Title of the Project: Bank customer churn model

Problem Statement:

1. Despite the continuous efforts of banks to attract and retain customers, the banking industry faces a persistent challenge in the form of customer churn, leading to financial losses and reduced customer satisfaction.

Project Objective:

1. The aim of this project is to analyze the customer churn rate for bank because it is useful to understand why the customers leave.
2. After Analyzing we need to train a Machine Learning Model which can find the key factors that significantly influence the customer churn or attrition.
3. In the end will choose the most reliable model that will attach a probability to the churn to make it easier for customer service to target right customer in order to minimize their efforts to prevent customers churn.

1.Label Data Encoding 2.Features Scalling 3.Handling Imbalance Data a) Random Under sampling b) Random Over Sampling 4.Support vector machine classifier 5.Grid search for Hyperparameter Tunning

Project Overview:

1. Churn refers to customers leaving a bank or discontinuing their banking services.
2. Banking Churn Analysis is a process of studying customer behavior in the banking industry to predict and understand customer attrition or churn.
3. Banking Churn Modeling aims to identify patterns and factors that contribute tocustomer churn, enabling banks to take proactive measures to retain customers and improve customer satisfaction.

About dataset: The bank customer churn dataset is a commonly used dataset for predicting customer churn in the banking industry. It contains information on bank customers who either left the bank or continue to be a customer.

Importing Required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading Dataset

```
df = pd.read_csv("https://github.com/YBI-Foundation/Dataset/raw/main/Bank%20Churn%20Modelling.csv")
```

Describe/ Analysis Data

```
df.head()
```

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	Num Produ
0	15634602	Hargrave	619	France	Female	42	2	0.00	
1	15647311	Hill	608	Spain	Female	41	1	83807.86	
2	15619304	Onio	502	France	Female	42	8	159660.80	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
```

```
---  ------            --------------  -----
 0   CustomerId        10000 non-null  int64
 1   Surname           10000 non-null  object
 2   CreditScore       10000 non-null  int64
 3   Geography         10000 non-null  object
 4   Gender            10000 non-null  object
 5   Age               10000 non-null  int64
 6   Tenure            10000 non-null  int64
 7   Balance           10000 non-null  float64
 8   Num Of Products   10000 non-null  int64
 9   Has Credit Card   10000 non-null  int64
 10  Is Active Member  10000 non-null  int64
 11  Estimated Salary  10000 non-null  float64
 12  Churn             10000 non-null  int64
dtypes: float64(2), int64(8), object(3)
memory usage: 1015.8+ KB
```

```
df.duplicated('CustomerId').sum()
```

```
0
```

```
df= df.set_index('CustomerId')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 15634602 to 15628319
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Surname           10000 non-null  object
 1   CreditScore       10000 non-null  int64
 2   Geography         10000 non-null  object
 3   Gender            10000 non-null  object
 4   Age               10000 non-null  int64
 5   Tenure            10000 non-null  int64
 6   Balance           10000 non-null  float64
 7   Num Of Products   10000 non-null  int64
 8   Has Credit Card   10000 non-null  int64
 9   Is Active Member  10000 non-null  int64
 10  Estimated Salary  10000 non-null  float64
 11  Churn             10000 non-null  int64
dtypes: float64(2), int64(7), object(3)
memory usage: 1015.6+ KB
```

Label Encoding

converting into catogorical values

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

```
France     5014
Germany    2509
Spain      2477
Name: Geography, dtype: int64
```

```
df.replace({'Geography': {'France':2, 'Germany':1, 'Spain':0}},inplace=True)
```

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

```
Male      5457
Female    4543
Name: Gender, dtype: int64
```

```
df.replace({'Gender': {'Male':0,'Female':1}},inplace=True)
```

```
df.replace({'Num Of Products': {1:0,2:1, 3:1, 4:1}},inplace=True)
```

```
#1-have the credit cards
#0-dont have the credit cards
df['Has Credit Card'].value_counts()
```

```
1    7055
0    2945
Name: Has Credit Card, dtype: int64
```

```
#1- active members
#0- not active members
df['Is Active Member'].value_counts()
```

```
1    5151
0    4849
Name: Is Active Member, dtype: int64
```

Feature Engineering

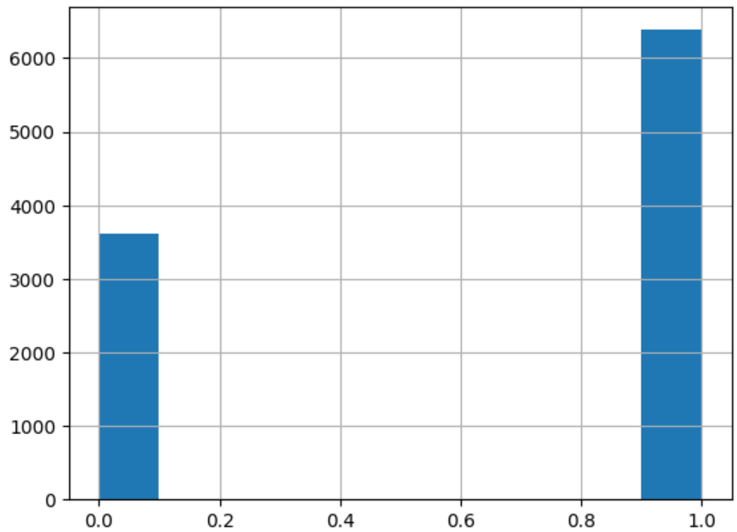
```
#1- zero bank balace left the bank
#0- zero bank balance still in bank
df.loc[(df['Balance']==0), 'Churn'].value_counts()
```

```
0    3117
1     500
Name: Churn, dtype: int64
```

```
df['Zero Balance'] = np.where(df['Balance']>0,1,0)
```

```
df['Zero Balance'].hist()
```

```
<Axes: >
```




```
df.groupby(['Churn', 'Geography']).count()
```

Churn	Geography	Surname	CreditScore	Gender	Age	Tenure	Balance	Num Of Products	Has Credit Card	Is Active Member	Estimated Salary	Z Bala
0	0	2064	2064	2064	2064	2064	2064	2064	2064	2064	2064	2
	1	1695	1695	1695	1695	1695	1695	1695	1695	1695	1695	1
	2	4204	4204	4204	4204	4204	4204	4204	4204	4204	4204	4
1	0	413	413	413	413	413	413	413	413	413	413	
	1	814	814	814	814	814	814	814	814	814	814	

Define Label and features

```
df.columns
```

```
Index(['Surname', 'CreditScore', 'Geography', 'Gender', 'Age', 'Tenure',
       'Balance', 'Num Of Products', 'Has Credit Card', 'Is Active Member',
       'Estimated Salary', 'Churn', 'Zero Balance'],
      dtype='object')
```

```
x= df.drop(['Surname','Churn'],axis=1)
```

```
y =df['Churn']
```

```
x.shape, y.shape
```

```
((10000, 11), (10000,))
```

Handling Imbalance Data

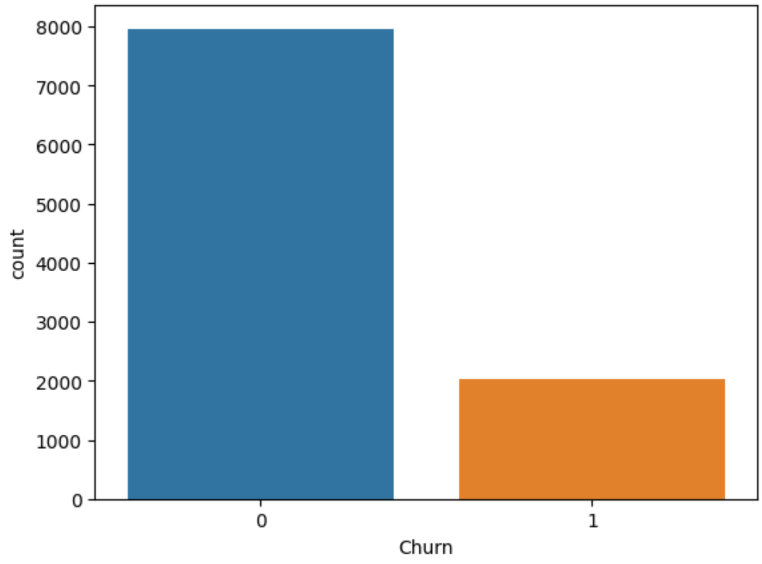
1.Undersampling

2.Oversampling

```
#1-left
#0- not left
df['Churn'].value_counts()
```

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

```
sns.countplot(x='Churn', data=df);
```




```
x.shape, y.shape
```

```
((10000, 11), (10000,))
```

Random under sampling

```
from imblearn.under_sampling import RandomUnderSampler
```

```
rus= RandomUnderSampler(random_state=2529)
```

```
x_rus, y_rus= rus.fit_resample(x,y)
```

```
x_rus.shape, y_rus.shape, x.shape, y.shape
```

```
((4074, 11), (4074,), (10000, 11), (10000,))
```

```
#1-left
#0- not left
y.value_counts()
```

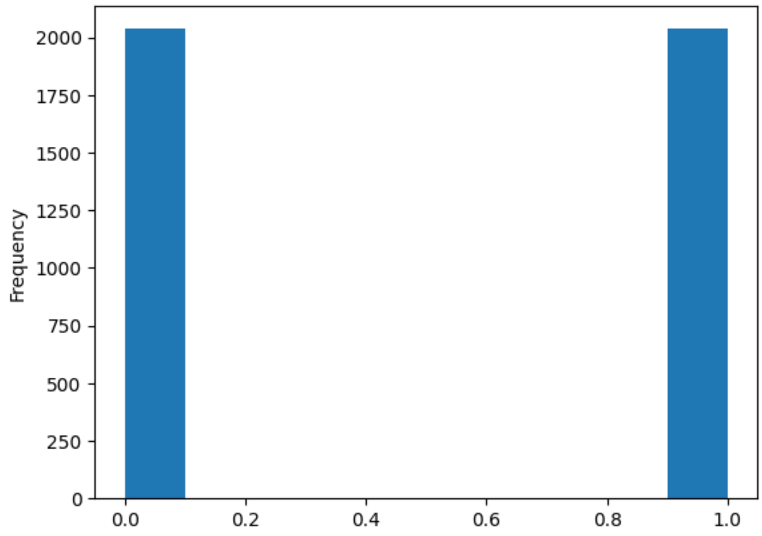
```
0    7963
1    2037
Name: Churn, dtype: int64
```

```
#after random under sampling
#1-left
#0- not left
y_rus.value_counts()
```

```
0    2037
1    2037
Name: Churn, dtype: int64
```

```
y_rus.plot(kind= 'hist')
```

```
<Axes: ylabel='Frequency'>
```



Random Over Sampling

```
from imblearn.over_sampling import RandomOverSampler
```

```
ros= RandomOverSampler(random_state=2529)
```

```
x_ros, y_ros= ros.fit_resample(x,y)
```

```
x_ros.shape, y_ros.shape, x.shape, y.shape
```

```
((15926, 11), (15926,), (10000, 11), (10000,))
```

```
#1-left
#0- not left
y.value_counts()
```

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

```
#after random over sampling
#1-left
#0- not left
y_ros.value_counts()
```

```
1    7963
0    7963
Name: Churn, dtype: int64
```

```
y_ros.plot(kind='hist')
```

```
<Axes: ylabel='Frequency'>
```

Train Test Split Method

```
from sklearn.model_selection import train_test_split
```

Split origanal Data

```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.3, random_state=2529)
```

Split Random Under sample Data

```
x_train_rus, x_test_rus, y_train_rus, y_test_rus = train_test_split(x_rus,y_rus, test_size=0.3, random_state=2529)
```

Split Random over sample Data

```
x_train_ros, x_test_ros, y_train_ros, y_test_ros = train_test_split(x_ros,y_ros, test_size=0.3, random_state=2529)
```

Standardize Features

Data preprocessing

```
from sklearn.preprocessing import StandardScaler
```

```
sc = StandardScaler()
```

Satandardize original data

```
x_train[['CreditScore', 'Age', 'Tenure','Balance','Estimated Salary']]= sc.fit_transform(x_train [['CreditScore', 'Age', 'Tenure','Balanc
```

```
x_test[['CreditScore', 'Age', 'Tenure','Balance','Estimated Salary']] = sc.fit_transform(x_test [['CreditScore', 'Age', 'Tenure','Balance
```

Satandardize Random under sample data

```
x_train_rus[['CreditScore', 'Age', 'Tenure','Balance','Estimated Salary']]= sc.fit_transform(x_train_rus [['CreditScore', 'Age', 'Tenure'
```

```
 x_test_rus[['CreditScore', 'Age', 'Tenure','Balance','Estimated Salary']] = sc.fit_transform(x_test_rus [['CreditScore', 'Age', 'Tenure'
```

Satandardize Random over sample data

```
x_train_ros[['CreditScore', 'Age', 'Tenure','Balance','Estimated Salary']]= sc.fit_transform(x_train_ros [['CreditScore', 'Age', 'Tenure'
```

```
x_test_ros[['CreditScore', 'Age', 'Tenure','Balance','Estimated Salary']] = sc.fit_transform(x_test_ros [['CreditScore', 'Age', 'Tenure'
```

Support vector Classifier

```
from sklearn.svm import SVC
svc =  SVC()
```

```
svc.fit(x_train, y_train)
```

```
▾ SVC
SVC()
```

```
y_pred= svc.predict(x_test)
```

Model Accuracy

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

```
confusion_matrix(y_test, y_pred)
```

```
array([[2381,   33],
       [ 436,  150]])
```

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.99      0.91      2414
           1       0.82      0.26      0.39       586

    accuracy                           0.84      3000
   macro avg       0.83      0.62      0.65      3000
weighted avg       0.84      0.84      0.81      3000
```

support vector machine accuracy is 0.84= 84%

recall is = 0.26 = 26%

Hyperparameter tunning

cross-valiidation

```
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

param_grid = {
    'C': [0.1, 1, 10],
    'gamma': [1, 0.1, 0.01],
    'kernel': ['rbf'],
    'class_weight': ['balanced']
}

grid = GridSearchCV(SVC(), param_grid, refit=True, verbose=2, cv=2)
grid.fit(x_train, y_train)
```

```
Fitting 2 folds for each of 9 candidates, totalling 18 fits
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   1.6s
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   2.3s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.8s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.2s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.2s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.3s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   1.4s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   1.4s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.0s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.0s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.1s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.9s
```

```
print(grid.best_estimator_)
```

```
SVC(C=10, class_weight='balanced', gamma=1)
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.0s
```

```
grid_predictions = grid.predict (x_test)
```

```
confusion_matrix(y_test, grid_predictions)
```

```
array([[2159,  255],
       [ 343,  243]])
```

```
print(classification_report(y_test, grid_predictions))
```

```
              precision    recall  f1-score   support

           0       0.86      0.89      0.88      2414
           1       0.49      0.41      0.45       586

    accuracy                           0.80      3000
   macro avg       0.68      0.65      0.66      3000
weighted avg       0.79      0.80      0.79      3000
```

accuracy = 0.80= 80% recall =0.41= 41%

Model with random under sampling

```
svc_rus= SVC()
```

```
svc_rus.fit(x_train_rus, y_train_rus)
```

```
▾ SVC
SVC()
```

```
y_pred_rus =svc_rus.predict(x_test_rus)
```

Model accuracy

```
confusion_matrix(y_test_rus, y_pred_rus)
```

```
array([[470, 157],
       [174, 422]])
```

```
print(classification_report(y_test_rus, y_pred_rus))
```

```
              precision    recall  f1-score   support

           0       0.73      0.75      0.74       627
           1       0.73      0.71      0.72       596

    accuracy                           0.73      1223
   macro avg       0.73      0.73      0.73      1223
weighted avg       0.73      0.73      0.73      1223
```

accuracy = 0.73= 73% recall =0.71= 71%

```
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

param_grid = {
    'C': [0.1, 1, 10],
    'gamma': [1, 0.1, 0.01],
    'kernel': ['rbf'],
    'class_weight': ['balanced']
}

grid_rus = GridSearchCV(SVC(), param_grid, refit=True, verbose=2, cv=2)
grid_rus.fit(x_train_rus, y_train_rus)
```

```
Fitting 2 folds for each of 9 candidates, totalling 18 fits
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   0.2s
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   0.2s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   0.2s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   0.2s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   0.2s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   0.2s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   0.3s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   0.2s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   0.2s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   0.2s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   0.2s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   0.2s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=   0.2s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=   0.3s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   0.2s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   0.2s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   0.2s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   0.2s
```

▸ **GridSearchCV**

▸ **estimator: SVC**

▸ SVC

```
print(grid_rus.best_estimator_)
```

```
SVC(C=1, class_weight='balanced', gamma=0.1)
```

```
grid_predictions_rus = grid_rus.predict (x_test_rus)
```

```
confusion_matrix(y_test_rus, y_pred_rus)
```

```
array([[470, 157],
       [174, 422]])
```

```
print(classification_report(y_test_rus, y_pred_rus))
```

```
              precision    recall  f1-score   support

           0       0.73      0.75      0.74       627
           1       0.73      0.71      0.72       596

    accuracy                           0.73      1223
   macro avg       0.73      0.73      0.73      1223
weighted avg       0.73      0.73      0.73      1223
```

Model with random over sampling

```
svc_ros= SVC()
```

```
svc_ros.fit(x_train_ros, y_train_ros)
```

▾ SVC

SVC()

```
y_pred_ros =svc_ros.predict(x_test_ros)
```

Model accuracy

```
confusion_matrix(y_test_ros, y_pred_ros)
```

```
array([[1823,  556],
       [ 626, 1773]])
```

```
print(classification_report(y_test_ros, y_pred_ros))
```

```
              precision    recall  f1-score   support

           0       0.74      0.77      0.76      2379
           1       0.76      0.74      0.75      2399

    accuracy                           0.75      4778
   macro avg       0.75      0.75      0.75      4778
weighted avg       0.75      0.75      0.75      4778
```

accuracy = 0.75= 75% recall =0.74= 74%

```
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

param_grid = {
    'C': [0.1, 1, 10],
    'gamma': [1, 0.1, 0.01],
    'kernel': ['rbf'],
    'class_weight': ['balanced']
}

grid_ros = GridSearchCV(SVC(), param_grid, refit=True, verbose=2, cv=2)
grid_ros.fit(x_train_ros, y_train_ros)
```

```
Fitting 2 folds for each of 9 candidates, totalling 18 fits
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   5.0s
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   8.7s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   3.3s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   5.3s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   7.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   4.9s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   6.6s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   3.2s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   2.5s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   3.0s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   3.6s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   2.6s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=   3.0s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=   3.4s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   3.8s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   2.8s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   2.7s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   2.6s
```

▸ **GridSearchCV**

▸ **estimator: SVC**

▸ SVC

```
print(grid_ros.best_estimator_)
```

```
SVC(C=10, class_weight='balanced', gamma=1)
```

```
grid_predictions_ros = grid_ros.predict (x_test_ros)
```

```
confusion_matrix(y_test_ros, grid_predictions_ros)
```

```
array([[2047,  332],
       [  68, 2331]])
```

```
print(classification_report(y_test_ros, grid_predictions_ros))
```

```
              precision    recall  f1-score   support

           0       0.97      0.86      0.91      2379
           1       0.88      0.97      0.92      2399

    accuracy                           0.92      4778
   macro avg       0.92      0.92      0.92      4778
weighted avg       0.92      0.92      0.92      4778
```

accuracy = 0.92= 92% recall =0.97= 97%

Results:

Normal Data

```
print(classification_report(y_test, y_pred))

              precision    recall  f1-score   support

           0       0.85      0.99      0.91      2414
           1       0.82      0.26      0.39       586

    accuracy                           0.84      3000
   macro avg       0.83      0.62      0.65      3000
weighted avg       0.84      0.84      0.81      3000
```

After Hyperparameter tunning

```
print(classification_report(y_test, grid_predictions))

              precision    recall  f1-score   support

           0       0.86      0.89      0.88      2414
           1       0.49      0.41      0.45       586

    accuracy                           0.80      3000
   macro avg       0.68      0.65      0.66      3000
weighted avg       0.79      0.80      0.79      3000
```

Random under sampling

```
print(classification_report(y_test_rus, y_pred_rus))

              precision    recall  f1-score   support

           0       0.73      0.75      0.74       627
           1       0.73      0.71      0.72       596

    accuracy                           0.73      1223
   macro avg       0.73      0.73      0.73      1223
weighted avg       0.73      0.73      0.73      1223
```

After Hyperparameter tunning On Random under sampler

```
print(classification_report(y_test_rus, y_pred_rus))

              precision    recall  f1-score   support

           0       0.73      0.75      0.74       627
           1       0.73      0.71      0.72       596

    accuracy                           0.73      1223
   macro avg       0.73      0.73      0.73      1223
weighted avg       0.73      0.73      0.73      1223
```

Random over sampling

```
print(classification_report(y_test_ros, y_pred_ros))

              precision    recall  f1-score   support

           0       0.74      0.77      0.76      2379
           1       0.76      0.74      0.75      2399
```

```
    accuracy                           0.75      4778
   macro avg       0.75      0.75      0.75      4778
weighted avg       0.75      0.75      0.75      4778
```

After Hyperparameter tunning On Random over sampler

```
print(classification_report(y_test_ros, grid_predictions_ros))
```

```
              precision    recall  f1-score   support

           0       0.97      0.86      0.91      2379
           1       0.88      0.97      0.92      2399

    accuracy                           0.92      4778
   macro avg       0.92      0.92      0.92      4778
weighted avg       0.92      0.92      0.92      4778
```

Churn Prediction:

In this classification problem, a lot of information about the consumers was provided, and the dataset was pretty clean with no missing values and no duplicate values. With only two classes in the objective feature (0: not churned, 1: churned), it was a binary classification challenge. The classes were imbalanced and the models were predicting all 0s in the target feature. We had employed the over-sampling technique to address this. we found repeated categorical values in some of the columns, We used LabelEncoder() to assign numerical values for categorical values.Later on, the Age, Balance and Vintage columns were scaled using standardscalar by projecting mean to zero and varience to one.

Some key lessons that the Bank can focus to bring down the churn rate:-

- 1.Greater percentage of females are likely to churn.
- 2.Customers who has not done any transaction in the past 3 months are more likely to churn.
- 3.Customers with credit card are more in number and are more likely to churn.
- Customers with poor credit ratings dominate the dataset and are also more likely to exit.
- 5.High-income customers are difficult to keep as they are more prone to churn.