# Risky Loaners Model

## Introduction

## **Loan Application Procedure**

How to identify potential bad loaners, whom having high loan risk from the loan application, before the loan is being approved and the loan is funded to the borrowers?



## **Define Prediction Target: Good and Bad Loan Grouping**

The distribution of Good Loan vs Bad Loan are 41% (12,135) vs 59% (17,383).

#### **Good Loan**

Loans that are paid according to the agreed term and predefined schedule as set by the lender.

#### **Loan Status:**

Paid Off Loan Settlement Paid Off

#### **Bad Loan**

Loans that carry a risk of default or are unlikely to be repaid according to the agreed term and predefined schedule. This leads to the possibility of cost incurred on third parties (i.e., Administrator, Legal fees) for late payments.

#### **Loan Status:**

Charged Off Paid Off Charged Off Internal Collection External Collection Settled Bankruptcy

## Analytics Model Methodology

### **Solution Overview**



## **Engineered Features**

**11** additional features are created to enrich data input and **7** categorical features are encoded.

	Payment	Loan	Clarity Writing	Recommended
		-State*		-Income -Employment Status
5		-Lead Type* -Pay Frequency*		
Score			-Inquiry on file current address conflict** -More than 3 inquires in the last 30 days** -Overall Match Result** -Name Address Match**	
5000	-Difference between Paid Off Amount and Original -# Previous Loan Scheduled Payment Amount -# Previous Bad Loan -# Previous is Collection -Existing Debt Amount (RM) -# Payment Count -Median of Success Payment -# of Success Payment -# of Failed Payment			-Debt to Income Ratio -Credit Card Payment History
	-Median of Failed Payment -Ratio of Failed over (RM) Success Payment			These features are not included as they are not available

<sup>\*</sup> One hot encoding is performed and Chi-Square Test is used to further select features that has relationship with the target

<sup>\*\*</sup> Label encoding is performed

Clarity Writing

consumer seen by Clarity (5,034)

-# of unique inquires for the

-# fraud indicators (5,049) -Max # of unique SSNs with any

-Clear Fraud Score (5.116)

-Inquiry/on-file current address

-Name Address Match (5,058)

bank account (5.049)

conflict, T/F (5,066)

(RM)

## **Strategies to Handle Missing Values**

A total **5,118** missing records were dropped with **24,400** records remained.

#### **Data Collected**

#### Payment Loan -# of Paid Off Loan (21) -Minutes from application to originated -Difference between Paid Off -# of Paid Off Loan **Amount and Original** -# Previous Loan Scheduled Payment Amount -Annual Percentage Rate -# Previous Bad Loan -Loan Amount -# Previous is Collection -Existing Debt Amount (RM) -Original Scheduled Paument Amount -# Payment Count -Median of Success Payment -# of Success Paument -Lead Cost -# of Failed Payment -Pay Frequency -Median of Failed Payment -State -Lead Tupe

### **Imputation Method**

#### Current

Records with missing values are dropped.

#### Recommended

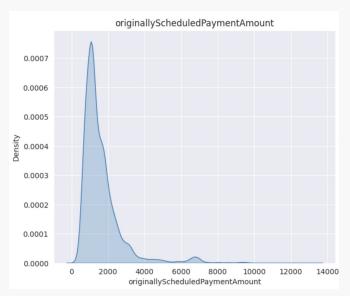
K-means missing values imputation methodology, provided with the following information:

- -More business context how Clarity Writing features (E.g. Clear Fraud Score) are calculated
- -Collect other dataset, such as transaction information, credit card payment historical records, if available

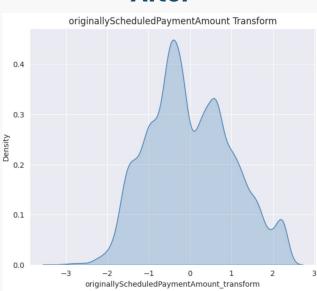
## **Data Transformation for Model Building Experiment**

15 statistically non-normal features are transformed to a more normally distributed features.

#### **Before**



#### After



#### **Explanation:**

- Perform Normality Test on Numerical Features
- For non-Normal features, perform following data transformation using following steps
  - a. Standard scaling the feature to have mean of 0 and standard deviation of 1
  - b. Min max scaling the feature to have a min of 0 and max of 1
  - c. Perform Yeo-Johnson transformation on the feature

## **Preliminary Data Exploration**

6 pairs of highly correlated features are identified from Correlation Analysis.

#### **Non-normal Dataset**

	level_0	level_1	correlation (	(Original)
34	thirtydaysago	ninetydaysago		0.802316
37	thirtydaysago	fifteendaysago		0.869999
167	sevendaysago	fifteendaysago		0.885578
346	loanAmount	originallyScheduledPaymentAmount		0.932922
446	prevLoan_cnt	prevPaidOff_cnt		0.992360

	level_0	level_1	correlation	(Original,	removed	derived	features
26	thirtydaysago	fifteendaysago					0.866266
101	sevendaysago	fifteendaysago					0.870926
181	loanAmount	$originally {\bf Scheduled Payment Amount}$					0.948468

#### **Transformed Dataset**

		<u> </u>	
	level_0	level_1	correlation (Transformed)
34	thirtydaysago	ninetydaysago	0.802316
37	thirtydaysago	fifteendaysago	0.869999
162	sevendaysago	fifteendaysago	0.885578
333	loanAmount_transform	$originally Scheduled Payment Amount\_transform$	0.910899
382	existDebt_amt_transform	prevPaidOff_cnt_transform	-0.875509
406	medFailed_paymentAmt_transform	numFailed_payment_transform	0.999999

	level_0	level_1	correlation	(Transformed,	removed deri	ved features	E
26	thirtydaysago	fifteendaysago				0.866266	0
101	sevendaysago	fifteendaysago				0.870926	
181	loanAmount_transform	$originally {\tt ScheduledPaymentAmount\_transform}$				0.915783	

#### **Explanation:**

oan

- 1. Number of unique inquiries for the consumer seen by clarity in the last 30 days is positively correlated to 90 days and 15 days
- 2. Number of unique inquiries for the consumer seen by clarity in the last 15 days is positively correlated to 30 days and 7 days
- 3. Loan Amount is positively correlated to originally Scheduled Payment Amount, apply to before transformed and after transformed

#### **Before Transform:**

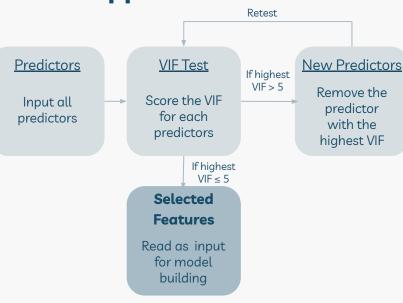
1. Previous loan count is positively correlated to Previous paid off loan count

#### **After Transform:**

- 1. Existing loan debt amount (RM) is negatively correlated to Previous paid off loan count
- 2. Median of Failed Payment Amount (RM) is positively correlated to Number of Failed payment

## Highly correlated Predictors are removed to prevent multicollinearity for model building

### **Approach A: VIF**



### **Approach B: Performance Metrics**

### <u>Predictors</u> <u>Random</u>

Input all lowly correlated predictors

#### **Predictors**

Input 1
highly
correlated
predictor

#### Random Forest Model

Model: Default Parameter

Build: Train dataset

Score: Test dataset

Replace the highly correlated predictor with another highly correlated predictor

#### Selected Features

Select the feature with highest model performance metrics in test data in each highly correlated pairs of predictors

Feature

Non-normal

**Transformed** 

#### Random Forest model has been selected as Final Model

Recall metric increased by 2.4% in in-time test and 1.8% in out-time validation upon Model Optimization.

Baseline Model Selection

Comparing Model Performance across 5 different default models

Recall AUC Logistic Regression 78.0% 63.0% SVM 74.9% 61.0% Random Forest 74.6% 63.2% **Gradient Boostina** 78.0% 63.6% 75.5% 63.1% **XGBoost** 

Logistic Regression 77.7% 63.1% SVM 76.0% 61.4% Random Forest 75.5% 63.4% Gradient Boostina 79.1% 64.2% i 74.5% 62.2% XGBoost

RF has the highest AUC in out-time validation dataset in both experiments.

Default RF Model

Comparing Model Performance after using feature elimination Approach (B) from step 1.

Recall AUC

**Random Forest** 

In-time test: 74.8% 63.4% Out-time validation: 88.1% 61.0%

**Random Forest** 

In-time test: 75.8% 63.3% Out-time validation: 87.2% 60.4% Final Model

Model Optimization

Huperparameter Tuning based on Grid search/Random Search CV for selected models from step 2.

Recall AUC

Random Forest

77.1% 63.4% In-time test: 89.2% 60.5% Out-time validation:

**Gradient Boostina** 

In-time test: 77.7% 63.8% Out-time validation: 88.6% 58.7% Remove Redundant Features and Retrain

Remove features with permutation importances ≤ 0 and retrain with the best model from step 3.



Final **Features** 

**Random Forest** 

Recall AUC

In-time test: 78.2% 62.9% Out-time validation: 89.0% 60.3%

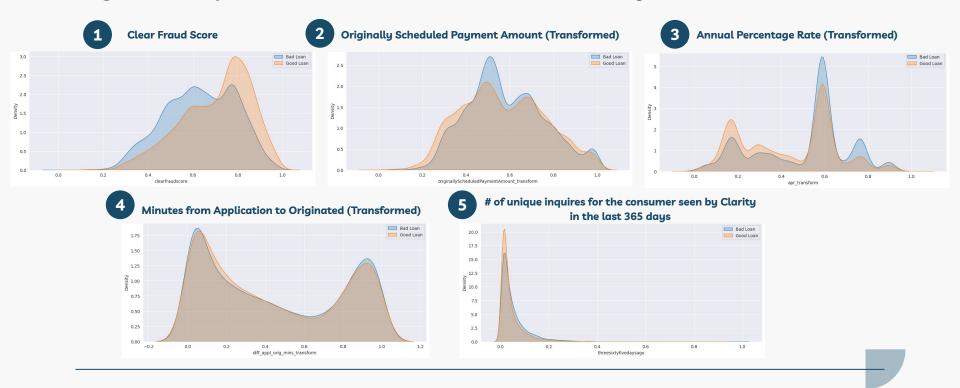
Feature

Engineering

Data

Insights

High feature importance has more distinctive distribution between good and bad loans.

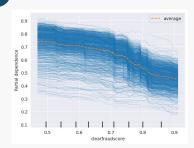


Feature

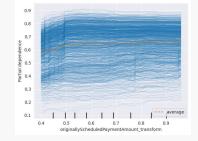
Engineering

## Top 5 Features Partial Dependence Plot based on Importances

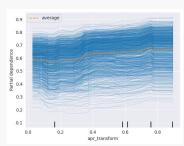
**Clear Fraud Score** 



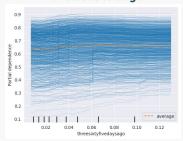
**Originally Scheduled Payment Amount (Transformed)** 



Annual Percentage Rate (Transformed)



# of unique inquires for the consumer seen by Clarity in the last 365 days



#### Explanation:

From the below Partial Dependence Plot, it is observed that

Feature

Selection

- The **higher** the Clear Fraud Score, the **lower** the loan risk
- The **higher** the Originally Scheduled Payment Amount Transform, the **higher** the loan risk
- The **higher** the Annual Percentage Rate (%), the **higher** the loan risk
- The **higher** the Number of unique inquiries for the consumer seen by Clarity in the last 365 days, the **higher** the loan risk

## **Business Impact**

## **\$246k** of Net Profit is Generated with Risky Loaners Model in 2017 Q1

Actual	Predicted	Loan Status	Loan Count	Loan Amount (USD)	Amount Collected as Scheduled Originally (USD)	Recovery Rate	Costs Rate	Revenue (USD)	Cost (USD)	Total (USD)
Good Loan	Good Loan	Paid Off Loan	326	\$281,007	\$739,503	100%	0%	\$458,496		\$458,496
Good Loan	Good Loan	Settlement Paid Off	1	\$400	\$1,336	100%	0%	\$936		\$936
Good Loan	<b>Bad Loan</b>	Paid Off Loan	693	\$487,503	\$1,480,469	100%	0%	\$992,966		\$992,966
Good Loan	<b>Bad Loan</b>	Settlement Paid Off	13	\$9,600	\$29,860	100%	0%	\$20,260		\$20,260
Bad Loan	Good Loan	Charged Off Paid Off	6	\$10,350	\$24,205	100%	20%		\$2,070	-\$2,070
Bad Loan	Good Loan	External Collection	8	\$5,075	\$13,244	60%	30%		\$3,553	-\$3,553
Bad Loan	Good Loan	Internal Collection	340	\$370,501	\$853,812	60%	15%		\$203,776	-\$203,776
Bad Loan	Good Loan	Settled Bankruptcy	8	\$7,500	\$15,954	60%	20%		\$4,500	-\$4,500
Bad Loan	Bad Loan	Charged Off	1	\$1,800	\$5,138	0%	20%		\$2,160	-\$2,160
Bad Loan	Bad Loan	Charged Off Paid Off	4	\$5,800	\$18,078	100%	20%		\$1,160	-\$1,160
Bad Loan	<b>Bad Loan</b>	External Collection	225	\$121,450	\$383,334	60%	30%		\$85,015	-\$85,015
Bad Loan	Bad Loan	Internal Collection	2678	\$1,793,106	\$5,241,509	60%	15%		\$986,208	-\$986,208
Bad Loan	Bad Loan	Settled Bankruptcy	22	\$13,000	\$34,647	60%	20%		\$7,800	-\$7,800

et Profit	\$176,417

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Bad Loan	Bad Loan	Settled Bankruptcy	22	\$13,000	\$34,647	60%	20%		\$0	\$0

#### Net Profit \$245.534

#### Assumptions:

Given that Recovery Rate for bad loans are set as 60%.

Costs for bad loans includes legal fees, external agency costs, administrative costs, write-offs and provisions, as well as unrecovered loan amounts.

Charged Off Paid Off are assumed to be 100% recovered, with no additional revenue generated.

## **Next Step**

## **Implementation Plan**

Model Deployment



Final Model Registry



CI/CD Pipeline



Code Repository

Operationalizing Predictive Model





Prediction Schedule



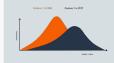


Prediction Result

Production Model Monitoring



Model Performance Metrics



Features Drift

## **Thank You**