Introduction

In this notebook, we conduct an end-to-end analysis of the **BankChurners** dataset (15 numerical & 8 categorical features) to understand and predict customer attrition in a competitive banking environment. Our objectives are to:

1. **Define the problem** — quantify the impact of high churn (revenue loss, weakened brand loyalty, costly replacements).

2. **Prepare the data** — remove irrelevant columns, handle outliers via IQR, and convert `Attrition_Flag` into a binary `Churn` label.

3. **Explore patterns (EDA)** — visualise distributions and joint relationships across demographics, transaction volume, utilisation ratios, and tenure.

4. **Rank features** — use correlation, F-score (ANOVA), and mutual information to identify top predictors such as `Total_Trans_Ct`, `Total_Trans_Amt`, and `Avg_Utilization_Ratio`.

5. **Build models** — train and compare Logistic Regression, Decision Tree, Random Forest, AdaBoost, XGBoost, SVM, and MLP to find the best churn-prediction engine.

6. **Derive insights & actions** — translate model outputs into targeted retention strategies (workshops, credit-rebuilding, personalised perks).

1. Setup

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency
import matplotlib.patches as mpatches
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier,
AdaBoostClassifier
from sklearn.metrics import (classification_report, confusion_matrix,
                             ConfusionMatrixDisplay, roc_curve,
roc_auc_score,
                             precision_recall_fscore_support)


plt.rcParams['figure.figsize'] = (10, 6)

import warnings
warnings.filterwarnings('ignore')
```

```python
print("Setup complete.")
```

```
Setup complete.
```

2. Data Loading

Ensure the **BankChurners.csv** file is in the same directory as this notebook.

```python
# Load the dataset
df = pd.read_csv("BankChurners.csv")

# Display the first 5 rows
df.head()
```

```
   CLIENTNUM     Attrition_Flag  Customer_Age Gender  Dependent_count  \
0  768805383  Existing Customer            45      M                3

1  818770008  Existing Customer            49      F                5

2  713982108  Existing Customer            51      M                3

3  769911858  Existing Customer            40      F                4

4  709106358  Existing Customer            40      M                3


  Education_Level Marital_Status Income_Category Card_Category  \
0     High School        Married     $60K - $80K          Blue
1        Graduate         Single  Less than $40K          Blue
2        Graduate        Married    $80K - $120K          Blue
3     High School        Unknown  Less than $40K          Blue
4      Uneducated        Married     $60K - $80K          Blue

   Months_on_book  ...  Credit_Limit  Total_Revolving_Bal
Avg_Open_To_Buy  \
0              39  ...       12691.0                  777
11914.0
1              44  ...        8256.0                  864
7392.0
2              36  ...        3418.0                    0
3418.0
3              34  ...        3313.0                 2517
796.0
4              21  ...        4716.0                    0
4716.0

   Total_Amt_Chng_Q4_Q1  Total_Trans_Amt  Total_Trans_Ct
Total_Ct_Chng_Q4_Q1  \
```

```
0                 1.335             1144             42
1.625
1                 1.541             1291             33
3.714
2                 2.594             1887             20
2.333
3                 1.405             1171             20
2.333
4                 2.175              816             28
2.500

   Avg_Utilization_Ratio  \
0                  0.061
1                  0.105
2                  0.000
3                  0.760
4                  0.000


Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_
mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1  \
0                                            0.000093

1                                            0.000057

2                                            0.000021

3                                            0.000134

4                                            0.000022



Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_
mon_Dependent_count_Education_Level_Months_Inactive_12_mon_2
0                                             0.99991

1                                             0.99994

2                                             0.99998

3                                             0.99987

4                                             0.99998


[5 rows x 23 columns]
```

3. Data Cleaning

3.1 Drop Unwanted Columns

We remove the following columns:

- `CLIENTNUM`
- Any columns generated by a Naive Bayes model (i.e., those starting with `Naive_Bayes_Classifier_...`)

```
# Define columns to drop
columns_to_drop = [
    'CLIENTNUM',

'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12
_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1',

'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12
_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_2'
]

# Drop the specified columns
df.drop(columns=columns_to_drop, inplace=True, errors='ignore')

print("Columns removed.")
df.head()
```

```
Columns removed.

      Attrition_Flag  Customer_Age Gender  Dependent_count
Education_Level  \
0  Existing Customer            45      M                3      High
School
1  Existing Customer            49      F                5
Graduate
2  Existing Customer            51      M                3
Graduate
3  Existing Customer            40      F                4      High
School
4  Existing Customer            40      M                3
Uneducated

  Marital_Status Income_Category Card_Category  Months_on_book  \
0        Married     $60K - $80K          Blue              39
1         Single  Less than $40K          Blue              44
2        Married    $80K - $120K          Blue              36
3        Unknown  Less than $40K          Blue              34
4        Married     $60K - $80K          Blue              21

   Total_Relationship_Count  Months_Inactive_12_mon
```

```
Contacts_Count_12_mon  \
0                          5                        1
3
1                          6                        1
2
2                          4                        1
0
3                          3                        4
1
4                          5                        1
0

   Credit_Limit  Total_Revolving_Bal  Avg_Open_To_Buy
Total_Amt_Chng_Q4_Q1  \
0       12691.0                  777          11914.0
1.335
1        8256.0                  864           7392.0
1.541
2        3418.0                    0           3418.0
2.594
3        3313.0                 2517            796.0
1.405
4        4716.0                    0           4716.0
2.175

   Total_Trans_Amt  Total_Trans_Ct  Total_Ct_Chng_Q4_Q1
Avg_Utilization_Ratio
0             1144              42                1.625
0.061
1             1291              33                3.714
0.105
2             1887              20                2.333
0.000
3             1171              20                2.333
0.760
4              816              28                2.500
0.000
```

3.2 Checking for Missing Values

We check for any missing values that might need to be addressed.

```python
# Check for missing values
missing_values = df.isnull().sum()
print("Missing Values in each column:")
print(missing_values)
```

```
Missing Values in each column:
Attrition_Flag              0
```

```
Customer_Age                0
Gender                      0
Dependent_count             0
Education_Level             0
Marital_Status              0
Income_Category             0
Card_Category               0
Months_on_book              0
Total_Relationship_Count    0
Months_Inactive_12_mon      0
Contacts_Count_12_mon       0
Credit_Limit                0
Total_Revolving_Bal         0
Avg_Open_To_Buy             0
Total_Amt_Chng_Q4_Q1        0
Total_Trans_Amt             0
Total_Trans_Ct              0
Total_Ct_Chng_Q4_Q1         0
Avg_Utilization_Ratio       0
dtype: int64
```

3.3 Create Numeric `Churn` Column

We keep the original `Attrition_Flag` for distribution plots. Then we create a numeric `Churn` column:

- `Existing Customer` → 0
- `Attrited Customer` → 1

```
# Map 'Attrition_Flag' to a binary numeric column 'Churn'
df['Churn'] = df['Attrition_Flag'].map({'Existing Customer': 0,
'Attrited Customer': 1})

print("Unique values in Attrition_Flag:",
df['Attrition_Flag'].unique())
print("Churn column created.")
df[['Attrition_Flag', 'Churn']].head()

Unique values in Attrition_Flag: ['Existing Customer' 'Attrited
Customer']
Churn column created.

      Attrition_Flag  Churn
0  Existing Customer      0
1  Existing Customer      0
2  Existing Customer      0
3  Existing Customer      0
4  Existing Customer      0
```

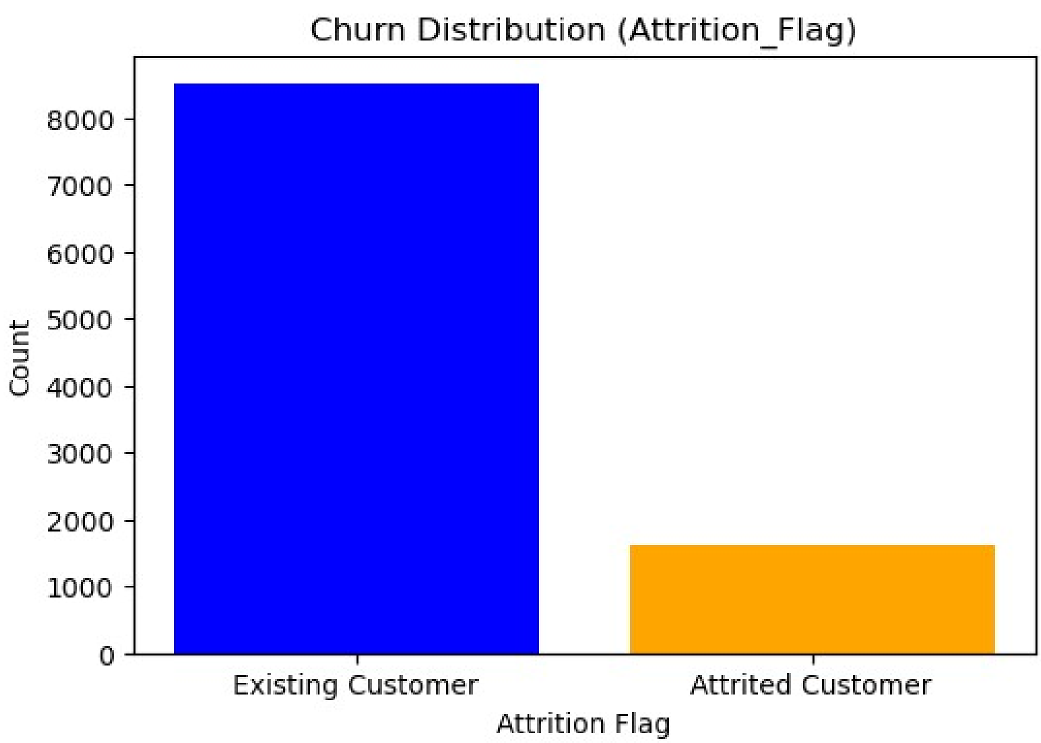
4. Exploratory Data Analysis (EDA)

4.1 Distribution of `Attrition_Flag`

We examine how many customers are attrited vs. existing.

```
# Check distribution of Attrition_Flag
if 'Attrition_Flag' in df.columns:
    churn_counts = df['Attrition_Flag'].value_counts()
    print(churn_counts)

    # Bar plot
    plt.figure(figsize=(6,4))
    plt.bar(churn_counts.index, churn_counts.values,
color=['blue','orange'])
    plt.title('Churn Distribution (Attrition_Flag)')
    plt.xlabel('Attrition Flag')
    plt.ylabel('Count')
    plt.show()
else:
    print("'Attrition_Flag' column not found.")
```

```
Attrition_Flag
Existing Customer    8500
Attrited Customer    1627
Name: count, dtype: int64
```



4.2 Outlier Removal

We remove outliers from all numeric columns **except** for `Churn`, using the IQR method.

```
# Create a copy for outlier removal
df_clean = df.copy()

# Identify numeric columns, excluding 'Churn'
numeric_cols =
df_clean.select_dtypes(include=[np.number]).columns.tolist()
if 'Churn' in numeric_cols:
    numeric_cols.remove('Churn')

# Remove outliers using IQR
for col in numeric_cols:
    Q1 = df_clean[col].quantile(0.25)
    Q3 = df_clean[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df_clean = df_clean[(df_clean[col] >= lower_bound) &
(df_clean[col] <= upper_bound)]

print("Original shape:", df.shape)
print("Cleaned shape:", df_clean.shape)

# Update df to the cleaned version
df = df_clean.copy()
```

```
Original shape: (10127, 21)
Cleaned shape: (6463, 21)
```

4.3 Data Overview (Post-Cleaning)

```
# View basic info after cleaning
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 6463 entries, 10 to 10125
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Attrition_Flag            6463 non-null   object
 1   Customer_Age              6463 non-null   int64
 2   Gender                    6463 non-null   object
 3   Dependent_count           6463 non-null   int64
 4   Education_Level           6463 non-null   object
 5   Marital_Status            6463 non-null   object
 6   Income_Category           6463 non-null   object
 7   Card_Category             6463 non-null   object
```

```
 8   Months_on_book            6463 non-null   int64
 9   Total_Relationship_Count  6463 non-null   int64
 10  Months_Inactive_12_mon    6463 non-null   int64
 11  Contacts_Count_12_mon     6463 non-null   int64
 12  Credit_Limit              6463 non-null   float64
 13  Total_Revolving_Bal       6463 non-null   int64
 14  Avg_Open_To_Buy           6463 non-null   float64
 15  Total_Amt_Chng_Q4_Q1      6463 non-null   float64
 16  Total_Trans_Amt           6463 non-null   int64
 17  Total_Trans_Ct            6463 non-null   int64
 18  Total_Ct_Chng_Q4_Q1       6463 non-null   float64
 19  Avg_Utilization_Ratio     6463 non-null   float64
 20  Churn                     6463 non-null   int64
dtypes: float64(5), int64(10), object(6)
memory usage: 1.1+ MB

# Summary statistics (including categorical columns)
df.describe(include='all')

           Attrition_Flag  Customer_Age Gender  Dependent_count  \
count                6463   6463.000000   6463      6463.000000
unique                  2           NaN      2              NaN
top     Existing Customer           NaN      F              NaN
freq                 5380           NaN   3988              NaN
mean                  NaN     46.384032    NaN         2.389138
std                   NaN      7.506139    NaN         1.272785
min                   NaN     26.000000    NaN         0.000000
25%                   NaN     41.000000    NaN         1.000000
50%                   NaN     46.000000    NaN         2.000000
75%                   NaN     52.000000    NaN         3.000000
max                   NaN     68.000000    NaN         5.000000

       Education_Level Marital_Status Income_Category Card_Category  \
count             6463           6463            6463          6463
unique               7              4               6             4
top           Graduate        Married  Less than $40K          Blue
freq              2006           2994            2677          6341
mean               NaN            NaN             NaN           NaN
std                NaN            NaN             NaN           NaN
min                NaN            NaN             NaN           NaN
25%                NaN            NaN             NaN           NaN
50%                NaN            NaN             NaN           NaN
75%                NaN            NaN             NaN           NaN
max                NaN            NaN             NaN           NaN

        Months_on_book  Total_Relationship_Count  ...
Contacts_Count_12_mon  \
count      6463.000000               6463.000000  ...
6463.000000
unique             NaN                       NaN  ...
```

```
NaN
top                 NaN                          NaN  ...
NaN
freq                NaN                          NaN  ...
NaN
mean          35.951106                     3.939192  ...
2.497138
std            7.036630                     1.514048  ...
0.930392
min           18.000000                     1.000000  ...
1.000000
25%           32.000000                     3.000000  ...
2.000000
50%           36.000000                     4.000000  ...
3.000000
75%           40.000000                     5.000000  ...
3.000000
max           53.000000                     6.000000  ...
4.000000

        Credit_Limit  Total_Revolving_Bal  Avg_Open_To_Buy  \
count    6463.000000          6463.000000      6463.000000
unique           NaN                  NaN              NaN
top              NaN                  NaN              NaN
freq             NaN                  NaN              NaN
mean     5084.608170          1140.233792      3944.374377
std      3921.874545           817.255076      3934.216696
min      1438.300000             0.000000        10.000000
25%      2264.000000             0.000000      1018.000000
50%      3359.000000          1250.000000      2229.000000
75%      6841.000000          1766.500000      5712.500000
max     19099.000000          2517.000000     16582.000000

        Total_Amt_Chng_Q4_Q1  Total_Trans_Amt  Total_Trans_Ct  \
count            6463.000000      6463.000000     6463.000000
unique                   NaN              NaN             NaN
top                      NaN              NaN             NaN
freq                     NaN              NaN             NaN
mean                0.728738      3593.651710       62.892155
std                 0.162697      1568.378776       19.472826
min                 0.293000       510.000000       10.000000
25%                 0.620000      2216.000000       46.000000
50%                 0.721000      3908.000000       67.000000
75%                 0.836000      4581.000000       79.000000
max                 1.193000      8454.000000      113.000000

        Total_Ct_Chng_Q4_Q1  Avg_Utilization_Ratio        Churn
count           6463.000000            6463.000000  6463.000000
unique                  NaN                    NaN          NaN
top                     NaN                    NaN          NaN
```

```
freq                      NaN                       NaN           NaN
mean                 0.687565                  0.320961      0.167569
std                  0.181285                  0.283666      0.373512
min                  0.207000                  0.000000      0.000000
25%                  0.569000                  0.000000      0.000000
50%                  0.689000                  0.260000      0.000000
75%                  0.808000                  0.570000      0.000000
max                  1.182000                  0.995000      1.000000

[11 rows x 21 columns]
```

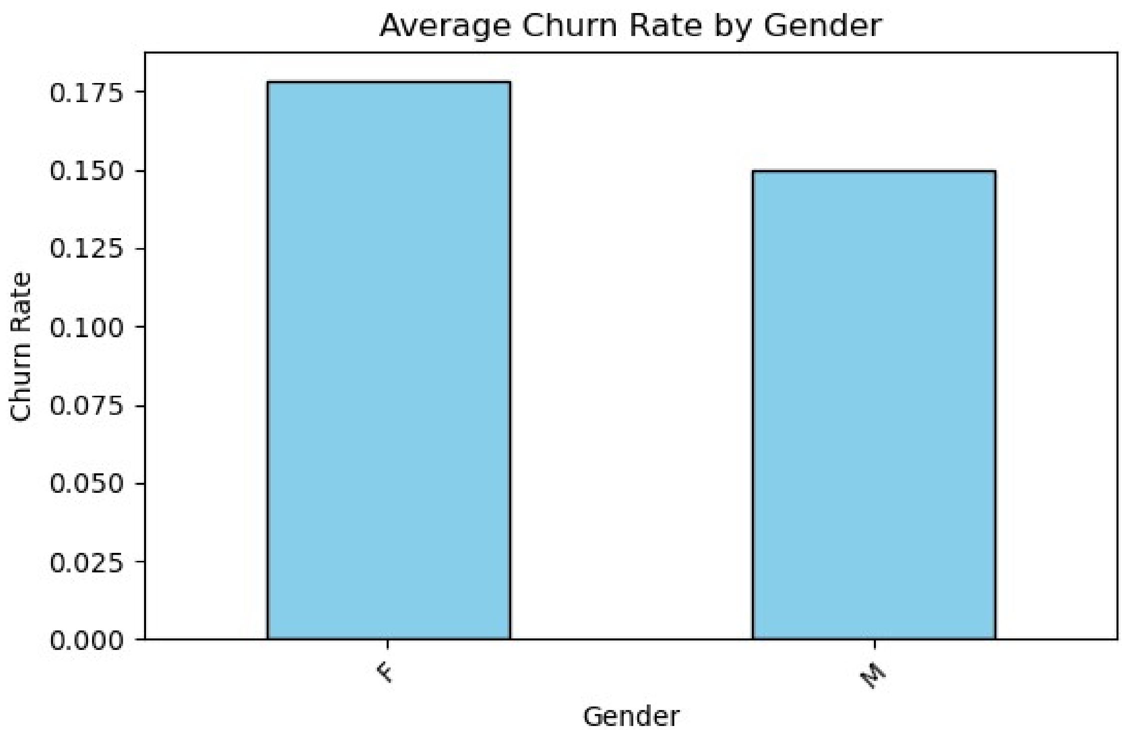
4.4 Categorical Analysis

We analyze the average churn rate for key categorical variables.

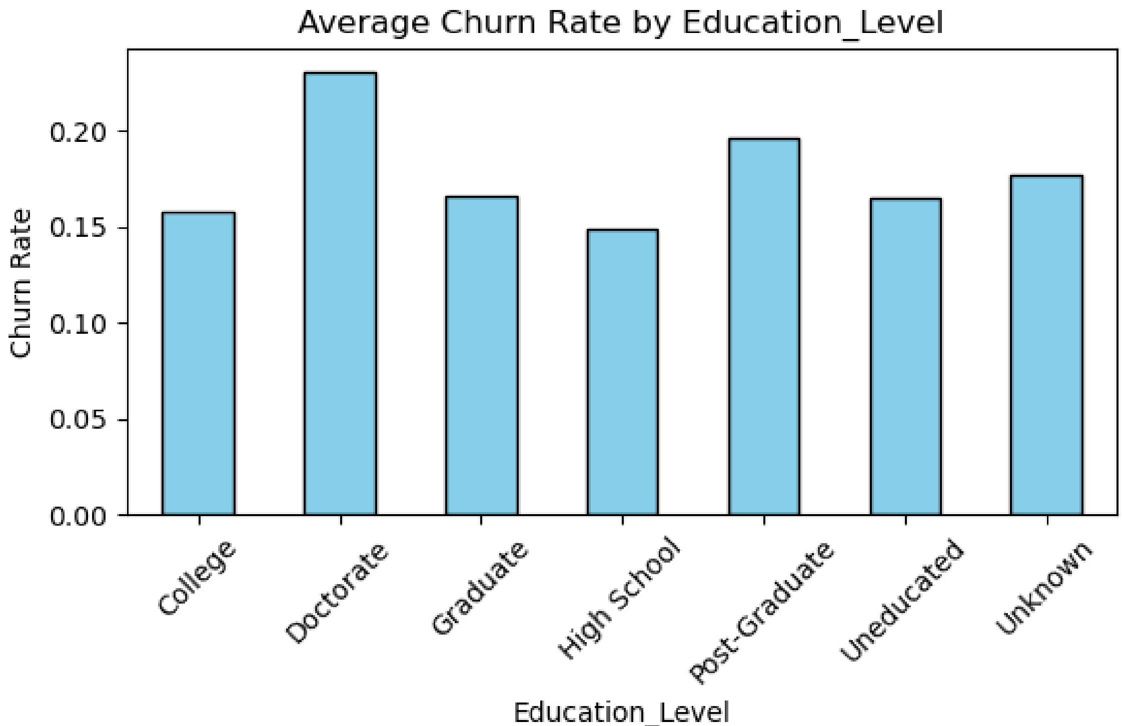
```
categorical_cols = ["Gender", "Education_Level", "Marital_Status",
"Income_Category", "Card_Category"]

for col in categorical_cols:
    if col in df.columns:
        print(f"=== Analysis for {col} ===")
        churn_rate = df.groupby(col)['Churn'].mean()
        print("Churn Rate by Category:")
        print(churn_rate)

        # Optional: Chi-square test
        contingency_table = pd.crosstab(df[col], df['Churn'])
        chi2, p, dof, expected = chi2_contingency(contingency_table)
        print(f"\nChi-square statistic: {chi2:.4f}")
        print(f"p-value: {p:.4f}")
        print(f"Degrees of freedom: {dof}")
        print("-" * 50)

        # Plot bar chart
        plt.figure(figsize=(6, 4))
        churn_rate.plot(kind='bar', color='skyblue',
edgecolor='black')
        plt.title(f"Average Churn Rate by {col}")
        plt.ylabel("Churn Rate")
        plt.xticks(rotation=45)
        plt.tight_layout()
        plt.show()
    else:
        print(f"Column {col} not found in DataFrame.")
```

```
=== Analysis for Gender ===
Churn Rate by Category:
Gender
F    0.178536
```

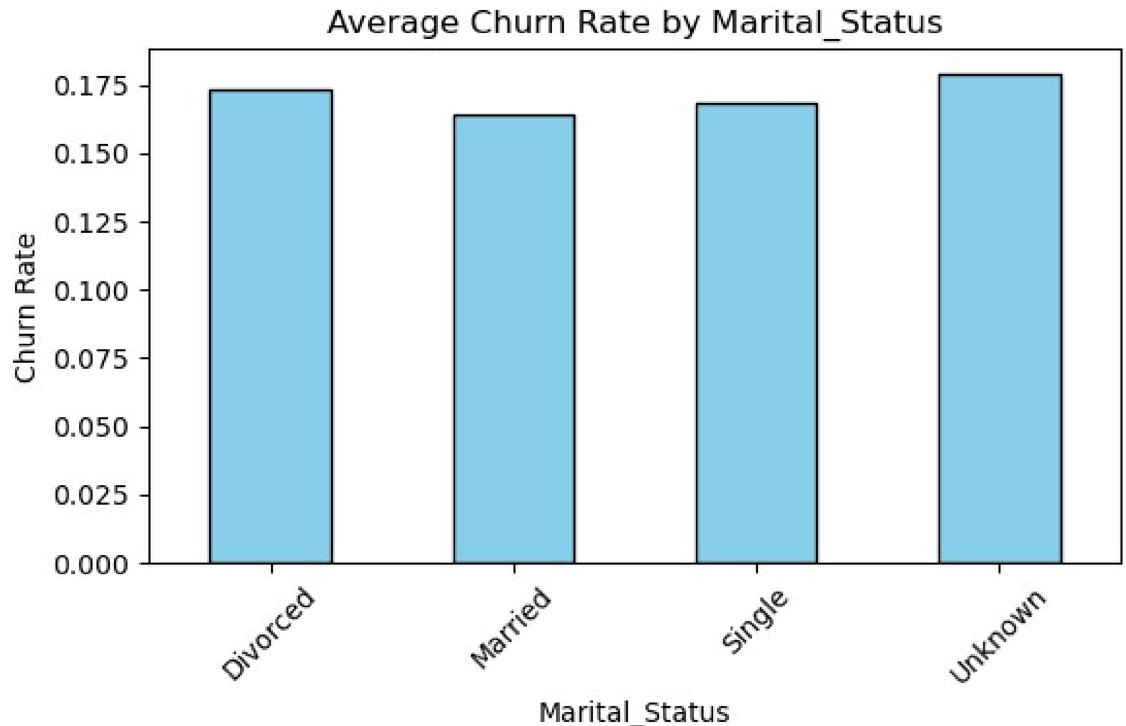
```
M    0.149899
Name: Churn, dtype: float64

Chi-square statistic: 8.7742
p-value: 0.0031
Degrees of freedom: 1
--------------------------------------------------
```



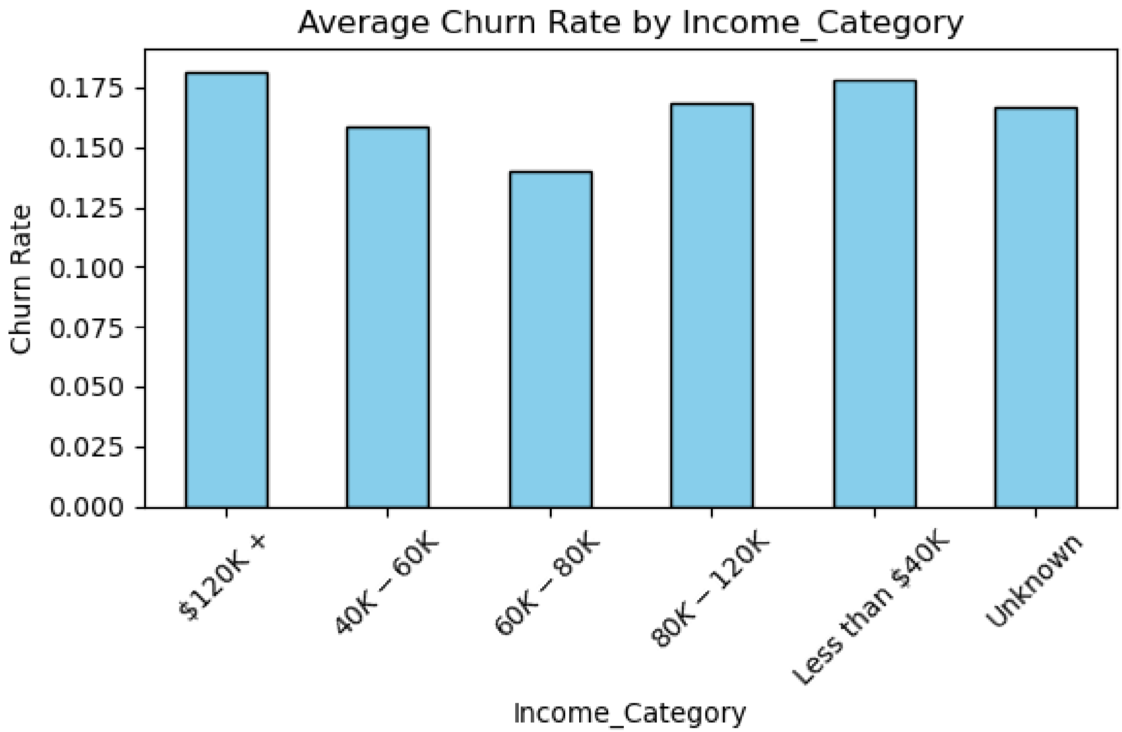

```
=== Analysis for Education_Level ===
Churn Rate by Category:
Education_Level
College          0.158133
Doctorate        0.230769
Graduate         0.166002
High School      0.148148
Post-Graduate    0.195652
Uneducated       0.164871
Unknown          0.177215
Name: Churn, dtype: float64

Chi-square statistic: 15.0267
p-value: 0.0201
Degrees of freedom: 6
--------------------------------------------------
```



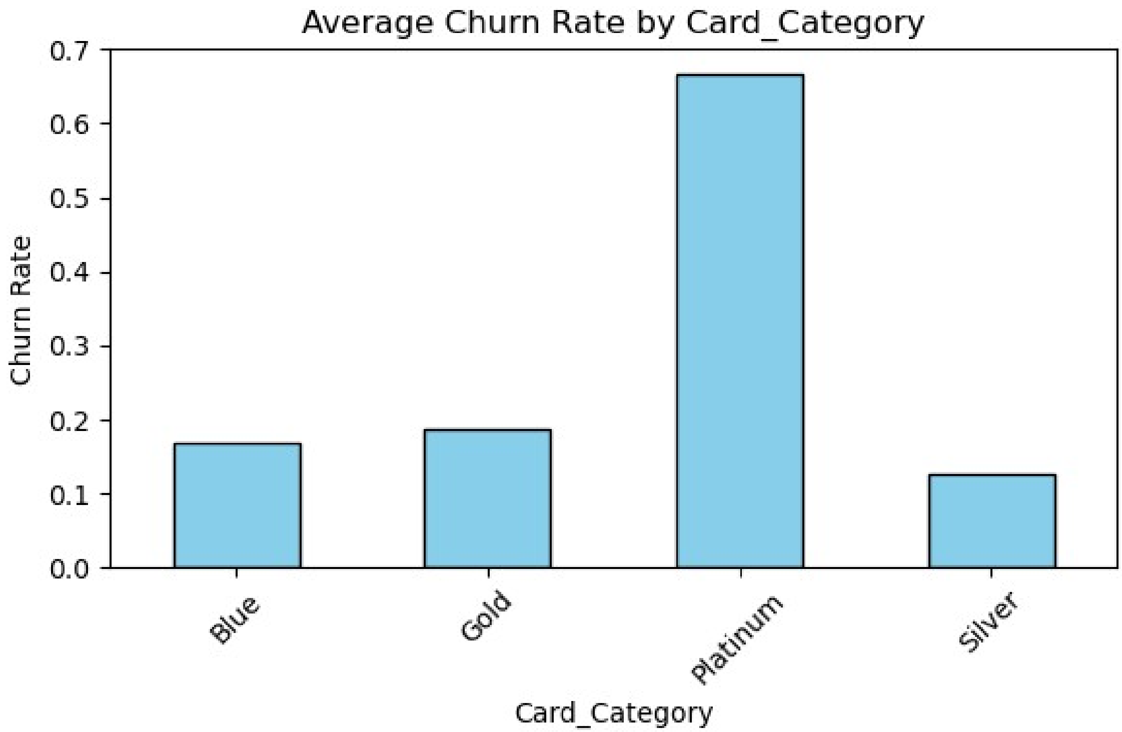

```
=== Analysis for Marital_Status ===
Churn Rate by Category:
Marital_Status
Divorced    0.173362
Married     0.163995
Single      0.168526
Unknown     0.179012
Name: Churn, dtype: float64

Chi-square statistic: 0.8607
p-value: 0.8349
Degrees of freedom: 3
--------------------------------------------------
```




```
=== Analysis for Income_Category ===
Churn Rate by Category:
Income_Category
$120K +           0.181818
$40K - $60K       0.158631
$60K - $80K       0.140199
$80K - $120K      0.168539
Less than $40K    0.178558
Unknown           0.167131
Name: Churn, dtype: float64

Chi-square statistic: 7.7728
p-value: 0.1692
Degrees of freedom: 5
--------------------------------------------------
```



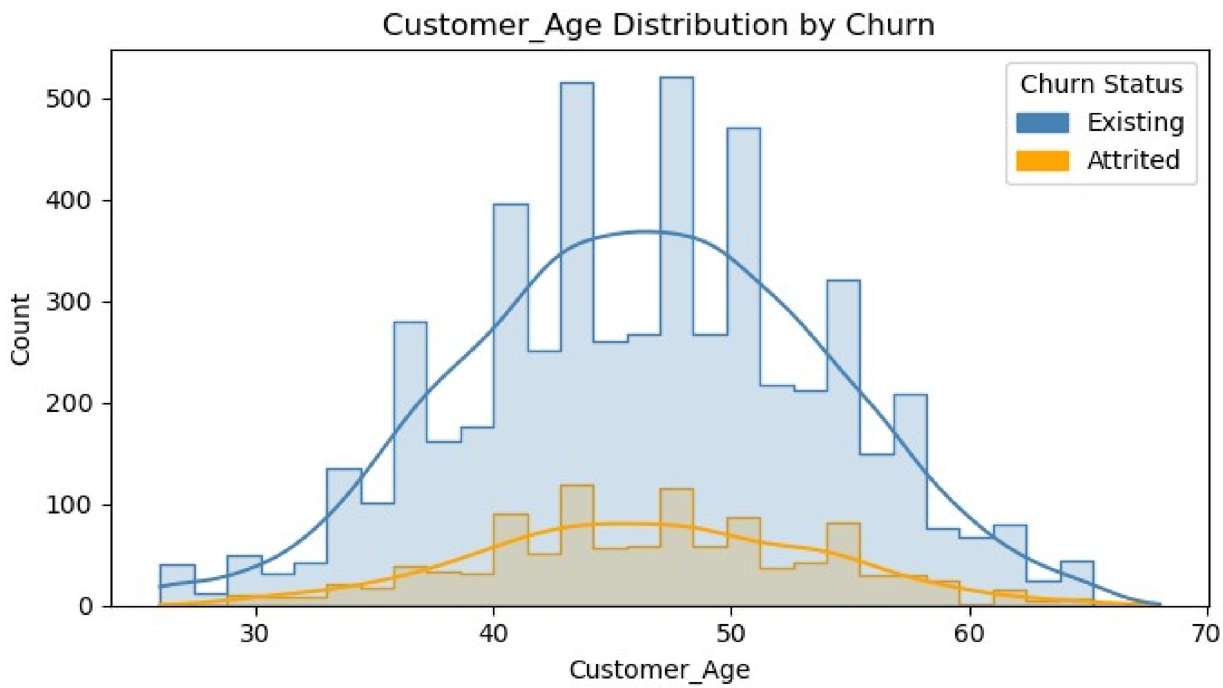

```
=== Analysis for Card_Category ===
Churn Rate by Category:
Card_Category
Blue        0.167955
Gold        0.187500
Platinum    0.666667
Silver      0.126214
Name: Churn, dtype: float64

Chi-square statistic: 6.6725
p-value: 0.0831
Degrees of freedom: 3
--------------------------------------------------
```

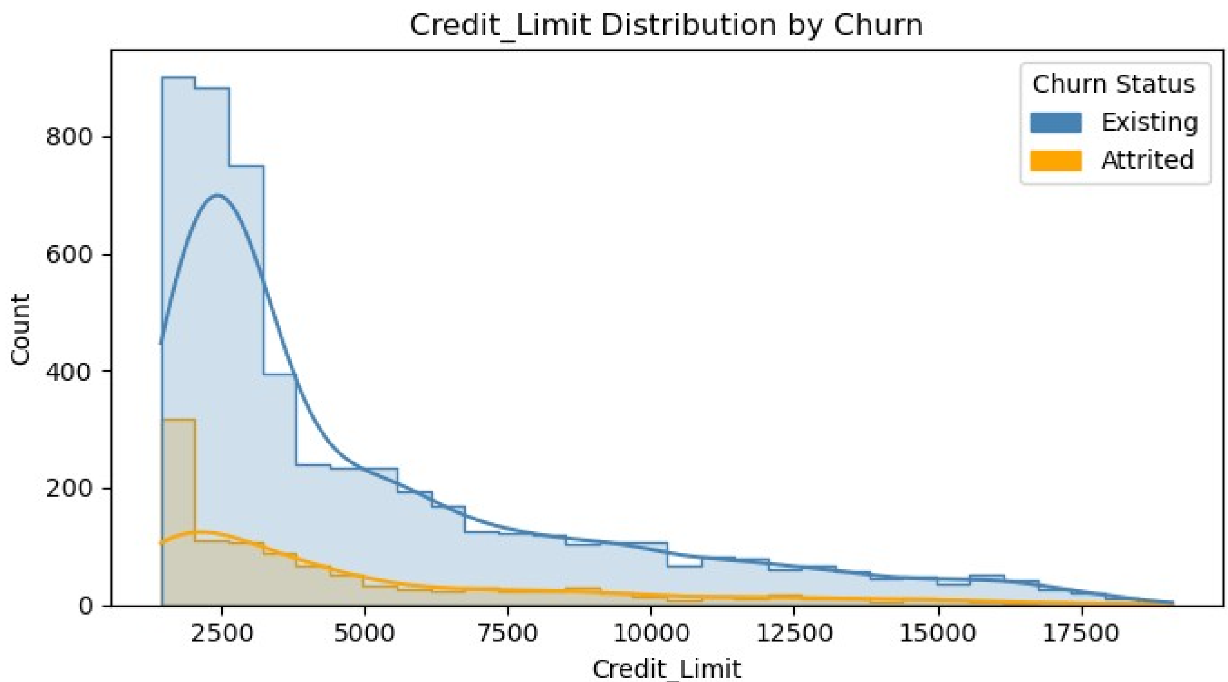


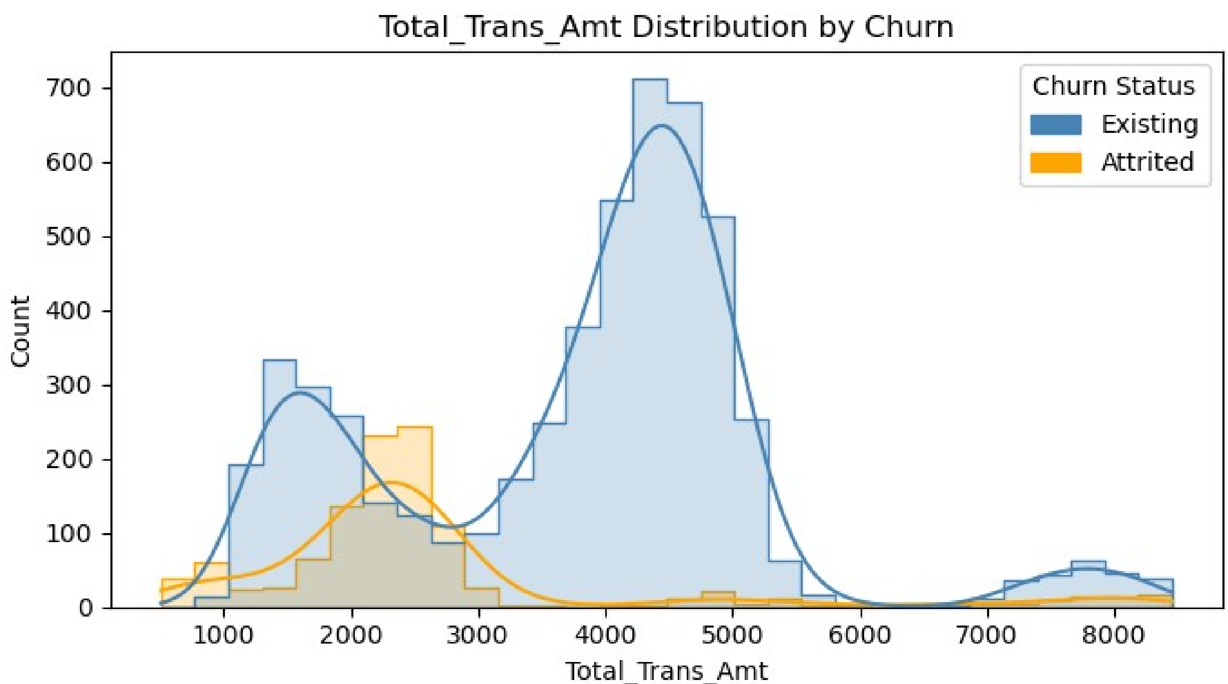
4.5 Numerical Feature Distributions

```
import matplotlib.patches as mpatches

numeric_cols = ["Customer_Age", "Credit_Limit", "Total_Trans_Amt"]

# Define custom legend patches
attrited_patch = mpatches.Patch(color='orange', label='Attrited')
existing_patch = mpatches.Patch(color='steelblue', label='Existing')

for col in numeric_cols:
    if col in df.columns:
        plt.figure(figsize=(7, 4))
        sns.histplot(
            data=df,
            x=col,
            hue='Churn',
            kde=True,
            bins=30,
            palette={1: 'orange', 0: 'steelblue'},
            element='step'
        )
        plt.title(f'{col} Distribution by Churn')
        plt.xlabel(col)
        plt.ylabel('Count')

        # Custom legend
```

```
        plt.legend(
            handles=[existing_patch, attrited_patch],
            title='Churn Status',
            loc='upper right'
        )

        plt.tight_layout()
        plt.show()
    else:
        print(f"Column {col} not found.")
```







4.6 Correlation Analysis

We compute the correlation matrix for numeric features and display the values in an annotated heatmap.

```
numeric_features = df.select_dtypes(include=[np.number])
corr_matrix = numeric_features.corr()
```

```
print("Correlation Matrix:")
print(corr_matrix)

plt.figure(figsize=(12, 10))
cax = plt.imshow(corr_matrix, cmap='coolwarm',
interpolation='nearest')
plt.colorbar(cax)
plt.xticks(range(len(corr_matrix.columns)), corr_matrix.columns,
rotation=90)
plt.yticks(range(len(corr_matrix.columns)), corr_matrix.columns)

# Annotate each cell
for i in range(len(corr_matrix.columns)):
    for j in range(len(corr_matrix.columns)):
        value = corr_matrix.iloc[i, j]
        plt.text(j, i, f"{value:.2f}", ha="center", va="center",
color="black")

plt.title('Correlation Matrix', pad=20)
plt.tight_layout()
plt.show()
```

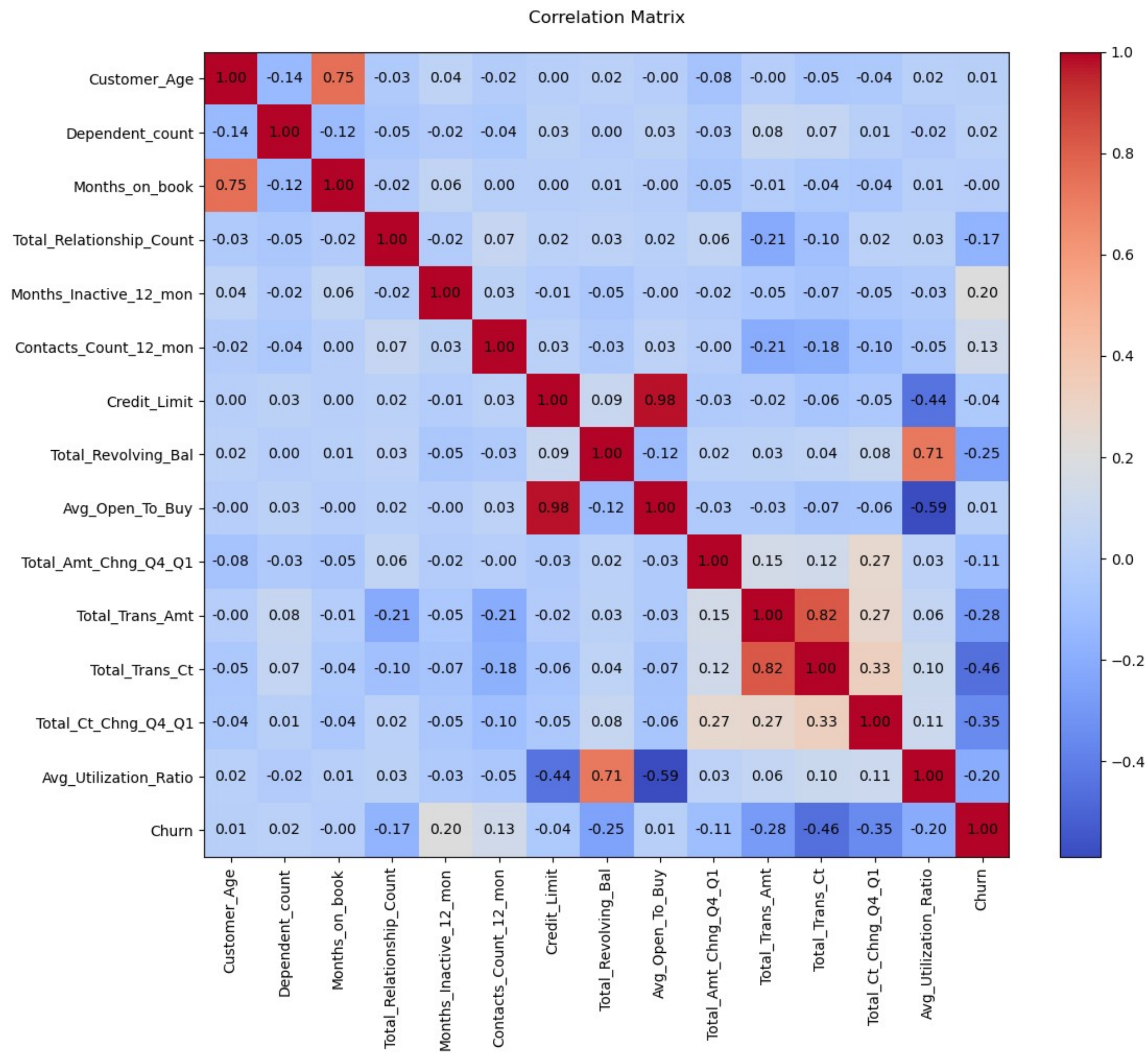
```
Correlation Matrix:
                          Customer_Age  Dependent_count
Months_on_book  \
Customer_Age                  1.000000        -0.135834
0.749380
Dependent_count              -0.135834         1.000000        -
0.118447
Months_on_book                0.749380        -0.118447
1.000000
Total_Relationship_Count     -0.027562        -0.053247        -
0.020789
Months_Inactive_12_mon        0.041709        -0.023846
0.059521
Contacts_Count_12_mon        -0.017703        -0.039636
0.001633
Credit_Limit                  0.001984         0.031626
0.002032
Total_Revolving_Bal           0.024946         0.000589
0.013704
Avg_Open_To_Buy              -0.003204         0.031405        -
0.000821
Total_Amt_Chng_Q4_Q1         -0.077916        -0.029982        -
0.054660
Total_Trans_Amt              -0.004178         0.083532        -
0.011554
Total_Trans_Ct               -0.045618         0.066685        -
0.040278
```

```
Total_Ct_Chng_Q4_Q1          -0.041602        0.009668       -
0.043758
Avg_Utilization_Ratio         0.018909       -0.019429
0.006541
Churn                         0.009278        0.024272       -
0.000709

                          Total_Relationship_Count
Months_Inactive_12_mon  \
Customer_Age                             -0.027562
0.041709
Dependent_count                          -0.053247                -
0.023846
Months_on_book                           -0.020789
0.059521
Total_Relationship_Count                  1.000000                -
0.017062
Months_Inactive_12_mon                   -0.017062
1.000000
Contacts_Count_12_mon                     0.069910
0.030453
Credit_Limit                              0.024691                -
0.010929
Total_Revolving_Bal                       0.033100                -
0.051495
Avg_Open_To_Buy                           0.017737                -
0.000198
Total_Amt_Chng_Q4_Q1                      0.057729                -
0.015678
Total_Trans_Amt                          -0.214060                -
0.047059
Total_Trans_Ct                           -0.096864                -
0.069923
Total_Ct_Chng_Q4_Q1                       0.024223                -
0.050469
Avg_Utilization_Ratio                     0.028920                -
0.034244
Churn                                    -0.166143
0.200456

                          Contacts_Count_12_mon  Credit_Limit  \
Customer_Age                          -0.017703      0.001984
Dependent_count                       -0.039636      0.031626
Months_on_book                         0.001633      0.002032
Total_Relationship_Count               0.069910      0.024691
Months_Inactive_12_mon                 0.030453     -0.010929
Contacts_Count_12_mon                  1.000000      0.025095
Credit_Limit                           0.025095      1.000000
Total_Revolving_Bal                   -0.032580      0.089066
```

```
Avg_Open_To_Buy                          0.031784     0.978361
Total_Amt_Chng_Q4_Q1                    -0.001769    -0.027540
Total_Trans_Amt                         -0.205141    -0.022577
Total_Trans_Ct                          -0.183845    -0.061805
Total_Ct_Chng_Q4_Q1                     -0.102562    -0.047357
Avg_Utilization_Ratio                   -0.049206    -0.442087
Churn                                    0.126290    -0.040464

                          Total_Revolving_Bal  Avg_Open_To_Buy  \
Customer_Age                         0.024946        -0.003204
Dependent_count                      0.000589         0.031405
Months_on_book                       0.013704        -0.000821
Total_Relationship_Count             0.033100         0.017737
Months_Inactive_12_mon              -0.051495        -0.000198
Contacts_Count_12_mon               -0.032580         0.031784
Credit_Limit                         0.089066         0.978361
Total_Revolving_Bal                  1.000000        -0.118943
Avg_Open_To_Buy                     -0.118943         1.000000
Total_Amt_Chng_Q4_Q1                 0.019511        -0.031507
Total_Trans_Amt                      0.031112        -0.028969
Total_Trans_Ct                       0.041654        -0.070264
Total_Ct_Chng_Q4_Q1                  0.080912        -0.064016
Avg_Utilization_Ratio                0.714490        -0.589121
Churn                               -0.250049         0.011606

                          Total_Amt_Chng_Q4_Q1  Total_Trans_Amt  \
Customer_Age                         -0.077916        -0.004178
Dependent_count                      -0.029982         0.083532
Months_on_book                       -0.054660        -0.011554
Total_Relationship_Count              0.057729        -0.214060
Months_Inactive_12_mon               -0.015678        -0.047059
Contacts_Count_12_mon                -0.001769        -0.205141
Credit_Limit                         -0.027540        -0.022577
Total_Revolving_Bal                   0.019511         0.031112
Avg_Open_To_Buy                      -0.031507        -0.028969
Total_Amt_Chng_Q4_Q1                  1.000000         0.145875
Total_Trans_Amt                       0.145875         1.000000
Total_Trans_Ct                        0.124872         0.823581
Total_Ct_Chng_Q4_Q1                   0.266692         0.270093
Avg_Utilization_Ratio                 0.033382         0.062679
Churn                                -0.105566        -0.282100

                          Total_Trans_Ct  Total_Ct_Chng_Q4_Q1  \
Customer_Age                   -0.045618            -0.041602
Dependent_count                 0.066685             0.009668
Months_on_book                 -0.040278            -0.043758
Total_Relationship_Count       -0.096864             0.024223
Months_Inactive_12_mon         -0.069923            -0.050469
Contacts_Count_12_mon          -0.183845            -0.102562
Credit_Limit                   -0.061805            -0.047357
```

Total_Revolving_Bal	0.041654	0.080912
Avg_Open_To_Buy	-0.070264	-0.064016
Total_Amt_Chng_Q4_Q1	0.124872	0.266692
Total_Trans_Amt	0.823581	0.270093
Total_Trans_Ct	1.000000	0.328686
Total_Ct_Chng_Q4_Q1	0.328686	1.000000
Avg_Utilization_Ratio	0.102378	0.109712
Churn	-0.456916	-0.351080

	Avg_Utilization_Ratio	Churn
Customer_Age	0.018909	0.009278
Dependent_count	-0.019429	0.024272
Months_on_book	0.006541	-0.000709
Total_Relationship_Count	0.028920	-0.166143
Months_Inactive_12_mon	-0.034244	0.200456
Contacts_Count_12_mon	-0.049206	0.126290
Credit_Limit	-0.442087	-0.040464
Total_Revolving_Bal	0.714490	-0.250049
Avg_Open_To_Buy	-0.589121	0.011606
Total_Amt_Chng_Q4_Q1	0.033382	-0.105566
Total_Trans_Amt	0.062679	-0.282100
Total_Trans_Ct	0.102378	-0.456916
Total_Ct_Chng_Q4_Q1	0.109712	-0.351080
Avg_Utilization_Ratio	1.000000	-0.204658
Churn	-0.204658	1.000000




```python
import pandas as pd
from sklearn.feature_selection import mutual_info_classif
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_selection import f_classif

# Step 1: Label Encode the categorical columns
label_encoder = LabelEncoder()

# Apply label encoding for each categorical column in the dataset
for column in df.select_dtypes(include=['object']).columns:
    df[column] = label_encoder.fit_transform(df[column])

# Split features and target
```

```python
X = df.drop(columns=['Churn'])  # Features
y = df['Churn']  # Target

# Step 2: Correlation Coefficient Calculation (Pearson Correlation)
correlation_scores = {}

for feature in X.columns:
    correlation_scores[feature] = X[feature].corr(y)  # Pearson
correlation

# Step 3: F-Score (ANOVA F-statistic) Calculation
f_scores, p_values = f_classif(X, y)

# Store the F-scores and their corresponding p-values
f_scores_dict = dict(zip(X.columns, f_scores))

# Step 4: Mutual Information Calculation
mutual_info = mutual_info_classif(X, y)

# Store the mutual information results
mi_scores = dict(zip(X.columns, mutual_info))

# Step 5: Rank the results from highest to lowest
sorted_correlation = sorted(correlation_scores.items(), key=lambda x:
abs(x[1]), reverse=True)
sorted_f_scores = sorted(f_scores_dict.items(), key=lambda x: x[1],
reverse=True)
sorted_mutual_info = sorted(mi_scores.items(), key=lambda x: x[1],
reverse=True)

# Step 6: Print the ranked results

# Print Correlation Coefficients ranked from highest to lowest
print("Correlation Coefficients ranked from highest to lowest:")
for feature, corr in sorted_correlation:
    print(f"{feature}: Correlation = {corr:.4f}")

# Print F-scores ranked from highest to lowest
print("\nF-Scores (ANOVA F-statistic) ranked from highest to lowest:")
for feature, f_score in sorted_f_scores:
    print(f"{feature}: F-Score = {f_score:.4f}")

# Print Mutual Information ranked from highest to lowest
print("\nMutual Information ranked from highest to lowest:")
for feature, mi in sorted_mutual_info:
    print(f"{feature}: Mutual Information = {mi:.4f}")
```

```
Correlation Coefficients ranked from highest to lowest:
Attrition_Flag: Correlation = -1.0000
Total_Trans_Ct: Correlation = -0.4569
Total_Ct_Chng_Q4_Q1: Correlation = -0.3511
```

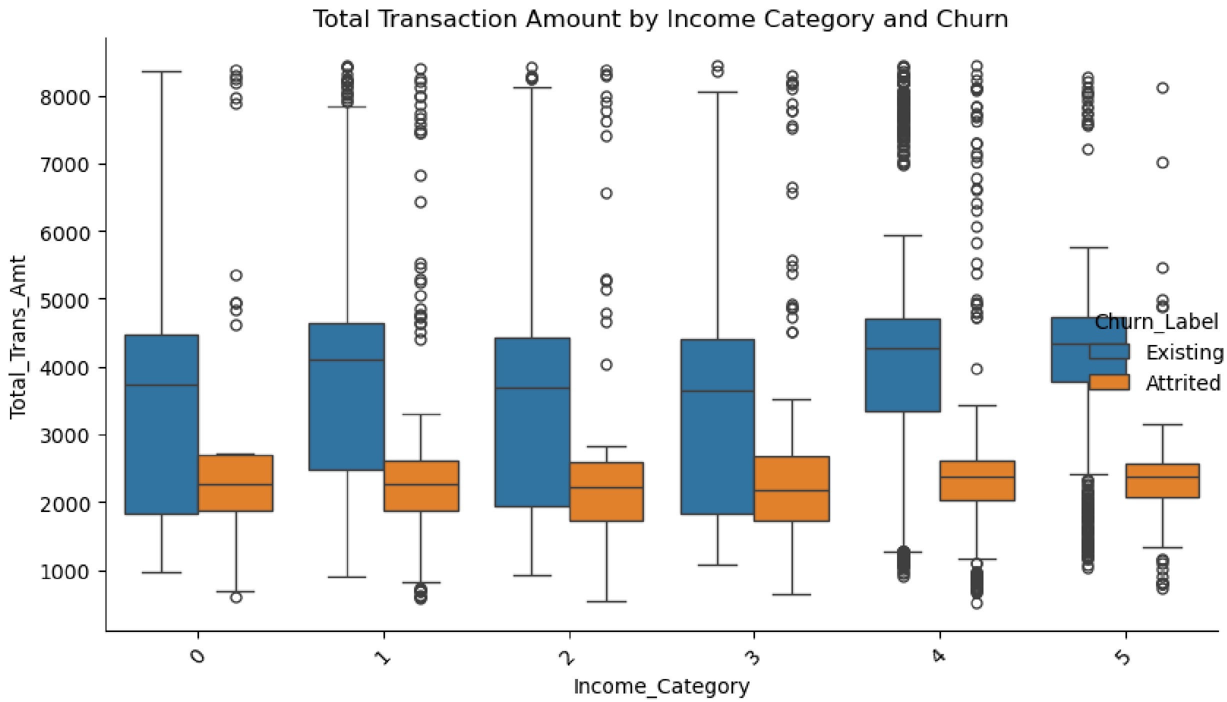
```
Total_Trans_Amt: Correlation = -0.2821
Total_Revolving_Bal: Correlation = -0.2500
Avg_Utilization_Ratio: Correlation = -0.2047
Months_Inactive_12_mon: Correlation = 0.2005
Total_Relationship_Count: Correlation = -0.1661
Contacts_Count_12_mon: Correlation = 0.1263
Total_Amt_Chng_Q4_Q1: Correlation = -0.1056
Credit_Limit: Correlation = -0.0405
Gender: Correlation = -0.0373
Dependent_count: Correlation = 0.0243
Income_Category: Correlation = 0.0177
Avg_Open_To_Buy: Correlation = 0.0116
Card_Category: Correlation = -0.0103
Customer_Age: Correlation = 0.0093
Marital_Status: Correlation = 0.0060
Education_Level: Correlation = 0.0035
Months_on_book: Correlation = -0.0007

F-Scores (ANOVA F-statistic) ranked from highest to lowest:
Attrition_Flag: F-Score = inf
Total_Trans_Ct: F-Score = 1704.7922
Total_Ct_Chng_Q4_Q1: F-Score = 908.3210
Total_Trans_Amt: F-Score = 558.6241
Total_Revolving_Bal: F-Score = 430.9144
Avg_Utilization_Ratio: F-Score = 282.4473
Months_Inactive_12_mon: F-Score = 270.4880
Total_Relationship_Count: F-Score = 183.4083
Contacts_Count_12_mon: F-Score = 104.7175
Total_Amt_Chng_Q4_Q1: F-Score = 72.8146
Credit_Limit: F-Score = 10.5963
Gender: F-Score = 8.9881
Dependent_count: F-Score = 3.8085
Income_Category: F-Score = 2.0217
Avg_Open_To_Buy: F-Score = 0.8703
Card_Category: F-Score = 0.6846
Customer_Age: F-Score = 0.5562
Marital_Status: F-Score = 0.2364
Education_Level: F-Score = 0.0805
Months_on_book: F-Score = 0.0033

Mutual Information ranked from highest to lowest:
Attrition_Flag: Mutual Information = 0.4526
Total_Trans_Amt: Mutual Information = 0.1872
Total_Trans_Ct: Mutual Information = 0.1570
Total_Ct_Chng_Q4_Q1: Mutual Information = 0.1100
Total_Revolving_Bal: Mutual Information = 0.0896
Avg_Utilization_Ratio: Mutual Information = 0.0480
Months_Inactive_12_mon: Mutual Information = 0.0303
Avg_Open_To_Buy: Mutual Information = 0.0211
```

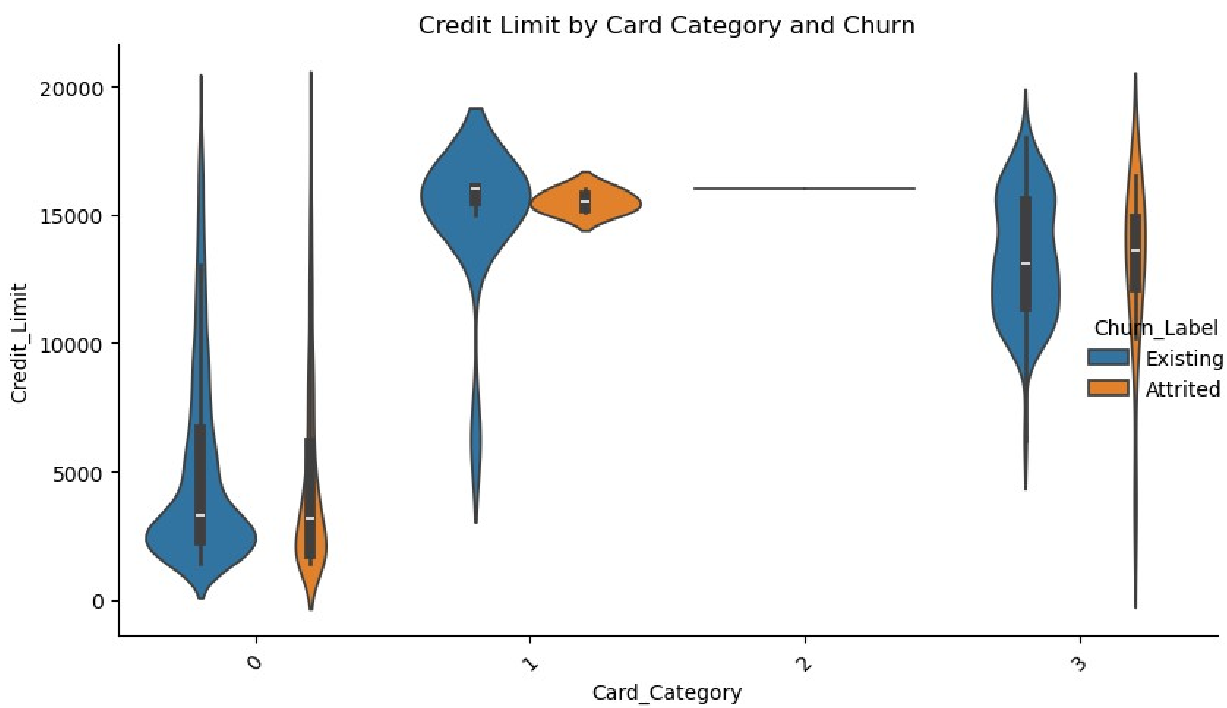
```
Total_Amt_Chng_Q4_Q1: Mutual Information = 0.0205
Total_Relationship_Count: Mutual Information = 0.0155
Dependent_count: Mutual Information = 0.0076
Contacts_Count_12_mon: Mutual Information = 0.0060
Credit_Limit: Mutual Information = 0.0057
Customer_Age: Mutual Information = 0.0042
Marital_Status: Mutual Information = 0.0042
Months_on_book: Mutual Information = 0.0040
Education_Level: Mutual Information = 0.0017
Income_Category: Mutual Information = 0.0012
Gender: Mutual Information = 0.0000
Card_Category: Mutual Information = 0.0000
```

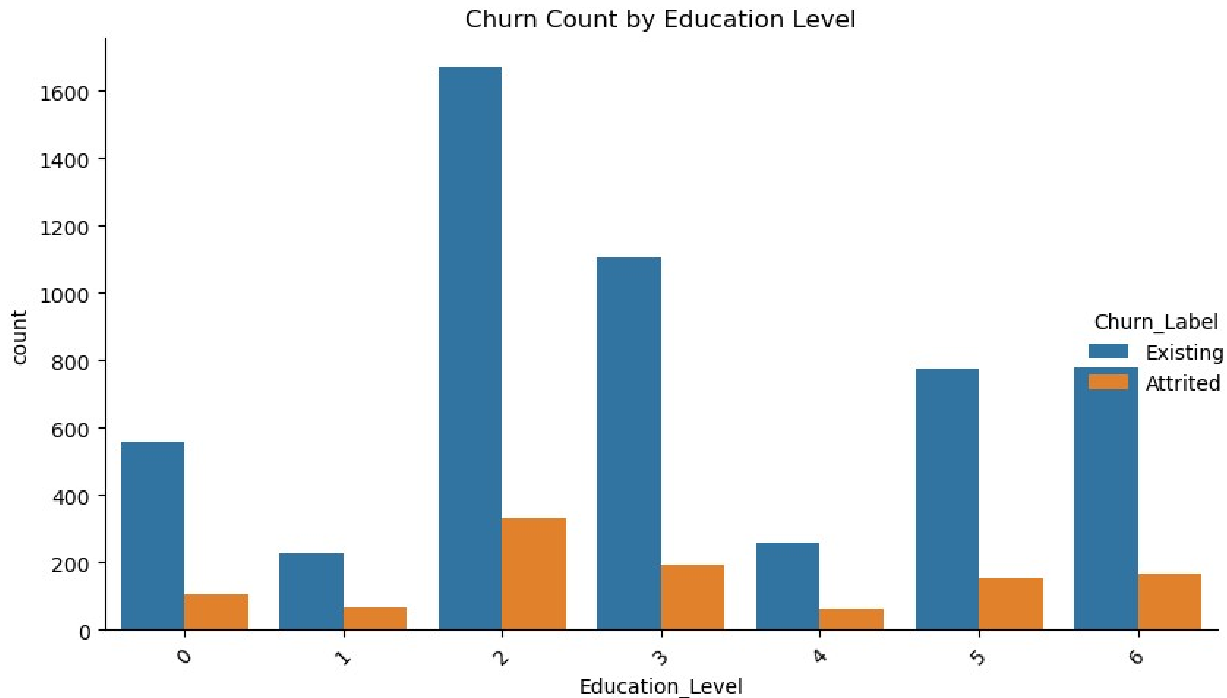
4.7 Join Plots and Cat Plots

We use Join Plots and Cat Plots to investigate the

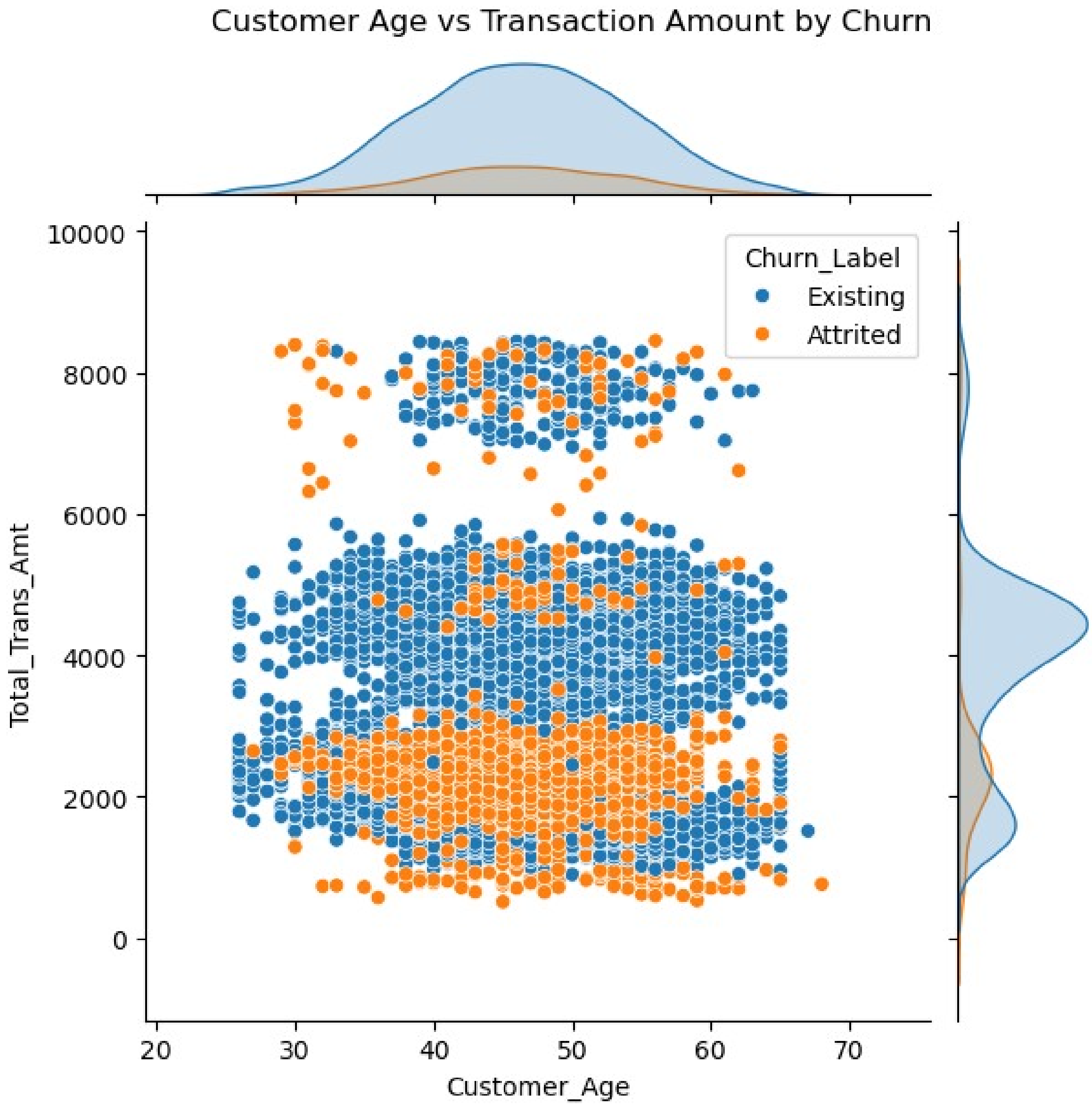
```
# Replace 0/1 in 'Churn' with descriptive labels
df['Churn_Label'] = df['Churn'].map({0: 'Existing', 1: 'Attrited'})

# 1. Transaction amount vs Income Category
sns.catplot(data=df, x="Income_Category", y="Total_Trans_Amt",
hue="Churn_Label", kind="box", height=5, aspect=1.5)
plt.title("Total Transaction Amount by Income Category and Churn")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# 2. Credit Limit by Card Category
sns.catplot(data=df, x="Card_Category", y="Credit_Limit",
hue="Churn_Label", kind="violin", height=5, aspect=1.5)
plt.title("Credit Limit by Card Category and Churn")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# 3. Count of customers by Education Level and Churn
sns.catplot(data=df, x="Education_Level", hue="Churn_Label",
kind="count", height=5, aspect=1.5)
plt.title("Churn Count by Education Level")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```


Total Transaction Amount by Income Category and Churn
Total_Trans_Amt
8000
7000
6000
5000
4000
3000
2000
1000
0
1
2
3
4
5
Income_Category
Churn_Label
Existing
Attrited

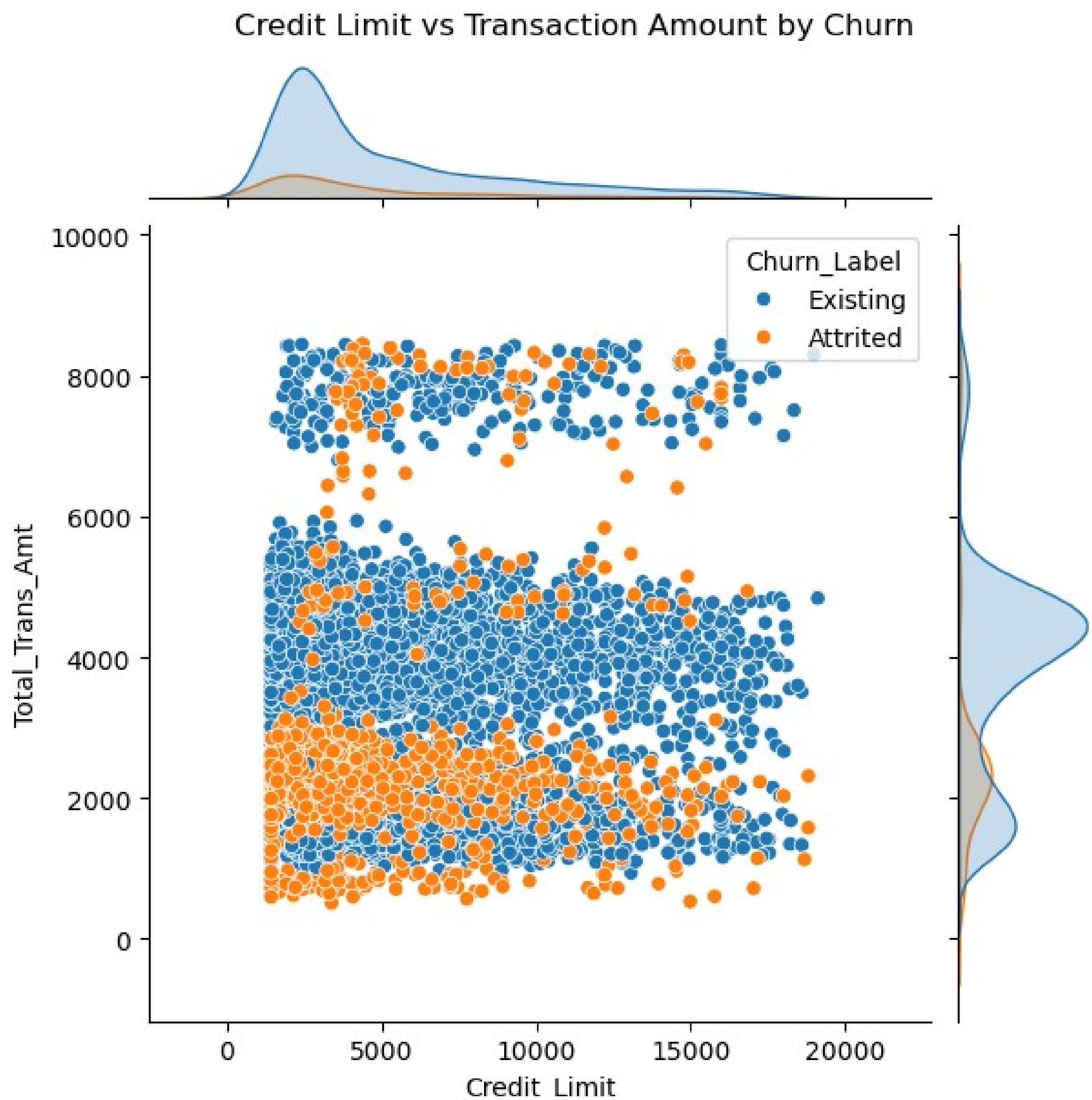

Credit Limit by Card Category and Churn
Credit_Limit
20000
15000
10000
5000
0
0
1
2
3
Card_Category
Churn_Label
Existing
Attrited




```
# Map churn values for clearer labels
df['Churn_Label'] = df['Churn'].map({0: 'Existing', 1: 'Attrited'})

# 1. Customer Age vs Total Transaction Amount
sns.jointplot(data=df, x="Customer_Age", y="Total_Trans_Amt",
hue="Churn_Label", kind="scatter", height=6)
plt.suptitle("Customer Age vs Transaction Amount by Churn", y=1.02)
plt.show()

# 2. Credit Limit vs Total Transaction Amount
sns.jointplot(data=df, x="Credit_Limit", y="Total_Trans_Amt",
hue="Churn_Label", kind="scatter", height=6)
plt.suptitle("Credit Limit vs Transaction Amount by Churn", y=1.02)
plt.show()
```



Customer Age vs Transaction Amount by Churn
Churn_Label
Existing
Attrited
Total_Trans_Amt
Customer_Age
10000
8000
6000
4000
2000
0
20
30
40
50
60
70



5. Predictive Modeling

We build logistic regression, random forest, **XGBoost**, and **AdaBoost** models to predict churn.

5.1 Data Preparation for Modeling

We:

- Drop `Attrition_Flag` from the dataset.
- One-hot encode the known categorical columns.
- Define features (`X`) and target (`y`).
- Perform a train-test split.

```
!pip install graphviz
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier,
AdaBoostClassifier
from sklearn.metrics import (classification_report, confusion_matrix,
                             ConfusionMatrixDisplay, roc_curve,
roc_auc_score,
                             precision_recall_fscore_support)
```

```
Requirement already satisfied: graphviz in
/opt/homebrew/anaconda3/lib/python3.12/site-packages (0.20.3)
```

```
import pandas as pd

# Load the CSV
df = pd.read_csv("BankChurners.csv")

# Drop the 'CLIENTNUM' column
df.drop(columns=['CLIENTNUM'], inplace=True)
df.drop(columns=['Naive_Bayes_Classifier_Attrition_Flag_Card_Category_
Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_
12_mon_1'], inplace=True)
df.drop(columns=['Naive_Bayes_Classifier_Attrition_Flag_Card_Category_
Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_
12_mon_2'], inplace=True)

# Select numeric and categorical columns
numeric_cols = df.select_dtypes(include=['int64', 'float64']).columns
categorical_cols = df.select_dtypes(include=['object']).columns

# Print unique values for each categorical column
for col in categorical_cols:
    print(f"Unique values in '{col}':")
    print(df[col].unique())
    print("-" * 50)
```

```
Unique values in 'Attrition_Flag':
['Existing Customer' 'Attrited Customer']
--------------------------------------------------
Unique values in 'Gender':
['M' 'F']
--------------------------------------------------
```

```
Unique values in 'Education_Level':
['High School' 'Graduate' 'Uneducated' 'Unknown' 'College' 'Post-
Graduate'
 'Doctorate']
--------------------------------------------------
Unique values in 'Marital_Status':
['Married' 'Single' 'Unknown' 'Divorced']
--------------------------------------------------
Unique values in 'Income_Category':
['$60K - $80K' 'Less than $40K' '$80K - $120K' '$40K - $60K' '$120K +'
 'Unknown']
--------------------------------------------------
Unique values in 'Card_Category':
['Blue' 'Gold' 'Silver' 'Platinum']
--------------------------------------------------
```

```python
cleaned_df = df.copy()
# Drop NA
cleaned_df.dropna()
# Drop duplicates
cleaned_df.drop_duplicates(inplace=True)

# IQR Filtering
for col in numeric_cols:
    Q1 = cleaned_df[col].quantile(0.25)
    Q3 = cleaned_df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    IQR_cleaned_df = cleaned_df[(cleaned_df[col] >= lower_bound) &
(cleaned_df[col] <= upper_bound)]

# Step 4: Check final shape after removing outliers
print("Cleaned dataset shape:", cleaned_df.shape)

# Optional: Save cleaned data
cleaned_df.to_csv("IQRcleaned_dataset.csv", index=False)
cleaned_df.head
```

```
Cleaned dataset shape: (10127, 20)
```

```
<bound method NDFrame.head of            Attrition_Flag  Customer_Age
Gender  Dependent_count  \
0      Existing Customer            45      M                3
1      Existing Customer            49      F                5
2      Existing Customer            51      M                3
3      Existing Customer            40      F                4
4      Existing Customer            40      M                3
...                  ...           ...    ...              ...
10122  Existing Customer            50      M                2
```

