MSIN0097 Individual Coursework - Credit Card Churn Prediction-2

April 19, 2024

Word Count: 1392

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf

from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪classification_report, roc_auc_score
from sklearn.metrics import roc_curve, precision_recall_curve, roc_auc_score,␣
↪PrecisionRecallDisplay,precision_recall_fscore_support
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.neural_network import MLPClassifier
from numpy import mean
from sklearn.datasets import make_classification
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RepeatedStratifiedKFold
from xgboost import XGBClassifier
from tensorflow.keras import layers, models, losses, metrics
from tensorflow.keras.datasets import mnist
from tensorflow import keras
```

Business Problem: A consumer credit card bank is facing the problem of customer attrition. The dataset contains a series of customer data including demographic characteristics and and historical activities, along with a variable 'Attrition_Flag' to label existing customer or attrited customer. The dataset is downloaded from Kaggle: https://www.kaggle.com/datasets/anwarsan/credit-card-bank-churn/data

Overall Strategy: The object is to build a predictive model to predict whether a customer will become attrited or not based on the information in the dataset. For those customers who are labeled as potentially attrited customer by the model, the bank could implement a series of customer retention strategies to prevent customer loss. For example, the bank could offer them discount on annual fee/interest rate or limited time bonus etc.

1 Get the Data

1.1 Download the Data

[4]:
```
data=pd.read_csv('credit_card_churn.csv')
data = data.iloc[:, 1:-2] #Delete last two column advised by the dataset␣
↪publication
```

1.2 Take a quick look at the data structure

[5]:
```
data.head()
```

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

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

   Total_Relationship_Count  Months_Inactive_12_mon  Contacts_Count_12_mon  \
0                         5                       1                      3
1                         6                       1                      2
2                         4                       1                      0
3                         3                       4                      1
4                         5                       1                      0

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

   Total_Trans_Amt  Total_Trans_Ct  Total_Ct_Chng_Q4_Q1  Avg_Utilization_Ratio
0             1144              42                1.625                  0.061
1             1291              33                3.714                  0.105
2             1887              20                2.333                  0.000
```

```
3          1171          20             2.333                 0.760
4           816          28             2.500                 0.000
```

[6]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 20 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Attrition_Flag            10127 non-null  object
 1   Customer_Age              10127 non-null  int64
 2   Gender                    10127 non-null  object
 3   Dependent_count           10127 non-null  int64
 4   Education_Level           10127 non-null  object
 5   Marital_Status            10127 non-null  object
 6   Income_Category           10127 non-null  object
 7   Card_Category             10127 non-null  object
 8   Months_on_book            10127 non-null  int64
 9   Total_Relationship_Count  10127 non-null  int64
 10  Months_Inactive_12_mon    10127 non-null  int64
 11  Contacts_Count_12_mon     10127 non-null  int64
 12  Credit_Limit              10127 non-null  float64
 13  Total_Revolving_Bal       10127 non-null  int64
 14  Avg_Open_To_Buy           10127 non-null  float64
 15  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 16  Total_Trans_Amt           10127 non-null  int64
 17  Total_Trans_Ct            10127 non-null  int64
 18  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 19  Avg_Utilization_Ratio     10127 non-null  float64
dtypes: float64(5), int64(9), object(6)
memory usage: 1.5+ MB
```

No Null value found in the dataset

[7]:

```
data.describe()
```

[7]:

```
       Customer_Age  Dependent_count  Months_on_book  \
count  10127.000000     10127.000000    10127.000000
mean      46.325960         2.346203       35.928409
std        8.016814         1.298908        7.986416
min       26.000000         0.000000       13.000000
25%       41.000000         1.000000       31.000000
50%       46.000000         2.000000       36.000000
75%       52.000000         3.000000       40.000000
max       73.000000         5.000000       56.000000

       Total_Relationship_Count  Months_Inactive_12_mon  \
```

```
count           10127.000000       10127.000000
mean                3.812580           2.341167
std                 1.554408           1.010622
min                 1.000000           0.000000
25%                 3.000000           2.000000
50%                 4.000000           2.000000
75%                 5.000000           3.000000
max                 6.000000           6.000000

       Contacts_Count_12_mon  Credit_Limit  Total_Revolving_Bal  \
count           10127.000000  10127.000000         10127.000000
mean                2.455317   8631.953698          1162.814061
std                 1.106225   9088.776650           814.987335
min                 0.000000   1438.300000             0.000000
25%                 2.000000   2555.000000           359.000000
50%                 2.000000   4549.000000          1276.000000
75%                 3.000000  11067.500000          1784.000000
max                 6.000000  34516.000000          2517.000000

       Avg_Open_To_Buy  Total_Amt_Chng_Q4_Q1  Total_Trans_Amt  Total_Trans_Ct  \
count     10127.000000          10127.000000     10127.000000    10127.000000
mean       7469.139637              0.759941      4404.086304       64.858695
std        9090.685324              0.219207      3397.129254       23.472570
min           3.000000              0.000000       510.000000       10.000000
25%        1324.500000              0.631000      2155.500000       45.000000
50%        3474.000000              0.736000      3899.000000       67.000000
75%        9859.000000              0.859000      4741.000000       81.000000
max       34516.000000              3.397000     18484.000000      139.000000

       Total_Ct_Chng_Q4_Q1  Avg_Utilization_Ratio
count         10127.000000           10127.000000
mean              0.712222               0.274894
std               0.238086               0.275691
min               0.000000               0.000000
25%               0.582000               0.023000
50%               0.702000               0.176000
75%               0.818000               0.503000
max               3.714000               0.999000
```

[8]:

```
# Plot distributions for all variables
plt.figure(figsize=(20, 27))
for i, col in enumerate(data.columns):
    plt.subplot(7, 3, i+1)
    if data[col].dtype == 'object':
        sns.countplot(x=data[col], data=data)  # countplot for categorical␣
↪variables
    else:
```

```
        sns.histplot(data[col])  # histplot for numerical variables
    plt.title(col)
    plt.xlabel('')
    plt.ylabel('')

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


Attrition_Flag
Existing Customer
Attrited Customer
Customer_Age
Gender
M
F
Dependent_count
Education_Level
High School
Graduate
Uneducated
Unknown
College
Post-Graduate
Doctorate
Marital_Status
Married
Single
Unknown
Divorced
Income_Category
60K − 80K
Less than $40K
80K − 120K
40K − 60K
$120K +
Unknown
Card_Category
Blue
Gold
Silver
Platinum
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

```
[9]: # Count the number of existing customers and calculate the percentage of␣
      ↪exsiting customers in the datset
     existing_count=data[(data['Attrition_Flag']=='Existing Customer')]
     existing_per = existing_count.shape[0]/data.shape[0]
     attrition_per = 1-existing_per
     print(existing_per)
     print(attrition_per)
```

```
0.8393403772094401
0.1606596227905599
```

From the first plot, I noticed that the dataset may have imbalanced classes since 84% of the sample are exsiting customers and only 16% are attrited customers. With the imbalanced classes, a model could get a pretty high accuracy just by predicting the majority class, but it may fail to capture the minority class. Below are some techiniques to solve the imlalanced classes:
1. Resampling techniques like undersampling or oversampling (undersampling discards potentially useful information and oversampling increases the likelihood of overfitting since it replicates the minority class event)
2. Use various performance metrics: accuracy can be misleading for imbalanced datasets. Confustion matrix, persision, recall, F1 score, and area under ROC curve could be used for model evaluation as well
3. Penalize algorithms (cost-Sensitive training) that increase the cost of classification mistakes in the minority class like Penalized-SVM and Weighted XGBoost
4. Use ensemble algorithms which performs well on imlalanced data like random forests and gradient boosted trees

Techinique 2,3,4 will be used in this project to solve imbalanced classes after analyzing the pros and cons of the 4 opitons.

1.3 Create a test set

```
[10]: # Split the data into train(80%) and test(20%) set
      # The train set will be used in model training, and the test set will be used␣
       ↪to generate predicted value and assess model performance
      train_set, test_set = train_test_split(data, test_size=0.2, random_state=42) #␣
       ↪set the random seed to ensure the same output every time
      print(len(train_set))
      print(len(test_set))
```

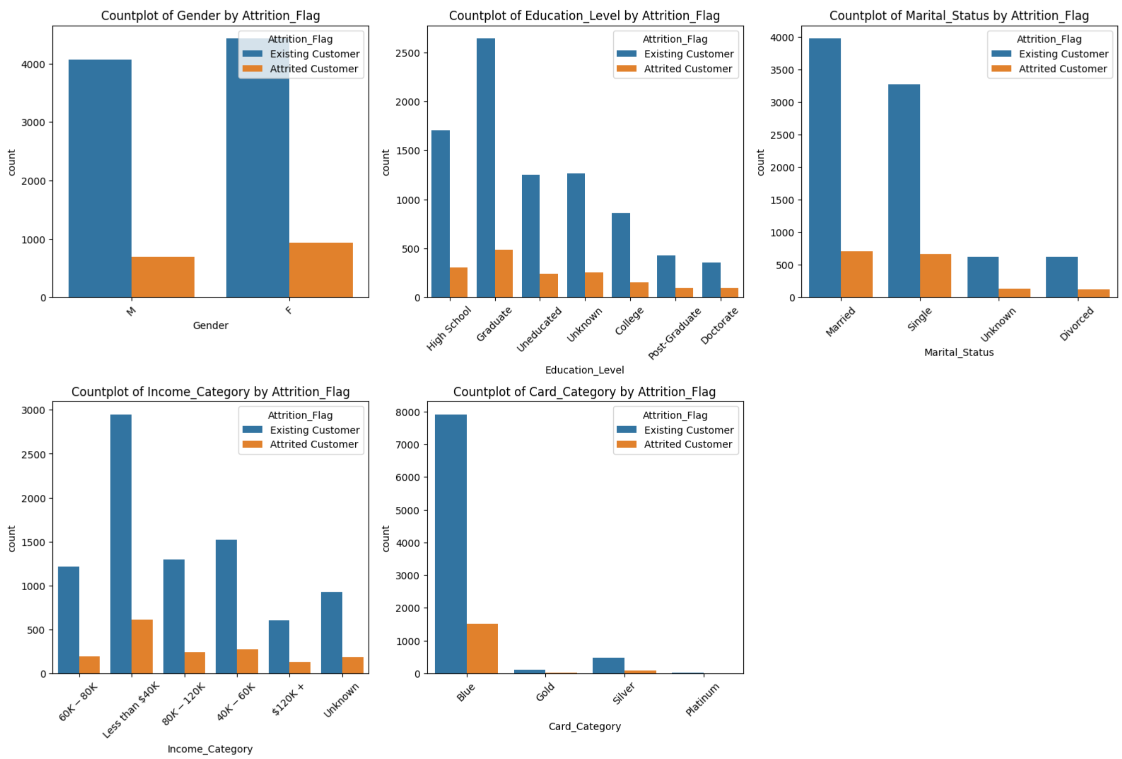
```
8101
2026
```

2 Discover and Visualize the Data to Gain Insights

2.1 Countplot plots of categorical variables by attrition flags

I want to see whether categorical variables have the same distribution for existing and attrited customers

[11]:
```python
df_categorical = data.select_dtypes(include='object').drop(columns=['Attrition_Flag']) # Generate a set of categorical variables
plt.figure(figsize=(16, 15))
for i, column in enumerate(df_categorical.columns, 1):
    plt.subplot(3, 3, i)
    sns.countplot(x=column, hue='Attrition_Flag', data=data)
    plt.title(f'Countplot of {column} by Attrition_Flag')
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



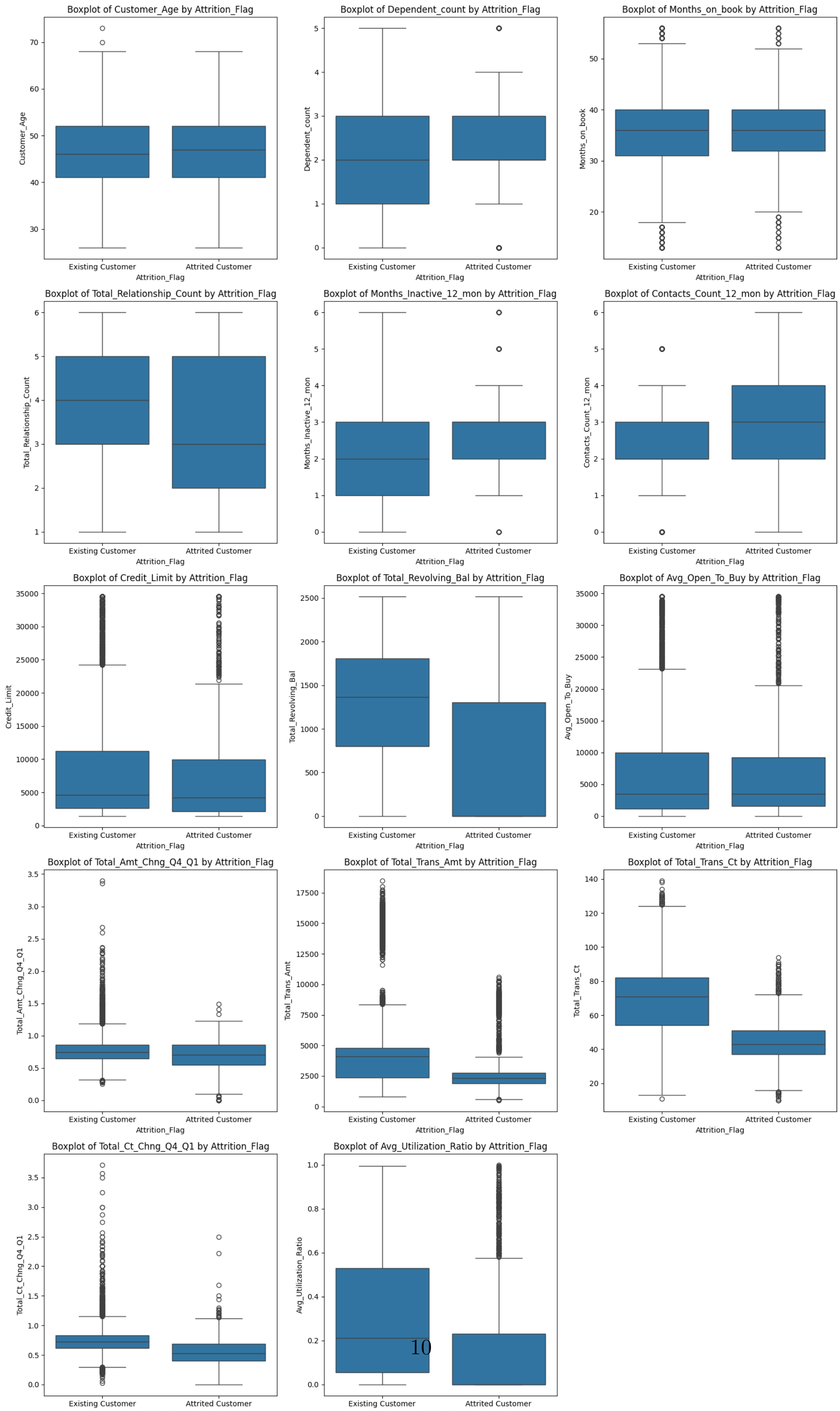
Some preliminary insights from EDA:
1. Married people are more likely to hold the card, followed by singles
2. Customers with graduate degree are more likely to hold the card, compared with other degrees
3. People whose income less than $40k are most likely to subscribe to the credit card

2.2 Box plots of numerical variables by attrition flags

I want to see whether numerical variables have the same distribution for existing and attrited customers

[12]:

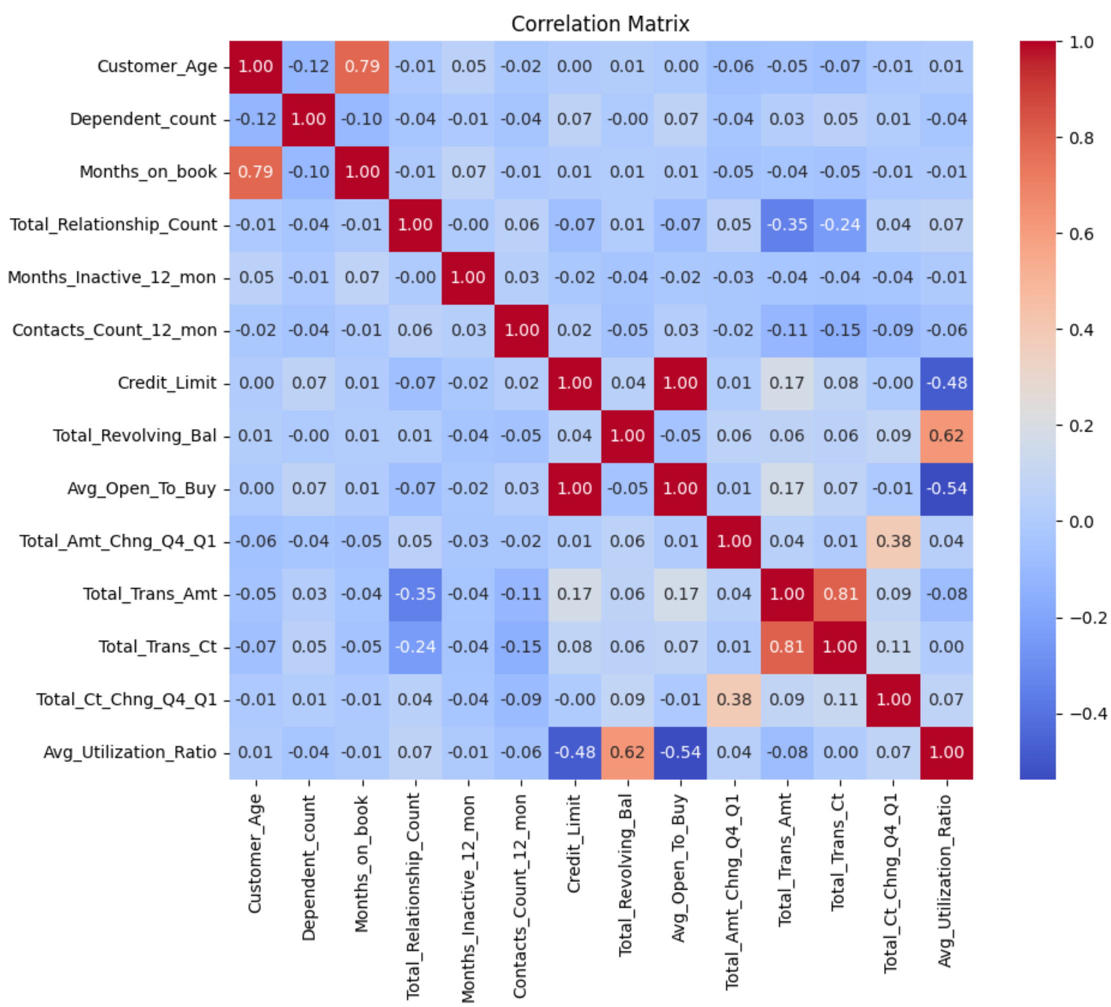
```
df_numerical = data.select_dtypes(include=['int64', 'float64']) # Generate a␣
↪set of numerical variables
plt.figure(figsize=(16, 27))
num_cols = len(df_numerical.columns)
rows = 5
cols = num_cols // rows + (num_cols % rows > 0)

for i, column in enumerate(df_numerical.columns, 1):
    plt.subplot(rows, cols, i)
    sns.boxplot(x='Attrition_Flag', y=column, data=data)
    plt.title(f'Boxplot of {column} by Attrition_Flag')
plt.tight_layout()
plt.show()
```


Boxplot of Customer_Age by Attrition_Flag
Customer_Age
Boxplot of Dependent_count by Attrition_Flag
Dependent_count
Boxplot of Months_on_book by Attrition_Flag
Months_on_book
Boxplot of Total_Relationship_Count by Attrition_Flag
Total_Relationship_Count
Boxplot of Months_Inactive_12_mon by Attrition_Flag
Months_Inactive_12_mon
Boxplot of Contacts_Count_12_mon by Attrition_Flag
Contacts_Count_12_mon
Boxplot of Credit_Limit by Attrition_Flag
Credit_Limit
Boxplot of Total_Revolving_Bal by Attrition_Flag
Total_Revolving_Bal
Boxplot of Avg_Open_To_Buy by Attrition_Flag
Avg_Open_To_Buy
Boxplot of Total_Amt_Chng_Q4_Q1 by Attrition_Flag
Total_Amt_Chng_Q4_Q1
Boxplot of Total_Trans_Amt by Attrition_Flag
Total_Trans_Amt
Boxplot of Total_Trans_Ct by Attrition_Flag
Total_Trans_Ct
Boxplot of Total_Ct_Chng_Q4_Q1 by Attrition_Flag
Total_Ct_Chng_Q4_Q1
Boxplot of Avg_Utilization_Ratio by Attrition_Flag
Avg_Utilization_Ratio
Existing Customer
Attrited Customer
Attrition_Flag

Some preliminary insights from EDA:
1. Attrited customers tend to have less product with the bank
2. Attrited customers tend to have more contacts with the bank in last 12 month
3. Attrited customers tend to have lower revalving balance and less transactions

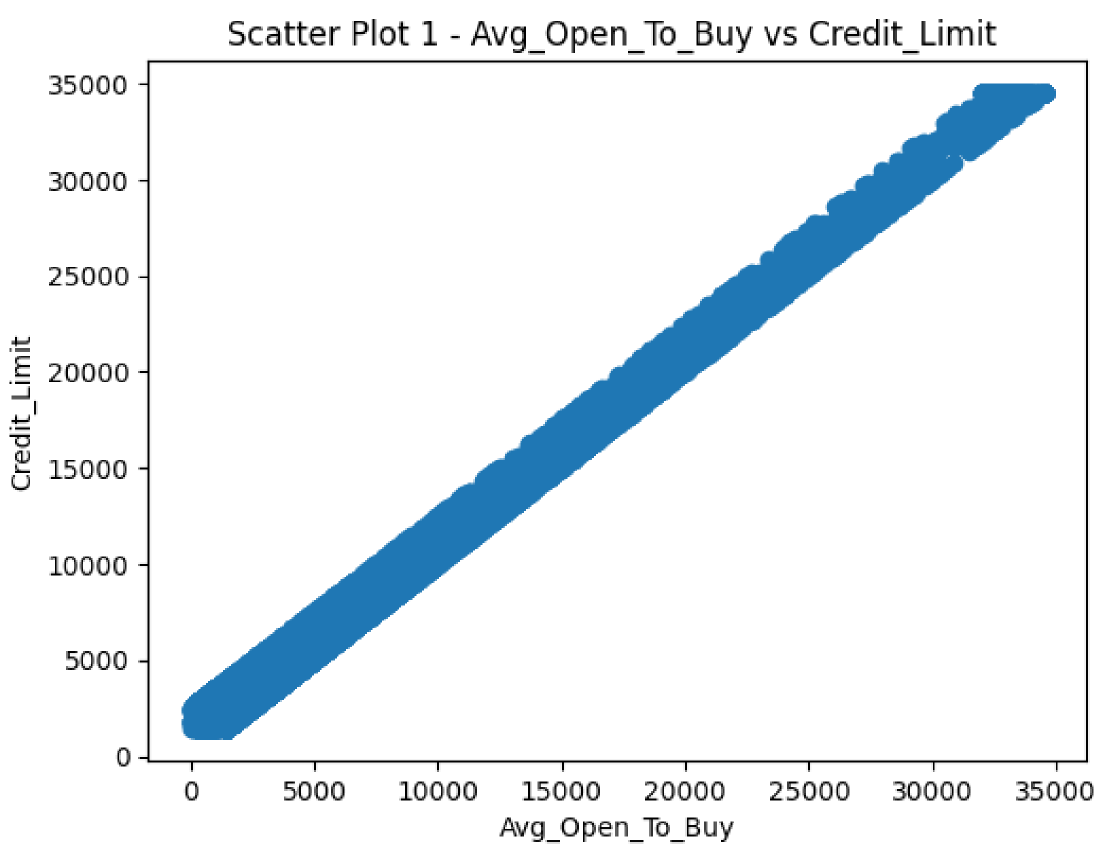
2.3 Looking for Correlations

[13]:
```python
# Plot correation matrix for all numerical variables
corr_matrix = df_numerical.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
↪annot_kws={"size": 10})
plt.title('Correlation Matrix')
plt.show()
```

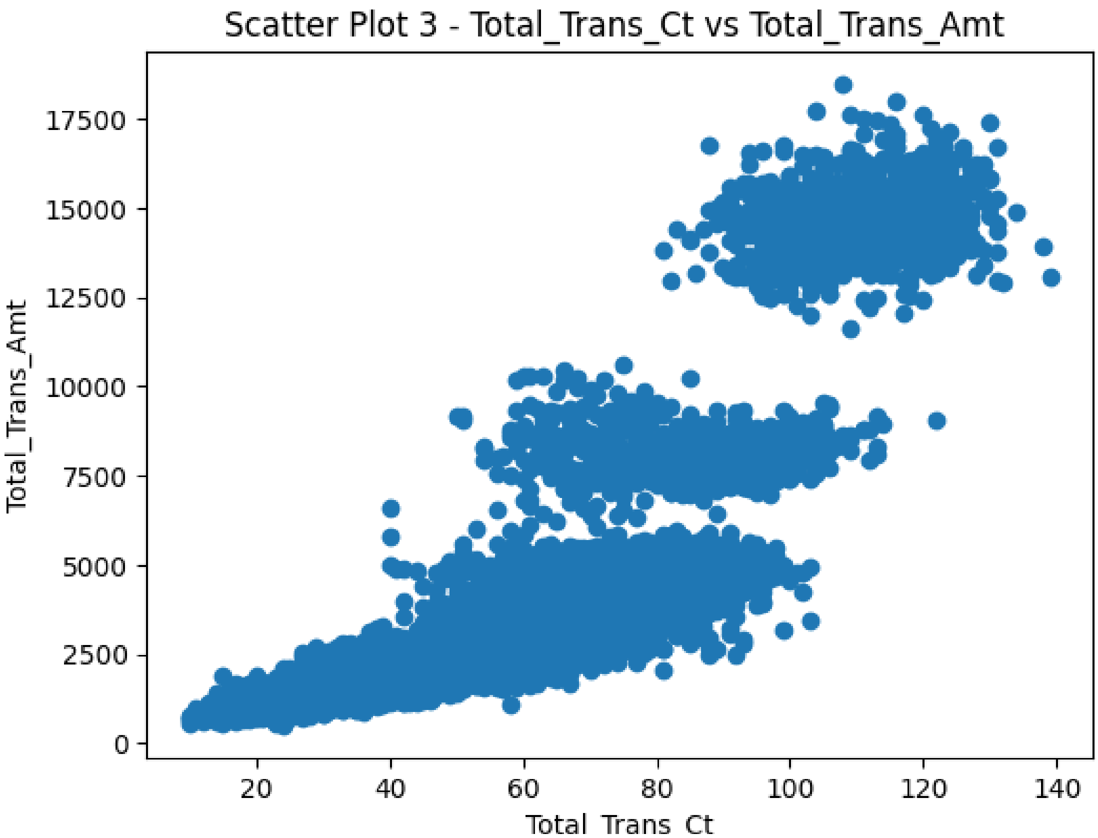


Three pairs of variables have high correlation(>=0.7) : Avg_Open_To_Buy & Credit_Limit, Months_on_book & Customer_Age, Total_Trans_Ct & Total_Trans_Amt. Scatter plot will be plotted to further investigate the correlation.

[14]:
```python
plt.scatter(df_numerical['Avg_Open_To_Buy'], df_numerical['Credit_Limit'])
plt.xlabel('Avg_Open_To_Buy')
plt.ylabel('Credit_Limit')
plt.title('Scatter Plot 1 - Avg_Open_To_Buy vs Credit_Limit ')
plt.show()

plt.scatter(df_numerical['Months_on_book'], df_numerical['Customer_Age'])
plt.xlabel('Months_on_book')
plt.ylabel('Customer_Age')
plt.title('Scatter Plot 2 - Months_on_book vs Customer_Age ')
plt.show()

plt.scatter(df_numerical['Total_Trans_Ct'], df_numerical['Total_Trans_Amt'])
plt.xlabel('Total_Trans_Ct')
plt.ylabel('Total_Trans_Amt')
plt.title('Scatter Plot 3 - Total_Trans_Ct vs Total_Trans_Amt ')
plt.show()
```




Scatter Plot 2 - Months_on_book vs Customer_Age
Customer_Age
Months_on_book
70
60
50
40
30
20
30
40
50



Due to the high colinearity indicated in the scatter plots above, I decide to delete Avg_Open_To_Buy, Customer_Age, and Total_Trans_Amt to reduce redundancy and improve stability and generalization of the model

[15]:
```
columns_to_exclude = ['Customer_Age','Avg_Open_To_Buy','Total_Trans_Amt']
data_new = data.drop(columns=columns_to_exclude)
```

3 Prepare the Data for Machine Learning Algorithms

[16]:
```
#Count number of rows that have at least one 'Unkown' value
filtered_df=data_new[(data_new['Income_Category']=='Unknown')|
                     (data_new['Education_Level']=='Unknown')|
                     (data_new['Marital_Status']=='Unknown')]
num_rows = filtered_df.shape[0]
print(num_rows)
```

3046

3.1 Data cleaning

Education_Level, Marital_Status, and Income_Category have 'Unknown' value, and there are 3046(~30% of the data) rows with at least one 'Unknown' value. There are several strategies dealing with 'Unkown' values: 1. Delete rows with 'Unknown' value 2. Replace with the mean, median, or mode of the respective feature. This is typically used for numerical features 3. Use machine learning algorithms to predict missing values based on other features. i.e. XGBoost

Giving large size of the dataset, I will chose option 1 to delete rows with missing values. If good results couldn't be obtained with the new dataset, I will seek other techniques for these 'Unknown' values.

[17]:
```
# Option 1 : Delete rows with 'Unknown' value
data_opt1 = data_new[(data_new['Income_Category'] != 'Unknown') &
                     (data_new['Education_Level'] != 'Unknown') &
                     (data_new['Marital_Status'] != 'Unknown')].copy()
```

[18]:
```
# ## Option 2: Replace 'Unknown' value with mode
# data_opt2=data_new.copy()
# mode_education= data_opt2['Education_Level'].mode()[0]
# mode_marital= data_opt2['Marital_Status'].mode()[0]
# mode_income= data_opt2['Income_Category'].mode()[0]
# data_opt2['Education_Level']=data_opt2['Education_Level'].
 ↪replace('Unknown',mode_education)
# data_opt2['Marital_Status']=data_opt2['Marital_Status'].
 ↪replace('Unknown',mode_marital)
# data_opt2['Income_Category']=data_opt2['Income_Category'].
 ↪replace('Unknown',mode_income)
# data_opt2.info()
```

[19]:
```
# Create rpreprocessor for x variables
categorical_features = ['Gender', 'Education_Level', 'Marital_Status',␣
 ↪'Income_Category', 'Card_Category']
numeric_features = ['Dependent_count', 'Months_on_book',␣
 ↪'Total_Relationship_Count',
       'Months_Inactive_12_mon', 'Contacts_Count_12_mon', 'Credit_Limit',
       'Total_Revolving_Bal', 'Total_Amt_Chng_Q4_Q1', 'Total_Trans_Ct',
       'Total_Ct_Chng_Q4_Q1', 'Avg_Utilization_Ratio']
preprocessor = ColumnTransformer(
    transformers=
    [
        ('num', StandardScaler(), numeric_features),  # standardize numerical␣
 ↪variables
        ('cat', OneHotEncoder(), categorical_features)  # encode categorical␣
 ↪variables
    ])
```

