

Machine Learning Assignment No.1

Que.1 Create a scatter plot between cylinder vs Co2Emission (green color)

Import the libraries

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

```
df = pd.read_csv("C:/Users/Lenovo/Documents/Data
Set/FuelConsumption.csv")
```

df

	MODEL	YEAR	MAKE	MODEL	VEHICLECLASS	ENGINE	SIZE
CYLINDERS \							
0	2014	ACURA	ILX	COMPACT	2.0		
4							
1	2014	ACURA	ILX	COMPACT	2.4		
4							
2	2014	ACURA	ILX HYBRID	COMPACT	1.5		
4							
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5		
6							
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5		
6							
...
...							

1062	2014	VOLVO	XC60 AWD	SUV - SMALL	3.0
6					
1063	2014	VOLVO	XC60 AWD	SUV - SMALL	3.2
6					
1064	2014	VOLVO	XC70 AWD	SUV - SMALL	3.0
6					
1065	2014	VOLVO	XC70 AWD	SUV - SMALL	3.2
6					
1066	2014	VOLVO	XC90 AWD	SUV - STANDARD	3.2
6					

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY
\				
0	AS5	Z	9.9	6.7
1	M6	Z	11.2	7.7

2	AV7	Z	6.0	5.8
3	AS6	Z	12.7	9.1
4	AS6	Z	12.1	8.7
...
1062	AS6	X	13.4	9.8
1063	AS6	X	13.2	9.5
1064	AS6	X	13.4	9.8
1065	AS6	X	12.9	9.3
1066	AS6	X	14.9	10.2

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255
4	10.6	27	244
...
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260
1066	12.8	22	294

[1067 rows x 13 columns]

df.head()

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINE SIZE	CYLINDERS	\
0	2014	ACURA	ILX	COMPACT	2.0	4	
1	2014	ACURA	ILX	COMPACT	2.4	4	
2	2014	ACURA	ILX HYBRID	COMPACT	1.5	4	
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5	6	
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5	6	

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY	\
0	AS5	Z	9.9	6.7	
1	M6	Z	11.2	7.7	
2	AV7	Z	6.0	5.8	
3	AS6	Z	12.7	9.1	

4	AS6	Z	12.1	8.7
---	-----	---	------	-----

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255
4	10.6	27	244

df.tail()

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINE SIZE
CYLINDERS \					
1062	2014	VOLVO	XC60 AWD	SUV - SMALL	3.0
6					
1063	2014	VOLVO	XC60 AWD	SUV - SMALL	3.2
6					
1064	2014	VOLVO	XC70 AWD	SUV - SMALL	3.0
6					
1065	2014	VOLVO	XC70 AWD	SUV - SMALL	3.2
6					
1066	2014	VOLVO	XC90 AWD	SUV - STANDARD	3.2
6					

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY
\				
1062	AS6	X	13.4	9.8
1063	AS6	X	13.2	9.5
1064	AS6	X	13.4	9.8
1065	AS6	X	12.9	9.3
1066	AS6	X	14.9	10.2

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260
1066	12.8	22	294

df.info

```
<bound method DataFrame.info of
VEHICLECLASS  ENGINE SIZE  CYLINDERS  \
0      2014  ACURA      ILX      COMPACT      2.0
4
```

1	2014	ACURA	ILX	COMPACT	2.4
4					
2	2014	ACURA	ILX HYBRID	COMPACT	1.5
4					
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5
6					
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5
6					
...
...					
1062	2014	VOLVO	XC60 AWD	SUV - SMALL	3.0
6					
1063	2014	VOLVO	XC60 AWD	SUV - SMALL	3.2
6					
1064	2014	VOLVO	XC70 AWD	SUV - SMALL	3.0
6					
1065	2014	VOLVO	XC70 AWD	SUV - SMALL	3.2
6					
1066	2014	VOLVO	XC90 AWD	SUV - STANDARD	3.2
6					

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY
\				
0	AS5	Z	9.9	6.7
1	M6	Z	11.2	7.7
2	AV7	Z	6.0	5.8
3	AS6	Z	12.7	9.1
4	AS6	Z	12.1	8.7
...
1062	AS6	X	13.4	9.8
1063	AS6	X	13.2	9.5
1064	AS6	X	13.4	9.8
1065	AS6	X	12.9	9.3
1066	AS6	X	14.9	10.2

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221

2	5.9	48	136
3	11.1	25	255
4	10.6	27	244
...
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260
1066	12.8	22	294

[1067 rows x 13 columns]>

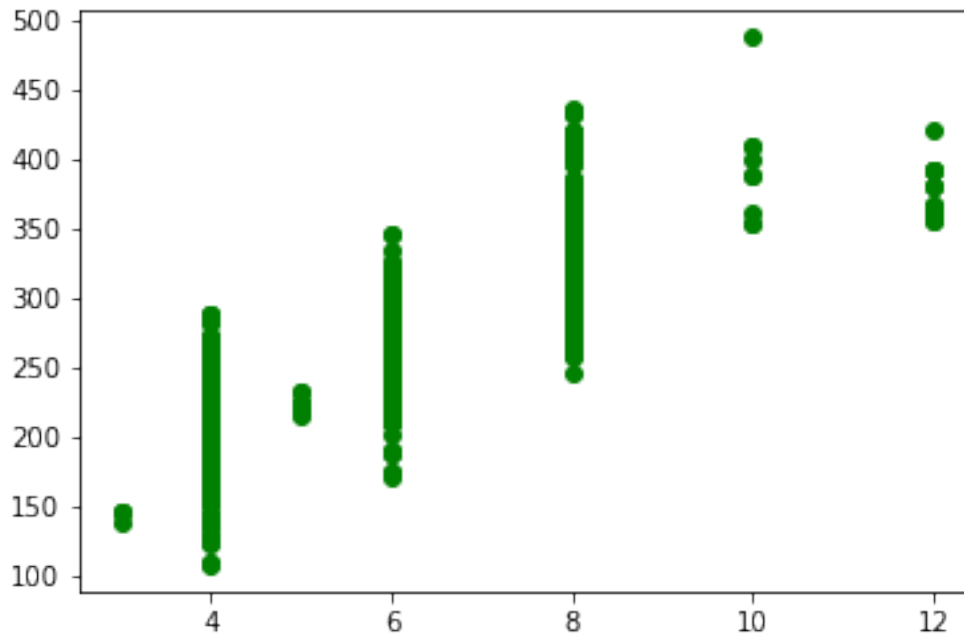
df.isnull().sum()

MODELYEAR	0
MAKE	0
MODEL	0
VEHICLECLASS	0
ENGINE SIZE	0
CYLINDERS	0
TRANSMISSION	0
FUELTYPE	0
FUELCONSUMPTION_CITY	0
FUELCONSUMPTION_HWY	0
FUELCONSUMPTION_COMB	0
FUELCONSUMPTION_COMB_MPG	0
CO2EMISSIONS	0

dtype: int64

plt.scatter(df['CYLINDERS'],df['CO2EMISSIONS'] , color = "green")

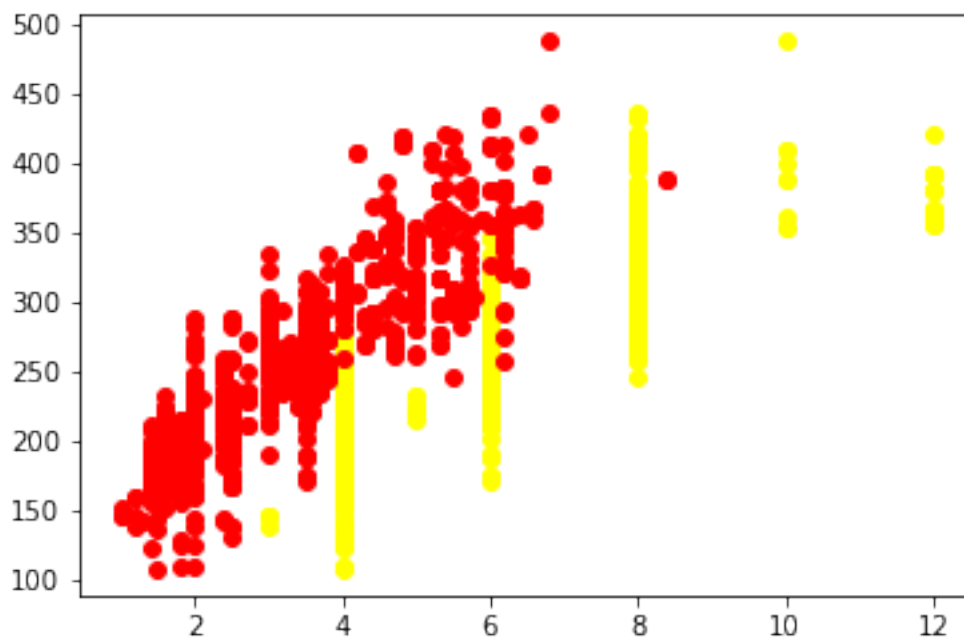
<matplotlib.collections.PathCollection at 0x21189b46b50>



Que.2 Using scatter plot compare data cylinder vs Co2Emission and Enginesize Vs Co2Emission using different colors

```
plt.scatter(df["CYLINDERS"],df["CO2EMISSIONS"], color='yellow')
plt.scatter(df["ENGINE_SIZE"],df["CO2EMISSIONS"],color='red')
```

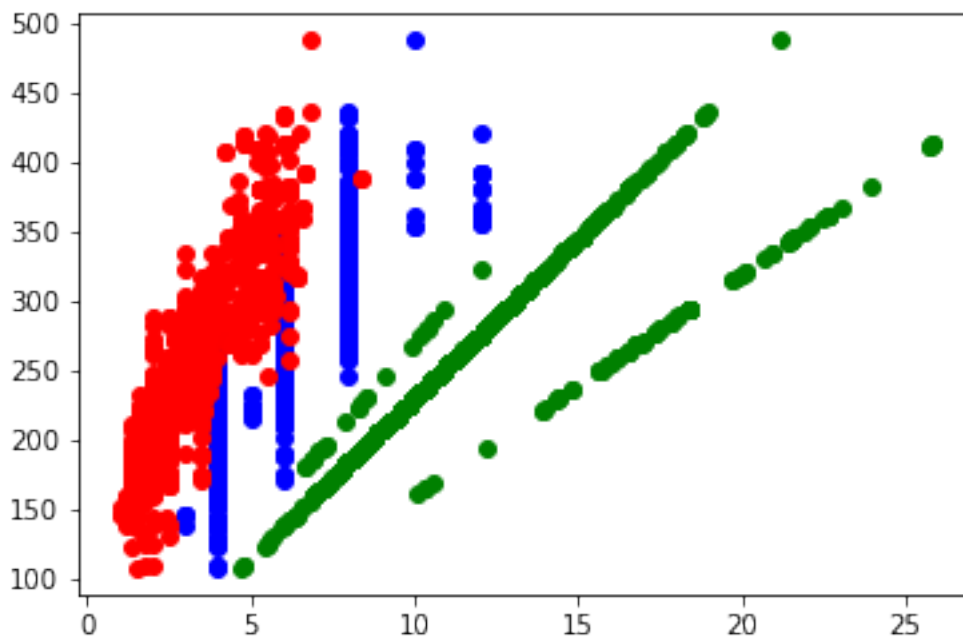
<matplotlib.collections.PathCollection at 0x21189c4ed60>



Que.3 Using scatter plot compare data cylinder vs Co2Emission and Enginesize Vs Co2Emission and FuelConsumption_comb Co2Emission using different colors

```
plt.scatter(df["CYLINDERS"],df["CO2EMISSIONS"], color="blue")
plt.scatter(df["ENGINE SIZE"],df["CO2EMISSIONS"],color='red')
plt.scatter(df["FUELCONSUMPTION_COMB"],df["CO2EMISSIONS"],
color='green')
```

<matplotlib.collections.PathCollection at 0x21189cd6520>



Que.4 Train your model with indepedent variable as cylinder and dependent variable as Co2Emission

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

```
df = pd.read_csv("C:/Users/Lenovo/Documents/Data
Set/FuelConsumption.csv")
```

df

	MODEL	YEAR	MAKE	MODEL	VEHICLECLASS	ENGINE SIZE
CYLINDERS \						
0	2014	ACURA	ILX	COMPACT	2.0	
4						
1	2014	ACURA	ILX	COMPACT	2.4	
4						

2	2014	ACURA	ILX HYBRID	COMPACT	1.5
4					
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5
6					
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5
6					
...
...					
1062	2014	VOLVO	XC60 AWD	SUV - SMALL	3.0
6					
1063	2014	VOLVO	XC60 AWD	SUV - SMALL	3.2
6					
1064	2014	VOLVO	XC70 AWD	SUV - SMALL	3.0
6					
1065	2014	VOLVO	XC70 AWD	SUV - SMALL	3.2
6					
1066	2014	VOLVO	XC90 AWD	SUV - STANDARD	3.2
6					

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY
\				
0	AS5	Z	9.9	6.7
1	M6	Z	11.2	7.7
2	AV7	Z	6.0	5.8
3	AS6	Z	12.7	9.1
4	AS6	Z	12.1	8.7
...
1062	AS6	X	13.4	9.8
1063	AS6	X	13.2	9.5
1064	AS6	X	13.4	9.8
1065	AS6	X	12.9	9.3
1066	AS6	X	14.9	10.2

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255

4	10.6	27	244
...
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260
1066	12.8	22	294

[1067 rows x 13 columns]

df.head()

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINESIZE	CYLINDERS	\
0	2014	ACURA	ILX	COMPACT	2.0	4	
1	2014	ACURA	ILX	COMPACT	2.4	4	
2	2014	ACURA	ILX HYBRID	COMPACT	1.5	4	
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5	6	
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5	6	

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY	\
0	AS5	Z	9.9	6.7	
1	M6	Z	11.2	7.7	
2	AV7	Z	6.0	5.8	
3	AS6	Z	12.7	9.1	
4	AS6	Z	12.1	8.7	

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255
4	10.6	27	244

df.tail()

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINESIZE
CYLINDERS \					
1062	2014	VOLVO	XC60 AWD	SUV - SMALL	3.0
6					
1063	2014	VOLVO	XC60 AWD	SUV - SMALL	3.2
6					
1064	2014	VOLVO	XC70 AWD	SUV - SMALL	3.0
6					
1065	2014	VOLVO	XC70 AWD	SUV - SMALL	3.2
6					
1066	2014	VOLVO	XC90 AWD	SUV - STANDARD	3.2
6					

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY
\				
1062	AS6	X	13.4	9.8

1063	AS6	X	13.2	9.5
1064	AS6	X	13.4	9.8
1065	AS6	X	12.9	9.3
1066	AS6	X	14.9	10.2

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260
1066	12.8	22	294

df.info

```
<bound method DataFrame.info of
VEHICLECLASS  ENGINE SIZE  CYLINDERS  \
0      2014  ACURA      ILX      COMPACT      2.0
4
1      2014  ACURA      ILX      COMPACT      2.4
4
2      2014  ACURA  ILX HYBRID      COMPACT      1.5
4
3      2014  ACURA      MDX 4WD      SUV - SMALL      3.5
6
4      2014  ACURA      RDX AWD      SUV - SMALL      3.5
6
...      ...      ...      ...      ...      ...
...
1062     2014  VOLVO      XC60 AWD      SUV - SMALL      3.0
6
1063     2014  VOLVO      XC60 AWD      SUV - SMALL      3.2
6
1064     2014  VOLVO      XC70 AWD      SUV - SMALL      3.0
6
1065     2014  VOLVO      XC70 AWD      SUV - SMALL      3.2
6
1066     2014  VOLVO      XC90 AWD      SUV - STANDARD      3.2
6
```

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY
0	AS5	Z	9.9	6.7
1	M6	Z	11.2	7.7

2	AV7	Z	6.0	5.8
3	AS6	Z	12.7	9.1
4	AS6	Z	12.1	8.7
...
1062	AS6	X	13.4	9.8
1063	AS6	X	13.2	9.5
1064	AS6	X	13.4	9.8
1065	AS6	X	12.9	9.3
1066	AS6	X	14.9	10.2

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255
4	10.6	27	244
...
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260
1066	12.8	22	294

[1067 rows x 13 columns]>

Data Exploration

Summarize the Data

df.describe()

	MODELYEAR	ENGINE SIZE	CYLINDERS	FUELCONSUMPTION_CITY \
count	1067.0	1067.000000	1067.000000	1067.000000
mean	2014.0	3.346298	5.794752	13.296532
std	0.0	1.415895	1.797447	4.101253
min	2014.0	1.000000	3.000000	4.600000
25%	2014.0	2.000000	4.000000	10.250000
50%	2014.0	3.400000	6.000000	12.600000
75%	2014.0	4.300000	8.000000	15.550000
max	2014.0	8.400000	12.000000	30.200000

	FUELCONSUMPTION_HWY	FUELCONSUMPTION_COMB
FUELCONSUMPTION_COMB_MPG \		
count	1067.000000	1067.000000
1067.000000		
mean	9.474602	11.580881
26.441425		
std	2.794510	3.485595
7.468702		
min	4.900000	4.700000
11.000000		
25%	7.500000	9.000000
21.000000		
50%	8.800000	10.900000
26.000000		
75%	10.850000	13.350000
31.000000		
max	20.500000	25.800000
60.000000		

	CO2EMISSIONS
count	1067.000000
mean	256.228679
std	63.372304
min	108.000000
25%	207.000000
50%	251.000000
75%	294.000000
max	488.000000

```
df[['MODELYEAR', 'ENGINE SIZE', 'CYLINDERS']]
```

	MODELYEAR	ENGINE SIZE	CYLINDERS
0	2014	2.0	4
1	2014	2.4	4
2	2014	1.5	4
3	2014	3.5	6
4	2014	3.5	6
...
1062	2014	3.0	6
1063	2014	3.2	6
1064	2014	3.0	6
1065	2014	3.2	6
1066	2014	3.2	6

```
[1067 rows x 3 columns]
```

```
df[['CYLINDERS', 'CO2EMISSIONS']]
```

	CYLINDERS	CO2EMISSIONS
0	4	196
1	4	221

2	4	136
3	6	255
4	6	244
...
1062	6	271
1063	6	264
1064	6	271
1065	6	260
1066	6	294

[1067 rows x 2 columns]

df

	MODEL	YEAR	MAKE	MODEL	VEHICLECLASS	ENGINE	SIZE
CYLINDERS	\						
0		2014	ACURA	ILX	COMPACT		2.0
4							
1		2014	ACURA	ILX	COMPACT		2.4
4							
2		2014	ACURA	ILX HYBRID	COMPACT		1.5
4							
3		2014	ACURA	MDX 4WD	SUV - SMALL		3.5
6							
4		2014	ACURA	RDX AWD	SUV - SMALL		3.5
6							
...	
...							
1062		2014	VOLVO	XC60 AWD	SUV - SMALL		3.0
6							
1063		2014	VOLVO	XC60 AWD	SUV - SMALL		3.2
6							
1064		2014	VOLVO	XC70 AWD	SUV - SMALL		3.0
6							
1065		2014	VOLVO	XC70 AWD	SUV - SMALL		3.2
6							
1066		2014	VOLVO	XC90 AWD	SUV - STANDARD		3.2
6							

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY
\				
0	AS5	Z	9.9	6.7
1	M6	Z	11.2	7.7
2	AV7	Z	6.0	5.8
3	AS6	Z	12.7	9.1
4	AS6	Z	12.1	8.7

...
1062	AS6	X	13.4	9.8
1063	AS6	X	13.2	9.5
1064	AS6	X	13.4	9.8
1065	AS6	X	12.9	9.3
1066	AS6	X	14.9	10.2

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255
4	10.6	27	244
...
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260
1066	12.8	22	294

[1067 rows x 13 columns]

```

cdf =
df[['ENGINE_SIZE', 'CYLINDERS', 'FUELCONSUMPTION_COMB', 'CO2EMISSIONS']]
cdf.head()

```

	ENGINE_SIZE	CYLINDERS	FUELCONSUMPTION_COMB	CO2EMISSIONS
0	2.0	4	8.5	196
1	2.4	4	9.6	221
2	1.5	4	5.9	136
3	3.5	6	11.1	255
4	3.5	6	10.6	244

```

cdf.tail()

```

	ENGINE_SIZE	CYLINDERS	FUELCONSUMPTION_COMB	CO2EMISSIONS
1062	3.0	6	11.8	271
1063	3.2	6	11.5	264
1064	3.0	6	11.8	271
1065	3.2	6	11.3	260
1066	3.2	6	12.8	294

