Project : Mercedes-Benz Greener Manufacturing

DESCRIPTION : Reduce the time a Mercedes-Benz spends on the test bench.

For this project we will use jupyter notebook. The description of the steps that are used to solve this problem are given along with the code below.

In [1]:
```
# import the required libraries
import numpy as np # Numpy
import pandas as pd # Pandas
import matplotlib.pyplot as plt # Matplotlib for visualization
%matplotlib inline
from sklearn.decomposition import PCA # Principal Component Analysis
from sklearn.model_selection import train_test_split # Train Test Split
from xgboost import XGBRegressor # XGBoost Regressor
from sklearn.metrics import mean_squared_error,r2_score # Model performance metrics
```

In [2]:
```
# Set working directory
import io
%cd "F:\Akshay\Simplilearn\Electives\Machine Learning\Projects\Mercedes-Benz Greener Manufacturing"
```

```
F:\Akshay\Simplilearn\Electives\Machine Learning\Projects\Mercedes-Benz Greener Manufacturing
```

In [3]:
```
# Read the train dataset
train = pd.read_csv('train.csv')
# First 5 records
train.head()
```

Out[3]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
0	0	130.81	k	v	at	a	d	u	j	o	...	0	0	1	0	0	0	0	0	0	0
1	6	88.53	k	t	av	e	d	y	l	o	...	1	0	0	0	0	0	0	0	0	0
2	7	76.26	az	w	n	c	d	x	j	x	...	0	0	0	0	0	0	1	0	0	0
3	9	80.62	az	t	n	f	d	x	l	e	...	0	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	0

5 rows × 378 columns

In [4]:
```
# Read the test dataset
test = pd.read_csv('test.csv')
# First 5 records
test.head()
```

Out[4]:

	ID	X0	X1	X2	X3	X4	X5	X6	X8	X10	...	X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
0	1	az	v	n	f	d	t	a	w	0	...	0	0	0	1	0	0	0	0	0	0
1	2	t	b	ai	a	d	b	g	y	0	...	0	0	1	0	0	0	0	0	0	0
2	3	az	v	as	f	d	a	j	j	0	...	0	0	0	1	0	0	0	0	0	0
3	4	az	l	n	f	d	z	l	n	0	...	0	0	0	1	0	0	0	0	0	0
4	5	w	s	as	c	d	y	i	m	0	...	1	0	0	0	0	0	0	0	0	0

5 rows × 377 columns

In [5]:
```
# Get the number of rows and columns in each dataframe
print(train.shape)
print(test.shape)
```

```
(4209, 378)
(4209, 377)
```

As we can see that there are 4209 rows in both train and test data and 378 columns in train and 377 columns in test data.

In [6]:
```
# Brief description of train data
train.describe()
```

Out[6]:

	ID	y	X10	X11	X12	X13	X14	X15	X16	X17	...	X375	X376	
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	4209.000000	4209.000000	4
mean	4205.960798	100.669318	0.013305	0.0	0.075077	0.057971	0.428130	0.000475	0.002613	0.007603	...	0.318841	0.057258	
std	2437.608688	12.679381	0.114590	0.0	0.263547	0.233716	0.494867	0.021796	0.051061	0.086872	...	0.466082	0.232363	
min	0.000000	72.110000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000	
25%	2095.000000	90.820000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000	
50%	4220.000000	99.150000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000	
75%	6314.000000	109.010000	0.000000	0.0	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	...	1.000000	0.000000	

	ID	y	X10	X11	X12	X13	X14	X15	X16	X17	...	X375	X376
max	8417.000000	265.320000	1.000000	0.0	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	1.000000	1.000000

8 rows × 370 columns

In [7]:
```
# Brief description of test data
test.describe()
```

Out[7]:

	ID	X10	X11	X12	X13	X14	X15	X16	X17	X18	...	X375	X3
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	4209.000000	4209.0000
mean	4211.039202	0.019007	0.000238	0.074364	0.061060	0.427893	0.000713	0.002613	0.008791	0.010216	...	0.325968	0.0496
std	2423.078926	0.136565	0.015414	0.262394	0.239468	0.494832	0.026691	0.051061	0.093357	0.100570	...	0.468791	0.2172
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.0000
25%	2115.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.0000
50%	4202.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.0000
75%	6310.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	...	1.000000	0.0000
max	8416.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	1.000000	1.0000

8 rows × 369 columns

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

In [8]:
```
train.isnull().sum().any()
```

Out[8]: False

In [9]:
```
test.isnull().sum().any()
```

Out[9]: False

From above analysis we can see that there are no null values in train as well as test dataset

Now we will look for the unique values that are present in each columns of the train and the test data

In [10]:

```
# Unique values for columns in train dataset
train_unique = train.dtypes.index
for i in train_unique:
    print(i,train[i].unique())
```

```
ID [   0    6    7 ... 8412 8415 8417]
y [130.81  88.53  76.26 ...  85.71 108.77  87.48]
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']
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']
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']
X3 ['a' 'e' 'c' 'f' 'd' 'b' 'g']
X4 ['d' 'b' 'c' 'a']
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']
X6 ['j' 'l' 'd' 'h' 'i' 'a' 'g' 'c' 'k' 'e' 'f' 'b']
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']
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X382 [0 1]
X383 [0 1]
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```
X384 [0 1]
X385 [0 1]
```

In [11]:

```python
# Unique values for columns in test dataset
test_unique = test.dtypes.index
for i in test_unique:
    print(i,test[i].unique())
```

```
ID [   1    2    3 ... 8413 8414 8416]
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']
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']
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']
X3 ['f' 'a' 'c' 'e' 'd' 'g' 'b']
X4 ['d' 'b' 'a' 'c']
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']
X6 ['a' 'g' 'j' 'l' 'i' 'd' 'f' 'h' 'c' 'k' 'e' 'b']
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']
X10 [0 1]
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X180 [0 1]
X181 [0 1]
X182 [0 1]
X183 [0 1]
X184 [0 1]
X185 [1 0]
X186 [0 1]
X187 [0 1]
```

```
X189 [0 1]
X190 [0 1]
X191 [0 1]
X192 [0 1]
X194 [1 0]
X195 [0 1]
X196 [0 1]
X197 [0 1]
X198 [0 1]
X199 [0 1]
X200 [0 1]
X201 [0 1]
X202 [0 1]
X203 [0 1]
X204 [1 0]
X205 [0 1]
X206 [0 1]
X207 [0 1]
X208 [0 1]
X209 [1 0]
X210 [0 1]
X211 [0 1]
X212 [0 1]
X213 [0 1]
X214 [0 1]
X215 [0 1]
X216 [0 1]
X217 [0 1]
X218 [1 0]
X219 [0 1]
X220 [1 0]
X221 [0 1]
X222 [0 1]
X223 [1 0]
X224 [0 1]
X225 [0 1]
X226 [0 1]
X227 [0 1]
X228 [0 1]
X229 [0 1]
X230 [0 1]
X231 [0 1]
X232 [1 0]
X233 [0 1]
X234 [0 1]
X235 [0 1]
X236 [0 1]
X237 [0 1]
X238 [0 1]
X239 [0 1]
```

```
X240 [0 1]
X241 [0 1]
X242 [0 1]
X243 [0 1]
X244 [0 1]
X245 [0 1]
X246 [1 0]
X247 [0 1]
X248 [0 1]
X249 [0 1]
X250 [1 0]
X251 [0 1]
X252 [0 1]
X253 [0 1]
X254 [0 1]
X255 [0 1]
X256 [1 0]
X257 [0]
X258 [0]
X259 [0 1]
X260 [0 1]
X261 [0 1]
X262 [0 1]
X263 [0 1]
X264 [0 1]
X265 [0 1]
X266 [0 1]
X267 [0 1]
X268 [0 1]
X269 [0 1]
X270 [0 1]
X271 [0 1]
X272 [1 0]
X273 [1 0]
X274 [0 1]
X275 [0 1]
X276 [1 0]
X277 [0 1]
X278 [0 1]
X279 [1 0]
X280 [0 1]
X281 [0 1]
X282 [0 1]
X283 [0 1]
X284 [0 1]
X285 [0 1]
X286 [1 0]
X287 [0 1]
X288 [0 1]
X289 [0 1]
```

```
X290 [0 1]
X291 [0 1]
X292 [0 1]
X293 [0 1]
X294 [0 1]
X295 [0]
X296 [0]
X297 [0 1]
X298 [0 1]
X299 [0 1]
X300 [0 1]
X301 [0 1]
X302 [0 1]
X304 [1 0]
X305 [0 1]
X306 [0 1]
X307 [0 1]
X308 [0 1]
X309 [0 1]
X310 [0 1]
X311 [0 1]
X312 [0 1]
X313 [0 1]
X314 [0 1]
X315 [0 1]
X316 [0 1]
X317 [0 1]
X318 [0 1]
X319 [0 1]
X320 [0 1]
X321 [0 1]
X322 [0 1]
X323 [0 1]
X324 [0 1]
X325 [0 1]
X326 [0 1]
X327 [0 1]
X328 [1 0]
X329 [0 1]
X330 [0 1]
X331 [0 1]
X332 [0 1]
X333 [0 1]
X334 [1 0]
X335 [0 1]
X336 [0 1]
X337 [0 1]
X338 [0 1]
X339 [0 1]
X340 [0 1]
```

```
X341 [0 1]
X342 [0 1]
X343 [0 1]
X344 [0 1]
X345 [0 1]
X346 [0 1]
X347 [0 1]
X348 [1 0]
X349 [0 1]
X350 [1 0]
X351 [0 1]
X352 [0 1]
X353 [0 1]
X354 [0 1]
X355 [0 1]
X356 [0 1]
X357 [0 1]
X358 [1 0]
X359 [0 1]
X360 [0 1]
X361 [1 0]
X362 [0 1]
X363 [1 0]
X364 [0 1]
X365 [0 1]
X366 [0 1]
X367 [0 1]
X368 [0 1]
X369 [0]
X370 [0 1]
X371 [0 1]
X372 [0 1]
X373 [0 1]
X374 [0 1]
X375 [0 1]
X376 [0 1]
X377 [0 1]
X378 [1 0]
X379 [0 1]
X380 [0 1]
X382 [0 1]
X383 [0 1]
X384 [0 1]
X385 [0 1]
```

So in above steps we extracted the columns and the unique values that are present in the train and test data.

Q.3 : Apply label encoder.

Here we will apply label encoder for object datatype columns of both train and test data

In [12]:
```
# Creating a new variable for object columns in train data
objectcols_train = train[['X0','X1','X2','X3','X4','X5','X6','X8']]
```

In [13]:
```
# Dropping the object columns in train data
train = train.drop(['X0','X1','X2','X3','X4','X5','X6','X8'],axis=1)
```

In [14]:
```
# Importing Label Encoder
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

In [15]:
```
# Applying Label Encoder on object columns
for i in objectcols_train:
    le.fit(objectcols_train[i])
    objectcols_train[i] = le.transform(objectcols_train[i])
```

In [16]:
```
# Take a look at object columns after label encoding
objectcols_train
```

Out[16]:

	X0	X1	X2	X3	X4	X5	X6	X8
0	32	23	17	0	3	24	9	14
1	32	21	19	4	3	28	11	14
2	20	24	34	2	3	27	9	23
3	20	21	34	5	3	27	11	4
4	20	23	34	5	3	12	3	13
...	...	...	...	...	...	...	...	...
4204	8	20	16	2	3	0	3	16
4205	31	16	40	3	3	0	7	7
4206	8	23	38	0	3	0	6	4
4207	9	19	25	5	3	0	11	20

	X0	X1	X2	X3	X4	X5	X6	X8
4208	46	19	3	2	3	0	6	22

4209 rows × 8 columns

In [17]:
```
# Joining the label encoded object columns back to the train data
train = pd.concat([train,objectcols_train],axis=1)
# First 5 records
train.head()
```

Out[17]:

	ID	y	X10	X11	X12	X13	X14	X15	X16	X17	...	X384	X385	X0	X1	X2	X3	X4	X5	X6	X8
0	0	130.81	0	0	0	1	0	0	0	0	...	0	0	32	23	17	0	3	24	9	14
1	6	88.53	0	0	0	0	0	0	0	0	...	0	0	32	21	19	4	3	28	11	14
2	7	76.26	0	0	0	0	0	0	0	1	...	0	0	20	24	34	2	3	27	9	23
3	9	80.62	0	0	0	0	0	0	0	0	...	0	0	20	21	34	5	3	27	11	4
4	13	78.02	0	0	0	0	0	0	0	0	...	0	0	20	23	34	5	3	12	3	13

5 rows × 378 columns

Now we will label encode the object columns in the test data

In [18]:
```
# Creating a new variable for object columns in test dataset
objectcols_test = test[['X0','X1','X2','X3','X4','X5','X6','X8']]
```

In [19]:
```
# Dropping the object columns from the test data
test = test.drop(['X0','X1','X2','X3','X4','X5','X6','X8'],axis=1)
```

In [20]:
```
# Importing the Label Encoder
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

In [21]:
```
# Applying Label encoder on object columns
```

```
for i in objectcols_test:
    le.fit(objectcols_test[i])
    objectcols_test[i] = le.transform(objectcols_test[i])
```

In [22]:

```
# Take a look at object columns after label encoding
objectcols_test
```

Out[22]:

	X0	X1	X2	X3	X4	X5	X6	X8
0	21	23	34	5	3	26	0	22
1	42	3	8	0	3	9	6	24
2	21	23	17	5	3	0	9	9
3	21	13	34	5	3	31	11	13
4	45	20	17	2	3	30	8	12
...	...	...	...	...	...	...	...	...
4204	6	9	17	5	3	1	9	4
4205	42	1	8	3	3	1	9	24
4206	47	23	17	5	3	1	3	22
4207	7	23	17	0	3	1	2	16
4208	42	1	8	2	3	1	6	17

4209 rows × 8 columns

In [23]:

```
# Joining the label encoded object columns back to the test data
test = pd.concat([test,objectcols_test],axis=1)
# First 5 records
test.head()
```

Out[23]:

	ID	X10	X11	X12	X13	X14	X15	X16	X17	X18	...	X384	X385	X0	X1	X2	X3	X4	X5	X6	X8
0	1	0	0	0	0	0	0	0	0	0	...	0	0	21	23	34	5	3	26	0	22
1	2	0	0	0	0	0	0	0	0	0	...	0	0	42	3	8	0	3	9	6	24
2	3	0	0	0	0	1	0	0	0	0	...	0	0	21	23	17	5	3	0	9	9

	ID	X10	X11	X12	X13	X14	X15	X16	X17	X18	...	X384	X385	X0	X1	X2	X3	X4	X5	X6	X8
3	4	0	0	0	0	0	0	0	0	0	...	0	0	21	13	34	5	3	31	11	13
4	5	0	0	0	0	1	0	0	0	0	...	0	0	45	20	17	2	3	30	8	12

5 rows × 377 columns

Here we have successfully label encoded the object datatype columns in both train and test data and now our data is ready for further analysis.

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

In [24]:
```
# Creating new variables for independent columns and dependent column and also dropping ID column as it not necessary for
# further analysis
X = train.drop(['ID','y'],axis=1)
y = train.y
```

In [25]:
```
# Now we will import Variance Threshold from sklearn that removes all low-variance features.
from sklearn.feature_selection import VarianceThreshold
var_thresh = VarianceThreshold(threshold=0) # Threshold = 0 to remove columns which have 0 variance
var_thresh.fit(X)
```

Out[25]:
```
VarianceThreshold(threshold=0)
```

In [26]:
```
# Get a mask, or integer index, of the features selected
X.columns[var_thresh.get_support()]
```

Out[26]:
```
Index(['X10', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17', 'X18', 'X19', 'X20',
       ...
       'X384', 'X385', 'X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8'],
      dtype='object', length=364)
```

In [27]:
```
# Now will store columns which have 0 variance in a new variable
constant_columns = [column for column in X.columns if column not in X.columns[var_thresh.get_support()]]
print(len(constant_columns)) # To check how many columns have 0 variance
```

```
12
```

In [28]:
```
# Getting the columns with 0 variance
for feature in constant_columns:
    print(feature)
```

```
X11
X93
X107
X233
X235
X268
X289
X290
X293
X297
X330
X347
```

The columns mentioned above have 0 variance so we will drop them from X in the next step

In [29]:
```
# Removing the 0 variance columns from X
X = X.drop(constant_columns,axis=1)
X
```

Out[29]:

	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	...	X384	X385	X0	X1	X2	X3	X4	X5	X6	X8
0	0	0	1	0	0	0	0	1	0	0	...	0	0	32	23	17	0	3	24	9	14
1	0	0	0	0	0	0	0	1	0	0	...	0	0	32	21	19	4	3	28	11	14
2	0	0	0	0	0	0	1	0	0	0	...	0	0	20	24	34	2	3	27	9	23
3	0	0	0	0	0	0	0	0	0	0	...	0	0	20	21	34	5	3	27	11	4
4	0	0	0	0	0	0	0	0	0	0	...	0	0	20	23	34	5	3	12	3	13
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4204	0	0	0	1	0	0	0	0	0	0	...	0	0	8	20	16	2	3	0	3	16
4205	0	0	0	0	0	0	0	0	0	0	...	0	0	31	16	40	3	3	0	7	7
4206	0	1	1	0	0	0	0	0	0	0	...	0	0	8	23	38	0	3	0	6	4
4207	0	0	0	1	0	0	0	0	0	0	...	0	0	9	19	25	5	3	0	11	20
4208	0	0	0	0	0	0	0	0	0	1	...	0	0	46	19	3	2	3	0	6	22

4209 rows × 364 columns

Now we will repeat the same procedure on test data

In [30]:
```
from sklearn.feature_selection import VarianceThreshold
var_thresh = VarianceThreshold(threshold=0) # Threshold = 0 to remove columns which have 0 variance
var_thresh.fit(test)
```

Out[30]:
```
VarianceThreshold(threshold=0)
```

In [31]:
```
# Get a mask, or integer index, of the features selected
test.columns[var_thresh.get_support()]
```

Out[31]:
```
Index(['ID', 'X10', 'X11', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17', 'X18',
       ...
       'X384', 'X385', 'X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8'],
      dtype='object', length=372)
```

In [32]:
```
# Now will store columns which have 0 variance in a new variable
constant_columns = [column for column in test.columns if column not in test.columns[var_thresh.get_support()]]
print(len(constant_columns)) # To check how many columns have 0 variance
```

```
5
```

In [33]:
```
# Getting the columns with 0 variance
for feature in constant_columns:
    print(feature)
```

```
X257
X258
X295
X296
X369
```

The columns mentioned above have 0 variance so we will drop them from test in the next step

In [34]:
```
# Removing the 0 variance columns from test data and also the ID column as it is not necessary for further analysis
test = test.drop(constant_columns,axis=1)
test = test.drop('ID',axis=1)
test
```

Out[34]:

	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	...	X384	X385	X0	X1	X2	X3	X4	X5	X6	X8
0	0	0	0	0	0	0	0	0	0	0	...	0	0	21	23	34	5	3	26	0	22

	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	...	X384	X385	X0	X1	X2	X3	X4	X5	X6	X8
1	0	0	0	0	0	0	0	0	0	1	...	0	0	42	3	8	0	3	9	6	24
2	0	0	0	0	1	0	0	0	0	0	...	0	0	21	23	17	5	3	0	9	9
3	0	0	0	0	0	0	0	0	0	0	...	0	0	21	13	34	5	3	31	11	13
4	0	0	0	0	1	0	0	0	0	0	...	0	0	45	20	17	2	3	30	8	12
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4204	0	0	0	0	1	0	0	0	0	0	...	0	0	6	9	17	5	3	1	9	4
4205	0	0	0	0	0	0	0	0	0	1	...	0	0	42	1	8	3	3	1	9	24
4206	0	0	0	0	1	0	0	0	0	0	...	0	0	47	23	17	5	3	1	3	22
4207	0	0	0	1	1	0	0	0	0	0	...	0	0	7	23	17	0	3	1	2	16
4208	0	0	0	0	0	0	0	0	0	1	...	0	0	42	1	8	2	3	1	6	17

4209 rows × 371 columns

In [35]:

```
# Now we will check the dimensions of X,y and test data
print('X-Dimension : ',X.shape)
print('y-Dimension : ',y.shape)
print('test-Dimension : ',test.shape)
```

```
X-Dimension :  (4209, 364)
y-Dimension :  (4209,)
test-Dimension :  (4209, 371)
```

From above we can see that the columns with 0 variance are removed from the train and test data

Now as we can see that after label encoding some of the columns have high values compared to other and as we are applying PCA on our data so we need to scale the data for better analysis.

For Scaling we will use the Standard Scaler from sklearn preprocessing

In [36]:
```
from sklearn.preprocessing import StandardScaler
SS = StandardScaler()
```

In [37]:
```
# Lets first apply Standard Scaler on X data
X['X0'] = SS.fit_transform(X[['X0']])
X['X1'] = SS.fit_transform(X[['X1']])
X['X2'] = SS.fit_transform(X[['X2']])
X['X3'] = SS.fit_transform(X[['X3']])
X['X4'] = SS.fit_transform(X[['X4']])
X['X5'] = SS.fit_transform(X[['X5']])
X['X6'] = SS.fit_transform(X[['X6']])
X['X8'] = SS.fit_transform(X[['X8']])
```

In [38]:
```
X.head() # First 5 records after scaling the data
```

Out[38]:

	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	...	X384	X385	X0	X1	X2	X3	X4	X5	X6	X8
0	0	0	1	0	0	0	0	1	0	0	...	0	0	0.163012	1.393488	-0.028122	-1.678270	0.028938	1.292117	0.751787	0.339445
1	0	0	0	0	0	0	0	1	0	0	...	0	0	0.163012	1.159021	0.155388	0.620969	0.028938	1.776974	1.437511	0.339445
2	0	0	0	0	0	0	1	0	0	0	...	0	0	-0.710560	1.510721	1.531709	-0.528650	0.028938	1.655760	0.751787	1.618389
3	0	0	0	0	0	0	0	0	0	0	...	0	0	-0.710560	1.159021	1.531709	1.195779	0.028938	1.655760	1.437511	-1.081605
4	0	0	0	0	0	0	0	0	0	0	...	0	0	-0.710560	1.393488	1.531709	1.195779	0.028938	-0.162454	-1.305384	0.197340

5 rows × 364 columns

In [39]:
```
# Now we will apply Standard Scalar on test data
test['X0'] = SS.fit_transform(test[['X0']])
test['X1'] = SS.fit_transform(test[['X1']])
test['X2'] = SS.fit_transform(test[['X2']])
test['X3'] = SS.fit_transform(test[['X3']])
test['X4'] = SS.fit_transform(test[['X4']])
test['X5'] = SS.fit_transform(test[['X5']])
test['X6'] = SS.fit_transform(test[['X6']])
test['X8'] = SS.fit_transform(test[['X8']])
```

In [40]:
```
test.head() # First 5 records after scaling the data
```

Out[40]:

	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	...	X384	X385	X0	X1	X2	X3	X4	X5	X6	X8
0	0	0	0	0	0	0	0	0	0	0	...	0	0	-0.625211	1.395760	1.586068	1.163082	0.036299	1.266652	-2.388888	1.488396
1	0	0	0	0	0	0	0	0	0	1	...	0	0	0.754609	-0.945199	-0.956445	-1.651020	0.036299	-0.695011	-0.296602	1.773477
2	0	0	0	0	1	0	0	0	0	0	...	0	0	-0.625211	1.395760	-0.076345	1.163082	0.036299	-1.733538	0.749541	-0.364632
3	0	0	0	0	0	0	0	0	0	0	...	0	0	-0.625211	0.225281	1.586068	1.163082	0.036299	1.843611	1.446970	0.205531
4	0	0	0	0	1	0	0	0	0	0	...	0	0	0.951726	1.044616	-0.076345	-0.525379	0.036299	1.728219	0.400827	0.062990

5 rows × 371 columns

Q.4 : Perform dimensionality reduction

We will use Principal Component Analysis (PCA) for dimensionality reduction.

First we will find out the optimum number of components for PCA so that the accuracy of the model will be maximum

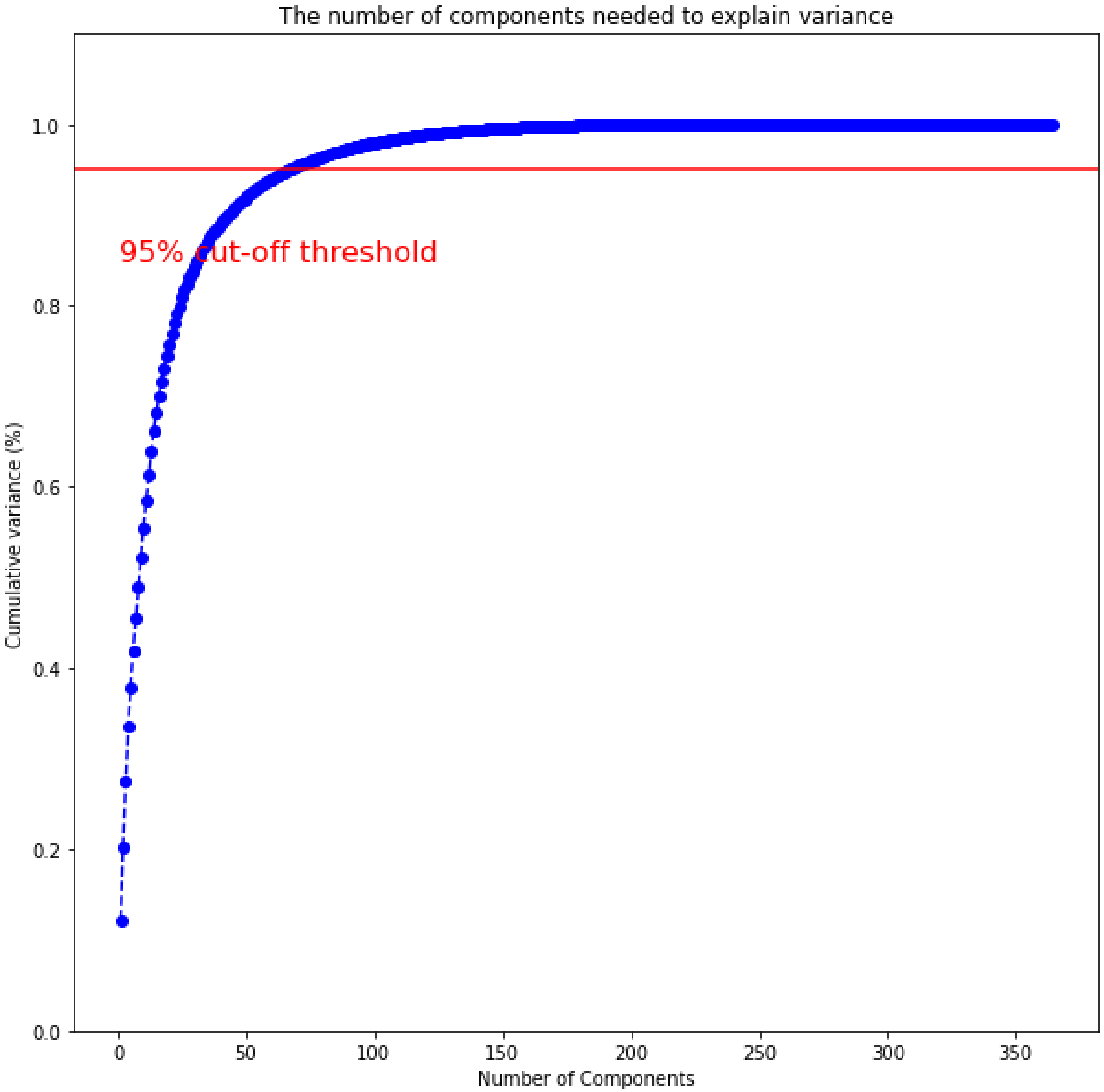
In [41]:
```
pca = PCA()
```

In [42]:
```
pca.fit(X)
```

Out[42]: PCA()

In [43]:
```
# Plotting the graph for optimum number of components
x_comp = np.arange(1, 365, step=1)
y_var = np.cumsum(pca.explained_variance_ratio_)
plt.figure(figsize=(10,10))
plt.ylim(0.0,1.1)
plt.plot(x_comp, y_var, marker='o', linestyle='--', color='b')
plt.xlabel('Number of Components')
```

```
plt.ylabel('Cumulative variance (%)')
plt.title('The number of components needed to explain variance')
plt.axhline(y=0.95, color='r', linestyle='-')
plt.text(0.5, 0.85, '95% cut-off threshold', color = 'red', fontsize=16)
plt.show()
```



It looks that for 95% we need the number of components between 60 to

70. So we will check the accuracy as well as RMSE and R2_Score of our model by using n_components as 0.95 components and we will use that to predict on the test data

In [44]:
```
# Using PCA with (n_components=0.95)
pca = PCA(n_components=0.95,svd_solver='auto')
```

In [45]:
```
# fitting PCA on X
pca.fit(X)
```

Out[45]:
```
PCA(n_components=0.95)
```

In [46]:
```
# Creating a new varible for transformed data
X_transformed = pd.DataFrame(pca.transform(X))
```

In [47]:
```
# Get the dimension of transformed data
X_transformed.shape
```

Out[47]:
```
(4209, 68)
```

In [48]:
```
# First 5 records
X_transformed.head()
```

Out[48]:

	0	1	2	3	4	5	6	7	8	9	...	58	59	60	61	62
0	0.313973	2.189802	2.117590	-0.065338	1.298016	-0.081501	0.190846	-1.591178	-0.437270	1.131222	...	-0.297913	0.929550	-0.319356	0.931352	-0.076276
1	-0.784066	-0.695754	1.208709	-0.239862	0.367869	-1.192245	-0.047564	-1.964055	-0.646133	1.676034	...	-0.103446	0.373455	0.147724	0.167174	0.102862
2	-1.944348	2.050056	2.924898	1.776213	-0.287656	-1.373386	3.786533	-0.623482	-0.481827	0.258289	...	-0.191323	-0.093491	-0.171269	0.281752	0.209978
3	-1.934820	0.822778	3.037489	2.956736	-1.455696	-2.191549	1.604562	-0.546356	-0.079549	0.036500	...	-0.109367	-0.015207	-0.163451	-0.125693	0.282807
4	-2.169094	0.603654	3.131980	2.602855	-1.551850	-1.665966	2.373468	1.302750	0.760940	-1.019324	...	0.041649	0.001472	0.133435	0.052521	0.324992

5 rows × 68 columns

In [49]:
```
# fitting PCA on test
pca.fit(test)
test_transformed = pd.DataFrame(pca.transform(test))
```

In [50]:
```
# Get dimension of the transformed data
test_transformed.shape
```

Out[50]: (4209, 68)

In [51]:
```
# First 5 Records
test_transformed.head()
```

Out[51]:

	0	1	2	3	4	5	6	7	8	9	...	58	59	60	61	62
0	-1.891260	0.344538	3.466406	1.917411	-1.317323	-1.686398	-0.947895	3.963974	-0.177529	-1.477851	...	-0.029105	0.266649	-0.014142	0.153464	-0.301432
1	4.175087	1.310735	0.527854	-1.034485	1.514685	1.445055	-0.161502	1.086963	-0.593352	1.222311	...	0.104767	0.048484	0.164372	0.017628	-0.116405
2	-1.988420	0.198563	1.101566	0.945251	-0.008231	-0.617490	0.346186	1.656466	-2.674321	0.154451	...	-0.351260	0.098849	0.028724	0.407329	-0.087659
3	-1.296248	0.177314	2.940011	2.862125	-1.486869	-2.194655	-1.761780	2.097380	-1.078638	0.017821	...	0.037204	0.215851	-0.043258	0.103153	-0.119684
4	-2.250654	0.507154	-1.602801	-1.648139	0.999834	-0.988460	-1.399337	-0.222853	0.729902	0.233054	...	0.290015	-0.059532	0.149463	0.028351	-0.092650

5 rows × 68 columns

As we can see that we need 68 columns in our data for accuracy to be 95%

Q.5 : Predict your test_df values using XGBoost.

In [52]:
```
# train test split
X_train, X_test, y_train, y_test = train_test_split(X_transformed, y, test_size=0.25, random_state=42)
```

In [53]:
```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(3156, 68)
(1053, 68)
(3156,)
(1053,)
```

In [54]:

```
XGB = XGBRegressor(learning_rate=0.01,n_estimators=5000,max_depth=4,min_child_weight=2, gamma=0, subsample=0.8,
                   colsample_bytree=0.8,reg_alpha=0.005,seed=27)
```

In [55]:

```
XGB.fit(X_train,y_train)
y_pred = XGB.predict(X_test)
print(XGB.score(X_train,y_train))
```

```
0.9448161061087406
```

In [56]:

```
print("RMSE :",np.sqrt(mean_squared_error(y_test,y_pred)))
print("R2 Score :",r2_score(y_test,y_pred))
```

```
RMSE : 9.675352519706323
R2 Score : 0.41100341473522095
```

From above analysis we can see that the model score is very good i.e.94.48% and RMSE is also small i.e 9.675 however the R2 Score is 0.411 which is somewhat good.

In [57]:

```
train_pred = pd.DataFrame({'Actual':y_test,'Predicted':y_pred})
train_pred.head(15)
```

Out[57]:

	Actual	Predicted
1073	97.94	95.233414
144	96.41	94.641479
2380	105.83	112.940292
184	79.09	77.344017
2587	108.69	113.367981
2768	94.60	97.796158
3697	84.48	95.543823

	Actual	Predicted
999	110.24	100.071259
2856	120.80	103.273911
2862	122.66	113.642799
2313	85.94	76.827133
3290	88.05	91.507500
3281	90.01	94.115486
2348	140.25	101.150414
166	98.25	92.680054

Above table gives us a good comparison of Actual Vs Predicted values and we can see that the our model has good accuracy.

Now we will predict the values based on the test data

In [58]:
```
predicted = XGB.predict(test_transformed)
predicted[:50]
```

Out[58]:
```
array([ 97.41057 , 103.53869 , 101.74826 ,  89.42028 , 118.691986,
        90.39269 , 107.90589 ,  92.42134 , 125.274605,  94.78106 ,
       123.88641 , 100.424355,  98.00963 ,  95.41308 ,  99.21417 ,
        98.58869 , 119.192375,  97.81834 ,  99.33622 ,  97.318634,
        97.81834 ,  97.81834 ,  93.92864 ,  98.51028 ,  89.59668 ,
       123.568924, 100.40258 ,  97.91276 , 101.41077 , 106.394   ,
       108.470695,  97.06113 , 113.44989 , 101.702225, 106.02058 ,
       100.609634,  91.60046 ,  98.73547 ,  95.237465,  99.91412 ,
       101.35742 ,  97.4928  , 104.141014, 103.477325, 122.714714,
       103.47554 ,  98.73547 ,  99.49108 , 109.68202 , 106.07846 ],
      dtype=float32)
```

Above array gives the first 50 predicted values on the test data

Summary :

1. We checked our data for columns that have zero variance and we found that there are 12 columns in the train data and 5 columns in the test data having a zero variance and we removed those for analysis purpose.

2. There were no null values in the train as well as test dataset and we also extracted unique values of the columns in train and test data.

3. We also applied Label Encoder on object datatype columns of train and test data and converted them to numeric for analysis purpose

4. We scaled our train and test data and also performed dimensionality reduction using Principal Component Analysis (PCA) we found out 68 features are necessary to achieve 95% accuracy

5. We used XGBoost Regressor and we got a pretty good accuracy and low RMSE on our model and we also predicted values on test data.