Capstone Project - 3
Credit Card Default Prediction

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Introduction

In today's world credit cards have become a lifeline to a lot of people so banks provide us with credit cards. Now we know the most common issue there is in providing these kind of deals are people not being able to pay the bills. These people are what we call "defaulters".

Problem Statement

Predicting whether a customer will default on his/her credit card

Data Summary

- X1 - Amount of credit(includes individual as well as family credit)
- X2 - Gender
- X3 - Education
- X4 - Marital Status
- X5 - Age
- X6 to X11 - History of past payments from April to September
- X12 to X17 - Amount of bill statement from April to September
- X18 to X23 - Amount of previous payment from April to September
- Y - Default payment

Approach Overview

Data Cleaning

Understanding and Cleaning

- Find information on documented columns values
- Clean data to get it ready for Analysis

Data Exploration

Graphical

- Examining the data with visualization

Modeling

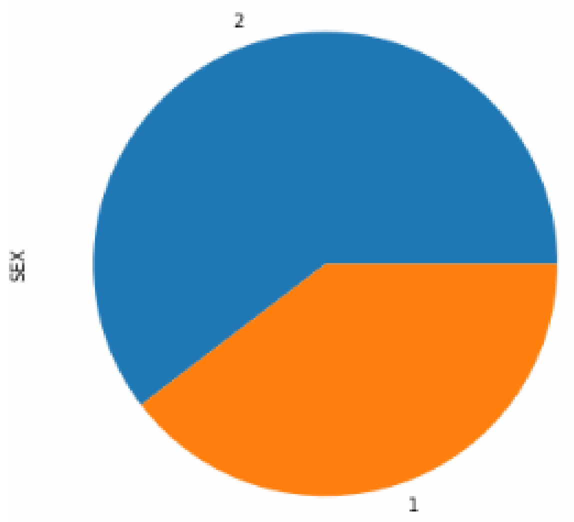
Machine Learning

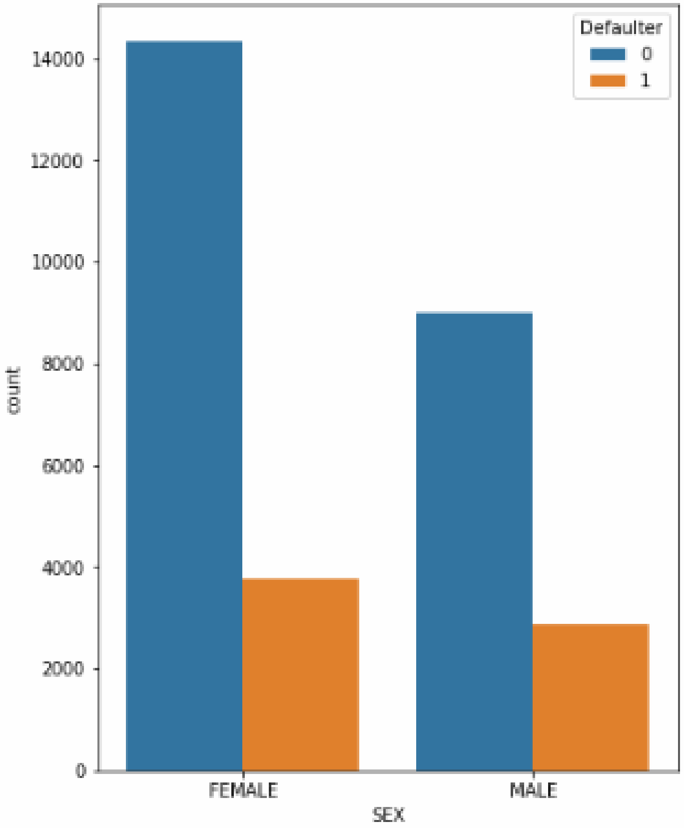
- Logistic
- SVM
- Random Forest
- XGBoost

Basic Exploration

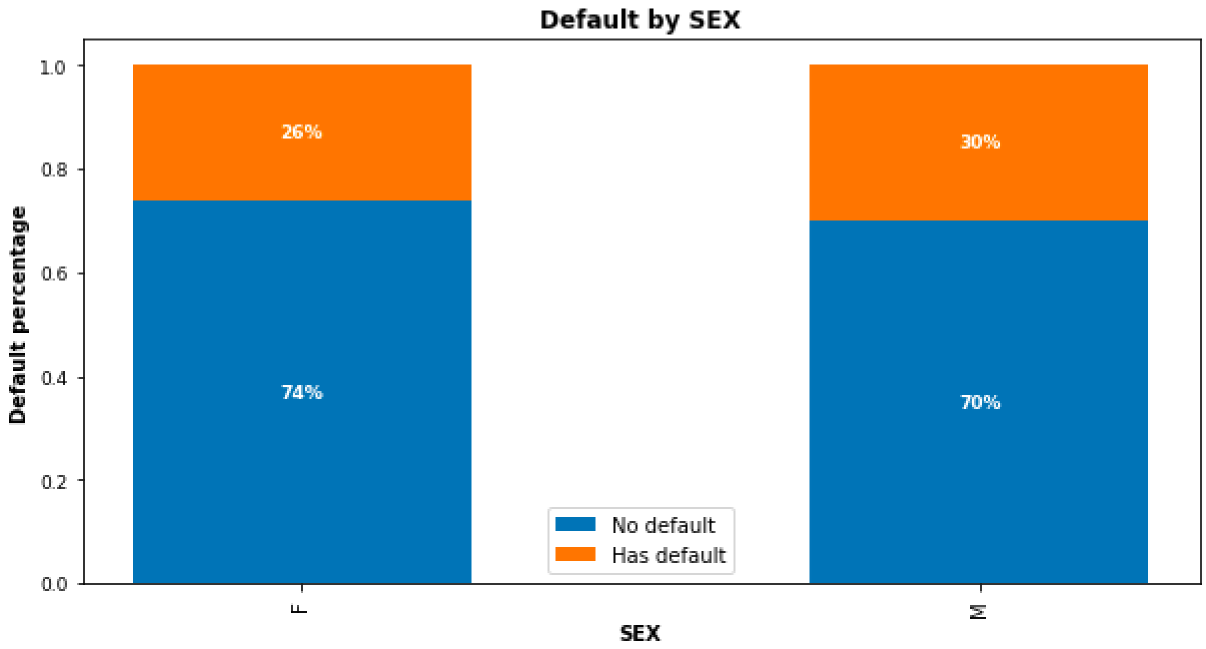
- Dataset for Taiwan.
- Data for 30000 customers.
- 6 Months payment and bill data available.
- No null data.
- 9 Categorical variables present.

