Project : Bank Churn Machine Learning Case Study

EXPOLATORY DATA ANALYSIS (EDA)

```
#Importing Basic Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
#To get the dataset from CSV file

df=pd.read_csv('/content/sample_data/Churn_Modelling.csv')
```

```
#To show the starting first 5 data

df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Ba
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	838
2	3	15619304	Onio	502	France	Female	42	8	1596
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	1255

```
#To check total no. of data (rows,columns) in the dataset

df.shape
```

```
(10000, 14)
```

```
#But here 'RowNumber', 'CustomerID' , 'Surname' are unwanted columns so delete them
# Remove three columns as index base

df.drop(df.columns[[0, 1, 2]], axis = 1, inplace = True)
```

```
#To show the starting first 5 data

df.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	619	France	Female	42	2	0.00	1	1
1	608	Spain	Female	41	1	83807.86	1	0
2	502	France	Female	42	8	159660.80	3	1
3	699	France	Female	39	1	0.00	2	0
4	850	Spain	Female	43	2	125510.82	1	1

```
#To check total no. of data (rows,columns) in the dataset

df.shape
```

```
(10000, 11)
```

```
#To check for Null values in dataset

df.isnull().sum()
```

```
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

```
#To recheck for Null values

df.dtypes
```

```
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

```
#Check Unique values in 'Geography' column

df['Geography'].unique()
```

```
array(['France', 'Spain', 'Germany'], dtype=object)
```

```
#Check Unique values in 'Gender' column

df['Gender'].unique()
```

```
array(['Female', 'Male'], dtype=object)
```

NOTE: Here Object type data also not contain null values so we can say that the given data doesn't contain Null Values

```
#Check for whether data is balanced or Imbalanced

df['Exited'].value_counts()
```

```
0    7963
1    2037
Name: Exited, dtype: int64
```

0 ----------> Not Exited

1 -----------> Yes Exited

We will need to balanced the data before giving to Machine Learning Algorithm because it will affect the accuracy of the model. After scaling we will balanced the data.

```
#Separate object type data and numeric type data from dataset df

df_num=df.select_dtypes(('float64','int64'))    #Numeric type data
df_cat=df.select_dtypes('object')             #Object type data
```

```
df_cat.dtypes
```

```
Geography    object
Gender       object
dtype: object
```

```
df_num.dtypes
```

```
CreditScore          int64
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

```
#Apply LableEncoder for converts object type data into numeric type

from sklearn.preprocessing import LabelEncoder
column=df_cat.columns
print(column)

for col in column:
    #Create object of LabelEncoder class
    le=LabelEncoder()
    df_cat[col]=le.fit_transform(df_cat[col])
```

```
Index(['Geography', 'Gender'], dtype='object')
```

```
df_cat.head()
```

	Geography	Gender
0	0	0
1	2	0
2	0	0
3	0	0
4	2	0

```
#To join both dataset df_num and df_cat and hold on new datafrome df_new

df_new=pd.concat([df_num,df_cat],axis=1)

#To show the starting first 5 data

df_new.head()
```

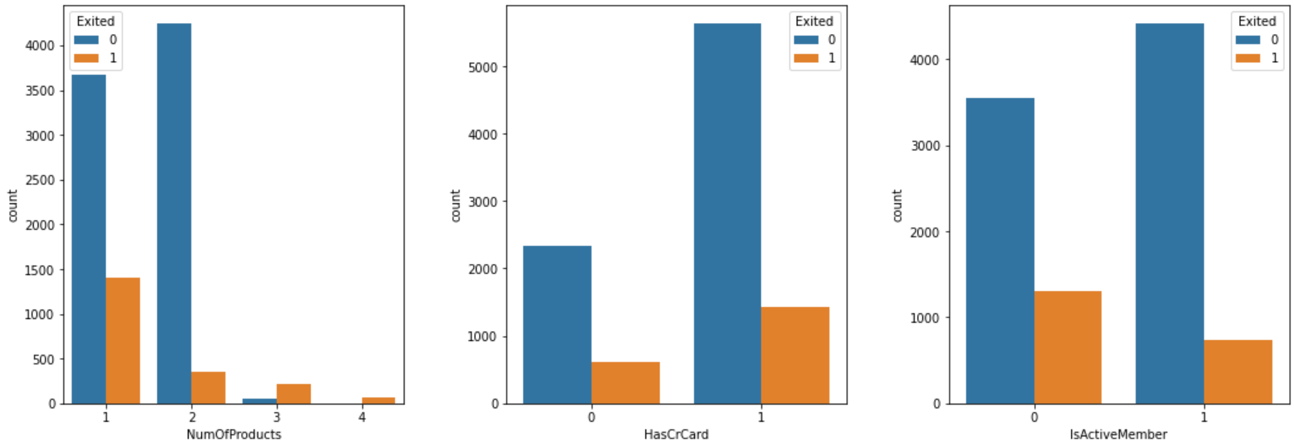
	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Est
0	619	42	2	0.00	1	1	1	
1	608	41	1	83807.86	1	0	1	
2	502	42	8	159660.80	3	1	0	
3	699	39	1	0.00	2	0	0	
4	850	43	2	125510.82	1	1	1	

DATA VISUALIZATION

```
_, ax = plt.subplots(1, 3, figsize=(18, 6))
plt.subplots_adjust(wspace=0.3)
```

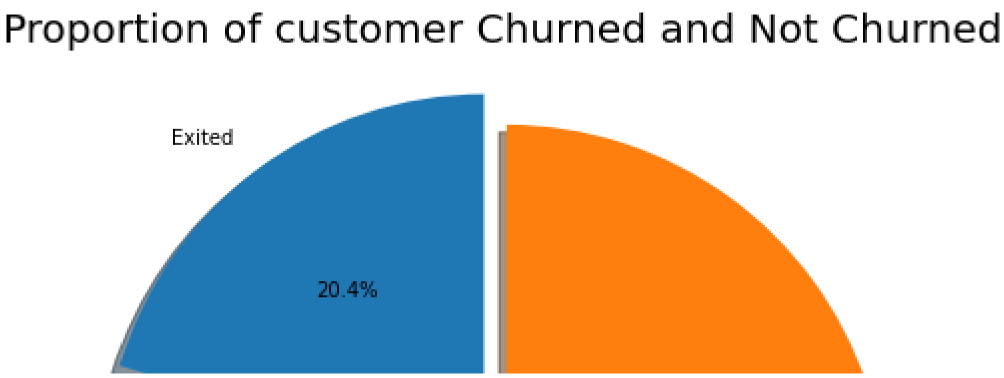
```
sns.countplot(x = "NumOfProducts", hue="Exited", data = df, ax= ax[0])
sns.countplot(x = "HasCrCard", hue="Exited", data = df, ax = ax[1])
sns.countplot(x = "IsActiveMember", hue="Exited", data = df, ax = ax[2])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa2e30e1b10>
```



Customer with 3 or 4 products are higher chances to Churn (Exit)

```
labels = 'Exited', 'Not Exited'
sizes = [df.Exited[df['Exited']==1].count(), df.Exited[df['Exited']==0].count()]
explode = (0, 0.1)
fig1, ax1 = plt.subplots(figsize=(10, 8))
ax1.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%',
        shadow=True, startangle=90)
ax1.axis('equal')
plt.title("Proportion of customer Churned and Not Churned", size = 20)
plt.show()
```



So about 20% of the customers have churned. So the baseline model could be to predict that 20% of the customers will churn.

SELECT INPUT(X) AND OUTPUT(Y) , TRAIN TEST SPLITING ,SCALING (StandardScaler), CREATING def FUNCTION FOR ALGORITHMS

```
#Select input and output from dataset

X=df_new.drop("Exited",axis=1)    #input

Y=df_new['Exited']          #output
```

```
X.head()
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Es
0	619	42	2	0.00	1	1	1	
1	608	41	1	83807.86	1	0	1	
2	502	42	8	159660.80	3	1	0	
3	699	39	1	0.00	2	0	0	
4	850	43	2	125510.82	1	1	1	

```
Y.head()
```

```
0    1
1    0
2    1
3    0
4    0
Name: Exited, dtype: int64
```

```
#train test split
```

```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.3,random_state=1)
```

```
#Scaling
from sklearn.preprocessing import StandardScaler
#create the object of StandardScaler class
ss=StandardScaler()
X_train=ss.fit_transform(X_train)             #fit is used to train the model
X_test=ss.transform(X_test)
```

```
#Create user defined function

def create_model(model): #Here model passing argument(object)

    model.fit(X_train,Y_train)  #Train the model with 70% data

    Y_pred=model.predict(X_test)   #Test the model with 30% data

    print(classification_report(Y_test,Y_pred))  #To generate Classification report
    print(confusion_matrix(Y_test,Y_pred))       #To generate Confusion matrix

    return model
```

```
from sklearn.metrics import classification_report,confusion_matrix
```

```
#Previously we have find that the data is imbalanced so we will need to balanced it before
#For Balancing the data we need to apply Sampling Technnique

#We will apply RandomOverSampler which is a type of Sampling Technique
#RandomOverSampler : inbuilt class : to increase means create duplicate records of minorit

from imblearn.over_sampling import RandomOverSampler
```

```
#before apply randomoversampler
Y_train.value_counts() #check if not balance
```

```
0    5590
1    1410
Name: Exited, dtype: int64
```

```
#Apply RandomOverSampler
#First create the object of class RandomOverSampler
ros=RandomOverSampler()
```

```
X_train,Y_train=ros.fit_resample(X_train,Y_train)
#here make a duplicate record from existing record of minority class
```

```
#Before apply randomoversample, check testing data
```

```
Y_test.value_counts()
```

```
0    2373
1     627
Name: Exited, dtype: int64
```

```
X_test,Y_test=ros.fit_resample(X_test,Y_test)          #fit_resample() inbuilt method of
```

```
#After apply randomversample , check testing data
Y_test.value_counts()
```

```
0    2373
1    2373
Name: Exited, dtype: int64
```

```
#Here data is balanced now so we can give our data to Machine Learning Algorithms
```

LOGISTIC REGRESSION

```
#Create a baseline model : logistic Regression
from sklearn.linear_model import LogisticRegression
```

```
#Create object of class LogisticRegression
lr=LogisticRegression()
```

```
#Call function
lr=create_model(lr)
```

```
              precision    recall  f1-score   support

           0       0.68      0.72      0.70      2373
           1       0.70      0.66      0.68      2373

    accuracy                           0.69      4746
   macro avg       0.69      0.69      0.69      4746
weighted avg       0.69      0.69      0.69      4746

[[1714  659]
 [ 802 1571]]
```

NOTE: Here LogisticRegression Algorithm gives about 0.69 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.72 and recall score of Class 1 is 0.66.

Lets, test the data with other models(Algorithms).

DECISION TREE CLASSIFIER

```
#Now perform dataset with the help of DecisionTreeClassifier
#Call DecisionTreeClassifier class

from sklearn.tree import DecisionTreeClassifier


#Create a object of class DecisionTreeClassifier
dt=DecisionTreeClassifier()


#call function
dt=create_model(dt)
```

```
              precision    recall  f1-score   support

           0       0.64      0.87      0.74      2373
           1       0.79      0.50      0.62      2373

    accuracy                           0.69      4746
   macro avg       0.72      0.69      0.68      4746
weighted avg       0.72      0.69      0.68      4746

[[2065  308]
 [1179 1194]]
```

```
#Here clearly understood that the model is overfit ,so reduced the overfitting situation w

#How to reduced a overfitting situation By using the Pruning technique There are 2 types o

#1. max_depth : inbulit parameter

#2. min_samples_leaf  : inbuilt parameter


#1.max_depth parameter
#Create object of DecisionTreeClassifier class and pass the parameter
#max_depth
dt1=DecisionTreeClassifier(max_depth=5,random_state=1)
#by default use inbuilt method gini index


#Call function
dt1=create_model(dt1)
```

```
              precision    recall  f1-score   support

           0       0.71      0.82      0.76      2373
           1       0.79      0.67      0.72      2373

    accuracy                           0.75      4746
   macro avg       0.75      0.75      0.74      4746
weighted avg       0.75      0.75      0.74      4746

[[1942  431]
 [ 779 1594]]
```

```
#Use second pruning tech .
#min_samples_leaf : Atleast 45-50 or more

##create object of DecisionTreeClassifier class
dt2=DecisionTreeClassifier(min_samples_leaf=50) #by default Gini index method
#min_samples_leaf =50 or more means not less than=45-50


#Call function
dt2=create_model(dt2)
```

```
              precision    recall  f1-score   support

           0       0.72      0.79      0.75      2373
           1       0.77      0.69      0.73      2373

    accuracy                           0.74      4746
   macro avg       0.74      0.74      0.74      4746
weighted avg       0.74      0.74      0.74      4746

[[1880  493]
 [ 734 1639]]
```

NOTE: Here DecisionTreeClassifier Algorithm without Pruning technique gives about 0.69 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.87 and recall score of Class 1 is 0.50.

Here DecisionTreeClassifier Algorithm with Pruning technique (max_depth parameter) gives about 0.75 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.82 and recall score of Class 1 is 0.67.

Here DecisionTreeClassifier Algorithm with Pruning technique with (min_samples_leaf) gives about 0.74 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.79 and recall score of Class 1 is 0.69.

Lets, test the data with other models(Algorithms).

RANDOM FOREST CLASSIFIER

```
#call Random Forest Tree from package

from sklearn.ensemble import RandomForestClassifier
#ensemble means to train the same dataset from multiple alorithm
```

```
#create object of RandomForestClassifier
rfc=RandomForestClassifier(n_estimators=10,max_features=10)
#n_estimators inbuilt parameter : no. of decision tree
#max n_estimators can be given<=100
#bydefault method gini index
```

```
#bydefault method gini index


#Call function
rfc=create_model(rfc)

                  precision    recall  f1-score   support

               0       0.65      0.92      0.76      2373
               1       0.87      0.50      0.64      2373

        accuracy                           0.71      4746
       macro avg       0.76      0.71      0.70      4746
    weighted avg       0.76      0.71      0.70      4746

     [[2190  183]
      [1179 1194]]
```

NOTE: Here RandomForestClassifier Algorithm gives about 0.71 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.92 and recall score of Class 1 is 0.50.

Lets, test the data with other models(Algorithms).

BOOSTING TECHNIQUE

Ensembling technique:

1. Random forest tree
2. Boosting technique

   A. ADA Boost : Adaptor Boosting

   B. Gradient Boost

   C. Extreme Gradient Boost

```
#Boosting Trechnique
#ADA Boost
from sklearn.ensemble import AdaBoostClassifier


ada=AdaBoostClassifier(n_estimators=9,random_state=1)
#n_estimators means no. of decision tree (depend on no. of input features)


#call function
ada=create_model(ada)

                  precision    recall  f1-score   support
```

```
               0       0.74      0.81      0.77      2373
               1       0.79      0.72      0.75      2373

        accuracy                           0.76      4746
       macro avg       0.76      0.76      0.76      4746
    weighted avg       0.76      0.76      0.76      4746

    [[1915  458]
     [ 672 1701]]
```

```
#Call GradientBoostingClassifier class from following package
from sklearn.ensemble import GradientBoostingClassifier


#create the object of GradientBoostingClassifier class
gbc=GradientBoostingClassifier(n_estimators=25,random_state=1)
#not can be <= 100     #n_estimators means no. of decision tree (depend on no. of input fe


#call function
gbc=create_model(gbc)
```

```
                  precision    recall  f1-score   support

               0       0.75      0.79      0.77      2373
               1       0.78      0.74      0.76      2373

        accuracy                           0.77      4746
       macro avg       0.77      0.77      0.77      4746
    weighted avg       0.77      0.77      0.77      4746

    [[1882  491]
     [ 615 1758]]
```

```
##Call Extreme Gradient Boosting (XGB) class from following package

from xgboost import XGBClassifier


#create object of class XGBClassifier
xgc=XGBClassifier(n_estimators=30,reg_alpha=1)
#reg means regularation : lambda or alpha
#automatic overfitting : reg means regularation and alpha or lambda :
#hyperparameter
#1 means True


#call function
xgc=create_model(xgc)
```

```
                  precision    recall  f1-score   support

               0       0.75      0.80      0.78      2373
               1       0.79      0.74      0.76      2373

        accuracy                           0.77      4746
       macro avg       0.77      0.77      0.77      4746
```

```
weighted avg       0.77      0.77      0.77      4746

[[1896  477]
 [ 618 1755]]
```

NOTE: Here ADA Boost Classifier Algorithm gives about 0.76 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.81 and recall score of Class 1 is 0.72.

Here Gradient Boost Classifier Algorithm gives about 0.77 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.79 and recall score of Class 1 is 0.74.

Here Extreme Gradient Classifier Algorithm gives about 0.77 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.80 and recall score of Class 1 is 0.74.

Lets, test the data with other models(Algorithms).

K-nn (KNeighborsClassifier) Algorithm:

```
#Use K-NN Algorithm
from sklearn.neighbors import KNeighborsClassifier


#Create the object of KNeighborsClassifier

knc= KNeighborsClassifier(n_neighbors=5, metric='minkowski', p=2)

#p=2 means Euclidean distance means sqrt(x2-x1)*2+(y2-y1)*2
#n_neighbors means k means select minimum point (always odd)



#call function
knc=create_model(knc)
```

```
              precision    recall  f1-score   support

           0       0.67      0.75      0.71      2373
           1       0.72      0.64      0.67      2373

    accuracy                           0.69      4746
   macro avg       0.70      0.69      0.69      4746
weighted avg       0.70      0.69      0.69      4746

[[1782  591]
 [ 866 1507]]
```

NOTE: Here KNeighborsClassifier Algorithm gives about 0.69 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.75 and recall score of Class 1 is 0.64.

Lets test the data with other models(Algorithms)

Support Vector Machine Algorithm

```
#Apply Support vector machine

from sklearn.svm import LinearSVC


#Create object of LinearSVC class
svc=LinearSVC(random_state=1)     #Hard margin by default means to outlier means # No over


#call function
svc=create_model(svc)
```

```
              precision    recall  f1-score   support

           0       0.68      0.72      0.70      2373
           1       0.70      0.66      0.68      2373

    accuracy                           0.69      4746
   macro avg       0.69      0.69      0.69      4746
weighted avg       0.69      0.69      0.69      4746

[[1716  657]
 [ 808 1565]]
```

```
#Here accuracy is 0.71 which is good but we can more better means can be possible ,model i
#because there can be no error on training time but error on testing time ,
#what do we do , add some external error on training time if create a object of LinearSVC

#Soft margin means to reduced overfitting situation means some error add on
#training time
#create object of LinearSVC class
svc1=LinearSVC(random_state=1,C=0.10)#soft margin
#always C means error parameter means to add external error on training time
#with the help of C parameter
#the value of C should be less than 1




#Call function

svc1=create_model(svc1)
```

```
              precision    recall  f1-score   support

           0       0.68      0.72      0.70      2373
```

```
               1       0.70      0.66      0.68      2373

        accuracy                           0.69      4746
       macro avg       0.69      0.69      0.69      4746
    weighted avg       0.69      0.69      0.69      4746

    [[1716  657]
     [ 808 1565]]
```

```
#Here data is non-linear so by changing the value of "C" above the accuracy not changes.


#if adding external error on training time but no any changes on score
#means given dataset in non-Linear can be possible , dataset is not linear means dataset i
#use Non-linear kernal function of SVM means 2 classes are not separatable with straight l

#There are 3 types of Kernal function of SVM

#1. Linear SVC  : use for linear data

#2. Non-Linear SVC : use for non-linear data

 #A. polynomial kernal function : increase the low dimension to high dimension
 #B. radial basis kernal function



#Kernel function : Converts low dimension data to high dimension data
#if we have 1 D array then converts 2D array and we have 2D array then to converts 3D arra

#polynomial Kernel function
#radial basis Kernel function

#both are used for non-linear data



#Give data to Polynomial kernel function , call inbuilt class SVC
from sklearn.svm import SVC
#SVC means support vector classifier


#create object of SVC class
svc=SVC(random_state=1,kernel='poly')


#call function
svc1=create_model(svc1)
```

```
                  precision    recall  f1-score   support

               0       0.68      0.72      0.70      2373
               1       0.70      0.66      0.68      2373

        accuracy                           0.69      4746
       macro avg       0.69      0.69      0.69      4746
    weighted avg       0.69      0.69      0.69      4746
```

```
[[1716  657]
 [ 808 1565]]
```

```
#Give dataset to radial basis means kernel=rbf
svc2=SVC(random_state=1,kernel='rbf')


#call function
svc2=create_model(svc2)
```

```
              precision    recall  f1-score   support

           0       0.74      0.80      0.77      2373
           1       0.78      0.73      0.75      2373

    accuracy                           0.76      4746
   macro avg       0.76      0.76      0.76      4746
weighted avg       0.76      0.76      0.76      4746

[[1887  486]
 [ 650 1723]]
```

NOTE: Here SupportVectorMachine Algorithm with hard margin gives about 0.69 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.72 and recall score of Class 1 is 0.66.

Here SupportVectorMachine Algorithm with soft margin gives about 0.69 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.72 and recall score of Class 1 is 0.66.

Here SupportVectorMachine Algorithm with Polynomial kernel function gives about 0.69 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.72 and recall score of Class 1 is 0.66.

Here SupportVectorMachine Algorithm with Radial basis Kernel function gives about 0.76 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.80 and recall score of Class 1 is 0.73.

Lets, test the data with other models(Algorithms).

Naive Bayes Classifier Algorithm

```
#Apply Navie Bayes Theorem (Classification theorem)
#1. Gaussian Naive Bayes theorem

from sklearn.naive_bayes import GaussianNB
#Inbuilt class GaussianNB
```

```
#create the object of class GaussianNB
#GaussianNB algorithm are applied on continuous Numerical value of input column

gnb=GaussianNB()


#call function

gnb=create_model(gnb)
```

```
              precision    recall  f1-score   support

           0       0.71      0.78      0.74      2373
           1       0.75      0.68      0.71      2373

    accuracy                           0.73      4746
   macro avg       0.73      0.73      0.73      4746
weighted avg       0.73      0.73      0.73      4746

[[1844  529]
 [ 759 1614]]
```

NOTE: Here Gaussian Naive Bayes Algorithm gives about 0.73 Accuracy score. But here in this case we have to focus on recall score, here recall score of Class 0 is 0.78 and recall score of Class 1 is 0.68.

CONCLUSION : Hence, we will recommend Extreme Gradient Classifier Algorithm for the given Dataset of Bank Churn.

0s completed at 1:38 AM