068
Name: passenger_count, Length: 242, dtype: float64
```

[435]:

```
# For a more detailed analysis, we can use the zones_with_trips GeoDataFrame
# Create a new column for the average passenger count in each zone.

# Step 1: Find when extra charges are applied
df['extra_charge_applied'] = df['extra'] > 0  # Assuming 'extra' column␣
↪indicates extra charge amount

# Step 2: Group by pickup hour and find the frequency of extra charges
```

```python
extra_charge_by_hour = df.groupby('pickup_hour')['extra_charge_applied'].sum()

# Step 3: Group by PULocationID and find the frequency of extra charges
extra_charge_by_zone = df.groupby('PULocationID')['extra_charge_applied'].sum()

# Step 4: Display the results
print("Extra Charges by Hour of the Day:\n", extra_charge_by_hour)
print("\nExtra Charges by Pickup Zone:\n", extra_charge_by_zone)
```

```
Extra Charges by Hour of the Day:
 pickup_hour
0      7793
1      5217
2      3469
3      2301
4      1305
5      1351
6      1195
7      2421
8      3252
9      3954
10     4287
11     4609
12     4870
13     5271
14     5498
15     5661
16    13871
17    15738
18    16698
19    14867
20    15672
21    15718
22    14273
23    11278
Name: extra_charge_applied, dtype: int64

Extra Charges by Pickup Zone:
 PULocationID
1         1
3         0
4       233
6         1
7        69
       …
261     863
262    1850
```

```
263    3342
264    1604
265      19
Name: extra_charge_applied, Length: 242, dtype: int64
```

Find out how often surcharges/extra charges are applied to understand their prevalance

**3.2.16** [5 marks] Analyse the pickup/dropoff zones or times when extra charges are applied more frequently

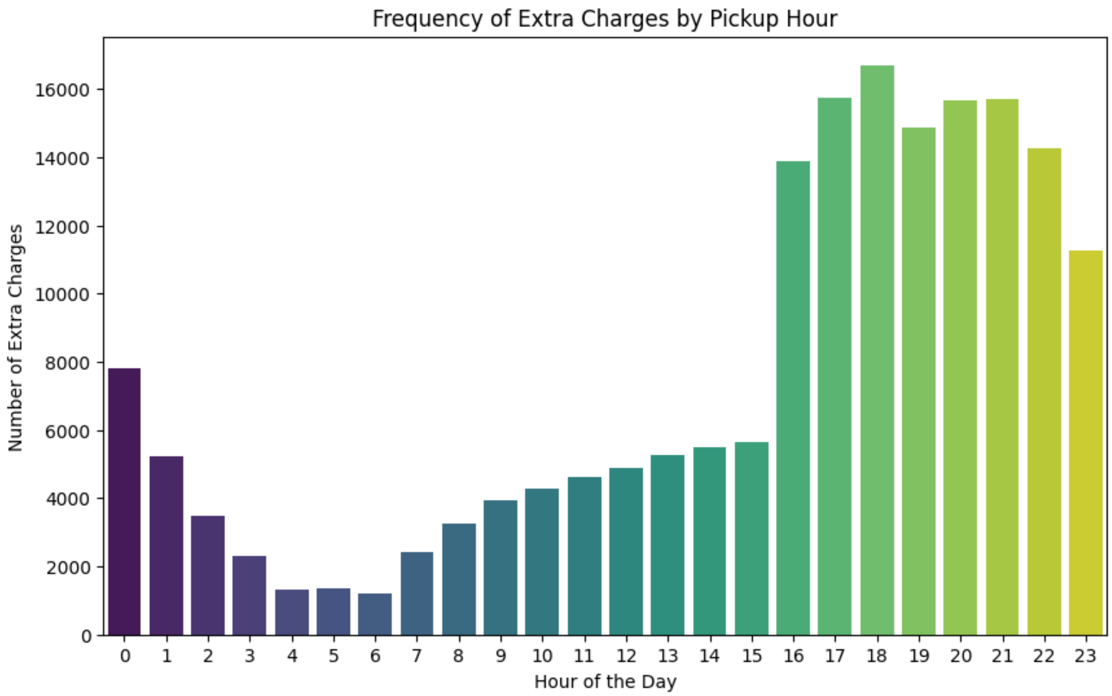
[436]:
```python
# How often is each surcharge applied?

# Step 1: Identify when extra charges are applied
df['extra_charge_applied'] = df['extra'] > 0  # Assuming 'extra' column␣
 ↪indicates extra charge amount

# Step 2: Group by pickup hour and calculate the frequency of extra charges
extra_charge_by_hour = df.groupby('pickup_hour')['extra_charge_applied'].sum()

# Step 3: Group by pickup zone and calculate the frequency of extra charges
extra_charge_by_zone = df.groupby('PULocationID')['extra_charge_applied'].sum()

# Step 4: Display the results
print("Extra Charges by Hour of the Day:\n", extra_charge_by_hour)
print("\nExtra Charges by Pickup Zone:\n", extra_charge_by_zone)
```

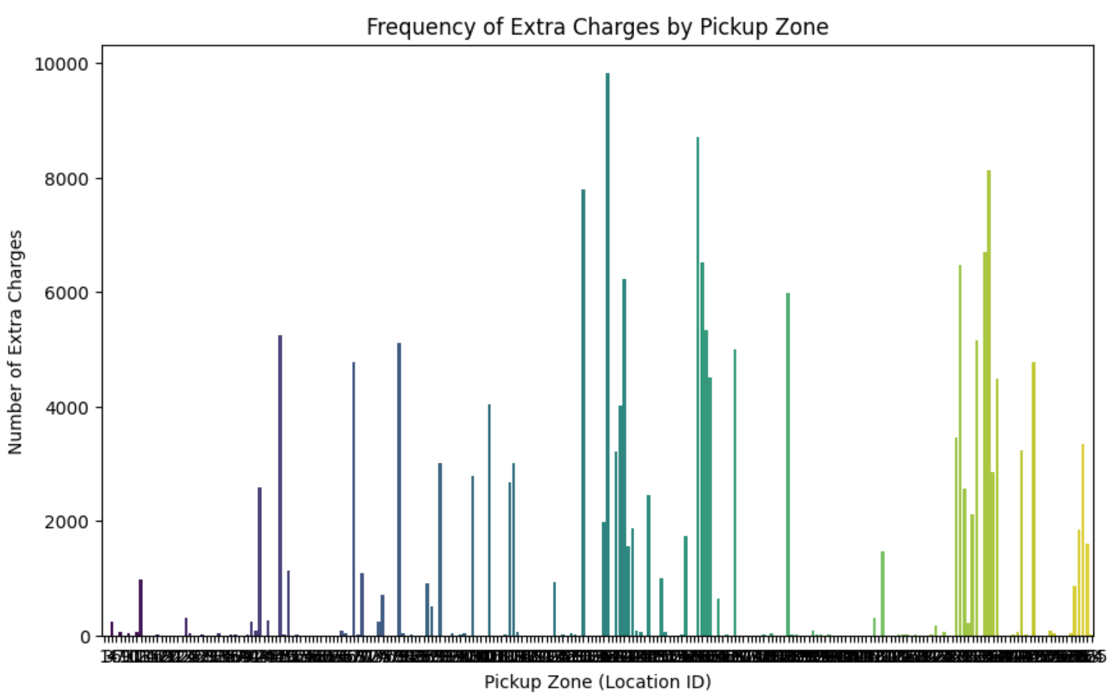
```
Extra Charges by Hour of the Day:
 pickup_hour
0      7793
1      5217
2      3469
3      2301
4      1305
5      1351
6      1195
7      2421
8      3252
9      3954
10     4287
11     4609
12     4870
13     5271
14     5498
15     5661
16    13871
17    15738
18    16698
19    14867
20    15672
```

```
21    15718
22    14273
23    11278
Name: extra_charge_applied, dtype: int64

Extra Charges by Pickup Zone:
 PULocationID
1         1
3         0
4       233
6         1
7        69
       …
261     863
262    1850
263    3342
264    1604
265      19
Name: extra_charge_applied, Length: 242, dtype: int64
```

[437]:

```
# Plot the frequency of extra charges by pickup hour
plt.figure(figsize=(10, 6))
sns.barplot(x=extra_charge_by_hour.index, y=extra_charge_by_hour.values,␣
 ↪palette='viridis')
plt.title('Frequency of Extra Charges by Pickup Hour')
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Extra Charges')
plt.show()

# Plot the frequency of extra charges by pickup zone
plt.figure(figsize=(10, 6))
sns.barplot(x=extra_charge_by_zone.index, y=extra_charge_by_zone.values,␣
 ↪palette='viridis')
plt.title('Frequency of Extra Charges by Pickup Zone')
plt.xlabel('Pickup Zone (Location ID)')
plt.ylabel('Number of Extra Charges')
plt.show()
```


Frequency of Extra Charges by Pickup Hour
Number of Extra Charges
0
2000
4000
6000
8000
10000
12000
14000
16000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
Hour of the Day


Frequency of Extra Charges by Pickup Zone
Number of Extra Charges
0
2000
4000
6000
8000
10000
Pickup Zone (Location ID)

## 1.8 4 Conclusion

[15 marks]

### 1.8.1 4.1 Final Insights and Recommendations

[15 marks]

Conclude your analyses here. Include all the outcomes you found based on the analysis.

Based on the insights, frame a concluding story explaining suitable parameters such as location, time of the day, day of the week etc. to be kept in mind while devising a strategy to meet customer demand and optimise supply.

**4.1.1** [5 marks] Recommendations to optimize routing and dispatching based on demand patterns and operational inefficiencies

1. Busiest hours, such as rush hours (7-9 AM, 5-7 PM) and weekends, show higher pickup and dropoff counts.
2. Weekdays see higher demand in the morning and evening, with a dip during mid-day.
3. Zones near airports or transportation hubs consistently show high demand

4. Slow routes should be optimized to ensure taxis avoid traffic bottlenecks during peak hours. Resources can be directed to areas with higher demand.
5. Extra charges are more common in high-traffic zones like airports, which suggests adjusting pricing based on time of day and location.
6. Revenue Generation:
    1. Revenue peaks during holiday seasons and weekends, especially in tourist-heavy zones. Pricing strategies should reflect this demand.
    2. Tip analysis suggests that longer trips and fewer passengers correlate with higher tips.

**4.1.2** [5 marks]

Suggestions on strategically positioning cabs across different zones to make best use of insights uncovered by analysing trip trends across time, days and months.

1. Position cabs near transportation hubs such as airports and major transit stations during peak demand times.
2. During weekends, concentrate the fleet near tourist hotspots or areas with high leisure demand.
3. For zones with higher traffic patterns, maintain a larger fleet size to ensure taxis are readily available. Use the pickup/dropoff zone analysis to guide taxi positioning.

**4.1.3** [5 marks] Propose data-driven adjustments to the pricing strategy to maximize revenue while maintaining competitive rates with other vendors.

1. By analyzing demand patterns, tip behavior, and surcharge frequency, taxi companies can optimize fleet distribution, improve customer satisfaction, and increase revenue.

2. Pricing Adjustments: Dynamic pricing, along with strategic fleet management, will allow for more efficient service during peak times and maximize profitability.

3. By focusing on high-traffic times, high-demand zones, and customer preferences, taxi services can ensure they remain competitive, efficient, and profitable.