Multivariate Analysis of Uber Driver Tipping Behavior

Aaron Hum - MAT 494 - Final Project

Introduction

Uber

Uber is a popular ride hailing, on-call taxi service app. Trip fares are calculated algorithmically through a dynamic pricing model paid to the driver where Uber takes a percentage. Then, after the ride, the rider chooses an amount they want to tip their driver.

Ride Variables and Tipping Behavior

Several variables go into a ride. First there is the circumstances of the trip itself including the day of the week, date, and time. Then there is the matter of the price of the trip, which is further broken down into fees for distance, time, wait time, surge pricing, promotional pricing, rewards pricing, long pickup fees, and cleaning fees. And finally there is tipping amount. This is the voluntary choice of the rider and (may) be affected by the previously mentioned variables.

Questions

Do the various circumstances of the ride, such as day of the week, date, or time of day, affect tip amount? Do riders tip more in the evening? On weekends?

Do the trip fares affect tip amount? Do riders tip more for longer/shorter distance trips? Do riders who experience extra fees (surge pricing, cleaning fee) tip less?

Do the given variables provide enough information to predict tipping behavior using data science models?

Data Source

I will use this dataset of Uber rides in Phoenix, AZ:

https://www.kaggle.com/datasets/procurator/55-weeks-of-uber-rides-in-phoenix-az?resource=download

Models and Numerical Methods

Linear Regression, Multiple Linear Regression, Logistic Regression

The Multiple Linear regrssion model will measure the tip amount, in the equation:

Y = Tip

X[1-18] = ['Base Fare','Distance','Time','Min Fare Supplement','Cancellation','Surge','Diamond Reward','Promotions','Total','Long Pickup

Fee','Optio0l Insurance','Consecutive Trips Promotion','Share Adjustment','Quest Promotion','Fare Adjustment','Platinum Reward','Cleaning Repairs']

B0 = Intercept, Bn = Slope of the regression line for each variable, e = error

Y = B0 + B1X1 + B2X2 + ... + B18X18 + e

Expectations

I expect that riders tip more on weekends and in the evening. I hypothesize that these riders are those coming back from a social outing, which may make them more susceptible to tipping higher amounts.

I expect higher fares, higher distance, and extra fees to all cause lower tips. This is due to the fact that that these trips already cost more, thus making the rider likely to tip less.

Finally, I expect that the data will be too varied and uncorrelated for the multiple linear regression or logistic regression models to produce accurate predictions.

Python Libraries in this Project

numpy: Numerical computations

pandas: Data manipulation

matplotlib: Data visualization

seaborn: Statistical data visualization

sklearn: Regression, machine learning, data analysis

```
# imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Uploading the Dataset

Upload 'phoenix_uber_trips.csv' from the data source.

```
# upload 'phoenix_uber_trips_modified.csv'
# "modified" refers to the modifications I did to the data including
replacing "NA" values with $0
from google.colab import files
uploaded = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving phoenix_uber_trips_modified.csv to phoenix_uber_trips_modified
(2).csv
```

```
dataset = pd.read_csv("phoenix_uber_trips_modified.csv")
dataset
```

```
     Driver 0me  Phone Number      Email  \
0      John Doe             0  jd@jd.com   
1      John Doe             0  jd@jd.com   
2      John Doe             0  jd@jd.com   
3      John Doe             0  jd@jd.com   
4      John Doe             0  jd@jd.com   
...         ...           ...        ...   
3099   John Doe             0  jd@jd.com   
3100   John Doe             0  jd@jd.com   
3101   John Doe             0  jd@jd.com   
3102   John Doe             0  jd@jd.com   
3103   John Doe             0  jd@jd.com   

                                 Date/Time  \
0        Thursday, April 18, 2019 10:24 PM   
1         Thursday, April 18, 2019 9:48 PM   
2           Friday, April 19, 2019 8:39 PM   
3          Friday, April 19, 2019 10:50 PM   
4        Wednesday, April 17, 2019 8:08 PM   
...                                    ...   
3099  Saturday, September 22, 2018 6:28 PM   
3100    Monday, September 24, 2018 5:32 PM   
3101  Saturday, September 22, 2018 6:48 PM   
3102    Monday, September 24, 2018 4:54 PM   
3103  Saturday, September 22, 2018 9:11 PM   

                                   Trip ID   Type  Base Fare  Distance  
Time  \
0     9bce9679-2755-4c90-9689-f2de69c8f817  UberX        0.3      0.97   
0.68   
1     bb83ec2b-fd4c-457d-ae92-0a216624d85b  UberX        0.3      4.10   
2.09   
2     42450298-7f34-4f5b-8283-3415fe7f15a0  UberX        0.3      4.40   
1.79   
3     6d5371a9-806f-4949-b506-edfffd985ff6  UberX        0.3      1.11   
0.60   
4     aaa4e703-53af-4b54-ae35-314684a1e330  UberX        0.3      1.10   
0.69   
...                                    ...    ...        ...       ...   
...   
3099  ffc28b2e-d7f5-4163-ba2a-1a4703c37097  UberX        0.3     10.95   
1.24   
3100  605fa173-7d88-4df4-9241-a9a14679cbae  UberX        0.3      0.92   
0.39   
3101  0bc6b8a2-775f-4c72-b85b-056db73b1d86  UberX        0.3     17.39   
1.95   
3102  b38bc746-5dac-4e56-996c-e462070ef1d9  UberX        0.3      0.36   
```

```
0.21
3103  daf728e0-ff5e-4f44-98c6-078ba3bd4d7f  UberX        0.3      4.46
0.92

      Min Fare Supplement  ...  Promotions  Total  Long Pickup Fee  \
0                    0.68  ...         0.0   2.73              0.0
1                    0.00  ...         0.0   9.86              0.0
2                    0.00  ...         0.0   6.87              0.0
3                    0.62  ...         0.0   2.97              0.0
4                    0.54  ...         0.0   7.74              0.0
...                   ...  ...         ...    ...              ...
3099                 0.00  ...         0.0  12.49              0.0
3100                 1.01  ...         0.0   6.87              0.0
3101                 0.00  ...         0.0  22.89              0.0
3102                 1.76  ...         0.0   2.97              0.0
3103                 0.00  ...         0.0   5.68              0.0

      Optio0l Insurance  Consecutive Trips Promotion  Share Adjustment
\
0                   0.0                          0.0               0.0

1                   0.0                          0.0               0.0

2                   0.0                          0.0               0.0

3                   0.0                          0.0               0.0

4                   0.0                          0.0               0.0

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

3099                0.0                          0.0               0.0

3100                0.0                          0.0               0.0

3101                0.0                          0.0               0.0

3102                0.0                          0.0               0.0

3103                0.0                          0.0               0.0


      Quest Promotion  Fare Adjustment  Platinum Reward  Cleaning
Repairs
0                 0.0              0.0              0.0
0.0
1                 0.0              0.0              0.0
0.0
2                 0.0              0.0              0.0
```

```
0.0
3                 0.0               0.0               0.0
0.0
4                 0.0               0.0               0.0
0.0
...               ...               ...               ...
...
3099              0.0               0.0               0.0
0.0
3100              0.0               0.0               0.0
0.0
3101              0.0               0.0               0.0
0.0
3102              0.0               0.0               0.0
0.0
3103              0.0               0.0               0.0
0.0

[3104 rows x 25 columns]
```

Examining the Dataset

```
# Examining the dataset
dataset.shape
dataset.info()
dataset.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3104 entries, 0 to 3103
Data columns (total 25 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Driver 0me                    3104 non-null   object
 1   Phone Number                  3104 non-null   int64
 2   Email                         3104 non-null   object
 3   Date/Time                     3104 non-null   object
 4   Trip ID                       3104 non-null   object
 5   Type                          3104 non-null   object
 6   Base Fare                     3104 non-null   float64
 7   Distance                      3104 non-null   float64
 8   Time                          3104 non-null   float64
 9   Min Fare Supplement           3104 non-null   float64
 10  Cancellation                  3104 non-null   float64
 11  Tip                           3104 non-null   float64
 12  Surge                         3104 non-null   float64
 13  Diamond Reward                3104 non-null   float64
 14  Wait Time                     3104 non-null   float64
 15  Promotions                    3104 non-null   float64
 16  Total                         3104 non-null   float64
 17  Long Pickup Fee               3104 non-null   float64
 18  Optio0l Insurance             3104 non-null   float64
```

```
 19  Consecutive Trips Promotion  3104 non-null   float64
 20  Share Adjustment             3104 non-null   float64
 21  Quest Promotion              3104 non-null   float64
 22  Fare Adjustment              3104 non-null   float64
 23  Platinum Reward              3104 non-null   float64
 24  Cleaning Repairs             3104 non-null   float64
dtypes: float64(19), int64(1), object(5)
memory usage: 606.4+ KB

  Driver 0me  Phone Number      Email
Date/Time  \
0   John Doe             0  jd@jd.com  Thursday, April 18, 2019 10:24
PM
1   John Doe             0  jd@jd.com   Thursday, April 18, 2019 9:48
PM
2   John Doe             0  jd@jd.com     Friday, April 19, 2019 8:39
PM
3   John Doe             0  jd@jd.com    Friday, April 19, 2019 10:50
PM
4   John Doe             0  jd@jd.com  Wednesday, April 17, 2019 8:08
PM

                                Trip ID   Type  Base Fare  Distance
Time  \
0  9bce9679-2755-4c90-9689-f2de69c8f817  UberX        0.3      0.97
0.68
1  bb83ec2b-fd4c-457d-ae92-0a216624d85b  UberX        0.3      4.10
2.09
2  42450298-7f34-4f5b-8283-3415fe7f15a0  UberX        0.3      4.40
1.79
3  6d5371a9-806f-4949-b506-edfffd985ff6  UberX        0.3      1.11
0.60
4  aaa4e703-53af-4b54-ae35-314684a1e330  UberX        0.3      1.10
0.69

   Min Fare Supplement  ...  Promotions  Total  Long Pickup Fee  \
0                 0.68  ...         0.0   2.73              0.0
1                 0.00  ...         0.0   9.86              0.0
2                 0.00  ...         0.0   6.87              0.0
3                 0.62  ...         0.0   2.97              0.0
4                 0.54  ...         0.0   7.74              0.0

   Optio0l Insurance  Consecutive Trips Promotion  Share Adjustment  \
0                0.0                          0.0               0.0
1                0.0                          0.0               0.0
2                0.0                          0.0               0.0
3                0.0                          0.0               0.0
4                0.0                          0.0               0.0

   Quest Promotion  Fare Adjustment  Platinum Reward  Cleaning Repairs
```

0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0

[5 rows x 25 columns]

Adding columns for Morning vs Evening, Day, and Weekend

```
# Functions to create the new columns
def GetMorningOrEvening(row):
  # print(row['Date/Time'].__contains__('AM'))
  # return 'test'
  if 'AM' in row['Date/Time']:
    return 'Morning'
  return 'Evening'

def GetDay(row):
  # print(row['Date/Time'].__contains__('Monday'))
  # return 'test'
  if 'Monday' in row['Date/Time']:
    return 'Monday'
  elif 'Tuesday' in row['Date/Time']:
    return 'Tuesday'
  elif 'Wednesday' in row['Date/Time']:
    return 'Wednesday'
  elif 'Thursday' in row['Date/Time']:
    return 'Thursday'
  elif 'Saturday' in row['Date/Time']:
    return 'Saturday'
  elif 'Saturday' in row['Date/Time']:
    return 'Saturday'
  return 'Sunday'

def GetWeekend(row):
  if 'Friday' in row['Date/Time'] or 'Saturday' in row['Date/Time'] or
'Sunday' in row['Date/Time']:
    return "Weekend"
  return "Weekday"

# Using the functions to create new columns
dataset['Morning or Evening'] = dataset.apply(lambda row:
GetMorningOrEvening(row), axis=1)
dataset['Day of the Week'] = dataset.apply(lambda row: GetDay(row),
```

```
axis=1)
dataset['Weekend'] = dataset.apply(lambda row: GetWeekend(row),
axis=1)

dataset

     Driver 0me  Phone Number      Email  \
0      John Doe             0  jd@jd.com
1      John Doe             0  jd@jd.com
2      John Doe             0  jd@jd.com
3      John Doe             0  jd@jd.com
4      John Doe             0  jd@jd.com
...         ...           ...        ...
3099   John Doe             0  jd@jd.com
3100   John Doe             0  jd@jd.com
3101   John Doe             0  jd@jd.com
3102   John Doe             0  jd@jd.com
3103   John Doe             0  jd@jd.com

                                 Date/Time  \
0        Thursday, April 18, 2019 10:24 PM
1         Thursday, April 18, 2019 9:48 PM
2           Friday, April 19, 2019 8:39 PM
3          Friday, April 19, 2019 10:50 PM
4        Wednesday, April 17, 2019 8:08 PM
...                                    ...
3099  Saturday, September 22, 2018 6:28 PM
3100    Monday, September 24, 2018 5:32 PM
3101  Saturday, September 22, 2018 6:48 PM
3102    Monday, September 24, 2018 4:54 PM
3103  Saturday, September 22, 2018 9:11 PM

                                   Trip ID   Type  Base Fare  Distance
Time  \
0     9bce9679-2755-4c90-9689-f2de69c8f817  UberX        0.3      0.97
0.68
1     bb83ec2b-fd4c-457d-ae92-0a216624d85b  UberX        0.3      4.10
2.09
2     42450298-7f34-4f5b-8283-3415fe7f15a0  UberX        0.3      4.40
1.79
3     6d5371a9-806f-4949-b506-edfffd985ff6  UberX        0.3      1.11
0.60
4     aaa4e703-53af-4b54-ae35-314684a1e330  UberX        0.3      1.10
0.69
...                                    ...    ...        ...       ...
...
3099  ffc28b2e-d7f5-4163-ba2a-1a4703c37097  UberX        0.3     10.95
1.24
3100  605fa173-7d88-4df4-9241-a9a14679cbae  UberX        0.3      0.92
0.39
```

```
3101  0bc6b8a2-775f-4c72-b85b-056db73b1d86  UberX        0.3     17.39
1.95
3102  b38bc746-5dac-4e56-996c-e462070ef1d9  UberX        0.3      0.36
0.21
3103  daf728e0-ff5e-4f44-98c6-078ba3bd4d7f  UberX        0.3      4.46
0.92

      Min Fare Supplement  ...  Optio0l Insurance  \
0                    0.68  ...                0.0
1                    0.00  ...                0.0
2                    0.00  ...                0.0
3                    0.62  ...                0.0
4                    0.54  ...                0.0
...                   ...  ...                ...
3099                 0.00  ...                0.0
3100                 1.01  ...                0.0
3101                 0.00  ...                0.0
3102                 1.76  ...                0.0
3103                 0.00  ...                0.0

      Consecutive Trips Promotion  Share Adjustment  Quest
Promotion  \
0                             0.0               0.0              0.0

1                             0.0               0.0              0.0

2                             0.0               0.0              0.0

3                             0.0               0.0              0.0

4                             0.0               0.0              0.0

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

3099                          0.0               0.0              0.0

3100                          0.0               0.0              0.0

3101                          0.0               0.0              0.0

3102                          0.0               0.0              0.0

3103                          0.0               0.0              0.0


      Fare Adjustment  Platinum Reward  Cleaning Repairs  Morning or
Evening  \
0                 0.0              0.0               0.0
Evening
```

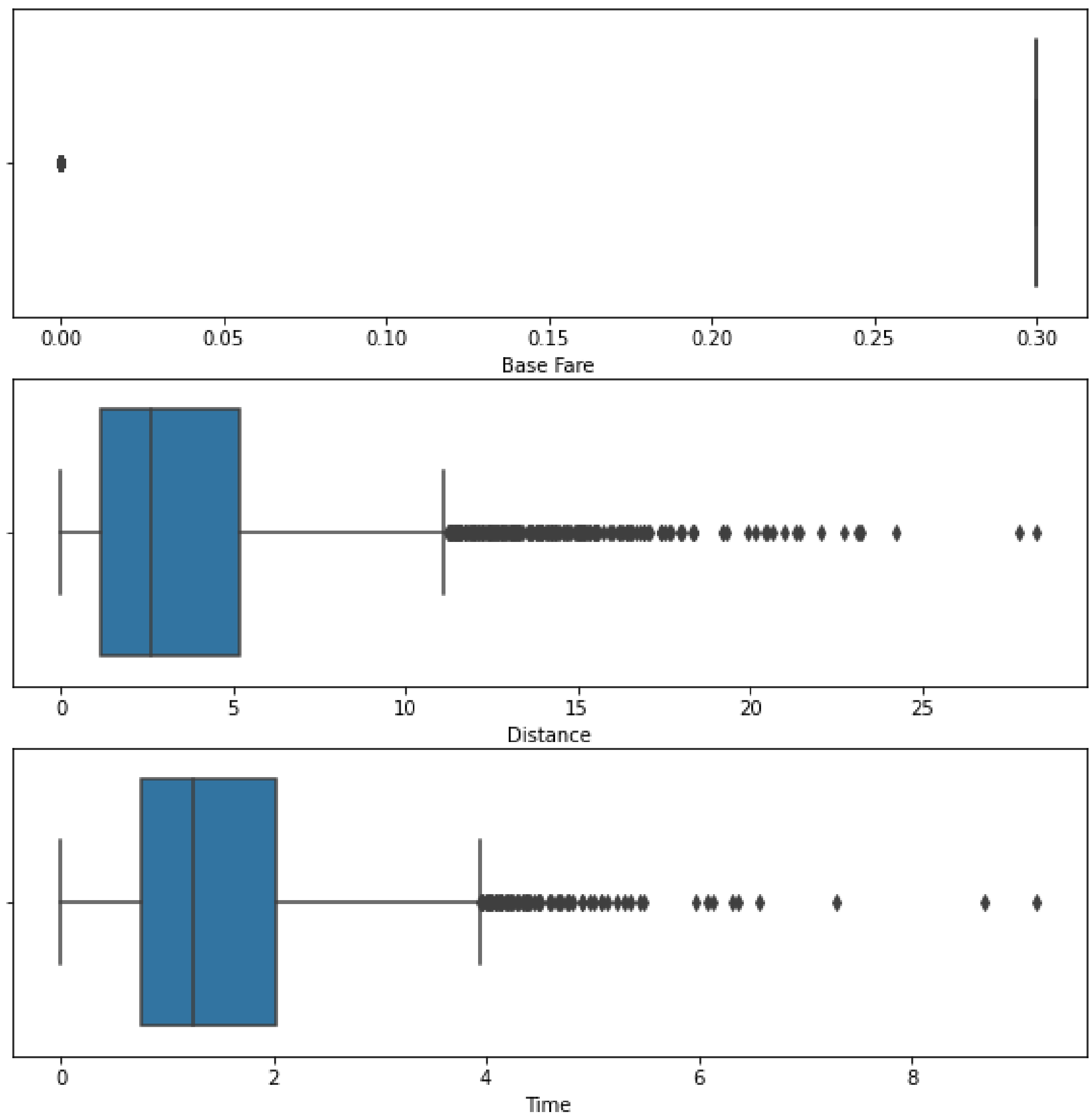
```
1                  0.0              0.0               0.0
Evening
2                  0.0              0.0               0.0
Evening
3                  0.0              0.0               0.0
Evening
4                  0.0              0.0               0.0
Evening
...                ...              ...               ...
...
3099               0.0              0.0               0.0
Evening
3100               0.0              0.0               0.0
Evening
3101               0.0              0.0               0.0
Evening
3102               0.0              0.0               0.0
Evening
3103               0.0              0.0               0.0
Evening

      Day of the Week  Weekend
0            Thursday  Weekday
1            Thursday  Weekday
2              Sunday  Weekend
3              Sunday  Weekend
4           Wednesday  Weekday
...               ...      ...
3099         Saturday  Weekend
3100           Monday  Weekday
3101         Saturday  Weekend
3102           Monday  Weekday
3103         Saturday  Weekend

[3104 rows x 28 columns]
```

Basic Plots, Data Visualization and Analysis

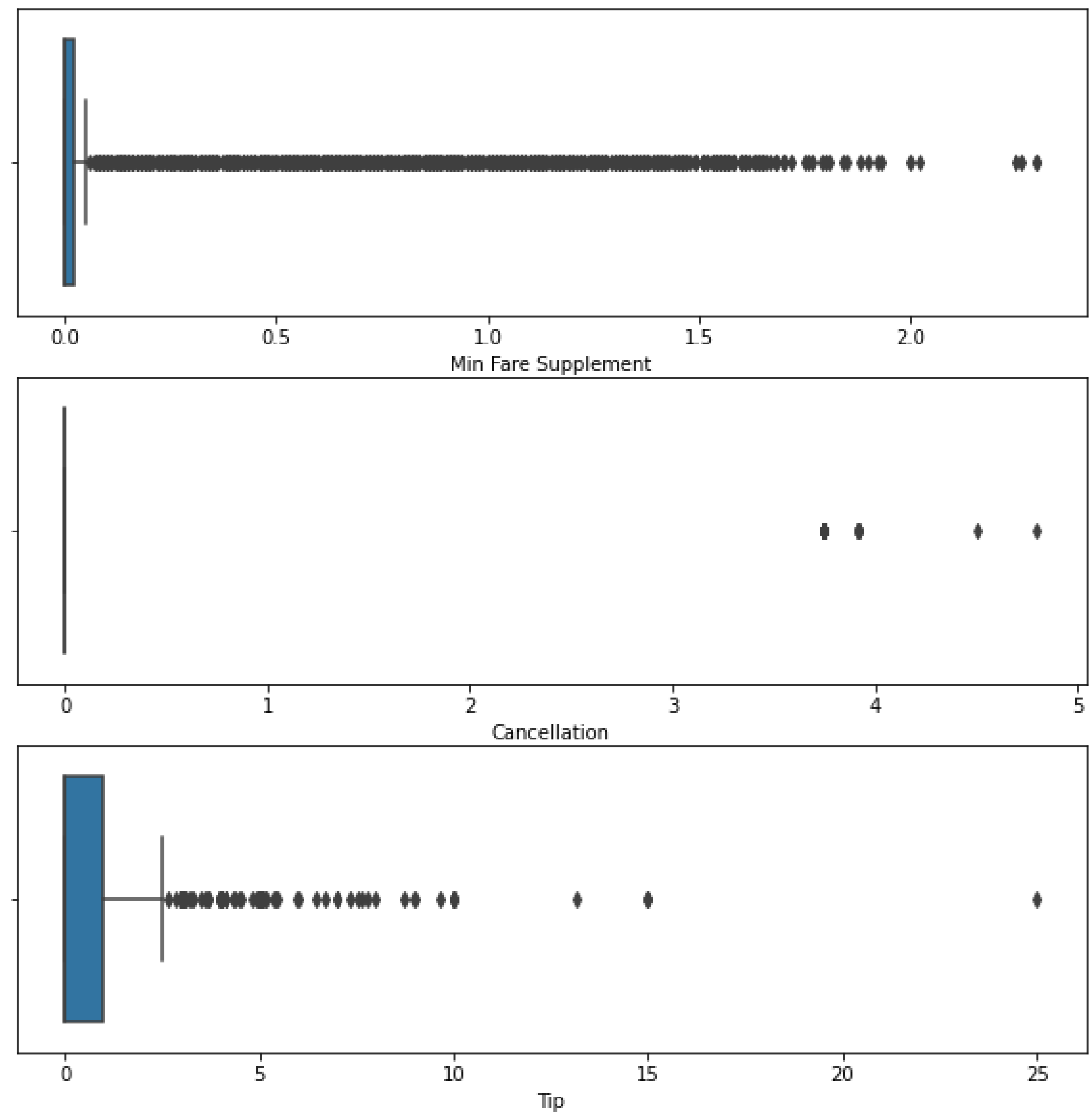
Using matplotlib and seaborn, I create several plots showing different aspects of the data.

Boxplots

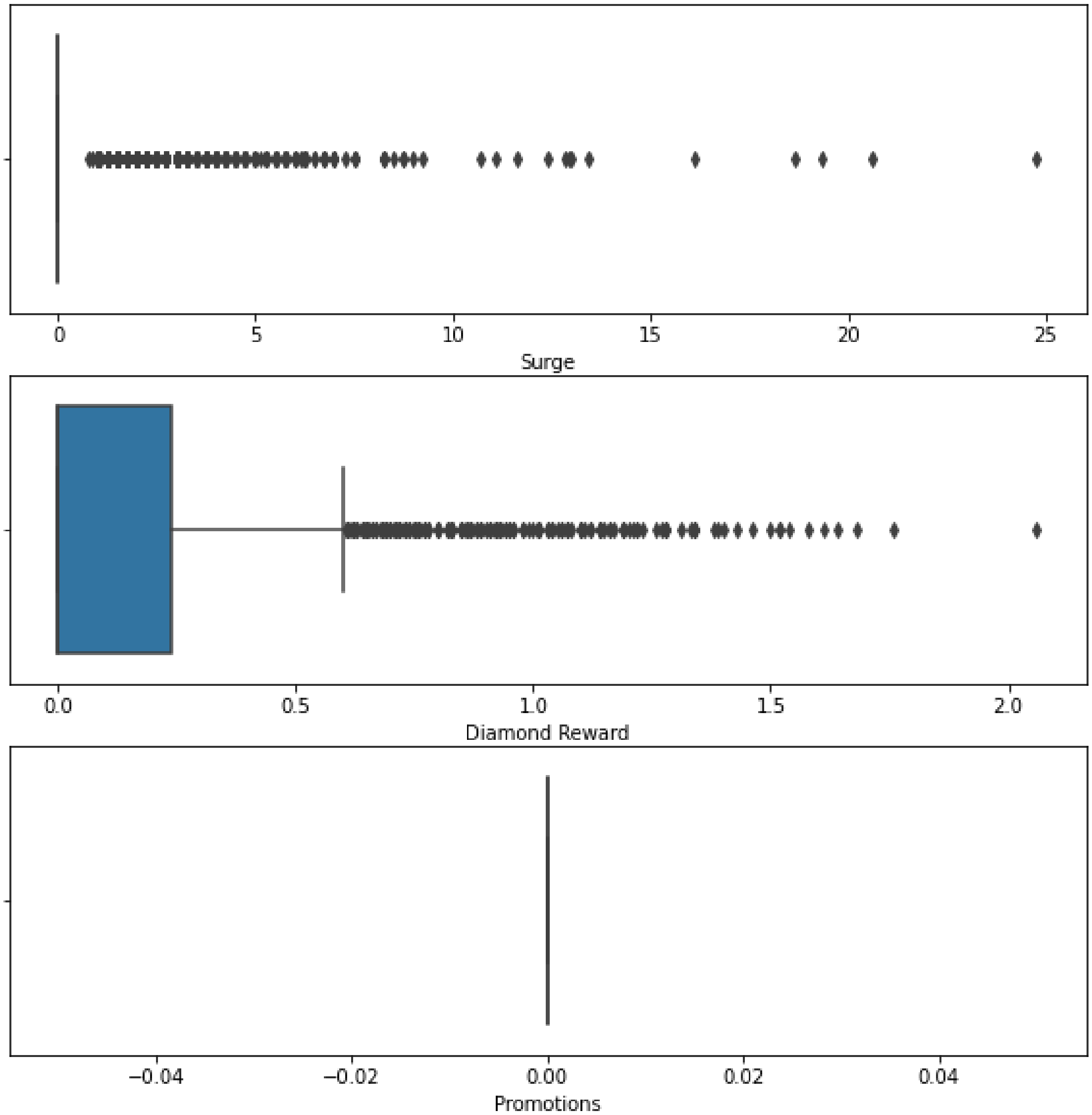
```
fig, axs = plt.subplots(3, figsize = (10,10))
plt1 = sns.boxplot(x = dataset['Base Fare'], ax = axs[0])
plt2 = sns.boxplot(x = dataset['Distance'], ax = axs[1])
plt3 = sns.boxplot(x = dataset['Time'], ax = axs[2])
```



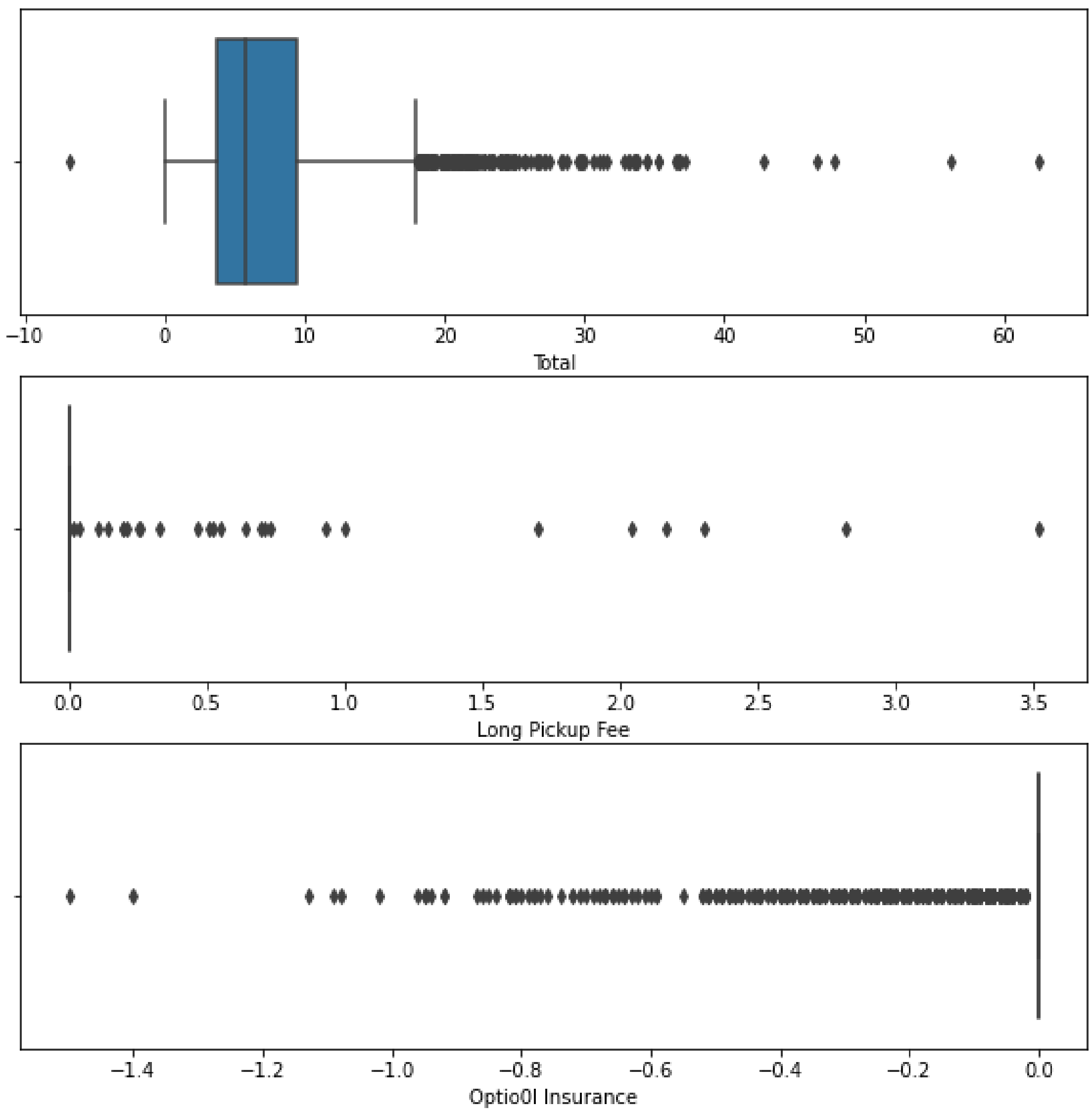

```
fig, axs = plt.subplots(3, figsize = (10,10))
plt4 = sns.boxplot(x = dataset['Min Fare Supplement'], ax = axs[0])
plt5 = sns.boxplot(x = dataset['Cancellation'], ax = axs[1])
plt6 = sns.boxplot(x = dataset['Tip'], ax = axs[2])
```



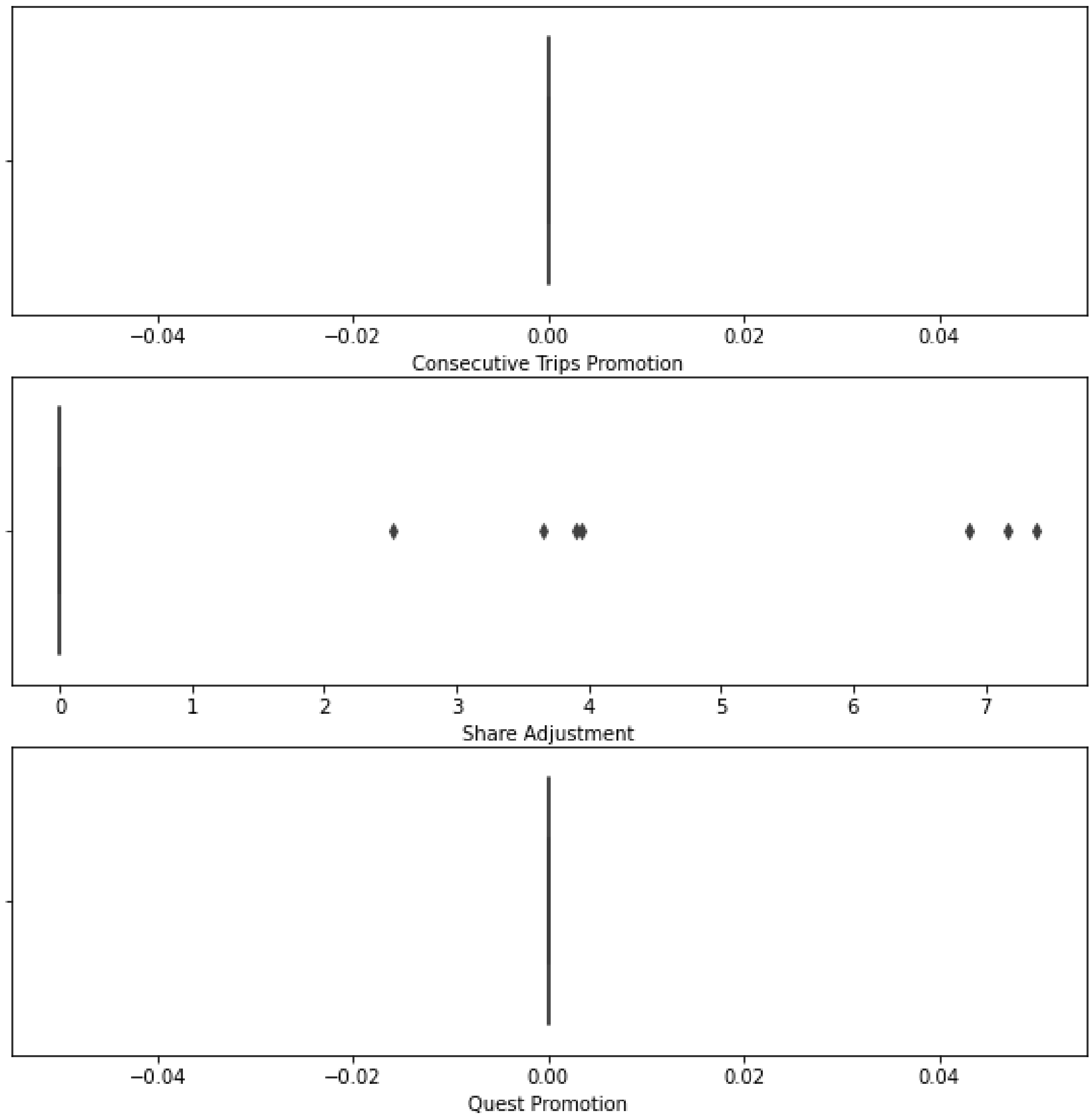

```
fig, axs = plt.subplots(3, figsize = (10,10))
plt7 = sns.boxplot(x = dataset['Surge'], ax = axs[0])
plt8 = sns.boxplot(x = dataset['Diamond Reward'], ax = axs[1])
plt9 = sns.boxplot(x = dataset['Promotions'], ax = axs[2])
```



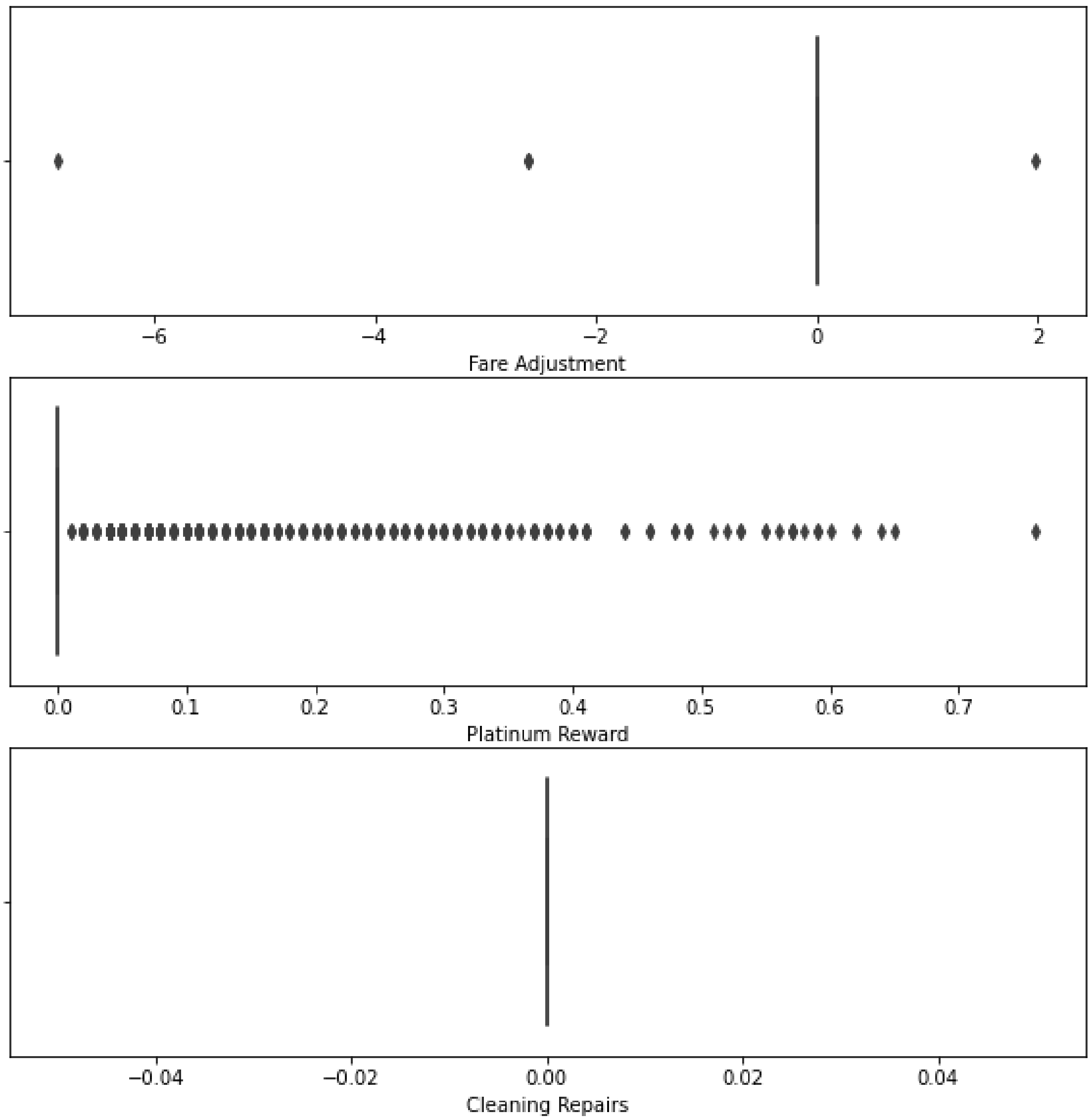

```
fig, axs = plt.subplots(3, figsize = (10,10))
plt10 = sns.boxplot(x = dataset['Total'], ax = axs[0])
plt11 = sns.boxplot(x = dataset['Long Pickup Fee'], ax = axs[1])
plt12 = sns.boxplot(x = dataset['Optio0l Insurance'], ax = axs[2])
```




```
fig, axs = plt.subplots(3, figsize = (10,10))
plt13 = sns.boxplot(x = dataset['Consecutive Trips Promotion'], ax =
axs[0])
plt14 = sns.boxplot(x = dataset['Share Adjustment'], ax = axs[1])
plt15 = sns.boxplot(x = dataset['Quest Promotion'], ax = axs[2])
```




```
fig, axs = plt.subplots(3, figsize = (10,10))
plt16 = sns.boxplot(x = dataset['Fare Adjustment'], ax = axs[0])
plt17 = sns.boxplot(x = dataset['Platinum Reward'], ax = axs[1])
plt18 = sns.boxplot(x = dataset['Cleaning Repairs'], ax = axs[2])
```



Boxplot Conclusions:

Base Fares are mostly 0.30 with negative outliers.

Distances are positively skewed with many positive outliers.

Times are positively skewed with many positive outliers.

Min Fare Supplements are positively skewed with many positive outliers.

Cancellations are mostly zero with positive outliers.

Tips are positively skewed with many positive outliers.

Surge pricings are mostly zero with many positive outliers.

Diamond Rewards are positively skewed with positive outliers.

Promotions are all zero.

Totals are positively skewed with many positive outliers and a single negative outlier.

Long Pickup Fees are mostly zero with positive outliers.

Optional Insurance are mostly zero with negative outliers.

Consecutive Trips Promotions are all zero.

Share Ajustments are mostly zero with positive outliers.

Quest Promotions are all zero.

Fare Adjustments are mostly zero with two negative and one positive outlier

Platinum Rewards are mostly zero with marginal positive outliers.

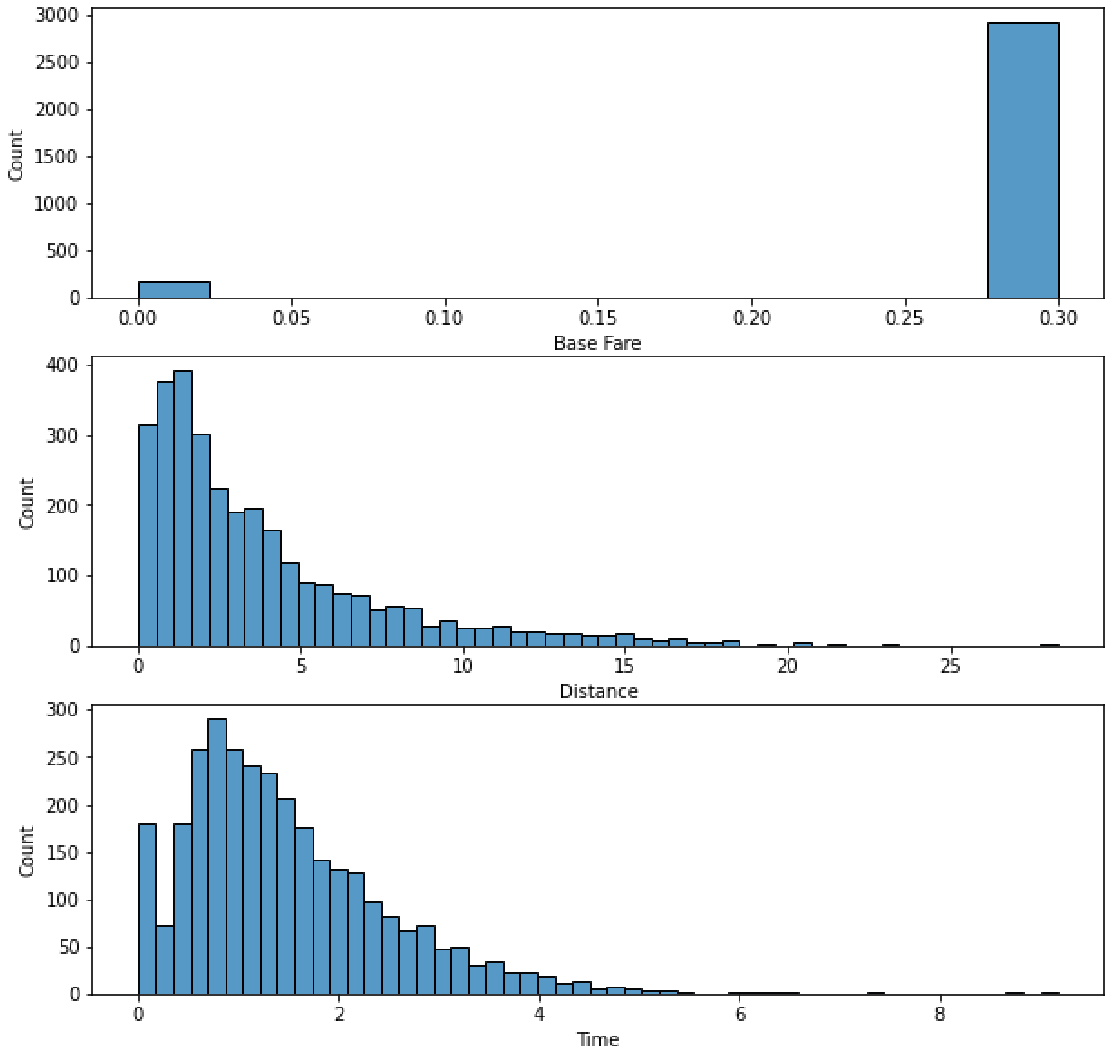
Cleaning Repairs are all zero.

Irrelavent variables conclusion

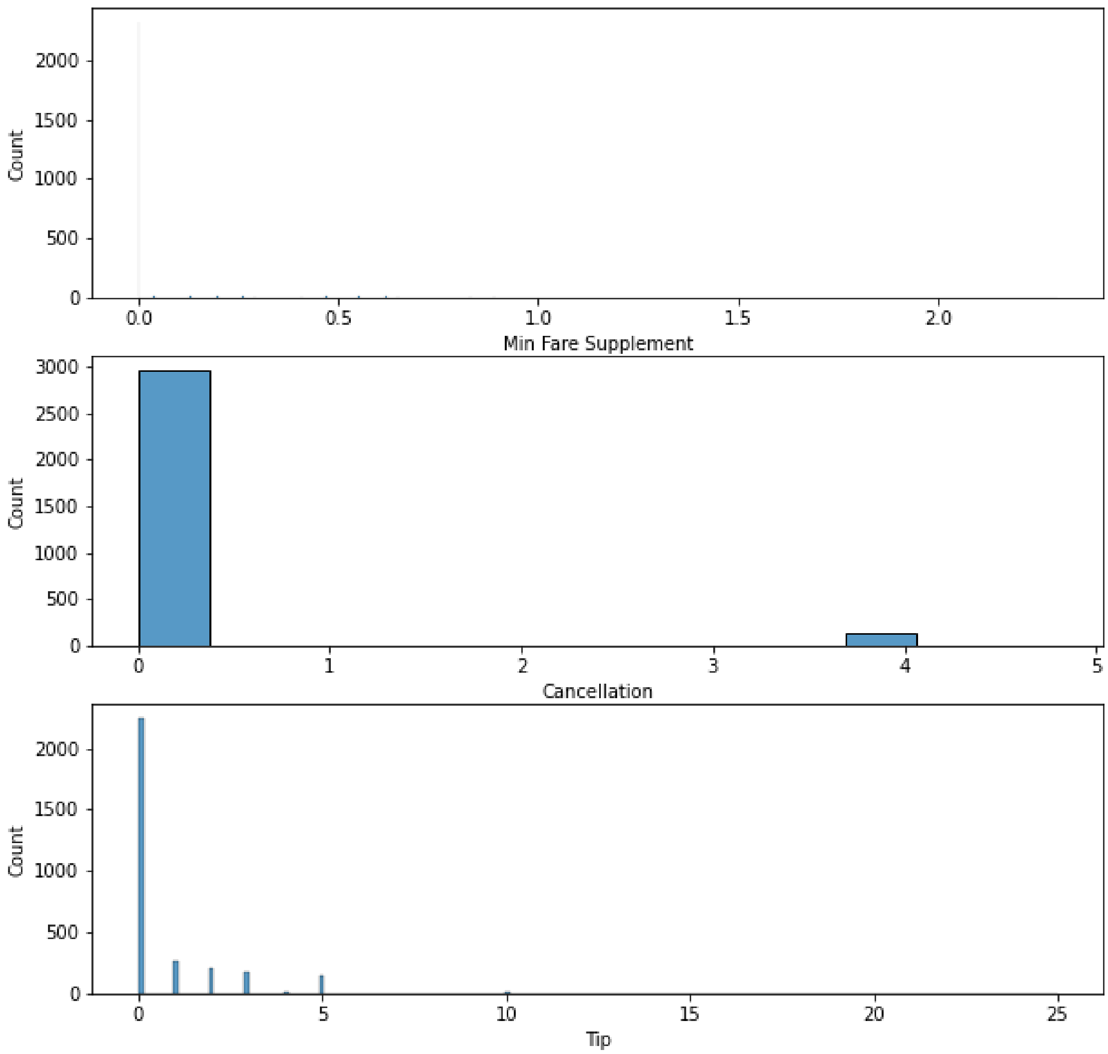
We can also determine that Promotions, Consecutive Trips Promotions, Quest Promotions, and Cleaning Repairs are irrelavent because they are all zero. We can therefore ignore them for further analysis

Histogram Plots

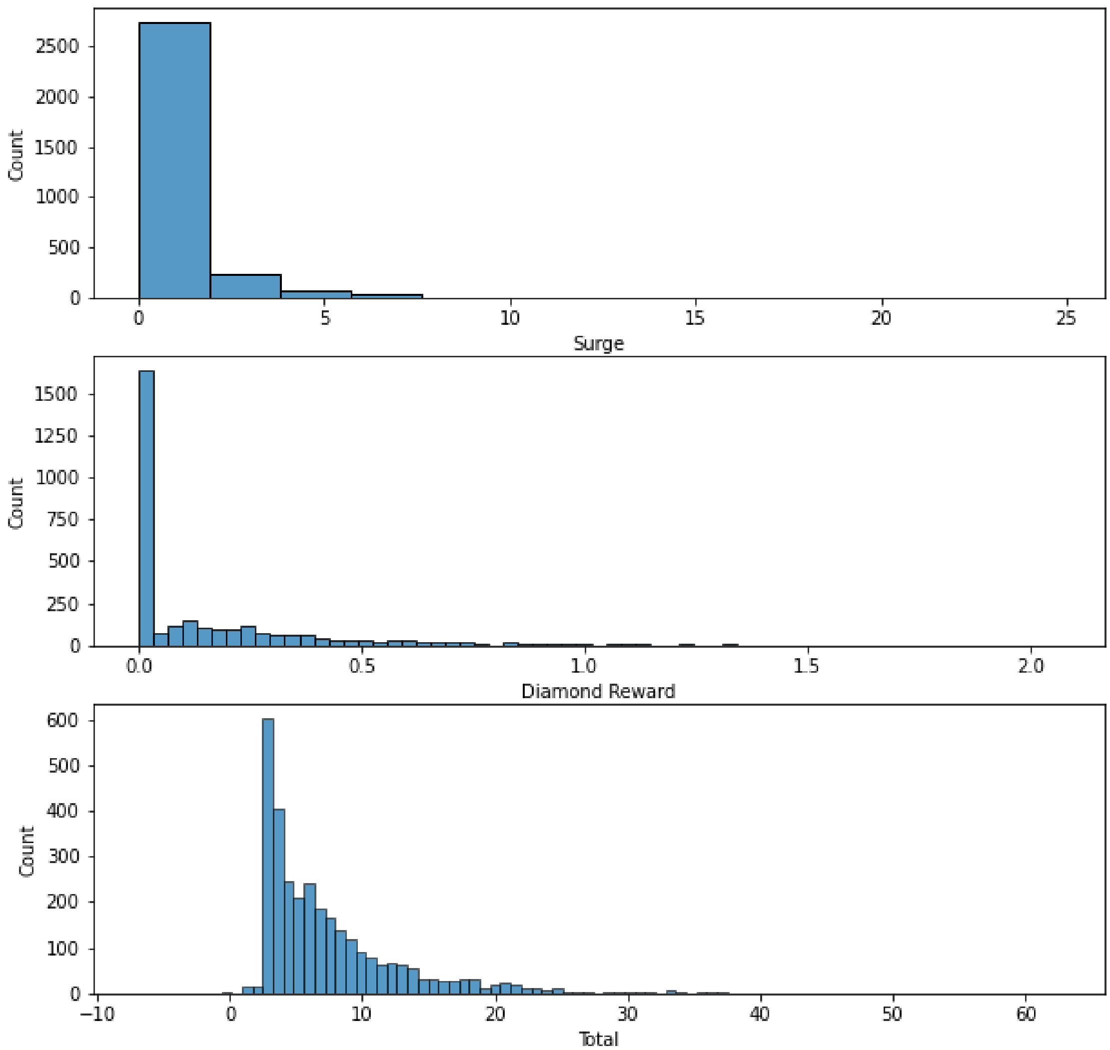
```
fig, axs = plt.subplots(3, figsize = (10,10))
plt0 = sns.histplot(x = dataset['Base Fare'], ax = axs[0])
plt1 = sns.histplot(x = dataset['Distance'], ax = axs[1])
plt2 = sns.histplot(x = dataset['Time'], ax = axs[2])
```



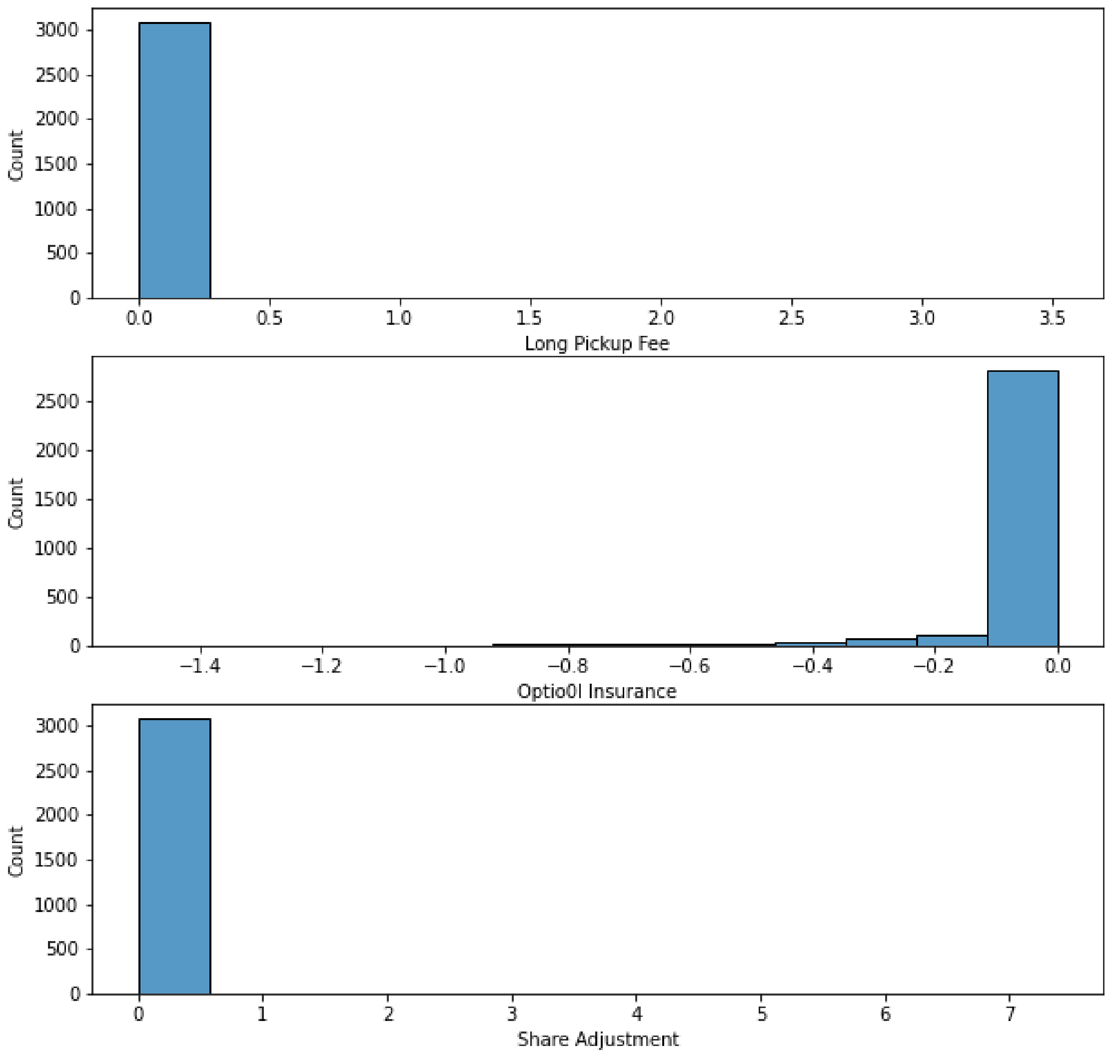

```
fig, axs = plt.subplots(3, figsize = (10,10))
plt3 = sns.histplot(x = dataset['Min Fare Supplement'], ax = axs[0])
plt4 = sns.histplot(x = dataset['Cancellation'], ax = axs[1])
plt5 = sns.histplot(x = dataset['Tip'], ax = axs[2])
```



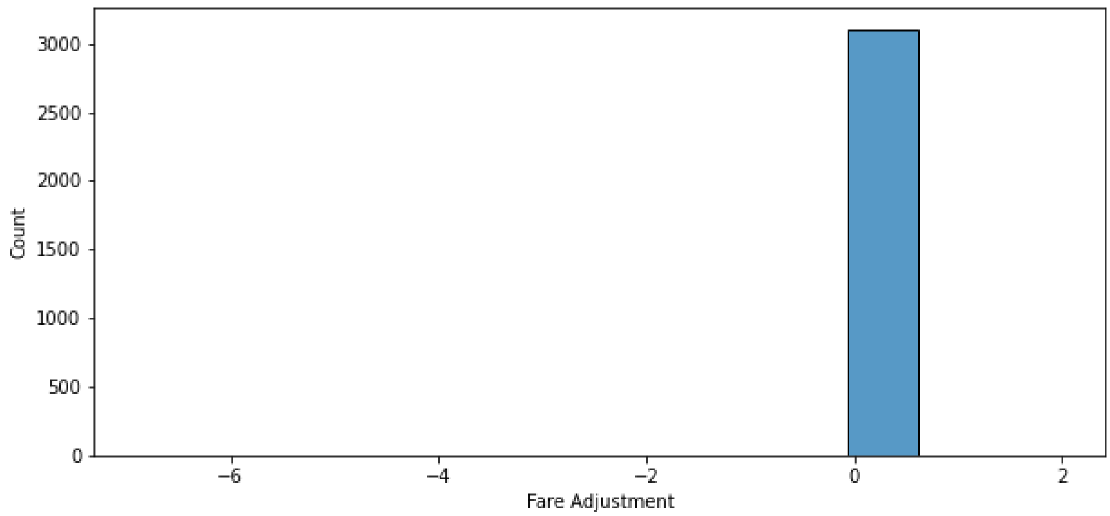

```
fig, axs = plt.subplots(3, figsize = (10,10))
plt6 = sns.histplot(x = dataset['Surge'], ax = axs[0])
plt7 = sns.histplot(x = dataset['Diamond Reward'], ax = axs[1])
plt8 = sns.histplot(x = dataset['Total'], ax = axs[2])
```

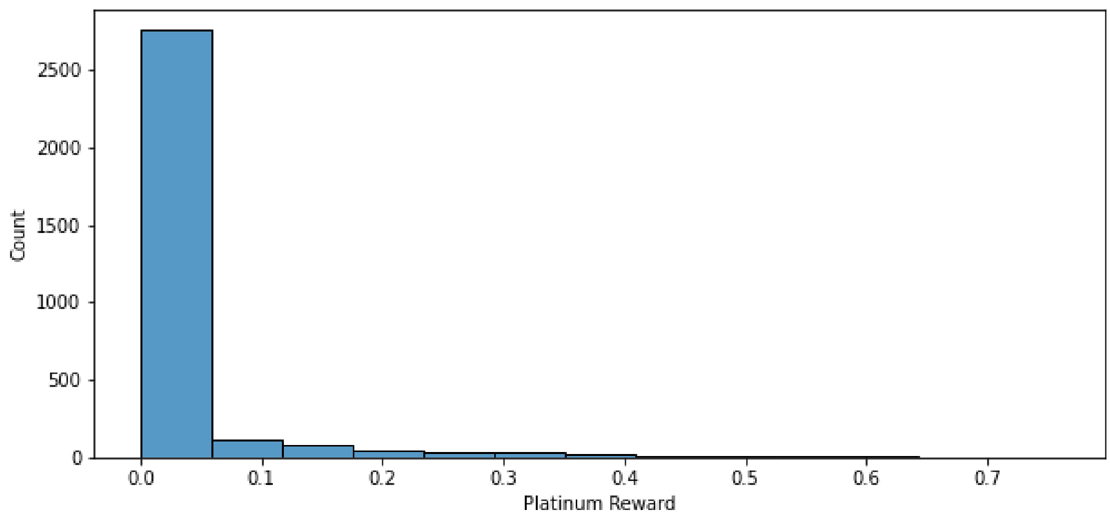



```
fig, axs = plt.subplots(3, figsize = (10,10))
plt9 = sns.histplot(x = dataset['Long Pickup Fee'], ax = axs[0])
plt10 = sns.histplot(x = dataset['Optio0l Insurance'], ax = axs[1])
plt11 = sns.histplot(x = dataset['Share Adjustment'], ax = axs[2])
```




```
fig, axs = plt.subplots(2, figsize = (10,10))
plt12 = sns.histplot(x = dataset['Fare Adjustment'], ax = axs[0])
plt13 = sns.histplot(x = dataset['Platinum Reward'], ax = axs[1])
```



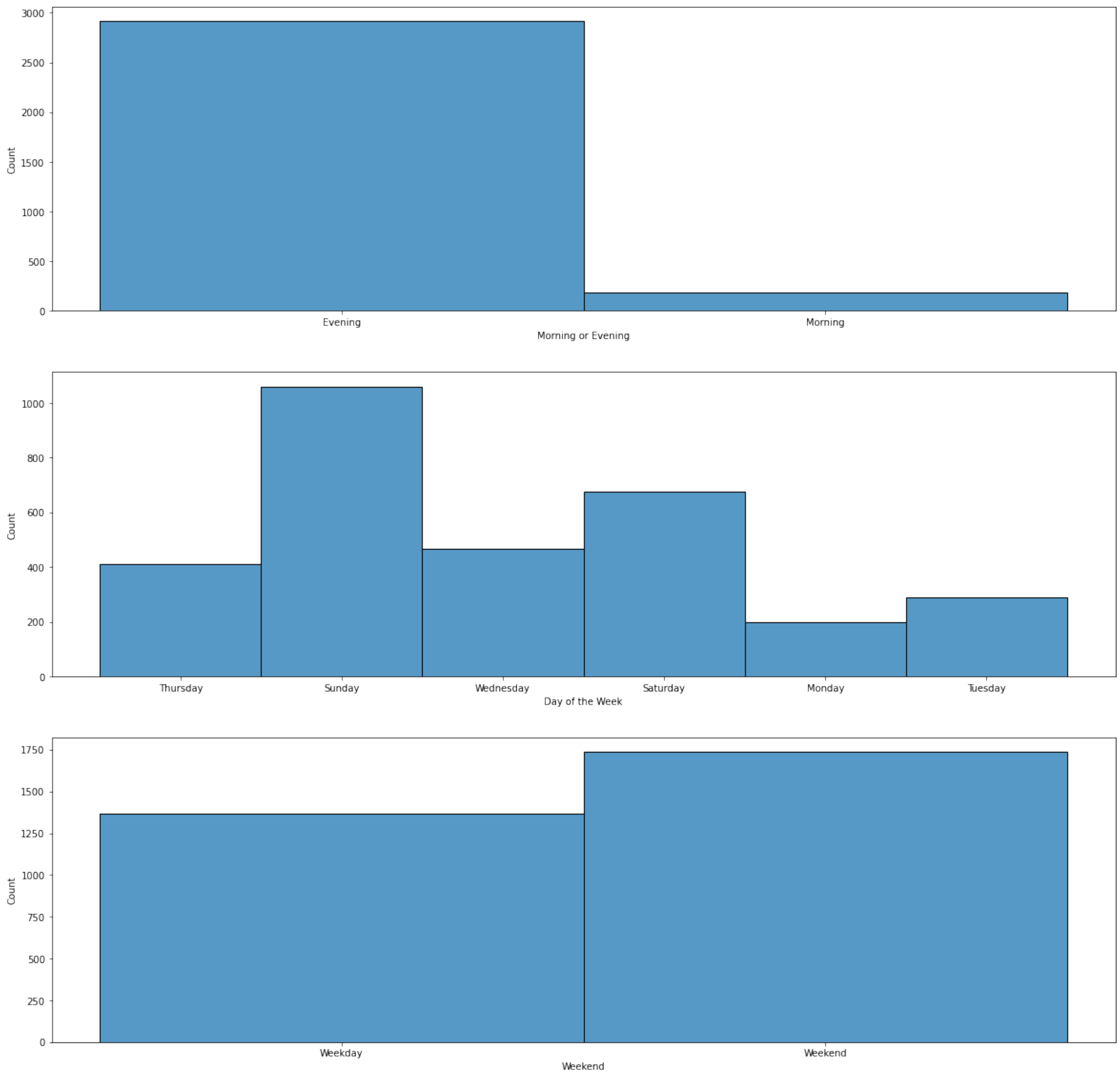


Histogram Conclusions:

Conclusions same as the boxplots.

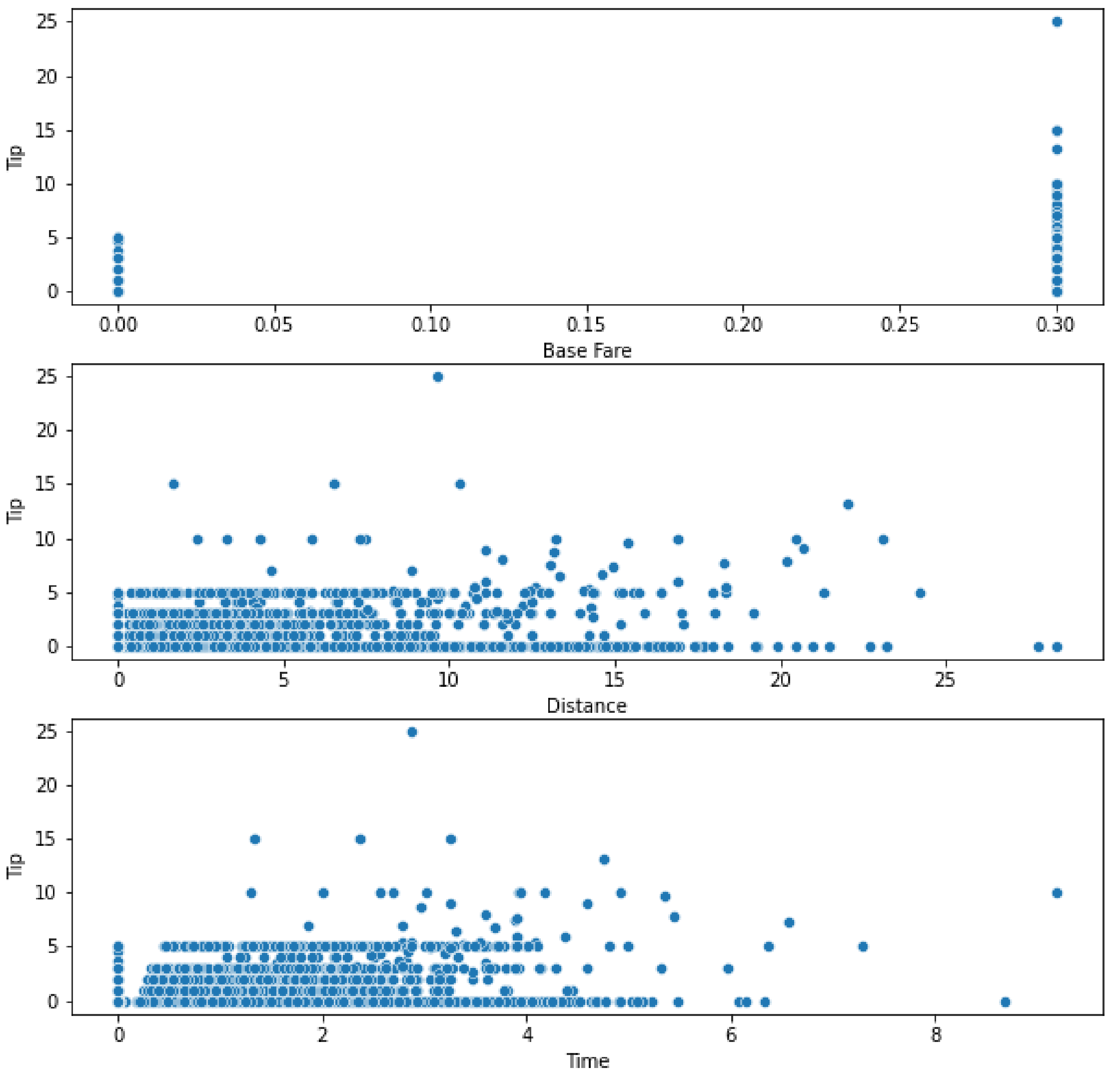
Histograms for non-numerical data

```
fig, axs = plt.subplots(3, figsize = (20,20))
plt0 = sns.histplot(x = dataset['Morning or Evening'], ax = axs[0])
plt1 = sns.histplot(x = dataset['Day of the Week'], ax = axs[1])
plt2 = sns.histplot(x = dataset['Weekend'], ax = axs[2])
```

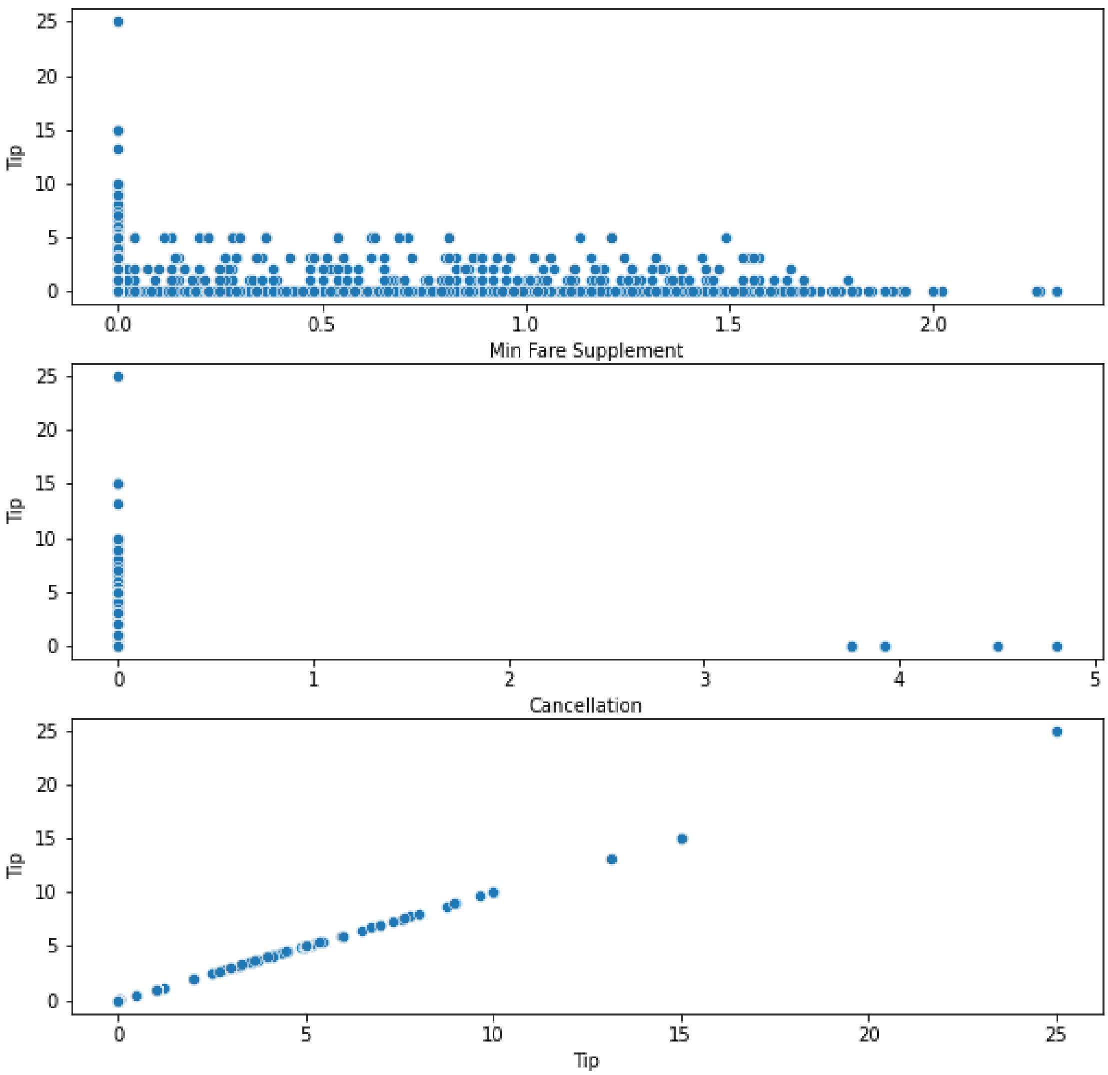


Scatter Plots

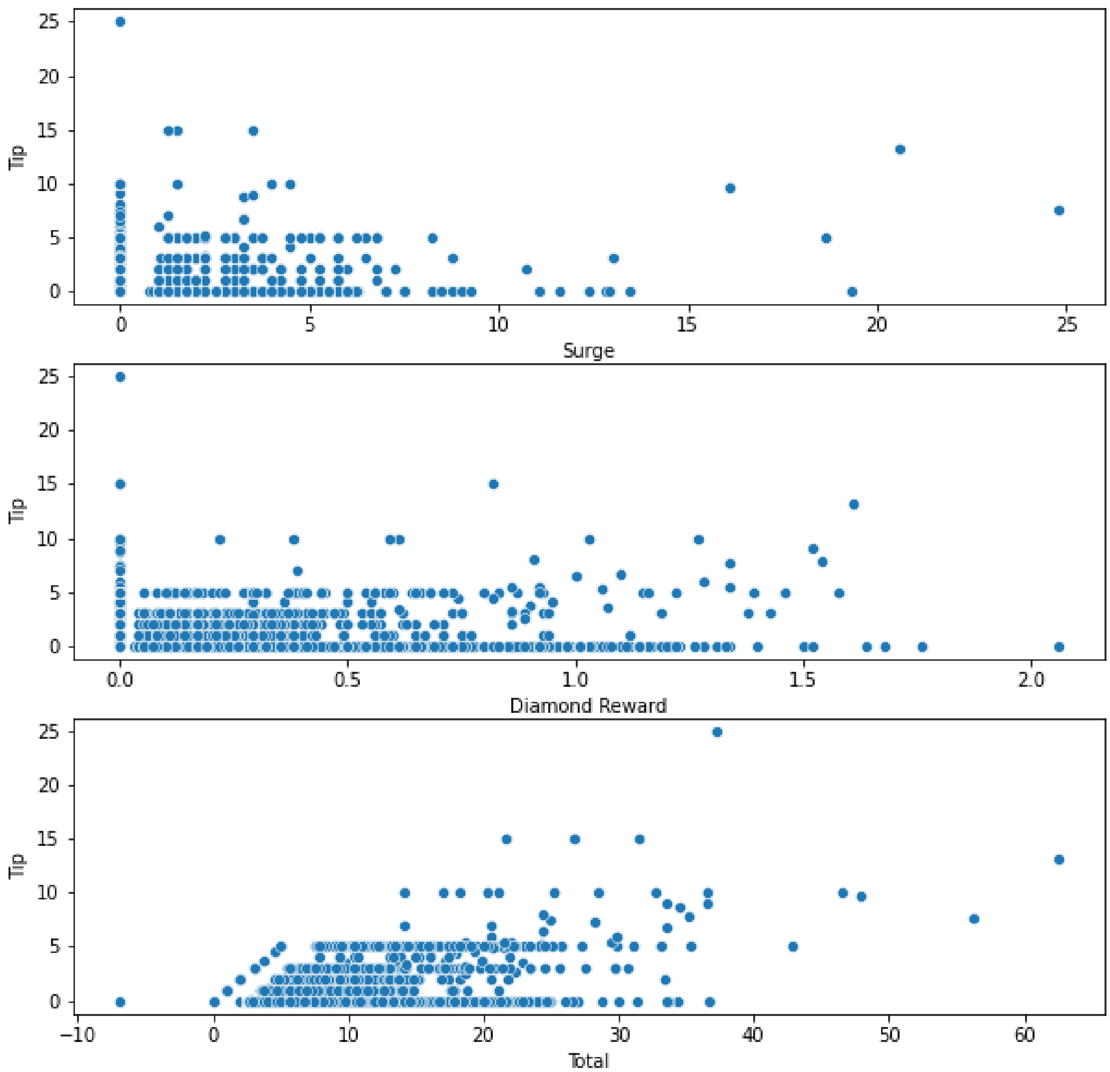
```
fig, axs = plt.subplots(3, figsize = (10,10))
plt0 = sns.scatterplot(x = dataset['Base Fare'], y = dataset['Tip'],
ax = axs[0])
plt1 = sns.scatterplot(x = dataset['Distance'], y = dataset['Tip'], ax
= axs[1])
plt2 = sns.scatterplot(x = dataset['Time'], y = dataset['Tip'], ax =
axs[2])
```



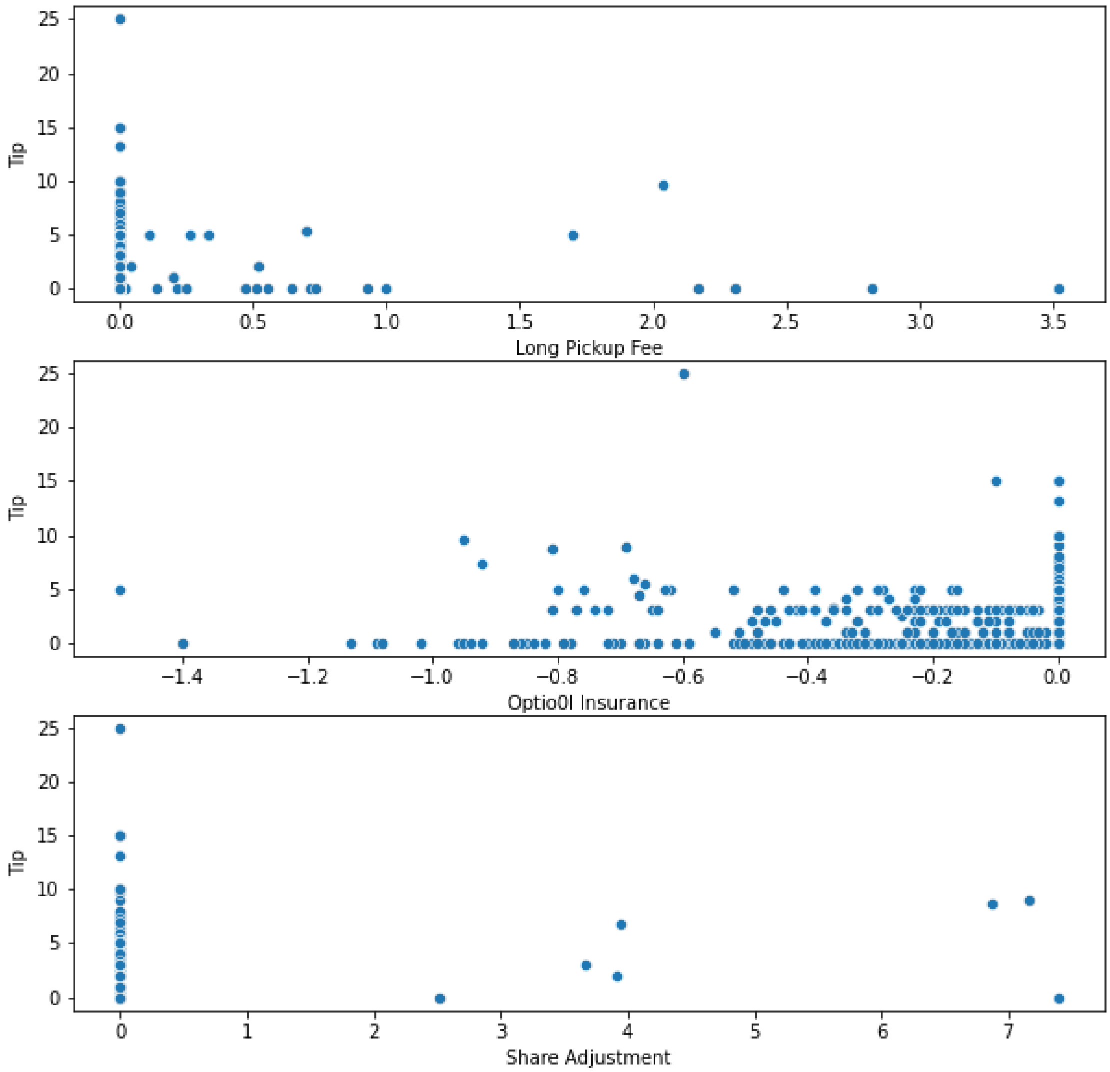

```
fig, axs = plt.subplots(3, figsize = (10,10))
plt3 = sns.scatterplot(x = dataset['Min Fare Supplement'], y =
dataset['Tip'], ax = axs[0])
plt4 = sns.scatterplot(x = dataset['Cancellation'], y =
dataset['Tip'], ax = axs[1])
plt5 = sns.scatterplot(x = dataset['Tip'], y = dataset['Tip'], ax =
axs[2])
```



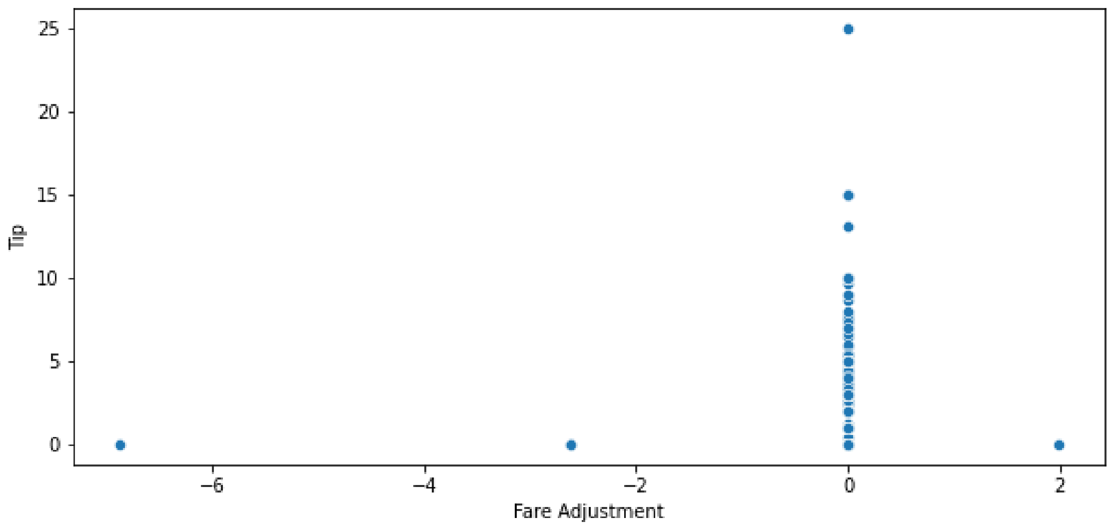

```
fig, axs = plt.subplots(3, figsize = (10,10))
plt6 = sns.scatterplot(x = dataset['Surge'], y = dataset['Tip'], ax =
axs[0])
plt7 = sns.scatterplot(x = dataset['Diamond Reward'], y =
dataset['Tip'], ax = axs[1])
plt8 = sns.scatterplot(x = dataset['Total'], y = dataset['Tip'], ax =
axs[2])
```

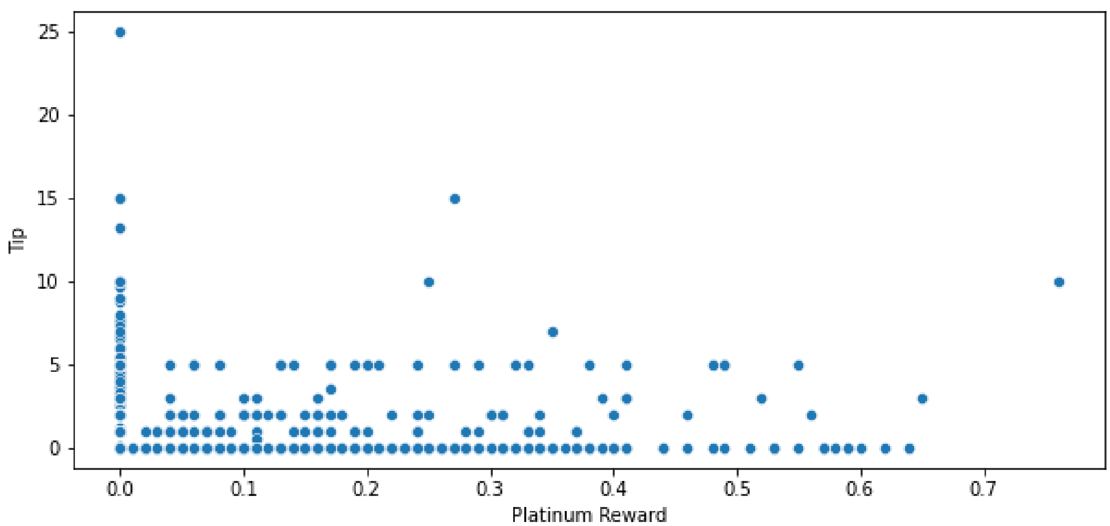



```
fig, axs = plt.subplots(3, figsize = (10,10))
plt9 = sns.scatterplot(x = dataset['Long Pickup Fee'], y =
dataset['Tip'], ax = axs[0])
plt10 = sns.scatterplot(x = dataset['Optio0l Insurance'], y =
dataset['Tip'], ax = axs[1])
plt11 = sns.scatterplot(x = dataset['Share Adjustment'], y =
dataset['Tip'], ax = axs[2])
```



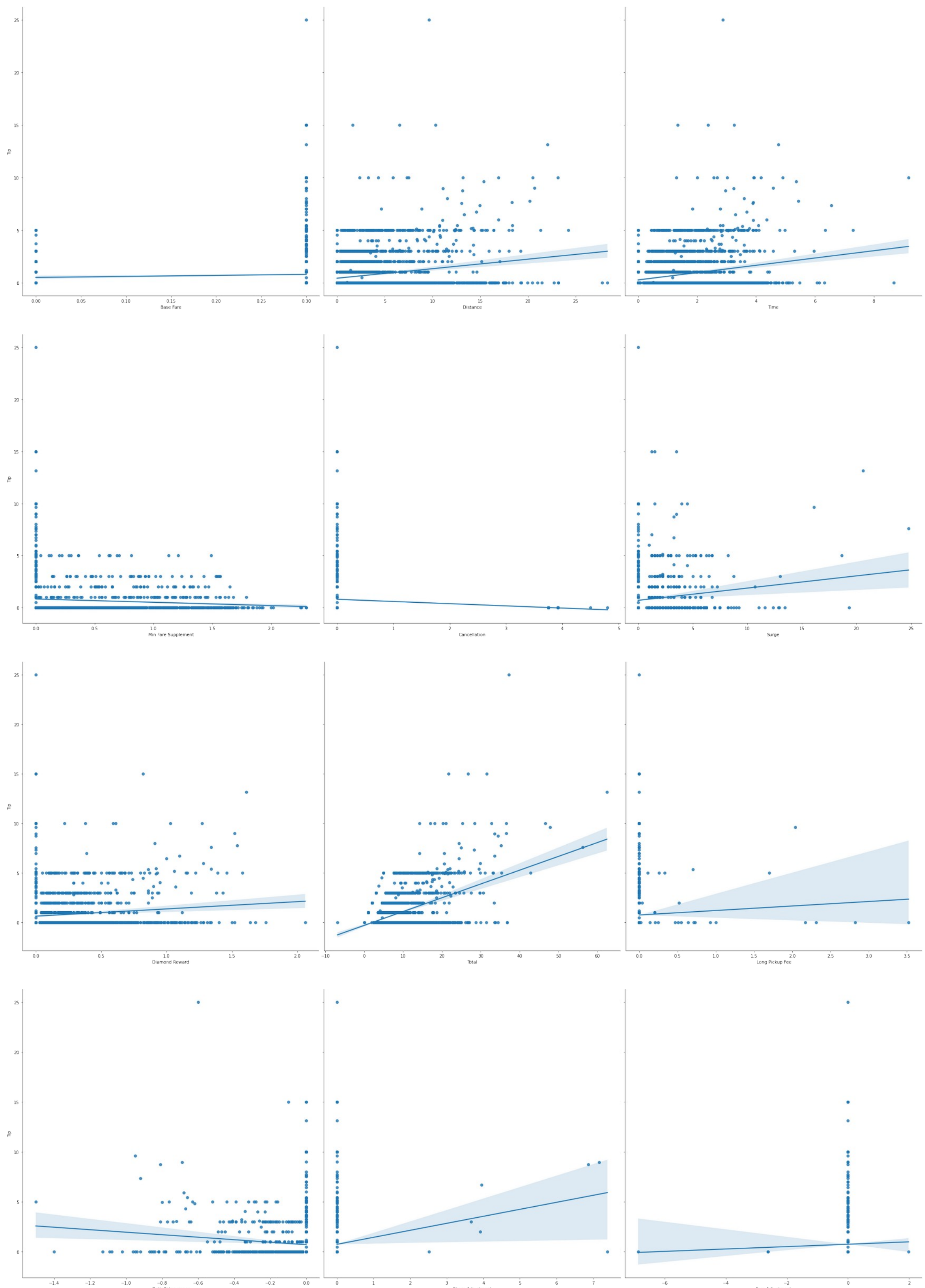

```
fig, axs = plt.subplots(2, figsize = (10,10))
plt12 = sns.scatterplot(x = dataset['Fare Adjustment'], y =
dataset['Tip'], ax = axs[0])
plt13 = sns.scatterplot(x = dataset['Platinum Reward'], y =
dataset['Tip'], ax = axs[1])
```

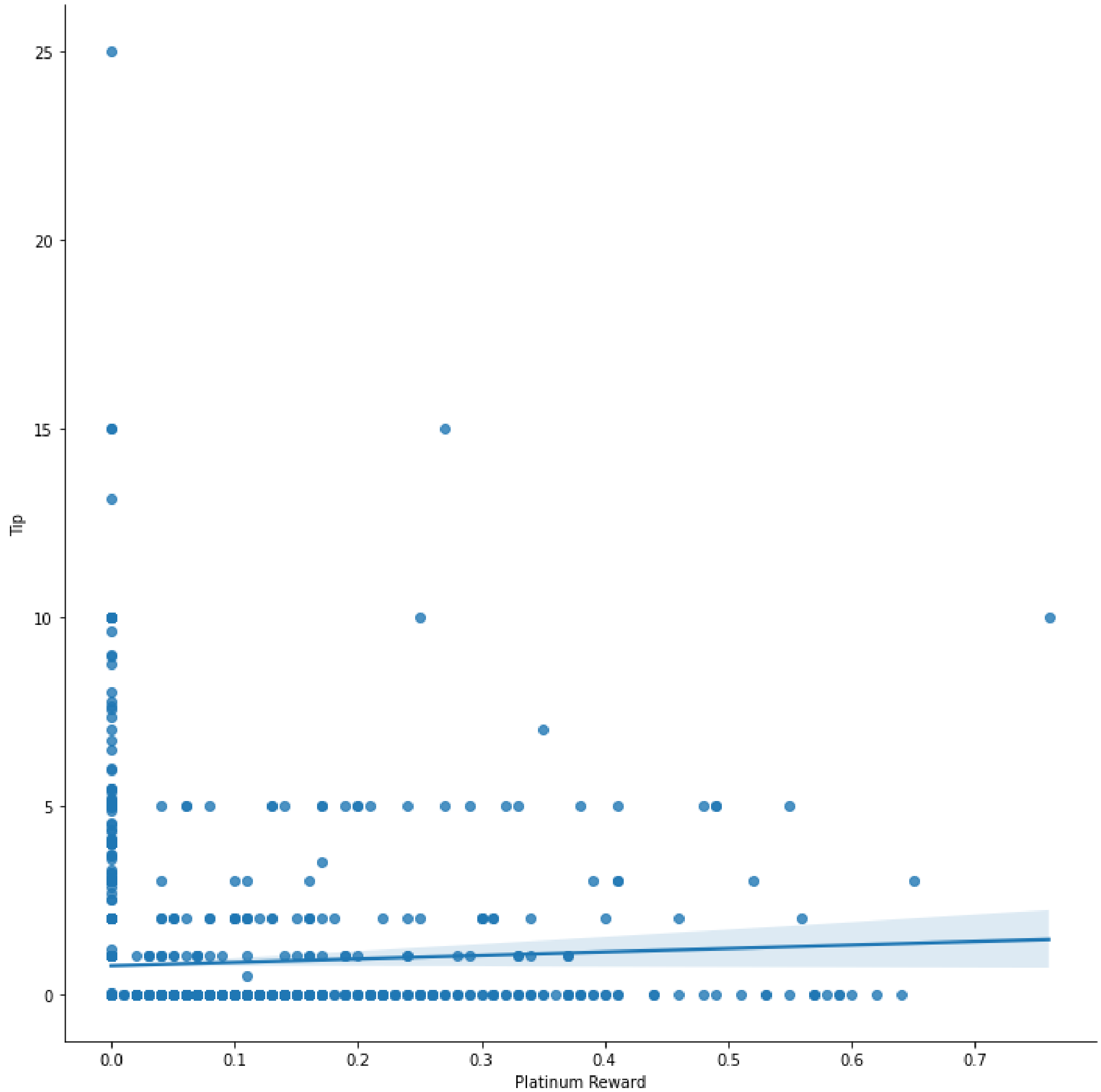





```
sns.pairplot(dataset, x_vars=['Base Fare','Distance','Time'],
y_vars='Tip', height=10, aspect=1, kind='reg')
sns.pairplot(dataset, x_vars=['Min Fare
Supplement','Cancellation','Surge'], y_vars='Tip', height=10,
aspect=1, kind='reg')
sns.pairplot(dataset, x_vars=['Diamond Reward','Total','Long Pickup
Fee'], y_vars='Tip', height=10, aspect=1, kind='reg')
sns.pairplot(dataset, x_vars=['Optio0l Insurance','Share
Adjustment','Fare Adjustment'], y_vars='Tip', height=10, aspect=1,
kind='reg')
sns.pairplot(dataset, x_vars=['Platinum Reward'], y_vars='Tip',
height=10, aspect=1, kind='reg')
```

```
<seaborn.axisgrid.PairGrid at 0x7f70d97cd590>
```


Tip
Base Fare
Distance
Time
Min Fare Supplement
Cancellation
Surge
Diamond Reward
Total
Long Pickup Fee
OptioOl Insurance
Share Adjustment
Fare Adjustment



Scatterplot Conclusions: Distance, Time, Surge, Diamond Reward, Total, and Share Adjustment have a positive correlation to Tip. Min Fare Supplement, Cancellation, and Optional Insurance have a negative correlation to Tip. Base fare, Fare Adjustment, and Platinum Reward have neutral correlation or no correlation to Tip.

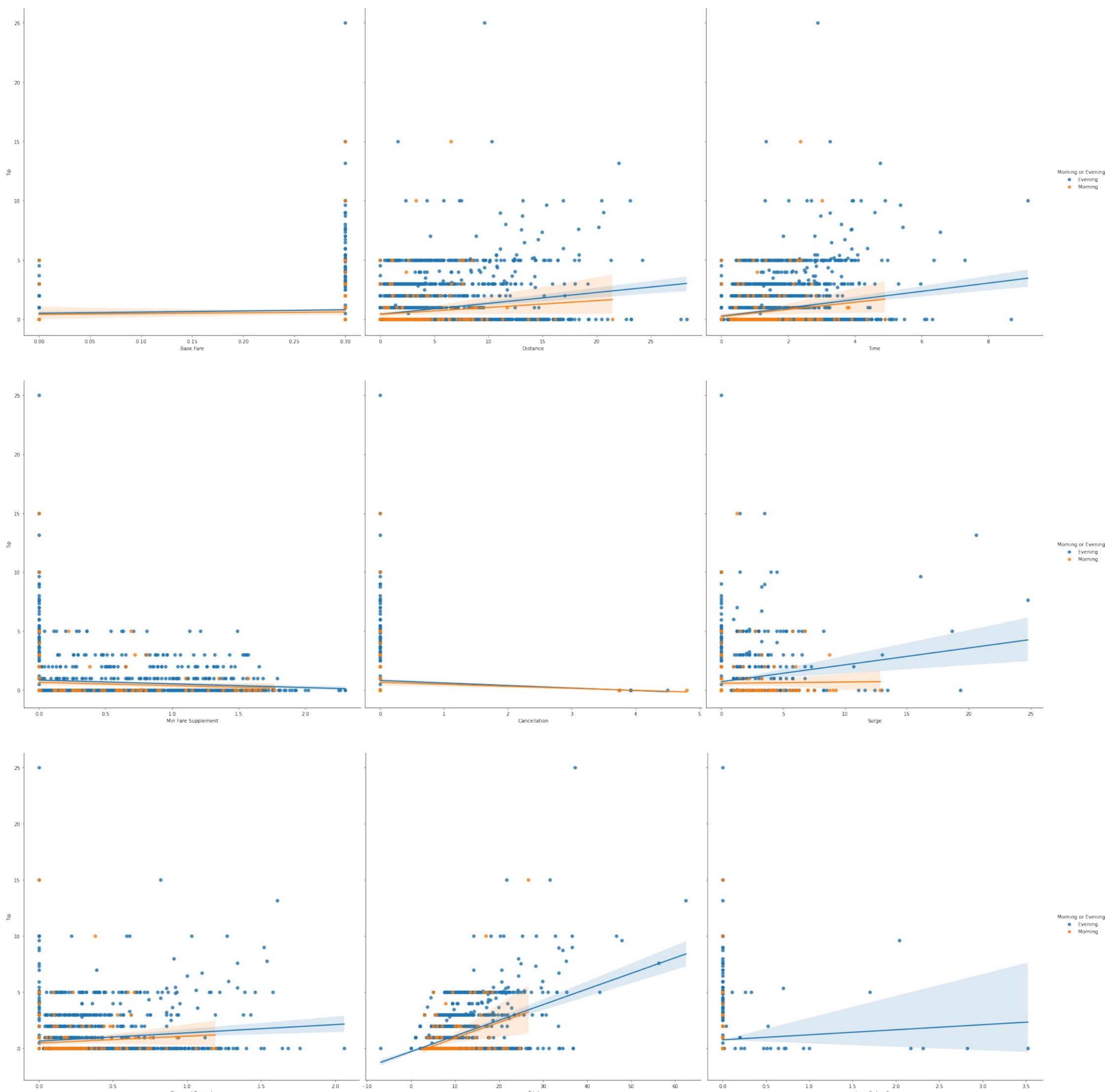
Scatterplots Showing Categorical Data

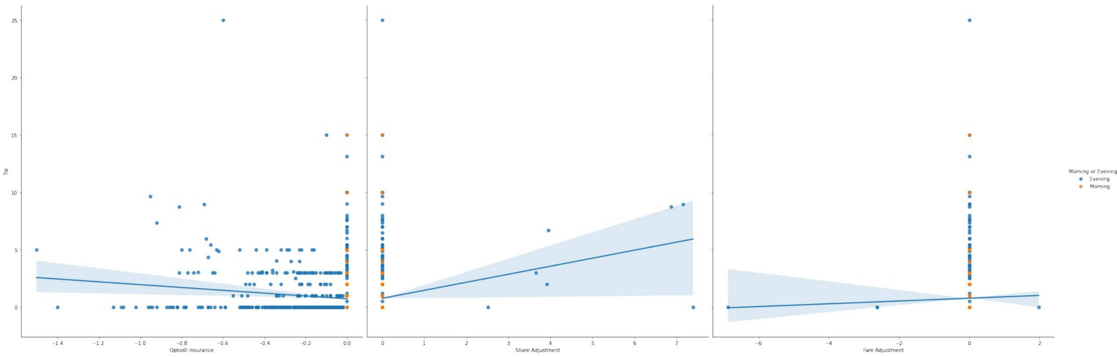
Morning vs Evening:

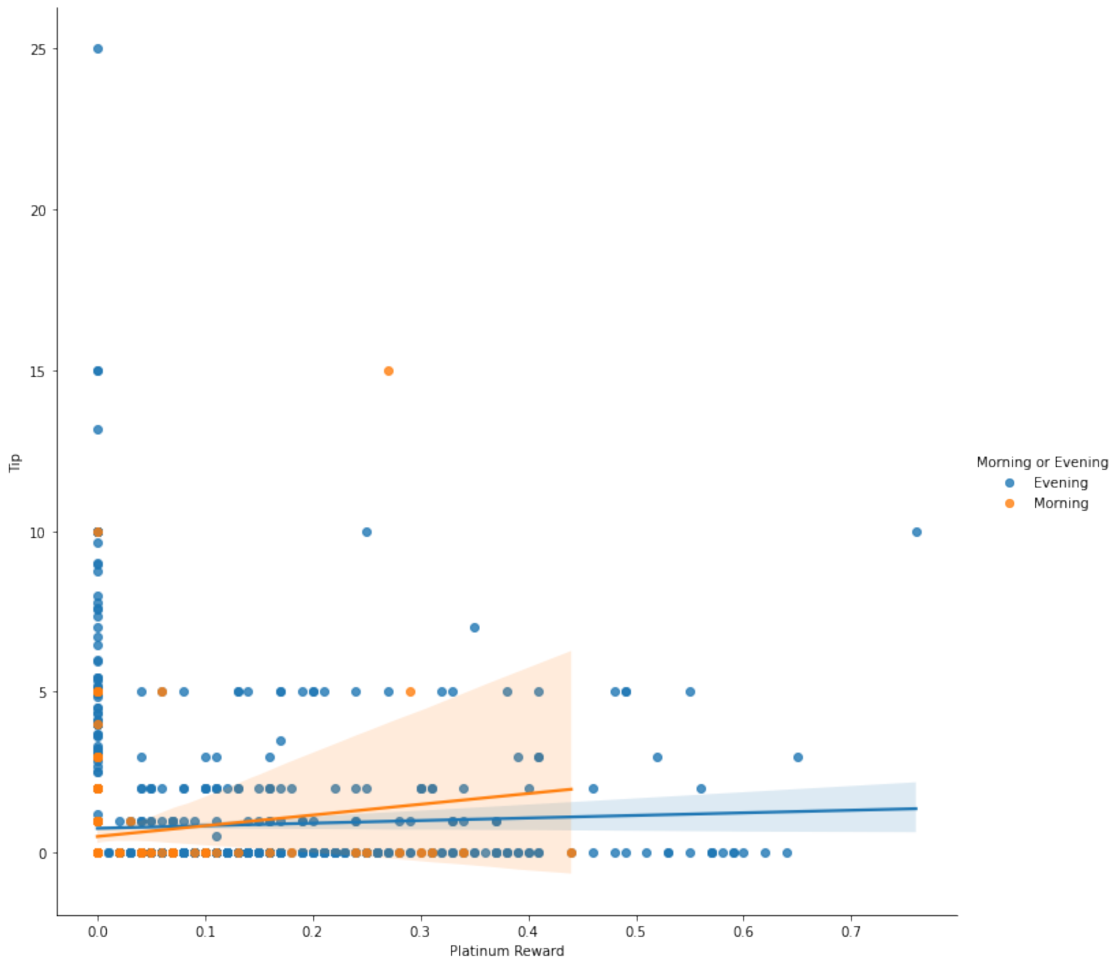
```
sns.pairplot(dataset, x_vars=['Base Fare','Distance','Time'],
y_vars='Tip', height=10, aspect=1, kind='reg', hue='Morning or
Evening')
sns.pairplot(dataset, x_vars=['Min Fare
Supplement','Cancellation','Surge'], y_vars='Tip', height=10,
aspect=1, kind='reg', hue='Morning or Evening')
sns.pairplot(dataset, x_vars=['Diamond Reward','Total','Long Pickup
Fee'], y_vars='Tip', height=10, aspect=1, kind='reg', hue='Morning or
```

```
Evening')
sns.pairplot(dataset, x_vars=['Optio0l Insurance','Share
Adjustment','Fare Adjustment'], y_vars='Tip', height=10, aspect=1,
kind='reg', hue='Morning or Evening')
sns.pairplot(dataset, x_vars=['Platinum Reward'], y_vars='Tip',
height=10, aspect=1, kind='reg', hue='Morning or Evening')
```

```
<seaborn.axisgrid.PairGrid at 0x7f70e5a5e710>
```





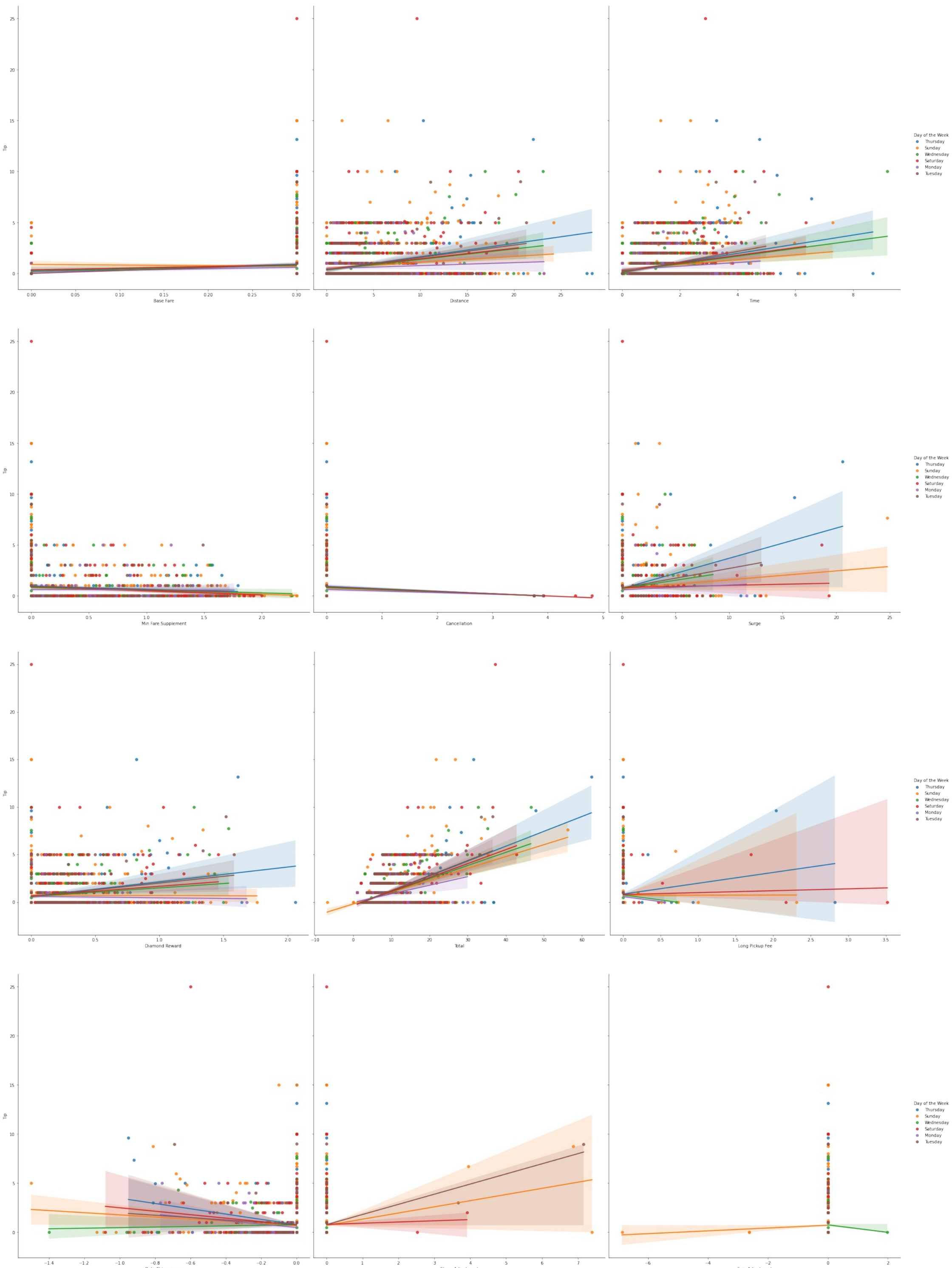


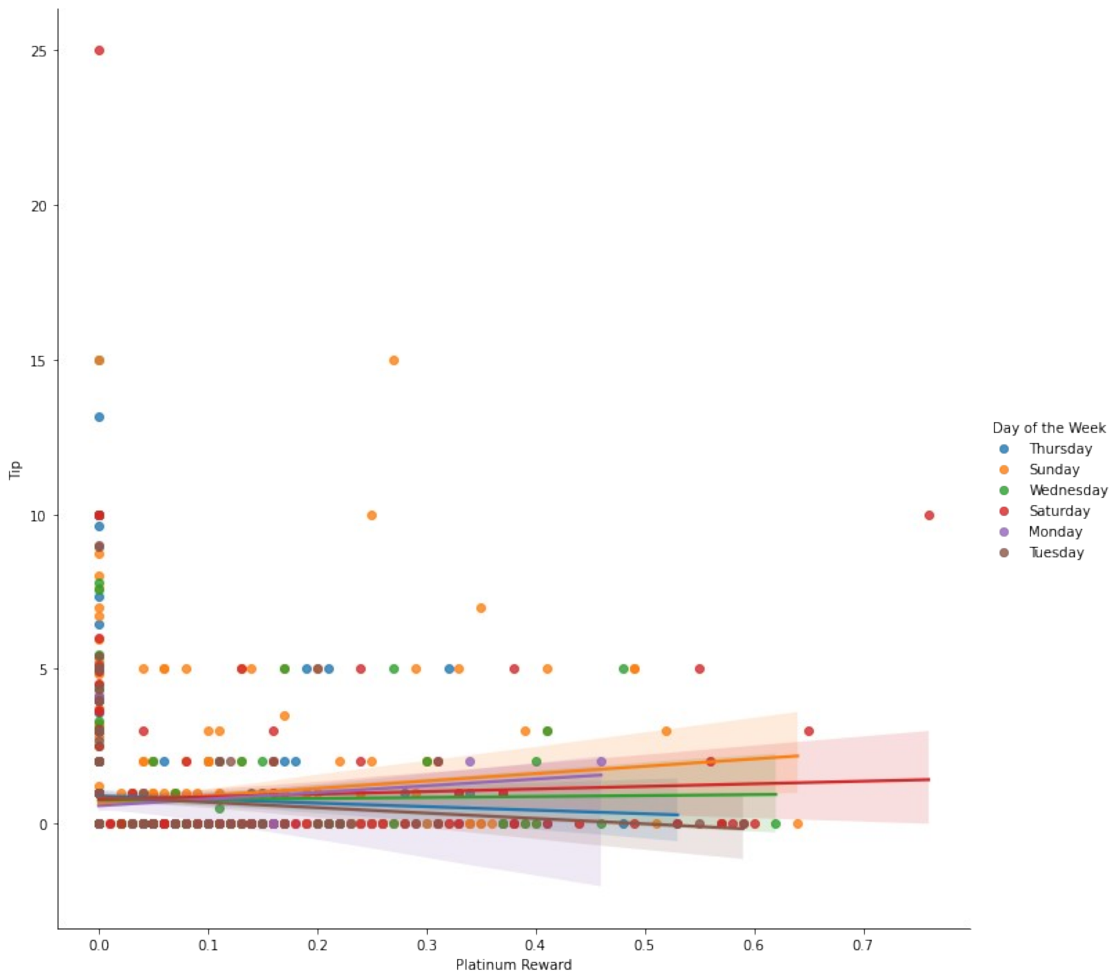
Day of the week

```
sns.pairplot(dataset, x_vars=['Base Fare','Distance','Time'],
y_vars='Tip', height=10, aspect=1, kind='reg', hue='Day of the Week')
sns.pairplot(dataset, x_vars=['Min Fare
Supplement','Cancellation','Surge'], y_vars='Tip', height=10,
aspect=1, kind='reg', hue='Day of the Week')
sns.pairplot(dataset, x_vars=['Diamond Reward','Total','Long Pickup
Fee'], y_vars='Tip', height=10, aspect=1, kind='reg', hue='Day of the
Week')
sns.pairplot(dataset, x_vars=['Optio0l Insurance','Share
```

```
Adjustment','Fare Adjustment'], y_vars='Tip', height=10, aspect=1,
kind='reg', hue='Day of the Week')
sns.pairplot(dataset, x_vars=['Platinum Reward'], y_vars='Tip',
height=10, aspect=1, kind='reg', hue='Day of the Week')
```

```
<seaborn.axisgrid.PairGrid at 0x7f70e302eb10>
```

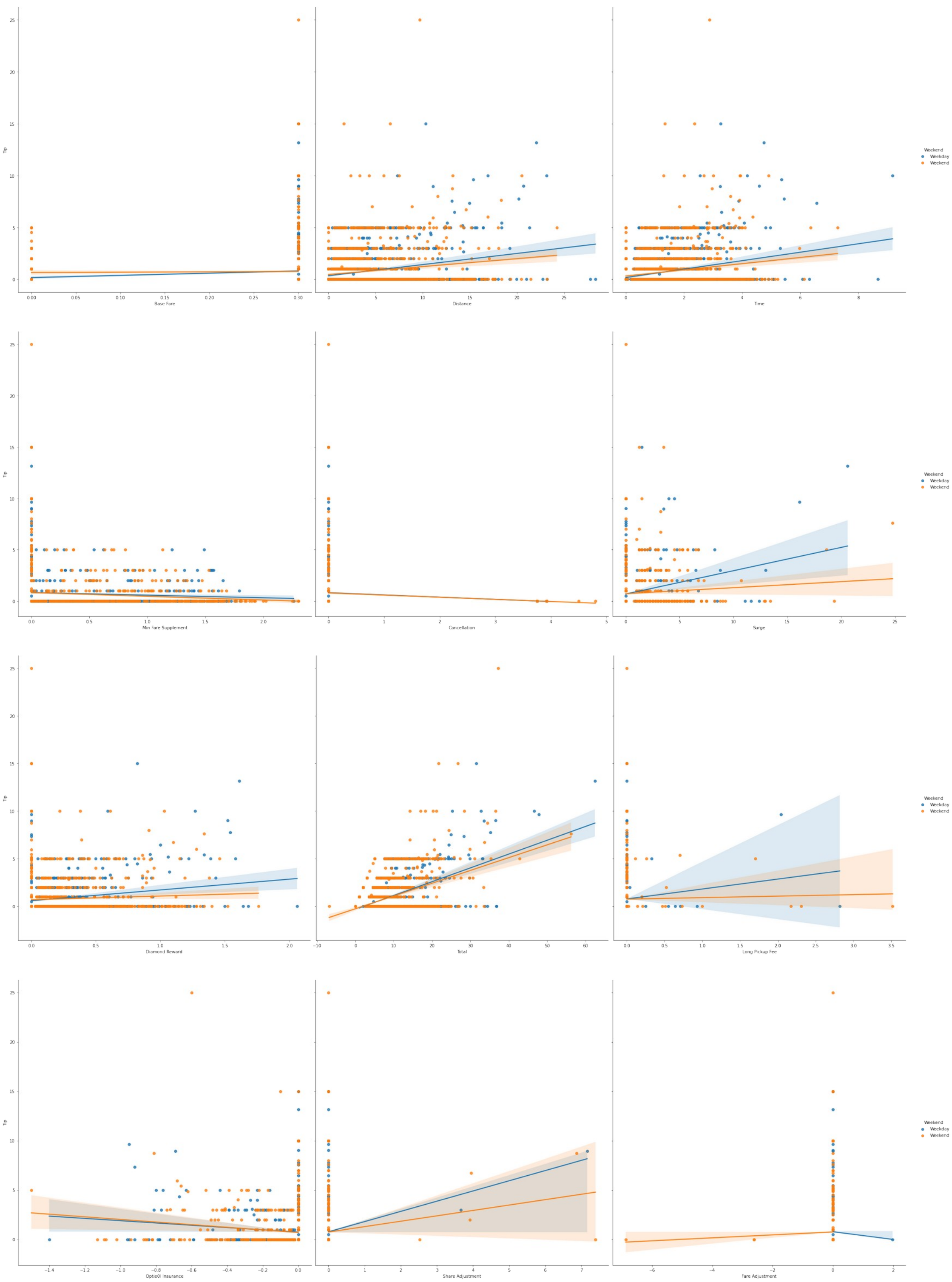




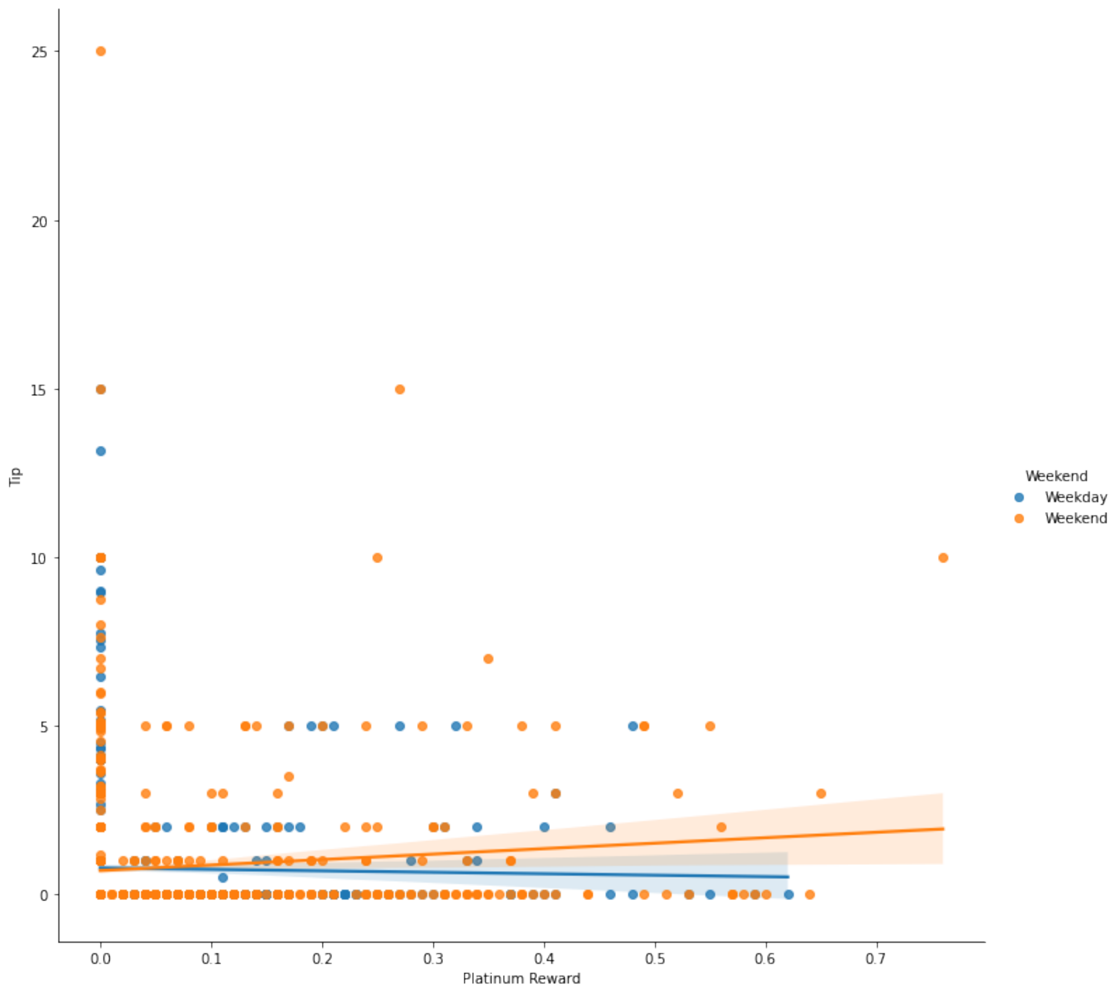
Weekend

```
sns.pairplot(dataset, x_vars=['Base Fare','Distance','Time'],
y_vars='Tip', height=10, aspect=1, kind='reg', hue='Weekend')
sns.pairplot(dataset, x_vars=['Min Fare
Supplement','Cancellation','Surge'], y_vars='Tip', height=10,
aspect=1, kind='reg', hue='Weekend')
sns.pairplot(dataset, x_vars=['Diamond Reward','Total','Long Pickup
Fee'], y_vars='Tip', height=10, aspect=1, kind='reg',hue='Weekend')
sns.pairplot(dataset, x_vars=['Optio0l Insurance','Share
Adjustment','Fare Adjustment'], y_vars='Tip', height=10, aspect=1,
kind='reg', hue='Weekend')
sns.pairplot(dataset, x_vars=['Platinum Reward'], y_vars='Tip',
height=10, aspect=1, kind='reg', hue='Weekend')
```

```
<seaborn.axisgrid.PairGrid at 0x7f70e2838190>
```



Tip
Base Fare
Distance
Time
Min Fare Supplement
Cancellation
Surge
Diamond Reward
Total
Long Pickup Fee
Optio0l Insurance
Share Adjustment
Fare Adjustment
Weekend
Weekday
Weekend



Weekend Conclusions: Effects from categorizing by morning vs evening, day of the week, or weekend vs weekend seem to be minimal.

Modeling

Using sklearn, I do linear regression and multiple regression modelling on the data.

Linear Regression

Imports for Linear Regression

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn import metrics
```

Creating the Linear Regression Models

```
# Create an array of all the datasets
x_var_names = ['Base Fare','Distance','Time','Min Fare
Supplement','Cancellation','Surge','Diamond Reward','Total','Long
Pickup Fee','Optio0l Insurance','Share Adjustment','Fare
Adjustment','Platinum Reward']
```

```
x = [0,0,0,0,0,0,0,0,0,0,0,0,0]
x[0] = dataset[['Base Fare']]
x[1] = dataset[['Distance']]
x[2] = dataset[['Time']]
x[3] = dataset[['Min Fare Supplement']]
x[4] = dataset[['Cancellation']]
x[5] = dataset[['Surge']]
x[6] = dataset[['Diamond Reward']]
x[7] = dataset[['Total']]
x[8] = dataset[['Long Pickup Fee']]
x[9] = dataset[['Optio0l Insurance']]
x[10] = dataset[['Share Adjustment']]
x[11] = dataset[['Fare Adjustment']]
x[12] = dataset[['Platinum Reward']]



y = dataset['Tip']

# Init arrays
x_train = [0,0,0,0,0,0,0,0,0,0,0,0,0]
x_test = [0,0,0,0,0,0,0,0,0,0,0,0,0]
y_train = [0,0,0,0,0,0,0,0,0,0,0,0,0]
y_test = [0,0,0,0,0,0,0,0,0,0,0,0,0]
reg = [0,0,0,0,0,0,0,0,0,0,0,0,0]
intercept = [0,0,0,0,0,0,0,0,0,0,0,0,0]
coefficient = [0,0,0,0,0,0,0,0,0,0,0,0,0]
eqs = [0,0,0,0,0,0,0,0,0,0,0,0,0]
y_pred_reg = [0,0,0,0,0,0,0,0,0,0,0,0,0]
x_pred_reg = [0,0,0,0,0,0,0,0,0,0,0,0,0]

for index, var in enumerate(x):
  x_train[index], x_test[index], y_train[index], y_test[index] =
train_test_split(x[index], y, test_size = 0.3, random_state = 99)

  reg[index] = LinearRegression()
  reg[index].fit(x_train[index], y_train[index])
  intercept[index] = reg[index].intercept_
  coefficient[index] = reg[index].coef_

  eqs[index] = 'Tip = %s + %s * (%s)'%
(intercept[index],coefficient[index],x_var_names[index])

for eq in eqs:
  print(eq)

Tip = 0.5252755905511916 + [0.85845382] * (Base Fare)
Tip = 0.45793579322093425 + [0.07885178] * (Distance)
Tip = 0.29670047398593746 + [0.3152301] * (Time)
Tip = 0.8309974902686637 + [-0.31960574] * (Min Fare Supplement)
```

```
Tip = 0.8024749462227033 + [-0.21271389] * (Cancellation)
Tip = 0.7076256830688059 + [0.11042091] * (Surge)
Tip = 0.6686178531808187 + [0.58781366] * (Diamond Reward)
Tip = -0.20312226055725868 + [0.12746508] * (Total)
Tip = 0.7648424850102665 + [0.38062147] * (Long Pickup Fee)
Tip = 0.7301408111223608 + [-0.94619132] * (Optio0l Insurance)
Tip = 0.7563093034404373 + [0.70096427] * (Share Adjustment)
Tip = 0.7680972124241997 + [0.09948674] * (Fare Adjustment)
Tip = 0.7356400861144413 + [1.3822777] * (Platinum Reward)
```

Prediction Based on the Model

```
# Testing Predictions
for index, var in enumerate(x):
  y_pred_reg[index] = reg[index].predict(x_test[index])

# Showing actual values vs predicted values of the data
predictionTable = pd.DataFrame({
    'Actual Value': y_test[0],
    x_var_names[0]: y_pred_reg[0],
    x_var_names[1]: y_pred_reg[1],
    x_var_names[2]: y_pred_reg[2],
    x_var_names[3]: y_pred_reg[3],
    x_var_names[4]: y_pred_reg[4],
    x_var_names[5]: y_pred_reg[5],
    x_var_names[6]: y_pred_reg[6],
    x_var_names[7]: y_pred_reg[7],
    x_var_names[8]: y_pred_reg[8],
    x_var_names[9]: y_pred_reg[9],
    x_var_names[10]: y_pred_reg[10],
    x_var_names[11]: y_pred_reg[11],
    x_var_names[12]: y_pred_reg[12],
    })

predictionTable
```

```
      Actual Value  Base Fare  Distance      Time  Min Fare Supplement
\
272            0.0   0.782812  1.081653  0.987054             0.830997

2091           2.0   0.782812  0.641660  0.697043             0.830997

2735           5.0   0.782812  0.591195  0.624540             0.830997

2296           0.0   0.782812  0.681086  0.662367             0.830997

187            0.0   0.782812  0.951548  1.021730             0.830997

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

2957           0.0   0.782812  1.644655  0.936618             0.830997
```

```
2852           0.0   0.782812  0.633775  0.608778             0.830997

307            1.0   0.782812  0.502093  0.485839             0.460255

2528           0.0   0.782812  0.527325  0.482686             0.556137

416            0.0   0.782812  0.711050  0.775850             0.830997


      Cancellation     Surge  Diamond Reward     Total  Long Pickup
Fee  \
272       0.802475  0.707626        1.027184  1.200268
0.764842
2091      0.802475  0.707626        0.668618  0.561668
0.764842
2735      0.802475  0.707626        0.668618  0.825521
0.764842
2296      0.802475  0.707626        0.809693  0.374295
0.764842
187       0.802475  0.956073        0.968403  1.314987
0.764842
...            ...       ...             ...       ...                ..
.
2957      0.802475  1.011283        0.668618  2.362750
0.764842
2852      0.802475  0.707626        0.668618  0.258301
0.764842
307       0.802475  0.707626        0.709765  0.267224
0.764842
2528      0.802475  0.707626        0.668618  0.125738
0.764842
416       0.802475  0.845652        0.839084  0.692957
0.764842

      Optio0l Insurance  Share Adjustment  Fare Adjustment  Platinum
Reward
272            0.730141          0.756309         0.768097
0.735640
2091           0.730141          0.756309         0.768097
0.873868
2735           0.730141          0.756309         0.768097
0.735640
2296           0.730141          0.756309         0.768097
0.735640
187            0.730141          0.756309         0.768097
0.735640
...                 ...               ...              ...
...
```

```
2957           0.730141          0.756309         0.768097
0.735640
2852           0.730141          0.756309         0.768097
0.873868
307            0.730141          0.756309         0.768097
0.735640
2528           0.777450          0.756309         0.768097
0.735640
416            0.730141          0.756309         0.768097
0.735640

[932 rows x 14 columns]
```

Accuracy of the Models

To test the accuracy, I will show the R squared values and error

```
# R squared value
for index, var in enumerate(x):
  r2 = reg[index].score(x[index],y)*100
  print('R squared value for %s model: %s'%(x_var_names[index], r2))

R squared value for Base Fare model: 0.16478825337008507
R squared value for Distance model: 4.50184533333442
R squared value for Time model: 4.735678507496988
R squared value for Min Fare Supplement model: 0.6675732024644776
R squared value for Cancellation model: 0.9581351408252337
R squared value for Surge model: 1.3449653930827754
R squared value for Diamond Reward model: 1.3362251889793009
R squared value for Total model: 23.886849262296607
R squared value for Long Pickup Fee model: 0.10071454670917968
R squared value for Optio0l Insurance model: 0.880623787211432
R squared value for Share Adjustment model: 1.1837072725825903
R squared value for Fare Adjustment model: 0.010013602078695616
R squared value for Platinum Reward model: 0.14343386843430617

for index, var in enumerate(x):
  mean_ab_er = metrics.mean_absolute_error(y_test[index],
y_pred_reg[index])
  mean_sq_er = metrics.mean_squared_error(y_test[index],
y_pred_reg[index])
  root_mean_er = mean_sq_er ** (1/2)
  print('Model: ', x_var_names[index])
  print('Mean absolute error: ',mean_ab_er)
  print('Mean square error: ', mean_sq_er)
  print('Root mean square: ', root_mean_er)

Model:  Base Fare
Mean absolute error:  1.106988156752214
Mean square error:  3.1583863850393876
Root mean square:  1.777184960840989
```

```
Model:  Distance
Mean absolute error:  1.077552732284949
Mean square error:  2.9879259931378828
Root mean square:  1.7285618279766226
Model:  Time
Mean absolute error:  1.0755747536369566
Mean square error:  2.995297441381452
Root mean square:  1.7306927634278282
Model:  Min Fare Supplement
Mean absolute error:  1.10587820490252
Mean square error:  3.1461397148360186
Root mean square:  1.7737360893988763
Model:  Cancellation
Mean absolute error:  1.091418074156296
Mean square error:  3.140143157506708
Root mean square:  1.772044908433956
Model:  Surge
Mean absolute error:  1.1088581702884774
Mean square error:  3.114468053023951
Root mean square:  1.7647855544014268
Model:  Diamond Reward
Mean absolute error:  1.0947671293494678
Mean square error:  3.10390407939484
Root mean square:  1.7617900213688464
Model:  Total
Mean absolute error:  0.9187129295949344
Mean square error:  2.2935904164746854
Root mean square:  1.5144604374082162
Model:  Long Pickup Fee
Mean absolute error:  1.107342713766335
Mean square error:  3.160499316505751
Root mean square:  1.777779321655461
Model:  Optio0l Insurance
Mean absolute error:  1.1028445664610391
Mean square error:  3.121913786012589
Root mean square:  1.766893824204666
Model:  Share Adjustment
Mean absolute error:  1.103050429698914
Mean square error:  3.164677917141994
Root mean square:  1.7789541638676343
Model:  Fare Adjustment
Mean absolute error:  1.10820938422187
Mean square error:  3.1645114956686005
Root mean square:  1.7789073881651627
Model:  Platinum Reward
Mean absolute error:  1.1126725436359963
Mean square error:  3.1795074601435664
Root mean square:  1.7831173433466365
```

Linear Regression Conclusion

Overall, these data do not seem to fit the linear regression model for any one variable, apart from Total, which achieved a fairly high R squared of 23.886849262296607

Multiple Linear Regression

Creating the Multiple Linear Regression Model

```
x = dataset[['Base Fare','Distance','Time','Min Fare
Supplement','Cancellation','Surge','Diamond Reward','Total','Long
Pickup Fee','Optio0l Insurance','Share Adjustment','Fare
Adjustment','Platinum Reward']]
y = dataset['Tip']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size =
0.3, random_state = 99)

mreg = LinearRegression()
mreg.fit(x_train, y_train)

LinearRegression()

mreg.coef_

array([-1.2291657 , -0.99157228, -0.98795922, -0.96853183, -
0.99432981,
       -0.99205252, -0.98286328,  0.98762502, -0.93599693, -
1.09106209,
       -1.01413615, -0.98563911, -1.02059491])

mreg.coef_

intercept = mreg.intercept_

eq = 'Tip = %s + %s * (Base Fare) + %s * (Distance) + %s * (Time) + %s
* (Min Fare Supplement) + %s * (Cancellation) + %s * (Surge) + %s *
(Diamond Reward) + %s * (Total) + %s * (Long Pickup Fee) + %s *
(Optio0l Insurance) + %s * (Share Adjustment) + %s * (Fare Adjustment)
+ %s * (Platinum Reward)'%(
    intercept,
    mreg.coef_[0],
    mreg.coef_[1],
    mreg.coef_[2],
    mreg.coef_[3],
    mreg.coef_[4],
    mreg.coef_[5],
    mreg.coef_[6],
    mreg.coef_[7],
    mreg.coef_[8],
    mreg.coef_[9],
    mreg.coef_[10],
```

```
    mreg.coef_[11],
    mreg.coef_[12],
    )
eq
```

{"type":"string"}

Prediction Based on the Model

```
y_pred_mreg = mreg.predict(x_test)
x_pred_mreg = mreg.predict(x_train)

prediction = pd.DataFrame({'Actual Value': y_test, 'Prediction':
y_pred_mreg})
prediction
```

```
      Actual Value  Prediction
272            0.0   -0.076218
2091           2.0    1.915163
2735           5.0    4.923444
2296           0.0   -0.057584
187            0.0    0.206231
...            ...         ...
2957           0.0   -0.119428
2852           0.0   -0.059598
307            1.0    0.960527
2528           0.0   -0.029247
416            0.0    0.389807

[932 rows x 2 columns]
```

Accuracy of the Model

To test the accuracy, I will show the R squared values and error.

```
# R squared value
r2 = mreg.score(x,y)*100

print('R squared value: ', r2)
```

```
R squared value:  98.75582386630697
```

```
mean_ab_er = metrics.mean_absolute_error(y_test, y_pred_mreg)
mean_sq_er = metrics.mean_squared_error(y_test, y_pred_mreg)
root_mean_er = mean_sq_er ** (1/2)

print('Mean absolute error: ', mean_ab_er)
print('Mean square error: ', mean_sq_er)
print('Root mean square error: ', root_mean_er)
```

```
Mean absolute error:  0.09340111101377355
Mean square error:  0.02820703880452539
Root mean square error:  0.16794951266534056
```

Multiple Linear Regression Conclusion

These data do seem to really fit the Multiple Linear Regression model, and it is coming up with very accurate predictions as seen by the R squared value of 98.75582386630697 and low errors.

Logistic Regression

Creating the Logistic Regression Model

Are 'Base Fare','Distance','Time','Min Fare Supplement','Cancellation','Surge','Diamond Reward','Total','Long Pickup Fee','Optio0l Insurance','Share Adjustment','Fare Adjustment','Platinum Reward', and 'Tip' good predictors of Evening vs Morning, Day of the week, and whether or not its a weekend?

Morning or Evening Logistic Regression

```
x = dataset[['Base Fare','Distance','Time','Min Fare
Supplement','Cancellation','Surge','Diamond Reward','Total','Long
Pickup Fee','Optio0l Insurance','Share Adjustment','Fare
Adjustment','Platinum Reward','Tip']]
y = dataset['Morning or Evening']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size =
0.3, random_state = 99)

lreg = LogisticRegression(solver='liblinear', random_state=99)
lreg.fit(x_train, y_train)

LogisticRegression(random_state=99, solver='liblinear')

lreg.coef_

array([[-0.68737466, -0.38901732, -0.67150933, -0.3127562 , -0.2065323
,
        -0.10585864,  0.23935202,  0.37239922, -1.18535351,
1.78892774,
        -0.56043042, -0.07721748,  0.84248209, -0.39773407]])
```

Prediction Based on the Model

```
y_pred_lreg = lreg.predict(x_test)

prediction = pd.DataFrame({'Actual Value': y_test, 'Prediction':
y_pred_lreg})
prediction

     Actual Value Prediction
272       Evening    Evening
2091      Evening    Evening
2735      Evening    Evening
2296      Evening    Evening
187       Evening    Evening
...           ...        ...
```

```
2957      Evening    Evening
2852      Evening    Evening
307       Evening    Evening
2528      Evening    Evening
416       Evening    Evening

[932 rows x 2 columns]
```

Accuracy of the Model

To test the accuracy, I will show the R squared values and error.

```
# R squared value
r2 = lreg.score(x,y)*100

print('R squared value: ', r2)

R squared value:  93.9110824742268
```

Morning or Evening Conclusion:

Overall the Logistic Regression Model is very good at predicting whether or not it is the evening or morning, getting an R squared value of 93.9110824742268.

Day of the Week Logistic Regression

```
x = dataset[['Base Fare','Distance','Time','Min Fare
Supplement','Cancellation','Surge','Diamond Reward','Total','Long
Pickup Fee','Optio0l Insurance','Share Adjustment','Fare
Adjustment','Platinum Reward','Tip']]
y = dataset['Day of the Week']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size =
0.3, random_state = 99)

lreg = LogisticRegression(solver='liblinear', random_state=99)
lreg.fit(x_train, y_train)

LogisticRegression(random_state=99, solver='liblinear')

lreg.coef_

array([[ 0.64963353,  0.62231331, -0.50398533,  0.10987221,
0.09699866,
         0.36724539, -0.20668122, -0.42281403,  0.05527316, -
0.28906995,
        -0.12980514,  0.48745946, -1.12373847,  0.37391944],
       [-0.4053081 ,  0.17667105,  0.07919387,  0.01686666,
0.24036667,
         0.29244819,  0.20076135, -0.15649621,  0.14681267,
0.29039727,
         0.06039048,  0.32342075,  0.36671177,  0.1404236 ],
       [-1.76543741, -0.20745053,  0.05648561, -0.06162545, -
```

```
0.32786558,
        -0.13354374,  0.16491256,  0.13535694, -0.15787854, -0.6441725
,
        -0.00438186, -0.88173778,  0.80471391, -0.14704612],
       [-0.06088747,  0.08490775,  0.3184495 ,  0.27899221,  0.1572865
,
         0.11794659, -0.1158632 , -0.11310708,  0.29459895,
0.68675116,
        -0.41537541,  0.27252953, -0.36269796,  0.11396306],
       [ 0.50483165, -0.16531718, -0.44854346, -0.65188063, -
0.21823936,
        -0.3548263 ,  0.09372239,  0.18038081, -0.56916059, -
0.20387818,
         0.17491159,  0.00698373,  0.38315414, -0.14491915],
       [ 0.0233908 , -0.02129712,  0.07440045,  0.21581439,
0.00243695,
        -0.22976308,  0.08820899,  0.01827765, -0.38334139,
0.21640612,
        -0.47048929,  0.96987551, -0.36853466, -0.00417432]])
```

Prediction Based on the Model

```
y_pred_lreg = lreg.predict(x_test)

prediction = pd.DataFrame({'Actual Value': y_test, 'Prediction':
y_pred_lreg})
prediction
```

```
     Actual Value Prediction
272      Thursday     Sunday
2091     Thursday     Sunday
2735     Saturday     Sunday
2296       Sunday     Sunday
187        Sunday     Sunday
...           ...        ...
2957    Wednesday   Saturday
2852     Saturday     Sunday
307       Tuesday     Sunday
2528      Tuesday     Sunday
416      Thursday     Sunday

[932 rows x 2 columns]
```

Accuracy of the Model

To test the accuracy, I will show the R squared values and error.

```
# R squared value
r2 = lreg.score(x,y)*100

print('R squared value: ', r2)
```

```
R squared value:  34.246134020618555
```

Day of the Week Conclusion:

Overall the Logistic Regression Model is not so good at predicting whether or not it is the evening or morning, getting an R squared value of 34.246134020618555.

Morning or Evening Logistic Regression

```
x = dataset[['Base Fare','Distance','Time','Min Fare
Supplement','Cancellation','Surge','Diamond Reward','Total','Long
Pickup Fee','Optio0l Insurance','Share Adjustment','Fare
Adjustment','Platinum Reward','Tip']]
y = dataset['Weekend']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size =
0.3, random_state = 99)

lreg = LogisticRegression(solver='liblinear', random_state=99)
lreg.fit(x_train, y_train)

LogisticRegression(random_state=99, solver='liblinear')

lreg.coef_

array([[-1.80578157, -0.06042382,  0.11347027, -0.02846011, -
0.09933103,
         0.11865059,  0.28315808,  0.01114352,  0.07831059, -
0.37818405,
         0.03885743, -0.8207992 ,  1.03549834, -0.0314501 ]])
```

Prediction Based on the Model

```
y_pred_lreg = lreg.predict(x_test)

prediction = pd.DataFrame({'Actual Value': y_test, 'Prediction':
y_pred_lreg})
prediction

     Actual Value Prediction
272       Weekday    Weekend
2091      Weekday    Weekend
2735      Weekend    Weekend
2296      Weekend    Weekend
187       Weekend    Weekend
...           ...        ...
2957      Weekday    Weekday
2852      Weekend    Weekend
307       Weekday    Weekend
2528      Weekday    Weekend
416       Weekday    Weekend

[932 rows x 2 columns]
```

Accuracy of the Model

To test the accuracy, I will show the R squared values and error.

```
# R squared value
r2 = lreg.score(x,y)*100

print('R squared value: ', r2)
```

```
R squared value:  56.66881443298969
```

Weekend Conclusion:

The Logistic Regression Model is pretty good at predicting whether or not it is the a weekend, getting an R squared value of 56.66881443298969, or getting it correct a little over half of the time.

Logistic Regression Conclusion

Overall, the Logistic Regression Models were very accurate at predicting whether it was evening or morning, relatively accurate at predicting if it was a weekend, and not very accurate at predicting the day of the week.

Summary and Conclusion

Overall, it seems that the given data doesn't fit very well into individual linear regression models for Tip value.

Conversely, the multiple regression model was able to make surprisingly accurate predictions of Tip value.

The logistc regression models were able to make some accurate predictions including evening or morning distinction, and whether or not it was a weekend, but they were not very accurate at predicting what day of the week it was.

I believe an improvement to this paper would be more data, as this dataset was taken from a single city of Phoenix, AZ, USA, and potentially other regions may cause the model to not be as accurate as tipping culture, and Uber rider usages vary in other places.

Additionally, this data was all taken prior to the COVID-19 Pandemic and the data may be no longer valid to compare to how post-pandemic riders tip, along with differing usage patterns due to telecommuting.