1 IMPORTING THE NECESSARY LIBRARIES

[31]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

2 UPLOADING THE DATASET(CSV FORMAT) TO THE WORKSPACE

[32]:
```
data=pd.read_csv('CO2_Emissions.csv')
```

[33]:
```
data
```

[33]:
```
      Engine Size(L)  Cylinders  Fuel Consumption City (L/100 km)  \
0                2.0          4                               9.9
1                2.4          4                              11.2
2                1.5          4                               6.0
3                3.5          6                              12.7
4                3.5          6                              12.1
…                 …         …                                 …
7380             2.0          4                              10.7
7381             2.0          4                              11.2
7382             2.0          4                              11.7
7383             2.0          4                              11.2
7384             2.0          4                              12.2

      Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100 km)  \
0                                 6.7                               8.5
1                                 7.7                               9.6
2                                 5.8                               5.9
3                                 9.1                              11.1
4                                 8.7                              10.6
…                                …                                 …
7380                              7.7                               9.4
7381                              8.3                               9.9
7382                              8.6                              10.3
```

```
7383                             8.3                              9.9
7384                             8.7                             10.7

      Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)
0                              33                  196
1                              29                  221
2                              48                  136
3                              25                  255
4                              27                  244
…                           …                  …
7380                           30                  219
7381                           29                  232
7382                           27                  240
7383                           29                  232
7384                           26                  248

[7385 rows x 7 columns]
```

3 EXPLORATORY DATA ANALYSIS

[34]:
```python
#I am renaming the columns as they have spaces between them,and also to improve␣
↪readability of features
data.rename(columns={ 'Engine Size(L)': 'engine_size','Cylinders':␣
↪'cylinders','Fuel Consumption City (L/100 km)': 'fuel_cons_city',
                      'Fuel Consumption Hwy (L/100 km)': 'fuel_cons_hwy','Fuel␣
↪Consumption Comb (L/100 km)': 'fuel_cons_comb',
                      'Fuel Consumption Comb (mpg)': 'fuel_cons_comb_mpg','CO2␣
↪Emissions(g/km)': 'co2'
                    } , inplace=True)
```

[35]:
```python
data.head()
```

[35]:
```
   engine_size  cylinders  fuel_cons_city  fuel_cons_hwy  fuel_cons_comb  \
0          2.0          4             9.9            6.7             8.5
1          2.4          4            11.2            7.7             9.6
2          1.5          4             6.0            5.8             5.9
3          3.5          6            12.7            9.1            11.1
4          3.5          6            12.1            8.7            10.6

   fuel_cons_comb_mpg  co2
0                  33  196
1                  29  221
2                  48  136
3                  25  255
4                  27  244
```

[36]:
```
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   engine_size        7385 non-null   float64
 1   cylinders          7385 non-null   int64
 2   fuel_cons_city     7385 non-null   float64
 3   fuel_cons_hwy      7385 non-null   float64
 4   fuel_cons_comb     7385 non-null   float64
 5   fuel_cons_comb_mpg 7385 non-null   int64
 6   co2                7385 non-null   int64
dtypes: float64(4), int64(3)
memory usage: 404.0 KB
None
```

[37]:
```
data.describe()
```

[37]:
```
       engine_size    cylinders  fuel_cons_city  fuel_cons_hwy  \
count  7385.000000  7385.000000     7385.000000    7385.000000
mean      3.160068     5.615030       12.556534       9.041706
std       1.354170     1.828307        3.500274       2.224456
min       0.900000     3.000000        4.200000       4.000000
25%       2.000000     4.000000       10.100000       7.500000
50%       3.000000     6.000000       12.100000       8.700000
75%       3.700000     6.000000       14.600000      10.200000
max       8.400000    16.000000       30.600000      20.600000

       fuel_cons_comb  fuel_cons_comb_mpg          co2
count     7385.000000         7385.000000  7385.000000
mean        10.975071           27.481652   250.584699
std          2.892506            7.231879    58.512679
min          4.100000           11.000000    96.000000
25%          8.900000           22.000000   208.000000
50%         10.600000           27.000000   246.000000
75%         12.600000           32.000000   288.000000
max         26.100000           69.000000   522.000000
```

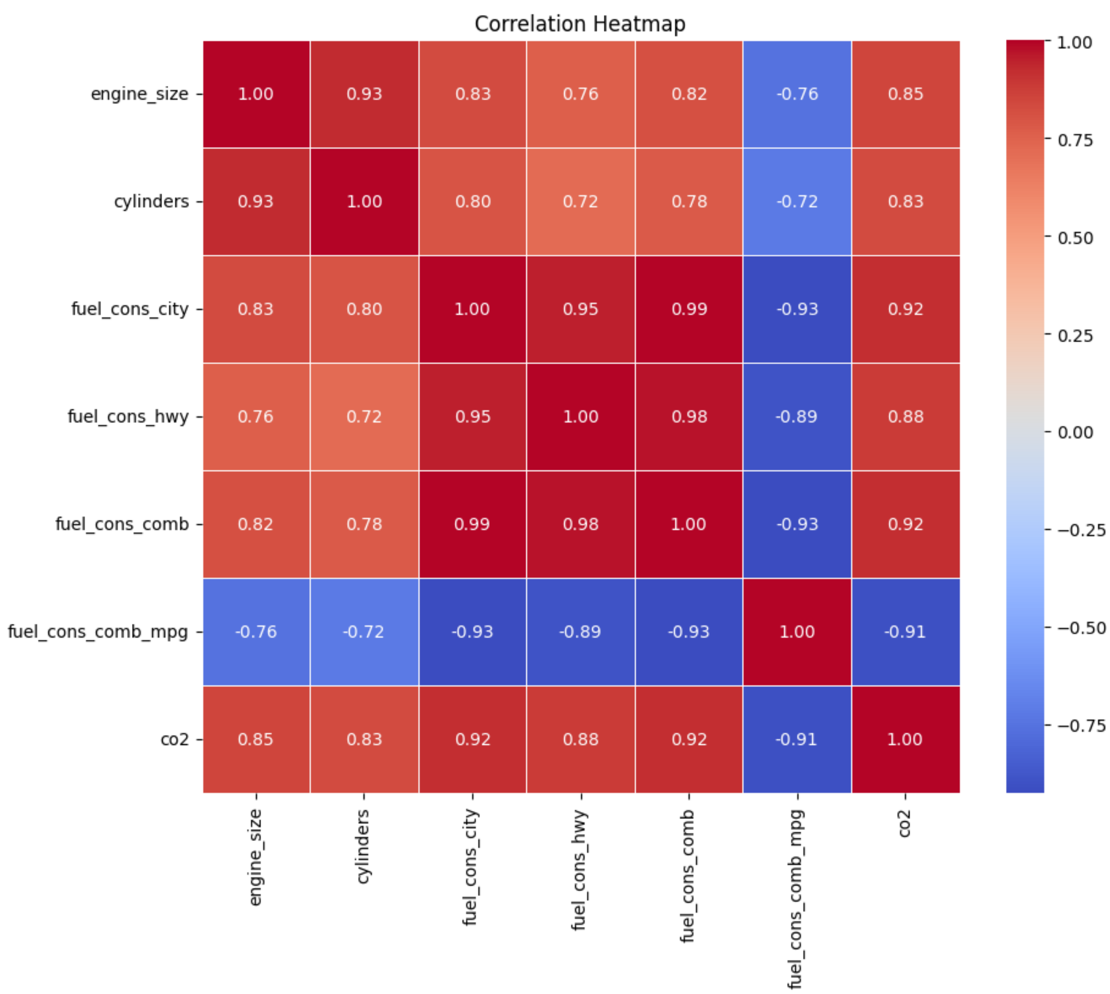
[38]:
```
data.shape
```

[38]:
```
(7385, 7)
```

[39]:
```
data.isnull().sum()
```

[39]:
```
engine_size          0
cylinders            0
fuel_cons_city       0
fuel_cons_hwy        0
fuel_cons_comb       0
fuel_cons_comb_mpg   0
co2                  0
dtype: int64
```

[40]:
```
import seaborn as sns
corr_matrix = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



[41]:
```
# Dropping the redundant features(which are highly correlated with each other)
data.drop(columns=['fuel_cons_city', 'fuel_cons_hwy', 'fuel_cons_comb_mpg'],␣
↪inplace=True)
```

[42]:
```
data
```

[42]:
```
      engine_size  cylinders  fuel_cons_comb  co2
0             2.0          4             8.5  196
1             2.4          4             9.6  221
2             1.5          4             5.9  136
3             3.5          6            11.1  255
4             3.5          6            10.6  244
…             …          …              …  …
7380          2.0          4             9.4  219
7381          2.0          4             9.9  232
7382          2.0          4            10.3  240
7383          2.0          4             9.9  232
7384          2.0          4            10.7  248

[7385 rows x 4 columns]
```

[43]:
```
x=data.iloc[:,:-1].values
y=data.iloc[:,-1].values
```

4 SCALING THE NECESSARY FEATURES

[44]:
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x=sc.fit_transform(x)
```

[45]:
```
x.shape
```

[45]:
```
(7385, 3)
```

[46]:
```
x
```

[46]:
```
array([[-0.85672099, -0.88340757, -0.85574185],
       [-0.5613172 , -0.88340757, -0.47542306],
       [-1.22597573, -0.88340757, -1.75467716],
       …,
       [-0.85672099, -0.88340757, -0.23340202],
       [-0.85672099, -0.88340757, -0.37169976],
       [-0.85672099, -0.88340757, -0.09510428]])
```

5 SPLITTING THE DATASET INTO TRAINING SET AND TEST SET

[47]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
```

6 Training the Multiple Linear Regression model on the Training set

[48]:
```
from sklearn.linear_model import LinearRegression
regressor=LinearRegression()
regressor.fit(x_train,y_train)
```

[48]:
```
LinearRegression()
```

7 Predicting the Test set results

[49]:
```
y_pred=regressor.predict(x_test)
```

[50]:
```
y_pred
```

[50]:
```
array([243.31052887, 200.93236303, 256.83307024, …, 228.66076015,
       170.66557481, 220.75232578])
```

8 EVALUATING THE MODEL NOW

[51]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score,␣
 ↪root_mean_squared_error
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = root_mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print the evaluation metrics
print(f"Mean Absolute Error: {mae:.2f}")
print(f"Mean Squared Error: {mse:.2f}")
print(f"Root Mean Squared Error: {rmse:.2f}")
print(f"R-squared: {r2:.2f}")
```

```
Mean Absolute Error: 13.56
Mean Squared Error: 421.59
Root Mean Squared Error: 20.53
R-squared: 0.88
```

9 VISUALISING THE RESULT

[52]:
```
import matplotlib.pyplot as plt
plt.scatter(y_test, y_pred)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs Predicted')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
plt.show()
```