```python
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from scipy.stats import chi2, chi2_contingency, ttest_ind, levene

# Loading Dataset
data= pd.read_csv('Bank-Records.csv')
data.head()
```

```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age
\
0          1    15634602  Hargrave          619    France  Female   42

1          2    15647311      Hill          608     Spain  Female   41

2          3    15619304      Onio          502    France  Female   42

3          4    15701354      Boni          699    France  Female   39

4          5    15737888  Mitchell          850     Spain  Female   43


   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1

   EstimatedSalary  Exited  Complain  Satisfaction Score Card Type  \
0        101348.88       1         1                   2   DIAMOND
1        112542.58       0         1                   3   DIAMOND
2        113931.57       1         1                   3   DIAMOND
3         93826.63       0         0                   5      GOLD
4         79084.10       0         0                   5      GOLD

   Point Earned
0           464
1           456
2           377
3           350
4           425
```

```python
print(data.shape)
print(f'There are {data.shape[0]} rows & {data.shape[1]} columns')
```

```
(10000, 18)
There are 10000 rows & 18 columns
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 18 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   RowNumber           10000 non-null  int64  
 1   CustomerId          10000 non-null  int64  
 2   Surname             10000 non-null  object 
 3   CreditScore         10000 non-null  int64  
 4   Geography           10000 non-null  object 
 5   Gender              10000 non-null  object 
 6   Age                 10000 non-null  int64  
 7   Tenure              10000 non-null  int64  
 8   Balance             10000 non-null  float64
 9   NumOfProducts       10000 non-null  int64  
 10  HasCrCard           10000 non-null  int64  
 11  IsActiveMember      10000 non-null  int64  
 12  EstimatedSalary     10000 non-null  float64
 13  Exited              10000 non-null  int64  
 14  Complain            10000 non-null  int64  
 15  Satisfaction Score  10000 non-null  int64  
 16  Card Type           10000 non-null  object 
 17  Point Earned        10000 non-null  int64  
dtypes: float64(2), int64(12), object(4)
memory usage: 1.4+ MB
```

Originally there are 12 integer columns, 2 float columns & 4 string columns

```
# Remove Columns RowNumber and CustomerId from dataset
data.drop(['RowNumber', 'CustomerId','Surname'], axis = 1, inplace = 
True)

# Changing data types
data['HasCrCard'] = data['HasCrCard'].astype('category')
data['IsActiveMember'] = data['IsActiveMember'].astype('category')
data['Exited'] = data['Exited'].astype('category')
data['Complain'] = data['Complain'].astype('category')
data['Satisfaction Score'] = data['Satisfaction 
Score'].astype('category')
data['Gender'] = data['Gender'].astype('category')
data['Geography'] = data['Geography'].astype('category')
data['Card Type'] = data['Card Type'].astype('category')

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 15 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   CreditScore         10000 non-null  int64
 1   Geography           10000 non-null  category
 2   Gender              10000 non-null  category
 3   Age                 10000 non-null  int64
 4   Tenure              10000 non-null  int64
 5   Balance             10000 non-null  float64
 6   NumOfProducts       10000 non-null  int64
 7   HasCrCard           10000 non-null  category
 8   IsActiveMember      10000 non-null  category
 9   EstimatedSalary     10000 non-null  float64
 10  Exited              10000 non-null  category
 11  Complain            10000 non-null  category
 12  Satisfaction Score  10000 non-null  category
 13  Card Type           10000 non-null  category
 14  Point Earned        10000 non-null  int64
dtypes: category(8), float64(2), int64(5)
memory usage: 626.3 KB
```

```
data.describe().T
```

```
                   count           mean           std     min
25%  \
CreditScore      10000.0     650.528800     96.653299  350.00
584.00
Age              10000.0      38.921800     10.487806   18.00
32.00
Tenure           10000.0       5.012800      2.892174    0.00
3.00
Balance          10000.0   76485.889288  62397.405202    0.00
0.00
NumOfProducts    10000.0       1.530200      0.581654    1.00
1.00
EstimatedSalary  10000.0  100090.239881  57510.492818   11.58
51002.11
Point Earned     10000.0     606.515100    225.924839  119.00
410.00

                       50%          75%        max
CreditScore        652.000     718.0000     850.00
Age                 37.000      44.0000      92.00
Tenure               5.000       7.0000      10.00
Balance          97198.540  127644.2400  250898.09
NumOfProducts        1.000       2.0000       4.00
EstimatedSalary  100193.915  149388.2475  199992.48
Point Earned       605.000     801.0000    1000.00
```

1. Minimum credit is 350 and maximum is 850. Average of credit is 650.5288
2. Given data is for age between 18 to 92.
3. Tenure is given between 0 to 10 years, where average tenure is 5 years
4. In given data balance of a customer is between 0 to 2 lakh 50 thousand.
5. There are maximum 4 products available
6. There are maximum 1000 points earned using credit card

```
data.describe(include = ['object','category'])
```

```
       Geography Gender  HasCrCard  IsActiveMember  Exited  
Complain  \
count      10000  10000      10000           10000   10000      10000   

unique         3      2          2               2       2          2   

top       France   Male          1               1       0          0   

freq        5014   5457       7055            5151    7962       7956   


        Satisfaction Score Card Type  
count                10000     10000  
unique                   5         4  
top                      3   DIAMOND  
freq                  2042      2507  
```

1. Three countries data is given. Most of the data is from France.
2. Mostly people has given satisfaction score 3.
3. There are 4 types of card. Most of the people uses DIAMOND card.

```
# Checking null values
data.isna().sum().sum()

0
```

There are no null values

```
# Checking duplicated values
data.duplicated().sum()

0
```

There are no duplicated values

```
numeric_columns = data.select_dtypes(include = ['int64', 'float64'])
numeric_columns

      CreditScore  Age  Tenure    Balance  NumOfProducts  
EstimatedSalary  \
0             619   42       2       0.00              1   
101348.88
```

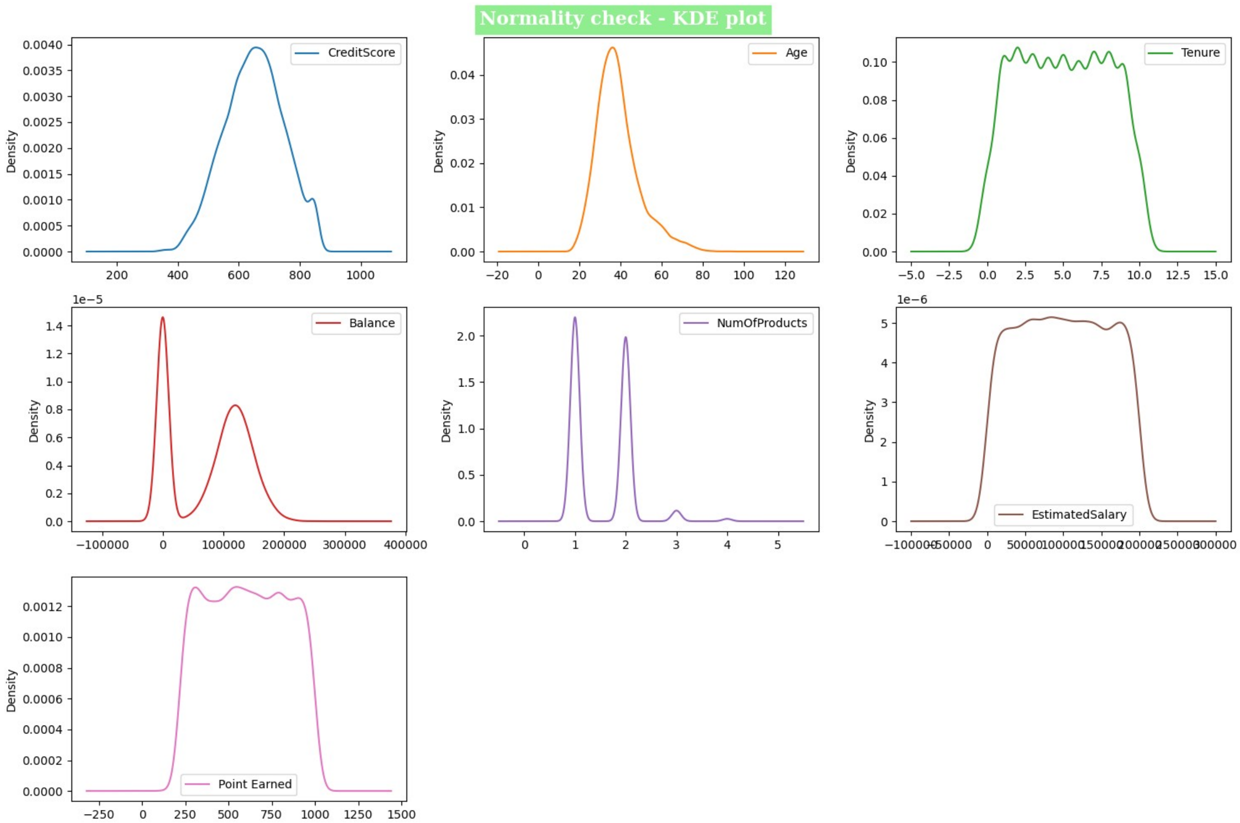
```
1               608   41        1   83807.86               1
112542.58
2               502   42        8  159660.80               3
113931.57
3               699   39        1       0.00               2
93826.63
4               850   43        2  125510.82               1
79084.10
...             ...  ...      ...        ...             ...
...
9995            771   39        5       0.00               2
96270.64
9996            516   35       10   57369.61               1
101699.77
9997            709   36        7       0.00               1
42085.58
9998            772   42        3   75075.31               2
92888.52
9999            792   28        4  130142.79               1
38190.78

      Point Earned
0              464
1              456
2              377
3              350
4              425
...            ...
9995           300
9996           771
9997           564
9998           339
9999           911

[10000 rows x 7 columns]
```

```
category_col = data.select_dtypes(exclude = ['int64', 'float64'])
category_col
```

```
     Geography  Gender HasCrCard IsActiveMember Exited Complain  \
0       France  Female         1              1      1        1
1        Spain  Female         0              1      0        1
2       France  Female         1              0      1        1
3       France  Female         0              0      0        0
4        Spain  Female         1              1      0        0
...        ...     ...       ...            ...    ...      ...
9995    France    Male         1              0      0        0
9996    France    Male         1              1      0        0
9997    France  Female         0              1      1        1
9998   Germany    Male         1              0      1        1
```

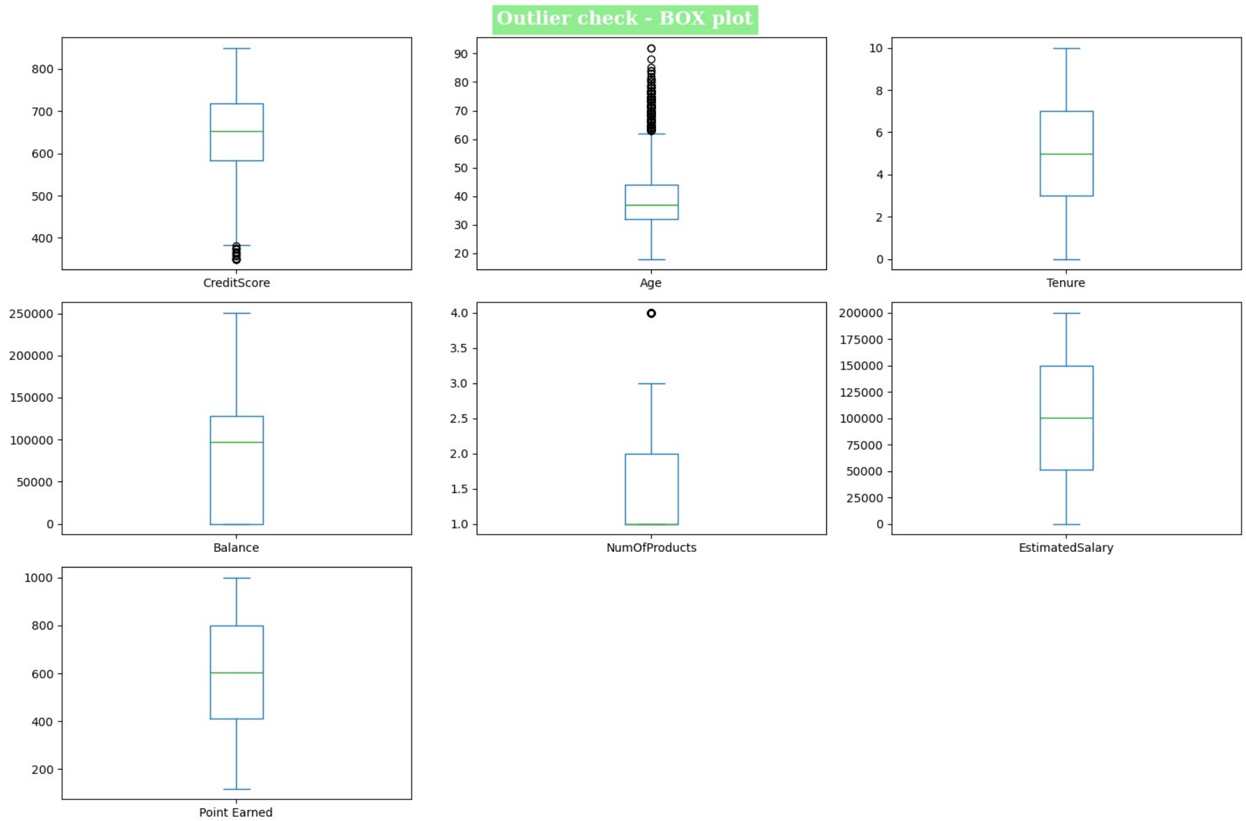
```
9999    France  Female         1              0      0        0

     Satisfaction Score Card Type
0                     2   DIAMOND
1                     3   DIAMOND
2                     3   DIAMOND
3                     5      GOLD
4                     5      GOLD
...                 ...       ...
9995                  1   DIAMOND
9996                  5  PLATINUM
9997                  3    SILVER
9998                  2      GOLD
9999                  3   DIAMOND

[10000 rows x 8 columns]
```

```
plt.rcParams['figure.figsize'] = [15, 10]

# Collect columns that are 'int64' or 'float64' dtype
numeric_cols = [col for col in data.columns if data[col].dtype in
['int64', 'float64']]

# Plot KDE for each numeric column
data[numeric_cols].plot(kind='kde', subplots=True, layout=(3, 3),
sharex=False)

# Set the overall title for the entire figure
plt.suptitle('Normality check - KDE plot', fontsize=16,
fontfamily='serif', fontweight='bold', backgroundcolor='lightgreen',
color='w')
plt.xticks(rotation = 90)
plt.tight_layout()  # Adjust the layout to make room for the suptitle
plt.show()
```



From above graph none of the columns except credit score & age are normally distributed

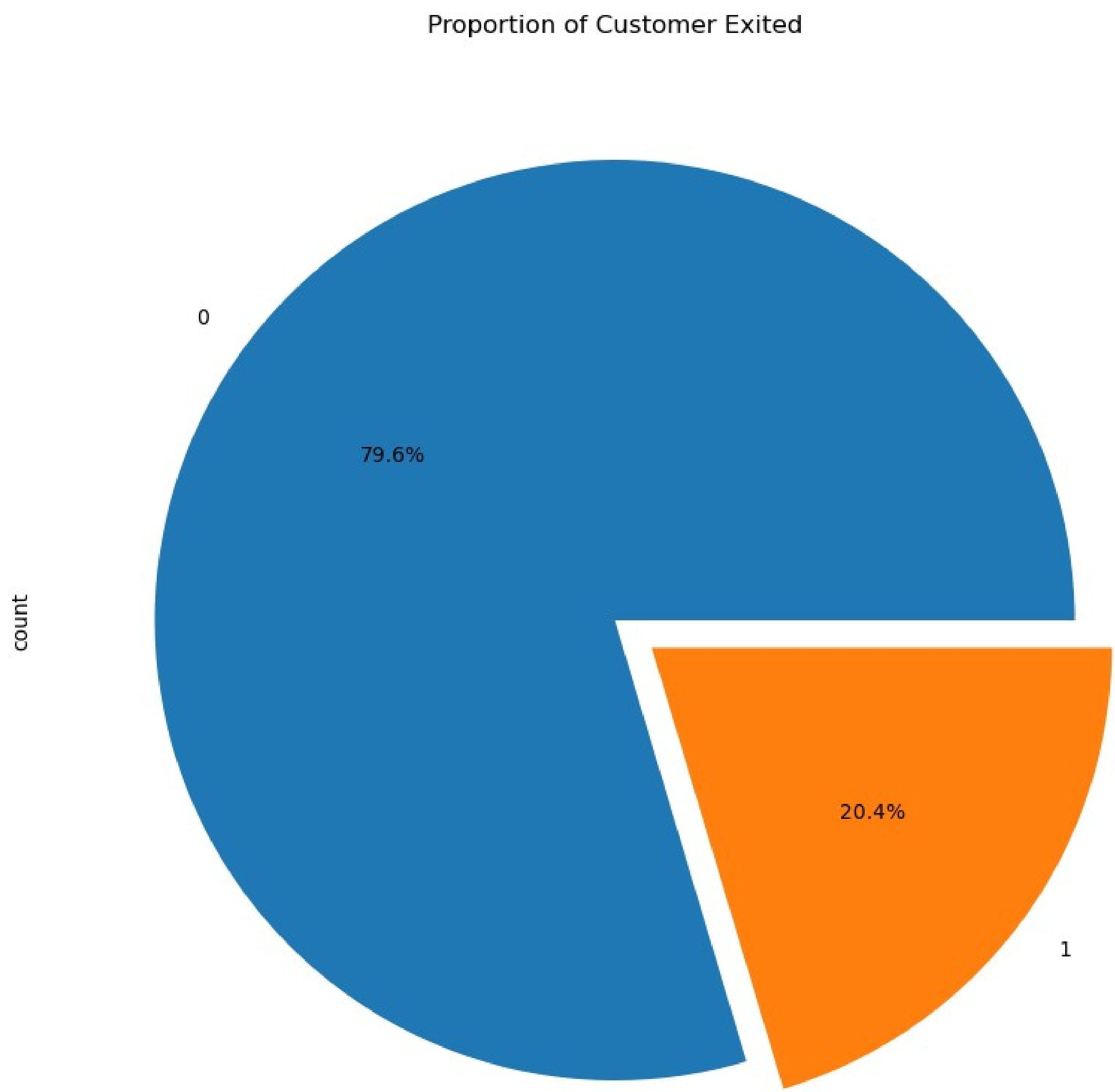
```
# Check Outliers in the numeric Data
plt.rcParams['figure.figsize'] = (15,10)
# Collect numeric col
numeric_col = [col for col in data.columns if data[col].dtypes in
['int64', 'float64']]

# Plot
data[numeric_col].plot(kind = 'box', subplots = True, layout = (3,3),
sharex = False)
# Set the overall title for the entire figure
plt.suptitle('Outlier check - BOX plot', fontsize=16,
fontfamily='serif', fontweight='bold', backgroundcolor='lightgreen',
color='w')
plt.xticks(rotation = 90)
plt.tight_layout()  # Adjust the layout to make room for the suptitle
plt.show()
```



There are outliers present in column age, credit score.

Only one outlier is there in no of Products

```
# Check proportion of customer exited
data['Exited'].value_counts().plot.pie(autopct = '%.1f%%', explode =
(0,0.1))
plt.title('Proportion of Customer Exited')
plt.show()
```

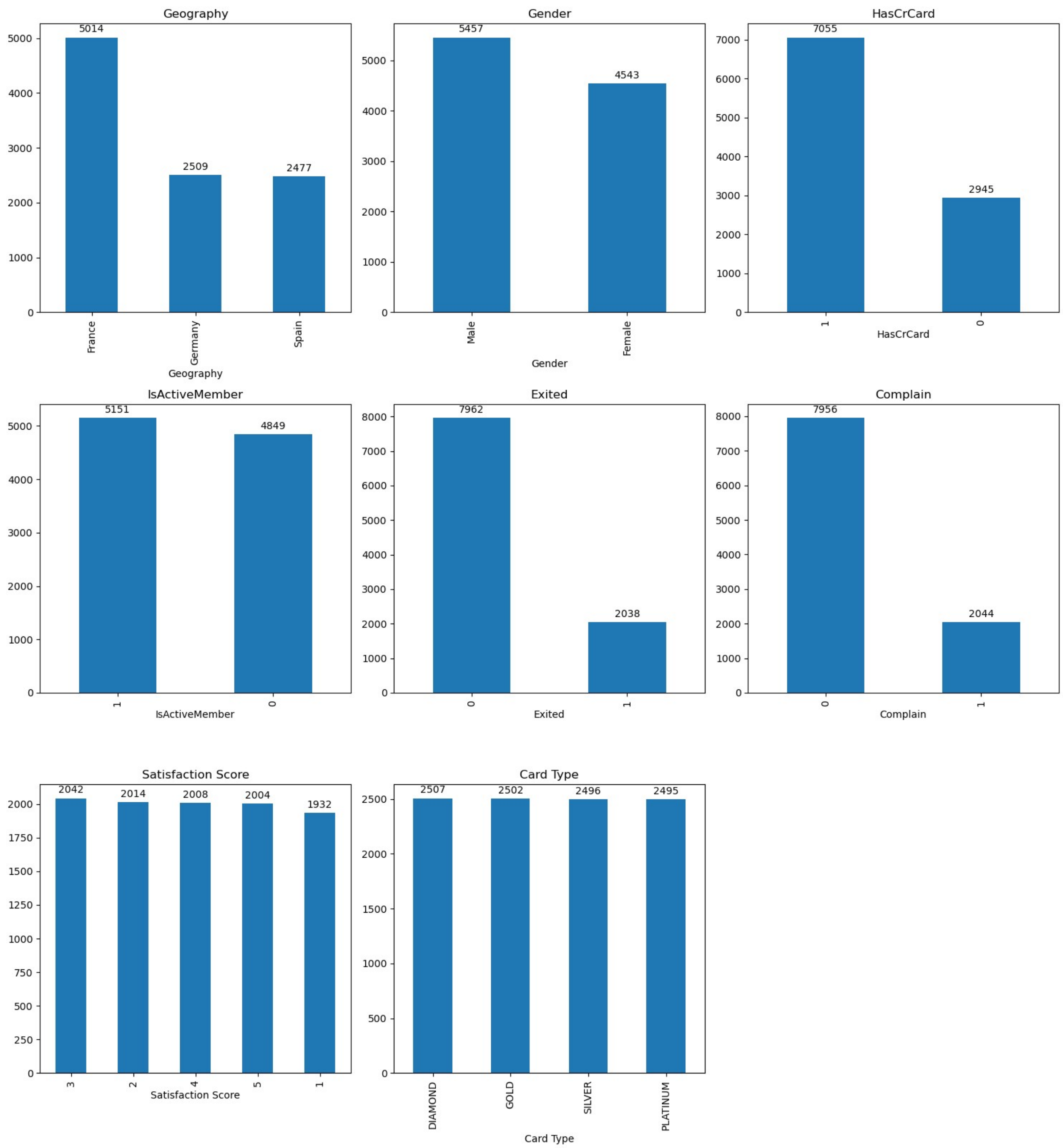


20.4 % of the customer have exited the bank

```
# Collect columns that are not 'int64' or 'float64' dtype
categorical_cols = [col for col in data.columns if data[col].dtype in
['category']]

# Calculate number of rows and columns for subplots
num_plots = len(categorical_cols)
nrows = (num_plots // 3) + 1 if num_plots % 3 != 0 else num_plots // 3
ncols = 3

# Create subplots
```

```
fig, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=(15, 18))
axes = axes.flatten()  # Flatten the 2D array of axes for easy
iteration

# Plot bar for each categorical column
for i, col in enumerate(categorical_cols):
    plot = data[col].value_counts().plot(kind='bar', ax=axes[i],
title=col)
    axes[i].set_xticklabels(axes[i].get_xticklabels(), rotation=90)


# Add values on top of bars
    for p in plot.patches:
        height = int(p.get_height())
        plot.annotate(f'{height}',
                      xy=(p.get_x()+ p.get_width() / 2, height),
                      xytext=(0, 3),  # 3 points vertical offset
                      textcoords='offset points',
                      ha='center', va='bottom')
# Hide any unused subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

# Set the overall title for the entire figure
fig.suptitle('Count check - BAR plot', fontsize=16,
fontfamily='serif', fontweight='bold', backgroundcolor='lightgreen',
color='w')

# Adjust the layout to make room for the suptitle
plt.tight_layout(rect=[0, 0.03, 1, 0.95])  # Adjust rect to not
overlap with suptitle
plt.show()
```

Count check - BAR plot



1. 5014 customers are from France followed by Germany and Spain who has 2509, 2477 customers respectively
2. 54% customers are male
3. 70.55% people uses credit card
4. 20% of the people have exited the bank

5. 20.44% of the people have filed the complain.

6. Most of the people (2042) have given satisfaction score 3 followed by scores 2, 4, 5, 1

7. Most of the people uses Diamond card(2507) & Gold(2503) followed by Silver & Platinum

```
# Checking the count in each categorical variable
for col in category_col:
    val = data[col].value_counts()
    print(val)
    print('*'*50)
```

```
Geography
France     5014
Germany    2509
Spain      2477
Name: count, dtype: int64
**************************************************
Gender
Male      5457
Female    4543
Name: count, dtype: int64
**************************************************
HasCrCard
1    7055
0    2945
Name: count, dtype: int64
**************************************************
IsActiveMember
1    5151
0    4849
Name: count, dtype: int64
**************************************************
Exited
0    7962
1    2038
Name: count, dtype: int64
**************************************************
Complain
0    7956
1    2044
Name: count, dtype: int64
**************************************************
Satisfaction Score
3    2042
2    2014
4    2008
5    2004
```

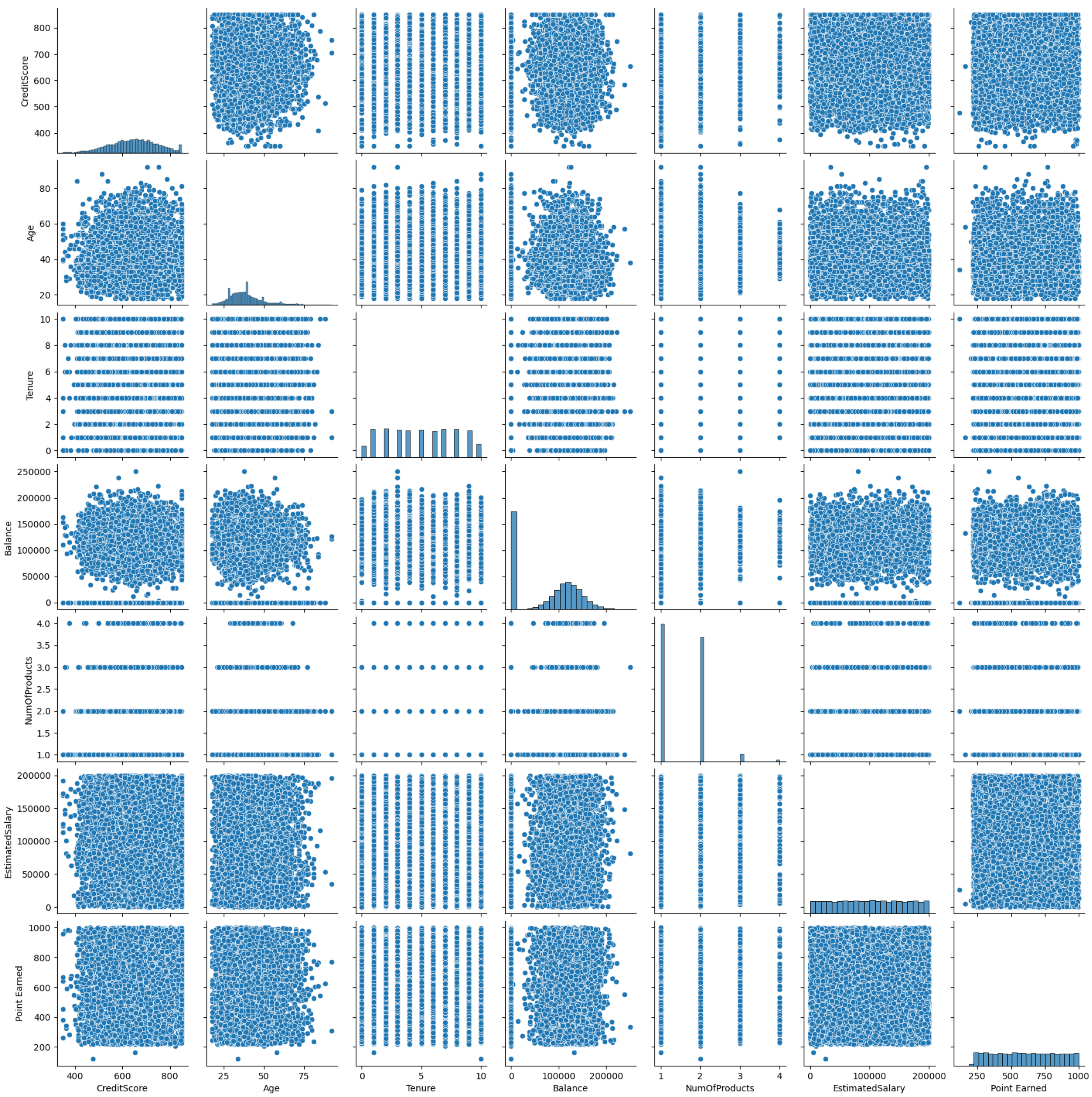
```
1    1932
Name: count, dtype: int64
**************************************************
Card Type
DIAMOND     2507
GOLD        2502
SILVER      2496
PLATINUM    2495
Name: count, dtype: int64
**************************************************
```

```python
# Correation check
numeric_columns.corr()
```

```
                 CreditScore       Age    Tenure   Balance   
NumOfProducts  \
CreditScore         1.000000 -0.003965  0.000842  0.006268   
0.012238   
Age                -0.003965  1.000000 -0.009997  0.028308      -
0.030680   
Tenure              0.000842 -0.009997  1.000000 -0.012254   
0.013444   
Balance             0.006268  0.028308 -0.012254  1.000000      -
0.304180   
NumOfProducts       0.012238 -0.030680  0.013444 -0.304180   
1.000000   
EstimatedSalary    -0.001384 -0.007201  0.007784  0.012797   
0.014204   
Point Earned        0.000077  0.002222 -0.010196  0.014608      -
0.015330   

                 EstimatedSalary  Point Earned  
CreditScore            -0.001384      0.000077  
Age                    -0.007201      0.002222  
Tenure                  0.007784     -0.010196  
Balance                 0.012797      0.014608  
NumOfProducts           0.014204     -0.015330  
EstimatedSalary         1.000000     -0.001515  
Point Earned           -0.001515      1.000000  
```

```python
sns.pairplot(numeric_columns)
```

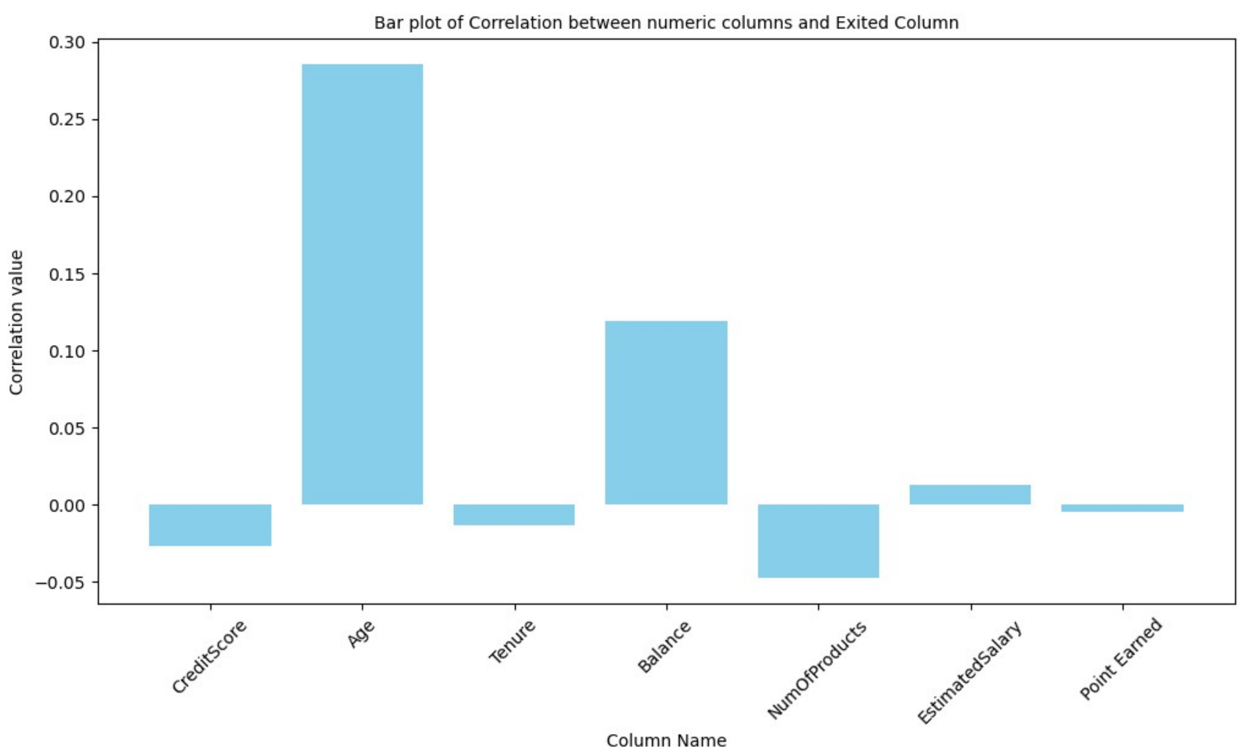
```
<seaborn.axisgrid.PairGrid at 0x12a2c5e9810>
```




```python
# Check correlation between exited variable and other numeric columns

numeric_col = [col for col in data.columns if data[col].dtypes in
['int64', 'float64']]
correlation = {}
for col in numeric_col:
    corr = data[col].corr(data['Exited'])
    correlation[col] = round(corr,4)
print(correlation)
```

```
{'CreditScore': -0.0268, 'Age': 0.2853, 'Tenure': -0.0137, 'Balance':
0.1186, 'NumOfProducts': -0.0476, 'EstimatedSalary': 0.0125, 'Point
Earned': -0.0046}
```

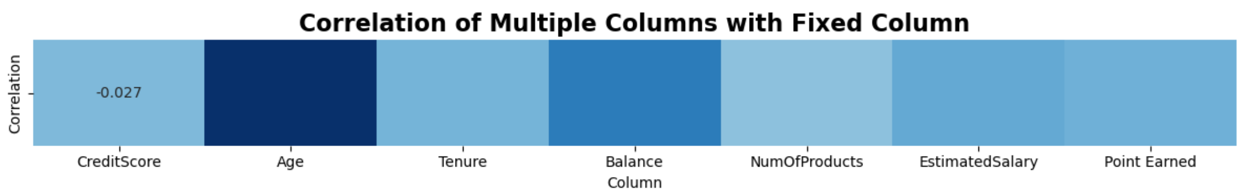
```
# Visualization of correlation between numeric columns with Exited
column

column = list(correlation.keys())
values = list(correlation.values())
# Plotting
plt.figure(figsize = (12,6))
plt.bar(column, values, color = 'skyblue')
# Title
plt.xticks(rotation = 45)
plt.title('Bar plot of Correlation between numeric columns and Exited
Column', fontsize = 10)
plt.ylabel('Correlation value')
plt.xlabel('Column Name')
plt.show()
```



1. There is positive correlation between age and people exiting the bank followed by balance
2. There is negative correlation between number of products purchased by customer and people exiting the bank, same is happening for credit score and tenure

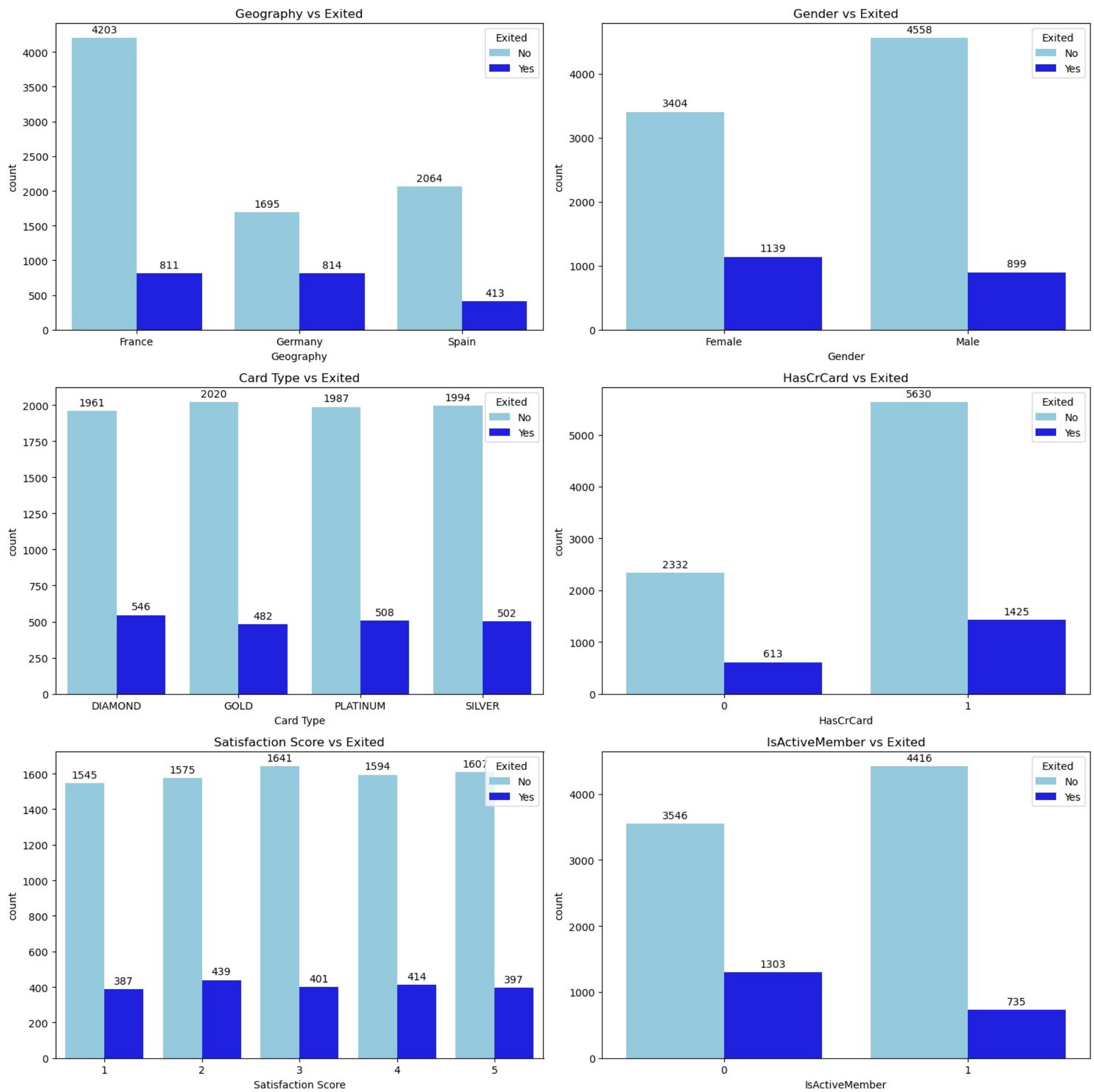
```
# Correlation heatmap
```

```
# Convert dictionary to DataFrame for heatmap
corr_df = pd.DataFrame(list(correlation.items()), columns=['Column',
'Correlation'])
corr_df = corr_df.set_index('Column').transpose()

# Create the heatmap
plt.figure(figsize=(12, 2))
sns.heatmap(corr_df, annot=True, cmap='Blues', center=0, cbar=False)

# Add title
plt.title('Correlation of Multiple Columns with Fixed Column',
fontsize=16, fontweight='bold')

# Show the plot
plt.tight_layout()
plt.show()
```



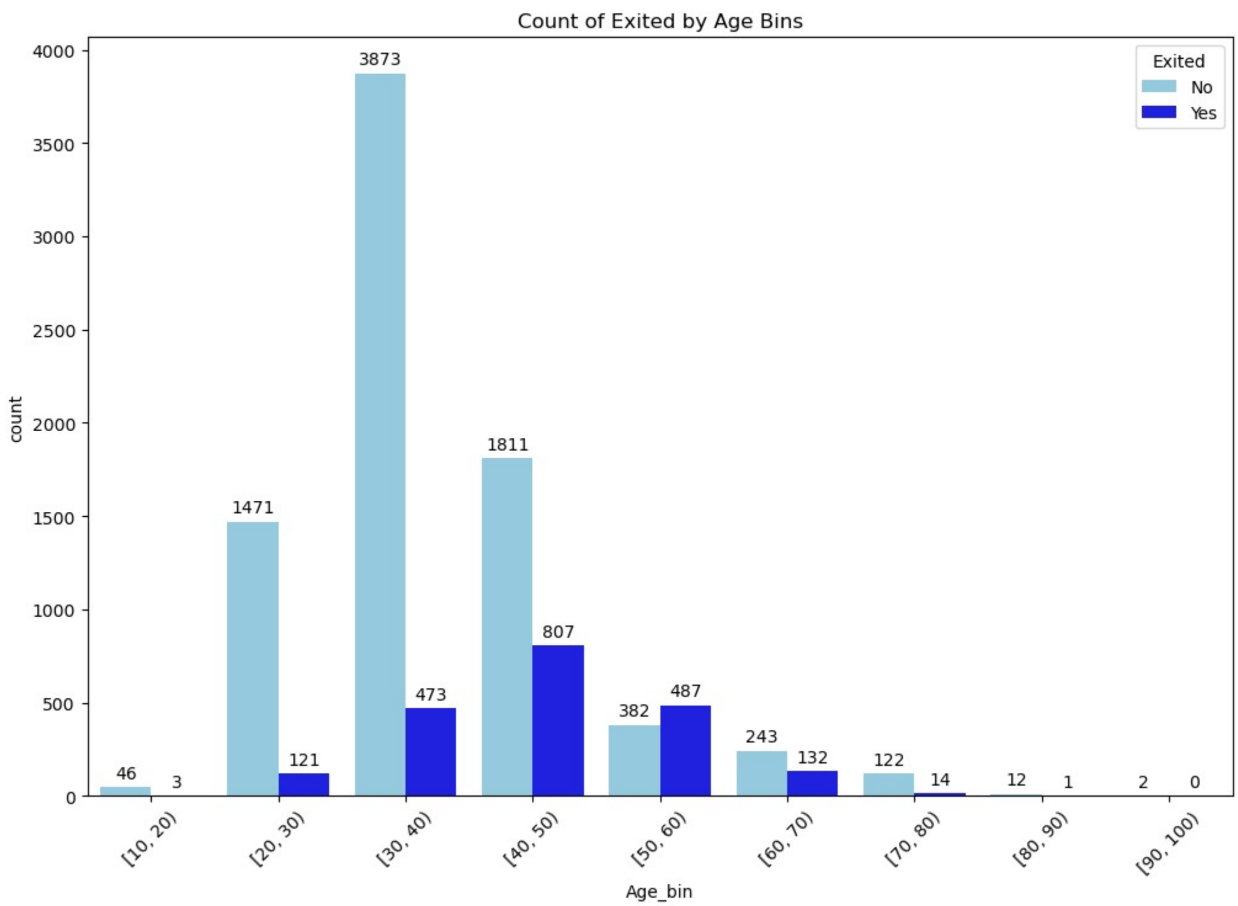

```
# Covert Exited column
dict1 = {1: 'Yes', 0: 'No'}
data['Exited'] = data['Exited'].map(dict1)

column = ['Geography', 'Gender', 'Card Type', 'HasCrCard',
'Satisfaction Score','IsActiveMember']
# Plotting category verses exited
# Calculate number of rows and columns for subplots
num_plots = len(column)
nrows = (num_plots + 1) // 2
ncols = 2
# Define custom colors for the hue categories
custom_palette = {'Yes': 'blue', 'No': 'skyblue'}

# Create subplots
fig, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=(15, 15))
axes = axes.flatten()  # Flatten the 2D array of axes for easy
iteration

for i, col in enumerate(column):
    plot = sns.countplot(data=data, x=col, hue='Exited',
ax=axes[i],palette = custom_palette)
    axes[i].set_title(f'{col} vs Exited')

 # Add values on top of bars
    for p in plot.patches:
```

```
        height = int(p.get_height())
        plot.annotate(f'{height}',
                      xy=(p.get_x()+ p.get_width() / 2, height),
                      xytext=(0, 3),  # 3 points vertical offset
                      textcoords='offset points',
                      ha='center', va='bottom')
plt.tight_layout()
plt.show()
```



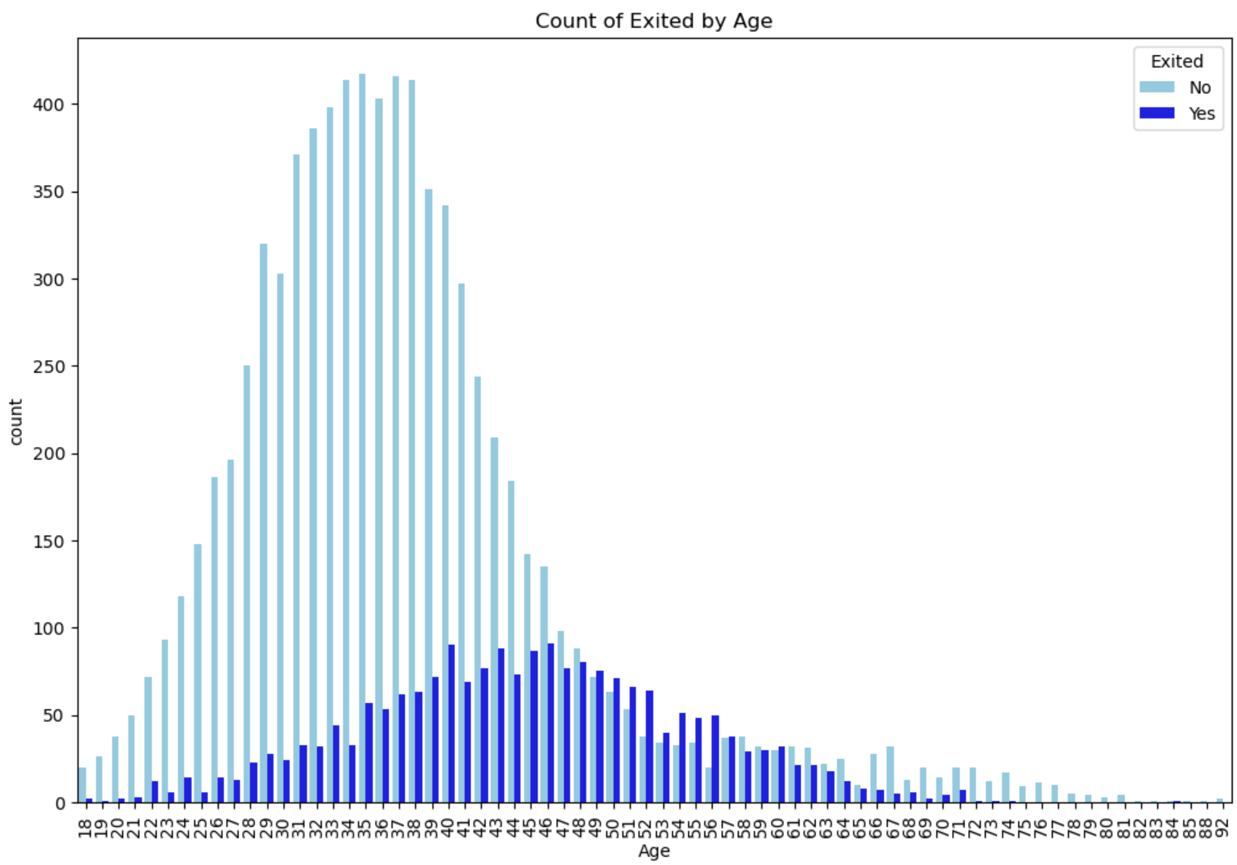

```
# Age vs Exited column
plt.figure(figsize = (12,8))
```

```python
bins = [10,20,30,40,50,60,70,80,90,100]
data['Age_bin'] = pd.cut(data.Age, bins = bins, right = False)
plot = sns.countplot(data = data, x = 'Age_bin', hue = 'Exited',
palette = {'Yes': 'blue', 'No': 'skyblue'})
# Add bin values on top of bars
for p in plot.patches:
    height = int(p.get_height())
    plot.annotate(f'{height}',
                  xy=(p.get_x() + p.get_width() / 2, height),
                  xytext=(0, 3),  # 3 points vertical offset
                  textcoords='offset points',
                  ha='center', va='bottom')

plt.title('Count of Exited by Age Bins')

plt.xticks(rotation= 45)
plt.show()
```



1. Most of the customers are from age group 30 to 40
2. Most of the customers who have left the bank are from age group 40 to 60
3. There are very few customers aged above 80

```python
plt.figure(figsize = (12,8))
sns.countplot(data = data, x = 'Age', hue = 'Exited', palette =
{'Yes': 'blue', 'No': 'skyblue'})
plt.xticks(rotation= 90)
plt.title('Count of Exited by Age')
plt.show()
```




```python
# Checking churn by geography
churn_by_geography = data.groupby('Geography')
['Exited'].value_counts(normalize=True)
churn_by_geography
```

```
Geography  Exited
France     No        0.838253
           Yes       0.161747
Germany    No        0.675568
           Yes       0.324432
Spain      No        0.833266
           Yes       0.166734
Name: proportion, dtype: float64
```

Geography and Customer Exit Rates:

1.In France, 16.17% of customers have exited, while 83.83% have not exited.

2.In Germany, 32.44% of customers have exited, while 67.56% have not exited.

3.In Spain, 16.67% of customers have exited, while 83.33% have not exited.

```
# checking churn by gender
churn_by_gender = data.groupby('Gender')
['Exited'].value_counts(normalize=True)
churn_by_gender
```

```
Gender  Exited
Female  No        0.749285
        Yes       0.250715
Male    No        0.835257
        Yes       0.164743
Name: proportion, dtype: float64
```

Gender and Customer Exit Rates:

1.Among female customers, 25.07% have exited, while 74.93% have not exited.

2.Among male customers, 16.47% have exited, while 83.53% have not exited.

```
# # checking churn by tenure
churn_by_tenure = data.groupby('Tenure')
['Exited'].value_counts(normalize = True)
churn_by_tenure
```

```
Tenure  Exited
0       No        0.769976
        Yes       0.230024
1       No        0.775845
        Yes       0.224155
2       No        0.808206
        Yes       0.191794
3       No        0.788900
        Yes       0.211100
4       No        0.794742
        Yes       0.205258
5       No        0.793478
        Yes       0.206522
6       No        0.797311
        Yes       0.202689
7       No        0.827821
        Yes       0.172179
8       No        0.807805
        Yes       0.192195
9       No        0.782520
        Yes       0.217480
10      No        0.793878
```

```
        Yes       0.206122
Name: proportion, dtype: float64
```

Most of the customer with tenure 0 have left the bank

```
# # checking churn by active number or not
churn_by_isacivemember = data.groupby('IsActiveMember')
['Exited'].value_counts(normalize = True)
churn_by_isacivemember

IsActiveMember  Exited
0               No        0.731285
                Yes       0.268715
1               No        0.857309
                Yes       0.142691
Name: proportion, dtype: float64
```

Active Membership and Customer Exit Rates:

1.Among inactive members, 26.87% have exited, while 73.13% have not exited.

2.Among active members, 14.27% have exited, while 85.73% have not exited.

```
# # checking churn by credit card
churn_by_creditcard = data.groupby('HasCrCard')
['Exited'].value_counts(normalize = True)
churn_by_creditcard

HasCrCard  Exited
0          No        0.791851
           Yes       0.208149
1          No        0.798016
           Yes       0.201984
Name: proportion, dtype: float64
```

Credit Card Ownership and Customer Exit Rates:

1.Among customers without a credit card, 20.81% have exited, while 79.19% have not exited.

2.Among customers with a credit card, 20.20% have exited, while 79.80% have not exited.

```
# # checking churn by satisfaction score
churn_by_satisfactionscore = data.groupby('Satisfaction Score')
['Exited'].value_counts(normalize = True)
churn_by_satisfactionscore

Satisfaction Score  Exited
1                   No        0.799689
                    Yes       0.200311
2                   No        0.782026
```

```
                    Yes       0.217974
3                   No        0.803624
                    Yes       0.196376
4                   No        0.793825
                    Yes       0.206175
5                   No        0.801896
                    Yes       0.198104
Name: proportion, dtype: float64
```

```
# Outlier Detection

column = ['CreditScore', 'NumOfProducts','Age']

for col in column:
    Q1= np.percentile(data[col], 25)
    Q3= np.percentile(data[col], 75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5*IQR
    print(f'lower Bound is {lower_bound}')
    upper_bound = Q3 + 1.5*IQR
    print(f'Upper Bound is {upper_bound}')
    thr = pd.DataFrame(data[col][(data[col] < lower_bound) |
(data[col] > upper_bound)])
    print(thr)
    print('*'*50)
```

```
lower Bound is 383.0
Upper Bound is 919.0
      CreditScore
7             376
942           376
1193          363
1405          359
1631          350
1838          350
1962          358
2473          351
2579          365
8154          367
8723          350
8762          350
9210          382
9356          373
9624          350
**************************************************
lower Bound is -0.5
Upper Bound is 3.5
      NumOfProducts
7                 4
```

```
70          4
1254        4
1469        4
1488        4
1701        4
1876        4
2124        4
2196        4
2285        4
2462        4
2499        4
2509        4
2541        4
2614        4
2617        4
2872        4
3152        4
3365        4
3841        4
4013        4
4014        4
4166        4
4260        4
4403        4
4511        4
4516        4
4606        4
4654        4
4748        4
4822        4
5010        4
5137        4
5235        4
5386        4
5700        4
5904        4
6150        4
6172        4
6279        4
6750        4
6875        4
7257        4
7457        4
7567        4
7698        4
7724        4
7729        4
8041        4
8590        4
```

```
8683                4
8850                4
8923                4
9215                4
9255                4
9323                4
9370                4
9411                4
9540                4
9565                4
**************************************************
lower Bound is 14.0
Upper Bound is 62.0
      Age
58     66
85     75
104    65
158    73
181    65
...   ...
9753   68
9765   64
9832   64
9894   77
9936   77

[359 rows x 1 columns]
**************************************************
```

HYPOTHESIS TESTING

Number Of Products Vs Customer Churn

H0 : There is no significant difference between the Number of products customer buying and exiting the bank

H1 : There is significant difference between the Number of products customer buying and exiting the bank

```
Products = pd.crosstab(data['NumOfProducts'], data['Exited'])
Products
```

Exited	No	Yes
NumOfProducts		
1	3675	1409
2	4241	349
3	46	220
4	0	60

```
chi_stat , p_value , dof , expected = chi2_contingency(Products)

print("chi_stat : ",chi_stat)
print("p_value : ",p_value)
print("dof : ",dof)
print("expected : ",expected)

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("There is significant difference between the Number of
products customer buying and exiting the bank")
else:
    print("Fail to Reject Ho")
    print("There is no significant difference between the Number of
products customer buying and exiting the bank")
```

```
chi_stat :  1501.5048306588592
p_value :  0.0
dof :  3
expected :  [[4047.8808 1036.1192]
 [3654.558   935.442 ]
 [ 211.7892   54.2108]
 [  47.772    12.228 ]]
Reject Ho
There is significant difference between the Number of products
customer buying and exiting the bank
```

There is significant difference between the Number of products customer buying and exiting the bank

Active Member Vs Customer Churn

H0: There is no association betweeen Active Customer and exiting the bank

H1: There is an association betweeen Active Customer and exiting the bank

```
active_member = pd.crosstab(data['IsActiveMember'], data['Exited'])
active_member
```

Exited	No	Yes
IsActiveMember		
0	3546	1303
1	4416	735

```
chi_stat , p_value , dof , expected = chi2_contingency(active_member)

print("chi_stat : ",chi_stat)
```

```
print("p_value : ",p_value)
print("dof : ",dof)
print("expected : ",expected)

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("There is an association betweeen Active Customer and 
exiting the bank.")
else:
    print("Fail to Reject Ho")
    print("There is no association betweeen Active Customer and 
exiting the bank")
```

```
chi_stat :  243.6948024819593
p_value :  6.1531674381134086e-55
dof :  1
expected :  [[3860.7738  988.2262]
 [4101.2262 1049.7738]]
Reject Ho
There is an association betweeen Active Customer and exiting the bank.
```

There is an association betweeen Active Customer and exiting the bank.

Balance Vs Customer Churn

H0: There is no significant difference between the mean balance of the customer who exited and not exited

H1: There is significant difference between the mean balance of the customer who exited and not exited

```
d_exited = data[data['Exited'] == 'Yes']['Balance']
d_stayed = data[data['Exited'] == 'No']['Balance']


stats, pval = ttest_ind(d_stayed, d_exited, equal_var = False)
print(f'Stats value: {stats}')
print(f'P value: {pval}')


alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("There is significant difference between the mean balance of 
the customer who exited and not exited")
else:
    print("Fail to Reject Ho")
```

```
    print("There is no significant difference between the mean balance of the customer who exited and not exited")
```

```
Stats value: -12.47802583232175
P value: 5.817634004614694e-35
Reject Ho
There is significant difference between the mean balance of the customer who exited and not exited
```

There is significant difference between the mean balance of the customer who exited and not exited

Credit Card Vs Customer Churn

H0: There is no impact of credit card on customer churn

H1: There is an impact of credit card on customer churn

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

Exited	No	Yes
HasCrCard		
0	2332	613
1	5630	1425

```
chi_stat , p_value , dof , expected = chi2_contingency(card)

print("chi_stat : ",chi_stat)
print("p_value : ",p_value)
print("dof : ",dof)
print("expected : ",expected)

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("There is an impact of credit card on customer churn")
else:
    print("Fail to Reject Ho")
    print("There is no impact of credit card on customer churn")
```

```
chi_stat :  0.4494039375253385
p_value :  0.5026181509009862
dof :  1
expected :  [[2344.809  600.191]
 [5617.191 1437.809]]
Fail to Reject Ho
There is no impact of credit card on customer churn
```

There is no impact of credit card on customer churn

Complain Vs Customer churn

H0: There is no effect of complaints on customer churn.

H1: There is an effect of complaints on customer churn.

```
complain = pd.crosstab(data.Complain, data.Exited)
complain
```

```
Exited      No   Yes
Complain
0         7952     4
1           10  2034
```

```
chi_stat , p_value , dof , expected = chi2_contingency(complain)

print("chi_stat : ",chi_stat)
print("p_value : ",p_value)
print("dof : ",dof)
print("expected : ",expected)

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("There is an effect of complaints on customer churn.")
else:
    print("Fail to Reject Ho")
    print("There is no affect of complain on customer churn")
```

```
chi_stat :  9907.907035880155
p_value :  0.0
dof :  1
expected :  [[6334.5672 1621.4328]
 [1627.4328  416.5672]]
Reject Ho
There is an effect of complaints on customer churn.
```

There is an effect of complaints on customer churn.

Satisfaction score Vs Customer churn

H0: There is no significant difference in satisfaction score of customer who have exited with complain and exited without complain

H1: There is significant difference in satisfaction score of customer who have exited with complain and exited without complain

```
exited_customers = data[data['Exited'] == 'Yes']

satis_com = pd.crosstab(exited_customers['Satisfaction Score'],
exited_customers['Complain'])

chi2, p_value, a, b = chi2_contingency(satis_com)

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("There is significant difference in satisfaction score of
customer who have exited with complain and exited without complain")
else:
    print("Fail to Reject Ho")
    print("There is no significant difference in satisfaction score of
customer who have exited with complain and exited without complain")

Fail to Reject Ho
There is no significant difference in satisfaction score of customer
who have exited with complain and exited without complain
```

There is no significant difference in satisfaction score of customer who have exited with complain and exited without complain

Card Type Vs Customer Churn

H0: There is no association between different card types and customers exiting the bank.

H1: There is an association between different card types and customers exiting the bank.

```
card = pd.crosstab(data['Card Type'], data['Exited'])
card

Exited        No   Yes
Card Type
DIAMOND     1961   546
GOLD        2020   482
PLATINUM    1987   508
SILVER      1994   502

chi_stat , p_value , dof , expected = chi2_contingency(card)

print("chi_stat : ",chi_stat)
print("p_value : ",p_value)

alpha = 0.05
```

```
if p_value< alpha:
    print("Reject Ho")
    print("There is an association between different card types and
customers exiting the bank.")
else:
    print("Fail to Reject Ho")
    print("There is no association between different card types and
customers exiting the bank.")
```

```
chi_stat :  5.053223027060927
p_value :  0.16794112067810177
Fail to Reject Ho
There is no association between different card types and customers
exiting the bank.
```

There is no association between different card types and customers exiting the bank.

Point Earned Vs Customer churn

H0: Points earned from credit card usage do not influence customer churn.

H1: Points earned from credit card usage does influence customer churn

```
p_churn = data[data.Exited == 'Yes']['Point Earned']
np_churn = data[data.Exited == 'No']['Point Earned']
```

Test for equal variances

H0: Variances are equal

H1: Variances are not equal

```
l_stat, p_val = levene(p_churn, np_churn)
print(f' P value: {p_val}')

alpha = 0.05
if p_val < alpha:
    print('Reject H0')
    print('Variances are not equal')

else:
    print('Fail to reject H0')
    print('Variances are equal')
```

```
 P value: 0.8176344750713012
Fail to reject H0
Variances are equal
```

```
t_stat, p_val = ttest_ind(p_churn, np_churn)
print(f' P value: {p_val}')

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("Points earned from credit card usage does influence
customer churn.")
else:
    print("Fail to Reject Ho")
    print("Points earned from credit card usage do not influence
customer churn.")
```

```
 P value: 0.6435350184288993
Fail to Reject Ho
Points earned from credit card usage do not influence customer churn.
```

Points earned from credit card usage do not influence customer churn.

Salary Vs Customer churn

H0: Estimated Salary does not influence customer churn decisions.

H1: Estimated Salary does influence customer churn decisions.

```
churn = data[data.Exited == 'Yes']['EstimatedSalary']
n_churn = data[data.Exited == 'No']['EstimatedSalary']
```

Equal variances test

H0: Variances are equal

H1: Variances are not equal

```
l_stat, p_val = levene(churn, n_churn)
print(f' P value: {p_val}')

alpha = 0.05
if p_val < alpha:
    print('Reject H0')
    print('Variances are not equal')

else:
    print('Fail to reject H0')
    print('Variances are equal')
```

```
 P value: 0.32105166125575746
Fail to reject H0
Variances are equal
```

```
t_stat, p_val = ttest_ind(churn, n_churn)
print(f' P value: {p_val}')

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("Estimated Salary does  influence customer churn 
decisions.")
else:
    print("Fail to Reject Ho")
    print("Estimated Salary does not influence customer churn 
decisions.")
```

```
 P value: 0.2117146135149097
Fail to Reject Ho
Estimated Salary does not influence customer churn decisions.
```

Estimated Salary does not influence customer churn decisions.

Age Vs Customer Churn

H0: There is no significant difference between the mean age of the customer who exited and not exited

H1: There is significant difference between the mean age of the customer who exited and not exited

```
a_exited = data[data['Exited'] == 'Yes']['Age']
a_stayed = data[data['Exited'] == 'No']['Age']
```

Equal variances test

H0: Variances are equal

H1: Variances are not equal

```
l_stat, p_val = levene(a_exited, a_stayed)
print(f' P value: {p_val}')

alpha = 0.05
if p_val < alpha:
    print('Reject H0')
    print('Variances are not equal')
```

```
else:
    print('Fail to reject H0')
    print('Variances are equal')
```

```
 P value: 0.000318344550440417
Reject H0
Variances are not equal
```

```
stats, pval = ttest_ind(a_stayed, a_exited, equal_var=False)

alpha = 0.05

if p_val < alpha:
    print('Reject H0')
    print('There is significant difference between the mean age of the customer who exited and not exited')
else:
    print('Fail to reject H0')
    print('There is no significant difference between the mean age of the customer who exited and not exited')
```

```
Reject H0
There is significant difference between the mean age of the customer who exited and not exited
```

There is significant difference between the mean age of the customer who exited and not exited

Gender Vs Customer Churn

H0: There is no association between the Gender and customer exiting the bank

H1: There is an association between the Gender and customer exiting the bank

```
gender = pd.crosstab(data.Exited, data.Gender)
gender
```

Gender	Female	Male
Exited		
No	3404	4558
Yes	1139	899

```
chi_stat , p_value , dof , expected = chi2_contingency(gender)

print("chi_stat : ",chi_stat)
print("p_value : ",p_value)

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
```

```
    print("There is an association between the Gender and customer exiting the bank")
else:
    print("Fail to Reject Ho")
    print("There is no association between the Gender and customers exiting the bank.")
```

```
chi_stat :  112.39655374778587
p_value :  2.9253677618642e-26
Reject Ho
There is an association between the Gender and customer exiting the bank
```

There is an association between the Gender and customer exiting the bank

Geography and Customer Churn

H0: There is no association between the geographical locations of the customer and exiting the Bank

H1: There is association between the geographical locations of the customer and exiting the Bank

```
geography = pd.crosstab(data.Exited, data.Geography)
geography
```

Geography	France	Germany	Spain
Exited			
No	4203	1695	2064
Yes	811	814	413

```
chi_stat , p_value , dof , expected = chi2_contingency(geography)

print("chi_stat : ",chi_stat)
print("p_value : ",p_value)

alpha = 0.05
if p_value< alpha:
    print("Reject Ho")
    print("There is an association between the geographical locations of the customer and exiting the Bank")
else:
    print("Fail to Reject Ho")
    print("There is no association between the geographical locations of the customer and exiting the Bank")
```

```
chi_stat :  300.6264011211942
p_value :  5.245736109572763e-66
```

```
Reject Ho
There is an association between the geographical locations of the
customer and exiting the Bank
```

There is an association between the geographical locations of the customer and exiting the Bank

```

```

Insights

1. Age Range: The age of customers ranges from 18 to 92 years.
2. Tenure: The tenure ranges from 0 to 10 years, with an average tenure of 5 years.
3. Balance: The balance of customers varies from 0 to 250,000.
4. Products: Customers can have up to 4 products.
5. Credit Card Points: Customers can earn up to 1,000 points using their credit cards.
6. Churn Rate: 20.4% of the customers have exited the bank.
7. Customer Distribution by Country: France: 5,014 customers Germany: 2,509 customers Spain: 2,477 customers
8. Gender Distribution: 54% of customers are male.
9. Credit Card Usage: 70.55% of customers use credit cards.
10. Complaint Filing: 20.44% of customers have filed complaints.
11. Satisfaction Scores: Most customers have given a satisfaction score of 3, followed by scores 2, 4, 5, and 1.
12. Card Usage: Most customers use Diamond cards (2,507) and Gold cards (2,503), followed by Silver and Platinum.
13. Customers in Germany have a higher exit rate compared to those in France and Spain.
14. Female customers have a higher exit rate compared to male customers.
15. Most customers with a tenure of 0 have left the bank.
16. Inactive members have a higher exit rate compared to active members.
17. There is no significant impact of credit card ownership on customer churn.
18. There is a significant difference in the number of products customers buy and their likelihood of exiting the bank.
19. There is an association between active membership and customer exit rates.

20. There is a significant difference between the mean balance of customers who exited and those who did not.
21. There is an association between geographical location and customer exit rates.
22. There is an association between gender and customer exit rates.

Recommendation

1. Target Germany for Retention: Develop strategies to address the higher churn rate in Germany, such as personalized customer engagement and addressing specific issues faced by German customers
2. Focus on Female Customers: Implement targeted retention strategies for female customers, such as personalized offers and improving customer service.
3. Engage New Customers: Develop programs to better engage new customers with a tenure of 0 years to reduce early churn.
4. Promote Active Membership: Encourage inactive members to become active through loyalty programs, rewards, and personalized engagement.
5. Comprehensive Retention Strategies: Implement broad strategies to improve overall customer satisfaction and retention, considering the insights on products, balance, and geographical differences