In [ ]:
```
!gdown 1q1Mh3Mm4kv1LitxWcdY6--gNHVmuAfPP
```

```
Downloading...
From: https://drive.google.com/uc?id=1q1Mh3Mm4kv1LitxWcdY6--gNHVmuAfPP
To: /content/Bank-Records.csv

  0% 0.00/837k [00:00<?, ?B/s]
100% 837k/837k [00:00<00:00, 106MB/s]
```

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

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

Out[ ]:

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure |
|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 15634602 | Hargrave | 619 | France | Female | 42 | 2 |
| **1** | 2 | 15647311 | Hill | 608 | Spain | Female | 41 | 1 |
| **2** | 3 | 15619304 | Onio | 502 | France | Female | 42 | 8 |
| **3** | 4 | 15701354 | Boni | 699 | France | Female | 39 | 1 |
| **4** | 5 | 15737888 | Mitchell | 850 | Spain | Female | 43 | 2 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| **9995** | 9996 | 15606229 | Obijiaku | 771 | France | Male | 39 | 5 |
| **9996** | 9997 | 15569892 | Johnstone | 516 | France | Male | 35 | 10 |
| **9997** | 9998 | 15584532 | Liu | 709 | France | Female | 36 | 7 |
| **9998** | 9999 | 15682355 | Sabbatini | 772 | Germany | Male | 42 | 3 |
| **9999** | 10000 | 15628319 | Walker | 792 | France | Female | 28 | 4 |

10000 rows × 18 columns

In [ ]:
```
data.shape
```

Out[ ]: (10000, 18)

In [ ]:
```
data.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 [ ]:
```
data['CustomerId'].nunique()
```

Out[ ]:
```
10000
```

# Performing Basic Exploring data analysis

In [ ]:
```
data[['CustomerId','Exited']]
```

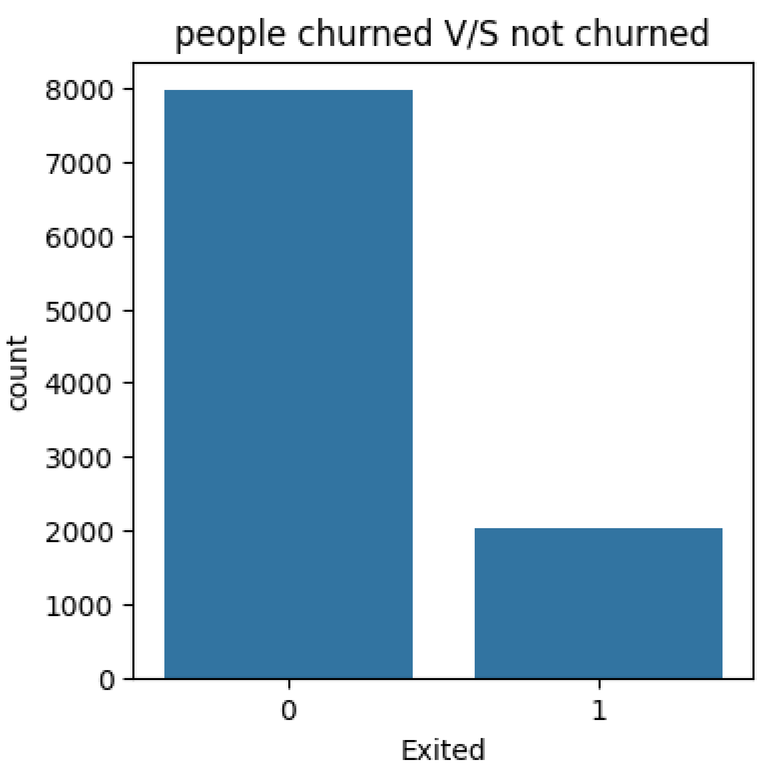
Out[ ]:

| | CustomerId | Exited |
|---|---|---|
| **0** | 15634602 | 1 |
| **1** | 15647311 | 0 |
| **2** | 15619304 | 1 |
| **3** | 15701354 | 0 |
| **4** | 15737888 | 0 |
| **...** | ... | ... |
| **9995** | 15606229 | 0 |
| **9996** | 15569892 | 0 |
| **9997** | 15584532 | 1 |
| **9998** | 15682355 | 1 |
| **9999** | 15628319 | 0 |

10000 rows × 2 columns

In [ ]:

```
plt.figure(figsize=(4,4))
sns.countplot(x = data['Exited'])
plt.title("people churned V/S not churned")
plt.show()
```




In [ ]:

```
data['Exited'].value_counts()
```

Out[ ]:
```
0    7962
1    2038
Name: Exited, dtype: int64
```

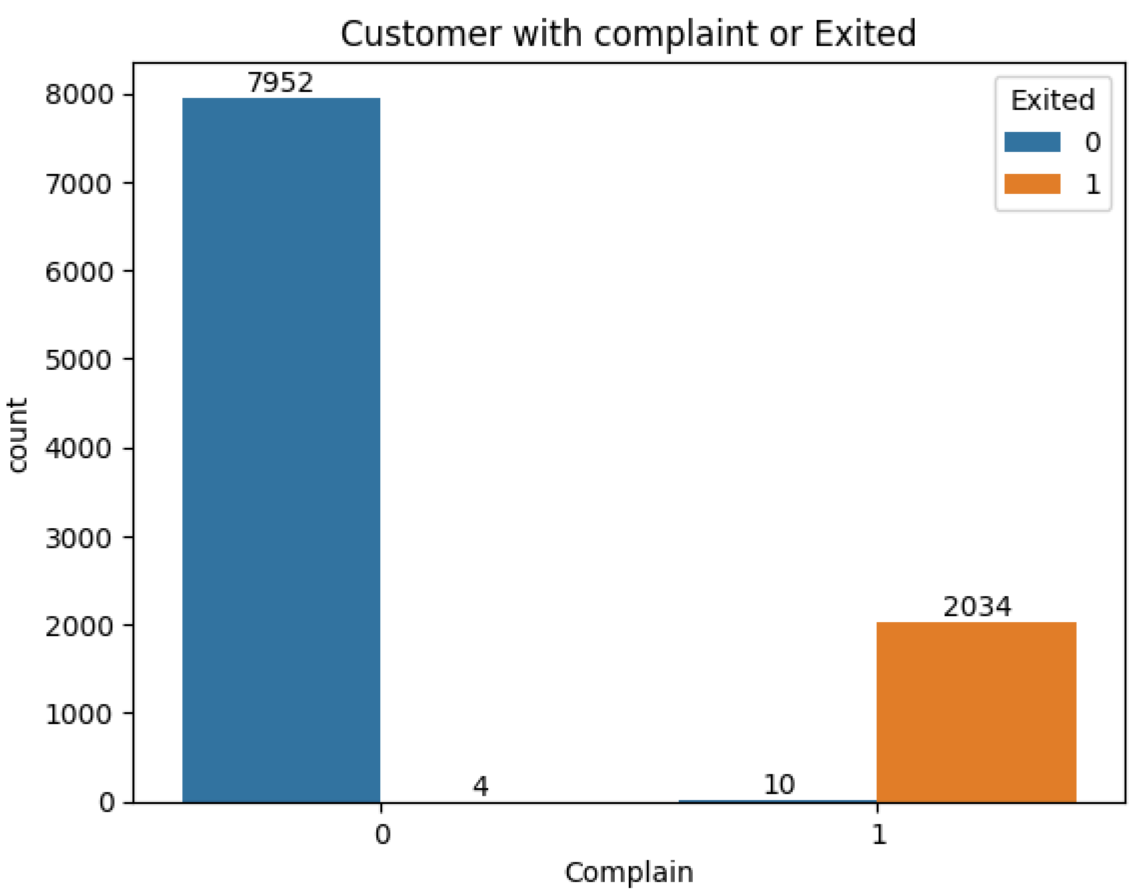
from above observation it is clear that 2038 people exited from bank and 7962 are still account holder at the bank out of 10000

In [ ]:
```
pd.crosstab(columns = data['Complain'],index = data['Exited'])
```

Out[ ]:

| Complain | 0 | 1 |
|---|---|---|
| **Exited** | | |
| **0** | 7952 | 10 |
| **1** | 4 | 2034 |

In [ ]:
```
ax1 = sns.countplot(x=data['Complain'],hue=data['Exited'])
for container in ax1.containers:
    ax1.bar_label(container)
plt.title('Customer with complaint or Exited')
plt.show()
```




out of 2038 customer churned there were 2034 customer who complained

In [ ]:
```
pd.crosstab(columns = data['Satisfaction Score'],index = data['Exited'])
```

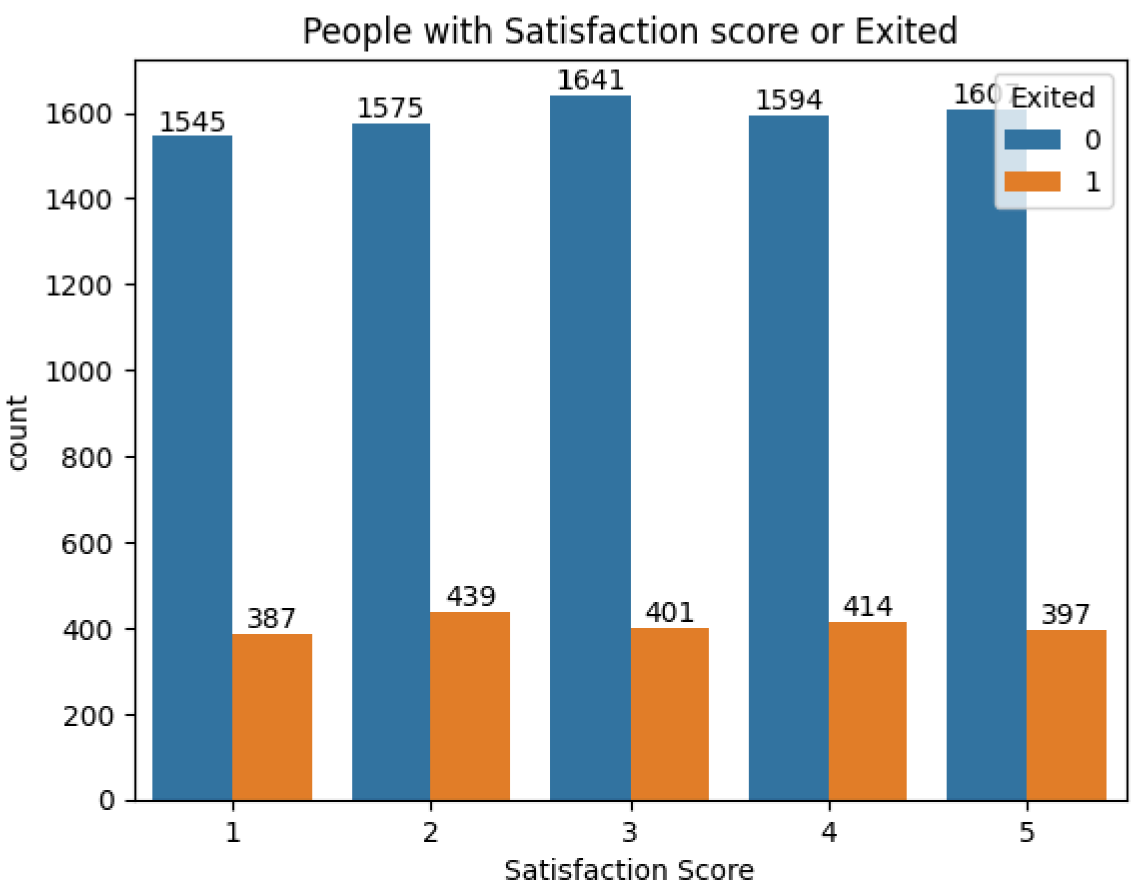
Out[ ]:

| Satisfaction Score | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| **Exited** | | | | | |
| **0** | 1545 | 1575 | 1641 | 1594 | 1607 |
| **1** | 387 | 439 | 401 | 414 | 397 |

In [ ]:

```
ax2 = sns.countplot(x=data['Satisfaction Score'],hue=data['Exited'])
for container in ax2.containers:
    ax2.bar_label(container)
plt.title('People with Satisfaction score or Exited')

plt.show()
```




In [ ]:

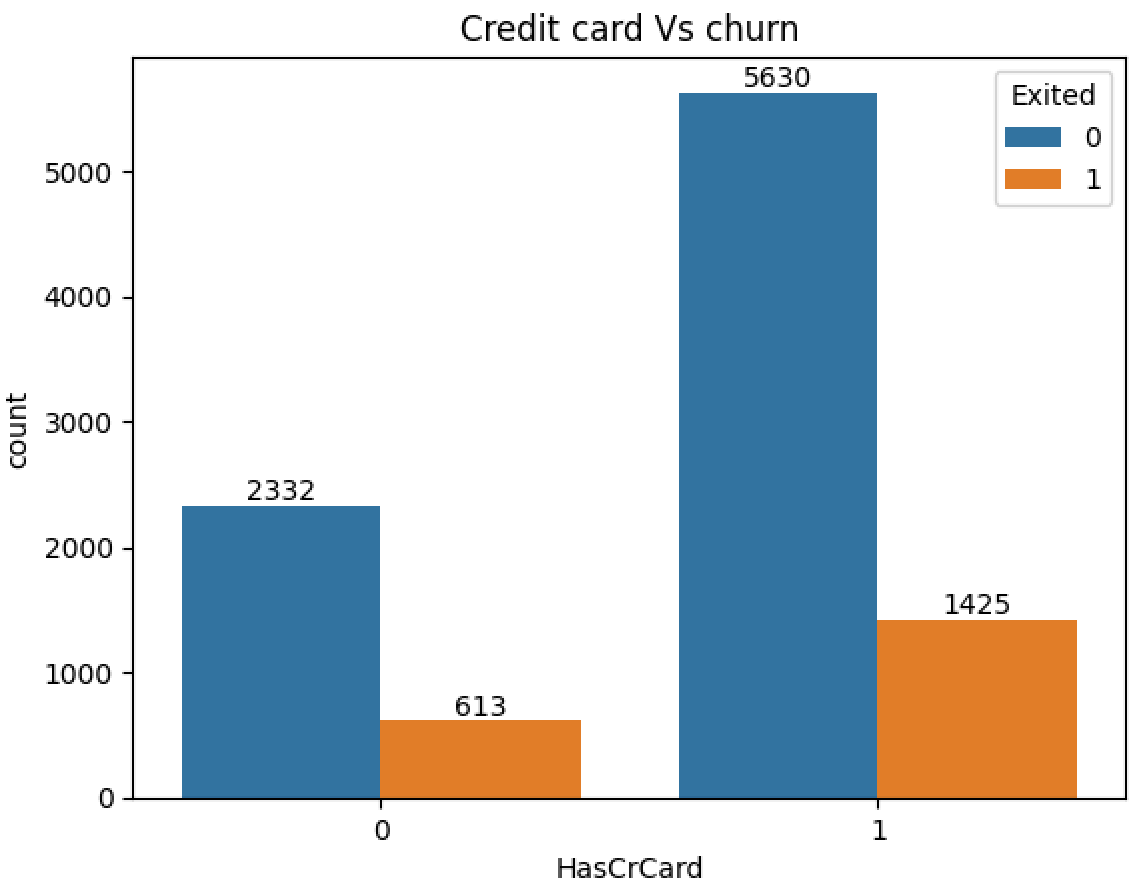
```
pd.crosstab(columns = data['HasCrCard'],index = data['Exited'])
```

Out[ ]:

| HasCrCard | 0 | 1 |
|---|---|---|
| **Exited** | | |
| **0** | 2332 | 5630 |
| **1** | 613 | 1425 |

from above observation it is cleared that people who have no card and exited were 613 and people with card and exited were 1425 which shows people having card exited more than who have no cards

In [ ]:
```
ax3 = sns.countplot(x = data['HasCrCard'],hue=data['Exited'])
for container in ax3.containers:
    ax3.bar_label(container)
plt.title("Credit card Vs churn")
plt.show()
```




In [ ]:
```
pd.crosstab(columns = data['Card Type'],index = data['Exited'])
```

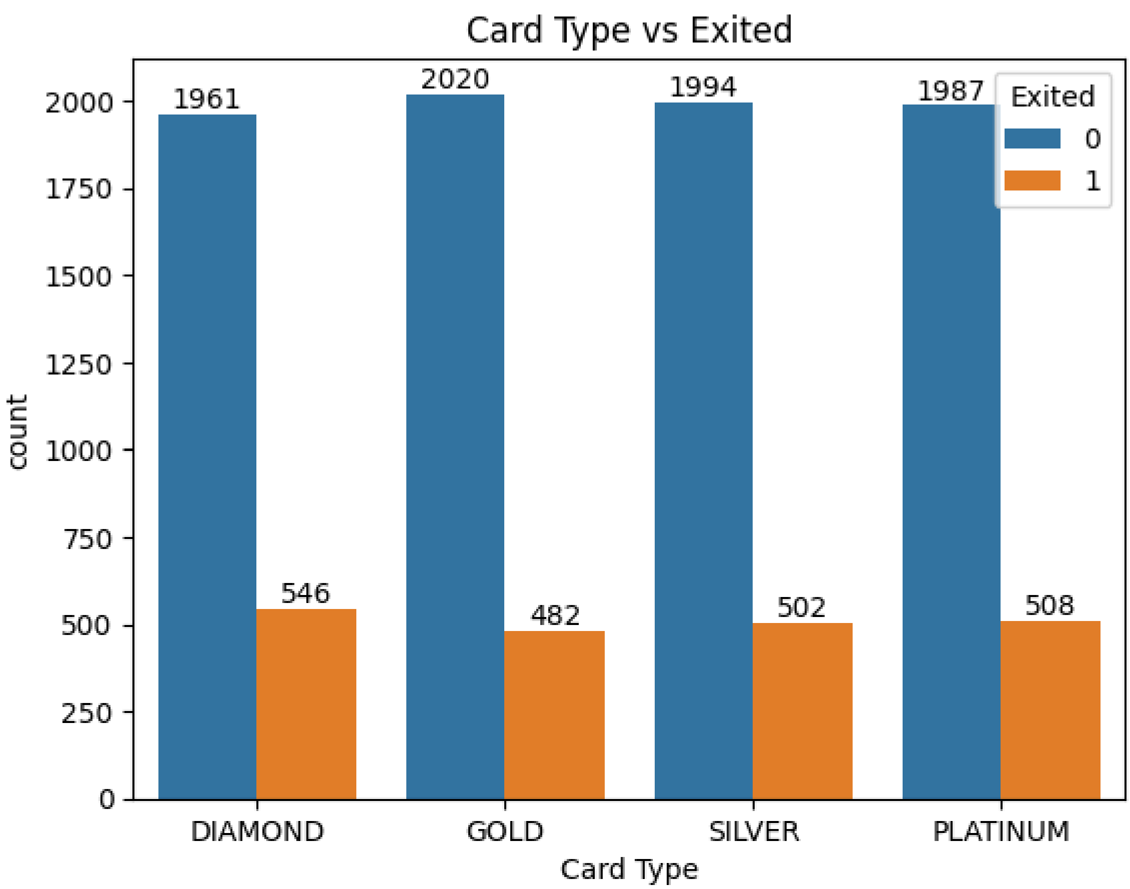
Out[ ]:

| Card Type | DIAMOND | GOLD | PLATINUM | SILVER |
|---|---|---|---|---|
| **Exited** | | | | |
| **0** | 1961 | 2020 | 1987 | 1994 |
| **1** | 546 | 482 | 508 | 502 |

from above observation we can see almost all different type of Card Type holders have Equally churned out

In [ ]:
```
ax4 = sns.countplot(x=data['Card Type'],hue=data['Exited'])
for container in ax4.containers:
```

```
    ax4.bar_label(container)
plt.title('Card Type vs Exited')
plt.show()
```




In [ ]:
```
data[data['Exited']== 1]['CreditScore'].max()
```

Out[ ]: 850

In [ ]:
```
bins =[300,400,500,600,700,800,900]
```

In [ ]:
```
credit_bin = pd.cut(data[data['Exited']== 1]['CreditScore'],bins)
```

In [ ]:
```
pd.crosstab(columns = credit_bin ,index = data['Exited'])
```

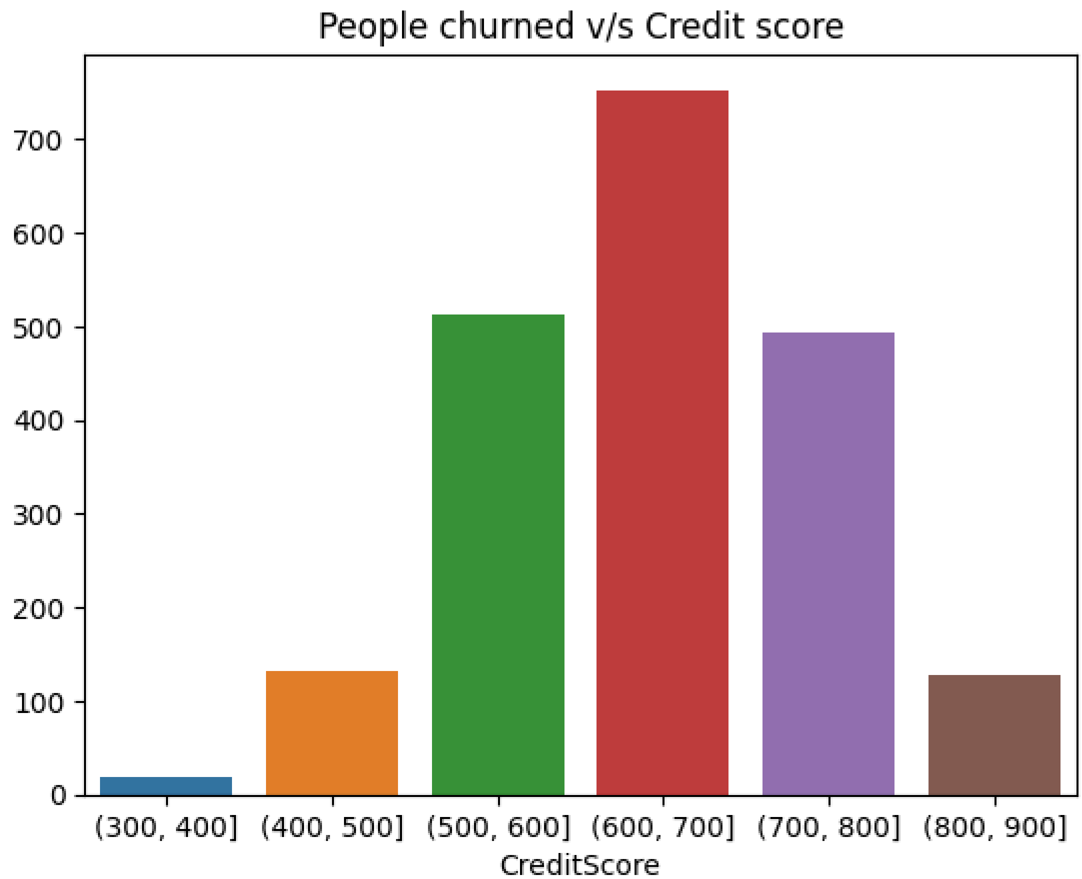
Out[ ]:

| CreditScore | (300, 400] | (400, 500] | (500, 600] | (600, 700] | (700, 800] | (800, 900] |
|---|---|---|---|---|---|---|
| **Exited** | | | | | | |
| **1** | 19 | 133 | 513 | 753 | 493 | 127 |

people with credit score in between 500 - 600 and 600-700 left the banking service the most

In [ ]:
```
sns.barplot(pd.crosstab(columns = credit_bin ,index = data['Exited']))
plt.title('People churned v/s Credit score')
```

Out[ ]: Text(0.5, 1.0, 'People churned v/s Credit score')




In [ ]:
```
pd.crosstab(columns = data['Gender'],index = data['Exited'])
```

Out[ ]:

| Gender | Female | Male |
|---|---|---|
| **Exited** | | |
| **0** | 3404 | 4558 |
| **1** | 1139 | 899 |

In [ ]:
```
pd.crosstab(columns = data['Geography'],index = data['Exited'])
```

Out[ ]:

| Geography | France | Germany | Spain |
|---|---|---|---|
| **Exited** | | | |
| **0** | 4203 | 1695 | 2064 |
| **1** | 811 | 814 | 413 |

In [ ]:
```
pd.crosstab(columns = data['Geography'],index = data['Gender'])
```

Out[ ]:

| Geography | France | Germany | Spain |
|---|---|---|---|
| **Gender** | | | |
| **Female** | 2261 | 1193 | 1089 |
| **Male** | 2753 | 1316 | 1388 |

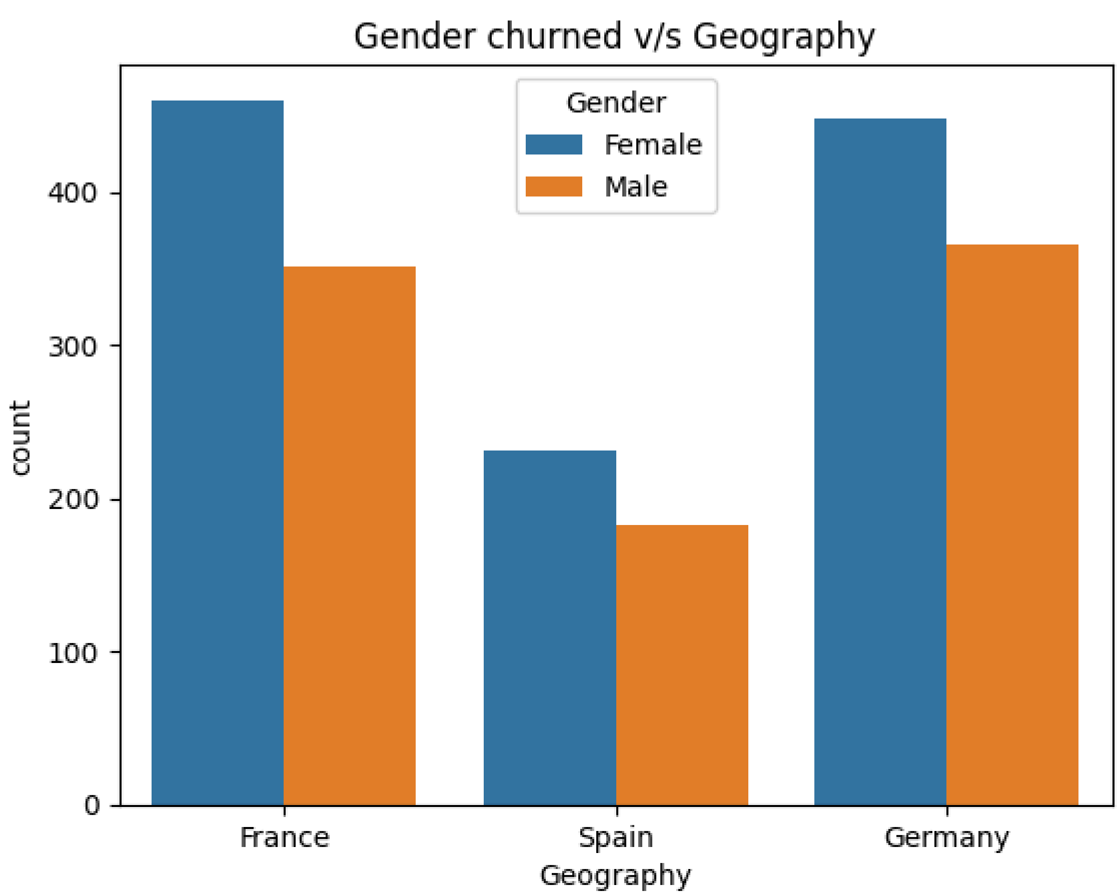
In [ ]:
```
pd.crosstab(columns = [data['Geography'],data['Gender']],index = data['Exited'])
```

Out[ ]:

| Geography | France | | Germany | | Spain | |
|---|---|---|---|---|---|---|
| **Gender** | **Female** | **Male** | **Female** | **Male** | **Female** | **Male** |
| **Exited** | | | | | | |
| **0** | 1801 | 2402 | 745 | 950 | 858 | 1206 |
| **1** | 460 | 351 | 448 | 366 | 231 | 182 |

In [ ]:
```
sns.countplot(x= data[data['Exited']==1]['Geography'],hue=data[data['Exited']==1]['
plt.title("Gender churned v/s Geography")
```

Out[ ]: Text(0.5, 1.0, 'Gender churned v/s Geography')



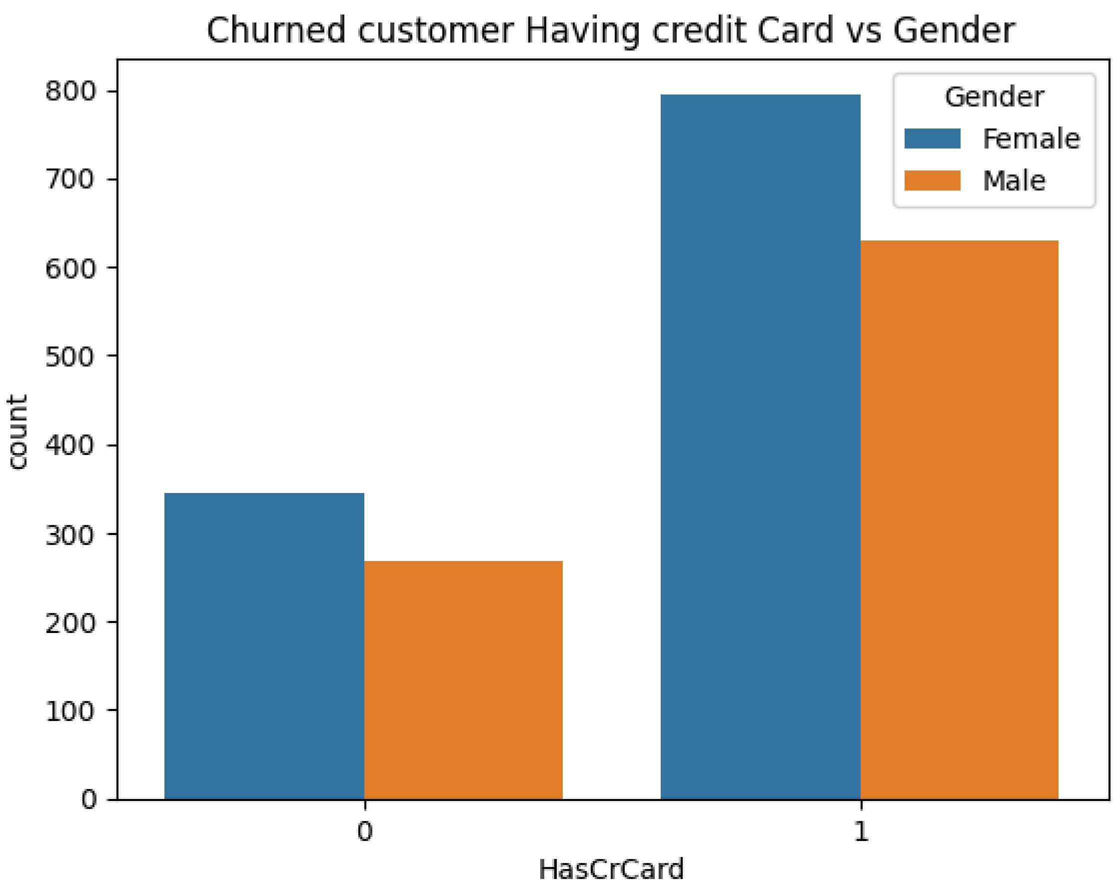

In [ ]:
```
pd.crosstab(columns = [data['HasCrCard'],data['Gender']],index = data['Exited'])
```

Out[ ]:

| HasCrCard | 0 | | 1 | |
|---|---|---|---|---|
| Gender | Female | Male | Female | Male |
| Exited | | | | |
| 0 | 1007 | 1325 | 2397 | 3233 |
| 1 | 344 | 269 | 795 | 630 |

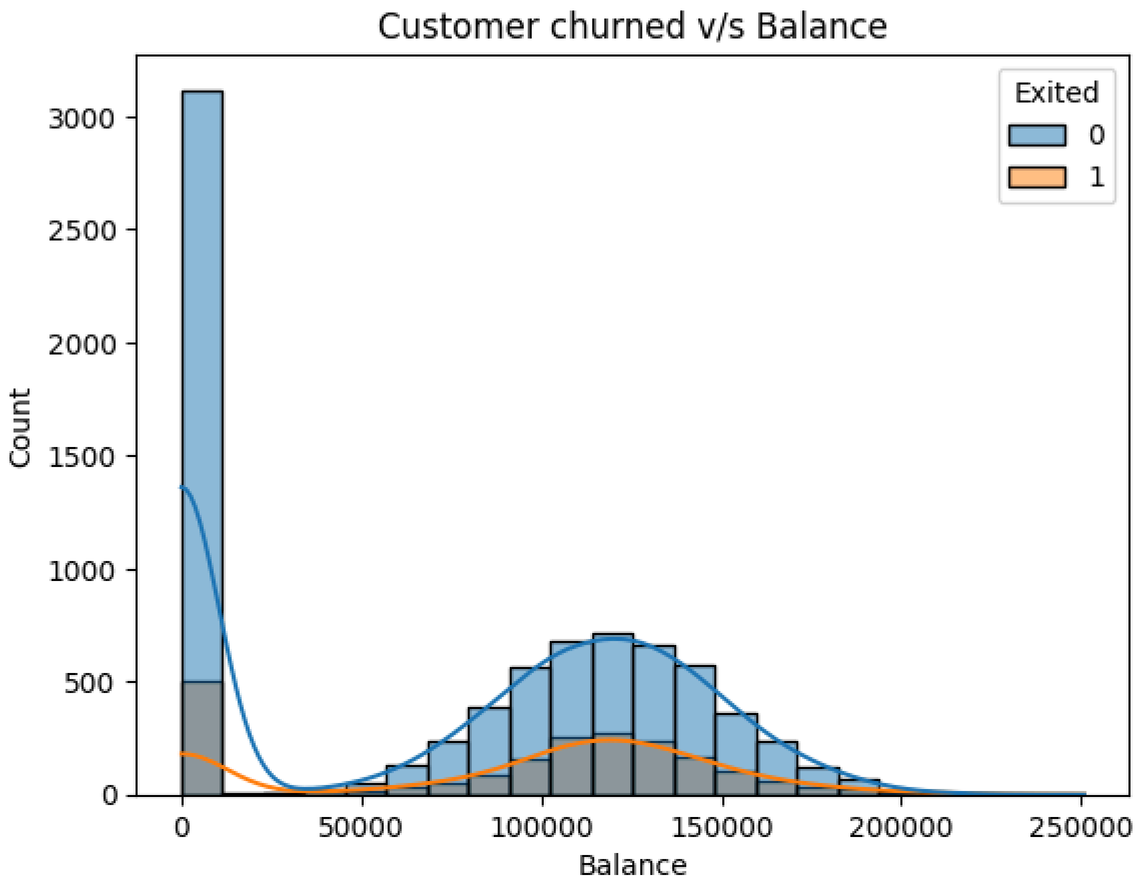
In [ ]:
```
sns.countplot(x = data[data['Exited'] == 1]['HasCrCard'] ,hue = data[data['Exited']
plt.title('Churned customer Having credit Card vs Gender')
```

Out[ ]: `Text(0.5, 1.0, 'Churned customer Having credit Card vs Gender')`



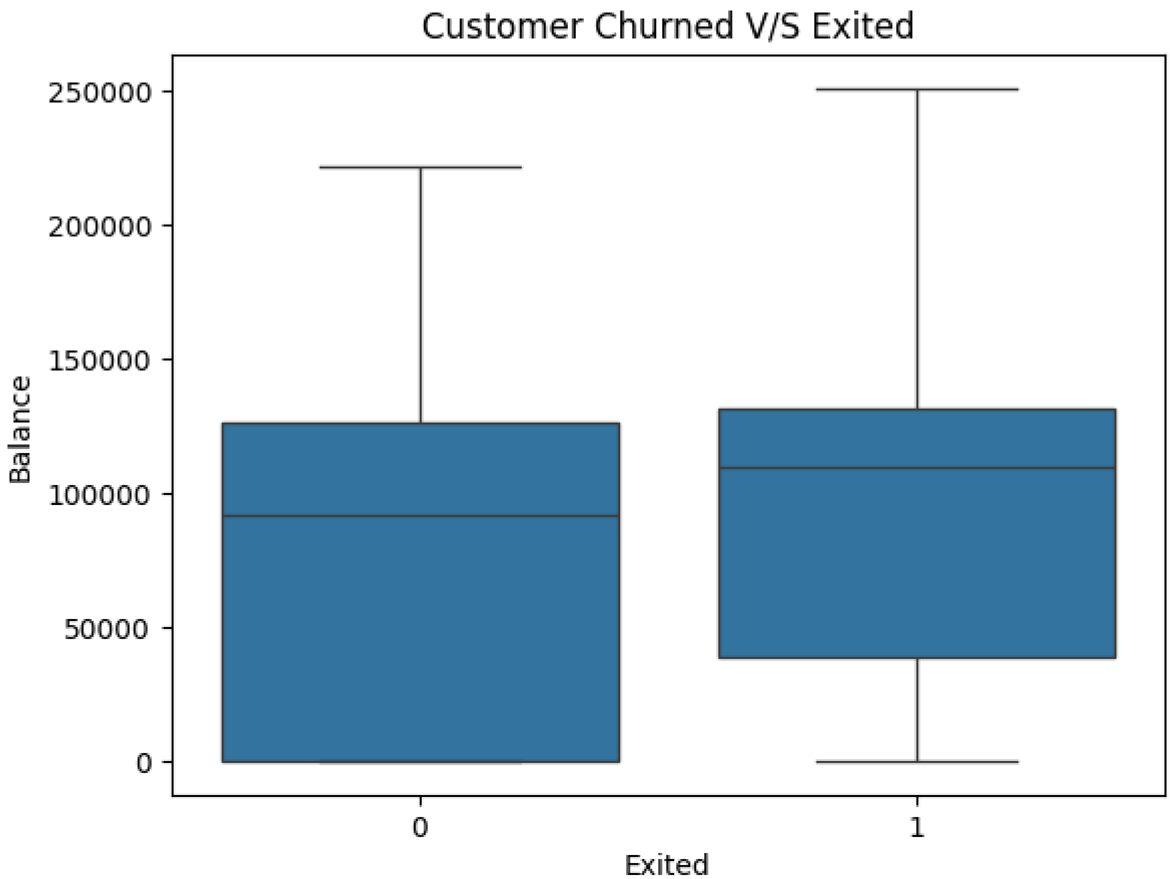

In [ ]:
```
sns.histplot(data = data, x= data['Balance'],hue =data['Exited'],kde =True)
plt.title('Customer churned v/s Balance')
```

Out[ ]: `Text(0.5, 1.0, 'Customer churned v/s Balance')`




In [ ]:
```
sns.boxplot(data=data,x=data['Exited'],y = data['Balance'])
plt.title("Customer Churned V/S Exited")
```

Out[ ]: Text(0.5, 1.0, 'Customer Churned V/S Exited')



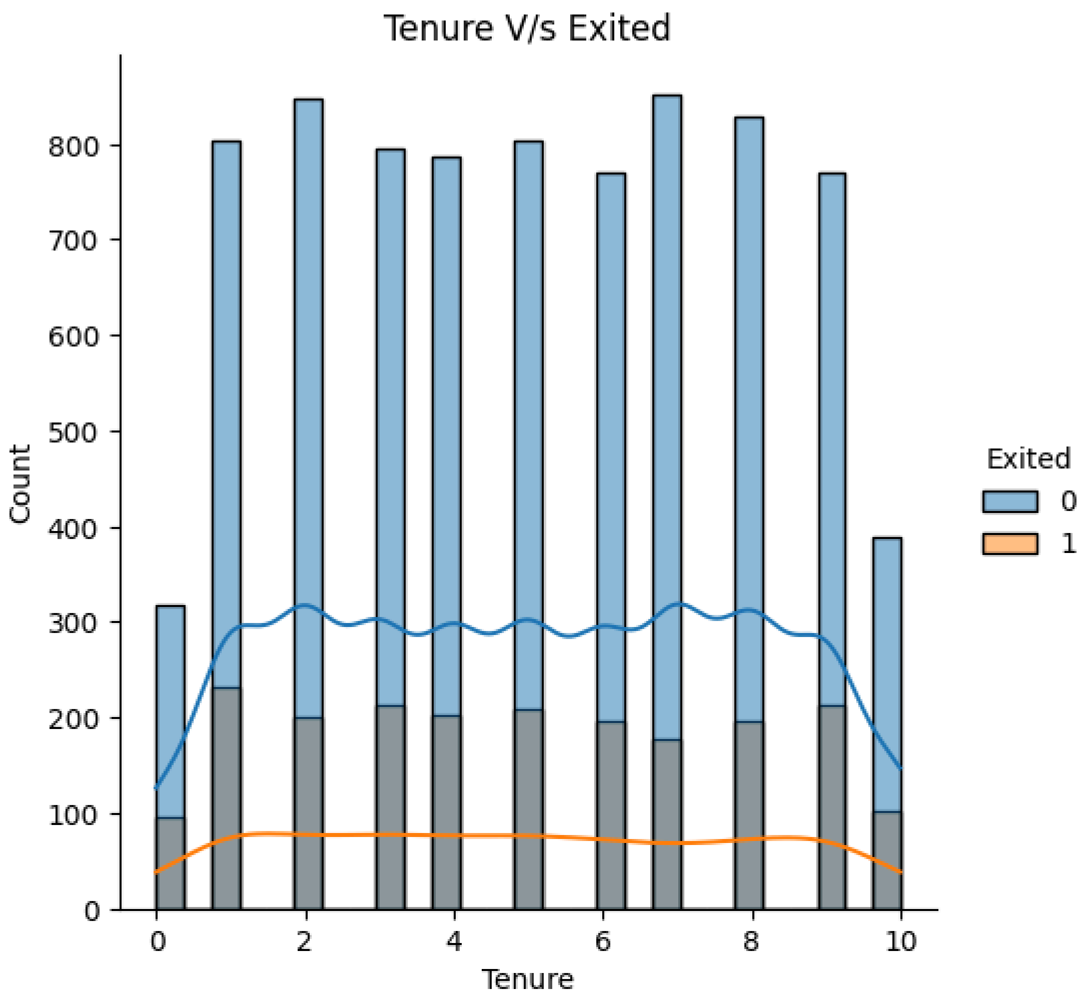

In [ ]:
```
pd.crosstab(columns = data['Tenure'],index = data['Exited'])
```

Out[ ]:

| Tenure | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Exited** | | | | | | | | | | | |
| **0** | 318 | 803 | 847 | 796 | 786 | 803 | 771 | 851 | 828 | 770 | 389 |
| **1** | 95 | 232 | 201 | 213 | 203 | 209 | 196 | 177 | 197 | 214 | 101 |

In [ ]:
```
sns.displot(x = data['Tenure'],hue = data['Exited'],kde =True)
plt.title('Tenure V/s Exited')
```

Out[ ]:
```
Text(0.5, 1.0, 'Tenure V/s Exited')
```



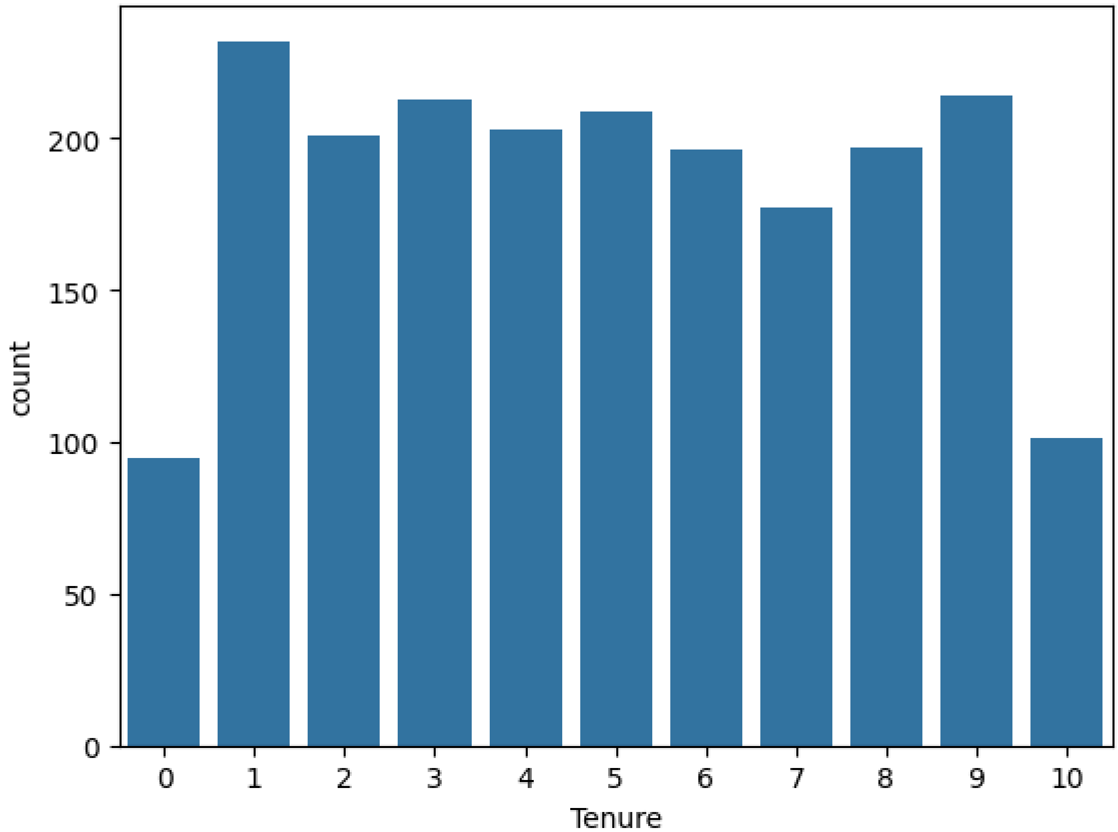

In [ ]:
```
data[data['Exited']==1]['Tenure'].value_counts().reset_index()
```

Out[ ]:

| | index | Tenure |
|---|---|---|
| **0** | 1 | 232 |
| **1** | 9 | 214 |
| **2** | 3 | 213 |
| **3** | 5 | 209 |
| **4** | 4 | 203 |
| **5** | 2 | 201 |
| **6** | 8 | 197 |
| **7** | 6 | 196 |
| **8** | 7 | 177 |
| **9** | 10 | 101 |
| **10** | 0 | 95 |

In [ ]:
```
sns.countplot(x =data[data['Exited']==1]['Tenure'])
```

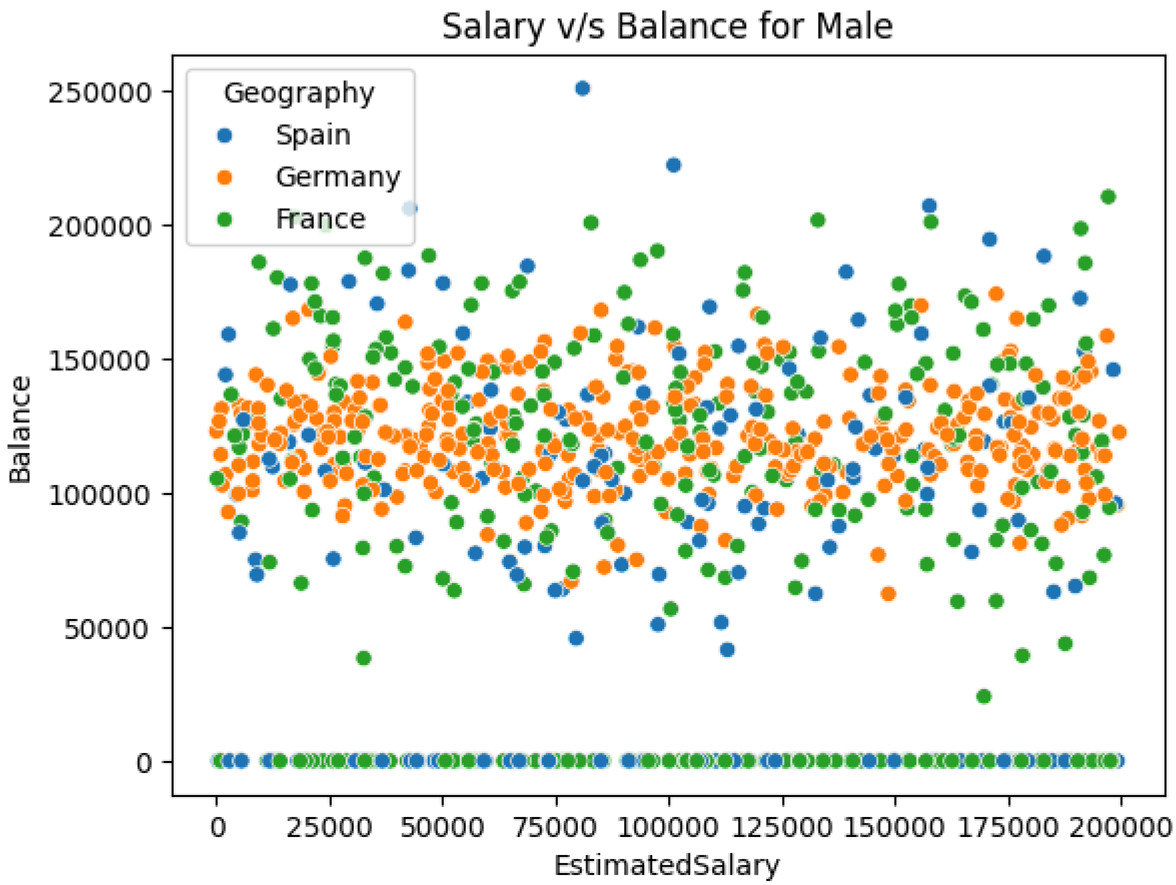
Out[ ]: <Axes: xlabel='Tenure', ylabel='count'>




### Lets check Estimated salary v/s balance of people w.r.t to Geography for different genders who left the bank

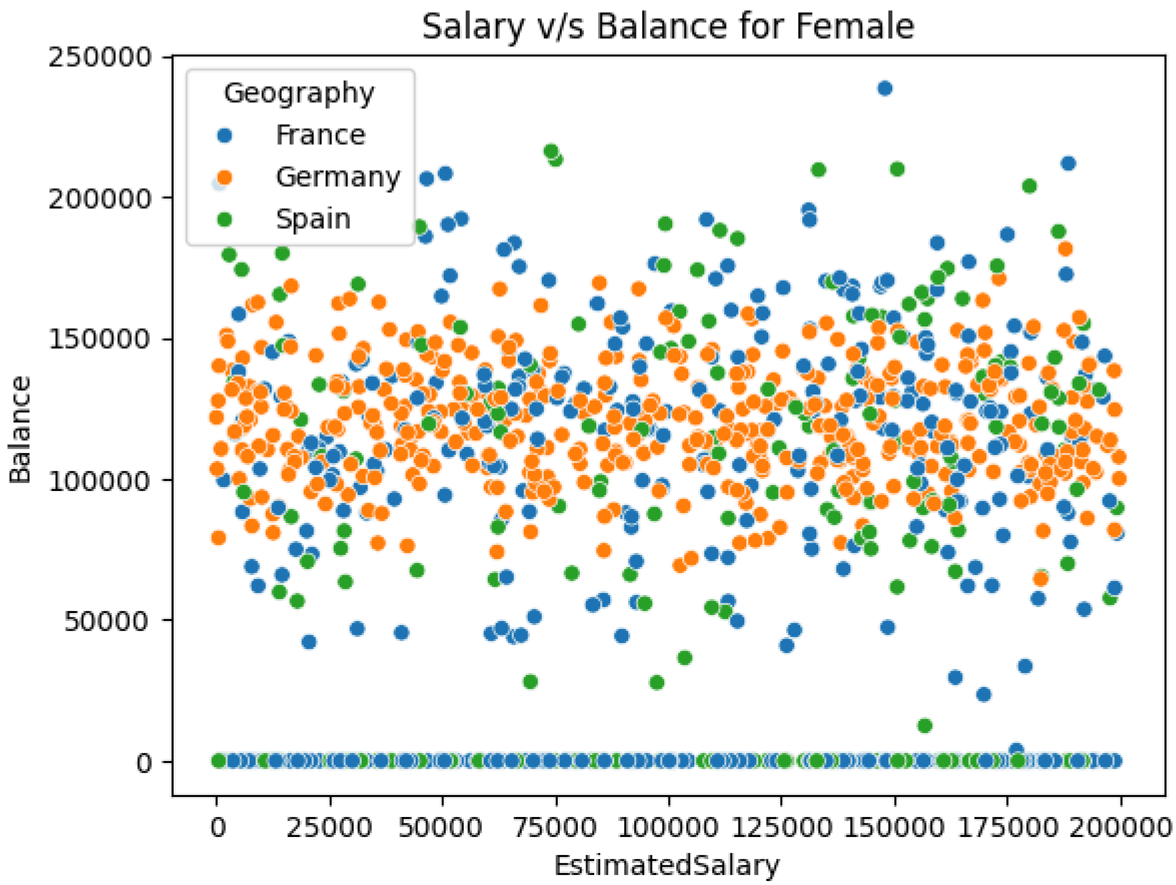
## Male

In [ ]:
```
ax = sns.scatterplot(x="EstimatedSalary", y="Balance",
                     hue="Geography",
                     data=data[(data['Exited']==1) & (data['Gender'] =='Male')])
ax.set_title('Salary v/s Balance for Male')
plt.show()
```




## Female

In [ ]:
```
ax = sns.scatterplot(x="EstimatedSalary", y="Balance",
                     hue="Geography",
                     data=data[(data['Exited']==1) & (data['Gender'] =='Female')])
ax.set_title('Salary v/s Balance for Female')
plt.show()
```




# lets create functions for our Hypothesis test inorder to check correlations

## Credit score vs Customer churn

we will use ANOVA for our hypothesis testing

In [ ]:
```
d1 = data [['CreditScore','Exited']]
d1
```

Out[ ]:

| | CreditScore | Exited |
|---|---|---|
| **0** | 619 | 1 |
| **1** | 608 | 0 |
| **2** | 502 | 1 |
| **3** | 699 | 0 |
| **4** | 850 | 0 |
| **...** | ... | ... |
| **9995** | 771 | 0 |
| **9996** | 516 | 0 |
| **9997** | 709 | 1 |
| **9998** | 772 | 1 |
| **9999** | 792 | 0 |

10000 rows × 2 columns

In [ ]:
```
from scipy.stats import f_oneway,kruskal,ttest_ind,chi2_contingency
```

Ho: Customer churn is independent of Credit score

Ha: customer churn is dependent on Credit score

In [ ]:
```
t_stats, p_value = ttest_ind(data[data['Exited'] == 0]['CreditScore'],data[data['Ex
print("t_stats :",t_stats)
print("p_value",p_value)
if p_value < 0.05:
  print("Null hypothesis is rejected")
else:
  print("Null hypothesis is accepted")
```

```
t_stats : 2.6778368664704235
p_value 0.0074220372427342435
Null hypothesis is rejected
```

# Age vs Customer churn

we will use ttest_ind

In [ ]:
```
data[['Age','Exited']]
```

Out[ ]:

| | Age | Exited |
|---|---|---|
| **0** | 42 | 1 |
| **1** | 41 | 0 |
| **2** | 42 | 1 |
| **3** | 39 | 0 |
| **4** | 43 | 0 |
| **...** | ... | ... |
| **9995** | 39 | 0 |
| **9996** | 35 | 0 |
| **9997** | 36 | 1 |
| **9998** | 42 | 1 |
| **9999** | 28 | 0 |

10000 rows × 2 columns

H0: Customer churn is independent of Age

Ha: Customer churn is dependent of Age

In [ ]:

```
t_stats, p_value = ttest_ind(data[data['Exited'] == 0]['Age'],data[data['Exited'] =
print("t_stats :",t_stats)
print("p_value",p_value)
if p_value < 0.05:
  print("Null hypothesis is rejected")
else:
  print("Null hypothesis is accepted")
```

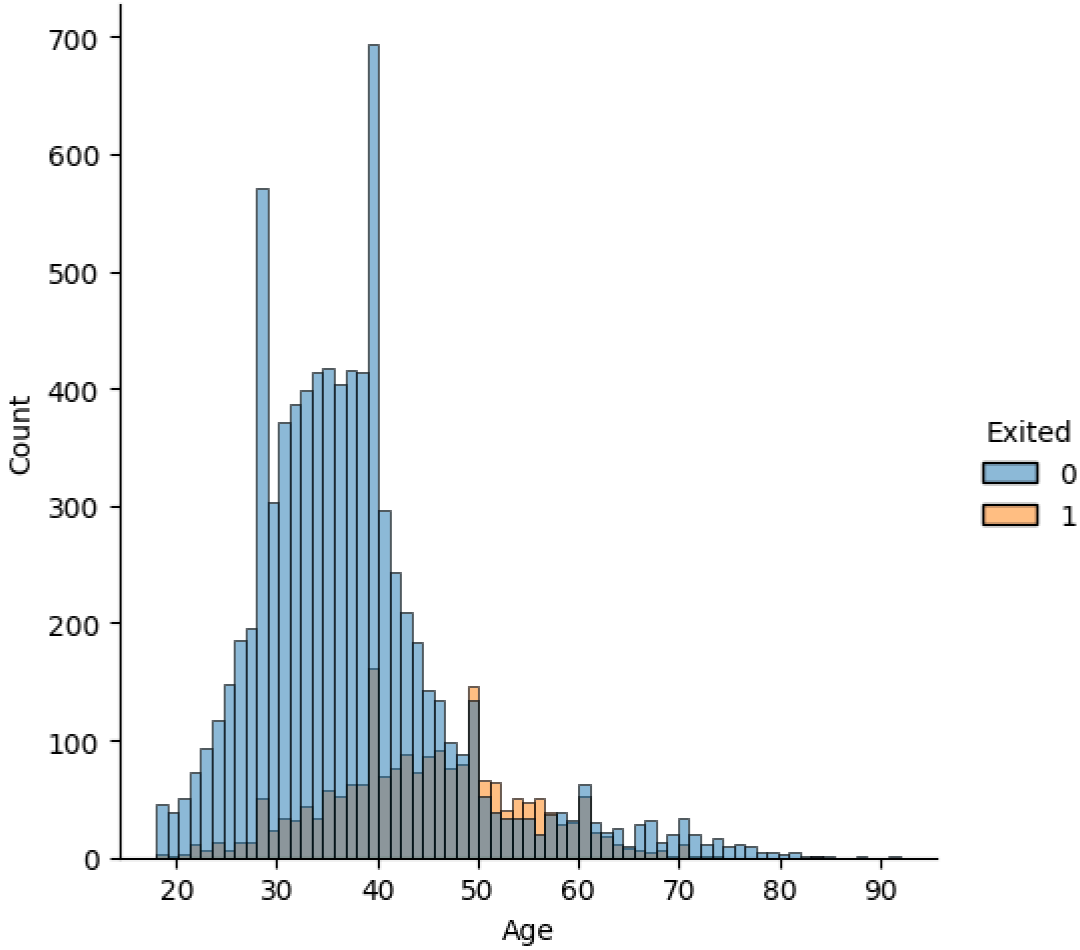
```
t_stats : -29.76379695489027
p_value 1.3467162476197306e-186
Null hypothesis is rejected
```

In [ ]:

```
plt.figure(figsize=(5, 5))
sns.displot(data=data, x="Age", hue="Exited")
```

Out[ ]: <seaborn.axisgrid.FacetGrid at 0x7e27fb94eb60>

<Figure size 500x500 with 0 Axes>




# Tenure V/s Customer churn

In [ ]:
```
data[['Tenure','Exited']]
```

Out[ ]:

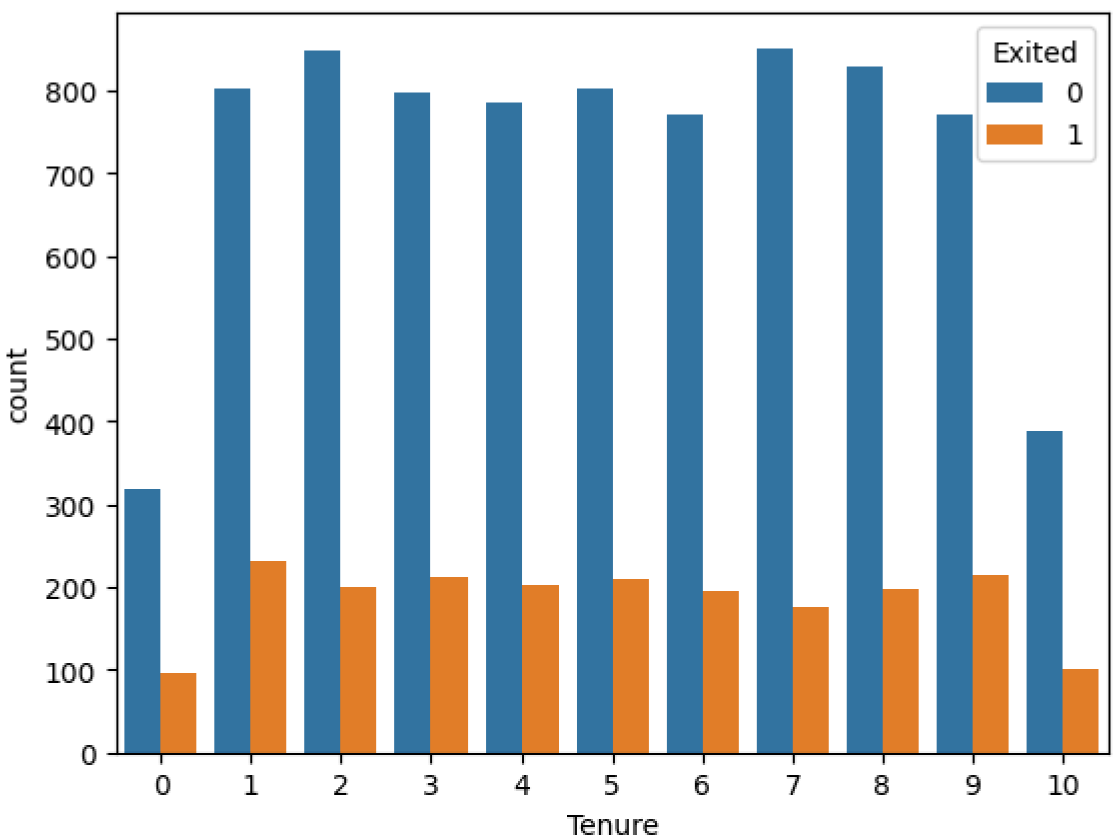
| | Tenure | Exited |
|---|---|---|
| **0** | 2 | 1 |
| **1** | 1 | 0 |
| **2** | 8 | 1 |
| **3** | 1 | 0 |
| **4** | 2 | 0 |
| **...** | ... | ... |
| **9995** | 5 | 0 |
| **9996** | 10 | 0 |
| **9997** | 7 | 1 |
| **9998** | 3 | 1 |
| **9999** | 4 | 0 |

10000 rows × 2 columns

In [ ]:

```
sns.countplot(x = data['Tenure'],hue = data['Exited'])
```

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




H0: Customer churn is independent of tenure

Ha: Customer churn is dependent of tenure

```
In [ ]: t_stats, p_value = ttest_ind(data[data['Exited'] == 0]['Tenure'],data[data['Exited'
        print("t_stats :",t_stats)
        print("p_value",p_value)
        if p_value < 0.05:
          print("Null hypothesis is rejected")
        else:
          print("Null hypothesis is accepted")
```

```
t_stats : 1.365570678788837
p_value 0.1721044754880606
Null hypothesis is accepted
```

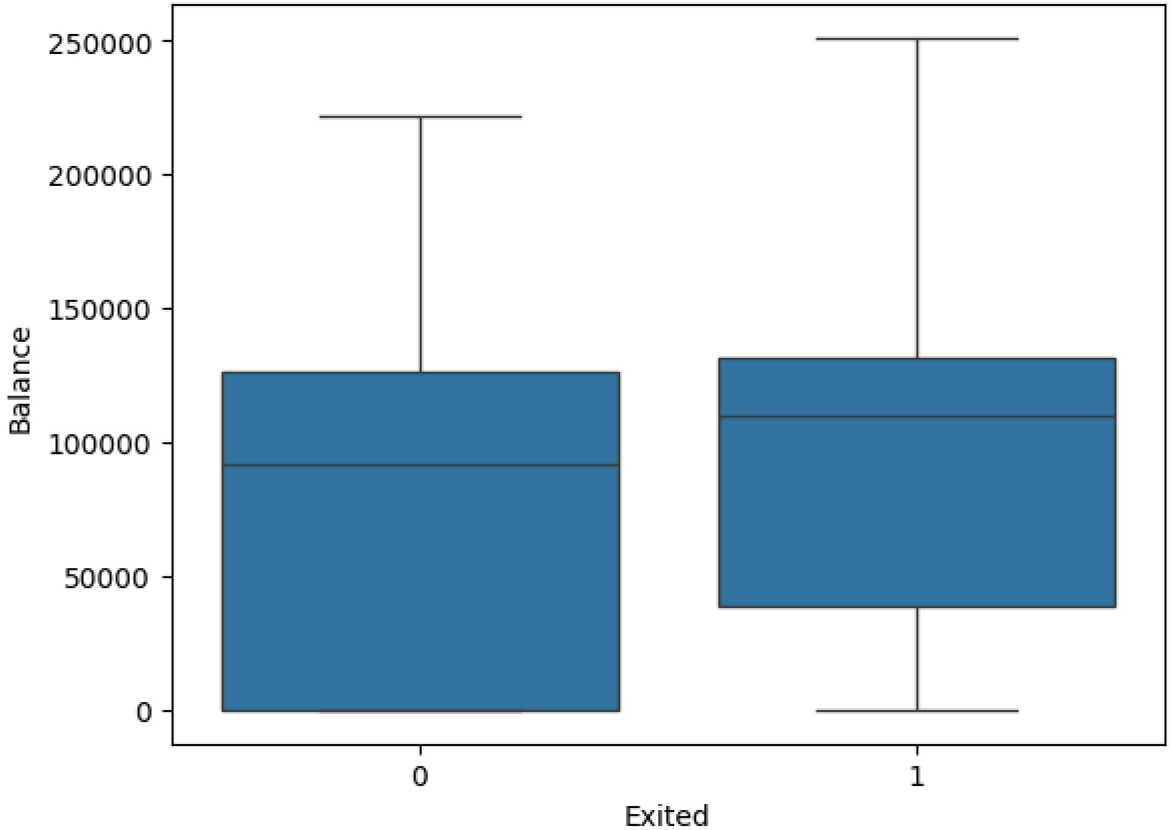
# Balance vs Customer Churn

```
In [ ]: print(" max Balance of person who churned ", data[data['Exited'] == 1]['Balance'].m
        print(" min Balance of person who churned ",data[data['Exited'] == 1]['Balance'].mi
        print(" max Balance of person who didn't churned ", data[data['Exited'] == 0]['Bala
        print(" min Balance of person who  didn't churned ",data[data['Exited'] == 0]['Bala
```

```
 max Balance of person who churned  250898.09
 min Balance of person who churned  0.0
 max Balance of person who didn't churned  221532.8
 min Balance of person who  didn't churned  0.0
```

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

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




from graphical observation it is Difficult to conclude about correlation of customer churn and their balance in account

Ho: Customer Churn is independent of Balance

Ha: Customer Churn is dependent of Balance

In [ ]:
```
t_stats, p_value = ttest_ind(data[data['Exited'] == 0]['Balance'],data[data['Exited
print("t_stats :",t_stats)
print("p_value",p_value)
if p_value < 0.05:
  print("Null hypothesis is rejected")
else:
  print("Null hypothesis is accepted")
```

```
t_stats : -11.940747722508185
p_value 1.2092076077156017e-32
Null hypothesis is rejected
```

# Geogrpahy v/s customer churn

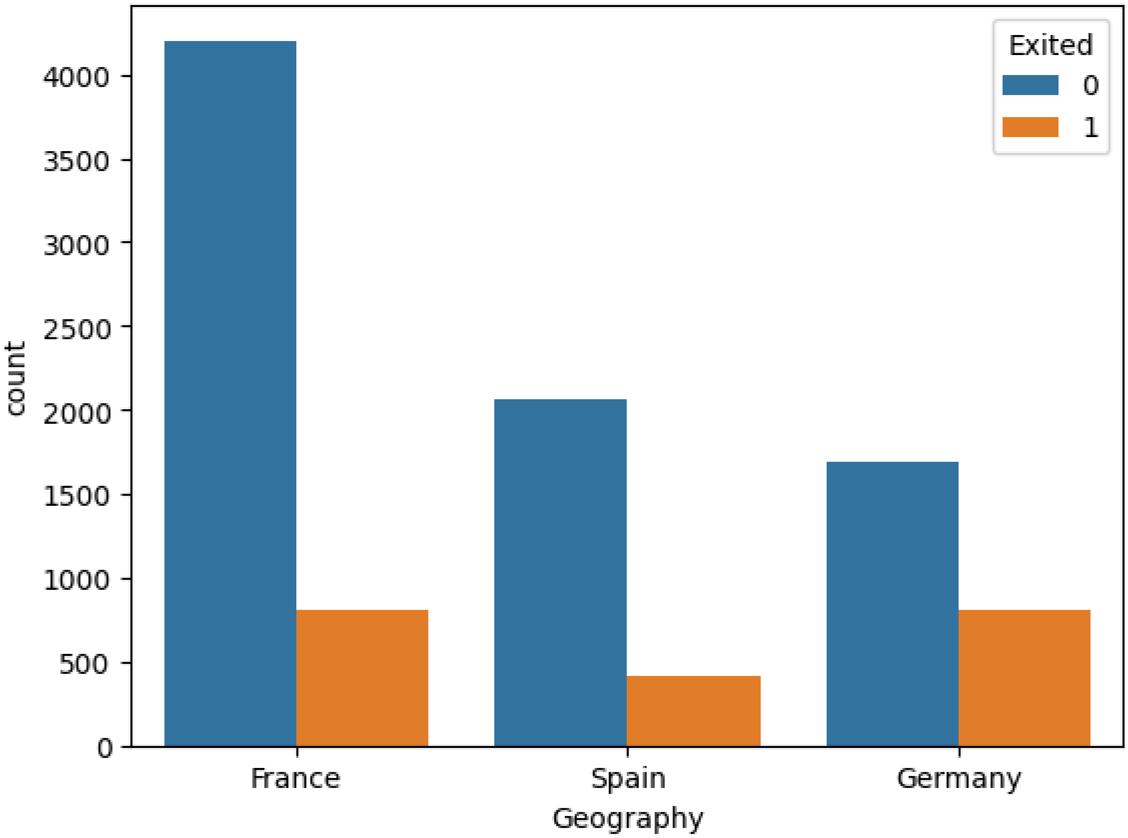
In [ ]:
```
GC = pd.crosstab(columns = data['Geography'],index = data['Exited'])
GC
```

Out[ ]:

| Geography | France | Germany | Spain |
|---|---|---|---|
| **Exited** | | | |
| **0** | 4203 | 1695 | 2064 |
| **1** | 811 | 814 | 413 |

In [ ]:
```
sns.countplot(x=data['Geography'],hue=data['Exited'])
```

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




Since this is a case of categorical - categorical we would apply chi2_contingency or Chi_square test of independence

H0: Geography and Customer churn are independent

Ha : Geography and Customer churn are dependent

In [ ]:
```
t_stats, p_value, dof, array = chi2_contingency (GC)
print("Result:",chi2_contingency (GC))
print("t_stats :",t_stats)
print("p_value",p_value)
if p_value < 0.05:
  print("Null hypothesis is rejected")
  print("Geography and Customer churn are dependent")

else:
```

```
    print("Null hypothesis is accepted")
    print("Geography and Customer churn are Independent")
```

```
Result: Chi2ContingencyResult(statistic=300.6264011211942, pvalue=5.245736109572763e
-66, dof=2, expected_freq=array([[3992.1468, 1997.6658, 1972.1874],
       [1021.8532,  511.3342,  504.8126]]))
t_stats : 300.6264011211942
p_value 5.245736109572763e-66
Null hypothesis is rejected
Geography and Customer churn are dependent
```

# Impact assessement of different features on Customer churn

# Gender and Customer Churn

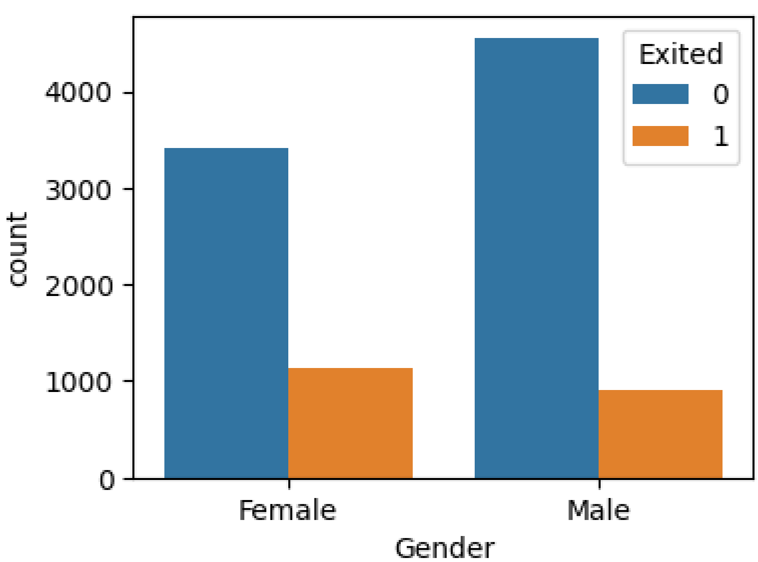
In [ ]:
```
Gec = pd.crosstab(columns = data['Gender'],index = data['Exited'])
Gec
```

Out[ ]:

| Gender | Female | Male |
|---|---|---|
| **Exited** | | |
| **0** | 3404 | 4558 |
| **1** | 1139 | 899 |

In [ ]:
```
plt.figure(figsize=(4,3))
sns.countplot(x=data['Gender'],hue=data['Exited'])
```

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




H0: Gender and Customer churn are independent

Ha : Gender and Customer churn are dependent

In [ ]:
```
t_stats, p_value, dof, array = chi2_contingency (Gec)
print("Result:",chi2_contingency (Gec))
print("t_stats :",t_stats)
print("p_value",p_value)
if p_value < 0.05:
  print("Null hypothesis is rejected")
  print("Gender and Customer churn are dependent")

else:
  print("Null hypothesis is accepted")
  print("Gender and Customer churn are Independent")
```

```
Result: Chi2ContingencyResult(statistic=112.39655374778587, pvalue=2.9253677618642e-26, dof=1, expected_freq=array([[3617.1366, 4344.8634],
       [ 925.8634, 1112.1366]]))
t_stats : 112.39655374778587
p_value 2.9253677618642e-26
Null hypothesis is rejected
Gender and Customer churn are dependent
```

# Impact of Credit Card on Churn rate

In [ ]:
```
Cc = pd.crosstab(columns = data['Card Type'],index = data['Exited'])
Cc
```

Out[ ]:

| Card Type | DIAMOND | GOLD | PLATINUM | SILVER |
|---|---|---|---|---|
| Exited | | | | |
| 0 | 1961 | 2020 | 1987 | 1994 |
| 1 | 546 | 482 | 508 | 502 |

H0: Credit Card and Customer churn are independent

Ha : Credit Card and Customer churn are dependent

In [ ]:
```
t_stats, p_value, dof, array = chi2_contingency (Gec)
print("Result:",chi2_contingency (Gec))
print("t_stats :",t_stats)
print("p_value",p_value)
if p_value < 0.05:
  print("Null hypothesis is rejected")
  print("Credit Card and Customer churn are dependent")

else:
  print("Null hypothesis is accepted")
  print("Credit Card and Customer churn are Independent")
```

```
Result: Chi2ContingencyResult(statistic=112.39655374778587, pvalue=2.9253677618642e-26, dof=1, expected_freq=array([[3617.1366, 4344.8634],
       [ 925.8634, 1112.1366]]))
t_stats : 112.39655374778587
p_value 2.9253677618642e-26
Null hypothesis is rejected
Credit Card and Customer churn are dependent
```

# Analayze Area for service improvement

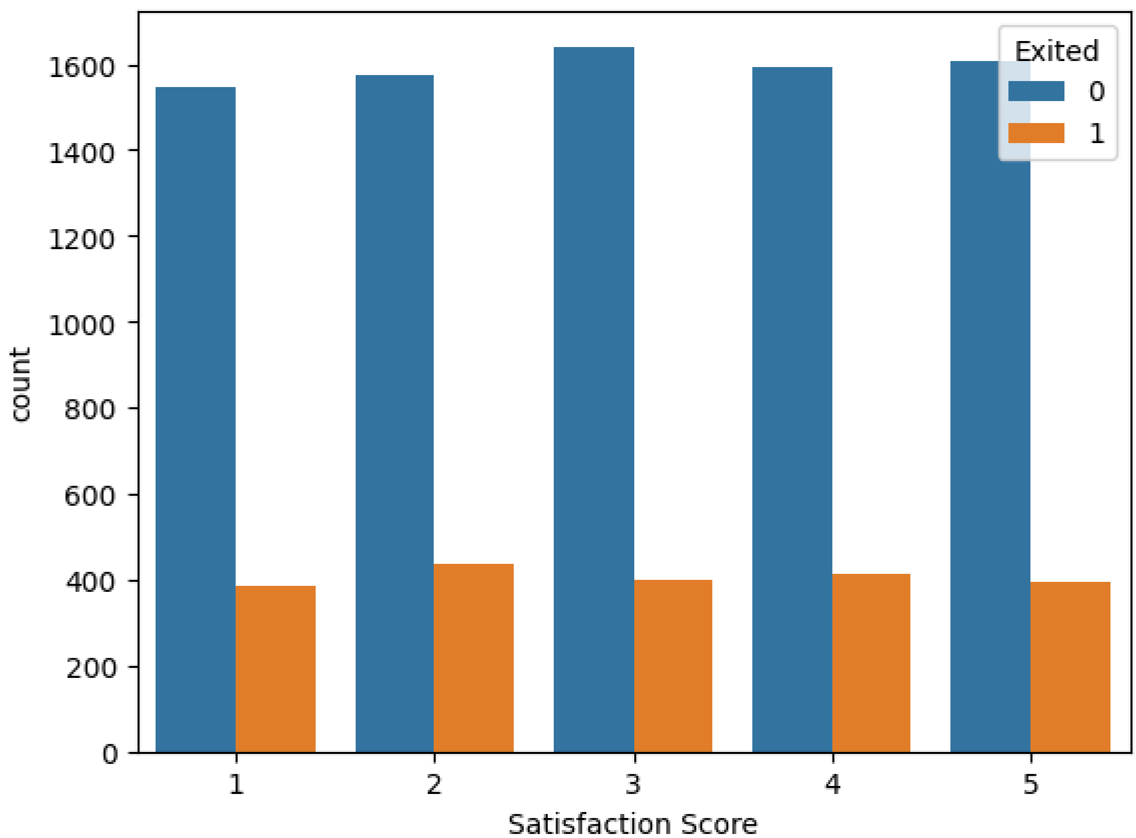
In [ ]:
```
pd.crosstab(columns = [data['Complain'],data['Satisfaction Score']],index = data['E
```

Out[ ]:

| Complain | 0 | | | | | 1 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Satisfaction Score** | **1** | **2** | **3** | **4** | **5** | **1** | **2** | **3** | **4** | **5** |
| **Exited** | | | | | | | | | | |
| **0** | 1544 | 1574 | 1636 | 1594 | 1604 | 1 | 1 | 5 | 0 | 3 |
| **1** | 1 | 2 | 0 | 1 | 0 | 386 | 437 | 401 | 413 | 397 |

In [ ]:
```
sns.countplot(x=data['Satisfaction Score'],hue= data['Exited'])
```

Out[ ]: <Axes: xlabel='Satisfaction Score', ylabel='count'>



people who raised the complaint and churned = 1 and their satisfaction score were 1 ,2 3, 4, 5

# Strategies for customer retenion strategies

In [ ]:
```
data_banking_behaviour = data.loc[data['Exited'] ==1,['CustomerId','Tenure','NumOfP
data_banking_behaviour
```

Out[ ]:

| | CustomerId | Tenure | NumOfProducts | EstimatedSalary | Balance |
|---|---|---|---|---|---|
| **0** | 15634602 | 2 | 1 | 101348.88 | 0.00 |
| **2** | 15619304 | 8 | 3 | 113931.57 | 159660.80 |
| **5** | 15574012 | 8 | 2 | 149756.71 | 113755.78 |
| **7** | 15656148 | 4 | 4 | 119346.88 | 115046.74 |
| **16** | 15737452 | 1 | 1 | 5097.67 | 132602.88 |
| **...** | ... | ... | ... | ... | ... |
| **9981** | 15672754 | 3 | 1 | 53445.17 | 152039.70 |
| **9982** | 15768163 | 7 | 1 | 115146.40 | 137145.12 |
| **9991** | 15769959 | 4 | 1 | 69384.71 | 88381.21 |
| **9997** | 15584532 | 7 | 1 | 42085.58 | 0.00 |
| **9998** | 15682355 | 3 | 2 | 92888.52 | 75075.31 |

2038 rows × 5 columns

In [ ]:
```
data_banking_behaviour['Spent'] = data_banking_behaviour['EstimatedSalary']* data_b
data_banking_behaviour
```

Out[ ]:

| | CustomerId | Tenure | NumOfProducts | EstimatedSalary | Balance | Spent |
|---|---|---|---|---|---|---|
| **0** | 15634602 | 2 | 1 | 101348.88 | 0.00 | 202697.76 |
| **2** | 15619304 | 8 | 3 | 113931.57 | 159660.80 | 751791.76 |
| **5** | 15574012 | 8 | 2 | 149756.71 | 113755.78 | 1084297.90 |
| **7** | 15656148 | 4 | 4 | 119346.88 | 115046.74 | 362340.78 |
| **16** | 15737452 | 1 | 1 | 5097.67 | 132602.88 | -127505.21 |
| **...** | ... | ... | ... | ... | ... | ... |
| **9981** | 15672754 | 3 | 1 | 53445.17 | 152039.70 | 8295.81 |
| **9982** | 15768163 | 7 | 1 | 115146.40 | 137145.12 | 668879.68 |
| **9991** | 15769959 | 4 | 1 | 69384.71 | 88381.21 | 189157.63 |
| **9997** | 15584532 | 7 | 1 | 42085.58 | 0.00 | 294599.06 |
| **9998** | 15682355 | 3 | 2 | 92888.52 | 75075.31 | 203590.25 |

2038 rows × 6 columns

In [ ]:
```
data_banking_behaviour[data_banking_behaviour['Balance'] < 0 ]
```

Out[ ]:

| CustomerId | Tenure | NumOfProducts | EstimatedSalary | Balance | Spent |
|---|---|---|---|---|---|

we don't have any negative balance account it shows we have no customer who have dfaulted while exiting the bank after using its service

In [ ]:
```
data_banking_behaviour[data_banking_behaviour['Spent'] < 0 ]
```

Out[ ]:

| | CustomerId | Tenure | NumOfProducts | EstimatedSalary | Balance | Spent |
|---|---|---|---|---|---|---|
| **16** | 15737452 | 1 | 1 | 5097.67 | 132602.88 | -127505.21 |
| **35** | 15794171 | 0 | 1 | 27822.99 | 134264.04 | -134264.04 |
| **54** | 15569590 | 1 | 1 | 40014.76 | 98495.72 | -58480.96 |
| **70** | 15703793 | 2 | 4 | 28373.86 | 133745.44 | -76997.72 |
| **127** | 15782688 | 0 | 1 | 46824.08 | 148507.24 | -148507.24 |
| **...** | ... | ... | ... | ... | ... | ... |
| **9863** | 15726179 | 5 | 2 | 3497.43 | 131433.33 | -113946.18 |
| **9882** | 15785490 | 3 | 1 | 16281.68 | 105229.72 | -56384.68 |
| **9920** | 15673020 | 3 | 1 | 738.88 | 204510.94 | -202294.30 |
| **9924** | 15578865 | 5 | 1 | 6985.34 | 107959.39 | -73032.69 |
| **9947** | 15732202 | 1 | 2 | 73124.53 | 83503.11 | -10378.58 |

350 rows × 6 columns

The above analysis shows the out of total people who left 350 are of people whose balance were more than their estimated salary according to Their bank tenure usage which speaks that apart from their estimated salary they have had more balance not from salary but from other assets

bank is at loss for loosing such customers

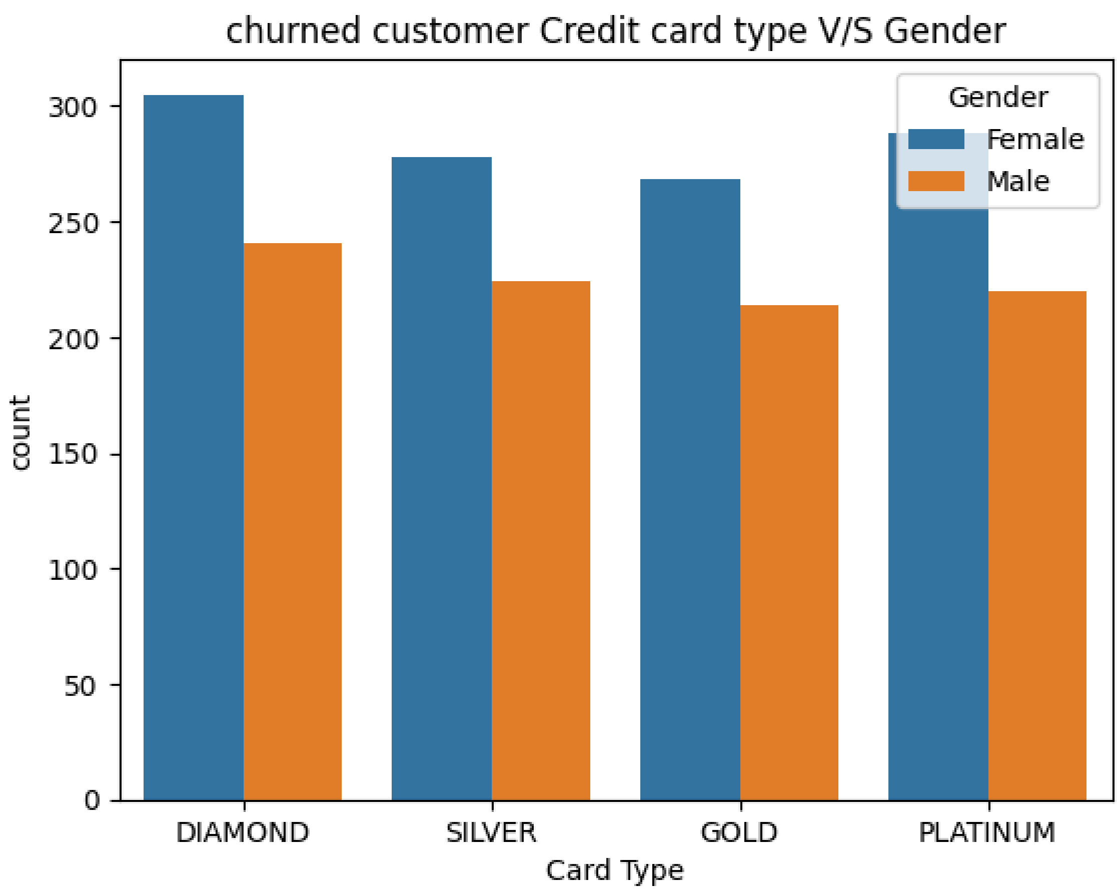
# Lets check the people whose balance were not zero or less but have complaint and churned out of the bank with different credit card

In [ ]:

```
sns.countplot(x = data[data['Exited'] == 1]['Card Type'],hue = data['Gender'])
plt.title("churned customer Credit card type V/S Gender")
```

Out[ ]:

```
Text(0.5, 1.0, 'churned customer Credit card type V/S Gender')
```




In [ ]:
```
data.loc[data['Exited']== 1,['Balance','Complain','Card Type','Satisfaction Score']]
```

Out[ ]:

| | Balance | Complain | Card Type | Satisfaction Score |
|---|---|---|---|---|
| **0** | 0.00 | 1 | DIAMOND | 2 |
| **2** | 159660.80 | 1 | DIAMOND | 3 |
| **5** | 113755.78 | 1 | DIAMOND | 5 |
| **7** | 115046.74 | 1 | DIAMOND | 2 |
| **16** | 132602.88 | 0 | SILVER | 2 |
| **...** | ... | ... | ... | ... |
| **9981** | 152039.70 | 1 | GOLD | 3 |
| **9982** | 137145.12 | 1 | GOLD | 4 |
| **9991** | 88381.21 | 1 | GOLD | 3 |
| **9997** | 0.00 | 1 | SILVER | 3 |
| **9998** | 75075.31 | 1 | GOLD | 2 |

2038 rows × 4 columns

In [ ]:
```
pd.crosstab(index = data[data['Exited'] == 1]['Card Type'],columns = data[data['Exi
```

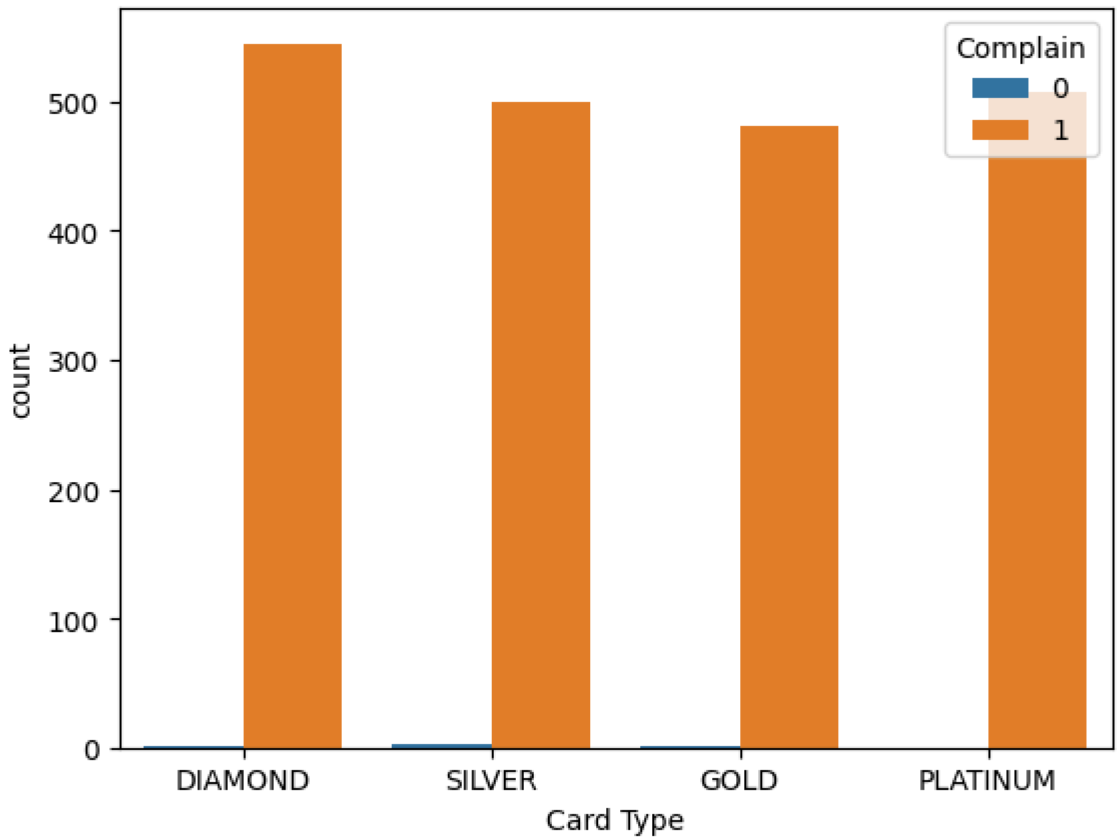
Out[ ]:

| | Complain | Card Type | 0 | 1 | All |
|---|---|---|---|---|---|
| **0** | | DIAMOND | 1 | 545 | 546 |
| **1** | | GOLD | 1 | 481 | 482 |
| **2** | | PLATINUM | 0 | 508 | 508 |
| **3** | | SILVER | 2 | 500 | 502 |
| **4** | | All | 4 | 2034 | 2038 |

In [ ]:

```
sns.countplot(x = data[data['Exited'] == 1]['Card Type'],hue = data[data['Exited']
```

Out[ ]: `<Axes: xlabel='Card Type', ylabel='count'>`



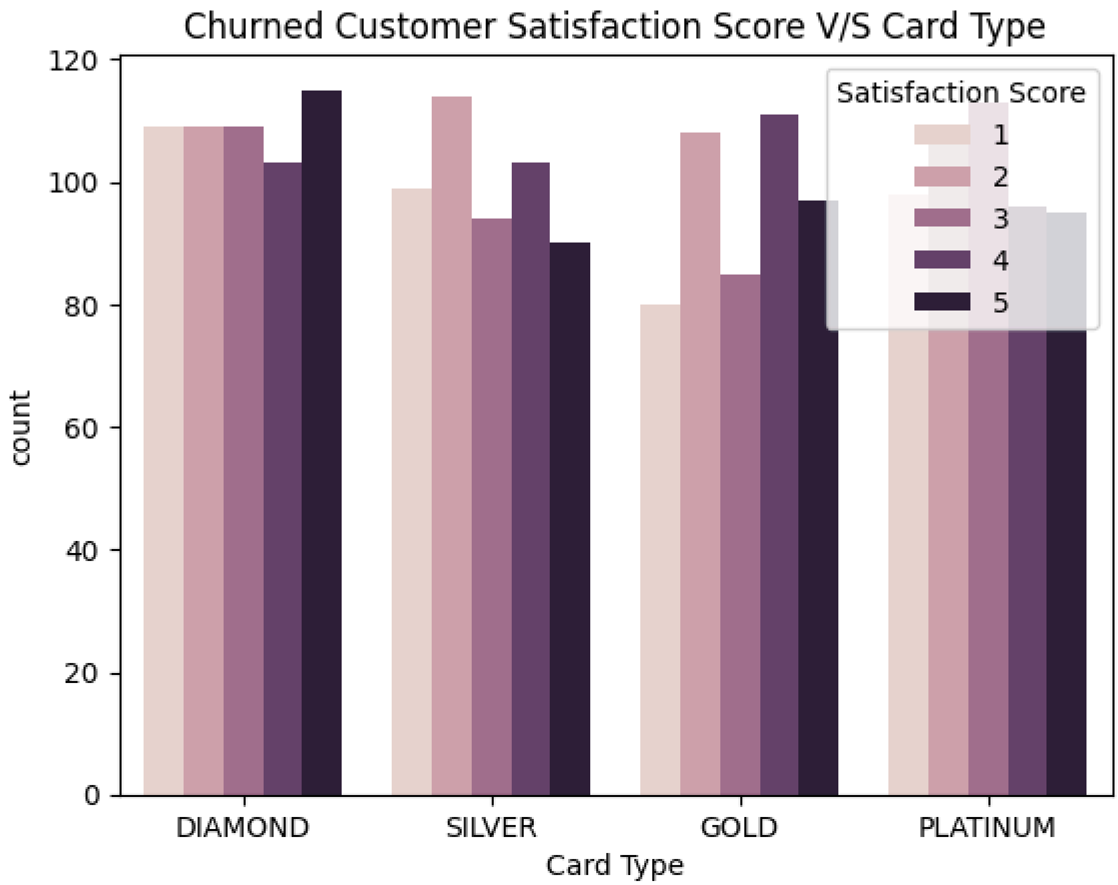

satisfaction score for Customer who churned out and have complained to banking services were visualize as below shown

In [ ]:

In [ ]:

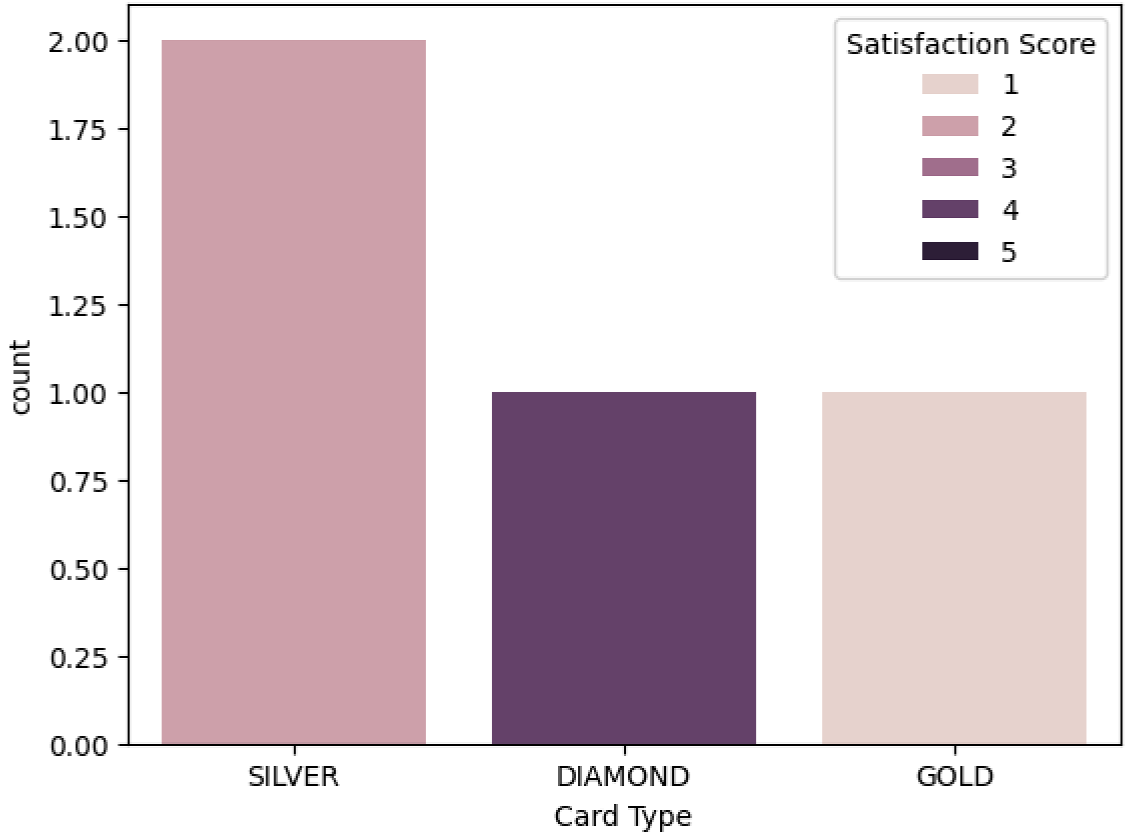
```
sns.countplot(x = data[(data['Exited'] ==1) & (data['Complain']==1)]['Card Type'],h
plt.title('Churned Customer Satisfaction Score V/S Card Type')
```

Out[ ]: `Text(0.5, 1.0, 'Churned Customer Satisfaction Score V/S Card Type')`




```
In [ ]: sns.countplot(x = data[(data['Exited'] ==1) & (data['Complain']==0)]['Card Type'],h
```

```
Out[ ]: <Axes: xlabel='Card Type', ylabel='count'>
```



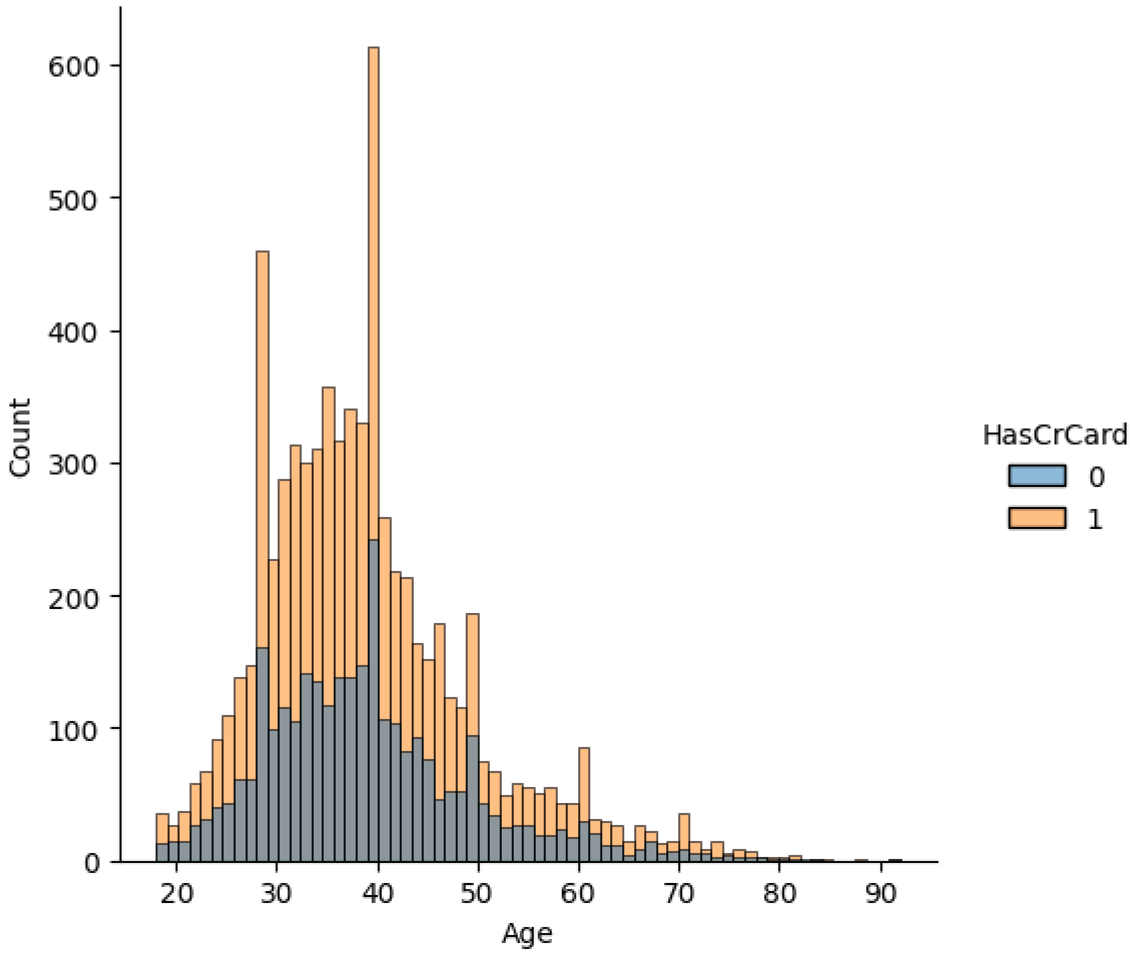

# Checking Credit card Age wise

In [ ]:

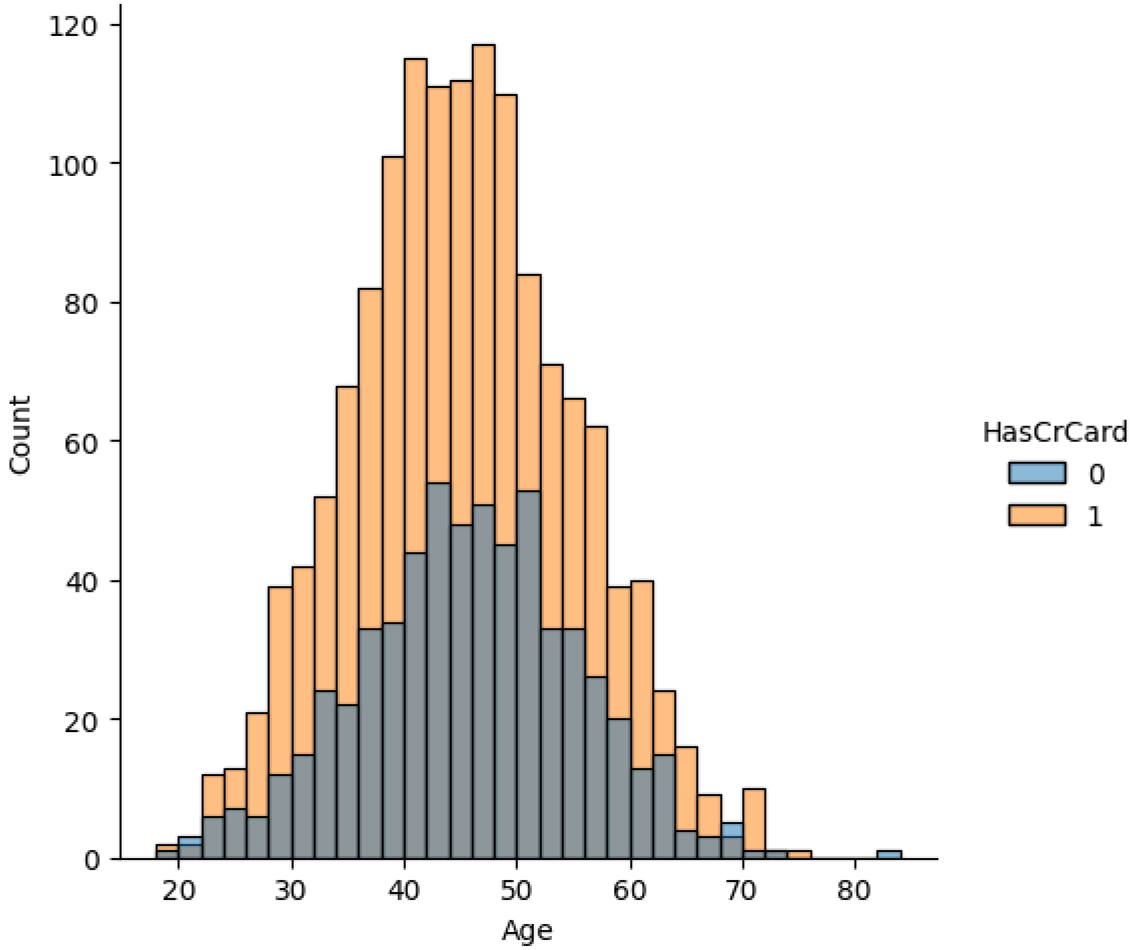
```
plt.figure(figsize=(5, 5))
sns.displot(data=data, x="Age", hue="HasCrCard")
plt.figure(figsize=(5, 5))  # Create a new figure
sns.displot(data=data[data["Exited"] == 1], x="Age", hue="HasCrCard")
plt.figure(figsize=(5, 5))
sns.displot(data=data[data["Exited"] == 1], x="Age", hue="IsActiveMember")
```

Out[ ]:

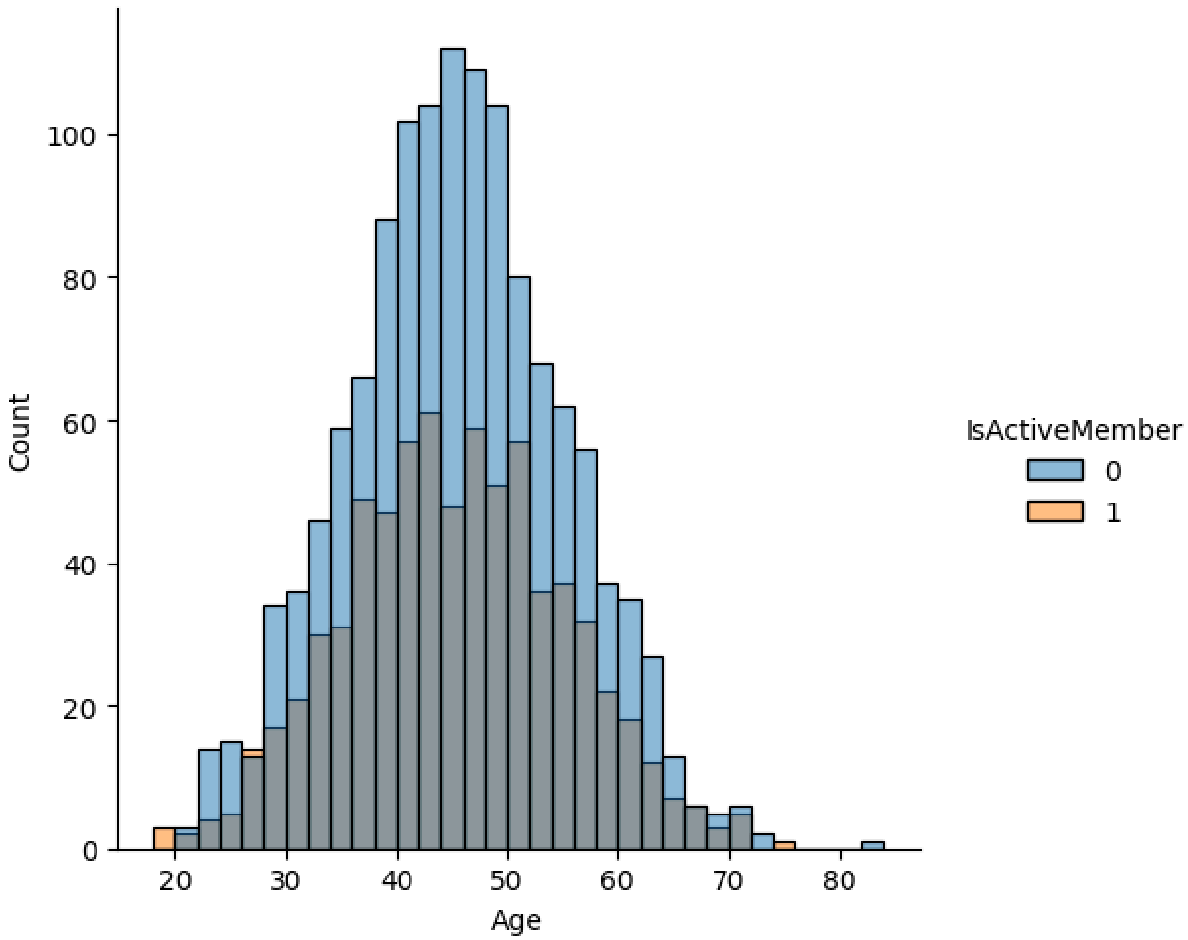
```
<seaborn.axisgrid.FacetGrid at 0x7e27f9820be0>
<Figure size 500x500 with 0 Axes>
```




<Figure size 500x500 with 0 Axes>




<Figure size 500x500 with 0 Axes>

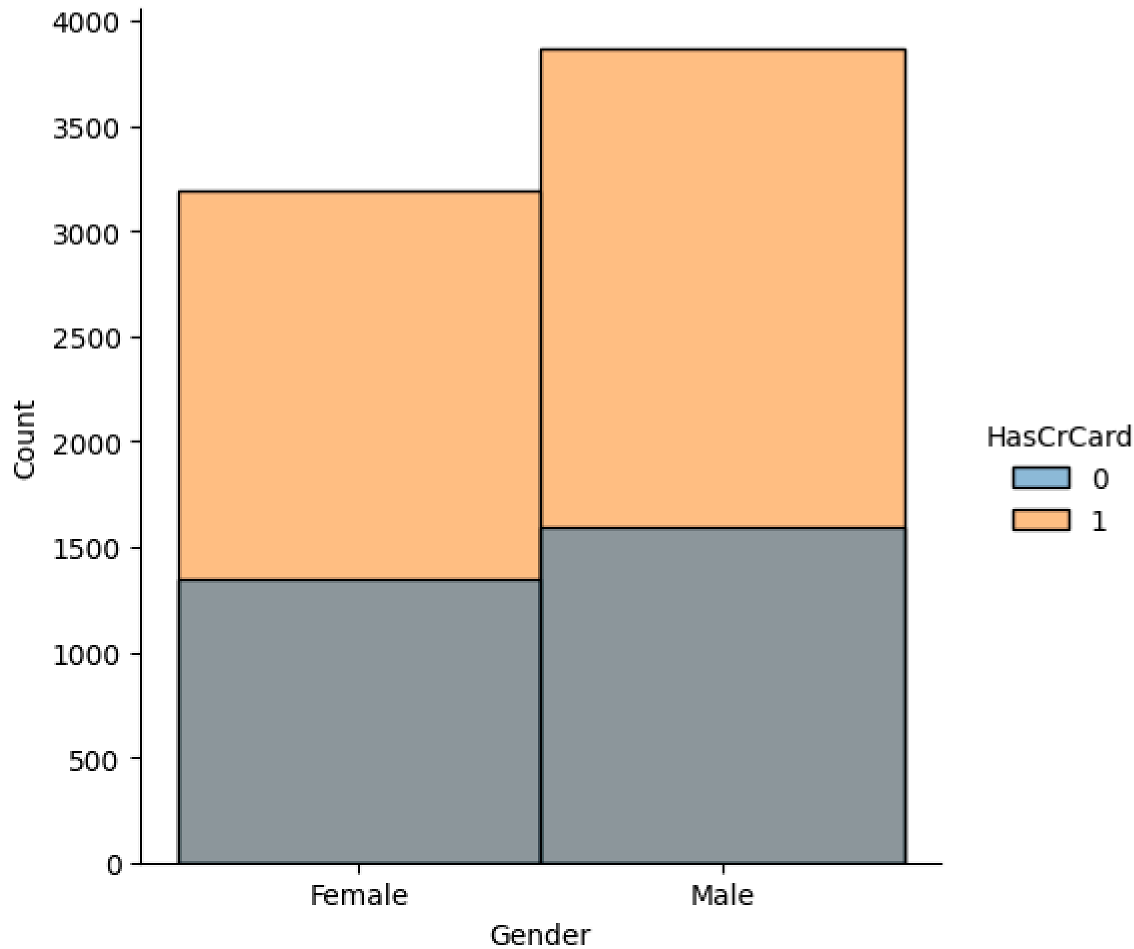



the people who churned were more active member in age group of 30-55.

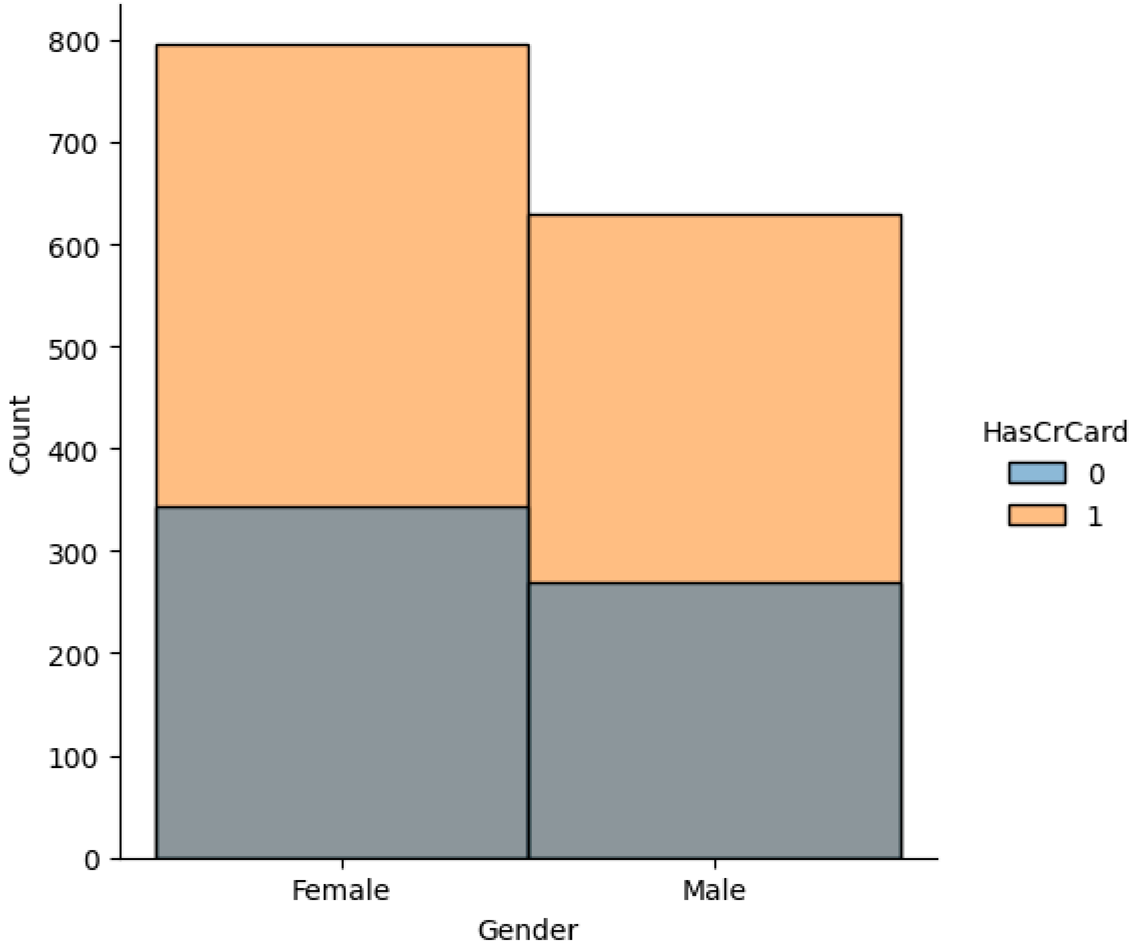
these are set of people who are customer of the bank now we will analyze customer who were churned were of

In [ ]:
```
plt.figure(figsize=(5, 5))
sns.displot(data=data, x="Gender", hue="HasCrCard")
plt.figure(figsize=(5, 5))  # Create a new figure
sns.displot(data=data[data["Exited"] == 1], x="Gender", hue="HasCrCard")
plt.figure(figsize=(5, 5))
sns.displot(data=data[data["Exited"] == 1], x="Gender", hue="IsActiveMember")
```

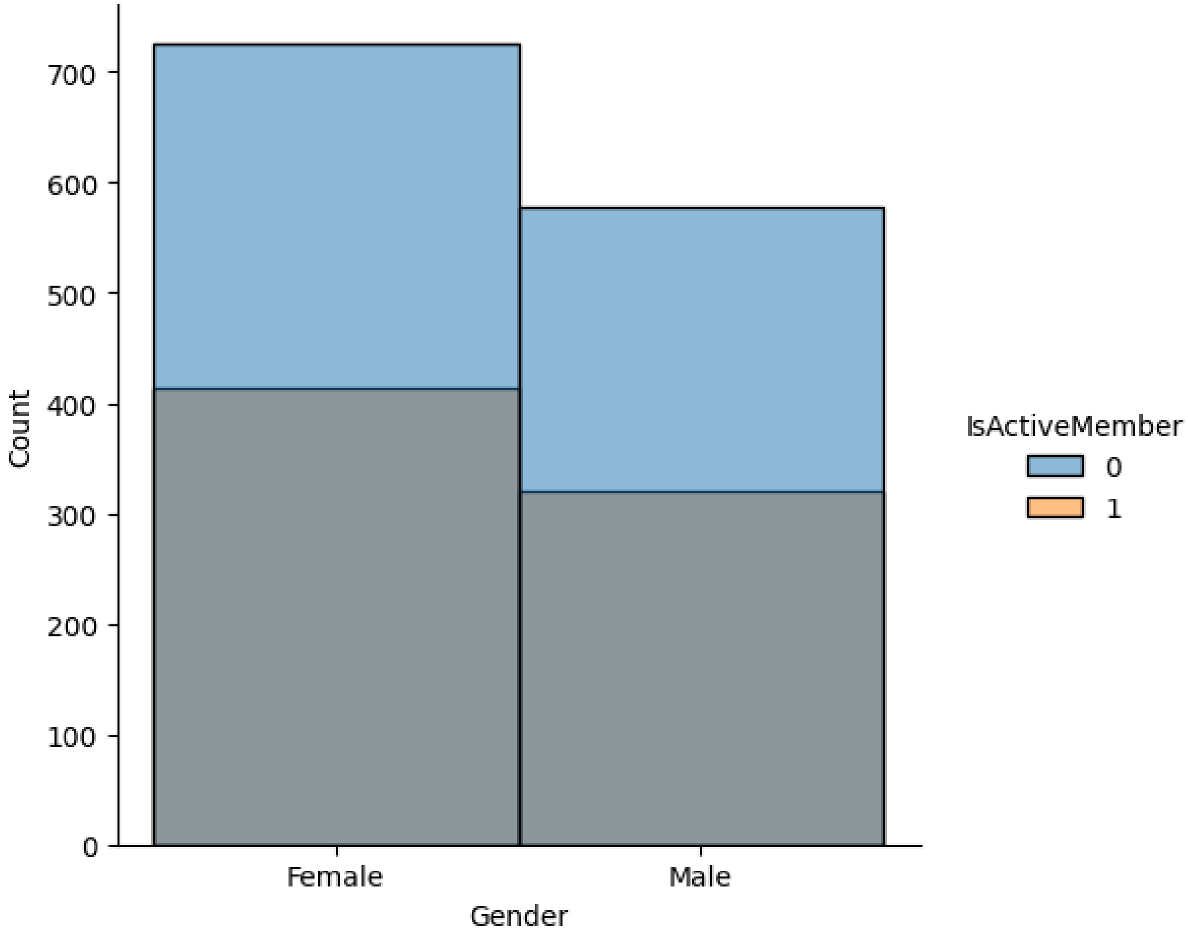
Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7e2800235540>
<Figure size 500x500 with 0 Axes>
```




```
<Figure size 500x500 with 0 Axes>
```




<Figure size 500x500 with 0 Axes>



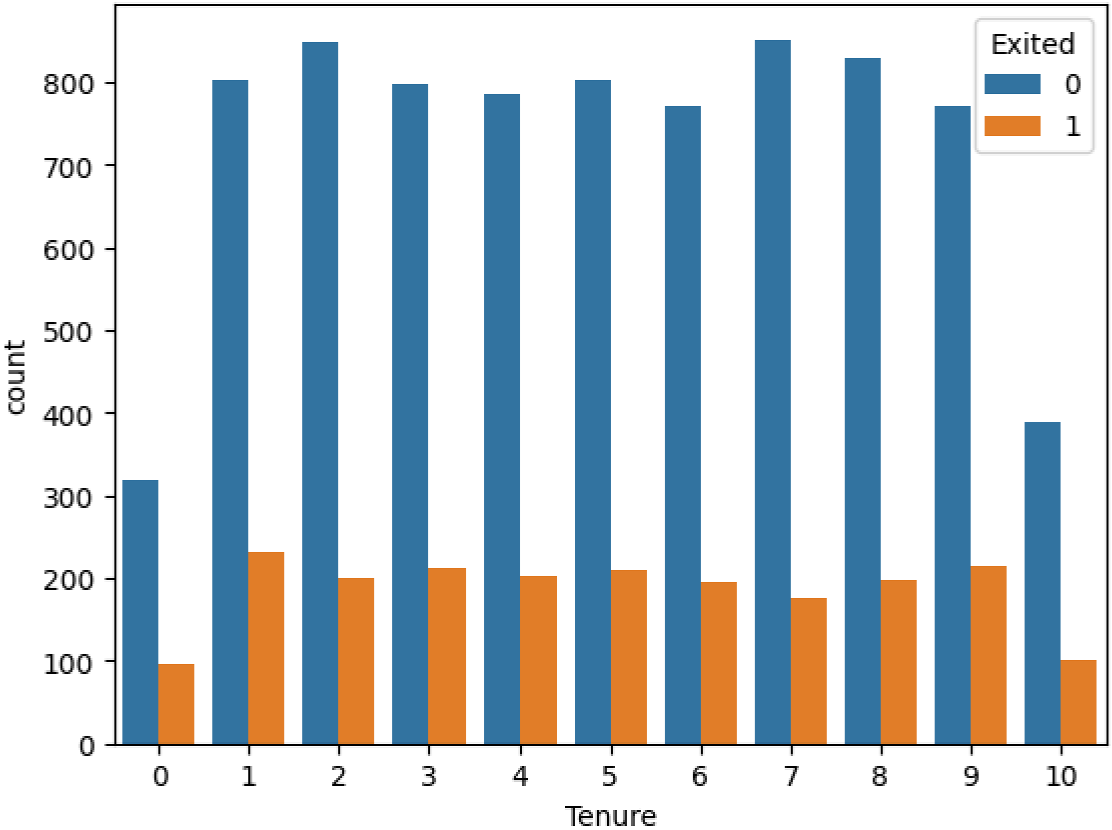

# Descriptive analysis

## Churn rate

for different type of tenures

In [ ]:
```
sns.countplot(x=data['Tenure'],hue= data['Exited'])
```

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




In [ ]:
```
pd.crosstab(columns = data['Tenure'],index= data['Exited'],margins = True)
```

Out[ ]:

| Tenure | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Exited** | | | | | | | | | | | | |
| **0** | 318 | 803 | 847 | 796 | 786 | 803 | 771 | 851 | 828 | 770 | 389 | 7962 |
| **1** | 95 | 232 | 201 | 213 | 203 | 209 | 196 | 177 | 197 | 214 | 101 | 2038 |
| **All** | 413 | 1035 | 1048 | 1009 | 989 | 1012 | 967 | 1028 | 1025 | 984 | 490 | 10000 |

In [ ]:
```
churn_data = pd.crosstab(columns = data['Tenure'],index= data['Exited'],normalize =
churn_data
```

Out[ ]:

| Tenure | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|---|
| **Exited** | | | | | | | | | |
| **0** | 0.769976 | 0.775845 | 0.808206 | 0.7889 | 0.794742 | 0.793478 | 0.797311 | 0.827821 | 0.807 |
| **1** | 0.230024 | 0.224155 | 0.191794 | 0.2111 | 0.205258 | 0.206522 | 0.202689 | 0.172179 | 0.192 |

In [ ]:
```

```

In [ ]:
```
churn_data[1:2].reset_index()
```

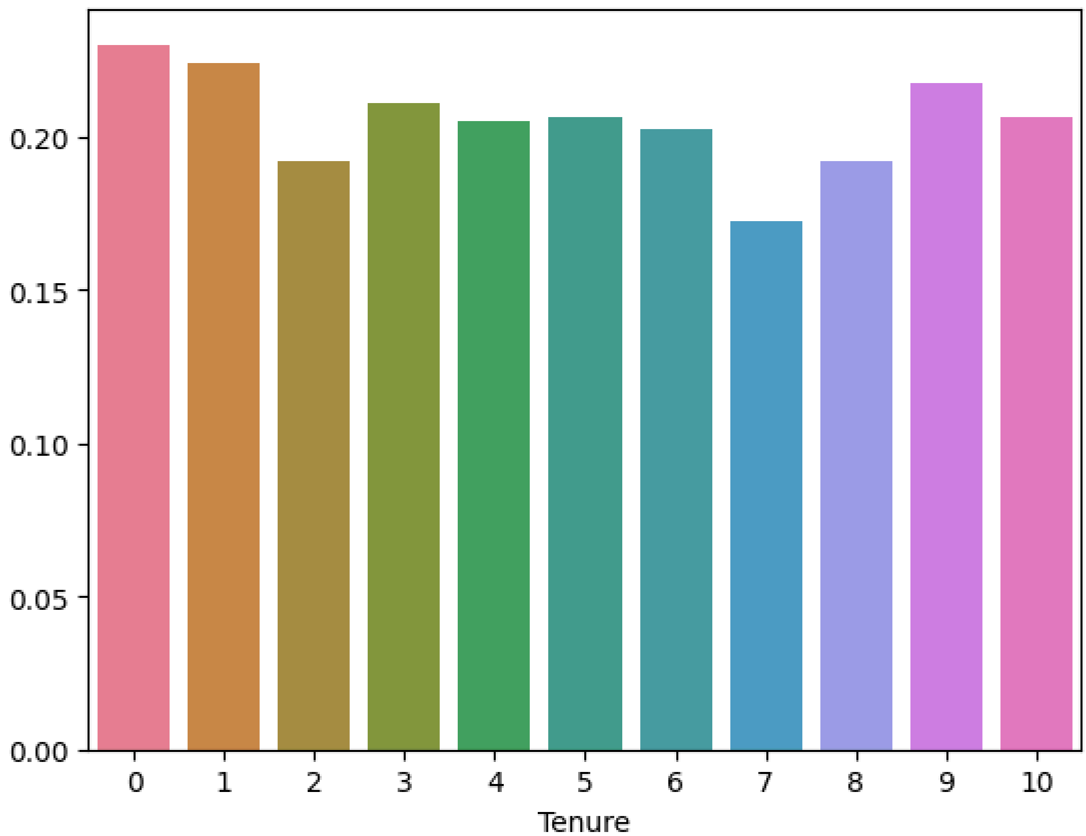
Out[ ]:

| Tenure | Exited | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0.230024 | 0.224155 | 0.191794 | 0.2111 | 0.205258 | 0.206522 | 0.202689 | 0.17217 |

from above table the 2nd rows show the churning rate for every different tenure

In [ ]:
```
sns.barplot(churn_data[1:2].reset_index().drop('Exited',axis = 1))
```

Out[ ]: <Axes: xlabel='Tenure'>




The Customer churning are dependent on Variables like Credit Score ,Age and Geography Tenure has no relation with customer who churned

**Recommendation:**

Focus on Customer with Credit score between 600-700 as they are more likely to churn. Keep a guard rail check on the 30-40 year of age people as they are loyal customers the Age from 40 – 50 were the mostly who churned so incentivize them too so they not churned in future Gender has an impact on churning so and incentives for gender can benefits the customer Focus on credit card service and bring innovation as people who left were most of who have credit card with them

# Observation & Recommendation:

The Customer churning are dependent on Variables like Credit Score ,Age and Geography, Balance Tenure has no relation with customer who churned

## Recommendation

Focus on Customer with Credit score between 600-700 as they are more likely to churn.

Keep a guard rail check on the 30-40 year of age people as they are loyal customers ,the Age from 40 – 50 were the mostly who churned so incentivize them too so they not churned in future

Gender has an impact on churning so an incentives for both gender can benefits the customer

Focus on credit card service and bring innovation as people who left were most of who have credit card with them

Geography especially France as most customer centric and Balance should be considered for predicting the next possible churn

# Conclusion

Customer leaving the bank makes a significant impact on firm reputation and leads to financial loss and in order to deal with this crisis a comprehensive data analysis needed for making an informed decision by decision makers