EDA_Assg_NYC_Taxi_Starter

June 25, 2025

1 New York City Yellow Taxi Data

1.1 Objective

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

1.2 Problem Statement

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

1.3 Tasks

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

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

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

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

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

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

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

1.4 Data Understanding

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

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

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

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

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

1.4.1 Data Description

You can find the data description here: Data Dictionary

Trip Records

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

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

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

Taxi Zones

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

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

This is covered in more detail in later sections.

1.5 1 Data Preparation

[5 marks]

1.5.1 Import Libraries

[140]:
```
# Import warnings
import warnings
```

[142]:
```
# Import the libraries you will be using for analysis
import numpy as np
import pandas as pd
import matplotlib as mlib
import matplotlib.pyplot as plt
import seaborn as sns
```

[144]:
```
# 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: 1.26.4
pandas version: 2.2.3
matplotlib version: 3.10.0
seaborn version: 0.13.2
```

1.5.2 1.1 Load the dataset

[5 marks]

You will see twelve files, one for each month.

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

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

[148]:
```
# Try loading one file
```

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

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

[150]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3041714 entries, 0 to 3066765
Data columns (total 19 columns):
 #   Column                 Dtype
---  ------                 -----
 0   VendorID               int64
 1   tpep_pickup_datetime   datetime64[us]
 2   tpep_dropoff_datetime  datetime64[us]
 3   passenger_count        float64
 4   trip_distance          float64
 5   RatecodeID             float64
 6   store_and_fwd_flag     object
 7   PULocationID           int64
 8   DOLocationID           int64
 9   payment_type           int64
```

```
 10  fare_amount            float64
 11  extra                  float64
 12  mta_tax                float64
 13  tip_amount             float64
 14  tolls_amount           float64
 15  improvement_surcharge  float64
 16  total_amount           float64
 17  congestion_surcharge   float64
 18  airport_fee            float64
dtypes: datetime64[us](2), float64(12), int64(4), object(1)
memory usage: 464.1+ MB
```

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

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

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:

```python
# 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.

[152]:
```python
# Sample the data
# It is recommmended to not load all the files at once to avoid memory overload



def extractMonthlySampleData (filePath):
    df = pd.read_parquet(filePath)  #'trip_records/2023-1.parquet'
    # Extract date and hour from pickup datetime
    df['pickup_date'] = df['tpep_pickup_datetime'].dt.date
    df['pickup_hour'] = df['tpep_pickup_datetime'].dt.hour
    df_group_day_hour = df.groupby(["pickup_date", "pickup_hour"])
    sample_df_rows = []

    for (pickup_date, pickup_hour), hour_data in df_group_day_hour:
            sampled = hour_data.sample(frac=0.05, random_state=42)
            sample_df_rows.append(sampled)

    monthly_sample = pd.concat(sample_df_rows, ignore_index=True)
    return monthly_sample
```

[156]:
```python
sample = extractMonthlySampleData ('2023-1.parquet')
sample.head()
```

[156]:
```
   VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
0         2  2022-12-31 23:51:30   2022-12-31 23:56:06              1.0
1         2  2023-01-01 00:07:18   2023-01-01 00:23:15              1.0
2         2  2023-01-01 00:16:41   2023-01-01 00:21:46              2.0
3         2  2023-01-01 00:14:03   2023-01-01 00:24:36              3.0
4         2  2023-01-01 00:24:30   2023-01-01 00:29:55              1.0

   trip_distance  RatecodeID store_and_fwd_flag  PULocationID  DOLocationID  \
0           0.86         1.0                  N           141           140
1           7.74         1.0                  N           138           256
2           1.24         1.0                  N           161           237
3           1.44         1.0                  N           237           141
4           0.54         1.0                  N           143           142

   payment_type  …  extra  mta_tax  tip_amount  tolls_amount  \
0             1  …    1.0      0.5        2.00           0.0
1             2  …    6.0      0.5        0.00           0.0
2             1  …    1.0      0.5        2.58           0.0
3             2  …    1.0      0.5        0.00           0.0
4             2  …    1.0      0.5        0.00           0.0

   improvement_surcharge  total_amount  congestion_surcharge  airport_fee  \
0                    1.0         13.50                   2.5         0.00
1                    1.0         41.15                   0.0         1.25
```

```
2                    1.0         15.48                       2.5          0.00
3                    1.0         16.40                       2.5          0.00
4                    1.0         11.50                       2.5          0.00

   pickup_date pickup_hour
0   2022-12-31          23
1   2023-01-01           0
2   2023-01-01           0
3   2023-01-01           0
4   2023-01-01           0

[5 rows x 21 columns]
```

[158]:
```
# from google.colab import drive
# drive.mount('/content/drive')
print(f"sample : {sample.shape}")
```

```
sample : (152087, 21)
```

[160]:
```
# 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\Sherry\UpgradExample\Datasets and Dictionary-NYC\Starter␣
 ↪Notebook - EDA NYC Taxi\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)

        # Reading the current file
```

```
        # 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()
        sampled_data = extractMonthlySampleData(file_path)
        print (f"file_name : {file_name}  sampled_data.shape:{sampled_data.
↪shape}")
        # Loop through dates and then loop through every hour of each date

            # Iterate through each hour of the selected date

                # Sample 5% of the hourly data randomly

                # add data of this hour to the dataframe

        # Concatenate the sampled data of all the dates to a single dataframe
        df =  pd.concat([df,sampled_data])
        print (f"file_name : {file_name}  df.shape:{df.shape}")
        #df = # we initialised this empty DF earlier

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

print("completed processing")
#df = pd.concat(df, ignore_index=True)
df.info()
```

```
file_name : 2023-1.parquet  sampled_data.shape:(152087, 21)
file_name : 2023-1.parquet  df.shape:(152087, 21)
file_name : 2023-10.parquet  sampled_data.shape:(174255, 21)
file_name : 2023-10.parquet  df.shape:(326342, 22)
file_name : 2023-11.parquet  sampled_data.shape:(165133, 21)
file_name : 2023-11.parquet  df.shape:(491475, 22)
file_name : 2023-12.parquet  sampled_data.shape:(166709, 21)
file_name : 2023-12.parquet  df.shape:(658184, 22)
file_name : 2023-2.parquet  sampled_data.shape:(168696, 21)
file_name : 2023-2.parquet  df.shape:(826880, 22)
file_name : 2023-3.parquet  sampled_data.shape:(163786, 21)
file_name : 2023-3.parquet  df.shape:(990666, 22)
file_name : 2023-4.parquet  sampled_data.shape:(139641, 21)
file_name : 2023-4.parquet  df.shape:(1130307, 22)
file_name : 2023-5.parquet  sampled_data.shape:(144458, 21)
file_name : 2023-5.parquet  df.shape:(1274765, 22)
file_name : 2023-6.parquet  sampled_data.shape:(162910, 21)
file_name : 2023-6.parquet  df.shape:(1437675, 22)
```

```
file_name : 2023-7.parquet  sampled_data.shape:(174068, 21)
file_name : 2023-7.parquet  df.shape:(1611743, 22)
file_name : 2023-8.parquet  sampled_data.shape:(143782, 21)
file_name : 2023-8.parquet  df.shape:(1755525, 22)
file_name : 2023-9.parquet  sampled_data.shape:(140875, 21)
file_name : 2023-9.parquet  df.shape:(1896400, 22)
file_name : sample-2023.parquet  sampled_data.shape:(94927, 22)
file_name : sample-2023.parquet  df.shape:(1991327, 22)
completed processing
<class 'pandas.core.frame.DataFrame'>
Index: 1991327 entries, 0 to 94926
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  pickup_date            object
 20  pickup_hour            int32
 21  Airport_fee            float64
dtypes: datetime64[us](2), float64(13), int32(1), int64(4), object(2)
memory usage: 341.8+ MB
```

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.

[178]:
```
df.to_csv('sample-2023-ex1.csv', index=False)
```

[162]:
```
# Store the df in csv/parquet
df.to_parquet('sample-2023-v1.parquet')
```

```python
print (df.shape)
```

```
(1991327, 22)
```

1.6 2 Data Cleaning

[30 marks]

Now we can load the new data directly.

[180]:
```python
# Load the new data file

df = pd.read_parquet('sample-2023-v1.parquet')
```

[182]:
```python
df.head()
```

[182]:
```
   VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
0         2  2022-12-31 23:51:30   2022-12-31 23:56:06              1.0
1         2  2023-01-01 00:07:18   2023-01-01 00:23:15              1.0
2         2  2023-01-01 00:16:41   2023-01-01 00:21:46              2.0
3         2  2023-01-01 00:14:03   2023-01-01 00:24:36              3.0
4         2  2023-01-01 00:24:30   2023-01-01 00:29:55              1.0

   trip_distance  RatecodeID store_and_fwd_flag  PULocationID  DOLocationID  \
0           0.86         1.0                  N           141           140
1           7.74         1.0                  N           138           256
2           1.24         1.0                  N           161           237
3           1.44         1.0                  N           237           141
4           0.54         1.0                  N           143           142

   payment_type  …  mta_tax  tip_amount  tolls_amount  \
0             1  …      0.5        2.00           0.0
1             2  …      0.5        0.00           0.0
2             1  …      0.5        2.58           0.0
3             2  …      0.5        0.00           0.0
4             2  …      0.5        0.00           0.0

   improvement_surcharge  total_amount  congestion_surcharge  airport_fee  \
0                    1.0         13.50                   2.5         0.00
1                    1.0         41.15                   0.0         1.25
2                    1.0         15.48                   2.5         0.00
3                    1.0         16.40                   2.5         0.00
4                    1.0         11.50                   2.5         0.00

   pickup_date  pickup_hour Airport_fee
0   2022-12-31           23         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]
```

[184]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1991327 entries, 0 to 94926
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  pickup_date            object
 20  pickup_hour            int32
 21  Airport_fee            float64
dtypes: datetime64[us](2), float64(13), int32(1), int64(4), object(2)
memory usage: 341.8+ 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

[186]:
```
# Fix the index and drop any columns that are not needed

df.reset_index(drop=True, inplace=True)
# All columns provide some information which can be useful
```

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.

[188]:
```
# Combine the two airport fee columns
print (df[(df['Airport_fee'].isnull()) & (df['airport_fee'].isnull())].shape)
print (df[(df['Airport_fee'].isnull()) & (df['airport_fee'].notnull())].shape)
print (df[(df['Airport_fee'].notnull()) & (df['airport_fee'].isnull())].shape)
print (df[(df['Airport_fee'].notnull()) & (df['airport_fee'].notnull())].shape)

df['airport_fee'] = df['airport_fee'].fillna(df['Airport_fee'])
print (df[(df['Airport_fee'].isnull()) & (df['airport_fee'].notnull())].shape)
# (Optional) Drop the duplicate column after merging
df.drop(columns='Airport_fee', inplace=True)

print(df['airport_fee'].isnull().sum())
```

```
(68132, 22)
(155904, 22)
(1767291, 22)
(0, 22)
(155904, 22)
68132
```

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

[190]:
```
# check where values of fare amount are negative


negative_fares = df[df['fare_amount'] < 0]
negative_fares.head()
print (negative_fares.shape)
```

```
(0, 21)
```

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

[ ]:
```
# Analyse RatecodeID for the negative fare amounts
## I have created sample multiple times but no fare amount was negative, though␣
↪there is total amount as negative but that is because of other negative␣
↪components
```

[210]:
```
# Find which columns have negative values

numeric_df = df.select_dtypes(include='number')
negative_columns = numeric_df.columns[(numeric_df < 0).any()]

print("Columns with negative values:", list(negative_columns))
```

```
Columns with negative values: ['extra', 'mta_tax', 'improvement_surcharge',
'total_amount', 'congestion_surcharge', 'airport_fee']
```

[224]:
```
# fix these negative values
# will use abs function to make negative to positive numbers
(df[negative_columns] < 0).sum()
df[negative_columns] = df[negative_columns].abs()
(df[negative_columns] < 0).sum()
```

[224]:
```
extra                    0
mta_tax                  0
improvement_surcharge    0
total_amount             0
congestion_surcharge     0
airport_fee              0
dtype: int64
```

1.6.1 2.2 Handling Missing Values

[10 marks]

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

[240]:
```
# Find the proportion of missing values in each column

print(f"proportion of values on percentage of records: \n {df.isnull().mean() *␣
↪100} ")
print(f"proportion of values on number of records: \n {df.isnull().sum()} ")
```

```
proportion of values on percentage of records:
 VendorID                 0.000000
tpep_pickup_datetime     0.000000
tpep_dropoff_datetime    0.000000
passenger_count          3.421437
trip_distance            0.000000
RatecodeID               3.421437
store_and_fwd_flag       3.421437
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     3.421437
airport_fee              3.421437
pickup_date              0.000000
pickup_hour              0.000000
dtype: float64
```

```
proportion of values on number of records:
 VendorID                    0
tpep_pickup_datetime        0
tpep_dropoff_datetime       0
passenger_count         68132
trip_distance               0
RatecodeID              68132
store_and_fwd_flag      68132
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    68132
airport_fee             68132
pickup_date                 0
pickup_hour                 0
dtype: int64
```

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

[266]:
```
# Display the rows with null values
null_rows = df[df.isnull().any(axis=1)]
print ("null_rows Shape: ", null_rows.shape)
print(null_rows.head(10))


# Impute NaN values in 'passenger_count'
most_commonly_used_value = df['passenger_count'].mode()[0]
print("most_commonly_used_value :",most_commonly_used_value)

print ("Before - number of nulls in passenger_count",df['passenger_count'].
 ↪isnull().sum())
df['passenger_count'].fillna(most_commonly_used_value, inplace=True)

print ("After setting the most_commonly_used_value - number of nulls in␣
 ↪passenger_count",df['passenger_count'].isnull().sum())
```

```
null_rows Shape:  (68132, 21)
     VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
5           2  2023-01-01 00:43:00   2023-01-01 01:01:00              NaN
16          2  2023-01-01 00:41:50   2023-01-01 01:14:50              NaN
43          2  2023-01-01 00:37:21   2023-01-01 00:54:18              NaN
```

```
44          2  2023-01-01 00:44:03   2023-01-01 01:13:49              NaN
47          2  2023-01-01 00:50:55   2023-01-01 01:19:06              NaN
53          2  2023-01-01 00:55:00   2023-01-01 01:07:00              NaN
70          1  2023-01-01 00:28:22   2023-01-01 00:41:25              NaN
78          1  2023-01-01 00:37:09   2023-01-01 00:58:16              NaN
105         2  2023-01-01 00:58:50   2023-01-01 01:17:07              NaN
126         2  2023-01-01 00:16:00   2023-01-01 00:38:00              NaN

     trip_distance  RatecodeID store_and_fwd_flag  PULocationID  DOLocationID  \
5            19.24         NaN               None            66           107
16           10.77         NaN               None           151           106
43            4.52         NaN               None           114           262
44            9.19         NaN               None           239           256
47            2.74         NaN               None            90            48
53            1.89         NaN               None           141           143
70            2.90         NaN               None           263           137
78            0.00         NaN               None            36             7
105           4.43         NaN               None            33            68
126           4.77         NaN               None            90           262

     payment_type  …  extra  mta_tax  tip_amount  tolls_amount  \
5               0  …    0.0      0.5        5.93          0.00
16              0  …    0.0      0.5       11.19          6.55
43              0  …    0.0      0.5        0.00          0.00
44              0  …    0.0      0.5        2.20          0.00
47              0  …    0.0      0.5        3.37          0.00
53              0  …    0.0      0.5        3.36          0.00
70              0  …    1.0      0.5        3.09          0.00
78              0  …    1.0      0.5        0.00          0.00
105             0  …    0.0      0.5        4.37          0.00
126             0  …    0.0      0.5        7.86          0.00

     improvement_surcharge  total_amount  congestion_surcharge  airport_fee  \
5                      1.0         35.57                   NaN          NaN
16                     1.0         67.12                   NaN          NaN
43                     1.0         29.38                   NaN          NaN
44                     1.0         46.20                   NaN          NaN
47                     1.0         25.85                   NaN          NaN
53                     1.0         20.16                   NaN          NaN
70                     1.0         23.69                   NaN          NaN
78                     1.0         32.00                   NaN          NaN
105                    1.0         33.50                   NaN          NaN
126                    1.0         39.28                   NaN          NaN

     pickup_date pickup_hour
5     2023-01-01           0
16    2023-01-01           0
43    2023-01-01           0
```

```
44     2023-01-01          0
47     2023-01-01          0
53     2023-01-01          0
70     2023-01-01          0
78     2023-01-01          0
105    2023-01-01          0
126    2023-01-01          0

[10 rows x 21 columns]
most_commonly_used_value : 1.0
Before - number of nulls in passenger_count 68132
After setting the most_commonly_used_value - number of nulls in passenger_count
0
```

```
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\419987922.py:12:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['passenger_count'].fillna(most_commonly_used_value, inplace=True)
```

Did you find zeroes in passenger_count? Handle these.

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

[278]:

```python
# Fix missing values in 'RatecodeID'

most_commonly_used_RatecodeID = 99
print("most_commonly_used_RatecodeID :",most_commonly_used_RatecodeID)

print ("Before the change- number of nulls in RatecodeID",df['RatecodeID'].
 ↪isnull().sum())
print ("will change the value with 99 which is equivalent to null/unknown")

df['RatecodeID'].fillna(most_commonly_used_RatecodeID, inplace=True)

print ("After setting the most_commonly_used_value - number of nulls in␣
 ↪passenger_count",df['passenger_count'].isnull().sum())
```

```
most_commonly_used_RatecodeID : 99
Before the change- number of nulls in RatecodeID 68132
will change the value with 99 which is equivalent to null/unknown
```

```
After setting the most_commonly_used_value - number of nulls in passenger_count
0
```

2.2.4 [3 marks] Impute NaN in `congestion_surcharge`

[288]:
```python
# handle null values in congestion_surcharge
# here i will be setting the value as 2.5 after summing up total␣
↪fare_amount,extra,mta_tax,tip_amount,tolls_amount,improvement_surcharge and␣
↪then subtracting it with Total. A very good finding was that most of the␣
↪congestion charge was missing.It should 2.5 as that is the most commonly␣
↪used value.

most_commonly_used_cs = df['congestion_surcharge'].mode()[0]
print(most_commonly_used_cs)

df['total_diff'] = df['total_amount'] - (
    df['fare_amount'] +
    df['extra'] +
    df['mta_tax'] +
    df['tip_amount'] +
    df['tolls_amount'] +
    df['improvement_surcharge']
)
```

```
2.5
```

[292]:
```python
check_cs = (df['congestion_surcharge'].isnull()) & (df['total_diff'] == 2.5)
print(f"Before - Rows available for update: {check_cs.sum()}")
df.loc[
    (df['congestion_surcharge'].isnull()) & (df['total_diff'] == 2.5),
    ['congestion_surcharge', 'airport_fee']
] = [2.5, 0.0]

check_cs = (df['congestion_surcharge'].isnull()) & (df['total_diff'] == 2.5)
print(f"After - Rows availablefor update: {check_cs.sum()}")
```

```
Before - Rows available for update: 49245
After - Rows availablefor update: 0
```

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

[296]:
```python
# Handle any remaining missing values
print("number of nulls with congestion_surcharge",df['congestion_surcharge'].
↪isnull().sum())

initial_rows = len(df)
df = df[df['congestion_surcharge'].notnull()]
print(f"Rows after removal: {len(df)} (Removed {initial_rows - len(df)} rows)")
```

```
print("number of nulls with congestion_surcharge",df['congestion_surcharge'].
 ↪isnull().sum())
print("number of nulls with airport_fee",df['airport_fee'].isnull().sum())
```

```
number of nulls with congestion_surcharge 18887
Rows after removal: 1972440 (Removed 18887 rows)
number of nulls with congestion_surcharge 0
number of nulls with airport_fee 0
```

[306]:

```
print(f"Before proportion of values on number of records: \n␣
 ↪{df['store_and_fwd_flag'].isnull().sum()} ")
most_commonly_used_store_and_fwd_flag = df['store_and_fwd_flag'].mode()[0]
# Will set the flag as N, as anyways I dont see much use of these column for␣
 ↪now. Can renmove this later if not used,
df['store_and_fwd_flag'].fillna('N', inplace=True)
print(f"After proportion of values on number of records: \n␣
 ↪{df['store_and_fwd_flag'].isnull().sum()} ")
```

```
Before proportion of values on number of records:
 49245
```

```
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\3598645282.py:4:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['store_and_fwd_flag'].fillna('N', inplace=True)
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\3598645282.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['store_and_fwd_flag'].fillna('N', inplace=True)
```

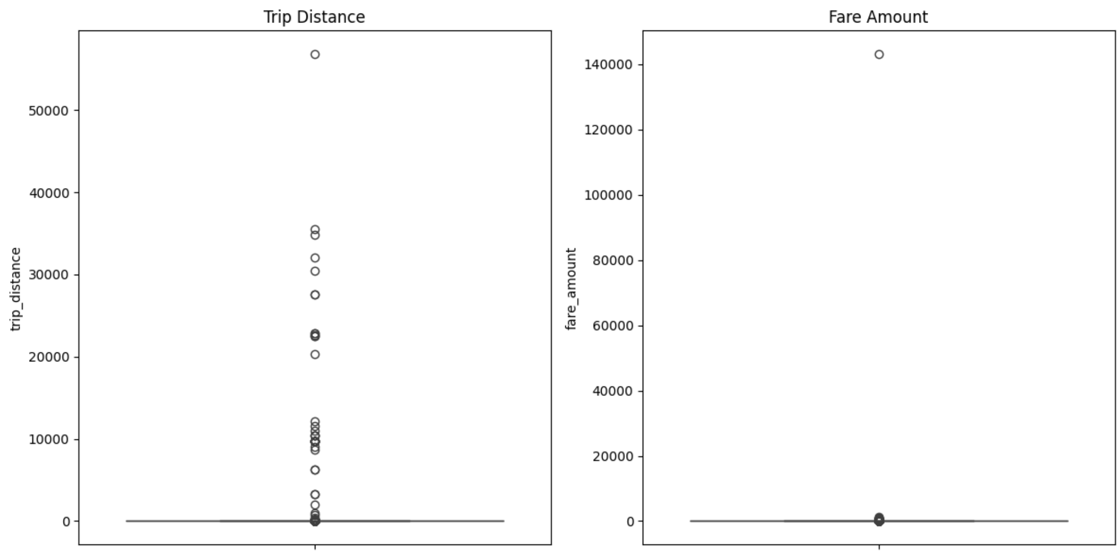
```
After proportion of values on number of records:
 0
```

1.6.2 2.3 Handling Outliers

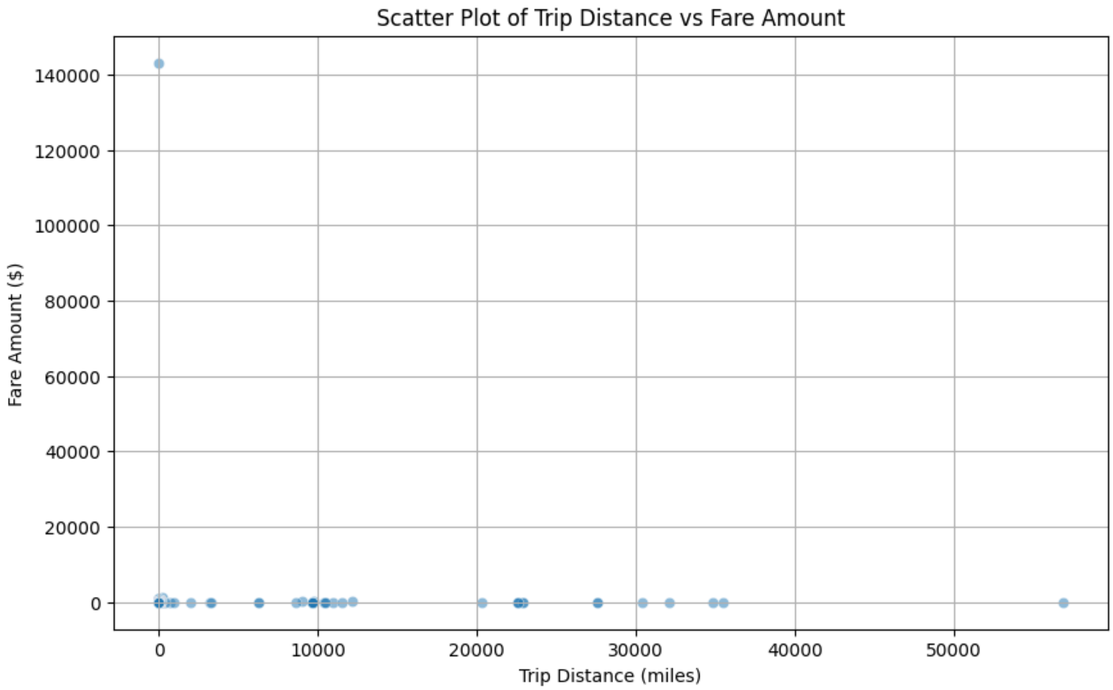
[10 marks]

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

[316]:
```
# Describe the data and check if there are any potential outliers present
# Check for potential out of place values in various columns

df.describe()

fig, axes = plt.subplots(1, 2, figsize=(12, 6))

# Box plot for trip_distance
sns.boxplot(y=df['trip_distance'], ax=axes[0])
axes[0].set_title("Trip Distance")

# Box plot for fare_amount
sns.boxplot(y=df['fare_amount'], ax=axes[1])
axes[1].set_title("Fare Amount")

plt.tight_layout()
plt.show()
```



[319]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='fare_amount', data=df, alpha=0.5)
plt.title("Scatter Plot of Trip Distance vs Fare Amount")
plt.xlabel("Trip Distance (miles)")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
```



[323]:
```
df['passenger_count'].value_counts()
```

[323]:
```
passenger_count
1.0    1495716
2.0     291012
3.0      72376
4.0      40387
0.0      31234
5.0      25004
6.0      16690
8.0         11
7.0          5
9.0          5
Name: count, dtype: int64
```

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.

[325]:
```
# remove passenger_count > 6
df = df[df['passenger_count'] <= 6]
```

[327]:
```
df['passenger_count'].value_counts()
```

[327]:
```
passenger_count
1.0    1495716
2.0     291012
3.0      72376
4.0      40387
0.0      31234
5.0      25004
6.0      16690
Name: count, dtype: int64
```

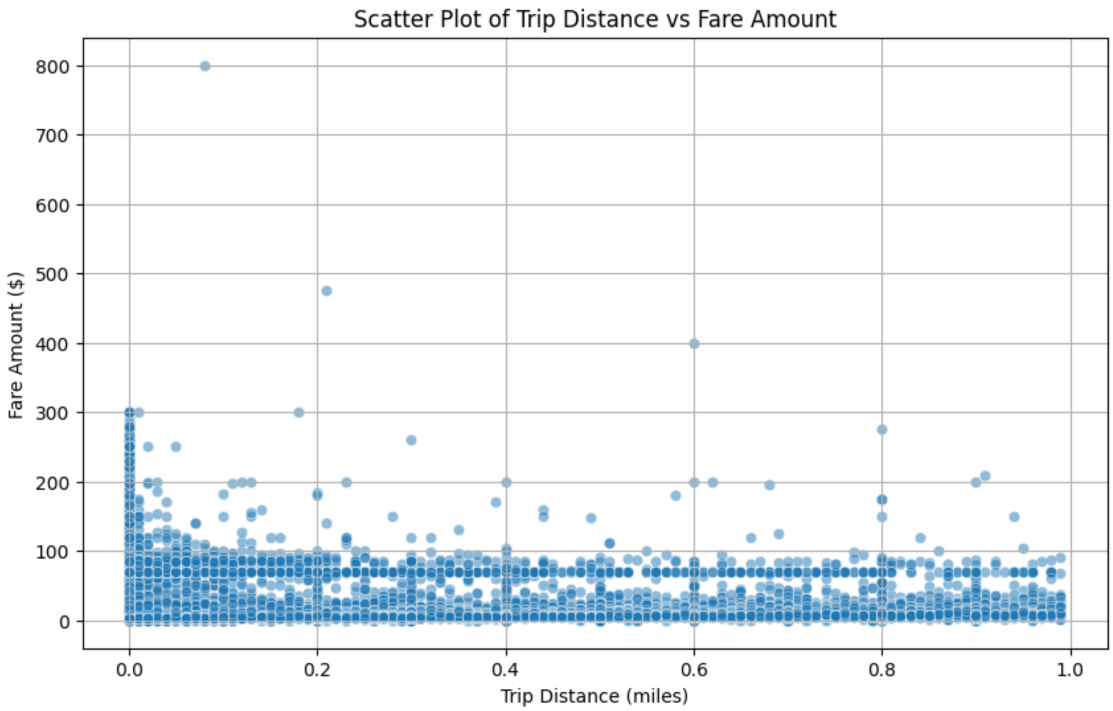
[339]:
```
# Continue with outlier handling
#  remove engtries with  trip_distance is  0 and fare_amount is more than 300
df = df[~((df['trip_distance'] == 0) & (df['fare_amount'] > 300))]
```

[341]:
```
# remove 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[~((df['trip_distance'] == 0) &
          (df['fare_amount'] == 0) &
          (df['PULocationID'] != df['DOLocationID']))]
```

[355]:
```
#Remove outlier Fare amounts
print(len( df[~(df['fare_amount'] > 1500)]))
df =  df[~(df['fare_amount'] > 1500)]
print(len( df[~(df['fare_amount'] > 1500)]))
```

```
1972319
1972319
```

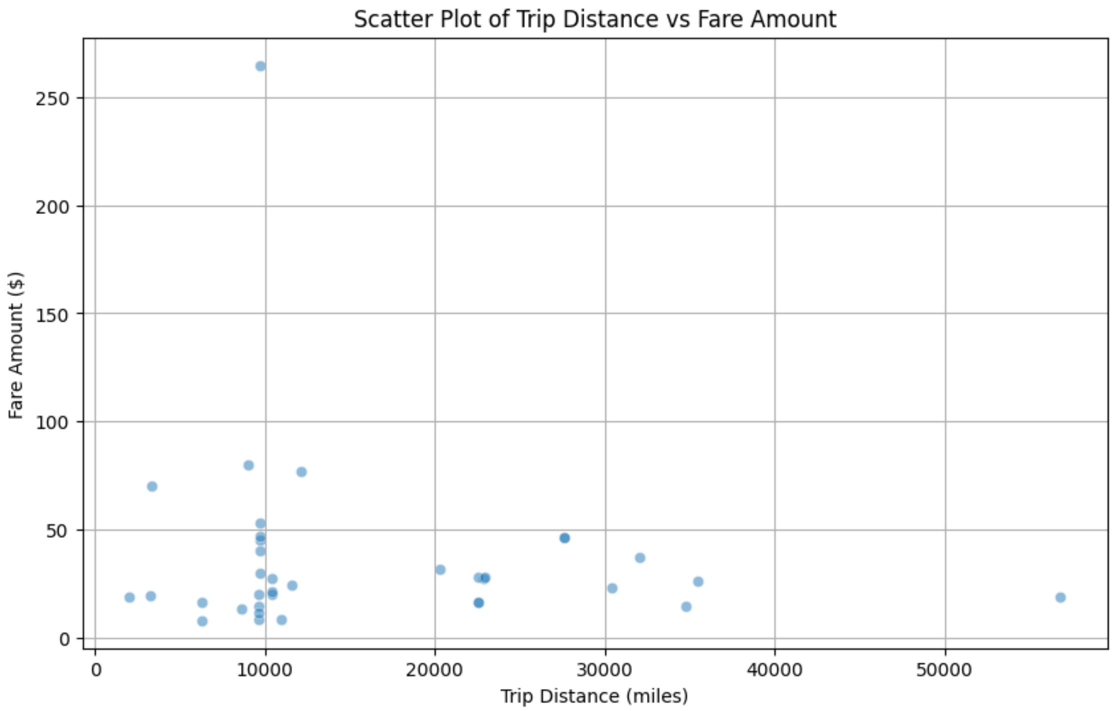
[359]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='fare_amount',␣
↪data=df[(df['trip_distance'] < 1)], alpha=0.5)
plt.title("Scatter Plot of Trip Distance vs Fare Amount")
plt.xlabel("Trip Distance (miles)")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
```



[361]:
```
# remove engtries with  trip_distance is around 0.8 and fare_amount is more␣
↪than 300
df = df[~((df['trip_distance'] < 0.8) & (df['fare_amount'] > 300))]
```

[367]:
```
# remove engtries with  trip_distance is  0.4 and fare_amount is more than 400
df = df[~((df['trip_distance'] < 0.4) & (df['fare_amount'] > 200))]
```

[371]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='fare_amount',␣
↪data=df[(df['trip_distance'] > 1000)], alpha=0.5)
plt.title("Scatter Plot of Trip Distance vs Fare Amount")
plt.xlabel("Trip Distance (miles)")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
```



[377]:
```
#  remove engtries with  trip_distance motre then 10000 and fare_amount is less␣
↪than 100
df = df[~((df['trip_distance'] > 10000) & (df['fare_amount'] < 200))]
```

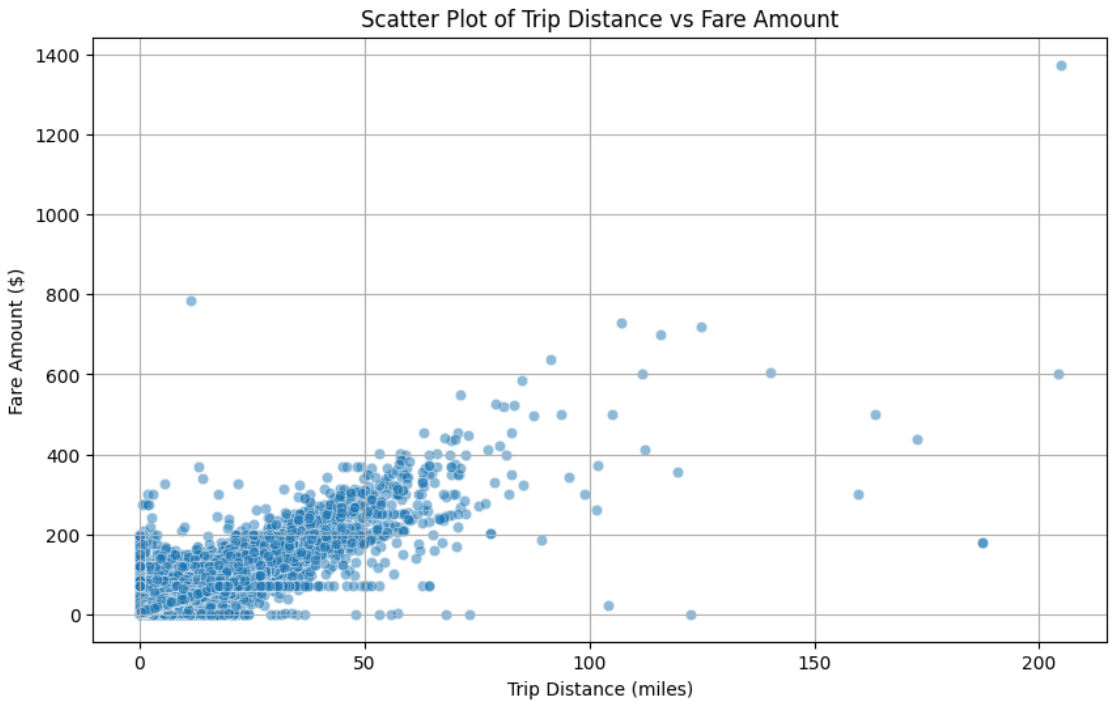
[393]:
```
#  remove engtries with  trip_distance motre then 250
print(len(df[~((df['trip_distance'] > 250))]))
df = df[~((df['trip_distance'] > 250))]
```

```
1972185
```

[383]:
```
df.shape
```

[383]:
```
(1972205, 22)
```

[395]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='fare_amount', data=df, alpha=0.5)
plt.title("Scatter Plot of Trip Distance vs Fare Amount")
plt.xlabel("Trip Distance (miles)")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
```



[400]:
```
# Do any columns need standardising?

df.describe().loc[['min', 'max']]
df["payment_type"].value_counts()
# 0 is flex fare type
```

[400]:
```
payment_type
1    1566923
2     332211
0      49225
4      14386
3       9440
Name: count, dtype: int64
```

1.7 3 Exploratory Data Analysis

[90 marks]

[402]:
```
df.columns.tolist()
```

[402]:
```
['VendorID',
 'tpep_pickup_datetime',
 'tpep_dropoff_datetime',
 'passenger_count',
 'trip_distance',
```

```
'RatecodeID',
'store_and_fwd_flag',
'PULocationID',
'DOLocationID',
'payment_type',
'fare_amount',
'extra',
'mta_tax',
'tip_amount',
'tolls_amount',
'improvement_surcharge',
'total_amount',
'congestion_surcharge',
'airport_fee',
'pickup_date',
'pickup_hour',
'total_diff']
```

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`: Numerical * `tpep_dropoff_datetime`: Numerical * `passenger_count`:Numerical * `trip_distance`:Numerical * `RatecodeID`: Categorical * `PULocationID`: Categorical * `DOLocationID`: Categorical * `payment_type`: Categorical * `pickup_hour`: Numerical * `trip_duration`: Numerical

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

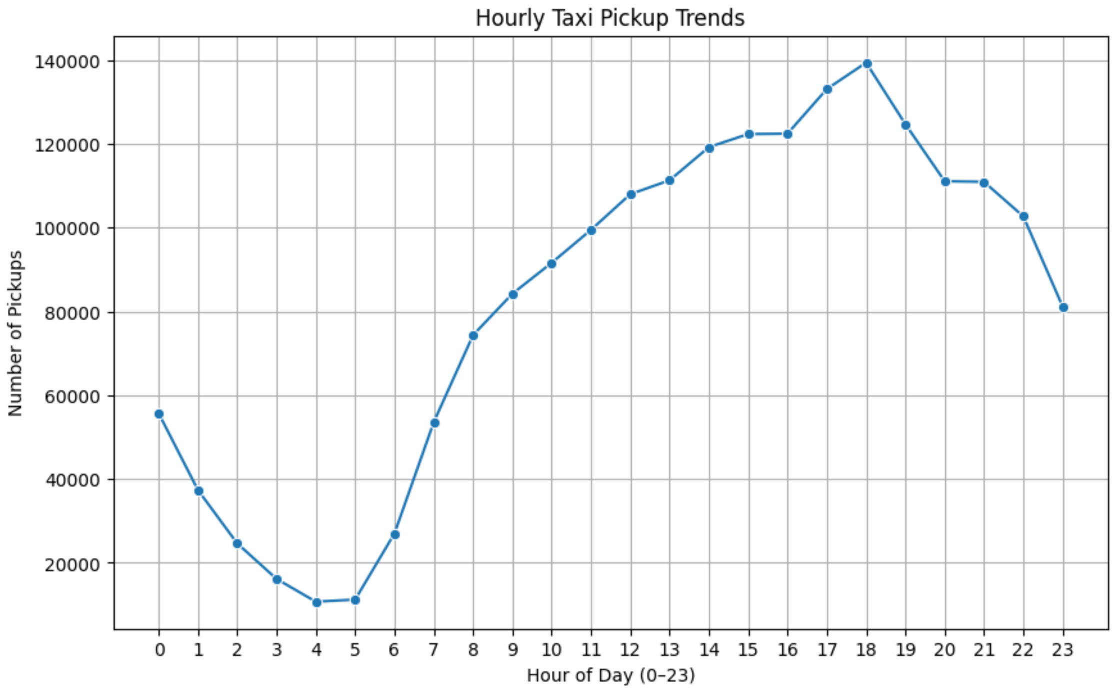
Ans: All the below are numerical

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

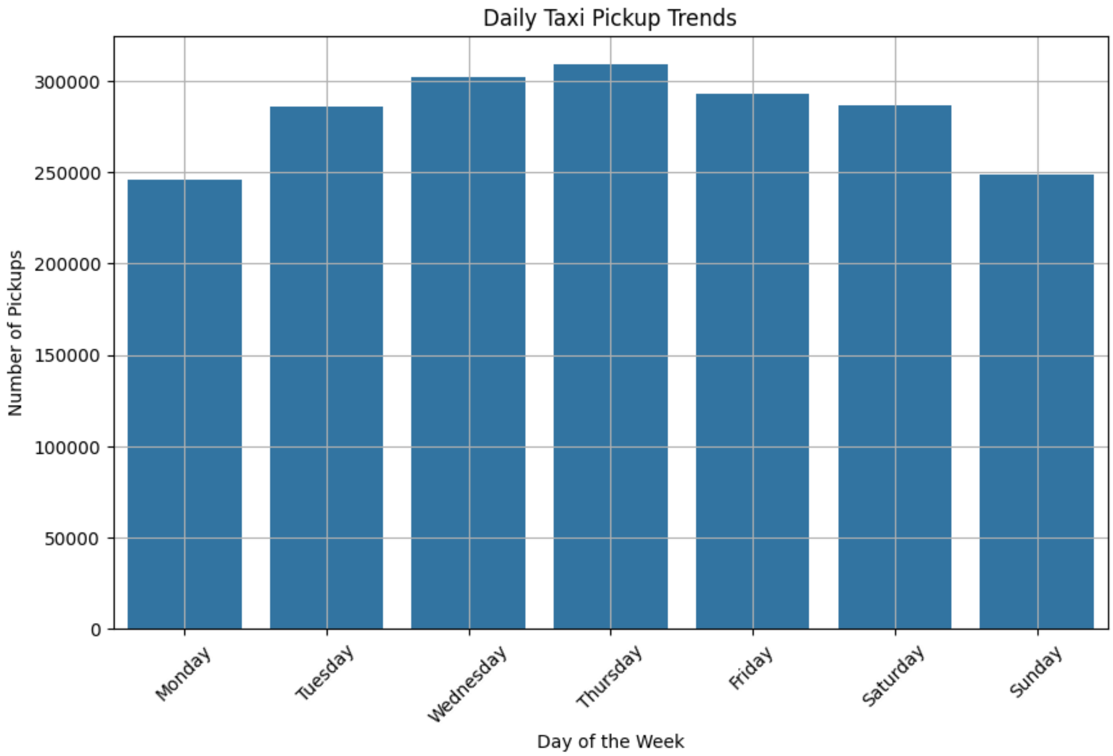
Temporal Analysis **3.1.2** [5 marks] Analyse the distribution of taxi pickups by hours, days of the week, and months.

[412]:
```
# Find and show the hourly trends in taxi pickups
# using line plot to look at the Pickup trends
hourly_trends = df['pickup_hour'].value_counts().sort_index()


plt.figure(figsize=(10, 6))
```

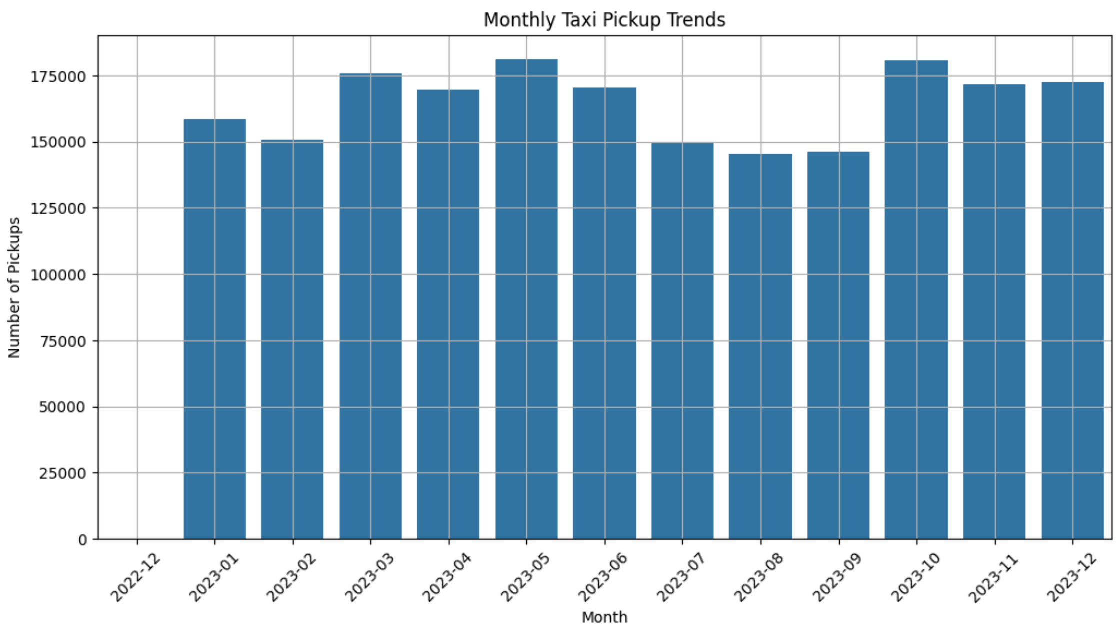
```python
sns.lineplot(x=hourly_trends.index, y=hourly_trends.values, marker='o')
plt.title("Hourly Taxi Pickup Trends")
plt.xlabel("Hour of Day (0-23)")
plt.ylabel("Number of Pickups")
plt.xticks(range(0, 24))
plt.grid(True)
plt.show()
```



[416]:
```python
# Find and show the daily trends in taxi pickups (days of the week)
df['pickup_day'] = df['tpep_pickup_datetime'].dt.day_name()

daily_counts = df['pickup_day'].value_counts().reindex([
    'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'
])


plt.figure(figsize=(10, 6))
sns.barplot(x=daily_counts.index, y=daily_counts.values)
plt.title("Daily Taxi Pickup Trends")
plt.xlabel("Day of the Week")
plt.ylabel("Number of Pickups")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



[418]:
```
# Show the monthly trends in pickups

df['pickup_month'] = df['tpep_pickup_datetime'].dt.to_period('M').astype(str)
monthly_counts = df['pickup_month'].value_counts().sort_index()

plt.figure(figsize=(12, 6))
sns.barplot(x=monthly_counts.index, y=monthly_counts.values)
plt.title("Monthly Taxi Pickup Trends")
plt.xlabel("Month")
plt.ylabel("Number of Pickups")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



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?

[420]:
```python
# Analyse the above parameters

cols_to_check = ['fare_amount', 'tip_amount', 'total_amount', 'trip_distance']

for col in cols_to_check:
    zero_count = (df[col] == 0).sum()
    negative_count = (df[col] < 0).sum()
    print(f"{col}: {zero_count} zeros, {negative_count} negatives")
```

```
fare_amount: 605 zeros, 0 negatives
tip_amount: 451627 zeros, 0 negatives
total_amount: 270 zeros, 0 negatives
trip_distance: 35884 zeros, 0 negatives
```

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?

[425]:
```python
# Create a df with non zero entries for the selected parameters.
# Removing only those rows which have fare_amount or total amount as zero.

df = df[~((df['fare_amount'] == 0) | (df['total_amount'] == 0))]
```

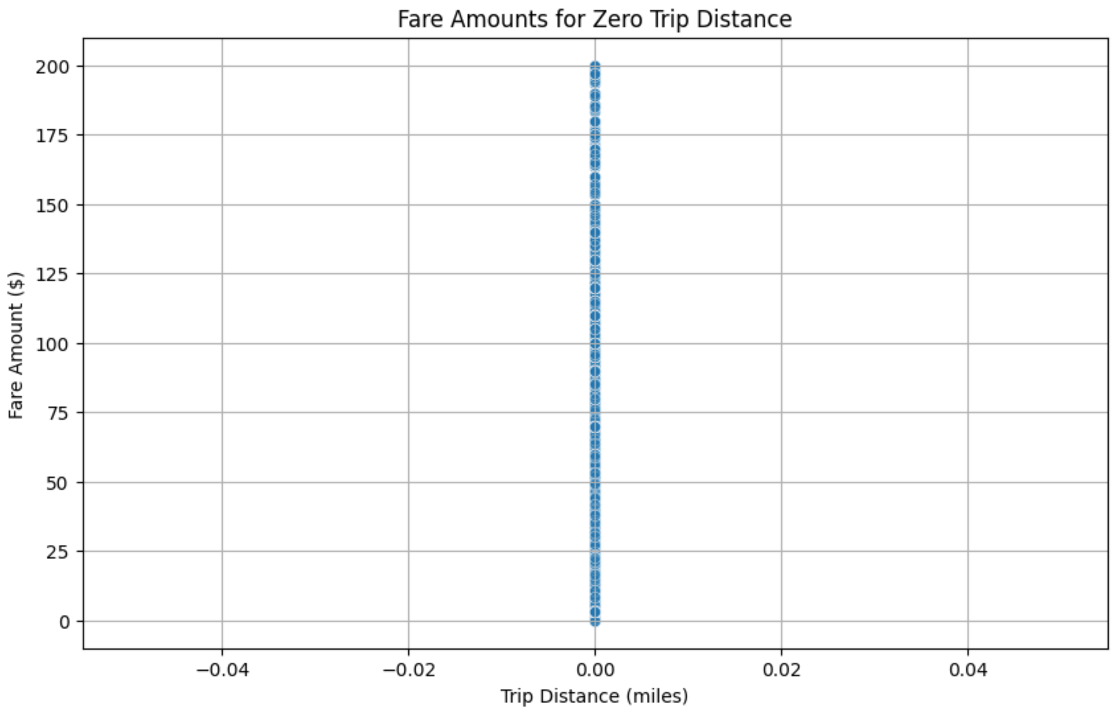
```python
for col in cols_to_check:
    zero_count = (df[col] == 0).sum()
    negative_count = (df[col] < 0).sum()
    print(f"{col}: {zero_count} zeros, {negative_count} negatives")
```

```
fare_amount: 0 zeros, 0 negatives
tip_amount: 451042 zeros, 0 negatives
total_amount: 0 zeros, 0 negatives
trip_distance: 35612 zeros, 0 negatives
```

[437]:
```python
zero_count = ((df['trip_distance'] == 0) & (df['fare_amount'] <= 25 )).sum()
total_count = len(df)
percentage = (zero_count / total_count) * 100

print(f"Percentage of zero trip_distance records: {percentage:.2f}%")
```

```
Percentage of zero trip_distance records: 1.23%
```

[427]:
```python
zero_distance_df = df[df['trip_distance'] == 0]

# Create scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='fare_amount', data=zero_distance_df,␣
 ↪alpha=0.6)
plt.title("Fare Amounts for Zero Trip Distance")
plt.xlabel("Trip Distance (miles)")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
```



[439]:
```
# only removing all the records with trip distance as 0 and amount less 25␣
↪dollars
df = df[~ ((df['trip_distance'] == 0) & (df['fare_amount'] <= 25 ))]
```

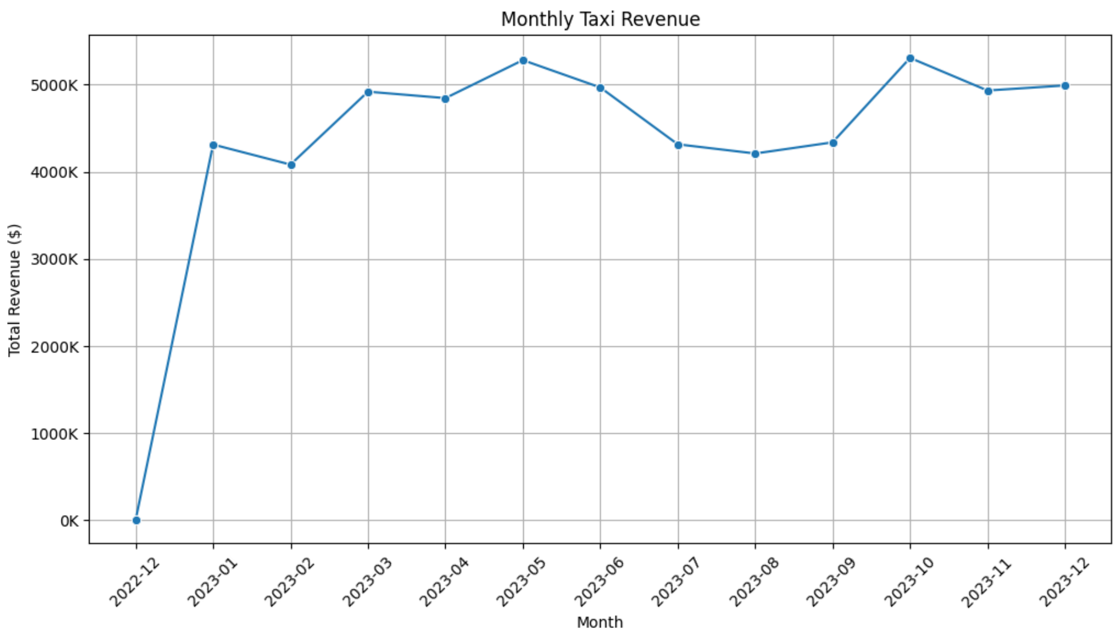
[441]:
```
zero_count = ((df['trip_distance'] == 0) ).sum()
total_count = len(df)
percentage = (zero_count / total_count) * 100

print(f"Percentage of zero trip_distance records: {percentage:.2f}%")
```

```
Percentage of zero trip_distance records: 0.58%
```

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

[449]:
```
# Group data by month and analyse monthly revenue
import matplotlib.ticker as ticker

monthly_revenue = df.groupby('pickup_month')['total_amount'].sum()
plt.figure(figsize=(12, 6))
sns.lineplot(x=monthly_revenue.index, y=monthly_revenue.values, marker='o')
plt.gca().yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: f'{x/
↪1000:.0f}K'))

plt.title("Monthly Taxi Revenue")
plt.xlabel("Month")
```

```
plt.ylabel("Total Revenue ($)")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



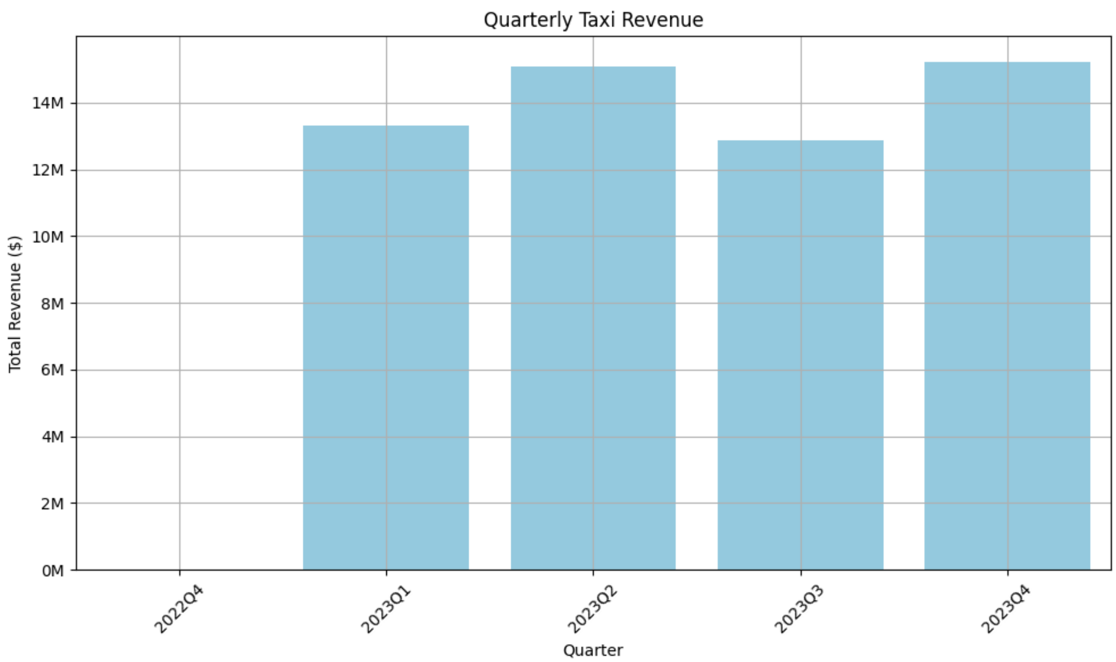
3.1.5 [3 marks] Show the proportion of each quarter of the year in the revenue

[451]:
```
# Calculate proportion of each quarter
df['pickup_quarter'] = df['tpep_pickup_datetime'].dt.to_period('Q')
quarterly_revenue = df.groupby('pickup_quarter')['total_amount'].sum()
annual_revenue = quarterly_revenue.sum()
quarterly_proportion = (quarterly_revenue / annual_revenue) * 100
print(quarterly_proportion.round(2))
```

```
pickup_quarter
2022Q4     0.00
2023Q1    23.56
2023Q2    26.72
2023Q3    22.76
2023Q4    26.96
Freq: Q-DEC, Name: total_amount, dtype: float64
```

[457]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x=quarterly_revenue.index.astype(str), y=quarterly_revenue.values,␣
↪color='skyblue')
plt.gca().yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: f'{x/
↪1000000:.0f}M'))
```

