Credit Card Default Risk Analysis

A Case Study of 3 Classification Algorithms

Teresa Nan
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Project mentor: Tommy Blanchard

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

* Image source: Google image

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

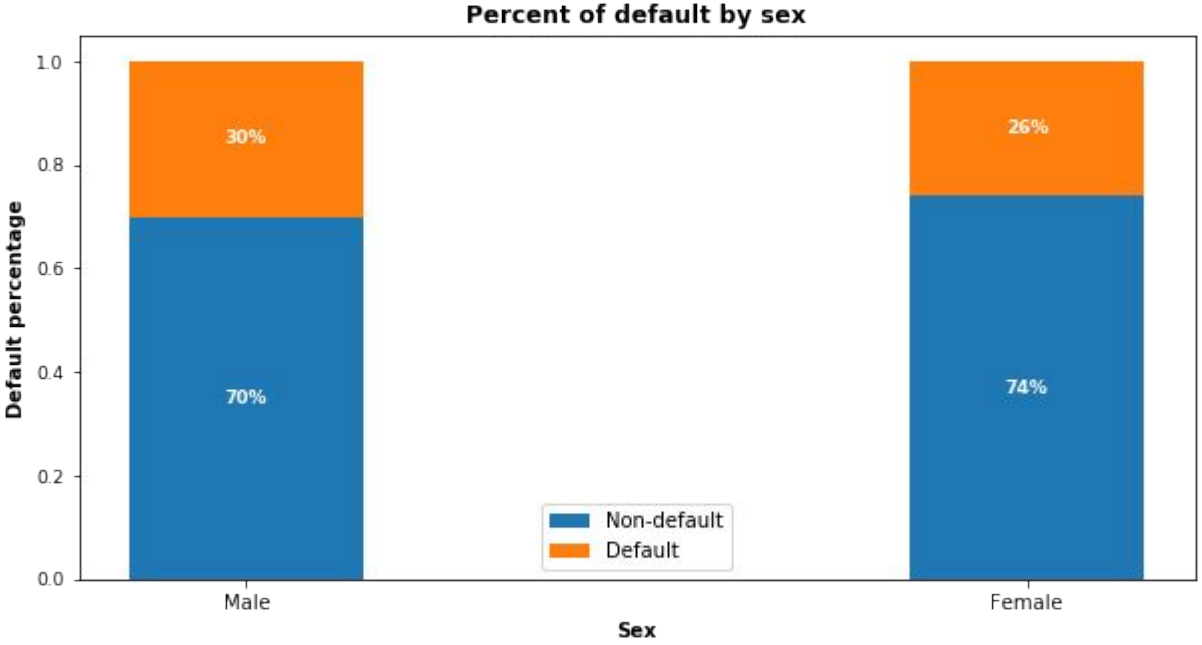
*Lichman, M. (2013). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.

Part 1

Exploratory Data Analysis

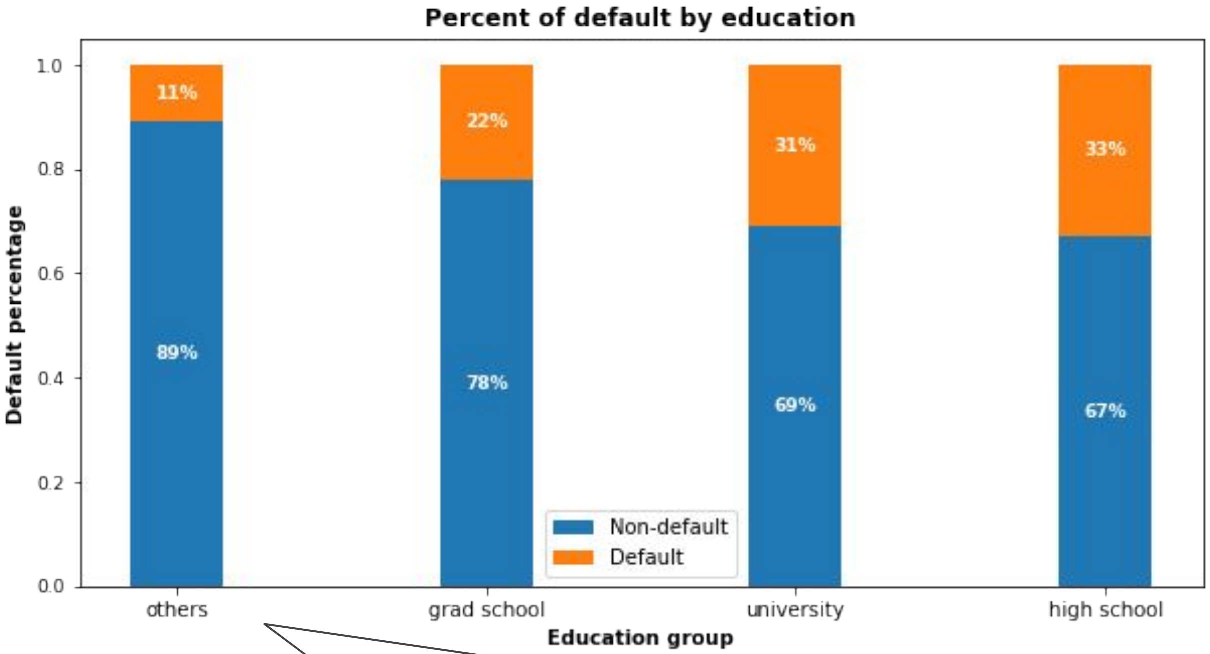
What demographic factors impact payment default risk?

Gender Variable



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

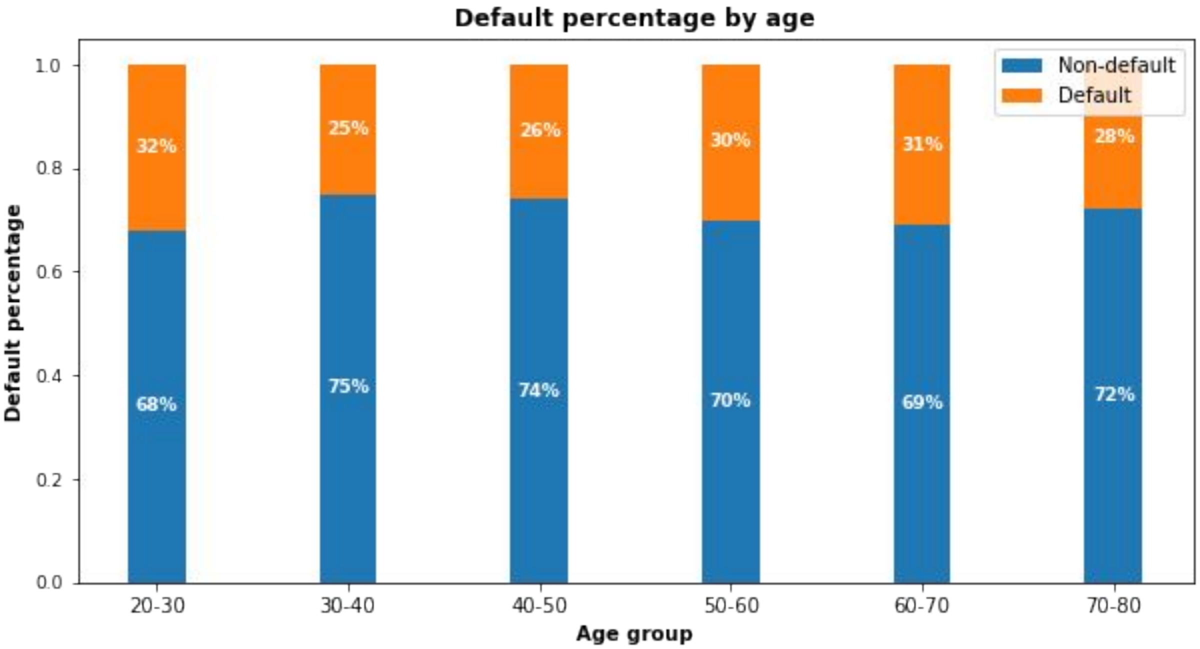
Education Variable



Higher education level, **lower** default risk.

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

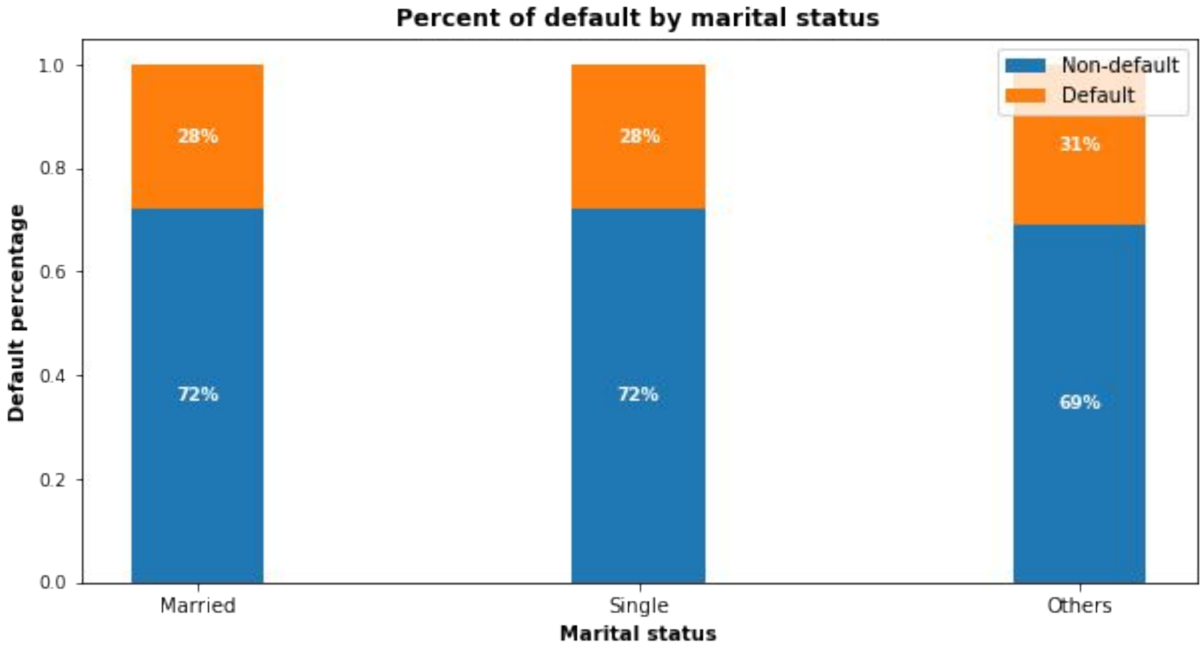
Age Variable



30-50:
Lowest risk

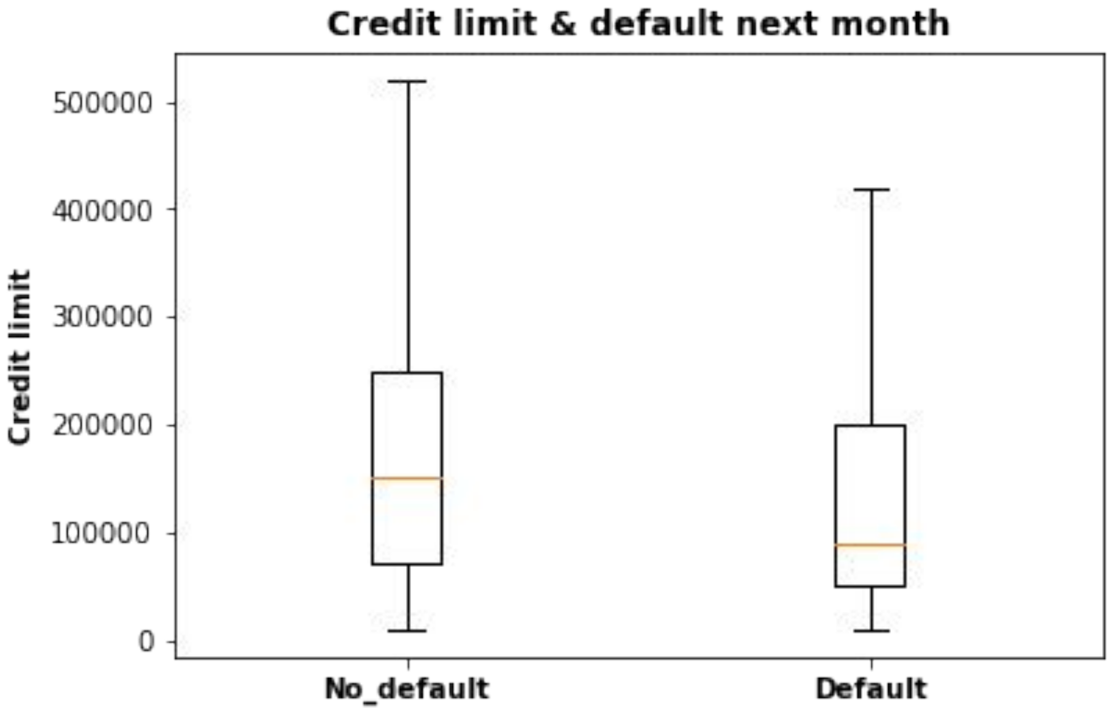
< 30 or >50:
Risk increases

Marital Status Variable



No significant correlations of default risk and marital status

Credit Limit Variable



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?

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

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

Fitting and Tuning

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

Model Evaluation

- 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.

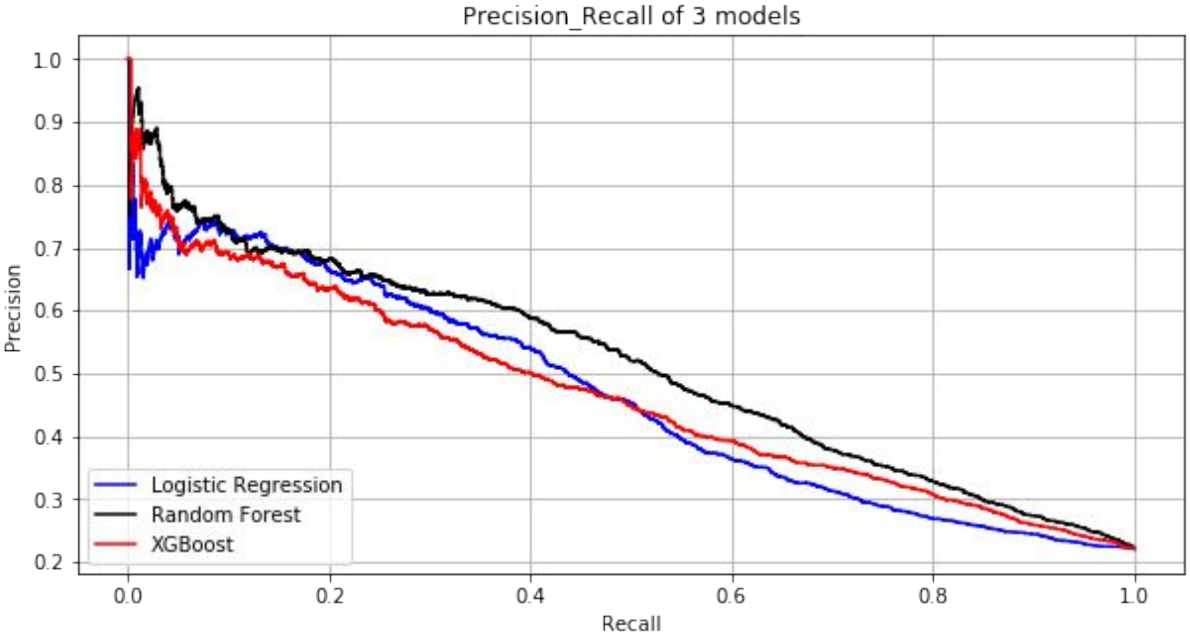
Model Comparisons

- 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	

Model Comparisons

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

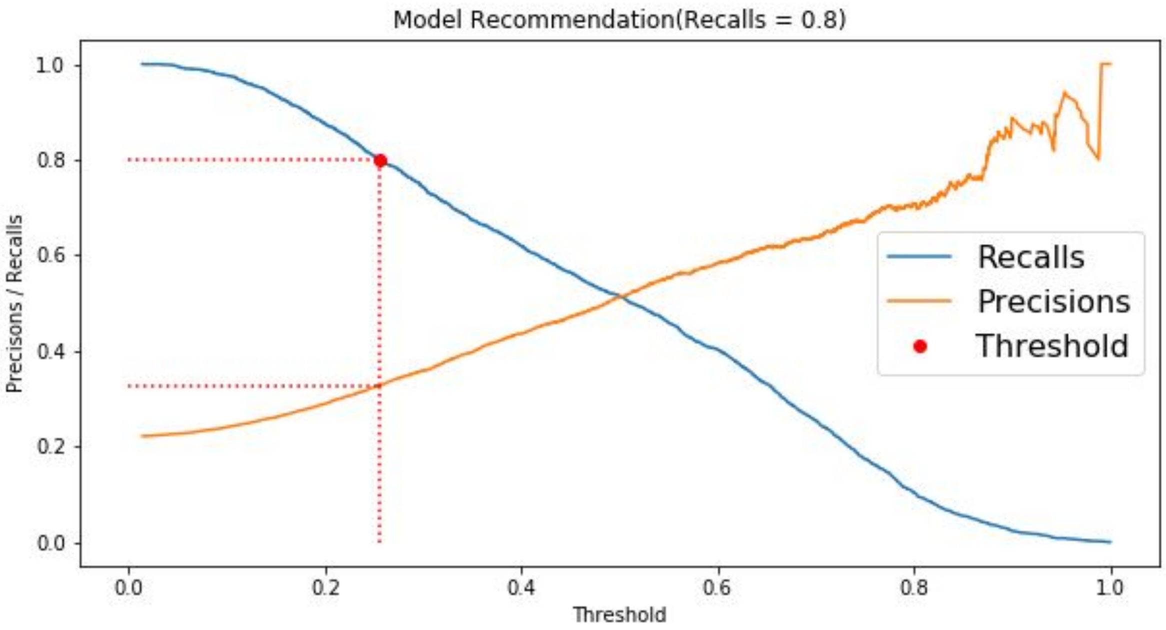


Terminology:

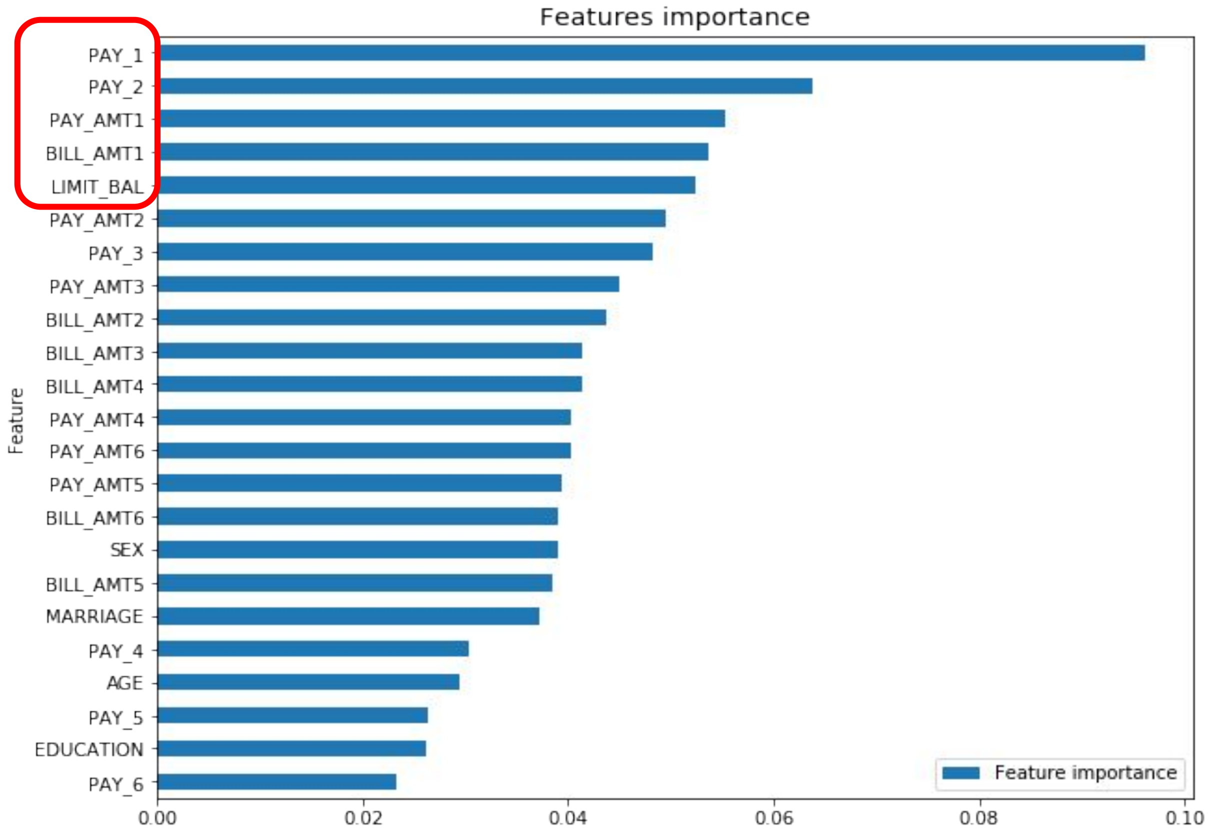
★ Recall: how many 1s are being identified?
★ Precision: Among all the 1s that are flagged, how many are truly 1s?
★ Precision and recall trade-off: high recall will cause low precision

Model Usage - Recommendation

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



Feature Importances



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.

Thank you!

Teresa Nan
Email: fenglin.nan@gmail.com
LinkedIn: https://www.linkedin.com/in/teresa-n-39287042/
Github: https://github.com/teresanan/capstone_project_credit_card_default/tree/master
Project report: https://github.com/teresanan/capstone_project_credit_card_default/blob/master/Final_Report.pdf