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

```
from google.colab import drive
drive.mount('/content/drive/')
```

```
Drive already mounted at /content/drive/; to attempt to forcibly remount, call drive.mou
```

Injesting The Data

```
train_data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/data/benz/train.csv')
test_data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/data/benz/test.csv')
```

Data Analysis

```
train_data.shape
```

```
(4209, 378)
```

```
test_data.shape
```

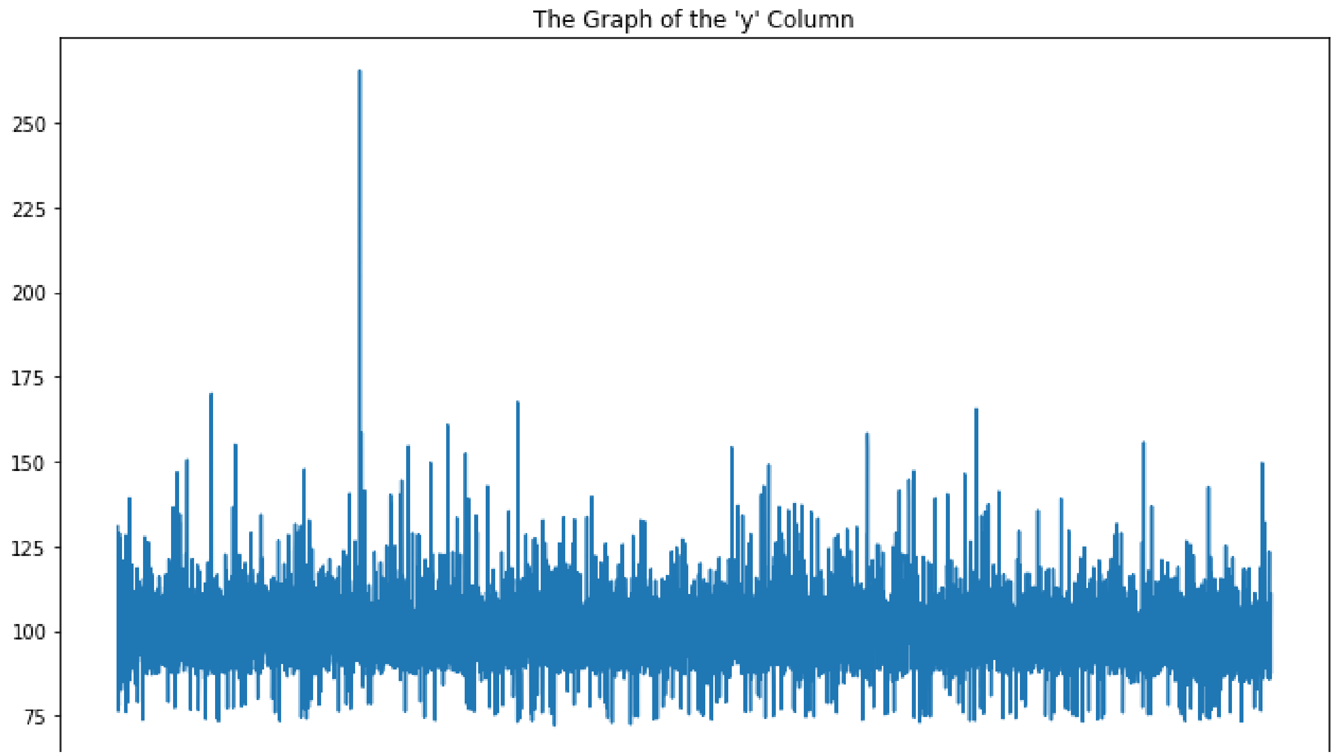
```
(4209, 377)
```

```
train_data.head()
```

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	X380	X
0	0	130.81	k	v	at	a	d	u	j	o	...	0	0	1	0	0	0	
1	6	88.53	k	t	av	e	d	y	l	o	...	1	0	0	0	0	0	
2	7	76.26	az	w	n	c	d	x	j	x	...	0	0	0	0	0	0	
3	9	80.62	az	t	n	f	d	x	l	e	...	0	0	0	0	0	0	
4	13	78.02	az	v	n	f	d	h	d	n	...	0	0	0	0	0	0	

5 rows × 378 columns

```
train_data['y'].plot(figsize=(12,7), title="The Graph of the 'y' Column");
```




```
1 test_data.head()
```

	ID	X0	X1	X2	X3	X4	X5	X6	X8	X10	...	X375	X376	X377	X378	X379	X380	X382
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	(

5 rows × 377 columns

```
1 train_data.dtypes
```

```
ID         int64
y        float64
X0        object
X1        object
X2        object
          ...
X380       int64
X382       int64
X383       int64
X384       int64
X385       int64
Length: 378, dtype: object
```

```
1 train_data.describe()
```

	ID	y	X10	X11	X12	X13	X1
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	4209.000000	4209.00000
mean	4205.960798	100.669318	0.013305	0.0	0.075077	0.057971	0.42813
std	2437.608688	12.679381	0.114590	0.0	0.263547	0.233716	0.49486
min	0.000000	72.110000	0.000000	0.0	0.000000	0.000000	0.00000
25%	2095.000000	90.820000	0.000000	0.0	0.000000	0.000000	0.00000
50%	4220.000000	99.150000	0.000000	0.0	0.000000	0.000000	0.00000
75%	6314.000000	109.010000	0.000000	0.0	0.000000	0.000000	1.00000
max	8417.000000	265.320000	1.000000	0.0	1.000000	1.000000	1.00000

8 rows × 370 columns

```
1 test_data.dtypes
```

```
ID       int64
X0      object
X1      object
X2      object
X3      object
         ...
X380     int64
X382     int64
X383     int64
X384     int64
X385     int64
Length: 377, dtype: object
```

```
1   test_data.describe()
```

	ID	X10	X11	X12	X13	X14	
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.(
std	2423.078926	0.138565	0.015414	0.262394	0.239468	0.494832	0.:

Checking Null Values

```
train_data.isnull().sum()
```

```
ID      0
y       0
X0      0
X1      0
X2      0
       ..
X380    0
X382    0
X383    0
X384    0
X385    0
Length: 378, dtype: int64
```

```
test_data.isnull().sum()
```

```
ID      0
X0      0
X1      0
X2      0
X3      0
       ..
X380    0
X382    0
X383    0
X384    0
X385    0
Length: 377, dtype: int64
```

```
train_data.describe(include='object')
```

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

Separating categorical and numeric feature

```
dictionary={}
dictionary['num'] = train_data.dtypes[train_data.dtypes=='int64'].index
dictionary['cat'] = train_data.dtypes[train_data.dtypes=='object'].index
dictionary
```

```
{'cat': Index(['X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8'], dtype='object'),
 'num': Index(['ID', 'X10', 'X11', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17', 'X18',
        ...
        'X375', 'X376', 'X377', 'X378', 'X379', 'X380', 'X382', 'X383', 'X384',
        'X385'],
       dtype='object', length=369)}
```

```
train_data['X376'].value_counts()
```

```
0    3968
1     241
Name: X376, dtype: int64
```

Finding and removing features with zero variance

```
da=[]
count=0
for i in dictionary['num']:
  if(np.var(train_data[i])==0):
    da.append(i)
print(da)
```

```
['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290', 'X293', 'X297', 'X330',
```

```
z=['ID','y']
da.extend(z)
print(da)
```

```
['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290', 'X293', 'X297', 'X330',
```

```
y_train=train_data['y'].values
ID_train=train_data['ID'].values
ID_test=test_data['ID'].values
```

```
da_test=['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290', 'X293', 'X297', 'X
```

```
X_train=train_data.drop(da,axis=1)
X_test=test_data.drop(da_test,axis=1)
```

```
X_train.shape
```

```
(4209, 364)
```

```
X_test.shape
```

```
(4209, 364)
```

Applying Label encoding on the categorical variables

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

```
#Train dataset
le0=LabelEncoder()
le1=LabelEncoder()
le2=LabelEncoder()
le3=LabelEncoder()
le4=LabelEncoder()
le5=LabelEncoder()
le6=LabelEncoder()
le8=LabelEncoder()
```

```
le0.fit(X_train['X0'])
le1.fit(X_train['X1'])
le2.fit(X_train['X2'])
le3.fit(X_train['X3'])
le4.fit(X_train['X4'])
le5.fit(X_train['X5'])
le6.fit(X_train['X6'])
le8.fit(X_train['X8'])
```

```
LabelEncoder()
```

```
#Test Dataset
let0=LabelEncoder()
let1=LabelEncoder()
let2=LabelEncoder()
let3=LabelEncoder()
let4=LabelEncoder()
let5=LabelEncoder()
let6=LabelEncoder()
let8=LabelEncoder()
```

```
#Test Dataset
let0.fit(X_test['X0'])
let1.fit(X_test['X1'])
let2.fit(X_test['X2'])
let3.fit(X_test['X3'])
```

```
let4.fit(X_test['X4'])
let5.fit(X_test['X5'])
let6.fit(X_test['X6'])
let8.fit(X_test['X8'])
```

```
LabelEncoder()
```

Transforming and replacing the categorical variables into 0s and 1s

```
#Train dataset
X_train['X0'] = le0.transform(X_train['X0'])
X_train['X1'] = le1.transform(X_train['X1'])
X_train['X2'] = le2.transform(X_train['X2'])
X_train['X3'] = le3.transform(X_train['X3'])
X_train['X4'] = le4.transform(X_train['X4'])
X_train['X5'] = le5.transform(X_train['X5'])
X_train['X6'] = le6.transform(X_train['X6'])
X_train['X8'] = le8.transform(X_train['X8'])
```

```
#Test dataset
X_test['X0'] = let0.transform(X_test['X0'])
X_test['X1'] = let1.transform(X_test['X1'])
X_test['X2'] = let2.transform(X_test['X2'])
X_test['X3'] = let3.transform(X_test['X3'])
X_test['X4'] = let4.transform(X_test['X4'])
X_test['X5'] = let5.transform(X_test['X5'])
X_test['X6'] = let6.transform(X_test['X6'])
X_test['X8'] = let8.transform(X_test['X8'])
```

```
X_train.head()
```

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	...	X375	X376	X377	X378	X379	X380	X3
0	32	23	17	0	3	24	9	14	0	0	...	0	0	1	0	0	0	
1	32	21	19	4	3	28	11	14	0	0	...	1	0	0	0	0	0	
2	20	24	34	2	3	27	9	23	0	0	...	0	0	0	0	0	0	
3	20	21	34	5	3	27	11	4	0	0	...	0	0	0	0	0	0	
4	20	23	34	5	3	12	3	13	0	0	...	0	0	0	0	0	0	

5 rows × 364 columns

```
X_test.head()
```

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	...	X375	X376	X377	X378	X379	X380	X38
0	21	23	34	5	3	26	0	22	0	0	...	0	0	0	1	0	0	
1	42	3	8	0	3	9	6	24	0	0	...	0	0	1	0	0	0	
2	21	23	17	5	3	0	9	9	0	0	...	0	0	0	1	0	0	
3	21	13	34	5	3	31	11	13	0	0	...	0	0	0	1	0	0	
4	45	20	17	2	3	30	8	12	0	0	...	1	0	0	0	0	0	

Perform dimensionality reduction on Train dataset

```
from sklearn.decomposition import PCA
pca = PCA(n_components=0.7)
pca.fit(X_train)
```

```
PCA(n_components=0.7)
```

```
pca.explained_variance_ratio_
```

```
array([0.38334782, 0.21388033, 0.13261866])
```

```
X_train_transformed = pca.transform(X_train)
X_test_transformed = pca.transform(X_test)
```

```
X_train_transformed.shape, X_test_transformed.shape
```

```
((4209, 3), (4209, 3))
```

```
pca.inverse_transform(X_train_transformed).shape
```

```
(4209, 364)
```

Split the datasets

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_train_transformed,y_train , random_
```

```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(3156, 3)
(1053, 3)
```

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

Evaluate with ensemble learning algorithms

```
import xgboost
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error
```

```
#Using XGBoost - The most powerful ensemble learning algorithm
start = time.time()
xgbr = xgboost.XGBRegressor()
xgbr.fit(X_train, y_train)

y_pred= xgbr.predict(X_test)
score = mean_squared_error(y_pred, y_test)
print('Score : ', score)
end = time.time()

print('\nRunTime : ', end - start)
```

```
[02:53:42] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now de
Score :  110.00614368130348

RunTime :  0.1572103500366211
```

```
#Using GradientBoost
start = time.time()
gbr = GradientBoostingRegressor()
gbr.fit(X_train, y_train)

y_pred= gbr.predict(X_test)
score = mean_squared_error(y_pred, y_test)
print('Score : ', score)
end = time.time()

print('\nRunTime : ', end - start)
```

```
Score :  111.54442824296098

RunTime :  0.3748013973236084
```

As seen above, XGBoost performs more efficiently than GradientBoost

0s completed at 10:53 PM