Project to Submit – Project 1

DESCRIPTION

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

Problem Statement Scenario:
Since the first automobile, the Benz Patent Motor Car in 1886, Mercedes-Benz has stood for important automotive innovations. These include the passenger safety cell with a crumple zone, the airbag, and intelligent assistance systems. Mercedes-Benz applies for nearly 2000 patents per year, making the brand the European leader among premium carmakers. Mercedes-Benz is the leader in the premium car industry. With a huge selection of features and options, customers can choose the customized Mercedes-Benz of their dreams.

To ensure the safety and reliability of every unique car configuration before they hit the road, the company's engineers have developed a robust testing system. As one of the world's biggest manufacturers of premium cars, safety and efficiency are paramount on Mercedes-Benz's production lines. However, optimizing the speed of their testing system for many possible feature combinations is complex and time-consuming without a powerful algorithmic approach.

You are required to reduce the time that cars spend on the test bench. Others will work with a dataset representing different permutations of features in a Mercedes-Benz car to predict the time it takes to pass testing. Optimal algorithms will contribute to faster testing, resulting in lower carbon dioxide emissions without reducing Mercedes-Benz's standards.

Following actions should be performed:

- If for any column(s), the variance is equal to zero, then you need to remove those variable(s).
- Check for null and unique values for test and train sets.
- Apply label encoder.
- Perform dimensionality reduction.
- Predict your test_df values using XGBoost.

Write Up:

Analysis Tasks to be performed:

1. Data was already divided into two files for training and test dataset.
2. Both had equal number of rows

In [5]:
```
train_df.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
```

In [6]:
```
test_df.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
```

In [7]:
```
train_df.describe()
```

Out[7]:

	ID	y	X10	X11	X12	X13	X14	X15	X16	X17	...	X375	X
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	4209.000000	4209.000
mean	4205.960798	100.669318	0.013305	0.0	0.075077	0.057971	0.428130	0.000475	0.002613	0.007603	...	0.318841	0.057
std	2437.608688	12.679381	0.114590	0.0	0.263547	0.233716	0.494867	0.021796	0.051061	0.086872	...	0.466082	0.232
min	0.000000	72.110000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000
25%	2095.000000	90.820000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000
50%	4220.000000	99.150000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000
75%	6314.000000	109.010000	0.000000	0.0	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	...	1.000000	0.000
max	8417.000000	265.320000	1.000000	0.0	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	1.000000	1.000

8 rows × 370 columns

In [8]:
```
test_df.describe()
```

Out[8]:

	ID	X10	X11	X12	X13	X14	X15	X16	X17	X18	...	X375	42
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	4209.000000	42
mean	4211.039202	0.019007	0.000238	0.074364	0.061060	0.427893	0.000713	0.002613	0.008791	0.010216	...	0.325968	
std	2423.078926	0.136565	0.015414	0.262394	0.239468	0.494832	0.026691	0.051061	0.093357	0.100570	...	0.468791	
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	
25%	2115.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	

3.
4. Training dataset as usual had y column which is the target column which was missing in test data set

In [9]:
```
print("Number of datapoints: ", train_df.shape[0])
print("Number of features: ", train_df.shape[1])
train_df.head()
```

```
Number of datapoints:  4209
Number of features:  378
```

Out[9]:

	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 [10]:
```
print("Number of datapoints: ", test_df.shape[0])
print("Number of features: ", test_df.shape[1])
test_df.head()
```

```
Number of datapoints:  4209
Number of features:  377
```

Out[10]:

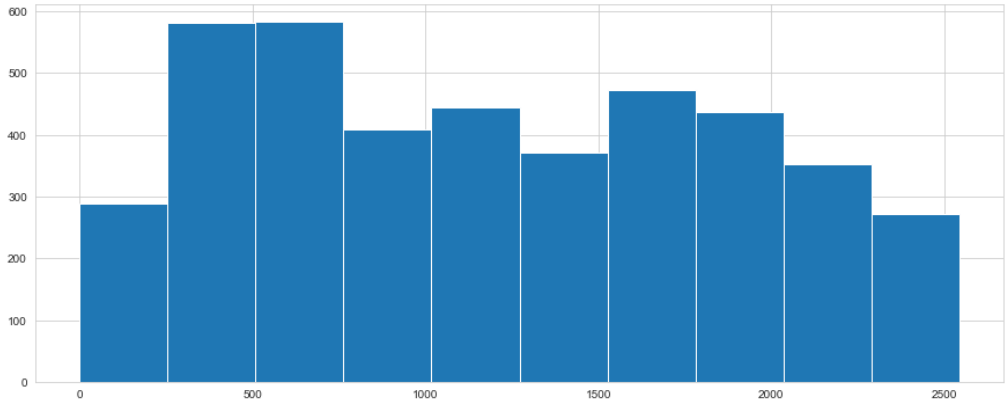
	ID	X0	X1	X2	X3	X4	X5	X6	X8	X10	...	X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
0	1	az	v	n	f	d	t	a	w	0	...	0	0	0	1	0	0	0	0	0	0
1	2	t	b	ai	a	d	b	g	y	0	...	0	0	1	0	0	0	0	0	0	0
2	3	az	v	as	f	d	a	j	j	0	...	0	0	0	1	0	0	0	0	0	0
3	4	az	l	n	f	d	z	l	n	0	...	0	0	0	1	0	0	0	0	0	0
4	5	w	s	as	c	d	y	i	m	0	...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

5 rows × 377 columns

5. Training data set had 369 binary features, 8 features which have datatype = ‘object’ is most probably categorical features and 1 remaining feature is our target variable i.e. ‘y’.

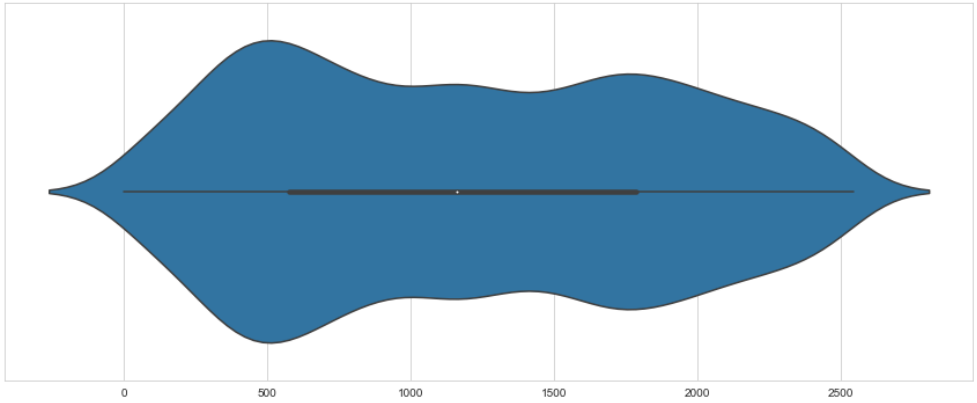
6. Performing univariate analysis on categorical features, to get the insight out of it. Any feature that has very low variance as compared to other categorical features, will be removed
7. Found 12 columns which had no variance. We removed them.
    1. Name = X11
    2. Name = X93
    3. Name = X107
    4. Name = X233
    5. Name = X235
    6. Name = X268
    7. Name = X289
    8. Name = X290
    9. Name = X293
    10. Name = X297
    11. Name = X330
    12. Name = X347
    13. No of columns which has zero variance = 12
8. Also checked for null, duplicate rows and unique values
9. Got the details of categorical columns and integers columns separatel
10. Then applied encoder
11. Then Summarize outcome (testing time) in training dataset (created box-plot to see how the data is spread)
12. On y, we plotted histogram & violin plot to see if there are any outliers.

Out[34]: <AxesSubplot:>



In [35]:
```
sns.violinplot(train_df['y'].values)
```

Out[35]: <AxesSubplot:>



13. Perform dimensionality reduction.
14. The methods at our disposal using linear algebra are:
15. Principal Components Analysis Singular Value Decomposition Non-Negative Matrix Factorization. Identified 6 main components.
16. Created the dataset to include only these components for further analysis
17. Before using XGBoost, checked the model with the following methods
    - Logistic Regression
    - KNN
    - SVM
    - Random Forest
18. None of the model was good. We tried XGBoost.
19. For the first time we got good >95% accuracy.
20. We further tested with different booster='dart', ‘gbliner’, ‘gbtree’. Gbtree gave the best result, and
21. We enhanced it further with K-fold.
22. We got predicted y with accuracy of 99.9%

Code:

Mercedes-Benz Greener Manufacturing

DESCRIPTION

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To ensure the safety and reliability of every unique car configuration before they hit the road, the company's engineers have developed a robust testing system. As one of the world's biggest manufacturers of premium cars, safety and efficiency are paramount on Mercedes-Benz's production lines. However, optimizing the speed of their testing system for many possible feature combinations is complex and time-consuming without a powerful algorithmic approach.

You are required to reduce the time that cars spend on the test bench. Others will work with a dataset representing different permutations of features in a Mercedes-Benz car to predict the time it takes to pass testing. Optimal algorithms will contribute to faster testing, resulting in lower carbon dioxide emissions without reducing Mercedes-Benz's standards.

Following actions should be performed:

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

Check for null and unique values for test and train sets.

Apply label encoder.

Perform dimensionality reduction.

Predict your test_df values using XGBoost.

The data set is already divided into train and test

```
import numpy as np

import pandas as pd
```

```
from datetime import datetime as dt
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 15, 6

import warnings
warnings.filterwarnings('ignore')

# importing csv module
import csv
# csv file name
train_df = pd.read_csv(r'D:\OneDrive\Studies\AI - ML\Python\Examples\ML Pracs\train.csv')

# importing csv module
import csv
# csv file name
test_df = pd.read_csv(r'D:\OneDrive\Studies\AI - ML\Python\Examples\ML Pracs\test.csv')

train_df.info()

test_df.info()

train_df.describe()

test_df.describe()

print("Number of datapoints: ", train_df.shape[0])
print("Number of features: ", train_df.shape[1])
train_df.head()
```

```
print("Number of datapoints: ", test_df.shape[0])
print("Number of features: ", test_df.shape[1])
test_df.head()

dtype_df = train_df.dtypes.reset_index()
dtype_df.columns = ["feature name","dtypes"]
dtype_df.groupby("dtypes").agg("count").reset_index()
```

there are 369 binary features,

8 features which have datatype = ‘object’ is most probably categorical features and

1 remaining feature is our target variable i.e. ‘y’.

Performing univariate analysis on categorical features, to get the insight out of it.

Any feature that has very low variance as compared to other categorical features, will be removed

```
dtype_df = test_df.dtypes.reset_index()
dtype_df.columns = ["feature name","dtypes"]
dtype_df.groupby("dtypes").agg("count").reset_index()
```

Question 1:

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

Starting with train and then with test data

```
variance = pow(train_df.drop(columns={'ID','y'}).std(),2).to_dict()

null_cnt = 0
for key, value in variance.items():
    if(value==0):
        print('Name = ',key)
        null_cnt = null_cnt+1
```

```
print('No of columns which has zero variance = ',null_cnt)


train_df = train_df.drop(columns={'X11','X93','X107','X233','X235','X268','X289','X290','X293','X297','X330','X347'})
train_df.shape


variance = pow(test_df.drop(columns={'ID'}).std(),2).to_dict()


null_cnt = 0
for key, value in variance.items():
    if(value==0):
        print('Name = ',key)
        null_cnt = null_cnt+1
print('No of columns which has zero variance = ',null_cnt)


train_df = train_df.drop(columns={'X257','X258','X295','X296','X369'})
train_df.shape
```

Question 2:

Check for null and unique values for test and train sets.

```
print(train_df.nunique())
print(test_df.nunique())


#Check for null value
print(train_df.isnull().sum().any())
print(test_df.isnull().sum().any())


train_df.describe(include='object')


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

```
dup_ID = train_df['ID'].duplicated().sum()
print(f"Here we have {dup_ID} duplicate IDs")
```

No null data, all unique values across the file listed.

Henceforth working with Train data only as it is the data that we would use for our model.

Question 3:

Apply label encoder.

No null variable. All the variables are categorical applying encoder

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for i in train_df.columns:
    train_df[i]=le.fit_transform(train_df[i])
```

```
train_df.head()
```

```
train_df.corr()
```

Summarize outcome (testing time) in training dataset

```
# Draw a vertical boxplot grouped
# by a categorical variable: X0
sns.set_style("whitegrid")
```

```
object_columns = test_df.describe(include='object').columns
print('\nobject columns:\n',object_columns)
cols = len(object_columns)
```

```
sns.boxplot(x = 'X0', y = 'y', data = train_df)


sns.boxplot(x = 'X1', y = 'y', data = train_df)


sns.boxplot(x = 'X2', y = 'y', data = train_df)


sns.boxplot(x = 'X3', y = 'y', data = train_df)


sns.boxplot(x = 'X4', y = 'y', data = train_df)


sns.boxplot(x = 'X5', y = 'y', data = train_df)


sns.boxplot(x = 'X6', y = 'y', data = train_df)


sns.boxplot(x = 'X8', y = 'y', data = train_df)


#Now the target y

train_df['y'].hist()


sns.violinplot(train_df['y'].values)
```

The data seems optimized. The removal of few data points which had no variance had optimized the y. No reason to test for any more outliers.

Idealy, this test is done first, but if variance 0 is removed, it increases the chances of y being optimized, with no outliers.

Dimensionality reduction refers to techniques for reducing the number of input variables in training data.

Fewer input dimensions often means correspondingly fewer parameters or a simpler structure in the machine learning model, referred to as degrees of freedom. A model with too many degrees of freedom is likely to overfit the training dataset and may not perform well on new data.

It is desirable to have simple models that generalize well, and in turn, input data with few input variables. This is particularly true for linear models where the number of inputs and the degrees of freedom of the model are often closely related.

Dimensionality reduction is a data preparation technique performed on data prior to modeling. It might be performed after data cleaning and data scaling and before training a predictive model.

Question 4: Perform dimensionality reduction.

The methods at our disposal using linear algebra are:

Principal Components Analysis

Singular Value Decomposition

Non-Negative Matrix Factorization

```
# Draw a vertical boxplot grouped

# by a categorical variable: X0

train_df.describe(include='int64')
```

```
bin_columns = train_df['ID']

print('\nobject columns:\n',bin_columns)
```

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

scaler.fit(train_df)

sdata = scaler.transform(train_df)

from sklearn.decomposition import PCA
```

```
sdata.shape


# lets take top 6 pca components
pca = PCA(n_components=6)
pca.fit(sdata)
x_pca = pca.transform(sdata)
x_pca.shape


# number of components
n_pcs= pca.components_.shape[0]
n_pcs



 # get the index of the most important feature on EACH component i.e. largest ⎵ ,→absolute value
# using LIST COMPREHENSION HERE
most_important = [np.abs(pca.components_[i]).argmax() for i in range(n_pcs)]
initial_feature_names = bin_columns
most_important



# using LIST COMPREHENSION HERE AGAIN
dic = {'PC{}'.format(i): most_important[i] for i in range(n_pcs)}


dic


pca.components_


explained_variance = pca.explained_variance_ratio_
explained_variance
#it is a measure of the variance of the data when projected onto that axis. The projection of each data point onto
the
```

#principal axes are the “principal components” of the data. .4 is the var of PCA

#and .179 is the var of PCA2

#Creating training and test data with only these columns

selected_columns = train_df[['ID', 'X325', 'X27', 'X180', 'X161', 'X309', 'X85', 'y']]

X_train = selected_columns.copy()

X_train.shape

X_train

#Now creating a df with only these 5 components

selected_columns = test_df[['ID', 'X325', 'X27', 'X180', 'X161', 'X309', 'X85']]

X_test = selected_columns.copy()

X_test.shape

X_test

#now will perfrom XGBoost

Predict your test_df values using XGBoost.

Model Selection

Logistic Regression

KNN

SVM

Random Forest

#Now splitting the data into train & test. Before that, identifying all input parameters as X, and output parameter as y

y_train=train_df['y']

```
y_train
```

```
y_train.shape
```

```
from sklearn.model_selection import learning_curve
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix

import xgboost as xgb
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split
```

```
X_train.shape
```

```
X_test.shape
```

```
y_train.shape
```

```
#We do not have X & y. Creating X
```

```
X = X_train
#X = pd.concat([X_train,X_test])
print(X)
```

```
X.shape
```

```
#y = pd.concat([y_train,y_train])
y = y_train
```

```
y.shape


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=72)


# Logistic Regression
logreg=LogisticRegression(solver='liblinear',multi_class='ovr')
logreg.fit(X_train,y_train)
y_pred=logreg.predict(X_test)
y_pred
#Accuracy Score
#print(metrics.accuracy_score(y_pred,y_train))
accuracy = (logreg.score(X_train,y_train))
print(accuracy)


# Logistic Regression
logreg=LogisticRegression(solver='lbfgs',multi_class='auto')
logreg.fit(X_train,y_train)
y_pred=logreg.predict(X_test)
y_pred
#Accuracy Score
#print(metrics.accuracy_score(y_pred,y_train))
accuracy = (logreg.score(X_train,y_train))
print(accuracy)


#SVM "Support Vector Classifier"
from sklearn.svm import SVC
svm = SVC(kernel='linear')


# fitting x samples and y classes
svm.fit(X_train,y_train)
y_pred = svm.predict(X_test)
```

```
from sklearn import metrics
accuracy = metrics.accuracy_score(y_test, y_pred)
print(accuracy)

#KNN with 5 neighbours
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred))

print(classification_report(y_test,pred))

knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred))

print(classification_report(y_test,pred))

avg_score=[]
for k in range(2,30):
   knn=KNeighborsClassifier(n_jobs=-1,n_neighbors=k)
   score=cross_val_score(knn,X_train,y_train,cv=5,n_jobs=-1,scoring='accuracy')
   avg_score.append(score.mean())

plt.figure(figsize=(12,8))
plt.plot(range(2,30),avg_score)
plt.xlabel("n_neighbours")
plt.ylabel("accuracy")
#plt.xticks(range(2,30,2))
```

```
#Random Forests Classifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score

rfc=RandomForestClassifier(n_jobs=-1,random_state=51)
rfc.fit(X_train,y_train)
print(rfc.score(X_test,y_test))
print(f1_score(y_test,rfc.predict(X_test),average='macro'))

#Till now SVM followed by Random forest is the leading model

from xgboost import XGBClassifier
from sklearn.metrics import mean_squared_error
from sklearn import svm
from xgboost import XGBClassifier
import xgboost as xgb

#Here, we are using XGBRegressor as a Machine Learning model to fit the data.
model = xgb.XGBRegressor(booster='dart', objective='reg:squarederror', num_class = 1,  eval_metric = 'merror',
n_estimators = 10, seed = 123)
model.fit(X_train, y_train)
print(); print(model)

# Predict the model
pred = model.predict(X_test)

# RMSE Computation
rmse = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE : % f" %(rmse))
```

```
expected_y  = y_test

predicted_y = model.predict(X_test)

print(metrics.r2_score(y_test, predicted_y))


predicted_y


#Here, we are using XGBRegressor as a Machine Learning model to fit the data.

model = xgb.XGBRegressor(booster='gblinear', objective='reg:squarederror', num_class = 1,  eval_metric = 'merror',
n_estimators = 10, seed = 123)

model.fit(X_train, y_train)

print(); print(model)


# Predict the model

pred = model.predict(X_test)


# RMSE Computation

rmse = np.sqrt(mean_squared_error(y_test, pred))

print("RMSE : % f" %(rmse))


expected_y  = y_test

predicted_y = model.predict(X_test)

print(metrics.r2_score(y_test, predicted_y))


#As we see gbliner is not the right model.

#Here, we are using XGBRegressor as a Machine Learning model to fit the data.

model = xgb.XGBRegressor(booster='gbtree', objective='reg:squarederror', num_class = 1,  eval_metric = 'merror',
n_estimators = 10, seed = 123)

model.fit(X_train, y_train)

print(); print(model)


# Predict the model
```

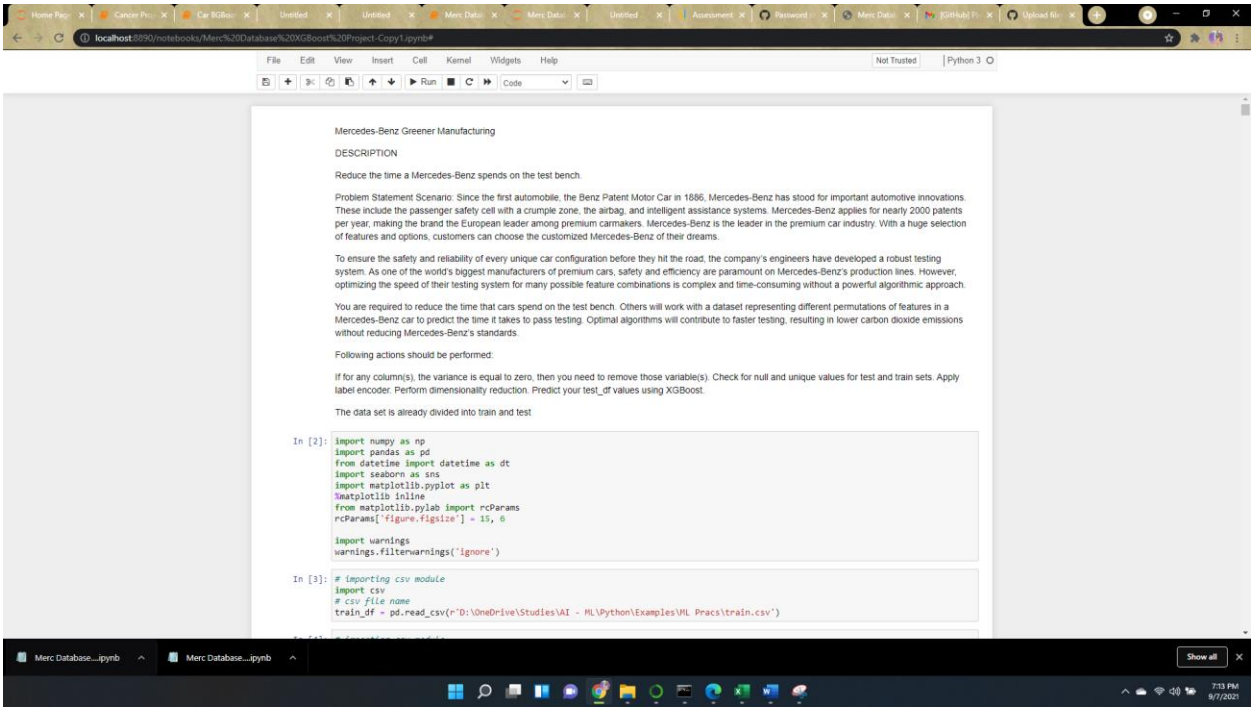
```
pred = model.predict(X_test)

# RMSE Computation
rmse = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE : % f" %(rmse))

expected_y  = y_test
predicted_y = model.predict(X_test)
print(metrics.r2_score(y_test, predicted_y))

model = xgb.XGBRegressor()
model.fit(X_train, y_train)
print(); print(model)

plt.figure(figsize=(10,10))
sns.regplot(expected_y, predicted_y, fit_reg=True, scatter_kws={"s": 100})

#e'll check the training accuracy with cross-validation and k-fold methods.
# Applying k-Fold Cross Validation
from sklearn.model_selection import cross_val_score, KFold

kfold = KFold(n_splits=10, shuffle=True)
kf_cv_scores = cross_val_score(model, X_train, y_train, cv=kfold )
print("K-fold CV average score: %.2f" % kf_cv_scores.mean())

#Now we have predicted the output by passing X_test and also stored real target in expected_y.
expected_y  = y_test
predicted_y = model.predict(X_test)
print(metrics.r2_score(expected_y, predicted_y))

#This is the best model so far
```

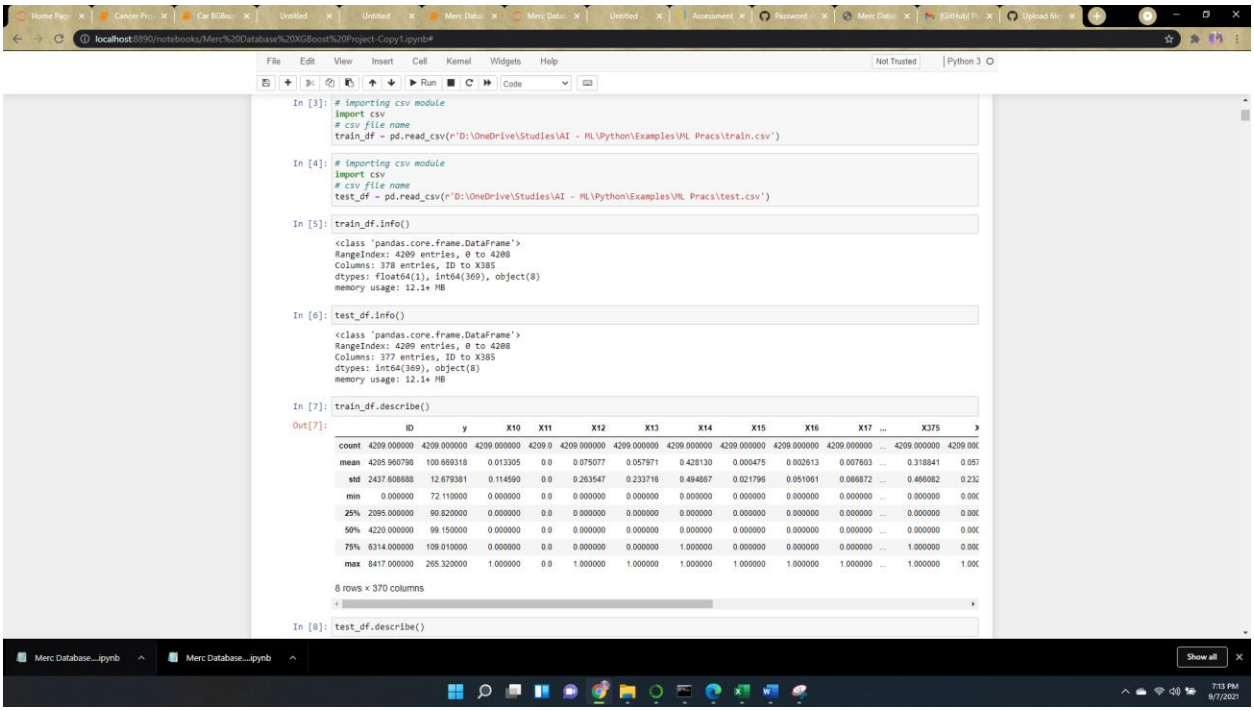
#Q 5. Predicting y with XGBoost

#Displaying predicted values

predicted_y

ScreenShots:



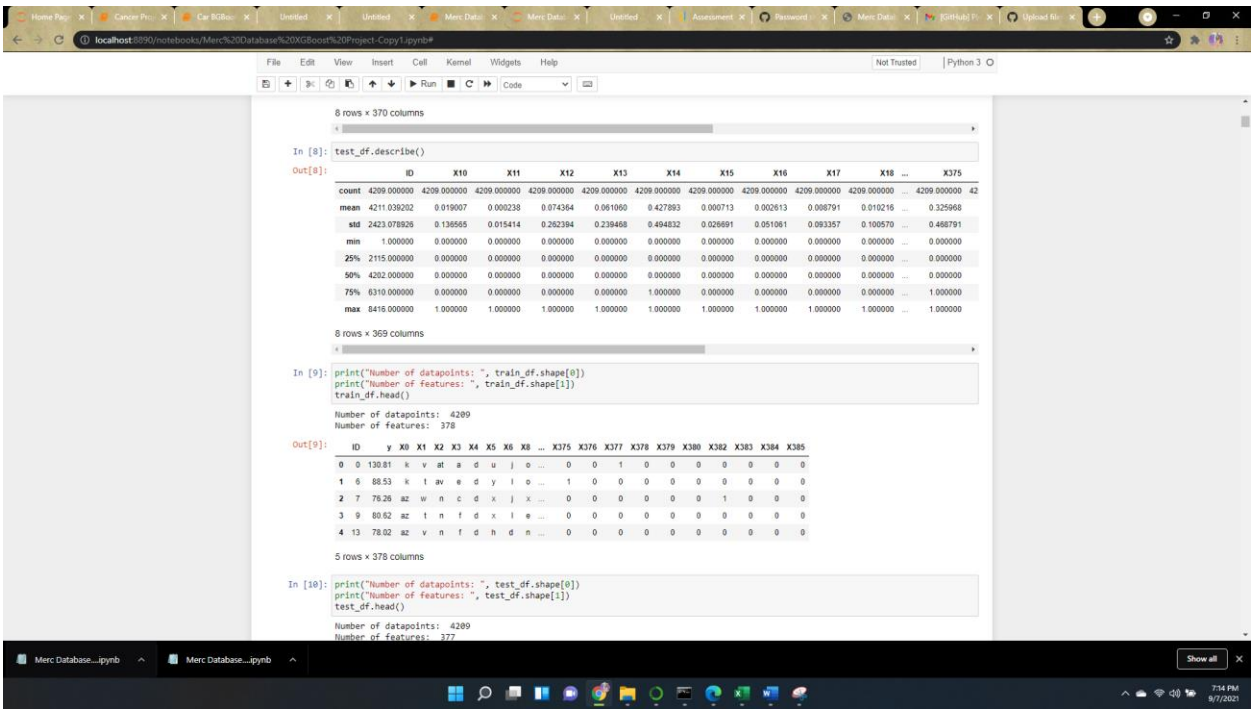


```
In [3]: # importing csv module
        import csv
        # csv file name
        train_df = pd.read_csv(r'D:\OneDrive\Studies\AI - ML\Python\Examples\ML Pracs\train.csv')

In [4]: # importing csv module
        import csv
        # csv file name
        test_df = pd.read_csv(r'D:\OneDrive\Studies\AI - ML\Python\Examples\ML Pracs\test.csv')

In [5]: train_df.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

In [6]: test_df.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

In [7]: train_df.describe()

Out[7]:
```

	ID	y	X10	X11	X12	X13	X14	X15	X16	X17	...	X375	X
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	4209.000000	4209.00
mean	4205.960798	100.669318	0.013305	0.0	0.075077	0.057971	0.428130	0.000475	0.002613	0.007603	...	0.318841	0.057
std	2437.608688	12.679381	0.114590	0.0	0.263547	0.233716	0.494867	0.021796	0.051061	0.086872	...	0.466082	0.232
min	0.000000	72.110000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.00
25%	2095.000000	90.820000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.00
50%	4220.000000	99.150000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.00
75%	6314.000000	109.010000	0.000000	0.0	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	...	1.000000	0.00
max	8417.000000	265.320000	1.000000	0.0	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	1.000000	1.00

8 rows × 370 columns

```
In [8]: test_df.describe()
```



```
        8 rows × 370 columns

In [8]: test_df.describe()

Out[8]:
```

	ID	X10	X11	X12	X13	X14	X15	X16	X17	X18	...	X375	42
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	4209.000000	
mean	4211.039202	0.019007	0.000238	0.074364	0.061060	0.427893	0.000713	0.002613	0.008791	0.010216	...	0.325968	
std	2423.079926	0.136565	0.015414	0.262394	0.239468	0.494832	0.026691	0.051061	0.093357	0.100570	...	0.468791	
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	
25%	2115.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	
50%	4202.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	
75%	6310.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	...	1.000000	
max	8416.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	1.000000	

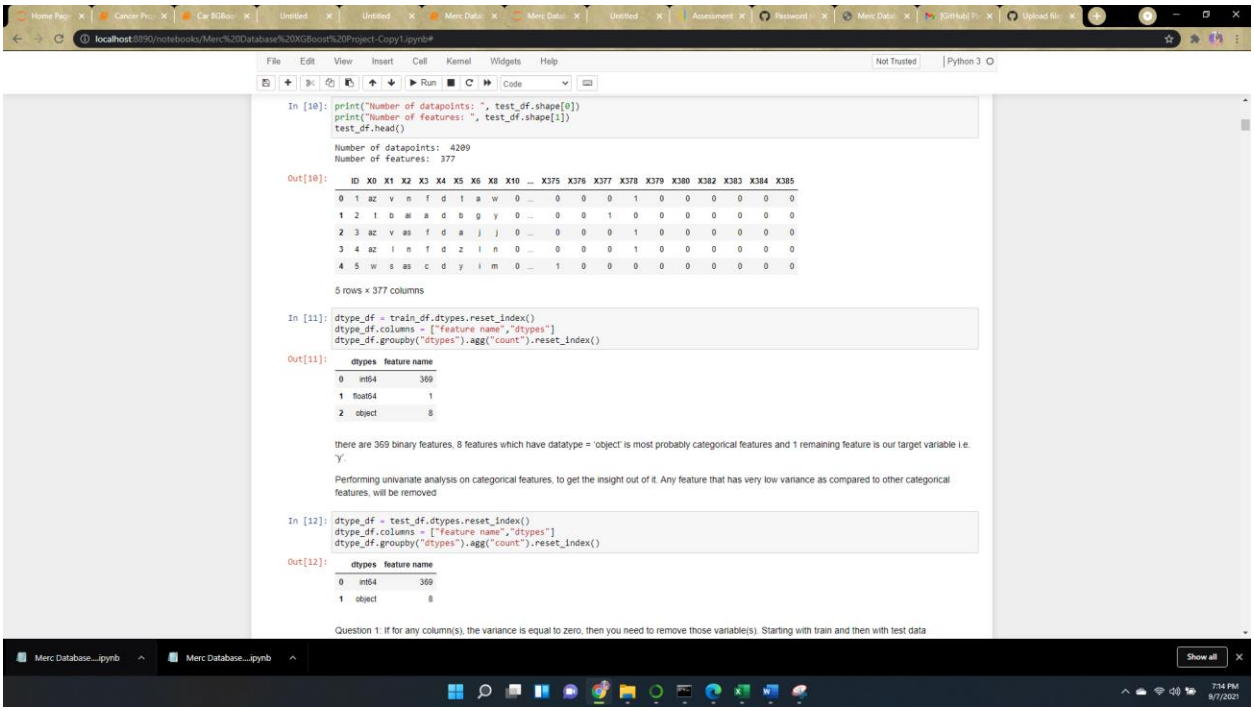
8 rows × 369 columns

```
In [9]: print("Number of datapoints: ", train_df.shape[0])
        print("Number of features: ", train_df.shape[1])
        train_df.head()

        Number of datapoints:  4209
        Number of features:  378

Out[9]:
```

	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 [10]: print("Number of datapoints: ", test_df.shape[0])
         print("Number of features: ", test_df.shape[1])
         test_df.head()

         Number of datapoints:  4209
         Number of features:  377
```



In [10]:
```
print("Number of datapoints: ", test_df.shape[0])
print("Number of features: ", test_df.shape[1])
test_df.head()
```

```
Number of datapoints:  4209
Number of features:  377
```

Out[10]:

	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 [11]:
```
dtype_df = train_df.dtypes.reset_index()
dtype_df.columns = ["feature name","dtypes"]
dtype_df.groupby("dtypes").agg("count").reset_index()
```

Out[11]:

	dtypes	feature name
0	int64	369
1	float64	1
2	object	8

there are 369 binary features, 8 features which have datatype = 'object' is most probably categorical features and 1 remaining feature is our target variable i.e. 'y'.

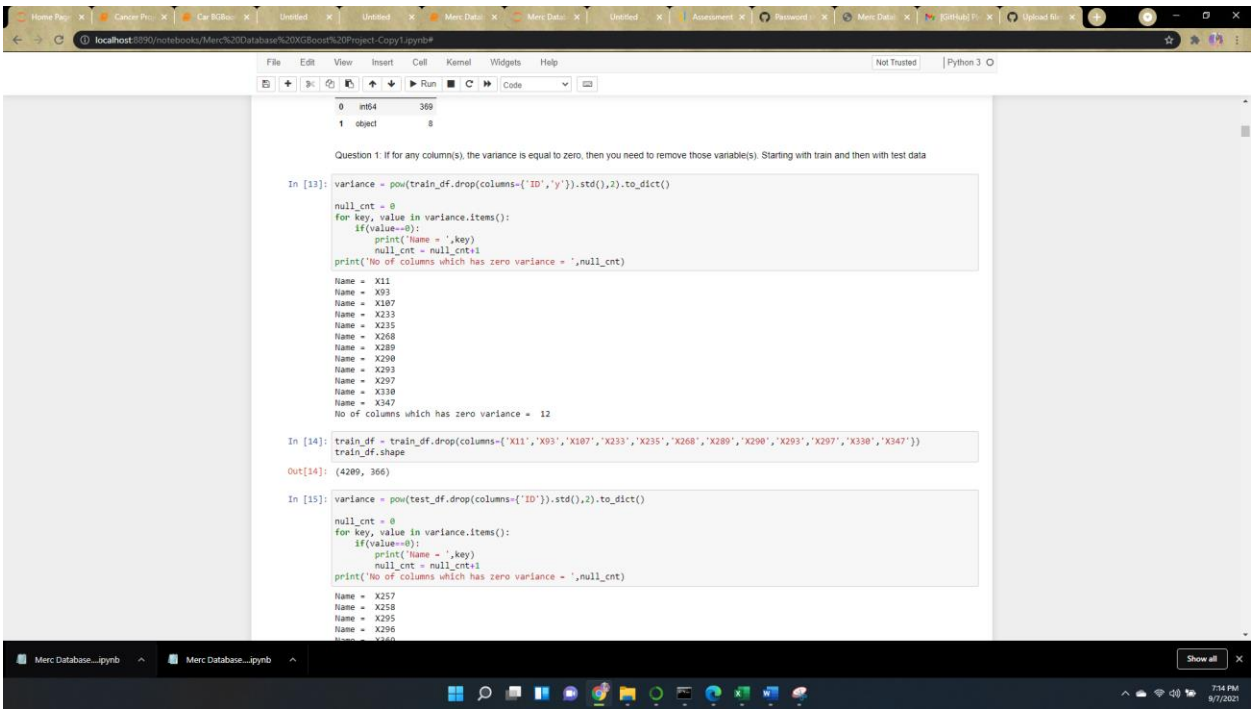
Performing univariate analysis on categorical features, to get the insight out of it. Any feature that has very low variance as compared to other categorical features, will be removed

In [12]:
```
dtype_df = test_df.dtypes.reset_index()
dtype_df.columns = ["feature name","dtypes"]
dtype_df.groupby("dtypes").agg("count").reset_index()
```

Out[12]:

	dtypes	feature name
0	int64	369
1	object	8

Question 1: If for any column(s), the variance is equal to zero, then you need to remove those variable(s). Starting with train and then with test data



In [13]:
```
variance = pow(train_df.drop(columns={'ID','y'}).std(),2).to_dict()

null_cnt = 0
for key, value in variance.items():
    if(value==0):
        print('Name = ',key)
        null_cnt = null_cnt+1
print('No of columns which has zero variance = ',null_cnt)
```

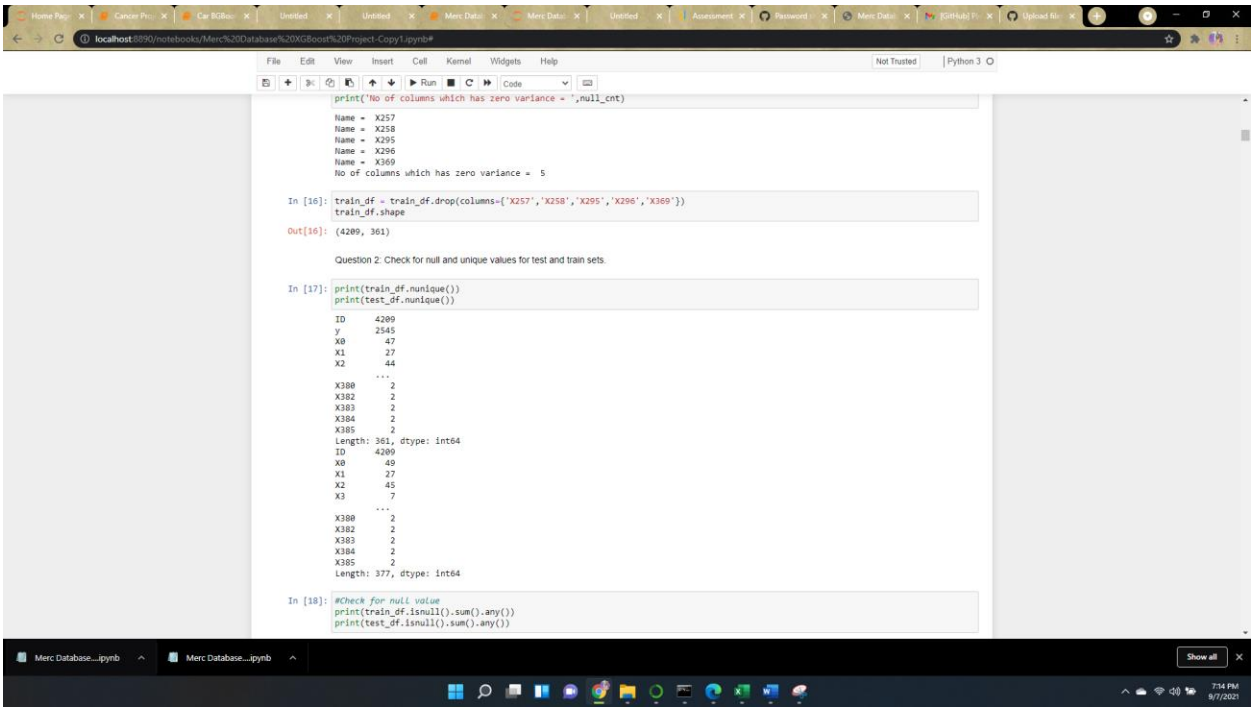
```
Name =  X11
Name =  X93
Name =  X107
Name =  X233
Name =  X235
Name =  X268
Name =  X289
Name =  X290
Name =  X293
Name =  X297
Name =  X330
Name =  X347
No of columns which has zero variance =  12
```

In [14]:
```
train_df = train_df.drop(columns={'X11','X93','X107','X233','X235','X268','X289','X290','X293','X297','X330','X347'})
train_df.shape
```

Out[14]:
```
(4209, 366)
```

In [15]:
```
variance = pow(test_df.drop(columns={'ID'}).std(),2).to_dict()

null_cnt = 0
for key, value in variance.items():
    if(value==0):
        print('Name = ',key)
        null_cnt = null_cnt+1
print('No of columns which has zero variance = ',null_cnt)
```

```
Name =  X257
Name =  X258
Name =  X295
Name =  X296
```



```
print('No of columns which has zero variance = ',null_cnt)
```

```
Name =  X257
Name =  X258
Name =  X295
Name =  X296
Name =  X369
No of columns which has zero variance =  5
```

In [16]:
```
train_df = train_df.drop(columns={'X257','X258','X295','X296','X369'})
train_df.shape
```

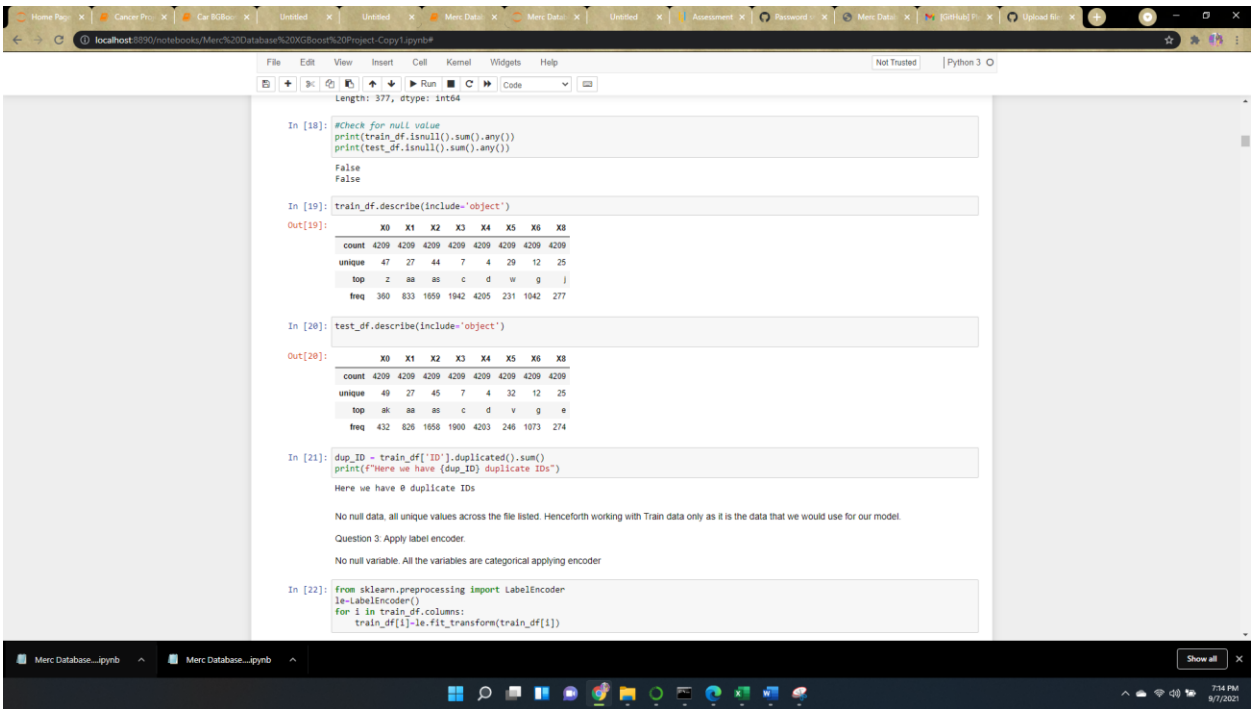
Out[16]: (4209, 361)

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

In [17]:
```
print(train_df.nunique())
print(test_df.nunique())
```

```
ID      4209
y       2545
X0        47
X1        27
X2        44
        ...
X380       2
X382       2
X383       2
X384       2
X385       2
Length: 361, dtype: int64
ID      4209
X0        49
X1        27
X2        45
X3         7
        ...
X380       2
X382       2
X383       2
X384       2
X385       2
Length: 377, dtype: int64
```

In [18]:
```
#Check for null value
print(train_df.isnull().sum().any())
print(test_df.isnull().sum().any())
```



```
Length: 377, dtype: int64
```

In [18]:
```
#Check for null value
print(train_df.isnull().sum().any())
print(test_df.isnull().sum().any())
```

```
False
False
```

In [19]:
```
train_df.describe(include='object')
```

Out[19]:

	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

In [20]:
```
test_df.describe(include='object')
```

Out[20]:

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

In [21]:
```
dup_ID = train_df['ID'].duplicated().sum()
print(f"Here we have {dup_ID} duplicate IDs")
```

```
Here we have 0 duplicate IDs
```

No null data, all unique values across the file listed. Henceforth working with Train data only as it is the data that we would use for our model.

Question 3: Apply label encoder.

No null variable. All the variables are categorical applying encoder

In [22]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for i in train_df.columns:
    train_df[i]=le.fit_transform(train_df[i])
```

```
In [22]: from sklearn.preprocessing import LabelEncoder
         le=LabelEncoder()
         for i in train_df.columns:
             train_df[i]=le.fit_transform(train_df[i])

In [23]: train_df.head()
```

Out[23]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
0	0	2466	32	23	17	0	3	24	9	14	...	0	0	1	0	0	0	0	0	0	0
1	1	366	32	21	19	4	3	28	11	14	...	1	0	0	0	0	0	0	0	0	0
2	2	69	20	24	34	2	3	27	9	23	...	0	0	0	0	0	0	1	0	0	0
3	3	133	20	21	34	5	3	27	11	4	...	0	0	0	0	0	0	0	0	0	0
4	4	106	20	23	34	5	3	12	3	13	...	0	0	0	0	0	0	0	0	0	0

5 rows × 361 columns

```
In [24]: train_df.corr()
```

Out[24]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378
ID	1.000000	-0.053835	-0.012938	0.085511	-0.022195	-0.032942	0.018940	0.649727	-0.017728	0.006444	...	0.045307	-0.079988	-0.022990	0.030387
y	-0.053835	1.000000	-0.235347	0.012417	0.111803	-0.153171	-0.015482	-0.035435	0.001477	-0.003473	...	0.021055	0.131811	0.055796	-0.226880
X0	-0.012938	-0.235347	1.000000	-0.271123	-0.139904	-0.070645	0.017988	0.012293	0.037549	0.047735	...	0.113272	0.070546	0.045173	-0.102136
X1	0.085511	0.012417	-0.271123	1.000000	0.088266	0.205657	-0.020724	0.046417	-0.079119	-0.000306	...	0.056874	-0.102424	-0.248791	0.145282
X2	-0.022195	0.111803	-0.139904	0.088266	1.000000	-0.093546	0.002289	-0.017722	0.065778	-0.069932	...	-0.174308	0.033697	0.122503	0.131974
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
X380	-0.013644	0.047247	-0.038618	-0.022360	0.006473	0.004166	0.002611	0.010434	-0.014059	0.009511	...	-0.061741	-0.022240	-0.061168	-0.013110
X382	-0.038092	-0.139801	-0.060401	0.120044	0.024392	-0.046271	0.002533	-0.031128	0.054548	-0.000996	...	-0.059883	-0.021571	-0.059327	-0.012716
X383	-0.009363	0.018200	-0.011174	-0.029253	-0.019873	-0.028280	0.001181	-0.007337	-0.021293	0.038712	...	-0.015413	-0.010059	0.035107	-0.005930
X384	-0.015531	-0.003465	0.009110	0.017603	-0.002614	0.007273	0.000631	0.007030	0.023867	0.008950	...	-0.014917	-0.005373	0.008694	-0.003168
X385	0.028997	-0.024460	0.011660	0.008356	-0.004529	0.045180	0.001093	0.032027	-0.021254	0.045040	...	0.055225	-0.009311	-0.025610	-0.005489

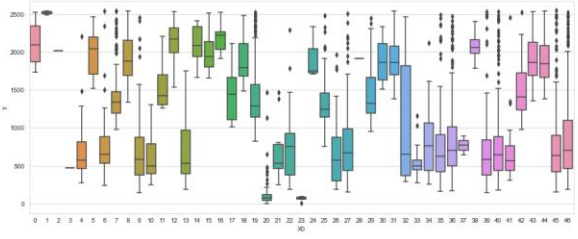
361 rows × 361 columns

Summarize outcome (testing time) in training dataset

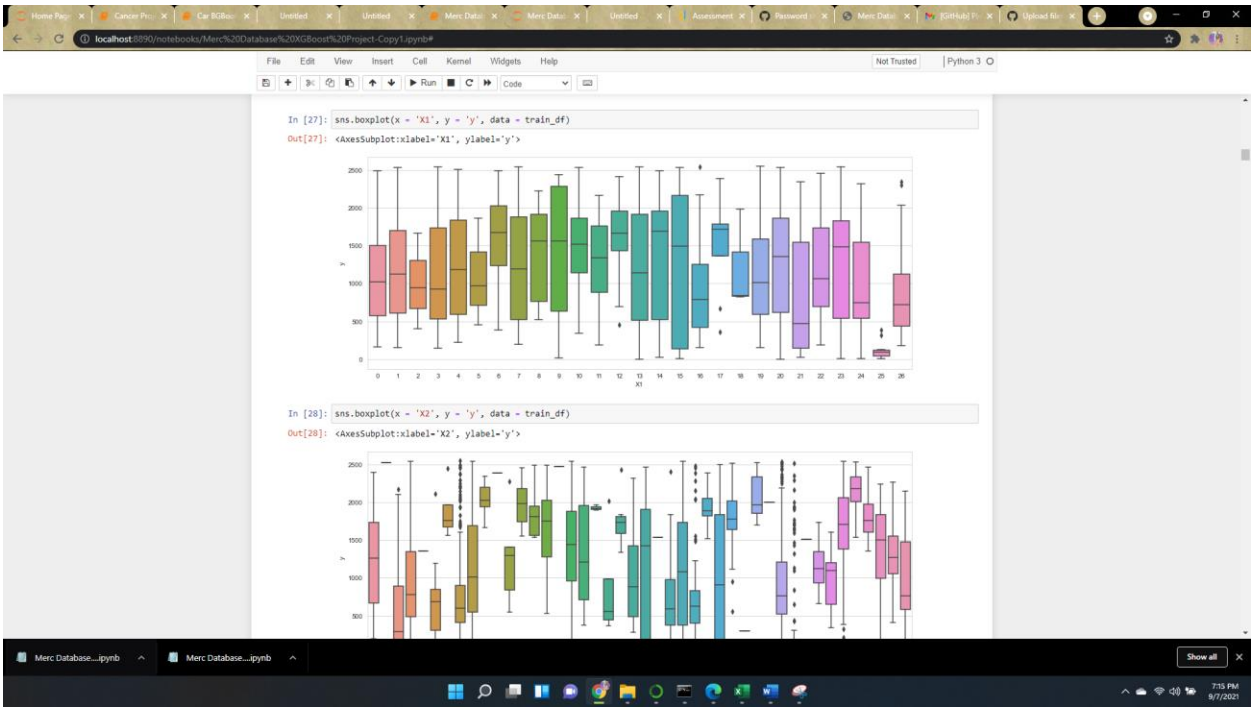
```
In [25]: # Draw a vertical boxplot grouped
```

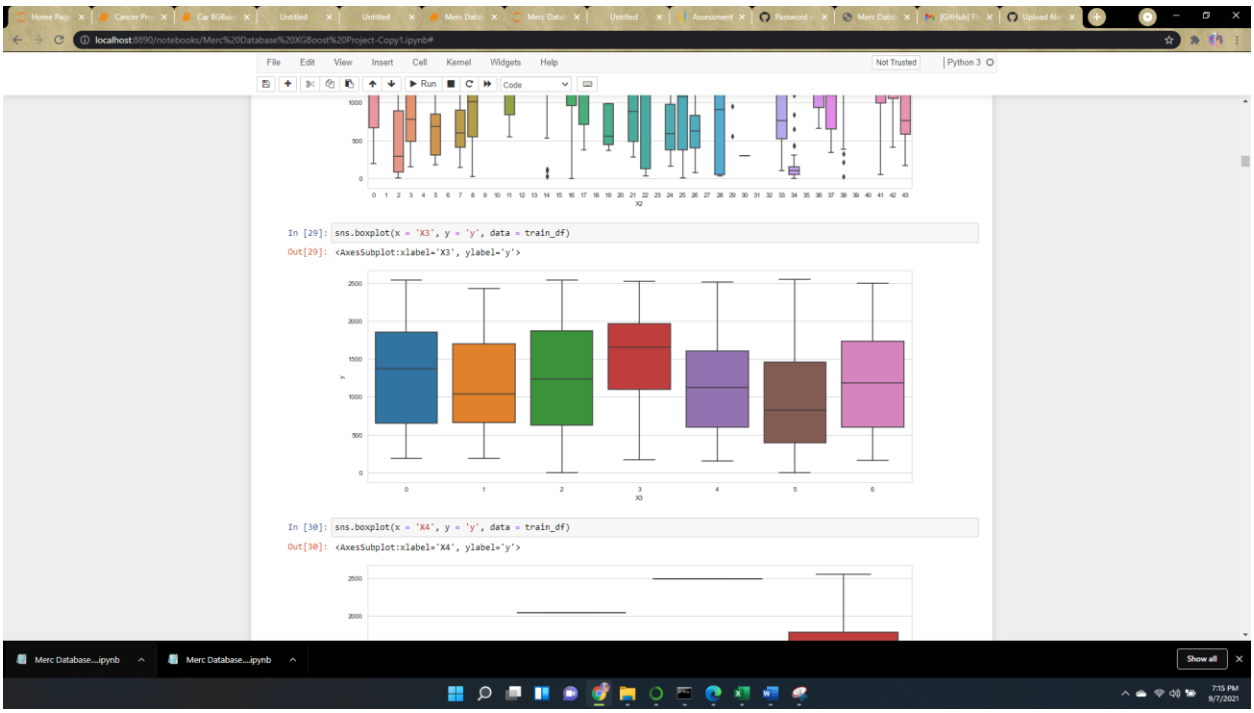

Summarize outcome (testing time) in training dataset

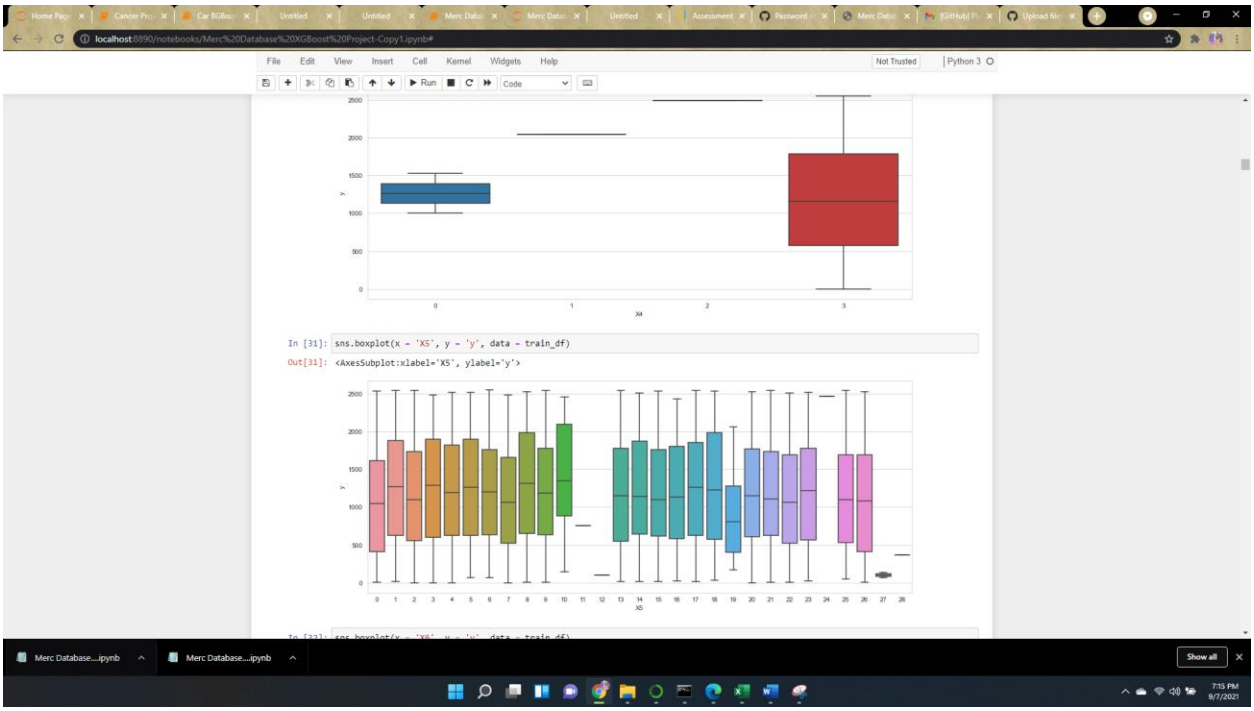
```
In [25]: # Draw a vertical boxplot grouped
         # by a categorical variable: X0
         sns.set_style("whitegrid")

         object_columns = test_df.describe(include='object').columns
         print('\nobject columns:\n',object_columns)
         cols = len(object_columns)


object columns:
 Index(['X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8'], dtype='object')

In [26]: sns.boxplot(x = 'X0', y = 'y', data = train_df)
Out[26]: <AxesSubplot:xlabel='X0', ylabel='y'>
```

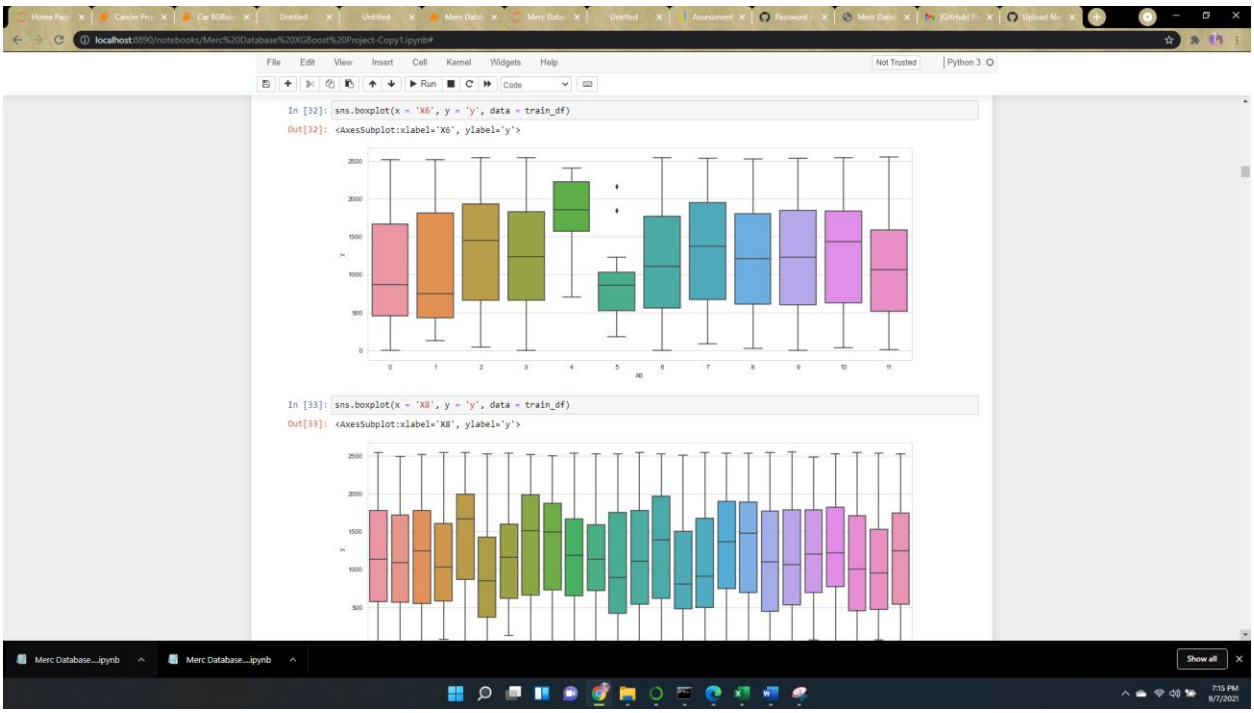



```
In [27]: sns.boxplot(x = 'X1', y = 'y', data = train_df)
Out[27]: <AxesSubplot:xlabel='X1', ylabel='y'>
```

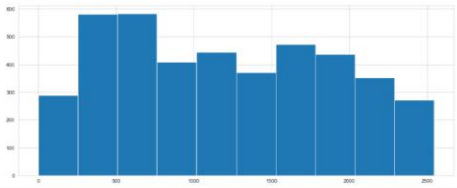

localhost:8890/notebooks/Merc%20Database%20XGBoost%20Project-Copy1.ipynb#
File Edit View Insert Cell Kernel Widgets Help
Not Trusted
Python 3
Run
Code
In [27]: sns.boxplot(x = 'X1', y = 'y', data = train_df)
Out[27]: <AxesSubplot:xlabel='X1', ylabel='y'>
In [28]: sns.boxplot(x = 'X2', y = 'y', data = train_df)
Out[28]: <AxesSubplot:xlabel='X2', ylabel='y'>
Merc Database....ipynb
Merc Database....ipynb
Show all
7:15 PM
9/7/2021


localhost:8890/notebooks/Merc%20Database%20XGBoost%20Project-Copy1.ipynb#
File Edit View Insert Cell Kernel Widgets Help
Not Trusted
Python 3
Run
Code
In [29]: sns.boxplot(x = 'X3', y = 'y', data = train_df)
Out[29]: <AxesSubplot:xlabel='X3', ylabel='y'>
In [30]: sns.boxplot(x = 'X4', y = 'y', data = train_df)
Out[30]: <AxesSubplot:xlabel='X4', ylabel='y'>
Merc Database....ipynb
Merc Database....ipynb
Show all
7:15 PM
9/7/2021

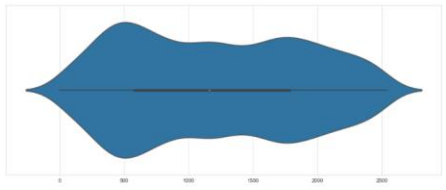

localhost:8890/notebooks/Merc%20Database%20XGBoost%20Project-Copy1.ipynb#
File Edit View Insert Cell Kernel Widgets Help
Not Trusted
Python 3
Run
Code
X4
In [31]: sns.boxplot(x = 'X5', y = 'y', data = train_df)
Out[31]: <AxesSubplot:xlabel='X5', ylabel='y'>
X5
Merc Database....ipynb
Merc Database....ipynb
Show all
7:15 PM
9/7/2021


localhost:8890/notebooks/Merc%20Database%20XGBoost%20Project-Copy1.ipynb#
File Edit View Insert Cell Kernel Widgets Help
Not Trusted
Python 3
Run
Code
In [32]: sns.boxplot(x = 'X6', y = 'y', data = train_df)
Out[32]: <AxesSubplot:xlabel='X6', ylabel='y'>
X6
In [33]: sns.boxplot(x = 'X8', y = 'y', data = train_df)
Out[33]: <AxesSubplot:xlabel='X8', ylabel='y'>
Merc Database....ipynb
Merc Database....ipynb
Show all
7:15 PM
9/7/2021

```
In [34]: #now the target y
         train_df['y'].hist()
Out[34]: <AxesSubplot:>
```



```
In [35]: sns.violinplot(train_df['y'].values)
Out[35]: <AxesSubplot:>
```



The data seems optimized. The removal of few data points which had no variance had optimized the y. No reason to test for any more outliers. Ideally, this test is done first, but if variance 0 is removed, it increases the chances of y being optimized, with no outliers.

Dimensionality reduction refers to techniques for reducing the number of input variables in training data. Fewer input dimensions often means correspondingly fewer parameters or a simpler structure in the machine learning model, referred to as degrees of freedom. A model with too many degrees of freedom is likely to overfit the training dataset and may not perform well on new data.

It is desirable to have simple models that generalize well, and in turn, input data with few input variables. This is particularly true for linear models where the number of inputs and the degrees of freedom of the model are often closely related.

Dimensionality reduction refers to techniques for reducing the number of input variables in training data. Fewer input dimensions often means correspondingly fewer parameters or a simpler structure in the machine learning model, referred to as degrees of freedom. A model with too many degrees of freedom is likely to overfit the training dataset and may not perform well on new data.

It is desirable to have simple models that generalize well, and in turn, input data with few input variables. This is particularly true for linear models where the number of inputs and the degrees of freedom of the model are often closely related.

Dimensionality reduction is a data preparation technique performed on data prior to modeling. It might be performed after data cleaning and data scaling and before training a predictive model.

Question 4: Perform dimensionality reduction.

The methods at our disposal using linear algebra are:

Principal Components Analysis Singular Value Decomposition Non-Negative Matrix Factorization

```
In [36]: # Draw a vertical boxplot grouped
         # by a categorical variable: X0
         train_df.describe(include='int64')
```

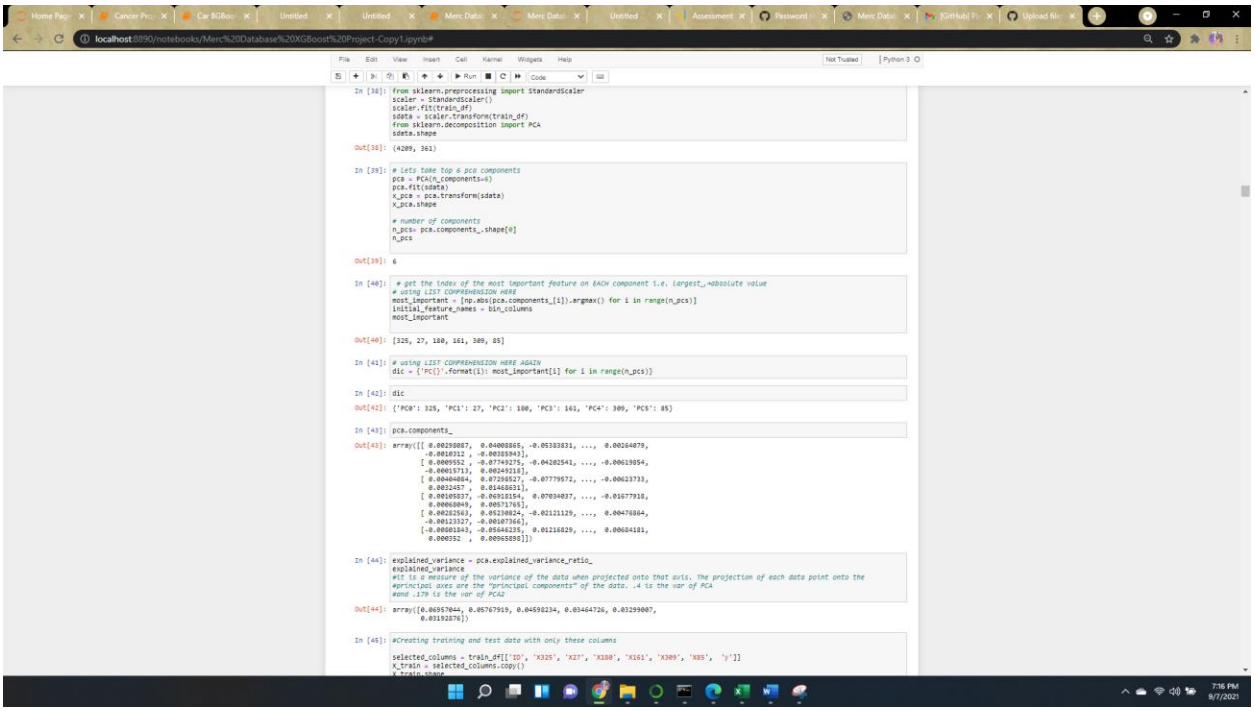
Out[36]:

	ID	y	X10	X12	X13	X14	X15	X16	X17	X18	...	X375
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	4209.000000
mean	2104.000000	1200.809931	0.013305	0.075077	0.057971	0.428130	0.000475	0.002613	0.007603	0.007840	...	0.318841
std	1215.177971	694.116229	0.114590	0.263647	0.233716	0.494987	0.021796	0.051061	0.086872	0.088208	...	0.466082
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000
25%	1052.000000	575.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000
50%	2104.000000	1161.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000
75%	3155.000000	1784.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	...	1.000000
max	4208.000000	2544.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	1.000000

8 rows × 353 columns

```
In [37]: bin_columns = train_df['ID']
         print('\nobject columns:\n',bin_columns)

object columns:
 0         0
1         1
2         2
3         3
4         4
        ...
4204    4204
4205    4205
4206    4206
4207    4207
4208    4208
Name: ID, Length: 4209, dtype: int64
```

```
In [38]: from sklearn.preprocessing import StandardScaler
         scaler = StandardScaler()
         scaler.fit(train_df)
         sdata = scaler.transform(train_df)
         from sklearn.decomposition import PCA
         sdata.shape
Out[38]: (4209, 361)
```



```
In [38]: from sklearn.preprocessing import StandardScaler
         scaler = StandardScaler()
         scaler.fit(train_df)
         sdata = scaler.transform(train_df)
         from sklearn.decomposition import PCA
         sdata.shape

Out[38]: (4209, 361)

In [39]: # Lets take top 6 pca components
         pca = PCA(n_components=6)
         pca.fit(sdata)
         X_pca = pca.transform(sdata)
         X_pca.shape

         # number of components
         n_pcs= pca.components_.shape[0]
         n_pcs

Out[39]: 6

In [40]: # get the index of the most important feature on EACH component i.e. largest_absolute value
         # using LIST COMPREHENSION HERE
         most_important = [np.abs(pca.components_[i]).argmax() for i in range(n_pcs)]
         initial_feature_names = bin_columns
         most_important

Out[40]: [325, 27, 180, 161, 309, 85]

In [41]: # using LIST COMPREHENSION HERE AGAIN
         dic = {'PC{}'.format(i): most_important[i] for i in range(n_pcs)}

In [42]: dic

Out[42]: {'PC0': 325, 'PC1': 27, 'PC2': 180, 'PC3': 161, 'PC4': 309, 'PC5': 85}

In [43]: pca.components_

Out[43]: array([[ 0.00259867,  0.04008865, -0.05383831, ...,  0.00264079,
                  -0.0018312 , -0.00355943],
                [ 0.0009552 , -0.07749275, -0.04282541, ..., -0.00619854,
                  -0.00015713,  0.00249218],
                [ 0.00404084,  0.07298527, -0.07779572, ..., -0.00623733,
                   0.0032457 ,  0.01468631],
                [ 0.00105837, -0.06911164,  0.07034037, ..., -0.01677918,
                   0.00068049,  0.00571765],
                [ 0.00282563,  0.05230824, -0.02121129, ...,  0.00476864,
                  -0.00123527, -0.00107366],
                [-0.00301843, -0.05646235,  0.01216829, ...,  0.00684181,
                   0.000252  ,  0.00965898]])

In [44]: explained_variance = pca.explained_variance_ratio_
         explained_variance
         #it is a measure of the variance of the data when projected onto that axis. The projection of each data point onto the
         #principal axes are the "principal components" of the data. .4 is the var of PCA
         #and .179 is the var of PCA2

Out[44]: array([0.06957044, 0.05767919, 0.04598234, 0.03464726, 0.03299007,
                0.03192876])

In [45]: #Creating training and test data with only these columns

         selected_columns = train_df[['ID', 'X325', 'X27', 'X180', 'X161', 'X309', 'X85',  'y']]
         X_train = selected_columns.copy()
         X_train.shape
         X_train
```

Out[45]:

	ID	X325	X27	X180	X161	X309	X85	y
0	0	0	0	0	0	0	1	2406
1	1	0	1	0	0	0	1	365
2	2	0	1	0	0	0	1	60
3	3	0	1	0	0	0	0	133
4	4	0	1	0	0	0	0	106
...	...	...	...	...	...	...	...	...
4204	4204	0	1	0	0	0	1	1657
4205	4205	0	0	0	0	0	0	1795
4206	4206	0	1	0	0	0	1	1801
4207	4207	0	0	0	0	0	0	280
4208	4208	0	0	0	0	0	0	1921

4209 rows × 8 columns

```
In [46]: #Now creating a df with only these 5 components

         selected_columns = test_df[['ID', 'X325', 'X27', 'X180', 'X161', 'X309', 'X85']]
         X_test = selected_columns.copy()
         X_test.shape
         X_test
```

Out[46]:

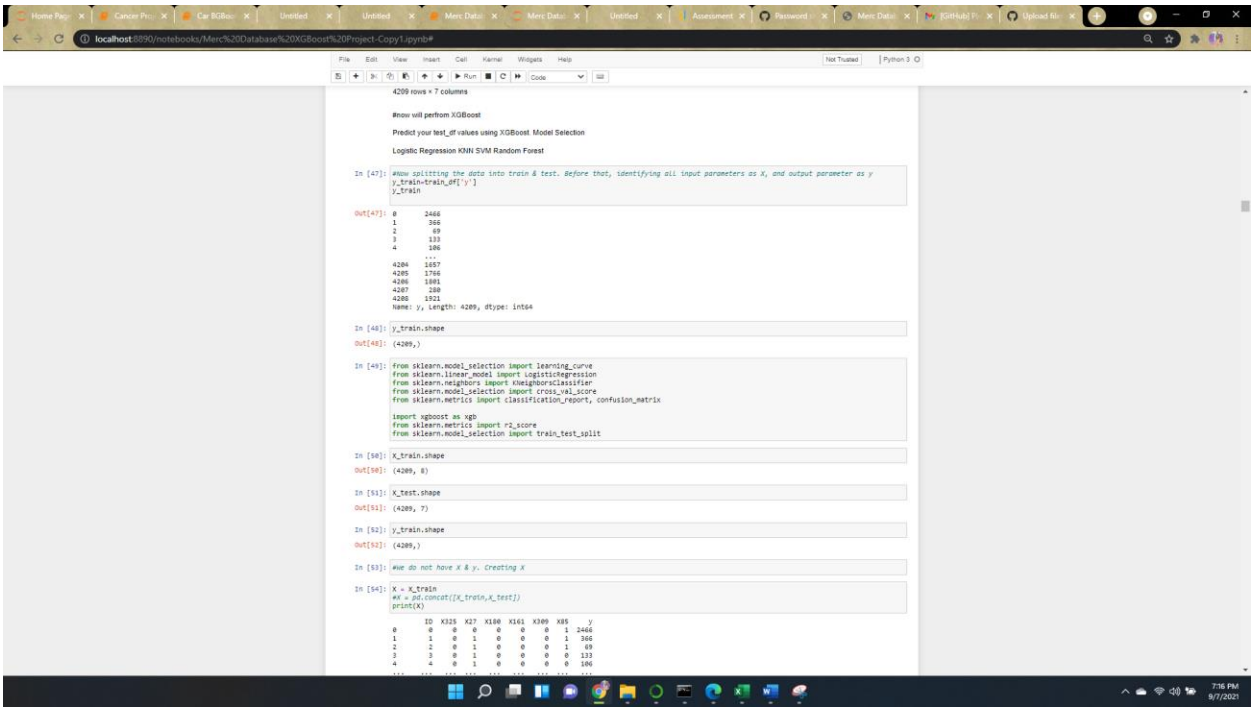
	ID	X325	X27	X180	X161	X309	X85
0	1	0	1	0	0	0	0
1	2	0	1	0	1	0	0
2	3	0	1	0	0	0	1
3	4	0	1	0	0	0	0
4	5	0	1	0	0	0	1
...	...	...	...	...	...	...	...
4204	8410	0	1	0	0	0	1
4205	8411	0	1	0	0	0	0
4206	8413	0	1	0	0	0	0
4207	8414	0	1	0	0	0	1
4208	8416	0	1	0	0	0	0

4209 rows × 7 columns

#now will perfrom XGBoost

Predict your test_df values using XGBoost. Model Selection

Logistic Regression KNN SVM Random Forest



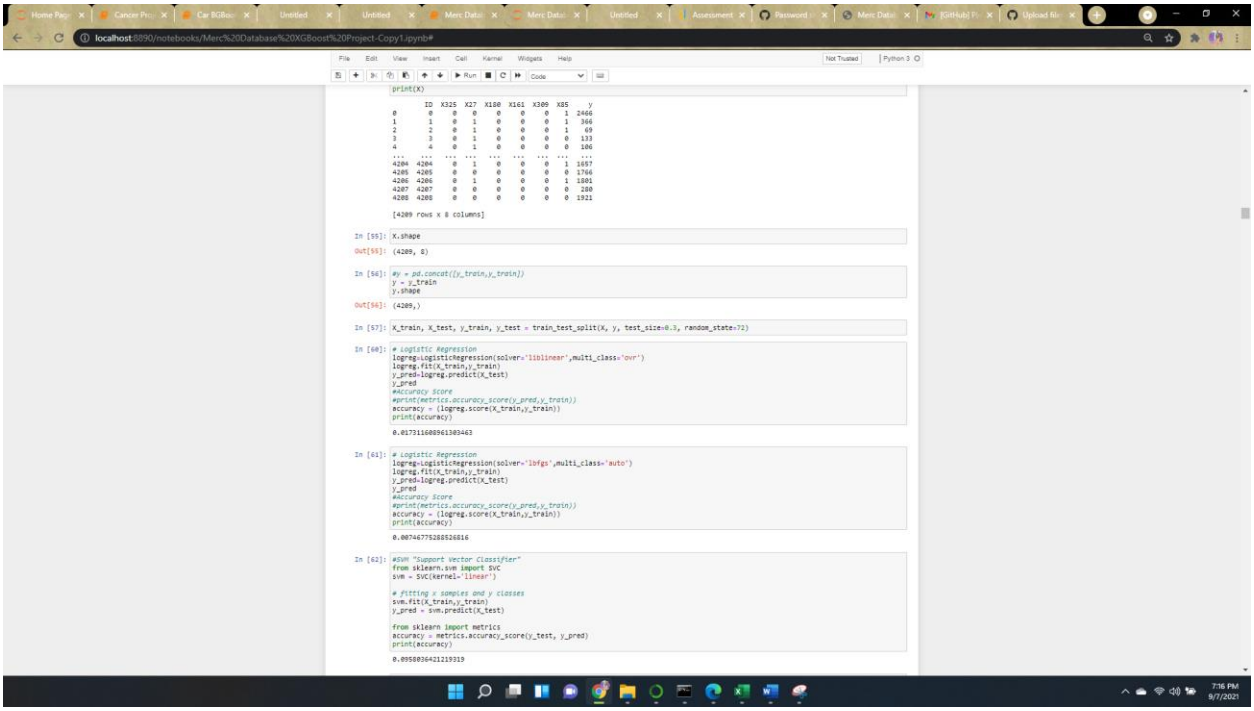
4209 rows × 7 columns

#now will perfrom XGBoost

Predict your test_df values using XGBoost. Model Selection

Logistic Regression KNN SVM Random Forest

```
In [47]: #Now splitting the data into train & test. Before that, identifying all input parameters as X, and output parameter as y
         y_train=train_df['y']
         y_train

Out[47]: 0       2466
         1        366
         2         69
         3        133
         4        106
                 ...
         4204    1657
         4205    1766
         4206    1801
         4207     280
         4208    1921
         Name: y, Length: 4209, dtype: int64

In [48]: y_train.shape

Out[48]: (4209,)

In [49]: from sklearn.model_selection import learning_curve
         from sklearn.linear_model import LogisticRegression
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.model_selection import cross_val_score
         from sklearn.metrics import classification_report, confusion_matrix

         import xgboost as xgb
         from sklearn.metrics import r2_score
         from sklearn.model_selection import train_test_split

In [50]: X_train.shape

Out[50]: (4209, 8)

In [51]: X_test.shape

Out[51]: (4209, 7)

In [52]: y_train.shape

Out[52]: (4209,)

In [53]: #we do not have X & y. Creating X

In [54]: X = X_train
         #X = pd.concat([X_train,X_test])
         print(X)

              ID  X325  X27  X180  X161  X309  X85     y
         0       0     0    0     0     0     1  2466
         1       1     0    1     0     0     1   366
         2       2     0    1     0     0     1    69
         3       3     0    1     0     0     0   133
         4       4     0    1     0     0     0   106
         ...   ...   ...  ...   ...   ...   ...   ...
```



```
         print(X)

              ID  X325  X27  X180  X161  X309  X85     y
         0       0     0    0     0     0     1  2466
         1       1     0    1     0     0     1   366
         2       2     0    1     0     0     1    69
         3       3     0    1     0     0     0   133
         4       4     0    1     0     0     0   106
         ...   ...   ...  ...   ...   ...   ...   ...
         4204  4204     0    1     0     0     1  1657
         4205  4205     0    0     0     0     0  1766
         4206  4206     0    1     0     0     1  1801
         4207  4207     0    0     0     0     0   280
         4208  4208     0    0     0     0     0  1921

         [4209 rows x 8 columns]

In [55]: X.shape

Out[55]: (4209, 8)

In [56]: #y = pd.concat([y_train,y_train])
         y = y_train
         y.shape

Out[56]: (4209,)

In [57]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=72)

In [60]: # Logistic Regression
         logreg=LogisticRegression(solver='liblinear',multi_class='ovr')
         logreg.fit(X_train,y_train)
         y_pred=logreg.predict(X_test)
         y_pred
         #Accuracy Score
         #print(metrics.accuracy_score(y_pred,y_train))
         accuracy = (logreg.score(X_train,y_train))
         print(accuracy)

         0.017311608961303463

In [61]: # Logistic Regression
         logreg=LogisticRegression(solver='lbfgs',multi_class='auto')
         logreg.fit(X_train,y_train)
         y_pred=logreg.predict(X_test)
         y_pred
         #Accuracy Score
         #print(metrics.accuracy_score(y_pred,y_train))
         accuracy = (logreg.score(X_train,y_train))
         print(accuracy)

         0.007467758856816

In [62]: #SVM "Support Vector Classifier"
         from sklearn.svm import SVC
         svm = SVC(kernel='linear')

         # fitting x samples and y classes
         svm.fit(X_train,y_train)
         y_pred = svm.predict(X_test)

         from sklearn import metrics
         accuracy = metrics.accuracy_score(y_test, y_pred)
         print(accuracy)

         0.0958036421219319
```

```
y_pred = svm.predict(X_test)

from sklearn import metrics
accuracy = metrics.accuracy_score(y_test, y_pred)
print(accuracy)
```

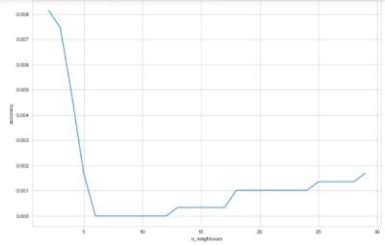
```
0.9958036421219319
```

In [67]:
```
#KNN with 5 neighbours
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred))
```

```
0.0023752969121140144
```

In [68]:
```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       0.00      0.00      0.00         0
           2       0.00      0.00      0.00         1
           3       0.00      0.00      0.00         0
           4       0.00      0.00      0.00         0
           5       0.00      0.00      0.00         0
           6       0.00      0.00      0.00         0
           8       0.00      0.00      0.00         0
          11       0.00      0.00      0.00         1
          12       0.00      0.00      0.00         0
          13       0.00      0.00      0.00         1
          14       0.00      0.00      0.00         0
          15       0.00      0.00      0.00         1
          16       0.00      0.00      0.00         1
          17       0.00      0.00      0.00         0
          19       0.00      0.00      0.00         1
          20       0.00      0.00      0.00         0
          22       0.00      0.00      0.00         1
          23       0.00      0.00      0.00         1
          24       0.00      0.00      0.00         1
          25       0.00      0.00      0.00         0
          27       0.00      0.00      0.00         0
          29       0.00      0.00      0.00         0
          30       0.00      0.00      0.00         1
          31       0.00      0.00      0.00         0
          32       0.00      0.00      0.00         0
          33       0.00      0.00      0.00         1
          34       0.00      0.00      0.00         1
          35       0.00      0.00      0.00         0
          41       0.00      0.00      0.00         0
          42       0.00      0.00      0.00         1
          46       0.00      0.00      0.00         0
          47       0.00      0.00      0.00         0
          48       0.00      0.00      0.00         1
          49       0.00      0.00      0.00         0
          51       0.00      0.00      0.00         1
          52       0.00      0.00      0.00         1
          53       0.00      0.00      0.00         1
          54       0.00      0.00      0.00         1
          60       0.00      0.00      0.00         1
          63       0.00      0.00      0.00         1
          64       0.00      0.00      0.00         1
          66       0.00      0.00      0.00         1
          67       0.00      0.00      0.00         0
          68       0.00      0.00      0.00         1
          69       0.00      0.00      0.00         0
          72       0.00      0.00      0.00         0
          75       0.00      0.00      0.00         1
          76       0.00      0.00      0.00         0
```



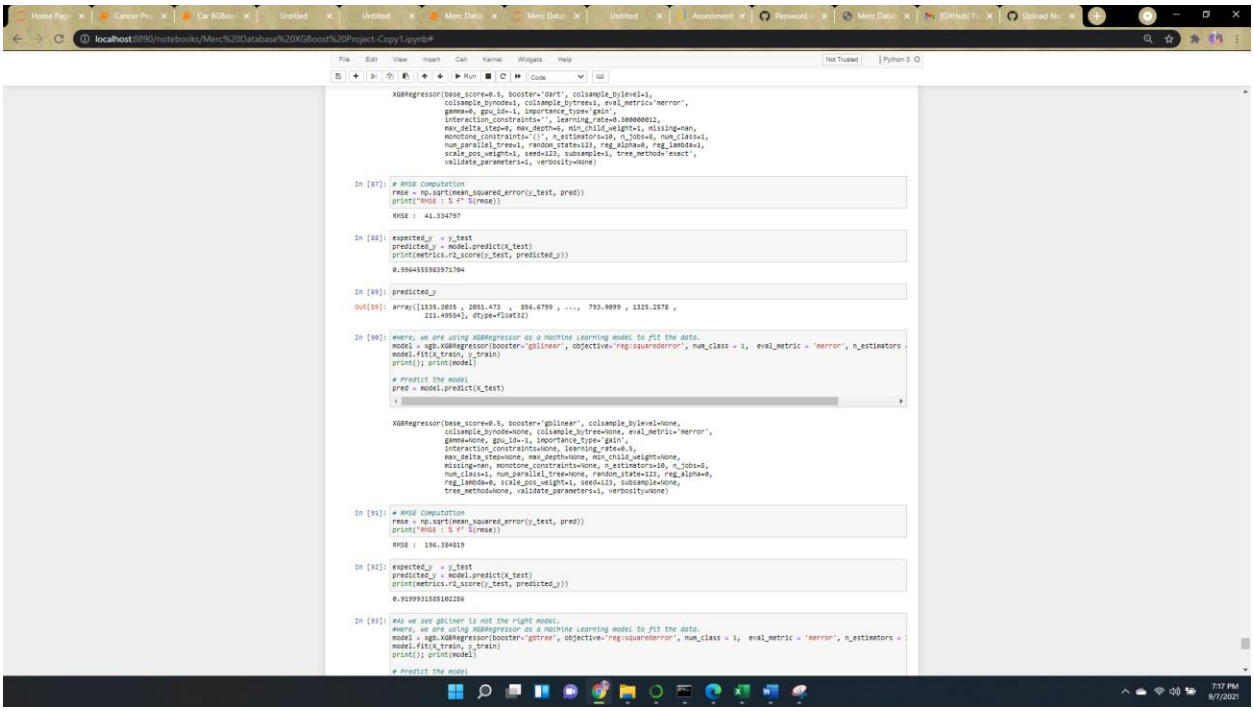
In [84]:
```
#Random Forests Classifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score

rfc=RandomForestClassifier(n_jobs=-1,random_state=51)
rfc.fit(X_train,y_train)
print(rfc.score(X_test,y_test))
print(f1_score(y_test,rfc.predict(X_test),average='macro'))
```

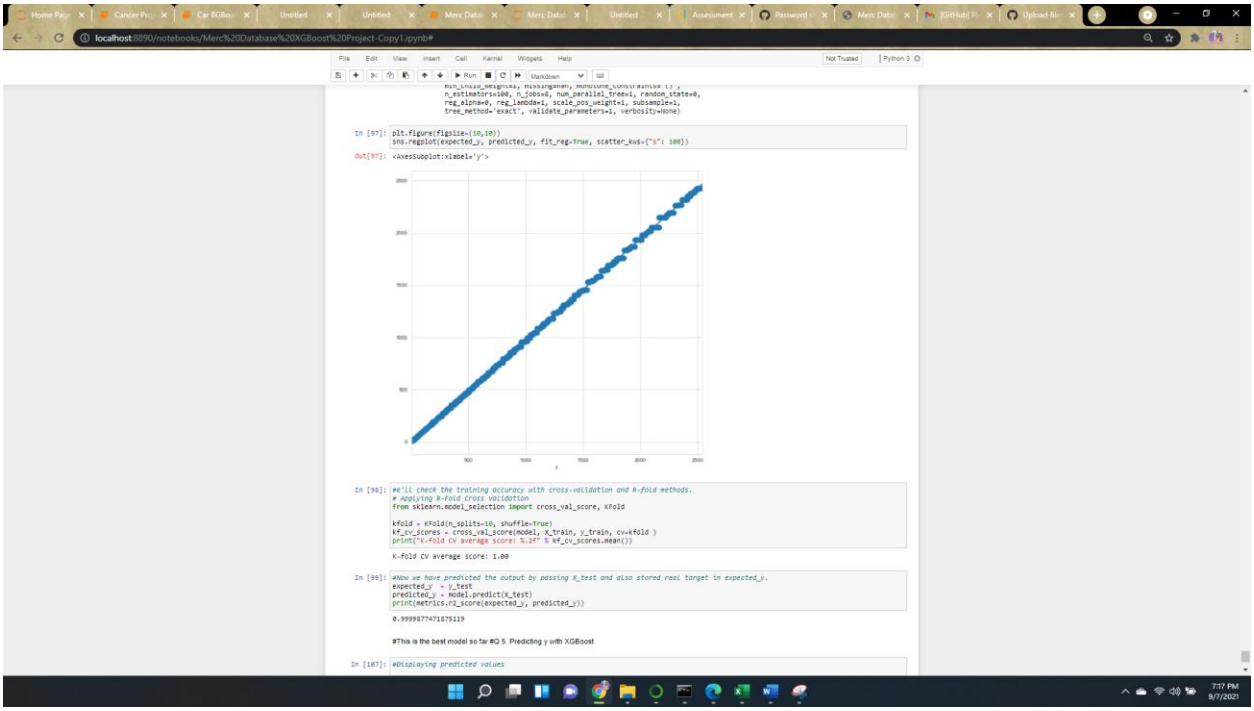
```
0.9213776722090261
0.8109586316626888942
```

In [85]:
```
#Till now SVM followed by Random forest is the leading model

from xgboost import XGBClassifier
from sklearn.metrics import mean_squared_error
from sklearn import svm
from xgboost import XGBClassifier
import xgboost as xgb
```

In [86]:
```
#Here, we are using XGBRegressor as a machine learning model to fit the data.
model = xgb.XGBRegressor(booster='dart', objective='reg:squarederror', num_class = 1,  eval_metric = 'merror', n_estimators = 10
model.fit(X_train, y_train)
print(); print(model)

# Predict the model
pred = model.predict(X_test)
```

```
XGBRegressor(base_score=0.5, booster='dart', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, eval_metric='merror',
             gamma=0, gpu_id=-1, importance_type='gain',
             interaction_constraints='', learning_rate=0.30000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=10, n_jobs=8, num_class=1,
             num_parallel_tree=1, random_state=123, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, seed=123, subsample=1, tree_method='exact',
```





Embedded File:

Python File:

Merc Database XGBoost Project.ipynb

Code hosted on GitHub :
https://github.com/ks-alokranjan/Simplilearn_ML