EDA for Classification Project – Customer Churn Dataset

1. Initial Setup & Data Overview

In [161…

```
import numpy as np
import pandas as pd
from pandas_summary import DataFrameSummary

import seaborn as sns
import matplotlib.pyplot as plt
from   scipy.stats import chi2_contingency, f_oneway
from math import log, e

import warnings
import random

pd.set_option('display.max_rows', 800)
pd.set_option('display.max_columns', 500)
%matplotlib inline
warnings.filterwarnings("ignore")
```

In [3]:

```
df = pd.read_csv(r'C:\Users\admin\Desktop\PYTHON LEARNING\jupyter noteboo
df.head()
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	8
2	3	15619304	Onio	502	France	Female	42	8	15
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	12

In [4]:

```
df.columns.tolist()
```

Out[4]:

```
['RowNumber',
 'CustomerId',
 'Surname',
 'CreditScore',
 'Geography',
 'Gender',
 'Age',
 'Tenure',
 'Balance',
 'NumOfProducts',
 'HasCrCard',
 'IsActiveMember',
```

```
 'EstimatedSalary',
 'Exited']
```

In [7]:
```
df.drop('RowNumber',axis = 1 , inplace = True)
```

In [49]:
```
df.shape
```

Out[49]:
```
(10000, 13)
```

2. Univariate Analysis

In [48]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   CustomerId       10000 non-null  int64  
 1   Surname          10000 non-null  object 
 2   CreditScore      10000 non-null  int64  
 3   Geography        10000 non-null  object 
 4   Gender           10000 non-null  object 
 5   Age              10000 non-null  int64  
 6   Tenure           10000 non-null  int64  
 7   Balance          10000 non-null  float64
 8   NumOfProducts    10000 non-null  int64  
 9   HasCrCard        10000 non-null  int64  
 10  IsActiveMember   10000 non-null  int64  
 11  EstimatedSalary  10000 non-null  float64
 12  Exited           10000 non-null  int64  
dtypes: float64(2), int64(8), object(3)
memory usage: 1015.8+ KB
```

In [8]:
```
df.describe()
```

Out[8]:

	CustomerId	CreditScore	Age	Tenure	Balance	NumO
count	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	1000
mean	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	
std	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	
min	1.556570e+07	350.000000	18.000000	0.000000	0.000000	
25%	1.562853e+07	584.000000	32.000000	3.000000	0.000000	
50%	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	
75%	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	
max	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	

In [11]:
```
numeric_df = df.select_dtypes(include='number')
dfs = DataFrameSummary(numeric_df)
```

```
dfs.columns_stats
```

Out[11]:

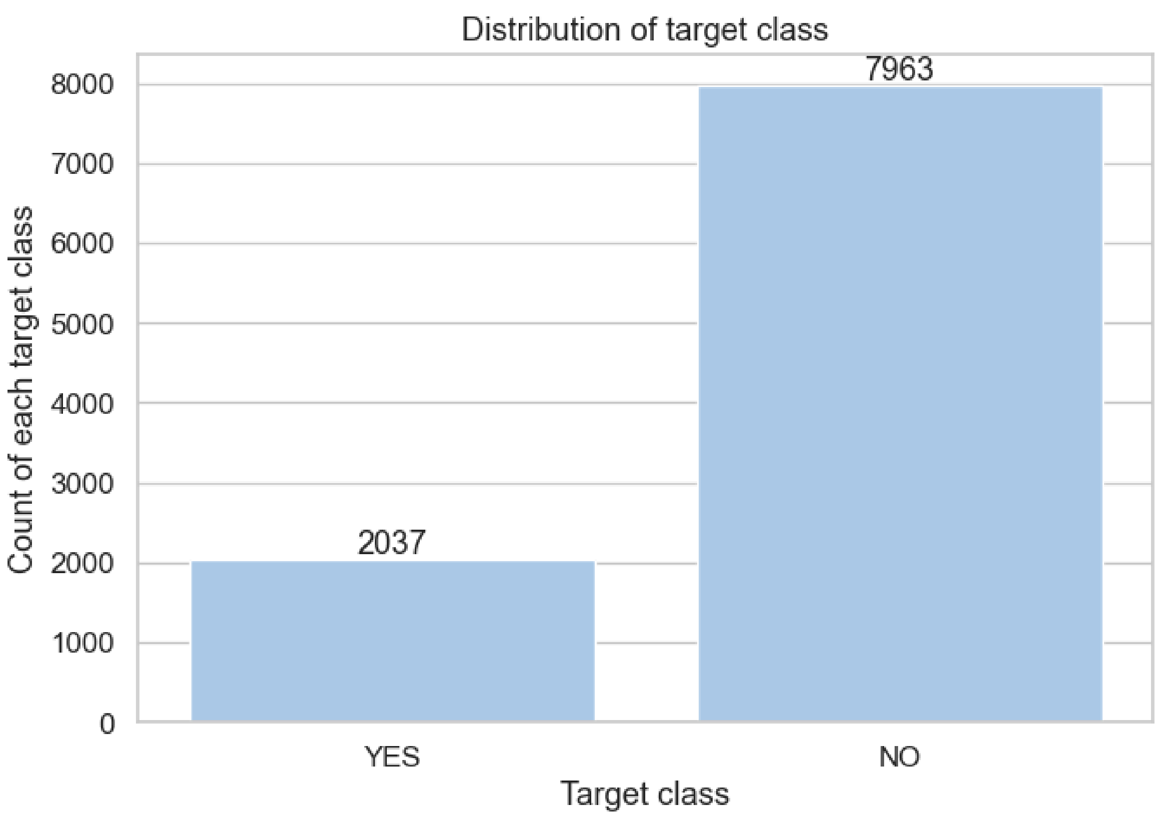
	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCı
counts	10000	10000	10000	10000	10000	10000	1
uniques	10000	460	70	11	6382	4	
missing	0	0	0	0	0	0	
missing_perc	0%	0%	0%	0%	0%	0%	
types	numeric	numeric	numeric	numeric	numeric	numeric	

Check if the target class is imbanced

In [14]:
```
df['Exited'].value_counts()
```

Out[14]:
```
Exited
0    7963
1    2037
Name: count, dtype: int64
```

In [160…
```
plt.figure(figsize = (7,5))
ax = sns.countplot(data = df,x = df['Exited'].map({1:'YES',0:'NO'}))
ax.bar_label(ax.containers[0])
plt.xlabel('Target class')
plt.ylabel('Count of each target class')
plt.title('Distribution of target class')
plt.tight_layout()
plt.show()
```



Checking impurity of y lable

In [47]:
```
from scipy.stats import entropy
ent = pd.value_counts(df['Exited'], normalize=True)
entropy(ent)
```

Out[47]:
```
0.505489127326179
```

Entropy of the target variable is 0.505, which indicates a moderate level of impurity or uncertainty in the class distribution. This means the classes are not perfectly balanced or perfectly pure — there is some mix, but one class likely dominates slightly.

3. Bivariate Analysis

In [52]:
```
numeric_df.columns.tolist()
```

Out[52]:
```
['CustomerId',
 'CreditScore',
 'Age',
 'Tenure',
 'Balance',
 'NumOfProducts',
 'HasCrCard',
 'IsActiveMember',
 'EstimatedSalary',
 'Exited']
```

In [54]:
```
remove_col = ['HasCrCard', 'IsActiveMember', 'Exited']
num_df = numeric_df.drop(columns=remove_col)
num_df.columns.tolist()
```

Out[54]:
```
['CustomerId',
 'CreditScore',
 'Age',
 'Tenure',
 'Balance',
 'NumOfProducts',
 'EstimatedSalary']
```

In [57]:
```
cat_df = df.columns.difference(num_df.columns)
cat_df = df[cat_df]
cat_df.drop('Exited',axis = 1,inplace = True)
cat_df.columns.tolist()
```

Out[57]:
```
['Gender', 'Geography', 'HasCrCard', 'IsActiveMember', 'Surname']
```

Chie Square Test

(For Categorical columns)

In [62]:
```
for col in cat_df.columns:
    contingency = pd.crosstab(cat_df[col], df['Exited'])
```

```
    if contingency.shape[0] > 1 and contingency.shape[1] > 1:
        chi2, p, dof, expected = chi2_contingency(contingency)

        significance = "Yes" if p < 0.05 else "No"

        print(f"Column: {col}")
        print(f"  Test Statistic: {chi2:.4f}")
        print(f"  p-value       : {p:.4f}")
        print(f"  Statistically Significant?  {significance}\n")
```

```
Column: Gender
  Test Statistic: 112.9186
  p-value       : 0.0000
  Statistically Significant?  Yes

Column: Geography
  Test Statistic: 301.2553
  p-value       : 0.0000
  Statistically Significant?  Yes

Column: HasCrCard
  Test Statistic: 0.4713
  p-value       : 0.4924
  Statistically Significant?  No

Column: IsActiveMember
  Test Statistic: 242.9853
  p-value       : 0.0000
  Statistically Significant?  Yes

Column: Surname
  Test Statistic: 2786.4142
  p-value       : 0.9720
  Statistically Significant?  No
```

The features Gender, Geography, and IsActiveMember were found to be statistically significant ($p < 0.05$) based on the Chi-Square test of independence. This suggests that they have a meaningful association with the target variable and may play an important role in predicting outcomes.

Statistically Significant Features ($p < 0.05$):

- Gender
- Geography
- IsActiveMember

ANOVA Test

(For Numerical Columns)

In [64]:

```
for col in num_df.columns:

    group_0 = df[df['Exited'] == 0][col].dropna()
    group_1 = df[df['Exited'] == 1][col].dropna()
```

```python
    f_stat, p = f_oneway(group_0, group_1)

    significance = "Yes" if p < 0.05 else "No"

    print(f"Column: {col}")
    print(f"  Test Statistic: {f_stat:.4f}")
    print(f"  p-value        : {p:.4f}")
    print(f"  Statistically Significant? {significance}\n")
```

```
Column: CustomerId
  Test Statistic: 0.3903
  p-value        : 0.5322
  Statistically Significant? No

Column: CreditScore
  Test Statistic: 7.3445
  p-value        : 0.0067
  Statistically Significant? Yes

Column: Age
  Test Statistic: 886.0633
  p-value        : 0.0000
  Statistically Significant? Yes

Column: Tenure
  Test Statistic: 1.9602
  p-value        : 0.1615
  Statistically Significant? No

Column: Balance
  Test Statistic: 142.4738
  p-value        : 0.0000
  Statistically Significant? Yes

Column: NumOfProducts
  Test Statistic: 22.9152
  p-value        : 0.0000
  Statistically Significant? Yes

Column: EstimatedSalary
  Test Statistic: 1.4633
  p-value        : 0.2264
  Statistically Significant? No
```

Based on the One-Way ANOVA test, the following numerical features were found to be statistically significant ($p < 0.05$) in relation to the target variable Exited. This indicates that the mean values of these features differ significantly between customers who exited and those who did not, making them potentially valuable for predictive modeling

Statistically Significant Features ($p < 0.05$):

- CreditScore
- Age
- Balance
- NumOfProducts

📈 Feature Significance Summary

We conducted statistical tests to identify which features have a meaningful association with the target variable `Exited`.

- **For categorical variables**, we used the **Chi-Square test of independence**.
- **For numerical variables**, we applied the **One-Way ANOVA test**.

🔹 Statistically Significant Categorical Features (Chi-Square Test)

These categorical variables showed a significant relationship ($p < 0.05$) with the target variable:

- `Gender`
- `Geography`
- `IsActiveMember`

🔹 Statistically Significant Numerical Features (One-Way ANOVA)

These numerical variables had significantly different means between exited and non-exited customers:

- `Age`
- `Balance`
- `CreditScore`
- `NumOfProducts`

> These features are strong candidates for inclusion in predictive models such as logistic regression, decision trees, or any supervised machine learning task focused on customer churn prediction.

4. Visual Analytics

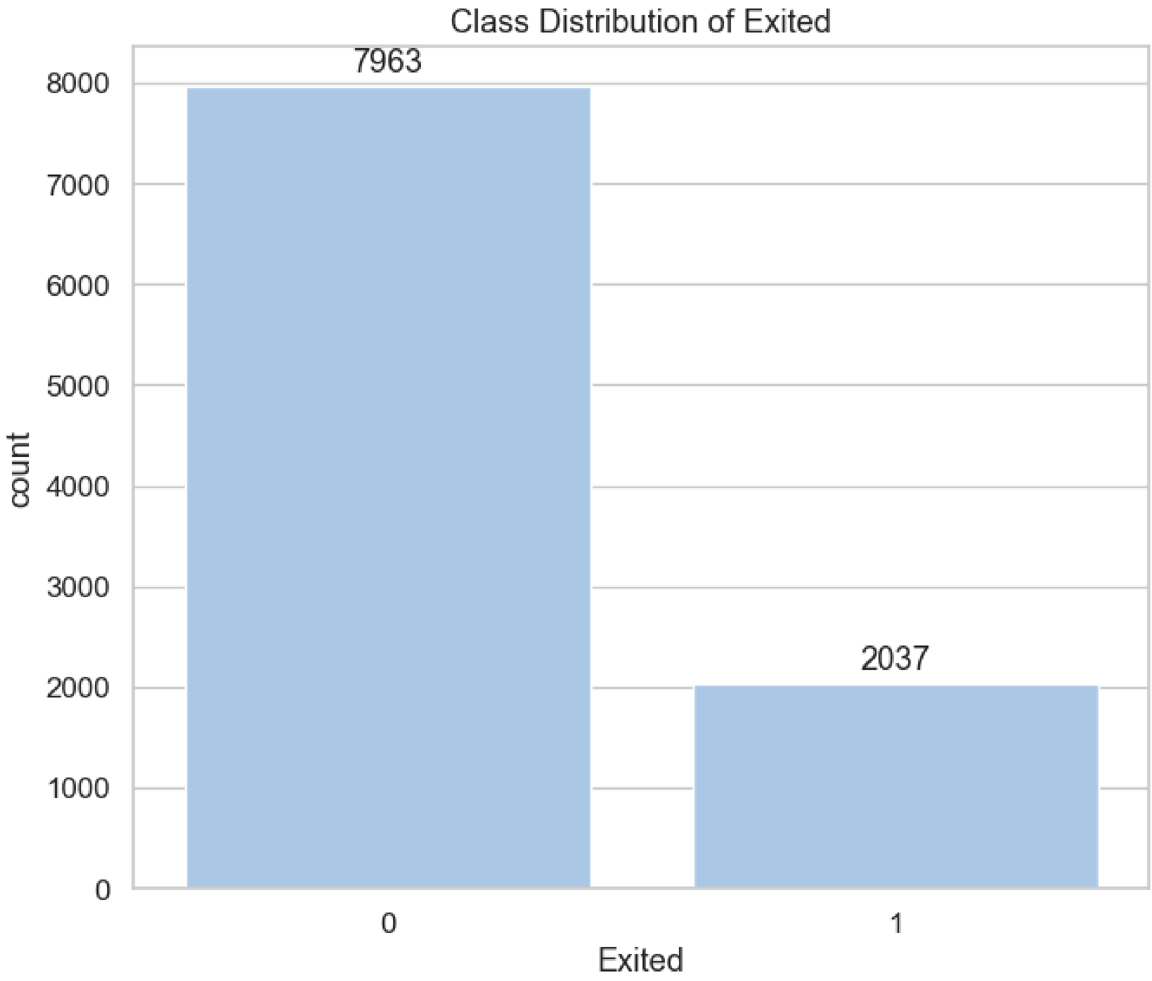
In [66]:
```
sns.set_theme(style="whitegrid", palette="pastel", font_scale=1.1)
sns.despine()
```

Categorical Features

Target Distribution

In [104…
```
plt.figure(figsize = (7,6))
ax = sns.countplot(x="Exited", data=df)
ax.bar_label(ax.containers[0],label_type='edge', padding=3, fmt='%d')
plt.title("Class Distribution of Exited")
```

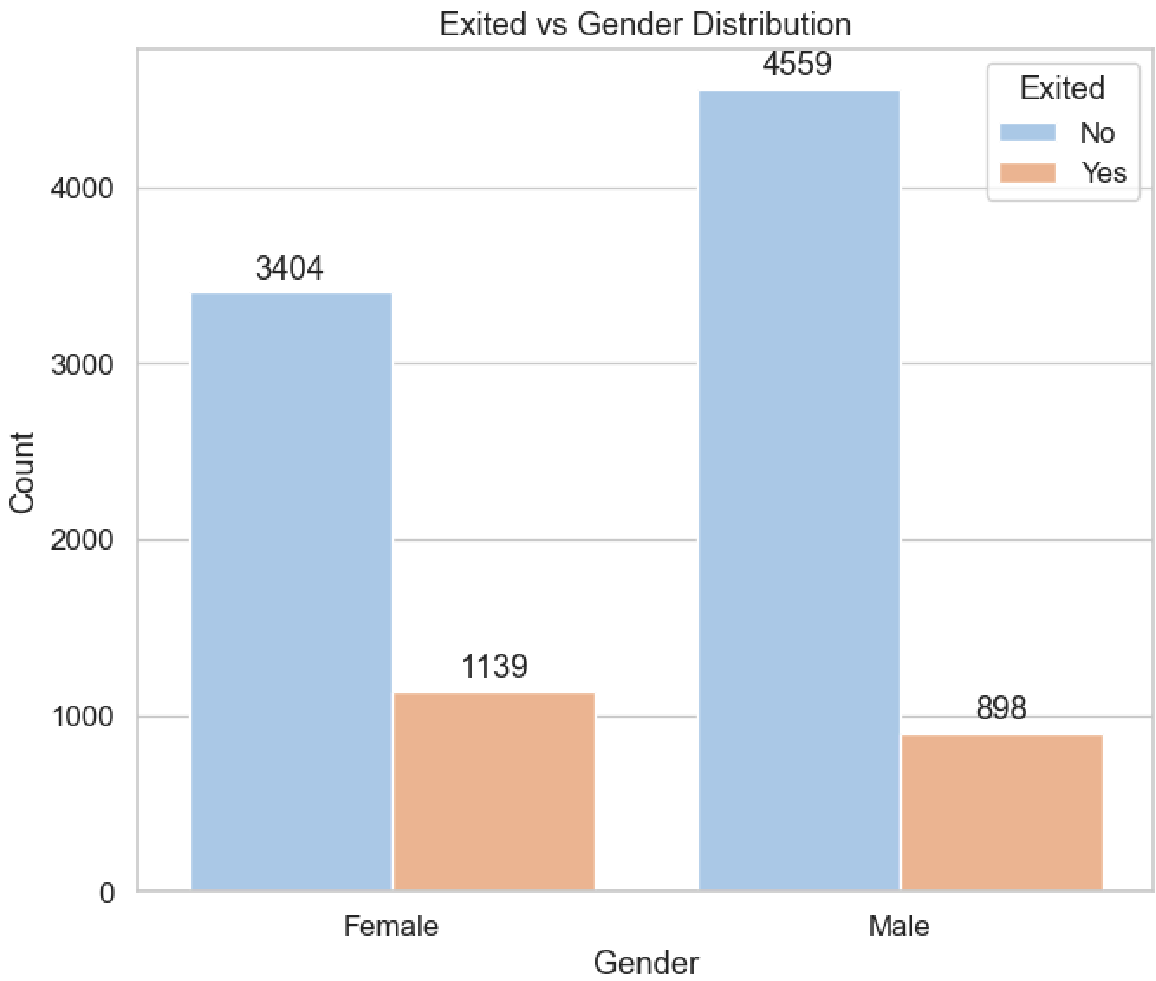
```
plt.tight_layout()
plt.show()
```



Gender

In [106…

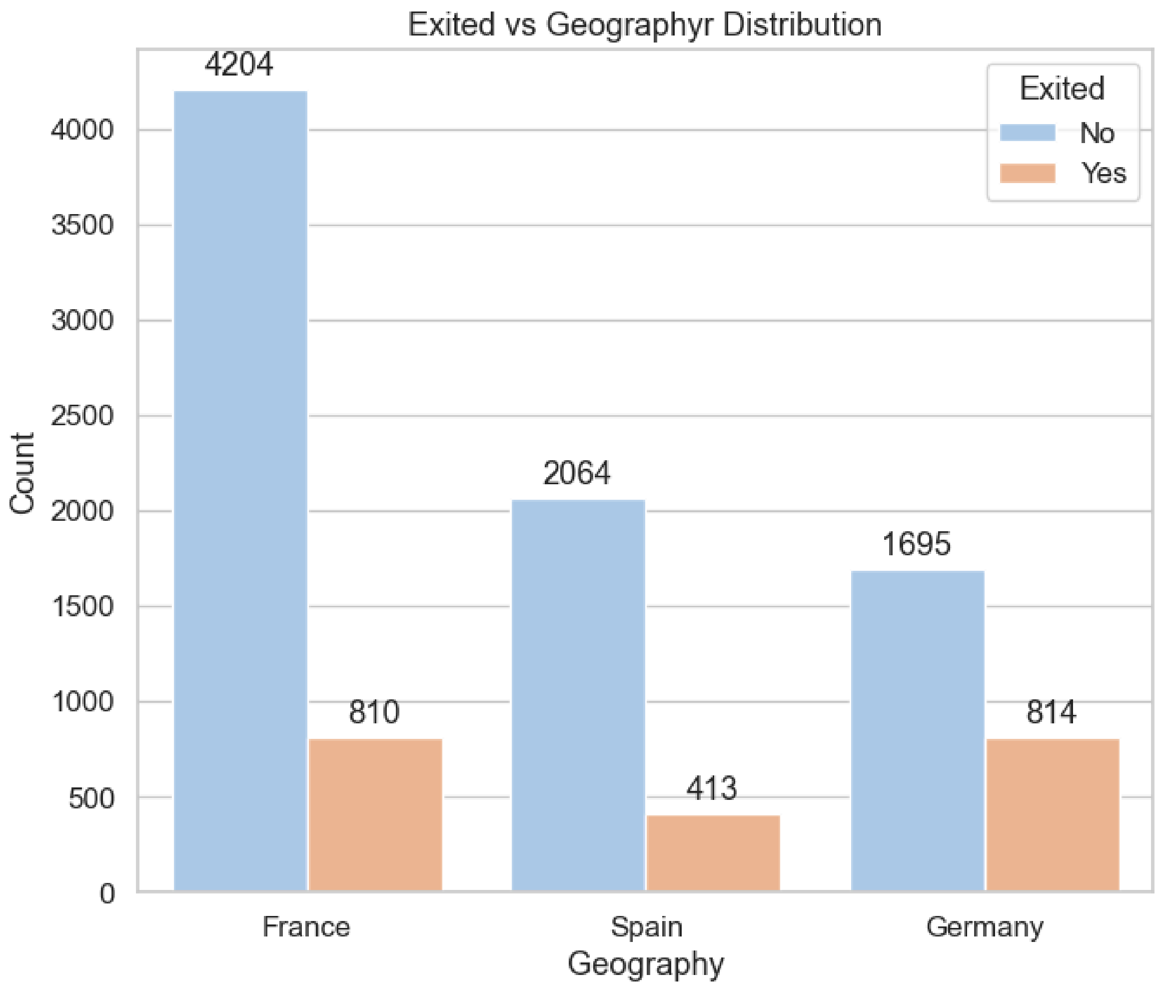
```
plt.figure(figsize = (7,6))
ax = sns.countplot(x="Gender", hue="Exited", data=df, palette="pastel")
for container in ax.containers:
    ax.bar_label(container, label_type='edge', padding=3, fmt='%d')
plt.title("Exited vs Gender Distribution")
plt.xlabel("Gender")
plt.ylabel("Count")
plt.legend(title="Exited", labels=["No", "Yes"])
plt.tight_layout()
plt.show()
```



Geography

In [107…

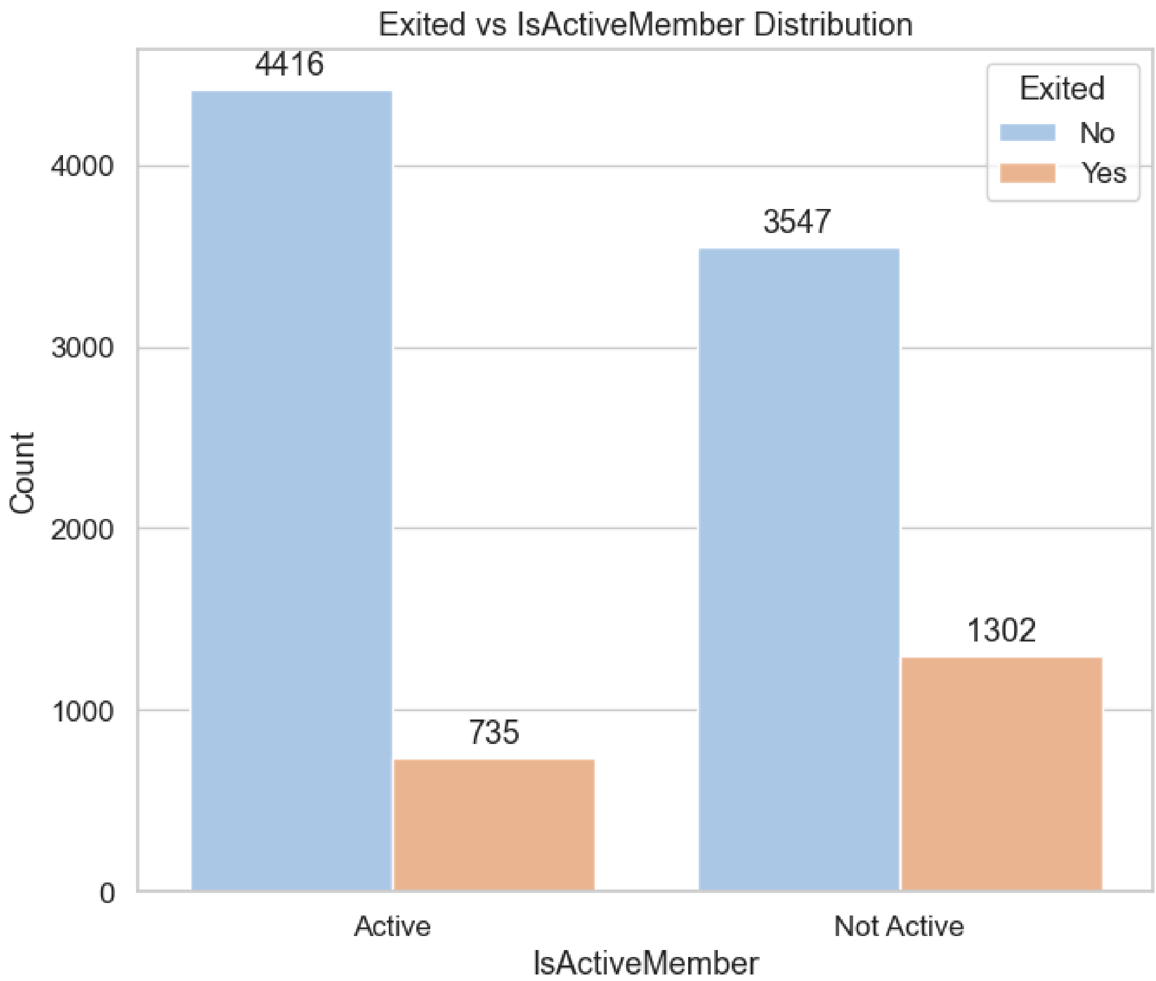
```
plt.figure(figsize = (7,6))
ax = sns.countplot(x="Geography", hue="Exited", data=df, palette="pastel"
for container in ax.containers:
    ax.bar_label(container, label_type='edge', padding=3, fmt='%d')
plt.title("Exited vs Geographyr Distribution")
plt.xlabel("Geography")
plt.ylabel("Count")
plt.legend(title="Exited", labels=["No", "Yes"])
plt.tight_layout()
plt.show()
```



IsActiveMemeber

In [109…

```
plt.figure(figsize = (7,6))
ax = sns.countplot(x=df["IsActiveMember"].map({0: "Not Active", 1: "Activ
for container in ax.containers:
    ax.bar_label(container, label_type='edge', padding=3, fmt='%d')
plt.title("Exited vs IsActiveMember Distribution")
plt.xlabel("IsActiveMember")
plt.ylabel("Count")
plt.legend(title="Exited", labels=["No", "Yes"])
plt.tight_layout()
plt.show()
```

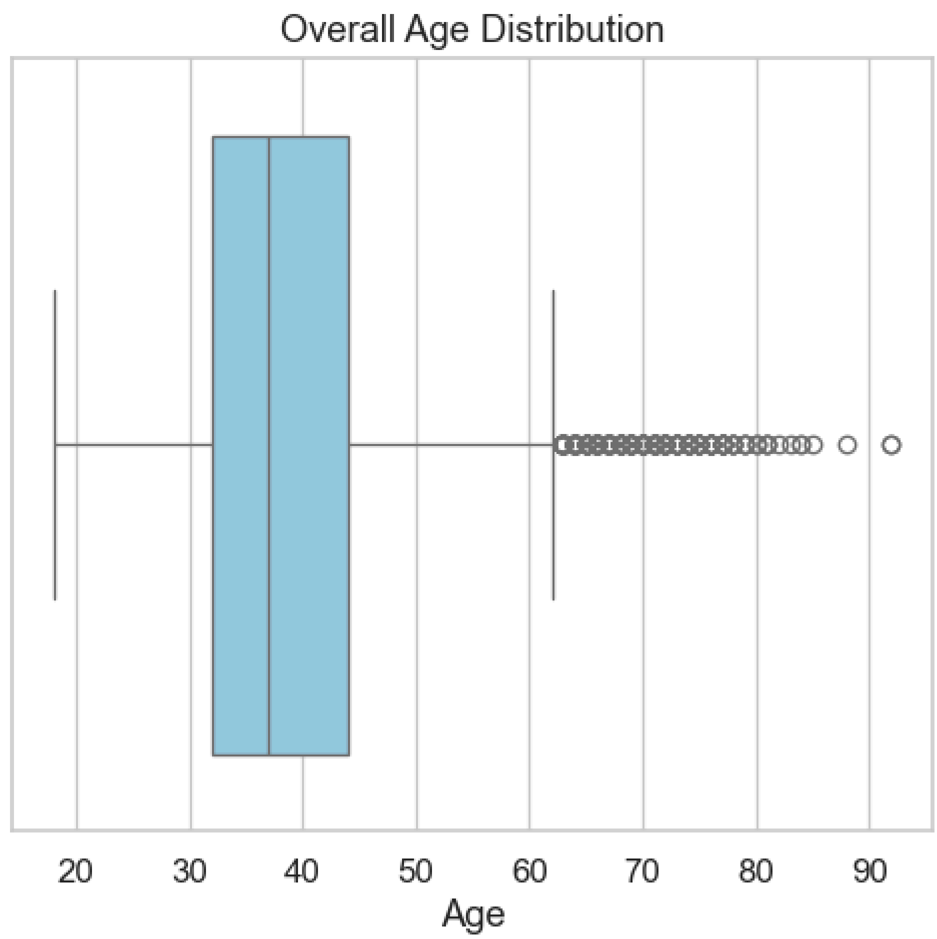


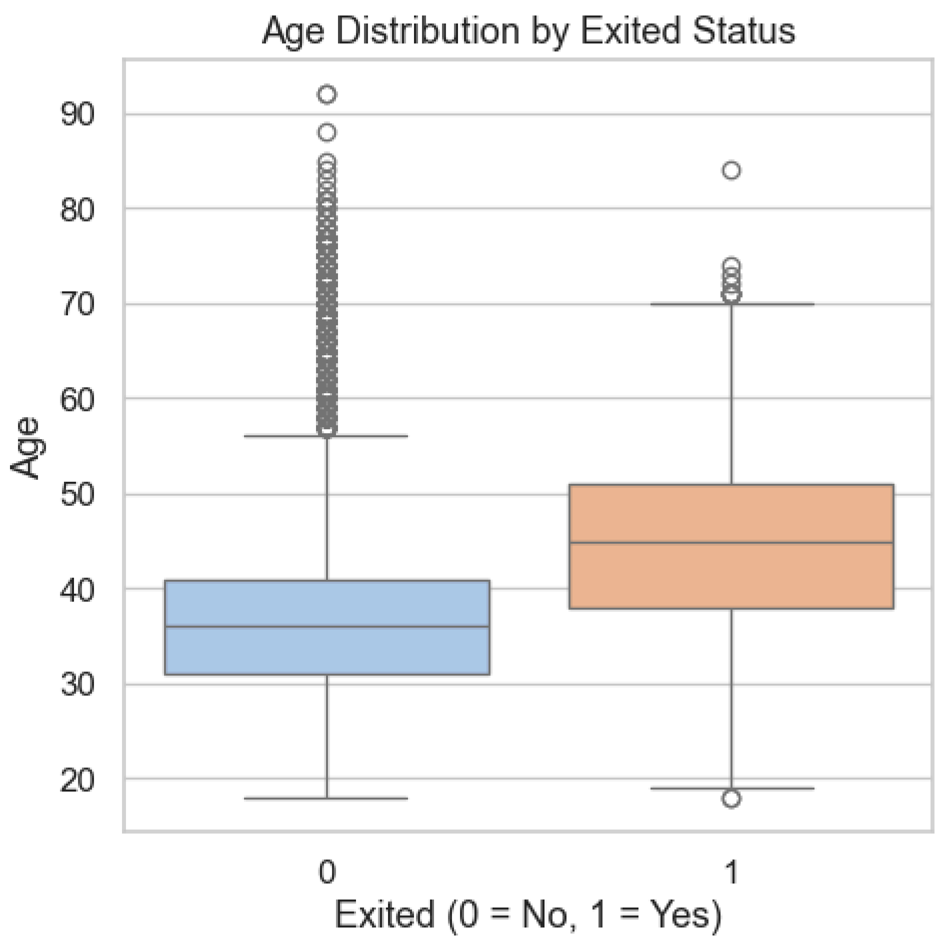
Numerical Features

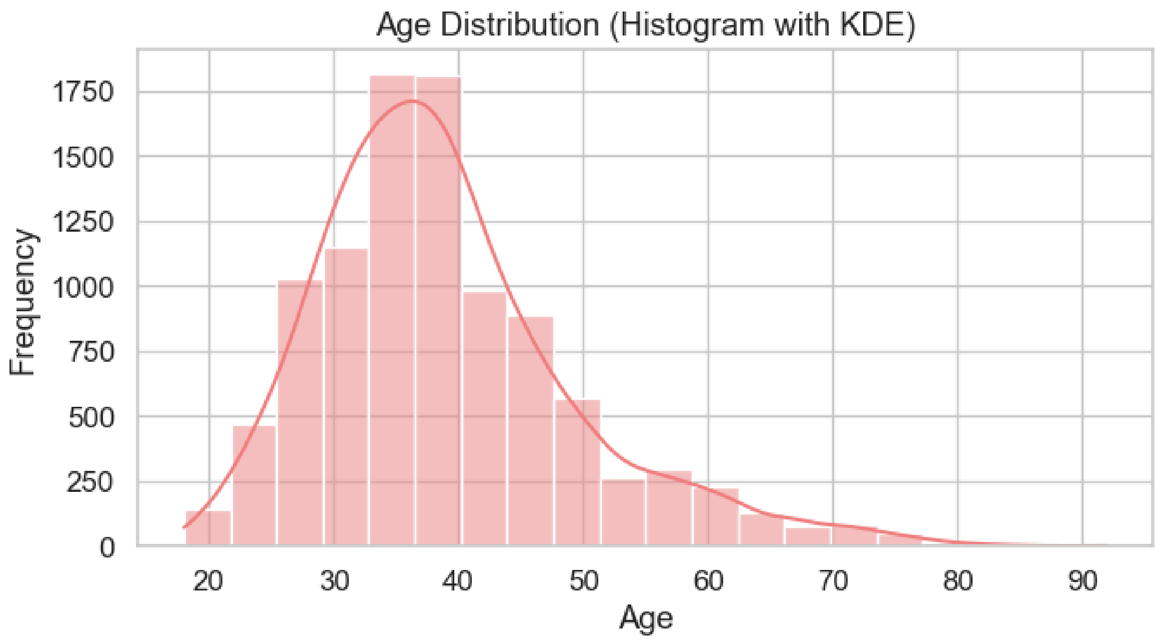
Age

In [143…

```
plt.figure(figsize=(5,5))
sns.boxplot(x=df["Age"], color='skyblue')
plt.title("Overall Age Distribution")
plt.xlabel("Age")
plt.ylabel("")
plt.tight_layout()
plt.show()

plt.figure(figsize=(5, 5))
sns.boxplot(x="Exited", y="Age", data=df, palette="pastel")
plt.title("Age Distribution by Exited Status")
plt.xlabel("Exited (0 = No, 1 = Yes)")
plt.ylabel("Age")
plt.tight_layout()
plt.show()

plt.figure(figsize=(7, 4))
sns.histplot(df['Age'], bins=20, kde=True, color='lightcoral')
plt.title("Age Distribution (Histogram with KDE)")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.tight_layout()
plt.show()
```


Overall Age Distribution
20
30
40
50
60
70
80
90
Age

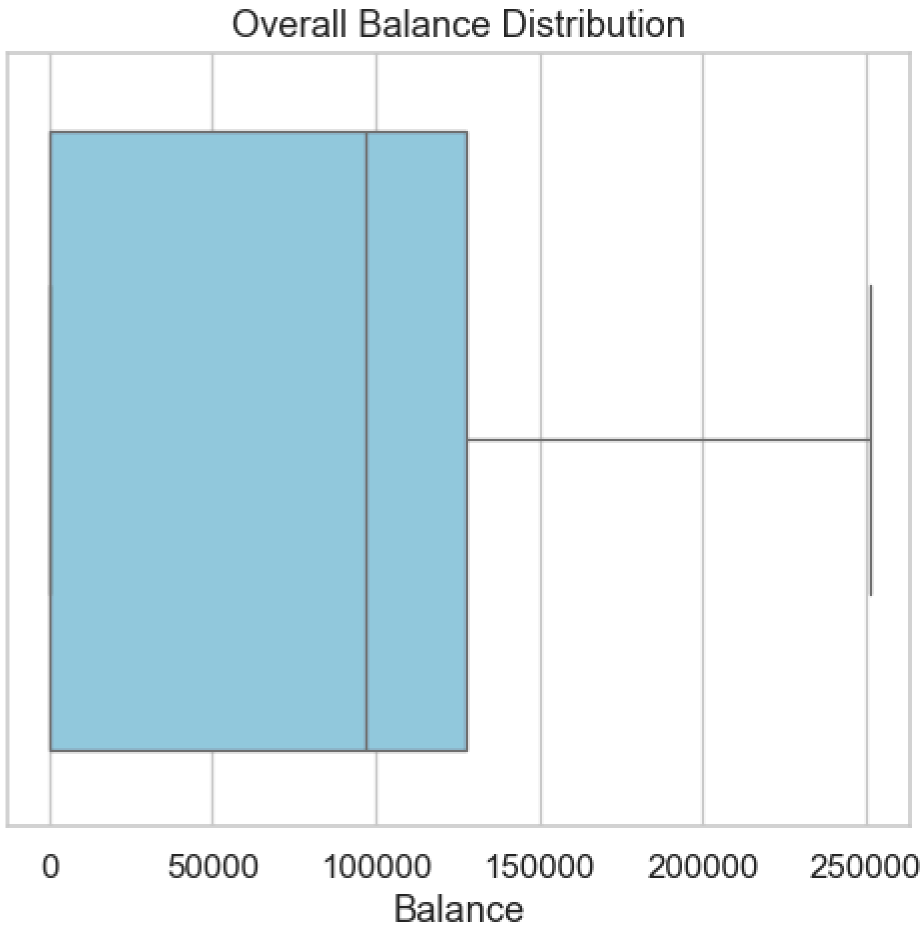

Age Distribution by Exited Status
90
80
70
60
50
40
30
20
Age
0
1
Exited (0 = No, 1 = Yes)

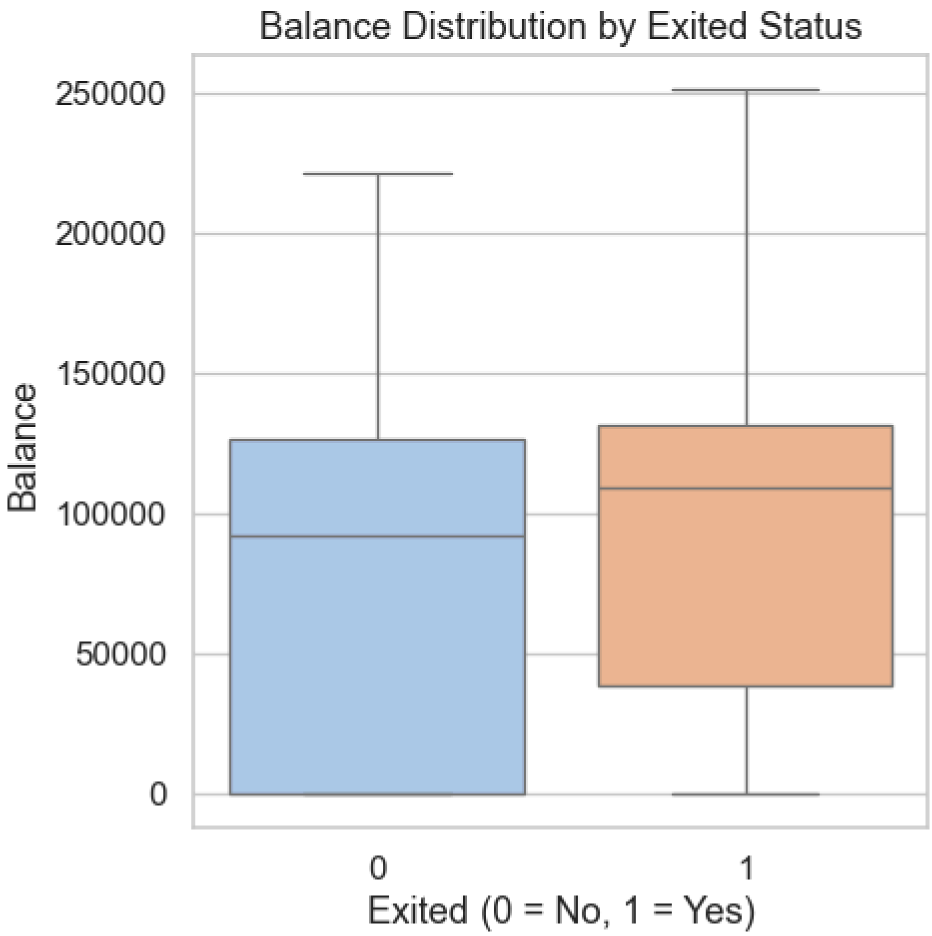


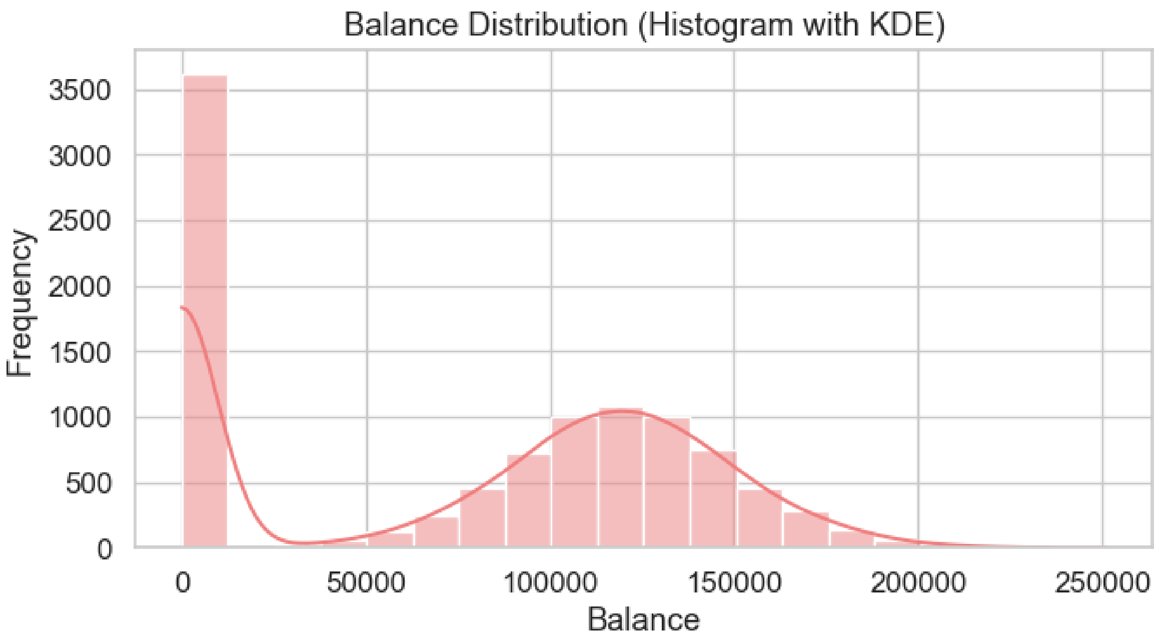
Balance

In [142…

```
plt.figure(figsize=(5,5))
sns.boxplot(x=df["Balance"], color='skyblue')
plt.title("Overall Balance Distribution")
plt.xlabel("Balance")
plt.ylabel("")
plt.tight_layout()
plt.show()

plt.figure(figsize=(5, 5))
sns.boxplot(x="Exited", y="Balance", data=df, palette="pastel")
plt.title("Balance Distribution by Exited Status")
plt.xlabel("Exited (0 = No, 1 = Yes)")
plt.ylabel("Balance")
plt.tight_layout()
plt.show()

plt.figure(figsize=(7, 4))
sns.histplot(df['Balance'], bins=20, kde=True, color='lightcoral')
plt.title("Balance Distribution (Histogram with KDE)")
plt.xlabel("Balance")
plt.ylabel("Frequency")
plt.tight_layout()
plt.show()
```


Overall Balance Distribution
0
50000
100000
150000
200000
250000
Balance


Balance Distribution by Exited Status
250000
200000
150000
100000
50000
0
Balance
0
1
Exited (0 = No, 1 = Yes)

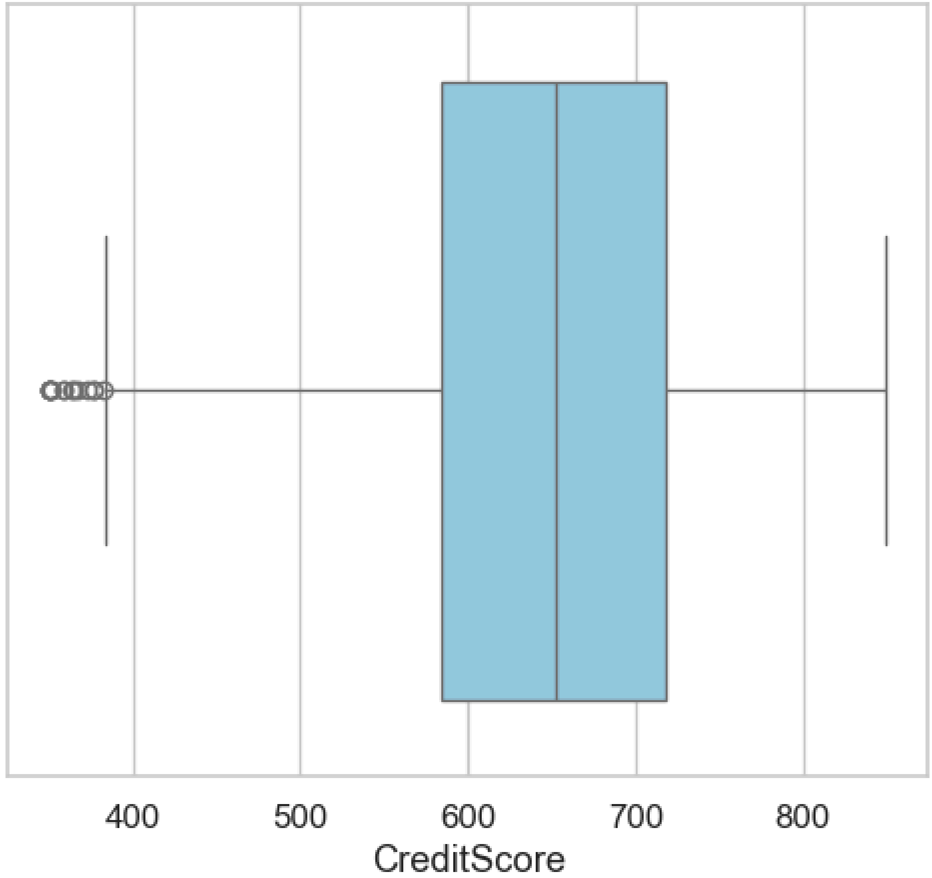


CreditScore

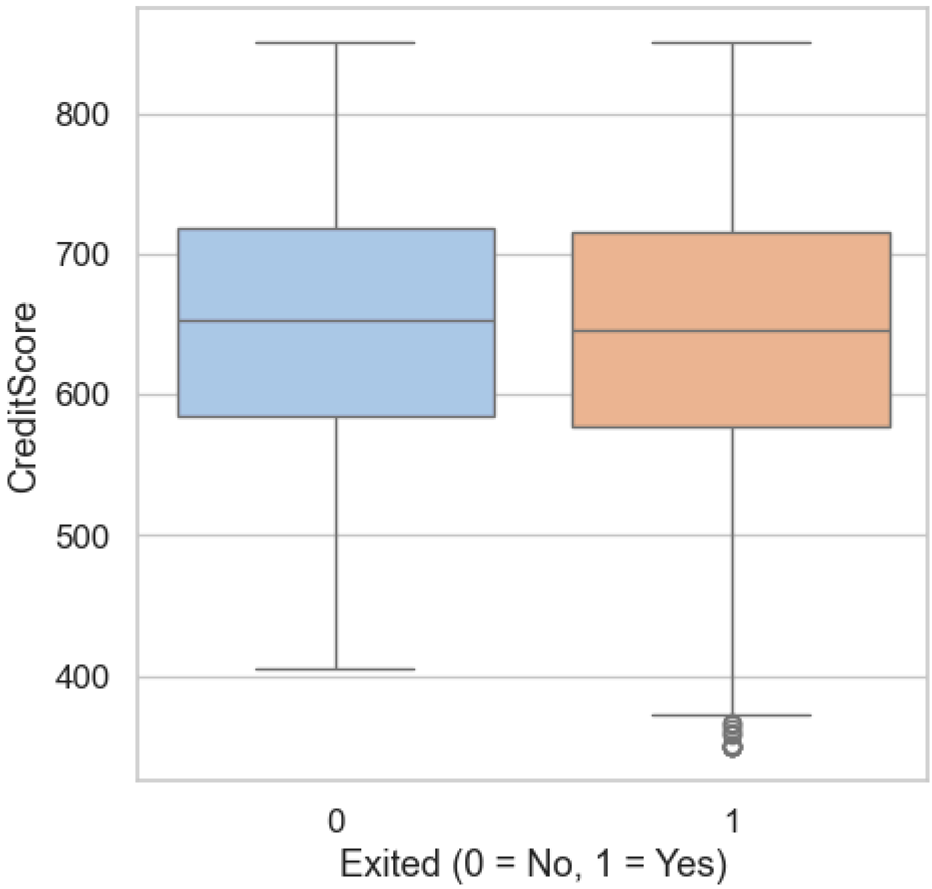
In [141…

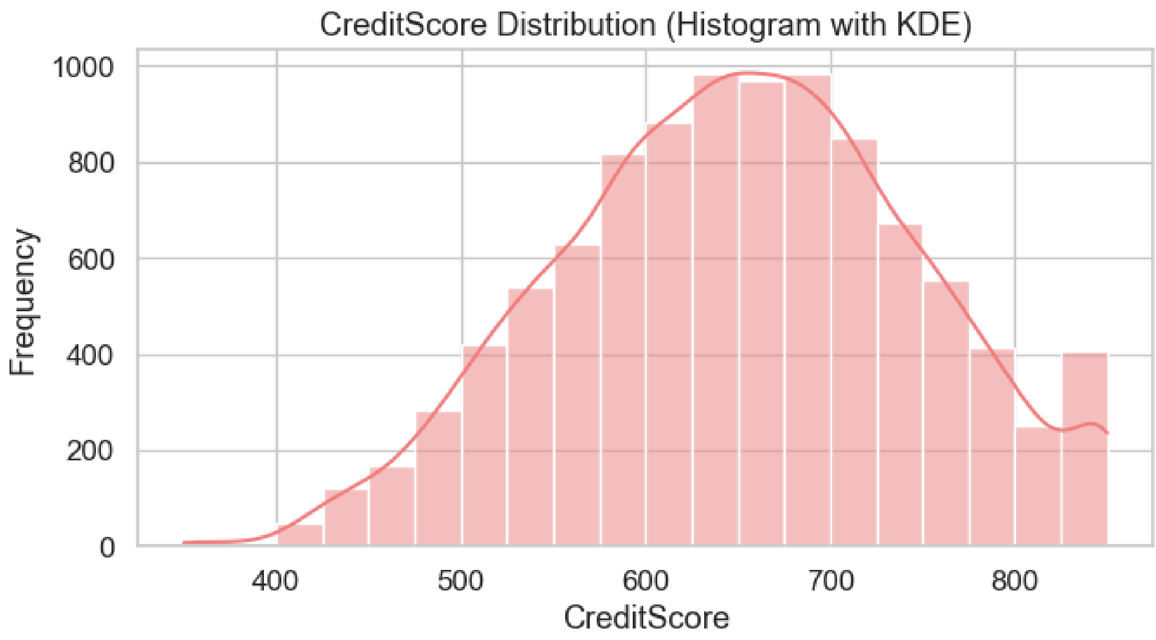
```
plt.figure(figsize=(5,5))
sns.boxplot(x=df["CreditScore"], color='skyblue')
plt.title("Overall CreditScore Distribution")
plt.xlabel("CreditScore")
plt.ylabel("")
plt.tight_layout()
plt.show()

plt.figure(figsize=(5, 5))
sns.boxplot(x="Exited", y="CreditScore", data=df, palette="pastel")
plt.title("CreditScore Distribution by Exited Status")
plt.xlabel("Exited (0 = No, 1 = Yes)")
plt.ylabel("CreditScore")
plt.tight_layout()
plt.show()

plt.figure(figsize=(7, 4))
sns.histplot(df['CreditScore'], bins=20, kde=True, color='lightcoral')
plt.title("CreditScore Distribution (Histogram with KDE)")
plt.xlabel("CreditScore")
plt.ylabel("Frequency")
plt.tight_layout()
plt.show()
```

Overall CreditScore Distribution



CreditScore Distribution by Exited Status

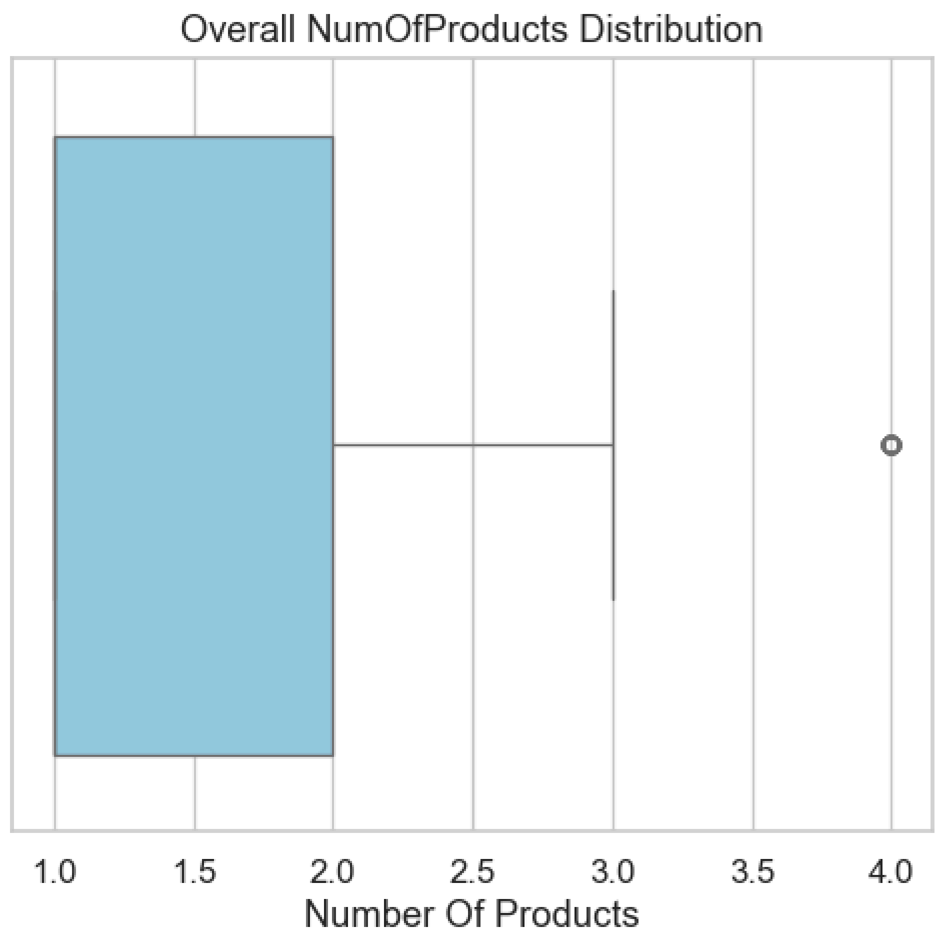


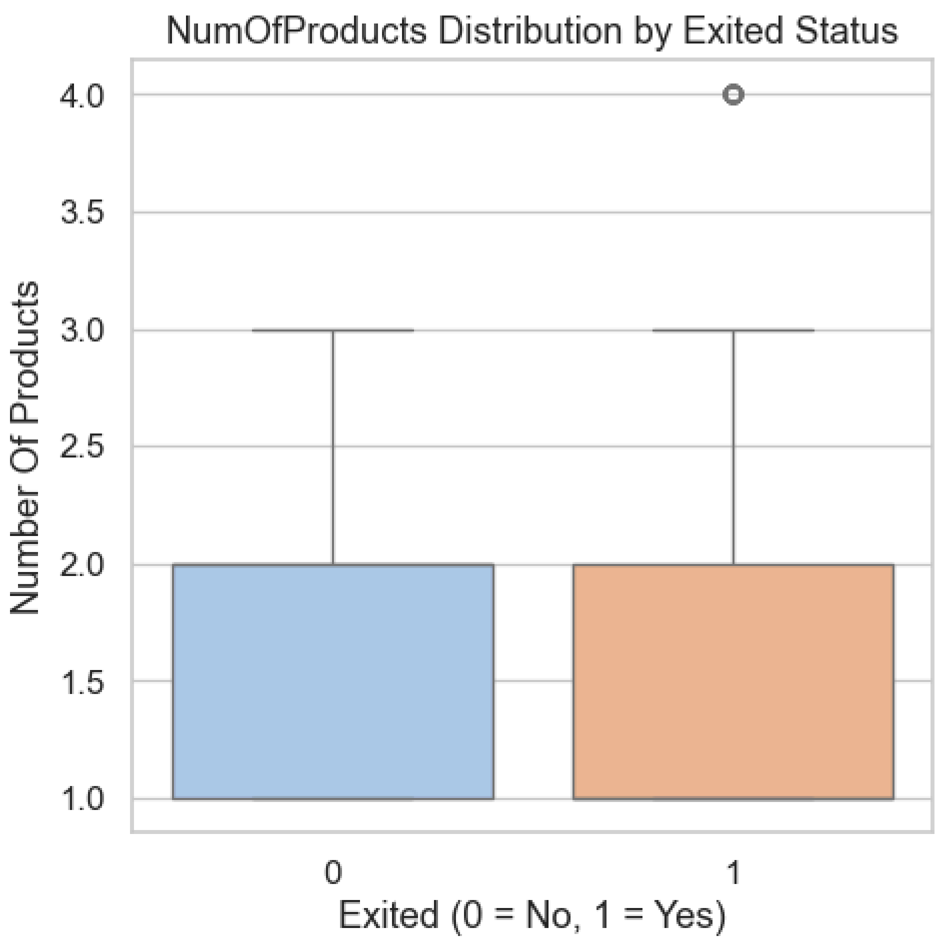


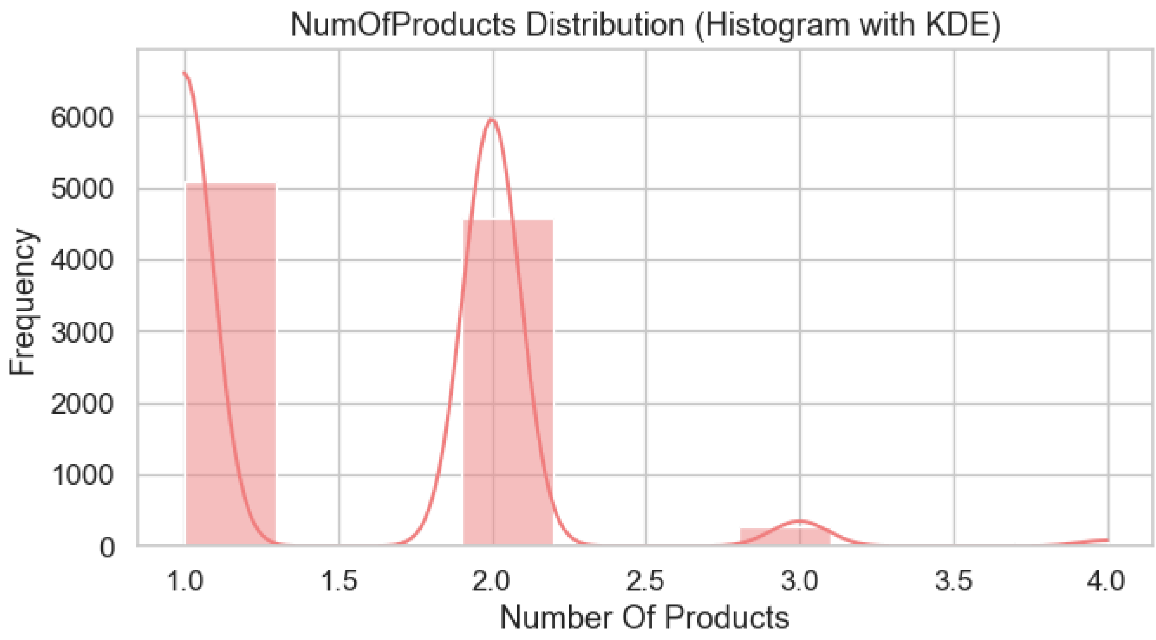
NumOfProducts

In [145…

```
plt.figure(figsize=(5,5))
sns.boxplot(x=df["NumOfProducts"], color='skyblue')
plt.title("Overall NumOfProducts Distribution")
plt.xlabel("Number Of Products")
plt.ylabel("")
plt.tight_layout()
plt.show()

plt.figure(figsize=(5, 5))
sns.boxplot(x="Exited", y="NumOfProducts", data=df, palette="pastel")
plt.title("NumOfProducts Distribution by Exited Status")
plt.xlabel("Exited (0 = No, 1 = Yes)")
plt.ylabel("Number Of Products")
plt.tight_layout()
plt.show()

plt.figure(figsize=(7, 4))
sns.histplot(df['NumOfProducts'], bins=10, kde=True, color='lightcoral')
plt.title("NumOfProducts Distribution (Histogram with KDE)")
plt.xlabel("Number Of Products")
plt.ylabel("Frequency")
plt.tight_layout()
plt.show()
```


Overall NumOfProducts Distribution
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Number Of Products


NumOfProducts Distribution by Exited Status
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Number Of Products
0
1
Exited (0 = No, 1 = Yes)



5. Data Pre-processing

A. Handling Missing Values

In [146…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   CustomerId       10000 non-null  int64  
 1   Surname          10000 non-null  object 
 2   CreditScore      10000 non-null  int64  
 3   Geography        10000 non-null  object 
 4   Gender           10000 non-null  object 
 5   Age              10000 non-null  int64  
 6   Tenure           10000 non-null  int64  
 7   Balance          10000 non-null  float64
 8   NumOfProducts    10000 non-null  int64  
 9   HasCrCard        10000 non-null  int64  
 10  IsActiveMember   10000 non-null  int64  
 11  EstimatedSalary  10000 non-null  float64
 12  Exited           10000 non-null  int64  
dtypes: float64(2), int64(8), object(3)
memory usage: 1015.8+ KB
```

After inspecting the dataset, we found that there are **no missing values** in any column.

Therefore, we are **skipping the missing value treatment step** in the data preprocessing pipeline.

> ✅ This ensures the integrity of our dataset and allows us to move directly to outlier detection and feature analysis.

B. Outlier Detection

In [151…

```
y = df['Exited']

x = df.drop(['Exited', 'CustomerId', 'Surname',
                   'Geography', 'Gender'], axis = 1)
x.head()
```

Out[151…

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Es
0	619	42	2	0.00	1	1	1	
1	608	41	1	83807.86	1	0	1	
2	502	42	8	159660.80	3	1	0	
3	699	39	1	0.00	2	0	0	
4	850	43	2	125510.82	1	1	1	

In [152…

```
from sklearn.neighbors import LocalOutlierFactor
model = LocalOutlierFactor()
yhat = model.fit_predict(x)
```

In [153…

```
# seect all rows that are outliers
outliers = yhat == -1

# select all rows that are not outliers
mask = yhat != -1
```

In [154…

```
# Outliers
pd.concat([x.iloc[outliers, :], y.iloc[outliers]], axis=1)
```

Out[154…

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember
343	543	22	8	0.00	2	0	0
520	850	35	1	211774.31	1	1	0
537	686	34	9	0.00	2	1	0
1533	850	37	3	212778.20	1	0	1
1791	702	35	8	14262.80	2	1	0
1830	506	37	5	0.00	2	1	1
1856	527	29	2	27755.97	1	1	0
2092	655	38	3	250898.09	3	0	1
2709	592	37	4	212692.97	1	0	0
3247	791	25	7	0.00	1	1	0
3280	583	57	3	238387.56	1	0	1

3588	489	40	3	221532.80	1	1	0
3920	634	43	3	212696.32	1	1	0
4062	559	45	8	24043.45	1	0	1
4533	850	39	6	206014.94	2	0	1
5048	707	42	2	16893.59	1	1	1
5568	693	38	7	198338.77	2	1	1
5686	644	46	6	12459.19	1	0	0
5742	832	61	2	0.00	1	0	1
6029	659	44	9	23503.31	1	0	1
6271	747	49	6	202904.64	1	1	1
6717	663	58	5	216109.88	1	0	1
6721	824	77	3	27517.15	2	0	1
7353	596	21	4	210433.08	2	0	1
8260	640	30	5	32197.64	1	0	1
8427	753	40	0	3768.69	2	1	0
8733	749	42	9	222267.63	1	0	0
8982	504	32	8	206663.75	1	0	0
9920	678	49	3	204510.94	1	0	1

In [155…

```
final_df = df.iloc[mask, :]
final_df.head()
```

Out[155…

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

In [157…

```
final_df.shape
```

Out[157…

```
(9971, 13)
```

🧠 EDA for Classification Project : Conclusion

Dataset: Customer Churn

This project focused on performing a comprehensive **Exploratory Data Analysis (EDA)** on a customer churn dataset, with the goal of identifying patterns and significant features that influence customer churn behavior.

✅ Summary of Steps

1. 🚀 Initial Setup & Data Overview

- Imported essential libraries: `pandas` , `numpy` , `seaborn` , `matplotlib`
- Loaded the **Customer Churn dataset**
- Explored basic structure using `.info()` , `.describe()` , and `.head()`
- Checked column types and understood variable categories (categorical vs numerical)
- Reviewed the target variable `Exited` for class balance

2. 📊 Univariate Analysis

- Explored individual distributions of key features
- Assessed value counts, skewness, and class balance

3. 🔗 Bivariate Statistical Testing

- Applied **Chi-Square Test** (categorical vs `Exited`)
- Applied **ANOVA Test** (numerical vs `Exited`)
- ✅ Selected only statistically significant features for further analysis

4. 📈 Visual Analytics (Seaborn)

- Clean and modern charts using `sns.set_theme()`
- Grouped bar plots for categorical features vs `Exited`
- Boxplots and histograms for numerical feature variation by `Exited`

5. 🚨 Missing Value Handling & Outlier Detection

- Checked for missing values
- ✅ No missing values found — skipped imputation
- Used **Local Outlier Factor (LOF)** on numerical features
- Identified and removed rows with extreme behavior
- Resulted in a more stable, high-quality dataset

📌 Key Insights

- ✅ **Gender**, **Geography**, and **IsActiveMember** were **statistically significant** categorical predictors of churn
- 📉 Customers with **higher Age** and **lower Balance** showed higher churn risk
- 🧠 Visual analysis aligned well with statistical test outcomes, increasing trust in the selected features

---

🏁 Final Notes

This EDA phase provides a **robust foundation for predictive modeling**.
The cleaned and statistically validated dataset is now ready for training classification models such as:

- Logistic Regression
- Random Forest
- XGBoost
- Gradient Boosting

> ✅ A well-executed EDA ensures data is **relevant, interpretable, and ready for machine learning**.

In [ ]:

```

```