MERCEDEZ BENZ PROJECT 1

In [7]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

pd.set_option("display.max.columns", None)
```

In [8]:
```
##Importing Data Set
traindata = pd.read_csv("/Downloads/input/mercedes-benz-greener-manufacturing/test.c
testdata = pd.read_csv("/Downloads/input/mercedes-benz-greener-manufacturing/test.cs

submission = pd.read_csv("/Downloads/input/mercedes-benz-greener-manufacturing/sampl
```

In [9]:
```
#Creating Variables for Identificaton of Data.
testdata['Type'] = "Test"
traindata['Type'] = "train"

#Merging Data Set
mergeddata = (pd.concat([traindata, testdata], ignore_index= True))
```

Exploratary Data Inspection

In [10]:
```
traindata.head()
```

Out[10]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	X10	X11	X12	X13	X14	X15	X16	X17	X18
0	0	130.81	k	v	at	a	d	u	j	o	0	0	0	1	0	0	0	0	1
1	6	88.53	k	t	av	e	d	y	l	o	0	0	0	0	0	0	0	0	1
2	7	76.26	az	w	n	c	d	x	j	x	0	0	0	0	0	0	0	1	0
3	9	80.62	az	t	n	f	d	x	l	e	0	0	0	0	0	0	0	0	0
4	13	78.02	az	v	n	f	d	h	d	n	0	0	0	0	0	0	0	0	0

In [11]:
```
traindata.describe()
```

Out[11]:

	ID	y	X10	X11	X12	X13	X14	
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	4209.000000	4209.000000	4209.0
mean	4205.960798	100.669318	0.013305	0.0	0.075077	0.057971	0.428130	0.0
std	2437.608688	12.679381	0.114590	0.0	0.263547	0.233716	0.494867	0.0
min	0.000000	72.110000	0.000000	0.0	0.000000	0.000000	0.000000	0.0
25%	2095.000000	90.820000	0.000000	0.0	0.000000	0.000000	0.000000	0.0
50%	4220.000000	99.150000	0.000000	0.0	0.000000	0.000000	0.000000	0.0
75%	6314.000000	109.010000	0.000000	0.0	0.000000	0.000000	1.000000	0.0

	ID	y	X10	X11	X12	X13	X14	
max	8417.000000	265.320000	1.000000	0.0	1.000000	1.000000	1.000000	1.(

In [12]:
```
## ID not seems relevant data, it seems a like serial number of records, so dropping
mergeddata.set_index('ID', inplace=True)
```

In [13]:
```
traindata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4209 entries, 0 to 4208
Columns: 379 entries, ID to Type
dtypes: float64(1), int64(369), object(9)
memory usage: 12.2+ MB
```

In [14]:
```
traindata.shape
```

Out[14]:
```
(4209, 379)
```

In [15]:
```
traindata.isnull().sum()
```

Out[15]:
```
ID      0
y       0
X0      0
X1      0
X2      0
       ..
X382    0
X383    0
X384    0
X385    0
Type    0
Length: 379, dtype: int64
```

In [16]:
```
traindata.isnull().sum().sum()
```

Out[16]:
```
0
```

In [17]:
```
traindata.isnull().values.any()
```

Out[17]:
```
False
```

In [18]:
```
traindata.var()
```

Out[18]:
```
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
```

In [19]:
```
testdata.var()
```

Out[19]:
```
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
```

Data PreProcessing

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

In [20]:
```
##Creating Variance dataframe
Numeric = pd.DataFrame(traindata.var())
Numeric = Numeric.transpose()
Numeric
```

Out[20]:

	ID	y	X10	X11	X12	X13	X14	X15	X16	X1
0	5.941936e+06	160.76671	0.013131	0.0	0.069457	0.054623	0.244893	0.000475	0.002607	0.0075

In [21]:
```
##Dropping variable from combined dataset which have 0 variance in training Set.
variables = Numeric.columns
variable = [ ]
numeric = traindata[variables]
var = numeric.var()
numeric = numeric.columns
variable = [ ]
for i in range(0,len(var)):
    if var[i] == 0:   #setting the threshold as 0
       variable.append(numeric[i])

mergeddata1 = mergeddata.drop(variable,axis=1)
mergeddata1.head()
```

Out[21]:

ID	y	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X2
0	130.81	k	v	at	a	d	u	j	o	0	0	1	0	0	0	0	1	0	

ID	y	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X
6	88.53	k	t	av	e	d	y	l	o	0	0	0	0	0	0	0	1	0	
7	76.26	az	w	n	c	d	x	j	x	0	0	0	0	0	0	1	0	0	
9	80.62	az	t	n	f	d	x	l	e	0	0	0	0	0	0	0	0	0	
13	78.02	az	v	n	f	d	h	d	n	0	0	0	0	0	0	0	0	0	

In [22]:
```
##Checcking Variance in Test Data
Numeric1 = pd.DataFrame(testdata.var())
Numeric1 = Numeric1.transpose()
Numeric1
```

Out[22]:

	ID	X10	X11	X12	X13	X14	X15	X16	X17	
0	5.871311e+06	0.01865	0.000238	0.068851	0.057345	0.244859	0.000712	0.002607	0.008715	0.01(

In [23]:
```
##Dropping variable from combined dataset which have 0 variance in Test Data Set.
variables = Numeric1.columns
variable = [ ]
numeric = testdata[variables]
var = numeric.var()
numeric = numeric.columns
variable = [ ]
for i in range(0,len(var)):
    if var[i] == 0:   #setting the threshold as 0
       variable.append(numeric[i])

mergeddata2 = mergeddata1.drop(variable,axis=1)
mergeddata2.head()
```

Out[23]:

ID	y	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X
0	130.81	k	v	at	a	d	u	j	o	0	0	1	0	0	0	0	1	0	
6	88.53	k	t	av	e	d	y	l	o	0	0	0	0	0	0	0	1	0	
7	76.26	az	w	n	c	d	x	j	x	0	0	0	0	0	0	1	0	0	
9	80.62	az	t	n	f	d	x	l	e	0	0	0	0	0	0	0	0	0	
13	78.02	az	v	n	f	d	h	d	n	0	0	0	0	0	0	0	0	0	

In [24]:
```
##Checking Categorical Data in DataFrame for train Data
traindata.describe(include=object)
```

Out[24]:

	X0	X1	X2	X3	X4	X5	X6	X8	Type

	X0	X1	X2	X3	X4	X5	X6	X8	Type
count	4209	4209	4209	4209	4209	4209	4209	4209	4209
unique	47	27	44	7	4	29	12	25	1
top	z	aa	as	c	d	v	g	j	train
freq	360	833	1659	1942	4205	231	1042	277	4209

Dropping X4 Variable as it has no variance as value 'd' count is 8408 which is almost 100% of variable.

In [25]:
```
mergeddata3 = mergeddata2.drop('X4',axis=1)
mergeddata3.head()
```

Out[25]:

ID	y	X0	X1	X2	X3	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	X
0	130.81	k	v	at	a	u	j	o	0	0	1	0	0	0	0	1	0	0	
6	88.53	k	t	av	e	y	l	o	0	0	0	0	0	0	0	1	0	0	
7	76.26	az	w	n	c	x	j	x	0	0	0	0	0	0	1	0	0	0	
9	80.62	az	t	n	f	x	l	e	0	0	0	0	0	0	0	0	0	0	
13	78.02	az	v	n	f	h	d	n	0	0	0	0	0	0	0	0	0	0	

In [26]:
```
##Checking Categorical Data in DataFrame for Test Data
testdata.describe(include=object)
```

Out[26]:

	X0	X1	X2	X3	X4	X5	X6	X8	Type
count	4209	4209	4209	4209	4209	4209	4209	4209	4209
unique	49	27	45	7	4	32	12	25	1
top	ak	aa	as	c	d	v	g	e	Test
freq	432	826	1658	1900	4203	246	1073	274	4209

Another variables has variation except X4 and it has bee already removed during checking of Traning Data Variance for Categorical Data

In [27]:
```
FinalData = mergeddata3.copy()
FinalData.head()
```

Out[27]:

ID	y	X0	X1	X2	X3	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	X

ID	y	X0	X1	X2	X3	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	X

ID																			
0	130.81	k	v	at	a	u	j	o	0	0	1	0	0	0	0	1	0	0
6	88.53	k	t	av	e	y	l	o	0	0	0	0	0	0	0	1	0	0
7	76.26	az	w	n	c	x	j	x	0	0	0	0	0	0	1	0	0	0
9	80.62	az	t	n	f	x	l	e	0	0	0	0	0	0	0	0	0	0
13	78.02	az	v	n	f	h	d	n	0	0	0	0	0	0	0	0	0	0

Step:2 - Check for null and unique values for test and train sets.

In [28]:
```
traindata.isna().sum()
```

Out[28]:
```
ID      0
y       0
X0      0
X1      0
X2      0
       ..
X382    0
X383    0
X384    0
X385    0
Type    0
Length: 379, dtype: int64
```

In [29]:
```
traindata.isnull().sum().sum()
```

Out[29]:
```
0
```

In [30]:
```
testdata.isna().sum()
```

Out[30]:
```
ID      0
X0      0
X1      0
X2      0
X3      0
       ..
X382    0
X383    0
X384    0
X385    0
Type    0
Length: 378, dtype: int64
```

In [31]:
```
testdata.isnull().sum().sum()
```

Out[31]:
```
0
```

Checking Categorical Value availablity between train and test data.

In [32]:
```
#Feature X0
X0Check = np.where(testdata.X0.isin(traindata.X0),'Match', traindata.X0)
X0Check = pd.Series(X0Check)
X0Check.value_counts()
```

Out[32]:
```
Match    4203
f           3
ak          1
z           1
n           1
dtype: int64
```

In [33]:
```
#Feature X1
X1Check = np.where(testdata.X1.isin(traindata.X1),'Match', traindata.X1)
X1Check = pd.Series(X1Check)
X1Check.value_counts()
```

Out[33]:
```
Match    4209
dtype: int64
```

In [34]:
```
#Feature X2
X2Check = np.where(testdata.X2.isin(traindata.X2),'Match', traindata.X2)
X2Check = pd.Series(X2Check)
X2Check.value_counts()
```

Out[34]:
```
Match    4195
as          7
ae          3
t           1
m           1
ai          1
n           1
dtype: int64
```

In [35]:
```
#Feature X3
X3Check = np.where(testdata.X3.isin(traindata.X3),'Match', traindata.X3)
X3Check = pd.Series(X3Check)
X3Check.value_counts()
```

Out[35]:
```
Match    4209
dtype: int64
```

In [36]:
```
#Feature X5
X5Check = np.where(testdata.X5.isin(traindata.X5),'Match', traindata.X5)
X5Check = pd.Series(X5Check)
X5Check.value_counts()
```

Out[36]:
```
Match    4205
x           2
y           1
u           1
dtype: int64
```

In [37]:
```
#Feature X6
X6Check = np.where(testdata.X6.isin(traindata.X6),'Match', traindata.X6)
```

```
X6Check = pd.Series(X6Check)
X6Check.value_counts()
```

Out[37]:
```
Match    4209
dtype: int64
```

In [38]:
```
#Feature X8
X8Check = np.where(testdata.X8.isin(traindata.X8),'Match', traindata.X8)
X8Check = pd.Series(X8Check)
X8Check.value_counts()
```

Out[38]:
```
Match    4209
dtype: int64
```

All Level are available in train data which is in test data except few ones which has low occurrance. I will leave it as is.

In [39]:
```
##Frequency observation of categorical column.

for column in traindata.select_dtypes(include=['object']).columns:
    display(pd.crosstab(index=traindata[column], columns='Observations%', normalize=
```

col_0	Observations%
X0	
a	0.498931
aa	0.047517
ab	0.023759
ac	0.023759
ad	0.332621
af	0.831551
ai	0.807793
aj	3.587550
ak	8.291756
al	1.591827
am	0.427655
ao	0.095034
ap	2.447137
aq	0.427655
as	0.237586
at	0.593965
au	0.261345
aw	0.380138
ax	0.451414

col_0	Observations%
X0	
ay	7.436446
az	4.157757
b	0.261345
ba	0.641483
bc	0.142552
c	0.071276
d	1.734379
e	0.760276
f	5.393205
g	0.023759
h	1.781896
i	0.427655
j	4.300309
k	0.261345
l	0.380138
m	0.807793
n	4.632929
o	6.391067
q	0.047517
r	0.237586
s	2.518413
t	7.270135
u	0.403896
v	0.855310
w	4.324067
x	7.127584
y	7.697790
z	8.553100

col_0	Observations%
X1	
a	3.397482
aa	19.790924
ab	0.071276
b	14.065099

col_0 X1	Observations%
c	2.874792
d	0.071276
e	0.784034
f	0.546448
g	0.142552
h	0.689000
i	4.822998
j	0.522689
k	0.403896
l	14.017581
m	0.760276
n	0.451414
o	1.948206
p	0.213828
q	0.071276
r	5.963412
s	14.207650
t	0.736517
u	0.879069
v	9.693514
w	1.235448
y	0.546448
z	1.092896

col_0 X2	Observations%
a	1.116655
aa	0.023759
ac	0.308862
ae	11.784272
af	0.023759
ag	0.451414
ah	0.095034
ai	9.859824
ak	6.296032

col_0	Observations%
X2	
al	0.118793
am	0.023759
an	0.118793
ao	0.475172
ap	0.261345
aq	1.496793
ar	0.023759
as	39.415538
at	0.142552
au	0.071276
av	0.095034
aw	0.190069
ay	1.282965
b	0.498931
c	0.023759
d	0.427655
e	1.924448
f	2.066999
g	0.285103
h	0.142552
i	0.593965
j	0.023759
k	0.593965
l	0.023759
m	8.719411
n	3.254930
o	0.023759
p	0.095034
q	0.118793
r	3.635068
s	2.233310
t	0.689000
x	0.237586
y	0.261345
z	0.451414

col_0 X3	Observations%
a	10.453789
b	1.354241
c	46.139225
d	6.889998
e	3.872654
f	25.564267
g	5.725826

col_0 X4	Observations%
a	0.047517
b	0.023759
c	0.023759
d	99.904966

col_0 X5	Observations%
aa	2.660965
ab	4.680447
ac	4.751722
ad	4.395343
ae	4.870516
af	4.466619
ag	4.846757
ah	2.304585
c	3.112378
d	5.084343
f	0.166310
g	0.023759
h	0.023759
i	4.918033
j	2.969827
k	4.205274
l	4.632929
m	4.941791
n	5.036826

col_0 X5	Observations%
o	0.475172
p	4.941791
q	5.226895
r	5.108102
s	5.084343
u	0.023759
v	5.488239
w	5.488239
x	0.047517
y	0.023759

col_0 X6	Observations%
a	4.894274
b	0.665241
c	0.902827
d	14.849133
e	0.285103
f	0.475172
g	24.756474
h	4.514136
i	11.594203
j	24.685198
k	1.021620
l	11.356617

col_0 X8	Observations%
a	4.989309
b	4.514136
c	2.375861
d	2.447137
e	5.345688
f	5.773343
g	3.088620
h	2.779758

col_0	Observations%
X8	
i	5.630791
j	6.581136
k	4.181516
l	2.399620
m	3.682585
n	5.749584
o	3.872654
p	2.375861
q	2.779758
r	5.203136
s	6.058446
t	2.827275
u	2.827275
v	4.609171
w	4.656688
x	2.494654
y	2.755999

col_0	Observations%
Type	
train	100.0

By looking the data, all input feature has sufficient variance.

In [40]:
```
##Frequency observation of numerical(binary) columns.