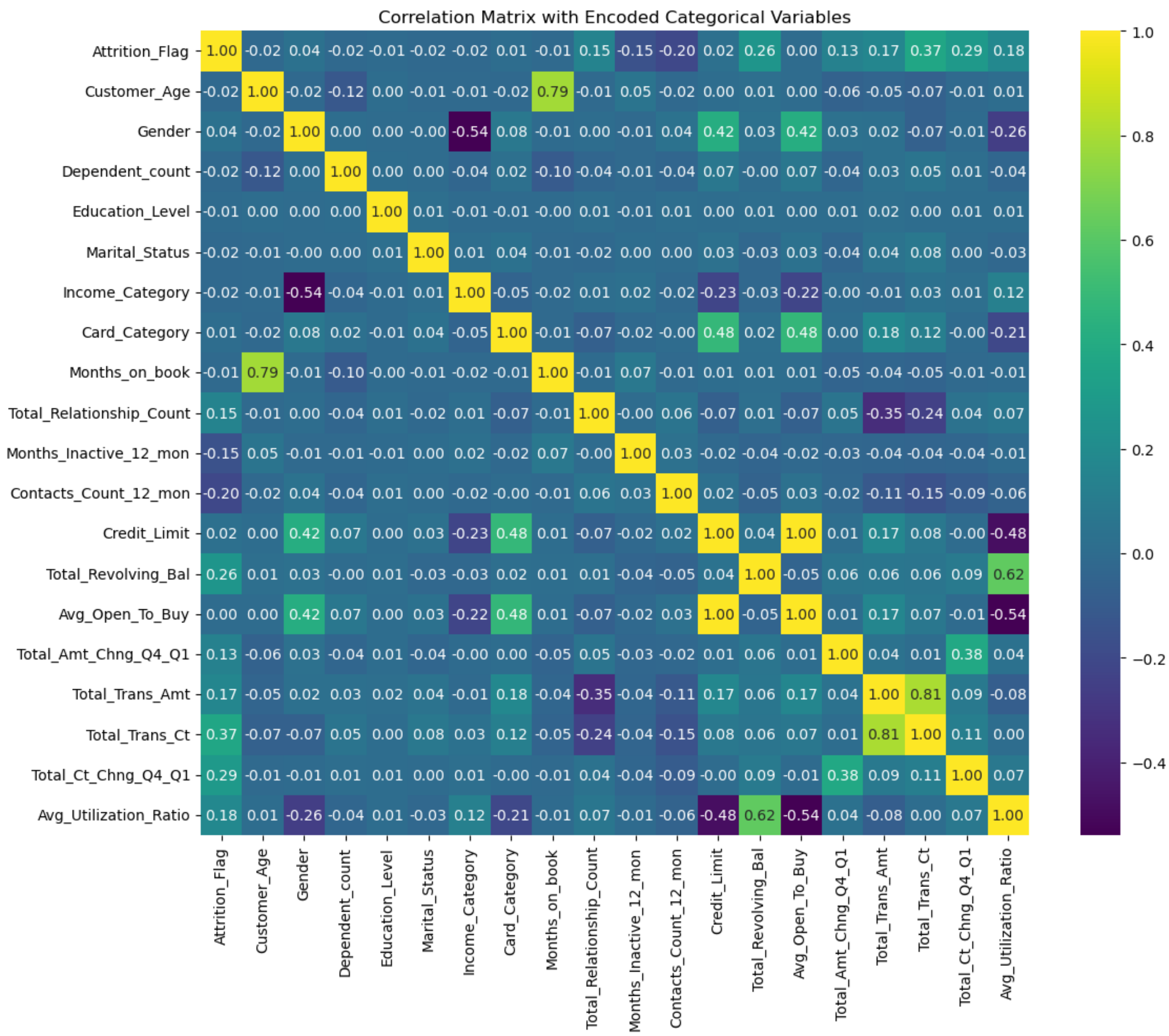
```
10123  Attrited Customer            41      M                2
10124  Attrited Customer            44      F                1
10125  Attrited Customer            30      M                2
10126  Attrited Customer            43      F                2

      Education_Level Marital_Status Income_Category Card_Category  \
0         High School        Married     $60K - $80K          Blue
1            Graduate         Single  Less than $40K          Blue
2            Graduate        Married    $80K - $120K          Blue
3         High School        Unknown  Less than $40K          Blue
4          Uneducated        Married     $60K - $80K          Blue
...               ...            ...             ...           ...
10122        Graduate         Single     $40K - $60K          Blue
10123         Unknown       Divorced     $40K - $60K          Blue
10124     High School        Married  Less than $40K          Blue
10125        Graduate        Unknown     $40K - $60K          Blue
10126        Graduate        Married  Less than $40K        Silver

       Months_on_book  Total_Relationship_Count
Months_Inactive_12_mon  \
0                  39                         5
1
1                  44                         6
1
2                  36                         4
1
3                  34                         3
4
4                  21                         5
1
...               ...                       ...                    ..
.
10122              40                         3
2
10123              25                         4
2
10124              36                         5
3
10125              36                         4
3
10126              25                         6
2

       Contacts_Count_12_mon  Credit_Limit  Total_Revolving_Bal  \
0                          3       12691.0                  777
1                          2        8256.0                  864
2                          0        3418.0                    0
3                          1        3313.0                 2517
4                          0        4716.0                    0
...                      ...           ...                  ...
```

```
10122                         3       4003.0                     1851
10123                         3       4277.0                     2186
10124                         4       5409.0                        0
10125                         3       5281.0                        0
10126                         4      10388.0                     1961

       Avg_Open_To_Buy  Total_Amt_Chng_Q4_Q1  Total_Trans_Amt
Total_Trans_Ct  \
0              11914.0                 1.335             1144
42
1               7392.0                 1.541             1291
33
2               3418.0                 2.594             1887
20
3                796.0                 1.405             1171
20
4               4716.0                 2.175              816
28
...                ...                   ...              ...
...
10122           2152.0                 0.703            15476
117
10123           2091.0                 0.804             8764
69
10124           5409.0                 0.819            10291
60
10125           5281.0                 0.535             8395
62
10126           8427.0                 0.703            10294
61

       Total_Ct_Chng_Q4_Q1  Avg_Utilization_Ratio
0                    1.625                  0.061
1                    3.714                  0.105
2                    2.333                  0.000
3                    2.333                  0.760
4                    2.500                  0.000
...                    ...                    ...
10122                0.857                  0.462
10123                0.683                  0.511
10124                0.818                  0.000
10125                0.722                  0.000
10126                0.649                  0.189

[10127 rows x 20 columns]>
```

5.2 Finding the Most Relevant Features

```
import pandas as pd
import seaborn as sns
```

```python
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder

# List of categorical columns as provided.
categorical_cols = [
    'Attrition_Flag',
    'Gender',
    'Education_Level',
    'Marital_Status',
    'Income_Category',
    'Card_Category'
]

# Create a copy of the DataFrame for encoding.
df_encoded = IQR_cleaned_df.copy()

# Apply label encoding to each categorical column.
le = LabelEncoder()
for col in categorical_cols:
    df_encoded[col] = le.fit_transform(df_encoded[col])

# Compute the correlation matrix for the entire DataFrame.
corr_matrix = df_encoded.corr()

# Create a heatmap for the correlation matrix.
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, cmap='viridis', annot=True, fmt=".2f")
plt.title('Correlation Matrix with Encoded Categorical Variables')
plt.xticks(rotation=90)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```



5.2.2 F-Score

```python
import pandas as pd
from sklearn.feature_selection import f_classif

# Assume df_encoded is your DataFrame with all features encoded,
including "Attrition_Flag".
# Define the target variable.
target = 'Attrition_Flag'

# Create X containing all features except the target variable,
# and y containing the target.
X = df_encoded.drop(columns=[target])
y = df_encoded[target]

# Compute F-scores and p-values using the ANOVA F-test.
F_values, p_values = f_classif(X, y)
```

```python
# Create a DataFrame to display the F-scores and p-values along with the feature names.
f_scores_df = pd.DataFrame({
    'Feature': X.columns,
    'F_score': F_values,
    'p_value': p_values
}).sort_values(by='F_score', ascending=False)

print("F-scores against Attrition_Flag:")
print(f_scores_df)
```

```
F-scores against Attrition_Flag:
                     Feature      F_score        p_value
16            Total_Trans_Ct  1620.121692   0.000000e+00
17       Total_Ct_Chng_Q4_Q1   930.078416  1.647725e-195
12       Total_Revolving_Bal   752.702408  6.630148e-160
10     Contacts_Count_12_mon   441.868050   4.697490e-96
18     Avg_Utilization_Ratio   332.876795   3.357689e-73
15           Total_Trans_Amt   296.227714   1.857439e-65
9     Months_Inactive_12_mon   240.910376   1.032664e-53
8   Total_Relationship_Count   233.072886   4.829281e-52
14      Total_Amt_Chng_Q4_Q1   176.961638   4.836643e-40
1                     Gender    14.085007   1.757076e-04
11              Credit_Limit     5.773729   1.628536e-02
2            Dependent_count     3.652825   5.600239e-02
4             Marital_Status     3.503085   6.128344e-02
0               Customer_Age     3.356074   6.698689e-02
5            Income_Category     3.131546   7.682098e-02
7             Months_on_book     1.897071   1.684370e-01
6              Card_Category     0.369161   5.434755e-01
3            Education_Level     0.312007   5.764636e-01
13           Avg_Open_To_Buy     0.000823   9.771161e-01
```

5.2.3 Mutual Information

```python
import pandas as pd
from sklearn.feature_selection import mutual_info_classif

# Assume df_encoded is your DataFrame with features encoded, including "Attrition_Flag".

# Define the target variable and feature set.
target = 'Attrition_Flag'
X = df_encoded.drop(columns=[target])
y = df_encoded[target]

# Compute the mutual information for each feature with respect to the target.
mi_values = mutual_info_classif(X, y, random_state=42)
```

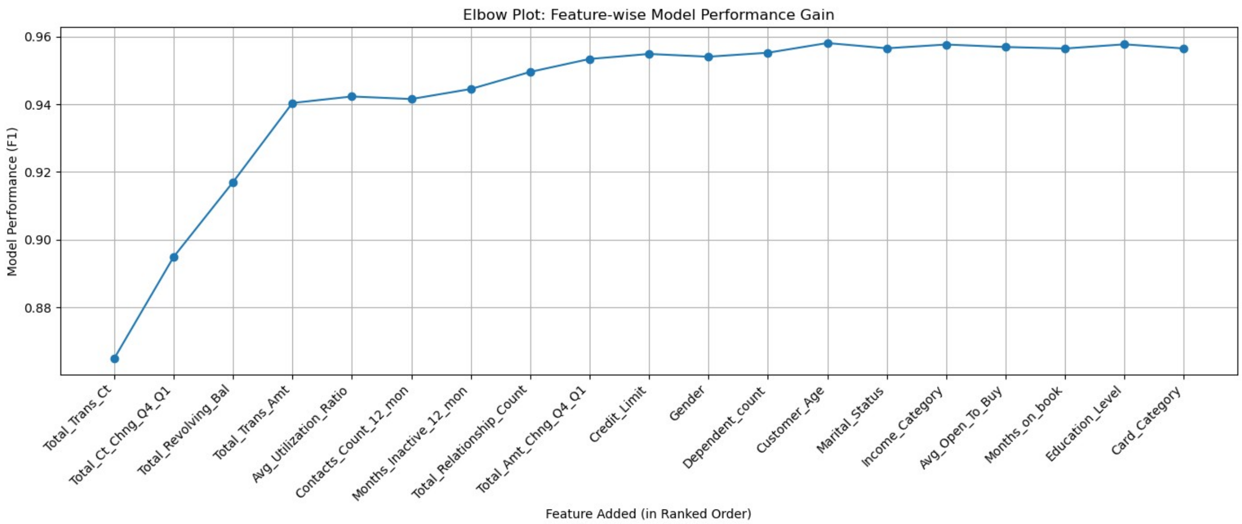
```
# Create a DataFrame to display the mutual information values along
with the feature names.
mi_df = pd.DataFrame({
    'Feature': X.columns,
    'Mutual_Information': mi_values
}).sort_values(by='Mutual_Information', ascending=False)

print("Mutual Information of each feature with Attrition_Flag:")
print(mi_df)
```

```
Mutual Information of each feature with Attrition_Flag:
                     Feature  Mutual_Information
15            Total_Trans_Amt            0.159579
16             Total_Trans_Ct            0.113819
17        Total_Ct_Chng_Q4_Q1            0.097490
12        Total_Revolving_Bal            0.081312
18      Avg_Utilization_Ratio            0.046084
14       Total_Amt_Chng_Q4_Q1            0.028307
10      Contacts_Count_12_mon            0.023935
13            Avg_Open_To_Buy            0.020645
9      Months_Inactive_12_mon            0.017864
8    Total_Relationship_Count            0.013571
11               Credit_Limit            0.009097
3             Education_Level            0.006701
7              Months_on_book            0.005862
4              Marital_Status            0.005622
2             Dependent_count            0.005081
0                Customer_Age            0.002752
1                      Gender            0.002016
6               Card_Category            0.001135
5             Income_Category            0.000975
```

5.2.4 Elbow Plot to Determine Minimum Columns Required

```
import pandas as pd
import numpy as np
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier  # or
LogisticRegression
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt

# --- Setup ---
# Your DataFrame with encoded categorical columns and target column
df = df_encoded.copy()
y = df['Attrition_Flag']

# Ranked features from previous combined ranking
ranked_features = [
    'Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1', 'Total_Revolving_Bal',
```

```python
'Total_Trans_Amt',
    'Avg_Utilization_Ratio', 'Contacts_Count_12_mon',
'Months_Inactive_12_mon',
    'Total_Relationship_Count', 'Total_Amt_Chng_Q4_Q1',
'Credit_Limit', 'Gender',
    'Dependent_count', 'Customer_Age', 'Marital_Status',
'Income_Category',
    'Avg_Open_To_Buy', 'Months_on_book', 'Education_Level',
'Card_Category'
]

# --- Model and scoring ---
model = RandomForestClassifier(random_state=42)
scoring_metric = 'f1'  # or 'accuracy'

# --- Elbow plot prep ---
scores = []
num_features_list = list(range(1, len(ranked_features) + 1))

for i in num_features_list:
    selected_features = ranked_features[:i]
    X = df[selected_features]

    # 5-fold cross-validation
    score = cross_val_score(model, X, y, cv=5,
scoring=scoring_metric).mean()
    scores.append(score)

# --- Plot ---
# --- Plot ---
plt.figure(figsize=(14, 6))
plt.plot(num_features_list, scores, marker='o')

# Set x-axis labels to the feature name added at each step
added_features = ranked_features  # Already ordered by importance
plt.xticks(ticks=num_features_list, labels=added_features,
rotation=45, ha='right')

plt.title('Elbow Plot: Feature-wise Model Performance Gain')
plt.xlabel('Feature Added (in Ranked Order)')
plt.ylabel(f'Model Performance ({scoring_metric.upper()})')
plt.grid(True)
plt.tight_layout()
plt.show()
```



6 Machine Learning Models

6.1 Logistic Regression

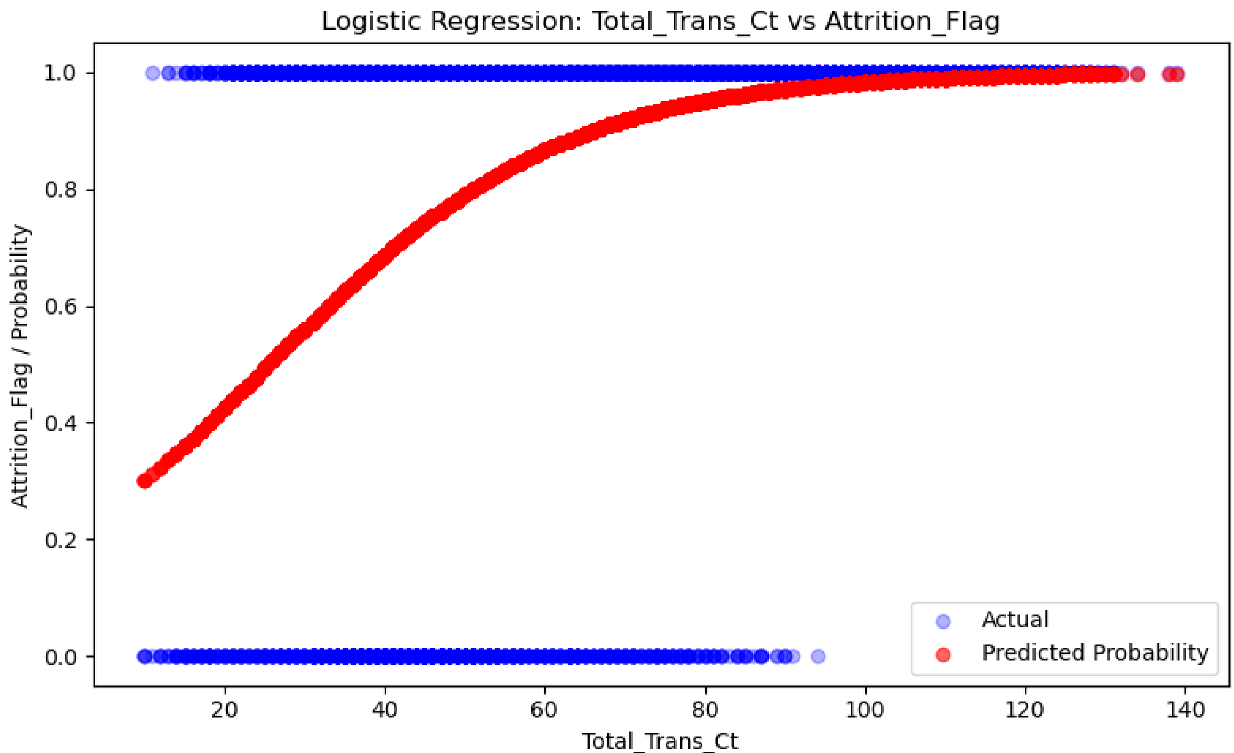
Logistic regression estimates the probability of an event occurring, such as voted or didn't vote, based on a given data set of independent variables.

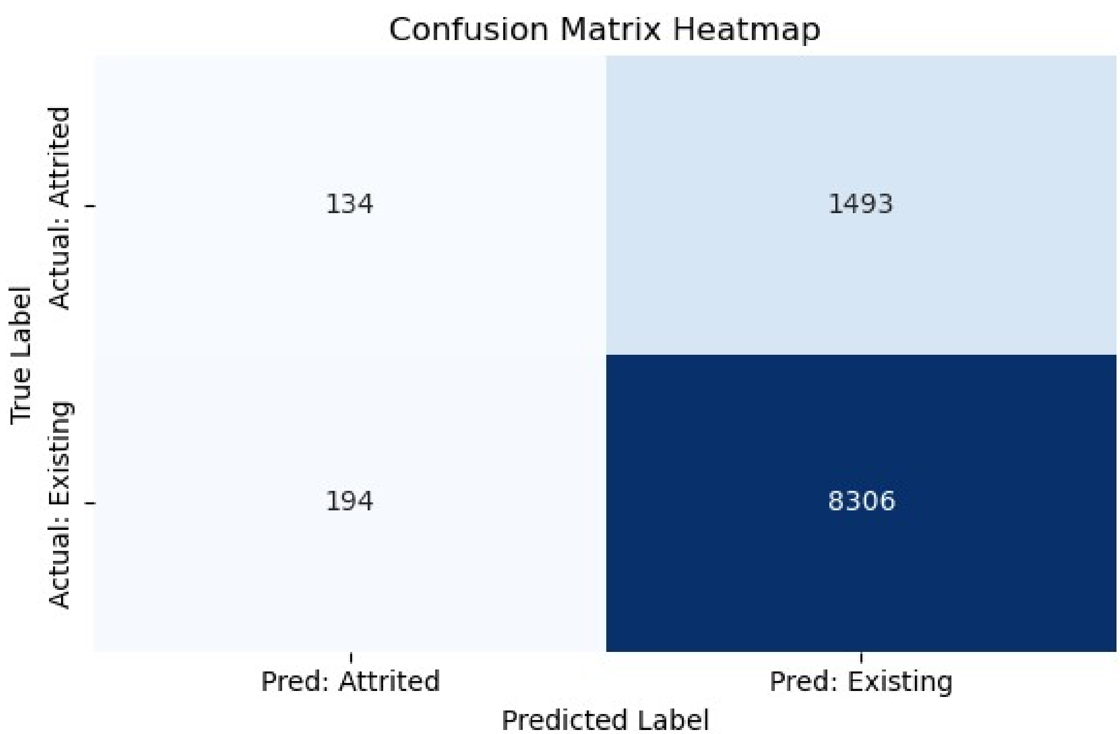
Logistic Regression: Attrition_Flag against Total_Trans_Ct

```
import pandas as pd
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Define X and y
X = df_encoded[['Total_Trans_Ct']]
y = df_encoded['Attrition_Flag']

# Fit logistic regression
logreg = LogisticRegression()
logreg.fit(X, y)

# Predict class and probabilities
y_pred_class = logreg.predict(X)
y_pred_proba = logreg.predict_proba(X)[:, 1]  # Probability of class 1
(Attrited)

# Evaluation metrics
acc = accuracy_score(y, y_pred_class)
auc = roc_auc_score(y, y_pred_proba)
cm = confusion_matrix(y, y_pred_class)
```

```python
print("Logistic Regression Results:")
print(f"Coefficient: {logreg.coef_[0][0]}")
print(f"Intercept: {logreg.intercept_[0]}")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc:.4f}")
print("Confusion Matrix:")
print(cm)

# --- Visual: Logistic Regression Curve ---
plt.figure(figsize=(8, 5))
plt.scatter(X, y, color='blue', alpha=0.3, label='Actual')
plt.scatter(X, y_pred_proba, color='red', alpha=0.6, label='Predicted
Probability')
plt.xlabel('Total_Trans_Ct')
plt.ylabel('Attrition_Flag / Probability')
plt.title('Logistic Regression: Total_Trans_Ct vs Attrition_Flag')
plt.legend()
plt.tight_layout()
plt.show()

# --- Visual: Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Pred: Attrited', 'Pred: Existing'],
            yticklabels=['Actual: Attrited', 'Actual: Existing'])
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()
```

```
Logistic Regression Results:
Coefficient: 0.05432217053505641
Intercept: -1.3909493448085435
Accuracy: 0.8334
ROC AUC Score: 0.7956
Confusion Matrix:
[[ 134 1493]
 [ 194 8306]]
```





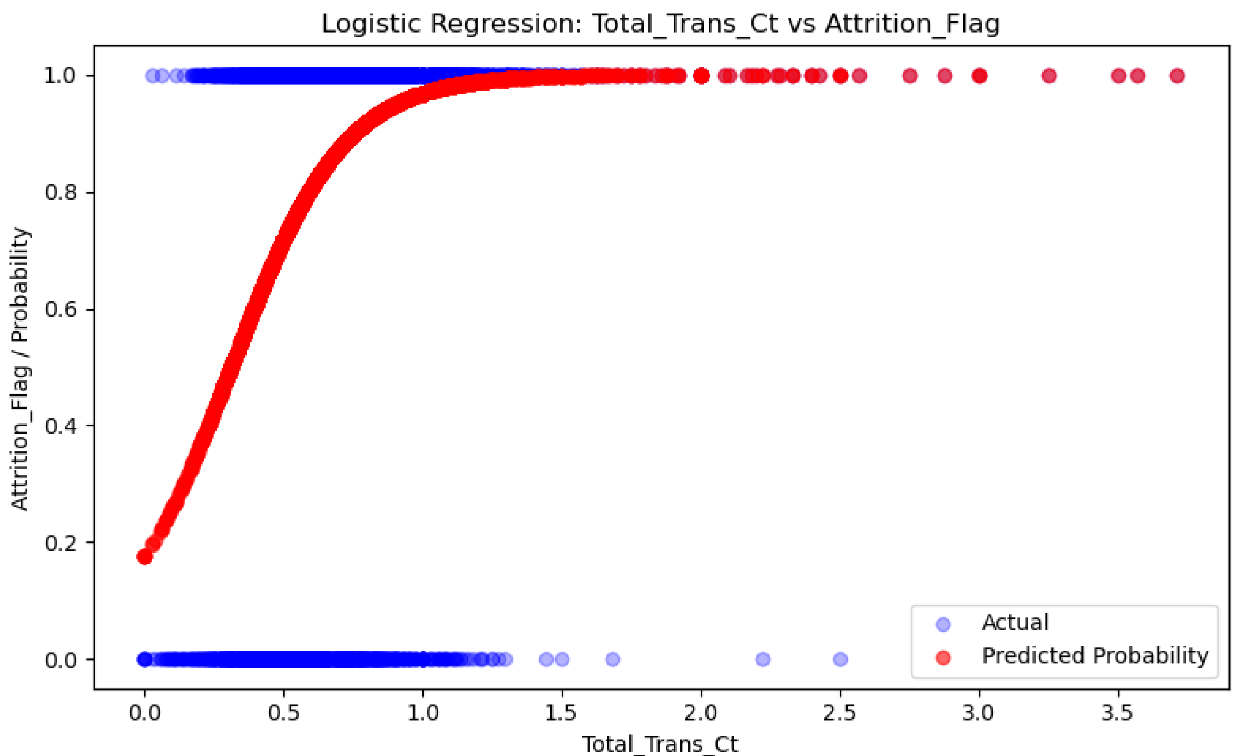
Logistic Regression: Attrition_Flag against Total_Ct_Chng_Q4_Q1

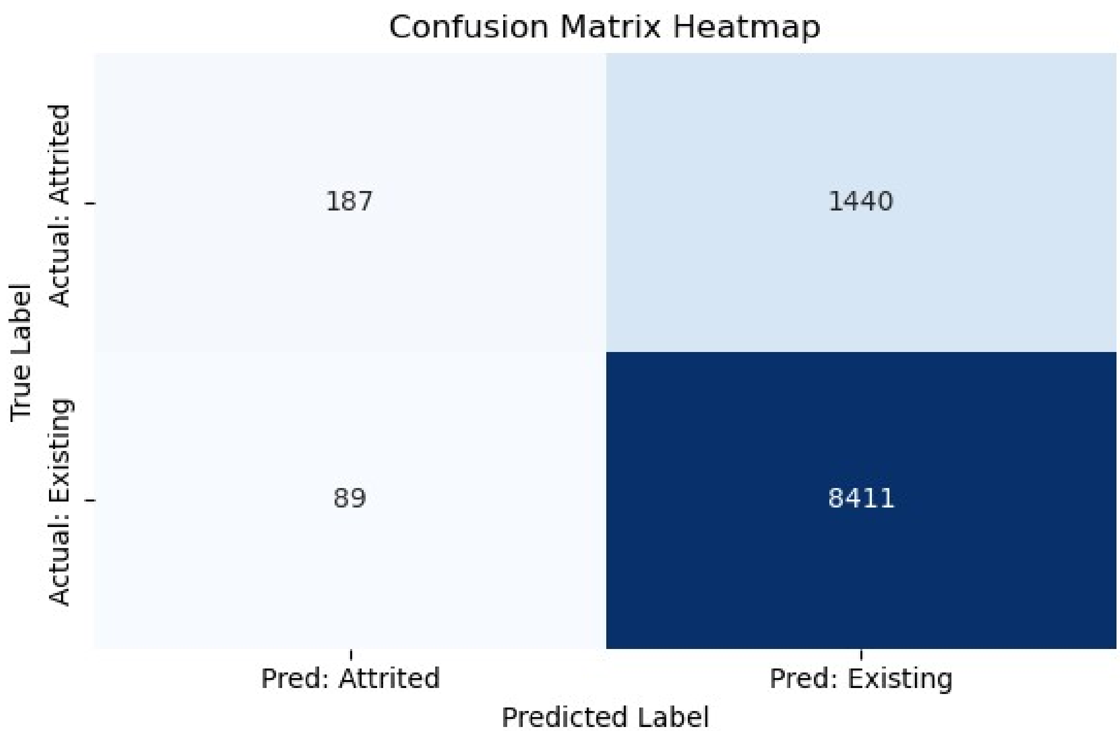
```
import pandas as pd
import numpy as np
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Define X and y
X = df_encoded[['Total_Ct_Chng_Q4_Q1']]
y = df_encoded['Attrition_Flag']

# Fit logistic regression
logreg = LogisticRegression()
logreg.fit(X, y)

# Predict class and probabilities
y_pred_class = logreg.predict(X)
y_pred_proba = logreg.predict_proba(X)[:, 1]  # Probability of class 1
(Attrited)

# Evaluation metrics
acc = accuracy_score(y, y_pred_class)
auc = roc_auc_score(y, y_pred_proba)
cm = confusion_matrix(y, y_pred_class)

print("Logistic Regression Results:")
print(f"Coefficient: {logreg.coef_[0][0]}")
print(f"Intercept: {logreg.intercept_[0]}")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc:.4f}")
print("Confusion Matrix:")
print(cm)

# --- Visual: Logistic Regression Curve ---
plt.figure(figsize=(8, 5))
plt.scatter(X, y, color='blue', alpha=0.3, label='Actual')
plt.scatter(X, y_pred_proba, color='red', alpha=0.6, label='Predicted
Probability')
plt.xlabel('Total_Trans_Ct')
plt.ylabel('Attrition_Flag / Probability')
plt.title('Logistic Regression: Total_Trans_Ct vs Attrition_Flag')
plt.legend()
plt.tight_layout()
plt.show()

# --- Visual: Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Pred: Attrited', 'Pred: Existing'],
            yticklabels=['Actual: Attrited', 'Actual: Existing'])
plt.title('Confusion Matrix Heatmap')
```

```
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()
```

```
Logistic Regression Results:
Coefficient: 4.965997692835299
Intercept: -1.5473791155267234
Accuracy: 0.8490
ROC AUC Score: 0.7453
Confusion Matrix:
[[ 187 1440]
 [  89 8411]]
```



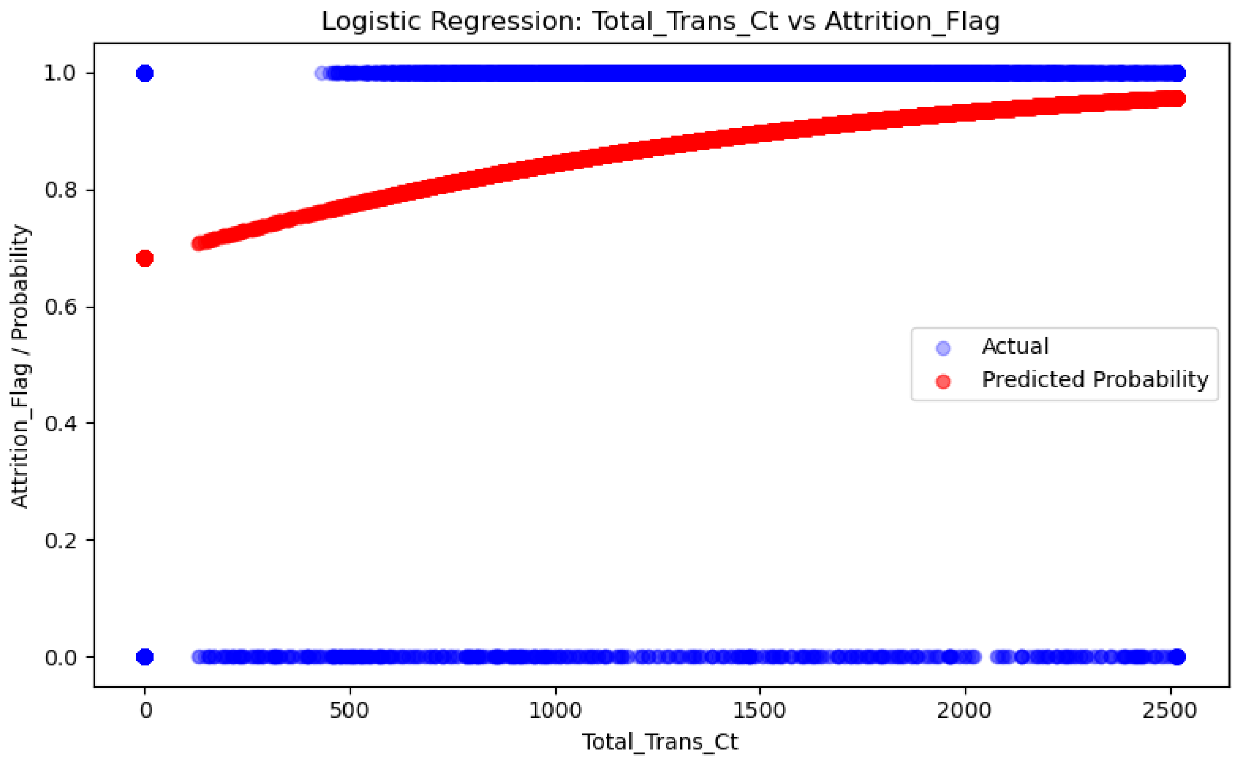


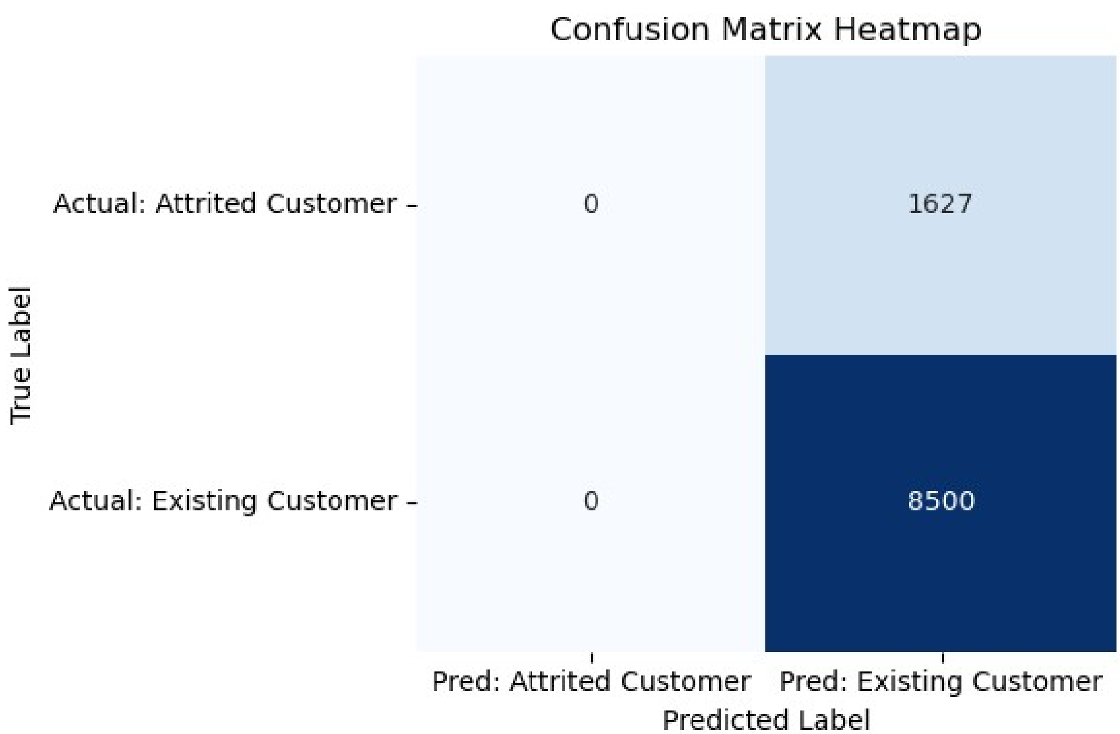
Logistic Regression: Attrition_Flag against Total_Revolving_Bal

```
import pandas as pd
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Define X and y
X = df_encoded[['Total_Revolving_Bal']]
y = df_encoded['Attrition_Flag']

# Fit logistic regression
logreg = LogisticRegression()
logreg.fit(X, y)

# Predict class and probabilities
y_pred_class = logreg.predict(X)
y_pred_proba = logreg.predict_proba(X)[:, 1]  # Probability of class 1
(Attrited)

# Evaluation metrics
acc = accuracy_score(y, y_pred_class)
auc = roc_auc_score(y, y_pred_proba)
cm = confusion_matrix(y, y_pred_class)
```

```python
print("Logistic Regression Results:")
print(f"Coefficient: {logreg.coef_[0][0]}")
print(f"Intercept: {logreg.intercept_[0]}")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc:.4f}")
print("Confusion Matrix:")
print(cm)

# --- Visual: Logistic Regression Curve ---
plt.figure(figsize=(8, 5))
plt.scatter(X, y, color='blue', alpha=0.3, label='Actual')
plt.scatter(X, y_pred_proba, color='red', alpha=0.6, label='Predicted
Probability')
plt.xlabel('Total_Trans_Ct')
plt.ylabel('Attrition_Flag / Probability')
plt.title('Logistic Regression: Total_Trans_Ct vs Attrition_Flag')
plt.legend()
plt.tight_layout()
plt.show()

# --- Visual: Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Pred: Attrited Customer', 'Pred: Existing
Customer'],
            yticklabels=['Actual: Attrited Customer', 'Actual:
Existing Customer'])
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()
```

```
Logistic Regression Results:
Coefficient: 0.0009275749206390263
Intercept: 0.7633947274499862
Accuracy: 0.8393
ROC AUC Score: 0.6877
Confusion Matrix:
[[   0 1627]
 [   0 8500]]
```





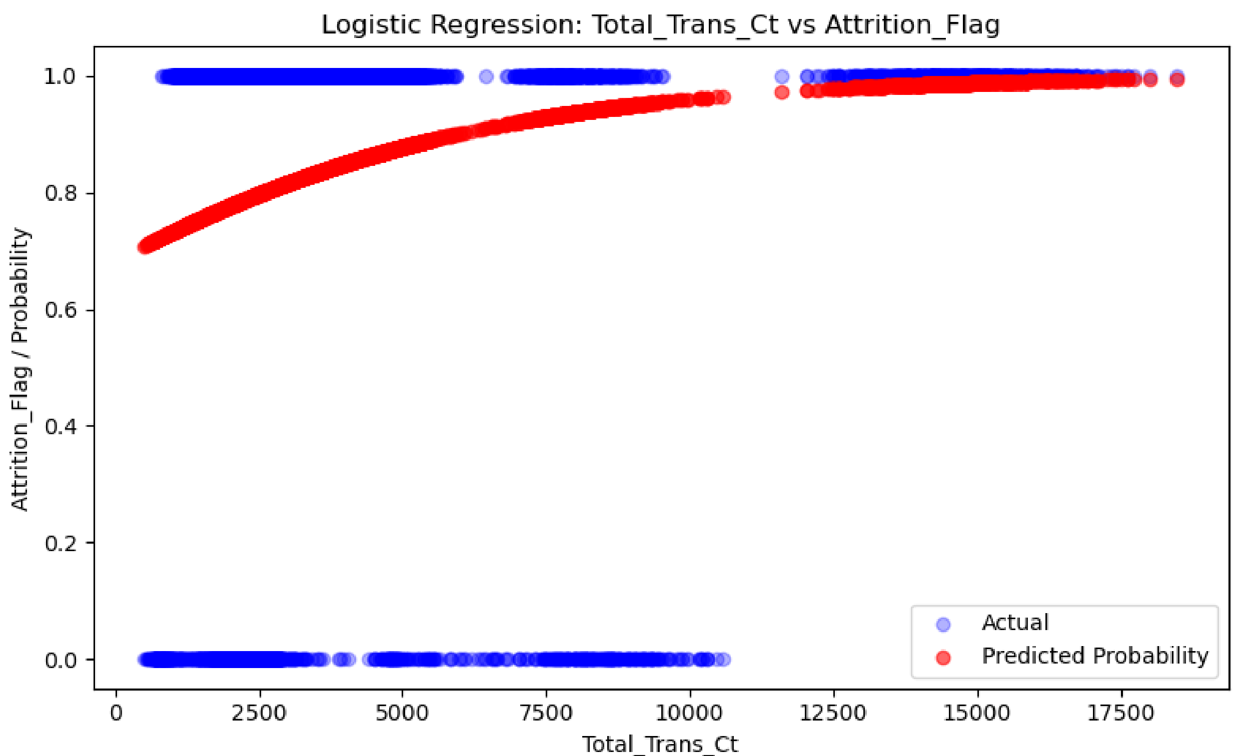
Logistic Regression: Attrition_Flag against Total_Trans_Amt

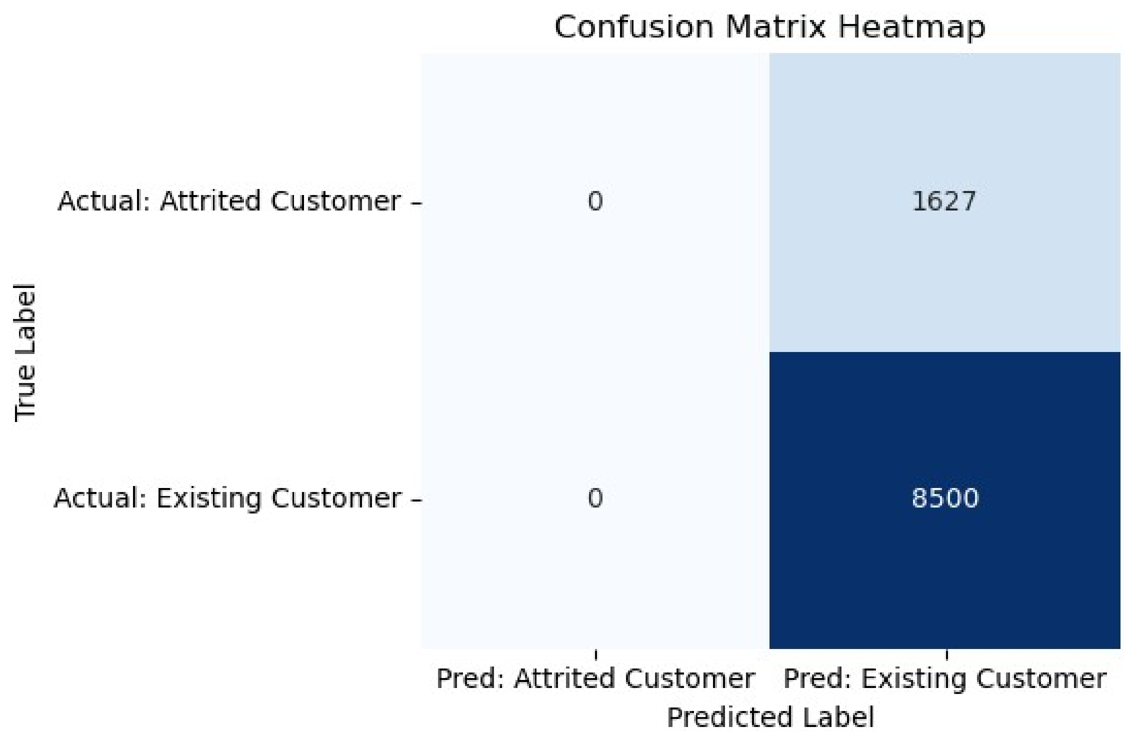
```
import pandas as pd
import numpy as np
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Define X and y
X = df_encoded[['Total_Trans_Amt']]
y = df_encoded['Attrition_Flag']

# Fit logistic regression
logreg = LogisticRegression()
logreg.fit(X, y)

# Predict class and probabilities
y_pred_class = logreg.predict(X)
y_pred_proba = logreg.predict_proba(X)[:, 1]  # Probability of class 1
(Attrited)

# Evaluation metrics
acc = accuracy_score(y, y_pred_class)
auc = roc_auc_score(y, y_pred_proba)
cm = confusion_matrix(y, y_pred_class)

print("Logistic Regression Results:")
print(f"Coefficient: {logreg.coef_[0][0]}")
print(f"Intercept: {logreg.intercept_[0]}")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc:.4f}")
print("Confusion Matrix:")
print(cm)

# --- Visual: Logistic Regression Curve ---
plt.figure(figsize=(8, 5))
plt.scatter(X, y, color='blue', alpha=0.3, label='Actual')
plt.scatter(X, y_pred_proba, color='red', alpha=0.6, label='Predicted
Probability')
plt.xlabel('Total_Trans_Ct')
plt.ylabel('Attrition_Flag / Probability')
plt.title('Logistic Regression: Total_Trans_Ct vs Attrition_Flag')
plt.legend()
plt.tight_layout()
plt.show()

# --- Visual: Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Pred: Attrited Customer', 'Pred: Existing
Customer'],
            yticklabels=['Actual: Attrited Customer', 'Actual:
```

```
Existing Customer'])
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()
```

```
Logistic Regression Results:
Coefficient: 0.00024092367759846606
Intercept: 0.7639090174091386
Accuracy: 0.8393
ROC AUC Score: 0.6759
Confusion Matrix:
[[   0 1627]
 [   0 8500]]
```





Logistic Regression: Attrition_Flag against df_encoded[['Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1', 'Total_Revolving_Bal', 'Total_Trans_Amt']]

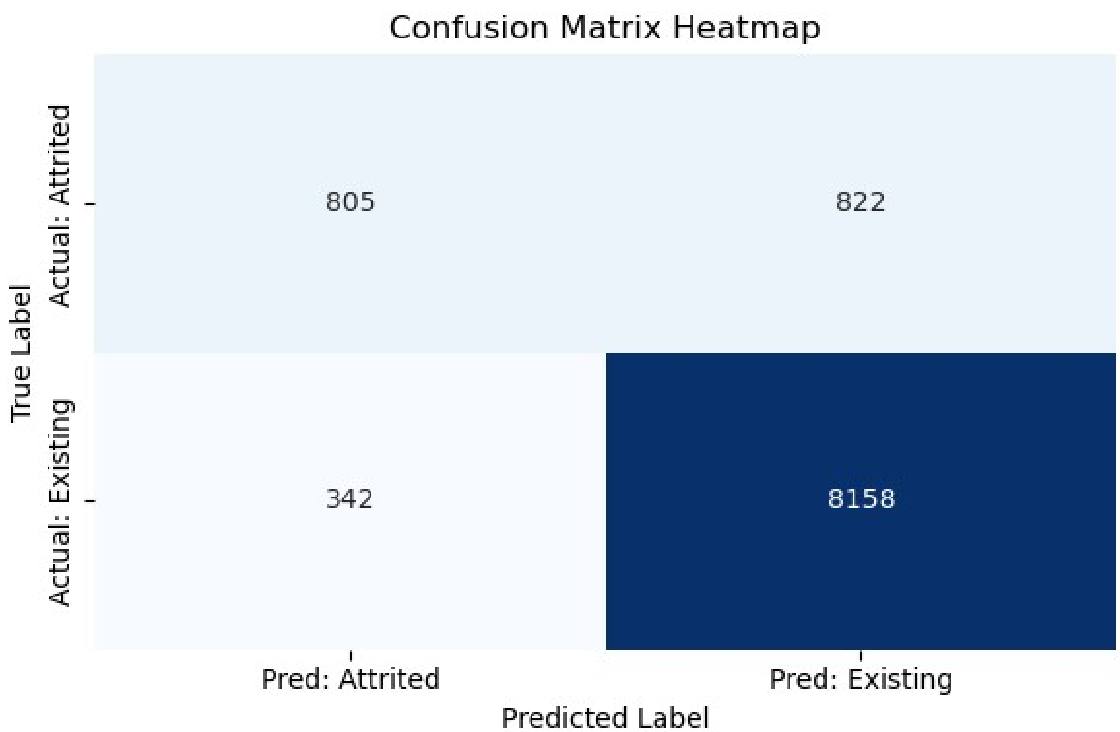
In view of the low accuracy and performance of single variables, we decided to use a multivariate feature to predict Attrition_Flag

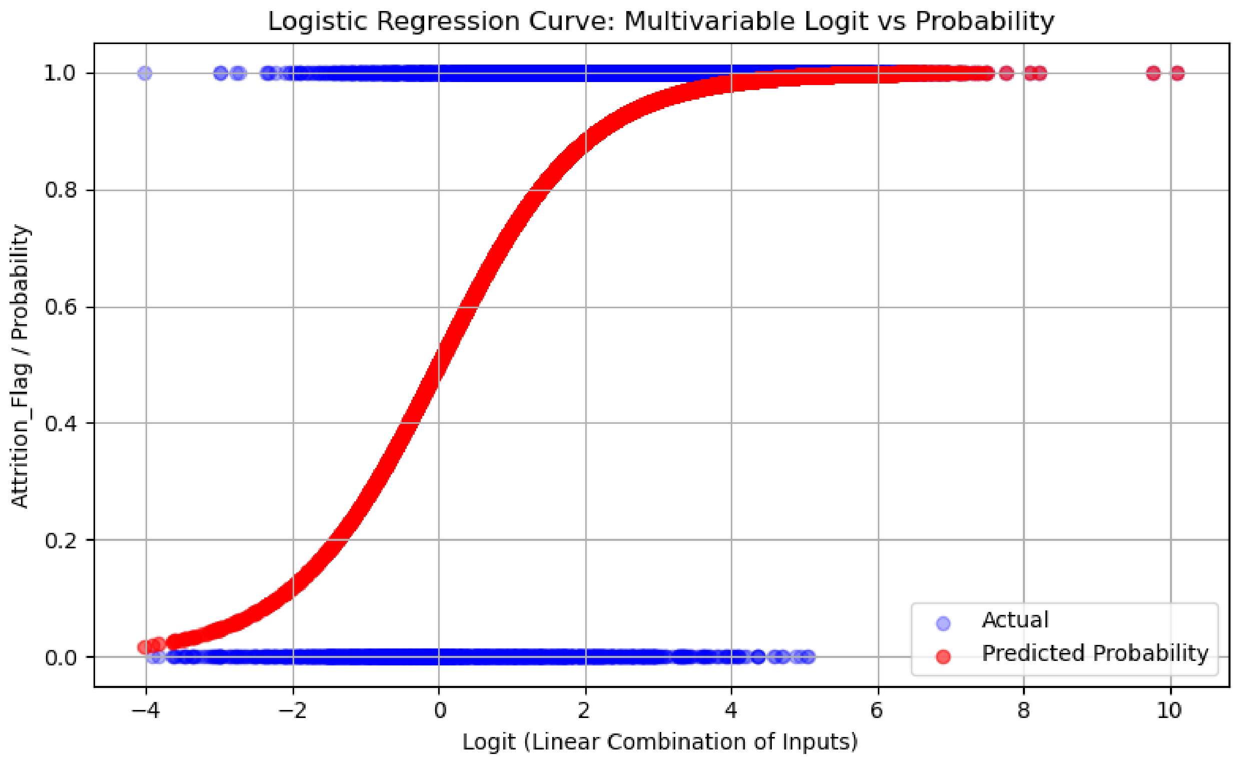
```
import pandas as pd
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Define X and y with 4 top-ranked features
X = df_encoded[['Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1',
'Total_Revolving_Bal', 'Total_Trans_Amt']]
y = df_encoded['Attrition_Flag']

# Fit logistic regression
logreg = LogisticRegression(max_iter=1000)  # Increase max_iter for
convergence
logreg.fit(X, y)

# Predict class and probabilities
y_pred_class = logreg.predict(X)
y_pred_proba = logreg.predict_proba(X)[:, 1]  # Probability of class 1
```

```python
(Attrited)

# Evaluation metrics
acc = accuracy_score(y, y_pred_class)
auc = roc_auc_score(y, y_pred_proba)
cm = confusion_matrix(y, y_pred_class)

print("Logistic Regression Results:")
for i, feature in enumerate(X.columns):
    print(f"Coefficient for {feature}: {logreg.coef_[0][i]:.4f}")
print(f"Intercept: {logreg.intercept_[0]:.4f}")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc:.4f}")
print("Confusion Matrix:")
print(cm)

# --- Visual: Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Pred: Attrited', 'Pred: Existing'],
            yticklabels=['Actual: Attrited', 'Actual: Existing'])
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()

# Compute linear combination (logit) manually
logit_values = np.dot(X, logreg.coef_[0]) + logreg.intercept_[0]

# Plot the sigmoid curve
plt.figure(figsize=(8, 5))
plt.scatter(logit_values, y, color='blue', alpha=0.3, label='Actual')
plt.scatter(logit_values, y_pred_proba, color='red', alpha=0.6,
label='Predicted Probability')
plt.xlabel('Logit (Linear Combination of Inputs)')
plt.ylabel('Attrition_Flag / Probability')
plt.title('Logistic Regression Curve: Multivariable Logit vs
Probability')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Logistic Regression Results:
Coefficient for Total_Trans_Ct: 0.1040
Coefficient for Total_Ct_Chng_Q4_Q1: 3.0909
Coefficient for Total_Revolving_Bal: 0.0010
Coefficient for Total_Trans_Amt: -0.0005
Intercept: -5.4061
```

```
Accuracy: 0.8851
ROC AUC Score: 0.8938
Confusion Matrix:
[[ 805  822]
 [ 342 8158]]
```



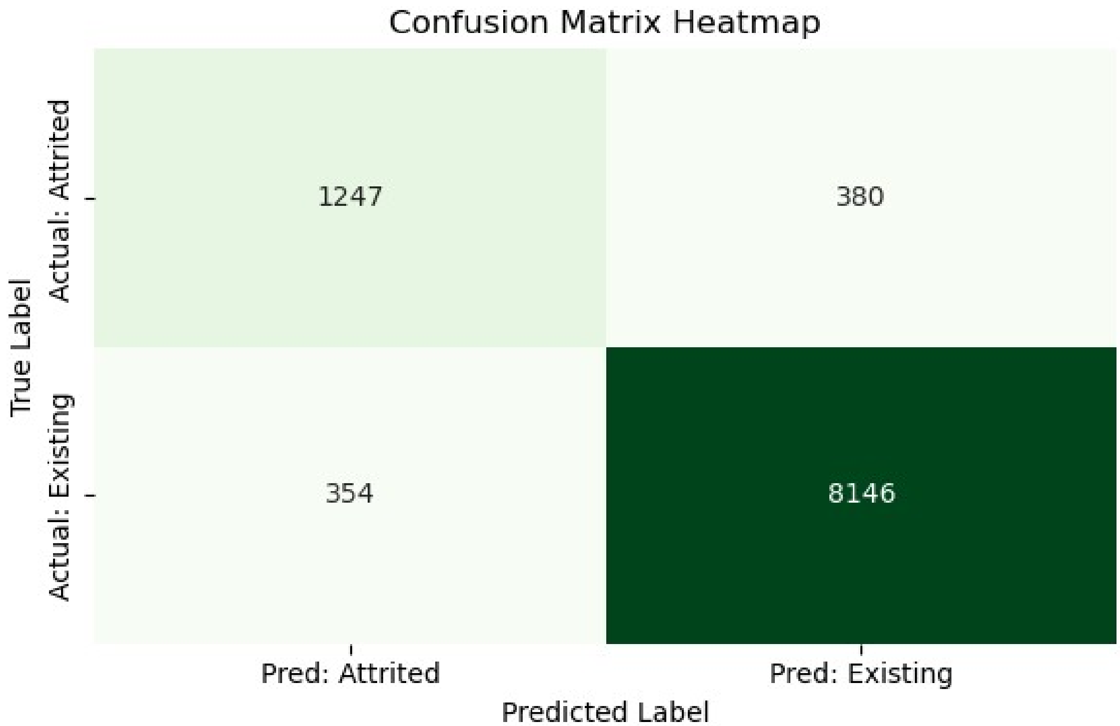


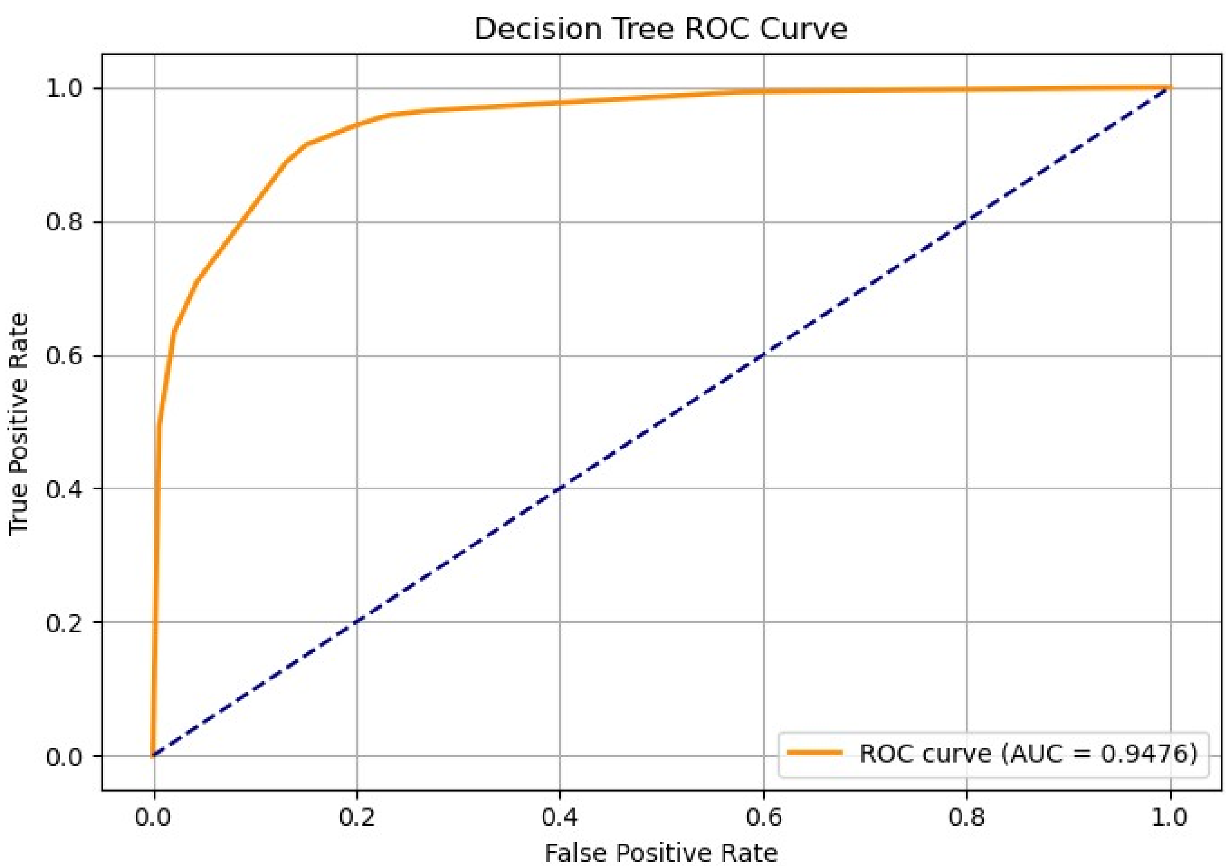
6.2 Decision Trees

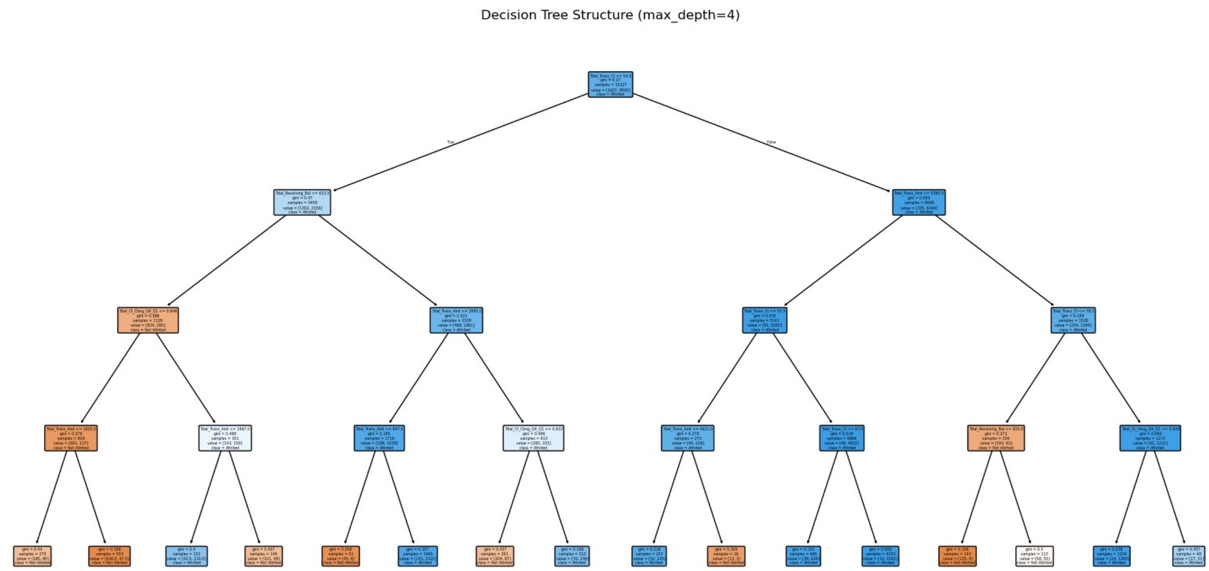
```
import pandas as pd
import numpy as np
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix, roc_curve, auc
import matplotlib.pyplot as plt
import seaborn as sns

# Define X and y with top 4 features
X = df_encoded[['Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1',
'Total_Revolving_Bal', 'Total_Trans_Amt']]
y = df_encoded['Attrition_Flag']

# Fit Decision Tree Classifier
tree_clf = DecisionTreeClassifier(max_depth=4, random_state=42)  # You
can tweak max_depth
tree_clf.fit(X, y)

# Predictions
y_pred_class = tree_clf.predict(X)
y_pred_proba = tree_clf.predict_proba(X)[:, 1]

# Evaluation metrics
acc = accuracy_score(y, y_pred_class)
auc_score = roc_auc_score(y, y_pred_proba)
```

```python
cm = confusion_matrix(y, y_pred_class)

print("Decision Tree Classifier Results:")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc_score:.4f}")
print("Confusion Matrix:")
print(cm)

# --- Visual: Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Greens', cbar=False,
            xticklabels=['Pred: Attrited', 'Pred: Existing'],
            yticklabels=['Actual: Attrited', 'Actual: Existing'])
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()

# --- Visual: ROC Curve ---
fpr, tpr, _ = roc_curve(y, y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC =
{roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Decision Tree ROC Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Visual: Decision Tree Structure ---
plt.figure(figsize=(16, 8))
plot_tree(tree_clf, feature_names=X.columns, class_names=['Not
Attrited', 'Attrited'],
          filled=True, rounded=True)
plt.title("Decision Tree Structure (max_depth=4)")
plt.tight_layout()
plt.show()
```

```
Decision Tree Classifier Results:
Accuracy: 0.9275
ROC AUC Score: 0.9476
Confusion Matrix:
[[1247  380]
 [ 354 8146]]
```


Confusion Matrix Heatmap
Actual: Attrited
Actual: Existing
True Label
1247
380
354
8146
Pred: Attrited
Pred: Existing
Predicted Label


Decision Tree ROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (AUC = 0.9476)



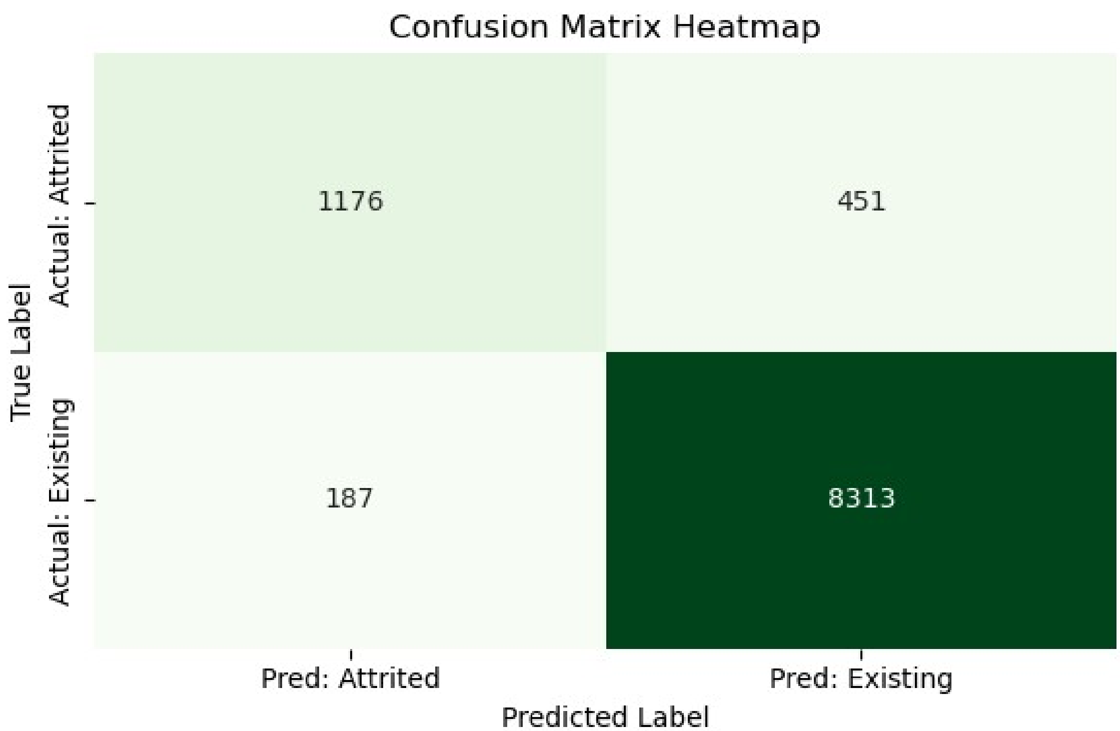
6.3 Bagging of Trees: Random Forest

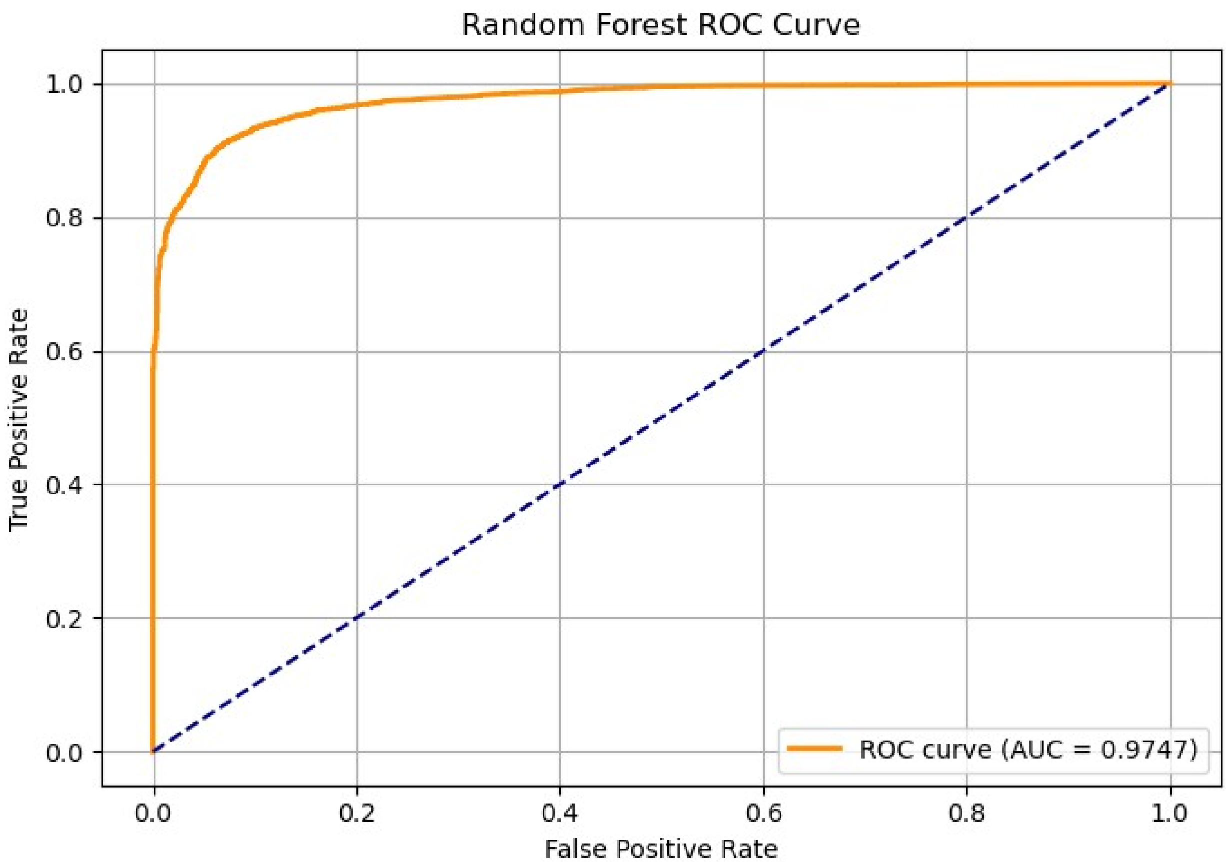
Random forest uses multiple decision trees to make predictions, improving accuracy and reducing overfitting.

```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix, roc_curve, auc
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt
import seaborn as sns

# Define X and y
X = df_encoded[['Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1',
'Total_Revolving_Bal', 'Total_Trans_Amt']]
y = df_encoded['Attrition_Flag']

# Fit Random Forest Classifier
rf_clf = RandomForestClassifier(n_estimators=100, max_depth=5,
random_state=42)
rf_clf.fit(X, y)

# Predictions
y_pred_class = rf_clf.predict(X)
y_pred_proba = rf_clf.predict_proba(X)[:, 1]

# Evaluation metrics
acc = accuracy_score(y, y_pred_class)
auc_score = roc_auc_score(y, y_pred_proba)
```

```python
cm = confusion_matrix(y, y_pred_class)

print("Random Forest Classifier Results:")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc_score:.4f}")
print("Confusion Matrix:")
print(cm)

# --- Visual: Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Greens', cbar=False,
            xticklabels=['Pred: Attrited', 'Pred: Existing'],
            yticklabels=['Actual: Attrited', 'Actual: Existing'])
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()

# --- Visual: ROC Curve ---
fpr, tpr, _ = roc_curve(y, y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC =
{roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Random Forest ROC Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Visual: Feature Importances ---
importances = rf_clf.feature_importances_
features = X.columns
indices = np.argsort(importances)[::-1]

plt.figure(figsize=(160, 80), dpi=200)
sns.barplot(x=importances[indices], y=features[indices],
palette='magma')
plt.title("Feature Importances (Random Forest)")
plt.xlabel("Importance Score")
plt.tight_layout()
plt.show()

# --- Visual: One Tree from the Random Forest ---
plt.figure(figsize=(20, 10))
```

```
plot_tree(rf_clf.estimators_[0],  # Plot the first tree in the forest
          feature_names=X.columns,
          class_names=['Not Attrited', 'Attrited'],
          filled=True, rounded=True, fontsize=8, )
plt.title("Example Tree from Random Forest")
plt.tight_layout()
plt.show()


Random Forest Classifier Results:
Accuracy: 0.9370
ROC AUC Score: 0.9747
Confusion Matrix:
[[1176  451]
 [ 187 8313]]
```




Random Forest ROC Curve
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.9747)
0.0
0.2
0.4
0.6
0.8
1.0

6.4 Boosting of Trees: AdaBoost

AdaBoost is an ensemble machine learning method that combines multiple weak learners to create a strong classifier or regressor. It works by iteratively training a sequence of models, where each new model focuses on instances incorrectly classified by previous models.

```python
import pandas as pd
import numpy as np
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix, roc_curve, auc, classification_report
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import plot_tree

# --- Define X and y ---
X = df_encoded[['Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1',
'Total_Revolving_Bal', 'Total_Trans_Amt']]
y = df_encoded['Attrition_Flag']

# --- Train-Test Split ---
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, stratify=y, random_state=42)

# --- Fit AdaBoost ---
ada_clf = AdaBoostClassifier(n_estimators=100, random_state=42)
ada_clf.fit(X_train, y_train)

# --- Predictions ---
y_pred = ada_clf.predict(X_test)
y_proba = ada_clf.predict_proba(X_test)[:, 1]

# --- Evaluation Metrics ---
acc = accuracy_score(y_test, y_pred)
auc_score = roc_auc_score(y_test, y_proba)
cm = confusion_matrix(y_test, y_pred)

print("=== AdaBoost Classifier Results ===")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc_score:.4f}")
print("Confusion Matrix:\n", cm)
print("\nClassification Report:\n", classification_report(y_test,
y_pred))

# --- Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Oranges', cbar=False,
            xticklabels=['Pred: Existing', 'Pred: Attrited'],
            yticklabels=['Actual: Existing', 'Actual: Attrited'])
```

```
plt.title('AdaBoost: Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.show()

# --- ROC Curve ---
fpr, tpr, _ = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label=f'AdaBoost ROC Curve (AUC = {roc_auc:.4f})',
color='crimson')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('AdaBoost ROC Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Feature Importances ---
if hasattr(ada_clf, 'feature_importances_'):
    importances = ada_clf.feature_importances_
    feature_names = X.columns
    indices = np.argsort(importances)[::-1]

    plt.figure(figsize=(8, 5))
    sns.barplot(x=importances[indices], y=feature_names[indices],
palette='magma')
    plt.title("AdaBoost Feature Importances")
    plt.xlabel("Importance Score")
    plt.tight_layout()
    plt.show()
else:
    print("AdaBoost base estimator does not expose
feature_importances_.")
```

6.5 Boosting of Trees: XGBoost

XGBoost, short for Extreme Gradient Boosting, is a popular and powerful open-source machine learning library used for both classification and regression tasks.

Compared to AdaBoost, XGBoost is a more complex algorithm that uses gradient descent to optimize the loss function

```
import pandas as pd
import numpy as np
```

```python
from xgboost import XGBClassifier, plot_tree
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix, roc_curve, auc, classification_report
import matplotlib.pyplot as plt
import seaborn as sns

# --- Define X and y ---
X = df_encoded[['Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1',
'Total_Revolving_Bal', 'Total_Trans_Amt']]
y = df_encoded['Attrition_Flag']

# --- Train-Test Split ---
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, stratify=y, random_state=42)

# --- Fit XGBoost Classifier ---
xgb_clf = XGBClassifier(
    n_estimators=100,
    learning_rate=0.1,
    max_depth=3,
    use_label_encoder=False,
    eval_metric='logloss',
    random_state=42
)
xgb_clf.fit(X_train, y_train)

# --- Predictions ---
y_pred = xgb_clf.predict(X_test)
y_proba = xgb_clf.predict_proba(X_test)[:, 1]

# --- Evaluation ---
acc = accuracy_score(y_test, y_pred)
auc_score = roc_auc_score(y_test, y_proba)
cm = confusion_matrix(y_test, y_pred)

print("=== XGBoost Classifier Results ===")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc_score:.4f}")
print("Confusion Matrix:\n", cm)
print("\nClassification Report:\n", classification_report(y_test,
y_pred))

# --- Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Purples', cbar=False,
            xticklabels=['Pred: Existing', 'Pred: Attrited'],
            yticklabels=['Actual: Existing', 'Actual: Attrited'])
plt.title('XGBoost: Confusion Matrix')
plt.xlabel('Predicted')
```

```
plt.ylabel('Actual')
plt.tight_layout()
plt.show()

# --- ROC Curve ---
fpr, tpr, _ = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, color='darkgreen', lw=2, label=f'ROC curve (AUC =
{roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('XGBoost: ROC Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Feature Importances ---
importances = xgb_clf.feature_importances_
features = X.columns
indices = np.argsort(importances)[::-1]

plt.figure(figsize=(8, 5))
sns.barplot(x=importances[indices], y=features[indices],
palette='viridis')
plt.title("XGBoost Feature Importances")
plt.xlabel("Importance Score")
plt.tight_layout()
plt.show()
```

6.6 Support Vector Machines (3-Dimensional)

A Support Vector Machine (SVM) is a supervised learning algorithm that can be used for classification and regression tasks.

It finds the best hyperplane to separate different classes of data points, maximizing the distance between the hyperplane and the closest data points of each class.

```
import numpy as np
import pandas as pd
import plotly.graph_objects as go
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.svm import SVC
from sklearn.metrics import (
    confusion_matrix, accuracy_score, precision_score, recall_score,
```

```
f1_score
)
from sklearn.preprocessing import StandardScaler

# --- Define X and y ---
X = df_encoded[['Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1',
'Total_Revolving_Bal']]
y = df_encoded['Attrition_Flag']

# --- Standardize Features ---
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# --- Train SVM with linear kernel ---
svm_clf = SVC(kernel='linear', random_state=42)
svm_clf.fit(X_scaled, y)

# --- Predict ---
y_pred = svm_clf.predict(X_scaled)

# --- Prepare DataFrame for Visualisation ---
X_3d = pd.DataFrame(X_scaled, columns=X.columns)
X_3d['Actual'] = y.values
X_3d['Predicted'] = y_pred

# --- Classification Outcome Tagging ---
def get_outcome(row):
    if row['Actual'] == 0 and row['Predicted'] == 0:
        return 'True Existing'
    elif row['Actual'] == 1 and row['Predicted'] == 1:
        return 'True Attrited'
    elif row['Actual'] == 1 and row['Predicted'] == 0:
        return 'False Existing'
    else:
        return 'False Attrited'

X_3d['Outcome'] = X_3d.apply(get_outcome, axis=1)

# --- Confusion Matrix Heatmap ---
cm = confusion_matrix(X_3d['Actual'], X_3d['Predicted'])
plt.figure(figsize=(6, 4))
sns.heatmap(
    cm, annot=True, fmt='d', cmap='YlOrRd', cbar=False,
    xticklabels=['Predicted Existing', 'Predicted Attrited'],
    yticklabels=['Actual Existing', 'Actual Attrited']
)
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted Label')
plt.ylabel('Actual Label')
plt.tight_layout()
```

```
plt.show()

# --- 3D Scatter Plot ---
color_map = {
    'True Attrited': 'green',
    'True Existing': 'red',
    'False Attrited': 'yellow',
    'False Existing': 'orange'
}

scatter = go.Scatter3d(
    x=X_3d['Total_Trans_Ct'],
    y=X_3d['Total_Ct_Chng_Q4_Q1'],
    z=X_3d['Total_Revolving_Bal'],
    mode='markers',
    marker=dict(
        size=5,
        color=[color_map[o] for o in X_3d['Outcome']],
        opacity=0.7
    ),
    text=X_3d['Outcome'],
    name='Classification Outcome'
)

# --- SVM Decision Hyperplane ---
x_range = np.linspace(X_3d['Total_Trans_Ct'].min(),
X_3d['Total_Trans_Ct'].max(), 10)
y_range = np.linspace(X_3d['Total_Ct_Chng_Q4_Q1'].min(),
X_3d['Total_Ct_Chng_Q4_Q1'].max(), 10)
xx, yy = np.meshgrid(x_range, y_range)

coef = svm_clf.coef_[0]
intercept = svm_clf.intercept_[0]
zz = (-coef[0] * xx - coef[1] * yy - intercept) / coef[2]

plane = go.Surface(
    x=xx, y=yy, z=zz,
    showscale=False,
    opacity=0.3,
    colorscale=[[0, 'red'], [1, 'red']],
    name='SVM Hyperplane'
)

# --- Combine & Render Plot ---
fig = go.Figure(data=[scatter, plane])
fig.update_layout(
    title='SVM Classification Outcome in 3D Feature
Space<br><sub>Green: True Attrited | Red: True Existing | Yellow:
False Attrited | Orange: False Existing</sub>',
    scene=dict(
```

```
        xaxis_title='Total_Trans_Ct',
        yaxis_title='Total_Ct_Chng_Q4_Q1',
        zaxis_title='Total_Revolving_Bal'
    ),
    width=1000,
    height=800,
    legend_title_text='Prediction Outcome',
    margin=dict(l=20, r=20, b=20, t=80)
)
fig.write_html("svm_3d_colored_outcome_with_heatmap.html")
fig.show()

# --- Evaluation Metrics ---
accuracy = accuracy_score(X_3d['Actual'], X_3d['Predicted'])
precision = precision_score(X_3d['Actual'], X_3d['Predicted'])
recall = recall_score(X_3d['Actual'], X_3d['Predicted'])
f1 = f1_score(X_3d['Actual'], X_3d['Predicted'])

print("SVM Performance Metrics:")
print(f"Accuracy : {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall   : {recall:.4f}")
print(f"F1 Score : {f1:.4f}")
```

6.7 Support Vector Machine (with dimensionality reduction using PCA)

Due to the poor performance of the 3D SVM, we decided to try Dimensionality Reduction with PCA first, before performing SVM again.

Indeed, it showed much better performance than the 3D SVM.

```
import pandas as pd
import numpy as np
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix, roc_curve, auc
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns

# --- Define X and y ---
X = df_encoded[['Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1',
'Total_Revolving_Bal', 'Total_Trans_Amt']]
y = df_encoded['Attrition_Flag']

# --- Standardize features ---
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```python
# --- Fit Support Vector Machine ---
svm_clf = SVC(kernel='rbf', probability=True, random_state=42)
svm_clf.fit(X_scaled, y)

# --- Predict ---
y_pred_class = svm_clf.predict(X_scaled)
y_pred_proba = svm_clf.predict_proba(X_scaled)[:, 1]

# --- Evaluation ---
acc = accuracy_score(y, y_pred_class)
auc_score = roc_auc_score(y, y_pred_proba)
cm = confusion_matrix(y, y_pred_class)

print("SVM Classifier Results:")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc_score:.4f}")
print("Confusion Matrix:")
print(cm)

# --- Confusion Matrix Heatmap ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Oranges', cbar=False,
            xticklabels=['Pred: Attrited', 'Pred: Existing'],
            yticklabels=['Actual: Attrited', 'Actual: Existing'])
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()

# --- ROC Curve ---
fpr, tpr, _ = roc_curve(y, y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, color='purple', lw=2, label=f'ROC curve (AUC =
{roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('SVM ROC Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()

# --- PCA Reduction for 2D Plot ---
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
```

```
# Refit SVM on PCA space for decision boundary visualization
svm_pca_clf = SVC(kernel='rbf', probability=True)
svm_pca_clf.fit(X_pca, y)

# --- Decision boundary plot in 2D (PCA) ---
x_min, x_max = X_pca[:, 0].min() - 1, X_pca[:, 0].max() + 1
y_min, y_max = X_pca[:, 1].min() - 1, X_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 500),
                     np.linspace(y_min, y_max, 500))
Z = svm_pca_clf.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, Z, alpha=0.3, cmap='coolwarm')
sns.scatterplot(x=X_pca[:, 0], y=X_pca[:, 1], hue=y, palette='Set1',
edgecolor='k')
plt.title('SVM Decision Regions (PCA-reduced 2D space)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Attrition_Flag')
plt.tight_layout()
plt.show()
```

6.8 Neural Network (MLPClassifier)

Lastly, We decided to try using a Neural Network to predict Attrition Rate.

```
import pandas as pd
import numpy as np
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, roc_auc_score,
confusion_matrix, roc_curve, auc, f1_score
import matplotlib.pyplot as plt
import seaborn as sns

# Define X and y
X = df_encoded[['Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1',
'Total_Revolving_Bal', 'Total_Trans_Amt']]
y = df_encoded['Attrition_Flag']

# --- Step 1: Standardize features for neural networks ---
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# --- Step 2: Define and train the neural network ---
mlp = MLPClassifier(hidden_layer_sizes=(16, 8), activation='relu',
solver='adam',
                    max_iter=500, random_state=42)
```

```
mlp.fit(X_scaled, y)

# --- Step 3: Predictions ---
y_pred_class = mlp.predict(X_scaled)
y_pred_proba = mlp.predict_proba(X_scaled)[:, 1]

# --- Step 4: Evaluation metrics ---
acc = accuracy_score(y, y_pred_class)
auc_score = roc_auc_score(y, y_pred_proba)
f1 = f1_score(y, y_pred_class)
cm = confusion_matrix(y, y_pred_class)

print("Neural Network (MLPClassifier) Results:")
print(f"Accuracy: {acc:.4f}")
print(f"ROC AUC Score: {auc_score:.4f}")
print(f"F1 Score: {f1:.4f}")
print("Confusion Matrix:")
print(cm)

# --- Step 5: Heatmap of Confusion Matrix ---
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Pred: Attrited', 'Pred: Existing'],
            yticklabels=['Actual: Attrited', 'Actual: Existing'])
plt.title('Confusion Matrix Heatmap (Neural Net)')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.tight_layout()
plt.show()

# --- Step 6: ROC Curve ---
fpr, tpr, _ = roc_curve(y, y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = 
{roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve (Neural Network)')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()
```

Conclusion

Our study delivered the following key takeaways:

- **Top churn drivers**:
    a. **Total_Trans_Ct** (highest correlation & F-score)

    b. **Total_Trans_Amt** (highest mutual information)

    c. **Avg_Utilization_Ratio**, **Total_Revolving_Bal**, **Contacts_Count_12_mon**.
- **Model performance**:
    – **XGBoost** led with **94.90% accuracy** and **F1 0.8323**.

    – **MLP Classifier** close behind at **94.48% accuracy** and **F1 0.8288**.

    – SVM (with PCA) and Random Forest also delivered strong results (~ 92–93% accuracy).
- **Recommended actions**:
    a. **Educational workshops** on account usage & budgeting.

    b. **Credit-rebuilding programmes** for high-utilisation customers.

    c. **Personalised retention perks** (cashback, loyalty bonuses).

    d. **Early-warning alerts** for at-risk segments identified via clustering.

By integrating deep EDA, robust feature ranking, and ensemble modelling, this framework equips banking teams to **anticipate** and **mitigate** churn—preserving revenue and strengthening customer loyalty.