Teesside University MSc Data Science

Machine Learning ICA

INTRODUCTION

Machine Learning Application for Bank Customer Churn Prediction

The dataset used in this project was gotten from https://www.kaggle.com/code/kmalit/bank-customer-churn-prediction/data

The aims of this work are:

1. Identify which factors contribute to customer churn using visualization packages.

2. Build a prediction model that will Classify if a customer is going to churn or not.

Importing Required Libraries

In [451…

```
import numpy as np
import pandas as pd


import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.preprocessing import PolynomialFeatures

from sklearn.ensemble import ExtraTreesClassifier

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score, confusion_matrix, roc_curve

from sklearn.metrics import classification_report,accuracy_score
```

Exploratory Data Analysis¶

Reading the data from the .csv dataset using pandas library

In [452…

```
dataFrame=pd.read_csv("Churn_Modelling.csv")
dataFrame.head(20)
```

Out[452]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProdu
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	
3	4	15701354	Boni	699	France	Female	39	1	0.00	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	
5	6	15574012	Chu	645	Spain	Male	44	8	113755.78	
6	7	15592531	Bartlett	822	France	Male	50	7	0.00	
7	8	15656148	Obinna	376	Germany	Female	29	4	115046.74	
8	9	15792365	He	501	France	Male	44	4	142051.07	
9	10	15592389	H?	684	France	Male	27	2	134603.88	
10	11	15767821	Bearce	528	France	Male	31	6	102016.72	
11	12	15737173	Andrews	497	Spain	Male	24	3	0.00	
12	13	15632264	Kay	476	France	Female	34	10	0.00	
13	14	15691483	Chin	549	France	Female	25	5	0.00	
14	15	15600882	Scott	635	Spain	Female	35	7	0.00	
15	16	15643966	Goforth	616	Germany	Male	45	3	143129.41	
16	17	15737452	Romeo	653	Germany	Male	58	1	132602.88	
17	18	15788218	Henderson	549	Spain	Female	24	9	0.00	
18	19	15661507	Muldrow	587	Spain	Male	45	6	0.00	
19	20	15568982	Hao	726	France	Female	24	6	0.00	

Basic insight from the dataset

In [453…

```
# getting the dimension of the dataFrame
dataFrame.shape
```

Out[453]:

```
(10000, 14)
```

The data frame has 10,000 rows with 14 columns.

In [ ]:

In [454…

```
dataFrame.dtypes # checking data type of the culumns
```

Out[454]:

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

In [ ]:

In [455…

```
# checking for missing values from each column
dataFrame.isnull().sum()
```

Out[455]:
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

In [456...
```
# unique value count of each column
dataFrame.nunique()
```

Out[456]:
```
RowNumber          10000
CustomerId         10000
Surname             2932
CreditScore          460
Geography              3
Gender                 2
Age                   70
Tenure                11
Balance             6382
NumOfProducts          4
HasCrCard              2
IsActiveMember         2
EstimatedSalary     9999
Exited                 2
dtype: int64
```

We will be dropping the columns that are irrelevant and will not be contributing to the model development

the following columns will be dropped

- RowNumber
- CustomerId
- Surname

In [457...
```
dataFrame = dataFrame.drop(["RowNumber", "CustomerId", "Surname"], axis = 1)
# First row display of whats left
dataFrame.head(1)
```

Out[457]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estimat
0	619	France	Female	42	2	0.0	1	1	1	1

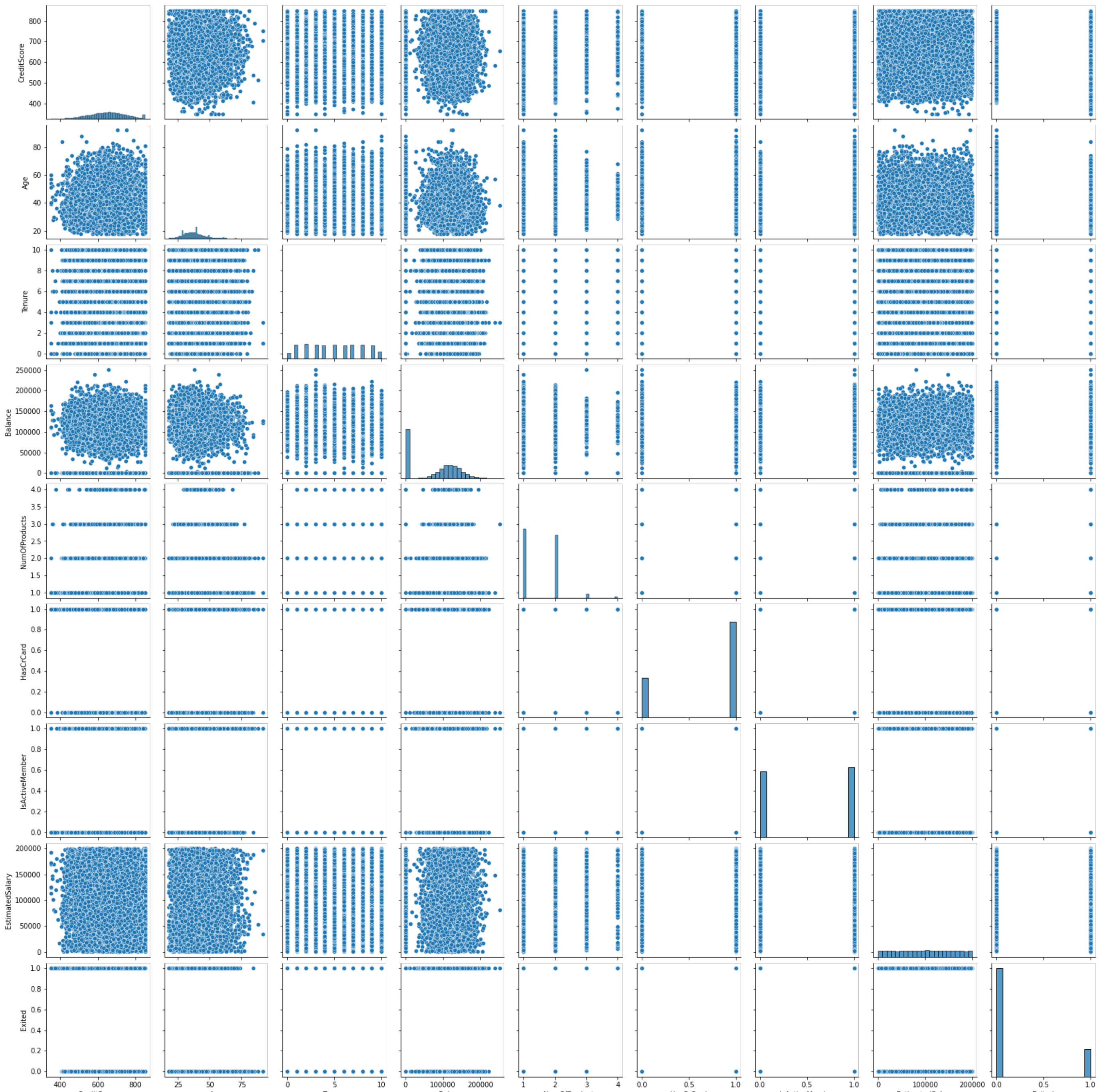
In [458...
```
# Re-checking for unique count of new columns
dataFrame.nunique()
```

Out[458]:
```
CreditScore         460
Geography             3
Gender                2
Age                  70
Tenure               11
Balance            6382
NumOfProducts         4
HasCrCard             2
IsActiveMember        2
EstimatedSalary    9999
Exited                2
dtype: int64
```

Visualization

In [459...
```
sns.pairplot(dataFrame)
```

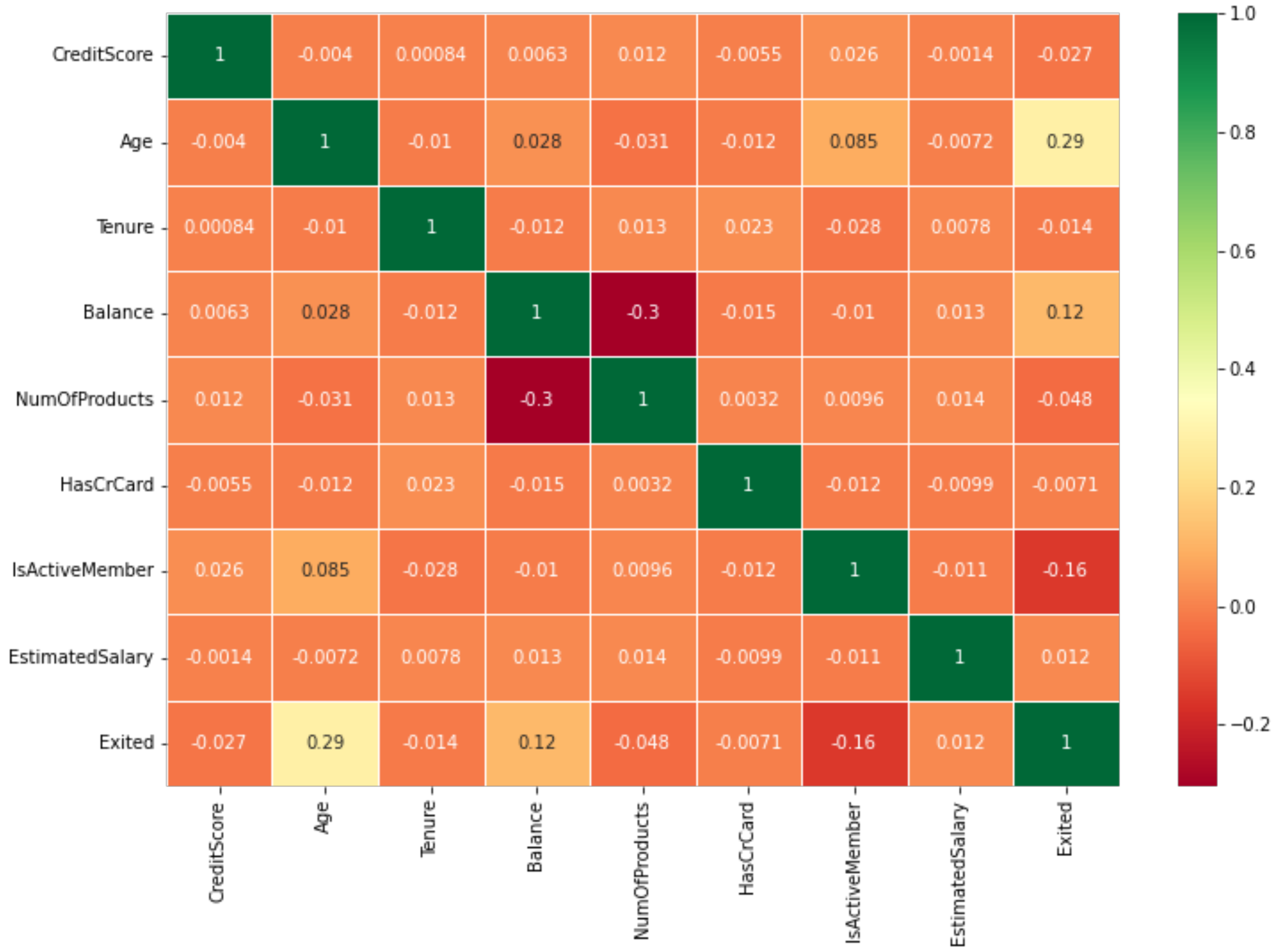
Out[459]: <seaborn.axisgrid.PairGrid at 0x155ac40a488>



Heat map showing Correlation

In [460…

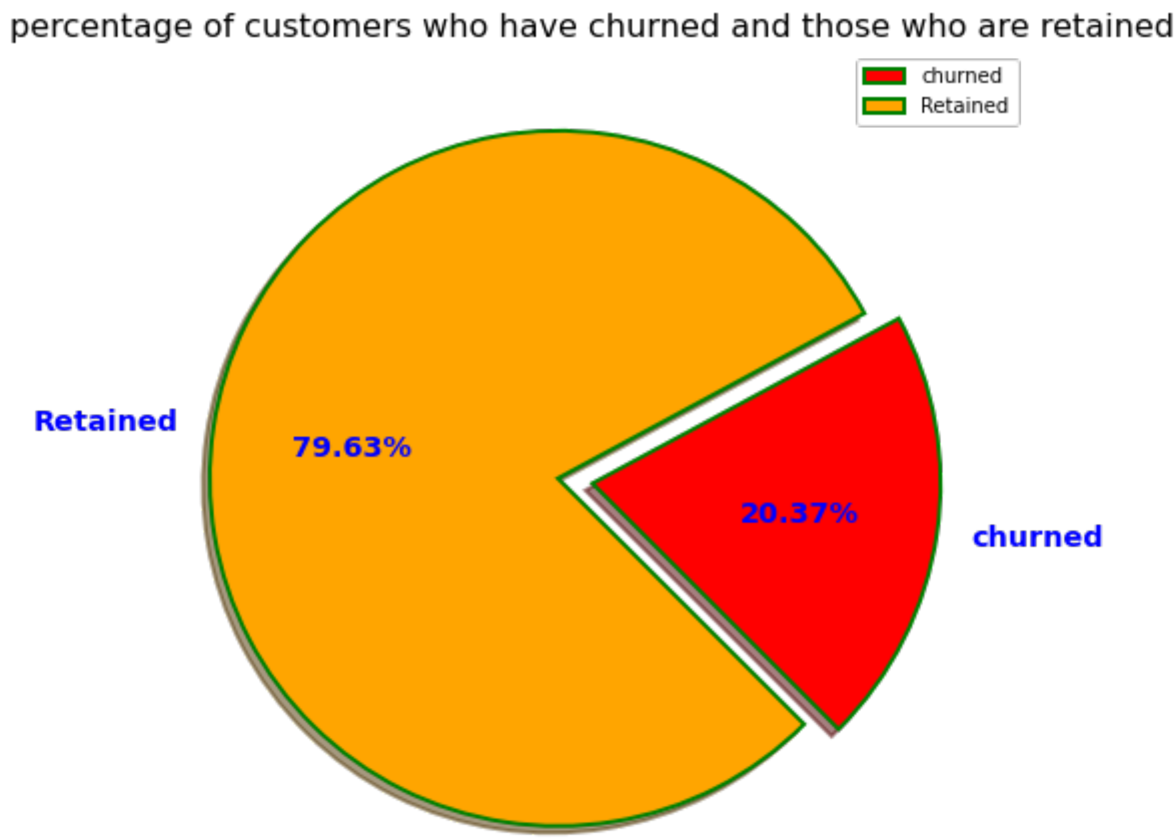
```
sns.heatmap(dataFrame.corr(),
annot=True,cmap='RdYlGn',linewidths=0.5)
#data.corr()-->correlation
matrixfig=plt.gcf()
matrixfig.set_size_inches(12,8)

plt.show()
```



Checking the percentage of churn and retain customer in the dataset

In [461…

```
sizes = [dataFrame.Exited[dataFrame['Exited']==1].count(),
          dataFrame.Exited[dataFrame['Exited']==0].count()
         ]
colors=['chocolate','darksalmon']
explode = (0, 0.1)
wp = { 'linewidth' : 2, 'edgecolor' : "green" }

plt.figure(figsize = (8, 8))
plt.pie(sizes, labels = ['churned', 'Retained'], autopct = '%.2f%%',
        explode=explode,
        colors=['red','orange'],
        shadow=True,
        startangle= -45,
        wedgeprops = wp,
        textprops = {'size' : 'x-large','fontweight' : 'bold', 'color' : 'b',}
       )

plt.legend()
plt.title("percentage of customers who have churned and those who are retained", fontsize = 16)
plt.show()
```



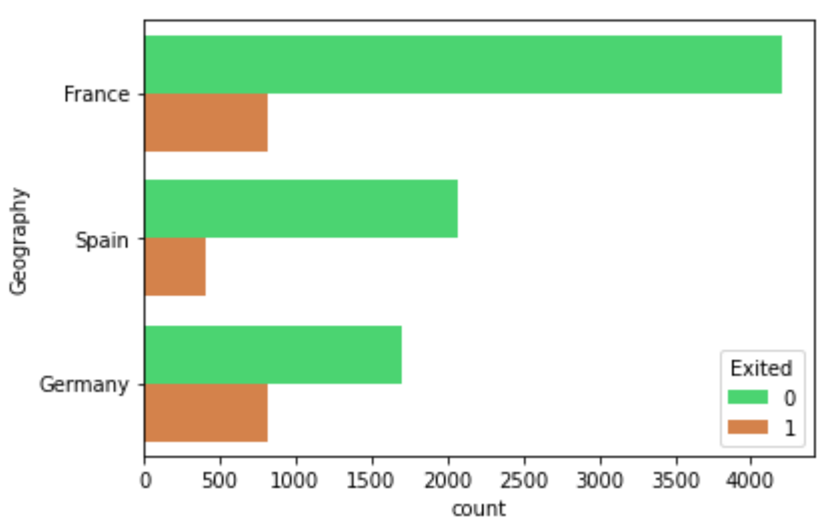
From the pie chart above, 20.37% of customers actually churn and 79.63% are retained Our focus will be on predicting on a higher Accuracy this percentage of customers will will churn

Visualizing categorical variables' impact on the target variable

In [462…

```
#plotting Geography variable on exited

sns.countplot(y='Geography', hue = 'Exited',
              data = dataFrame,
              palette=['#34eb67',"#eb7d34"]
             )
```

Out[462]: <AxesSubplot:xlabel='count', ylabel='Geography'>

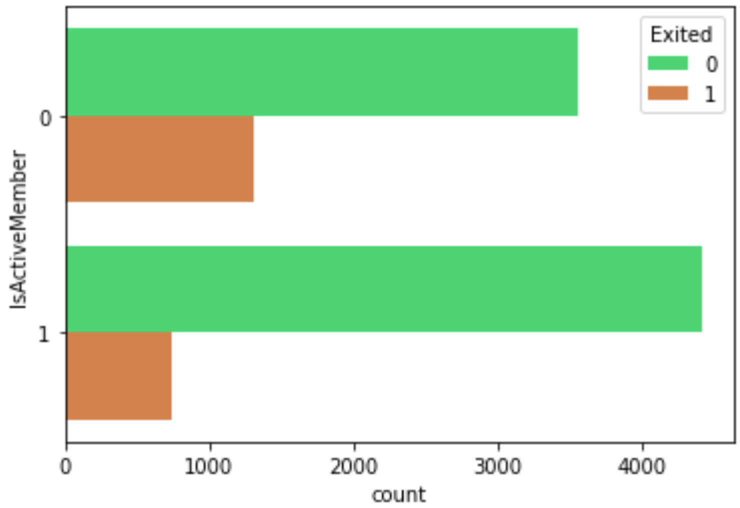


Although the majority of consumers are from France, the number of churned customers cannot be determined solely on their region.

In [463…

```
#plot IsActiveMember variable on exited
sns.countplot(y='IsActiveMember',
              hue = 'Exited',data = dataFrame,
              palette=['#34eb67',"#eb7d34"]
             )
```

Out[463]: <AxesSubplot:xlabel='count', ylabel='IsActiveMember'>



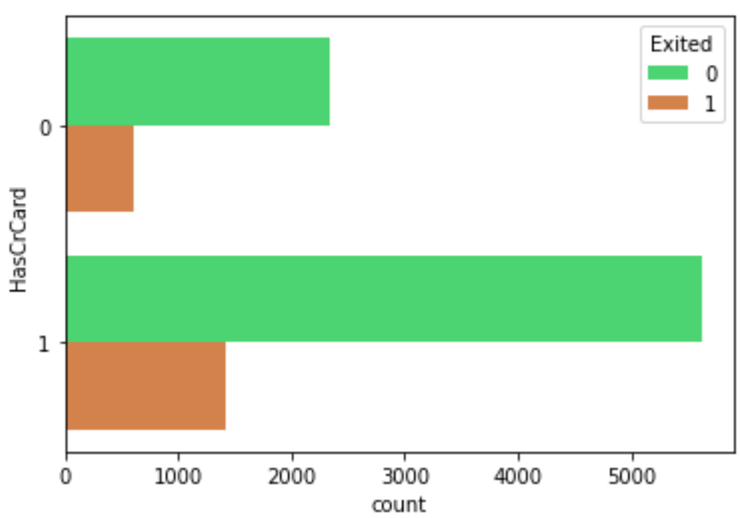
The Active Members have lower churn while the Inactive Members have a greater churn.

There is a reason for consern as the number of Inactive Members is very large. the bank needs to look into it.

In [464…

```
#plot HasCrCard variable on exited
sns.countplot(y='HasCrCard',
              hue = 'Exited',data = dataFrame,
              palette=['#34eb67',"#eb7d34"]
             )
```

Out[464]: <AxesSubplot:xlabel='count', ylabel='HasCrCard'>

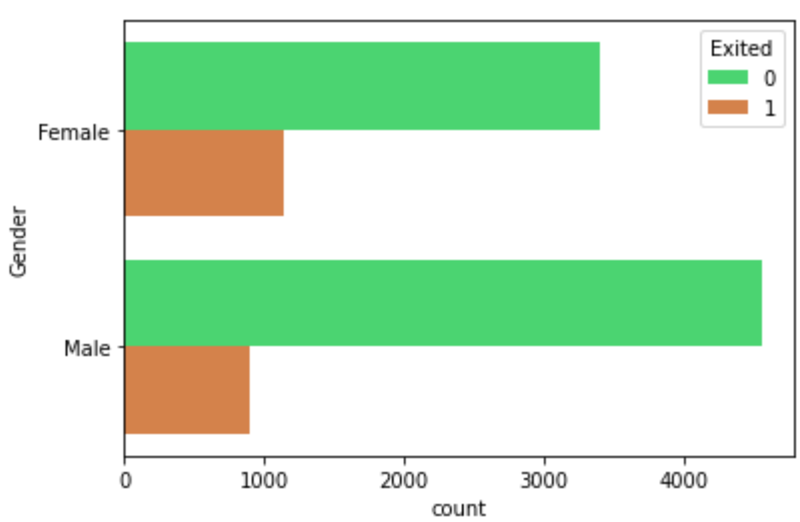


The majority of churned consumers are ones that uses credit cards.

In [465…

```
#plot Gender variable on exited
sns.countplot(y='Gender', hue = 'Exited',
              data = dataFrame,
              palette=['#34eb67',"#eb7d34"]
             )
```

Out[465]: <AxesSubplot:xlabel='count', ylabel='Gender'>

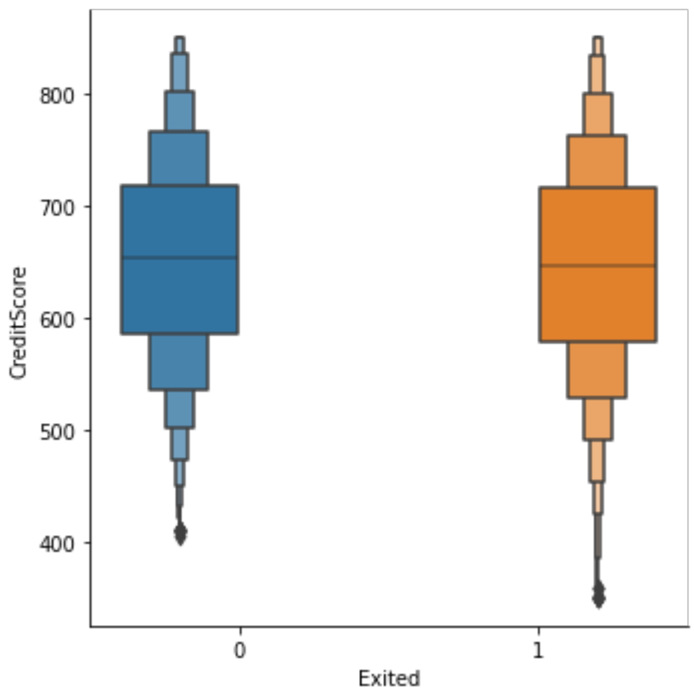


The number of female clients who are churning outnumbers the number of male consumers.

checking the effect of continuous variable on target variable

In [466…
```
#plot CreditScore variable on exited
sns.catplot(y='CreditScore',x = 'Exited', hue = 'Exited',kind="boxen",data = dataFrame)
```

Out[466]: <seaborn.axisgrid.FacetGrid at 0x155bce90448>

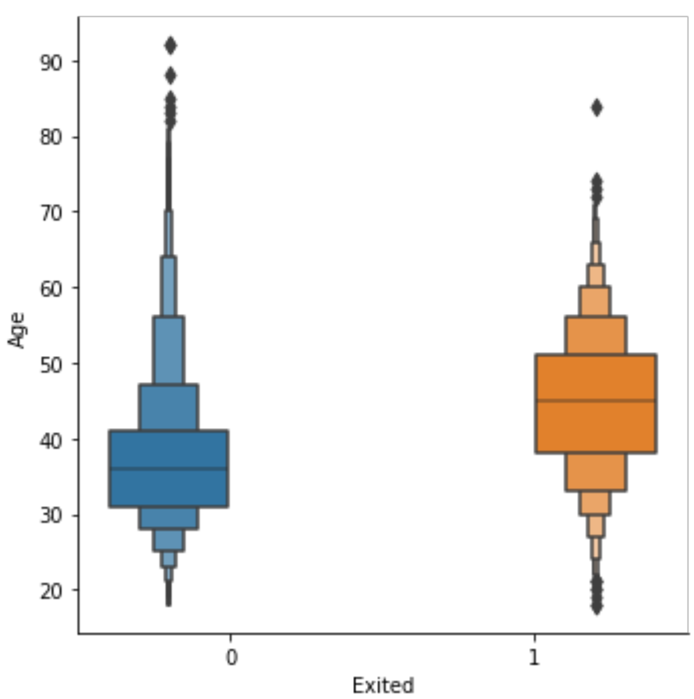


In [ ]:

There is no discernible variation in the credit score distribution between retained and churned customers.

In [467…
```
#plot Age variable on exited
sns.catplot(y='Age',x = 'Exited', hue = 'Exited',kind="boxen",data = dataFrame)
```

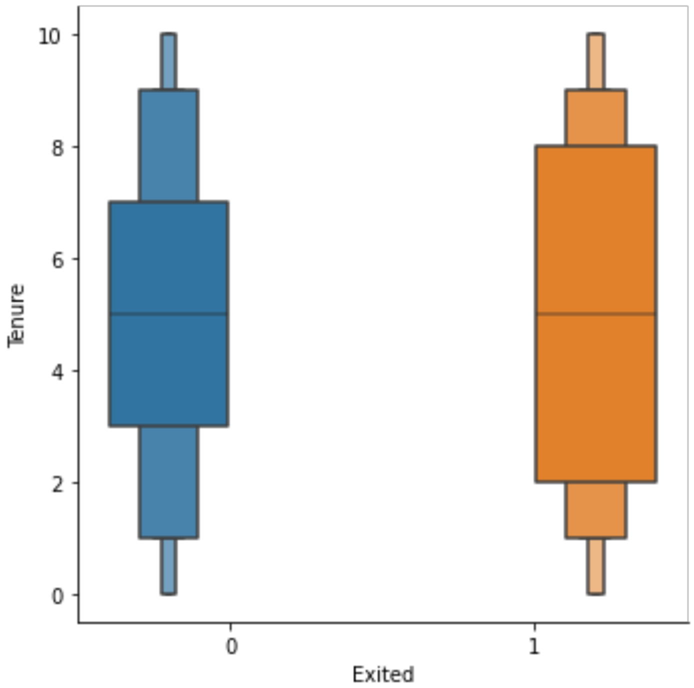
Out[467]: <seaborn.axisgrid.FacetGrid at 0x155bd2534c8>



The older customers are churning more than the younger customers

In [468…
```
#plot Tenure variable on exited
sns.catplot(y='Tenure',x = 'Exited',kind="boxen", hue = 'Exited',data = dataFrame)
```

Out[468]: <seaborn.axisgrid.FacetGrid at 0x155bd24cac8>



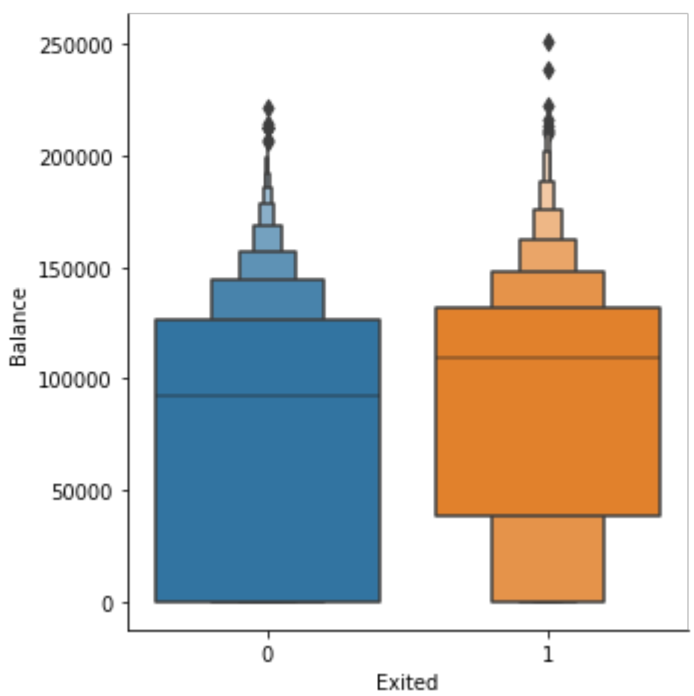
The customers on either extreme end are more likely to churn compared to those that are of average tenure.

In [469…

```
#plot Balance variable on exited
sns.catplot(y='Balance',x = 'Exited', kind = 'boxen',data = dataFrame)
```

Out[469]:

```
<seaborn.axisgrid.FacetGrid at 0x155c6501348>
```



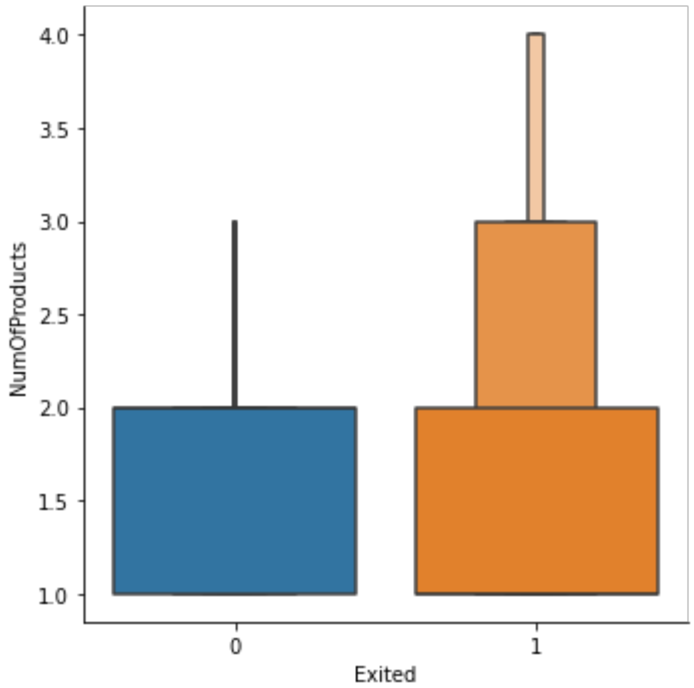
Customers with high balance are chuning.

In [470…

```
# plot NumOfProducts variable on exited
sns.catplot(y='NumOfProducts',x = 'Exited', kind = 'boxen',data = dataFrame)
```

Out[470]:

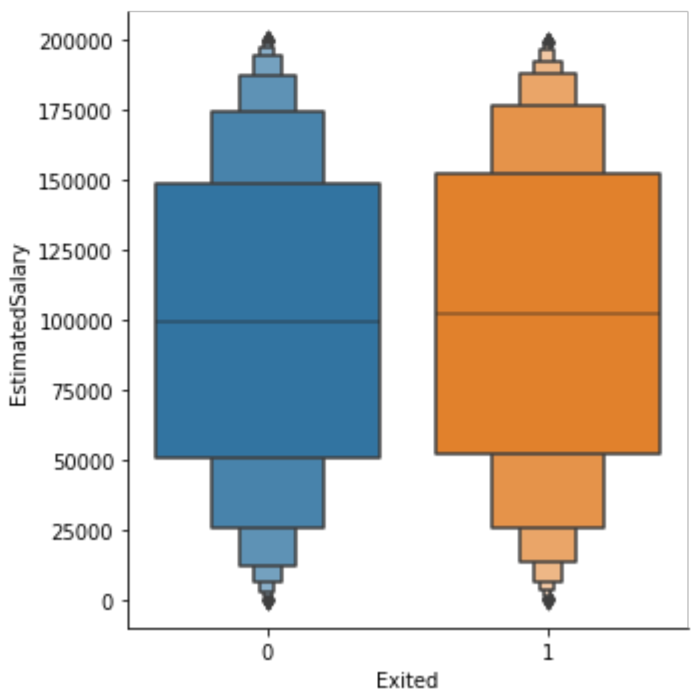
```
<seaborn.axisgrid.FacetGrid at 0x155c76e4408>
```



Customers with 3 products are churning.

In [471…
```
#plot EstimatedSalary variable on exited
sns.catplot(y='EstimatedSalary',x = 'Exited', kind = 'boxen',data = dataFrame)
```

Out[471]:
```
<seaborn.axisgrid.FacetGrid at 0x155c76ec4c8>
```



salary has no significant effect on target variable.

Feature engineering

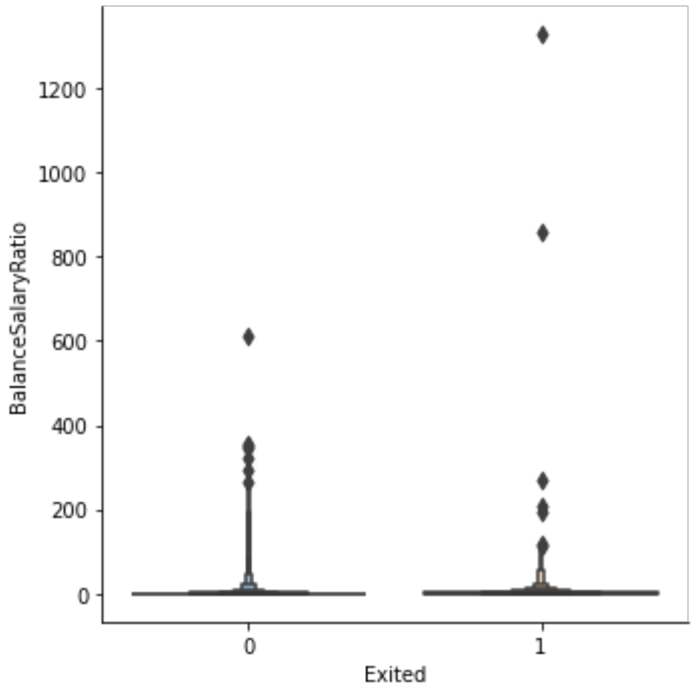
Divide the data into two sets: training and testing.

In [472…
```
# Split Train, test data
df_train = dataFrame.sample(frac=0.8,random_state=200)
df_test = dataFrame.drop(df_train.index)
print("Train Dataset:",df_train.shape)
print("Test Dataset:",df_test.shape)
```

```
Train Dataset: (8000, 11)
Test Dataset: (2000, 11)
```

In [473…
```
import matplotlib.pyplot as plt
df_train['BalanceSalaryRatio'] = df_train.Balance/df_train.EstimatedSalary
sns.catplot(y='BalanceSalaryRatio',x = 'Exited', kind = 'boxen',data = df_train)
```

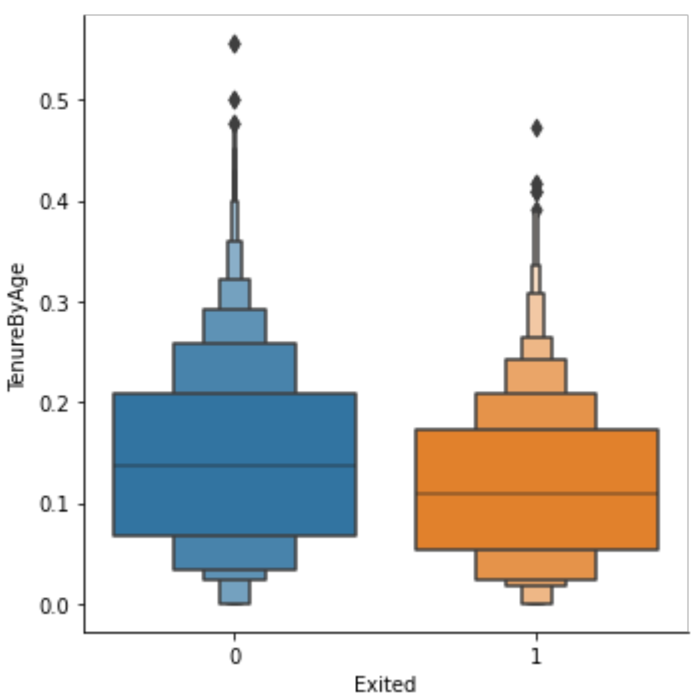
Out[473]:
```
<seaborn.axisgrid.FacetGrid at 0x155c77fc608>
```



Customer departure is unaffected by salary ratio.

In [474…

```
# Given that tenure is a 'function' of age, we create a new column aiming to standardize tenure
df_train['TenureByAge'] = df_train.Tenure/(df_train.Age)
sns.catplot(y='TenureByAge',x = 'Exited', kind = 'boxen',data = df_train)
#plt.ylim(-1, 5)
plt.show()
```



In [ ]:

Customer with low tenure are churning

In [475…

```
# we create a column to capture credit score given age to take into account credit behaviour
df_train['CreditScoreGivenAge'] = df_train.CreditScore/(df_train.Age)
```

In [476…

```
# Cheking the dataframe
df_train.head(2)
```

Out[476]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Est
8159	461	Spain	Female	25	6	0.00	2	1	1	
6332	619	France	Female	35	4	90413.12	1	1	1	

Data preparation¶

In [477…

```
# Re-arranging the columns by data type
continuous_cols = ['CreditScore',  'Age', 'Tenure', 'Balance','NumOfProducts', 'EstimatedSalary'
                   'TenureByAge','CreditScoreGivenAge']
cate_cols = ['HasCrCard', 'IsActiveMember','Geography', 'Gender']
df_train = df_train[['Exited'] + continuous_cols + cate_cols]
df_train.head()
```

Out[477]:

	Exited	CreditScore	Age	Tenure	Balance	NumOfProducts	EstimatedSalary	BalanceSalaryRatio	TenureE
8159	0	461	25	6	0.00	2	15306.29	0.000000	0.2
6332	0	619	35	4	90413.12	1	20555.21	4.398550	0.1
8895	0	699	40	8	122038.34	1	102085.35	1.195454	0.2
5351	0	558	41	2	124227.14	1	111184.67	1.117305	0.0
4314	0	638	34	5	133501.36	1	155643.04	0.857741	0.1

In [478…

```
#For the one hot variables, we convert 0 to -1
df_train.loc[df_train.HasCrCard == 0, 'HasCrCard'] = -1
df_train.loc[df_train.IsActiveMember == 0, 'IsActiveMember'] = -1
df_train.head()
```

Out[478]:

	Exited	CreditScore	Age	Tenure	Balance	NumOfProducts	EstimatedSalary	BalanceSalaryRatio	TenureE
8159	0	461	25	6	0.00	2	15306.29	0.000000	0.2
6332	0	619	35	4	90413.12	1	20555.21	4.398550	0.1
8895	0	699	40	8	122038.34	1	102085.35	1.195454	0.2
5351	0	558	41	2	124227.14	1	111184.67	1.117305	0.0
4314	0	638	34	5	133501.36	1	155643.04	0.857741	0.1

In [479…

```
# One hot encode the categorical variables -1
lst = ['Geography', 'Gender']
remove = list()
for x in lst:
    if (df_train[x].dtype == np.str or df_train[x].dtype == np.object):
        for y in df_train[x].unique():
            df_train[x+'_'+y] = np.where(df_train[x] == y,1,-1)
        remove.append(x)
df_train = df_train.drop(remove, axis=1)
df_train.head()
```

```
C:\Users\HP\Desktop\pyprog\data_sc_env\lib\site-packages\ipykernel_launcher.py:5: DeprecationWa
rning: `np.str` is a deprecated alias for the builtin `str`. To silence this warning, use `str`
by itself. Doing this will not modify any behavior and is safe. If you specifically wanted the
numpy scalar type, use `np.str_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.2
0.0-notes.html#deprecations
  """
C:\Users\HP\Desktop\pyprog\data_sc_env\lib\site-packages\ipykernel_launcher.py:5: DeprecationWa
rning: `np.object` is a deprecated alias for the builtin `object`. To silence this warning, use
`object` by itself. Doing this will not modify any behavior and is safe.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.2
0.0-notes.html#deprecations
  """
```

Out[479]:

	Exited	CreditScore	Age	Tenure	Balance	NumOfProducts	EstimatedSalary	BalanceSalaryRatio	TenureE
8159	0	461	25	6	0.00	2	15306.29	0.000000	0.2
6332	0	619	35	4	90413.12	1	20555.21	4.398550	0.1
8895	0	699	40	8	122038.34	1	102085.35	1.195454	0.2
5351	0	558	41	2	124227.14	1	111184.67	1.117305	0.0
4314	0	638	34	5	133501.36	1	155643.04	0.857741	0.1

Data normalization

In [480…

```
# create a minimum and Maximum scale for the continuous variables
minVec = df_train[continuous_cols].min().copy()
maxVec = df_train[continuous_cols].max().copy()
df_train[continuous_cols] = (df_train[continuous_cols]-minVec)/(maxVec-minVec)
df_train.head()
```

Out[480]:

	Exited	CreditScore	Age	Tenure	Balance	NumOfProducts	EstimatedSalary	BalanceSalaryRatio	Tenu
8159	0	0.222	0.094595	0.6	0.000000	0.333333	0.076118	0.000000	
6332	0	0.538	0.229730	0.4	0.360358	0.000000	0.102376	0.003317	
8895	0	0.698	0.297297	0.8	0.486406	0.000000	0.510225	0.000901	
5351	0	0.416	0.310811	0.2	0.495130	0.000000	0.555744	0.000843	
4314	0	0.576	0.216216	0.5	0.532094	0.000000	0.778145	0.000647	

Data preparation pipeline for test dataset

In [481…

```
def DfPrepPipeline(df_predict,df_train_Cols,minVec,maxVec):
    # this section adds new features
    df_predict['BalanceSalaryRatio'] = df_predict.Balance/df_predict.EstimatedSalary
    df_predict['TenureByAge'] = df_predict.Tenure/(df_predict.Age - 18)
    df_predict['CreditScoreGivenAge'] = df_predict.CreditScore/(df_predict.Age - 18)

    # Reordering of the columns
    cont_cols = ['CreditScore','Age','Tenure','Balance',
                 'NumOfProducts','EstimatedSalary','BalanceSalaryRatio',
                 'TenureByAge','CreditScoreGivenAge'
                ]
    cat_cols = ['HasCrCard','IsActiveMember',"Geography", "Gender"]
    df_predict = df_predict[['Exited'] + cont_cols + cat_cols]

    # Changing the '0's in categorical variables to '-1's
    df_predict.loc[df_predict.HasCrCard == 0, 'HasCrCard'] = -1
    df_predict.loc[df_predict.IsActiveMember == 0, 'IsActiveMember'] = -1

    # performing one-hot-encoding to th categorical variables
    lst = ["Geography", "Gender"]
    remove = list()
    for x in lst:
        for y in df_predict[x].unique():
            df_predict[x+'_'+y] = np.where(df_predict[x] == y,1,-1)
        remove.append(x)
    df_predict = df_predict.drop(remove, axis=1)

    # making sure all one-hot-encoded variables in the train data appears in the subsequent datc
    L = list(set(df_train_Cols) - set(df_predict.columns))
    for l in L:
        df_predict[str(l)] = -1

    # MinMax scaling coontinuous variables based on min and max from the train data
    df_predict[cont_cols] = (df_predict[cont_cols]-minVec)/(maxVec-minVec)
    # Ensure that The variables are ordered in the same way as was ordered in the train set
    df_predict = df_predict[df_train_Cols]
    return df_predict
```

Model Fitting

models

I will be working with the following models

- Logistic regression
- Random Forest
- Ensemble models(XGboost)
- KNN

In [482…

```
# Make the data transformation for test data
df_test = DfPrepPipeline(df_test,df_train.columns,minVec,maxVec)
df_test = df_test.mask(np.isinf(df_test))
df_test = df_test.dropna()
df_test.shape
```

Out[482]:

```
(1996, 17)
```

Splitting train and test dataset into x and y

In [483…

```
#Splitting train dataset into x and y
x_train=df_train.loc[:, df_train.columns != 'Exited']
y_train=df_train.Exited
#Splitting test dataset into x and y
x_test=df_test.loc[:, df_test.columns != 'Exited']
y_test=df_test.Exited
```

Fine tuning to get right value of k using test dataset

In [484…

```
# try K=1 through K=20 and record testing accuracy
k_range = range(1, 20)

# We can create Python dictionary using [] or dict()
scores = []

# We use a loop through the range 1 to 26
# We append the scores in the dictionary
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(df_train.loc[:, df_train.columns != 'Exited'],df_train.Exited)
    y_pred = knn.predict(x_test)
    scores.append(accuracy_score(df_test.Exited, y_pred))

print(scores)
```

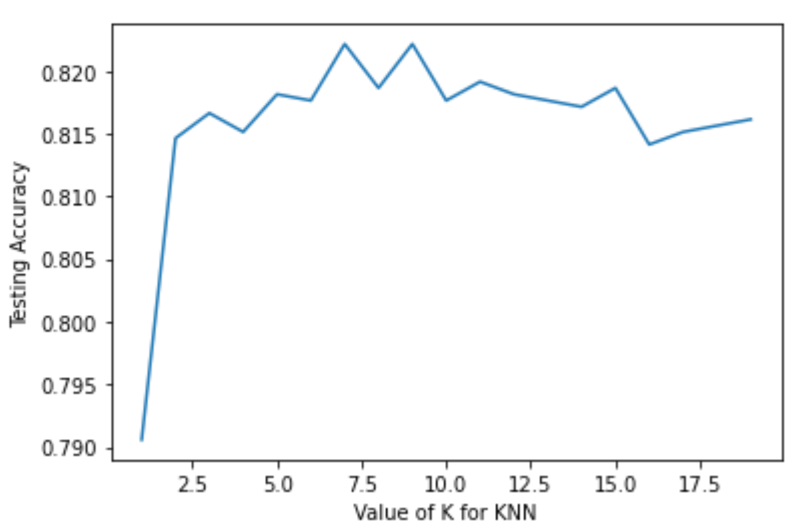
```
[0.7905811623246493, 0.814629258517034, 0.8166332665330661, 0.8151302605210421, 0.8181362725450
901, 0.8176352705410822, 0.8221442885771543, 0.8186372745490982, 0.8221442885771543, 0.81763527
05410822, 0.8191382765531062, 0.8181362725450901, 0.8176352705410822, 0.8171342685370742, 0.818
6372745490982, 0.814128256513026, 0.8151302605210421, 0.8156312625250501, 0.8161322645290581]
```

In [485…

```
# plot the relationship between K and testing accuracy
# plt.plot(x_axis, y_axis)
plt.plot(k_range, scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Testing Accuracy')
```

Out[485]:

```
Text(0, 0.5, 'Testing Accuracy')
```



From the above chart, the K value with the highest value of accuracy is 7

KNeighborsClassifier

In [486…

```
knn_model = KNeighborsClassifier(n_neighbors=7)
knn_model.fit(x_train,y_train)
```

Out[486]: KNeighborsClassifier(n_neighbors=7)

KNN model Training Results

In [502…
```
train_preds = knn_model.predict(x_train)
print(classification_report(y_train,train_preds))
```

```
              precision    recall  f1-score   support

           0       0.86      0.97      0.91      6353
           1       0.77      0.41      0.53      1647

    accuracy                           0.85      8000
   macro avg       0.82      0.69      0.72      8000
weighted avg       0.84      0.85      0.84      8000
```

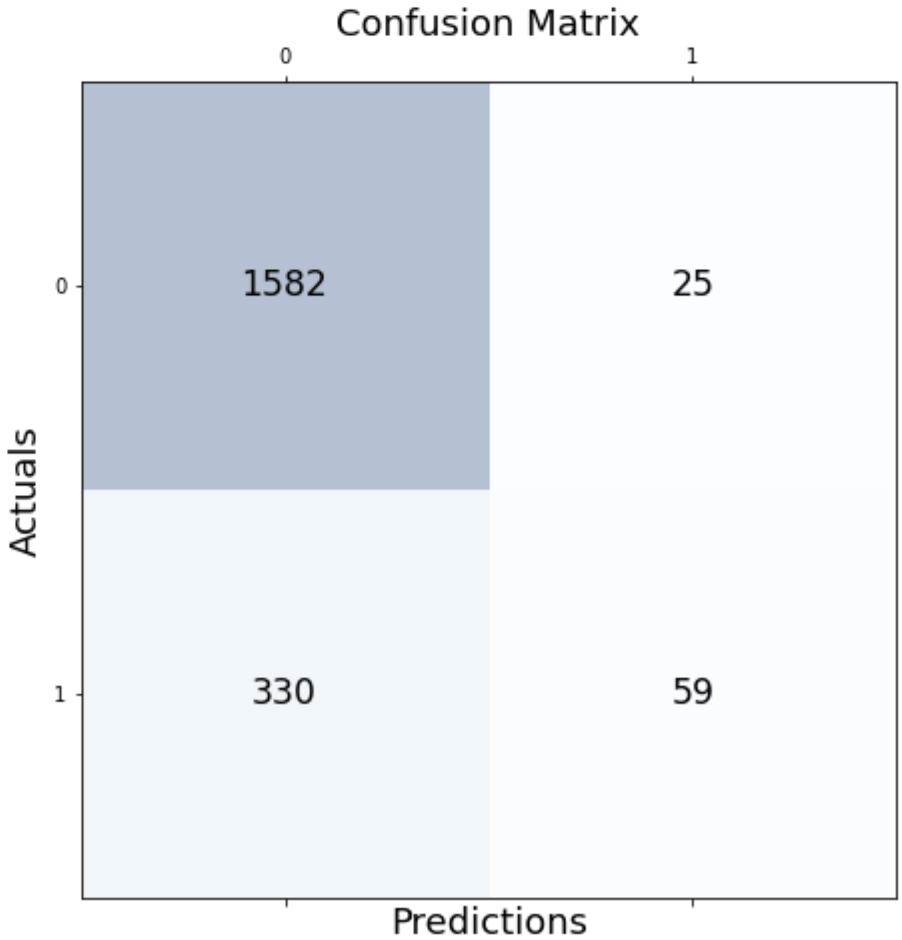
KNN model Test Results

In [504…
```
test_preds_knn = knn_model.predict(x_test)
print(classification_report(y_test,test_preds))
```

```
              precision    recall  f1-score   support

           0       0.83      0.98      0.90      1607
           1       0.70      0.15      0.25       389

    accuracy                           0.82      1996
   macro avg       0.76      0.57      0.57      1996
weighted avg       0.80      0.82      0.77      1996
```

KNN test confusion matrix

In [505…
```
y_pred_hp_rf = knn_model.predict(x_test)
cf_matrix = confusion_matrix(y_test,y_pred_hp_rf)

fig, ax = plt.subplots(figsize=(7.5, 7.5))
ax.matshow(cf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(cf_matrix.shape[0]):
    for j in range(cf_matrix.shape[1]):
        ax.text(x=j, y=i,s=cf_matrix[i, j], va='center', ha='center', size='xx-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```



logistic regression with pol 2 kernel

In [487…

```
# Fit logistic regression with pol 2 kernel
poly2 = PolynomialFeatures(degree=2)
df_train_pol2 = poly2.fit_transform(x_train)
log_pol2 = LogisticRegression(solver='liblinear')
log_pol2.fit(df_train_pol2,y_train)
```

Out[487]:

```
LogisticRegression(solver='liblinear')
```

Logistic regression model Training Results

In [506…

```
print(classification_report(y_train,  log_pol2.predict(df_train_pol2)))
```

```
              precision    recall  f1-score   support

           0       0.86      0.98      0.91      6353
           1       0.80      0.38      0.52      1647

    accuracy                           0.85      8000
   macro avg       0.83      0.68      0.72      8000
weighted avg       0.85      0.85      0.83      8000
```

Logistic Regression model Test Results

In [507…

```
poly2 = PolynomialFeatures(degree=2)
df_test_pol2 = poly2.fit_transform(x_test)

pol2_prob=log_pol2.predict(df_test_pol2)
print(classification_report(y_test,  log_pol2.predict(df_test_pol2)))
```

```
              precision    recall  f1-score   support

           0       0.85      0.87      0.86      1607
           1       0.42      0.39      0.40       389

    accuracy                           0.78      1996
   macro avg       0.64      0.63      0.63      1996
weighted avg       0.77      0.78      0.77      1996
```

In [ ]:

RandomForestClassifier

In [488…

```
# Fit Random Forest classifier
RF = RandomForestClassifier(n_estimators=1000,min_samples_leaf=4, min_samples_split=2,max_featur
RF.fit(x_train,y_train)
```

Out[488]:

```
RandomForestClassifier(max_features=16, min_samples_leaf=4, n_estimators=1000)
```

Random Forest model Training Results

In [509…

```
print(classification_report(y_train,  RF.predict(x_train)))
```

```
              precision    recall  f1-score   support

           0       0.94      0.99      0.96      6353
           1       0.94      0.74      0.83      1647

    accuracy                           0.94      8000
   macro avg       0.94      0.86      0.89      8000
weighted avg       0.94      0.94      0.93      8000
```

Random Forest model Test Results

In [510…

```
rf_prob=RF.predict(x_test)

print(classification_report(y_test,  RF.predict(x_test)))
```

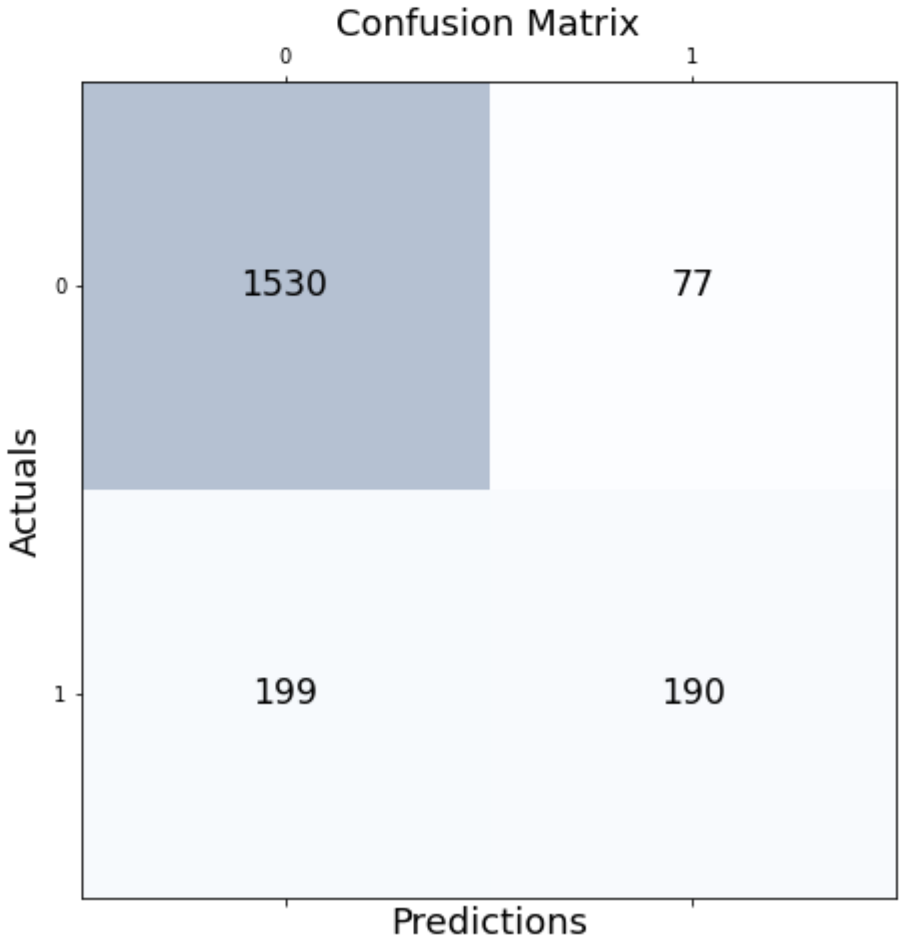
```
              precision    recall  f1-score   support

           0       0.88      0.95      0.92      1607
           1       0.71      0.49      0.58       389

    accuracy                           0.86      1996
   macro avg       0.80      0.72      0.75      1996
weighted avg       0.85      0.86      0.85      1996
```

Random Forest test Confusion matrix

In [511…

```
y_pred_hp_rf = RF.predict(x_test)
cf_matrix = confusion_matrix(y_test,y_pred_hp_rf)

print(cf_matrix)

fig, ax = plt.subplots(figsize=(7.5, 7.5))
ax.matshow(cf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(cf_matrix.shape[0]):
    for j in range(cf_matrix.shape[1]):
        ax.text(x=j, y=i,s=cf_matrix[i, j], va='center', ha='center', size='xx-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```

```
[[1530   77]
 [ 199  190]]
```



XGBClassifier

In [489…

```
# Extreme Gradient Boost Classifier
XGB = XGBClassifier(gamma=0.01, learning_rate=0.08555,eval_metric="logloss")
XGB.fit(x_train,y_train)
```

```
C:\Users\HP\Desktop\pyprog\data_sc_env\lib\site-packages\xgboost\sklearn.py:1224: UserWarning:
The use of label encoder in XGBClassifier is deprecated and will be removed in a future releas
e. To remove this warning, do the following: 1) Pass option use_label_encoder=False when constr
ucting XGBClassifier object; and 2) Encode your labels (y) as integers starting with 0, i.e. 0,
1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
```

Out[489]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              eval_metric='logloss', gamma=0.01, gpu_id=-1,
              importance_type=None, interaction_constraints='',
              learning_rate=0.08555, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=4, num_parallel_tree=1, predictor='auto',
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              subsample=1, tree_method='exact', validate_parameters=1,
              verbosity=None)
```

XGboost model Training Results

In [493…

```
print(classification_report(y_train,  XGB.predict(x_train)))
```

```
              precision    recall  f1-score   support

           0       0.90      0.98      0.94      6353
           1       0.88      0.60      0.71      1647

    accuracy                           0.90      8000
   macro avg       0.89      0.79      0.83      8000
weighted avg       0.90      0.90      0.89      8000
```

From the classification reports of models above, the best model that gives a decent balance of the recall and precision is the random forest where According to the fit on the training set, with a precision score on 1's of 0.94, out of all customers that the model thinks would churn, 94 percent do indeed churn, and with a recall score on 1's of 0.74, the model is able to highlight 74 percent of all those that churned.

XGboost model Test Results

In [499…

```
xgb_prob= XGB.predict(x_test)
print(classification_report(y_test,  XGB.predict(x_test)))
```

```
              precision    recall  f1-score   support

           0       0.89      0.97      0.92      1607
           1       0.77      0.49      0.60       389

    accuracy                           0.87      1996
   macro avg       0.83      0.73      0.76      1996
weighted avg       0.86      0.87      0.86      1996
```

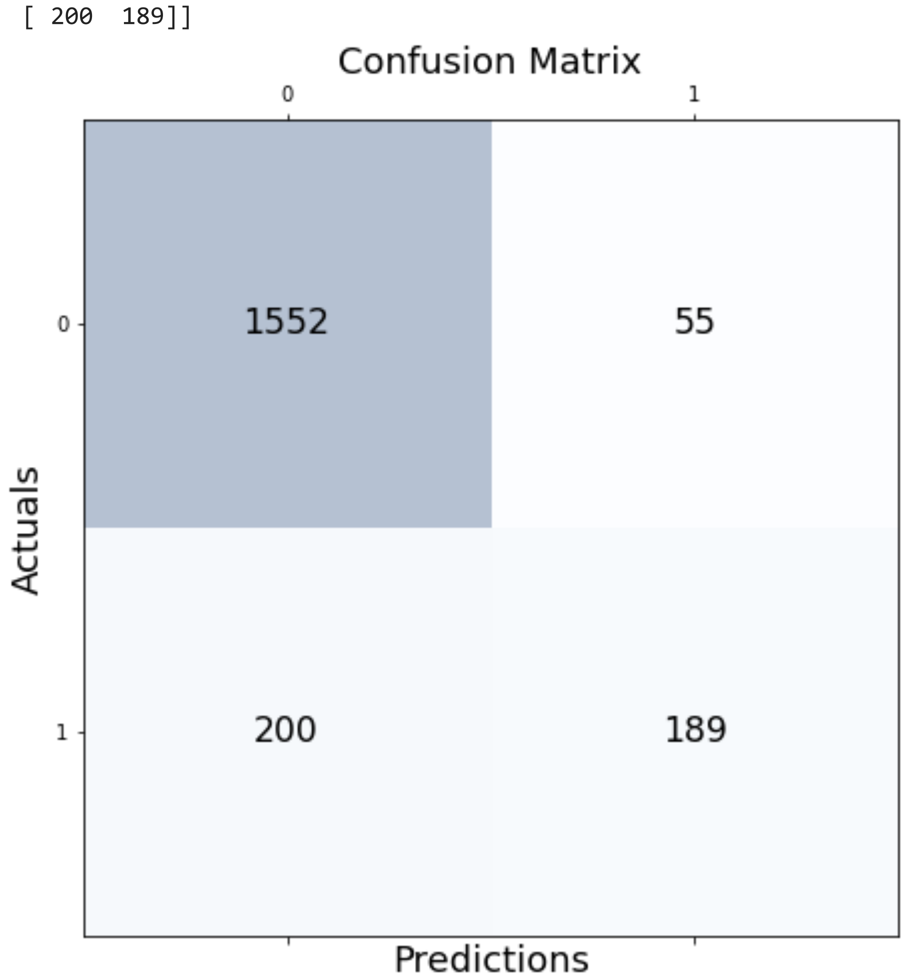
The XGBoost ensembles method, with an overall accuracy of 87 percent and a precision score of 77 percent on 1's, and a recall score of 49 percent on 1's, is the best model that gives the highest overall accuracy with a decent balance of recall and precision, according to the classification reports of models above.

XGboost Test Confusion matrix

In [500…

```
y_pred_hp_rf = XGB.predict(x_test)
cf_matrix = confusion_matrix(y_test,y_pred_hp_rf)

print(cf_matrix)

fig, ax = plt.subplots(figsize=(7.5, 7.5))
ax.matshow(cf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(cf_matrix.shape[0]):
    for j in range(cf_matrix.shape[1]):
        ax.text(x=j, y=i,s=cf_matrix[i, j], va='center', ha='center', size='xx-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```

```
[[1552   55]
 [ 200  189]]
```

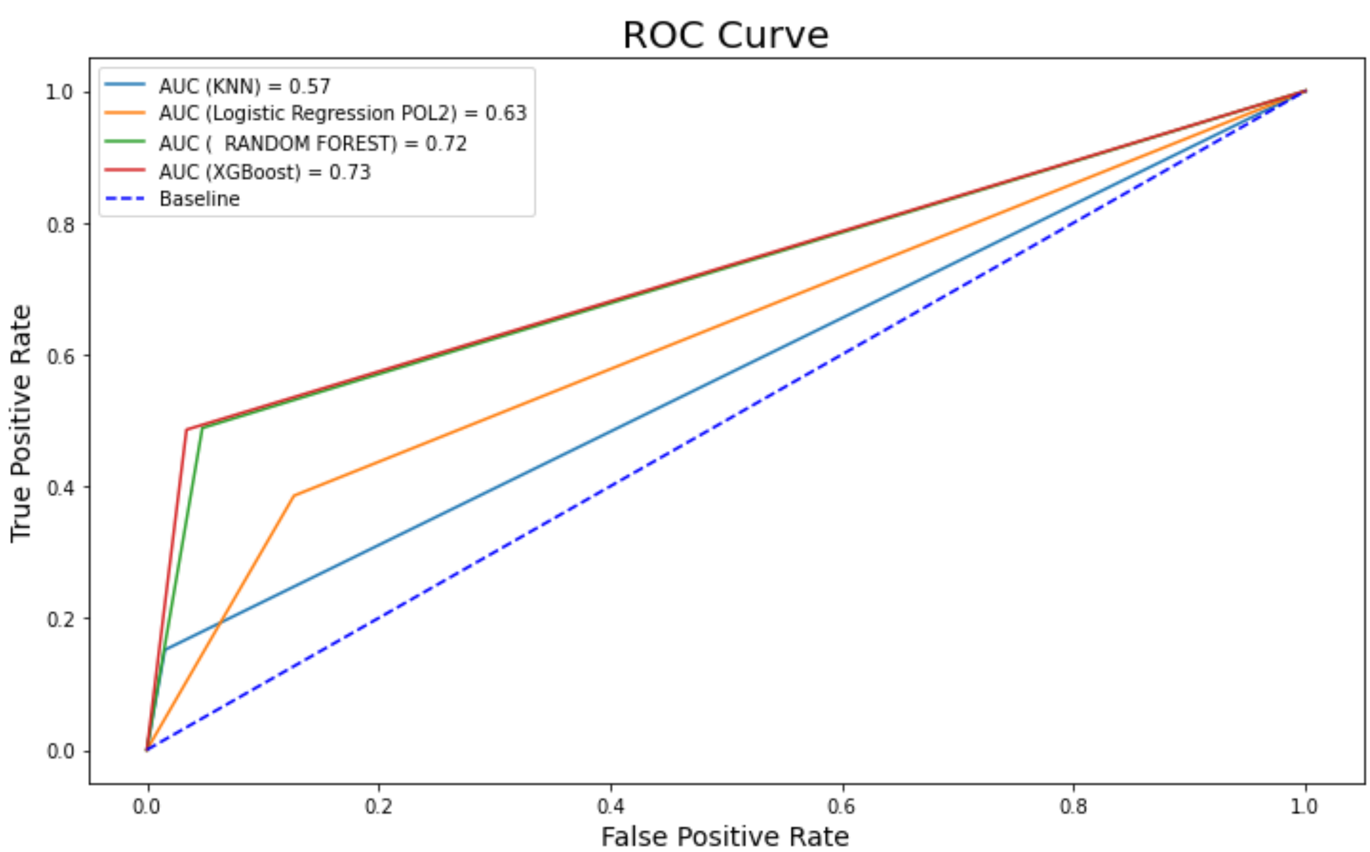


In [ ]:

Creating an Accuracy Plot of all the models used

In [501…

```
accuracy_lr = roc_auc_score(y_test,test_preds_knn)
fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test,test_preds_knn)

accuracy_pol = roc_auc_score(y_test,pol2_prob)
fpr_pol, tpr_pol, thresholds_pol = roc_curve(y_test,pol2_prob)

accuracy_rf = roc_auc_score(y_test,rf_prob)
fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test,rf_prob)

accuracy_xgb = roc_auc_score(y_test,xgb_prob)
fpr_xgb, tpr_xgb, thresholds_xgb = roc_curve(y_test,xgb_prob)

plt.figure(figsize=(12, 7))
plt.plot(fpr_lr, tpr_lr, label=f'AUC (KNN) = {accuracy_lr:.2f}')
plt.plot(fpr_pol, tpr_pol, label=f'AUC (Logistic Regression POL2) = {accuracy_pol:.2f}')
plt.plot(fpr_rf, tpr_rf, label=f'AUC (  RANDOM FOREST) = {accuracy_rf:.2f}')
plt.plot(fpr_xgb, tpr_xgb, label=f'AUC (XGBoost) = {accuracy_xgb:.2f}')
plt.plot([0, 1], [0, 1], color='blue', linestyle='--', label='Baseline')
plt.title('ROC Curve', size=20)
plt.xlabel('False Positive Rate', size=14)
plt.ylabel('True Positive Rate', size=14)
plt.legend();
```



In [ ]:

Conclusion

On the test dataset, the model's f1-score for predicting churned customers is slightly higher. Even while the model is very accurate, it still misses 40% of those who end up churning. However, it is in our best interests to predict which clients are likely to churn so that a plan may be put in place to prevent it. Retraining the model with more data over time, while working with the model to save the 60% percent that may have churned, could enhance the accuracy.

In [ ]: