

CSCA 5622

Introduction to Machine

Learning: Supervised Learning

Default of Credit Card Clients

Purpose

- The purpose of Default of Credit Card Client kaggle project is to build a supervised Machine learning model that predicts whether a credit card client will default on their payment in the next month.
- This is a binary classification problem based on real world financial and demographic data from clients in Taiwan, collected between April and Sept 2005.
- Multiple algorithms like Logistic Regression, Random Forest Classifier, XGBoost and SVC were trained and evaluated.

Data Source Citation

1. UCI Machine Learning Repository:

Yeh, I. (2009). Default of Credit Card Clients [Dataset]. UCI Machine Learning Repository. <https://doi.org/10.24432/C55S3H>.

2. Kaggle Platform:

The dataset was accessed from the Kaggle platform:

Default of Credit Card Clients Dataset. (n.d.). [Www.kaggle.com](http://www.kaggle.com).
<https://www.kaggle.com/datasets/uciml/default-of-credit-card-clients-dat>

Data Source

Data Size:

- Number of rows: 30,000
- Number of features: 25

Data Types:

3 Categorical features and the remaining Numerical features.

- Education
- Sex
- Marriage

Data Cleaning

- The dataset contains 3 categorical variables: Education, Sex and Marriage
- Rare or undefined values in Education([0,5,6]) were grouped under category 4, and Marriage value 0 was reassigned to 3 (“Others”)
- The column PAY_0 was renamed to PAY_1 for consistency with other payment status features.
- The dataset contains no missing values or duplicate entries, ensuring data integrity.
- A significant class imbalance exists, with the majority of samples belonging to class 0 (non-default). Techniques such as resampling or SMOTE may be applied to address this imbalance.

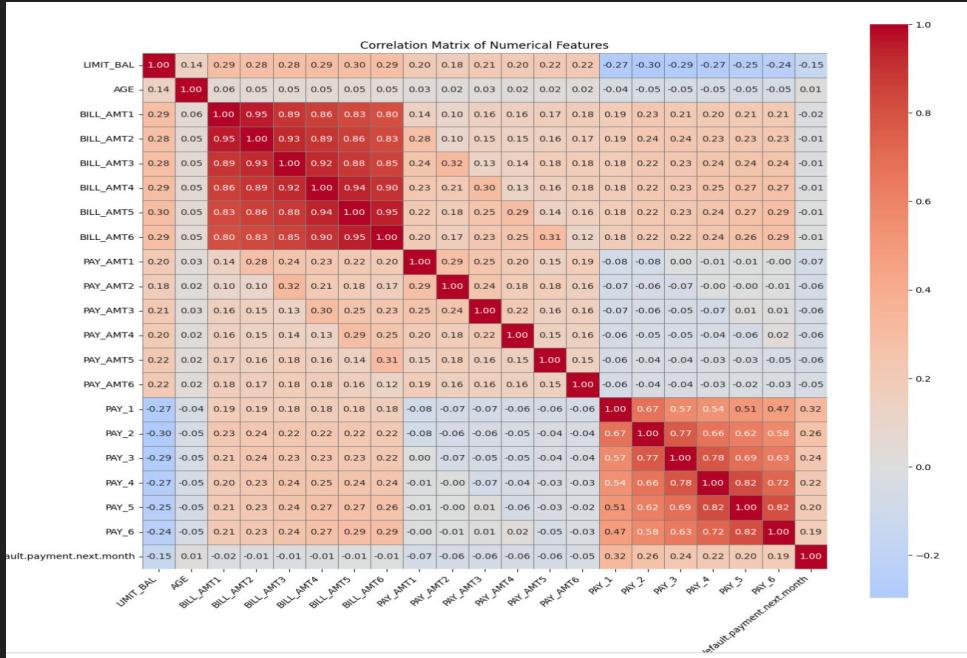
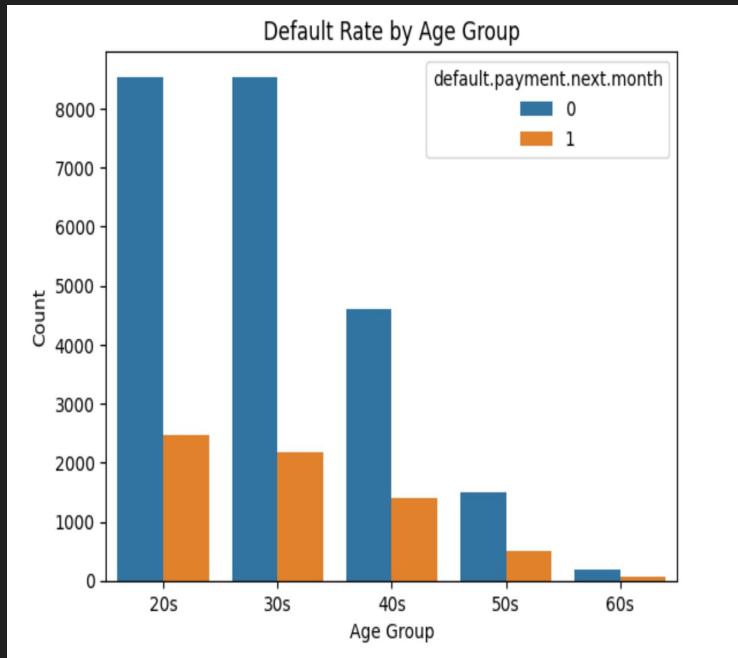
Exploratory Data Analysis

- **Categorical Feature Distributions:** The three categorical variables—EDUCATION, MARRIAGE, and SEX—were analyzed and visualized to understand their relationship with default status.
- **Gender vs. Default Status:** Although females make up 60% of the dataset, males show a higher default rate (24% of all males). Class 0 (non-default) dominates both genders due to class imbalance.
- **Education Levels:** Most clients, both defaulters and non-defaulters, belong to the Graduate School and University categories. Other education levels contribute minimally, likely due to sparse data.

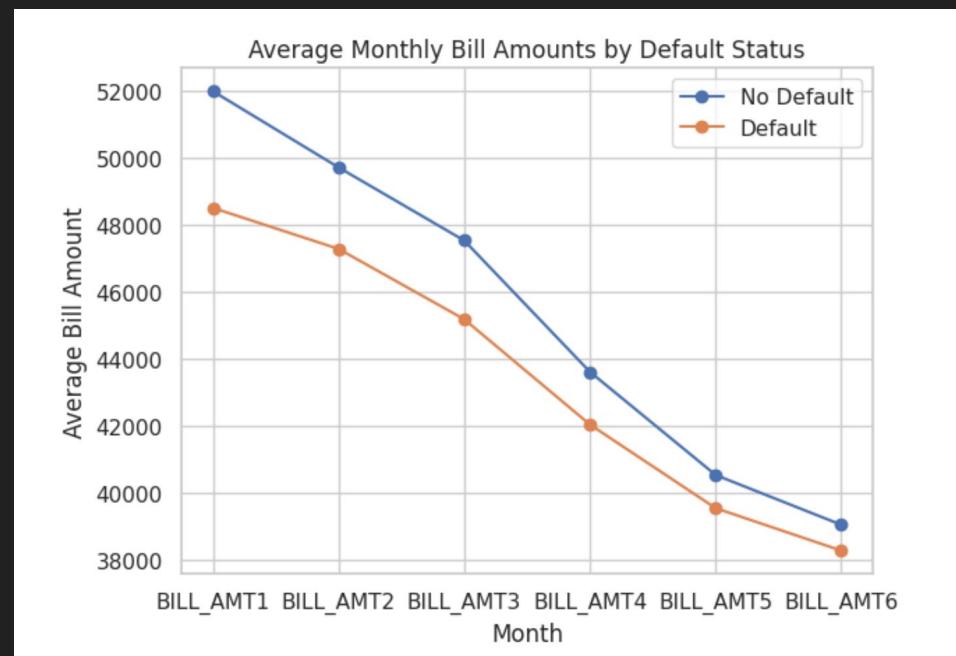
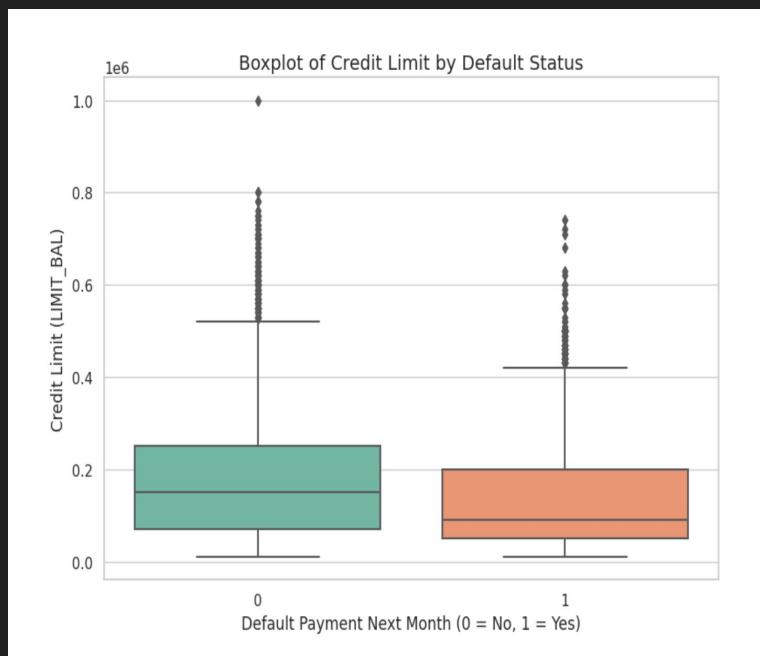
Exploratory Data Analysis(Contd.)

- Marriage Status: Defaulters are primarily found in the 'Single' and 'Married' groups.
- Age Distribution: Age was binned for visualization; clients in their 20s show the highest default rate, possibly due to limited savings.
- Correlation Insights: LIMIT_BAL and PAY_1 show strong correlation with default status, indicating their predictive importance.
- Compute Variance Inflation factor to check Multicollinearity
- Check Outliers by Credit Limit
- Credit Limit Patterns: Non-defaulters tend to have higher and more flexible credit limits; defaulters are assigned lower limits, reflecting risk-based credit allocation.
- Perform Statistical Tests like chi square tests(Categorical columns) and Anova Test (Numerical columns)
- Kde plot on the strongest predictor

Exploratory Data Analysis(Contd.)



Exploratory Data Analysis(Contd.)



ML PipeLine

- Data Preprocessing
- Separate Features & Target and Train/Test/Validation Split
- Feature Selection and Scaling
- Handle Class Imbalance
- Model Training and Evaluation
- Model Performance Summary
- Implementing the best model on Testset
- Conclusion

Model Training and Evaluation

Default Credit Card Clients project has been trained on the following 4 Supervised learning algorithms:

- Logistic Regression
- Random Forest Classifier
- XGBoost
- SVC

Model Optimization Summary

- Applied hyperparameter tuning to each model using GridSearch/Randomized CV to identify optimal settings.
- Select the best threshold value for classification and recalculated accuracy.
- Preformed Cross-validation on each model to compute the mean F1 score ensuring robust performance evaluation.
- Compared tuned models against baseline versions to assess improvements in recall, F1 score and ROC-AUC.
- Visualized performance metrics to support final model selection.

Logistic Regression(Baseline Model)

Baseline Logistic Regression Model

Accuracy:0.69

Precision:0.38

Recall:0.66

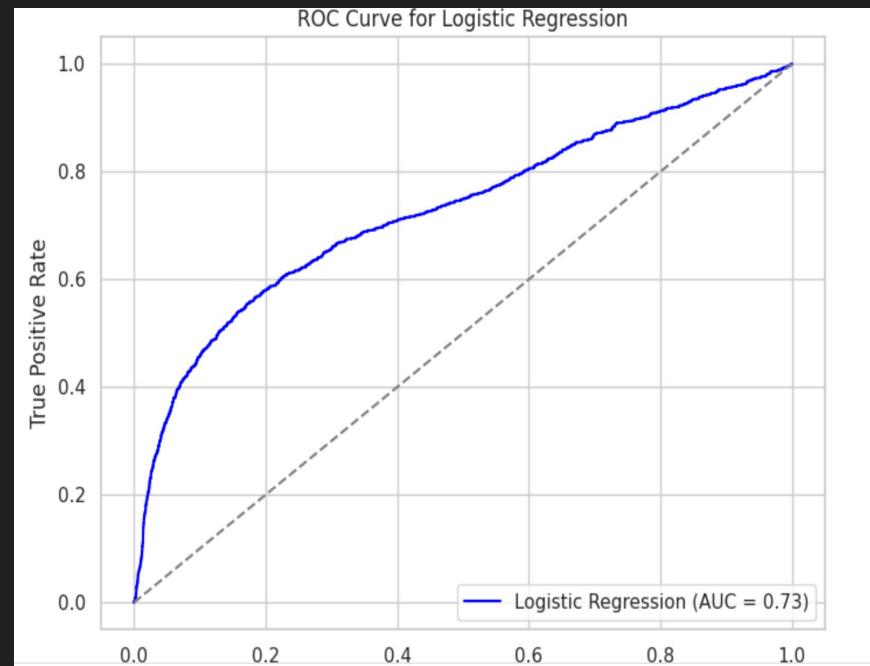
F1 Score:0.48

ROC AUC:0.73

Confusion Matrix:

`[[3276 1397]`

`[457 870]]`



Logistic Regression (HyperTuned Model)

Best Params: {'C': 1, 'penalty': 'l2', 'solver': 'liblinear'}

GridSearchCV Logistic Regression Model

Accuracy: 0.72

Precision: 0.41

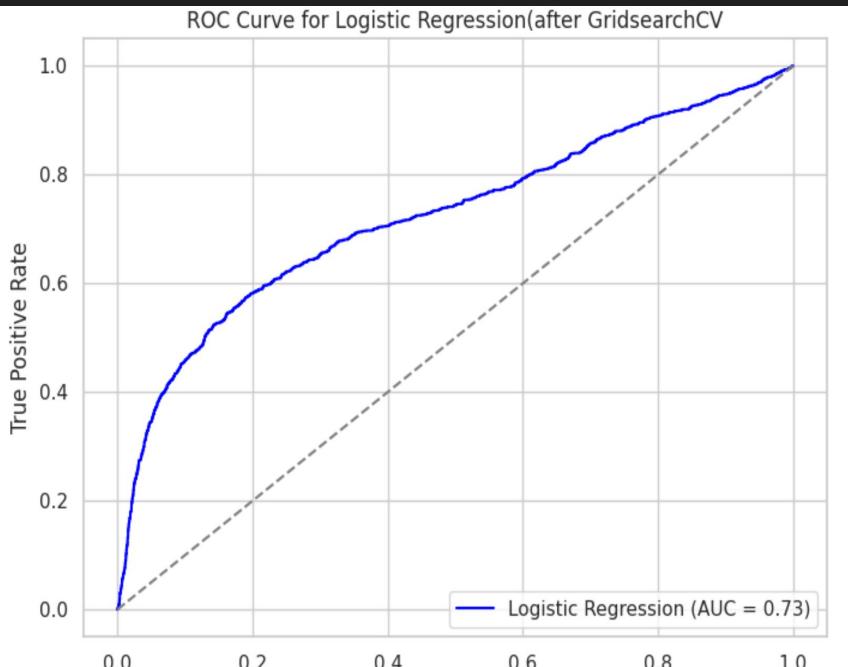
Recall: 0.59

F1 Score: 0.48

ROC AUC: 0.73

Confusion Matrix:

```
[[3561 1112]
 [ 549  778]]
```



Logistic Regression(Best Threshold)

Best Threshold Value 0.5677309148324262

Optimized Threshold Logistic Regression Model

Accuracy:0.79

Precision:0.52

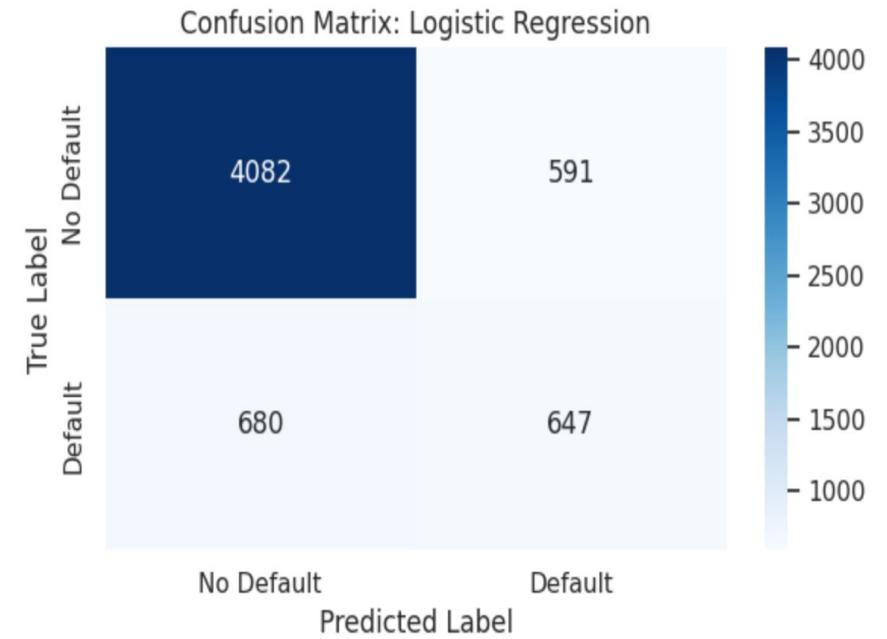
Recall:0.49

F1 Score:0.50

Confusion Matrix:

[[4082 591]

[680 647]]



Random Forest Classifier(Baseline Model)

Random Forest Classifier

Accuracy:0.81

Precision:0.66

Recall:0.34

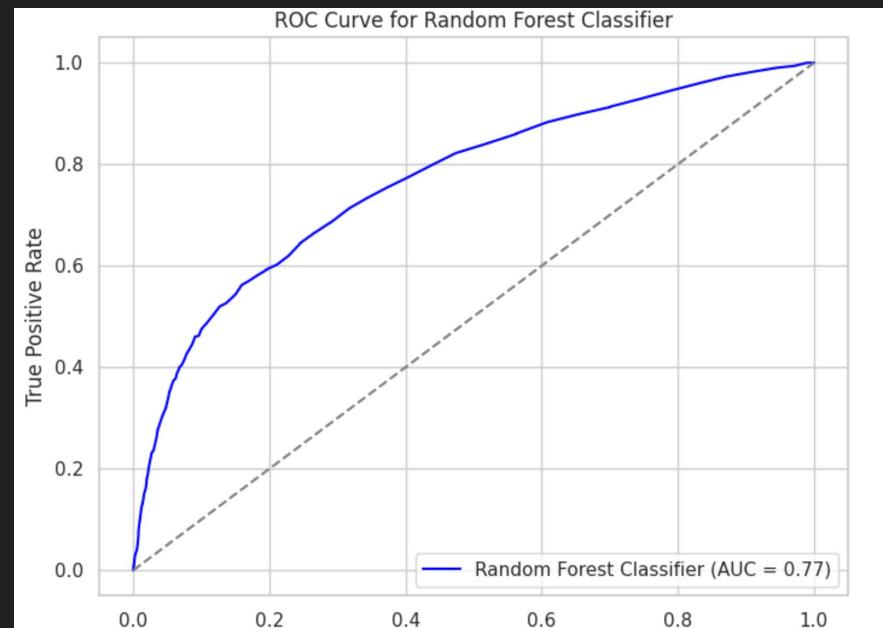
F1 Score:0.44

ROC AUC:0.77

Confusion Matrix:

