Assignment_1

August 21, 2024

[1]:
```python
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.metrics import r2_score, mean_squared_error

# Load the dataset
data = pd.read_csv("uber.csv")

data
```

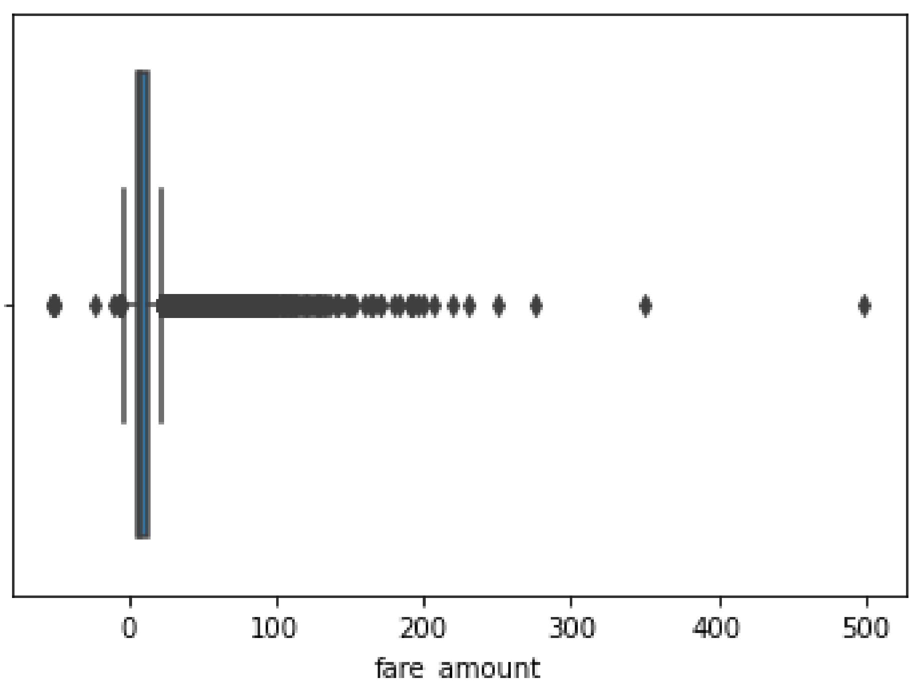
[1]:
```
        Unnamed: 0                          key  fare_amount  \
0         24238194   2015-05-07 19:52:06.0000003          7.5
1         27835199   2009-07-17 20:04:56.0000002          7.7
2         44984355  2009-08-24 21:45:00.00000061         12.9
3         25894730   2009-06-26 08:22:21.0000001          5.3
4         17610152  2014-08-28 17:47:00.000000188         16.0
…              …                             …          …
199995    42598914  2012-10-28 10:49:00.00000053          3.0
199996    16382965   2014-03-14 01:09:00.0000008          7.5
199997    27804658  2009-06-29 00:42:00.00000078         30.9
199998    20259894   2015-05-20 14:56:25.0000004         14.5
199999    11951496  2010-05-15 04:08:00.00000076         14.1

                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
…                           …               …              …
199995  2012-10-28 10:49:00 UTC        -73.987042        40.739367
199996  2014-03-14 01:09:00 UTC        -73.984722        40.736837
199997  2009-06-29 00:42:00 UTC        -73.986017        40.756487
```

```
199998  2015-05-20 14:56:25 UTC        -73.997124        40.725452
199999  2010-05-15 04:08:00 UTC        -73.984395        40.720077

        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
…                     …                …               …
199995         -73.986525         40.740297                1
199996         -74.006672         40.739620                1
199997         -73.858957         40.692588                2
199998         -73.983215         40.695415                1
199999         -73.985508         40.768793                1

[200000 rows x 9 columns]
```

[2]:
```
# 1. Pre-process the dataset

# Remove unnecessary column
data["pickup_datetime"] = pd.to_datetime(data["pickup_datetime"])

missing_values = data.isnull().sum()
print("Missing values in the dataset:")
print(missing_values)

# Handle missing values
# We can choose to drop rows with missing values or fill them with appropriate␣
↪values.

data.dropna(inplace=True)

# To fill missing values with the mean value of the column:
# data.fillna(data.mean(), inplace=True)

# Ensure there are no more missing values
missing_values = data.isnull().sum()
print("Missing values after handling:")
print(missing_values)

# 2. Identify outliers
# visualization to detect outliers.
sns.boxplot(x=data["fare_amount"])
plt.show()
```

```
Missing values in the dataset:
```

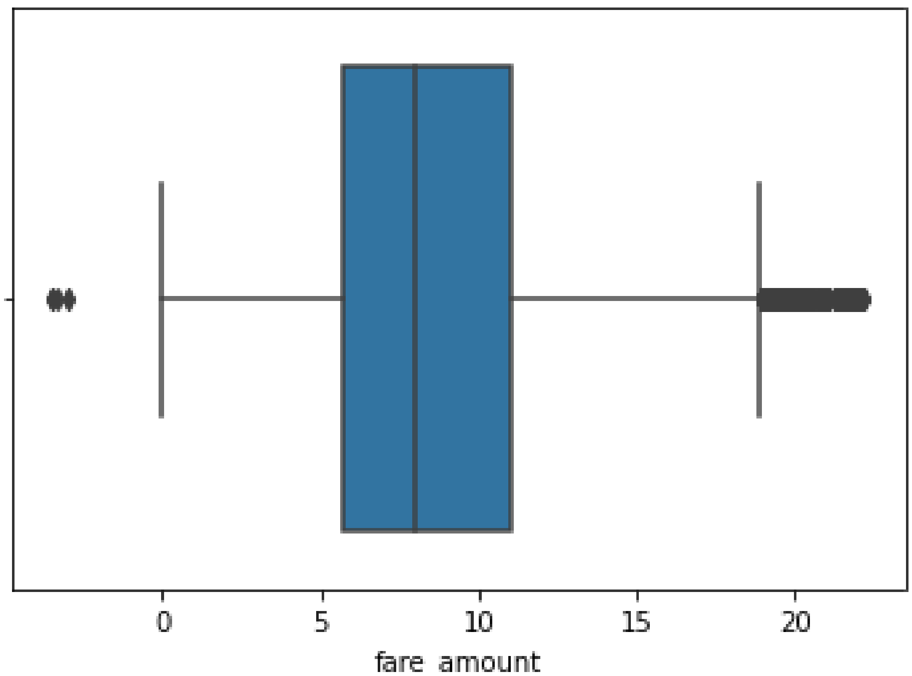
```
Unnamed: 0            0
key                   0
fare_amount           0
pickup_datetime       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude     1
dropoff_latitude      1
passenger_count       0
dtype: int64
Missing values after handling:
Unnamed: 0            0
key                   0
fare_amount           0
pickup_datetime       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude     0
dropoff_latitude      0
passenger_count       0
dtype: int64
```



[3]:

```
# Calculate the IQR for the 'fare_amount' column
Q1 = data["fare_amount"].quantile(0.25)
Q3 = data["fare_amount"].quantile(0.75)
```

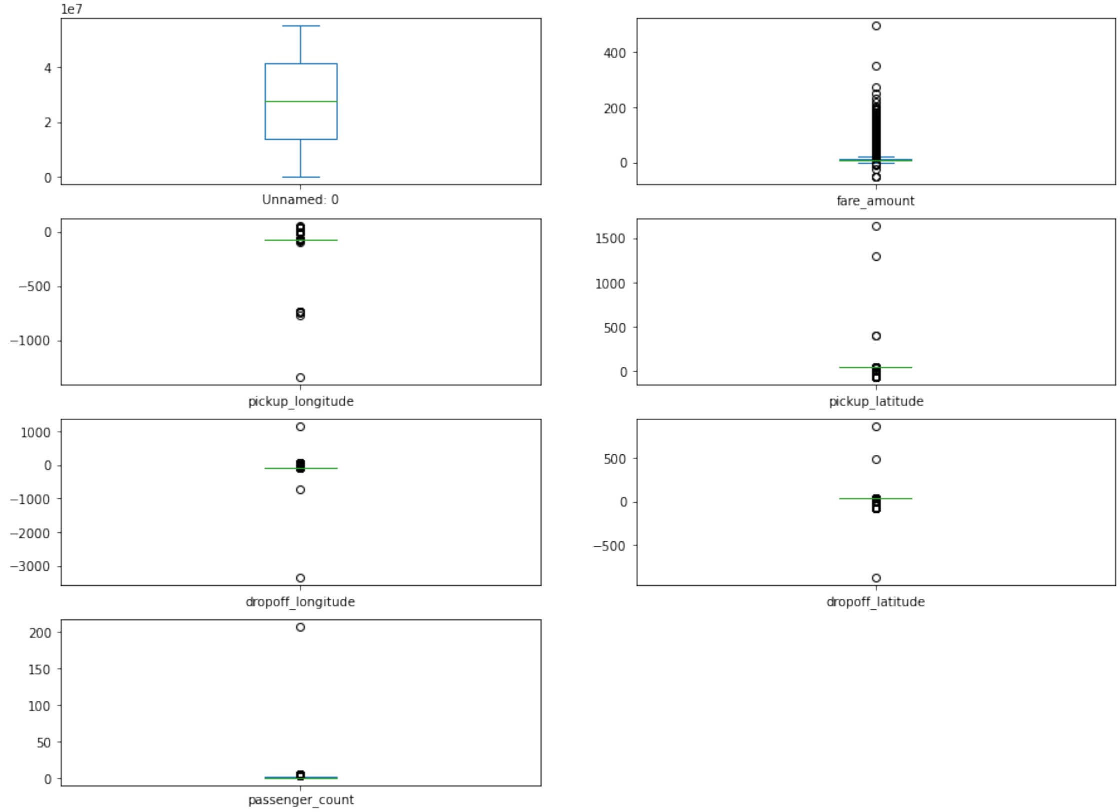
```
IQR = Q3 - Q1

# Define a threshold (e.g., 1.5 times the IQR) to identify outliers
threshold = 1.5
lower_bound = Q1 - threshold * IQR
upper_bound = Q3 + threshold * IQR

# Remove outliers
data_no_outliers = data[(data["fare_amount"] >= lower_bound) &
 ↪(data["fare_amount"] <= upper_bound)]

# Visualize the 'fare_amount' distribution without outliers
sns.boxplot(x=data_no_outliers["fare_amount"])
plt.show()
```



[4]:
```
data.plot(kind="box",subplots=True, layout=(7, 2), figsize=(15, 20))
```

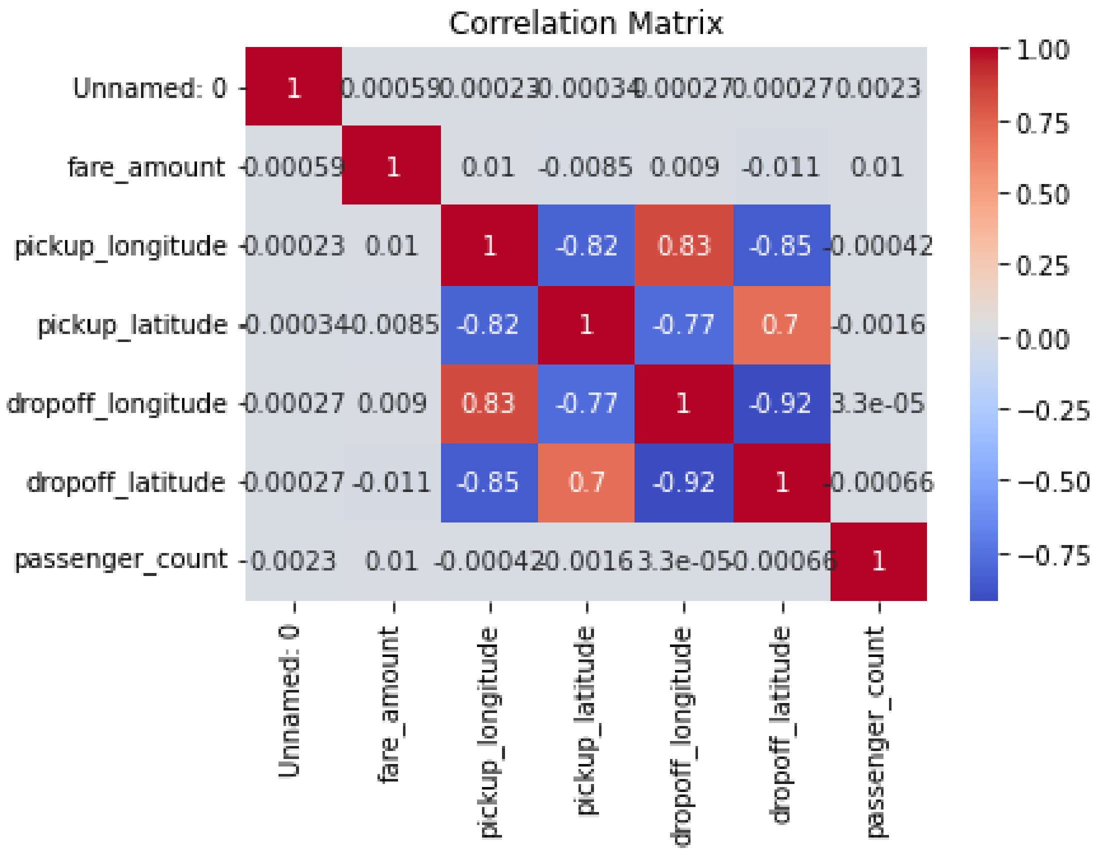
[4]:
```
Unnamed: 0              AxesSubplot(0.125,0.787927;0.352273x0.0920732)
fare_amount          AxesSubplot(0.547727,0.787927;0.352273x0.0920732)
pickup_longitude        AxesSubplot(0.125,0.677439;0.352273x0.0920732)
pickup_latitude      AxesSubplot(0.547727,0.677439;0.352273x0.0920732)
dropoff_longitude       AxesSubplot(0.125,0.566951;0.352273x0.0920732)
dropoff_latitude     AxesSubplot(0.547727,0.566951;0.352273x0.0920732)
passenger_count         AxesSubplot(0.125,0.456463;0.352273x0.0920732)
```

```
dtype: object
```



[5]:

```
# 3. Check the correlation
# Determine the correlation between features and the target variable␣
↪(fare_amount).
numeric_data = data.select_dtypes(include=[int, float])

# Calculate the correlation matrix
correlation_matrix = numeric_data.corr()

# Plot the heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



[6]:
```
# 4. Implement linear regression and random forest regression models
# Split the data into features and target variable
X = data[['pickup_longitude', 'pickup_latitude', 'dropoff_longitude',␣
↪'dropoff_latitude', 'passenger_count']]
y = data['fare_amount']  #Target

y
```

[6]:
```
0          7.5
1          7.7
2         12.9
3          5.3
4         16.0
          …
199995     3.0
199996     7.5
199997    30.9
199998    14.5
199999    14.1
Name: fare_amount, Length: 199999, dtype: float64
```

[7]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[8]:
```
# Create and train the linear regression model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

[8]:
```
LinearRegression()
```

[9]:
```
# Create and train the random forest regression model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

[9]:
```
RandomForestRegressor(random_state=42)
```

[10]:
```
# 5. Evaluate the models
# Predict the values
y_pred_lr = lr_model.predict(X_test)
y_pred_lr
print("Linear Model:",y_pred_lr)
y_pred_rf = rf_model.predict(X_test)
print("Random Forest Model:", y_pred_rf)
```

```
Linear Model: [11.29237916 11.29171388 11.5718662  … 11.29183291 11.43252639
 11.29190248]
Random Forest Model: [ 9.26    5.043   12.577   …  6.8057 11.264   8.304 ]
```

[11]:
```
# Calculate R-squared (R2) and Root Mean Squared Error (RMSE) for both models
r2_lr = r2_score(y_test, y_pred_lr)
rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
```

[12]:
```
# Compare the scores
print("Linear Regression - R2:", r2_lr)
print("Linear Regression - RMSE:", rmse_lr)
```

```
Linear Regression - R2: 0.00034152697863043535
Linear Regression - RMSE: 10.197470623964248
```

[13]:
```
r2_rf = r2_score(y_test, y_pred_rf)
rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))

print("Random Forest Regression R2:", r2_rf)
print("Random Forest Regression RMSE:",rmse_rf)
```

```
Random Forest Regression R2: 0.701102567545169
Random Forest Regression RMSE: 5.576063738722296
```

[14]:

```
# Overall Analysis

# The Random Forest Regression model has significantly improved the predictive␣
↪performance.
# An R-squared (R2) value of approximately 0.701 and a Root Mean Squared Error␣
↪(RMSE)
# of approximately 5.575 indicate that the Random Forest model is capturing a␣
↪substantial portion
# of the variance in the target variable and providing more accurate␣
↪predictions compared to the linear regression model.
```

[ ]:

```

```