

Machine Learning Assignment No.2

Que.1 By Taking reference of the Housing Price Dataset plot each independent variable with the dependent variable and store the name of independent variable in a list which show non linear behavior

```
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	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							
...
...							
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
MoSold								
\								
0	Lvl	AllPub	...	0	NaN	NaN	NaN	0

```

2
1      Lvl      AllPub  ...      0      NaN      NaN      NaN      0
5
2      Lvl      AllPub  ...      0      NaN      NaN      NaN      0
9
3      Lvl      AllPub  ...      0      NaN      NaN      NaN      0
2
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.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 = df.drop("LotFrontage",axis=1) # Independent variable
```

```
df
```

	Id	MSSubClass	MSZoning	LotArea	Street	Alley	LotShape
LandContour \							
0	1	60	RL	8450	Pave	NaN	Reg
Lvl							
1	2	20	RL	9600	Pave	NaN	Reg
Lvl							
2	3	60	RL	11250	Pave	NaN	IR1
Lvl							
3	4	70	RL	9550	Pave	NaN	IR1
Lvl							
4	5	60	RL	14260	Pave	NaN	IR1
Lvl							
...
...							
1455	1456	60	RL	7917	Pave	NaN	Reg
Lvl							
1456	1457	20	RL	13175	Pave	NaN	Reg
Lvl							
1457	1458	70	RL	9042	Pave	NaN	Reg
Lvl							
1458	1459	20	RL	9717	Pave	NaN	Reg
Lvl							
1459	1460	20	RL	9937	Pave	NaN	Reg
Lvl							

	Utilities	LotConfig	...	PoolArea	PoolQC	Fence	MiscFeature
MiscVal \							
0	AllPub	Inside	...	0	NaN	NaN	NaN
0							
1	AllPub	FR2	...	0	NaN	NaN	NaN
0							
2	AllPub	Inside	...	0	NaN	NaN	NaN
0							
3	AllPub	Corner	...	0	NaN	NaN	NaN
0							
4	AllPub	FR2	...	0	NaN	NaN	NaN

```

0
...      ...      ...      ...      ...      ...      ...      ...
..
1455     AllPub     Inside     ...      0      NaN      NaN      NaN
0
1456     AllPub     Inside     ...      0      NaN     MnPrv      NaN
0
1457     AllPub     Inside     ...      0      NaN     GdPrv      Shed
2500
1458     AllPub     Inside     ...      0      NaN      NaN      NaN
0
1459     AllPub     Inside     ...      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 80 columns]
```

```
df.shape
```

```
(1460, 80)
```

```
X = df.drop("SalePrice",axis = 1) # Independent variable
X
```

```

      Id  MSSubClass  MSZoning  LotArea  Street  Alley  LotShape
LandContour \
0         1         60        RL     8450    Pave    NaN        Reg
Lv1
1         2         20        RL     9600    Pave    NaN        Reg
Lv1
2         3         60        RL    11250    Pave    NaN        IR1
Lv1
3         4         70        RL     9550    Pave    NaN        IR1
Lv1
4         5         60        RL    14260    Pave    NaN        IR1
Lv1
...      ...      ...      ...      ...      ...      ...      ...
...
1455    1456         60        RL     7917    Pave    NaN        Reg

```

Lvl							
1456	1457	20	RL	13175	Pave	NaN	Reg
Lvl							
1457	1458	70	RL	9042	Pave	NaN	Reg
Lvl							
1458	1459	20	RL	9717	Pave	NaN	Reg
Lvl							
1459	1460	20	RL	9937	Pave	NaN	Reg
Lvl							

	Utilities	LotConfig	...	ScreenPorch	PoolArea	PoolQC	Fence
MiscFeature \							
0	AllPub	Inside	...	0	0	NaN	NaN
NaN							
1	AllPub	FR2	...	0	0	NaN	NaN
NaN							
2	AllPub	Inside	...	0	0	NaN	NaN
NaN							
3	AllPub	Corner	...	0	0	NaN	NaN
NaN							
4	AllPub	FR2	...	0	0	NaN	NaN
NaN							
...
...							
1455	AllPub	Inside	...	0	0	NaN	NaN
NaN							
1456	AllPub	Inside	...	0	0	NaN	MnPrv
NaN							
1457	AllPub	Inside	...	0	0	NaN	GdPrv
Shed							
1458	AllPub	Inside	...	0	0	NaN	NaN
NaN							
1459	AllPub	Inside	...	0	0	NaN	NaN
NaN							

	MiscVal	MoSold	YrSold	SaleType	SaleCondition
0	0	2	2008	WD	Normal
1	0	5	2007	WD	Normal
2	0	9	2008	WD	Normal
3	0	2	2006	WD	Abnorml
4	0	12	2008	WD	Normal
...
1455	0	8	2007	WD	Normal
1456	0	2	2010	WD	Normal
1457	2500	5	2010	WD	Normal
1458	0	4	2010	WD	Normal
1459	0	6	2008	WD	Normal

[1460 rows x 79 columns]


```
Y = df["SalePrice"] #dependent variables only target column will be in Y
```

```
Y
```

```
0      208500
1      181500
2      223500
3      140000
4      250000
```

```
...
1455    175000
1456    210000
1457    266500
1458    142125
1459    147500
```

```
Name: SalePrice, Length: 1460, dtype: int64
```

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

```
Y
```

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

```
X.head()
```

	Id	MSSubClass	MSZoning	LotArea	Street	Alley	LotShape	LandContour
0	1	60	RL	8450	Pave	NaN	Reg	Lvl
1	2	20	RL	9600	Pave	NaN	Reg	Lvl
2	3	60	RL	11250	Pave	NaN	IR1	Lvl
3	4	70	RL	9550	Pave	NaN	IR1	Lvl
4	5	60	RL	14260	Pave	NaN	IR1	Lvl

	Utilities	LotConfig	...	ScreenPorch	PoolArea	PoolQC	Fence
0	AllPub	Inside	...	0	0	NaN	NaN
1	AllPub	FR2	...	0	0	NaN	NaN

2	AllPub	Inside	...	0	0	NaN	NaN
NaN							
3	AllPub	Corner	...	0	0	NaN	NaN
NaN							
4	AllPub	FR2	...	0	0	NaN	NaN
NaN							

	MiscVal	MoSold	YrSold	SaleType	SaleCondition
0	0	2	2008	WD	Normal
1	0	5	2007	WD	Normal
2	0	9	2008	WD	Normal
3	0	2	2006	WD	Abnorml
4	0	12	2008	WD	Normal

[5 rows x 79 columns]

```
# separate dataset into train and test
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(
    X,
    Y,
    test_size=0.3,
    random_state=50)
```

X_train.shape, X_test.shape

((1022, 79), (438, 79))

X_train

	Id	MSSubClass	MSZoning	LotArea	Street	Alley	LotShape
LandContour \							
175	176	20	RL	12615	Pave	NaN	Reg
Lvl							
1408	1409	70	RM	7740	Pave	NaN	Reg
Lvl							
1148	1149	50	RM	5700	Pave	NaN	Reg
Lvl							
861	862	190	RL	11625	Pave	NaN	Reg
Lvl							
220	221	20	RL	8990	Pave	NaN	IR1
Lvl							
...
...							
229	230	120	RL	3182	Pave	NaN	Reg
Lvl							
70	71	20	RL	13651	Pave	NaN	IR1
Lvl							
132	133	20	RL	7388	Pave	NaN	Reg
Lvl							
1313	1314	60	RL	14774	Pave	NaN	IR1

Lvl							
109	110	20	RL	11751	Pave	NaN	IR1
Lvl							
	Utilities	LotConfig	...	ScreenPorch	PoolArea	PoolQC	Fence
MiscFeature \							
175	AllPub	Corner	...	0	0	NaN	MnPrv
NaN							
1408	AllPub	Inside	...	168	0	NaN	NaN
NaN							
1148	AllPub	Inside	...	0	0	NaN	NaN
NaN							
861	AllPub	Inside	...	0	0	NaN	NaN
NaN							
220	AllPub	Inside	...	0	0	NaN	NaN
NaN							
...
...							
229	AllPub	Inside	...	0	0	NaN	NaN
NaN							
70	AllPub	Inside	...	0	0	NaN	NaN
NaN							
132	AllPub	Corner	...	0	0	NaN	NaN
NaN							
1313	AllPub	Corner	...	0	0	NaN	NaN
NaN							
109	AllPub	Inside	...	0	0	NaN	MnPrv
NaN							

	MiscVal	MoSold	YrSold	SaleType	SaleCondition
175	0	6	2007	WD	Normal
1408	0	6	2010	WD	Normal
1148	0	8	2008	WD	Normal
861	0	4	2010	WD	Normal
220	0	4	2006	New	Partial
...
229	0	5	2009	WD	Normal
70	0	2	2007	WD	Normal
132	0	7	2007	WD	Normal
1313	0	5	2010	WD	Normal
109	0	1	2010	COD	Normal

[1022 rows x 79 columns]

X_train.corr()

	Id	MSSubClass	LotArea	OverallQual
OverallCond \				
Id	1.000000	0.025180	-0.042861	-0.017525
0.027990				

MSSubClass 0.078168	0.025180	1.000000	-0.114367	0.018828	-
LotArea 0.002465	-0.042861	-0.114367	1.000000	0.097441	-
OverallQual 0.111293	-0.017525	0.018828	0.097441	1.000000	-
OverallCond 1.000000	0.027990	-0.078168	-0.002465	-0.111293	
YearBuilt 0.387111	-0.012989	0.042625	0.015185	0.577101	-
YearRemodAdd 0.078987	-0.013134	0.053252	0.026488	0.555213	
MasVnrArea 0.114867	-0.068046	0.025975	0.104614	0.414165	-
BsmtFinSF1 0.056106	-0.006606	-0.079230	0.224503	0.230208	-
BsmtFinSF2 0.049775	-0.022122	-0.088294	0.116479	-0.042107	
BsmtUnfSF 0.138530	0.016729	-0.129546	-0.013383	0.307859	-
TotalBsmtSF 0.179180	0.001622	-0.245195	0.266075	0.534580	-
1stFlrSF 0.154743	-0.000038	-0.256829	0.293272	0.470704	-
2ndFlrSF 0.005361	-0.006532	0.292979	0.042529	0.303157	
LowQualFinSF 0.043748	-0.048756	0.059712	-0.007210	-0.036297	
GrLivArea 0.106192	-0.009664	0.057437	0.251388	0.595486	-
BsmtFullBath 0.079731	-0.000926	0.000866	0.171255	0.085237	-
BsmtHalfBath 0.121766	-0.044217	-0.001635	0.049252	-0.037835	
FullBath 0.216317	-0.011373	0.113428	0.140051	0.552090	-
HalfBath 0.071881	0.002378	0.182245	0.001082	0.276522	-
BedroomAbvGr 0.013135	0.008400	-0.033968	0.128956	0.107916	-
KitchenAbvGr 0.106891	0.006342	0.236044	-0.009992	-0.195035	-
TotRmsAbvGrd 0.101754	-0.000633	0.027472	0.182974	0.435719	-
Fireplaces 0.045240	-0.036304	-0.083865	0.280601	0.385690	-
GarageYrBlt 0.302170	-0.003349	0.110443	-0.032688	0.557026	-
GarageCars 0.202612	0.018369	-0.034364	0.140119	0.605606	-

GarageArea 0.161514	0.015167	-0.093700	0.165381	0.577165	-
WoodDeckSF 0.002512	-0.045645	0.010248	0.169479	0.247537	-
OpenPorchSF 0.026936	0.004472	0.013227	0.069652	0.299579	-
EnclosedPorch 0.106672	0.013902	-0.011002	-0.024140	-0.105834	
3SsnPorch 0.024791	-0.075026	-0.064610	0.011642	0.016132	
ScreenPorch 0.036087	0.010995	-0.042803	0.028306	0.063606	
PoolArea 0.028996	0.020920	-0.007767	0.088009	0.101894	-
MiscVal 0.079555	-0.004467	0.000907	0.035375	-0.035628	
MoSold 0.002778	0.024806	-0.006537	-0.013137	0.066265	
YrSold 0.048223	0.009276	-0.021893	-0.014502	-0.014671	

	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	
BsmtFinSF2 \ Id 0.022122	-0.012989	-0.013134	-0.068046	-0.006606	-
MSSubClass 0.088294	0.042625	0.053252	0.025975	-0.079230	-
LotArea 0.116479	0.015185	0.026488	0.104614	0.224503	
OverallQual 0.042107	0.577101	0.555213	0.414165	0.230208	-
OverallCond 0.049775	-0.387111	0.078987	-0.114867	-0.056106	
YearBuilt 0.046764	1.000000	0.598748	0.308525	0.252258	-
YearRemodAdd 0.057883	0.598748	1.000000	0.171563	0.136949	-
MasVnrArea 0.063710	0.308525	0.171563	1.000000	0.263987	-
BsmtFinSF1 0.042417	0.252258	0.136949	0.263987	1.000000	-
BsmtFinSF2 1.000000	-0.046764	-0.057883	-0.063710	-0.042417	
BsmtUnfSF 0.208535	0.145947	0.147399	0.114849	-0.502190	-
TotalBsmtSF 0.113599	0.394536	0.270313	0.369768	0.537806	
1stFlrSF 0.117595	0.285877	0.232418	0.355018	0.454542	
2ndFlrSF	0.029176	0.161668	0.176942	-0.141532	-

0.113736					
LowQualFinSF	-0.169594	-0.068087	-0.070230	-0.042055	
0.011049					
GrLivArea	0.220770	0.299572	0.401767	0.215477	-
0.006091					
BsmtFullBath	0.184121	0.110194	0.066960	0.647734	
0.165378					
BsmtHalfBath	-0.047195	-0.010370	0.042605	0.044331	
0.057414					
FullBath	0.475584	0.444591	0.283784	0.054317	-
0.083134					
HalfBath	0.260997	0.194512	0.190178	-0.003646	-
0.023659					
BedroomAbvGr	-0.048401	-0.039360	0.104784	-0.102588	-
0.016352					
KitchenAbvGr	-0.159160	-0.164545	-0.035418	-0.082943	-
0.036257					
TotRmsAbvGrd	0.117424	0.197051	0.295755	0.065795	-
0.036636					
Fireplaces	0.155521	0.116917	0.263209	0.266428	
0.054814					
GarageYrBlt	0.813789	0.651013	0.231085	0.150479	-
0.097642					
GarageCars	0.527617	0.418037	0.346576	0.218608	-
0.028433					
GarageArea	0.477330	0.387689	0.362806	0.298668	-
0.017958					
WoodDeckSF	0.228017	0.226514	0.207229	0.177238	
0.057041					
OpenPorchSF	0.201400	0.256033	0.103869	0.110250	
0.014051					
EnclosedPorch	-0.416450	-0.177672	-0.131871	-0.109477	
0.026815					
3SsnPorch	0.011016	0.025054	0.032758	-0.004082	-
0.030257					
ScreenPorch	-0.009983	-0.026060	0.047905	0.064097	
0.091784					
PoolArea	0.005994	0.039571	0.035591	0.236978	
0.042001					
MiscVal	-0.039418	-0.009489	-0.040046	-0.004573	-
0.002470					
MoSold	0.025161	0.022081	-0.020837	-0.043953	-
0.012785					
YrSold	-0.029227	0.034888	-0.018832	0.019368	
0.021047					

	...	GarageArea	WoodDeckSF	OpenPorchSF	EnclosedPorch
\					
Id	...	0.015167	-0.045645	0.004472	0.013902

MSSubClass	...	-0.093700	0.010248	0.013227	-0.011002
LotArea	...	0.165381	0.169479	0.069652	-0.024140
OverallQual	...	0.577165	0.247537	0.299579	-0.105834
OverallCond	...	-0.161514	-0.002512	-0.026936	0.106672
YearBuilt	...	0.477330	0.228017	0.201400	-0.416450
YearRemodAdd	...	0.387689	0.226514	0.256033	-0.177672
MasVnrArea	...	0.362806	0.207229	0.103869	-0.131871
BsmtFinSF1	...	0.298668	0.177238	0.110250	-0.109477
BsmtFinSF2	...	-0.017958	0.057041	0.014051	0.026815
BsmtUnfSF	...	0.183632	0.026537	0.118611	-0.011277
TotalBsmtSF	...	0.491643	0.234292	0.239787	-0.116877
1stFlrSF	...	0.497726	0.222607	0.189023	-0.079051
2ndFlrSF	...	0.152533	0.117434	0.204863	0.081864
LowQualFinSF	...	-0.054352	-0.000270	-0.015534	0.085925
GrLivArea	...	0.489400	0.261650	0.307754	0.016677
BsmtFullBath	...	0.169224	0.155536	0.081407	-0.059105
BsmtHalfBath	...	-0.036467	0.028290	-0.020259	-0.019276
FullBath	...	0.410229	0.222691	0.259877	-0.117271
HalfBath	...	0.193076	0.111364	0.212537	-0.097562
BedroomAbvGr	...	0.079784	0.071997	0.085638	0.021797
KitchenAbvGr	...	-0.049193	-0.087300	-0.050643	0.043848
TotRmsAbvGrd	...	0.358110	0.194187	0.229790	0.000650
Fireplaces	...	0.275484	0.228026	0.158219	-0.020807
GarageYrBlt	...	0.562112	0.220969	0.241712	-0.314456

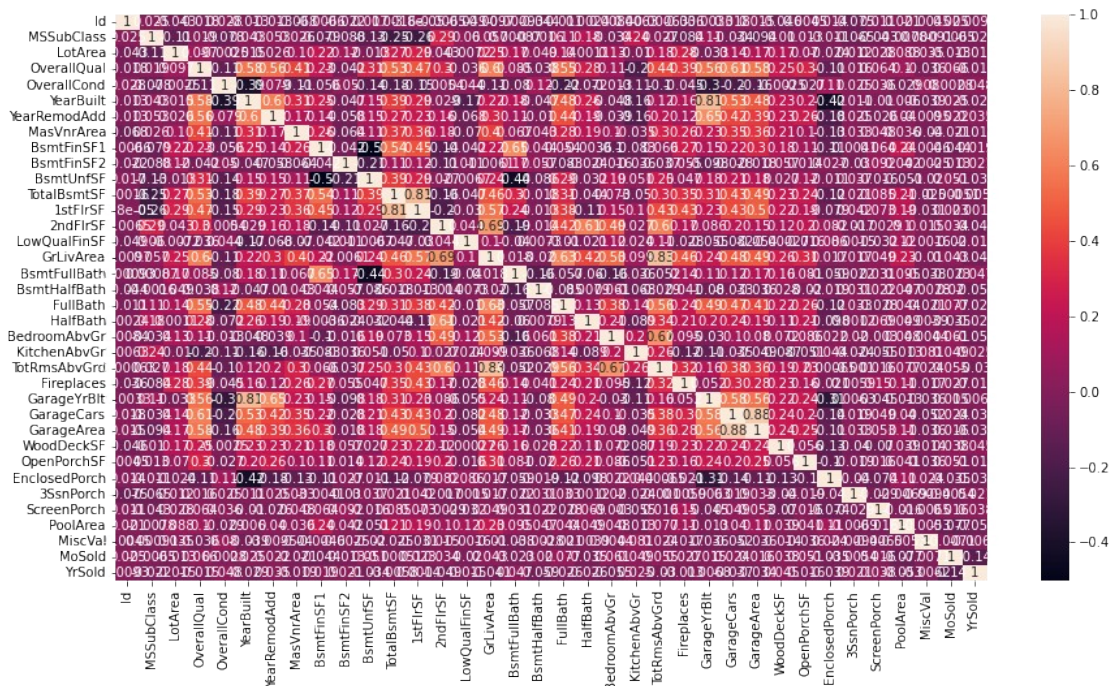
GarageCars	...	0.879030	0.242454	0.198639	-0.136279
GarageArea	...	1.000000	0.239356	0.253631	-0.108896
WoodDeckSF	...	0.239356	1.000000	0.055852	-0.132687
OpenPorchSF	...	0.253631	0.055852	1.000000	-0.104518
EnclosedPorch	...	-0.108896	-0.132687	-0.104518	1.000000
3SsnPorch	...	0.033450	-0.040471	-0.019403	-0.039606
ScreenPorch	...	0.053370	-0.070333	0.016460	-0.074408
PoolArea	...	0.106756	0.039455	0.041268	0.109545
MiscVal	...	-0.035755	-0.014213	-0.036254	0.023738
MoSold	...	0.015672	0.038213	0.051491	-0.035075
YrSold	...	-0.033988	0.045145	-0.016294	-0.039395

	3SsnPorch	ScreenPorch	PoolArea	MiscVal	MoSold
YrSold					
Id	-0.075026	0.010995	0.020920	-0.004467	0.024806
0.009276					
MSSubClass	-0.064610	-0.042803	-0.007767	0.000907	-0.006537
0.021893					-
LotArea	0.011642	0.028306	0.088009	0.035375	-0.013137
0.014502					-
OverallQual	0.016132	0.063606	0.101894	-0.035628	0.066265
0.014671					-
OverallCond	0.024791	0.036087	-0.028996	0.079555	0.002778
0.048223					
YearBuilt	0.011016	-0.009983	0.005994	-0.039418	0.025161
0.029227					-
YearRemodAdd	0.025054	-0.026060	0.039571	-0.009489	0.022081
0.034888					
MasVnrArea	0.032758	0.047905	0.035591	-0.040046	-0.020837
0.018832					-
BsmtFinSF1	-0.004082	0.064097	0.236978	-0.004573	-0.043953
0.019368					
BsmtFinSF2	-0.030257	0.091784	0.042001	-0.002470	-0.012785
0.021047					
BsmtUnfSF	0.036599	-0.016374	-0.050625	-0.019717	0.050622
0.034031					-
TotalBsmtSF	0.021133	0.084885	0.214770	-0.025406	-0.000514
0.005826					-

1stFlrSF	0.041808	0.072976	0.188889	-0.030553	0.022552	
0.001376						
2ndFlrSF	-0.016551	-0.002855	0.100149	0.015084	0.034486	-
0.049469						
LowQualFinSF	0.001540	-0.031614	0.116828	-0.001580	-0.019975	-
0.015037						
GrLivArea	0.017369	0.048856	0.232607	-0.010262	0.043444	-
0.041178						
BsmtFullBath	-0.021664	0.030538	0.094942	-0.038425	-0.022647	
0.047220						
BsmtHalfBath	0.031338	0.021563	0.047085	-0.002763	0.019802	-
0.058886						
FullBath	0.033250	-0.028500	0.044232	-0.020825	0.076741	-
0.025906						
HalfBath	0.001197	0.069264	0.048676	0.003928	-0.034601	-
0.026238						
BedroomAbvGr	0.019734	-0.003015	0.048259	0.004437	0.061194	-
0.054573						
KitchenAbvGr	-0.023562	-0.055461	-0.013256	0.080628	0.048652	
0.025447						
TotRmsAbvGrd	-0.001018	0.015995	0.076767	0.023662	0.054622	-
0.029951						
Fireplaces	0.005923	0.149292	0.105683	-0.017496	0.026723	-
0.013111						
GarageYrBlt	0.006252	-0.044522	-0.012544	-0.035604	0.014729	
0.006770						
GarageCars	0.019429	0.049214	0.039868	-0.051857	0.023925	-
0.037423						
GarageArea	0.033450	0.053370	0.106756	-0.035755	0.015672	-
0.033988						
WoodDeckSF	-0.040471	-0.070333	0.039455	-0.014213	0.038213	
0.045145						
OpenPorchSF	-0.019403	0.016460	0.041268	-0.036254	0.051491	-
0.016294						
EnclosedPorch	-0.039606	-0.074408	0.109545	0.023738	-0.035075	-
0.039395						
3SsnPorch	1.000000	-0.028835	-0.006892	-0.009439	-0.005406	
0.020883						
ScreenPorch	-0.028835	1.000000	-0.016223	-0.006470	0.015864	
0.038272						
PoolArea	-0.006892	-0.016223	1.000000	-0.005311	-0.077185	-
0.052822						
MiscVal	-0.009439	-0.006470	-0.005311	1.000000	-0.007057	-
0.006154						
MoSold	-0.005406	0.015864	-0.077185	-0.007057	1.000000	-
0.141790						
YrSold	0.020883	0.038272	-0.052822	-0.006154	-0.141790	
1.000000						

[36 rows x 36 columns]

