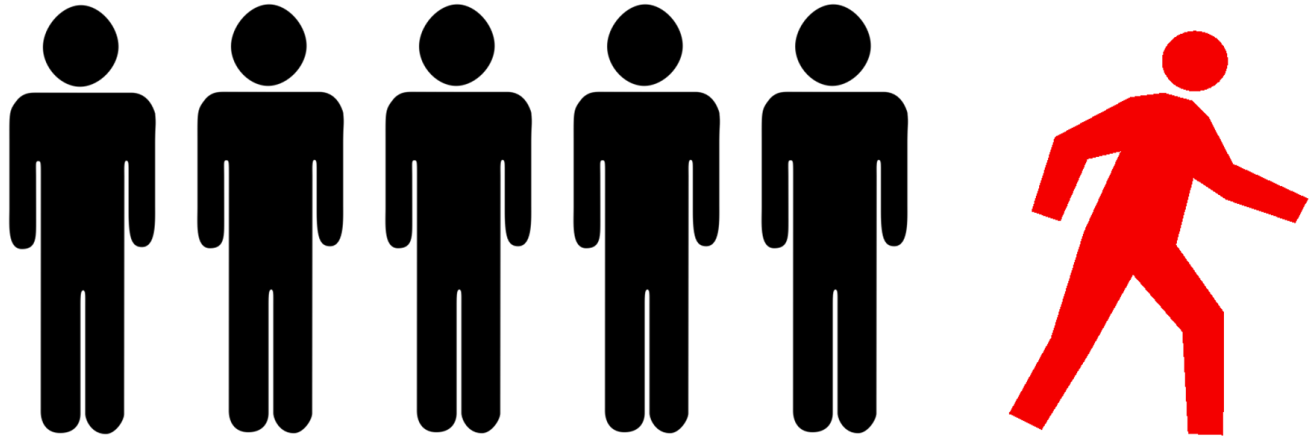


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▼ BANK CUSTOMER CHURN MODEL



▼ Learning Objective

1. Data Encoding
2. Feature Scaling
3. Handling Imbalance Data a. Random Under Sampling b. Random Over Sampling
4. Support Vector Machine Classifier
5. Grid Search for Hyperparameter Tuning

▼ Import Library

```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

▼ Import Data

```
df = pd.read_csv('http://github.com/YBI-Foundation/Dataset/raw/main/Bank%20Churn%20Modelling
```

```
df.head()
```

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	Num Of Products
0	15634602	Hargrave	619	France	Female	42	2	0.00	1
1	15647311	Hill	608	Spain	Female	41	1	83807.86	1
2	15619304	Onio	502	France	Female	42	8	159660.80	3
3	15701354	Boni	699	France	Female	39	1	0.00	1
4	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1

```
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
```

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

```
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
```

▼ Encoding

```
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['Num Of Products'].value_counts()
```

```
1      5084
2      4590
3       266
```

```
4      60
```

```
Name: Num Of Products, dtype: int64
```

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

```
df['Has Credit Card'].value_counts()
```

```
1      7055
```

```
0      2945
```

```
Name: Has Credit Card, dtype: int64
```

```
df['Is Active Member'].value_counts()
```

```
1      5151
```

```
0      4849
```

```
Name: Is Active Member, dtype: int64
```

```
df.loc[(df['Balance']==0), 'Churn'].value_counts()
```

```
0      3117
```

```
1       500
```

```
Name: Churn, dtype: int64
```

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

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

		Surname	CreditScore	Gender	Age	Tenure	Balance	Num Of Products	Has Credit Card
Churn	Geography								
0	0	2064	2064	2064	2064	2064	2064	2064	2064
	1	1695	1695	1695	1695	1695	1695	1695	1695
	2	4204	4204	4204	4204	4204	4204	4204	4204
1	0	413	413	413	413	413	413	413	413
	1	814	814	814	814	814	814	814	814
	2	810	810	810	810	810	810	810	810

▼ 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'],
      dtype='object')
```

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

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

```
X.shape, y.shape
```

```
((10000, 10), (10000,))
```

▼ Handling Imbalance Data

Class imbalance is a common problem in machine learning, especially in classification problems as machine learning algorithms are designed to maximize accuracy and reduce errors. If the data set is imbalanced then in such cases, just by predicting the majority class we get a pretty high accuracy, but fails to capture the minority class, which is most often the point of creating the model in the first place. Like in 1. fraud detection 2. spam filtering 3. disease screening 4. online sales churn 5. advertising click-throughs

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

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

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



X.shape, y.shape

```
((10000, 10), (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, 10), (4074,)), (10000, 10), (10000,))
```

```
y.value_counts()
```

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

```
y_rus.value_counts()
```

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

▼ 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, 10), (15926,)), (10000, 10), (10000,))
```

```
y.value_counts()
```

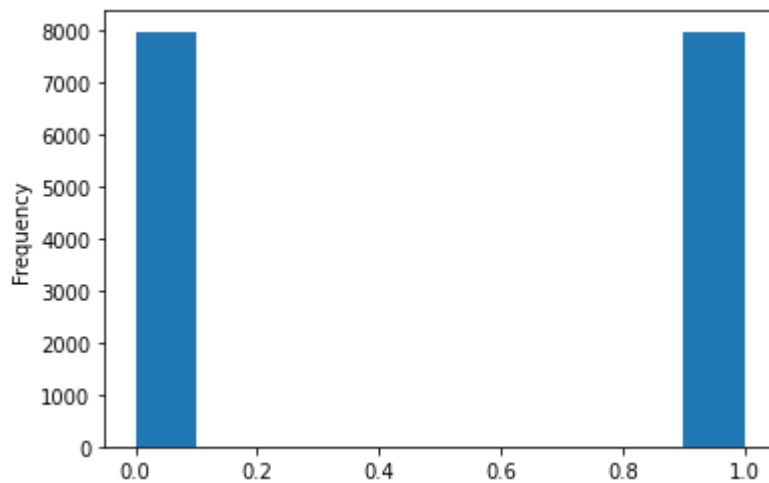
```
0    7963
1    2037
Name: Churn, dtype: int64
```

```
y_ros.value_counts()
```

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

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f90754bfad0>
```



▼ Train Test Split

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

▼ Split Original Data

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=25)
```

▼ Split Random Under Sampler Data

```
X_train_rus, X_test_rus, y_train_rus, y_test_rus = train_test_split(X_rus, y_rus, test_size=
```

▼ 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=
```

▼ Standardize Feature

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

```
sc = StandardScaler()
```

▼ Standardize Original Data

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

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

▼ Standardize Random Over Sample Data

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

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

▼ Support Vector Machine Classifier

```
from sklearn.svm import SVC
```

```
svc= SVC()
```

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

```
SVC()
```



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

▼ Model Accuracy

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

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

```
array([[2372,  47],
       [ 420, 161]])
```

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

	precision	recall	f1-score	support
0	0.85	0.98	0.91	2419
1	0.77	0.28	0.41	581
accuracy			0.84	3000
macro avg	0.81	0.63	0.66	3000
weighted avg	0.83	0.84	0.81	3000

```
from sklearn.model_selection import GridSearchCV
```

```
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= 2.6s
[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=0.1, kernel=rbf; total time= 1.2s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time= 1.1s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time= 1.3s
[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= 1.1s
[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= 1.1s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time= 1.3s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time= 1.3s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time= 1.1s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time= 1.1s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time= 1.1s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time= 1.1s
GridSearchCV(cv=2, estimator=SVC(),
              param_grid={'C': [0.1, 1, 10], 'class_weight': ['balanced'],
                           'gamma': [1, 0.1, 0.01], 'kernel': ['rbf']},
              verbose=2)
```

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

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

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

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

```
array([[2166, 253],
       [ 362, 219]])
```

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

	precision	recall	f1-score	support
0	0.86	0.90	0.88	2419
1	0.46	0.38	0.42	581
accuracy			0.80	3000
macro avg	0.66	0.64	0.65	3000
weighted avg	0.78	0.80	0.79	3000

▼ Model with Random Under Sampling

```
svc_rus = SVC()
```

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

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

▼ Model Accuracy

```
confusion_matrix(y_test_rus, y_pred_rus)

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

▼ Hyperparameter Tunning

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

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

print(grid_rus.best_estimator_)

grid_predictions_rus = grid_rus.predict(X_test_rus)
```

▼ Model with Random Over Sampling

```
svc_ros = SVC()

svc_ros.fit(X_train_ros, y_train_ros)

y_pred_ros = svc__ros.predict(X_test_ros)
```

▼ Model Accuracy

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

▼ Hyperparameter Tunning

```
param_grid = {'C': [0.1, 1, 10],
```

```
'gamma': [1,0.1,0.01],  
'kernel': ['rbf'],  
'class_weight' : ['branched']}]}
```

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

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

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

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

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

```
print(classification_report(y_test_rus,grid_predictions_rus))
```