

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 model. 5. Evaluate the model using R2, RMSE, etc. Use Uber Dataset: <https://www.kaggle.com/datasets/yasserh/uber-fares-dataset>

```
In [20]: import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [21]: data = pd.read_csv("C:/Users/Atharva/OneDrive/Desktop/uber.csv")
print(data.head())
```

	Unnamed: 0	key	fare_amount	\
0	24238194	2015-05-07 19:52:06.000000	7.5	
1	27835199	2009-07-17 20:04:56.000000	7.7	
2	44984355	2009-08-24 21:45:00.000000	12.9	
3	25894730	2009-06-26 08:22:21.000000	5.3	
4	17610152	2014-08-28 17:47:00.000000	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	

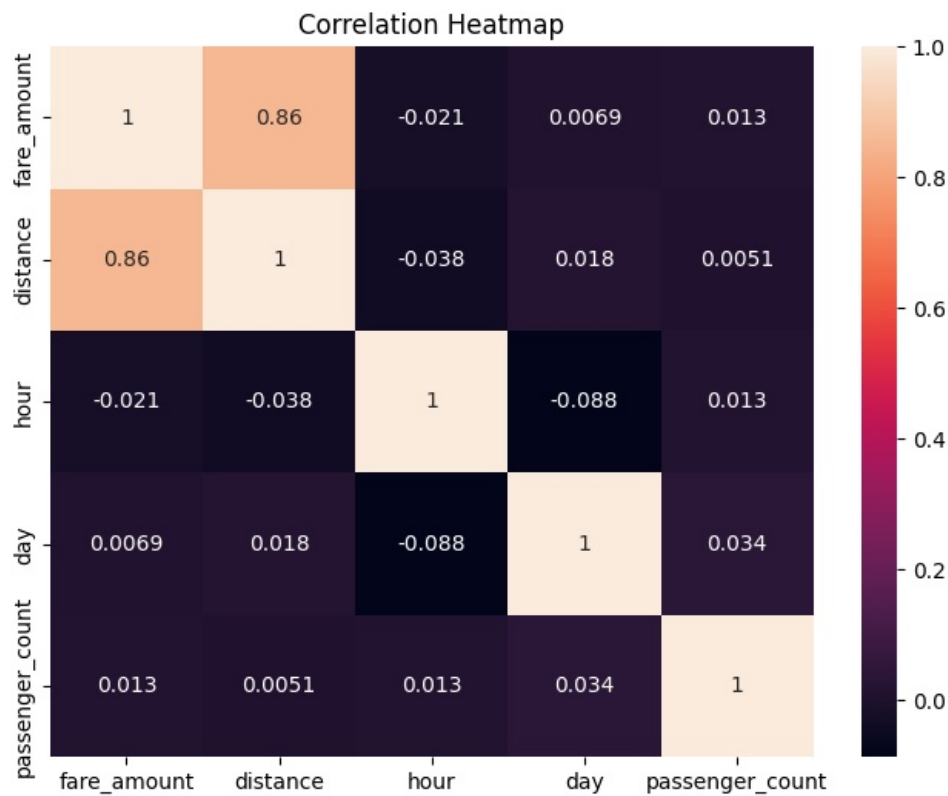
	dropoff_longitude	dropoff_latitude	passenger_count
0	-73.999512	40.723217	1
1	-73.994710	40.750325	1
2	-73.962565	40.772647	1
3	-73.965316	40.803349	3
4	-73.973082	40.761247	5

```
In [22]: # Pre-process dataset
data.dropna(inplace=True) # Drop missing values
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'])
data['hour'] = data['pickup_datetime'].dt.hour
data['day'] = data['pickup_datetime'].dt.dayofweek
```

```
In [23]: # Calculate distance
data['distance'] = np.sqrt((data['dropoff_longitude'] - data['pickup_longitude'])**2 +
                           (data['dropoff_latitude'] - data['pickup_latitude'])**2)
```

```
In [24]: # Filter outliers based on distance and fare
data = data[(data['distance'] < data['distance'].quantile(0.99)) &
            (data['fare_amount'] < data['fare_amount'].quantile(0.99))]
```

```
In [25]: # Check correlation
plt.figure(figsize=(8, 6))
sns.heatmap(data[['fare_amount', 'distance', 'hour', 'day', 'passenger_count']].corr(), annot=True)
plt.title("Correlation Heatmap")
plt.show()
```



```
In [26]: # Prepare data for training
X = data[['distance', 'hour', 'day', 'passenger_count']]
y = data['fare_amount']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
In [27]: # Train Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
```

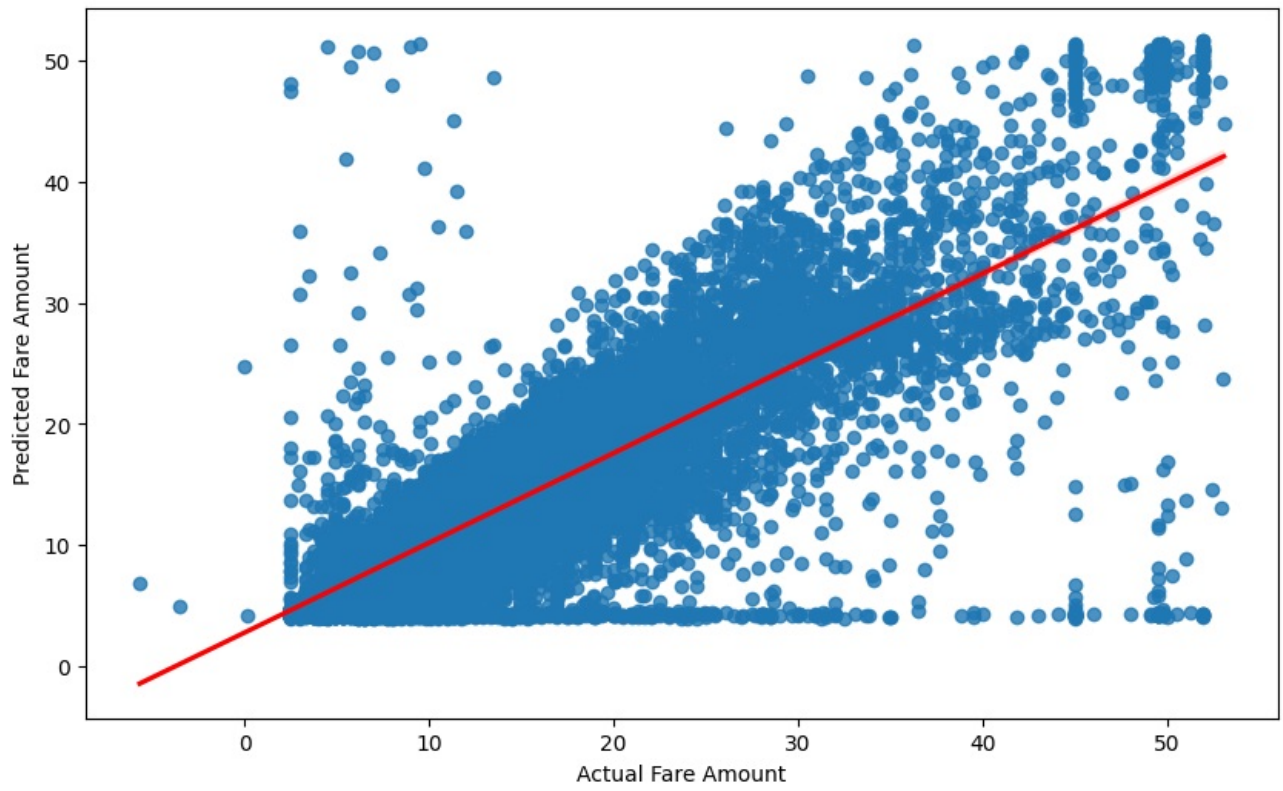
```
Out[27]: LinearRegression
LinearRegression()
```

```
In [28]: # Evaluate model
y_pred = model.predict(X_test)
print("R2 Score:", r2_score(y_test, y_pred))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred)))
print("MAE:", mean_absolute_error(y_test, y_pred))
```

```
R2 Score: 0.7318091906005604
RMSE: 3.9063550842642774
MAE: 2.273437684878074
```

```
In [29]: # Plot actual vs. predicted values
plt.figure(figsize=(10, 6))
sns.regplot(x=y_test, y=y_pred, line_kws={'color': 'red'})
plt.xlabel("Actual Fare Amount")
plt.ylabel("Predicted Fare Amount")
plt.title("Actual vs. Predicted Fare Amounts")
plt.show()
```

Actual vs. Predicted Fare Amounts



In []:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js