```
import seaborn as sns
import matplotlib.pyplot as plt
#Using Pearson Correlation
plt.figure(figsize=(15,8))
cor = X_train.corr()
sns.heatmap(cor, annot=True)
plt.show()
```



with the following function we can select highly correlated features
it will remove the first feature that is correlated with anything
other feature

```
def correlation(dataset, threshold): # X_train,0.3
    col_corr = set() # Set of all the names of correlated columns
    col_corr_lst = []
    print(f"set initial {col_corr}")
    print(f"list initial {col_corr_lst}")
    corr_arr = dataset.corr() # corr_arr is my correlaion matrix which
    is 2d
    for row in range(len(corr_arr)):
        for col in range(row):
            if abs(corr_arr.iloc[row, col]) > threshold: # we are
            interested in absolute coeff value
                colname = corr_arr.columns[row] # getting the name of
                column
                col_corr_lst.append(colname)
                col_corr.add(colname)
                print(f"colname name which is correlated is
                {colname}")
```

```

        print(f"set {col_corr}")
        print(f"lst {col_corr_lst}")

    print(f"list is {col_corr_lst}")
    return col_corr

corr_features = correlation(X_train, 0.3)#data,threshold
len(set(corr_features))

set initial set()
list initial []
colname name which is correlated is YearBuilt
set {'YearBuilt'}
lst ['YearBuilt']
colname name which is correlated is YearBuilt
set {'YearBuilt'}
lst ['YearBuilt', 'YearBuilt']
colname name which is correlated is YearRemodAdd
set {'YearRemodAdd', 'YearBuilt'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd']
colname name which is correlated is YearRemodAdd
set {'YearRemodAdd', 'YearBuilt'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd']
colname name which is correlated is MasVnrArea
set {'YearRemodAdd', 'YearBuilt', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea']
colname name which is correlated is MasVnrArea
set {'YearRemodAdd', 'YearBuilt', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea']
colname name which is correlated is BsmtUnfSF
set {'YearRemodAdd', 'YearBuilt', 'BsmtUnfSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF']
colname name which is correlated is BsmtUnfSF
set {'YearRemodAdd', 'YearBuilt', 'BsmtUnfSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF']
colname name which is correlated is TotalBsmtSF
set {'YearBuilt', 'YearRemodAdd', 'BsmtUnfSF', 'TotalBsmtSF',
'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',

```

```

'TotalBsmtSF']
colname name which is correlated is TotalBsmtSF
set {'YearBuilt', 'YearRemodAdd', 'BsmtUnfSF', 'TotalBsmtSF',
'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF']
colname name which is correlated is TotalBsmtSF
set {'YearBuilt', 'YearRemodAdd', 'BsmtUnfSF', 'TotalBsmtSF',
'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF']
colname name which is correlated is TotalBsmtSF
set {'YearBuilt', 'YearRemodAdd', 'BsmtUnfSF', 'TotalBsmtSF',
'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF']
colname name which is correlated is 1stFlrSF
set {'YearBuilt', '1stFlrSF', 'YearRemodAdd', 'BsmtUnfSF',
'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF']
colname name which is correlated is 1stFlrSF
set {'YearBuilt', '1stFlrSF', 'YearRemodAdd', 'BsmtUnfSF',
'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF']
colname name which is correlated is 1stFlrSF
set {'YearBuilt', '1stFlrSF', 'YearRemodAdd', 'BsmtUnfSF',
'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF']
colname name which is correlated is 2ndFlrSF
set {'YearBuilt', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd', 'BsmtUnfSF',
'TotalBsmtSF', 'MasVnrArea'}

```

```

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF']
colname name which is correlated is GrLivArea
set {'YearBuilt', 'GrLivArea', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd',
'BsmtUnfSF', 'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea']
colname name which is correlated is GrLivArea
set {'YearBuilt', 'GrLivArea', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd',
'BsmtUnfSF', 'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea']
colname name which is correlated is GrLivArea
set {'YearBuilt', 'GrLivArea', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd',
'BsmtUnfSF', 'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea']
colname name which is correlated is GrLivArea
set {'YearBuilt', 'GrLivArea', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd',
'BsmtUnfSF', 'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea']
colname name which is correlated is BsmtFullBath
set {'YearBuilt', 'GrLivArea', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',

```



```
colname name which is correlated is FullBath
set {'YearBuilt', 'GrLivArea', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'FullBath', 'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath']
colname name which is correlated is FullBath
set {'YearBuilt', 'GrLivArea', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'FullBath', 'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath']
colname name which is correlated is FullBath
set {'YearBuilt', 'GrLivArea', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'FullBath', 'TotalBsmtSF', 'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath']
colname name which is correlated is HalfBath
set {'YearBuilt', 'GrLivArea', '1stFlrSF', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
```


'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr']

colname name which is correlated is TotRmsAbvGrd

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF', '2ndFlrSF',
'YearRemodAdd', 'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath',
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd']

colname name which is correlated is TotRmsAbvGrd

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF', '2ndFlrSF',
'YearRemodAdd', 'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath',
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd']

colname name which is correlated is TotRmsAbvGrd

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF', '2ndFlrSF',
'YearRemodAdd', 'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath',
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
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'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd']

colname name which is correlated is TotRmsAbvGrd

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF', '2ndFlrSF',
'YearRemodAdd', 'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath',
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
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'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',

[illegible]

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'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',  
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces']
```

colname name which is correlated is Fireplaces

```
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',  
'Fireplaces', '2ndFlrSF', 'YearRemodAdd', 'BsmtFullBath', 'BsmtUnfSF',  
'HalfBath', 'FullBath', 'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}
```

```
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',  
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',  
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'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',  
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',  
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',  
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',  
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',  
'Fireplaces']
```

colname name which is correlated is Fireplaces

```
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',  
'Fireplaces', '2ndFlrSF', 'YearRemodAdd', 'BsmtFullBath', 'BsmtUnfSF',  
'HalfBath', 'FullBath', 'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}
```

```
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',  
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',  
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',  
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'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',  
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',  
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',  
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',  
'Fireplaces', 'Fireplaces']
```

colname name which is correlated is GarageYrBlt

```
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',  
'GarageYrBlt', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',  
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',  
'MasVnrArea', 'BedroomAbvGr'}
```

```
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',  
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',  
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',  
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',  
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
```

'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt']

colname name which is correlated is GarageYrBlt

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt']

colname name which is correlated is GarageYrBlt

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',
'GarageYrBlt']

colname name which is correlated is GarageYrBlt

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',

'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',
'GarageYrBlt', 'GarageYrBlt']

colname name which is correlated is GarageYrBlt

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',
'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt']

colname name which is correlated is GarageYrBlt

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
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'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',
'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt']

colname name which is correlated is GarageCars

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea', 'BedroomAbvGr'}

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lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',  
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',  
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'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',  
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',  
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',  
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',  
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',  
'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt',  
'GarageCars']
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colname name which is correlated is GarageCars

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set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',  
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'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',  
'MasVnrArea', 'BedroomAbvGr'}
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lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
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'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',  
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',  
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',  
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',  
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'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt',  
'GarageCars', 'GarageCars']
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colname name which is correlated is GarageCars

```
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',  
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'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',  
'MasVnrArea', 'BedroomAbvGr'}
```

```
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
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'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',  
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',  
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',  
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',  
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',  
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',
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```

'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt',
'GarageCars', 'GarageCars', 'GarageCars']
colname name which is correlated is GarageCars
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea', 'BedroomAbvGr'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
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'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',
'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt',
'GarageCars', 'GarageCars', 'GarageCars', 'GarageCars']
colname name which is correlated is GarageCars
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea', 'BedroomAbvGr'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
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'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
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'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
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'GarageCars', 'GarageCars', 'GarageCars', 'GarageCars', 'GarageCars']
colname name which is correlated is GarageCars
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
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'MasVnrArea', 'BedroomAbvGr'}
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'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',  
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'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt',  
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'GarageCars']
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colname name which is correlated is GarageCars

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set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',  
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lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
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'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',  
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',  
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'GarageCars', 'GarageCars']
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colname name which is correlated is GarageCars

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set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',  
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',  
'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',  
'MasVnrArea', 'BedroomAbvGr'}
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lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
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'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',  
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',  
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'GarageCars', 'GarageCars', 'GarageCars']
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colname name which is correlated is GarageCars
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
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'BsmtFullBath', 'BsmtUnfSF', 'HalfBath', 'FullBath', 'TotalBsmtSF',
'MasVnrArea', 'BedroomAbvGr'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
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colname name which is correlated is GarageCars
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lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
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colname name which is correlated is GarageCars
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lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
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colname name which is correlated is GarageArea

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
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'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
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'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
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colname name which is correlated is GarageArea

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'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
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colname name which is correlated is GarageArea

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'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
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colname name which is correlated is GarageArea

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
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'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
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colname name which is correlated is GarageArea

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'GarageArea', 'HalfBath', 'FullBath',
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

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lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',  
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',  
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colname name which is correlated is GarageArea

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set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',  
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',  
'BsmtFullBath', 'BsmtUnfSF', 'GarageArea', 'HalfBath', 'FullBath',  
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}
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lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
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colname name which is correlated is GarageArea

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set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',  
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'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}
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lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',  
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'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
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'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',
'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt',
'GarageCars', 'GarageCars', 'GarageCars', 'GarageCars', 'GarageCars',
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'GarageCars', 'GarageArea', 'GarageArea', 'GarageArea', 'GarageArea',
'GarageArea', 'GarageArea', 'GarageArea']

colname name which is correlated is GarageArea

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'GarageArea', 'HalfBath', 'FullBath',
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
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'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
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colname name which is correlated is GarageArea

set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'GarageArea', 'HalfBath', 'FullBath',
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}

lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
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'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
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'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt',
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'GarageCars', 'GarageArea', 'GarageArea', 'GarageArea', 'GarageArea',
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colname name which is correlated is GarageArea
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'GarageArea', 'HalfBath', 'FullBath',
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
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'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
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'GarageArea', 'GarageArea', 'GarageArea', 'GarageArea', 'GarageArea',
'GarageArea']

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```

colname name which is correlated is GarageArea
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'Fireplaces', '2ndFlrSF', 'YearRemodAdd',
'BsmtFullBath', 'BsmtUnfSF', 'GarageArea', 'HalfBath', 'FullBath',
'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
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'GarageArea']

```

```

'GarageArea', 'GarageArea']
colname name which is correlated is OpenPorchSF
set {'YearBuilt', 'GrLivArea', 'TotRmsAbvGrd', '1stFlrSF',
'GarageYrBlt', 'GarageCars', 'OpenPorchSF', 'Fireplaces', '2ndFlrSF',
'YearRemodAdd', 'BsmtFullBath', 'BsmtUnfSF', 'GarageArea', 'HalfBath',
'FullBath', 'TotalBsmtSF', 'MasVnrArea', 'BedroomAbvGr'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',
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'GarageArea', 'GarageArea', 'OpenPorchSF']

```

```

colname name which is correlated is EnclosedPorch
set {'YearBuilt', 'TotRmsAbvGrd', 'GarageCars', '2ndFlrSF',
'TotalBsmtSF', 'BedroomAbvGr', 'GrLivArea', 'GarageYrBlt',
'Fireplaces', 'BsmtFullBath', 'EnclosedPorch', '1stFlrSF',
'OpenPorchSF', 'YearRemodAdd', 'HalfBath', 'MasVnrArea', 'BsmtUnfSF',
'GarageArea', 'FullBath'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
'BsmtFullBath', 'BsmtFullBath', 'BsmtFullBath', 'FullBath',
'FullBath', 'FullBath', 'FullBath', 'FullBath', 'FullBath',
'FullBath', 'HalfBath', 'HalfBath', 'BedroomAbvGr', 'BedroomAbvGr',
'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
'TotRmsAbvGrd', 'Fireplaces', 'Fireplaces', 'Fireplaces',
'Fireplaces', 'Fireplaces', 'GarageYrBlt', 'GarageYrBlt',
'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt', 'GarageYrBlt',
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'GarageCars', 'GarageArea', 'GarageArea', 'GarageArea', 'GarageArea',
'GarageArea', 'GarageArea', 'GarageArea', 'GarageArea', 'GarageArea',
'GarageArea', 'GarageArea', 'OpenPorchSF', 'EnclosedPorch']

```

```

colname name which is correlated is EnclosedPorch
set {'YearBuilt', 'TotRmsAbvGrd', 'GarageCars', '2ndFlrSF',

```



```

'TotalBsmtSF', 'BedroomAbvGr', 'GrLivArea', 'GarageYrBlt',
'Fireplaces', 'BsmtFullBath', 'EnclosedPorch', '1stFlrSF',
'OpenPorchSF', 'YearRemodAdd', 'HalfBath', 'MasVnrArea', 'BsmtUnfSF',
'GarageArea', 'FullBath'}
lst ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
'MasVnrArea', 'MasVnrArea', 'BsmtUnfSF', 'BsmtUnfSF', 'TotalBsmtSF',
'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF', 'TotalBsmtSF',
'1stFlrSF', '1stFlrSF', '1stFlrSF', '1stFlrSF', '2ndFlrSF',
'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea', 'GrLivArea',
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list is ['YearBuilt', 'YearBuilt', 'YearRemodAdd', 'YearRemodAdd',
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'BedroomAbvGr', 'TotRmsAbvGrd', 'TotRmsAbvGrd', 'TotRmsAbvGrd',
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'GarageArea', 'GarageArea', 'OpenPorchSF', 'EnclosedPorch',
'EnclosedPorch']

```

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corr_features

```

{'1stFlrSF',
'2ndFlrSF',
'BedroomAbvGr',
'BsmtFullBath',

```

```

'BsmtUnfSF',
'EnclosedPorch',
'Fireplaces',
'FullBath',
'GarageArea',
'GarageCars',
'GarageYrBlt',
'GrLivArea',
'HalfBath',
'MasVnrArea',
'OpenPorchSF',
'TotRmsAbvGrd',
'TotalBsmtSF',
'YearBuilt',
'YearRemodAdd'}

```

```

X_train.drop(corr_features,axis=1,inplace = True)
X_test.drop(corr_features,axis=1,inplace = True)

```

```

X_train

```

	Id	MSSubClass	MSZoning	LotArea	Street	Alley	LotShape
LandContour \							
175	176	20	RL	12615	Pave	NaN	Reg
Lvl							
1408	1409	70	RM	7740	Pave	NaN	Reg
Lvl							
1148	1149	50	RM	5700	Pave	NaN	Reg
Lvl							
861	862	190	RL	11625	Pave	NaN	Reg
Lvl							
220	221	20	RL	8990	Pave	NaN	IR1
Lvl							
...
...							
229	230	120	RL	3182	Pave	NaN	Reg
Lvl							
70	71	20	RL	13651	Pave	NaN	IR1
Lvl							
132	133	20	RL	7388	Pave	NaN	Reg
Lvl							
1313	1314	60	RL	14774	Pave	NaN	IR1
Lvl							
109	110	20	RL	11751	Pave	NaN	IR1
Lvl							
	Utilities	LotConfig	...	ScreenPorch	PoolArea	PoolQC	Fence
MiscFeature \							
175	AllPub	Corner	...	0	0	NaN	MnPrv
NaN							
1408	AllPub	Inside	...	168	0	NaN	NaN

NaN							
1148	AllPub	Inside	...	0	0	NaN	NaN
NaN							
861	AllPub	Inside	...	0	0	NaN	NaN
NaN							
220	AllPub	Inside	...	0	0	NaN	NaN
NaN							
...
...							
229	AllPub	Inside	...	0	0	NaN	NaN
NaN							
70	AllPub	Inside	...	0	0	NaN	NaN
NaN							
132	AllPub	Corner	...	0	0	NaN	NaN
NaN							
1313	AllPub	Corner	...	0	0	NaN	NaN
NaN							
109	AllPub	Inside	...	0	0	NaN	MnPrv
NaN							

	MiscVal	MoSold	YrSold	SaleType	SaleCondition
175	0	6	2007	WD	Normal
1408	0	6	2010	WD	Normal
1148	0	8	2008	WD	Normal
861	0	4	2010	WD	Normal
220	0	4	2006	New	Partial
...
229	0	5	2009	WD	Normal
70	0	2	2007	WD	Normal
132	0	7	2007	WD	Normal
1313	0	5	2010	WD	Normal
109	0	1	2010	COD	Normal

[1022 rows x 60 columns]

X_test

	Id	MSSubClass	MSZoning	LotArea	Street	Alley	LotShape
LandContour	\						
930	931	20	RL	8925	Pave	NaN	IR1
HLS							
530	531	80	RL	10200	Pave	NaN	Reg
Lvl							
1291	1292	160	RM	1680	Pave	NaN	Reg
Lvl							
1385	1386	50	RM	5436	Pave	NaN	Reg
Lvl							
305	306	20	RL	10386	Pave	NaN	Reg
Lvl							
...

...							
1307	1308	20	RL	8072	Pave	NaN	Reg
Lvl							
1078	1079	120	RM	4435	Pave	NaN	Reg
Lvl							
1244	1245	70	RL	11435	Pave	NaN	IR1
HLS							
406	407	50	RL	10480	Pave	NaN	Reg
Lvl							
1459	1460	20	RL	9937	Pave	NaN	Reg
Lvl							

	Utilities	LotConfig	...	ScreenPorch	PoolArea	PoolQC	Fence
MiscFeature \							
930	AllPub	Inside	...	0	0	NaN	NaN
NaN							
530	AllPub	Inside	...	0	0	NaN	NaN
NaN							
1291	AllPub	Inside	...	0	0	NaN	NaN
NaN							
1385	AllPub	Inside	...	0	0	NaN	MnPrv
NaN							
305	AllPub	Inside	...	0	0	NaN	NaN
NaN							
...
...							
1307	AllPub	Inside	...	0	0	NaN	NaN
NaN							
1078	AllPub	Inside	...	0	0	NaN	NaN
NaN							
1244	AllPub	Corner	...	0	0	NaN	NaN
NaN							
406	AllPub	Inside	...	0	0	NaN	NaN
NaN							
1459	AllPub	Inside	...	0	0	NaN	NaN
NaN							

	MiscVal	MoSold	YrSold	SaleType	SaleCondition
930	0	7	2009	WD	Normal
530	0	8	2008	WD	Abnorml
1291	0	2	2009	WD	Normal
1385	0	5	2010	WD	Normal
305	0	7	2007	WD	Normal
...
1307	0	5	2009	WD	Normal
1078	0	5	2006	WD	Normal
1244	0	6	2006	WD	Normal
406	0	3	2008	WD	Normal
1459	0	6	2008	WD	Normal

[438 rows x 60 columns]

```
df =  
df.drop(["Alley", "1stFlrSF", "2ndFlrSF", "BedroomAbvGr", "BsmtFullBath", "  
BsmtUnfSF", "EnclosedPorch", "Fireplaces", "FullBath", "GarageArea", "Garag  
eCars", "GarageYrBlt", "GrLivArea", "HalfBath", "MasVnrArea", "OpenPorchSF"  
, "TotRmsAbvGrd", "TotalBsmtSF", "YearBuilt", "YearRemodAdd", "MSZoning", "L  
otConfig", "Neighborhood", "PoolQC", "Fence", "MiscFeature", "YrSold", "Sale  
Type", "SaleCondition", "Condition1", "Condition2", "BldgType", "HouseStyle  
, "RoofStyle", "RoofMatl", "Exterior1st", "Exterior2nd", "MasVnrType", "Ext  
erQual", "ExterCond", "Foundation", "BsmtQual", "BsmtCond", "BsmtExposure",  
"BsmtFinType1", "BsmtFinType2", "Heating", "HeatingQC", "CentralAir", "Elec  
trical", "KitchenQual", "Functional", "FireplaceQu", "GarageType", "GarageF  
inish", "GarageQual", "GarageCond", "PavedDrive", "LandSlope", "Street", "Lo  
tShape", "LandContour", "Utilities"], axis = 1)  
df
```

		Id	MSSubClass	LotArea	OverallQual	OverallCond	BsmtFinSF1
\	0	1	60	8450	7	5	706
	1	2	20	9600	6	8	978
	2	3	60	11250	7	5	486
	3	4	70	9550	7	5	216
	4	5	60	14260	8	5	655

	1455	1456	60	7917	6	5	0
	1456	1457	20	13175	6	6	790
	1457	1458	70	9042	7	9	275
	1458	1459	20	9717	5	6	49
	1459	1460	20	9937	5	6	830

		BsmtFinSF2	LowQualFinSF	BsmtHalfBath	KitchenAbvGr	WoodDeckSF
\	0	0	0	0	1	0
	1	0	0	1	1	298

2	0	0	0	1	0
3	0	0	0	1	0
4	0	0	0	1	192
...
1455	0	0	0	1	0
1456	163	0	0	1	349
1457	0	0	0	1	0
1458	1029	0	0	1	366
1459	290	0	0	1	736

	3SsnPorch	ScreenPorch	PoolArea	MiscVal	MoSold	SalePrice
0	0	0	0	0	2	208500
1	0	0	0	0	5	181500
2	0	0	0	0	9	223500
3	0	0	0	0	2	140000
4	0	0	0	0	12	250000
...
1455	0	0	0	0	8	175000
1456	0	0	0	0	2	210000
1457	0	0	0	2500	5	266500
1458	0	0	0	0	4	142125
1459	0	0	0	0	6	147500

[1460 rows x 17 columns]

df.isnull().sum()

Id	0
MSSubClass	0
LotArea	0
OverallQual	0
OverallCond	0
BsmtFinSF1	0
BsmtFinSF2	0
LowQualFinSF	0
BsmtHalfBath	0
KitchenAbvGr	0
WoodDeckSF	0
3SsnPorch	0
ScreenPorch	0

```
PoolArea      0
MiscVal       0
MoSold        0
SalePrice     0
dtype: int64
```

```
X = df[['MSSubClass',
'LotArea',"OverallQual","OverallCond","BsmtFinSF1","BsmtFinSF2","LowQualFinSF","BsmtHalfBath","KitchenAbvGr","WoodDeckSF","3SsnPorch","ScreenPorch","PoolArea","MiscVal","MoSold"]].values #independent variable
X[0:5]
```

```
array([[ 60, 8450, 7, 5, 706, 0, 0, 0, 1,
        0, 0, 0, 0, 2],
 [ 20, 9600, 6, 8, 978, 0, 0, 1, 1,
 298, 0, 0, 0, 5],
 [ 60, 11250, 7, 5, 486, 0, 0, 0, 1,
 0, 0, 0, 0, 9],
 [ 70, 9550, 7, 5, 216, 0, 0, 0, 1,
 0, 0, 0, 0, 2],
 [ 60, 14260, 8, 5, 655, 0, 0, 0, 1,
 192, 0, 0, 0, 12]], dtype=int64)
```

```
Y = df[["SalePrice"]]
```

```
Y
```

```
      SalePrice
0      208500
1      181500
2      223500
3      140000
4      250000
...
1455     175000
1456     210000
1457     266500
1458     142125
1459     147500
```

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

```
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, 15)
```

```
X_test.shape
```

(292, 15)

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([[ -0.85469057, -0.0242262 , -0.78256106, ..., -0.07684505,
        -0.11595495,  0.24559339],
       [ -0.85469057, -0.18471992,  0.63894954, ..., -0.07684505,
        -0.11595495, -0.49181812],
       [  0.09911675,  0.29260181,  2.77121545, ..., -0.07684505,
        -0.11595495, -0.12311237],
       ...,
       [ -0.85469057, -0.10082087, -0.07180576, ..., -0.07684505,
        -0.11595495, -0.86052387],
       [ -0.85469057, -0.28343067, -0.78256106, ..., -0.07684505,
        -0.11595495,  0.24559339],
       [ -0.85469057, -0.01966095,  0.63894954, ..., -0.07684505,
        -0.11595495, -0.12311237]])
```

X_test

```
array([[ 0.09911675, -0.17731408, -0.07180576, ..., -0.07684505,
        -0.11595495,  0.61429914],
       [ 0.09911675, -0.01154496,  0.63894954, ..., -0.07684505,
        -0.11595495,  0.98300489],
       [ 0.33756858, -0.11299485, -0.78256106, ..., -0.07684505,
        -0.11595495, -0.12311237],
       ...,
       [ 0.09911675, -0.2562421 , -0.07180576, ..., -0.07684505,
        -0.11595495,  2.08912215],
       [ 1.52982773, -0.26192329, -0.07180576, ..., -0.07684505,
        -0.11595495,  0.24559339],
       [ 0.09911675, -0.14353127,  0.63894954, ..., -0.07684505,
        -0.11595495, -0.12311237]])
```

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],  
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       [-2.75214745e-01],  
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       [-3.47912898e-01],
```

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[1.36006388e-01]])

Multiple Regression Model

```
from sklearn import linear_model
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:  [-9.63766304e-17]
Coefficient :  [[-9.02873132e-02  9.87258038e-02  7.27431899e-01 -
2.45253111e-03
 1.50082091e-01  9.31031720e-03  7.51810841e-03 -3.46707655e-03
 4.88886019e-02  1.01349908e-01  3.38783711e-02  5.96773472e-02
 5.10781326e-03  5.93216756e-04 -1.01065850e-02]]

regr.intercept_
array([-9.63766304e-17])

regr.coef_
array([[ -9.02873132e-02,  9.87258038e-02,  7.27431899e-01,
        -2.45253111e-03,  1.50082091e-01,  9.31031720e-03,
         7.51810841e-03, -3.46707655e-03,  4.88886019e-02,
         1.01349908e-01,  3.38783711e-02,  5.96773472e-02,
         5.10781326e-03,  5.93216756e-04, -1.01065850e-02]])

regr.coef_[0][0]
-0.09028731320937944

regr.coef_[0][1]
0.0987258037893155

y_pred = regr.predict(X_test)

y_pred
array([[ -0.33722427],
       [ 0.31952841],
       [-0.60598383],
       [-0.43255507],
       [-0.2066125 ],
       [-0.07160902],
       [ 0.6781571 ],
       [-1.10503171],
       [ 0.21028814],
       [-1.23931036],
       [-0.814138 ],
       [ 0.4244962 ],
       [-0.5451187 ],
```

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```
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[-0.56171185],
[-0.15478399],
[-0.43828999],
[-0.26238376],
[-0.37192232],
[ 0.39365457]])
```

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

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

```
R2 Score : 70.281267555182 %
```

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

```
Mean absolute error: 0.3459234130131204
```

```
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 : 70.281267555182 % '
```

Apply Lasso Regression to cover the overfitting and underfitting problem

```
from sklearn.linear_model import Lasso

L = Lasso(alpha = 1)

L.fit(X_train,Y_train)

Lasso(alpha=1)

ypred1 = L.predict(X_test)

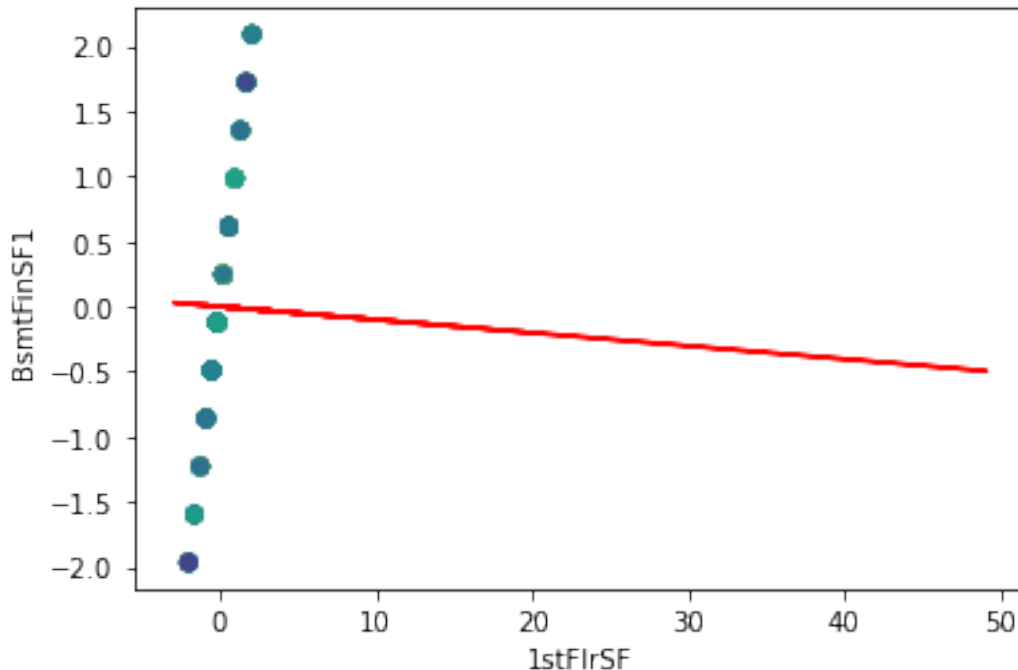
from sklearn.metrics import r2_score
print("R2-score",r2_score(Y_test,ypred1))
print(f"Mean absolute error: {np.mean(np.absolute(ypred1 - Y_test))}")
# pred - actual

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

Plots

```
import matplotlib.pyplot as plt
plt.scatter(X_test[:,14],X_test[:,-1], c = y_pred)
plt.plot(X_test, regr.coef_[0][14]*X_test + regr.intercept_[0], 'r') #
y = mx+c
plt.xlabel("1stFlrSF")
plt.ylabel("BsmtFinSF1")

Text(0, 0.5, 'BsmtFinSF1')
```



This Independent variable shows the Non-Linear Relationship

```
lst = ["MSSubClass",
'LotArea', 'OverallQual', 'OverallCond', 'BsmtFinSF1', 'BsmtFinSF2', 'LowQualFinSF', 'BsmtHalfBath', 'KitchenAbvGr', "WoodDeckSF", "3SsnPorch", "ScreenPorch", "PoolArea", "MiscVal", "MoSold"]
```

```
lst
```

```
["MSSubClass",
'LotArea', 'OverallQual', 'OverallCond', 'BsmtFinSF1', 'BsmtFinSF2', 'LowQualFinSF', 'BsmtHalfBath', 'KitchenAbvGr',
'WoodDeckSF',
'3SsnPorch',
'ScreenPorch',
'PoolArea',
'MiscVal',
'MoSold']
```

Ans : All the Independent Variable shows the Non-Linear Relationship

Que.2 Columns which showed non linear behavior apply Polynomial Linear Regression to it ...

Note : If there is None column which is showing Non Linear Behavior you can take anyone of the column as independent variable and apply Polynomial Linear Regression to it

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

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

```
# take a look at the dataset
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.shape
```

```
(1067, 13)
```

```
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	ENGINE SIZE	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
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

```

```

df =
df.drop(["MODELYEAR", "MAKE", "MODEL", "VEHICLECLASS", "TRANSMISSION", "FUE
LTYPE"],axis = 1)

```

```

df

```

	ENGINE SIZE	CYLINDERS	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY
0	2.0	4	9.9	6.7
1	2.4	4	11.2	7.7
2	1.5	4	6.0	5.8
3	3.5	6	12.7	9.1
4	3.5	6	12.1	8.7
...
1062	3.0	6	13.4	9.8
1063	3.2	6	13.2	9.5
1064	3.0	6	13.4	9.8
1065	3.2	6	12.9	9.3
1066	3.2	6	14.9	10.2

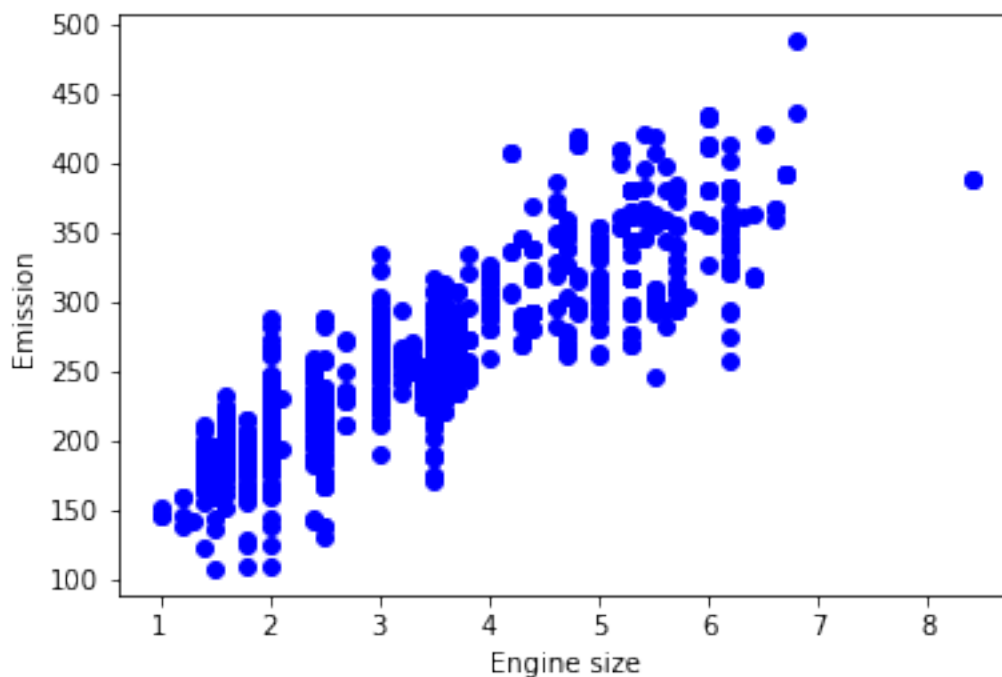
	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255
4	10.6	27	244
...
1062	11.8	24	271
1063	11.5	25	264
1064	11.8	24	271
1065	11.3	25	260

```
[1067 rows x 7 columns]
```

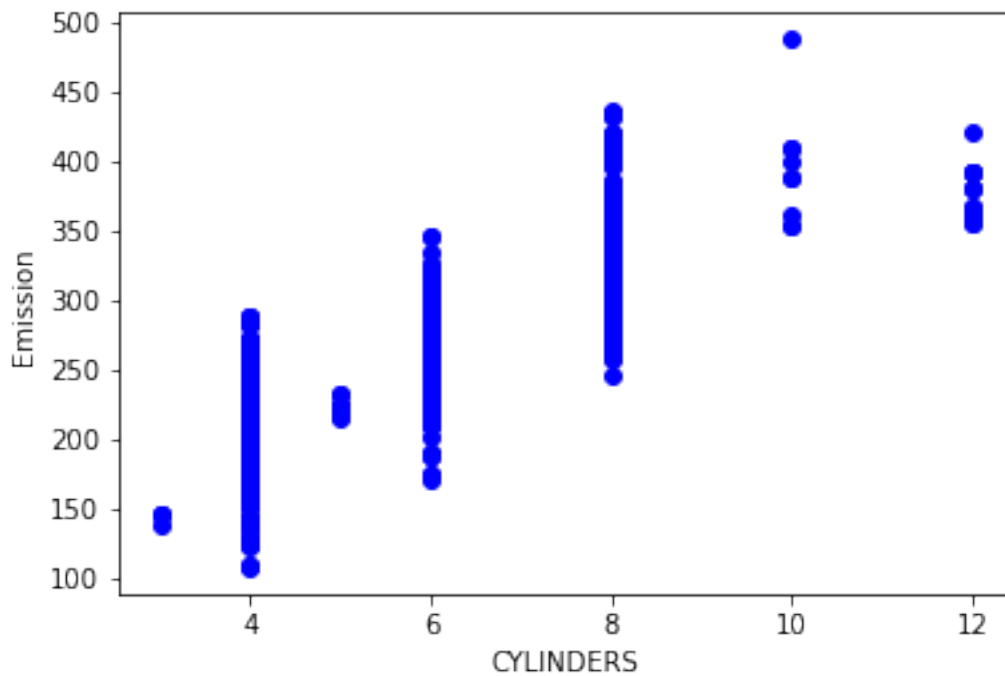
```
cdf =  
df[['ENGINE_SIZE', 'CYLINDERS', 'FUELCONSUMPTION_COMB', 'CO2EMISSIONS']]  
cdf.head(9)
```

	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
5	3.5	6	10.0	230
6	3.5	6	10.1	232
7	3.7	6	11.1	255
8	3.7	6	11.6	267

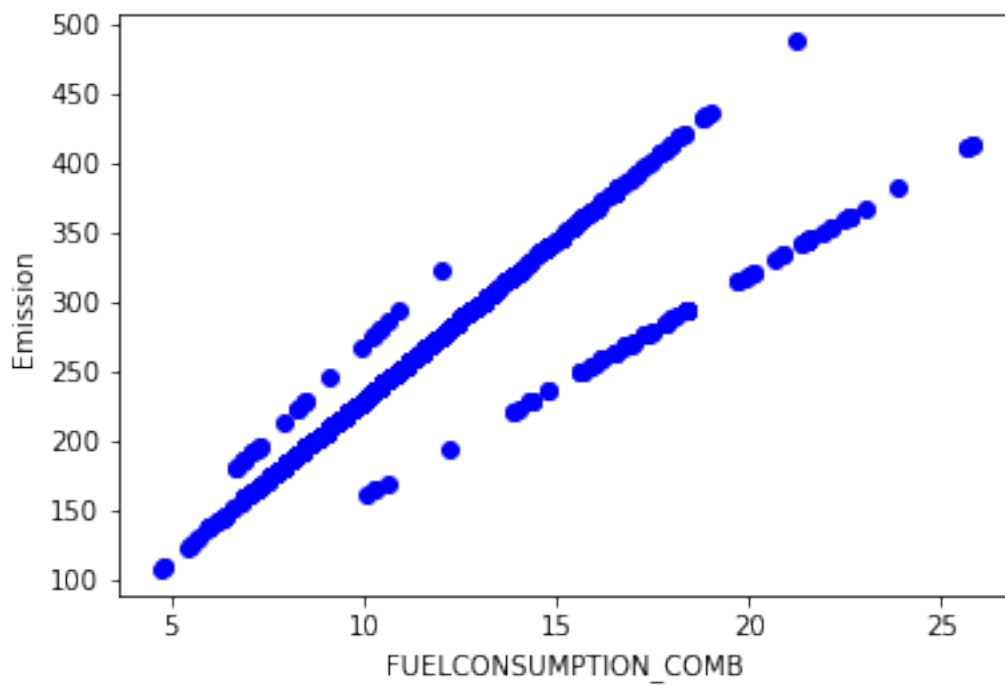
```
plt.scatter(cdf.ENGINE_SIZE, cdf.CO2EMISSIONS, color='blue')  
plt.xlabel("Engine size")  
plt.ylabel("Emission")  
plt.show()
```



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



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



Apply polynomial regression on Fuelconsumption_Comb

Creating train and test dataset

```
len(cdf)
```

```
1067
```

```
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]
```

```
msk = np.random.rand(len(df)) < 0.8
```

```
msk
```

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

```
msk = np.random.rand(len(df)) < 0.8
```

```
train = cdf[msk]
```

```
test = cdf[~msk]
```

```
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
4	3.5	6	10.6	244
5	3.5	6	10.0	230
...
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

```
[855 rows x 4 columns]
```

test

	ENGINE SIZE	CYLINDERS	FUEL CONSUMPTION_COMB	CO2 EMISSIONS
3	3.5	6	11.1	255
12	5.9	12	15.6	359
23	2.0	4	10.0	230
34	4.0	8	12.5	288
39	3.0	6	11.2	258
...
1053	2.0	4	10.7	246
1056	2.5	5	9.7	223
1057	2.5	5	10.1	232
1059	3.2	6	10.2	235
1060	3.0	6	11.5	264

[212 rows x 4 columns]

Polynomial Regression

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn import linear_model
train_x = np.asanyarray(train[['FUELCONSUMPTION_COMB']]) #independent
train_y = np.asanyarray(train[['CO2EMISSIONS']]) #dependent
#training -> train_x, train_y
test_x = np.asanyarray(test[['FUELCONSUMPTION_COMB']])
test_y = np.asanyarray(test[['CO2EMISSIONS']])
#y_hat=prediction -> test_x
#evaluation -> test_y, y_hat
train_x
```

```
array([[ 8.5],
       [ 9.6],
       [ 5.9],
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       [14.7],
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       [ 8.8],
       [10. ],
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```

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```

```
train_x[0:5]
```

```
array([[ 8.5],  
       [ 9.6],  
       [ 5.9],  
       [10.6],  
       [10. ]])
```

```
poly = PolynomialFeatures(degree=2)  
train_x_poly = poly.fit_transform(train_x)  
train_x_poly
```

```
array([[ 1. ,  8.5 , 72.25],  
       [ 1. ,  9.6 , 92.16],  
       [ 1. ,  5.9 , 34.81],
```

```

'''
[ 1. , 11.8 , 139.24],
[ 1. , 11.3 , 127.69],
[ 1. , 12.8 , 163.84]])

clf = linear_model.LinearRegression()
train_y_ = clf.fit(train_x_poly, train_y)
# The coefficients
print ('Coefficients: ', clf.coef_)
print ('Intercept: ', clf.intercept_)

Coefficients: [[ 0.          39.81542284 -0.87453348]]
Intercept: [-76.35808794]

import numpy as np

np.arange(0,10,1)

array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

np.arange(0,10,0.5)

array([0. , 0.5, 1. , 1.5, 2. , 2.5, 3. , 3.5, 4. , 4.5, 5. , 5.5,
6. ,
      6.5, 7. , 7.5, 8. , 8.5, 9. , 9.5])

print(clf.intercept_, "----", clf.coef_)

[-76.35808794] ---- [[ 0.          39.81542284 -0.87453348]]

clf.intercept_[0]

-76.35808794149165

clf.coef_[0][0]

0.0

clf.coef_[0][1]

39.81542284160467

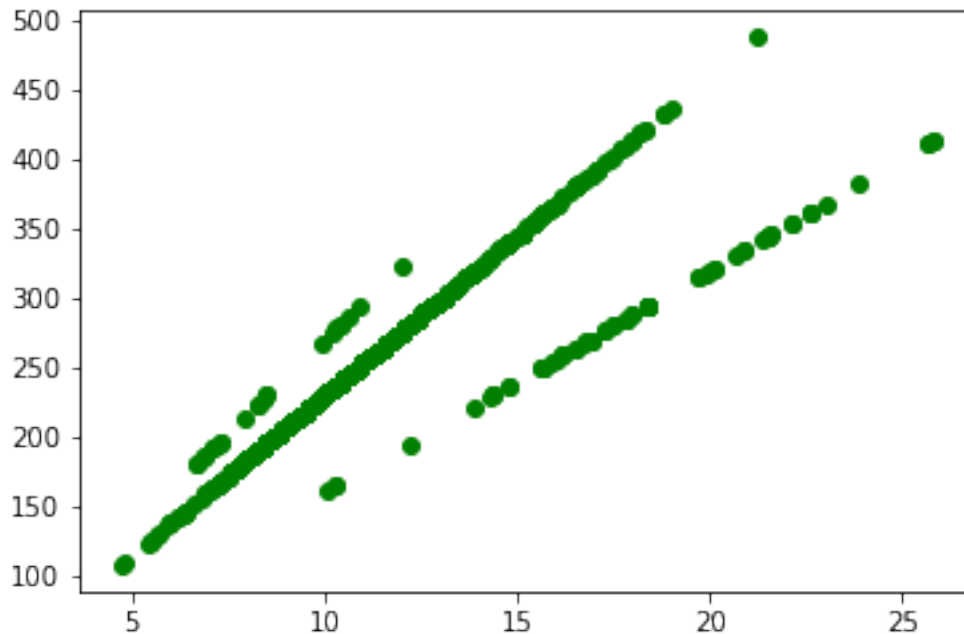
clf.coef_[0][2]

-0.8745334755747078

plt.scatter(train.FUELCONSUMPTION_COMB, train.CO2EMISSIONS,
color='green')

<matplotlib.collections.PathCollection at 0x19e677ff4f0>

```

```
XX = np.arange(0, 10, .1)
```

```
XX
```

```
array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. , 1.1,
1.2,
      1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2. , 2.1, 2.2, 2.3, 2.4,
2.5,
      2.6, 2.7, 2.8, 2.9, 3. , 3.1, 3.2, 3.3, 3.4, 3.5, 3.6, 3.7,
3.8,
      3.9, 4. , 4.1, 4.2, 4.3, 4.4, 4.5, 4.6, 4.7, 4.8, 4.9, 5. ,
5.1,
      5.2, 5.3, 5.4, 5.5, 5.6, 5.7, 5.8, 5.9, 6. , 6.1, 6.2, 6.3,
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9. ,
      9.1, 9.2, 9.3, 9.4, 9.5, 9.6, 9.7, 9.8, 9.9])
```

```
#y = b + m1xx + m2xx**2
```

```
yy = clf.intercept_[0]+ clf.coef_[0][1]*XX+ clf.coef_[0]
[2]*np.power(XX, 2)
```

```
yy
```

```
array([-7.63580879e+01, -7.23852910e+01, -6.84299847e+01, -
6.44921691e+01,
      -6.05718442e+01, -5.66690099e+01, -5.27836663e+01, -
4.89158134e+01,
```

```

-4.50654511e+01, -4.12325795e+01, -3.74171986e+01, -
3.36193083e+01,
-2.98389087e+01, -2.60759998e+01, -2.23305816e+01, -
1.86026540e+01,
-1.48922171e+01, -1.11992709e+01, -7.52381529e+00, -
3.86585039e+00,
-2.25376161e-01, 3.39760740e+00, 7.00310029e+00,
1.05911025e+01,
1.41616141e+01, 1.77146349e+01, 2.12501652e+01,
2.47682047e+01,
2.82687536e+01, 3.17518118e+01, 3.52173793e+01,
3.86654562e+01,
4.20960424e+01, 4.55091379e+01, 4.89047427e+01,
5.22828569e+01,
5.56434804e+01, 5.89866133e+01, 6.23122555e+01,
6.56204070e+01,
6.89110678e+01, 7.21842380e+01, 7.54399175e+01,
7.86781063e+01,
8.18988045e+01, 8.51020120e+01, 8.82877288e+01,
9.14559549e+01,
9.46066904e+01, 9.77399352e+01, 1.00855689e+02,
1.03953953e+02,
1.07034726e+02, 1.10098008e+02, 1.13143799e+02,
1.16172100e+02,
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1.28110397e+02,
1.31051244e+02, 1.33974601e+02, 1.36880467e+02,
1.39768842e+02,
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1.75726072e+02, 1.78369578e+02, 1.80995594e+02,
1.83604118e+02,
1.86195152e+02, 1.88768696e+02, 1.91324748e+02,
1.93863311e+02,
1.96384382e+02, 1.98887963e+02, 2.01374053e+02,
2.03842652e+02,
2.06293761e+02, 2.08727379e+02, 2.11143506e+02,
2.13542143e+02,
2.15923289e+02, 2.18286944e+02, 2.20633109e+02,
2.22961783e+02,
2.25272966e+02, 2.27566659e+02, 2.29842861e+02,
2.32101572e+02])

```

```

import matplotlib.pyplot as plt
plt.scatter(train.FUELCONSUMPTION_COMB, train.CO2EMISSIONS,
color='green')

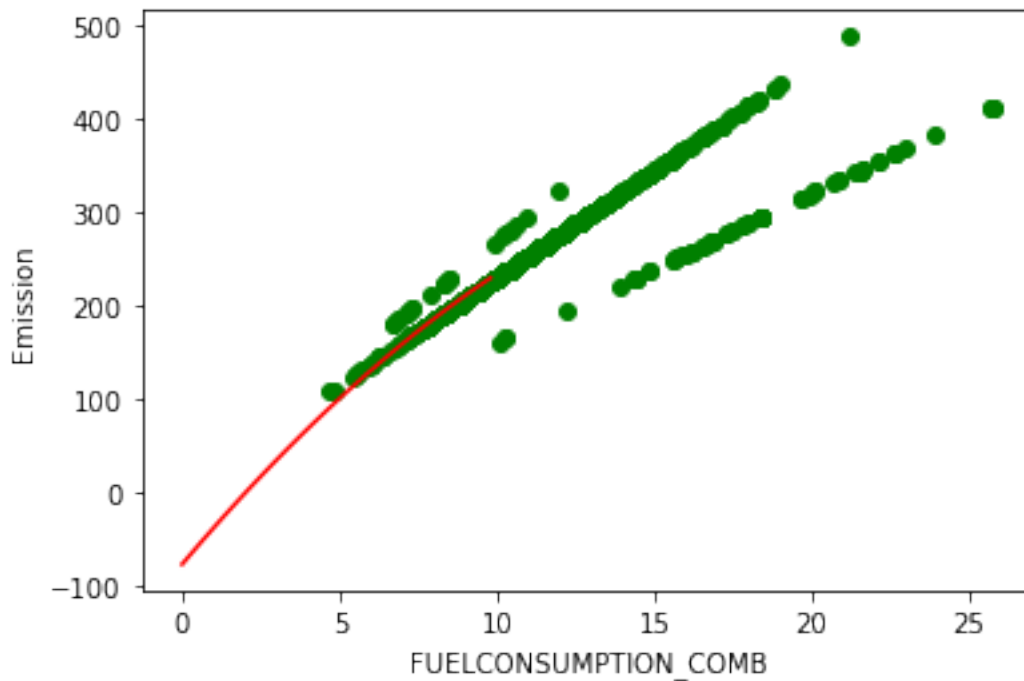
```

```

XX = np.arange(0, 10 , 0.2)
yy = clf.intercept_[0]+ clf.coef_[0][1]*XX+ clf.coef_[0]
[2]*np.power(XX, 2)
plt.plot(XX, yy, 'r' )
plt.xlabel("FUELCONSUMPTION_COMB")
plt.ylabel("Emission")

Text(0, 0.5, 'Emission')

```



Evaluation

```

from sklearn.metrics import r2_score

test_x_poly = poly.fit_transform(test_x)
test_x
array([[11.1],
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test_x_poly

```
array([[ 1. , 11.1 , 123.21],
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       [ 1. , 11.2 , 125.44],
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       [ 1. , 9.1 , 82.81],
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       [ 1. , 9.9 , 98.01],
       [ 1. , 10. , 100. ],
       [ 1. , 9.9 , 98.01],
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       [ 1. , 12.2 , 148.84],
       [ 1. , 12.7 , 161.29],
       [ 1. , 14.7 , 216.09],
       [ 1. , 14.7 , 216.09],
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       [ 1. , 11. , 121. ],
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       [ 1. , 16.5 , 272.25],
       [ 1. , 10.2 , 104.04],
       [ 1. , 11.2 , 125.44],
       [ 1. , 10.8 , 116.64],
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       [ 1. , 16.5 , 272.25],
```



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[ 1. , 14.9 , 222.01],
[ 1. , 7.6 , 57.76],
[ 1. , 6.6 , 43.56],
[ 1. , 7. , 49. ],
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[ 1. , 8.9 , 79.21],
[ 1. , 8. , 64. ],
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[ 1. , 9. , 81. ],
[ 1. , 10.2 , 104.04],
[ 1. , 10.3 , 106.09],
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[ 1. , 16.5 , 272.25],
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[1. , 17.4 , 302.76],
[1. , 17.3 , 299.29],
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[1. , 10.6 , 112.36],
[1. , 11. , 121.],
[1. , 12.3 , 151.29],
[1. , 11.4 , 129.96],
[1. , 12.3 , 151.29],

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[ 1. , 12.7 , 161.29],
[ 1. , 10.7 , 114.49],
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[ 1. , 7.8 , 60.84],
[ 1. , 7.3 , 53.29],
[ 1. , 9. , 81. ],
[ 1. , 9. , 81. ],
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[ 1. , 10.9 , 118.81],
[ 1. , 9.3 , 86.49],
[ 1. , 11.1 , 123.21],
[ 1. , 8.6 , 73.96],
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[ 1. , 10.9 , 118.81],
[ 1. , 14. , 196. ],
[ 1. , 9.8 , 96.04],
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[ 1. , 12.7 , 161.29],
[ 1. , 11.3 , 127.69],
[ 1. , 15.4 , 237.16],
[ 1. , 15.9 , 252.81],
[ 1. , 16. , 256. ],
[ 1. , 11.2 , 125.44],
[ 1. , 7.8 , 60.84],
[ 1. , 9.8 , 96.04],
[ 1. , 6.9 , 47.61],
[ 1. , 8.2 , 67.24],
[ 1. , 4.8 , 23.04],
[ 1. , 11.9 , 141.61],
```

```
[ 1. , 11.8 , 139.24],
[ 1. , 11.3 , 127.69],
[ 1. , 9.8 , 96.04],
[ 1. , 9.7 , 94.09],
[ 1. , 9.8 , 96.04],
[ 1. , 6.9 , 47.61],
[ 1. , 9.2 , 84.64],
[ 1. , 8.6 , 73.96],
[ 1. , 10.8 , 116.64],
[ 1. , 10.7 , 114.49],
[ 1. , 9.7 , 94.09],
[ 1. , 10.1 , 102.01],
[ 1. , 10.2 , 104.04],
[ 1. , 11.5 , 132.25]])
```

```
pred = clf.predict(test_x_poly)
```

```
print(f"Mean absolute error: {np.mean(np.absolute(pred - test_y))}")
print(f"Residual sum of squares (MSE): {np.mean((pred - test_y) **
2)}")
print(f"R2-score: {r2_score(pred , test_y)}")
```

```
Mean absolute error: 13.976264079815174
Residual sum of squares (MSE): 699.408567190187
R2-score: 0.8066327979825534
```

New predictions get value of Engine Size transform it and then predict

```
transformed_data = poly.fit_transform([[3.25]])
```

```
transformed_data
```

```
array([[ 1. , 3.25 , 10.5625]])
```

```
clf.predict(transformed_data)
```

```
#clf.predict([[3.15]])
```

```
array([[43.80477646]])
```

Ans : The best accuracy is 80.66%

Que.3 : Apply multi Linear regression to the Housing Price Data Set

Note : You can take any number of Independent Variable Note : You

need to make 3 models atleast with different number of indepent

variable Note : Try to get the best possible accuracy

```
import numpy as np
import pandas as pd
```

```
import matplotlib.pyplot as plt
from sklearn import preprocessing
```

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

```
df
```

	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							
...
...							
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]
```

```
cdf = df[["1stFlrSF", "2ndFlrSF", "OpenPorchSF", "SalePrice"]]
```

```
cdf
```

```

      1stFlrSF  2ndFlrSF  OpenPorchSF  SalePrice
0          856      854          61    208500
1         1262         0           0    181500
2          920      866          42    223500
3          961      756          35    140000
4         1145     1053          84    250000
...      ...   ...      ...      ...
1455        953      694          40    175000
1456       2073         0           0    210000
1457       1188     1152          60    266500
1458       1078         0           0    142125
1459       1256         0          68    147500

```

```
[1460 rows x 4 columns]
```

```
cdf.head()
```

```

      1stFlrSF  2ndFlrSF  OpenPorchSF  SalePrice
0          856      854          61    208500
1         1262         0           0    181500
2          920      866          42    223500
3          961      756          35    140000
4         1145     1053          84    250000

```

```
cdf.tail()
```

	1stFlrSF	2ndFlrSF	OpenPorchSF	SalePrice
1455	953	694	40	175000
1456	2073	0	0	210000
1457	1188	1152	60	266500
1458	1078	0	0	142125
1459	1256	0	68	147500

```
cdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 4 columns):
#   Column          Non-Null Count  Dtype
---  ---
0   1stFlrSF        1460 non-null   int64
1   2ndFlrSF        1460 non-null   int64
2   OpenPorchSF     1460 non-null   int64
3   SalePrice       1460 non-null   int64
dtypes: int64(4)
memory usage: 45.8 KB
```

```
cdf.describe()
```

	1stFlrSF	2ndFlrSF	OpenPorchSF	SalePrice
count	1460.000000	1460.000000	1460.000000	1460.000000
mean	1162.626712	346.992466	46.660274	180921.195890
std	386.587738	436.528436	66.256028	79442.502883
min	334.000000	0.000000	0.000000	34900.000000
25%	882.000000	0.000000	0.000000	129975.000000
50%	1087.000000	0.000000	25.000000	163000.000000
75%	1391.250000	728.000000	68.000000	214000.000000
max	4692.000000	2065.000000	547.000000	755000.000000

```
cdf.isnull().sum()
```

```
1stFlrSF      0
2ndFlrSF      0
OpenPorchSF    0
SalePrice     0
dtype: int64
```

```
X = np.asarray(df[["1stFlrSF", "2ndFlrSF", "OpenPorchSF"]]) #
Independent Variable
```

```
X
```

```
array([[ 856,  854,  61],
       [1262,   0,   0],
       [ 920,  866,  42],
       ...,
       [1188, 1152,  60],
```

```
[1078, 0, 0],  
[1256, 0, 68]], dtype=int64)
```

```
set(df["1stFlrSF"])
```

```
{334,  
372,  
438,  
480,  
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2392,
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2411,
2444,

```

2515,
2524,
2633,
2898,
3138,
3228,
4692}

set(df['GarageCars'])

{0, 1, 2, 3, 4}

Y = np.asarray(df[["SalePrice"]].values) # Dependent Variable
Y
array([[208500],
       [181500],
       [223500],
       ...,
       [266500],
       [142125],
       [147500]], dtype=int64)

```

Creating Train and Test dataset

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, 3)

X_test.shape
(292, 3)

Y_train.shape
(1168, 1)

Y_test.shape
(292, 1)

```

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

```
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       ...,
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       [-0.52651394, -0.78522929, -0.69929179],
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```

X_test

```
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Y_test

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```

Multiple Regression Model

```

from sklearn import linear_model
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: [-1.22690901e-16]
Coefficient : [[0.67069037 0.42959836 0.07104694]]

```

```
regr.intercept_
```

```
array([-1.22690901e-16])
```

```
regr.coef_
```

```
array([[0.67069037, 0.42959836, 0.07104694]])
```

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

```
0.6706903674798578
```

```
regr.coef_[0][1]
```

```
0.4295983638014665
```

```
regr.coef_[0][2]
```

```
0.07104693987752371
```

```
y_pred = regr.predict(X_test)
```

```
y_pred
```

```
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[-0.17392476],
[0.42578843],
[0.04932569],
[-0.57583711],
[0.21308976],
[-0.09785813],
[-1.18318506],
[-0.74183747],
[0.3441466],
[-0.09823583],
[2.15469392],
[0.69287993],
[0.57710372],

```
[ 1.37428485],  
[-0.72405832],  
[-0.16930562],  
[ 1.47263763],  
[-0.75200076],  
[-0.67238834],  
[ 1.13667681],  
[-0.29886344],  
[ 0.24242893],  
[-0.70125451],  
[-0.8706099 ],  
[-0.78926614],  
[-0.80281719],  
[ 0.1377436 ],  
[ 1.60811761],  
[ 0.31095902],  
[ 1.78754935],  
[ 0.29502405],  
[-0.11455412],  
[-0.90853723],  
[-1.02640951],  
[-0.0168563 ],  
[-0.95880072],  
[ 0.49808937],  
[-0.45379286],  
[ 0.01901777],  
[-0.17554541],  
[-0.31836716],  
[-0.52938352],  
[-0.43555892],  
[-0.3952941 ],  
[-0.58470533],  
[-0.40853016],  
[-0.37533169],  
[ 0.33828563],  
[ 0.66184205],  
[-0.43693885],  
[-0.93832769],  
[-0.819756 ],  
[ 0.63084735],  
[ 0.43699981],  
[ 0.1122797 ]])
```

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

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

```
R2 Score : 65.71391638689818 %
```

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

Mean absolute error: 0.3503742187252111

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

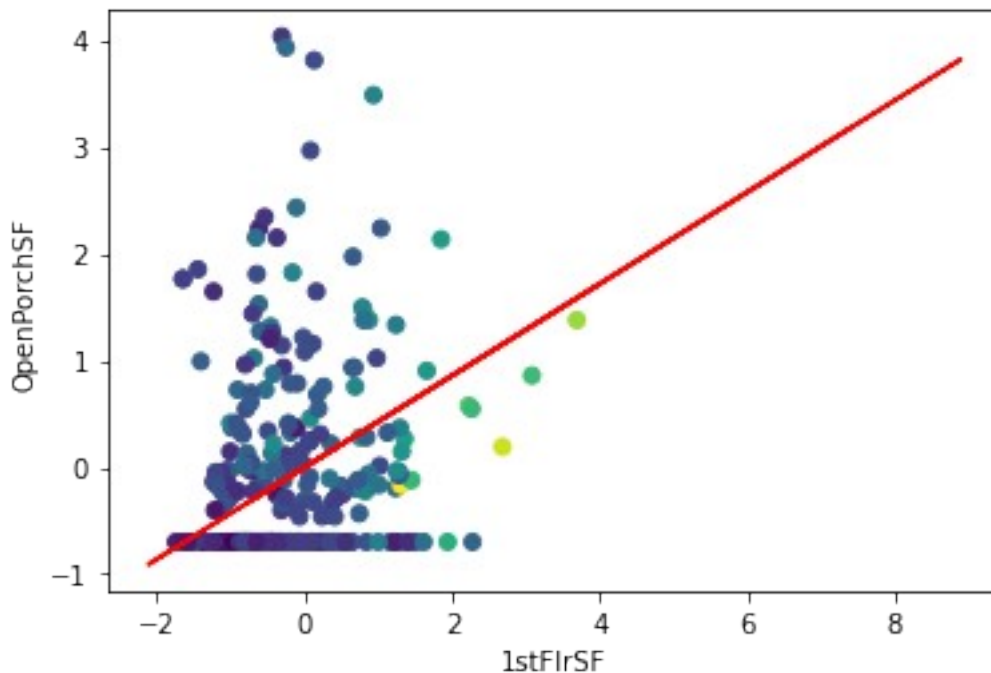
Residual sum of squares (MSE): 0.25

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

R2 Score : 65.71391638689818 %

Plot Outputs

```
import matplotlib.pyplot as plt
plt.scatter(X_test[:,0],X_test[:,2],c=Y_test)
plt.plot(X_train, regr.coef_[0][1]*X_train + regr.intercept_[0], 'r')
#  $y = mx + c$ 
plt.xlabel("1stFlrSF")
plt.ylabel("OpenPorchSF")
Text(0, 0.5, 'OpenPorchSF')
```



```
from sklearn.linear_model import Lasso
L = Lasso(alpha = 1)
L.fit(X_train,Y_train)
Lasso(alpha=1)
ypred2 = L.predict(X_test)
```

```

from sklearn.metrics import r2_score
print("R2-score",r2_score(Y_test,ypred2))
print(f"Mean absolute error : {np.mean(np.absolute(ypred2 - Y_test))}")
# pred - actual

```

R2-score -0.004908518792945626

Mean absolute error: 0.6243935831081134

2nd Model

```

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import preprocessing

```

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

```
df
```

	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							
...
...							
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
MoSold  \

```

0	Lvl	AllPub	...	0	NaN	NaN	NaN	0
2								
1	Lvl	AllPub	...	0	NaN	NaN	NaN	0
5								
2	Lvl	AllPub	...	0	NaN	NaN	NaN	0
9								
3	Lvl	AllPub	...	0	NaN	NaN	NaN	0
2								
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.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.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

```

```
cdf1 = df[["MSSubClass", "MoSold", "LotArea", "SalePrice"]]
```

```
cdf1
```

	MSSubClass	MoSold	LotArea	SalePrice
0	60	2	8450	208500
1	20	5	9600	181500
2	60	9	11250	223500
3	70	2	9550	140000
4	60	12	14260	250000
...
1455	60	8	7917	175000
1456	20	2	13175	210000
1457	70	5	9042	266500
1458	20	4	9717	142125
1459	20	6	9937	147500

```
[1460 rows x 4 columns]
```

```
cdf1.head()
```

	MSSubClass	MoSold	LotArea	SalePrice
0	60	2	8450	208500
1	20	5	9600	181500
2	60	9	11250	223500
3	70	2	9550	140000
4	60	12	14260	250000

```
cdf1.tail()
```

	MSSubClass	MoSold	LotArea	SalePrice
1455	60	8	7917	175000
1456	20	2	13175	210000
1457	70	5	9042	266500
1458	20	4	9717	142125
1459	20	6	9937	147500

```
cdf1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 4 columns):
#   Column      Non-Null Count  Dtype
---  -
0   MSSubClass   1460 non-null   int64
1   MoSold       1460 non-null   int64
2   LotArea      1460 non-null   int64
3   SalePrice    1460 non-null   int64
dtypes: int64(4)
memory usage: 45.8 KB
```

```
cdf1.describe()
```

	MSSubClass	MoSold	LotArea	SalePrice
count	1460.000000	1460.000000	1460.000000	1460.000000
mean	56.897260	6.321918	10516.828082	180921.195890
std	42.300571	2.703626	9981.264932	79442.502883
min	20.000000	1.000000	1300.000000	34900.000000
25%	20.000000	5.000000	7553.500000	129975.000000
50%	50.000000	6.000000	9478.500000	163000.000000
75%	70.000000	8.000000	11601.500000	214000.000000
max	190.000000	12.000000	215245.000000	755000.000000

```
cdf1.isnull().sum()
```

```
MSSubClass    0
MoSold         0
LotArea        0
SalePrice      0
dtype: int64
```

```
X = df[["MSSubClass", "MoSold", "LotArea"]]
```

```
X
```

	MSSubClass	MoSold	LotArea
0	60	2	8450
1	20	5	9600
2	60	9	11250
3	70	2	9550
4	60	12	14260
...
1455	60	8	7917
1456	20	2	13175
1457	70	5	9042
1458	20	4	9717
1459	20	6	9937

```
[1460 rows x 3 columns]
```

```
Y = df[["SalePrice"]]
```

Y

	SalePrice
0	208500
1	181500
2	223500
3	140000
4	250000
...	...
1455	175000
1456	210000
1457	266500
1458	142125
1459	147500

[1460 rows x 1 columns]

Creating Train and Test Dataset

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, 3)

X_test.shape

(292, 3)

Y_train.shape

(1168, 1)

Y_test.shape

(292, 1)

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([[ -0.85469057,  0.24559339, -0.0242262 ],
       [ -0.85469057, -0.49181812, -0.18471992],
       [  0.09911675, -0.12311237,  0.29260181],
       ...,
       [ -0.85469057, -0.86052387, -0.10082087],
       [ -0.85469057,  0.24559339, -0.28343067],
       [ -0.85469057, -0.12311237, -0.01966095]])
```

```
X_test
```

```
array([[ 9.91167493e-02,  6.14299139e-01, -1.77314083e-01],
       [ 9.91167493e-02,  9.83004891e-01, -1.15449627e-02],
       [ 3.37568579e-01, -1.23112366e-01, -1.12994853e-01],
       [-8.54690568e-01, -1.96664113e+00,  6.61456757e-03],
       [ 9.91167493e-02, -1.22922962e+00,  1.33629830e-01],
       [ 9.91167493e-02, -1.23112366e-01, -1.32168882e-01],
       [ 9.91167493e-02, -4.91818118e-01,  1.86789572e-01],
       [-8.54690568e-01,  1.72041640e+00, -3.68648575e-01],
       [ 9.91167493e-02,  1.72041640e+00,  2.44717459e-01],
       [-1.39335080e-01,  1.72041640e+00,  6.65714526e-02],
       [-1.39335080e-01,  2.45593386e-01, -6.18215305e-01],
       [ 1.52982773e+00, -1.23112366e-01, -4.28402561e-01],
       [-8.54690568e-01,  2.45593386e-01, -3.07778642e-01],
       [-8.54690568e-01, -1.23112366e-01,  7.26584460e-02],
       [ 2.48363504e+00, -1.23112366e-01, -7.47056665e-01],
       [ 9.91167493e-02, -1.23112366e-01, -1.98212760e-01],
       [-8.54690568e-01,  9.83004891e-01, -1.59966152e-01],
       [-1.39335080e-01,  1.72041640e+00, -4.41692496e-01],
       [-8.54690568e-01,  2.45593386e-01, -3.25228023e-01],
       [ 4.56794493e-01,  2.45593386e-01, -5.14736417e-01],
       [ 2.48363504e+00,  1.35171064e+00, -8.26390479e-01],
       [ 9.91167493e-02,  9.83004891e-01, -2.30676725e-01],
       [-1.39335080e-01,  2.45593386e-01,  5.07168325e-01],
       [-8.54690568e-01, -4.91818118e-01,  1.56557505e-01],
       [ 1.52982773e+00,  9.83004891e-01, -3.69155825e-01],
       [-1.39335080e-01,  6.14299139e-01, -5.96707928e-01],
       [ 3.37568579e-01,  2.45593386e-01,  2.09190021e-02],
       [-8.54690568e-01, -1.23112366e-01, -1.03762913e-01],
       [-8.54690568e-01, -1.23112366e-01, -3.13865635e-01],
       [ 6.95246323e-01, -1.23112366e-01,  1.20542794e-01],
       [ 5.76020408e-01, -1.23112366e-01,  5.64386063e-01],
       [ 9.91167493e-02,  2.45593386e-01, -3.61972860e-02],
       [ 9.91167493e-02,  2.45593386e-01,  4.61008625e-01],
       [ 9.91167493e-02, -4.91818118e-01,  1.98659209e-01],
       [ 1.52982773e+00,  1.35171064e+00, -6.64577905e-01],
       [ 2.48363504e+00,  1.72041640e+00, -9.04303995e-01],
```

[3.37568579e-01, 1.72041640e+00, -3.13865635e-01],
[3.37568579e-01, 2.45593386e-01, 2.56789996e-01],
[-8.54690568e-01, -1.23112366e-01, 2.79616222e-01],
[-6.16238739e-01, 1.72041640e+00, -4.53866483e-01],
[1.52982773e+00, 9.83004891e-01, -7.51926260e-01],
[-8.54690568e-01, -4.91818118e-01, 2.51413152e-01],
[1.52982773e+00, -1.22922962e+00, -3.85692157e-01],
[-6.16238739e-01, -1.23112366e-01, -2.52995701e-01],
[-8.54690568e-01, -1.23112366e-01, -1.51545811e-01],
[9.91167493e-02, 2.45593386e-01, 2.48755478e-02],
[9.91167493e-02, -4.91818118e-01, 1.70639062e-02],
[2.48363504e+00, -1.23112366e-01, -8.08129499e-01],
[1.52982773e+00, -4.91818118e-01, -7.51926260e-01],
[9.91167493e-02, -1.23112366e-01, 4.35323510e+00],
[1.52982773e+00, -8.60523870e-01, -5.61099017e-01],
[-1.39335080e-01, -1.23112366e-01, -5.36040894e-01],
[9.91167493e-02, 2.45593386e-01, 1.65687995e-01],
[-1.39335080e-01, -1.96664113e+00, -1.86464550e-02],
[-8.54690568e-01, 2.45593386e-01, -1.70821290e-01],
[-1.39335080e-01, -1.23112366e-01, -2.22560734e-01],
[-8.54690568e-01, -1.23112366e-01, 4.04906836e-01],
[-8.54690568e-01, -4.91818118e-01, -2.06734551e-01],
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[-8.54690568e-01, 1.35171064e+00, -1.38357325e-01],
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```

Multiple Regression Model

```

from sklearn import linear_model
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: [3.82889473e-17]
Coefficient : [[-0.05383768  0.04488339  0.24819609]]

```

```
regr.intercept_
```

```
array([3.82889473e-17])
```

```
regr.coef_
```

```
array([[-0.05383768,  0.04488339,  0.24819609]])
```

```
regr.coef_[0][1]
```

```
0.044883387796239835
```

```
regr.coef_[0][2]
```

```
0.2481960930581826
```

```
y_pred = regr.predict(X_test)
```

```
y_pred
```

```

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from sklearn.metrics import r2_score

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

accuracy : 9.092114450354227 %

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

Mean absolute error: 0.5837743155131746

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

Residual sum of squares (MSE): 0.66

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

```

accuracy : 9.092114450354227 %

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)

ypred = L.predict(X_test)

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

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

regr.fit (Independent and Dependent Variable)

```
regr.fit(X_train, Y_train)

LinearRegression()

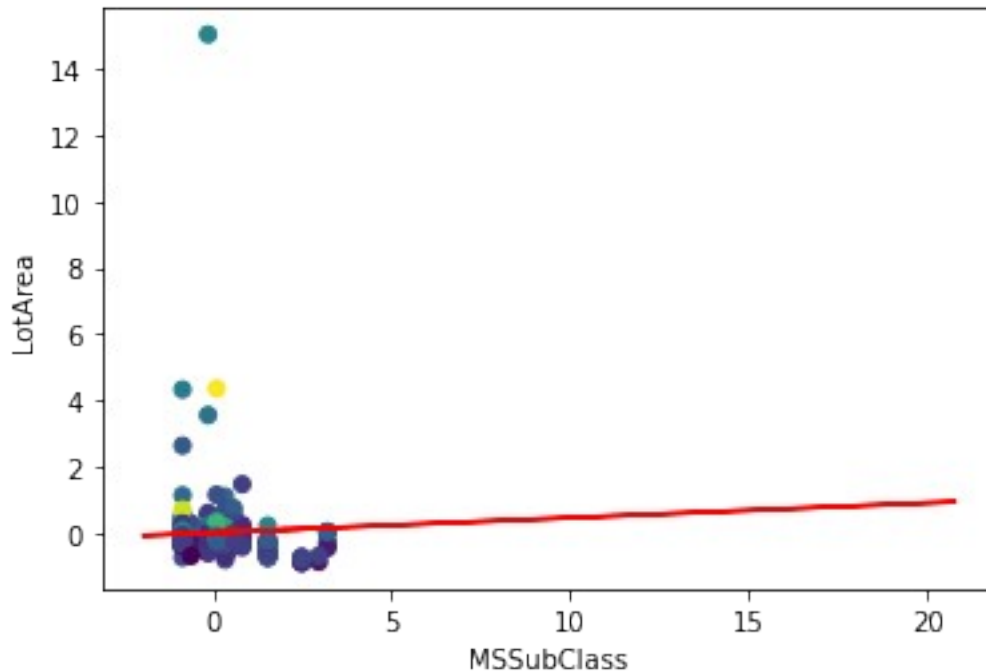
# The coefficients
print ('Coefficients: ', regr.coef_)
print ('Intercept: ',regr.intercept_)

Coefficients:  [[-0.05383768  0.04488339  0.24819609]]
Intercept:  [3.82889473e-17]
```

Plot Outputs

```
import matplotlib.pyplot as plt
plt.scatter(X_test[:,0],X_test[:,2],c=Y_test)
plt.plot(X_train, regr.coef_[0][1]*X_train + regr.intercept_[0], 'r')
#y = mx+c
plt.xlabel("MSSubClass")
plt.ylabel("LotArea")

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



3rd Model

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

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

```
df
```

	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							
...
...							
1455	1456	60	RL	62.0	7917	Pave	NaN
Reg							
1456	1457	20	RL	85.0	13175	Pave	NaN
Reg							

1457 Reg	1458	70	RL	66.0	9042	Pave	NaN
1458 Reg	1459	20	RL	68.0	9717	Pave	NaN
1459 Reg	1460	20	RL	75.0	9937	Pave	NaN

	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.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.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

```

```

cdf2 = df[["OverallCond", "OverallQual", "MiscVal", "SalePrice"]]

```

```

cdf2

```

	OverallCond	OverallQual	MiscVal	SalePrice
0	5	7	0	208500
1	8	6	0	181500
2	5	7	0	223500
3	5	7	0	140000
4	5	8	0	250000
...
1455	5	6	0	175000
1456	6	6	0	210000
1457	9	7	2500	266500
1458	6	5	0	142125
1459	6	5	0	147500

```

[1460 rows x 4 columns]

```

```

X = df[["OverallCond", "OverallQual", "MiscVal"]] # Independent Variable

```

```

X

```

	OverallCond	OverallQual	MiscVal
0	5	7	0
1	8	6	0
2	5	7	0
3	5	7	0
4	5	8	0
...
1455	5	6	0
1456	6	6	0

1457	9	7	2500
1458	6	5	0
1459	6	5	0

[1460 rows x 3 columns]

```
Y = df[["SalePrice"]]
```

Y

	SalePrice
0	208500
1	181500
2	223500
3	140000
4	250000
...	...
1455	175000
1456	210000
1457	266500
1458	142125
1459	147500

[1460 rows x 1 columns]

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, 3)

Y_train.shape

(1168, 1)

X_test.shape

(292, 3)

Y_test.shape

(292, 1)

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([[ -0.5039999 , -0.78256106, -0.11595495],
       [ -0.5039999 ,  0.63894954, -0.11595495],
       [ -0.5039999 ,  2.77121545, -0.11595495],
       ...,
       [  0.39063822, -0.07180576, -0.11595495],
       [ -0.5039999 , -0.78256106, -0.11595495],
       [ -0.5039999 ,  0.63894954, -0.11595495]])
```

Y_train

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

X_test

```
array([[ -0.5039999 , -0.07180576, -0.11595495],
       [  0.39063822,  0.63894954, -0.11595495],
       [  1.28527634, -0.78256106, -0.11595495],
       [  0.39063822, -0.78256106, -0.11595495],
       [ -0.5039999 , -0.07180576, -0.11595495],
       [ -0.5039999 , -0.07180576, -0.11595495],
       [ -0.5039999 ,  0.63894954, -0.11595495],
       [  0.39063822, -1.49331636,  1.46830692],
       [ -0.5039999 ,  0.63894954, -0.11595495],
       [ -0.5039999 , -1.49331636, -0.11595495],
       [ -0.5039999 , -0.78256106, -0.11595495],
       [ -0.5039999 ,  0.63894954, -0.11595495],
       [ -0.5039999 , -0.78256106, -0.11595495],
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```

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Y_test

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```

Multiple Regression Model

```

from sklearn import linear_model
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:  [-5.45294703e-17]
Coefficient :  [[-0.00535786  0.79887333  0.01851957]]

```

```
regr.intercept_
```

```
array([-5.45294703e-17])
```

```
regr.coef_
```

```
array([[-0.00535786,  0.79887333,  0.01851957]])
```

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

```
-0.005357859174442641
```

```
regr.coef_[0][1]
```

```
0.7988733281398422
```

```
regr.coef_[0][2]
```

```
0.01851956792706759
```

```
y_pred = regr.predict(X_test)
```

```
y_pred
```

```

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[-0.06639747],
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[0.83834439],


```

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[-0.62940758],
[-0.05681078],
[-0.05681078],
[-0.05681078],
[-0.05681078],
[ 0.51099267]])

from sklearn.metrics import r2_score

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

R2 Score : 55.15103204321362 %

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

Mean absolute error: 0.4076871161048974

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

```

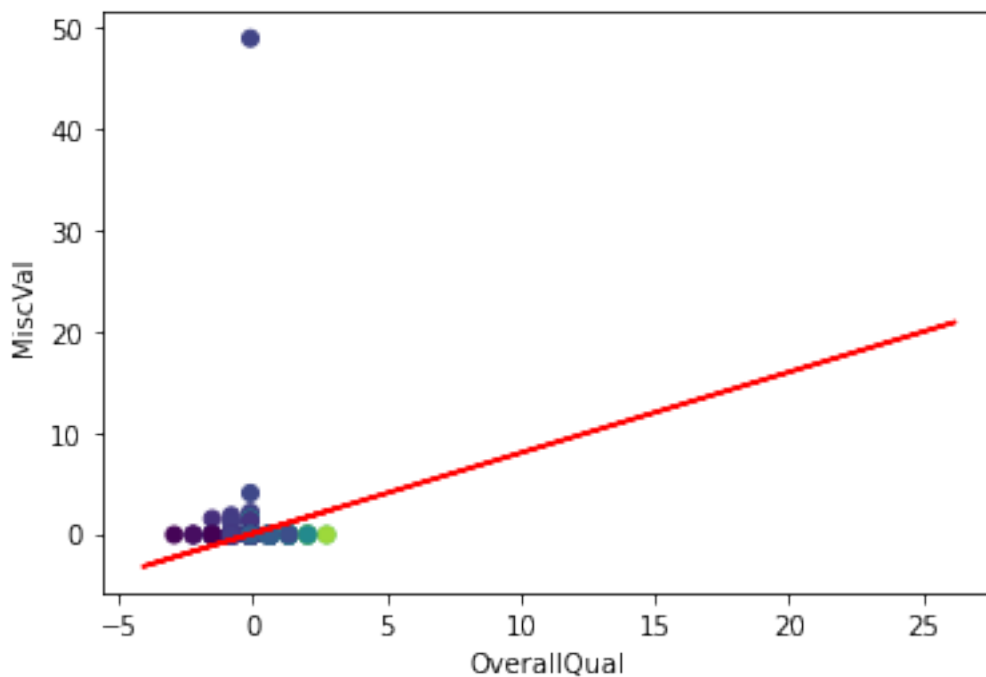
Residual sum of squares (MSE): 0.33

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

```
accuracy : 55.15103204321362 %
```

Plot Outputs

```
import matplotlib.pyplot as plt
plt.scatter(X_test[:,1],X_test[:,2],c=Y_test)
plt.plot(X_train, regr.coef_[0][1]*X_train + regr.intercept_[0], 'r')
#y = mx+c
plt.xlabel("OverallQual")
plt.ylabel("MiscVal")
Text(0, 0.5, 'MiscVal')
```



Ans : The best possible accuracy is having the 1st model that is R2 Score is 65.71%.

Que.4 We are providing you churn dataset and we expect you to apply logistic regression on it and try to change the hyperparameters so that you can get the best possible accuracy

```
import pandas as pd
import numpy as np
```

```
from sklearn import preprocessing
import matplotlib.pyplot as plt
```

```
churn_df = pd.read_csv("C:/Users/Lenovo/Documents/Data  
Set/ChurnData.csv")  
churn_df.head()
```

	tenure	age	address	income	ed	employ	equip	callcard
0	11.0	33.0	7.0	136.0	5.0	5.0	0.0	1.0
1	33.0	33.0	12.0	33.0	2.0	0.0	0.0	0.0
2	23.0	30.0	9.0	30.0	1.0	2.0	0.0	0.0
3	38.0	35.0	5.0	76.0	2.0	10.0	1.0	1.0
4	7.0	35.0	14.0	80.0	2.0	15.0	0.0	1.0

longmon	...	pager	internet	callwait	confer	ebill	loglong
0 4.40	...	1.0	0.0	1.0	1.0	0.0	1.482
3.033							
1 9.45	...	0.0	0.0	0.0	0.0	0.0	2.246
3.240							
2 6.30	...	0.0	0.0	0.0	1.0	0.0	1.841
3.240							
3 6.05	...	1.0	1.0	1.0	1.0	1.0	1.800
3.807							
4 7.10	...	0.0	0.0	1.0	1.0	0.0	1.960
3.091							

	lninc	custcat	churn
0	4.913	4.0	1.0
1	3.497	1.0	1.0
2	3.401	3.0	0.0
3	4.331	4.0	0.0
4	4.382	3.0	0.0

[5 rows x 28 columns]

Data Pre-Processing and Selection

```
churn_df = churn_df[['tenure', 'age', 'address', 'income', 'ed',  
                    'employ', 'equip', 'callcard', 'wireless', 'churn']]  
churn_df.head()
```

```
tenure  age  address  income  ed  employ  equip  callcard
wireless \
```

```

0    11.0  33.0      7.0  136.0  5.0      5.0  0.0      1.0
1.0
1    33.0  33.0     12.0   33.0  2.0      0.0  0.0      0.0
0.0
2    23.0  30.0      9.0   30.0  1.0      2.0  0.0      0.0
0.0
3    38.0  35.0      5.0   76.0  2.0     10.0  1.0      1.0
1.0
4      7.0  35.0     14.0   80.0  2.0     15.0  0.0      1.0
0.0

```

```

      churn
0      1.0
1      1.0
2      0.0
3      0.0
4      0.0

```

```

churn_df['churn'] = churn_df['churn'].astype('int')
churn_df.head()

```

```

      tenure  age  address  income  ed  employ  equip  callcard
wireless \
0    11.0  33.0      7.0   136.0  5.0      5.0  0.0      1.0
1.0
1    33.0  33.0     12.0   33.0  2.0      0.0  0.0      0.0
0.0
2    23.0  30.0      9.0   30.0  1.0      2.0  0.0      0.0
0.0
3    38.0  35.0      5.0   76.0  2.0     10.0  1.0      1.0
1.0
4      7.0  35.0     14.0   80.0  2.0     15.0  0.0      1.0
0.0

```

```

      churn
0      1
1      1
2      0
3      0
4      0

```

```

churn_df.shape # No. of rows nd no. of cols

```

```

(200, 10)

```

```

churn_df.columns

```

```

Index(['tenure', 'age', 'address', 'income', 'ed', 'employ', 'equip',
      'callcard', 'wireless', 'churn'],
      dtype='object')

```

```
churn_df.info() #how many null/empty values present
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype
---  -
 0   tenure      200 non-null    float64
 1   age         200 non-null    float64
 2   address     200 non-null    float64
 3   income      200 non-null    float64
 4   ed          200 non-null    float64
 5   employ      200 non-null    float64
 6   equip       200 non-null    float64
 7   callcard    200 non-null    float64
 8   wireless    200 non-null    float64
 9   churn       200 non-null    int32
dtypes: float64(9), int32(1)
memory usage: 15.0 KB
```

```
churn_df.isnull().sum()
```

```
tenure      0
age          0
address     0
income      0
ed           0
employ       0
equip        0
callcard     0
wireless     0
churn        0
dtype: int64
```

```
#independent variable
```

```
#asarray is used to convert columns to same data type to the array
X = np.asarray(churn_df[['tenure', 'age', 'address', 'income', 'ed',
                          'employ', 'equip']]) # Independent variable
X[0:1] # 0,1,2,3,4,5,6
```

```
array([[ 11.,  33.,   7., 136.,   5.,   5.,   0.]])
```

```
# Dependent variable
```

```
y = np.asarray(churn_df['churn']) # Dependent variable
y [0:10]
```

```
array([1, 1, 0, 0, 0, 0, 0, 0, 0, 0])
```

Also we Normalize the Dataset

For the values are for 1 to 10 and some are the 10 to 100 range that's why we have to convert that values in the range

```
X[0:5]
```

```
array([[ 11.,  33.,   7., 136.,   5.,   5.,   0.],
       [ 33.,  33.,  12.,  33.,   2.,   0.,   0.],
       [ 23.,  30.,   9.,  30.,   1.,   2.,   0.],
       [ 38.,  35.,   5.,  76.,   2.,  10.,   1.],
       [  7.,  35.,  14.,  80.,   2.,  15.,   0.]])
```

```
from sklearn import preprocessing
```

```
X = preprocessing.StandardScaler().fit(X).transform(X)
```

```
X[0:1]
```

```
array([[ -1.13518441, -0.62595491, -0.4588971 ,  0.4751423 ,  1.6961288
        ,
        -0.58477841, -0.85972695]])
```

Train Test Dataset

```
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=200) # Trainingsize = 80%, Test = 20%
print ('Train set:', X_train.shape, y_train.shape)
print ('Test set:', X_test.shape, y_test.shape)
```

```
Train set: (160, 7) (160,)
```

```
Test set: (40, 7) (40,)
```

Modeling (Logistic Regression with Scikit-learn)

Lets build our model using LogisticRegression from Scikit-learn package. This function implements logistic regression and can use different numerical optimizers to find parameters, including 'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga' solvers. You can find extensive information about the pros and cons of these optimizers if you search it in internet.

```
from sklearn.linear_model import LogisticRegression
LR = LogisticRegression(solver='sag')
LR.fit(X_train,y_train) # Training
LR
```

```
LogisticRegression(solver='sag')
```

```

yhat = LR.predict(X_test)#only questions passed and answers are saved for evaluation
yhat[:5]

array([1, 0, 0, 0, 0])

yhat_prob = LR.predict_proba(X_test)
yhat_prob[:5]

array([[0.25580103, 0.74419897],
       [0.79835828, 0.20164172],
       [0.97099194, 0.02900806],
       [0.96104168, 0.03895832],
       [0.78135768, 0.21864232]])

```

Evaluation

```

from sklearn.metrics import f1_score
f1_score(y_test, yhat) #actualvale, predvalue

```

0.75

churn_df

	tenure	age	address	income	ed	employ	equip	callcard
wireless \								
0	11.0	33.0	7.0	136.0	5.0	5.0	0.0	1.0
1.0								
1	33.0	33.0	12.0	33.0	2.0	0.0	0.0	0.0
0.0								
2	23.0	30.0	9.0	30.0	1.0	2.0	0.0	0.0
0.0								
3	38.0	35.0	5.0	76.0	2.0	10.0	1.0	1.0
1.0								
4	7.0	35.0	14.0	80.0	2.0	15.0	0.0	1.0
0.0								
...
...								
195	55.0	44.0	24.0	83.0	1.0	23.0	0.0	1.0
0.0								
196	34.0	23.0	3.0	24.0	1.0	7.0	0.0	1.0
0.0								
197	6.0	32.0	10.0	47.0	1.0	10.0	0.0	1.0
0.0								
198	24.0	30.0	0.0	25.0	4.0	5.0	0.0	1.0
1.0								
199	61.0	50.0	16.0	190.0	2.0	22.0	1.0	1.0
1.0								

	churn
0	1

1	1
2	0
3	0
4	0
..	...
195	0
196	0
197	0
198	1
199	0

[200 rows x 10 columns]

X_test

```
array([[ -1.18150902e+00, -1.00927084e+00, -2.61522001e-01,
        -1.01476095e-03,  9.16299467e-01, -1.03245566e+00,
         1.16316000e+00],
       [ -2.08692340e-01,  3.70666503e-01,  1.12010367e+00,
         5.37589130e-01,  9.16299467e-01,  3.10576093e-01,
        -8.59726954e-01],
       [  9.95747358e-01,  1.44395110e+00,  8.24041023e-01,
        -4.77171824e-01, -6.43359200e-01,  1.87744647e+00,
        -8.59726954e-01],
       [  1.69061641e+00,  2.59389889e+00,  3.58729236e+00,
        -4.77171824e-01, -6.43359200e-01, -4.72859097e-01,
        -8.59726954e-01],
       [  1.61904490e-01, -1.31592358e+00, -9.52334835e-01,
        -3.83501582e-01, -6.43359200e-01, -6.96697723e-01,
        -8.59726954e-01],
       [  9.03098150e-01,  8.30645618e-01,  1.02141612e+00,
         4.04889621e-01, -1.42318853e+00,  1.98936579e+00,
        -8.59726954e-01],
       [  4.39852113e-01, -1.46924996e+00, -9.52334835e-01,
        -3.05443047e-01,  9.16299467e-01, -1.14437497e+00,
         1.16316000e+00],
       [  1.69061641e+00,  2.59389889e+00,  2.50172933e+00,
        -3.28860608e-01, -1.42318853e+00,  3.78007479e+00,
        -8.59726954e-01],
       [  1.41266879e+00,  1.59727748e+00,  1.90960405e+00,
        -2.19578659e-01, -6.43359200e-01, -6.96697723e-01,
        -8.59726954e-01],
       [  1.08839657e+00,  1.06063518e+00,  1.71222895e+00,
        -2.58607926e-01,  1.36470133e-01,  1.20593060e+00,
        -8.59726954e-01],
       [  1.55164260e+00,  3.70666503e-01,  6.26665928e-01,
        -7.12674424e-02, -6.43359200e-01,  9.82091970e-01,
        -8.59726954e-01],
       [ -1.59843045e+00, -8.55944470e-01, -8.53647287e-01,
         4.67336448e-01,  9.16299467e-01, -8.08617036e-01,
```


1.16316000e+00],
[-7.64587585e-01, -7.02618098e-01, 3.45406417e-02,
-3.22381749e-02, 9.16299467e-01, -5.84778410e-01,
1.16316000e+00],
[1.64429181e+00, 5.23992875e-01, 1.31747876e+00,
1.66163203e+00, 1.36470133e-01, 9.82091970e-01,
-8.59726954e-01],
[3.93527509e-01, 2.94003318e-01, 7.25353475e-01,
1.00461334e-01, -1.42318853e+00, 1.20593060e+00,
-8.59726954e-01],
[-9.96210604e-01, -1.16259721e+00, -1.05102238e+00,
-3.91307435e-01, -6.43359200e-01, -1.14437497e+00,
-8.59726954e-01],
[-5.79289170e-01, 6.77319247e-01, -1.05102238e+00,
5.92230104e-01, 9.16299467e-01, -2.49020471e-01,
-8.59726954e-01],
[1.50531800e+00, 8.30645618e-01, 5.27978380e-01,
3.50248646e-01, -1.42318853e+00, 1.54168853e+00,
-8.59726954e-01],
[4.39852113e-01, -1.08593403e+00, -8.53647287e-01,
-2.82025487e-01, 1.36470133e-01, -9.20536348e-01,
-8.59726954e-01],
[-1.08885981e+00, -1.31592358e+00, -9.52334835e-01,
-4.38142556e-01, -1.42318853e+00, -1.14437497e+00,
-8.59726954e-01],
[1.59796721e+00, -4.72628541e-01, -7.54959740e-01,
-2.11772805e-01, -6.43359200e-01, -1.37101158e-01,
-8.59726954e-01],
[1.69061641e+00, 1.06063518e+00, 1.21879121e+00,
5.36262135e-02, 1.36470133e-01, 1.65360785e+00,
1.16316000e+00],
[-8.10912189e-01, -5.49291726e-01, -7.54959740e-01,
-2.58607926e-01, -6.43359200e-01, 4.22495406e-01,
-8.59726954e-01],
[-1.36680743e+00, -9.32607656e-01, -7.54959740e-01,
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-8.59726954e-01],
[-1.27415823e+00, -1.46924996e+00, -8.53647287e-01,
-3.91307435e-01, 9.16299467e-01, -1.14437497e+00,
-8.59726954e-01],
[1.32001958e+00, -1.23926040e+00, -7.54959740e-01,
6.79109254e-03, 1.36470133e-01, -9.20536348e-01,
1.16316000e+00],
[3.47202905e-01, -9.32607656e-01, -7.54959740e-01,
-3.28860608e-01, -1.42318853e+00, 3.10576093e-01,
-8.59726954e-01],
[-4.40315359e-01, -8.55944470e-01, -7.54959740e-01,
6.79109254e-03, 1.36470133e-01, -3.60939784e-01,
1.16316000e+00],
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```

2.24027995e-02, 9.16299467e-01, -2.51818454e-02,
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1.16316000e+00],
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-2.97637194e-01, -1.42318853e+00, -3.60939784e-01,
-8.59726954e-01],
[ 3.47202905e-01, 1.40676946e-01, -8.53647287e-01,
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1.16316000e+00],
[ 7.64124339e-01, 6.40137602e-02, 5.27978380e-01,
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-8.59726954e-01],
[ 1.22737038e+00, 2.67056208e+00, 8.24041023e-01,
-3.13248901e-01, 1.36470133e-01, 8.70172658e-01,
-8.59726954e-01],
[ 5.32501320e-01, -8.93126115e-02, 4.29290832e-01,
4.04889621e-01, 9.16299467e-01, 1.98656780e-01,
1.16316000e+00],
[ 1.61904490e-01, 4.47329689e-01, -1.05102238e+00,
-5.56557354e-02, 9.16299467e-01, -2.51818454e-02,
-8.59726954e-01],
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1.23878895e-01, 9.16299467e-01, -1.03245566e+00,
1.16316000e+00],
[-1.22783362e+00, -1.26494257e-02, 3.45406417e-02,
-2.82025487e-01, 9.16299467e-01, -8.08617036e-01,
1.16316000e+00],
[ 4.86176716e-01, 2.94003318e-01, 3.45406417e-02,
1.62908162e-01, 1.36470133e-01, 7.58253345e-01,
1.16316000e+00]])

```

X_test[:,1] *#1 index col values*

```

array([-1.00927084, 0.3706665 , 1.4439511 , 2.59389889, -
1.31592358,
0.83064562, -1.46924996, 2.59389889, 1.59727748,
1.06063518,
0.3706665 , -0.85594447, -0.7026181 , 0.52399288,
0.29400332,
-1.16259721, 0.67731925, 0.83064562, -1.08593403, -
1.31592358,
-0.47262854, 1.06063518, -0.54929173, -0.93260766, -
1.46924996,
-1.2392604 , -0.93260766, -0.85594447, -0.54929173, -
0.62595491,
1.21396155, 0.14067695, 0.06401376, 2.67056208, -

```

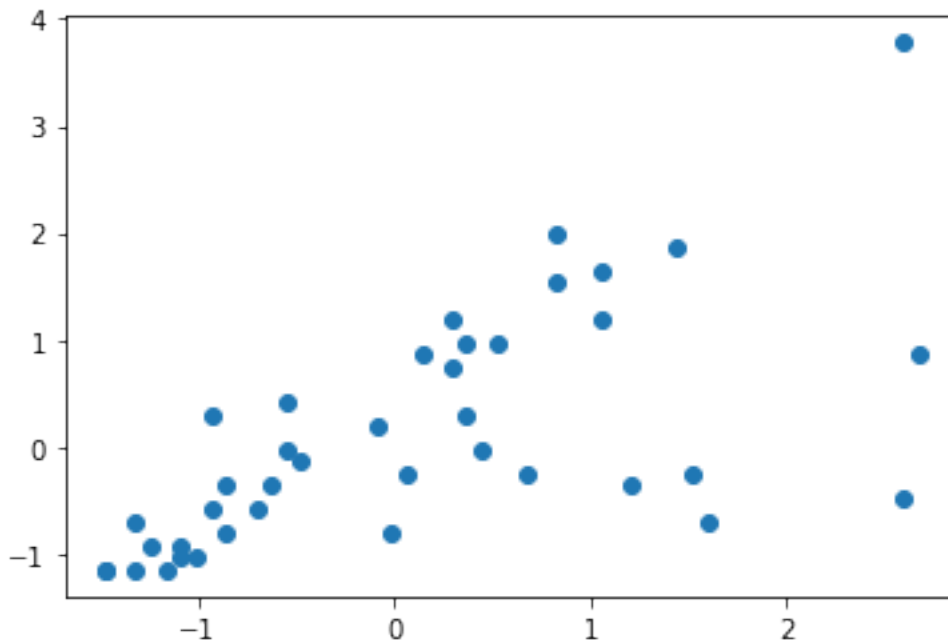
```

0.08931261,
    0.44732969,  1.52061429, -1.08593403, -0.01264943,
0.29400332])
X_test[:, -2] #2nd last column values

array([-1.03245566,  0.31057609,  1.87744647, -0.4728591 , -
0.69669772,
    1.98936579, -1.14437497,  3.78007479, -0.69669772,
1.2059306 ,
    0.98209197, -0.80861704, -0.58477841,  0.98209197,
1.2059306 ,
   -1.14437497, -0.24902047,  1.54168853, -0.92053635, -
1.14437497,
   -0.13710116,  1.65360785,  0.42249541, -0.58477841, -
1.14437497,
   -0.92053635,  0.31057609, -0.36093978, -0.02518185, -
0.36093978,
   -0.36093978,  0.87017266, -0.24902047,  0.87017266,
0.19865678,
   -0.02518185, -0.24902047, -1.03245566, -0.80861704,
0.75825334])

plt.scatter(X_test[:, 1], X_test[:, -2])
<matplotlib.collections.PathCollection at 0x1c2aaec3550>

```

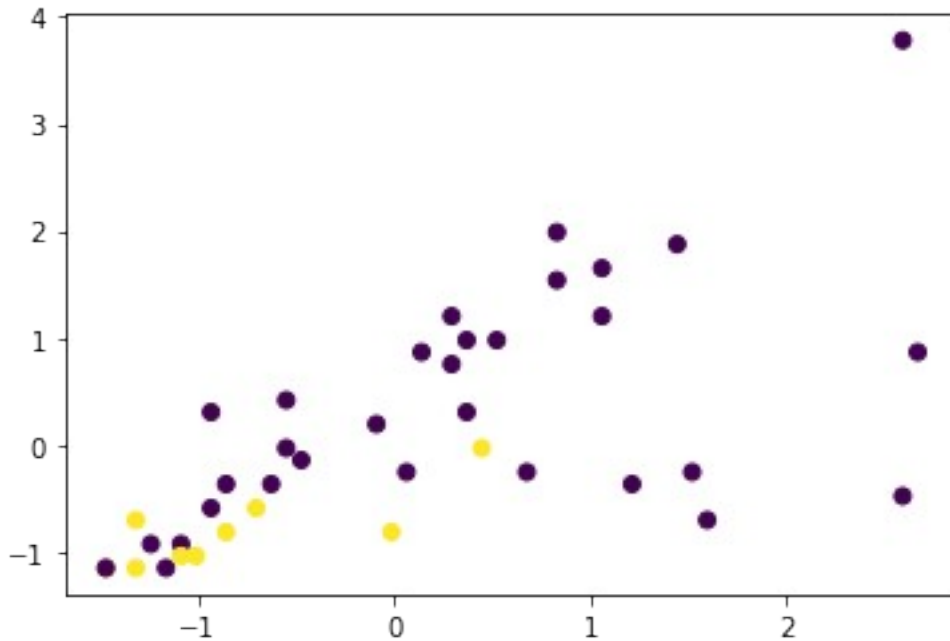


```

import matplotlib.pyplot as plt
plt.scatter(X_test[:, 1], X_test[:, -2], c = y_test) #coloring based on
actual values

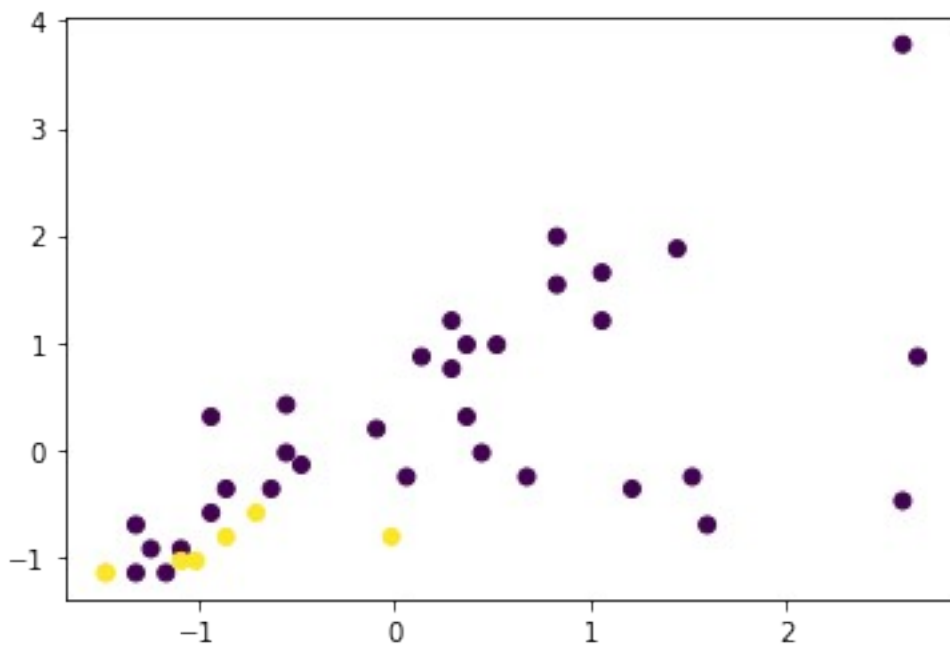
```

```
<matplotlib.collections.PathCollection at 0x1c2aafc2910>
```



```
import matplotlib.pyplot as plt  
plt.scatter(X_test[:,1],X_test[:,-2],c = yhat)
```

```
<matplotlib.collections.PathCollection at 0x1c2ab032430>
```



```
from sklearn.linear_model import LogisticRegression  
LR = LogisticRegression(solver='newton-cg')
```

```
LR.fit(X_train,y_train) # Training
LR
LogisticRegression(solver='newton-cg')
yhat = LR.predict(X_test)#only questions passed and answers are saved
for evaluation
yhat[:5]
array([1, 0, 0, 0, 0])
yhat_prob = LR.predict_proba(X_test)
yhat_prob[:5]
array([[0.25573477, 0.74426523],
       [0.79831414, 0.20168586],
       [0.97100876, 0.02899124],
       [0.96102166, 0.03897834],
       [0.78136144, 0.21863856]])
from sklearn.metrics import f1_score
f1_score(y_test, yhat) #actualvale,predvalue
0.75
```

	tenure	age	address	income	ed	employ	equip	callcard
0	11.0	33.0	7.0	136.0	5.0	5.0	0.0	1.0
1	33.0	33.0	12.0	33.0	2.0	0.0	0.0	0.0
2	23.0	30.0	9.0	30.0	1.0	2.0	0.0	0.0
3	38.0	35.0	5.0	76.0	2.0	10.0	1.0	1.0
4	7.0	35.0	14.0	80.0	2.0	15.0	0.0	1.0
..
195	55.0	44.0	24.0	83.0	1.0	23.0	0.0	1.0
196	34.0	23.0	3.0	24.0	1.0	7.0	0.0	1.0
197	6.0	32.0	10.0	47.0	1.0	10.0	0.0	1.0
198	24.0	30.0	0.0	25.0	4.0	5.0	0.0	1.0
199	61.0	50.0	16.0	190.0	2.0	22.0	1.0	1.0

	churn
0	1
1	1
2	0
3	0
4	0
..	...
195	0
196	0
197	0
198	1
199	0

[200 rows x 10 columns]

X_test

```
array([[ -1.18150902e+00,  -1.00927084e+00,  -2.61522001e-01,
        -1.01476095e-03,   9.16299467e-01,  -1.03245566e+00,
         1.16316000e+00],
       [ -2.08692340e-01,   3.70666503e-01,   1.12010367e+00,
         5.37589130e-01,   9.16299467e-01,   3.10576093e-01,
        -8.59726954e-01],
       [  9.95747358e-01,   1.44395110e+00,   8.24041023e-01,
        -4.77171824e-01,  -6.43359200e-01,   1.87744647e+00,
        -8.59726954e-01],
       [  1.69061641e+00,   2.59389889e+00,   3.58729236e+00,
        -4.77171824e-01,  -6.43359200e-01,  -4.72859097e-01,
        -8.59726954e-01],
       [  1.61904490e-01,  -1.31592358e+00,  -9.52334835e-01,
        -3.83501582e-01,  -6.43359200e-01,  -6.96697723e-01,
        -8.59726954e-01],
       [  9.03098150e-01,   8.30645618e-01,   1.02141612e+00,
         4.04889621e-01,  -1.42318853e+00,   1.98936579e+00,
        -8.59726954e-01],
       [  4.39852113e-01,  -1.46924996e+00,  -9.52334835e-01,
        -3.05443047e-01,   9.16299467e-01,  -1.14437497e+00,
         1.16316000e+00],
       [  1.69061641e+00,   2.59389889e+00,   2.50172933e+00,
        -3.28860608e-01,  -1.42318853e+00,   3.78007479e+00,
        -8.59726954e-01],
       [  1.41266879e+00,   1.59727748e+00,   1.90960405e+00,
        -2.19578659e-01,  -6.43359200e-01,  -6.96697723e-01,
        -8.59726954e-01],
       [  1.08839657e+00,   1.06063518e+00,   1.71222895e+00,
        -2.58607926e-01,   1.36470133e-01,   1.20593060e+00,
        -8.59726954e-01],
       [  1.55164260e+00,   3.70666503e-01,   6.26665928e-01,
        -7.12674424e-02,  -6.43359200e-01,   9.82091970e-01,
        -8.59726954e-01],
```

[-1.59843045e+00, -8.55944470e-01, -8.53647287e-01,
4.67336448e-01, 9.16299467e-01, -8.08617036e-01,
1.16316000e+00],
[-7.64587585e-01, -7.02618098e-01, 3.45406417e-02,
-3.22381749e-02, 9.16299467e-01, -5.84778410e-01,
1.16316000e+00],
[1.64429181e+00, 5.23992875e-01, 1.31747876e+00,
1.66163203e+00, 1.36470133e-01, 9.82091970e-01,
-8.59726954e-01],
[3.93527509e-01, 2.94003318e-01, 7.25353475e-01,
1.00461334e-01, -1.42318853e+00, 1.20593060e+00,
-8.59726954e-01],
[-9.96210604e-01, -1.16259721e+00, -1.05102238e+00,
-3.91307435e-01, -6.43359200e-01, -1.14437497e+00,
-8.59726954e-01],
[-5.79289170e-01, 6.77319247e-01, -1.05102238e+00,
5.92230104e-01, 9.16299467e-01, -2.49020471e-01,
-8.59726954e-01],
[1.50531800e+00, 8.30645618e-01, 5.27978380e-01,
3.50248646e-01, -1.42318853e+00, 1.54168853e+00,
-8.59726954e-01],
[4.39852113e-01, -1.08593403e+00, -8.53647287e-01,
-2.82025487e-01, 1.36470133e-01, -9.20536348e-01,
-8.59726954e-01],
[-1.08885981e+00, -1.31592358e+00, -9.52334835e-01,
-4.38142556e-01, -1.42318853e+00, -1.14437497e+00,
-8.59726954e-01],
[1.59796721e+00, -4.72628541e-01, -7.54959740e-01,
-2.11772805e-01, -6.43359200e-01, -1.37101158e-01,
-8.59726954e-01],
[1.69061641e+00, 1.06063518e+00, 1.21879121e+00,
5.36262135e-02, 1.36470133e-01, 1.65360785e+00,
1.16316000e+00],
[-8.10912189e-01, -5.49291726e-01, -7.54959740e-01,
-2.58607926e-01, -6.43359200e-01, 4.22495406e-01,
-8.59726954e-01],
[-1.36680743e+00, -9.32607656e-01, -7.54959740e-01,
-4.38142556e-01, -6.43359200e-01, -5.84778410e-01,
-8.59726954e-01],
[-1.27415823e+00, -1.46924996e+00, -8.53647287e-01,
-3.91307435e-01, 9.16299467e-01, -1.14437497e+00,
-8.59726954e-01],
[1.32001958e+00, -1.23926040e+00, -7.54959740e-01,
6.79109254e-03, 1.36470133e-01, -9.20536348e-01,
1.16316000e+00],
[3.47202905e-01, -9.32607656e-01, -7.54959740e-01,
-3.28860608e-01, -1.42318853e+00, 3.10576093e-01,
-8.59726954e-01],
[-4.40315359e-01, -8.55944470e-01, -7.54959740e-01,
6.79109254e-03, 1.36470133e-01, -3.60939784e-01,

```

1.16316000e+00],
[-2.33939249e-02, -5.49291726e-01, -4.58897097e-01,
 2.24027995e-02, 9.16299467e-01, -2.51818454e-02,
-8.59726954e-01],
[-1.16043132e-01, -6.25954912e-01, 3.45406417e-02,
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 1.16316000e+00],
[ 8.10448943e-01, 1.21396155e+00, 1.31747876e+00,
-2.97637194e-01, -1.42318853e+00, -3.60939784e-01,
-8.59726954e-01],
[ 3.47202905e-01, 1.40676946e-01, -8.53647287e-01,
-1.57131831e-01, 9.16299467e-01, 8.70172658e-01,
 1.16316000e+00],
[ 7.64124339e-01, 6.40137602e-02, 5.27978380e-01,
-3.75695728e-01, 1.36470133e-01, -2.49020471e-01,
-8.59726954e-01],
[ 1.22737038e+00, 2.67056208e+00, 8.24041023e-01,
-3.13248901e-01, 1.36470133e-01, 8.70172658e-01,
-8.59726954e-01],
[ 5.32501320e-01, -8.93126115e-02, 4.29290832e-01,
 4.04889621e-01, 9.16299467e-01, 1.98656780e-01,
 1.16316000e+00],
[ 1.61904490e-01, 4.47329689e-01, -1.05102238e+00,
-5.56557354e-02, 9.16299467e-01, -2.51818454e-02,
-8.59726954e-01],
[ 1.69061641e+00, 1.52061429e+00, 2.20566669e+00,
-1.10296710e-01, -1.42318853e+00, -2.49020471e-01,
-8.59726954e-01],
[-1.62367736e-01, -1.08593403e+00, -8.53647287e-01,
 1.23878895e-01, 9.16299467e-01, -1.03245566e+00,
 1.16316000e+00],
[-1.22783362e+00, -1.26494257e-02, 3.45406417e-02,
-2.82025487e-01, 9.16299467e-01, -8.08617036e-01,
 1.16316000e+00],
[ 4.86176716e-01, 2.94003318e-01, 3.45406417e-02,
 1.62908162e-01, 1.36470133e-01, 7.58253345e-01,
 1.16316000e+00]])

```

`X_test[:,1]` *#1 index col values*

```

array([-1.00927084,  0.3706665 ,  1.4439511 ,  2.59389889, -
 1.31592358,
        0.83064562, -1.46924996,  2.59389889,  1.59727748,
 1.06063518,
        0.3706665 , -0.85594447, -0.7026181 ,  0.52399288,
 0.29400332,
       -1.16259721,  0.67731925,  0.83064562, -1.08593403, -
 1.31592358,
       -0.47262854,  1.06063518, -0.54929173, -0.93260766, -
 1.46924996,
       -1.2392604 , -0.93260766, -0.85594447, -0.54929173, -

```



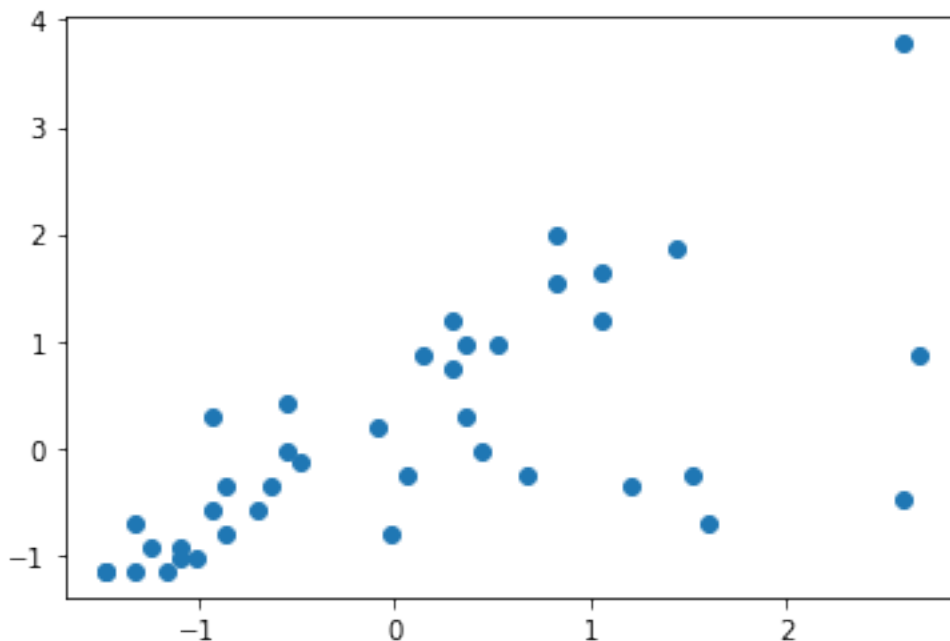
```
0.62595491,
    1.21396155,  0.14067695,  0.06401376,  2.67056208, -
0.08931261,
    0.44732969,  1.52061429, -1.08593403, -0.01264943,
0.29400332])
```

```
X_test[:, -2] #2nd last column values
```

```
array([-1.03245566,  0.31057609,  1.87744647, -0.4728591 , -
0.69669772,
    1.98936579, -1.14437497,  3.78007479, -0.69669772,
1.2059306 ,
    0.98209197, -0.80861704, -0.58477841,  0.98209197,
1.2059306 ,
    -1.14437497, -0.24902047,  1.54168853, -0.92053635, -
1.14437497,
    -0.13710116,  1.65360785,  0.42249541, -0.58477841, -
1.14437497,
    -0.92053635,  0.31057609, -0.36093978, -0.02518185, -
0.36093978,
    -0.36093978,  0.87017266, -0.24902047,  0.87017266,
0.19865678,
    -0.02518185, -0.24902047, -1.03245566, -0.80861704,
0.75825334])
```

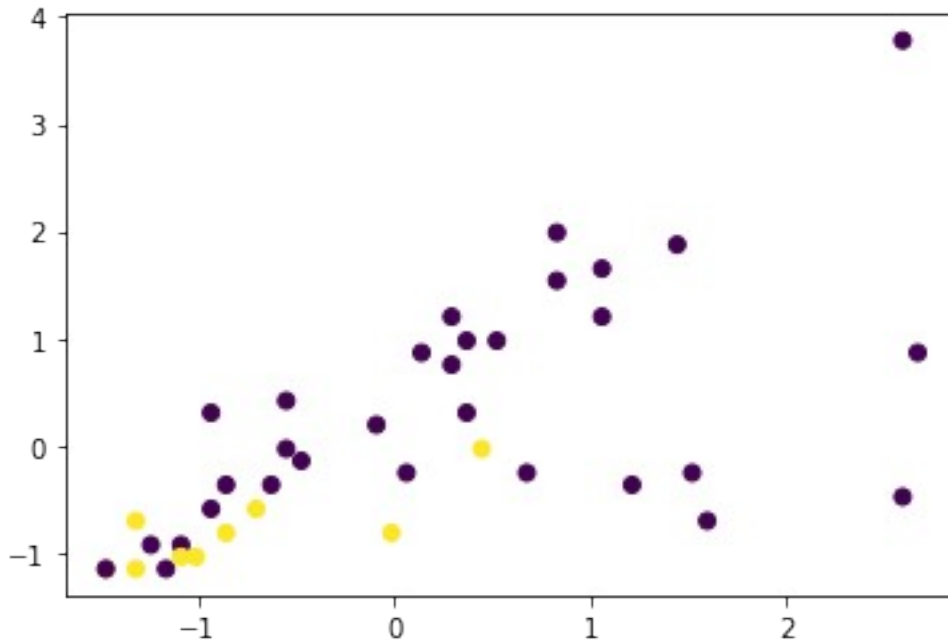
```
plt.scatter(X_test[:, 1], X_test[:, -2])
```

```
<matplotlib.collections.PathCollection at 0x1c2ab094e80>
```



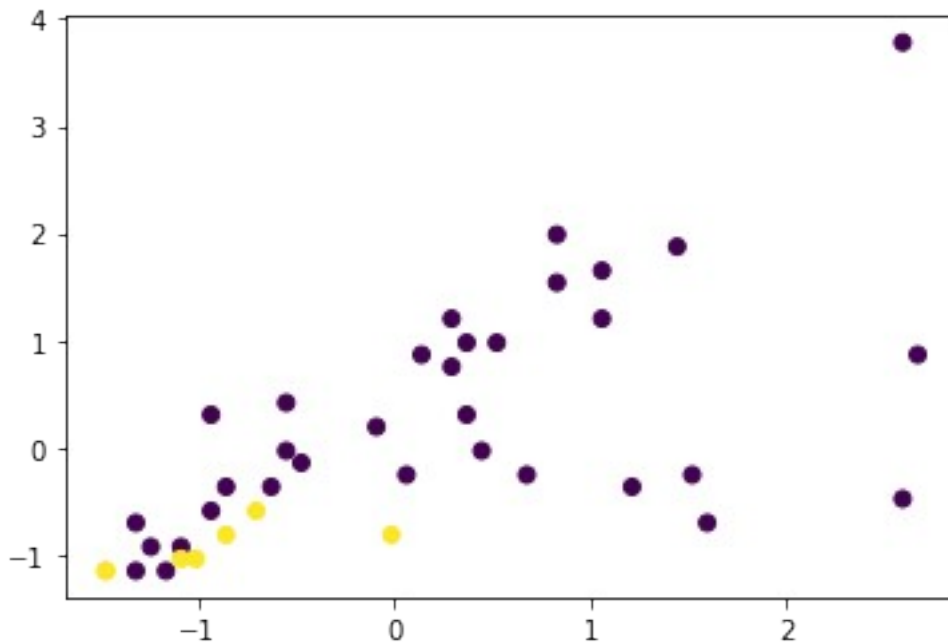
```
import matplotlib.pyplot as plt
plt.scatter(X_test[:,1],X_test[:,-2],c = y_test) #coloring based on  
actual values
```

<matplotlib.collections.PathCollection at 0x1c2ab0fc1f0>



```
import matplotlib.pyplot as plt
plt.scatter(X_test[:,1],X_test[:,-2],c = yhat)
```

<matplotlib.collections.PathCollection at 0x1c2ab1556d0>



```

from sklearn.linear_model import LogisticRegression
LR = LogisticRegression(solver='saga')
LR.fit(X_train,y_train) # Training
LR

LogisticRegression(solver='saga')

from sklearn.metrics import f1_score
f1_score(y_test, yhat) #actualvare,predvalue

0.75

from sklearn.linear_model import LogisticRegression
LR = LogisticRegression(solver='lbfgs')
LR.fit(X_train,y_train) # Training
LR

LogisticRegression()

from sklearn.metrics import f1_score
f1_score(y_test, yhat) #actualvare,predvalue

0.75

from sklearn.linear_model import LogisticRegression
LR = LogisticRegression(solver='liblinear')
LR.fit(X_train,y_train) # Training
LR

LogisticRegression(solver='liblinear')

from sklearn.metrics import f1_score
f1_score(y_test, yhat) #actualvare,predvalue

0.75

```

Ans : The Best possible accuracy will be 75%

Que 5 : We are providing you the cell dataset and we expect you to use all the independent variables for creating the SVM machine learning model and change the hyperparameters so that you can get the best accuracy

```

import pandas as pd
import numpy as np
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

```

```
cell_df = pd.read_csv("C:/Users/Lenovo/Documents/Data
Set/cell_samples.csv")
cell_df.head()
```

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	
BareNuc \							
0	1000025	5	1	1	1	2	1
1	1002945	5	4	4	5	7	10
2	1015425	3	1	1	1	2	2
3	1016277	6	8	8	1	3	4
4	1017023	4	1	1	3	2	1

	BlandChrom	NormNucl	Mit	Class
0	3	1	1	2
1	3	2	1	2
2	3	1	1	2
3	3	7	1	2
4	3	1	1	2

```
cell_df.tail()
```

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BareNuc
\							
694	776715	3	1	1	1	3	2
695	841769	2	1	1	1	2	1
696	888820	5	10	10	3	7	3
697	897471	4	8	6	4	3	4
698	897471	4	8	8	5	4	5

	BlandChrom	NormNucl	Mit	Class
694	1	1	1	2
695	1	1	1	2
696	8	10	2	4
697	10	6	1	4
698	10	4	1	4

```
cell_df
```

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BareNuc
\							

0	1000025	5	1	1	1	2	1
1	1002945	5	4	4	5	7	10
2	1015425	3	1	1	1	2	2
3	1016277	6	8	8	1	3	4
4	1017023	4	1	1	3	2	1
..
694	776715	3	1	1	1	3	2
695	841769	2	1	1	1	2	1
696	888820	5	10	10	3	7	3
697	897471	4	8	6	4	3	4
698	897471	4	8	8	5	4	5

	BlandChrom	NormNucl	Mit	Class
0	3	1	1	2
1	3	2	1	2
2	3	1	1	2
3	3	7	1	2
4	3	1	1	2
..
694	1	1	1	2
695	1	1	1	2
696	8	10	2	4
697	10	6	1	4
698	10	4	1	4

[699 rows x 11 columns]

Data pre-processing and selection

```
cell_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 699 entries, 0 to 698
Data columns (total 11 columns):
#   Column      Non-Null Count  Dtype
---  -
0   ID           699 non-null    int64
1   Clump        699 non-null    int64
```

```

2   UnifSize      699 non-null    int64
3   UnifShape     699 non-null    int64
4   MargAdh       699 non-null    int64
5   SingEpiSize   699 non-null    int64
6   BareNuc       699 non-null    object
7   BlandChrom    699 non-null    int64
8   NormNucl      699 non-null    int64
9   Mit           699 non-null    int64
10  Class         699 non-null    int64

```

```
dtypes: int64(10), object(1)
```

```
memory usage: 60.2+ KB
```

```
cell_df.describe()
```

	ID	Clump	UnifSize	UnifShape	MargAdh	\
count	6.990000e+02	699.000000	699.000000	699.000000	699.000000	
mean	1.071704e+06	4.417740	3.134478	3.207439	2.806867	
std	6.170957e+05	2.815741	3.051459	2.971913	2.855379	
min	6.163400e+04	1.000000	1.000000	1.000000	1.000000	
25%	8.706885e+05	2.000000	1.000000	1.000000	1.000000	
50%	1.171710e+06	4.000000	1.000000	1.000000	1.000000	
75%	1.238298e+06	6.000000	5.000000	5.000000	4.000000	
max	1.345435e+07	10.000000	10.000000	10.000000	10.000000	

	SingEpiSize	BlandChrom	NormNucl	Mit	Class
count	699.000000	699.000000	699.000000	699.000000	699.000000
mean	3.216023	3.437768	2.866953	1.589413	2.689557
std	2.214300	2.438364	3.053634	1.715078	0.951273
min	1.000000	1.000000	1.000000	1.000000	2.000000
25%	2.000000	2.000000	1.000000	1.000000	2.000000
50%	2.000000	3.000000	1.000000	1.000000	2.000000
75%	4.000000	5.000000	4.000000	1.000000	4.000000
max	10.000000	10.000000	10.000000	10.000000	4.000000

```
cell_df.drop('BareNuc',axis = 1,inplace = True)
```

```
cell_df
```

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize
BlandChrom \						
0	1000025	5	1	1	1	2
3						
1	1002945	5	4	4	5	7
3						
2	1015425	3	1	1	1	2
3						
3	1016277	6	8	8	1	3
3						
4	1017023	4	1	1	3	2
3						
..

```

...
694 776715 3 1 1 1 3
1
695 841769 2 1 1 1 2
1
696 888820 5 10 10 3 7
8
697 897471 4 8 6 4 3
10
698 897471 4 8 8 5 4
10

```

```

      NormNucl  Mit  Class
0          1    1     2
1          2    1     2
2          1    1     2
3          7    1     2
4          1    1     2
..      ...    ...    ...
694         1    1     2
695         1    1     2
696        10    2     4
697         6    1     4
698         4    1     4

```

[699 rows x 10 columns]

```

feature_df = cell_df[['Clump', 'UnifSize', 'UnifShape', 'MargAdh',
'SingEpiSize', 'BlandChrom', 'NormNucl', 'Mit']]
feature_df # Independent Variable

```

```

      Clump  UnifSize  UnifShape  MargAdh  SingEpiSize  BlandChrom
NormNucl \
0          5          1          1          1          2          3
1
1          5          4          4          5          7          3
2
2          3          1          1          1          2          3
1
3          6          8          8          1          3          3
7
4          4          1          1          3          2          3
1
..      ...      ...      ...      ...      ...      ...
...
694       3          1          1          1          3          1
1
695       2          1          1          1          2          1
1
696       5         10         10          3          7          8

```

```

10
697      4      8      6      4      3      10
6
698      4      8      8      5      4      10
4

```

```

      Mit
0      1
1      1
2      1
3      1
4      1
..    ...
694    1
695    1
696    2
697    1
698    1

```

```
[699 rows x 8 columns]
```

```
feature_df.dtypes
```

```

Clump      int64
UnifSize   int64
UnifShape  int64
MargAdh    int64
SingEpiSize int64
BlandChrom int64
NormNucl   int64
Mit        int64

```

```
dtype: object
```

```
X = np.asarray(feature_df) # Independent variable independent variable
array got created
```

```
X[0:5] # show me elements from zeroth row to 5th row
```

```

array([[5, 1, 1, 1, 2, 3, 1, 1],
       [5, 4, 4, 5, 7, 3, 2, 1],
       [3, 1, 1, 1, 2, 3, 1, 1],
       [6, 8, 8, 1, 3, 3, 7, 1],
       [4, 1, 1, 3, 2, 3, 1, 1]], dtype=int64)

```

```

cell_df['Class'] = cell_df['Class'].astype('int')
y = np.asarray(cell_df['Class']) # Dependent variable
y [0:5]

```

```
array([2, 2, 2, 2, 2])
```


Train/Test dataset

```
X_train, X_test, y_train, y_test = train_test_split(X, y,  
test_size=0.2, random_state=50)  
print ('Train set:', X_train.shape, y_train.shape)  
print ('Test set:', X_test.shape, y_test.shape)
```

```
Train set: (559, 8) (559,)  
Test set: (140, 8) (140,)
```

Modeling (SVM with Scikit-learn)

The SVM algorithm offers a choice of kernel functions for performing its processing. Basically, mapping data into a higher dimensional space is called kernelling. The mathematical function used for the transformation is known as the kernel function, and can be of different types, such as:

1.Linear

2.Polynomial

3.Radial basis function (RBF)

4.Sigmoid

Each of these functions has its characteristics, its pros and cons, and its equation, but as there's no easy way of knowing which function performs best with any given dataset, we usually choose different functions in turn and compare the results. Let's just use the default, **RBF (Radial Basis Function)** for this lab.

```
from sklearn import svm  
clf = svm.SVC(kernel='poly')  
clf.fit(X_train, y_train) # Question and Answers  
  
SVC(kernel='poly')
```

```
yhat = clf.predict(X_test) # Question
yhat [0:5]

array([2, 2, 2, 2, 2])
```

Evaluation

```
from sklearn.metrics import f1_score
f1_score(y_test, yhat, average='weighted')
```

```
0.9425054112554112
```

```
# write your code here
```

```
clf2 = svm.SVC(kernel='rbf')
clf2.fit(X_train, y_train)
yhat2 = clf2.predict(X_test)
print("Avg F1-score: %.4f" % f1_score(y_test, yhat2,
average="weighted"))
```

```
Avg F1-score: 0.9714
```

```
# write your code here
```

```
clf2 = svm.SVC(kernel='linear')
clf2.fit(X_train, y_train)
yhat2 = clf2.predict(X_test)
print("Avg F1-score: %.4f" % f1_score(y_test, yhat2,
average="weighted"))
```

```
Avg F1-score: 0.9644
```

```
cell_df
```

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize
BlandChrom \						
0	1000025	5	1	1	1	2
3						
1	1002945	5	4	4	5	7
3						
2	1015425	3	1	1	1	2
3						
3	1016277	6	8	8	1	3
3						
4	1017023	4	1	1	3	2
3						
..
...						
694	776715	3	1	1	1	3
1						
695	841769	2	1	1	1	2

```

1
696 888820      5      10      10      3      7
8
697 897471      4       8       6      4      3
10
698 897471      4       8       8      5      4
10

```

```

      NormNucl  Mit  Class
0           1    1     2
1           2    1     2
2           1    1     2
3           7    1     2
4           1    1     2
..          ...  ...   ...
694          1    1     2
695          1    1     2
696         10    2     4
697          6    1     4
698          4    1     4

```

```
[699 rows x 10 columns]
```

```
X_test
```

```

array([[4, 1, 1, ..., 2, 1, 1],
       [2, 3, 1, ..., 1, 1, 1],
       [5, 3, 1, ..., 2, 1, 1],
       ...,
       [5, 8, 7, ..., 5, 7, 1],
       [2, 1, 1, ..., 2, 1, 1],
       [1, 2, 3, ..., 1, 1, 1]], dtype=int64)

```

```
X_test.shape
```

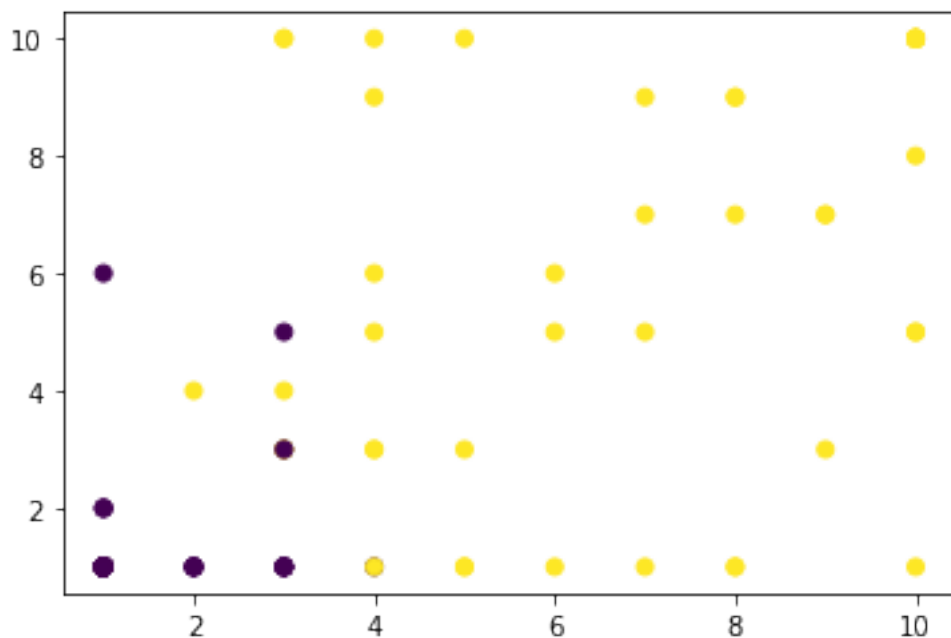
```
(140, 8)
```

```

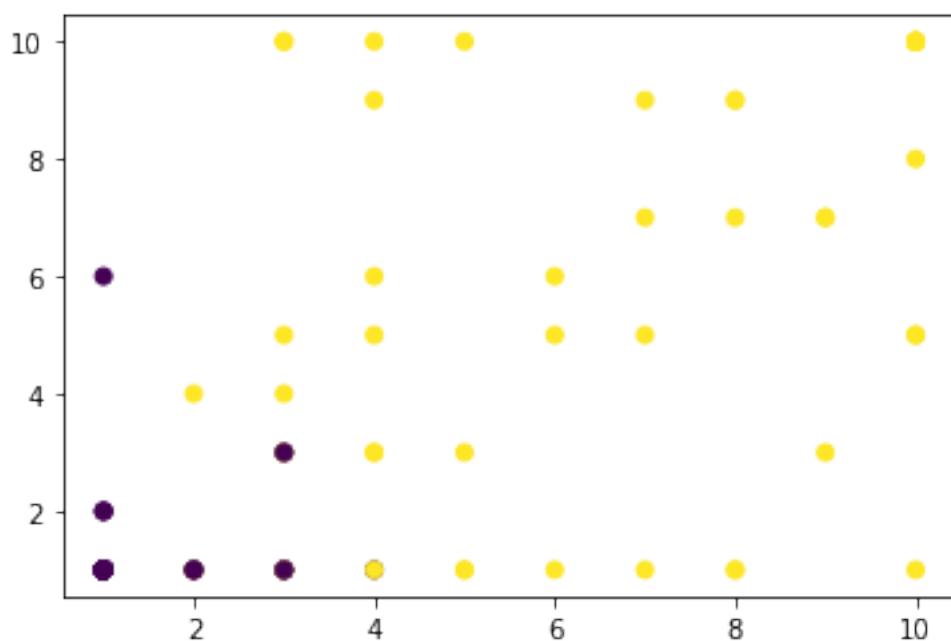
import matplotlib.pyplot as plt
plt.scatter(X_test[:,1],X_test[:,-2],c=y_test)

```

```
<matplotlib.collections.PathCollection at 0x1c2ab1e0190>
```



```
import matplotlib.pyplot as plt
plt.scatter(X_test[:,1],X_test[:,2],c=yhat2)
<matplotlib.collections.PathCollection at 0x1c2ab222ee0>
```



cell_df

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize
BlandChrom \						
0	1000025	5	1	1	1	2
3						

1	1002945	5	4	4	5	7
3						
2	1015425	3	1	1	1	2
3						
3	1016277	6	8	8	1	3
3						
4	1017023	4	1	1	3	2
3						
..
...						
694	776715	3	1	1	1	3
1						
695	841769	2	1	1	1	2
1						
696	888820	5	10	10	3	7
8						
697	897471	4	8	6	4	3
10						
698	897471	4	8	8	5	4
10						

	NormNucl	Mit	Class
0	1	1	2
1	2	1	2
2	1	1	2
3	7	1	2
4	1	1	2
..
694	1	1	2
695	1	1	2
696	10	2	4
697	6	1	4
698	4	1	4

[699 rows x 10 columns]

```
clf2.predict([[6,13,13,5,7,3,2,4]])
```

```
array([4])
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=50)
from sklearn import svm
clf = svm.SVC(kernel='poly')
clf.fit(X_train, y_train) #Training Model
training_pred = clf.predict(X_train)
print(f"training accuracy is {f1_score(y_train, training_pred,
average='weighted') }")
```

training accuracy is 0.9676813490496357

```
yhat = clf.predict(X_test) #final
from sklearn.metrics import f1_score

print(f"testing accuracy is {f1_score(y_test, yhat,
average='weighted') }")

testing accuracy is 0.9425054112554112
```

Best accuracy can be give the hyperparameter is rbf (Radial Basis Function) = 97.14 %

Que 6 : Take the same cell Dataset and instead of SVM apply logistic regression in it.

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

cell_df = pd.read_csv("C:/Users/Lenovo/Documents/Data
Set/cell_samples.csv")
cell_df.head()
```

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	
BareNuc \							
0	1000025	5	1	1	1	2	1
1	1002945	5	4	4	5	7	10
2	1015425	3	1	1	1	2	2
3	1016277	6	8	8	1	3	4
4	1017023	4	1	1	3	2	1

	BlandChrom	NormNucl	Mit	Class
0	3	1	1	2
1	3	2	1	2
2	3	1	1	2
3	3	7	1	2
4	3	1	1	2

```
cell_df.tail()
```

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BareNuc
\							
694	776715	3	1	1	1	3	2

695	841769	2	1	1	1	2	1
696	888820	5	10	10	3	7	3
697	897471	4	8	6	4	3	4
698	897471	4	8	8	5	4	5

	BlandChrom	NormNucl	Mit	Class
694	1	1	1	2
695	1	1	1	2
696	8	10	2	4
697	10	6	1	4
698	10	4	1	4

```
set(cell_df['Class'])
```

```
{2, 4}
```

```
cell_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 699 entries, 0 to 698
Data columns (total 11 columns):
#   Column                Non-Null Count  Dtype
---  -
0   ID                    699 non-null    int64
1   Clump                 699 non-null    int64
2   UnifSize              699 non-null    int64
3   UnifShape             699 non-null    int64
4   MargAdh               699 non-null    int64
5   SingEpiSize           699 non-null    int64
6   BareNuc               699 non-null    object
7   BlandChrom            699 non-null    int64
8   NormNucl              699 non-null    int64
9   Mit                   699 non-null    int64
10  Class                 699 non-null    int64
dtypes: int64(10), object(1)
memory usage: 60.2+ KB
```

```
cell_df.isnull().sum()
```

ID	0
Clump	0
UnifSize	0
UnifShape	0
MargAdh	0
SingEpiSize	0
BareNuc	0

```

BlandChrom      0
NormNucl        0
Mit             0
Class           0
dtype: int64

```

```
cell_df.drop('BareNuc',axis = 1,inplace = True)
```

```
cell_df
```

	ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize
BlandChrom \						
0	1000025	5	1	1	1	2
3						
1	1002945	5	4	4	5	7
3						
2	1015425	3	1	1	1	2
3						
3	1016277	6	8	8	1	3
3						
4	1017023	4	1	1	3	2
3						
..
...						
694	776715	3	1	1	1	3
1						
695	841769	2	1	1	1	2
1						
696	888820	5	10	10	3	7
8						
697	897471	4	8	6	4	3
10						
698	897471	4	8	8	5	4
10						

	NormNucl	Mit	Class
0	1	1	2
1	2	1	2
2	1	1	2
3	7	1	2
4	1	1	2
..
694	1	1	2
695	1	1	2
696	10	2	4
697	6	1	4
698	4	1	4

```
[699 rows x 10 columns]
```



```
cell_df =
cell_df[["Clump", "UnifSize", "UnifShape", "MargAdh", "SingEpiSize", "Bland
Chrom", "NormNucl", "Mit", "Class"]]
cell_df.head()
```

	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BlandChrom
NormNucl \						
0	5	1	1	1	2	3
1						
1	5	4	4	5	7	3
2						
2	3	1	1	1	2	3
1						
3	6	8	8	1	3	3
7						
4	4	1	1	3	2	3
1						

	Mit	Class
0	1	2
1	1	2
2	1	2
3	1	2
4	1	2

```
cell_df.tail()
```

	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BlandChrom
NormNucl \						
694	3	1	1	1	3	1
1						
695	2	1	1	1	2	1
1						
696	5	10	10	3	7	8
10						
697	4	8	6	4	3	10
6						
698	4	8	8	5	4	10
4						

	Mit	Class
694	1	2
695	1	2
696	2	4
697	1	4
698	1	4

```
cell_df.shape
```

```
(699, 9)
```

```

cell_df.columns

Index(['Clump', 'UnifSize', 'UnifShape', 'MargAdh', 'SingEpiSize',
      'BlandChrom', 'NormNucl', 'Mit', 'Class'],
      dtype='object')

# Independent variable
# asarray is used to concert columns to same data type to the array
X =
np.asarray(cell_df[["Clump","UnifSize","UnifShape","MargAdh","SingEpiS
ize","BlandChrom","NormNucl","Mit"]]) # independent variable
X[0:1]#0,1,2,3,4

array([[5, 1, 1, 1, 2, 3, 1, 1]], dtype=int64)

# Dependent variable
y = np.asarray(cell_df['Class']) #dependent variable
y [0:9]

array([2, 2, 2, 2, 2, 4, 2, 2, 2], dtype=int64)

X[0:5]

array([[5, 1, 1, 1, 2, 3, 1, 1],
      [5, 4, 4, 5, 7, 3, 2, 1],
      [3, 1, 1, 1, 2, 3, 1, 1],
      [6, 8, 8, 1, 3, 3, 7, 1],
      [4, 1, 1, 3, 2, 3, 1, 1]], dtype=int64)

```

Train/Test dataset

```

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=200) # trainingsize = 80% test = 20%
print ('Train set:', X_train.shape, y_train.shape)
print ('Test set:', X_test.shape, y_test.shape)

```

Train set: (559, 8) (559,)

Test set: (140, 8) (140,)

Modeling (Logistic Regression with Scikit-learn)

Lets build our model using LogisticRegression from Scikit-learn package. This function implements logistic regression and can use different numerical optimizers to find parameters, including 'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga' solvers. You can find extensive information about the pros and cons of these optimizers if you search it in internet.

```
from sklearn.linear_model import LogisticRegression
LR = LogisticRegression(solver='saga')
LR.fit(X_train,y_train) # training
LR

C:\Users\Lenovo\anaconda3\lib\site-packages\sklearn\linear_model\
_sag.py:352: ConvergenceWarning: The max_iter was reached which means
the coef_ did not converge
  warnings.warn(

LogisticRegression(solver='saga')

yhat = LR.predict(X_test)# only questions passed and answers are saved
for evaluation
yhat[:5]

array([4, 2, 4, 4, 2], dtype=int64)

yhat_prob = LR.predict_proba(X_test)
yhat_prob[:5]

array([[0.20679859, 0.79320141],
       [0.68021412, 0.31978588],
       [0.21399263, 0.78600737],
       [0.00104075, 0.99895925],
       [0.52621739, 0.47378261]])
```

Evaluation

```
from sklearn.metrics import f1_score
f1_score(y_test, yhat, average='weighted') # actualvalue,predvalue

0.9498499911759516

cell_df

      Clump  UnifSize  UnifShape  MargAdh  SingEpiSize  BlandChrom
NormNucl  \
0          5          1          1          1          2          3
```

1						
1	5	4	4	5	7	3
2						
2	3	1	1	1	2	3
1						
3	6	8	8	1	3	3
7						
4	4	1	1	3	2	3
1						
..
...						
694	3	1	1	1	3	1
1						
695	2	1	1	1	2	1
1						
696	5	10	10	3	7	8
10						
697	4	8	6	4	3	10
6						
698	4	8	8	5	4	10
4						

	Mit	Class
0	1	2
1	1	2
2	1	2
3	1	2
4	1	2
..
694	1	2
695	1	2
696	2	4
697	1	4
698	1	4

[699 rows x 9 columns]

X_test

```
array([[10, 4, 3, ..., 5, 3, 2],
       [ 5, 1, 2, ..., 2, 1, 1],
       [10, 4, 2, ..., 4, 3, 10],
       ...,
       [ 4, 3, 3, ..., 3, 3, 1],
       [ 5, 5, 5, ..., 4, 3, 1],
       [10, 5, 7, ..., 8, 9, 1]], dtype=int64)
```

X_test[:,1] *#1 index col values .*

```
array([ 4, 1, 4, 7, 3, 1, 1, 8, 1, 10, 1, 5, 1, 1, 1, 3,
1,
```

```

1,      3,  8,  1,  1,  1,  1,  1,  1,  1,  7,  9,  1,  1,  1,  1,  2,
1,      1,  9, 10,  1,  1,  1,  5,  1, 10,  6,  1, 10, 10,  3, 10,  1,
1,      1,  1,  1,  3,  1,  5,  5,  1,  8,  1,  1,  7,  5,  1,  1,  2,
1,      4,  1,  7,  4,  1,  1,  3,  1,  4,  1,  1,  1,  1,  4,  1,  5,
1,      1,  2,  1,  1,  6,  1,  5,  1,  1,  1,  1,  1,  1,  1,  1,  1,
2,      1,  1,  1,  1,  2,  1, 10,  1,  4,  1,  7,  3,  4,  1,  1,  1,
6,      3,  6,  1,  1,  1,  1, 10, 10,  1,  1,  6,  8,  1,  1,  1,  1,
10,     2,  3,  5,  5], dtype=int64)

```

```

X_test[:, -2] #2nd last column values

```

```

array([ 3,  1,  3, 10,  1,  1,  1,  1,  1,  3,  1,  4,  1,  1,  1,  6,
1,      1, 10,  1,  1,  1,  1,  1,  1,  1,  4,  2,  1,  1,  1,  1,  3,
2,      1,  7,  3,  1,  1,  1,  1,  1,  3,  7,  1,  7, 10,  4,  1,  1,
1,      1,  1,  1,  1,  2,  4,  5,  1,  8,  1,  1,  8,  3,  1,  1,  2,
1,      3,  1, 10,  1,  1,  1,  1,  1,  1,  1,  1,  1,  3,  1,  9,
1,      1,  1,  1,  1, 10,  1,  3,  1,  2,  1,  1,  1,  1,  1,  1,
1,      1,  1,  3,  1,  1,  1,  8,  1, 10,  1, 10,  4,  2,  1,  1,  1,
5,      1, 10,  1,  1,  1,  1,  8,  3,  1,  1, 10,  9,  1,  1,  1,  1,
3,      1,  3,  3,  9], dtype=int64)

```

```

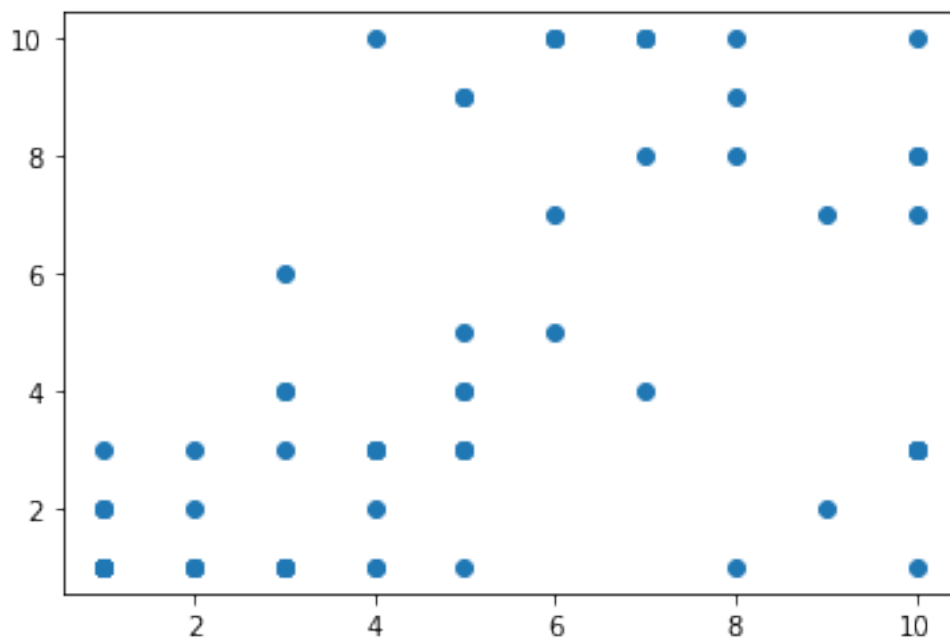
plt.scatter(X_test[:, 1], X_test[:, -2])

```

```

<matplotlib.collections.PathCollection at 0x1c2ac2742e0>

```



cell_df

	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BlandChrom
NormNucl \						
0	5	1	1	1	2	3
1	5	4	4	5	7	3
2	3	1	1	1	2	3
3	6	8	8	1	3	3
4	4	1	1	3	2	3
...
694	3	1	1	1	3	1
695	2	1	1	1	2	1
696	5	10	10	3	7	8
697	4	8	6	4	3	10
698	4	8	8	5	4	10

	Mit	Class
0	1	2
1	1	2

```

2      1      2
3      1      2
4      1      2
..     ...    ...
694    1      2
695    1      2
696    2      4
697    1      4
698    1      4

```

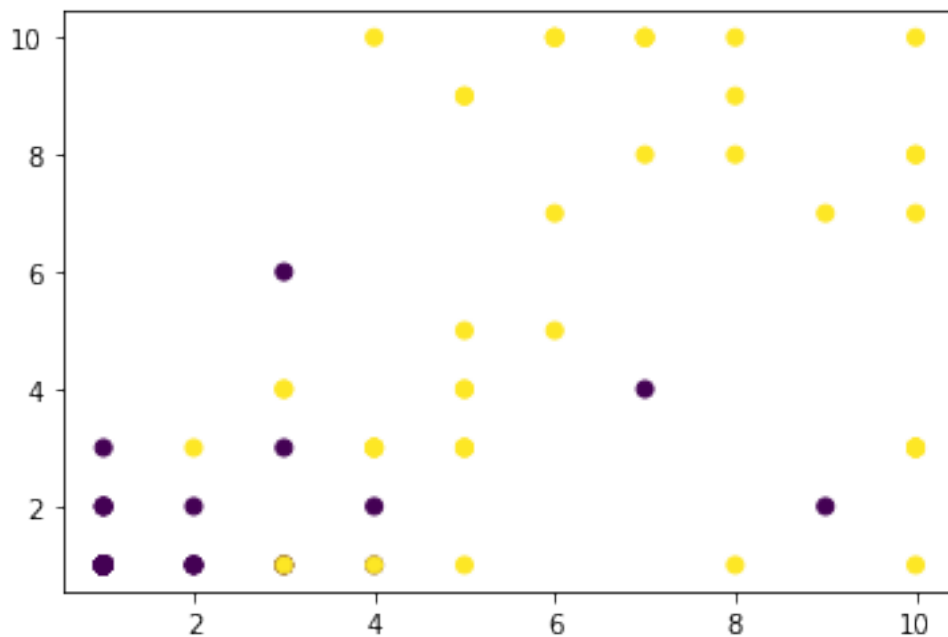
```
[699 rows x 9 columns]
```

```

import matplotlib.pyplot as plt
plt.scatter(X_test[:,1],X_test[:,-2],c = y_test) # Coloring based on
actual values

```

```
<matplotlib.collections.PathCollection at 0x1c2ac2d7970>
```

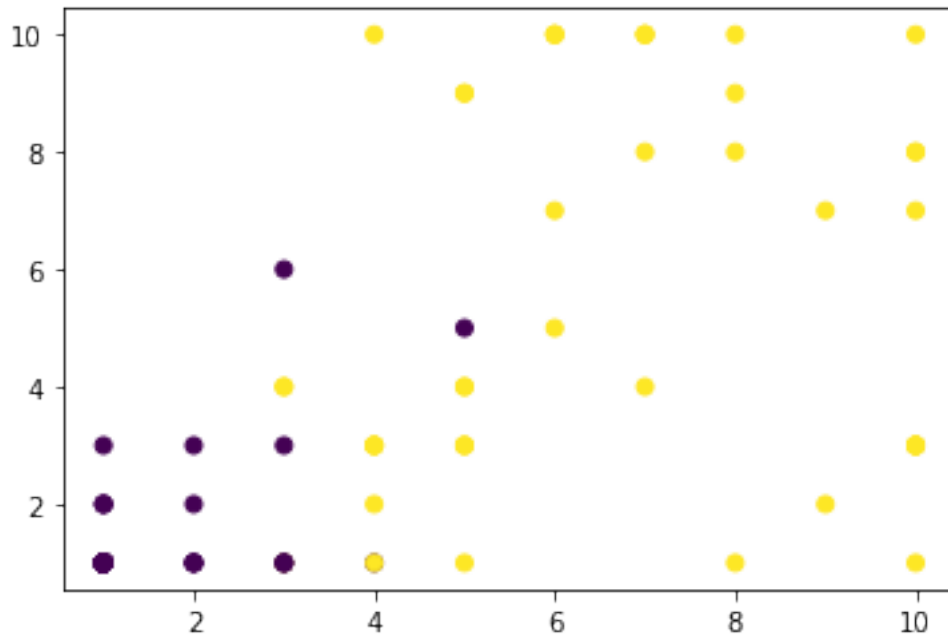


```

import matplotlib.pyplot as plt
plt.scatter(X_test[:,1],X_test[:,-2],c = yhat)

```

```
<matplotlib.collections.PathCollection at 0x1c2ac331f10>
```



Q7 : We are providing you a dataset apart from churn and cell dataset which is titanic dataset remove unnecessary column which are not usefull with aspect of machine learning and apply label encoding where ever its necessary and store processed data into your memory

Dependent Column : Survived

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

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

titanic_df

	Unnamed: 0	PassengerId	Survived	Pclass	\
0	0	1	0	3	
1	1	2	1	1	
2	2	3	1	3	
3	3	4	1	1	
4	4	5	0	3	
...	
707	885	886	0	3	
708	886	887	0	2	
709	887	888	1	1	
710	889	890	1	1	


```

711      890      891      0      3

SibSp \
0      Braund, Mr. Owen Harris      male  22.0
1
1      Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2      Heikkinen, Miss. Laina      female  26.0
0
3      Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4      Allen, Mr. William Henry      male  35.0
0
..      ...      ...      ...
...
707      Rice, Mrs. William (Margaret Norton)  female  39.0
0
708      Montvila, Rev. Juozas      male  27.0
0
709      Graham, Miss. Margaret Edith      female  19.0
0
710      Behr, Mr. Karl Howell      male  26.0
0
711      Dooley, Mr. Patrick      male  32.0
0

```

```

Parch      Ticket      Fare Embarked
0      0      A/5 21171      7.2500      S
1      0      PC 17599      71.2833      C
2      0      STON/O2. 3101282      7.9250      S
3      0      113803      53.1000      S
4      0      373450      8.0500      S
..      ...      ...      ...      ...
707      5      382652      29.1250      Q
708      0      211536      13.0000      S
709      0      112053      30.0000      S
710      0      111369      30.0000      C
711      0      370376      7.7500      Q

```

[712 rows x 12 columns]

titanic_df.head()

```

Unnamed: 0      PassengerId      Survived      Pclass \
0      0      1      0      3
1      1      2      1      1
2      2      3      1      3
3      3      4      1      1
4      4      5      0      3

```

SibSp \	Name	Sex	Age
0	Braund, Mr. Owen Harris	male	22.0
1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0
1	Heikkinen, Miss. Laina	female	26.0
2	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0
0	Allen, Mr. William Henry	male	35.0

	Parch	Ticket	Fare	Embarked
0	0	A/5 21171	7.2500	S
1	0	PC 17599	71.2833	C
2	0	STON/O2. 3101282	7.9250	S
3	0	113803	53.1000	S
4	0	373450	8.0500	S

titanic_df.tail()

	Unnamed: 0	PassengerId	Survived	Pclass \
707	885	886	0	3
708	886	887	0	2
709	887	888	1	1
710	889	890	1	1
711	890	891	0	3

Ticket \	Name	Sex	Age	SibSp	Parch
707 Rice, Mrs. William (Margaret Norton) 382652	female	39.0	0	5	
708 Montvila, Rev. Juozas 211536	male	27.0	0	0	
709 Graham, Miss. Margaret Edith 112053	female	19.0	0	0	
710 Behr, Mr. Karl Howell 111369	male	26.0	0	0	
711 Dooley, Mr. Patrick 370376	male	32.0	0	0	

	Fare	Embarked
707	29.125	Q
708	13.000	S
709	30.000	S
710	30.000	C
711	7.750	Q

```
titanic_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 712 entries, 0 to 711
Data columns (total 12 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Unnamed: 0      712 non-null   int64
1   PassengerId     712 non-null   int64
2   Survived        712 non-null   int64
3   Pclass          712 non-null   int64
4   Name            712 non-null   object
5   Sex             712 non-null   object
6   Age            712 non-null   float64
7   SibSp           712 non-null   int64
8   Parch           712 non-null   int64
9   Ticket          712 non-null   object
10  Fare            712 non-null   float64
11  Embarked        712 non-null   object
dtypes: float64(2), int64(6), object(4)
memory usage: 66.9+ KB
```

```
titanic_df.isnull().sum()
```

```
Unnamed: 0      0
PassengerId     0
Survived         0
Pclass          0
Name            0
Sex             0
Age            0
SibSp           0
Parch           0
Ticket          0
Fare            0
Embarked        0
dtype: int64
```

```
titanic_df.shape
```

```
(712, 12)
```

```
titanic_df = titanic_df.drop(["Name", "Ticket", "Unnamed: 0", "PassengerId", "Age"], axis = 1)
```

```
titanic_df
```

	Survived	Pclass	Sex	SibSp	Parch	Fare	Embarked
0	0	3	male	1	0	7.2500	S
1	1	1	female	1	0	71.2833	C
2	1	3	female	0	0	7.9250	S
3	1	1	female	1	0	53.1000	S

4	0	3	male	0	0	8.0500	S
...
707	0	3	female	0	5	29.1250	Q
708	0	2	male	0	0	13.0000	S
709	1	1	female	0	0	30.0000	S
710	1	1	male	0	0	30.0000	C
711	0	3	male	0	0	7.7500	Q

[712 rows x 7 columns]

```
X =
titanic_df[["Pclass", "Sex", "SibSp", "Parch", "Fare", "Embarked"]].values
```

X

```
array([[3, 'male', 1, 0, 7.25, 'S'],
       [1, 'female', 1, 0, 71.2833, 'C'],
       [3, 'female', 0, 0, 7.925, 'S'],
       ...,
       [1, 'female', 0, 0, 30.0, 'S'],
       [1, 'male', 0, 0, 30.0, 'C'],
       [3, 'male', 0, 0, 7.75, 'Q']], dtype=object)
```

Label Encoding

```
from sklearn import preprocessing
le_Sex = preprocessing.LabelEncoder()
le_Sex.fit(['female', 'male'])
X[:,1] = le_Sex.transform(X[:,1]) # I AM UPDATING MY FIRST COLUMN
FROM F,M TO 0,1
```

```
le_Embarked = preprocessing.LabelEncoder()
le_Embarked.fit(['S', 'C', 'Q'])
X[:,5] = le_Embarked.transform(X[:,5]) # I AM UPDATING MY SECOND
COLUMN FROM S,C,Q TO 0,1,2
```

X[0:6]

```
array([[3, 1, 1, 0, 7.25, 2],
       [1, 0, 1, 0, 71.2833, 0],
       [3, 0, 0, 0, 7.925, 2],
       [1, 0, 1, 0, 30.0, 2],
       [3, 1, 0, 0, 8.05, 2],
       [1, 1, 0, 0, 30.0, 2]], dtype=object)
```

X

```
array([[3, 1, 1, 0, 7.25, 2],
       [1, 0, 1, 0, 71.2833, 0],
       [3, 0, 0, 0, 7.925, 2],
```

```

        ...,
        [1, 0, 0, 0, 30.0, 2],
        [1, 1, 0, 0, 30.0, 0],
        [3, 1, 0, 0, 7.75, 1]], dtype=object)

Y = titanic_df[["Survived"]]

Y

```

	Survived
0	0
1	1
2	1
3	1
4	0
...	...
707	0
708	0
709	1
710	1
711	0

```

[712 rows x 1 columns]

set(titanic_df[["Survived"]])

{0, 1}

from sklearn import preprocessing
X = preprocessing.StandardScaler().fit(X).transform(X)

X

```

```

array([[ 0.90859974,  0.75613751,  0.52251079, -0.50678737, -
 0.51637992,
         0.51958818],
       [-1.48298257, -1.32251077,  0.52251079, -0.50678737, -
 0.69404605,
        -2.04948671],
       [ 0.90859974, -1.32251077, -0.55271372, -0.50678737, -
 0.50362035,
         0.51958818],
       ...,
       [-1.48298257, -1.32251077, -0.55271372, -0.50678737, -
 0.08633507,
         0.51958818],
       [-1.48298257,  0.75613751, -0.55271372, -0.50678737, -
 0.08633507,
        -2.04948671],
       [ 0.90859974,  0.75613751, -0.55271372, -0.50678737, -
 0.50692839,
        -0.76494927]])

```

```
from sklearn import preprocessing
Y = preprocessing.StandardScaler().fit(Y).transform(Y)
```

Y

```
array([[ -0.82416338],
       [ 1.21335165],
       [ 1.21335165],
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       [-0.82416338],
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       [-0.82416338]])
```

[illegible]

[illegible]

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```

Que.8 Use that processed titanic dataset and apply svm in it

Train and Test Dataset

```
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=100)
print ('Train set:', X_train.shape, Y_train.shape)
print ('Test set:', X_test.shape, Y_test.shape)

```

```

Train set: (569, 6) (569, 1)
Test set: (143, 6) (143, 1)

```

```
X_train
```

```

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```

```
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```

X_test

```
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[-0.82416338],
[1.21335165],


```

        [ 1.21335165],
        [ 1.21335165],
        [ 1.21335165],
        [-0.82416338],
        [-0.82416338],
        [-0.82416338],
        [-0.82416338]])

from sklearn import preprocessing
from sklearn import utils

#convert y values to categorical values
value = preprocessing.LabelEncoder()
Y_train_transformed = value.fit_transform(Y_train)

#view transformed values
print(Y_train_transformed)

[0 0 0 0 1 1 0 1 1 1 1 0 1 0 1 0 1 0 0 1 0 0 1 1 0 0 0 1 1 1 0 0 1
 1 0
 0 1 1 1 0 0 1 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0
 1 1
 1 0 1 1 0 1 0 0 0 1 0 0 1 0 0 0 1 1 0 0 1 0 1 1 0 0 1 1 0 1 1 1 0 1 0
 0 0
 0 1 0 1 0 0 1 0 1 1 0 0 0 0 1 1 0 0 0 0 0 1 1 0 0 0 0 0 1 0 0 0 0 1 0
 1 1
 0 0 1 0 0 0 1 1 0 0 0 0 1 0 0 0 0 0 1 0 1 1 0 0 0 0 1 1 1 1 0 0 1 0 0
 1 0
 0 1 0 1 1 0 1 1 0 1 1 1 1 0 1 0 0 1 0 1 1 1 1 1 0 0 1 0 1 1 1 1 1 1
 1 0
 1 1 0 0 1 0 1 0 1 1 0 0 0 0 0 1 1 0 1 1 1 1 0 1 0 0 0 0 0 0 0 1 0 0 1
 1 0
 1 1 0 1 0 1 0 0 0 0 1 0 1 1 0 1 0 1 0 0 0 1 1 1 1 0 1 0 1 0 0 0 0 1 0
 0 0
 0 0 0 0 0 1 0 1 0 1 0 0 1 1 1 0 0 0 0 1 1 0 0 0 0 0 0 1 0 1 0 0 0 0 1
 0 1
 0 1 1 1 0 1 0 0 1 0 0 0 0 0 1 0 0 1 1 0 1 0 1 1 1 0 0 0 1 1 0 0 1 0 0
 0 0
 0 0 0 1 1 1 0 1 0 0 1 0 1 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 1 0 0 1
 0 1
 0 0 0 0 0 0 0 1 0 0 0 0 1 1 0 0 1 1 0 1 1 0 0 1 0 0 1 0 1 1 0 1 1 0 0
 1 1
 0 0 1 1 0 1 1 0 0 0 1 0 1 0 1 0 1 1 0 0 1 0 0 0 0 1 1 1 0 0 0 0 0 1 1
 0 0
 0 1 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 1 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0 0 0
 0 1
 1 0 0 0 0 1 1 0 0 1 0 0 0 1 1 0 0 0 1 1 0 1 0 1 0 0 0 0 0 0 0 0 0 1 1
 1 0
 0 0 0 0 0 0 1 0 0 0 0 0 0 1]

```

```
C:\Users\Lenovo\anaconda3\lib\site-packages\sklearn\preprocessing\
_label.py:115: DataConversionWarning: A column-vector y was passed
when a 1d array was expected. Please change the shape of y to
(n_samples, ), for example using ravel().
```

```
y = column_or_1d(y, warn=True)
```

```
from sklearn import preprocessing
from sklearn import utils
```

```
#convert y values to categorical values
```

```
value = preprocessing.LabelEncoder()
```

```
Y_test_transformed = value.fit_transform(Y_test)
```

```
#view transformed values
```

```
print(Y_test_transformed)
```

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

Modelling (Scikit-Learn)

```
from sklearn import svm
```

```
clf = svm.SVC(kernel='rbf')
```

```
clf.fit(X_train, Y_train_transformed) # question and answers
```

```
SVC()
```

```
yhat = clf.predict(X_test) #question
```

```
yhat [0:5]
```

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

Evaluation

```
from sklearn.metrics import f1_score
```

```
f1_score(Y_test_transformed, yhat) #actualvale, predvalue
```

```
0.6923076923076923
```

```
from sklearn import svm
```

```
clf2 = svm.SVC(kernel='linear')
```

```
clf2.fit(X_train, Y_train_transformed)
```

```
yhat2 = clf2.predict(X_test)
```

```
yhat2
```

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

```
from sklearn.metrics import f1_score
```

```
f1_score(Y_test_transformed, yhat2) #actualvale,predvalue
```

```
0.7627118644067797
```

```
from sklearn import svm
```

```
clf = svm.SVC(kernel='poly')
```

```
clf.fit(X_train, Y_train_transformed) # question and answers
```

```
SVC(kernel='poly')
```

```
yhat3 = clf.predict(X_test) #question
```

```
yhat3 [0:5]
```

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

Evaluation

```
from sklearn.metrics import f1_score
```

```
f1_score(Y_test_transformed, yhat)
```

```
0.6923076923076923
```

Ans: The possible accuracy gives the kernel as linear that is 76.27%