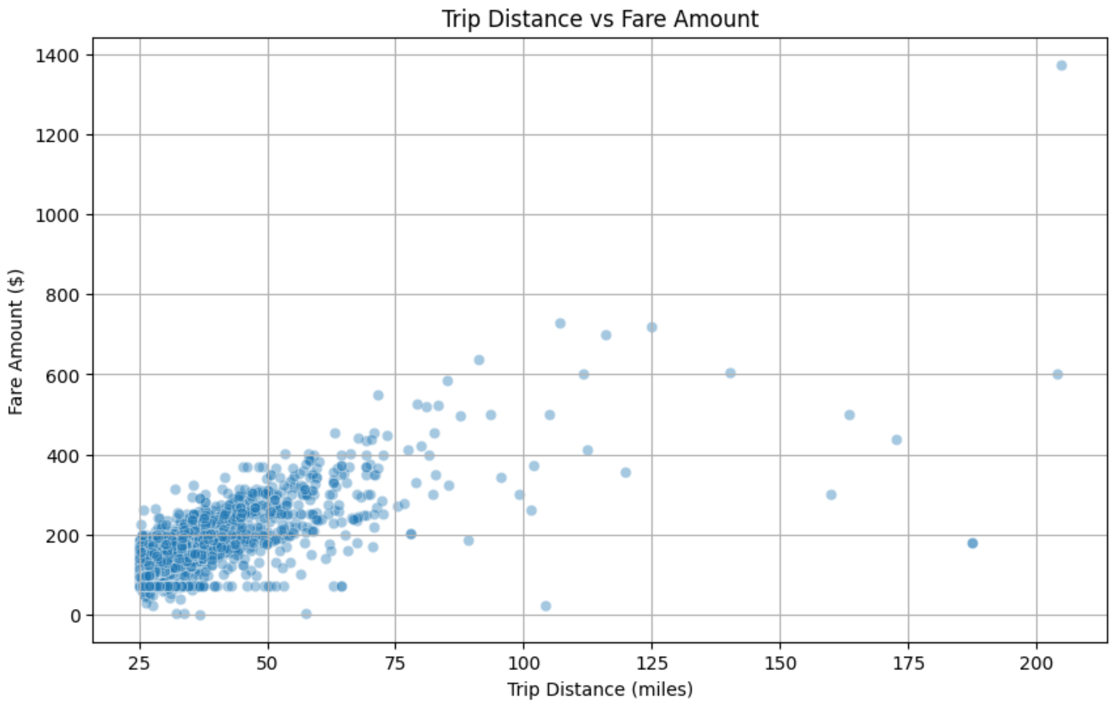
```
plt.title("Quarterly Taxi Revenue")
plt.xlabel("Quarter")
plt.ylabel("Total Revenue ($)")
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



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

[463]:
```
# Show how trip fare is affected by distance
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='fare_amount', 
 ↪data=df[(df['trip_distance'] > 25)], alpha=0.4)
plt.title("Trip Distance vs Fare Amount")
plt.xlabel("Trip Distance (miles)")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
```



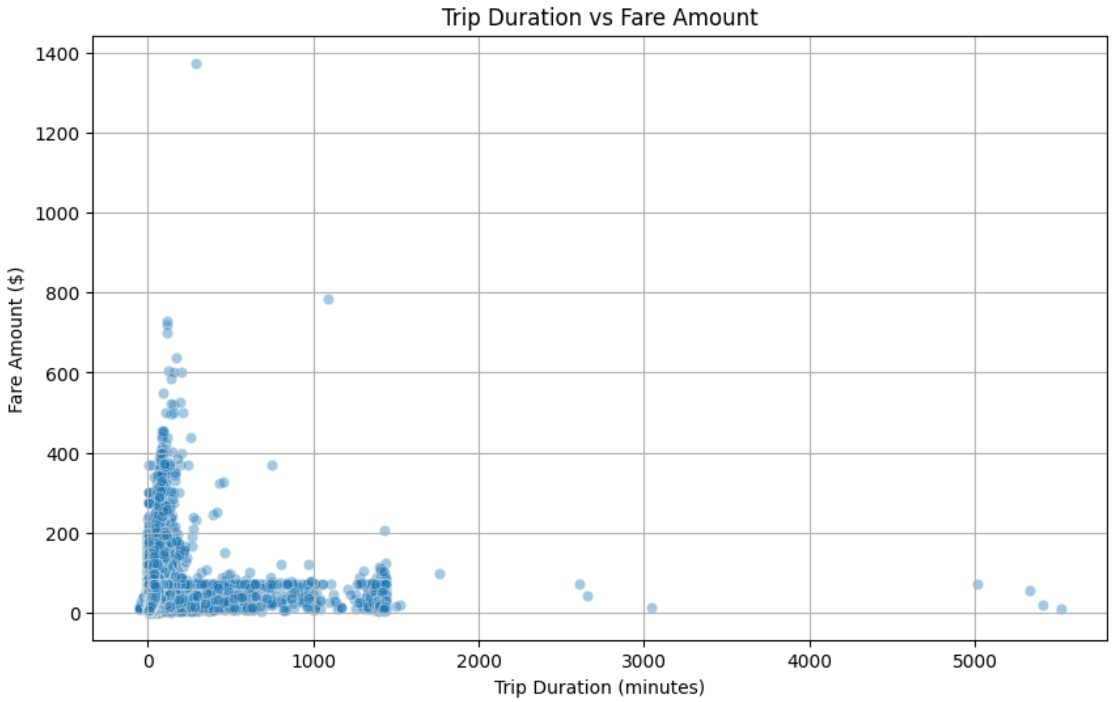
3.1.7 [5 marks] Find and visualise the correlation between: 1. `fare_amount` and trip duration (pickup time to dropoff time) 2. `fare_amount` and `passenger_count` 3. `tip_amount` and `trip_distance`

[467]:
```
df.columns
```

[467]:
```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge', 'airport_fee', 'pickup_date',
       'pickup_hour', 'total_diff', 'pickup_day', 'pickup_month',
       'pickup_quarter'],
      dtype='object')
```

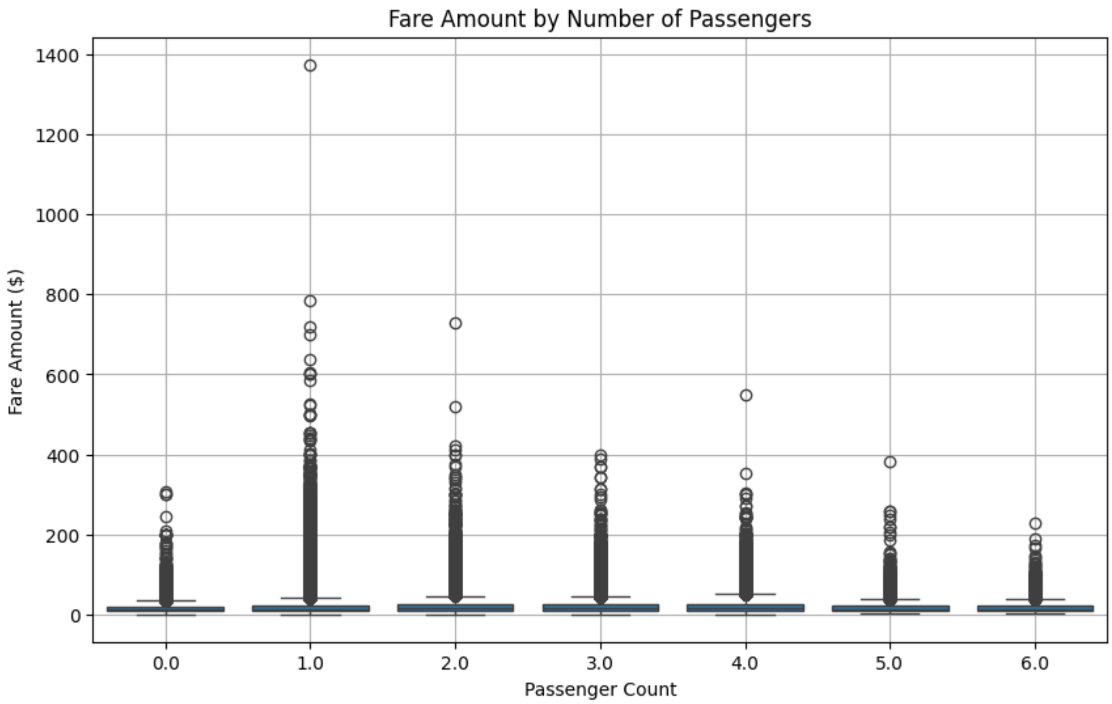
[469]:
```
# Show relationship between fare and trip duration
df['trip_duration'] = (df['tpep_dropoff_datetime'] -
 ↪df['tpep_pickup_datetime']).dt.total_seconds() / 60
plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_duration', y='fare_amount', data=df, alpha=0.4)
plt.title("Trip Duration vs Fare Amount")
plt.xlabel("Trip Duration (minutes)")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
```

```
plt.show()
```

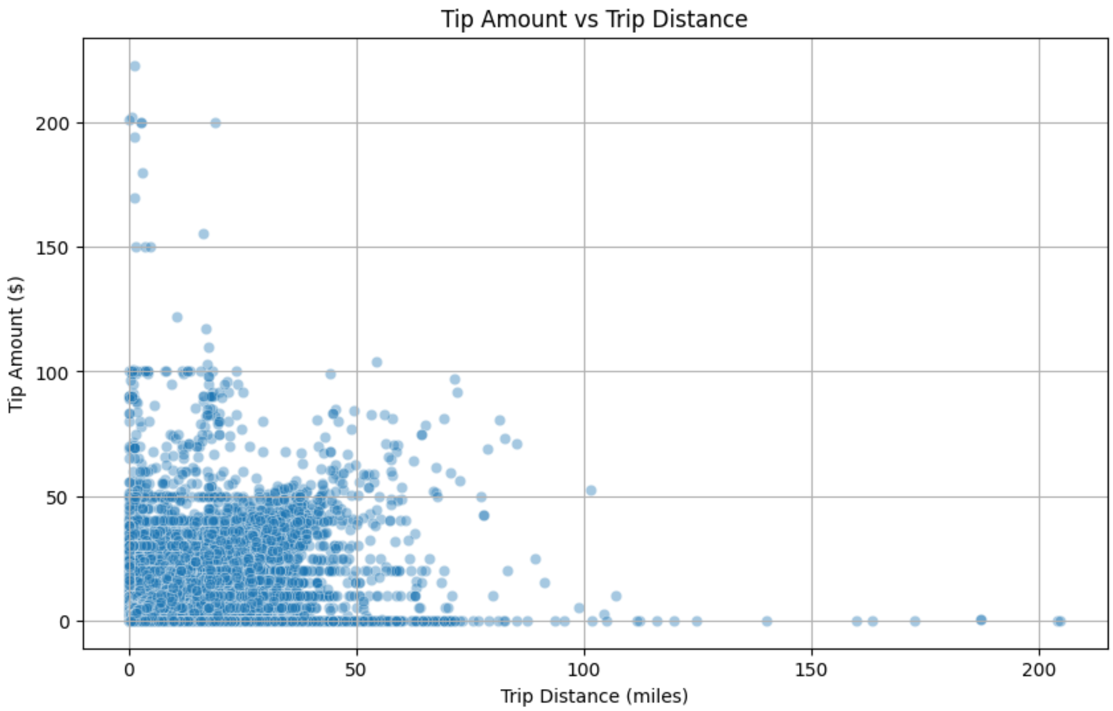


[475]:

```
# Show relationship between fare and number of passengers

plt.figure(figsize=(10, 6))
sns.boxplot(x='passenger_count', y='fare_amount', data=df)
plt.title("Fare Amount by Number of Passengers")
plt.xlabel("Passenger Count")
plt.ylabel("Fare Amount ($)")
plt.grid(True)
plt.show()
```



[477]:
```python
# Show relationship between tip and trip distance

plt.figure(figsize=(10, 6))
sns.scatterplot(x='trip_distance', y='tip_amount', data=df, alpha=0.4)
plt.title("Tip Amount vs Trip Distance")
plt.xlabel("Trip Distance (miles)")
plt.ylabel("Tip Amount ($)")
plt.grid(True)
plt.show()
```

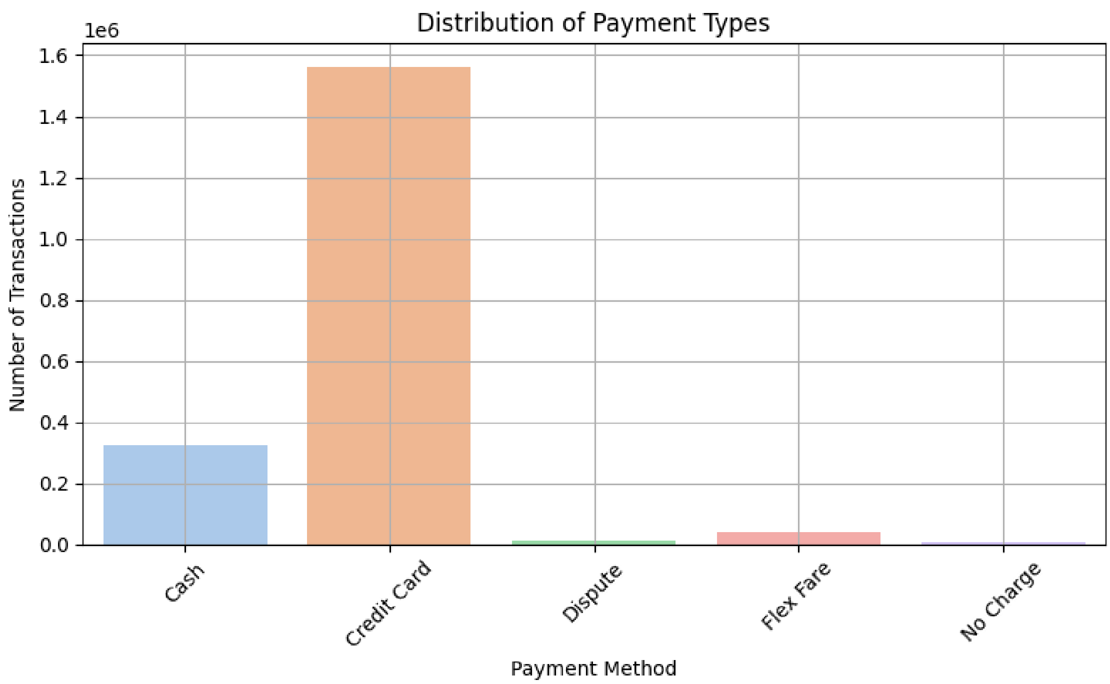


3.1.8 [3 marks] Analyse the distribution of different payment types (`payment_type`)

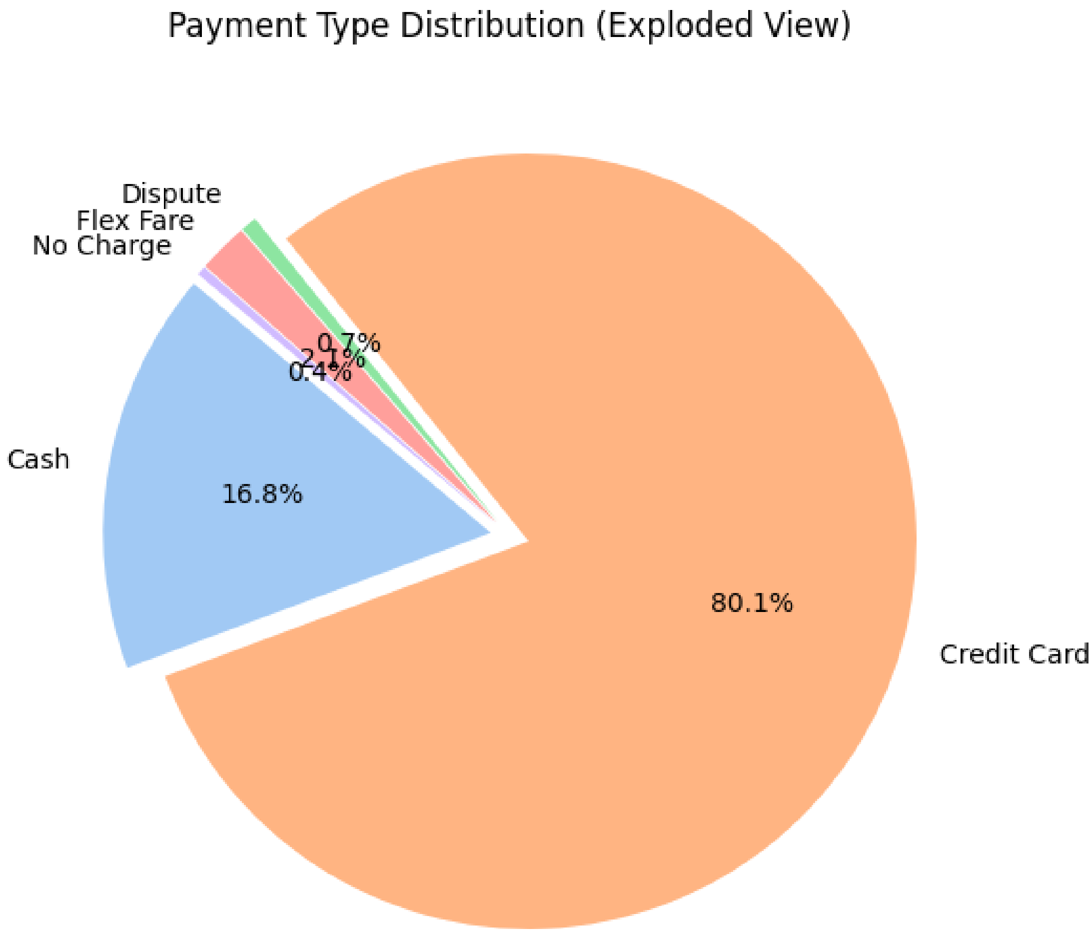
[485]:
```
payment_labels = {
    0: 'Flex Fare',
    1: 'Credit Card',
    2: 'Cash',
    3: 'No Charge',
    4: 'Dispute'
}
df['payment_type_label'] = df['payment_type'].map(payment_labels)
```

[487]:
```
# Analyse the distribution of different payment types (payment_type).

payment_counts = df['payment_type_label'].value_counts().sort_index()

plt.figure(figsize=(8, 5))
sns.barplot(x=payment_counts.index, y=payment_counts.values, palette='pastel')
plt.title("Distribution of Payment Types")
plt.xlabel("Payment Method")
plt.ylabel("Number of Transactions")
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\3317766951.py:6:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=payment_counts.index, y=payment_counts.values, palette='pastel')
```



[491]:
```
explode = [0.05] * len(payment_counts)  # Adjust the value for more/less␣
 ↪separation

# Plot pie chart
plt.figure(figsize=(6, 6))
plt.pie(payment_counts.values,
        labels=payment_counts.index,
        autopct='%1.1f%%',
        startangle=140,
        explode=explode,
        colors=sns.color_palette('pastel'))

plt.title("Payment Type Distribution (Exploded View)")
plt.tight_layout()
plt.show()
```



- 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

[493]:
```
!pip install geopandas
```

```
Collecting geopandas
  Downloading geopandas-1.1.0-py3-none-any.whl.metadata (2.3 kB)
Requirement already satisfied: numpy>=1.24 in
c:\users\sherry\anaconda3\lib\site-packages (from geopandas) (1.26.4)
Collecting pyogrio>=0.7.2 (from geopandas)
  Downloading pyogrio-0.11.0-cp312-cp312-win_amd64.whl.metadata (5.4 kB)
Requirement already satisfied: packaging in
c:\users\sherry\appdata\roaming\python\python312\site-packages (from geopandas)
(24.2)
Requirement already satisfied: pandas>=2.0.0 in
c:\users\sherry\appdata\roaming\python\python312\site-packages (from geopandas)
(2.2.3)
Collecting pyproj>=3.5.0 (from geopandas)
  Downloading pyproj-3.7.1-cp312-cp312-win_amd64.whl.metadata (31 kB)
Collecting shapely>=2.0.0 (from geopandas)
  Downloading shapely-2.1.1-cp312-cp312-win_amd64.whl.metadata (7.0 kB)
Requirement already satisfied: python-dateutil>=2.8.2 in
c:\users\sherry\appdata\roaming\python\python312\site-packages (from
pandas>=2.0.0->geopandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
c:\users\sherry\appdata\roaming\python\python312\site-packages (from
pandas>=2.0.0->geopandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in
c:\users\sherry\appdata\roaming\python\python312\site-packages (from
pandas>=2.0.0->geopandas) (2024.2)
Requirement already satisfied: certifi in
c:\users\sherry\appdata\roaming\python\python312\site-packages (from
pyogrio>=0.7.2->geopandas) (2025.1.31)
Requirement already satisfied: six>=1.5 in
c:\users\sherry\appdata\roaming\python\python312\site-packages (from python-
dateutil>=2.8.2->pandas>=2.0.0->geopandas) (1.17.0)
```

```
Downloading geopandas-1.1.0-py3-none-any.whl (338 kB)
Downloading pyogrio-0.11.0-cp312-cp312-win_amd64.whl (19.2 MB)
   ---------------------------------------- 0.0/19.2 MB ? eta -:--:--
   -------- ------------------------------- 4.2/19.2 MB 22.9 MB/s eta 0:00:01
   ------------------- -------------------- 9.2/19.2 MB 23.8 MB/s eta 0:00:01
   -------------------------- ------------- 12.6/19.2 MB 20.7 MB/s eta 0:00:01
   ----------------------------------- ---- 17.0/19.2 MB 21.1 MB/s eta 0:00:01
   ---------------------------------------- 19.2/19.2 MB 20.9 MB/s eta 0:00:00
Downloading pyproj-3.7.1-cp312-cp312-win_amd64.whl (6.3 MB)
   ---------------------------------------- 0.0/6.3 MB ? eta -:--:--
   ---------------------------- ----------- 4.5/6.3 MB 24.4 MB/s eta 0:00:01
   ---------------------------------------- 6.3/6.3 MB 19.2 MB/s eta 0:00:00
Downloading shapely-2.1.1-cp312-cp312-win_amd64.whl (1.7 MB)
   ---------------------------------------- 0.0/1.7 MB ? eta -:--:--
   ---------------------------------------- 1.7/1.7 MB 22.9 MB/s eta 0:00:00
Installing collected packages: shapely, pyproj, pyogrio, geopandas
Successfully installed geopandas-1.1.0 pyogrio-0.11.0 pyproj-3.7.1 shapely-2.1.1


[notice] A new release of pip is available: 24.3.1 -> 25.1.1
[notice] To update, run: python.exe -m pip install --upgrade pip
```

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

[499]:
```python
import geopandas as gpd


# Read the shapefile using geopandas
zones = gpd.read_file(r"C:\Users\Sherry\UpgradExample\Datasets and␣
↪Dictionary-NYC\Starter Notebook - EDA NYC Taxi\taxi_zones\taxi_zones.shp")
# read the .shp file using gpd
zones.head()
```

[499]:
```
   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.

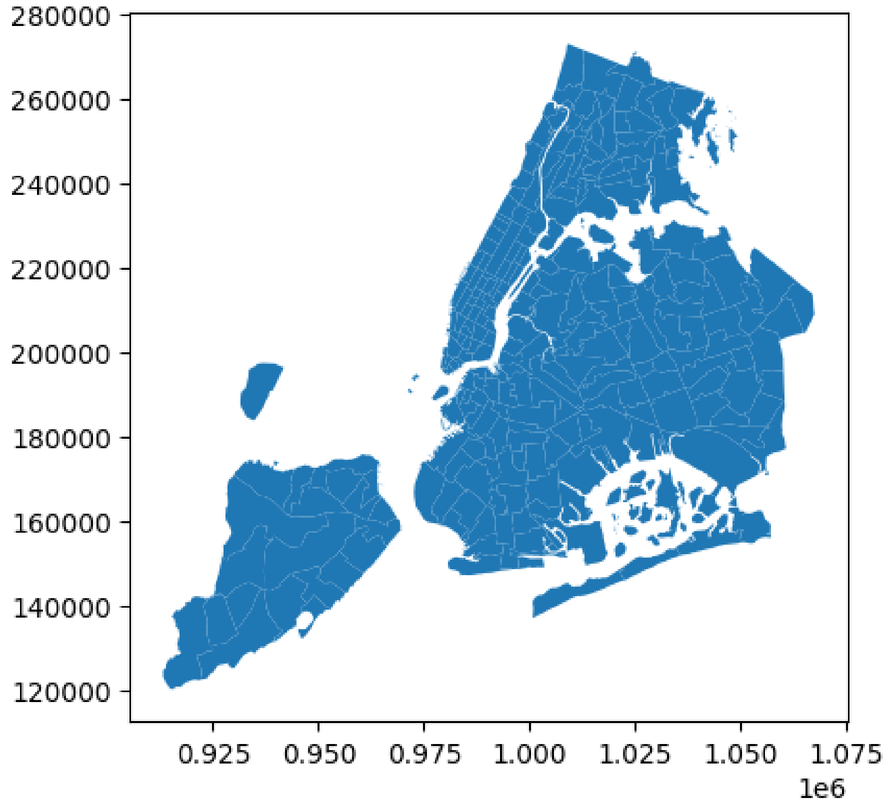
The geometric parameters like shape length, shape area and geometry are used to plot the zones on a map.

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

[501]:
```
print(zones.info())
zones.plot()
```

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

[501]: `<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.

[503]:
```
# Merge zones and trip records using locationID and PULocationID

df = df.merge(zones[['LocationID', 'zone', 'borough']], how='left',␣
↪left_on='PULocationID', right_on='LocationID')
```

[507]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1947483 entries, 0 to 1947482
Data columns (total 30 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  pickup_date            object
 20  pickup_hour            int32
 21  total_diff             float64
 22  pickup_day             object
 23  pickup_month           object
 24  pickup_quarter         period[Q-DEC]
 25  trip_duration          float64
 26  payment_type_label     object
 27  LocationID             float64
 28  zone                   object
 29  borough                object
dtypes: datetime64[us](2), float64(15), int32(1), int64(4), object(7),
period[Q-DEC](1)
memory usage: 438.3+ MB
```

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

[511]:

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

pickup = df['PULocationID'].value_counts().rename_axis('LocationID').
 ↪reset_index(name='pickup_count')
dropoff = df['DOLocationID'].value_counts().rename_axis('LocationID').
 ↪reset_index(name='dropoff_count')

# Merge and fill missing values with 0
location_trip_counts = pd.merge(pickup, dropoff, on='LocationID', how='outer').
 ↪fillna(0)

# Calculate total trips
location_trip_counts['total_trips'] = location_trip_counts['pickup_count'] +␣
 ↪location_trip_counts['dropoff_count']
location_trip_counts
```

[511]:
```
     LocationID  pickup_count  dropoff_count  total_trips
0             1         198.0         5593.0       5791.0
1             2           2.0            4.0          6.0
2             3          39.0          164.0        203.0
3             4        2273.0         7370.0       9643.0
4             5          13.0           34.0         47.0
..          …           …             …            …
256         261       10289.0         9280.0      19569.0
257         262       25874.0        30149.0      56023.0
258         263       37490.0        40052.0      77542.0
259         264       17096.0        18275.0      35371.0
260         265         890.0         8016.0       8906.0

[261 rows x 4 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.

[514]:
```python
# Merge trip counts back to the zones GeoDataFrame

zones = zones.merge(location_trip_counts, on='LocationID', how='left')
zones.head()
```

[514]:
```
   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…

   pickup_count  dropoff_count  total_trips
0         198.0         5593.0       5791.0
1           2.0            4.0          6.0
2          39.0          164.0        203.0
3        2273.0         7370.0       9643.0
4          13.0           34.0         47.0
```

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.

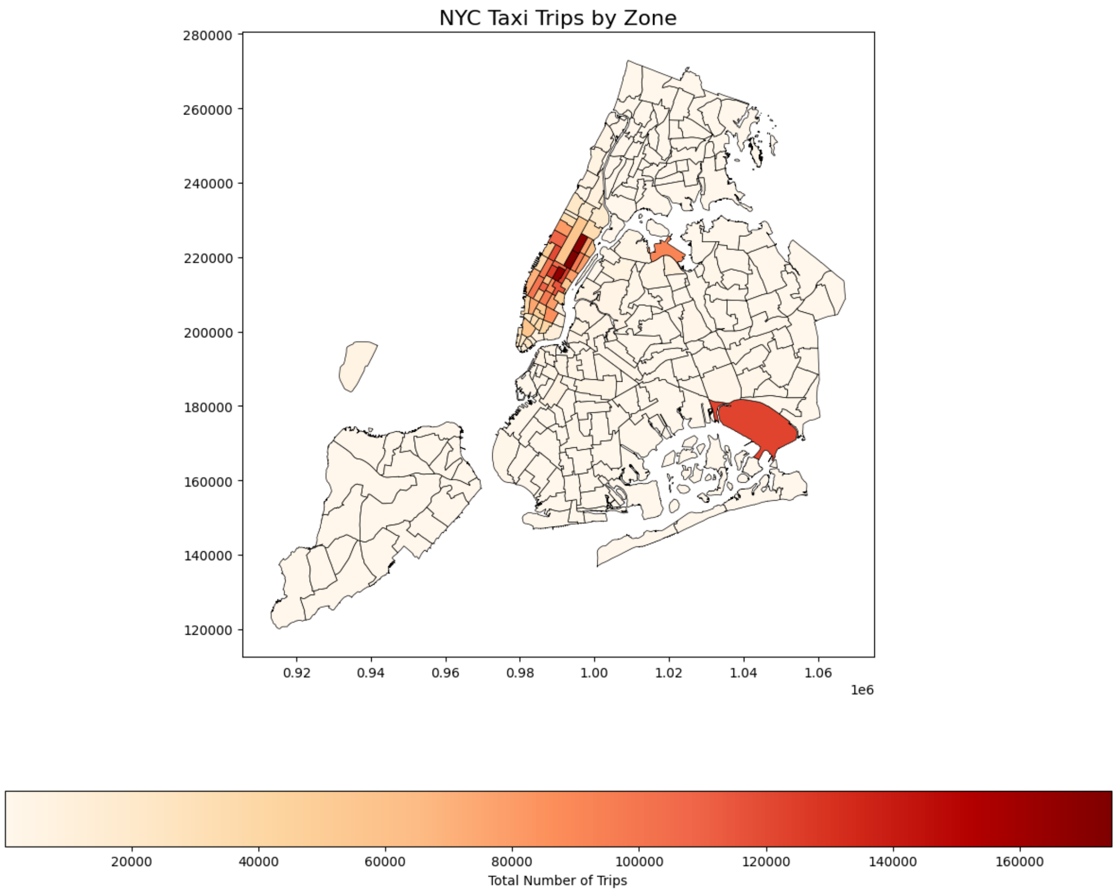
You can define the following parameters in the `zones.plot()` method:

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

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

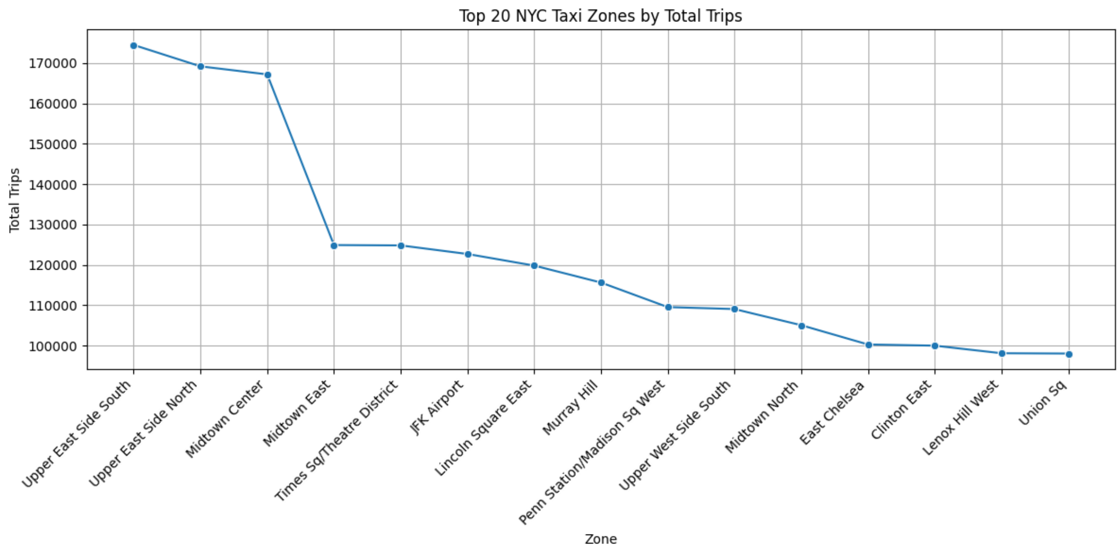
3.1.13 [3 marks] Plot a color-coded map showing zone-wise trips

[520]:
```python
# Define figure and axis
fig, ax = plt.subplots(1, 1, figsize=(12, 10))


# Plot the map and display it
zones.plot(column='total_trips',
           cmap='OrRd',
           legend=True,
           edgecolor='black',
           linewidth=0.5,
           ax=ax,
           legend_kwds={
               'label': "Total Number of Trips",
               'orientation': "horizontal"  # or "vertical"
           })

ax.set_title("NYC Taxi Trips by Zone", fontsize=16)
plt.tight_layout()
plt.show()
```



[524]:
```python
# can you try displaying the zones DF sorted by the number of trips?



sorted_zones = zones.sort_values(by='total_trips', ascending=False)

# Plot top 20 zones (or adjust as needed)
plt.figure(figsize=(12, 6))
sns.lineplot(
    x=sorted_zones['zone'].head(15),
    y=sorted_zones['total_trips'].head(15),
    marker='o'
)

plt.title("Top 20 NYC Taxi Zones by Total Trips")
plt.xlabel("Zone")
plt.ylabel("Total Trips")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.grid(True)
```

```
plt.show()
```



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)

[526]:
```
# Find routes which have the slowest speeds at different times of the day

df['trip_duration_hr'] = df['trip_duration'] / 60  # convert minutes to hours
df['speed_mph'] = df['trip_distance'] / df['trip_duration_hr']
```

[540]:
```
negative_speed_rows = df[df['speed_mph'] < 0]
len(negative_speed_rows)
#remove negative speed rows from the data set
df = df[df['speed_mph'] >= 0]
```

[528]:
```
def get_time_of_day(hour):
    if 5 <= hour < 12:
        return 'Morning'
    elif 12 <= hour < 17:
        return 'Afternoon'
    elif 17 <= hour < 21:
        return 'Evening'
    else:
        return 'Night'

df['time_of_day'] = df['pickup_hour'].apply(get_time_of_day)
df['route'] = df['zone'] + "   " + df['DOLocationID'].astype(str)
```

[528]:
```
                                   route time_of_day  speed_mph
0        Allerton/Pelham Gardens   10     Morning  17.387074
1       Allerton/Pelham Gardens   119     Evening   0.000000
2       Allerton/Pelham Gardens   133     Morning   0.000000
3       Allerton/Pelham Gardens   137     Morning  14.452188
4       Allerton/Pelham Gardens   142       Night  12.731092
…                                  …         …          …
44716             Yorkville West   95       Night  33.024821
44717             Yorkville West   97   Afternoon  16.922724
44718             Yorkville West   97     Evening  18.859933
44719             Yorkville West   97     Morning  21.771459
44720             Yorkville West   97       Night  23.045805

[44721 rows x 3 columns]
```

[542]:
```
route_speeds = df[(df['speed_mph'] > 0)].groupby(['route',␣
 ↪'time_of_day'])['speed_mph'].mean().reset_index()
route_speeds
```

[542]:
```
                                   route time_of_day  speed_mph
0        Allerton/Pelham Gardens   10     Morning  17.387074
1       Allerton/Pelham Gardens   137     Morning  14.452188
2       Allerton/Pelham Gardens   142       Night  12.731092
3       Allerton/Pelham Gardens   147   Afternoon  14.716981
4       Allerton/Pelham Gardens   163     Morning  17.384074
…                                  …         …          …
43366             Yorkville West   95       Night  33.024821
43367             Yorkville West   97   Afternoon  16.922724
43368             Yorkville West   97     Evening  18.859933
```

```
43369            Yorkville West   97     Morning  21.771459
43370            Yorkville West   97       Night  23.045805

[43371 rows x 3 columns]
```

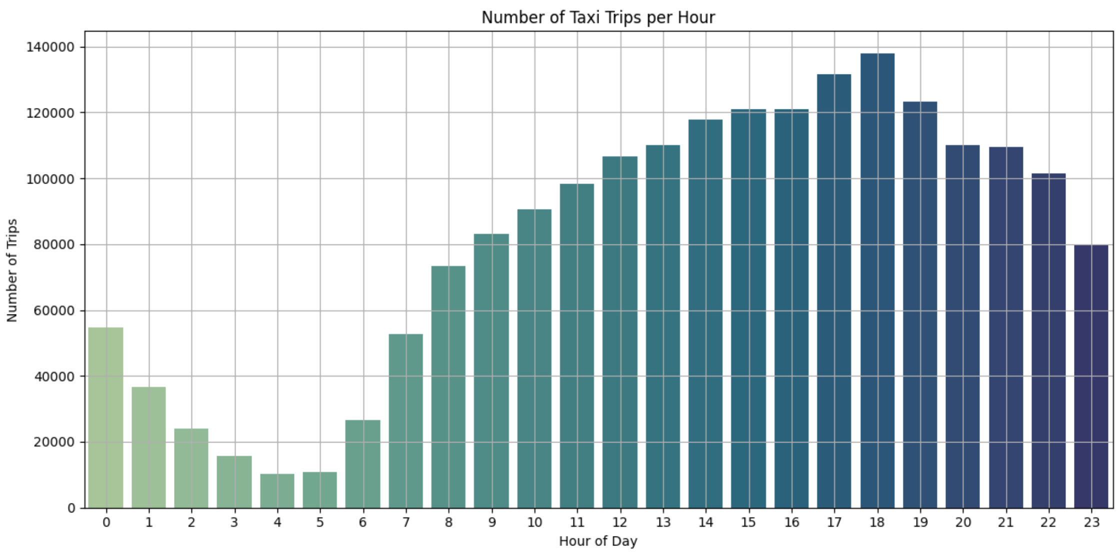
[546]:
```
#Below are the slowest routes at different time of day
slowest_routes = route_speeds.sort_values(['time_of_day', 'speed_mph']).
 ↪groupby('time_of_day').head(1)
print(slowest_routes)
```

```
                                    route time_of_day  speed_mph
16515               Howard Beach   129   Afternoon   0.072029
39723  Washington Heights North   264     Evening   0.007772
4109                Central Park   10     Morning   0.022236
15307    Greenwich Village North   235       Night   0.048105
```

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.

[561]:
```
# Visualise the number of trips per hour and find the busiest hour

hourly_counts = df['pickup_hour'].value_counts().sort_index()

# Plot
plt.figure(figsize=(12, 6))
sns.barplot(x=hourly_counts.index, y=hourly_counts.values,hue=hourly_counts.
 ↪index, palette='crest', legend=False)

plt.title("Number of Taxi Trips per Hour")
plt.xlabel("Hour of Day")
plt.ylabel("Number of Trips")
plt.xticks(range(0, 24))
plt.grid(True)
plt.tight_layout()
plt.show()
```



Busiest time is between 6 - 7 PM.

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

[565]:
```
hourly_counts = df['pickup_hour'].value_counts().sort_values(ascending=False)
top_5_hours = hourly_counts.head(5)


# 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
estimated_top_5 = (top_5_hours / sample_fraction).astype(int)

print("Estimated Total Trips in Top 5 Busiest Hours:")
print(estimated_top_5)
```

```
Estimated Total Trips in Top 5 Busiest Hours:
pickup_hour
18    2755620
17    2629080
19    2466940
16    2420800
15    2420100
Name: count, dtype: int32
```

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

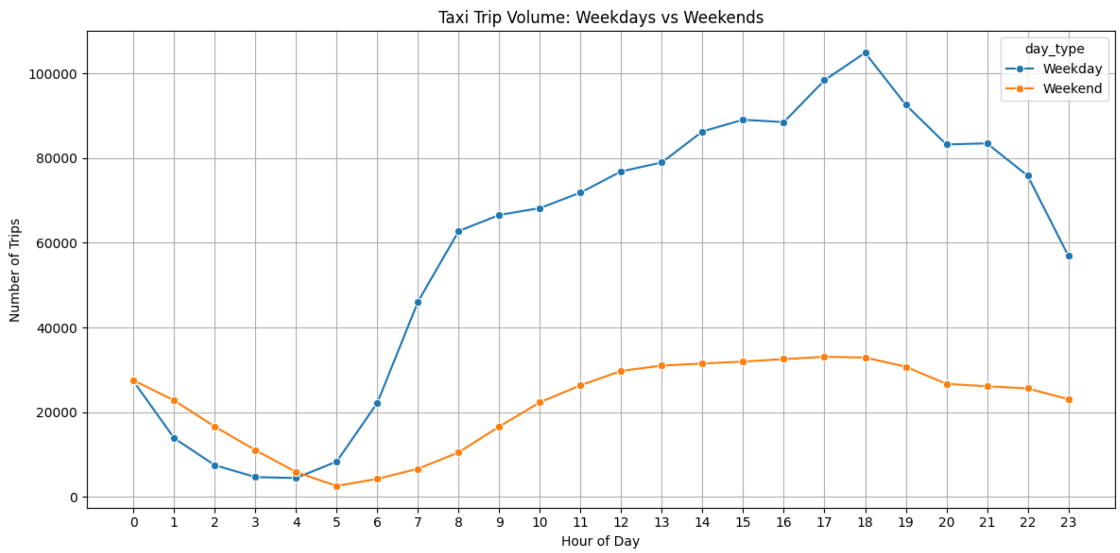
[568]:
```
# Compare traffic trends for the week days and weekends
df['pickup_dayofweek'] = df['tpep_pickup_datetime'].dt.dayofweek  # Monday=0,␣
↪Sunday=6
df['day_type'] = df['pickup_dayofweek'].apply(lambda x: 'Weekend' if x >= 5␣
↪else 'Weekday')
```

[570]:
```
hourly_trends = df.groupby(['pickup_hour', 'day_type']).size().
↪reset_index(name='trip_count')
hourly_trends.head(10)
```

[570]:

	pickup_hour	day_type	trip_count
0	0	Weekday	27286
1	0	Weekend	27518
2	1	Weekday	13865
3	1	Weekend	22779
4	2	Weekday	7496
5	2	Weekend	16592
6	3	Weekday	4694
7	3	Weekend	11059
8	4	Weekday	4478
9	4	Weekend	5874

[572]:
```
plt.figure(figsize=(12, 6))
sns.lineplot(data=hourly_trends, x='pickup_hour', y='trip_count',␣
↪hue='day_type', marker='o')

plt.title("Taxi Trip Volume: Weekdays vs Weekends")
plt.xlabel("Hour of Day")
plt.ylabel("Number of Trips")
plt.xticks(range(0, 24))
plt.grid(True)
plt.tight_layout()
plt.show()
```



Trends on weekday vs Weekend There is more traffic at late night 12 AM during weekends vs the weekadys. In general between 4 to 11 PM traffic is high on weekdays may be because of business or employees travelling to there home.

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.

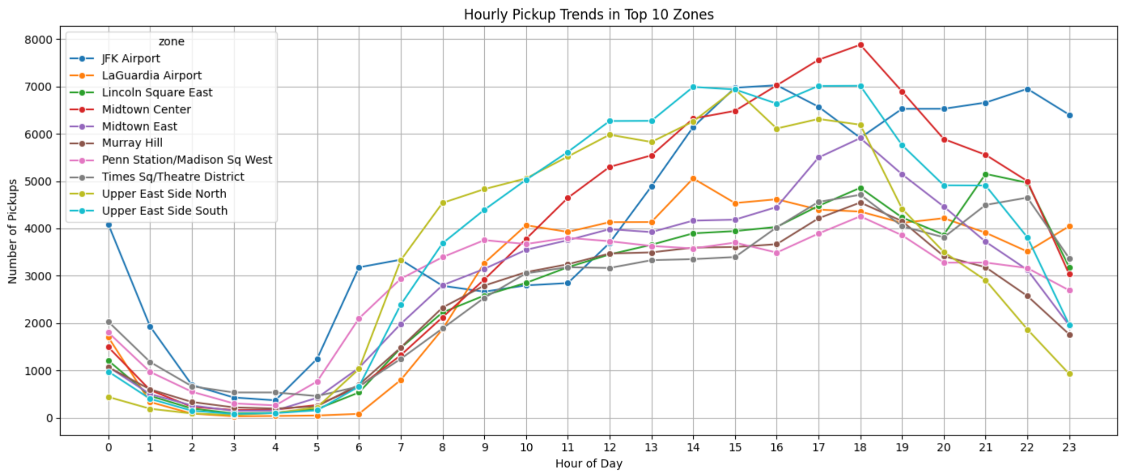
[579]:
```
# Find top 10 pickup and dropoff zones

pickup_hourly = df.groupby(['zone', 'pickup_hour']).size().
  ↪reset_index(name='pickup_count')
dropoff_hourly = df.groupby(['DOLocationID', 'pickup_hour']).size().
  ↪reset_index(name='dropoff_count')
dropoff_hourly = dropoff_hourly.merge(zones[['LocationID', 'zone']],␣
  ↪left_on='DOLocationID', right_on='LocationID', how='left')
dropoff_hourly.drop(columns='LocationID', inplace=True)

top_pickup_zones = pickup_hourly.groupby('zone')['pickup_count'].sum().
  ↪nlargest(10).index
print (top_pickup_zones)
top_dropoff_zones = dropoff_hourly.groupby('zone')['dropoff_count'].sum().
  ↪nlargest(10).index
print (top_dropoff_zones)
```

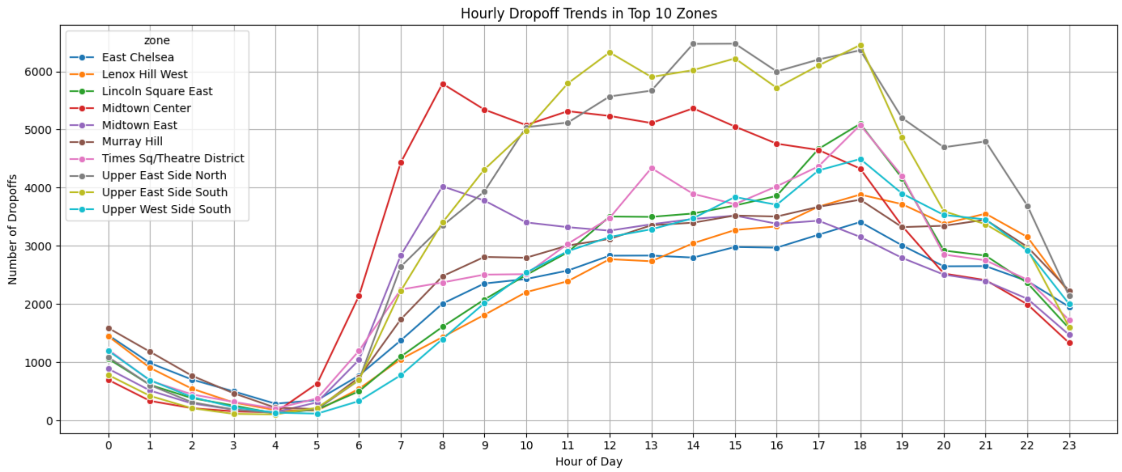
```
Index(['JFK Airport', 'Upper East Side South', 'Midtown Center',
       'Upper East Side North', 'Midtown East', 'LaGuardia Airport',
       'Penn Station/Madison Sq West', 'Times Sq/Theatre District',
```

```
       'Lincoln Square East', 'Murray Hill'],
      dtype='object', name='zone')
Index(['Upper East Side North', 'Upper East Side South', 'Midtown Center',
       'Times Sq/Theatre District', 'Murray Hill', 'Midtown East',
       'Lincoln Square East', 'Upper West Side South', 'Lenox Hill West',
       'East Chelsea'],
      dtype='object', name='zone')
```

[582]:

```
pickup_top = pickup_hourly[pickup_hourly['zone'].isin(top_pickup_zones)]
dropoff_top = dropoff_hourly[dropoff_hourly['zone'].isin(top_dropoff_zones)]

# Plot pickup trends
plt.figure(figsize=(14, 6))
sns.lineplot(data=pickup_top, x='pickup_hour', y='pickup_count', hue='zone',␣
 ↪marker='o')
plt.title("Hourly Pickup Trends in Top 10 Zones")
plt.xlabel("Hour of Day")
plt.ylabel("Number of Pickups")
plt.xticks(range(0, 24))
plt.grid(True)
plt.tight_layout()
plt.show()

# Plot dropoff trends
plt.figure(figsize=(14, 6))
sns.lineplot(data=dropoff_top, x='pickup_hour', y='dropoff_count', hue='zone',␣
 ↪marker='o')
plt.title("Hourly Dropoff Trends in Top 10 Zones")
plt.xlabel("Hour of Day")
plt.ylabel("Number of Dropoffs")
plt.xticks(range(0, 24))
plt.grid(True)
plt.tight_layout()
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.

[640]:
```
# Find the top 10 and bottom 10 pickup/dropoff ratios

pickup_counts = df.groupby('PULocationID').size().reset_index(name='pickup_count')
pickup_counts.rename(columns={'PULocationID': 'LocationID'}, inplace=True)
# Count dropoffs
dropoff_counts = df.groupby('DOLocationID').size().reset_index(name='dropoff_count')
dropoff_counts.rename(columns={'DOLocationID': 'LocationID'}, inplace=True)
# Merge counts
zone_counts = pd.merge(pickup_counts, dropoff_counts, on='LocationID', how='outer').fillna(0)
```

```
# Avoid division by zero
zone_counts = zone_counts[(zone_counts['dropoff_count'] > 0) &␣
↪(zone_counts['pickup_count'] > 0)]

# Compute pickup/dropoff ratio
zone_counts['pickup_dropoff_ratio'] = zone_counts['pickup_count'] /␣
↪zone_counts['dropoff_count']

#Add zone column
zone_counts = zone_counts.merge(zones[['LocationID', 'zone']], on='LocationID',␣
↪how='left')

# Top 10 highest ratios
top10 = zone_counts.sort_values(by='pickup_dropoff_ratio', ascending=False).
↪head(10)

# Bottom 10 lowest ratios
bottom10 = zone_counts.sort_values(by='pickup_dropoff_ratio', ascending=True).
↪head(10)

print("Top 10 Pickup/Dropoff Ratios:")
print(top10[['zone', 'pickup_count', 'dropoff_count', 'pickup_dropoff_ratio']])

print("\n Bottom 10 Pickup/Dropoff Ratios:")
print(bottom10[['zone', 'pickup_count', 'dropoff_count',␣
↪'pickup_dropoff_ratio']])
```

```
Top 10 Pickup/Dropoff Ratios:
                           zone  pickup_count  dropoff_count  \
69                East Elmhurst        8681.0          943.0
126                 JFK Airport      100661.0        21981.0
132           LaGuardia Airport       67284.0        24361.0
179  Penn Station/Madison Sq West      66844.0        42673.0
108        Greenwich Village South     25903.0        18780.0
41                 Central Park       32558.0        23716.0
239                West Village       43322.0        32497.0
156                Midtown East       69352.0        55550.0
155              Midtown Center       90851.0        76350.0
98             Garment District       31913.0        26822.0

     pickup_dropoff_ratio
69               9.205726
126              4.579455
132              2.761956
179              1.566424
108              1.379286
```

```
41                1.372828
239               1.333108
156               1.248461
155               1.189928
98                1.189807

 Bottom 10 Pickup/Dropoff Ratios:
                                    zone  pickup_count  dropoff_count  \
247                      Windsor Terrace          27.0          814.0
0                         Newark Airport         198.0         5593.0
109                  Grymes Hill/Clifton           1.0           25.0
26   Breezy Point/Fort Tilden/Riis Beach           2.0           43.0
95              Forest Park/Highland Park          3.0           62.0
122                     Inwood Hill Park           6.0          115.0
44                           City Island           3.0           56.0
191                            Ridgewood          60.0         1060.0
242                           Whitestone          23.0          377.0
192  Riverdale/North Riverdale/Fieldston          42.0          659.0

     pickup_dropoff_ratio
247              0.033170
0                0.035401
109              0.040000
26               0.046512
95               0.048387
122              0.052174
44               0.053571
191              0.056604
242              0.061008
192              0.063733
```

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

[652]:
```python
# 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

# Define night hours (11 PM to 5 AM)
night_hours = list(range(0, 5)) + [23]
# [0, 1, 2, 3, 4, 23] as 4 hour window will have traffic till 4:59 mins
# Filter the DataFrame
night_df = df[df['pickup_hour'].isin(night_hours)]

# Count pickups
night_pickups = night_df.groupby('PULocationID').size().
 ↪reset_index(name='pickup_count')
night_pickups.rename(columns={'PULocationID': 'LocationID'}, inplace=True)
# Count dropoffs
```

```
night_dropoffs = night_df.groupby('DOLocationID').size().
 ↪reset_index(name='dropoff_count')
night_dropoffs.rename(columns={'DOLocationID': 'LocationID'}, inplace=True)

# Merge pickup and dropoff counts
night_traffic = pd.merge(night_pickups, night_dropoffs, on='LocationID',␣
 ↪how='outer').fillna(0)

# Calculate total traffic
night_traffic['total_night_traffic'] = night_traffic['pickup_count'] +␣
 ↪night_traffic['dropoff_count']

#Add zone column
night_traffic = night_traffic.merge(zones[['LocationID', 'zone']],␣
 ↪on='LocationID', how='left')

# Sort by total traffic
top_night_zones = night_traffic.sort_values(by='total_night_traffic',␣
 ↪ascending=False).head(10)
print(top_night_zones)

top_night_pickup_zones = night_traffic.sort_values(by='pickup_count',␣
 ↪ascending=False).head(10)
print(top_night_pickup_zones)

top_night_dropoff_zones = night_traffic.sort_values(by='dropoff_count',␣
 ↪ascending=False).head(10)
print(top_night_dropoff_zones)
```

```
     LocationID  pickup_count  dropoff_count  total_night_traffic  \
78           79       16558.0           8800              25358.0
242         249       13337.0           5190              18527.0
46           48       10464.0           7122              17586.0
127         132       13912.0           1147              15059.0
143         148       10341.0           4629              14970.0
223         230        8308.0           4583              12891.0
67           68        6247.0           5882              12129.0
109         114        9365.0           2672              12037.0
103         107        5778.0           5979              11757.0
159         164        6414.0           4259              10673.0

                          zone
78                East Village
242               West Village
46                Clinton East
127                JFK Airport
143            Lower East Side
```

```
223  Times Sq/Theatre District
67                East Chelsea
109    Greenwich Village South
103                   Gramercy
159              Midtown South
     LocationID  pickup_count  dropoff_count  total_night_traffic  \
78           79       16558.0           8800              25358.0
127         132       13912.0           1147              15059.0
242         249       13337.0           5190              18527.0
46           48       10464.0           7122              17586.0
143         148       10341.0           4629              14970.0
109         114        9365.0           2672              12037.0
223         230        8308.0           4583              12891.0
181         186        6572.0           3698              10270.0
159         164        6414.0           4259              10673.0
67           68        6247.0           5882              12129.0

                             zone
78                   East Village
127                   JFK Airport
242                  West Village
46                   Clinton East
143               Lower East Side
109       Greenwich Village South
223     Times Sq/Theatre District
181  Penn Station/Madison Sq West
159                 Midtown South
67                   East Chelsea
     LocationID  pickup_count  dropoff_count  total_night_traffic  \
78           79       16558.0           8800              25358.0
46           48       10464.0           7122              17586.0
165         170        4173.0           6444              10617.0
103         107        5778.0           5979              11757.0
67           68        6247.0           5882              12129.0
136         141        3408.0           5557               8965.0
256         263        3442.0           5297               8739.0
242         249       13337.0           5190              18527.0
232         239        2745.0           4639               7384.0
143         148       10341.0           4629              14970.0

                 zone
78       East Village
46       Clinton East
165       Murray Hill
103          Gramercy
67       East Chelsea
136   Lenox Hill West
256    Yorkville West
```

```
242          West Village
232  Upper West Side South
143        Lower East Side
```

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.

[654]:
```python
# Filter for night hours (11 PM to 5 AM)

def get_time_period(hour):
    return 'Night' if hour in [23, 0, 1, 2, 3, 4] else 'Day'

df['time_period'] = df['pickup_hour'].apply(get_time_period)
revenue_by_period = df.groupby('time_period')['total_amount'].sum().
 ↪reset_index()
total_revenue = revenue_by_period['total_amount'].sum()

# Add revenue share column
revenue_by_period['revenue_share'] = revenue_by_period['total_amount'] /␣
 ↪total_revenue
print(revenue_by_period)
```

```
  time_period  total_amount  revenue_share
0         Day   50032020.54       0.885585
1       Night    6464009.88       0.114415
```

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.

[656]:
```python
# Analyse the fare per mile per passenger for different passenger counts

df_nonzerotrip = df[(df['trip_distance'] > 0) & (df['passenger_count'] > 0)]
df_nonzerotrip['fare_per_mile_per_passenger'] = df_nonzerotrip['total_amount'] /
 ↪ (df_nonzerotrip['trip_distance'] * df_nonzerotrip['passenger_count'])

fare_stats = df_nonzerotrip.
 ↪groupby('passenger_count')['fare_per_mile_per_passenger'].agg(['mean',␣
 ↪'median', 'count']).reset_index()
print(fare_stats)
```

```
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\1008790237.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_nonzerotrip['fare_per_mile_per_passenger'] = df_nonzerotrip['total_amount']
/ (df_nonzerotrip['trip_distance'] * df_nonzerotrip['passenger_count'])
```

	passenger_count	mean	median	count
0	1.0	16.642746	11.394958	1465055
1	2.0	9.308108	5.486631	288161
2	3.0	5.748642	3.705356	71576
3	4.0	5.848518	2.708333	39462
4	5.0	2.761556	2.245989	24882
5	6.0	2.214246	1.891815	16616

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

[668]:
```
# Compare the average fare per mile for different days and for different times␣
↪of the day

# Calculate fare per mile
df_nonzerotrip['fare_per_mile'] = df_nonzerotrip['total_amount'] /␣
↪df_nonzerotrip['trip_distance']

fare_by_day = df_nonzerotrip.groupby('pickup_day')['fare_per_mile'].mean().
↪reindex([
    'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'
])

fare_by_hour = df_nonzerotrip.groupby('pickup_hour')['fare_per_mile'].mean()

print("Fare by Day",fare_by_day)
print("Fare by hour", fare_by_hour)
```

```
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\3179039869.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_nonzerotrip['fare_per_mile'] = df_nonzerotrip['total_amount'] /
df_nonzerotrip['trip_distance']
```

```
Fare by Day pickup_day
Monday       16.690505
Tuesday      17.435274
Wednesday    17.045675
Thursday     17.121152
Friday       16.881214
Saturday     16.122162
```

```
Sunday       18.050026
Name: fare_per_mile, dtype: float64
Fare by hour pickup_hour
0     15.745927
1     17.019776
2     15.368973
3     16.752811
4     18.852770
5     20.698345
6     15.582748
7     14.966662
8     15.315742
9     15.502052
10    15.781852
11    16.267838
12    17.185356
13    17.479966
14    16.763815
15    18.039635
16    21.347213
17    19.408165
18    18.569847
19    18.463796
20    15.037497
21    14.701038
22    15.384210
23    16.047008
Name: fare_per_mile, dtype: float64
```

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

[674]:

```python
# Compare fare per mile for different vendors
df_nonzerotrip

vendor_fares = df_nonzerotrip.groupby('VendorID')['fare_per_mile'].agg(['mean',
 'median', 'count']).reset_index()
print(vendor_fares)
```

```
   VendorID       mean     median    count
0         1  13.308087  11.407407   476121
1         2  18.279316  11.274725  1429624
2         6  12.064572   9.900990        7
```

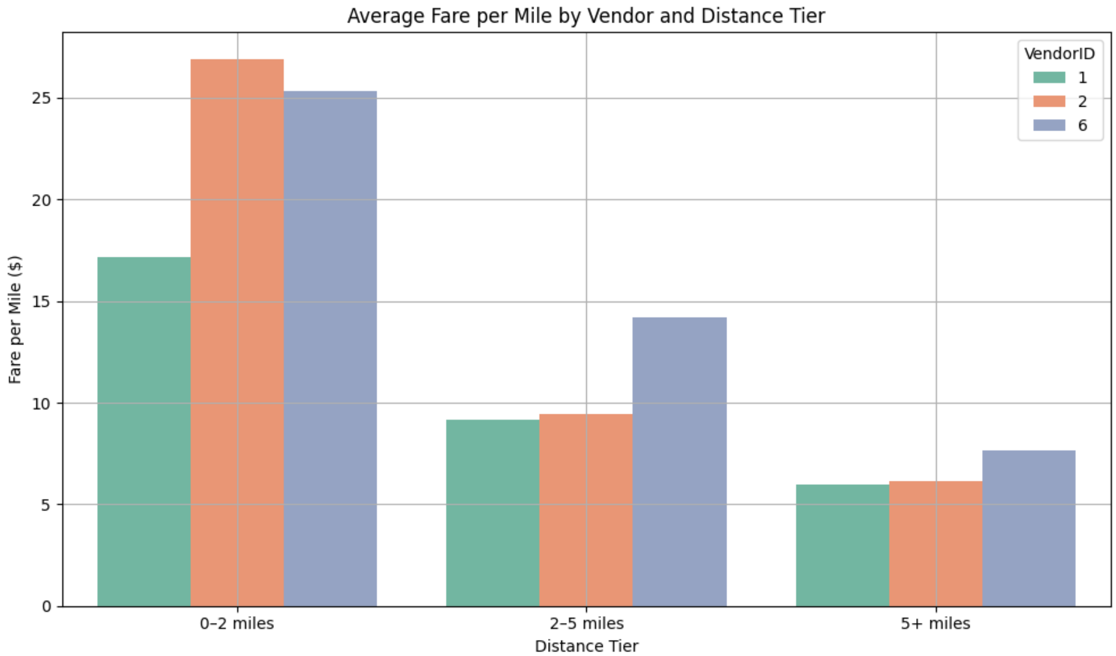
3.2.12 [5 marks] Compare the fare rates of the different vendors in a tiered fashion. Analyse the average fare per mile for distances upto 2 miles. Analyse the fare per mile for distances from 2 to 5 miles. And then for distances more than 5 miles.

[678]:

```
# 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_nonzerotrip['distance_tier'] = df_nonzerotrip['trip_distance'].
↪apply(distance_tier)
tiered_fares = df_nonzerotrip.groupby(['VendorID',␣
↪'distance_tier'])['fare_per_mile'].mean().reset_index()
print (tiered_fares)
plt.figure(figsize=(10, 6))
sns.barplot(data=tiered_fares, x='distance_tier', y='fare_per_mile',␣
↪hue='VendorID', palette='Set2')

plt.title("Average Fare per Mile by Vendor and Distance Tier")
plt.xlabel("Distance Tier")
plt.ylabel("Fare per Mile ($)")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\3727777382.py:10:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_nonzerotrip['distance_tier'] =
df_nonzerotrip['trip_distance'].apply(distance_tier)
```

	VendorID	distance_tier	fare_per_mile
0	1	0-2 miles	17.187697
1	1	2-5 miles	9.184617
2	1	5+ miles	5.990546
3	2	0-2 miles	26.878538
4	2	2-5 miles	9.460546
5	2	5+ miles	6.155048
6	6	0-2 miles	25.333333
7	6	2-5 miles	14.214047
8	6	5+ miles	7.672644



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?

[686]:
```
#  Analyze tip percentages based on distances, passenger counts and pickup times
df['tip_percent'] = (df['tip_amount'] / df['total_amount']) * 100
df['distance_tier'] = df['trip_distance'].apply(distance_tier)
tip_by_distance = df.groupby('distance_tier')['tip_percent'].mean().
 ↪reset_index()
print(tip_by_distance)
tip_by_passenger = df[df['passenger_count'] > 0].
 ↪groupby('passenger_count')['tip_percent'].mean().reset_index()
print(tip_by_passenger)
tip_by_hour = df.groupby('pickup_hour')['tip_percent'].mean().reset_index()
print(tip_by_hour)
```

```
  distance_tier  tip_percent
0     0-2 miles    12.053035
1     2-5 miles    12.234527
2      5+ miles    11.280166
   passenger_count  tip_percent
0              1.0    12.082660
1              2.0    11.771686
2              3.0    11.358086
3              4.0    10.466442
4              5.0    12.116323
```

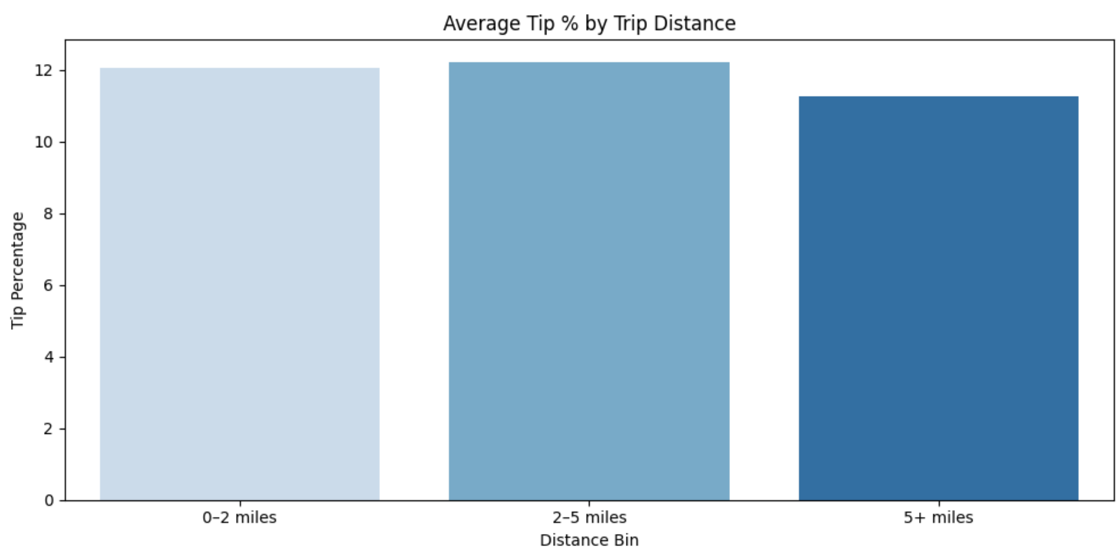
```
5              6.0    12.209256
    pickup_hour  tip_percent
0             0    11.861455
1             1    11.832382
2             2    11.639764
3             3    11.179685
4             4    10.346102
5             5    10.136287
6             6    11.023918
7             7    11.850445
8             8    12.181061
9             9    12.033606
10           10    11.762246
11           11    11.756538
12           12    11.761377
13           13    11.705225
14           14    11.766097
15           15    11.749014
16           16    11.774628
17           17    12.041503
18           18    12.224745
19           19    12.194702
20           20    12.404647
21           21    12.545225
22           22    12.461128
23           23    12.092979
```

[688]:

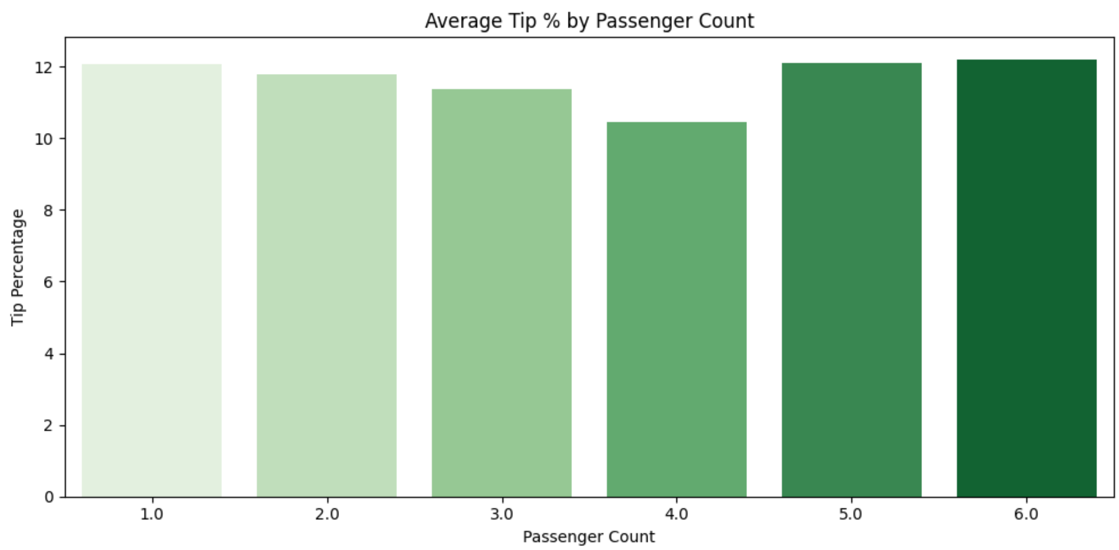
```
# Distance
plt.figure(figsize=(10, 5))
sns.barplot(data=tip_by_distance, x='distance_tier', y='tip_percent',␣
↪palette='Blues')
plt.title("Average Tip % by Trip Distance")
plt.ylabel("Tip Percentage")
plt.xlabel("Distance Bin")
plt.tight_layout()
plt.show()

# Passenger Count
plt.figure(figsize=(10, 5))
sns.barplot(data=tip_by_passenger, x='passenger_count', y='tip_percent',␣
↪palette='Greens')
plt.title("Average Tip % by Passenger Count")
plt.ylabel("Tip Percentage")
plt.xlabel("Passenger Count")
plt.tight_layout()
plt.show()
```

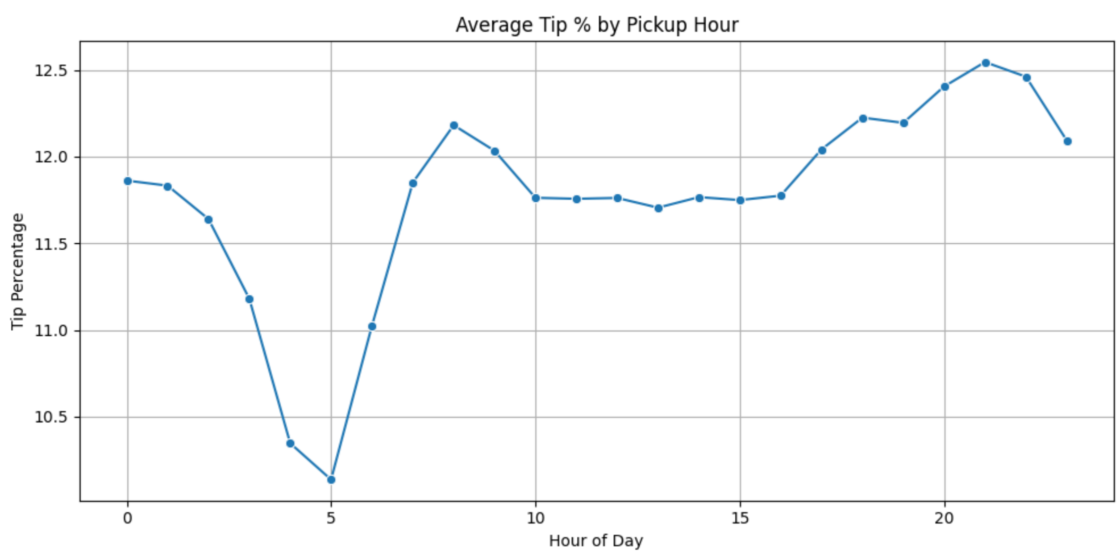
```
# Pickup Hour
plt.figure(figsize=(10, 5))
sns.lineplot(data=tip_by_hour, x='pickup_hour', y='tip_percent', marker='o')
plt.title("Average Tip % by Pickup Hour")
plt.xlabel("Hour of Day")
plt.ylabel("Tip Percentage")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\895667400.py:3:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=tip_by_distance, x='distance_tier', y='tip_percent',
palette='Blues')
```




```
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\895667400.py:12:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=tip_by_passenger, x='passenger_count', y='tip_percent',
palette='Greens')
```





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

[712]:
```
# Count drop-offs by DOLocationID
dropoff_counts = df['DOLocationID'].value_counts()

# Get the location with the maximum drop-offs
max_dropoff_location = dropoff_counts.idxmax()
max_dropoff_count = dropoff_counts.max()
print(dropoff_counts)
```

```
print(f"Location ID with most drop-offs: {max_dropoff_location}␣
↪({max_dropoff_count:,} trips)")
print("zone is ", zones[zones['LocationID'] == max_dropoff_location]['zone'].
↪values[0])
```

```
DOLocationID
236    86548
237    82371
161    76350
230    59943
170    57654
       …
84         9
187        7
204        6
2          4
99         3
Name: count, Length: 260, dtype: int64
Location ID with most drop-offs: 236 (86,548 trips)
zone is  Upper East Side North
```

[716]:

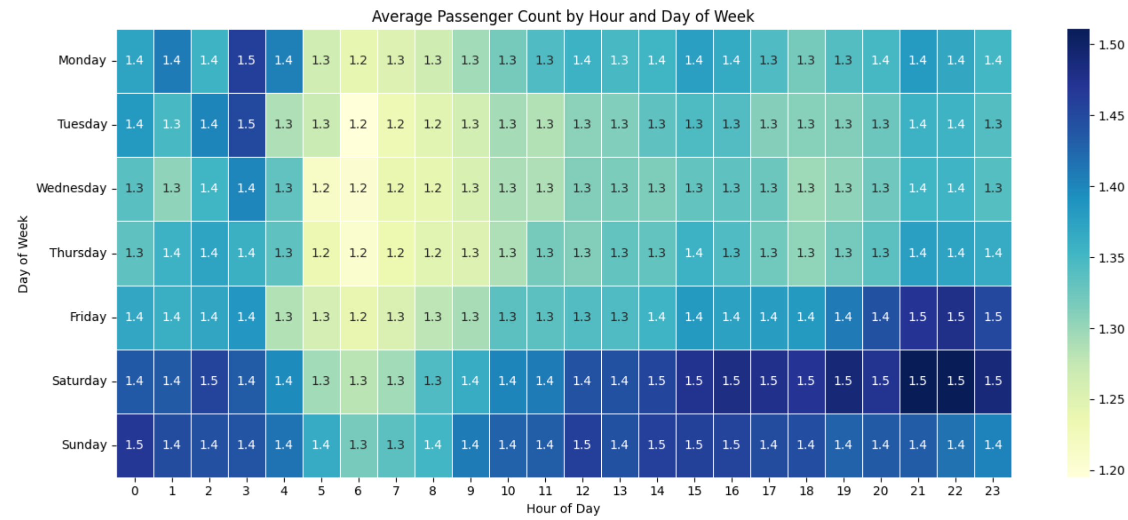
```
# Compare trips with tip percentage < 10% to trips with tip percentage > 25%
low_tip = df[df['tip_percent'] < 10]
high_tip = df[df['tip_percent'] > 25]

comparison = pd.DataFrame({
    'Low Tip (<10%)': {
        'Avg Fare': low_tip['total_amount'].median(),
        'Avg Distance': low_tip['trip_distance'].median(),
        'Avg Duration (min)': low_tip['trip_duration'].median(),
        'Avg Tip %': low_tip['tip_percent'].mean(),
        'Median Passengers Count': low_tip['passenger_count'].median(),
        'Maximum Drop off': zones[zones['LocationID'] ==␣
↪low_tip['DOLocationID'].value_counts().idxmax()]['zone'].values[0],
        'Maximum Pick up':zones[zones['LocationID'] == low_tip['PULocationID'].
↪value_counts().idxmax()]['zone'].values[0],
        'Trip Count': len(low_tip)
    },
    'High Tip (>25%)': {
        'Avg Fare': high_tip['total_amount'].median(),
        'Avg Distance': high_tip['trip_distance'].median(),
        'Avg Duration (min)': high_tip['trip_duration'].median(),
        'Avg Tip %': high_tip['tip_percent'].mean(),
        'Median Passengers Count': high_tip['passenger_count'].median(),
        'Maximum Drop off':zones[zones['LocationID'] ==␣
↪high_tip['DOLocationID'].value_counts().idxmax()]['zone'].values[0],
```

```
        'Maximum Pick up':zones[zones['LocationID'] == high_tip['PULocationID'].
↪value_counts().idxmax()]['zone'].values[0],
        'Trip Count': len(high_tip)
    }
})
print(comparison)
```

```
                              Low Tip (<10%)          High Tip (>25%)
Avg Fare                                19.6                     21.0
Avg Distance                             1.8                     1.17
Avg Duration (min)                      13.1                      8.3
Avg Tip %                           2.452221                34.486054
Median Passengers Count                  1.0                      1.0
Maximum Drop off       Upper East Side South    Upper East Side North
Maximum Pick up                  JFK Airport  Times Sq/Theatre District
Trip Count                            655277                     9581
```

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

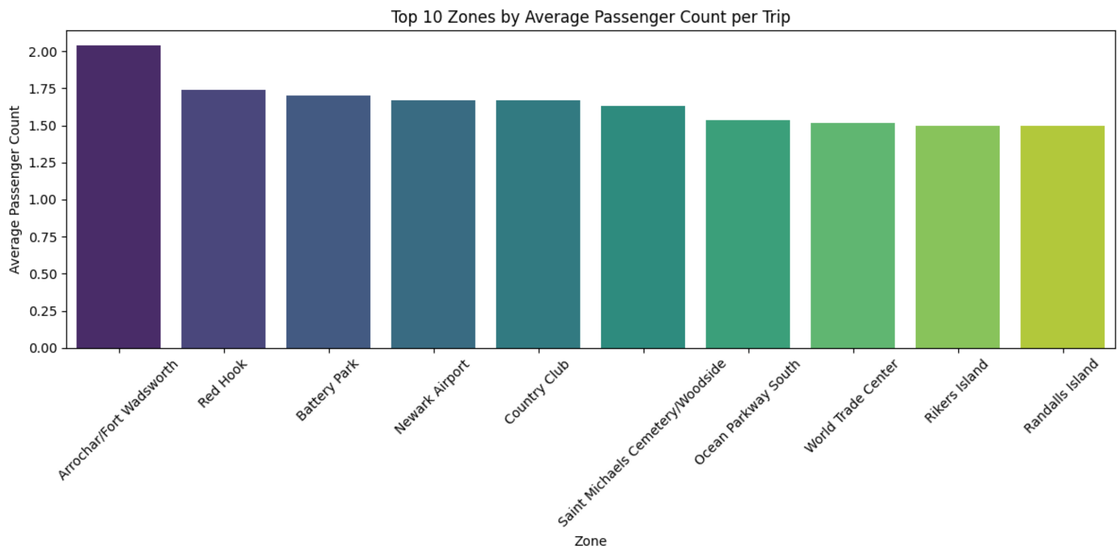
[718]:
```
# See how passenger count varies across hours and days

# Average passenger count by hour and day
passenger_trends = df.groupby(['pickup_day', 'pickup_hour'])['passenger_count'].
↪mean().reset_index()

# Pivot for heatmap
pivot_table = passenger_trends.pivot(index='pickup_day', columns='pickup_hour',␣
↪values='passenger_count')

ordered_days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
↪'Saturday', 'Sunday']
pivot_table = pivot_table.reindex(ordered_days)

# Plot
plt.figure(figsize=(14, 6))
sns.heatmap(pivot_table, cmap='YlGnBu', annot=True, fmt=".1f", linewidths=0.5)

plt.title("Average Passenger Count by Hour and Day of Week")
plt.xlabel("Hour of Day")
plt.ylabel("Day of Week")
plt.tight_layout()
plt.show()
```



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

[720]:
```python
# How does passenger count vary across zones

zone_passenger_stats = df.groupby('zone')['passenger_count'].agg(['mean', 'median', 'sum', 'count']).reset_index()
zone_passenger_stats = zone_passenger_stats.sort_values(by='mean', ascending=False)

top_zones = zone_passenger_stats.head(10)

plt.figure(figsize=(12, 6))
sns.barplot(data=top_zones, x='zone', y='mean', palette='viridis')
plt.title("Top 10 Zones by Average Passenger Count per Trip")
plt.ylabel("Average Passenger Count")
plt.xlabel("Zone")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
C:\Users\Sherry\AppData\Local\Temp\ipykernel_11388\4228150114.py:9:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=top_zones, x='zone', y='mean', palette='viridis')
```



[724]:
```python
# 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.
avg_passenger = df.groupby('zone')['passenger_count'].mean().
 ↪reset_index(name='avg_passenger_count')
zones_with_trips = zones.merge(avg_passenger, on='zone', how='left')
```

[724]:
```
     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
..        …         …         …                      …         …
258       259    0.126750    0.000395       Woodlawn/Wakefield         259
259       260    0.133514    0.000422                 Woodside         260
260       261    0.027120    0.000034       World Trade Center         261
261       262    0.049064    0.000122           Yorkville East         262
262       263    0.037017    0.000066           Yorkville West         263

           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…
..             …                                                 …
258          Bronx  POLYGON ((1025414.782 270986.139, 1025138.624 …
259         Queens  POLYGON ((1011466.966 216463.005, 1011545.889 …
```

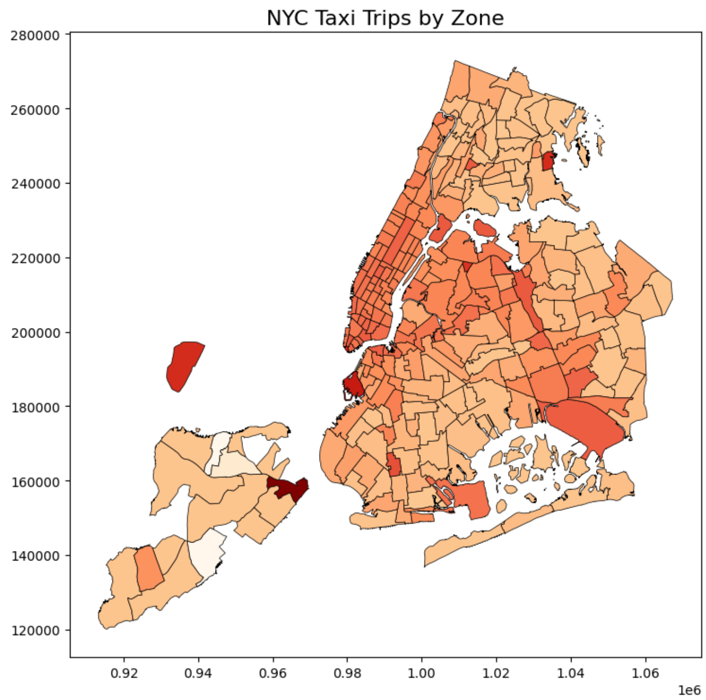
```
260      Manhattan  POLYGON ((980555.204 196138.486, 980570.792 19…
261      Manhattan  MULTIPOLYGON (((999804.795 224498.527, 999824…
262      Manhattan  POLYGON ((997493.323 220912.386, 997355.264 22…

     pickup_count  dropoff_count  total_trips  avg_passenger_count
0           198.0         5593.0       5791.0             1.666667
1             2.0            4.0          6.0             1.000000
2            39.0          164.0        203.0             1.025641
3          2273.0         7370.0       9643.0             1.354158
4            13.0           34.0         47.0             1.000000
..            …              …            …                   …
258          48.0          212.0        260.0             1.104167
259         328.0         1398.0       1726.0             1.290520
260       10289.0         9280.0      19569.0             1.514677
261       25874.0        30149.0      56023.0             1.299126
262       37490.0        40052.0      77542.0             1.312758

[263 rows x 11 columns]
```

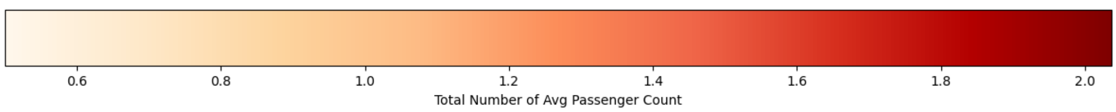
[728]:

```python
# Define figure and axis
fig, ax = plt.subplots(1, 1, figsize=(12, 10))


# Plot the map and display it
zones_with_trips.plot(column='avg_passenger_count',
           cmap='OrRd',
           legend=True,
           edgecolor='black',
           linewidth=0.5,
           ax=ax,
           legend_kwds={
               'label': "Total Number of Avg Passenger Count",
               'orientation': "horizontal"  # or "vertical"
           })

ax.set_title("NYC Taxi Trips by Zone", fontsize=16)
plt.tight_layout()
plt.show()
```





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

[730]:
```
surcharge_cols = ['extra', 'mta_tax', 'improvement_surcharge',␣
 ↪'congestion_surcharge']

# Count how often each surcharge is applied (non-zero)
surcharge_stats = {
    col: {
        'applied_count': (df[col] > 0).sum(),
        'total_trips': len(df),
        'prevalence_percent': 100 * (df[col] > 0).mean()
    }
    for col in surcharge_cols
}


surcharge_df = pd.DataFrame(surcharge_stats).T
print(surcharge_df)
```

```
                       applied_count  total_trips  prevalence_percent
```

```
extra                          1188170.0    1947260.0           61.017532
mta_tax                        1931825.0    1947260.0           99.207348
improvement_surcharge          1947049.0    1947260.0           99.989164
congestion_surcharge           1807575.0    1947260.0           92.826587
```

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

[732]:
```
df.rename(columns={'zone': 'pickup_zone'}, inplace=True)
```

[734]:
```
# Merge dropoff zone names into df
df = df.merge(zones[['LocationID', 'zone']], left_on='DOLocationID',␣
 ↪right_on='LocationID', how='left')

# Rename the merged column to 'dropoff_zone'
df.rename(columns={'zone': 'dropoff_zone'}, inplace=True)
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
Cell In[734], line 8
      5 df.rename(columns={'zone': 'dropoff_zone'}, inplace=True)
      7 # Optionally drop the extra LocationID column if not needed
----> 8 df.drop(columns='LocationID', inplace=True)

File ~\AppData\Roaming\Python\Python312\site-packages\pandas\core\frame.py:5581 ␣
 ↪in DataFrame.drop(self, labels, axis, index, columns, level, inplace, errors)
   5433 def drop(
   5434     self,
   5435     labels: IndexLabel | None = None,
   (…)
   5442     errors: IgnoreRaise = "raise",
   5443 ) -> DataFrame | None:
   5444     """
   5445     Drop specified labels from rows or columns.
   5446 
   (…)
   5579             weight  1.0     0.8
   5580     """
-> 5581     return super().drop(
   5582         labels=labels,
   5583         axis=axis,
   5584         index=index,
   5585         columns=columns,
   5586         level=level,
   5587         inplace=inplace,
   5588         errors=errors,
   5589     )
```

```
File ~\AppData\Roaming\Python\Python312\site-packages\pandas\core\generic.py:
 ↪4788, in NDFrame.drop(self, labels, axis, index, columns, level, inplace,␣
 ↪errors)
   4786 for axis, labels in axes.items():
   4787     if labels is not None:
-> 4788         obj = obj._drop_axis(labels, axis, level=level, errors=errors)
   4790 if inplace:
   4791     self._update_inplace(obj)

File ~\AppData\Roaming\Python\Python312\site-packages\pandas\core\generic.py:
 ↪4830, in NDFrame._drop_axis(self, labels, axis, level, errors, only_slice)
   4828         new_axis = axis.drop(labels, level=level, errors=errors)
   4829     else:
-> 4830         new_axis = axis.drop(labels, errors=errors)
   4831     indexer = axis.get_indexer(new_axis)
   4833 # Case for non-unique axis
   4834 else:

File ~\AppData\Roaming\Python\Python312\site-packages\pandas\core\indexes\base.
 ↪py:7070, in Index.drop(self, labels, errors)
   7068 if mask.any():
   7069     if errors != "ignore":
-> 7070         raise KeyError(f"{labels[mask].tolist()} not found in axis")
   7071     indexer = indexer[~mask]
   7072 return self.delete(indexer)

KeyError: "['LocationID'] not found in axis"
```

[738]:
```
df.drop(columns='LocationID_y', inplace=True)
```

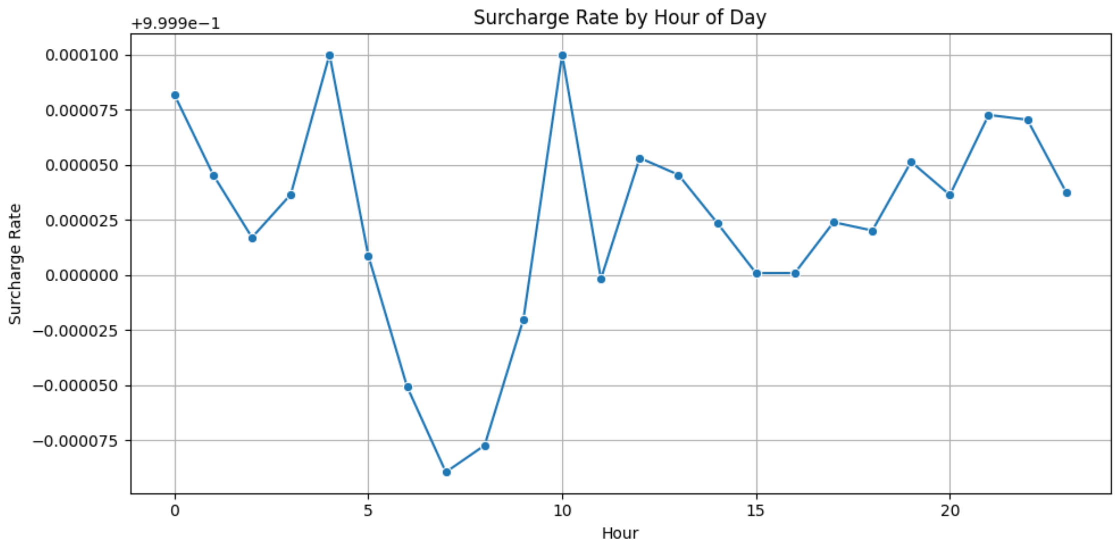
[740]:
```
# How often is each surcharge applied?
df['has_surcharge'] = df[surcharge_cols].sum(axis=1) > 0
# Pickup zones
pickup_surcharge = df.groupby('pickup_zone')['has_surcharge'].mean().
 ↪reset_index(name='pickup_surcharge_rate')

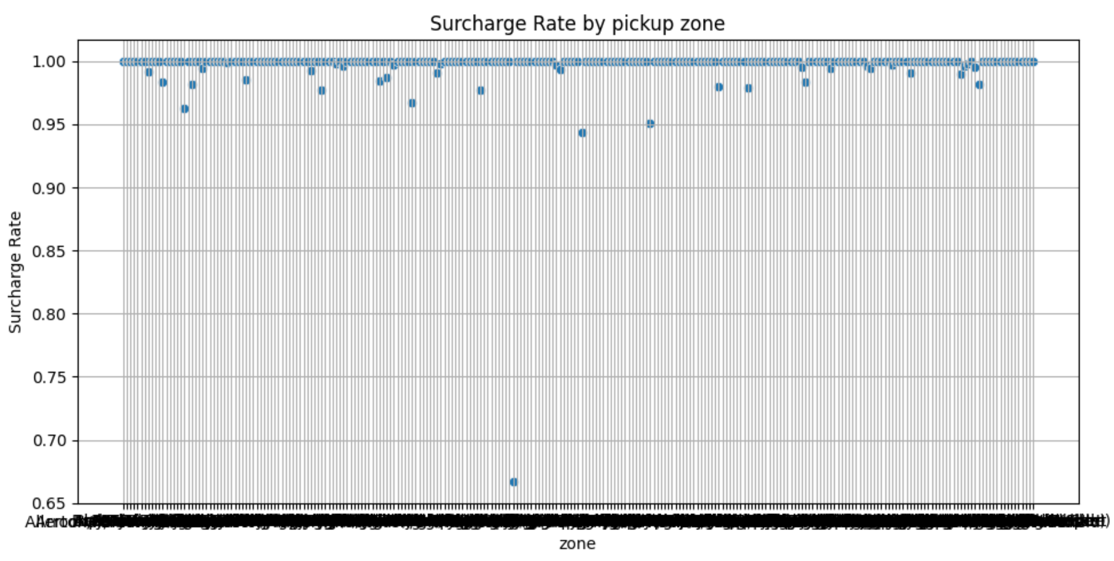
# Dropoff zones (if you have dropoff zone names)
dropoff_surcharge = df.groupby('dropoff_zone')['has_surcharge'].mean().
 ↪reset_index(name='dropoff_surcharge_rate')
```

[742]:
```
hourly_surcharge = df.groupby('pickup_hour')['has_surcharge'].mean().
 ↪reset_index(name='surcharge_rate')
```

[748]:
```
# By hour
plt.figure(figsize=(10, 5))
sns.lineplot(data=hourly_surcharge, x='pickup_hour', y='surcharge_rate',␣
 ↪marker='o')
```

```
plt.title("Surcharge Rate by Hour of Day")
plt.xlabel("Hour")
plt.ylabel("Surcharge Rate")
plt.grid(True)
plt.tight_layout()
plt.show()
```





1.8 4 Conclusion

[15 marks]

1.8.1 4.1 Final Insights and Recommendations

[15 marks]

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

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

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

[ ]:
```
- Plan for taxis to be available between 2 PM and 7 PM on weekdays, when demand␣
↪is typically at its highest.
- For nighttime operations, schedule taxis between 12 AM and 5 AM on weekends,␣
↪as demand tends to be significantly higher during these hours.
- When planning for holidays, prioritize either Monday or Sunday, as pickup␣
↪volume is generally lower on these days.
- May and October usually see a surge in pickup demand, so plan fleet␣
↪availability accordingly.
- Focus on shorter trips lasting less than 2 to 3 hours to maximize turnaround␣
↪and efficiency.
- Since most customers prefer paying by credit card, ensure that taxis are␣
↪equipped with card payment facilities.
```

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.

[ ]:
```
- Position your taxis in high-demand zones such as Upper East Side South, Upper␣
↪East Side North, and Midtown Center, where both pickups and drop-offs are␣
↪consistently high.
- Avoid scheduling pickups and drop-offs on slower routes based on time-of-day␣
↪variations. This insight can be communicated to drivers to help them choose␣
↪the fastest available routes.
- Since demand peaks between 5 PM and 7 PM, plan for efficient routing during␣
↪this window to improve turnaround time.
- By analyzing hourly pickup and drop-off trends, you can better estimate the␣
↪likelihood of securing a fare in specific areas.
- Certain zones-like East Elmhurst, JFK Airport, and LaGuardia Airport-show␣
↪high pickup-to-drop-off ratios. Taxis should prioritize trips to and from␣
↪these areas.
- Based on nighttime pickup and drop-off patterns, taxis can strategically plan␣
↪their routes to maximize efficiency during late hours
```

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

```
[ ]: - Based on hourly pickup and drop-off zone trends, dynamic pricing strategies
     ↪can be developed.
     - During high-demand periods—especially between 5 PM and 7 PM—fares can be
     ↪adjusted upward to optimize revenue.
     - To maximize earnings, prioritize daytime operations over nighttime, as demand
     ↪is typically higher during the day.
     - Fare pricing should reflect peak demand at specific hours throughout the day.
     - Vendor 1 may increase rates for both shorter and longer trips.
     - Vendor 2 can focus fare adjustments on trips longer than 2 miles.
     - Revenue is generally higher during March, April, May, June, October,
     ↪November, and December compared to other months.
     - If planning vehicle servicing or holidays, February is ideal, as it tends to
     ↪have the lowest revenue. Further analysis of pickup times and zones may help
     ↪boost revenue in off-peak months.
     - Trips under 50 miles tend to be more profitable. Avoid assigning taxis to
     ↪longer routes, as longer duration doesn't always mean higher earnings.
     - Tips are typically higher for shorter trips, whereas between 3 AM and 7 AM,
     ↪tip amounts are significantly lower.
     - Surcharges are least common from 5 AM to 9 AM, which could impact fare
     ↪planning during early morning hours.
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