Analyzing Customer Churn and Credit Scores: A Case Study in Banking

Background :

Bank customer churn, also known as customer attrition, refers to the phenomenon where customers stop doing business with a bank or switch to another bank. Churn is a critical metric for banks as it directly impacts their customer base and revenue. The dataset represents bank customer information for churn analysis. Each row in the dataset corresponds to a specific customer and contains several features or attributes that describe them.

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import scipy.stats as stats
import seaborn as sns
import matplotlib.pyplot as plt
```

1. Import “Bank Churn” data and check dimension, top 5 rows and bottom 5 rows of the data frame .

In [2]:
```
data = pd.read_csv("Bank Churn.csv")
```

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 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  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [4]:
```
data.head()
```

Out[4]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	N
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 [5]:
```
data.tail()
```

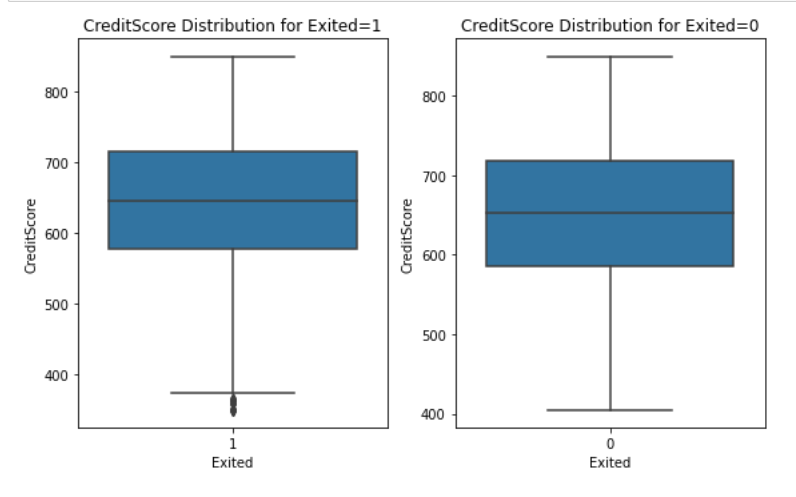
Out[5]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balanc
9995	9996	15606229	Obijiaku	771	France	Male	39	5	0.0
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.6
9997	9998	15584532	Liu	709	France	Female	36	7	0.0
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.3
9999	10000	15628319	Walker	792	France	Female	28	4	130142.7

2. Check if the distribution of “CreditScore” is symmetric for Exited=1 and Exited=0. Obtain box-whisker plot and estimate the values of skewness.

In [6]:
```
data_exited_1 = data[data['Exited'] == 1]
data_exited_0 = data[data['Exited'] == 0]
```

In [7]:
```
# Create box-whisker plots for 'CreditScore' for each group
# Create a figure with two subplots for the box plots
plt.figure(figsize=(8, 5))

# Box plot for Exited=1
plt.subplot(1, 2, 1)
sns.boxplot(x='Exited', y='CreditScore', data=data_exited_1)
plt.title('CreditScore Distribution for Exited=1')

# Box plot for Exited=0
plt.subplot(1, 2, 2)
sns.boxplot(x='Exited', y='CreditScore', data=data_exited_0)
plt.title('CreditScore Distribution for Exited=0')

# Adjust the layout
plt.tight_layout()

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



In [8]:
```
# Calculate skewness for each group
skewness_exited_1 = stats.skew(data_exited_1['CreditScore'])
skewness_exited_0 = stats.skew(data_exited_0['CreditScore'])

print(f"Skewness for Exited=1: {skewness_exited_1:.2f}")
print(f"Skewness for Exited=0: {skewness_exited_0:.2f}")
```

```
Skewness for Exited=1: -0.14
Skewness for Exited=0: -0.05
```

Observation :

The box-whisker plots and values of skewness clearly indicate symmetric distribution of Credit Score

3. Summarize “CreditScore” using count and appropriate measure of central tendency by “Exited”

In [9]:
```
summary_credit_score = data.groupby('Exited')['CreditScore'].agg(['count', 'mean'])

# Rename the columns for clarity
summary_credit_score = summary_credit_score.rename(columns={
    'count': 'Count',
    'mean': 'Mean'})

summary_credit_score.round(2)
```

Out[9]:

Exited	Count	Mean
0	7963	651.85
1	2037	645.35

4. Obtain cross table of Geography vs Exited(count and proportions)

In [10]:
```
# Create a cross table of 'Geography' vs. 'Exited' with counts
cross_table = pd.crosstab(data['Geography'], data['Exited'], margins=True, margins_name='Total')

# Calculate proportions
cross_table_proportions = cross_table.div(cross_table['Total'], axis=0) * 100

# Rename the columns for clarity
cross_table = cross_table.rename(columns={0: 'Not Exited', 1: 'Exited'})
cross_table_proportions = cross_table_proportions.rename(columns={0: 'Not Exited (%)', 1: 'Exited (%)'})

# Display the cross table and proportions
print("Cross Table (Counts):\n")
print(cross_table)

print("\nCross Table (Proportions):\n")
print(cross_table_proportions.round(2))
```

```
Cross Table (Counts):

Exited     Not Exited  Exited  Total
Geography                           
France           4204     810   5014
Germany          1695     814   2509
Spain            2064     413   2477
Total            7963    2037  10000

Cross Table (Proportions):

Exited     Not Exited (%)  Exited (%)  Total
Geography                                   
France              83.85       16.15  100.0
Germany             67.56       32.44  100.0
Spain               83.33       16.67  100.0
Total               79.63       20.37  100.0
```

Observation :

Churn rates vary significantly: France and Spain have similar rates, while Germany’s is notably higher.

5. Obtain Correlation Coefficient between CreditScore and Estimated Salary and interpret.

In [11]:
```
correlation_coefficient = data['CreditScore'].corr(data['EstimatedSalary'])
correlation_coefficient.round(4)
```

Out[11]: -0.0014

Observation :

The correlation coefficient of approximately -0.0014 suggests a very weak, near-zero correlation between CreditScore and Estimated Salary. These variables appear largely unrelated.

6. Derive a new variable as CreditScore_Cat=1 if >=650;0 if <650

In [12]:
```
data['CreditScore_Cat'] = np.where(data['CreditScore']>=650,1,0)
data.head()
```

Out[12]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	N
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	

7. Obtain cross table of CreditScore_Cat vs Exited

In [13]:
```
# Create a cross table of 'CreditScore_Cat' vs. 'Exited' with counts, excluding the "Total" row
cross_table = pd.crosstab(data['CreditScore_Cat'], data['Exited'], margins=False)

# Calculate proportions
cross_table_proportions = (cross_table.div(cross_table.sum(axis=1), axis=0) * 100).round(2)

# Rename the columns for clarity
cross_table.columns = ['Not Exited', 'Exited']
cross_table_proportions.columns = ['Not Exited (%)', 'Exited (%)']

# Concatenate the counts and proportions side by side
result_table = pd.concat([cross_table, cross_table_proportions], axis=1)

# Display the combined table
print(result_table)
```

```
                 Not Exited  Exited  Not Exited (%)  Exited (%)
CreditScore_Cat                                                
0                      3851    1049           78.59       21.41
1                      4112     988           80.63       19.37
```

Observation :

Customers with a CreditScore_Cat 0 have a slightly higher exit rate (21.4%) compared to those with a CreditScore_Cat 1, who have a lower exit rate (19.4%).

8. Create a subset of 300 customers with highest Credit Score and check how they are spread over Geography

In [14]:
```
# Sort the data by 'CreditScore' in descending order and select the top 300 rows
top_300_customers = data.sort_values(by='CreditScore', ascending=False).head(300)

# Create a cross table to check the distribution of these customers over 'Geography'
geo_distribution_top_300 = pd.crosstab(top_300_customers['Geography'], columns='Count')

# Display the cross table
print("Geography Distribution of Top 500 Customers:")
print(geo_distribution_top_300)
```

```
Geography Distribution of Top 500 Customers:
col_0      Count
Geography       
France       150
Germany       80
Spain         70
```

Observation:

Among the top 300 customers with the highest Credit Scores, the majority are from France, followed by Germany and Spain

9. Summarize “CreditScore” using count, mean and median by Geography+Gender

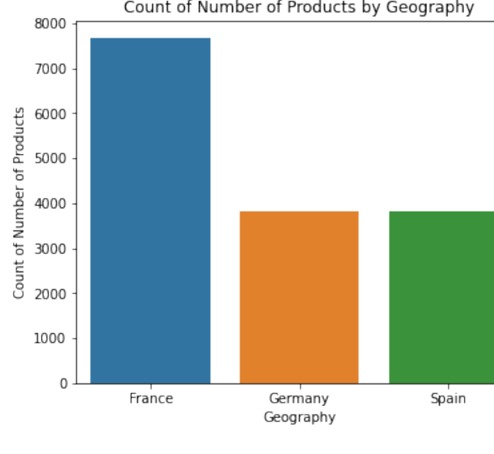
In [15]:
```
# Group the data by 'Geography' and 'Gender', and calculate count, mean, and median for 'CreditScore'
summary_credit_score = data.groupby(['Geography', 'Gender'])['CreditScore'].agg(['count', 'mean', 'median'])

# Reset the index to make the result more readable
summary_credit_score = summary_credit_score.reset_index()

# Rename the columns for clarity
summary_credit_score = summary_credit_score.rename(columns={
    'count': 'Count',
    'mean': 'Mean',
    'median': 'Median'
})

# Display the summary
print(summary_credit_score)
```

```
  Geography  Gender  Count        Mean  Median
0    France  Female   2261  649.185759   652.0
1    France    Male   2753  650.064657   653.0
2   Germany  Female   1193  653.093881   651.0
3   Germany    Male   1316  649.966565   650.5
4     Spain  Female   1089  651.769513   653.0
5     Spain    Male   1388  650.992075   650.0
```

10. Analyze Geography and Number of Products and comment

In [16]:
```
# Count the number of products for each combination of Geography
product_count_by_geography = data.groupby('Geography')['NumOfProducts'].sum().reset_index()
print(product_count_by_geography)
# Create a bar plot to show the count of number of products by Geography
plt.figure(figsize=(6, 5))
sns.barplot(x='Geography', y='NumOfProducts', data=product_count_by_geography)
plt.title('Count of Number of Products by Geography')
plt.xlabel('Geography')
plt.ylabel('Count of Number of Products')
plt.show()
```

```
  Geography  NumOfProducts
0    France           7676
1   Germany           3813
2     Spain           3813
```



Observation:

France has the highest number of products, while Spain and Germany have the same count.