Capstone Project
Credit Card Default Prediction

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Content

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 (1 = male; 2 = female).
- X3 - Education (1 = graduate school; 2 = university; 3 = high school; 4 = others)
- X4 - Marital Status (1 = married; 2 = single; 3 = others)
- X5 - Age(year).
- 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 next month

Pipeline

AI

Data Cleaning

Understanding and Cleaning

- Null value analysis
- Outlier Treatment

Data Exploration

Graphical

- Univariate analysis with visualization
- Bivariate Analysis
- with visualization

Modeling

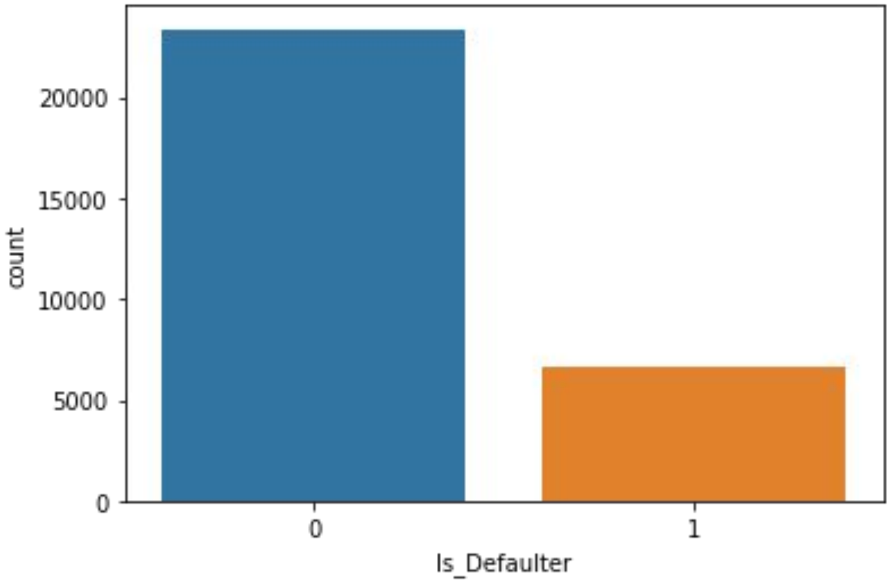
Machine Learning

- Logistic regression
- SVM
- Decision tree
- Random Forest
- XGBoost
- CatBoost
- Lightgbm

Basic Exploration

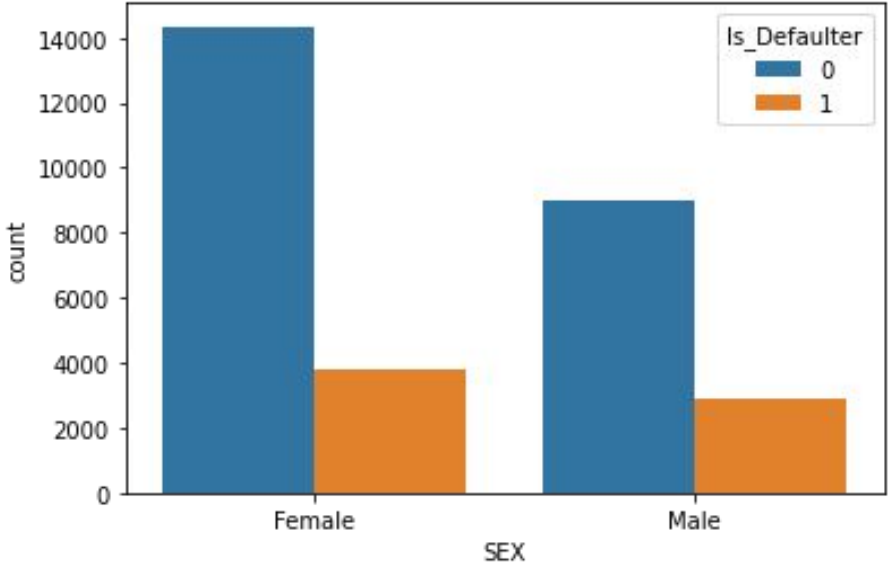
- Data of 30000 customers.
- 6 Months payment and bill data.
- No null data.
- 9 Categorical variables present.
- Various undocumented/wrong labels were present

Defaulter Distribution



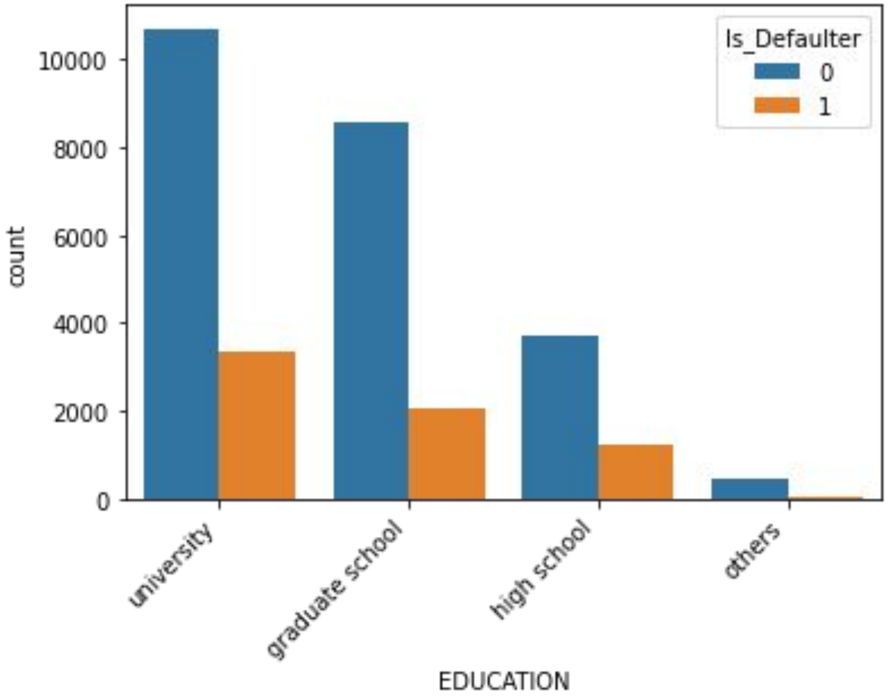
index	Is_Defaulter
0	77.88
1	22.12

Gender Distribution



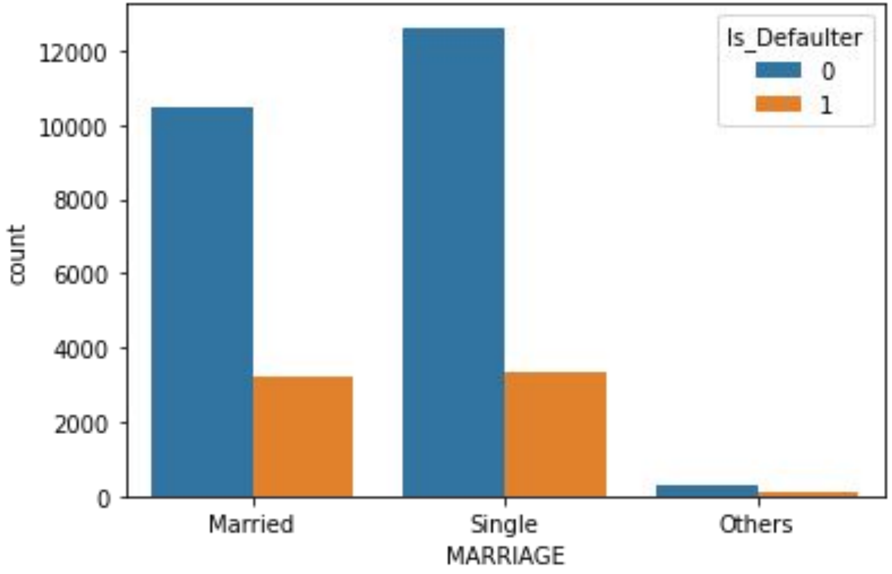
	SEX	Is_Defaulter
0	Female	20.776281
1	Male	24.167227

Education Distribution



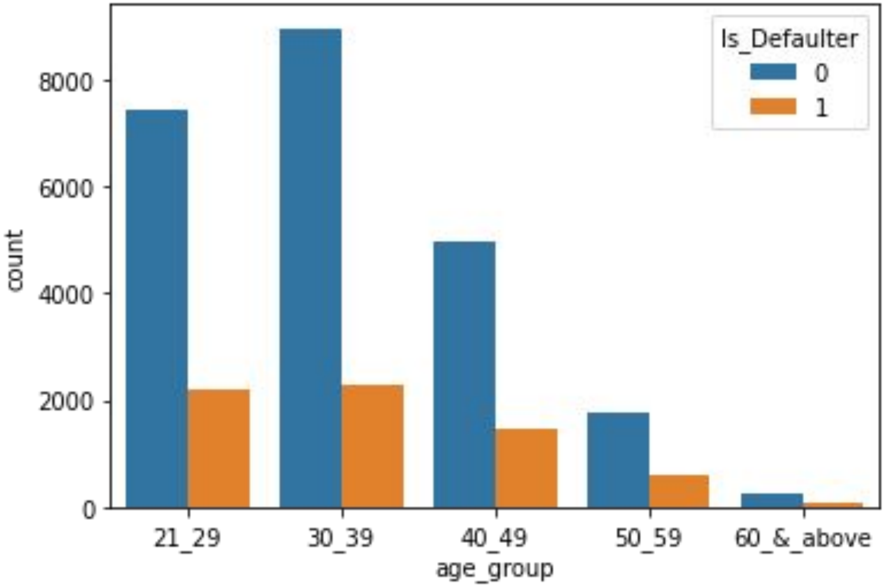
EDUCATION	Is_Defaulter
high school	25.157616
university	23.734854
graduate school	19.234766
others	7.051282

Marital Distributions



MARRIAGE	Is_Defaulter
Others	23.607427
Married	23.471704
Single	20.928339

Age Distribution



age_group	Is_Defaulter
60_&_above	28.318584
50_59	24.861170
40_49	22.973391
21_29	22.842587
30_39	20.252714

Modeling Overview

- Supervised learning
  - Binary Classification
- Imbalance data with 22% defaulters

Models Used:

- Logistic Regression
- Decision Trees
- Random Forest
- SVM
- XGBoost
- CatBoost
- LightGBM

Modeling Steps

Data Preprocessing

- Feature selection
- Feature engineering
- Train test data split(75%-25%)
- SMOTE oversampling

Data Fitting and Tuning

- Start with default model parameters
- Hyperparameter tuning
- Measure scores on training & test data

Model Evaluation

- Model testing
- Compare models

Logistic Modelling

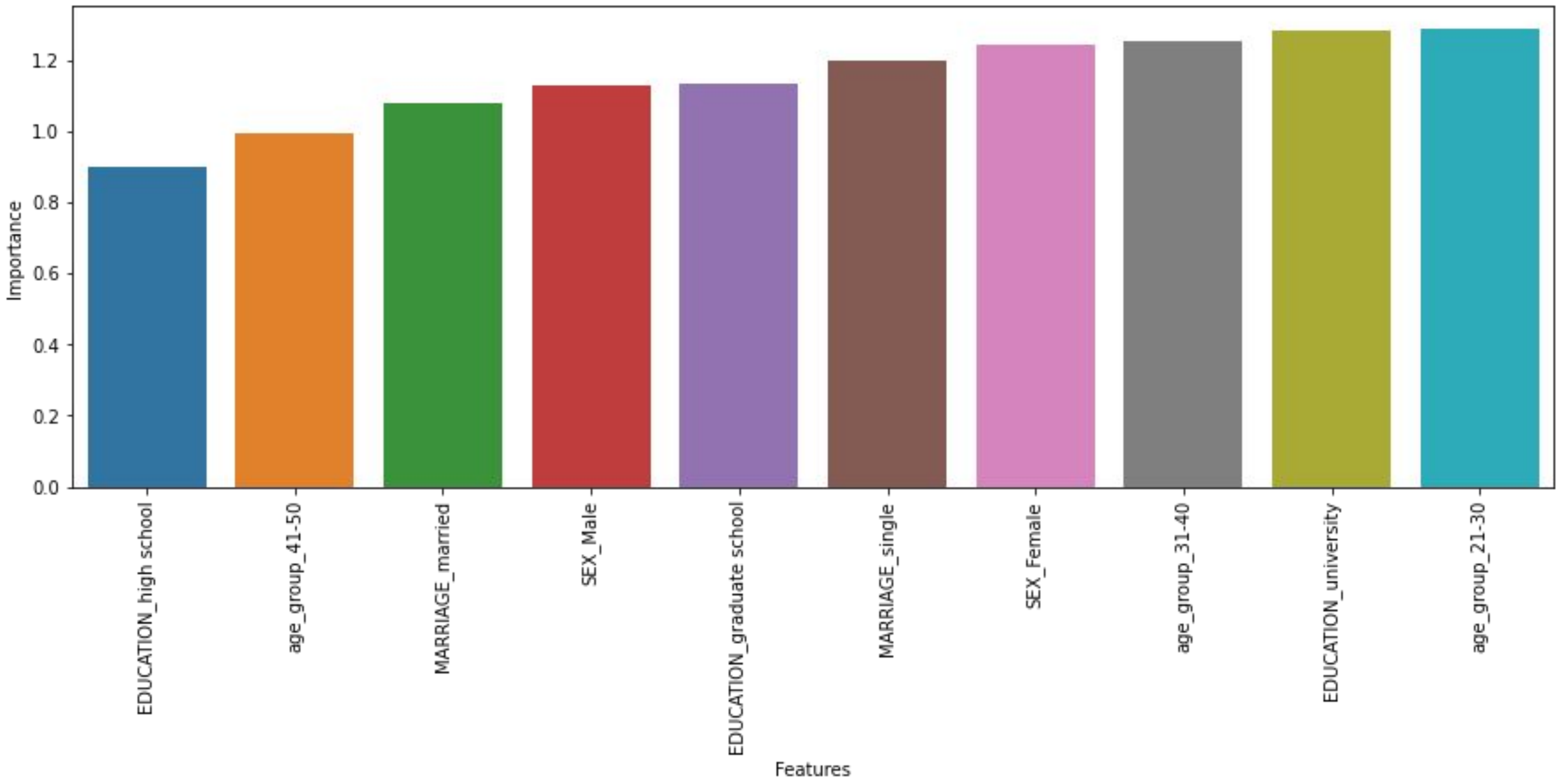
Parameters :

- C = 0.01
- Penalty = L2

Classification Report

	precision	recall	f1-score
0	0.81	0.97	0.88
1	0.96	0.77	0.85
accuracy			0.87

Logistic feature importances



Decision tree

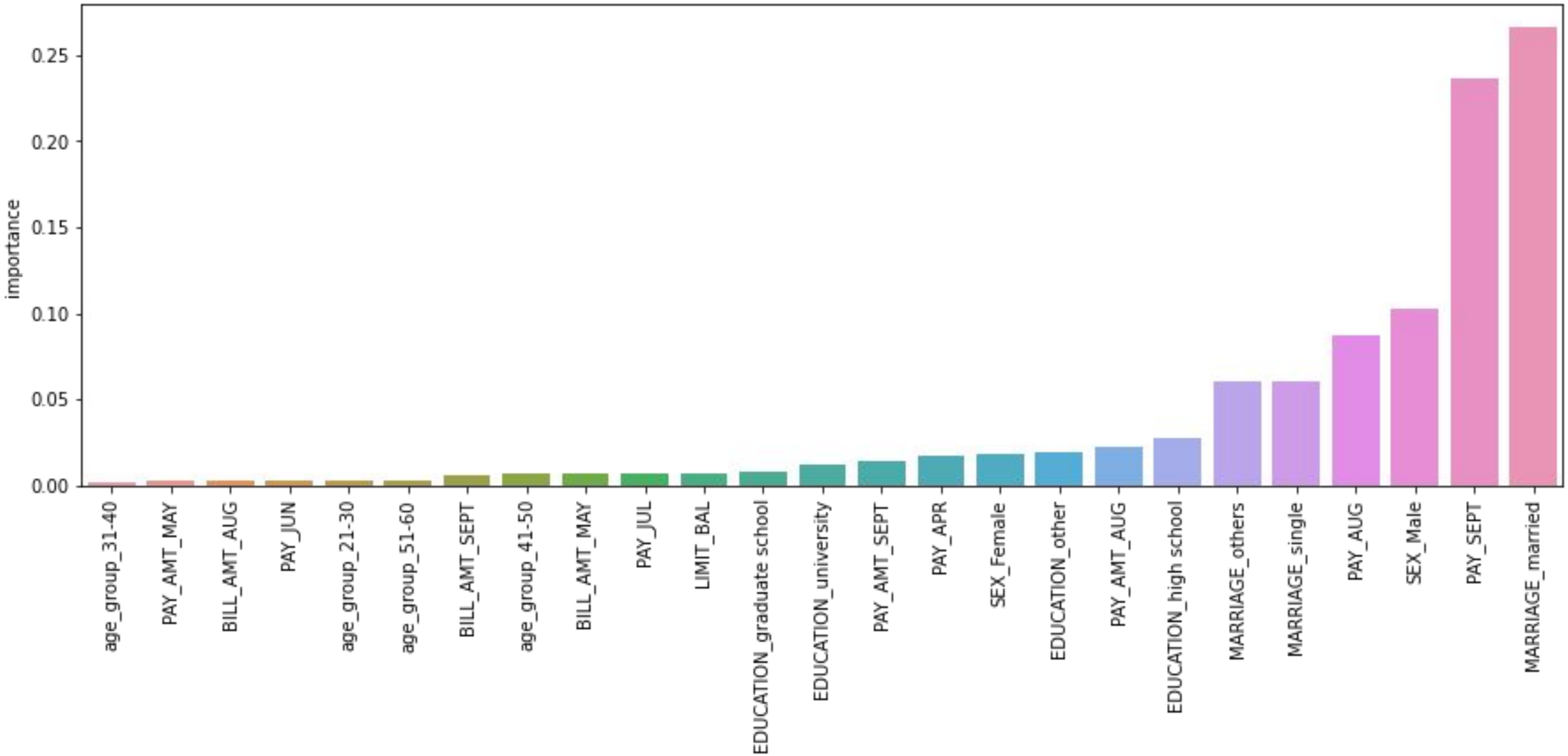
Parameters :

- max_depth=10
- max_leaf_nodes=45
- criterion= Entropy

Classification Report

	precision	recall	f1-score
0	0.77	0.93	0.84
1	0.91	0.72	0.81
accuracy			0.83

Decision tree feature importances



SVM Modelling

Parameters

C = 10

Kernel = ‘rbf’

Classification Report

	precision	recall	f1-score
0	0.82	0.96	0.88
1	0.95	0.79	0.86
accuracy			0.87

Random Forest Metrics

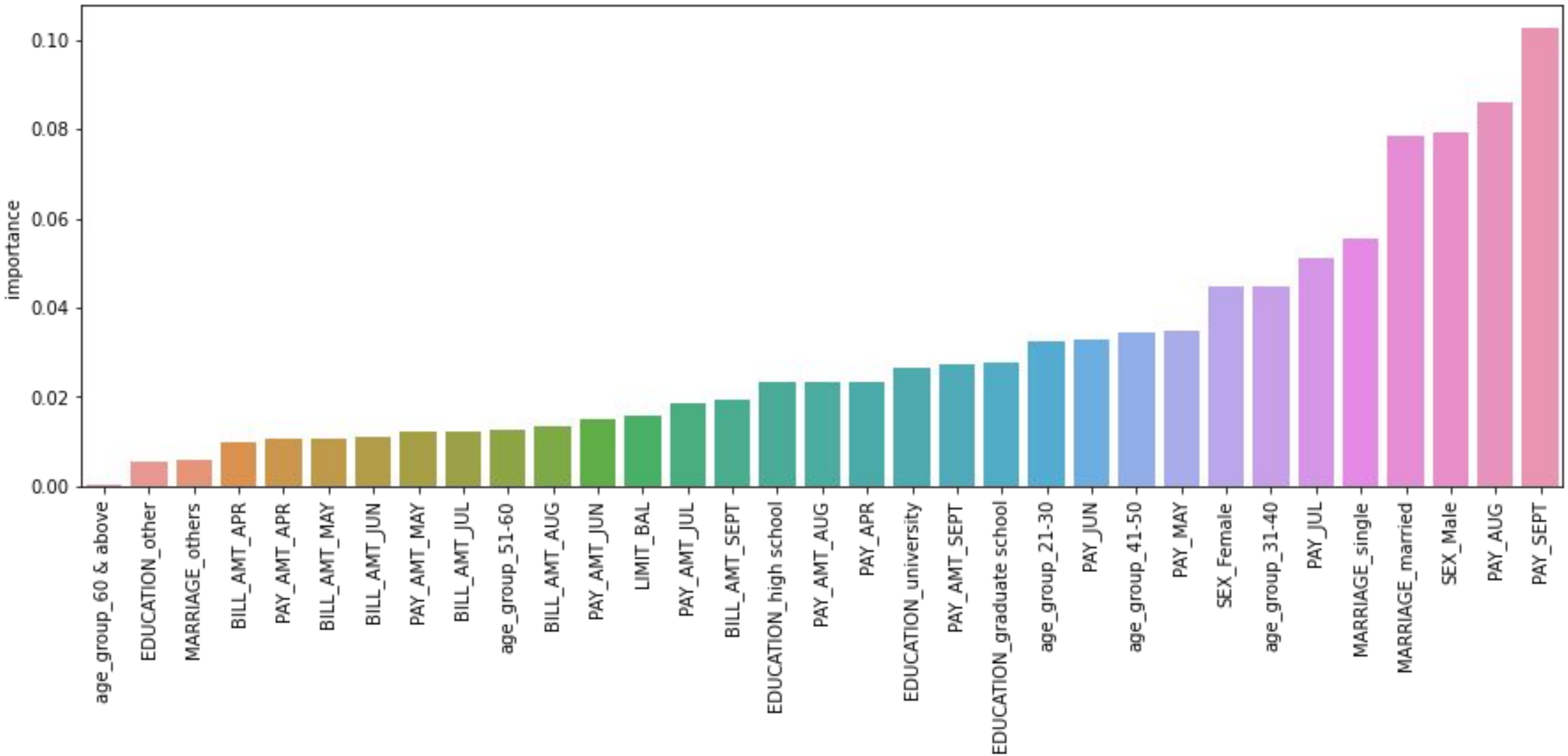
Parameters :

- max_depth=9
- n_estimators=200
- criterion: entropy

Classification Report

	precision	recall	f1-score
0	0.85	0.89	0.87
1	0.89	0.85	0.87
accuracy			0.87

Random Forest feature importances



XGBoost Modelling

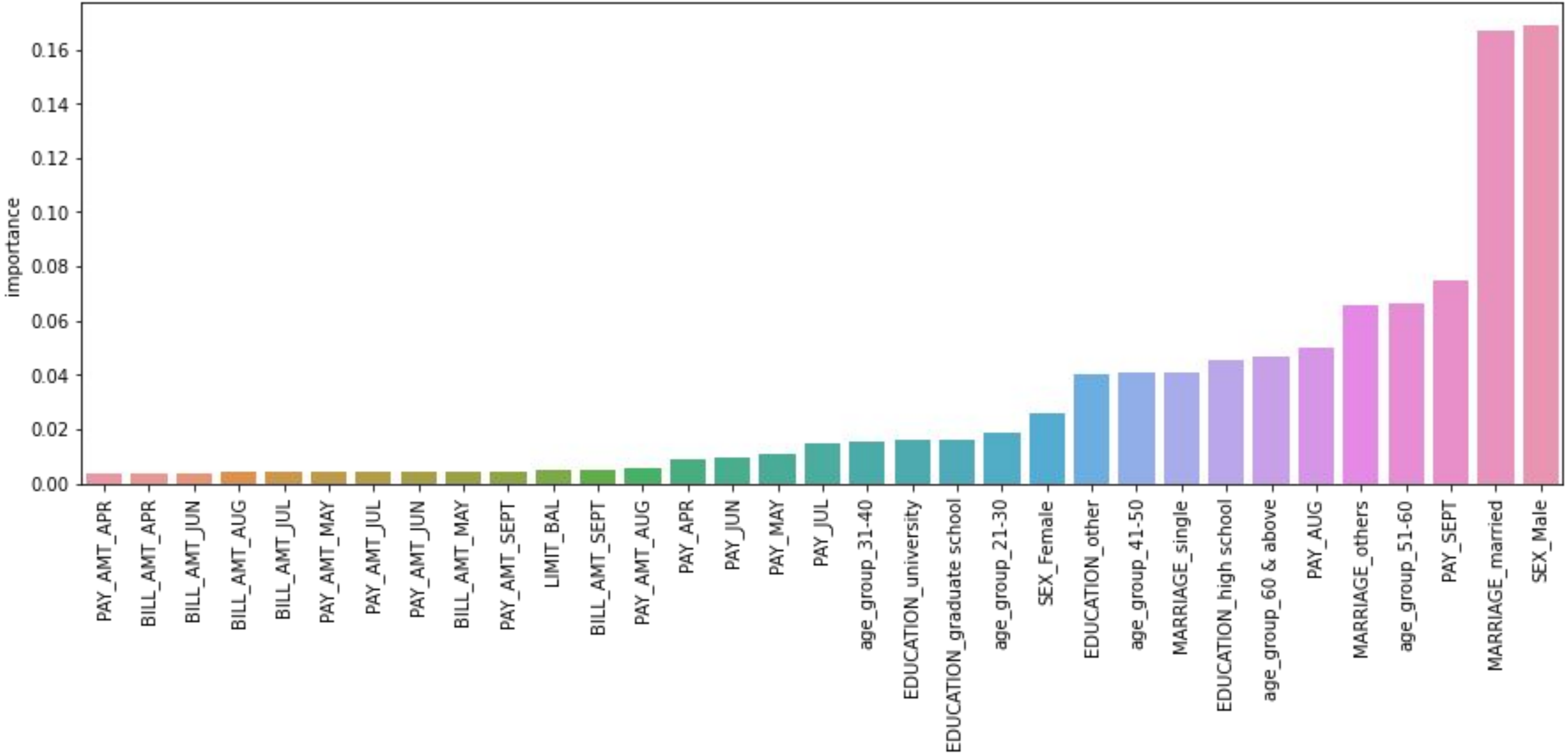
Parameters :

