ML Assignment 1

October 12, 2023

1 LP3 Group B Assignment 1

1.1 Predict the price of the Uber ride from a given pickup point to the agreed drop-off location.

1.1.1 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

[1]:

```python
#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
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In [1], line 2
      1 #Importing required libraries
----> 2 import matplotlib.pyplot as plt
      3 import numpy as np
      4 import pandas as pd

ModuleNotFoundError: No module named 'matplotlib'
```

[ ]:

```python
df = pd.read_csv('uber.csv') #Reading CSV file
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.dtypes #Checking Datatypes.
```

```
[ ]: 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
```

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

```
[ ]: 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
```

```
[ ]: 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()
```

```
[ ]:    fare_amount          pickup_datetime  pickup_longitude  pickup_latitude  \
     0          7.5  2015-05-07 19:52:06 UTC        -73.999817        40.738354
     1          7.7  2009-07-17 20:04:56 UTC        -73.994355        40.728225
     2         12.9  2009-08-24 21:45:00 UTC        -74.005043        40.740770
     3          5.3  2009-06-26 08:22:21 UTC        -73.976124        40.790844
     4         16.0  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
```

```
[ ]: 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)**2)) #Calculationg the Distance␣
      ↪using Haversine Formula
         return distance

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

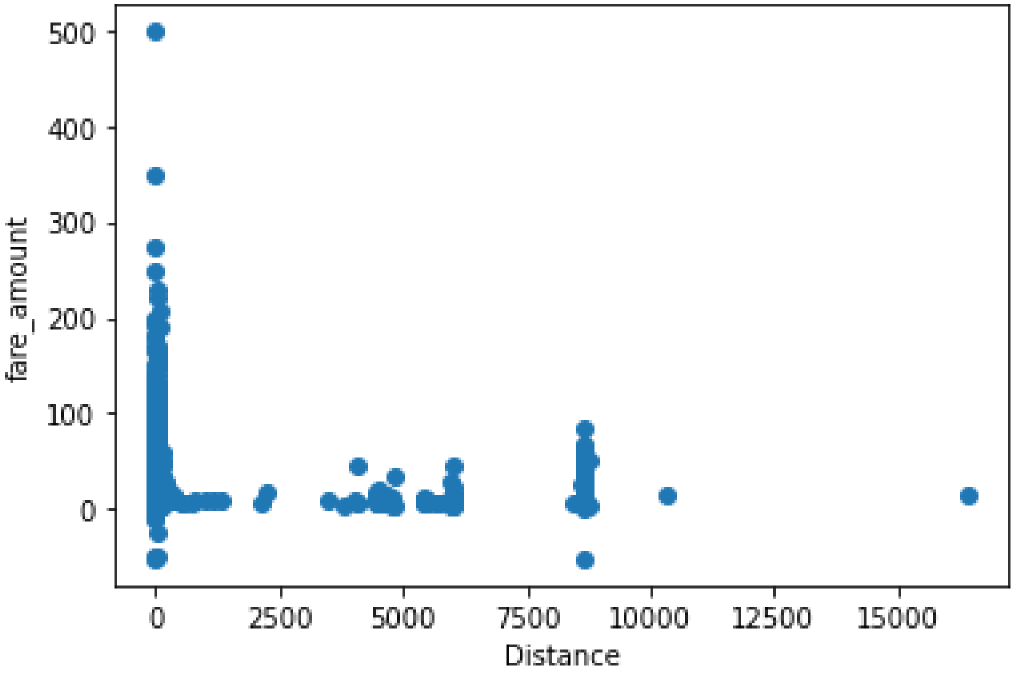
```
[ ]:    fare_amount          pickup_datetime  pickup_longitude  pickup_latitude  \
     0          7.5  2015-05-07 19:52:06 UTC        -73.999817        40.738354
     1          7.7  2009-07-17 20:04:56 UTC        -73.994355        40.728225
     2         12.9  2009-08-24 21:45:00 UTC        -74.005043        40.740770
     3          5.3  2009-06-26 08:22:21 UTC        -73.976124        40.790844
     4         16.0  2014-08-28 17:47:00 UTC        -73.925023        40.744085

        dropoff_longitude  dropoff_latitude  passenger_count  Distance
     0         -73.999512         40.723217                1      1.68
     1         -73.994710         40.750325                1      2.46
     2         -73.962565         40.772647                1      5.04
```

```
3          -73.965316         40.803349                 3       1.66
4          -73.973082         40.761247                 5       4.48
```

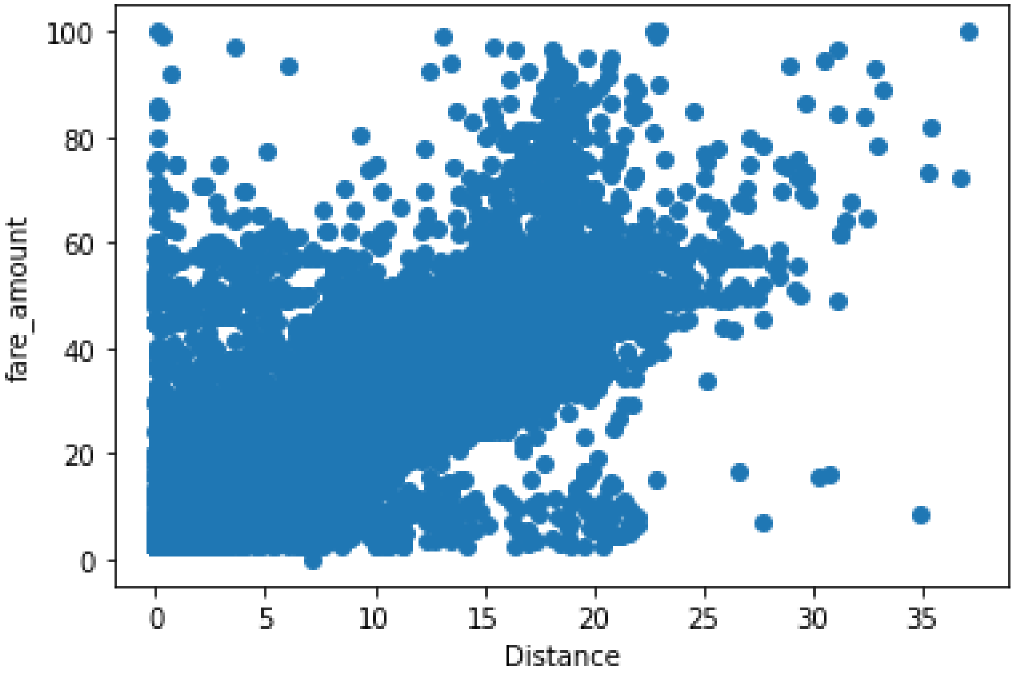
[ ]:
```python
#Plotting a scatter plot to check for outliers.
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

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



[ ]:
```python
#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 Distance.
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

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



```
[ ]: #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)
```

```
[ ]: 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)))
```

[ ]:

```
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
```

[ ]:

```
#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 passed 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
```

[ ]: