Credit Card Users Churn Prediction

Problem Statement

The Thera bank recently saw a steep decline in the number of credit card users. Credit cards are a good source of money for banks because of several types of fees charged by the banks, such as annual fees, balance transfer costs, cash advance fees, late payment fees, international transaction fees, and others. Some costs are assessed to all users regardless of consumption, while others are assessed only under specific conditions.

Customers leaving credit card services would result in a loss for the bank, so the bank wants to analyse customer data to identify customers who will leave their credit card services and the reasons for doing so – so that the bank can improve in those areas.

You as a Data scientist at Thera bank need to come up with a classification model that will help the bank improve its services so that customers do not renounce their credit cards. **You need to identify the best possible model that will give the required performance**.

Dataset Description

- **CLIENTNUM** - Client number. Unique identifier for the customer holding the account
- **Attrition_Flag** - Internal event (customer activity) variable - if the account is closed then "Attrited Customer" else "Existing Customer"
- **Customer_Age** - Age in Years
- **Gender** - Gender of the account holder
- **Dependent_count** - Number of dependents
- **Education_Level** - Educational Qualification of the account holder - Graduate, High School, Unknown, Uneducated, College(refers to college student), Post-Graduate, Doctorate
- **Marital_Status** - Marital Status of the account holder
- **Income_Category** - Annual Income Category of the account holder
- **Card_Category** - Type of Card
- **Months_on_book** - Period of relationship with the bank (in months)
- **Total_Relationship_Count** - Total no. of products held by the customer
- **Months_Inactive_12_mon** - No. of months inactive in the last 12 months

- **Contacts_Count_12_mon** - No. of Contacts in the last 12 months
- **Credit_Limit** - Credit Limit on the Credit Card
- **Total_Revolving_Bal** - Total Revolving Balance on the Credit Card
- **Avg_Open_To_Buy** - Open to Buy Credit Line (Average of last 12 months)
- **Total_Amt_Chng_Q4_Q1** - Change in Transaction Amount (Q4 over Q1)
- **Total_Trans_Amt** - Total Transaction Amount (Last 12 months)
- **Total_Trans_Ct** - Total Transaction Count (Last 12 months)
- **Total_Ct_Chng_Q4_Q1** - Change in Transaction Count (Q4 over Q1)
- **Avg_Utilization_Ratio** - Average Card Utilization Ratio

What is a Revolving Balance?

- If we don't pay the balance of the revolving credit account in full every month, the unpaid portion carries over to the next month. That's called a revolving balance.

What is the Average Open to buy?

- 'Open to Buy' means the amount left on your credit card to use. Now, this column represents the average of this value for the last 12 months.

What is the Average utilization Ratio?

- The Avg_Utilization_Ratio represents how much of the available credit the customer spent. This is useful for calculating credit scores.

Relation b/w Avg_Open_To_Buy, Credit_Limit and Avg_Utilization_Ratio:

- (Avg_Open_To_Buy / Credit_Limit) + Avg_Utilization_Ratio = 1

Importing the libraries and overview of the dataset

In [154…

```python
# Libraries to help with reading and manipulating data
import pandas as pd
import numpy as np

# Libaries to help with data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Removes the limit for the number of displayed columns
pd.set_option("display.max_columns", None)
# Sets the limit for the number of displayed rows
pd.set_option("display.max_rows", 200)
# Setting the precision of floating numbers to 5 decimal points
pd.set_option("display.float_format", lambda x: "%.5f" % x)

# To tune model, get different metric scores, and split data
from sklearn.metrics import (
    f1_score,
    accuracy_score,
    recall_score,
    precision_score,
    confusion_matrix,
    roc_auc_score,
    classification_report,
    precision_recall_curve
)
from sklearn import metrics

from sklearn.model_selection import train_test_split, StratifiedKFold, cross

# To be used for data scaling and one hot encoding
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncode

# To impute missing values
from sklearn.impute import SimpleImputer

# To help with model building
from sklearn.linear_model import LogisticRegression

# To build classification models
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression


# For tuning the model
from sklearn.model_selection import GridSearchCV

# To supress warnings
import warnings
warnings.filterwarnings("ignore")
```

Loading Data

In [155…
```
# from google.colab import drive
# drive.mount('/content/drive')
```

In [156…
```
# Loading the dataset
churn = pd.read_csv("/content/Mydrive/MyDrive/BankChurners.csv")
```

In [157…
```
# Checking the number of rows and columns in the data
churn.shape
```

Out[157…
```
(10127, 21)
```

Observations:

- There are **10127 observations and 21 columns** in the dataset.

Data Overview

In [158…

```
# Let's create a copy of the data
data = churn.copy()
```

In [159…

```
# Let's view the first 5 rows of the data
data.head()
```

Out[159…

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_L
0	768805383	Existing Customer	45	M	3	High Sc
1	818770008	Existing Customer	49	F	5	Grac
2	713982108	Existing Customer	51	M	3	Grac
3	769911858	Existing Customer	40	F	4	High Sc
4	709106358	Existing Customer	40	M	3	Uneduc

In [160…

```
# Let's view the last 5 rows of the data
data.tail()
```

Out[160…

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Educati
10122	772366833	Existing Customer	50	M	2	
10123	710638233	Attrited Customer	41	M	2	
10124	716506083	Attrited Customer	44	F	1	Hi
10125	717406983	Attrited Customer	30	M	2	
10126	714337233	Attrited Customer	43	F	2	

Checking the info of the dataset

In [161…

```
# Let's check the data types of the columns in the dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   CLIENTNUM                 10127 non-null  int64  
 1   Attrition_Flag            10127 non-null  object 
 2   Customer_Age              10127 non-null  int64  
 3   Gender                    10127 non-null  object 
 4   Dependent_count           10127 non-null  int64  
 5   Education_Level           8608 non-null   object 
 6   Marital_Status            9378 non-null   object 
 7   Income_Category           10127 non-null  object 
 8   Card_Category             10127 non-null  object 
 9   Months_on_book            10127 non-null  int64  
 10  Total_Relationship_Count  10127 non-null  int64  
 11  Months_Inactive_12_mon    10127 non-null  int64  
 12  Contacts_Count_12_mon     10127 non-null  int64  
 13  Credit_Limit              10127 non-null  float64
 14  Total_Revolving_Bal       10127 non-null  int64  
 15  Avg_Open_To_Buy           10127 non-null  float64
 16  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 17  Total_Trans_Amt           10127 non-null  int64  
 18  Total_Trans_Ct            10127 non-null  int64  
 19  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 20  Avg_Utilization_Ratio     10127 non-null  float64
dtypes: float64(5), int64(10), object(6)
memory usage: 1.6+ MB
```

Observations:

- There are missing values in the Education_Level and Marital_Status.
- Five columns are of the object type, and the remaining columns are all numerical.

Checking for Duplicate values and Missing Values

In [162…

```python
# Let's check for duplicate values in the data
data.duplicated().sum()
```

Out[162…

```
0
```

In [163…

```python
# Let's check for missing values in the data
round(data.isnull().sum() / data.isnull().count() * 100, 2)
```

```
Out[163…  CLIENTNUM                    0.00000
          Attrition_Flag               0.00000
          Customer_Age                 0.00000
          Gender                       0.00000
          Dependent_count              0.00000
          Education_Level             15.00000
          Marital_Status               7.40000
          Income_Category              0.00000
          Card_Category                0.00000
          Months_on_book               0.00000
          Total_Relationship_Count     0.00000
          Months_Inactive_12_mon       0.00000
          Contacts_Count_12_mon        0.00000
          Credit_Limit                 0.00000
          Total_Revolving_Bal          0.00000
          Avg_Open_To_Buy              0.00000
          Total_Amt_Chng_Q4_Q1         0.00000
          Total_Trans_Amt              0.00000
          Total_Trans_Ct               0.00000
          Total_Ct_Chng_Q4_Q1          0.00000
          Avg_Utilization_Ratio        0.00000
          dtype: float64
```

Observations:

- Education_Level has 15% missing values
- Marital_Status has 7% missing values

Univariate analysis of numerical columns

```
In [164…  # Let's view the statistical summary of the numerical columns in the data
          data.describe().T
```

Out [164…

	count	mean	std	
CLIENTNUM	10127.00000	739177606.33366	36903783.45023	708082083.
Customer_Age	10127.00000	46.32596	8.01681	26.
Dependent_count	10127.00000	2.34620	1.29891	0.
Months_on_book	10127.00000	35.92841	7.98642	13.
Total_Relationship_Count	10127.00000	3.81258	1.55441	1.
Months_Inactive_12_mon	10127.00000	2.34117	1.01062	0.
Contacts_Count_12_mon	10127.00000	2.45532	1.10623	0.
Credit_Limit	10127.00000	8631.95370	9088.77665	1438.
Total_Revolving_Bal	10127.00000	1162.81406	814.98734	0.
Avg_Open_To_Buy	10127.00000	7469.13964	9090.68532	3.
Total_Amt_Chng_Q4_Q1	10127.00000	0.75994	0.21921	0.
Total_Trans_Amt	10127.00000	4404.08630	3397.12925	510.
Total_Trans_Ct	10127.00000	64.85869	23.47257	10.
Total_Ct_Chng_Q4_Q1	10127.00000	0.71222	0.23809	0.
Avg_Utilization_Ratio	10127.00000	0.27489	0.27569	0.

Observations:

- **CLIENTNUM:** It is a unique identifier for customers and can be dropped as it wouldn't add any information to our analysis.
- **Customer_Age:** Average age of customers is 46 years and it has a wide range from 26 to 73 years.
- **Dependent_count:** On average the customers in the data have 2 dependents and a maximum of 5 dependents.
- **Months_on_book:** All the customers of the bank have at least been with them for a year and 50% of the customers for at least 3 years.
- **Total_Relationship_Count:** All customers use at least one product of the bank, whereas 75% of customers use 5 or fewer products of the bank.
- **Months_Inactive_12_mon:** On average customers were inactive for two months in the past 12 months - this shows that the bank customers are active in transactions or usage of cards it would be interesting to see if high inactivity leads to churning of a customer.
- **Contacts_Count_12_mon:** On average bank and customers interacted twice in the past 12 months.
- **Credit_Limit:** There's a huge difference between the third quartile and maximum value. The range of credit limit is very wide from 1438 to 34516, customers with

high credit limit might be outliers.

- **Total_Revolving_Bal:** Average revolving balance of customers is 1162, there's not much difference in the third quartile and maximum value.
- **Avg_Open_To_Buy:** Average amount that goes unused by the customers is 7469, the range is very wide for this variable and the extreme values(min and max) might be outliers.
- **Total_Amt_Chng_Q4_Q1:** For 75% of the customers the transaction amount in Q4 was less than the transaction amount in Q1 (as value is equal to ~0.9).
- **Total_Trans_Amt:** Average transaction amount of last 12 months is 4404, some customers spent as little as 510 while some customers made the transaction of more than 18k.
- **Total_Trans_Ct:** On average customers made 64 or fewer transactions while 75% of the customers made 81 transactions.
- **Total_Ct_Chng_Q4_Q1:** For 75% of the customers the number of transactions in Q4 was less than the transactions made in Q1.
- **Avg_Utilization_Ratio:** On average customers used ~27% of the available credit amount of their card, with 75% of the customers utilizing 50% or less of their available credit amount.

Univariate analysis for categorical variables

In [165…

```
data.describe(include=["object"]).T
```

Out[165…

	count	unique	top	freq
Attrition_Flag	10127	2	Existing Customer	8500
Gender	10127	2	F	5358
Education_Level	8608	6	Graduate	3128
Marital_Status	9378	3	Married	4687
Income_Category	10127	6	Less than $40K	3561
Card_Category	10127	4	Blue	9436

In [166…

```
# Printing the % sub categories of each category

for i in data.describe(include=["object"]).columns:
    print("Unique values in", i, "are :")
    print(data[i].value_counts())
    print("*" * 50)
```

```
Unique values in Attrition_Flag are :
Attrition_Flag
Existing Customer    8500
Attrited Customer    1627
Name: count, dtype: int64
**************************************************
Unique values in Gender are :
Gender
F    5358
M    4769
Name: count, dtype: int64
**************************************************
Unique values in Education_Level are :
Education_Level
Graduate         3128
High School      2013
Uneducated       1487
College          1013
Post-Graduate     516
Doctorate         451
Name: count, dtype: int64
**************************************************
Unique values in Marital_Status are :
Marital_Status
Married     4687
Single      3943
Divorced     748
Name: count, dtype: int64
**************************************************
Unique values in Income_Category are :
Income_Category
Less than $40K    3561
$40K - $60K       1790
$80K - $120K      1535
$60K - $80K       1402
abc               1112
$120K +            727
Name: count, dtype: int64
**************************************************
Unique values in Card_Category are :
Card_Category
Blue        9436
Silver       555
Gold         116
Platinum      20
Name: count, dtype: int64
**************************************************
```

Observations:

- Most of the records are for existing customers.
- Most of the bank's customers are female.
- Most customers are graduates.
- Most customers are married.
- Most customers are in the income group of less than $40k

- Most customers have blue card.
- 'abc' value of Income_Category can be considered and treated as **missing values.**

Data Preprocessing

In [167…
```
# CLIENTNUM consists of uniques ID for clients and hence will not add value

data.drop(["CLIENTNUM"], axis=1, inplace=True)
```

In [168…
```
## Encoding Existing and Attrited customers to 0 and 1 respectively, for ana

data["Attrition_Flag"].replace("Existing Customer", 0, inplace=True)
data["Attrition_Flag"].replace("Attrited Customer", 1, inplace=True)
```

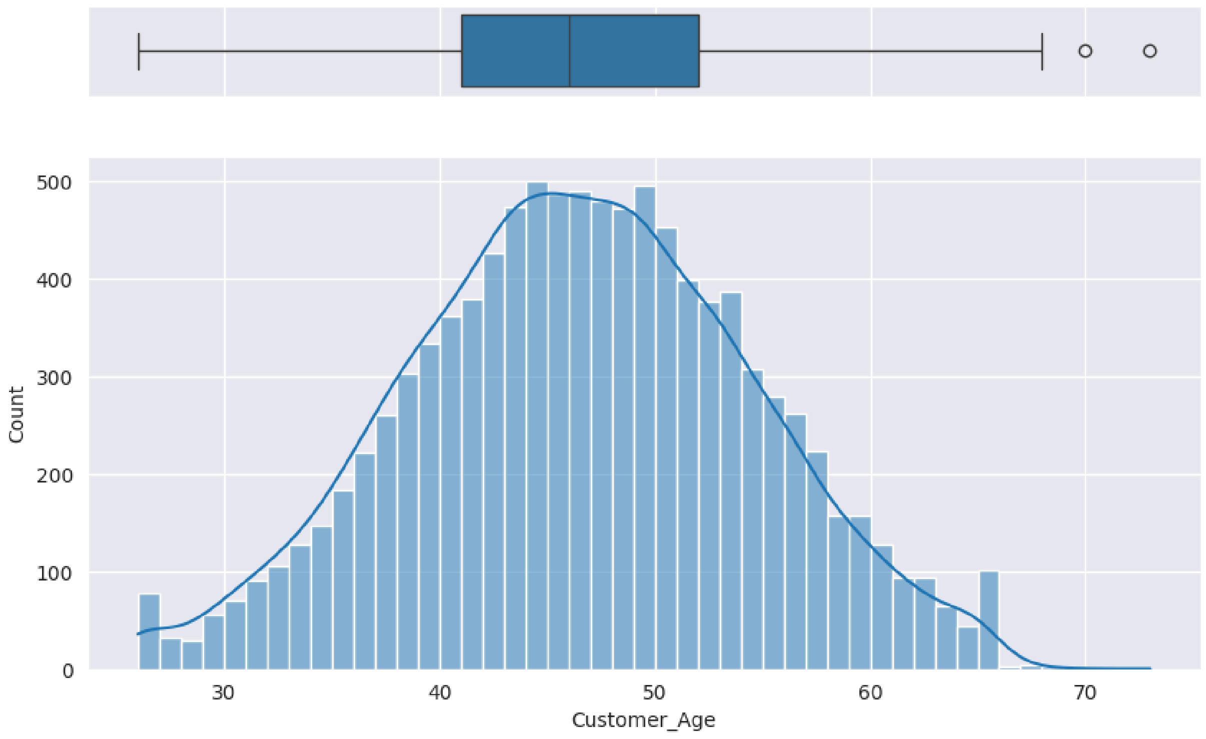
Exploratory Data Analysis

Univariate analysis

Let's explore these variables in some more depth by observing their distributions

1.Customer_Age:

In [169…
```
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={'height_rat
sns.set_style("darkgrid")

# Add a graph in each part
sns.boxplot(data=data, x="Customer_Age", ax=ax_box)
sns.histplot(data=data, x="Customer_Age", kde=True, ax=ax_hist)
ax_box.set(xlabel='Customer Age')

plt.show()
```



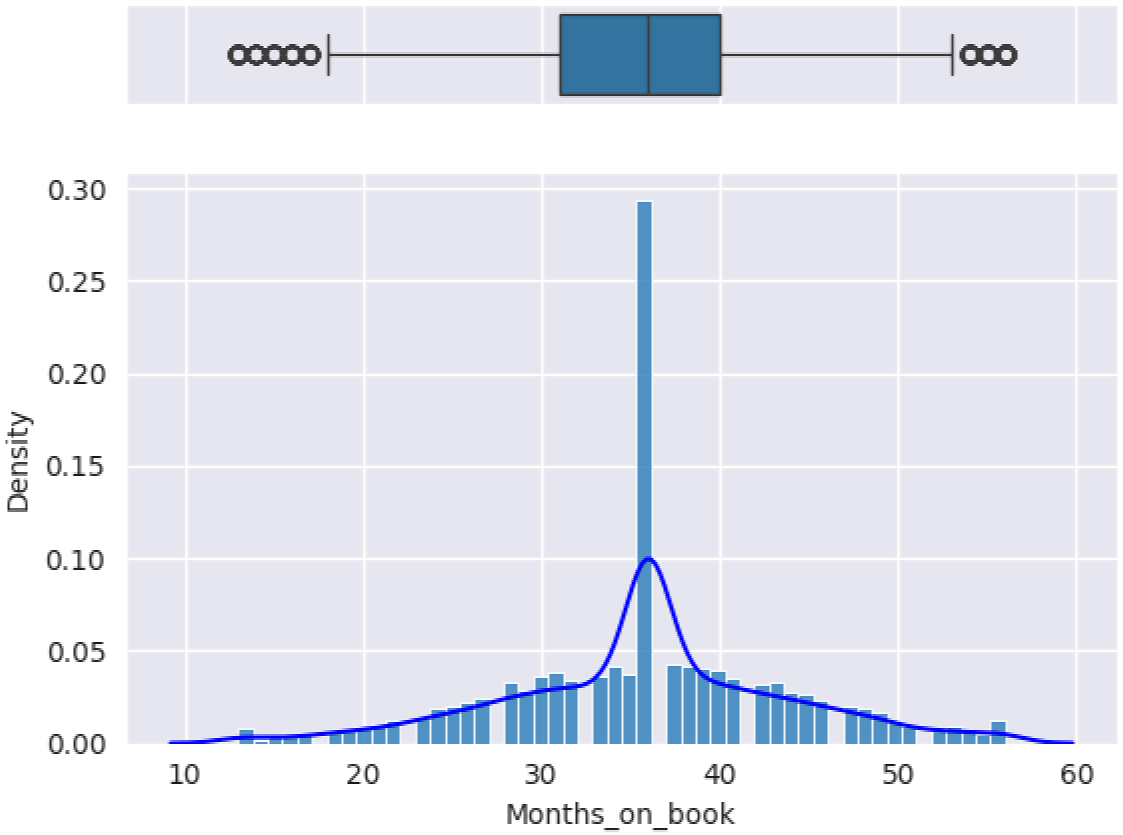
Observations:

- The distribution of Customer_Age is normally distributed with mean and median at 46 years.
- From the boxplot, we can see that there are a few outliers.