for column in traindata.select_dtypes(include=['int64']).columns:
    display(pd.crosstab(index=traindata[column], columns='Observations%', normalize=
```

col_0	Observations%
ID	
0	0.023759
6	0.023759
7	0.023759
9	0.023759
13	0.023759

col_0	Observations%
ID	
...	...
8405	0.023759
8406	0.023759
8412	0.023759
8415	0.023759
8417	0.023759

4209 rows × 1 columns

col_0	Observations%
X10	
0	98.669518
1	1.330482

col_0	Observations%
X11	
0	100.0

col_0	Observations%
X12	
0	92.492278
1	7.507722

col_0	Observations%
X13	
0	94.202899
1	5.797101

col_0	Observations%
X14	
0	57.18698
1	42.81302

col_0	Observations%
X15	
0	99.952483
1	0.047517

col_0	Observations%

col_0	Observations%
X16	
0	99.738655
1	0.261345

col_0	Observations%
X17	
0	99.239724
1	0.760276

col_0	Observations%
X18	
0	99.215966
1	0.784034

col_0	Observations%
X19	
0	90.045141
1	9.954859

col_0	Observations%
X20	
0	85.721074
1	14.278926

col_0	Observations%
X21	
0	99.738655
1	0.261345

col_0	Observations%
X22	
0	91.304348
1	8.695652

col_0	Observations%
X23	
0	97.933001
1	2.066999

col_0	Observations%
X24	
0	99.809931
1	0.190069

col_0	Observations%
X26	
0	99.501069
1	0.498931

col_0	Observations%
X27	
0	31.741506
1	68.258494

col_0	Observations%
X28	
0	96.74507
1	3.25493

col_0	Observations%
X29	
0	95.699691
1	4.300309

col_0	Observations%
X30	
0	99.548586
1	0.451414

col_0	Observations%
X31	
0	76.764077
1	23.235923

col_0	Observations%
X32	
0	98.883345
1	1.116655

col_0	Observations%

col_0 X33	Observations%
0	99.976241
1	0.023759

col_0 X34	Observations%
0	99.453552
1	0.546448

col_0 X35	Observations%
0	76.764077
1	23.235923

col_0 X36	Observations%
0	99.548586
1	0.451414

col_0 X37	Observations%
0	76.764077
1	23.235923

col_0 X38	Observations%
0	96.673794
1	3.326206

col_0 X39	Observations%
0	99.976241
1	0.023759

col_0 X40	Observations%
0	99.928724
1	0.071276

col_0	Observations%
X41	
0	98.859587
1	1.140413

col_0	Observations%
X42	
0	99.976241
1	0.023759

col_0	Observations%
X43	
0	92.777382
1	7.222618

col_0	Observations%
X44	
0	98.859587
1	1.140413

col_0	Observations%
X45	
0	74.673319
1	25.326681

col_0	Observations%
X46	
0	40.270848
1	59.729152

col_0	Observations%
X47	
0	98.717035
1	1.282965

col_0	Observations%
X48	
0	97.76669
1	2.23331

col_0	Observations%

col_0 X49	Observations%
0	87.788073
1	12.211927

col_0 X50	Observations%
0	78.59349
1	21.40651

col_0 X51	Observations%
0	27.821335
1	72.178665

col_0 X52	Observations%
0	95.770967
1	4.229033

col_0 X53	Observations%
0	99.311
1	0.689

col_0 X54	Observations%
0	95.652174
1	4.347826

col_0 X55	Observations%
0	99.477311
1	0.522689

col_0 X56	Observations%
0	97.885483
1	2.114517

col_0	Observations%
X57	
0	98.669518
1	1.330482

col_0	Observations%
X58	
0	42.504158
1	57.495842

col_0	Observations%
X59	
0	99.928724
1	0.071276

col_0	Observations%
X60	
0	99.857448
1	0.142552

col_0	Observations%
X61	
0	4.609171
1	95.390829

col_0	Observations%
X62	
0	99.406035
1	0.593965

col_0	Observations%
X63	
0	98.859587
1	1.140413

col_0	Observations%
X64	
0	62.485151
1	37.514849

col_0	Observations%

col_0	Observations%
X65	
0	99.786172
1	0.213828

col_0	Observations%
X66	
0	97.291518
1	2.708482

col_0	Observations%
X67	
0	99.809931
1	0.190069

col_0	Observations%
X68	
0	92.658589
1	7.341411

col_0	Observations%
X69	
0	97.006415
1	2.993585

col_0	Observations%
X70	
0	8.006652
1	91.993348

col_0	Observations%
X71	
0	89.641245
1	10.358755

col_0	Observations%
X73	
0	98.004277
1	1.995723

col_0	Observations%
X74	
0	0.071276
1	99.928724

col_0	Observations%
X75	
0	96.388691
1	3.611309

col_0	Observations%
X76	
0	95.652174
1	4.347826

col_0	Observations%
X77	
0	98.740794
1	1.259206

col_0	Observations%
X78	
0	99.429793
1	0.570207

col_0	Observations%
X79	
0	97.481587
1	2.518413

col_0	Observations%
X80	
0	5.298171
1	94.701829

col_0	Observations%
X81	
0	77.096698
1	22.903302

col_0	Observations%

col_0	Observations%
X82	
0	98.28938
1	1.71062

col_0	Observations%
X83	
0	99.881207
1	0.118793

col_0	Observations%
X84	
0	89.641245
1	10.358755

col_0	Observations%
X85	
0	59.182704
1	40.817296

col_0	Observations%
X86	
0	99.857448
1	0.142552

col_0	Observations%
X87	
0	99.904966
1	0.095034

col_0	Observations%
X88	
0	99.287242
1	0.712758

col_0	Observations%
X89	
0	99.928724
1	0.071276

col_0	Observations%
X90	
0	99.263483
1	0.736517

col_0	Observations%
X91	
0	99.83369
1	0.16631

col_0	Observations%
X92	
0	99.904966
1	0.095034

col_0	Observations%
X93	
0	100.0

col_0	Observations%
X94	
0	99.263483
1	0.736517

col_0	Observations%
X95	
0	99.976241
1	0.023759

col_0	Observations%
X96	
0	24.186268
1	75.813732

col_0	Observations%
X97	
0	99.572345
1	0.427655

col_0	Observations%
X98	

col_0 X98	Observations%
0	5.749584
1	94.250416

col_0 X99	Observations%
0	99.14469
1	0.85531

col_0 X100	Observations%
0	30.981231
1	69.018769

col_0 X101	Observations%
0	6.438584
1	93.561416

col_0 X102	Observations%
0	99.311
1	0.689

col_0 X103	Observations%
0	21.549062
1	78.450938

col_0 X104	Observations%
0	99.809931
1	0.190069

col_0 X105	Observations%
0	99.762414
1	0.237586

col_0	Observations%

col_0	Observations%
X106	
0	98.693276
1	1.306724

col_0	Observations%
X107	
0	100.0

col_0	Observations%
X108	
0	98.526966
1	1.473034

col_0	Observations%
X109	
0	95.961036
1	4.038964

col_0	Observations%
X110	
0	99.904966
1	0.095034

col_0	Observations%
X111	
0	2.518413
1	97.481587

col_0	Observations%
X112	
0	99.714897
1	0.285103

col_0	Observations%
X113	
0	97.76669
1	2.23331

col_0	Observations%

col_0	Observations%
X114	
0	85.388453
1	14.611547

col_0	Observations%
X115	
0	71.442148
1	28.557852

col_0	Observations%
X116	
0	80.327869
1	19.672131

col_0	Observations%
X117	
0	95.081967
1	4.918033

col_0	Observations%
X118	
0	37.776194
1	62.223806

col_0	Observations%
X119	
0	37.776194
1	62.223806

col_0	Observations%
X120	
0	4.229033
1	95.770967

col_0	Observations%
X122	
0	99.287242
1	0.712758

col_0	Observations%
X123	
0	99.738655
1	0.261345

col_0	Observations%
X124	
0	99.952483
1	0.047517

col_0	Observations%
X125	
0	99.691138
