Bank_Churn_Analysis

August 5, 2025

1 STEP 1: Import & QA the data

Import & join two customer data tables, then remove duplicate rows & columns and fill in missing values.

Import/Open both tables in the "Bank_Churn_Messy.xlsx" file

[ ]:
```
from google.colab import files

uploaded = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving Bank_Churn_Messy.xlsx to Bank_Churn_Messy (2).xlsx
```

[ ]:
```
import pandas as pd

churn_cust_info = pd.read_excel("Bank_Churn_Messy.xlsx")

churn_cust_info.head()
```

[ ]:

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	\
0	15634602	Hargrave	619	FRA	Female	42.0	2	
1	15647311	Hill	608	Spain	Female	41.0	1	
2	15619304	Onio	502	French	Female	42.0	8	
3	15701354	Boni	699	FRA	Female	39.0	1	
4	15737888	Mitchell	850	Spain	Female	43.0	2	

	EstimatedSalary
0	€101348.88
1	€112542.58
2	€113931.57
3	€93826.63
4	€79084.1

[ ]:
```
churn_acct_info = pd.read_excel("Bank_Churn_Messy.xlsx", sheet_name=1)

churn_acct_info.head()
```

[ ]:

	CustomerId	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	\
0	15634602	€0.0	1	Yes	2	Yes	
1	15634602	€0.0	1	Yes	2	Yes	
2	15647311	€83807.86	1	Yes	1	Yes	
3	15619304	€159660.8	3	No	8	No	
4	15701354	€0.0	2	No	1	No	

	Exited
0	1
1	1
2	0
3	1
4	0

Used a left join "Accounttt_Info" to "Customer_Info" using the "CustomerID" column.

[ ]:
```
churn_df = churn_cust_info.merge(churn_acct_info, how="left", on="CustomerId")

churn_df.head()
```

[ ]:

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure_x	\
0	15634602	Hargrave	619	FRA	Female	42.0	2	
1	15634602	Hargrave	619	FRA	Female	42.0	2	
2	15647311	Hill	608	Spain	Female	41.0	1	
3	15619304	Onio	502	French	Female	42.0	8	
4	15701354	Boni	699	FRA	Female	39.0	1	

	EstimatedSalary	Balance	NumOfProducts	HasCrCard	Tenure_y	\
0	€101348.88	€0.0	1	Yes	2	
1	€101348.88	€0.0	1	Yes	2	
2	€112542.58	€83807.86	1	Yes	1	
3	€113931.57	€159660.8	3	No	8	
4	€93826.63	€0.0	2	No	1	

	IsActiveMember	Exited
0	Yes	1
1	Yes	1
2	Yes	0
3	No	1
4	No	0

Check for and remove duplicated rows and columns.

[ ]:
```
churn_df = churn_df.drop("Tenure_y", axis=1).rename({"Tenure_x":"Tenure"},␣
↪axis=1).drop_duplicates()

churn_df.head()
```

[ ]:

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	\
0	15634602	Hargrave	619	FRA	Female	42.0	2	
2	15647311	Hill	608	Spain	Female	41.0	1	
3	15619304	Onio	502	French	Female	42.0	8	
4	15701354	Boni	699	FRA	Female	39.0	1	
5	15737888	Mitchell	850	Spain	Female	43.0	2	

	EstimatedSalary	Balance	NumOfProducts	HasCrCard	IsActiveMember	Exited
0	€101348.88	€0.0	1	Yes	Yes	1
2	€112542.58	€83807.86	1	Yes	Yes	0
3	€113931.57	€159660.8	3	No	No	1
4	€93826.63	€0.0	2	No	No	0
5	€79084.1	€125510.82	1	Yes	Yes	0

[ ]:
```
churn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10000 entries, 0 to 10000
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CustomerId       10000 non-null  int64
 1   Surname          9997 non-null   object
 2   CreditScore      10000 non-null  int64
 3   Geography        10000 non-null  object
 4   Gender           10000 non-null  object
 5   Age              9997 non-null   float64
 6   Tenure           10000 non-null  int64
 7   EstimatedSalary  10000 non-null  object
 8   Balance          10000 non-null  object
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  object
 11  IsActiveMember   10000 non-null  object
 12  Exited           10000 non-null  int64
dtypes: float64(1), int64(5), object(7)
memory usage: 1.1+ MB
```

2 STEP 2: Clean the Data

Clean the data by fixing inconsistencies in labeling, handling erroneous values, and fixing currency fields.

Checked the data types for each column and make any necessary fixes.

[ ]:
```
churn_df.head()
```

[ ]:
```
   CustomerId   Surname  CreditScore Geography  Gender   Age  Tenure  \
0    15634602  Hargrave          619       FRA  Female  42.0       2
2    15647311      Hill          608     Spain  Female  41.0       1
3    15619304      Onio          502    French  Female  42.0       8
4    15701354      Boni          699       FRA  Female  39.0       1
5    15737888  Mitchell          850     Spain  Female  43.0       2

  EstimatedSalary     Balance  NumOfProducts HasCrCard IsActiveMember  Exited
0      €101348.88        €0.0              1       Yes            Yes       1
2      €112542.58   €83807.86              1       Yes            Yes       0
3      €113931.57   €159660.8              3        No             No       1
4       €93826.63        €0.0              2        No             No       0
5        €79084.1  €125510.82              1       Yes            Yes       0
```

[ ]:
```
#churn_df["EstimatedSalary"] = churn_df["EstimatedSalary"].str.replace("€", "").
↪astype(float)

churn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10000 entries, 0 to 10000
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CustomerId       10000 non-null  int64
 1   Surname          9997 non-null   object
 2   CreditScore      10000 non-null  int64
 3   Geography        10000 non-null  object
 4   Gender           10000 non-null  object
 5   Age              9997 non-null   float64
 6   Tenure           10000 non-null  int64
 7   EstimatedSalary  10000 non-null  object
 8   Balance          10000 non-null  object
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  object
 11  IsActiveMember   10000 non-null  object
 12  Exited           10000 non-null  int64
dtypes: float64(1), int64(5), object(7)
memory usage: 1.1+ MB
```

[ ]:
```
#churn_df["Balance"] = churn_df["Balance"].str.replace("€", "").astype(float)

churn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10000 entries, 0 to 10000
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
```

```
---  ------           --------------  -----
 0   CustomerId       10000 non-null  int64
 1   Surname          9997 non-null   object
 2   CreditScore      10000 non-null  int64
 3   Geography        10000 non-null  object
 4   Gender           10000 non-null  object
 5   Age              9997 non-null   float64
 6   Tenure           10000 non-null  int64
 7   EstimatedSalary  10000 non-null  object
 8   Balance          10000 non-null  object
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  object
 11  IsActiveMember   10000 non-null  object
 12  Exited           10000 non-null  int64
dtypes: float64(1), int64(5), object(7)
memory usage: 1.1+ MB
```

[ ]:
```
churn_df[churn_df.isna().any(axis=1) == True]
```

[ ]:
```
      CustomerId Surname  CreditScore Geography  Gender  Age  Tenure  \
29      15728693     NaN          574   Germany  Female  NaN       3
122     15580203     NaN          674     Spain    Male  NaN       6
9390    15756954     NaN          538    France  Female  NaN       2

     EstimatedSalary     Balance  NumOfProducts HasCrCard IsActiveMember  \
29          -€999999  €141349.43              1       Yes             Yes
122         -€999999  €120193.42              1        No              No
9390        -€999999        €0.0              1       Yes             Yes

      Exited
29         0
122        0
9390       0
```

[ ]:
```
churn_df = churn_df.fillna(value={"Surname": "MISSING", "Age": churn_df["Age"].
 ↪median})

churn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10000 entries, 0 to 10000
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CustomerId       10000 non-null  int64
 1   Surname          10000 non-null  object
 2   CreditScore      10000 non-null  int64
 3   Geography        10000 non-null  object
```

```
 4   Gender           10000 non-null  object
 5   Age              10000 non-null  object
 6   Tenure           10000 non-null  int64
 7   EstimatedSalary  10000 non-null  object
 8   Balance          10000 non-null  object
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  object
 11  IsActiveMember   10000 non-null  object
 12  Exited           10000 non-null  int64
dtypes: int64(5), object(8)
memory usage: 1.1+ MB
```

[ ]:
```
churn_df.iloc[[28, 121, 9389]]
```

[ ]:

	CustomerId	Surname	CreditScore	Geography	Gender	\
29	15728693	MISSING	574	Germany	Female	
122	15580203	MISSING	674	Spain	Male	
9390	15756954	MISSING	538	France	Female	

		Age	Tenure	\
29	<bound method Series.median of 0	42.0\n…	3	
122	<bound method Series.median of 0	42.0\n…	6	
9390	<bound method Series.median of 0	42.0\n…	2	

	EstimatedSalary	Balance	NumOfProducts	HasCrCard	IsActiveMember	\
29	-€999999	€141349.43	1	Yes	Yes	
122	-€999999	€120193.42	1	No	No	
9390	-€999999	€0.0	1	Yes	Yes	

	Exited
29	0
122	0
9390	0

Profile the numeric columns in the data. Are there any extreme or non-sensical values? If so, impute them with the median of the column.

[ ]:
```
churn_df.describe()
```

[ ]:

	CustomerId	CreditScore	Tenure	NumOfProducts	Exited
count	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000
mean	1.569094e+07	650.528800	5.012800	1.530200	0.203700
std	7.193619e+04	96.653299	2.892174	0.581654	0.402769
min	1.556570e+07	350.000000	0.000000	1.000000	0.000000
25%	1.562853e+07	584.000000	3.000000	1.000000	0.000000
50%	1.569074e+07	652.000000	5.000000	1.000000	0.000000
75%	1.575323e+07	718.000000	7.000000	2.000000	0.000000
max	1.581569e+07	850.000000	10.000000	4.000000	1.000000

Checked the values in the "Geography" column and combine any variations in country names to a single value per country.

[ ]:
```
churn_df["Geography"].value_counts()
```

[ ]:
```
Geography
Germany    2509
Spain      2477
France     1741
French     1655
FRA        1618
Name: count, dtype: int64
```

[ ]:
```
import numpy as np


churn_df["Geography"] = np.where(churn_df["Geography"].isin(["FRA", "France",␣
 ↪"French"]), "France", churn_df["Geography"])

churn_df["Geography"].value_counts()
```

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

[ ]:
```
churn_df = (
    pd.read_excel("Bank_Churn_Messy.xlsx")
    .merge(pd.read_excel("Bank_Churn_Messy.xlsx", sheet_name=1), how="left",␣
 ↪on="CustomerId")
    .drop_duplicates()
    .drop("Tenure_y", axis=1)
    .rename({"Tenure_x": "Tenure"}, axis=1)
    .assign(
        EstimatedSalary=lambda x: x["EstimatedSalary"].str.replace("€", "").
 ↪astype("float"),
        Balance=lambda x: x["Balance"].str.replace("€", "").astype("float"),
        Geography=lambda x: np.where(x["Geography"].isin(["FRA", "France",␣
 ↪"French"]), "France", x["Geography"]),
     )
    .assign(EstimatedSalary= lambda x: x["EstimatedSalary"].replace(-999999,␣
 ↪x["EstimatedSalary"].median()))
)

churn_df = churn_df.fillna(value={"Surname": "MISSING", "Age": churn_df["Age"].
 ↪median()})
```

```
churn_df.head()
```

[ ]:

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	\
0	15634602	Hargrave	619	France	Female	42.0	2	
2	15647311	Hill	608	Spain	Female	41.0	1	
3	15619304	Onio	502	France	Female	42.0	8	
4	15701354	Boni	699	France	Female	39.0	1	
5	15737888	Mitchell	850	Spain	Female	43.0	2	

	EstimatedSalary	Balance	NumOfProducts	HasCrCard	IsActiveMember	Exited
0	101348.88	0.00	1	Yes	Yes	1
2	112542.58	83807.86	1	Yes	Yes	0
3	113931.57	159660.80	3	No	No	1
4	93826.63	0.00	2	No	No	0
5	79084.10	125510.82	1	Yes	Yes	0

3 STEP 3: Explore the data (EDA)

Explore the target variable and look at feature-target relationships for categorical and numeric fields.

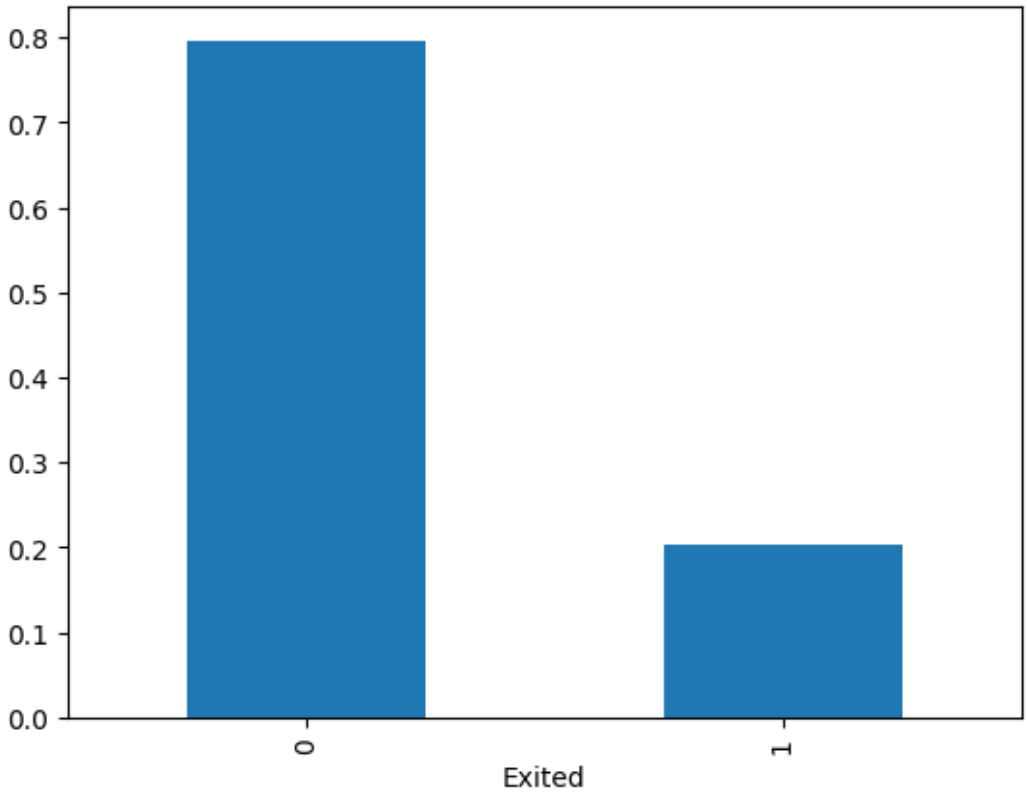
*** Built a bar chart displaying the count of churners (Exited=1) vs. non-churners (Exited=0)***

```
churn_df["Exited"].value_counts(normalize=True).plot.bar()
```

[ ]:

```
<Axes: xlabel='Exited'>
```

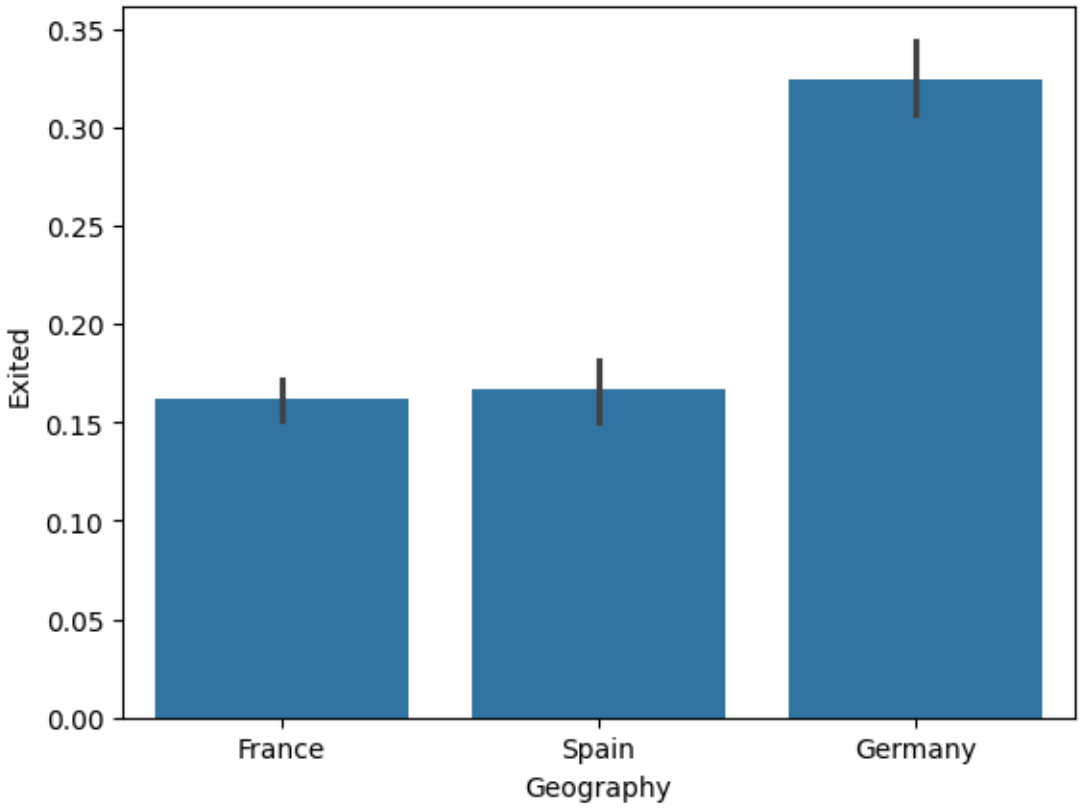
[ ]:

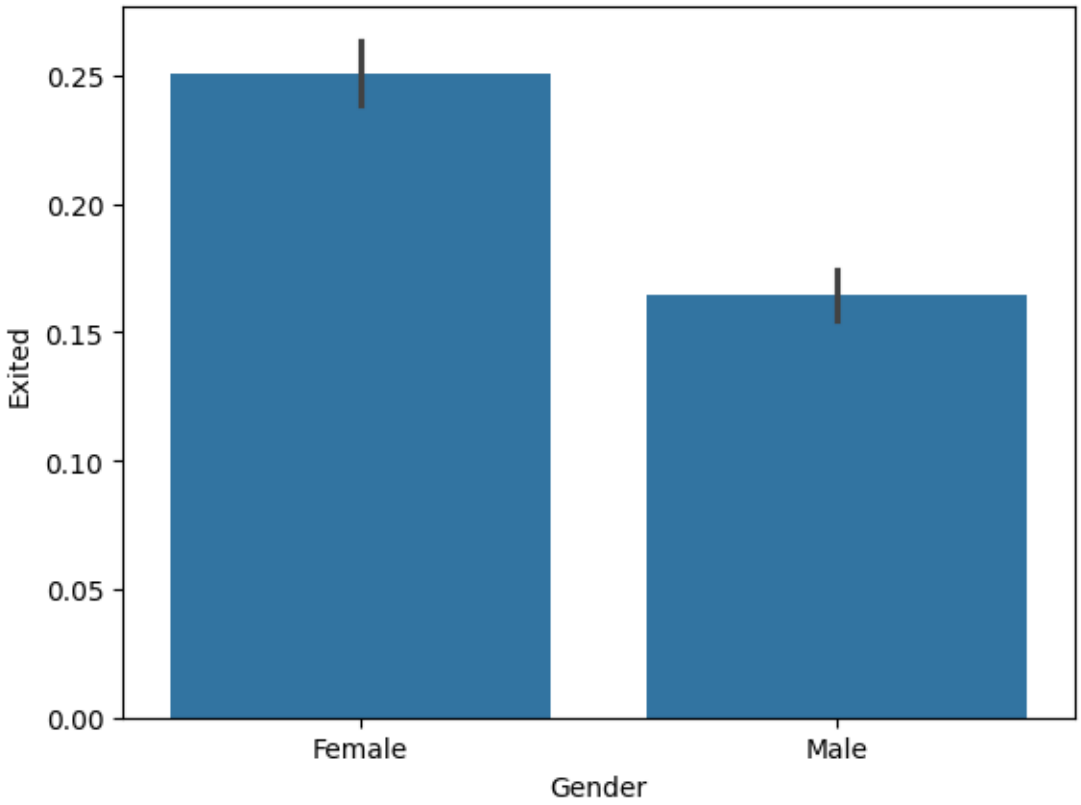


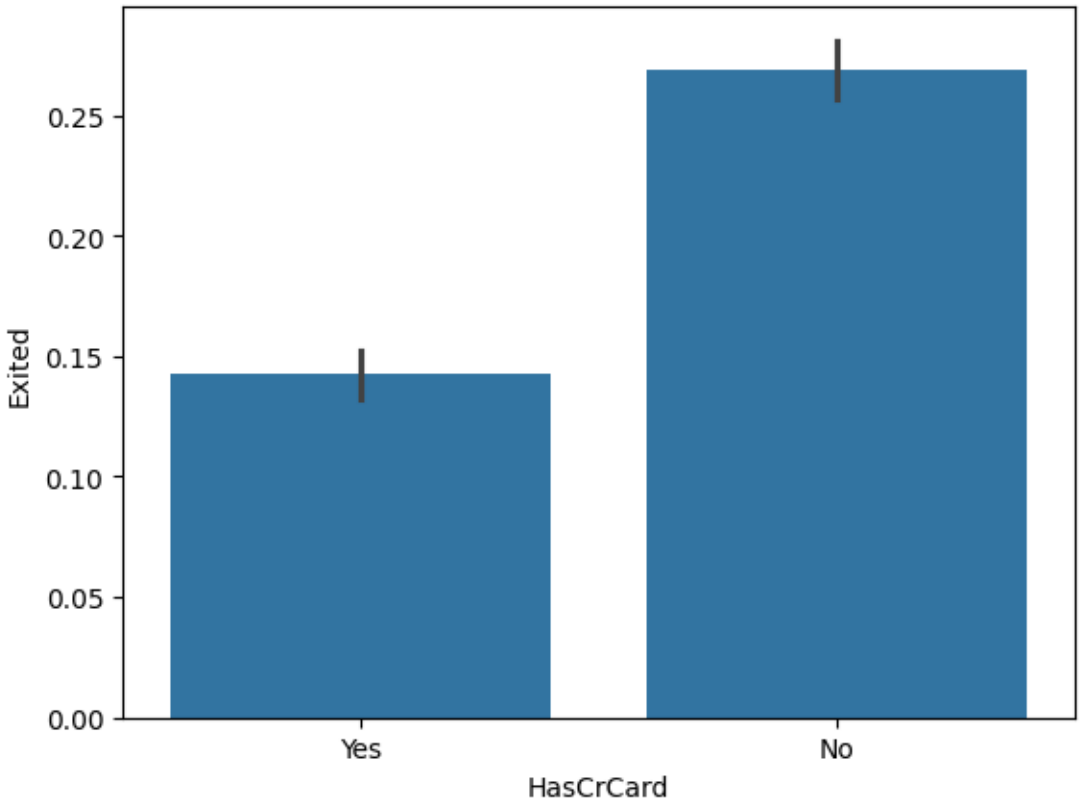
Explored the categorical variables vs. the target, and looked at the percentage of Churners by "Geography" and "Gender"

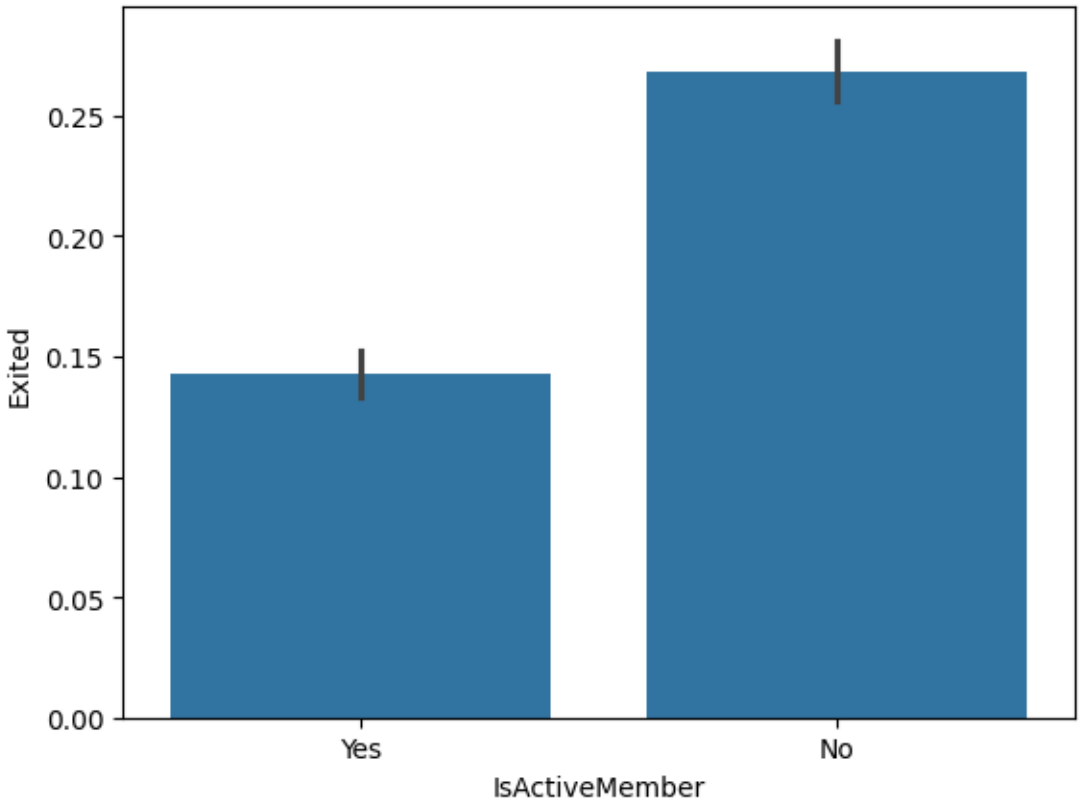
[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt

for col in churn_df.drop("Surname", axis=1).select_dtypes("object"):
    sns.barplot(data=churn_df, x=col, y="Exited")
    plt.show()
```


0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Exited
France
Spain
Germany
Geography


0.25
0.20
0.15
0.10
0.05
0.00
Exited
Female
Male
Gender


0.25
0.20
0.15
0.10
0.05
0.00
Exited
Yes
No
HasCrCard



[ ]:
```
churn_df.select_dtypes("object")
```

[ ]:

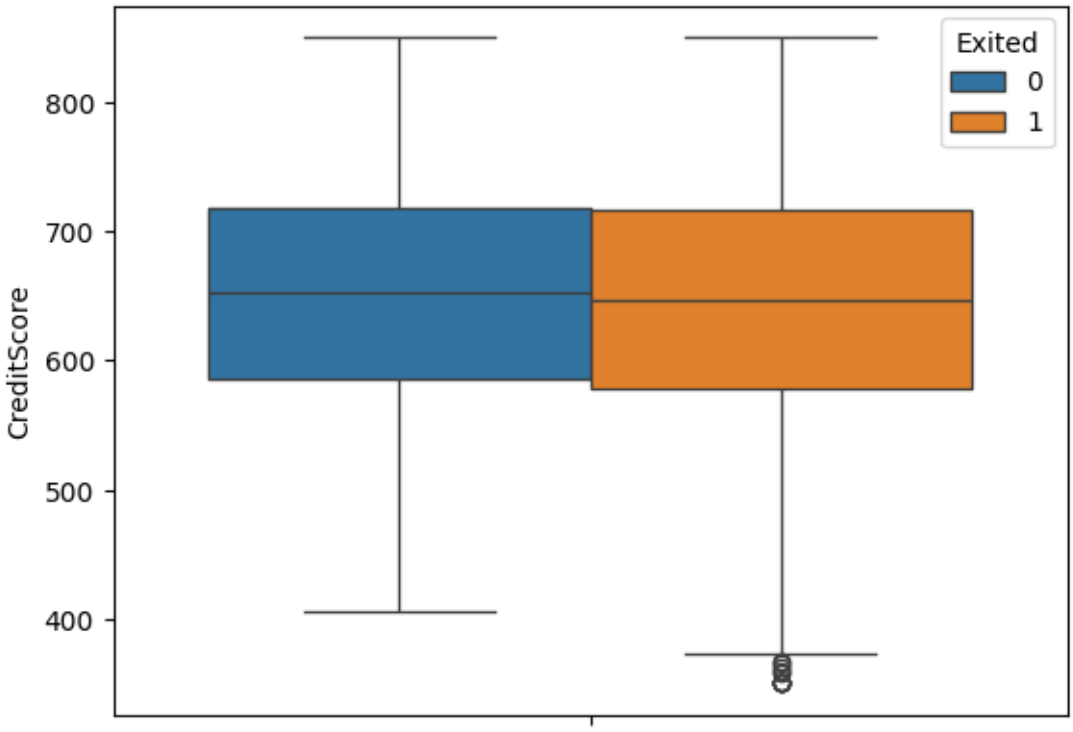
	Surname	Geography	Gender	HasCrCard	IsActiveMember
0	Hargrave	France	Female	Yes	Yes
2	Hill	Spain	Female	Yes	Yes
3	Onio	France	Female	No	No
4	Boni	France	Female	No	No
5	Mitchell	Spain	Female	Yes	Yes
…	…	…	…	…	…
9996	Obijiaku	France	Male	No	No
9997	Johnstone	France	Male	Yes	Yes
9998	Liu	France	Female	Yes	Yes
9999	Sabbatini	Germany	Male	No	No
10000	Walker	France	Female	No	No

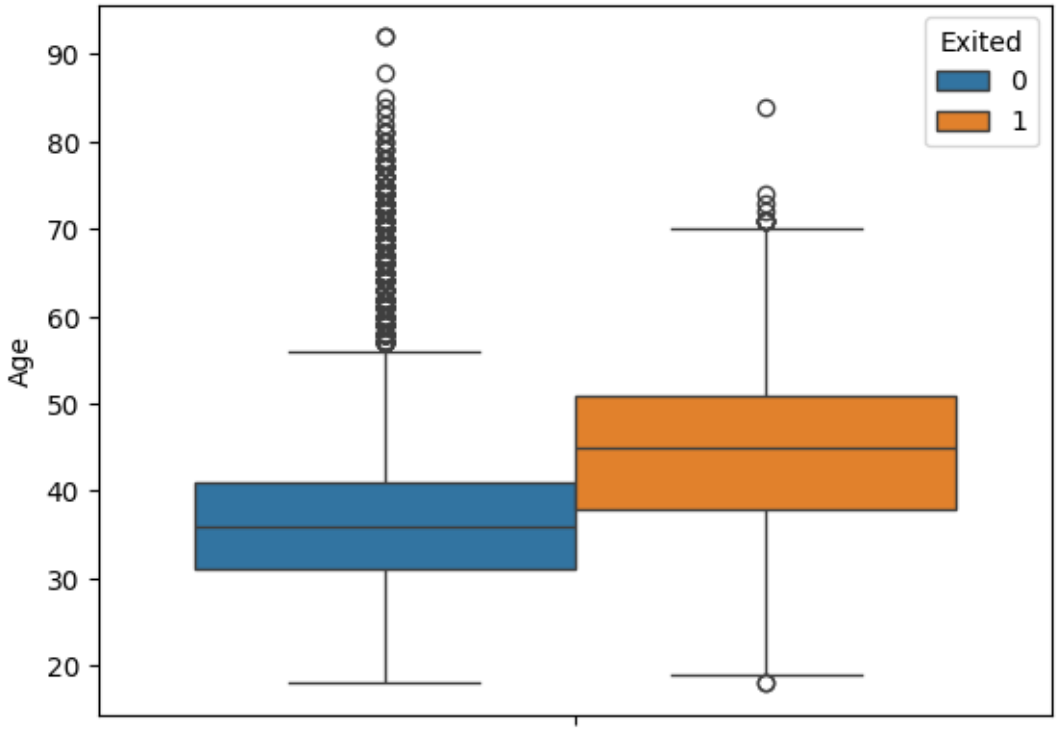
[10000 rows x 5 columns]

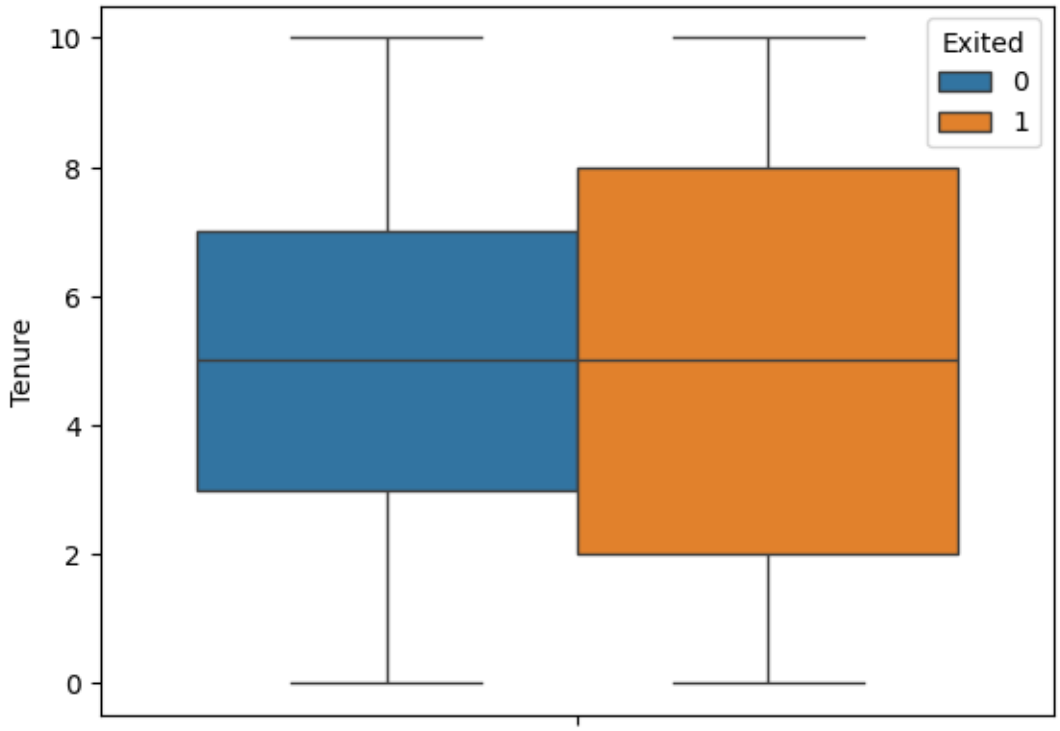
Built box plots for each numeric field, broken out by churners vs. non-churners.

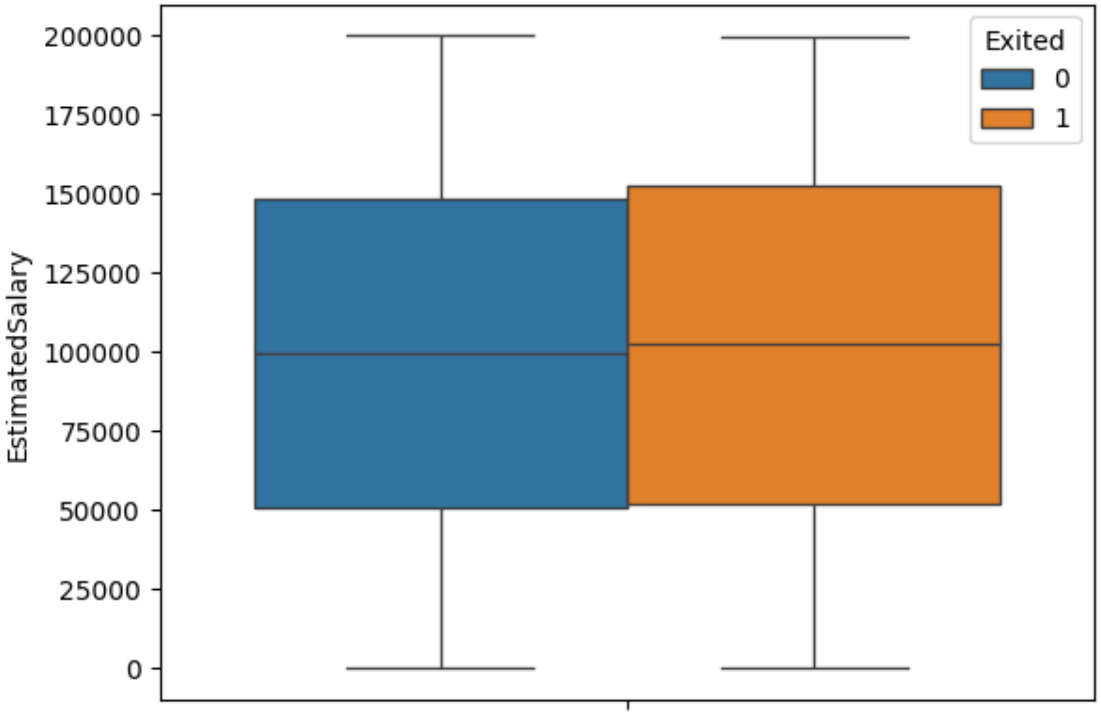
[ ]:
```
for col in churn_df.drop("CustomerId", axis=1).select_dtypes("number"):
    sns.boxplot(data=churn_df, y=col, hue="Exited")
```

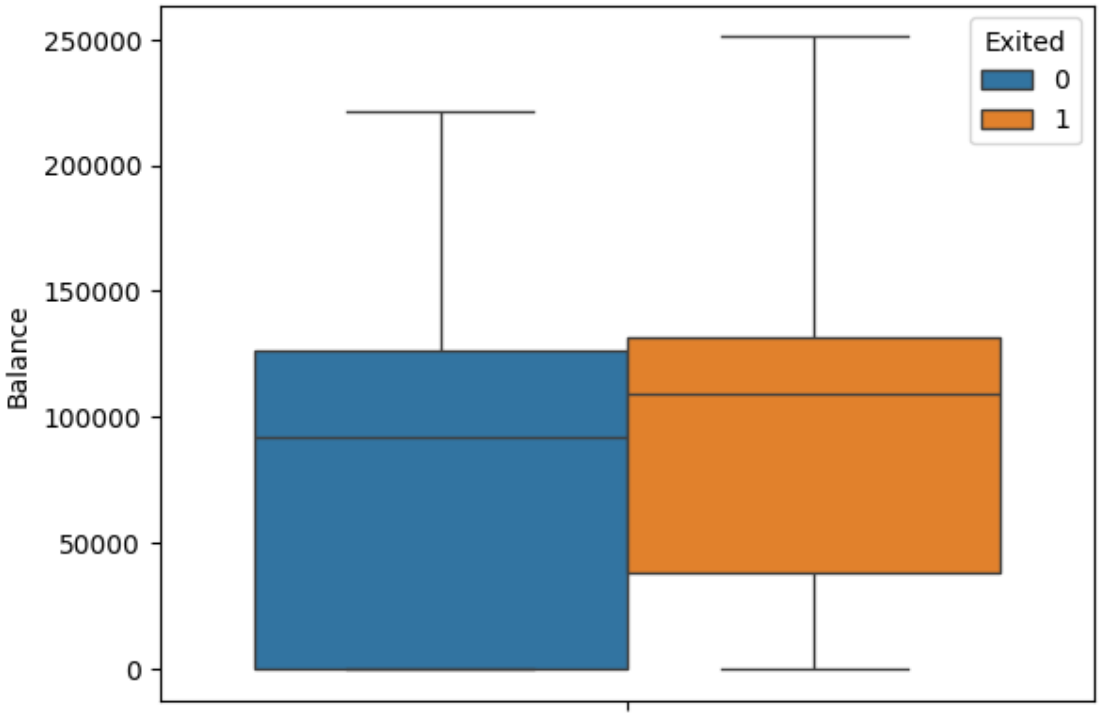
```
    plt.show()
```

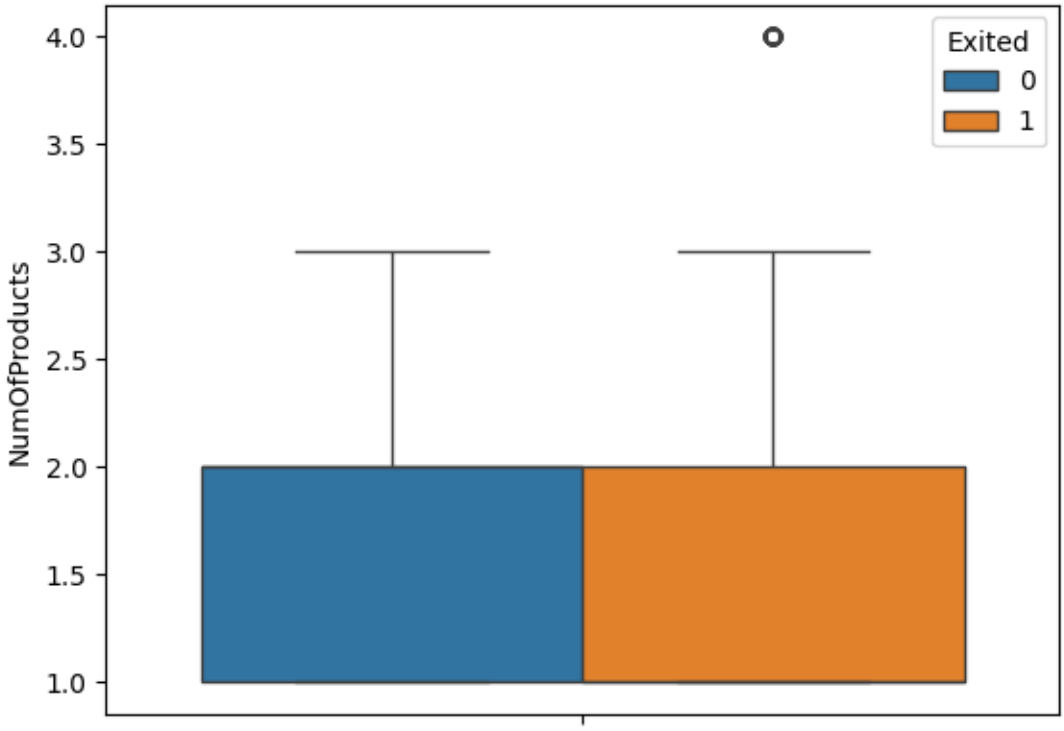

Exited
0
1
800
700
600
500
400
CreditScore


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


Exited
0
1
Tenure
10
8
6
4
2
0

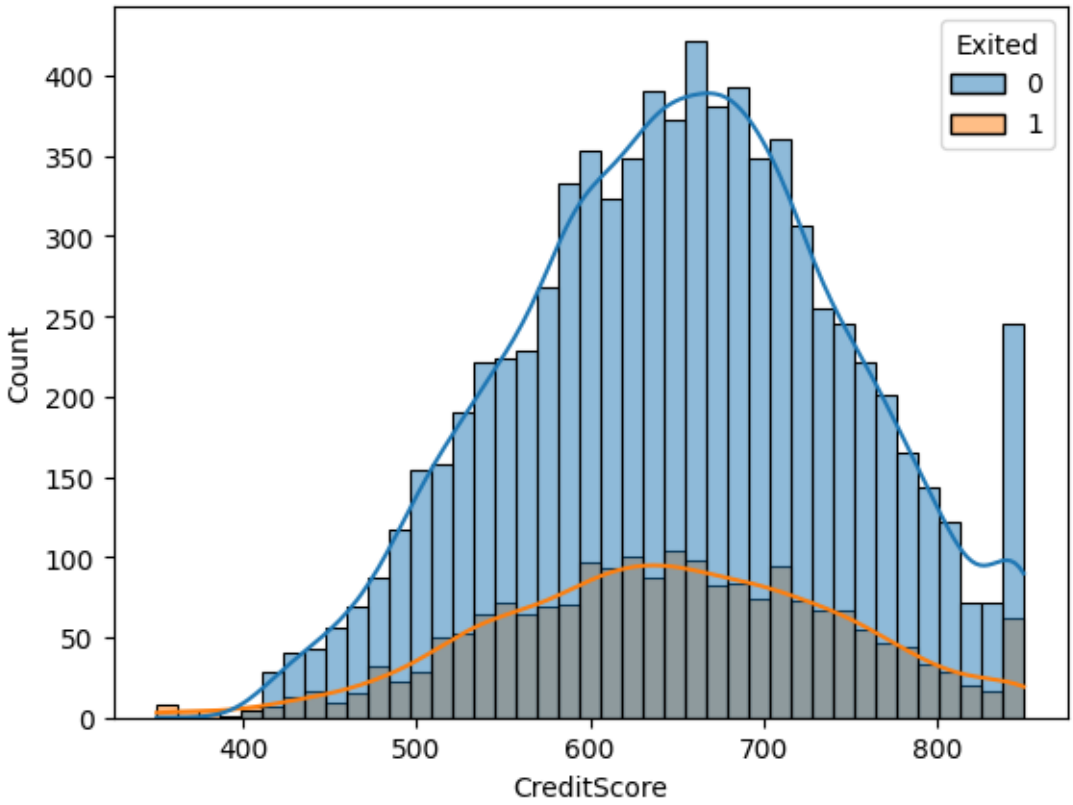

Exited
0
1
EstimatedSalary
200000
175000
150000
125000
100000
75000
50000
25000
0

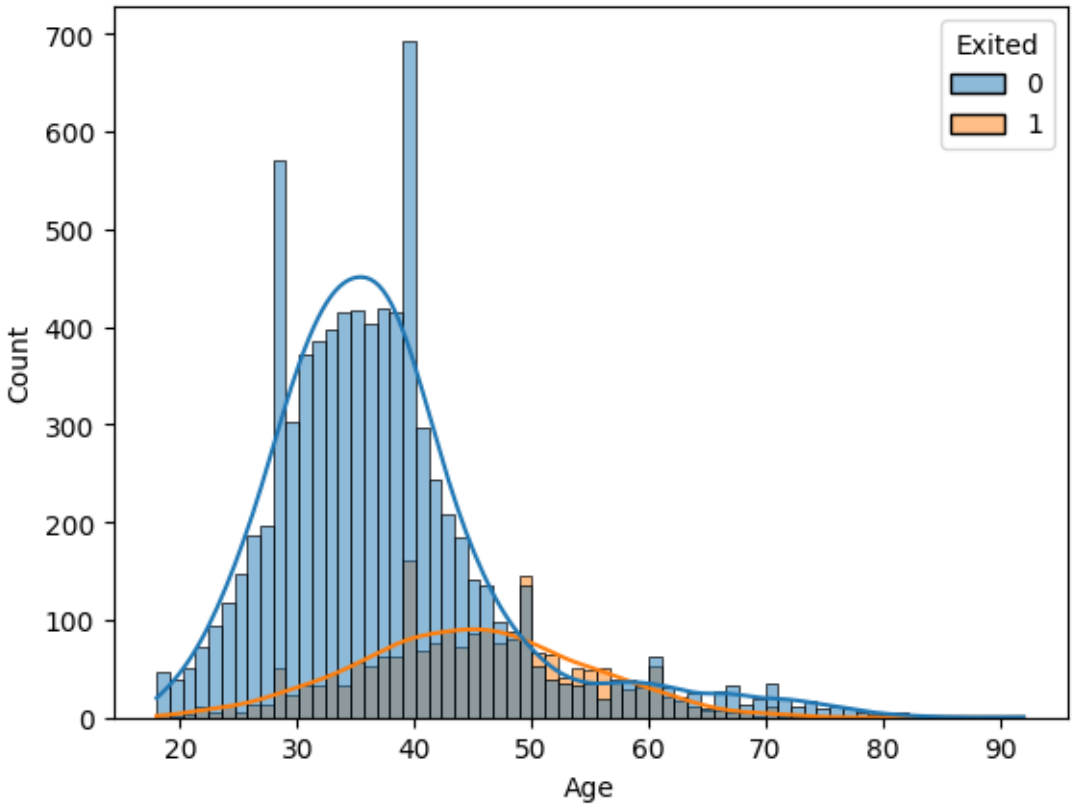

Exited
0
1
250000
200000
150000
100000
50000
0
Balance

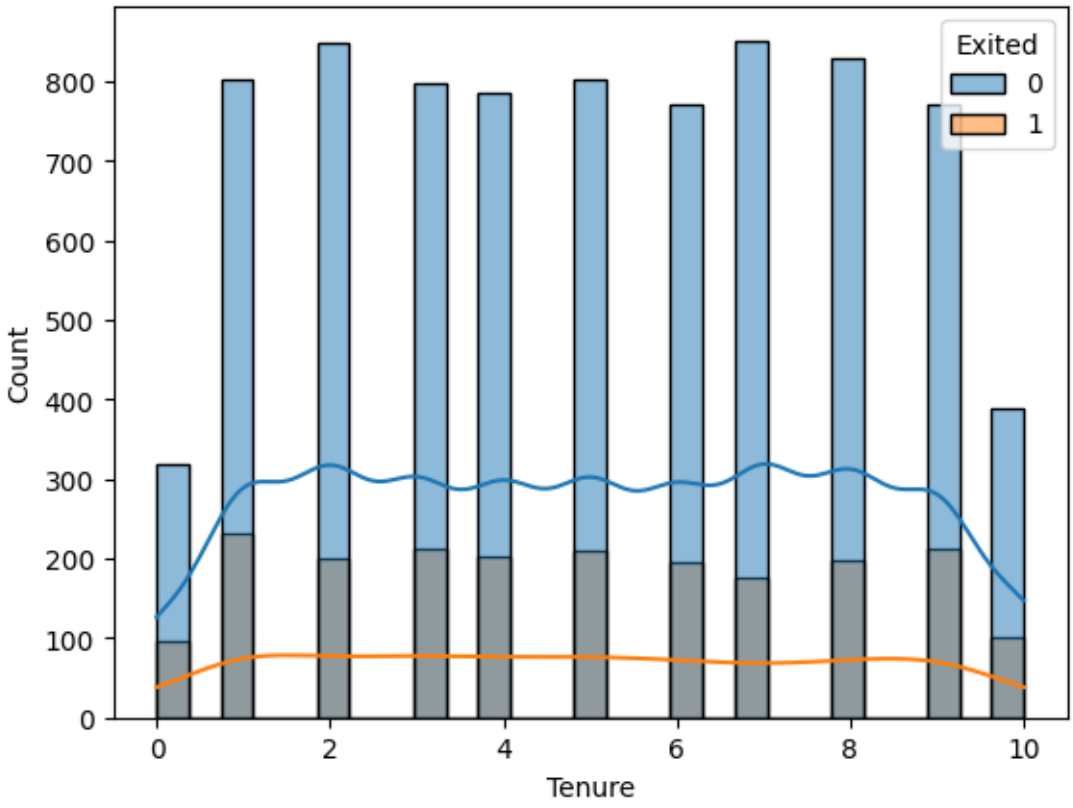

Exited
0
1
4.0
3.5
3.0
2.5
2.0
1.5
1.0
NumOfProducts

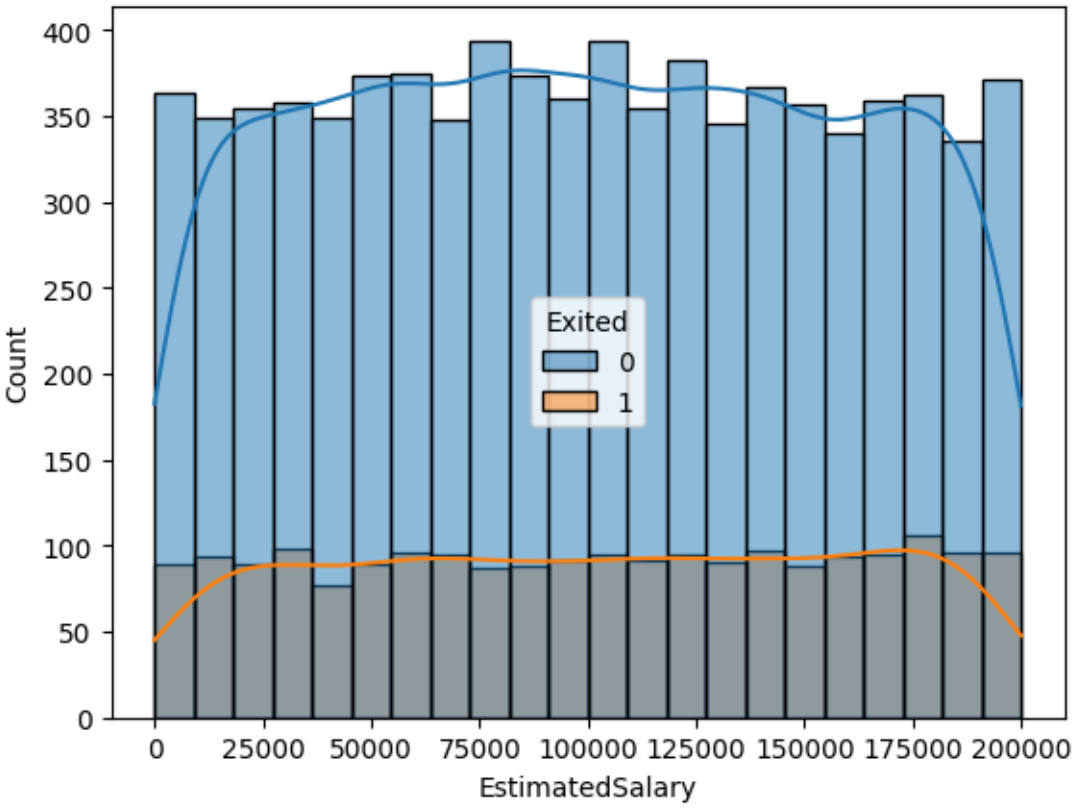
Built histograms for each numeric. fieeeld, broken out by churners vs. non-churners.

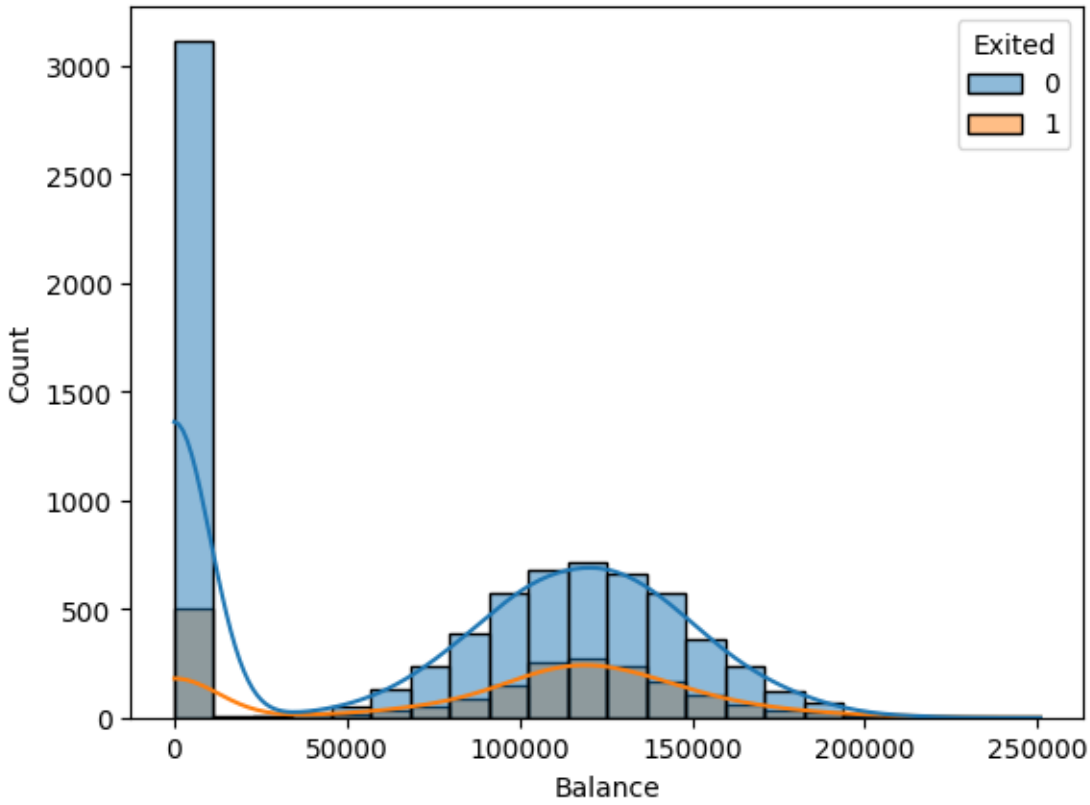
[ ]:
```
for col in churn_df.drop("CustomerId", axis=1).select_dtypes("number"):
    sns.histplot(data=churn_df, x=col, hue="Exited", kde=True)
    plt.show()
```

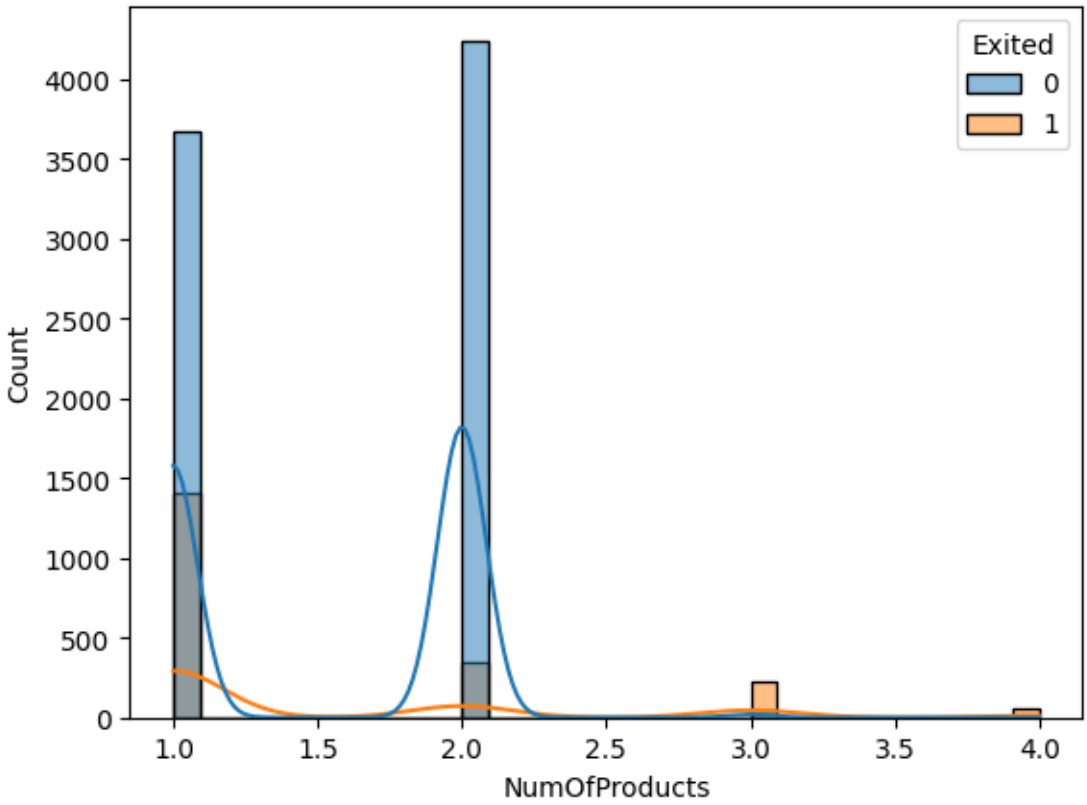

Exited
0
1
Count
CreditScore
0
50
100
150
200
250
300
350
400
400
500
600
700
800

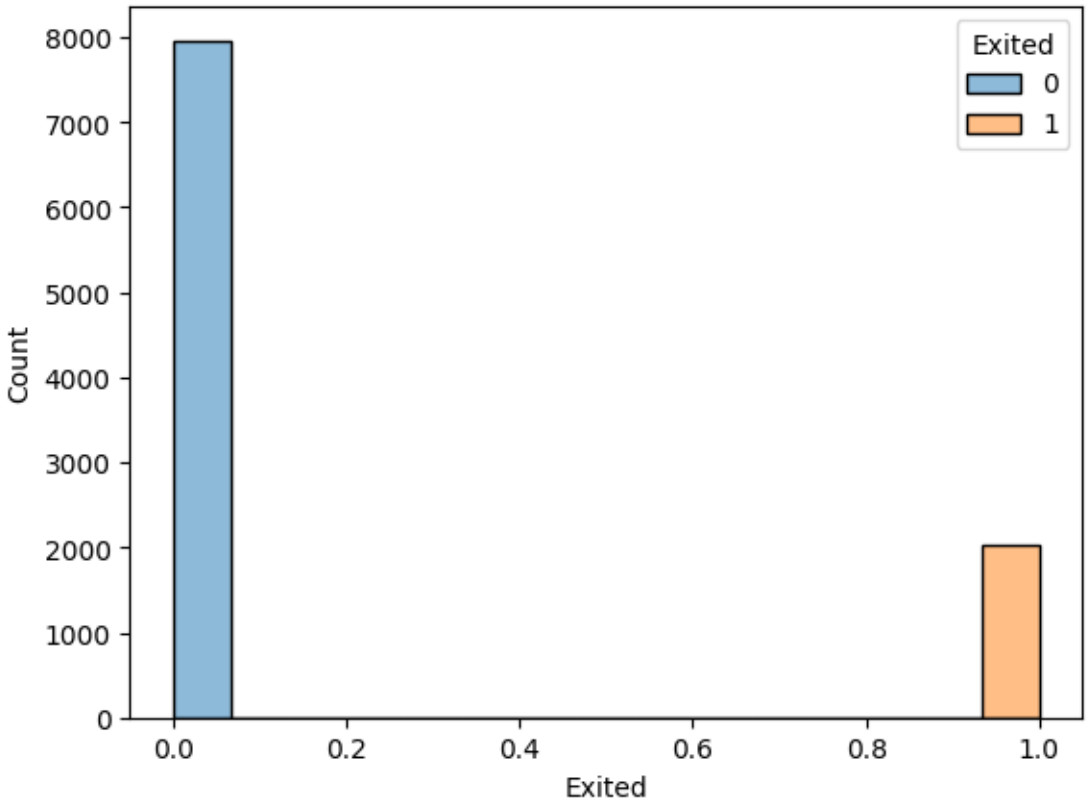

Exited
0
1
Count
Age
0
100
200
300
400
500
600
700
20
30
40
50
60
70
80
90


Exited
0
1
Count
0
100
200
300
400
500
600
700
800
0
2
4
6
8
10
Tenure


Count
EstimatedSalary
Exited
0
1
0
50
100
150
200
250
300
350
400
0
25000
50000
75000
100000
125000
150000
175000
200000


Exited
0
1
Count
3000
2500
2000
1500
1000
500
0
0
50000
100000
150000
200000
250000
Balance


Exited
0
1
Count
4000
3500
3000
2500
2000
1500
1000
500
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
NumOfProducts



4 STEP 4: Data Preparaion and Feature Engineering

Prepared the data for modeling through feature selection, feature engineering, and data splitting.

Created a dataset that excludes any columns that aren't be suitable for modeling.

[ ]:
```
modeling_df= churn_df.drop(["CustomerId", "Surname"], axis=1)

modeling_df.head()
```

[ ]:

	CreditScore	Geography	Gender	Age	Tenure	EstimatedSalary	Balance	\
0	619	France	Female	42.0	2	101348.88	0.00	
2	608	Spain	Female	41.0	1	112542.58	83807.86	
3	502	France	Female	42.0	8	113931.57	159660.80	
4	699	France	Female	39.0	1	93826.63	0.00	
5	850	Spain	Female	43.0	2	79084.10	125510.82	

	NumOfProducts	HasCrCard	IsActiveMember	Exited
0	1	Yes	Yes	1
2	1	Yes	Yes	0
3	3	No	No	1

```
4              2        No             No       0
5              1       Yes            Yes       0
```

Created dummy variables for categorical fields.

[ ]:
```
modeling_df = pd.get_dummies(modeling_df, drop_first=True)
```

Created a new "balance_v_income" feature, which divides a customer's bank balance by their estimated salary, then visualize that feature vs. churn status.

[ ]:
```
modeling_df["Balance_v_Sal"] = modeling_df["Balance"] /␣
↪modeling_df["EstimatedSalary"]

modeling_df.head()
```

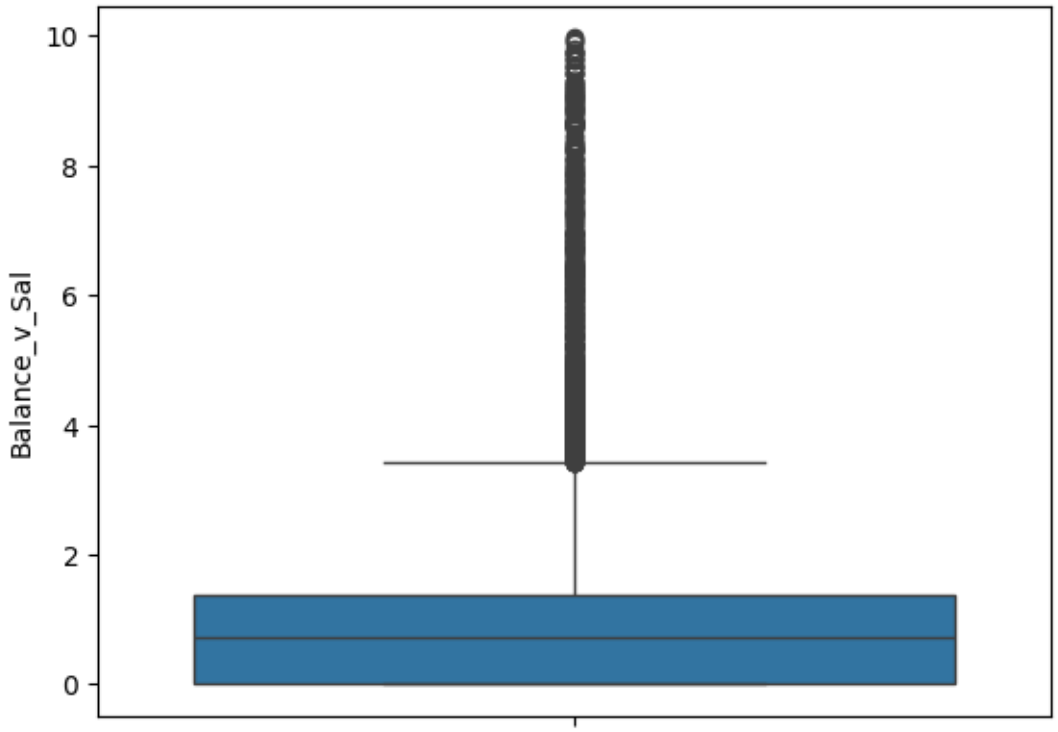
[ ]:
```
   CreditScore   Age  Tenure  EstimatedSalary    Balance  NumOfProducts  \
0          619  42.0       2        101348.88       0.00              1
2          608  41.0       1        112542.58   83807.86              1
3          502  42.0       8        113931.57  159660.80              3
4          699  39.0       1         93826.63       0.00              2
5          850  43.0       2         79084.10  125510.82              1

   Exited  Geography_Germany  Geography_Spain  Gender_Male  HasCrCard_Yes  \
0       1              False            False        False           True
2       0              False             True        False           True
3       1              False            False        False          False
4       0              False            False        False          False
5       0              False             True        False           True

   IsActiveMember_Yes  Balance_v_Sal
0                True       0.000000
2                True       0.744677
3               False       1.401375
4               False       0.000000
5                True       1.587055
```

[ ]:
```
sns.boxplot(data=modeling_df.query("Balance_v_Sal < 10"), y="Balance_v_Sal")
```

[ ]:
```
<Axes: ylabel='Balance_v_Sal'>
```



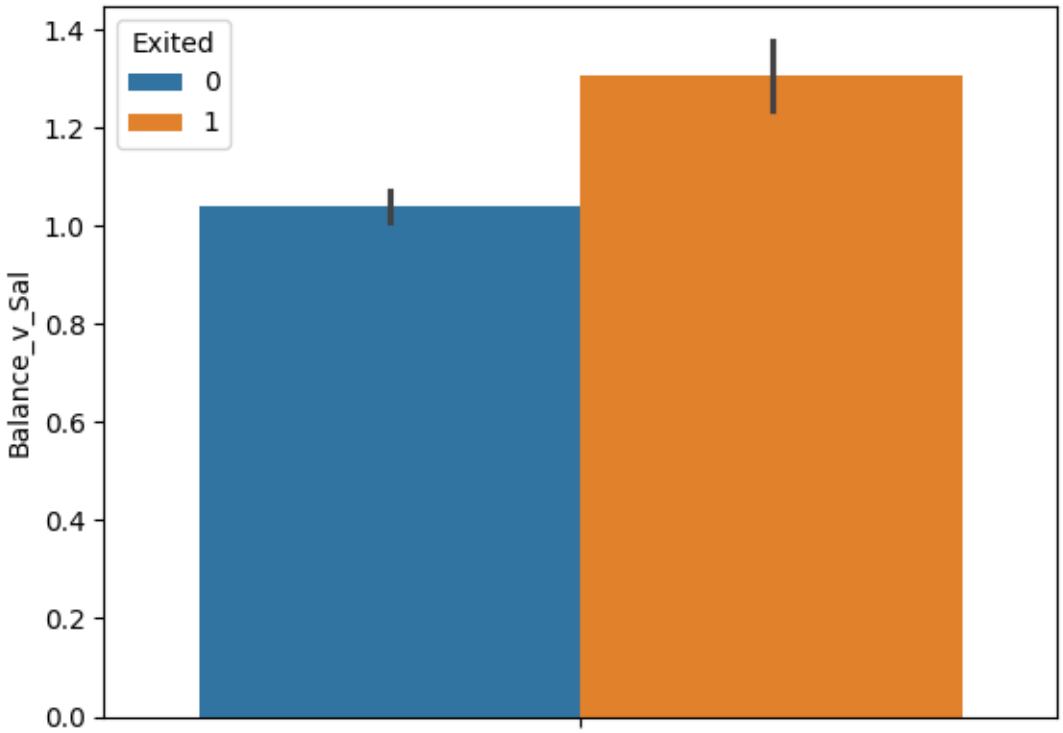
[ ]:
```
modeling_df.describe()
```

[ ]:
```
         CreditScore           Age        Tenure  EstimatedSalary  \
count  10000.000000  10000.000000  10000.000000     10000.000000
mean     650.528800     38.921500      5.012800    100092.252506
std       96.653299     10.487552      2.892174     57510.146401
min      350.000000     18.000000      0.000000        11.580000
25%      584.000000     32.000000      3.000000     51002.110000
50%      652.000000     37.000000      5.000000    100196.062500
75%      718.000000     44.000000      7.000000    149388.247500
max      850.000000     92.000000     10.000000    199992.480000

             Balance  NumOfProducts        Exited  Balance_v_Sal
count   10000.000000   10000.000000  10000.000000   10000.000000
mean    76485.889288       1.530200      0.203700       3.878703
std     62397.405202       0.581654      0.402769     108.337260
min         0.000000       1.000000      0.000000       0.000000
25%         0.000000       1.000000      0.000000       0.000000
50%     97198.540000       1.000000      0.000000       0.747002
75%    127644.240000       2.000000      0.000000       1.514022
max    250898.090000       4.000000      1.000000   10614.655440
```

[ ]:
```
sns.barplot(data=modeling_df.query("Balance_v_Sal < 10"), y="Balance_v_Sal",␣
↪hue="Exited")
```

[ ]:
```
<Axes: ylabel='Balance_v_Sal'>
```



[ ]:
```

```