New York City Yellow Taxi Data

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.

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.

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

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.

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

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
Store_and_fwd_flag	This flag indicates whether the trip

Field Name	description
	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.

---

1 Data Preparation

[5 marks]

Import Libraries

```
# Import warnings
import warnings
warnings.filterwarnings("ignore")

# 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

# 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: 2.2.4
pandas version: 2.2.3
matplotlib version: 3.10.0
seaborn version: 0.13.2
```

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')`

```
# Try loading one file
df = pd.read_parquet(r'C:\Users\CSG\Desktop\upgrad\EDA-Assignment\
Datasets and Dictionary-NYC\Datasets and Dictionary\trip_records\2023-
1.parquet')
```

```
df.info()
df.head()
```

```
<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

   VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
0         2  2023-01-01 00:32:10   2023-01-01 00:40:36
1.0
1         2  2023-01-01 00:55:08   2023-01-01 01:01:27
1.0
2         2  2023-01-01 00:25:04   2023-01-01 00:37:49
1.0
3         1  2023-01-01 00:03:48   2023-01-01 00:13:25
0.0
4         2  2023-01-01 00:10:29   2023-01-01 00:21:19
1.0

   trip_distance  RatecodeID store_and_fwd_flag  PULocationID
DOLocationID  \
0           0.97         1.0                  N           161
141
1           1.10         1.0                  N            43
237
2           2.51         1.0                  N            48
```

```
238
3            1.90         1.0                   N           138
7
4            1.43         1.0                   N           107
79

   payment_type  fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
0             2          9.3   1.00      0.5        0.00           0.0

1             1          7.9   1.00      0.5        4.00           0.0

2             1         14.9   1.00      0.5       15.00           0.0

3             1         12.1   7.25      0.5        0.00           0.0

4             1         11.4   1.00      0.5        3.28           0.0


   improvement_surcharge  total_amount  congestion_surcharge
airport_fee
0                    1.0         14.30                   2.5
0.00
1                    1.0         16.90                   2.5
0.00
2                    1.0         34.90                   2.5
0.00
3                    1.0         20.85                   0.0
1.25
4                    1.0         19.68                   2.5
0.00
```

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.

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?)

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.

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

# from google.colab import drive
# drive.mount('/content/drive')

# 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
import os

# Select the folder having data files
os.chdir(r'C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and
Dictionary-NYC\Datasets and Dictionary\trip_records')

# 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)
        print(file_path)
        # Reading the current file
        monthly_data = pd.read_parquet(file_path)
        #Extracting the data
        monthly_data['date'] =
monthly_data['tpep_pickup_datetime'].dt.date
        monthly_data['hour'] =
monthly_data['tpep_pickup_datetime'].dt.hour

        # We will store the sampled data for the current date in this
df by appending the sampled data from each hour to this
        # 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_data['date'].unique():
            daily_data=monthly_data[monthly_data['date'] ==
date].copy()
            # Iterate through each hour of the selected date
            for hour in range(24):
                hour_data=daily_data[monthly_data['hour'] == hour]
                # Sample 5% of the hourly data randomly
                if not hour_data.empty:
                    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

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

# Reset index after combining all months
df.reset_index(drop=True, inplace=True)

# Show summary of sampled dataset
print(df.head())
```

```
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-1.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-10.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-11.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-12.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-2.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-3.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-4.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-5.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-6.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-7.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-8.parquet
C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets and Dictionary-
NYC\Datasets and Dictionary\trip_records\2023-9.parquet
   VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
0         2  2023-01-01 00:07:18   2023-01-01 00:23:15
1.0
1         2  2023-01-01 00:16:41   2023-01-01 00:21:46
2.0
2         2  2023-01-01 00:14:03   2023-01-01 00:24:36
3.0
3         2  2023-01-01 00:24:30   2023-01-01 00:29:55
1.0
4         2  2023-01-01 00:43:00   2023-01-01 01:01:00
NaN

   trip_distance  RatecodeID store_and_fwd_flag  PULocationID
DOLocationID  \
0           7.74         1.0                  N           138
256
1           1.24         1.0                  N           161
237
2           1.44         1.0                  N           237
141
3           0.54         1.0                  N           143
142
4          19.24         NaN               None            66
107
```

```
   payment_type  ...  mta_tax  tip_amount  tolls_amount  \
0             2  ...      0.5        0.00           0.0
1             1  ...      0.5        2.58           0.0
2             2  ...      0.5        0.00           0.0
3             2  ...      0.5        0.00           0.0
4             0  ...      0.5        5.93           0.0

   improvement_surcharge  total_amount  congestion_surcharge
airport_fee  \
0                    1.0         41.15                   0.0
1.25
1                    1.0         15.48                   2.5
0.00
2                    1.0         16.40                   2.5
0.00
3                    1.0         11.50                   2.5
0.00
4                    1.0         35.57                   NaN
NaN

         date  hour Airport_fee
0  2023-01-01     0         NaN
1  2023-01-01     0         NaN
2  2023-01-01     0         NaN
3  2023-01-01     0         NaN
4  2023-01-01     0         NaN

[5 rows x 22 columns]
```

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.

```
#Above code took around 5 min time to read all the 12 folders with 5 %
# Store the df in csv/parquet
df.to_parquet(r'C:\Users\CSG\Desktop\upgrad\EDA-Assignment\Datasets
and Dictionary-NYC\Datasets and Dictionary\Filtered_data\
trip_records.parquet',index=False)
```

2. Data Cleaning

[30 marks]

Now we can load the new data directly.

```
# Load the new data file
df = pd.read_parquet(r'C:\Users\CSG\Desktop\upgrad\EDA-Assignment\
```

```
Datasets and Dictionary-NYC\Datasets and Dictionary\Filtered_data\
trip_records.parquet')
```

```
df.head()
```

```
   VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
0         2  2023-01-01 00:07:18   2023-01-01 00:23:15
1.0
1         2  2023-01-01 00:16:41   2023-01-01 00:21:46
2.0
2         2  2023-01-01 00:14:03   2023-01-01 00:24:36
3.0
3         2  2023-01-01 00:24:30   2023-01-01 00:29:55
1.0
4         2  2023-01-01 00:43:00   2023-01-01 01:01:00
NaN

   trip_distance  RatecodeID store_and_fwd_flag  PULocationID
DOLocationID  \
0           7.74         1.0                  N           138
256
1           1.24         1.0                  N           161
237
2           1.44         1.0                  N           237
141
3           0.54         1.0                  N           143
142
4          19.24         NaN               None            66
107

   payment_type  ...  mta_tax  tip_amount  tolls_amount  \
0             2  ...      0.5        0.00           0.0
1             1  ...      0.5        2.58           0.0
2             2  ...      0.5        0.00           0.0
3             2  ...      0.5        0.00           0.0
4             0  ...      0.5        5.93           0.0

   improvement_surcharge  total_amount  congestion_surcharge
airport_fee  \
0                    1.0         41.15                   0.0
1.25
1                    1.0         15.48                   2.5
0.00
2                    1.0         16.40                   2.5
0.00
3                    1.0         11.50                   2.5
0.00
4                    1.0         35.57                   NaN
NaN
```

```
         date  hour Airport_fee
0  2023-01-01     0         NaN
1  2023-01-01     0         NaN
2  2023-01-01     0         NaN
3  2023-01-01     0         NaN
4  2023-01-01     0         NaN

[5 rows x 22 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1896400 entries, 0 to 1896399
Data columns (total 22 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
 19  date                   object
 20  hour                   int32
 21  Airport_fee            float64
dtypes: datetime64[us](2), float64(13), int32(1), int64(4), object(2)
memory usage: 311.1+ 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

```
# Fix the index and drop any columns that are not needed
#Fix the index
df = df.reset_index(drop=True)
#Drop any columns
#column store_and_fwd_flag can be dropped
df = df.drop(columns=['store_and_fwd_flag'], errors='ignore')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1896400 entries, 0 to 1896399
Data columns (total 21 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   PULocationID           int64
 7   DOLocationID           int64
 8   payment_type           int64
 9   fare_amount            float64
 10  extra                  float64
 11  mta_tax                float64
 12  tip_amount             float64
 13  tolls_amount           float64
 14  improvement_surcharge  float64
 15  total_amount           float64
 16  congestion_surcharge   float64
 17  airport_fee            float64
 18  date                   object
 19  hour                   int32
 20  Airport_fee            float64
dtypes: datetime64[us](2), float64(13), int32(1), int64(4), object(1)
memory usage: 296.6+ MB
```

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.

```
# Combine the two airport fee columns
df["Airport_fee"] = df["airport_fee"].fillna(0) +
df["Airport_fee"].fillna(0)  # Merge values into one single column
Airport_fee
df.drop(columns=["airport_fee"], inplace=True)  # Drop the extra
column
df.info()
#combines two similarly named columns, 'airport_fee' and
'Airport_fee', by summing their values into a single 'Airport_fee'
```

```
column, then safely removes the duplicate 'airport_fee' column to
clean the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1896400 entries, 0 to 1896399
Data columns (total 20 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   PULocationID           int64
 7   DOLocationID           int64
 8   payment_type           int64
 9   fare_amount            float64
 10  extra                  float64
 11  mta_tax                float64
 12  tip_amount             float64
 13  tolls_amount           float64
 14  improvement_surcharge  float64
 15  total_amount           float64
 16  congestion_surcharge   float64
 17  date                   object
 18  hour                   int32
 19  Airport_fee            float64
dtypes: datetime64[us](2), float64(12), int32(1), int64(4), object(1)
memory usage: 282.1+ MB
```

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

```
# check where values of fare amount are negative
df[df["fare_amount"] < 0.0] #No negative Fare Amount
```

```
Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee]
Index: []
```

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

```
# Analyse RatecodeID for the negative fare amounts
df[df["fare_amount"] < 0.0]["RatecodeID"].value_counts()
```

```
Series([], Name: count, dtype: int64)
```

```python
# Find which columns have negative values
negative_columns =
df.select_dtypes(include=['number']).columns[(df.select_dtypes(include
=['number']) < 0).any()]
print(negative_columns)
```

```
Index(['extra', 'mta_tax', 'improvement_surcharge', 'total_amount',
       'congestion_surcharge', 'Airport_fee'],
      dtype='object')
```

```python
# fix these negative values
#Column Extra
df[df["extra"] < 0]
```

```
        VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
184944         2  2023-10-06 22:24:42   2023-10-06 22:25:38
2.0
300725         2  2023-10-27 14:51:03   2023-10-27 14:51:11
1.0
361257         2  2023-11-06 22:37:04   2023-11-06 22:37:55
1.0

        trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
184944           0.03         1.0           161           161
2
300725           0.00         1.0           265           265
2
361257           0.03         1.0           229           229
2

        fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
184944          0.0   -1.0     -0.5         0.0           0.0
300725          3.0   -2.5      0.0         0.0           0.0
361257          0.0   -1.0     -0.5         0.0           0.0

        improvement_surcharge  total_amount  congestion_surcharge
date  \
184944                   -1.0          -5.0                  -2.5
2023-10-06
300725                    1.0           4.0                   0.0
2023-10-27
361257                   -1.0          -5.0                  -2.5
2023-11-06

        hour  Airport_fee
184944    22          0.0
```

```
300725    14          0.0
361257    22          0.0

#As there are only 3 columns which are negative ,we can either delete
them which is 3/1896400  which is very minimal or replace the values
with 1 and 0.5.
#As per data dictionary,the column 'extra' can hold only 0.5(Overnight
Surcharge-Applied from 8:00 PM to 6:00 AM) and 1 value(Rush Hour
Surcharge → $1.00 Applied only on weekdays from 4:00 PM to 8:00 PM).

#writing a small function to replace  the negative  value those with
overright surcharge value and rush hour charge value based on
tpep_pickup_datetime
def apply_surcharge(pickup_datetime):
    hour = pickup_datetime.hour
    weekday = pickup_datetime.weekday()  #monday-0 and #sunday-6
    # Rush Hour Surcharge: Weekdays (Mon-Fri) from 16:00-20:00
    if weekday < 5 and 16 <= hour < 20:
        return 1.00
    # Overnight Surcharge: Every day from 20:00-06:00
    elif hour >= 20 or hour < 6:
        return 0.50
    # No surcharge outside these hours
    return 0.00
# Apply only to negative extra values
df.loc[df["extra"] < 0, "extra"] = df.loc[df["extra"] < 0,
"tpep_pickup_datetime"].apply(apply_surcharge)

df[df["extra"] < 0]

Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee]
Index: []

#Handling mtax column
df[df["mta_tax"]< 0]

         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
9093            2  2023-01-03 14:24:45   2023-01-03 14:25:14
1.0
77200           2  2023-01-17 12:37:35   2023-01-17 13:24:00
1.0
77920           2  2023-01-17 15:03:44   2023-01-17 15:36:28
1.0
86509           2  2023-01-19 09:50:26   2023-01-19 09:58:13
```

```
1.0
117837         2  2023-01-25 11:10:37   2023-01-25 11:11:02
1.0
...          ...                  ...                   ...
...
1653357        2  2023-07-11 14:13:25   2023-07-11 15:24:35
1.0
1658058        2  2023-07-12 12:32:03   2023-07-12 12:32:13
4.0
1734702        2  2023-07-27 17:56:27   2023-07-27 18:00:12
1.0
1762681        2  2023-09-02 18:29:48   2023-09-02 18:30:13
3.0
1774112        2  2023-09-05 15:32:01   2023-09-05 15:43:35
1.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
9093              0.00         2.0           132           132
2
77200            17.68         2.0           230           132
2
77920             4.12         1.0           239           168
2
86509             0.50         1.0           161            43
2
117837            0.02         2.0           170           233
2
...                ...         ...           ...           ...
...
1653357           9.50         1.0           181            13
2
1658058           0.00         2.0            48            48
2
1734702           0.66         1.0           113           234
2
1762681           0.00         2.0            74            74
2
1774112           0.01         1.0           161           170
2

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
9093             0.0    0.0     -0.5         0.0           0.0
77200            0.0    0.0     -0.5         0.0           0.0
77920            0.0    0.0     -0.5         0.0           0.0
86509            0.0    0.0     -0.5         0.0           0.0
117837           0.0    0.0     -0.5         0.0           0.0
...              ...    ...      ...         ...           ...
1653357          0.0    0.0     -0.5         0.0           0.0
```

```
1658058          0.0    0.0     -0.5          0.0           0.0
1734702          0.0    0.0     -0.5          0.0           0.0
1762681          0.0    0.0     -0.5          0.0           0.0
1774112          0.0    0.0     -0.5          0.0           0.0

         improvement_surcharge  total_amount  congestion_surcharge  \
9093                      -1.0         -5.25                  -2.5
77200                     -1.0         -4.00                  -2.5
77920                     -1.0         -4.00                  -2.5
86509                     -1.0         -4.00                  -2.5
117837                    -1.0         -4.00                  -2.5
...                        ...           ...                   ...
1653357                   -1.0         -4.00                  -2.5
1658058                   -1.0         -4.00                  -2.5
1734702                   -1.0         -4.00                  -2.5
1762681                   -1.0         -1.50                   0.0
1774112                   -1.0         -4.00                  -2.5

               date  hour  Airport_fee
9093     2023-01-03    14        -1.25
77200    2023-01-17    12         0.00
77920    2023-01-17    15         0.00
86509    2023-01-19     9         0.00
117837   2023-01-25    11         0.00
...             ...   ...          ...
1653357  2023-07-11    14         0.00
1658058  2023-07-12    12         0.00
1734702  2023-07-27    17         0.00
1762681  2023-09-02    18         0.00
1774112  2023-09-05    15         0.00

[73 rows x 20 columns]
```

```
df["mta_tax"].value_counts()
```

```
mta_tax
 0.50    1878456
 0.00      17797
-0.50         73
 0.80         52
 0.05         17
 4.00          2
 0.30          1
 3.50          1
 2.50          1
Name: count, dtype: int64
```

```
# replacing all the negative values with $0.50 MTA tax as it is
automatically triggered based on the metered rate in use i.e., 73
```

```
records will be made 0.50
df.loc[df['mta_tax'] < 0, 'mta_tax'] = 0.50

df["mta_tax"].value_counts()

mta_tax
0.50    1878529
0.00      17797
0.80         52
0.05         17
4.00          2
0.30          1
3.50          1
2.50          1
Name: count, dtype: int64

#handling improvement charge
df[df["improvement_surcharge"]< 0]

         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
3966            2  2023-01-02 05:12:19   2023-01-02 05:41:45
1.0
9093            2  2023-01-03 14:24:45   2023-01-03 14:25:14
1.0
77200           2  2023-01-17 12:37:35   2023-01-17 13:24:00
1.0
77920           2  2023-01-17 15:03:44   2023-01-17 15:36:28
1.0
86509           2  2023-01-19 09:50:26   2023-01-19 09:58:13
1.0
...           ...                  ...                   ...
...
1734702         2  2023-07-27 17:56:27   2023-07-27 18:00:12
1.0
1742776         2  2023-07-29 03:47:56   2023-07-29 03:48:34
4.0
1762681         2  2023-09-02 18:29:48   2023-09-02 18:30:13
3.0
1774112         2  2023-09-05 15:32:01   2023-09-05 15:43:35
1.0
1893750         2  2023-09-30 16:35:07   2023-09-30 16:35:13
1.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
3966             17.07         3.0           142             1
2
9093              0.00         2.0           132           132
2
```

```
77200              17.68          2.0            230            132
2
77920               4.12          1.0            239            168
2
86509               0.50          1.0            161             43
2
...                  ...          ...            ...            ...
...
1734702             0.66          1.0            113            234
2
1742776             0.00          5.0             79             79
4
1762681             0.00          2.0             74             74
2
1774112             0.01          1.0            161            170
2
1893750             0.00          5.0            141            141
2

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
3966             0.0    0.0      0.0         0.0           0.0
9093             0.0    0.0      0.5         0.0           0.0
77200            0.0    0.0      0.5         0.0           0.0
77920            0.0    0.0      0.5         0.0           0.0
86509            0.0    0.0      0.5         0.0           0.0
...              ...    ...      ...         ...           ...
1734702          0.0    0.0      0.5         0.0           0.0
1742776          0.0    0.0      0.0         0.0           0.0
1762681          0.0    0.0      0.5         0.0           0.0
1774112          0.0    0.0      0.5         0.0           0.0
1893750          0.0    0.0      0.0         0.0           0.0

         improvement_surcharge  total_amount  congestion_surcharge  \
3966                      -1.0         -1.00                   0.0
9093                      -1.0         -5.25                  -2.5
77200                     -1.0         -4.00                  -2.5
77920                     -1.0         -4.00                  -2.5
86509                     -1.0         -4.00                  -2.5
...                        ...           ...                   ...
1734702                   -1.0         -4.00                  -2.5
1742776                   -1.0         -3.50                  -2.5
1762681                   -1.0         -1.50                   0.0
1774112                   -1.0         -4.00                  -2.5
1893750                   -1.0         -3.50                  -2.5

               date  hour  Airport_fee
3966     2023-01-02     5         0.00
9093     2023-01-03    14        -1.25
77200    2023-01-17    12         0.00
77920    2023-01-17    15         0.00
```

```
86509    2023-01-19     9         0.00
...             ...   ...          ...
1734702  2023-07-27    17         0.00
1742776  2023-07-29     3         0.00
1762681  2023-09-02    18         0.00
1774112  2023-09-05    15         0.00
1893750  2023-09-30    16         0.00

[78 rows x 20 columns]
```

```
df["improvement_surcharge"].value_counts()
```

```
improvement_surcharge
 1.0    1894141
 0.3       1283
 0.0        898
-1.0         78
Name: count, dtype: int64
```

```
# replacing all the negative values with 1 as it has occured most of the time and has its a very minimal value
df.loc[df['improvement_surcharge'] < 0, 'improvement_surcharge'] = 1.0

df[df["improvement_surcharge"] < 0]
```

```
Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime, passenger_count, trip_distance, RatecodeID, PULocationID, DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount, tolls_amount, improvement_surcharge, total_amount, congestion_surcharge, date, hour, Airport_fee]
Index: []
```

```
#handling total_amount
df[df["total_amount"] < 0]
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime passenger_count  \
3966            2  2023-01-02 05:12:19   2023-01-02 05:41:45 1.0
9093            2  2023-01-03 14:24:45   2023-01-03 14:25:14 1.0
77200           2  2023-01-17 12:37:35   2023-01-17 13:24:00 1.0
77920           2  2023-01-17 15:03:44   2023-01-17 15:36:28 1.0
86509           2  2023-01-19 09:50:26   2023-01-19 09:58:13 1.0
...           ...                  ...                   ... ...
1734702         2  2023-07-27 17:56:27   2023-07-27 18:00:12
```

```
1.0
1742776         2  2023-07-29 03:47:56   2023-07-29 03:48:34
4.0
1762681         2  2023-09-02 18:29:48   2023-09-02 18:30:13
3.0
1774112         2  2023-09-05 15:32:01   2023-09-05 15:43:35
1.0
1893750         2  2023-09-30 16:35:07   2023-09-30 16:35:13
1.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
3966             17.07         3.0           142             1
2
9093              0.00         2.0           132           132
2
77200            17.68         2.0           230           132
2
77920             4.12         1.0           239           168
2
86509             0.50         1.0           161            43
2
...                ...         ...           ...           ...
...
1734702           0.66         1.0           113           234
2
1742776           0.00         5.0            79            79
4
1762681           0.00         2.0            74            74
2
1774112           0.01         1.0           161           170
2
1893750           0.00         5.0           141           141
2

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
3966             0.0    0.0      0.0         0.0           0.0
9093             0.0    0.0      0.5         0.0           0.0
77200            0.0    0.0      0.5         0.0           0.0
77920            0.0    0.0      0.5         0.0           0.0
86509            0.0    0.0      0.5         0.0           0.0
...              ...    ...      ...         ...           ...
1734702          0.0    0.0      0.5         0.0           0.0
1742776          0.0    0.0      0.0         0.0           0.0
1762681          0.0    0.0      0.5         0.0           0.0
1774112          0.0    0.0      0.5         0.0           0.0
1893750          0.0    0.0      0.0         0.0           0.0

         improvement_surcharge  total_amount  congestion_surcharge  \
3966                       1.0         -1.00                   0.0
```

```
9093                         1.0        -5.25                      -2.5
77200                        1.0        -4.00                      -2.5
77920                        1.0        -4.00                      -2.5
86509                        1.0        -4.00                      -2.5
...                          ...          ...                       ...
1734702                      1.0        -4.00                      -2.5
1742776                      1.0        -3.50                      -2.5
1762681                      1.0        -1.50                       0.0
1774112                      1.0        -4.00                      -2.5
1893750                      1.0        -3.50                      -2.5

               date  hour  Airport_fee
3966     2023-01-02     5         0.00
9093     2023-01-03    14        -1.25
77200    2023-01-17    12         0.00
77920    2023-01-17    15         0.00
86509    2023-01-19     9         0.00
...             ...   ...          ...
1734702  2023-07-27    17         0.00
1742776  2023-07-29     3         0.00
1762681  2023-09-02    18         0.00
1774112  2023-09-05    15         0.00
1893750  2023-09-30    16         0.00

[78 rows x 20 columns]
```

```
df.loc[df['total_amount'] < 0, 'total_amount'] =
df.loc[df['total_amount'] < 0, 'total_amount'].abs() # replace the
negative values with its own absolute values i.e.,-5.75 to 5.75

df[df["total_amount"] < 0]
```

```
Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee]
Index: []
```

```
#handling congestion_surcharge
df[df["congestion_surcharge"] < 0]
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
9093            2  2023-01-03 14:24:45   2023-01-03 14:25:14
1.0
77200           2  2023-01-17 12:37:35   2023-01-17 13:24:00
1.0
77920           2  2023-01-17 15:03:44   2023-01-17 15:36:28
1.0
```

```
86509               2  2023-01-19 09:50:26   2023-01-19 09:58:13
1.0
117837              2  2023-01-25 11:10:37   2023-01-25 11:11:02
1.0
120029              2  2023-01-25 18:52:24   2023-01-25 19:06:34
1.0
182975              2  2023-10-06 16:38:25   2023-10-06 16:39:09
2.0
184944              2  2023-10-06 22:24:42   2023-10-06 22:25:38
2.0
194896              2  2023-10-08 19:17:28   2023-10-08 19:20:11
1.0
241978              2  2023-10-17 13:44:31   2023-10-17 13:44:37
2.0
267977              2  2023-10-21 18:01:24   2023-10-21 18:16:52
2.0
341633              2  2023-11-03 15:51:42   2023-11-03 15:53:00
1.0
358634              2  2023-11-06 14:30:56   2023-11-06 15:18:30
1.0
361257              2  2023-11-06 22:37:04   2023-11-06 22:37:55
1.0
377312              2  2023-11-09 18:20:22   2023-11-09 18:26:46
2.0
394759              2  2023-11-12 14:34:25   2023-11-12 15:08:43
2.0
430572              2  2023-11-18 16:32:18   2023-11-18 16:32:48
1.0
444033              2  2023-11-21 09:55:48   2023-11-21 10:22:57
1.0
488863              2  2023-11-30 17:25:50   2023-11-30 18:02:33
1.0
541046              2  2023-12-09 08:34:26   2023-12-09 08:34:35
1.0
557871              2  2023-12-12 06:57:09   2023-12-12 07:16:37
1.0
604717              2  2023-12-19 15:33:14   2023-12-19 16:05:27
2.0
648645              2  2023-12-29 17:32:20   2023-12-29 17:33:49
1.0
711296              2  2023-03-10 16:18:09   2023-03-10 16:49:43
3.0
736319              2  2023-03-20 12:10:40   2023-03-20 13:03:14
1.0
896231              2  2023-06-13 12:09:53   2023-06-13 12:48:21
1.0
938415              2  2023-06-21 09:02:24   2023-06-21 09:07:21
1.0
940700              2  2023-06-21 16:01:44   2023-06-21 17:11:47
```

```
1.0
952127          2  2023-06-23 15:19:43   2023-06-23 15:36:43
1.0
961390          2  2023-06-25 05:59:41   2023-06-25 06:08:22
2.0
984075          2  2023-06-29 17:52:22   2023-06-29 18:11:03
1.0
989979          2  2023-06-30 21:37:09   2023-06-30 21:46:00
2.0
998118          2  2023-08-02 16:04:37   2023-08-02 16:04:44
2.0
998197          2  2023-08-02 16:57:03   2023-08-02 17:15:42
1.0
1018792         2  2023-08-06 23:08:49   2023-08-06 23:21:25
1.0
1061724         2  2023-08-16 14:37:18   2023-08-16 14:37:38
2.0
1103578         2  2023-08-25 21:14:13   2023-08-25 21:19:14
1.0
1124730         2  2023-08-30 19:11:33   2023-08-30 19:37:35
2.0
1126623         2  2023-08-31 09:50:00   2023-08-31 09:51:28
1.0
1136263         2  2023-02-02 08:12:32   2023-02-02 08:24:59
1.0
1204192         2  2023-02-15 10:55:02   2023-02-15 11:56:22
1.0
1293365         2  2023-04-04 16:24:21   2023-04-04 16:24:28
4.0
1315110         2  2023-04-12 19:12:27   2023-04-12 19:37:09
1.0
1377689         2  2023-04-24 12:48:38   2023-04-24 12:48:44
1.0
1503406         2  2023-05-15 15:16:08   2023-05-15 15:16:22
2.0
1523752         2  2023-05-14 23:47:22   2023-05-14 23:57:43
6.0
1532470         2  2023-05-17 13:27:33   2023-05-17 14:25:24
1.0
1590233         2  2023-05-27 12:45:20   2023-05-27 12:45:26
2.0
1608308         2  2023-05-31 14:52:23   2023-05-31 15:54:56
2.0
1620491         2  2023-07-03 14:46:17   2023-07-03 15:03:59
1.0
1653357         2  2023-07-11 14:13:25   2023-07-11 15:24:35
1.0
1658058         2  2023-07-12 12:32:03   2023-07-12 12:32:13
4.0
```

```
1734702         2  2023-07-27 17:56:27   2023-07-27 18:00:12
1.0
1742776         2  2023-07-29 03:47:56   2023-07-29 03:48:34
4.0
1774112         2  2023-09-05 15:32:01   2023-09-05 15:43:35
1.0
1893750         2  2023-09-30 16:35:07   2023-09-30 16:35:13
1.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
9093              0.00         2.0           132           132
2
77200            17.68         2.0           230           132
2
77920             4.12         1.0           239           168
2
86509             0.50         1.0           161            43
2
117837            0.02         2.0           170           233
2
120029            1.75         1.0           140           163
2
182975            0.01         2.0           107           107
2
184944            0.03         1.0           161           161
2
194896            0.53         1.0           237           237
2
241978            0.00         2.0           140           140
2
267977            2.40         1.0           137           145
2
341633            0.21         2.0           246           246
2
358634           16.92         2.0           170           132
2
361257            0.03         1.0           229           229
2
377312            0.79         1.0           143           143
2
394759            1.97         1.0           162           249
2
430572            0.02         1.0           164           164
4
444033            0.65         1.0            43           186
2
488863            1.72         1.0           236           161
2
```

```
541046              0.00          2.0           107           137
2
557871              3.30          1.0           164           239
2
604717              5.83          1.0           186            87
2
648645              0.02          1.0           161           161
2
711296              6.94          1.0            88           230
2
736319             16.11          2.0           132           170
2
896231              5.25          1.0            50           226
2
938415              0.96          1.0           249           234
2
940700             12.56          2.0           132           114
2
952127              2.14          1.0           142           164
2
961390              1.09          2.0            90           170
2
984075              2.93          1.0           246           239
2
989979              1.38          2.0           249           186
2
998118              0.01          2.0           237           237
2
998197              3.31          1.0           238           263
2
1018792             2.25          1.0            79           107
2
1061724             0.00          2.0           142           142
2
1103578             0.54          2.0           238           238
2
1124730             8.92          1.0           138           234
2
1126623             0.00          1.0           186            68
2
1136263             2.12          1.0           236           161
2
1204192            12.34          1.0           138           230
2
1293365             0.00          1.0           264           264
2
1315110             3.61          1.0            68           232
2
1377689             0.00          5.0           140             7
```

```
2
1503406          0.00        2.0           107           107
2
1523752          3.66        1.0           170           263
2
1532470          5.44        1.0           144           238
2
1590233          0.01        2.0           163            43
2
1608308         17.37        2.0           132           132
2
1620491          2.58        1.0           163           238
2
1653357          9.50        1.0           181            13
2
1658058          0.00        2.0            48            48
2
1734702          0.66        1.0           113           234
2
1742776          0.00        5.0            79            79
4
1774112          0.01        1.0           161           170
2
1893750          0.00        5.0           141           141
2

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
9093             0.0    0.0      0.5         0.0           0.0
77200            0.0    0.0      0.5         0.0           0.0
77920            0.0    0.0      0.5         0.0           0.0
86509            0.0    0.0      0.5         0.0           0.0
117837           0.0    0.0      0.5         0.0           0.0
120029           0.0    0.0      0.5         0.0           0.0
182975           0.0    0.0      0.5         0.0           0.0
184944           0.0    0.5      0.5         0.0           0.0
194896           0.0    0.0      0.5         0.0           0.0
241978           0.0    0.0      0.5         0.0           0.0
267977           0.0    0.0      0.5         0.0           0.0
341633           0.0    0.0      0.5         0.0           0.0
358634           0.0    0.0      0.5         0.0           0.0
361257           0.0    0.5      0.5         0.0           0.0
377312           0.0    0.0      0.5         0.0           0.0
394759           0.0    0.0      0.5         0.0           0.0
430572           0.0    0.0      0.5         0.0           0.0
444033           0.0    0.0      0.5         0.0           0.0
488863           0.0    0.0      0.5         0.0           0.0
541046           0.0    0.0      0.5         0.0           0.0
557871           0.0    0.0      0.5         0.0           0.0
604717           0.0    0.0      0.5         0.0           0.0
```

```
648645          0.0    0.0      0.5        0.0          0.0
711296          0.0    0.0      0.5        0.0          0.0
736319          0.0    0.0      0.5        0.0          0.0
896231          0.0    0.0      0.5        0.0          0.0
938415          0.0    0.0      0.5        0.0          0.0
940700          0.0    0.0      0.5        0.0          0.0
952127          0.0    0.0      0.5        0.0          0.0
961390          0.0    0.0      0.5        0.0          0.0
984075          0.0    0.0      0.5        0.0          0.0
989979          0.0    0.0      0.5        0.0          0.0
998118          0.0    0.0      0.5        0.0          0.0
998197          0.0    0.0      0.5        0.0          0.0
1018792         0.0    0.0      0.5        0.0          0.0
1061724         0.0    0.0      0.5        0.0          0.0
1103578         0.0    0.0      0.5        0.0          0.0
1124730         0.0    0.0      0.5        0.0          0.0
1126623         0.0    0.0      0.5        0.0          0.0
1136263         0.0    0.0      0.5        0.0          0.0
1204192         0.0    0.0      0.5        0.0          0.0
1293365         0.0    0.0      0.5        0.0          0.0
1315110         0.0    0.0      0.5        0.0          0.0
1377689         0.0    0.0      0.0        0.0          0.0
1503406         0.0    0.0      0.5        0.0          0.0
1523752         0.0    0.0      0.5        0.0          0.0
1532470         0.0    0.0      0.5        0.0          0.0
1590233         0.0    0.0      0.5        0.0          0.0
1608308         0.0    0.0      0.5        0.0          0.0
1620491         0.0    0.0      0.5        0.0          0.0
1653357         0.0    0.0      0.5        0.0          0.0
1658058         0.0    0.0      0.5        0.0          0.0
1734702         0.0    0.0      0.5        0.0          0.0
1742776         0.0    0.0      0.0        0.0          0.0
1774112         0.0    0.0      0.5        0.0          0.0
1893750         0.0    0.0      0.0        0.0          0.0

         improvement_surcharge  total_amount  congestion_surcharge  \
9093                       1.0          5.25                  -2.5
77200                      1.0          4.00                  -2.5
77920                      1.0          4.00                  -2.5
86509                      1.0          4.00                  -2.5
117837                     1.0          4.00                  -2.5
120029                     1.0          4.00                  -2.5
182975                     1.0          4.00                  -2.5
184944                     1.0          5.00                  -2.5
194896                     1.0          4.00                  -2.5
241978                     1.0          4.00                  -2.5
267977                     1.0          4.00                  -2.5
341633                     1.0          4.00                  -2.5
358634                     1.0          4.00                  -2.5
```

361257	1.0	5.00	-2.5
377312	1.0	4.00	-2.5
394759	1.0	4.00	-2.5
430572	1.0	4.00	-2.5
444033	1.0	4.00	-2.5
488863	1.0	4.00	-2.5
541046	1.0	4.00	-2.5
557871	1.0	4.00	-2.5
604717	1.0	4.00	-2.5
648645	1.0	4.00	-2.5
711296	1.0	4.00	-2.5
736319	1.0	5.25	-2.5
896231	1.0	4.00	-2.5
938415	1.0	4.00	-2.5
940700	1.0	5.75	-2.5
952127	1.0	4.00	-2.5
961390	1.0	4.00	-2.5
984075	1.0	4.00	-2.5
989979	1.0	4.00	-2.5
998118	1.0	4.00	-2.5
998197	1.0	4.00	-2.5
1018792	1.0	4.00	-2.5
1061724	1.0	4.00	-2.5
1103578	1.0	4.00	-2.5
1124730	1.0	5.75	-2.5
1126623	1.0	4.00	-2.5
1136263	1.0	4.00	-2.5
1204192	1.0	5.25	-2.5
1293365	1.0	4.00	-2.5
1315110	1.0	4.00	-2.5
1377689	1.0	3.50	-2.5
1503406	1.0	4.00	-2.5
1523752	1.0	4.00	-2.5
1532470	1.0	4.00	-2.5
1590233	1.0	4.00	-2.5
1608308	1.0	5.75	-2.5
1620491	1.0	4.00	-2.5
1653357	1.0	4.00	-2.5
1658058	1.0	4.00	-2.5
1734702	1.0	4.00	-2.5
1742776	1.0	3.50	-2.5
1774112	1.0	4.00	-2.5
1893750	1.0	3.50	-2.5

	date	hour	Airport_fee
9093	2023-01-03	14	-1.25
77200	2023-01-17	12	0.00
77920	2023-01-17	15	0.00
86509	2023-01-19	9	0.00

117837	2023-01-25	11	0.00
120029	2023-01-25	18	0.00
182975	2023-10-06	16	0.00
184944	2023-10-06	22	0.00
194896	2023-10-08	19	0.00
241978	2023-10-17	13	0.00
267977	2023-10-21	18	0.00
341633	2023-11-03	15	0.00
358634	2023-11-06	14	0.00
361257	2023-11-06	22	0.00
377312	2023-11-09	18	0.00
394759	2023-11-12	14	0.00
430572	2023-11-18	16	0.00
444033	2023-11-21	9	0.00
488863	2023-11-30	17	0.00
541046	2023-12-09	8	0.00
557871	2023-12-12	6	0.00
604717	2023-12-19	15	0.00
648645	2023-12-29	17	0.00
711296	2023-03-10	16	0.00
736319	2023-03-20	12	-1.25
896231	2023-06-13	12	0.00
938415	2023-06-21	9	0.00
940700	2023-06-21	16	-1.75
952127	2023-06-23	15	0.00
961390	2023-06-25	5	0.00
984075	2023-06-29	17	0.00
989979	2023-06-30	21	0.00
998118	2023-08-02	16	0.00
998197	2023-08-02	16	0.00
1018792	2023-08-06	23	0.00
1061724	2023-08-16	14	0.00
1103578	2023-08-25	21	0.00
1124730	2023-08-30	19	-1.75
1126623	2023-08-31	9	0.00
1136263	2023-02-02	8	0.00
1204192	2023-02-15	10	-1.25
1293365	2023-04-04	16	0.00
1315110	2023-04-12	19	0.00
1377689	2023-04-24	12	0.00
1503406	2023-05-15	15	0.00
1523752	2023-05-14	23	0.00
1532470	2023-05-17	13	0.00
1590233	2023-05-27	12	0.00
1608308	2023-05-31	14	-1.75
1620491	2023-07-03	14	0.00
1653357	2023-07-11	14	0.00
1658058	2023-07-12	12	0.00
1734702	2023-07-27	17	0.00
1742776	2023-07-29	3	0.00

```
1774112  2023-09-05    15         0.00
1893750  2023-09-30    16         0.00
```

```python
df["congestion_surcharge"].value_counts()
```

```
congestion_surcharge
 2.5    1690572
 0.0     140897
-2.5         56
 0.5          1
Name: count, dtype: int64
```

```python
df.loc[df['congestion_surcharge'] < 0, 'congestion_surcharge'] = 2.50
# since majority of the values is 2.50 ,we can replace -2.50 with 2.50
```

```python
df[df["congestion_surcharge"] < 0]
```

```
Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee]
Index: []
```

```python
#handling Airport_fee
df[df["Airport_fee"] < 0]
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
9093            2  2023-01-03 14:24:45   2023-01-03 14:25:14
1.0
239893          2  2023-10-17 00:56:18   2023-10-17 00:56:35
1.0
240472          2  2023-10-17 08:39:40   2023-10-17 08:41:19
1.0
354781          2  2023-11-05 17:01:32   2023-11-05 19:03:35
1.0
390002          2  2023-11-11 18:50:47   2023-11-11 19:40:33
4.0
456757          2  2023-11-22 15:44:42   2023-11-22 15:45:57
1.0
592821          2  2023-12-17 08:10:57   2023-12-17 08:28:46
1.0
725836          2  2023-03-13 11:40:22   2023-03-13 11:51:53
1.0
736319          2  2023-03-20 12:10:40   2023-03-20 13:03:14
1.0
940700          2  2023-06-21 16:01:44   2023-06-21 17:11:47
1.0
1124730         2  2023-08-30 19:11:33   2023-08-30 19:37:35
```

```
2.0
1204192         2  2023-02-15 10:55:02   2023-02-15 11:56:22
1.0
1299057         2  2023-04-10 18:40:15   2023-04-10 18:44:09
1.0
1456503         2  2023-05-09 17:05:56   2023-05-09 17:24:59
1.0
1608308         2  2023-05-31 14:52:23   2023-05-31 15:54:56
2.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
9093              0.00         2.0           132           132
2
239893            0.06         1.0           132           132
2
240472            0.29         1.0           138            70
2
354781          122.46         4.0           132           265
2
390002           20.06         2.0           132           151
2
456757            0.05         2.0           132           132
4
592821           11.27         1.0           132            70
2
725836            3.49         1.0           138           253
2
736319           16.11         2.0           132           170
2
940700           12.56         2.0           132           114
2
1124730           8.92         1.0           138           234
2
1204192          12.34         1.0           138           230
2
1299057           0.36         1.0           132           132
2
1456503           8.35         1.0           132           222
2
1608308          17.37         2.0           132           132
2

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
9093             0.0    0.0      0.5         0.0           0.0
239893           0.0    0.0      0.5         0.0           0.0
240472           0.0    0.0      0.5         0.0           0.0
354781           0.0    0.0      0.0         0.0           0.0
390002           0.0    0.0      0.5         0.0           0.0
```

456757	0.0	0.0	0.5	0.0	0.0
592821	0.0	0.0	0.5	0.0	0.0
725836	0.0	0.0	0.5	0.0	0.0
736319	0.0	0.0	0.5	0.0	0.0
940700	0.0	0.0	0.5	0.0	0.0
1124730	0.0	0.0	0.5	0.0	0.0
1204192	0.0	0.0	0.5	0.0	0.0
1299057	0.0	0.0	0.5	0.0	0.0
1456503	0.0	0.0	0.5	0.0	0.0
1608308	0.0	0.0	0.5	0.0	0.0

	improvement_surcharge	total_amount	congestion_surcharge \
9093	1.0	5.25	2.5
239893	1.0	3.25	0.0
240472	1.0	3.25	0.0
354781	1.0	2.75	0.0
390002	1.0	3.25	0.0
456757	1.0	3.25	0.0
592821	1.0	3.25	0.0
725836	1.0	2.75	0.0
736319	1.0	5.25	2.5
940700	1.0	5.75	2.5
1124730	1.0	5.75	2.5
1204192	1.0	5.25	2.5
1299057	1.0	3.25	0.0
1456503	1.0	3.25	0.0
1608308	1.0	5.75	2.5

	date	hour	Airport_fee
9093	2023-01-03	14	-1.25
239893	2023-10-17	0	-1.75
240472	2023-10-17	8	-1.75
354781	2023-11-05	17	-1.75
390002	2023-11-11	18	-1.75
456757	2023-11-22	15	-1.75
592821	2023-12-17	8	-1.75
725836	2023-03-13	11	-1.25
736319	2023-03-20	12	-1.25
940700	2023-06-21	16	-1.75
1124730	2023-08-30	19	-1.75
1204192	2023-02-15	10	-1.25
1299057	2023-04-10	18	-1.75
1456503	2023-05-09	17	-1.75
1608308	2023-05-31	14	-1.75

```
# from data dictonary the airport fee is fixed $1.25 for both
LaGuardia(pulocationid=132)and John F. Kennedy Airports
(pulocationid=138):googled the pulocation id it,so replacing
nullvalues with 1.25
```

```
df.loc[(df["PULocationID"].isin([132, 138])) & (df["Airport_fee"] <
0), "Airport_fee"] = 1.25

df[df["Airport_fee"] < 0]

Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee]
Index: []
```

2.2 Handling Missing Values

[10 marks]

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

```
# Find the proportion of missing values in each column
df.isnull().mean()*100

VendorID                 0.000000
tpep_pickup_datetime     0.000000
tpep_dropoff_datetime    0.000000
passenger_count          3.420903
trip_distance            0.000000
RatecodeID               3.420903
PULocationID             0.000000
DOLocationID             0.000000
payment_type             0.000000
fare_amount              0.000000
extra                    0.000000
mta_tax                  0.000000
tip_amount               0.000000
tolls_amount             0.000000
improvement_surcharge    0.000000
total_amount             0.000000
congestion_surcharge     3.420903
date                     0.000000
hour                     0.000000
Airport_fee              0.000000
dtype: float64
```

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

```
# Display the rows with null values
# Impute NaN values in 'passenger_count'
#Replacing NaN values with 1.0 because every ride must have at least
```

```
one passenger (a taxi cannot be empty).
df["passenger_count"].fillna(1.0, inplace=True)
df.isnull().sum()
```

```
VendorID                     0
tpep_pickup_datetime         0
tpep_dropoff_datetime        0
passenger_count              0
trip_distance                0
RatecodeID               64874
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     64874
date                         0
hour                         0
Airport_fee                  0
dtype: int64
```

Did you find zeroes in passenger_count? Handle these.

```
df[df["passenger_count"]==0]
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
118             2  2023-01-01 00:47:28   2023-01-01 00:47:32
0.0
192             1  2023-01-01 00:50:09   2023-01-01 01:14:29
0.0
197             1  2023-01-01 00:23:01   2023-01-01 00:32:42
0.0
234             1  2023-01-01 00:42:48   2023-01-01 00:52:02
0.0
235             1  2023-01-01 00:58:49   2023-01-01 01:04:32
0.0
...           ...                  ...                   ...
...
1895962         1  2023-09-30 22:09:45   2023-09-30 22:14:52
0.0
1895986         1  2023-09-30 22:42:00   2023-09-30 22:56:02
0.0
1896083         1  2023-09-30 23:04:02   2023-09-30 23:05:11
```

```
0.0
1896224         1  2023-09-30 23:26:07   2023-09-30 23:38:31
0.0
1896326         1  2023-09-30 23:34:15   2023-09-30 23:39:31
0.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
118                0.0         5.0           232           232
1
192                3.0         1.0           237            90
1
197                2.4         1.0            43           166
1
234                1.0         1.0           162           161
1
235                0.7         1.0           186           234
1
...                ...         ...           ...           ...
...
1895962            0.7         1.0           142           230
1
1895986            2.5         1.0           144            33
1
1896083            0.2         1.0            50            50
1
1896224            1.3         1.0           161           100
1
1896326            1.1         1.0           263            75
1

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
118             14.0    0.0      0.0         0.0           0.0
192             22.6    3.5      0.5         6.9           0.0
197             12.8    3.5      0.5         2.2           0.0
234             10.0    3.5      0.5         1.5           0.0
235              6.5    3.5      0.5         2.3           0.0
...              ...    ...      ...         ...           ...
1895962          6.5    3.5      0.5         2.3           0.0
1895986         15.6    3.5      0.5         4.1           0.0
1896083          3.7    3.5      0.5         1.0           0.0
1896224         12.1    3.5      0.5         3.4           0.0
1896326          7.9    3.5      0.5         3.2           0.0

         improvement_surcharge  total_amount  congestion_surcharge  \
118                        1.0          15.0                   0.0
192                        1.0          34.5                   2.5
197                        1.0          20.0                   2.5
234                        1.0          16.5                   2.5
235                        1.0          13.8                   2.5
```

```
...                           ...           ...                      ...
1895962                       1.0          13.8                      2.5
1895986                       1.0          24.7                      2.5
1896083                       1.0           9.7                      2.5
1896224                       1.0          20.5                      2.5
1896326                       1.0          16.1                      2.5

               date  hour  Airport_fee
118      2023-01-01     0          0.0
192      2023-01-01     0          0.0
197      2023-01-01     0          0.0
234      2023-01-01     0          0.0
235      2023-01-01     0          0.0
...             ...   ...          ...
1895962  2023-09-30    22          0.0
1895986  2023-09-30    22          0.0
1896083  2023-09-30    23          0.0
1896224  2023-09-30    23          0.0
1896326  2023-09-30    23          0.0

[29681 rows x 20 columns]
```

```python
 #There are 29681 records with zero values in passenger count ,as
mentioned earlier every ride must atleast have 1 passenger and the
most occurance of passenger count is also 1.0 hence replacing it with
1
df.loc[df['passenger_count'] == 0, 'passenger_count'] = 1.0
df[df["passenger_count"]==0]
```

```
Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee]
Index: []
```

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

```python
# Fix missing values in 'RatecodeID'
df.isnull().sum()
```

```
VendorID                     0
tpep_pickup_datetime         0
tpep_dropoff_datetime        0
passenger_count              0
trip_distance                0
RatecodeID               64874
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     64874
date                         0
hour                         0
Airport_fee                  0
dtype: int64
```

```python
df["RatecodeID"].value_counts()
```

```
RatecodeID
1.0     1729259
2.0       71670
99.0      10472
5.0       10275
3.0        6124
4.0        3723
6.0           3
Name: count, dtype: int64
```

```python
#since RatecodeID is categorical (1-6 codes), replacing NaN with the most common value (mode) is a good approach
df["RatecodeID"].fillna(df["RatecodeID"].mode()[0], inplace=True)
```

2.2.4 [3 marks] Impute NaN in `congestion_surcharge`

```python
# handle null values in congestion_surcharge
df.isnull().sum()
```

```
VendorID                     0
tpep_pickup_datetime         0
tpep_dropoff_datetime        0
passenger_count              0
trip_distance                0
RatecodeID                   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       64874
date                           0
hour                           0
Airport_fee                    0
dtype: int64
```

```
df["congestion_surcharge"].value_counts()
```

```
congestion_surcharge
2.5    1690628
0.0     140897
0.5          1
Name: count, dtype: int64
```

```
#Replacing NaN with the most common value (mode) with
Congestion_surcharge
df["congestion_surcharge"].fillna(df["congestion_surcharge"].mode()
[0], inplace=True)
```

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

```
# Handle any remaining missing values
df.isnull().sum()
```

```
VendorID                 0
tpep_pickup_datetime     0
tpep_dropoff_datetime    0
passenger_count          0
trip_distance            0
RatecodeID               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
date                     0
hour                     0
Airport_fee              0
dtype: int64
```

2.3 Handling Outliers

[10 marks]

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

```
# Describe the data and check if there are any potential outliers
present
# Check for potential out of place values in various columns
df.describe()
```

```
           VendorID        tpep_pickup_datetime
tpep_dropoff_datetime  \
count  1.896400e+06                     1896400
1896400
mean   1.733026e+00  2023-07-02 19:59:52.930795  2023-07-02
20:17:18.919563
min    1.000000e+00         2022-12-31 23:51:30         2022-12-31
23:56:06
25%    1.000000e+00  2023-04-02 16:10:08.750000  2023-04-02
16:27:43.500000
50%    2.000000e+00  2023-06-27 15:44:22.500000         2023-06-27
16:01:15
75%    2.000000e+00         2023-10-06 19:37:45         2023-10-06
19:53:39
max    6.000000e+00         2023-12-31 23:57:51         2024-01-01
20:50:55
std    4.476401e-01                         NaN
NaN

       passenger_count  trip_distance    RatecodeID  PULocationID  \
count     1.896400e+06   1.896400e+06  1.896400e+06  1.896400e+06
mean      1.372236e+00   3.858293e+00  1.612981e+00  1.652814e+02
min       1.000000e+00   0.000000e+00  1.000000e+00  1.000000e+00
25%       1.000000e+00   1.050000e+00  1.000000e+00  1.320000e+02
50%       1.000000e+00   1.790000e+00  1.000000e+00  1.620000e+02
75%       1.000000e+00   3.400000e+00  1.000000e+00  2.340000e+02
max       9.000000e+00   1.263605e+05  9.900000e+01  2.650000e+02
std       8.644038e-01   1.294085e+02  7.267261e+00  6.400038e+01

       DOLocationID  payment_type   fare_amount         extra
mta_tax  \
count  1.896400e+06  1.896400e+06  1.896400e+06  1.896400e+06
1.896400e+06
mean   1.640515e+02  1.163817e+00  1.991935e+01  1.588021e+00
4.953181e-01
min    1.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
0.000000e+00
25%    1.140000e+02  1.000000e+00  9.300000e+00  0.000000e+00
5.000000e-01
```

```
50%    1.620000e+02  1.000000e+00  1.350000e+01  1.000000e+00
5.000000e-01
75%    2.340000e+02  1.000000e+00  2.190000e+01  2.500000e+00
5.000000e-01
max    2.650000e+02  4.000000e+00  1.431635e+05  2.080000e+01
4.000000e+00
std    6.980207e+01  5.081384e-01  1.055371e+02  1.829197e+00
4.845942e-02

         tip_amount  tolls_amount  improvement_surcharge  total_amount
\
count  1.896400e+06  1.896400e+06           1.896400e+06  1.896400e+06

mean   3.547011e+00  5.965338e-01           9.990529e-01  2.898216e+01

min    0.000000e+00  0.000000e+00           0.000000e+00  0.000000e+00

25%    1.000000e+00  0.000000e+00           1.000000e+00  1.596000e+01

50%    2.850000e+00  0.000000e+00           1.000000e+00  2.100000e+01

75%    4.420000e+00  0.000000e+00           1.000000e+00  3.094000e+01

max    2.230800e+02  1.430000e+02           1.000000e+00  1.431675e+05

std    4.054882e+00  2.187878e+00           2.835735e-02  1.064161e+02


       congestion_surcharge          hour   Airport_fee
count          1.896400e+06  1.896400e+06  1.896400e+06
mean           2.314256e+00  1.426504e+01  1.380319e-01
min            0.000000e+00  0.000000e+00  0.000000e+00
25%            2.500000e+00  1.100000e+01  0.000000e+00
50%            2.500000e+00  1.500000e+01  0.000000e+00
75%            2.500000e+00  1.900000e+01  0.000000e+00
max            2.500000e+00  2.300000e+01  1.750000e+00
std            6.556359e-01  5.807381e+00  4.575733e-01
```

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.

```
# remove passenger_count > 6
df[df["passenger_count"] > 6]

         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
88797           2  2023-01-19 16:33:22   2023-01-19 17:57:32
8.0
230693          2  2023-10-15 08:11:40   2023-10-15 08:39:01
7.0
261244          2  2023-10-20 16:55:31   2023-10-20 16:56:27
7.0
485300          2  2023-11-30 00:13:36   2023-11-30 00:13:39
8.0
511725          2  2023-12-04 15:32:03   2023-12-04 15:32:08
9.0
546188          2  2023-12-09 22:01:38   2023-12-09 22:01:40
8.0
612517          2  2023-12-20 19:26:27   2023-12-20 19:33:17
9.0
624897          2  2023-12-22 23:00:21   2023-12-22 23:00:24
8.0
631419          2  2023-12-26 17:38:04   2023-12-26 17:38:06
8.0
885785          2  2023-06-11 11:53:08   2023-06-11 11:53:29
9.0
1059918         2  2023-08-16 06:10:57   2023-08-16 06:49:47
8.0
1082350         2  2023-08-21 01:53:09   2023-08-21 01:53:11
8.0
1171036         2  2023-02-08 23:26:39   2023-02-08 23:26:51
9.0
1233147         2  2023-02-19 17:19:13   2023-02-19 17:57:24
9.0
1333135         2  2023-04-09 09:22:54   2023-04-09 09:23:22
7.0
1401814         2  2023-04-21 16:44:17   2023-04-21 16:44:19
8.0
1421730         2  2023-04-28 02:24:47   2023-04-28 02:25:01
8.0
1597591         2  2023-05-29 02:35:04   2023-05-29 02:35:16
7.0
1679906         2  2023-07-16 16:33:55   2023-07-16 16:34:00
8.0
```

```
1846867         2  2023-09-18 13:07:26   2023-09-18 14:05:27
8.0
1848113         2  2023-09-18 17:26:13   2023-09-18 17:52:25
7.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
88797            18.30         5.0           230           132
1
230693            7.60         5.0           246           195
1
261244           16.17         5.0           132           132
1
485300            0.00         5.0            90           264
1
511725            0.00         5.0           132           132
1
546188            0.00         5.0            79           264
1
612517            0.07         5.0           112           112
2
624897            0.09         5.0           236           236
1
631419            0.45         5.0           216           264
1
885785            0.00         5.0           138           138
1
1059918          19.03         5.0           132            75
1
1082350           0.00         5.0           264           264
2
1171036           0.13         5.0           231           231
1
1233147          16.79         5.0           186             1
1
1333135           0.00         5.0           125           125
1
1401814           0.00         5.0           264           264
1
1421730           0.00         5.0            87            87
2
1597591           0.00         5.0           256           256
1
1679906           0.00         5.0           233           233
1
1846867          31.71         5.0            48           219
1
1848113           5.11         5.0           246           265
1
```

	fare_amount	extra	mta_tax	tip_amount	tolls_amount	\
88797	85.00	0.0	0.5	19.11	6.55	
230693	70.00	0.0	0.5	18.50	0.00	
261244	74.00	0.0	0.0	0.00	13.00	
485300	86.00	0.0	0.5	5.00	0.00	
511725	90.00	0.0	0.5	18.65	0.00	
546188	87.00	0.0	0.5	17.70	0.00	
612517	92.00	0.0	0.5	0.00	0.00	
624897	85.00	0.0	0.5	17.30	0.00	
631419	85.00	0.0	0.5	17.30	0.00	
885785	95.00	5.0	0.0	0.00	0.00	
1059918	82.00	0.0	0.5	15.00	6.94	
1082350	82.00	0.0	0.0	0.00	0.00	
1171036	95.55	0.0	0.5	19.91	0.00	
1233147	90.00	0.0	0.0	18.00	14.75	
1333135	80.00	0.0	0.5	0.00	21.25	
1401814	86.00	0.0	0.0	10.10	0.00	
1421730	85.00	0.0	0.5	0.00	0.00	
1597591	75.00	0.0	0.0	0.02	0.00	
1679906	88.00	0.0	0.5	17.90	0.00	
1846867	88.90	0.0	0.5	10.00	11.19	
1848113	70.00	0.0	0.0	0.00	0.00	

	improvement_surcharge	total_amount	congestion_surcharge	\
88797	1.0	114.66	2.5	
230693	1.0	92.50	2.5	
261244	1.0	88.00	0.0	
485300	1.0	92.50	0.0	
511725	1.0	111.90	0.0	
546188	1.0	106.20	0.0	
612517	1.0	93.50	0.0	
624897	1.0	103.80	0.0	
631419	1.0	103.80	0.0	
885785	1.0	102.75	0.0	
1059918	1.0	105.44	0.0	
1082350	1.0	83.00	0.0	
1171036	1.0	119.46	2.5	
1233147	1.0	123.75	0.0	
1333135	1.0	105.25	2.5	
1401814	1.0	97.10	0.0	
1421730	1.0	89.00	2.5	
1597591	1.0	76.02	0.0	
1679906	1.0	107.40	0.0	
1846867	1.0	114.09	2.5	
1848113	1.0	71.00	0.0	

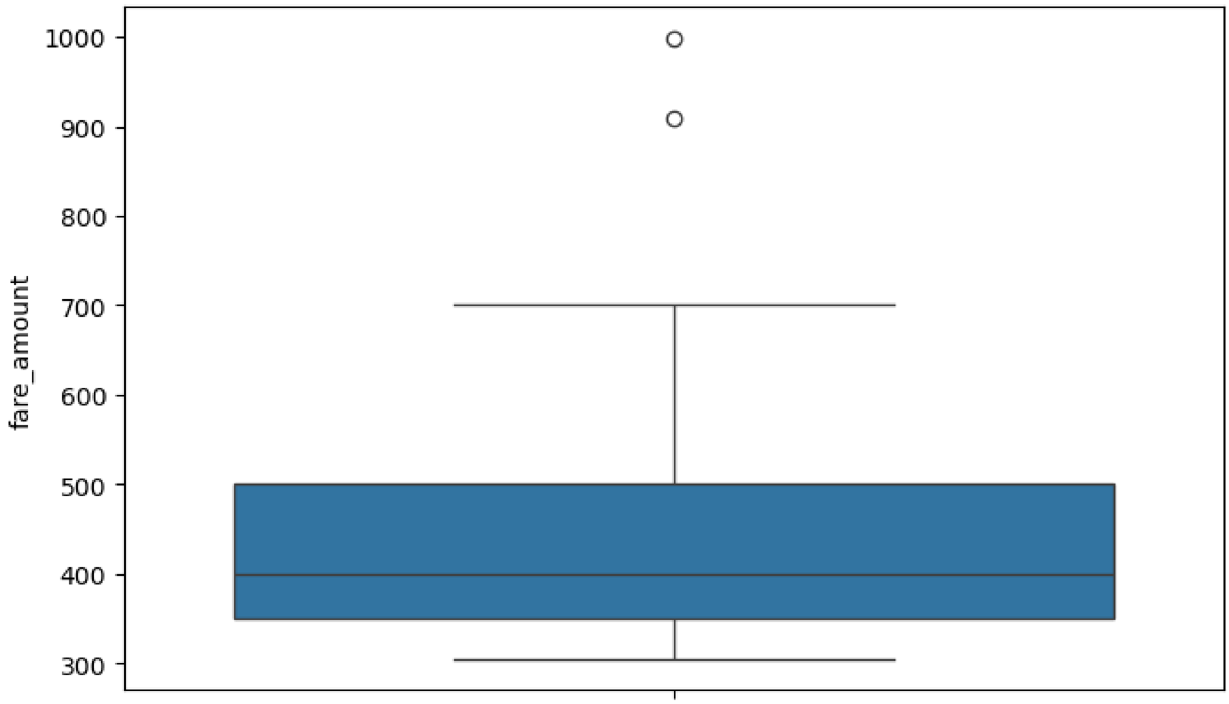
	date	hour	Airport_fee
88797	2023-01-19	16	0.00
230693	2023-10-15	8	0.00

```
261244   2023-10-20    16          0.00
485300   2023-11-30     0          0.00
511725   2023-12-04    15          1.75
546188   2023-12-09    22          0.00
612517   2023-12-20    19          0.00
624897   2023-12-22    23          0.00
631419   2023-12-26    17          0.00
885785   2023-06-11    11          1.75
1059918  2023-08-16     6          0.00
1082350  2023-08-21     1          0.00
1171036  2023-02-08    23          0.00
1233147  2023-02-19    17          0.00
1333135  2023-04-09     9          0.00
1401814  2023-04-21    16          0.00
1421730  2023-04-28     2          0.00
1597591  2023-05-29     2          0.00
1679906  2023-07-16    16          0.00
1846867  2023-09-18    13          0.00
1848113  2023-09-18    17          0.00
```

```
df.shape[0]#1896400
df=df[~(df["passenger_count"] > 6)] #21
df.shape[0]#1896379
```

```
1896379
```

```
# Continue with outlier handling
#Entries where trip_distance is nearly 0 and fare_amount is more than 
300
outliers1 = df[(df["trip_distance"] <= 0.01) & (df["fare_amount"] > 
300)]

# Create a boxplot for the fare_amount column
plt.figure(figsize=(8, 5))
sns.boxplot(y=outliers1["fare_amount"])
plt.show()
```




```
#There are outliers above $700, values reaching  $900, and even $1000
for trip_distance <=0.01.
df[(df["trip_distance"] <= 0.01) & (df["fare_amount"] > 700)]

         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
38085           1  2023-01-09 16:17:32   2023-01-09 16:20:41
1.0
1171493         1  2023-02-09 07:37:30   2023-02-09 07:39:13
1.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
38085              0.0         5.0           141           141
3
1171493            0.0         5.0           246           246
4

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
38085          999.0    0.0      0.0         0.0           0.0
1171493        910.0    0.0      0.0         0.0           0.0

         improvement_surcharge  total_amount  congestion_surcharge  \
38085                      1.0        1000.0                   0.0
1171493                    1.0         911.0                   0.0

               date  hour  Airport_fee
```

```
38085    2023-01-09    16          0.0
1171493  2023-02-09     7          0.0
```

```
#High fare amount for 0.00  distance and pickup and drop time is also
minimal ,so its better to remove these records from the sample
df.shape[0]#1896379
df=df[~((df["trip_distance"] <= 0.01) & (df["fare_amount"] > 700))]#4
df.shape[0]#1896377
```

```
1896377
```

```
#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)
df[(df["trip_distance"] == 0) & (df["fare_amount"] == 0) &
(df["PULocationID"] != df["DOLocationID"])]
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
43681           1  2023-01-10 19:28:41   2023-01-10 20:14:48
1.0
83048           1  2023-01-18 15:42:00   2023-01-18 15:42:00
1.0
83247           1  2023-01-18 16:23:49   2023-01-18 16:23:49
1.0
90721           1  2023-01-19 21:57:21   2023-01-19 22:17:44
1.0
142069          1  2023-01-29 18:33:14   2023-01-29 18:33:14
1.0
...           ...                  ...                   ...
...
1718458         1  2023-07-24 14:14:22   2023-07-24 14:14:22
1.0
1735378         1  2023-07-27 18:59:15   2023-07-27 18:59:15
2.0
1844320         1  2023-09-17 20:40:48   2023-09-17 20:40:48
1.0
1854559         2  2023-09-19 21:27:12   2023-09-19 21:27:48
1.0
1887230         1  2023-09-29 11:12:42   2023-09-29 11:12:42
1.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
43681              0.0         1.0           127            91
1
83048              0.0         1.0           161           264
2
83247              0.0         1.0           239           264
2
```

```
90721                0.0         1.0           170           75
0
142069               0.0         5.0           261          264
2
...                  ...         ...           ...          ...
...
1718458              0.0         1.0           229          264
4
1735378              0.0         5.0           231          264
2
1844320              0.0         5.0            79          264
2
1854559              0.0         1.0             7          193
1
1887230              0.0         5.0           128          264
2

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
43681            0.0    0.0      0.0         0.0           0.0
83048            0.0    0.0      0.0         0.0           0.0
83247            0.0    0.0      0.0         0.0           0.0
90721            0.0    0.0      0.0         0.0           0.0
142069           0.0    0.0      0.0         0.0           0.0
...              ...    ...      ...         ...           ...
1718458          0.0    0.0      0.0         0.0           0.0
1735378          0.0    5.0      0.0         0.0           0.0
1844320          0.0    0.0      0.0         0.0           0.0
1854559          0.0    0.0      0.0         0.0           0.0
1887230          0.0    0.0      0.0         0.0           0.0

         improvement_surcharge  total_amount  congestion_surcharge  \
43681                      0.0           0.0                   0.0
83048                      0.0           0.0                   0.0
83247                      0.0           0.0                   0.0
90721                      0.0           2.0                   2.5
142069                     0.0           0.0                   0.0
...                        ...           ...                   ...
1718458                    0.0           0.0                   0.0
1735378                    0.0           5.0                   2.5
1844320                    0.0           0.0                   0.0
1854559                    0.0           0.0                   0.0
1887230                    0.0           0.0                   0.0

               date  hour  Airport_fee
43681    2023-01-10    19          0.0
83048    2023-01-18    15          0.0
83247    2023-01-18    16          0.0
90721    2023-01-19    21          0.0
142069   2023-01-29    18          0.0
...             ...   ...          ...
```

```
1718458  2023-07-24    14          0.0
1735378  2023-07-27    18          0.0
1844320  2023-09-17    20          0.0
1854559  2023-09-19    21          0.0
1887230  2023-09-29    11          0.0

[63 rows x 20 columns]
```

```
#it indicates data inconsistency,both trip distance and fare amount is 0.Fare amount can be adjusted by total fare-(all other taxes and fares),but we cannot estimate trip distance as its only 63 records we can delete it.
df.shape[0]#1896377
df=df[~((df["trip_distance"] <= 0.0) & (df["fare_amount"] == 0) & (df["PULocationID"] != df["DOLocationID"]))]#63 records
df.shape[0]#1896314
```

```
1896314
```

```
#Entries where trip_distance is more than 250 miles.
df[df["trip_distance"] > 250.0]
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime  
passenger_count  \
30438           2  2023-01-07 20:02:05   2023-01-07 20:07:10
1.0
111442          2  2023-01-24 06:27:00   2023-01-24 07:18:00
1.0
136826          2  2023-01-28 18:16:37   2023-01-28 18:41:22
1.0
137589          2  2023-01-28 20:39:00   2023-01-28 20:59:00
1.0
152189          2  2023-10-01 00:05:00   2023-10-01 00:19:00
1.0
316935          2  2023-10-30 07:13:00   2023-10-30 07:33:00
1.0
439631          2  2023-11-20 11:46:00   2023-11-20 12:30:00
1.0
539719          2  2023-12-08 23:45:00   2023-12-09 00:14:00
1.0
547189          2  2023-12-10 01:11:00   2023-12-10 01:25:00
1.0
550654          2  2023-12-10 17:10:00   2023-12-10 17:12:00
1.0
632702          1  2023-12-27 06:00:00   2023-12-27 07:22:13
1.0
651837          2  2023-12-30 13:24:39   2023-12-30 14:07:52
1.0
672226          2  2023-03-02 15:45:34   2023-03-02 16:00:45
1.0
```

```
685422          2  2023-03-03 19:47:00   2023-03-03 20:05:00
1.0
712683          2  2023-03-10 19:12:22   2023-03-10 19:18:55
1.0
817826          2  2023-03-30 14:07:00   2023-03-30 15:32:00
1.0
839768          2  2023-06-03 06:23:00   2023-06-03 06:31:00
1.0
895099          2  2023-06-13 09:59:00   2023-06-13 10:12:00
1.0
943709          2  2023-06-22 06:34:00   2023-06-22 06:47:00
1.0
967196          2  2023-06-26 13:45:44   2023-06-26 13:51:12
2.0
990505          2  2023-06-30 23:40:00   2023-07-01 00:11:00
1.0
1071471         1  2023-08-18 14:26:43   2023-08-18 15:04:09
1.0
1159551         2  2023-02-06 19:56:52   2023-02-06 20:33:55
2.0
1180941         2  2023-02-10 19:53:45   2023-02-10 20:01:48
2.0
1204921         2  2023-02-15 13:06:00   2023-02-15 13:40:00
1.0
1214416         2  2023-02-17 07:17:00   2023-02-17 07:25:00
1.0
1219208         2  2023-02-17 22:36:00   2023-02-17 23:00:00
1.0
1234357         2  2023-02-19 22:06:00   2023-02-19 22:22:00
1.0
1337908         2  2023-04-17 10:56:00   2023-04-17 11:25:00
1.0
1407060         2  2023-04-22 14:58:35   2023-04-22 15:23:03
1.0
1445157         2  2023-05-08 15:22:51   2023-05-08 16:02:16
1.0
1482063         2  2023-05-11 19:43:07   2023-05-11 20:01:07
1.0
1508956         2  2023-05-12 15:12:50   2023-05-12 16:03:58
1.0
1579201         2  2023-05-25 11:10:00   2023-05-25 11:35:00
1.0
1586514         2  2023-05-26 16:22:00   2023-05-26 16:56:00
1.0
1598683         2  2023-05-29 13:13:00   2023-05-29 14:23:00
1.0
1649781         2  2023-07-10 17:33:19   2023-07-10 19:14:56
1.0
1661245         2  2023-07-12 21:05:00   2023-07-12 21:10:00
```

```
1.0
1664701         2  2023-07-13 15:38:02   2023-07-13 16:09:33
1.0
1669836         2  2023-07-14 15:32:30   2023-07-14 16:18:58
1.0
1696966         2  2023-07-20 04:22:00   2023-07-20 04:42:00
1.0
1737698         2  2023-07-28 08:10:00   2023-07-28 08:47:00
1.0
1803062         2  2023-09-10 13:44:00   2023-09-10 14:16:00
1.0
1841392         1  2023-09-17 07:23:50   2023-09-17 07:48:20
1.0
1853724         2  2023-09-19 19:36:56   2023-09-19 19:48:16
1.0
1872165         2  2023-09-26 19:41:43   2023-09-26 20:01:00
1.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
30438           721.26         1.0           145             7
1
111442         3253.99         1.0           230            90
0
136826         2003.03         1.0            48           113
0
137589        10451.89         1.0           142           224
0
152189        34804.51         1.0           263           151
0
316935         4547.48         1.0           143           136
0
439631        22869.37         1.0           179           237
0
539719        22414.00         1.0            65           188
0
547189        35482.69         1.0           224            33
0
550654        33133.96         1.0           142           142
0
632702          969.10        99.0           258           265
1
651837         9021.10         1.0           132            49
1
672226         9674.01         1.0           161            68
1
685422         7094.16         1.0            75            42
0
712683        10961.43         1.0           140           263
```

					2
817826	12133.27	1.0	50	132	0
839768	26217.98	1.0	231	68	0
895099	22528.82	1.0	116	239	0
943709	22562.67	1.0	151	237	0
967196	6262.99	1.0	75	238	1
990505	20314.00	1.0	237	248	0
1071471	56823.80	99.0	71	39	1
1159551	3317.68	2.0	132	186	1
1180941	9673.76	1.0	264	142	1
1204921	2942.93	1.0	231	166	0
1214416	8645.77	1.0	238	230	0
1219208	11551.95	1.0	41	170	0
1234357	6284.45	1.0	186	236	0
1337908	7914.69	1.0	89	227	0
1407060	403.66	1.0	144	237	1
1445157	9678.97	1.0	138	161	1
1482063	9675.03	1.0	68	231	1
1508956	9678.78	1.0	138	116	2
1579201	10433.95	1.0	116	238	0
1586514	27586.37	1.0	230	17	0
1598683	126360.46	1.0	265	132	0
1649781	9717.11	1.0	216	265	4
1661245	30430.04	1.0	263	263	0
1664701	9679.36	1.0	138	234	1

```
1669836       9677.04         1.0           138           263
1
1696966      32053.26         1.0             4           138
0
1737698      22576.01         1.0           151           137
0
1803062      22910.92         1.0           163           223
0
1841392      10452.60        99.0           159           254
1
1853724       9674.07         1.0           233           186
1
1872165       9678.34         1.0           138           197
1

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
30438           7.90    0.0      0.5        2.00          0.00
111442         19.24    0.0      0.5        4.51          0.00
136826         18.87    0.0      0.5        3.00          0.00
137589         19.94    0.0      0.5        4.79          0.00
152189         14.45    0.0      0.5        3.69          0.00
316935         36.47    0.0      0.5        4.05          0.00
439631         27.39    0.0      0.5        0.00          0.00
539719         21.69    0.0      0.5        4.64          0.00
547189         25.91    0.0      0.5        4.49          0.00
550654         12.02    0.0      0.5        2.40          0.00
632702         25.50    0.0      0.5        0.00          0.00
651837         80.00    0.0      0.5        3.00          0.00
672226         14.20    0.0      0.5        2.00          0.00
685422         18.81    0.0      0.5        0.00          0.00
712683          8.60    2.5      0.5        0.00          0.00
817826         77.00    0.0      0.5       16.20          0.00
839768         10.63    0.0      0.5        2.93          0.00
895099         17.42    0.0      0.5        0.37          0.00
943709         16.32    0.0      0.5        2.03          0.00
967196          7.90    0.0      0.5        1.88          0.00
990505         31.47    0.0      0.5        7.09          0.00
1071471        18.50    0.0      0.5        0.00          0.00
1159551        70.00    5.0      0.5       17.11          6.55
1180941         8.60    2.5      0.5        1.50          0.00
1204921        26.49    0.0      0.5        4.63          0.00
1214416        13.34    0.0      0.5        4.34          0.00
1219208        24.03    0.0      0.5        5.61          0.00
1234357        16.00    0.0      0.5        0.00          0.00
1337908        19.85    0.0      0.5        0.00          0.00
1407060        24.00    0.0      0.5        2.00          0.00
1445157        45.00    0.0      0.5        2.39          6.55
1482063        19.80    2.5      0.5        7.89          0.00
1508956        47.10    0.0      0.5        0.00          6.55
```

```
1579201        21.25    0.0       0.5        0.00          0.00
1586514        46.43    0.0       0.5        0.00          6.55
1598683        85.52    0.0       0.5       20.71          6.55
1649781       264.80    2.5       0.5        0.00          0.00
1661245        23.01    0.0       0.5        0.00          0.00
1664701        40.10    5.0       0.5       10.00          6.55
1669836        52.70    5.0       0.5       13.15          6.55
1696966        36.90    0.0       0.5        8.18          0.00
1737698        28.19    0.0       0.5        3.00          0.00
1803062        27.66    0.0       0.5        6.33          0.00
1841392        27.50    0.0       0.5        0.00          0.00
1853724        11.40    2.5       0.5        4.47          0.00
1872165        29.60    7.5       0.5        7.72          0.00

         improvement_surcharge  total_amount  congestion_surcharge  \
30438                      1.0         11.40                   0.0
111442                     0.3         27.05                   2.5
136826                     1.0         25.87                   2.5
137589                     1.0         28.73                   2.5
152189                     1.0         22.14                   2.5
316935                     1.0         44.52                   2.5
439631                     1.0         31.39                   2.5
539719                     1.0         27.83                   2.5
547189                     1.0         34.40                   2.5
550654                     1.0         18.42                   2.5
632702                     1.0         27.00                   0.0
651837                     1.0         88.75                   2.5
672226                     1.0         20.20                   2.5
685422                     1.0         20.31                   2.5
712683                     1.0         15.10                   2.5
817826                     1.0         97.20                   2.5
839768                     1.0         17.56                   2.5
895099                     1.0         21.79                   2.5
943709                     1.0         22.35                   2.5
967196                     1.0         11.28                   0.0
990505                     1.0         42.56                   2.5
1071471                    1.0         20.00                   0.0
1159551                    1.0        103.91                   2.5
1180941                    1.0         16.60                   2.5
1204921                    0.3         34.42                   2.5
1214416                    1.0         21.68                   2.5
1219208                    1.0         33.64                   2.5
1234357                    1.0         20.00                   2.5
1337908                    1.0         21.35                   2.5
1407060                    1.0         30.00                   2.5
1445157                    1.0         57.94                   2.5
1482063                    1.0         34.19                   2.5
1508956                    1.0         55.15                   0.0
1579201                    1.0         25.25                   2.5
```

1586514	1.0	56.98	2.5
1598683	1.0	114.28	2.5
1649781	1.0	271.30	2.5
1661245	1.0	27.01	2.5
1664701	1.0	67.40	2.5
1669836	1.0	80.65	0.0
1696966	1.0	49.08	2.5
1737698	1.0	35.19	2.5
1803062	1.0	37.99	2.5
1841392	1.0	29.00	0.0
1853724	1.0	22.37	2.5
1872165	1.0	48.07	0.0

	date	hour	Airport_fee
30438	2023-01-07	20	0.00
111442	2023-01-24	6	0.00
136826	2023-01-28	18	0.00
137589	2023-01-28	20	0.00
152189	2023-10-01	0	0.00
316935	2023-10-30	7	0.00
439631	2023-11-20	11	0.00
539719	2023-12-08	23	0.00
547189	2023-12-10	1	0.00
550654	2023-12-10	17	0.00
632702	2023-12-27	6	0.00
651837	2023-12-30	13	1.75
672226	2023-03-02	15	0.00
685422	2023-03-03	19	0.00
712683	2023-03-10	19	0.00
817826	2023-03-30	14	0.00
839768	2023-06-03	6	0.00
895099	2023-06-13	9	0.00
943709	2023-06-22	6	0.00
967196	2023-06-26	13	0.00
990505	2023-06-30	23	0.00
1071471	2023-08-18	14	0.00
1159551	2023-02-06	19	1.25
1180941	2023-02-10	19	0.00
1204921	2023-02-15	13	0.00
1214416	2023-02-17	7	0.00
1219208	2023-02-17	22	0.00
1234357	2023-02-19	22	0.00
1337908	2023-04-17	10	0.00
1407060	2023-04-22	14	0.00
1445157	2023-05-08	15	0.00
1482063	2023-05-11	19	0.00
1508956	2023-05-12	15	0.00
1579201	2023-05-25	11	0.00
1586514	2023-05-26	16	0.00

```
1598683  2023-05-29    13         0.00
1649781  2023-07-10    17         0.00
1661245  2023-07-12    21         0.00
1664701  2023-07-13    15         1.75
1669836  2023-07-14    15         1.75
1696966  2023-07-20     4         0.00
1737698  2023-07-28     8         0.00
1803062  2023-09-10    13         0.00
1841392  2023-09-17     7         0.00
1853724  2023-09-19    19         0.00
1872165  2023-09-26    19         1.75
```

```
df.shape[0]#1896314
df=df[~(df["trip_distance"] > 250.0)]#46
df.shape[0]#1896268
```

```
1896268
```

```
#Entries where payment_type is 0 (there is no payment_type 0 defined
in the data dictionary)
df[df["payment_type"]==0]
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
4               2  2023-01-01 00:43:00   2023-01-01 01:01:00
1.0
15              2  2023-01-01 00:41:50   2023-01-01 01:14:50
1.0
42              2  2023-01-01 00:37:21   2023-01-01 00:54:18
1.0
43              2  2023-01-01 00:44:03   2023-01-01 01:13:49
1.0
46              2  2023-01-01 00:50:55   2023-01-01 01:19:06
1.0
...           ...                  ...                   ...
...
1896343         1  2023-09-30 23:18:31   2023-09-30 23:30:35
1.0
1896356         1  2023-09-30 23:42:07   2023-10-01 00:05:22
1.0
1896369         1  2023-09-30 23:59:39   2023-10-01 00:15:03
1.0
1896376         1  2023-09-30 23:47:09   2023-10-01 00:03:01
1.0
1896387         1  2023-09-30 23:17:34   2023-09-30 23:30:46
1.0

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
4                19.24         1.0            66           107
```

```
0
15                10.77         1.0           151           106
0
42                 4.52         1.0           114           262
0
43                 9.19         1.0           239           256
0
46                 2.74         1.0            90            48
0
...                 ...         ...           ...           ...
...
1896343            0.00         1.0            43           229
0
1896356            0.00         1.0           255           209
0
1896369            0.00         1.0           137           249
0
1896376            3.50         1.0           233           144
0
1896387            0.00         1.0           231            90
0

         fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
4              25.64    0.0      0.5        5.93          0.00
15             45.38    0.0      0.5       11.19          6.55
42             25.38    0.0      0.5        0.00          0.00
43             40.00    0.0      0.5        2.20          0.00
46             18.48    0.0      0.5        3.37          0.00
...              ...    ...      ...         ...           ...
1896343        12.55    0.0      0.5        0.00          0.00
1896356        34.02    0.0      0.5        0.00          0.00
1896369        21.50    0.0      0.5        0.00          0.00
1896376        21.28    0.0      0.5        0.00          0.00
1896387        15.68    0.0      0.5        0.00          0.00

         improvement_surcharge  total_amount  congestion_surcharge  \
4                          1.0         35.57                   2.5
15                         1.0         67.12                   2.5
42                         1.0         29.38                   2.5
43                         1.0         46.20                   2.5
46                         1.0         25.85                   2.5
...                        ...           ...                   ...
1896343                    1.0         16.55                   2.5
1896356                    1.0         38.02                   2.5
1896369                    1.0         25.50                   2.5
1896376                    1.0         25.28                   2.5
1896387                    1.0         19.68                   2.5

               date  hour  Airport_fee
4        2023-01-01     0          0.0
```

```
15       2023-01-01     0          0.0
42       2023-01-01     0          0.0
43       2023-01-01     0          0.0
46       2023-01-01     0          0.0
...             ...   ...          ...
1896343  2023-09-30    23          0.0
1896356  2023-09-30    23          0.0
1896369  2023-09-30    23          0.0
1896376  2023-09-30    23          0.0
1896387  2023-09-30    23          0.0

[64844 rows x 20 columns]
```

```
#There are 64844 records with payment_type as zero,that is almost
3.41% so deleting these records is not a wise decision ,instead of
this we can replace the value to 5 as its known as unknown
df.loc[df["payment_type"]==0, "payment_type"] = 5
df[df["payment_type"]==0] # 0 columns
```

```
Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee]
Index: []
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1896268 entries, 0 to 1896399
Data columns (total 20 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   PULocationID           int64
 7   DOLocationID           int64
 8   payment_type           int64
 9   fare_amount            float64
 10  extra                  float64
 11  mta_tax                float64
 12  tip_amount             float64
 13  tolls_amount           float64
 14  improvement_surcharge  float64
 15  total_amount           float64
```

```
 16  congestion_surcharge    float64
 17  date                    object
 18  hour                    int32
 19  Airport_fee             float64
dtypes: datetime64[us](2), float64(12), int32(1), int64(4), object(1)
memory usage: 296.6+ MB
```

```
#Do any columns need standardising?
#Passenger_count can be changed from float to int as the content is a
whole number it can be changed into int
df["passenger_count"] = df["passenger_count"].astype(int)
```

3 Exploratory Data Analysis

[90 marks]

```
df.columns.tolist()
```

```
['VendorID',
 'tpep_pickup_datetime',
 'tpep_dropoff_datetime',
 'passenger_count',
 'trip_distance',
 'RatecodeID',
 'PULocationID',
 'DOLocationID',
 'payment_type',
 'fare_amount',
 'extra',
 'mta_tax',
 'tip_amount',
 'tolls_amount',
 'improvement_surcharge',
 'total_amount',
 'congestion_surcharge',
 'date',
 'hour',
 'Airport_fee']
```

3.1 General EDA: Finding Patterns and Trends

[40 marks]

3.1.1 [3 marks] Categorise the varaibles into Numerical or Categorical.

- `VendorID`: Categorical
- `tpep_pickup_datetime`: datetime
- `tpep_dropoff_datetime`: datetime
- `passenger_count`:Numerical

- `trip_distance`:Numerical
- `RatecodeID`:Ordinal Categorical
- `PULocationID`:Ordinal Categorical
- `DOLocationID`:Ordinal Categorical
- `payment_type`:Oridinal Categorical
- `pickup_hour`:Categorical
- `trip_duration`:Numerical

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`

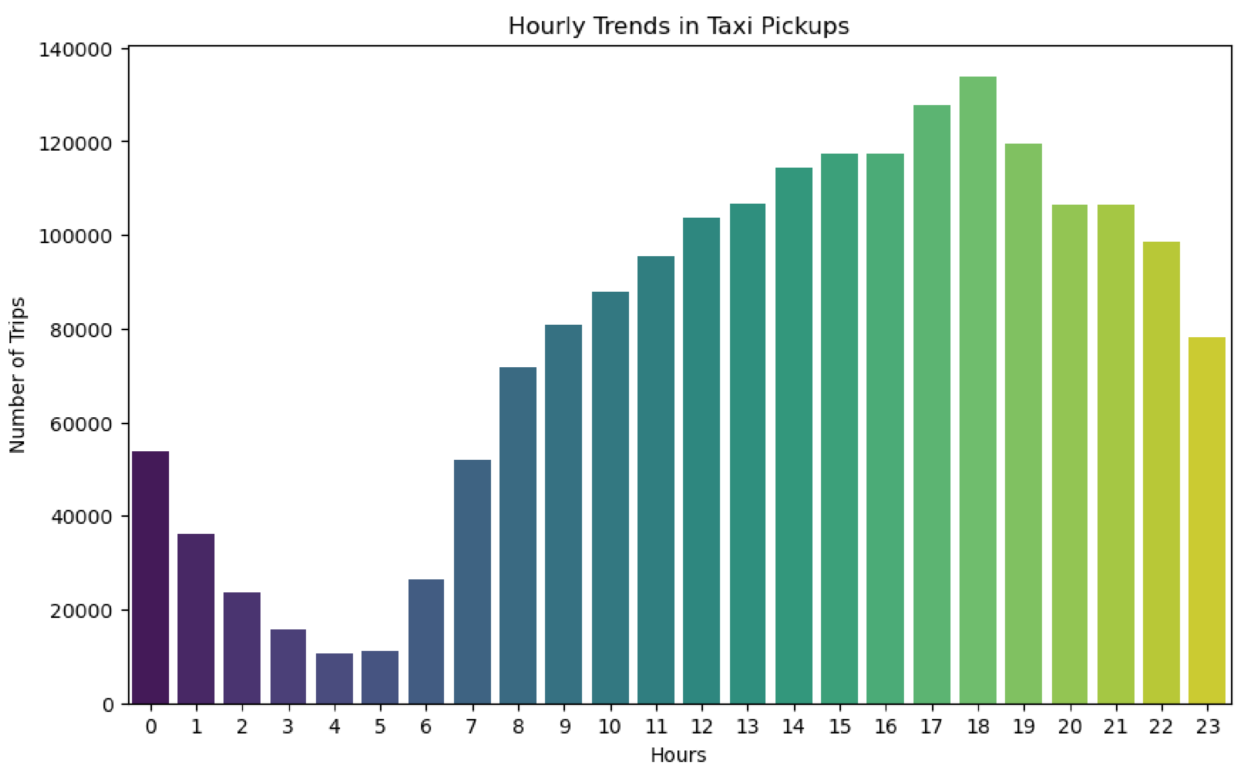
  #The monetary parameters listed are Numerical. They represent continuous monetary amounts and are used for calculations such as totals, averages, or comparisons.

Temporal Analysis

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

```
# Find and show the hourly trends in taxi pickups
#we have dervied hour column from tpep_pickup_dateeime,we can group
the count based on hour
hourly_trends=df.groupby("hour").size()
print(hourly_trends)
plt.figure(figsize=(10,6))
sns.barplot(x=hourly_trends.index, y=hourly_trends.values,
palette="viridis")
plt.xlabel("Hours")
plt.ylabel("Number of Trips")
plt.title("Hourly Trends in Taxi Pickups")
plt.show()

hour
0       53675
1       36027
2       23766
3       15675
4       10634
5       11135
6       26322
7       51822
```

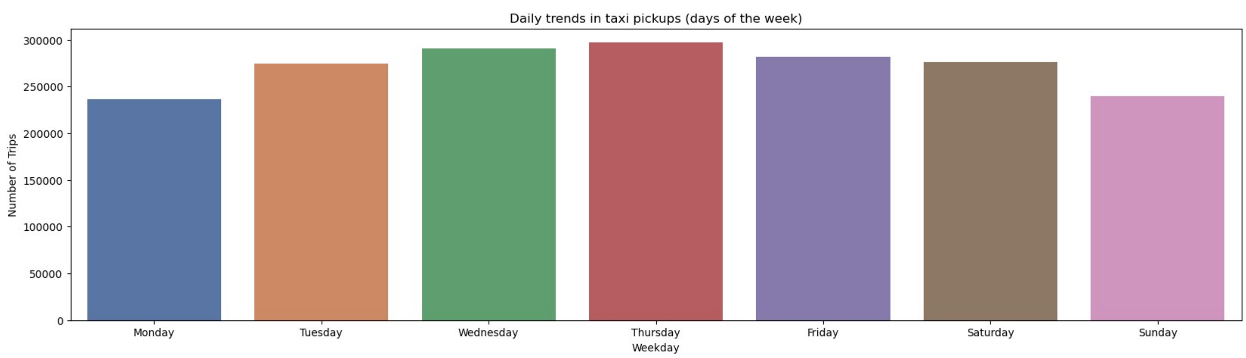
```
8        71809
9        80986
10       87909
11       95426
12      103585
13      106799
14      114453
15      117397
16      117501
17      127859
18      133934
19      119652
20      106582
21      106494
22       98682
23       78144
dtype: int64
```




```
#The graph shows that there are more number of trips during the 18th
hour(6PM),followed by 17th hour(5PM)and the least at 4AM

# Find and show the daily trends in taxi pickups (days of the week)
df["weekday"] = df["tpep_pickup_datetime"].dt.day_name()#to get the
day of week
weekdays_order = ["Monday", "Tuesday", "Wednesday", "Thursday",
```

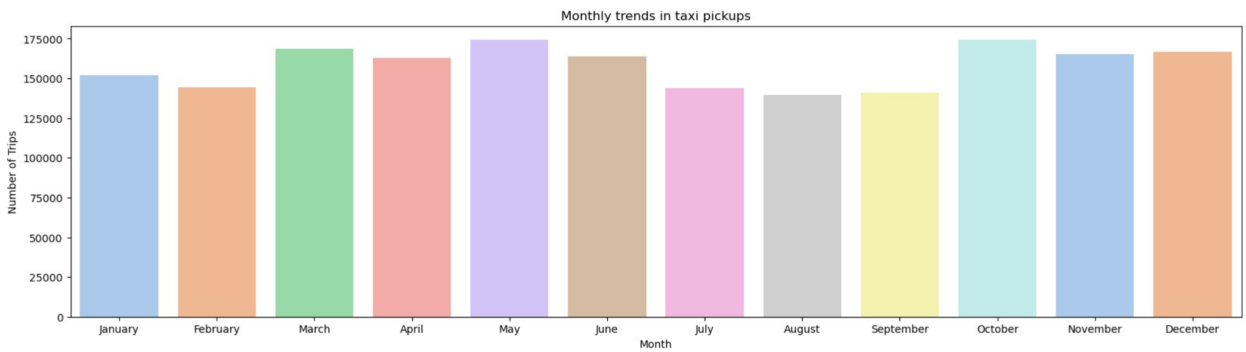
```
"Friday", "Saturday", "Sunday"]
daily_trends=df.groupby("weekday").size().reindex(weekdays_order)
print(daily_trends)
plt.figure(figsize=(20,5))
sns.barplot(x=daily_trends.index, y=daily_trends.values,
palette="deep")
plt.xlabel("Weekday")
plt.ylabel("Number of Trips")
plt.title("Daily trends in taxi pickups (days of the week)")
plt.show()
```

```
weekday
Monday       236300
Tuesday      274267
Wednesday    290493
Thursday     297287
Friday       282172
Saturday     276138
Sunday       239611
dtype: int64
```




```
The above chart depicts that there are more number of trips on
Thursday,followed by Wednesday and Monday has least trips.

# Show the monthly trends in pickups
df["Month"] = df["tpep_pickup_datetime"].dt.month_name()#to get the
month
month_order = ["January", "February", "March", "April", "May", "June",
"July","August","September","October","November","December"]
month_trends=df.groupby("Month").size().reindex(month_order)
print(month_trends)
plt.figure(figsize=(20,5))
sns.barplot(x=month_trends.index, y=month_trends.values,
palette="pastel")
plt.xlabel("Month")
plt.ylabel("Number of Trips")
plt.title("Monthly trends in taxi pickups")
plt.show()
```

```
Month
January      152075
February     144445
March        168689
April        162899
May          174057
June         163772
July         143771
August       139637
September    140867
October      174240
November     165124
December     166692
dtype: int64
```




```
The above chart depicts that there are more number of trips in the
month of October,followed by May and August has least trips.
```

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?

```
# Analyse the above parameters
df[df["fare_amount"]<=0] # 588 columns
df[df["tip_amount"]<=0] # 435873 columns
df[df["total_amount"]<=0] # 264 columns
df[df["trip_distance"]<=0] # 37657 columns

         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
77              1  2023-01-01 00:37:09   2023-01-01 00:58:16
1
118             2  2023-01-01 00:47:28   2023-01-01 00:47:32
1
127             1  2023-01-01 00:45:06   2023-01-01 00:54:06
1
236             1  2023-01-01 00:53:00   2023-01-01 01:07:31
```

```
1
280            2  2023-01-01 01:34:06   2023-01-01 01:34:14
2
...          ...                  ...                   ...
...
1896356        1  2023-09-30 23:42:07   2023-10-01 00:05:22
1
1896359        2  2023-09-30 23:15:27   2023-09-30 23:22:37
2
1896368        1  2023-09-30 23:13:43   2023-09-30 23:14:07
1
1896369        1  2023-09-30 23:59:39   2023-10-01 00:15:03
1
1896387        1  2023-09-30 23:17:34   2023-09-30 23:30:46
1

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
77                 0.0         1.0            36             7
5
118                0.0         5.0           232           232
1
127                0.0         1.0            48            48
2
236                0.0         1.0           141            79
1
280                0.0         5.0           265           265
1
...                ...         ...           ...           ...
...
1896356            0.0         1.0           255           209
5
1896359            0.0         1.0           264           264
1
1896368            0.0         5.0           148           148
1
1896369            0.0         1.0           137           249
5
1896387            0.0         1.0           231            90
5

         fare_amount  ...  tip_amount  tolls_amount
improvement_surcharge  \
77             27.50  ...        0.00           0.0
1.0
118            14.00  ...        0.00           0.0
1.0
127             8.60  ...        0.00           0.0
1.0
```

```
236            12.80  ...        4.45           0.0
1.0
280            50.00  ...       10.20           0.0
1.0
...              ...  ...         ...           ...
...
1896356        34.02  ...        0.00           0.0
1.0
1896359         7.90  ...        1.55           0.0
1.0
1896368        10.00  ...        0.00           0.0
1.0
1896369        21.50  ...        0.00           0.0
1.0
1896387        15.68  ...        0.00           0.0
1.0

         total_amount  congestion_surcharge        date  hour
Airport_fee  \
77              32.00                   2.5  2023-01-01     0
0.0
118             15.00                   0.0  2023-01-01     0
0.0
127             13.60                   2.5  2023-01-01     0
0.0
236             22.25                   2.5  2023-01-01     0
0.0
280             61.20                   0.0  2023-01-01     1
0.0
...               ...                   ...         ...   ...
...
1896356         38.02                   2.5  2023-09-30    23
0.0
1896359         14.45                   2.5  2023-09-30    23
0.0
1896368         11.00                   0.0  2023-09-30    23
0.0
1896369         25.50                   2.5  2023-09-30    23
0.0
1896387         19.68                   2.5  2023-09-30    23
0.0

          weekday      Month
77         Sunday    January
118        Sunday    January
127        Sunday    January
236        Sunday    January
280        Sunday    January
...           ...        ...
```

```
1896356  Saturday  September
1896359  Saturday  September
1896368  Saturday  September
1896369  Saturday  September
1896387  Saturday  September

[37657 rows x 22 columns]
```

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

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?

```
# Create a df with non zero entries for the selected parameters.
#Fare Amount
df[df["fare_amount"]<=0]#588 rows
#fare amount is a parameter which is calculated from the trip distance
and ratecodeid ,as we dont know the ratecode against the ratecodeid
value we can't fix these ones and as the number count is
588/1896268~0.03% we can delete it

        VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
3119           1  2023-01-01 19:16:54   2023-01-01 19:17:15
1
3966           2  2023-01-02 05:12:19   2023-01-02 05:41:45
1
5039           1  2023-01-02 13:44:07   2023-01-02 13:48:36
1
7701           2  2023-01-03 08:27:38   2023-01-03 08:59:16
1
9093           2  2023-01-03 14:24:45   2023-01-03 14:25:14
1
...          ...                  ...                   ...
...
1879753        1  2023-09-28 07:00:00   2023-09-28 07:54:54
1
1881612        2  2023-09-28 13:50:44   2023-09-28 13:50:44
1
1888608        1  2023-09-29 16:12:01   2023-09-29 16:13:12
1
1892743        1  2023-09-30 13:22:42   2023-09-30 13:33:41
1
1893750        2  2023-09-30 16:35:07   2023-09-30 16:35:13
1

        trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
```

```
3119                0.00          2.0             261             261
3
3966               17.07          3.0             142               1
2
5039                0.00          1.0             145             145
1
7701                8.34          1.0             161             244
2
9093                0.00          2.0             132             132
2
...                  ...          ...             ...             ...
...
1879753             3.00         99.0              95             216
1
1881612             0.00         99.0             233             233
2
1888608             0.00          1.0             237             237
3
1892743             2.00          5.0             142              48
3
1893750             0.00          5.0             141             141
2

         fare_amount  ...  tip_amount  tolls_amount
improvement_surcharge  \
3119             0.0  ...         0.0           0.0
0.0
3966             0.0  ...         0.0           0.0
1.0
5039             0.0  ...         0.0           0.0
0.0
7701             0.0  ...         0.0           0.0
1.0
9093             0.0  ...         0.0           0.0
1.0
...              ...  ...         ...           ...
...
1879753          0.0  ...         0.0           0.0
0.0
1881612          0.0  ...        14.2           0.0
1.0
1888608          0.0  ...         0.0           0.0
0.0
1892743          0.0  ...         0.0           0.0
1.0
1893750          0.0  ...         0.0           0.0
1.0

         total_amount  congestion_surcharge       date  hour
```

```
Airport_fee  \
3119             0.00                    0.0  2023-01-01    19
0.00
3966             1.00                    0.0  2023-01-02     5
0.00
5039             0.00                    0.0  2023-01-02    13
0.00
7701             4.00                    2.5  2023-01-03     8
0.00
9093             5.25                    2.5  2023-01-03    14
1.25
...               ...                    ...         ...   ...
...
1879753          0.00                    0.0  2023-09-28     7
0.00
1881612         18.20                    2.5  2023-09-28    13
0.00
1888608          0.00                    0.0  2023-09-29    16
0.00
1892743          1.00                    0.0  2023-09-30    13
0.00
1893750          3.50                    2.5  2023-09-30    16
0.00

          weekday      Month
3119       Sunday    January
3966       Monday    January
5039       Monday    January
7701      Tuesday    January
9093      Tuesday    January
...           ...        ...
1879753  Thursday  September
1881612  Thursday  September
1888608    Friday  September
1892743  Saturday  September
1893750  Saturday  September

[588 rows x 22 columns]
```

```
df.shape[0]#1896268
df=df[~(df["fare_amount"] <=0)] #588
df.shape[0]#1873933
```

```
1895680
```

```
#Tip_Amount
df[df["tip_amount"]<=0]#435303 rows
#tip_amount is not mandatory fee,its optional ,a passenger can pay tip
or else no ,it is valid to have a tip amount as zero ,hence  it’s not
```

```
an error or a missing value,deleting these rows can significantly
delete a good chunck of data which is approx 22%
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
0               2  2023-01-01 00:07:18   2023-01-01 00:23:15
1
2               2  2023-01-01 00:14:03   2023-01-01 00:24:36
3
3               2  2023-01-01 00:24:30   2023-01-01 00:29:55
1
10              2  2023-01-01 00:14:47   2023-01-01 00:20:18
1
16              2  2023-01-01 00:56:42   2023-01-01 01:00:25
1
...           ...                  ...                   ...
...
1896387         1  2023-09-30 23:17:34   2023-09-30 23:30:46
1
1896388         1  2023-09-30 23:41:35   2023-10-01 00:04:10
1
1896389         2  2023-09-30 23:53:03   2023-10-01 00:13:48
1
1896390         2  2023-09-30 23:37:17   2023-09-30 23:46:07
1
1896398         1  2023-09-30 23:26:31   2023-10-01 00:04:05
2

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
0                 7.74         1.0           138           256
2
2                 1.44         1.0           237           141
2
3                 0.54         1.0           143           142
2
10                0.78         1.0           237           229
2
16                0.74         1.0           229           141
1
...                ...         ...           ...           ...
...
1896387           0.00         1.0           231            90
5
1896388           2.80         1.0            79           186
3
1896389           9.65         1.0           132           225
2
1896390           0.86         1.0           164           233
2
```

```
1896398           13.20          1.0           164             14
2

         fare_amount  ...  tip_amount  tolls_amount
improvement_surcharge  \
0              32.40  ...         0.0           0.0
1.0
2              11.40  ...         0.0           0.0
1.0
3               6.50  ...         0.0           0.0
1.0
10              7.20  ...         0.0           0.0
1.0
16              5.80  ...         0.0           0.0
1.0
...              ...  ...         ...           ...
...
1896387        15.68  ...         0.0           0.0
1.0
1896388        17.70  ...         0.0           0.0
1.0
1896389        39.40  ...         0.0           0.0
1.0
1896390         9.30  ...         0.0           0.0
1.0
1896398        54.80  ...         0.0           0.0
1.0

         total_amount  congestion_surcharge        date  hour
Airport_fee  \
0               41.15                   0.0  2023-01-01     0
1.25
2               16.40                   2.5  2023-01-01     0
0.00
3               11.50                   2.5  2023-01-01     0
0.00
10              12.20                   2.5  2023-01-01     0
0.00
16              10.80                   2.5  2023-01-01     0
0.00
...               ...                   ...         ...   ...
...
1896387         19.68                   2.5  2023-09-30    23
0.00
1896388         22.70                   2.5  2023-09-30    23
0.00
1896389         43.65                   0.0  2023-09-30    23
1.75
1896390         14.30                   2.5  2023-09-30    23
```

```
0.00
1896398        59.80                  2.5  2023-09-30    23
0.00

          weekday      Month
0          Sunday    January
2          Sunday    January
3          Sunday    January
10         Sunday    January
16         Sunday    January
...           ...        ...
1896387  Saturday  September
1896388  Saturday  September
1896389  Saturday  September
1896390  Saturday  September
1896398  Saturday  September

[435303 rows x 22 columns]
```

```
df[df["total_amount"]<=0]
#we have deleted rows where fare_amount == 0, then rows with
total_amount == 0 would also be affected, since total fare is largely
dependent on fare_amount.
```

```
Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee, weekday, Month]
Index: []

[0 rows x 22 columns]
```

```
df[df["trip_distance"]<=0]#37395
df[(df["trip_distance"] == 0) & (df["PULocationID"] !=
df["DOLocationID"])]#21749 records where the pickup and drop locations
are different but there trip_distance is zero ,we can drop it.
```

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
77              1  2023-01-01 00:37:09   2023-01-01 00:58:16
1
236             1  2023-01-01 00:53:00   2023-01-01 01:07:31
1
372             1  2023-01-01 01:51:10   2023-01-01 02:19:45
1
378             1  2023-01-01 01:51:26   2023-01-01 02:16:59
1
432             2  2023-01-01 01:34:23   2023-01-01 01:50:21
```

```
2
...            ...                  ...                   ...
...
1896306         1  2023-09-30 23:58:41   2023-10-01 00:04:27
1
1896343         1  2023-09-30 23:18:31   2023-09-30 23:30:35
1
1896356         1  2023-09-30 23:42:07   2023-10-01 00:05:22
1
1896369         1  2023-09-30 23:59:39   2023-10-01 00:15:03
1
1896387         1  2023-09-30 23:17:34   2023-09-30 23:30:46
1

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
77                 0.0         1.0            36             7
5
236                0.0         1.0           141            79
1
372                0.0        99.0            74            77
1
378                0.0         1.0           246           262
5
432                0.0         1.0            43            79
1
...                ...         ...           ...           ...
...
1896306            0.0         1.0           239           143
5
1896343            0.0         1.0            43           229
5
1896356            0.0         1.0           255           209
5
1896369            0.0         1.0           137           249
5
1896387            0.0         1.0           231            90
5

         fare_amount  ...  tip_amount  tolls_amount
improvement_surcharge  \
77             27.50  ...        0.00          0.00
1.0
236            12.80  ...        4.45          0.00
1.0
372            41.20  ...        0.00          6.55
1.0
378            74.78  ...        0.00          0.00
1.0
```

```
432            13.50  ...        3.70          0.00
1.0
...              ...  ...         ...           ...
...
1896306        11.33  ...        0.00          0.00
1.0
1896343        12.55  ...        0.00          0.00
1.0
1896356        34.02  ...        0.00          0.00
1.0
1896369        21.50  ...        0.00          0.00
1.0
1896387        15.68  ...        0.00          0.00
1.0

        total_amount  congestion_surcharge        date  hour
Airport_fee  \
77             32.00                   2.5  2023-01-01     0
0.0
236            22.25                   2.5  2023-01-01     0
0.0
372            49.25                   0.0  2023-01-01     1
0.0
378            78.78                   2.5  2023-01-01     1
0.0
432            22.20                   2.5  2023-01-01     1
0.0
...              ...                   ...         ...   ...
...
1896306        15.33                   2.5  2023-09-30    23
0.0
1896343        16.55                   2.5  2023-09-30    23
0.0
1896356        38.02                   2.5  2023-09-30    23
0.0
1896369        25.50                   2.5  2023-09-30    23
0.0
1896387        19.68                   2.5  2023-09-30    23
0.0

          weekday      Month
77         Sunday    January
236        Sunday    January
372        Sunday    January
378        Sunday    January
432        Sunday    January
...           ...        ...
1896306  Saturday  September
1896343  Saturday  September
```

```
1896356   Saturday  September
1896369   Saturday  September
1896387   Saturday  September

[21749 rows x 22 columns]
```

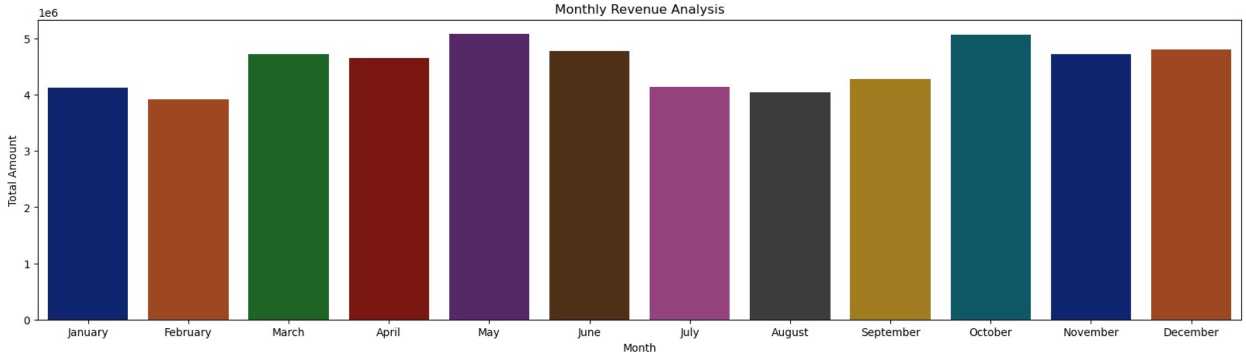
```
df.shape[0]#1895680
df = df[~((df["trip_distance"] == 0) & (df["PULocationID"] !=
df["DOLocationID"]))]#deleting 21749 records
df.shape[0]#1873931
```

```
1873931
```

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

```
# Group data by month and analyse monthly revenue
monthly_revenue = df.groupby('Month')
['total_amount'].sum().reindex(month_order)
print(monthly_revenue)
plt.figure(figsize=(20,5))
sns.barplot(x=monthly_revenue.index, y=monthly_revenue.values,
palette="dark")
plt.xlabel("Month")
plt.ylabel("Total Amount")
plt.title("Monthly Revenue Analysis")
plt.show()
```

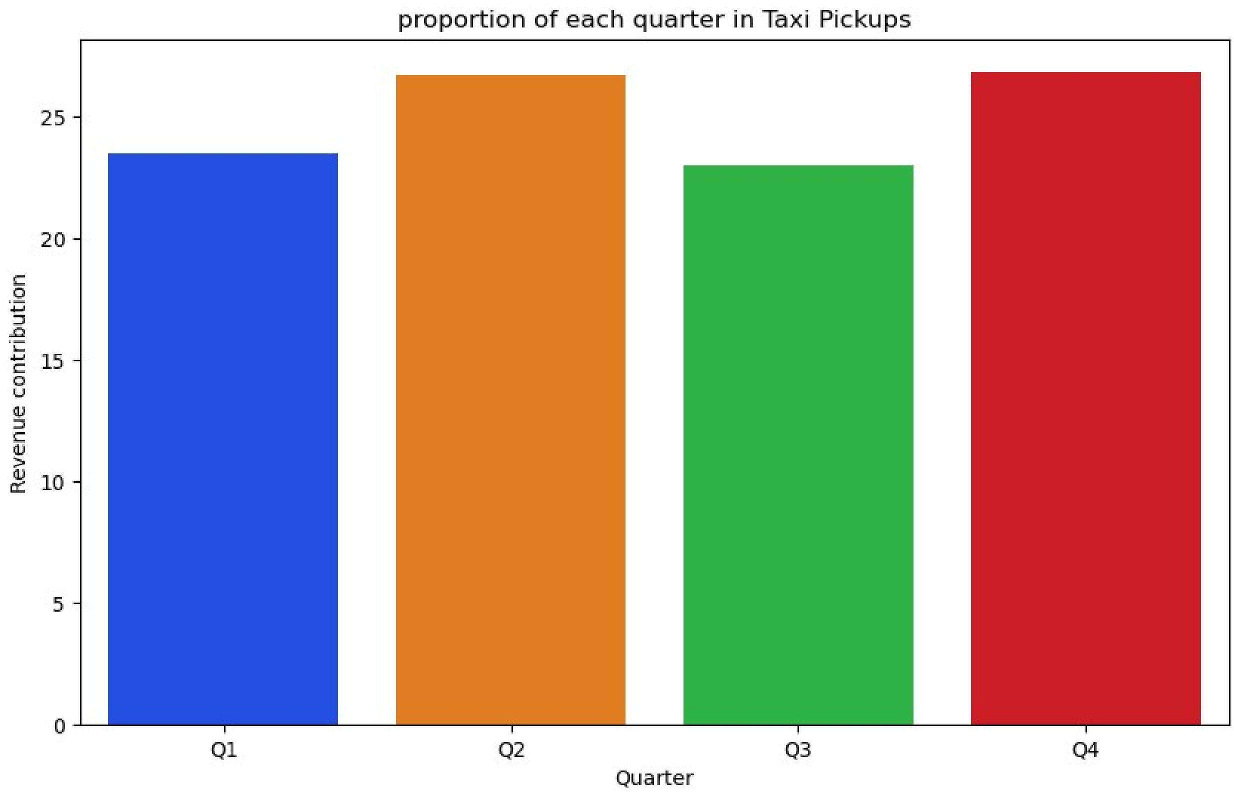
```
Month
January      4131381.44
February     3913296.87
March        4723659.81
April        4654899.33
May          5082964.13
June         4783075.39
July         4145495.23
August       4042054.16
September    4286502.36
October      5066785.10
November     4718641.44
December     4800854.19
Name: total_amount, dtype: float64
```




```
#As observed earlier in section 3.1.2, there were a higher number of
trips in the months of May and October. Consequently, the revenue
generated during these months was also higher.
```

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

```
# Calculate proportion of each quarter
df['quarter'] = 'Q' +
df['tpep_pickup_datetime'].dt.quarter.astype(str)
quarter_order = ["Q1","Q2","Q3","Q4"]
quarter_revenue=df.groupby('quarter')
['total_amount'].sum().reindex(quarter_order)
print(quarter_revenue)
quarter_proportion = (quarter_revenue / quarter_revenue.sum()) * 100
print(quarter_proportion)
plt.figure(figsize=(10,6))
sns.barplot(x=quarter_proportion.index, y=quarter_proportion.values,
palette="bright")
plt.xlabel("Quarter")
plt.ylabel("Revenue contribution")
plt.title("proportion of each quarter in Taxi Pickups")
plt.show()

quarter
Q1    12768338.12
Q2    14520938.85
Q3    12474051.75
Q4    14586280.73
Name: total_amount, dtype: float64
quarter
Q1    23.492971
Q2    26.717651
Q3    22.951502
Q4    26.837876
Name: total_amount, dtype: float64
```

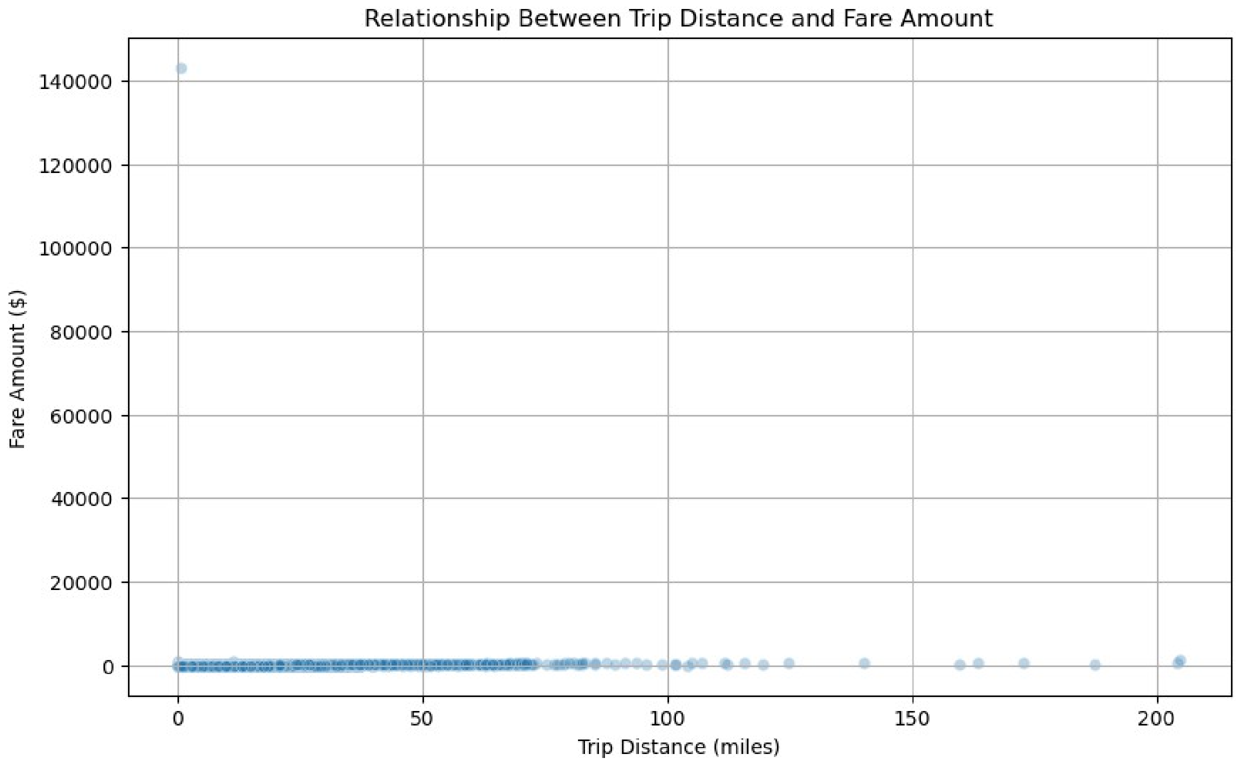



```
Quarter 4 has yelded good revenue.
```

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

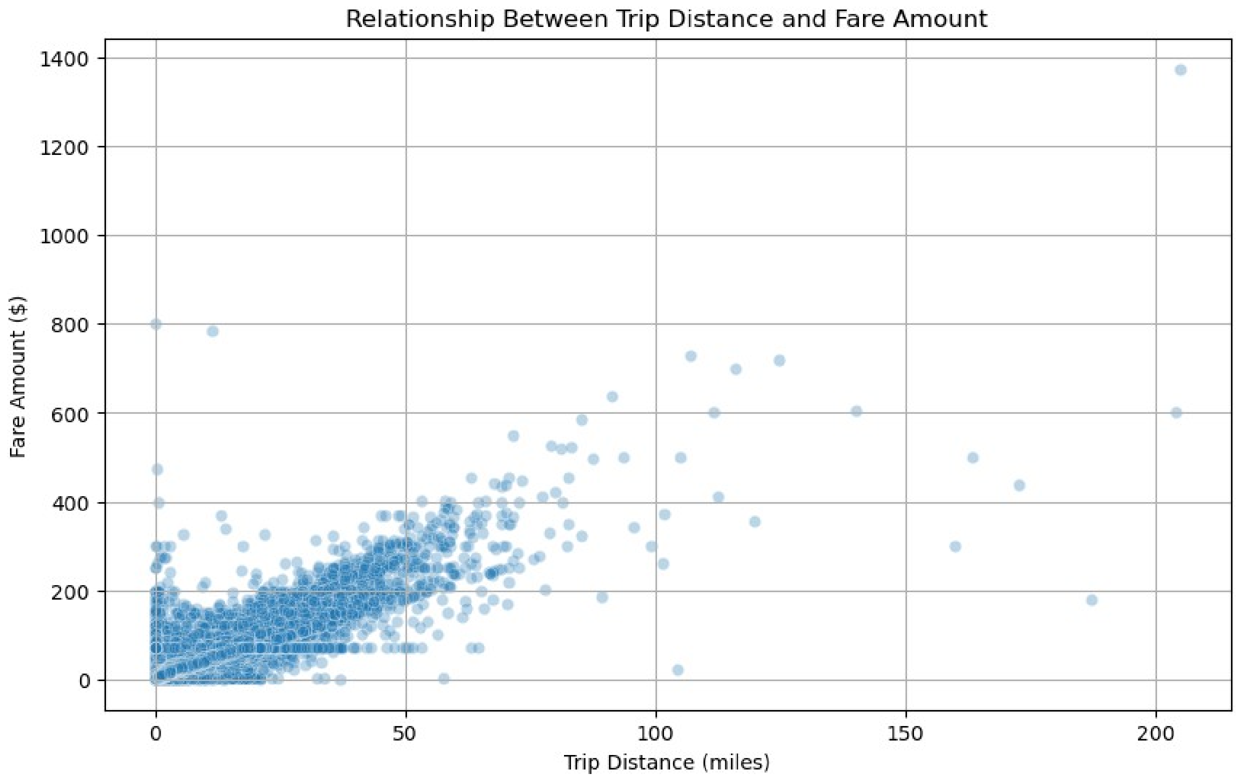
Hint: You can leave out the trips with trip_distance = 0

```
# Show how trip fare is affected by distance
trip_distance=df[~(df["trip_distance"] == 0)]
plt.figure(figsize=(10, 6))
sns.scatterplot(data=trip_distance, x="trip_distance",
y="fare_amount", alpha=0.3)
plt.title("Relationship Between Trip Distance and Fare Amount")
plt.xlabel("Trip Distance (miles)")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
```




```
#the above figure shows some extreme outliers of a fare amount so we
can delete the record then plot the graph
df[(df["fare_amount"]>=120000)]

         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
1772349         1  2023-09-05 10:16:13   2023-09-05 10:20:56
1

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
1772349            0.7         1.0           249            90
2

         fare_amount  ...  tolls_amount  improvement_surcharge
total_amount  \
1772349    143163.45  ...           0.0                    1.0
143167.45

         congestion_surcharge        date  hour  Airport_fee  weekday
\
1772349                   2.5  2023-09-05    10          0.0  Tuesday


             Month  quarter
1772349  September       Q3
```

```
[1 rows x 23 columns]

df=df[~(df["fare_amount"]>=120000)]
df[(df["fare_amount"]>=120000)]

Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee, weekday, Month,
quarter]
Index: []

[0 rows x 23 columns]

# Show how trip fare is affected by distance
trip_distance=df[~(df["trip_distance"] == 0)]
plt.figure(figsize=(10, 6))
sns.scatterplot(data=trip_distance, x="trip_distance",
y="fare_amount", alpha=0.3)
plt.title("Relationship Between Trip Distance and Fare Amount")
plt.xlabel("Trip Distance (miles)")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
correlation =
trip_distance['trip_distance'].corr(trip_distance['fare_amount'])
print(f"Correlation between trip_distance and fare_amount:
{correlation:.3f}")
```




```
Correlation between trip_distance and fare_amount: 0.943

#There’s a clear upward trend — as trip distance increases, the fare
amount generally increases. This is expected, as longer trips
typically cost more.
#Most data points are clustered between 0 and 30 miles, indicating
that the majority of taxi rides are short to medium distance.
#There are some outliers with very high fares (over $1000) and
unusually long distances (over 200 miles). These could represent rare,
special-case trips such as out-of-city airport transfers or long-
distance private hires.
```

3.1.7 [5 marks] Find and visualise the correlation between:

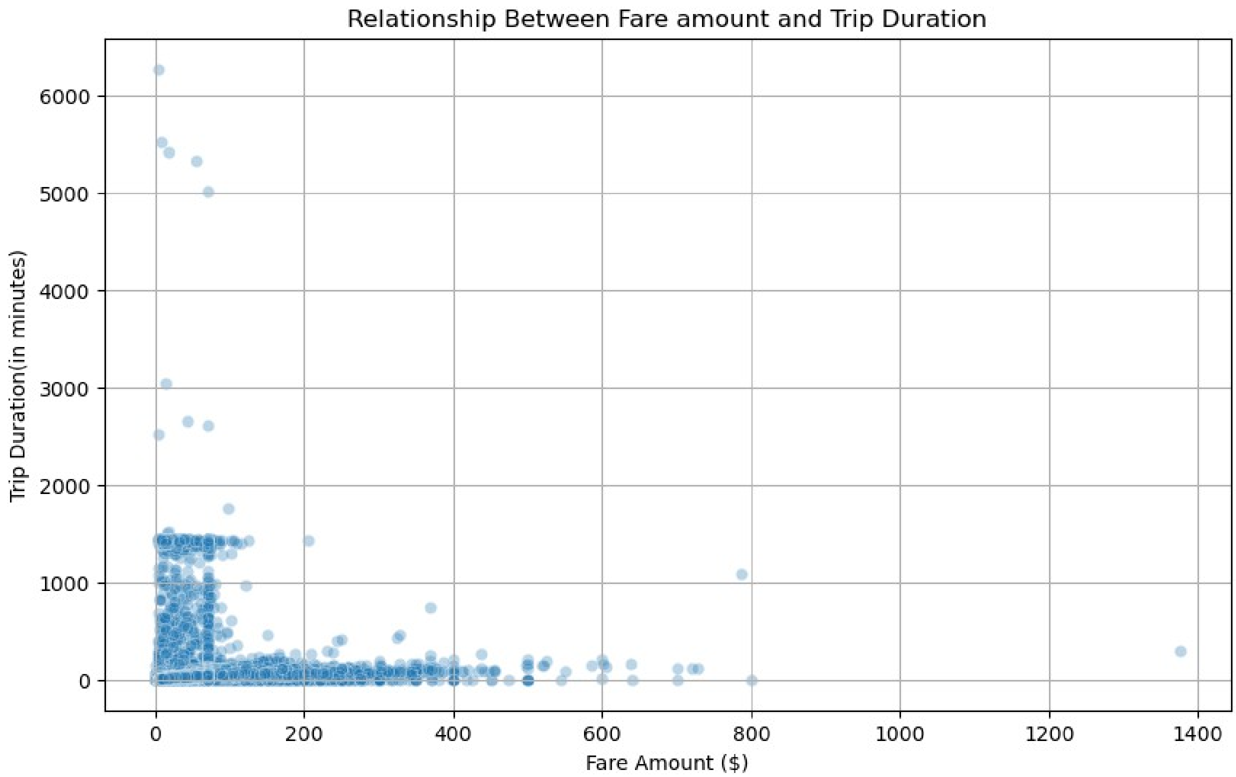
1. `fare_amount` and trip duration (pickup time to dropoff time)
2. `fare_amount` and `passenger_count`
3. `tip_amount` and `trip_distance`

```
# Show relationship between fare and trip duration
df["trip_duration"] = (df["tpep_dropoff_datetime"] -
df["tpep_pickup_datetime"]).dt.total_seconds() / 60
df[(df["trip_duration"] < 0)]#checking for neagtive trip
duration,deleting the records--114 records

         VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
```

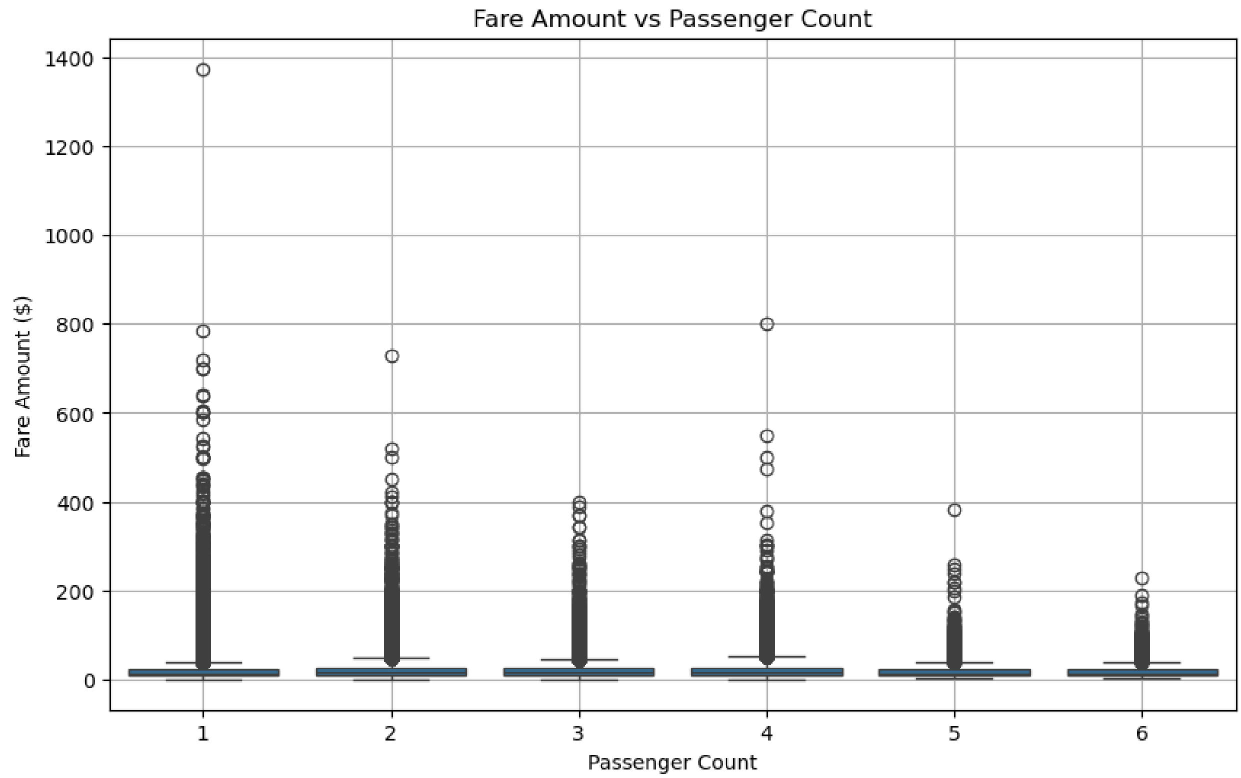
```
176789          6  2023-10-05 16:10:14   2023-10-05 16:10:03
1
183835          6  2023-10-06 19:10:49   2023-10-06 19:10:33
1
204130          6  2023-10-10 19:10:57   2023-10-10 19:10:36
1
236815          6  2023-10-16 13:10:43   2023-10-16 13:10:23
1
252924          6  2023-10-19 10:10:42   2023-10-19 10:10:22
1
...           ...                  ...                   ...
...
1811429         6  2023-09-12 06:09:25   2023-09-12 06:09:22
1
1856219         6  2023-09-20 10:09:24   2023-09-20 10:09:18
1
1856700         6  2023-09-20 12:09:49   2023-09-20 12:09:26
1
1861988         6  2023-09-21 11:09:43   2023-09-21 11:09:14
1
1876498         6  2023-09-27 16:09:51   2023-09-27 16:09:32
1

         trip_distance  RatecodeID  PULocationID  DOLocationID
payment_type  \
176789            7.50         1.0           265           196
5
183835           14.26         1.0           265           220
5
204130            3.88         1.0           265           261
5
236815            1.72         1.0           265            32
5
252924            6.04         1.0           265            75
5
...                ...         ...           ...           ...
...
1811429          17.29         1.0           265            65
5
1856219           3.74         1.0           265            92
5
1856700           5.29         1.0           265           258
5
1861988           6.60         1.0           265           259
5
1876498           2.39         1.0           265            66
5

         fare_amount  ...  improvement_surcharge  total_amount  \
```

```
176789        54.20  ...                      0.3        55.00
183835        66.89  ...                      0.3        67.69
204130        27.20  ...                      0.3        28.00
236815        15.20  ...                      0.3        16.00
252924        40.22  ...                      0.3        41.02
...             ...  ...                      ...          ...
1811429       47.09  ...                      0.3        47.89
1856219       31.20  ...                      0.3        32.00
1856700       17.38  ...                      0.3        18.18
1861988       36.14  ...                      0.3        36.94
1876498       15.28  ...                      0.3        16.08

         congestion_surcharge        date  hour  Airport_fee
weekday  \
176789                    2.5  2023-10-05    16          0.0
Thursday
183835                    2.5  2023-10-06    19          0.0
Friday
204130                    2.5  2023-10-10    19          0.0
Tuesday
236815                    2.5  2023-10-16    13          0.0
Monday
252924                    2.5  2023-10-19    10          0.0
Thursday
...                       ...         ...   ...          ...         ..
.
1811429                   2.5  2023-09-12     6          0.0
Tuesday
1856219                   2.5  2023-09-20    10          0.0
Wednesday
1856700                   2.5  2023-09-20    12          0.0
Wednesday
1861988                   2.5  2023-09-21    11          0.0
Thursday
1876498                   2.5  2023-09-27    16          0.0
Wednesday

             Month  quarter  trip_duration
176789     October       Q4      -0.183333
183835     October       Q4      -0.266667
204130     October       Q4      -0.350000
236815     October       Q4      -0.333333
252924     October       Q4      -0.333333
...            ...      ...            ...
1811429  September       Q3      -0.050000
1856219  September       Q3      -0.100000
1856700  September       Q3      -0.383333
1861988  September       Q3      -0.483333
1876498  September       Q3      -0.316667
```

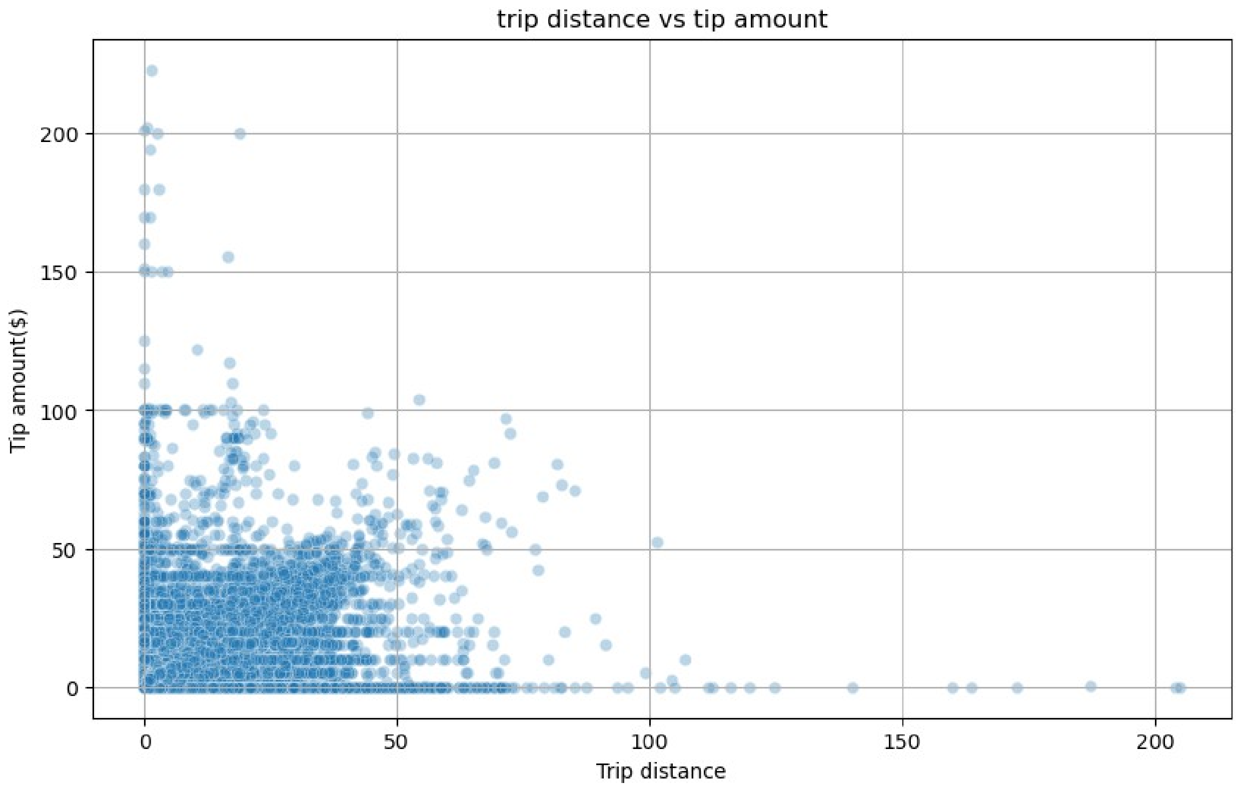
```
[114 rows x 24 columns]

df=df[~(df["trip_duration"] < 0)]
df[(df["trip_duration"] < 0)]

Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee, weekday, Month,
quarter, trip_duration]
Index: []

[0 rows x 24 columns]

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x="fare_amount", y="trip_duration",
alpha=0.3)
plt.title("Relationship Between Fare amount and Trip Duration")
plt.xlabel("Fare Amount ($)")
plt.ylabel("Trip Duration(in minutes)")
plt.grid(True)
plt.show()
correlation = df['fare_amount'].corr(df['trip_duration'])
print(f"Correlation between fare_amount and trip_duration:
{correlation:.3f}")
```




```
Correlation between fare_amount and trip_duration: 0.267

#Most trips have shorter durations (under 1000 minutes) and correspond
to lower fare amounts (under $200). This cluster shows typical,
everyday rides.

# Show relationship between fare and number of passengers
df[(df["passenger_count"] == 0)]
plt.figure(figsize=(10, 6))
sns.boxplot(x='passenger_count', y='fare_amount', data=df)
plt.title("Fare Amount vs Passenger Count")
plt.xlabel("Passenger Count")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
correlation = df['fare_amount'].corr(df['passenger_count'])
print(f"Correlation between fare_amount and passenger_count:
{correlation:.3f}")
```




```
Correlation between fare_amount and passenger_count: 0.042

#The distribution of fare amounts is still quite similar across all
valid passenger counts.The medians remain close, indicating no strong
effect of passenger count on the typical fare.

# Show relationship between tip and trip distance
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x="trip_distance", y="tip_amount", alpha=0.3)
plt.title("trip distance vs tip amount")
plt.xlabel("Trip distance")
plt.ylabel("Tip amount($)")
plt.grid(True)
plt.show()
correlation = df['trip_distance'].corr(df['tip_amount'])
print(f"Correlation between fare_amount and passenger_count:
{correlation:.3f}")
```



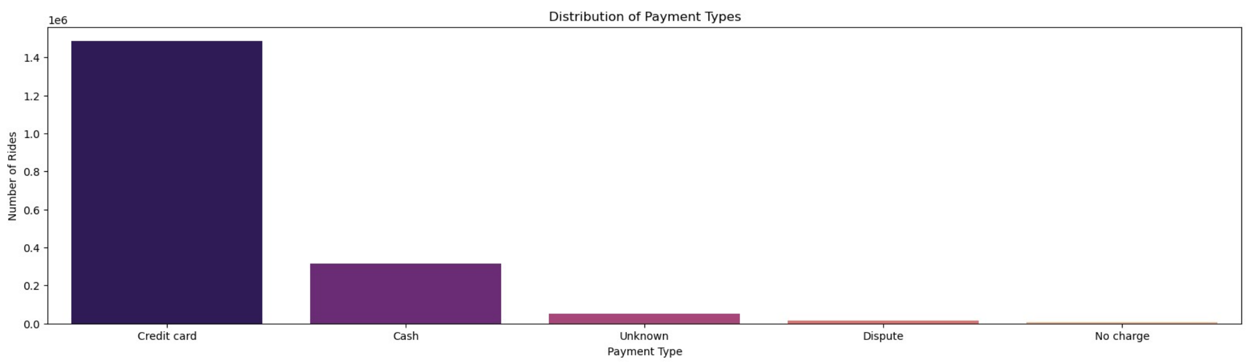

```
Correlation between fare_amount and passenger_count: 0.574

#Majority of trips fall under 50 miles in distance and $0–$50 in tip amount , indicating most trips are relatively short and modestly tipped.
```

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

```
# Analyse the distribution of different payment types (payment_type).
payment_type_labels = {
    1: 'Credit card',
    2: 'Cash',
    3: 'No charge',
    4: 'Dispute',
    5: 'Unknown'
}

df['payment_type_label'] = df['payment_type'].map(payment_type_labels)

# Count and sort
payment_counts = df['payment_type_label'].value_counts()
print(payment_counts)
# Plot
plt.figure(figsize=(20, 5))
sns.barplot(x=payment_counts.index,
```

```
y=payment_counts.values,palette="magma")
plt.title("Distribution of Payment Types")
plt.ylabel("Number of Rides")
plt.xlabel("Payment Type")
plt.show()
```

```
payment_type_label
Credit card    1486409
Cash            314751
Unknown          50675
Dispute          13396
No charge         8702
Name: count, dtype: int64
```



- 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

Requirement already satisfied: geopandas in c:\users\csg\anaconda3\
envs\py3132_env\lib\site-packages (1.0.1)
Requirement already satisfied: numpy>=1.22 in c:\users\csg\anaconda3\
envs\py3132_env\lib\site-packages (from geopandas) (2.2.4)
Requirement already satisfied: pyogrio>=0.7.2 in c:\users\csg\
anaconda3\envs\py3132_env\lib\site-packages (from geopandas) (0.10.0)
Requirement already satisfied: packaging in c:\users\csg\anaconda3\
envs\py3132_env\lib\site-packages (from geopandas) (24.2)
Requirement already satisfied: pandas>=1.4.0 in c:\users\csg\
anaconda3\envs\py3132_env\lib\site-packages (from geopandas) (2.2.3)
Requirement already satisfied: pyproj>=3.3.0 in c:\users\csg\
anaconda3\envs\py3132_env\lib\site-packages (from geopandas) (3.7.1)
Requirement already satisfied: shapely>=2.0.0 in c:\users\csg\
anaconda3\envs\py3132_env\lib\site-packages (from geopandas) (2.1.0)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\csg\
anaconda3\envs\py3132_env\lib\site-packages (from pandas>=1.4.0-
>geopandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\csg\anaconda3\
envs\py3132_env\lib\site-packages (from pandas>=1.4.0->geopandas)
(2024.1)
Requirement already satisfied: tzdata>=2022.7 in c:\users\csg\
anaconda3\envs\py3132_env\lib\site-packages (from pandas>=1.4.0-
>geopandas) (2023.3)
Requirement already satisfied: certifi in c:\users\csg\anaconda3\envs\
py3132_env\lib\site-packages (from pyogrio>=0.7.2->geopandas)
(2025.1.31)
Requirement already satisfied: six>=1.5 in c:\users\csg\anaconda3\
envs\py3132_env\lib\site-packages (from python-dateutil>=2.8.2-
>pandas>=1.4.0->geopandas) (1.16.0)
```

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

```
import geopandas as gpd


# Read the shapefile using geopandas
zones = gpd.read_file(r'C:\Users\CSG\Desktop\upgrad\EDA-Assignment\
```

```
Datasets and Dictionary-NYC\Datasets and Dictionary\taxi_zones\
taxi_zones.shp')
zones.head()
```

```
   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.

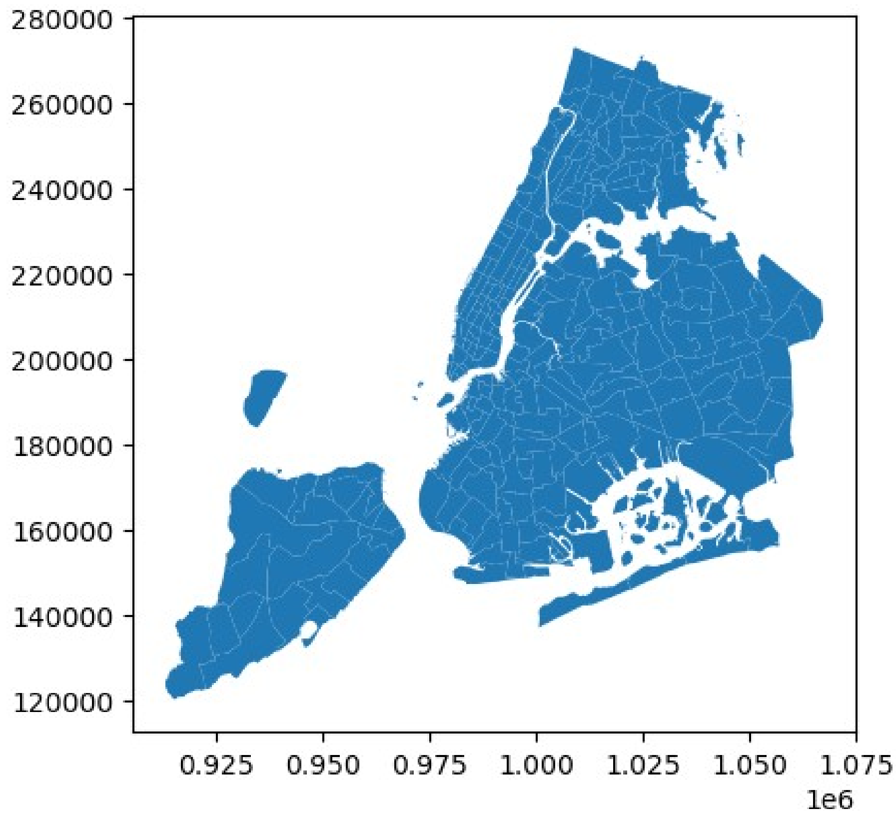
The geometric parameters like shape length, shape area and geometry are used to plot the zones on a map.

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

```
print(zones.info())
zones = gpd.GeoDataFrame(zones, geometry='geometry')
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

<Axes: >
```



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

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

```
# Merge zones and trip records using locationID and PULocationID
df=pd.merge(left=df,right=zones, how='left', left_on='PULocationID',
right_on='LocationID')
df.head()

   VendorID tpep_pickup_datetime tpep_dropoff_datetime
passenger_count  \
0         2  2023-01-01 00:07:18   2023-01-01 00:23:15
1
1         2  2023-01-01 00:16:41   2023-01-01 00:21:46
2
2         2  2023-01-01 00:14:03   2023-01-01 00:24:36
```

```
3
3         2  2023-01-01 00:24:30   2023-01-01 00:29:55
1
4         2  2023-01-01 00:43:00   2023-01-01 01:01:00
1

   trip_distance  RatecodeID  PULocationID  DOLocationID  payment_type
\
0           7.74         1.0           138           256             2

1           1.24         1.0           161           237             1

2           1.44         1.0           237           141             2

3           0.54         1.0           143           142             2

4          19.24         1.0            66           107             5


   fare_amount  ...  quarter  trip_duration  payment_type_label
OBJECTID  \
0        32.40  ...       Q1      15.950000                Cash
138.0
1         7.90  ...       Q1       5.083333         Credit card
161.0
2        11.40  ...       Q1      10.550000                Cash
237.0
3         6.50  ...       Q1       5.416667                Cash
143.0
4        25.64  ...       Q1      18.000000             Unknown
66.0

   Shape_Leng  Shape_Area                   zone LocationID    borough
\
0    0.107467    0.000537      LaGuardia Airport      138.0     Queens

1    0.035804    0.000072         Midtown Center      161.0  Manhattan

2    0.042213    0.000096  Upper East Side South      237.0  Manhattan

3    0.054180    0.000151    Lincoln Square West      143.0  Manhattan

4    0.054633    0.000108     DUMBO/Vinegar Hill       66.0   Brooklyn


                                            geometry
0  MULTIPOLYGON (((1019904.219 225677.983, 102031...
1  POLYGON ((991081.026 214453.698, 990952.644 21...
2  POLYGON ((993633.442 216961.016, 993507.232 21...
3  POLYGON ((989338.1 223572.253, 989368.225 2235...
4  POLYGON ((990055.507 196472.349, 990004.46 196...
```

```
[5 rows x 32 columns]
```

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

```
# Group data by location and calculate the number of trips
trip_count =
df.groupby("LocationID").size().reset_index(name="trip_count")
print(trip_count)
```

```
     LocationID  trip_count
0           1.0         203
1           2.0           2
2           3.0          35
3           4.0        2238
4           5.0          10
..          ...         ...
250       259.0          45
251       260.0         354
252       261.0        9844
253       262.0       24999
254       263.0       35921

[255 rows x 2 columns]
```

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.

```
# Merge trip counts back to the zones GeoDataFrame

zones=pd.merge(left=trip_count,right=zones, how='left',
left_on='LocationID', right_on='LocationID')
zones.head()
```

```
   LocationID  trip_count  OBJECTID  Shape_Leng  Shape_Area  \
0         1.0         203         1    0.116357    0.000782
1         2.0           2         2    0.433470    0.004866
2         3.0          35         3    0.084341    0.000314
3         4.0        2238         4    0.043567    0.000112
4         5.0          10         5    0.092146    0.000498

                      zone        borough  \
0           Newark Airport            EWR
1              Jamaica Bay         Queens
2  Allerton/Pelham Gardens          Bronx
3            Alphabet City      Manhattan
4            Arden Heights  Staten Island

                                            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...
```

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)

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.

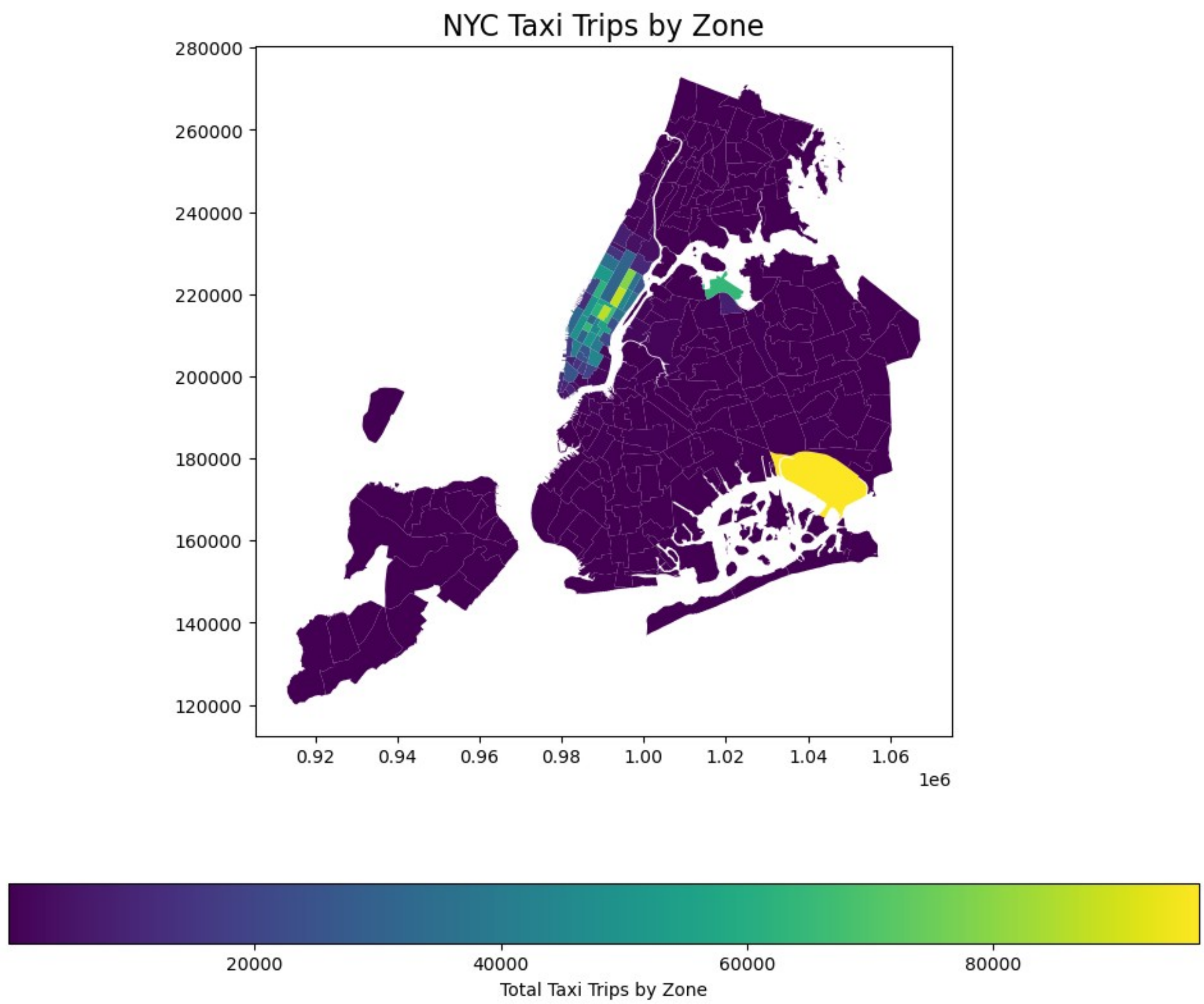
You can define the following parameters in the `zones.plot()` method:

```
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

```
# Define figure and axis
fig, ax = plt.subplots(1, 1, figsize = (12, 10))
# Plot the map and display it
zones = gpd.GeoDataFrame(zones, geometry='geometry')
zones.plot(
    column='trip_count',
    cmap='viridis',
    linewidth=0.8,
    ax=ax,
    legend=True,
    legend_kwds={'label': "Total Taxi Trips by Zone", 'orientation':
"horizontal"}
)
ax.set_title("NYC Taxi Trips by Zone", fontsize=16)
plt.show()
```




```
# can you try displaying the zones DF sorted by the number of trips?
zones_sorted = zones.sort_values(by='trip_count', ascending=False)
print(zones_sorted)
```

```
     LocationID  trip_count  OBJECTID  Shape_Leng  Shape_Area  \
125       132.0       96691       132    0.245479    0.002038   
229       237.0       88166       237    0.042213    0.000096   
154       161.0       86914       161    0.035804    0.000072   
228       236.0       79176       236    0.044252    0.000103   
155       162.0       66342       162    0.035270    0.000048   
..          ...         ...       ...         ...         ...   
82         84.0           1        84    0.233624    0.002074   
108       115.0           1       115    0.116169    0.000373   
165       172.0           1       172    0.118476    0.000658   
213       221.0           1       221    0.166218    0.000890   
237       245.0           1       245    0.095983    0.000466   

                                      zone        borough  \
125                            JFK Airport         Queens  
```

```
229               Upper East Side South      Manhattan
154                      Midtown Center      Manhattan
228               Upper East Side North      Manhattan
155                        Midtown East      Manhattan
..                                  ...            ...
82   Eltingville/Annadale/Prince's Bay  Staten Island
108                 Grymes Hill/Clifton  Staten Island
165              New Dorp/Midland Beach  Staten Island
213                           Stapleton  Staten Island
237                      West Brighton  Staten Island

                                               geometry
125  MULTIPOLYGON (((1032791.001 181085.006, 103283...
229  POLYGON ((993633.442 216961.016, 993507.232 21...
154  POLYGON ((991081.026 214453.698, 990952.644 21...
228  POLYGON ((995940.048 221122.92, 995812.322 220...
155  POLYGON ((992224.354 214415.293, 992096.999 21...
..                                                ...
82   POLYGON ((939754.454 131548.91, 939802.804 131...
108  POLYGON ((961850.466 167915.309, 961831.926 16...
165  POLYGON ((960204.812 146820.751, 960103.437 14...
213  POLYGON ((963349.728 171627.581, 963397.759 17...
237  POLYGON ((957085.564 172591.26, 957142.385 172...

[256 rows x 8 columns]
```

```
zones.sort_values(by='trip_count', ascending=True)
```

```
     PULocationID  passenger_count  LocationID  trip_count
OBJECTID  \
26             27         1.000000        27.0         1.0      27.0

83             84         1.000000        84.0         1.0      84.0

108           115         1.000000       115.0         1.0     115.0

165           172         1.000000       172.0         1.0     172.0

236           245         1.000000       245.0         1.0     245.0

..            ...              ...         ...         ...       ...

228           237         1.336469       237.0     88166.0     237.0

125           132         1.497062       132.0     96691.0     132.0

56             57         1.000000         NaN         NaN       NaN

255           264         1.345379         NaN         NaN       NaN

256           265         1.216643         NaN         NaN       NaN
```

```
     Shape_Leng  Shape_Area                               zone  \
26     0.202509    0.001341  Breezy Point/Fort Tilden/Riis Beach
83     0.233624    0.002074    Eltingville/Annadale/Prince's Bay
108    0.116169    0.000373                 Grymes Hill/Clifton
165    0.118476    0.000658              New Dorp/Midland Beach
236    0.095983    0.000466                      West Brighton
..          ...         ...                                 ...
228    0.042213    0.000096             Upper East Side South
125    0.245479    0.002038                         JFK Airport
56          NaN         NaN                                 NaN
255         NaN         NaN                                 NaN
256         NaN         NaN                                 NaN

           borough                                           geometry

26          Queens  POLYGON ((1021692.969 147138.664, 1021883.624 ...

83   Staten Island  POLYGON ((939754.454 131548.91, 939802.804 131...

108  Staten Island  POLYGON ((961850.466 167915.309, 961831.926 16...

165  Staten Island  POLYGON ((960204.812 146820.751, 960103.437 14...

236  Staten Island  POLYGON ((957085.564 172591.26, 957142.385 172...

..             ...                                                ...

228      Manhattan  POLYGON ((993633.442 216961.016, 993507.232 21...

125         Queens  MULTIPOLYGON (((1032791.001 181085.006, 103283...

56             NaN                                               None

255            NaN                                               None

256            NaN                                               None


[257 rows x 10 columns]
```

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*)

```
# Find routes which have the slowest speeds at different times of the day
#grouping the pickuplocation and droplocation and hour and calculating the avg trip_distance and avg trip_duration
route_hour=df.groupby(['PULocationID', 'DOLocationID', 'hour']).agg({
    'trip_distance': 'mean',
    'trip_duration': 'mean'
}).reset_index()
route_hour['avg_speed']=route_hour['trip_distance']/route_hour['trip_duration']
#route_hour.sort_values(by='avg_speed').head(200)
route_hour[route_hour['PULocationID'] !=
route_hour['DOLocationID']].sort_values(by='avg_speed').head(200)
```

```
        PULocationID  DOLocationID  hour  trip_distance  trip_duration  \
107868           232            65    13       0.490000    5522.433333

120895           243           264    17       0.180000    1389.550000

9374              43            10    10       0.020000      53.966667

36261            100             7     8       0.220000     334.433333

7514              40            65    21       1.120000    1434.433333

...              ...           ...   ...            ...            ...

93905            193           140    10       0.400000      38.816667

36931            100            98    21       8.920000     865.066667
```

```
95043                209                25    22          3.054000     296.033333

31426                 88                 1    17         14.850000    1435.200000

123724               249                13     4          2.238571     212.161905


        avg_speed
107868   0.000089
120895   0.000130
9374     0.000371
36261    0.000658
7514     0.000781
...           ...
93905    0.010305
36931    0.010311
95043    0.010316
31426    0.010347
123724   0.010551

[200 rows x 6 columns]
```

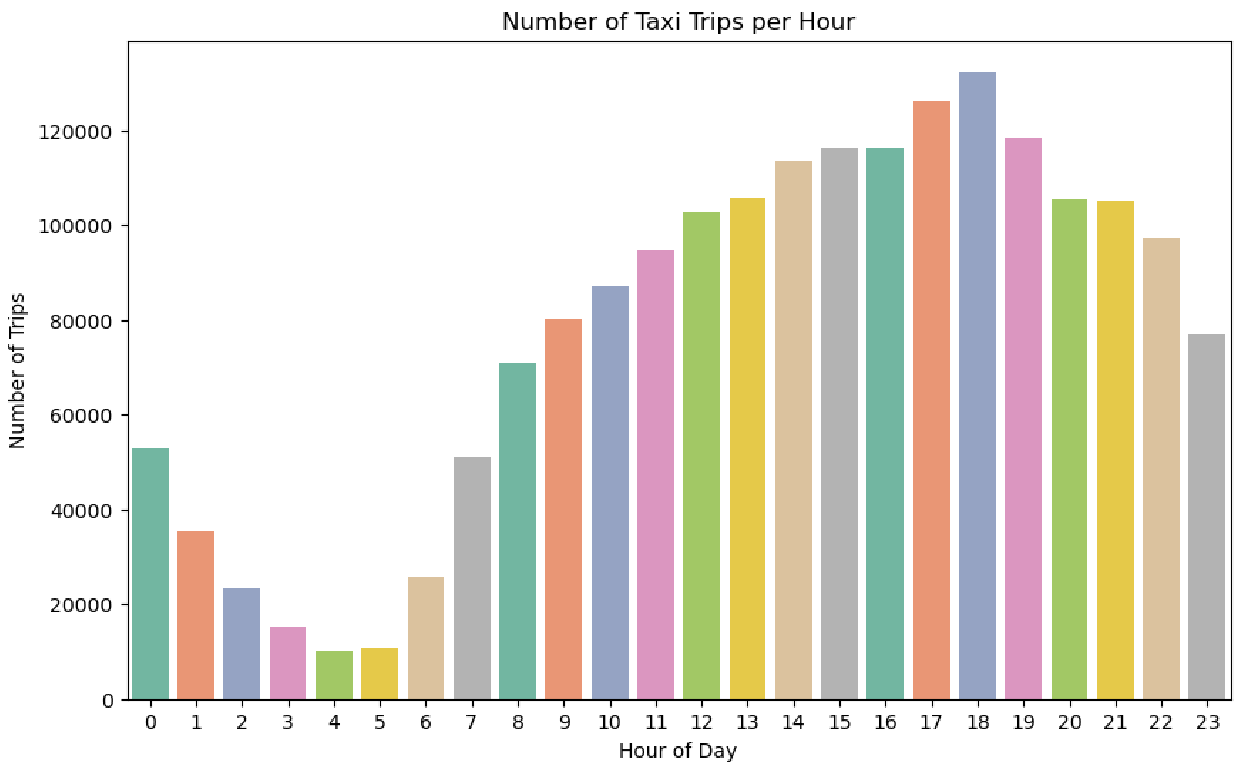
How does identifying high-traffic, high-demand routes help us?

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.

```
# Visualise the number of trips per hour and find the busiest hour
trips_per_hour = df['hour'].value_counts().sort_index()
print(trips_per_hour)
plt.figure(figsize=(10, 6))
sns.barplot(x=trips_per_hour.index,
y=trips_per_hour.values,palette="Set2")
plt.title("Number of Taxi Trips per Hour")
plt.xlabel("Hour of Day")
plt.ylabel("Number of Trips")
plt.show()
#busiest hour using idmax() function
print(f"Busiest hour of the day is: {trips_per_hour.idxmax()}:00 with
number of trips: {trips_per_hour.max()}")
```

```
hour
0      52731
1      35377
2      23279
3      15326
4      10261
5      10827
6      25814
```

```
7        50940
8        70781
9        80237
10       87240
11       94618
12      102653
13      105774
14      113431
15      116304
16      116395
17      126355
18      132307
19      118306
20      105485
21      105264
22       97326
23       76902
Name: count, dtype: int64
```




```
Busiest hour of the day is: 18:00 with number of trips: 132307
```

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

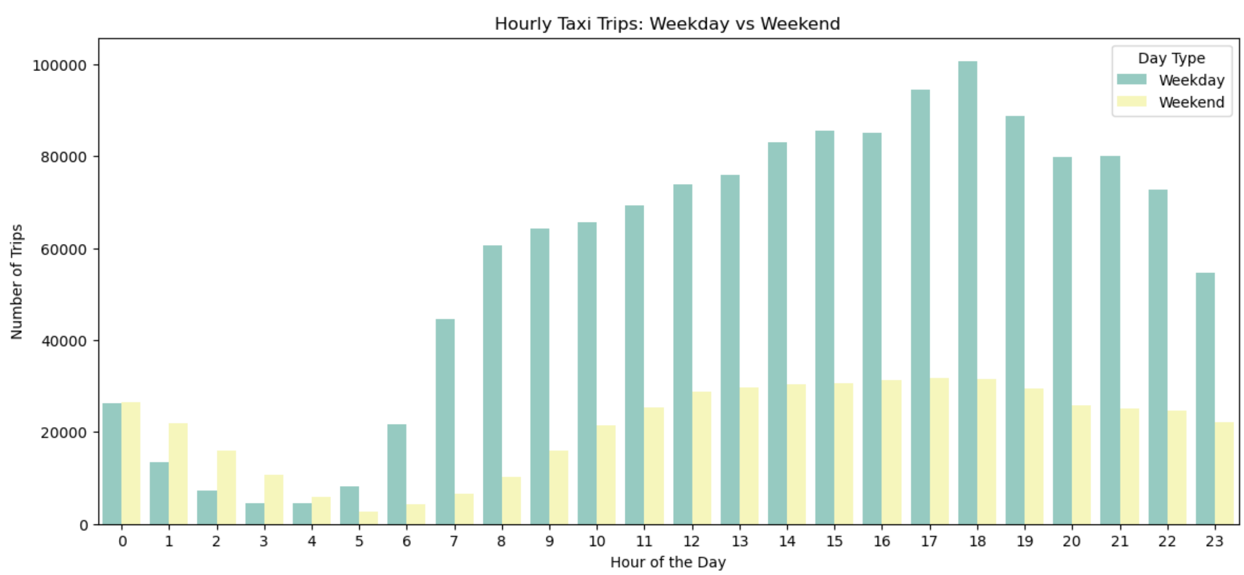
3.2.3 [2 mark] Find the actual number of trips in the five busiest hours

```
# Scale up the number of trips

# Fill in the value of your sampling fraction and use that to scale up the numbers
sample_fraction =0.05#[5%]
scaled_trips=trips_per_hour/sample_fraction
scaled_trips.sort_values(ascending=False).head(5)
```

```
hour
18    2646140.0
17    2527100.0
19    2366120.0
16    2327900.0
15    2326080.0
Name: count, dtype: float64
```

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

```
# Compare traffic trends for the week days and weekends
df['day_type'] = df['weekday'].apply(lambda x: 'Weekend' if x in ['Saturday', 'Sunday'] else 'Weekday')
hour_daytype = df.groupby(['hour', 'day_type']).size().reset_index(name='num_trips')
plt.figure(figsize=(14, 6))
sns.barplot(x='hour', y='num_trips', hue='day_type', data=hour_daytype, palette='Set3')
plt.title("Hourly Taxi Trips: Weekday vs Weekend")
plt.xlabel("Hour of the Day")
plt.ylabel("Number of Trips")
plt.legend(title='Day Type')
plt.show()
```

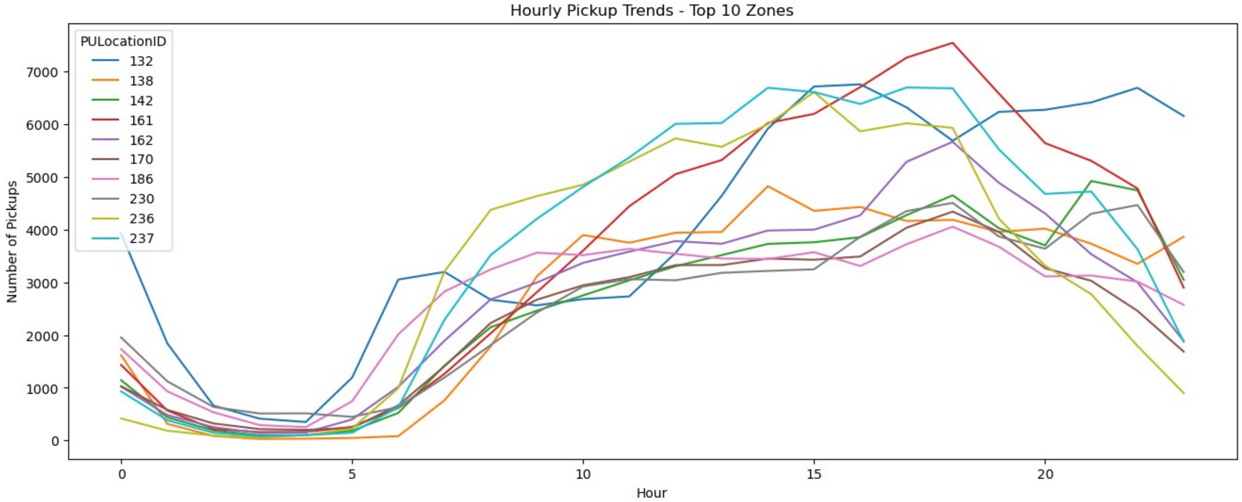


```
#There's a clear peak in the evening hours (around 17:00–19:00), likely due to post-work commute or travel,Overall, weekdays show a gradual rise from 6 AM, peaking in the late afternoon/evening.
#Trip counts are more evenly distributed on weekends, with moderate activity throughout the day,Late night and early morning hours (12 AM – 3 AM) have higher trip volumes than weekdays, possibly reflecting nightlife or late outings.
```

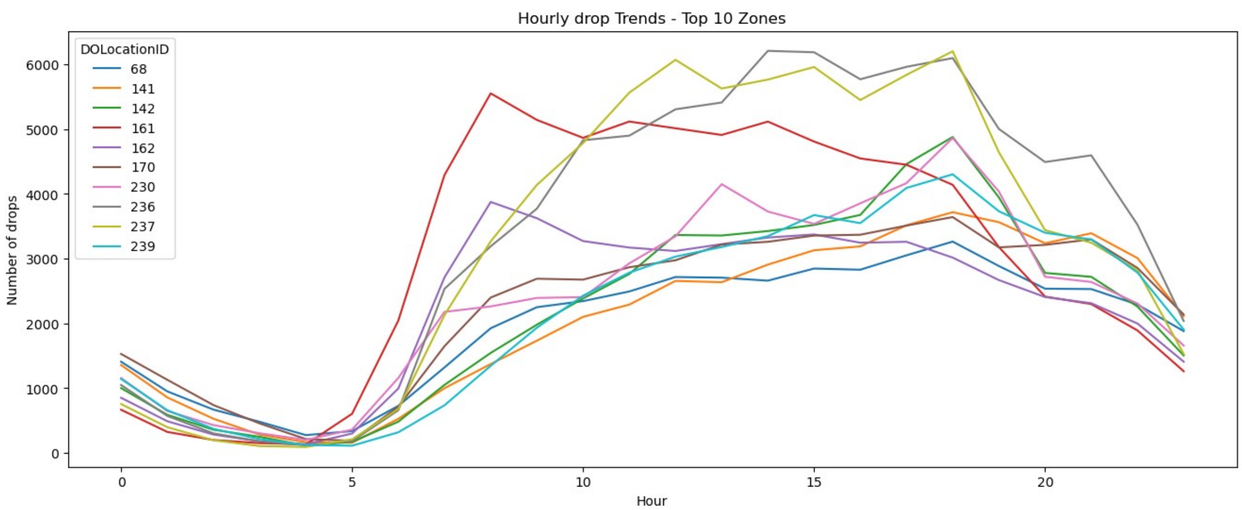
What can you infer from the above patterns? How will finding busy and quiet hours for each day help us?

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.

```
# Find top 10 pickup and dropoff zones
# Find top 10 pickup and dropoff zones
top_pu_zones = df['PULocationID'].value_counts().head(10).index
#Find top 10 dropoff zones
top_do_zones = df['DOLocationID'].value_counts().head(10).index

pickup_df = df[df['PULocationID'].isin(top_pu_zones)]
dropoff_df = df[df['DOLocationID'].isin(top_do_zones)]

# Group pickup and dropoff data by hour and location
pickup_trends = pickup_df.groupby(['hour',
'PULocationID']).size().reset_index(name='pickup_count')
dropoff_trends = dropoff_df.groupby(['hour',
'DOLocationID']).size().reset_index(name='dropoff_count')

#Pickup trend
plt.figure(figsize=(16, 6))
sns.lineplot(data=pickup_trends, x='hour', y='pickup_count',
hue='PULocationID', palette='tab10')
plt.title("Hourly Pickup Trends - Top 10 Zones")
plt.xlabel("Hour")
plt.ylabel("Number of Pickups")
plt.legend(title='PULocationID')
plt.show()
```




```
#drop trend
plt.figure(figsize=(16, 6))
sns.lineplot(data=dropoff_trends, x='hour', y='dropoff_count',
hue='DOLocationID', palette='tab10')
plt.title("Hourly drop Trends - Top 10 Zones")
plt.xlabel("Hour")
plt.ylabel("Number of drops")
plt.legend(title='DOLocationID')
plt.show()
```



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.

```
# Find the top 10 and bottom 10 pickup/dropoff ratios

pickup_counts = df['PULocationID'].value_counts()
dropoff_counts = df['DOLocationID'].value_counts()
```

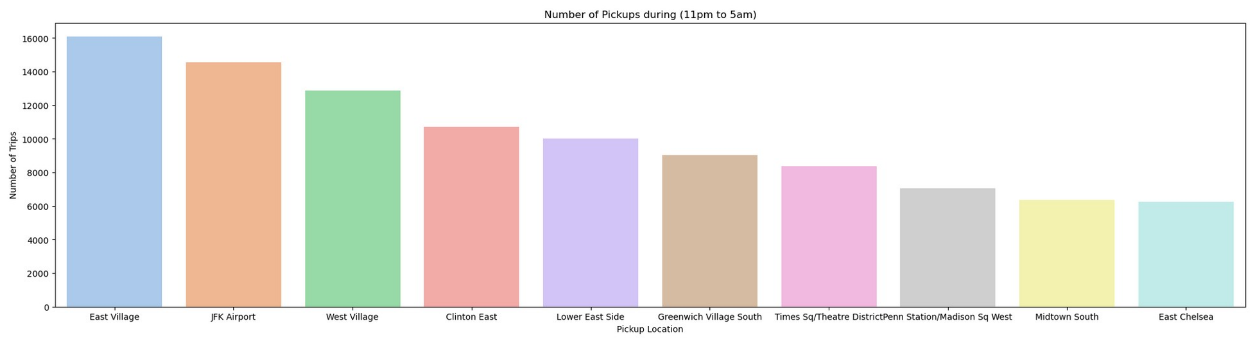
```python
# Combine into a single DataFrame
zone_stats = pd.DataFrame({
    'pickup_count': pickup_counts,
    'dropoff_count': dropoff_counts
}).fillna(0)  # Fill missing values with 0

# Calculate pickup/dropoff ratio
zone_stats['pickup_dropoff_ratio'] = zone_stats['pickup_count'] /
(zone_stats['dropoff_count'] + 1)  # +1 to avoid division by zero

# Sort and get top 10 and bottom 10
top_10 = zone_stats.sort_values(by='pickup_dropoff_ratio',
ascending=False).head(10)
bottom_10 = zone_stats.sort_values(by='pickup_dropoff_ratio').head(10)

print("Top 10 Pickup/Dropoff Ratios:")
print(top_10)

print("\nBottom 10 Pickup/Dropoff Ratios:")
print(bottom_10)
```

```
Top 10 Pickup/Dropoff Ratios:
     pickup_count  dropoff_count  pickup_dropoff_ratio
70         8343.0          990.0              8.418769
132       96691.0        22604.0              4.277417
138       64318.0        24445.0              2.631023
199           2.0            0.0              2.000000
186       63911.0        40851.0              1.564452
114       24774.0        18007.0              1.375722
43        31134.0        22725.0              1.369973
249       41386.0        31111.0              1.330226
162       66342.0        53261.0              1.245578
161       86914.0        73136.0              1.188373

Bottom 10 Pickup/Dropoff Ratios:
     pickup_count  dropoff_count  pickup_dropoff_ratio
30            0.0           18.0              0.000000
176           0.0           12.0              0.000000
99            0.0            3.0              0.000000
27            1.0           38.0              0.025641
221           1.0           36.0              0.027027
245           1.0           31.0              0.031250
1           203.0         5720.0              0.035483
115           1.0           24.0              0.040000
257          36.0          786.0              0.045743
46            3.0           49.0              0.060000
```

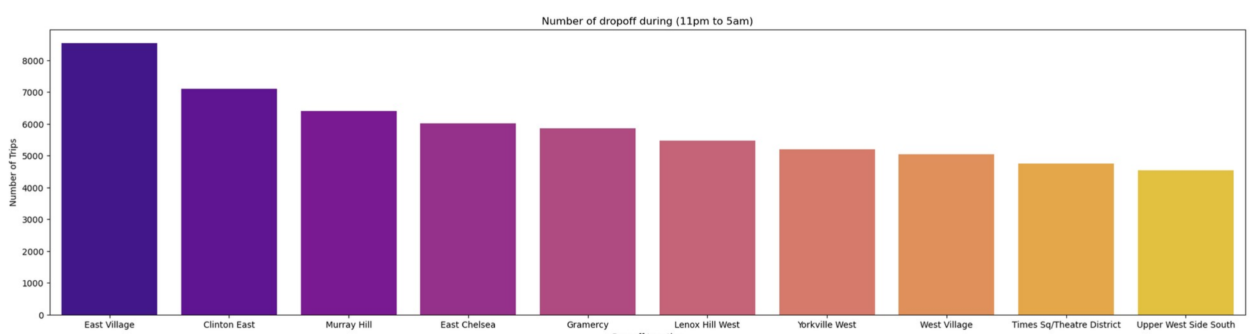
3.2.7 [3 marks] Identify zones with high pickup and dropoff traffic during night hours (11PM to 5AM)

```
# 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
night_hours = df[(df["hour"] == 23) | (df["hour"] <= 5)]

# Get top 10 pickup zone IDs by frequency
top_pickups =
night_hours['PULocationID'].value_counts().head(10).reset_index()
top_pickups.columns = ['PULocationID', 'pickup_count']

# Merge with zone names
top_pickups = top_pickups.merge(zones[['LocationID', 'zone']],
left_on='PULocationID', right_on='LocationID', how='left')

# Display result
print("Top Pickups during during (11pm to 5am)")
print(top_pickups[['PULocationID', 'zone', 'pickup_count']])


plt.figure(figsize=(25, 6))
sns.barplot(x=top_pickups.zone,
y=top_pickups.pickup_count,palette="pastel")
plt.title("Number of Pickups during (11pm to 5am)")
plt.xlabel("Pickup Location")
plt.ylabel("Number of Trips")
plt.show()



# Get top 10 drop zone IDs by frequency
top_dropoff =
night_hours['DOLocationID'].value_counts().head(10).reset_index()
top_dropoff.columns = ['DOLocationID', 'drop_count']

top_dropoff = top_dropoff.merge(zones[['LocationID', 'zone']],
left_on='DOLocationID', right_on='LocationID', how='left')

# Display result
print(top_dropoff[['DOLocationID', 'zone', 'drop_count']])

plt.figure(figsize=(25, 6))
sns.barplot(x=top_dropoff.zone,
y=top_dropoff.drop_count,palette="plasma")
plt.title("Number of dropoff during (11pm to 5am)")
plt.xlabel("Dropoff Location")
plt.ylabel("Number of Trips")
plt.show()
```

```
Top Pickups during during (11pm to 5am)
   PULocationID                         zone  pickup_count
0            79                 East Village         16098
1           132                  JFK Airport         14548
2           249                 West Village         12871
3            48                 Clinton East         10696
4           148              Lower East Side         10002
5           114      Greenwich Village South          9013
6           230    Times Sq/Theatre District          8380
7           186  Penn Station/Madison Sq West         7059
8           164                Midtown South          6344
9            68                 East Chelsea          6242
```




```
   DOLocationID                       zone  drop_count
0            79               East Village        8544
1            48               Clinton East        7100
2           170                Murray Hill        6395
3            68               East Chelsea        6005
4           107                   Gramercy        5851
5           141            Lenox Hill West        5462
6           263             Yorkville West        5202
7           249               West Village        5050
8           230  Times Sq/Theatre District        4759
9           239      Upper West Side South        4530
```

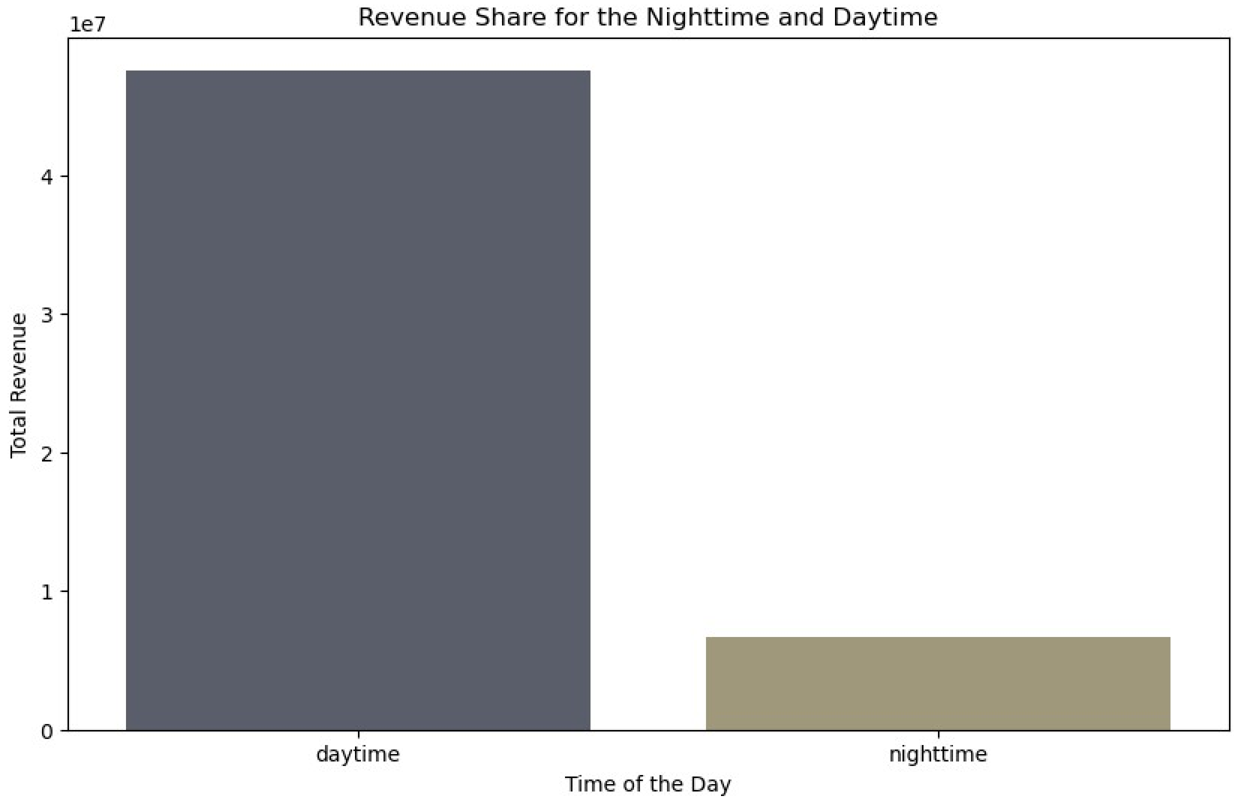


Now, let us find the revenue share for the night time hours and the day time hours. After this, we will move to deciding a pricing strategy.

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

```
# Filter for night hours (11 PM to 5 AM)
df['time_of_the_day'] = df['hour'].apply(lambda x: 'nighttime' if x in
[23,0,1,2,3,4,5] else 'daytime')
revenue_Share=df.groupby('time_of_the_day')
['total_amount'].sum().reset_index()
revenue_Share.columns=['time_of_the_day', 'Total_Revenue']
print(revenue_Share)
plt.figure(figsize=(10, 6))
sns.barplot(data=revenue_Share,x='time_of_the_day',
y='Total_Revenue',palette='cividis')
plt.title("Revenue Share for the Nighttime and Daytime")
plt.xlabel("Time of the Day")
plt.ylabel("Total Revenue")
plt.show()
```

```
  time_of_the_day  Total_Revenue
0         daytime    47563732.78
1       nighttime     6644568.46
```



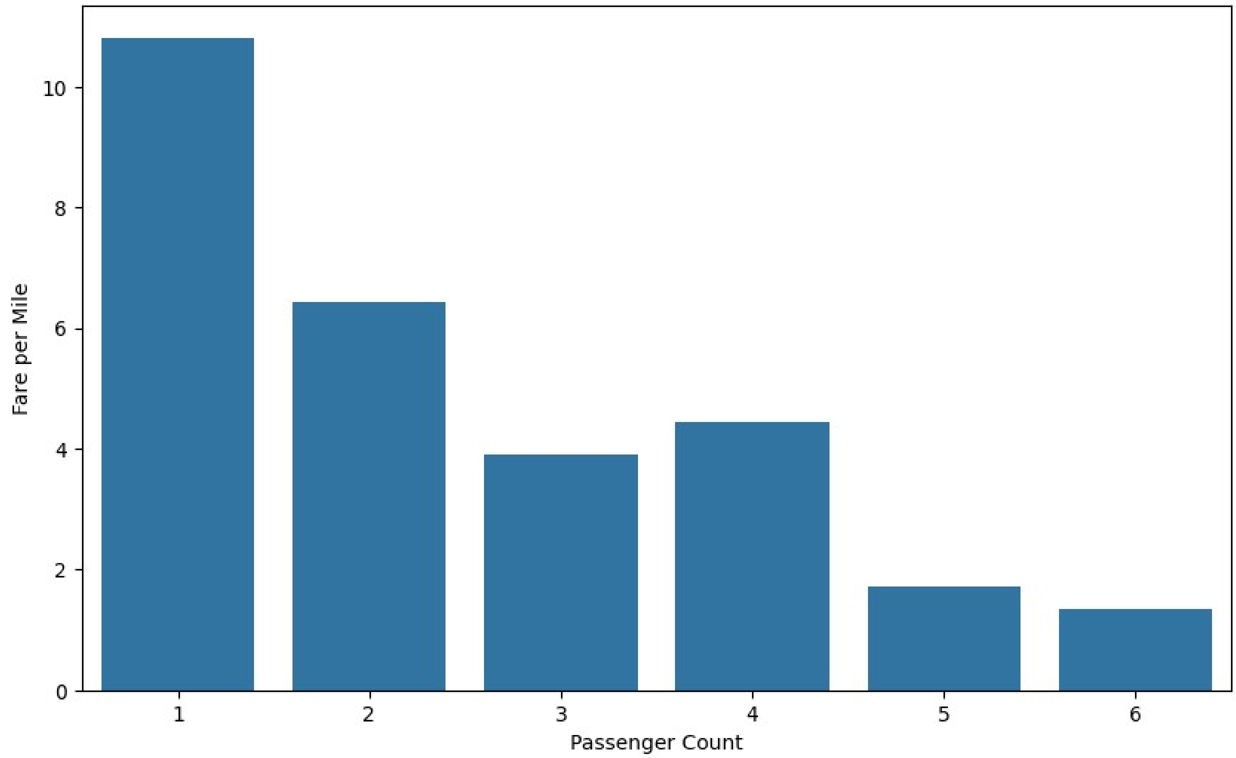
Pricing Strategy

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.

```
# Analyse the fare per mile per passenger for different passenger counts
# Analyse the fare per mile per passenger for different passenger counts
df_filtered = df[(df['trip_distance'] > 0) & (df['passenger_count'] > 0)]
df_filtered['fare_per_mile_per_passenger'] =
df_filtered['fare_amount'] / (df_filtered['trip_distance'] *
df_filtered['passenger_count'])
revenue_Share=df_filtered.groupby('passenger_count')
['fare_per_mile_per_passenger'].mean().reset_index()
print(revenue_Share)
plt.figure(figsize=(10,6))
sns.barplot(data=revenue_Share,x='passenger_count',y='fare_per_mile_per_passenger')
plt.xlabel('Passenger Count')
plt.ylabel('Fare per Mile')
plt.show()
```

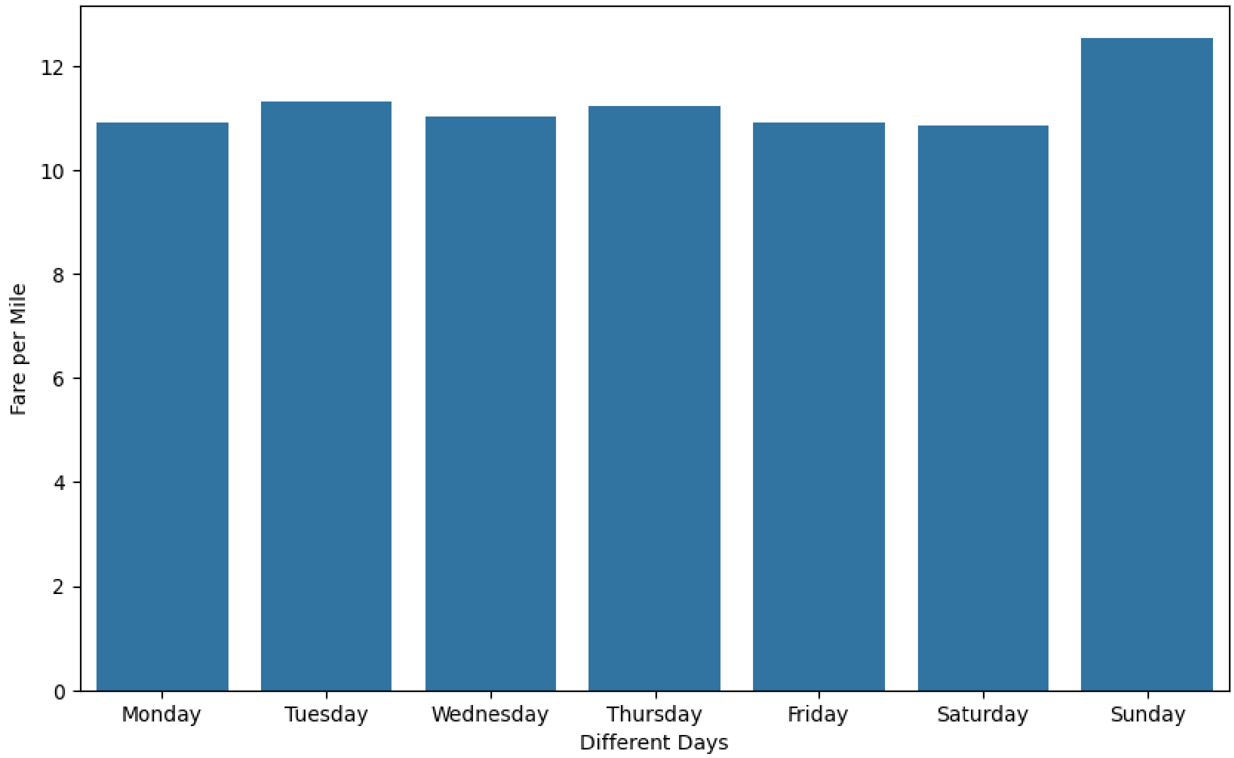
	passenger_count	fare_per_mile_per_passenger
0	1	10.819636
1	2	6.435831
2	3	3.908175
3	4	4.442612
4	5	1.709582
5	6	1.350748



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

```
# Compare the average fare per mile for different days and for
different times of the day
df_filtered['fare_per_mile']=df_filtered['fare_amount'] /
(df_filtered['trip_distance'])
weekdays_order = ["Monday", "Tuesday", "Wednesday", "Thursday",
"Friday", "Saturday", "Sunday"]
avg_fare_different_days=df_filtered.groupby('weekday')
['fare_per_mile'].mean().loc[weekdays_order].reset_index()
print(avg_fare_different_days)
plt.figure(figsize=(10,6))
sns.barplot(data=avg_fare_different_days,x='weekday',y='fare_per_mile'
)
plt.xlabel('Different Days')
plt.ylabel('Fare per Mile')
plt.show()
```

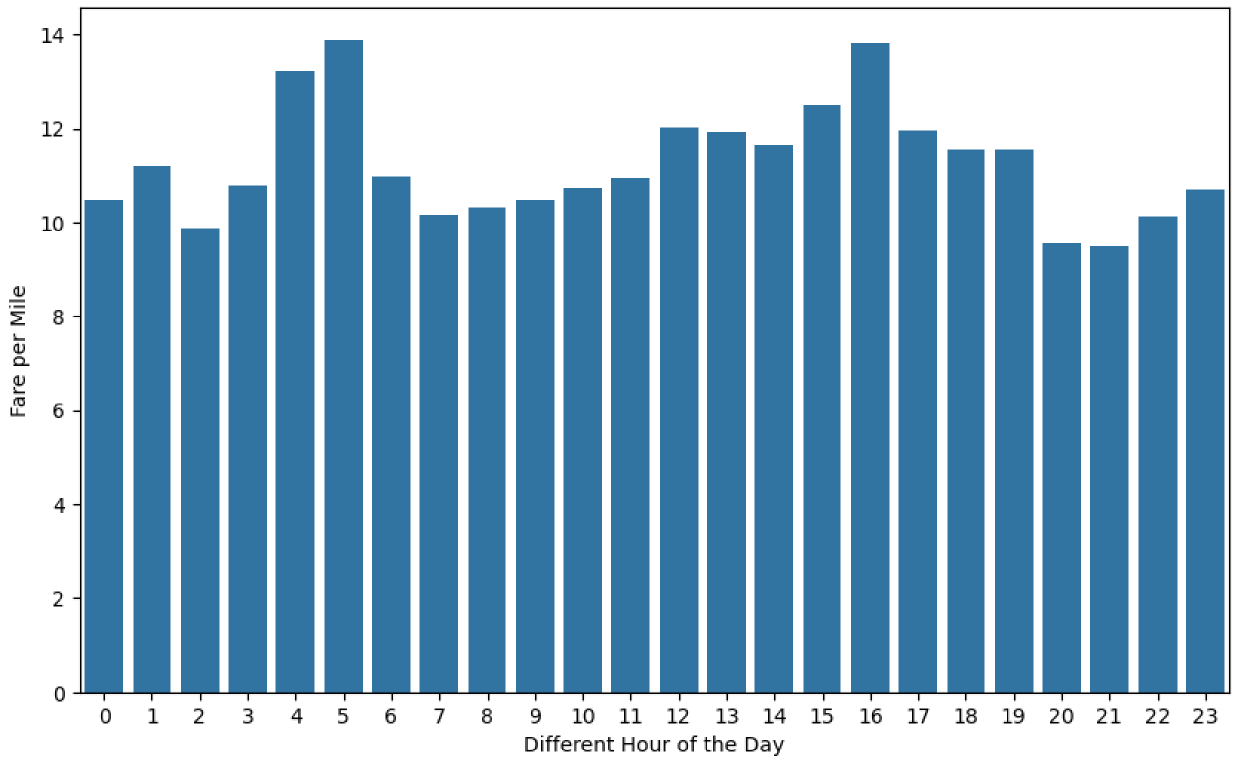
```
     weekday  fare_per_mile
0     Monday      10.927990
1    Tuesday      11.324551
2  Wednesday      11.041058
3   Thursday      11.241392
4     Friday      10.904955
5   Saturday      10.873127
6     Sunday      12.550587
```




```
avg_fare_different_hours=df_filtered.groupby('hour')
['fare_per_mile'].mean().reset_index()
print(avg_fare_different_hours)
plt.figure(figsize=(10,6))
sns.barplot(data=avg_fare_different_hours,x='hour',y='fare_per_mile')
plt.xlabel('Different Hour of the Day')
plt.ylabel('Fare per Mile')
plt.show()
```

	hour	fare_per_mile
0	0	10.468009
1	1	11.211110
2	2	9.875171
3	3	10.802813
4	4	13.230628
5	5	13.894166
6	6	10.988200
7	7	10.164931
8	8	10.307984
9	9	10.466128
10	10	10.739090
11	11	10.939953
12	12	12.011519
13	13	11.939303
14	14	11.635168
15	15	12.498288

```
16    16       13.817297
17    17       11.966133
18    18       11.547573
19    19       11.552982
20    20        9.561032
21    21        9.485384
22    22       10.125980
23    23       10.711245
```

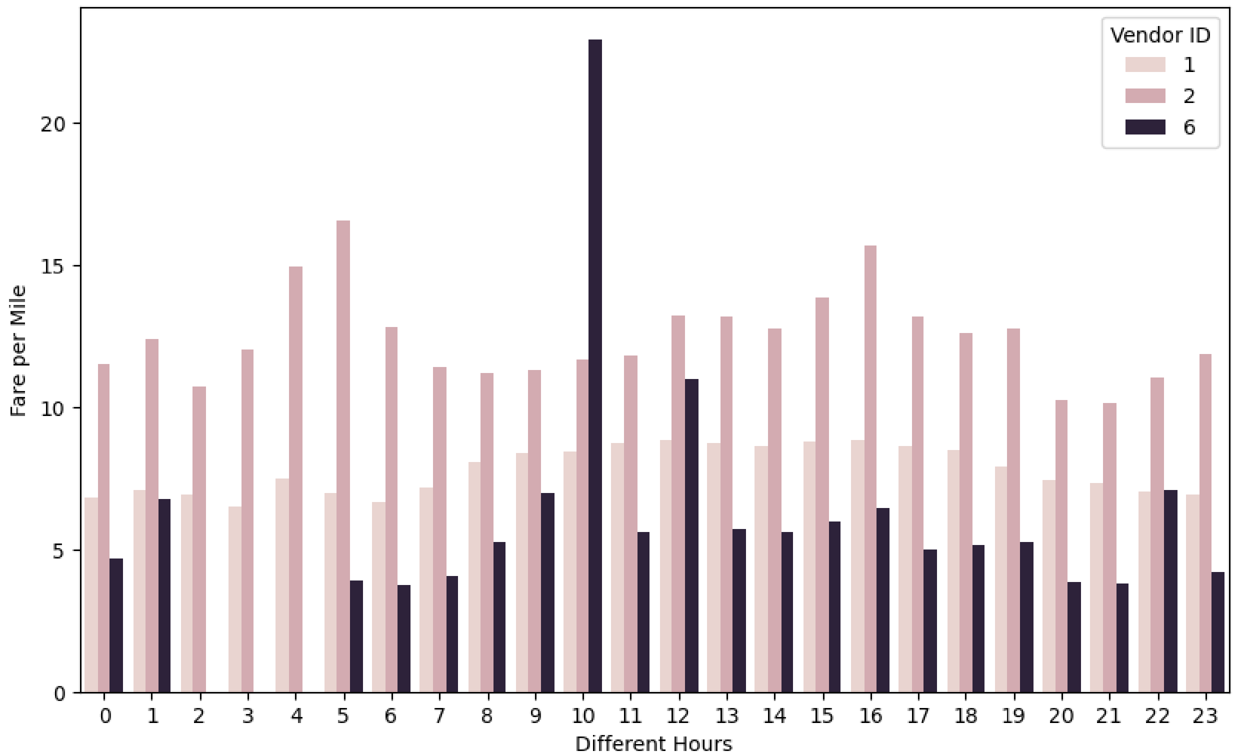


3.2.11 [3 marks] Analyse the average fare per mile for the different vendors for different hours of the day

```python
# Compare fare per mile for different vendors
vendor_id_hour=df_filtered.groupby(['VendorID','hour'])
['fare_per_mile'].mean().reset_index()
print(vendor_id_hour)
plt.figure(figsize=(10,6))
sns.barplot(data=vendor_id_hour,x='hour',y='fare_per_mile',hue='Vendor
ID')
plt.xlabel('Different Hours')
plt.ylabel('Fare per Mile')
plt.legend(title="Vendor ID")
plt.show()
```

```
    VendorID  hour  fare_per_mile
0          1     0       6.795081
```

```
1          1     1        7.055755
2          1     2        6.932000
3          1     3        6.510311
4          1     4        7.498874
..       ...   ...             ...
64         6    19        5.251338
65         6    20        3.828599
66         6    21        3.790070
67         6    22        7.059671
68         6    23        4.208472

[69 rows x 3 columns]
```

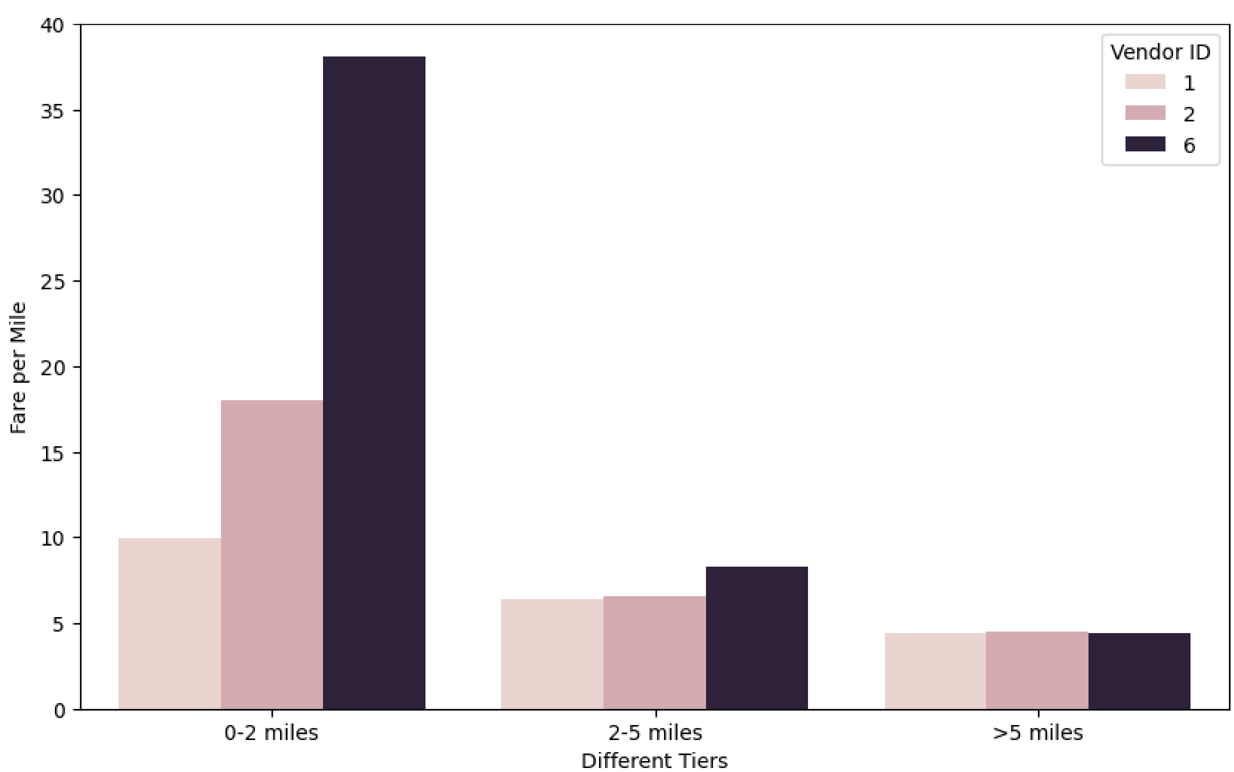


3.2.12 [5 marks] Compare the fare rates of the different vendors in a tiered fashion. Analyse the average fare per mile for distances upto 2 miles. Analyse the fare per mile for distances from 2 to 5 miles. And then for distances more than 5 miles.

```python
# Defining distance tiers
def distance_tier(dist):
    if dist <= 2:
        return '0-2 miles'
    elif dist <= 5:
        return '2-5 miles'
    else:
        return '>5 miles'
```

```
df_filtered['distance_tier'] =
df_filtered['trip_distance'].apply(distance_tier)
fare_analysis = df_filtered.groupby(['VendorID', 'distance_tier'])
['fare_per_mile'].mean().reset_index()
fare_analysis = fare_analysis.sort_values(by=['distance_tier',
'VendorID'])
print(fare_analysis)
plt.figure(figsize=(10,6))
sns.barplot(data=fare_analysis,x='distance_tier',y='fare_per_mile',hue
='VendorID')
plt.xlabel('Different Tiers')
plt.ylabel('Fare per Mile')
plt.legend(title="Vendor ID")
plt.show()
```

	VendorID	distance_tier	fare_per_mile
0	1	0-2 miles	9.912013
3	2	0-2 miles	18.023912
6	6	0-2 miles	38.122035
1	1	2-5 miles	6.382525
4	2	2-5 miles	6.538501
7	6	2-5 miles	8.294061
2	1	>5 miles	4.426744
5	2	>5 miles	4.490938
8	6	>5 miles	4.367008



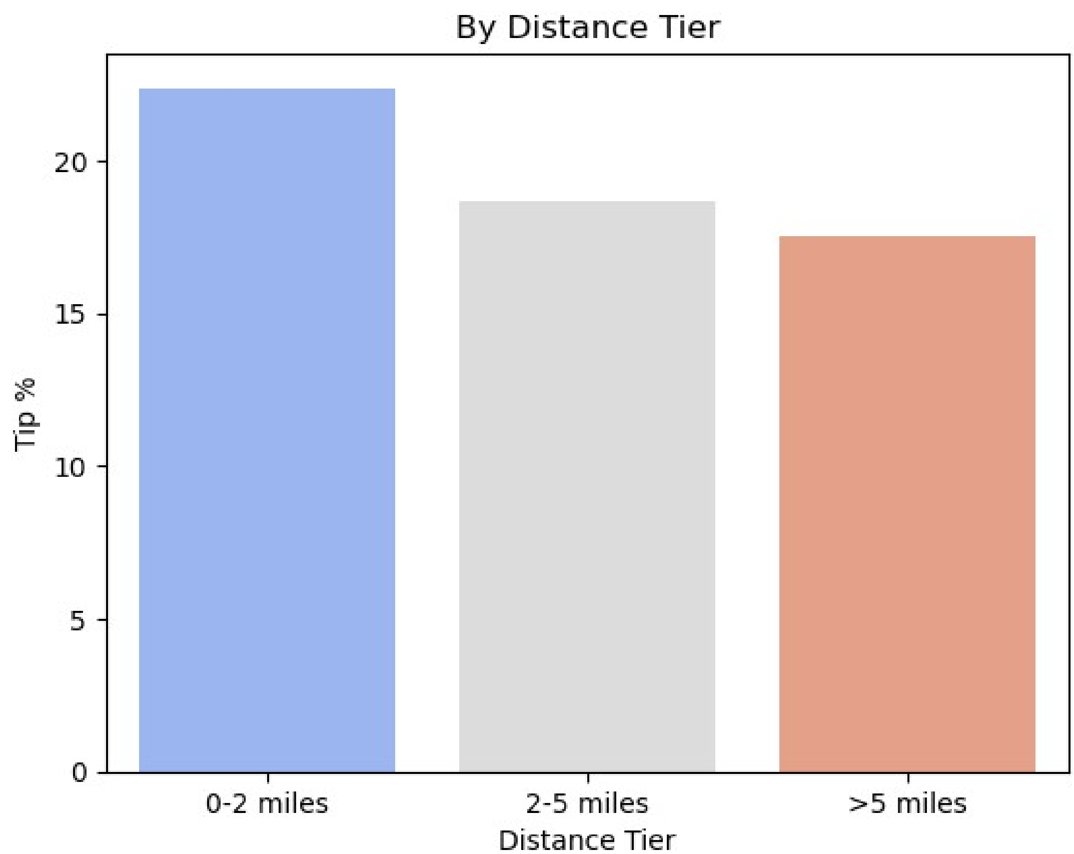
Customer Experience and Other Factors

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?

```
df[df["fare_amount"] == 0]

Empty DataFrame
Columns: [VendorID, tpep_pickup_datetime, tpep_dropoff_datetime,
passenger_count, trip_distance, RatecodeID, PULocationID,
DOLocationID, payment_type, fare_amount, extra, mta_tax, tip_amount,
tolls_amount, improvement_surcharge, total_amount,
congestion_surcharge, date, hour, Airport_fee, weekday, Month,
quarter, trip_duration, payment_type_label, OBJECTID, Shape_Leng,
Shape_Area, zone, LocationID, borough, geometry, day_type,
time_of_the_day]
Index: []

[0 rows x 34 columns]

#  Analyze tip percentages based on distances, passenger counts and
pickup times

df_filtered['tip_percentage'] =
(df_filtered['tip_amount']/df_filtered['fare_amount'])*100

#based on trip distances
tip_by_distance = df_filtered.groupby('distance_tier')
['tip_percentage'].mean().reset_index()
print(tip_by_distance)
sns.barplot(data=tip_by_distance, x='distance_tier',
y='tip_percentage', palette='coolwarm')
plt.title("By Distance Tier")
plt.ylabel("Tip %")
plt.xlabel("Distance Tier")

plt.show()


#based on passenger counts
tip_by_customer=df_filtered.groupby('passenger_count')
['tip_percentage'].mean().reset_index()
print(tip_by_customer)

sns.barplot(data=tip_by_customer, x='passenger_count',
y='tip_percentage', palette='Blues')
plt.title("By Passenger Count")
plt.ylabel("Tip %")
plt.xlabel("Passenger Count")

plt.show()
```

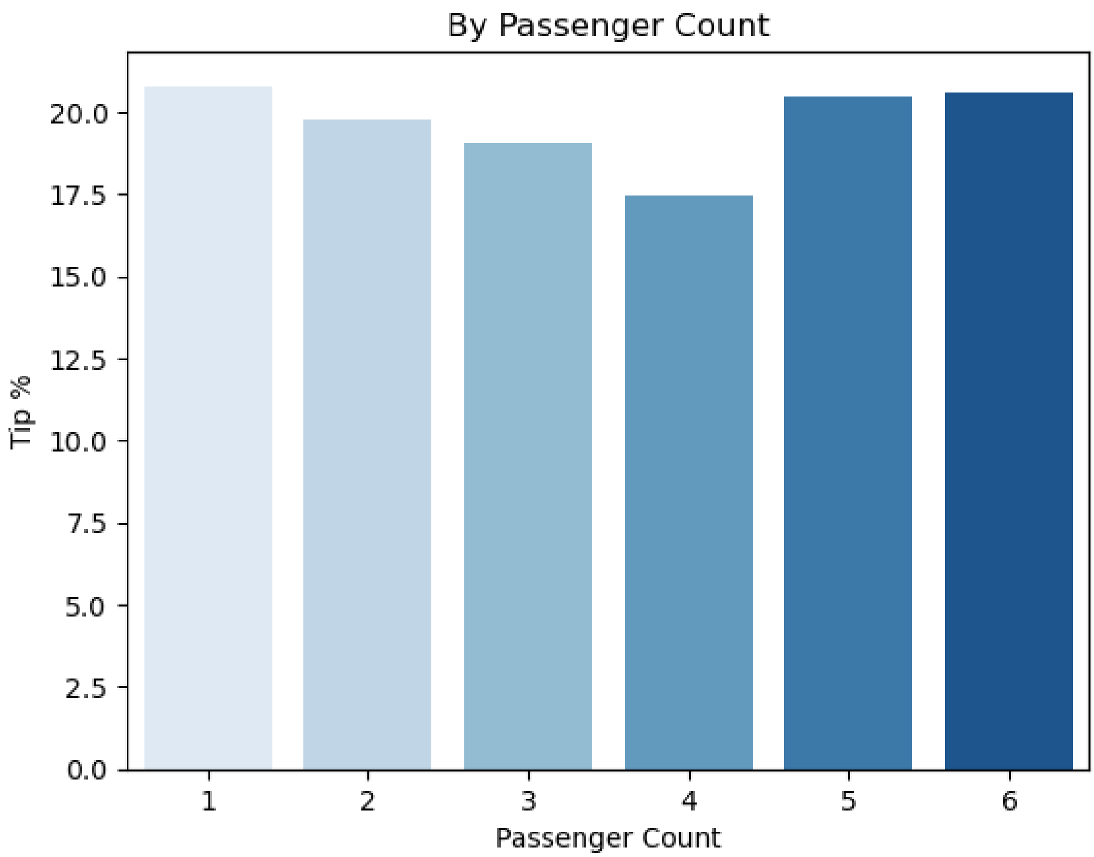
```
#based on hour
tip_by_hour = df_filtered.groupby('hour')
['tip_percentage'].mean().reset_index()
print(tip_by_hour)

sns.lineplot(data=tip_by_hour, x='hour', y='tip_percentage')
plt.title("By Hour of Day")
plt.ylabel("Tip %")
plt.xlabel("Hour")

plt.show()
```

```
  distance_tier  tip_percentage
0     0-2 miles       22.364552
1     2-5 miles       18.631551
2      >5 miles       17.523800
```



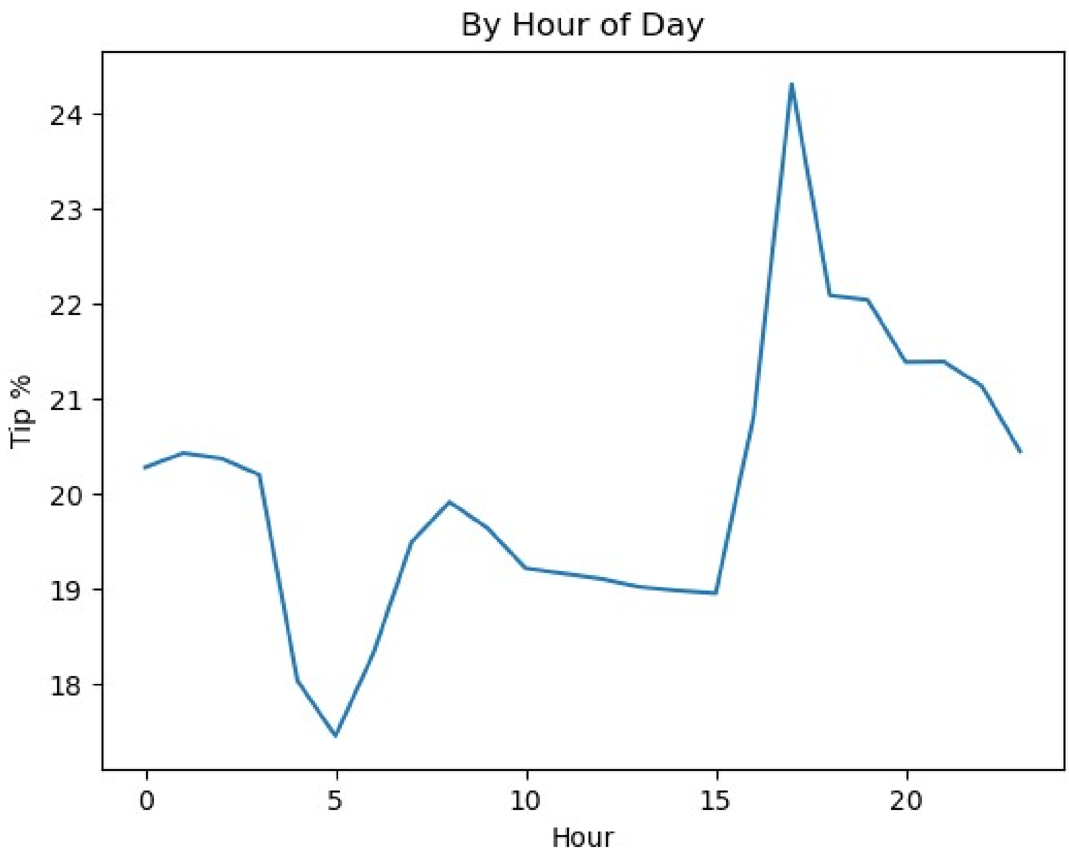

```
   passenger_count  tip_percentage
0                1       20.779341
1                2       19.730210
2                3       19.027092
3                4       17.454155
```

4	5	20.491740
5	6	20.602921



	hour	tip_percentage
0	0	20.283104
1	1	20.432968
2	2	20.376030
3	3	20.204433
4	4	18.042224
5	5	17.461459
6	6	18.331031
7	7	19.498217
8	8	19.918841
9	9	19.644564
10	10	19.223425
11	11	19.166608
12	12	19.111539
13	13	19.026891
14	14	18.987558
15	15	18.960154
16	16	20.822130
17	17	24.307098

```
18    18        22.088533
19    19        22.039225
20    20        21.386189
21    21        21.390538
22    22        21.137194
23    23        20.453246
```



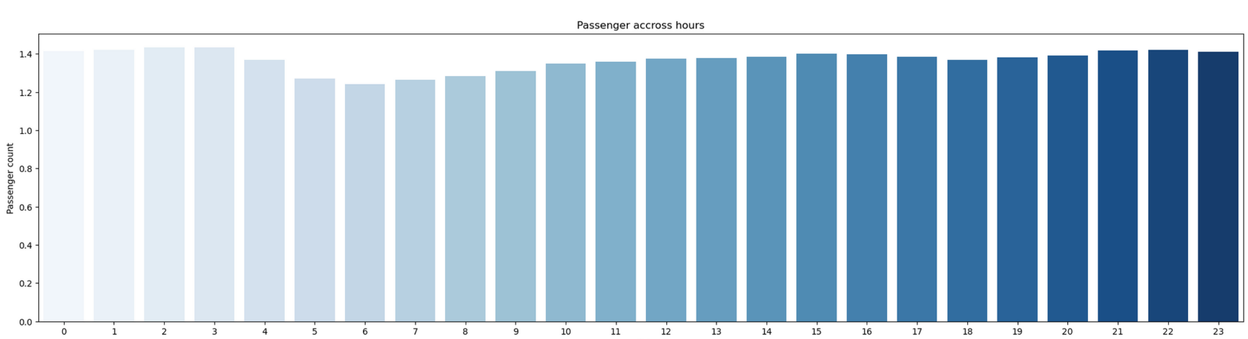
Additional analysis [optional]: Let's try comparing cases of low tips with cases of high tips to find out if we find a clear aspect that drives up the tipping behaviours

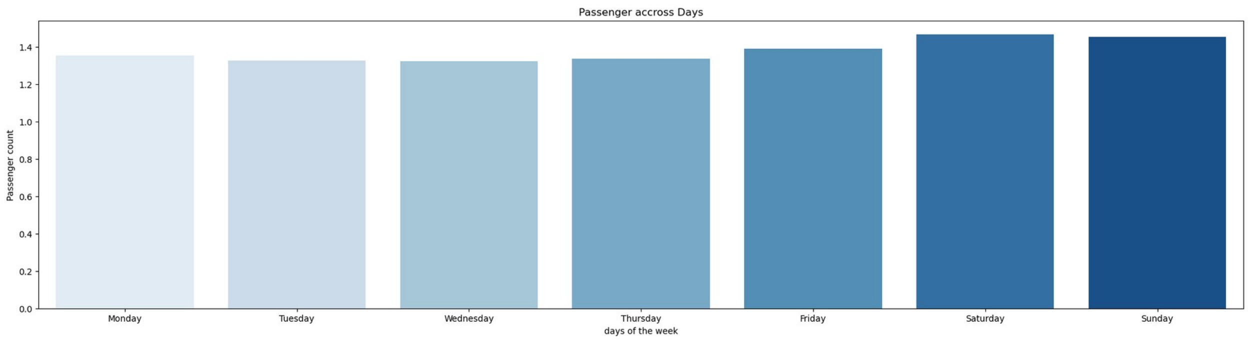
```
# Compare trips with tip percentage < 10% to trips with tip percentage
> 25%

low_tips=df_filtered[df_filtered['tip_percentage'] < 10]
high_tips=df_filtered[df_filtered['tip_percentage'] > 25]

print("Average values for low tip trips (<10%)")
print(low_tips[['trip_distance', 'fare_amount', 'passenger_count',
'hour']].mean())

print("\nAverage values for high tip trips (>25%)")
print(high_tips[['trip_distance', 'fare_amount', 'passenger_count',
'hour']].mean())
```

```
Average values for low tip trips (<10%)
trip_distance       3.938108
fare_amount        21.667735
passenger_count     1.417360
hour               13.919788
dtype: float64

Average values for high tip trips (>25%)
trip_distance       2.310641
fare_amount        14.440777
passenger_count     1.358733
hour               14.594737
dtype: float64
```

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

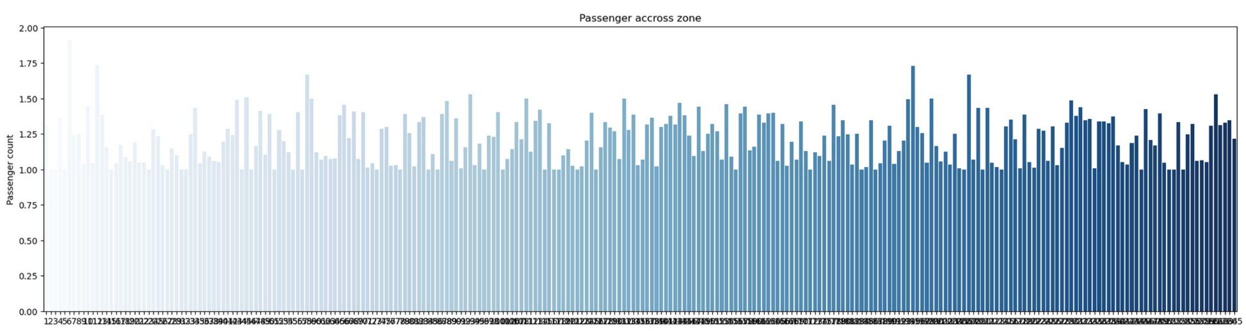
```
# See how passenger count varies across hours and days
#passenger count accross hours
passenger_count_hour=df_filtered.groupby('hour')
['passenger_count'].mean().reset_index()
plt.figure(figsize=(25,6))
sns.barplot(data=passenger_count_hour,x='hour',y='passenger_count',pal
ette='Blues')
plt.xlabel('Hours of the day')
plt.ylabel('Passenger count')
plt.title("Passenger accross hours")
plt.show()

#passenger count accross days
passenger_count_days=df_filtered.groupby('weekday')
['passenger_count'].mean().loc[weekdays_order].reset_index()
plt.figure(figsize=(25,6))
sns.barplot(data=passenger_count_days,x='weekday',y='passenger_count',
palette='Blues')
plt.xlabel('days of the week')
plt.ylabel('Passenger count')
plt.title("Passenger accross Days")
plt.show()
```





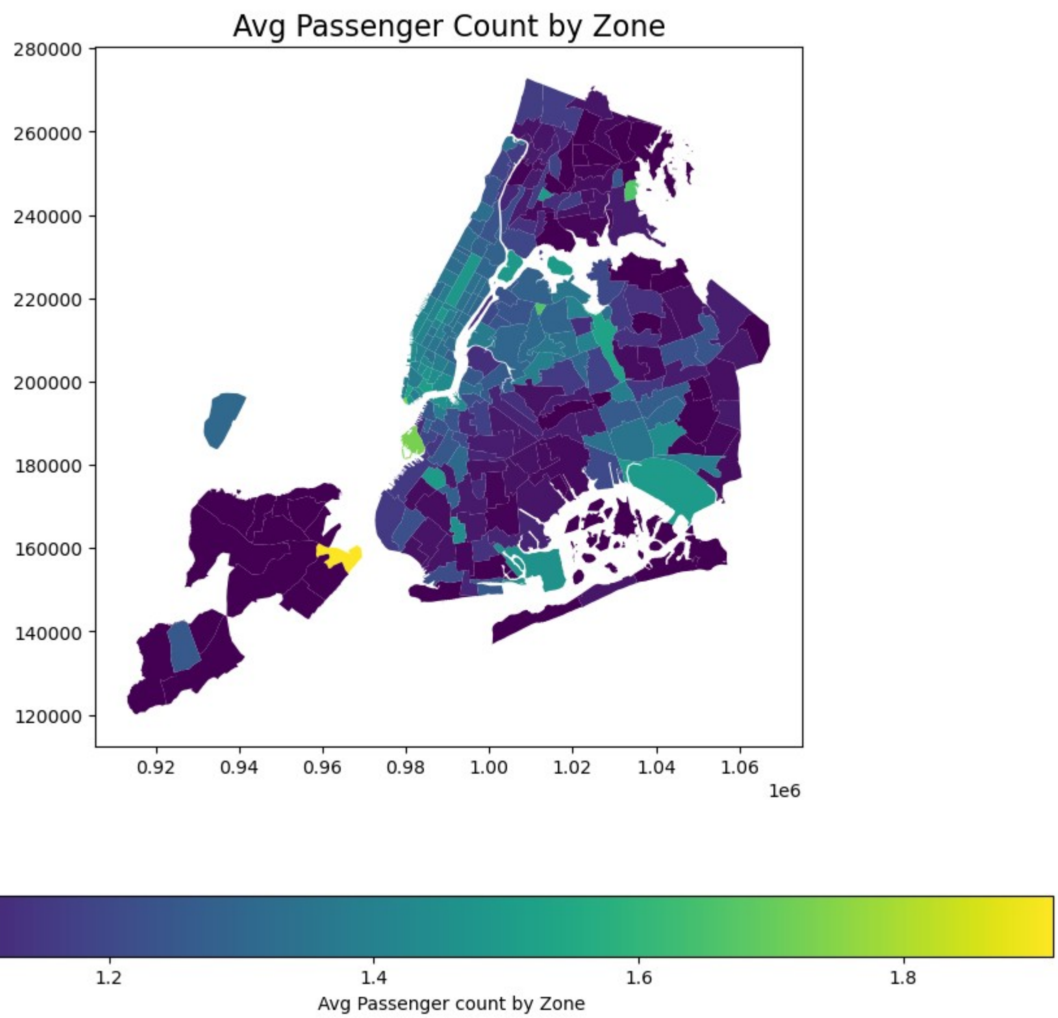
3.2.15 [2 marks] Analyse the variation of passenger counts across zones

```
# How does passenger count vary across zones
passenger_count_zone=df_filtered.groupby('PULocationID')
['passenger_count'].mean().reset_index()
plt.figure(figsize=(25,6))
sns.barplot(data=passenger_count_zone,x='PULocationID',y='passenger_co
unt',palette='Blues')
plt.xlabel('zone')
plt.ylabel('Passenger count')
plt.title("Passenger accross zone")
plt.show()
```




```
# 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.
zones.head()
zones=pd.merge(left=passenger_count_zone,right=zones, how='left',
left_on='PULocationID', right_on='LocationID')
fig, ax = plt.subplots(1, 1, figsize = (12, 10))
zones = gpd.GeoDataFrame(zones, geometry='geometry')
zones.plot(
    column='passenger_count',
    cmap='viridis',
    linewidth=0.8,
    ax=ax,
    legend=True,
    legend_kwds={'label': " Avg Passenger count by Zone",
```

```
'orientation': "horizontal"}
)
ax.set_title("Avg Passenger Count by Zone", fontsize=16)
plt.show()
```



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

```
# How often is each surcharge applied?
pickup_surcharge = df.groupby(['PULocationID',
'congestion_surcharge']).size().reset_index(name='count')
pickup_surcharge = pickup_surcharge.sort_values(by='count',
ascending=False)
print(pickup_surcharge.head(10))

drop_surcharge = df.groupby(['DOLocationID',
'congestion_surcharge']).size().reset_index(name='count')
```

```python
drop_surcharge = drop_surcharge.sort_values(by='count',
ascending=False)
print(drop_surcharge.head(10))

hour_surcharge = df.groupby(['hour',
'congestion_surcharge']).size().reset_index(name='count')
hour_surcharge = hour_surcharge.sort_values(by='count',
ascending=False)
print(hour_surcharge.head(10))
```

```
     PULocationID  congestion_surcharge  count
435           237                   2.5  87965
293           161                   2.5  86272
433           236                   2.5  78809
295           162                   2.5  65933
336           186                   2.5  63536
256           142                   2.5  61806
421           230                   2.5  61145
311           170                   2.5  55033
297           163                   2.5  53844
439           239                   2.5  51918
     DOLocationID  congestion_surcharge  count
460           236                   2.5  82203
462           237                   2.5  78799
312           161                   2.5  72959
448           230                   2.5  57237
330           170                   2.5  55048
314           162                   2.5  53136
274           142                   2.5  52480
466           239                   2.5  52364
272           141                   2.5  49346
134            68                   2.5  47218
    hour  congestion_surcharge   count
38    18                   2.5  124543
36    17                   2.5  118161
40    19                   2.5  110802
33    16                   2.5  107661
31    15                   2.5  107613
29    14                   2.5  105087
27    13                   2.5   98475
42    20                   2.5   98353
44    21                   2.5   98269
25    12                   2.5   95761
```

4 Conclusion

[15 marks]

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

```
"""Prioritize dispatch during peak hours (6–8 PM on weekdays) to high-demand zones like Midtown, JFK, and LaGuardia.Reroute or reduce supply during low-demand hours (3–5 AM) and redistribute cabs toward zones with nightlife like East/West Village.
Avoid slow routes by analyzing and avoiding origin-destination pairs with low average speeds during rush hours.Weekend dispatching should be more spread out and balanced, with added focus on nightlife zones (East Village, West Village)"""
```

```
'Prioritize dispatch during peak hours (6–8 PM on weekdays) to high-demand zones like Midtown, JFK, and LaGuardia.Reroute or reduce supply during low-demand hours (3–5 AM) and redistribute cabs toward zones with nightlife like East/West Village.\nAvoid slow routes by analyzing and avoiding origin-destination pairs with low average speeds during rush hours.Weekend dispatching should be more spread out and balanced, with added focus on nightlife zones (East Village, West Village)'
```

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.

```
"""Based on the analysis, it is evident that zones such as JFK Airport, west village, and Times Square consistently rank among the top locations for pickups. During night hours (11 PM–5 AM), neighborhoods like East Village, Clinton East, and Murray Hill experience a notable increase in activity, highlighting late-night travel demand in nightlife and residential areas. Zone-wise heatmaps further confirm a strong clustering of trip demand in specific geographic regions.
To optimize cab distribution, strategic positioning should be adopted based on time and day trends. During daytime hours (6 AM–4 PM), cabs should be concentrated in high-traffic commercial and commuter hubs such as Times Square, and JFK Airport to capture office-hour and airport-related traffic. For late-night operations (11 PM–3 AM), a shift in focus toward nightlife-centric areas like East Village, West
```

```
Village, and Clinton East is recommended to meet high drop-off demand
from restaurants, bars, and clubs.
On weekends, where trip volumes are more evenly spread throughout the
day, cab distribution should be balanced across popular entertainment
districts and tourist attractions to ensure service availability.
Additionally, data indicates strong round-trip activity, particularly
around airports, where the same pickup and drop-off zones are common.
This suggests that cabs can be strategically queued at airports to
take advantage of steady inbound and outbound traffic, enabling faster
turnaround times and maximizing earnings."""
```

```
'Based on the analysis, it is evident that zones such as JFK Airport,
west village, and Times Square consistently rank among the top
locations for pickups. During night hours (11 PM–5 AM), neighborhoods
like East Village, Clinton East, and Murray Hill experience a notable
increase in activity, highlighting late-night travel demand in
nightlife and residential areas. Zone-wise heatmaps further confirm a
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Village, and Clinton East is recommended to meet high drop-off demand
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indicates strong round-trip activity, particularly around airports,
where the same pickup and drop-off zones are common. This suggests
that cabs can be strategically queued at airports to take advantage of
steady inbound and outbound traffic, enabling faster turnaround times
and maximizing earnings.'
```

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

```
"""From the analysis, it's evident that fare per mile decreases as
trip distance increases, with short trips (0–2 miles) being the most
frequent and showing the highest fare-per-mile. This indicates a clear
opportunity for flat-rate pricing on short-distance rides to simplify
fares and attract more passengers.
Additionally, Vendor 6 consistently charges the highest fare per mile,
while Vendor 1 offers more stable pricing, highlighting potential
pricing competitiveness among vendors.
Tips tend to be higher for solo-passenger, short trips, especially
during evening rush hours (4–6 PM). While daytime contributes more to
total revenue, nighttime trips (3–5 AM) have a higher fare per mile,
```

```
suggesting premium pricing opportunities in those hours.
Based on these insights, the following pricing strategy adjustments
are recommended:
•	Introduce flat fare tiers for trips under 2 miles to encourage
high-frequency short rides.
•	Implement surge pricing in high-demand zones such as JFK,
Midtown, and Times Square during peak hours, supported by zone-level
trip density data.
•	Adjust pricing by time of day, capitalizing on early morning (3–5
AM) and evening peak periods for enhanced profitability."""
```

```
"From the analysis, it's evident that fare per mile decreases as trip distance increases, with short trips (0–2 miles) being the most frequent and showing the highest fare-per-mile. This indicates a clear opportunity for flat-rate pricing on short-distance rides to simplify fares and attract more passengers.\nAdditionally, Vendor 6 consistently charges the highest fare per mile, while Vendor 1 offers more stable pricing, highlighting potential pricing competitiveness among vendors.\nTips tend to be higher for solo-passenger, short trips, especially during evening rush hours (4–6 PM). While daytime contributes more to total revenue, nighttime trips (3–5 AM) have a higher fare per mile, suggesting premium pricing opportunities in those hours.\nBased on these insights, the following pricing strategy adjustments are recommended:\n•\tIntroduce flat fare tiers for trips under 2 miles to encourage high-frequency short rides.\n•\tImplement surge pricing in high-demand zones such as JFK, Midtown, and Times Square during peak hours, supported by zone-level trip density data.\n•\tAdjust pricing by time of day, capitalizing on early morning (3–5 AM) and evening peak periods for enhanced profitability."
```