Capstone Project

CREDIT CARD DEFAULT PREDICTION

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Problems to Resolve

Problem Statement

- ML applications focused on credit score predicting.
- Relying on credit scores and credit history.
- Miss valuable customers with no credit history. I.e. immigrants.
- Regulatory constraints on banking industry forbids some ML algorithms.

Purpose of Project

- Conduct quantitative analysis on credit default risk by applying three interpretable machine learning models without utilizing credit score or credit history.

Who Should Care?

Credit Card Companies

Commercial Banks

Approach Overview

Data Cleaning → **Data Exploration** → **Predictive Modeling**

Understand and Clean
- Find information on undocumented columns values
- Clean data to get it ready for analysis

Graphical and Statistical
- Exam data with visualization
- Verify findings with statistical tests

Machine Learning
- Logistic Regression
- Random Forest
- XGBoost

Data Acquisition

Dataset

- Default Payments of Credit Card Clients in Taiwan from 2005
- Source: Public dataset from Kaggle.
- Original Source: UCI Machine Learning Repository*

Why This Dataset?

- Real credit card data
- Comprehensive and complete
- 30,000 customers
- Usage of 6 months
- Age from 20-79
- Demographic factors
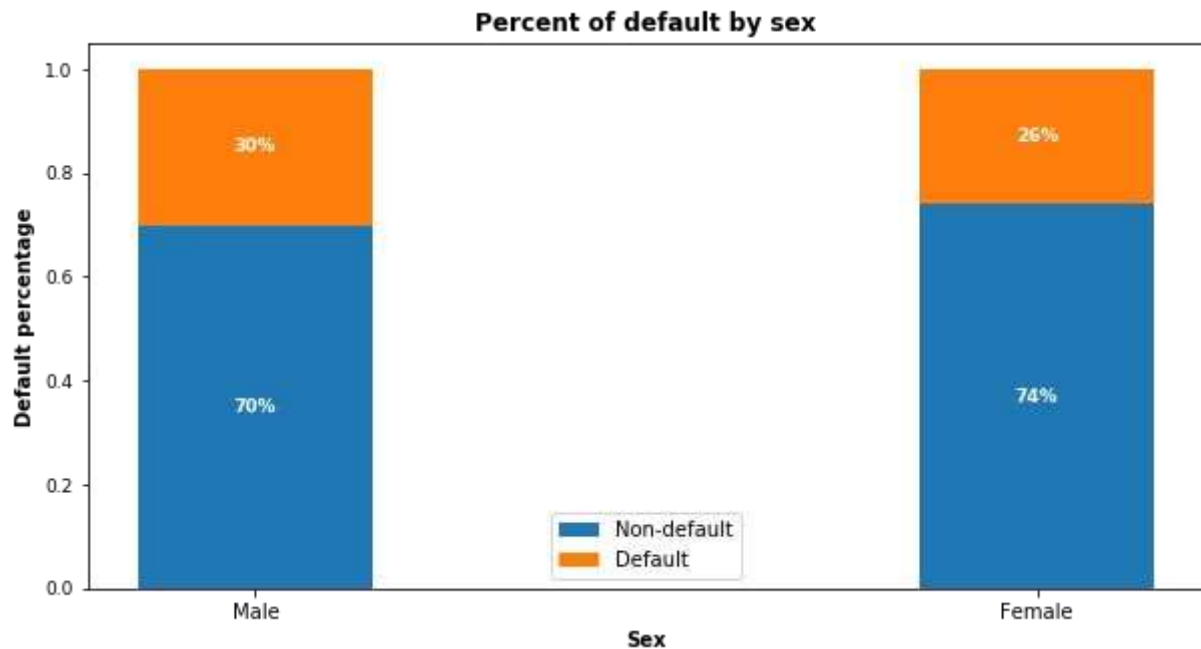- No credit score or credit history

