churn_bank

April 19, 2023

Contexto:

Somos un banco que dispone de una base de datos con una gran cantidad de información sobre nuestros clientes. Nuestro objetivo es ayudar a los analistas a predecir la tasa de abandono de estos clientes para así poder reducirla. La base de datos incluye información demográfica como la edad, el sexo, el estado civil y la categoría de ingresos. También contiene información sobre el tipo de tarjeta, el número de meses en cartera y los periodos inactivos. Además, dispone de datos clave sobre el comportamiento de gasto de los clientes que se acercan a su decisión de cancelación. Entre esta última información hay el saldo total renovable, el límite de crédito, la tasa media de apertura a la compra y métricas analizables como el importe total del cambio del cuarto trimestre al primero o el índice medio de utilización.

Frente a este conjunto de datos podemos capturar información actualizada que puede determinar la estabilidad de la cuenta a largo plazo o su salida inminente.

Dataset:

CLIENTNUM: Identificador único para cada cliente. (Integer) Attrition_Flag: Indicador de si el cliente ha abandonado el banco o se queda (Boolean) Attrited Customer -> 0 Existing Customer -> 1 Customer_Age: Edad del cliente. (Integer) Gender: Sexo del cliente. (String) Dependent_count: Número de personas a cargo que tiene el cliente. (Integer) Education_Level: Nivel educativo del cliente. (String) Marital_Status: Marital status of customer. (String Income_Category: Categoría de ingresos del cliente. (String Card_Category: Tipo de tarjeta del cliente. (String Months_on_book: El tiempo que el cliente ha estado en los libros. (Integer Total_Relationship_Count: Número total de relaciones que tiene el cliente con el proveedor de la tarjeta de crédito. (Integer Months_Inactive_12_mon: Número de meses que el cliente ha estado inactivo en los últimos doce meses.(Integer Contacts_Count_12_mon: Número de contactos que ha tenido el cliente en los últimos doce meses. (Integer Credit_Limit: Límite de crédito del cliente. (Integer Total_Revolving_Bal: Saldo renovable total del cliente. (Integer Avg_Open_To_Buy: Ratio medio de apertura a la compra del cliente. (Integer Total_Amt_Chng_Q4_Q1: Importe total cambiado del trimestre 4 al trimestre 1. (Integer Total_Trans_Amt: Importe total de la transacción. (Integer Total_Trans_Ct: Recuento total de transacciones. (Integer Total_Ct_Chng_Q4_Q1: Recuento total cambiado del trimestre 4 al trimestre 1. (Integer Avg_Utilization_Ratio: Ratio de utilización media del cliente. (Integer Months_Inactive_12_mon: Número de meses que el cliente ha estado inactivo en los últimos doce meses. (Integer Contacts_Count_12_mon: Número de contactos que ha tenido el cliente en los últimos doce meses. (Integer Credit_Limit: Límite de crédito del cliente. (Integer Total_Revolving_Bal: Saldo rotativo total del cliente. (Integer Avg_Open_To_Buy: Ratio medio de apertura a compra del cliente. (Integer) Total_Amt_Chng_Q4_Q1: Importe total cambiado del trimestre 4 al trimestre 1. (Integer) Total_Trans_Amt: Importe total de la transacción. (Integer) Total_Trans_Ct: Recuento total de transacciones.. (Integer) Total_Ct_Chng_Q4_Q1: Recuento total cambiado del trimestre 4 al trimestre 1. (Integer) Avg_Utilization_Ratio: Ratio de utilización media del cliente. (Integer)

1 Libraries

[1]:
```
#uncomment to install libraries in google colab
#!pip install category_encoders
#!pip install -U imbalanced-learn
```

[2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use('ggplot')
%matplotlib inline
import math
import pickle
from xgboost import XGBClassifier
from xgboost import plot_importance
import category_encoders as ce
from sklearn.preprocessing import StandardScaler,RobustScaler
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline
from sklearn.model_selection import (train_test_split,
                                      StratifiedKFold,
                                    GridSearchCV)
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.metrics import (mean_squared_error,
                             confusion_matrix,roc_curve,classification_report,
                            roc_auc_score,
                             accuracy_score,f1_score)
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
import json
```

2 Functions

[3]:
```
#1 get the number of rows for the plot
def plot_template(n_cols,features):
    n_rows = math.ceil(len(features)/n_cols)
    return n_rows
```

[4]:
```
#2 get the reltion between two features
def attrited_feature(df,target,feature):
    attr = df[[target,feature]].groupby([feature]).mean().sort_values(by=target)
    return attr
```

[5]:
```
#3 plot the attrition value in relation with a feature
def plot_target_attrition(df,col):
    plt.figure(figsize=(8,5))
    sns.barplot(data=df,x=df.index,y=col)
    plt.tight_layout()
    plt.xticks(rotation=90)
    plt.title("Attrition by {}".format(df.index.name))
    plt.show()

```

[6]:
```
#4 plot confusion matrix and roc

def␣
 ↪subplots_ROC_CM(main_title,rtitle,mtitle,mod,accuracy,auc,matrix,model,Xtest,ytest,label):
 ↪
    fig , axes = plt.subplots(1,2,figsize=(10,8))


    y_pred_prob1_rs = mod.predict_proba(Xtest)[:,1]
    fpr1_rs, tpr1_rs, thresholds1_rs = roc_curve(ytest, y_pred_prob1_rs)
    axes[0].plot([0, 1], [0, 1], 'k--')
    axes[0].plot(fpr1_rs, tpr1_rs, label=label)
    axes[0].legend(loc="best")
    axes[0].set_xlabel('False Positive Rate')
    axes[0].set_ylabel('True Positive Rate')
    axes[0].set_title(rtitle + "\n" +
              "AUC : {0:.2%}".format(accuracy.get(model)))


    group_counts = ["{0:0.0f}".format(v) for v in matrix.flatten()]
    group_percentages = ["{0:.2%}".format(value)
                     for value in matrix.flatten()/np.sum(matrix)]
    labels = [f"{ant1}\n{ant2}" for ant1, ant2 in␣
 ↪zip(group_counts,group_percentages)]
    labels = np.asarray(labels).reshape(2,2)
    ax = sns.heatmap(matrix, annot=labels, fmt='',
                cmap='Blues', ax=axes[1])
    axes[1].set_title(mtitle + "\n" + "Accuracy Score: {0:.2%}".format(auc.
 ↪get(model)))
    axes[1].set_xlabel('\nPredicted Values')
    axes[1].set_ylabel('Actual Values ')
    axes[1].xaxis.set_ticklabels(['False','True'])
```

```
    axes[1].yaxis.set_ticklabels(['False','True'])

    plt.suptitle(main_title,size=17, weight='bold')
    plt.show()
```

[7]:
```
#5 get the item from the dict

def get_value(item):
    return item[1]
```

3 Load Data

[8]:
```
data_train = pd.read_csv("https://storage.googleapis.com/challenges_events/\
03_2023/Pre-Selection%20JOBarcelona/Data/supply_chain_train.
 ↪csv",index_col="train_idx")

data_train.head(10).T
```

[8]:
```
train_idx                          0            1                2  \
CLIENTNUM                  713071383    714246333        718206783
Customer_Age                      54           58               45
Gender                             F            F                F
Dependent_count                    1            4                4
Education_Level              Unknown  High School          Unknown
Marital_Status                Single      Married           Single
Income_Category              Unknown      Unknown   Less than $40K
Card_Category                   Blue         Blue             Gold
Months_on_book                    36           48               36
Total_Relationship_Count           1            1                6
Months_Inactive_12_mon             3            4                1
Contacts_Count_12_mon              3            3                3
Credit_Limit                  3723.0       5396.0          15987.0
Total_Revolving_Bal             1728         1803             1648
Avg_Open_To_Buy               1995.0       3593.0          14339.0
Total_Amt_Chng_Q4_Q1           0.595        0.493            0.732
Total_Trans_Amt                 8554         2107             1436
Total_Trans_Ct                    99           39               36
Total_Ct_Chng_Q4_Q1            0.678        0.393             1.25
Avg_Utilization_Ratio          0.464        0.334            0.103
Attrition_Flag                     1            0                1

train_idx                               3            4                5  \
CLIENTNUM                       721096983    720028683        778942233
Customer_Age                           34           49               60
Gender                                  F            F                F
Dependent_count                         2            2                0
```

```
Education_Level                Graduate  High School       Doctorate
Marital_Status                   Single      Married         Married
Income_Category          Less than $40K  $40K - $60K  Less than $40K
Card_Category                      Blue         Blue            Blue
Months_on_book                       36           39              45
Total_Relationship_Count              4            5               5
Months_Inactive_12_mon                3            3               2
Contacts_Count_12_mon                 4            4               4
Credit_Limit                     3625.0       2720.0          1438.3
Total_Revolving_Bal                2517         1926             648
Avg_Open_To_Buy                  1108.0        794.0           790.3
Total_Amt_Chng_Q4_Q1              1.158        0.602           0.477
Total_Trans_Amt                    2616         3806            1267
Total_Trans_Ct                       46           61              27
Total_Ct_Chng_Q4_Q1                 1.3        0.794           1.077
Avg_Utilization_Ratio             0.694        0.708           0.451
Attrition_Flag                        1            1               1

train_idx                         6            7               8  \
CLIENTNUM                 708682908    720670458       719952408
Customer_Age                     43           52              30
Gender                            F            F               M
Dependent_count                   4            2               0
Education_Level             Unknown      Unknown        Graduate
Marital_Status               Single       Single         Married
Income_Category             Unknown  $40K - $60K  Less than $40K
Card_Category                  Blue         Blue            Blue
Months_on_book                   28           45              36
Total_Relationship_Count          2            3               3
Months_Inactive_12_mon            2            1               3
Contacts_Count_12_mon             1            3               2
Credit_Limit                 2838.0       3476.0          2550.0
Total_Revolving_Bal            1934         1560            1623
Avg_Open_To_Buy               904.0       1916.0           927.0
Total_Amt_Chng_Q4_Q1          0.873        0.894            0.65
Total_Trans_Amt                8644         3496            1870
Total_Trans_Ct                   87           58              51
Total_Ct_Chng_Q4_Q1           0.554        0.871           0.275
Avg_Utilization_Ratio         0.681        0.449           0.636
Attrition_Flag                    1            1               1

train_idx                             9
CLIENTNUM                     708412758
Customer_Age                         33
Gender                                F
Dependent_count                       3
Education_Level                Graduate
```

```
Marital_Status                          Single
Income_Category                 Less than $40K
Card_Category                             Blue
Months_on_book                              36
Total_Relationship_Count                     5
Months_Inactive_12_mon                       2
Contacts_Count_12_mon                        3
Credit_Limit                            1457.0
Total_Revolving_Bal                          0
Avg_Open_To_Buy                         1457.0
Total_Amt_Chng_Q4_Q1                     0.677
Total_Trans_Amt                           2200
Total_Trans_Ct                              45
Total_Ct_Chng_Q4_Q1                      0.364
Avg_Utilization_Ratio                      0.0
Attrition_Flag                               0
```

[9]:

```
data = data_train.copy()
```

[10]:

```
test = pd.read_csv("https://storage.googleapis.com/challenges_events/\
03_2023/Pre-Selection%20JOBarcelona/Data/supply_chain_test.
 ↪csv",index_col="test_idx")

test
```

[10]:

```
           CLIENTNUM  Customer_Age Gender  Dependent_count Education_Level  \
test_idx
0          719455083            48      F                3      Uneducated
1          773503308            59      M                1      Uneducated
2          715452408            37      F                2        Graduate
3          711264033            47      M                3       Doctorate
4          718943508            42      M                3         Unknown
…                …           …    …              …             …
2021       814776033            34      M                2        Graduate
2022       720444408            35      F                1         College
2023       720503508            44      F                1      Uneducated
2024       721217283            27      M                0        Graduate
2025       770920908            39      F                0         Unknown

         Marital_Status Income_Category Card_Category  Months_on_book  \
test_idx
0                Single  Less than $40K          Blue              39
1                Single  Less than $40K          Blue              53
2              Divorced  Less than $40K          Blue              36
3              Divorced     $40K - $60K          Blue              36
4                Single    $80K - $120K          Blue              33
…                 …             …           …             …
```

```
2021           Single    $80K - $120K         Blue              29
2022           Single  Less than $40K         Blue              25
2023         Divorced  Less than $40K         Blue              37
2024           Single         $120K +         Blue              17
2025           Single     $40K - $60K       Silver              26

          Total_Relationship_Count  Months_Inactive_12_mon  \
test_idx
0                                4                       3
1                                5                       5
2                                4                       3
3                                4                       2
4                                3                       3
…                              …                       …
2021                             3                       1
2022                             2                       2
2023                             1                       2
2024                             6                       2
2025                             1                       1

          Contacts_Count_12_mon  Credit_Limit  Total_Revolving_Bal  \
test_idx
0                             4        2991.0                 1508
1                             4        2192.0                 1569
2                             3        1734.0                  987
3                             3        4786.0                 1516
4                             2        3714.0                 2170
…                           …           …                  …
2021                          3       13395.0                 1678
2022                          4        2231.0                 1791
2023                          3        5594.0                 1235
2024                          2        8713.0                 1354
2025                          1       22054.0                 1146

          Avg_Open_To_Buy  Total_Amt_Chng_Q4_Q1  Total_Trans_Amt  \
test_idx
0                  1483.0                 0.703             3734
1                   623.0                 0.706             4010
2                   747.0                 0.879             4727
3                  3270.0                 0.940             4973
4                  1544.0                 0.524             1454
…                   …                   …                …
2021              11717.0                 1.006             2650
2022                440.0                 0.820             2576
2023               4359.0                 0.549             5220
2024               7359.0                 0.558             2094
2025              20908.0                 0.842             8055
```

```
          Total_Trans_Ct  Total_Ct_Chng_Q4_Q1  Avg_Utilization_Ratio
test_idx
0                     64                0.882                  0.504
1                     79                0.717                  0.716
2                     67                0.914                  0.569
3                     74                0.850                  0.317
4                     35                0.522                  0.584
…                    …                   …                    …
2021                  69                0.865                  0.125
2022                  42                0.750                  0.803
2023                  75                0.829                  0.221
2024                  36                0.333                  0.155
2025                  82                0.673                  0.052

[2026 rows x 20 columns]
```

4 Exploratory Data Analysis

[11]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8101 entries, 0 to 8100
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   CLIENTNUM                 8101 non-null   int64
 1   Customer_Age              8101 non-null   int64
 2   Gender                    8101 non-null   object
 3   Dependent_count           8101 non-null   int64
 4   Education_Level           8101 non-null   object
 5   Marital_Status            8101 non-null   object
 6   Income_Category           8101 non-null   object
 7   Card_Category             8101 non-null   object
 8   Months_on_book            8101 non-null   int64
 9   Total_Relationship_Count  8101 non-null   int64
 10  Months_Inactive_12_mon    8101 non-null   int64
 11  Contacts_Count_12_mon     8101 non-null   int64
 12  Credit_Limit              8101 non-null   float64
 13  Total_Revolving_Bal       8101 non-null   int64
 14  Avg_Open_To_Buy           8101 non-null   float64
 15  Total_Amt_Chng_Q4_Q1      8101 non-null   float64
 16  Total_Trans_Amt           8101 non-null   int64
 17  Total_Trans_Ct            8101 non-null   int64
 18  Total_Ct_Chng_Q4_Q1       8101 non-null   float64
 19  Avg_Utilization_Ratio     8101 non-null   float64
```

```
 20  Attrition_Flag            8101 non-null   int64  
dtypes: float64(5), int64(11), object(5)
memory usage: 1.4+ MB
```

[12]:
```
columns = data.columns
binary_cols = []
for col in columns:
    if data[col].value_counts().shape[0] == 2:
        binary_cols.append(col)
binary_cols
```

[12]:
```
['Gender', 'Attrition_Flag']
```

[13]:
```
numeric_cols = data.select_dtypes(include=['number'])
cat_cols = data.select_dtypes(include=[object])
```

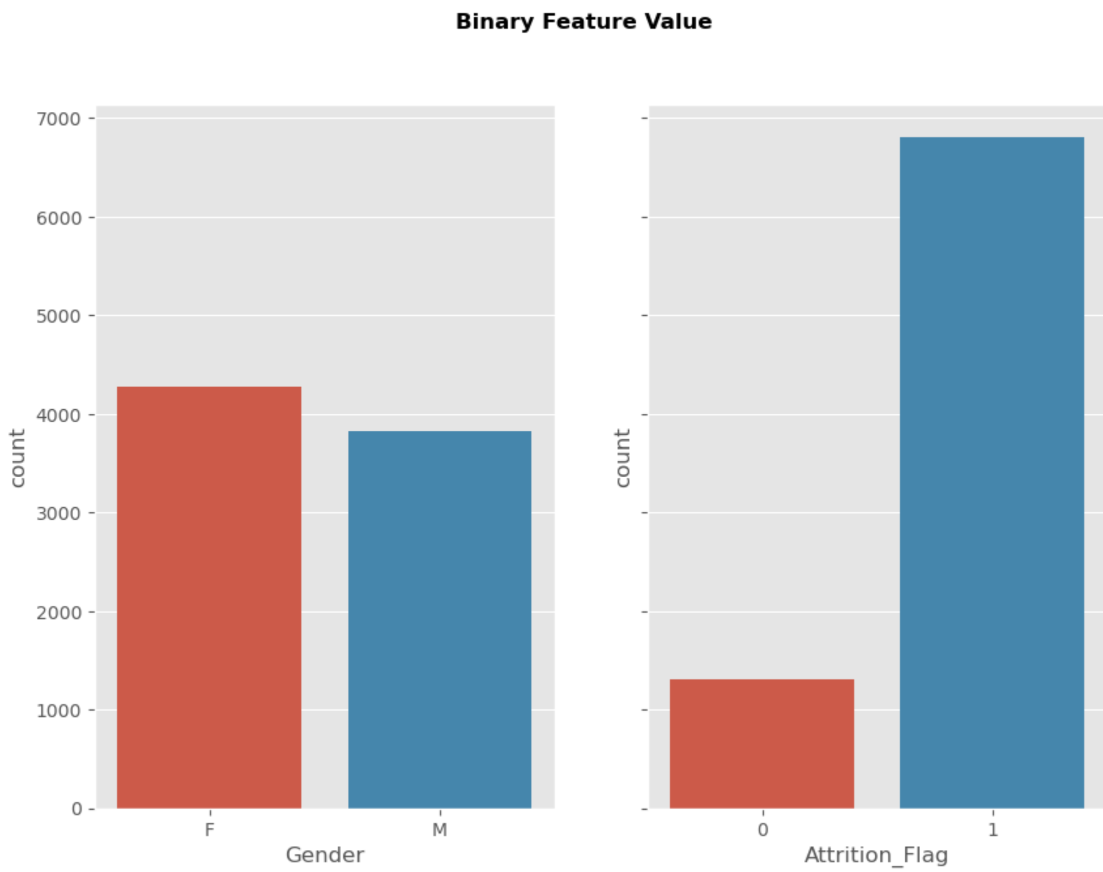
[14]:
```
mult_categories_cols = list(set(columns).difference(binary_cols,numeric_cols))
mult_categories_cols
```

[14]:
```
['Income_Category', 'Card_Category', 'Marital_Status', 'Education_Level']
```

[15]:
```
numeric_categories_cols = list(set(numeric_cols).difference(binary_cols))
numeric_categories_cols
```

[15]:
```
['Total_Trans_Amt',
 'Customer_Age',
 'Avg_Utilization_Ratio',
 'CLIENTNUM',
 'Months_Inactive_12_mon',
 'Total_Amt_Chng_Q4_Q1',
 'Total_Revolving_Bal',
 'Months_on_book',
 'Credit_Limit',
 'Total_Relationship_Count',
 'Total_Trans_Ct',
 'Dependent_count',
 'Contacts_Count_12_mon',
 'Total_Ct_Chng_Q4_Q1',
 'Avg_Open_To_Buy']
```

[16]:
```
fig, axes = plt.subplots(1, 2, figsize=(10, 7), sharey=True)

for i, col in enumerate(binary_cols):
    ax = axes.flat[i]
    sns.countplot(x= data[col],ax=ax)
plt.suptitle("Binary Feature Value",fontweight='bold')
plt.show()
```

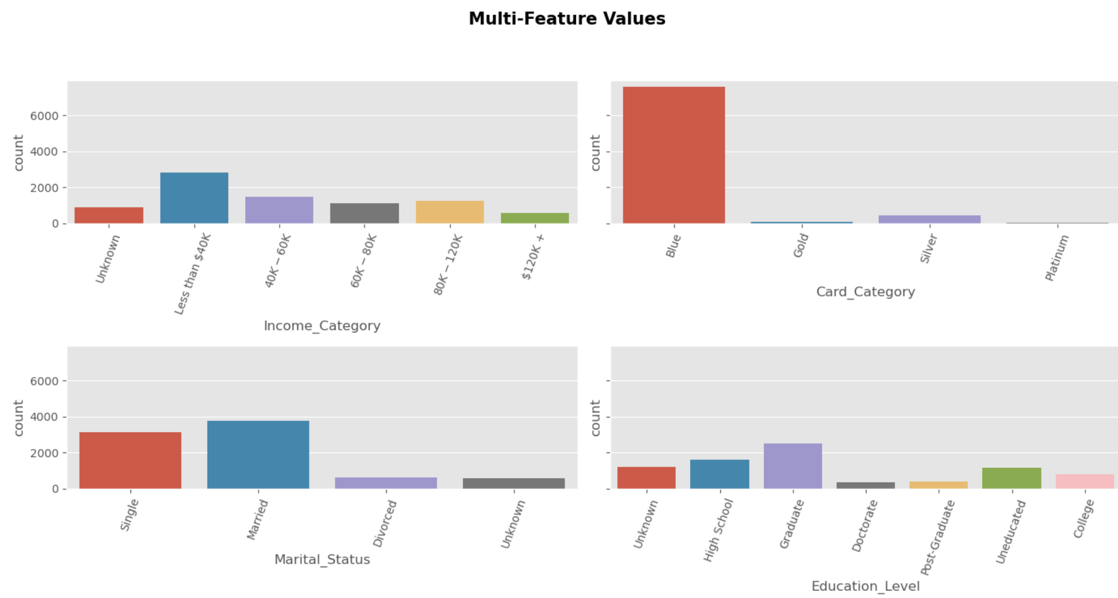


[17]:
```
n_cols = 2

n_rows = plot_template(n_cols,mult_categories_cols)
n_rows
```

[17]: 2

[18]:
```
fig, axes = plt.subplots(n_rows,n_cols, figsize=(3.5 * 4, 3.5 *n_rows),␣
↪sharey=True)

for i, col in enumerate(mult_categories_cols):
    ax = axes.flat[i]
    sns.countplot(x= data[col],ax=ax)


for ax in axes.flatten():
    plt.sca(ax)
    plt.xticks(rotation = 70)
```

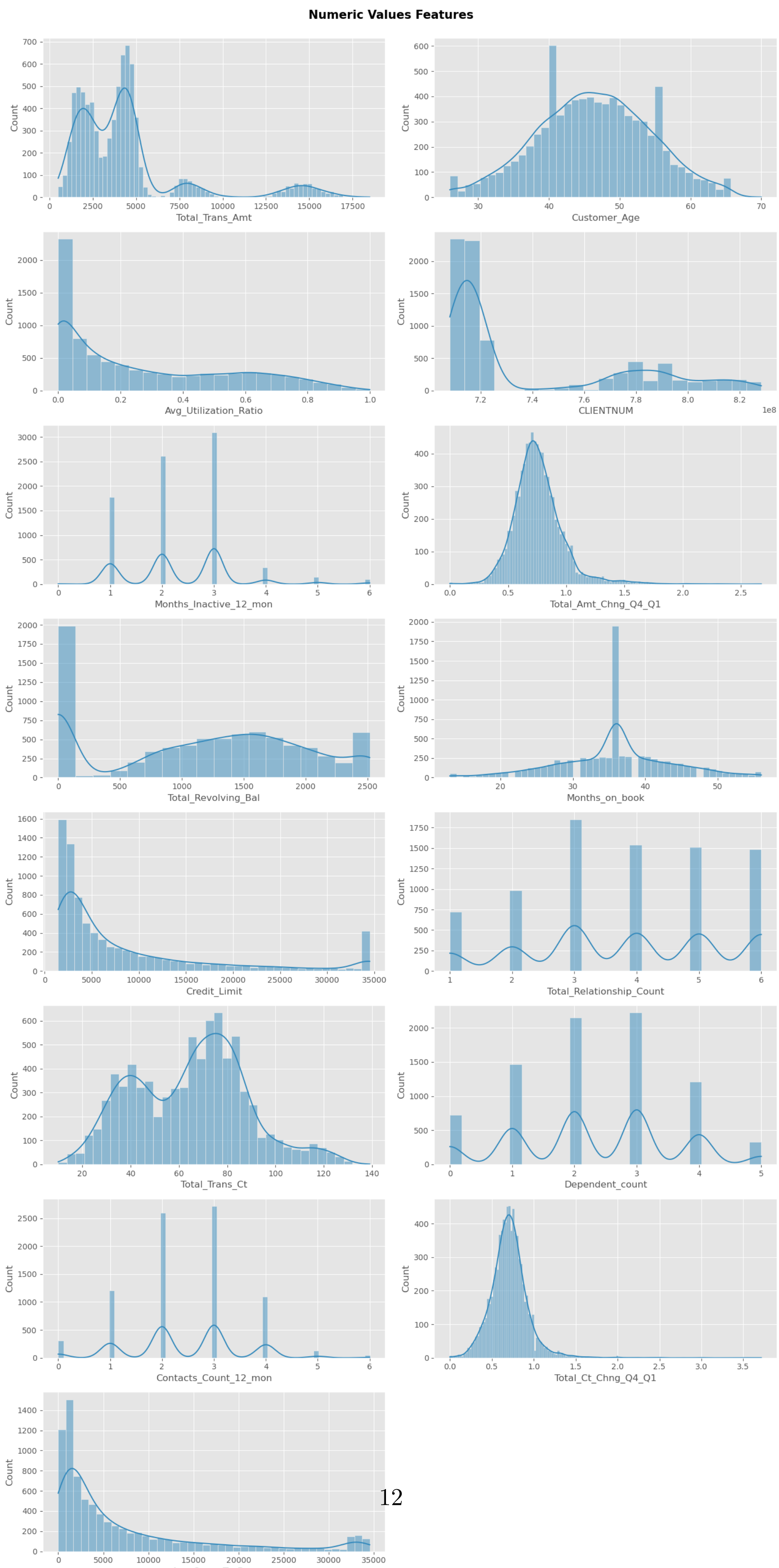
```
plt.suptitle("Multi-Feature Values", y=1.05,fontsize=15,fontweight='bold')
plt.tight_layout()
plt.show()
```



[19]:
```
n_rows = plot_template(n_cols,numeric_categories_cols)
n_rows
```

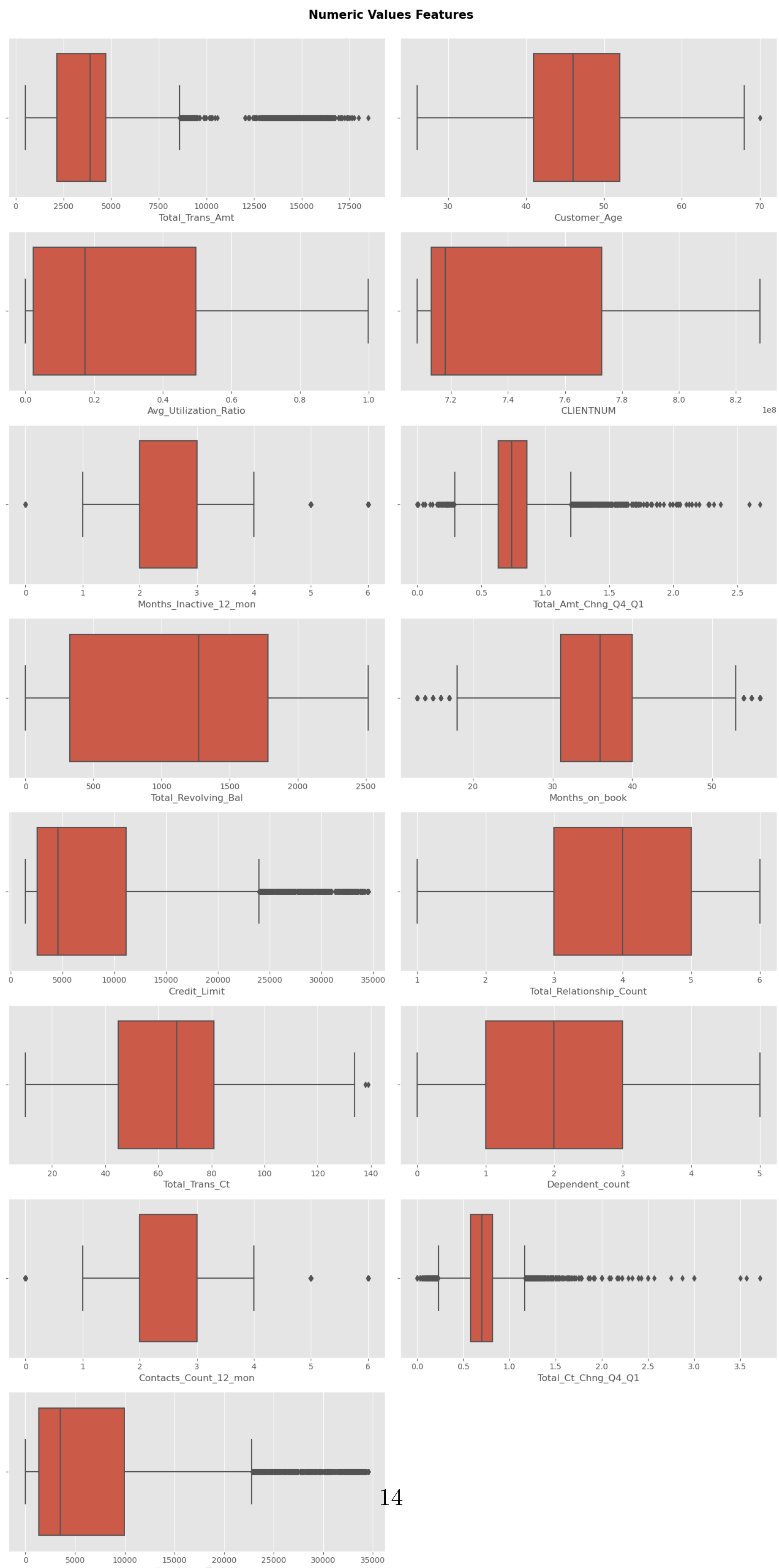
[19]: 8

[20]:
```
fig, axes = plt.subplots(n_rows,n_cols, figsize=(3.5 * 4, 3.5 *n_rows))

for i, col in enumerate(numeric_categories_cols):
    ax = axes.flat[i]
    sns.histplot(x= data[col],kde=True,ax=ax)

plt.suptitle("Numeric Values Features", y=1,fontsize=15,fontweight='bold')
axes[-1, -1].axis('off')
plt.tight_layout()
plt.show()
```


Numeric Values Features
Count
Total_Trans_Amt
Customer_Age
Avg_Utilization_Ratio
CLIENTNUM
1e8
Months_Inactive_12_mon
Total_Amt_Chng_Q4_Q1
Total_Revolving_Bal
Months_on_book
Credit_Limit
Total_Relationship_Count
Total_Trans_Ct
Dependent_count
Contacts_Count_12_mon
Total_Ct_Chng_Q4_Q1
Avg_Open_To_Buy

[21]:

```
fig, axes = plt.subplots(n_rows,n_cols, figsize=(3.5 * 4, 3.5 *n_rows))

for i, col in enumerate(numeric_categories_cols):
    ax = axes.flat[i]
    sns.boxplot(x= data[col],ax=ax)

plt.suptitle("Numeric Values Features", y=1,fontsize=15,fontweight='bold')
axes[-1, -1].axis('off')
plt.tight_layout()
plt.show()
```


Numeric Values Features
Total_Trans_Amt
Customer_Age
Avg_Utilization_Ratio
CLIENTNUM
1e8
Months_Inactive_12_mon
Total_Amt_Chng_Q4_Q1
Total_Revolving_Bal
Months_on_book
Credit_Limit
Total_Relationship_Count
Total_Trans_Ct
Dependent_count
Contacts_Count_12_mon
Total_Ct_Chng_Q4_Q1
Avg_Open_To_Buy

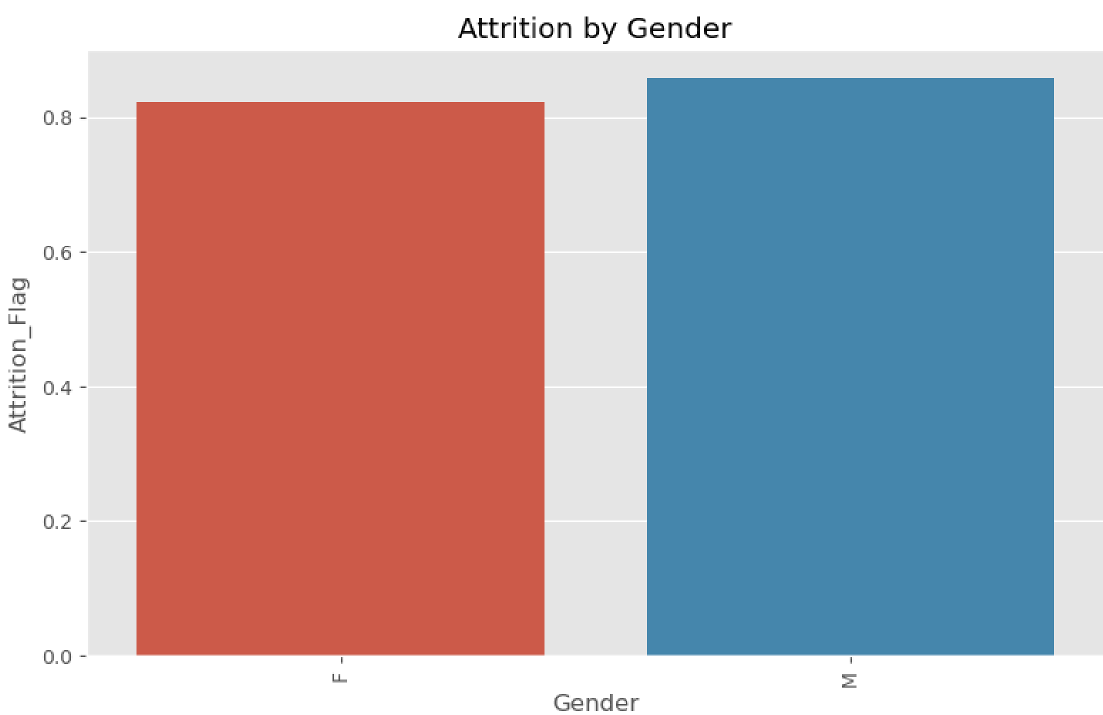
It would be interesting to see the behavior of the variables with the attrition flag.

4.1 Categorical Features

[22]:
```
gender_attrition = attrited_feature(data,'Attrition_Flag','Gender')
gender_attrition
```

[22]:
```
        Attrition_Flag
Gender
F             0.823090
M             0.857928
```

[23]:
```
plot_target_attrition(gender_attrition,'Attrition_Flag')
```

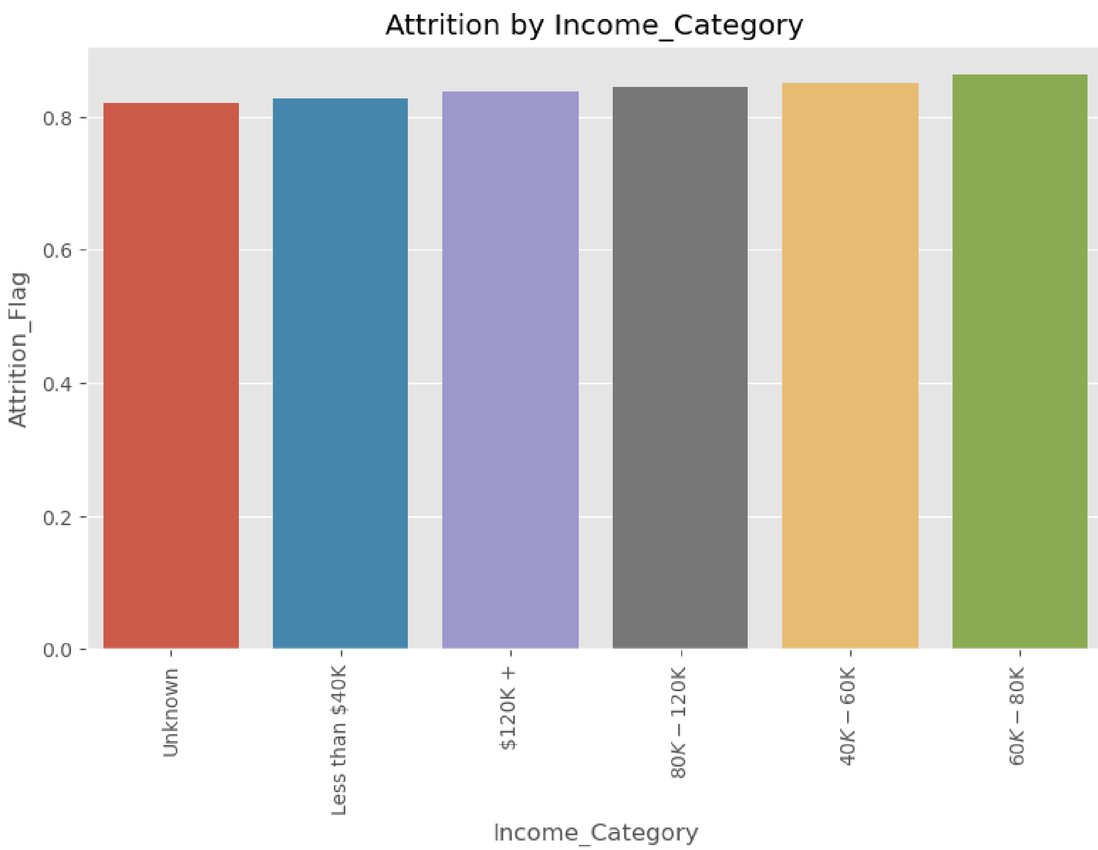


[24]:
```
card_category_attrition =␣
 ↪attrited_feature(data,'Attrition_Flag',mult_categories_cols[0])
card_category_attrition
```

[24]:
```
                 Attrition_Flag
Income_Category
Unknown                0.821147
```

```
Less than $40K         0.827881
$120K +                0.838435
$80K - $120K           0.843977
$40K - $60K            0.851342
$60K - $80K            0.863636
```

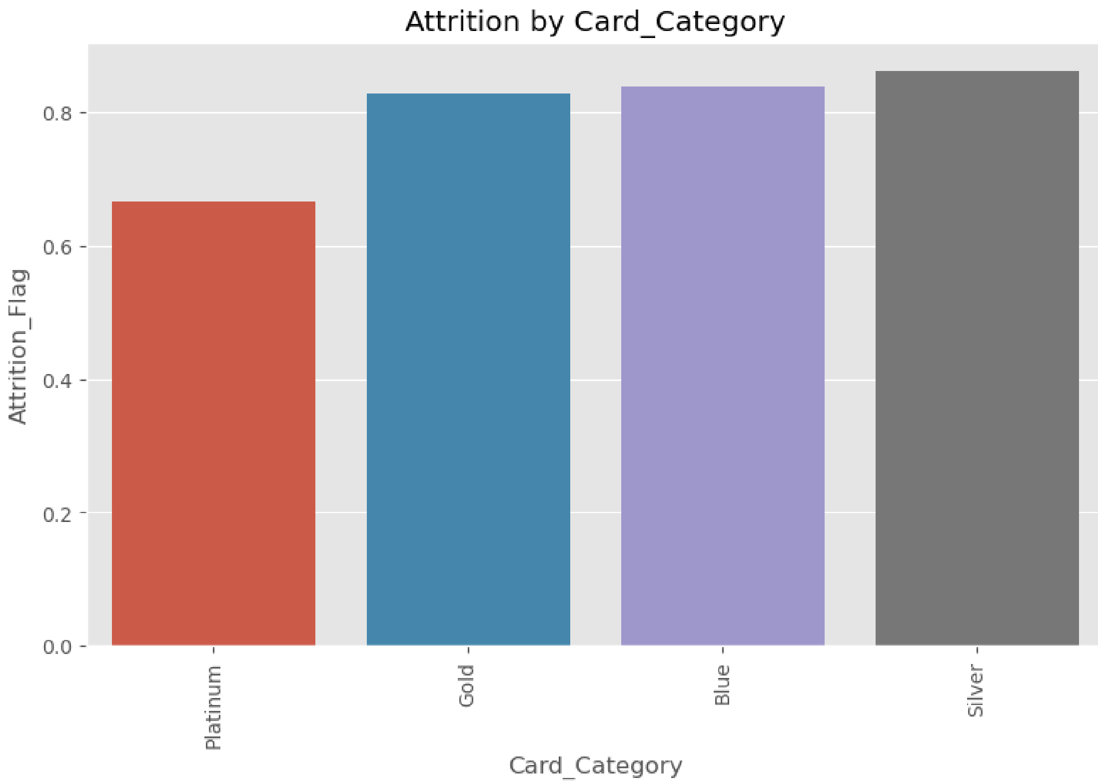
[25]:
```python
plot_target_attrition(card_category_attrition,'Attrition_Flag')
```



[26]:
```python
income_attrition =␣
↪attrited_feature(data,'Attrition_Flag',mult_categories_cols[1])
income_attrition
```

[26]:
```
               Attrition_Flag
Card_Category
Platinum             0.666667
Gold                 0.827957
Blue                 0.838693
Silver               0.862385
```

[27]:
```python
plot_target_attrition(income_attrition,'Attrition_Flag')
```

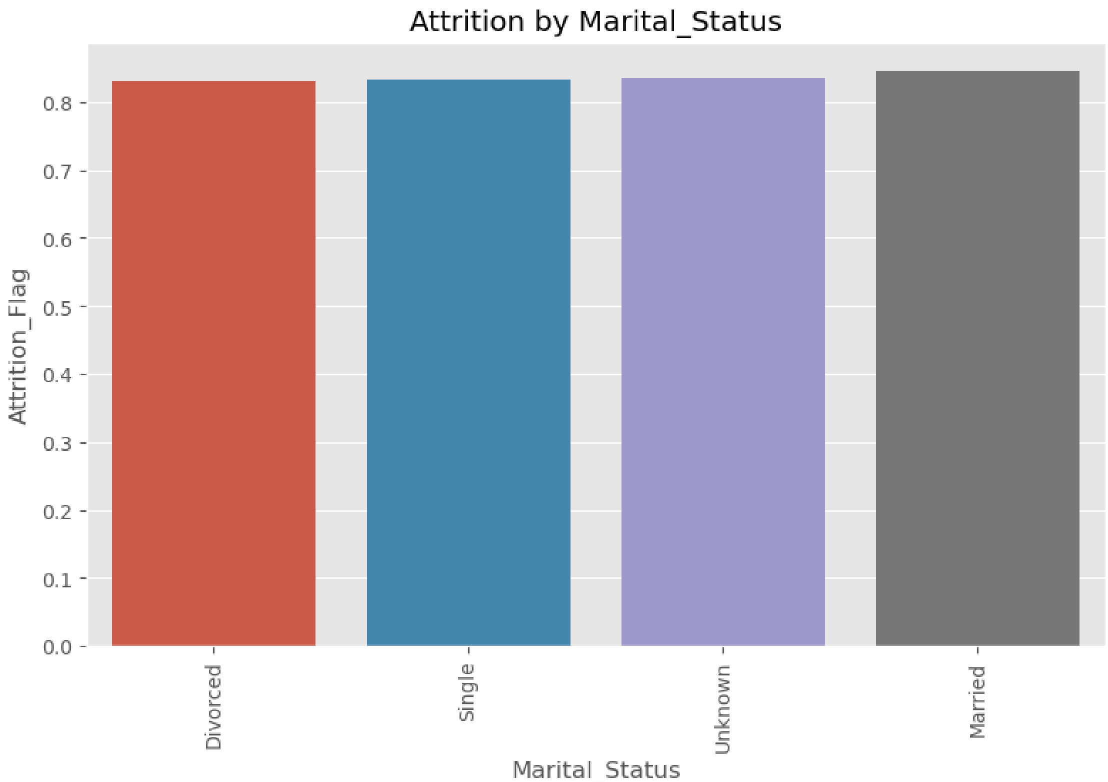


[28]:
```
education_level_attrition =␣
↪attrited_feature(data,'Attrition_Flag',mult_categories_cols[2])
education_level_attrition
```

[28]:

	Attrition_Flag
Marital_Status	
Divorced	0.831424
Single	0.833333
Unknown	0.835924
Married	0.846562

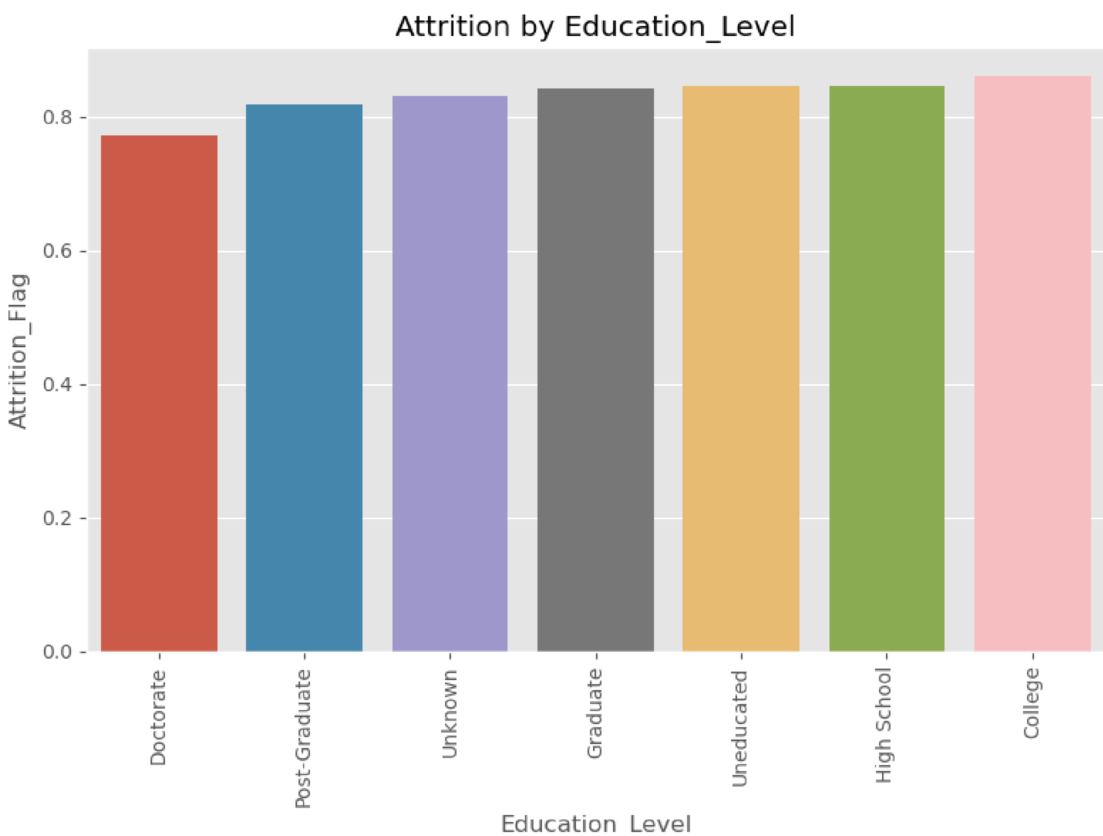
[29]:
```
plot_target_attrition(education_level_attrition,'Attrition_Flag')
```



[30]:
```
marital_status_attrition =␣
 ↪attrited_feature(data,'Attrition_Flag',mult_categories_cols[3])
marital_status_attrition
```

[30]:
```
                 Attrition_Flag
Education_Level
Doctorate              0.771831
Post-Graduate          0.818182
Unknown                0.831535
Graduate               0.842168
Uneducated             0.845431
High School            0.846819
College                0.860294
```

[31]:
```
plot_target_attrition(marital_status_attrition,'Attrition_Flag')
```



4.2 Numeric Features

[32]:
```
for i in numeric_categories_cols:
    print(i,attrited_feature(data,'Attrition_Flag',i).describe())
```

```
Total_Trans_Amt        Attrition_Flag
count     4462.000000
mean         0.823347
std          0.348259
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
Customer_Age        Attrition_Flag
count       44.000000
mean         0.852584
std          0.078781
min          0.500000
25%          0.832231
50%          0.844726
```

```
75%          0.874344
max          1.000000
Avg_Utilization_Ratio        Attrition_Flag
count      943.000000
mean         0.881510
std          0.206084
min          0.000000
25%          0.833333
50%          1.000000
75%          1.000000
max          1.000000
CLIENTNUM        Attrition_Flag
count     8101.000000
mean         0.839526
std          0.367068
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
Months_Inactive_12_mon        Attrition_Flag
count         7.000000
mean          0.755196
std           0.189499
min           0.363636
25%           0.740961
50%           0.798611
75%           0.843011
max           0.956180
Total_Amt_Chng_Q4_Q1        Attrition_Flag
count     1089.000000
mean         0.813661
std          0.266016
min          0.000000
25%          0.750000
50%          0.909091
75%          1.000000
max          1.000000
Total_Revolving_Bal        Attrition_Flag
count     1883.000000
mean         0.887529
std          0.260863
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
Months_on_book        Attrition_Flag
```

```
count       44.000000
mean         0.845314
std          0.044243
min          0.714286
25%          0.823432
50%          0.848812
75%          0.871630
max          0.925926
Credit_Limit        Attrition_Flag
count     5325.000000
mean         0.845085
std          0.337039
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
Total_Relationship_Count        Attrition_Flag
count        6.000000
mean         0.825264
std          0.074599
min          0.722843
25%          0.766316
50%          0.851069
75%          0.880784
max          0.897849
Total_Trans_Ct        Attrition_Flag
count      126.000000
mean         0.823723
std          0.242963
min          0.000000
25%          0.724476
50%          0.955398
75%          1.000000
max          1.000000
Dependent_count        Attrition_Flag
count        6.000000
mean         0.840738
std          0.010474
min          0.827183
25%          0.835099
50%          0.839425
75%          0.845405
max          0.857338
Contacts_Count_12_mon        Attrition_Flag
count        7.000000
mean         0.720160
std          0.334339
```

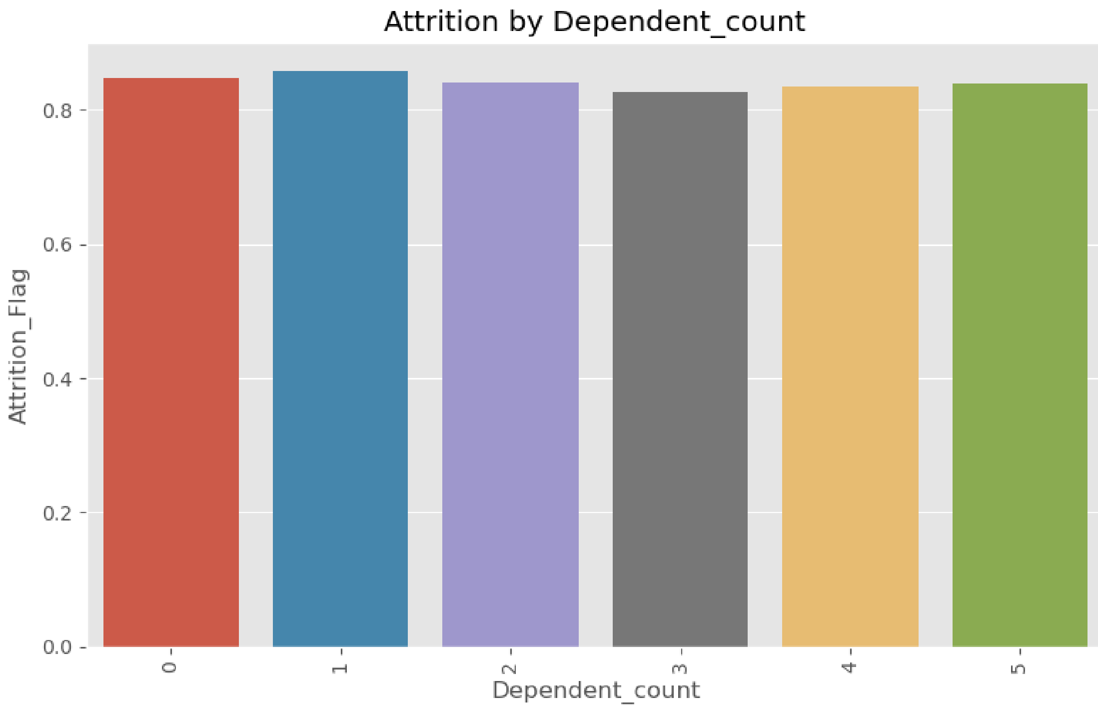
```
min           0.000000
25%           0.724335
50%           0.793446
75%           0.904311
max           0.990385
Total_Ct_Chng_Q4_Q1        Attrition_Flag
count       795.000000
mean          0.818918
std           0.282779
min           0.000000
25%           0.750000
50%           1.000000
75%           1.000000
max           1.000000
Avg_Open_To_Buy        Attrition_Flag
count      5757.000000
mean          0.842429
std           0.342053
min           0.000000
25%           1.000000
50%           1.000000
75%           1.000000
max           1.000000
```

[33]:
```
Dependent_count_attrition =␣
↪attrited_feature(data,'Attrition_Flag','Dependent_count')
Dependent_count_attrition
```

[33]:

	Attrition_Flag
Dependent_count	
3	0.827183
4	0.834158
5	0.837920
2	0.840930
0	0.846897
1	0.857338

[34]:
```
plot_target_attrition(Dependent_count_attrition,'Attrition_Flag')
```

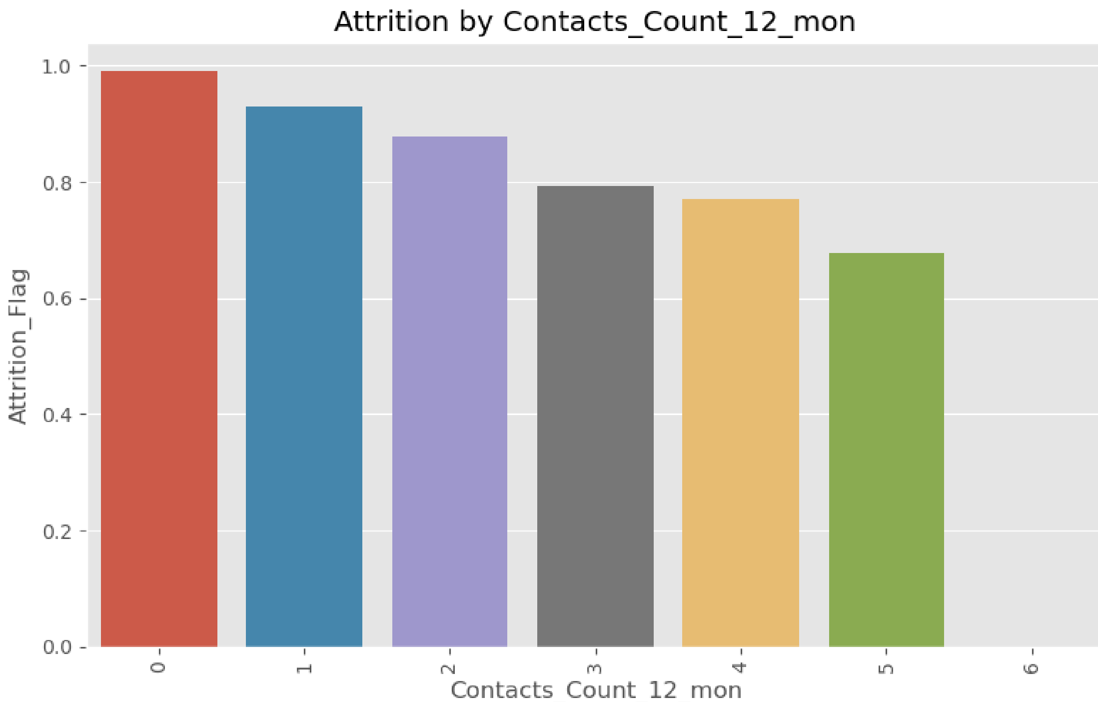


[35]:
```
Contacts_Count_12_mon_attrition =␣
↪attrited_feature(data,'Attrition_Flag','Contacts_Count_12_mon')
Contacts_Count_12_mon_attrition
```

[35]:

Contacts_Count_12_mon	Attrition_Flag
6	0.000000
5	0.676692
4	0.771978
3	0.793446
2	0.879045
1	0.929577
0	0.990385

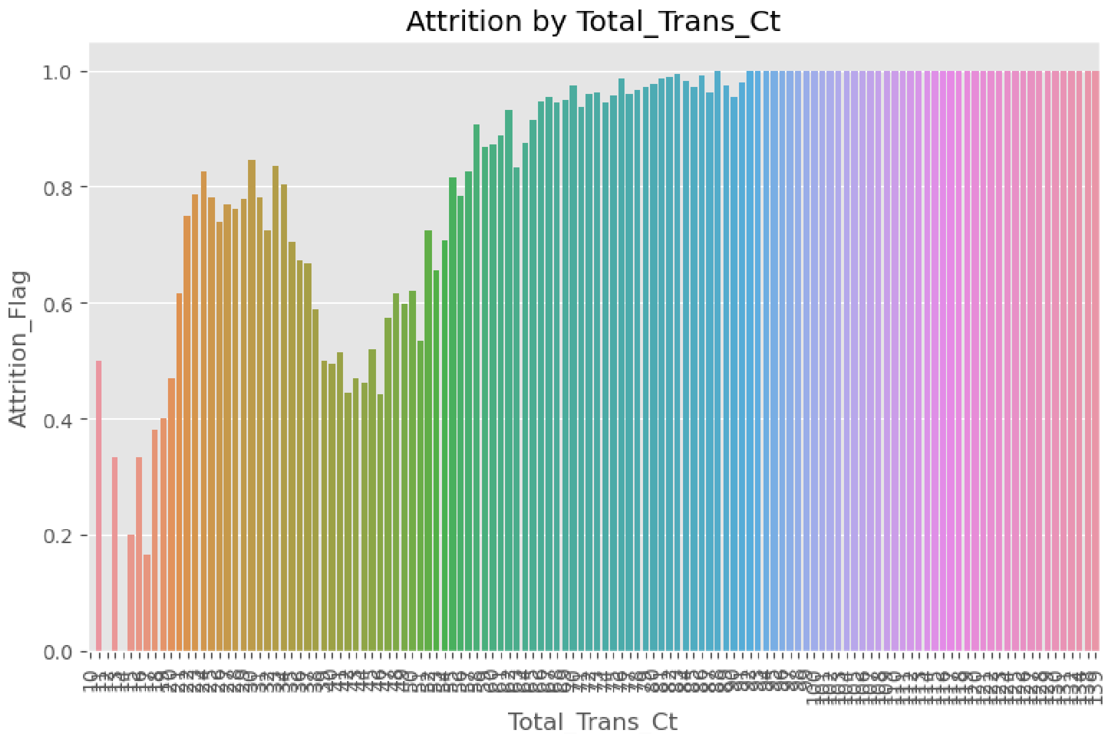
[36]:
```
plot_target_attrition(Contacts_Count_12_mon_attrition,'Attrition_Flag')
```



[37]:
```
Total_Trans_Ct_attrition =␣
↪attrited_feature(data,'Attrition_Flag','Total_Trans_Ct')
Total_Trans_Ct_attrition
```

[37]:
```
                Attrition_Flag
Total_Trans_Ct
10                    0.000000
12                    0.000000
14                    0.000000
17                    0.166667
15                    0.200000
…                          …
108                   1.000000
109                   1.000000
110                   1.000000
100                   1.000000
139                   1.000000

[126 rows x 1 columns]
```

[38]:
```
plot_target_attrition(Total_Trans_Ct_attrition,'Attrition_Flag')
```

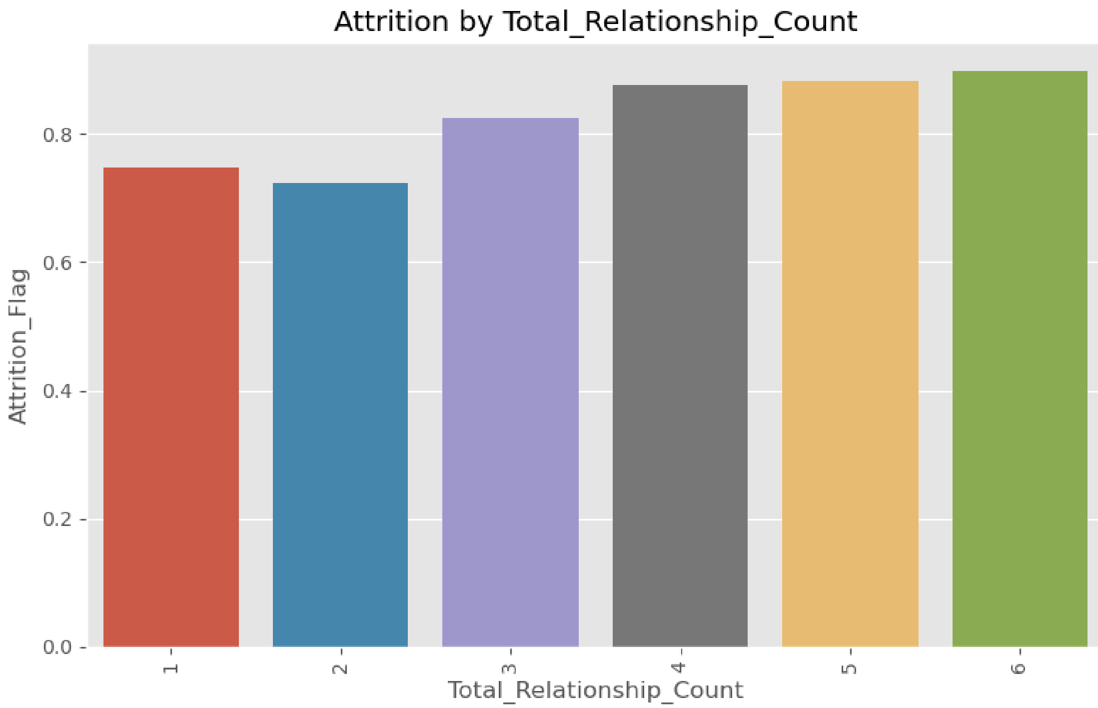


[39]:
```
Total_Relationship_Count_attrition =␣
 ↪attrited_feature(data,'Attrition_Flag','Total_Relationship_Count')
Total_Relationship_Count_attrition
```

[39]:

Total_Relationship_Count	Attrition_Flag
2	0.722843
1	0.746556
3	0.825594
4	0.876543
5	0.882197
6	0.897849

[40]:
```
plot_target_attrition(Total_Relationship_Count_attrition,'Attrition_Flag')
```



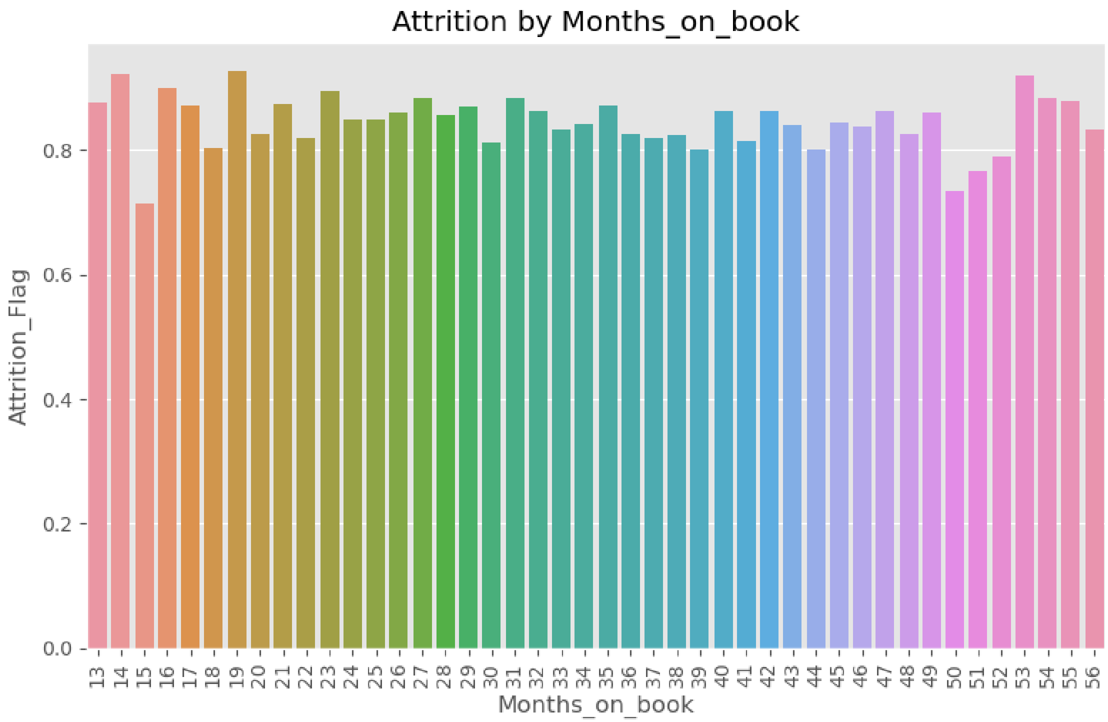

```
[41]: Months_on_book_attrition =␣
      ↪attrited_feature(data,'Attrition_Flag','Months_on_book')
      Months_on_book_attrition
```

[41]:

Months_on_book	Attrition_Flag
15	0.714286
50	0.735632
51	0.765625
52	0.788462
39	0.800725
44	0.802139
18	0.804348
30	0.813043
41	0.814815
37	0.818841
22	0.819277
38	0.824818
20	0.825397
48	0.827068
36	0.827179
33	0.832000
56	0.833333
46	0.838710

```
43                   0.839623
34                   0.842697
45                   0.844920
24                   0.848000
25                   0.849624
28                   0.856522
49                   0.859649
26                   0.861111
42                   0.861905
40                   0.862454
32                   0.863071
47                   0.863309
29                   0.869792
17                   0.870968
35                   0.871094
21                   0.873239
13                   0.877193
55                   0.878788
31                   0.882353
27                   0.883721
54                   0.883721
23                   0.894737
16                   0.900000
53                   0.920635
14                   0.923077
19                   0.925926
```

[42]:
```
plot_target_attrition(Months_on_book_attrition,'Attrition_Flag')
```

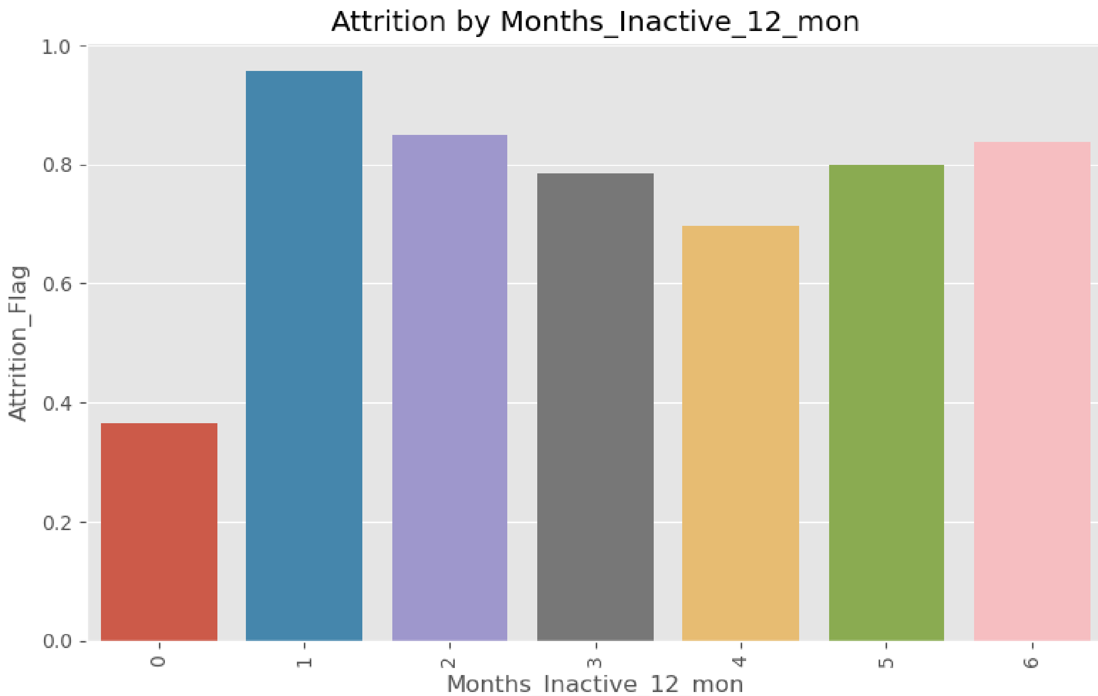


[43]:
```
Months_Inactive_12_mon_attrition =␣
  ↪attrited_feature(data,'Attrition_Flag','Months_Inactive_12_mon')
Months_Inactive_12_mon_attrition
```

[43]:

	Attrition_Flag
Months_Inactive_12_mon	
0	0.363636
4	0.696532
3	0.785391
5	0.798611
6	0.836538
2	0.849483
1	0.956180

[44]:
```
plot_target_attrition(Months_Inactive_12_mon_attrition,'Attrition_Flag')
```



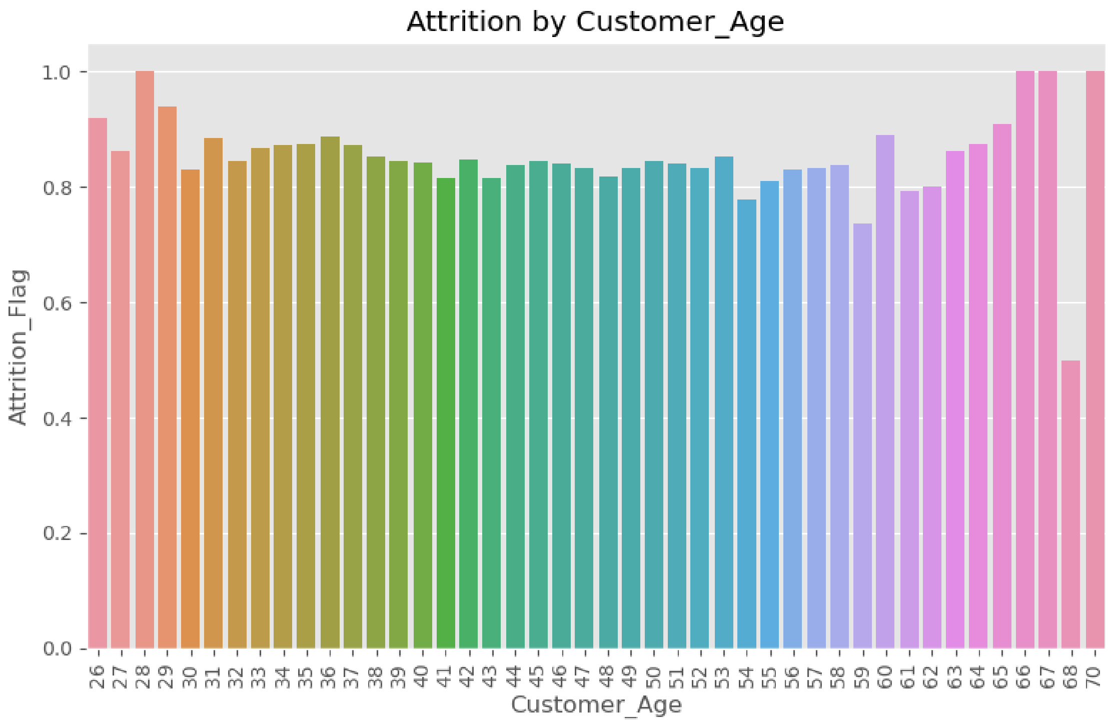
[45]:
```
Customer_Age_attrition = attrited_feature(data,'Attrition_Flag','Customer_Age')
Customer_Age_attrition
```

[45]:
```
              Attrition_Flag
Customer_Age
68                  0.500000
59                  0.735537
54                  0.779592
61                  0.794521
62                  0.800000
55                  0.811404
41                  0.814570
43                  0.816712
48                  0.817204
30                  0.830189
56                  0.830189
49                  0.832911
47                  0.833333
57                  0.833333
52                  0.833333
44                  0.836788
58                  0.838462
51                  0.840000
46                  0.841310
```

```
40                    0.843333
32                    0.844444
50                    0.844687
39                    0.844765
45                    0.846154
42                    0.846626
38                    0.852590
53                    0.853821
63                    0.862069
27                    0.863636
33                    0.867347
37                    0.872549
34                    0.873016
35                    0.874126
64                    0.875000
31                    0.884615
36                    0.886905
60                    0.888889
65                    0.909091
26                    0.920635
29                    0.940000
28                    1.000000
66                    1.000000
67                    1.000000
70                    1.000000
```

[46]:

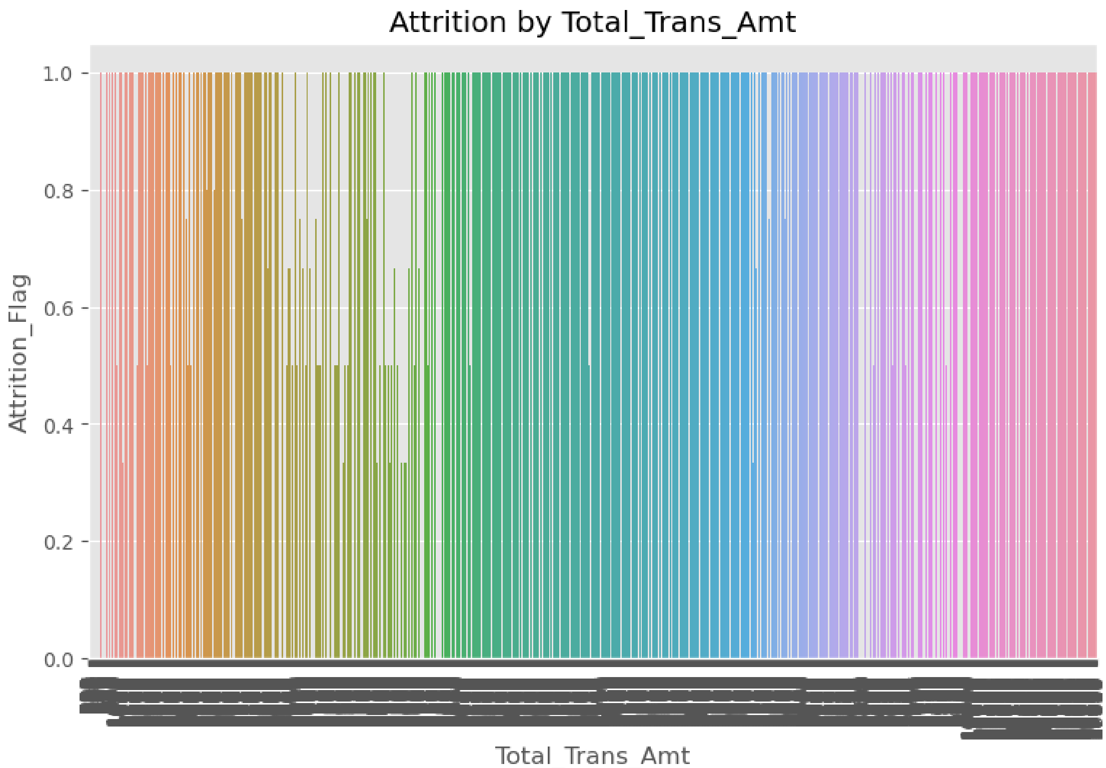
```
plot_target_attrition(Customer_Age_attrition,'Attrition_Flag')
```



[47]:
```
Total_Trans_Amt_attrition =␣
↪attrited_feature(data,'Attrition_Flag','Total_Trans_Amt')
Total_Trans_Amt_attrition
```

[47]:
```
                 Attrition_Flag
Total_Trans_Amt
510                         0.0
2430                        0.0
2427                        0.0
2426                        0.0
2424                        0.0
…                             …
3693                        1.0
3694                        1.0
3695                        1.0
3660                        1.0
18484                       1.0

[4462 rows x 1 columns]
```

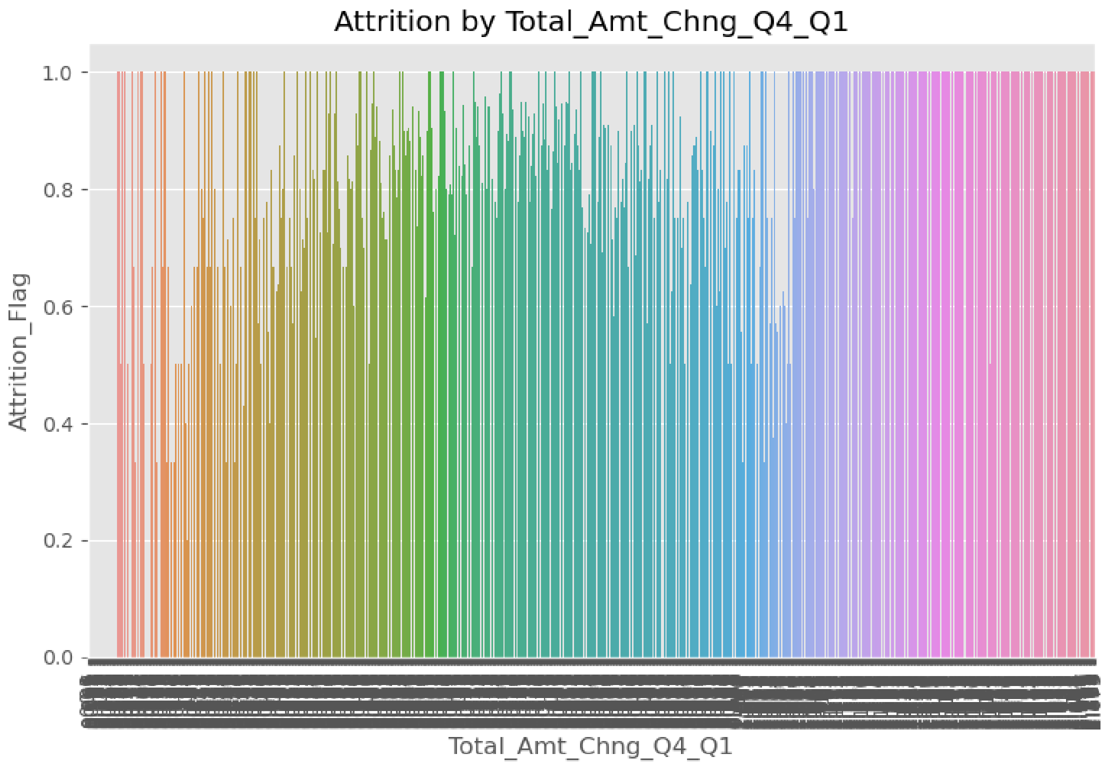
[48]:
```
plot_target_attrition( Total_Trans_Amt_attrition,'Attrition_Flag')
```



[49]:
```
Total_Amt_Chng_Q4_Q1_attrition =␣
↪attrited_feature(data,'Attrition_Flag','Total_Amt_Chng_Q4_Q1')
Total_Amt_Chng_Q4_Q1_attrition
```

[49]:
```
                      Attrition_Flag
Total_Amt_Chng_Q4_Q1
0.000                            0.0
0.439                            0.0
0.304                            0.0
0.305                            0.0
1.203                            0.0
…                                …
1.065                            1.0
1.064                            1.0
1.063                            1.0
1.077                            1.0
2.675                            1.0

[1089 rows x 1 columns]
```

[50]:
```
plot_target_attrition(Total_Amt_Chng_Q4_Q1_attrition,'Attrition_Flag')
```



5 Split the Data

[51]:
```
X = data.drop(columns=['CLIENTNUM','Attrition_Flag'])
y = data['Attrition_Flag']
seed = 13
```

[52]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=seed)
```

6 Preprocessing Data

[53]:
```
cat_cols.columns.to_list()
```

[53]:
```
['Gender',
 'Education_Level',
 'Marital_Status',
 'Income_Category',
 'Card_Category']
```

[54]:
```
#encode the categorical values
enc = ce.TargetEncoder(cols=cat_cols.columns,smoothing=11).fit(X_train[cat_cols.
 ↪columns],y_train)
X_train[cat_cols.columns] = enc.transform(X_train[cat_cols.columns])
```

[55]:
```
X_test[cat_cols.columns] = enc.transform(X_test[cat_cols.columns])
```

[56]:
```
X_train.head().T
```

[56]:
```
train_idx                          802          4121         3083          6160  \
Customer_Age                 45.000000     55.000000    29.000000     47.000000
Gender                        0.855063      0.824137     0.855063      0.855063
Dependent_count               3.000000      1.000000     0.000000      5.000000
Education_Level               0.843642      0.843642     0.843642      0.859177
Marital_Status                0.828299      0.828299     0.846585      0.846585
Income_Category               0.863014      0.823635     0.863014      0.829218
Card_Category                 0.838528      0.838528     0.838528      0.838528
Months_on_book               38.000000     42.000000    36.000000     34.000000
Total_Relationship_Count      1.000000      6.000000     3.000000      3.000000
Months_Inactive_12_mon        3.000000      3.000000     3.000000      1.000000
Contacts_Count_12_mon         1.000000      2.000000     4.000000      2.000000
Credit_Limit               3751.000000   2517.000000  1459.000000  17603.000000
Total_Revolving_Bal        1869.000000   1257.000000   590.000000   1063.000000
Avg_Open_To_Buy            1882.000000   1260.000000   869.000000  16540.000000
Total_Amt_Chng_Q4_Q1          0.926000      0.834000     1.164000      1.065000
Total_Trans_Amt            9497.000000   4528.000000  2229.000000   2902.000000
Total_Trans_Ct              106.000000     75.000000    52.000000     64.000000
Total_Ct_Chng_Q4_Q1           0.710000      0.786000     1.080000      0.641000
Avg_Utilization_Ratio         0.498000      0.499000     0.404000      0.060000

train_idx                           509
Customer_Age                  41.000000
Gender                         0.855063
Dependent_count                2.000000
Education_Level                0.836798
Marital_Status                 0.828299
Income_Category                0.838614
Card_Category                  0.838528
Months_on_book                28.000000
Total_Relationship_Count       1.000000
Months_Inactive_12_mon         2.000000
Contacts_Count_12_mon          3.000000
Credit_Limit               13679.000000
Total_Revolving_Bal         2267.000000
Avg_Open_To_Buy            11412.000000
Total_Amt_Chng_Q4_Q1           1.232000
Total_Trans_Amt            15180.000000
```

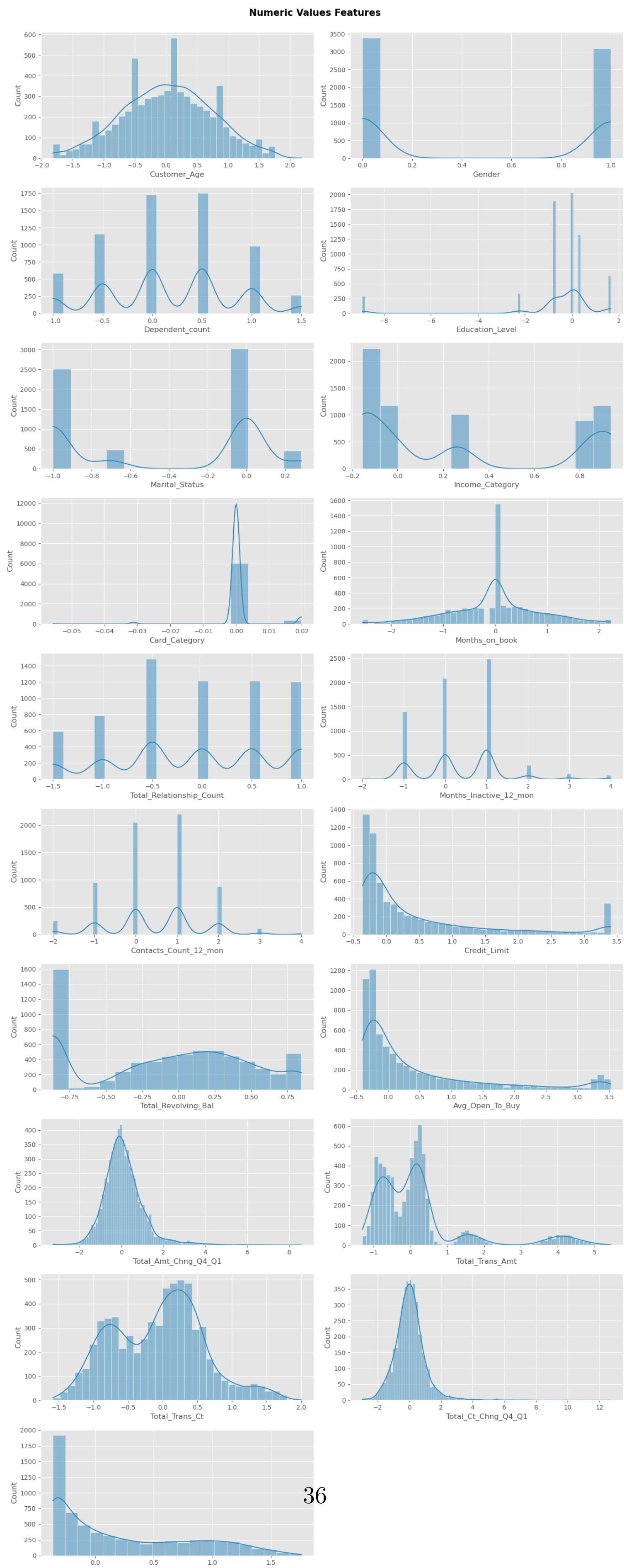
```
Total_Trans_Ct              103.000000
Total_Ct_Chng_Q4_Q1           0.689000
Avg_Utilization_Ratio         0.166000
```

[57]:
```
#scaler = StandardScaler()
scaler = RobustScaler()

# transform data
X_train[X_train.columns] = scaler.fit_transform(X_train)
X_test[X_test.columns] = scaler.transform(X_test)
```

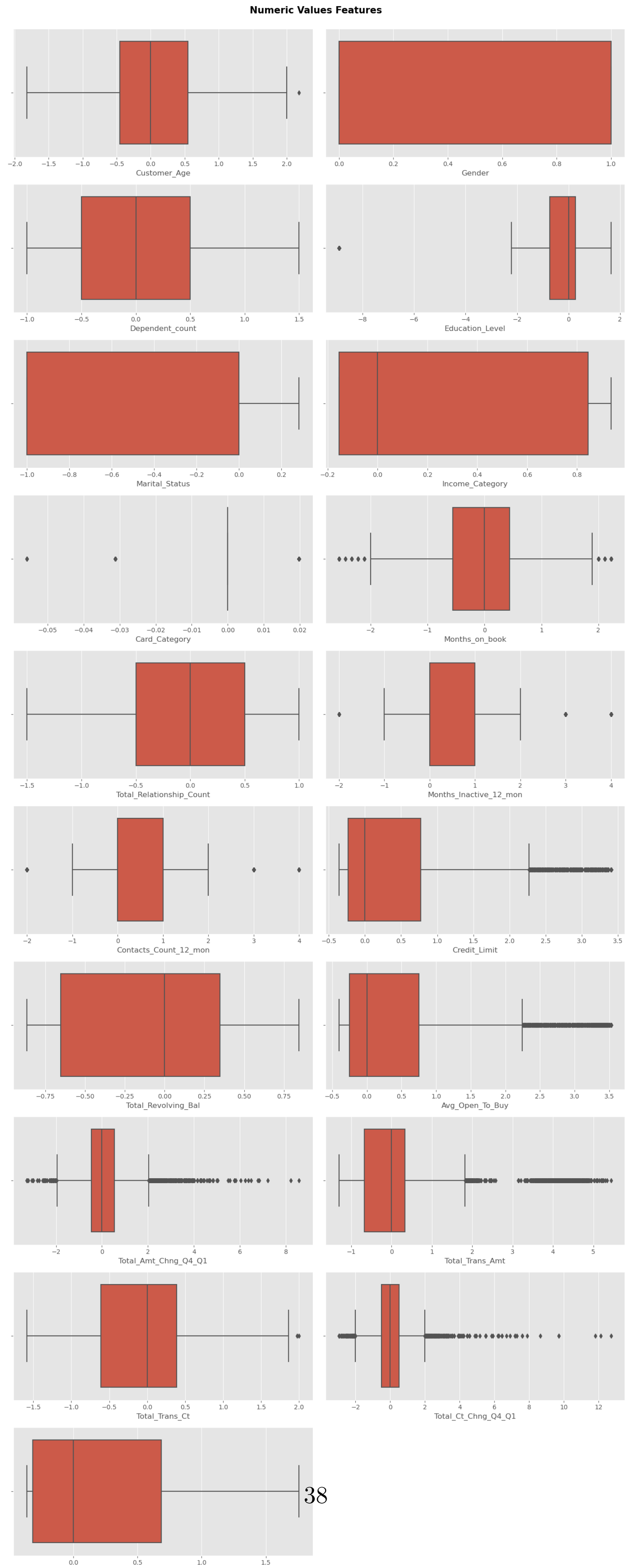
[58]:
```
n_rows = plot_template(n_cols,X_train.columns)
n_rows
```

[58]:
```
10
```

[59]:
```
fig, axes = plt.subplots(n_rows,n_cols, figsize=(3.5 * 4, 3.5 *n_rows))

for i, col in enumerate(X_train):
    ax = axes.flat[i]
    sns.histplot(x= X_train[col],kde=True,ax=ax)

plt.suptitle("Numeric Values Features", y=1,fontsize=15,fontweight='bold')
axes[-1, -1].axis('off')
plt.tight_layout()
plt.show()
```


Numeric Values Features
Count
Customer_Age
Gender
Dependent_count
Education_Level
Marital_Status
Income_Category
Card_Category
Months_on_book
Total_Relationship_Count
Months_Inactive_12_mon
Contacts_Count_12_mon
Credit_Limit
Total_Revolving_Bal
Avg_Open_To_Buy
Total_Amt_Chng_Q4_Q1
Total_Trans_Amt
Total_Trans_Ct
Total_Ct_Chng_Q4_Q1
Avg_Utilization_Ratio

[60]:
```
fig, axes = plt.subplots(n_rows,n_cols, figsize=(3.5 * 4, 3.5 *n_rows))

for i, col in enumerate(X_train.columns):
    ax = axes.flat[i]
    sns.boxplot(x= X_train[col],ax=ax)

plt.suptitle("Numeric Values Features", y=1,fontsize=15,fontweight='bold')
axes[-1, -1].axis('off')
plt.tight_layout()
plt.show()
```


Numeric Values Features
Customer_Age
Gender
Dependent_count
Education_Level
Marital_Status
Income_Category
Card_Category
Months_on_book
Total_Relationship_Count
Months_Inactive_12_mon
Contacts_Count_12_mon
Credit_Limit
Total_Revolving_Bal
Avg_Open_To_Buy
Total_Amt_Chng_Q4_Q1
Total_Trans_Amt
Total_Trans_Ct
Total_Ct_Chng_Q4_Q1
Avg_Utilization_Ratio

Balance Data

[61]:
```
over = SMOTE(sampling_strategy='not majority',random_state=17)
under = RandomUnderSampler(sampling_strategy='not majority')
steps = [('o', over), ('u', under)]
pipeline = Pipeline(steps=steps)

X_train_sm,y_train_sm = pipeline.fit_resample(X_train,y_train)
```

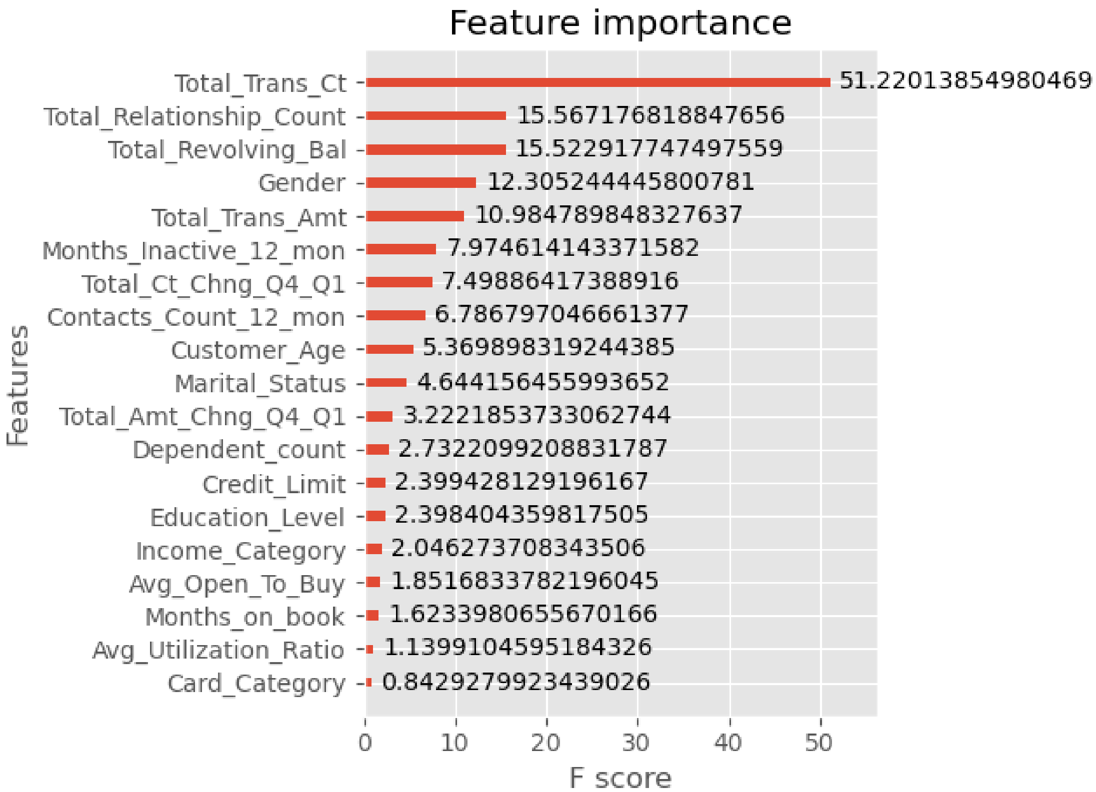
[62]:
```
X_train_sm.shape[0],y_train_sm.shape[0],X_test.shape[0],y_test.shape[0]
```

[62]:
```
(10872, 10872, 1621, 1621)
```

7 Feature Selection

[63]:
```
features = XGBClassifier()
features.fit(X_train_sm, y_train_sm)

plt.figure(figsize=(10,6))
plot_importance(features,height=0.3,importance_type='gain')
plt.tight_layout()
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



[64]:
```
features_importance_names = features.get_booster().
↪get_score(importance_type='gain')
features_importance_names
```

[64]:
```
{'Customer_Age': 5.369898319244385,
 'Gender': 12.305244445800781,
 'Dependent_count': 2.7322099208831787,
 'Education_Level': 2.398404359817505,
 'Marital_Status': 4.644156455993652,
 'Income_Category': 2.046273708343506,
 'Card_Category': 0.8429279923439026,
 'Months_on_book': 1.6233980655670166,
 'Total_Relationship_Count': 15.567176818847656,
 'Months_Inactive_12_mon': 7.974614143371582,
 'Contacts_Count_12_mon': 6.786797046661377,
 'Credit_Limit': 2.399428129196167,
 'Total_Revolving_Bal': 15.522917747497559,
 'Avg_Open_To_Buy': 1.8516833782196045,
 'Total_Amt_Chng_Q4_Q1': 3.2221853733062744,
 'Total_Trans_Amt': 10.984789848327637,
 'Total_Trans_Ct': 51.22013854980469,
```

```
 'Total_Ct_Chng_Q4_Q1': 7.49886417388916,
 'Avg_Utilization_Ratio': 1.1399104595184326}
```

[65]:
```
#use function (5) to get the tupple from the list and then sort it
features_importance_names_list = list(features_importance_names.items())
features_importance_names_list.sort(key = get_value,reverse=True)
```

[66]:
```
features_importance_names_list
```

[66]:
```
[('Total_Trans_Ct', 51.22013854980469),
 ('Total_Relationship_Count', 15.567176818847656),
 ('Total_Revolving_Bal', 15.522917747497559),
 ('Gender', 12.305244445800781),
 ('Total_Trans_Amt', 10.984789848327637),
 ('Months_Inactive_12_mon', 7.974614143371582),
 ('Total_Ct_Chng_Q4_Q1', 7.49886417388916),
 ('Contacts_Count_12_mon', 6.786797046661377),
 ('Customer_Age', 5.369898319244385),
 ('Marital_Status', 4.644156455993652),
 ('Total_Amt_Chng_Q4_Q1', 3.2221853733062744),
 ('Dependent_count', 2.7322099208831787),
 ('Credit_Limit', 2.399428129196167),
 ('Education_Level', 2.398404359817505),
 ('Income_Category', 2.046273708343506),
 ('Avg_Open_To_Buy', 1.8516833782196045),
 ('Months_on_book', 1.6233980655670166),
 ('Avg_Utilization_Ratio', 1.1399104595184326),
 ('Card_Category', 0.8429279923439026)]
```

[67]:
```
#get only the first value of the tupple
features_sorted_names = []

for i in features_importance_names_list:
    features_sorted_names.append(i[0])

features_sorted_names
```

[67]:
```
['Total_Trans_Ct',
 'Total_Relationship_Count',
 'Total_Revolving_Bal',
 'Gender',
 'Total_Trans_Amt',
 'Months_Inactive_12_mon',
 'Total_Ct_Chng_Q4_Q1',
 'Contacts_Count_12_mon',
 'Customer_Age',
 'Marital_Status',
```

```
 'Total_Amt_Chng_Q4_Q1',
 'Dependent_count',
 'Credit_Limit',
 'Education_Level',
 'Income_Category',
 'Avg_Open_To_Buy',
 'Months_on_book',
 'Avg_Utilization_Ratio',
 'Card_Category']
```

[74]:
```
#define the columns with least value
drop_cols = features_sorted_names[9:]
drop_cols
```

[74]:
```
['Marital_Status',
 'Total_Amt_Chng_Q4_Q1',
 'Dependent_count',
 'Credit_Limit',
 'Education_Level',
 'Income_Category',
 'Avg_Open_To_Buy',
 'Months_on_book',
 'Avg_Utilization_Ratio',
 'Card_Category']
```

[75]:
```
X_train_ = X_train_sm.drop(columns=drop_cols)
y_train_ = y_train_sm
```

[76]:
```
X_test_ = X_test.drop(columns=drop_cols)
y_test_ = y_test
```

8 Model Creation

8.1 Random Forest

[77]:
```
rf = RandomForestClassifier(random_state= seed)
```

[78]:
```
 # Hyperparameter Tuning
parameters_rf = {
    'n_estimators': [10,100, 200,500],
    'max_depth' : [2, 5, 7,10,20,25],
    'min_samples_split': [12,20,40],
    'criterion':['gini', 'entropy'],
    'bootstrap': [True, False]
}
```

[79]:
```
skfold = StratifiedKFold(n_splits=6,shuffle=True,random_state=seed)
```

[80]:
```
gridRf = GridSearchCV(rf, parameters_rf, cv=skfold)
```

[81]:
```
y_rf_score = gridRf.fit(X_train_, y_train_)
```

[82]:
```
gridRf.best_score_
```

[82]:
```
0.9734179543782192
```

[83]:
```
#best parameters
gridRf.best_params_
```

[83]:
```
{'bootstrap': False,
 'criterion': 'entropy',
 'max_depth': 20,
 'min_samples_split': 12,
 'n_estimators': 500}
```

[84]:
```
best_stimator_grid_rf = gridRf.best_estimator_
best_stimator_grid_rf
```

[84]:
```
RandomForestClassifier(bootstrap=False, criterion='entropy', max_depth=20,
                       min_samples_split=12, n_estimators=500, random_state=13)
```

[85]:
```
y_rf_pred = gridRf.predict(X_test_)
```

[86]:
```
report_rf = classification_report(y_test_, y_rf_pred,output_dict=True)
df_report_rf = pd.DataFrame(report_rf).T
df_report_rf
```

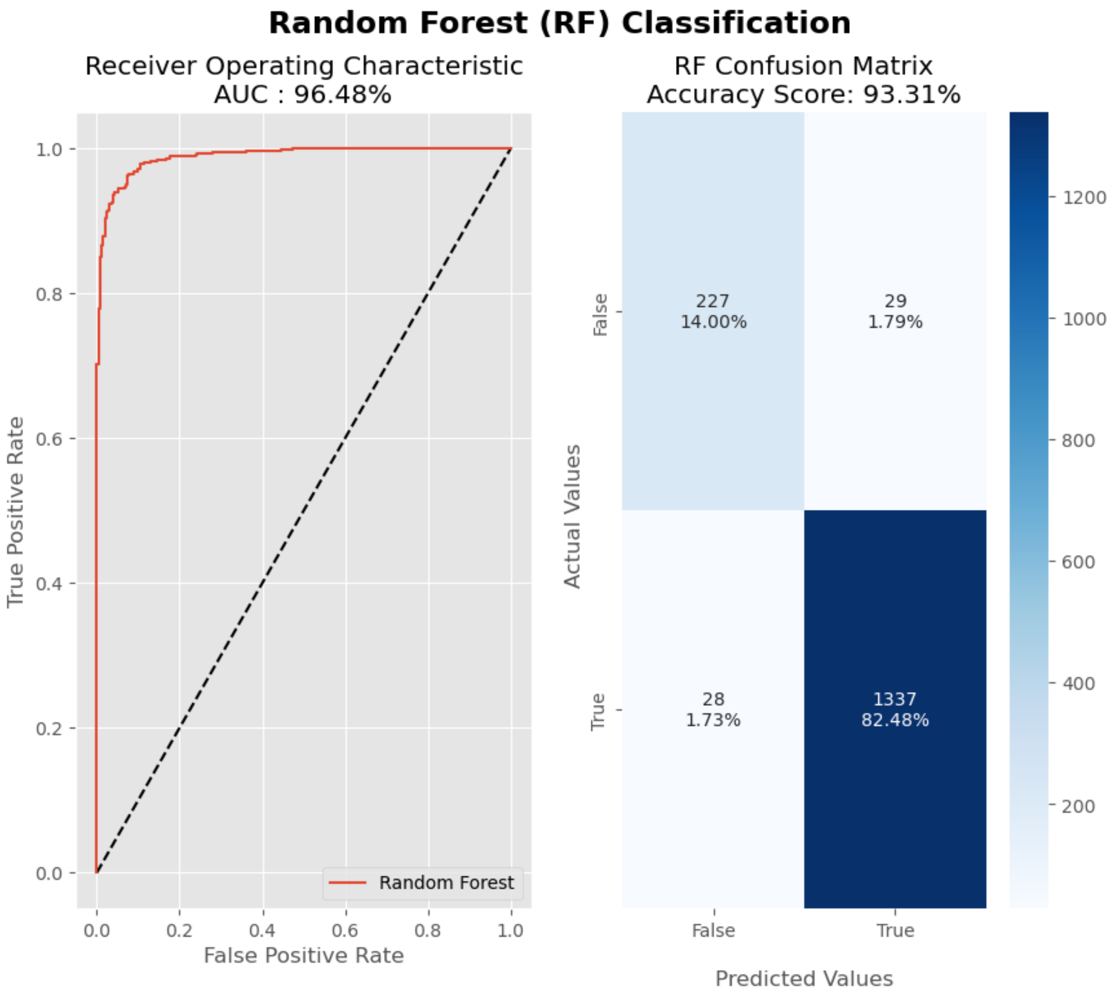
[86]:

	precision	recall	f1-score	support
0	0.890196	0.886719	0.888454	256.000000
1	0.978770	0.979487	0.979129	1365.000000
accuracy	0.964837	0.964837	0.964837	0.964837
macro avg	0.934483	0.933103	0.933791	1621.000000
weighted avg	0.964782	0.964837	0.964809	1621.000000

[87]:
```
#Confusion matrix
conf_matrix_rf = confusion_matrix(y_test_, y_rf_pred)
#Accuracy
acu_rf = accuracy_score(y_test_, y_rf_pred)
#AUC
auc_rf = roc_auc_score(y_test_, y_rf_pred)
```

[88]:
```
acmod_rf = {"RF_y_test":round(acu_rf,4)}
aucmod_rf = {"RF_y_test":round(auc_rf,4)}
```

[89]:
```
#run the functiona (4)
subplots_ROC_CM("Random Forest (RF) Classification","Receiver Operating␣
↪Characteristic",
                "RF Confusion Matrix",
                gridRf.
↪best_estimator_,acmod_rf,aucmod_rf,conf_matrix_rf,"RF_y_test",X_test_,y_test_,"Random␣
↪Forest")
```



8.2 Stochastic Gradient Descent (SDG)

[90]:
```
sdg = SGDClassifier(random_state= seed)
```

[91]:
```
# Hyperparameter Tuning
parameters_sdg = {
    'penalty':['l2', 'l1', 'elasticnet'],
    'learning_rate': ['constant','optimal','invscaling','adaptive'],
```

```
    'loss': ['log_loss','modified_huber'],
    'alpha': list(range(1,50,1)) ,
    'fit_intercept': [True,False],
    'max_iter': [5000]

}
```

[92]:
```
gridSdg = GridSearchCV(sdg, parameters_sdg, cv=skfold)
```

[93]:
```
y_sdg_score = gridSdg.fit(X_train_, y_train_)
```

```
/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py:372: FitFailedWarning:
12348 fits failed out of a total of 14112.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
10584 fits failed with the following error:
Traceback (most recent call last):
  File "/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py", line 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/opt/anaconda3/lib/python3.9/site-
packages/sklearn/linear_model/_stochastic_gradient.py", line 883, in fit
    return self._fit(
  File "/opt/anaconda3/lib/python3.9/site-
packages/sklearn/linear_model/_stochastic_gradient.py", line 649, in _fit
    self._validate_params()
  File "/opt/anaconda3/lib/python3.9/site-
packages/sklearn/linear_model/_stochastic_gradient.py", line 149, in
_validate_params
    raise ValueError("eta0 must be > 0")
ValueError: eta0 must be > 0

--------------------------------------------------------------------------------
1764 fits failed with the following error:
Traceback (most recent call last):
  File "/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_validation.py", line 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/opt/anaconda3/lib/python3.9/site-
packages/sklearn/linear_model/_stochastic_gradient.py", line 883, in fit
    return self._fit(
```

```
  File "/opt/anaconda3/lib/python3.9/site-
packages/sklearn/linear_model/_stochastic_gradient.py", line 649, in _fit
    self._validate_params()
  File "/opt/anaconda3/lib/python3.9/site-
packages/sklearn/linear_model/_stochastic_gradient.py", line 162, in
_validate_params
    raise ValueError("The loss %s is not supported. " % self.loss)
ValueError: The loss log_loss is not supported.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/opt/anaconda3/lib/python3.9/site-
packages/sklearn/model_selection/_search.py:969: UserWarning: One or more of the
test scores are non-finite: [nan nan nan … nan nan nan]
  warnings.warn(
```

[94]:
```
gridSdg.best_score_
```

[94]:
```
0.8084988962472406
```

[95]:
```
#best parameters
gridSdg.best_params_
```

[95]:
```
{'alpha': 1,
 'fit_intercept': True,
 'learning_rate': 'optimal',
 'loss': 'modified_huber',
 'max_iter': 5000,
 'penalty': 'l2'}
```

[96]:
```
best_estimator_grid_sdg = gridSdg.best_estimator_
best_estimator_grid_sdg
```

[96]:
```
SGDClassifier(alpha=1, loss='modified_huber', max_iter=5000, random_state=13)
```

[97]:
```
y_sdg_pred = gridSdg.predict(X_test_)
```

[98]:
```
report_sdg = classification_report(y_test_, y_sdg_pred,output_dict=True)
df_report_sdg = pd.DataFrame(report_sdg).T
df_report_sdg
```

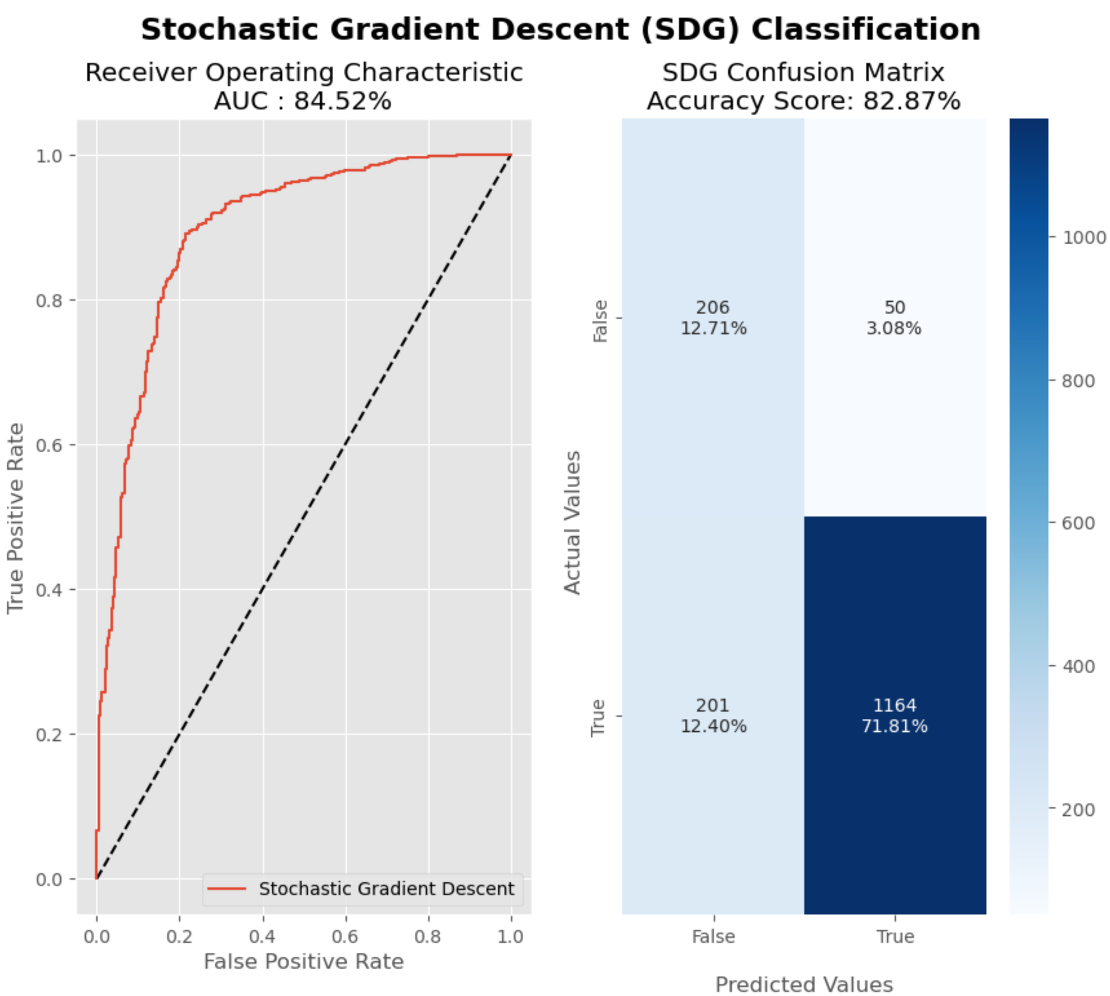
[98]:

	precision	recall	f1-score	support
0	0.506143	0.804688	0.621418	256.000000
1	0.958814	0.852747	0.902675	1365.000000
accuracy	0.845157	0.845157	0.845157	0.845157
macro avg	0.732478	0.828717	0.762047	1621.000000
weighted avg	0.887325	0.845157	0.858257	1621.000000

[99]:
```
#Confusion matrix
conf_matrix_sdg = confusion_matrix(y_test, y_sdg_pred)
#Accuracy
acu_sdg = accuracy_score(y_test, y_sdg_pred)
#AUC
auc_sdg = roc_auc_score(y_test, y_sdg_pred)
```

[100]:
```
acmod_sdg = {"SDG_y_test":round(acu_sdg,4)}
aucmod_sdg = {"SDG_y_test":round(auc_sdg,4)}
```

[101]:
```
#run the functiona (4)
subplots_ROC_CM("Stochastic Gradient Descent (SDG) Classification","Receiver␣
↪Operating Characteristic",
                "SDG Confusion Matrix",
                gridSdg.
↪best_estimator_,acmod_sdg,aucmod_sdg,conf_matrix_sdg,"SDG_y_test",X_test_,y_test_,"Stochast
↪Gradient Descent")
```



8.3 XGBoost

[102]:
```
xgbc = XGBClassifier(random_state= seed)
```

[103]:
```
# Hyperparameter Tuning
parameters_xgbc = {
              'objective':['binary:logistic'],
              'learning_rate': [0.0001,0.001,0.01,0.1],
              'max_depth': [2,4,7,15],
              'subsample': [0.1,0.5,0.8],
              'colsample_bytree': [0.1,0.5,0.7],
              'n_estimators': [100,300,500,1000],
}
```

[104]:
```
gridXgbc = GridSearchCV(xgbc, parameters_xgbc, cv=skfold)
```

[105]:
```
 y_xgbc_score = gridXgbc.fit(X_train_, y_train_)
```

[106]:
```
 gridXgbc.best_score_
```

[106]:
```
0.978476821192053
```

[107]:
```
#best parameters
gridXgbc.best_params_
```

[107]:
```
{'colsample_bytree': 0.5,
 'learning_rate': 0.1,
 'max_depth': 15,
 'n_estimators': 500,
 'objective': 'binary:logistic',
 'subsample': 0.8}
```

[108]:
```
best_estimator_grid_xgbc = gridXgbc.best_estimator_
best_estimator_grid_xgbc
```

[108]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.5, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=15, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=500, n_jobs=None, num_parallel_tree=None,
```

```
                predictor=None, random_state=13, …)
```

[109]:
```
y_xgbc_pred = gridXgbc.predict(X_test_)
```

[110]:
```
report_xgbc = classification_report(y_test_, y_xgbc_pred,output_dict=True)
df_report_xgbc = pd.DataFrame(report_xgbc).T
df_report_xgbc
```

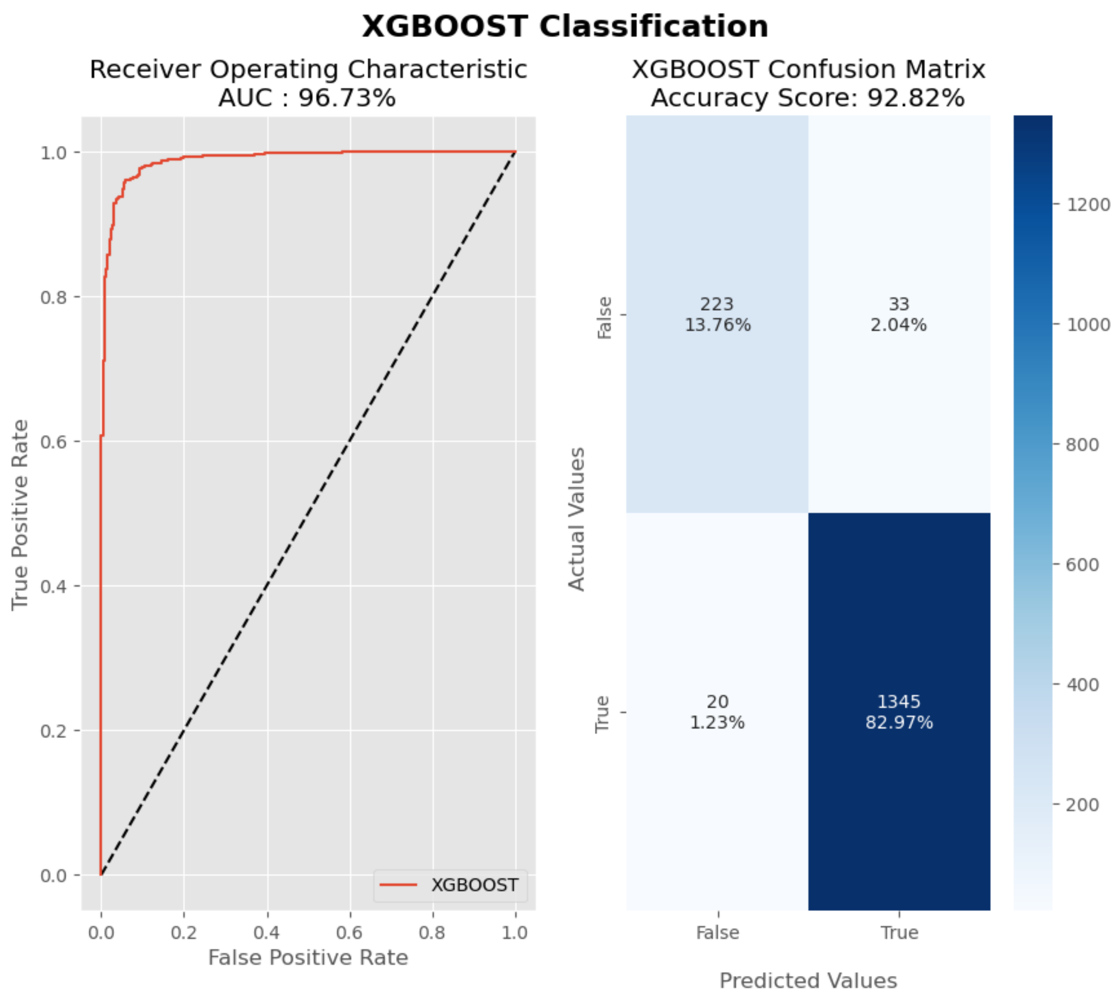
[110]:

	precision	recall	f1-score	support
0	0.917695	0.871094	0.893788	256.000000
1	0.976052	0.985348	0.980678	1365.000000
accuracy	0.967304	0.967304	0.967304	0.967304
macro avg	0.946874	0.928221	0.937233	1621.000000
weighted avg	0.966836	0.967304	0.966956	1621.000000

[111]:
```
#Confusion matrix
conf_matrix_xgbc = confusion_matrix(y_test_, y_xgbc_pred)
#Accuracy
acu_xgbc = accuracy_score(y_test_, y_xgbc_pred)
#AUC
auc_xgbc = roc_auc_score(y_test_, y_xgbc_pred)
```

[112]:
```
acmod_xgbc = {"XGBC_y_test":round(acu_xgbc,4)}
aucmod_xgbc = {"XGBC_y_test":round(auc_xgbc,4)}
```

[113]:
```
#run the functiona (9)
subplots_ROC_CM("XGBOOST Classification","Receiver Operating Characteristic",
                "XGBOOST Confusion Matrix",
                gridXgbc.
  ↪best_estimator_,acmod_xgbc,aucmod_xgbc,conf_matrix_xgbc,"XGBC_y_test",X_test_,y_test_,"XGBO
```



9 Select Model

[138]:
```
Accuracy = {"RF":acu_rf,"SDG":acu_sdg,"XGBC":acu_xgbc}
AUC = {"RF":auc_rf,"SDG":auc_sdg,"XGBC":auc_xgbc}
F1_score = {"RF":df_report_rf.iloc[3,2],
            "SDG":df_report_sdg.iloc[3,2],"XGBC":df_report_xgbc.iloc[3,2]}
```

[139]:
```
df_report_rf
```

[139]:

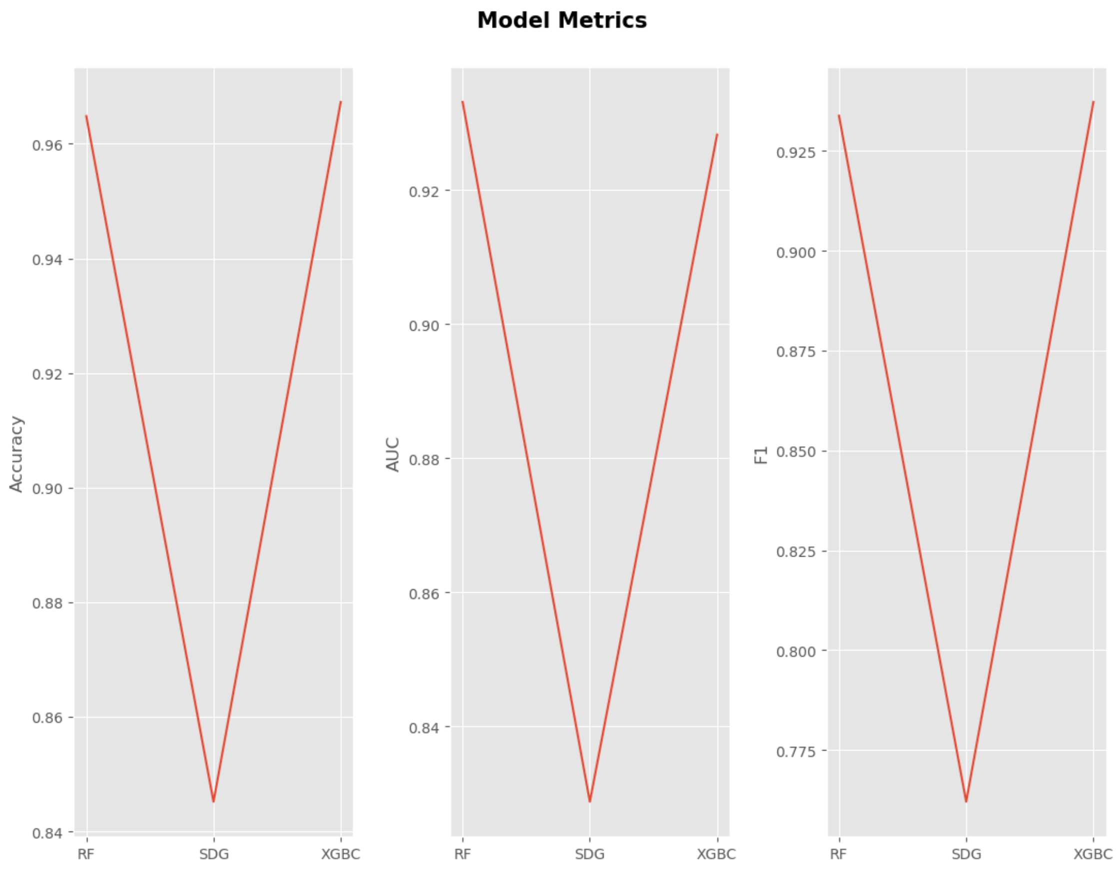
	precision	recall	f1-score	support
0	0.890196	0.886719	0.888454	256.000000
1	0.978770	0.979487	0.979129	1365.000000
accuracy	0.964837	0.964837	0.964837	0.964837
macro avg	0.934483	0.933103	0.933791	1621.000000
weighted avg	0.964782	0.964837	0.964809	1621.000000

[140]:
```
metrics_models = pd.
 ↪DataFrame([Accuracy,AUC,F1_score],index=["Accuracy","AUC","F1"]).T
metrics_models
```

[140]:

	Accuracy	AUC	F1
RF	0.964837	0.933103	0.933791
SDG	0.845157	0.828717	0.762047
XGBC	0.967304	0.928221	0.937233

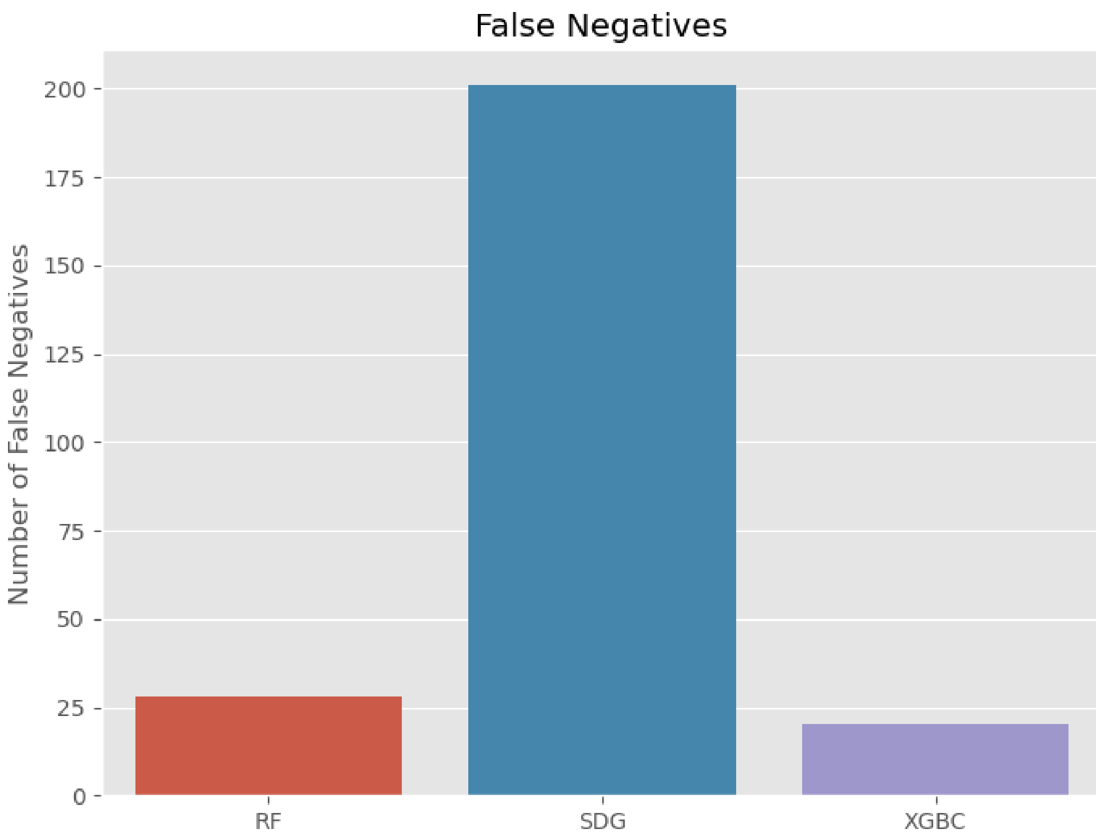
[141]:
```
fig,axes= plt.subplots(1,3,figsize=(11,8))

for i,col in enumerate(metrics_models.columns):
    sns.lineplot(data=metrics_models[col],ax=axes[i] )

plt.tight_layout()
plt.suptitle("Model Metrics", fontsize = 15, fontweight = "bold", y=1.05)
plt.show()
```



[120]:
```
false_Negative = [conf_matrix_rf[1,0],
                  conf_matrix_sdg[1,0],conf_matrix_xgbc[1,0]]
```

```
false_Negative_S = pd.Series(false_Negative,name="FN",index=["RF","SDG","XGBC"])
```

[147]:
```
fig  = plt.figure(figsize=(8, 6))
sns.barplot(x=false_Negative_S.index,y=false_Negative_S.values)
plt.ylabel("Number of False Negatives")
plt.title("False Negatives")
plt.show()
```



The RF and XGB model have almost the same f1, with the XGB being slightly higher, but has a greater reduction of false negatives. XGB will be chosen because of its slight increase in f1 but undoubtedly the reduction in false negatives is something of great importance as it represents customers that the model classifies as satisfied with the bank's service but are really customers who are likely to cease using the bank's services.

10 Test

[122]:
```
X_Test = test.copy().drop(columns='CLIENTNUM')
```

[123]:
```
test_cat_cols = X_Test.select_dtypes(object).columns
test_cat_cols
```

[123]: Index(['Gender', 'Education_Level', 'Marital_Status', 'Income_Category',
       'Card_Category'],
      dtype='object')

[124]:
```
X_Test[test_cat_cols] = enc.transform(X_Test[test_cat_cols])
```

[125]:
```
X_Test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2026 entries, 0 to 2025
Data columns (total 19 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Customer_Age              2026 non-null   int64
 1   Gender                    2026 non-null   float64
 2   Dependent_count           2026 non-null   int64
 3   Education_Level           2026 non-null   float64
 4   Marital_Status            2026 non-null   float64
 5   Income_Category           2026 non-null   float64
 6   Card_Category             2026 non-null   float64
 7   Months_on_book            2026 non-null   int64
 8   Total_Relationship_Count  2026 non-null   int64
 9   Months_Inactive_12_mon    2026 non-null   int64
 10  Contacts_Count_12_mon     2026 non-null   int64
 11  Credit_Limit              2026 non-null   float64
 12  Total_Revolving_Bal       2026 non-null   int64
 13  Avg_Open_To_Buy           2026 non-null   float64
 14  Total_Amt_Chng_Q4_Q1      2026 non-null   float64
 15  Total_Trans_Amt           2026 non-null   int64
 16  Total_Trans_Ct            2026 non-null   int64
 17  Total_Ct_Chng_Q4_Q1       2026 non-null   float64
 18  Avg_Utilization_Ratio     2026 non-null   float64
dtypes: float64(10), int64(9)
memory usage: 316.6 KB
```

[126]:
```
X_Test[X_Test.columns] = scaler.transform(X_Test)
```

[127]:
```
X_Test = X_Test.drop(columns=drop_cols)
```

[144]:
```
final_model_prediction = gridXgbc.predict(X_Test)
```

[145]:
```
#create Series with predictions
final_prediction_series = pd.Series(data = final_model_prediction,␣
 ↪name='target')
final_prediction_series
```

[145]:
```
0       1
1       1
2       1
3       1
4       1
       ..
2021    1
2022    0
2023    1
2024    1
2025    1
Name: target, Length: 2026, dtype: int64
```

[146]:
```
#convert series to json file
json_dict = {'target': final_prediction_series.to_dict()}
with open('predictions.json', 'w') as f:
    json.dump(json_dict, f)
```