In [49]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

from scipy.stats import chi2_contingency, ttest_ind
```

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
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
Complain              0
Satisfaction Score    0
Card Type             0
Point Earned          0
dtype: int64
```

In [5]:
```
df = pd.read_csv('Bank-Records.csv')
df.head()
```

Out[5]:

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

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 18 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  
 14  Complain            10000 non-null  int64  
 15  Satisfaction Score  10000 non-null  int64  
 16  Card Type           10000 non-null  object 
 17  Point Earned        10000 non-null  int64  
dtypes: float64(2), int64(12), object(4)
memory usage: 1.4+ MB
```

In [7]:
```
df.describe(include = 'object')
```

Out[7]:

	Surname	Geography	Gender	Card Type
count	10000	10000	10000	10000
unique	2932	3	2	4
top	Smith	France	Male	DIAMOND
freq	32	5014	5457	2507

In [8]:
```
df.describe()
```

Out[8]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estima
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	100(
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	1000!
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	575
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	510
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	1001!
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	1493
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	1999!

In [9]:
```
df.drop(columns = {'RowNumber', 'CustomerId', 'Surname'}, axis = 1, inplace =True)
```

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

Out[10]:

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

In [11]:
```
df['HasCrCard'].replace({0 : 'No', 1 : 'Yes'}, inplace = True)
```

In [12]:
```
df['IsActiveMember'].replace({0 : 'No', 1 : 'Yes'}, inplace = True)
df['Exited'].replace({0 : 'No', 1 : 'Yes'}, inplace = True)
df['Complain'].replace({0 : 'No', 1 : 'Yes'}, inplace = True)
```

In [13]:
```
df.head()
```

Out[13]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Sati
0	619	France	Female	42	2	0.00	1	Yes	Yes	101348.88	Yes	Yes	
1	608	Spain	Female	41	1	83807.86	1	No	Yes	112542.58	No	Yes	
2	502	France	Female	42	8	159660.80	3	Yes	No	113931.57	Yes	Yes	
3	699	France	Female	39	1	0.00	2	No	No	93826.63	No	No	
4	850	Spain	Female	43	2	125510.82	1	Yes	Yes	79084.10	No	No	

Non Graphical Analysis

In [14]:
```
columnss = ['Geography', 'Gender', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'Exited', 'Complain', 'Satisfaction Score', 'Card Type']
for i in columnss:
  print(df.value_counts(i))
  print('\n')
```

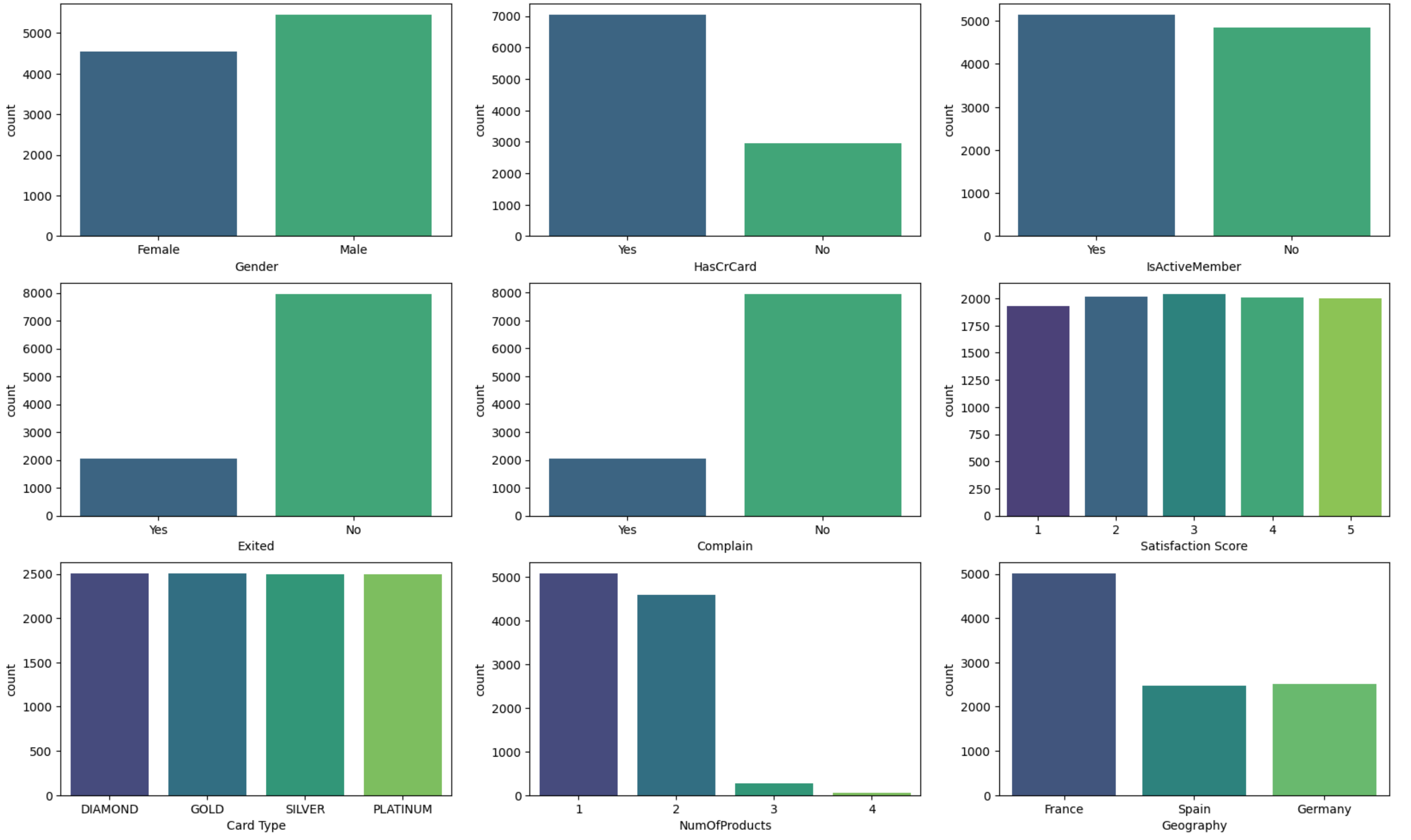
```
Geography
France     5014
Germany    2509
Spain      2477
Name: count, dtype: int64


Gender
Male      5457
Female    4543
Name: count, dtype: int64


NumOfProducts
1    5084
2    4590
3     266
4      60
Name: count, dtype: int64


HasCrCard
Yes    7055
No     2945
Name: count, dtype: int64


IsActiveMember
Yes    5151
No     4849
Name: count, dtype: int64


Exited
No     7962
Yes    2038
Name: count, dtype: int64


Complain
```

```
No     7956
Yes    2044
Name: count, dtype: int64


Satisfaction Score
3    2042
2    2014
4    2008
5    2004
1    1932
Name: count, dtype: int64


Card Type
DIAMOND     2507
GOLD        2502
SILVER      2496
PLATINUM    2495
Name: count, dtype: int64
```

- 50% Customers are from France
- 70% Customer have Credit Card
- There seems to be more Male as compared to Females but by small margin
- Complain and Exited seems to have some corelation since they have same numbers
- Marginally have large number of active members as compared to non-active members

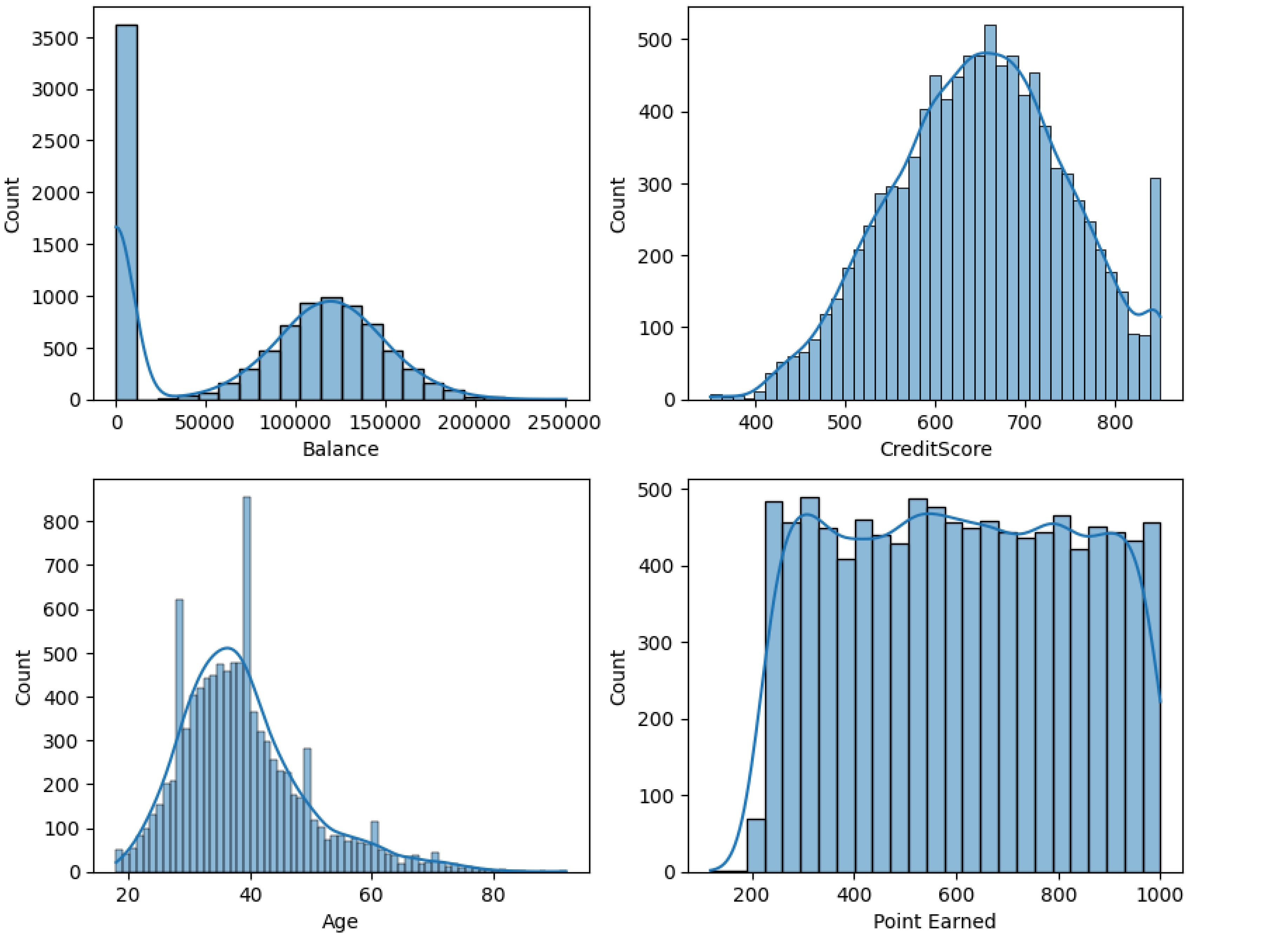
Univariate Analysis:

In [15]:
```
fig, axs = plt.subplots(nrows = 3, ncols = 3, figsize = (20,12))
sns.countplot(data = df, x = 'Gender', ax = axs[0,0], palette = 'viridis')
sns.countplot(data = df, x = 'HasCrCard', ax = axs[0,1], palette = 'viridis')
sns.countplot(data = df, x = 'IsActiveMember', ax = axs[0,2], palette = 'viridis')
sns.countplot(data = df, x = 'Exited', ax = axs[1,0], palette = 'viridis')
sns.countplot(data = df, x = 'Complain', ax = axs[1,1], palette = 'viridis')
sns.countplot(data = df, x = 'Satisfaction Score', ax = axs[1,2], palette = 'viridis')
sns.countplot(data = df, x = 'Card Type', ax = axs[2,0], palette = 'viridis')
sns.countplot(data = df, x = 'NumOfProducts', ax = axs[2,1], palette = 'viridis')
sns.countplot(data = df, x = 'Geography', ax = axs[2,2], palette = 'viridis')
plt.show()
```



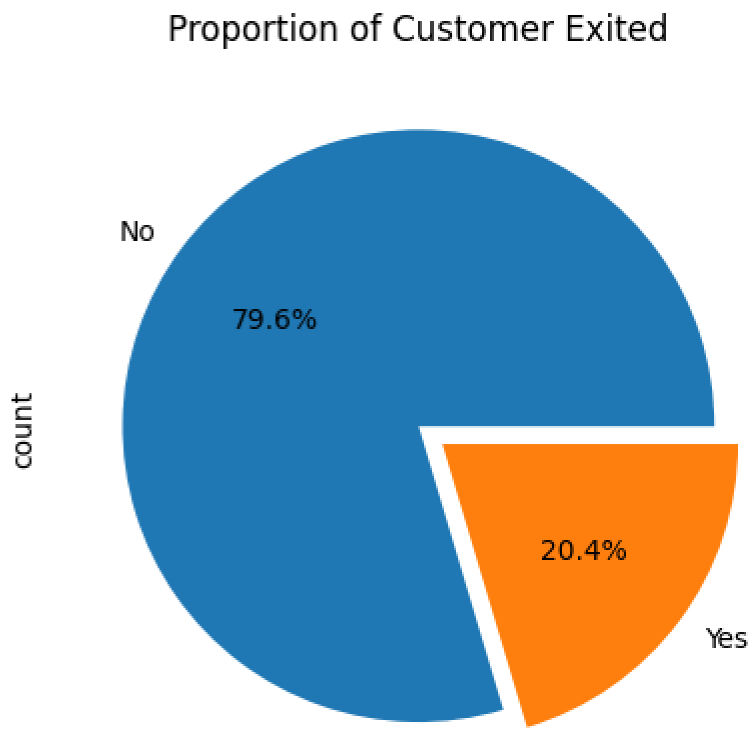
count
Female
Male
Gender
Yes
No
HasCrCard
IsActiveMember
Exited
Complain
1
2
3
4
5
Satisfaction Score
DIAMOND
GOLD
SILVER
PLATINUM
Card Type
NumOfProducts
France
Spain
Germany
Geography

In [16]:
```
fig, axs = plt.subplots(nrows = 2, ncols = 2, figsize = (10,8))
sns.histplot(data = df, x = 'Balance', kde = True, ax = axs[0,0])
sns.histplot(data = df, x = 'CreditScore', kde = True, ax = axs[0,1])
sns.histplot(data = df, x = 'Age', kde = True, ax = axs[1,0])
sns.histplot(data = df, x = 'Point Earned', kde = True, ax = axs[1,1])
plt.show()
```


Count
Balance
0
50000
100000
150000
200000
250000
3500
3000
2500
2000
1500
1000
500
Count
CreditScore
400
500
600
700
800
300
200
100
Count
Age
20
40
60
80
900
700
600
Count
Point Earned
1000

- 3.7k Customer have around 0 Balance account
- More number of people have age around 40

In [17]:
```
df['Exited'].value_counts().plot.pie(autopct = '%.1f%%', explode = (0,0.1))
plt.title('Proportion of Customer Exited')
plt.show()
```



- There is 20% Churn Rate

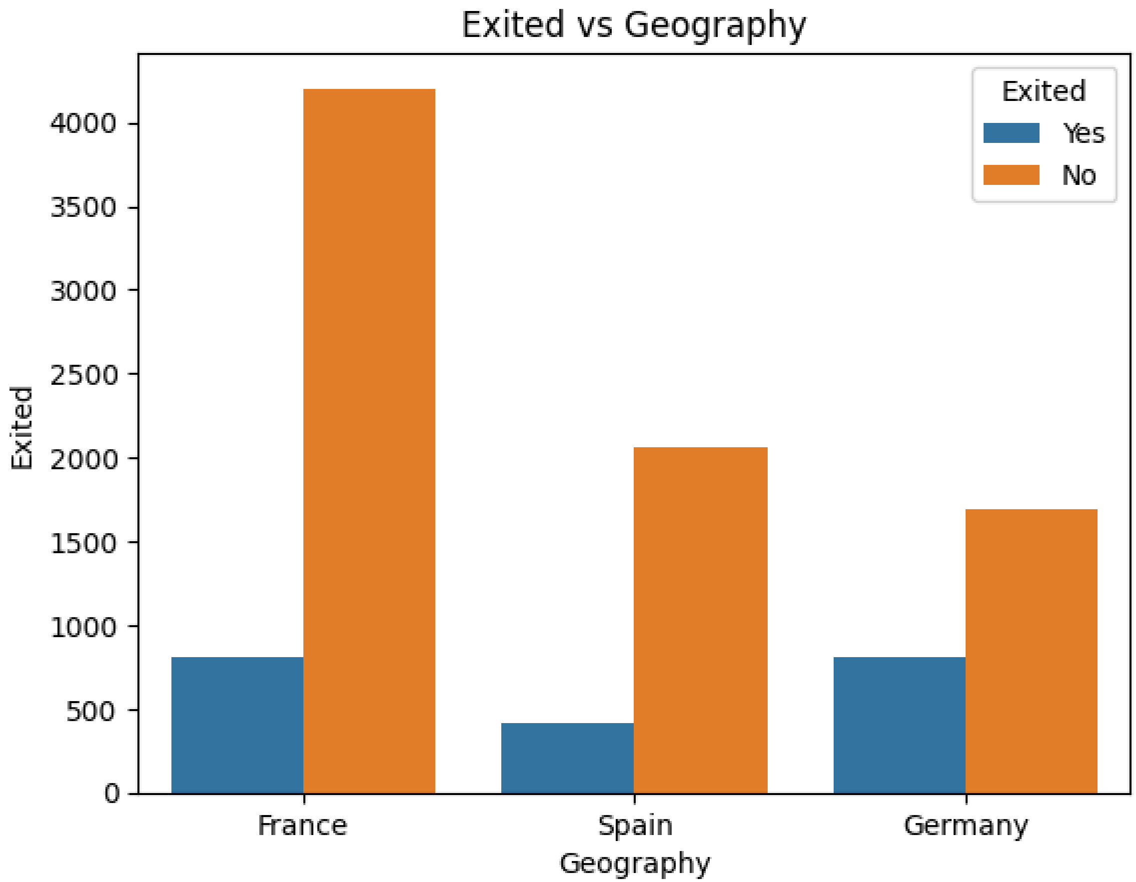
Bivariate Analysis

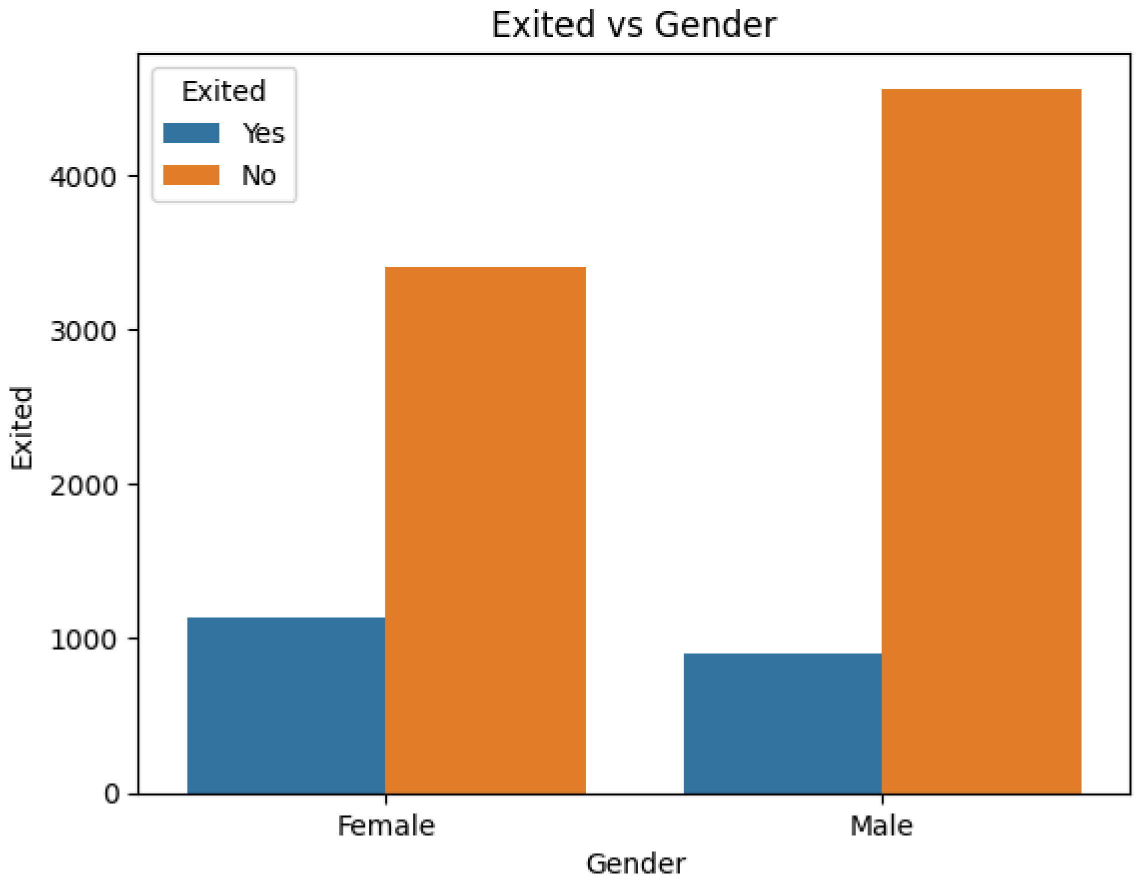
In [18]:
```
df.head()
```

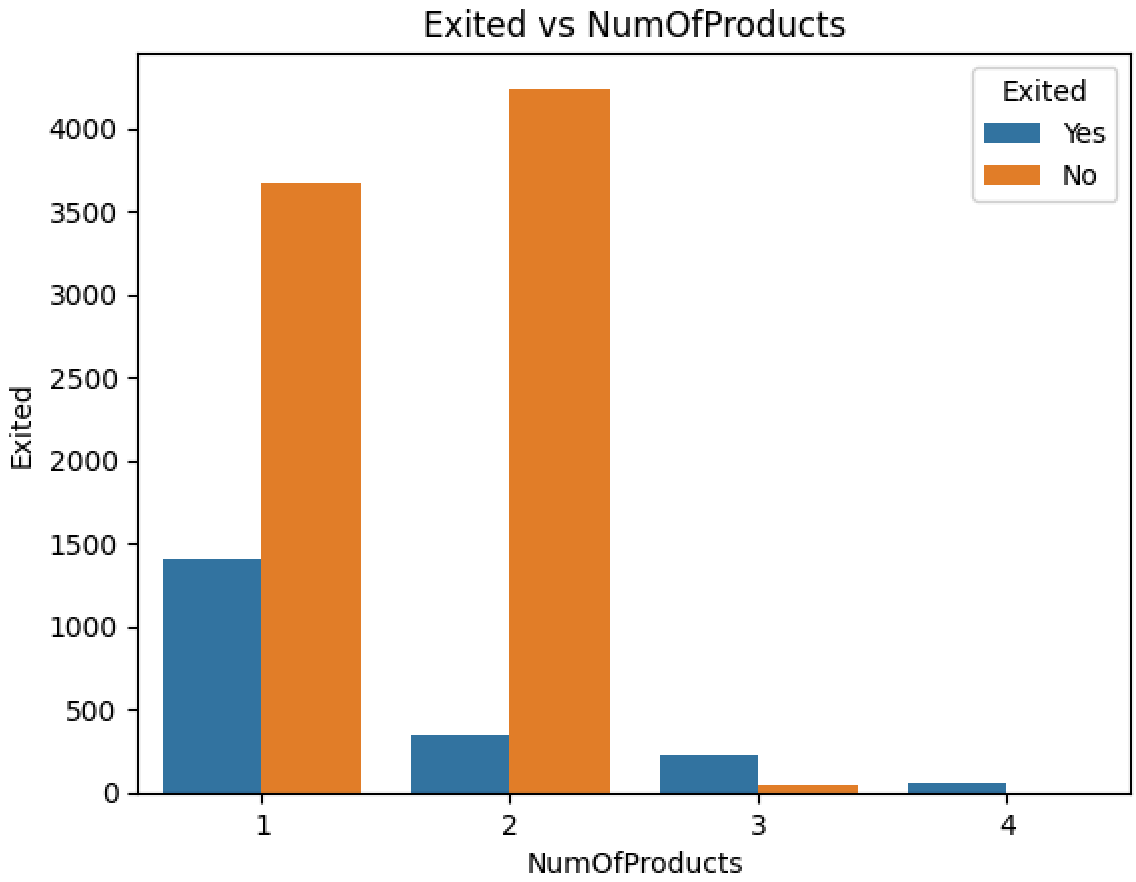
Out[18]:

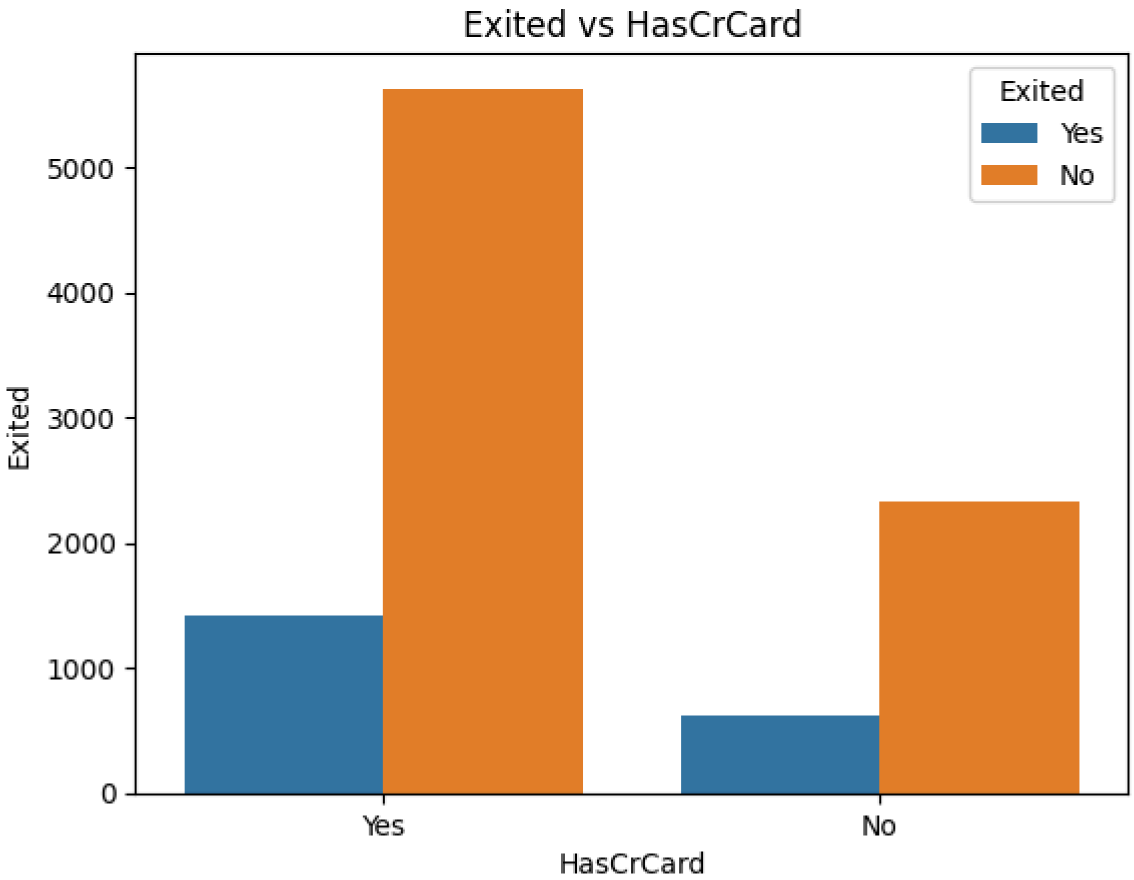
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Sati
0	619	France	Female	42	2	0.00	1	Yes	Yes	101348.88	Yes	Yes	
1	608	Spain	Female	41	1	83807.86	1	No	Yes	112542.58	No	Yes	
2	502	France	Female	42	8	159660.80	3	Yes	No	113931.57	Yes	Yes	
3	699	France	Female	39	1	0.00	2	No	No	93826.63	No	No	
4	850	Spain	Female	43	2	125510.82	1	Yes	Yes	79084.10	No	No	

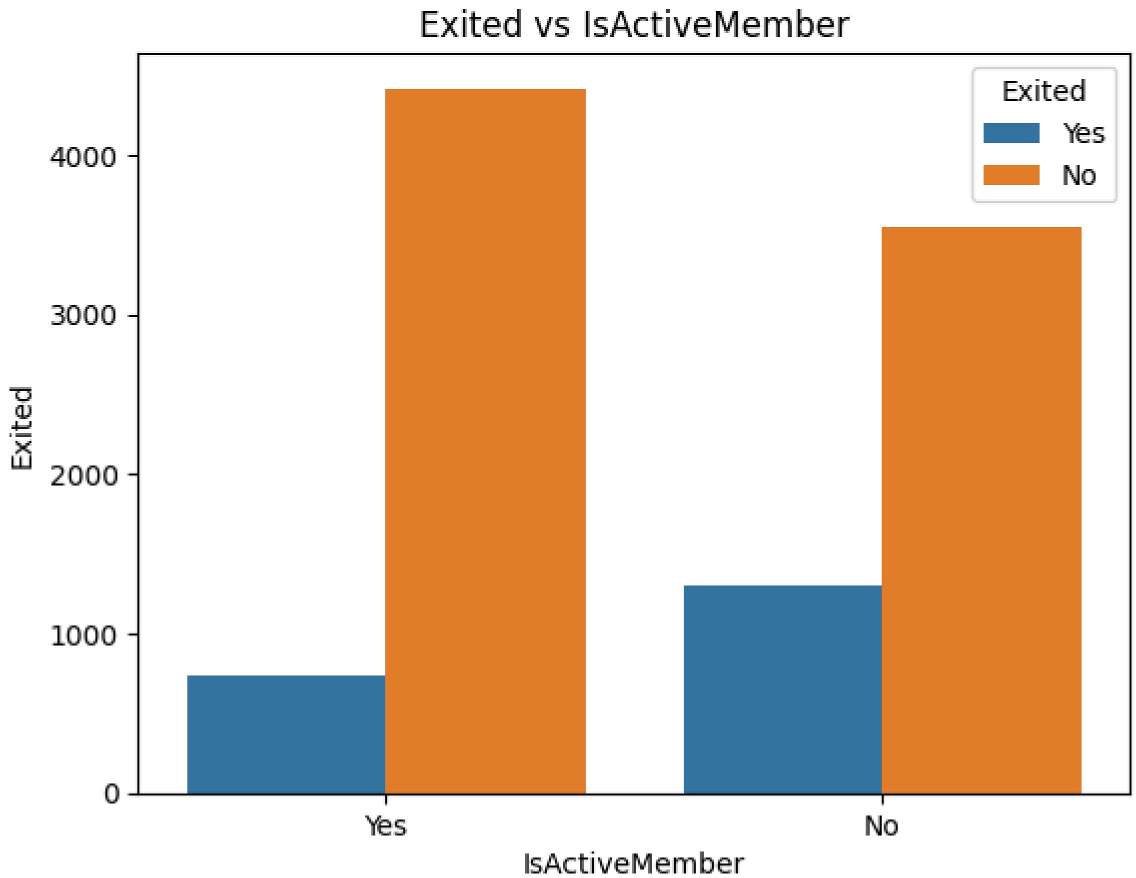
In [19]:
```
s = ['Geography','Gender','NumOfProducts','HasCrCard','IsActiveMember','Complain','Satisfaction Score','Card Type','Te
nure']

