# Capstone Project

(SUPERVISED ML – CLASSIFICATION)

# Credit Card Default Prediction


**INDIVIDUAL PROJECT**


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~ UNDER THE GUIDANCE OF ALMABETTER TEAM

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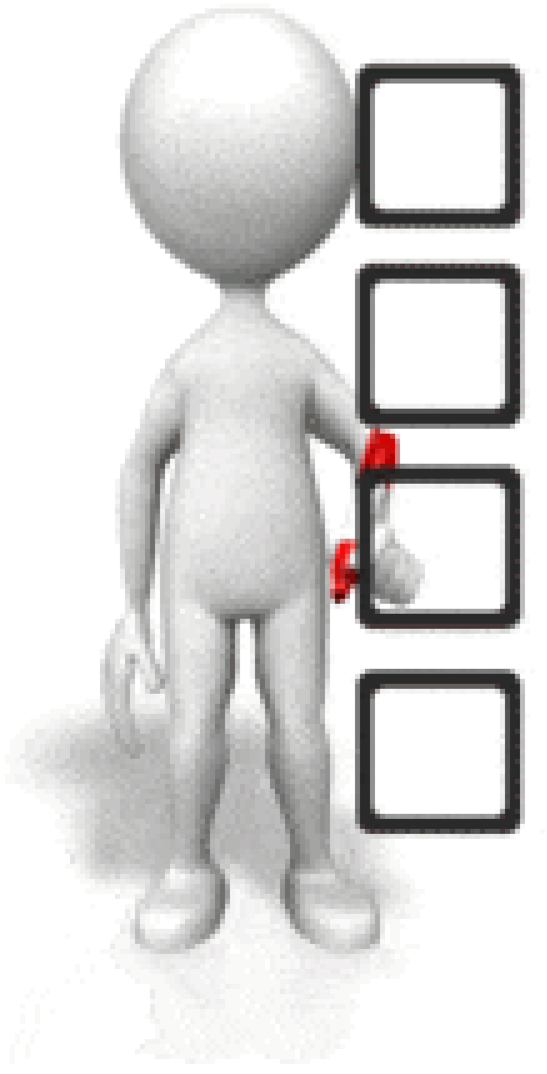
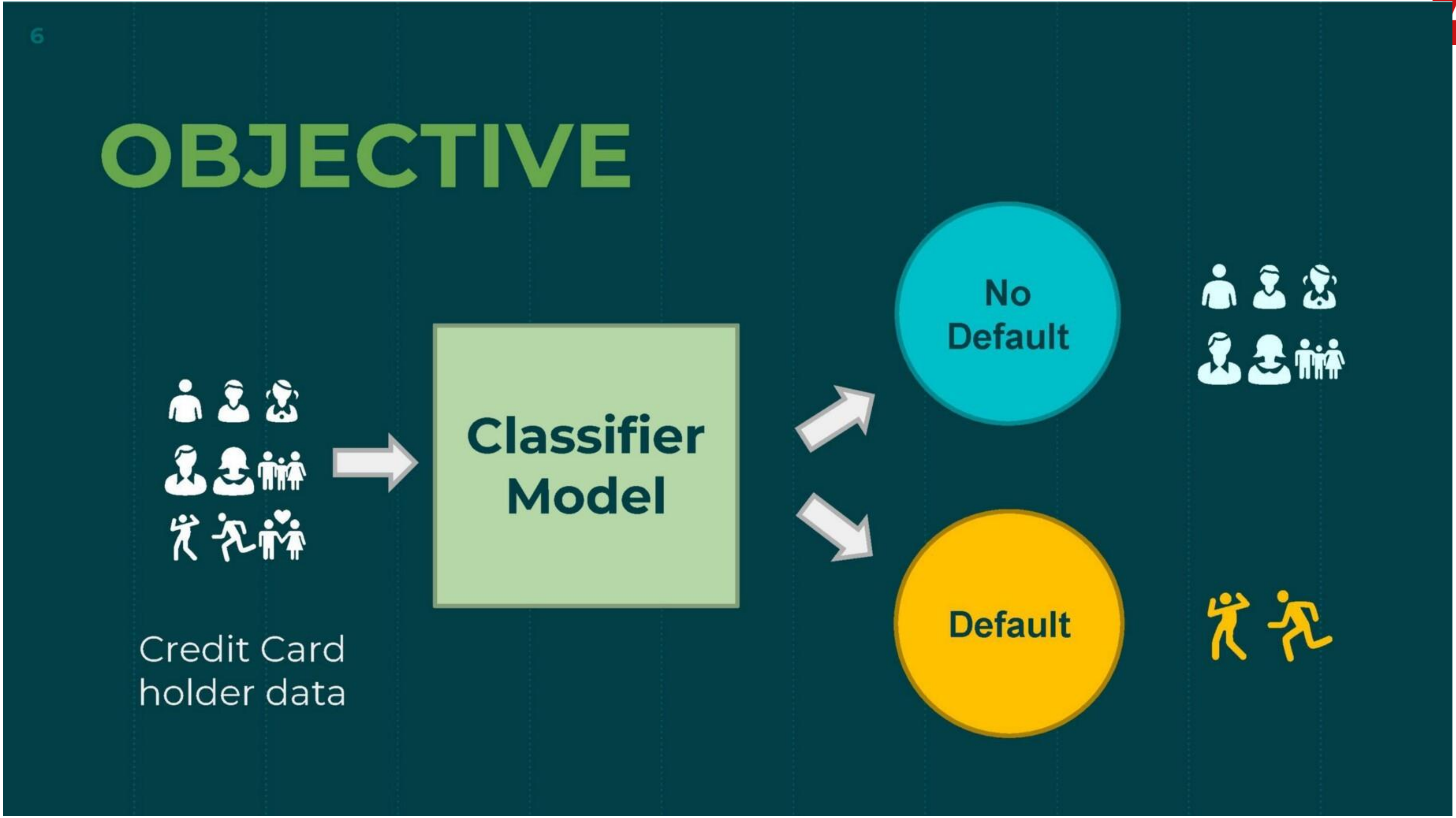


# PROBLEM STATEMENT

- This project is aimed at predicting the case of customers default payments in Taiwan. From the perspective of risk management, the result of predictive accuracy of the estimated probability of default will be more valuable than the binary result of classification - credible or not credible clients.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OBJECTIVE
Classifier Model
No Default
Default
Credit Card holder data

# ROAD MAP

**EDA**
- Data distribution of features
- Check Correlation
- Feature Engineering

**Model building**
- Using SMOTE Technique
- Data transformation
- Fitting & Prediction
- Evaluation matrices

**Model validation**
- Model selection
- Feature importance
- Conclusion

# INTRODUCTION

The basic idea of this capstone project is to use the Supervised Machine Learning - Classification to predict customers default payments in Taiwan. Here we have previous 6 month transaction bills and statements as our major information to classify defaulter.

Based on these features we will be predicting our target variable i.e. credit card defaulters. By using concepts like model validation, we will came to know which features are important and how much they contribute to our target variable.

# DATA DESCRIPTION

- *ID: ID of each client*
- *LIMIT_BAL: Amount of given credit in NT dollars (includes individual and family/supplementary credit)*
- *SEX: Gender (1 = male, 2 = female)*
- *EDUCATION: (1 = graduate school, 2 = university, 3 = high school, 0,4,5,6 = others)*
- *MARRIAGE: Marital status (1 = married, 2 = single, 3 = others)*
- *AGE: Age in years*
- Scale for PAY_0 to PAY_6 :

  *(-2 = No consumption, -1 = paid in full, 0 = use of revolving credit (paid minimum only),*

  *1 = payment delay for one month, 2 = payment delay for two months,*

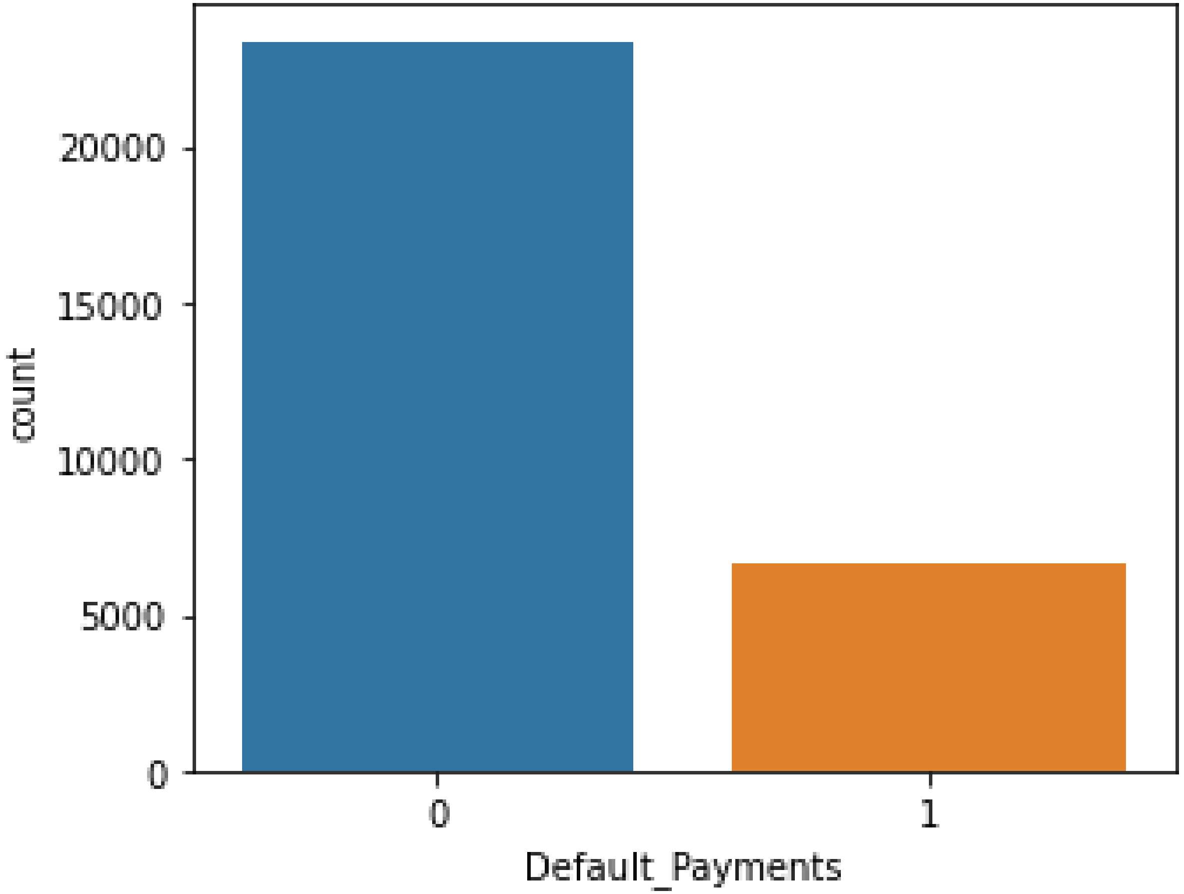
  *… 8 = payment delay for eight months, 9 = payment delay for nine months and above*)
- *PAY_0 to PAY_6: Repayment status in (September, 2005), (August, 2005)…..(April, 2005)*
- *BILL_AMT1 to BILL_AMT6: Amount of bill statement in (September, 2005), (August, 2005)…..(April, 2005)*
- *PAY_AMT1 to PAY_AMT6: Amount of previous payment in (September, 2005), (August, 2005)…..(April, 2005)*
- *Default payment next month: Default payment (1=yes, 0=no)*

# EDA

**Data distribution of target variable**

- ❑ Non-Defaulter(0) -**78%**
- ❑ Defaulter(1) – **22%**

**22%** of customers has default payment next month and We Have Imbalance Dataset

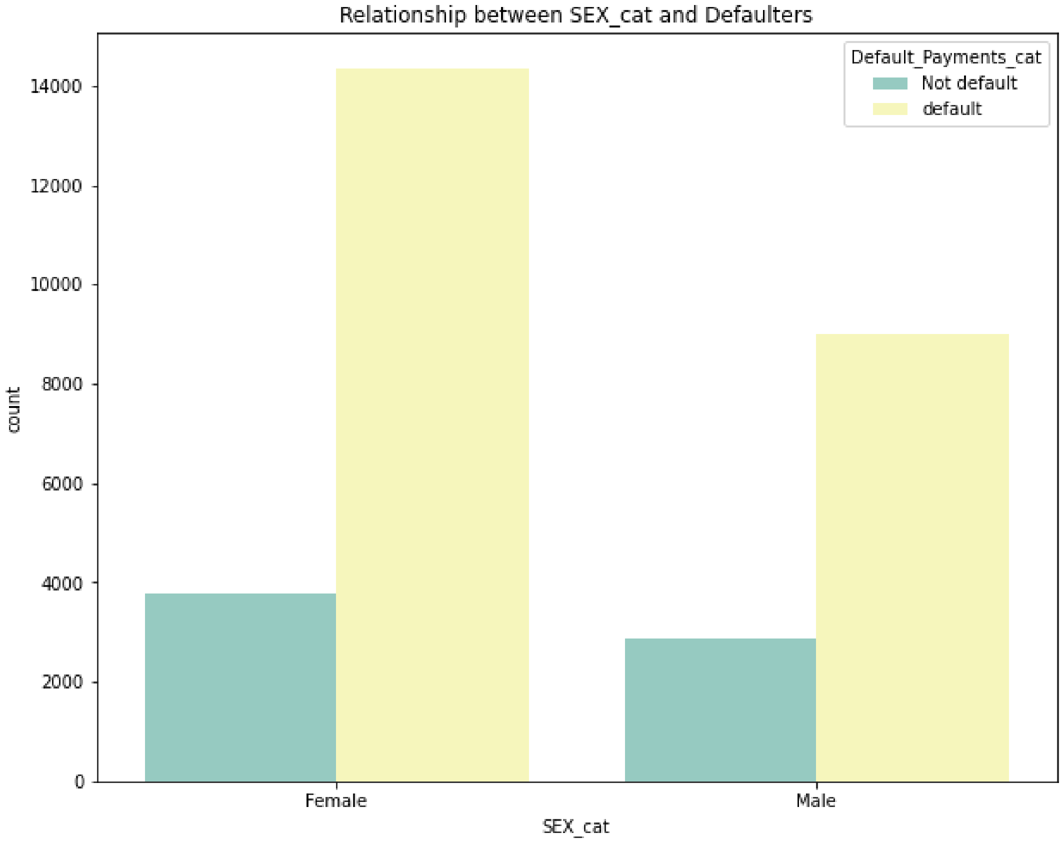


# EDA

## SEX Column According to Target Variable

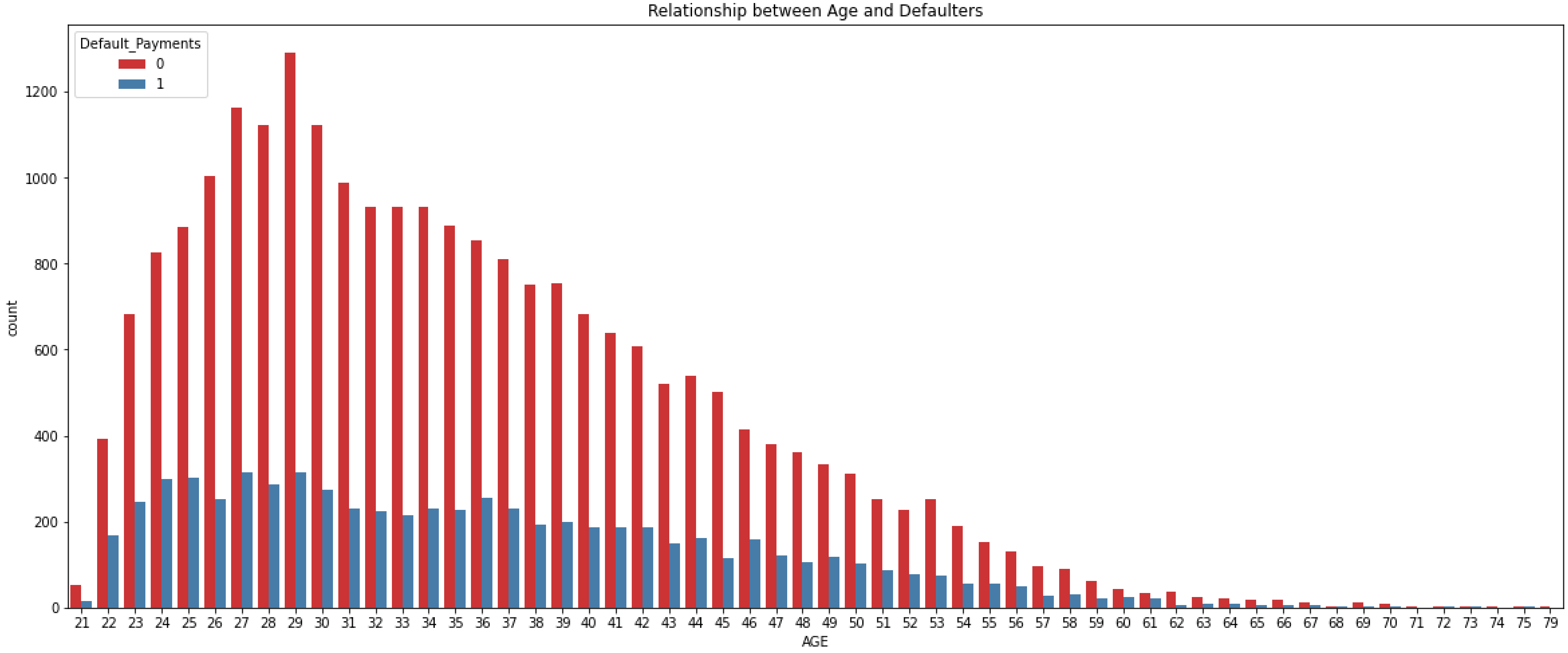
| SEX<br>Default_Payments | Male | Female | All |
|---|---|---|---|
| **Non-default** | 0.758328 | 0.792237 | 0.7788 |
| **Default** | 0.241672 | 0.207763 | 0.2212 |
| **All** | 1.000000 | 1.000000 | 1.0000 |

Female : Non Default - 76%, Default 24%
Male : Non Default - 78%, Default 22%
Females have lower default risk than males in this dataset.



# EDA

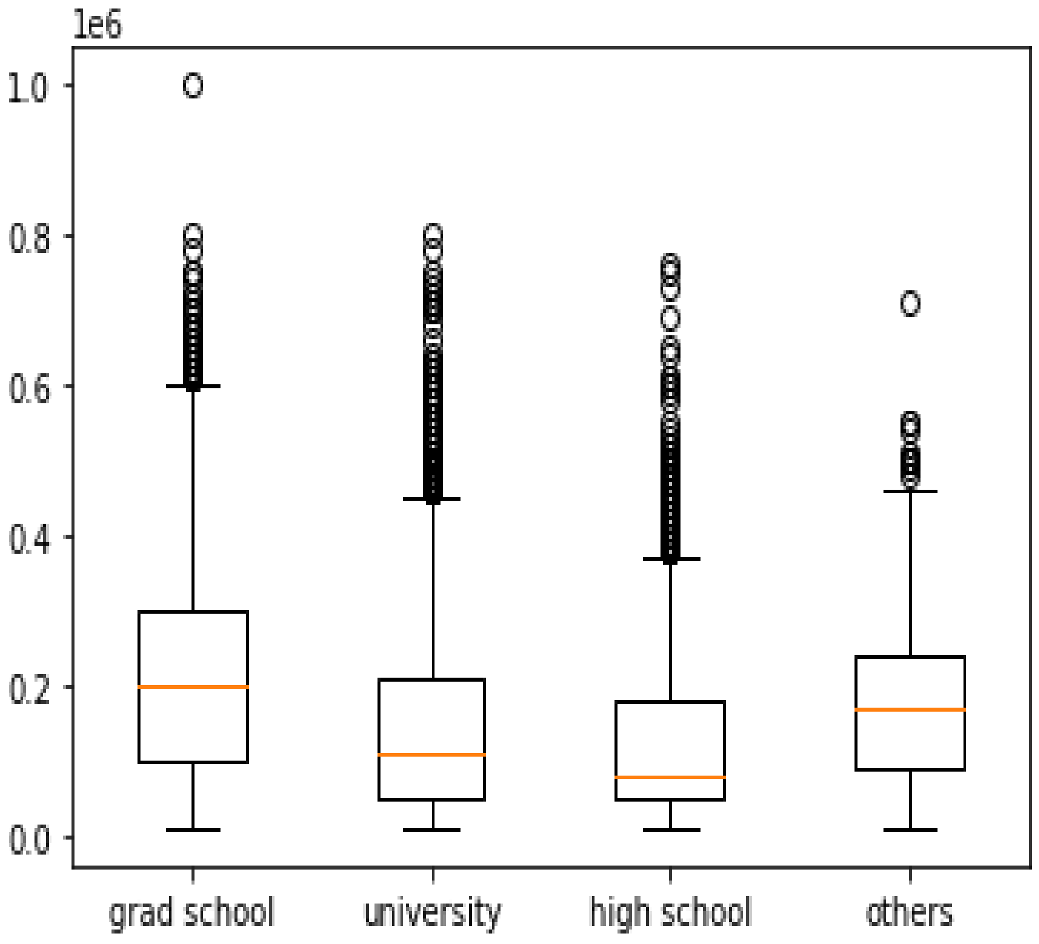
## Analysis on AGE feature

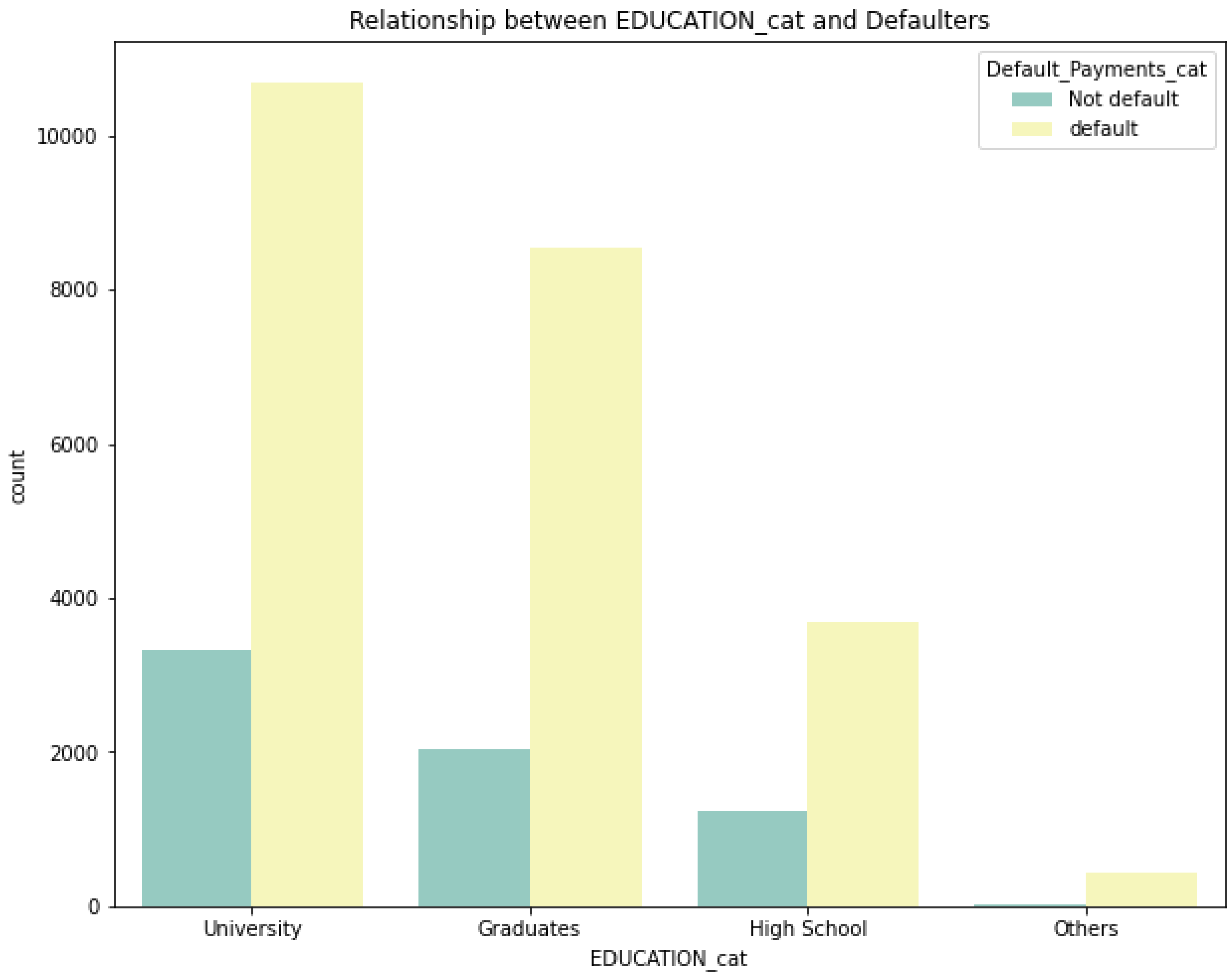



- ❑ 20 to 45 years customer are on average for defaulters
- ❑ Age above 60 years are almost defaulters

# EDA

**Analysis on Education feature**



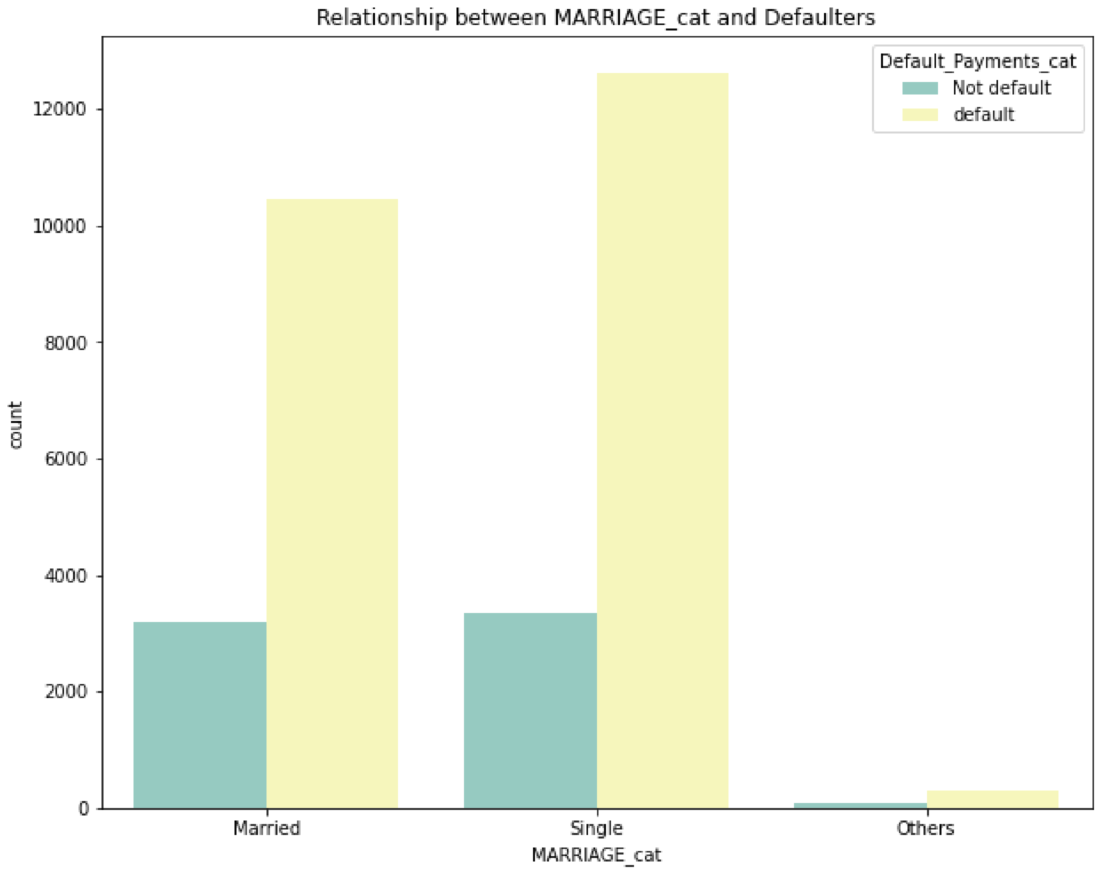




- Customer which had education at University level has more user as well as defaulters

# EDA

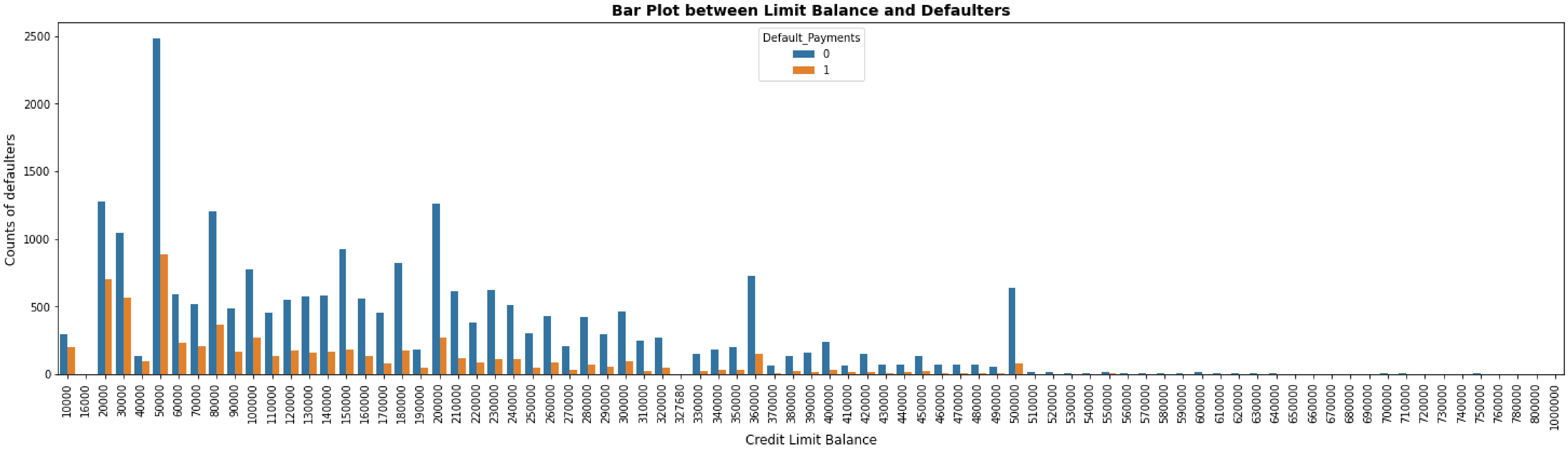
## Analysis on MARRIAGE feature

- ❑ Married customer count is greater of all
- ❑ Married and single defaulter customers does not have much difference but, married customers takes lead for defaulters



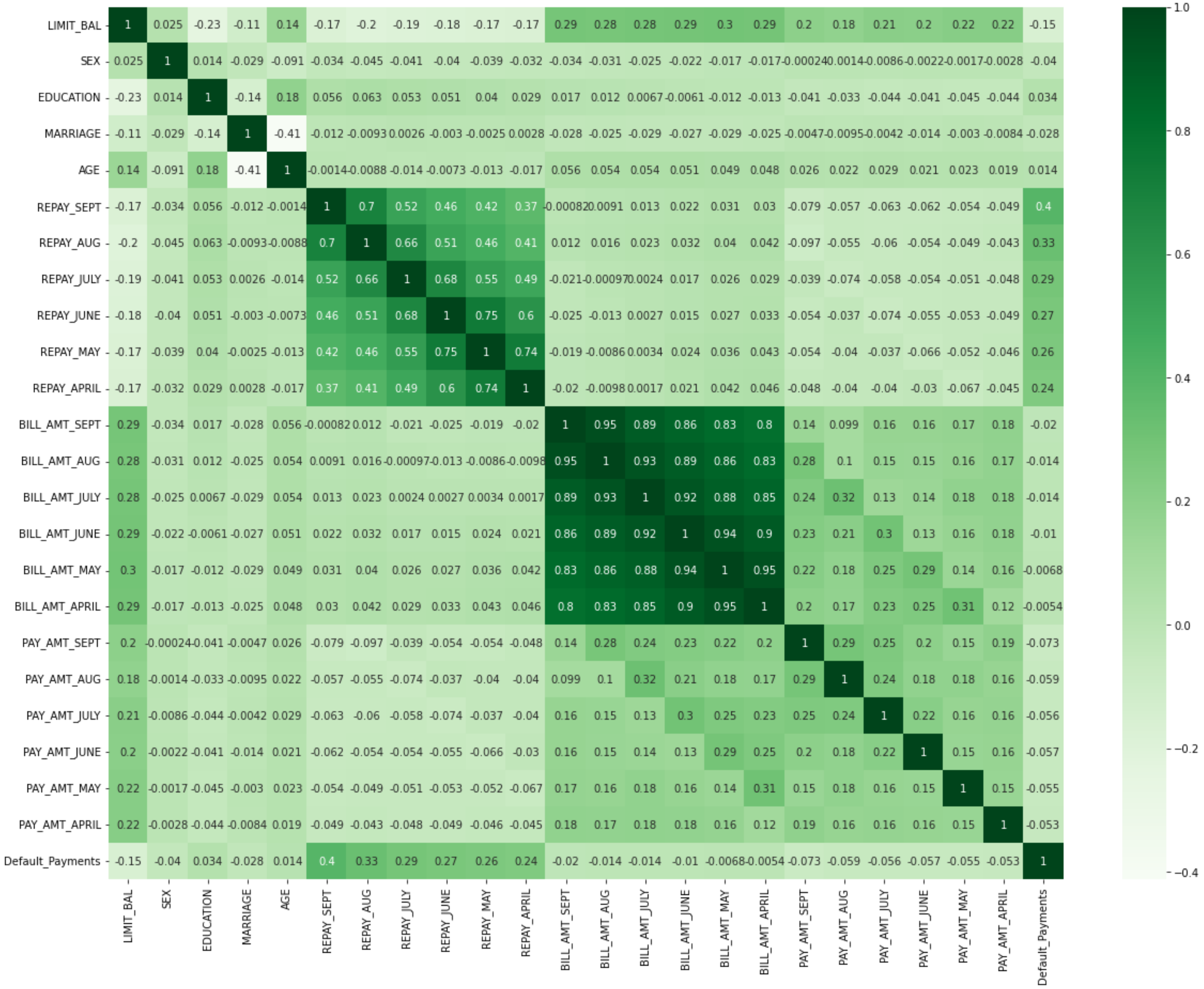
# EDA

## Analysis on Limit Balance  feature




- ❑ Most of the Defaulter are lies between 20K to 50K. And Then Average defaulter are in between 60K to 3L.

## Correlation Heat Map




- Here most of the categories have correlated with each other, because all those are previous transaction of customer
- Bill amount of 6 months have high Correlation with each other.

# Feature Engineering:

**STANDARD SCALER:**

Scaling Independent variable with StanardScaler()

**SMOTE -** Synthetic Minority Oversampling Technique:

Over Sampling of Target Variable with SMOTE Technique to over come Imbalance of the Dataset.

**TRAIN TEST SPLIT:**

Splitting Dataset into Training Dataset for Model Training.

Testing Dataset for Model Testing.

**Target Variable before SMOTE**

**Target Variable after SMOTE**

# FITTING VARIOUS MODEL

1. Logistic Regression
2. Support Vector Classifier
3. K-Nearest Neighbors Classifier
4. Random forest Classifier
5. XG Boosting Classifier

# MODEL PERFORMANCE COMPARISION

Evaluation matrices for all the models without Hyperparameter Tuning

| | Model | accuracy | precision | recall | f1_score_ | roc_auc_score |
|---|---|---|---|---|---|---|
| 0 | Logistic Regression_train | 70.49 | 78.06 | 56.71 | 65.70 | 70.44 |
| 1 | Logistic Regression_test | 70.08 | 77.76 | 56.91 | 65.72 | 70.19 |
| 2 | Support Vector Machine_train | 72.35 | 77.94 | 62.08 | 69.11 | 72.31 |
| 3 | Support Vector Machine_test | 71.37 | 76.94 | 61.71 | 68.49 | 71.45 |
| 4 | KNN_train | 85.01 | 79.77 | 93.68 | 86.17 | 85.04 |
| 5 | KNN_test | 76.79 | 72.21 | 87.72 | 79.21 | 76.70 |
| 6 | RandomForest_train | 99.97 | 99.98 | 99.96 | 99.97 | 99.97 |
| 7 | RandomForest_test | 84.34 | 86.35 | 81.87 | 84.05 | 84.36 |
| 8 | XGBClassifier_train | 79.48 | 84.76 | 71.70 | 77.69 | 79.45 |
| 9 | XGBClassifier_test | 78.33 | 83.42 | 71.15 | 76.80 | 78.39 |

- ❑ Logistic Regression, SVM and XGB Classifier have good performance.
- ❑ KNN and Random Forest Overfitting with the model.

# MODEL PERFORMANCE COMPARISION

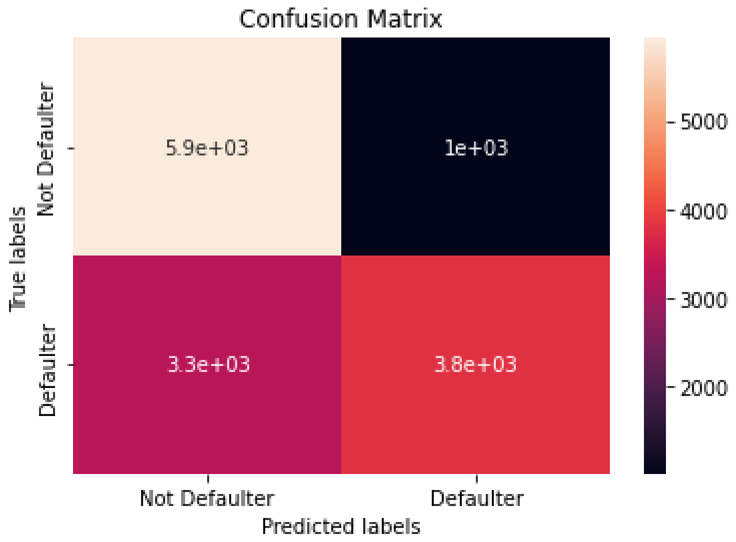
Evaluation matrices for all the models with Hyperparameter Tuning

| Model | accuracy | precision | recall | f1_score_ | roc_auc_score |
|---|---|---|---|---|---|
| Logistic_train_hyper | 69.88 | 79.08 | 53.76 | 64.01 | 69.82 |
| Logistic_test_hyper | 69.36 | 78.64 | 53.83 | 63.91 | 69.48 |
| knn_train_hyper | 89.27 | 84.26 | 96.50 | 89.96 | 89.30 |
| knn_test_hyper | 78.56 | 73.74 | 89.27 | 80.77 | 78.48 |
| Random Forest_train_hyper | 76.25 | 81.15 | 68.18 | 74.10 | 76.23 |
| Random Forest_test_hyper | 74.56 | 79.29 | 67.03 | 72.65 | 74.62 |
| XG Boosting Train_hyper | 90.44 | 94.78 | 85.52 | 89.91 | 90.42 |
| XG Boosting Test_hyper | 86.06 | 89.94 | 81.46 | 85.49 | 86.10 |

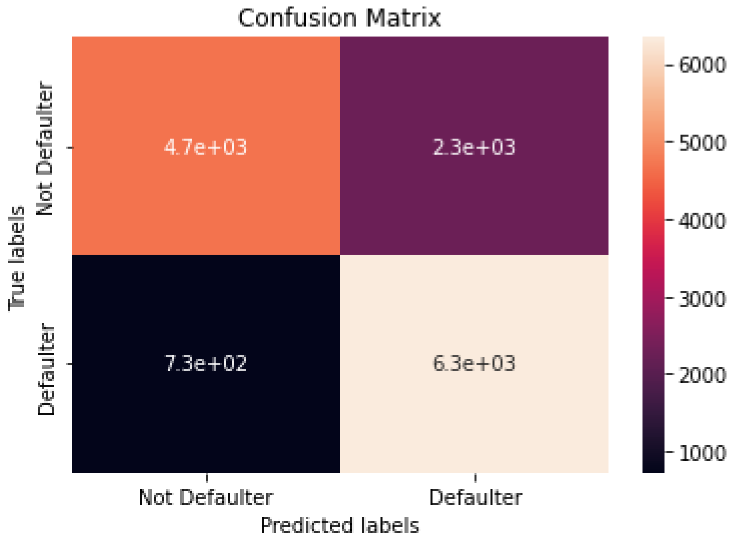
- ❑ Random Forest and XGB Classifier have good performance.
- ❑ KNN Overfitting with the model and Logistic Regression have low performance compared to others.

# Confusion matrices of all Testing Model

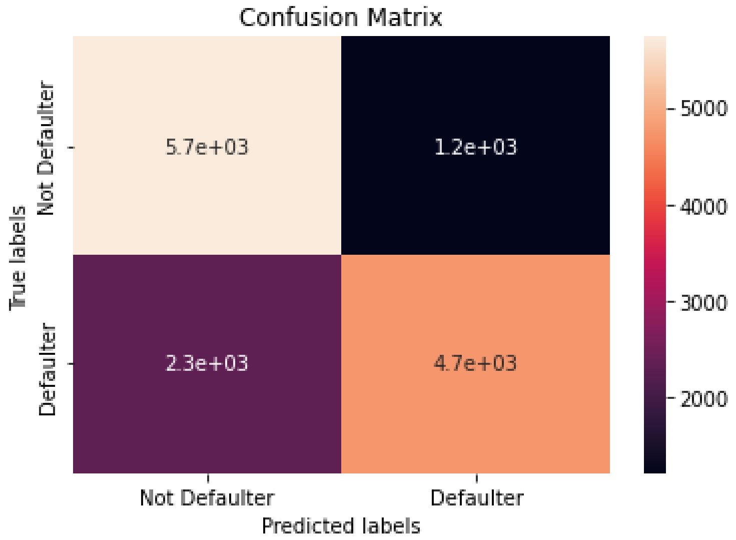
## LR



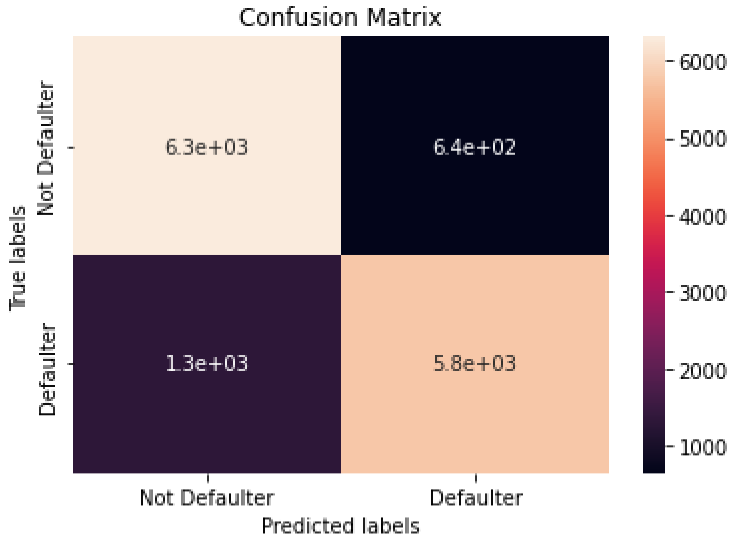

## KNN




## RF

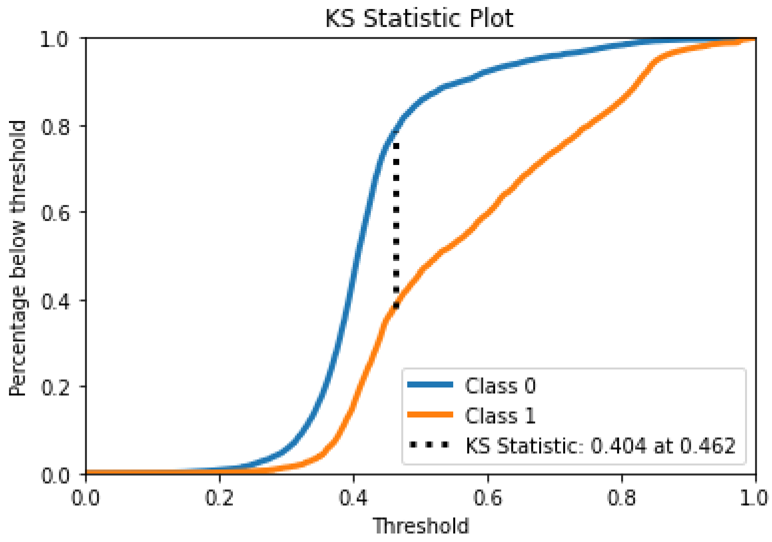



## XGB

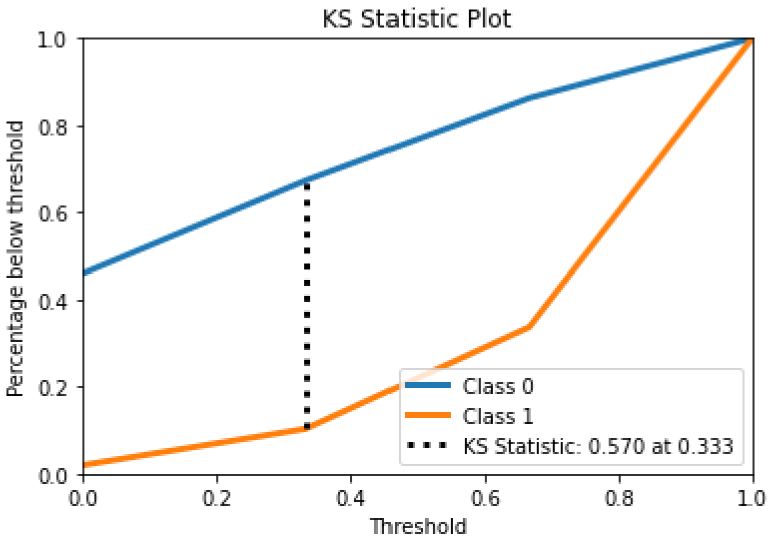


# KS Statistics of all Testing Model

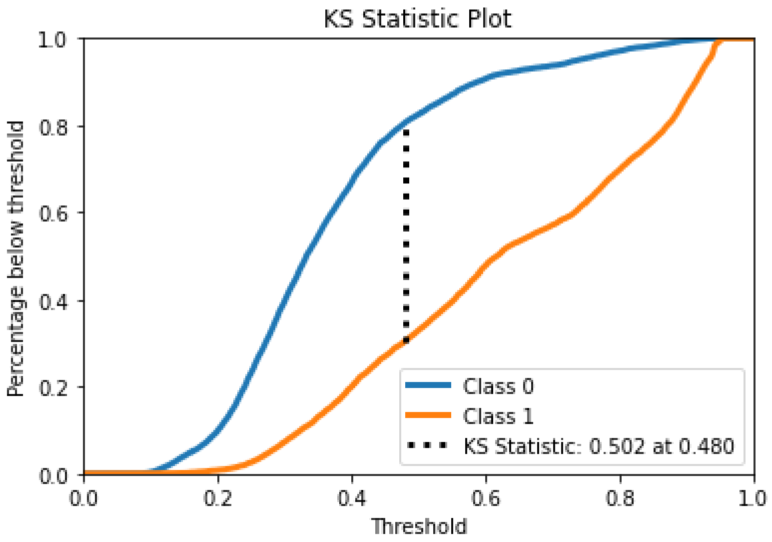
**LR**



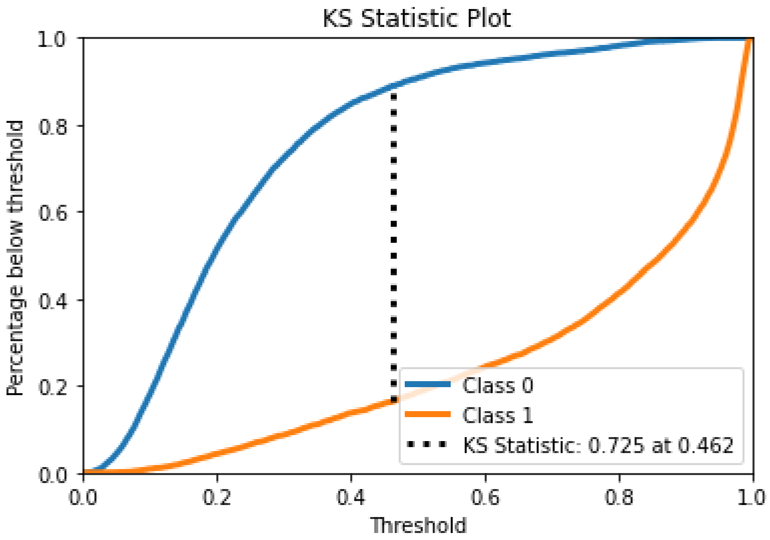

**KNN**




**RF**




**XGB**



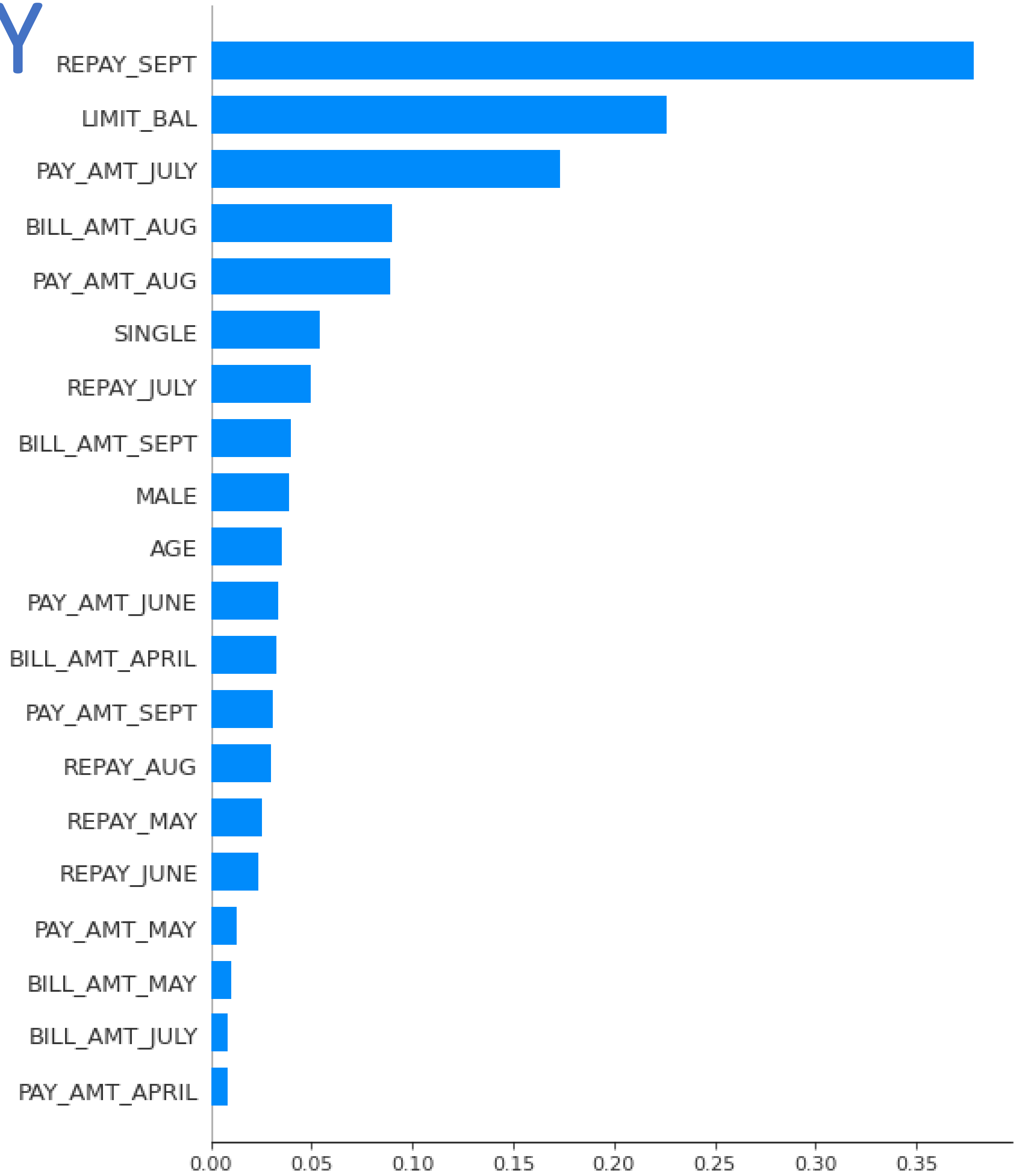
# MODEL VALIDATION

- By observing Evaluation matrices for all the models-
  - ❑Logistic Regression model scores Low Performance as compared to other
  - ❑KNN looking at the scores this models are over fitting and we can't conclude with respect to accuracy.
  - ❑SVC Model is good with accuracy, but they are not best with its recall score compare to others.
  - ❑XGB Classifier and Random forest have High precision, high Recall value and high KS Statistic compared to others .

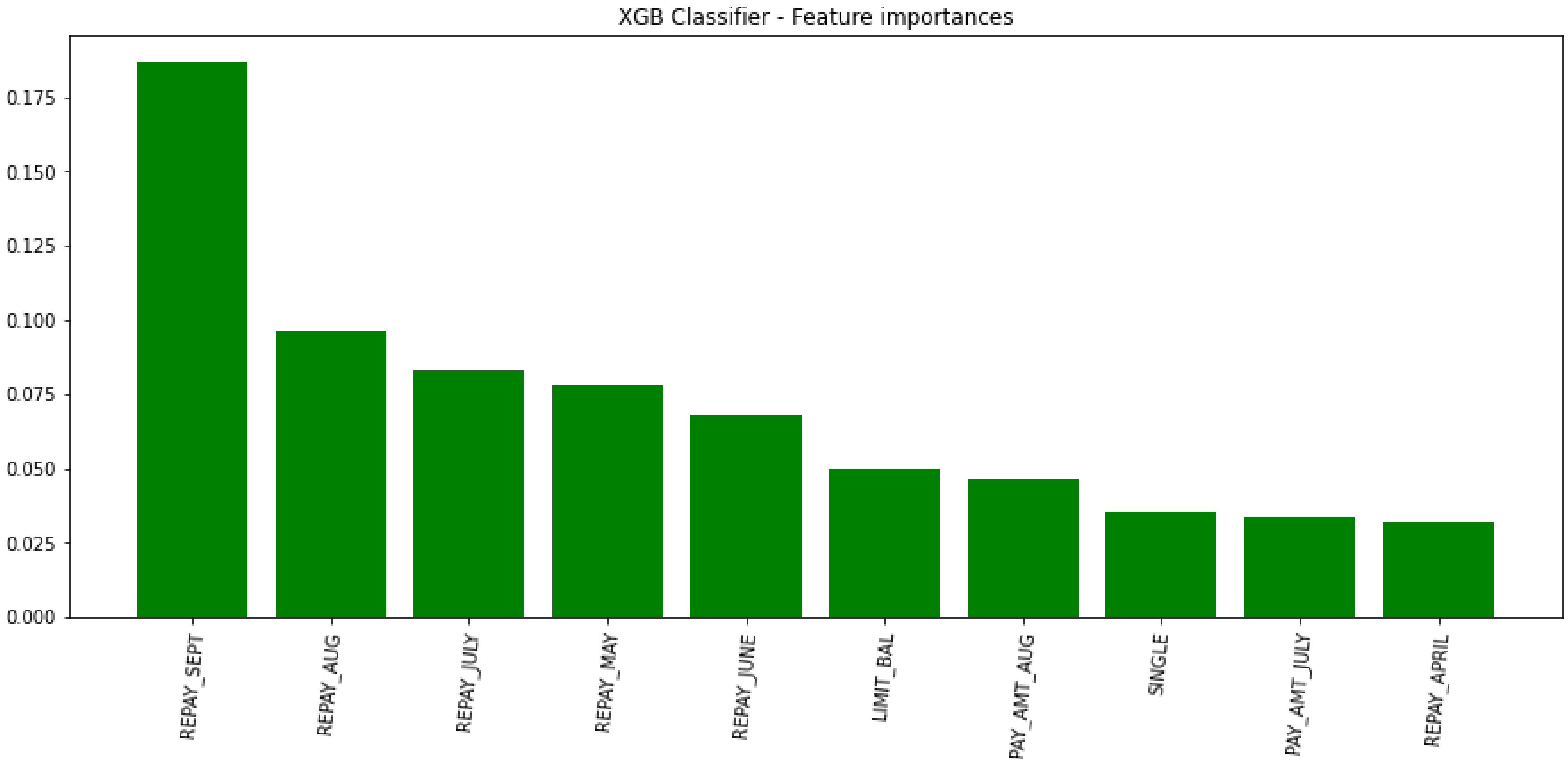
# MODEL EXPLAINABILITY

**1. Using SHAP**

as per the SHAP technique REPAY_SEP and LIMIT _BAL are the most important feature to predict target variable.



# Feature Importance



# CONCLUSION

- From entire Project analysis of ML Model, we got some evident that XGB Classifier will perform better among all the models for the Credit Card Default Prediction, since the recall score was best for this model.

- Repayment of September and Limit balance are the features contributes heavily to predict our target variable.

Thank You