NYU

Loan Portfolio Prediction

Final Presentation

5/13/2024

Team Introduction

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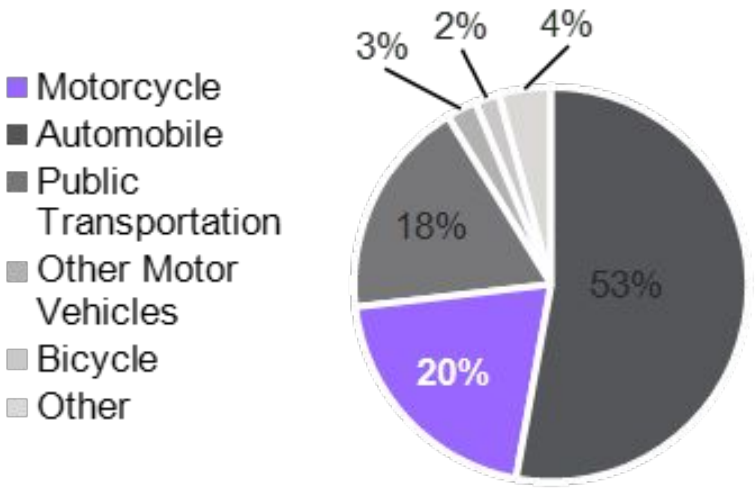
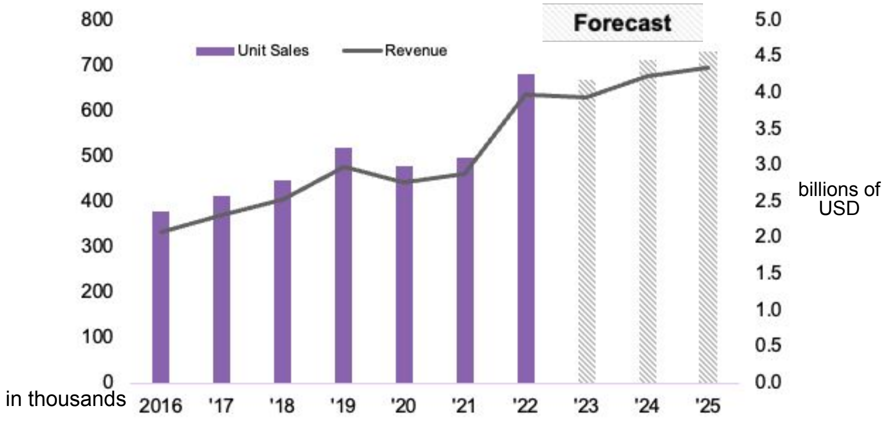
Market Overview

Transportation Breakdown in Malaysia



Source: Statista Market Insights

Motorcycle Market Trend in Malaysia



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Business Overview

Company Overview

- **Our capstone team is focused on a loan portfolio prediction project with a finance company in Malaysia who specializes in motorcycle loans**
- **The company's value proposition lies in providing:**
  - Accessible financial solutions
  - Facilitating mobility
  - Enhancing lifestyle choices for customers
- **By offering financing solutions, the company plays a pivotal role in helping customers to purchase motorcycles**

Loan Comparison

Auto Loan and Motorcycle Loan Comparison		
	Auto Loan	Motorcycle Loan
Target Customer	Individuals looking to purchase a car	Individuals looking to purchase a motorcycle
Loan Amount	High (Average USD $10,000)	Low (Average USD $2,500)
Term	12 ~ 108 months (Average 90 months)	12 ~ 60 months (Average 48 months)
Customer Credit	Generally stable	Generally lower
Interest Rate	Average 8%	Average 10%

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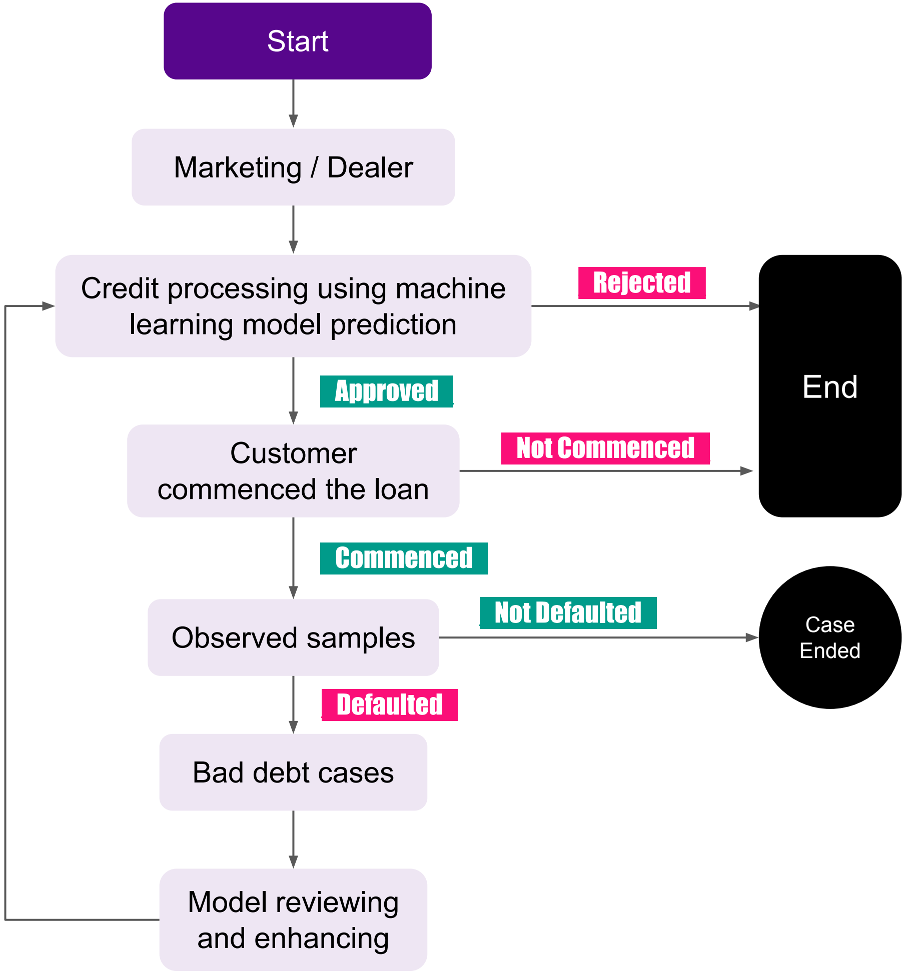
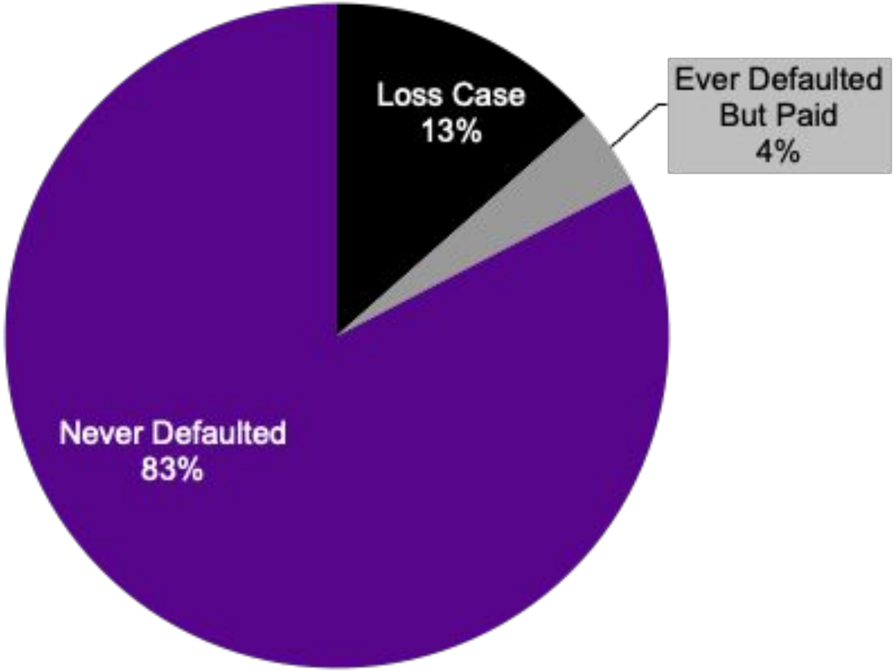
Customer Journey Flowchart



Loss Caused by Lost Cases



Number of lost cases : 7460

Average loss per lost case : USD 1971

Total amount lent to lost cases : Million USD 14.7

Defaulter - Lost case

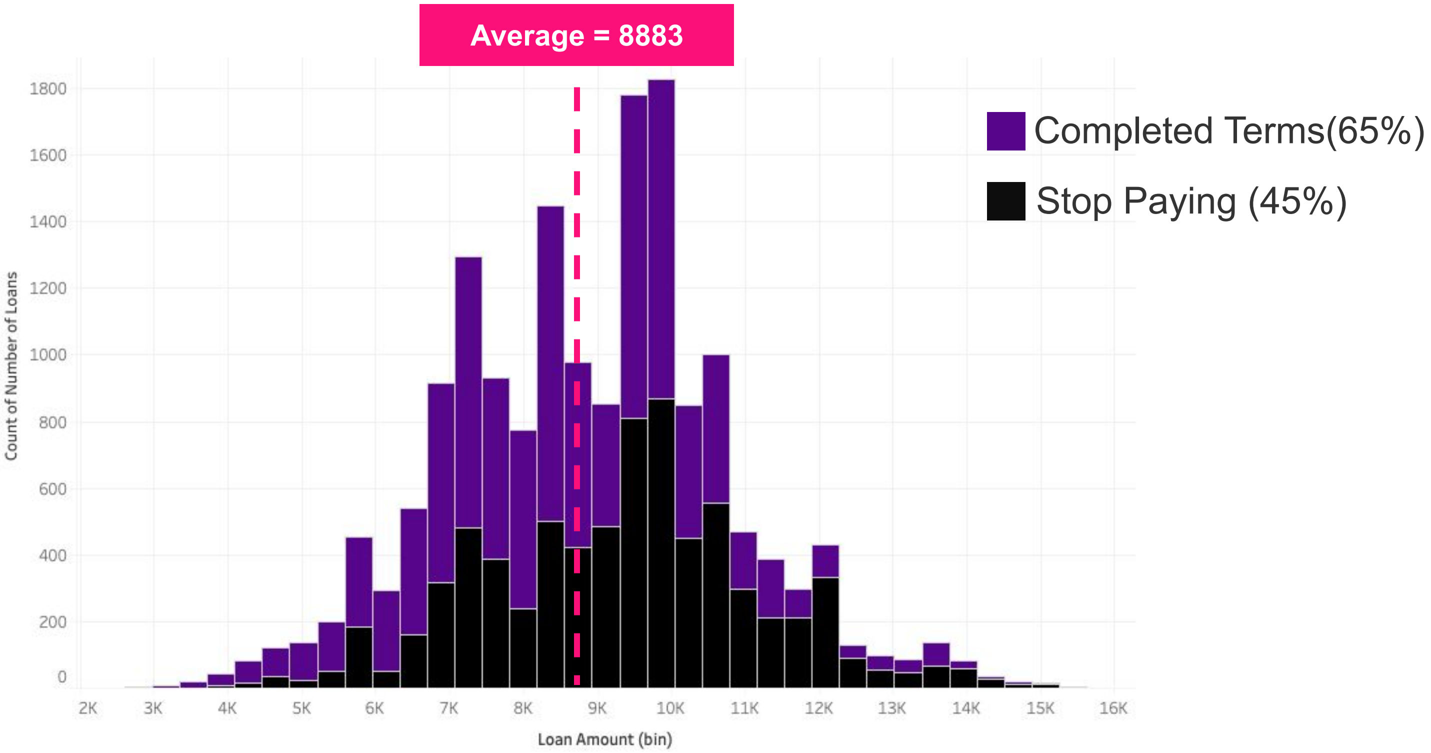
Defaulter : Customer missed paying 3 consecutive installments

Lost case : Customer completely stopped paying back

Models Built

	Default	Lost
Yes / no	Default or not	Lost case or not
When?	Default when?	Lost when?

Key Finding 1 : Loan Amount Distribution



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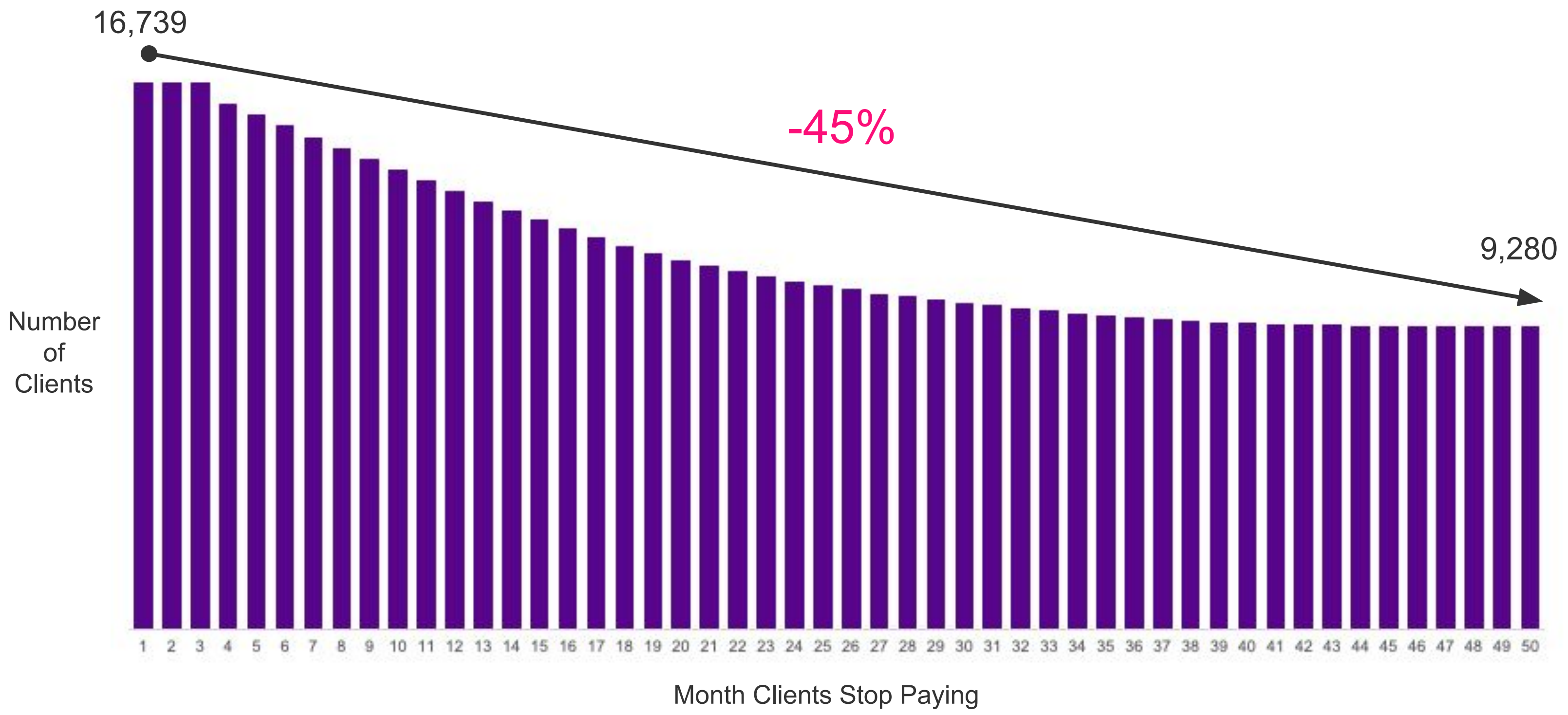
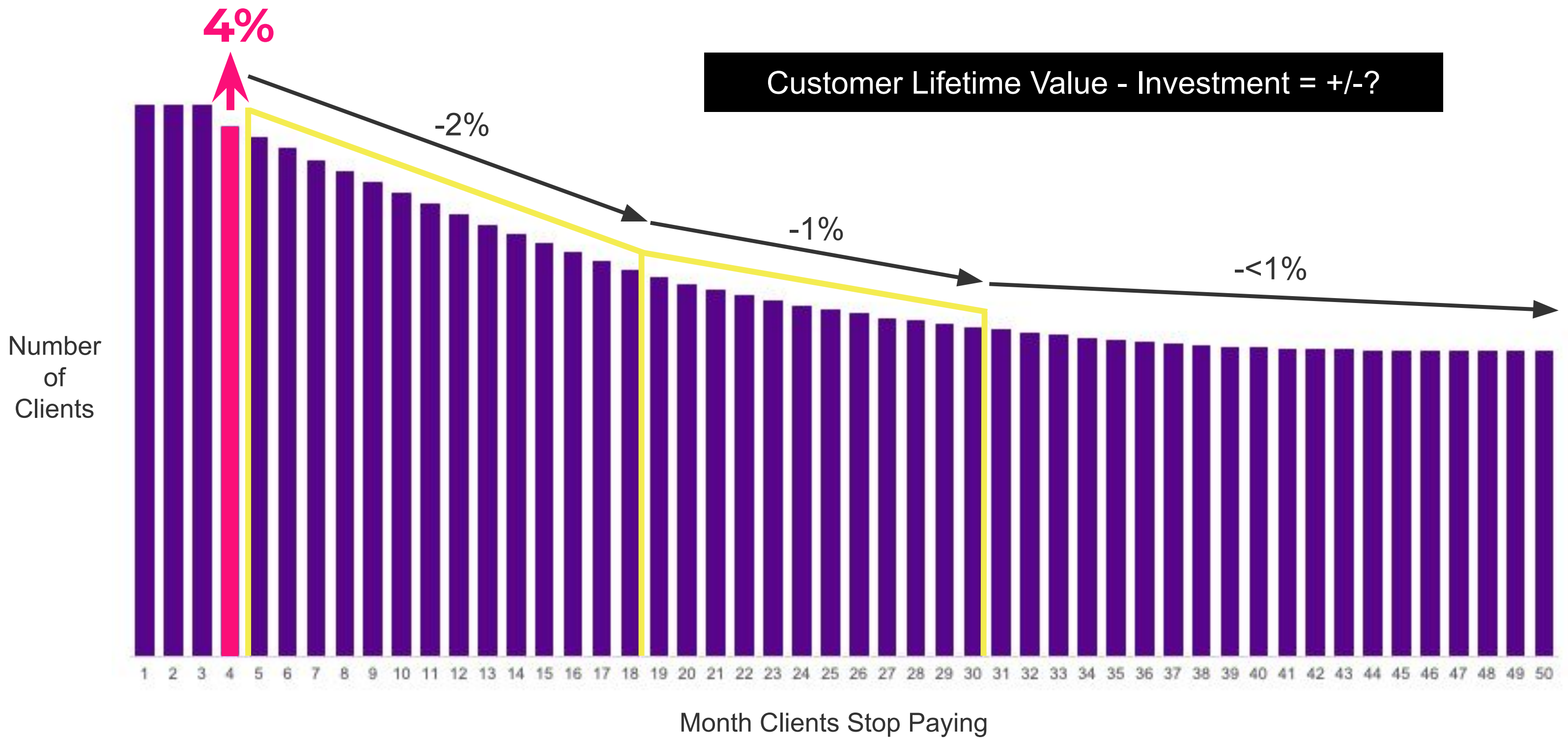
Key Finding 2 : High Churn Rate



Key Finding 2 : Client Attrition Speed



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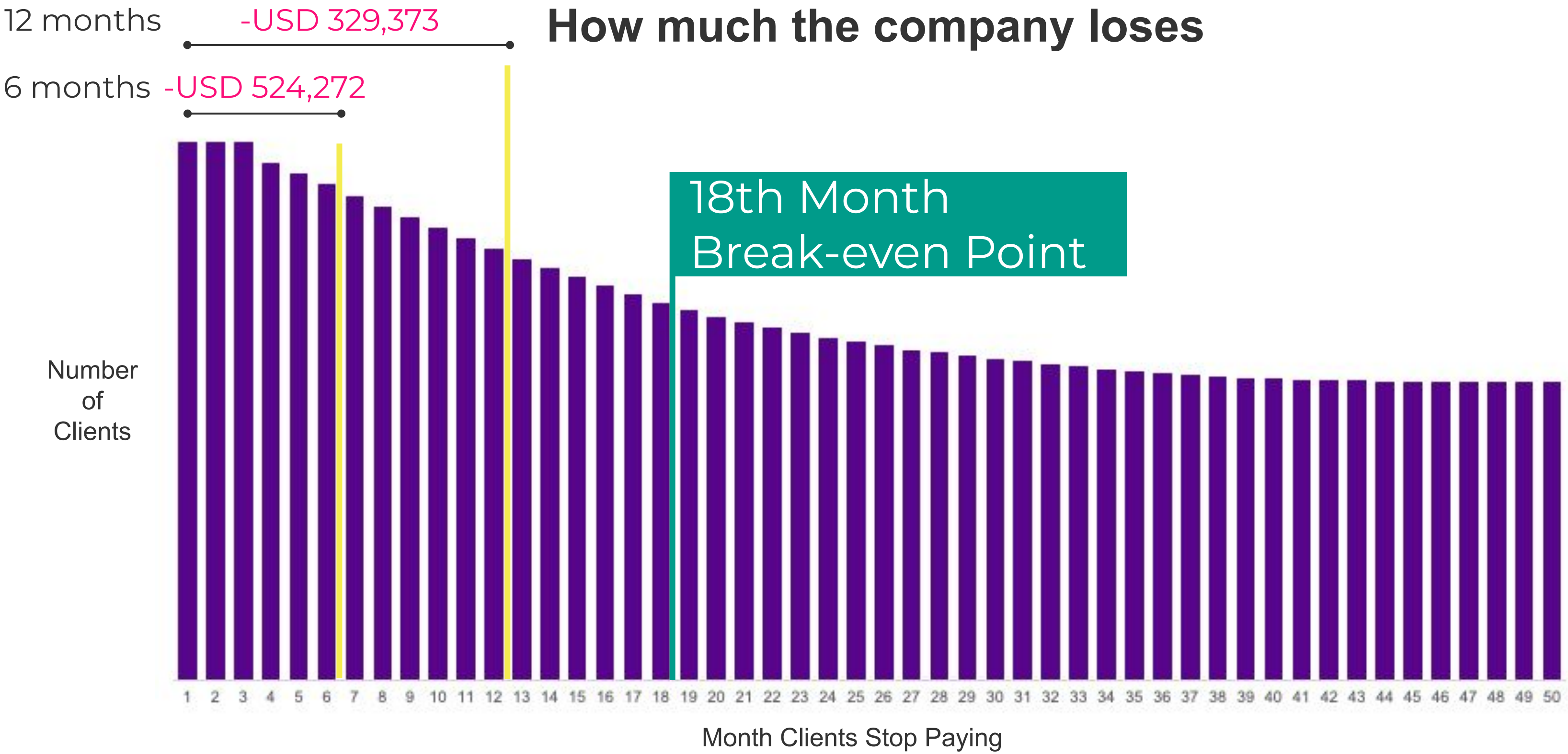
Key Finding 2 :How much loses are

How much the company loses



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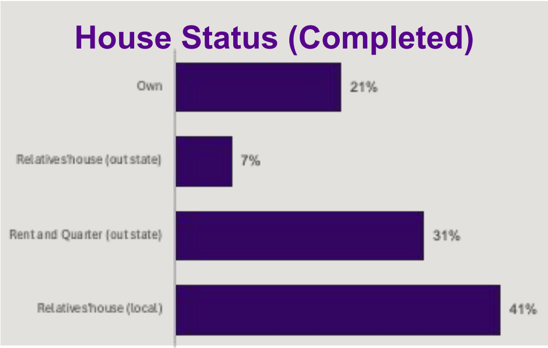
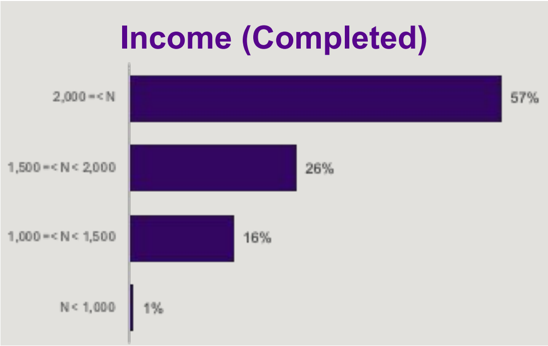
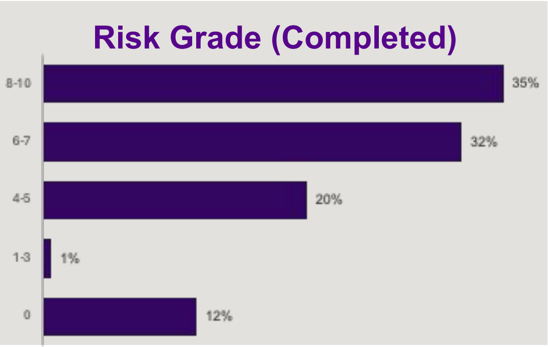
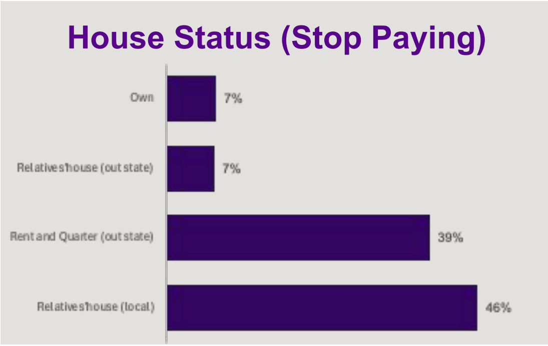
Key Finding 3

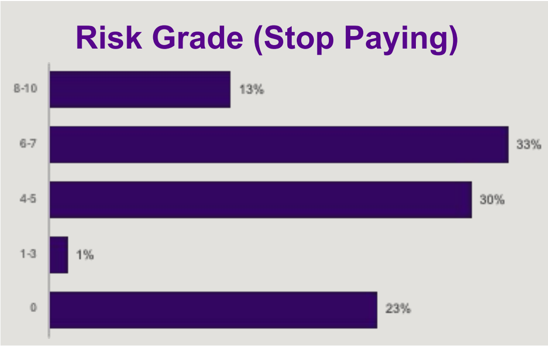
Complete Loan Terms VS. Stop Paying



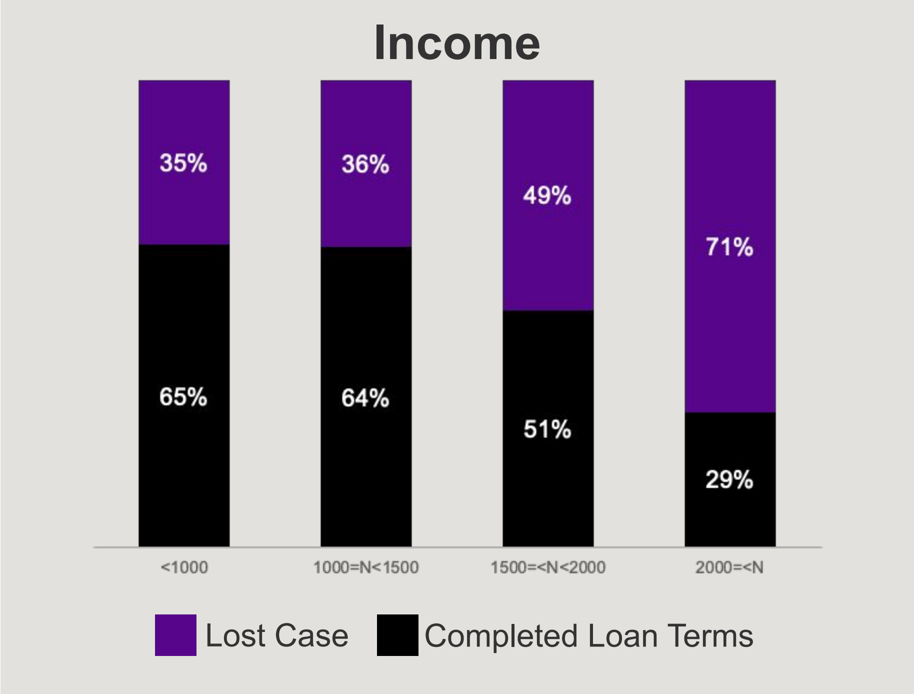


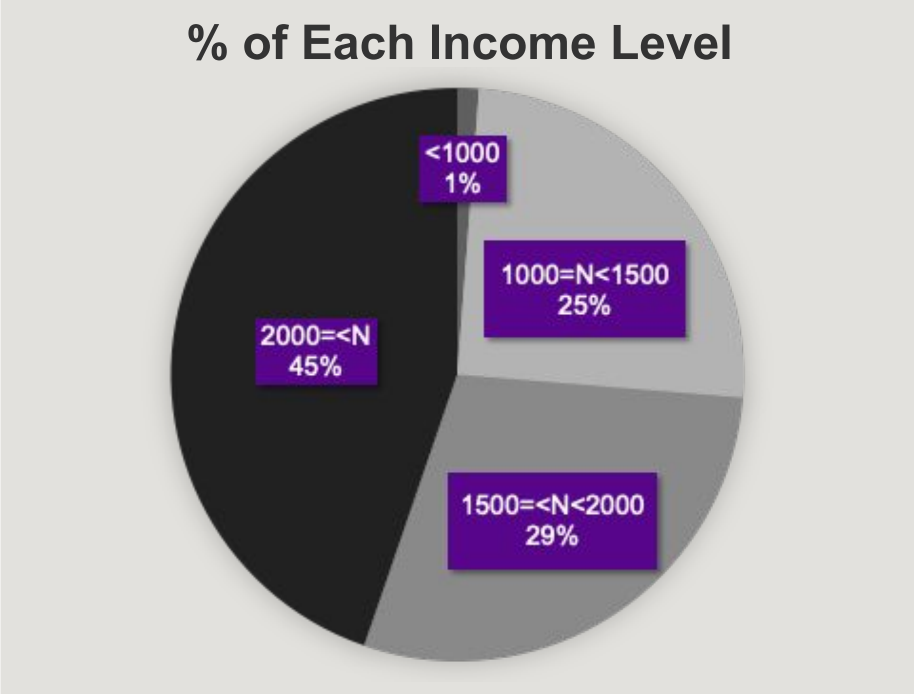






Key Finding 3





Higher income, lesser default rate.

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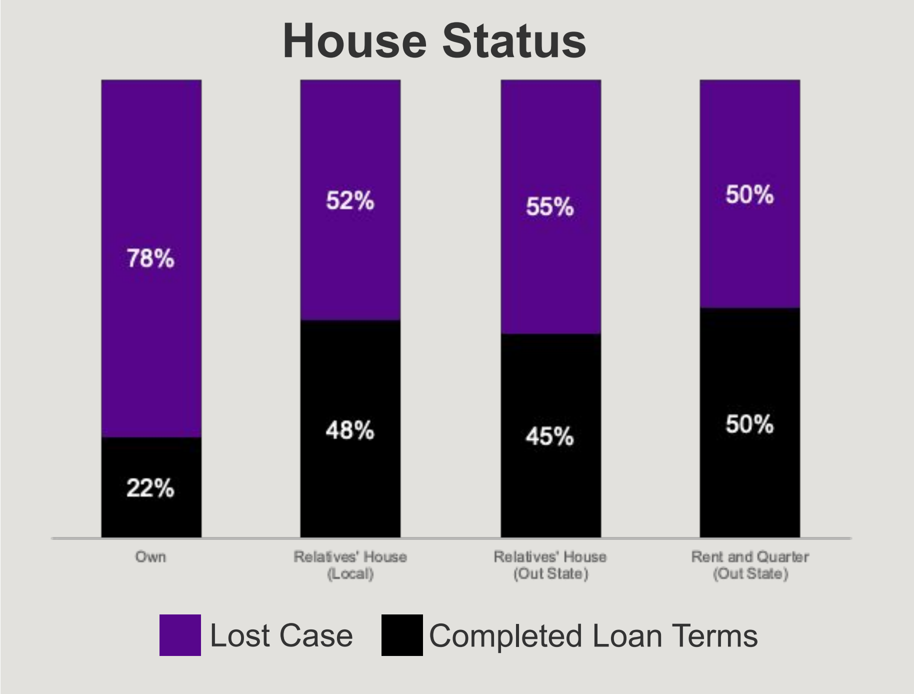
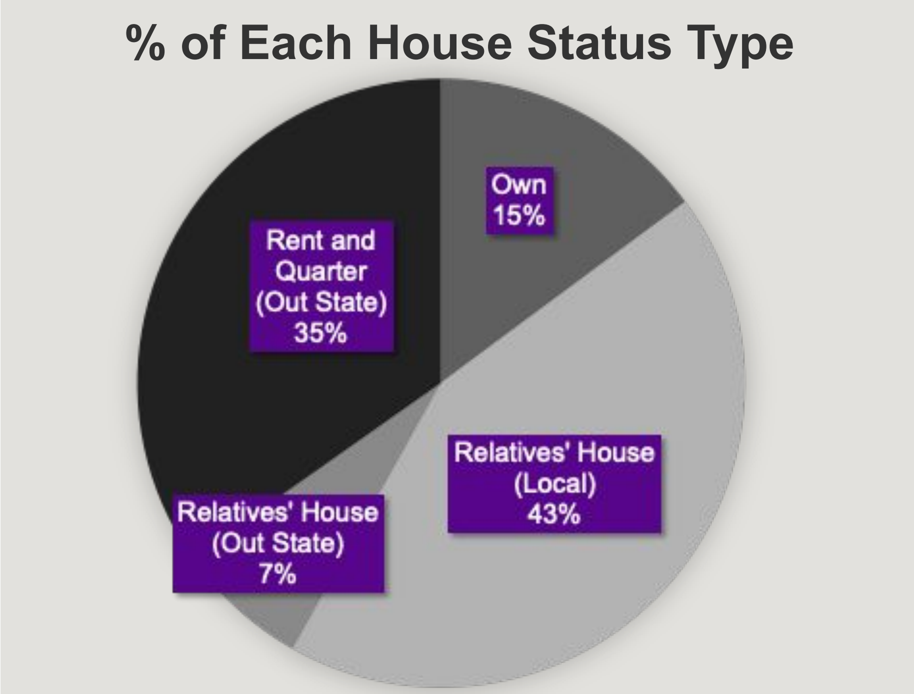
Key Finding 3





Clients owning a house have less change to stop paying.

Project Objective

Challenges

- High competition
- Intense finance competition
- More non-performing loans

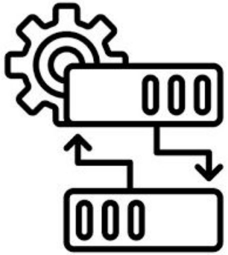
Goals

- Reduce losses from clients stop paying
- Spot clients’ profile causing loss
- Identify potential clients’ characteristics

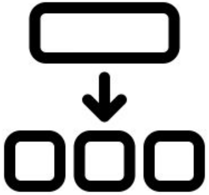
Features Selection : Correlation & SelectKBest

Total 34
Chose 8 Variables

Multicollinearity
& redundancy

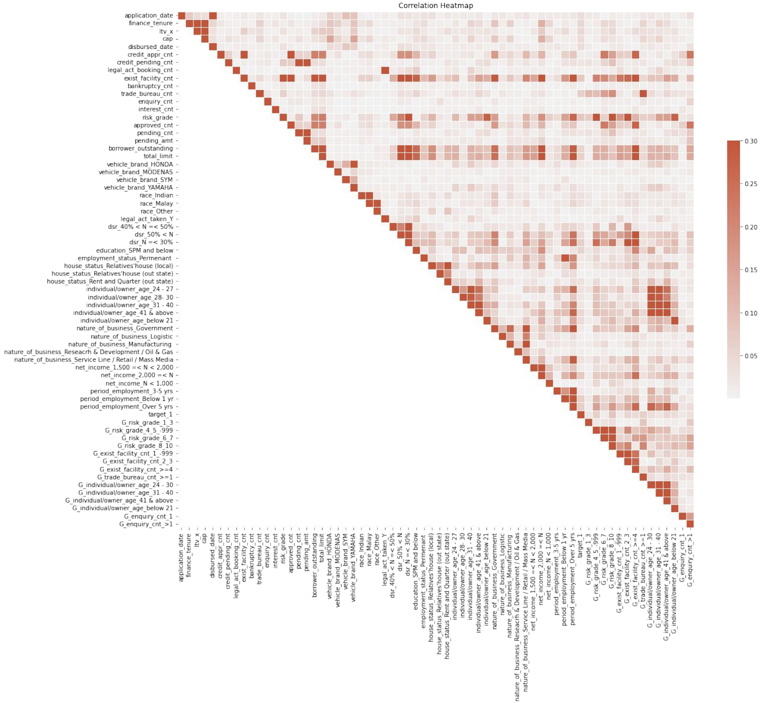


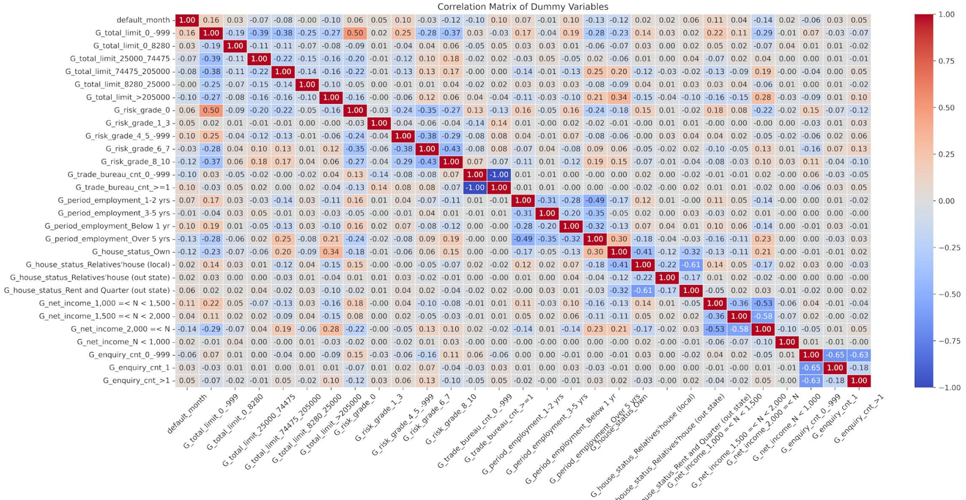
Chi-squared Test
Categorical



Anova Test
(Analysis of variance)
Numeric

Feature selection - Correlation heatmaps





Description of Our Data

Loan Default

Risk Grade

Credit range of the applicant form by 3rd party credit agency

House Status

Applicant's housing situation (own, rent, relative, etc.)

Net Income

Applicant's net income per month in Malaysian Ringgits

Employment Period

How long has the applicant been employed

Loan Amount

Total initial borrowing amount

Enquiry Count

Count of how many times this customer requested for a loan in past 12 months

Trade Bureau

Count of how many other financial obligations this customer has with Companies like Telephone bill, and etc

Model Development Overview

Loan Defaulter/lost case Prediction

- Machine learning algorithms tried
  - Random Forest
  - Decision Tree
  - Logistic Regression
  - XGBoost
- Logistic Regression model was the optimal prediction model for our business needs

Cost/Benefit Matrix

For every $100

Prediction/Actual	Non-Default	Default
Non-Default	**$23.65**	**($73.95)**
Default	**$0**	**$0**

Model	Accuracy	Delta performance	Expected Value
Random Forest	**66%**	**-20%**	**$134,360**
Decision Tree	**83%**	**-2%**	**$166,770**
Logistic Regression	**93%**	**8%**	**$191,040**
XGBoost	**59%**	**-26%**	**$148,345**

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Model Development Overview

Default/Lost Case Month Prediction

Approach	Objective	Expectation
Decision tree	Identify potential defaulters, then initiate proactive measures to minimize defaults.	Minimize loss from defaulters

Model Development Overview

Loan Default / lost month Prediction

```
Original Data:

Decision Tree Performance:
Mean Absolute Error: 9.256702412868632
Mean Squared Error: 146.02077747989276
Root Mean Squared Error: 12.083905721243143

New applicant's original default_month is: 7
Decision Tree Prediction for New Applicant: [10.]
```

```
New applicant's original default_month is: 25
Decision Tree Prediction for New Applicant: [25.]
```

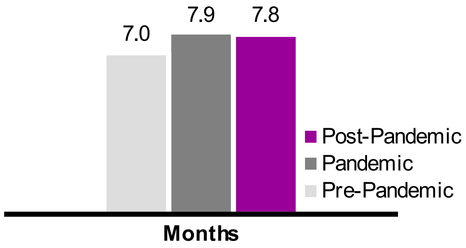
```
New applicant's original default_month is: 19
Decision Tree Prediction for New Applicant: [21.]
```

Causal Inference

Natural experiment

- A natural experiment analysis was conducted to determine if the Covid-19 pandemic affected loan defaults
- Three time periods were assessed (before, during, after) to determine impact using statistical and regression approaches
- **Results show that borrowers were more likely to default during and after the pandemic, despite improvement in time to default**

Time period	Logistic coefficient	Odds ratio
Pre-pandemic	-0.493	0.61
Post-pandemic	**0.541**	**1.71**



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Causal Inference

Counterfactual experiment - Total limit

- **0_8280 to 8280_25000 - Level 2**
- **Performance Improvement : 17.7%**
- **Not Zero/too little previous loans, Not too many other loans**

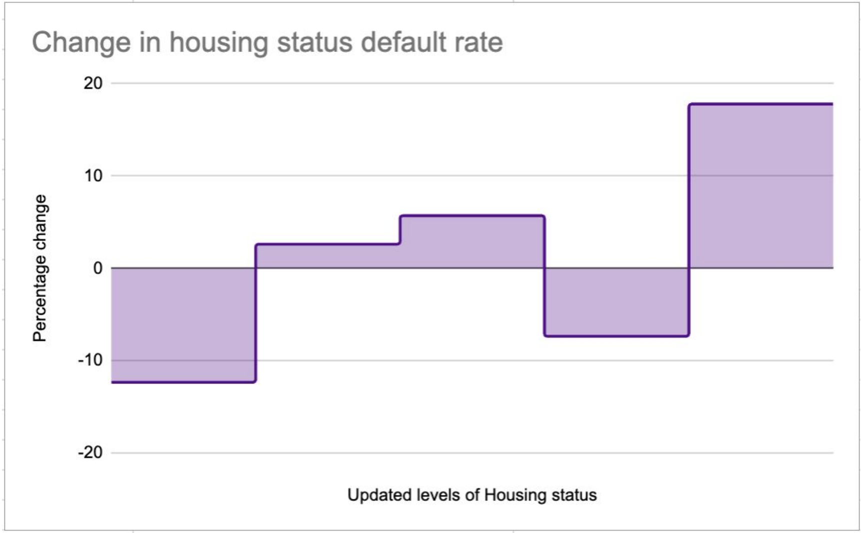
- **8280_25000 to 25000_74475 dropped performance by 24.48%**

Causal Inference

Counterfactual experiment - Housing

- **Rent to Own - Level 4**
- **Performance Improvement : 15.8%**
- **Not Zero/too little previous loans,**
  Not too many other loans