2.Months_on_book

In [170…

```
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_rat
sns.boxplot(data=data, x="Months_on_book", ax=ax_box)
sns.histplot(data=data, x="Months_on_book", ax=ax_hist, stat='density')
sns.kdeplot(data=data, x="Months_on_book", ax=ax_hist, color='blue')
ax_box.set(xlabel='Months_on_book')
plt.show()
```

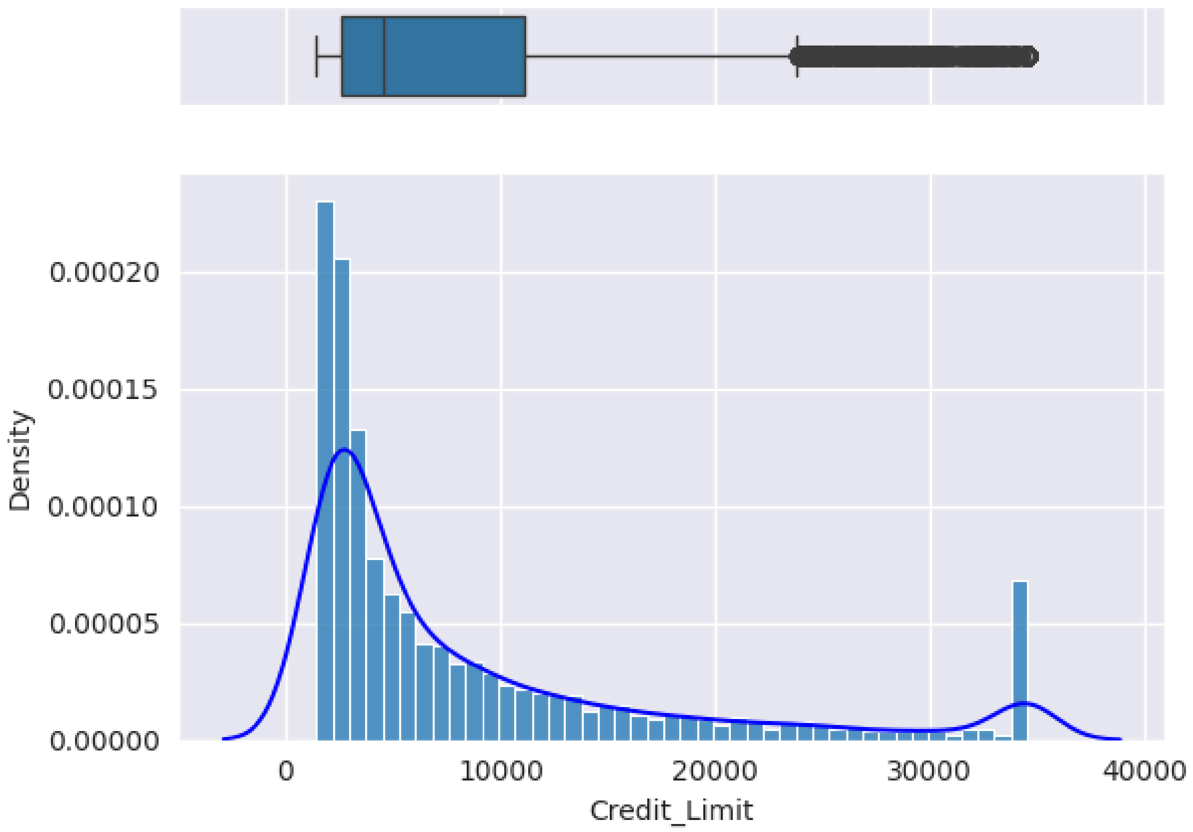


Observations:

- Most customers are with the bank for 3 years.
- From the boxplot, we can see that there are outliers on both sides of the whiskers.

3.Credit_Limit

In [171…
```
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_rat
sns.boxplot(data=data, x="Credit_Limit", ax=ax_box)
sns.histplot(data=data, x="Credit_Limit", ax=ax_hist, stat='density')
sns.kdeplot(data=data, x="Credit_Limit", ax=ax_hist, color='blue')
ax_box.set(xlabel='Credit_Limit')
plt.show()
```



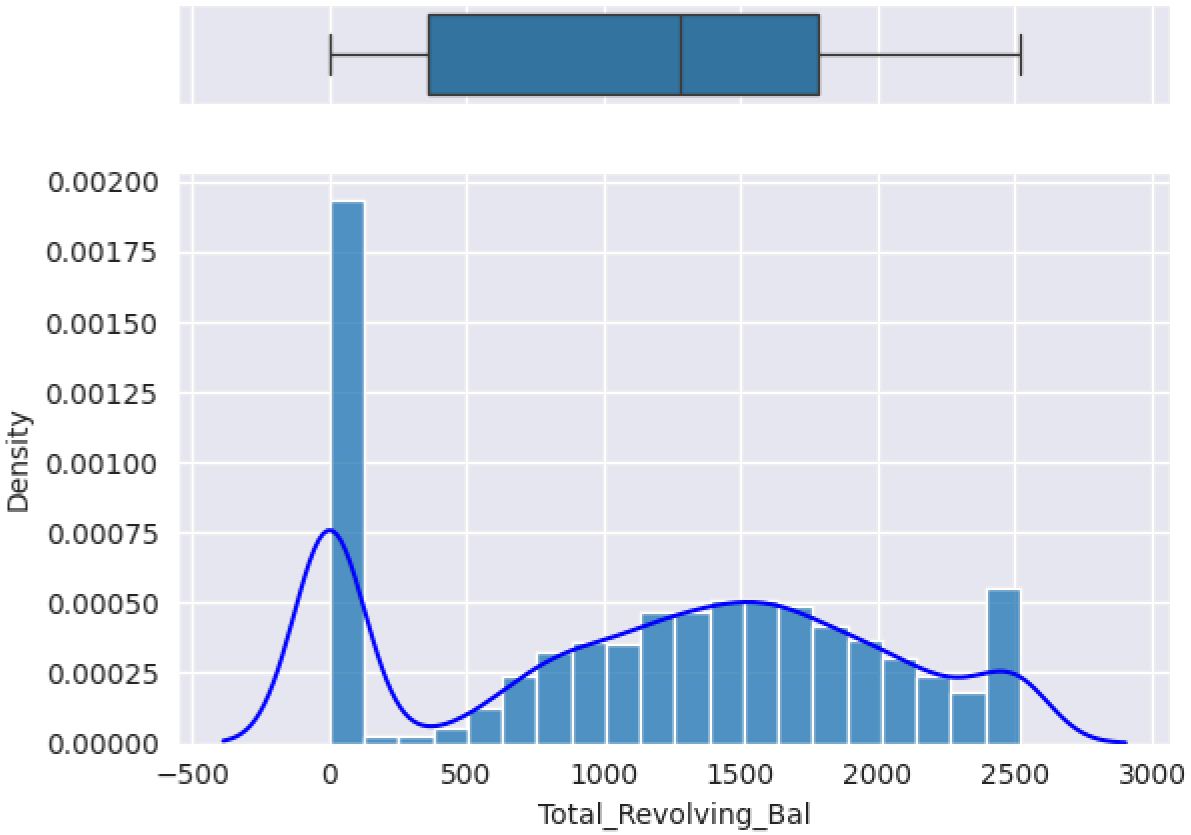
Observations:

- The distribution of the Credit_Limit is skewed to the right.
- There are quite a few customers with a maximum Credit Limit of 35000.
- 50% of the customers of the bank have a credit limit of less than <5000.

4.Total_Revolving_Bal

In [172…

```
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_rat
sns.boxplot(data=data, x="Total_Revolving_Bal", ax=ax_box)
sns.histplot(data=data, x="Total_Revolving_Bal", ax=ax_hist, stat='density')
sns.kdeplot(data=data, x="Total_Revolving_Bal", ax=ax_hist, color='blue')
ax_box.set(xlabel='Total_Revolving_Bal')
plt.show()
```

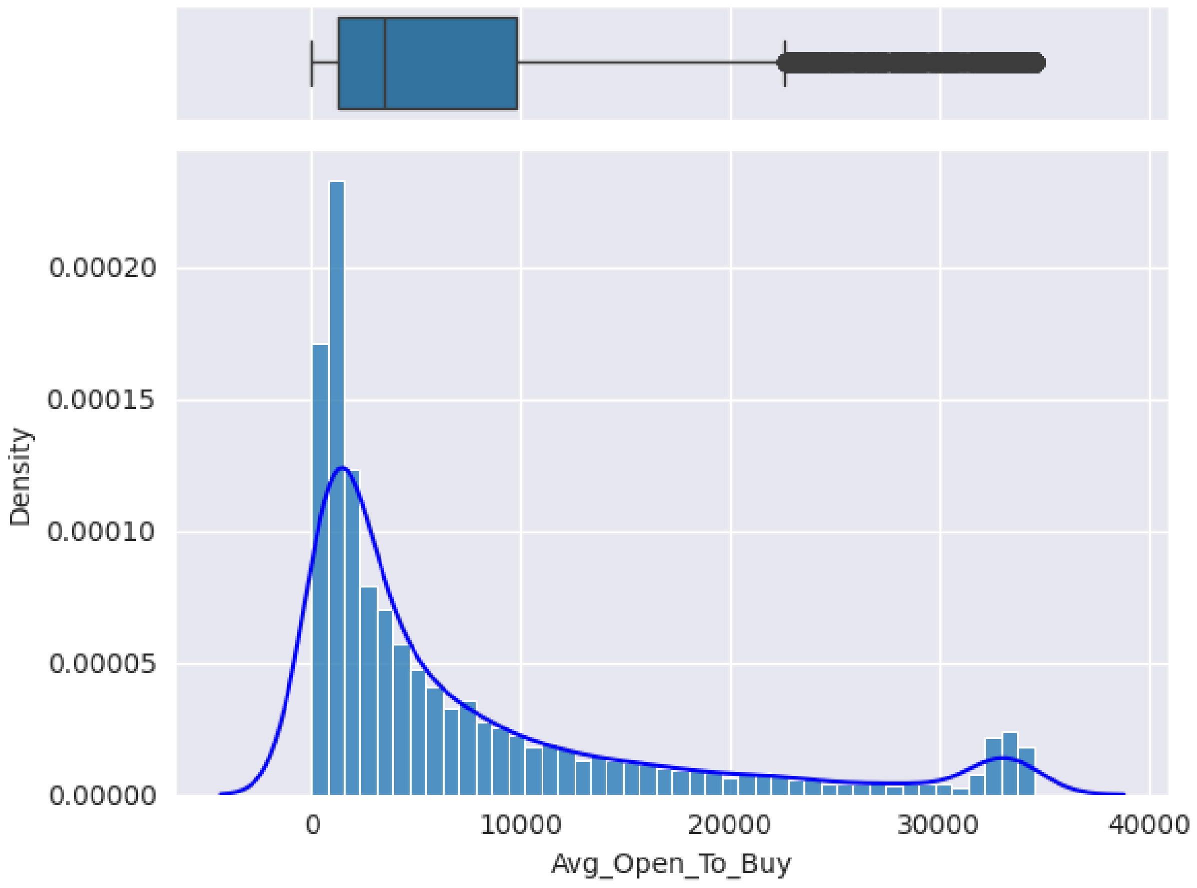


Observations:

- Most customers pay the complete dues of credit card and have 0 revolving balance.
- There are quite a few customers with a revolving balance of 2500.

5.Avg_Open_To_Buy

In [173…
```
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_rat
sns.boxplot(data=data, x="Avg_Open_To_Buy", ax=ax_box)
sns.histplot(data=data, x="Avg_Open_To_Buy", ax=ax_hist, stat='density')
sns.kdeplot(data=data, x="Avg_Open_To_Buy", ax=ax_hist, color='blue')
ax_box.set(xlabel='')
ax_hist.set_xlabel('Avg_Open_To_Buy')
plt.tight_layout()
plt.show()
```

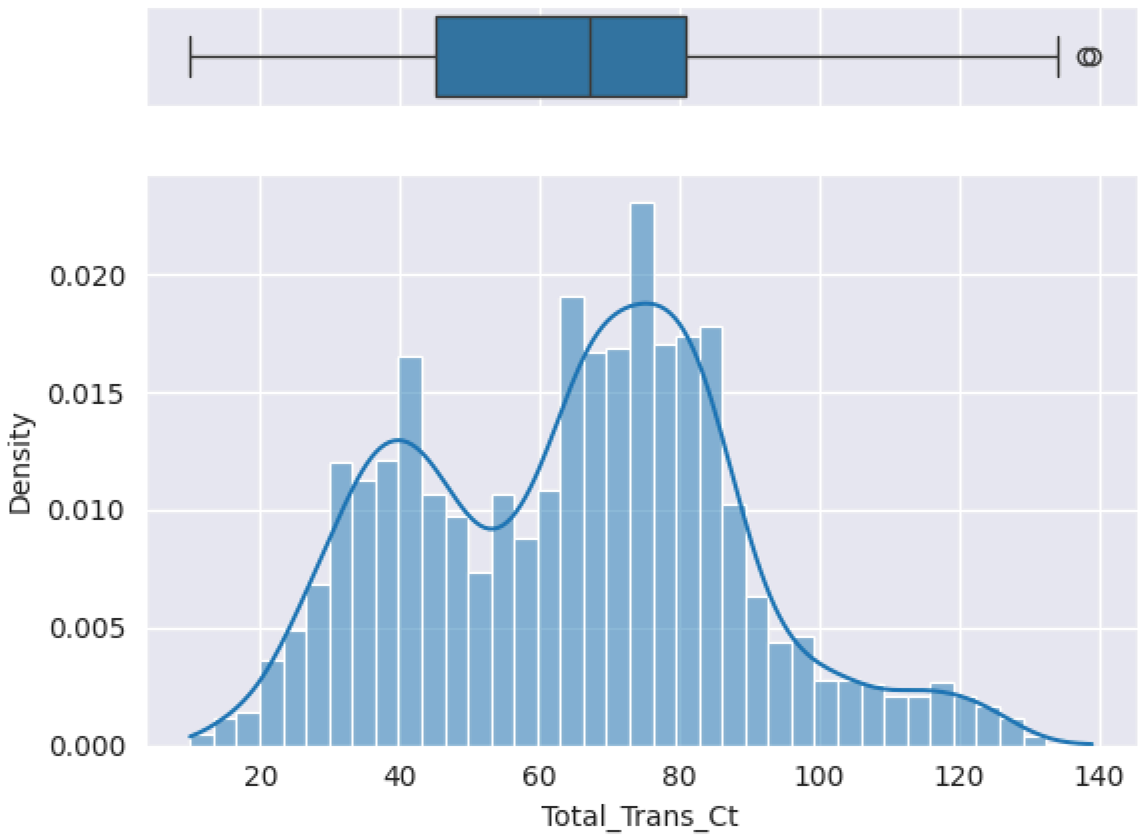


Observations:

- The distribution of the Avg_Open_To_Buy column is right-skewed.
- A right-skewed distribution indicates that most customers used a big part of their limit while only a few customers (on the right tail) were left with a majority of their credit amount.

6.Total_Trans_Ct

```
In [174…  f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_rat
          sns.boxplot(data=data, x=data["Total_Trans_Ct"], ax=ax_box)
          sns.histplot(data["Total_Trans_Ct"], ax=ax_hist, kde=True, stat="density")
          ax_box.set(xlabel='Total_Trans_Ct')
          plt.show()
```

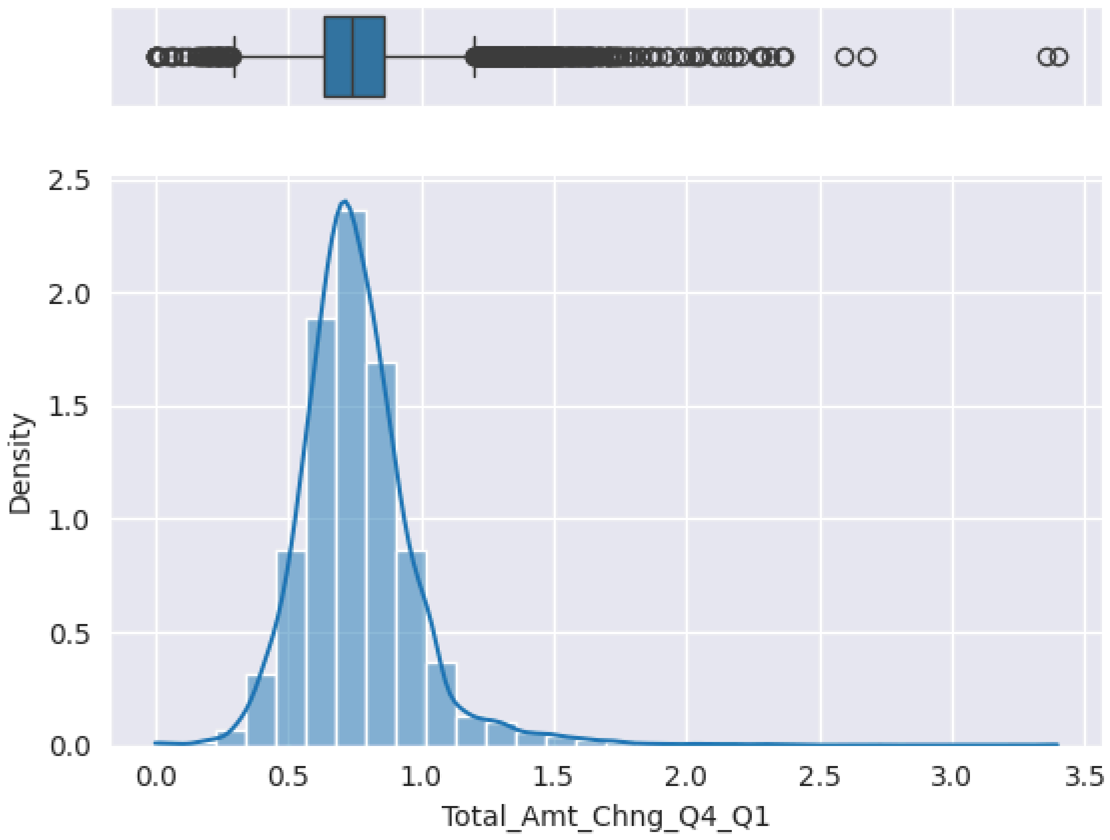


Observations:

- The distribution of Total_Trans_Ct shows two peaks on 40 and 80 transactions in a year which indicates that customers used credit cards 3 to 6 times a month to make transactions.

7.Total_Amt_Chng_Q4_Q1

In [175…
```
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_rat
sns.boxplot(data=data, x=data["Total_Amt_Chng_Q4_Q1"], ax=ax_box)
sns.histplot(data["Total_Amt_Chng_Q4_Q1"], ax=ax_hist, kde=True, stat="densi
ax_box.set(xlabel='Total_Amt_Chng_Q4_Q1')
plt.show()
```



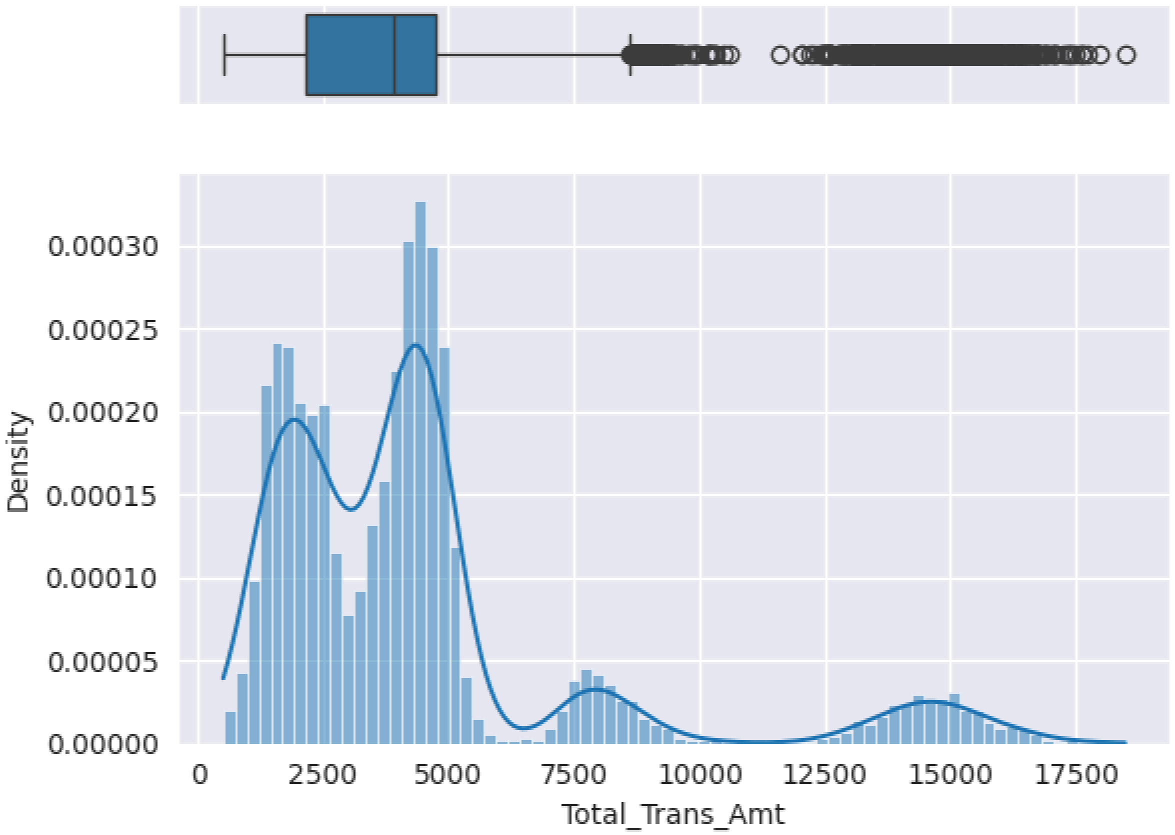
Observations:

- The distribution of Total_Amt_Chng_Q4_Q1 looks normally distributed but there's a slight skew towards the right.
- From the boxplot, we can see that there are outliers on both sides of the whiskers.

8.Total_Trans_Amt

In [176…

```
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_rat
sns.boxplot(data=data, x=data["Total_Trans_Amt"], ax=ax_box)
sns.histplot(data=data["Total_Trans_Amt"], ax=ax_hist, kde=True, stat='densi
ax_box.set(xlabel='Total_Trans_Amt')
plt.show()
```



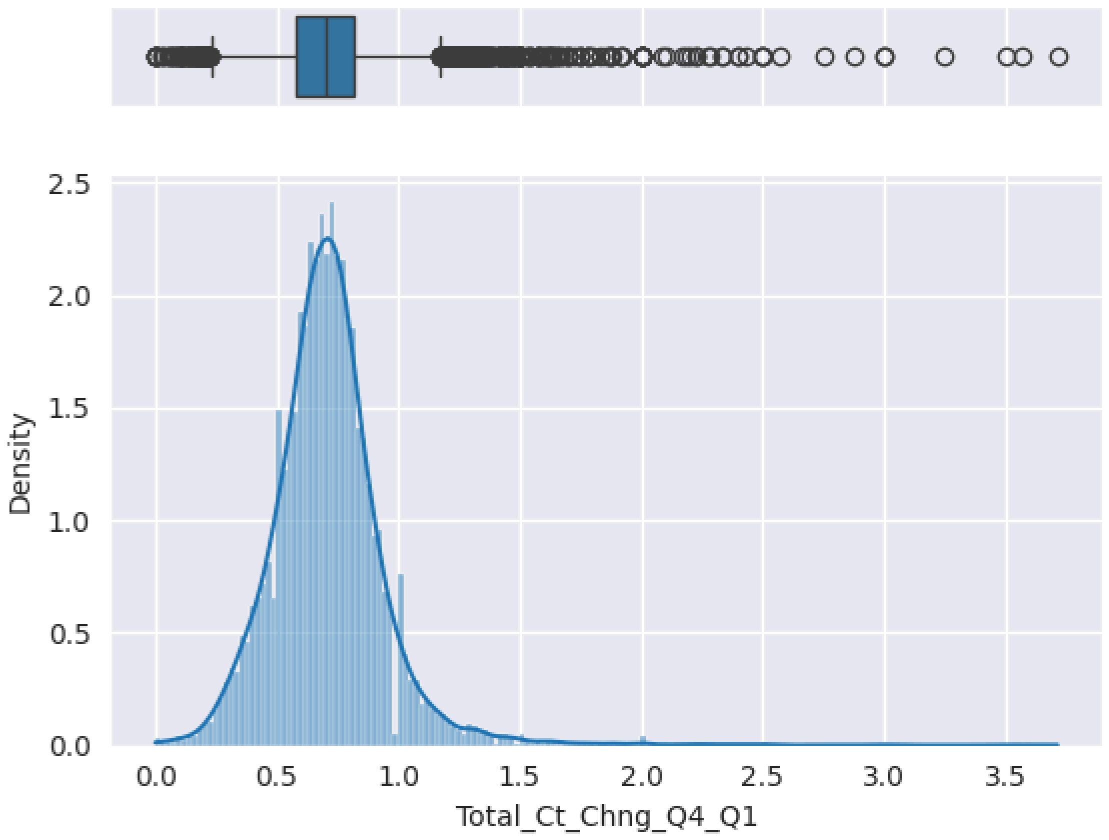
Observations:

- The distribution of Total_Trans_Amt is skewed to the right.
- Data shows two peaks at total transaction amounts, one around 2500 and the other around the mean value of 4500.
- From the boxplot, we can see that there are outliers - customers with more than ~8000 total transaction amounts are being considered as outliers.
- It would be interesting to check if the customers spending less with the card are the ones churning or the ones spending more are churning, if the latter is the case then there is a problem for the bank as it is losing valuable customers.

9.Total_Ct_Chng_Q4_Q1

In [177…

```
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_rat
sns.boxplot(data=data, x=data["Total_Ct_Chng_Q4_Q1"], ax=ax_box)
sns.histplot(data=data["Total_Ct_Chng_Q4_Q1"], ax=ax_hist, kde=True, stat='c
ax_box.set(xlabel='Total_Ct_Chng_Q4_Q1')
plt.show()
```



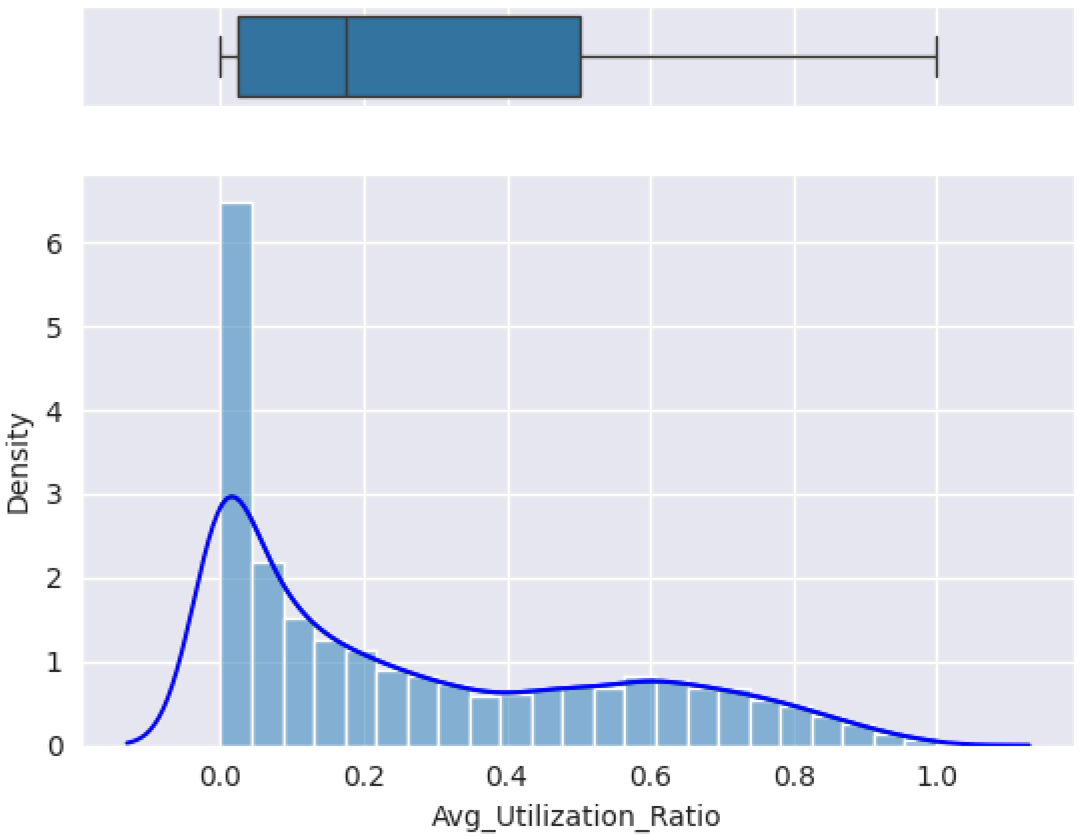
Observations:

- The distribution of Total_Ct_Chng_Q4_Q1 looks normally distributed but there's a slight skew towards the right.
- From the boxplot, we can see that there are outliers on both sides of the whiskers.

10.Avg_Utilization_Ratio

In [178…

```
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_rat
sns.boxplot(data=data, x="Avg_Utilization_Ratio", ax=ax_box)
sns.histplot(data=data, x="Avg_Utilization_Ratio", ax=ax_hist, kde=True, sta
sns.kdeplot(data=data, x="Avg_Utilization_Ratio", ax=ax_hist, color='blue')
ax_box.set(xlabel='Avg_Utilization_Ratio')
plt.show()
```



Observations:

- The distribution of Avg_Utilization_Ratio is skewed to the right.
- This distribution is not a positive sign for the bank as most of the customers are not utilizing their credit amount.

Credit limit, Average open to buy and Average utilization ratio are right-skewed.

1. **Open to buy** means how much credit a customer is left with

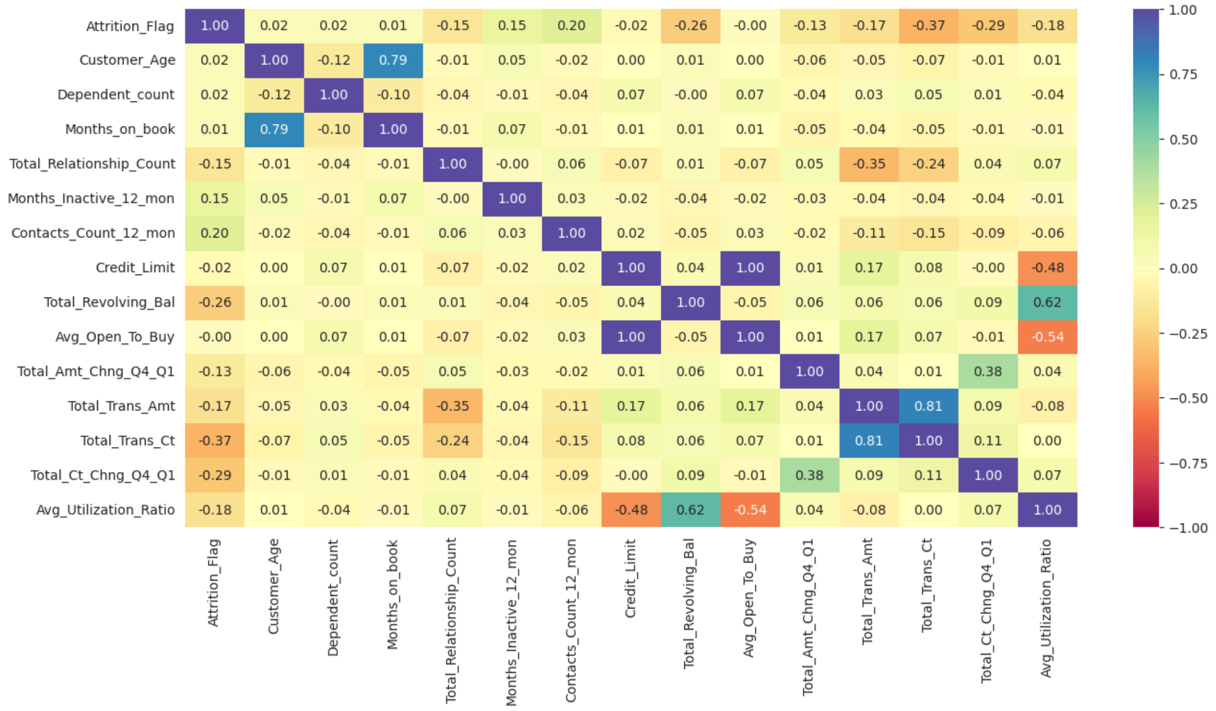
   - Low values of Open to buy could represent either
     - Customers have low credit limits
     - Customers are spending a lot so they are left less open to buy
2. **Average utilization ratio** = (1 - (open to buy/credit limit))

   - Low values of the Average utilization ratio represents
     - (Open to buy/credit limit) is nearly equal to 1 -> Open to buy is nearly equal to the credit limit -> customers are spending less using their credit cards
3. **Credit limit** is also right-skewed which represents - most of the customers have low credit limits

Based on the three variables, we can conclude that the majority of customers have low credit limits and are not utilizing their credit cards frequently. Now this statement justifies the right skewness for all the three variables.

Bivariate Analysis

```
In [179…  numeric_data = data.select_dtypes(include=['float64', 'int64'])
          plt.figure(figsize=(15, 7))
          sns.heatmap(numeric_data.corr(), annot=True, vmin=-1, vmax=1, fmt=".2f", cma
          plt.show()
```



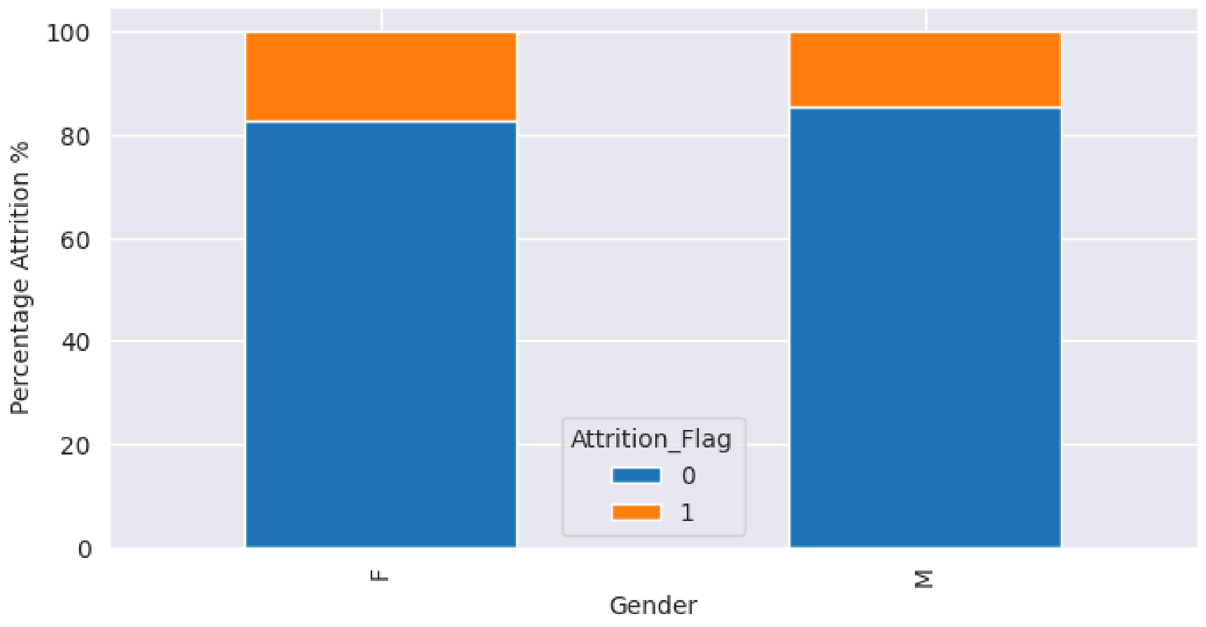
Observations:

- Attrition_Flag shows a bit of a negative correlation with **Total_Trans_Ct (total transactions)** and **Total_Trans_Amt (total transaction amount)**.
- There's a strong positive correlation between **Months_on_book** and **Customer_Age**, **Total_Revolving_Bal** and **Avg_Utilization_Ratio**, **Total_Trans_Amt** and **Total_Trans_Ct**.
- There's a negative correlation of **Total_Relationship_count** with **Total_Trans_Amt** and **Total_Trans_Ct**, **Avg_Utilization_Ratio** with **Avg_Open_To_Buy** and **Credit_Limit**.

Attrition_Flag vs Gender

```
In [180…  (pd.crosstab(data['Gender'],data['Attrition_Flag'],normalize='index')*100).p
          plt.ylabel('Percentage Attrition %')
```

```
Out[180…  Text(0, 0.5, 'Percentage Attrition %')
```



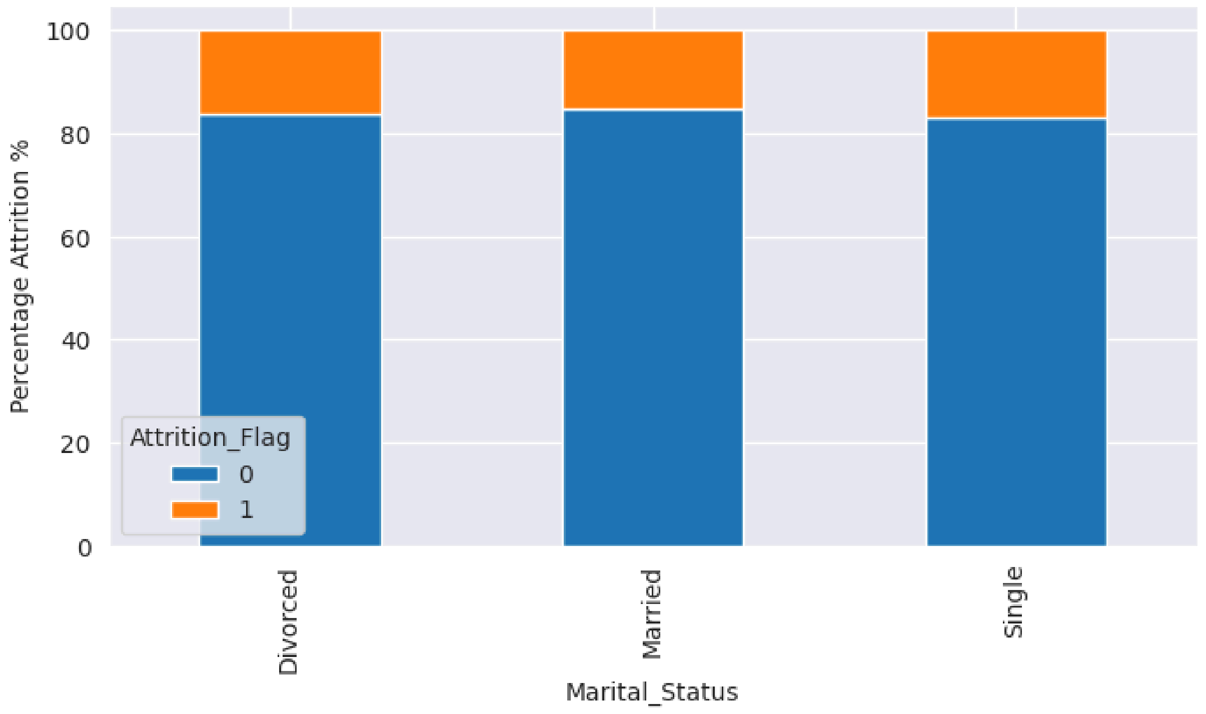
Observations:

- There's not much difference in attrition percentages for Males and Females.
- ~20% of both Males and Females attrite.

Attrition_Flag vs Marital_Status

```
In [181…  (pd.crosstab(data['Marital_Status'],data['Attrition_Flag'],normalize='index'
          plt.ylabel('Percentage Attrition %')
```

```
Out[181…  Text(0, 0.5, 'Percentage Attrition %')
```



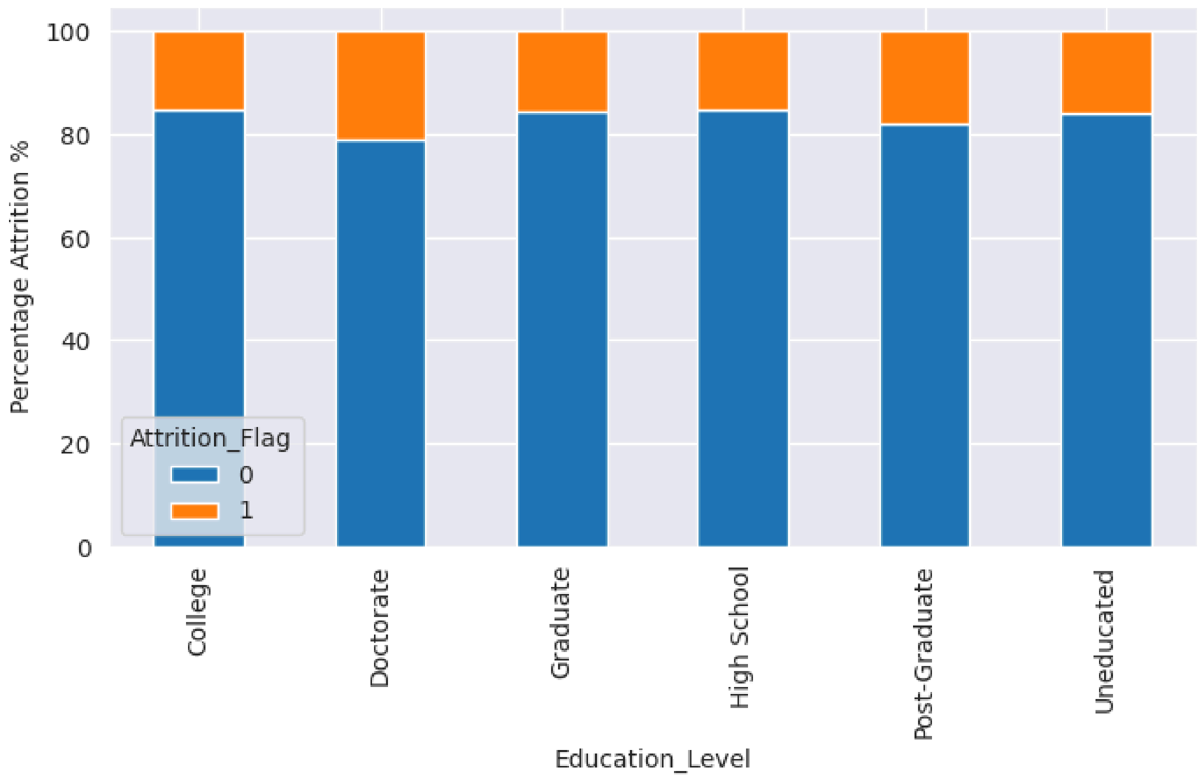
Observations:

- There's not much difference in attrition percentages for Marital_Status.
- ~20% of Singles, Divorced attrite.
- Married customers attrite the least.

Attrition_Flag vs Education_Level

```
In [182…  (pd.crosstab(data['Education_Level'],data['Attrition_Flag'],normalize='index
          plt.ylabel('Percentage Attrition %')
```

```
Out[182…  Text(0, 0.5, 'Percentage Attrition %')
```



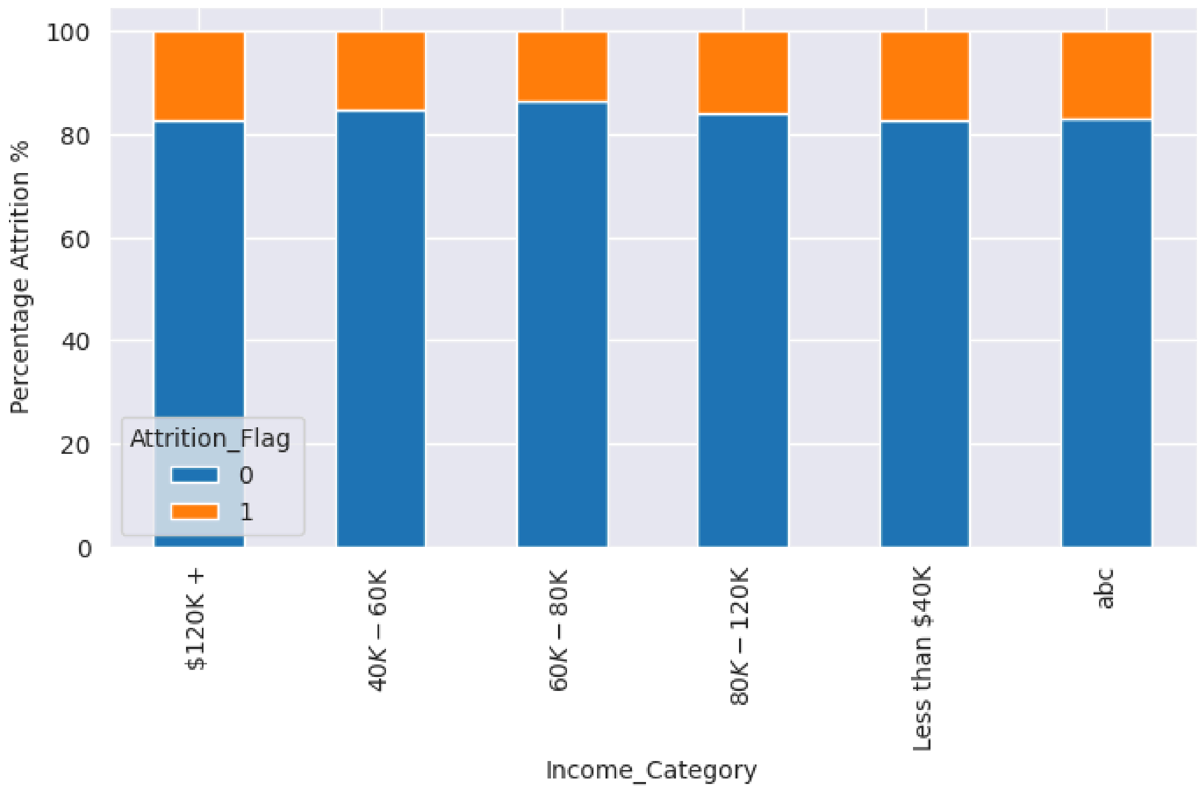
Observations:

- Customers with higher education - Doctorates and Post Graduates are the ones most (~20% for both education levels) attriting.

Attrition_Flag vs Income_Category

```
In [183…  (pd.crosstab(data['Income_Category'],data['Attrition_Flag'],normalize='index
          plt.ylabel('Percentage Attrition %')
```

```
Out[183…  Text(0, 0.5, 'Percentage Attrition %')
```



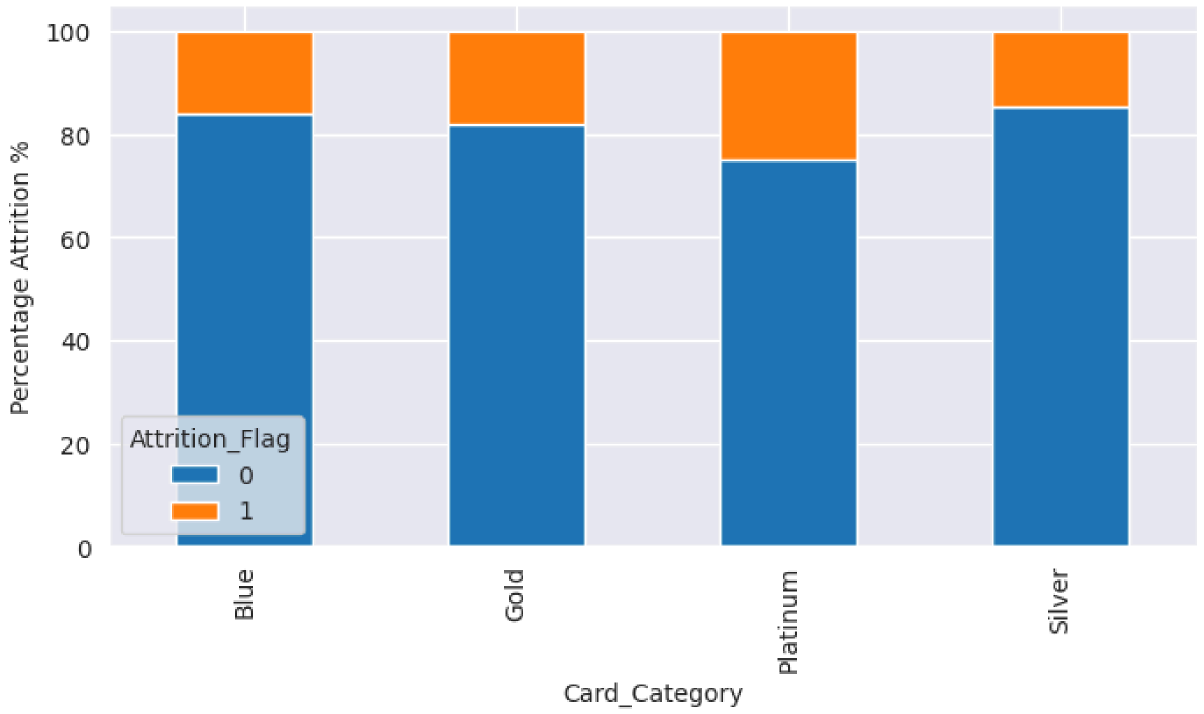
Observations:

- The customers from two extreme income groups - Earning less than 40K and Earning more than 120k+ are the ones attriting the most.

Attrition_Flag vs Card_Category

In [184…
```
(pd.crosstab(data['Card_Category'],data['Attrition_Flag'],normalize='index')
plt.ylabel('Percentage Attrition %')
```

Out[184…
```
Text(0, 0.5, 'Percentage Attrition %')
```



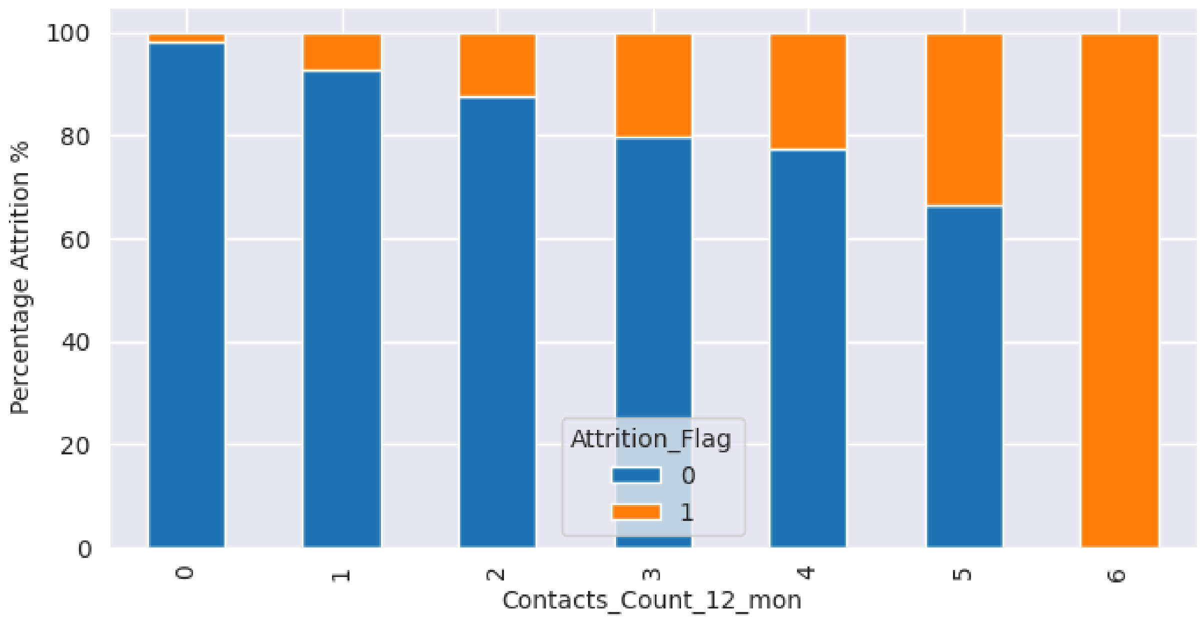
Observations:

- ~35% of attrition is amongst the customers with platinum cards followed by ~30% attrition in Gold cards.
- Customers with Platinum and Gold cards are our premium customers and the highest attrition for these customers is alarming as they are using the premium card provided by the bank.

Attrition_Flag vs Contacts_Count_12_mon

In [185…
```
(pd.crosstab(data['Contacts_Count_12_mon'],data['Attrition_Flag'],normalize=
plt.ylabel('Percentage Attrition %')
```

Out[185…
```
Text(0, 0.5, 'Percentage Attrition %')
```



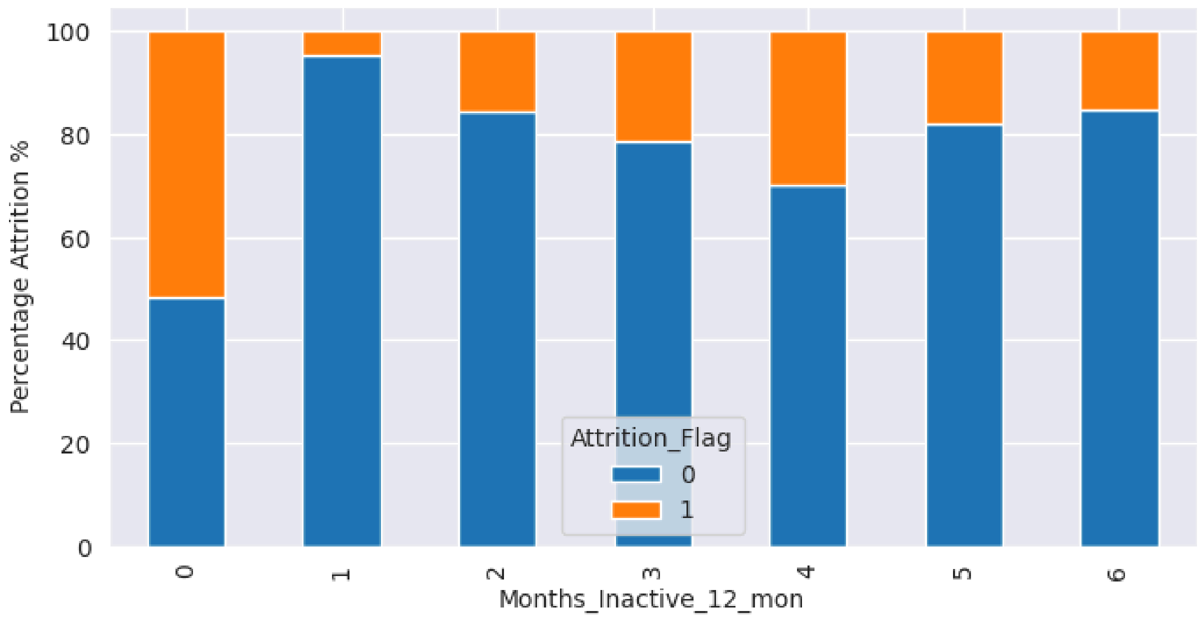
Observations:

- Highest attrition is among the customers who interacted the most with the bank.
- This signifies that the bank is not able to resolve the problems faced by customers leading to attrition.
- A preliminary step to identify attriting customers would be to look out for customers who have reached out to them repeatedly.

Attrition_Flag vs Months_Inactive_12_mon

```
In [186…  (pd.crosstab(data['Months_Inactive_12_mon'],data['Attrition_Flag'],normalize
          plt.ylabel('Percentage Attrition %')
```

```
Out[186…  Text(0, 0.5, 'Percentage Attrition %')
```



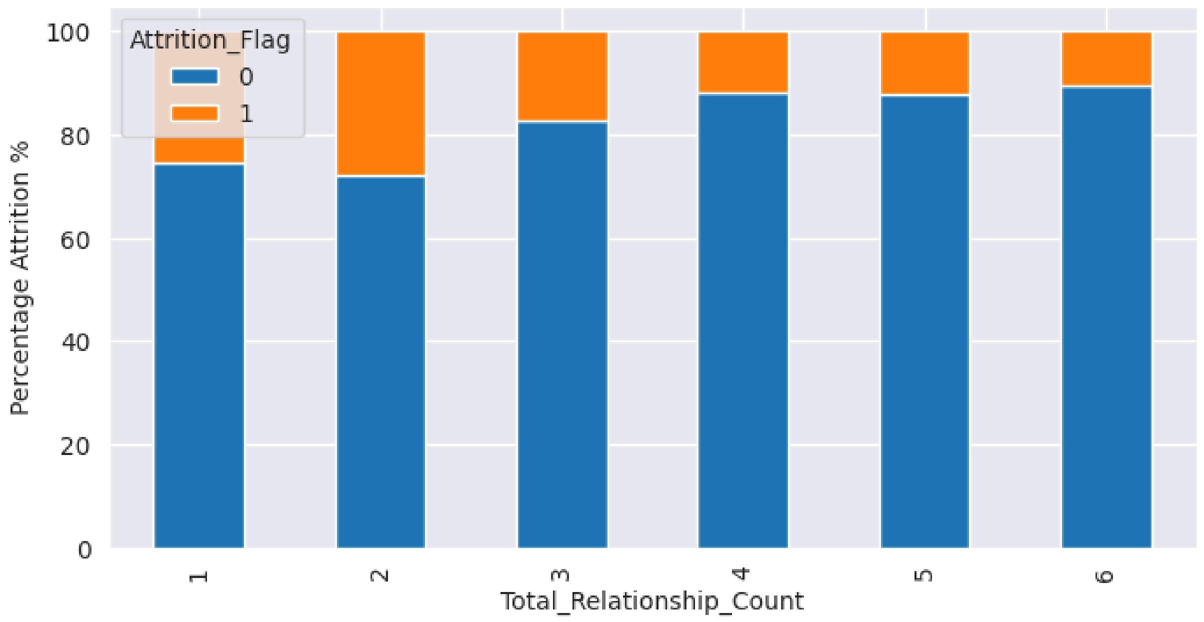
Observations:

- As inactivity increases attrition also increases (2-4 months).
- The interpretation from here for 0 months to 6 months is difficult as customers who recently used the card attrited the most while those who were inactive for 6 months attrited less.

Attrition_Flag vs Total_Relationship_Count

```
In [187…  (pd.crosstab(data['Total_Relationship_Count'],data['Attrition_Flag'],normali
          plt.ylabel('Percentage Attrition %')
```

```
Out[187…  Text(0, 0.5, 'Percentage Attrition %')
```



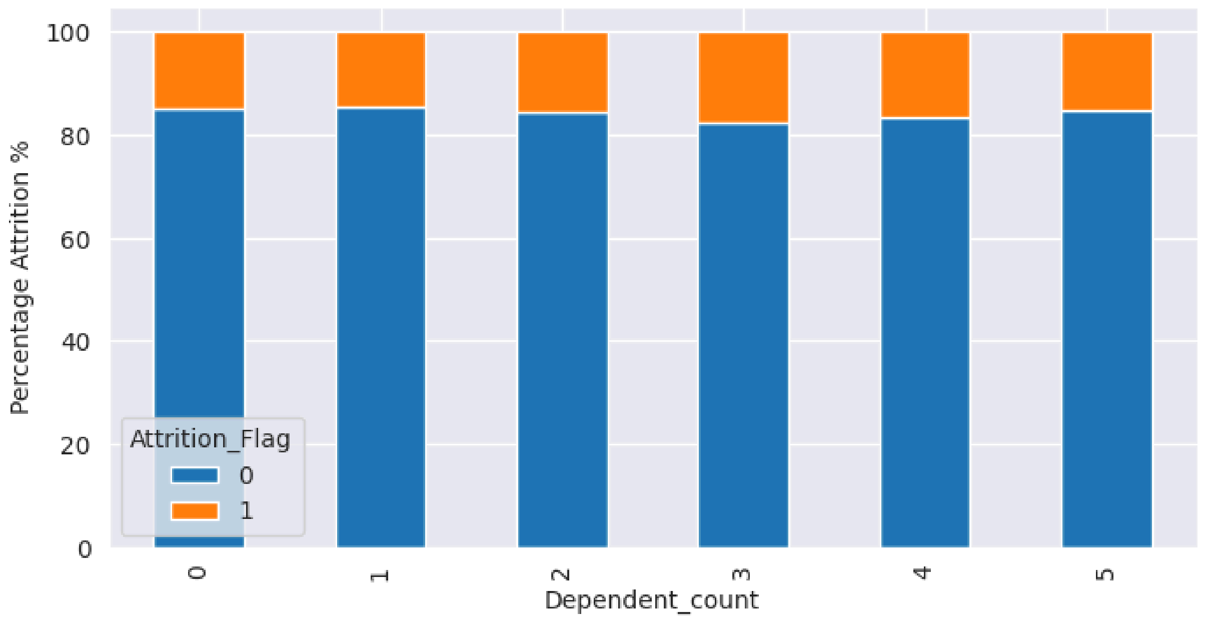
Observations:

- Attrition is highest among the customers who are using 1 or 2 products offered by the bank - together they constitute ~55% of the attrition.
- Customers who use more than 3 products are the ones least attriting, such customers might be more financially stable and actively invest in different services provided by the bank.

Attrition_Flag vs Dependent_count

```
In [188…  (pd.crosstab(data['Dependent_count'],data['Attrition_Flag'],normalize='index
          plt.ylabel('Percentage Attrition %')
```

```
Out[188…  Text(0, 0.5, 'Percentage Attrition %')
```



Observations:

- More the number of dependents more is the attrition, more responsibilities might lead to financial instability in such customers.
- Attrition is fairly low for customers with 0 or 1 dependents.

Let's find the percentage of outliers, in each column of the data, using IQR.

In [189…

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

# Calculate quartiles and IQR
Q1 = numeric_data.quantile(0.25)
Q3 = numeric_data.quantile(0.75)
IQR = Q3 - Q1

# Find lower and upper bounds for outliers
lower = Q1 - 1.5 * IQR
upper = Q3 + 1.5 * IQR
```

In [190…

```
(
    (data.select_dtypes(include=["float64", "int64"]) < lower)
    | (data.select_dtypes(include=["float64", "int64"]) > upper)
).sum() / len(data) * 100
```

```
Out[190…  Attrition_Flag              16.06596
          Customer_Age                 0.01975
          Dependent_count              0.00000
          Months_on_book               3.81159
          Total_Relationship_Count     0.00000
          Months_Inactive_12_mon       3.26849
          Contacts_Count_12_mon        6.21112
          Credit_Limit                 9.71660
          Total_Revolving_Bal          0.00000
          Avg_Open_To_Buy              9.50923
          Total_Amt_Chng_Q4_Q1         3.91034
          Total_Trans_Amt              8.84764
          Total_Trans_Ct               0.01975
          Total_Ct_Chng_Q4_Q1          3.89059
          Avg_Utilization_Ratio        0.00000
          dtype: float64
```

Observations:

- After identifying outliers, we can decide whether to remove/treat them or not. It depends on one's approach, here we are not going to treat them as there will be outliers in real case scenario (in age, the total amount of transactions, number of transactions, etc) and we would want our model to learn the underlying pattern for such customers.

Missing value imputation

- We will first replace 'abc' values with 'np.nan' in Income_Category.
- We will impute missing values in all 3 columns using mode.

```
In [191…  data1 = data.copy()
```

```
In [192…  data1["Income_Category"].replace("abc", np.nan, inplace=True)
```

```
In [193…  data1.isna().sum()
```

```
Out[193…
Attrition_Flag                 0
Customer_Age                   0
Gender                         0
Dependent_count                0
Education_Level             1519
Marital_Status               749
Income_Category             1112
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
```

Separating the independent variables (X) and the dependent variable (Y)

In [194…

```
X = data1.drop(["Attrition_Flag"], axis=1)
y = data1["Attrition_Flag"]
```

Splitting the data into 70% train and 30% test set

Some classification problems can exhibit a large imbalance in the distribution of the target classes: for instance there could be several times more negative samples than positive samples. In such cases it is recommended to use the **stratified sampling** technique to ensure that relative class frequencies are approximately preserved in each train and validation fold.

In [195…

```
# Splitting the data
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_stat
```

Missing Values Imputation

In [196…

```
# Columns to impute
reqd_col_for_impute = ["Education_Level", "Marital_Status", "Income_Category

# Simple Imputer with Mode
imputer = SimpleImputer(strategy="most_frequent")

# Fit and transform the train data
X_train[reqd_col_for_impute] = imputer.fit_transform(X_train[reqd_col_for_im

# Transform the test data
X_test[reqd_col_for_impute] = imputer.transform(X_test[reqd_col_for_impute])
```

In [197…
```
# Checking that no column has missing values in train or test sets
print(X_train.isna().sum())
print("-" * 30)
print(X_test.isna().sum())
```

```
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
------------------------------
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
```

Observations:

- All missing values have been treated.

In [198…
```
cols = X_train.select_dtypes(include=["object", "category"])
for i in cols.columns:
    print(X_train[i].value_counts())
    print("*" * 30)
```

```
Gender
F    3770
M    3318
Name: count, dtype: int64
******************************
Education_Level
Graduate         3247
High School      1425
Uneducated       1031
College           709
Post-Graduate     364
Doctorate         312
Name: count, dtype: int64
******************************
Marital_Status
Married     3815
Single      2771
Divorced     502
Name: count, dtype: int64
******************************
Income_Category
Less than $40K    3273
$40K - $60K       1254
$80K - $120K      1084
$60K - $80K        974
$120K +            503
Name: count, dtype: int64
******************************
Card_Category
Blue        6621
Silver       375
Gold          78
Platinum      14
Name: count, dtype: int64
******************************
```

In [199…

```python
cols = X_test.select_dtypes(include=["object", "category"])
for i in cols.columns:
    print(X_train[i].value_counts())
    print("*" * 30)
```

```
Gender
F    3770
M    3318
Name: count, dtype: int64
******************************
Education_Level
Graduate         3247
High School      1425
Uneducated       1031
College           709
Post-Graduate     364
Doctorate         312
Name: count, dtype: int64
******************************
Marital_Status
Married     3815
Single      2771
Divorced     502
Name: count, dtype: int64
******************************
Income_Category
Less than $40K    3273
$40K - $60K       1254
$80K - $120K      1084
$60K - $80K        974
$120K +            503
Name: count, dtype: int64
******************************
Card_Category
Blue        6621
Silver       375
Gold          78
Platinum      14
Name: count, dtype: int64
******************************
```

Encoding categorical variables

In [200…

```
X_train = pd.get_dummies(X_train, drop_first=True)
X_test = pd.get_dummies(X_test, drop_first=True)
print(X_train.shape, X_test.shape)
```

```
(7088, 29) (3039, 29)
```

Observations:

- After encoding there are 29 columns.

In [201…

```
X_train.head()
```

Out[201…

	Customer_Age	Dependent_count	Months_on_book	Total_Relationship_Count
4124	50	1	43	6
4686	50	0	36	3
1276	26	0	13	6
6119	65	0	55	3
2253	46	3	35	6

Model evaluation criterion

The model can make two types of wrong predictions:

1. Predicting a customer will attrite and the customer doesn't attrite.
2. Predicting a customer will not attrite and the customer attrites.

Which case is more important?

- Predicting that customer will not attrite but he attrites i.e. losing on a valuable customer or asset.

How to reduce this loss i.e the need to reduce False Negatives?

- **Bank would want `Recall` to be maximized**, greater the Recall higher the chances of minimizing false negatives. Hence, the focus should be on increasing Recall or minimizing the false negatives or in other words identifying the true positives (i.e. Class 1) so that the bank can retain their valuable customers by identifying the customers who are at risk of attrition.

Also, let's create a function to calculate and print the classification report and confusion matrix so that we don't have to rewrite the same code repeatedly for each model.

In [202…

```
# Creating metric function

def metrics_score(actual, predicted):
    print(classification_report(actual, predicted))
    cm = confusion_matrix(actual, predicted)
    plt.figure(figsize=(8,5))
    sns.heatmap(cm, annot=True,  fmt='.2f', xticklabels=['Not Attrite', 'Att
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    plt.show()
```

Building the model

We will be building 4 different models:

- **Logistic Regression**
- **Support Vector Machine(SVM)**
- **Decision Tree**
- **Random Forest**

Logistic Regression Model

- Logistic Regression is a supervised learning algorithm that is used for **binary classification problems** i.e. where the dependent variable is categorical and has only two possible values. In logistic regression, we use the sigmoid function to calculate the probability of an event y, given some features x as:

```
P(y)=1/(1 + exp(-x))
```

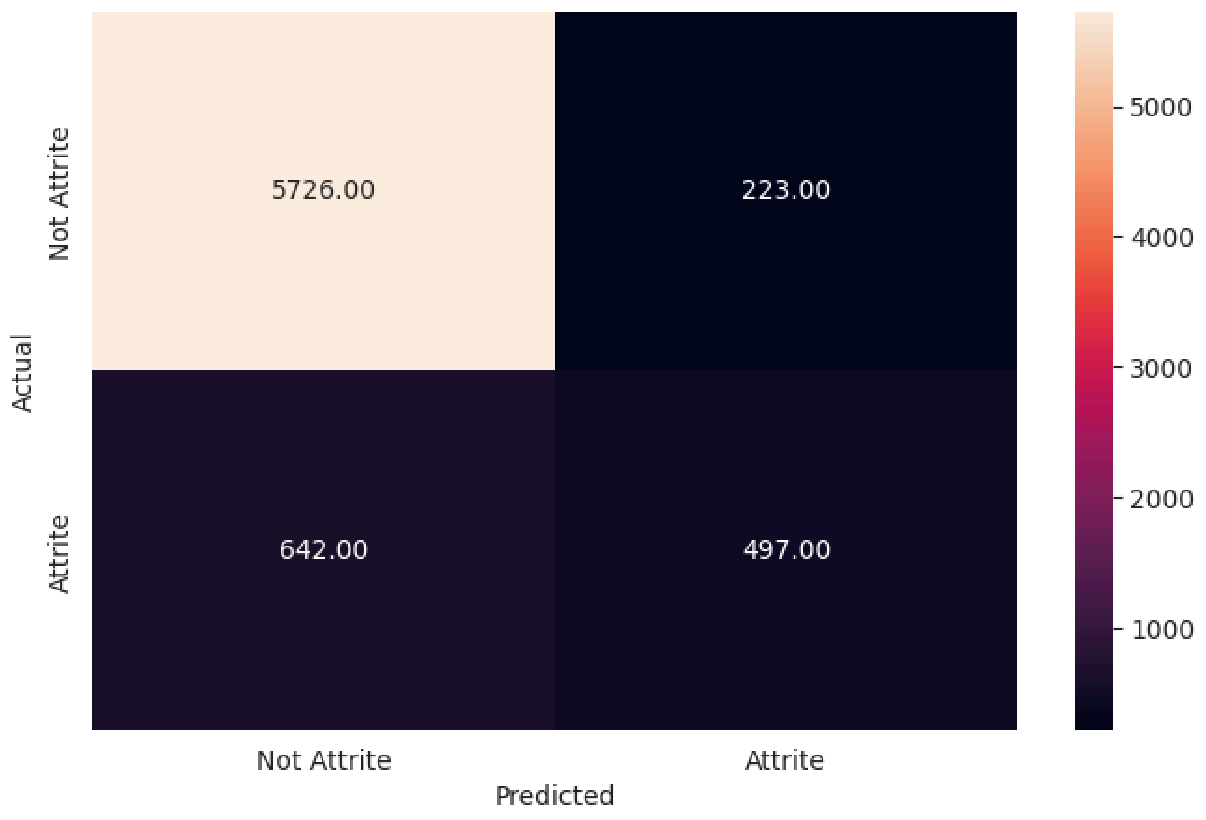
In [203…
```
# Fitting logistic regression model

lg = LogisticRegression()
lg.fit(X_train,y_train)
```

Out[203…
```
▾ LogisticRegression
LogisticRegression()
```

Let's check the model performance

In [204…
```
# Checking the performance on the training data

y_pred_train = lg.predict(X_train)

metrics_score(y_train, y_pred_train)
```

```
              precision    recall  f1-score   support

           0       0.90      0.96      0.93      5949
           1       0.69      0.44      0.53      1139

    accuracy                           0.88      7088
   macro avg       0.79      0.70      0.73      7088
weighted avg       0.87      0.88      0.87      7088
```



- The reported average includes the macro average which averages the unweighted mean per label, and the weighted average i.e. averaging the support-weighted mean per label.
- In classification, the class of interest is considered the positive class. Here, the class of interest is 1 i.e. identifying the customers who are at risk of attrition.

Reading the confusion matrix (clockwise):

- True Negative (Actual=0, Predicted=0): Model predicts that a customer would not attrite and the customer does not attrite

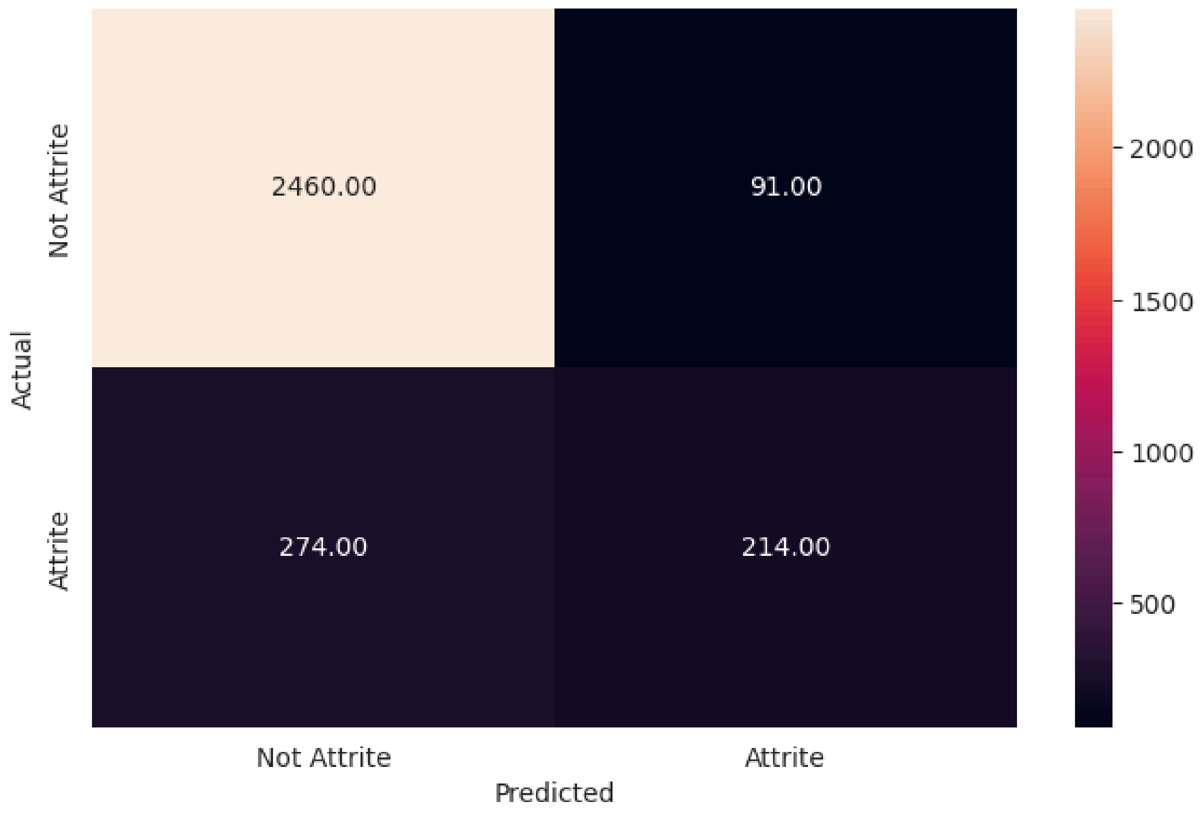
- False Positive (Actual=0, Predicted=1): Model predicts that a customer would attrite but the customer does not attrite

- False Negative (Actual=1, Predicted=0): Model predicts that a customer would not attrite but the customer attrites

- True Positive (Actual=1, Predicted=1): Model predicts that a customer would attrite and the customer attrites

In [205…
```
# Checking the performance on the test dataset

y_pred_test = lg.predict(X_test)

metrics_score(y_test, y_pred_test)
```

```
              precision    recall  f1-score   support

           0       0.90      0.96      0.93      2551
           1       0.70      0.44      0.54       488

    accuracy                           0.88      3039
   macro avg       0.80      0.70      0.74      3039
weighted avg       0.87      0.88      0.87      3039
```



Observations:

- **We are getting an accuracy of around 90%** on train and test dataset.
- However, **the recall for this model is only around 44% for class 1 on train and test dataset.**
- As the recall is low, **this model will not perform well** in differentiating out those customers who have a high chance of leaving the bank, meaning it will eventually not help in reducing the attrition rate.
- As we can see from the Confusion Matrix, **this model fails to identify the majority of customers who will attrite.**

Let's check the coefficients and find which variables are leading to attrition and which can help to reduce the attrition:

In [206…
```
# Printing the coefficients of logistic regression

cols=X_train.columns
```

```
coef_lg=lg.coef_

pd.DataFrame(coef_lg,columns=cols).T.sort_values(by=0,ascending=False)
```

Out[206…

	0
Contacts_Count_12_mon	0.31531
Months_Inactive_12_mon	0.24919
Dependent_count	0.20002
Customer_Age	0.11755
Income_Category_Less than $40K	0.05269
Marital_Status_Single	0.04579
Education_Level_Graduate	0.01085
Education_Level_Post-Graduate	0.00870
Education_Level_Doctorate	0.00737
Education_Level_Uneducated	0.00455
Card_Category_Silver	0.00365
Card_Category_Gold	0.00318
Income_Category_$40K-$60K	0.00264
Card_Category_Platinum	0.00175
Avg_Utilization_Ratio	0.00137
Total_Trans_Amt	0.00038
Avg_Open_To_Buy	0.00034
Education_Level_High School	-0.00032
Credit_Limit	-0.00035
Total_Revolving_Bal	-0.00068
Income_Category_$80K-$120K	-0.00609
Total_Amt_Chng_Q4_Q1	-0.01180
Income_Category_$60K-$80K	-0.01614
Marital_Status_Married	-0.01957
Gender_M	-0.03225
Total_Ct_Chng_Q4_Q1	-0.05203
Months_on_book	-0.09103
Total_Trans_Ct	-0.09617
Total_Relationship_Count	-0.21321

Observations:

Features which positively affect on the attrition rate are:

- Contacts_Count_12_mon
- Months_Inactive_12_mon
- Dependent_count
- Customer_Age
- Income_Category_Less than $40K
- Marital_Status_Single
- Education_Level_Graduate
- Education_Level_Post-Graduate
- Education_Level_Doctorate
- Avg_Utilization_Ratio

Features which negatively affect on the attrition rate are:

- Total_Relationship_Count
- Total_Trans_Ct
- Months_on_book
- Total_Ct_Chng_Q4_Q1
- Marital_Status_Married
- Income_Category_ 60K– 80K
- Total_Amt_Chng_Q4_Q1

Observations:

- Based on the Logistic Regression model, **Contacts_Count_12_mon is the most important feature** in detecting whether a customer would attrite or not. So, the highest attrition is among the customers who interacted the most with the bank.

This signifies that the bank is not able to resolve the problems faced by customers leading to attrition

- **This model also suggests that attrition is dependent on the customers' activity.** As inactivity increases attrition also increases.

- **Dependent_count is an important variable in predicting the attrition rate.** As more the number of dependents more is the attrition, more responsibilities might lead to financial instability in such customers.

- Education level of customers also have some interesting outcome. Customers with higher education - Doctorates and Post Graduates are the ones most attriting.

- The customers belonging to the income group - Earning less than 40K are the ones attriting the most.

- Other features which appear to affect the chances of attrition are Marital Status, Avg Utilization ratio.
- The model also captures the **inverse relation between Total_Relationship_Count and attrition** - suggesting customer who uses more number of products from the bank are the ones least attriting, such customers might be more financially stable and actively invest in different services provided by the bank.
- **Customers who are doing more transactions with the bank have a lower chance of attrition**, a conclusion that makes sense since Less number of transactions leads to higher attrition.
- From Total_Ct_Chng_Q4_Q1 and Total_Amt_Chng_Q4_Q1 it's clear that Customers who didn't attrite showed less variability across Q4 to Q1 as compared to the ones who attrited.

The coefficients of the **logistic regression** model give us the **log of odds**, which is hard to interpret in the real world. We can convert the **log of odds into real odds** by taking its exponential.

In [207…

```
# Finding the odds
odds = np.exp(lg.coef_[0])

# Adding the odds to a dataframe and sorting the values
pd.DataFrame(odds, X_train.columns, columns=['odds']).sort_values(by='odds',
```

Out[207…

	odds
Contacts_Count_12_mon	1.37069
Months_Inactive_12_mon	1.28299
Dependent_count	1.22143
Customer_Age	1.12474
Income_Category_Less than $40K	1.05410
Marital_Status_Single	1.04686
Education_Level_Graduate	1.01091
Education_Level_Post-Graduate	1.00874
Education_Level_Doctorate	1.00739
Education_Level_Uneducated	1.00456
Card_Category_Silver	1.00366
Card_Category_Gold	1.00319
Income_Category_$40K-$60K	1.00265
Card_Category_Platinum	1.00176
Avg_Utilization_Ratio	1.00137
Total_Trans_Amt	1.00038
Avg_Open_To_Buy	1.00034
Education_Level_High School	0.99968
Credit_Limit	0.99965
Total_Revolving_Bal	0.99932
Income_Category_$80K-$120K	0.99392
Total_Amt_Chng_Q4_Q1	0.98827
Income_Category_$60K-$80K	0.98399
Marital_Status_Married	0.98062
Gender_M	0.96826
Total_Ct_Chng_Q4_Q1	0.94930
Months_on_book	0.91299
Total_Trans_Ct	0.90831
Total_Relationship_Count	0.80799

Observations

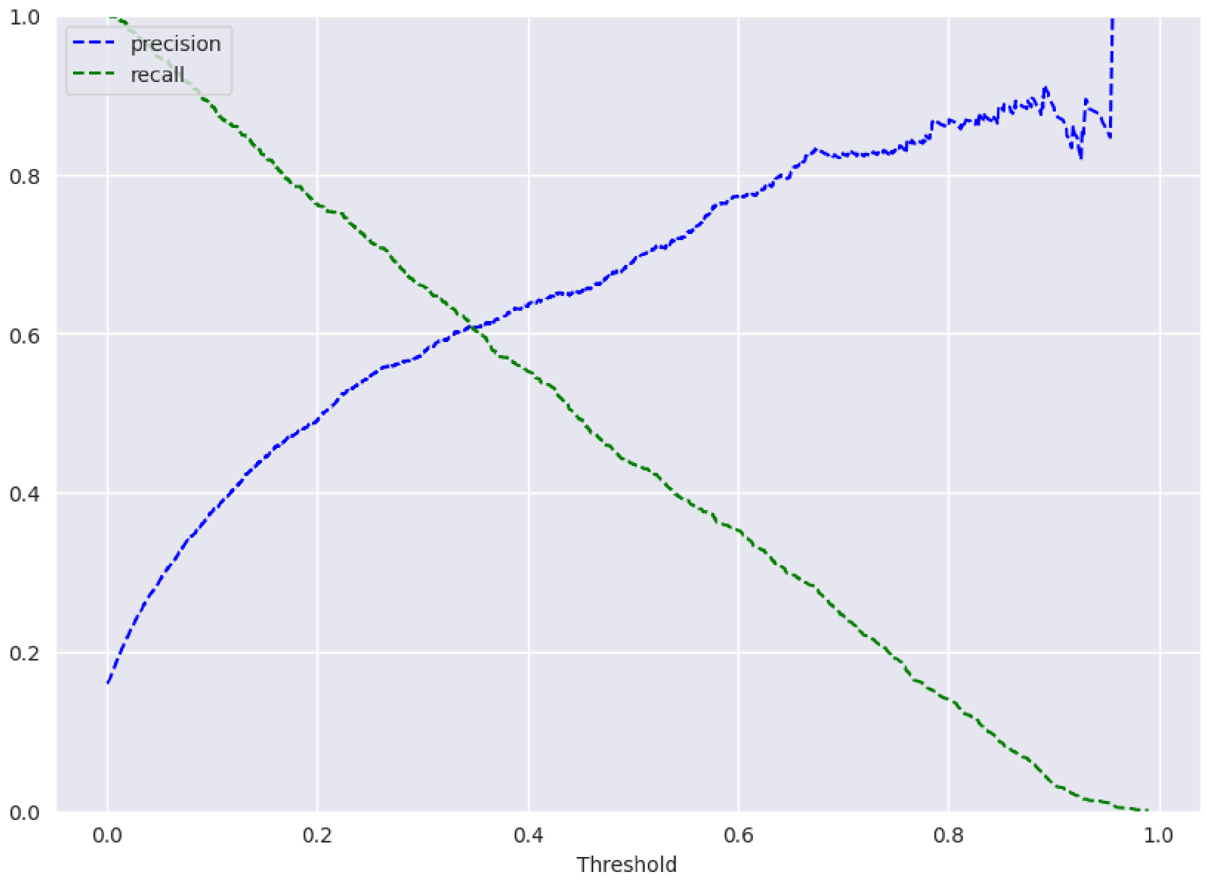
- The odds of a customers contacting with the bank more to attrite are **1.3 times** the odds of one who is not, probably due to the fact that the bank is not able to resolve the problems faced by customers leading to attrition.
- The odds of a customer being inactive to attrite are **1.2 times** the odds of a customer who is actively in touch with bank.
- The odds of a customer with more dependent attriting are **1.2 times** the odds of a customer with less or no dependent.

Precision-Recall Curve for logistic regression

Precision-Recall curves summarize the trade-off between the true positive rate and the positive predictive value for a predictive model using different probability thresholds.

In [208…

```
# Predict_proba gives the probability of each observation belonging to each

y_scores_lg=lg.predict_proba(X_train)

precisions_lg, recalls_lg, thresholds_lg = precision_recall_curve(y_train, y

# Plot values of precisions, recalls, and thresholds
plt.figure(figsize=(10,7))
plt.plot(thresholds_lg, precisions_lg[:-1], 'b--', label='precision')
plt.plot(thresholds_lg, recalls_lg[:-1], 'g--', label = 'recall')
plt.xlabel('Threshold')
plt.legend(loc='upper left')
plt.ylim([0,1])
plt.show()
```



```
In [209…  # Calculating the exact threshold where precision and recall are equal.

          for i in np.arange(len(thresholds_lg)):
              if precisions_lg[i]==recalls_lg[i]:
                  print(thresholds_lg[i])
```

```
0.34806960434560535
```

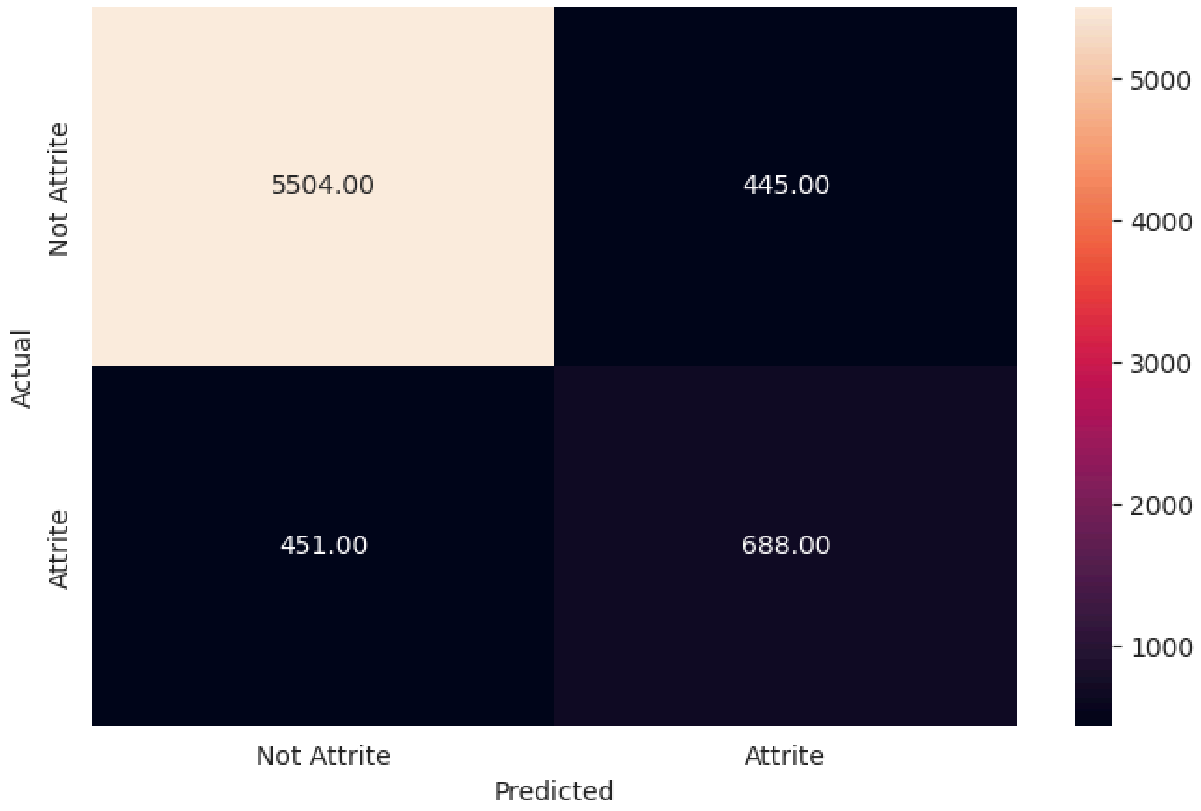
Observation:

- We can see that precision and recall are balanced for a threshold of about ~**0.35**.

Let's find out the performance of the model at this threshold

```
In [210…  optimal_threshold=.35
          y_pred_train = lg.predict_proba(X_train)
          metrics_score(y_train, y_pred_train[:,1]>optimal_threshold)
```

```
              precision    recall  f1-score   support

           0       0.92      0.93      0.92      5949
           1       0.61      0.60      0.61      1139

    accuracy                           0.87      7088
   macro avg       0.77      0.76      0.77      7088
weighted avg       0.87      0.87      0.87      7088
```



Observations:

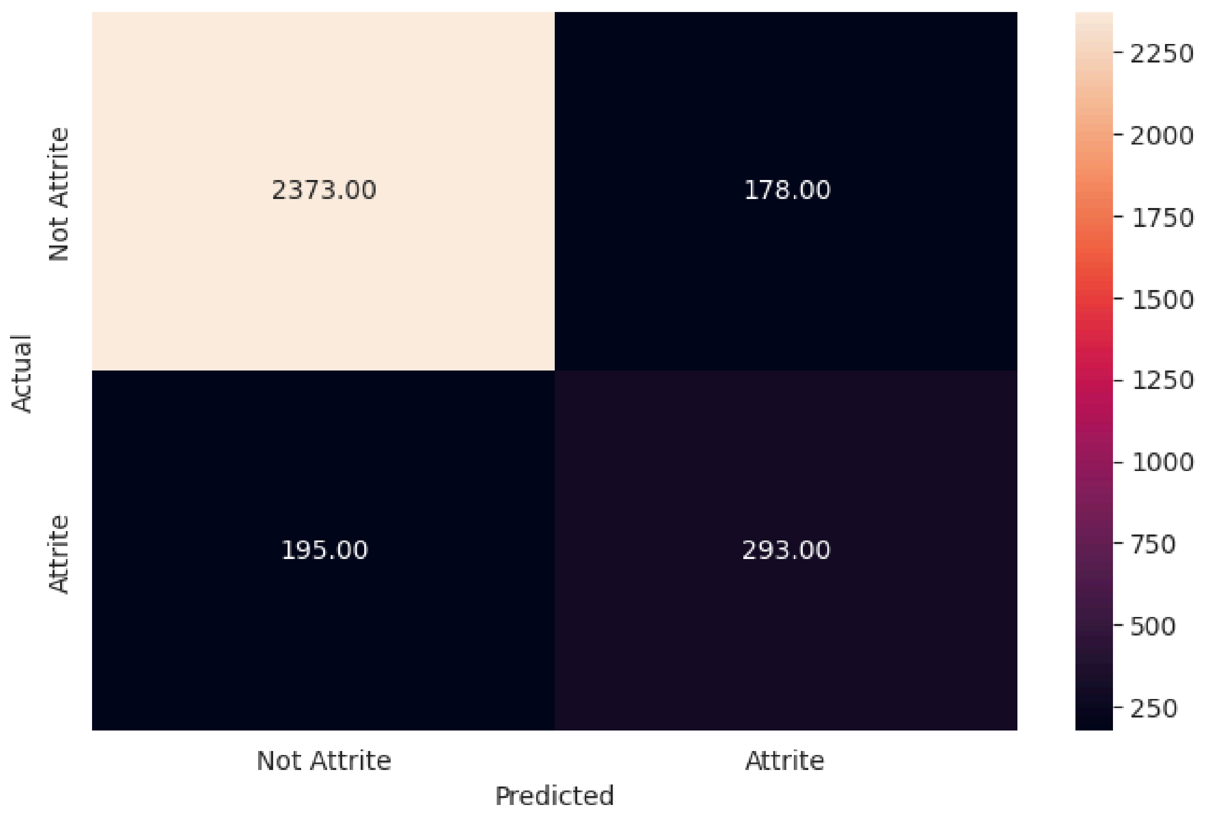
- The model performance has improved. The recall has increased significantly for class 1.

Let's check the performance on the test data.

In [211…

```
optimal_threshold1=.35
y_pred_test = lg.predict_proba(X_test)
metrics_score(y_test, y_pred_test[:,1]>optimal_threshold1)
```

```
              precision    recall  f1-score   support

           0       0.92      0.93      0.93      2551
           1       0.62      0.60      0.61       488

    accuracy                           0.88      3039
   macro avg       0.77      0.77      0.77      3039
weighted avg       0.88      0.88      0.88      3039
```



Observation:

- The model is giving a **similar performance on the test and train data** i.e. the model is giving a generalized performance.
- **The recall of the test data has increased significantly** while at the same time, the precision has decreased slightly, which is to be expected while adjusting the threshold.
- The average recall and precision for the model are good but let's see if we can get better performance using other algorithms.

Support Vector Machines

In [212…
```
# To Speed-Up SVM training.

scaling = MinMaxScaler(feature_range=(-1,1)).fit(X_train)
X_train_scaled = scaling.transform(X_train)
X_test_scaled = scaling.transform(X_test)
```

Let's build the models using the two of the widely used kernel functions:

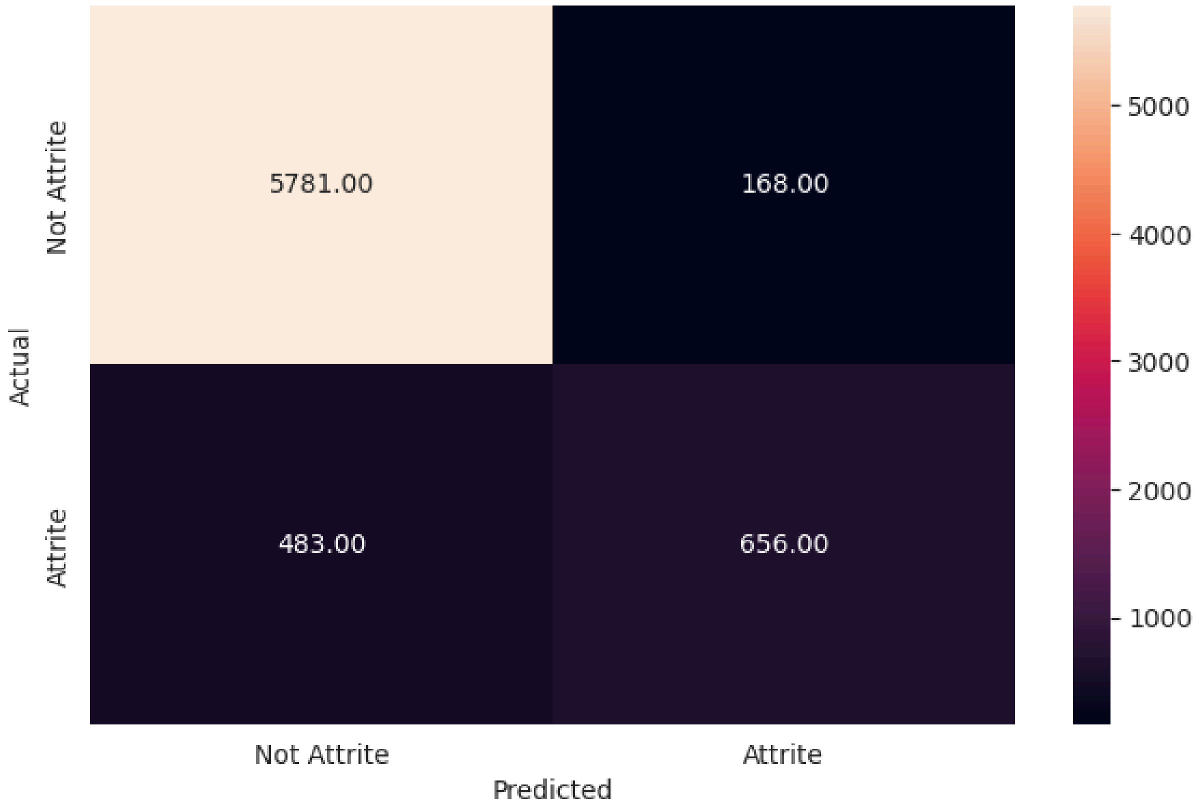
1. **Linear Kernel**
2. **RBF Kernel**

Linear Kernel

```
In [213…  # Fitting SVM
          svm = SVC(kernel = 'linear') # Linear kernel or linear decision boundary
          model = svm.fit(X = X_train_scaled, y = y_train)
```

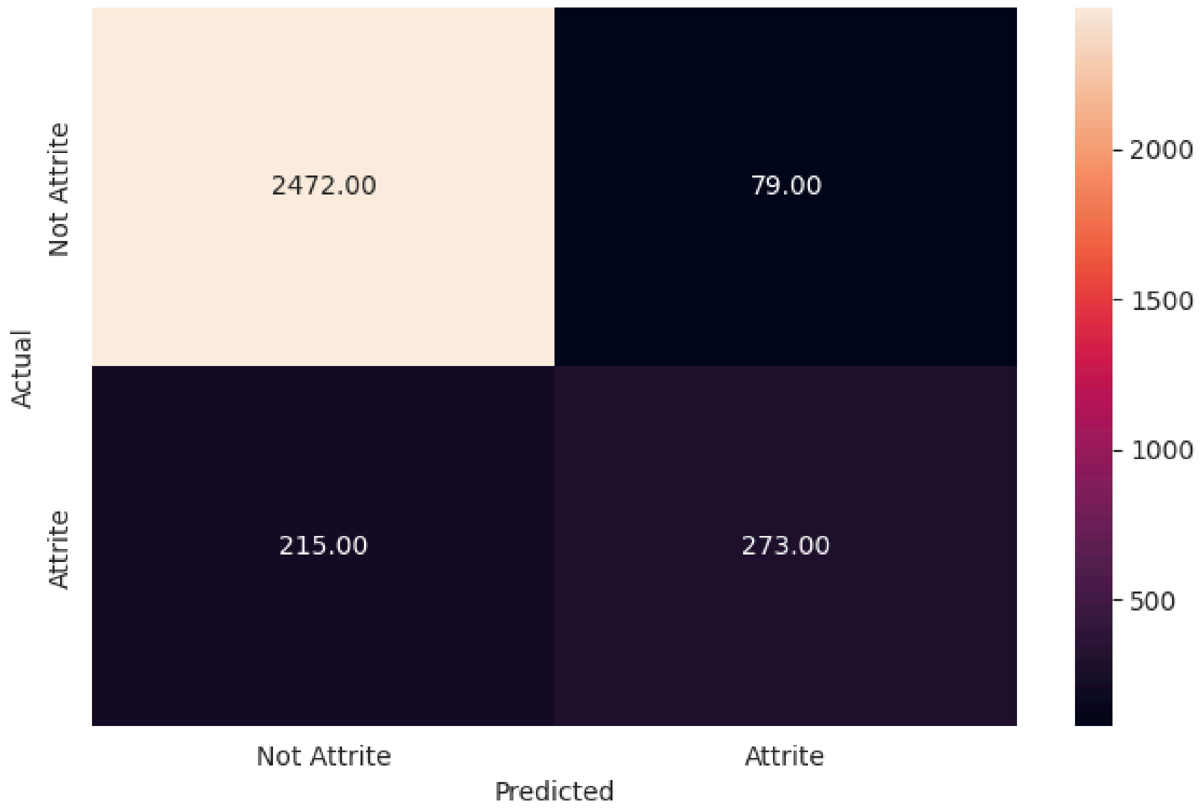
```
In [214…  y_pred_train_svm = model.predict(X_train_scaled)

          metrics_score(y_train, y_pred_train_svm)
```

```
              precision    recall  f1-score   support

           0       0.92      0.97      0.95      5949
           1       0.80      0.58      0.67      1139

    accuracy                           0.91      7088
   macro avg       0.86      0.77      0.81      7088
weighted avg       0.90      0.91      0.90      7088
```



```
In [215…  # Checking performance on the test data
          y_pred_test_svm = model.predict(X_test_scaled)
          metrics_score(y_test, y_pred_test_svm)
```

```
              precision    recall  f1-score   support

           0       0.92      0.97      0.94      2551
           1       0.78      0.56      0.65       488

    accuracy                           0.90      3039
   macro avg       0.85      0.76      0.80      3039
weighted avg       0.90      0.90      0.90      3039
```

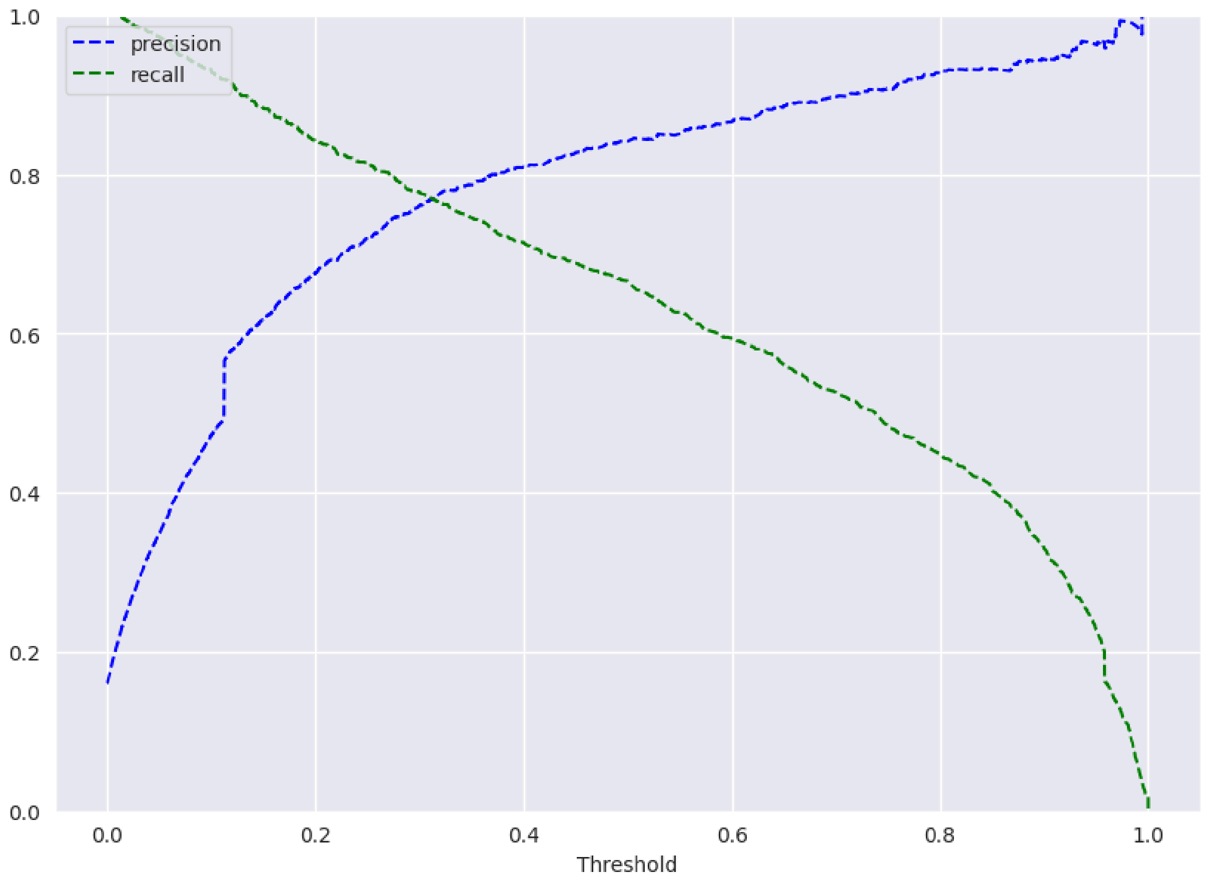


- SVM model with linear kernel is not overfitting as the accuracy is around 90% for both train and test dataset.
- Recall of class 1 for the model is only around 55% which implies our model will not correctly predict the customers who are likely to attrite.
- The precision is quite good and the model will help to find true positive and will save the cost and energy of the bank.

RBF Kernel

In [216…

```
svm_rbf=SVC(kernel='rbf',probability=True)
svm_rbf.fit(X_train_scaled,y_train)
y_scores_svm=svm_rbf.predict_proba(X_train_scaled) # Predict_proba gives the


precisions_svm, recalls_svm, thresholds_svm = precision_recall_curve(y_trair

# Plot values of precisions, recalls, and thresholds
plt.figure(figsize=(10,7))
plt.plot(thresholds_svm, precisions_svm[:-1], 'b--', label='precision')
plt.plot(thresholds_svm, recalls_svm[:-1], 'g--', label = 'recall')
plt.xlabel('Threshold')
plt.legend(loc='upper left')
plt.ylim([0,1])
plt.show()
```



In [217…

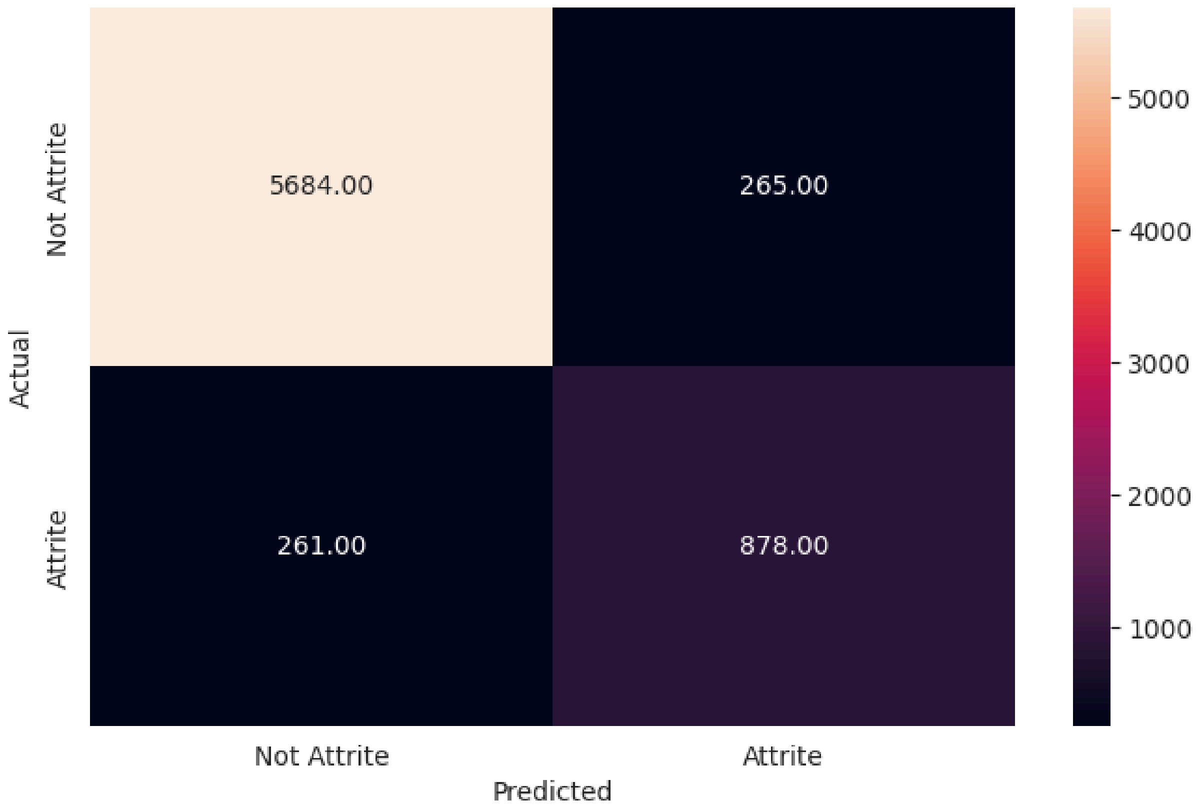
```
# Calculating the exact threshold where precision and recall are equal.
for i in np.arange(len(thresholds_svm)):
    if precisions_svm[i]==recalls_svm[i]:
        print(thresholds_svm[i])
```

```
0.3122015685746674
```

In [218…

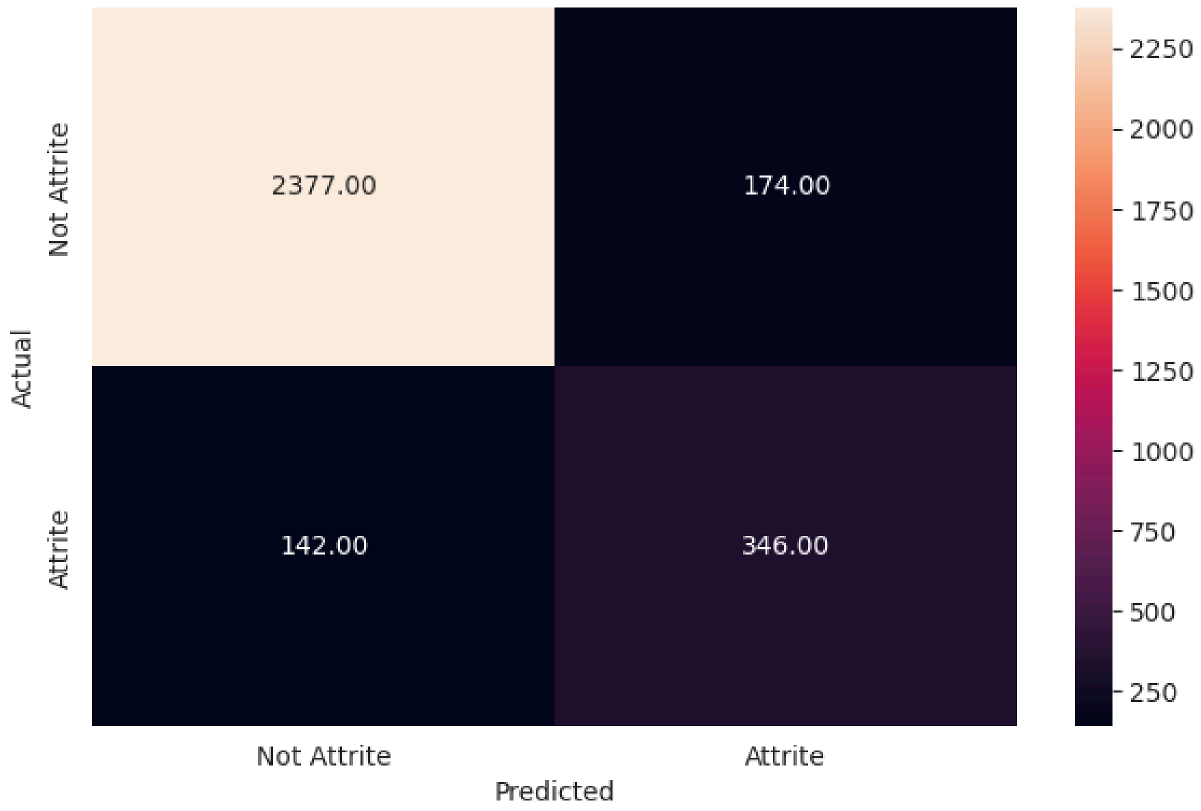
```
optimal_threshold1=0.31
y_pred_train = svm_rbf.predict_proba(X_train_scaled)

metrics_score(y_train, y_pred_train[:,1]>optimal_threshold1)
```

```
              precision    recall  f1-score   support

           0       0.96      0.96      0.96      5949
           1       0.77      0.77      0.77      1139

    accuracy                           0.93      7088
   macro avg       0.86      0.86      0.86      7088
weighted avg       0.93      0.93      0.93      7088
```



```
In [219…  y_pred_test = svm_rbf.predict_proba(X_test_scaled)

          metrics_score(y_test, y_pred_test[:,1]>optimal_threshold1)
```

```
              precision    recall  f1-score   support

           0       0.94      0.93      0.94      2551
           1       0.67      0.71      0.69       488

    accuracy                           0.90      3039
   macro avg       0.80      0.82      0.81      3039
weighted avg       0.90      0.90      0.90      3039
```



Observations:

- At the optimal threshold of .31, the model performance has improved significantly. The recall has improved from 0.55 to .77 which is a ~20% increase and the model is giving good generalized results.
- Moreover, the kernel used to create this is rbf, hence model is performing good with non-linear kernel.
- As the recall is good, **this model will perform well** in differentiating out those customers who have a high chance of leaving the bank, meaning it will eventually help in reducing the attrition rate.

Decision Tree

In [220…

```
# Building decision tree model

model_dt= DecisionTreeClassifier(random_state=1,max_depth=8)
model_dt.fit(X_train, y_train)
```

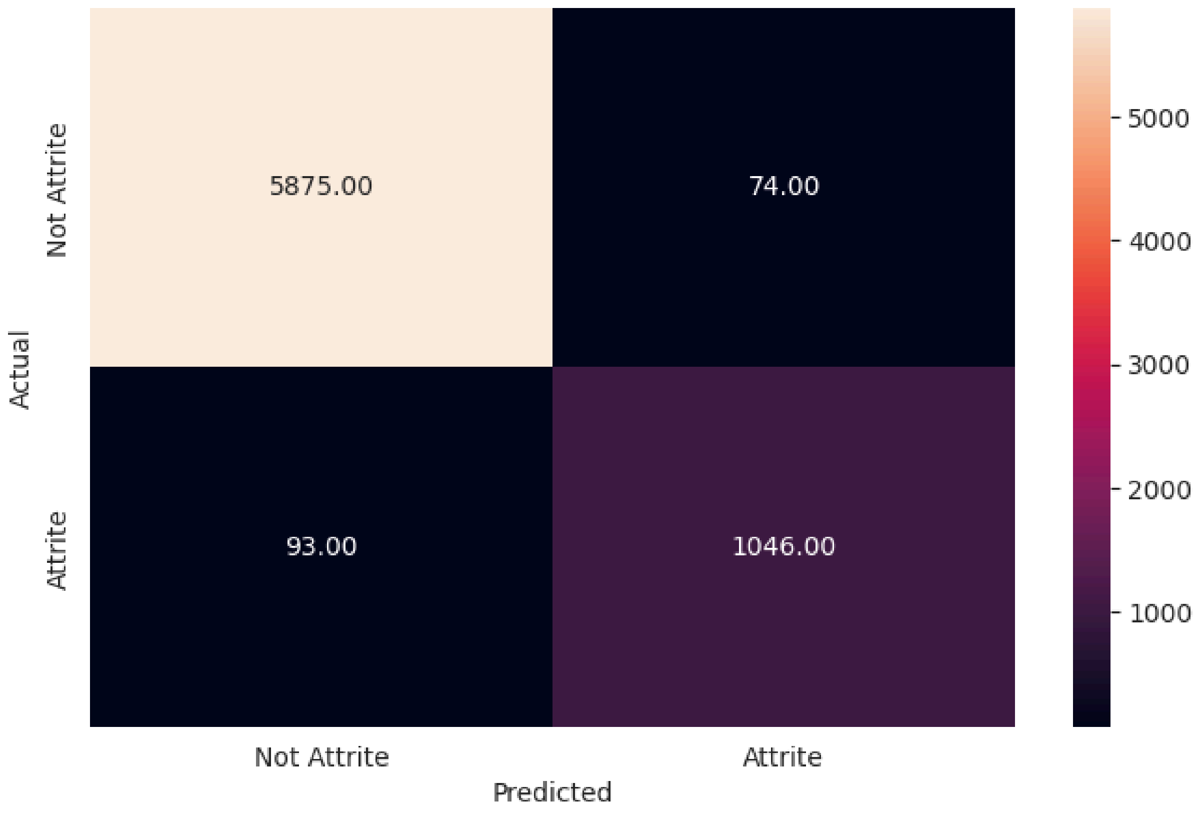
Out[220…

```
▾                DecisionTreeClassifier
DecisionTreeClassifier(max_depth=8, random_state=1)
```

Let's check the model performance of decision tree

```
In [221…  # Checking performance on the training dataset

          pred_train_dt = model_dt.predict(X_train)

          metrics_score(y_train, pred_train_dt)
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      5949
           1       0.93      0.92      0.93      1139

    accuracy                           0.98      7088
   macro avg       0.96      0.95      0.96      7088
weighted avg       0.98      0.98      0.98      7088
```



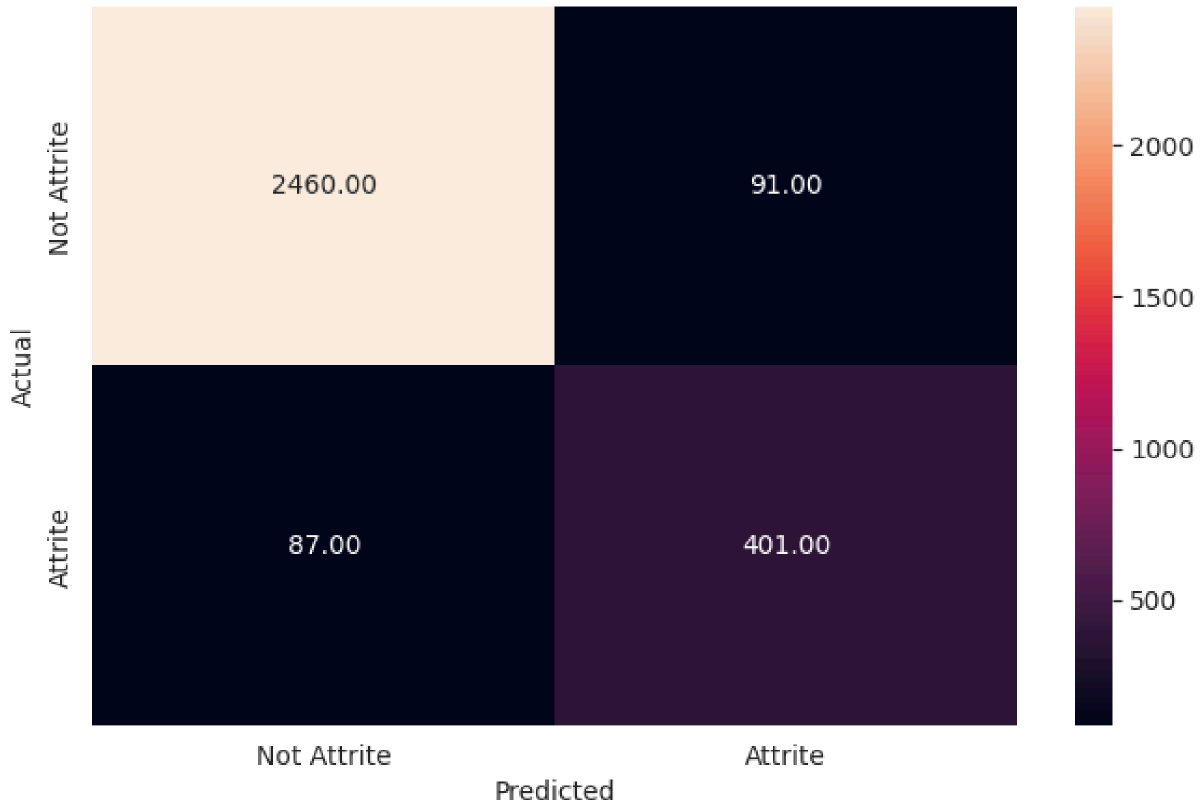
Observation:

- Model has performed very well on the training set.
- As we know a decision tree will continue to grow and classify each data point correctly if no restrictions are applied as the trees will learn all the patterns in the training set.

Let's check the performance on test data to see if the model is overfitting.

```
In [222…  pred_test_dt = model_dt.predict(X_test)
          metrics_score(y_test, pred_test_dt)
```

```
              precision    recall  f1-score   support

           0       0.97      0.96      0.97      2551
           1       0.82      0.82      0.82       488

    accuracy                           0.94      3039
   macro avg       0.89      0.89      0.89      3039
weighted avg       0.94      0.94      0.94      3039
```



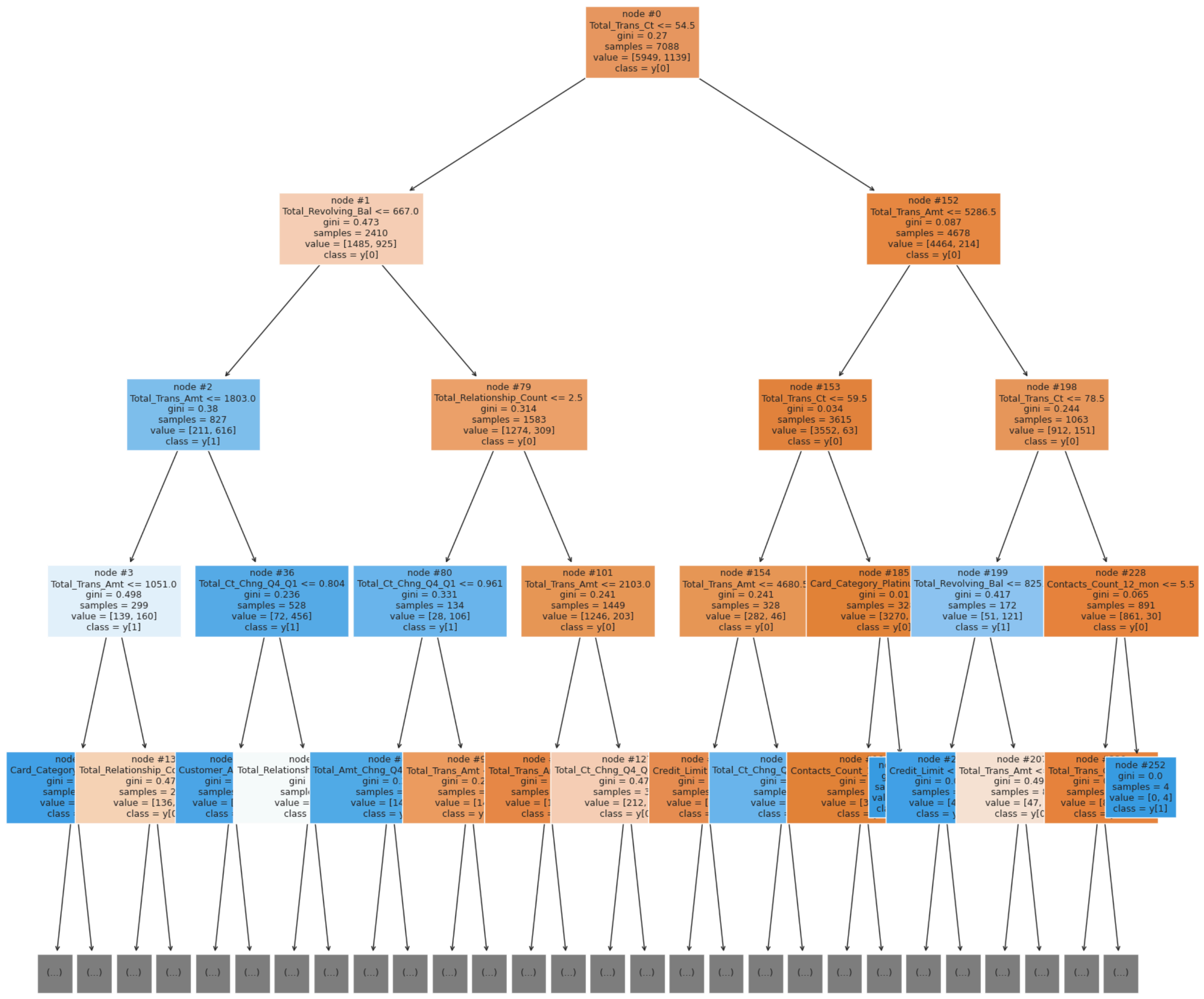
Observation:

- The decision tree model is slightly overfitting the data here.
- We can tune the hyperparameters to increase the performance and reduce overfitting.

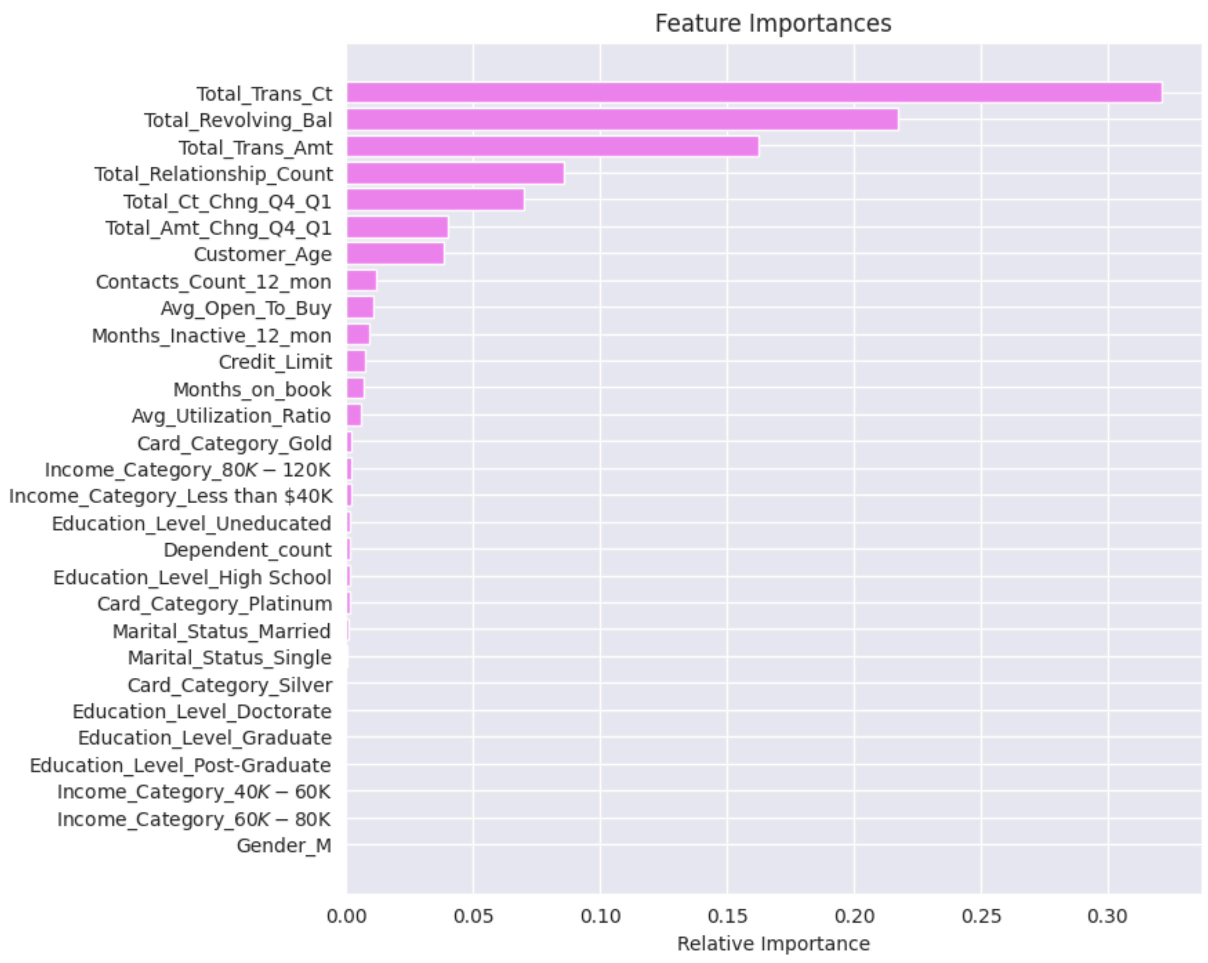
Let's visualize the decision tree and observe the decision rules:

In [223…

```
features = list(X_train.columns)

plt.figure(figsize=(20,20))
from sklearn import tree
tree.plot_tree(model_dt,feature_names=features,max_depth =4, filled=True,for
plt.show()
```



```
In [224…  # Importance of features in the tree building

          feature_names = list(X_train.columns)
          importances = model_dt.feature_importances_
          indices = np.argsort(importances)

          plt.figure(figsize=(8, 8))
          plt.title("Feature Importances")
          plt.barh(range(len(indices)), importances[indices], color="violet", align="c
          plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
          plt.xlabel("Relative Importance")
          plt.show()
```



Observation:

- **So,Total_Trans_Ct is the most important feature followed by Total_Revolving_Bal and Total_Trans_Amt** which makes sense. Customers who are doing more transactions with the bank have lower chance of attrition.
- **Total_Ct_Chng_Q4_Q1, Total_Relationship_Count, Total_Amt_Chng_Q4_Q1 are also important factors** .

Random Forest

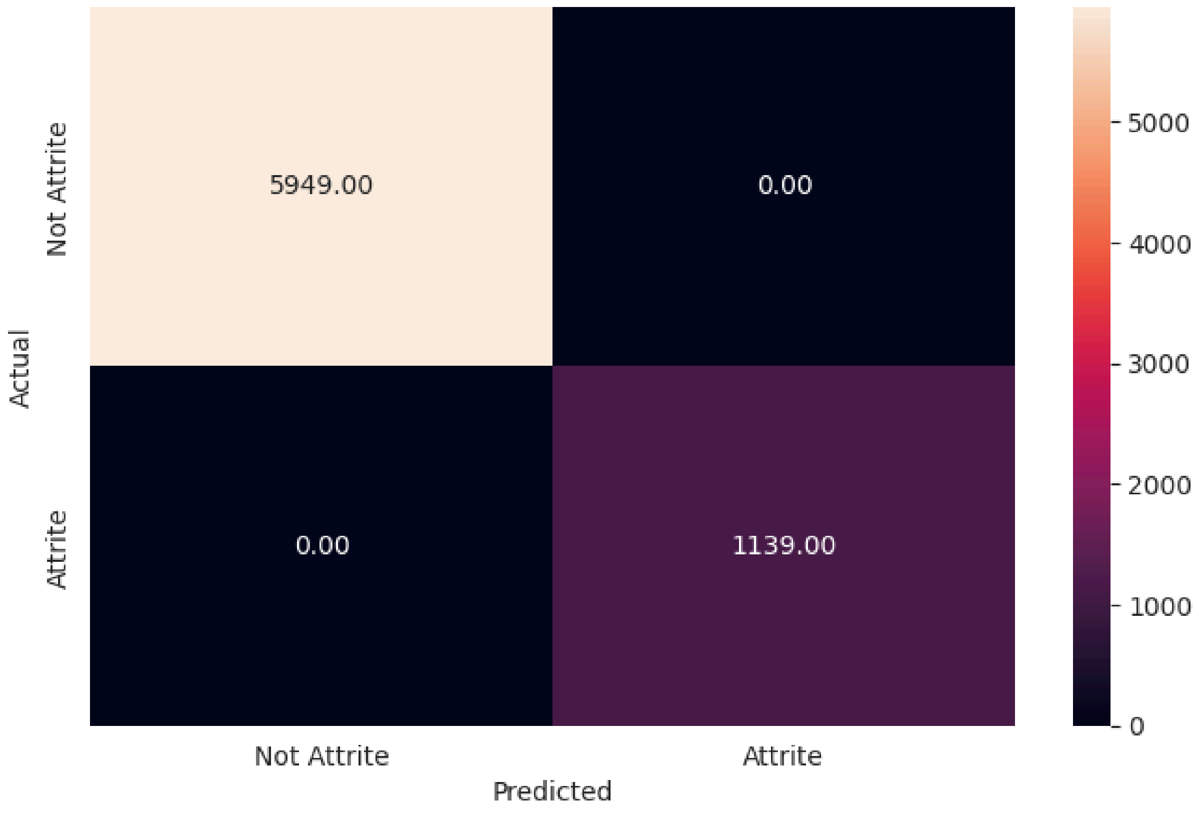
In [225…
```
# Fitting the Random Forest classifier on the training data
rf_estimator = RandomForestClassifier(random_state = 1)

rf_estimator.fit(X_train, y_train)
```

Out[225…
```
▾ RandomForestClassifier
RandomForestClassifier(random_state=1)
```

In [226…
```
# Checking performance on the training data
y_pred_train_rf = rf_estimator.predict(X_train)
```

```
metrics_score(y_train, y_pred_train_rf)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      5949
           1       1.00      1.00      1.00      1139

    accuracy                           1.00      7088
   macro avg       1.00      1.00      1.00      7088
weighted avg       1.00      1.00      1.00      7088
```

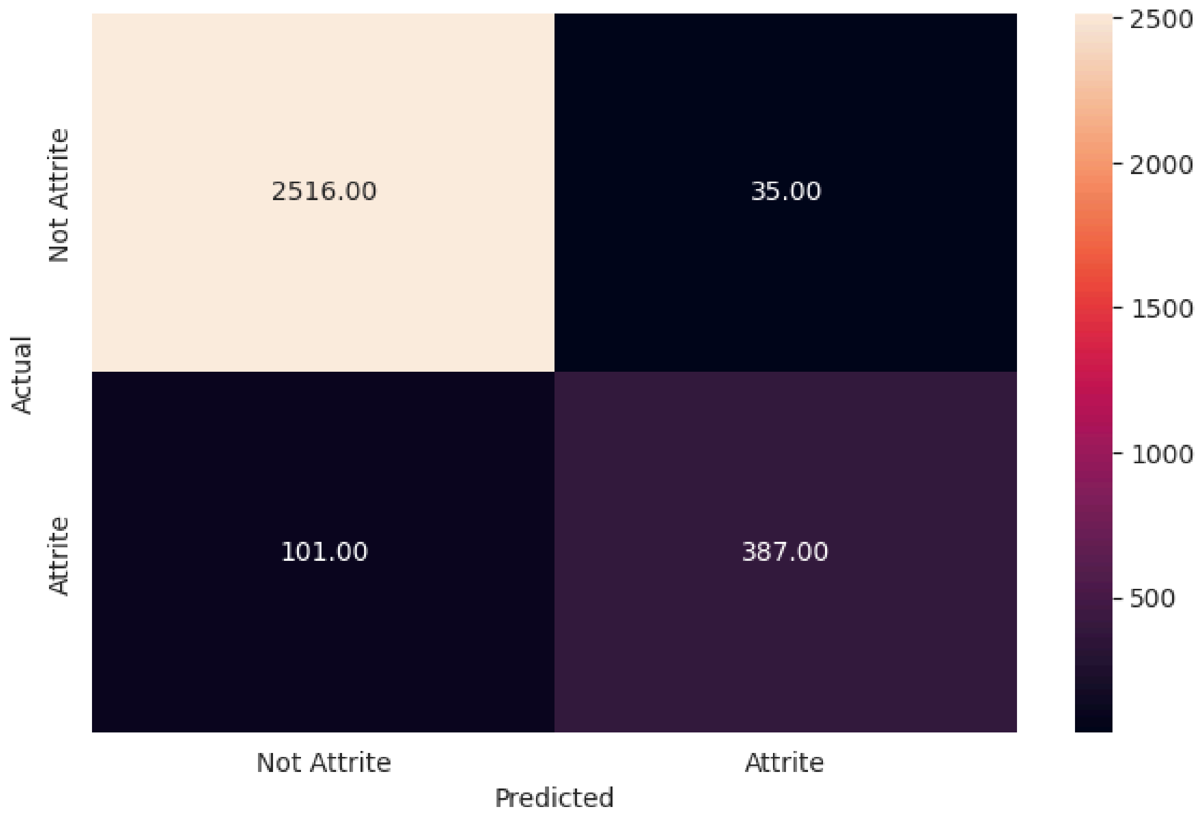


Observation:

- For all the metrics in the training dataset, the Random Forest gives a 100% score.

```
In [227…
# Checking performance on the testing data
y_pred_test_rf = rf_estimator.predict(X_test)

metrics_score(y_test, y_pred_test_rf)
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.97      2551
           1       0.92      0.79      0.85       488

    accuracy                           0.96      3039
   macro avg       0.94      0.89      0.91      3039
weighted avg       0.95      0.96      0.95      3039
```



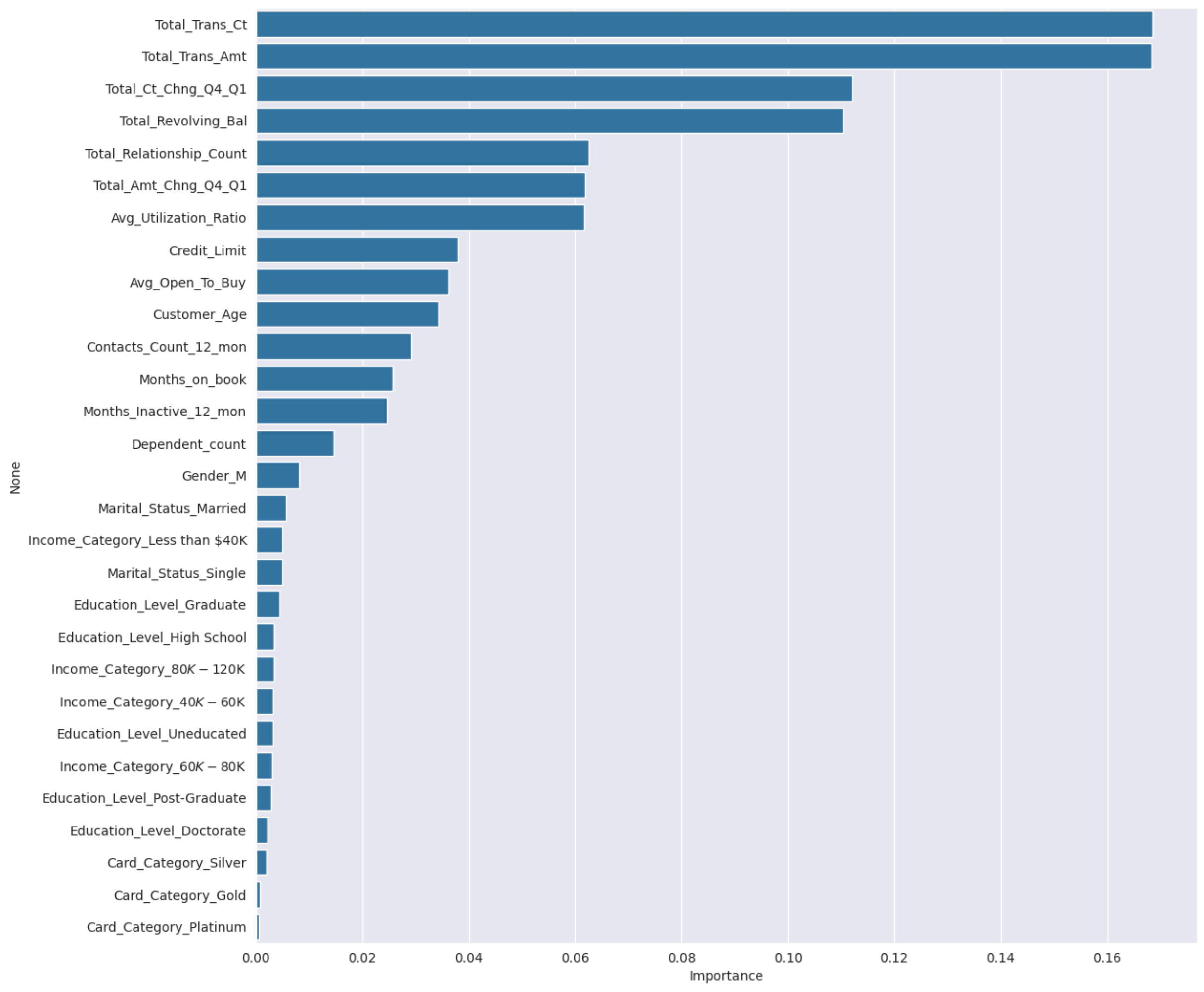
Observations:

- The Random Forest classifier **seems to be overfitting the training data**. The recall on the training data is 1, while the recall on the test data is only ~ 0.80 for class 1.
- Precision is high for the test data as well.

Let's check the feature importance of the Random Forest

In [228…
```
importances = rf_estimator.feature_importances_

columns = X_train.columns

importance_df = pd.DataFrame(importances, index = columns, columns = ['Impor

plt.figure(figsize = (13, 13))

sns.barplot(x = importance_df.Importance, y = importance_df.index)
```

Out[228…
```
<Axes: xlabel='Importance', ylabel='None'>
```



Observations:

- The Random Forest further verifies the results from the decision tree that the most important features are `Total_Trans_ct` and `Total_Trans_Amt`.

Business Recommendations:

- We have been able to build a predictive model:

  a) that the bank can deploy to identify customers who are at risk of attrition.

  b) that the bank can use to find the key causes that drive attrition.

  c) based on which the bank can take appropriate actions to build better retention policies for customers.

- Factors that drive attrition - Total_Trans_Ct, Total_Revolving_Bal, Total_Trans_Amt, Total_Relationship_Count
- Total_Trans_Ct: Less number of transactions in a year leads to attrition of a customer - to increase the usage of cards the bank can provide offers like

cashback, special discounts on the purchase of something, etc so that customers feel motivated to use their cards.

- Total_Revolving_Bal: Customers with less total revolving balance are the ones who attrited, such customers must have cleared their dues and opted out of the credit card service. After the customer has cleared the dues bank can ask for feedback on their experience and get to the cause of attrition.
- Total_Trans_Amt: Less number of transactions can lead to less transaction amount and eventually leads to customer attrition - Bank can provide offers on the purchase of costlier items which in turn will benefit the customers and bank both.
- Total_Relationship_Count: Attrition is highest among the customers who are using 1 or 2 products offered by the bank - together they constitute ~55% of the attrition - Bank should investigate here to find the problems customers are facing with these products. Customer support, or more transparency can help in retaining customers.
- Female customers should be the target customers for any kind of marketing campaign as they are the ones who utilize their credits, make more and higher amount transactions. But their credit limit is less, so increasing the credit limit for such customers can profit the bank.
- Months_Inactive: As inactivity increases the attrition also increases. 2-4 months of inactivity are the biggest contributors of attrition - Bank can send automated messages to engage customers, these messages can be about their monthly activity, new offers or services, etc.
- Highest attrition is among the customers who interacted/reached out the most with/to the bank, this indicates that the bank is not able to resolve the problems faced by customers leading to attrition - a feedback collection system can be set up to check if the customers are satisfied with the resolution provided, if not, the bank should act upon it accordingly.