In [1]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```python
df = pd.read_csv('Churn_Modelling.csv')
df.head()
```

Out[2]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance
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

In [3]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [4]:
```
df.describe(include='all')
```

Out[4]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age
count	10000.00000	1.000000e+04	10000	10000.000000	10000	10000	10000.000000
unique	NaN	NaN	2932	NaN	3	2	NaN
top	NaN	NaN	Smith	NaN	France	Male	NaN
freq	NaN	NaN	32	NaN	5014	5457	NaN
mean	5000.50000	1.569094e+07	NaN	650.528800	NaN	NaN	38.921800
std	2886.89568	7.193619e+04	NaN	96.653299	NaN	NaN	10.487806
min	1.00000	1.556570e+07	NaN	350.000000	NaN	NaN	18.000000
25%	2500.75000	1.562853e+07	NaN	584.000000	NaN	NaN	32.000000
50%	5000.50000	1.569074e+07	NaN	652.000000	NaN	NaN	37.000000
75%	7500.25000	1.575323e+07	NaN	718.000000	NaN	NaN	44.000000
max	10000.00000	1.581569e+07	NaN	850.000000	NaN	NaN	92.000000

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
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
```

Dropping Irrelevant Features

In [6]:
```
df.columns
```

Out[6]:
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

In [7]:
```python
df = df.drop(['RowNumber', 'CustomerId', 'Surname'],axis=1)
```

In [8]:
```python
df.head()
```

Out[8]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActi
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	

Encoding Categorical Data

In [9]:
```python
df = pd.get_dummies(df,drop_first = True)
```

In [10]:
```python
df.head()
```

Out[10]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estimated
0	619	42	2	0.00	1	1	1	1013
1	608	41	1	83807.86	1	0	1	1125
2	502	42	8	159660.80	3	1	0	1139
3	699	39	1	0.00	2	0	0	938
4	850	43	2	125510.82	1	1	1	790

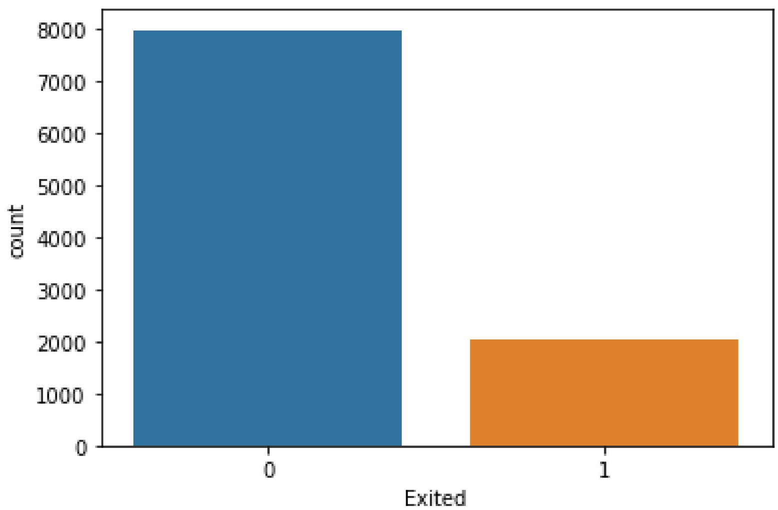
Some insights about the target variable

In [11]:
```python
df['Exited'].value_counts()
```

Out[11]:
```
0    7963
1    2037
Name: Exited, dtype: int64
```

In [12]:
```python
sns.countplot(df['Exited'])
```

Out[12]: <AxesSubplot:xlabel='Exited', ylabel='count'>



In [13]:
```python
X = df.drop('Exited',axis=1)
y = df['Exited']
```

Handling Imbalanced Data with SMOTE

In [14]:
```python
from imblearn.over_sampling import SMOTE
```

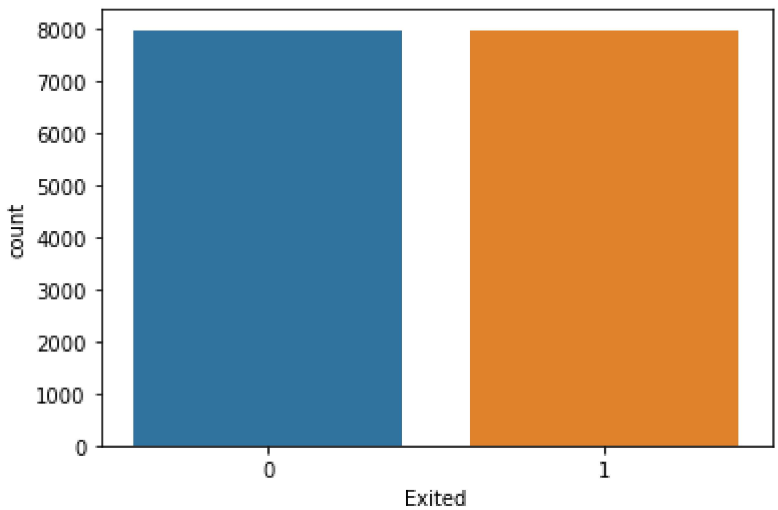
In [15]:
```python
X_res, y_res = SMOTE().fit_resample(X,y)
```

In [16]:
```python
y_res.value_counts()
```

Out[16]:
```
1    7963
0    7963
Name: Exited, dtype: int64
```

In [17]:
```
sns.countplot(y_res)
```

Out[17]: <AxesSubplot:xlabel='Exited', ylabel='count'>



Splitting The Dataset into Training Set and Test Set

In [18]:
```
from sklearn.model_selection import train_test_split
```

In [19]:
```
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.
```

Feature Scaling

In [20]:
```
from sklearn.preprocessing import StandardScaler
```

In [21]:
```
sc = StandardScaler()
```

In [22]:
```
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [23]:
```
X_train
```

Out[23]:
```
array([[ 0.75877907, -0.8982394 ,  0.78677282, ..., -0.575693  ,
         2.16445251, -0.84390722],
       [-0.68402381, -0.7976025 ,  1.15294588, ..., -0.575693  ,
        -0.4620106 ,  1.18496439],
       [-1.32891298,  0.2087665 ,  0.78677282, ..., -0.575693  ,
         2.16445251,  1.18496439],
       ...,
       [-0.00634367,  0.0074927 ,  0.42059976, ..., -0.575693  ,
        -0.4620106 , -0.84390722],
       [ 0.47459063, -0.9988763 , -1.41026556, ..., -0.575693  ,
        -0.4620106 ,  1.18496439],
       [ 1.63320506,  2.22150449, -1.41026556, ..., -0.575693  ,
        -0.4620106 , -0.84390722]])
```

Logistic Regression

In [24]:
```
from sklearn.linear_model import LogisticRegression
```

In [25]:
```
log = LogisticRegression()
```

In [26]:
```
log.fit(X_train, y_train)
```

Out[26]:
```
LogisticRegression()
```

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In [27]:
```
y_pred1 = log.predict(X_test)
```

In [28]:
```
from sklearn.metrics import accuracy_score
```

In [29]:
```
accuracy_score(y_test,y_pred1)
```

Out[29]:
```
0.7748011720385098
```

In [30]:
```
from sklearn.metrics import precision_score, recall_score, f1_score
```

In [31]:
```
precision_score(y_test, y_pred1)
```

Out[31]:
```
0.7582957804178615
```

In [32]:
```
recall_score(y_test, y_pred1)
```

Out[32]:
```
0.79204107830552
```

In [33]:
```
f1_score(y_test,y_pred1)
```
Out[33]: 0.7748011720385098

SVC

In [34]:
```
from sklearn import svm
```
In [35]:
```
svm = svm.SVC()
```
In [36]:
```
svm.fit(X_train,y_train)
```
Out[36]: SVC()

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In [37]:
```
y_pred2=svm.predict(X_test)
```
In [38]:
```
accuracy_score(y_test, y_pred2)
```
Out[38]: 0.8287986605274174

In [39]:
```
precision_score(y_test, y_pred2)
```
Out[39]: 0.8214134574693187

In [40]:
```
recall_score(y_test, y_pred2)
```
Out[40]: 0.8305519897304237

In [41]:
```
f1_score(y_test,y_pred2)
```
Out[41]: 0.8259574468085107

KNeighbors Classifier

In [42]:
```
from sklearn.neighbors import KNeighborsClassifier
```
In [43]:
```
knn = KNeighborsClassifier()
```

In [44]:
```
knn.fit(X_train,y_train)
```

Out[44]:
```
KNeighborsClassifier()
```

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In [45]:
```
y_pred3=knn.predict(X_test)
```

In [46]:
```
accuracy_score(y_test, y_pred3)
```

Out[46]:
```
0.8080786940142319
```

In [47]:
```
precision_score(y_test, y_pred3)
```

Out[47]:
```
0.785829307568438
```

In [48]:
```
recall_score(y_test, y_pred3)
```

Out[48]:
```
0.8352588789045785
```

In [49]:
```
f1_score(y_test,y_pred3)
```

Out[49]:
```
0.8097904998962872
```

Desicion Tree Classifier

In [50]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [51]:
```
dt = DecisionTreeClassifier()
```

In [52]:
```
dt.fit(X_train, y_train)
```

Out[52]:
```
DecisionTreeClassifier()
```

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In [53]:
```
y_pred4=dt.predict(X_test)
```

In [54]:
```
accuracy_score(y_test, y_pred4)
```

Out[54]:
```
0.7986605274173294
```

In [55]:
```
precision_score(y_test, y_pred4)
```
Out[55]: 0.7804977560179519

In [56]:
```
recall_score(y_test, y_pred4)
```
Out[56]: 0.8185708172871202

In [57]:
```
f1_score(y_test,y_pred4)
```
Out[57]: 0.7990810359231411

Random Forest Classifier

In [58]:
```
from sklearn.ensemble import RandomForestClassifier
```
In [59]:
```
rf = RandomForestClassifier()
```
In [60]:
```
rf.fit(X_train,y_train)
```
Out[60]: RandomForestClassifier()

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In [61]:
```
y_pred5=rf.predict(X_test)
```
In [62]:
```
accuracy_score(y_test,y_pred5)
```
Out[62]: 0.8503557974047719

In [63]:
```
precision_score(y_test, y_pred5)
```
Out[63]: 0.8407563025210084

In [64]:
```
recall_score(y_test, y_pred5)
```
Out[64]: 0.8562259306803595

In [65]:
```
f1_score(y_test,y_pred5)
```
Out[65]: 0.8484206063175749

Gradient Boosting Classifier

In [66]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

In [67]:
```
gbc = GradientBoostingClassifier()
```

In [68]:
```
gbc.fit(X_train, y_train)
```

Out[68]:
```
GradientBoostingClassifier()
```

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In [69]:
```
y_pred6=gbc.predict(X_test)
```

In [70]:
```
accuracy_score(y_test,y_pred6)
```

Out[70]:
```
0.8340309753034743
```

In [71]:
```
precision_score(y_test,y_pred6)
```

Out[71]:
```
0.8307626392459297
```

In [72]:
```
recall_score(y_test,y_pred6)
```

Out[72]:
```
0.8296961916987591
```

In [73]:
```
f1_score(y_test,y_pred6)
```

Out[73]:
```
0.8302290730036395
```

XGBoost

In [86]:
```
import xgboost as xgb

model_xgb = xgb.XGBClassifier(random_state=42, verbosity = 0)
model_xgb.fit(X_train, y_train)
```

Out[86]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=Fals
e,
              gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=8,
              num_parallel_tree=1, predictor='auto', random_state=42,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=0)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [87]:
```
y_pred7=model_xgb.predict(X_test)
```

In [88]:
```
accuracy_score(y_test,y_pred7)
```

Out[88]: 0.8522394307241523

In [89]:
```
precision_score(y_test,y_pred7)
```

Out[89]: 0.8382413936126089

In [90]:
```
recall_score(y_test,y_pred6)
```

Out[90]: 0.8296961916987591

In [91]:
```
f1_score(y_test,y_pred6)
```

Out[91]: 0.8302290730036395

Accuracy Summary

In [92]:
```
performance_summary = pd.DataFrame({
    'Model':['LR','SVC','KNN','DT','RF','GBC','XGB'],
    'ACC':[accuracy_score(y_test,y_pred1),
           accuracy_score(y_test,y_pred2),
           accuracy_score(y_test,y_pred3),
           accuracy_score(y_test,y_pred4),
           accuracy_score(y_test,y_pred5),
           accuracy_score(y_test,y_pred6),
           accuracy_score(y_test,y_pred7)
          ]
})
```

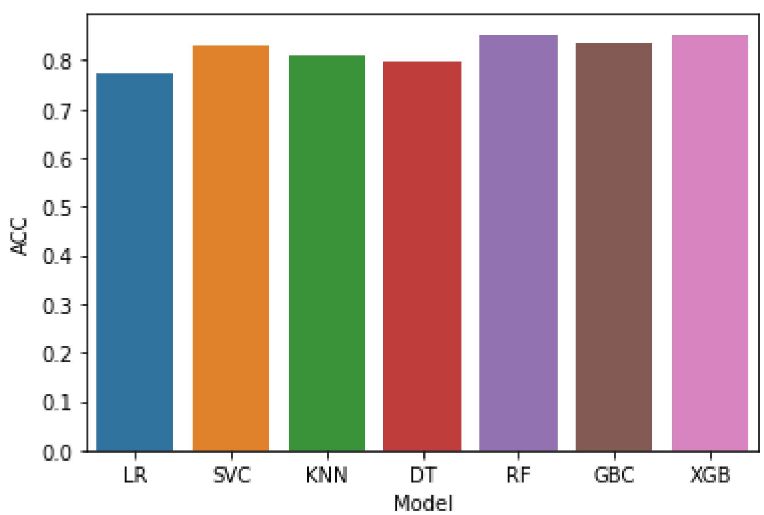
In [93]:
```
performance_summary
```

Out[93]:

	Model	ACC
0	LR	0.774801
1	SVC	0.828799
2	KNN	0.808079
3	DT	0.798661
4	RF	0.850356
5	GBC	0.834031
6	XGB	0.852239

In [94]:
```
sns.barplot(performance_summary['Model'],performance_summary['ACC'])
```

Out[94]: <AxesSubplot:xlabel='Model', ylabel='ACC'>



As we can see, XGBoost Classifier has highest accuracy

In [95]:
```
performance_summary = pd.DataFrame({
    'Model':['LR','SVC','KNN','DT','RF','GBC','XGB'],
    'PRECISION':[precision_score(y_test,y_pred1),
           precision_score(y_test,y_pred2),
           precision_score(y_test,y_pred3),
           precision_score(y_test,y_pred4),
           precision_score(y_test,y_pred5),
           precision_score(y_test,y_pred6),
            precision_score(y_test,y_pred6)
          ]
})
```

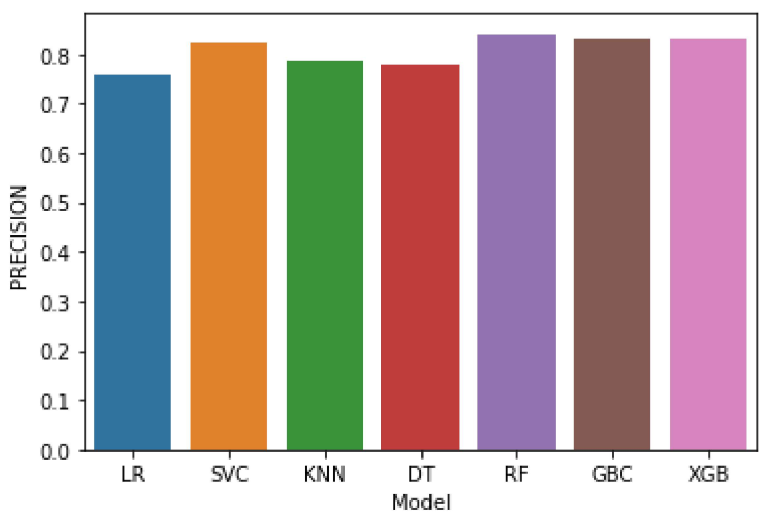
In [96]:
```
performance_summary
```

Out[96]:

	Model	PRECISION
0	LR	0.758296
1	SVC	0.821413
2	KNN	0.785829
3	DT	0.780498
4	RF	0.840756
5	GBC	0.830763
6	XGB	0.830763

In [97]:
```
sns.barplot(performance_summary['Model'],performance_summary['PRECISION'])
```

Out[97]: <AxesSubplot:xlabel='Model', ylabel='PRECISION'>



Saving the best model, XGBoost

In [80]:
```
X_train = sc.fit_transform(X_train)
```

In [98]:
```
model_xgb.fit(X_res,y_res)
```

Out[98]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=Fals
e,
              gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=8,
              num_parallel_tree=1, predictor='auto', random_state=42,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=0)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [99]:
```
import joblib
```

In [100]:
```
joblib.dump(model_xgb, 'churn_predict_model')
```

Out[100]:
```
['churn_predict_model']
```

In [101]:
```
model = joblib.load('churn_predict_model')
```

In [85]:
```
df.columns
```

Out[85]:
```
Index(['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCar
d',
       'IsActiveMember', 'EstimatedSalary', 'Exited', 'Geography_Germany',
       'Geography_Spain', 'Gender_Male'],
      dtype='object')
```