Bank Customers Churn Analysis

Term Project Milestone 1: Data Selection and EDA

Introduction

Customer churn is the most important factor for banks and other financial institutions. The main reason for this is retaining the existing customer is more cost-effective and also more profitable. The rapid advancement in technology and the invention of new banking services have also made it more important for banks to understand which factors influence customer churn and develop effective strategies to minimize it. In this context, the applications of Artificial Intelligence (AI) and machine learning can be used to predict customer churn and can provide valuable insights and help banks take proactive steps to retain a maximum number of their customers. The main purpose of this object is to develop a classification model that can predict whether a bank customer will churn or not with the highest accuracy. The dataset used in this task is obtained from Kaggle. The dataset contains information about various customer attributes such as demographics, and financial and account-related activities. We can find factors that influence customer churn by analyzing this dataset and can provide recommendations for the bank to reduce customer churn and improve customer retention rate and satisfaction. The dataset used in this task is related to the bank customers churn and has been obtained from the kaggle. The link of the dataset is given below:
https://www.kaggle.com/datasets/santoshd3/bank-customers
The dataset contains various customer attributes which be used to identify factors that influence customer churn and develop effective strategies to minimize it. There are 14 attributes in the dataset which are:
RowNumber: The row number in the dataset.
CustomerId: Unique id of the customer.
Surname: Last name of the customer.
CreditScore: Credit Score of the customer.
Country: Country of the Customer (e.g., France, Germany, Spain).
Gender: Customer's gender (Male/Female).
Age: Age of customer's in years.
Tenure: The number of years customer has been with the bank.
Balance: Customer's account balance.
NumOfProducts: Number of banking products the customer uses (e.g., loans, credit cars, etc.).
HasCrCard: Binary variable indicating whether customer has credit car (1) or not (0).
IsActiveMember: A binary variable indicating whether the customer is an active member (1) or not (0).
EstimatedSalary: The Customer's estimated annual salary.
HasCrCard: Binary variable indicating whether customer has credit car (1) or not.
The dataset used in this project is well described and provides the necessary information to

developer the customer churn prediction model. Although the additional data can enhanced the analysis, the existing dataset is sufficient for building a comprehensive classification model.

Exploring the data

In [43]:
```
#import necessary packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
import yellowbrick
from sklearn.model_selection import train_test_split #used to split data into training
```

In [2]:
```
df = pd.read_csv("Churn Modeling.csv")
df.head()
```

Out[2]:

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

In [3]:
```
df.shape
```

Out[3]:
```
(10000, 14)
```

Observations

- There are total 10000 rows and 14 columns.
- Some columns like RowNumber, CustomerId, Surname are not very useful.
- The Exited column is target column with value 1 means the customer churned out and value 0 mean the customer didn't churn.
- The dataset has mix of numerical and categorical variables.

In [4]:
```
#data type of each column
df.dtypes
```

Out[4]:
```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

In [5]:
```
#summary statistics for numerical variables
df.describe()
```

Out[5]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfP
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4

In [6]:
```
#summary statistics for categroical variables
df.describe(include = 'object')
```

Out[6]:

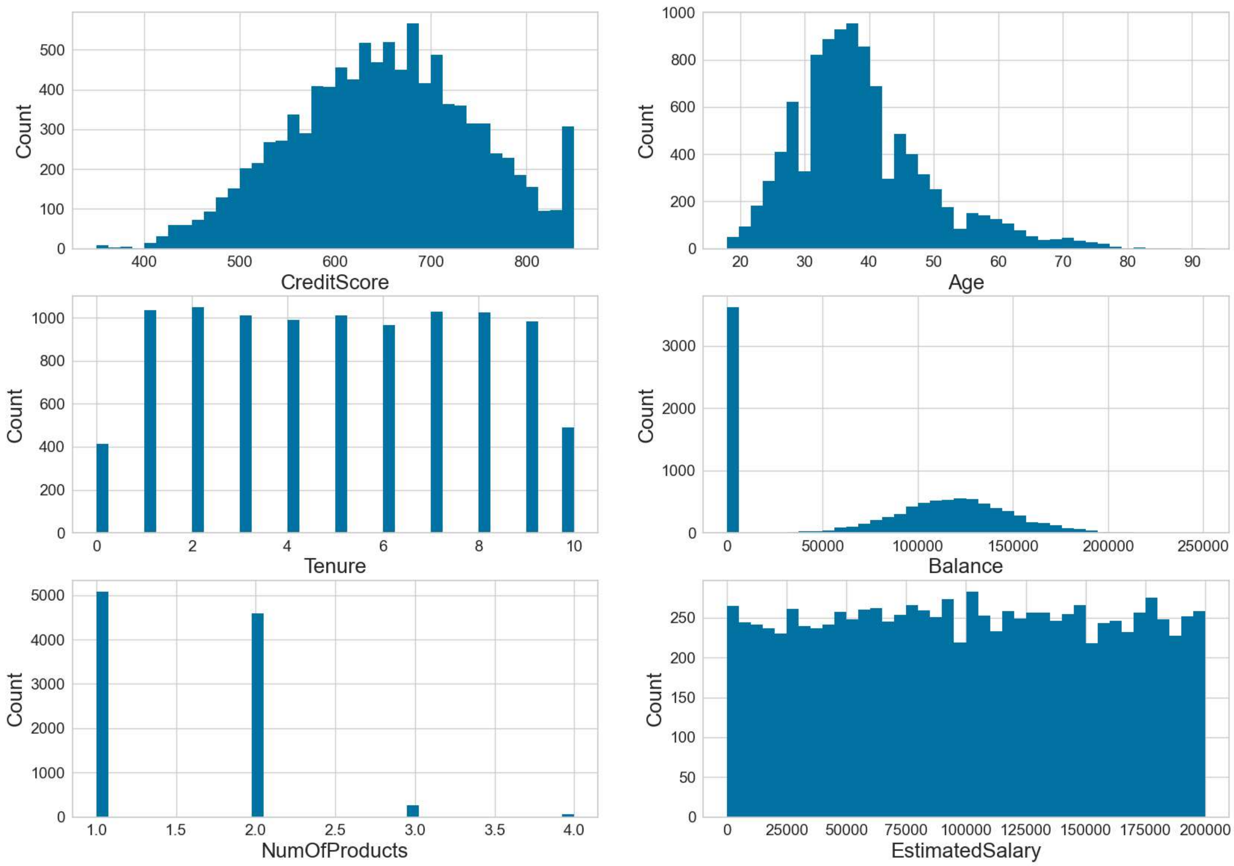
	Surname	Geography	Gender
count	10000	10000	10000
unique	2932	3	2
top	Smith	France	Male
freq	32	5014	5457

Observations

- There are no missing values in the data.

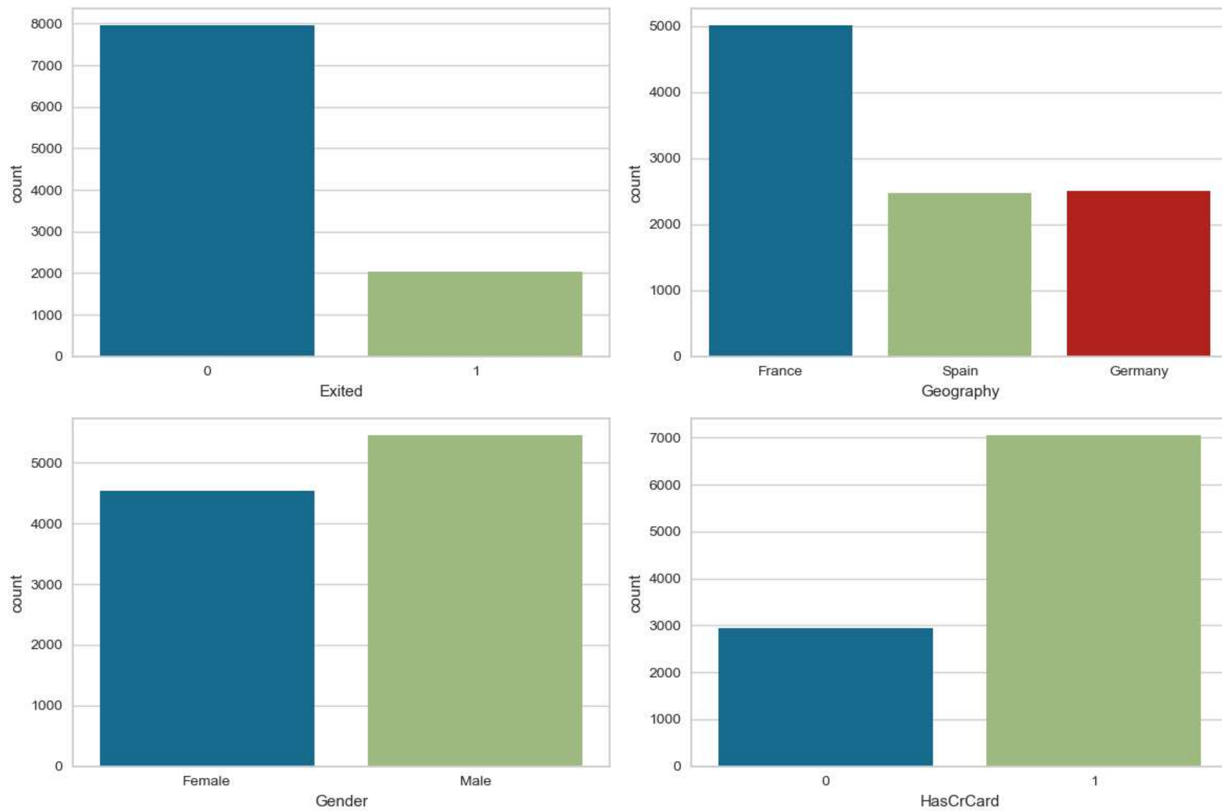
In [7]:
```
#histograms for numerical features
plt.rcParams['figure.figsize'] = (20, 14)
# make subplots
fig, axes = plt.subplots(nrows = 3, ncols = 2)
```

```
#numerical fatures
num_features = ['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProducts',
                'EstimatedSalary']
xaxes = num_features
yaxes = ['Count', 'Count', 'Count', 'Count', 'Count', 'Count']
# draw histograms
axes = axes.ravel()
for idx, ax in enumerate(axes):
    ax.hist(df[num_features[idx]].dropna(), bins=40)
    ax.set_xlabel(xaxes[idx], fontsize=20)
    ax.set_ylabel(yaxes[idx], fontsize=20)
    ax.tick_params(axis='both', labelsize=15)
plt.show()
```



In [8]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Set the figure size
plt.figure(figsize=(12, 8))

# Plot 1 - Exited
plt.subplot(2, 2, 1)
sns.countplot(data=df, x='Exited')

# Plot 2 - Geography
plt.subplot(2, 2, 2)
sns.countplot(data=df, x='Geography')

# Plot 3 - Gender
plt.subplot(2, 2, 3)
sns.countplot(data=df, x='Gender')
```

```
# Plot 4 - HasCrCard
plt.subplot(2, 2, 4)
sns.countplot(data=df, x='HasCrCard')

# Adjust the spacing between subplots
plt.tight_layout()

# Display the plots
plt.show()
```

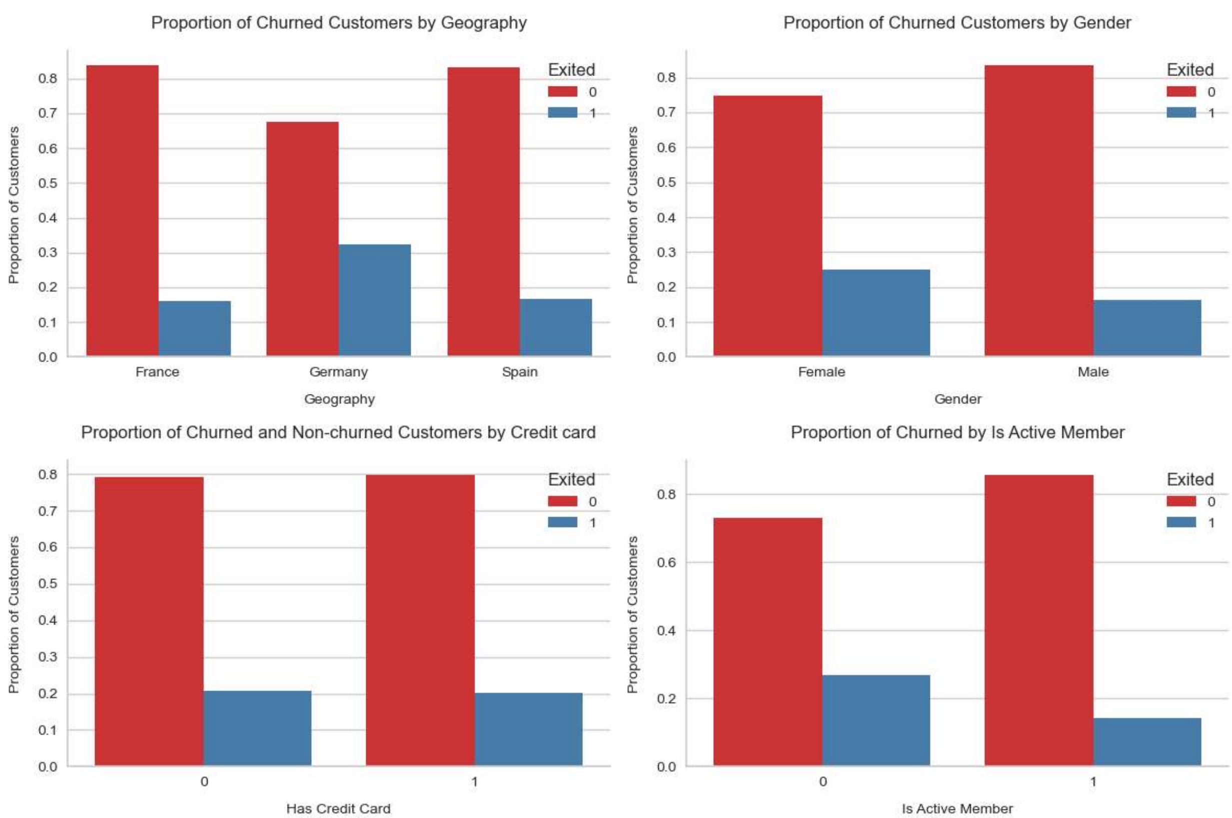


Observations

- Most of the customers in the dataset didn't churn out.
- Very few customers in the dataset churned out.
- Most of the customers in the dataset are from Germany.
- There are more male customers in the dataset as compare to female customers.
- Most of the customers in the dataset has credit card.

In [9]:
```
# plotting distribution of customers churn by geography
geography_churn = pd.crosstab(df['Geography'], df['Exited'], normalize='index').reset_
geography_churn_melted = pd.melt(geography_churn, id_vars='Geography', var_name='Exite
plt.figure(figsize=(12, 8))
plt.subplot(2, 2, 1)
ax = sns.barplot(x='Geography', y='Proportion', hue='Exited', data=geography_churn_mel
plt.xlabel("Geography", fontsize=10, labelpad=10)
plt.ylabel("Proportion of Customers", fontsize=10, labelpad=10)
plt.title("Proportion of Churned Customers by Geography", fontsize=12, pad=15)
sns.despine(top=True, right=True)
plt.subplot(2,2,2)
#plotting relationship between Gender and Customers Churn
gender_churn = pd.crosstab(df['Gender'], df['Exited'], normalize='index').reset_index(
```

```
gender_churn_melted = pd.melt(gender_churn, id_vars='Gender', var_name='Exited', value
ax = sns.barplot(data=gender_churn_melted,x='Gender', y='Proportion', hue='Exited', pa
plt.xlabel("Gender", fontsize=10, labelpad=10)
plt.ylabel("Proportion of Customers", fontsize=10, labelpad=10)
plt.title("Proportion of Churned Customers by Gender", fontsize=12, pad=15)
sns.despine(top=True, right=True)
#plotting relationship between Gender and Customers Churn
plt.subplot(2,2,3)
card_churn = pd.crosstab(df['HasCrCard'], df['Exited'], normalize='index').reset_index
gender_churn_melted = pd.melt(card_churn, id_vars='HasCrCard', var_name='Exited', valu
ax = sns.barplot(x='HasCrCard', y='Proportion', hue='Exited', data=gender_churn_meltec
plt.xlabel("Has Credit Card", fontsize=10, labelpad=10)
plt.ylabel("Proportion of Customers", fontsize=10, labelpad=10)
plt.title("Proportion of Churned and Non-churned Customers by Credit card", fontsize=1
sns.despine(top=True, right=True)
#plotting relationship between Is Active Member and Customers Churn
plt.subplot(2,2, 4)
active_churn = pd.crosstab(df['IsActiveMember'], df['Exited'], normalize='index').rese
gender_churn_melted = pd.melt(active_churn, id_vars='IsActiveMember', var_name='Exitec
gender_churn_melted
ax = sns.barplot(x='IsActiveMember', y='Proportion', hue='Exited', data=gender_churn_n
plt.xlabel("Is Active Member", fontsize=10, labelpad=10)
plt.ylabel("Proportion of Customers", fontsize=10, labelpad=10)
plt.title("Proportion of Churned by Is Active Member", fontsize=12, pad=15)
sns.despine(top=True, right=True)
plt.tight_layout()

plt.show()
```

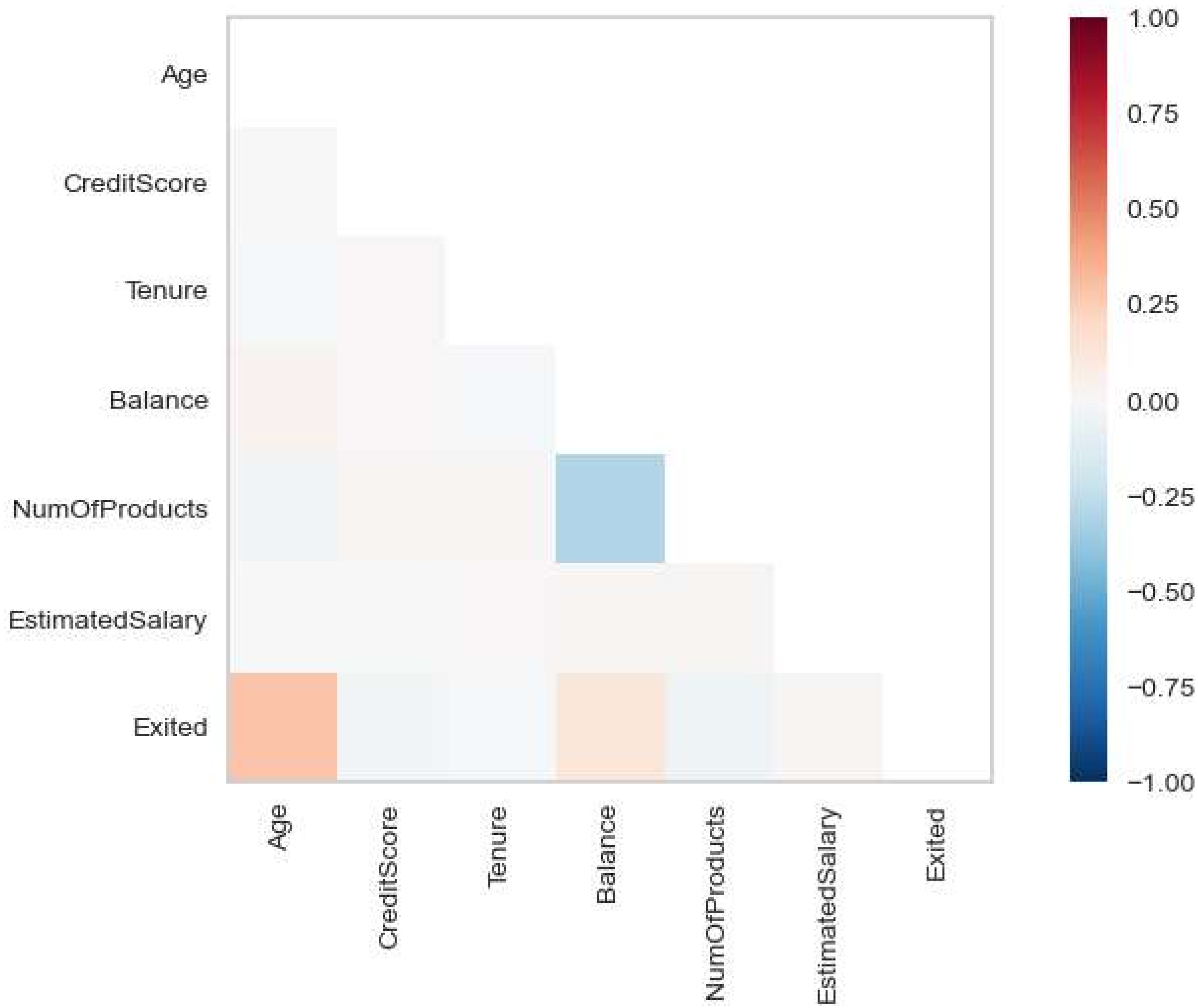


Observations

- Highest proportion of customers from Germany have churned out.
- Second highest proportion of customers from Spain have churned out.

- Proportion of churned customers varied by geographical location.
- This could play an important role for predicting whether the customer will churn out or not.
- Female customers are more likely to churn out as compare to male customers.
- Non-Active customers are more likely to churn out as compare to active customers.

In [10]:
```
%matplotlib inline
plt.rcParams['figure.figsize'] = (10, 5)

heat_map_features = ['Age', 'CreditScore', 'Tenure', 'Balance', 'NumOfProducts',
                     'EstimatedSalary', 'Exited']
# import the package for visulization of the correlation
from yellowbrick.features import Rank2D

# extract the numpy arrays from the data frame
X = df[heat_map_features].values

# instantiate the visualizer
heat_map = Rank2D(features=heat_map_features, algorithm='pearson')
heat_map.fit_transform(X) #fit and tranform the data for the heat map
plt.show()
```



Observations

- The numerical variables that are correlation with Exited are Age, Balance and Number of Products.