Gender Distribution



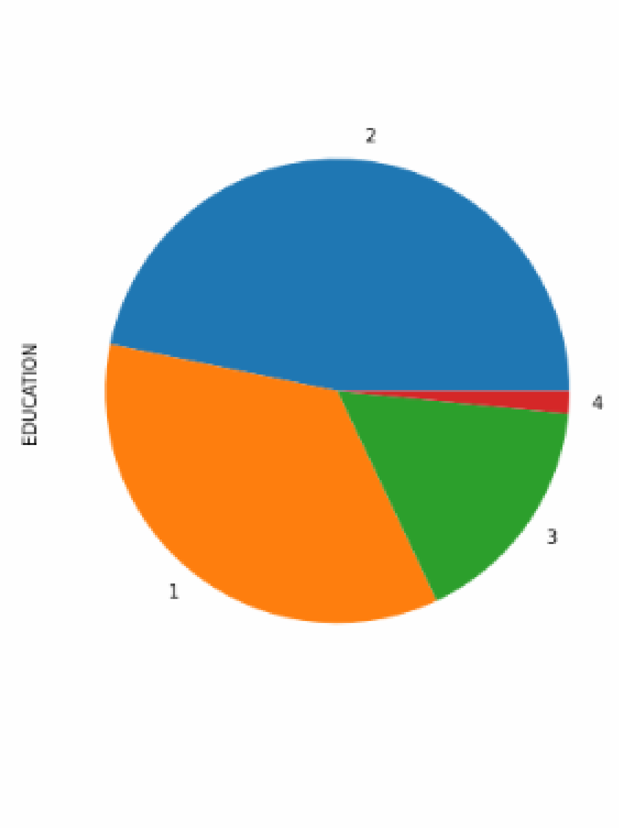


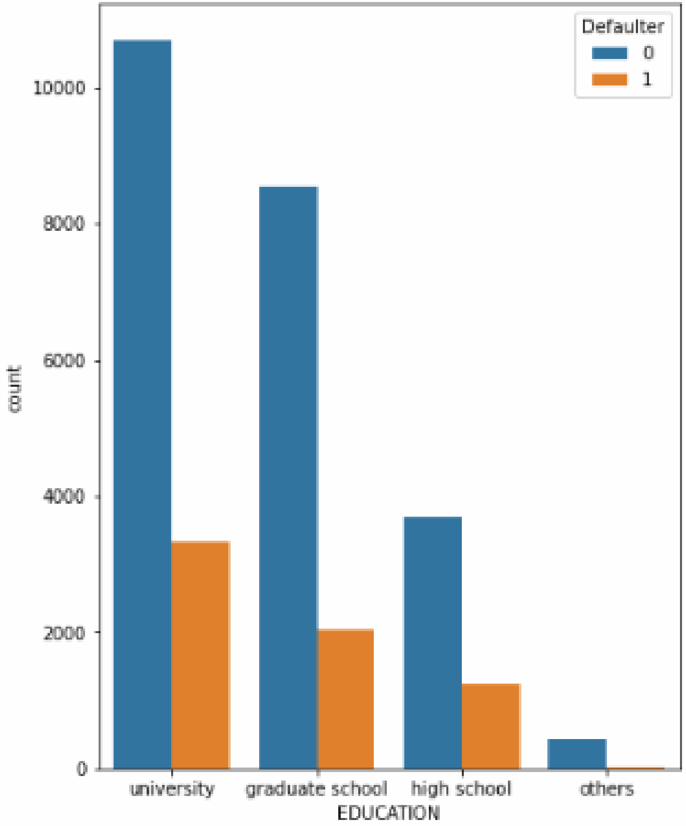
Gender wise defaulters



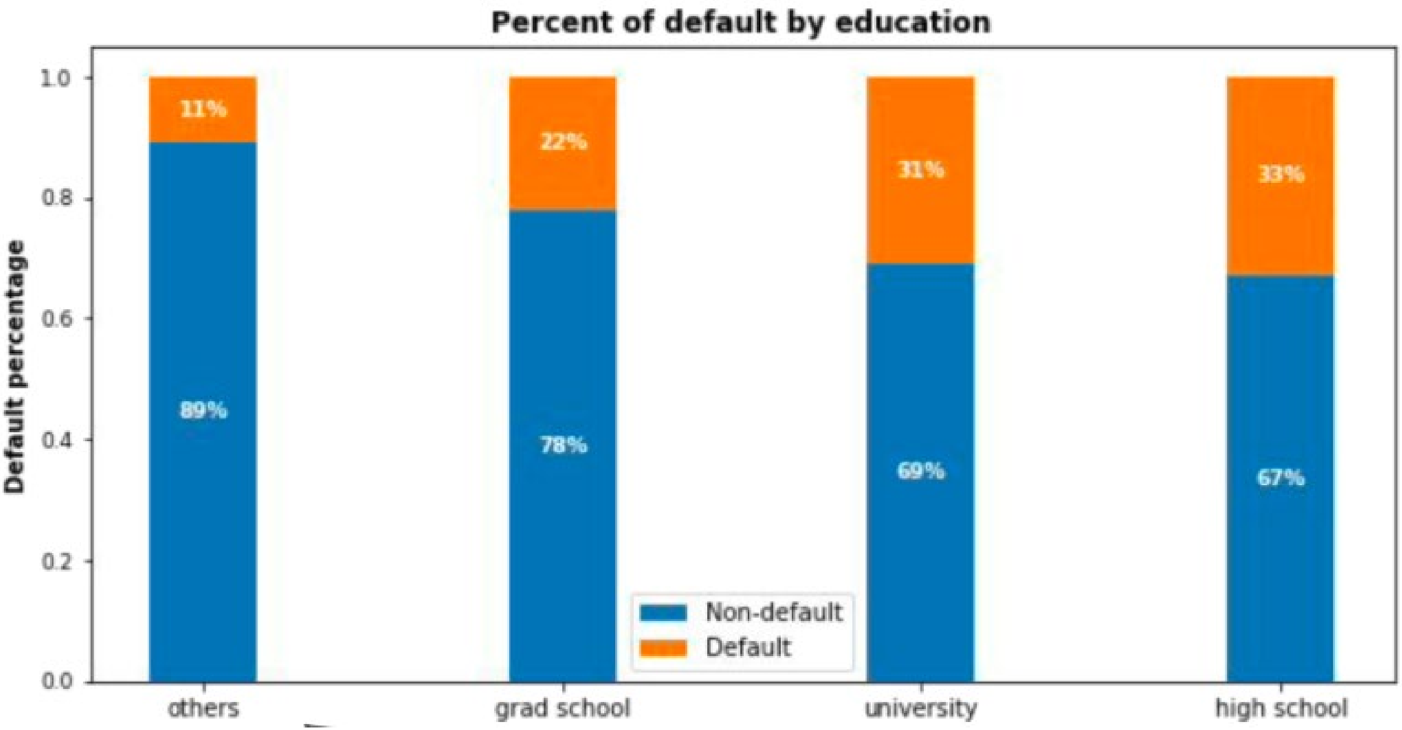
30% of Males and **26%** of Females are defaulters

Education Distribution



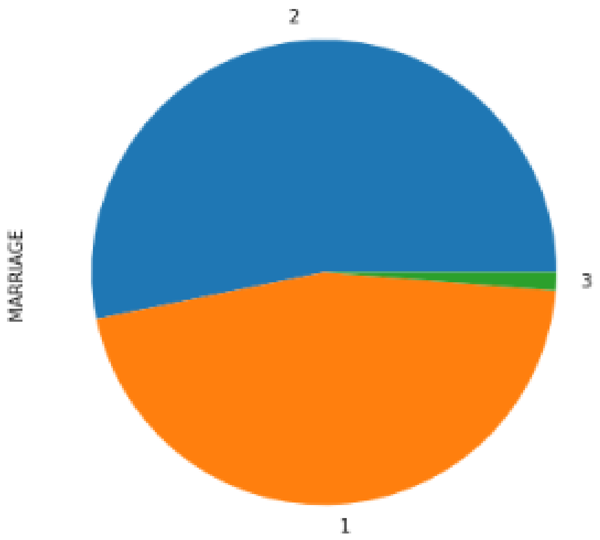


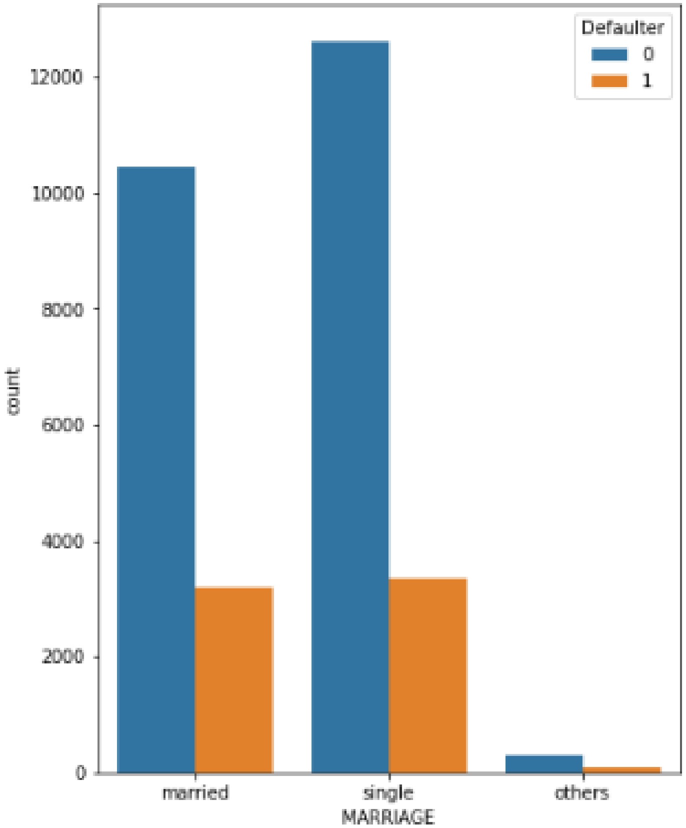
Education wise defaulters



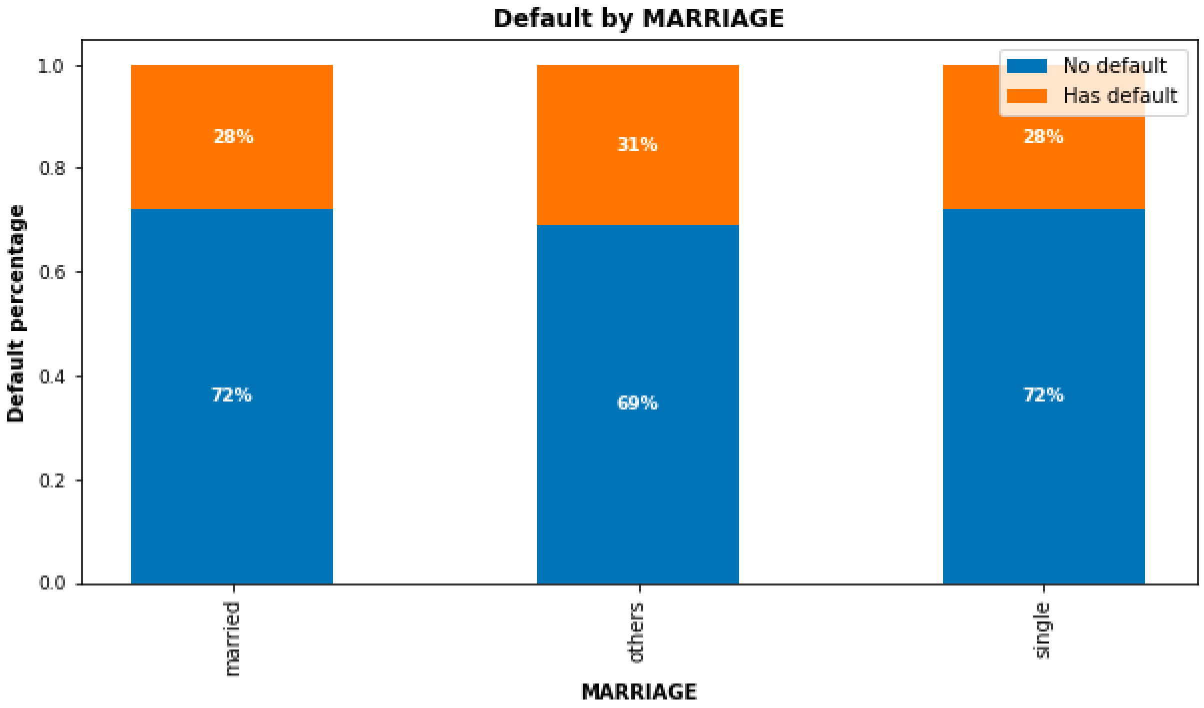
Higher Education level, lower Default Risk

Marital Distributions



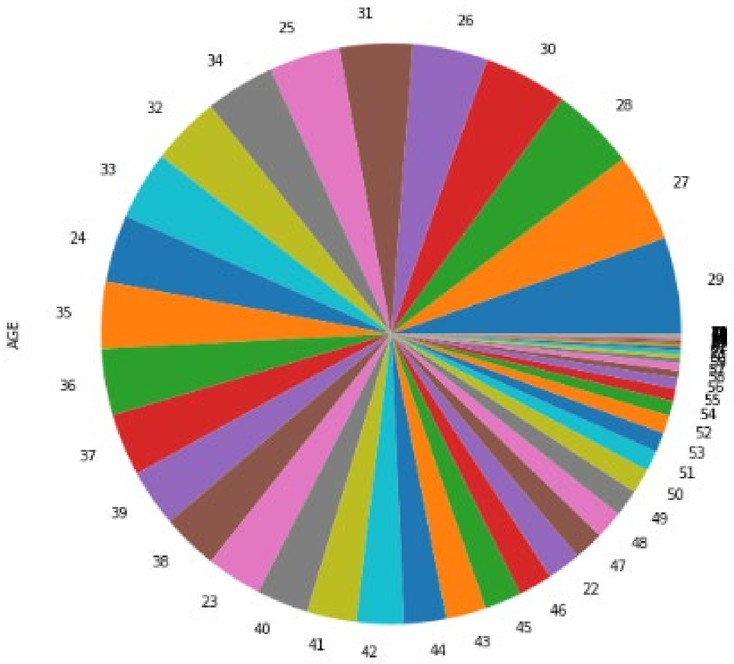


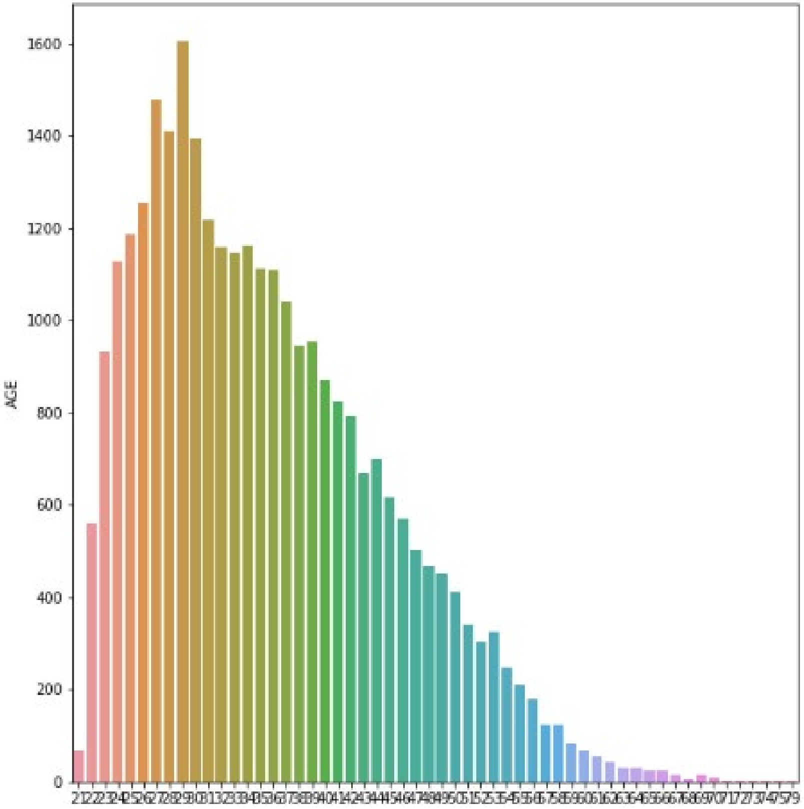
Marital Status



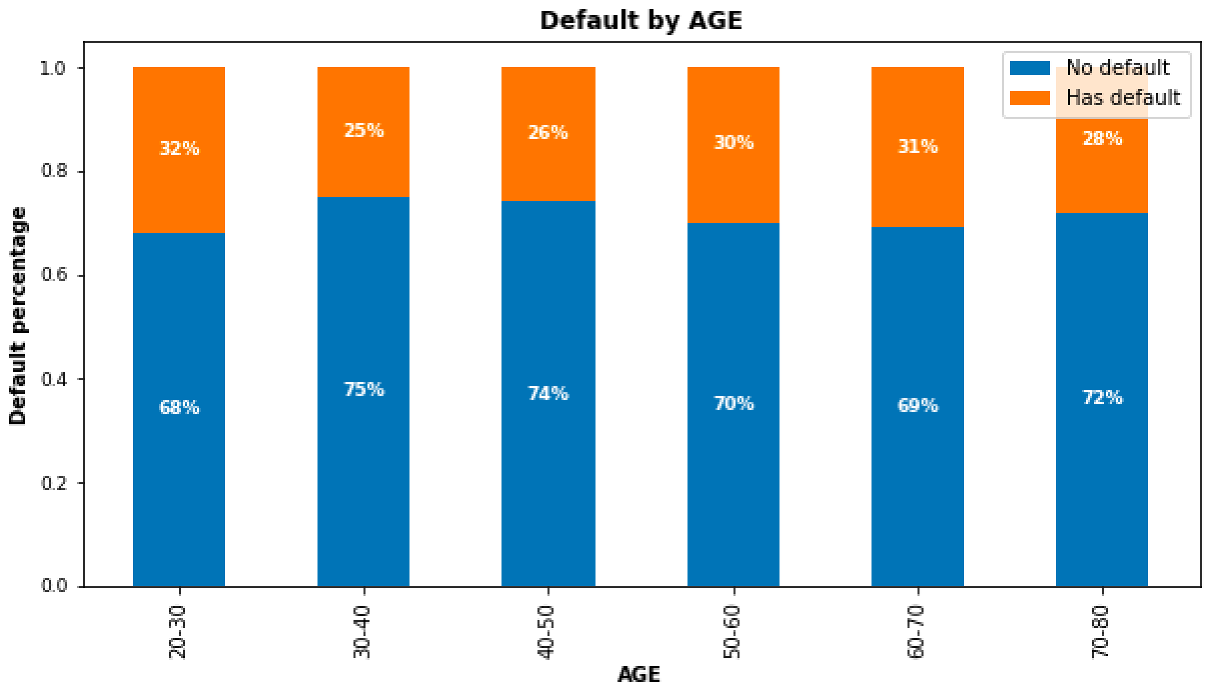
No
Significant correlation of default risk and marital status

Age Distribution





Age wise defaulters



30 t0 50:
Lowest Risk

<30 and >50:
Risk Increases

Modeling Overview

- Supervised learning/Binary Classification
- Imbalance data with 78% non-defaulters and 22% defaulters

Models Used:

- Logistic Regression
- Knn
- Decision Trees
- Random Forest
- SVM
- XGBoost
- Naive Bayes

Modeling Steps

Data Preprocessing

- Feature selection
- Feature engineering
- Train test data split(80%-20%)
- SMOTE oversampling

Data Fitting and Tuning

- Start with default model parameters
- Hyperparameter tuning
- Measure RUC-AOC on training data

Model Evaluation

- Model testing
- Precision_Recall Score
- Compare with the other models

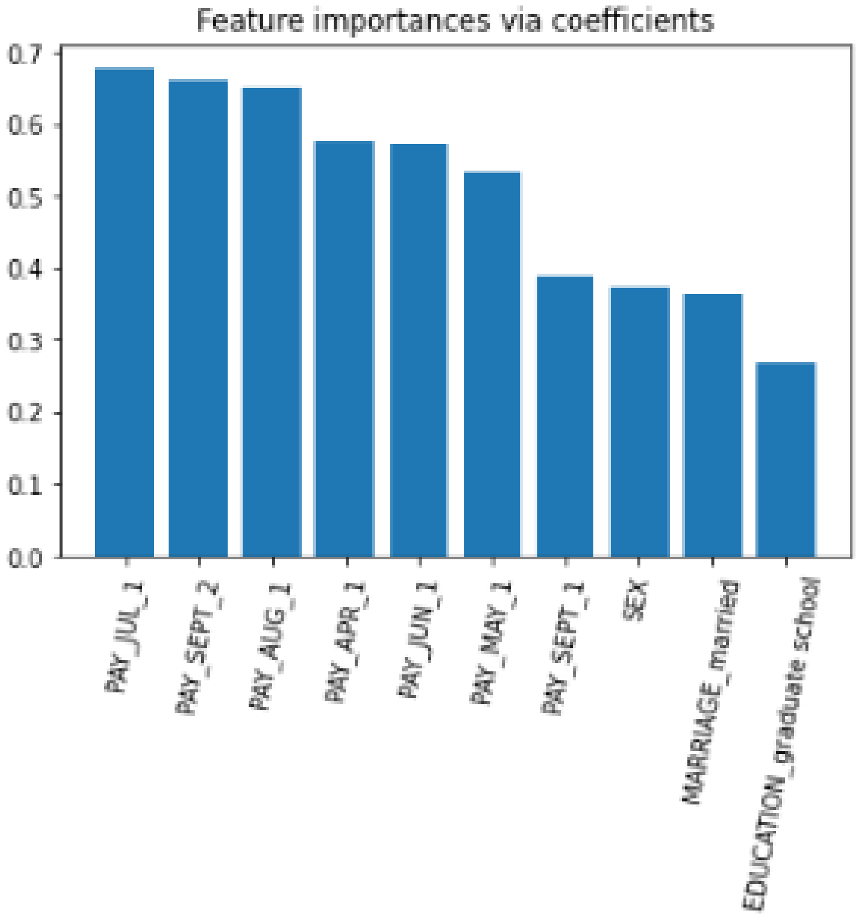
Logistic Modelling

Parameters :

- C = 0.01
- Penalty = L2

```
The accuracy on test data is  0.756371182154205
The precision on test data is  0.696368352788586
The recall on test data is  0.791304347826086
The f1 on test data is  0.740807174887892
The roc_score on train data is  0.760114888132589
```

Logistic feature importances



SVM Modelling

Parameters

C = 10

Kernel = ‘rbf’

```
The accuracy on test data is  0.7812074443940081
The precision on test data is  0.7229571984435798
The recall on test data is  0.8182618907809748
The f1 on test data is  0.7676628563558738
The roc_score on train data is  0.7850747251558493
```

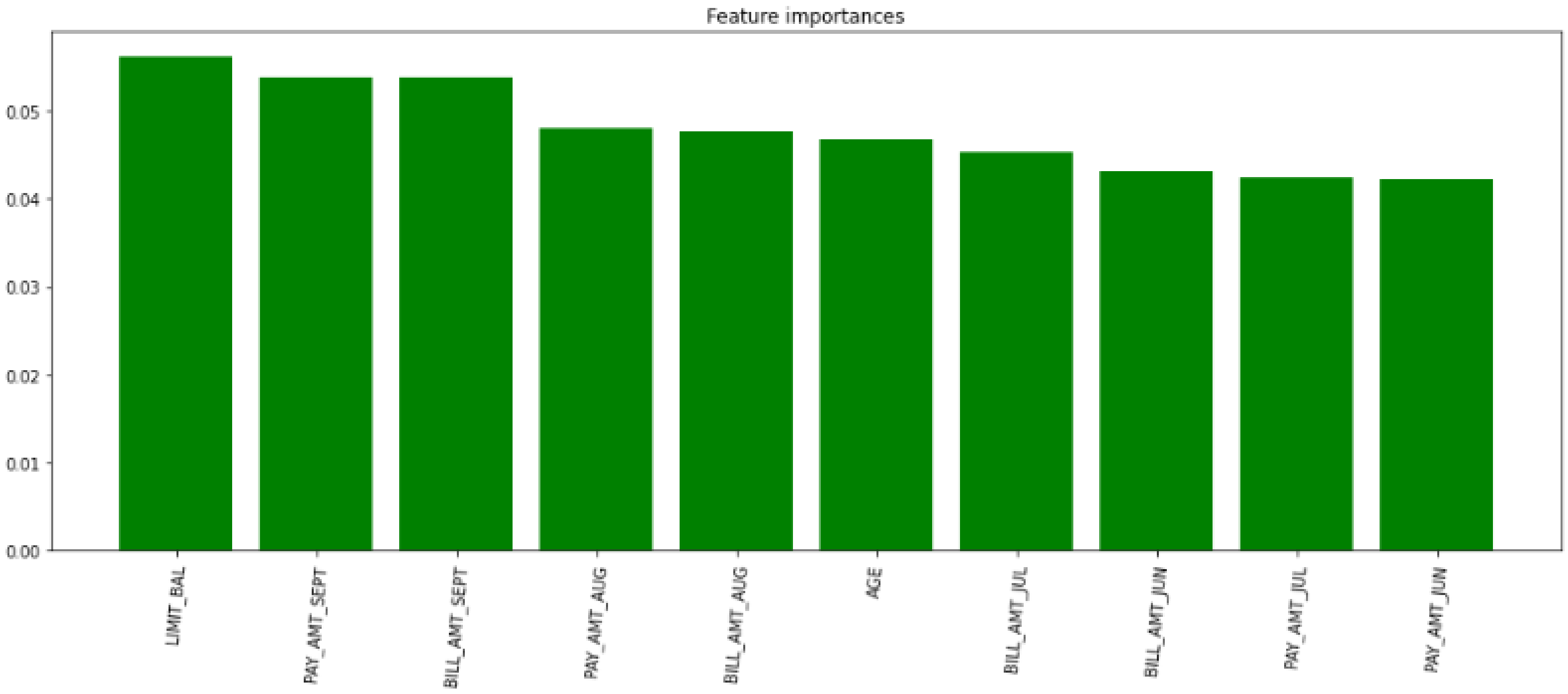
Random Forest Metrics

Parameters :

- max_depth=30
- n_estimators=150

```
The accuracy on test data is  0.8357434667012515
The precision on test data is  0.8051880674448768
The recall on test data is  0.8575770133996409
The f1 on test data is  0.8305572279082214
The roc_score on test data is  0.8370016575186912
```

Random Forest feature importances



AI

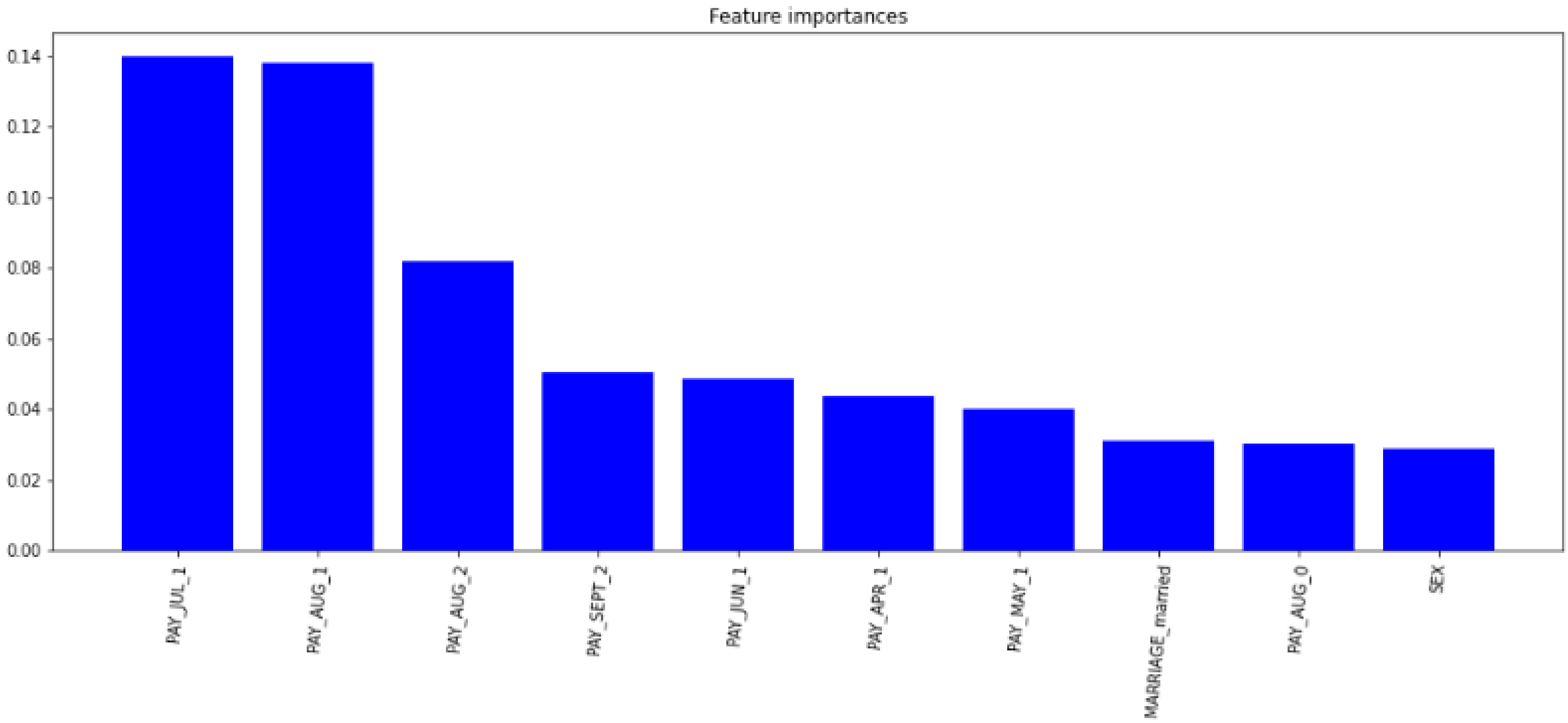
XGBoost Modelling

Parameters :

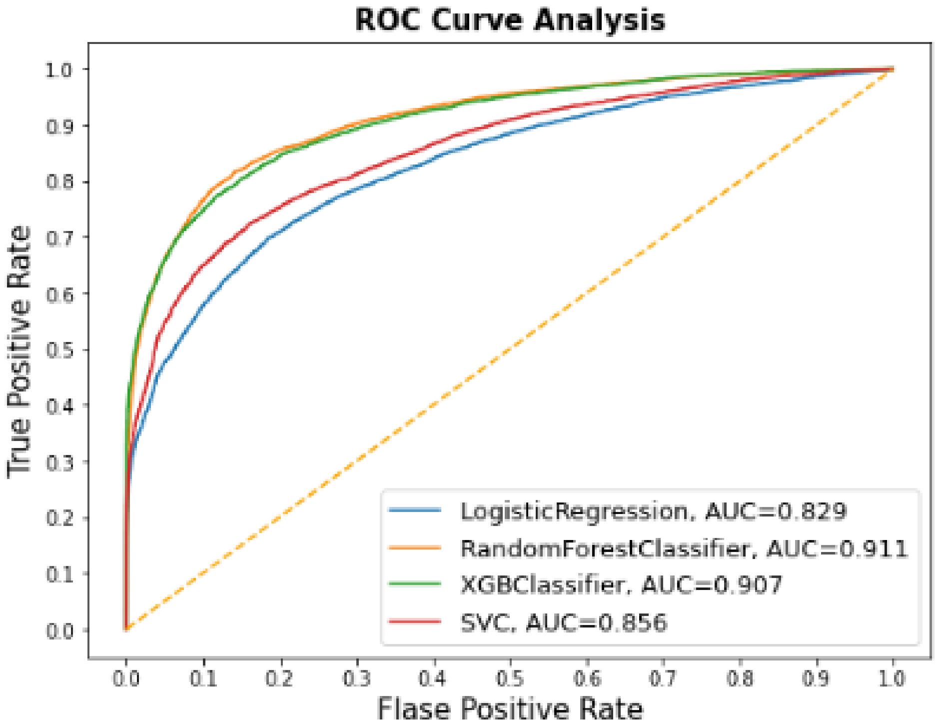
- max_depth= 15
- min_child_weight= 8

```
The accuracy on test data is  0.8271188638869075
The precision on test data is  0.7859922178988327
The recall on test data is  0.856416054267948
The f1 on test data is  0.8196943054240496
The roc_score on train data is  0.8293464333652503
```

X Gradient Boosting feature importances



AUC-ROC curve comparision



Challenges

- Understanding the columns.
- Feature engineering.
- Getting a higher accuracy on the models.

Conclusion

- XGBoost provided us the best results giving us a recall of 85 percent(meaning out of 100 defaulters 85 will be correctly caught by XGBoost)
- Random Forest also had good score as well but leads to overfit the data.
- Logistic regression being the least accurate with a recall of 79.

Classifier	Train Accuracy	Test Accuracy	Precision Score	Recall Score	F1 Score
Logistic Regression	0.754017	0.756371	0.696368	0.791304	0.740807
SVC	0.809851	0.781207	0.722957	0.818262	0.767663
Random Forest CLf	0.998754	0.835743	0.805188	0.857577	0.830557
Xgboost Clf	0.912607	0.827119	0.785992	0.856416	0.819694

Thank You

Q & A