[[4440 233]

[882 445]]



Random Forest Classifier(HyperTuned Model)

GridSearchCV Random Forest Classifier Model

Accuracy:0.79

Precision:0.53

Recall:0.55

F1 Score:0.54

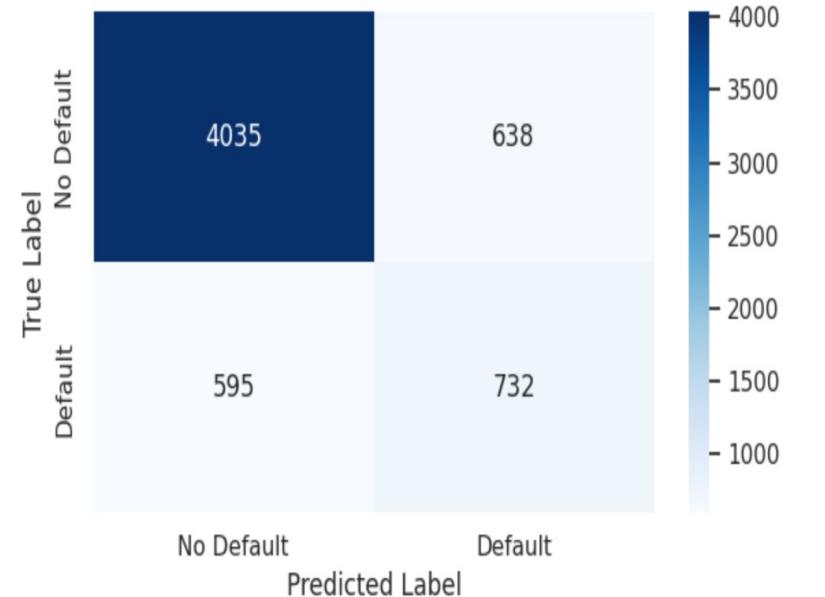
ROC AUC:0.78

Confusion Matrix:

[[4035 638]

[595 732]]

Confusion Matrix: Random Forest Classifier



Random Forest Classifier(Best Threshold)

Best Threshold Value 0.5033772300746544

Optimized Threshold Random Forest Classifier Model

Accuracy:0.80

Precision:0.54

Recall:0.55

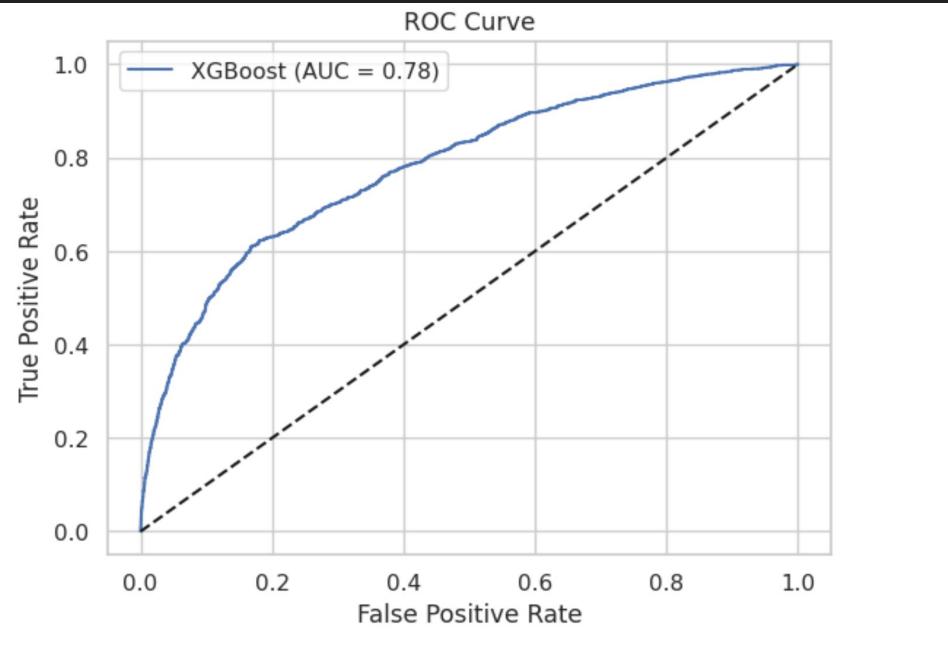
F1 Score:0.54

Confusion Matrix:

```
[[4045  628]
 [ 597  730]]
```

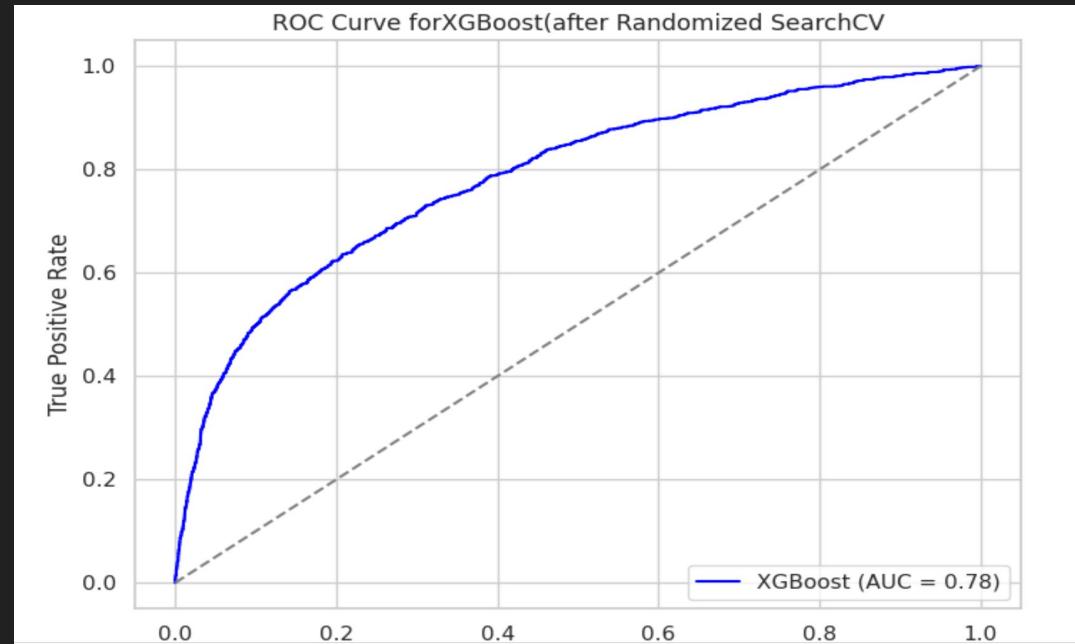
XGBoost (Baseline Model)

XGBoost Classifier
Accuracy: 0.82
Precision: 0.69
Recall: 0.36
F1 Score: 0.47
ROC AUC: 0.78
Confusion Matrix:
[[4458 215]
 [851 476]]



XGBoost (HyperTuned Model)

XGBoost Classifier
Accuracy: 0.82
Precision: 0.69
Recall: 0.36
F1 Score: 0.47
ROC AUC: 0.78
Confusion Matrix:
[[4458 215]
 [851 476]]



XGBoost (Best Threshold)

```
Best Threshold Value 0.2799016
Optimized Threshold XGBClassifier Model
Accuracy:0.80
Precision:0.54
Recall:0.55
F1 Score:0.54
Confusion Matrix:
 [[4045  628]
 [ 598  729]]
```

SVC(Baseline Model)

