LP3 Group B Assignment 1

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]:
```
#Importing required libraries
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
```

In [2]:
```
df = pd.read_csv('uber.csv') #Reading CSV file
df.head()
```

Out[2]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	p
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	

In [3]:
```
df.dtypes #Checking Datatypes.
```

Out[3]:
```
Unnamed: 0             int64
key                   object
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

In [4]:
```
df.isnull().sum() #Checking for Null Values.
```

Out[4]:
```
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
```

In [5]:

```
df.drop(['Unnamed: 0','key'],axis=1,inplace=True) #Dropping first coloumnn as it is irrelevant.
df.dropna(axis=0,inplace=True) #Dropping the rows with null values.
df.head()
```

Out[5]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	1
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	1
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	1
3	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	3
4	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	5

In [6]:

```
def haversine (lon_1, lon_2, lat_1, lat_2): #Function to find the distance using the coordinates
    lon_1, lon_2, lat_1, lat_2 = map(np.radians, [lon_1, lon_2, lat_1, lat_2]) #Converting Degrees to Radians
    diff_lon = lon_2 - lon_1
    diff_lat = lat_2 - lat_1
    distance = 2 * 6371 * np.arcsin(np.sqrt(np.sin(diff_lat/2.0)**2+np.cos(lat_1)*np.cos(lat_2)*np.sin(diff_lon/2.0
    return distance

df['Distance']= haversine(df['pickup_longitude'],df['dropoff_longitude'],df['pickup_latitude'],df['dropoff_latitude
df['Distance'] = df['Distance'].astype(float).round(2) #Rounding-off to 2 decimals
df.head()
```

Out[6]:

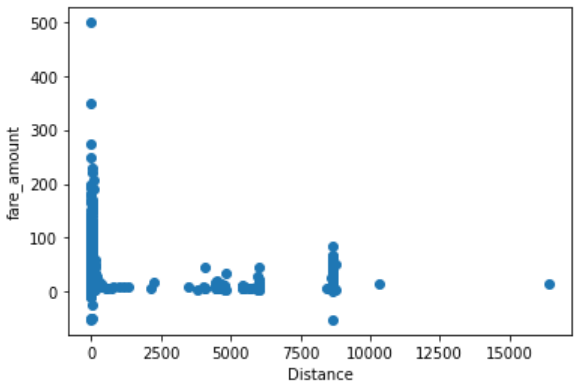
	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	Distance
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	1	1.68
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	1	2.46
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	1	5.04
3	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	3	1.66
4	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	5	4.48

In [7]:

```
#Plotting a scatter plot to check for outliers.
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

Out[7]:

```
Text(0, 0.5, 'fare_amount')
```

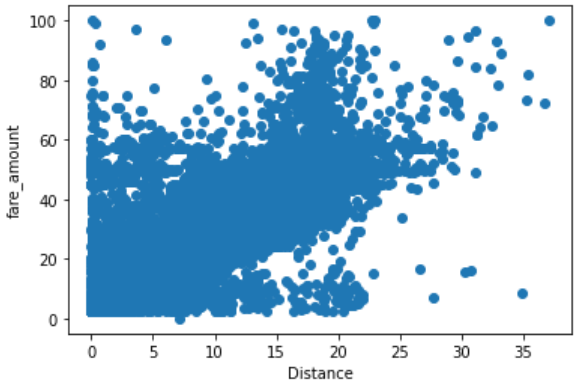


In [8]:

```
#Dealing with Outliers via removing rows with too large Distance and 0 or lesser distance.
df.drop(df[df['Distance']>60].index, inplace=True)
df.drop(df[df['Distance']==0].index, inplace=True)
df.drop(df[df['Distance']<0].index, inplace=True)
#Dealing with Outliers via removing rows with 0 or lesser fare amounts.
df.drop(df[df['fare_amount']==0].index, inplace=True)
df.drop(df[df['fare_amount']<0].index, inplace=True)
#Dealing with Outliers via removing rows with non-plausible fare amounts and distance travelled.
df.drop(df[df['Distance']>100].index, inplace=True)
df.drop(df[df['fare_amount']>100].index, inplace=True)
df.drop(df[(df['fare_amount']>100) & (df['Distance']<1)].index, inplace = True )
df.drop(df[(df['fare_amount']<100) & (df['Distance']>100)].index, inplace = True )
#Plotting a Scatter Plot to check for any more outliers and also to show correlation between Fare Amount and Distan
plt.scatter(df['Distance'], df['fare_amount'])
```

```
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

Out[8]:
```
Text(0, 0.5, 'fare_amount')
```



In [9]:
```
#Preprocessing the Data Using Standard Scaler in range of -1 to 1
x = df['Distance'].values.reshape(-1, 1)        #Independent Variable
y = df['fare_amount'].values.reshape(-1, 1)     #Dependent Variable
std = StandardScaler()
Y = std.fit_transform(y)
X = std.fit_transform(x)
#Splitting the data into training and testing set
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=1)
```

In [10]:
```
def apply_model(model): #Model to print the metrics of the various prediction models
    model.fit(X_train,Y_train)
    print("Training score = ",model.score(X_train,Y_train))
    print("Testing score = ",model.score(X_test,Y_test))
    print("Accuracy = ",model.score(X_test,Y_test))
    Y_pred = model.predict(X_test)
    print("Predicted values:\n",Y_pred)
    print("Mean Absolute Error =", metrics.mean_absolute_error(Y_test, Y_pred))
    print("Mean Squared Error =", metrics.mean_squared_error(Y_test, Y_pred))
    print("Root Mean Squared Error =", np.sqrt(metrics.mean_squared_error(Y_test, Y_pred)))
```

In [11]:
```
lr = LinearRegression()
apply_model(lr)
```

```
Training score =  0.8023890708990102
Testing score =  0.800134921063358
Accuracy =  0.800134921063358
Predicted values:
 [[-0.0856421 ]
 [ 1.40250073]
 [ 0.1072653 ]
 ...
 [-0.17833787]
 [-0.42636167]
 [-0.37124527]]
Mean Absolute Error = 0.243543639885431
Mean Squared Error = 0.19732734085539588
Root Mean Squared Error = 0.44421542167668593
```

In [12]:
```
#Random Forest Model
rf = RandomForestRegressor(n_estimators=100, random_state=10)
apply_model(rf)
```

```
C:\Users\candr\AppData\Local\Temp\ipykernel_7216\3813684645.py:2: DataConversionWarning: A column-vector y was passe
d when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  model.fit(X_train,Y_train)
Training score =  0.8250567049453948
Testing score =  0.7931312012692804
Accuracy =  0.7931312012692804
Predicted values:
 [-0.10304075  1.80284551  0.08764113 ... -0.21391608 -0.42011423
 -0.37785255]
Mean Absolute Error = 0.24703500001737674
Mean Squared Error = 0.20424213262599705
Root Mean Squared Error = 0.4519315574575392
```

In [ ]: