IÉSEG SCHOOL OF MANAGEMENT

EMPOWERING CHANGEMAKERS FOR A BETTER SOCIETY

# STATISTICAL & MACHINE LEARNING

## Group Project

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# OUR TEAM

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# PROJECT OVERVIEW

**Problem Description:** Credit card delinquency rose from 1.54% to 1.62% in the 4th quarter of 2021*. It is still under 2% of historic low, however the total amount of delinquencies has a major impact on the lending bank.

**Project Description:** Predict if the client will be able to pay the credit card bill in the upcoming month to help the lending bank take pro-active actions against the client to avoid any losses.

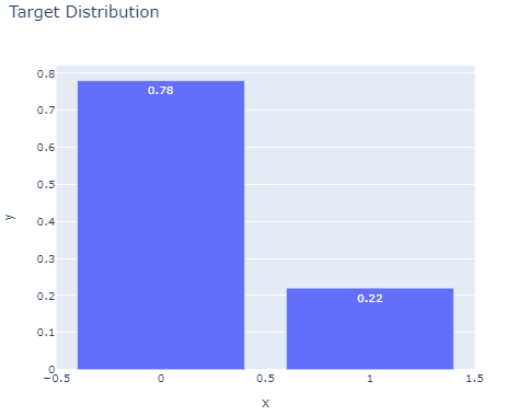
**Solution Approach:** Use past data from clients' payment and default history and build a ML based solution to predict risky clients who may default in the next month.

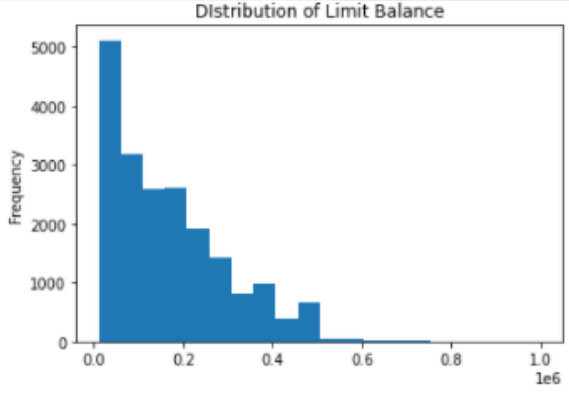
** Source: https://www.federalreserve.gov/releases/chargeoff/delallsa.htm*

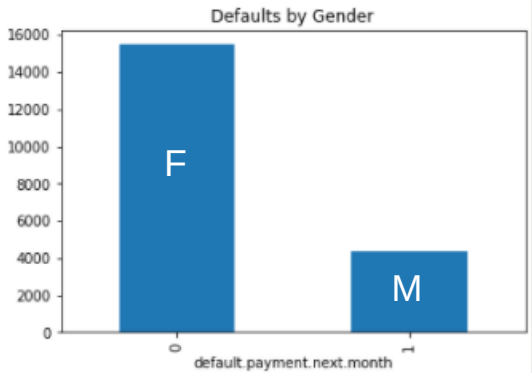
# Overview

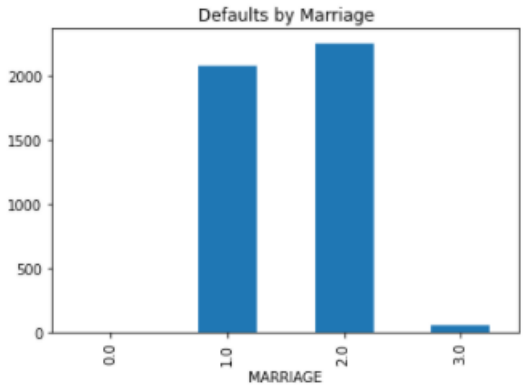
- Predictive modeling pipeline
- Interpretating the results
- Kaggle competition

# Exploratory Data Analysis



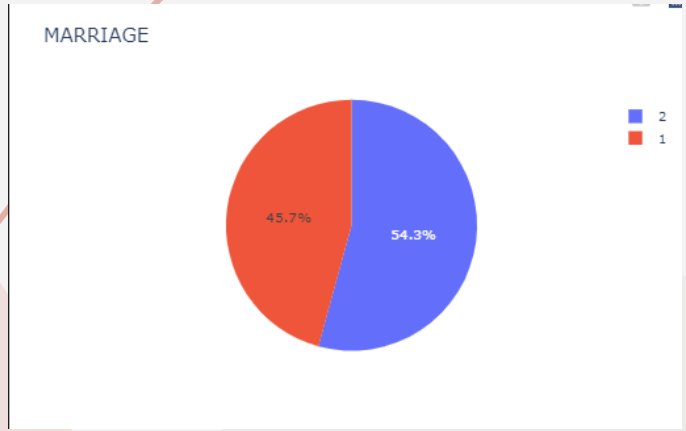



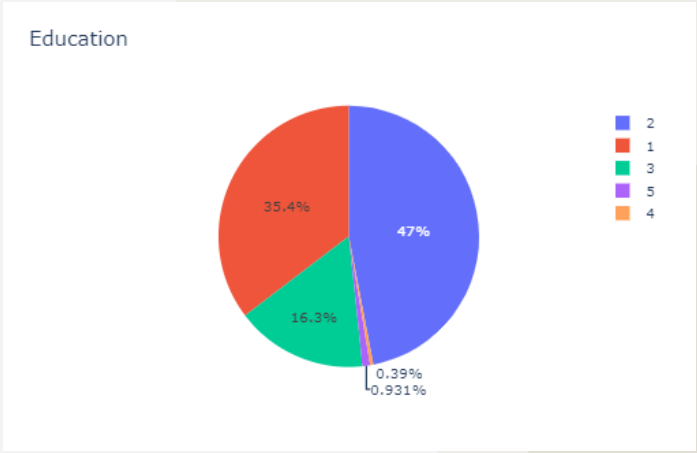



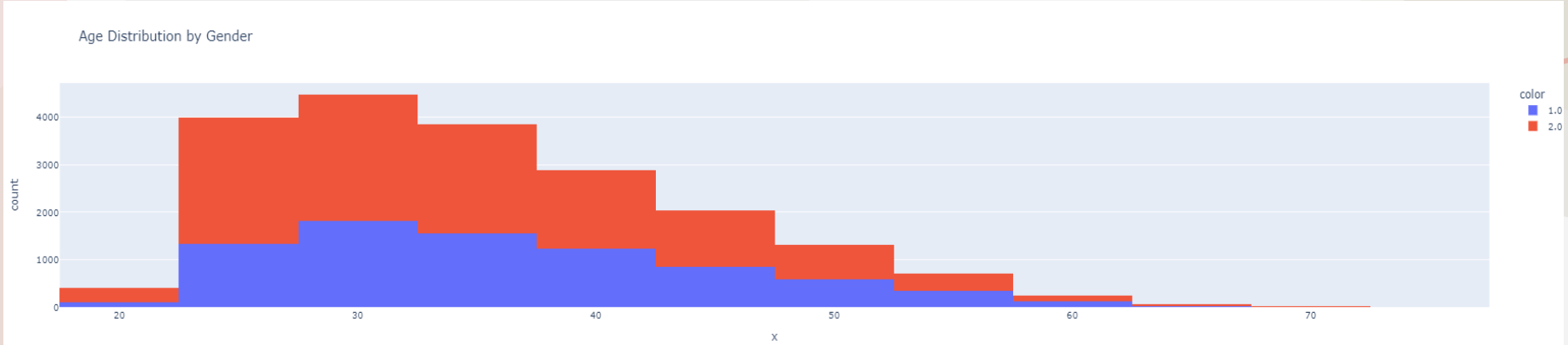




**Marital status:** 1=married, 2=single,

# Exploratory Data Analysis



# Data Preprocessing

## Error Correction

- Constant variables
- Missing values
- Outliers
- Encode categorical

## Feature Engineering

- Correlation test
- Mutual information
- Polynomial terms

## Value Transformation

- Re-mapping
- Decision tree discretization
- Equal frequency discretization
- Equal width discretization

## Value Representation

- Dummy encoding
- Incidence replacement
- WoE conversion

# Feature Engineering

01

Correlation Test

02

Mutual Information

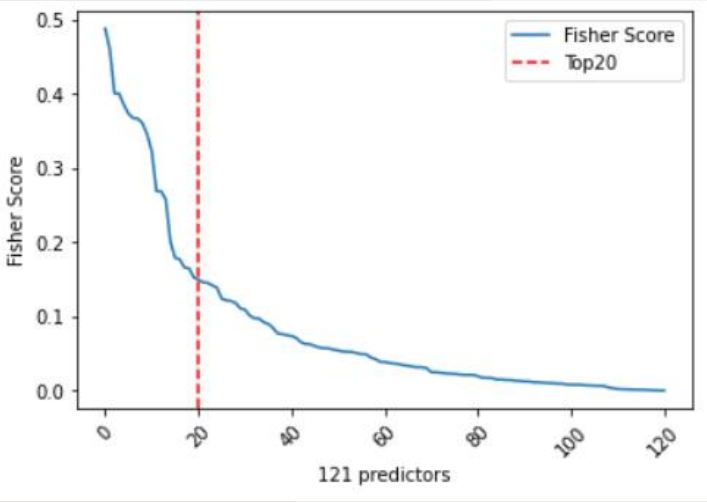
03

Polynomial Terms

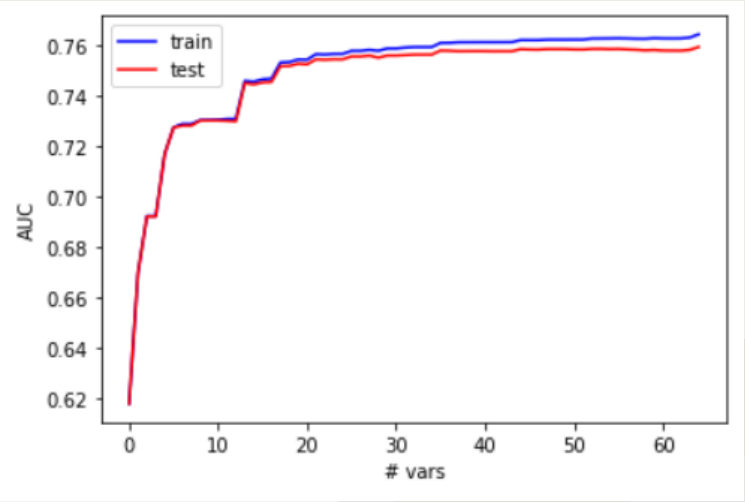
04

Dummy Encoding

# Feature Selection



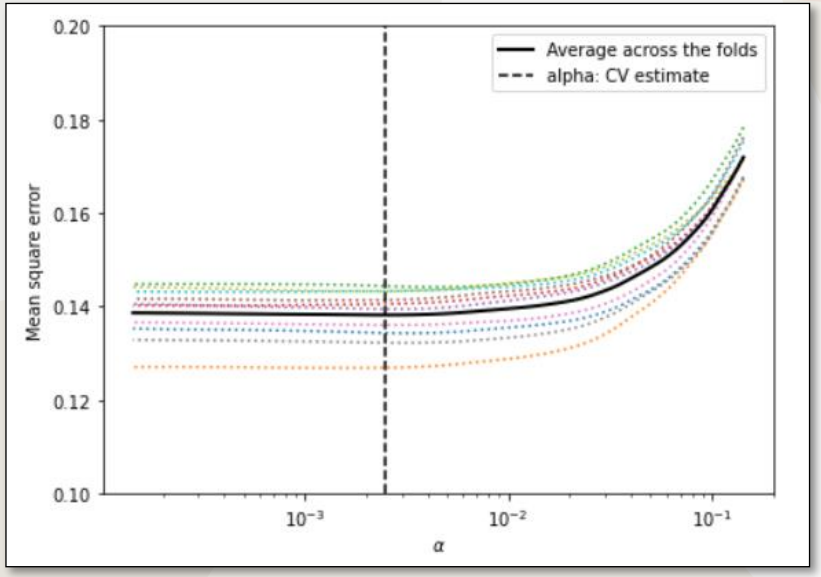

Top 20 Variables based on Fisher's Score




Scores drops and flatlines after 20+ variables, best at ~20 variables

Fisher Score

# Feature Selection




Lasso

**Alpha = 0.00233**

Calculate coefficients and remove features with coefficient equals 0

# Feature Selection

## Feature Selection Method 1 (Lasso)

Select all features that had coefficients different from 0 to fit in the model

## Feature Selection Method 2 (Fisher + Lasso + Manual Stepwise)

1. Select top features based on the Fisher's Score
2. Add one more feature from lasso method and monitor the change in AUC
3. If AUC improves and there is no sign of overfitting, we keep that feature
4. Add one more feature and repeat steps 1 to 4

# Selected Features

For final feature selection, we used a combination of methods that gave us the best results, these methods and the features selected using them are outlined below:

| Feature | Description | Selection Method |
|---|---|---|
| PAY_0_4.0 | Repayment Month | Fisher's Score / Lasso |
| PAY_2_4.0 | Repayment Month | Fisher's Score / Lasso |
| PAY_3_4.0 | Repayment Month | Fisher's Score |
| PAY_0_2.0 | Repayment Month | Fisher's Score / Lasso |
| PAY_4_4.0 | Repayment Month | Fisher's Score / Lasso |
| PAY_5_3.0 | Repayment Month | Fisher's Score / Lasso |
| PAY_6_3.0 | Repayment Month | Fisher's Score / Lasso |
| PAY_2_2.0 | Repayment Month | Fisher's Score |
| Age | Age | Step wise / Lasso |
| Age_sq | 2nd degree Polynomial of Age | Step wise |
| Limit_Bal | Scaled Limit Balance | Step wise / Lasso |
| PAY_0_1.0<br>PAY_0_2.0<br>PAY_0_3.0<br>PAY_0_5.0, PAY_0_6.0,<br>PAY_0_7.0, PAY_0_10.0 | Dummy representation of payment months | Lasso |
| PAY_2_3.0,<br>PAY_2_5.0, PAY_2_7.0,<br>PAY_2_8.0 | Dummy representation of payment months | Lasso |
| PAY_3_5.0,PAY_3_8.0,<br>PAY_3_11.0 | Dummy representation of payment months | Lasso |

| Feature | Description | Selection Method |
|---|---|---|
| BILL_AMT2,<br>BILL_AMT3_na | | Lasso |
| PAY_AMT1,<br>PAY_AMT2,<br>PAY_AMT3,<br>PAY_AMT4,<br>PAY_AMT5,<br>PAY_AMT6,<br>PAY_AMT3_na,<br>PAY_AMT5_na | Payment Amount of previous payment | Lasso |
| SEX_1.0 | Dummy rep of Sex | Lasso |
| EDUCATION_2.0,<br>EDUCATION_4.0,<br>EDUCATION_5.0 | Dummy rep of Education | Lasso |
| MARRIAGE_1.0,<br>MARRIAGE_3.0 | Dummy rep of Marriage | Lasso |
| AGE_na | Dummy rep - Missing Age | Lasso |
| PAY_4_1.0,<br>PAY_4_3.0 | Dummy rep for payments | Lasso |

# Model Benchmarking

| | Logistic Regression | Cat Boost Classifier | LGBM Classifier | XGB Classifier | Stacked Ensemble (Auto ML) | AdaBoost Classifier | MLP Classifier | Voting + Stacked Ensemble |
|---|---|---|---|---|---|---|---|---|
| **AUC Train** | **76.9%** | **87.2%** | **84.4%** | **83.0%** | **74.6%** | **82.9%** | **84.0%** | **N/A** |
| **AUC Validation** | **76.3%** | **76.8%** | **77.5%** | **77.3%** | **75.4%** | **77.5%** | **76.7%** | **N/A** |
| **AUC Test (Kaggle)** | **N/A** | **78.9%** | **79.2%** | **76.07%** | **72.3%** | **N/A** | **77.9%** | **79.2%** |

*N/A = Not Submitted on Kaggle*

** Note AUC on 5 folds cross validation*

# Model Selection

Best Scoring Model based on Kaggle Test Set

## Mean (Voting Ensemble + AdaBoost)

LightGBM


CatBoost

Logistic Regression

# Model Selection

## Best Scoring Model Parameters

1. LGBMClassifier(boosting_type='gbdt', random_state=1, learning_rate= 0.1, max_depth= 5, num_leaves= 10, objective = 'binary', reg_alpha= 0.8, reg_lambda= 1)

2. RandomForestClassifier(n_estimators=300)

3. CatBoostClassifier(verbose=0, learning_rate=0.009, depth=16)

4. LogisticRegression(C=2, max_iter= 1000, penalty= 'l1', solver= 'liblinear’)

5. AdaBoostClassifier(base_estimator=RandomForestClassifier(), max_depth=4, min_samples_leaf=5, n_estimators=250, learning_rate=0.01)

# Hyper-parameter Tuning

## Using GRID Search & Cross Validation

### Logistic Regression

| | |
|---|---|
| penalty | l1, l2 |
| C (Inverse of regularization strength) | 0.01, 0.1, 0.5, 1, 2 |

### LightGBM

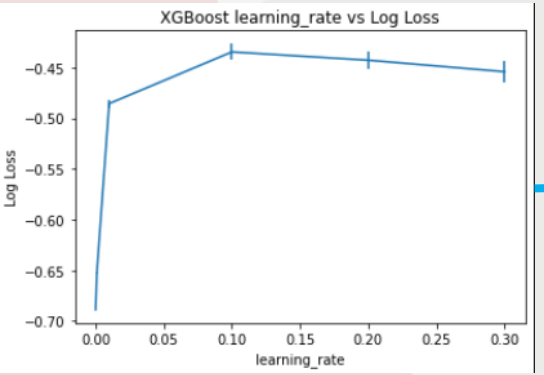
| | |
|---|---|
| learning rate | 0.01, 0.05, 0.1 |
| maximum tree leaves | 10, 12, 15, 20 |
| maximum tree depth | 5, 8 |
| L1 regularization term on weights | 0.8, 1 |
| L2 regularization term on weights | 1, 1.2, 1.3, 1.4 |

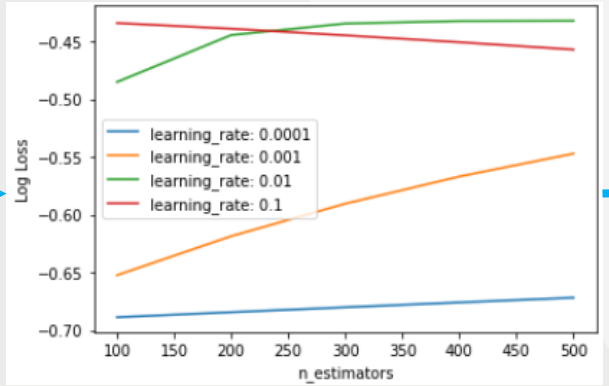
Examples of grid search parameters we used to tune our models

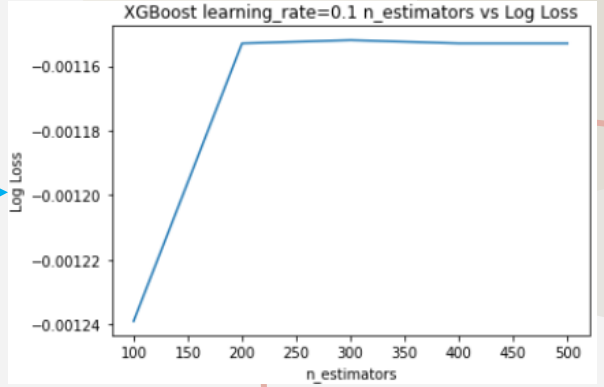
Multiple iterations of Grid Search and Cross Validation were performed to find the best parameters without over or under fitting

# Hyper-parameter Tuning
# Our Approach

1. Understand impact learning rate has on the performance
2. Monitor the learning rate and number of estimators
3. Re-visit the performance of learning rate vs number of estimators



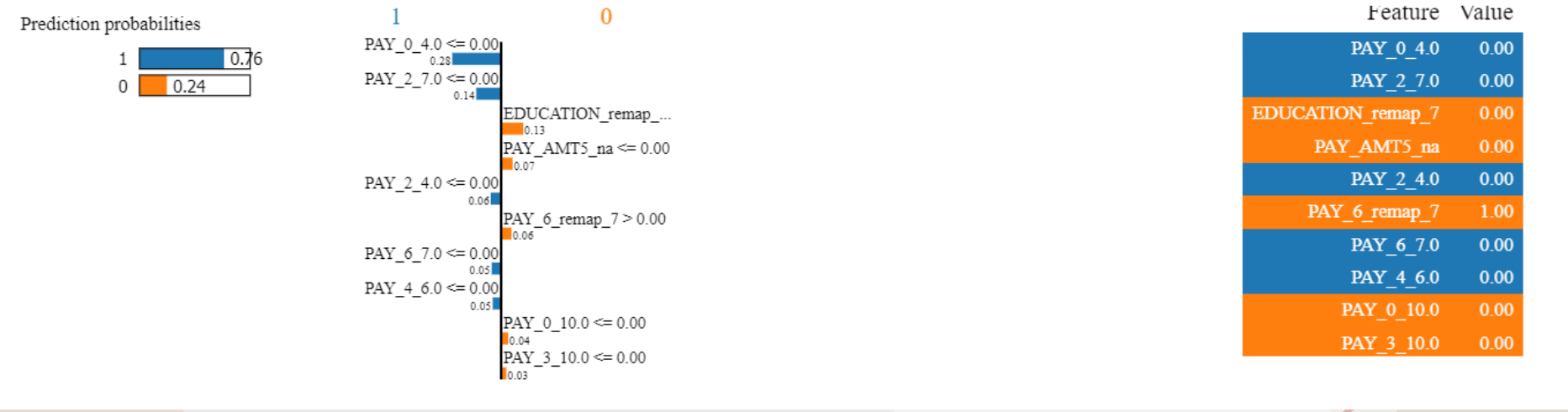

**Our approach was similar for tuning all models: tune 1 parameter → monitor its impact on other parameters → Adjust and tune next parameter*

# Model Interpretation using LIME

LIME (Locally Interpretable Model Agnostic Explanations) is a method that fits a surrogate glassbox model around the decision space of any Blackbox model's prediction.

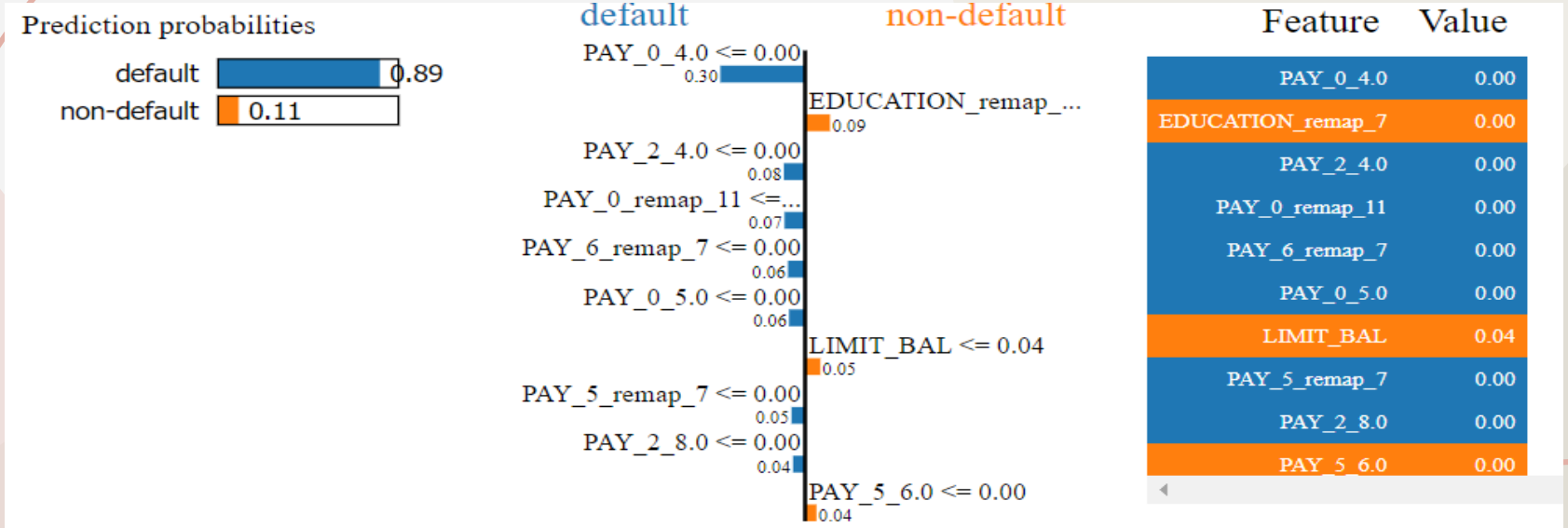
LIME works by generating synthetic data which gets evaluated by the Blackbox system, and ultimately used as a training set for the glass box model.

# Model Interpretation - XGBoost




Higher the value of the variables in Blue and lower the value of the variables in Orange will push the target variable towards 1

# Model Interpretation - LGBM




Higher the value of the variables in Blue and lower the value of the variables in Orange will push the target variable towards 1

# Conclusion

Higher the education of the clients the lower the probability of default

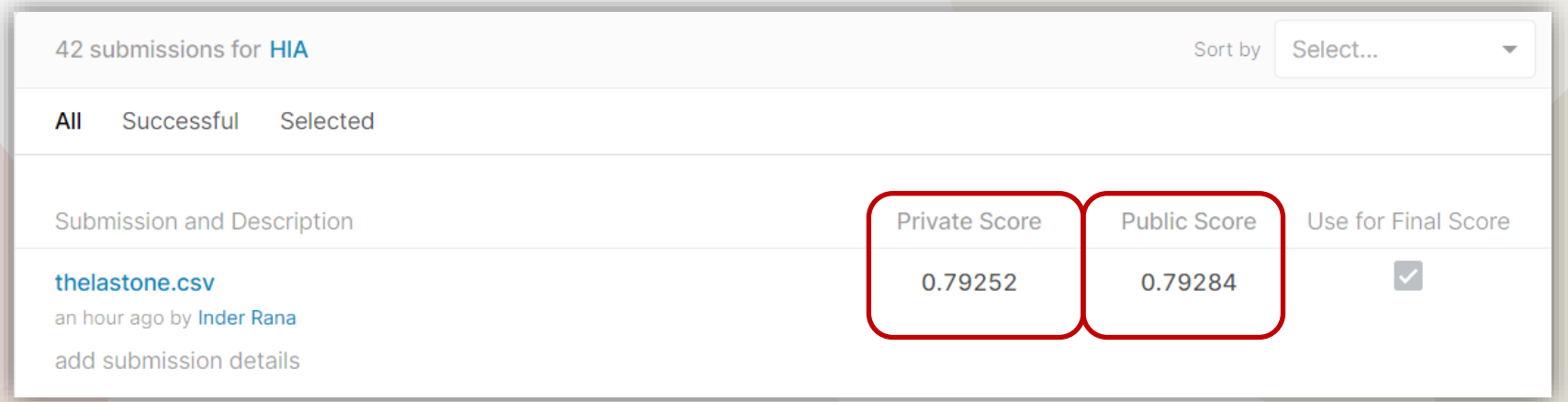
Lower the limit balance, lower the probability of default

# Conclusion

Based on the features in our dataset we noticed the following:

- Almost all models (except Logistic Regression) tend to overfit very easily if we use a lot of features.
- Logistic Regression was one of the best models in terms of Train/Test AUC stability of 76% AUC.
- Boosting models performed the best and even better when combined using voting and stacking methods.
- Although an ensemble performed better, we would still recommend using Logistic Regression model as the difference in the performance is only 3% and Logistic Regression model is very fast, simple and easy to explain compared to an ensemble.

# Kaggle Competition



# Recommendations

- Banks can adapt the customer’s limit based on default predictions
- Lending institution can send proactive notifications to the clients who are probable to default next month.
- Banks can offer short term loan to the clients with probability of default in order to pay for the credit card and avoid high interest rates.
- Use Education as one of the inputs while assigning limit balance

# THANKS!

# References


- ML Pipeline template and functions: Minh Phan – IESEG School of Management
- Presentation theme, icons and graphics: Slidesgo, IconsFlaticon, Freepik
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