Task 3: Customer Churn Prediction

```
Develop a model to predict customer churn for a subscription￾based service or business. Use historic
al customer data, including features like usage behavior and customer demographics, and try algorith
ms like Logistic Regression, Random Forests, or Gradient Boosting to predict churn.
```

In [2]:
```
## Importing necessary libraries

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

Data Collection

In [3]:
```
## Read The Data

data = pd.read_csv("./Customer Churn Dataset/Churn_Modelling.csv")
```

In [4]:
```
data.head()
```

Out[4]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActive
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	

In [5]:
```
## Check for basic info
data.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 [6]:
```
## Check basic statistic
data.describe(include = "all")
```

Out[6]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfPr
count	10000.00000	1.000000e+04	10000	10000.000000	10000	10000	10000.000000	10000.000000	10000.000000	10000.0
unique	NaN	NaN	2932	NaN	3	2	NaN	NaN	NaN	
top	NaN	NaN	Smith	NaN	France	Male	NaN	NaN	NaN	
freq	NaN	NaN	32	NaN	5014	5457	NaN	NaN	NaN	
mean	5000.50000	1.569094e+07	NaN	650.528800	NaN	NaN	38.921800	5.012800	76485.889288	1.5
std	2886.89568	7.193619e+04	NaN	96.653299	NaN	NaN	10.487806	2.892174	62397.405202	0.5
min	1.00000	1.556570e+07	NaN	350.000000	NaN	NaN	18.000000	0.000000	0.000000	1.0
25%	2500.75000	1.562853e+07	NaN	584.000000	NaN	NaN	32.000000	3.000000	0.000000	1.0
50%	5000.50000	1.569074e+07	NaN	652.000000	NaN	NaN	37.000000	5.000000	97198.540000	1.0
75%	7500.25000	1.575323e+07	NaN	718.000000	NaN	NaN	44.000000	7.000000	127644.240000	2.0
max	10000.00000	1.581569e+07	NaN	850.000000	NaN	NaN	92.000000	10.000000	250898.090000	4.0

Data Cleaning

In [7]:
```
## Check for missing values or nan values

data.isna().sum()
```

Out[7]:
```
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 [8]:
```
## Check for any duplicates rows

data.duplicated().sum()
```

Out[8]:
```
0
```

In [9]:
```
## Remove unnecessary rows

data.drop(["RowNumber","CustomerId"],axis = 1, inplace = True)
data.head()
```

Out[9]:

	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88
1	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63
4	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

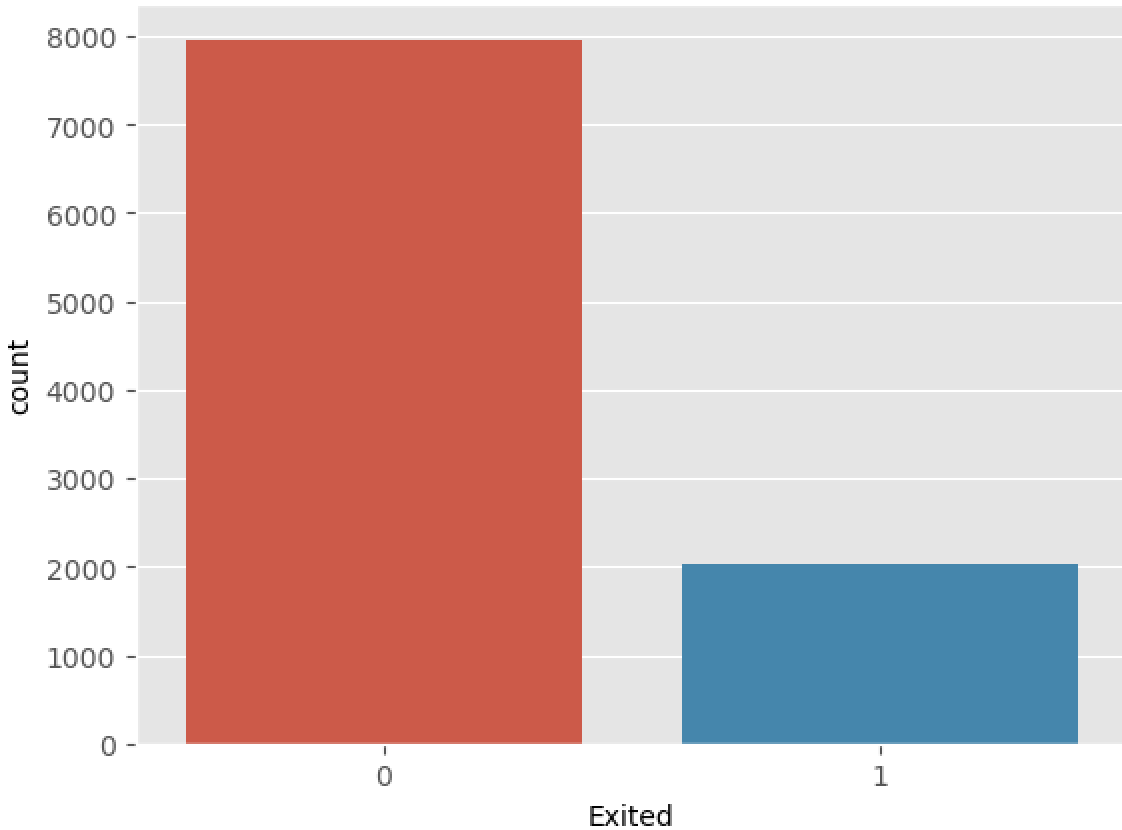
In [10]:
```
# Check for Data Imbalance

data["Exited"].value_counts() ## There is imbalance data
```

Out[10]:
```
0    7963
1    2037
Name: Exited, dtype: int64
```

Data Visualization

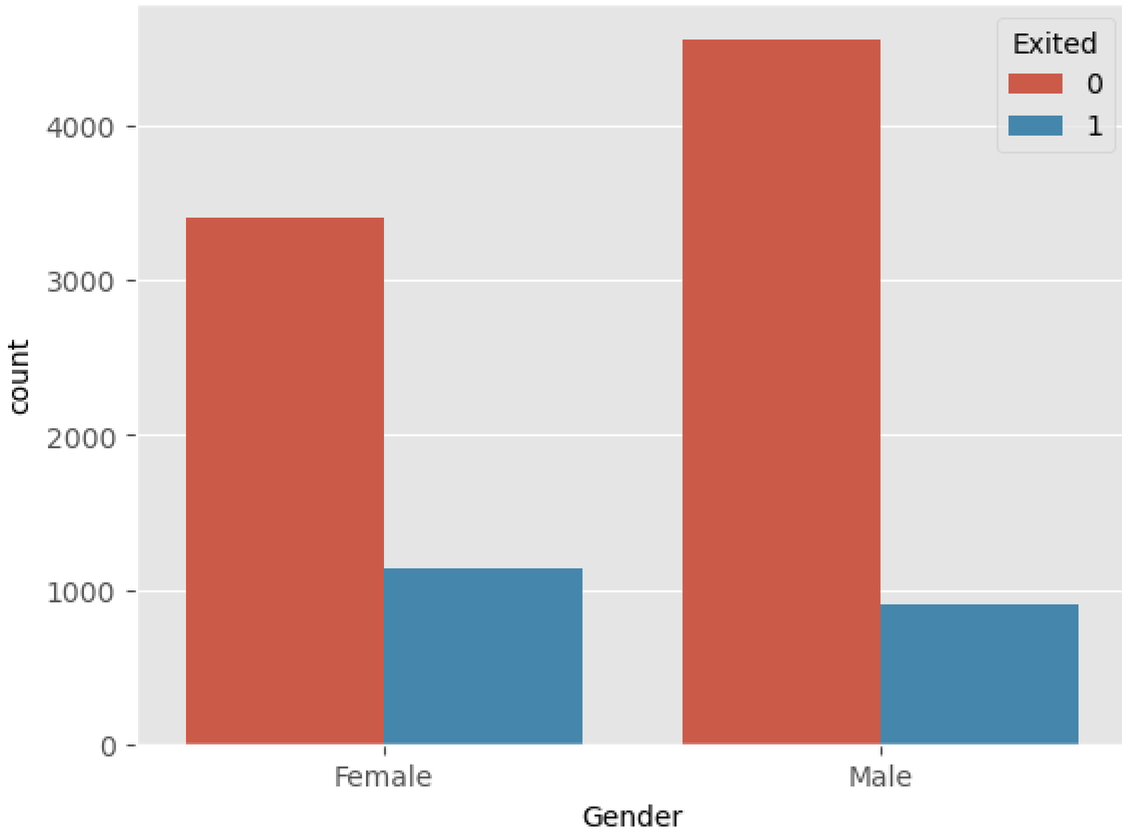
In [11]:
```
## View the Label data for imbalance data
plt.style.use("ggplot")
sns.countplot(x = data["Exited"])
```

Out[11]:
```
<Axes: xlabel='Exited', ylabel='count'>
```



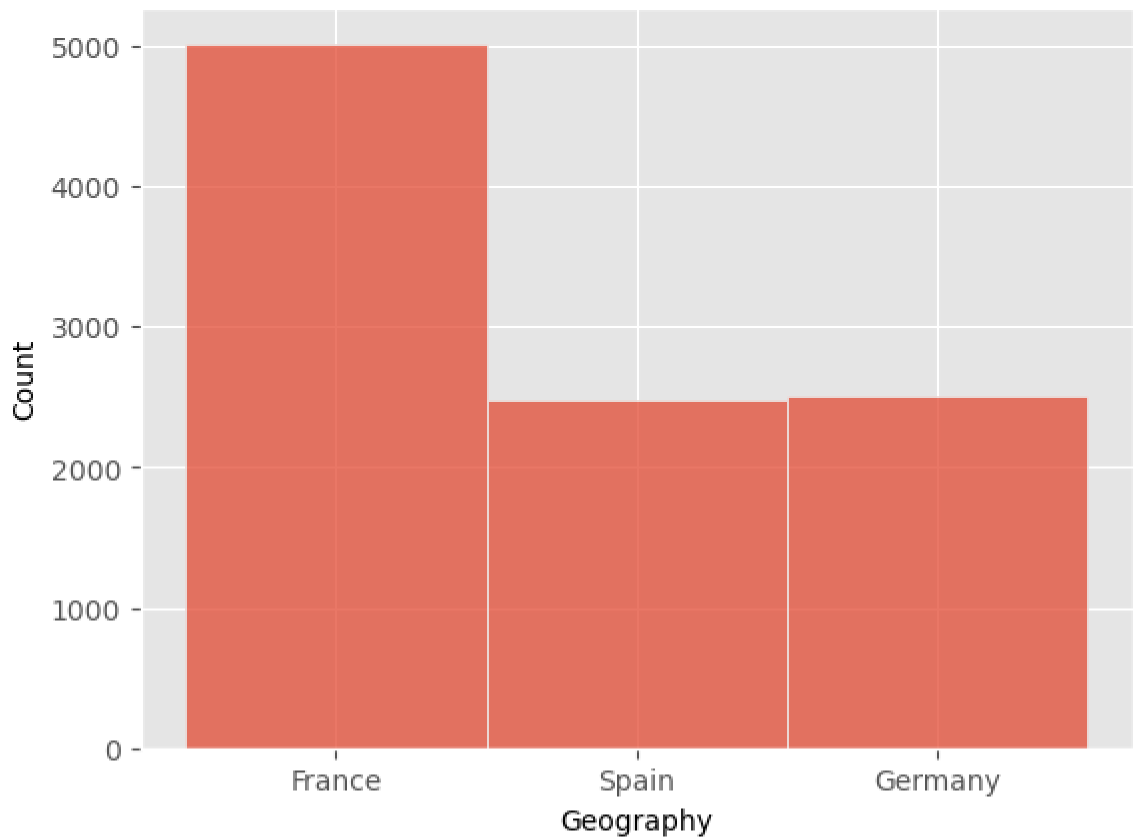
In [12]:
```
## View the GEnder
plt.style.use("ggplot")
sns.countplot(x = data["Gender"],hue = "Exited" ,data = data)
```

Out[12]:
```
<Axes: xlabel='Gender', ylabel='count'>
```



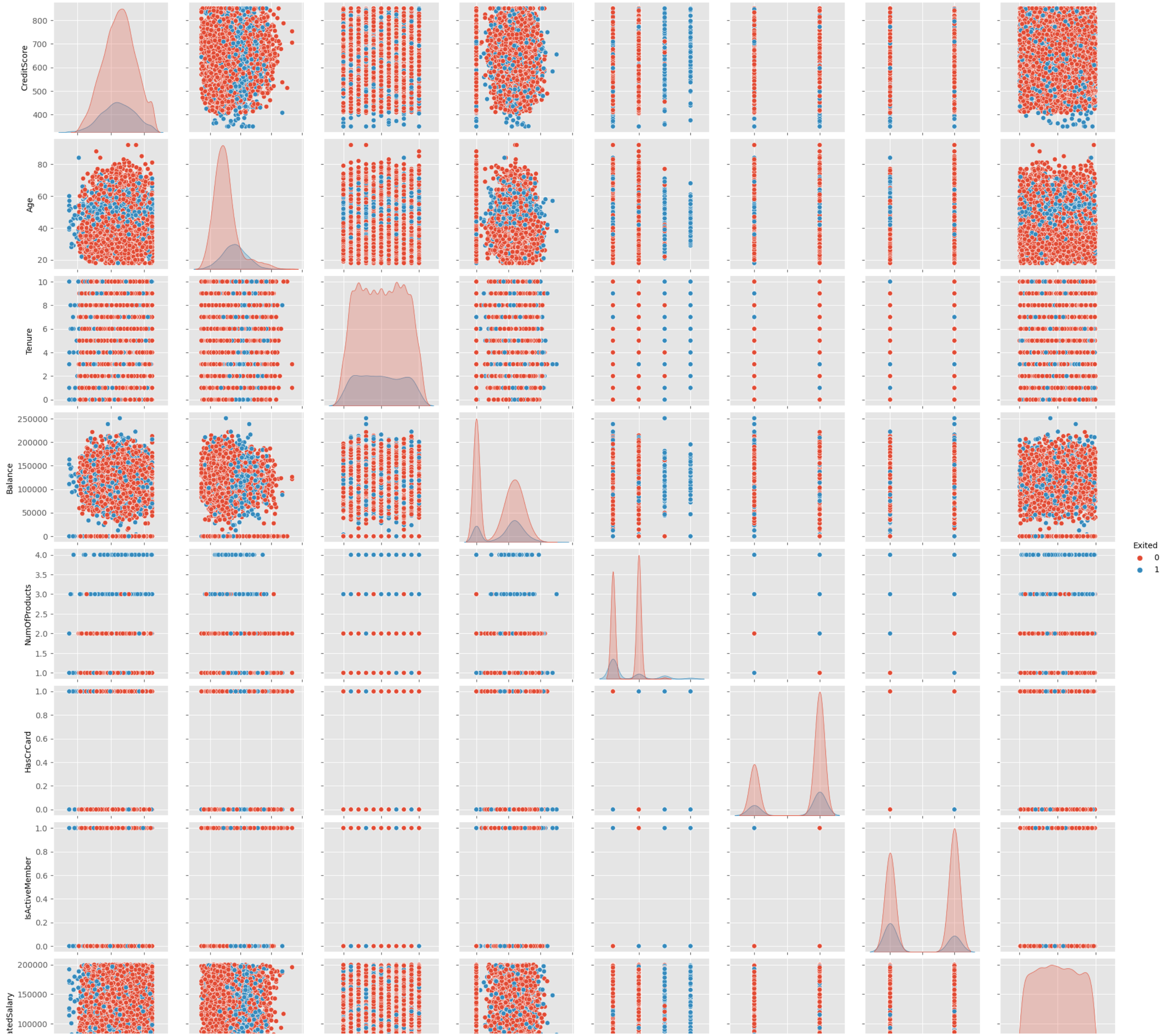
In [13]:
```
## Plot the geography of data
sns.histplot(x ="Geography" ,data =data)
```

Out[13]: <Axes: xlabel='Geography', ylabel='Count'>

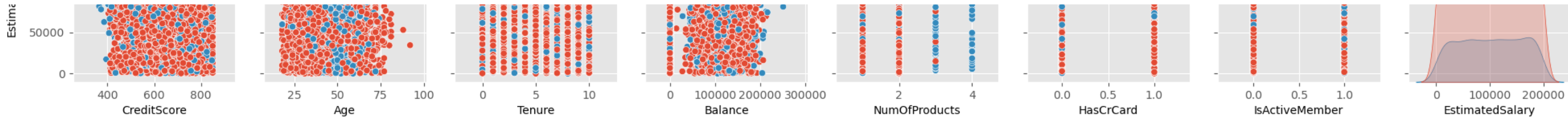


In [14]:
```
## Pair plot basic understanding
sns.pairplot(data ,hue = "Exited")
```

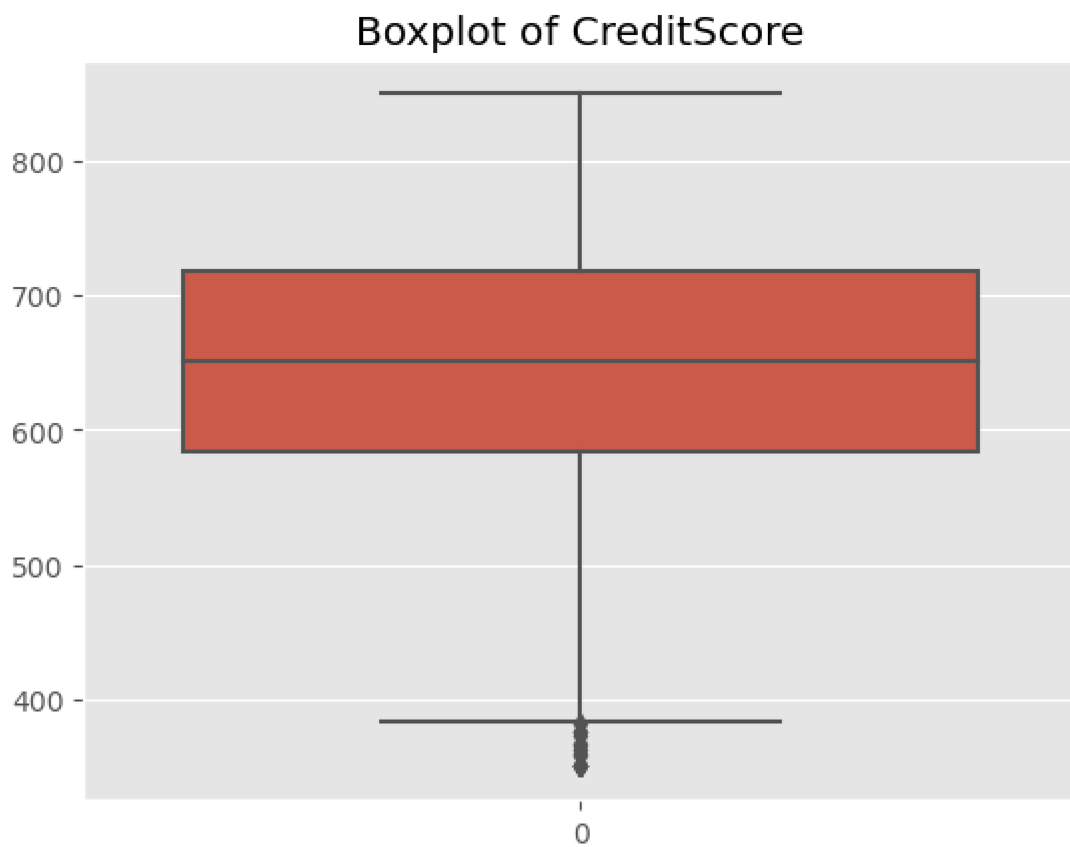
Out[14]:
```
<seaborn.axisgrid.PairGrid at 0x25afc55c9d0>
```

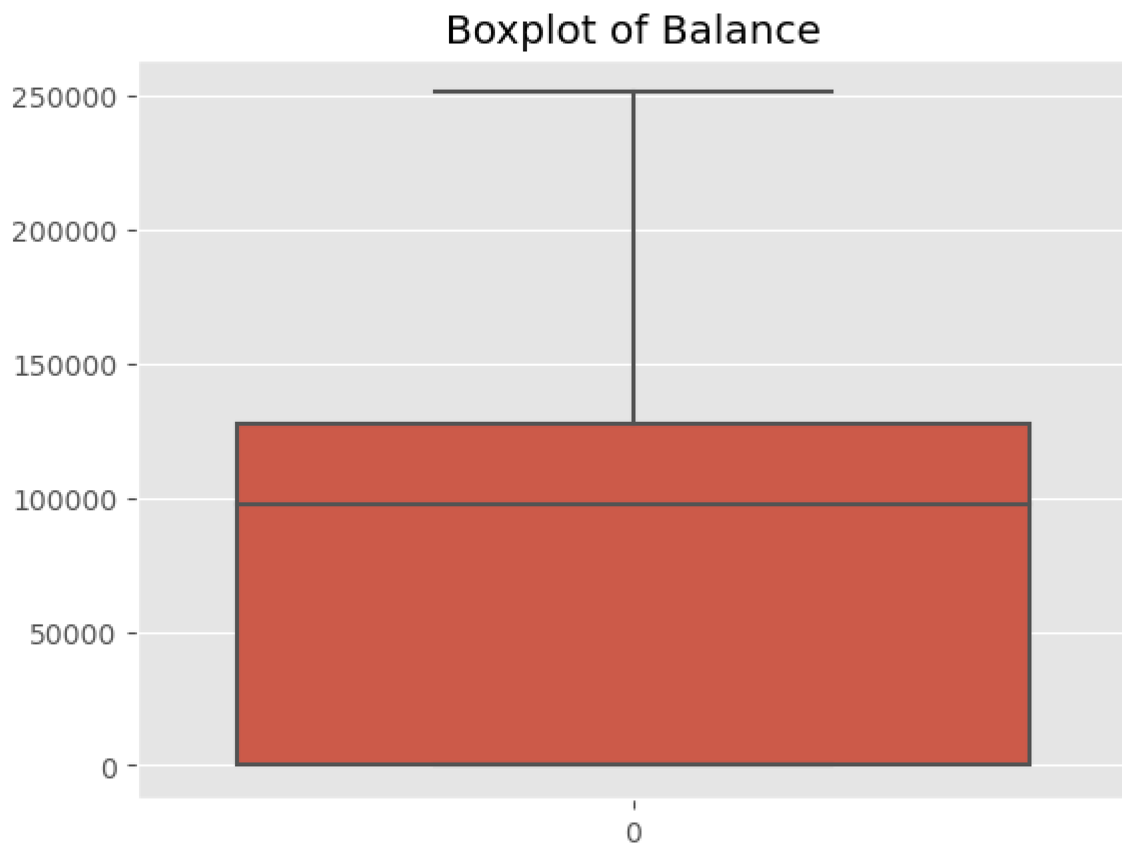


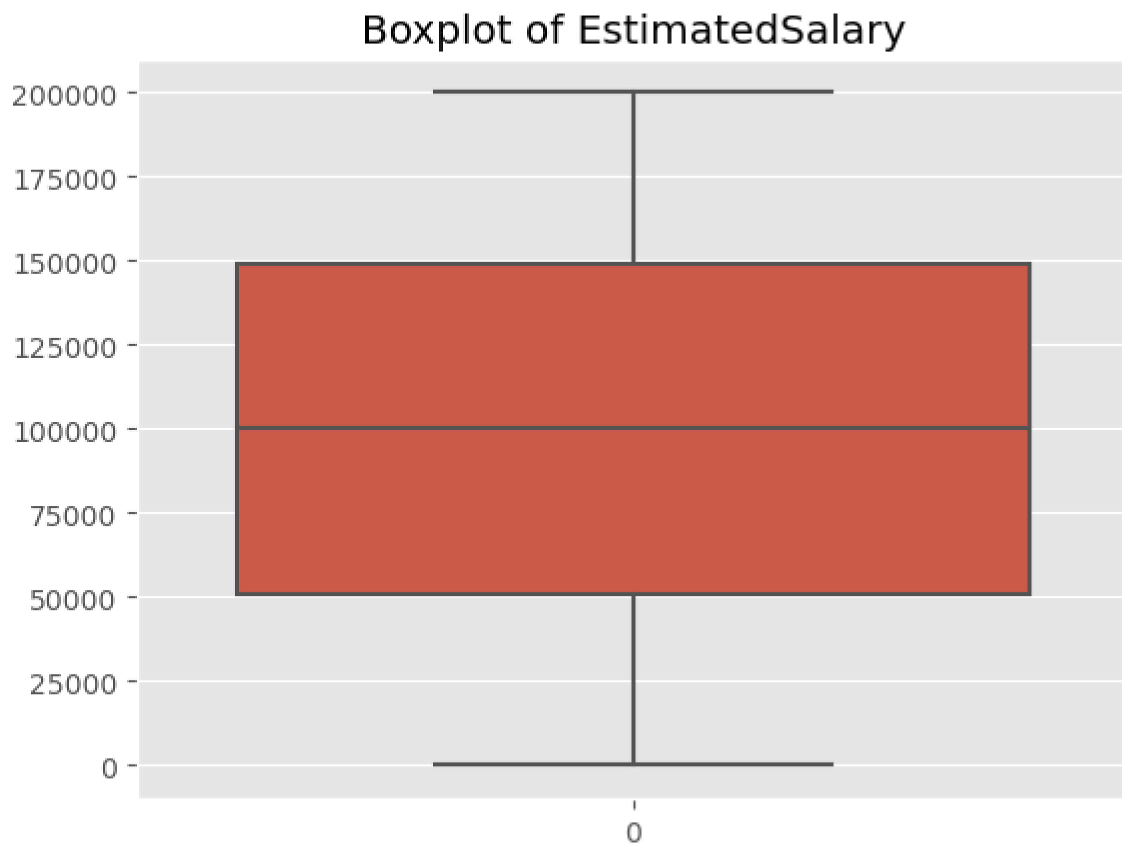
CreditScore
Age
Tenure
Balance
NumOfProducts
HasCrCard
IsActiveMember
atedSalary
Exited
0
1


50000
0
400
600
800
CreditScore
25
50
75
100
Age
0
5
10
Tenure
0
100000
200000
300000
Balance
2
4
NumOfProducts
0.0
0.5
1.0
HasCrCard
0.0
0.5
1.0
IsActiveMember
0
100000
200000
EstimatedSalary

In [15]:
```
## check for outliers in numerical data using box plot

