

# Project\_Mercedes-Benz Greener Manufacturing

May 25, 2022

## 1 Mercedes-Benz Greener Manufacturing

```
[1]: # Import Require library

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

```
[2]: import warnings
warnings.filterwarnings('ignore')
```

### 1.0.1 Load the Train and Test dataset

```
[3]: # Load the "Train.csv" file

data_train = pd.read_csv('train.csv')
data_train.head()
```

```
[3]:
```

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	\
0	0	130.81	k	v	at	a	d	u	j	o	...	0	0	1	0	0	
1	6	88.53	k	t	av	e	d	y	l	o	...	1	0	0	0	0	
2	7	76.26	az	w	n	c	d	x	j	x	...	0	0	0	0	0	
3	9	80.62	az	t	n	f	d	x	l	e	...	0	0	0	0	0	
4	13	78.02	az	v	n	f	d	h	d	n	...	0	0	0	0	0	

	X380	X382	X383	X384	X385
0	0	0	0	0	0
1	0	0	0	0	0
2	0	1	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

[5 rows x 378 columns]

```
[4]: # Load the "Test.csv" file
```

```
data_test = pd.read_csv('test.csv')
data_test.head()
```

```
[4]:
```

	ID	X0	X1	X2	X3	X4	X5	X6	X8	X10	...	X375	X376	X377	X378	X379	X380	\
0	1	az	v	n	f	d	t	a	w	0	...	0	0	0	1	0	0	
1	2	t	b	ai	a	d	b	g	y	0	...	0	0	1	0	0	0	
2	3	az	v	as	f	d	a	j	j	0	...	0	0	0	1	0	0	
3	4	az	l	n	f	d	z	l	n	0	...	0	0	0	1	0	0	
4	5	w	s	as	c	d	y	i	m	0	...	1	0	0	0	0	0	

	X382	X383	X384	X385
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

[5 rows x 377 columns]

```
[5]: print('Train Data Size:',data_train.shape)
      print('Test Data Size:',data_test.shape)
```

Train Data Size: (4209, 378)

Test Data Size: (4209, 377)

## 1.0.2 Exploratory Data Analysis:

```
[6]: # Check the columns in Train dataset
```

```
data_train.columns
```

```
[6]: Index(['ID', 'y', 'X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8',
          ...,
          'X375', 'X376', 'X377', 'X378', 'X379', 'X380', 'X382', 'X383', 'X384',
          'X385'],
          dtype='object', length=378)
```

```
[7]: # Check the columns in Test dataset
```

```
data_test.columns
```

```
[7]: Index(['ID', 'X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8', 'X10',
          ...,
          'X375', 'X376', 'X377', 'X378', 'X379', 'X380', 'X382', 'X383', 'X384',
          'X385'],
          dtype='object', length=377)
```

```
[8]: # Check the information of train dataset
```

```
data_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 4209 entries, 0 to 4208  
Columns: 378 entries, ID to X385  
dtypes: float64(1), int64(369), object(8)  
memory usage: 12.1+ MB
```

```
[9]: # Check the information of test dataset
```

```
data_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 4209 entries, 0 to 4208  
Columns: 377 entries, ID to X385  
dtypes: int64(369), object(8)  
memory usage: 12.1+ MB
```

```
[10]: data_train.describe()
```

```
[10]:
```

	ID	y	X10	X11	X12	\
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	
mean	4205.960798	100.669318	0.013305	0.0	0.075077	
std	2437.608688	12.679381	0.114590	0.0	0.263547	
min	0.000000	72.110000	0.000000	0.0	0.000000	
25%	2095.000000	90.820000	0.000000	0.0	0.000000	
50%	4220.000000	99.150000	0.000000	0.0	0.000000	
75%	6314.000000	109.010000	0.000000	0.0	0.000000	
max	8417.000000	265.320000	1.000000	0.0	1.000000	

	X13	X14	X15	X16	X17	...	\
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	
mean	0.057971	0.428130	0.000475	0.002613	0.007603	...	
std	0.233716	0.494867	0.021796	0.051061	0.086872	...	
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	0.000000	0.000000	0.000000	0.000000	...	
75%	0.000000	1.000000	0.000000	0.000000	0.000000	...	
max	1.000000	1.000000	1.000000	1.000000	1.000000	...	

	X375	X376	X377	X378	X379	\
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	
mean	0.318841	0.057258	0.314802	0.020670	0.009503	
std	0.466082	0.232363	0.464492	0.142294	0.097033	
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	0.000000	0.000000	0.000000	0.000000
75%	1.000000	0.000000	1.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

	X380	X382	X383	X384	X385
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000
mean	0.008078	0.007603	0.001663	0.000475	0.001426
std	0.089524	0.086872	0.040752	0.021796	0.037734
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	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

[8 rows x 370 columns]

```
[11]: data_test.describe()
```

```
[11]:
```

	ID	X10	X11	X12	X13 \
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000
mean	4211.039202	0.019007	0.000238	0.074364	0.061060
std	2423.078926	0.136565	0.015414	0.262394	0.239468
min	1.000000	0.000000	0.000000	0.000000	0.000000
25%	2115.000000	0.000000	0.000000	0.000000	0.000000
50%	4202.000000	0.000000	0.000000	0.000000	0.000000
75%	6310.000000	0.000000	0.000000	0.000000	0.000000
max	8416.000000	1.000000	1.000000	1.000000	1.000000

	X14	X15	X16	X17	X18 ... \
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000 ...
mean	0.427893	0.000713	0.002613	0.008791	0.010216 ...
std	0.494832	0.026691	0.051061	0.093357	0.100570 ...
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	0.000000	0.000000	0.000000	0.000000 ...
75%	1.000000	0.000000	0.000000	0.000000	0.000000 ...
max	1.000000	1.000000	1.000000	1.000000	1.000000 ...

	X375	X376	X377	X378	X379 \
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000
mean	0.325968	0.049656	0.311951	0.019244	0.011879
std	0.468791	0.217258	0.463345	0.137399	0.108356
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	0.000000	0.000000	0.000000	0.000000
75%	1.000000	0.000000	1.000000	0.000000	0.000000

max	1.000000	1.000000	1.000000	1.000000	1.000000
	X380	X382	X383	X384	X385
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000
mean	0.008078	0.008791	0.000475	0.000713	0.001663
std	0.089524	0.093357	0.021796	0.026691	0.040752
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	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

[8 rows x 369 columns]

## 2 1. If for any column(s), the variance is equal to zero, then you need to remove those variable(s).

```
[12]: # Check the variance of train dataset
```

```
data_train.var()
```

```
[12]: ID      5.941936e+06
      y      1.607667e+02
      X10    1.313092e-02
      X11    0.000000e+00
      X12    6.945713e-02
      ...
      X380    8.014579e-03
      X382    7.546747e-03
      X383    1.660732e-03
      X384    4.750593e-04
      X385    1.423823e-03
      Length: 370, dtype: float64
```

```
[13]: # Check the variance of test dataset
```

```
data_test.var()
```

```
[13]: ID      5.871311e+06
      X10    1.865006e-02
      X11    2.375861e-04
      X12    6.885074e-02
      X13    5.734498e-02
      ...
      X380    8.014579e-03
      X382    8.715481e-03
```

```

X383    4.750593e-04
X384    7.124196e-04
X385    1.660732e-03
Length: 369, dtype: float64

```

```
[14]: # Check variance is equal to zero variables from train dataset
```

```
data_train.var()[data_train.var() == 0].index.values
```

```
[14]: array(['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290',
        'X293', 'X297', 'X330', 'X347'], dtype=object)
```

```
[15]: # Check variance is equal to zero variables from test dataset
```

```
data_test.var()[data_test.var() == 0].index.values
```

```
[15]: array(['X257', 'X258', 'X295', 'X296', 'X369'], dtype=object)
```

```
[16]: # Removed the variance is equal to zero variables from train dataset
```

```
data_train = data_train.drop(['X11', 'X93', 'X107', 'X233', 'X235', 'X268',
    ↪ 'X289', 'X290',
                                'X293', 'X297', 'X330', 'X347'],axis=1)
data_train.head()
```

```
[16]:
```

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	\
0	0	130.81	k	v	at	a	d	u	j	o	...	0	0	1	0	0	
1	6	88.53	k	t	av	e	d	y	l	o	...	1	0	0	0	0	
2	7	76.26	az	w	n	c	d	x	j	x	...	0	0	0	0	0	
3	9	80.62	az	t	n	f	d	x	l	e	...	0	0	0	0	0	
4	13	78.02	az	v	n	f	d	h	d	n	...	0	0	0	0	0	

	X380	X382	X383	X384	X385
0	0	0	0	0	0
1	0	0	0	0	0
2	0	1	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

```
[5 rows x 366 columns]
```

```
[17]: # Removed the variance is equal to zero variables from test dataset
```

```
data_test = data_test.drop(['X11', 'X93', 'X107', 'X233', 'X235', 'X268',
    ↪ 'X289', 'X290',
                                'X293', 'X297', 'X330', 'X347'],axis=1)
data_test.head()
```

```
[17]:
```

	ID	X0	X1	X2	X3	X4	X5	X6	X8	X10	...	X375	X376	X377	X378	X379	X380	\
0	1	az	v	n	f	d	t	a	w	0	...	0	0	0	1	0	0	
1	2	t	b	ai	a	d	b	g	y	0	...	0	0	1	0	0	0	
2	3	az	v	as	f	d	a	j	j	0	...	0	0	0	1	0	0	
3	4	az	l	n	f	d	z	l	n	0	...	0	0	0	1	0	0	
4	5	w	s	as	c	d	y	i	m	0	...	1	0	0	0	0	0	

	X382	X383	X384	X385
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

[5 rows x 365 columns]

```
[18]: # After removal variance is equal to zero check the shape of the train dataset
data_train.shape
```

```
[18]: (4209, 366)
```

```
[19]: # After removal variance is equal to zero check the shape of the test dataset
data_test.shape
```

```
[19]: (4209, 365)
```

```
[20]: data_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4209 entries, 0 to 4208
Columns: 366 entries, ID to X385
dtypes: float64(1), int64(357), object(8)
memory usage: 11.8+ MB
```

### 3 2. Check for null and unique values for test and train sets.

```
[21]: # Check the unique value of train dataset.

for columns in data_train:
    print('Train data Unique Values:',columns,data_train[columns].unique(),
          'Train data Unique Value Shape:',data_train[columns].unique().shape)
```

```
Train data Unique Values: ID [ 0 6 7 ... 8412 8415 8417] Train data
Unique Value Shape: (4209,)
Train data Unique Values: y [130.81 88.53 76.26 ... 85.71 108.77 87.48]
```

```

Train data Unique Value Shape: (2545,)
Train data Unique Values: X0 ['k' 'az' 't' 'al' 'o' 'w' 'j' 'h' 's' 'n' 'ay' 'f'
'x' 'y' 'aj' 'ak' 'am'
'z' 'q' 'at' 'ap' 'v' 'af' 'a' 'e' 'ai' 'd' 'aq' 'c' 'aa' 'ba' 'as' 'i'
'r' 'b' 'ax' 'bc' 'u' 'ad' 'au' 'm' 'l' 'aw' 'ao' 'ac' 'g' 'ab'] Train data
Unique Value Shape: (47,)
Train data Unique Values: X1 ['v' 't' 'w' 'b' 'r' 'l' 's' 'aa' 'c' 'a' 'e' 'h'
'z' 'j' 'o' 'u' 'p' 'n'
'i' 'y' 'd' 'f' 'm' 'k' 'g' 'q' 'ab'] Train data Unique Value Shape: (27,)
Train data Unique Values: X2 ['at' 'av' 'n' 'e' 'as' 'aq' 'r' 'ai' 'ak' 'm' 'a'
'k' 'ae' 's' 'f' 'd'
'ag' 'ay' 'ac' 'ap' 'g' 'i' 'aw' 'y' 'b' 'ao' 'al' 'h' 'x' 'au' 't' 'an'
'z' 'ah' 'p' 'am' 'j' 'q' 'af' 'l' 'aa' 'c' 'o' 'ar'] Train data Unique Value
Shape: (44,)
Train data Unique Values: X3 ['a' 'e' 'c' 'f' 'd' 'b' 'g'] Train data Unique
Value Shape: (7,)
Train data Unique Values: X4 ['d' 'b' 'c' 'a'] Train data Unique Value Shape:
(4,)
Train data Unique Values: X5 ['u' 'y' 'x' 'h' 'g' 'f' 'j' 'i' 'd' 'c' 'af' 'ag'
'ab' 'ac' 'ad' 'ae'
'ah' 'l' 'k' 'n' 'm' 'p' 'q' 's' 'r' 'v' 'w' 'o' 'aa'] Train data Unique Value
Shape: (29,)
Train data Unique Values: X6 ['j' 'l' 'd' 'h' 'i' 'a' 'g' 'c' 'k' 'e' 'f' 'b']
Train data Unique Value Shape: (12,)
Train data Unique Values: X8 ['o' 'x' 'e' 'n' 's' 'a' 'h' 'p' 'm' 'k' 'd' 'i'
'v' 'j' 'b' 'q' 'w' 'g'
'y' 'l' 'f' 'u' 'r' 't' 'c'] Train data Unique Value Shape: (25,)
Train data Unique Values: X10 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X12 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X13 [1 0] Train data Unique Value Shape: (2,)
Train data Unique Values: X14 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X15 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X16 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X17 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X18 [1 0] Train data Unique Value Shape: (2,)
Train data Unique Values: X19 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X20 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X21 [1 0] Train data Unique Value Shape: (2,)
Train data Unique Values: X22 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X23 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X24 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X26 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X27 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X28 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X29 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X30 [0 1] Train data Unique Value Shape: (2,)
Train data Unique Values: X31 [1 0] Train data Unique Value Shape: (2,)
Train data Unique Values: X32 [0 1] Train data Unique Value Shape: (2,)

```



[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]



```
[22]: # Check the unique value of test dataset.
```

```
for columns in data_test:
    print('Test Data Unique Values:',columns,data_test[columns].unique(),
          'Test Data Unique Value Shape:',data_test[columns].unique().shape)
```

```
Test Data Unique Values: ID [ 1 2 3 ... 8413 8414 8416] Test Data Unique
Value Shape: (4209,)
Test Data Unique Values: X0 ['az' 't' 'w' 'y' 'x' 'f' 'ap' 'o' 'ay' 'al' 'h' 'z'
'aj' 'd' 'v' 'ak'
'ba' 'n' 'j' 's' 'af' 'ax' 'at' 'aq' 'av' 'm' 'k' 'a' 'e' 'ai' 'i' 'ag'
'b' 'am' 'aw' 'as' 'r' 'ao' 'u' 'l' 'c' 'ad' 'au' 'bc' 'g' 'an' 'ae' 'p'
'bb'] Test Data Unique Value Shape: (49,)
Test Data Unique Values: X1 ['v' 'b' 'l' 's' 'aa' 'r' 'a' 'i' 'p' 'c' 'o' 'm'
'z' 'e' 'h' 'w' 'g' 'k'
'y' 't' 'u' 'd' 'j' 'q' 'n' 'f' 'ab'] Test Data Unique Value Shape: (27,)
Test Data Unique Values: X2 ['n' 'ai' 'as' 'ae' 's' 'b' 'e' 'ak' 'm' 'a' 'aq'
'ag' 'r' 'k' 'aj' 'ay'
'ao' 'an' 'ac' 'af' 'ax' 'h' 'i' 'f' 'ap' 'p' 'au' 't' 'z' 'y' 'aw' 'd'
'at' 'g' 'am' 'j' 'x' 'ab' 'w' 'q' 'ah' 'ad' 'al' 'av' 'u'] Test Data Unique
Value Shape: (45,)
Test Data Unique Values: X3 ['f' 'a' 'c' 'e' 'd' 'g' 'b'] Test Data Unique Value
Shape: (7,)
Test Data Unique Values: X4 ['d' 'b' 'a' 'c'] Test Data Unique Value Shape: (4,)
Test Data Unique Values: X5 ['t' 'b' 'a' 'z' 'y' 'x' 'h' 'g' 'f' 'j' 'i' 'd' 'c'
'af' 'ag' 'ab' 'ac'
'ad' 'ae' 'ah' 'l' 'k' 'n' 'm' 'p' 'q' 's' 'r' 'v' 'w' 'o' 'aa'] Test Data
Unique Value Shape: (32,)
Test Data Unique Values: X6 ['a' 'g' 'j' 'l' 'i' 'd' 'f' 'h' 'c' 'k' 'e' 'b']
Test Data Unique Value Shape: (12,)
Test Data Unique Values: X8 ['w' 'y' 'j' 'n' 'm' 's' 'a' 'v' 'r' 'o' 't' 'h' 'c'
'k' 'p' 'u' 'd' 'g'
'b' 'q' 'e' 'l' 'f' 'i' 'x'] Test Data Unique Value Shape: (25,)
Test Data Unique Values: X10 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X12 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X13 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X14 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X15 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X16 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X17 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X18 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X19 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X20 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X21 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X22 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X23 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X24 [0 1] Test Data Unique Value Shape: (2,)
```



[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```

Test Data Unique Values: X379 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X380 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X382 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X383 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X384 [0 1] Test Data Unique Value Shape: (2,)
Test Data Unique Values: X385 [0 1] Test Data Unique Value Shape: (2,)

```

```
[23]: # Check null (NaN) or Missing value in train dataset.
```

```
data_train.isna().any()
```

```

[23]: ID      False
      y      False
      X0      False
      X1      False
      X2      False
      ...
      X380    False
      X382    False
      X383    False
      X384    False
      X385    False
      Length: 366, dtype: bool

```

```
[24]: data_train.isna().sum().any()
```

```
[24]: False
```

```
[25]: # Check null (NaN) of Missing value in test dataset.
```

```
data_test.isna().any()
```

```

[25]: ID      False
      X0      False
      X1      False
      X2      False
      X3      False
      ...
      X380    False
      X382    False
      X383    False
      X384    False
      X385    False
      Length: 365, dtype: bool

```

```
[26]: data_test.isna().sum().any()
```



[26]: False

- As we can say that there is no Null (NaN or Missing values) values available in Train as well as Test dataset.

```
[27]: data_train.isna().any()[data_train.isna().any()].index.values
```

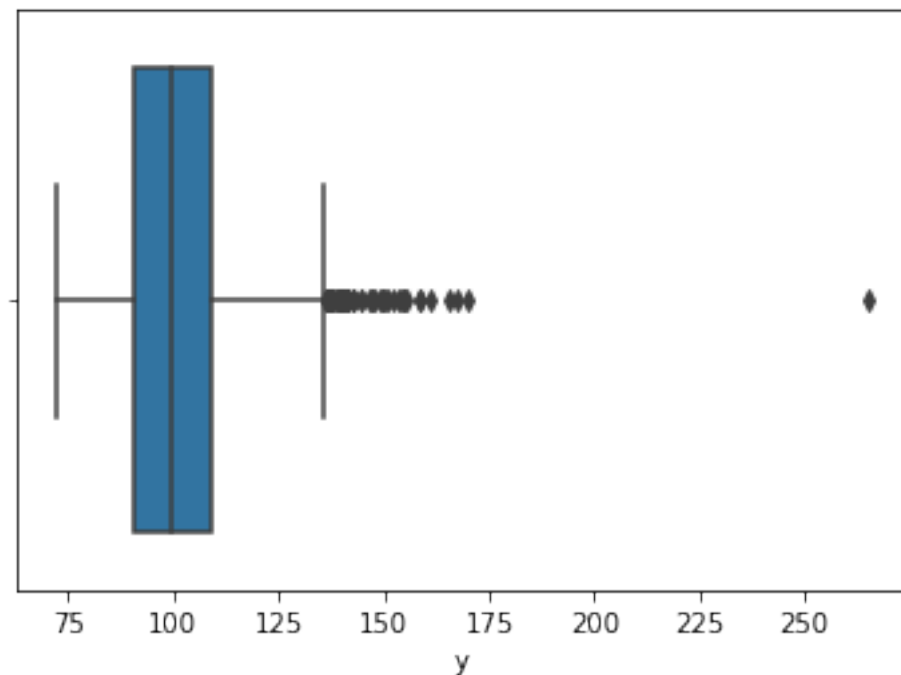
[27]: array([], dtype=object)

```
[28]: data_test.isna().any()[data_test.isna().any()].index.values
```

[28]: array([], dtype=object)

```
[29]: # Find out the outliers in dataset  
sns.boxplot(data_train['y'])
```

[29]: <AxesSubplot:xlabel='y'>



```
[30]: # Treatment on outliers  
  
#Import required library  
  
from scipy import stats
```

```

iqr = stats.iqr(data_train['y'])

q1 = data_train['y'].quantile(0.25)
q3 = data_train['y'].quantile(0.75)

upperbound = q3 + 1.5*(iqr)
lowerbound = q1 - 1.5*(iqr)

print('Q1 is:',q1)
print('Q3 is:',q3)
print('Upper Bound is:',upperbound)
print('Lower Bound is:',lowerbound)

```

```

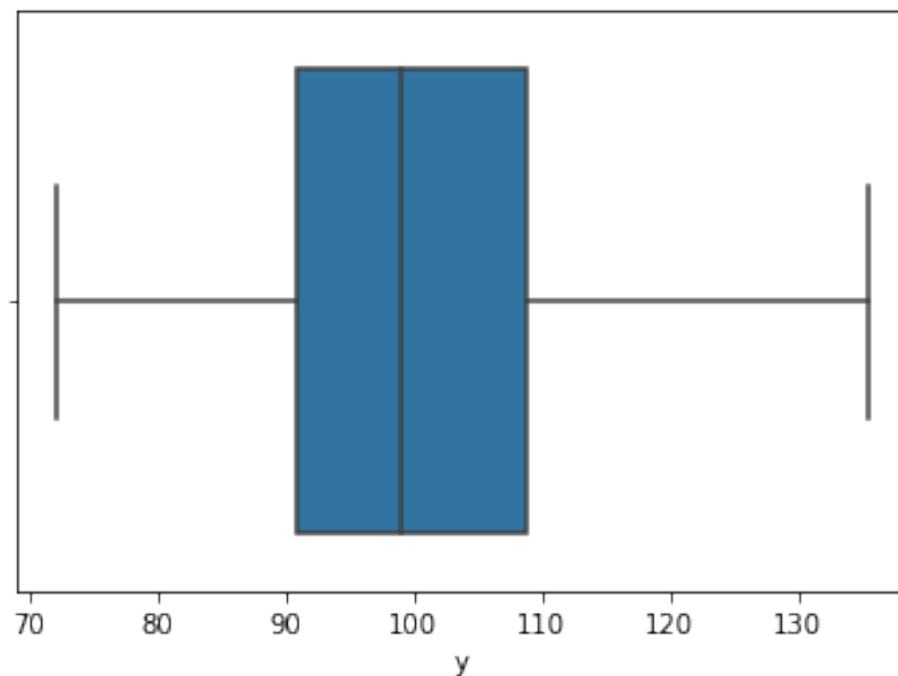
Q1 is: 90.82
Q3 is: 109.01
Upper Bound is: 136.29500000000002
Lower Bound is: 63.534999999999975

```

```
[31]: data_train = data_train[(data_train['y']<136.295)]
```

```
[32]: sns.boxplot(data_train['y'])
```

```
[32]: <AxesSubplot:xlabel='y'>
```



- Outliers found in higher side in y column hence removed the outliers from the train dataset

```
[33]: # Check the correlation between the train dataset.
```

```
data_train.corr()
```

```
[33]:
```

	ID	y	X10	X12	X13	X14	X15	\
ID	1.000000	-0.050630	0.001390	0.059408	-0.035614	-0.026758	0.002207	
y	-0.050630	1.000000	-0.024244	0.089837	0.052033	0.216901	0.026882	
X10	0.001390	-0.024244	1.000000	-0.033155	-0.028975	-0.101005	-0.002563	
X12	0.059408	0.089837	-0.033155	1.000000	0.215648	-0.245361	-0.006225	
X13	-0.035614	0.052033	-0.028975	0.215648	1.000000	-0.085463	-0.005440	
...	...	...	...	...	...	...	...	
X380	-0.013824	0.050207	-0.010606	-0.005432	0.023198	0.007861	-0.001991	
X382	-0.038549	-0.173845	-0.010287	-0.024990	-0.021839	0.012860	-0.001931	
X383	-0.006331	-0.002986	-0.004053	-0.009846	-0.008605	0.026104	-0.000761	
X384	-0.015481	-0.004021	-0.002563	-0.006225	0.041500	0.025370	-0.000481	
X385	0.029146	-0.022945	-0.004441	-0.010787	-0.009427	0.043964	-0.000834	
	X16	X17	X18	...	X375	X376	X377	\
ID	-0.036778	-0.038549	-0.030057	...	0.046756	-0.083687	-0.023784	
y	0.057175	-0.173845	-0.008593	...	0.031648	0.125295	0.065368	
X10	-0.006016	-0.010287	-0.010287	...	0.166474	-0.028719	-0.074593	
X12	-0.014614	-0.024990	-0.024990	...	-0.111403	-0.069763	0.030725	
X13	-0.012772	-0.021839	-0.010061	...	-0.169490	-0.060967	0.357497	
...	...	...	...	...	...	...	...	
X380	-0.004675	-0.007994	-0.007994	...	-0.062043	-0.022318	-0.061460	
X382	-0.004535	1.000000	0.086723	...	-0.060176	-0.021646	-0.059610	
X383	-0.001787	-0.003055	-0.003055	...	-0.008814	-0.008528	0.021355	
X384	-0.001130	-0.001931	-0.001931	...	-0.014990	-0.005392	0.008776	
X385	-0.001957	-0.003347	-0.003347	...	0.055620	-0.009344	-0.025731	
	X378	X379	X380	X382	X383	X384	X385	
ID	0.030264	0.022330	-0.013824	-0.038549	-0.006331	-0.015481	0.029146	
y	-0.281230	0.069033	0.050207	-0.173845	-0.002986	-0.004021	-0.022945	
X10	-0.017077	-0.011367	-0.010606	-0.010287	-0.004053	-0.002563	-0.004441	
X12	-0.015895	-0.027612	-0.005432	-0.024990	-0.009846	-0.006225	-0.010787	
X13	-0.036252	-0.024130	0.023198	-0.021839	-0.008605	0.041500	-0.009427	
...	...	...	...	...	...	...	...	
X380	-0.013270	-0.008833	1.000000	-0.007994	-0.003150	-0.001991	-0.003451	
X382	-0.012871	-0.008567	-0.007994	1.000000	-0.003055	-0.001931	-0.003347	
X383	-0.005071	-0.003375	-0.003150	-0.003055	1.000000	-0.000761	-0.001319	
X384	-0.003206	-0.002134	-0.001991	-0.001931	-0.000761	1.000000	-0.000834	
X385	-0.005556	-0.003698	-0.003451	-0.003347	-0.001319	-0.000834	1.000000	

[358 rows x 358 columns]

```
[34]: # Check the correlation between the test dataset.
```

```
data_test.corr()
```

```
[34]:
```

	ID	X10	X12	X13	X14	X15	X16	\
ID	1.000000	-0.016166	0.043162	0.017910	-0.036099	0.005100	-0.024482	
X10	-0.016166	1.000000	-0.039453	-0.035496	-0.120379	-0.003717	-0.007125	
X12	0.043162	-0.039453	1.000000	0.283228	-0.245127	-0.007570	-0.014509	
X13	0.017910	-0.035496	0.283228	1.000000	-0.076145	-0.006811	-0.013054	
X14	-0.036099	-0.120379	-0.245127	-0.076145	1.000000	-0.023097	-0.044269	
...	...	...	...	...	...	...	...	
X380	0.012520	-0.012561	-0.025578	0.054582	0.007787	-0.002410	-0.004619	
X382	-0.021581	-0.013108	-0.016991	-0.024015	0.000864	-0.002515	-0.004821	
X383	-0.001625	-0.003035	-0.006180	-0.005560	0.025212	-0.000582	-0.001116	
X384	0.013948	-0.003717	-0.007570	-0.006811	0.030881	-0.000713	-0.001367	
X385	0.026357	-0.005681	-0.011569	-0.010408	0.047195	-0.001090	-0.002089	
	X17	X18	X19	...	X375	X376	X377	\
ID	-0.021581	-0.010920	-0.020800	...	0.024007	-0.087891	0.004271	
X10	-0.013108	-0.014142	-0.049351	...	0.189023	-0.031817	-0.086214	
X12	-0.016991	-0.028796	-0.100493	...	-0.148812	-0.064790	0.080843	
X13	-0.024015	-0.025908	-0.090413	...	-0.177340	-0.058291	0.359450	
X14	0.000864	-0.087862	-0.306620	...	0.107496	0.043260	-0.139742	
...	...	...	...	...	...	...	...	
X380	-0.008498	0.043621	-0.023568	...	-0.062756	-0.020628	-0.060764	
X382	1.000000	0.066366	-0.033389	...	-0.065490	-0.021526	-0.063411	
X383	-0.002053	-0.002215	-0.007730	...	-0.015163	-0.004984	0.008850	
X384	-0.002515	-0.002713	-0.009469	...	0.000420	-0.006105	0.020448	
X385	-0.003844	-0.004147	-0.014471	...	0.058691	-0.009330	-0.027482	
	X378	X379	X380	X382	X383	X384	X385	
ID	-0.002939	0.031762	0.012520	-0.021581	-0.001625	0.013948	0.026357	
X10	-0.019498	-0.015262	-0.012561	-0.013108	-0.003035	-0.003717	-0.005681	
X12	-0.006747	-0.022720	-0.025578	-0.016991	-0.006180	-0.007570	-0.011569	
X13	-0.035722	-0.027961	0.054582	-0.024015	-0.005560	-0.006811	-0.010408	
X14	-0.051238	0.113487	0.007787	0.000864	0.025212	0.030881	0.047195	
...	...	...	...	...	...	...	...	
X380	-0.012641	-0.009895	1.000000	-0.008498	-0.001968	-0.002410	-0.003683	
X382	-0.013192	-0.010326	-0.008498	1.000000	-0.002053	-0.002515	-0.003844	
X383	-0.003054	-0.002391	-0.001968	-0.002053	1.000000	-0.000582	-0.000890	
X384	-0.003741	-0.002928	-0.002410	-0.002515	-0.000582	1.000000	-0.001090	
X385	-0.005717	-0.004475	-0.003683	-0.003844	-0.000890	-0.001090	1.000000	

```
[357 rows x 357 columns]
```

```
[35]: # ID column not required for modeling hence removed from both dataset.
```

```
data_train.drop('ID',axis=1,inplace=True)
data_test.drop('ID',axis=1,inplace=True)
```

```
[36]: # Shuffle or Split the train dataset in input and output feature.
```

```
features = data_train.drop('y',axis=1)
target = data_train[['y']]
```

## 4 3. Apply label encoder.

### 4.0.1 Train Dataset

```
[37]: # Find out the categorical values in train dataset.
```

```
dictionary={}
dictionary['categorical']=features.dtypes[features.dtypes=='object'].index
dictionary
```

```
[37]: {'categorical': Index(['X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8'],
dtype='object')}
```

- In train data found some columns in categorical form so convert in numerical form by using Label Encoder

```
[38]: # Categorical value convert in numeric form for modeling by using Label Encoder
↳ (Ordinal)
```

```
from sklearn.preprocessing import LabelEncoder
```

```
[39]: le_X0 = LabelEncoder()
le_X1 = LabelEncoder()
le_X2 = LabelEncoder()
le_X3 = LabelEncoder()
le_X4 = LabelEncoder()
le_X5 = LabelEncoder()
le_X6 = LabelEncoder()
le_X8 = LabelEncoder()
```

```
[40]: features['X0'] = le_X0.fit_transform(features['X0'])
features['X1'] = le_X1.fit_transform(features['X1'])
features['X2'] = le_X2.fit_transform(features['X2'])
features['X3'] = le_X3.fit_transform(features['X3'])
features['X4'] = le_X4.fit_transform(features['X4'])
features['X5'] = le_X5.fit_transform(features['X5'])
features['X6'] = le_X6.fit_transform(features['X6'])
features['X8'] = le_X8.fit_transform(features['X8'])
```

```
[41]: features.head(10)
```

```
[41]:
```

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	...	X375	X376	X377	X378	\
0	32	23	16	0	3	24	9	14	0	0	...	0	0	1	0	
1	32	21	18	4	3	28	11	14	0	0	...	1	0	0	0	
2	20	24	33	2	3	27	9	23	0	0	...	0	0	0	0	
3	20	21	33	5	3	27	11	4	0	0	...	0	0	0	0	
4	20	23	33	5	3	12	3	13	0	0	...	0	0	0	0	
5	40	3	24	2	3	11	7	18	0	0	...	0	0	1	0	
6	9	19	24	5	3	10	7	18	0	0	...	0	0	0	0	
7	36	13	15	5	3	10	9	0	0	0	...	0	0	0	0	
8	43	20	15	4	3	10	8	7	0	0	...	1	0	0	0	
9	31	3	13	2	3	10	0	4	0	0	...	0	0	1	0	

	X379	X380	X382	X383	X384	X385
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	1	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	0	0	0	0	0	0

[10 rows x 364 columns]

#### 4.0.2 Test Dataset

```
[42]: dictionary={}
dictionary['cat']=data_test.dtypes[data_test.dtypes=='object'].index
dictionary
```

```
[42]: {'cat': Index(['X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8'], dtype='object')}
```

- In test data found some columns in categorical form so convert in numerical form by using Label Encoder

```
[43]: le_X0 = LabelEncoder()
le_X1 = LabelEncoder()
le_X2 = LabelEncoder()
le_X3 = LabelEncoder()
le_X4 = LabelEncoder()
le_X5 = LabelEncoder()
le_X6 = LabelEncoder()
le_X8 = LabelEncoder()
```

```
[44]: data_test['X0'] = le_X0.fit_transform(data_test['X0'])
data_test['X1'] = le_X1.fit_transform(data_test['X1'])
data_test['X2'] = le_X2.fit_transform(data_test['X2'])
data_test['X3'] = le_X3.fit_transform(data_test['X3'])
data_test['X4'] = le_X4.fit_transform(data_test['X4'])
data_test['X5'] = le_X5.fit_transform(data_test['X5'])
data_test['X6'] = le_X6.fit_transform(data_test['X6'])
data_test['X8'] = le_X8.fit_transform(data_test['X8'])
```

```
[45]: data_test.head(10)
```

```
[45]:
```

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	...	X375	X376	X377	X378	\
0	21	23	34	5	3	26	0	22	0	0	...	0	0	0	1	
1	42	3	8	0	3	9	6	24	0	0	...	0	0	1	0	
2	21	23	17	5	3	0	9	9	0	0	...	0	0	0	1	
3	21	13	34	5	3	31	11	13	0	0	...	0	0	0	1	
4	45	20	17	2	3	30	8	12	0	0	...	1	0	0	0	
5	47	1	8	4	3	29	6	18	0	0	...	1	0	0	0	
6	46	3	4	3	3	29	3	24	0	0	...	0	0	0	0	
7	29	20	4	2	3	14	3	0	0	0	...	0	0	1	0	
8	12	13	38	2	3	14	9	13	0	0	...	0	0	0	0	
9	38	23	17	5	3	13	5	21	0	0	...	0	0	0	0	

	X379	X380	X382	X383	X384	X385
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	1	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	0	0	0	0	0	0

[10 rows x 364 columns]

```
[46]: # More variation in dataset hence rescaling the values by using standard scaler
      ↪ (range 0 to 1).

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

features = scaler.fit_transform(features)
```

```
[47]: # Import required library

from sklearn.model_selection import train_test_split

# Split the train dataset in training and testing from.

xtrain,xtest,ytrain,ytest = train_test_split(features,target,test_size=0.
↪25,random_state=10)
```

```
[48]: # Check shape of the data.
```

```
print(xtrain.shape)
print(xtest.shape)
print(ytrain.shape)
print(ytest.shape)
```

```
(3119, 364)
(1040, 364)
(3119, 1)
(1040, 1)
```

## 5 4. Perform dimensionality reduction (PCA).

```
[49]: # Import required library

from sklearn.decomposition import PCA
```

```
[50]: pca = PCA(n_components=0.95)
```

```
[51]: xtrain_transform = pca.fit_transform(xtrain)
xtest_transform = pca.transform(xtest)
```

```
[52]: pca.explained_variance_ratio_
```

```
[52]: array([0.07019274, 0.05729392, 0.04609237, 0.03515298, 0.03375958,
0.03292353, 0.02905596, 0.02185832, 0.02104466, 0.0177154 ,
0.01656399, 0.01553658, 0.01492109, 0.01405254, 0.01393377,
0.01305241, 0.01184265, 0.01118177, 0.01083652, 0.01068139,
0.01012464, 0.00943591, 0.0088153 , 0.00873972, 0.00813892,
0.00795704, 0.00786851, 0.00752673, 0.0074265 , 0.00727647,
0.00693622, 0.00674369, 0.00669274, 0.00652471, 0.00644761,
0.00623725, 0.00609012, 0.00592114, 0.00580969, 0.00577976,
0.00556441, 0.00549373, 0.00542699, 0.00520633, 0.00516627,
0.0050948 , 0.00497358, 0.00495062, 0.00489009, 0.00471821,
0.00466741, 0.00463163, 0.00453932, 0.00444688, 0.00435878,
0.00430327, 0.00423754, 0.00416412, 0.00412734, 0.00409017,
```



```
0.00406457, 0.00400174, 0.00396979, 0.0039042 , 0.00385469,
0.00381901, 0.0037737 , 0.00373333, 0.00366122, 0.00358136,
0.0035554 , 0.00349281, 0.00348558, 0.00340535, 0.00337646,
0.00334585, 0.00333005, 0.00328155, 0.00320043, 0.00317289,
0.00314952, 0.00311033, 0.00309291, 0.0030509 , 0.00302206,
0.00297985, 0.00292358, 0.00287127, 0.00282779, 0.00281652,
0.00278533, 0.00275123, 0.00272304, 0.00268221, 0.00266552,
0.00263688, 0.00260685, 0.00256342, 0.00255046, 0.00252926,
0.00251445, 0.0024949 , 0.00245533, 0.00244842, 0.00242278,
0.00239232, 0.00236028, 0.00234539, 0.00230195, 0.00228297,
0.00226582, 0.00221066, 0.00220342, 0.00215847, 0.00211229,
0.00211003, 0.00207315, 0.00204617, 0.00199182, 0.00195448,
0.00194303, 0.00191564, 0.00187583, 0.0018657 , 0.0018458 ,
0.00181042, 0.00177961, 0.0017544 , 0.0017379 , 0.00171343,
0.00168156, 0.00167204, 0.00164478, 0.00161469, 0.00159322,
0.00155612, 0.0015177 , 0.00149996, 0.00146936, 0.00143128,
0.00140798, 0.00139064, 0.00137898])
```

```
[53]: print(xtrain_transform.shape)
      print(xtest_transform.shape)
```

```
(3119, 143)
(1040, 143)
```

```
[54]: xtrain_transform
```

```
[54]: array([[10.61283975, -2.47702013,  0.82357088, ...,  0.53083803,
          0.29588805, -1.14707981],
        [-2.17584734, -1.08495605,  0.59481737, ..., -0.12867998,
          0.01131092,  0.4324378 ],
        [-2.73604686,  0.15089878,  2.7461672 , ...,  0.40397308,
         -0.07231659, -0.28202867],
        ...,
        [-2.12381216, -3.91014979, -6.81306636, ..., -0.53600069,
          0.27311935,  0.23946768],
        [-1.09391938,  0.32794205,  2.96897123, ..., -0.56746158,
         -0.6645795 , -1.05995913],
        [-0.29338825, -1.43396707, -3.31466989, ...,  0.85925952,
          0.24446146, -0.60080401]])
```

```
[55]: # Linear Regression applied
      #Import required library

      from sklearn.linear_model import LinearRegression
```

```
[56]: model = LinearRegression()
```

```
model.fit(xtrain_transform,ytrain)
ypred = model.predict(xtest_transform)
```

```
[57]: from sklearn.metrics import
      ↪mean_absolute_error,mean_squared_error,r2_score,accuracy_score
```

```
[58]: print('Mean Absolute Error = ',mean_absolute_error(ytest,ypred))
      print('Mean Squared Error = ',mean_squared_error(ytest,ypred))
      print('Root Mean Squared Error = ',np.sqrt(mean_squared_error(ytest,ypred)))
      print('R2 Score = ',r2_score(ytest,ypred))
```

```
Mean Absolute Error =  5.159089114357101
Mean Squared Error =  51.137287254097004
Root Mean Squared Error =  7.151033998947075
R2 Score =  0.6069512538830951
```

- Got R2 score is 0.6069 by applying Linear Regression.

## 6 5. Predict your test\_df values using XGBoost.

```
[59]: #Import required library

      from xgboost import XGBRegressor
```

```
[60]: xgb_rg = XGBRegressor(booster = 'gblinear')
```

```
[61]: xgb_rg.fit(xtrain_transform, ytrain)
```

```
[61]: XGBRegressor(base_score=0.5, booster='gblinear', colsample_bylevel=None,
                  colsample_bynode=None, colsample_bytree=None,
                  enable_categorical=False, gamma=None, gpu_id=-1,
                  importance_type=None, interaction_constraints=None,
                  learning_rate=0.5, max_delta_step=None, max_depth=None,
                  min_child_weight=None, missing=nan, monotone_constraints=None,
                  n_estimators=100, n_jobs=4, num_parallel_tree=None, predictor=None,
                  random_state=0, reg_alpha=0, reg_lambda=0, scale_pos_weight=1,
                  subsample=None, tree_method=None, validate_parameters=1,
                  verbosity=None)
```

```
[62]: xgb_preds = xgb_rg.predict(xtest_transform)
```

```
[63]: print('Mean Absolute Error = ',mean_absolute_error(xgb_preds,ytest))
      print('Mean Squared Error = ',mean_squared_error(xgb_preds, ytest))
      print('Root Mean Squared Error = ',np.sqrt(mean_squared_error(xgb_preds,
      ↪ytest)))
      print('R2 Score = ',r2_score(ytest,xgb_preds))
```

```
Mean Absolute Error = 5.159087237724891
Mean Squared Error = 51.13726496280257
Root Mean Squared Error = 7.151032440340526
R2 Score = 0.6069514252172781
```

- Got R2 score is 0.6069 by applying XGBoost (XGBRegressor).

```
[64]: # Applied Ridge Regressor (for checking R2 score)
```

```
from sklearn.linear_model import Ridge
```

```
[65]: ridge_model = Ridge()
```

```
[66]: ridge_model.fit(xtrain_transform,ytrain)
```

```
[66]: Ridge()
```

```
[67]: ridge_preds = ridge_model.predict(xtest_transform)
```

```
[68]: print('Mean Absolute Error = ',mean_absolute_error(ridge_preds,ytest))
      print('Mean Squared Error = ',mean_squared_error(ridge_preds, ytest))
      print('Root Mean Squared Error = ',np.sqrt(mean_squared_error(ridge_preds,
      ↪ytest)))
      print('R2 Score = ',r2_score(ytest,ridge_preds))
```

```
Mean Absolute Error = 5.159036828040949
Mean Squared Error = 51.135617930582214
Root Mean Squared Error = 7.1509172789637425
R2 Score = 0.6069640845502967
```

- Got R2 score is 0.6069 by applying Ridge Regressor.
- R2 score values found same in Linear Regressor, XGBoost and Ridge Regressor.

### 6.0.1 Find out the predicted values by using XGBoost on test data

```
[69]: pca.fit(data_test)
```

```
[69]: PCA(n_components=0.95)
```

```
[70]: test_transform = pca.transform(data_test)
```

```
[71]: pred_xgbr = xgb_rg.predict(test_transform)
```

```
[72]: pred_xgbr
```

```
[72]: array([112.495605, 103.38444 , 85.74017 , ..., 81.08352 , 104.7797 ,
          91.61079 ], dtype=float32)
```

```
[73]: pred_xgbr.shape
```

```
[73]: (4209,)
```

```
[74]: preds_xgbreg = pd.DataFrame(pred_xgbr, index = data_test.index)
preds_xgbreg = preds_xgbreg.rename(columns = {0:'Predict_values'})
```

```
[75]: # Predicted values by using XGBoost

preds_xgbreg
```

```
[75]:      Predict_values
0      112.495605
1      103.384438
2       85.740173
3      107.230255
4      104.222031
...
4204     97.012054
4205     93.501297
4206     81.083519
4207    104.779701
4208     91.610786

[4209 rows x 1 columns]
```

```
[76]: test_predict = pd.concat([data_test,preds_xgbreg],axis = 1)
test_predict
```

```
[76]:      X0  X1  X2  X3  X4  X5  X6  X8  X10  X12  ...  X376  X377  X378  X379  \
0      21  23  34   5   3  26   0  22   0   0  ...   0    0    1    0
1      42   3   8   0   3   9   6  24   0   0  ...   0    1    0    0
2      21  23  17   5   3   0   9   9   0   0  ...   0    0    1    0
3      21  13  34   5   3  31  11  13   0   0  ...   0    0    1    0
4      45  20  17   2   3  30   8  12   0   0  ...   0    0    0    0
...
4204     6   9  17   5   3   1   9   4   0   0  ...   0    0    0    0
4205    42   1   8   3   3   1   9  24   0   0  ...   1    0    0    0
4206    47  23  17   5   3   1   3  22   0   0  ...   0    0    0    0
4207     7  23  17   0   3   1   2  16   0   0  ...   0    1    0    0
4208    42   1   8   2   3   1   6  17   0   0  ...   0    0    0    0

      X380  X382  X383  X384  X385  Predict_values
0         0     0     0     0     0      112.495605
1         0     0     0     0     0      103.384438
2         0     0     0     0     0       85.740173
3         0     0     0     0     0      107.230255
```

4		0	0	0	0	0	104.222031
...	...	...	...	...	...	...	
4204		0	0	0	0	0	97.012054
4205		0	0	0	0	0	93.501297
4206		0	0	0	0	0	81.083519
4207		0	0	0	0	0	104.779701
4208		0	0	0	0	0	91.610786

[4209 rows x 365 columns]

[ ]: