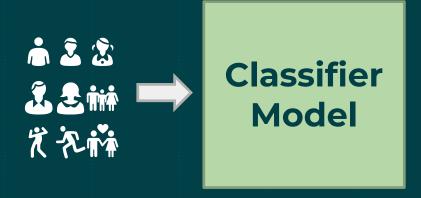




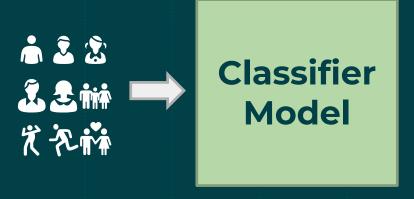
How do we properly assess if someone is going to be a credit risk?

#### **OBJECTIVE**



Credit Card holder data

#### **OBJECTIVE**



Credit Card holder data











#### **OBJECTIVE**





More **consistency** to loaning process





**Telltale signs** of a potential defaulter

# The Data

Dataset information



# 30,000 clients

## 24 variables

- Age
- Gender
- Marriage
- Education

- April to September, 2005
- Bill Statements
- Payment amount
- Repayment status

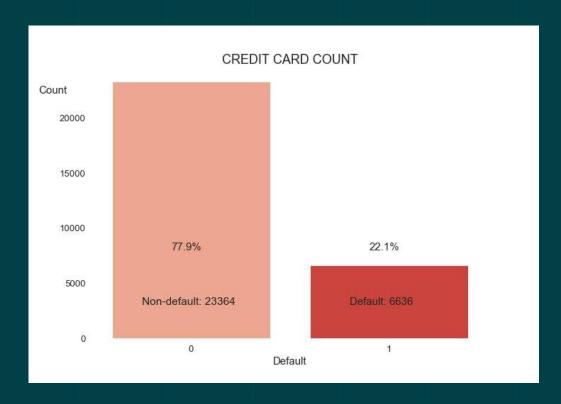


# Data Pre-Processing

Target Skew



#### **TARGET SKEW**

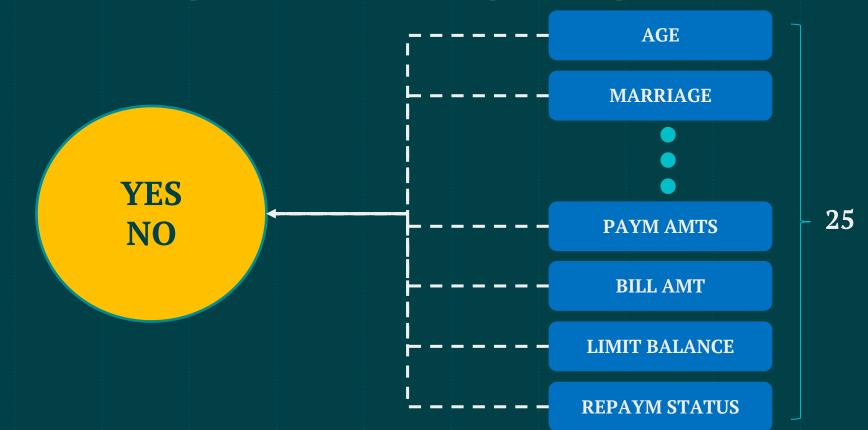


Class imbalance

22% Defaulters

Taken into account

#### DATASET FEATURES



# Methodology<sup>5</sup>

Models Used

F1

Train/Cross-Validation

Results of best model from Train/Cross-Validation

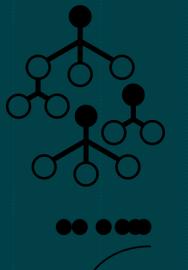
Threshold Tuning

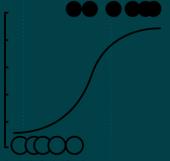
Final Train/Test

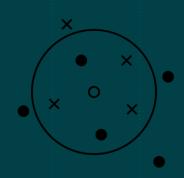


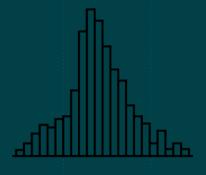
#### **Models Used**

- Gaussian Naïve Bayes
- Logistic Regression
- K-Nearest Neighbors
- Decision Tree
- Random Forest
- Linear SVC









#### **Model Evaluation**

- o F1 Score
- Harmonic mean of *Precison* and *Recall*
- Best value at 1, worst value at 0

```
F1 Score = 

2 x (Precision x Recall)

Precision + Recall
```

#### Recall

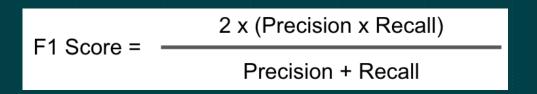
Out of **ALL** the defaulters, how many did the model actually get right?

#### **Precision**

How accurate the model is based on it's own predictions

#### **Model Evaluation**

- o F1 Score
- Harmonic mean of *Precison* and *Recall*
- Best value at 1, worst value at 0



#### Recall

Out of **ALL** the defaulters, how many did the model actually get right?

#### **Precision**

How accurate the model is based on it's own predictions

60% Train Data

20% Holdout Data

20% Validation Data

5-fold Cross-Validation

60% Train 20% Val 20% Test

Vanilla Dataset

Models	Fl
GaussianNB	0.40
Logistic Reg	0.0
K-NN	0.24
Decision Tre	0.39
Random Forest	0.40
Linear SVC	0.01

60% Train

20% Val

Vanilla Dataset

Models	Fl
GaussianNB	0.40
Logistic Reg	0.0
K-NN	0.24
Decision Tre	0.39
Random Forest	0.40
Linear SVC	0.01

60% Train

20% Val

Vanilla Dataset

Models	Fl
GaussianNB	0.40
Logistic Reg	0.0
K-NN	0.24
Decision Tre	0.39
Random Forest	0.40
Linear SVC	0.01

Must improve F1 Score

60% Train

20% Val

Vanilla Dataset

Oversample

Dataset

Undersample

Dataset

**SMOTE** 

Dataset

**Account for Class Imbalance** 

60% Train

20% Val

Un-Scale scaled **Undersample Oversample SMOTE** Vanilla Dataset Dataset Dataset Dataset

#### **Account for Class Imbalance**

60% Train

20% Val

### **Preliminary Results**

Models	FI
GaussianNB	0.40
Logistic Reg	0
K-NN	0.24
Decision Tre	0.39
Random Forest	0.40
Linear SVC	0.01

Vanilla Dataset

60% Train

20% Val

### **Preliminary Results**

Scale

Vanilla Dataset

Models	F1
GaussianNB	0.40
Logistic Reg	0
K-NN	0.24
Decision Tre	0.39
Random Forest	0.40
Linear SVC	0.01



F1 Improved	
0.52	
0.35	
0.42	
0.40	
0.41	
0.27	

60% Train

20% Val

## **Preliminary Results**

Scale

Vanilla Dataset

Models	FI	F1 Improved
GaussianNB	0.40	0.52
Logistic Reg	0	0.35
K-NN	0.24	0.42
Decision Tre	0.39	0.40
Random Forest	0.40	0.41
Linear SVC	0.01	0.27

60% Train

20% Val

#### Further increase F1

Scale

Vanilla Dataset

Models	F1
GaussianNB	0.40
Logistic Reg	0
K-NN	0.24
Decision Tre	0.39
Random Forest	0.40
Linear SVC	0.01



F1 Improved	
0.52	
0.35	
0.42	
0.40	
0.41	
0.27	

#### **Next highest two**

60% Train

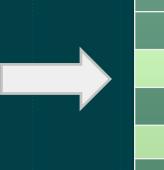
20% Val

#### Further increase F1

Scale

Vanilla Dataset

Models	FI
GaussianNB	0.40
Logistic Reg	0
K-NN	0.24
Decision Tre	0.39
Random Forest	0.40
Linear SVC	0.01



F1 Improved	
0.52	
0.35	
0.42	
0.40	
0.41	
0.27	

#### **Hyper-Parameter Tune**

60% Train

20% Val

#### **Post-Hyper Tuning**

Scale

Models	F1 Improved
GaussianNB	0.52
K-NN	0.42
Random Forest	0.41



Vanilla Dataset

No significant improvement in F1 score

60% Train

20% Val

#### **Post-Hyper Tuning**

Scale

Models	F1 Improved
GaussianNB	0.52
K-NN	0.42
Random Forest	0.4



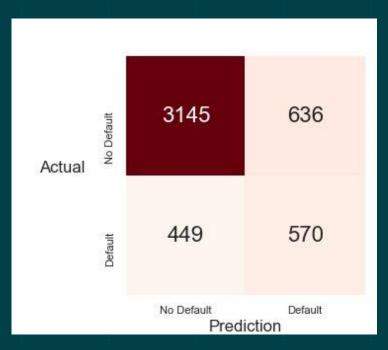
Vanilla Dataset

GaussianNB Chosen F1 = 0.52

60% Train

20% Val

#### GaussianNB Train/CV Results

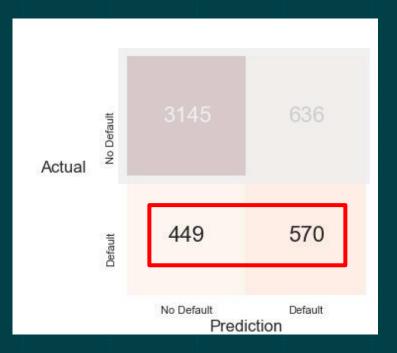


Threshold = 0.5

60% Train

20% Val

#### GaussianNB Train/CV Results



Threshold = 0.5

Test/CV Recall = 0.56

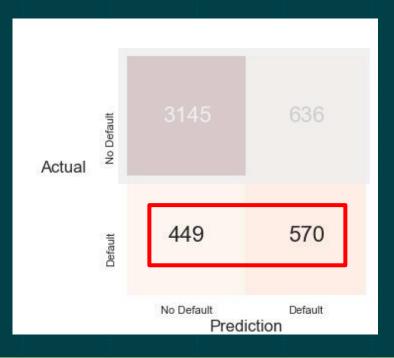
Only captures 56% of all the defaulters

44% not captured

60% Train

20% Val

#### GaussianNB Train/CV Results

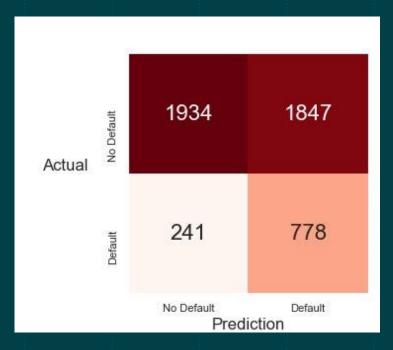


Need for further optimization

60% Train

20% Val

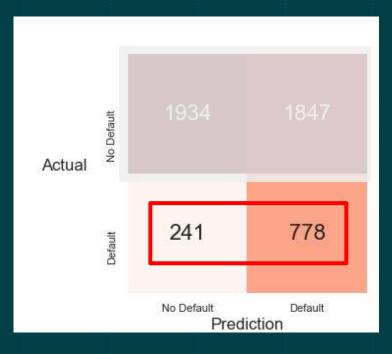
#### **Threshold Optimization**



Threshold = **0.25** 

60% Train 20% Val 20% Test

### Threshold Optimization



Threshold = **0.25** 

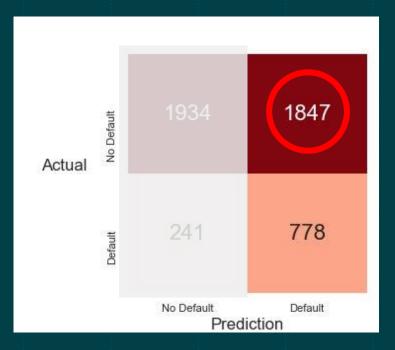
Test/CV Recall = **0.76** 

Improved to 76%

60% Train

20% Val

#### Threshold Optimization

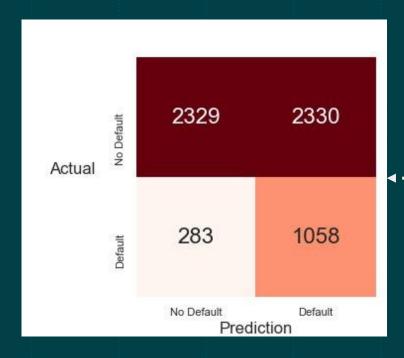


Trade-off: More False Positive Predictions

Higher recall outweighs cost of inconveniencing more people

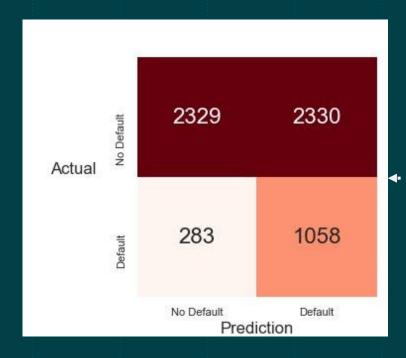
60% Train 20% Val 20% Test





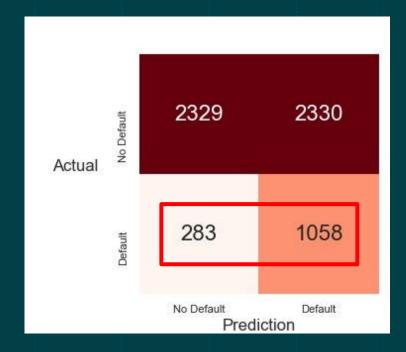
Train on 80% data

80% Train

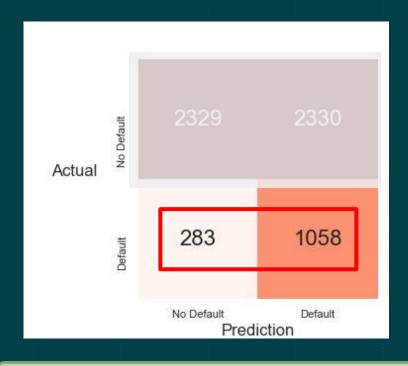


Test on 20% unseen data

80% Train 20% Test



80% Train



79%

80% Train

# Future Work







FEATURE ENGINEER



FEATURE SELECTION





HYPERPARAMETER TUNING



OTHER MODELS

# Questions?





www.linkedin.com/in/seow-xian-jin



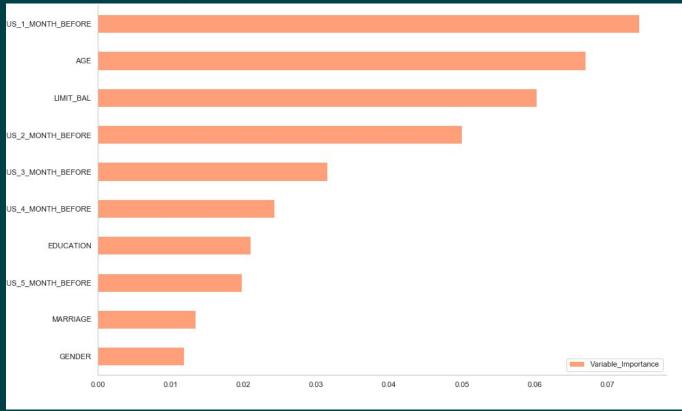
github.com/xianjinseow92/projects



xianjinseow92@gmail.com

# APPENDIX

#### Feature Importance



#### **Model Evaluation**

- o F1 Score
- Harmonic mean of Precison and Recall
- Considers both to compute score
- Best value at 1, worst value at 0

#### **Precision**

How accurate the model is from all it's own predictions

#### Recall

Out of all the defaulters, how many did the model actually get right?