ML_1

November 10, 2025

[102]:
```
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
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
```

[103]:
```
# Load the dataset (change path if needed)
df = pd.read_csv(r"C:\Users\suraj\OneDrive\Desktop\LP3-master\ML\datasets\uber.
↪csv")
# Display first 5 rows
df.head()
```

[103]:
```
   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
```

[104]:
```python
# Remove missing values
df = df.dropna()

# Keep only positive fare values
df = df[df['fare_amount'] > 0]

# Convert pickup_datetime to datetime format
df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'], errors='coerce')
df = df.dropna(subset=['pickup_datetime'])

# Create a simple distance feature (approximation)
df['distance'] = ((df['dropoff_longitude'] - df['pickup_longitude'])**2 +
                  (df['dropoff_latitude'] - df['pickup_latitude'])**2)**0.5

# Remove rows where distance is 0
df = df[df['distance'] > 0]

print("Data after preprocessing:", df.shape)
df.head()
```

```
Data after preprocessing: (194347, 10)
```

[104]:
```
   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+00:00        -73.999817        40.738354
1 2009-07-17 20:04:56+00:00        -73.994355        40.728225
2 2009-08-24 21:45:00+00:00        -74.005043        40.740770
3 2009-06-26 08:22:21+00:00        -73.976124        40.790844
4 2014-08-28 17:47:00+00:00        -73.925023        40.744085

   dropoff_longitude  dropoff_latitude  passenger_count  distance
0         -73.999512         40.723217                1  0.015140
1         -73.994710         40.750325                1  0.022103
2         -73.962565         40.772647                1  0.053109
3         -73.965316         40.803349                3  0.016528
4         -73.973082         40.761247                5  0.051031
```

[105]:
```python
# Remove extreme outliers using IQR method on fare_amount
Q1 = df['fare_amount'].quantile(0.25)
Q3 = df['fare_amount'].quantile(0.75)
IQR = Q3 - Q1
low = Q1 - 1.5 * IQR
```

```python
high = Q3 + 1.5 * IQR
df = df[(df['fare_amount'] >= low) & (df['fare_amount'] <= high)]

# Remove unrealistic distance values (greater than 5 degrees ~ 500 km)
df = df[df['distance'] < 0.04]

print("Data after removing outliers:", df.shape)
df.head()
```

```
Data after removing outliers: (146319, 10)
```

[105]:

```
    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
3     25894730   2009-06-26 08:22:21.0000001          5.3
8     15822268  2012-02-17 09:32:00.00000043          9.7
10     2205147   2015-05-22 17:32:27.0000004          6.5

             pickup_datetime  pickup_longitude  pickup_latitude  \
0  2015-05-07 19:52:06+00:00        -73.999817        40.738354
1  2009-07-17 20:04:56+00:00        -73.994355        40.728225
3  2009-06-26 08:22:21+00:00        -73.976124        40.790844
8  2012-02-17 09:32:00+00:00        -73.975187        40.745767
10 2015-05-22 17:32:27+00:00        -73.974388        40.746952

    dropoff_longitude  dropoff_latitude  passenger_count  distance
0          -73.999512         40.723217                1  0.015140
1          -73.994710         40.750325                1  0.022103
3          -73.965316         40.803349                3  0.016528
8          -74.002720         40.743537                1  0.027623
10         -73.988586         40.729805                1  0.022262
```

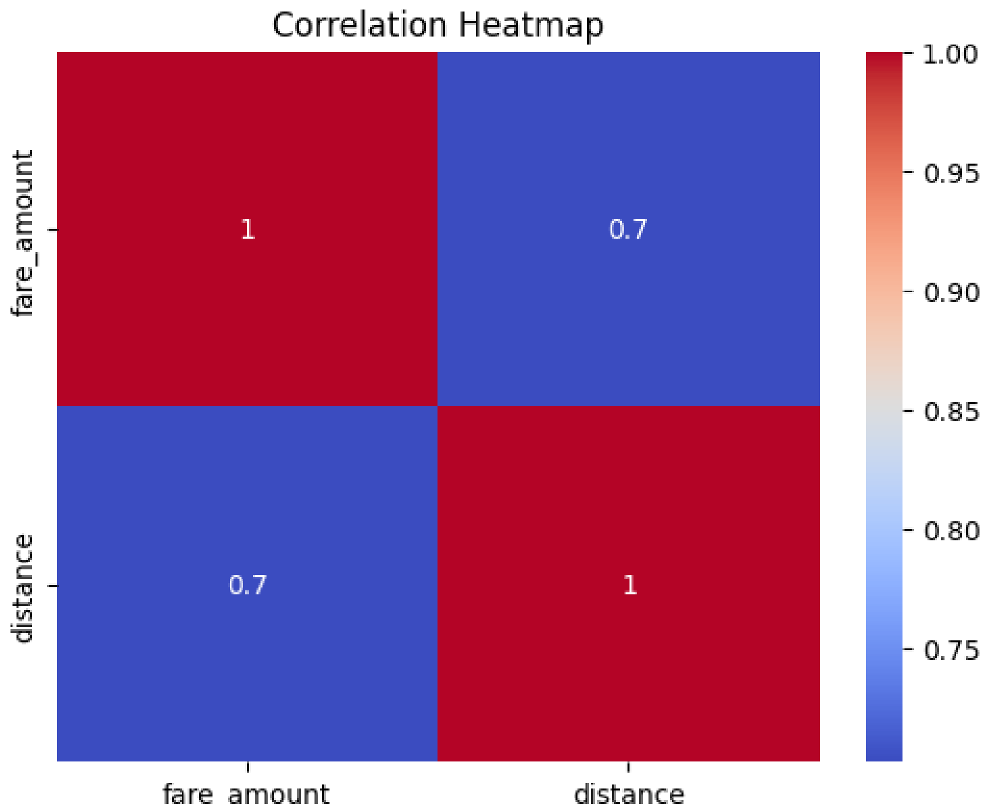
[106]:

```python
# Select numerical columns for correlation
corr = df[['fare_amount', 'distance']].corr()

# Print correlation
print("Correlation Matrix:")
print(corr)

# Plot heatmap
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```

```
Correlation Matrix:
             fare_amount  distance
fare_amount     1.000000  0.702447
distance        0.702447  1.000000
```



[107]:
```
# Extract time-based features
df['hour'] = df['pickup_datetime'].dt.hour
df['weekday'] = df['pickup_datetime'].dt.weekday
df['month'] = df['pickup_datetime'].dt.month

# Keep only useful columns
df = df[['fare_amount', 'distance', 'hour', 'weekday', 'month']]
df.head()
```

[107]:

	fare_amount	distance	hour	weekday	month
0	7.5	0.015140	19	3	5
1	7.7	0.022103	20	4	7
3	5.3	0.016528	8	4	6
8	9.7	0.027623	9	4	2
10	6.5	0.022262	17	4	5

[108]:
```
corr = df.corr()
print(corr)
```

```
             fare_amount  distance      hour   weekday     month
fare_amount     1.000000  0.702447  0.026125 -0.004165  0.038995
```

```
distance        0.702447  1.000000  0.013780  0.023288  0.007521
hour            0.026125  0.013780  1.000000 -0.076056 -0.002268
weekday        -0.004165  0.023288 -0.076056  1.000000 -0.010123
month           0.038995  0.007521 -0.002268 -0.010123  1.000000
```

[109]:

```python
# Define features and target
X = df[['distance', 'hour', 'weekday', 'month']]
y = df['fare_amount']

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42)

print("Training data:", X_train.shape)
print("Testing data:", X_test.shape)
```

```
Training data: (117055, 4)
Testing data: (29264, 4)
```

[110]:

```python
# Scale features for Linear Regression
scaler = StandardScaler()
X_train_s = scaler.fit_transform(X_train)
X_test_s = scaler.transform(X_test)

# Train Linear Regression
lr = LinearRegression()
lr.fit(X_train_s, y_train)

# Predict
y_pred_lr = lr.predict(X_test_s)
```

[111]:

```python
# Train Random Forest Regressor
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train_s, y_train)

# Predict
y_pred_rf = rf.predict(X_test_s)
```

[123]:

```python
# Define evaluation function
def evaluate(y_true, y_pred):
    r2 = r2_score(y_true, y_pred)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    mae = mean_absolute_error(y_true, y_pred)
    return round(r2, 4), round(rmse, 2), round(mae, 2)

# Evaluate both models
r2_lr, rmse_lr, mae_lr = evaluate(y_test, y_pred_lr)
r2_rf, rmse_rf, mae_rf = evaluate(y_test, y_pred_rf)
```

```python
# Create comparison table
results = pd.DataFrame({
    'Model': ['Linear Regression', 'Random Forest'],
    'R2 Score': [r2_lr, r2_rf],
    'RMSE': [rmse_lr, rmse_rf],
    'MAE': [mae_lr, mae_rf]
})

print("Model Comparison Results:")
display(results)
```

```
Model Comparison Results:

               Model  R2 Score  RMSE   MAE
0  Linear Regression    0.4982  2.09  1.47
1      Random Forest    0.4700  2.15  1.53
```

[ ]:

```

```