CSE343: Machine Learning Assignmnet 1

Section C (Algorithm implementation using packages)

Q3. Implementation of linear regression using libraries:- Split the dataset into 80:20 (train:test)

Dataset: CO2 Emissions Dataset

- Importing the required libraries

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA
from sklearn.linear_model import SGDRegressor
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.metrics import mean_squared_error, r2_score,
mean_absolute_error
```

- Reading the dataset

```
data = pd.read_csv('CO2 Emissions.csv')
new_data = data.drop(['Make', 'Model','Vehicle Class', 'Transmission',
'Fuel Type'], axis = 1)
scaled_data = StandardScaler().fit_transform(new_data)
# new_data = StandardScaler().fit_transform(new_data)
headers = ['Engine Size(L)', 'Cylinders',
       'Fuel Consumption City (L/100 km)',
       'Fuel Consumption Hwy (L/100 km)', 'Fuel Consumption Comb
(L/100 km)',
       'Fuel Consumption Comb (mpg)']
categorical_data = data[['Make', 'Model','Vehicle Class',
'Transmission', 'Fuel Type']]
data.head()
# headers

    Make       Model Vehicle Class  Engine Size(L)  Cylinders
Transmission  \
0  ACURA         ILX       COMPACT             2.0          4
AS5
1  ACURA         ILX       COMPACT             2.4          4
M6
2  ACURA  ILX HYBRID       COMPACT             1.5          4
```

```
AV7
3  ACURA     MDX 4WD   SUV - SMALL             3.5          6
AS6
4  ACURA     RDX AWD   SUV - SMALL             3.5          6
AS6

  Fuel Type  Fuel Consumption City (L/100 km)  \
0         Z                               9.9
1         Z                              11.2
2         Z                               6.0
3         Z                              12.7
4         Z                              12.1

   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


   Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)
0                           33                  196
1                           29                  221
2                           48                  136
3                           25                  255
4                           27                  244
```

```
data['Make'].unique()
```

```
array(['ACURA', 'ALFA ROMEO', 'ASTON MARTIN', 'AUDI', 'BENTLEY',
'BMW',
       'BUICK', 'CADILLAC', 'CHEVROLET', 'CHRYSLER', 'DODGE', 'FIAT',
       'FORD', 'GMC', 'HONDA', 'HYUNDAI', 'INFINITI', 'JAGUAR',
'JEEP',
       'KIA', 'LAMBORGHINI', 'LAND ROVER', 'LEXUS', 'LINCOLN',
'MASERATI',
       'MAZDA', 'MERCEDES-BENZ', 'MINI', 'MITSUBISHI', 'NISSAN',
       'PORSCHE', 'RAM', 'ROLLS-ROYCE', 'SCION', 'SMART', 'SRT',
'SUBARU',
       'TOYOTA', 'VOLKSWAGEN', 'VOLVO', 'GENESIS', 'BUGATTI'],
      dtype=object)
```

```
data['Model'].unique()
```

```
array(['ILX', 'ILX HYBRID', 'MDX 4WD', ...,
       'Tacoma 4WD D-Cab TRD Off-Road/Pro', 'Atlas Cross Sport 
4MOTION',
       'XC40 T4 AWD'], dtype=object)
```

```
data['Vehicle Class'].unique()
```

```
array(['COMPACT', 'SUV - SMALL', 'MID-SIZE', 'TWO-SEATER', 
'MINICOMPACT',
       'SUBCOMPACT', 'FULL-SIZE', 'STATION WAGON - SMALL',
       'SUV - STANDARD', 'VAN - CARGO', 'VAN - PASSENGER',
       'PICKUP TRUCK - STANDARD', 'MINIVAN', 'SPECIAL PURPOSE 
VEHICLE',
       'STATION WAGON - MID-SIZE', 'PICKUP TRUCK - SMALL'], 
dtype=object)
```

```
data['Transmission'].unique()
```

```
array(['AS5', 'M6', 'AV7', 'AS6', 'AM6', 'A6', 'AM7', 'AV8', 'AS8', 
'A7',
       'A8', 'M7', 'A4', 'M5', 'AV', 'A5', 'AS7', 'A9', 'AS9', 'AV6',
       'AS4', 'AM5', 'AM8', 'AM9', 'AS10', 'A10', 'AV10'], 
dtype=object)
```

```
data['Fuel Type'].unique()
```

```
array(['Z', 'D', 'X', 'E', 'N'], dtype=object)
```

```
data.isnull().sum()
```

```
Make                                0
Model                               0
Vehicle Class                       0
Engine Size(L)                      0
Cylinders                           0
Transmission                        0
Fuel Type                           0
Fuel Consumption City (L/100 km)    0
Fuel Consumption Hwy (L/100 km)     0
Fuel Consumption Comb (L/100 km)    0
Fuel Consumption Comb (mpg)         0
CO2 Emissions(g/km)                 0
dtype: int64
```

The given data doesn't have any null data in the dataframe.

```
# x = data[['Engine Size(L)']]
# y = data[['CO2 Emissions(g/km)']]
```

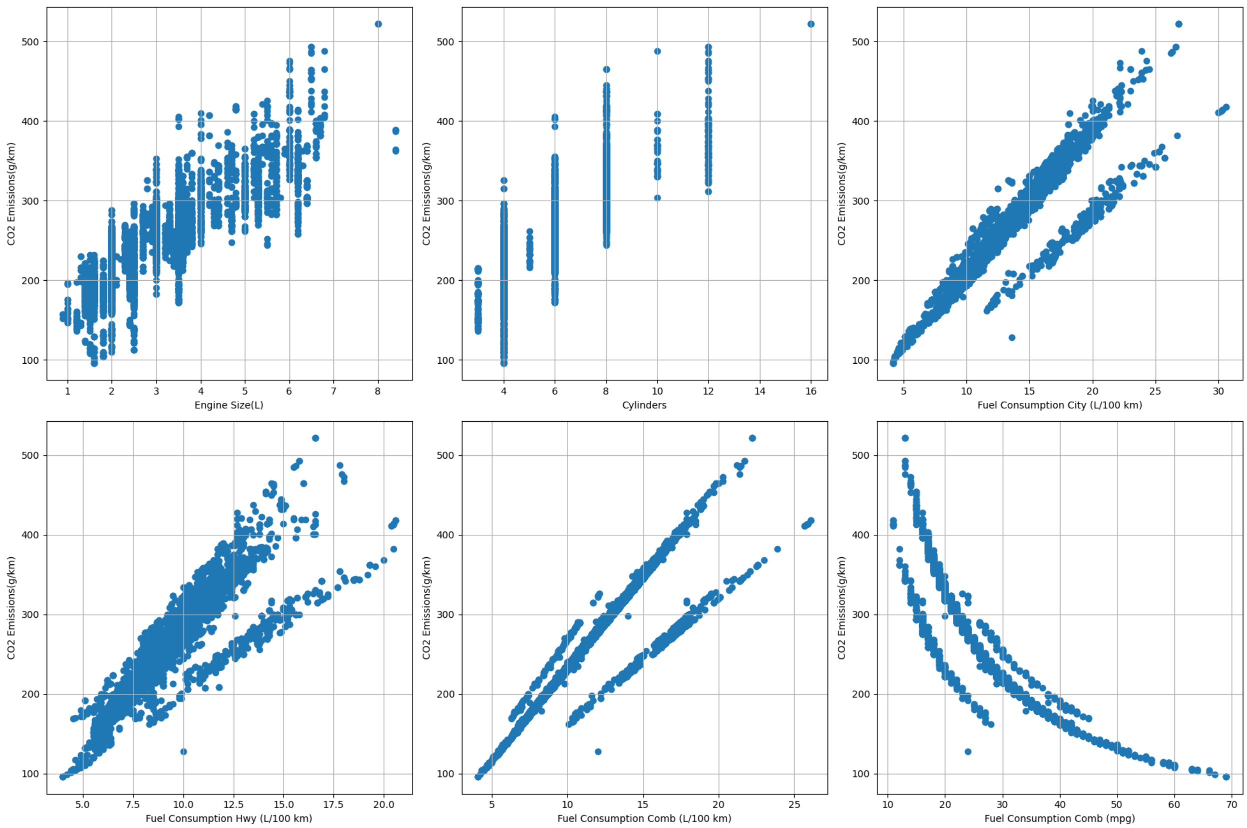
```
# plt.scatter(x, y, color='blue')
# plt.xlabel('Engine Size(L)')
# plt.ylabel('CO2 Emissions(g/km)')
```

Part A.

• Scatter plots of the dataset.

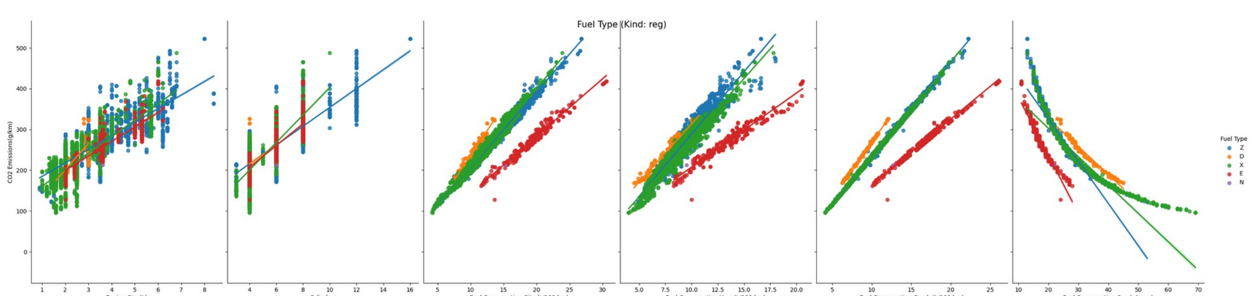
1. Scatter Plot is a graph in which the values of two variables are plotted along two axes, the pattern of the resulting points revealing any correlation present.

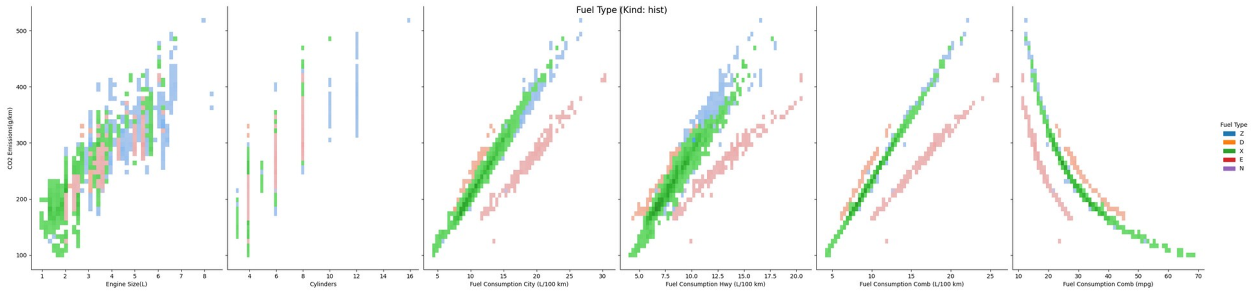
```
fig, axis = plt.subplots(2, 3, figsize=(18, 12))

axis[0, 0].scatter(data['Engine Size(L)'], data['CO2 
Emissions(g/km)'])
axis[0, 0].set(xlabel='Engine Size(L)', ylabel='CO2 Emissions(g/km)')
axis[0, 0].grid(True)

axis[0, 1].scatter(data['Cylinders'], data['CO2 Emissions(g/km)'])
axis[0, 1].set(xlabel='Cylinders', ylabel='CO2 Emissions(g/km)')
axis[0, 1].grid(True)

axis[0, 2].scatter(data['Fuel Consumption City (L/100 km)'], data['CO2 
Emissions(g/km)'])
axis[0, 2].set(xlabel='Fuel Consumption City (L/100 km)', ylabel='CO2 
Emissions(g/km)')
axis[0, 2].grid(True)

axis[1, 0].scatter(data['Fuel Consumption Hwy (L/100 km)'], data['CO2 
Emissions(g/km)'])
axis[1, 0].set(xlabel='Fuel Consumption Hwy (L/100 km)', ylabel='CO2 
Emissions(g/km)')
axis[1, 0].grid(True)

axis[1, 1].scatter(data['Fuel Consumption Comb (L/100 km)'], data['CO2 
Emissions(g/km)'])
axis[1, 1].set(xlabel='Fuel Consumption Comb (L/100 km)', ylabel='CO2 
Emissions(g/km)')
axis[1, 1].grid(True)

axis[1, 2].scatter(data['Fuel Consumption Comb (mpg)'], data['CO2 
Emissions(g/km)'])
axis[1, 2].set(xlabel='Fuel Consumption Comb (mpg)', ylabel='CO2 
Emissions(g/km)')
axis[1, 2].grid(True)

plt.tight_layout() #to automatically adjust subplot parameters without 
overlapping
plt.show()
```

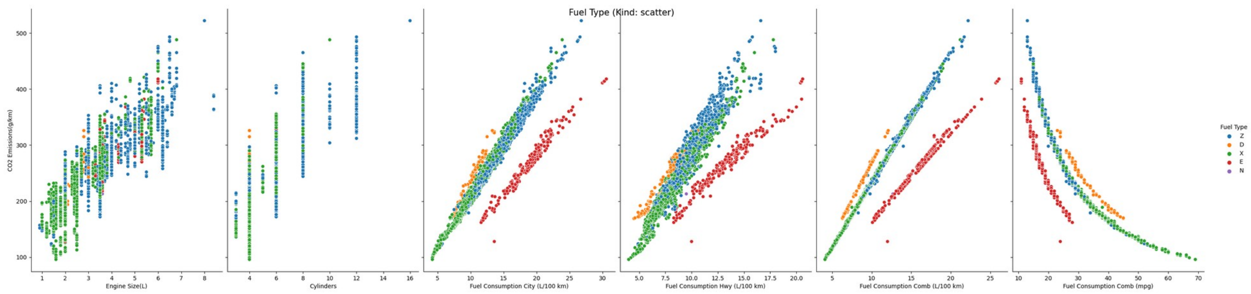


- Pair Plots of the dataset.
  1. A pairs plot allows us to see both distribution of single variables and relationships between two variables.
  2. If the parameter is crowded at a particular value, it is not suitable for regression analysis.

```
#List of Pair Plot Types ('kde' also)
pptypes = ['reg', 'hist', 'scatter']

for kind in pptypes:
    sns.pairplot(data, x_vars=headers, y_vars='CO2 Emissions(g/km)',
height=7, aspect=0.7, kind=kind, hue='Fuel Type')
    # sns.pairplot(data, x_vars=headers, y_vars='CO2 Emissions(g/km)',
height=7, aspect=0.7, kind=kind, hue='Transmission')
    plt.suptitle(f'Fuel Type (Kind: {kind})', fontsize=15)
    plt.show()
```

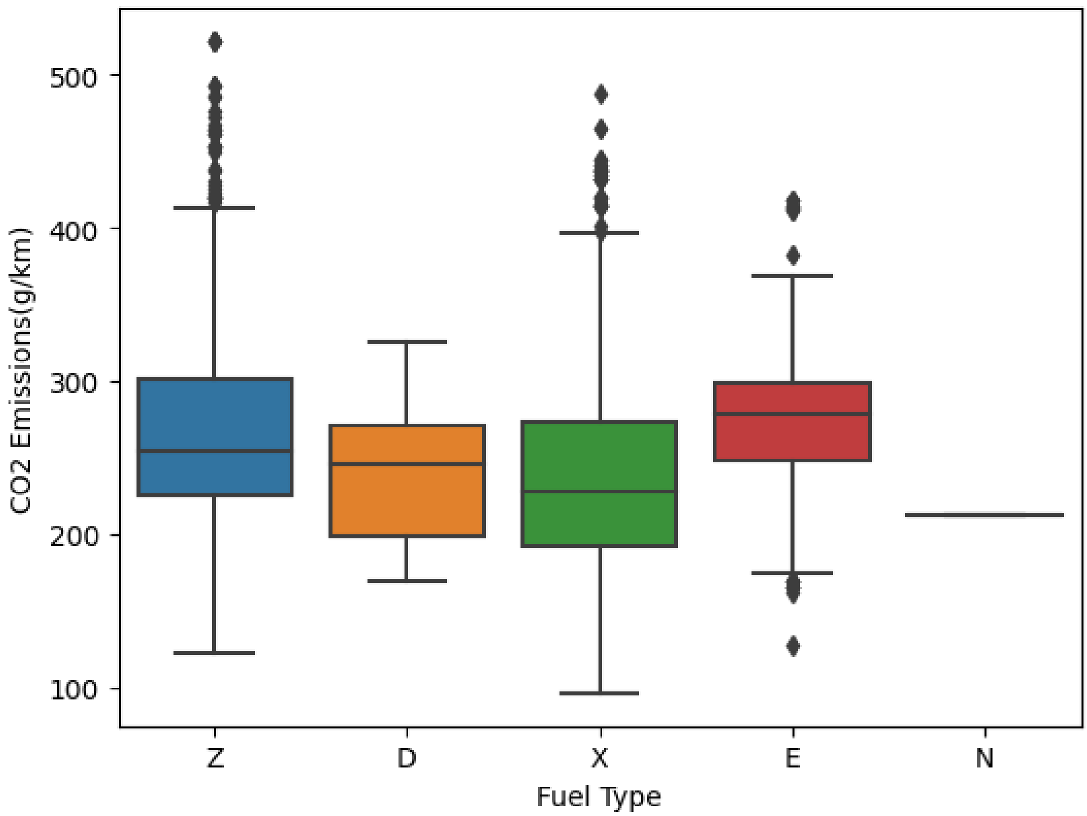




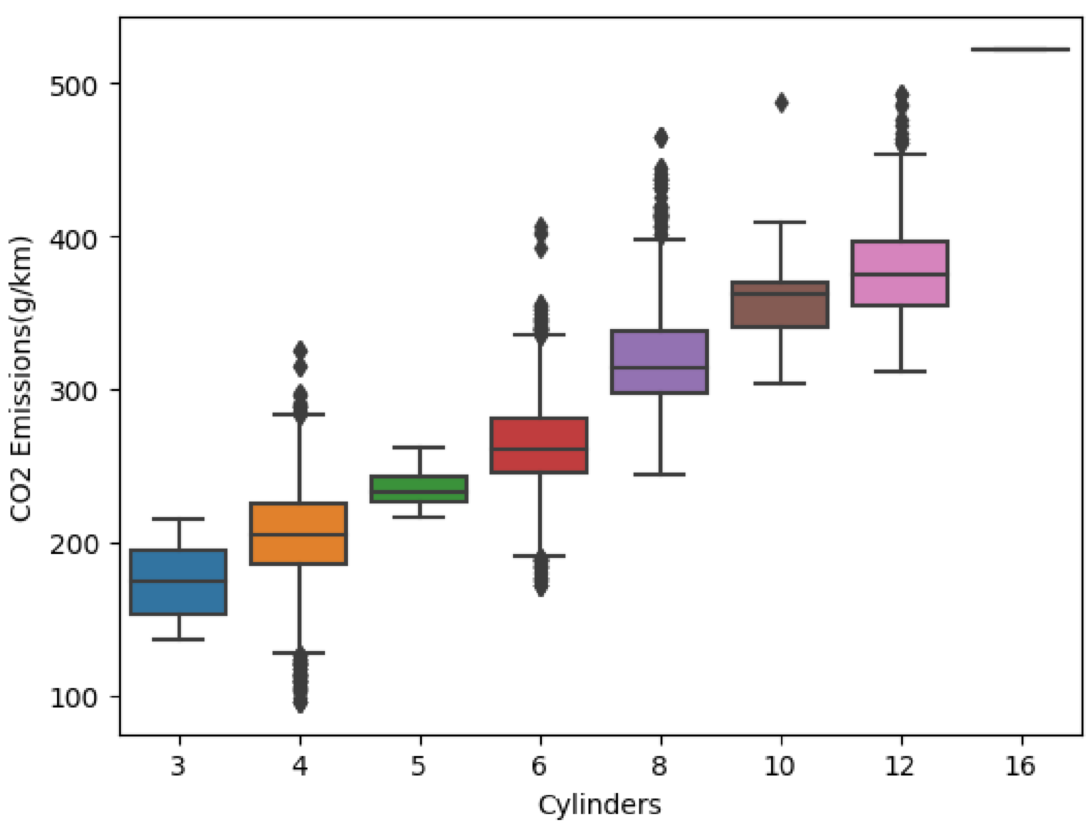


- Box plots of the dataset. (aka Box and Whisker Plot)
    1. It helps us to vizualize the distribution of the data by quartile, outliners and median.

```
sns.boxplot(data=data, x='Fuel Type', y='CO2 Emissions(g/km)')
plt.show()
sns.boxplot(data=data, x='Cylinders', y='CO2 Emissions(g/km)')
plt.show()

# Dropped other categorical columns because of intense unique values
```



CO2 Emissions(g/km)
100
200
300
400
500
Z
D
X
E
N
Fuel Type

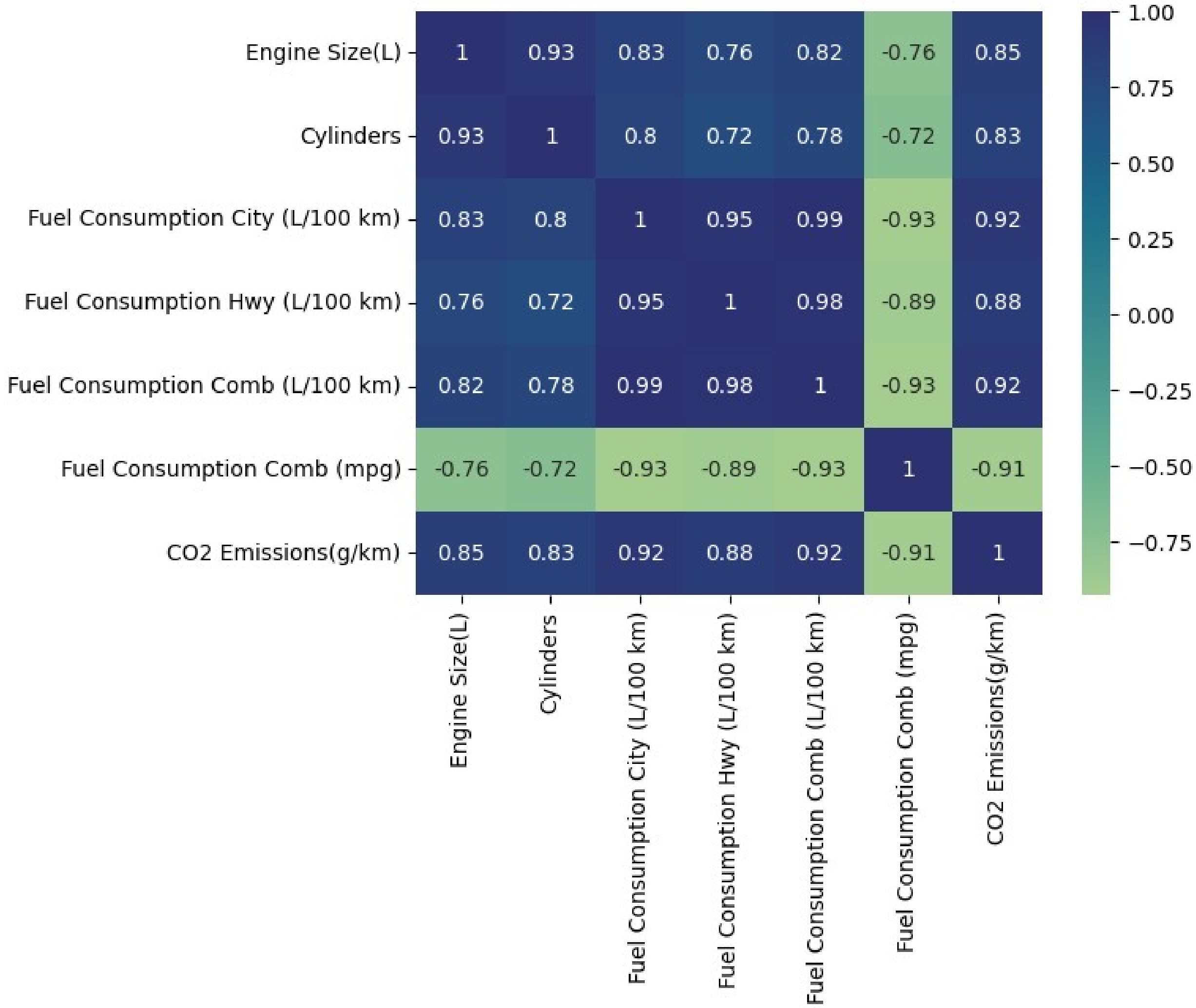


CO2 Emissions(g/km)
100
200
300
400
500
3
4
5
6
8
10
12
16
Cylinders

Correlation Heatmap of the dataset.

1. A correlation heatmap uses colored cells, typically in a monochromatic scale, to show a 2D correlation matrix (table) between two discrete dimensions or event types.
2. It is very important in Feature Selection.

```
correlation = new_data.corr() #corr() is used to identify the realtionships between variables. It generates a correlation matrix.
sns.heatmap(correlation, cmap='crest', annot=True)
plt.show()
```



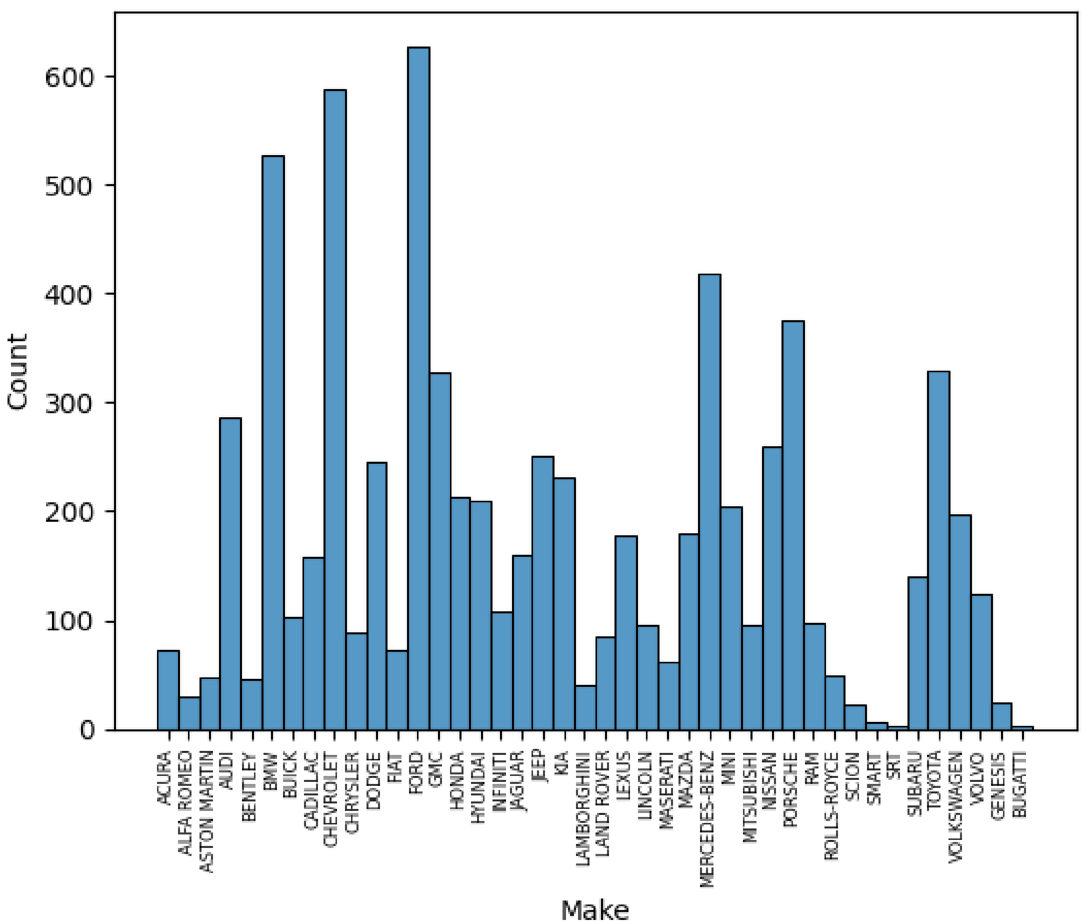
• Histogram

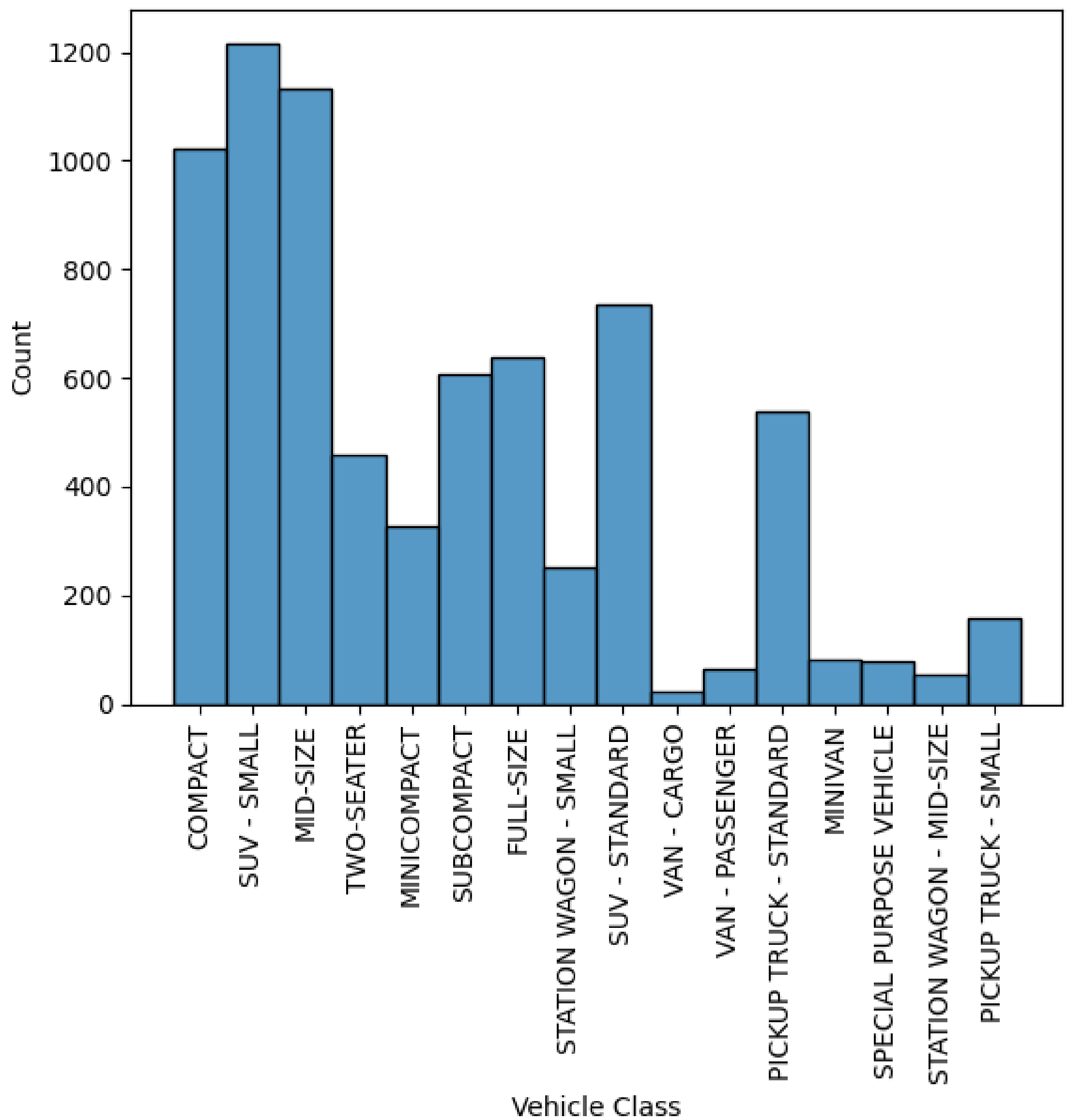
1. A histogram is a graphical display of data using bars of different heights.
2. In a histogram, each bar groups numbers into ranges. Taller bars show that more data falls in that range.

```
data.describe()
```

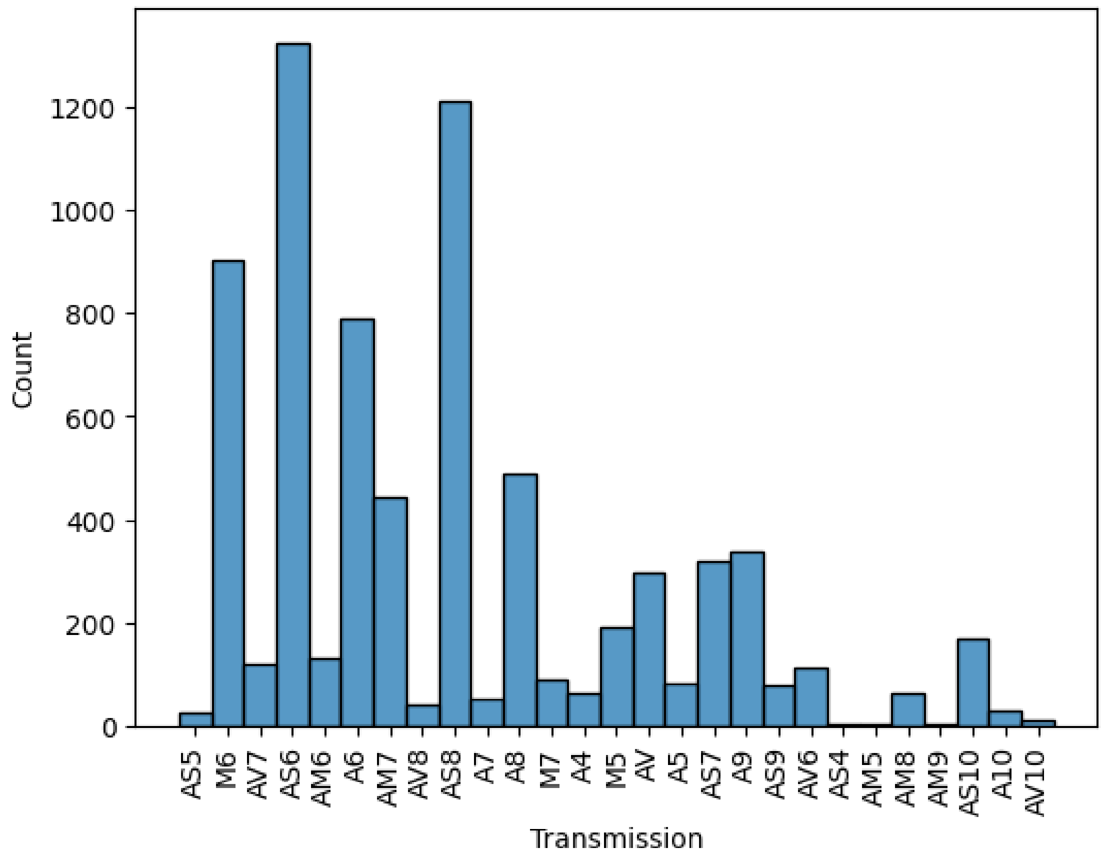
```
       Engine Size(L)    Cylinders  Fuel Consumption City (L/100
km)  \
count     7385.000000  7385.000000                          7385.000000

mean         3.160068     5.615030                            12.556534

std          1.354170     1.828307                             3.500274

min          0.900000     3.000000                             4.200000

25%          2.000000     4.000000                            10.100000

50%          3.000000     6.000000                            12.100000

75%          3.700000     6.000000                            14.600000

max          8.400000    16.000000                            30.600000


       Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100
km)  \
count                      7385.000000
7385.000000
mean                          9.041706
10.975071
std                           2.224456
2.892506
min                           4.000000
4.100000
25%                           7.500000
8.900000
50%                           8.700000
10.600000
75%                          10.200000
12.600000
max                          20.600000
26.100000

       Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)
count                  7385.000000          7385.000000
mean                     27.481652           250.584699
std                       7.231879            58.512679
min                      11.000000            96.000000
25%                      22.000000           208.000000
50%                      27.000000           246.000000
75%                      32.000000           288.000000
max                      69.000000           522.000000

sns.histplot(data=data, x='Make')
plt.xticks(rotation=90, fontsize=6)
```

```
plt.show()
# sns.histplot(data=data, x='Model')
# plt.xticks(rotation=90)
# plt.show()
sns.histplot(data=data, x='Vehicle Class')
plt.xticks(rotation=90)
plt.show()
sns.histplot(data=data, x='Transmission')
plt.xticks(rotation=90)
plt.show()

#Dropped other categorical columns because of high unique values.
```



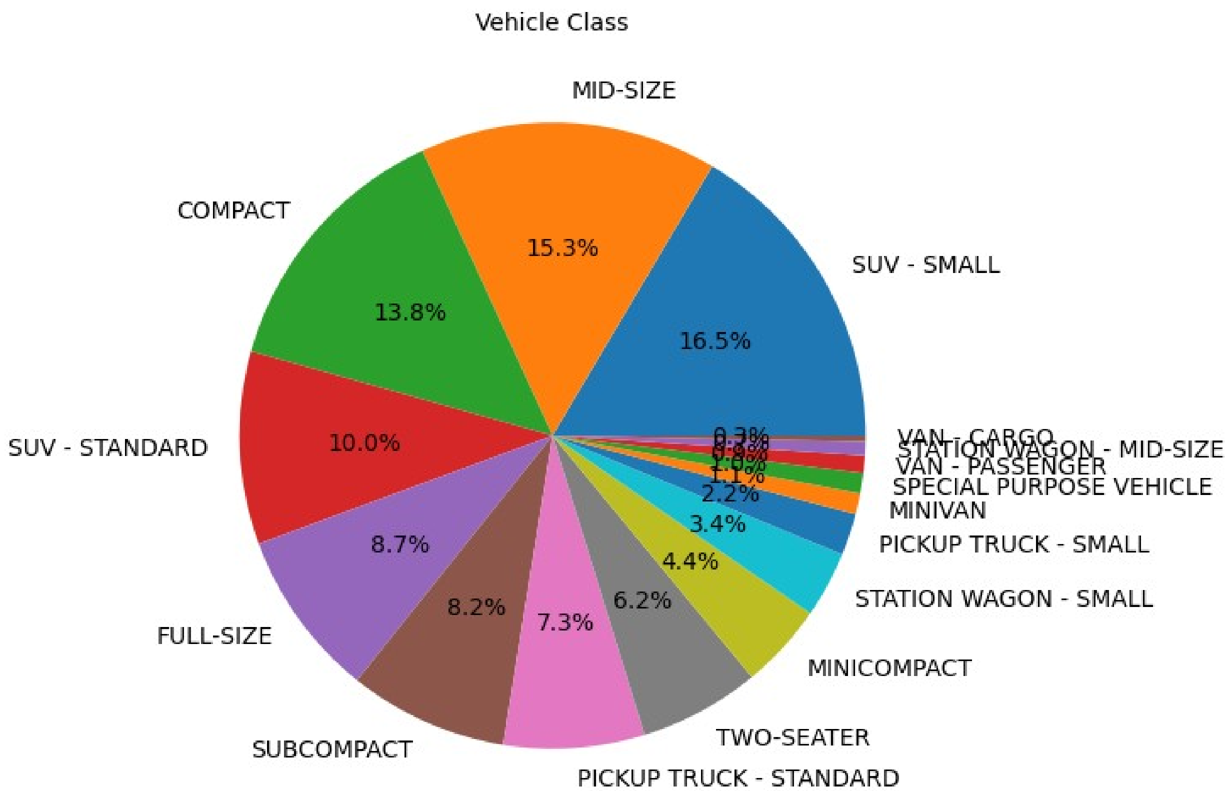


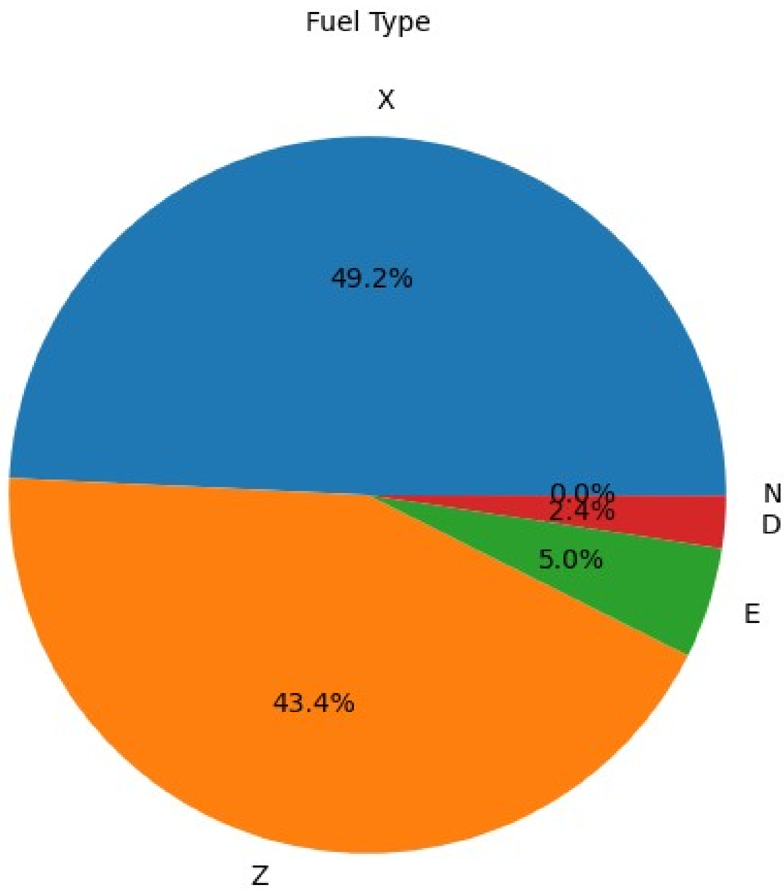
Count
0
200
400
600
800
1000
1200
COMPACT
SUV - SMALL
MID-SIZE
TWO-SEATER
MINICOMPACT
SUBCOMPACT
FULL-SIZE
STATION WAGON - SMALL
SUV - STANDARD
VAN - CARGO
VAN - PASSENGER
PICKUP TRUCK - STANDARD
MINIVAN
SPECIAL PURPOSE VEHICLE
STATION WAGON - MID-SIZE
PICKUP TRUCK - SMALL
Vehicle Class



- Pie Chart of the dataset.
  1. A pie chart is a circular statistical graphic, which is divided into slices to illustrate numerical proportion.

```
plt.figure(figsize=(6, 6))
plt.pie(data['Vehicle Class'].value_counts(), labels=data['Vehicle
Class'].value_counts().index, autopct='%1.1f%%')
plt.title('Vehicle Class', fontsize=10)
plt.show()

# plt.figure(figsize=(8, 8))
# plt.pie(data['Transmission'].value_counts(),
labels=data['Transmission'].value_counts().index, autopct='%1.1f%%')
# plt.title('Transmission', fontsize=10)
# plt.show()

plt.figure(figsize=(6, 6))
plt.pie(data['Fuel Type'].value_counts(), labels=data['Fuel
Type'].value_counts().index, autopct='%1.1f%%')
plt.title('Fuel Type', fontsize=10)
plt.show()

#Dropped other categorical columns because of high unique values.
```


Vehicle Class
MID-SIZE
15.3%
COMPACT
13.8%
SUV - SMALL
16.5%
SUV - STANDARD
10.0%
FULL-SIZE
8.7%
SUBCOMPACT
8.2%
PICKUP TRUCK - STANDARD
7.3%
TWO-SEATER
6.2%
MINICOMPACT
4.4%
STATION WAGON - SMALL
3.4%
PICKUP TRUCK - SMALL
2.2%
MINIVAN
SPECIAL PURPOSE VEHICLE
VAN - PASSENGER
STATION WAGON - MID-SIZE
VAN - CARGO



Insights:

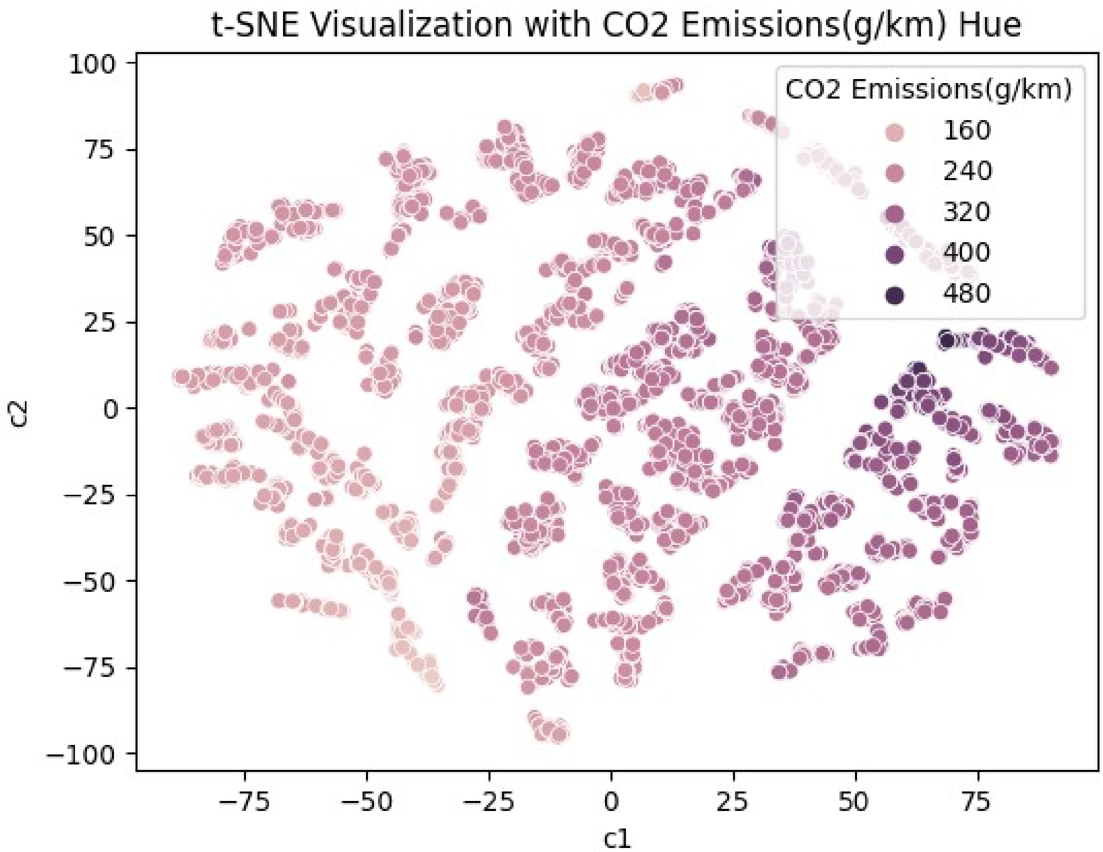
1. Categorical Values like Make and Model have very high unique data points so it can be dropped and will have very minimal effect on the models.
2. The scatter plots show a positive linear relationship between two numerical variables.
3. Box plots indicate the presence of outliers in certain numerical features.
4. Histograms reveal that a particular numerical feature follows a skewed distribution.
5. Categorical distribution plots display an imbalanced distribution among categories.
6. The correlation heatmap highlights a strong positive correlation between two numerical variables.

Part B.

TSNE (t-distributed stochastic neighbour embedding)

```
model = TSNE(n_components=2, random_state=0)
tsne_data = model.fit_transform(scaled_data) #this fits the transformation model to the input data (scaled_data) and then applies the transformation to the data, returning the transformed dataset.
tsne_df = pd.DataFrame(tsne_data, columns=['c1', 'c2'])
```

```
sns.scatterplot(x='c1', y='c2', data=tsne_df, hue= data['CO2
Emissions(g/km)'])
plt.title('t-SNE Visualization with CO2 Emissions(g/km) Hue')
plt.show()
```



Insight on t-SNE

1. t-SNE is effective at revealing separability in data when the data is high-dimensional, leading to well separated clusters after dimensionality reduction.
2. It may not perform well when data lacks clear clusters or have noise, resulting in fuzzy clusters.

Observation:

Here we can see clear cluster formation of the dataframes. Hence, we can conclude that this dataset can be further used to prepare ml model. Otherwise, in case of bad clustering and more noise, we avoid to further proceed on creating models and focus more on preprocessing of the data.

Part C.

Preprocessing on the data

```
x = data.drop("CO2 Emissions(g/km)", axis=1)
y = data["CO2 Emissions(g/km)"]

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=0)

encoder = LabelEncoder()
x_train['Make'] = encoder.fit_transform(x_train['Make'])
x_train['Model'] = encoder.fit_transform(x_train['Model'])
x_train['Vehicle Class'] = encoder.fit_transform(x_train['Vehicle
Class'])
x_train['Transmission'] =
encoder.fit_transform(x_train['Transmission'])
x_train['Fuel Type'] = encoder.fit_transform(x_train['Fuel Type'])

x_test['Make'] = encoder.fit_transform(x_test['Make'])
x_test['Model'] = encoder.fit_transform(x_test['Model'])
x_test['Vehicle Class'] = encoder.fit_transform(x_test['Vehicle
Class'])
x_test['Transmission'] = encoder.fit_transform(x_test['Transmission'])
x_test['Fuel Type'] = encoder.fit_transform(x_test['Fuel Type'])

x_train.head()

      Make  Model  Vehicle Class  Engine Size(L)  Cylinders
Transmission  \
1095     3    213             10             2.0          4
8
3538     9   1542              6             5.3          8
3
2377     8    330              0             2.5          4
17
3414     5    256              0             4.4          8
17
880     32    171              3             3.4          6
26

      Fuel Type  Fuel Consumption City (L/100 km)  \
1095          4                              10.1
3538          1                              19.7
2377          3                              10.6
3414          4                              14.7
880           4                              12.4

      Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100
km)  \
1095                              7.5
8.9
3538                             13.9
17.1
```

```
2377                              7.3
9.1
3414                              9.7
12.5
880                               8.6
10.7

      Fuel Consumption Comb (mpg)
1095                           32
3538                           17
2377                           31
3414                           23
880                            26

#Scaling the data
x_train = StandardScaler().fit_transform(x_train)
x_test = StandardScaler().fit_transform(x_test)

#We typically scale only the input features (x) because scaling the
target variable (y) may alter its interpretation and evaluation
metrics, which are based on the original scale of y.

#The code scales the features in both the training and test datasets
independently, ensuring that they have zero mean and unit variance.
#It's important to fit and transform each dataset separately to
prevent data leakage from the test set to the training set.

X_train = x_train #used in part g
X_test = x_test #used in part g
Y_test = y_test #used in part g
Y_train = y_train #used in part g

model = LinearRegression()
model.fit(x_train, y_train)

y_test_pred = model.predict(x_test)
y_train_pred = model.predict(x_train)

n_train = len(y_train) #number of datapoints (training)
n_test = len(y_test) #number of datapoints (testing)
p_train = x_train.shape[1] #training set features dimentionality
p_test = x_test.shape[1] #testing set features dimentionality

print('Train set metrics')
print('Mean Squared Error:', metrics.mean_squared_error(y_train,
y_train_pred))
print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_train, y_train_pred)))
print('R2 Score:', metrics.r2_score(y_train, y_train_pred))
print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(y_train,
```

```
y_train_pred))*(n_train-1)/(n_train-p_train-1)))
print('Mean Absolute Error:', metrics.mean_absolute_error(y_train,
y_train_pred))
print('Accuracy:', model.score(x_train, y_train)*100, '%')

print('\nTest set metrics')
print('Mean Squared Error:', metrics.mean_squared_error(y_test,
y_test_pred))
print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_test, y_test_pred)))
print('R2 Score:', metrics.r2_score(y_test, y_test_pred))
print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(y_test,
y_test_pred))*(n_test-1)/(n_test-p_test-1)))
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test,
y_test_pred))
print('Accuracy:', model.score(x_test, y_test)*100, '%')
```

```
Train set metrics
Mean Squared Error: 285.8901655194361
Root Mean Squared Error: 16.908286888961758
R2 Score: 0.9164709697704508
Adjusted R2 Score: 0.9163151320274853
Mean Absolute Error: 11.0699529734518
Accuracy: 91.64709697704508 %

Test set metrics
Mean Squared Error: 317.4664749909796
Root Mean Squared Error: 17.81758892193272
R2 Score: 0.9073258800490117
Adjusted R2 Score: 0.9066300334145674
Mean Absolute Error: 11.423256847158251
Accuracy: 90.73258800490117 %
```

Part D.

PCA

```
for i in range(4,12,2):
    pca = PCA(n_components=i)
    x_train_pca = pca.fit_transform(x_train)
    x_test_pca = pca.transform(x_test)

    model = LinearRegression()
    model.fit(x_train_pca, y_train)

    y_test_pred = model.predict(x_test_pca)
    y_train_pred = model.predict(x_train_pca)

    n_train = len(y_train) #number of datapoints (training)
```

```
    n_test = len(y_test) #number of datapoints (testing)
    p_train = x_train_pca.shape[1] #training set features 
dimentionality
    p_test = x_test_pca.shape[1] #testing set features dimentionality

    print(f'\nFor N={i}')
    print('-----------------------------------')
    print(f'Train set metrics')
    print('Mean Squared Error:', metrics.mean_squared_error(y_train, 
y_train_pred))
    print('Root Mean Squared Error:', 
np.sqrt(metrics.mean_squared_error(y_train, y_train_pred)))
    print('R2 Score:', metrics.r2_score(y_train, y_train_pred))
    print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(y_train, 
y_train_pred))*(n_train-1)/(n_train-p_train-1)))
    print('Mean Absolute Error:', metrics.mean_absolute_error(y_train, 
y_train_pred))
    print('Accuracy:', model.score(x_train_pca, y_train)*100)
    print('-----------------------------------')
    print('Test set metrics')
    print('Mean Squared Error:', metrics.mean_squared_error(y_test, 
y_test_pred))
    print('Root Mean Squared Error:', 
np.sqrt(metrics.mean_squared_error(y_test, y_test_pred)))
    print('R2 Score:', metrics.r2_score(y_test, y_test_pred))
    print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(y_test, 
y_test_pred))*(n_test-1)/(n_test-p_test-1)))
    print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, 
y_test_pred))
    print('Accuracy:', model.score(x_test_pca, y_test)*100)
    print('-----------------------------------')
```

```
For N=4
-----------------------------------
Train set metrics
Mean Squared Error: 303.8928264328678
Root Mean Squared Error: 17.432522090416747
R2 Score: 0.911211100810222
Adjusted R2 Score: 0.9111509355388754
Mean Absolute Error: 11.814640746145644
Accuracy: 91.12111008102221
-----------------------------------
Test set metrics
Mean Squared Error: 332.61255251693336
Root Mean Squared Error: 18.2376685055117
R2 Score: 0.9029044701805615
Adjusted R2 Score: 0.9026406236321391
Mean Absolute Error: 11.988212275546745
Accuracy: 90.29044701805616
```

```
----------------------------------

For N=6
----------------------------------
Train set metrics
Mean Squared Error: 300.23963788932804
Root Mean Squared Error: 17.32742444477332
R2 Score: 0.9122784593034152
Adjusted R2 Score: 0.9121892660744406
Mean Absolute Error: 11.810816362443703
Accuracy: 91.22784593034152
----------------------------------
Test set metrics
Mean Squared Error: 329.992217794494
Root Mean Squared Error: 18.165687925165233
R2 Score: 0.9036693925692515
Adjusted R2 Score: 0.903276206416473
Mean Absolute Error: 12.051709230732502
Accuracy: 90.36693925692515
----------------------------------

For N=8
----------------------------------
Train set metrics
Mean Squared Error: 286.8886882708372
Root Mean Squared Error: 16.937788765681226
R2 Score: 0.9161792296298442
Adjusted R2 Score: 0.9160655550811136
Mean Absolute Error: 11.097077830396486
Accuracy: 91.61792296298442
----------------------------------
Test set metrics
Mean Squared Error: 319.9426236351788
Root Mean Squared Error: 17.886940029954225
R2 Score: 0.9066030481453422
Adjusted R2 Score: 0.9060940729308754
Mean Absolute Error: 11.485843867907114
Accuracy: 90.66030481453421
----------------------------------

For N=10
----------------------------------
Train set metrics
Mean Squared Error: 285.9466230777012
Root Mean Squared Error: 16.9099563298579
R2 Score: 0.9164544744668001
Adjusted R2 Score: 0.9163127998432063
Mean Absolute Error: 11.071850856527009
Accuracy: 91.64544744668001
----------------------------------
```

```
Test set metrics
Mean Squared Error: 317.45151736815427
Root Mean Squared Error: 17.81716917380969
R2 Score: 0.9073302464455956
Adjusted R2 Score: 0.9066981198865615
Mean Absolute Error: 11.430870464717804
Accuracy: 90.73302464455956
----------------------------------
```

Insights

- As we increase the number of components, the accuracy of the model increases.
- The accuracy of the model is highest when the number of components is 10.
- The accuracy of the model is lowest when the number of components is 4.
- We will discuss about overfitting in further parts below.

Part E

```
data=pd.read_csv("CO2 Emissions.csv")
categorical_data = ['Make', 'Model', 'Vehicle Class', 'Transmission',
'Fuel Type']

oneHotEncoder = OneHotEncoder(sparse_output=False, drop='first')
#sparse_output: It specifies that the output of OneHotEncoder should
be a dense matrix instead of a sparse matrix.
#drop: Drops the first category in each feature to avoid
multicollinearity in one-hot encoded features, which is often used in
linear models.

encoded_cols = oneHotEncoder.fit_transform(data[categorical_data])
encoded_df = pd.DataFrame(encoded_cols,
columns=oneHotEncoder.get_feature_names_out(categorical_data))
new_data = pd.concat([data, encoded_df], axis=1)

new_data.drop(categorical_data, axis=1, inplace=True)

x = new_data.drop("CO2 Emissions(g/km)", axis=1)
y = new_data["CO2 Emissions(g/km)"]

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=0)

model = LinearRegression()
model.fit(x_train, y_train)

y_test_pred = model.predict(x_test)
y_train_pred = model.predict(x_train)
```

```python
n_train = len(y_train) #number of datapoints (training)
n_test = len(y_test) #number of datapoints (testing)
p_train = x_train.shape[1] #training set features dimentionality
p_test = x_test.shape[1] #testing set features dimentionality

print('Train set metrics')
print('Mean Squared Error:', metrics.mean_squared_error(y_train,
y_train_pred))
print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_train, y_train_pred)))
print('R2 Score:', metrics.r2_score(y_train, y_train_pred))
print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(y_train,
y_train_pred))*(n_train-1)/(n_train-p_train-1)))
print('Mean Absolute Error:', metrics.mean_absolute_error(y_train,
y_train_pred))
print('Accuracy:', model.score(x_train, y_train)*100)

print('\nTest set metrics')
print('Mean Squared Error:', metrics.mean_squared_error(y_test,
y_test_pred))
print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_test, y_test_pred)))
print('R2 Score:', metrics.r2_score(y_test, y_test_pred))
print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(y_test,
y_test_pred))*(n_test-1)/(n_test-p_test-1)))
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test,
y_test_pred))
print('Accuracy:', model.score(x_test, y_test)*100)
```

```
Train set metrics
Mean Squared Error: 8.781171936372138
Root Mean Squared Error: 2.9633042260915663
R2 Score: 0.9974343896202535
Adjusted R2 Score: 0.9959726121410677
Mean Absolute Error: 1.929030403545279
Accuracy: 99.74343896202535

Test set metrics
Mean Squared Error: 3.194788632517709e+19
Root Mean Squared Error: 5652246130.979886
R2 Score: -9326157193650528.0
Adjusted R2 Score: 2.0606898230281708e+16
Mean Absolute Error: 919345348.4739655
Accuracy: -9.326157193650528e+17
```

Insights:

- As we can clearly see the overfitting of the model, we can conclude that one hot encoding is not suitable for this dataset.

• The immense rmse and r2 score of the test set is due to the overfitting of the model.

Part F.

```
for i in [10, 50, 100, 500, 1000, 1500, 2000]:
    pca = PCA(n_components=i)
    x_train_pca = pca.fit_transform(x_train)
    x_test_pca = pca.transform(x_test)

    model = LinearRegression()
    model.fit(x_train_pca, y_train)

    y_test_pred = model.predict(x_test_pca)
    y_train_pred = model.predict(x_train_pca)

    n_train = len(y_train) #number of datapoints (training)
    n_test = len(y_test) #number of datapoints (testing)
    p_train = x_train_pca.shape[1] #training set features
dimentionality
    p_test = x_test_pca.shape[1] #testing set features dimentionality

    print(f'\nFor N={i}')
    print('----------------------------------')
    print(f'Train set metrics')
    print('Mean Squared Error:', metrics.mean_squared_error(y_train,
y_train_pred))
    print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_train, y_train_pred)))
    print('R2 Score:', metrics.r2_score(y_train, y_train_pred))
    print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(y_train,
y_train_pred))*(n_train-1)/(n_train-p_train-1)))
    print('Mean Absolute Error:', metrics.mean_absolute_error(y_train,
y_train_pred))
    print('Accuracy:', model.score(x_train_pca, y_train)*100)
    print('----------------------------------')
    print('Test set metrics')
    print('Mean Squared Error:', metrics.mean_squared_error(y_test,
y_test_pred))
    print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_test, y_test_pred)))
    print('R2 Score:', metrics.r2_score(y_test, y_test_pred))
    print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(y_test,
y_test_pred))*(n_test-1)/(n_test-p_test-1)))
    print('Mean Absolute Error:', metrics.mean_absolute_error(y_test,
y_test_pred))
    print('Accuracy:', model.score(x_test_pca, y_test)*100)
    print('----------------------------------')
```

```
For N=10
```

```
----------------------------------
Train set metrics
Mean Squared Error: 318.9972575556904
Root Mean Squared Error: 17.86049432562521
R2 Score: 0.9067980127224731
Adjusted R2 Score: 0.9066399628881886
Mean Absolute Error: 11.422064236739313
Accuracy: 90.6798012722473
----------------------------------
Test set metrics
Mean Squared Error: 332.1828967112781
Root Mean Squared Error: 18.225885347803494
R2 Score: 0.9030298943648697
Adjusted R2 Score: 0.9023684338898688
Mean Absolute Error: 11.390642280420433
Accuracy: 90.30298943648697
----------------------------------

For N=50
----------------------------------
Train set metrics
Mean Squared Error: 106.13165738592912
Root Mean Squared Error: 10.302022004729418
R2 Score: 0.96899132783391
Adjusted R2 Score: 0.9687266132004279
Mean Absolute Error: 6.2911794147927464
Accuracy: 96.899132783391
----------------------------------
Test set metrics
Mean Squared Error: 108.44039077127758
Root Mean Squared Error: 10.413471600349116
R2 Score: 0.9683443179877341
Adjusted R2 Score: 0.9672343712131105
Mean Absolute Error: 6.2895750267278006
Accuracy: 96.83443179877341
----------------------------------

For N=100
----------------------------------
Train set metrics
Mean Squared Error: 23.641449883703732
Root Mean Squared Error: 4.862247410786882
R2 Score: 0.9930926361932796
Adjusted R2 Score: 0.9929736872728953
Mean Absolute Error: 3.01258802790337
Accuracy: 99.30926361932796
----------------------------------
Test set metrics
Mean Squared Error: 20.938339657528967
```

```
Root Mean Squared Error: 4.575843054293817
R2 Score: 0.9938877256218897
Adjusted R2 Score: 0.9934435196351084
Mean Absolute Error: 3.056058056999726
Accuracy: 99.38877256218896
----------------------------------

For N=500
----------------------------------
Train set metrics
Mean Squared Error: 20.665959115164775
Root Mean Squared Error: 4.545982744706008
R2 Score: 0.9939619905409588
Adjusted R2 Score: 0.9934036393795901
Mean Absolute Error: 2.7658767544121448
Accuracy: 99.39619905409587
----------------------------------
Test set metrics
Mean Squared Error: 19.744150314405864
Root Mean Squared Error: 4.4434390188688155
R2 Score: 0.9942363307665177
Adjusted R2 Score: 0.991283631364119
Mean Absolute Error: 2.9623792435490834
Accuracy: 99.42363307665177
----------------------------------

For N=1000
----------------------------------
Train set metrics
Mean Squared Error: 16.545679561008075
Root Mean Squared Error: 4.06763808136959
R2 Score: 0.9951658198325611
Adjusted R2 Score: 0.9941806598228935
Mean Absolute Error: 2.5947000461380987
Accuracy: 99.51658198325612
----------------------------------
Test set metrics
Mean Squared Error: 18.79472637172878
Root Mean Squared Error: 4.335288499249938
R2 Score: 0.994513484530078
Adjusted R2 Score: 0.9829871915260403
Mean Absolute Error: 2.9452931495154435
Accuracy: 99.45134845300781
----------------------------------

For N=1500
----------------------------------
Train set metrics
Mean Squared Error: 13.853321291972986
Root Mean Squared Error: 3.7220050096652186
```

```
R2 Score: 0.9959524508621189
Adjusted R2 Score: 0.9945747962882996
Mean Absolute Error: 2.297793724298839
Accuracy: 99.59524508621189
----------------------------------
Test set metrics
Mean Squared Error: 20.179745290306354
Root Mean Squared Error: 4.492187138834084
R2 Score: 0.9941091728326042
Adjusted R2 Score: 1.3622858707948386
Mean Absolute Error: 2.9581702842873847
Accuracy: 99.41091728326043
----------------------------------

For N=2000
----------------------------------
Train set metrics
Mean Squared Error: 8.781045105766136
Root Mean Squared Error: 2.963282825814326
R2 Score: 0.9974344266765738
Adjusted R2 Score: 0.9961211052926853
Mean Absolute Error: 1.9291885462118314
Accuracy: 99.74344266765738
----------------------------------
Test set metrics
Mean Squared Error: 3.3871965417337546e+21
Root Mean Squared Error: 58199626645.99967
R2 Score: -9.887830159550732e+17
Adjusted R2 Score: 2.785197960972687e+18
Mean Absolute Error: 12006728231.577263
Accuracy: -9.887830159550731e+19
----------------------------------
```

Insights:

• Applying PCA to one-hot encoded categorical variables reduces the number of features, simplifying the model and potentially improving its generalization performance by reducing the risk of overfitting.

• As seen for N=1500, model performs best with accuracy of 99.59876460411795%. Where when we increase N to 2000, accuracy drops drastically to -9.887830159550731e+19%, because of the overfitting of the model.

Conclusion: the model performs best for N=1500.

Part G.

L1 and L2 regularization

```
linearModel = LinearRegression()
linearModel.fit(X_train, Y_train)

lassoModel = Lasso(alpha=0.1)
lassoModel.fit(X_train, Y_train)

ridgeModel = Ridge(alpha=0.1)
ridgeModel.fit(X_train, Y_train)

# Function to calculate metrics
def calculate_metrics(a, b, modelType):
    mse = mean_squared_error(a, b)
    rmse = np.sqrt(mse)
    r2 = r2_score(a, b)
    n_train = len(a)
    p_train = X_train.shape[1]
    adjusted_r2 = 1 - ((1 - r2) * (n_train - 1) / (n_train - p_train -
1))
    mae = mean_absolute_error(a, b)
    accuracy = r2*100
    print(f'\n{modelType} Model Metrics')
    print('-----------------------------------')
    print('Mean Squared Error:', mse)
    print('Root Mean Squared Error:', rmse)
    print('R2 Score:', r2)
    print('Adjusted R2 Score:', adjusted_r2)
    print('Mean Absolute Error:', mae)
    print('Accuracy:', accuracy)
    print('-----------------------------------')

# Calculate metrics for each model on both train and test datasets
calculate_metrics(Y_train, linearModel.predict(X_train), 'Linear')
calculate_metrics(Y_test, linearModel.predict(X_test), 'Linear')

calculate_metrics(Y_train, lassoModel.predict(X_train), 'Lasso')
calculate_metrics(Y_test, lassoModel.predict(X_test), 'Lasso')

calculate_metrics(Y_train, ridgeModel.predict(X_train), 'Ridge')
calculate_metrics(Y_test, ridgeModel.predict(X_test), 'Ridge')
```

```
Linear Model Metrics
----------------------------------
Mean Squared Error: 285.8901655194361
```

```
Root Mean Squared Error: 16.908286888961758
R2 Score: 0.9164709697704508
Adjusted R2 Score: 0.9163151320274853
Mean Absolute Error: 11.0699529734518
Accuracy: 91.64709697704508
----------------------------------

Linear Model Metrics
----------------------------------
Mean Squared Error: 317.4664749909796
Root Mean Squared Error: 17.81758892193272
R2 Score: 0.9073258800490117
Adjusted R2 Score: 0.9066300334145674
Mean Absolute Error: 11.423256847158251
Accuracy: 90.73258800490117
----------------------------------

Lasso Model Metrics
----------------------------------
Mean Squared Error: 286.01368877470134
Root Mean Squared Error: 16.91193923755349
R2 Score: 0.9164348797646811
Adjusted R2 Score: 0.9162789746896152
Mean Absolute Error: 11.06973418738236
Accuracy: 91.64348797646811
----------------------------------

Lasso Model Metrics
----------------------------------
Mean Squared Error: 316.9163922897592
Root Mean Squared Error: 17.802145721506697
R2 Score: 0.90748645898963
Adjusted R2 Score: 0.9067918180673679
Mean Absolute Error: 11.394372569213427
Accuracy: 90.748645898963
----------------------------------

Ridge Model Metrics
----------------------------------
Mean Squared Error: 285.89090902411556
Root Mean Squared Error: 16.908308875346332
R2 Score: 0.9164707525393868
Adjusted R2 Score: 0.9163149143911394
Mean Absolute Error: 11.070026959889601
Accuracy: 91.64707525393868
----------------------------------

Ridge Model Metrics
----------------------------------
Mean Squared Error: 317.457983104965
```

```
Root Mean Squared Error: 17.817350619689925
R2 Score: 0.9073283589818286
Adjusted R2 Score: 0.9066325309605318
Mean Absolute Error: 11.423862834780278
Accuracy: 90.73283589818286
----------------------------------
```

Insights:

• The models show consistent performance with similar Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values.

• High R2 and adjusted R2 scores indicate the models' ability to explain a significant portion of variance in the target variable and high accuracy.

• Mean Absolute Error (MAE) values indicate that the models have relatively small average prediction errors.

• Regularization techniques (Lasso and Ridge) show similar performance to the standard linear model in this context.

Part H.

```
sdg_reg = SGDRegressor(max_iter=1000, random_state=0, alpha=0.01)
sdg_reg.fit(X_train, Y_train)

y_test_pred = sdg_reg.predict(X_test)
y_train_pred = sdg_reg.predict(X_train)

n_train = len(Y_train) #number of datapoints (training)
n_test = len(Y_test) #number of datapoints (testing)
p_train = x_train.shape[1] #training set features dimentionality
p_test = x_test.shape[1] #testing set features dimentionality

print('Train set metrics')
print('Mean Squared Error:', metrics.mean_squared_error(Y_train,
y_train_pred))
print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(Y_train, y_train_pred)))
print('R2 Score:', metrics.r2_score(Y_train, y_train_pred))
print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(Y_train,
y_train_pred))*(n_train-1)/(n_train-p_train-1)))
print('Mean Absolute Error:', metrics.mean_absolute_error(Y_train,
y_train_pred))
print('Accuracy:', sdg_reg.score(X_train, y_train)*100)

print('\nTest set metrics')
print('Mean Squared Error:', metrics.mean_squared_error(Y_test,
y_test_pred))
print('Root Mean Squared Error:',
```

```
np.sqrt(metrics.mean_squared_error(Y_test, y_test_pred)))
print('R2 Score:', metrics.r2_score(Y_test, y_test_pred))
print('Adjusted R2 Score:', 1 - ((1-metrics.r2_score(Y_test,
y_test_pred))*(n_test-1)/(n_test-p_test-1)))
print('Mean Absolute Error:', metrics.mean_absolute_error(Y_test,
y_test_pred))
print('Accuracy:', sdg_reg.score(X_test, Y_test)*100)

Train set metrics
Mean Squared Error: 289.555621675842
Root Mean Squared Error: 17.016333966981314
R2 Score: 0.9154000270273269
Adjusted R2 Score: 0.8671985011029552
Mean Absolute Error: 11.411300979268002
Accuracy: 91.54000270273269

Test set metrics
Mean Squared Error: 319.292257723116
Root Mean Squared Error: 17.868750871930473
R2 Score: 0.9067929015418252
Adjusted R2 Score: 1.2059486187489012
Mean Absolute Error: 11.644577031079605
Accuracy: 90.67929015418252
```

Insights:

- SGDRegression and other (Linear, Lasso and Rigde) models almost perform similar with accuracy of nearly 91%

- It is used for large-scale linear regression tasks with potentially millions of data points because it can efficiently optimize linear models. It differs from Lasso and Ridge regression by optimizing linear models using stochastic gradient descent, which is suitable for large datasets, and it doesn't perform L1 or L2 regularization by default unless explicitly specified.