- max_depth= 9
- n_estimators=150

Classification Report

	precision	recall	f1-score
0	0.84	0.94	0.89
1	0.93	0.82	0.87
accuracy			0.88

X Gradient Boosting feature importances



CatBoost

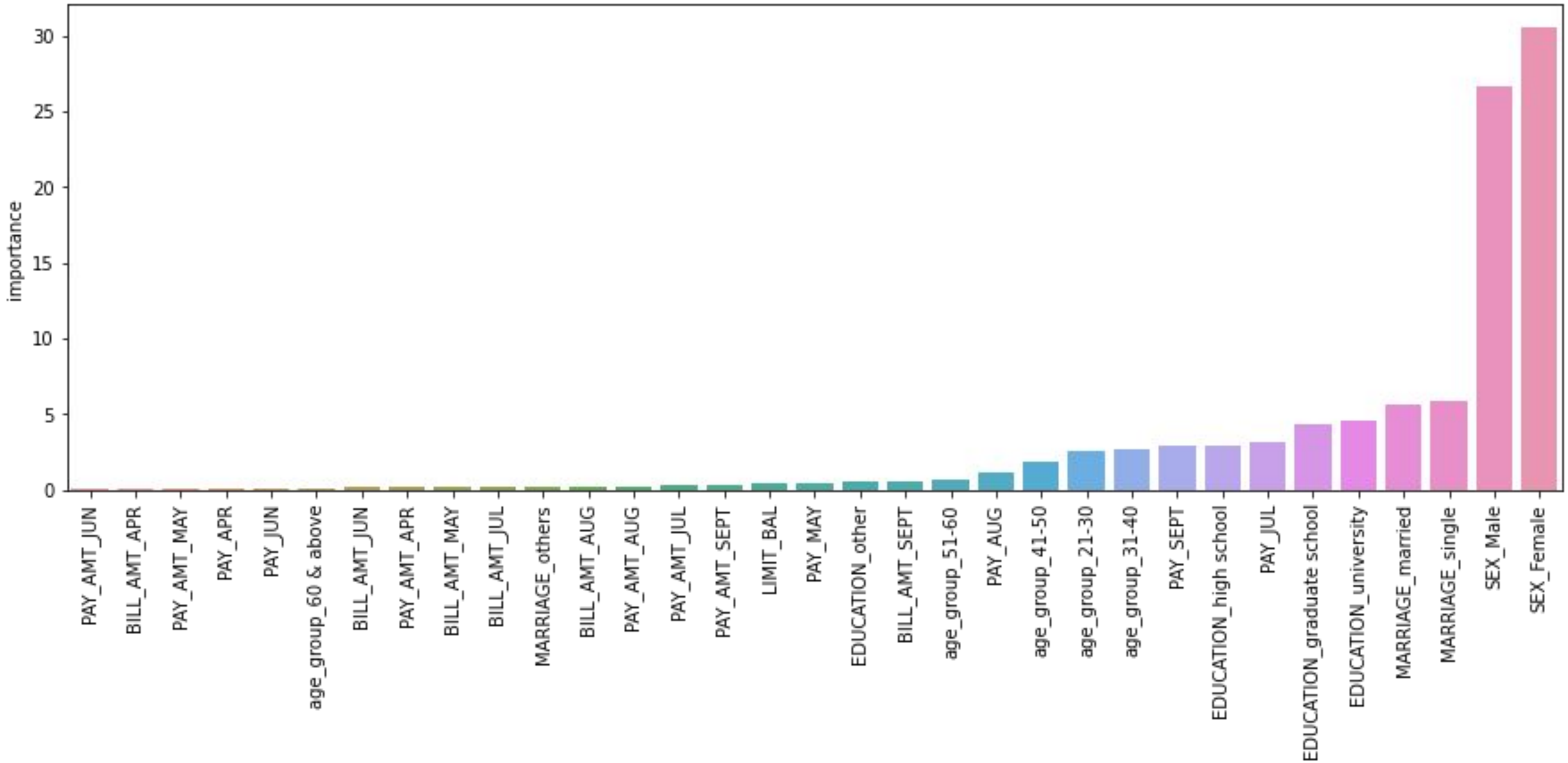
Parameters :

- max_depth=3,
- n_estimators: 150

Classification Report

	precision	recall	f1-score
0	0.83	0.95	0.88
1	0.94	0.80	0.86
accuracy			0.87

CatBoost feature importances



LightGBM

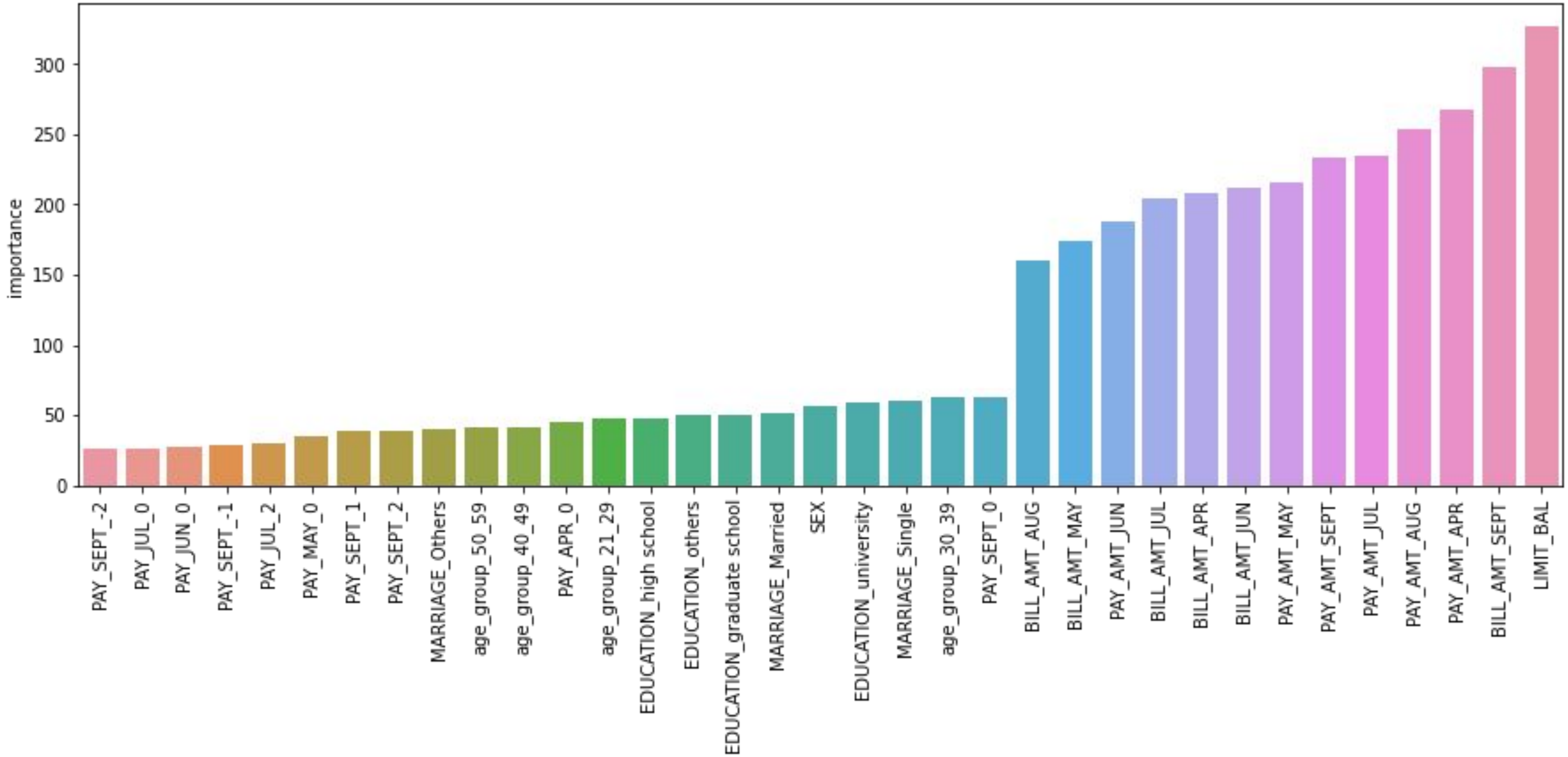
Parameters :

- max_depth=7
- n_estimators: 150

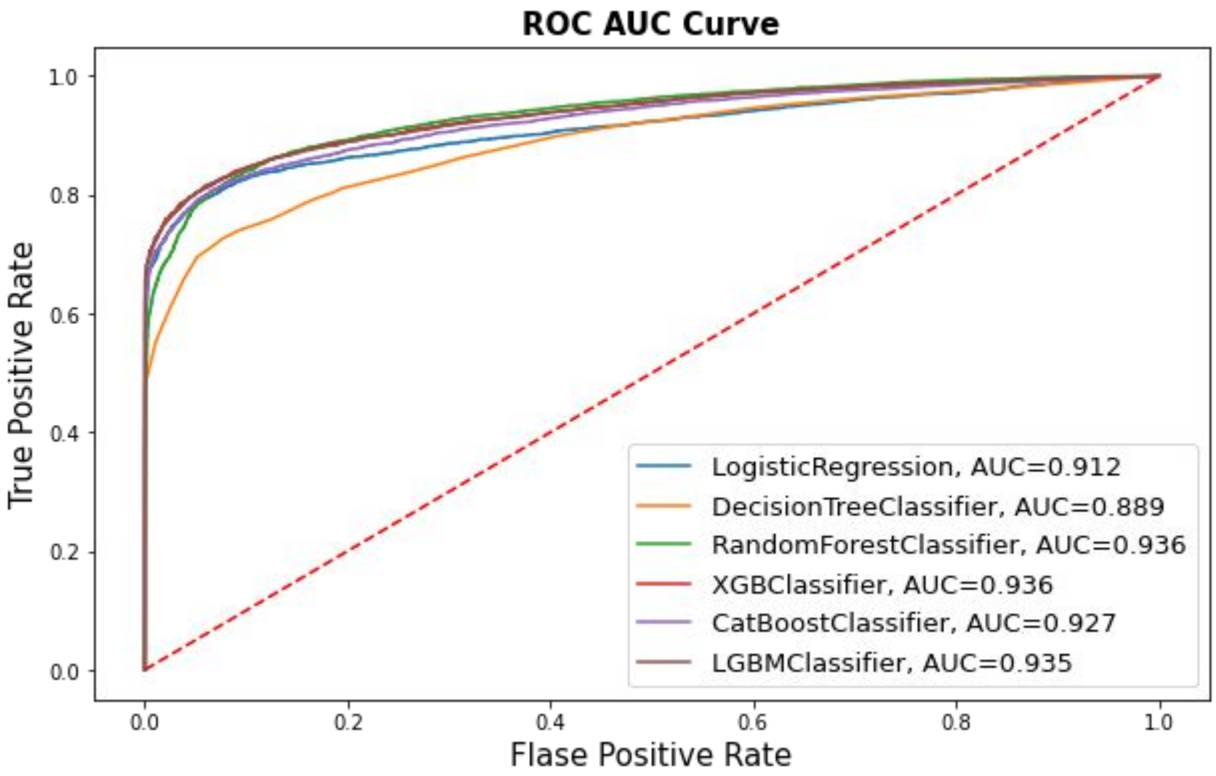
Classification Report

	precision	recall	f1-score
0	0.84	0.94	0.88
1	0.93	0.82	0.87
accuracy			0.88

LightGBM feature importance



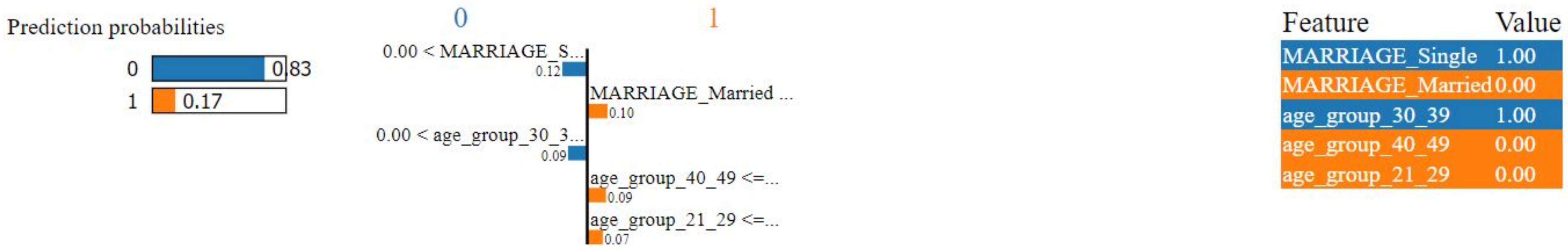
AUC-ROC curve comparison



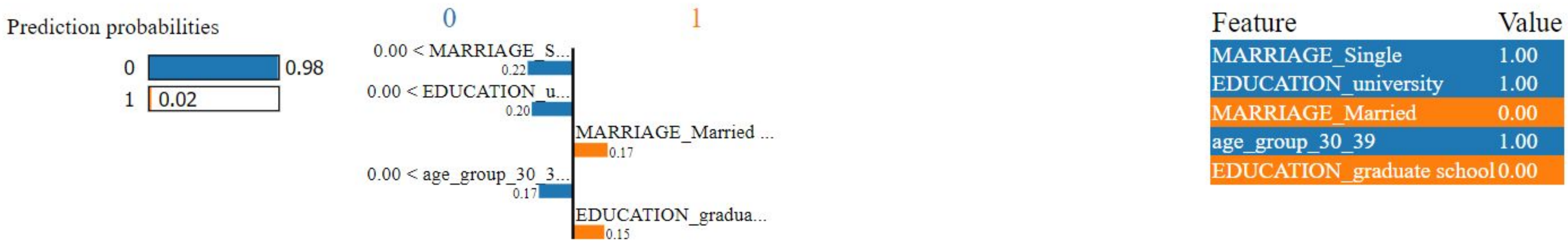
Score Matrix

	Models	accuracy	precision	recall	f1	roc_auc
0	Logestic Regrestion	0.863511	0.953632	0.766049	0.849610	0.864155
1	grid_log_regg	0.864115	0.950053	0.770512	0.850915	0.864734
2	Desision Tree	0.823428	0.891674	0.738929	0.808147	0.823986
3	Random forest	0.874482	0.902152	0.841916	0.870994	0.874697
4	grid random forest	0.869730	0.901749	0.831789	0.865357	0.869981
5	SVM	0.869039	0.943051	0.787333	0.858185	0.869579
6	Grid SVM	0.868435	0.931076	0.797631	0.859203	0.868903
7	XGboost	0.867312	0.921249	0.805184	0.859315	0.867722
8	Grid Xgboost	0.875173	0.925092	0.818229	0.868385	0.875549
9	CATBoost	0.872927	0.926877	0.811535	0.865379	0.873332
10	Grid Catboost	0.869039	0.912519	0.818229	0.862805	0.869375
11	LightGBM	0.876469	0.932337	0.813594	0.868928	0.876884
12	Grid LightGBM	0.877332	0.933320	0.814452	0.869844	0.877748

Model Explainability - LIME



Random forest



XGBoost

Challenges

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

Conclusion

- The default rate is higher for males, increases as the education increases, also increases as the age of a person increases. i.e clients whose age over 60 was higher than mid-age and young people.

- In all of these models, our recall revolves in the range of 76 to 84%.with the best fit model as random forest

Thank You