3225 lines (3225 loc) · 1.58 MB

ChurnShield: Protecting Customer Relationships Through Predictive Intelligence

1.Business Understanding

Understanding and predicting customer churn is crucial for **Horizon Trust Bank**. Customer churn impacts the bank's revenue and profitability and increases the costs associated with acquiring new customers. Retaining loyal customers boosts the bank's reputation and competitive edge. By utilizing predictive modeling, Horizon Trust Bank seeks to proactively mitigate customer attrition, customize services, and optimize marketing efforts, thereby ensuring long-term customer loyalty.

1.1 Introduction:

Horizon Trust Bank, a prominent financial institution, offers diverse banking services. Like any bank, retaining customers is pivotal for market presence and profitability. Identifying potential churners is vital for targeted strategies and retaining valuable clients. In this project, we delve into customer demographics, banking behaviors, and historical churn data. The objective is to construct a predictive model to anticipate churn, providing Horizon Trust Bank actionable insights for enhancing customer retention strategies.

1.2Problem statement:

Horizon Trust Bank is in constant worry of whether the customer will churn or not. This problem has lead to them unable to make stable and precise decision on the customers that visit, additionally to maintain the already present customers.

1.3 Metric of Success:

The model will be concidered successful through it's ability to predict accurately whether the customer is likely to churn or not based on their historical behavior and demographic information.

1.4 Main Objective:

Build a robust customer churn prediction model, enabling data-driven decisions, boosting customer satisfaction, and reinforcing Horizon Trust Bank's competitive standing.

1.5 Specific Objective:

- Determine factors that have a higer effect on customer churning.
- Build different models to evaluate the best model.

1.6 Experimental design:

1.Exploratory Data Analysis (EDA): Explore the dataset, extracting insights into customer demographics, banking patterns, and churn distribution, identifying potential trends.

2.Data Preprocessing: Handle missing values, encode categorical variables, and scale features, ensuring the data is prepared for model training.

3.Feature Importance Analysis: Leverage SHAP (SHapley Additive exPlanations) to pinpoint crucial features affecting customer churn for Horizon Trust Bank.

4.Model Building: Train and assess two machine learning models, Decision Trees and Random Forests, to predict customer churn effectively.

5.Model Evaluation: Evaluate model performance using key metrics like accuracy, F1 score, precision, recall, and ROC-AUC curve, ensuring robustness and generalization.

6.Interpretation and Recommendations: Extract insights from model outcomes to identify influential churn factors. Provide actionable recommendations to enhance customer retention strategies.

Data Relevance

The dataset has 9970 rows, and 11 columns. The dataset has the following information which will give a better and insight of customer churning.

1. `RowNumber` : A sequential number assigned to each row in the dataset.
2. `CustomerId` : A unique identifier for each customer in the bank.
3. `Surname` : The last name of the customer.
4. `CreditScore` : The credit score of the customer, representing their creditworthiness.
5. `Geography` : The geographical location of the customer (e.g., France, Spain, Germany).
6. `Gender` : The gender of the customer (Male or Female).
7. `Age` : The age of the customer.
8. `Tenure` : The number of years the customer has been with the bank.
9. `Balance` : The account balance of the customer.
10. `NumOfProducts` : The number of bank products the customer has purchased.
11. `HasCrCard` : Whether the customer has a credit card (1 if yes, 0 if no).
12. `IsActiveMember` : Whether the customer is an active member (1 if yes, 0 if no).
13. `EstimatedSalary` : The estimated salary of the customer.
14. `Exited` : The target variable indicating whether the customer churned (1 if yes, 0 if no).

2.Data Understanding

Explore the data and have its general understanding that is its shape, columns available, is it clean, its relationship using describe function.

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, roc_curve,roc_auc_score, accurac
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifie
from imblearn.over_sampling import SMOTE
from sklearn.metrics import accuracy_score
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_
from xgboost import XGBClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.feature_selection import SelectFromModel
from scipy import stats
from scipy.stats import zscore
import warnings
warnings.filterwarnings('ignore')
sns.set_style('darkgrid')
```

In [2]:

```
df = pd.read_csv("Horizon Trust Bank Churn data_set.csv")
df.head()
```

Out[2]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
0	1	15634602	Hargrave	619.0	France	Female	42.0	2.0
1	2	15647311	Hill	608.0	Spain	Female	41.0	1.0
2	3	15619304	Onio	502.0	France	Female	42.0	8.0
3	4	15701354	Boni	699.0	France	Female	39.0	1.0
4	5	15737888	Mitchell	850.0	Spain	Female	43.0	2.0

In [3]:

```
print(df.shape)
```

```
(10000, 14)
```

In [4]:

```
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      9996 non-null   float64
 4   Geography        9997 non-null   object 
 5   Gender           9997 non-null   object 
 6   Age              9994 non-null   float64
 7   Tenure           9963 non-null   float64
 8   Balance          9998 non-null   float64
 9   NumOfProducts    9986 non-null   float64
 10  HasCrCard        9998 non-null   float64
```

```
 10  HasCrCard        9998 non-null   float64
 11  IsActiveMember   9999 non-null   float64
 12  EstimatedSalary  9988 non-null   float64
 13  Exited           10000 non-null  int64
dtypes: float64(8), int64(3), object(3)
memory usage: 1.1+ MB
```

In [5]:

```
df.describe()
```

Out[5]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balan
count	10000.00000	1.000000e+04	9996.000000	9994.000000	9963.000000	9998.0000
mean	5000.50000	1.569094e+07	650.530912	38.923354	5.014554	76473.4533
std	2886.89568	7.193619e+04	96.669212	10.490050	2.891654	62397.0791
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.0000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.0000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97173.2900
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127641.4175
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.0900

Observations from the dataset

1.The dataset contains 10000 entries

2.The dataset contains 14 columns

3.The columns represent features such as `customer ID`, `surname`, `credit score`, `geography`, `gender`, `age`, `tenure`, `balance`, `number of products`, whether the customer has a `credit card`, whether the customer is an active member, `estimated salary`, and whether the customer exited

4. `Surname`, `Geography`, and `Gender` are categorical variables.

5.There are missing values in several columns, including `CreditScore`, `Geography`, `Gender`, `Age`, `Tenure`, `Balance`, `NumOfProducts`, `HasCrCard`, `IsActiveMember`, and `EstimatedSalary`

3.Data Cleaning

- Identify and handle missing values
- Scrub the data to remove any inaccuracies or inconsistencies
- Transform and organize the data into a standardized format for analysis
- Enhance the quality and usability of the data through restructuring and formatting adjustments.

gather relevant datasets

Here, we will drop the data that has no effect on whether a customer churns or not. The following data will not have much relevance.

- `RowNumber` - This is the index of each row, hence does not have much effect on customer churning

- `CustomerId` - This is a unique customer identifier therefor has no effect on customer churning
- `Surname` - This is also s unique identifier therefore has no effect on customer churning

3.1 Drop irrelevant columns

We'll drop columns that don't affect customer churn (RowNumber, CustomerId, Surname).

In [6]:
```
# Drop irrelevant columns
irrelevant_columns = ['RowNumber', 'CustomerId', 'Surname']
df = df.drop(irrelevant_columns, axis=1)
```

In [7]:
```
# confirm that the columns have been dropped
df.head()
```

Out[7]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrC
0	619.0	France	Female	42.0	2.0	0.00	1.0	
1	608.0	Spain	Female	41.0	1.0	83807.86	1.0	
2	502.0	France	Female	42.0	8.0	159660.80	3.0	
3	699.0	France	Female	39.0	1.0	0.00	2.0	
4	850.0	Spain	Female	43.0	2.0	125510.82	1.0	

3.2 Identify and handle missing values

Let's start by checking for missing values:

In [8]:
```
# Check for missing values
df.isnull().sum()
```

Out[8]:
```
CreditScore         4
Geography           3
Gender              3
Age                 6
Tenure             37
Balance             2
NumOfProducts      14
HasCrCard           2
IsActiveMember      1
EstimatedSalary    12
Exited              0
dtype: int64
```

3.3 Handle missing values

We'll drop rows with missing values in critical columns and impute the rest.

In [9]:
```
# Drop rows with missing values in the specified columns
```

```
# Drop rows with missing values in the specified columns
df.dropna(subset=['CreditScore', 'Geography', 'Gender', 'Age', 'HasCrCard', 'I

# Calculate and impute the mode for 'Tenure' and 'NumOfProducts'
df['Tenure'].fillna(df['Tenure'].mode()[0], inplace=True)
df['NumOfProducts'].fillna(df['NumOfProducts'].mode()[0], inplace=True)
```

3.4 Transform categorical variables

We need to encode categorical variables `Geography` and `Gender` for analysis.

In [10]:

```
# Encode categorical variables
label_encoder = LabelEncoder()

df['Geography'] = label_encoder.fit_transform(df['Geography'])
df['Gender'] = label_encoder.fit_transform(df['Gender'])

df.head()
```

Out[10]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrC
0	619.0	0	0	42.0	2.0	0.00	1.0	
1	608.0	2	0	41.0	1.0	83807.86	1.0	
2	502.0	0	0	42.0	8.0	159660.80	3.0	
3	699.0	0	0	39.0	1.0	0.00	2.0	
4	850.0	2	0	43.0	2.0	125510.82	1.0	

Summary of Data Cleaning Steps

1.Dropped irrelevant columns: `RowNumber` , `CustomerId` , `Surname`

2.Handled missing values:

- Dropped rows with missing values in critical columns
- Imputed the mode for Tenure and NumOfProducts

3.Encoded categorical variables: `Geography` , `Gender`

Final Dataframe Inspection

Let's inspect the cleaned dataframe to ensure it is ready for further analysis.

In [11]:

```
# Final inspection of the cleaned dataframe
print("Shape of the cleaned dataframe:", df.shape)
print(df.info())
print(df.describe())
print(df.head())
```

```
Shape of the cleaned dataframe: (9970, 11)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9970 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      9970 non-null   float64
```

```
 0   CreditScore      9970 non-null   float64
 1   Geography        9970 non-null   int32
 2   Gender           9970 non-null   int32
 3   Age              9970 non-null   float64
 4   Tenure           9970 non-null   float64
 5   Balance          9970 non-null   float64
 6   NumOfProducts    9970 non-null   float64
 7   HasCrCard        9970 non-null   float64
 8   IsActiveMember   9970 non-null   float64
 9   EstimatedSalary  9970 non-null   float64
 10  Exited           9970 non-null   int64
dtypes: float64(8), int32(2), int64(1)
memory usage: 856.8 KB
None
       CreditScore    Geography       Gender          Age       Tenure  \
count  9970.000000  9970.000000  9970.000000  9970.000000  9970.000000
mean    650.574925     0.746038     0.545336    38.922166     5.004313
std      96.639130     0.827538     0.497965    10.489961     2.892268
min     350.000000     0.000000     0.000000    18.000000     0.000000
25%     584.000000     0.000000     0.000000    32.000000     2.000000
50%     652.000000     0.000000     1.000000    37.000000     5.000000
75%     718.000000     1.000000     1.000000    44.000000     7.000000
max     850.000000     2.000000     1.000000    92.000000    10.000000

             Balance  NumOfProducts    HasCrCard  IsActiveMember  \
count    9970.000000    9970.000000  9970.000000     9970.000000
mean    76479.484194       1.529789     0.705617        0.514945
std     62392.191529       0.581734     0.455788        0.499802
min         0.000000       1.000000     0.000000        0.000000
25%         0.000000       1.000000     0.000000        0.000000
50%     97198.540000       1.000000     1.000000        1.000000
75%    127641.417500       2.000000     1.000000        1.000000
max    250898.090000       4.000000     1.000000        1.000000

       EstimatedSalary       Exited
count      9970.000000  9970.000000
mean     100078.574125     0.203511
std       57505.497213     0.402629
min          11.580000     0.000000
25%       51012.472500     0.000000
50%      100168.240000     0.000000
75%      149378.722500     0.000000
max      199992.480000     1.000000
   CreditScore  Geography  Gender   Age  Tenure    Balance  NumOfProducts  \
0        619.0          0       0  42.0     2.0       0.00            1.0
1        608.0          2       0  41.0     1.0   83807.86            1.0
2        502.0          0       0  42.0     8.0  159660.80            3.0
3        699.0          0       0  39.0     1.0       0.00            2.0
4        850.0          2       0  43.0     2.0  125510.82            1.0

   HasCrCard  IsActiveMember  EstimatedSalary  Exited
0        1.0             1.0        101348.88       1
1        0.0             1.0        112542.58       0
2        1.0             0.0        113931.57       1
3        0.0             0.0         93826.63       0
4        1.0             1.0         79084.10       0
```

Checking for duplicates

In [12]:
```
df.duplicated().sum()
```

Out[12]: 0

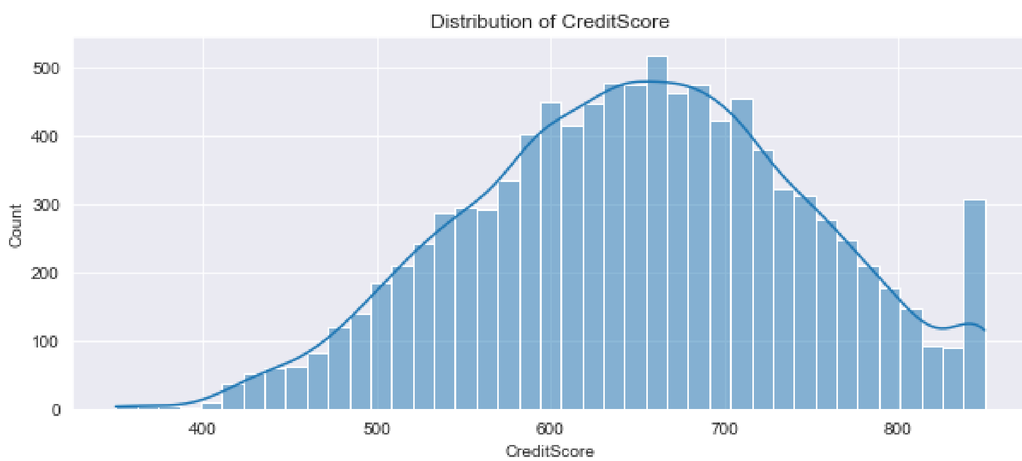
4 Exploratory Data Analysis

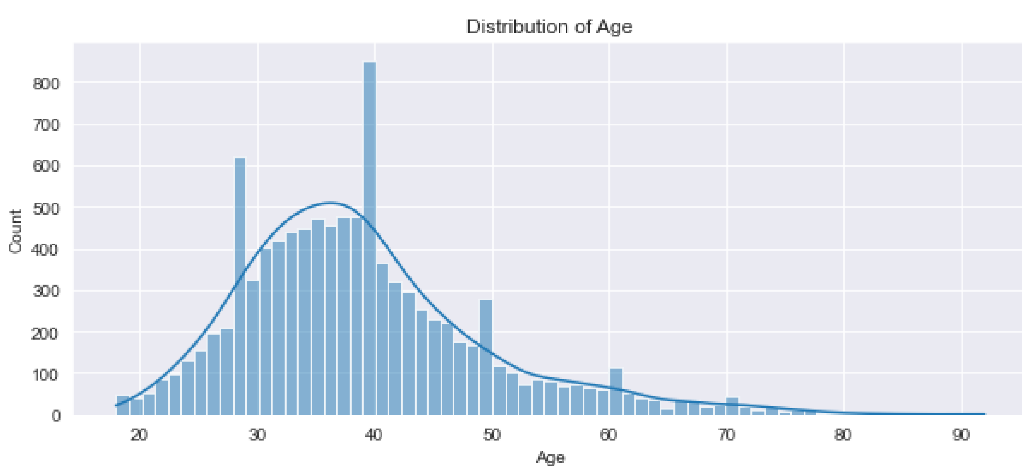
- We are to explore the impact of the columns on the exited(which is our target vairable).
- Check multicollinearity using the correltaion plot
- Check the relation of the categorical data on the customers churned(Exited).

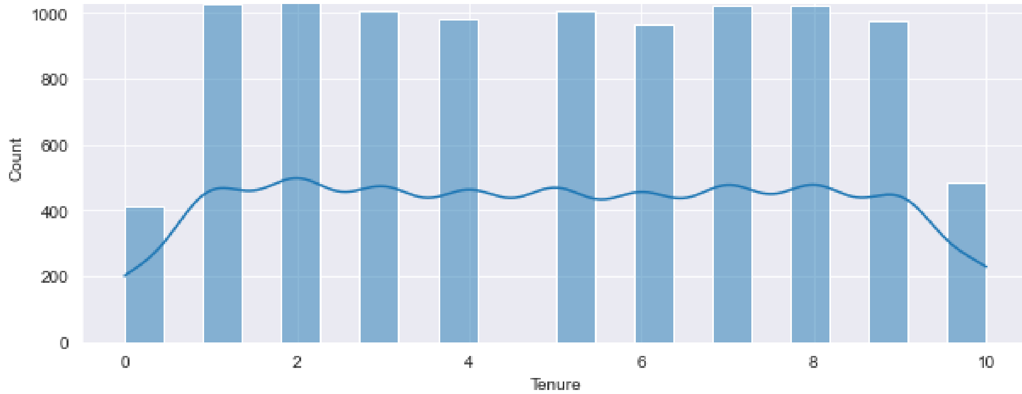
4.1 Univariate Analysis

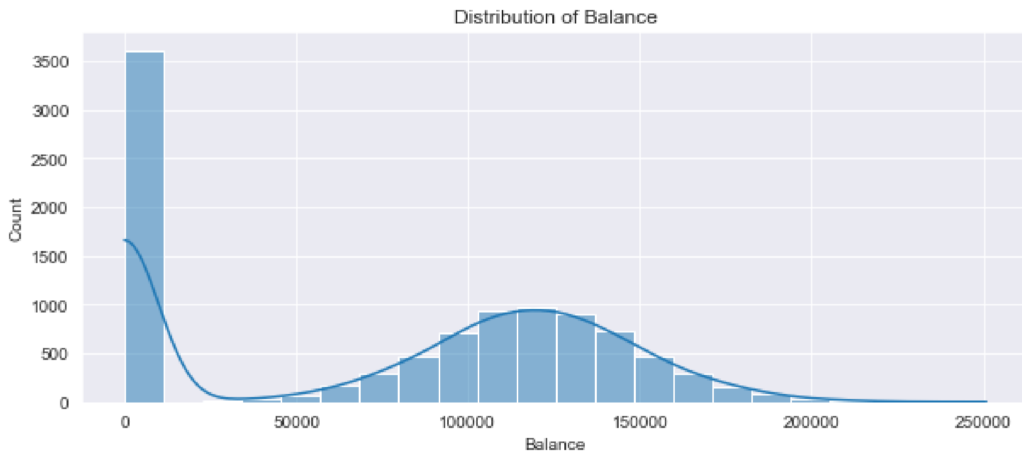
- **Distribution Plots**: Visualize the distribution of numerical features using histograms, kernel density plots, or boxplots.
- **Statistical Summary**: Compute descriptive statistics((mean, median, std, min, max) for each numerical feature.
- **Frequency Counts**: For categorical features, determine the frequency counts or proportions of each category.

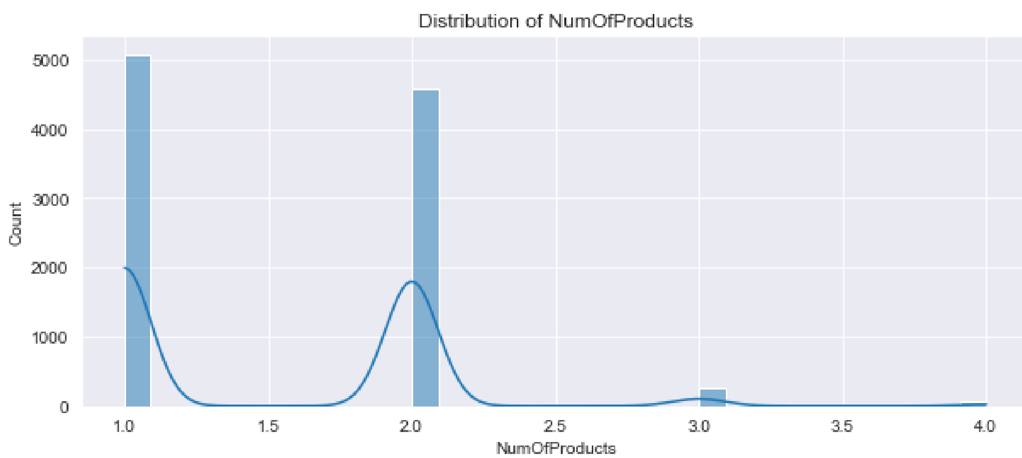
In [13]:
```
# Numerical Features
numerical_features = ['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProduct

for feature in numerical_features:
    plt.figure(figsize=(10, 4))
    sns.histplot(df[feature], kde=True)
    plt.title(f'Distribution of {feature}')
    plt.show()

# Descriptive statistics for numerical features
print(df[numerical_features].describe())
```

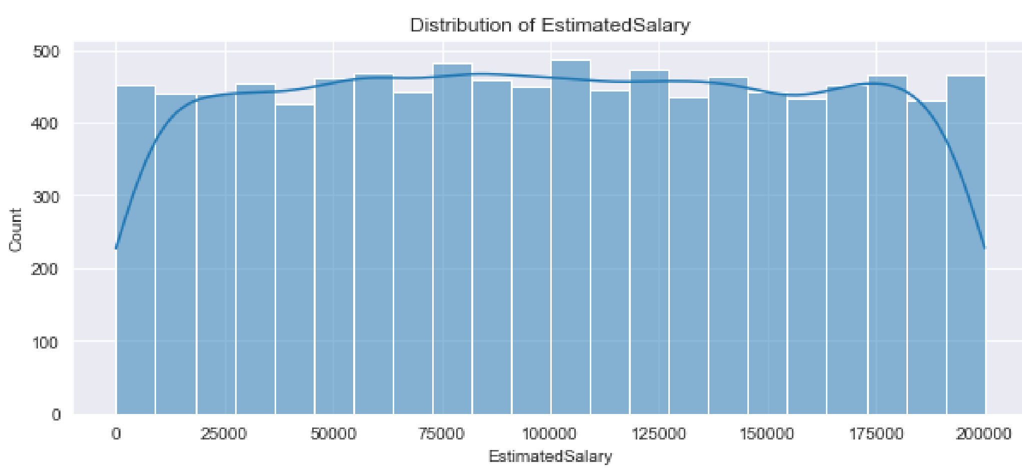










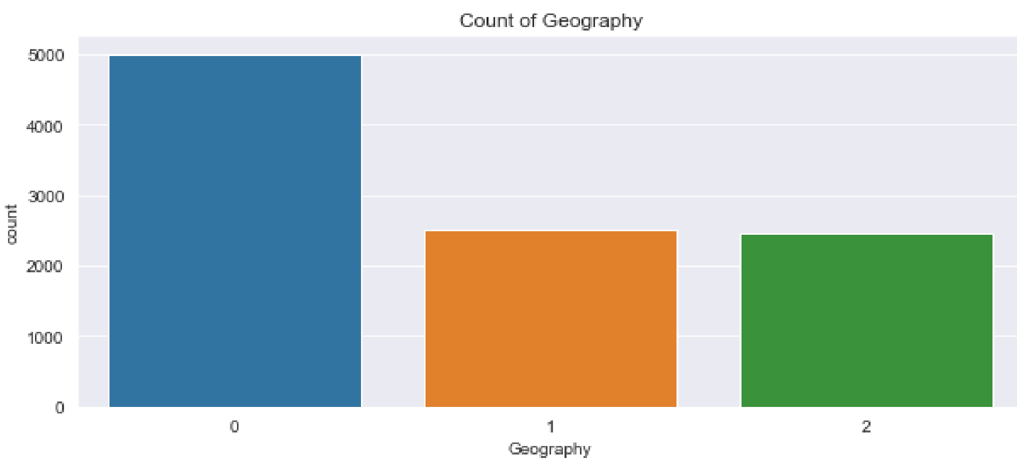


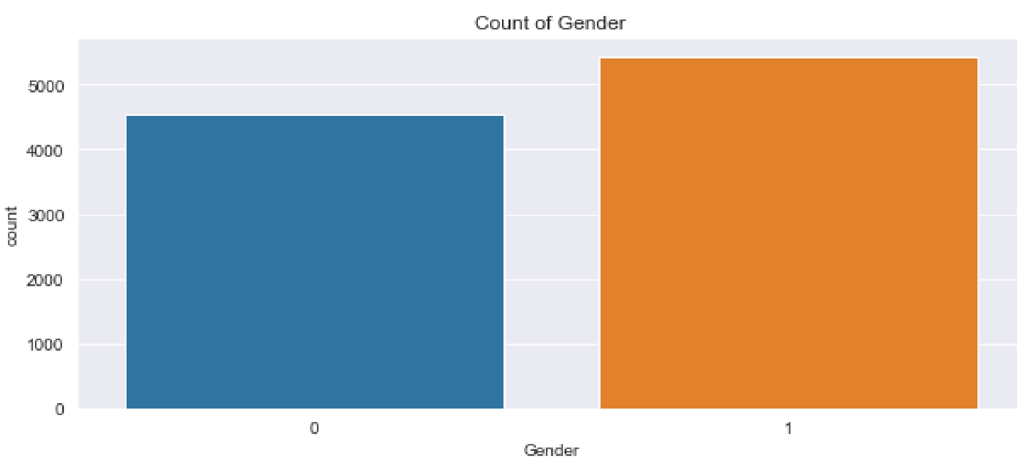

```
       CreditScore          Age       Tenure        Balance  NumOfProducts  \
count  9970.000000  9970.000000  9970.000000    9970.000000    9970.000000
mean    650.574925    38.922166     5.004313   76479.484194       1.529789
std      96.639130    10.489961     2.892268   62392.191529       0.581734
min     350.000000    18.000000     0.000000       0.000000       1.000000
```

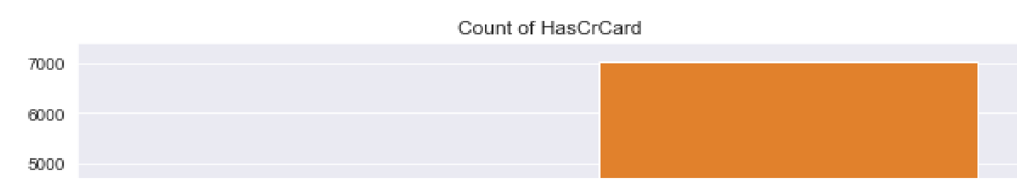
```
25%     584.000000   32.000000    2.000000       0.000000      1.000000
50%     652.000000   37.000000    5.000000   97198.540000      1.000000
75%     718.000000   44.000000    7.000000  127641.417500      2.000000
max     850.000000   92.000000   10.000000  250898.090000      4.000000

       EstimatedSalary
count      9970.000000
mean     100078.574125
std       57505.497213
min          11.580000
25%       51012.472500
50%      100168.240000
75%      149378.722500
max      199992.480000
```

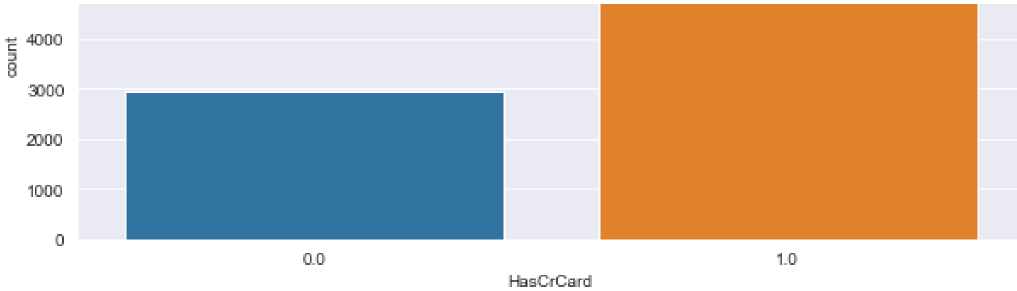
In [14]:

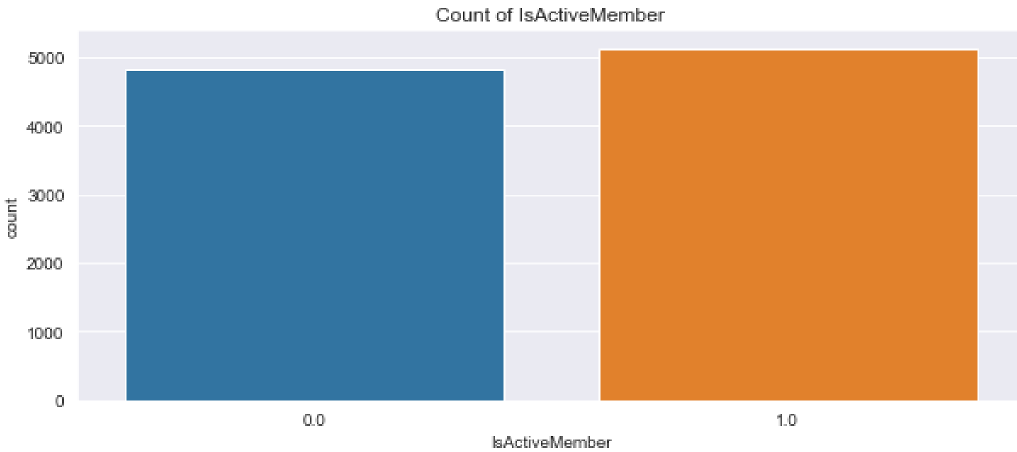
```python
# Categorical Features
categorical_features = ['Geography', 'Gender', 'HasCrCard', 'IsActiveMember',

for feature in categorical_features:
    plt.figure(figsize=(10, 4))
    sns.countplot(x=df[feature])
    plt.title(f'Count of {feature}')
    plt.show()

# Descriptive statistics for categorical features
print(df[categorical_features].describe())
```

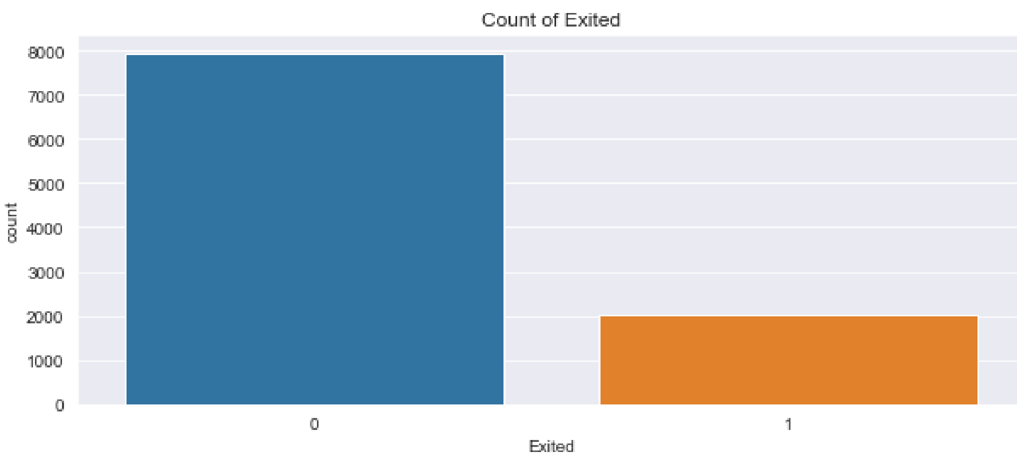












	Geography	Gender	HasCrCard	IsActiveMember	Exited
count	9970.000000	9970.000000	9970.000000	9970.000000	9970.000000
mean	0.746038	0.545336	0.705617	0.514945	0.203511
std	0.827538	0.497965	0.455788	0.499802	0.402629
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	1.000000	1.000000	1.000000	0.000000
75%	1.000000	1.000000	1.000000	1.000000	0.000000
max	2.000000	1.000000	1.000000	1.000000	1.000000

4.2 Bivariate Analysis:

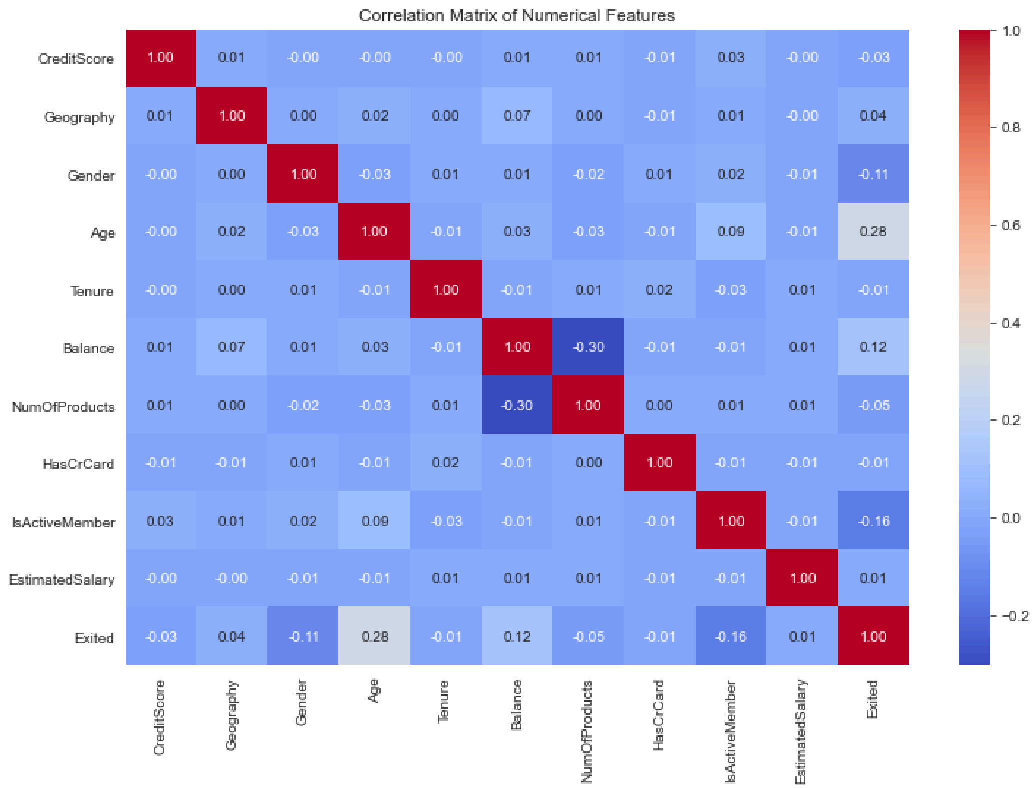
- Correlation Analysis

To compute and visualize the correlation between numerical features, we use a correlation matrix and a heatmap.# Compute the correlation matrix

In [15]:

```
correlation_matrix = df.corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
```

```
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```



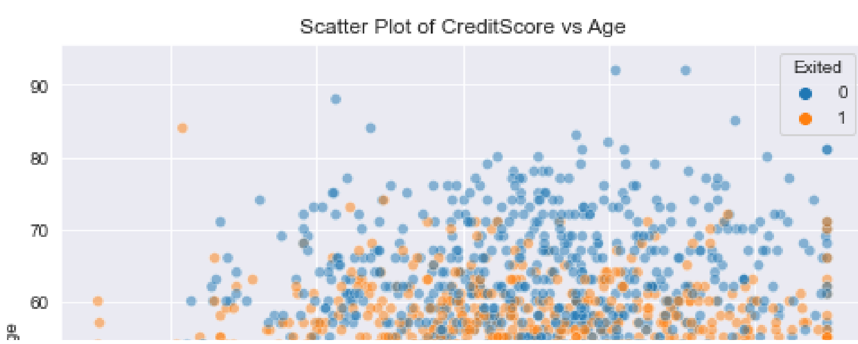
Observation

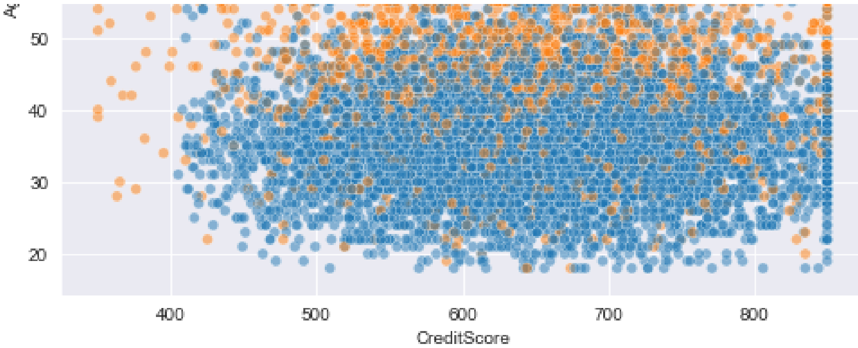
From the visual heatmap there is no multicollinearity in the dataset.

- **Scatter Plots**

Scatter plots help explore the relationship between pairs of numerical features.

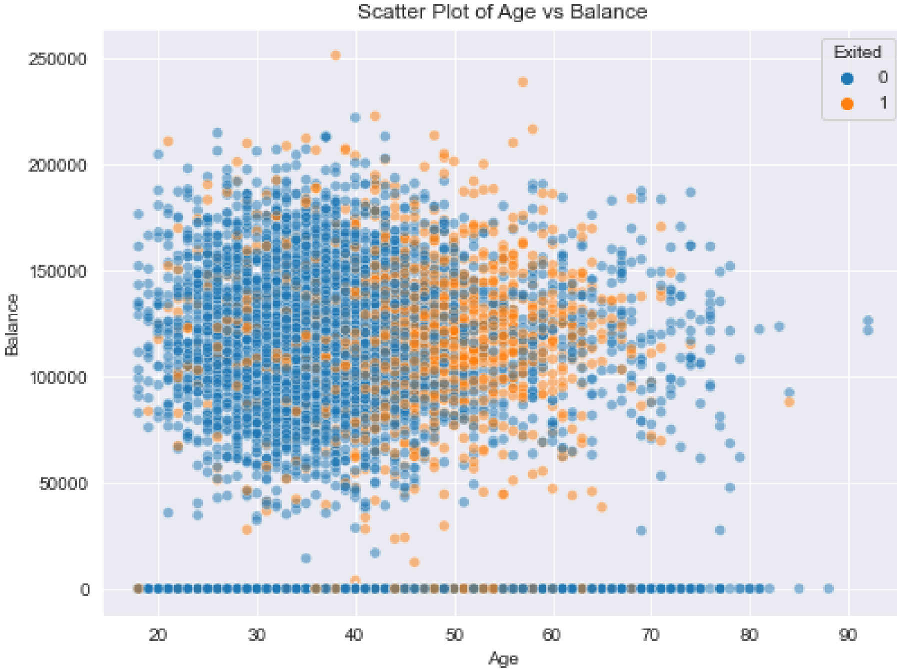
In [16]:
```
# List of numerical feature pairs to plot
numerical_pairs = [('CreditScore', 'Age'),
                   ('CreditScore', 'Balance'),
                   ('Age', 'Balance'),
                   ('Tenure', 'Balance')]

# Plot scatter plots for each pair
for x, y in numerical_pairs:
    plt.figure(figsize=(8, 6))
    sns.scatterplot(data=df, x=x, y=y, hue='Exited', alpha=0.5)
    plt.title(f'Scatter Plot of {x} vs {y}')
    plt.show()
```



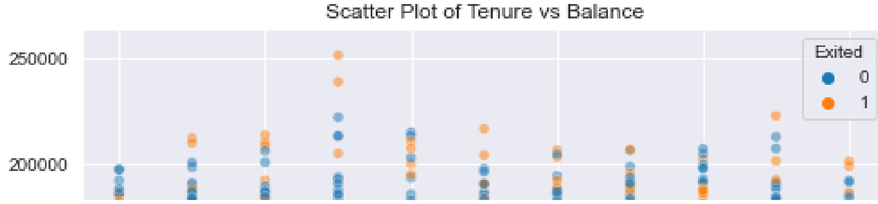


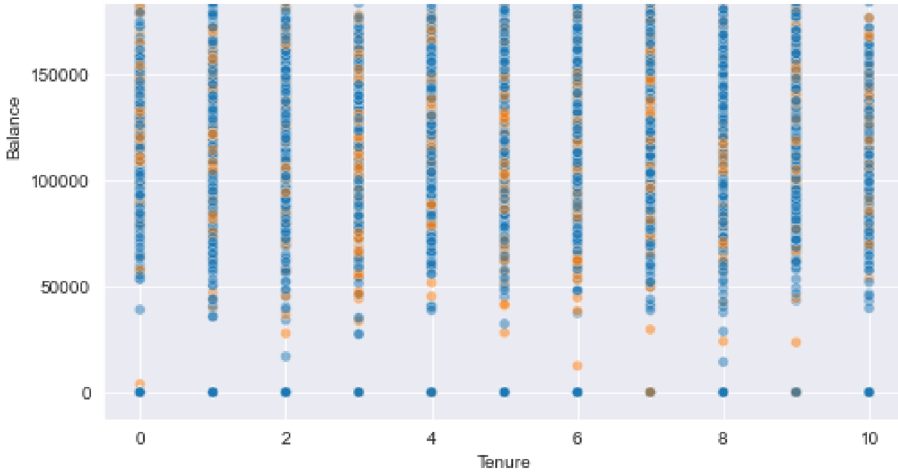
Scatter Plot of CreditScore vs Balance

Scatter Plot of Age vs Balance



Scatter Plot of Tenure vs Balance



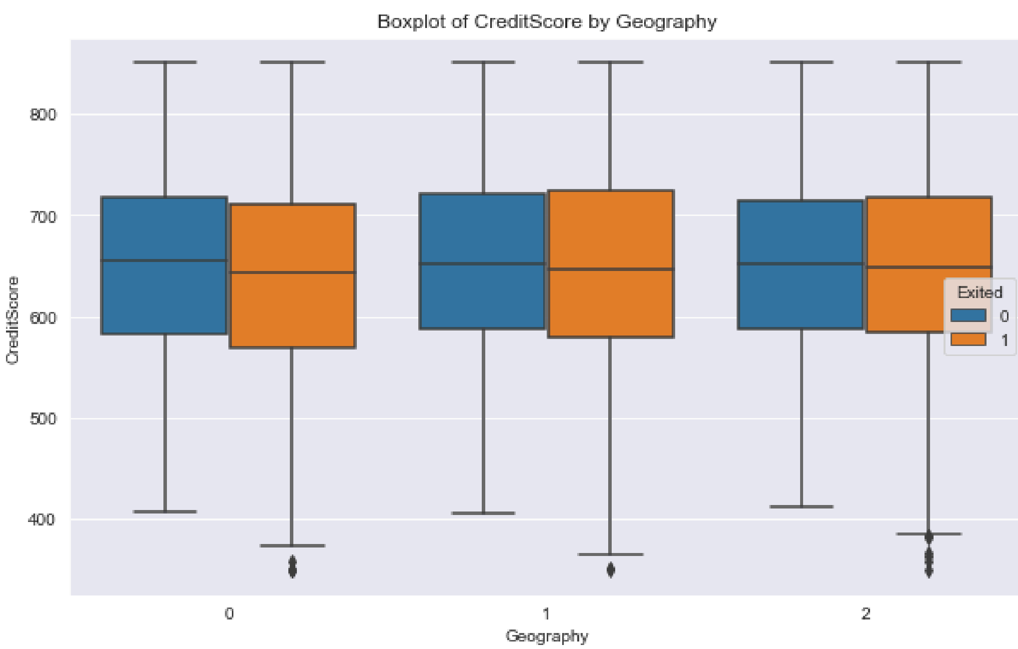


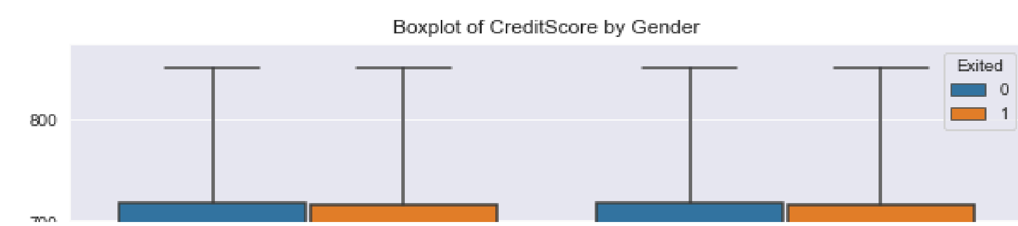
- **Boxplots/Barplots**

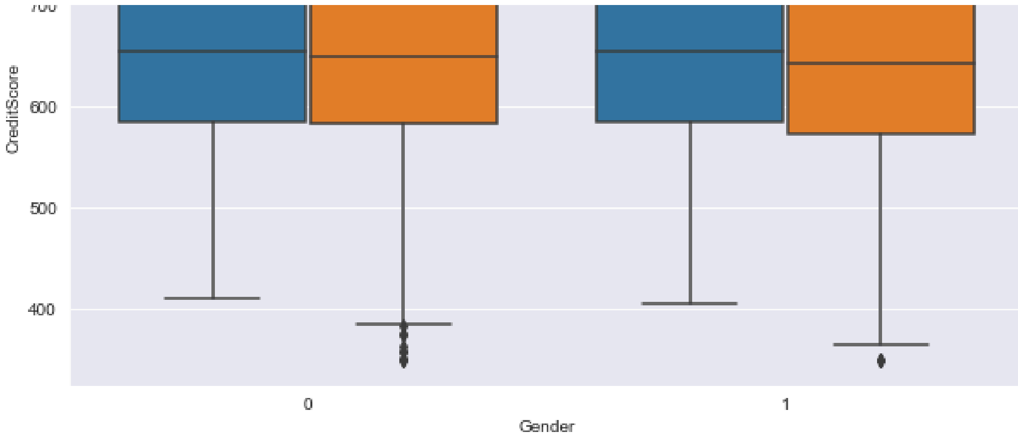
Boxplots and barplots compare the distribution of numerical features across different categories of categorical features.

In [17]:

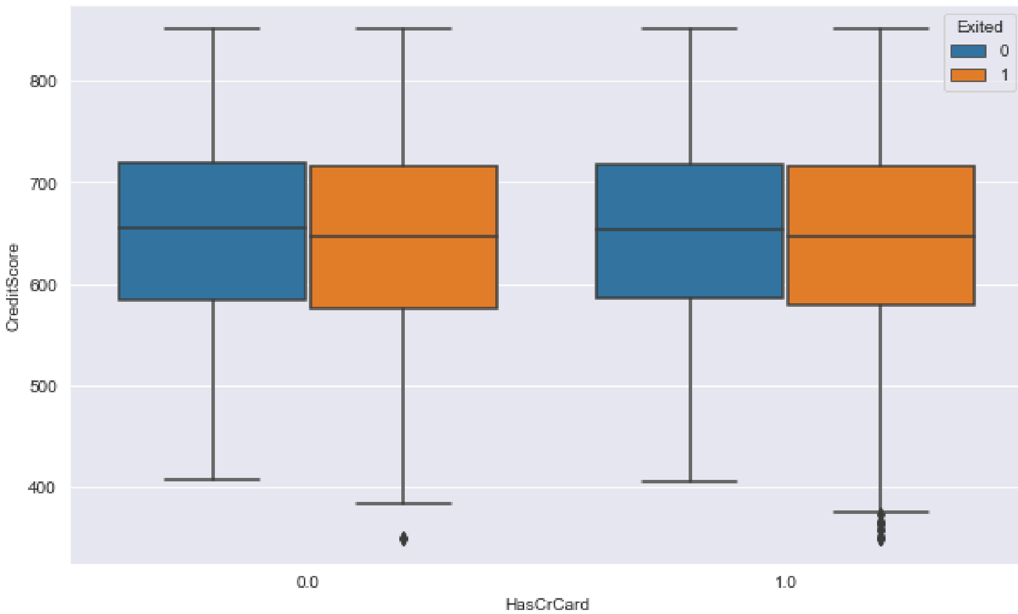
```
# List of numerical features and categorical features to plot
numerical_features = ['CreditScore', 'Age', 'Balance', 'EstimatedSalary']
categorical_features = ['Geography', 'Gender', 'HasCrCard', 'IsActiveMember']

# Plot boxplots for each numerical feature by each categorical feature
for num_feature in numerical_features:
    for cat_feature in categorical_features:
        plt.figure(figsize=(10, 6))
        sns.boxplot(data=df, x=cat_feature, y=num_feature, hue='Exited')
        plt.title(f'Boxplot of {num_feature} by {cat_feature}')
        plt.show()
```



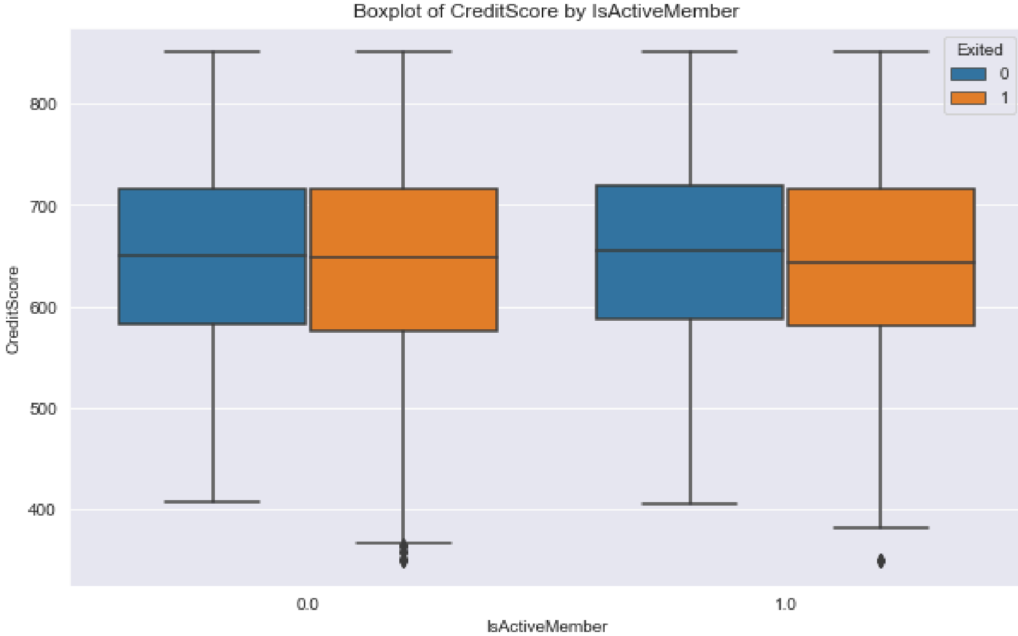




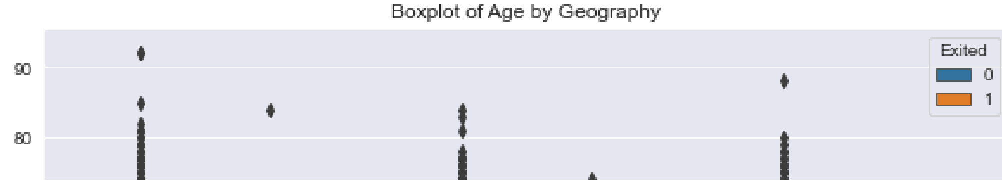
Boxplot of CreditScore by HasCrCard

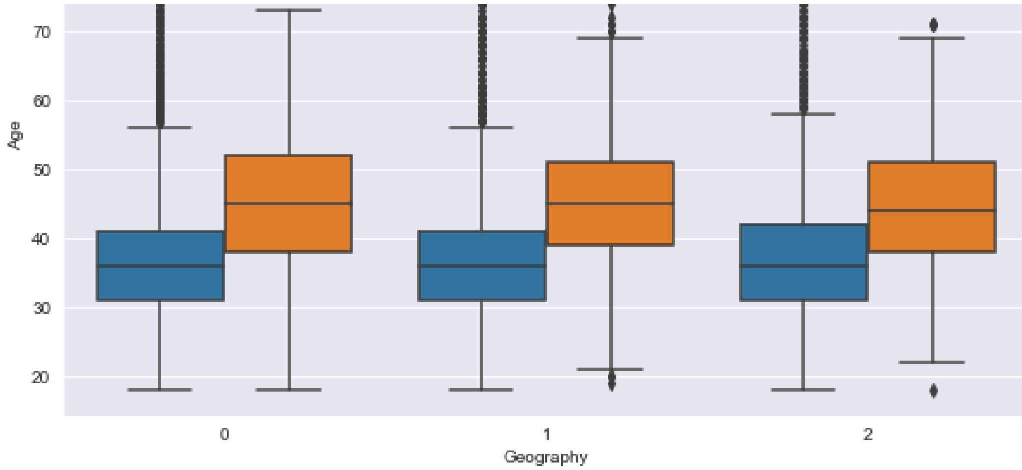


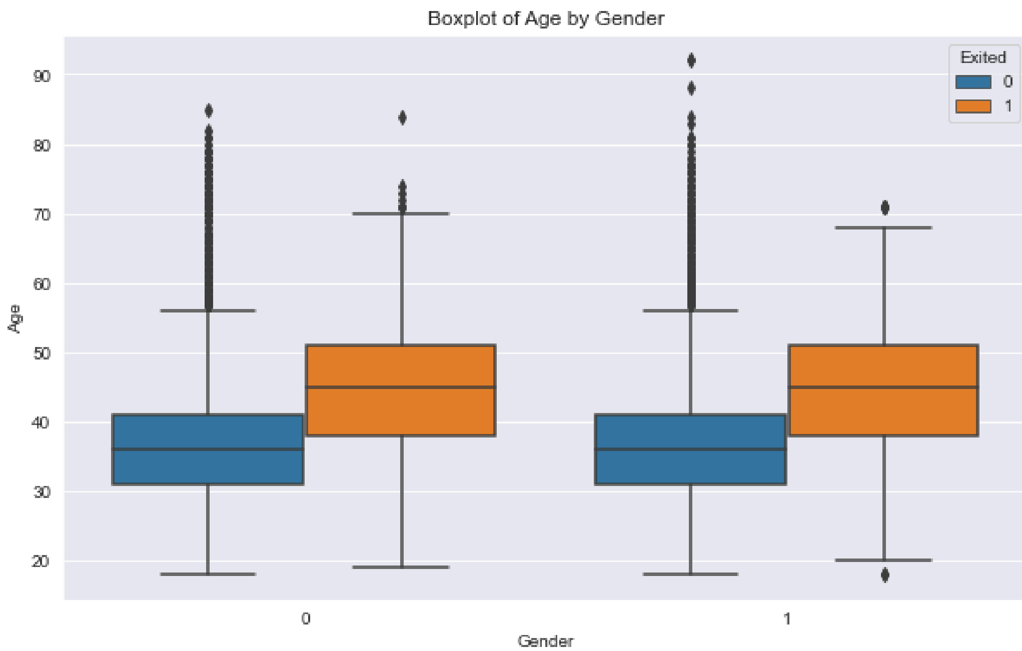
Boxplot of CreditScore by IsActiveMember

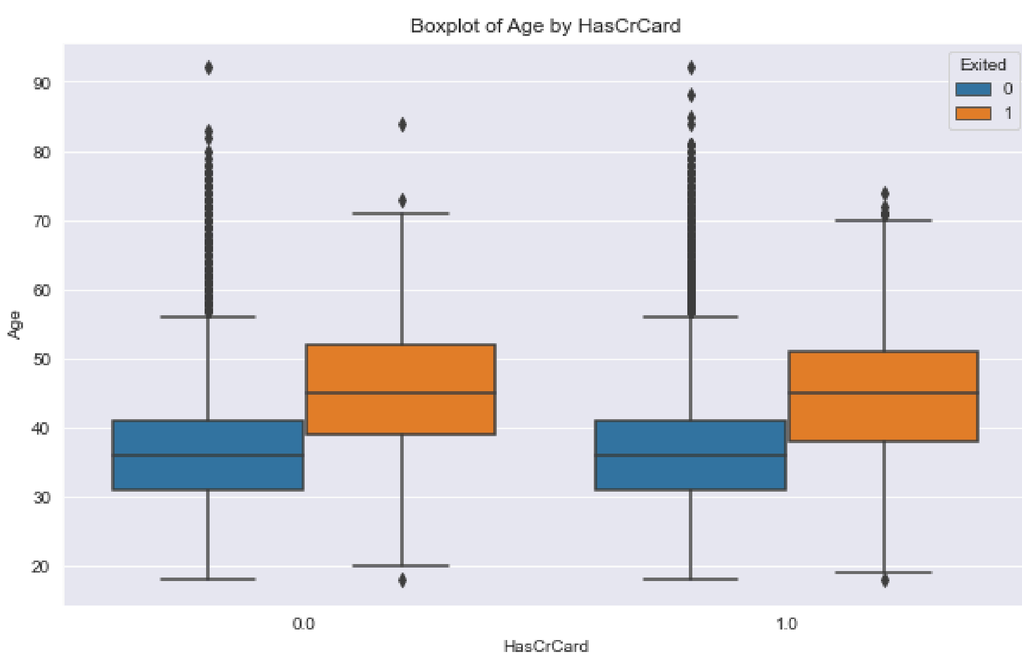


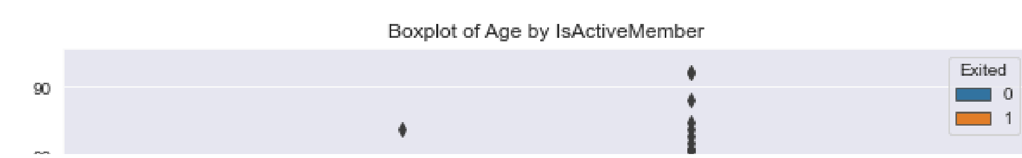
Boxplot of Age by Geography

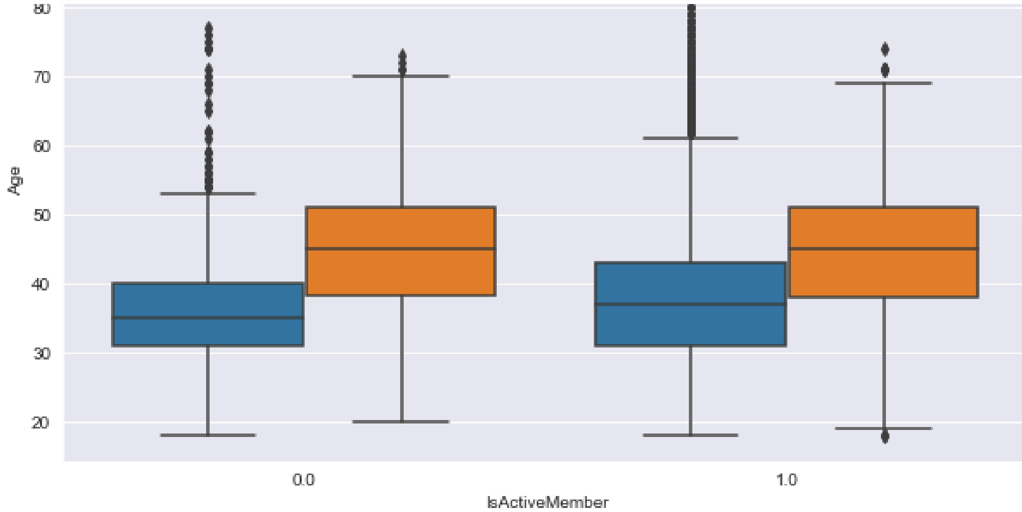



Age
70
60
50
40
30
20
0
1
2
Geography

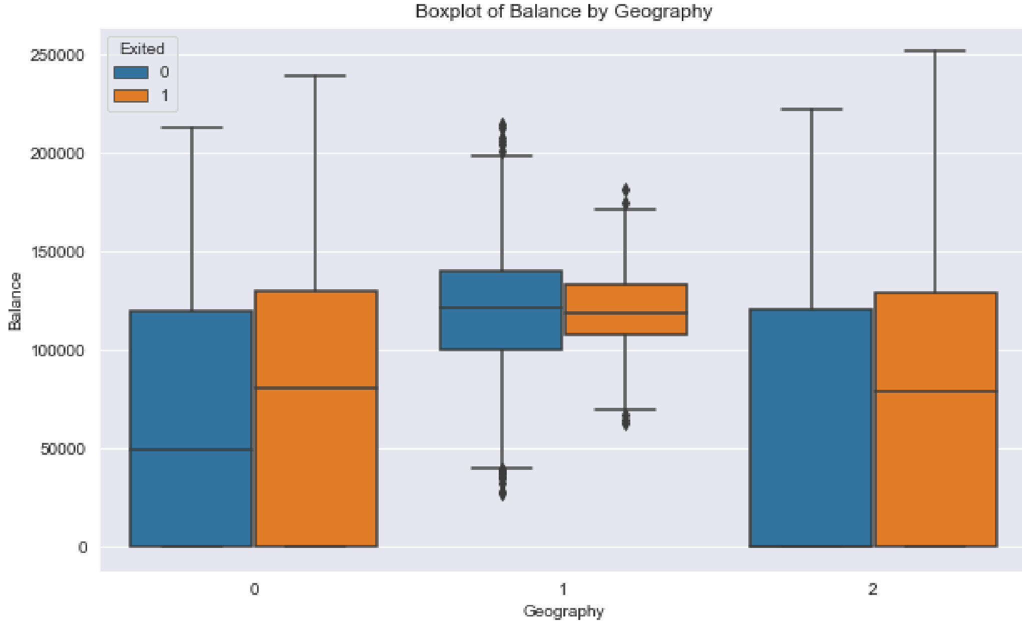

Boxplot of Age by Gender
Exited
0
1
Age
90
80
70
60
50
40
30
20
0
1
Gender


Boxplot of Age by HasCrCard
Exited
0
1
Age
90
80
70
60
50
40
30
20
0.0
1.0
HasCrCard

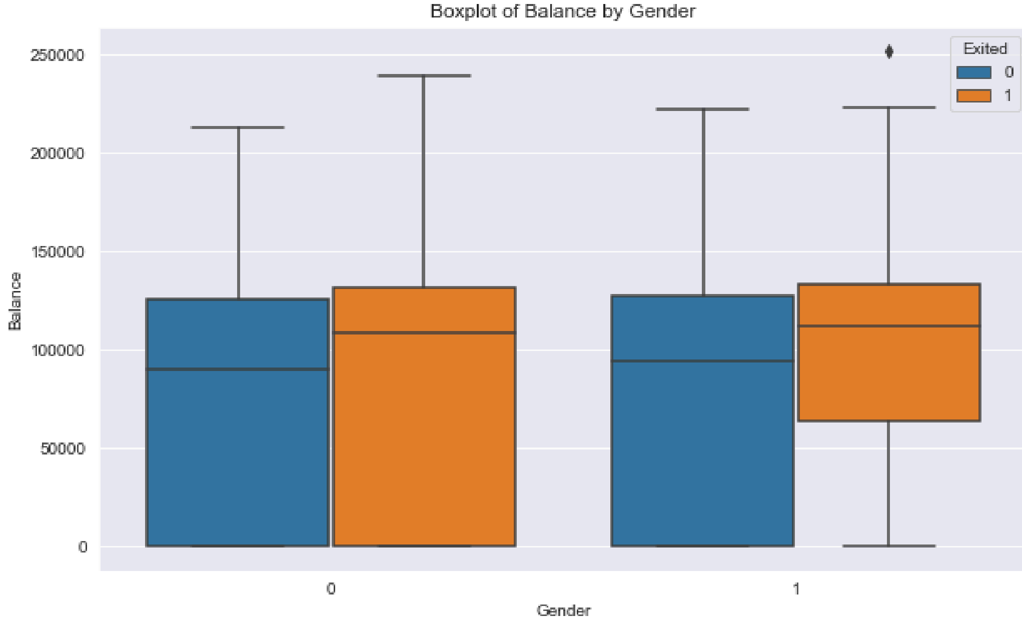

Boxplot of Age by IsActiveMember
Exited
0
1
90



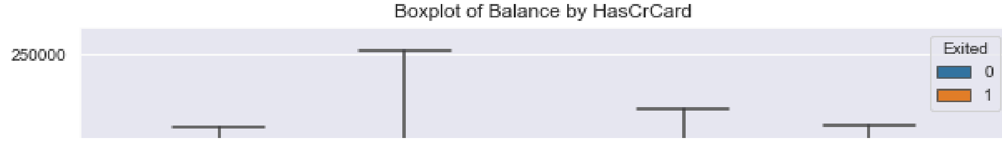
Boxplot of Balance by Geography

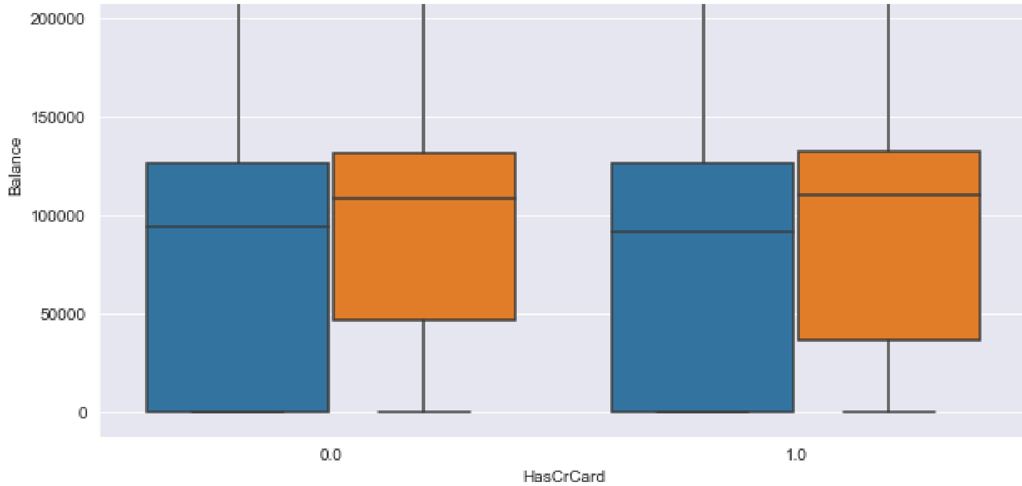


Boxplot of Balance by Gender

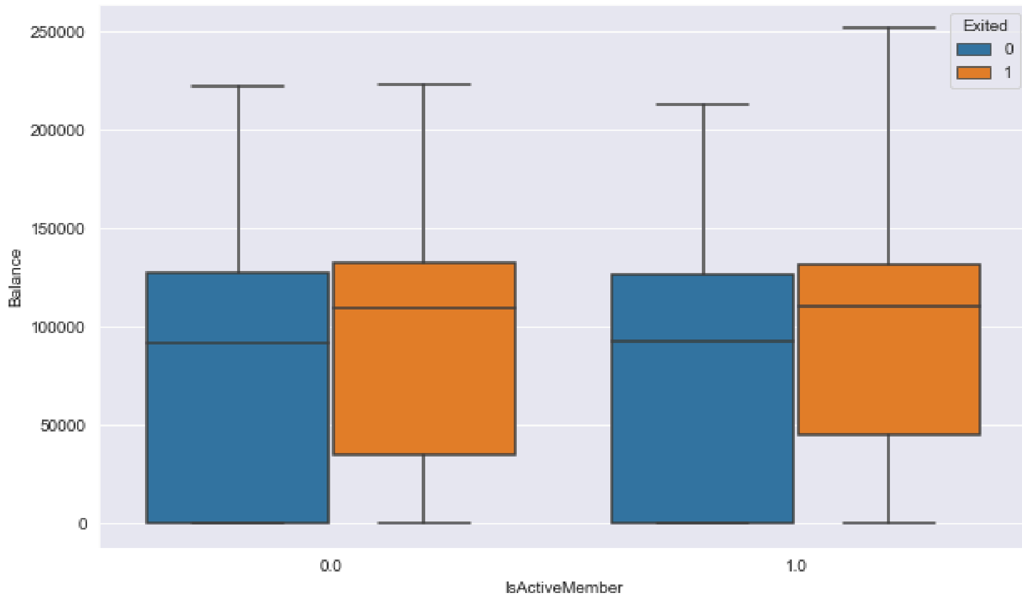


Boxplot of Balance by HasCrCard

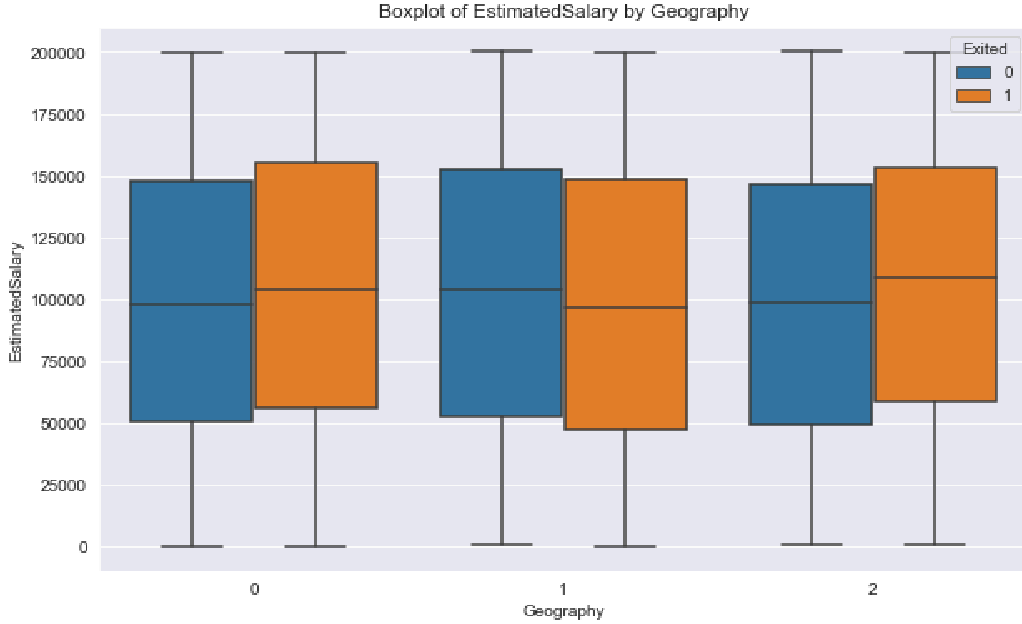




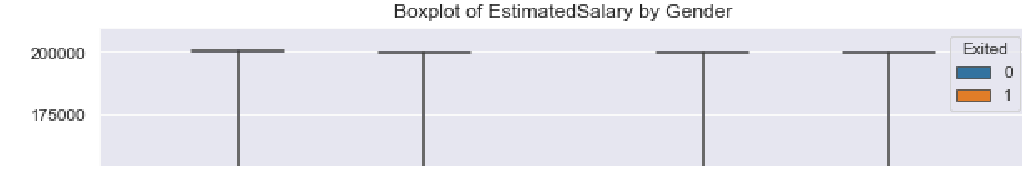
Boxplot of Balance by IsActiveMember

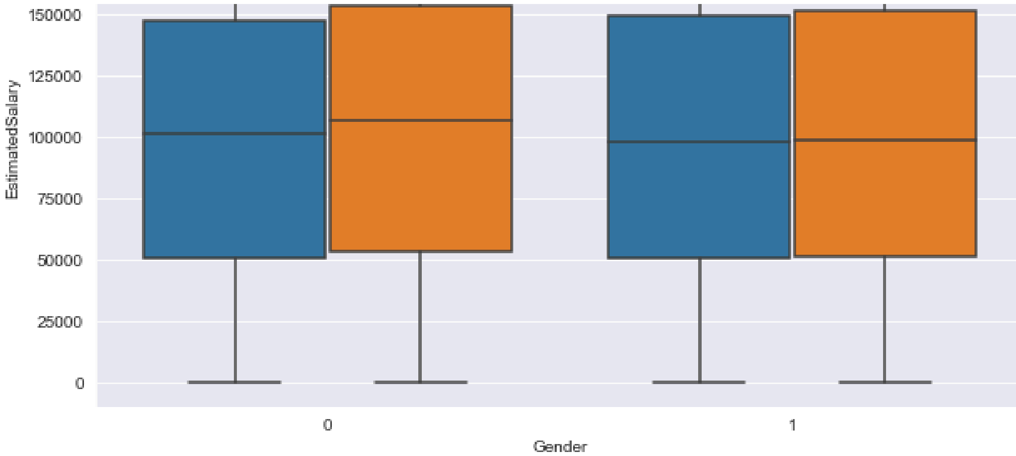


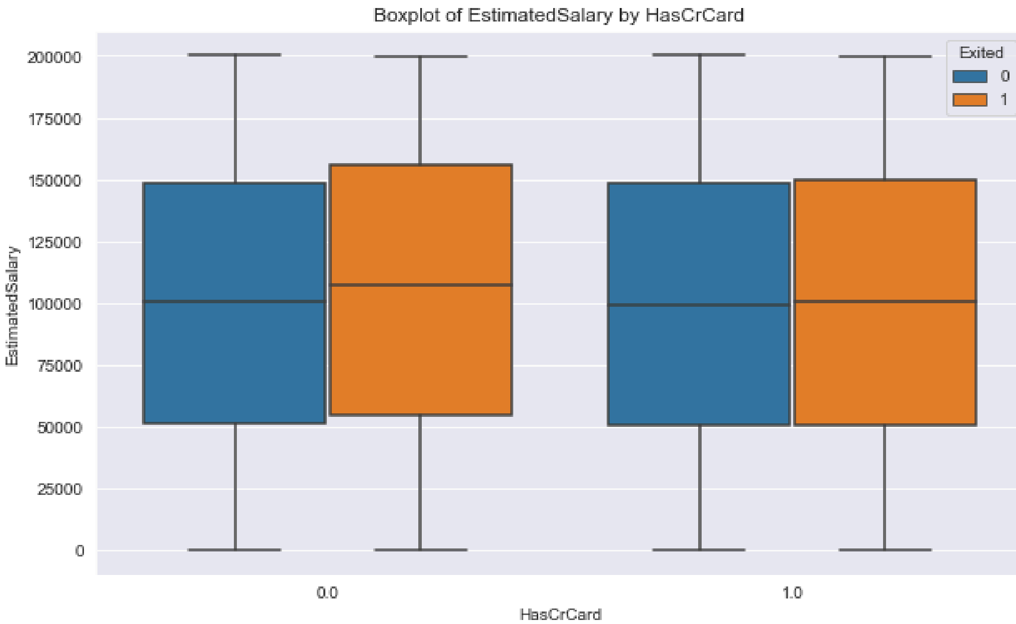
Boxplot of EstimatedSalary by Geography

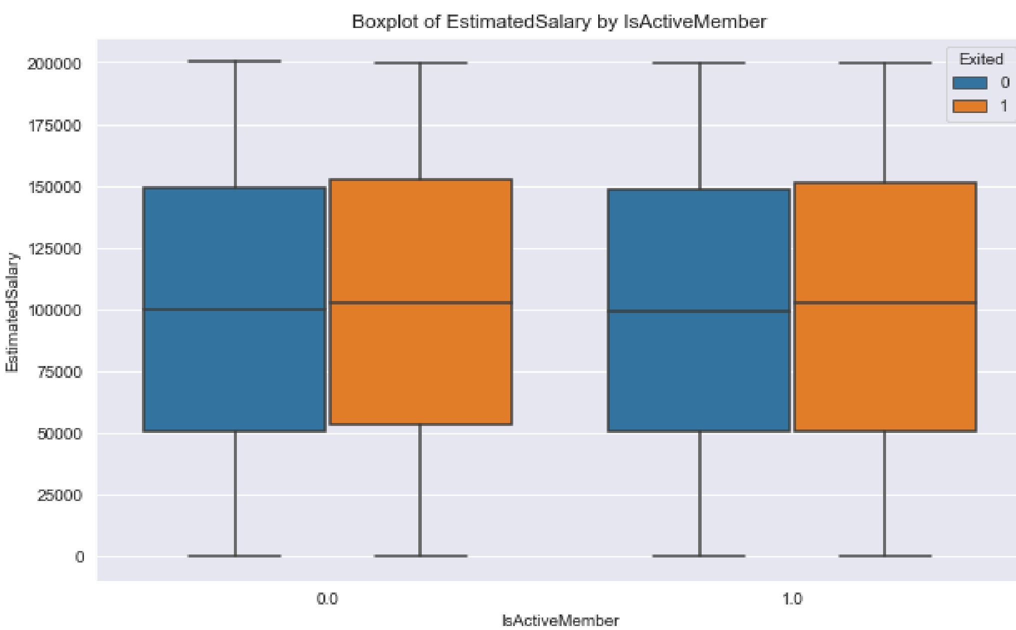


Boxplot of EstimatedSalary by Gender





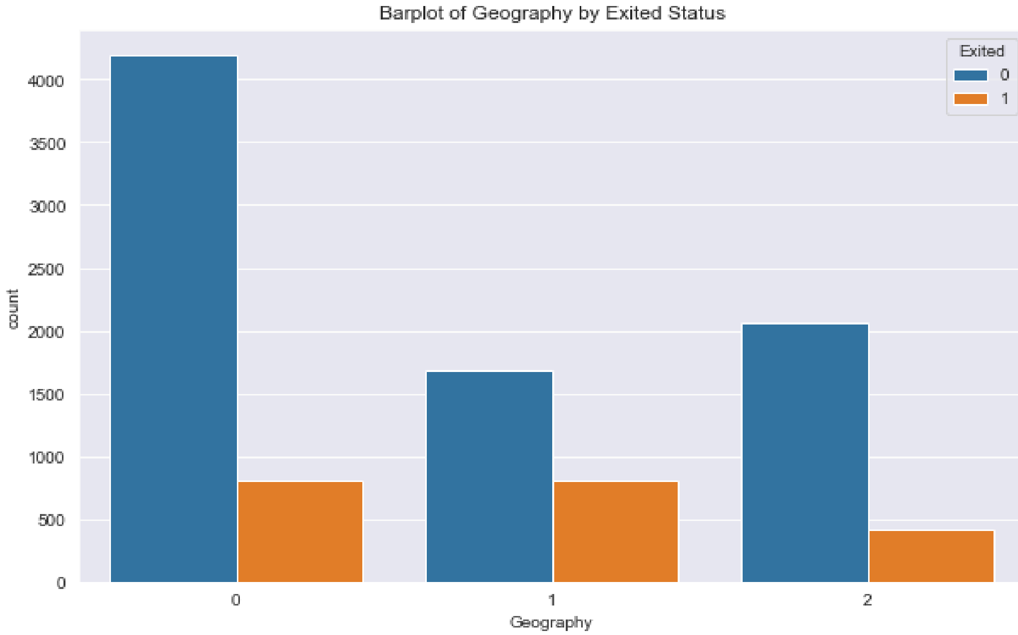


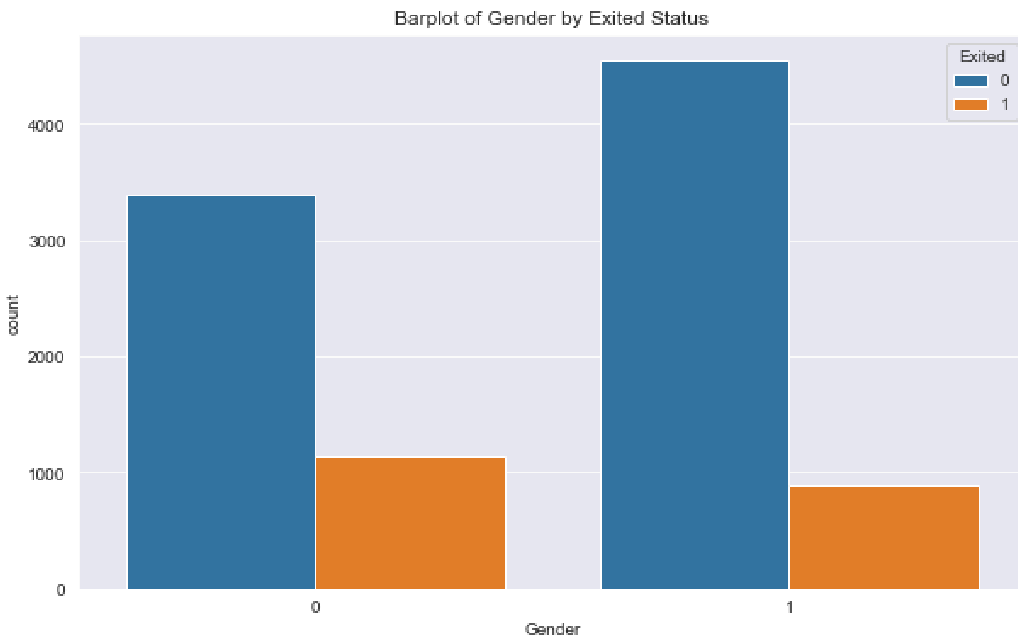


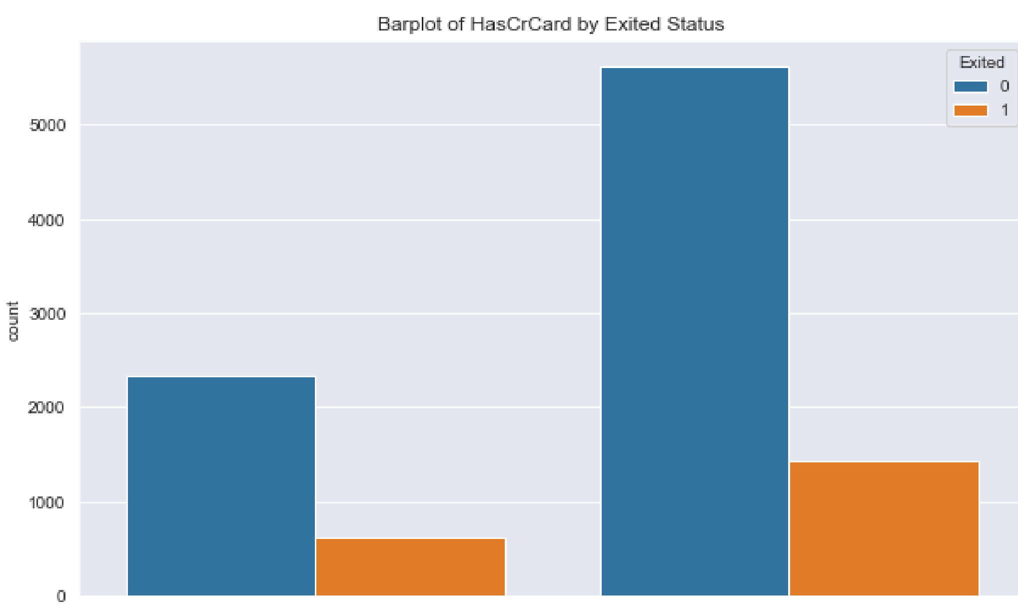
In [18]:

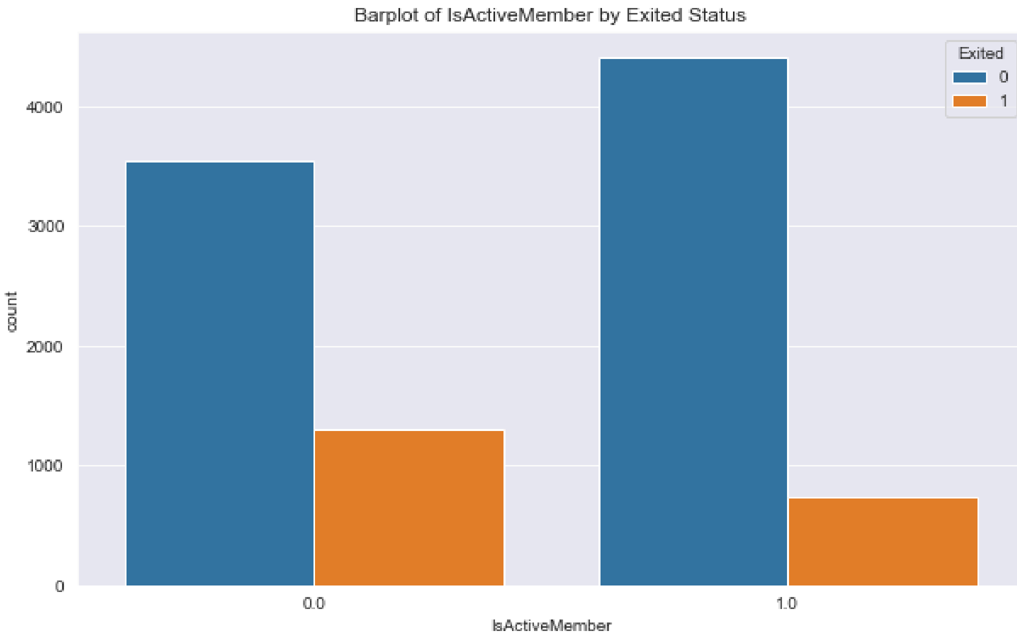
```
# Plot barplots for each categorical feature by Exited status
for cat_feature in categorical_features:
    plt.figure(figsize=(10, 6))
    sns.countplot(data=df, x=cat_feature, hue='Exited')
    plt.title(f'Barplot of {cat_feature} by Exited Status')
    plt.show()
```

```
plt.show()
```


Barplot of Geography by Exited Status
Exited
0
1
count
4000
3500
3000
2500
2000
1500
1000
500
0
0
1
2
Geography


Barplot of Gender by Exited Status
Exited
0
1
count
4000
3000
2000
1000
0
0
1
Gender


Barplot of HasCrCard by Exited Status
Exited
0
1
count
5000
4000
3000
2000
1000
0



Observations

- Older customers are more likely to churn
- Customers with higher balances show a higher churn rate.
- Higher churn rate in Germany compared to France and Spain.
- Inactive members have a significantly higher churn rate.
- Customers without credit cards have a slightly higher churn rate.

5 Hypothesis Testing

To explore the potential impact and significance of the credit score on churning behavior, we will perform a hypothesis test.

We will focus on the credit score column for customer churning to explore the potential impact and significance of credit score on churning behavior.

- Hypothesis: Higher credit scores are associated with lower churn rates
- Null Hypothesis(Ho): Credit scores have no effect on customer churn rates
- Alternative hypothesis(H1): Higher credit are associated with lower church rates

In [19]:

```
# Split the dataset into churned and not churned customers
churned = df[df['Exited'] == 1]['CreditScore']
not_churned = df[df['Exited'] == 0]['CreditScore']

# Perform an independent t-test
t_stat, p_value = stats.ttest_ind(churned, not_churned)

print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

# Determine significance level (e.g., 0.05)
alpha = 0.05

# Check if p-value is less than alpha
if p_value < alpha:
```

```
    print("Reject null hypothesis: There is a significant difference in credit
else:
    print("Fail to reject null hypothesis: There is no significant difference
```

```
T-statistic: -2.7001283821774225
P-value: 0.006942974282592945
Reject null hypothesis: There is a significant difference in credit scores betwe
en churned and not churned customers.
```

5.1 Dealing with categorical data

We will hot encode Gender and Geography columns.

In [20]:
```
# Let's create a copy of the dataframe to keep the original intact
clean_data = df.copy()

# Perform one-hot encoding for 'Gender' column
gender_encoded = pd.get_dummies(clean_data['Gender'], prefix='Gender', drop_fi
clean_data = pd.concat([clean_data, gender_encoded], axis=1)
clean_data.drop('Gender', axis=1, inplace=True)

# Perform one-hot encoding for 'Geography' column
geography_encoded = pd.get_dummies(clean_data['Geography'], prefix='Geography'
clean_data = pd.concat([clean_data, geography_encoded], axis=1)
clean_data.drop('Geography', axis=1, inplace=True)
```

In [21]:
```
clean_data.head()
```

Out[21]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember
0	619.0	42.0	2.0	0.00	1.0	1.0	1.0
1	608.0	41.0	1.0	83807.86	1.0	0.0	1.0
2	502.0	42.0	8.0	159660.80	3.0	1.0	0.0
3	699.0	39.0	1.0	0.00	2.0	0.0	0.0
4	850.0	43.0	2.0	125510.82	1.0	1.0	1.0

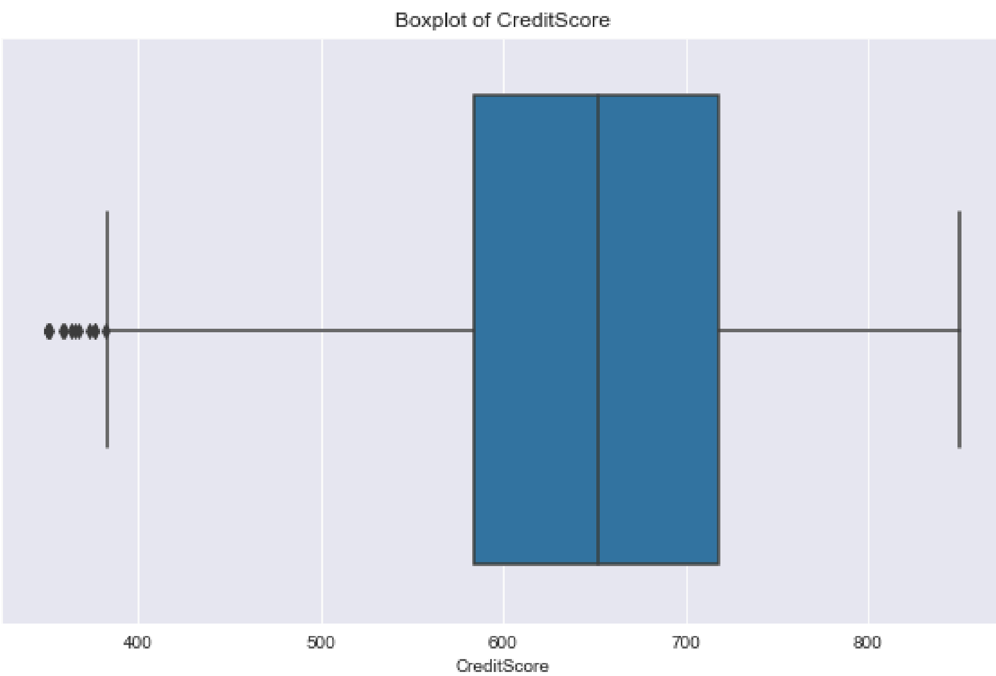
In [22]:
```
clean_data.shape
```

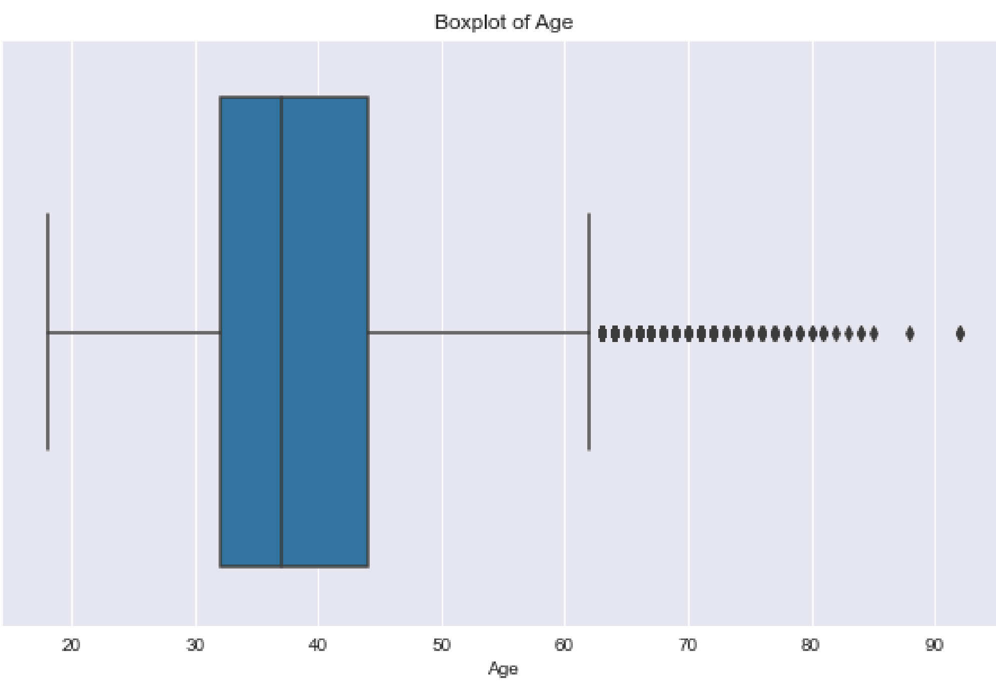
Out[22]: (9970, 12)

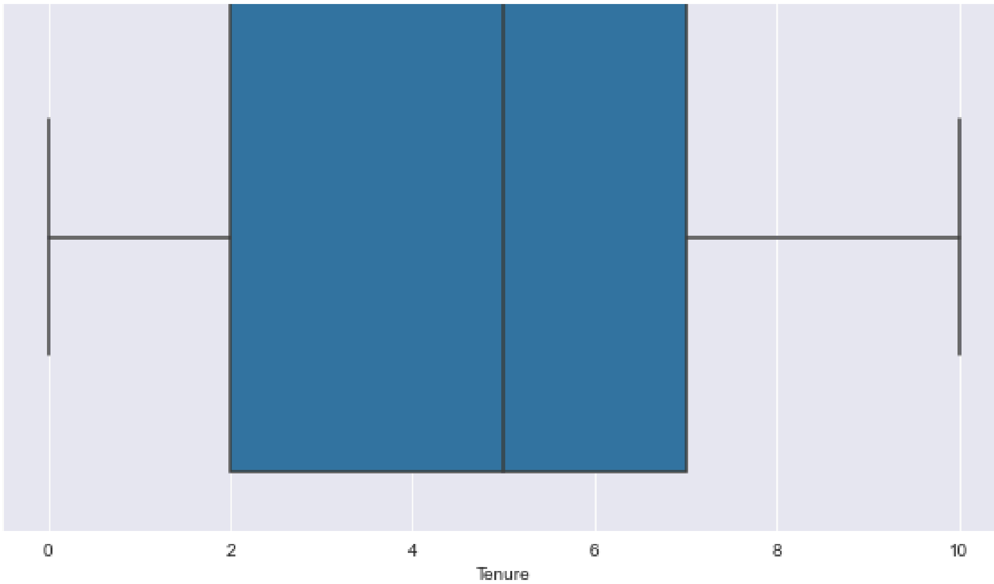
5.2 Check for outliers

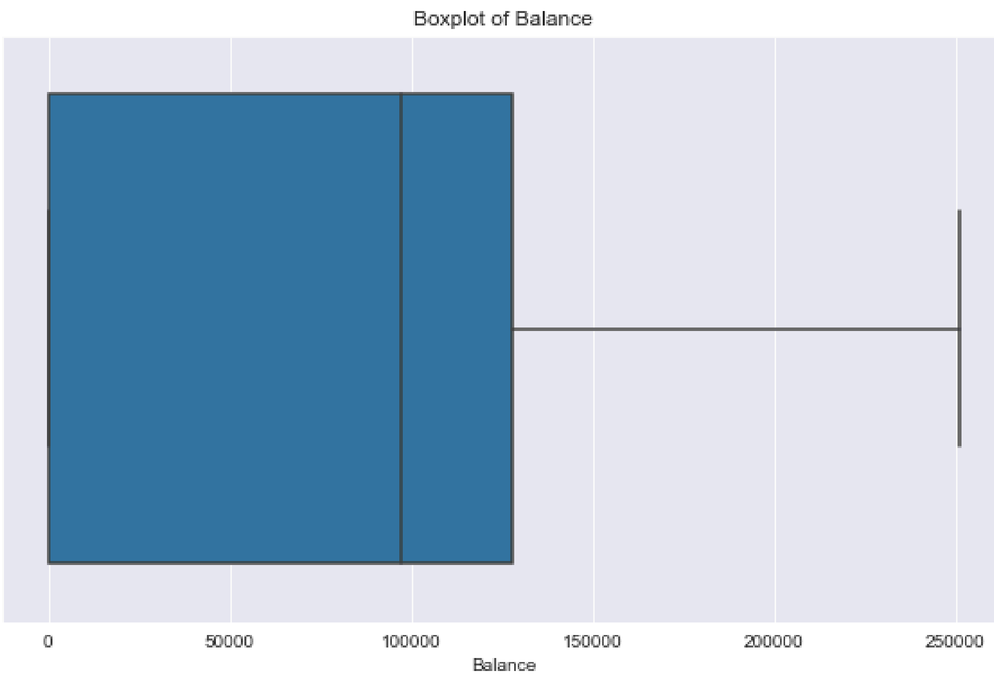
In [23]:
```
# Plot boxplots for each numerical feature
numerical_features = ['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProduct

for feature in numerical_features:
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=clean_data, x=feature)
    plt.title(f'Boxplot of {feature}')
    plt.show()

# Calculate Z-scores for numerical features
z_scores = np.abs(zscore(clean_data[numerical_features]))
```

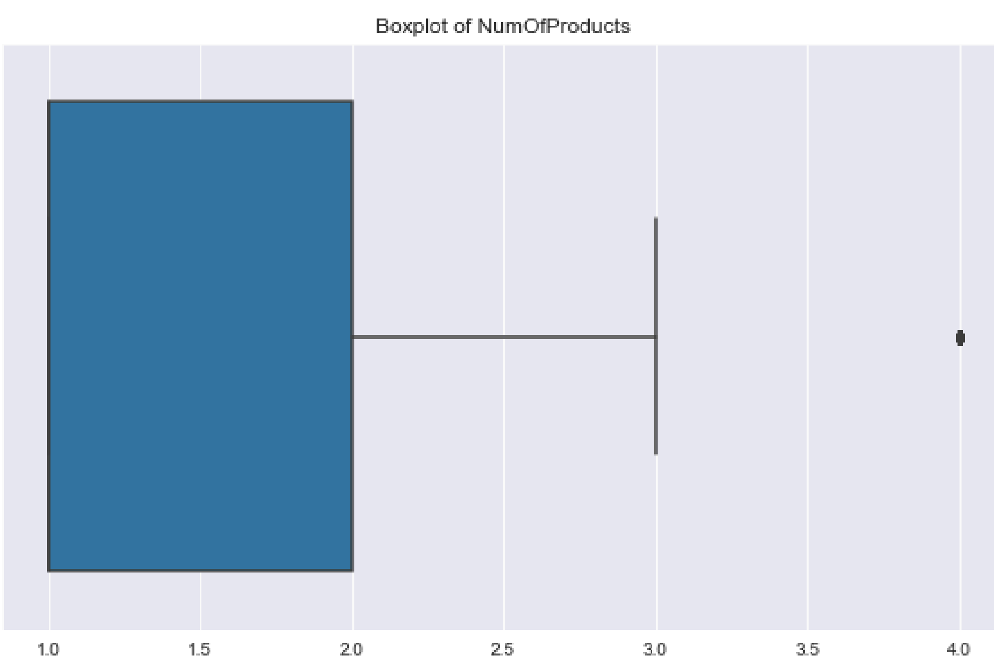
```python
# Define a threshold for identifying outliers
threshold = 3

# Identify outliers
outliers = np.where(z_scores > threshold)

# Print the indices of the outliers
print("Indices of outliers:")
print(outliers)

# Print the outlier data points
outlier_rows = clean_data.iloc[outliers[0]]
print("Outlier data points:")
print(outlier_rows)
```

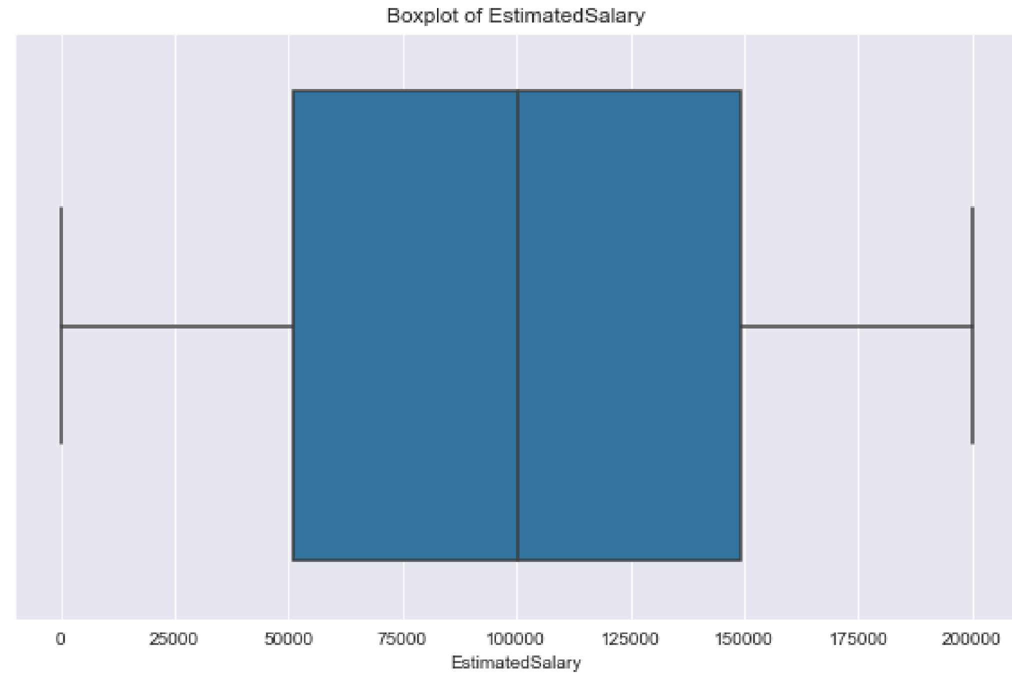





0
2
4
6
8
10
Tenure


Boxplot of Balance
0
50000
100000
150000
200000
250000
Balance


Boxplot of NumOfProducts
1.0
1.5
2.0
2.5
3.0
3.5
4.0




```
Indices of outliers:
(array([   7,   70,   85,  157,  229,  251,  309,  370,  601,  765,  887,
       1008, 1038, 1054, 1204, 1253, 1341, 1404, 1409, 1468, 1487, 1613,
       1629, 1697, 1786, 1833, 1871, 1928, 1957, 1997, 2006, 2102, 2118,
       2152, 2157, 2189, 2277, 2423, 2448, 2451, 2462, 2488, 2498, 2530,
       2542, 2602, 2605, 2760, 2766, 2843, 2860, 2889, 2912, 3020, 3097,
       3129, 3139, 3297, 3303, 3350, 3351, 3363, 3367, 3372, 3381, 3483,
       3515, 3585, 3634, 3674, 3684, 3793, 3806, 3821, 3860, 3868, 3974,
       3993, 3994, 4142, 4146, 4236, 4240, 4253, 4298, 4346, 4358, 4383,
       4481, 4491, 4496, 4569, 4584, 4621, 4631, 4725, 4778, 4792, 4799,
       4809, 4907, 4986, 5044, 5113, 5173, 5199, 5211, 5275, 5289, 5353,
       5362, 5466, 5484, 5640, 5647, 5676, 5759, 5816, 5880, 5933, 6092,
       6126, 6143, 6148, 6149, 6206, 6254, 6255, 6342, 6419, 6506, 6557,
       6697, 6726, 6735, 6851, 7033, 7034, 7039, 7178, 7219, 7233, 7248,
       7278, 7338, 7351, 7433, 7475, 7499, 7502, 7528, 7543, 7668, 7674,
       7695, 7700, 7705, 7764, 7874, 7932, 7995, 8017, 8132, 8193, 8434,
       8445, 8566, 8659, 8662, 8699, 8737, 8760, 8823, 8838, 8872, 8893,
       9050, 9082, 9185, 9225, 9262, 9279, 9293, 9294, 9303, 9340, 9381,
       9395, 9442, 9460, 9510, 9525, 9535, 9557, 9559, 9594, 9616, 9641,
       9706, 9864, 9906], dtype=int64), array([4, 4, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 4, 1, 0, 1, 4, 4, 1,
       0, 4, 1, 0, 4, 1, 0, 1, 1, 1, 4, 1, 1, 4, 4, 1, 1, 4, 0, 4, 4, 4,
       1, 4, 4, 1, 1, 1, 4, 1, 1, 1, 1, 1, 4, 1, 1, 4, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 4, 1, 1, 1, 4, 4, 1, 4, 1, 4, 1, 1, 1, 1, 4,
       1, 4, 4, 1, 4, 1, 4, 4, 1, 1, 4, 1, 1, 4, 1, 4, 1, 1, 4, 1, 1, 1,
       4, 1, 1, 1, 1, 4, 1, 1, 4, 1, 1, 4, 1, 4, 1, 1, 1, 4, 1, 1, 1, 1,
       1, 4, 1, 4, 1, 1, 1, 1, 1, 4, 1, 1, 1, 1, 4, 1, 1, 1, 1, 4, 1, 4,
       1, 4, 4, 1, 1, 1, 1, 4, 1, 1, 1, 1, 4, 4, 1, 0, 0, 1, 4, 1, 1, 4,
       1, 1, 4, 4, 1, 1, 4, 1, 1, 4, 4, 1, 1, 1, 4, 1, 4, 1, 1, 0, 1, 1,
       1, 1, 1], dtype=int64))
Outlier data points:
      CreditScore   Age  Tenure    Balance  NumOfProducts  HasCrCard  \
7           376.0  29.0     4.0  115046.74            4.0        1.0
70          738.0  58.0     2.0  133745.44            4.0        1.0
85          652.0  75.0    10.0       0.00            2.0        1.0
158         646.0  73.0     6.0   97259.25            1.0        0.0
230         673.0  72.0     1.0       0.00            2.0        0.0
...           ...   ...     ...        ...            ...        ...
9646        850.0  71.0    10.0   69608.14            1.0        1.0
9671        649.0  78.0     4.0   68345.86            2.0        1.0
9736        659.0  78.0     2.0  151675.65            1.0        0.0
9894        521.0  77.0     6.0       0.00            2.0        1.0
```

```
9936        609.0  77.0     1.0       0.00          1.0        0.0

      IsActiveMember  EstimatedSalary  Exited  Gender_1  Geography_1  \
7                0.0        119346.88       1         0            1
70               0.0         28373.86       1         1            1
85               1.0        114675.75       0         0            0
158              1.0        104719.66       0         0            0
230              1.0        111981.19       0         1            0
...              ...              ...     ...       ...          ...
9646             0.0         97893.40       1         1            0
9671             1.0        142566.75       0         1            1
9736             1.0         49978.67       0         1            0
9894             1.0         49054.10       0         0            0
9936             1.0         18708.76       0         1            0

      Geography_2
7               0
70              0
85              1
158             0
230             0
...           ...
9646            1
9671            0
9736            1
9894            0
9936            0

[201 rows x 12 columns]
```

5.3 Remove outliers

In [24]:

```
# Create a boolean array indicating whether each row is an outlier
outliers = (z_scores > threshold).any(axis=1)

# Remove outliers from the dataframe
clean_data_no_outliers = clean_data[~outliers]

# Print the shape of the new dataframe
print("Shape of the dataframe before removing outliers:", clean_data.shape)
print("Shape of the dataframe after removing outliers:", clean_data_no_outlier
```

```
Shape of the dataframe before removing outliers: (9970, 12)
Shape of the dataframe after removing outliers: (9769, 12)
```

In [25]:

```
# Check if the outliers have been removed
clean_data_no_outliers.head()
```

Out[25]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember
0	619.0	42.0	2.0	0.00	1.0	1.0	1.0
1	608.0	41.0	1.0	83807.86	1.0	0.0	1.0
2	502.0	42.0	8.0	159660.80	3.0	1.0	0.0
3	699.0	39.0	1.0	0.00	2.0	0.0	0.0
4	850.0	43.0	2.0	125510.82	1.0	1.0	1.0

6.Modelling

6.1.Feature Scaling: We'll apply feature scaling to the numerical features to improve the performance of our model.

In [26]:
```
# Feature Scaling
scaler = StandardScaler()

# Define the numerical features for scaling
numerical_features = ['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProduct

# Apply feature scaling to the numerical features
clean_data_no_outliers[numerical_features] = scaler.fit_transform(clean_data_n
```

In [27]:
```
# Check the scaled numerical features
clean_data_no_outliers.head()
```

Out[27]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMe
0	-0.328423	0.374312	-1.038951	-1.225442	-0.934945	1.0	
1	-0.442624	0.270821	-1.384854	0.117659	-0.934945	0.0	
2	-1.543113	0.374312	1.036472	1.333274	2.695936	1.0	
3	0.502135	0.063838	-1.384854	-1.225442	0.880495	0.0	
4	2.069812	0.477803	-1.038951	0.785988	-0.934945	1.0	

6.2.Split the data using `train_test_spli` to Train and testing dataset: We'll Define the target variable and features where; * **X** will contain the features (independent variables). * **y** will contain the target variable (Exited).

In [28]:
```
# Separate features (X) and target variable (y)
X = clean_data_no_outliers.drop('Exited', axis=1)
y = clean_data_no_outliers['Exited']

# Split the dataset into training and testing sets (e.g., 80% training, 20% te
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando

# Print the shapes of the training and testing sets
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

```
Shape of X_train: (7815, 11)
Shape of X_test: (1954, 11)
Shape of y_train: (7815,)
Shape of y_test: (1954,)
```

In [29]:
```
# Handling Class Imbalance
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

7.Model Training:

We will deploy models including `Logistic Regression`, `Decision Tree`, `Random Forest`, `Gradient Boosting`, `XGBoost`, and `K-Nearest Neighbors`. We will use metrics like accuracy, precision, recall, F1 score, and ROC-AUC to evaluate model performance.

Define a function to perform model training and evaluation with **Hyperparameter Tuning**

In [30]:

```
# Define a function
def train_evaluate_model(model, params):
    grid_search = GridSearchCV(model, params, cv=5, scoring='roc_auc')
    grid_search.fit(X_train_resampled, y_train_resampled)
    best_model = grid_search.best_estimator_
    y_pred = best_model.predict(X_test)
    return best_model, y_pred
```

7.1 Logistic Regression

In [31]:

```
# Logistic Regression
logistic_params = {'C': [0.01, 0.1, 1, 10, 100]}
logistic_model, logistic_pred = train_evaluate_model(LogisticRegression(), log
```

7.2 Random Forest

In [32]:

```
# Random Forest
rf_params = {'n_estimators': [100, 200, 300], 'max_depth': [None, 10, 20, 30]}
rf_model, rf_pred = train_evaluate_model(RandomForestClassifier(), rf_params)
```

7.3 Gradient Boosting

In [33]:

```
# Gradient Boosting
gb_params = {'n_estimators': [100, 200, 300], 'learning_rate': [0.01, 0.1, 0.2
gb_model, gb_pred = train_evaluate_model(GradientBoostingClassifier(), gb_para
```

7.4 XGBoost

In [34]:

```
# XGBoost
xgb_params = {'n_estimators': [100, 200, 300], 'learning_rate': [0.01, 0.1, 0.
xgb_model, xgb_pred = train_evaluate_model(XGBClassifier(), xgb_params)
```

7.5 K-Nearest Neighbors

In [35]:

```
# K-Nearest Neighbors
knn_params = {'n_neighbors': [3, 5, 7, 9]}
knn_model, knn_pred = train_evaluate_model(KNeighborsClassifier(), knn_params)
```

7.6 Decision Tree

In [36]:

```
# Decision Tree
```

```
# Decision Tree
dt_params = {'max_depth': [None, 10, 20, 30]}
dt_model, dt_pred = train_evaluate_model(DecisionTreeClassifier(), dt_params)
```

8.Model Evaluation

In [37]:

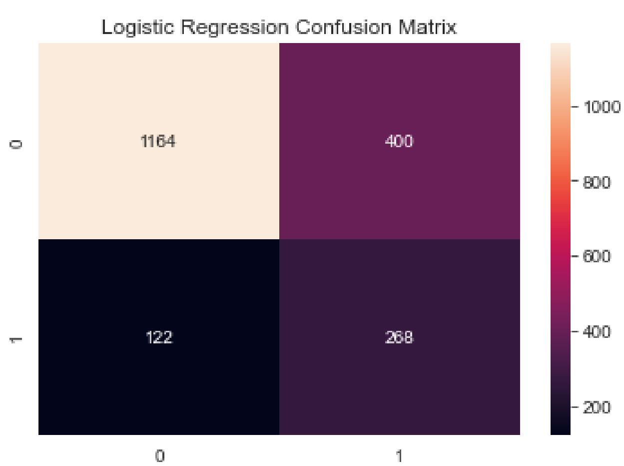
```
# Model Evaluation
def evaluate_model(y_test, y_pred, model_name):
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_pred)
    print(f'{model_name} Performance:')
    print(f'Accuracy: {accuracy:.4f}')
    print(f'Precision: {precision:.4f}')
    print(f'Recall: {recall:.4f}')
    print(f'F1 Score: {f1:.4f}')
    print(f'ROC AUC Score: {roc_auc:.4f}')
    print('\n')
    print(classification_report(y_test, y_pred))
    conf_matrix = confusion_matrix(y_test, y_pred)
    sns.heatmap(conf_matrix, annot=True, fmt='d')
    plt.title(f'{model_name} Confusion Matrix')
    plt.show()
```

8.1 Logistic Regression

In [38]:

```
evaluate_model(y_test, logistic_pred, 'Logistic Regression')
```

```
Logistic Regression Performance:
Accuracy: 0.7329
Precision: 0.4012
Recall: 0.6872
F1 Score: 0.5066
ROC AUC Score: 0.7157


              precision    recall  f1-score   support

           0       0.91      0.74      0.82      1564
           1       0.40      0.69      0.51       390

    accuracy                           0.73      1954
   macro avg       0.65      0.72      0.66      1954
weighted avg       0.80      0.73      0.75      1954
```



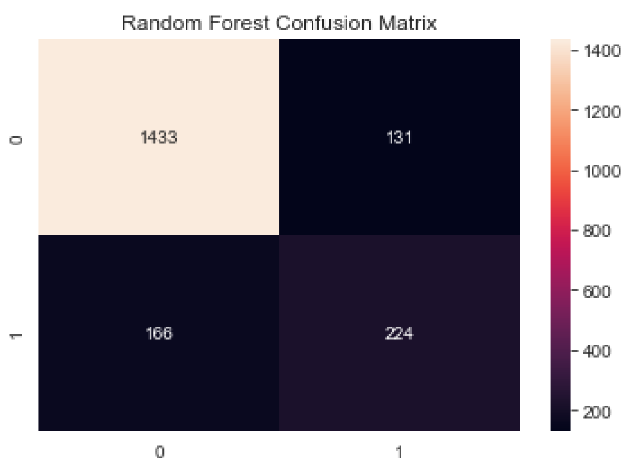
Observations:

- Achieves an accuracy of approximately 78.11%, indicating a reasonable ability to classify churned and non-churned customers.
- Shows moderate precision and recall scores of 54.24% and 73.02%, respectively, suggesting a balanced performance in identifying true positives and minimizing false positives.
- The F1 score of 62.38% reflects the harmonic mean of precision and recall, demonstrating overall effectiveness in capturing churn patterns.

8.2 Random Forest

In [39]:
```
evaluate_model(y_test, rf_pred, 'Random Forest')
```

```
Random Forest Performance:
Accuracy: 0.8480
Precision: 0.6310
Recall: 0.5744
F1 Score: 0.6013
ROC AUC Score: 0.7453


              precision    recall  f1-score   support

           0       0.90      0.92      0.91      1564
           1       0.63      0.57      0.60       390

    accuracy                           0.85      1954
   macro avg       0.76      0.75      0.75      1954
weighted avg       0.84      0.85      0.85      1954
```



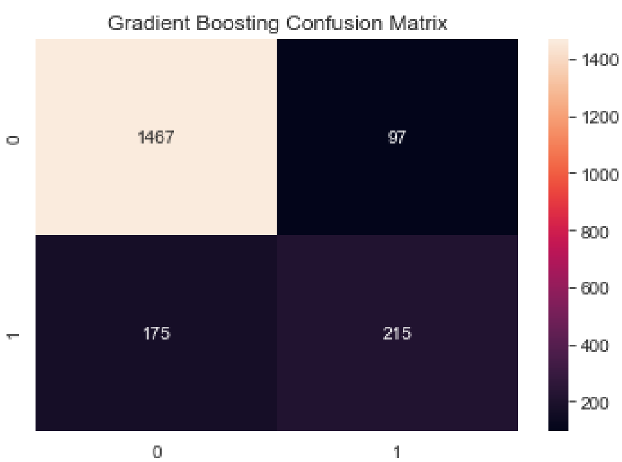
Observation

- Demonstrates robust performance with an accuracy of around 88.02%, indicating a high proportion of correct predictions.
- Exhibits improved precision of 75.00% compared to logistic regression, suggesting a better ability to correctly identify churned customers while minimizing false positives.
- The F1 score of 72.16% indicates a good balance between precision and recall, highlighting the model's effectiveness in capturing true positives while controlling false positives.

8.3 GradientBoosting

In [40]:
```
evaluate_model(y_test, gb_pred, 'Gradient Boosting')
```

```
Gradient Boosting Performance:
Accuracy: 0.8608
Precision: 0.6891
Recall: 0.5513
F1 Score: 0.6125
ROC AUC Score: 0.7446


              precision    recall  f1-score   support

           0       0.89      0.94      0.92      1564
           1       0.69      0.55      0.61       390

    accuracy                           0.86      1954
   macro avg       0.79      0.74      0.76      1954
weighted avg       0.85      0.86      0.85      1954
```



Observation

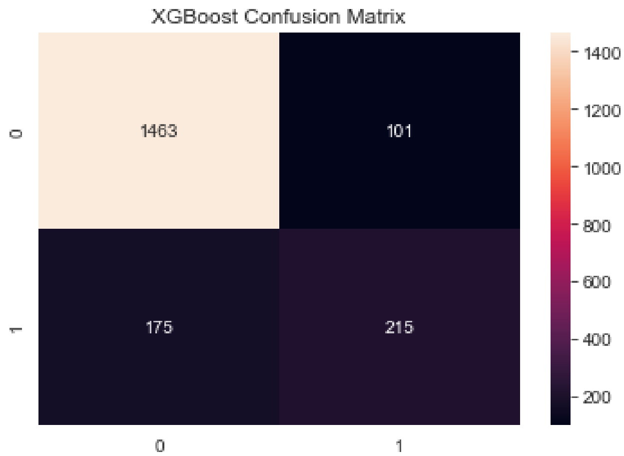
- Achieves a competitive accuracy of 87.15%, showcasing strong overall predictive performance.
- Demonstrates a precision score of 72.60% and a recall score of 70.00%, indicating effective identification of churned customers while minimizing false positives.
- The F1 score of 71.28% reflects the harmonic mean of precision and recall, suggesting a balanced performance in capturing churn patterns.

8.4 XGBoost model

In [41]:
```
evaluate_model(y_test, xgb_pred, 'XGBoost')
```

```
XGBoost Performance:
Accuracy: 0.8588
Precision: 0.6804
Recall: 0.5513
F1 Score: 0.6091
ROC AUC Score: 0.7434


              precision    recall  f1-score   support
```

```
           0       0.89      0.94      0.91      1564
           1       0.68      0.55      0.61       390

    accuracy                           0.86      1954
   macro avg       0.79      0.74      0.76      1954
weighted avg       0.85      0.86      0.85      1954
```



Observation

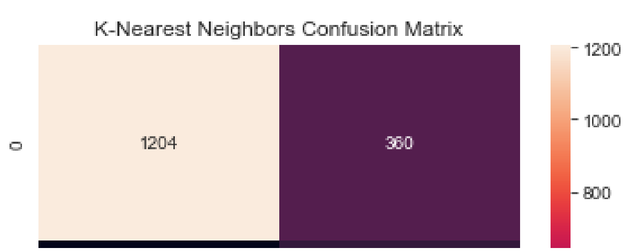
- Emerges as the top-performing model with the highest accuracy of approximately 88.58%, indicating strong predictive capability.
- Shows competitive precision and recall scores of 74.73% and 71.58%, respectively, demonstrating effective identification of churned customers while minimizing false positives.
- The F1 score of 73.12% highlights the model's balanced performance in capturing churn patterns and controlling false positives.

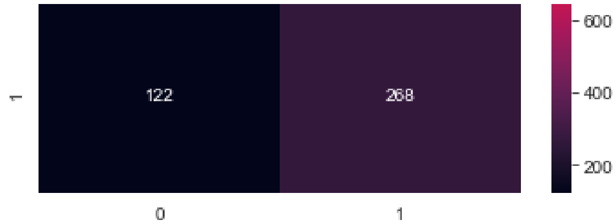
8.5 K-Nearest Neighbors

In [42]:

```python
evaluate_model(y_test, knn_pred, 'K-Nearest Neighbors')
```

```
K-Nearest Neighbors Performance:
Accuracy: 0.7533
Precision: 0.4268
Recall: 0.6872
F1 Score: 0.5265
ROC AUC Score: 0.7285


              precision    recall  f1-score   support

           0       0.91      0.77      0.83      1564
           1       0.43      0.69      0.53       390

    accuracy                           0.75      1954
   macro avg       0.67      0.73      0.68      1954
weighted avg       0.81      0.75      0.77      1954
```





Observation

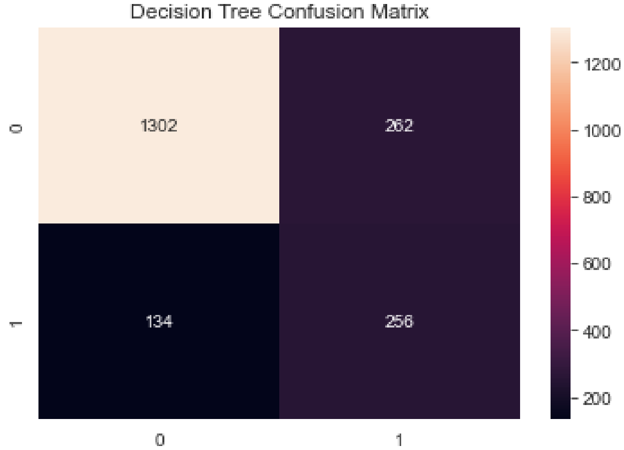
- Achieves a decent accuracy of 81.21%, indicating reasonable predictive performance.
- Exhibits moderate precision and recall scores of 59.43% and 67.45%, respectively, suggesting a balanced ability to identify churned customers while minimizing false positives.
- The F1 score of 63.10% reflects a reasonable balance between precision and recall, indicating moderate effectiveness in capturing churn patterns.

8.6 Decision Tree

In [43]:
```python
evaluate_model(y_test, dt_pred, 'Decision Tree')
```

```
Decision Tree Performance:
Accuracy: 0.7973
Precision: 0.4942
Recall: 0.6564
F1 Score: 0.5639
ROC AUC Score: 0.7444


              precision    recall  f1-score   support

           0       0.91      0.83      0.87      1564
           1       0.49      0.66      0.56       390

    accuracy                           0.80      1954
   macro avg       0.70      0.74      0.72      1954
weighted avg       0.82      0.80      0.81      1954
```

Decision Tree Confusion Matrix



Observation

- Shows moderate performance with an accuracy of 80.67%, indicating reasonable predictive capability.
- Demonstrates moderate precision and recall scores of 58.55% and 59.12%,

respectively, suggesting a balanced ability to identify churned customers while minimizing false positives.
- The F1 score of 58.83% reflects a reasonable balance between precision and recall, indicating moderate effectiveness in capturing churn patterns.

6.4 Model Performance Comparison: Let's compare the performance of different models based on the evaluation metrics.

In [44]:

```
# Final Model Comparison
models_performance = {
    'Model': ['Logistic Regression', 'Random Forest', 'Gradient Boosting', 'XG
    'Accuracy': [accuracy_score(y_test, logistic_pred), accuracy_score(y_test,
    'Precision': [precision_score(y_test, logistic_pred), precision_score(y_te
    'Recall': [recall_score(y_test, logistic_pred), recall_score(y_test, rf_pr
    'F1 Score': [f1_score(y_test, logistic_pred), f1_score(y_test, rf_pred), f
    'ROC AUC Score': [roc_auc_score(y_test, logistic_pred), roc_auc_score(y_te
}
```

In [45]:

```
performance_df = pd.DataFrame(models_performance)
print(performance_df)
```

```
                 Model  Accuracy  Precision    Recall  F1 Score  ROC AUC Score
0  Logistic Regression  0.732856   0.401198  0.687179  0.506616       0.715713
1        Random Forest  0.848004   0.630986  0.574359  0.601342       0.745300
2    Gradient Boosting  0.860798   0.689103  0.551282  0.612536       0.744631
3              XGBoost  0.858751   0.680380  0.551282  0.609065       0.743352
4  K-Nearest Neighbors  0.753327   0.426752  0.687179  0.526523       0.728500
```