

# HOME CREDIT

*Kamu Bisa!*

## VIRTUAL INTERNSHIP EXPERIENCE (VIX)

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# PROBLEM RESEARCH

- Problem : How do you help the assessment team examine customer loans?
- Goal : Increase the speed of filing inspection without increasing costs
- Objective : Create a system to help loan assessments automatically
- Business Metrics : daily resolved applications & average resolved time



# DATA PREPROCESSING

## Data Cleaning

Check Data Duplicate  
Check Missing Data

## Feature Selection

Split Data Train (80:20)  
Categorical (Chi Square)  
Numerical (ANOVA)

## Feature Engineering

Simple Imputer  
OHE with dummy  
creation

## Feature Engineering

WoE Binning  
Information Value (IV)

<https://towardsdatascience.com/feature-selection-and-eda-in-python-c6c4eb1058a3>

<https://towardsdatascience.com/how-to-develop-a-credit-risk-model-and-scorecard-91335fc01f03>

<https://medium.com/@finntanweelip/feature-selection-in-credit-scoring-b0eee604cd51>

# DATASET

01

application\_train has 307511 rows and 122 columns

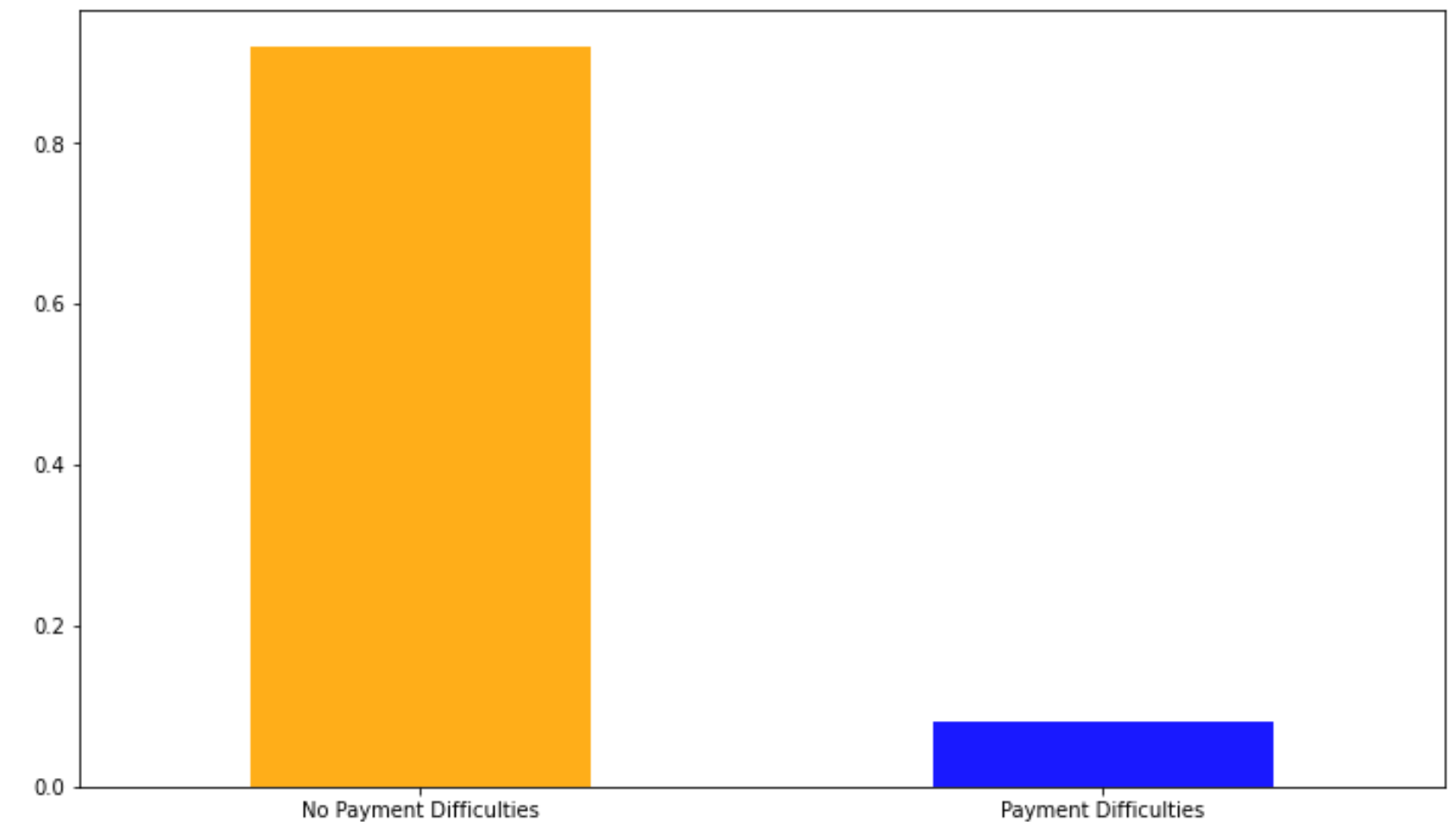
- Float64 : 65
- Int64 : 41
- Object : 16

02

application\_test has 48744 rows and 121 columns

- Float64 : 65
- Int64 : 40
- Object : 16

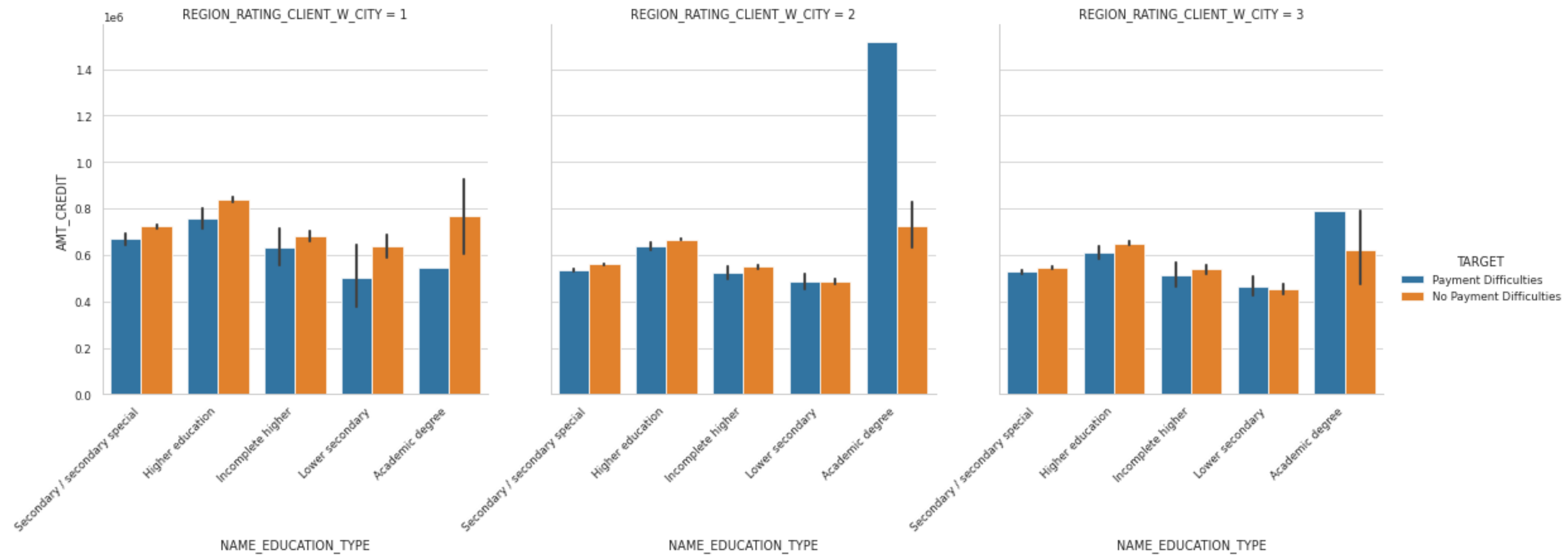
The Distribution of Clients Repayment Abilities



Column Target from application\_train

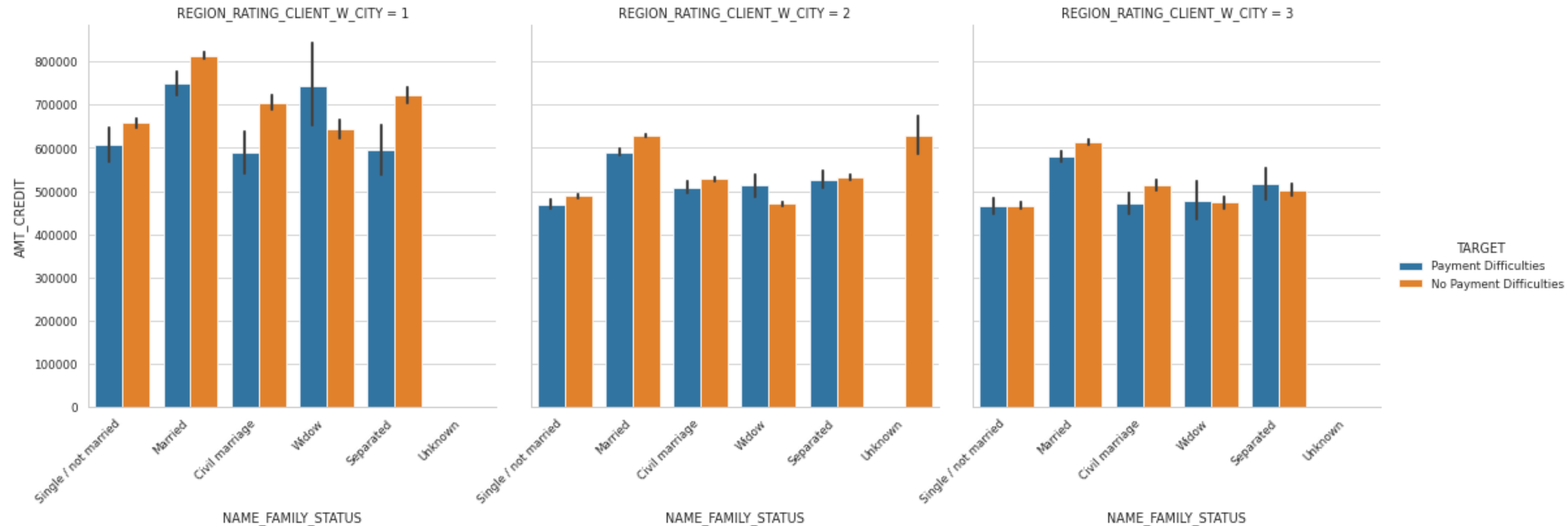
- No Payment Difficulties : 92%
- Payment Difficulties : 8%

# DATA VIZ AND BUSINESS INSIGHT



For clients who have an **academic degree** and live in **an area with a rating of 2**, have **problems repaying loans** for **higher credit amounts**. And, clients with the **same degree** but **living in a region with a rating of 3** have **problems repaying loans** for moderate amounts of loan credit.

# DATA VIZ AND BUSINESS INSIGHT



- Clients who are **widowed, whether domiciled** in areas with a rating of 1, 2, or 3, have **difficulty paying off loans** for **moderate to high loan amounts**.
- Clients who have **separate family status**, and live in **areas rated 3**, have **problems repaying loans** for a **moderate amount of loan credit** compared to clients who live in areas rated 1 or 2.



# MACHINE LEARNING & EVALUATION

## Modelling

Class\_Weight = Balance  
Woe\_transform

## Pipeline

```
Pipeline(steps=[('woe', woe_transform), ('model', dt)])
```

## Cross Validation

```
RepeatedStratifiedKfold  
N_split = 5  
N_repeats = 3  
Random_state = 42
```

## Evaluation

Models	MEAN AUROC	GINI
Decision Tree	0.54	0.07
Logistic Regression	0.73	0.46

I think the **feature we selected** isn't the best feature to model a credit scorecard. But, **0.73 is acceptable for the baseline**. (Hosmer & Lemeshow (2013). Applied logistic regression. p.177)

# SCORECARD



## General

BASE(intercept) = 569

Min score = 300

Max score = 850

REGION_POPULATION_RELATIVE	SCORE
<0.0147	2
0.0147-0.0292	1
0.0292-0.0436	-2
0.0436-0.0581	1
>0.0581	-1

AMT_CREDIT	SCORE
<846000	-3
846000-1647000	1
1647000-2448000	10
2448000-3249000	3
>3249000	-11

YEAR_LAST_PHONE_CHANGE	SCORE
<2	-7
2-4	-3
4-6	1
6-8	4
8-10	5
>10	0

NAME_EDUCATION_TYPE	SCORE
Academic degree	53
Higher education	4
Incomplete higher	-8
Lower secondary	-30
Secondary / secondary special	-19

NAME_FAMILY_STATUS	SCORE
Single or Unknown	-2
Civil marriage	-4
Married	6
Separated	-3
Widow	3

YEAR_ID_PUBLISH	SCORE
<4	-11
4-8	-7
8-12	-4
12-16	4
>16	18

NAME_INCOME_TYPE	SCORE
Businessman or Commercial Associate	10
Pensioner or maternity leave	9
Student or unemployed	-48
State servant	24
Working	5

FLAG_DOCUMENT_3	SCORE
0	8
1	-8

REG_CITY_NOT_LIVE_CITY	SCORE
0	6
1	-6

CODE_GENDER	SCORE
M	-10
F or XNA	10

REGION_RATING_CLIENT_W_CITY	SCORE
0	0
1	18
2	9

EXT_SOURCE_2	SCORE
<0.0855	-52
0.0855-0.171	-34
0.171-0.256	-24
0.256-0.342	-13
0.342-0.427	-5
0.427-0.513	3
0.513-0.598	10
0.598-0.684	20
0.684-0.769	37
>0.769	56

YEAR_REGISTRATION	SCORE
<17	-4
17-34	-1
34-51	-4
>51	8

YEAR_BIRTH (AGE)	SCORE
<30	-2
30-40	-10
40-50	-2
50-60	6
>60	8

EXT_SOURCE_3	SCORE
<0.0901	-65
0.0901-0.18	-48
0.18-0.269	-32
0.269-0.359	-14
0.359-0.448	-1
0.448-0.538	5
0.538-0.627	25
0.627-0.717	35
0.717-0.806	46
>0.806	50





# PREDICTION



## General

BASE(intercept) = 569

Min score = 300

Max score = 850

## Application\_test

48744 applicants

## Model

Logistic Regression

AUC 0.73

Recall 0.96

## Threshold

0.5

## Best Threshold

0.29957

### Threshold = 0.5

Accept Score	N Approved	N Rejected	Approval Rate	Rejection Rate
569.0	40097	21406	0.651952	0.348048

### Best Threshold

Accept Score	N Approved	N Rejected	Approval Rate	Rejection Rate
524.0	55529	5974	0.902867	0.097133

Threshold 0.5 would result in a **very high rejection rate** with a corresponding **loss of business**.

Accordingly, we will stick with **our ideal threshold** and the corresponding **Credit Score of 524**



# BUSINESS RECOMMENDATION

## Possible Scenarios:

- Full automation  
Submissions are instantly accepted/rejected based on the output of the model
- Auto-reject  
Submissions that may be bad immediately rejected.  
If not, it needs to be checked manually first by the assessment team
- Partial Auto-reject & Auto-approve  
Submissions that may be bad immediately rejected.  
Submissions that are highly likely to be good are immediately accepted.  
If it's still 'gray', just checked manually by the assessment team

## Metrics Impact

Business Metrics	Before	After
Daily resolved applications	10.000	50.000
Average resolved time	50 hours	1 hour