SVC

Accuracy:0.78

Precision:0.50

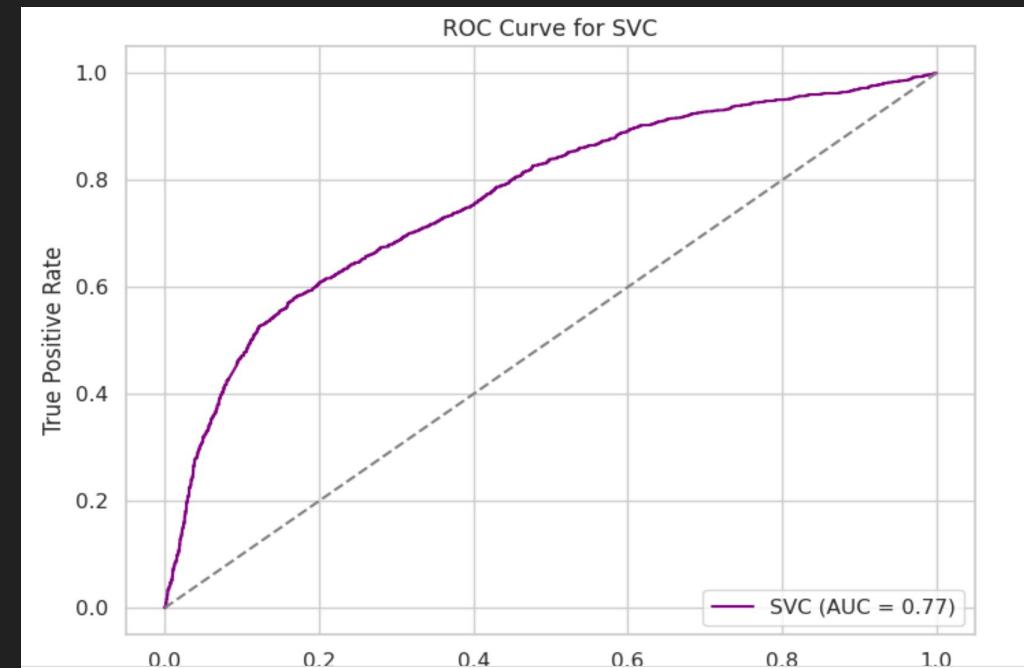
Recall:0.58

F1 Score:0.54

ROC AUC:0.77

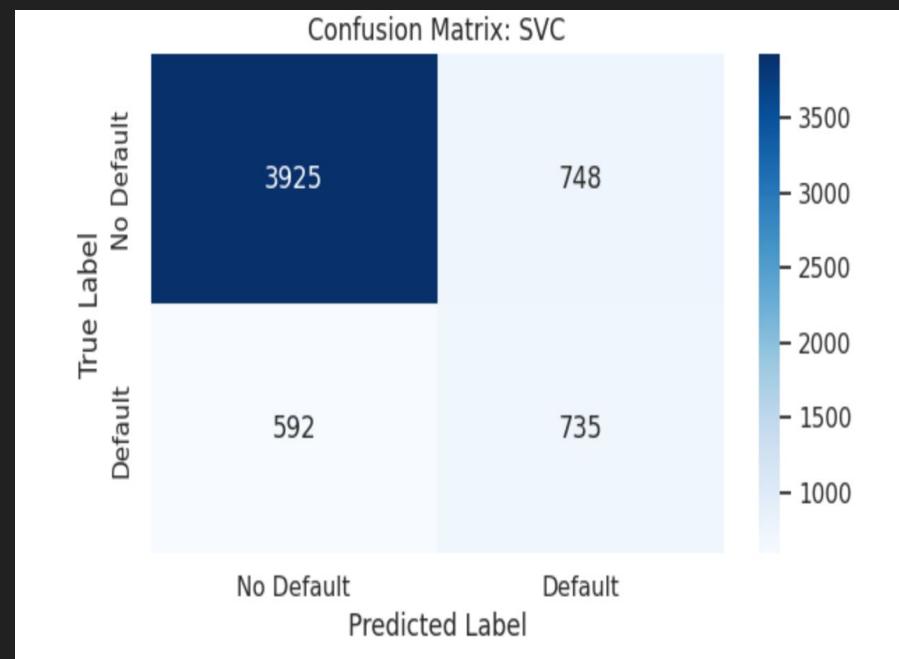
Confusion Matrix:

```
[[3908  765]
 [ 561  766]]
```



SVC(HyperTuned Model)

```
GridSearchCV SVC Model  
Accuracy:0.78  
Precision:0.50  
Recall:0.55  
F1 Score:0.52  
ROC AUC:0.76  
Confusion Matrix:  
[[3925  748]  
 [ 592  735]]
```



SVC(Best Threshold)

Best Threshold Value 0.5683945102249383

Optimized Threshold SVC Model

Accuracy:0.81

Precision:0.69

Recall:0.23

F1 Score:0.35

Confusion Matrix:

```
[[4533 140]
 [1020 307]]
```

Model Performance Summary

... Model Performance Summary:

	Accuracy	Precision	Recall	F1 Score	ROC AUC
Logistic Regression	0.724	0.413	0.587	0.485	0.725
Random Forest	0.814	0.656	0.335	0.444	0.773
XGBoost	0.822	0.689	0.359	0.472	0.781
SVC	0.779	0.500	0.577	0.536	0.766

Hypertuned Model Performance Summary:

	Accuracy	Precision	Recall	F1 Score	ROC AUC
Logistic Regression(after HT)	0.723	0.412	0.586	0.484	0.725
Random Forest(after HT)	0.794	0.534	0.552	0.543	0.777
XGBoost (after HT)	0.822	0.694	0.353	0.468	0.784
SVC (after HT)	0.777	0.496	0.554	0.523	0.759

Optimized Threshold Model Performance Summary:

	Accuracy	Precision	Recall	\
Logistic Regression(Optimized Threshold)	0.788	0.523	0.488	
Random Forest(Optimized Threshold)	0.796	0.538	0.550	
XGBoost (Optimized Threshold)	0.796	0.537	0.549	
SVC (Optimized Threshold)	0.807	0.687	0.231	

	F1 Score	ROC AUC
Logistic Regression(Optimized Threshold)	0.504	0.725
Random Forest(Optimized Threshold)	0.544	0.777
XGBoost (Optimized Threshold)	0.543	0.784
SVC (Optimized Threshold)	0.346	0.759

Validation Summary:

	Mean	CV	F1
Logistic Regression	0.706		
Random Forest Classifier	0.536		
XGBoost	0.471		
SVC	0.534		

Implementing the Best Model on the Test set - RFC(Optimized Threshold)

Optimized Threshold Random Forest TestSet

Accuracy:0.80

Precision:0.54

Recall:0.55

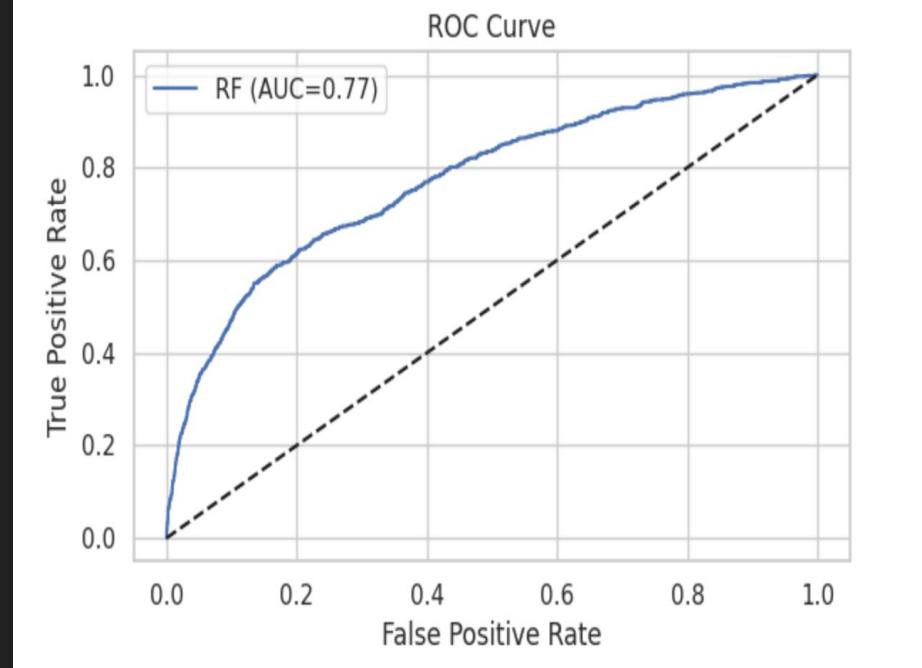
F1 Score:0.54

ROC AUC:0.77

Confusion Matrix:

$\begin{bmatrix} 4042 & 631 \end{bmatrix}$

$\begin{bmatrix} 597 & 730 \end{bmatrix}$



Conclusion

Key Learnings:

- 1) Threshold Optimization is essential for imbalanced datasets. Optimizing threshold(0.5) for Random Forest and XGBOOST significantly improve their recall and F1 scores.
- 2) Other Metrics like F1 Score, Recall , Precision, ROC AUC should be taken for imbalance data sets other than accuracy.
- 3) Cross Validation reveals true model stability. Though Logistic Regression has the highest CV (0.7) it lacked in the other metrics. XGBOOST has the lowest CV score 0.4 showing it is more sensitive to data splits. Random Forest showed strong performance.
- 4) Ensemble models like XGBOOST and Random Forest showed better performance than the other 2 models.
- 5) Confusion Matrix Importance should be given to False positives and False negatives for this imbalanced dataset than accuracy.

Highlights:

- 1)EDA has been done on the data set and found that the class is imbalanced.So, SMOTE and class weight='balanced' techniques were used.
- 2)Data preprocessing and scaling were done on the numerical and categorical columns.
- 3)Evaluated models across Baseline,Hyperparameter Tuning , Optimized threshold and Cross Validation.
- 4)Best Overall Model: Random Forest(Optimized Threshold) Random Forest(Optimized Threshold)
0.796(accuracy),0.538(precision), 0.550(recall),0.544 (F1 SCORE) and ROC AUC (0.777)
- 5)Random Forest Classifier(Optimized Threshold) was applied on the test set and the below metric were calculated.

Optimized Threshold Random Forest TestSet Accuracy:0.80 Precision:0.54 Recall:0.55 F1 Score:0.54 ROC AUC:0.77
Confusion Matrix: [[4042 631] [597 730]]
- 6)Out of 6000 samples in the testset, we can see that 4772 samples have been predicted accurately.

Things to Improve

- 1)Feature Engineering - Model performance can be improved by adding more features, domain specific variables
- 2)Advanced Ensemble methods like LightBOOST and also other models like knn can be implemented.
- 3)Have to address False negatives since this is very expensive. This can be done using cost sensitive learning.
- 4)For improving code usability, Pipeline models can be used.

References

- <https://seaborn.pydata.org/generated/seaborn.kdeplot.html>
- <https://www.geeksforgeeks.org/python/detecting-multicollinearity-with-vif-python/>
- <https://www.geeksforgeeks.org/mathematics/chi-square-test/>
- https://github.com/HillidatullImi/EDA-and-Machine-Learning-Default-of-Credit-Card-Clients/blob/main/EDA_and_Machine_Learning_Default_of_Credit_Card_Clients.ipynb

Links

Github Link:

[MS-AI/Pathway Machine Learning: Theory & Hands-On Practice with Python Specialization/CSCA 5622: Introduction to Machine Learning: Supervised Learning /Module 7 - Final Project at main · kmadhu181090/MS-AI](https://github.com/kmadhu181090/MS-AI)

Video Presentation Link:

<https://youtu.be/eFIQEvEVZxM>

THANK YOU