```
# Since LabelEncoder() will encode on alphabet order, attrited customers will␣
↪be encoded 0.
# I want to label attrited customers as positive(1), so I manually encode the y␣
↪variable.
data_opt1['Attrition_Flag']=data_opt1['Attrition_Flag'].replace({'Existing␣
↪Customer':0,'Attrited Customer':1}).astype(int)
```

```
/var/folders/t7/j5jl86t54kjg319qghzc7l_h0000gn/T/ipykernel_68206/1586075494.py:1
6: FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  data_opt1['Attrition_Flag']=data_opt1['Attrition_Flag'].replace({'Existing
Customer':0,'Attrited Customer':1}).astype(int)
```

[20]:

```
data_opt1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7081 entries, 0 to 10126
Data columns (total 17 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Attrition_Flag            7081 non-null   int64
 1   Gender                    7081 non-null   object
 2   Dependent_count           7081 non-null   int64
 3   Education_Level           7081 non-null   object
 4   Marital_Status            7081 non-null   object
 5   Income_Category           7081 non-null   object
 6   Card_Category             7081 non-null   object
 7   Months_on_book            7081 non-null   int64
 8   Total_Relationship_Count  7081 non-null   int64
 9   Months_Inactive_12_mon    7081 non-null   int64
 10  Contacts_Count_12_mon     7081 non-null   int64
 11  Credit_Limit              7081 non-null   float64
 12  Total_Revolving_Bal       7081 non-null   int64
 13  Total_Amt_Chng_Q4_Q1      7081 non-null   float64
 14  Total_Trans_Ct            7081 non-null   int64
 15  Total_Ct_Chng_Q4_Q1       7081 non-null   float64
 16  Avg_Utilization_Ratio     7081 non-null   float64
dtypes: float64(4), int64(8), object(5)
memory usage: 995.8+ KB
```

4 Select and Train a Model

[21]:

```
# Define the explantory and dependent variables and the train and test set
columns_to_exclude = ['Attrition_Flag']
X = data_opt1.drop(columns=columns_to_exclude)
```

```
y=data_opt1['Attrition_Flag']
#Split the data set into train(80%) and test(20%) dataset
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
 ↪2,random_state=42)
print(len(X_train),len(X_test)) # Print the size of train and test dataset
```

```
5664 1417
```

[22]:
```
#Preprocess the X_train and X_test datasets
X_train_preproc = preprocessor.fit_transform(X_train)
X_test_preproc = preprocessor.transform(X_test)
```

4.1 Logistic Regression

[23]:
```
# Fit the logistic regression model using the train set
log_reg=LogisticRegression()
log_reg.fit(X_train_preproc, y_train)
```

[23]:
```
LogisticRegression()
```

[24]:
```
#Use the trained model to predict y value
y_pred_lr=log_reg.predict(X_test_preproc)

#Calculate y_score for AUC
y_score_lr = log_reg.predict_proba(X_test_preproc)[:, 1]
```

[25]:
```
#Generate performance metrics
accuracy_lr = accuracy_score(y_test, y_pred_lr)
conf_matrix_lr = confusion_matrix(y_test, y_pred_lr)
classification_rep_lr = classification_report(y_test, y_pred_lr)
auc_lr=roc_auc_score(y_test, y_score_lr)

print(f"Test accuracy: \n  {accuracy_lr:.2%}")
print ("Confusion Matrix : \n", conf_matrix_lr)
print("\nClassification Report: : \n",classification_rep_lr)
print(f"AUC: \n  {auc_lr:.2%}")
```

```
Test accuracy:
  90.26%
Confusion Matrix :
 [[1169   36]
 [ 102  110]]

Classification Report: :
               precision    recall  f1-score   support

           0       0.92      0.97      0.94      1205
           1       0.75      0.52      0.61       212
```

```
    accuracy                           0.90      1417
   macro avg       0.84      0.74      0.78      1417
weighted avg       0.89      0.90      0.89      1417

AUC:
  90.92%
```

The logistic regression model has a 90.26% accuracy which is pretty high. However, I noticed that the model has a very high f1-score for the majority class(0 or existing customers) but a low f1-score for the minority class(1 or attrited customers). The object of the project is to model to identify the potential attrited customers, so I want to reduce the false negative cases(attrited but predicted as existing). As a result, a model with a high recall rate (TP/(TP+FN)) is desired. Clearly, the logistic model with 52% recall rate is not satisfying.

4.2 Penalized-SVM

Increasing the cost of classification mistakes in the minority class is a technique to deal with dataset with inbalanced classese. A popular algorithm is Penalized-SVM. During training, the argument class_weight='balanced' could be used to penalize mistakes on the minority class by an amount proportional to how under-represented it is.

[26]:
```
# Fit the model
svc = SVC(class_weight='balanced' ,probability=True)
#class_weight='balanced' to penalize mistakes on the minority class by an␣
↪amount proportional to how under-represented it is.
svc.fit(X_train_preproc, y_train)
```

[26]:
```
SVC(class_weight='balanced', probability=True)
```

[27]:
```
# Generate the predicted y value and calculate the y_score
y_pred_svc=svc.predict(X_test_preproc)
y_score_svc= svc.predict_proba(X_test_preproc)[:, 1]
```

[28]:
```
#Generate performance metrics
accuracy_svc = accuracy_score(y_test, y_pred_svc)
conf_matrix_svc = confusion_matrix(y_test, y_pred_svc)
classification_rep_svc = classification_report(y_test, y_pred_svc)
auc_svc=roc_auc_score(y_test, y_score_svc)

print(f"Test accuracy: \n  {accuracy_svc:.2%}")
print ("Confusion Matrix : \n", conf_matrix_svc)
print("\nClassification Report: : \n",classification_rep_svc)
print(f"AUC: \n  {auc_svc:.2%}")
```

```
Test accuracy:
  89.98%
Confusion Matrix :
 [[1094  111]
```

```
 [  31  181]]

Classification Report: :
               precision    recall  f1-score   support

           0       0.97      0.91      0.94      1205
           1       0.62      0.85      0.72       212

    accuracy                           0.90      1417
   macro avg       0.80      0.88      0.83      1417
weighted avg       0.92      0.90      0.91      1417

AUC:
  95.11%
```

Even though the test accuracy of the Penalized-SVM model is a little bit lower than the Logistic Regression model, the AUC slightly increases and the recall rate increases significantly by 33%. However, the precision(TP/(TP+FP)) of the model is only 62%, which means ~40% of the attrited customers predicted by the model are exsiting customers. Offering discount/bonus to these customers may lead to profit reduction.

4.3 Random Forest

[29]:
```
# Fit the model
random_forest = RandomForestClassifier(random_state=42)
random_forest.fit(X_train_preproc, y_train)
```

[29]:
```
RandomForestClassifier(random_state=42)
```

[30]:
```
# Generate the predicted y value and calculate the y_score
y_pred_rf=random_forest.predict(X_test_preproc)
y_score_rf = random_forest.predict_proba(X_test_preproc)[:, 1]
```

[31]:
```
#Generate performance metrics
accuracy_rf = accuracy_score(y_test, y_pred_rf)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
classification_rep_rf = classification_report(y_test, y_pred_rf)
auc_rf=roc_auc_score(y_test, y_score_rf)

print(f"Test accuracy: \n  {accuracy_rf:.2%}")
print ("Confusion Matrix : \n", conf_matrix_rf)
print("\nClassification Report: : \n",classification_rep_rf)
print(f"AUC: \n  {auc_rf:.2%}")
```

```
Test accuracy:
  92.94%
Confusion Matrix :
 [[1181   24]
 [  76  136]]
```

```
Classification Report: :
              precision    recall  f1-score   support

           0       0.94      0.98      0.96      1205
           1       0.85      0.64      0.73       212

    accuracy                           0.93      1417
   macro avg       0.89      0.81      0.85      1417
weighted avg       0.93      0.93      0.93      1417

AUC:
  95.79%
```

Even though the Random Forest model has a higher accuracy and AUC compared to the Penalized-SVM model, the recall rate (64%) is pretty low.

4.4 XGBoost

Extreme Gradient Boosting(XGBoost) is a machine-learning algorithm based on the gradient boosting(GBM) algorithm. However, a few differences of XGBoost make it better than GBM in terms of performance and speed. 1. Regularization: XGBoost implements regularization in its alogrithm to avoid overfitting, whereas GBM doesn't. 2. Parallelization: GBM tends to have a slower training time than the XGBoost because the latter algorithm implements parallelization during the training process. 3. Missing Data Handling: XGBoost has its own in-built missing data handler, whereas GBM doesn't. 4. In-Built Cross-Validation: XGBoost has an in-built Cross-Validation that could improve the model generalization and robustness.

[32]:
```python
# Fit the model
xgboost = XGBClassifier()
# scale_pos_weight can be used to train a class-weighted or cost-sensitive␣
↪version of XGBoost for imbalanced classification.
# a fast way to estimate this value using # majority class/ # minority class.␣
↪Based on the data exploration, I have 84%/16%=5.25
xgboost.fit(X_train_preproc,y_train)
```

[32]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, …)
```

[33]:
```python
# Generate the predicted y value and calculate the y_score
y_pred_xgb = xgboost.predict(X_test_preproc)
y_score_xgb = xgboost.predict_proba(X_test_preproc)[:, 1]
```

[34]:
```python
#Generate performance metrics
accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
conf_matrix_xgb = confusion_matrix(y_test, y_pred_xgb)
classification_rep_xgb = classification_report(y_test, y_pred_xgb)
auc_xgb=roc_auc_score(y_test, y_score_xgb)

print(f"Test accuracy: \n  {accuracy_xgb:.2%}")
print ("Confusion Matrix : \n", conf_matrix_xgb)
print("\nClassification Report: : \n",classification_rep_xgb)
print(f"AUC: \n  {auc_xgb:.2%}")
```

```
Test accuracy:
  93.72%
Confusion Matrix :
 [[1167   38]
 [  51  161]]

Classification Report: :
               precision    recall  f1-score   support

           0       0.96      0.97      0.96      1205
           1       0.81      0.76      0.78       212

    accuracy                           0.94      1417
   macro avg       0.88      0.86      0.87      1417
weighted avg       0.94      0.94      0.94      1417

AUC:
  96.89%
```

XGBoost has a highest test accuracy, f1 score, and AUC among all models.

4.5 MLP

[36]:
```python
# Define MLP model
mlp = models.Sequential([
    layers.Dense(64, activation='relu', input_shape=(X_train_preproc.
 ↪shape[1],)),
    layers.Dense(32, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])



# Compile the model
```

```
mlp.compile(optimizer='sgd',
              loss=keras.losses.BinaryCrossentropy(),
              metrics=[keras.metrics.AUC()]) # Use AUC as the metrics

# Train the model
mlp.fit(X_train_preproc, y_train, epochs=250, batch_size=128)
```

```
Epoch 1/250

/opt/anaconda3/lib/python3.11/site-packages/keras/src/layers/core/dense.py:86:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

45/45                 0s 372us/step -
auc: 0.5532 - loss: 0.6147
Epoch 2/250
45/45                 0s 388us/step -
auc: 0.6831 - loss: 0.4605
Epoch 3/250
45/45                 0s 310us/step -
auc: 0.7568 - loss: 0.4030
Epoch 4/250
45/45                 0s 308us/step -
auc: 0.7955 - loss: 0.3711
Epoch 5/250
45/45                 0s 309us/step -
auc: 0.8160 - loss: 0.3541
Epoch 6/250
45/45                 0s 305us/step -
auc: 0.8325 - loss: 0.3518
Epoch 7/250
45/45                 0s 324us/step -
auc: 0.8365 - loss: 0.3282
Epoch 8/250
45/45                 0s 309us/step -
auc: 0.8503 - loss: 0.3343
Epoch 9/250
45/45                 0s 304us/step -
auc: 0.8564 - loss: 0.3190
Epoch 10/250
45/45                 0s 306us/step -
auc: 0.8759 - loss: 0.3150
Epoch 11/250
45/45                 0s 310us/step -
auc: 0.8676 - loss: 0.3071
Epoch 12/250
45/45                 0s 317us/step -
```

```
auc: 0.8815 - loss: 0.3015
Epoch 13/250
45/45              0s 309us/step -
auc: 0.8809 - loss: 0.2901
Epoch 14/250
45/45              0s 301us/step -
auc: 0.8934 - loss: 0.2814
Epoch 15/250
45/45              0s 305us/step -
auc: 0.8791 - loss: 0.2860
Epoch 16/250
45/45              0s 308us/step -
auc: 0.8877 - loss: 0.2766
Epoch 17/250
45/45              0s 315us/step -
auc: 0.8926 - loss: 0.2750
Epoch 18/250
45/45              0s 306us/step -
auc: 0.9030 - loss: 0.2718
Epoch 19/250
45/45              0s 315us/step -
auc: 0.8985 - loss: 0.2710
Epoch 20/250
45/45              0s 305us/step -
auc: 0.8933 - loss: 0.2763
Epoch 21/250
45/45              0s 309us/step -
auc: 0.8966 - loss: 0.2740
Epoch 22/250
45/45              0s 303us/step -
auc: 0.8928 - loss: 0.2720
Epoch 23/250
45/45              0s 303us/step -
auc: 0.9010 - loss: 0.2618
Epoch 24/250
45/45              0s 312us/step -
auc: 0.9058 - loss: 0.2624
Epoch 25/250
45/45              0s 308us/step -
auc: 0.9014 - loss: 0.2654
Epoch 26/250
45/45              0s 301us/step -
auc: 0.9120 - loss: 0.2538
Epoch 27/250
45/45              0s 315us/step -
auc: 0.9080 - loss: 0.2563
Epoch 28/250
45/45              0s 300us/step -
```

```
auc: 0.9025 - loss: 0.2592
Epoch 29/250
45/45             0s 308us/step -
auc: 0.9030 - loss: 0.2540
Epoch 30/250
45/45             0s 304us/step -
auc: 0.9032 - loss: 0.2561
Epoch 31/250
45/45             0s 305us/step -
auc: 0.9089 - loss: 0.2516
Epoch 32/250
45/45             0s 305us/step -
auc: 0.9134 - loss: 0.2505
Epoch 33/250
45/45             0s 344us/step -
auc: 0.9068 - loss: 0.2549
Epoch 34/250
45/45             0s 361us/step -
auc: 0.9167 - loss: 0.2423
Epoch 35/250
45/45             0s 318us/step -
auc: 0.9151 - loss: 0.2450
Epoch 36/250
45/45             0s 318us/step -
auc: 0.8954 - loss: 0.2649
Epoch 37/250
45/45             0s 324us/step -
auc: 0.9077 - loss: 0.2472
Epoch 38/250
45/45             0s 320us/step -
auc: 0.9151 - loss: 0.2422
Epoch 39/250
45/45             0s 333us/step -
auc: 0.9187 - loss: 0.2395
Epoch 40/250
45/45             0s 306us/step -
auc: 0.9130 - loss: 0.2498
Epoch 41/250
45/45             0s 293us/step -
auc: 0.9148 - loss: 0.2399
Epoch 42/250
45/45             0s 307us/step -
auc: 0.9135 - loss: 0.2513
Epoch 43/250
45/45             0s 303us/step -
auc: 0.9106 - loss: 0.2539
Epoch 44/250
45/45             0s 302us/step -
```

```
auc: 0.9149 - loss: 0.2497
Epoch 45/250
45/45              0s 301us/step -
auc: 0.9152 - loss: 0.2432
Epoch 46/250
45/45              0s 315us/step -
auc: 0.9190 - loss: 0.2402
Epoch 47/250
45/45              0s 308us/step -
auc: 0.9178 - loss: 0.2492
Epoch 48/250
45/45              0s 296us/step -
auc: 0.9255 - loss: 0.2381
Epoch 49/250
45/45              0s 299us/step -
auc: 0.9130 - loss: 0.2443
Epoch 50/250
45/45              0s 329us/step -
auc: 0.9129 - loss: 0.2441
Epoch 51/250
45/45              0s 294us/step -
auc: 0.9130 - loss: 0.2439
Epoch 52/250
45/45              0s 286us/step -
auc: 0.9203 - loss: 0.2312
Epoch 53/250
45/45              0s 289us/step -
auc: 0.9188 - loss: 0.2353
Epoch 54/250
45/45              0s 298us/step -
auc: 0.9202 - loss: 0.2381
Epoch 55/250
45/45              0s 300us/step -
auc: 0.9206 - loss: 0.2405
Epoch 56/250
45/45              0s 298us/step -
auc: 0.9199 - loss: 0.2377
Epoch 57/250
45/45              0s 306us/step -
auc: 0.9273 - loss: 0.2284
Epoch 58/250
45/45              0s 291us/step -
auc: 0.9157 - loss: 0.2531
Epoch 59/250
45/45              0s 309us/step -
auc: 0.9112 - loss: 0.2493
Epoch 60/250
45/45              0s 283us/step -
```

```
auc: 0.9170 - loss: 0.2423
Epoch 61/250
45/45            0s 282us/step -
auc: 0.9200 - loss: 0.2350
Epoch 62/250
45/45            0s 286us/step -
auc: 0.9214 - loss: 0.2425
Epoch 63/250
45/45            0s 281us/step -
auc: 0.9132 - loss: 0.2477
Epoch 64/250
45/45            0s 292us/step -
auc: 0.9242 - loss: 0.2292
Epoch 65/250
45/45            0s 307us/step -
auc: 0.9247 - loss: 0.2350
Epoch 66/250
45/45            0s 287us/step -
auc: 0.9173 - loss: 0.2344
Epoch 67/250
45/45            0s 286us/step -
auc: 0.9254 - loss: 0.2272
Epoch 68/250
45/45            0s 282us/step -
auc: 0.9304 - loss: 0.2280
Epoch 69/250
45/45            0s 300us/step -
auc: 0.9258 - loss: 0.2315
Epoch 70/250
45/45            0s 303us/step -
auc: 0.9166 - loss: 0.2381
Epoch 71/250
45/45            0s 289us/step -
auc: 0.9254 - loss: 0.2331
Epoch 72/250
45/45            0s 297us/step -
auc: 0.9259 - loss: 0.2278
Epoch 73/250
45/45            0s 285us/step -
auc: 0.9243 - loss: 0.2310
Epoch 74/250
45/45            0s 284us/step -
auc: 0.9231 - loss: 0.2371
Epoch 75/250
45/45            0s 299us/step -
auc: 0.9246 - loss: 0.2292
Epoch 76/250
45/45            0s 288us/step -
```

```
auc: 0.9286 - loss: 0.2235
Epoch 77/250
45/45            0s 290us/step -
auc: 0.9203 - loss: 0.2332
Epoch 78/250
45/45            0s 288us/step -
auc: 0.9312 - loss: 0.2256
Epoch 79/250
45/45            0s 309us/step -
auc: 0.9213 - loss: 0.2361
Epoch 80/250
45/45            0s 290us/step -
auc: 0.9237 - loss: 0.2307
Epoch 81/250
45/45            0s 296us/step -
auc: 0.9256 - loss: 0.2304
Epoch 82/250
45/45            0s 287us/step -
auc: 0.9289 - loss: 0.2241
Epoch 83/250
45/45            0s 291us/step -
auc: 0.9302 - loss: 0.2255
Epoch 84/250
45/45            0s 290us/step -
auc: 0.9302 - loss: 0.2255
Epoch 85/250
45/45            0s 322us/step -
auc: 0.9288 - loss: 0.2253
Epoch 86/250
45/45            0s 304us/step -
auc: 0.9290 - loss: 0.2224
Epoch 87/250
45/45            0s 299us/step -
auc: 0.9233 - loss: 0.2234
Epoch 88/250
45/45            0s 287us/step -
auc: 0.9328 - loss: 0.2243
Epoch 89/250
45/45            0s 323us/step -
auc: 0.9291 - loss: 0.2207
Epoch 90/250
45/45            0s 290us/step -
auc: 0.9241 - loss: 0.2192
Epoch 91/250
45/45            0s 290us/step -
auc: 0.9279 - loss: 0.2235
Epoch 92/250
45/45            0s 295us/step -
```

```
auc: 0.9364 - loss: 0.2149
Epoch 93/250
45/45            0s 289us/step -
auc: 0.9228 - loss: 0.2338
Epoch 94/250
45/45            0s 286us/step -
auc: 0.9304 - loss: 0.2197
Epoch 95/250
45/45            0s 292us/step -
auc: 0.9342 - loss: 0.2171
Epoch 96/250
45/45            0s 301us/step -
auc: 0.9303 - loss: 0.2225
Epoch 97/250
45/45            0s 295us/step -
auc: 0.9303 - loss: 0.2261
Epoch 98/250
45/45            0s 296us/step -
auc: 0.9303 - loss: 0.2283
Epoch 99/250
45/45            0s 287us/step -
auc: 0.9346 - loss: 0.2177
Epoch 100/250
45/45            0s 288us/step -
auc: 0.9319 - loss: 0.2122
Epoch 101/250
45/45            0s 290us/step -
auc: 0.9347 - loss: 0.2180
Epoch 102/250
45/45            0s 311us/step -
auc: 0.9326 - loss: 0.2237
Epoch 103/250
45/45            0s 324us/step -
auc: 0.9330 - loss: 0.2185
Epoch 104/250
45/45            0s 286us/step -
auc: 0.9284 - loss: 0.2180
Epoch 105/250
45/45            0s 290us/step -
auc: 0.9359 - loss: 0.2092
Epoch 106/250
45/45            0s 303us/step -
auc: 0.9297 - loss: 0.2216
Epoch 107/250
45/45            0s 291us/step -
auc: 0.9341 - loss: 0.2164
Epoch 108/250
45/45            0s 291us/step -
```

```
auc: 0.9419 - loss: 0.2003
Epoch 109/250
45/45            0s 295us/step -
auc: 0.9347 - loss: 0.2226
Epoch 110/250
45/45            0s 309us/step -
auc: 0.9356 - loss: 0.2170
Epoch 111/250
45/45            0s 290us/step -
auc: 0.9368 - loss: 0.2133
Epoch 112/250
45/45            0s 288us/step -
auc: 0.9344 - loss: 0.2176
Epoch 113/250
45/45            0s 295us/step -
auc: 0.9343 - loss: 0.2176
Epoch 114/250
45/45            0s 288us/step -
auc: 0.9318 - loss: 0.2206
Epoch 115/250
45/45            0s 290us/step -
auc: 0.9290 - loss: 0.2198
Epoch 116/250
45/45            0s 290us/step -
auc: 0.9375 - loss: 0.2132
Epoch 117/250
45/45            0s 287us/step -
auc: 0.9403 - loss: 0.2072
Epoch 118/250
45/45            0s 296us/step -
auc: 0.9390 - loss: 0.2093
Epoch 119/250
45/45            0s 288us/step -
auc: 0.9384 - loss: 0.2158
Epoch 120/250
45/45            0s 322us/step -
auc: 0.9344 - loss: 0.2192
Epoch 121/250
45/45            0s 289us/step -
auc: 0.9398 - loss: 0.2131
Epoch 122/250
45/45            0s 284us/step -
auc: 0.9313 - loss: 0.2184
Epoch 123/250
45/45            0s 290us/step -
auc: 0.9345 - loss: 0.2155
Epoch 124/250
45/45            0s 296us/step -
```

```
auc: 0.9388 - loss: 0.2159
Epoch 125/250
45/45            0s 286us/step -
auc: 0.9448 - loss: 0.2044
Epoch 126/250
45/45            0s 285us/step -
auc: 0.9403 - loss: 0.2136
Epoch 127/250
45/45            0s 279us/step -
auc: 0.9444 - loss: 0.1997
Epoch 128/250
45/45            0s 290us/step -
auc: 0.9430 - loss: 0.2036
Epoch 129/250
45/45            0s 296us/step -
auc: 0.9421 - loss: 0.2116
Epoch 130/250
45/45            0s 287us/step -
auc: 0.9359 - loss: 0.2082
Epoch 131/250
45/45            0s 303us/step -
auc: 0.9383 - loss: 0.2121
Epoch 132/250
45/45            0s 286us/step -
auc: 0.9427 - loss: 0.2053
Epoch 133/250
45/45            0s 296us/step -
auc: 0.9470 - loss: 0.1998
Epoch 134/250
45/45            0s 284us/step -
auc: 0.9378 - loss: 0.2150
Epoch 135/250
45/45            0s 283us/step -
auc: 0.9487 - loss: 0.1940
Epoch 136/250
45/45            0s 283us/step -
auc: 0.9385 - loss: 0.2175
Epoch 137/250
45/45            0s 287us/step -
auc: 0.9462 - loss: 0.2029
Epoch 138/250
45/45            0s 291us/step -
auc: 0.9437 - loss: 0.1997
Epoch 139/250
45/45            0s 288us/step -
auc: 0.9442 - loss: 0.2067
Epoch 140/250
45/45            0s 287us/step -
```

```
auc: 0.9451 - loss: 0.2021
Epoch 141/250
45/45            0s 285us/step -
auc: 0.9409 - loss: 0.2138
Epoch 142/250
45/45            0s 293us/step -
auc: 0.9516 - loss: 0.1895
Epoch 143/250
45/45            0s 296us/step -
auc: 0.9464 - loss: 0.2019
Epoch 144/250
45/45            0s 325us/step -
auc: 0.9435 - loss: 0.2052
Epoch 145/250
45/45            0s 302us/step -
auc: 0.9474 - loss: 0.2022
Epoch 146/250
45/45            0s 289us/step -
auc: 0.9468 - loss: 0.2099
Epoch 147/250
45/45            0s 303us/step -
auc: 0.9481 - loss: 0.2008
Epoch 148/250
45/45            0s 296us/step -
auc: 0.9507 - loss: 0.1950
Epoch 149/250
45/45            0s 293us/step -
auc: 0.9411 - loss: 0.2060
Epoch 150/250
45/45            0s 287us/step -
auc: 0.9451 - loss: 0.2053
Epoch 151/250
45/45            0s 293us/step -
auc: 0.9434 - loss: 0.2033
Epoch 152/250
45/45            0s 285us/step -
auc: 0.9560 - loss: 0.1878
Epoch 153/250
45/45            0s 292us/step -
auc: 0.9528 - loss: 0.1944
Epoch 154/250
45/45            0s 295us/step -
auc: 0.9504 - loss: 0.1943
Epoch 155/250
45/45            0s 297us/step -
auc: 0.9463 - loss: 0.2032
Epoch 156/250
45/45            0s 295us/step -
```

```
auc: 0.9437 - loss: 0.2062
Epoch 157/250
45/45            0s 273us/step -
auc: 0.9514 - loss: 0.1958
Epoch 158/250
45/45            0s 279us/step -
auc: 0.9481 - loss: 0.2030
Epoch 159/250
45/45            0s 277us/step -
auc: 0.9458 - loss: 0.2028
Epoch 160/250
45/45            0s 279us/step -
auc: 0.9504 - loss: 0.1961
Epoch 161/250
45/45            0s 278us/step -
auc: 0.9521 - loss: 0.1901
Epoch 162/250
45/45            0s 317us/step -
auc: 0.9479 - loss: 0.2005
Epoch 163/250
45/45            0s 294us/step -
auc: 0.9447 - loss: 0.2032
Epoch 164/250
45/45            0s 300us/step -
auc: 0.9484 - loss: 0.1906
Epoch 165/250
45/45            0s 277us/step -
auc: 0.9451 - loss: 0.2056
Epoch 166/250
45/45            0s 290us/step -
auc: 0.9481 - loss: 0.1922
Epoch 167/250
45/45            0s 357us/step -
auc: 0.9504 - loss: 0.1869
Epoch 168/250
45/45            0s 302us/step -
auc: 0.9501 - loss: 0.1897
Epoch 169/250
45/45            0s 321us/step -
auc: 0.9505 - loss: 0.2026
Epoch 170/250
45/45            0s 309us/step -
auc: 0.9534 - loss: 0.1888
Epoch 171/250
45/45            0s 302us/step -
auc: 0.9586 - loss: 0.1830
Epoch 172/250
45/45            0s 316us/step -
```

```
auc: 0.9482 - loss: 0.1874
Epoch 173/250
45/45            0s 294us/step -
auc: 0.9521 - loss: 0.1924
Epoch 174/250
45/45            0s 329us/step -
auc: 0.9491 - loss: 0.1944
Epoch 175/250
45/45            0s 296us/step -
auc: 0.9517 - loss: 0.1916
Epoch 176/250
45/45            0s 291us/step -
auc: 0.9498 - loss: 0.1971
Epoch 177/250
45/45            0s 290us/step -
auc: 0.9602 - loss: 0.1778
Epoch 178/250
45/45            0s 283us/step -
auc: 0.9558 - loss: 0.1840
Epoch 179/250
45/45            0s 286us/step -
auc: 0.9511 - loss: 0.1863
Epoch 180/250
45/45            0s 286us/step -
auc: 0.9540 - loss: 0.1926
Epoch 181/250
45/45            0s 291us/step -
auc: 0.9552 - loss: 0.1861
Epoch 182/250
45/45            0s 289us/step -
auc: 0.9540 - loss: 0.1869
Epoch 183/250
45/45            0s 289us/step -
auc: 0.9514 - loss: 0.1905
Epoch 184/250
45/45            0s 292us/step -
auc: 0.9555 - loss: 0.1893
Epoch 185/250
45/45            0s 289us/step -
auc: 0.9526 - loss: 0.1906
Epoch 186/250
45/45            0s 309us/step -
auc: 0.9486 - loss: 0.1975
Epoch 187/250
45/45            0s 308us/step -
auc: 0.9553 - loss: 0.1846
Epoch 188/250
45/45            0s 312us/step -
```

```
auc: 0.9536 - loss: 0.1914
Epoch 189/250
45/45            0s 293us/step -
auc: 0.9545 - loss: 0.1845
Epoch 190/250
45/45            0s 284us/step -
auc: 0.9548 - loss: 0.1868
Epoch 191/250
45/45            0s 289us/step -
auc: 0.9596 - loss: 0.1759
Epoch 192/250
45/45            0s 284us/step -
auc: 0.9480 - loss: 0.1917
Epoch 193/250
45/45            0s 284us/step -
auc: 0.9537 - loss: 0.1877
Epoch 194/250
45/45            0s 286us/step -
auc: 0.9547 - loss: 0.1898
Epoch 195/250
45/45            0s 287us/step -
auc: 0.9551 - loss: 0.1859
Epoch 196/250
45/45            0s 285us/step -
auc: 0.9565 - loss: 0.1867
Epoch 197/250
45/45            0s 286us/step -
auc: 0.9563 - loss: 0.1874
Epoch 198/250
45/45            0s 289us/step -
auc: 0.9541 - loss: 0.1852
Epoch 199/250
45/45            0s 285us/step -
auc: 0.9592 - loss: 0.1758
Epoch 200/250
45/45            0s 287us/step -
auc: 0.9592 - loss: 0.1729
Epoch 201/250
45/45            0s 289us/step -
auc: 0.9531 - loss: 0.1897
Epoch 202/250
45/45            0s 287us/step -
auc: 0.9559 - loss: 0.1878
Epoch 203/250
45/45            0s 296us/step -
auc: 0.9574 - loss: 0.1787
Epoch 204/250
45/45            0s 287us/step -
```

```
auc: 0.9546 - loss: 0.1871
Epoch 205/250
45/45            0s 282us/step -
auc: 0.9574 - loss: 0.1821
Epoch 206/250
45/45            0s 289us/step -
auc: 0.9650 - loss: 0.1677
Epoch 207/250
45/45            0s 290us/step -
auc: 0.9534 - loss: 0.1886
Epoch 208/250
45/45            0s 283us/step -
auc: 0.9511 - loss: 0.1916
Epoch 209/250
45/45            0s 284us/step -
auc: 0.9551 - loss: 0.1893
Epoch 210/250
45/45            0s 288us/step -
auc: 0.9590 - loss: 0.1751
Epoch 211/250
45/45            0s 299us/step -
auc: 0.9570 - loss: 0.1856
Epoch 212/250
45/45            0s 291us/step -
auc: 0.9587 - loss: 0.1843
Epoch 213/250
45/45            0s 299us/step -
auc: 0.9597 - loss: 0.1766
Epoch 214/250
45/45            0s 286us/step -
auc: 0.9607 - loss: 0.1776
Epoch 215/250
45/45            0s 283us/step -
auc: 0.9614 - loss: 0.1744
Epoch 216/250
45/45            0s 294us/step -
auc: 0.9589 - loss: 0.1829
Epoch 217/250
45/45            0s 295us/step -
auc: 0.9598 - loss: 0.1763
Epoch 218/250
45/45            0s 287us/step -
auc: 0.9621 - loss: 0.1727
Epoch 219/250
45/45            0s 290us/step -
auc: 0.9557 - loss: 0.1849
Epoch 220/250
45/45            0s 282us/step -
```

```
auc: 0.9597 - loss: 0.1756
Epoch 221/250
45/45            0s 292us/step -
auc: 0.9561 - loss: 0.1860
Epoch 222/250
45/45            0s 286us/step -
auc: 0.9561 - loss: 0.1848
Epoch 223/250
45/45            0s 303us/step -
auc: 0.9612 - loss: 0.1743
Epoch 224/250
45/45            0s 297us/step -
auc: 0.9612 - loss: 0.1744
Epoch 225/250
45/45            0s 304us/step -
auc: 0.9621 - loss: 0.1701
Epoch 226/250
45/45            0s 292us/step -
auc: 0.9600 - loss: 0.1729
Epoch 227/250
45/45            0s 285us/step -
auc: 0.9600 - loss: 0.1732
Epoch 228/250
45/45            0s 281us/step -
auc: 0.9613 - loss: 0.1722
Epoch 229/250
45/45            0s 288us/step -
auc: 0.9629 - loss: 0.1729
Epoch 230/250
45/45            0s 285us/step -
auc: 0.9562 - loss: 0.1781
Epoch 231/250
45/45            0s 287us/step -
auc: 0.9569 - loss: 0.1834
Epoch 232/250
45/45            0s 284us/step -
auc: 0.9589 - loss: 0.1773
Epoch 233/250
45/45            0s 289us/step -
auc: 0.9615 - loss: 0.1771
Epoch 234/250
45/45            0s 295us/step -
auc: 0.9563 - loss: 0.1776
Epoch 235/250
45/45            0s 292us/step -
auc: 0.9635 - loss: 0.1707
Epoch 236/250
45/45            0s 287us/step -
```

```
auc: 0.9625 - loss: 0.1730
Epoch 237/250
45/45              0s 288us/step -
auc: 0.9616 - loss: 0.1724
Epoch 238/250
45/45              0s 286us/step -
auc: 0.9651 - loss: 0.1722
Epoch 239/250
45/45              0s 298us/step -
auc: 0.9672 - loss: 0.1610
Epoch 240/250
45/45              0s 291us/step -
auc: 0.9598 - loss: 0.1740
Epoch 241/250
45/45              0s 285us/step -
auc: 0.9625 - loss: 0.1732
Epoch 242/250
45/45              0s 313us/step -
auc: 0.9601 - loss: 0.1819
Epoch 243/250
45/45              0s 283us/step -
auc: 0.9611 - loss: 0.1708
Epoch 244/250
45/45              0s 290us/step -
auc: 0.9630 - loss: 0.1699
Epoch 245/250
45/45              0s 286us/step -
auc: 0.9615 - loss: 0.1779
Epoch 246/250
45/45              0s 291us/step -
auc: 0.9614 - loss: 0.1764
Epoch 247/250
45/45              0s 285us/step -
auc: 0.9612 - loss: 0.1743
Epoch 248/250
45/45              0s 288us/step -
auc: 0.9663 - loss: 0.1665
Epoch 249/250
45/45              0s 291us/step -
auc: 0.9589 - loss: 0.1789
Epoch 250/250
45/45              0s 294us/step -
auc: 0.9614 - loss: 0.1696
```

```
[36]: <keras.src.callbacks.history.History at 0x287b03710>
```

[37]:
```
# Generate the predicted probability of y
y_score_mlp = mlp.predict(X_test_preproc)

# Convert probability to y value
y_pred_mlp = (y_score_mlp > 0.5).astype(int)

# Generate the test loss and AUC
test_loss, auc_mlp=mlp.evaluate(X_test_preproc, y_test)
```

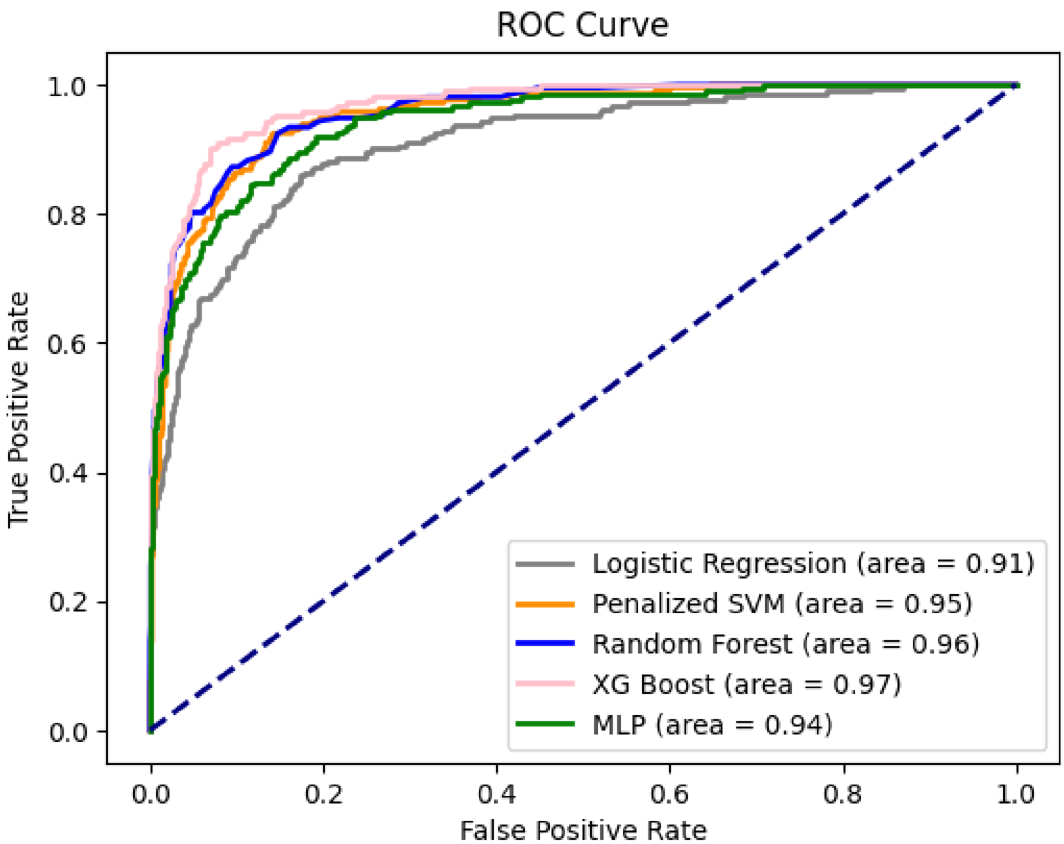
```
45/45              0s 480us/step
45/45              0s 304us/step -
auc: 0.9505 - loss: 0.1855
```

[38]:
```
#Generate performance metrics
accuracy_mlp = accuracy_score(y_test, y_pred_mlp)
conf_matrix_mlp = confusion_matrix(y_test, y_pred_mlp)
classification_rep_mlp = classification_report(y_test, y_pred_mlp)
# auc_mlp=roc_auc_score(y_test, y_score_mlp)

print(f"Test accuracy: \n  {accuracy_mlp:.2%}")
print ("Confusion Matrix : \n", conf_matrix_mlp)
print("\nClassification Report: : \n",classification_rep_mlp)
print(f"AUC: \n  {auc_mlp:.2%}")
```

```
Test accuracy:
  92.52%
Confusion Matrix :
 [[1174   31]
 [  75  137]]

Classification Report: :
               precision    recall  f1-score   support

           0       0.94      0.97      0.96      1205
           1       0.82      0.65      0.72       212

    accuracy                           0.93      1417
   macro avg       0.88      0.81      0.84      1417
weighted avg       0.92      0.93      0.92      1417

AUC:
  94.09%
```

4.6 Model Selection

[39]:
```
# Calculate ROC Curve
fpr_lr, tpr_lr, thresholds = roc_curve(y_test, y_score_lr)
fpr_svc, tpr_svc, thresholds = roc_curve(y_test, y_score_svc)
fpr_rf, tpr_rf, thresholds = roc_curve(y_test, y_score_rf)
fpr_xgb, tpr_xgb, thresholds = roc_curve(y_test, y_score_xgb)
fpr_mlp, tpr_mlp, thresholds = roc_curve(y_test, y_score_mlp)

# Plot ROC Curve
plt.figure()
plt.plot(fpr_lr, tpr_lr, color='gray', lw=2, label='Logistic Regression (area =␣
↪%0.2f)' % auc_lr)
plt.plot(fpr_svc, tpr_svc, color='darkorange', lw=2, label='Penalized SVM (area␣
↪= %0.2f)' % auc_svc)
plt.plot(fpr_rf, tpr_rf, color='blue', lw=2, label='Random Forest (area = %0.
↪2f)' % auc_rf)
plt.plot(fpr_xgb, tpr_xgb, color='pink', lw=2, label='XG Boost (area = %0.2f)'␣
↪% auc_xgb)
plt.plot(fpr_mlp, tpr_mlp, color='green', lw=2, label='MLP (area = %0.2f)' %␣
↪auc_mlp)

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



XG Boos has the best performance based on the AUC and F1 score. As a result, I want to select the XGBoost and fine-tune the model to get a higer recall if possible.

5 Fine-Tune the Model

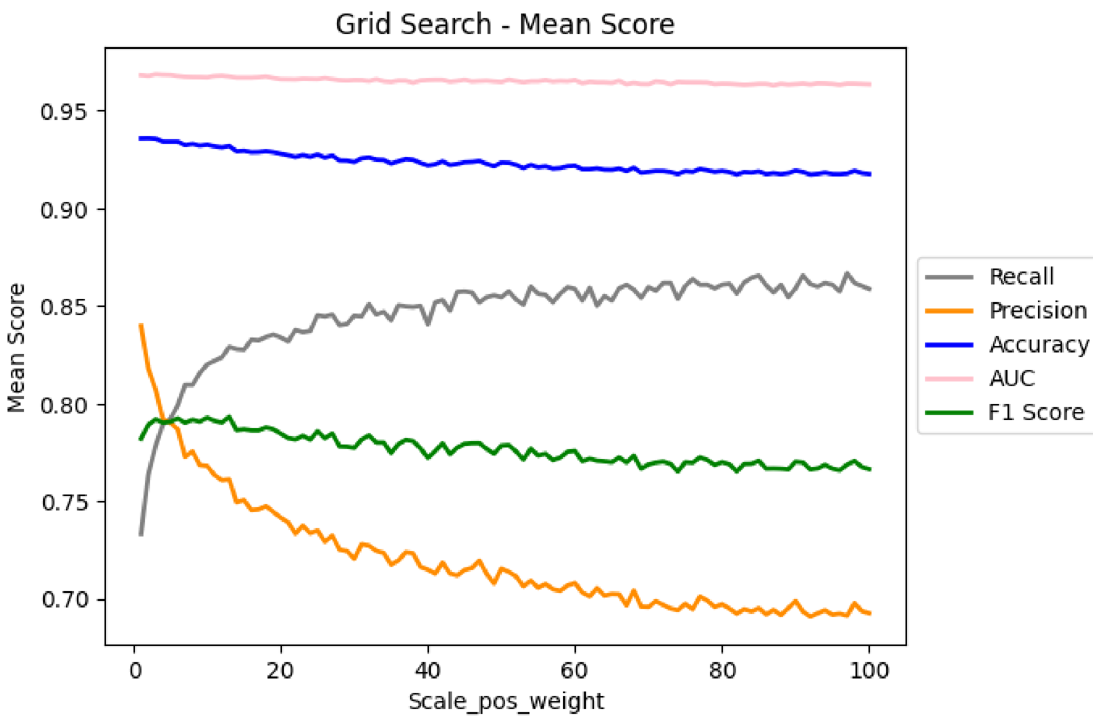
5.1 Grid Search

In this section, I want to search the optimized scale_pos_weight which is a hyperparameter in XGBoost with the effect of weighing the balance of positive examples(minority class), relative to negative examples(majority class) when boosting decision trees. It has by default value 1. A sensible default value to set for the scale_pos_weight hyperparameter is the inverse of the class distribution. For example, for a dataset with a 1 to 100 ratio for examples in the minority to majority classes, the scale_pos_weight can be set to 100. This will give classification errors made by the model on the minority class 100 times more impact, and in turn, 100 times more correction than errors made on the majority class.

[40]:
```
# Preprocess X variables
X_preproc = preprocessor.transform(X)
# Define model
model = XGBClassifier()
```

```
# Define grid - all integers between 1 and 100
weights = list(range(1, 101))
param_grid = dict(scale_pos_weight=weights)
# Define evaluation procedure
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=42)
# Define grid search based on different scoring method(recall,precision,f1␣
↪score, accuracy, AUC)
grid_recall = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1,␣
↪cv=cv, scoring='recall')
grid_precision = GridSearchCV(estimator=model, param_grid=param_grid,␣
↪n_jobs=-1, cv=cv, scoring='precision')
grid_f1 = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1,␣
↪cv=cv, scoring='f1')
grid_accuracy = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1,␣
↪cv=cv, scoring='accuracy')
grid_auc = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1,␣
↪cv=cv, scoring='roc_auc')

# Execute the grid search
grid_result_recall = grid_recall.fit(X_preproc,y)
grid_result_precision = grid_precision.fit(X_preproc,y)
grid_result_f1 = grid_f1.fit(X_preproc,y)
grid_result_accuracy = grid_accuracy.fit(X_preproc,y)
grid_result_auc = grid_auc.fit(X_preproc,y)

# Save the mean core by different weight
means_recall = grid_result_recall.cv_results_['mean_test_score']
means_precision = grid_result_precision.cv_results_['mean_test_score']
means_f1 = grid_result_f1.cv_results_['mean_test_score']
means_accuracy = grid_result_accuracy.cv_results_['mean_test_score']
means_auc = grid_result_auc.cv_results_['mean_test_score']
```

[41]:
```
# Plot the mean score by different weight
plt.figure()
plt.plot(weights, means_recall, color='gray', lw=2, label='Recall')
plt.plot(weights, means_precision, color='darkorange', lw=2, label='Precision' )
plt.plot(weights, means_accuracy, color='blue', lw=2, label='Accuracy')
plt.plot(weights, means_auc, color='pink', lw=2, label='AUC' )
plt.plot(weights, means_f1, color='green', lw=2, label='F1 Score')

plt.xlabel('Scale_pos_weight')
plt.ylabel('Mean Score')
plt.title('Grid Search - Mean Score')
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.show()
```



From the plot above, I observed that averaged recall(TP/(TP+FN)) increases as the scale_pos_weight increases, which means the model becomes more powerful to identify the attrited customers as scale_pos_weight increases. However, the precision decreases as the scale_pos_weight increases because the increase in penalty on minority samples may lead the model to classify more samples as positive, thereby increasing the false positive rate and decreasing precision, and also accuracy and AUC.

In this project, the bank wants to identify potential attrited customers and take actions to avoid customer loss, but the bank doesn't want to give ' win back offer' to too many existing customers since the offers reduces their profit. As a result, I want to find a balance between recall and precision in the model, and the f1 score could be a good metric as it is the weighted average of recall and precision.

[42]:
```
# Report the best configuration
print("Best: %f using %s" % (grid_result_f1.best_score_, grid_result_f1.
 ↪best_params_))
```

```
Best: 0.793146 using {'scale_pos_weight': 13}
```

5.2 Evaluate the Model on the Test Set

[43]:
```
# Fit the model
xgboost = XGBClassifier(scale_pos_weight=13)
xgboost.fit(X_train_preproc,y_train)
```

[43]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, …)
```

[44]:
```
# Generate the predicted y value and calculate the y_score
y_pred_xgb = xgboost.predict(X_test_preproc)
y_score_xgb = xgboost.predict_proba(X_test_preproc)[:, 1]
```

[45]:
```
#Generate performance metrics
accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
conf_matrix_xgb = confusion_matrix(y_test, y_pred_xgb)
classification_rep_xgb = classification_report(y_test, y_pred_xgb)
auc_xgb=roc_auc_score(y_test, y_score_xgb)

print(f"Test accuracy: \n  {accuracy_xgb:.2%}")
print ("Confusion Matrix : \n", conf_matrix_xgb)
print("\nClassification Report: : \n",classification_rep_xgb)
print(f"AUC: \n  {auc_xgb:.2%}")
```

```
Test accuracy:
  93.15%
Confusion Matrix :
 [[1142   63]
 [  34  178]]

Classification Report: :
               precision    recall  f1-score   support

           0       0.97      0.95      0.96      1205
           1       0.74      0.84      0.79       212

    accuracy                           0.93      1417
   macro avg       0.85      0.89      0.87      1417
weighted avg       0.94      0.93      0.93      1417

AUC:
  97.01%
```

6 Conclusion

I have successfully trained a model with an accuracy of 93.15% and an AUC of 97.01%. This model can effectively identify 84% of customers who will close their credit cards. However, within the customers identified as attrited, 26% actually do not close their cards. A trade-off relationship is observed between the precision and recall of this model. Therefore, further evaluation is needed to compare the cost of customer churn with the reduction in profit from offering promotions to customers who will not churn. If the cost of customer churn is greater, the model's scale_pos_weight should be increased to improve its recall. Conversely, if the reduction in profit from offering promotions to customers who will not churn is greater, the model's scale_pos_weight should be adjusted downwards to improve precision.