

```
In [138... # Predict the price of the Uber ride from a given pickup point to the agreed drop-o
# Location. Perform following tasks:
# 1. Pre-process the dataset.
# 2. Identify outliers.
# 3. Check the correlation.
# 4. Implement Linear regression and ridge, Lasso regression models.
# 5. Evaluate the models and compare their respective scores like R2, RMSE, etc.
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```
In [139... 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
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import mean_squared_error, r2_score
from math import radians, cos, sin, asin, sqrt
```

```
In [140... uber = pd.read_csv('uber.csv')
uber.head()
```

```
Out[140...      Unnamed: 0   key  fare_amount  pickup_datetime  pickup_longitude  pickup_
0          24238194 2015-05-07           7.5  2015-05-07
19:52:06.00000003 19:52:06 UTC    -73.999817        40
1          27835199 2009-07-17           7.7  2009-07-17
20:04:56.00000002 20:04:56 UTC    -73.994355        40
2          44984355 2009-08-24          12.9  2009-08-24
21:45:00.00000061 21:45:00 UTC    -74.005043        40
3          25894730 2009-06-26           5.3  2009-06-26
08:22:21.00000001 08:22:21 UTC    -73.976124        40
4          17610152 2014-08-28          16.0  2014-08-28
17:47:00.0000000188 17:47:00 UTC    -73.925023        40
```



```
In [141... print("Number of columns: ", uber.shape[1])
print("Number of rows: ", uber.shape[0])
```

```
Number of columns: 9
Number of rows: 200000
```

```
In [142... uber.columns
```

```
Out[142... Index(['Unnamed: 0', 'key', 'fare_amount', 'pickup_datetime',
       'pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

```
In [143... uber.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
```

```
In [144... print("Missing values: ", uber.isnull().sum())
```

```
Missing 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
```

```
In [145... uber = uber.drop(['Unnamed: 0', 'key'], axis=1)
uber.head()
```

```
Out[145...      fare_amount  pickup_datetime  pickup_longitude  pickup_latitude  dropoff_longitude  dr
 0            7.5    2015-05-07
                 19:52:06 UTC      -73.999817      40.738354     -73.999512
 1            7.7    2009-07-17
                 20:04:56 UTC      -73.994355      40.728225     -73.994710
 2           12.9    2009-08-24
                 21:45:00 UTC      -74.005043      40.740770     -73.962565
 3            5.3    2009-06-26
                 08:22:21 UTC      -73.976124      40.790844     -73.965316
 4           16.0    2014-08-28
                 17:47:00 UTC      -73.925023      40.744085     -73.973082
```



```
In [146... uber['pickup_datetime'] = pd.to_datetime(uber['pickup_datetime'], errors='coerce')
```

```
In [147... uber = uber.dropna(subset=['pickup_datetime'])
```

```
In [148...]: uber = uber.dropna(subset=['dropoff_longitude', 'dropoff_latitude'])
```

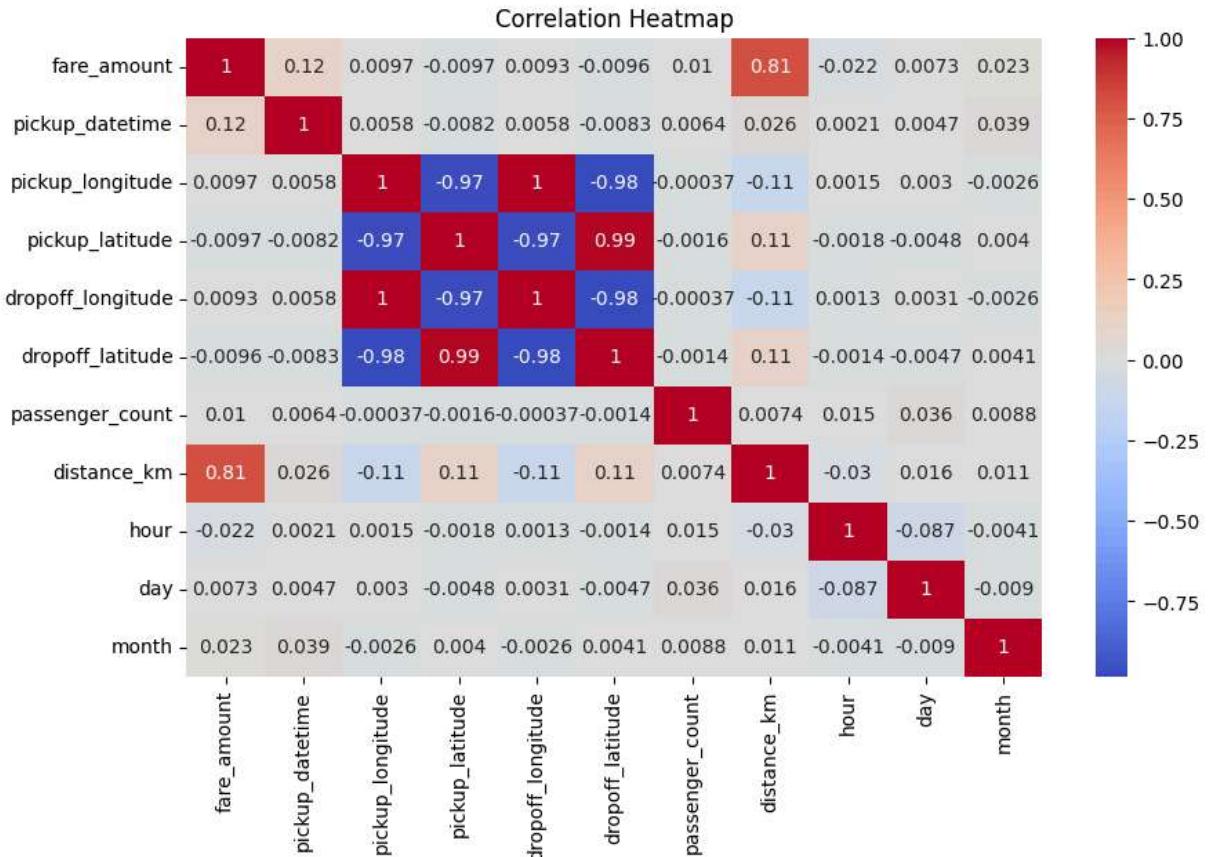
```
In [149...]: # Data Engineering
def haversine(lon1, lat1, lon2, lat2):
    lon1, lat1, lon2, lat2 = map(radians, [lon1, lat1, lon2, lat2])
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = sin(dlat/2)**2 + cos(lat1)*cos(lat2)*sin(dlon/2)**2
    c = 2 * asin(sqrt(a))
    km = 6371 * c
    return km
```

```
In [150...]: uber['distance_km'] = uber.apply(lambda row: haversine(
    row['pickup_longitude'], row['pickup_latitude'],
    row['dropoff_longitude'], row['dropoff_latitude']), axis=1)
```

```
In [151...]: uber['hour'] = uber['pickup_datetime'].dt.hour
uber['day'] = uber['pickup_datetime'].dt.dayofweek      # Monday=0, Sunday=6
uber['month'] = uber['pickup_datetime'].dt.month
```

```
In [152...]: #Outliers
uber = uber[(uber['fare_amount'] > 0) & (uber['fare_amount'] < 500)]
uber = uber[(uber['passenger_count'] > 0) & (uber['passenger_count'] <= 6)]
uber = uber[(uber['distance_km'] < 100)]
```

```
In [153...]: plt.figure(figsize=(10,6))
sns.heatmap(uber.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



In [154...]

```
# Prepare Data
X = uber[['pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
           'dropoff_latitude', 'passenger_count', 'distance_km',
           'hour', 'day', 'month']]
y = uber['fare_amount']
```

In [155...]

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [156...]

```
#Train models
lr = LinearRegression()
ridge = Ridge(alpha=1.0)
lasso = Lasso(alpha=0.1)

lr.fit(X_train, y_train)
ridge.fit(X_train, y_train)
lasso.fit(X_train, y_train)
```

Out[156...]

```
▼ Lasso ⓘ ?  
Lasso(alpha=0.1)
```

In [157...]

```
#Predictions
y_pred_lr = lr.predict(X_test)
y_pred_ridge = ridge.predict(X_test)
y_pred_lasso = lasso.predict(X_test)
```

```
In [158...]: # Evaluate models
def evaluate_model(y_true, y_pred, model_name):
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    r2 = r2_score(y_true, y_pred)
    print(f"{model_name} --> RMSE: {rmse:.2f}, R2: {r2:.3f}")


```

```
In [159...]: evaluate_model(y_test, y_pred_lr, "Linear Regression")
evaluate_model(y_test, y_pred_ridge, "Ridge Regression")
evaluate_model(y_test, y_pred_lasso, "Lasso Regression")
```

Linear Regression --> RMSE: 5.48, R2: 0.695

Ridge Regression --> RMSE: 5.48, R2: 0.695

Lasso Regression --> RMSE: 5.51, R2: 0.691