*Lichman, M. (2013). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.
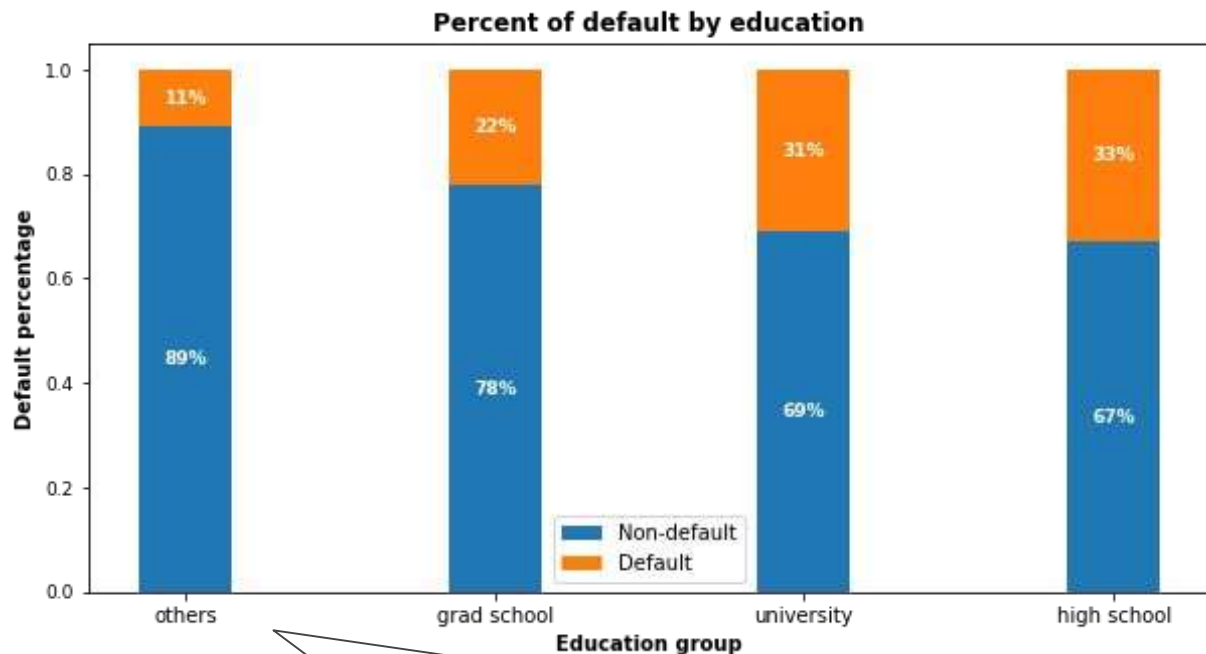
Part 1

Exploratory Data Analysis

What demographic factors impact payment default risk?

Gender Variable

Percent of default by sex

30% of males and **26%** of females have payment default.

Education Variable

Percent of default by education
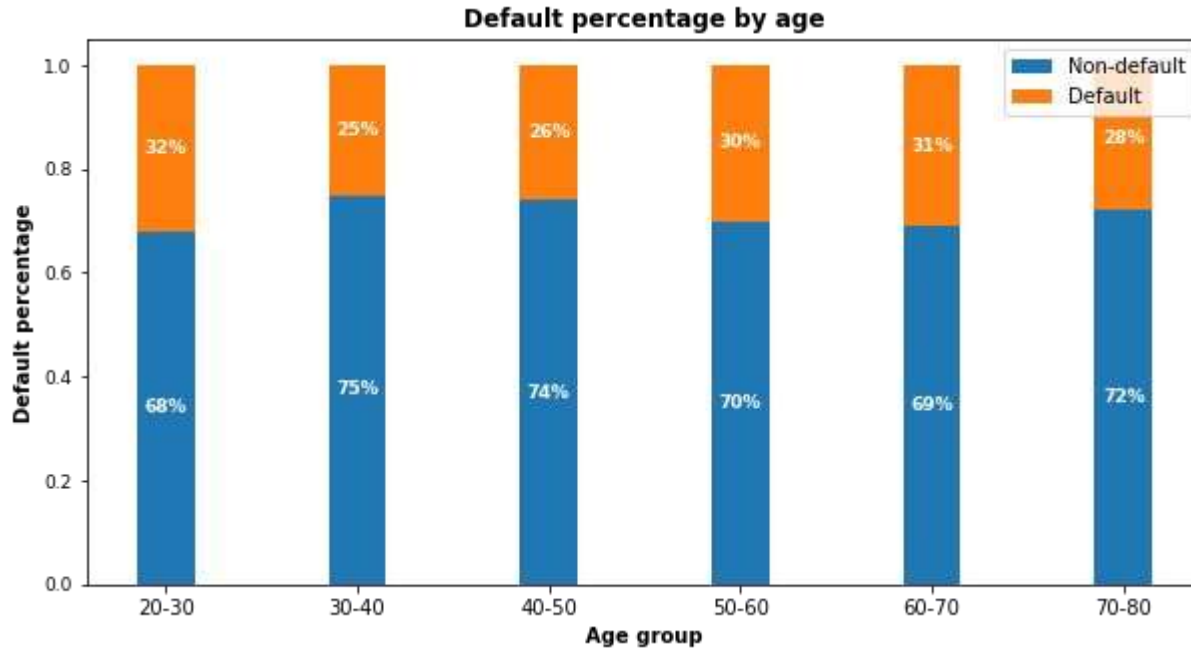
Higher education level, **lower** default risk.

"Others" only consists 1.56% of total customers even if they appear to have the least default.

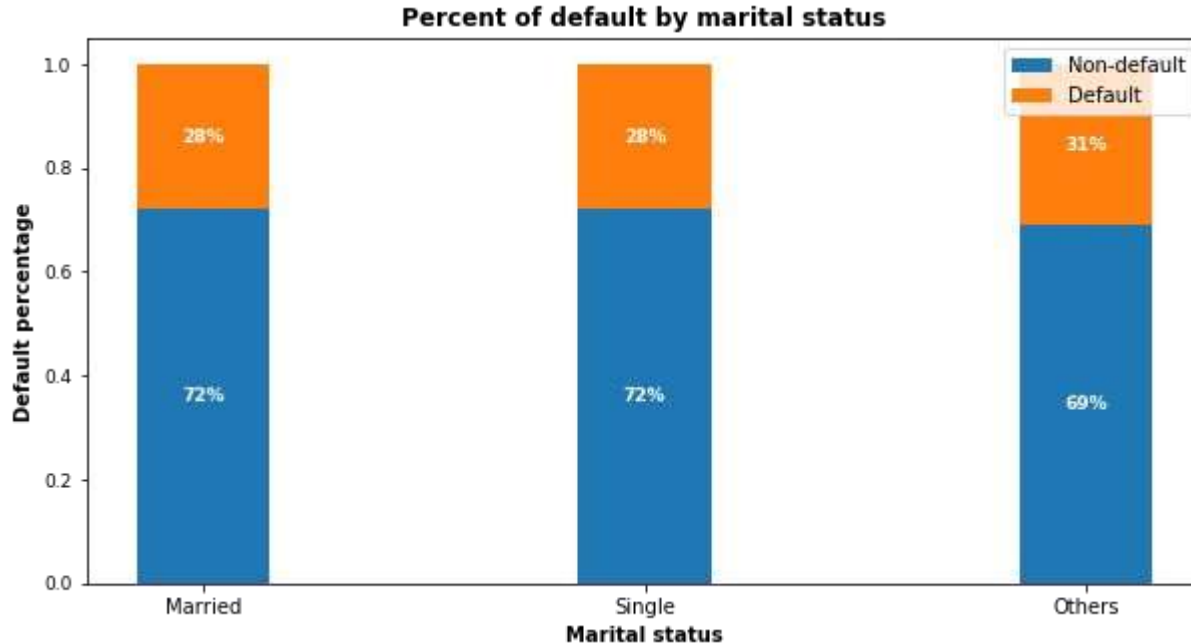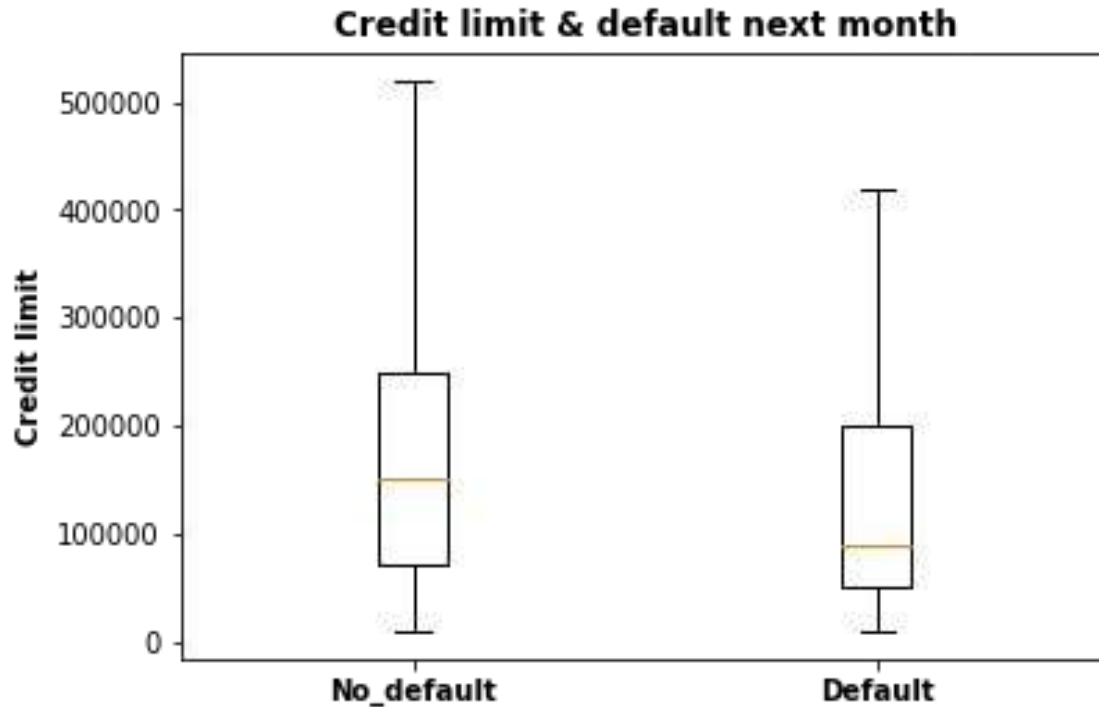# Age Variable

Default percentage by age

30-50:
Lowest risk

< 30 or >50:
Risk increases

Marital Status Variable

Percent of default by marital status

No significant correlations of default risk and marital status

Credit Limit Variable

Credit limit & default next month

Higher credit limits,

lower default risk.

EDA Summary

- Demographic factors that impact default risk are:

  - Education: Higher education is associated with lower default risk.

  - Age: Customers aged 30-50 have the lowest default risk.

  - Sex: Females have lower default risk than males in this dataset.

  - Credit limit: Higher credit limit is associated with lower default risk.

Part 2

Predictive Modeling

What precision and recall scores can the models achieve?

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Modeling Overview

Define Problem: Supervised learning / binary classification

Imbalanced Classes: 78% non-default vs. 22% default

Tools Used: Scikit learn library and imblearn

Models Applied: Logistic Regression / Random Forest / XGBoost

Modeling Steps

Data Preprocessing	Fitting and Tuning	Model Evaluation

- Feature selection
- Feature engineering
- Train-test data splitting (70%/30%)
- Training data rescaling
- SMOTE oversampling

- Start with default model parameters
- Hyperparameters tuning
- Measure ROC_AUC on training data

- Models testing
- Precision_Recall score
- Compare with sklearn dummy classifier
- Compare within the 3 models

Correct Imbalanced Classes

- Fit every model without and with SMOTE oversampling for comparison.
- Training AUC scores improved significantly with SMOTE.

Models	AUC Without SMOTE	AUC With SMOTE
Logistic Regression	0.726	0.797
Random Forest	0.764	0.916
XGBoost	0.762	0.899

Hyperparameters Tuning

- **K-Fold Cross Validation** to get average performance on the folds.

- **Randomized Search** on Logistic Regression since C has large search space.

- **Grid Search** on Random Forest on limited parameters combinations.

- **Randomized Search** on XGBoost because multiple hyperparameters to tune.

Model Comparisons

- Compare the models to Scikit-learn's dummy classifier.
- All models performed better than dummy model.

Models	Precision	Recall	F1 Score	Conclusion
Dummy Model	0.217	0.500	0.303	**Benchmark**
Logistic Regression	0.384	0.566	0.457	**Best recall**
Random Forest	0.513	0.514	0.514	**Best F1**
XGBoost	0.444	0.505	0.474	

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Model Comparisons

- Compare within 3 models.
- Random Forest (black line) has the best precision_recall score.
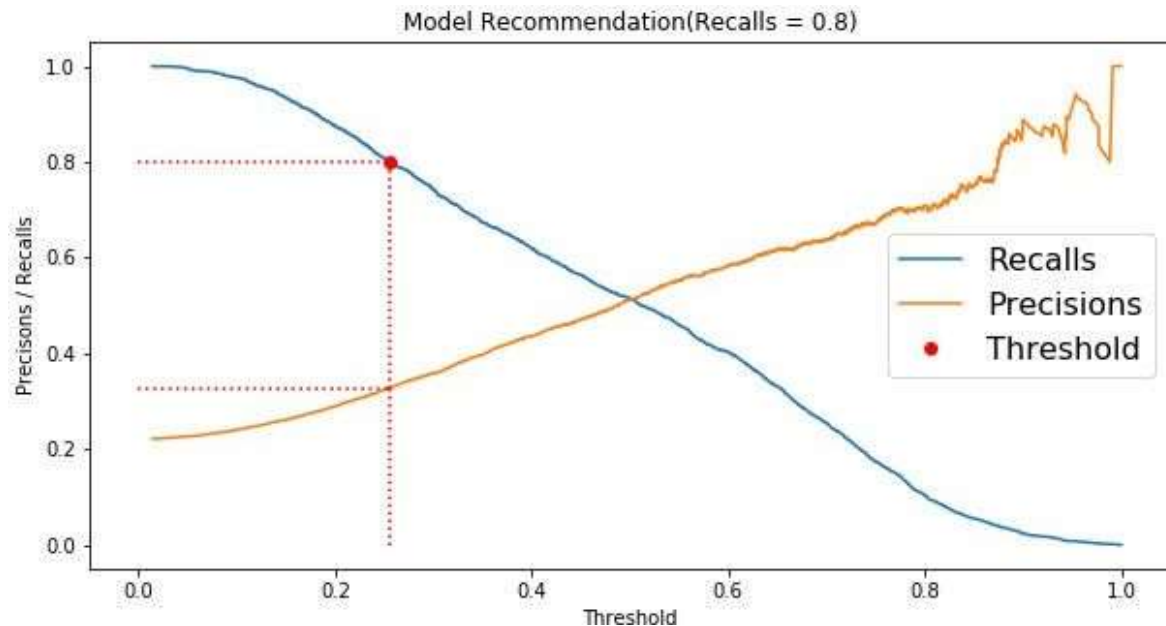

Precision_Recall of 3 models
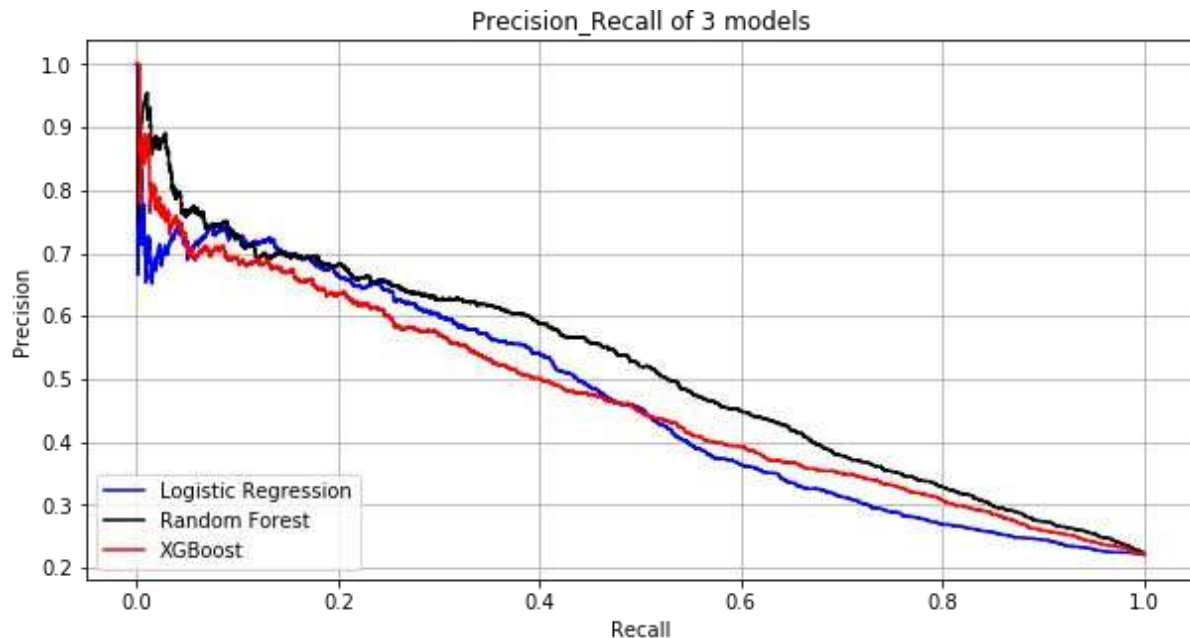
Terminology:

★ Recall: how many 1s are being identified?

★ Precision: Among all the 1s that are flagged, how many are truly 1s?

★ Precision and recall trade-off: high recall will cause low precision

Model Usage - Recommendation

- I.e. recall = 0.8. Threshold can be adjusted to reach higher recall.

Model Recommendation(Recalls = 0.8)

Feature Importances

Features importance
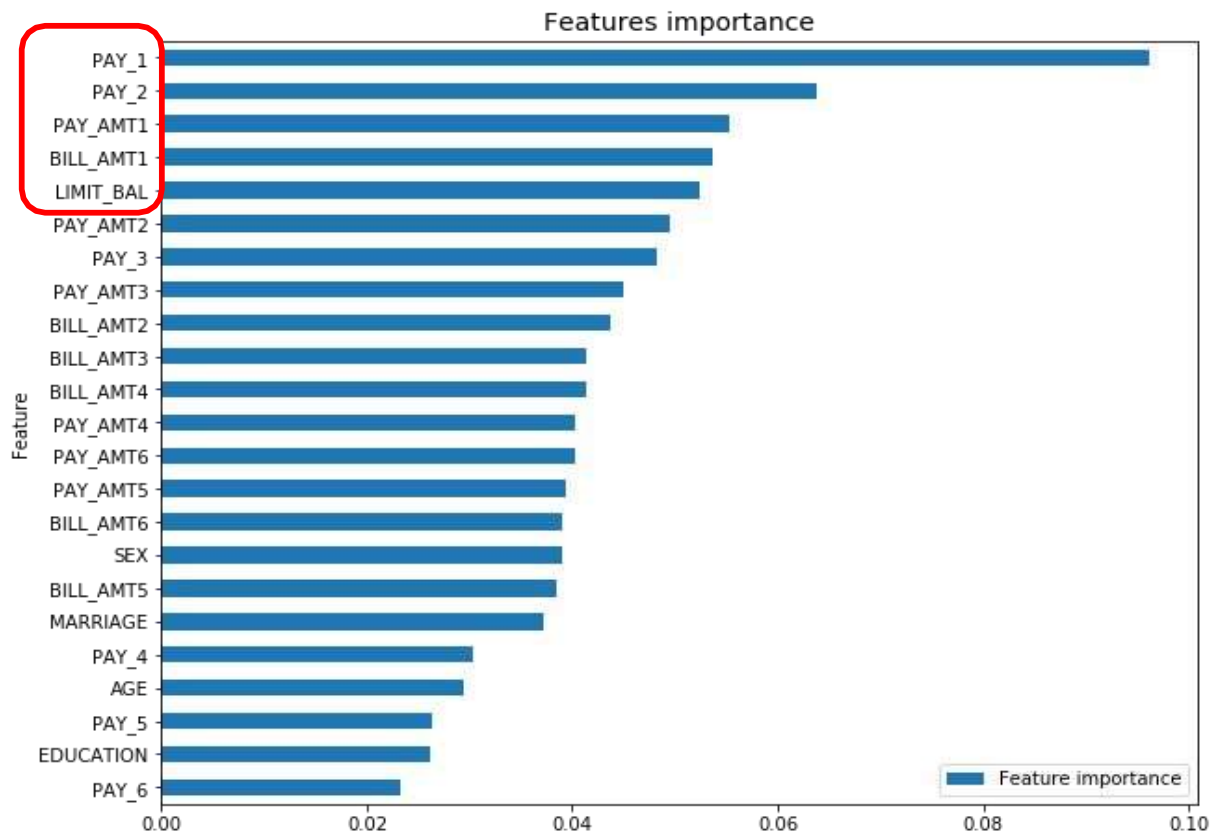
Best model Random Forest feature importances plot.

- ★ PAY_1: most recent month's payment status.
- ★ PAY_2: the month prior to current month's payment status.
- ★ BILL_AMT1: most recent month's bill amount.
- ★ LIMIT_BAL: credit limit

Limitations & Future Work

Limitations

- Best model Random Forest can only detect 51% of default.
- Model can only be served as an aid in decision making instead of replacing human decision.
- Used only 30,000 records and not from US consumers.

Future Work

- Models are not exhaustive. Other models could perform better.
- Get more computational resources to tune XGBoost parameters.
- Acquire US customer data and more useful features.I.e.customer income.

Conclusions

- Recent 2 payment status and credit limit are the strongest default predictors.
- Dormant customers can also have default risk.
- Random Forest has the best precision and recall balance.
- Higher recall can be achieved if low precision is acceptable.
- Model can be served as an aid to human decision.
- Suggest output probabilities rather than predictions.
- Model can be improved with more data and computational resources.