Retention Risk Assesment

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PHASE 1

Retention Risk Assessment

QUESTION 1:

Problem Statement:

Customer churn can be considered as a crucial problem in the banking industry in which customers decide to stop the utilization of the bank's services due to several reasons. The objective of the project is coming up with a binary classification model that would be used effectively in predicting whether a customer is likely to churn based on the historic data of customers. By analyzing factors such as account balance, transaction history, credit score, and customer demographics, we aim to identify which customers are at high risk of leaving the bank.

Contribution:

This can make all the difference for the bank in its efforts toward customer retention, thereby reducing the costs of acquiring new customers. Precise prediction of churn allows the bank to take proactive measures toward forestalling the event, done through offering incentives in a personalized way or simply improving their customer service where dissatisfaction seems most evident.

Why is this crucial?

Retaining customers is less expensive than acquiring new ones, and the customer loss may further lead to reduction of profits, especially when such high-value customers are involved. Knowing what generates churn will help provide strategic input to the bank in its endeavor for improvement of services and overall customer satisfaction, leading to long-term profitability and growth.

QUESTION 2:

Research Questions:

1. *Do gender differences (male vs. female) play a role in customer exit rates?*
    - *Significance:* Men and women may have different banking requirements, leading to different churn behaviors. Knowing these trends may allow banks to offer gender-specific products and services.
2. *How does a customer's credit score influence their likelihood of exiting the bank?*
    - *Significance:* A poor credit score may signal financial difficulties, putting these consumers at danger of leaving. Understanding this relationship can help banks develop targeted retention initiatives.
3. *How does the number of banking products a customer uses (e.g., loans, credit cards) affect their likelihood of exiting?*
    - *Significance:* Customers who purchase more products may be more engaged and less inclined to depart. Understanding this could help banks encourage clients to try new products as a retention strategy.
4. *How does a customer's age influence their decision to leave the bank?*
    - *Significance:* Different age groups may have distinct banking demands, with younger clients being more willing to move banks, while older customers may want stability.
5. *Are active members less likely to exit compared to inactive members?*
    - *Significance:* Active interaction with financial services may indicate loyalty. Encouraging more activity may lessen turnover.
6. *Is there a relationship between estimated salary and the likelihood of a customer exiting the bank?*
    - *Significance:* Customers with varying income levels may exhibit distinct financial behaviors, influencing their loyalty to a bank. This information can assist banks in designing goods and services to meet the needs of people with different income levels.
7. *Does having a credit card correlate with a customer's likelihood to exit the bank?*
    - *Significance:* A credit card could indicate a deeper level of interaction with the bank. Understanding this can help banks assess whether boosting credit card adoption can improve client retention.
8. *Does the tenure of a customer (length of time they have been with the bank) impact their retention?*

- *Significance:* Long-term consumers may have built a stronger relationship with the bank. Knowing if tenure influences churn can help steer loyalty programs designed to retain long-term customers.

Questions in question 2 and EDA are done by : Jai Advitheeya Lella : 1,8 Niharika Reddy Katakam Prashanthi : 2,5 Prathyusha Reddy Allam : 3,4 Kundavaram Joseph Sujith Kumar : 6,7

In [ ]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency

# Load the training data
data = pd.read_csv('train.csv')

# Split the data into training and testing sets
train_data, test_data = train_test_split(data, test_size=0.2, random_state=42)


# Print the number of rows in each DataFrame
print("Number of records in Train Data:", train_data.shape[0])
print("Number of records in Test Data:", test_data.shape[0])

# Print the columns of the training dataset
print("Train Data Columns:")
print(train_data.columns)

# Print the columns of the test dataset
print("Test Data Columns:")
print(test_data.columns)
```

```
Number of records in Train Data: 132027
Number of records in Test Data: 33007
Train Data Columns:
Index(['id', 'CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender',
       'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
Test Data Columns:
Index(['id', 'CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender',
       'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

In [ ]:

```python
# Debug: Print initial shape of the data
print("Initial Train Data Shape:", train_data.shape)
print("Initial Test Data Shape:", test_data.shape)

# 1. Remove Duplicates
train_data.drop_duplicates(inplace=True)
test_data.drop_duplicates(inplace=True)

# Debug: Print shape after removing duplicates
print("Train Data Shape after removing duplicates:", train_data.shape)
print("Test Data Shape after removing duplicates:", test_data.shape)

# Ensure both train and test data have the same columns before handling missing values
all_columns = set(train_data.columns).union(set(test_data.columns))
train_data = train_data.reindex(columns=all_columns)
test_data = test_data.reindex(columns=all_columns)

# Debug: Print shape after reindexing
print("Train Data Shape after reindexing:", train_data.shape)
print("Test Data Shape after reindexing:", test_data.shape)
```

```
Initial Train Data Shape: (132027, 14)
Initial Test Data Shape: (33007, 14)
Train Data Shape after removing duplicates: (132027, 14)
Test Data Shape after removing duplicates: (33007, 14)
Train Data Shape after reindexing: (132027, 14)
Test Data Shape after reindexing: (33007, 14)
```

In [ ]:
```python
# 2. Handle Missing Values
# Separate numeric and categorical columns
numeric_cols = train_data.select_dtypes(include=[np.number]).columns
categorical_cols = train_data.select_dtypes(exclude=[np.number]).columns

# Fill missing values for numeric columns with the mean
train_data[numeric_cols] = train_data[numeric_cols].fillna(train_data[numeric_cols].mean())
test_data[numeric_cols] = test_data[numeric_cols].fillna(test_data[numeric_cols].mean())

# Debug: Print shape after filling missing values for numeric columns
print("Train Data Shape after filling missing numeric values:", train_data.shape)
print("Test Data Shape after filling missing numeric values:", test_data.shape)

# Fill missing values for categorical columns with the mode (if any)
if not categorical_cols.empty:
    if not train_data[categorical_cols].mode().empty:
        train_data[categorical_cols] = train_data[categorical_cols].fillna(train_data[categorical_cols].mode().iloc[0])
    if not test_data[categorical_cols].mode().empty:
        test_data[categorical_cols] = test_data[categorical_cols].fillna(test_data[categorical_cols].mode().iloc[0])

# Debug: Print shape after filling missing values for categorical columns
print("Train Data Shape after filling missing categorical values:", train_data.shape)
print("Test Data Shape after filling missing categorical values:", test_data.shape)
```

```
Train Data Shape after filling missing numeric values: (132027, 14)
Test Data Shape after filling missing numeric values: (33007, 14)
Train Data Shape after filling missing categorical values: (132027, 14)
Test Data Shape after filling missing categorical values: (33007, 14)
```

In [ ]:
```python
# 3. Set Proper Precision
pd.set_option('display.precision', 2)
```

In [ ]:
```python
# 4. Remove Outliers
# Define a function to remove outliers based on the IQR method

# Define numerical_columns
numerical_columns = ['CreditScore', 'Age', 'Balance', 'EstimatedSalary']
def remove_outliers(df, columns):
    for col in columns:
        Q1 = df[col].quantile(0.25)
```

```python
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        df = df[~((df[col] < (Q1 - 1.5 * IQR)) | (df[col] > (Q3 + 1.5 * IQR)))]
    return df

train_data = remove_outliers(train_data, numerical_columns)
test_data = remove_outliers(test_data, numerical_columns)

# Debug: Print shape after removing outliers
print("Train Data Shape after removing outliers:", train_data.shape)
print("Test Data Shape after removing outliers:", test_data.shape)
```

```
Train Data Shape after removing outliers: (126706, 14)
Test Data Shape after removing outliers: (31684, 14)
```

In [ ]:

```python
# 4. Show General Characteristics of the Data
print("Train Data Description:")
print(train_data.describe())

print("\nTest Data Description:")
print(test_data.describe())
```

Train Data Description:

	Exited	EstimatedSalary	HasCrCard	Age	NumOfProducts	\
count	126706.0	126706.00	126706.00	126706.00	126706.00	
mean	0.2	112855.68	0.75	37.11	1.56	
std	0.4	50195.96	0.43	7.37	0.54	
min	0.0	11.58	0.00	18.00	1.00	
25%	0.0	74850.84	1.00	32.00	1.00	
50%	0.0	118711.75	1.00	37.00	2.00	
75%	0.0	155641.46	1.00	41.00	2.00	
max	1.0	199992.48	1.00	57.00	4.00	

	CustomerId	CreditScore	id	IsActiveMember	Balance	\
count	1.27e+05	126706.00	126706.00	126706.00	126706.00	
mean	1.57e+07	657.19	82400.74	0.49	55404.91	
std	7.14e+04	79.37	47689.83	0.50	62823.23	
min	1.56e+07	430.00	1.00	0.00	0.00	
25%	1.56e+07	598.00	41070.50	0.00	0.00	
50%	1.57e+07	660.00	82427.50	0.00	0.00	
75%	1.58e+07	710.00	123731.75	1.00	119961.48	
max	1.58e+07	850.00	165033.00	1.00	250898.09	

	Tenure
count	126706.00
mean	5.03
std	2.81
min	0.00
25%	3.00
50%	5.00
75%	7.00
max	10.00

Test Data Description:

	Exited	EstimatedSalary	HasCrCard	Age	NumOfProducts	\
count	31684.0	31684.00	31684.00	31684.00	31684.00	
mean	0.2	112321.62	0.76	37.14	1.56	
std	0.4	50275.16	0.43	7.36	0.55	
min	0.0	11.80	0.00	18.00	1.00	
25%	0.0	74556.10	1.00	32.00	1.00	
50%	0.0	117948.00	1.00	37.00	2.00	
75%	0.0	154767.34	1.00	41.00	2.00	
max	1.0	199992.48	1.00	57.00	4.00	

```
       CustomerId  CreditScore         id  IsActiveMember    Balance   Tenure
count    3.17e+04     31684.00   31684.00        31684.00   31684.00  31684.00
mean     1.57e+07       655.53   82874.22            0.49   54768.85      5.02
std      7.15e+04        79.61   47397.84            0.50   62594.99      2.79
min      1.56e+07       428.00       0.00            0.00       0.00      0.00
25%      1.56e+07       597.00   41894.50            0.00       0.00      3.00
50%      1.57e+07       658.00   82949.50            0.00       0.00      5.00
75%      1.58e+07       710.00  123786.50            1.00  119278.01      7.00
max      1.58e+07       850.00  165028.00            1.00  250898.09     10.00
```

In [ ]:

```python
# 5. Calculate Measures of Spread for Numeric Columns Only
train_variance = train_data[numeric_cols].var()
train_std_dev = train_data[numeric_cols].std()
train_iqr = train_data[numeric_cols].quantile(0.75) - train_data[numeric_cols].quantile(0.25)

print("\nTrain Data Variance:")
print(train_variance)

print("\nTrain Data Standard Deviation:")
print(train_std_dev)

print("\nTrain Data Interquartile Range (IQR):")
print(train_iqr)

# Debug: Print columns to check if 'Gender' and 'Geography' exist
print("\nTrain Data Columns:")
print(train_data.columns)

print("\nTest Data Columns:")
print(test_data.columns)
```

```
Train Data Variance:
Exited             1.63e-01
EstimatedSalary    2.52e+09
HasCrCard          1.85e-01
Age                5.43e+01
NumOfProducts      2.97e-01
CustomerId         5.09e+09
CreditScore        6.30e+03
id                 2.27e+09
IsActiveMember     2.50e-01
Balance            3.95e+09
Tenure             7.88e+00
dtype: float64

Train Data Standard Deviation:
Exited                 0.40
EstimatedSalary    50195.96
HasCrCard              0.43
Age                    7.37
NumOfProducts          0.54
CustomerId         71355.60
CreditScore           79.37
id                 47689.83
IsActiveMember         0.50
Balance            62823.23
Tenure                 2.81
dtype: float64

Train Data Interquartile Range (IQR):
Exited                  0.00
EstimatedSalary     80790.62
HasCrCard               0.00
Age                     9.00
NumOfProducts           1.00
CustomerId         123751.00
CreditScore           112.00
id                  82661.25
IsActiveMember          1.00
Balance            119961.48
Tenure                  4.00
dtype: float64
```

```
Train Data Columns:
Index(['Exited', 'EstimatedSalary', 'HasCrCard', 'Age', 'Geography',
       'NumOfProducts', 'Surname', 'Gender', 'CustomerId', 'CreditScore', 'id',
       'IsActiveMember', 'Balance', 'Tenure'],
      dtype='object')

Test Data Columns:
Index(['Exited', 'EstimatedSalary', 'HasCrCard', 'Age', 'Geography',
       'NumOfProducts', 'Surname', 'Gender', 'CustomerId', 'CreditScore', 'id',
       'IsActiveMember', 'Balance', 'Tenure'],
      dtype='object')
```

In [ ]:

```
# 6. Handle any remaining NaN or infinite values
print("\nShape before dropping NaNs:")
print("Train Data Shape:", train_data.shape)
print("Test Data Shape:", test_data.shape)

# Debug: Check for NaN or infinite values in numerical columns
print("\nNaN values in train_data:")
print(train_data[numeric_cols].isna().sum())

print("\nNaN values in test_data:")
print(test_data[numeric_cols].isna().sum())

print("\nInfinite values in train_data:")
print(np.isinf(train_data[numeric_cols]).sum())

print("\nInfinite values in test_data:")
print(np.isinf(test_data[numeric_cols]).sum())

# Replace infinite values with NaN
train_data.replace([np.inf, -np.inf], np.nan, inplace=True)
test_data.replace([np.inf, -np.inf], np.nan, inplace=True)

# Debug: Print shape after replacing infinite values
print("Train Data Shape after replacing infinite values:", train_data.shape)
print("Test Data Shape after replacing infinite values:", test_data.shape)

# Fill remaining NaN values with the mean of the column
train_data[numeric_cols] = train_data[numeric_cols].fillna(train_data[numeric_cols].mean())
```

```
test_data[numeric_cols] = test_data[numeric_cols].fillna(test_data[numeric_cols].mean())

print("\nShape after filling NaNs:")
print("Train Data Shape:", train_data.shape)
print("Test Data Shape:", test_data.shape)

# Check if DataFrames are empty
if train_data.empty or test_data.empty:
    raise ValueError("Train or test data is empty after cleaning. Please check the data for NaN or infinite values.")
```

```
Shape before dropping NaNs:
Train Data Shape: (126706, 14)
Test Data Shape: (31684, 14)

NaN values in train_data:
Exited             0
EstimatedSalary    0
HasCrCard          0
Age                0
NumOfProducts      0
CustomerId         0
CreditScore        0
id                 0
IsActiveMember     0
Balance            0
Tenure             0
dtype: int64

NaN values in test_data:
Exited             0
EstimatedSalary    0
HasCrCard          0
Age                0
NumOfProducts      0
CustomerId         0
CreditScore        0
id                 0
IsActiveMember     0
Balance            0
Tenure             0
dtype: int64

Infinite values in train_data:
Exited             0
EstimatedSalary    0
HasCrCard          0
Age                0
NumOfProducts      0
CustomerId         0
CreditScore        0
id                 0
```

```
IsActiveMember     0
Balance            0
Tenure             0
dtype: int64

Infinite values in test_data:
Exited             0
EstimatedSalary    0
HasCrCard          0
Age                0
NumOfProducts      0
CustomerId         0
CreditScore        0
id                 0
IsActiveMember     0
Balance            0
Tenure             0
dtype: int64
Train Data Shape after replacing infinite values: (126706, 14)
Test Data Shape after replacing infinite values: (31684, 14)

Shape after filling NaNs:
Train Data Shape: (126706, 14)
Test Data Shape: (31684, 14)
```

In [ ]:

```
# 8. Normalize Numerical Features
scaler = StandardScaler()
numerical_columns = ['CreditScore', 'Age', 'Balance', 'EstimatedSalary']
train_data[numerical_columns] = scaler.fit_transform(train_data[numerical_columns])
test_data[numerical_columns] = scaler.transform(test_data[numerical_columns])

# Debug: Print shape after normalization
print("Train Data Shape after normalization:", train_data.shape)
print("Test Data Shape after normalization:", test_data.shape)
```

```
Train Data Shape after normalization: (126706, 14)
Test Data Shape after normalization: (31684, 14)
```

In [ ]:

```
# 9. Separate Features and Target Variable
X_train = train_data.drop('Exited', axis=1)
y_train = train_data['Exited'].values.reshape(-1, 1)
```

```python
X_test = test_data.drop('Exited', axis=1)
y_test = test_data['Exited'].values.reshape(-1, 1)

# Debug: Print shape after separating features and target variable
print("X_train Shape:", X_train.shape)
print("y_train Shape:", y_train.shape)
print("X_test Shape:", X_test.shape)
print("y_test Shape:", y_test.shape)
```

```
X_train Shape: (126706, 13)
y_train Shape: (126706, 1)
X_test Shape: (31684, 13)
y_test Shape: (31684, 1)
```

In [ ]:

```python
# 10. Remove Highly Correlated Features (Excluding String Columns)
def remove_highly_correlated_features(df, threshold=0.9):
    # Select only numerical columns for correlation analysis
    numeric_df = df.select_dtypes(include=[np.number])

    corr_matrix = numeric_df.corr().abs()
    upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
    to_drop = [column for column in upper.columns if any(upper[column] > threshold)]

    # Drop highly correlated numerical columns from the original dataframe
    df = df.drop(columns=to_drop)
    return df

train_data = remove_highly_correlated_features(train_data)
test_data = remove_highly_correlated_features(test_data)

# Debug: Print shape after removing highly correlated features
print("Train Data Shape after removing highly correlated features:", train_data.shape)
print("Test Data Shape after removing highly correlated features:", test_data.shape)
```

```
Train Data Shape after removing highly correlated features: (126706, 14)
Test Data Shape after removing highly correlated features: (31684, 14)
```

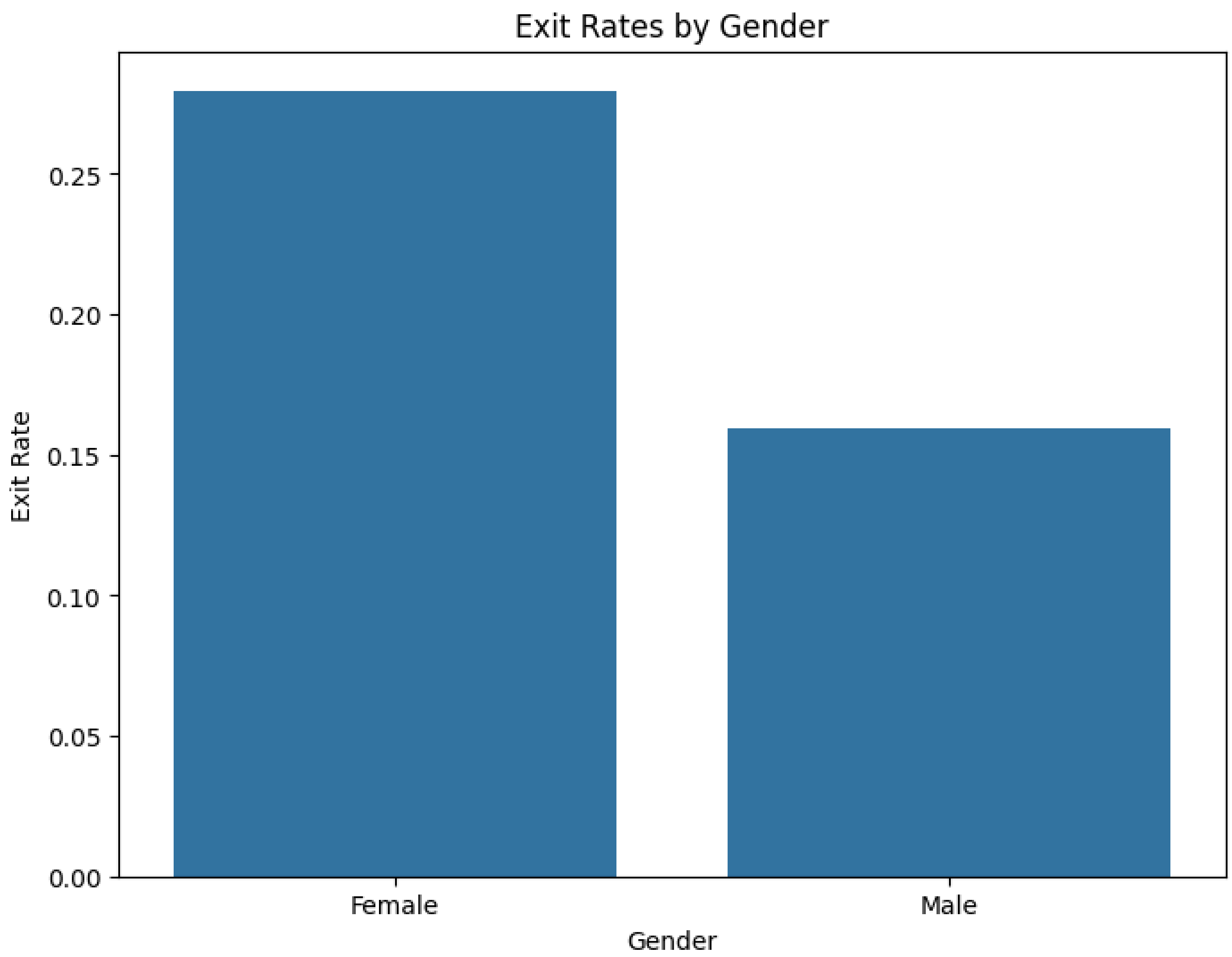
EDA

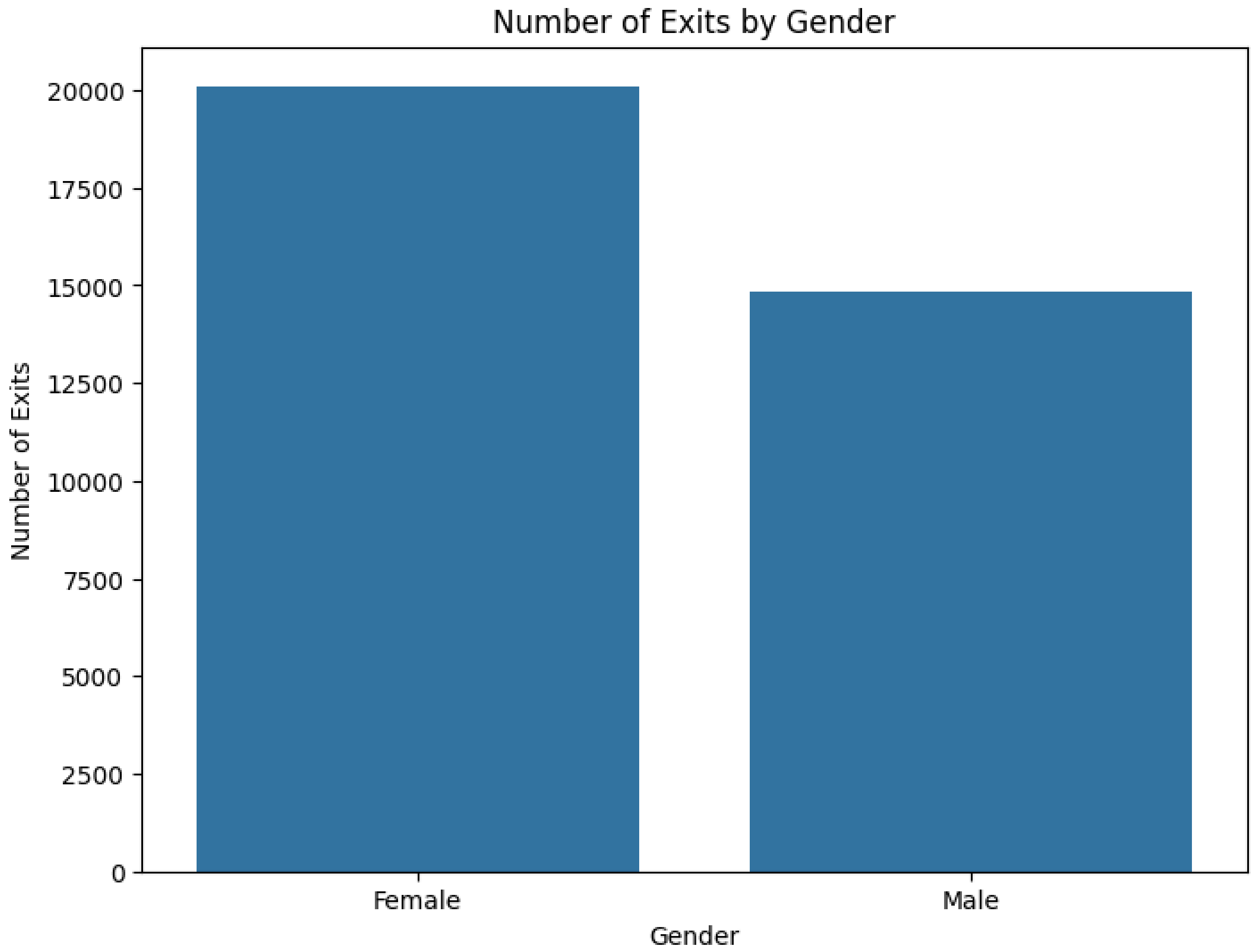
1

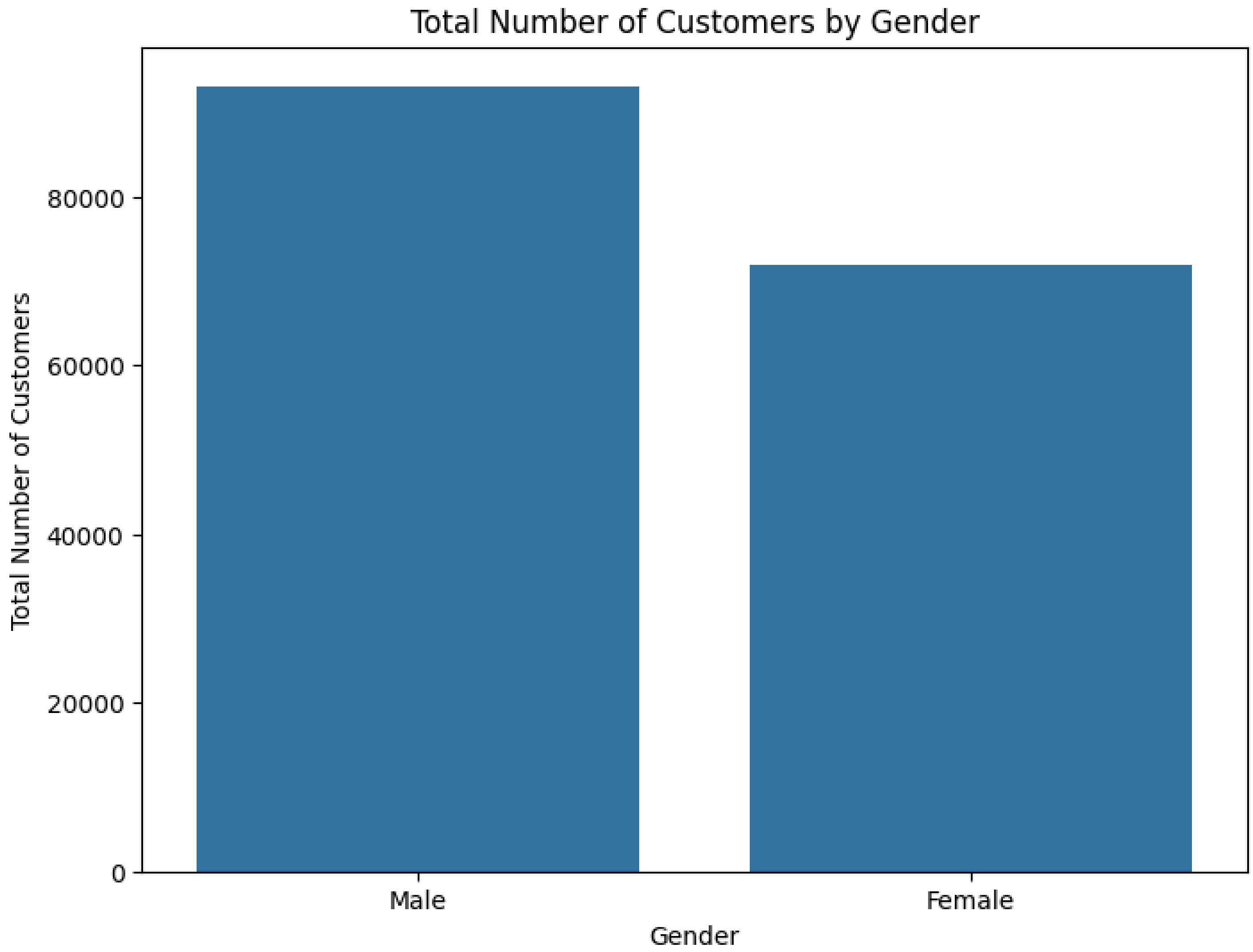
In [ ]:

```
# Calculate the exit rates for male and female customers
gender_exit_rate = data.groupby('Gender')['Exited'].mean()
print("Exit Rates by Gender:\n", gender_exit_rate)

# Calculate the count of exits for male and female customers
gender_exit_count = data.groupby('Gender')['Exited'].sum()
print("Exit Counts by Gender:\n", gender_exit_count)

# Calculate the total number of male and female customers
gender_total_count = data['Gender'].value_counts()
print("Total Counts by Gender:\n", gender_total_count)


# Plot the exit rates for male and female customers
plt.figure(figsize=(8, 6))
sns.barplot(x=gender_exit_rate.index, y=gender_exit_rate.values)
plt.xlabel('Gender')
plt.ylabel('Exit Rate')
plt.title('Exit Rates by Gender')
plt.show()

# Plot the count of exits for male and female customers
plt.figure(figsize=(8, 6))
sns.barplot(x=gender_exit_count.index, y=gender_exit_count.values)
plt.xlabel('Gender')
plt.ylabel('Number of Exits')
plt.title('Number of Exits by Gender')
plt.show()

# Plot the total number of male and female customers
plt.figure(figsize=(8, 6))
sns.barplot(x=gender_total_count.index, y=gender_total_count.values)
plt.xlabel('Gender')
plt.ylabel('Total Number of Customers')
plt.title('Total Number of Customers by Gender')
plt.show()
```

```
Exit Rates by Gender:
 Gender
Female    0.28
Male      0.16
Name: Exited, dtype: float64
Exit Counts by Gender:
 Gender
Female    20105
Male      14816
Name: Exited, dtype: int64
Total Counts by Gender:
 Gender
Male      93150
Female    71884
Name: count, dtype: int64
```


Exit Rates by Gender
Exit Rate
0.00
0.05
0.10
0.15
0.20
0.25
Female
Male
Gender


Number of Exits by Gender
Number of Exits
20000
17500
15000
12500
10000
7500
5000
2500
0
Female
Male
Gender



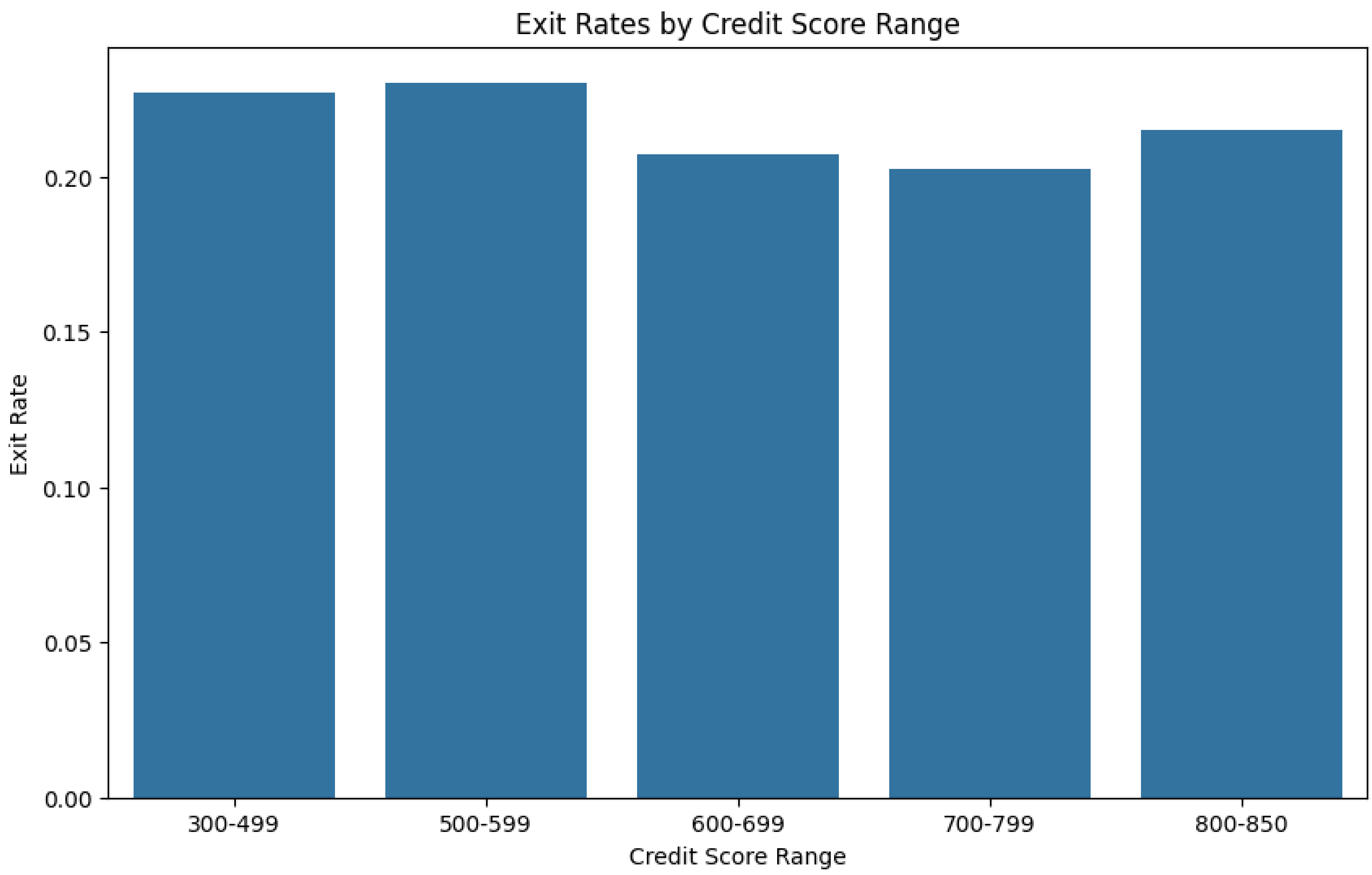
2

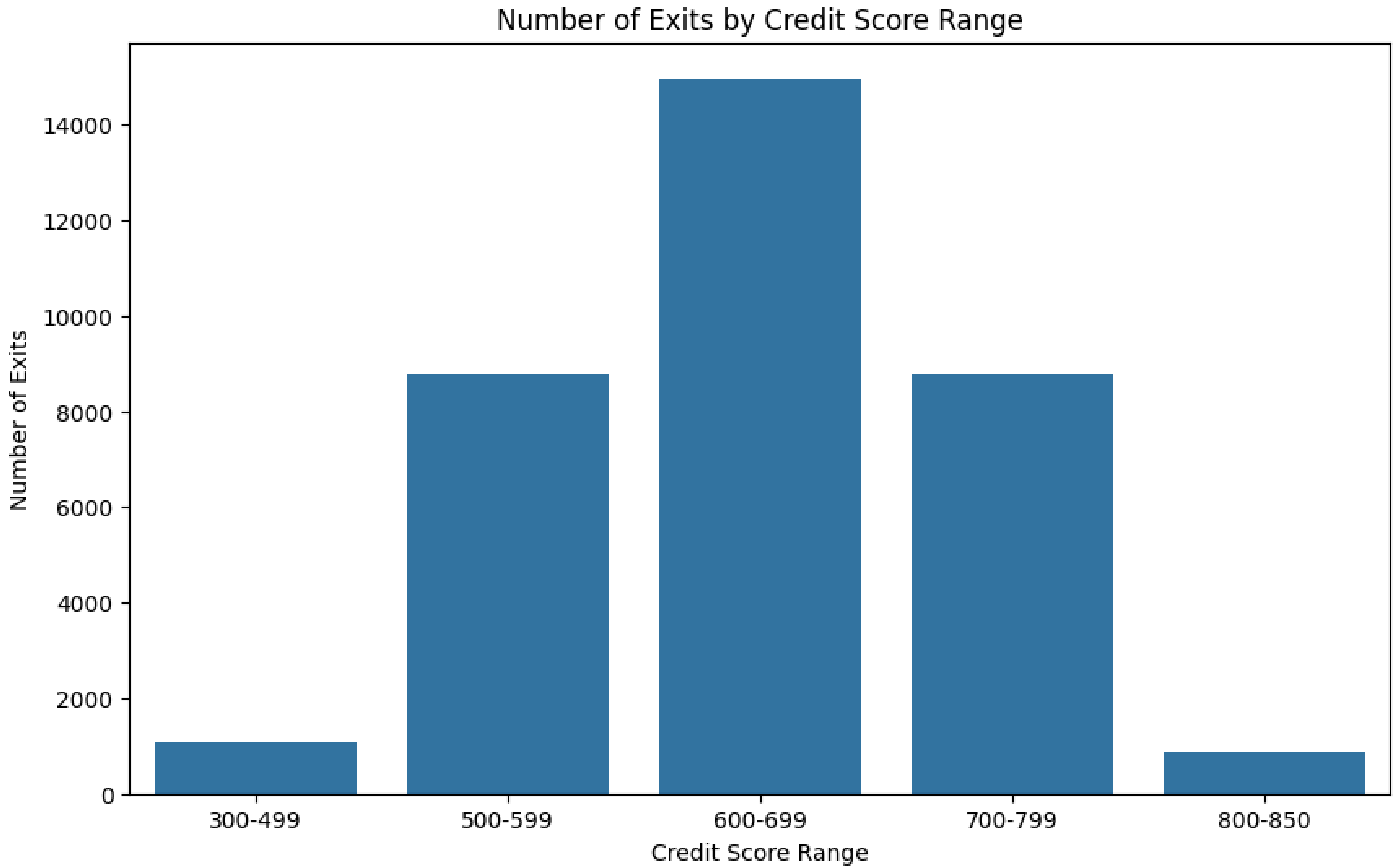
```
# Create bins for credit scores
bins = [300, 500, 600, 700, 800, 850]
labels = ['300-499', '500-599', '600-699', '700-799', '800-850']
data['CreditScoreRange'] = pd.cut(data['CreditScore'], bins=bins, labels=labels, right=False)
```

```python
# Calculate the exit rates for different credit score ranges
credit_score_exit_rate = data.groupby('CreditScoreRange')['Exited'].mean()
print("Exit Rates by Credit Score Range:\n", credit_score_exit_rate)

# Calculate the count of exits for different credit score ranges
credit_score_exit_count = data.groupby('CreditScoreRange')['Exited'].sum()
print("Exit Counts by Credit Score Range:\n", credit_score_exit_count)

# Calculate the total number of customers in different credit score ranges
credit_score_total_count = data['CreditScoreRange'].value_counts().sort_index()
print("Total Counts by Credit Score Range:\n", credit_score_total_count)


# Plot the exit rates for different credit score ranges
plt.figure(figsize=(10, 6))
sns.barplot(x=credit_score_exit_rate.index, y=credit_score_exit_rate.values)
plt.xlabel('Credit Score Range')
plt.ylabel('Exit Rate')
plt.title('Exit Rates by Credit Score Range')
plt.show()

# Plot the count of exits for different credit score ranges
plt.figure(figsize=(10, 6))
sns.barplot(x=credit_score_exit_count.index, y=credit_score_exit_count.values)
plt.xlabel('Credit Score Range')
plt.ylabel('Number of Exits')
plt.title('Number of Exits by Credit Score Range')
plt.show()

# Plot the total number of customers in different credit score ranges
plt.figure(figsize=(10, 6))
sns.barplot(x=credit_score_total_count.index, y=credit_score_total_count.values)
plt.xlabel('Credit Score Range')
plt.ylabel('Total Number of Customers')
plt.title('Total Number of Customers by Credit Score Range')
plt.show()
```

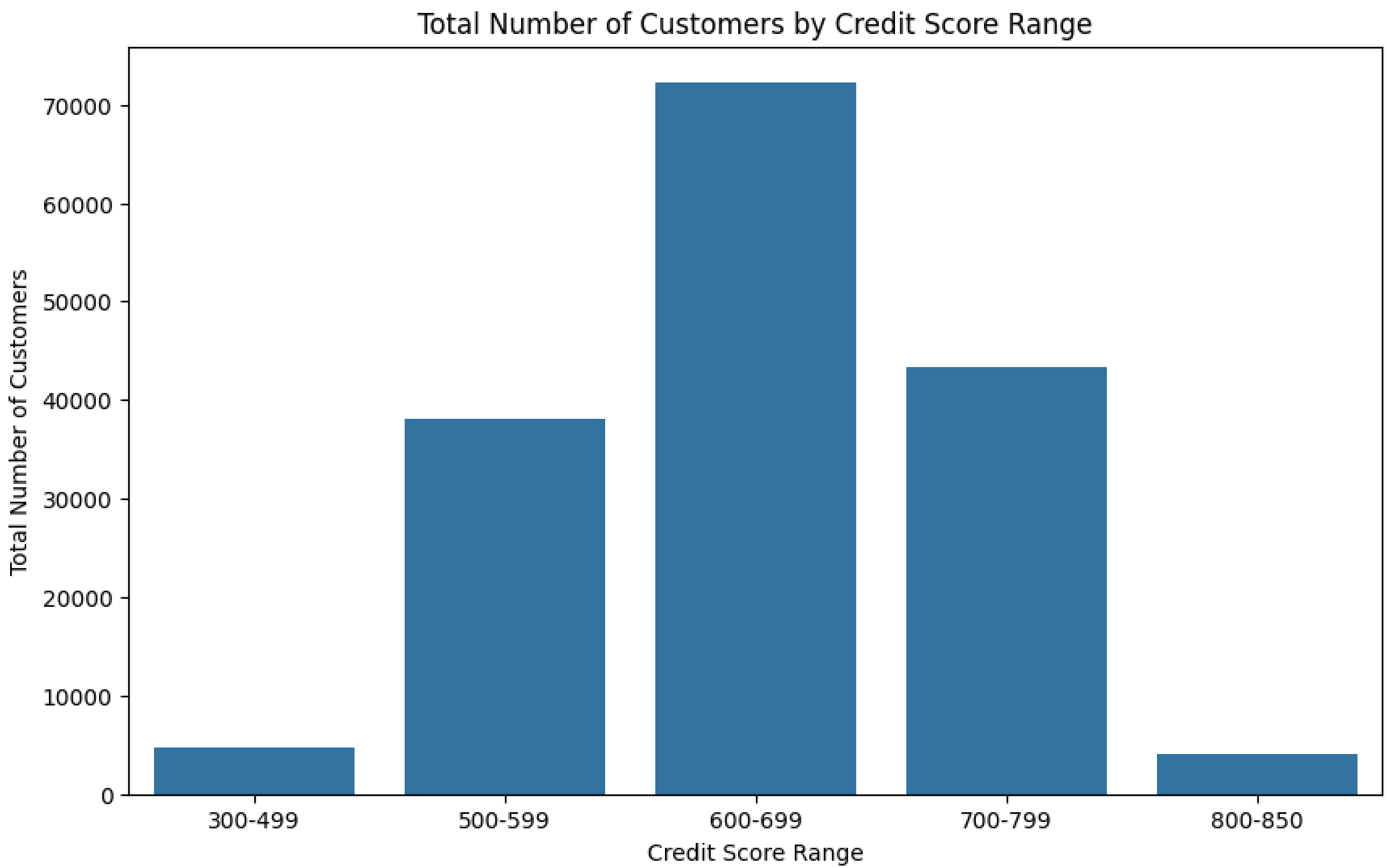
```
Exit Rates by Credit Score Range:
 CreditScoreRange
300-499    0.23
500-599    0.23
600-699    0.21
700-799    0.20
800-850    0.22
Name: Exited, dtype: float64
Exit Counts by Credit Score Range:
 CreditScoreRange
300-499     1073
500-599     8775
600-699    14967
700-799     8754
800-850      882
Name: Exited, dtype: int64
Total Counts by Credit Score Range:
 CreditScoreRange
300-499     4732
500-599    38108
600-699    72286
700-799    43275
800-850     4101
Name: count, dtype: int64
```

```
C:\Users\jaiad\AppData\Local\Temp\ipykernel_14172\1370137640.py:7: FutureWarning: The default of observed=False is deprecated a
nd will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to ad
opt the future default and silence this warning.
  credit_score_exit_rate = data.groupby('CreditScoreRange')['Exited'].mean()
C:\Users\jaiad\AppData\Local\Temp\ipykernel_14172\1370137640.py:11: FutureWarning: The default of observed=False is deprecated
and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to a
dopt the future default and silence this warning.
  credit_score_exit_count = data.groupby('CreditScoreRange')['Exited'].sum()
```


Exit Rates by Credit Score Range
Exit Rate
0.00
0.05
0.10
0.15
0.20
300-499
500-599
600-699
700-799
800-850
Credit Score Range



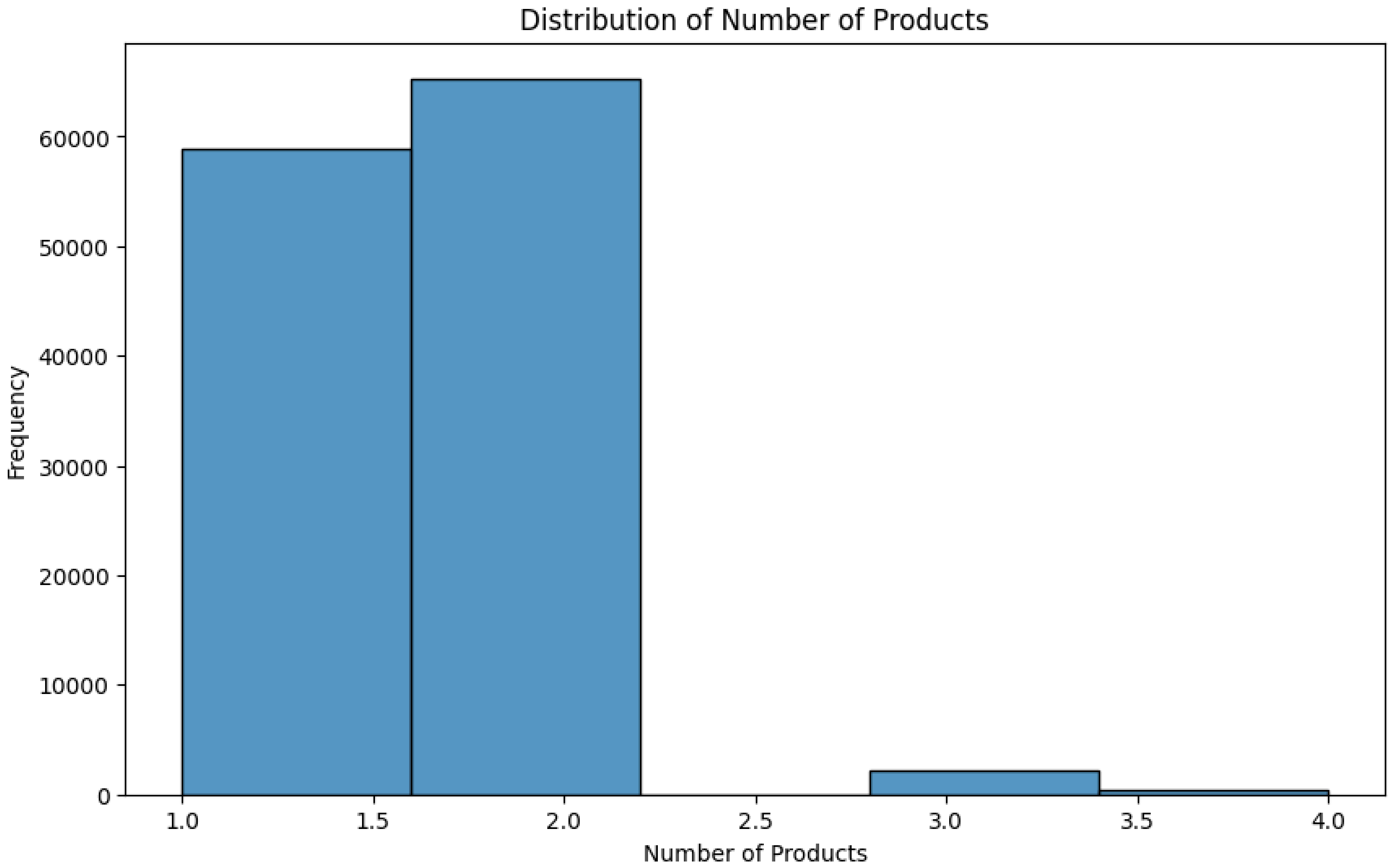
Number of Exits by Credit Score Range
Number of Exits
14000
12000
10000
8000
6000
4000
2000
0
300-499
500-599
600-699
700-799
800-850
Credit Score Range



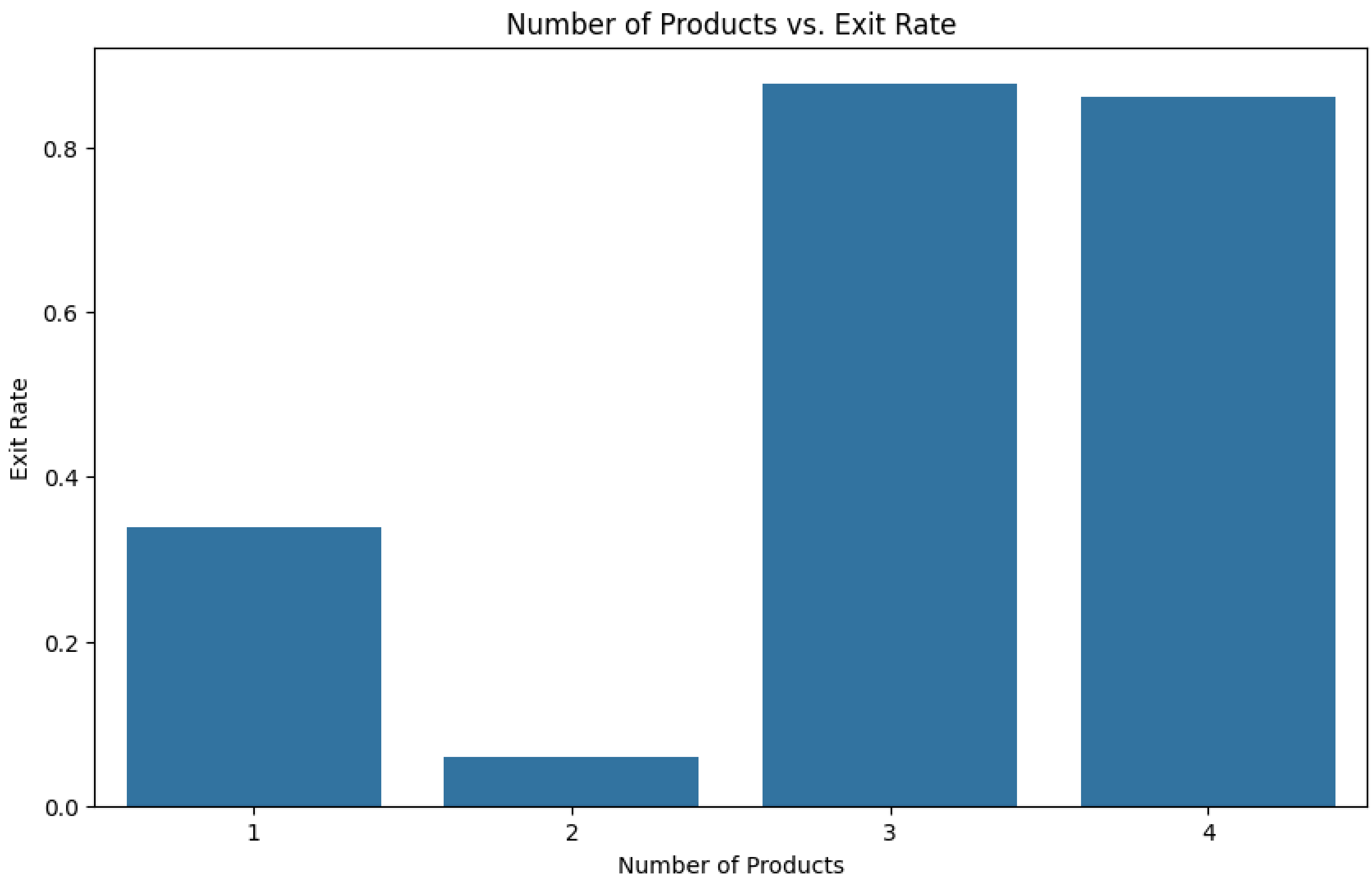
3

In [ ]:
```
# Histogram of number of products
plt.figure(figsize=(10, 6))
sns.histplot(train_data['NumOfProducts'], bins=5, kde=False)
plt.title('Distribution of Number of Products')
```

```python
plt.xlabel('Number of Products')
plt.ylabel('Frequency')
plt.show()

# Bar plot of number of products vs. exit
plt.figure(figsize=(10, 6))
sns.barplot(x='NumOfProducts', y='Exited', data=train_data, ci=None)
plt.title('Number of Products vs. Exit Rate')
plt.xlabel('Number of Products')
plt.ylabel('Exit Rate')
plt.show()


# Create a contingency table
contingency_table = pd.crosstab(train_data['NumOfProducts'], train_data['Exited'])

# Perform chi-square test
chi2, p, dof, expected = chi2_contingency(contingency_table)
print(f'Chi-square test statistic: {chi2}')
print(f'p-value: {p}')

# Interpretation
if p < 0.05:
    print("There is a significant relationship between the number of products and customer exit.")
else:
    print("There is no significant relationship between the number of products and customer exit.")
```




```
C:\Users\jaiad\AppData\Local\Temp\ipykernel_14172\593253213.py:11: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(x='NumOfProducts', y='Exited', data=train_data, ci=None)
```

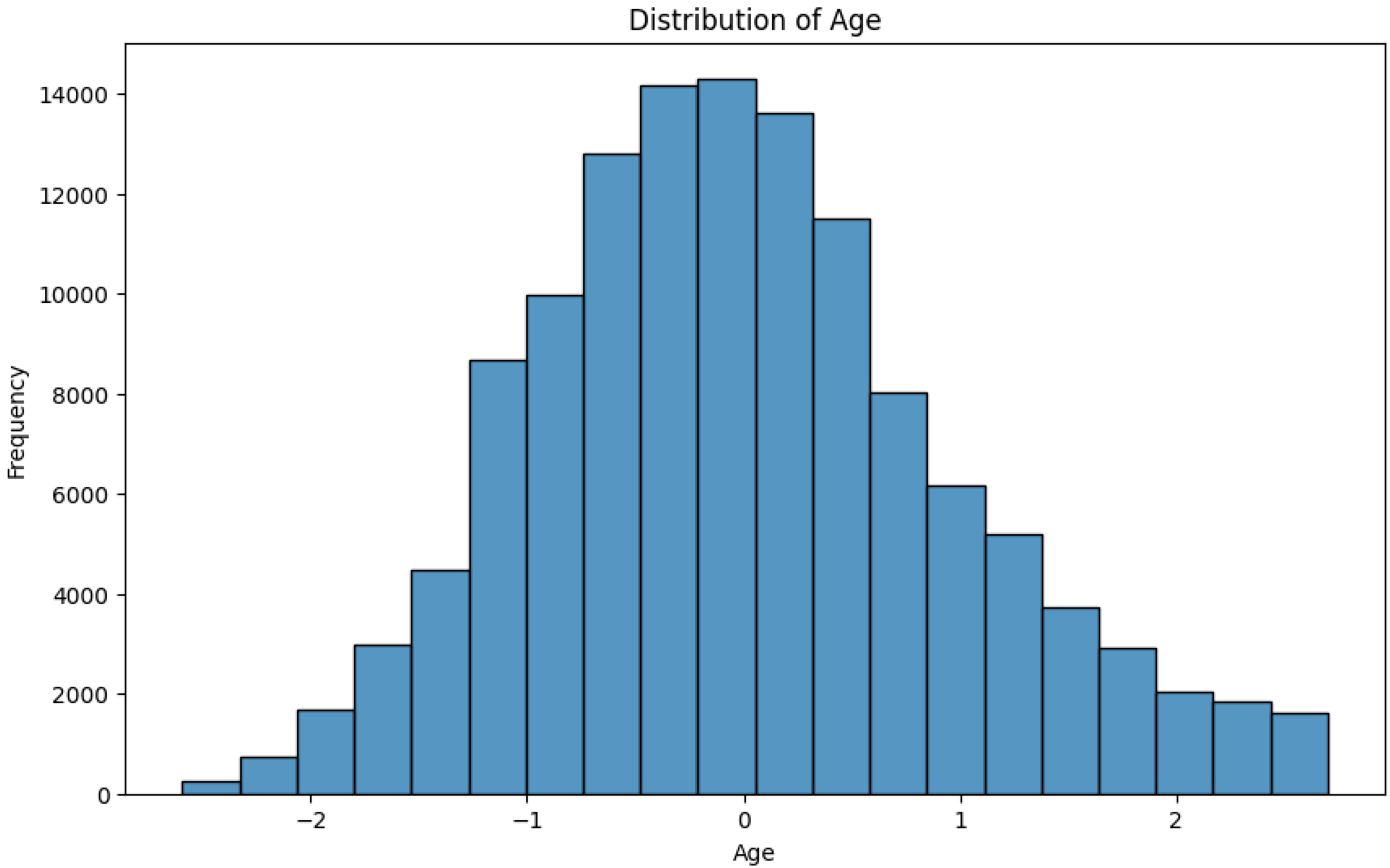



```
Chi-square test statistic: 21944.14794910601
p-value: 0.0
There is a significant relationship between the number of products and customer exit.
```

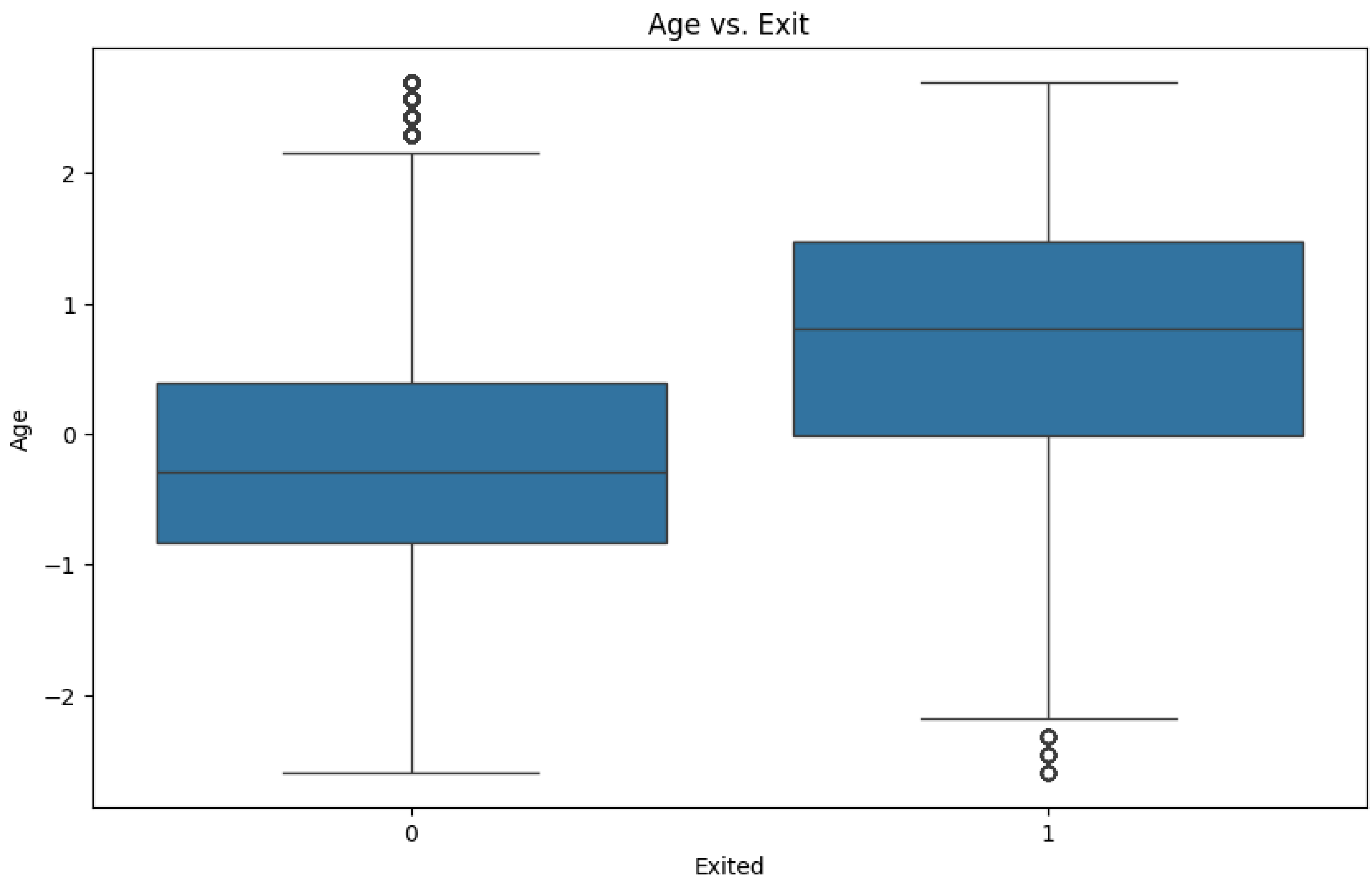
In [ ]:

```
#  Data Visualization
# Histogram of age
plt.figure(figsize=(10, 6))
sns.histplot(train_data['Age'], bins=20, kde=False)
```

```python
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()

# Bar plot of age vs. exit
plt.figure(figsize=(10, 6))
sns.boxplot(x='Exited', y='Age', data=train_data)
plt.title('Age vs. Exit')
plt.xlabel('Exited')
plt.ylabel('Age')
plt.show()

# Statistical Analysis
# Create age bins
train_data['AgeGroup'] = pd.cut(train_data['Age'], bins=[0, 20, 30, 40, 50, 60, 70, 80, 90, 100], labels=['0-20', '21-30', '31

# Create a contingency table
contingency_table = pd.crosstab(train_data['AgeGroup'], train_data['Exited'])

# Perform chi-square test
chi2, p, dof, expected = chi2_contingency(contingency_table)
print(f'Chi-square test statistic: {chi2}')
print(f'p-value: {p}')

# Interpretation
if p < 0.05:
    print("There is a significant relationship between age and customer exit.")
else:
    print("There is no significant relationship between age and customer exit.")
```



Distribution of Age
Frequency
Age
0
2000
4000
6000
8000
10000
12000
14000
−2
−1
0
1
2



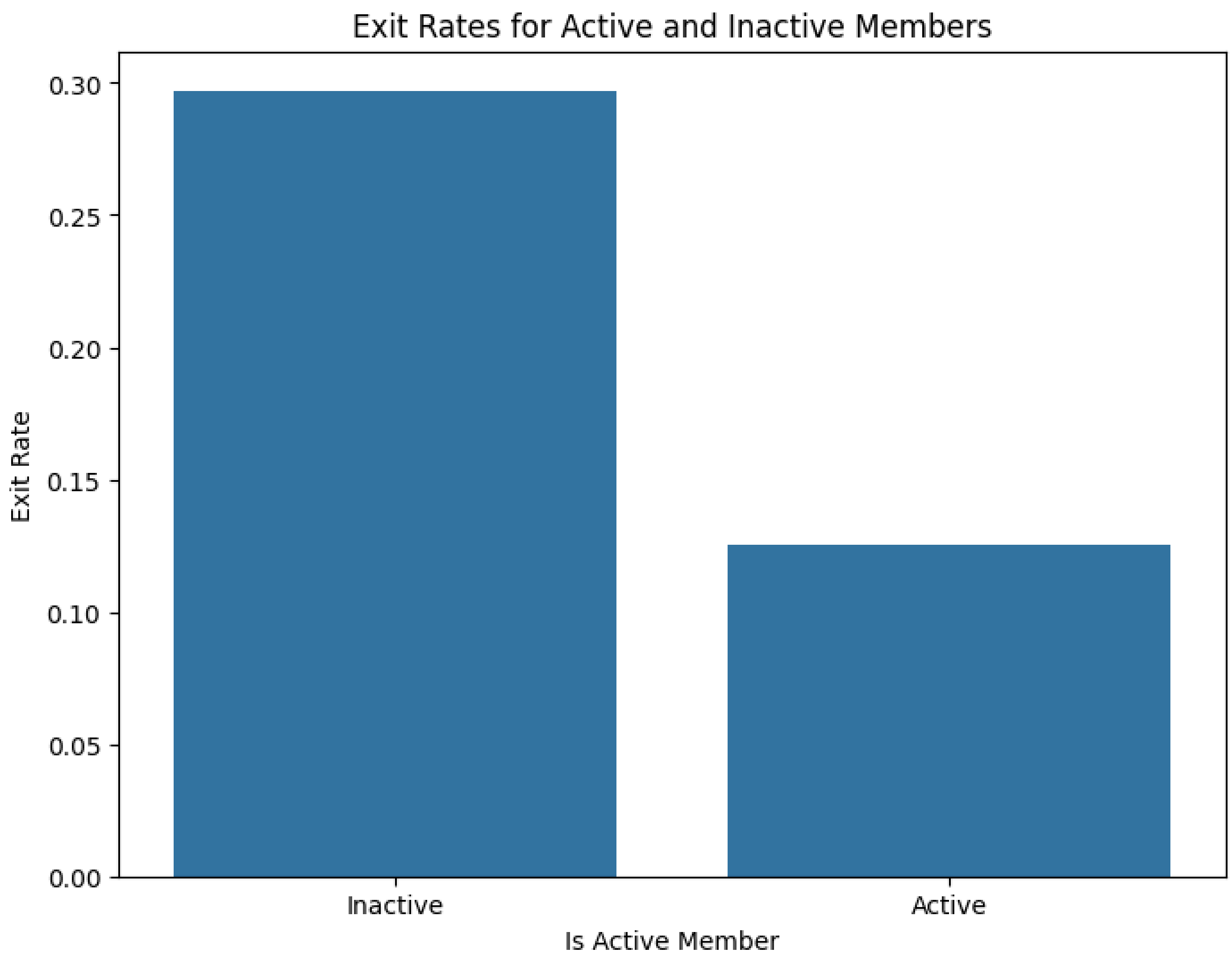

```
Chi-square test statistic: 0.0
p-value: 1.0
There is no significant relationship between age and customer exit.
```

In [ ]:

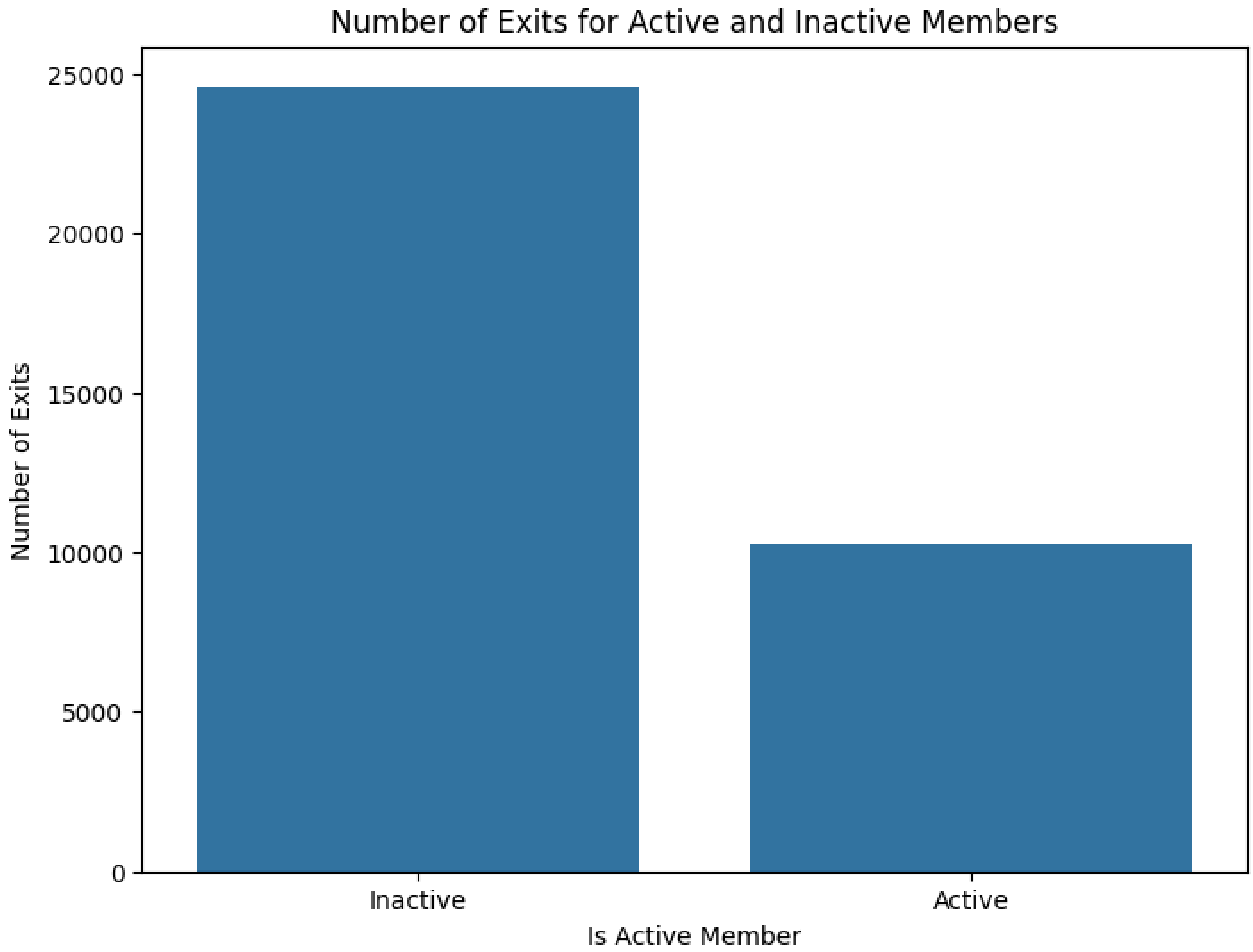
```
#5
# Calculate the exit rates for active and inactive members
exit_rates = data.groupby('IsActiveMember')['Exited'].mean()
print(exit_rates)
```

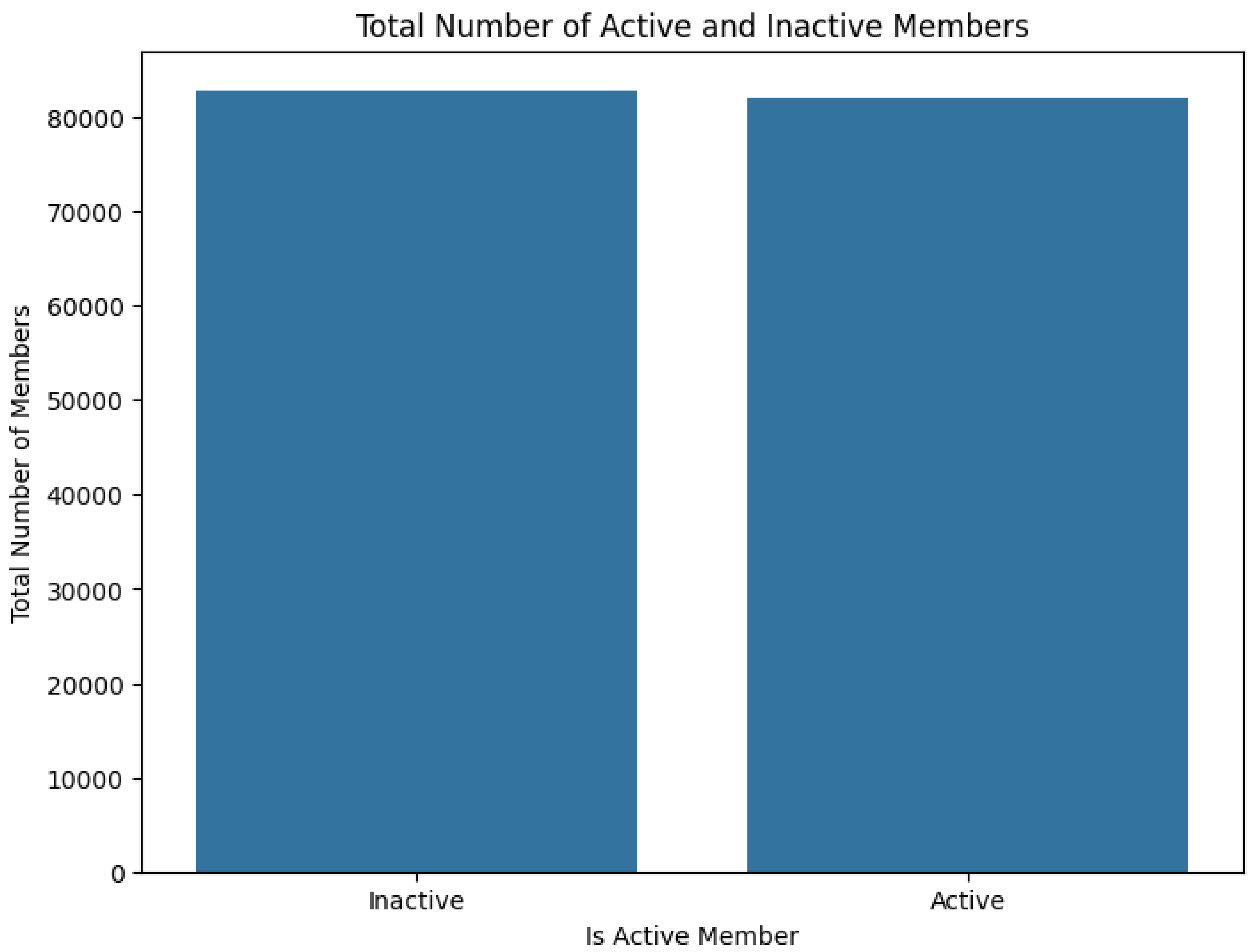
```
# Calculate the count of exits for active and inactive members
exit_counts = data.groupby('IsActiveMember')['Exited'].sum()
print(exit_counts)

# Calculate the total number of active and inactive members
total_counts = data['IsActiveMember'].value_counts()
print(total_counts)


# Plot the exit rates for active and inactive members
plt.figure(figsize=(8, 6))
sns.barplot(x=exit_rates.index, y=exit_rates.values)
plt.xlabel('Is Active Member')
plt.ylabel('Exit Rate')
plt.title('Exit Rates for Active and Inactive Members')
plt.xticks([0, 1], ['Inactive', 'Active'])
plt.show()

# Plot the count of exits for active and inactive members
plt.figure(figsize=(8, 6))
sns.barplot(x=exit_counts.index, y=exit_counts.values)
plt.xlabel('Is Active Member')
plt.ylabel('Number of Exits')
plt.title('Number of Exits for Active and Inactive Members')
plt.xticks([0, 1], ['Inactive', 'Active'])
plt.show()

# Plot the total number of active and inactive members
plt.figure(figsize=(8, 6))
sns.barplot(x=total_counts.index, y=total_counts.values)
plt.xlabel('Is Active Member')
plt.ylabel('Total Number of Members')
plt.title('Total Number of Active and Inactive Members')
plt.xticks([0, 1], ['Inactive', 'Active'])
plt.show()
```

```
IsActiveMember
0.0    0.30
1.0    0.13
Name: Exited, dtype: float64
IsActiveMember
0.0    24624
1.0    10297
Name: Exited, dtype: int64
IsActiveMember
0.0    82885
1.0    82149
Name: count, dtype: int64
```



Exit Rates for Active and Inactive Members
Exit Rate
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Inactive
Active
Is Active Member

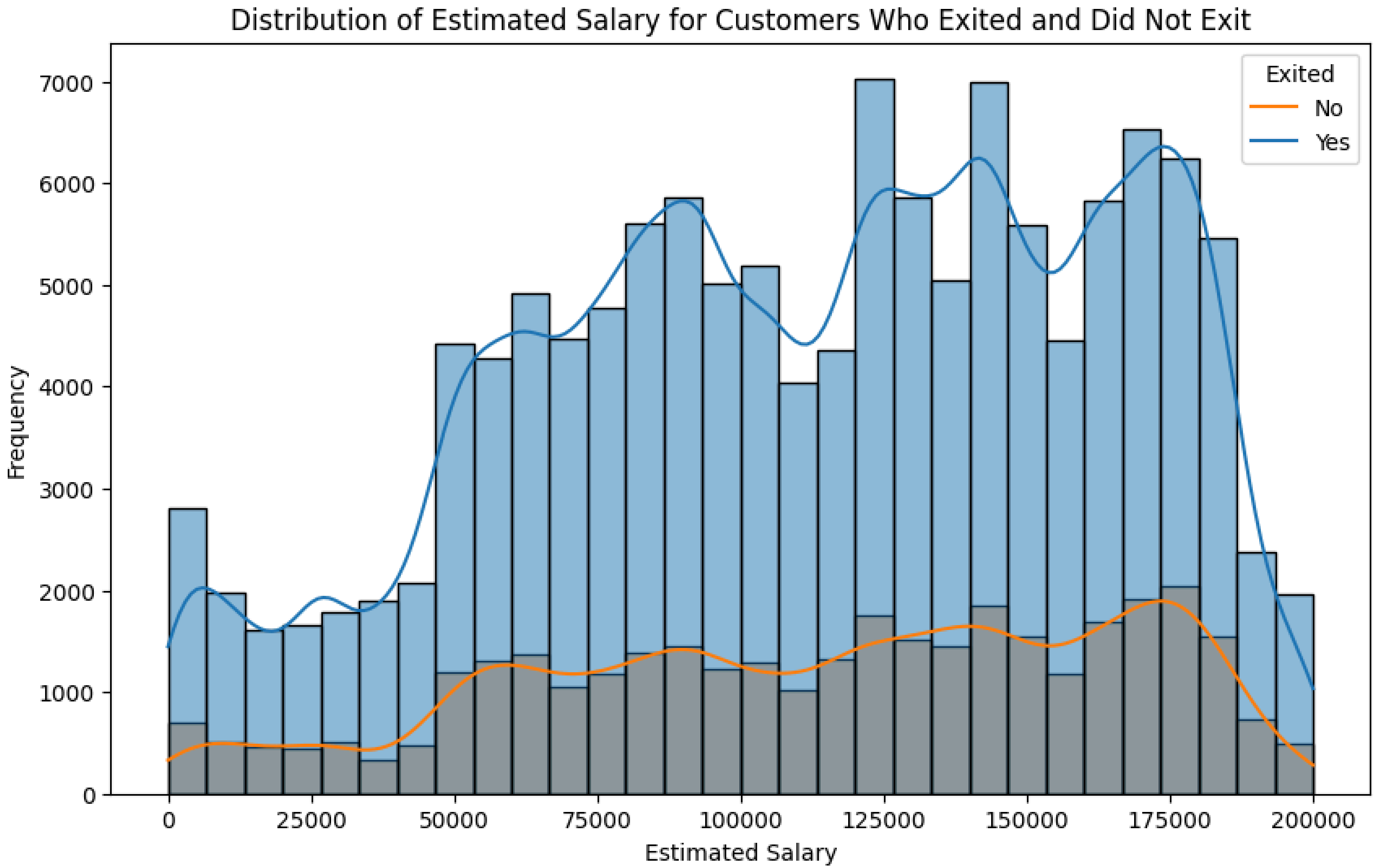

Number of Exits for Active and Inactive Members
25000
20000
15000
10000
5000
0
Number of Exits
Inactive
Active
Is Active Member

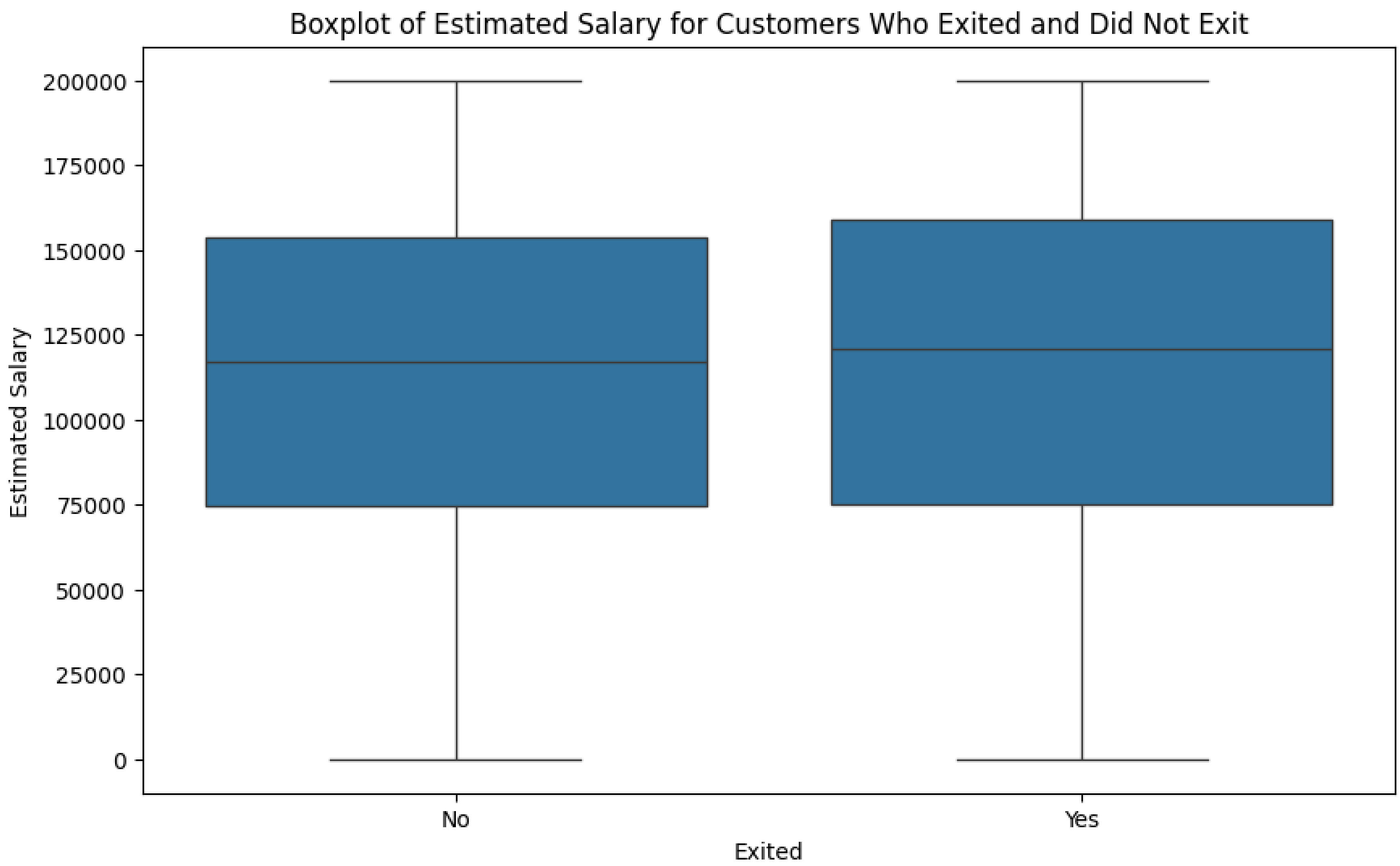


In [ ]:
```
#6
# Calculate the mean estimated salary for customers who exited and those who did not
salary_exit_mean = data.groupby('Exited')['EstimatedSalary'].mean()
print("Mean Estimated Salary:\n", salary_exit_mean)

# Calculate the median estimated salary for customers who exited and those who did not
salary_exit_median = data.groupby('Exited')['EstimatedSalary'].median()
```

```python
print("Median Estimated Salary:\n", salary_exit_median)

# Calculate the distribution of estimated salary for customers who exited and those who did not
salary_exit_distribution = data.groupby('Exited')['EstimatedSalary'].describe()
print("Estimated Salary Distribution:\n", salary_exit_distribution)

# Plot the distribution of estimated salary for customers who exited and those who did not
plt.figure(figsize=(10, 6))
sns.histplot(data=data, x='EstimatedSalary', hue='Exited', kde=True, bins=30)
plt.xlabel('Estimated Salary')
plt.ylabel('Frequency')
plt.title('Distribution of Estimated Salary for Customers Who Exited and Did Not Exit')
plt.legend(title='Exited', labels=['No', 'Yes'])
plt.show()

# Boxplot to compare the estimated salary for customers who exited and those who did not
plt.figure(figsize=(10, 6))
sns.boxplot(x='Exited', y='EstimatedSalary', data=data)
plt.xlabel('Exited')
plt.ylabel('Estimated Salary')
plt.title('Boxplot of Estimated Salary for Customers Who Exited and Did Not Exit')
plt.xticks([0, 1], ['No', 'Yes'])
plt.show()
```

```
Mean Estimated Salary:
 Exited
0    112084.29
1    114402.50
Name: EstimatedSalary, dtype: float64
Median Estimated Salary:
 Exited
0    116977.89
1    120892.96
Name: EstimatedSalary, dtype: float64
Estimated Salary Distribution:
            count       mean       std    min       25%        50%        75%  \
Exited
0       130113.0  112084.29  50214.66  11.58  74425.41  116977.89  153727.32
1        34921.0  114402.50  50542.03  11.58  74965.44  120892.96  158750.53

              max
Exited
0       199992.48
1       199992.48
```


Distribution of Estimated Salary for Customers Who Exited and Did Not Exit
Frequency
0
1000
2000
3000
4000
5000
6000
7000
0
25000
50000
75000
100000
125000
150000
175000
200000
Estimated Salary
Exited
No
Yes

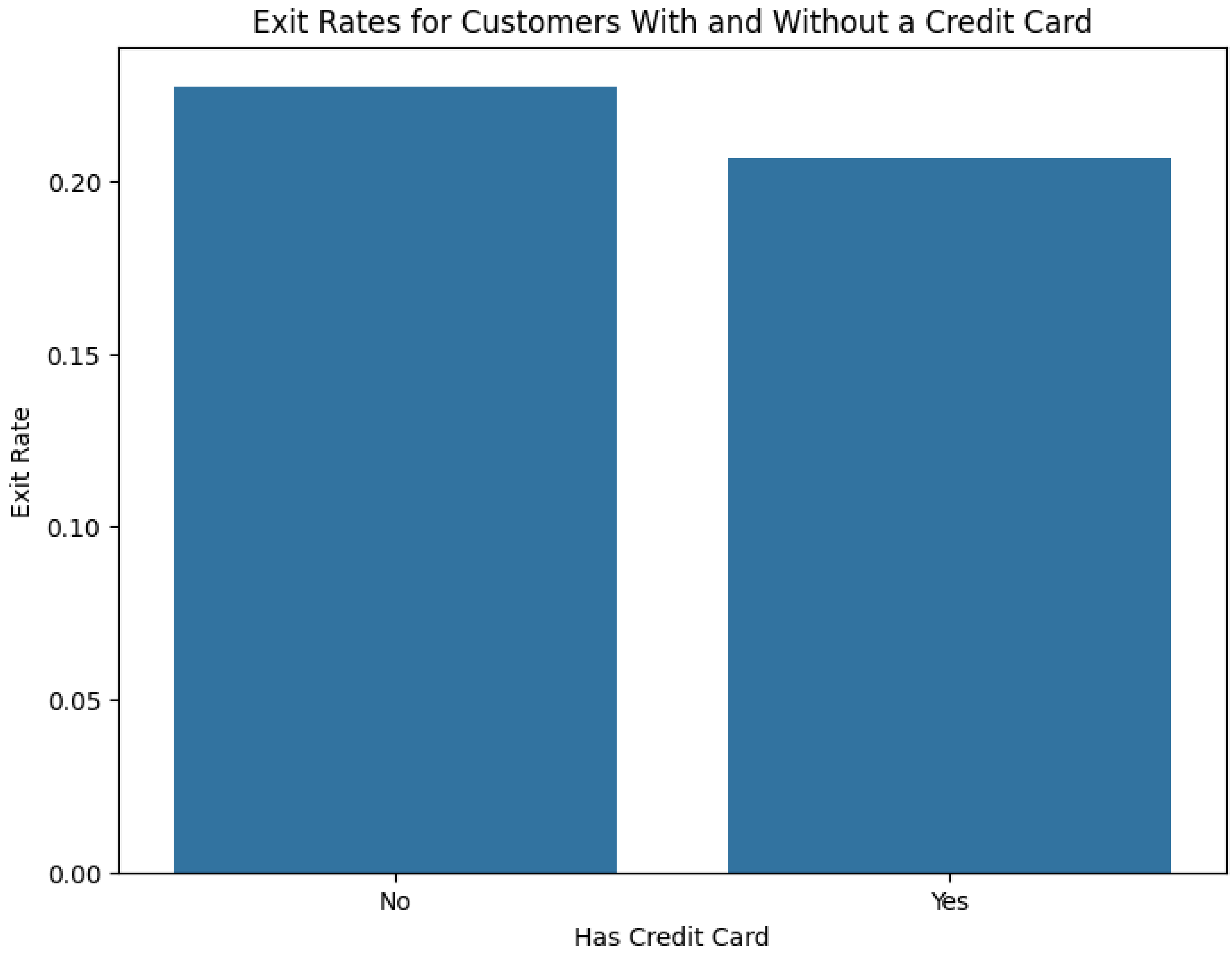


In [ ]:

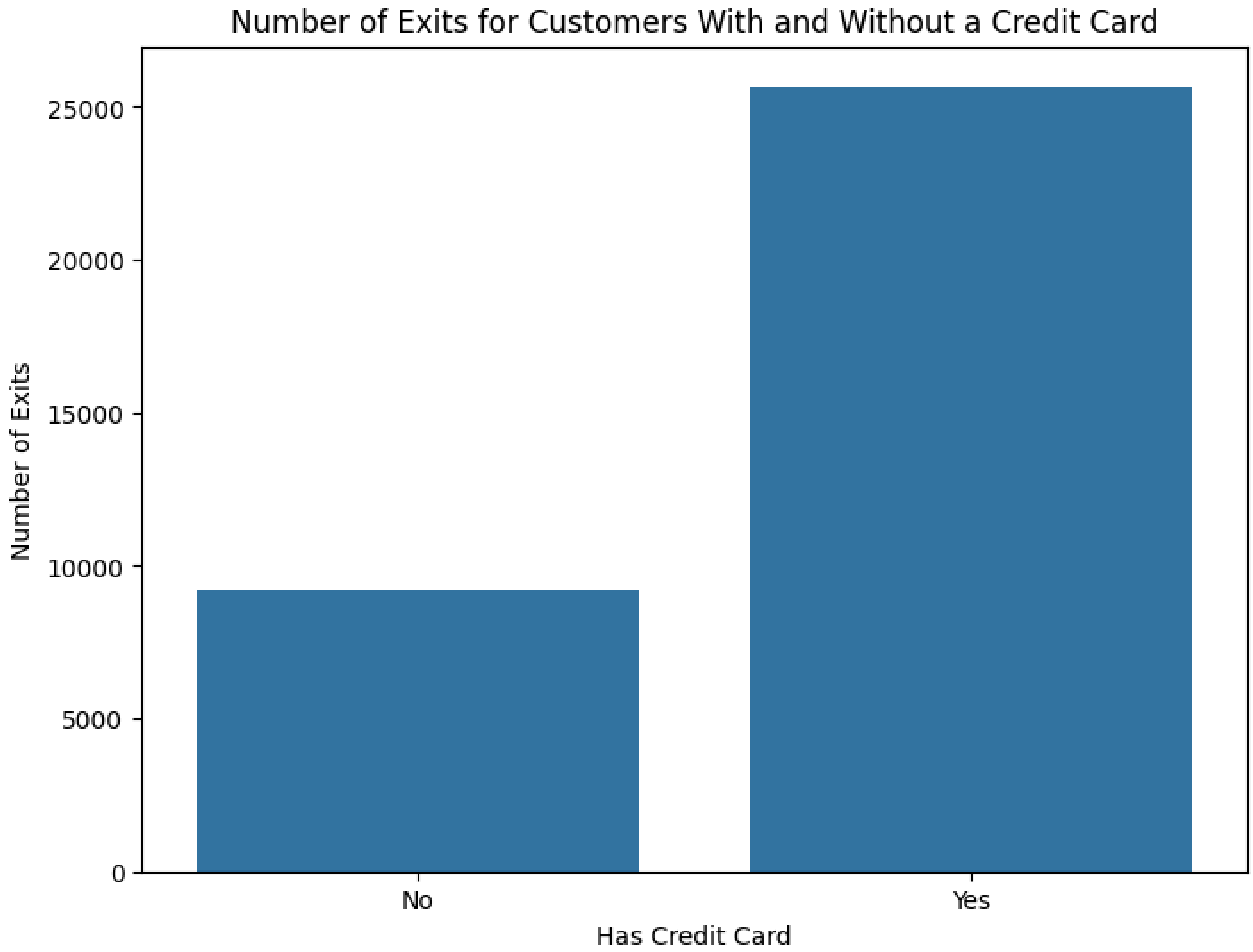
```
#7
#  Calculate the exit rates for customers with and without a credit card
credit_card_exit_rate = data.groupby('HasCrCard')['Exited'].mean()
print("Exit Rates:\n", credit_card_exit_rate)

# Calculate the count of exits for customers with and without a credit card
credit_card_exit_count = data.groupby('HasCrCard')['Exited'].sum()
```

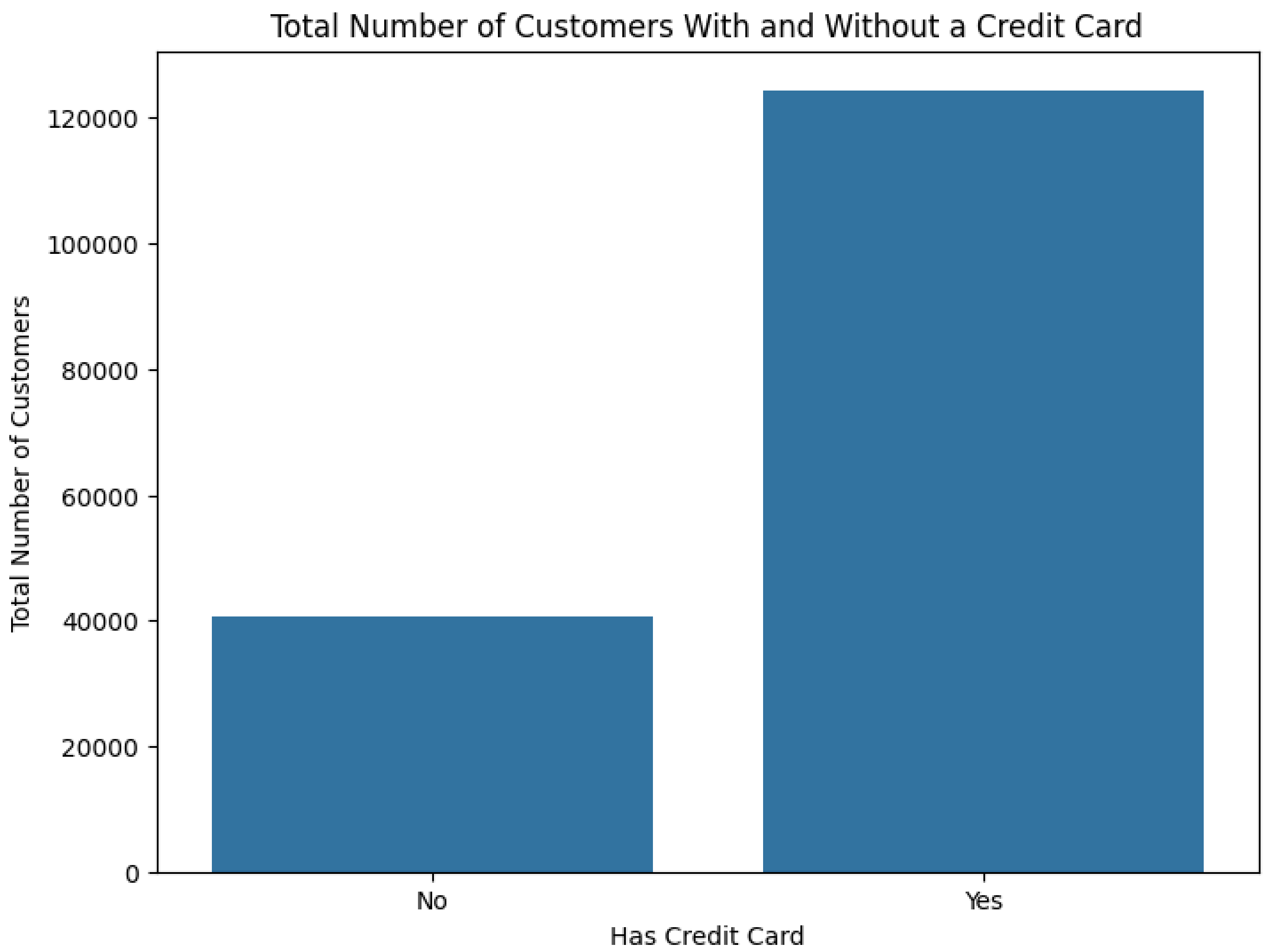
```python
print("Exit Counts:\n", credit_card_exit_count)

# Calculate the total number of customers with and without a credit card
credit_card_total_count = data['HasCrCard'].value_counts()
print("Total Counts:\n", credit_card_total_count)


# Plot the exit rates for customers with and without a credit card
plt.figure(figsize=(8, 6))
sns.barplot(x=credit_card_exit_rate.index, y=credit_card_exit_rate.values)
plt.xlabel('Has Credit Card')
plt.ylabel('Exit Rate')
plt.title('Exit Rates for Customers With and Without a Credit Card')
plt.xticks([0, 1], ['No', 'Yes'])
plt.show()

# Plot the count of exits for customers with and without a credit card
plt.figure(figsize=(8, 6))
sns.barplot(x=credit_card_exit_count.index, y=credit_card_exit_count.values)
plt.xlabel('Has Credit Card')
plt.ylabel('Number of Exits')
plt.title('Number of Exits for Customers With and Without a Credit Card')
plt.xticks([0, 1], ['No', 'Yes'])
plt.show()

# Plot the total number of customers with and without a credit card
plt.figure(figsize=(8, 6))
sns.barplot(x=credit_card_total_count.index, y=credit_card_total_count.values)
plt.xlabel('Has Credit Card')
plt.ylabel('Total Number of Customers')
plt.title('Total Number of Customers With and Without a Credit Card')
plt.xticks([0, 1], ['No', 'Yes'])
plt.show()
```

```
Exit Rates:
 HasCrCard
0.0    0.23
1.0    0.21
Name: Exited, dtype: float64
Exit Counts:
 HasCrCard
0.0     9235
1.0    25686
Name: Exited, dtype: int64
Total Counts:
 HasCrCard
1.0    124428
0.0     40606
Name: count, dtype: int64
```



Exit Rates for Customers With and Without a Credit Card
0.20
0.15
0.10
0.05
0.00
Exit Rate
No
Yes
Has Credit Card


Number of Exits for Customers With and Without a Credit Card
Number of Exits
25000
20000
15000
10000
5000
0
No
Yes
Has Credit Card

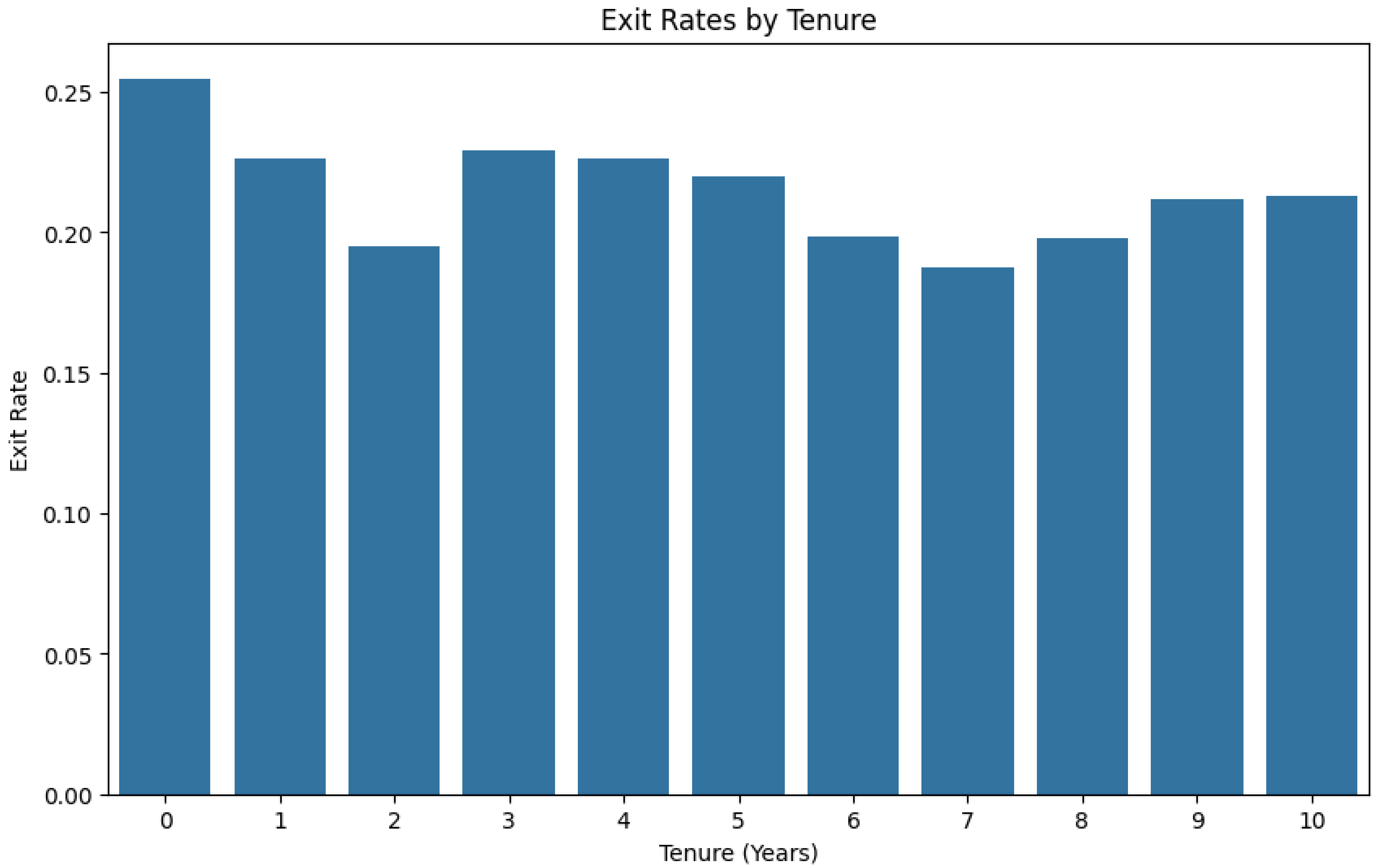


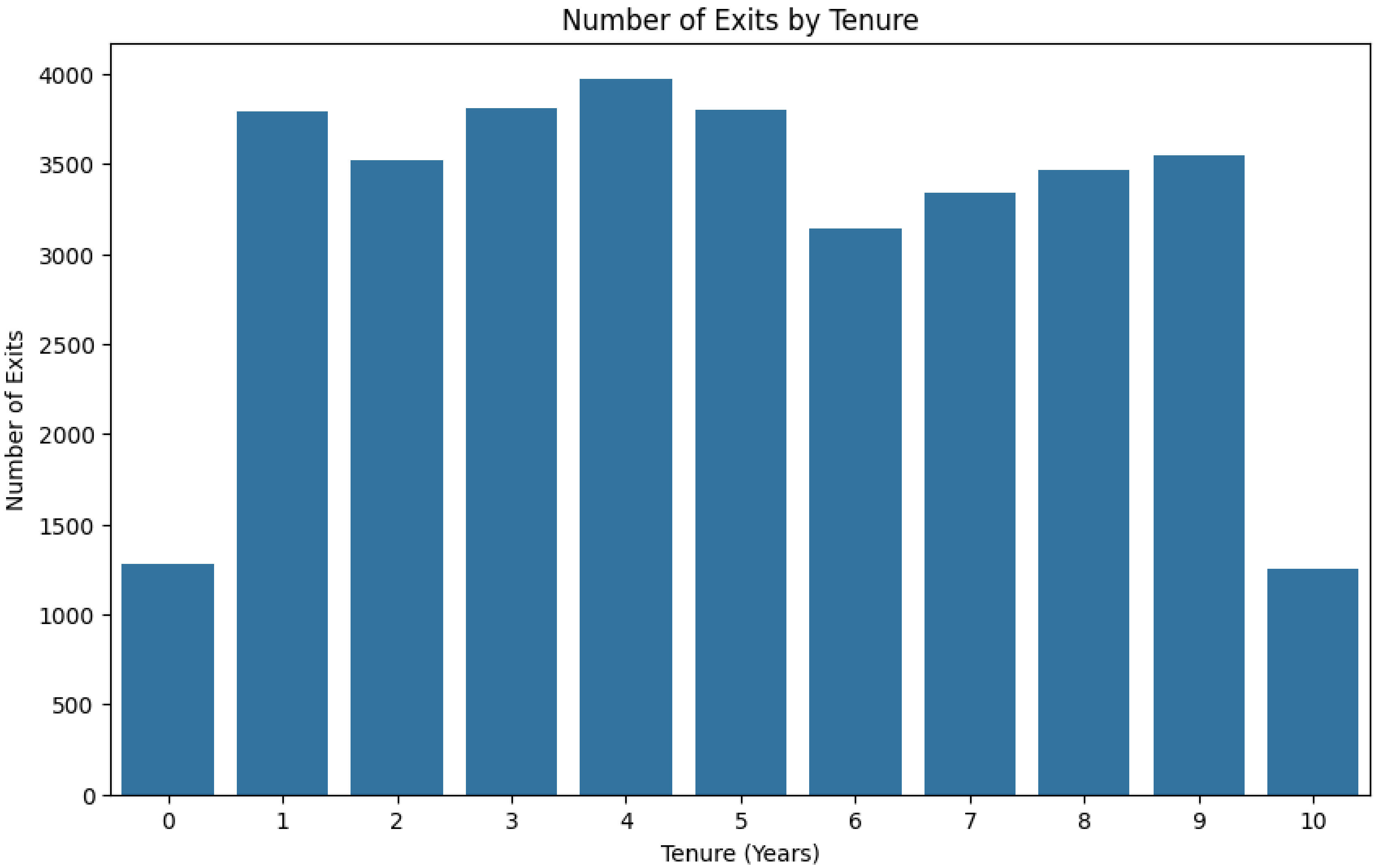
In [ ]:
```
# 8
#  Calculate the exit rates for different tenure groups
tenure_exit_rate = data.groupby('Tenure')['Exited'].mean()
print("Exit Rates by Tenure:\n", tenure_exit_rate)

# Calculate the count of exits for different tenure groups
tenure_exit_count = data.groupby('Tenure')['Exited'].sum()
```

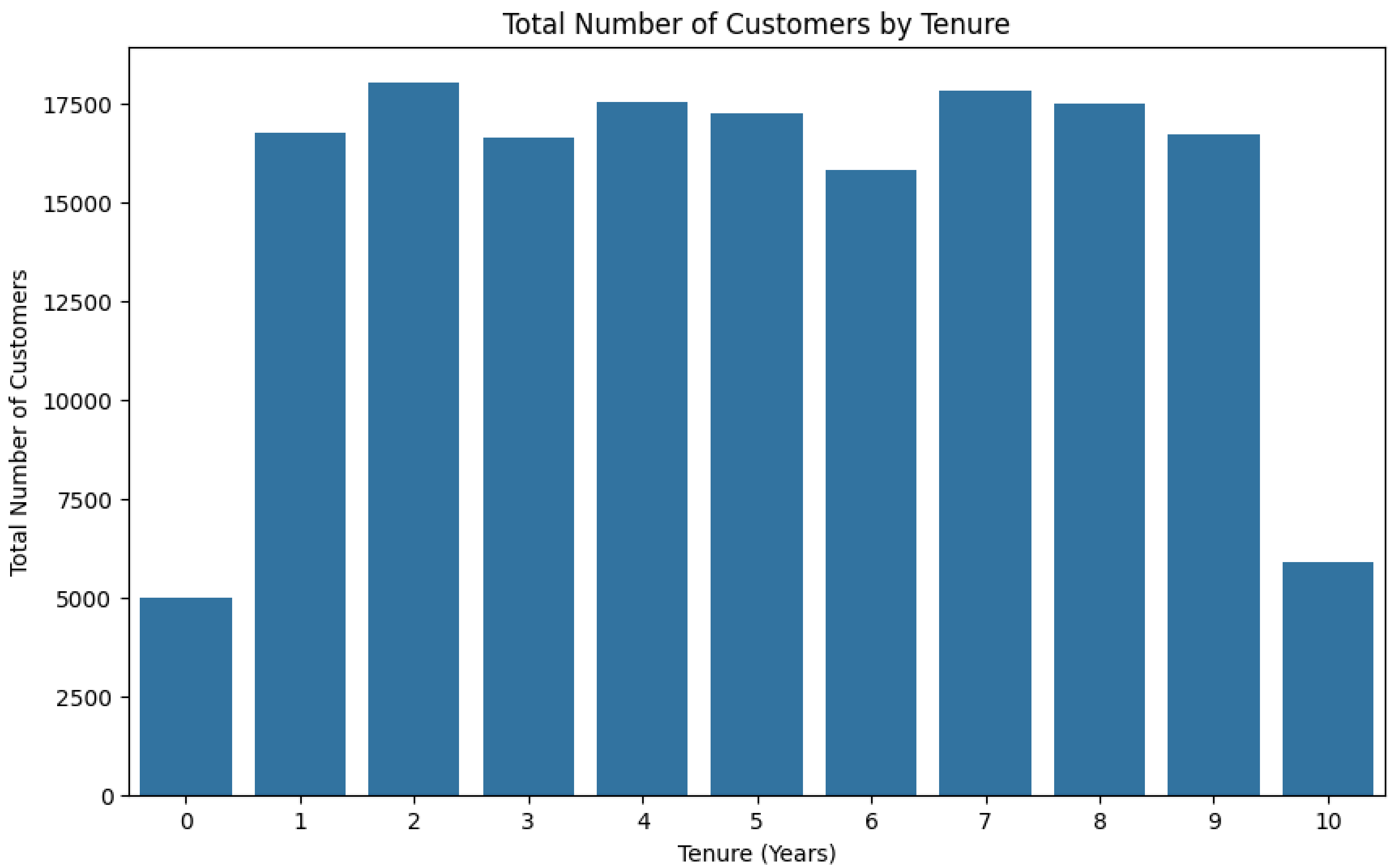
```python
print("Exit Counts by Tenure:\n", tenure_exit_count)

# Calculate the total number of customers in different tenure groups
tenure_total_count = data['Tenure'].value_counts().sort_index()
print("Total Counts by Tenure:\n", tenure_total_count)


# Plot the exit rates for different tenure groups
plt.figure(figsize=(10, 6))
sns.barplot(x=tenure_exit_rate.index, y=tenure_exit_rate.values)
plt.xlabel('Tenure (Years)')
plt.ylabel('Exit Rate')
plt.title('Exit Rates by Tenure')
plt.show()

# Plot the count of exits for different tenure groups
plt.figure(figsize=(10, 6))
sns.barplot(x=tenure_exit_count.index, y=tenure_exit_count.values)
plt.xlabel('Tenure (Years)')
plt.ylabel('Number of Exits')
plt.title('Number of Exits by Tenure')
plt.show()

# Plot the total number of customers in different tenure groups
plt.figure(figsize=(10, 6))
sns.barplot(x=tenure_total_count.index, y=tenure_total_count.values)
plt.xlabel('Tenure (Years)')
plt.ylabel('Total Number of Customers')
plt.title('Total Number of Customers by Tenure')
plt.show()
```

```
Exit Rates by Tenure:
 Tenure
0     0.25
1     0.23
2     0.19
3     0.23
4     0.23
5     0.22
6     0.20
7     0.19
8     0.20
9     0.21
10    0.21
Name: Exited, dtype: float64
Exit Counts by Tenure:
 Tenure
0     1276
1     3790
2     3516
3     3810
4     3974
5     3800
6     3145
7     3341
8     3468
9     3544
10    1257
Name: Exited, dtype: int64
Total Counts by Tenure:
 Tenure
0      5007
1     16760
2     18045
3     16630
4     17554
5     17268
6     15822
7     17810
8     17520
9     16709
```

```
10     5909
Name: count, dtype: int64
```




Number of Exits by Tenure
Number of Exits
4000
3500
3000
2500
2000
1500
1000
500
0
0
1
2
3
4
5
6
7
8
9
10
Tenure (Years)



PHASE 2

In [ ]:
```
# Separate features (X) and target (y)
X = df.drop(['Exited', 'id', 'CustomerId', 'Surname'], axis=1)  # Dropping unnecessary columns
y = df['Exited']
```

```python
# Create train-test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Verify columns
print("Columns after split:")
print(X_train.columns.tolist())
```

```
Columns after split:
['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSa
lary']
```

In [ ]:

```python
from sklearn.preprocessing import LabelEncoder, StandardScaler
import pandas as pd

# 1. Encode Gender using Label Encoder
label_encoder = LabelEncoder()
X_train['Gender'] = label_encoder.fit_transform(X_train['Gender'])
X_test['Gender'] = label_encoder.transform(X_test['Gender'])

# 2. One-Hot Encode Geography
geography_dummies_train = pd.get_dummies(X_train['Geography'], prefix='Geography')
geography_dummies_test = pd.get_dummies(X_test['Geography'], prefix='Geography')

# Drop one category (France) to avoid multicollinearity
geography_dummies_train = geography_dummies_train.drop('Geography_France', axis=1)
geography_dummies_test = geography_dummies_test.drop('Geography_France', axis=1)

# Add dummy variables to the datasets
X_train = pd.concat([X_train, geography_dummies_train], axis=1)
X_test = pd.concat([X_test, geography_dummies_test], axis=1)

# Drop the original Geography column
X_train = X_train.drop('Geography', axis=1)
X_test = X_test.drop('Geography', axis=1)

# 3. Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
# Convert to DataFrame to maintain column names
X_train_scaled = pd.DataFrame(X_train_scaled, columns=X_train.columns)
X_test_scaled = pd.DataFrame(X_test_scaled, columns=X_test.columns)

# Verify the final shape and data types
print("\nFinal shape of training data:", X_train_scaled.shape)
print("Final columns:", X_train_scaled.columns.tolist())
```

```
Final shape of training data: (132027, 11)
Final columns: ['CreditScore', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'Estimated
Salary', 'Geography_Germany', 'Geography_Spain']
```

Logistic Regression

In [ ]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_auc_score

# Train Logistic Regression
lr_model = LogisticRegression(random_state=42)
lr_model.fit(X_train_scaled, y_train)

# Make predictions
lr_pred = lr_model.predict(X_test_scaled)
lr_pred_proba = lr_model.predict_proba(X_test_scaled)[:,1]

# Evaluate the model
print("Logistic Regression Results:")
print("--------------------------")
print(f"Accuracy: {accuracy_score(y_test, lr_pred):.4f}")
print(f"ROC-AUC: {roc_auc_score(y_test, lr_pred_proba):.4f}")
print("\nClassification Report:")
print(classification_report(y_test, lr_pred))
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, lr_pred))
```

```
Logistic Regression Results:
---------------------------
Accuracy: 0.8356
ROC-AUC: 0.8180

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.95      0.90     26052
           1       0.70      0.39      0.50      6955

    accuracy                           0.84     33007
   macro avg       0.78      0.67      0.70     33007
weighted avg       0.82      0.84      0.82     33007


Confusion Matrix:
[[24877  1175]
 [ 4253  2702]]
```

Gradient Boosting

In [ ]:

```
from sklearn.ensemble import GradientBoostingClassifier

# Train Gradient Boosting model
print("Training Gradient Boosting model...")
gb_model = GradientBoostingClassifier(random_state=42)
gb_model.fit(X_train_scaled, y_train)

# Make predictions
gb_pred = gb_model.predict(X_test_scaled)
gb_pred_proba = gb_model.predict_proba(X_test_scaled)[:,1]

# Evaluate the model
print("\nGradient Boosting Results:")
print("------------------------")
print(f"Accuracy: {accuracy_score(y_test, gb_pred):.4f}")
print(f"ROC-AUC: {roc_auc_score(y_test, gb_pred_proba):.4f}")
print("\nClassification Report:")
```

```
print(classification_report(y_test, gb_pred))
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, gb_pred))
```

```
Training Gradient Boosting model...

Gradient Boosting Results:
------------------------
Accuracy: 0.8663
ROC-AUC: 0.8899

Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.95      0.92     26052
           1       0.75      0.55      0.63      6955

    accuracy                           0.87     33007
   macro avg       0.82      0.75      0.78     33007
weighted avg       0.86      0.87      0.86     33007


Confusion Matrix:
[[24796  1256]
 [ 3158  3797]]
```

markdown

Model Selection and Analysis for Retention Risk Assessment

In our Retention Risk Assessment project, we aimed to predict customer churn, identifying which customers are likely to leave the bank. To tackle this, we chose two machine learning models: **Logistic Regression** and **Gradient Boosting**. Here's a closer look at why we selected these models and an analysis of their results.

Why We Chose These Models

1. **Logistic Regression**:

- **Simplicity and Interpretability**: Logistic Regression is straightforward, offering clear insights into how different features affect the likelihood of a customer churning. This interpretability is especially useful for stakeholders who need to understand the reasoning behind predictions.
- **Establishing a Baseline**: Logistic Regression serves as a reliable baseline model in binary classification problems like this one. It allows us to set a standard accuracy level and directly compare it to more complex models.
- **Efficiency**: Logistic Regression is computationally efficient, making it a good starting point to explore the dataset's predictive potential quickly.

2. **Gradient Boosting**:

- **Higher Predictive Power**: Gradient Boosting is an ensemble model that combines multiple weaker models to improve performance. This approach often leads to better accuracy, especially on complex datasets like those involved in customer churn.
- **Capturing Complex Relationships**: Unlike Logistic Regression, Gradient Boosting can uncover non-linear patterns in data, which are likely important in predicting customer behavior.
- **Handling Imbalanced Data**: Since churn datasets are often imbalanced (more non-churning than churning customers), Gradient Boosting's flexibility in handling varying data distributions makes it well-suited to the task.

Results Analysis

After training and testing these models on our bank churn dataset, we achieved the following metrics:

- **Logistic Regression**:
  - **Accuracy**: 83.56%
  - **ROC-AUC**: 81.80%
- **Gradient Boosting**:
  - **Accuracy**: 86.63%
  - **ROC-AUC**: 88.99%

1. **Accuracy Comparison**:

- Gradient Boosting achieved a slightly higher accuracy (86.63%) compared to Logistic Regression (83.56%). This suggests that Gradient Boosting was more effective at correctly identifying both churning and non-churning customers, likely due to its ability to capture more nuanced patterns in the data.

2. **ROC-AUC Comparison**:

- The ROC-AUC score, which measures the model's ability to distinguish between classes, was also higher for Gradient Boosting (88.99%) than for Logistic Regression (81.80%). This improved discrimination is valuable for our project, as it reflects a stronger ability to identify potential churners with confidence.

Conclusion

Using both Logistic Regression and Gradient Boosting gave us complementary insights. Logistic Regression provided a solid, interpretable baseline, while Gradient Boosting achieved higher accuracy and captured complex relationships in the data. Together, these models give us a well-rounded perspective on customer churn, supporting our goal to make informed decisions in our retention strategies.