```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import scipy.stats as stats
import seaborn

#Extracting the data
df = pd.read_csv("./CO2 Emission by
Vehicles/CO2_Emissions_Canada.csv")

df.head()
```

```
    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
```

Pre-Processing

```
# Checking null values
df.isna().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
```

```
#Checking null values
(df == '?').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
```

```
# unique values for different column
df.nunique()
```

```
Make                                      42
Model                                   2053
Vehicle Class                             16
Engine Size(L)                            51
Cylinders                                  8
Transmission                              27
Fuel Type                                  5
Fuel Consumption City (L/100 km)         211
Fuel Consumption Hwy (L/100 km)          143
Fuel Consumption Comb (L/100 km)         181
```

```
Fuel Consumption Comb (mpg)           54
CO2 Emissions(g/km)                  331
dtype: int64
```

```
len(df)
```

```
7385
```

```python
# I want to encode all the string data column
# So I will drop the model column because there are many different
data which will create so many columns
df.drop(axis = "columns", labels = "Model", inplace=True)
```

```
df.head()
```

```
    Make Vehicle Class  Engine Size(L)  Cylinders Transmission Fuel
Type  \
0  ACURA       COMPACT             2.0          4          AS5
Z
1  ACURA       COMPACT             2.4          4           M6
Z
2  ACURA       COMPACT             1.5          4          AV7
Z
3  ACURA   SUV - SMALL             3.5          6          AS6
Z
4  ACURA   SUV - SMALL             3.5          6          AS6
Z

   Fuel Consumption City (L/100 km)  Fuel Consumption Hwy (L/100
km)  \
0                               9.9                               6.7

1                              11.2                               7.7

2                               6.0                               5.8

3                              12.7                               9.1

4                              12.1                               8.7


   Fuel Consumption Comb (L/100 km)  Fuel Consumption Comb (mpg)  \
0                               8.5                           33
1                               9.6                           29
2                               5.9                           48
3                              11.1                           25
4                              10.6                           27

   CO2 Emissions(g/km)
0                  196
```

```
1                  221
2                  136
3                  255
4                  244
```

```
df.nunique()
```

```
Make                                  42
Vehicle Class                         16
Engine Size(L)                        51
Cylinders                              8
Transmission                          27
Fuel Type                              5
Fuel Consumption City (L/100 km)     211
Fuel Consumption Hwy (L/100 km)      143
Fuel Consumption Comb (L/100 km)     181
Fuel Consumption Comb (mpg)           54
CO2 Emissions(g/km)                  331
dtype: int64
```

```
df["Vehicle Class"].value_counts()
```

```
SUV - SMALL                 1217
MID-SIZE                    1133
COMPACT                     1022
SUV - STANDARD               735
FULL-SIZE                    639
SUBCOMPACT                   606
PICKUP TRUCK - STANDARD      538
TWO-SEATER                   460
MINICOMPACT                  326
STATION WAGON - SMALL        252
PICKUP TRUCK - SMALL         159
MINIVAN                       80
SPECIAL PURPOSE VEHICLE       77
VAN - PASSENGER               66
STATION WAGON - MID-SIZE      53
VAN - CARGO                   22
Name: Vehicle Class, dtype: int64
```

```
# Checking the duplicated data
df.duplicated().sum()
```

```
2171
```

```
#dropping the duplicate data
df.drop(axis = "rows", labels = df.index[df.duplicated()], inplace =
True)
```

```
len(df)
```

```
5214
```

```
df.describe()

       Engine Size(L)    Cylinders  Fuel Consumption City (L/100 
km)  \
count     5214.000000  5214.000000                             5214.000000   

mean         3.129900     5.552934                               12.544687   

std          1.355553     1.823861                                3.584654   

min          0.900000     3.000000                                4.200000   

25%          2.000000     4.000000                               10.000000   

50%          3.000000     6.000000                               12.000000   

75%          3.700000     6.000000                               14.500000   

max          8.400000    16.000000                               30.600000   


       Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100 
km)  \
count                      5214.000000                              
5214.000000   
mean                          9.043402                              
10.969141   
std                           2.324962                              
2.984861   
min                           4.000000                              
4.100000   
25%                           7.400000                              
8.800000   
50%                           8.600000                              
10.500000   
75%                          10.200000                              
12.600000   
max                          20.600000                              
26.100000   

       Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)  
count                  5214.000000          5214.000000  
mean                     27.582278           249.550249  
std                       7.331877            59.478890  
min                      11.000000            96.000000  
25%                      22.000000           206.000000  
50%                      27.000000           244.000000  
75%                      32.000000           286.000000  
max                      69.000000           522.000000  
```

```python
df['Make'].value_counts()
```

```
FORD             528
CHEVROLET        458
BMW              340
MERCEDES-BENZ    338
TOYOTA           242
GMC              240
AUDI             221
PORSCHE          202
NISSAN           191
KIA              180
VOLKSWAGEN       179
HYUNDAI          167
HONDA            141
CADILLAC         138
JEEP             129
DODGE            122
MAZDA            119
LEXUS            116
MINI             114
SUBARU           111
VOLVO            106
BUICK             87
INFINITI          85
LINCOLN           77
MITSUBISHI        71
JAGUAR            58
RAM               56
CHRYSLER          51
LAND ROVER        51
ACURA             47
MASERATI          41
FIAT              36
ROLLS-ROYCE       34
BENTLEY           33
LAMBORGHINI       27
ASTON MARTIN      27
SCION             21
GENESIS           14
ALFA ROMEO        10
SMART              4
SRT                1
BUGATTI            1
Name: Make, dtype: int64
```

```python
df.head()
```

```
    Make Vehicle Class  Engine Size(L)  Cylinders Transmission Fuel
Type  \
0  ACURA       COMPACT             2.0          4          AS5
```

```
Z
1  ACURA       COMPACT            2.4          4           M6
Z
2  ACURA       COMPACT            1.5          4          AV7
Z
3  ACURA   SUV - SMALL            3.5          6          AS6
Z
4  ACURA   SUV - SMALL            3.5          6          AS6
Z

   Fuel Consumption City (L/100 km)  Fuel Consumption Hwy (L/100
km)  \
0                               9.9                              6.7

1                              11.2                              7.7

2                               6.0                              5.8

3                              12.7                              9.1

4                              12.1                              8.7


   Fuel Consumption Comb (L/100 km)  Fuel Consumption Comb (mpg)  \
0                               8.5                           33
1                               9.6                           29
2                               5.9                           48
3                              11.1                           25
4                              10.6                           27

   CO2 Emissions(g/km)
0                  196
1                  221
2                  136
3                  255
4                  244
```

```
df.nunique()
```

```
Make                                  42
Vehicle Class                         16
Engine Size(L)                        51
Cylinders                              8
Transmission                          27
Fuel Type                              5
Fuel Consumption City (L/100 km)     211
Fuel Consumption Hwy (L/100 km)      143
Fuel Consumption Comb (L/100 km)     181
Fuel Consumption Comb (mpg)           54
```

```
CO2 Emissions(g/km)                  331
dtype: int64
```

```python
# I will one hot encode all the string data columns
column_names_to_one_hot = ["Make", "Vehicle Class", "Transmission",
"Fuel Type"]

df = pd.get_dummies(df, columns=column_names_to_one_hot)

#Standardizing all the data except the columns whose value is either 1
or 0 and the target column
labels = ["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)"]
for i in labels:
    df[i] = (df[i]- df[i].mean())/df[i].std()
df.head()
```

```
   Engine Size(L)  Cylinders  Fuel Consumption City (L/100 km)  \
0       -0.833535  -0.851454                         -0.737780
1       -0.538452  -0.851454                         -0.375123
2       -1.202388  -0.851454                         -1.825752
3        0.273025   0.245120                          0.043327
4        0.273025   0.245120                         -0.124053

   Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100
km)  \
0                        -1.007931                         -0.827221

1                        -0.577817                         -0.458695

2                        -1.395034                         -1.698284

3                         0.024343                          0.043841

4                        -0.147702                         -0.123671


   Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)  Make_ACURA  \
0                     0.738927                  196           1
1                     0.193364                  221           1
2                     2.784788                  136           1
3                    -0.352199                  255           1
4                    -0.079417                  244           1

   Make_ALFA ROMEO  Make_ASTON MARTIN  ...  Transmission_AV7  \
0                0                  0  ...                 0
1                0                  0  ...                 0
2                0                  0  ...                 1
3                0                  0  ...                 0
```

```
4                 0                  0  ...                 0

   Transmission_AV8  Transmission_M5  Transmission_M6  Transmission_M7
\
0                 0                0                0                0

1                 0                0                1                0

2                 0                0                0                0

3                 0                0                0                0

4                 0                0                0                0


   Fuel Type_D  Fuel Type_E  Fuel Type_N  Fuel Type_X  Fuel Type_Z
0            0            0            0            0            1
1            0            0            0            0            1
2            0            0            0            0            1
3            0            0            0            0            1
4            0            0            0            0            1

[5 rows x 97 columns]
```

```
#dropping Fuel_type_N because there is only one data sample for it
df.drop(axis = "columns", labels = "Fuel Type_N", inplace=True)

df.head()
```

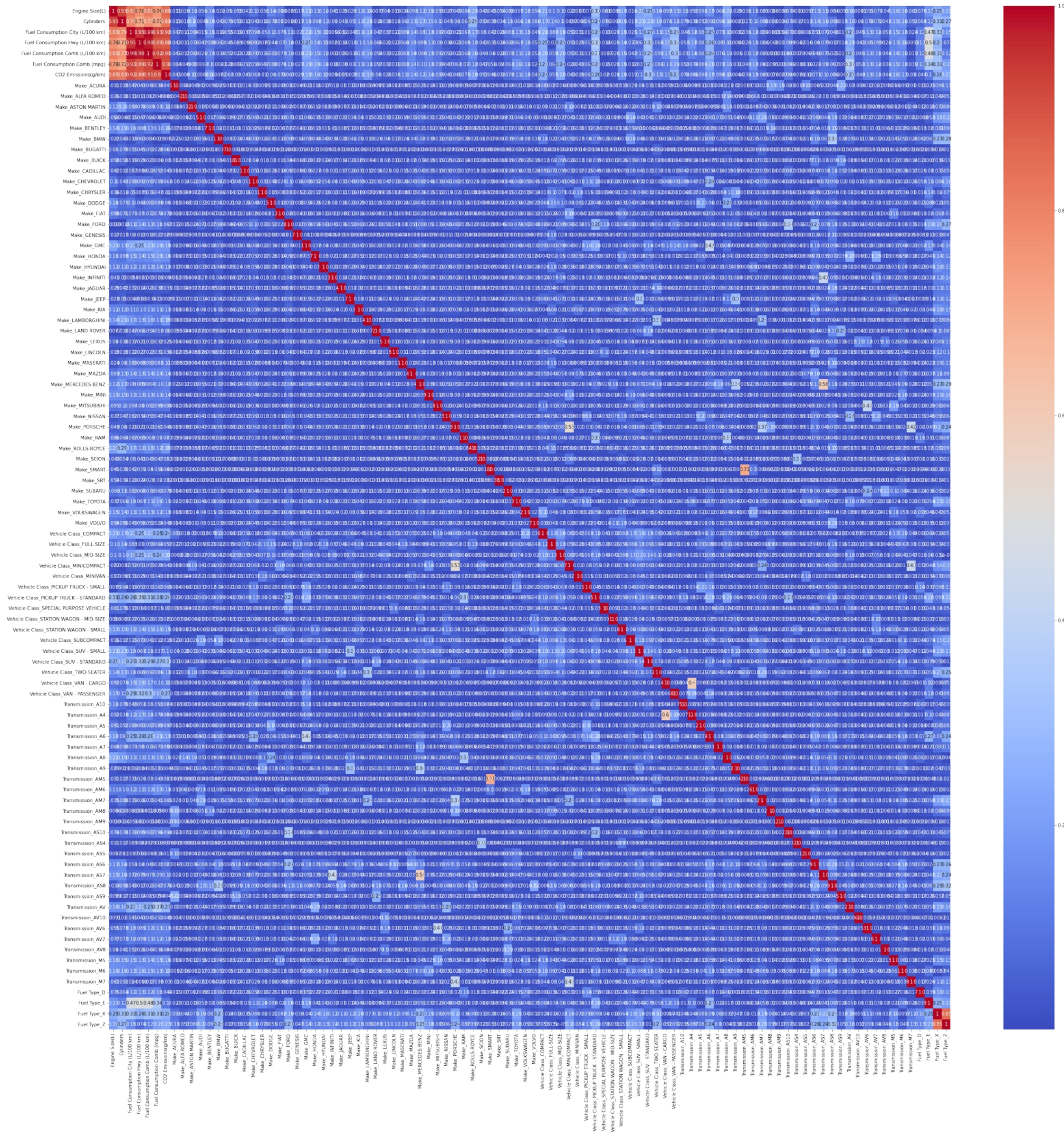
```
   Engine Size(L)  Cylinders  Fuel Consumption City (L/100 km)  \
0       -0.833535  -0.851454                         -0.737780
1       -0.538452  -0.851454                         -0.375123
2       -1.202388  -0.851454                         -1.825752
3        0.273025   0.245120                          0.043327
4        0.273025   0.245120                         -0.124053

   Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100
km)  \
0                        -1.007931                         -0.827221

1                        -0.577817                         -0.458695

2                        -1.395034                         -1.698284

3                         0.024343                          0.043841

4                        -0.147702                         -0.123671
```

```
   Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)  Make_ACURA  \
0                     0.738927                  196           1
1                     0.193364                  221           1
2                     2.784788                  136           1
3                    -0.352199                  255           1
4                    -0.079417                  244           1

   Make_ALFA ROMEO  Make_ASTON MARTIN  ...  Transmission_AV6  \
0                0                  0  ...                 0
1                0                  0  ...                 0
2                0                  0  ...                 0
3                0                  0  ...                 0
4                0                  0  ...                 0

   Transmission_AV7  Transmission_AV8  Transmission_M5
Transmission_M6  \
0                 0                 0                0
0
1                 0                 0                0
1
2                 1                 0                0
0
3                 0                 0                0
0
4                 0                 0                0
0

   Transmission_M7  Fuel Type_D  Fuel Type_E  Fuel Type_X  Fuel Type_Z

0                0            0            0            0            1

1                0            0            0            0            1

2                0            0            0            0            1

3                0            0            0            0            1

4                0            0            0            0            1


[5 rows x 96 columns]
```

```
# Matrix that will tell that the target value is most related to which
feature
corr_df = abs(df.corr())

# As we can see the target value is most related to Fuel Consumption
City (L/100 km) feature
```

```
plt.figure(figsize=(40,40))
seaborn.heatmap(corr_df, cmap='coolwarm',annot=True)
#Heatmap plot
```

```
<AxesSubplot:>
```



Splitting into train and test

```
#splitting the data into train and test data
rain_data = df.sample(frac = 0.65, random_state = 50)
test_data = df.drop(train_data.index)

X = train_data.drop(axis = "columns", labels = "CO2
Emissions(g/km)").to_numpy().astype(np.float64)
Y = train_data["CO2 Emissions(g/km)"].to_numpy().astype(np.float64)
```

```
X_test = test_data.drop(axis = "columns", labels = "CO2
Emissions(g/km)").to_numpy().astype(np.float64)
Y_test = test_data["CO2
Emissions(g/km)"].to_numpy().astype(np.float64)


# X = X.to_numpy().astype(np.float64)
# X_test = stats.zscore(X_test)
```

Closed form Solution for Multivariate

```
# Concatenating 1 in X for the bias feature
X_train = np.zeros((X.shape[0], X.shape[1] + 1))
X_train[:, 0] = 1
X_train[:, 1:] = X
X_tst = np.zeros((X_test.shape[0], X_test.shape[1] + 1))
X_tst[:, 0] = 1
X_tst[:, 1:] = X_test
```

W = (X^TX)^{-1}(X^TY)

```
W = np.dot(np.linalg.pinv(X_train), Y)
```

Ypred = XW

```
Y_pred = np.matmul(X_tst, W)
```

```
Y_pred
```

```
array([232.76299016, 216.61884313, 231.92609232, ..., 218.64314291,
       209.3561013 , 249.28661251])
```

```
# Calculating Mean Square Error for the test Data
MSE = np.sum((Y_pred - Y_test)**2)/Y_test.shape[0]
```

```
MSE
```

```
33.43676338547167
```

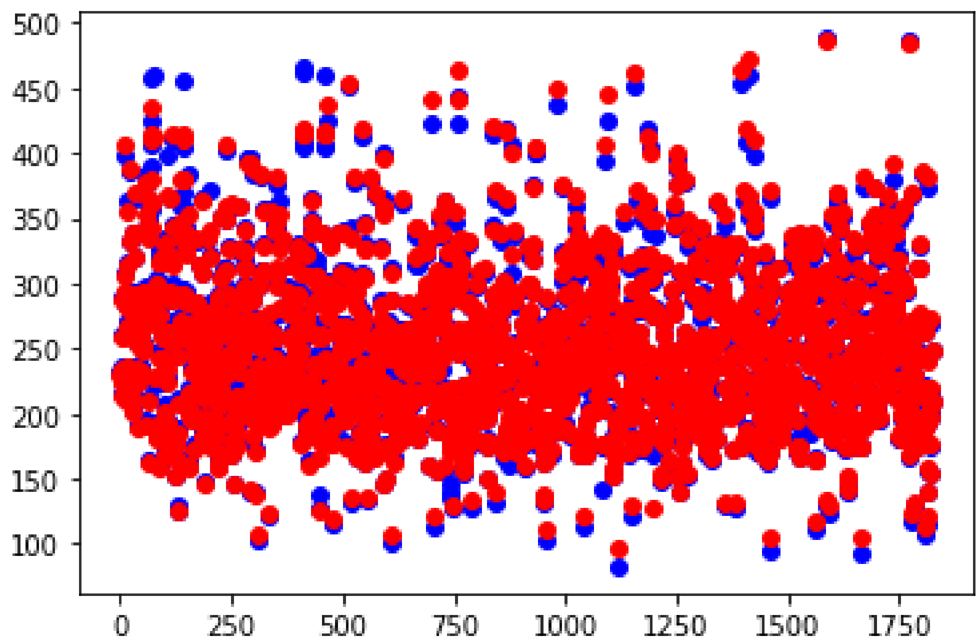
```
# Calculating Mean absolute error for the test Data
MAE = np.sum(np.absolute(Y_pred - Y_test)/Y_test.shape[0])
```

```
MAE
```

```
3.3556689786700193
```

```
indexes = [i for i in range(len(Y_pred))]
plt.scatter(x=indexes, y=Y_pred, color='blue') #blue for prediction
indexes = [i for i in range(len(Y_test))]
plt.scatter(x=indexes, y=Y_test, color='red') # Red for data sample
```

```
<matplotlib.collections.PathCollection at 0x7f133ffed130>
```



As we know see the target value is most related to Fuel Consumption City (L/100 km)

So we will explore univariate(Closed form) for this feature

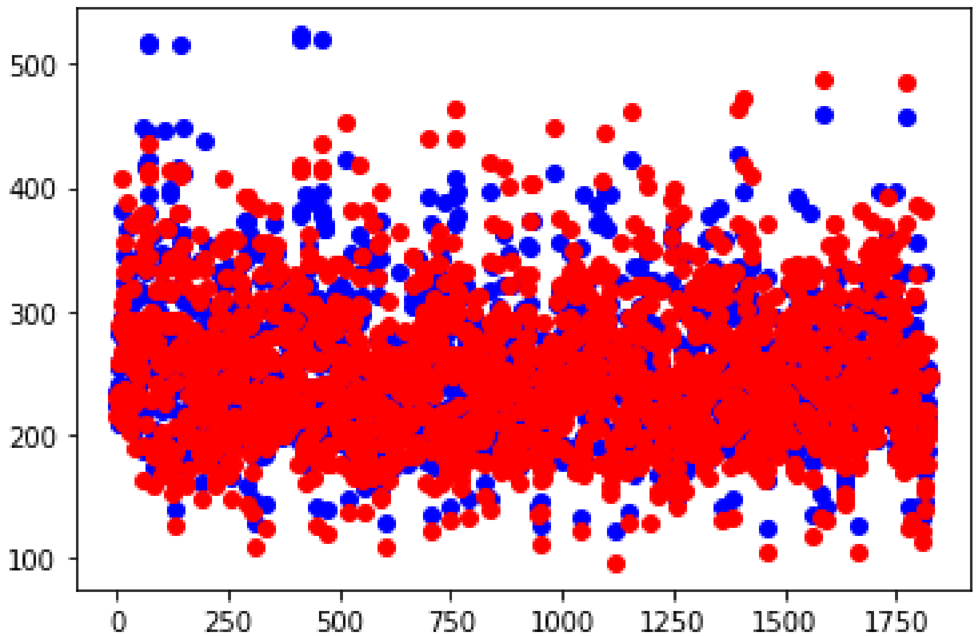
```
x = train_data["Fuel Consumption City (L/100
km)"].to_numpy().astype(np.float64)
x_test = test_data["Fuel Consumption City (L/100
km)"].to_numpy().astype(np.float64)
train_points = x.shape[0]
test_points = x_test.shape[0]
x = x.reshape((train_points, 1))
x_test = x_test.reshape((test_points, 1))

# Adding 1 column in x and x_test for the bias term
x_trn = np.zeros((x.shape[0], x.shape[1] + 1))
x_trn[:, 0] = 1
x_trn[:, 1:] = x
x_tst = np.zeros((x_test.shape[0], x_test.shape[1] + 1))
x_tst[:, 0] = 1
x_tst[:, 1:] = x_test

w = np.dot(np.linalg.pinv(x_trn), Y)

y_pred = np.matmul(x_tst, w)

MSE = np.sum((y_pred - Y_test)**2)/Y_test.shape[0]

MSE

584.5049533453364

MAE = np.sum(np.absolute(y_pred - Y_test)/Y_test.shape[0])
```

```
MAE
```

```
15.099668576572157
```

```python
indexes = [i for i in range(len(y_pred))]
plt.scatter(x=indexes, y=y_pred, color='blue') #blue for prediction
indexes = [i for i in range(len(Y_test))]
plt.scatter(x=indexes, y=Y_test, color='red') # Red for data sample
```

```
<matplotlib.collections.PathCollection at 0x7f133fae4490>
```



Gradient Descent Solution for Multivariate

J(W) = Summation(Y - XW)

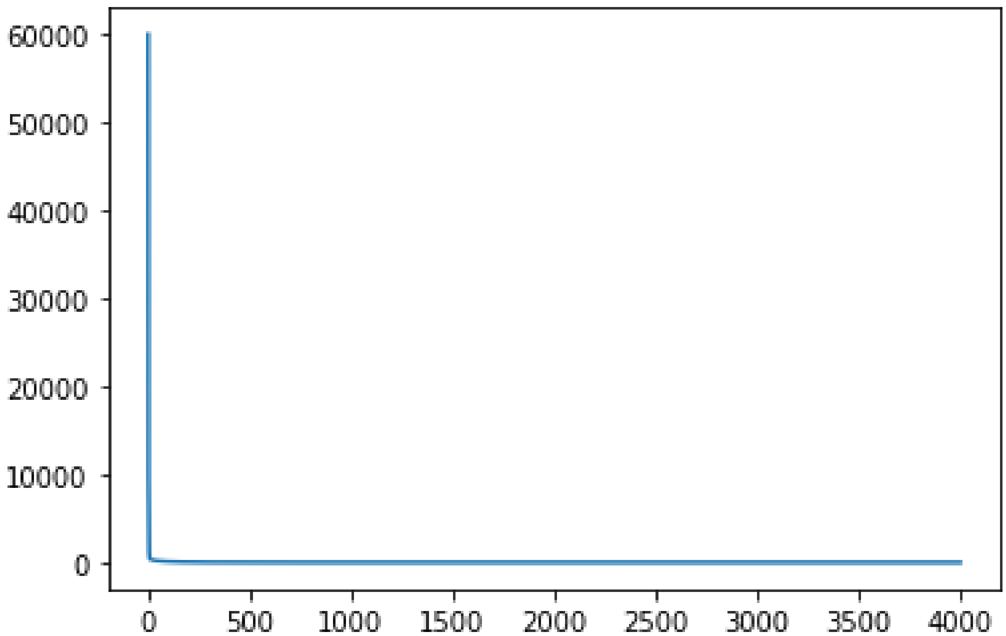
W_new = W_old - lr*dJ/dW

```python
lr = 0.12 # learning rate
iterations = 4000 # number of iterations|

n_points = Y.shape[0] # number of data points
W_grd = np.random.uniform(low = -12, high = 12, size =
X_train.shape[1]) # weight vector
costs = []

for i in range(iterations):
    Yhat = X_train@W_grd #y_prediction
    cost = np.mean((Y-Yhat)**2)
    costs.append(cost)
    W_grd[0] = W_grd[0] + lr*(1/n_points)*2*(np.sum(Y-X_train@W_grd))
    for j in range(1, W_grd.shape[0]): #for all features
```

```
        W_grd[j] = W_grd[j] + (2*lr/n_points)*(np.sum((Y-
X_train@W_grd)*X_train.T[j]))
```

```
plt.plot(costs)
```

```
[<matplotlib.lines.Line2D at 0x7f133fc41580>]
```



Inference for the test data

```
Y_pred_test = X_tst@W_grd#inference
MSE = np.sum((Y_pred_test - Y_test)**2)/Y_test.shape[0]# Calculating
MSE
MSE
```

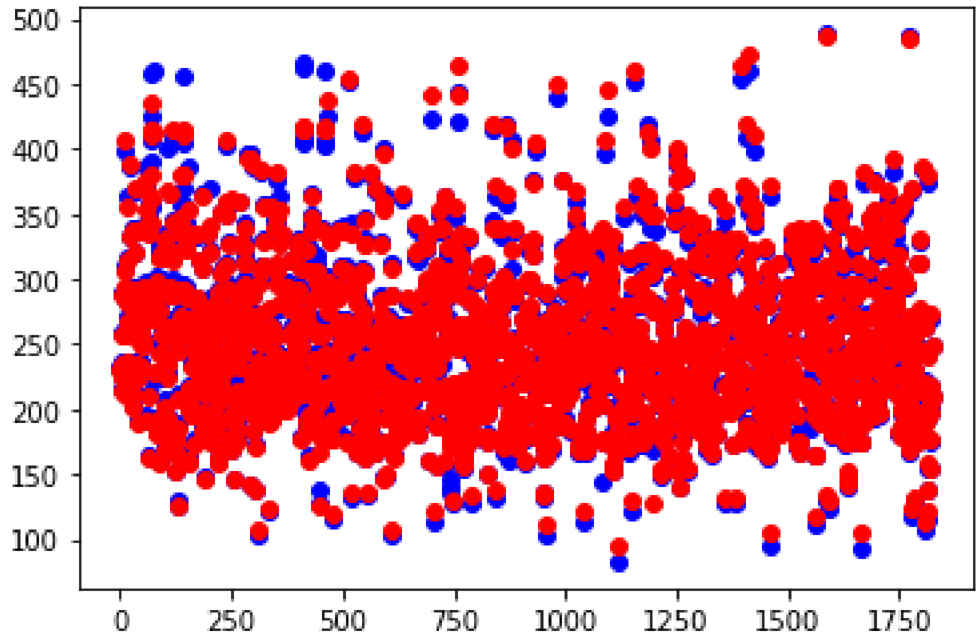
```
33.73400359812629
```

```
MAE = np.sum(np.absolute(X_tst@W_grd - Y_test)/Y_test.shape[0])#
Calculating MAE
MAE
```

```
3.345690962703453
```

```
indexes = [i for i in range(len(Y_pred_test))]
plt.scatter(x=indexes, y=Y_pred_test, color='blue') #blue for
prediction
indexes = [i for i in range(len(Y_test))]
plt.scatter(x=indexes, y=Y_test, color='red') # Red for data sample
```

```
<matplotlib.collections.PathCollection at 0x7f133fb2d6d0>
```



As we know see the target value is most related to Fuel Consumption City (L/100 km)

So we will explore univariate(Gradient Descent) for this feature

```
n_points = Y.shape[0] # number of data points
m_disc, b_disc = np.random.uniform(low = -12, high = 12, size = 2)

lr = 0.1
iterations = 50000

for i in range(iterations):
  yhat = m_disc*x + b_disc#y=mx+c
  db = (1/n_points)*(-2*np.sum(Y) + 2*b_disc*n_points +
2*m_disc*np.sum(x))
  dm = (1/n_points)*(-2*Y.T@x + 2*b_disc*np.sum(x) + 2*m_disc*x.T@x)
  m_disc = m_disc - lr*dm
  b_disc = b_disc -lr*db

y_grd_pred = m_disc*x_test + b_disc
print(y_grd_pred[0].shape)
print(Y_test)
```

```
(1,)
[230. 214. 230. ... 219. 210. 248.]
```

```
MSE_test = 0
for i in range(0, len(Y_test)):
    MSE_test += pow((Y_test[i] - y_grd_pred[i]), 2)
MSE_test /= len(Y_test)
float(MSE_test)
```

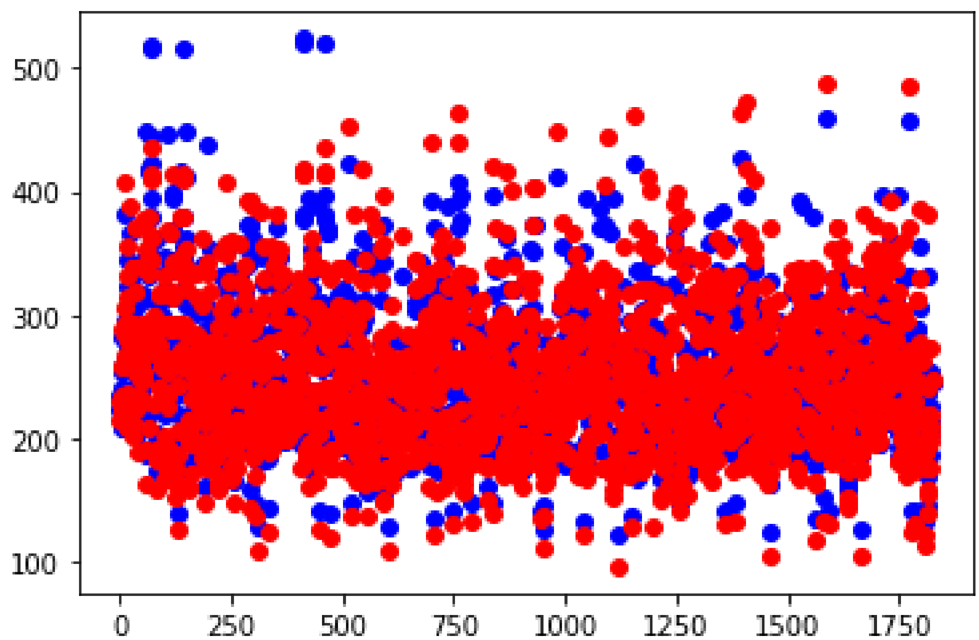
```
584.5049533453365
```

```
MAE_test = 0
for i in range(0, len(Y_test)):
    MAE_test += abs((Y_test[i] - y_grd_pred[i]))
MAE_test /= len(Y_test)
float(MAE_test)
# from sklearn.metrics import mean_absolute_error
# mean_absolute_error(y_grd_pred, Y_test)
```

```
15.099668576572203
```

```
indexes = [i for i in range(len(y_grd_pred))]
plt.scatter(x=indexes, y=y_grd_pred, color='blue') #blue for
prediction
indexes = [i for i in range(len(Y_test))]
plt.scatter(x=indexes, y=Y_test, color='red') # Red for data sample
```

```
<matplotlib.collections.PathCollection at 0x7f133ff61910>
```



Classification

```
#Extracting Data
main_df = pd.read_csv("./Heart Disease Dataset/heart.csv")
main_df.head()
```

```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak
slope  \
0   52    1   0       125   212    0        1      168      0      1.0
2
1   53    1   0       140   203    1        0      155      1      3.1
0
2   70    1   0       145   174    0        1      125      1      2.6
```

```
0
3   61   1   0      148   203   0        1      161       0      0.0
2
4   62   0   0      138   294   1        1      106       0      1.9
1

   ca  thal  target
0   2     3       0
1   0     3       0
2   0     3       0
3   1     3       0
4   3     2       0
```

Pre-processing

```
#Checking Null values
main_df.isna().sum()
```

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

```
(main_df == '?').sum()
```

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

```python
#Checking null values
main_df.duplicated().sum()
```

```
723
```

```python
#Dropping null values
main_df.drop(axis = "rows", labels =
main_df.index[main_df.duplicated()], inplace = True)
```

```python
#Checking unique values for all columns
main_df.nunique()
```

```
age          41
sex           2
cp            4
trestbps     49
chol        152
fbs           2
restecg       3
thalach      91
exang         2
oldpeak      40
slope         3
ca            5
thal          4
target        2
dtype: int64
```

```python
main_df["cp"].value_counts()
```

```
0    143
2     86
1     50
3     23
Name: cp, dtype: int64
```

```python
main_df["restecg"].value_counts()
```

```
1    151
0    147
2      4
Name: restecg, dtype: int64
```

```python
main_df["slope"].value_counts()
```

```
2    141
1    140
0     21
Name: slope, dtype: int64
```

```python
main_df["ca"].value_counts()
```

```
0    175
1     65
2     38
3     20
4      4
Name: ca, dtype: int64
```

```
main_df["thal"].value_counts()
```

```
2    165
3    117
1     18
0      2
Name: thal, dtype: int64
```

```
main_df["target"].value_counts()
```

```
1    164
0    138
Name: target, dtype: int64
```

One Hot Encoding

```
#one hot encoding of the column for which different values are not
that much
one_hot_encode_labels = ["cp", "restecg", "slope", "ca", "thal"]
main_df = pd.get_dummies(main_df, columns=one_hot_encode_labels)
```

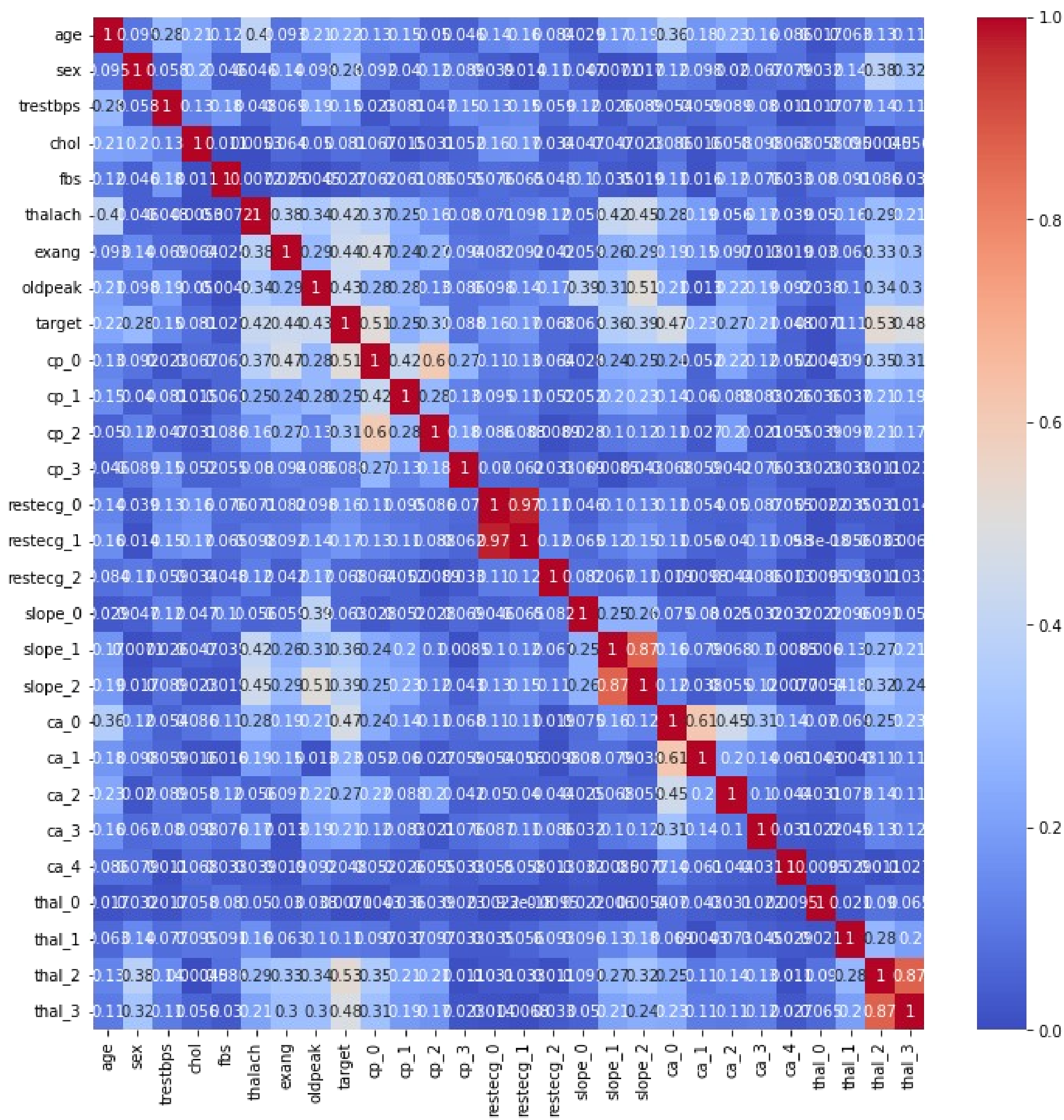
```
#standardize all the column except the column which take values either
0 or 1 and the target column
columns_to_standardize = ["age", "trestbps", "chol", "thalach",
"oldpeak"]
for i in columns_to_standardize:
    main_df[i] = (main_df[i]-main_df[i].mean())/main_df[i].std()
main_df.head()
```

```
        age  sex  trestbps      chol  fbs   thalach  exang   oldpeak
target  \
0 -0.267522    1 -0.375932 -0.666622    0  0.804700      0 -0.037063
0
1 -0.157000    1  0.478117 -0.840523    1  0.237102      1  1.771019
0
2  1.721875    1  0.762800 -1.400872    0 -1.072740      1  1.340523
0
3  0.727176    1  0.933609 -0.840523    0  0.499070      0 -0.898054
0
4  0.837698    0  0.364243  0.917813    1 -1.902307      0  0.737829
0

   cp_0  ...  slope_2  ca_0  ca_1  ca_2  ca_3  ca_4  thal_0  thal_1
thal_2  \
0     1  ...        1     0     0     1     0     0       0       0
```

```
0
1     1  ...        0     1     0     0     0     0       0       0
0
2     1  ...        0     1     0     0     0     0       0       0
0
3     1  ...        1     0     1     0     0     0       0       0
0
4     1  ...        0     0     0     0     1     0       0       0
1

   thal_3
0       1
1       1
2       1
3       1
4       0

[5 rows x 28 columns]
```

```python
#Getting the correlation Matrix
corr_df2 = abs(main_df.corr())

plt.figure(figsize=(12,12))
seaborn.heatmap(corr_df2, cmap='coolwarm',annot=True)
#Heatmap plot
```

```
<AxesSubplot:>
```



Splitting the data into test and train

```
data_train = main_df.sample(frac = 0.65, random_state = 50) # frac = 0.65
data_test = main_df.drop(data_train.index)

X_cls = data_train.drop(axis = "columns", labels = "target").to_numpy().astype(np.float64)
Y_cls = data_train["target"].to_numpy().astype(np.float64)
X_cls_test = data_test.drop(axis = "columns", labels = "target").to_numpy().astype(np.float64)
Y_cls_test = data_test["target"].to_numpy().astype(np.float64)

#Adding the column of 1 in X for the bias term
Y_count = data_train["target"].nunique() # different values that target can take
```

```python
X_cls_train = np.zeros((X_cls.shape[0], X_cls.shape[1]+1))
X_cls_train[:,0] = 1
X_cls_train[:,1:] = X_cls
X_cls_test2 = np.zeros((X_cls_test.shape[0], X_cls_test.shape[1]+1))
X_cls_test2[:,0] = 1
X_cls_test2[:,1:] = X_cls_test
```

```python
#Initializing the weight vector
W_cls = np.ones((X_cls_train.shape[1], 1))
print(W_cls.shape)
```

```
(28, 1)
```

Gradient descent for Logistic Regression

```python
#Sigmoid function
def sigmoid(z):
    return 1/(1+np.exp(-z))
```

```python
yhat = sigmoid(np.dot(X_cls_train, W_cls))
print(yhat.shape)
```

```
(196, 1)
```

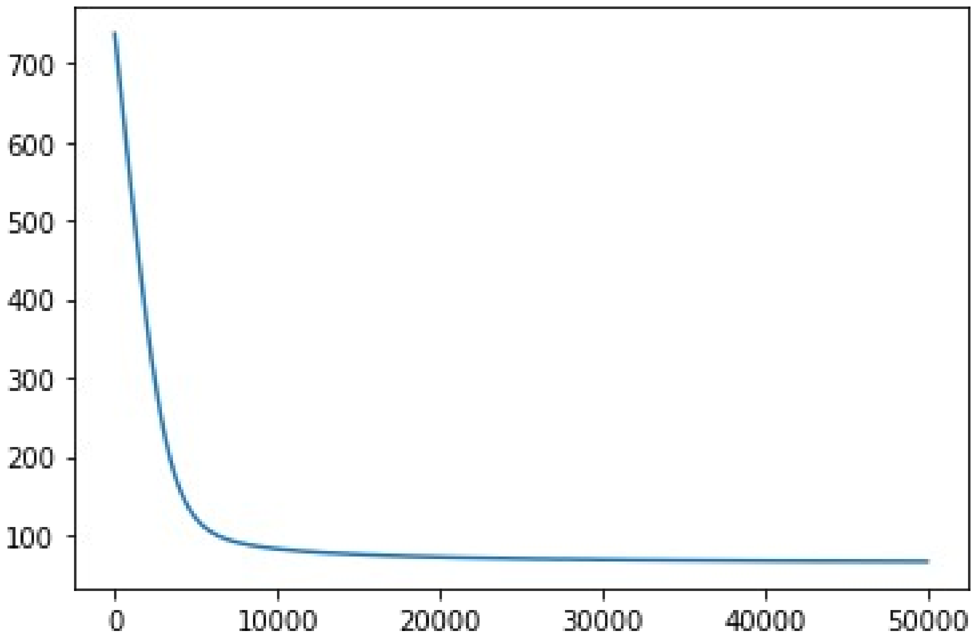
```python
alpha = 0.001
itr = 50000
```

```python
#Calculating entropy for the cost
def Entropy(a, b, c):
    return((np.sum(a*np.log(sigmoid(np.dot(b, c))) + (1-a)*np.log(1-
sigmoid(np.dot(b, c)))))*(-1))
```

```python
m_points = X_cls_train.shape[0]
Y_cls = Y_cls.reshape(m_points, 1)
costs2 = []
for i in range(itr):
    cost2 = Entropy(Y_cls, X_cls_train, W_cls)
    costs2.append(cost2)
    yhat = sigmoid(np.dot(X_cls_train, W_cls))
    dw = (1/m_points)*np.dot(X_cls_train.T, (yhat - Y_cls))
    W_cls = W_cls - alpha*dw
```

```python
plt.plot(costs2)
```

```
[<matplotlib.lines.Line2D at 0x7f133f6a77f0>]
```




```
#Mx = P(Y=1|X_i)
Mx = sigmoid(np.dot(X_cls_test2, W_cls))
print(Mx.shape)
print(W_cls.shape)
print(X_cls_train.shape)
print(W_cls)
```

```
(106, 1)
(28, 1)
(196, 28)
[[-0.89630574]
 [ 0.04131164]
 [-1.084774  ]
 [-0.27935924]
 [-0.25970519]
 [ 0.55574427]
 [ 0.52609796]
 [-0.38725861]
 [-0.22071462]
 [-0.63145964]
 [ 0.69782388]
 [ 1.04053436]
 [ 0.99679566]
 [-0.06378392]
 [ 0.24467949]
 [ 0.9227987 ]
 [ 0.6409081 ]
 [-0.31946484]
 [ 0.78225101]
 [ 1.4758835 ]
```

```
 [-0.11451448]
 [-0.01983725]
 [ 0.65848715]
 [ 1.10367533]
 [ 0.8885408 ]
 [ 0.69008655]
 [ 1.06685473]
 [-0.54178781]]
```

```python
#Initializing yprd
yprd = np.zeros(Mx.shape)
#Classifying into 0 or 1
for i in range(Mx.shape[0]):
    if(Mx[i] > 0.5):
        yprd[i] = 1
    else:
        yprd[i] = 0

print(yprd)
```

```
[[0.]
 [0.]
 [1.]
 [0.]
 [0.]
 [1.]
 [1.]
 [0.]
 [1.]
 [0.]
 [1.]
 [1.]
 [0.]
 [1.]
 [1.]
 [0.]
 [1.]
 [1.]
 [1.]
 [0.]
 [0.]
 [1.]
 [1.]
 [1.]
 [1.]
 [1.]
 [1.]
 [0.]
 [0.]
 [1.]
 [0.]
```

```
[0.]
[1.]
[0.]
[1.]
[1.]
[0.]
[0.]
[0.]
[0.]
[0.]
[0.]
[1.]
[0.]
[1.]
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[0.]
[1.]
[0.]
[1.]
[1.]
[1.]
[1.]
[1.]
[0.]
[1.]
[1.]
```

```
 [0.]
 [0.]
 [1.]
 [0.]
 [0.]
 [1.]
 [0.]
 [1.]
 [0.]
 [0.]
 [1.]
 [1.]
 [0.]
 [1.]
 [1.]
 [1.]
 [1.]
 [0.]
 [1.]
 [1.]
 [0.]
 [0.]
 [1.]
 [1.]
 [1.]]
```

```
from sklearn.metrics import accuracy_score
accuracy_score(Y_cls_test, yprd)
```

```
0.8679245283018868
```

Implementing F1 score

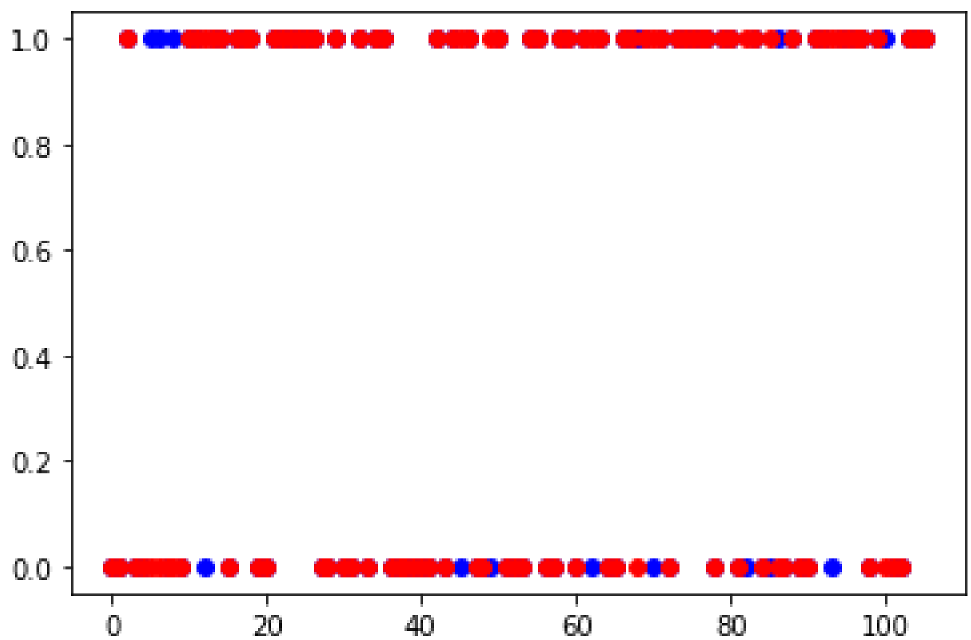
```
def confusion_matrix_mod(Y, Y_pred):
    Y = pd.Series(Y, name='Actual')
    Y_pred = pd.Series(Y_pred, name='Predicted')
    confusionMatrix = pd.crosstab(Y, Y_pred, rownames=['Actual'], 
colnames=['Predicted'], margins=True)
    return confusionMatrix

def calculateParams(confusionMatrix, rows):
    TP = 0
    FP = 0
    FN = 0
    for i in range(rows):
        TP += confusionMatrix[i][i]
        FP += confusionMatrix[rows][i] - confusionMatrix[i][i]
        FN += confusionMatrix[i][rows] - confusionMatrix[i][i]
    return TP, FP, FN
```

```
def calculate_f1_score(TP, FP, FN):
    precision = TP/(TP+FP)
    recall = TP/(TP+FN)
    f1 = (2*precision*recall)/(precision+recall)
    return f1

#reshaping yprd to 1 dimension
yprd = yprd.reshape(yprd.shape[0])

confusionMatrix = confusion_matrix_mod(Y_cls_test, yprd)
confusionMatrix = confusionMatrix.to_numpy()

TP, FP, FN = calculateParams(confusionMatrix, Y_count)
f1_score = calculate_f1_score(TP, FP, FN)
print(f1_score)
```

```
0.8679245283018869
```

```
# As we can see this F1 score is matching with scikit learn F1 score

indexes = [i for i in range(len(yprd))]
plt.scatter(x=indexes, y=yprd, color='blue') #blue for prediction
indexes = [i for i in range(len(Y_cls_test))]
plt.scatter(x=indexes, y=Y_cls_test, color='red') # Red for data
sample
```

```
<matplotlib.collections.PathCollection at 0x7f133f648a60>
```



Classification Naive Bayes

```
#Importing pandas and numpy library
import numpy as np
```

```
import pandas as pd
import matplotlib.pyplot as plt

# Extracting data
data = pd.read_csv("./Heart Disease Dataset/heart.csv")
data.head()
```

```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak
slope  \
0   52    1   0       125   212    0        1      168      0      1.0
2
1   53    1   0       140   203    1        0      155      1      3.1
0
2   70    1   0       145   174    0        1      125      1      2.6
0
3   61    1   0       148   203    0        1      161      0      0.0
2
4   62    0   0       138   294    1        1      106      0      1.9
1

   ca  thal  target
0   2     3       0
1   0     3       0
2   0     3       0
3   1     3       0
4   3     2       0
```

```
#checking for How many duplicate data are there
data.duplicated().sum()
```

```
723
```

```
# Dropping all the duplicate rows
data.drop(axis = "rows", labels = data.index[data.duplicated()],
inplace = True)

# Standardizing all the given columns except the columns which take
either 0 or 1 value and the target column
columns_to_standardize = ["age", "trestbps", "chol", "thalach",
"oldpeak", "cp", "restecg", "slope", "ca", "thal"]
for i in columns_to_standardize:
    data[i] = (data[i]-data[i].mean())/data[i].std()
data.head()
```

```
        age  sex        cp  trestbps      chol  fbs   restecg
thalach  \
0 -0.267522    1 -0.933658 -0.375932 -0.666622    0  0.900163
0.804700
1 -0.157000    1 -0.933658  0.478117 -0.840523    1 -1.000880
0.237102
2  1.721875    1 -0.933658  0.762800 -1.400872    0  0.900163 -
1.072740
```

```
3  0.727176    1 -0.933658  0.933609 -0.840523    0  0.900163
0.499070
4  0.837698    0 -0.933658  0.364243  0.917813    1  0.900163 -
1.902307

   exang   oldpeak     slope        ca      thal  target
0      0 -0.037063  0.977891  1.272867  1.118111       0
1      1  1.771019 -2.267418 -0.713727  1.118111       0
2      1  1.340523 -2.267418 -0.713727  1.118111       0
3      0 -0.898054  0.977891  0.279570  1.118111       0
4      0  0.737829 -0.644764  2.266164 -0.513143       0

# Splitting the data into train and test in the ratio 65:35
data_training = data.sample(frac = 0.65, random_state = 50) # frac =
0.65
data_testing = data.drop(data_training.index)

# For the X values we are dropping the target column and converting
that dataframe into numpy array
X_class = data_training.drop(axis = "columns", labels =
"target").to_numpy().astype(np.float64)
Y_class = data_training["target"].to_numpy().astype(np.float64)
X_class_test = data_testing.drop(axis = "columns", labels =
"target").to_numpy().astype(np.float64)
Y_class_test = data_testing["target"].to_numpy().astype(np.float64)

data_0 = data_training.loc[data_training['target'] == 0] # Data sample
entries for which the target value is 0
data_1 = data_training.loc[data_training['target'] == 1] # Data sample
entries for which the target value is 0
data_num_0 = data_0.drop(axis = "columns", labels =
"target").to_numpy().astype(np.float64)# dropping the target column
and converting into numpy
data_num_1 = data_1.drop(axis = "columns", labels =
"target").to_numpy().astype(np.float64)# dropping the target column
and converting into numpy

data_0.head()

          age  sex        cp  trestbps      chol  fbs   restecg
thalach  \
69   0.837698    0 -0.933658  1.616849 -1.594095    0 -1.000880 -
0.199512
429 -0.820132    1  1.004244 -1.343855 -0.067628    0  0.900163
0.106117
113  0.285088    1 -0.933658 -1.229981  1.710030    0  0.900163 -
0.286835
67  -1.372742    1 -0.933658  0.250370  1.323582    0  0.900163 -
1.072740
39   0.285088    1  1.004244 -0.205123 -0.338141    0 -1.000880
0.018795
```

```
     exang   oldpeak     slope        ca      thal  target
69       0  4.440091 -2.267418  2.266164  1.118111       0
429      0 -0.898054  0.977891 -0.713727 -0.513143       0
113      1  1.684920 -0.644764  0.279570  1.118111       0
67       1  0.651730 -0.644764 -0.713727 -2.144396       0
39       0 -0.553657 -0.644764  0.279570  1.118111       0
```

```
data_1.head()
```

```
          age  sex        cp  trestbps      chol  fbs   restecg
thalach  \
137  1.058743    0 -0.933658  2.755581  1.516806    0  0.900163
0.193440
521  0.395610    1  0.035293 -0.375932 -0.512043    0  0.900163 -
0.243174
41  -0.046478    1  1.004244 -0.660615  0.222207    0 -1.000880 -
0.112190
549  1.500831    1  1.004244 -0.774489  0.589332    0  0.900163
0.062456
355 -0.930654    0 -0.933658  0.364243 -0.067628    0 -1.000880
0.106117

     exang   oldpeak     slope        ca      thal  target
137      1 -0.898054  0.977891 -0.713727 -0.513143       1
521      0 -0.553657 -0.644764  3.259461  1.118111       1
41       0 -0.553657 -0.644764 -0.713727  1.118111       1
549      0 -0.037063  0.977891  0.279570  1.118111       1
355      1 -0.898054 -0.644764 -0.713727 -0.513143       1
```

We fit a gausian for each class and each feature column

```
# Initializing means array wich will store a mean for each gausian
means = np.zeros((Y_count, X_class.shape[1]))
print(means.shape)
```

```
(2, 13)
```

```
# Initializing stdDev array wich will store a standard deviation for
each gausian
stdDev = np.zeros((Y_count, X_class.shape[1]))
print(stdDev.shape)
```

```
(2, 13)
```

```
# Calculating and assigning the mean for each class feature and each
class label
for i in range(X_class.shape[1]):#for each feature
    means[0][i] = np.mean(data_num_0[:, i])# for both class label 0
and 1
    means[1][i] = np.mean(data_num_1[:, i])
```

```
# Calculating and assigning the mean for each class feature and each
class label
for i in range(X_class.shape[1]): # for each feature
    stdDev[0][i] = np.std(data_num_0[:,i])# for both class label 0 and
1
    stdDev[1][i] = np.std(data_num_1[:,i])
```

```
print(means)
```

```
[[ 0.22922001  0.83516484 -0.45450662  0.23285127  0.14003409
0.15384615
  -0.16525691 -0.41494056  0.56043956  0.34801807 -0.3416302
0.36689315
   0.41900218]
 [-0.23173379  0.57142857  0.39518911 -0.08582686 -0.11768243
0.11428571
   0.08543001  0.39927253  0.17142857 -0.31749961  0.34428326 -
0.32586782
  -0.32671367]]
```

```
print(stdDev)
```

```
[[0.87107981 0.37103171 0.88984151 1.15866351 0.9648036  0.36080121
  0.98474199 0.9349954  0.49633362 1.11862152 0.92894434 1.03759013
  1.11198152]
 [1.0089806  0.49487166 0.93854888 0.94696286 0.87149665 0.31815796
  0.94077205 0.77847098 0.37688303 0.74975025 0.9888053  0.82816631
  0.75727802]]
```

```
def normal_distribution(z, mean, dev):
    return((1/dev*np.sqrt(2*np.pi))*np.exp((-1/2)*((z-
mean)**2)/dev**2))
```

Inference for the Test data

```
count_1 = data_testing["target"].sum() # number of 1's in the test
data
count_0 = len(data_testing["target"])-count_1 # number of 1's in the
test data
```

(PI for k=1 to m(P(X[i, k])|y_i = c_j))*P(y_i = c_j)

```
Probability = np.zeros((X_class_test.shape[0], 1)) # Initializing the
numpy array to store the classification value
for i in range(X_class_test.shape[0]): # for all data samples
    prob_0 = 1
    prob_1 = 1
    for j in range(X_class_test.shape[1]): # for all data features
        prob_0 = prob_0*normal_distribution(X_class_test[i, j],
means[0, j], stdDev[0, j])*(count_0/(count_0+count_1))
        prob_1 = prob_1*normal_distribution(X_class_test[i, j],
means[1, j], stdDev[1, j])*(count_1/(count_0+count_1))
```

```
    #Classification according to which class label has higher
probability
    if(prob_0 > prob_1):
        Probability[i] = 0
    else:
        Probability[i] = 1

print(Probability)

[[1.]
 [0.]
 [1.]
 [0.]
 [0.]
 [1.]
 [1.]
 [1.]
 [0.]
 [0.]
 [1.]
 [1.]
 [0.]
 [1.]
 [1.]
 [0.]
 [1.]
 [1.]
 [1.]
 [0.]
 [0.]
 [1.]
 [1.]
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```

```
from sklearn.metrics import accuracy_score
accuracy_score(Y_class_test, Probability)
```

```
0.8113207547169812
```

```
#reshaping yprd to 1 dimension
Probability = Probability.reshape(Probability.shape[0])
```

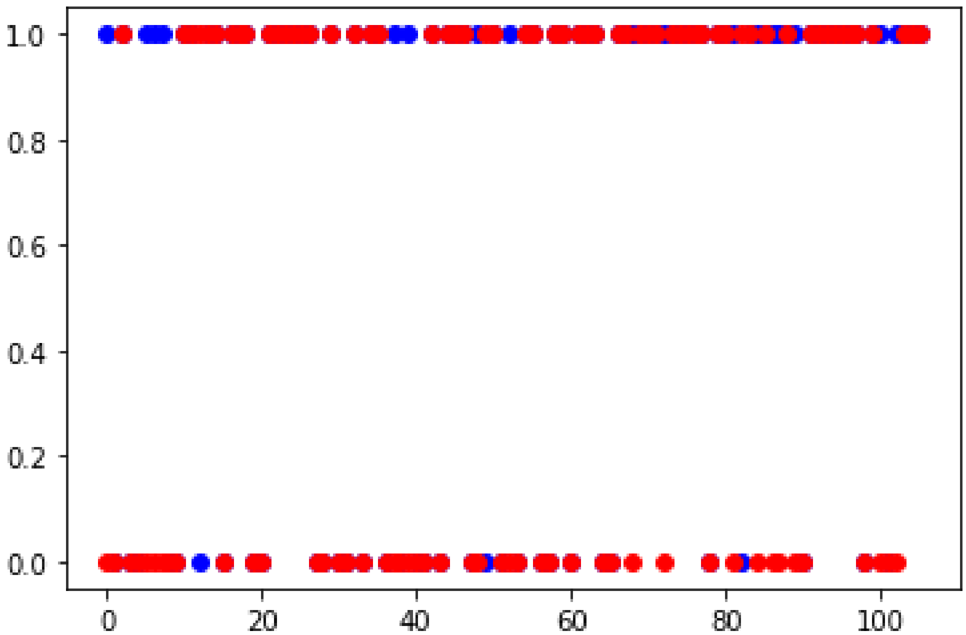
```
# Implementing F1 score
confusionMatrix = confusion_matrix_mod(Y_class_test, Probability)
confusionMatrix = confusionMatrix.to_numpy()

TP, FP, FN = calculateParams(confusionMatrix, Y_count)
f1_score = calculate_f1_score(TP, FP, FN)
print(f1_score)
```

```
0.8113207547169812
```

```
# As we can see this F1 score is matching with scikit learn F1 score
```

```
indexes = [i for i in range(len(Probability))]
plt.scatter(x=indexes, y=Probability, color='blue') #blue for
prediction
indexes = [i for i in range(len(Y_class_test))]
plt.scatter(x=indexes, y=Y_class_test, color='red') # Red for data
sample
```

```
<matplotlib.collections.PathCollection at 0x7f133f54ea00>
```



1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
80
100