Bank Customer Churn Prediction

`Author:` Prashant Sharma
`Date:` 20.December.2024
`Dataset:` Bank Customer Churn Prediction

About Dataset (Meta data)

Context

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

Content

Column Descriptions:

- `Customer ID:` A unique identifier for each customer.
- `Surname:` The customer's surname or last name.
- `Credit Score:` A numerical value representing the customer's credit score.
- `Geography:` The country where the customer resides (France, Spain or Germany).
- `Gender:` The customer's gender (Male or Female).
- `Age:` The customer's age.
- `Tenure:` The number of years the customer has been with the bank.
- `Balance:` The customer's account balance.
- `NumOfProducts:` The number of bank products the customer uses (e.g., savings account, credit card).

- `MonthsHasCrCard`: Whether the customer has a credit card (1 = yes, 0 = no).
- `IsActiveMember`: Whether the customer is an active member (1 = yes, 0 = no).
- `EstimatedSalary`: The estimated salary of the customer.
- `Exited`: Whether the customer has churned (1 = yes, 0 = no).

Import Libraries

In [1]:

```
# Import libraries

# Data manipulation and analysis
import numpy as np
import pandas as pd

# Data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Machine learning models and utilities
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

Load the Dataset

In [2]:

```python
df = pd.read_csv('Data/Customer.csv')
# Show top 10 rows
df.head(10)
```

Out[2]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	1	15634602	Hargrave	619	France	Female	42.0	2	0.00	1	1.0
1	2	15647311	Hill	608	Spain	Female	41.0	1	83807.86	1	0.0
2	3	15619304	Onio	502	France	Female	42.0	8	159660.80	3	1.0
3	4	15701354	Boni	699	France	Female	39.0	1	0.00	2	0.0
4	5	15737888	Mitchell	850	Spain	Female	43.0	2	125510.82	1	NaN
5	6	15574012	Chu	645	Spain	Male	44.0	8	113755.78	2	1.0
6	7	15592531	Bartlett	822	NaN	Male	50.0	7	0.00	2	1.0
7	8	15656148	Obinna	376	Germany	Female	29.0	4	115046.74	4	1.0
8	9	15792365	He	501	France	Male	44.0	4	142051.07	2	0.0
9	10	15592389	H?	684	France	Male	NaN	2	134603.88	1	1.0

Data Preprocessing

In [3]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10002 entries, 0 to 10001
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10002 non-null  int64  
 1   CustomerId       10002 non-null  int64  
 2   Surname          10002 non-null  object 
 3   CreditScore      10002 non-null  int64  
 4   Geography        10001 non-null  object 
 5   Gender           10002 non-null  object 
 6   Age              10001 non-null  float64
 7   Tenure           10002 non-null  int64  
 8   Balance          10002 non-null  float64
 9   NumOfProducts    10002 non-null  int64  
 10  HasCrCard        10001 non-null  float64
 11  IsActiveMember   10001 non-null  float64
 12  EstimatedSalary  10002 non-null  float64
 13  Exited           10002 non-null  int64  
dtypes: float64(5), int64(6), object(3)
memory usage: 1.1+ MB
```

`There are some categorical columns too in the dataset`

- `Categorical Columns:` Surname, Geography, Gender

In [4]:
```
df.describe()
```

Out[4]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard
count	10002.000000	1.000200e+04	10002.000000	10001.000000	10002.000000	10002.000000	10002.000000	10001.000000
mean	5001.499600	1.569093e+07	650.555089	38.922311	5.012498	76491.112875	1.530194	0.705529
std	2887.472338	7.193177e+04	96.661615	10.487200	2.891973	62393.474144	0.581639	0.455827
min	1.000000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.000000
25%	2501.250000	1.562852e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.000000
50%	5001.500000	1.569073e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.000000
75%	7501.750000	1.575323e+07	718.000000	44.000000	7.000000	127647.840000	2.000000	1.000000
max	10000.000000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.000000

In [5]:

```
#Checking the data shape
df.shape
```

Out[5]: (10002, 14)

In [6]:

```
# Check for missing values in the dataset
df.isnull().sum()
```

Out[6]:
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          1
Gender             0
Age                1
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          1
IsActiveMember     1
EstimatedSalary    0
Exited             0
dtype: int64
```

```
There are some missing values in the columns: Geography, Age, HasCrCard, IsActiveMember
```

As there are only one-one missing values in each columns so we dropping it

In [7]:
```
df.dropna(inplace=True)
```

In [8]:
```
df.head(10)
```

Out[8]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	1	15634602	Hargrave	619	France	Female	42.0	2	0.00	1	1.0
1	2	15647311	Hill	608	Spain	Female	41.0	1	83807.86	1	0.0
2	3	15619304	Onio	502	France	Female	42.0	8	159660.80	3	1.0
3	4	15701354	Boni	699	France	Female	39.0	1	0.00	2	0.0
5	6	15574012	Chu	645	Spain	Male	44.0	8	113755.78	2	1.0
7	8	15656148	Obinna	376	Germany	Female	29.0	4	115046.74	4	1.0
10	11	15767821	Bearce	528	France	Male	31.0	6	102016.72	2	0.0
11	12	15737173	Andrews	497	Spain	Male	24.0	3	0.00	2	1.0
12	13	15632264	Kay	476	France	Female	34.0	10	0.00	2	1.0
13	14	15691483	Chin	549	France	Female	25.0	5	0.00	2	0.0

In [9]:

```
df.shape
```

Out[9]:

```
(9998, 14)
```

In [10]:

```
df.isnull().sum()
```

Out[10]:
```
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
```

Now there are no missing values in the dataset

In [11]:
```
# Check NaN values in the entire dataset
nan_values = df.isna().sum()
print("NaN values in each column:\n", nan_values)
```

```
NaN values in each column:
 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
```

There are no nan values too

In [12]:

```
# Check unique values in categorical columns
print("Surname:", df['Surname'].unique())
print("Geography:", df['Geography'].unique())
print("Gender:", df['Gender'].unique())
```

```
Surname: ['Hargrave' 'Hill' 'Onio' ... 'Kashiwagi' 'Aldridge' 'Burbidge']
Geography: ['France' 'Spain' 'Germany']
Gender: ['Female' 'Male']
```

In [13]:

```
df.head(10)
```

Out[13]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	1	15634602	Hargrave	619	France	Female	42.0	2	0.00	1	1.0
1	2	15647311	Hill	608	Spain	Female	41.0	1	83807.86	1	0.0
2	3	15619304	Onio	502	France	Female	42.0	8	159660.80	3	1.0
3	4	15701354	Boni	699	France	Female	39.0	1	0.00	2	0.0
5	6	15574012	Chu	645	Spain	Male	44.0	8	113755.78	2	1.0
7	8	15656148	Obinna	376	Germany	Female	29.0	4	115046.74	4	1.0
10	11	15767821	Bearce	528	France	Male	31.0	6	102016.72	2	0.0
11	12	15737173	Andrews	497	Spain	Male	24.0	3	0.00	2	1.0
12	13	15632264	Kay	476	France	Female	34.0	10	0.00	2	1.0
13	14	15691483	Chin	549	France	Female	25.0	5	0.00	2	0.0

In [14]:

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

There was no use of these columns for churn prediction so we have dropped it

In [15]:

```
df.head(10)
```

Out[15]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	Female	42.0	2	0.00	1	1.0	1.0	101348.88
1	608	Spain	Female	41.0	1	83807.86	1	0.0	1.0	112542.58
2	502	France	Female	42.0	8	159660.80	3	1.0	0.0	113931.57
3	699	France	Female	39.0	1	0.00	2	0.0	0.0	93826.63
5	645	Spain	Male	44.0	8	113755.78	2	1.0	0.0	149756.71
7	376	Germany	Female	29.0	4	115046.74	4	1.0	0.0	119346.88
10	528	France	Male	31.0	6	102016.72	2	0.0	0.0	80181.12
11	497	Spain	Male	24.0	3	0.00	2	1.0	0.0	76390.01
12	476	France	Female	34.0	10	0.00	2	1.0	0.0	26260.98
13	549	France	Female	25.0	5	0.00	2	0.0	0.0	190857.79

Exploratory Data Analysis (EDA)

In [16]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 9998 entries, 0 to 10001
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      9998 non-null   int64
 1   Geography        9998 non-null   object
 2   Gender           9998 non-null   object
 3   Age              9998 non-null   float64
 4   Tenure           9998 non-null   int64
 5   Balance          9998 non-null   float64
 6   NumOfProducts    9998 non-null   int64
 7   HasCrCard        9998 non-null   float64
 8   IsActiveMember   9998 non-null   float64
 9   EstimatedSalary  9998 non-null   float64
 10  Exited           9998 non-null   int64
dtypes: float64(5), int64(4), object(2)
memory usage: 937.3+ KB
```

Analysis of Geography Column

In [17]:

```
# Find the values of Geography column
df['Geography'].value_counts()
```

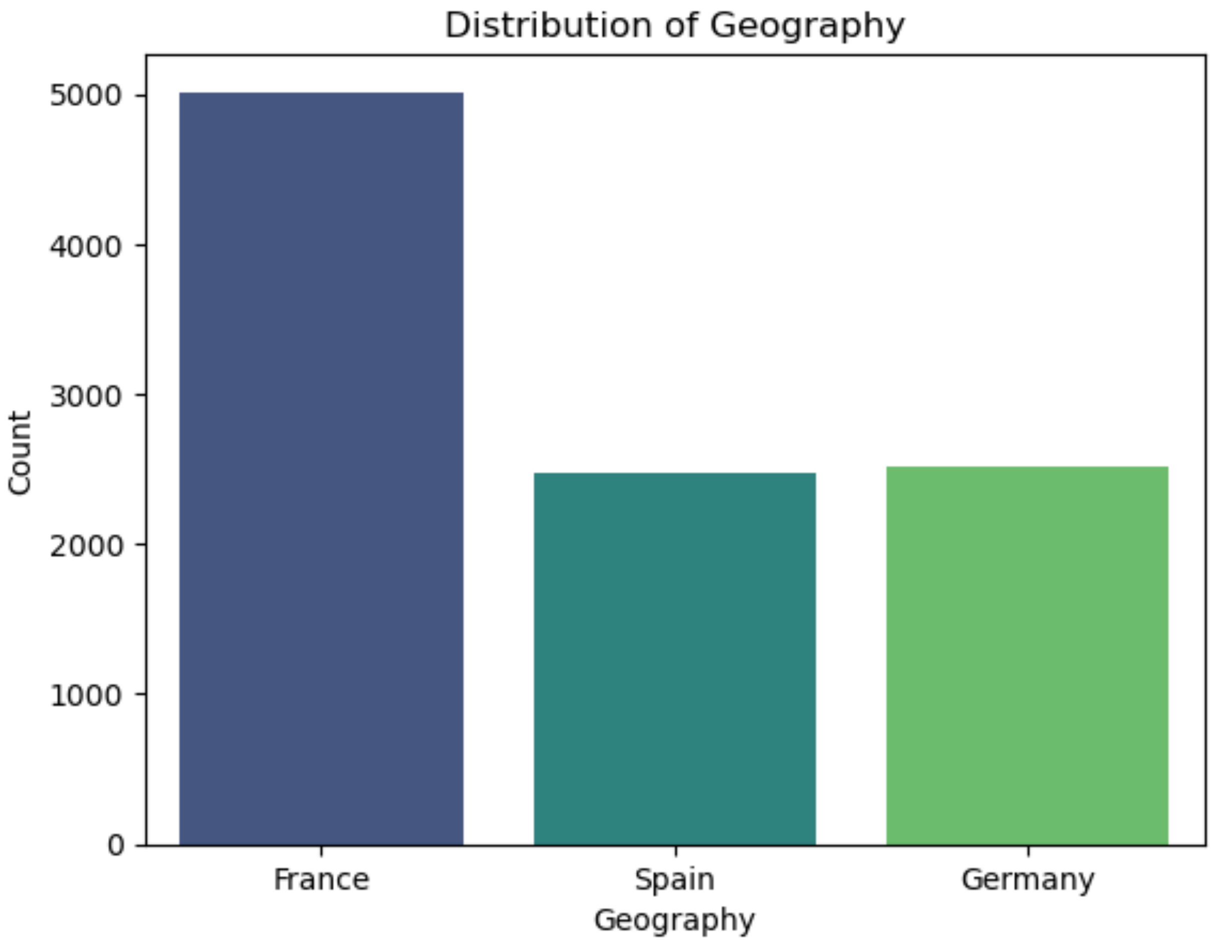
Out[17]:

```
Geography
France     5012
Germany    2510
Spain      2476
Name: count, dtype: int64
```

In [18]:

```
sns.countplot(x='Geography', data=df, palette='viridis')
plt.title('Distribution of Geography')
plt.xlabel('Geography')
```

```
plt.ylabel('Count')
plt.show()
```



Most of the customers are from France followed by Spain and Germany

Exploring Gender Column

In [19]:

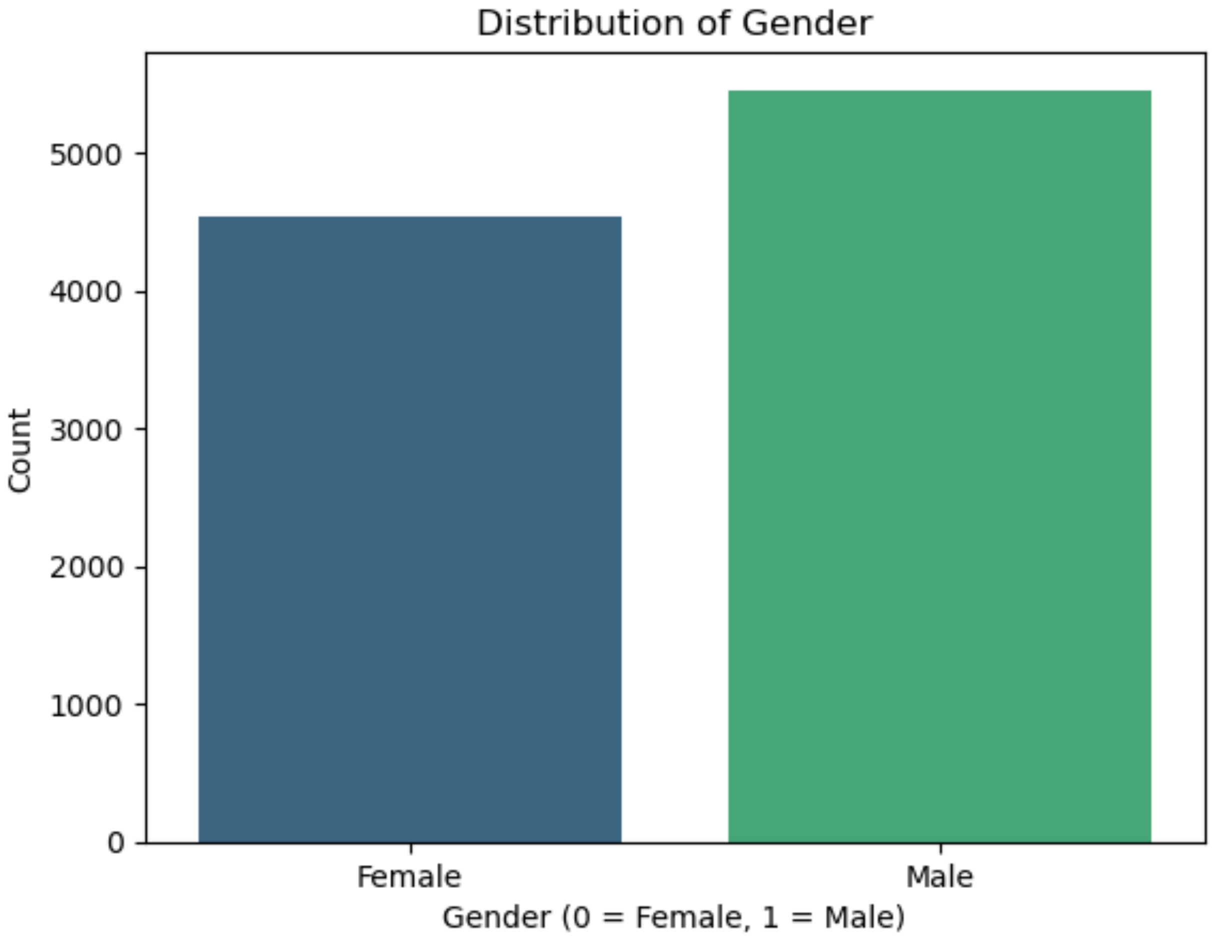
```
# Find the values of Geography column
df['Gender'].value_counts()
```

Out[19]:

```
Gender
Male      5455
Female    4543
Name: count, dtype: int64
```

In [20]:

```
sns.countplot(x='Gender', data=df, palette='viridis')
plt.title('Distribution of Gender')
plt.xlabel('Gender (0 = Female, 1 = Male)')
plt.ylabel('Count')
plt.show()
```



Most of the customers are male

In [21]:

```
# calculating the percentage fo male and female value counts in the data

male_count = 5455
female_count = 4543
```

```
total_count = male_count + female_count

# calculate percentages
male_percentage = (male_count/total_count)*100
female_percentages = (female_count/total_count)*100

# display the results
print(f'Male percentage in the data: {male_percentage:.2f}%')
print(f'Female percentage in the data: {female_percentages:.2f}%')
```

```
Male percentage in the data: 54.56%
Female percentage in the data: 45.44%
```

Males are more than 50% in the dataset

Exploring Age Column

In [22]:

```
print('Age Summary Statistics:')
df['Age'].describe()
```

```
Age Summary Statistics:
```

Out[22]:

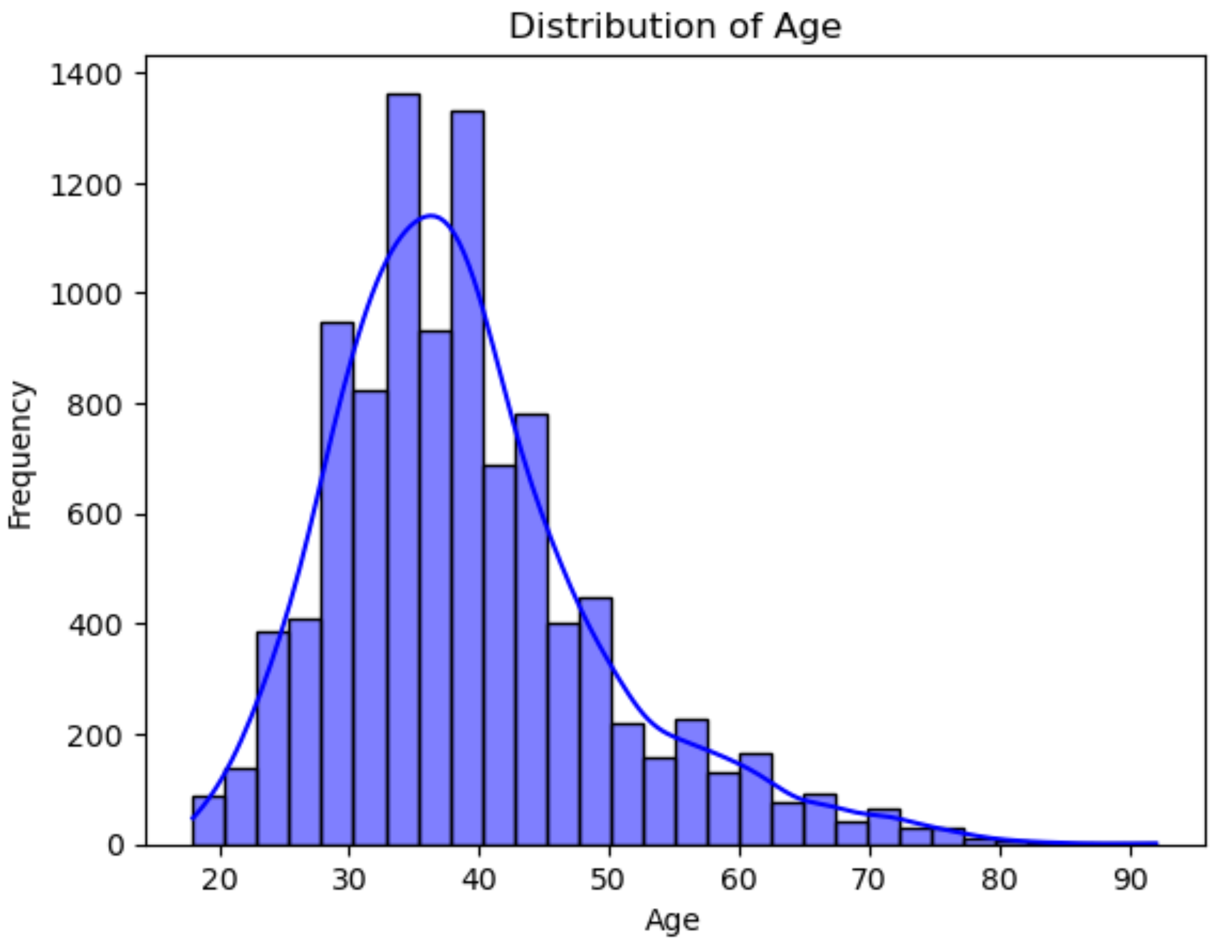
```
count    9998.000000
mean       38.920287
std        10.487986
min        18.000000
25%        32.000000
50%        37.000000
75%        44.000000
max        92.000000
Name: Age, dtype: float64
```

In [23]:

```
df['Age'].min(), df['Age'].max()
```

Out[23]: (18.0, 92.0)

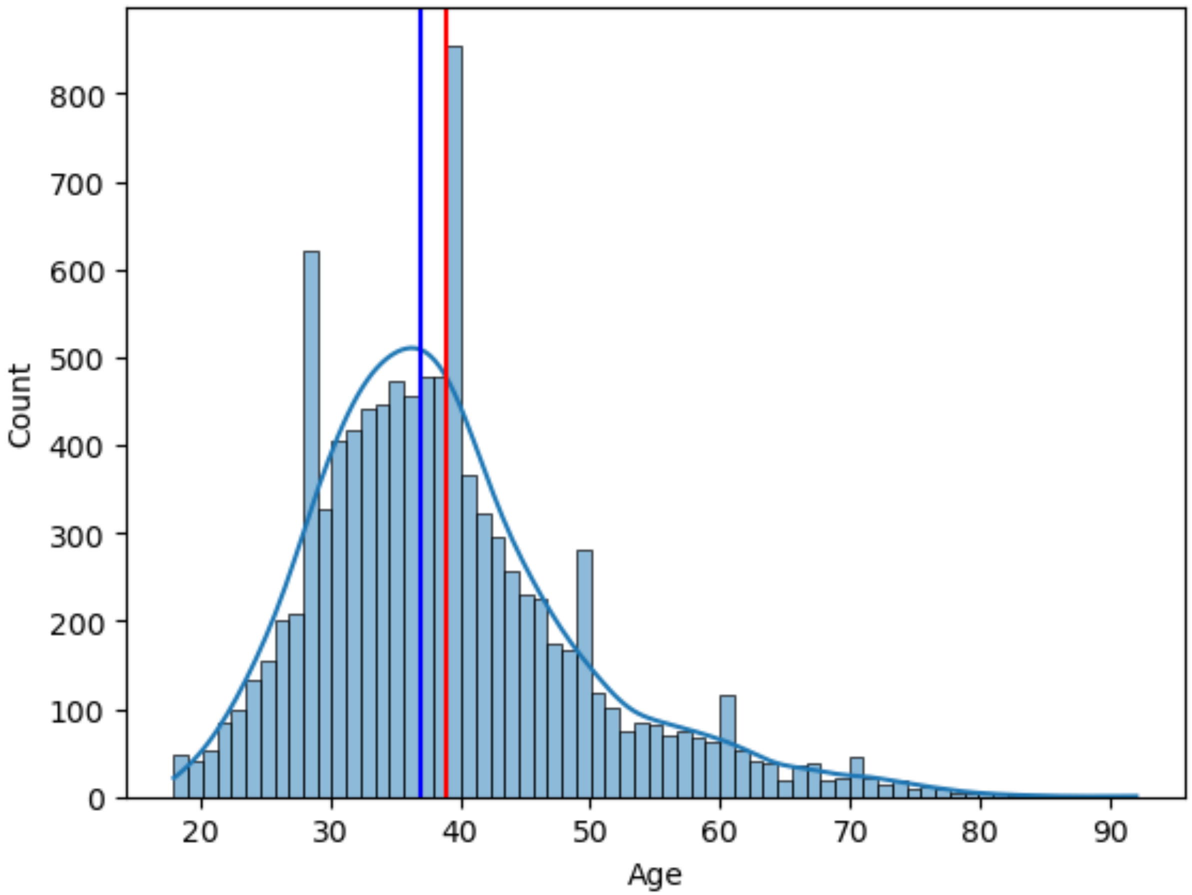
In [24]:
```
sns.histplot(df['Age'], kde=True, bins=30, color='blue')
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



In [25]:

```
sns.histplot(df['Age'], kde=True)
plt.axvline(df['Age'].mean(), color='Red')
plt.axvline(df['Age'].median(), color= 'orange')
plt.axvline(df['Age'].mode()[0], color='Blue')

# print the value of mean, median and mode of age column
print('Mean', df['Age'].mean())
print('Median', df['Age'].median())
print('Mode', df['Age'].mode())
```

```
Mean 38.920287057411485
Median 37.0
Mode 0    37.0
Name: Age, dtype: float64
```



Analysis of IsActiveMember Column

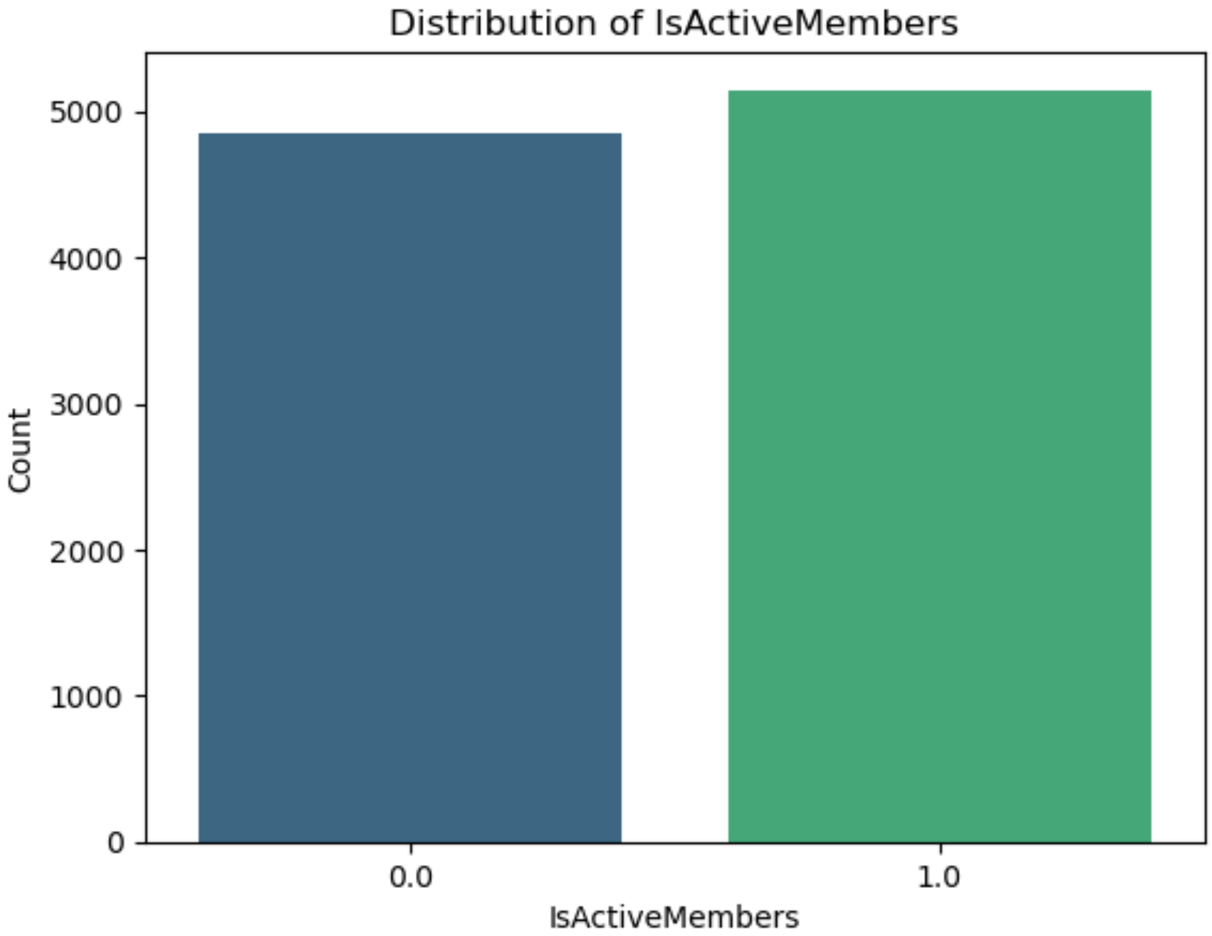
In [26]:

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

Out[26]:
```
IsActiveMember
1.0    5147
0.0    4851
Name: count, dtype: int64
```

Most of the users in the dataset are active

In [27]:
```
sns.countplot(x='IsActiveMember', data=df, palette='viridis')
plt.title('Distribution of IsActiveMembers')
plt.xlabel('IsActiveMembers')
plt.ylabel('Count')
plt.show()
```


Distribution of IsActiveMembers
Count
5000
4000
3000
2000
1000
0
0.0
1.0
IsActiveMembers

In [28]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 9998 entries, 0 to 10001
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   CreditScore      9998 non-null   int64  
 1   Geography        9998 non-null   object 
 2   Gender           9998 non-null   object 
 3   Age              9998 non-null   float64
 4   Tenure           9998 non-null   int64  
 5   Balance          9998 non-null   float64
 6   NumOfProducts    9998 non-null   int64  
 7   HasCrCard        9998 non-null   float64
 8   IsActiveMember   9998 non-null   float64
 9   EstimatedSalary  9998 non-null   float64
 10  Exited           9998 non-null   int64  
dtypes: float64(5), int64(4), object(2)
memory usage: 937.3+ KB
```

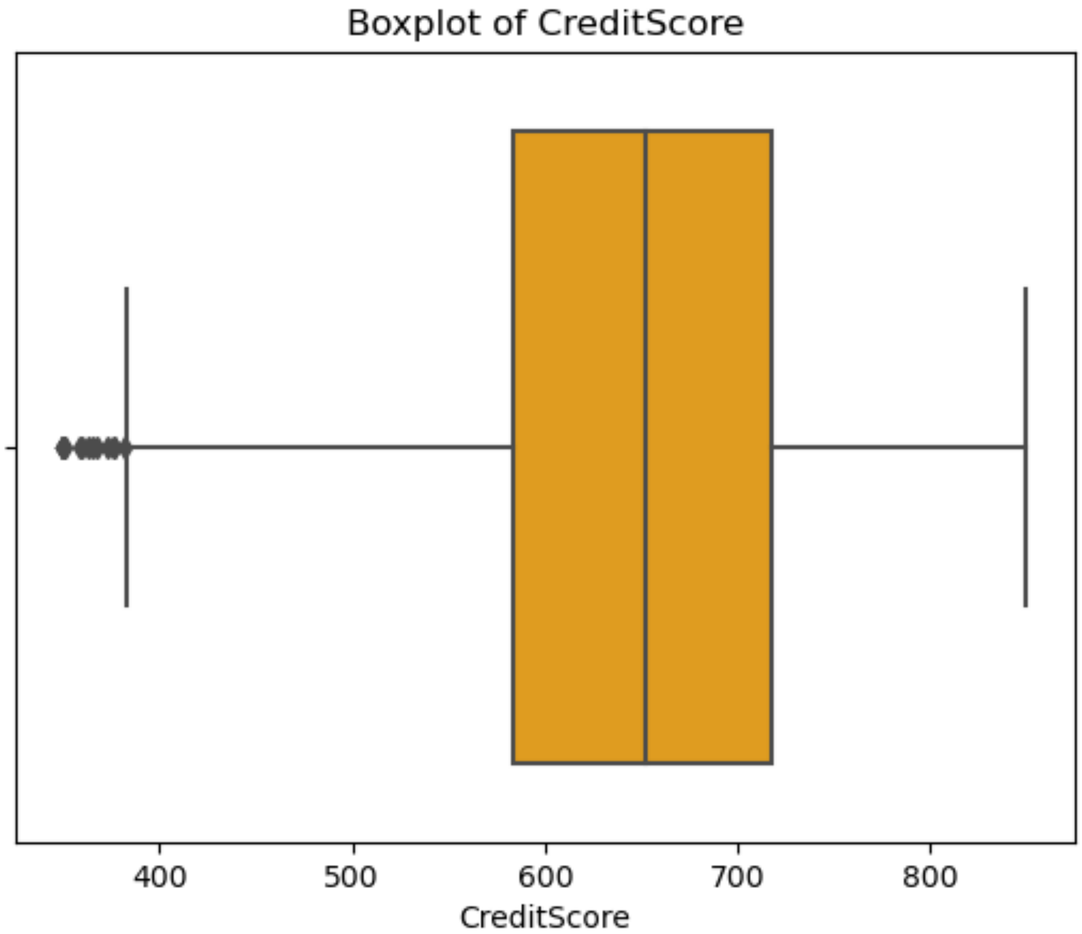
Identifying and Handling Outliers

In [29]:

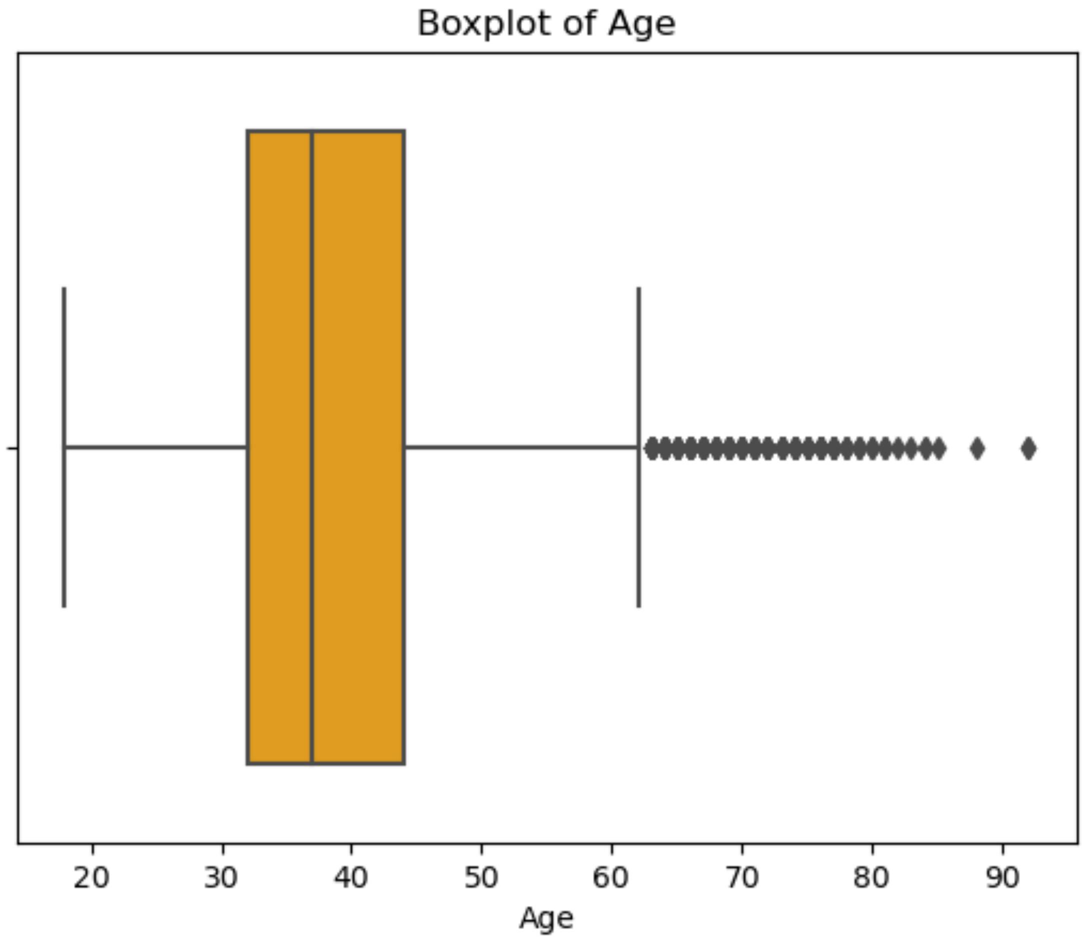
```
# List of numerical columns
numerical_columns = ['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember',
for col in numerical_columns:
    # Calculate Q1, Q3, and IQR
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Identify outliers
    outliers = df[(df[col] < lower_bound) | (df[col] > upper_bound)]
    print(f"Column: {col}")
```

```
    print(f"Number of outliers: {outliers.shape[0]}")

    # Visualization
    sns.boxplot(x=df[col], color='orange')
    plt.title(f'Boxplot of {col}')
    plt.xlabel(col)
    plt.show()

    # Handle outliers: Remove rows with outliers
    df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
    print(f"After handling outliers, dataset shape: {df.shape}")
```

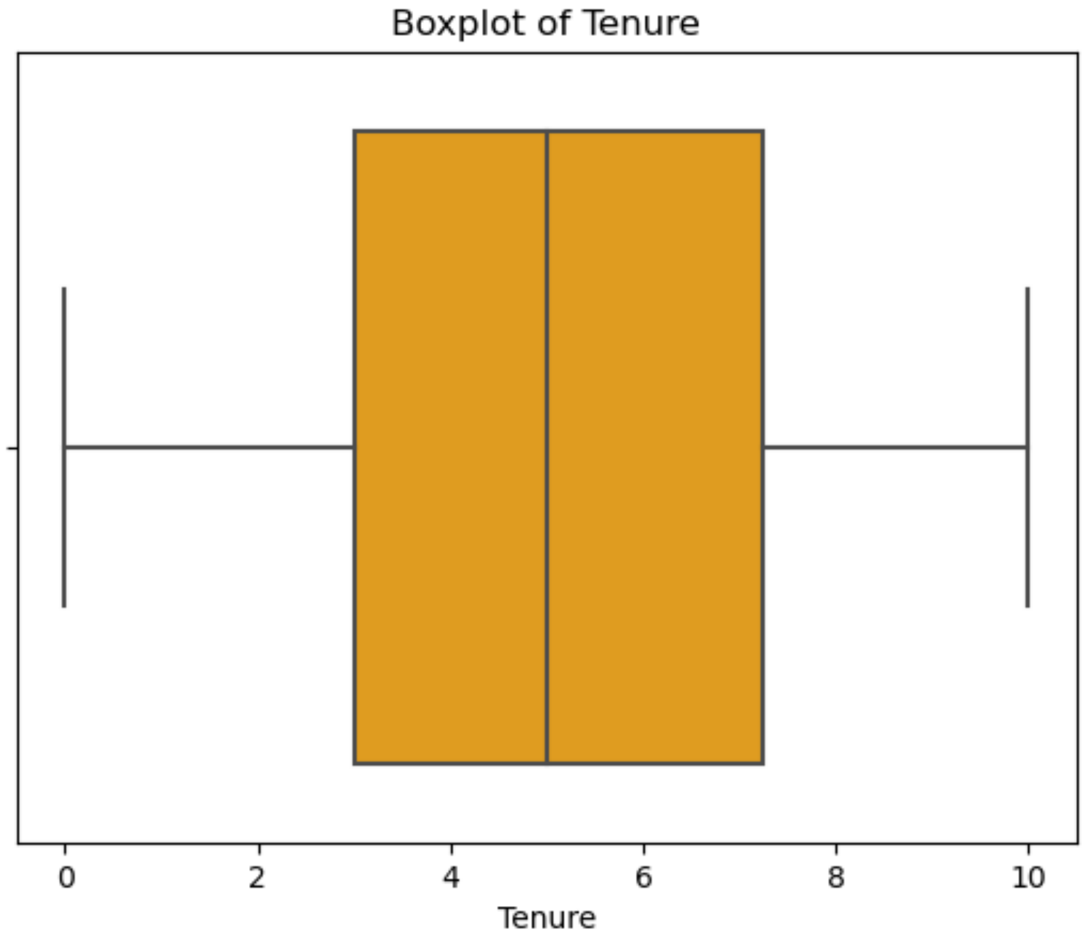
```
Column: CreditScore
Number of outliers: 15
```



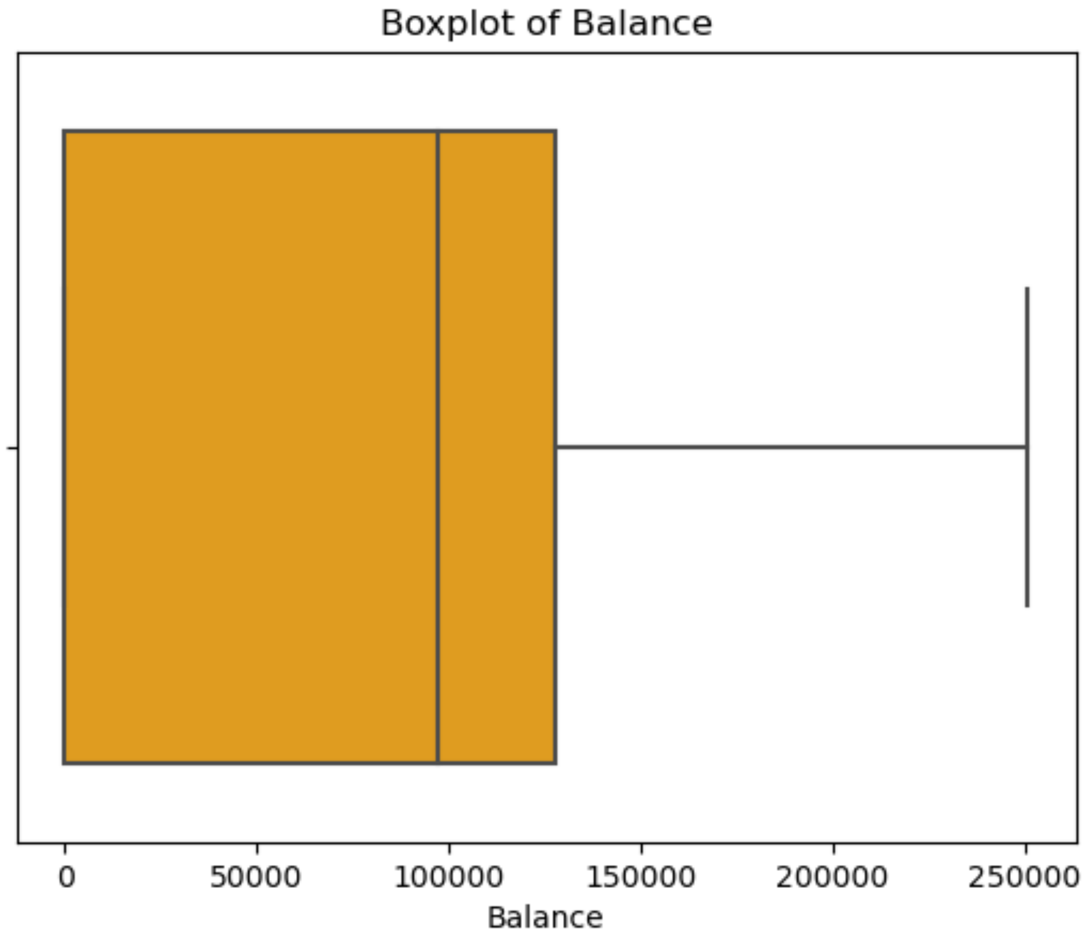

```
After handling outliers, dataset shape: (9983, 11)
Column: Age
Number of outliers: 359
```



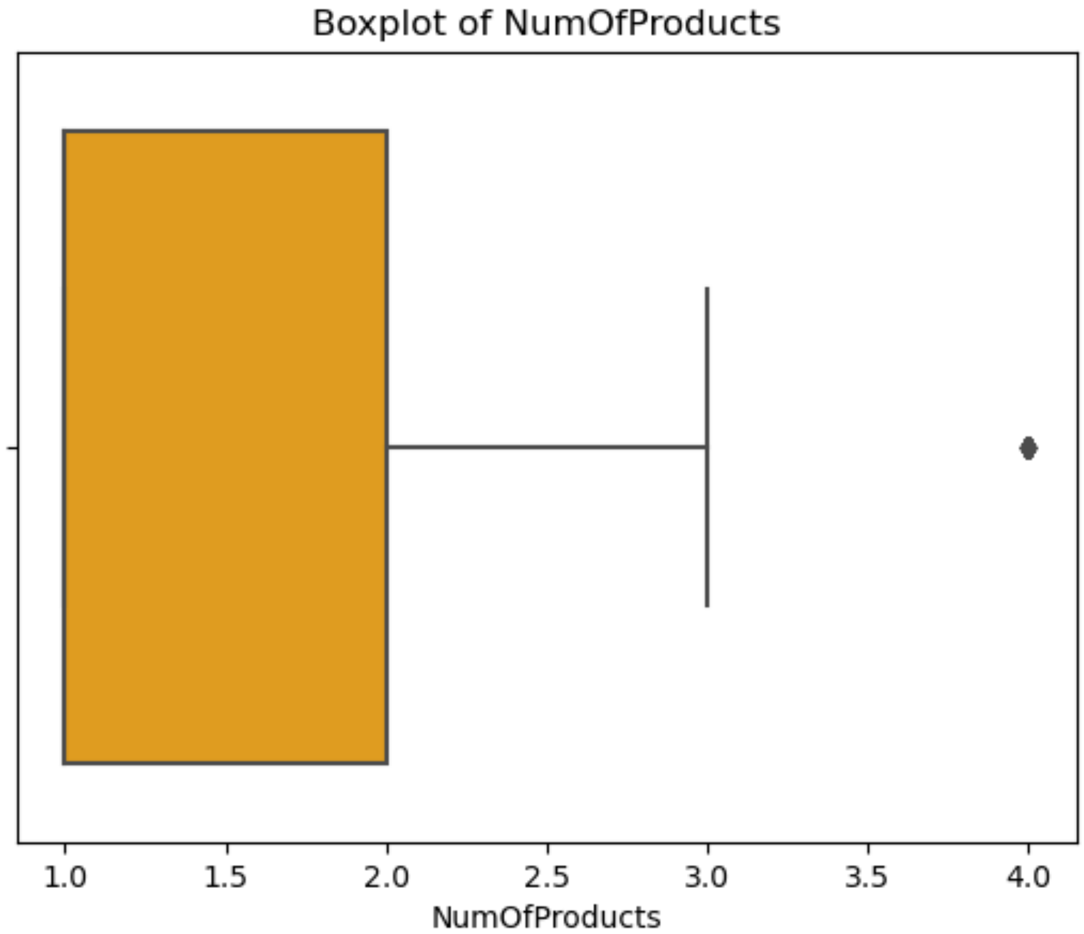

```
After handling outliers, dataset shape: (9624, 11)
Column: Tenure
Number of outliers: 0
```



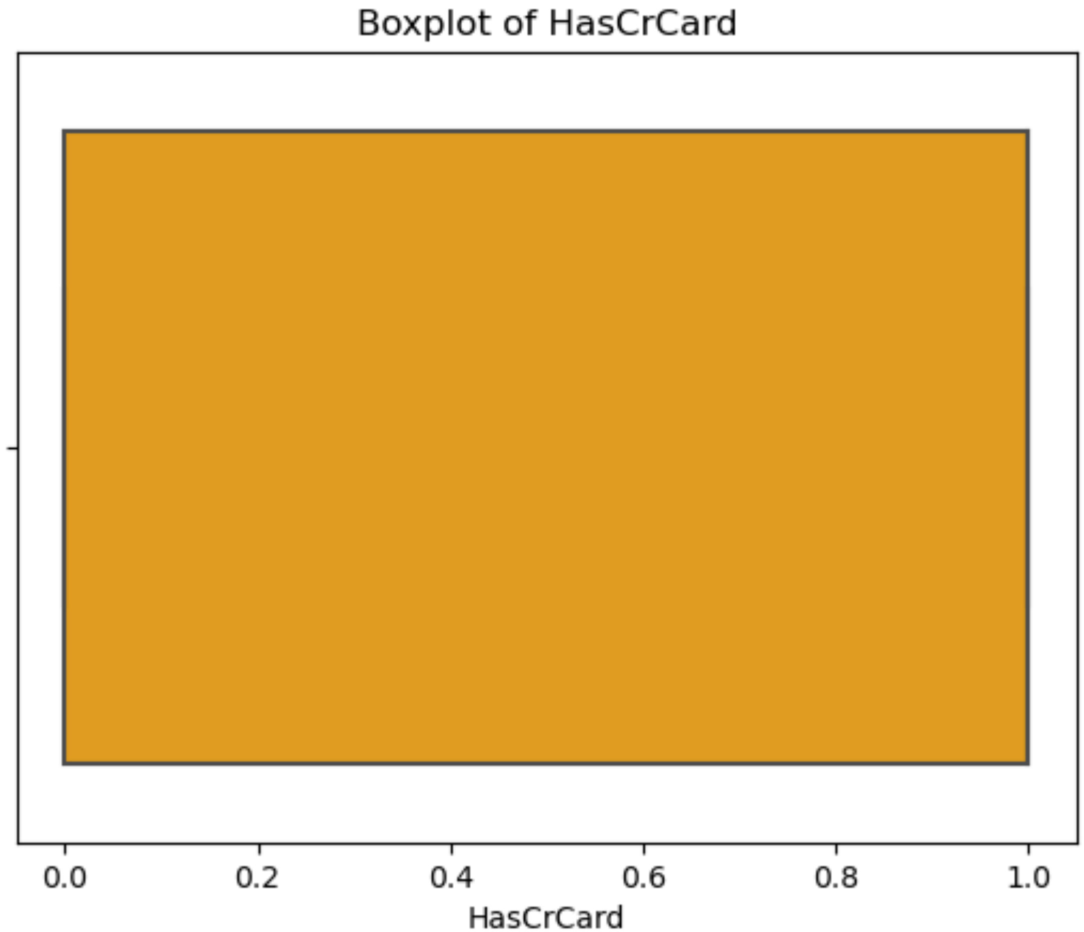

```
After handling outliers, dataset shape: (9624, 11)
Column: Balance
Number of outliers: 0
```



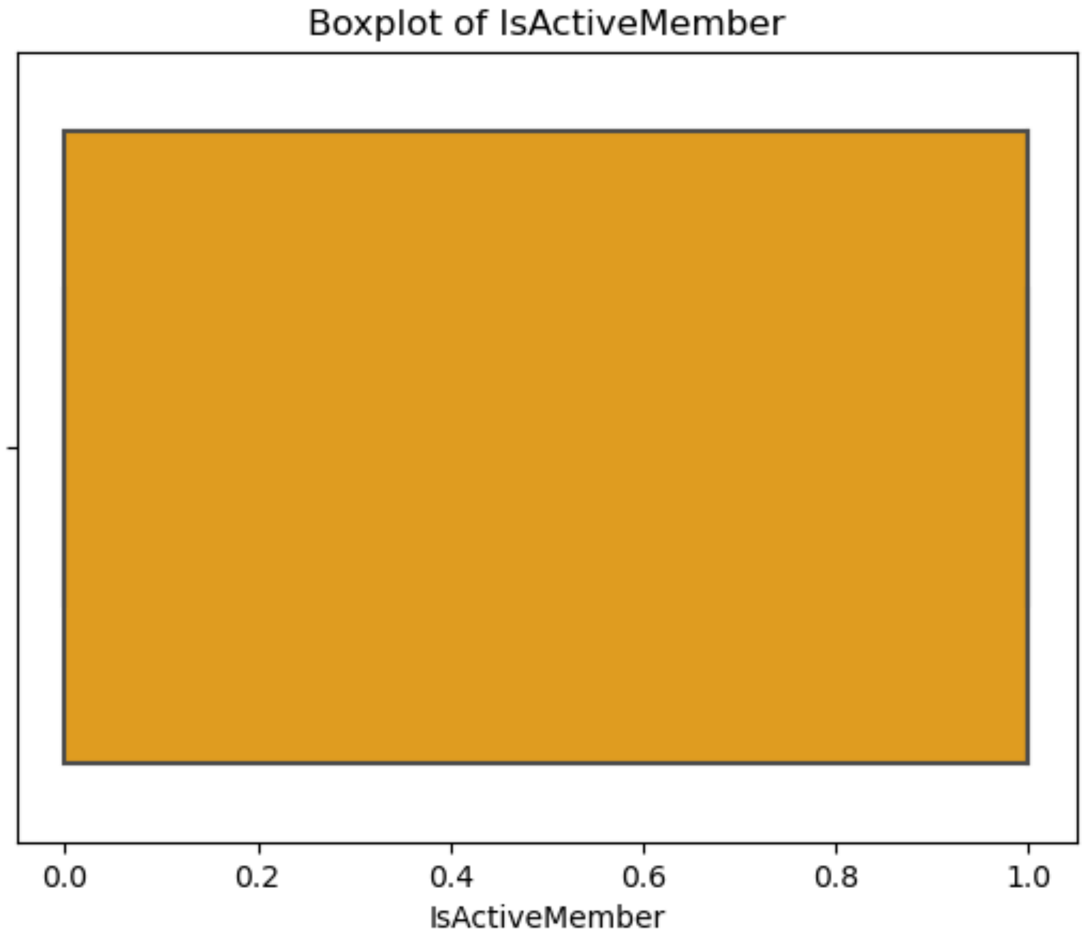

```
After handling outliers, dataset shape: (9624, 11)
Column: NumOfProducts
Number of outliers: 58
```



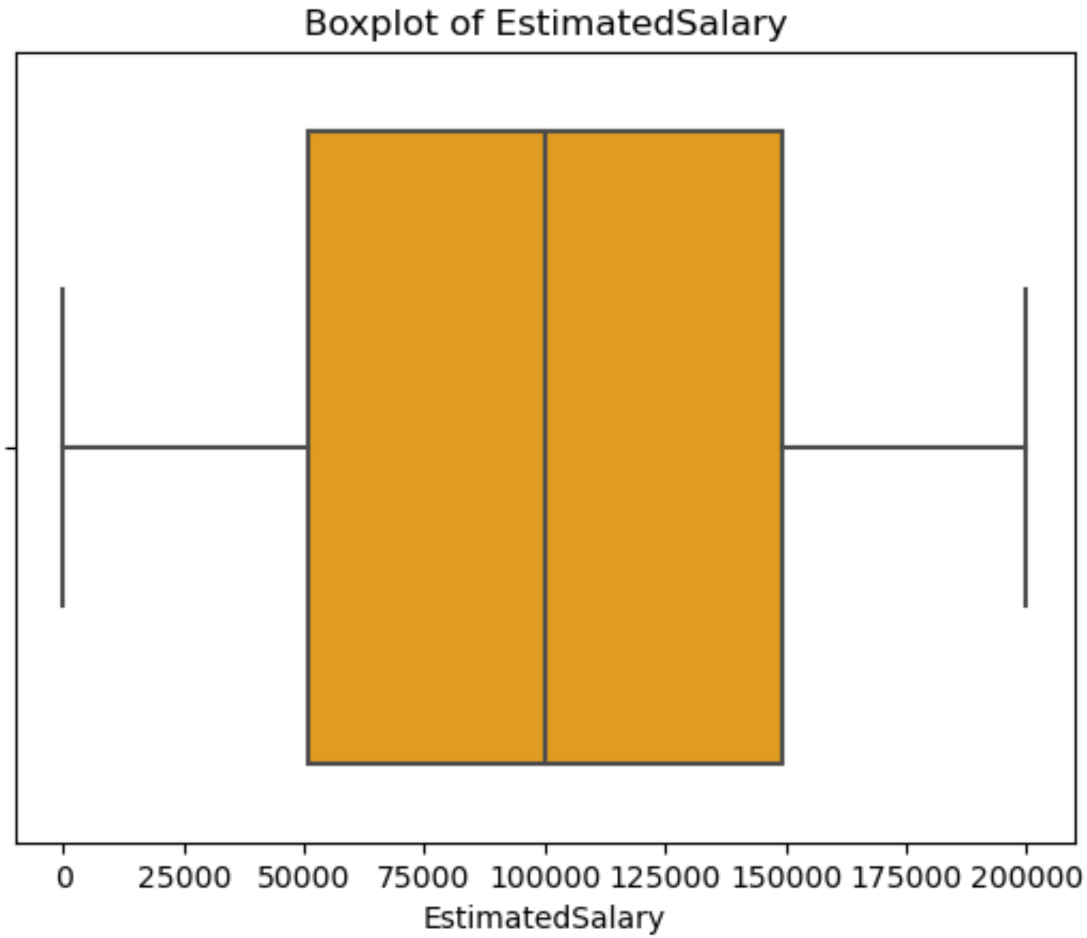

```
After handling outliers, dataset shape: (9566, 11)
Column: HasCrCard
Number of outliers: 0
```




```
After handling outliers, dataset shape: (9566, 11)
Column: IsActiveMember
Number of outliers: 0
```




```
After handling outliers, dataset shape: (9566, 11)
Column: EstimatedSalary
Number of outliers: 0
```




```
After handling outliers, dataset shape: (9566, 11)
```

All outliers in the numerical columns have been successfully identified and handled.

In [30]:

```python
df.shape
```

Out[30]:

```
(9566, 11)
```

In [31]:
```
df.head(10)
```

Out[31]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	Female	42.0	2	0.00	1	1.0	1.0	101348.88
1	608	Spain	Female	41.0	1	83807.86	1	0.0	1.0	112542.58
2	502	France	Female	42.0	8	159660.80	3	1.0	0.0	113931.57
3	699	France	Female	39.0	1	0.00	2	0.0	0.0	93826.63
5	645	Spain	Male	44.0	8	113755.78	2	1.0	0.0	149756.71
10	528	France	Male	31.0	6	102016.72	2	0.0	0.0	80181.12
11	497	Spain	Male	24.0	3	0.00	2	1.0	0.0	76390.01
12	476	France	Female	34.0	10	0.00	2	1.0	0.0	26260.98
13	549	France	Female	25.0	5	0.00	2	0.0	0.0	190857.79
14	635	Spain	Female	35.0	7	0.00	2	1.0	1.0	65951.65

```
Analysis of plotting
```

> - Everything seems fine and there are no outliers in the columns.
> - Columns are cleaned from outliers and also there are no missing values in the dataset.
> - The next step is Feature Selection but before that we need to encode the categorical columns.

In [32]:
```
# label Encoding

from sklearn.preprocessing import LabelEncoder
```

```
# List of categorical columns to encode
categorical_columns = ['Geography', 'Gender']

# Initialize the LabelEncoder
le = LabelEncoder()

# Apply Label Encoding to each categorical column
for col in categorical_columns:
    df[col] = le.fit_transform(df[col])
```

In [33]:

```
df.head(10)
```

Out[33]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	0	0	42.0	2	0.00	1	1.0	1.0	101348.88
1	608	2	0	41.0	1	83807.86	1	0.0	1.0	112542.58
2	502	0	0	42.0	8	159660.80	3	1.0	0.0	113931.57
3	699	0	0	39.0	1	0.00	2	0.0	0.0	93826.63
5	645	2	1	44.0	8	113755.78	2	1.0	0.0	149756.71
10	528	0	1	31.0	6	102016.72	2	0.0	0.0	80181.12
11	497	2	1	24.0	3	0.00	2	1.0	0.0	76390.01
12	476	0	0	34.0	10	0.00	2	1.0	0.0	26260.98
13	549	0	0	25.0	5	0.00	2	0.0	0.0	190857.79
14	635	2	0	35.0	7	0.00	2	1.0	1.0	65951.65

Now everything is good to go for feature selections

Feature Selection

In [34]:

```
import pandas as pd
from sklearn.feature_selection import SelectKBest, chi2

X = df.drop('Exited', axis=1)
y = df['Exited']

# Apply SelectKBest with Chi-Square Test
best_features = SelectKBest(score_func=chi2, k=5)
fit = best_features.fit(X, y)

# Get top 5 feature names
selected_features = X.columns[fit.get_support()]
print("Top 5 Features Selected:", selected_features)

# Feature Scores
feature_scores = pd.DataFrame({'Feature': X.columns, 'Score': fit.scores_})
feature_scores = feature_scores.sort_values(by='Score', ascending=False)
print("\nFeature Scores:\n", feature_scores)
```

```
Top 5 Features Selected: Index(['Gender', 'Age', 'Balance', 'IsActiveMember', 'EstimatedSalary'], dtype='object')

Feature Scores:
            Feature         Score
5           Balance  6.456268e+06
9   EstimatedSalary  2.268202e+04
3               Age  2.449916e+03
8    IsActiveMember  9.994814e+01
2            Gender  4.682741e+01
0       CreditScore  4.073225e+01
6     NumOfProducts  2.264400e+01
1         Geography  1.159640e+01
4            Tenure  3.257325e+00
7         HasCrCard  1.640134e-01
```

In [35]:

```
# Filter dataset with selected features
selected_features = X[selected_features]
```

Machine Learning Model and Evaluation

In [36]:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

In [37]:

```
#Split Dataset
X = selected_features
y= df[['Exited']]
X_train, X_test, y_train, y_test =train_test_split(X, y, test_size=0.3)
y_train = y_train.values.ravel()  # Converts y_train to a 1D array
y_test = y_test.values.ravel()    # Converts y_test to a 1D array
```

In [38]:

```
# Initialize and train the model
logistic_model = LogisticRegression(max_iter=1000, random_state=42)
logistic_model.fit(X_train, y_train)

# Make predictions
logistic_preds = logistic_model.predict(X_test)

# Evaluate
print("Logistic Regression Accuracy:", accuracy_score(y_test, logistic_preds))
print(classification_report(y_test, logistic_preds))
```

```
Logistic Regression Accuracy: 0.8268292682926829
              precision    recall  f1-score   support

           0       0.85      0.96      0.90      2323
           1       0.61      0.25      0.36       547

    accuracy                           0.83      2870
   macro avg       0.73      0.61      0.63      2870
weighted avg       0.80      0.83      0.80      2870
```

In [39]:

```
# Initialize and train the model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Make predictions
rf_preds = rf_model.predict(X_test)

# Evaluate
print("Random Forest Accuracy:", accuracy_score(y_test, rf_preds))
print(classification_report(y_test, rf_preds))
```

```
Random Forest Accuracy: 0.8153310104529616
              precision    recall  f1-score   support

           0       0.85      0.93      0.89      2323
           1       0.53      0.31      0.39       547

    accuracy                           0.82      2870
   macro avg       0.69      0.62      0.64      2870
weighted avg       0.79      0.82      0.80      2870
```

In [40]:

```
# Initialize and train the model
xgb_model = XGBClassifier(eval_metric='logloss', random_state=42)
xgb_model.fit(X_train, y_train)

# Make predictions
xgb_preds = xgb_model.predict(X_test)

# Evaluate
print("XGBoost Accuracy:", accuracy_score(y_test, xgb_preds))
print(classification_report(y_test, xgb_preds))
```

```
XGBoost Accuracy: 0.8222996515679443
              precision    recall  f1-score   support

           0       0.85      0.95      0.90      2323
           1       0.56      0.30      0.39       547

    accuracy                           0.82      2870
   macro avg       0.71      0.62      0.64      2870
weighted avg       0.80      0.82      0.80      2870
```

Maximum Accuracy we got from Logistic Regression i.e 82% so we taking that model for further consideration

Saving the Logistic Regression model for future prediction

In [41]:

```
import joblib

# Check the type of the model
print(type(logistic_model))

# Save the model
joblib.dump(logistic_model, 'model.pkl')
print("Model saved successfully!")
```

```
<class 'sklearn.linear_model._logistic.LogisticRegression'>
Model saved successfully!
```