1	0.308862

col_0	Observations%
X126	
0	96.103588
1	3.896412

col_0	Observations%
X127	
0	50.487052
1	49.512948

col_0	Observations%
X128	
0	4.157757
1	95.842243

col_0	Observations%
X129	
0	87.740556
1	12.259444

col_0	Observations%
X130	
0	95.842243
1	4.157757

col_0	Observations%

col_0	Observations%
X130	
X131	
0	97.339035
1	2.660965

col_0	Observations%
X132	
0	31.147541
1	68.852459

col_0	Observations%
X133	
0	87.574246
1	12.425754

col_0	Observations%
X134	
0	97.76669
1	2.23331

col_0	Observations%
X135	
0	97.291518
1	2.708482

col_0	Observations%
X136	
0	4.347826
1	95.652174

col_0	Observations%
X137	
0	41.815158
1	58.184842

col_0	Observations%
X138	
0	95.913519
1	4.086481

col_0	Observations%
X139	
0	90.947969
1	9.052031

col_0	Observations%
X140	
0	95.961036
1	4.038964

col_0	Observations%
X141	
0	98.574483
1	1.425517

col_0	Observations%
X142	
0	22.974578
1	77.025422

col_0	Observations%
X143	
0	96.174863
1	3.825137

col_0	Observations%
X144	
0	19.196959
1	80.803041

col_0	Observations%
X145	
0	99.857448
1	0.142552

col_0	Observations%
X146	
0	95.913519
1	4.086481

col_0	Observations%

col_0	Observations%
X147	
0	97.76669
1	2.23331

col_0	Observations%
X148	
0	95.509622
1	4.490378

col_0	Observations%
X150	
0	20.765027
1	79.234973

col_0	Observations%
X151	
0	91.4469
1	8.5531

col_0	Observations%
X152	
0	96.768829
1	3.231171

col_0	Observations%
X153	
0	99.928724
1	0.071276

col_0	Observations%
X154	
0	79.11618
1	20.88382

col_0	Observations%
X155	
0	92.349727
1	7.650273

col_0	Observations%
X156	
0	28.272749
1	71.727251

col_0	Observations%
X157	
0	71.727251
1	28.272749

col_0	Observations%
X158	
0	77.025422
1	22.974578

col_0	Observations%
X159	
0	98.645759
1	1.354241

col_0	Observations%
X160	
0	99.881207
1	0.118793

col_0	Observations%
X161	
0	80.232834
1	19.767166

col_0	Observations%
X162	
0	95.913519
1	4.086481

col_0	Observations%
X163	
0	69.660252
1	30.339748

col_0	Observations%

col_0	Observations%
X164	
0	93.751485
1	6.248515

col_0	Observations%
X165	
0	99.548586
1	0.451414

col_0	Observations%
X166	
0	96.673794
1	3.326206

col_0	Observations%
X167	
0	99.904966
1	0.095034

col_0	Observations%
X168	
0	72.915182
1	27.084818

col_0	Observations%
X169	
0	99.334759
1	0.665241

col_0	Observations%
X170	
0	97.576622
1	2.423378

col_0	Observations%
X171	
0	34.259919
1	65.740081

col_0	Observations%
X172	
0	99.406035
1	0.593965

col_0	Observations%
X173	
0	99.025897
1	0.974103

col_0	Observations%
X174	
0	98.265621
1	1.734379

col_0	Observations%
X175	
0	97.76669
1	2.23331

col_0	Observations%
X176	
0	98.28938
1	1.71062

col_0	Observations%
X177	
0	94.986933
1	5.013067

col_0	Observations%
X178	
0	44.262295
1	55.737705

col_0	Observations%
X179	
0	95.20076
1	4.79924

col_0	Observations%

col_0	Observations%
X180	
0	84.200523
1	15.799477

col_0	Observations%
X181	
0	90.615348
1	9.384652

col_0	Observations%
X182	
0	89.3799
1	10.6201

col_0	Observations%
X183	
0	99.596104
1	0.403896

col_0	Observations%
X184	
0	99.857448
1	0.142552

col_0	Observations%
X185	
0	98.12307
1	1.87693

col_0	Observations%
X186	
0	46.40057
1	53.59943

col_0	Observations%
X187	
0	57.947256
1	42.052744

col_0	Observations%
X189	
0	8.458066
1	91.541934

col_0	Observations%
X190	
0	99.976241
1	0.023759

col_0	Observations%
X191	
0	52.91043
1	47.08957

col_0	Observations%
X192	
0	99.762414
1	0.237586

col_0	Observations%
X194	
0	53.59943
1	46.40057

col_0	Observations%
X195	
0	98.835828
1	1.164172

col_0	Observations%
X196	
0	98.97838
1	1.02162

col_0	Observations%
X197	
0	96.768829
1	3.231171

col_0	Observations%

col_0	Observations%
X198	
0	97.695415
1	2.304585

col_0	Observations%
X199	
0	99.714897
1	0.285103

col_0	Observations%
X200	
0	99.334759
1	0.665241

col_0	Observations%
X201	
0	82.228558
1	17.771442

col_0	Observations%
X202	
0	75.86125
1	24.13875

col_0	Observations%
X203	
0	98.313139
1	1.686861

col_0	Observations%
X204	
0	99.976241
1	0.023759

col_0	Observations%
X205	
0	0.023759
1	99.976241

col_0	Observations%
X206	
0	98.075552
1	1.924448

col_0	Observations%
X207	
0	99.976241
1	0.023759

col_0	Observations%
X208	
0	93.703968
1	6.296032

col_0	Observations%
X209	
0	10.144928
1	89.855072

col_0	Observations%
X210	
0	99.976241
1	0.023759

col_0	Observations%
X211	
0	98.503207
1	1.496793

col_0	Observations%
X212	
0	99.453552
1	0.546448

col_0	Observations%
X213	
0	99.809931
1	0.190069

col_0	Observations%

col_0	Observations%
X214	
0	99.311
1	0.689

col_0	Observations%
X215	
0	90.140176
1	9.859824

col_0	Observations%
X216	
0	99.406035
1	0.593965

col_0	Observations%
X217	
0	99.263483
1	0.736517

col_0	Observations%
X218	
0	68.757425
1	31.242575

col_0	Observations%
X219	
0	93.252554
1	6.747446

col_0	Observations%
X220	
0	43.882157
1	56.117843

col_0	Observations%
X221	
0	99.192207
1	0.807793

col_0	Observations%
X222	
0	97.76669
1	2.23331

col_0	Observations%
X223	
0	44.476123
1	55.523877

col_0	Observations%
X224	
0	68.258494
1	31.741506

col_0	Observations%
X225	
0	90.306486
1	9.693514

col_0	Observations%
X226	
0	96.768829
1	3.231171

col_0	Observations%
X227	
0	99.691138
1	0.308862

col_0	Observations%
X228	
0	96.103588
1	3.896412

col_0	Observations%
X229	
0	3.991447
1	96.008553

col_0	Observations%

col_0	Observations%
X230	
0	99.477311
1	0.522689

col_0	Observations%
X231	
0	98.384414
1	1.615586

col_0	Observations%
X232	
0	95.699691
1	4.300309

col_0	Observations%
X233	
0	100.0

col_0	Observations%
X234	
0	79.828938
1	20.171062

col_0	Observations%
X235	
0	100.0

col_0	Observations%
X236	
0	99.952483
1	0.047517

col_0	Observations%
X237	
0	99.334759
1	0.665241

col_0	Observations%
X238	

col_0	Observations%
X238	
0	8.38679
1	91.61321

col_0	Observations%
X239	
0	99.311
1	0.689

col_0	Observations%
X240	
0	99.714897
1	0.285103

col_0	Observations%
X241	
0	90.282727
1	9.717273

col_0	Observations%
X242	
0	99.263483
1	0.736517

col_0	Observations%
X243	
0	99.287242
1	0.712758

col_0	Observations%
X244	
0	89.641245
1	10.358755

col_0	Observations%
X245	
0	99.928724
1	0.071276

col_0	Observations%

X246	Observations%
0	59.063911
1	40.936089

col_0	Observations%
X247	
0	75.86125
1	24.13875

col_0	Observations%
X248	
0	99.857448
1	0.142552

col_0	Observations%
X249	
0	99.239724
1	0.760276

col_0	Observations%
X250	
0	44.713709
1	55.286291

col_0	Observations%
X251	
0	60.584462
1	39.415538

col_0	Observations%
X252	
0	99.928724
1	0.071276

col_0	Observations%
X253	
0	99.857448
1	0.142552

col_0	Observations%
X254	
0	99.477311
1	0.522689

col_0	Observations%
X255	
0	98.051794
1	1.948206

col_0	Observations%
X256	
0	92.682347
1	7.317653

col_0	Observations%
X257	
0	99.976241
1	0.023759

col_0	Observations%
X258	
0	99.762414
1	0.237586

col_0	Observations%
X259	
0	99.976241
1	0.023759

col_0	Observations%
X260	
0	99.976241
1	0.023759

col_0	Observations%
X261	
0	58.04229
1	41.95771

col_0	Observations%

col_0	Observations%
X262	
X262	
0	99.857448
1	0.142552

col_0	Observations%
X263	
X263	
0	4.300309
1	95.699691

col_0	Observations%
X264	
X264	
0	96.05607
1	3.94393

col_0	Observations%
X265	
X265	
0	9.455928
1	90.544072

col_0	Observations%
X266	
X266	
0	99.857448
1	0.142552

col_0	Observations%
X267	
X267	
0	99.097173
1	0.902827

col_0	Observations%
X268	
X268	
0	100.0

col_0	Observations%
X269	
X269	
0	99.952483
1	0.047517

col_0	Observations%

col_0	Observations%
X270	
0	99.976241
1	0.023759

col_0	Observations%
X271	
0	99.786172
1	0.213828

col_0	Observations%
X272	
0	96.246139
1	3.753861

col_0	Observations%
X273	
0	27.987646
1	72.012354

col_0	Observations%
X274	
0	99.002138
1	0.997862

col_0	Observations%
X275	
0	27.322404
1	72.677596

col_0	Observations%
X276	
0	96.151105
1	3.848895

col_0	Observations%
X277	
0	99.857448
1	0.142552

col_0	Observations%
X278	
0	99.952483
1	0.047517

col_0	Observations%
X279	
0	95.699691
1	4.300309

col_0	Observations%
X280	
0	99.976241
1	0.023759

col_0	Observations%
X281	
0	99.738655
1	0.261345

col_0	Observations%
X282	
0	99.596104
1	0.403896

col_0	Observations%
X283	
0	85.934901
1	14.065099

col_0	Observations%
X284	
0	95.88976
1	4.11024

col_0	Observations%
X285	
0	79.425042
1	20.574958

col_0	Observations%

X286	Observations%
X286	
0	94.535519
1	5.464481

col_0	Observations%
X287	
0	98.408173
1	1.591827

col_0	Observations%
X288	
0	99.976241
1	0.023759

col_0	Observations%
X289	
0	100.0

col_0	Observations%
X290	
0	100.0

col_0	Observations%
X291	
0	98.954621
1	1.045379

col_0	Observations%
X292	
0	99.097173
1	0.902827

col_0	Observations%
X293	
0	100.0

col_0	Observations%
X294	
0	87.50297

col_0	Observations%
X294	
1	12.49703

col_0	Observations%
X295	
0	99.976241
1	0.023759

col_0	Observations%
X296	
0	99.976241
1	0.023759

col_0	Observations%
X297	
0	100.0

col_0	Observations%
X298	
0	99.548586
1	0.451414

col_0	Observations%
X299	
0	99.548586
1	0.451414

col_0	Observations%
X300	
0	79.306249
1	20.693751

col_0	Observations%
X301	
0	95.319553
1	4.680447

col_0	Observations%
X302	
0	98.859587

col_0	Observations%
X302	
1	1.140413

col_0	Observations%
X304	
0	7.578997
1	92.421003

col_0	Observations%
X305	
0	98.669518
1	1.330482

col_0	Observations%
X306	
0	95.628415
1	4.371585

col_0	Observations%
X307	
0	99.786172
1	0.213828

col_0	Observations%
X308	
0	99.049656
1	0.950344

col_0	Observations%
X309	
0	99.287242
1	0.712758

col_0	Observations%
X310	
0	99.738655
1	0.261345

col_0	Observations%
X311	

col_0 X311	Observations%
0	40.152055
1	59.847945

col_0 X312	Observations%
0	99.572345
1	0.427655

col_0 X313	Observations%
0	69.897838
1	30.102162

col_0 X314	Observations%
0	56.830601
1	43.169399

col_0 X315	Observations%
0	97.125208
1	2.874792

col_0 X316	Observations%
0	80.446662
1	19.553338

col_0 X317	Observations%
0	99.239724
1	0.760276

col_0 X318	Observations%
0	99.928724
1	0.071276

col_0	Observations%

col_0	Observations%
X319	
X319	
0	99.952483
1	0.047517

col_0	Observations%
X320	
X320	
0	99.287242
1	0.712758

col_0	Observations%
X321	
X321	
0	76.122594
1	23.877406

col_0	Observations%
X322	
X322	
0	97.814208
1	2.185792

col_0	Observations%
X323	
X323	
0	99.073414
1	0.926586

col_0	Observations%
X324	
X324	
0	42.504158
1	57.495842

col_0	Observations%
X325	
X325	
0	99.429793
1	0.570207

col_0	Observations%
X326	
X326	
0	96.768829
1	3.231171

col_0	Observations%
X327	
0	87.170349
1	12.829651

col_0	Observations%
X328	
0	95.984794
1	4.015206

col_0	Observations%
X329	
0	56.474222
1	43.525778

col_0	Observations%
X330	
0	100.0

col_0	Observations%
X331	
0	94.392967
1	5.607033

col_0	Observations%
X332	
0	99.928724
1	0.071276

col_0	Observations%
X333	
0	97.60038
1	2.39962

col_0	Observations%
X334	
0	53.741981
1	46.258019

col_0	Observations%
X335	

col_0 X335	Observations%
0	99.643621
1	0.356379

col_0 X336	Observations%
0	87.265384
1	12.734616

col_0 X337	Observations%
0	48.348776
1	51.651224

col_0 X338	Observations%
0	99.311
1	0.689

col_0 X339	Observations%
0	99.976241
1	0.023759

col_0 X340	Observations%
0	97.76669
1	2.23331

col_0 X341	Observations%
0	99.192207
1	0.807793

col_0 X342	Observations%
0	97.76669
1	2.23331

col_0	Observations%

col_0	Observations%
X343	
0	92.159658
1	7.840342

col_0	Observations%
X344	
0	99.14469
1	0.85531

col_0	Observations%
X345	
0	97.76669
1	2.23331

col_0	Observations%
X346	
0	95.248278
1	4.751722

col_0	Observations%
X347	
0	100.0

col_0	Observations%
X348	
0	5.274412
1	94.725588

col_0	Observations%
X349	
0	95.509622
1	4.490378

col_0	Observations%
X350	
0	66.120219
1	33.879781

col_0	Observations%

X350	Observations%

X351	
0	70.277976
1	29.722024

col_0	Observations%
X352	
0	94.583036
1	5.416964

col_0	Observations%
X353	
0	99.786172
1	0.213828

col_0	Observations%
X354	
0	79.710145
1	20.289855

col_0	Observations%
X355	
0	61.962461
1	38.037539

col_0	Observations%
X356	
0	82.01473
1	17.98527

col_0	Observations%
X357	
0	99.881207
1	0.118793

col_0	Observations%
X358	
0	57.305773
1	42.694227

col_0	Observations%
X359	
0	96.816346
1	3.183654

col_0	Observations%
X360	
0	92.349727
1	7.650273

col_0	Observations%
X361	
0	3.397482
1	96.602518

col_0	Observations%
X362	
0	47.968639
1	52.031361

col_0	Observations%
X363	
0	24.613923
1	75.386077

col_0	Observations%
X364	
0	99.714897
1	0.285103

col_0	Observations%
X365	
0	99.714897
1	0.285103

col_0	Observations%
X366	
0	99.881207
1	0.118793

col_0	Observations%

col_0	Observations%
X367	
0	94.820622
1	5.179378

col_0	Observations%
X368	
0	93.727726
1	6.272274

col_0	Observations%
X369	
0	99.952483
1	0.047517

col_0	Observations%
X370	
0	99.334759
1	0.665241

col_0	Observations%
X371	
0	98.574483
1	1.425517

col_0	Observations%
X372	
0	99.952483
1	0.047517

col_0	Observations%
X373	
0	98.075552
1	1.924448

col_0	Observations%
X374	
0	77.263008
1	22.736992

col_0	Observations%
X375	
0	68.115942
1	31.884058

col_0	Observations%
X376	
0	94.274174
1	5.725826

col_0	Observations%
X377	
0	68.519838
1	31.480162

col_0	Observations%
X378	
0	97.933001
1	2.066999

col_0	Observations%
X379	
0	99.049656
1	0.950344

col_0	Observations%
X380	
0	99.192207
1	0.807793

col_0	Observations%
X382	
0	99.239724
1	0.760276

col_0	Observations%
X383	
0	99.83369
1	0.16631

col_0	Observations%

X384	Observations%
X384	
0	99.952483
1	0.047517

col_0	Observations%
X385	
0	99.857448
1	0.142552

We have already removed those columns which has 0 variance in Final Data.

Data Seggragation from Merged Data - Train and Test Data

In [50]:
```
FinalData.head()
```

Out[50]:

ID	y	X0	X1	X2	X3	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	X
0	130.81	k	v	at	a	u	j	o	0	0	1	0	0	0	0	1	0	0	
6	88.53	k	t	av	e	y	l	o	0	0	0	0	0	0	0	1	0	0	
7	76.26	az	w	n	c	x	j	x	0	0	0	0	0	0	1	0	0	0	
9	80.62	az	t	n	f	x	l	e	0	0	0	0	0	0	0	0	0	0	
13	78.02	az	v	n	f	h	d	n	0	0	0	0	0	0	0	0	0	0	

In [51]:
```
FinalTrainData = FinalData[FinalData['Type']=='train'].drop('Type',axis=1)
FinalTrainData.shape
```

Out[51]:
```
(4209, 359)
```

In [52]:
```
FinalTrainData.head()
```

Out[52]:

ID	y	X0	X1	X2	X3	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	X
0	130.81	k	v	at	a	u	j	o	0	0	1	0	0	0	0	1	0	0	
6	88.53	k	t	av	e	y	l	o	0	0	0	0	0	0	0	1	0	0	
7	76.26	az	w	n	c	x	j	x	0	0	0	0	0	0	1	0	0	0	

ID	y	X0	X1	X2	X3	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	X
9	80.62	az	t	n	f	x	l	e	0	0	0	0	0	0	0	0	0	0	
13	78.02	az	v	n	f	h	d	n	0	0	0	0	0	0	0	0	0	0	

In [53]:
```
FinalTestData = FinalData[FinalData['Type']=='Test'].drop(['y','Type'],axis=1)
FinalTestData.shape
```

Out[53]: (4209, 358)

In [55]:
```
FinalTestData.head()
```

Out[55]:

ID	X0	X1	X2	X3	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X2
1	az	v	n	f	t	a	w	0	0	0	0	0	0	0	0	0	0	0	
2	t	b	ai	a	b	g	y	0	0	0	0	0	0	0	0	1	0	0	
3	az	v	as	f	a	j	j	0	0	0	1	0	0	0	0	0	0	0	
4	az	l	n	f	z	l	n	0	0	0	0	0	0	0	0	0	0	0	
5	w	s	as	c	y	i	m	0	0	0	1	0	0	0	0	0	0	0	

Step: - 3 Label Encoder Application

In [56]:
```
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from boruta import BorutaPy
import xgboost as xgb
import seaborn as sns
from scipy.stats import skew
from sklearn.metrics import mean_squared_error as MSE
from sklearn.metrics import mean_absolute_error as MAE
from sklearn.metrics import r2_score as rsq
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
import statistics as sts
le = preprocessing.LabelEncoder()
```

In [57]:
```
#Apply Lables Encoder on Non-Numerical Categorical Data.
FinalTrainData['X0']=le.fit_transform(FinalTrainData['X0'])
FinalTrainData['X1']=le.fit_transform(FinalTrainData['X1'])
FinalTrainData['X2']=le.fit_transform(FinalTrainData['X2'])
FinalTrainData['X3']=le.fit_transform(FinalTrainData['X3'])
FinalTrainData['X5']=le.fit_transform(FinalTrainData['X5'])
FinalTrainData['X6']=le.fit_transform(FinalTrainData['X6'])
FinalTrainData['X8']=le.fit_transform(FinalTrainData['X8'])
```

In [58]:
```
FinalTrainData.head()
```

Out[58]:

ID	y	X0	X1	X2	X3	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	X
0	130.81	32	23	17	0	24	9	14	0	0	1	0	0	0	0	1	0	0	
6	88.53	32	21	19	4	28	11	14	0	0	0	0	0	0	0	1	0	0	
7	76.26	20	24	34	2	27	9	23	0	0	0	0	0	0	1	0	0	0	
9	80.62	20	21	34	5	27	11	4	0	0	0	0	0	0	0	0	0	0	
13	78.02	20	23	34	5	12	3	13	0	0	0	0	0	0	0	0	0	0	

In [59]:
```
##Since after label encoding, categorical feature has higher value in terms of numbe
stscale=StandardScaler()
FinalTrainData['X0']=stscale.fit_transform(FinalTrainData[['X0']])
FinalTrainData['X1']=stscale.fit_transform(FinalTrainData[['X1']])
FinalTrainData['X2']=stscale.fit_transform(FinalTrainData[['X2']])
FinalTrainData['X3']=stscale.fit_transform(FinalTrainData[['X3']])
FinalTrainData['X5']=stscale.fit_transform(FinalTrainData[['X5']])
FinalTrainData['X6']=stscale.fit_transform(FinalTrainData[['X6']])
FinalTrainData['X8']=stscale.fit_transform(FinalTrainData[['X8']])
```

In [60]:
```
FinalTrainData.head()
```

Out[60]:

ID	y	X0	X1	X2	X3	X5	X6	X8	X10	X12	X1
0	130.81	0.163012	1.393488	-0.028122	-1.678270	1.292117	0.751787	0.339445	0	0	
6	88.53	0.163012	1.159021	0.155388	0.620969	1.776974	1.437511	0.339445	0	0	
7	76.26	-0.710560	1.510721	1.531709	-0.528650	1.655760	0.751787	1.618389	0	0	
9	80.62	-0.710560	1.159021	1.531709	1.195779	1.655760	1.437511	-1.081605	0	0	
13	78.02	-0.710560	1.393488	1.531709	1.195779	-0.162454	-1.305384	0.197340	0	0	

In [61]:
```
FinalTrainData.shape
```

Out[61]:
```
(4209, 359)
```

In [62]:
```
FinalTrainData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4209 entries, 0 to 8417
Columns: 359 entries, y to X385
dtypes: float64(8), int64(351)
memory usage: 11.6 MB
```

Task:4 Feature Selection/Dimensionality Reduction

using Boruta Package

In [63]:
```
##Preparing data for Feature and Label.
X =FinalTrainData.drop('y', axis=1)
y=FinalTrainData['y']
X.shape,y.shape
```

Out[63]:
```
((4209, 358), (4209,))
```

In [64]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.2, random_s
print("Shape of X_train is " , X_train.shape)
print("Shape of y_train is " , y_train.shape)
print("====================================")
print("Shape of X_test is " , X_test.shape)
print("Shape of y_test is " , y_test.shape)
```

```
Shape of X_train is  (3367, 358)
Shape of y_train is  (3367,)
====================================
Shape of X_test is  (842, 358)
Shape of y_test is  (842,)
```

Boruta Package Application on Training Data

In [66]:
```
mymodel=xgb.XGBRegressor()
```

In [67]:
```
selfeat=BorutaPy(mymodel, n_estimators='auto', verbose=2, random_state=1)
```

In [68]:
```
selfeat.fit(np.array(X),np.array(y))
```

```
Iteration:      1 / 100
Confirmed:      0
Tentative:      358
Rejected:       0
Iteration:      2 / 100
Confirmed:      0
Tentative:      358
Rejected:       0
Iteration:      3 / 100
Confirmed:      0
Tentative:      358
Rejected:       0
Iteration:      4 / 100
Confirmed:      0
Tentative:      358
Rejected:       0
Iteration:      5 / 100
Confirmed:      0
Tentative:      358
Rejected:       0
Iteration:      6 / 100
Confirmed:      0
Tentative:      358
Rejected:       0
Iteration:      7 / 100
Confirmed:      0
Tentative:      358
```

```
Rejected:       0
Iteration:      8 / 100
Confirmed:      0
Tentative:      11
Rejected:       347
Iteration:      9 / 100
Confirmed:      6
Tentative:      5
Rejected:       347
Iteration:      10 / 100
Confirmed:      6
Tentative:      5
Rejected:       347
Iteration:      11 / 100
Confirmed:      6
Tentative:      5
Rejected:       347
Iteration:      12 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      13 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      14 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      15 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      16 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      17 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      18 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      19 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      20 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      21 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      22 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      23 / 100
Confirmed:      6
Tentative:      4
```

```
Rejected:       348
Iteration:      24 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      25 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      26 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      27 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      28 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      29 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      30 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      31 / 100
Confirmed:      6
Tentative:      4
Rejected:       348
Iteration:      32 / 100
Confirmed:      7
Tentative:      3
Rejected:       348
Iteration:      33 / 100
Confirmed:      7
Tentative:      3
Rejected:       348
Iteration:      34 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      35 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      36 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      37 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      38 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      39 / 100
Confirmed:      8
Tentative:      2
```

```
Rejected:       348
Iteration:      40 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      41 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      42 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      43 / 100
Confirmed:      8
Tentative:      2
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Iteration:      44 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      45 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      46 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      47 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      48 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      49 / 100
Confirmed:      8
Tentative:      2
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Iteration:      50 / 100
Confirmed:      8
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Iteration:      51 / 100
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Iteration:      52 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      53 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      54 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      55 / 100
Confirmed:      8
Tentative:      2
```

```
Rejected:       348
Iteration:      56 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      57 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      58 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      59 / 100
Confirmed:      8
Tentative:      2
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Iteration:      60 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      61 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      62 / 100
Confirmed:      8
Tentative:      2
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Iteration:      63 / 100
Confirmed:      8
Tentative:      2
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Iteration:      64 / 100
Confirmed:      8
Tentative:      2
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Iteration:      65 / 100
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Iteration:      66 / 100
Confirmed:      8
Tentative:      2
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Iteration:      67 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      68 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      69 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      70 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      71 / 100
Confirmed:      8
Tentative:      2
```

```
Rejected:       348
Iteration:      72 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      73 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      74 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      75 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      76 / 100
Confirmed:      8
Tentative:      2
Rejected:       348
Iteration:      77 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      78 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      79 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      80 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      81 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      82 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      83 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      84 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      85 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      86 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      87 / 100
Confirmed:      8
Tentative:      1
```

```
Rejected:       349
Iteration:      88 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      89 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      90 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      91 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      92 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      93 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      94 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      95 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      96 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      97 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      98 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
Iteration:      99 / 100
Confirmed:      8
Tentative:      1
Rejected:       349


BorutaPy finished running.

Iteration:      100 / 100
Confirmed:      8
Tentative:      1
Rejected:       349
```

Out[68]:

```
BorutaPy(estimator=XGBRegressor(base_score=0.5, booster='gbtree',
                                colsample_bylevel=1, colsample_bynode=1,
                                colsample_bytree=1, gamma=0, gpu_id=-1,
                                importance_type='gain',
                                interaction_constraints='',
                                learning_rate=0.300000012, max_delta_step=0,
                                max_depth=6, min_child_weight=1, missing=nan,
```

```
                                monotone_constraints='()', n_estimators=70,
                                n_jobs=4, num_parallel_tree=1,
                                random_state=667832358, reg_alpha=0,
                                reg_lambda=1, scale_pos_weight=1, subsample=1,
                                tree_method='exact', validate_parameters=1,
                                verbosity=None),
                  n_estimators='auto',
                  random_state=RandomState(MT19937) at 0x7F3539D9C270, verbose=2)
```

In [70]:

```
#Boruta Result
selected_rf_features = pd.DataFrame({'Feature':list(X_train.columns),
                                     'Ranking':selfeat.ranking_,
                                   'Support':selfeat.support_})
Feature= selected_rf_features.copy()
Confimred = Feature[Feature['Ranking']==1]#Confirmed
Tentative = Feature[Feature['Ranking']==2]#Tentative
print(Confimred.head(10))
print(Tentative.head())
```

```
    Feature  Ranking  Support
24      X29        1     True
110    X118        1     True
118    X127        1     True
178    X189        1     True
222    X236        1     True
245    X261        1     True
290    X314        1     True
291    X315        1     True
   Feature  Ranking  Support
56     X61        2    False
```

8 Features has been confimred thru Boruta as Important feature, we will move with these 8 feature for modeling.

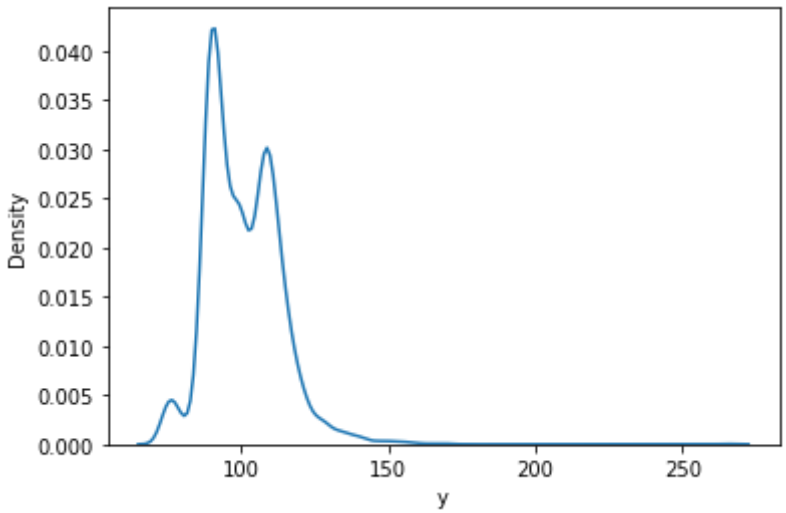
In [72]:

```
#Final Model with with Confirmed Feature
FinData1=FinalTrainData[['y','X189','X315','X314','X118','X261','X29','X127','X236']]
```

In [74]:

```
##Target Value Data Distribution Review
sns.kdeplot(FinData1.y)
```

Out[74]: <AxesSubplot:xlabel='y', ylabel='Density'>



By Looking the graph data seems to be skewed, lets check it by stats.

In [77]:
```
##Stats Checking
print('The Median Value of Target Variable is:',sts.median(FinData1.y))
print('The Mean Value of Target Variable is:',round(sts.mean(FinData1.y),2))
print('The Skewness of Target Variable is:',round(skew(FinData1.y),2))
```

```
The Median Value of Target Variable is: 99.15
The Mean Value of Target Variable is: 100.67
The Skewness of Target Variable is: 1.21
```

Data seems to be normally distributed as per stats as skewness is below threashold (<3%).

In [79]:
```
#Creating Train Test Model for XG Booster Model.
X =FinData1.drop('y', axis=1)
y=FinData1['y']
X.shape,y.shape
X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.2, random_s
print("Shape of X_train is " , X_train.shape)
print("Shape of y_train is " , y_train.shape)
print("====================================")
print("Shape of X_test is " , X_test.shape)
print("Shape of y_test is " , y_test.shape)
```

```
Shape of X_train is  (3367, 8)
Shape of y_train is  (3367,)
====================================
Shape of X_test is  (842, 8)
Shape of y_test is  (842,)
```

In [81]:
```
##Xgb Model
import random
random.seed(111)
xgb_mymodel = xgb.XGBRegressor(max_depth=3, n_estimators=100, n_jobs=2,
                               objectvie='reg:squarederror', booster='gbtree',
                               random_state=42, learning_rate=0.05)
```

In [82]:
```
#Fitting the Data
xgb_mymodel.fit(X_train, y_train)
```

```
[07:34:53] WARNING: ../src/learner.cc:573:
Parameters: { "objectvie" } might not be used.

  This may not be accurate due to some parameters are only used in language bindings
but
  passed down to XGBoost core.  Or some parameters are not used but slip through thi
s
  verification. Please open an issue if you find above cases.
```

Out[82]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.05, max_delta_step=0, max_depth=3,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=2, num_parallel_tree=1,
```

```
objectvie='reg:squarederror', random_state=42, reg_alpha=0,
reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
validate_parameters=1, verbosity=None)
```

In [84]:
```
##Prediction on Test Data for accuracy
preds = xgb_mymodel.predict(X_test)
```

In [85]:
```
#Evalution of Model on Test Data
rmse = np.sqrt(MSE(y_test, preds))
mae=MAE(y_test, preds)
mse = MSE(y_test, preds)
R2SQ=rsq(y_test, preds)
adjRSq = 1 - (1-R2SQ)*(len(y_test)-1)/(len(y_test)-X.shape[1]-1)
diff = pd.DataFrame({'Actual': y_test, 'Predicted': preds,'Error':y_test -preds})
print("The Root Mean Squared Error is: ",round(rmse,2))
print("The Mean Absolute Error is: ",round(mae,2))
print("The Mean Squared is Error is: ",round(mse,2))
print("The RSquared value is:",round(R2SQ,2))
print("The Adj RSquared value is:",round(adjRSq,2))
print("The Max Error value is:",round(diff.Error.min(),2))
print("The Max Error value is:",round(diff.Error.max(),2))
```

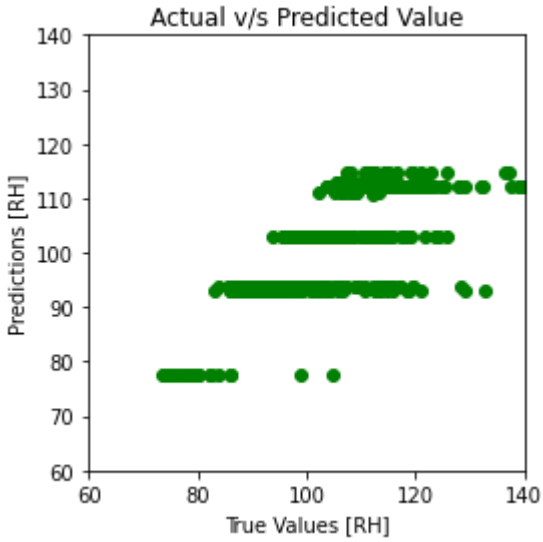
```
The Root Mean Squared Error is:  7.72
The Mean Absolute Error is:  5.11
The Mean Squared is Error is:  59.63
The RSquared value is: 0.59
The Adj RSquared value is: 0.59
The Max Error value is: -9.95
The Max Error value is: 44.23
```

In [86]:
```
y_test.describe()
```

Out[86]:
```
count    842.000000
mean     100.685511
std       12.067912
min       73.700000
25%       91.020000
50%       98.915000
75%      108.970000
max      169.910000
Name: y, dtype: float64
```

RMSE and Adjusted RSquared seems okay in respect of test data Mean and Standard deviation.

In [87]:
```
#Plotting Actual V/s Predicted Value
plt.scatter(y_test, preds,color = "Green")
plt.xlabel('True Values [RH]')
plt.ylabel('Predictions [RH]')
plt.grid(False)
plt.axis('equal')
plt.axis('square')
plt.xlim(60,140)
plt.ylim(60,140)
plt.title("Actual v/s Predicted Value")
plt.show()
```



Step:4 Predict your test_df values using XGBoost.

Standardization of Test Data for actual prediction

In [88]:
```
ActTestData=FinalTestData[['X189','X315','X314','X118','X261','X29','X127','X236']]
ActTestData.head()
```

Out[88]:

ID	X189	X315	X314	X118	X261	X29	X127	X236
1	0	0	0	0	0	1	0	0
2	1	0	0	1	0	0	1	0
3	0	0	0	0	0	1	0	0
4	0	0	0	0	0	1	0	0
5	1	0	1	1	1	0	0	0

In [89]:
```
ActTestData.describe()
```

Out[89]:

	X189	X315	X314	X118	X261	X29	X127
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000
mean	0.921834	0.025422	0.448325	0.622238	0.437871	0.038964	0.486101
std	0.268464	0.157421	0.497382	0.484885	0.496184	0.193532	0.499866
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000
75%	1.000000	0.000000	1.000000	1.000000	1.000000	0.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

In [91]:
```
##Prediction on Actual Data
ActualTestPred = xgb_mymodel.predict(ActTestData)
```

In [93]:
```
ActualTestPred
```

Out[93]:
```
array([ 77.410965,  93.83903 ,  77.410965, ...,  93.179054, 112.0005  ,
        93.83903 ], dtype=float32)
```

In [94]:
```
TestID = np.array(testdata['ID'])
FinalPred = pd.DataFrame({'ID': TestID, 'y': ActualTestPred})
FinalPred.head()
```

Out[94]:

	ID	y
0	1	77.410965
1	2	93.839027
2	3	77.410965
3	4	77.410965
4	5	112.000504

In [95]:
```
##Save the predicted values
FinalPred.to_csv('TestDataSubmission.csv', index=False)
```

End of Project: Thank You