for i in s:
    sns.countplot(data = df, x = i, hue = 'Exited')
    plt.title(f'Exited vs {i}')
    plt.xlabel(i)
    plt.ylabel('Exited')
    plt.show()
```

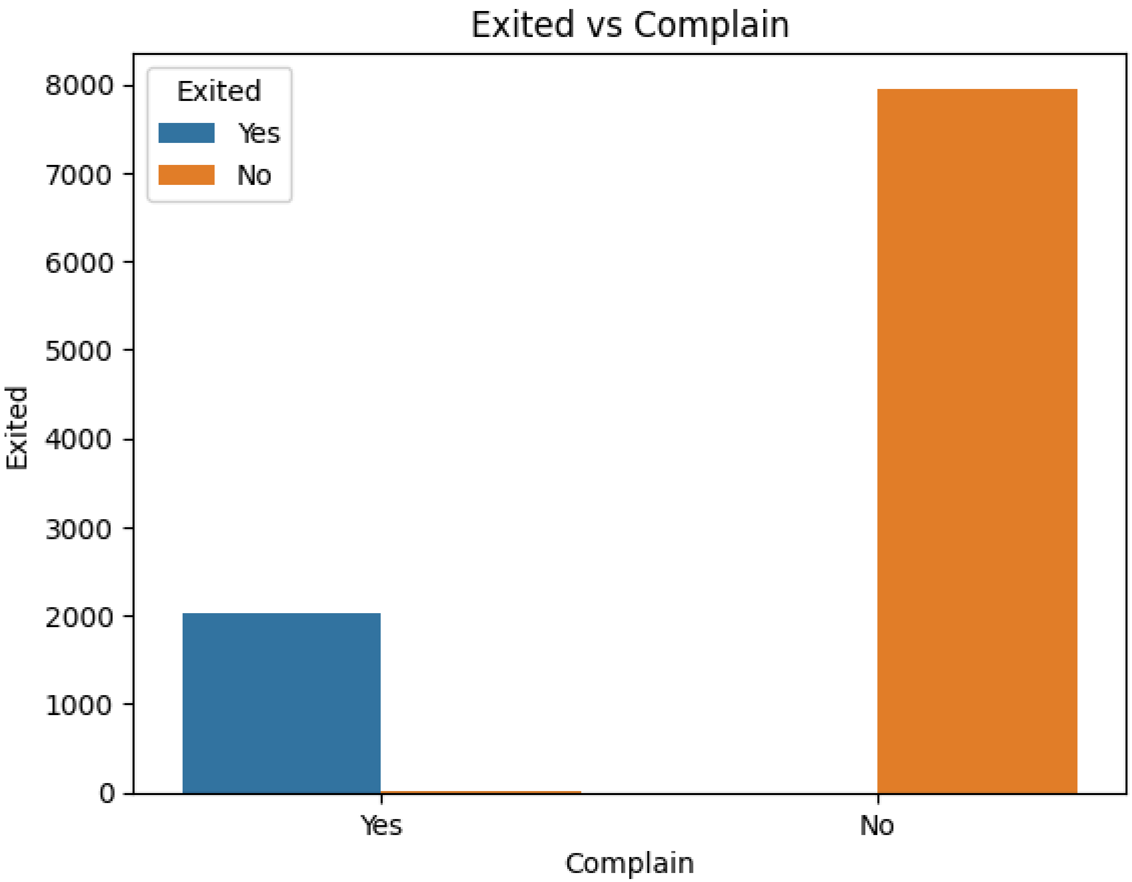

Exited vs Geography
Exited
Yes
No
4000
3500
3000
2500
2000
1500
1000
500
0
Exited
France
Spain
Germany
Geography

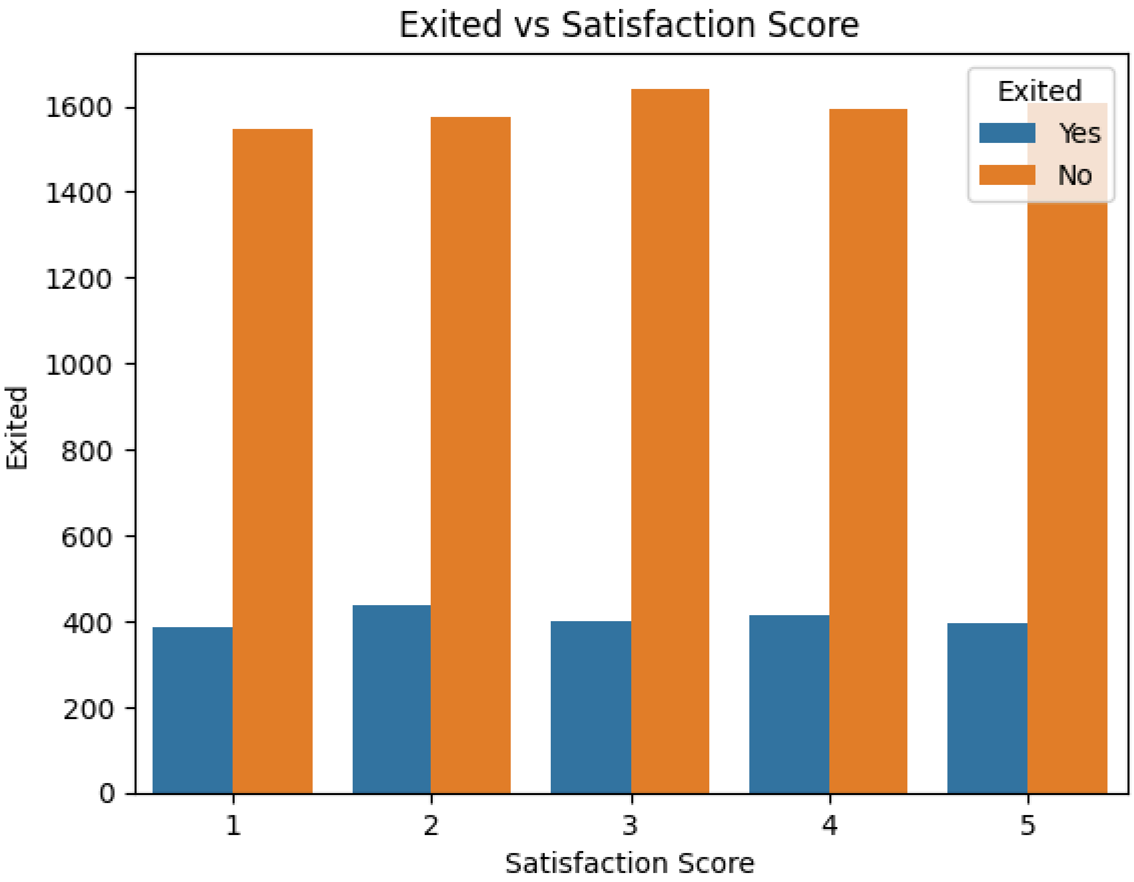

Exited vs Gender
Exited
Yes
No
4000
3000
2000
1000
0
Exited
Female
Male
Gender

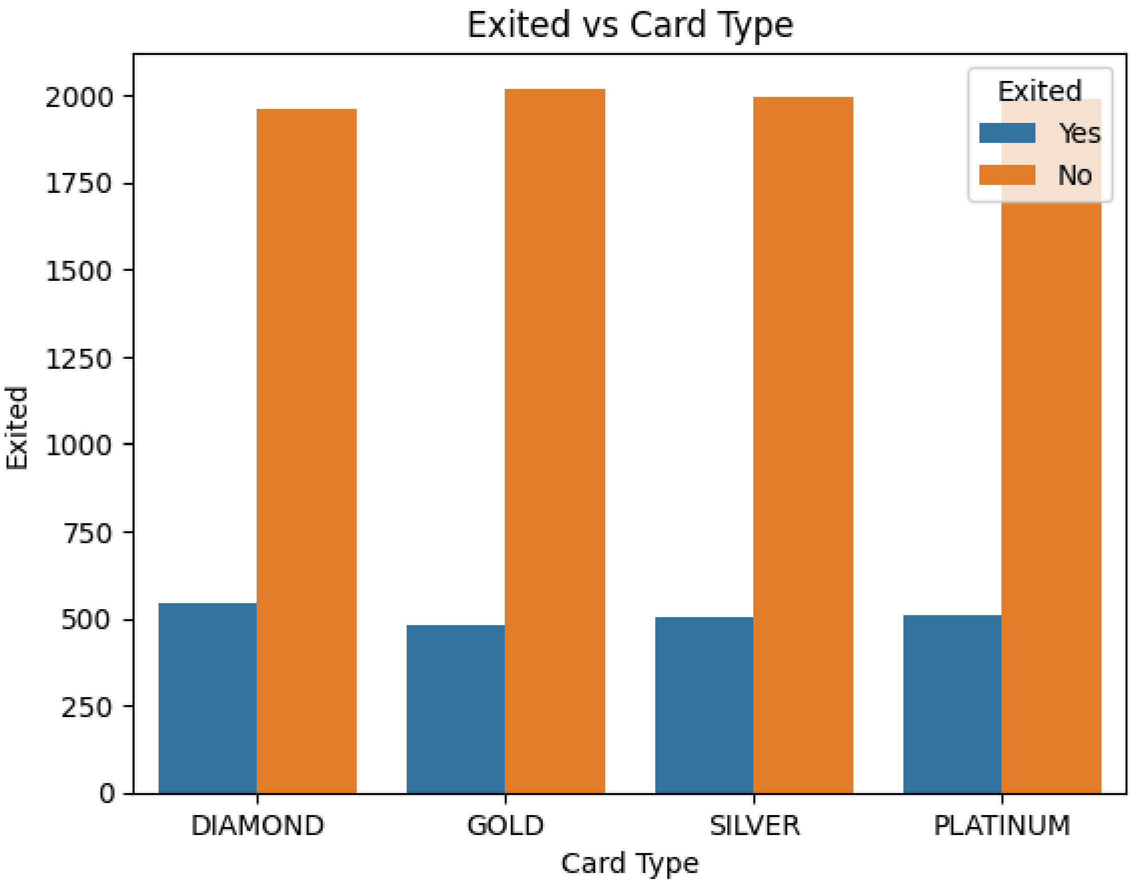

Exited vs NumOfProducts
Exited
Yes
No
4000
3500
3000
2500
2000
1500
1000
500
0
Exited
1
2
3
4
NumOfProducts

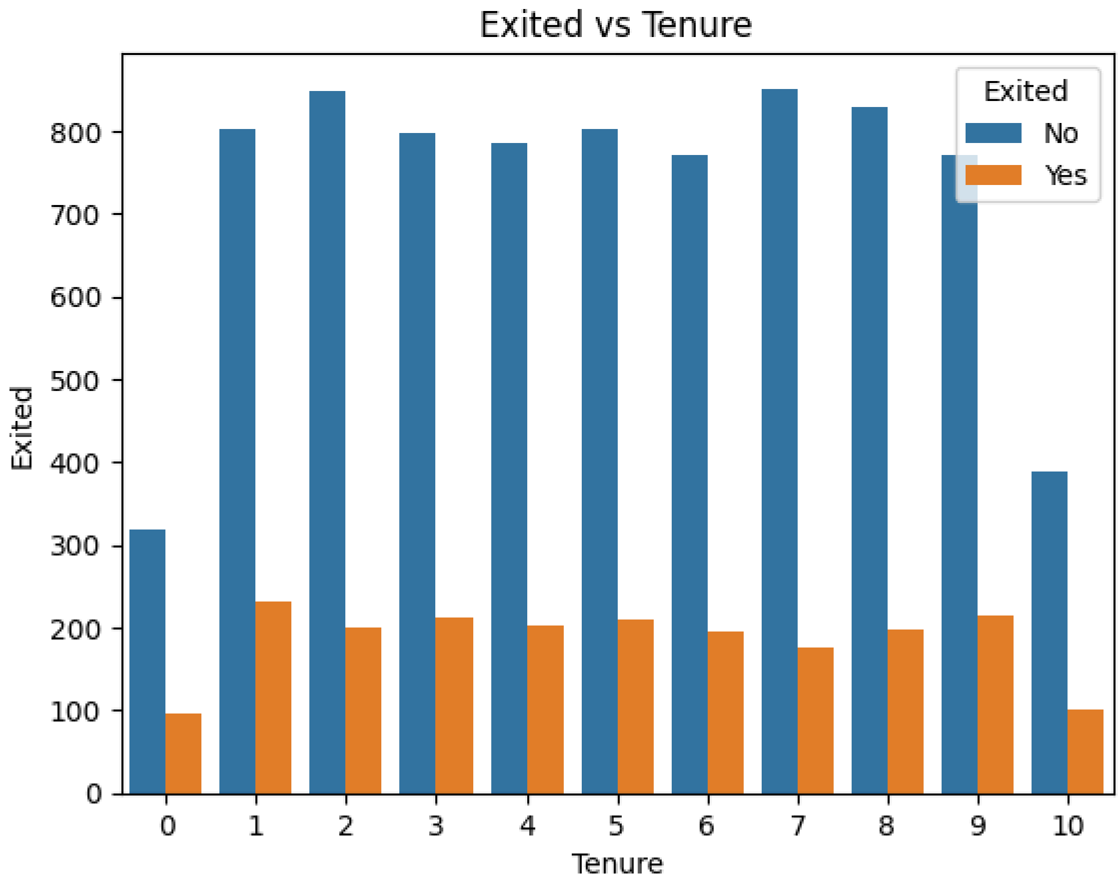

Exited vs HasCrCard
Exited
Yes
No
5000
4000
3000
2000
1000
0
Exited
Yes
No
HasCrCard


Exited vs IsActiveMember
Exited
Yes
No
4000
3000
2000
1000
0
Exited
Yes
No
IsActiveMember

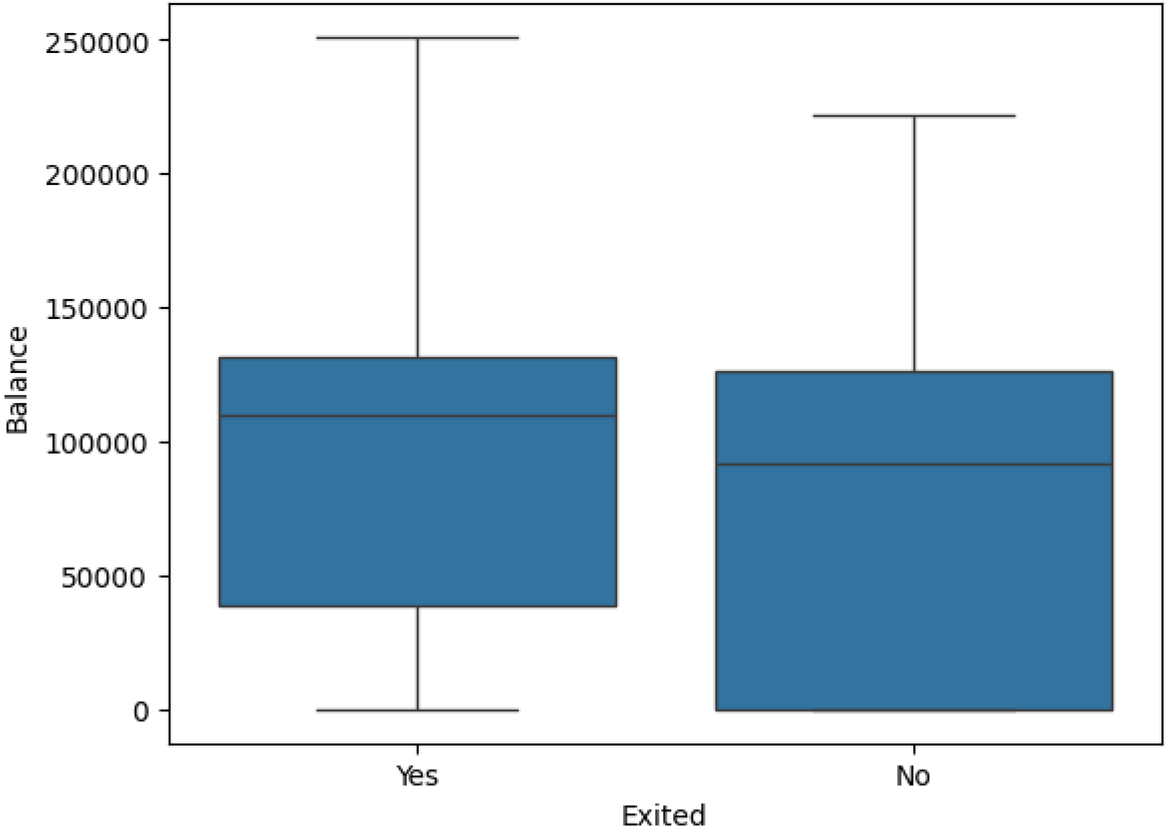

Exited vs Complain
Exited
Yes
No
8000
7000
6000
5000
4000
3000
2000
1000
0
Exited
Yes
No
Complain


Exited vs Satisfaction Score
Exited
Yes
No
1600
1400
1200
1000
800
600
400
200
0
Exited
1
2
3
4
5
Satisfaction Score

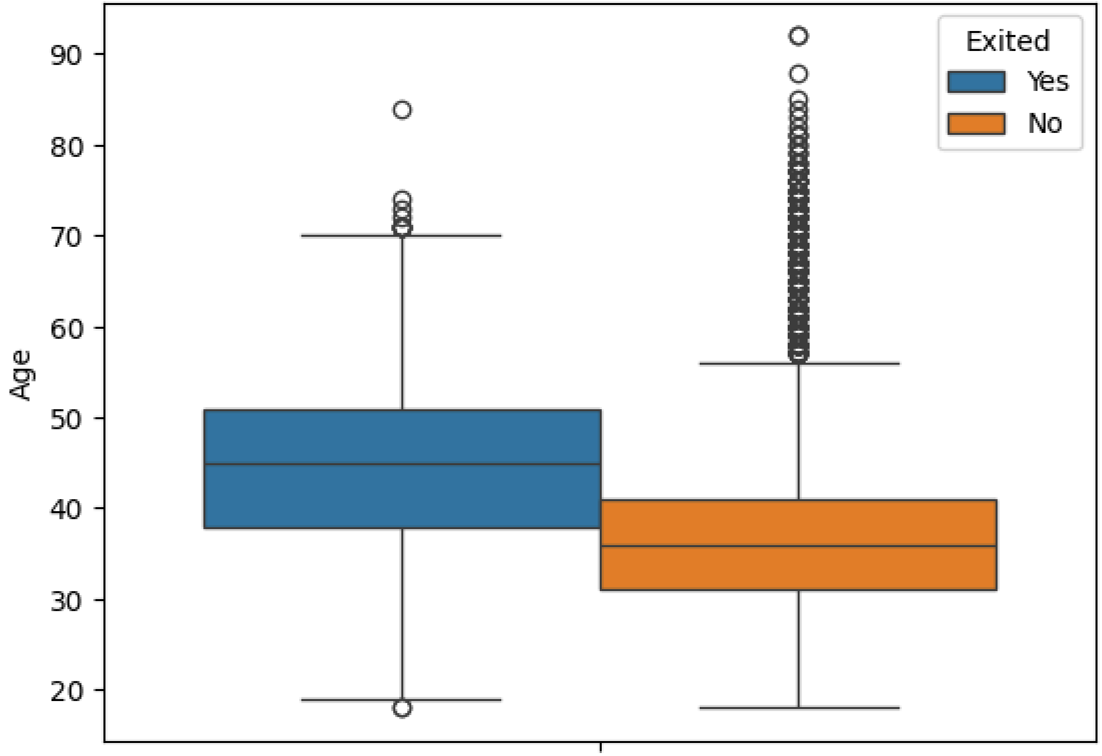

Exited vs Card Type
Exited
Yes
No
0
250
500
750
1000
1250
1500
1750
2000
DIAMOND
GOLD
SILVER
PLATINUM
Card Type


Exited vs Tenure
Exited
No
Yes
800
700
600
500
400
300
200
100
0
Exited
0
1
2
3
4
5
6
7
8
9
10
Tenure

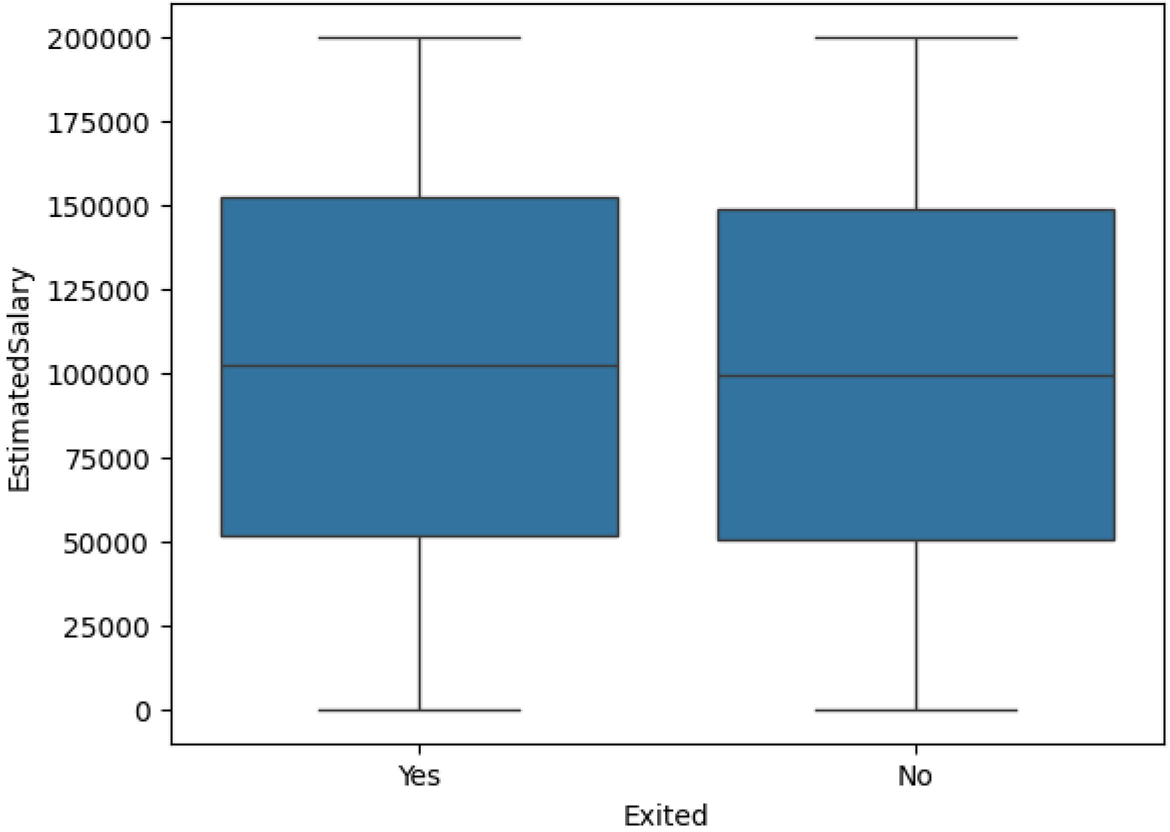
In [20]:
```
sns.boxplot(data = df, y = 'Balance', x = 'Exited')
plt.show()
```



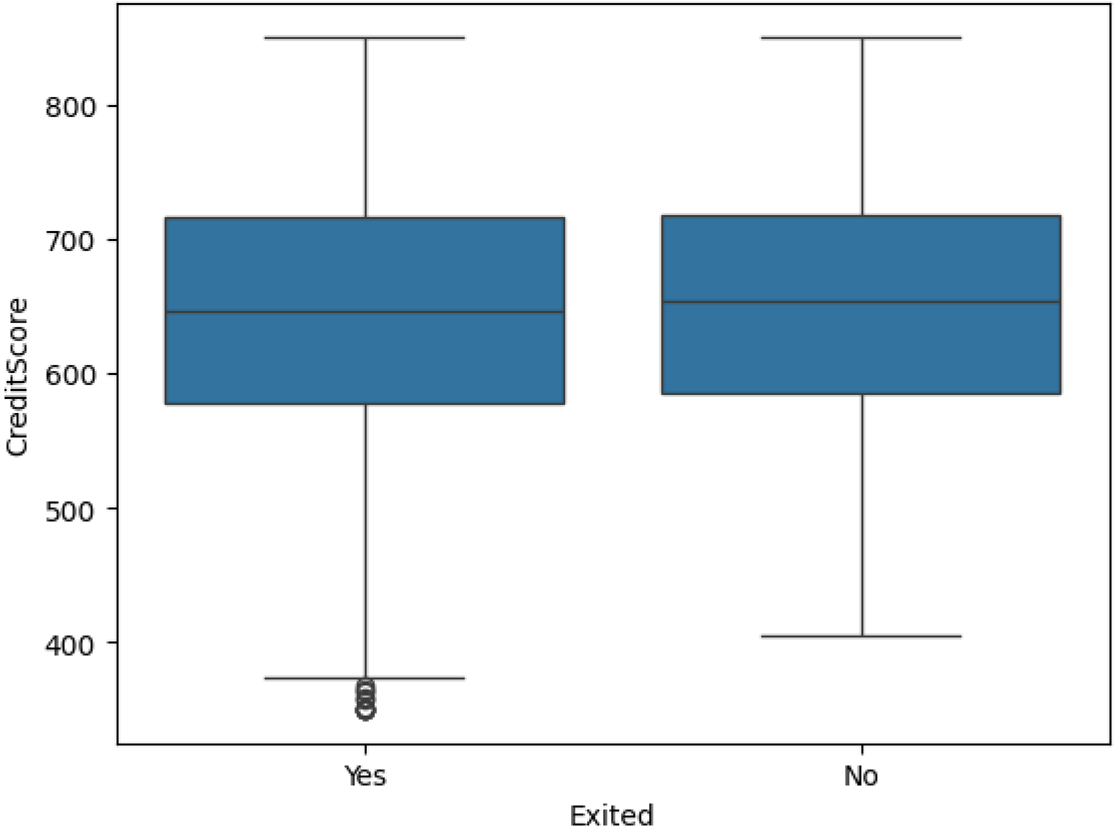
In [21]:
```
sns.boxplot(data = df, y = 'Age', hue = 'Exited')
plt.show()
```



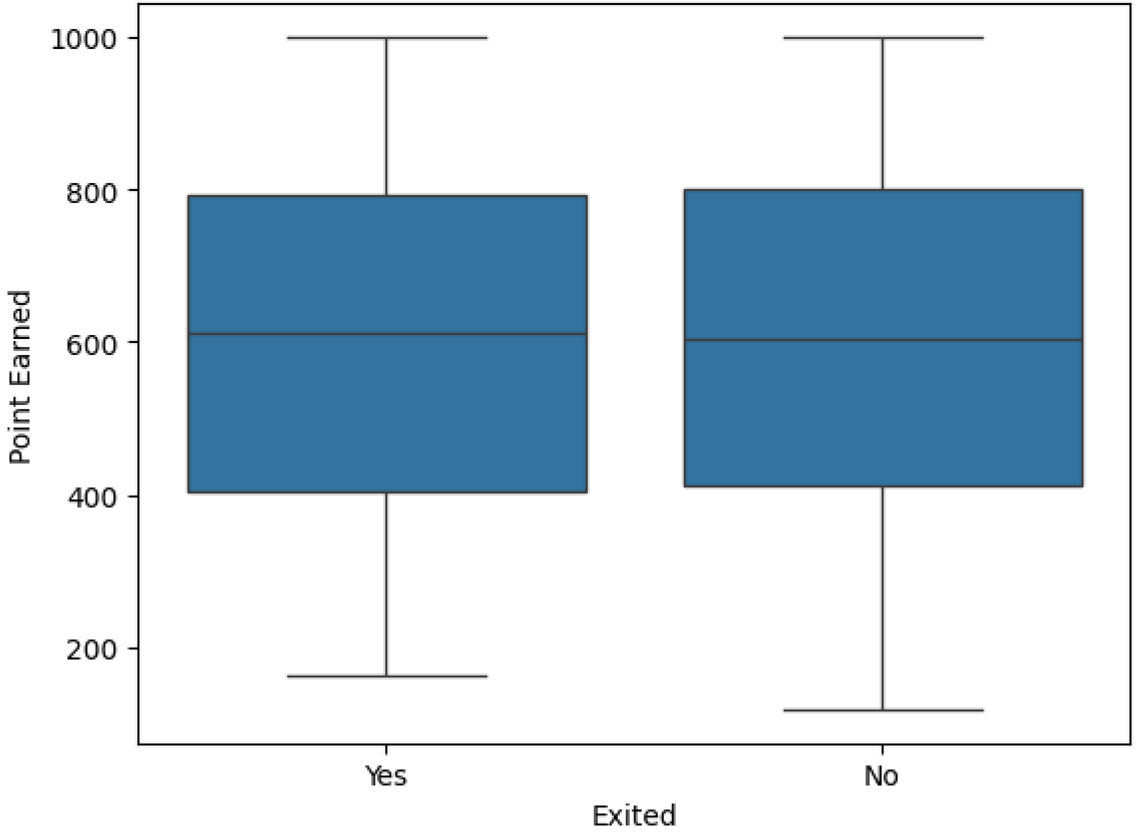
In [22]:
```
sns.boxplot(data = df, y = 'EstimatedSalary', x = 'Exited')
plt.show()
```



In [23]:
```
sns.boxplot(data = df, x = 'Exited', y = 'CreditScore')
plt.show()
```

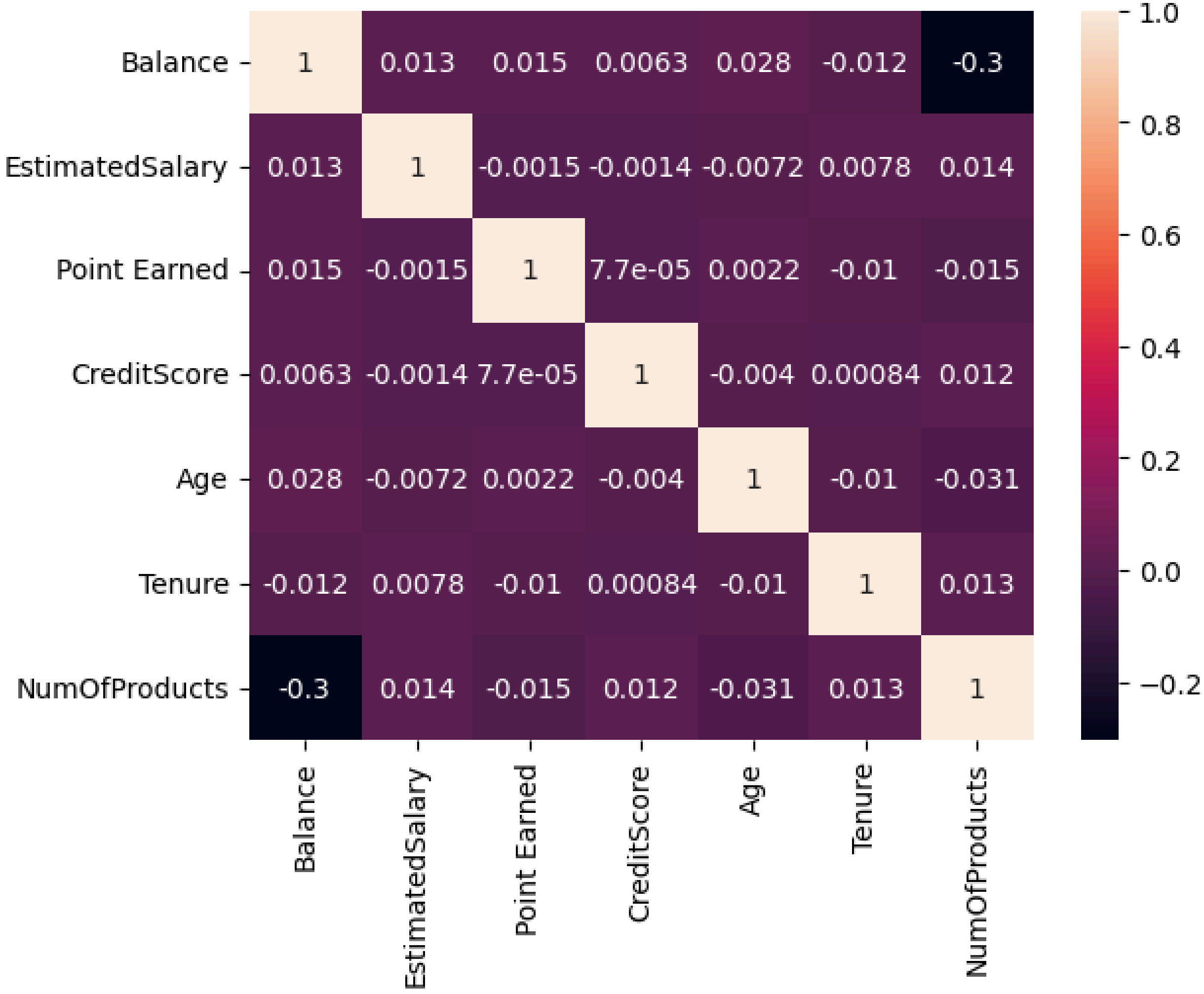


In [24]:
```
sns.boxplot(data = df, x = 'Exited', y = 'Point Earned')
plt.show()
```



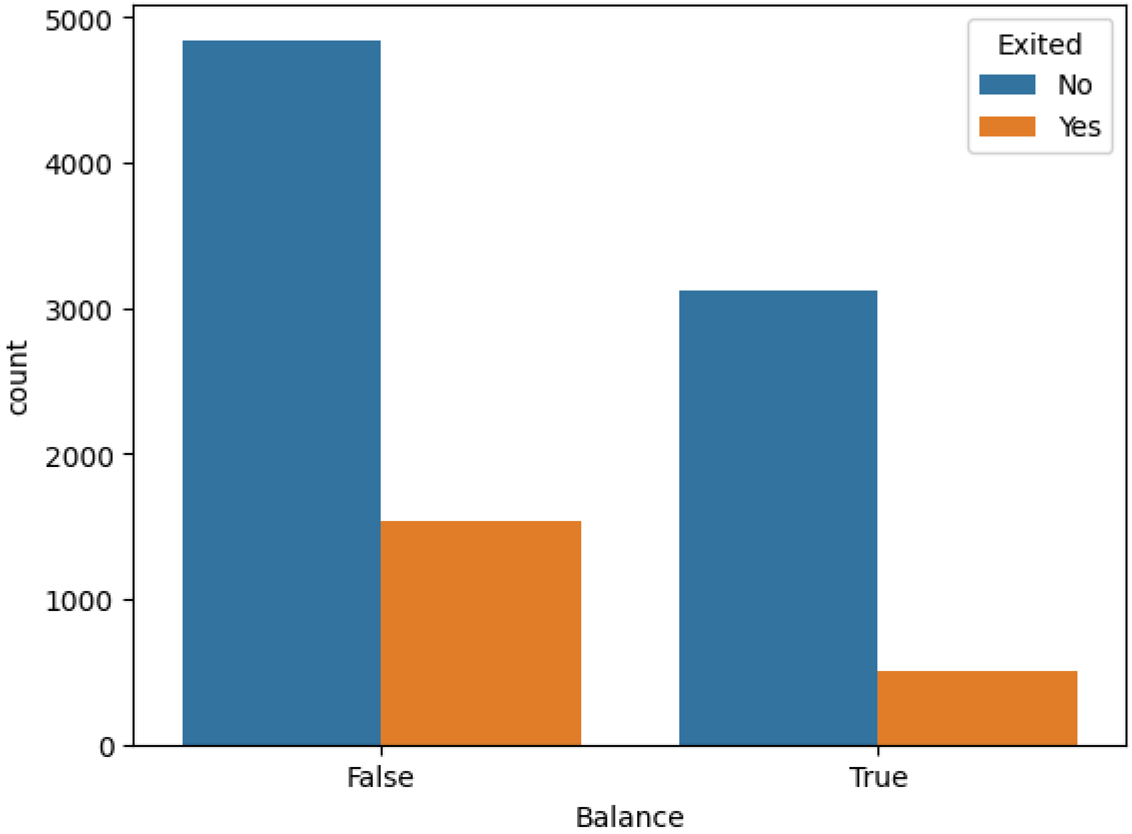
Correlation between the fields

In [25]:
```
numeric_corr = ['Balance','EstimatedSalary', 'Point Earned', 'CreditScore', 'Age', 'Tenure', 'NumOfProducts']
corr = df[numeric_corr].corr()
sns.heatmap(data = corr, annot = True)
plt.show()
```



0 Balance Customer

In [26]:
```
sns.countplot(data = df, x = df['Balance'] == 0, hue = 'Exited')
plt.show()
```



In [27]:
```
total_zero_balance = ((df['Balance'] == 0) & (df['Exited'] == 1)).sum()
total_zero_balance
```

Out[27]: 0

Churn Rate

For Categorical Columns

In [28]:
```
df.head()
```

Out[28]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Sati
0	619	France	Female	42	2	0.00	1	Yes	Yes	101348.88	Yes	Yes	
1	608	Spain	Female	41	1	83807.86	1	No	Yes	112542.58	No	Yes	
2	502	France	Female	42	8	159660.80	3	Yes	No	113931.57	Yes	Yes	
3	699	France	Female	39	1	0.00	2	No	No	93826.63	No	No	
4	850	Spain	Female	43	2	125510.82	1	Yes	Yes	79084.10	No	No	

In [29]:
```
df['Exited'].replace({'No' : 0, 'Yes' : 1}, inplace = True)
```

In [30]:
```
geography_churn_rate = df.groupby('Geography')['Exited'].mean() * 100
geography_churn_rate
```

Out[30]:
```
Geography
France      16.174711
Germany     32.443204
Spain       16.673395
Name: Exited, dtype: float64
```

In [31]:
```
gender_churn_rate = df.groupby('Gender')['Exited'].mean() * 100
gender_churn_rate
```

Out[31]:
```
Gender
Female    25.071539
Male      16.474253
Name: Exited, dtype: float64
```

In [32]:
```
tenure_churn_rate = df.groupby('Tenure')['Exited'].mean() * 100