for i in ["CreditScore","Balance","EstimatedSalary"]:
    sns.boxplot(data[i])
    plt.title(f"Boxplot of {i}")
    plt.show()
```




Boxplot of Balance
250000
200000
150000
100000
50000
0
0



In [16]:
```
data.head()
```

Out[16]:

	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88
1	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63
4	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

Data Preprocessing

With Imbalance data

In [17]:
```
## Import necessary libraries for preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder , StandardScaler
from sklearn.compose import ColumnTransformer

encoder = OneHotEncoder()
scaler = StandardScaler()

categ = ["Surname","Geography","Gender","NumOfProducts","HasCrCard","IsActiveMember"]
numeric = ["CreditScore","Age","Tenure","Balance","EstimatedSalary"]

transf = ColumnTransformer([("cat",encoder,categ),
                              ("num",scaler, numeric)])
x = data.drop("Exited" ,axis = 1)
y = data["Exited"]

transformX = transf.fit_transform(x)

print("transformX shape :",transformX.shape)
print("y shape :",y.shape)
```

```
transformX shape : (10000, 2950)
y shape : (10000,)
```

In [18]:
```
## Split the data to train test

x_train ,x_test ,y_train ,y_test = train_test_split (transformX ,y ,test_size = 0.2 ,random_state = 42)
```

Model Selection

In [19]:
```
## Import neceesary model for evaluation
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier ,GradientBoostingClassifier

from sklearn.metrics import accuracy_score,classification_report ,confusion_matrix ,precision_score ,recall_s
```

In [20]:
```
## Create a function to test models
def model_train_testing(model):
    model.fit(x_train,y_train)
    y_preds= model.predict(x_test)

    print("\nAccuracy Score : " ,accuracy_score(y_test ,y_preds))
    print("\nPrecision Score : " ,precision_score(y_test ,y_preds))
    print("\nRecall Score : " ,recall_score(y_test ,y_preds))
    print("\nConfusion Matrix : \n" ,confusion_matrix(y_test ,y_preds))
    print("\nClassification_report  :\n " ,classification_report(y_test ,y_preds))
```

In [21]:
```
print(10* "-", "LogisticRegression " ,10* "-")

## LogisticRegression with imbalance data
lr = LogisticRegression()
model_train_testing(lr)

print(30* "-", "RandomForestClassifier " ,30* "-")

## RandomForestClassifier with imbalance data
rf = RandomForestClassifier()
model_train_testing(rf)


print(30* "-", "  GradientBoostingClassifier " ,30* "-")
## GradientBoostingClassifier without dealing with imbalance data
gc = GradientBoostingClassifier()
model_train_testing(gc)
```

```
---------- LogisticRegression  ----------

C:\Users\Barcha\anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/prep
rocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/
stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

```
Accuracy Score :  0.8455

Precision Score :  0.6944444444444444

Recall Score :  0.3816793893129771

Confusion Matrix :
 [[1541   66]
 [ 243  150]]

Classification_report  :
               precision    recall  f1-score   support

           0       0.86      0.96      0.91      1607
           1       0.69      0.38      0.49       393

    accuracy                           0.85      2000
   macro avg       0.78      0.67      0.70      2000
weighted avg       0.83      0.85      0.83      2000

------------------------------ RandomForestClassifier  ------------------------------

Accuracy Score :  0.868

Precision Score :  0.8208955223880597

Recall Score :  0.4198473282442748

Confusion Matrix :
 [[1571   36]
 [ 228  165]]

Classification_report  :
               precision    recall  f1-score   support

           0       0.87      0.98      0.92      1607
           1       0.82      0.42      0.56       393

    accuracy                           0.87      2000
   macro avg       0.85      0.70      0.74      2000
weighted avg       0.86      0.87      0.85      2000
```

```
------------------------------   GradientBoostingClassifier  ------------------------------

Accuracy Score :  0.864

Precision Score :  0.7531380753138075

Recall Score :  0.4580152671755725

Confusion Matrix :
 [[1548   59]
 [ 213  180]]

Classification_report  :
                precision    recall  f1-score   support

           0       0.88      0.96      0.92      1607
           1       0.75      0.46      0.57       393

    accuracy                           0.86      2000
   macro avg       0.82      0.71      0.74      2000
weighted avg       0.85      0.86      0.85      2000
```

Without Imbalance Data using OverSampling

In [22]:
```
## Import necessary libraries for preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder , StandardScaler
from sklearn.compose import ColumnTransformer
from imblearn.over_sampling import SMOTE

encoder = OneHotEncoder()
scaler = StandardScaler()

categ = ["Surname","Geography","Gender","NumOfProducts","HasCrCard","IsActiveMember"]
numeric = ["CreditScore","Age","Tenure","Balance","EstimatedSalary"]

transf = ColumnTransformer([("cat",encoder,categ),
                            ("num",scaler, numeric)])


x = data.drop("Exited" ,axis = 1)
y = data["Exited"]

## tranform data
transformX = transf.fit_transform(x )


## Oversampling
sampler= SMOTE()
x_sampled ,y_sampled = sampler.fit_resample(transformX ,y)



print("x_sampled shape :",x_sampled.shape)
print("y_sampled shape :",y_sampled.shape)


## Split the data to train test

x_train ,x_test ,y_train ,y_test = train_test_split (x_sampled ,y_sampled ,test_size = 0.2 ,random_state = 42
```

```
x_sampled shape : (15926, 2950)
y_sampled shape : (15926,)
```

In [23]:
```
## Train and test

print(10* "-", "LogisticRegression " ,10* "-")

## LogisticRegression with imbalance data
lr = LogisticRegression()
model_train_testing(lr)

print(30* "-", "RandomForestClassifier " ,30* "-")

## RandomForestClassifier with imbalance data
rf = RandomForestClassifier()
model_train_testing(rf)


print(30* "-", "  GradientBoostingClassifier " ,30* "-")
## GradientBoostingClassifier without dealing with imbalance data
gc = GradientBoostingClassifier()
model_train_testing(gc)
```

```
---------- LogisticRegression  ----------

C:\Users\Barcha\anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/prep
rocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/
stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

```
Accuracy Score :  0.812617702448211

Precision Score :  0.7914634146341464

Recall Score :  0.8358016741790084

Confusion Matrix :
 [[1291  342]
 [ 255 1298]]

Classification_report  :
                precision    recall  f1-score   support

           0       0.84      0.79      0.81      1633
           1       0.79      0.84      0.81      1553

    accuracy                           0.81      3186
   macro avg       0.81      0.81      0.81      3186
weighted avg       0.81      0.81      0.81      3186

------------------------------ RandomForestClassifier  ------------------------------

Accuracy Score :  0.9422473320778405

Precision Score :  0.9459283387622149

Recall Score :  0.9349645846748229

Confusion Matrix :
 [[1550   83]
 [ 101 1452]]

Classification_report  :
                precision    recall  f1-score   support

           0       0.94      0.95      0.94      1633
           1       0.95      0.93      0.94      1553

    accuracy                           0.94      3186
   macro avg       0.94      0.94      0.94      3186
weighted avg       0.94      0.94      0.94      3186
```

```
------------------------------   GradientBoostingClassifier  ------------------------------

Accuracy Score :  0.8490269930947897

Precision Score :  0.8494132985658409

Recall Score :  0.8390212491951062

Confusion Matrix :
 [[1402  231]
 [ 250 1303]]

Classification_report  :
                precision    recall  f1-score   support

           0       0.85      0.86      0.85      1633
           1       0.85      0.84      0.84      1553

    accuracy                           0.85      3186
   macro avg       0.85      0.85      0.85      3186
weighted avg       0.85      0.85      0.85      3186
```

Thank you😉

In [ ]: