Regression for CO2.data

In [1]:

```
#import packages
import numpy as np
import pandas as pd
import seaborn as sn
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (10,6)

df=pd.read_csv("CO2_Emissions_Canada.csv")
df.head()
```

Out[1]:

	Make	Model	Vehicle Class	Engine Size(L)	Cylinders	Transmission	Fuel Type	Fuel Consumption City (L/100 km)	Fuel Consumption Hwy (L/100 km)	Fuel Consumption Comb (L/100 km)	F Consumpt Comb (m
0	ACURA	ILX	COMPACT	2.0	4	AS5	Z	9.9	6.7	8.5	
1	ACURA	ILX	COMPACT	2.4	4	M6	Z	11.2	7.7	9.6	
2	ACURA	ILX HYBRID	COMPACT	1.5	4	AV7	Z	6.0	5.8	5.9	
3	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS6	Z	12.7	9.1	11.1	
4	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS6	Z	12.1	8.7	10.6	

Swapping function

In [2]:

```
#swapping columns, shifting target column as first column
def swap_columns(df, c1, c2):
    col_list = list(df.columns)
    x, y = col_list.index(c1), col_list.index(c2)
    col_list[y], col_list[x] = col_list[x], col_list[y]
    df = df[col_list]
    return df
```

In [3]:

```
def mean_absolute_error(y_true,predictions):
  return np.mean(np.abs(y_true - predictions))
```

In [4]:

```
#analysing the data and checking for null values
df.head()
df.isna().sum()
df.nunique()
len(df)
```

Out[4]:

```
7385
```

In [5]:

```
#shifting co2 emissions column as first column
```

```
df=swap_columns(df,"Make","CO2 Emissions(g/km)")
df.nunique()
```

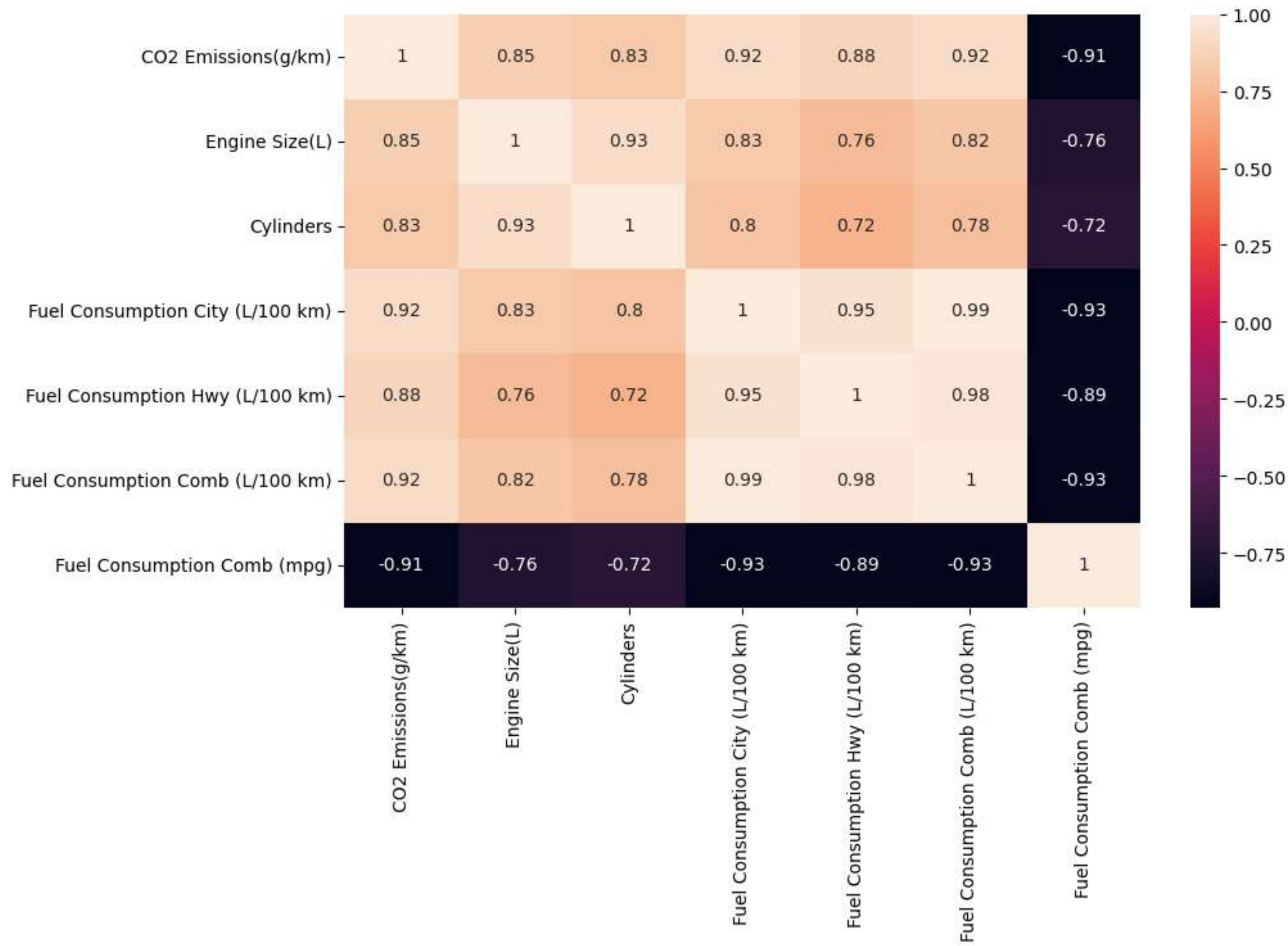
Out[5]:

```
CO2 Emissions(g/km)                  331
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
Make                                  42
dtype: int64
```

Correlation matrix

In [6]:

```
#correlation matrix
corrMatrix = df.corr()
sn.heatmap(corrMatrix, annot=True)
plt.show()
```



PREPROCESSING

Removing columns... and one hot encoding..

In [7]:

```
#removing unnecessary columns from dataframe
df.drop(axis="columns", labels="Make", inplace=True)
df.drop(axis="columns", labels="Model", inplace=True)
df.drop(axis="columns", labels="Vehicle Class", inplace=True)
#df.drop(axis="columns", labels="Transmission", inplace=True)

#using one hot encoding for fuel type and transmission columns
column_names_to_one_hot=["Fuel Type","Transmission"]
df = pd.get_dummies(df, columns=column_names_to_one_hot)
df.head()
```

Out[7]:

	CO2 Emissions(g/km)	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)	Fuel Type_D	Fuel Type_E	Fuel Type_N	...
0	196	2.0	4	9.9	6.7	8.5	33	0	0	0	...
1	221	2.4	4	11.2	7.7	9.6	29	0	0	0	...
2	136	1.5	4	6.0	5.8	5.9	48	0	0	0	...
3	255	3.5	6	12.7	9.1	11.1	25	0	0	0	...
4	244	3.5	6	12.1	8.7	10.6	27	0	0	0	...

5 rows × 39 columns

removing duplicates...

In [8]:

```
#removing duplicates
df.duplicated().sum()
df.drop(axis="rows", labels=df.index[df.duplicated()], inplace=True)
df.duplicated().sum()
df.shape[1]
```

Out[8]:

39

Seperating target column and features

In [9]:

```
#seperating X and Y
# adding a column of 1's
#X=np.ones((len(df),40))

X=df.iloc[:,1:df.shape[1]+1]

#standarize the data and a add a column of 1's as a constant
X = (X - X.mean())/X.std()
X.insert(df.shape[1]-1, "Const", [1]*len(X), True)
Y=df.iloc[:,0]
#print(X)
```

Splitting train and test data

In [10]:

```
#splitting data
np.random.seed(94)
arr = np.random.rand(X.shape[0])
split = arr < np.percentile(arr,89)
X_train = X[split]
Y_train = Y[split]
```

```
X_test =  X[~split]
Y_test = Y[~split]
```

UNIVARIATE LINEAR REGRESSION : CLOSED FORM

data for univariate regression

In [11]:

```
#column -3rd as the correclation bw 3 (or 5th) is greater with CO2 emissions
X_uni = df.iloc[:,[3]]
X_uni = (X_uni - X_uni.mean())/X_uni.std()
X_uni.insert(1, "Const", [1]*len(X_uni), True)
X_uni.nunique()
X_uni_tr=X_uni[split]
X_uni_te=X_uni[~split]
```

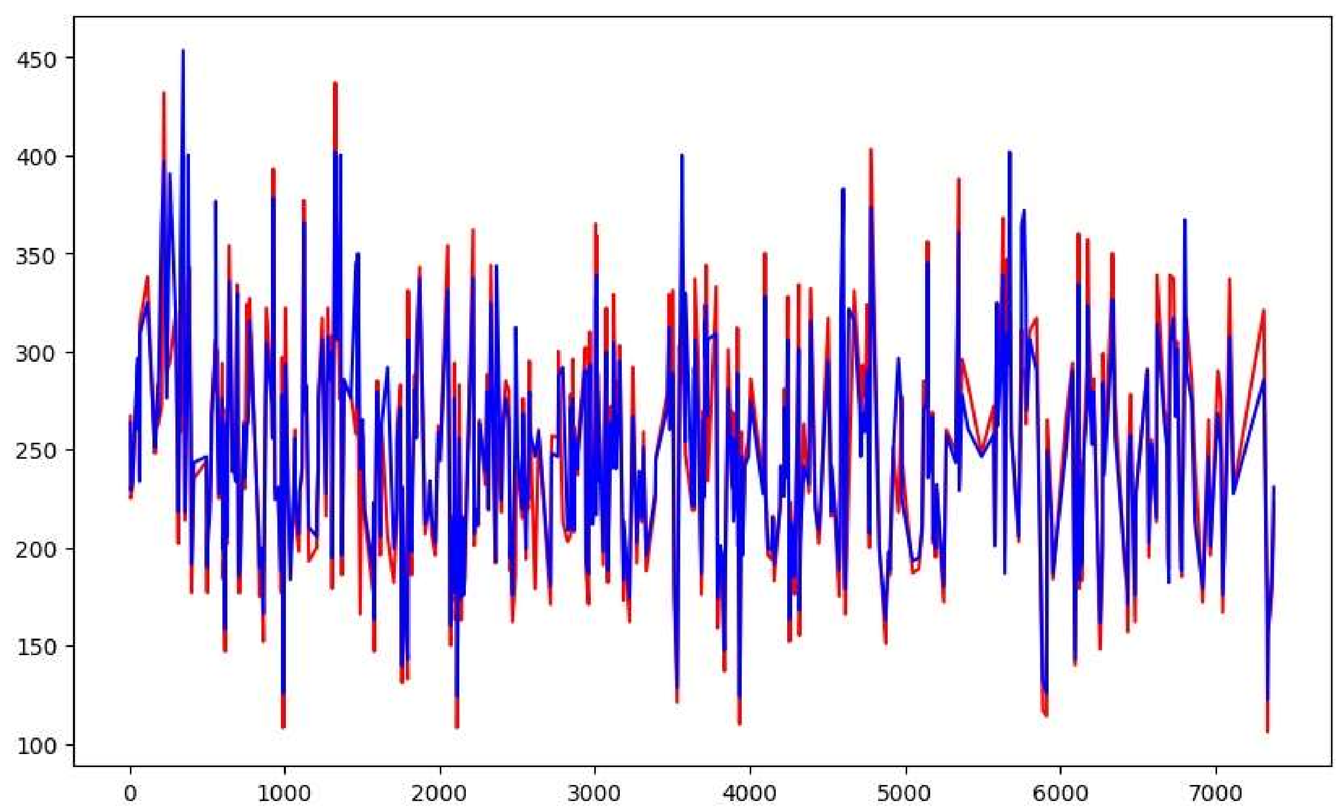
In [12]:

```
#formula for closed form regression
weightx= np.linalg.inv(X_uni_tr.T@X_uni_tr)@(X_uni_tr.T@Y_train)

Y_pred = (  X_uni_te @ weightx)
#print(Y_pred)
```

In [13]:

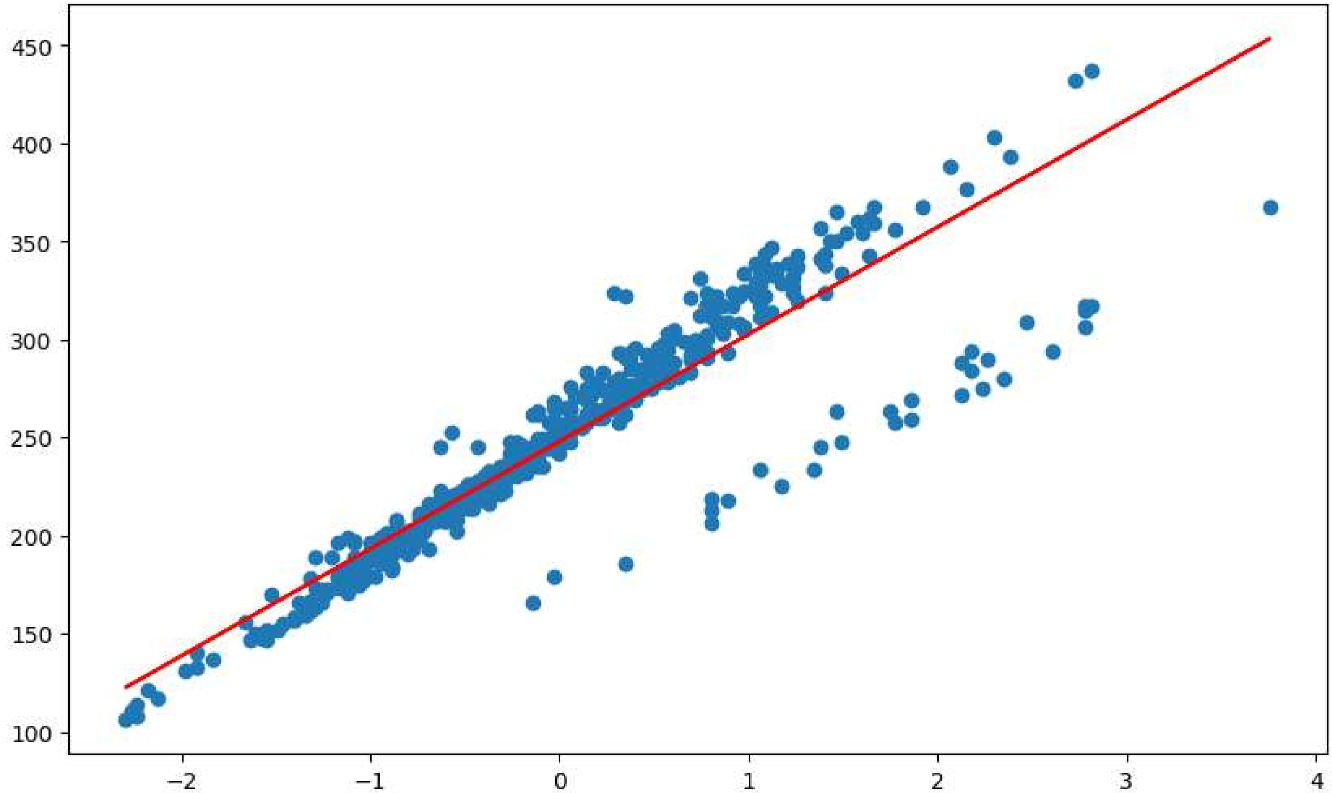
```
plt.plot(Y_test, color = "red")
plt.plot(Y_pred, color = "blue")
MSE = np.square(np.subtract(Y_test,Y_pred)).mean()
print("Mean Square Error: ", MSE)
mae=mean_absolute_error(Y_test,Y_pred)
#print(mae)
print("Mean Absolute Error: ", mae)
```

```
Mean Square Error:  594.0381937126144
Mean Absolute Error:  14.663427474262262
```



In [14]:

```
plt.scatter(X_test.loc[:,"Fuel Consumption City (L/100 km)"],Y_test)
plt.plot(X_test.loc[:,"Fuel Consumption City (L/100 km)"],Y_pred,color="red")
plt.show()
```



MULTIVARIATE LINEAR REGRESSION : Closed form

heart of linear regression

In [15]:

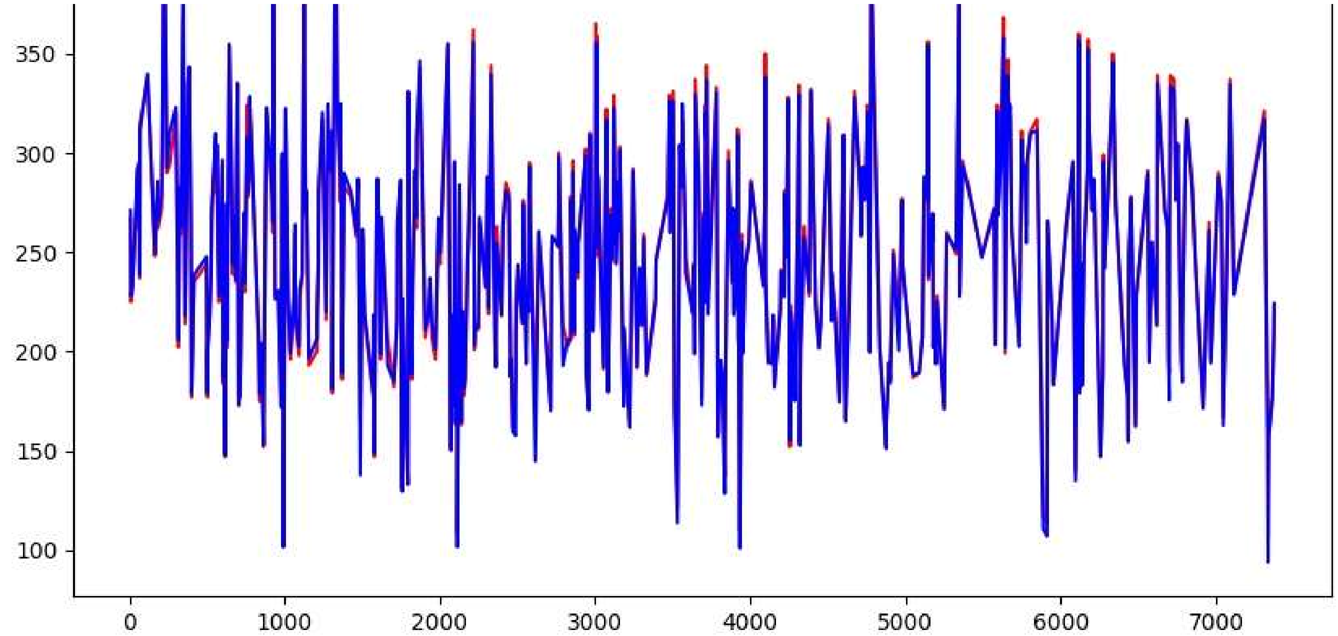
```
mat=X_train.T@X_train
ir=np.identity(X_train.shape[1])
ir+=0.0001
mat+=ir
mat=np.linalg.inv(mat)
mat=mat@(X_train.T@Y_train)
Y_pred=X_test@mat
```

Plot b/w predicted data and actual data

In [16]:

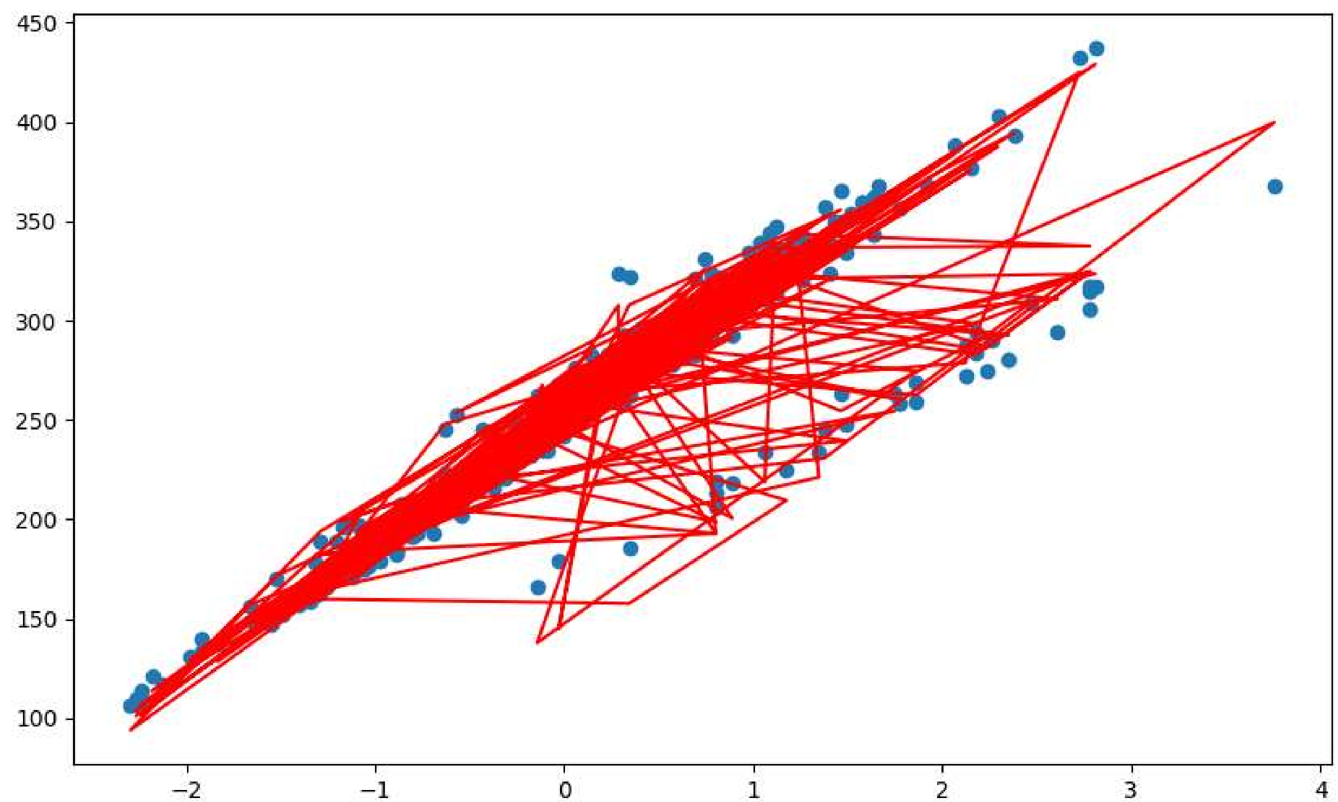
```
#print(mat)
plt.plot(Y_test, color = "red")
plt.plot(Y_pred, color = "blue")
MSE = np.square(np.subtract(Y_test,Y_pred)).mean()
print("Mean Square Error ", MSE)
mae=mean_absolute_error(Y_test,Y_pred)
print("Mean Absolute Error: ", mae)
#print(mae)
```

```
Mean Square Error  26.876641213389586
Mean Absolute Error:  3.2472669670416523
```



In [17]:

```
plt.scatter(X_test.loc[:,"Fuel Consumption City (L/100 km)"],Y_test)
plt.plot(X_test.loc[:,"Fuel Consumption City (L/100 km)"],Y_pred,color="red")
plt.show()
```



Gradient descent

UNIVARIATE LINEAR REGRESSION : gradient descent

In [18]:

```
l_rate=0.01

X_uni_tr=X.iloc[:,[3]]
X_uni_te=X.iloc[:,[3]]
```

```
X_uni_tr.insert(1, "Const", [1]*len(X_uni_tr), True)
X_uni_te.insert(1, "Const", [1]*len(X_uni_te), True)
X_uni_tr=X_uni_tr[split]
X_uni_te=X_uni_te[~split]

rows=X_uni_tr.shape[0]
```

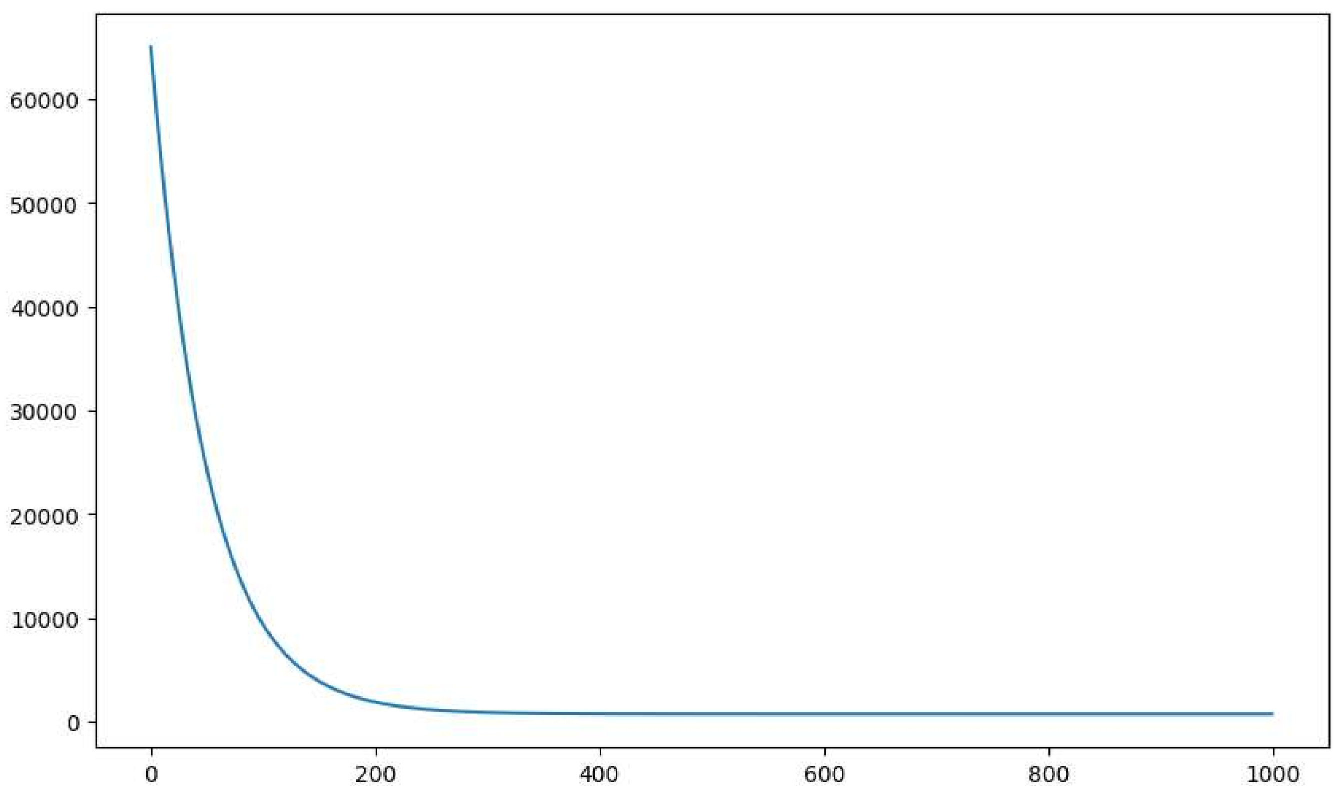
In [19]:

```
#W=np.random.uniform(low=0,high=2,size=2)
W=[0,0]
costs=[]

#W is the co efficients or the predicted co-relation
#grad is the gradient that to be reduced..

for i in range(1000):
    y_t=X_uni_tr@W
    #print(Y_train)
    #print(y_t)
    cost=np.mean((y_t-Y_train)**2)
    costs.append(cost)
    grad=(X_uni_tr.T)@(y_t-Y_train)
    W=W-1*l_rate/rows*grad

Y_pred=X_uni_te@W
#print(Y_pred)
```

In [20]:

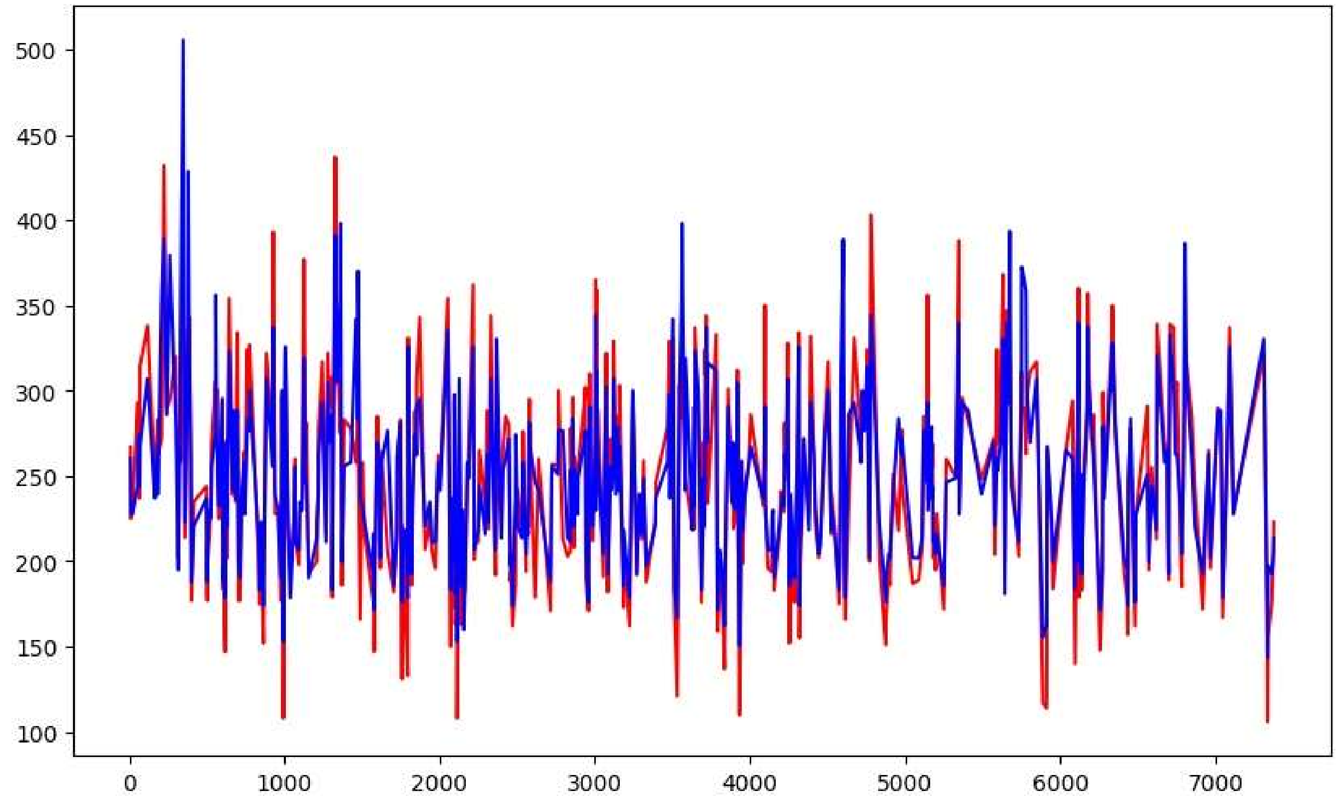
```
MSE = np.square(np.subtract(Y_test,Y_pred)).mean()
print("Mean Square Error : ", MSE)
plt.plot(costs)

mae=mean_absolute_error(Y_test,Y_pred)
#print(mae)
print("Mean Absolute Error: ", mae)
plt.show()
```

```
Mean Square Error :  756.1140717688158
Mean Absolute Error:  18.766331411368277
```



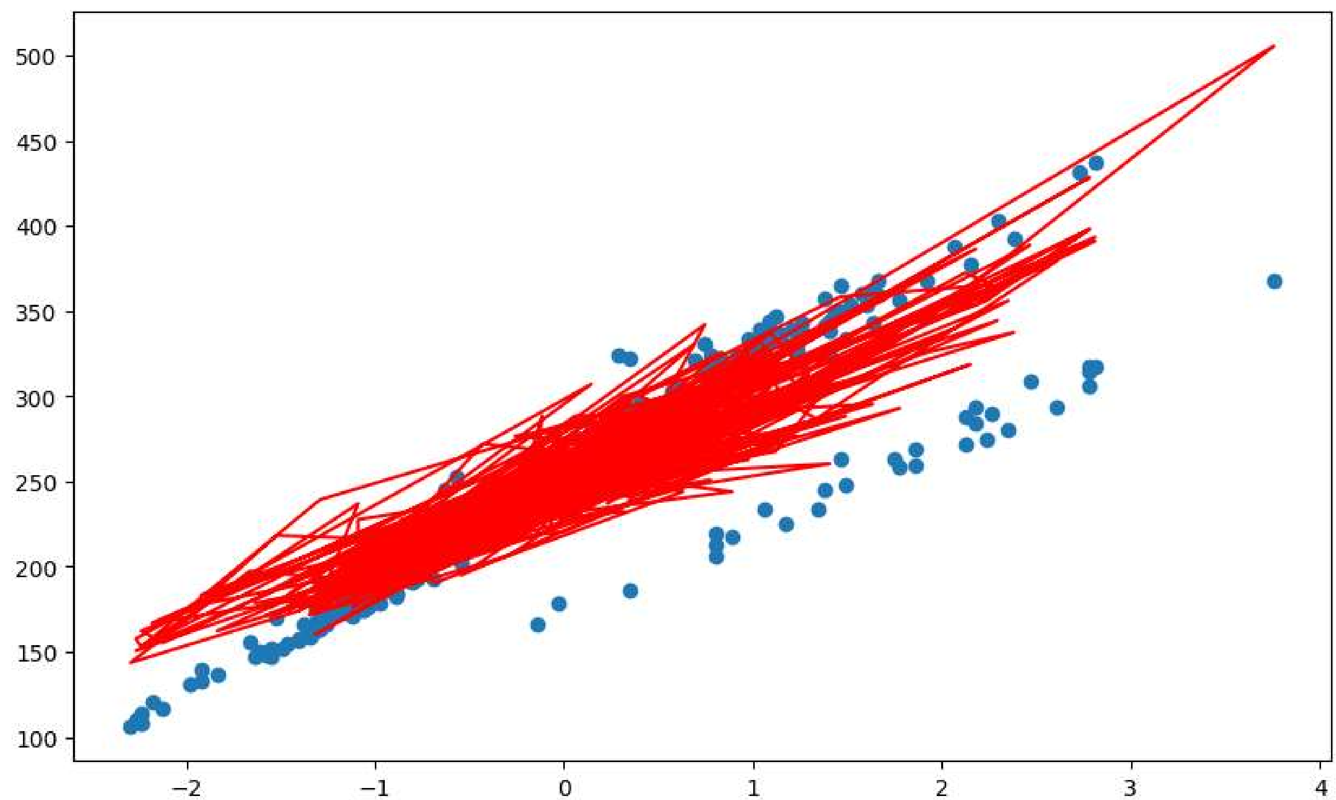
In [21]:

```
plt.plot(Y_test, color = "red")
plt.plot(Y_pred, color = "blue")
plt.show()
```



In [22]:

```
plt.scatter(X_test.loc[:,"Fuel Consumption City (L/100 km)"],Y_test)
plt.plot(X_test.loc[:,"Fuel Consumption City (L/100 km)"],Y_pred,color="red")
plt.show()
```



MULTIVARIATE LINEAR REGRESSION : gradient descent

In [23]:

```
#learning rate
l_rate=0.003

rows=X_train.shape[0]
#print(X_uni_tr.shape[1])

#a row of random values bw 0 and 1
W=np.random.uniform(low=0,high=1,size=X_train.shape[1])

#storing costs
costs=[]
```

In [24]:

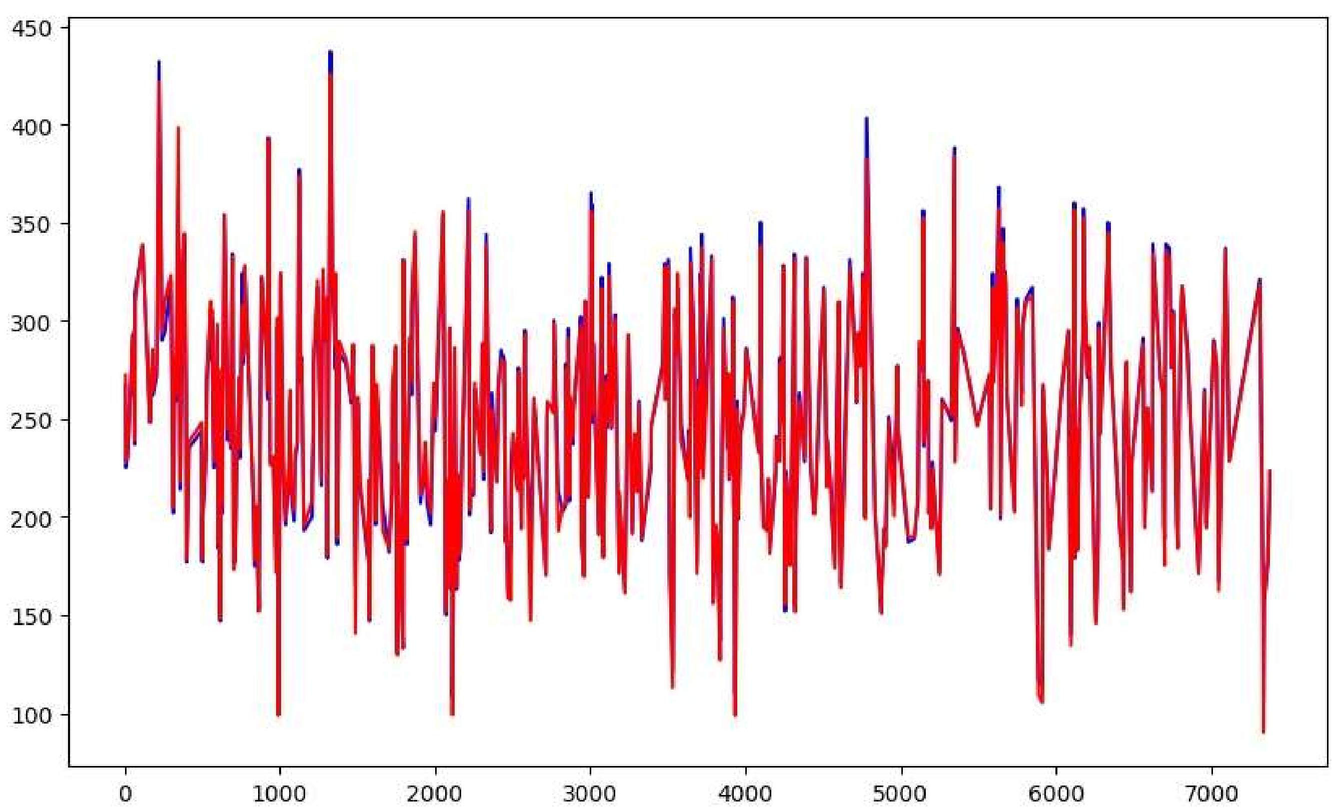
```
for i in range(10000):
    y_t=X_train@W
    cost=np.mean((y_t-Y_train)**2)
    costs.append(cost)
    grad=(X_train.T)@(y_t-Y_train)
    W=W-1*l_rate/rows*grad

#optimising W as the iteration goes on....
Y_pred=X_test@W
#print(Y_pred)
```

plot for *actual(blue)* and *predicted(red)*

In [25]:

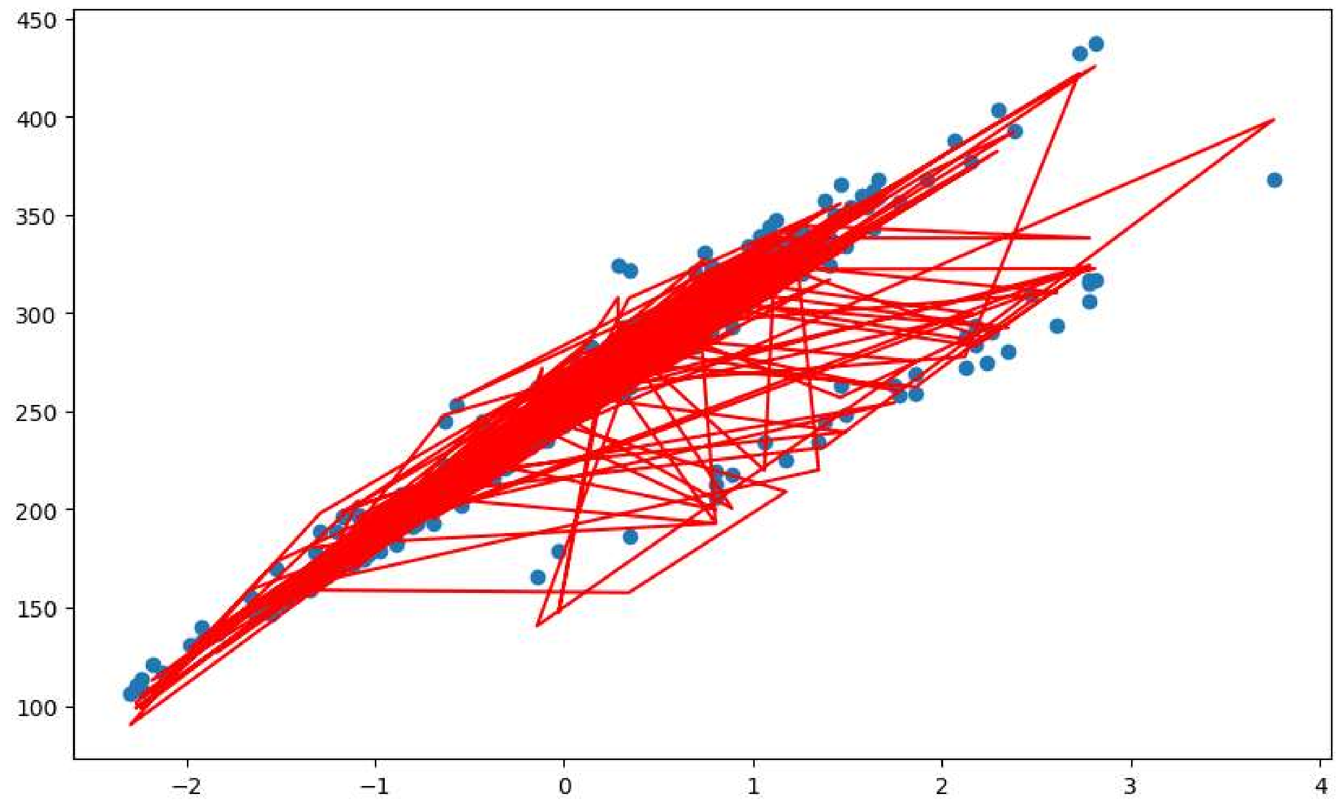
```
MSE = np.square(np.subtract(Y_test,Y_pred)).mean()
print("Mean Square", MSE)
plt.plot( Y_test,color="blue")
plt.plot(Y_pred, color="red")

mae=mean_absolute_error(Y_test,Y_pred)
print("Mean Absolute Error: ", mae)
```

```
Mean Square 28.835648093593942
Mean Absolute Error:  3.473828618910859
```



In [26]:

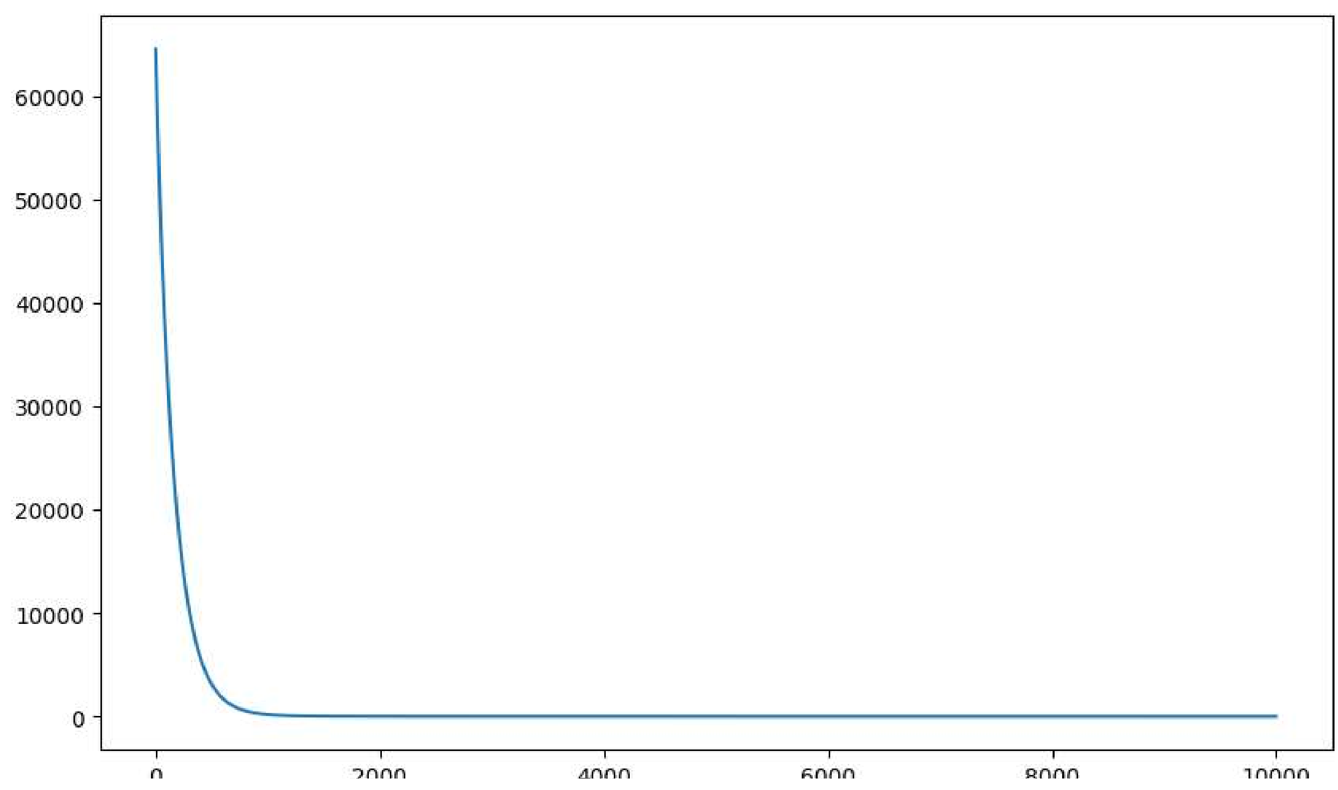
```
plt.scatter(X_test.loc[:,"Fuel Consumption City (L/100 km)"],Y_test)
plt.plot(X_test.loc[:,"Fuel Consumption City (L/100 km)"],Y_pred,color="red")
plt.show()
```



plot of costs...

In [27]:

```
plt.show()

#plotting costs
plt.plot(costs)
plt.show()
```



0
2000
4000
6000
8000
10000