tenure_churn_rate
```

Out[32]:
```
Tenure
0     23.002421
1     22.415459
2     19.179389
3     21.110010
4     20.525784
5     20.652174
6     20.268873
7     17.217899
8     19.219512
9     21.747967
10    20.612245
Name: Exited, dtype: float64
```

In [33]:
```
numofpro_churn_rate = df.groupby('NumOfProducts')['Exited'].mean() * 100
numofpro_churn_rate
```

Out[33]:
```
NumOfProducts
1     27.714398
2      7.603486
3     82.706767
4    100.000000
Name: Exited, dtype: float64
```

In [34]:
```
hascard_churn_rate = df.groupby('HasCrCard')['Exited'].mean() * 100
hascard_churn_rate
```

Out[34]:
```
HasCrCard
No     20.814941
Yes    20.198441
Name: Exited, dtype: float64
```

In [35]:
```
IsActiveMember_churn_rate = df.groupby('IsActiveMember')['Exited'].mean() * 100
IsActiveMember_churn_rate
```

Out[35]:
```
IsActiveMember
No     26.871520
Yes    14.269074
Name: Exited, dtype: float64
```

In [36]:
```
Complain_churn_rate = df.groupby('Complain')['Exited'].mean() * 100
Complain_churn_rate
```

Out[36]:
```
Complain
No      0.050277
Yes    99.510763
Name: Exited, dtype: float64
```

In [37]:
```
Satisfaction_Score_churn_rate = df.groupby('Satisfaction Score')['Exited'].mean() * 100
Satisfaction_Score_churn_rate
```

Out[37]:
```
Satisfaction Score
1    20.031056
2    21.797418
3    19.637610
4    20.617530
5    19.810379
Name: Exited, dtype: float64
```

In [38]:
```
Card_Type_churn_rate = df.groupby('Card Type')['Exited'].mean() * 100
Card_Type_churn_rate
```

Out[38]:
```
Card Type
DIAMOND     21.779019
GOLD        19.264588
PLATINUM    20.360721
SILVER      20.112179
Name: Exited, dtype: float64
```

In [39]:
```
bins = [18,30,45,58,75,93]
labels = ['18-29','30-44','45-57','58-74','75-92']

df['Age_bin'] = pd.cut(df['Age'], bins = bins, labels = labels, right = False)
df.head()
```

Out[39]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Sati
0	619	France	Female	42	2	0.00	1	Yes	Yes	101348.88	1	Yes	
1	608	Spain	Female	41	1	83807.86	1	No	Yes	112542.58	0	Yes	
2	502	France	Female	42	8	159660.80	3	Yes	No	113931.57	1	Yes	
3	699	France	Female	39	1	0.00	2	No	No	93826.63	0	No	
4	850	Spain	Female	43	2	125510.82	1	Yes	Yes	79084.10	0	No	

In [40]:
```
Age_bin_churn_rate = df.groupby('Age_bin')['Exited'].mean() * 100
Age_bin_churn_rate
```

Out[40]:
```
Age_bin
18-29     7.556368
30-44    14.454228
45-57    49.732938
58-74    34.109817
75-92     1.851852
Name: Exited, dtype: float64
```

For Numerical Columns

In [41]:
```
CreditScore_churn_rate = df[df['Exited'] == 1]['CreditScore'].mean() * 100
print(f'Churned Customer for Credit Score: {CreditScore_churn_rate}')

CreditScore_churn_rate = df[df['Exited'] == 0]['CreditScore'].mean() * 100
print(f'Non Churned Customer for Credit Score: {CreditScore_churn_rate}')
```

```
Churned Customer for Credit Score: 64541.462217860644
Non Churned Customer for Credit Score: 65183.78548103492
```

In [42]:
```
Age_churn_rate = df[df['Exited'] == 1]['Age'].mean() * 100
print(f'Churned Customer for Age: {Age_churn_rate}')

Age_churn_rate = df[df['Exited'] == 0]['Age'].mean() * 100
print(f'Non Churned Customer for Age: {Age_churn_rate}')
```

```
Churned Customer for Age: 4483.562315996075
Non Churned Customer for Age: 3740.8063300678223
```

In [43]:
```
Balance_churn_rate = df[df['Exited'] == 1]['Balance'].mean() * 100
print(f'Churned Customer for Balance: {Balance_churn_rate}')

Balance_churn_rate = df[df['Exited'] == 0]['Balance'].mean() * 100
print(f'Non Churned Customer for Balance: {Balance_churn_rate}')
```

```
Churned Customer for Balance: 9110947.600588812
Non Churned Customer for Balance: 7274275.066314995
```

In [44]:
```
EstimatedSalary_churn_rate = df[df['Exited'] == 1]['EstimatedSalary'].mean() * 100
print(f'Churned Customer for EstimatedSalary: {EstimatedSalary_churn_rate}')

EstimatedSalary_churn_rate = df[df['Exited'] == 0]['EstimatedSalary'].mean() * 100
print(f'Non Churned Customer for EstimatedSalary: {EstimatedSalary_churn_rate}')
```

```
Churned Customer for EstimatedSalary: 10150990.878312068
Non Churned Customer for EstimatedSalary: 9972685.314117055
```

- It is cleared that 99% complaints are not resolved
- Germany have higher churn rate
- Females are more likey to churn
- Those with 3 or more number of products are more likely to churn

Hypothesis Testing

∇ Satisfaction Score Vs Complain

- Null Hypothesis : There is no significant difference in satisfaction score of customer who have exited with complain and exited without complain
- Alternative Hypothesis : There is significant difference in satisfaction score of customer who have exited with complain and exited without complain

In [58]:
```
satis_com = pd.crosstab(df[df['Exited'] == 1]['Satisfaction Score'], df['Complain'])

chi2, pval, a, b = chi2_contingency(satis_com)
alpha = 0.05

if pval<alpha :
  print('Reject Null Hypothesis')
else:
  print('Failed to Reject Null Hypothesis')
```

```
Failed to Reject Null Hypothesis
```

- There is significant difference in satisfaction score of customer who have exited with complain and exited without complain

∇ Geography and Customer Churn

- Null Hypothesis : There is no association between the geographical locations of the customer and exiting the Bank
- Alternative Hypothesis : There is association between the geographical locations of the customer and exiting the Bank

In [61]:
```
geo_exit = pd.crosstab(df['Exited'], df['Geography'])

stest, pval, a, b = chi2_contingency(geo_exit)
alpha = 0.05

if pval < alpha :
  print('Reject Null Hypothesis')
else:
  print('Failed to Reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

- There is association between the geographical locations of the customer and exiting the Bank

∇ Gender Vs Customer Churn

- Null Hypothesis : There is no association between the Gender and customer exiting the bank
- Alternative Hypothesis : These is association between the Gender and customer exiting the bank

In [63]:
```
gen_exit = pd.crosstab(df['Exited'], df['Gender'])

stest, pval, a, b = chi2_contingency(gen_exit)
alpha = 0.05

if pval < alpha :
  print('Reject Null Hypothesis')
else:
  print('Failed to Reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

- These is association between the Gender and customer exiting the bank

∇ Number Of Products Vs Customer Churn

Null Hypothesis : There is no significant difference between the Number of products customer buying and exiting the bank

Alternative Hypothesis : There is significant difference between the Number of products customer buying and exiting the bank

In [65]:
```
num_exit = pd.crosstab(df['Exited'], df['NumOfProducts'])

stest, pval, a, b = chi2_contingency(num_exit)
alpha = 0.05

if pval < alpha :
  print('Reject Null Hypothesis')
else:
  print('Failed to Reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

- There is significant difference between the Number of products customer buying and exiting the bank

IsActiveMember Vs Customer Churn

- Null Hypothesis : There is no association betweeen Active Customer and exiting the bank
- Alternative Hypothesis : There is an association betweeen Active Customer and exiting the bank

In [66]:
```
act_exit = pd.crosstab(df['Exited'], df['IsActiveMember'])

stest, pval, a, b = chi2_contingency(act_exit)
alpha = 0.05

if pval < alpha :
  print('Reject Null Hypothesis')
else:
  print('Failed to Reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

- There is an association betweeen Active Customer and exiting the bank

Complain Vs Customer Churn

- Null Hypothesis : There is no association between complain by customers and exiting the bank
- Alternative Hypothesis : There is association between complain by customers and exiting the bank

In [67]:
```
com_exit = pd.crosstab(df['Exited'], df['Complain'])

stest, pval, a, b = chi2_contingency(com_exit)
alpha = 0.05

if pval < alpha :
  print('Reject Null Hypothesis')
else:
  print('Failed to Reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

- There is association between complain by customers and exiting the bank

∇ Credit Score Vs Customer Churn

Null Hypothesis : There is no significant difference between the mean of credit score who exited the bank and not exited the bank

Alternative Hypothesis : There is significant difference between the mean of credit score who exited the bank and not exited the bank

In [78]:
```
c_exited = df[df['Exited'] == 1]['CreditScore']
c_stayed = df[df['Exited'] == 0]['CreditScore']

alpha = 0.05
stats, pval = ttest_ind(c_stayed, c_exited, equal_var = False)

if pval < alpha :
  print('Reject Null Hypothesis')
else:
  print('Failed to Reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

- There is significant difference between the mean of credit score who exited the bank and not exited the bank

∇ Age Vs Customer Churn

- Null Hypothesis : There is no significant difference between the mean age of the customer who exited and not exited
- Alternative Hypothesis : There is significant difference between the mean age of the customer who exited and not exited

In [79]:
```
a_exited = df[df['Exited'] == 1]['Age']
a_stayed = df[df['Exited'] == 0]['Age']

alpha = 0.05
stats, pval = ttest_ind(a_stayed, a_exited, equal_var = False)

if pval < alpha :
  print('Reject Null Hypothesis')
else:
  print('Failed to Reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

- There is significant difference between the mean age of the customer who exited and not exited

∇ Balance Vs Customer Churn

- Null Hypothesis : There is no significant difference between the mean balance of the customer who exited and not exited
- Alternative Hypothesis : There is significant difference between the mean balance of the customer who exited and not exited

In [80]:
```
b_exited = df[df['Exited'] == 1]['Balance']
b_stayed = df[df['Exited'] == 0]['Balance']

alpha = 0.05
stats, pval = ttest_ind(b_stayed, b_exited, equal_var = False)

if pval < alpha :
  print('Reject Null Hypothesis')
else:
  print('Failed to Reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

- There is significant difference between the mean balance of the customer who exited and not exited

Actionable Insights

- **Expand Marketing Efforts in Germany and Spain**: Since 50% of customers are from France, focus marketing campaigns on Germany and Spain to boost customer acquisition in these regions.
- **Develop Targeted Offers for Female Customers**: Introduce specific products or offers aimed at attracting more female customers to balance the customer demographics.
- **Enhance After-Sales Service**: Address the fact that almost 99% of customers who filed complaints have left the bank by significantly improving the after-sales service experience.
- **Create Retention Strategies for Multi-Product Holders**: Implement targeted retention strategies for customers with three or more products, as they have a higher churn rate.
- **Engage Zero Balance Account Holders**: Investigate why approximately 3,000 accounts have zero balance and develop offers or incentives to engage these customers and encourage account usage.
- **Financial Counseling for At-Risk Customers**: Analyze factors influencing customer exit versus retention and offer financial counseling to customers in vulnerable salary brackets to reduce churn.

In [ ]: