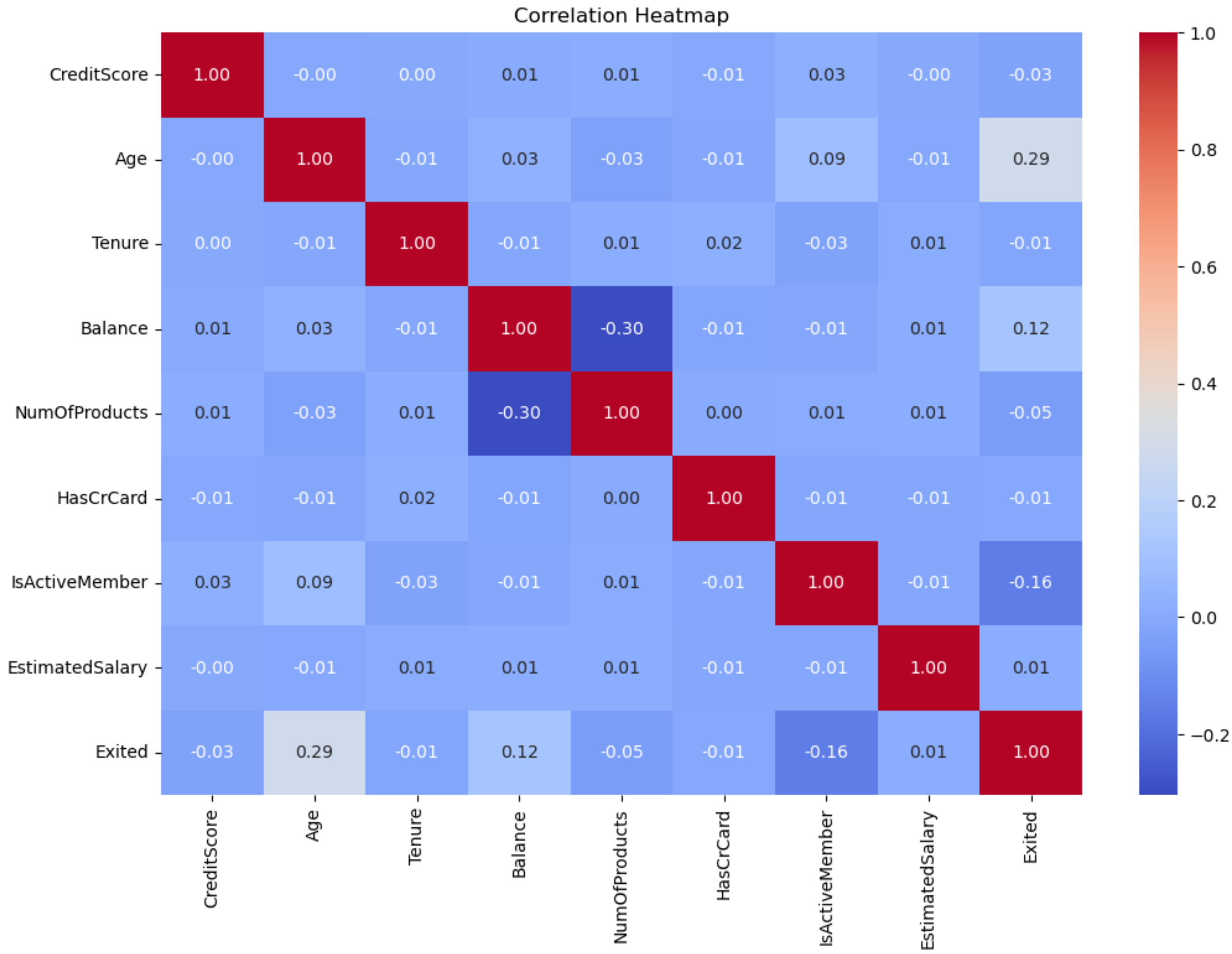
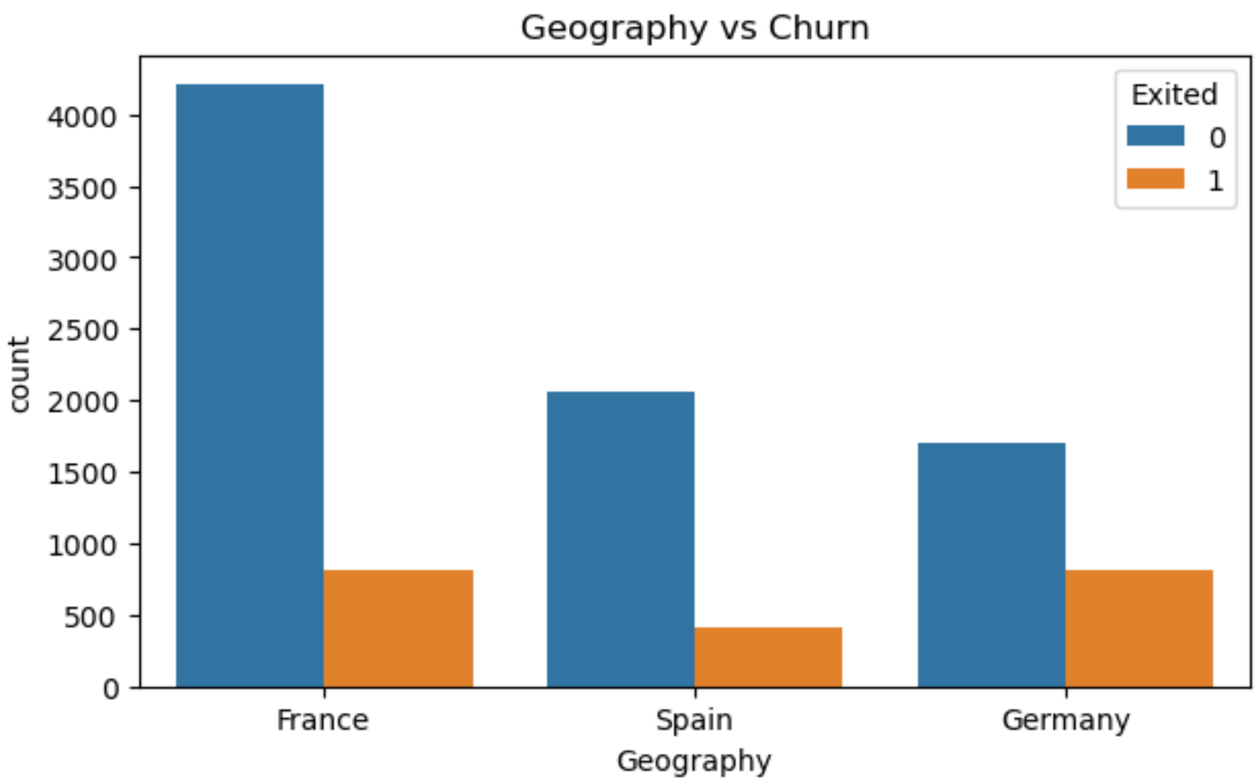
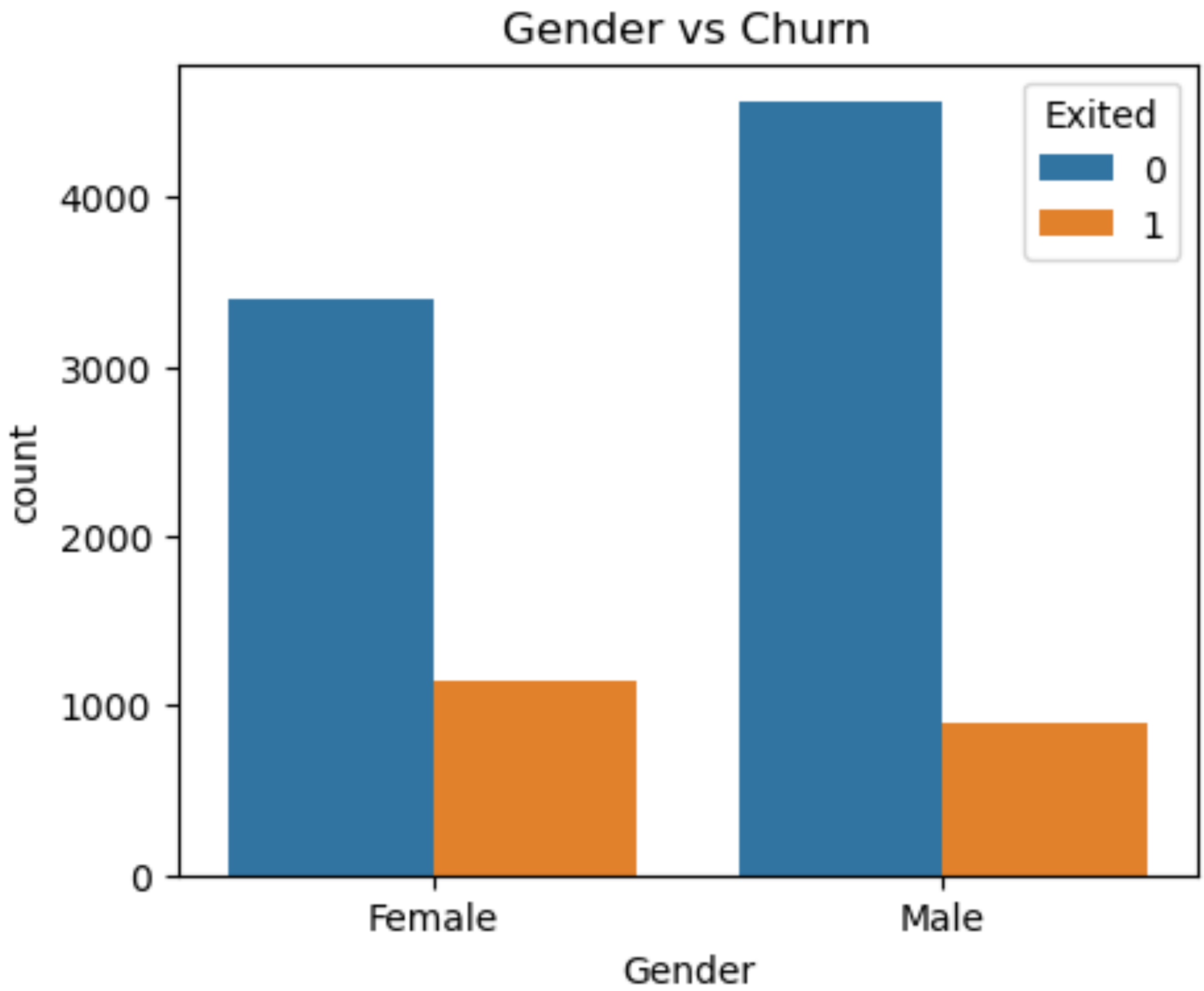
```
📌 Shape: (10000, 11)
📌 Columns: ['CreditScore', 'Geography', 'Gender', 'Age',
'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
'IsActiveMember', 'EstimatedSalary', 'Exited']
📌 Data Types:
 CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
📌 Missing Values:
 CreditScore       0
Geography         0
Gender            0
Age               0
Tenure            0
Balance           0
NumOfProducts     0
HasCrCard         0
IsActiveMember    0
EstimatedSalary   0
Exited            0
dtype: int64
📌 Summary Stats:
         CreditScore           Age        Tenure
Balance  NumOfProducts  \
count  10000.000000  10000.000000  10000.000000
10000.000000   10000.000000
mean     650.528800     38.921800      5.012800
76485.889288       1.530200
std       96.653299     10.487806      2.892174
62397.405202       0.581654
min      350.000000     18.000000      0.000000
0.000000       1.000000
25%      584.000000     32.000000      3.000000
0.000000       1.000000
50%      652.000000     37.000000      5.000000
97198.540000       1.000000
```

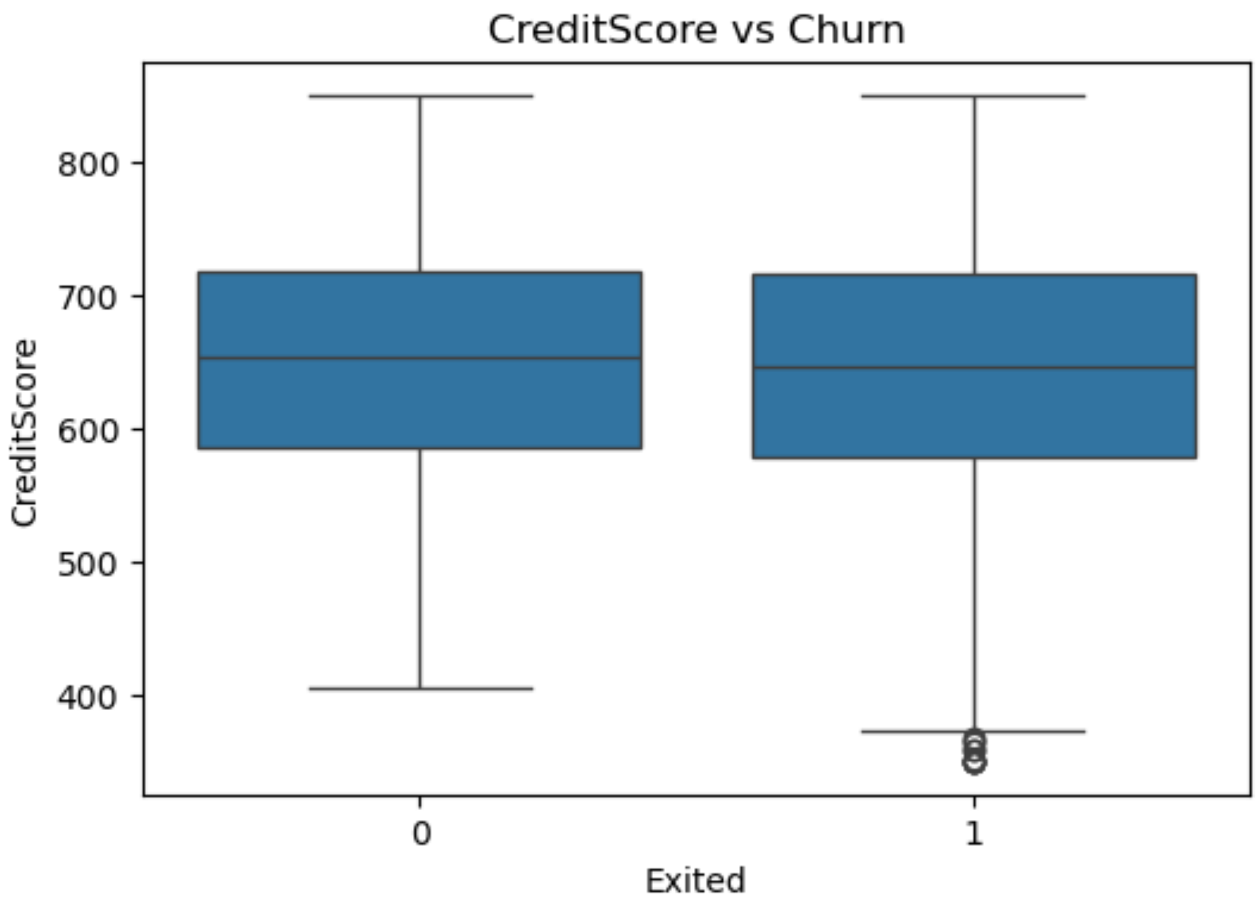
```
75%       718.000000     44.000000      7.000000
127644.240000       2.000000
max       850.000000     92.000000     10.000000
250898.090000       4.000000

         HasCrCard  IsActiveMember  EstimatedSalary
Exited
count  10000.00000    10000.000000     10000.000000
10000.000000
mean       0.70550        0.515100    100090.239881
0.203700
std        0.45584        0.499797     57510.492818
0.402769
min        0.00000        0.000000        11.580000
0.000000
25%        0.00000        0.000000     51002.110000
0.000000
50%        1.00000        1.000000    100193.915000
0.000000
75%        1.00000        1.000000    149388.247500
0.000000
max        1.00000        1.000000    199992.480000
1.000000
📌 Target Distribution:
 Exited
0    79.63
1    20.37
Name: proportion, dtype: float64
```

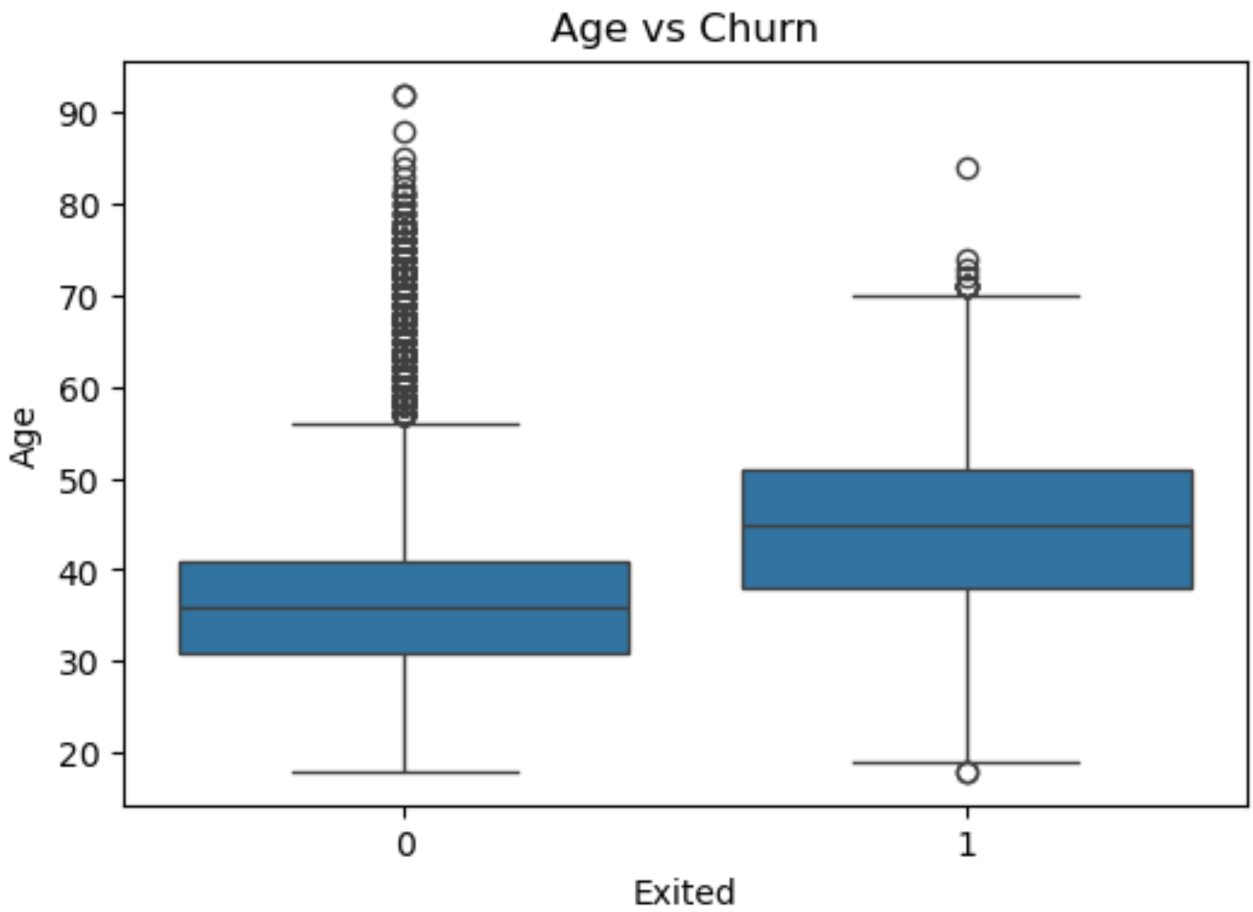

Correlation Heatmap
CreditScore
Age
Tenure
Balance
NumOfProducts
HasCrCard
IsActiveMember
EstimatedSalary
Exited
1.00 -0.00 0.00 0.01 0.01 -0.01 0.03 -0.00 -0.03
-0.00 1.00 -0.01 0.03 -0.03 -0.01 0.09 -0.01 0.29
0.00 -0.01 1.00 -0.01 0.01 0.02 -0.03 0.01 -0.01
0.01 0.03 -0.01 1.00 -0.30 -0.01 -0.01 0.01 0.12
0.01 -0.03 0.01 -0.30 1.00 0.00 0.01 0.01 -0.05
-0.01 -0.01 0.02 -0.01 0.00 1.00 -0.01 -0.01 -0.01
0.03 0.09 -0.03 -0.01 0.01 -0.01 1.00 -0.01 -0.16
-0.00 -0.01 0.01 0.01 0.01 -0.01 -0.01 1.00 0.01
-0.03 0.29 -0.01 0.12 -0.05 -0.01 -0.16 0.01 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

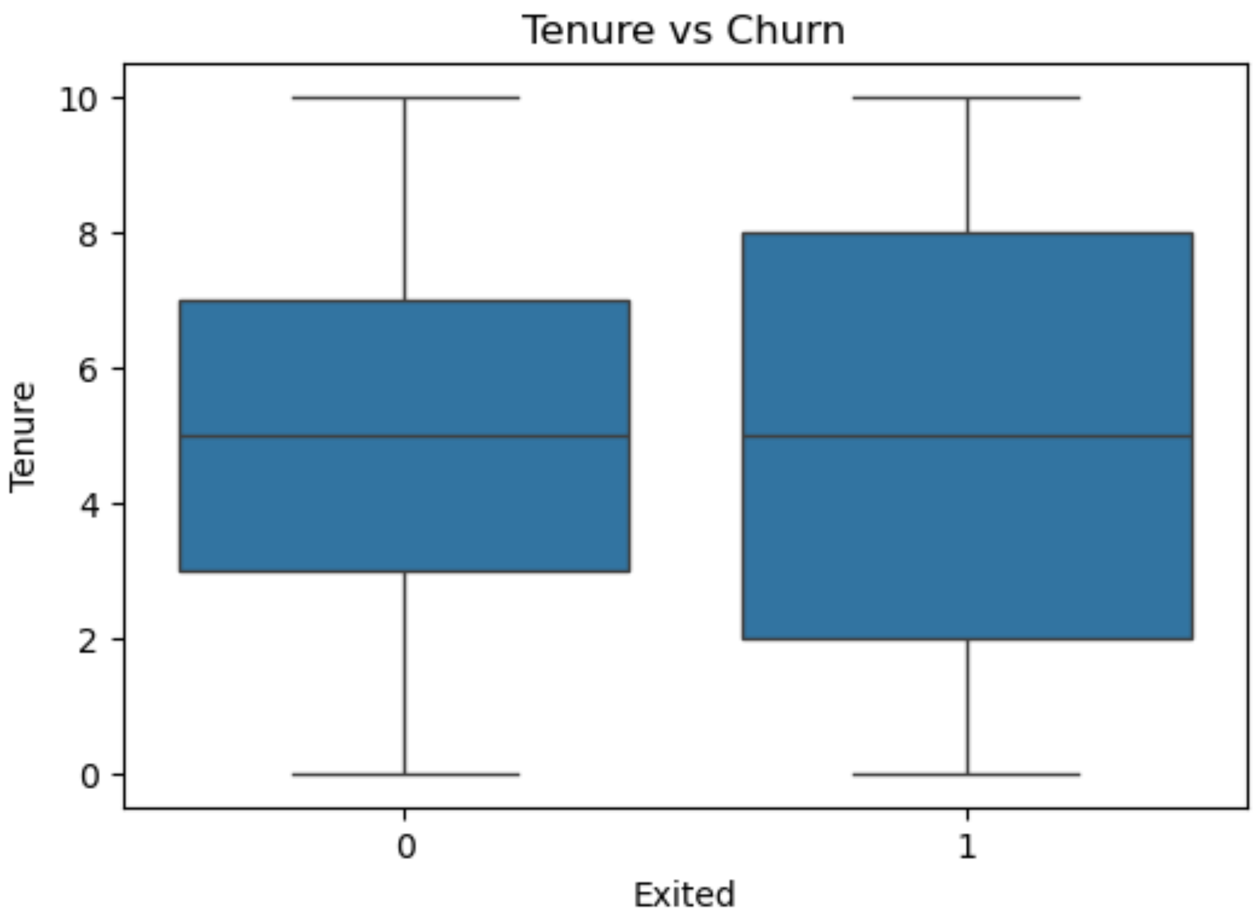

Geography vs Churn
Exited
0
1
count
4000
3500
3000
2500
2000
1500
1000
500
0
France
Spain
Germany
Geography



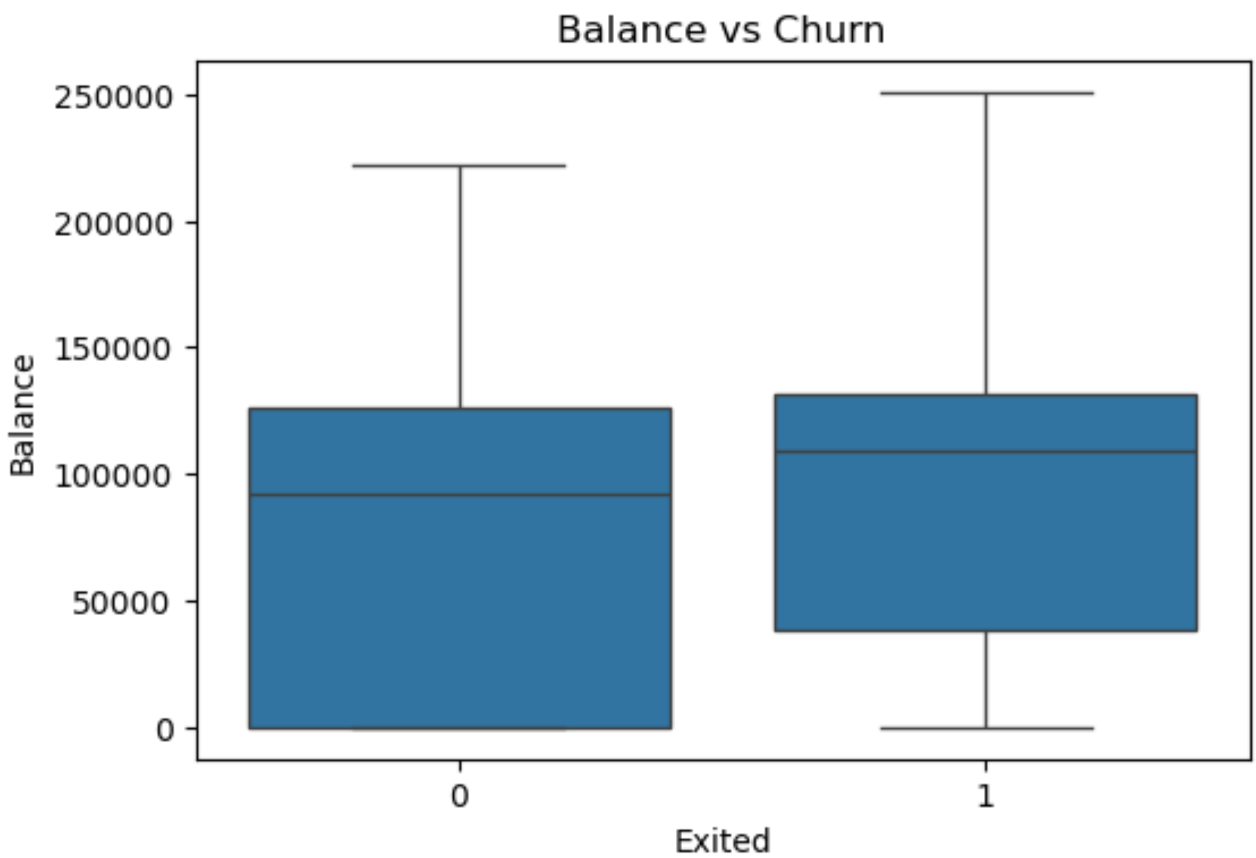
Gender vs Churn
Exited
0
1
4000
3000
2000
1000
0
count
Female
Male
Gender


CreditScore vs Churn
CreditScore
800
700
600
500
400
0
1
Exited

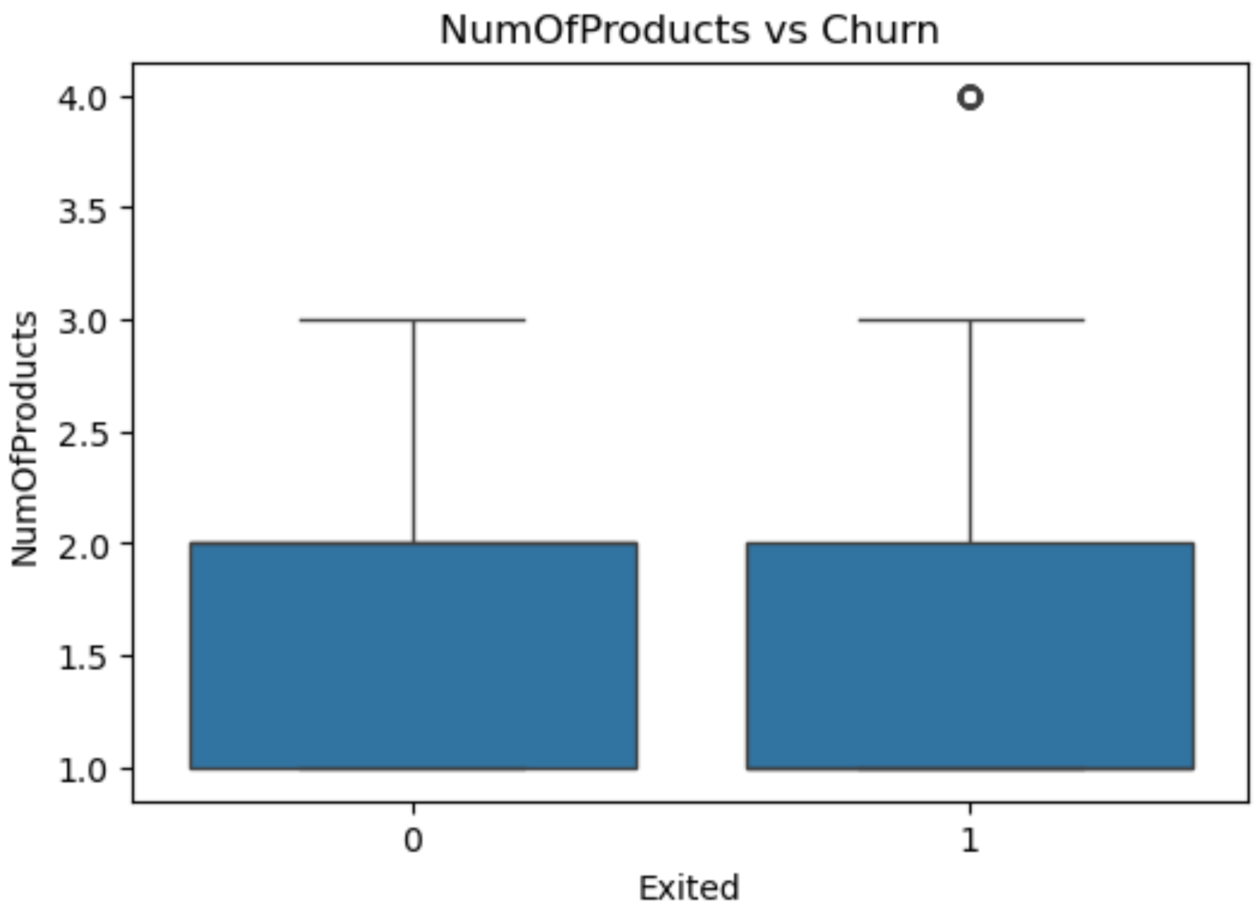

Age vs Churn
Age
90
80
70
60
50
40
30
20
0
1
Exited

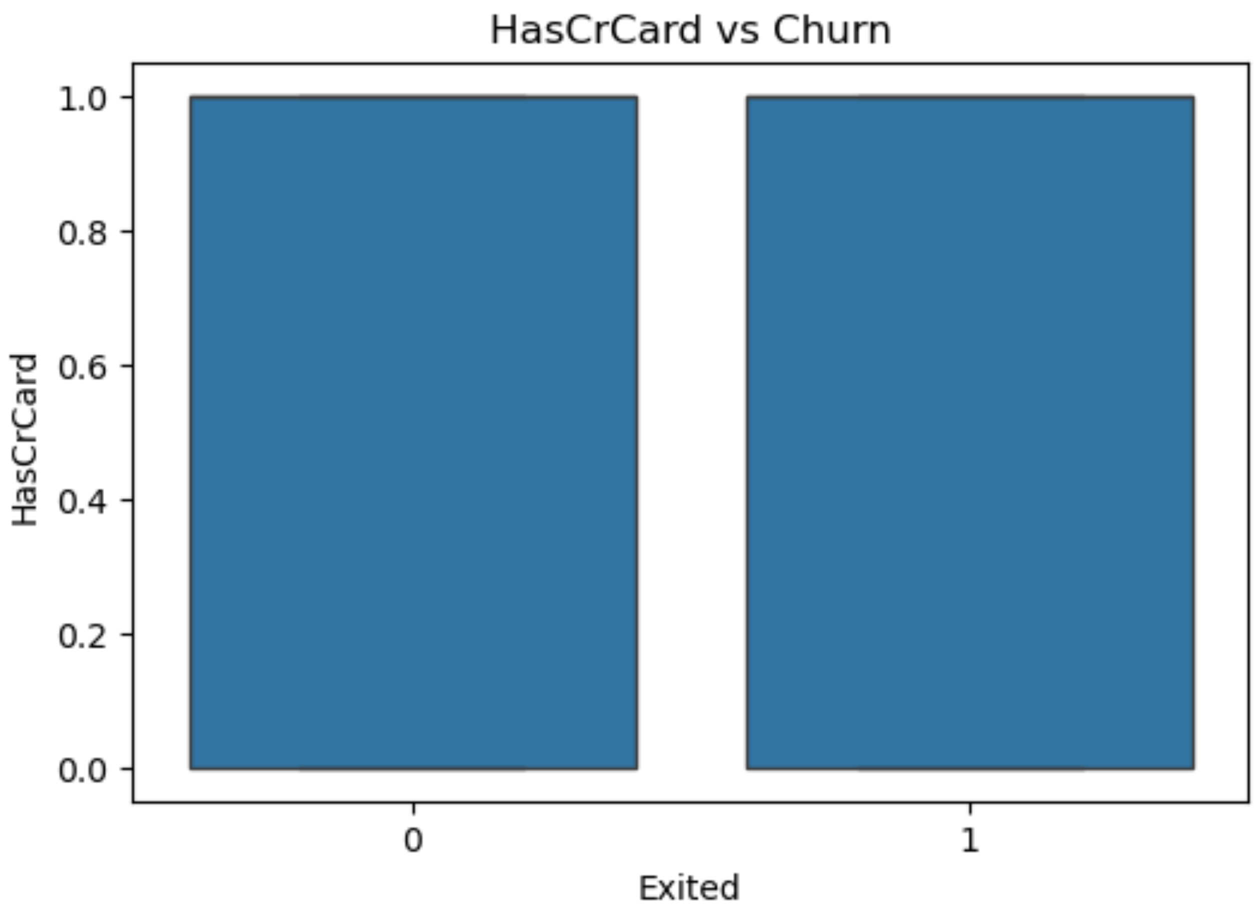


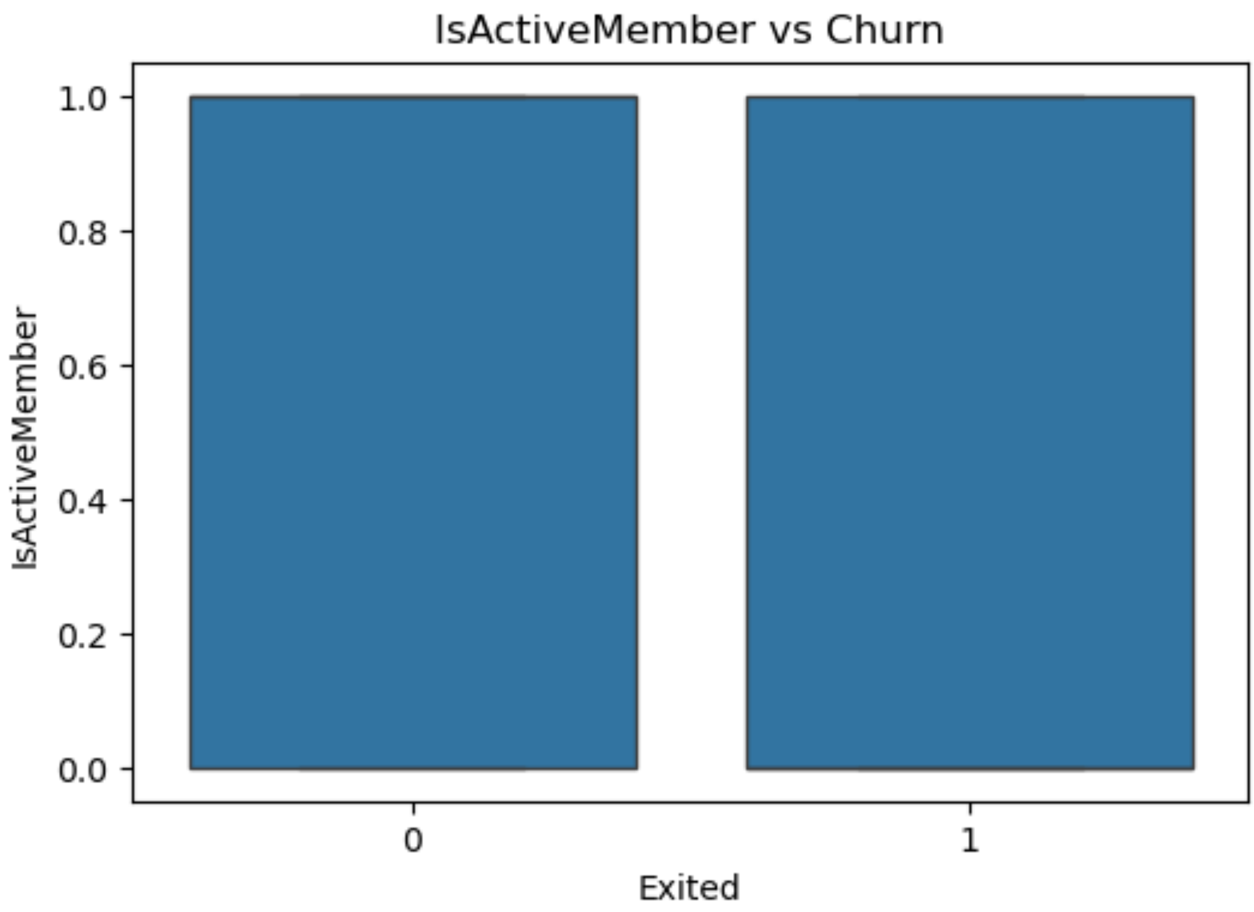
Tenure vs Churn
10
8
6
4
2
0
Tenure
0
1
Exited

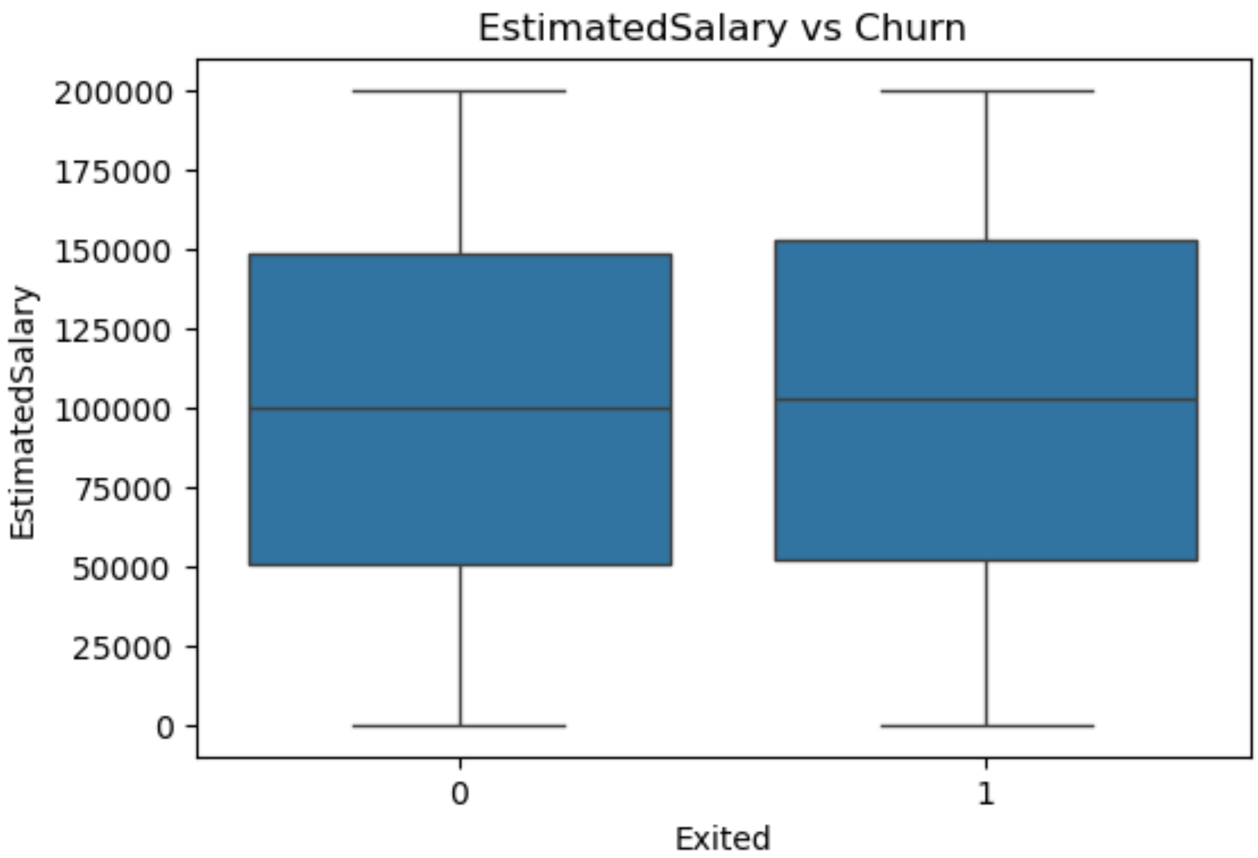


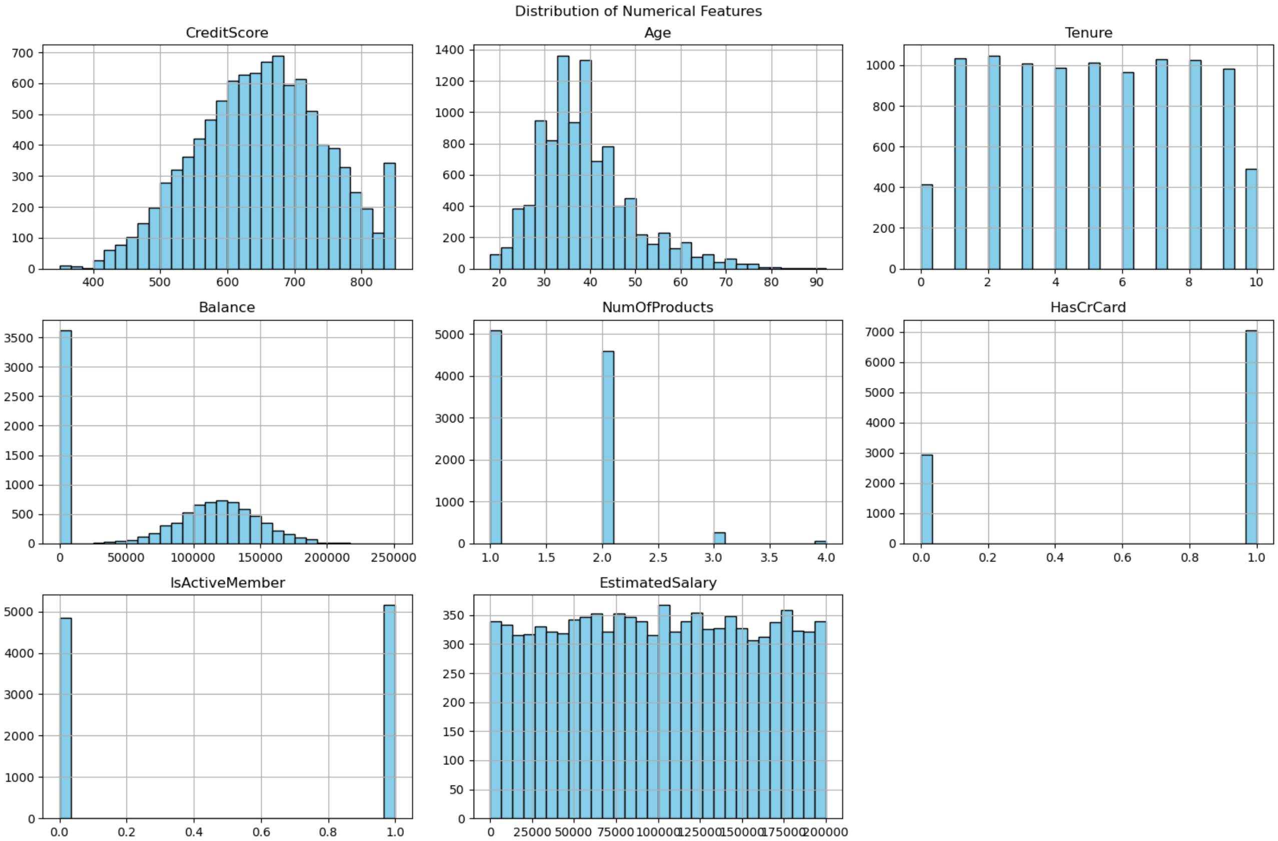
Balance vs Churn
250000
200000
150000
100000
50000
0
Balance
0
1
Exited

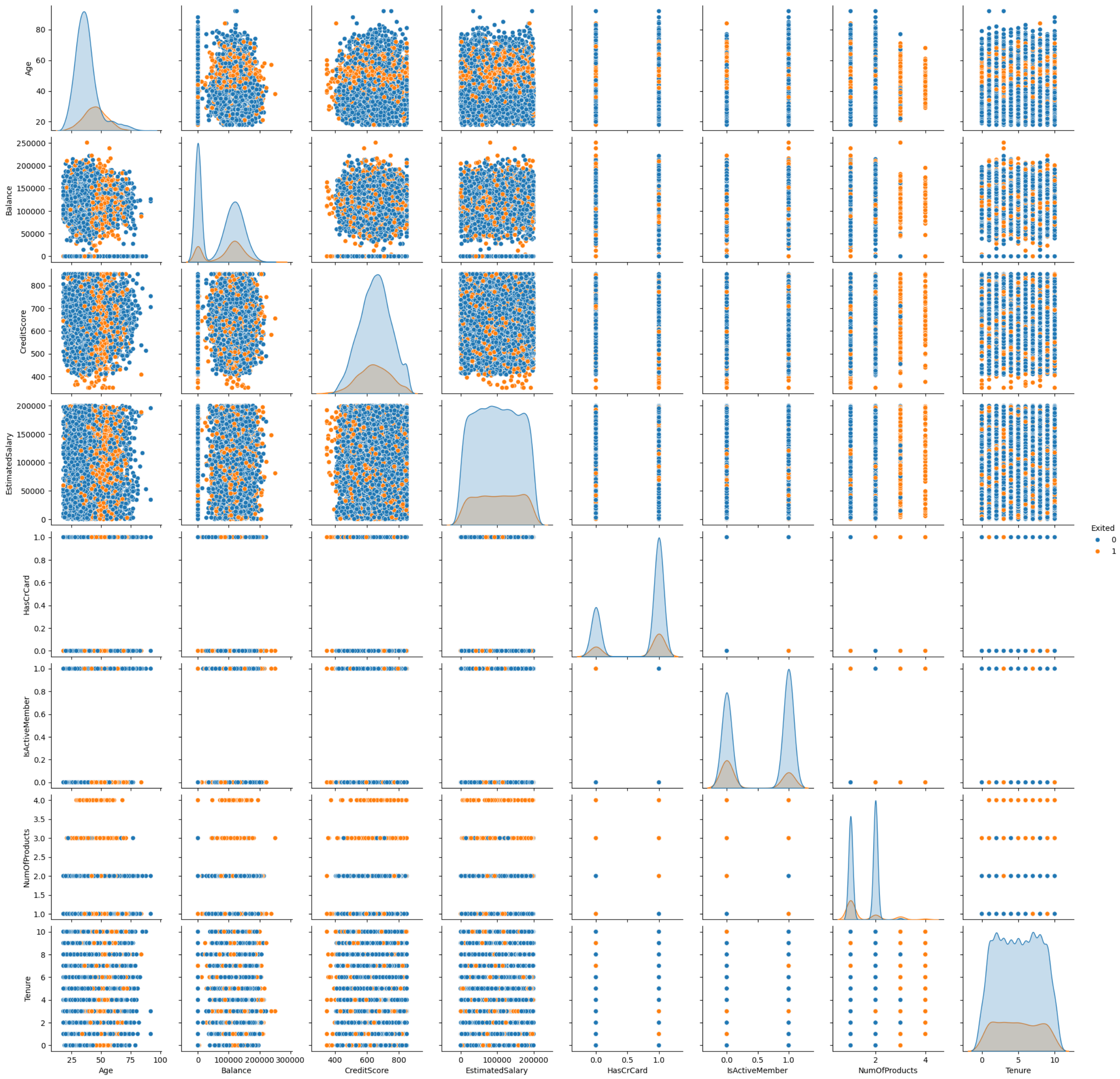

NumOfProducts vs Churn
4.0
3.5
3.0
2.5
2.0
1.5
1.0
NumOfProducts
0
1
Exited


HasCrCard vs Churn
1.0
0.8
0.6
0.4
0.2
0.0
HasCrCard
0
1
Exited


IsActiveMember vs Churn
1.0
0.8
0.6
0.4
0.2
0.0
IsActiveMember
0
1
Exited


EstimatedSalary vs Churn
200000
175000
150000
125000
100000
75000
50000
25000
0
EstimatedSalary
0
1
Exited

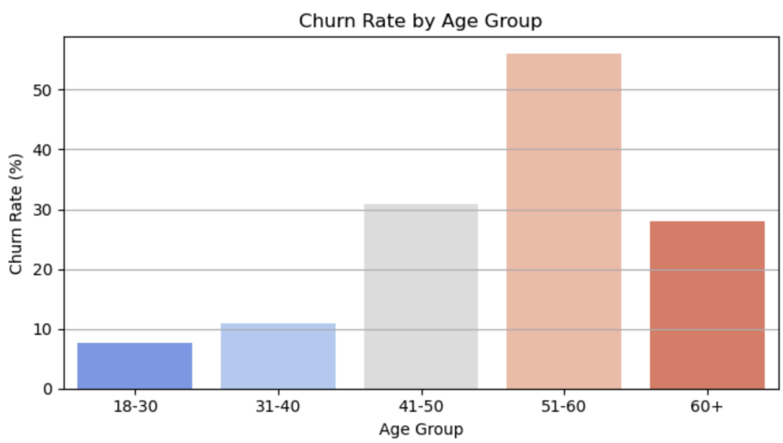

Distribution of Numerical Features
CreditScore
Age
Tenure
Balance
NumOfProducts
HasCrCard
IsActiveMember
EstimatedSalary



Top 5 inferences that can be concluded:

1. Older Customers Are More Likely to Leave:

Age is the factor that determines the timeline of the customer. More aged people are more often to leave the bank as they have grew old.

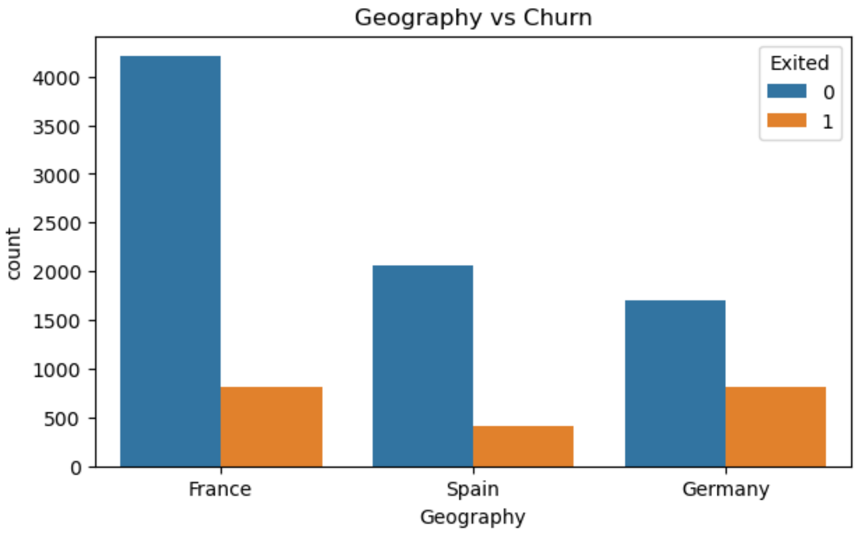


This bar plot clearly shows that people aged between 51-60 churn more.
Reasons could be: Older clients might feel neglected or find services complicated.
Action that bank can take: Launch special care programs for senior customers to keep them engaged. Also provide home services for better engagement.

2. Inactive Members Are At High Risk:
Inactive members is a major factor as it determines the customer's interest in the bank. They might have plans to join other banks if they are active.
Action that bank can take: Send push notifications to these specific users or special offers for re-engagement.

3. Higher the salary still likely to churn:
Customers with high salaries still churned if their balance or product usage was low. Just because someone earns more doesn't mean they'll stay.
Actions: Use models to identify rich but inactive customers and pitch them premium services before they leave.

4. Geographical factors:
Customers in Germany are more likely to churn. This might be due to the services provided their is not liked by the customer's.
Actions: Conduct surveys to enhance customer experience.



5. Few Products = Higher Risk of Leaving:
People using only one product of the bank like saving account or current account or loans only had double the churn rate than those using 2 or more. The more services a customer uses, the more loyal they become.
Actions: Make customer aware of all other services or products also so they can become loyal to the bank.

Overall feature importance: