```
!pip install haversine
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
import seaborn as sns
import statsmodels
import statsmodels.formula.api as smf
import statsmodels.api as sm
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
%matplotlib inline
from haversine import haversine, Unit
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

```
Defaulting to user installation because normal site-packages is not
writeable
Requirement already satisfied: haversine in c:\users\prem\appdata\
roaming\python\python311\site-packages (2.8.1)
```

```
df = pd.read_csv(r'uber.csv')
df.head()
```

```
   Unnamed: 0                            key  fare_amount  \
0    24238194    2015-05-07 19:52:06.0000003          7.5
1    27835199    2009-07-17 20:04:56.0000002          7.7
2    44984355   2009-08-24 21:45:00.00000061         12.9
3    25894730    2009-06-26 08:22:21.0000001          5.3
4    17610152  2014-08-28 17:47:00.000000188         16.0

           pickup_datetime  pickup_longitude  pickup_latitude  \
0  2015-05-07 19:52:06 UTC        -73.999817        40.738354
1  2009-07-17 20:04:56 UTC        -73.994355        40.728225
2  2009-08-24 21:45:00 UTC        -74.005043        40.740770
3  2009-06-26 08:22:21 UTC        -73.976124        40.790844
4  2014-08-28 17:47:00 UTC        -73.925023        40.744085

   dropoff_longitude  dropoff_latitude  passenger_count
0         -73.999512         40.723217                1
1         -73.994710         40.750325                1
2         -73.962565         40.772647                1
3         -73.965316         40.803349                3
4         -73.973082         40.761247                5
```

```
df.shape
```

```
(200000, 9)
```

```python
df.isnull().sum()
```

```
Unnamed: 0           0
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

```python
df.describe()
```

```
         Unnamed: 0    fare_amount  pickup_longitude  pickup_latitude  \
count  2.000000e+05  200000.000000     200000.000000    200000.000000   

mean   2.771250e+07      11.359955        -72.527638        39.935885   

std    1.601382e+07       9.901776         11.437787         7.720539   

min    1.000000e+00     -52.000000      -1340.648410       -74.015515   

25%    1.382535e+07       6.000000        -73.992065        40.734796   

50%    2.774550e+07       8.500000        -73.981823        40.752592   

75%    4.155530e+07      12.500000        -73.967154        40.767158   

max    5.542357e+07     499.000000         57.418457      1644.421482   


       dropoff_longitude  dropoff_latitude  passenger_count
count      199999.000000     199999.000000    200000.000000
mean          -72.525292         39.923890         1.684535
std            13.117408          6.794829         1.385997
min         -3356.666300       -881.985513         0.000000
25%           -73.991407         40.733823         1.000000
50%           -73.980093         40.753042         1.000000
75%           -73.963658         40.768001         2.000000
max          1153.572603        872.697628       208.000000
```

```python
r1null = df[df['dropoff_latitude'].isnull()]
print(r1null)
```

```
       Unnamed: 0                            key  fare_amount  \
87946    32736015  2013-07-02 03:51:57.0000001         24.1
```

```
                pickup_datetime  pickup_longitude  pickup_latitude  \
87946  2013-07-02 03:51:57 UTC        -73.950581        40.779692

       dropoff_longitude  dropoff_latitude  passenger_count
87946                NaN               NaN                0

r2null = df[df['dropoff_longitude'].isnull()]
print(r2null)

       Unnamed: 0                           key  fare_amount  \
87946    32736015  2013-07-02 03:51:57.0000001         24.1

                pickup_datetime  pickup_longitude  pickup_latitude  \
87946  2013-07-02 03:51:57 UTC        -73.950581        40.779692

       dropoff_longitude  dropoff_latitude  passenger_count
87946                NaN               NaN                0

df=df.dropna()

df.isnull().sum()

Unnamed: 0           0
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64

df.shape

(199999, 9)

df['key'] = pd.to_datetime(df['key'])

df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'])

df.info()

<class 'pandas.core.frame.DataFrame'>
Index: 199999 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         199999 non-null  int64
 1   key                199999 non-null  datetime64[ns]
 2   fare_amount        199999 non-null  float64
 3   pickup_datetime    199999 non-null  datetime64[ns, UTC]
```

```
 4   pickup_longitude   199999 non-null  float64
 5   pickup_latitude    199999 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    199999 non-null  int64
dtypes: datetime64[ns, UTC](1), datetime64[ns](1), float64(5),
int64(2)
memory usage: 15.3 MB
```

```
print(df['pickup_latitude'].min())
print(df['pickup_longitude'].min())
print(df['dropoff_latitude'].min())
print(df['dropoff_longitude'].min())
print()
print(df['pickup_latitude'].max())
print(df['pickup_longitude'].max())
print(df['dropoff_latitude'].max())
print(df['dropoff_longitude'].max())
```

```
-74.01551500000001
-1340.64841
-881.9855130000001
-3356.6663

1644.421482
57.418457
872.6976279999999
1153.5726029999998
```

```
# US Latitude Longitude ranges from (24 to 49 Latitude) and (-66 to -
125 Longitude)
# Delete latitude and longitude falling outside this range
lat = [24, 49]
lon = [-66, -125]

#delete = (df['pickup_latitude'] < 24) | (df['pickup_latitude'] > 49 )

df['invalid_pic_latitude'] = ((df['pickup_latitude'] < lat[0]) |
(df['pickup_latitude'] > lat[1]))
df['invalid_pic_longitude'] = ((df['pickup_longitude'] > lon[0]) |
(df['pickup_longitude'] < lon[1]))
df['invalid_drop_latitude'] = ((df['dropoff_latitude'] < lat[0]) |
(df['dropoff_latitude'] > lat[1]))
df['invalid_drop_longitude'] = ((df['dropoff_longitude'] > lon[0]) |
(df['dropoff_longitude'] < lon[1]))

df['invalid_pic_latitude'] = df['invalid_pic_latitude'].astype(int)
df['invalid_pic_longitude'] = df['invalid_pic_longitude'].astype(int)
df['invalid_drop_latitude'] = df['invalid_drop_latitude'].astype(int)
```

```
df['invalid_drop_longitude'] =
df['invalid_drop_longitude'].astype(int)

df[(df['invalid_pic_latitude']==1) | (df['invalid_pic_longitude']==1)
| (df['invalid_drop_latitude']==1) |
(df['invalid_drop_longitude']==1)].head()

     Unnamed: 0                           key  fare_amount  \
7      44195482 2012-12-11 13:52:00.000000290          2.5
11      6379048 2011-05-23 22:15:00.000000860          8.5
65     21993993 2014-05-05 19:27:00.000000340          6.0
92      1454546 2011-12-02 14:07:00.000000207          6.1
120    17358122 2010-08-20 19:39:48.000000300          6.5

              pickup_datetime  pickup_longitude  pickup_latitude  \
7   2012-12-11 13:52:00+00:00               0.0              0.0
11  2011-05-23 22:15:00+00:00               0.0              0.0
65  2014-05-05 19:27:00+00:00               0.0              0.0
92  2011-12-02 14:07:00+00:00               0.0              0.0
120 2010-08-20 19:39:48+00:00               0.0              0.0

     dropoff_longitude  dropoff_latitude  passenger_count  \
7                  0.0               0.0                1
11                 0.0               0.0                1
65                 0.0               0.0                1
92                 0.0               0.0                1
120                0.0               0.0                1

     invalid_pic_latitude  invalid_pic_longitude
invalid_drop_latitude  \
7                       1                      1
1
11                      1                      1
1
65                      1                      1
1
92                      1                      1
1
120                     1                      1
1

     invalid_drop_longitude
7                         1
11                        1
65                        1
92                        1
120                       1

df = df[(df['invalid_pic_latitude']!=1)]
df = df[(df['invalid_pic_longitude']!=1)]
```

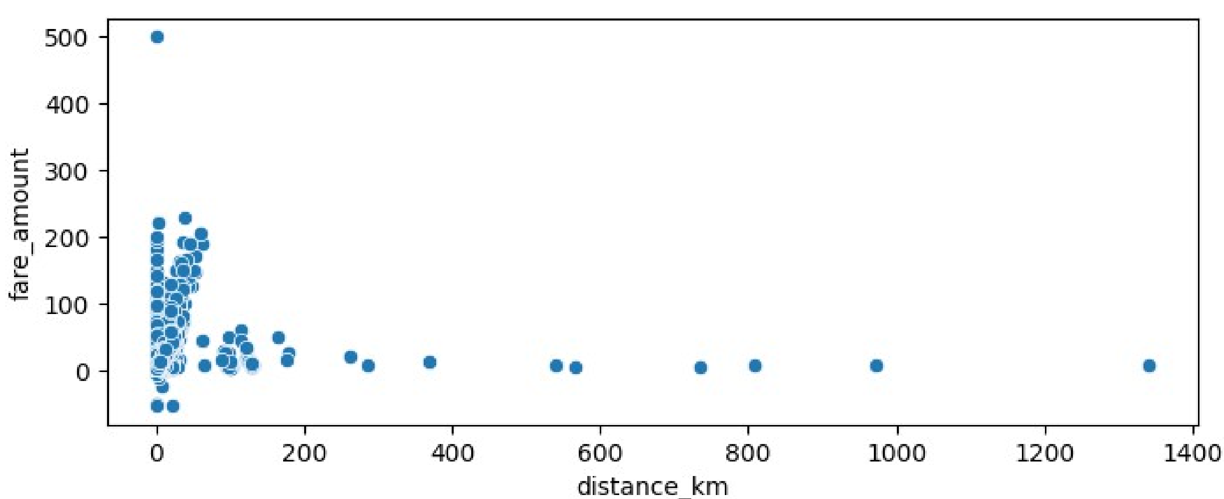
```
df = df[(df['invalid_drop_latitude']!=1)]
df = df[(df['invalid_drop_longitude']!=1)]

df.head()

   Unnamed: 0                            key  fare_amount  \
0    24238194 2015-05-07 19:52:06.000000300          7.5
1    27835199 2009-07-17 20:04:56.000000200          7.7
2    44984355 2009-08-24 21:45:00.000000610         12.9
3    25894730 2009-06-26 08:22:21.000000100          5.3
4    17610152 2014-08-28 17:47:00.000000188         16.0

            pickup_datetime  pickup_longitude  pickup_latitude  \
0 2015-05-07 19:52:06+00:00        -73.999817        40.738354
1 2009-07-17 20:04:56+00:00        -73.994355        40.728225
2 2009-08-24 21:45:00+00:00        -74.005043        40.740770
3 2009-06-26 08:22:21+00:00        -73.976124        40.790844
4 2014-08-28 17:47:00+00:00        -73.925023        40.744085

   dropoff_longitude  dropoff_latitude  passenger_count
invalid_pic_latitude  \
0         -73.999512         40.723217                1
0
1         -73.994710         40.750325                1
0
2         -73.962565         40.772647                1
0
3         -73.965316         40.803349                3
0
4         -73.973082         40.761247                5
0

   invalid_pic_longitude  invalid_drop_latitude
invalid_drop_longitude
0                      0                      0
0
1                      0                      0
0
2                      0                      0
0
3                      0                      0
0
4                      0                      0
0

df['distance_km'] = df.apply(lambda row:
haversine((row['pickup_latitude'], row['pickup_longitude']),
(row['dropoff_latitude'], row['dropoff_longitude']),

unit=Unit.KILOMETERS), axis=1)
```

```python
#df['distance_mi'] = df.apply(lambda row:
haversine((row['pickup_latitude'], row['pickup_longitude']),
(row['dropoff_latitude'], row['dropoff_longitude']),
#                                                    unit=Unit.MILES),
axis=1)

print(df['pickup_latitude'].min())
print(df['pickup_longitude'].min())
print(df['dropoff_latitude'].min())
print(df['dropoff_longitude'].min())
print()
print(df['pickup_latitude'].max())
print(df['pickup_longitude'].max())
print(df['dropoff_latitude'].max())
print(df['dropoff_longitude'].max())
```

```
32.005119
-89.93333299999999
37.53309
-75.458978633981

48.01876
-67.37035999999999
45.031598
-69.046738
```

```python
plt.figure(figsize = (8,3))
sns.scatterplot(data = df, x = 'distance_km', y = 'fare_amount')
```

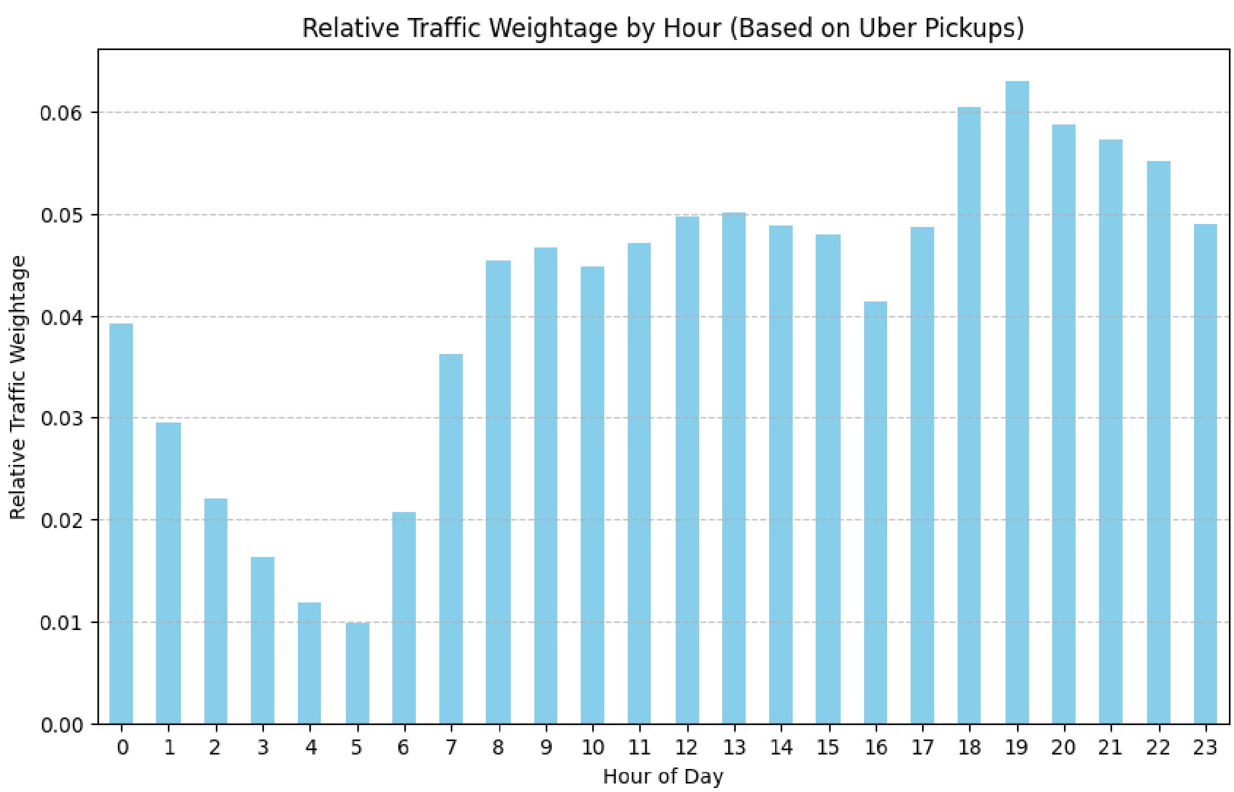
```
<Axes: xlabel='distance_km', ylabel='fare_amount'>
```




```python
df.drop(columns='invalid_pic_latitude', inplace=True)
df.drop(columns='invalid_pic_longitude', inplace=True)
```

```
df.drop(columns='invalid_drop_latitude', inplace=True)
df.drop(columns='invalid_drop_longitude', inplace=True)

df.head()

   Unnamed: 0                            key  fare_amount  \
0    24238194 2015-05-07 19:52:06.000000300          7.5
1    27835199 2009-07-17 20:04:56.000000200          7.7
2    44984355 2009-08-24 21:45:00.000000610         12.9
3    25894730 2009-06-26 08:22:21.000000100          5.3
4    17610152 2014-08-28 17:47:00.000000188         16.0

            pickup_datetime  pickup_longitude  pickup_latitude  \
0 2015-05-07 19:52:06+00:00        -73.999817        40.738354
1 2009-07-17 20:04:56+00:00        -73.994355        40.728225
2 2009-08-24 21:45:00+00:00        -74.005043        40.740770
3 2009-06-26 08:22:21+00:00        -73.976124        40.790844
4 2014-08-28 17:47:00+00:00        -73.925023        40.744085

   dropoff_longitude  dropoff_latitude  passenger_count  distance_km
0         -73.999512         40.723217                1     1.683325
1         -73.994710         40.750325                1     2.457593
2         -73.962565         40.772647                1     5.036384
3         -73.965316         40.803349                3     1.661686
4         -73.973082         40.761247                5     4.475456

df.shape

(195860, 10)

#distance, duration, traffic conditions, time of day, and demand

df['Hour'] = df['pickup_datetime'].dt.hour
hourly_pickups = df.groupby('Hour').size()
normalized_traffic_weightage = hourly_pickups / hourly_pickups.sum()
df['Traffic_Weitage'] = df['Hour'].map(normalized_traffic_weightage)
print("Peak Traffic Hours (Based on Uber Pickups):\n",
normalized_traffic_weightage)

plt.figure(figsize=(10, 6))
normalized_traffic_weightage.plot(kind='bar', color='skyblue')
plt.title('Relative Traffic Weightage by Hour (Based on Uber
Pickups)')
plt.xlabel('Hour of Day')
plt.ylabel('Relative Traffic Weightage')
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

Peak Traffic Hours (Based on Uber Pickups):
 Hour
```

```
0     0.039207
1     0.029506
2     0.022097
3     0.016282
4     0.011809
5     0.009818
6     0.020704
7     0.036148
8     0.045456
9     0.046717
10    0.044833
11    0.047095
12    0.049709
13    0.050077
14    0.048897
15    0.048009
16    0.041443
17    0.048627
18    0.060416
19    0.063055
20    0.058736
21    0.057286
22    0.055116
23    0.048958
dtype: float64
```



```
df.head()
```

```
   Unnamed: 0                           key  fare_amount  \
0    24238194 2015-05-07 19:52:06.000000300          7.5
1    27835199 2009-07-17 20:04:56.000000200          7.7
2    44984355 2009-08-24 21:45:00.000000610         12.9
3    25894730 2009-06-26 08:22:21.000000100          5.3
4    17610152 2014-08-28 17:47:00.000000188         16.0

            pickup_datetime  pickup_longitude  pickup_latitude  \
0 2015-05-07 19:52:06+00:00        -73.999817        40.738354
1 2009-07-17 20:04:56+00:00        -73.994355        40.728225
2 2009-08-24 21:45:00+00:00        -74.005043        40.740770
3 2009-06-26 08:22:21+00:00        -73.976124        40.790844
4 2014-08-28 17:47:00+00:00        -73.925023        40.744085

   dropoff_longitude  dropoff_latitude  passenger_count  distance_km
Hour  \
0         -73.999512         40.723217                1     1.683325
19
1         -73.994710         40.750325                1     2.457593
20
2         -73.962565         40.772647                1     5.036384
21
3         -73.965316         40.803349                3     1.661686
8
4         -73.973082         40.761247                5     4.475456
17

   Traffic_Weitage
0         0.063055
1         0.058736
2         0.057286
3         0.045456
4         0.048627
```

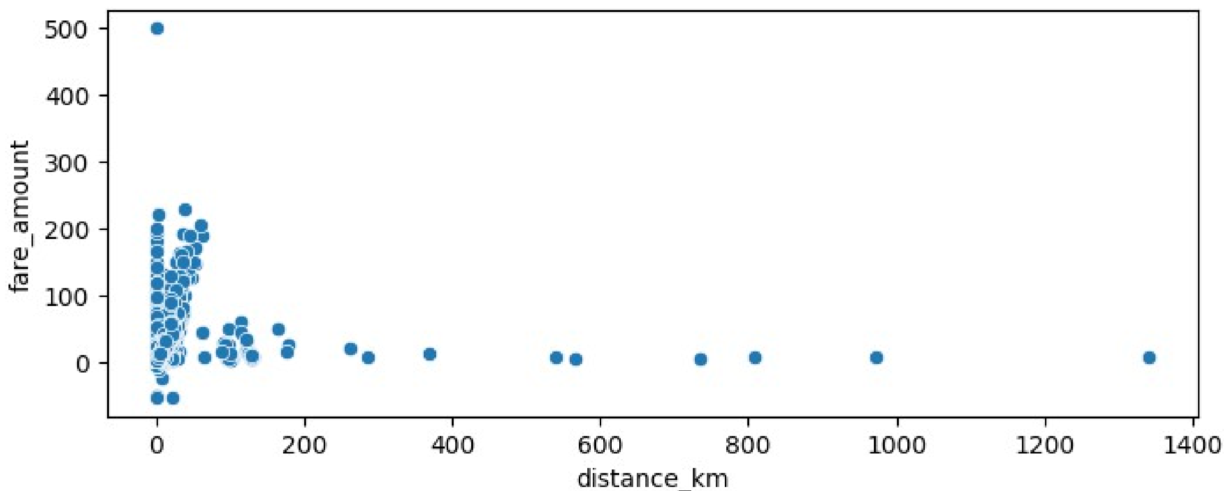
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 195860 entries, 0 to 199999
Data columns (total 12 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         195860 non-null  int64
 1   key                195860 non-null  datetime64[ns]
 2   fare_amount        195860 non-null  float64
 3   pickup_datetime    195860 non-null  datetime64[ns, UTC]
 4   pickup_longitude   195860 non-null  float64
 5   pickup_latitude    195860 non-null  float64
 6   dropoff_longitude  195860 non-null  float64
```

```
 7   dropoff_latitude   195860 non-null  float64
 8   passenger_count    195860 non-null  int64
 9   distance_km        195860 non-null  float64
 10  Hour               195860 non-null  int32
 11  Traffic_Weitage    195860 non-null  float64
dtypes: datetime64[ns, UTC](1), datetime64[ns](1), float64(7),
int32(1), int64(2)
memory usage: 18.7 MB
```

```python
plt.figure(figsize = (8,3))
sns.scatterplot(data = df, x = 'distance_km', y = 'fare_amount')
```

```
<Axes: xlabel='distance_km', ylabel='fare_amount'>
```




```python
# Deleting passenger count which is greater than 6
condition = df['passenger_count'] > 6
df = df[~condition]
df.shape
```

```
(195859, 12)
```

```python
# Deleting distance_km which is greater than 2000
condition = df['distance_km'] > 2000
df = df[~condition]
df.shape
```

```
(195859, 12)
```

```python
# Deleting fare_amount which is less than 10
condition = df['fare_amount'] <= 10
df = df[~condition]
df.shape
```

```
(73426, 12)
```

```
# Deleting 0 passenger count
condition = df['passenger_count'] == 0
df = df[~condition]
df.shape
```

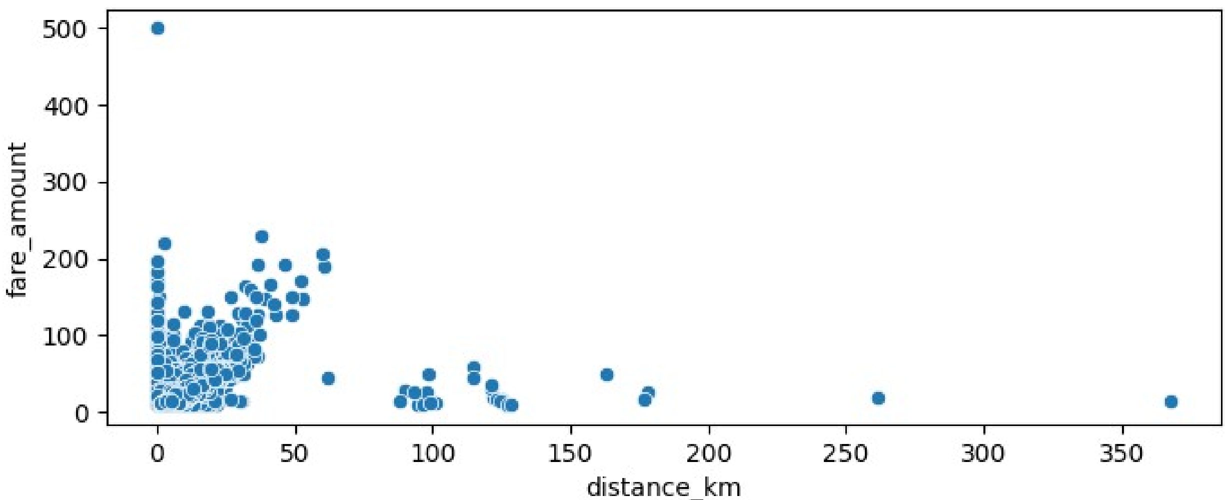
```
(73216, 12)
```

```
# Deleting 0 distance_km
condition = df['distance_km'] == 0
df = df[~condition]
df.shape
```

```
(72688, 12)
```

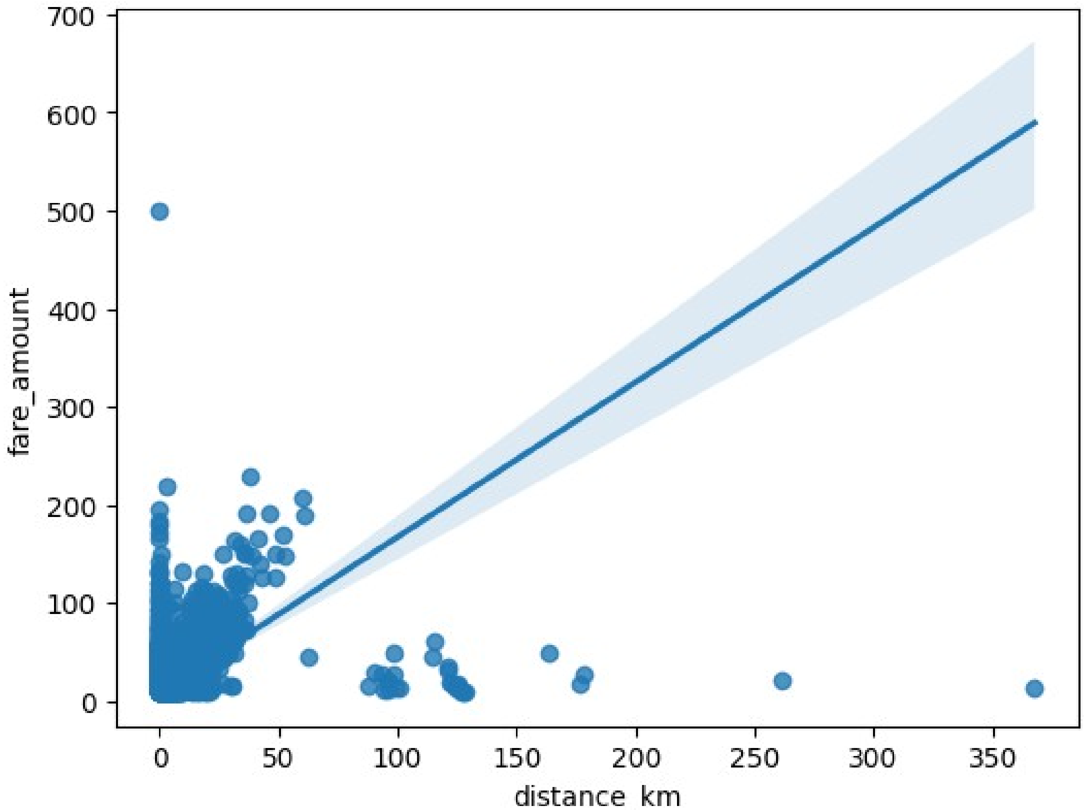
```
plt.figure(figsize = (8,3))
sns.scatterplot(data = df, x = 'distance_km', y = 'fare_amount')
```

```
<Axes: xlabel='distance_km', ylabel='fare_amount'>
```



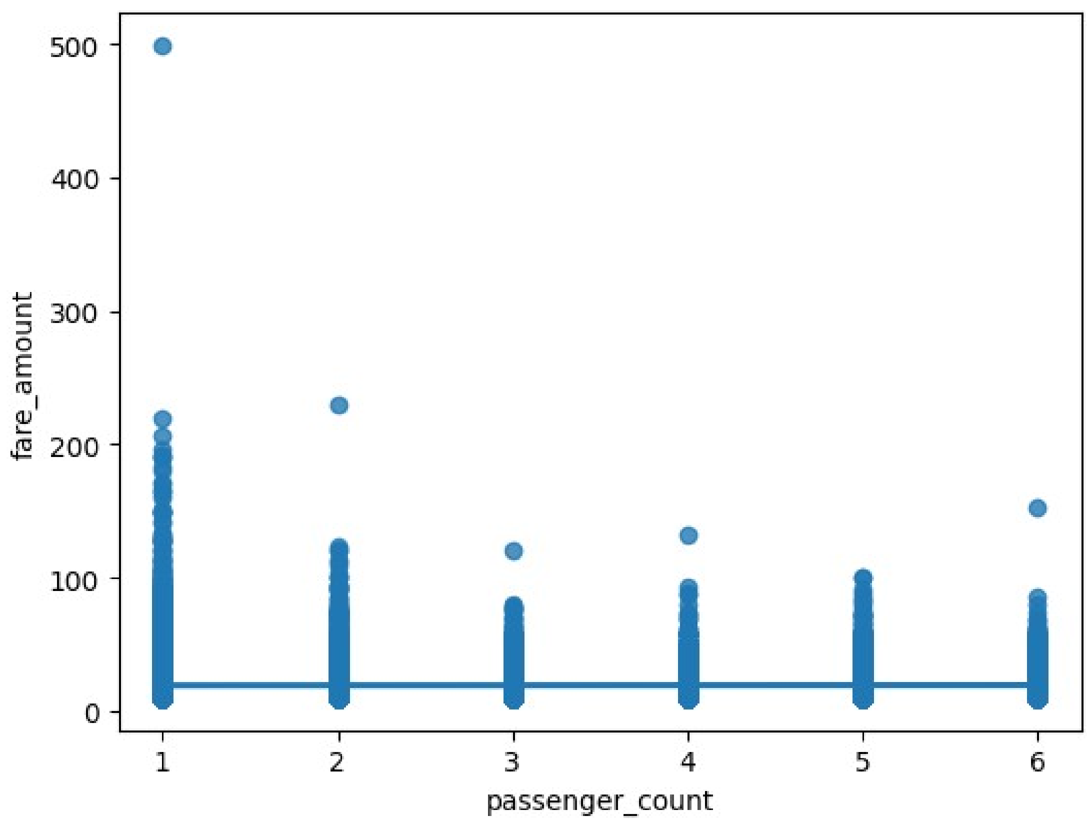

```
sns.regplot(x='distance_km', y='fare_amount', data=df)
```

```
<Axes: xlabel='distance_km', ylabel='fare_amount'>
```




```
sns.regplot(x='passenger_count', y='fare_amount', data=df)
```

```
<Axes: xlabel='passenger_count', ylabel='fare_amount'>
```



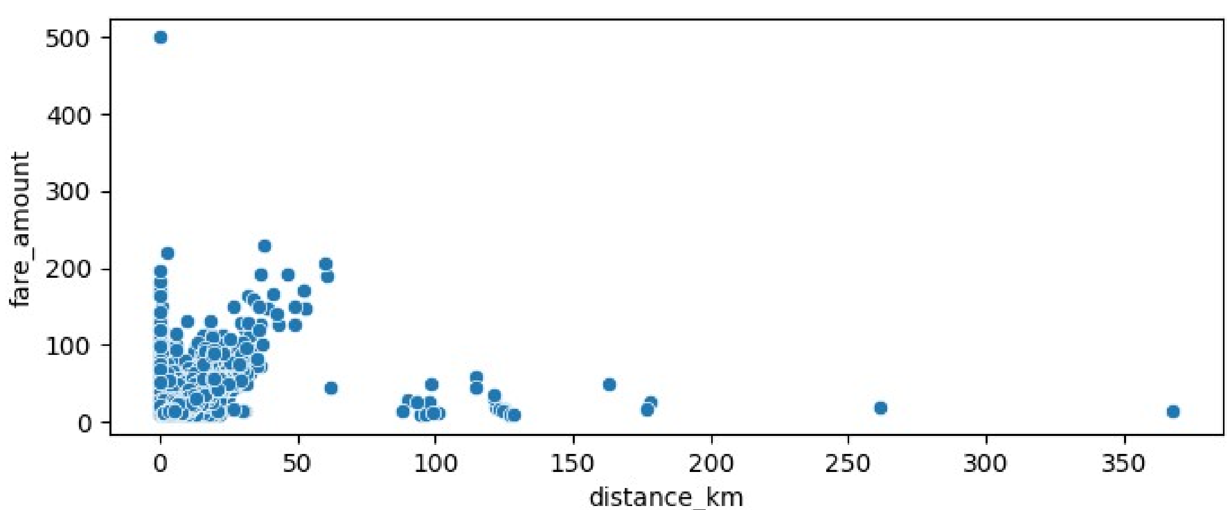

```
df.describe()

         Unnamed: 0                            key   fare_amount  \
count  7.268800e+04                          72688  72688.000000
mean   2.769841e+07  2012-06-29 13:26:22.654358784     19.201118
min    1.000000e+00  2009-01-01 01:59:17.000000100     10.100000
25%    1.383361e+07  2010-12-09 08:46:12.000000512     12.000000
50%    2.772307e+07  2012-09-11 22:19:00.000000256     14.500000
75%    4.153312e+07  2014-01-30 08:35:55.750000384     21.000000
max    5.542167e+07  2015-06-30 23:40:39.000000100    499.000000
std    1.600440e+07                            NaN     12.160614

       pickup_longitude  pickup_latitude  dropoff_longitude
dropoff_latitude  \
count      72688.000000     72688.000000       72688.000000
72688.000000
mean         -73.967812        40.746885         -73.966096
40.746809
min          -75.426904        39.610299         -75.458979
37.533090
25%          -73.993040        40.729664         -73.991539
40.723875
50%          -73.981861        40.751772         -73.978227
40.751926
```

```
75%          -73.962867        40.768650         -73.955159
40.769141
max          -71.896038        42.478467         -71.718700
42.464187
std            0.053375         0.035029           0.053175
0.045432

       passenger_count   distance_km          Hour  Traffic_Weitage
count     72688.000000  72688.000000  72688.000000     72688.000000
mean          1.711094      6.168671     13.315320         0.046653
min           1.000000      0.000084      0.000000         0.009818
25%           1.000000      3.287484      9.000000         0.044833
50%           1.000000      4.744799     14.000000         0.048627
75%           2.000000      7.268739     19.000000         0.055116
max           6.000000    367.442653     23.000000         0.063055
std           1.321225      5.321041      6.706105         0.012063
```

```
df.head()
```

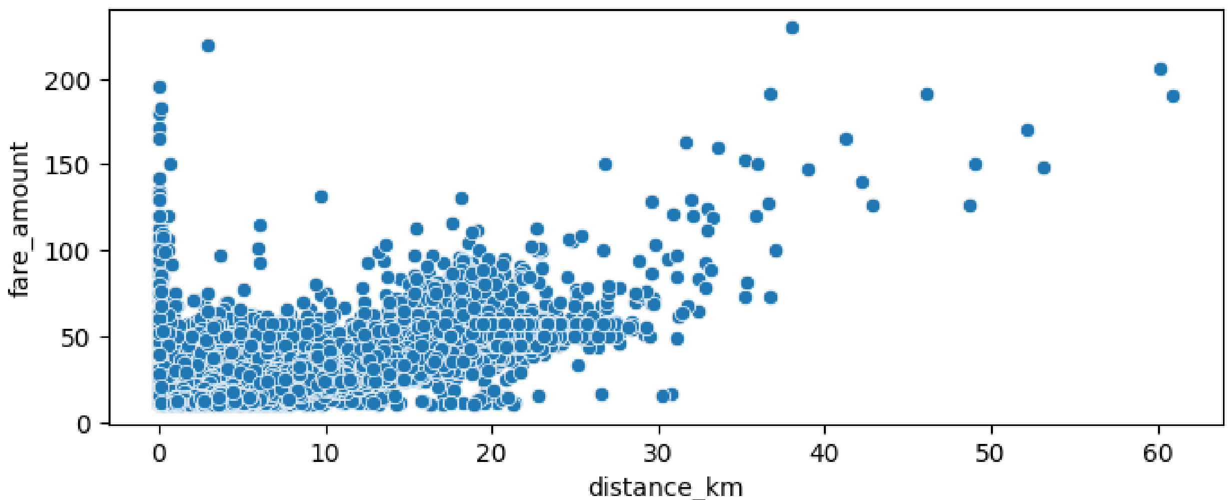
```
    Unnamed: 0                           key  fare_amount  \
2     44984355 2009-08-24 21:45:00.000000610         12.9
4     17610152 2014-08-28 17:47:00.000000188         16.0
6     48725865 2014-10-12 07:04:00.000000200         24.5
9     50611056 2012-03-29 19:06:00.000000273         12.5
13    13012786 2011-06-25 11:19:00.000000102         10.9

             pickup_datetime  pickup_longitude  pickup_latitude  \
2  2009-08-24 21:45:00+00:00        -74.005043        40.740770
4  2014-08-28 17:47:00+00:00        -73.925023        40.744085
6  2014-10-12 07:04:00+00:00        -73.961447        40.693965
9  2012-03-29 19:06:00+00:00        -74.001065        40.741787
13 2011-06-25 11:19:00+00:00        -73.953352        40.767382

    dropoff_longitude  dropoff_latitude  passenger_count  distance_km
Hour  \
2          -73.962565         40.772647                1     5.036384
21
4          -73.973082         40.761247                5     4.475456
17
6          -73.871195         40.774297                5    11.731031
7
9          -73.963040         40.775012                1     4.889424
19
13         -73.972510         40.796137                1     3.581256
11

    Traffic_Weitage
2          0.057286
4          0.048627
6          0.036148
```

```
9          0.063055
13         0.047095

df.drop(columns=['Unnamed: 0', 'key', 'pickup_longitude',
'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude'],
inplace=True)
df.head()

    fare_amount           pickup_datetime  passenger_count
distance_km  Hour  \
2          12.9 2009-08-24 21:45:00+00:00                1
5.036384    21
4          16.0 2014-08-28 17:47:00+00:00                5
4.475456    17
6          24.5 2014-10-12 07:04:00+00:00                5
11.731031     7
9          12.5 2012-03-29 19:06:00+00:00                1
4.889424    19
13         10.9 2011-06-25 11:19:00+00:00                1
3.581256    11

    Traffic_Weitage
2          0.057286
4          0.048627
6          0.036148
9          0.063055
13         0.047095

#sns.pairplot(df)

plt.figure(figsize = (8,3))
sns.scatterplot(data = df, x = 'distance_km', y = 'fare_amount')

<Axes: xlabel='distance_km', ylabel='fare_amount'>
```



```python
# Deleting outliers of distance>50 and fare_amount < 100.  They are outliers
condition = (df['distance_km'] > 50) & (df['fare_amount'] < 100)
df = df[~condition]

# Deleting outliers of fare_amount>300 as its distance from the above chart is close to 0
condition = df['fare_amount'] > 300
df = df[~condition]

plt.figure(figsize = (8,3))
sns.scatterplot(data = df, x = 'distance_km', y = 'fare_amount')
```

```
<Axes: xlabel='distance_km', ylabel='fare_amount'>
```




```python
df['Fare_Km'] = df['fare_amount']/df['distance_km']

df.head()
```

```
    fare_amount            pickup_datetime  passenger_count
distance_km  Hour  \
2          12.9 2009-08-24 21:45:00+00:00                1
5.036384    21
4          16.0 2014-08-28 17:47:00+00:00                5
4.475456    17
6          24.5 2014-10-12 07:04:00+00:00                5
11.731031     7
9          12.5 2012-03-29 19:06:00+00:00                1
4.889424    19
13         10.9 2011-06-25 11:19:00+00:00                1
3.581256    11

    Traffic_Weitage   Fare_Km
2          0.057286  2.561361
```

```
4           0.048627  3.575055
6           0.036148  2.088478
9           0.063055  2.556539
13          0.047095  3.043625
```

```
df.sort_values(by='Fare_Km', ascending=False).head()
```

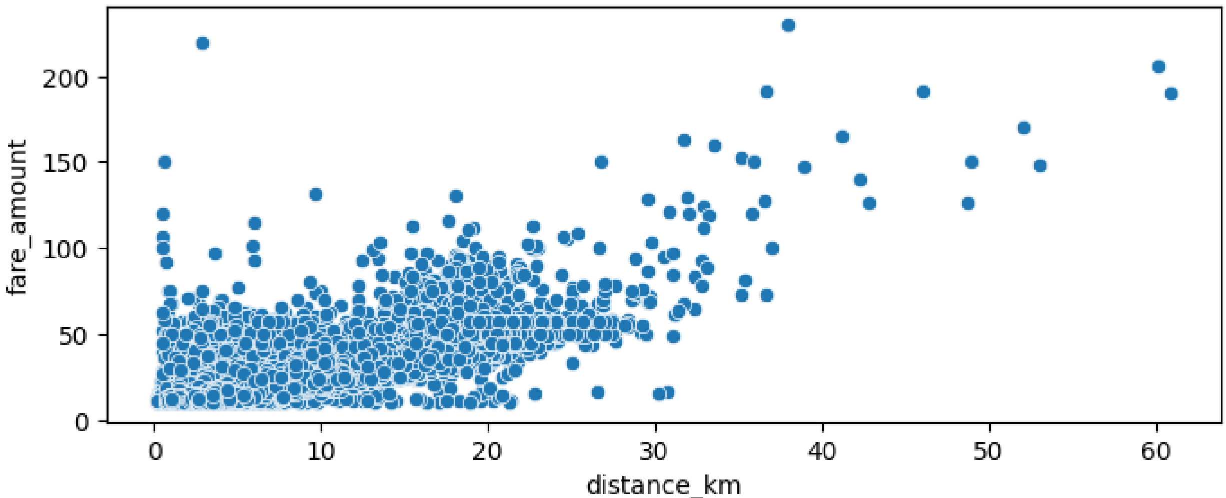
```
        fare_amount           pickup_datetime  passenger_count
distance_km  \
11301         113.0 2013-12-06 02:17:00+00:00                2
0.000169
14116          52.0 2014-01-25 03:31:46+00:00                1
0.000084
198655         52.0 2014-08-31 20:02:06+00:00                1
0.000084
1531           50.0 2009-05-28 19:40:00+00:00                1
0.000084
163148         45.0 2012-04-11 22:34:15+00:00                1
0.000084

        Hour  Traffic_Weitage        Fare_Km
11301      2         0.022097  667984.103674
14116      3         0.016282  617216.290511
198655    20         0.058736  616348.773783
1531      19         0.063055  593853.871246
163148    22         0.055116  534246.314443
```

```
# Deleting fare_km>50 and distance_km<0.5. They are outliers
condition = (df['Fare_Km'] > 50) & (df['distance_km'] < 0.5)
df = df[~condition]
df.shape
```

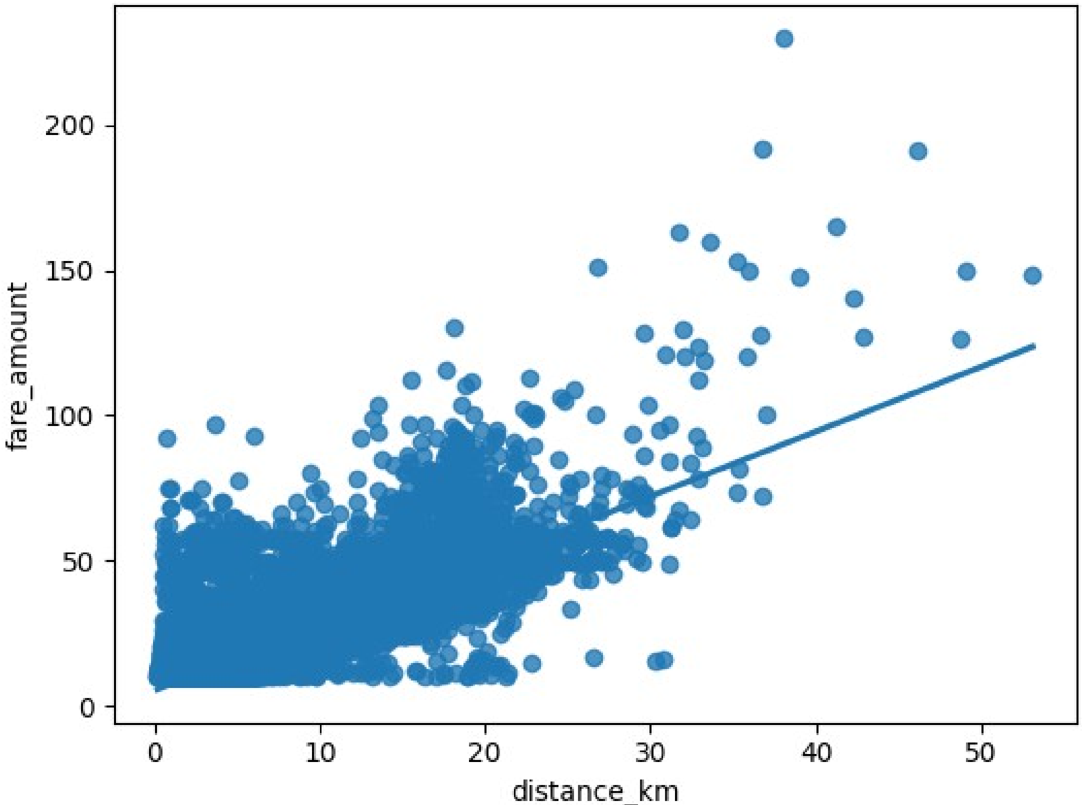
```
(72070, 7)
```

```
plt.figure(figsize = (8,3))
sns.scatterplot(data = df, x = 'distance_km', y = 'fare_amount')
```

```
<Axes: xlabel='distance_km', ylabel='fare_amount'>
```

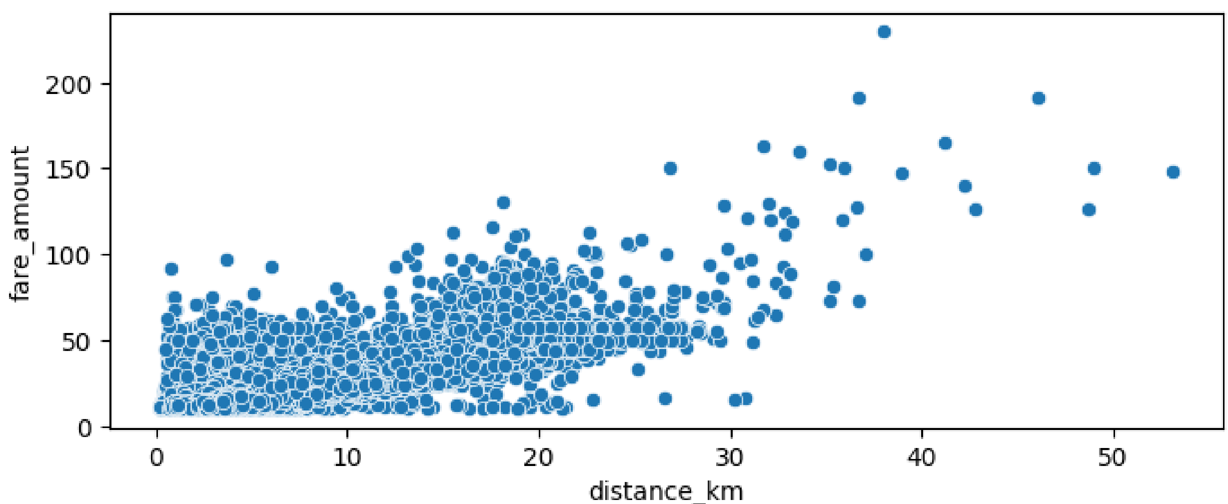



```python
# Deleting fare_amount>100 and distance_km<10. They are outliers
condition=(df['fare_amount'] > 100) & (df['distance_km'] < 10)
df = df[~condition]

# Deleting fare_amount>150 and distance_km>50. They are outliers
condition = (df['fare_amount'] > 150) & (df['distance_km'] > 50)
df = df[~condition]

sns.regplot(x='distance_km', y='fare_amount', data=df)

<Axes: xlabel='distance_km', ylabel='fare_amount'>
```




```
plt.figure(figsize = (8,3))
sns.scatterplot(data = df, x = 'distance_km', y = 'fare_amount')
```

```
<Axes: xlabel='distance_km', ylabel='fare_amount'>
```

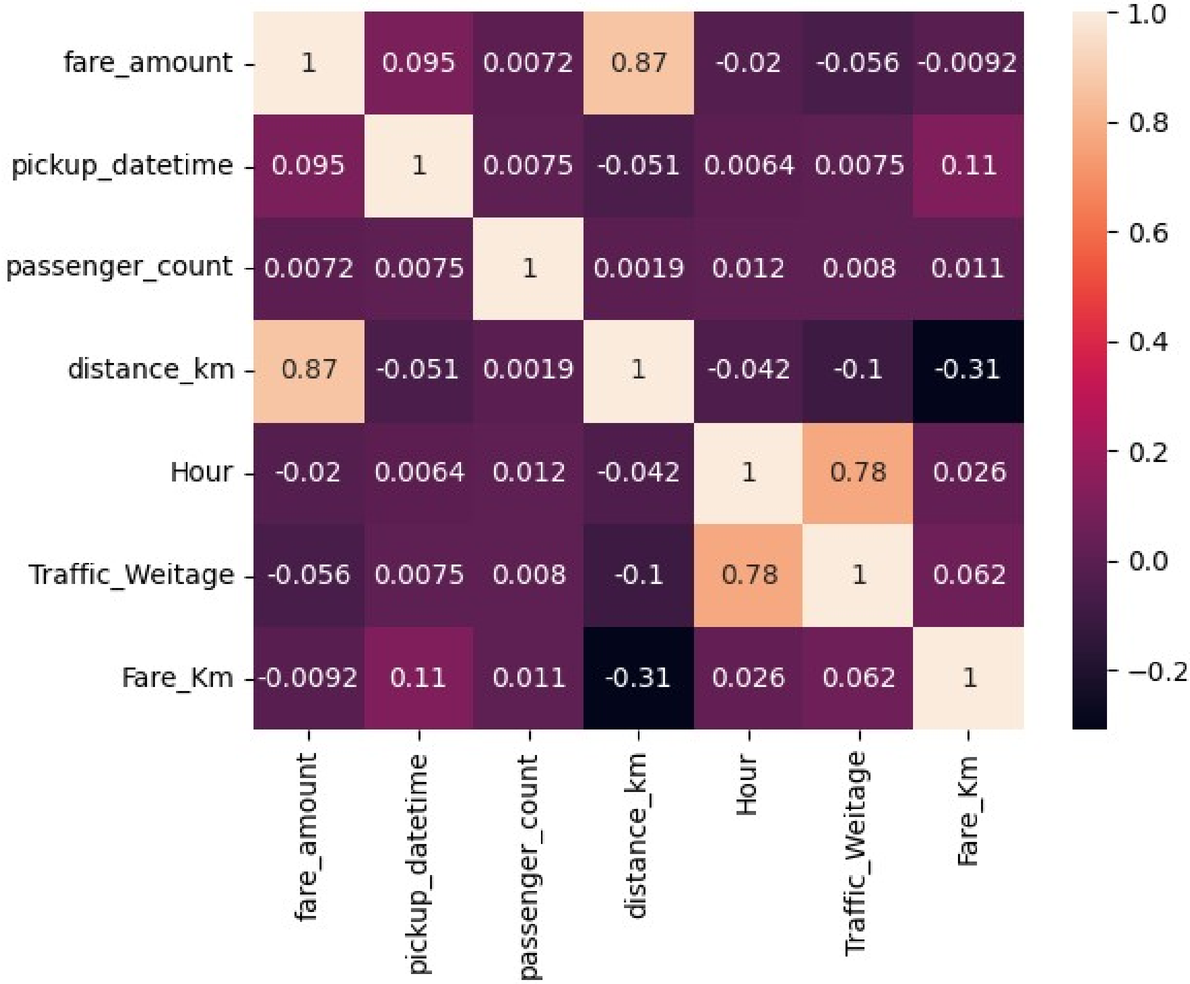



```
df.corr()
```

```
                  fare_amount  pickup_datetime  passenger_count
distance_km  \
fare_amount          1.000000         0.095435         0.007221
0.865596
pickup_datetime      0.095435         1.000000         0.007534     -
0.050902
passenger_count      0.007221         0.007534         1.000000
0.001854
distance_km          0.865596        -0.050902         0.001854
1.000000
Hour                -0.020000         0.006373         0.012281     -
0.041984
Traffic_Weitage     -0.055798         0.007550         0.008014     -
0.104752
Fare_Km             -0.009215         0.113492         0.010614     -
0.310038

                     Hour  Traffic_Weitage   Fare_Km
fare_amount     -0.020000        -0.055798 -0.009215
pickup_datetime  0.006373         0.007550  0.113492
passenger_count  0.012281         0.008014  0.010614
distance_km     -0.041984        -0.104752 -0.310038
Hour             1.000000         0.777955  0.026051
Traffic_Weitage  0.777955         1.000000  0.061969
Fare_Km          0.026051         0.061969  1.000000
```

```
sns.heatmap(df.corr(), annot=True)
```

```
<Axes: >
```




```
# Create X & y
# Create train and test datasets (70-30)%
# Train the model on the training set (learn the coefficients)
# Evaluate the model

df.head()

    fare_amount           pickup_datetime  passenger_count 
distance_km  Hour  \
2           12.9 2009-08-24 21:45:00+00:00                1
5.036384    21
4           16.0 2014-08-28 17:47:00+00:00                5
4.475456    17
6           24.5 2014-10-12 07:04:00+00:00                5
11.731031     7
9           12.5 2012-03-29 19:06:00+00:00                1
4.889424    19
13          10.9 2011-06-25 11:19:00+00:00                1
3.581256    11
```

```
    Traffic_Weitage   Fare_Km
2          0.057286  2.561361
4          0.048627  3.575055
6          0.036148  2.088478
9          0.063055  2.556539
13         0.047095  3.043625
```

```
df.drop(labels='pickup_datetime', axis=1, inplace=True)
```

```
df.head()
```

```
    fare_amount  passenger_count  distance_km  Hour  Traffic_Weitage
Fare_Km
2          12.9                1     5.036384    21         0.057286
2.561361
4          16.0                5     4.475456    17         0.048627
3.575055
6          24.5                5    11.731031     7         0.036148
2.088478
9          12.5                1     4.889424    19         0.063055
2.556539
13         10.9                1     3.581256    11         0.047095
3.043625
```

```
X = df.drop(labels='fare_amount', axis=1)
y = df['fare_amount']
```

```
X.head()
```

```
    passenger_count  distance_km  Hour  Traffic_Weitage   Fare_Km
2                 1     5.036384    21         0.057286  2.561361
4                 5     4.475456    17         0.048627  3.575055
6                 5    11.731031     7         0.036148  2.088478
9                 1     4.889424    19         0.063055  2.556539
13                1     3.581256    11         0.047095  3.043625
```

```
y.head()
```

```
2     12.9
4     16.0
6     24.5
9     12.5
13    10.9
Name: fare_amount, dtype: float64
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=0)
```

```
print(len(X_train))
print(len(X_test))
```

```
50441
21618
```

```
print(len(y_train))
print(len(y_test))
```

```
50441
21618
```

## Numerical Predictors - statsmodels

Model 1

```
# Create and train a linear regression model for the data and view its summary
# Note: The objective is to predict 'fare_amount' using 'passenger_count'
# Note: Using all the data for analytical purpose but when building models generally only training data is used
lrmodel_1 = smf.ols('fare_amount ~ passenger_count', data=df)
lrmodel_1 = lrmodel_1.fit()
print(lrmodel_1.summary())
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:            fare_amount   R-squared:
0.000
Model:                            OLS   Adj. R-squared:
0.000
Method:                 Least Squares   F-statistic:
3.757
Date:                Mon, 22 Apr 2024   Prob (F-statistic):
0.0526
Time:                        17:50:54   Log-Likelihood:            -
2.7900e+05
No. Observations:               72059   AIC:
5.580e+05
Df Residuals:                   72057   BIC:
5.580e+05
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
=============
                      coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
```

```
-------------
Intercept          18.9350      0.071    267.346      0.000
18.796      19.074
passenger_count     0.0634      0.033      1.938      0.053      -
0.001      0.128
======================================================================
========
Omnibus:                    41851.955   Durbin-Watson:
2.016
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
482702.594
Skew:                           2.614   Prob(JB):
0.00
Kurtosis:                      14.552   Cond. No.
4.05
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

Model 2

```
# Create and train a linear regression model for the data and view its
summary
# Note: The objective is to predict 'fare_amount' using 'distance_km'
lrmodel_2 = smf.ols('fare_amount ~ distance_km', data=df)
lrmodel_2 = lrmodel_2.fit()
print(lrmodel_2.summary())

                            OLS Regression Results

======================================================================
========
Dep. Variable:            fare_amount   R-squared:
0.749
Model:                            OLS   Adj. R-squared:
0.749
Method:                 Least Squares   F-statistic:
2.153e+05
Date:                Mon, 22 Apr 2024   Prob (F-statistic):
0.00
Time:                        17:50:54   Log-Likelihood:             -
2.2916e+05
No. Observations:               72059   AIC:
4.583e+05
Df Residuals:                   72057   BIC:
```

```
4.583e+05
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
=========
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
---------
Intercept       5.2994      0.037    144.374      0.000       5.227
5.371
distance_km     2.2298      0.005    464.021      0.000       2.220
2.239
======================================================================
========
Omnibus:                    53688.225   Durbin-Watson:
2.001
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
2539509.483
Skew:                           3.122   Prob(JB):
0.00
Kurtosis:                      31.404   Cond. No.
13.1
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

Model 3

```
# Create and train a linear regression model for the data and view its
summary
# Note: The objective is to predict 'fare_amount' using 'Hour'
lrmodel_3 = smf.ols('fare_amount ~ Hour', data=df)
lrmodel_3 = lrmodel_3.fit()
print(lrmodel_3.summary())

                            OLS Regression Results

======================================================================
========
Dep. Variable:            fare_amount   R-squared:
0.000
Model:                            OLS   Adj. R-squared:
```

```
0.000
Method:                 Least Squares   F-statistic:
28.84
Date:                Mon, 22 Apr 2024   Prob (F-statistic):
7.90e-08
Time:                        17:50:54   Log-Likelihood:            -
2.7898e+05
No. Observations:               72059   AIC:
5.580e+05
Df Residuals:                   72057   BIC:
5.580e+05
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
Intercept     19.5056      0.096    202.544      0.000      19.317
19.694
Hour          -0.0347      0.006     -5.370      0.000      -0.047
-0.022
======================================================================
========
Omnibus:                    41863.218   Durbin-Watson:
2.016
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
483004.175
Skew:                           2.615   Prob(JB):
0.00
Kurtosis:                      14.555   Cond. No.
33.3
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

Model 4

```
# Create and train a linear regression model for the data and view its
summary
# Note: The objective is to predict 'fare_amount' using
'Traffic_Weitage'
```

```
lrmodel_4 = smf.ols('fare_amount ~ Traffic_Weitage', data=df)
lrmodel_4 = lrmodel_4.fit()
print(lrmodel_4.summary())
```

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:            fare_amount   R-squared:
0.003
Model:                            OLS   Adj. R-squared:
0.003
Method:                 Least Squares   F-statistic:
225.0
Date:                Mon, 22 Apr 2024   Prob (F-statistic):
8.58e-51
Time:                        17:50:54   Log-Likelihood:             -
2.7888e+05
No. Observations:               72059   AIC:
5.578e+05
Df Residuals:                   72057   BIC:
5.578e+05
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
=============
                      coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
-------------
Intercept          21.5546      0.173    124.686      0.000
21.216      21.893
Traffic_Weitage   -53.8005      3.586    -15.001      0.000     -
60.830     -46.771
==============================================================================
========
Omnibus:                    41911.124   Durbin-Watson:
2.015
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
487049.303
Skew:                           2.616   Prob(JB):
0.00
Kurtosis:                      14.612   Cond. No.
83.1
==============================================================================
========

Notes:
```

```
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

Model 5

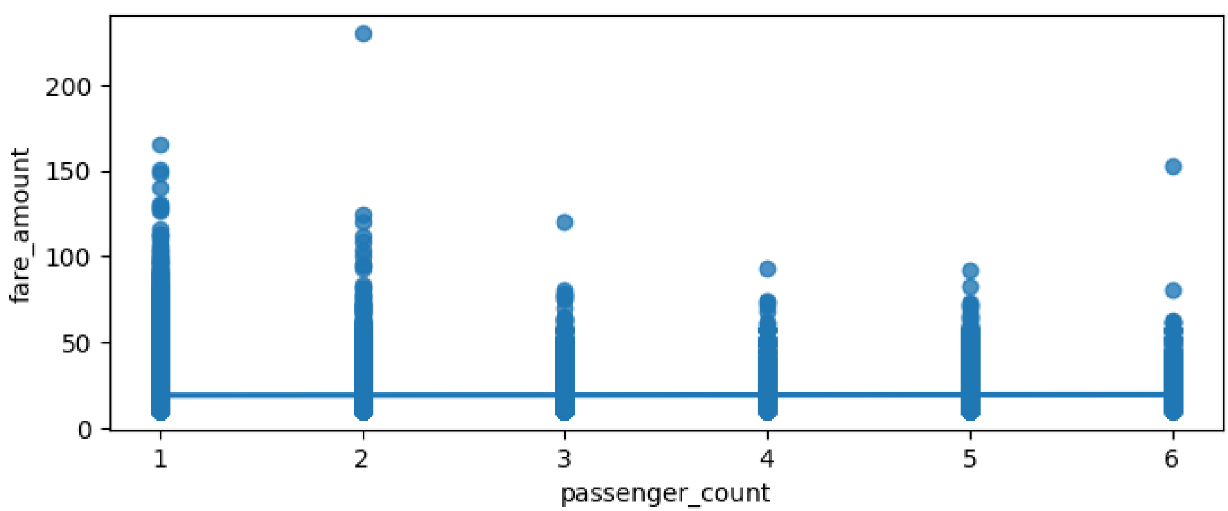
```
# Create and train a linear regression model for the data and view its
summary
# Note: The objective is to predict 'fare_amount' using 'Fare_Km'
lrmodel_5 = smf.ols('fare_amount ~ Fare_Km', data=df)
lrmodel_5 = lrmodel_5.fit()
print(lrmodel_5.summary())

                            OLS Regression Results

==============================================================================
========
Dep. Variable:            fare_amount   R-squared:
0.000
Model:                            OLS   Adj. R-squared:
0.000
Method:                 Least Squares   F-statistic:
6.120
Date:                Mon, 22 Apr 2024   Prob (F-statistic):
0.0134
Time:                        17:50:54   Log-Likelihood:            -
2.7899e+05
No. Observations:               72059   AIC:
5.580e+05
Df Residuals:                   72057   BIC:
5.580e+05
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
Intercept     19.1821      0.071    271.062      0.000      19.043
19.321
Fare_Km       -0.0370      0.015     -2.474      0.013      -0.066
-0.008
==============================================================================
========
Omnibus:                    41907.158   Durbin-Watson:
2.016
```

```
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
484710.118
Skew:                           2.618   Prob(JB):
0.00
Kurtosis:                      14.577   Cond. No.
7.96
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

## Numerical Predictors - sklearn

Model 1

```
lr_model_1 = LinearRegression()
lr_model_1 = lr_model_1.fit(X=X_train[['passenger_count']], y=y_train)

plt.figure(figsize = (8,3))
sns.regplot(x=X_train[['passenger_count']], y=y_train)

<Axes: xlabel='passenger_count', ylabel='fare_amount'>
```




```
# Look at the intercept and coefficient values
print('Intercept :', lr_model_1.intercept_)
print('Coefficient :', lr_model_1.coef_[0])

Intercept : 18.92385919144963
Coefficient : 0.06348161054262817
```

The coefficient obtained here as well as the consequent linear model are almost the same as the one we saw before

```
# Obtain predictions on the testing data set
lr_model_1.predict(X_test[['passenger_count']])
```

```
array([18.9873408 , 18.9873408 , 18.9873408 , ..., 19.05082241,
       18.9873408 , 18.9873408 ])
```

```
# General predictive performance of the model
pd.DataFrame(index = X_test.index, data = {'Truths': y_test,
                                           'Predictions':
lr_model_1.predict(X_test[['passenger_count']])}).head()
```

| | Truths | Predictions |
|---|---|---|
| 96575 | 11.3 | 18.987341 |
| 179699 | 19.5 | 18.987341 |
| 52608 | 10.5 | 18.987341 |
| 152591 | 15.7 | 18.987341 |
| 17045 | 11.5 | 18.987341 |

```
# Summarize the performance of the model on the test data using RMSE and MAPE
y_pred_lr_list = lr_model_1.predict(X_test[['passenger_count']])
rmse = np.sqrt(mean_squared_error(y_true = y_test, y_pred =
y_pred_lr_list))
mape = np.mean(np.abs(y_test - y_pred_lr_list)/y_test)*100

rmse = np.round(rmse,2)
mape = np.round(mape,2)

performance_df = pd.DataFrame(index=[0],
                              data = {'Model': 'SLR passenger_count',
'RMSE': rmse, 'MAPE': mape})
performance_df.set_index(keys='Model', inplace=True)
performance_df
```

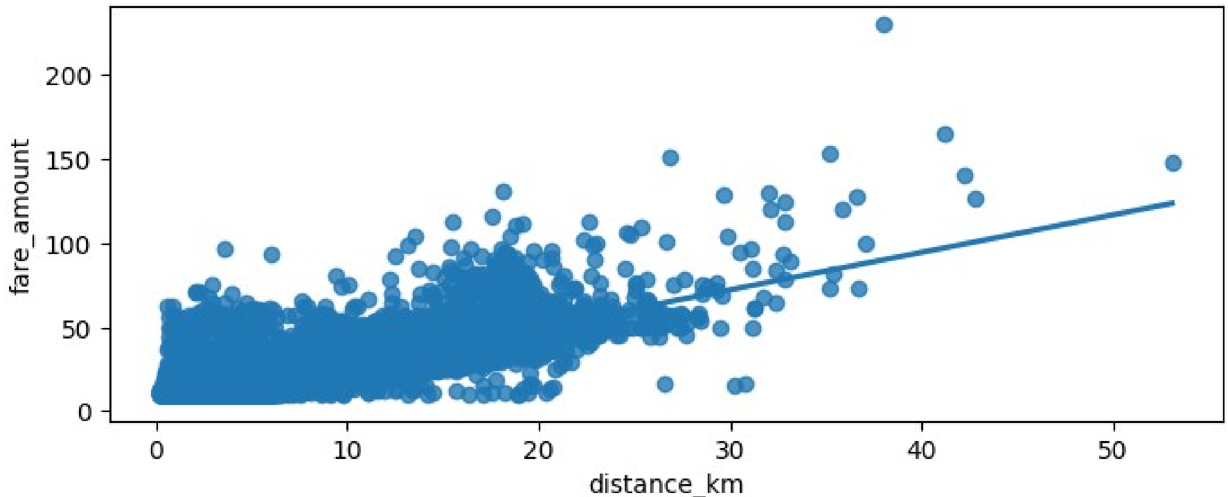
| | RMSE | MAPE |
|---|---|---|
| Model | | |
| SLR passenger_count | 11.73 | 43.5 |

## Model 2

```
# Create and train a linear regression model for the data and view its summary
# Note: The objective is to predict 'fare_amount' using
'passenger_count'
# Note: Using only the training data
lr_model_2 = LinearRegression()
lr_model_2 = lr_model_2.fit(X_train[['distance_km']], y_train)
```

```
# Create a regression plot for this model
plt.figure(figsize = (8,3))
sns.regplot(x = X_train[['distance_km']], y=y_train)
```

```
<Axes: xlabel='distance_km', ylabel='fare_amount'>
```




```
# Look at the intercept and coefficient values
print('Intercept: ', lr_model_2.intercept_)
print('Coefficient: ', lr_model_2.coef_[0])
```

```
Intercept:  5.320648742653468
Coefficient:  2.227040821706897
```

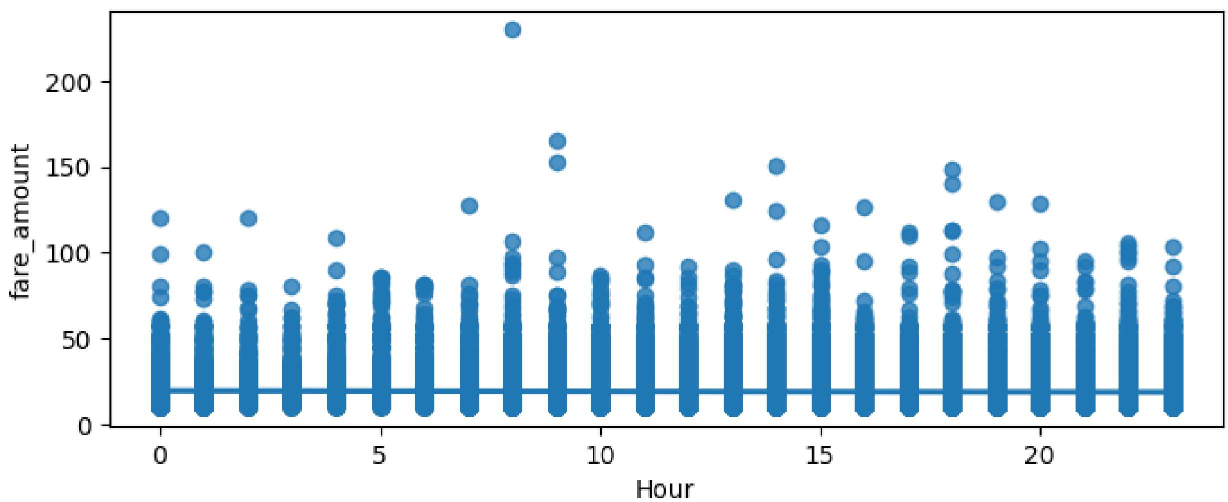
```
# Summarize the performance of the model on the test data using RMSE
and MAPE
y_pred_lr_list = lr_model_2.predict(X_test[['distance_km']])
rmse = np.sqrt(mean_squared_error(y_true=y_test,
y_pred=y_pred_lr_list))
mape = np.mean(np.abs(y_test-y_pred_lr_list)/y_test) * 100

rmse = np.round(rmse,2)
mape = np.round(mape,2)

performance_df_temp = pd.DataFrame(index=[0],
                                   data={'Model': 'SLR distance_km',
'RMSE': rmse, 'MAPE': mape})

performance_df_temp.set_index(keys='Model', inplace=True)
performance_df = pd.concat(objs=[performance_df, performance_df_temp])
performance_df
```

```
                      RMSE   MAPE
Model
```

```
SLR passenger_count  11.73  43.50
SLR distance_km       5.88  19.85
```

## Model 3

```
# Create and train a linear regression model for the data and view its
summary
# Note: The objective is to predict 'fare_amount' using
'passenger_count'
# Note: Using only the training data
lr_model_3 = LinearRegression()
lr_model_3 = lr_model_3.fit(X_train[['Hour']], y_train)

# Create a regression plot for this model
plt.figure(figsize = (8,3))
sns.regplot(x = X_train[['Hour']], y=y_train)

<Axes: xlabel='Hour', ylabel='fare_amount'>
```




```
# Look at the intercept and coefficient values
print('Intercept: ', lr_model_3.intercept_)
print('Coefficient: ', lr_model_3.coef_[0])

Intercept:  19.46661084810246
Coefficient:  -0.032606531128210686

# Summarize the performance of the model on the test data using RMSE
and MAPE
y_pred_lr_list = lr_model_3.predict(X_test[['Hour']])
rmse = np.sqrt(mean_squared_error(y_true=y_test,
y_pred=y_pred_lr_list))
mape = np.mean(np.abs(y_test-y_pred_lr_list)/y_test) * 100
```

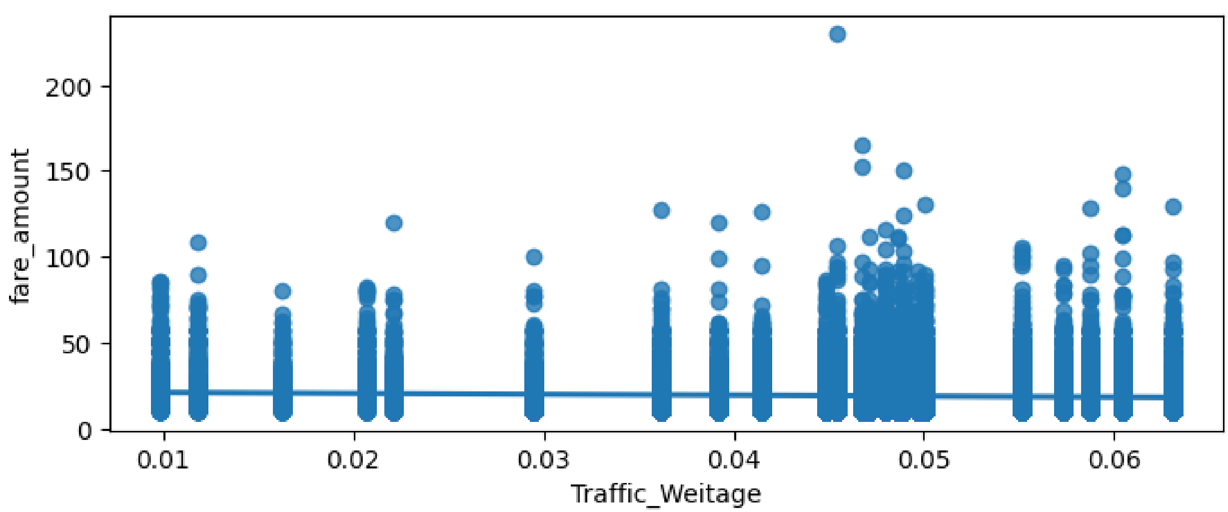
```
rmse = np.round(rmse,2)
mape = np.round(mape,2)

performance_df_temp = pd.DataFrame(index=[0],
                                  data={'Model': 'SLR Hour', 'RMSE':
rmse, 'MAPE': mape})

performance_df_temp.set_index(keys='Model', inplace=True)
performance_df = pd.concat(objs=[performance_df, performance_df_temp])
performance_df
```

| Model | RMSE | MAPE |
|---|---|---|
| SLR passenger_count | 11.73 | 43.50 |
| SLR distance_km | 5.88 | 19.85 |
| SLR Hour | 11.73 | 43.46 |

## Model 4

```
# Create and train a linear regression model for the data and view its
summary
# Note: The objective is to predict 'fare_amount' using
'passenger_count'
# Note: Using only the training data
lr_model_4 = LinearRegression()
lr_model_4 = lr_model_4.fit(X_train[['Traffic_Weitage']], y_train)

# Create a regression plot for this model
plt.figure(figsize = (8,3))
sns.regplot(x = X_train[['Traffic_Weitage']], y=y_train)
```

```
<Axes: xlabel='Traffic_Weitage', ylabel='fare_amount'>
```



```
# Look at the intercept and coefficient values
print('Intercept: ', lr_model_4.intercept_)
print('Coefficient: ', lr_model_4.coef_[0])
```

```
Intercept:  21.516912194962305
Coefficient:  -53.23144347261573
```

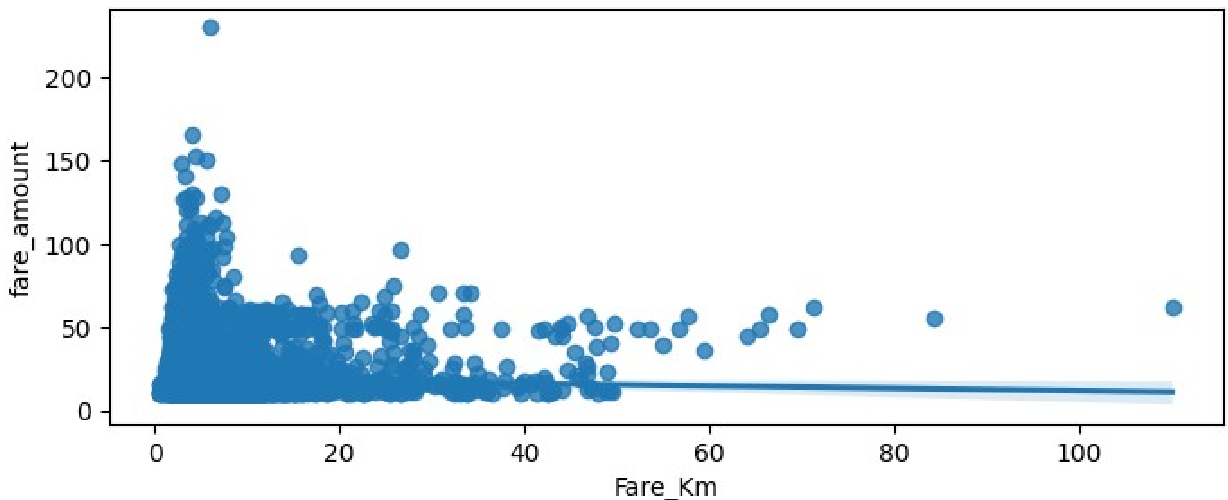
```
# Summarize the performance of the model on the test data using RMSE
and MAPE
y_pred_lr_list = lr_model_4.predict(X_test[['Traffic_Weitage']])
rmse = np.sqrt(mean_squared_error(y_true=y_test,
y_pred=y_pred_lr_list))
mape = np.mean(np.abs(y_test-y_pred_lr_list)/y_test) * 100

rmse = np.round(rmse,2)
mape = np.round(mape,2)

performance_df_temp = pd.DataFrame(index=[0],
                                  data={'Model': 'SLR
Traffic_Weitage', 'RMSE': rmse, 'MAPE': mape})

performance_df_temp.set_index(keys='Model', inplace=True)
performance_df = pd.concat(objs=[performance_df, performance_df_temp])
performance_df
```

| Model | RMSE | MAPE |
|---|---|---|
| SLR passenger_count | 11.73 | 43.50 |
| SLR distance_km | 5.88 | 19.85 |
| SLR Hour | 11.73 | 43.46 |
| SLR Traffic_Weitage | 11.71 | 43.33 |

## Model 5

```
# Create and train a linear regression model for the data and view its
summary
# Note: The objective is to predict 'fare_amount' using
'passenger_count'
# Note: Using only the training data
lr_model_5 = LinearRegression()
lr_model_5 = lr_model_5.fit(X_train[['Fare_Km']], y_train)

# Create a regression plot for this model
plt.figure(figsize = (8,3))
sns.regplot(x = X_train[['Fare_Km']], y=y_train)
```

```
<Axes: xlabel='Fare_Km', ylabel='fare_amount'>
```




```
# Look at the intercept and coefficient values
print('Intercept: ', lr_model_5.intercept_)
print('Coefficient: ', lr_model_5.coef_[0])

Intercept:  19.31016779649253
Coefficient:  -0.07445089197929841

# Summarize the performance of the model on the test data using RMSE
and MAPE
y_pred_lr_list = lr_model_5.predict(X_test[['Fare_Km']])
rmse = np.sqrt(mean_squared_error(y_true=y_test,
y_pred=y_pred_lr_list))
mape = np.mean(np.abs(y_test-y_pred_lr_list)/y_test) * 100

rmse = np.round(rmse,2)
mape = np.round(mape,2)

performance_df_temp = pd.DataFrame(index=[0],
                                   data={'Model': 'SLR Fare_Km',
'RMSE': rmse, 'MAPE': mape})

performance_df_temp.set_index(keys='Model', inplace=True)
performance_df = pd.concat(objs=[performance_df, performance_df_temp])
performance_df
```

| | RMSE | MAPE |
|---|---|---|
| Model | | |
| SLR passenger_count | 11.73 | 43.50 |
| SLR distance_km | 5.88 | 19.85 |
| SLR Hour | 11.73 | 43.46 |
| SLR Traffic_Weitage | 11.71 | 43.33 |
| SLR Fare_Km | 11.73 | 43.43 |

Out of 5 different models, distance_km has the least RMSE and MAPE values. It seems that distance_km is a good predictor of fare_amount