```
Predict the price of the Uber ride from a given pickup point to the agreed
drop-off location.
Perform following tasks:
1. Pre-process the dataset.
2. Identify outliers.
3. Check the correlation.
4. Implement linear regression and random forest regression models.
5. Evaluate the models and compare their respective scores like R2, RMSE,
etc.
Dataset link: https://www.kaggle.com/datasets/yasserh/uber-fares-dataset
```

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
```

In [2]:
```
df = pd.read_csv('uber.csv')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   Unnamed: 0         200000 non-null  int64  
 1   key                200000 non-null  object 
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object 
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64  
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

#Preprocess the data

In [3]:
```
df.shape
```

Out[3]:
```
(200000, 9)
```

In [4]:
```
df.head()
```

Out[4]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitud
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.73835
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.72822
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.74077
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.79084
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.74408

In [5]:
```
df.isnull()
```

Out[5]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	drop
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
...	...	...	...	...	...	...	
199995	False	False	False	False	False	False	
199996	False	False	False	False	False	False	
199997	False	False	False	False	False	False	
199998	False	False	False	False	False	False	
199999	False	False	False	False	False	False	

200000 rows × 9 columns

In [6]:
```
df.drop(columns=["Unnamed: 0", "key"], inplace=True)
df.head()
```

Out[6]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_la
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.7
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.7
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.7
3	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.8
4	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.7

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

In [8]:
```
df['dropoff_latitude'].fillna(value=df['dropoff_latitude'].mean(),inplace = Tr
df['dropoff_longitude'].fillna(value=df['dropoff_longitude'].median(),inplace
```

In [9]:
```
df.dtypes
```

Out[9]:
```
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

In [10]:
```
# From the above output, we see that the data type of 'pickup_datetime' is 'ob
# But 'pickup_datetime'is a date time stamp variable, which is wrongly interpr
```

In [11]:
```
df.pickup_datetime = pd.to_datetime(df.pickup_datetime)
df.dtypes
```

Out[11]:
```
fare_amount                       float64
pickup_datetime      datetime64[ns, UTC]
pickup_longitude                  float64
pickup_latitude                   float64
dropoff_longitude                 float64
dropoff_latitude                  float64
passenger_count                     int64
dtype: object
```

In [12]:
```
# we will extract time feature from the 'pickup_datetime'
# we will add a variable which measures the distance between pickup and drop
```

In [13]:
```
df = df.assign(hour = df.pickup_datetime.dt.hour,
               day = df.pickup_datetime.dt.day,
               month = df.pickup_datetime.dt.month,
               year = df.pickup_datetime.dt.year,
               dayofweek = df.pickup_datetime.dt.dayofweek)
```

In [14]:
```
df
```

Out[14]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	drop
0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	
1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	
3	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.790844	-73.965316	
4	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.744085	-73.973082	
...	...	...	...	...	...	
199995	3.0	2012-10-28 10:49:00+00:00	-73.987042	40.739367	-73.986525	
199996	7.5	2014-03-14 01:09:00+00:00	-73.984722	40.736837	-74.006672	
199997	30.9	2009-06-29 00:42:00+00:00	-73.986017	40.756487	-73.858957	
199998	14.5	2015-05-20 14:56:25+00:00	-73.997124	40.725452	-73.983215	
199999	14.1	2010-05-15 04:08:00+00:00	-73.984395	40.720077	-73.985508	

200000 rows × 12 columns

In [15]:
```
df = df.drop(["pickup_datetime"], axis =1)
df
```

Out[15]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passe
0	7.5	-73.999817	40.738354	-73.999512	40.723217	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	
4	16.0	-73.925023	40.744085	-73.973082	40.761247	
...	...	...	...	...	...	
199995	3.0	-73.987042	40.739367	-73.986525	40.740297	
199996	7.5	-73.984722	40.736837	-74.006672	40.739620	
199997	30.9	-73.986017	40.756487	-73.858957	40.692588	
199998	14.5	-73.997124	40.725452	-73.983215	40.695415	
199999	14.1	-73.984395	40.720077	-73.985508	40.768793	

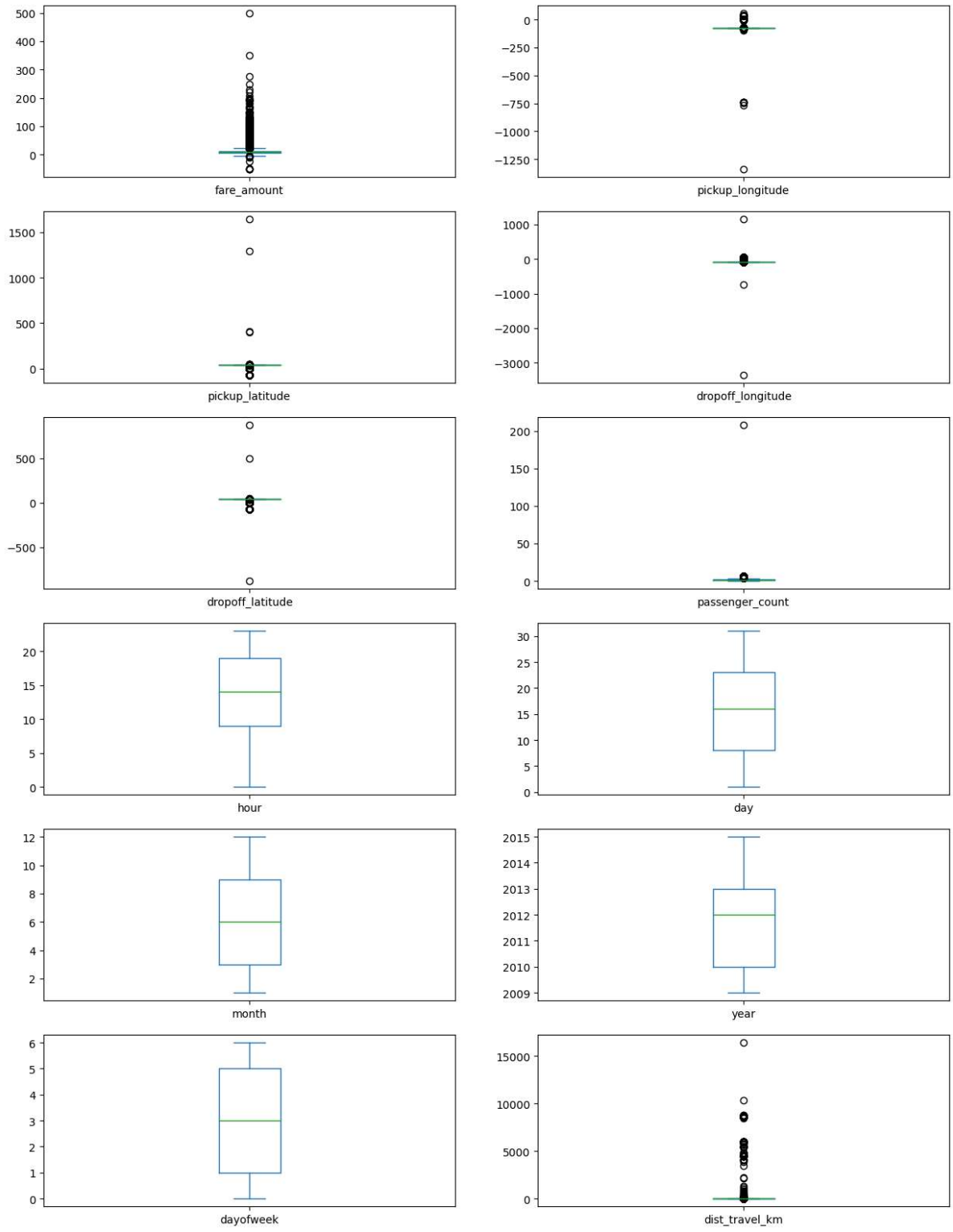
200000 rows × 11 columns

In [16]:
```
# function to calculate the travel distance from the longitudes and latitudes
from math import *

def distance_formula(longitude1, latitude1, longitude2, latitude2):
    travel_dist = []

    for pos in range (len(longitude1)):
        lon1, lan1, lon2, lan2 = map(radians, [longitude1[pos], latitude1[pos]
        dist_lon = lon2 - lon1
        dist_lan = lan2 - lan1

        a = sin(dist_lan/2)**2 + cos(lan1) * cos(lan2) * sin(dist_lon/2)**2

        #radius of earth = 6371
        c = 2 * asin(sqrt(a)) * 6371
        travel_dist.append(c)

    return  travel_dist
```

In [17]:
```
df['dist_travel_km'] = distance_formula(df.pickup_longitude.to_numpy(), df.pic
```

```
# Identify Outliers
```

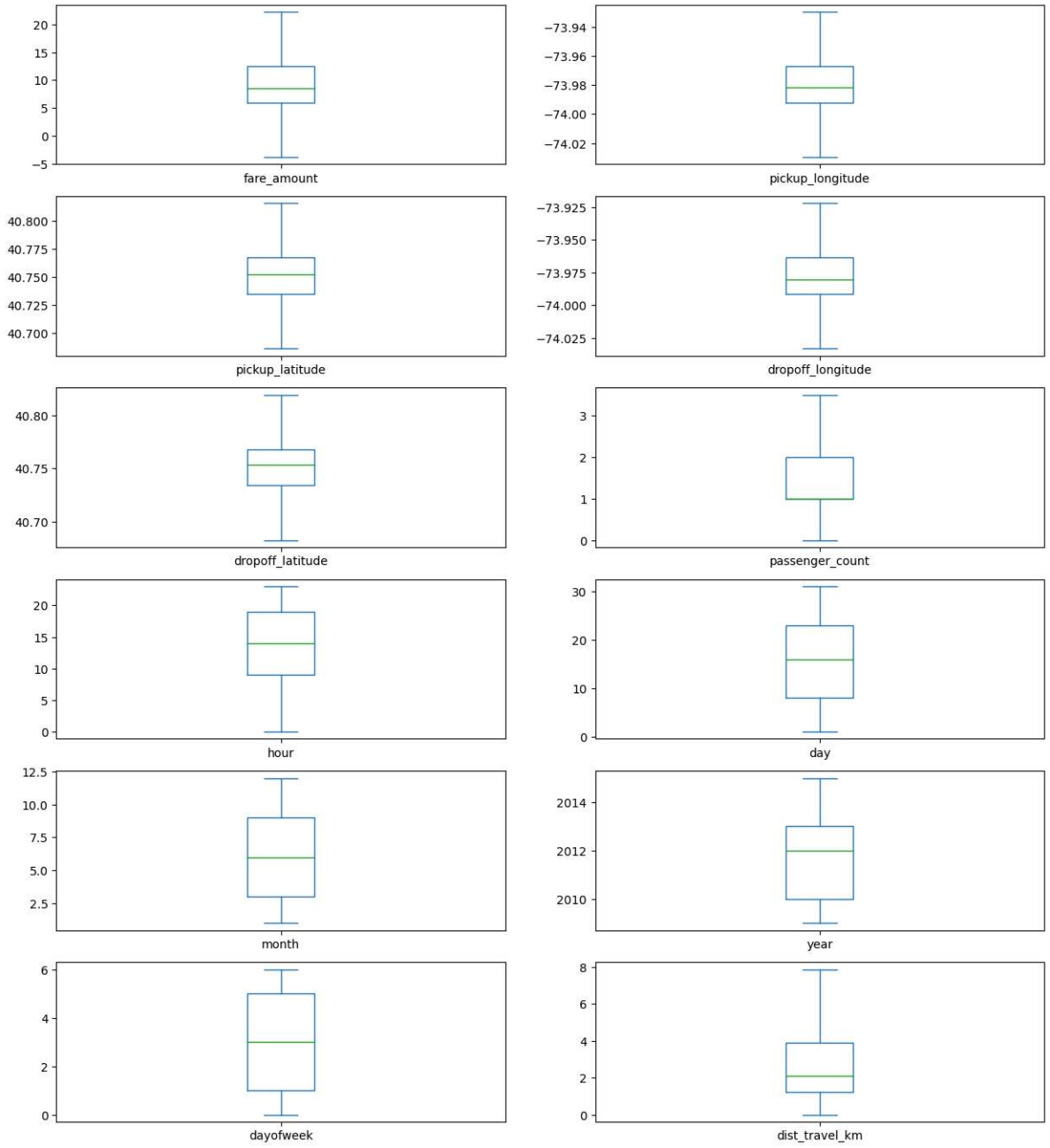
In [18]:
```
df.plot(kind = "box",subplots = True,layout = (6,2),figsize=(15,20)) #Boxplot
plt.show()
```



In [19]:
```
#Using the InterQuartile Range to fill the values
def remove_outlier(df1 , col):
    Q1 = df1[col].quantile(0.25)
    Q3 = df1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_whisker = Q1-1.5*IQR
    upper_whisker = Q3+1.5*IQR
    df[col] = np.clip(df1[col] , lower_whisker , upper_whisker)
    return df1

def treat_outliers_all(df1 , col_list):
    for c in col_list:
        df1 = remove_outlier(df , c)
    return df1
```

In [20]:
```
df = treat_outliers_all(df , df.iloc[: , 0::])
```

In [21]:
```
#Boxplot shows that dataset is free from outliers
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20))
plt.show()
```



Check the correlation

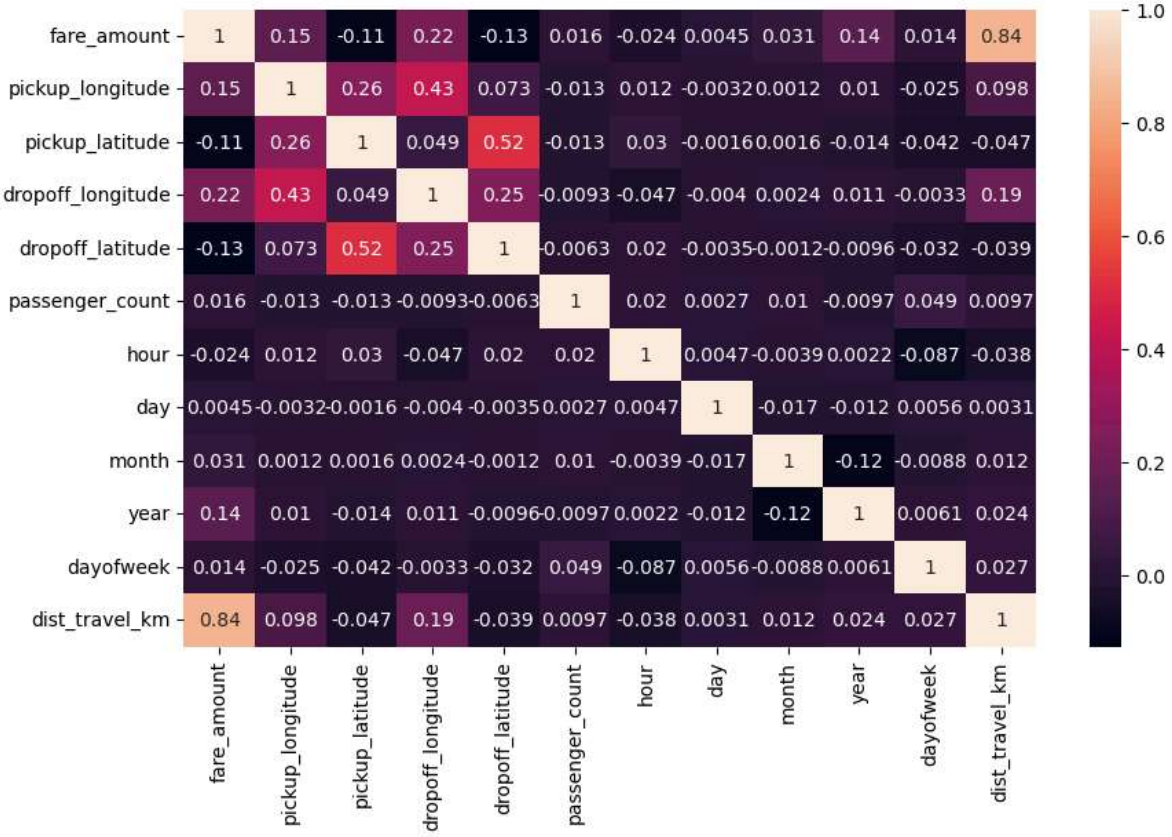
In [22]:
```
#Function to find the correlation
corr = df.corr()
corr
```

Out[22]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latit
fare_amount	1.000000	0.154069	-0.110842	0.218675	-0.125
pickup_longitude	0.154069	1.000000	0.259497	0.425619	0.073
pickup_latitude	-0.110842	0.259497	1.000000	0.048889	0.515
dropoff_longitude	0.218675	0.425619	0.048889	1.000000	0.245
dropoff_latitude	-0.125898	0.073290	0.515714	0.245667	1.000
passenger_count	0.015778	-0.013213	-0.012889	-0.009303	-0.006
hour	-0.023623	0.011579	0.029681	-0.046558	0.019
day	0.004534	-0.003204	-0.001553	-0.004007	-0.003
month	0.030817	0.001169	0.001562	0.002391	-0.001
year	0.141277	0.010198	-0.014243	0.011346	-0.009
dayofweek	0.013652	-0.024652	-0.042310	-0.003336	-0.031
dist_travel_km	0.844374	0.098094	-0.046812	0.186531	-0.038

In [23]:
```
fig,axis = plt.subplots(figsize = (10,6))
sns.heatmap(df.corr(),annot = True) #Correlation Heatmap (Light values means h
```

Out[23]: <Axes: >



Implement linear regression and random forest regression models.

In [25]:
```
# Dividing the dataset into feature and target values
df_x = df[['pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_l
df_y = df['fare_amount']
```

In [26]:
```
# Dividing the dataset into training and testing dataset
x_train, x_test, y_train, y_test = train_test_split(df_x, df_y, test_size=0.2,
```

In [27]:
```
df
```

Out[27]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passe
0	7.50	-73.999817	40.738354	-73.999512	40.723217	
1	7.70	-73.994355	40.728225	-73.994710	40.750325	
2	12.90	-74.005043	40.740770	-73.962565	40.772647	
3	5.30	-73.976124	40.790844	-73.965316	40.803349	
4	16.00	-73.929786	40.744085	-73.973082	40.761247	
...	...	...	...	...	...	
199995	3.00	-73.987042	40.739367	-73.986525	40.740297	
199996	7.50	-73.984722	40.736837	-74.006672	40.739620	
199997	22.25	-73.986017	40.756487	-73.922036	40.692588	
199998	14.50	-73.997124	40.725452	-73.983215	40.695415	
199999	14.10	-73.984395	40.720077	-73.985508	40.768793	

200000 rows × 12 columns

In [28]:
```
from sklearn.linear_model import LinearRegression

# initialize the linear regression model
reg = LinearRegression()

# Train the model with our training data
reg.fit(x_train, y_train)
```

Out[28]:
```
LinearRegression()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [29]:
```
y_pred_lin = reg.predict(x_test)
print(y_pred_lin)
```

```
[ 6.27615184  5.09986098  9.43641238 ... 11.07663949 12.15392248
 11.41496075]
```

In [30]:
```
from sklearn.ensemble import RandomForestRegressor

#Here n_estimators means number of trees you want to build before making the p
rf = RandomForestRegressor(n_estimators=100)
rf.fit(x_train,y_train)
```

Out[30]:
```
RandomForestRegressor()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [31]:
```
y_pred_rf = rf.predict(x_test)
print(y_pred_rf)
```

```
[ 4.8275  6.758   9.145  ... 11.255  11.064  13.5   ]
```

Evaluate the models and compare their respective scores like R2, RMSE, etc

In [32]:
```
cols = ['Model', 'RMSE', 'R-Squared']

# create a empty dataframe of the colums
# columns: specifies the columns to be selected
result_tabulation = pd.DataFrame(columns = cols)
```

In [37]:
```
from sklearn import metrics
from sklearn.metrics import r2_score

# Assuming y_test and y_pred_lin are already defined
reg_RMSE = np.sqrt(metrics.mean_squared_error(y_test, y_pred_lin))
reg_squared = r2_score(y_test, y_pred_lin)

# Creating the full_metrics Series
full_metrics = pd.Series({'Model': "Linear Regression", 'RMSE': reg_RMSE, 'R-S

# Convert full_metrics Series to a DataFrame for proper concatenation
full_metrics_df = full_metrics.to_frame().T

# If result_tabulation is an empty DataFrame or pre-existing DataFrame, we con
# Ensure that result_tabulation is a DataFrame
result_tabulation = pd.concat([result_tabulation, full_metrics_df], ignore_ind

# Print the result table
print(result_tabulation)
```

```
               Model      RMSE R-Squared
0  Linear Regression  2.703957  0.753906
```

In [38]:
```
from sklearn import metrics
from sklearn.metrics import r2_score

# Assuming y_test and y_pred_rf are already defined
rf_RMSE = np.sqrt(metrics.mean_squared_error(y_test, y_pred_rf))
rf_squared = r2_score(y_test, y_pred_rf)

# Creating the full_metrics Series
full_metrics = pd.Series({'Model': "Random Forest", 'RMSE': rf_RMSE, 'R-Square

# Convert the Series to a DataFrame for proper concatenation
full_metrics_df = full_metrics.to_frame().T

# Concatenate the new metrics with the existing result_tabulation DataFrame
result_tabulation = pd.concat([result_tabulation, full_metrics_df], ignore_ind

# Print the result table
print(result_tabulation)
```

```
               Model      RMSE R-Squared
0  Linear Regression  2.703957  0.753906
1      Random Forest  2.362658   0.81211
```