Creating train and test dataset

`cdf`

	ENGINE SIZE	CYLINDERS	FUEL CONSUMPTION_COMB	CO2 EMISSIONS
0	2.0	4	8.5	196
1	2.4	4	9.6	221
2	1.5	4	5.9	136
3	3.5	6	11.1	255
4	3.5	6	10.6	244
...
1062	3.0	6	11.8	271
1063	3.2	6	11.5	264
1064	3.0	6	11.8	271
1065	3.2	6	11.3	260
1066	3.2	6	12.8	294

`[1067 rows x 4 columns]`

`len(cdf)`

`1067`

`msk = np.random.rand(len(cdf)) <= 0.80 #80% #len 1067 #853`

`msk`

`array([True, True, True, ..., True, True, True])`

`~msk`

`array([False, False, False, ..., False, False, False])`

`len(msk)`

`1067`

`len(~msk)`

`1067`

`train = cdf[msk] #80% of rows are your training example`

`test = cdf[~msk] #rest of the data out of the msk are for testing data
#~not`

`train.shape`

`(845, 4)`

`test.shape`

`(222, 4)`

`train`

	ENGINE SIZE	CYLINDERS	FUEL CONSUMPTION_COMB	CO2 EMISSIONS
0	2.0	4	8.5	196
1	2.4	4	9.6	221
2	1.5	4	5.9	136
3	3.5	6	11.1	255
4	3.5	6	10.6	244
...
1062	3.0	6	11.8	271
1063	3.2	6	11.5	264
1064	3.0	6	11.8	271
1065	3.2	6	11.3	260
1066	3.2	6	12.8	294

[845 rows x 4 columns]

test

	ENGINE SIZE	CYLINDERS	FUEL CONSUMPTION_COMB	CO2 EMISSIONS
5	3.5	6	10.0	230
7	3.7	6	11.1	255
9	2.4	4	9.2	212
13	5.9	12	15.6	359
19	2.0	4	8.8	202
...
1041	2.0	4	6.9	186
1045	2.5	5	9.7	223
1046	2.5	5	9.8	225
1047	3.6	6	10.8	248
1052	2.0	4	11.6	267

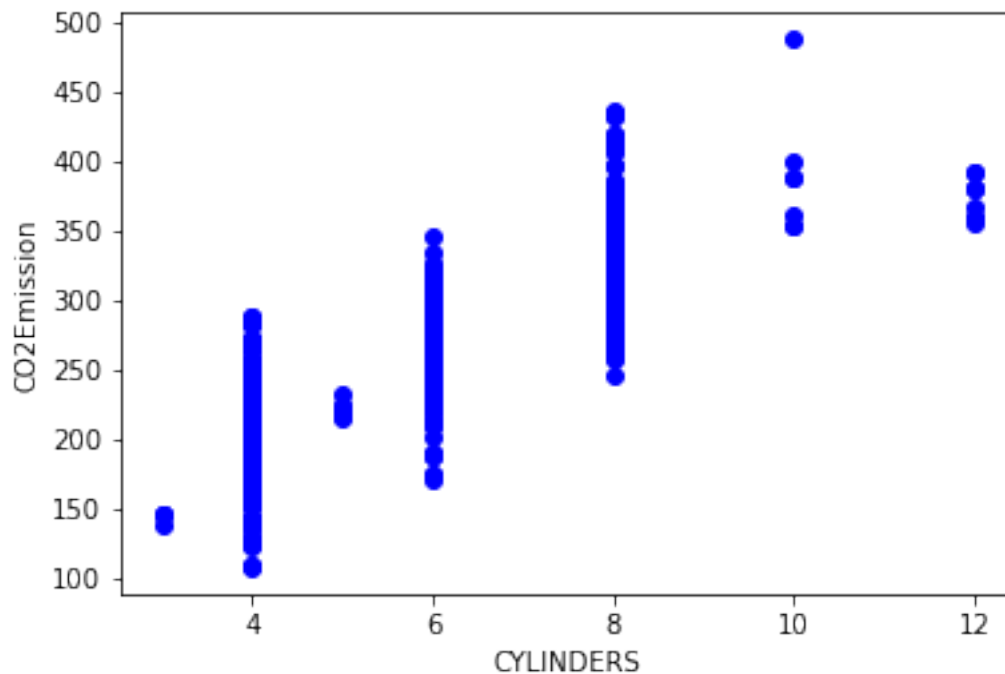
[222 rows x 4 columns]

Simple Regression Model

Linear Regression fits a linear model with coefficients $B = (B_1, \dots, B_n)$ to minimize the 'residual sum of squares' between the actual value y in the dataset, and the predicted value \hat{y} using linear approximation.

Train data distribution

```
plt.scatter(train.CYLINDERS, train.CO2EMISSIONS, color='blue')
plt.xlabel("CYLINDERS")
plt.ylabel("CO2Emission")
plt.show()
```

Modeling

Using sklearn package to model data.

```
train[['CYLINDERS']]
```

```

      CYLINDERS
0             4
1             4
2             4
3             6
4             6
...          ...
1062          6
1063          6
1064          6
1065          6
1066          6

```

```
[845 rows x 1 columns]
```

```
train[['CO2EMISSIONS']]
```

```

      CO2EMISSIONS
0             196
1             221
2             136
3             255

```

4	244
...	...
1062	271
1063	264
1064	271
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y = np.asarray(train[['CO2EMISSIONS']])

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from sklearn import linear_model

# y = mx + c == y is dependent variable, x is the data(indep. variable) m is COEFFICIENT and c is INTERCEPT

regr = linear_model.LinearRegression()

regr

LinearRegression()

train.shape

(845, 4)

test.shape

(222, 4)

train_x = np.asanyarray(train[['CYLINDERS']]) #x represents independent variables
train_y = np.asanyarray(train[['CO2EMISSIONS']]) #y represent dependent variable

train_x # All Values of Cylinders column this will be used for training

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```

regr.fit(independentvariable,dependentvariable)

```
regr.fit(train_x, train_y)
```

```
LinearRegression()
```

```
# The coefficients
```

```
print ('Coefficients: ', regr.coef_)
```

```
print ('Intercept: ',regr.intercept_)
```

```
Coefficients:  [[30.70676327]]
```

```
Intercept:  [78.19444198]
```

```
regr.coef_
```

```
array([[30.70676327]])
```

```
regr.intercept_
```

```
array([78.19444198])
```

```
regr.coef_[0][0]
```

```
30.706763266880237
```

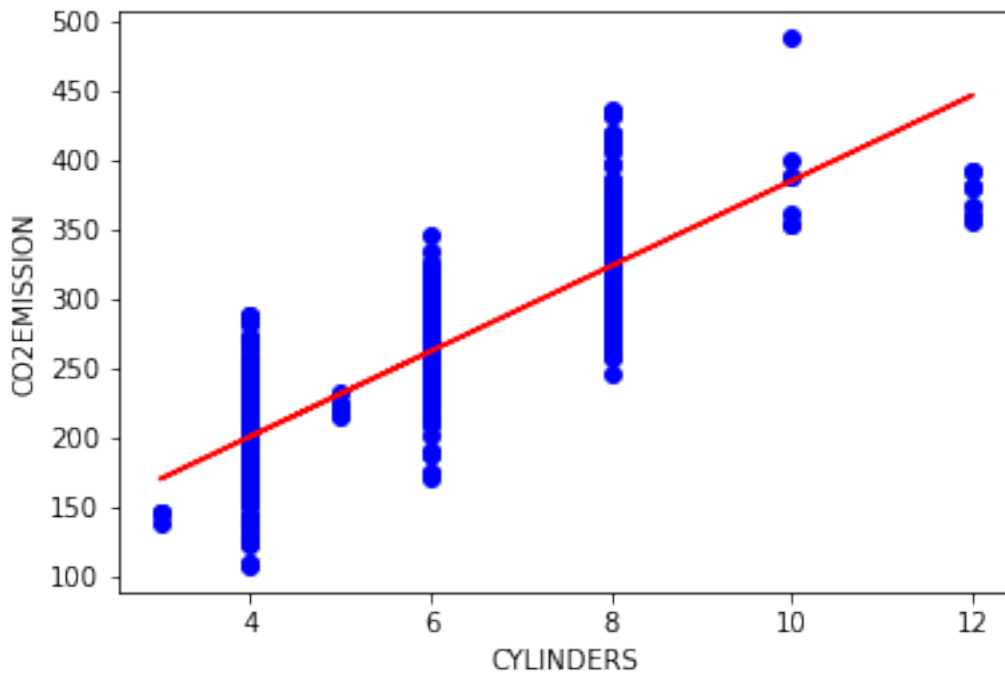
```
regr.intercept_[0]
```

```
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```


Plot Outputs

```
plt.scatter(train.CYLINDERS, train.CO2EMISSIONS, color='blue')
plt.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], 'r')
#y = mx+c
plt.xlabel("CYLINDERS")
plt.ylabel("CO2EMISSION")

Text(0, 0.5, 'CO2EMISSION')
```



Evaluation

```
test_x = np.asanyarray(test[['CYLINDERS']]) #question in exam
Questions
test_y = np.asanyarray(test[['CO2EMISSIONS']])#(ACTUAL answers)

test_x.shape #independent variable data for testing
(222, 1)

test_y.shape #dependent variable for testing
(222, 1)

predicted_y = regr.predict(test_x) #whatever answeerr will be generated
will be stored in predicted_y predicted

predicted_y
array([[262.43502158],
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```
test_y.shape
```

```
(222, 1)
```

```
predicted_y.shape
```

```
(222, 1)
```

```
from sklearn.metrics import r2_score
```

```
print(f"Mean absolute error: {np.mean(np.absolute(predicted_y - test_y))} ")# pred - actual
```

```
Mean absolute error: 26.218296344468087
```

```
print("Residual sum of squares (MSE): %.2f" % np.mean((predicted_y - test_y) **2))
```

```
Residual sum of squares (MSE): 1109.97
```

```
from sklearn.metrics import r2_score
```

```
print(f"R2-score:{r2_score(test_y , predicted_y)*100} %") # Most accurate thing or evaluation metrics
```

```
R2-score:72.38654274529334 %
```

Apply Lasso Regression to cover the overfitting and underfitting problem

```
from sklearn.linear_model import Lasso
```

```
L = Lasso(alpha = 1)
```

```

L.fit(train_x,train_y)

Lasso(alpha=1)

y_pred1 = L.predict(test_x)

from sklearn.metrics import r2_score
print("R2-score",r2_score(test_y,y_pred1))
print(f"Mean absolute error: {np.mean(np.absolute(y_pred1 - test_y))}")
# pred - actual

R2-score 0.7256514539177052
Mean absolute error: 68.97569534677652

```

Que.5 Train another model with independent variable as FuelConsumption_comb and dependent variable as Co2Emission

```

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv("C:/Users/Lenovo/Documents/Data Set/FuelConsumption.csv")

```

df

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINE SIZE
CYLINDERS \					
0	2014	ACURA	ILX	COMPACT	2.0
4					
1	2014	ACURA	ILX	COMPACT	2.4
4					
2	2014	ACURA	ILX HYBRID	COMPACT	1.5
4					
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5
6					
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5
6					
...
...					
1062	2014	VOLVO	XC60 AWD	SUV - SMALL	3.0
6					
1063	2014	VOLVO	XC60 AWD	SUV - SMALL	3.2
6					
1064	2014	VOLVO	XC70 AWD	SUV - SMALL	3.0
6					
1065	2014	VOLVO	XC70 AWD	SUV - SMALL	3.2
6					
1066	2014	VOLVO	XC90 AWD	SUV - STANDARD	3.2

6

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY
\				
0	AS5	Z	9.9	6.7
1	M6	Z	11.2	7.7
2	AV7	Z	6.0	5.8
3	AS6	Z	12.7	9.1
4	AS6	Z	12.1	8.7
...
1062	AS6	X	13.4	9.8
1063	AS6	X	13.2	9.5
1064	AS6	X	13.4	9.8
1065	AS6	X	12.9	9.3
1066	AS6	X	14.9	10.2

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255
4	10.6	27	244
...
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260
1066	12.8	22	294

[1067 rows x 13 columns]

df.head()

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINE SIZE	CYLINDERS	\
0	2014	ACURA	ILX	COMPACT	2.0	4	
1	2014	ACURA	ILX	COMPACT	2.4	4	
2	2014	ACURA	ILX HYBRID	COMPACT	1.5	4	
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5	6	

4	2014	ACURA	RDX AWD	SUV - SMALL	3.5	6
---	------	-------	---------	-------------	-----	---

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY	\
0	AS5	Z	9.9	6.7	
1	M6	Z	11.2	7.7	
2	AV7	Z	6.0	5.8	
3	AS6	Z	12.7	9.1	
4	AS6	Z	12.1	8.7	

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255
4	10.6	27	244

df.tail()

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINE SIZE
CYLINDERS \					
1062	2014	VOLVO	XC60 AWD	SUV - SMALL	3.0
6					
1063	2014	VOLVO	XC60 AWD	SUV - SMALL	3.2
6					
1064	2014	VOLVO	XC70 AWD	SUV - SMALL	3.0
6					
1065	2014	VOLVO	XC70 AWD	SUV - SMALL	3.2
6					
1066	2014	VOLVO	XC90 AWD	SUV - STANDARD	3.2
6					

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY	\
1062	AS6	X	13.4	9.8	
1063	AS6	X	13.2	9.5	
1064	AS6	X	13.4	9.8	
1065	AS6	X	12.9	9.3	
1066	AS6	X	14.9	10.2	

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260
1066	12.8	22	294

```
df.describe()
```

	MODELYEAR	ENGINE SIZE	CYLINDERS	FUELCONSUMPTION_CITY \
count	1067.0	1067.000000	1067.000000	1067.000000
mean	2014.0	3.346298	5.794752	13.296532
std	0.0	1.415895	1.797447	4.101253
min	2014.0	1.000000	3.000000	4.600000
25%	2014.0	2.000000	4.000000	10.250000
50%	2014.0	3.400000	6.000000	12.600000
75%	2014.0	4.300000	8.000000	15.550000
max	2014.0	8.400000	12.000000	30.200000

	FUELCONSUMPTION_HWY	FUELCONSUMPTION_COMB
FUELCONSUMPTION_COMB_MPG \		
count	1067.000000	1067.000000
1067.000000		
mean	9.474602	11.580881
26.441425		
std	2.794510	3.485595
7.468702		
min	4.900000	4.700000
11.000000		
25%	7.500000	9.000000
21.000000		
50%	8.800000	10.900000
26.000000		
75%	10.850000	13.350000
31.000000		
max	20.500000	25.800000
60.000000		

	CO2EMISSIONS
count	1067.000000
mean	256.228679
std	63.372304
min	108.000000
25%	207.000000
50%	251.000000
75%	294.000000
max	488.000000

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 1067 entries, 0 to 1066
```

```
Data columns (total 13 columns):
```

#	Column	Non-Null Count	Dtype
0	MODELYEAR	1067 non-null	int64
1	MAKE	1067 non-null	object
2	MODEL	1067 non-null	object

```

3  VEHICLECLASS      1067 non-null  object
4  ENGINESIZE        1067 non-null  float64
5  CYLINDERS         1067 non-null  int64
6  TRANSMISSION      1067 non-null  object
7  FUELTYPE          1067 non-null  object
8  FUELCONSUMPTION_CITY  1067 non-null  float64
9  FUELCONSUMPTION_HWY  1067 non-null  float64
10 FUELCONSUMPTION_COMB  1067 non-null  float64
11 FUELCONSUMPTION_COMB_MPG  1067 non-null  int64
12 CO2EMISSIONS      1067 non-null  int64
dtypes: float64(4), int64(4), object(5)
memory usage: 108.5+ KB

```

```
df.isnull().sum()
```

```

MODELYEAR      0
MAKE            0
MODEL          0
VEHICLECLASS    0
ENGINESIZE      0
CYLINDERS       0
TRANSMISSION    0
FUELTYPE        0
FUELCONSUMPTION_CITY  0
FUELCONSUMPTION_HWY  0
FUELCONSUMPTION_COMB  0
FUELCONSUMPTION_COMB_MPG  0
CO2EMISSIONS    0
dtype: int64

```

```
df[['MODELYEAR', 'ENGINESIZE', 'CYLINDERS']]
```

```

      MODELYEAR  ENGINESIZE  CYLINDERS
0          2014          2.0           4
1          2014          2.4           4
2          2014          1.5           4
3          2014          3.5           6
4          2014          3.5           6
...          ...          ...         ...
1062         2014          3.0           6
1063         2014          3.2           6
1064         2014          3.0           6
1065         2014          3.2           6
1066         2014          3.2           6

```

```
[1067 rows x 3 columns]
```

```
df[["FUELCONSUMPTION_COMB", "CO2EMISSIONS"]]
```

```

      FUELCONSUMPTION_COMB  CO2EMISSIONS
0                8.5           196

```

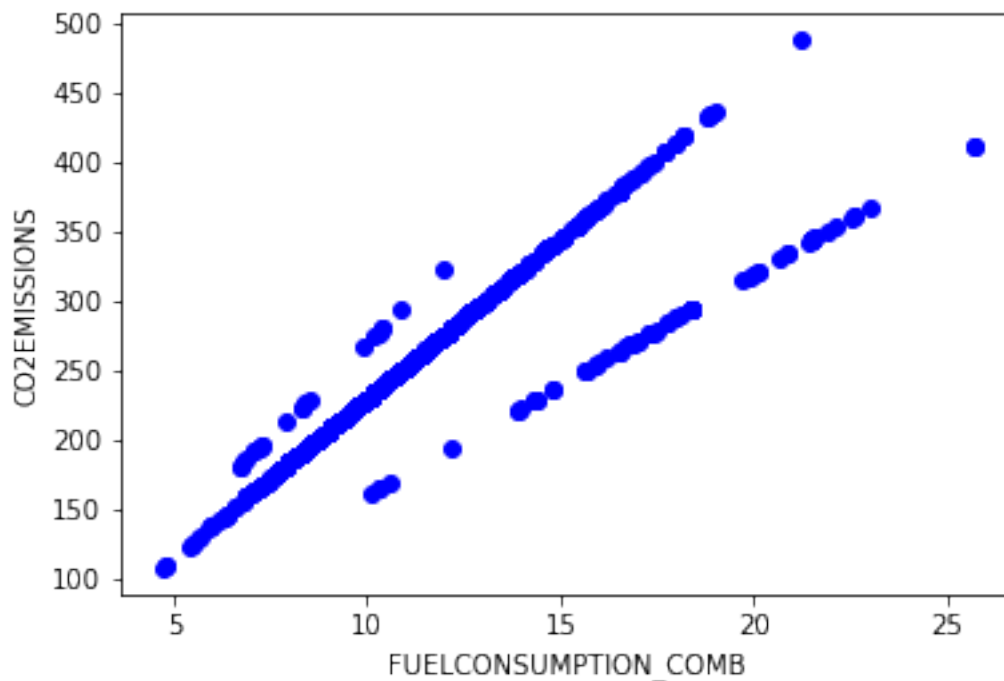
1	9.6	221
2	5.9	136
3	11.1	255
4	10.6	244
...
1062	11.8	271
1063	11.5	264
1064	11.8	271
1065	11.3	260
1066	12.8	294

[1067 rows x 2 columns]

Simple Regression Model

Train Data Distribution

```
plt.scatter(train.FUELCONSUMPTION_COMB, train.CO2EMISSIONS,
            color='blue')
plt.xlabel("FUELCONSUMPTION_COMB")
plt.ylabel("CO2EMISSIONS")
plt.show()
```



Modelling

```
train[['FUELCONSUMPTION_COMB']]
```

	FUELCONSUMPTION_COMB
0	8.5
1	9.6
2	5.9
3	11.1
4	10.6
...	...
1062	11.8
1063	11.5
1064	11.8
1065	11.3
1066	12.8

[845 rows x 1 columns]

train[['CO2EMISSIONS']]

	CO2EMISSIONS
0	196
1	221
2	136
3	255
4	244
...	...
1062	271
1063	264
1064	271
1065	260
1066	294

[845 rows x 1 columns]

np.asarray(train[['FUELCONSUMPTION_COMB']])

```
array([[ 8.5],
       [ 9.6],
       [ 5.9],
       [11.1],
       [10.6],
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y = np.asarray(train[['CO2EMISSIONS']]) # Dependent Variable
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from sklearn import linear_model

# y = mx + c == y is dependent variable, x is the data(indep.
variable) m is COEFFICIENT and c is INTERCEPT

regr = linear_model.LinearRegression()

regr

LinearRegression()

train.shape

(845, 4)

test.shape

(222, 4)

train_x = np.asanyarray(train[['FUELCONSUMPTION_COMB']]) #x represents
independent variables
train_y = np.asanyarray(train[['CO2EMISSIONS']]) #y represent
dependent variable

train_x # All Values of FUELCONSUMPTION_COMB column this will be used
for training

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[232],  
[264],  
[235],  
[264],  
[258],  
[271],  
[264],  
[271],  
[260],  
[294]], dtype=int64)
```

regr.fit(independentvariable,dependentvariable)

regr.fit(train_x,train_y)

LinearRegression()

```

# The coefficients
print ('Coefficients: ', regr.coef_)
print ('Intercept: ',regr.intercept_)

Coefficients:  [[16.37691523]]
Intercept:  [66.31999663]

regr.coef_
array([[16.37691523]])

regr.intercept_
array([66.31999663])

regr.coef_[0][0]
16.37691522903722

regr.intercept_[0]
66.31999662763249

```

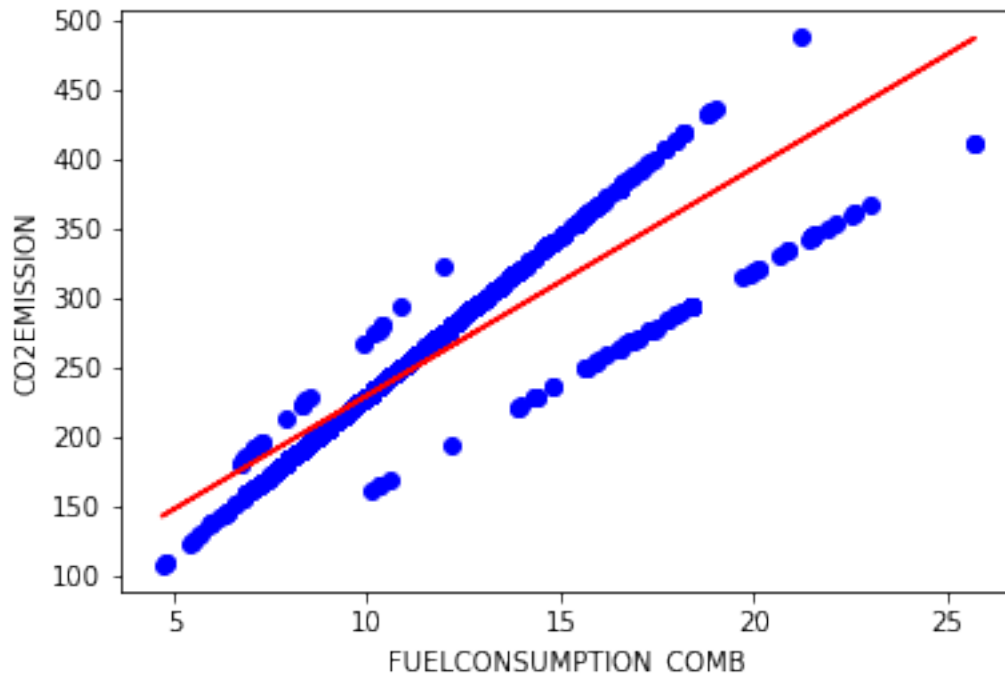
Plot Outputs

```

plt.scatter(train.FUELCONSUMPTION_COMB, train.CO2EMISSIONS,
color='blue')
plt.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], 'r')
#  $y = mx + c$ 
plt.xlabel("FUELCONSUMPTION_COMB")
plt.ylabel("CO2EMISSION")

Text(0, 0.5, 'CO2EMISSION')

```



Evaluation

```
test_x = np.asanyarray(test[['FUELCONSUMPTION_COMB']]) #question in exam Questions
```

```
test_y = np.asanyarray(test[['CO2EMISSIONS']])  #(ACTUAL answers)
```

```
test_x.shape # Independent variable data for testing
```

```
(222, 1)
```

```
test_y.shape # Dependent variable data for testing
```

```
(222, 1)
```

```
predicted_y = regr.predict(test_x) #whatever answer will be generated will be stored in predicted_y predicted
```

```
predicted_y
```

```
array([[230.08914892],
       [248.10375567],
       [216.98761673],
       [321.7998742 ],
       [210.43685064],
       [230.08914892],
       [233.36453196],
       [249.74144719],
       [323.43756572],
       [216.98761673],
       [215.34992521],
```

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[200.61070151],
[223.53838283],

```

[212.07454217],
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[185.8714778 ],
[231.72684044],
[225.17607435],
[179.32071171],
[179.32071171],
[225.17607435],
[226.81376587],
[243.1906811 ],
[256.29221328]])

test_y.shape

(222, 1)

predicted_y.shape

(222, 1)

from sklearn.metrics import r2_score
print(f"Mean absolute error: {np.mean(np.absolute(predicted_y -
test_y))} ")# pred - actual

Mean absolute error: 20.0264532711564

print("Residual sum of squares (MSE): %.2f" % np.mean((predicted_y -
test_y) **2))

Residual sum of squares (MSE): 822.80

from sklearn.metrics import r2_score
print(f"R2-score:{r2_score(test_y ,predicted_y)*100} %") # Most
accurate thing or evaluation metrics

R2-score:79.53048969001148 %

```

Apply Lasso Regression to cover the overfitting and underfitting problem

```

from sklearn.linear_model import Lasso

L = Lasso(alpha=1)

L.fit(train_x,train_y)

Lasso(alpha=1)

ypred2 = L.predict(test_x)

from sklearn.metrics import r2_score
print("R2-score",r2_score(test_y,ypred2))

```

```
print(f"Mean absolute error: {np.mean(np.absolute(ypred2 - test_y))}
")# pred - actual
```

R2-score 0.7956622176158492

Mean absolute error: 67.56303603234201

Que.6 Train your model on different train test ratio and train the models and note down there accuracies

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
```

```
Bill_Authentication = pd.read_csv("C:/Users/Lenovo/Documents/Data
Set/bill_authentication.csv")
```

```
Bill_Authentication
```

	Variance	Skewness	Curtosis	Entropy	Class
0	3.62160	8.66610	-2.8073	-0.44699	0
1	4.54590	8.16740	-2.4586	-1.46210	0
2	3.86600	-2.63830	1.9242	0.10645	0
3	3.45660	9.52280	-4.0112	-3.59440	0
4	0.32924	-4.45520	4.5718	-0.98880	0
...
1367	0.40614	1.34920	-1.4501	-0.55949	1
1368	-1.38870	-4.87730	6.4774	0.34179	1
1369	-3.75030	-13.45860	17.5932	-2.77710	1
1370	-3.56370	-8.38270	12.3930	-1.28230	1
1371	-2.54190	-0.65804	2.6842	1.19520	1

[1372 rows x 5 columns]

```
Bill_Authentication.head()
```

	Variance	Skewness	Curtosis	Entropy	Class
0	3.62160	8.6661	-2.8073	-0.44699	0
1	4.54590	8.1674	-2.4586	-1.46210	0
2	3.86600	-2.6383	1.9242	0.10645	0
3	3.45660	9.5228	-4.0112	-3.59440	0
4	0.32924	-4.4552	4.5718	-0.98880	0

```
Bill_Authentication.tail()
```

	Variance	Skewness	Curtosis	Entropy	Class
1367	0.40614	1.34920	-1.4501	-0.55949	1
1368	-1.38870	-4.87730	6.4774	0.34179	1
1369	-3.75030	-13.45860	17.5932	-2.77710	1
1370	-3.56370	-8.38270	12.3930	-1.28230	1
1371	-2.54190	-0.65804	2.6842	1.19520	1

```
X = Bill_Authentication[["Variance", "Skewness", "Curtosis", "Entropy"]]
# Indepandant Variable
```

X

	Variance	Skewness	Curtosis	Entropy
0	3.62160	8.66610	-2.8073	-0.44699
1	4.54590	8.16740	-2.4586	-1.46210
2	3.86600	-2.63830	1.9242	0.10645
3	3.45660	9.52280	-4.0112	-3.59440
4	0.32924	-4.45520	4.5718	-0.98880
...
1367	0.40614	1.34920	-1.4501	-0.55949
1368	-1.38870	-4.87730	6.4774	0.34179
1369	-3.75030	-13.45860	17.5932	-2.77710
1370	-3.56370	-8.38270	12.3930	-1.28230
1371	-2.54190	-0.65804	2.6842	1.19520

[1372 rows x 4 columns]

```
Y = Bill_Authentication[["Class"]]
```

Y

	Class
0	0
1	0
2	0
3	0
4	0
...	...
1367	1
1368	1
1369	1
1370	1
1371	1

[1372 rows x 1 columns]

Setting up Decision Tree

```
from sklearn.model_selection import train_test_split
X_trainset, X_testset, Y_trainset, Y_testset = train_test_split(X, Y,
test_size=0.2, random_state=500)
```

Modelling

```
ClassTree = DecisionTreeClassifier(criterion="entropy", max_depth = 4)
ClassTree # it shows the default parameters
```

```
DecisionTreeClassifier(criterion='entropy', max_depth=4)
ClassTree.fit(X_trainset,Y_trainset)
DecisionTreeClassifier(criterion='entropy', max_depth=4)
```

Prediction

Let's make some predictions on the testing dataset and store it into a variable called predTree

```
Y_pred = ClassTree.predict(X_testset)
```

Y_pred

```
array([[1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1,
1,
      1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0,
0,
      0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1,
0,
      0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0,
1,
      1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1,
0,
      0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0,
1,
      1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1,
0,
      1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0,
1,
      0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0,
1,
      1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0,
0,
      0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1,
1,
      1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1,
0,
      0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0], dtype=int64)
```

```
# You can print out predTree and y_testset if you want to visually
compare the prediction to the actual values.
```

```
print (Y_pred [0:5])# Predicted by the ml model
print (Y_testset [0:5])# Actual values we have
```

```
[1 0 1 1 0]
      Class
```

```

816      1
316      0
762      1
1128     1
232      0

```

```
print (Y_testset [0:5])
```

```

      Class
816      1
316      0
762      1
1128     1
232      0

```

Evaluation

Next, let's import metrics from sklearn and check the accuracy of our model.

```

from sklearn import metrics
print("DecisionTrees's Accuracy: ", metrics.accuracy_score(Y_testset,
Y_pred))

```

```
DecisionTrees's Accuracy:  0.9490909090909091
```

```
Bill_Authentication.head()
```

	Variance	Skewness	Curtosis	Entropy	Class
0	3.62160	8.6661	-2.8073	-0.44699	0
1	4.54590	8.1674	-2.4586	-1.46210	0
2	3.86600	-2.6383	1.9242	0.10645	0
3	3.45660	9.5228	-4.0112	-3.59440	0
4	0.32924	-4.4552	4.5718	-0.98880	0

```
Bill_Authentication.tail()
```

	Variance	Skewness	Curtosis	Entropy	Class
1367	0.40614	1.34920	-1.4501	-0.55949	1
1368	-1.38870	-4.87730	6.4774	0.34179	1
1369	-3.75030	-13.45860	17.5932	-2.77710	1
1370	-3.56370	-8.38270	12.3930	-1.28230	1
1371	-2.54190	-0.65804	2.6842	1.19520	1

```
ClassTree.predict([[3,4,-4,3]])
```

```
C:\Users\Lenovo\anaconda3\lib\site-packages\sklearn\base.py:450:
```

```
UserWarning: X does not have valid feature names, but
```

```
DecisionTreeClassifier was fitted with feature names
```

```
warnings.warn(
```

```
array([1], dtype=int64)
```

```
max(Bill_Authentication['Variance'])
```

6.8248

```
min(Bill_Authentication['Variance'])
```

-7.0421

```
X_testset[0:5]
```

	Variance	Skewness	Curtosis	Entropy
816	-4.8554	-5.903700	10.9818	-0.821990
316	5.7353	5.280800	-2.2598	0.075416
762	-1.3971	3.319100	-1.3927	-1.994800
1128	-2.1802	3.379100	-1.2256	-2.662100
232	2.2596	-0.033118	4.7355	-0.277600

```
Y_testset = np.array(Y_testset)
```

$$\bar{Y}_{\text{testset}}$$

```
array([[1],
```

 $[0],$

[1],

[1],

 $[0],$

[1],

[1],

[1],

 $[0],$

[1],

[0],
[1]

[1],

[1],
[2].
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[1].

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$$\begin{bmatrix} 1 \\ 1 \end{bmatrix},$$
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[0]

[0],
[0]

$$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$$
$$\begin{bmatrix} 1 \\ 1 \end{bmatrix},$$
$$\begin{bmatrix} 1 \\ 0 \end{bmatrix},$$

[10],
[11].

$$\begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

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X_testset

	Variance	Skewness	Curtosis	Entropy
816	-4.8554	-5.903700	10.98180	-0.821990
316	5.7353	5.280800	-2.25980	0.075416

```

762    -1.3971  3.319100  -1.39270 -1.994800
1128    -2.1802  3.379100  -1.22560 -2.662100
232     2.2596 -0.033118   4.73550 -0.277600
...
1122    -2.0285  3.846800  -0.63435 -1.175000
141     1.7317 -0.347650   4.19050 -0.991380
633     4.4295 -2.350700   1.70480  0.909460
428     3.4246 -0.146930   0.80342  0.291360
277     1.3638 -4.775900   8.41820 -1.883600

```

```
[275 rows x 4 columns]
```

```
X_testset = X_testset.values
```

```
X_testset
```

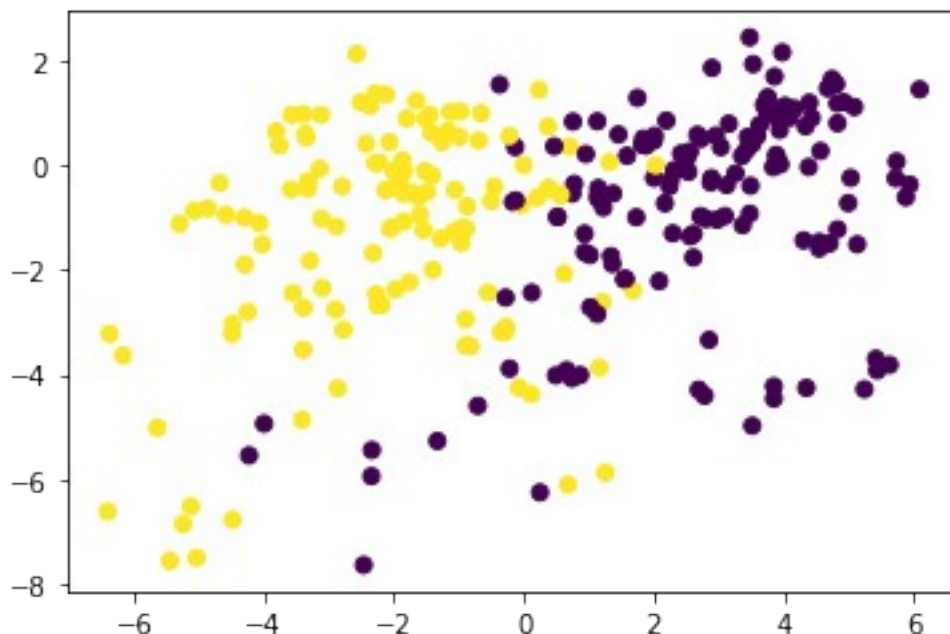
```

array([[ -4.8554,  -5.9037,  10.9818,  -0.82199 ],
       [  5.7353,   5.2808,  -2.2598,   0.075416],
       [ -1.3971,   3.3191,  -1.3927,  -1.9948 ],
       ...,
       [  4.4295,  -2.3507,   1.7048,   0.90946 ],
       [  3.4246,  -0.14693,   0.80342,   0.29136 ],
       [  1.3638,  -4.7759,   8.4182,  -1.8836 ]])

```

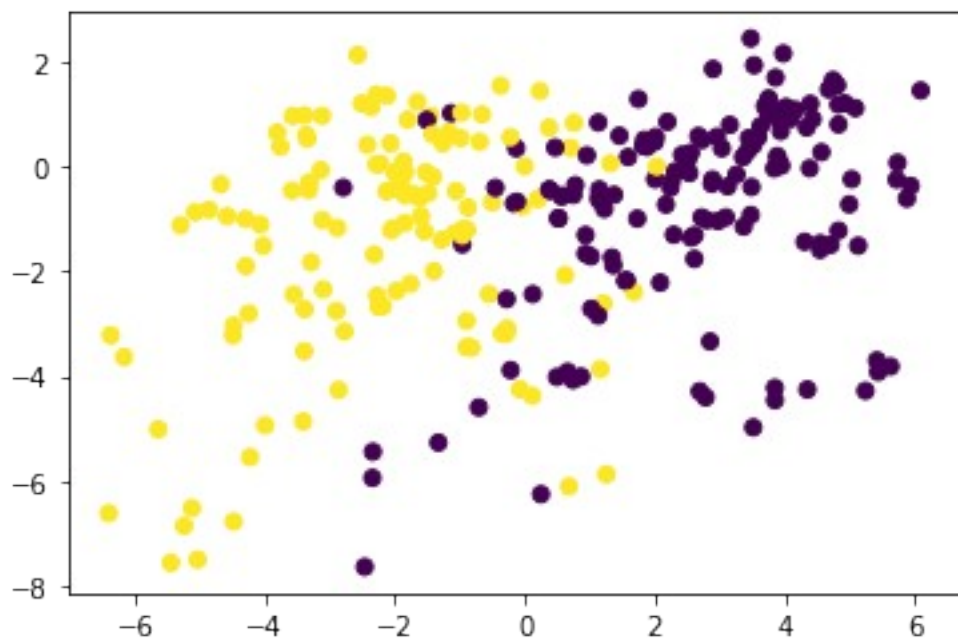
```
plt.scatter(X_testset[:,0],X_testset[:,-1], c = Y_pred)
```

```
<matplotlib.collections.PathCollection at 0x2118c333d00>
```



```
plt.scatter(X_testset[:,0],X_testset[:,-1], c = Y_testset)
```

```
<matplotlib.collections.PathCollection at 0x2118c3aa250>
```



For the accuracy of training and testing are

1) When take training data 80% and testing data 20% then accuracy is 94.90%

2) When take training data 70% and testing data the 30% then accuracy is 96.35%

3) When take training data is 60% and testing data is 40% then accuracy is 96.90%

4) When take training data 50% and testing data 50% then accuracy is 96.50%

Que.7 we are providing you another dataset regarding housing prediction to need to apply Linear Regression on atleast 5 pairs of independent and dependent variable and store their accuracy and then make a plot of those accuracy. Note : Dependent Variable is SalesPrice

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

```
df = pd.read_csv("C:/Users/Lenovo/Documents/Data Set/housing.csv")
```

```
df
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley
LotShape \							
0 Reg	1	60	RL	65.0	8450	Pave	NaN
1 Reg	2	20	RL	80.0	9600	Pave	NaN
2 IR1	3	60	RL	68.0	11250	Pave	NaN
3 IR1	4	70	RL	60.0	9550	Pave	NaN
4 IR1	5	60	RL	84.0	14260	Pave	NaN

...
1455	1456	60	RL	62.0	7917	Pave	NaN
Reg							
1456	1457	20	RL	85.0	13175	Pave	NaN
Reg							
1457	1458	70	RL	66.0	9042	Pave	NaN
Reg							
1458	1459	20	RL	68.0	9717	Pave	NaN
Reg							
1459	1460	20	RL	75.0	9937	Pave	NaN
Reg							

	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature
MiscVal \							
0	Lvl	AllPub	...	0	NaN	NaN	NaN
0							
1	Lvl	AllPub	...	0	NaN	NaN	NaN
0							
2	Lvl	AllPub	...	0	NaN	NaN	NaN
0							
3	Lvl	AllPub	...	0	NaN	NaN	NaN
0							
4	Lvl	AllPub	...	0	NaN	NaN	NaN
0							
...
...							
1455	Lvl	AllPub	...	0	NaN	NaN	NaN
0							
1456	Lvl	AllPub	...	0	NaN	MnPrv	NaN
0							
1457	Lvl	AllPub	...	0	NaN	GdPrv	Shed
2500							
1458	Lvl	AllPub	...	0	NaN	NaN	NaN
0							
1459	Lvl	AllPub	...	0	NaN	NaN	NaN
0							

	MoSold	YrSold	SaleType	SaleCondition	SalePrice
0	2	2008	WD	Normal	208500
1	5	2007	WD	Normal	181500
2	9	2008	WD	Normal	223500
3	2	2006	WD	Abnorml	140000
4	12	2008	WD	Normal	250000
...
1455	8	2007	WD	Normal	175000
1456	2	2010	WD	Normal	210000
1457	5	2010	WD	Normal	266500
1458	4	2010	WD	Normal	142125
1459	6	2008	WD	Normal	147500

[1460 rows x 81 columns]

df.head()

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape
0	1	60	RL	65.0	8450	Pave	NaN	Reg
1	2	20	RL	80.0	9600	Pave	NaN	Reg
2	3	60	RL	68.0	11250	Pave	NaN	IR1
3	4	70	RL	60.0	9550	Pave	NaN	IR1
4	5	60	RL	84.0	14260	Pave	NaN	IR1

	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal
0	Lvl	AllPub	...	0	NaN	NaN	NaN	0
2	Lvl	AllPub	...	0	NaN	NaN	NaN	0
5	Lvl	AllPub	...	0	NaN	NaN	NaN	0
9	Lvl	AllPub	...	0	NaN	NaN	NaN	0
3	Lvl	AllPub	...	0	NaN	NaN	NaN	0
2	Lvl	AllPub	...	0	NaN	NaN	NaN	0
4	Lvl	AllPub	...	0	NaN	NaN	NaN	0
12								

	YrSold	SaleType	SaleCondition	SalePrice
0	2008	WD	Normal	208500
1	2007	WD	Normal	181500
2	2008	WD	Normal	223500
3	2006	WD	Abnorml	140000
4	2008	WD	Normal	250000

[5 rows x 81 columns]

df.tail()

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley
LotShape							
1455	1456	60	RL	62.0	7917	Pave	NaN
Reg							
1456	1457	20	RL	85.0	13175	Pave	NaN
Reg							
1457	1458	70	RL	66.0	9042	Pave	NaN
Reg							

1458	1459	20	RL	68.0	9717	Pave	NaN
Reg							
1459	1460	20	RL	75.0	9937	Pave	NaN
Reg							

	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature
MiscVal \							
1455	Lvl	AllPub	...	0	NaN	NaN	NaN
0							
1456	Lvl	AllPub	...	0	NaN	MnPrv	NaN
0							
1457	Lvl	AllPub	...	0	NaN	GdPrv	Shed
2500							
1458	Lvl	AllPub	...	0	NaN	NaN	NaN
0							
1459	Lvl	AllPub	...	0	NaN	NaN	NaN
0							

	MoSold	YrSold	SaleType	SaleCondition	SalePrice
1455	8	2007	WD	Normal	175000
1456	2	2010	WD	Normal	210000
1457	5	2010	WD	Normal	266500
1458	4	2010	WD	Normal	142125
1459	6	2008	WD	Normal	147500

[5 rows x 81 columns]

df.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 1460 entries, 0 to 1459

Data columns (total 81 columns):

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	Id	1460 non-null	int64
1	MSSubClass	1460 non-null	int64
2	MSZoning	1460 non-null	object
3	LotFrontage	1201 non-null	float64
4	LotArea	1460 non-null	int64
5	Street	1460 non-null	object
6	Alley	91 non-null	object
7	LotShape	1460 non-null	object
8	LandContour	1460 non-null	object
9	Utilities	1460 non-null	object
10	LotConfig	1460 non-null	object
11	LandSlope	1460 non-null	object
12	Neighborhood	1460 non-null	object
13	Condition1	1460 non-null	object
14	Condition2	1460 non-null	object
15	BldgType	1460 non-null	object

16	HouseStyle	1460	non-null	object
17	OverallQual	1460	non-null	int64
18	OverallCond	1460	non-null	int64
19	YearBuilt	1460	non-null	int64
20	YearRemodAdd	1460	non-null	int64
21	RoofStyle	1460	non-null	object
22	RoofMatl	1460	non-null	object
23	Exterior1st	1460	non-null	object
24	Exterior2nd	1460	non-null	object
25	MasVnrType	1452	non-null	object
26	MasVnrArea	1452	non-null	float64
27	ExterQual	1460	non-null	object
28	ExterCond	1460	non-null	object
29	Foundation	1460	non-null	object
30	BsmtQual	1423	non-null	object
31	BsmtCond	1423	non-null	object
32	BsmtExposure	1422	non-null	object
33	BsmtFinType1	1423	non-null	object
34	BsmtFinSF1	1460	non-null	int64
35	BsmtFinType2	1422	non-null	object
36	BsmtFinSF2	1460	non-null	int64
37	BsmtUnfSF	1460	non-null	int64
38	TotalBsmtSF	1460	non-null	int64
39	Heating	1460	non-null	object
40	HeatingQC	1460	non-null	object
41	CentralAir	1460	non-null	object
42	Electrical	1459	non-null	object
43	1stFlrSF	1460	non-null	int64
44	2ndFlrSF	1460	non-null	int64
45	LowQualFinSF	1460	non-null	int64
46	GrLivArea	1460	non-null	int64
47	BsmtFullBath	1460	non-null	int64
48	BsmtHalfBath	1460	non-null	int64
49	FullBath	1460	non-null	int64
50	HalfBath	1460	non-null	int64
51	BedroomAbvGr	1460	non-null	int64
52	KitchenAbvGr	1460	non-null	int64
53	KitchenQual	1460	non-null	object
54	TotRmsAbvGrd	1460	non-null	int64
55	Functional	1460	non-null	object
56	Fireplaces	1460	non-null	int64
57	FireplaceQu	770	non-null	object
58	GarageType	1379	non-null	object
59	GarageYrBlt	1379	non-null	float64
60	GarageFinish	1379	non-null	object
61	GarageCars	1460	non-null	int64
62	GarageArea	1460	non-null	int64
63	GarageQual	1379	non-null	object
64	GarageCond	1379	non-null	object
65	PavedDrive	1460	non-null	object

```

66 WoodDeckSF      1460 non-null    int64
67 OpenPorchSF     1460 non-null    int64
68 EnclosedPorch   1460 non-null    int64
69 3SsnPorch       1460 non-null    int64
70 ScreenPorch     1460 non-null    int64
71 PoolArea        1460 non-null    int64
72 PoolQC          7 non-null       object
73 Fence           281 non-null     object
74 MiscFeature      54 non-null      object
75 MiscVal          1460 non-null    int64
76 MoSold           1460 non-null    int64
77 YrSold           1460 non-null    int64
78 SaleType         1460 non-null    object
79 SaleCondition    1460 non-null    object
80 SalePrice        1460 non-null    int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB

```

```
df.describe()
```

	Id	MSSubClass	LotFrontage	LotArea
OverallQual \				
count	1460.000000	1460.000000	1201.000000	1460.000000
1460.000000				
mean	730.500000	56.897260	70.049958	10516.828082
6.099315				
std	421.610009	42.300571	24.284752	9981.264932
1.382997				
min	1.000000	20.000000	21.000000	1300.000000
1.000000				
25%	365.750000	20.000000	59.000000	7553.500000
5.000000				
50%	730.500000	50.000000	69.000000	9478.500000
6.000000				
75%	1095.250000	70.000000	80.000000	11601.500000
7.000000				
max	1460.000000	190.000000	313.000000	215245.000000
10.000000				

	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea
BsmtFinSF1 ... \				
count	1460.000000	1460.000000	1460.000000	1452.000000
1460.000000 ...				
mean	5.575342	1971.267808	1984.865753	103.685262
443.639726 ...				
std	1.112799	30.202904	20.645407	181.066207
456.098091 ...				
min	1.000000	1872.000000	1950.000000	0.000000
0.000000 ...				
25%	5.000000	1954.000000	1967.000000	0.000000

```

0.000000 ...
50%      5.000000 1973.000000 1994.000000 0.000000
383.500000 ...
75%      6.000000 2000.000000 2004.000000 166.000000
712.250000 ...
max      9.000000 2010.000000 2010.000000 1600.000000
5644.000000 ...

```

```

      WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch
ScreenPorch \
count 1460.000000 1460.000000 1460.000000 1460.000000
1460.000000
mean   94.244521  46.660274   21.954110   3.409589
15.060959
std   125.338794  66.256028   61.119149   29.317331
55.757415
min     0.000000   0.000000   0.000000   0.000000
0.000000
25%     0.000000   0.000000   0.000000   0.000000
0.000000
50%     0.000000  25.000000   0.000000   0.000000
0.000000
75%    168.000000  68.000000   0.000000   0.000000
0.000000
max    857.000000 547.000000  552.000000  508.000000
480.000000

```

```

      PoolArea      MiscVal      MoSold      YrSold
SalePrice
count 1460.000000 1460.000000 1460.000000 1460.000000
1460.000000
mean   2.758904  43.489041   6.321918 2007.815753
180921.195890
std   40.177307 496.123024   2.703626   1.328095
79442.502883
min     0.000000   0.000000   1.000000 2006.000000
34900.000000
25%     0.000000   0.000000   5.000000 2007.000000
129975.000000
50%     0.000000   0.000000   6.000000 2008.000000
163000.000000
75%     0.000000   0.000000   8.000000 2009.000000
214000.000000
max    738.000000 15500.000000 12.000000 2010.000000
755000.000000

```

[8 rows x 38 columns]

```
df.isnull().sum()
```

```
Id          0
MSSubClass  0
MSZoning    0
LotFrontage 259
LotArea     0
...
MoSold      0
YrSold      0
SaleType    0
SaleCondition 0
SalePrice   0
Length: 81, dtype: int64
```

```
df[["1stFlrSF"]]
```

```
      1stFlrSF
0         856
1        1262
2         920
3         961
4        1145
...
1455        953
1456       2073
1457       1188
1458       1078
1459       1256
```

```
[1460 rows x 1 columns]
```

```
df[["2ndFlrSF"]]
```

```
      2ndFlrSF
0         854
1          0
2         866
3         756
4        1053
...
1455        694
1456          0
1457       1152
1458          0
1459          0
```

```
[1460 rows x 1 columns]
```

```
df[["OpenPorchSF"]]
```

```
      OpenPorchSF
0             61
```

1	0
2	42
3	35
4	84
...	...
1455	40
1456	0
1457	60
1458	0
1459	68

[1460 rows x 1 columns]

df[["BsmtFinSF1"]]

	BsmtFinSF1
0	706
1	978
2	486
3	216
4	655
...	...
1455	0
1456	790
1457	275
1458	49
1459	830

[1460 rows x 1 columns]

set(df['1stFlrSF'])

```
{334,
 372,
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2515,  
2524,  
2633,  
2898,  
3138,  
3228,  
4692}
```

```
X =  
df[["1stFlrSF", "2ndFlrSF", "OpenPorchSF", "PoolArea", "BsmtFinSF1"]].values  
# Independent variable
```

```
X
```

```
array([[ 856,  854,  61,  0,  706],  
       [1262,   0,   0,  0,  978],  
       [ 920,  866,  42,  0,  486],  
       ...,  
       [1188, 1152,  60,  0,  275],  
       [1078,   0,   0,  0,   49],  
       [1256,   0,  68,  0,  830]], dtype=int64)
```

```
Y = df[["SalePrice"]].values # Dependent Variable
```

Y

```
array([[208500],
       [181500],
       [223500],
       ...,
       [266500],
       [142125],
       [147500]], dtype=int64)
```

Splitting the dataset into the Training set and Test set

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size =
0.2, random_state = 500)
```

X_train.shape

(1168, 5)

X_test.shape

(292, 5)

Feature Scaling

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
sc_Y = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
Y_train = sc_Y.fit_transform(Y_train)
Y_test = sc_Y.transform(Y_test)
```

X_train

```
array([[ 0.10235513, -0.78522929,  0.94757715, -0.07684505, -
0.53193612],
       [ 0.60747084, -0.78522929,  0.85855721, -0.07684505, -
0.90231314],
       [ 1.40050251,  0.52565775,  3.36595228, -0.07684505, -
1.90633593],
       ...,
       [ 1.15804697, -0.78522929, -0.69929179, -0.07684505,  0.3716251
],
       [-0.52651394, -0.78522929, -0.69929179, -0.07684505, -
0.41651219],
       [ 0.49634538, -0.78522929, -0.69929179, -0.07684505, -
0.95361266]])
```

X_test

```
array([[ -1.06951333,  0.9456955 , -0.18000879, -0.07684505, -
 0.95361266],
       [ -0.19061199,  1.21341187,  0.32443755, -0.07684505, -
 0.09220812],
       [ -0.72098349,  0.9595429 , -0.69929179, -0.07684505, -
 0.12854528],
       ...,
       [ -0.4128629 ,  2.11580066, -0.01680556, -0.07684505, -
 0.95361266],
       [  1.12016329, -0.78522929,  0.32443755, -0.07684505, -
 0.60092842],
       [ -0.73613696,  1.31034366,  0.60633404, -0.07684505,
 0.39941234]])
```

Y_train

```
array([[ -0.47654967],
       [  0.04412298],
       [  3.30843421],
       ...,
       [ -0.52555415],
       [ -0.75955057],
       [ -0.36628958]])
```

Y_test

```
array([[ -9.79900262e-02],
       [  2.83019842e-01],
       [ -4.33670746e-01],
       [ -5.56181958e-01],
       [ -9.67649141e-02],
       [  6.24996610e-02],
       [  6.07674553e-01],
       [ -7.52199896e-01],
       [  4.91288902e-01],
       [ -2.49903929e-01],
       [ -2.75214745e-01],
       [  5.15791144e-01],
       [ -5.90485097e-01],
       [ -5.13303034e-01],
       [ -7.22626718e-02],
       [  4.07981278e-01],
       [  1.23755267e-01],
       [ -6.66442048e-01],
       [ -3.81603481e-01],
       [ -9.54343396e-01],
       [ -3.41787337e-01],
       [  4.90234277e-02],
       [  5.28042265e-01],
```


[5.26817153e-01],
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[ 1.36006388e-01]])
```

Multiple Regression Model

```
from sklearn import linear_model
from sklearn.linear_model import Lasso
regr = linear_model.LinearRegression()
regr.fit(X_train, Y_train)#training func question + answers
# The coefficients
print ('Intercept: ',regr.intercept_)
print ('Coefficient : ',regr.coef_)

Intercept:  [-8.10072062e-17]
Coefficient :  [[ 0.60519595  0.44512289  0.06762205 -0.05752323
 0.16796952]]

regr.intercept_

array([-8.10072062e-17])

regr.coef_

array([[ 0.60519595,  0.44512289,  0.06762205, -0.05752323,
 0.16796952]])

regr.coef_[0][0]

0.6051959545443171

regr.coef_[0][1]

0.44512289318862164

regr.coef_[0][3]
```

-0.05752322506300601

y_pred = regr.predict(X_test)

y_pred

```
array([[ -0.39424447],
       [  0.43563115],
       [ -0.07368063],
       [ -0.09273092],
       [ -0.36267396],
       [  0.05064675],
       [  0.20328702],
       [ -0.8909513 ],
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       [  0.04391717],
       [ -0.29435498],
       [  0.02776111],
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       [ -0.30049126],
       [ -0.32029542],
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       [ -0.706152  ],
       [ -0.93373737],
       [ -0.57429101],
       [ -0.18820504],
       [ -0.2201243 ],
       [  0.27443221],
       [ -0.49368059],
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```

```
from sklearn.metrics import r2_score
```

```
print(f"R2 Score : {r2_score(Y_test,y_pred)*100} % ")
```

R2 Score : 69.52190340964152 %

```
print(f"Mean absolute error: {np.mean(np.absolute(y_pred - Y_test))}  
")#pred - actual
```

Mean absolute error: 0.3362259554459409

```
print("Residual sum of squares (MSE): %.2f" % np.mean((y_pred -  
Y_test) **2))
```

Residual sum of squares (MSE): 0.22

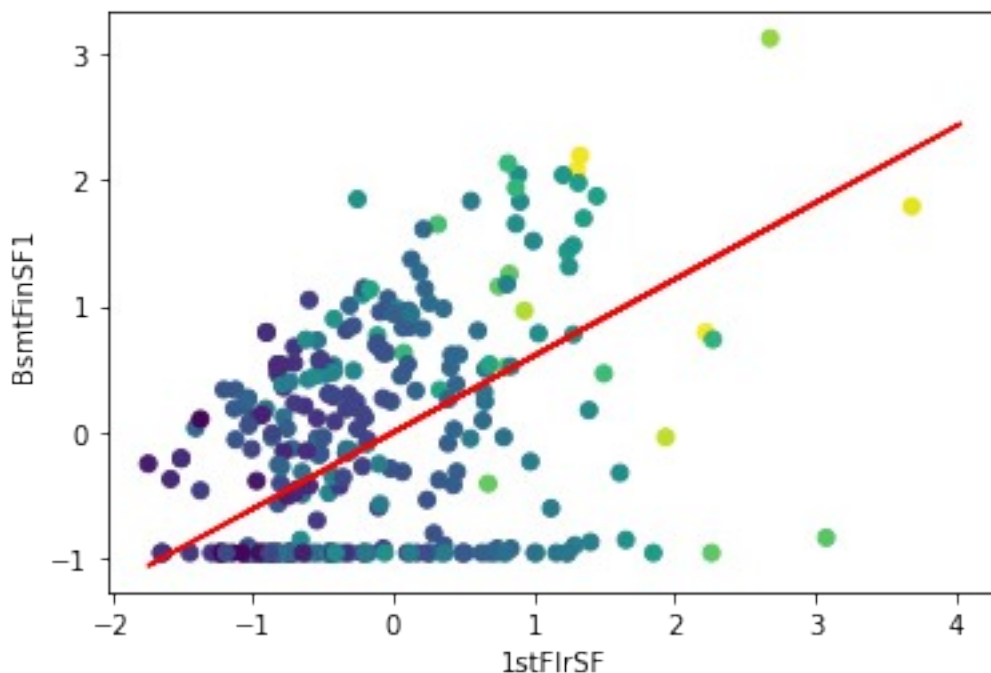
```
accuracy = (f"accuracy : {r2_score(Y_test,y_pred)*100} % ")
```

accuracy

'accuracy : 69.52190340964152 % '

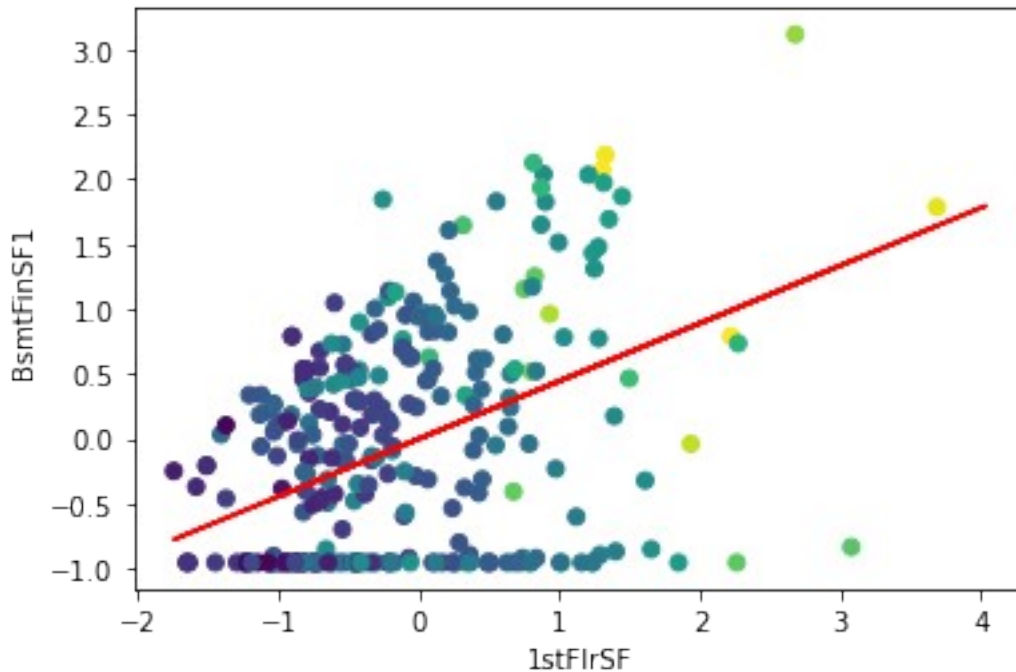
Plots

```
import matplotlib.pyplot as plt  
plt.scatter(X_test[:,0],X_test[:,-1], c = y_pred)  
plt.plot(X_test, regr.coef_[0][0]*X_test + regr.intercept_[0], 'r') #  
y = mx+c  
plt.xlabel("1stFlrSF")  
plt.ylabel("BsmtFinSF1")  
Text(0, 0.5, 'BsmtFinSF1')
```



```
import matplotlib.pyplot as plt  
plt.scatter(X_test[:,0],X_test[:,-1], c = y_pred)
```

```
plt.plot(X_test, regr.coef_[0][1]*X_test + regr.intercept_[0], 'r') #y
= mx+c
plt.xlabel("1stFlrSF")
plt.ylabel("BsmtFinSF1")
Text(0, 0.5, 'BsmtFinSF1')
```



Apply Lasso Regression to cover overfitting and undefitting Problem

```
from sklearn.linear_model import Lasso

L = Lasso(alpha = 1)
L.fit(X_train,Y_train)
Lasso(alpha=1)
ypred3 = L.predict(X_test)

from sklearn.metrics import r2_score
print("R2-score",r2_score(Y_test,ypred3))
print(f"Mean absolute error: {np.mean(np.absolute(ypred3 - Y_test))}")# pred - actual

R2-score -0.004908518792945626
Mean absolute error: 0.6243935831081134
```