- **Own to rent showed inverse effect**

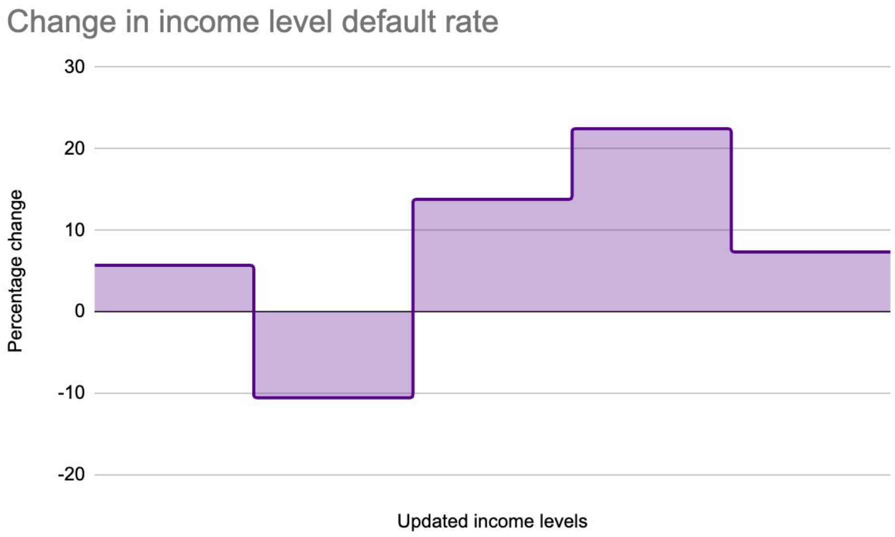


Causal Inference

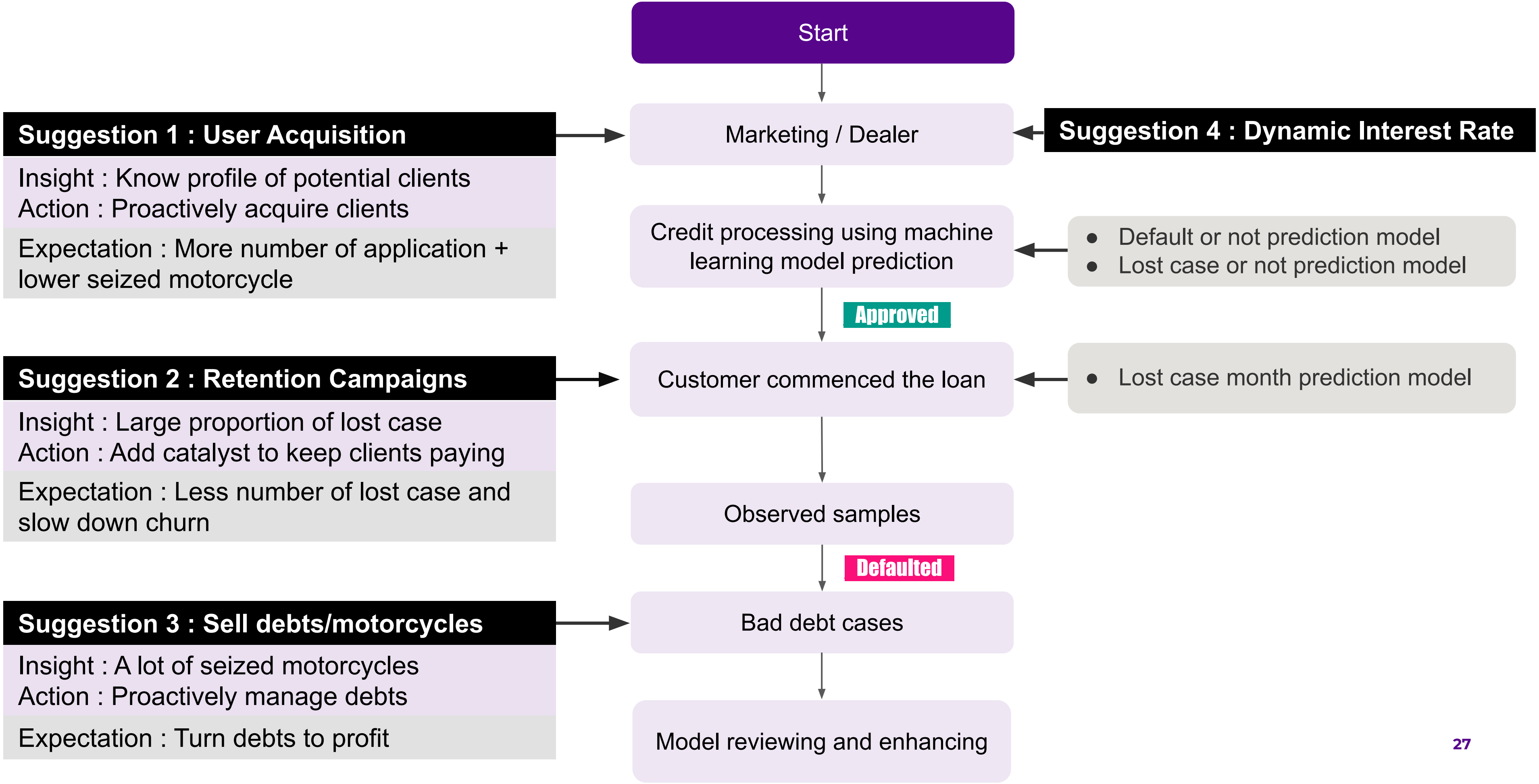
Counterfactual experiment - Income level

- 1000 < N < 1500 to 1500 < N < 2000

  - Level 3
- Performance Improvement : 22.5%
- Level 4 to 3 also has shown improvement in performance
- Level 3 to 4, performance dropped



Suggestions Overview



Suggestion 1 : Use Acquisition

Now

100%
Agents = Motorcycle Shops

Limitation

Characteristics of clients depend on locations of motorcycle shops.

Proactive User Acquisition

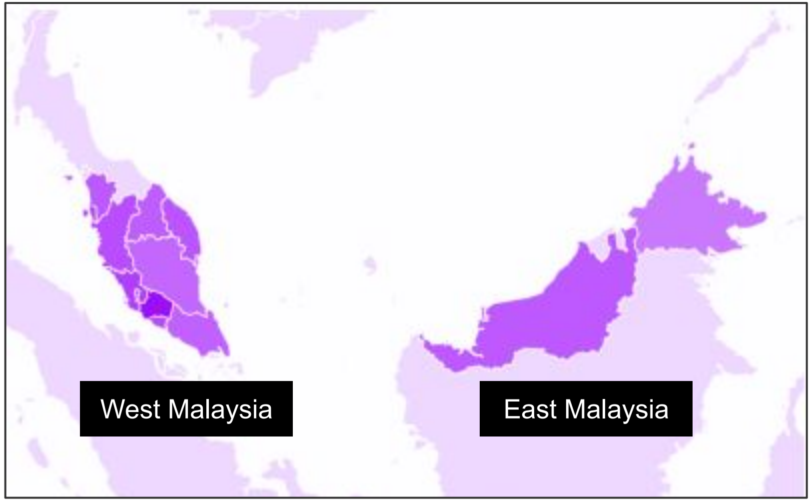
- The company website
- Offline Activities

Solution

Physical shops will not be a barrier for reaching out to better quality clients.

Suggestion 1 : Use Acquisition

Areas people search using keyword “motorcycle loan”



Source : Google Trend

Try to find best placements to acquire potential prospects

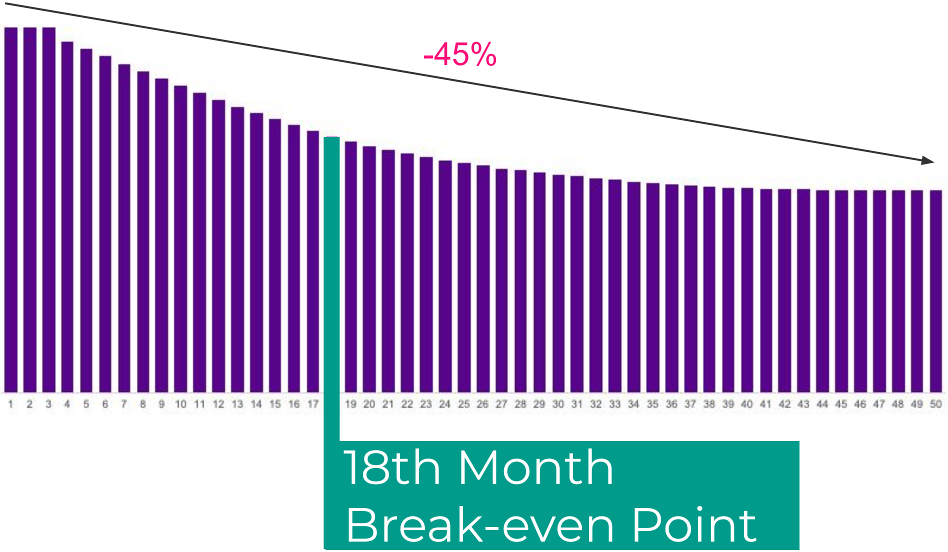
Client ID	Income	House Status	UTM Tag
00001	**2000=<N**	**Own**	abc_dotcom
00002	1000=N< 1500	Relatives' House (Local)	KOL1
00003	1500=<N <2000	Own	campaign24
00004	**2000=<N**	**Own**	abc_park

Try different approaches and use UTM tags to help identify best placements

Suggestion 2 : Retention Campaigns

Expectations

- Reduce client attrition to below 45%
- Prolong lifetime until 18th month or more



Promotions

- Discount on interest
- Reward system

Reward Size < Expected Profit

Positive Reinforcement
+
Take action before loss happens

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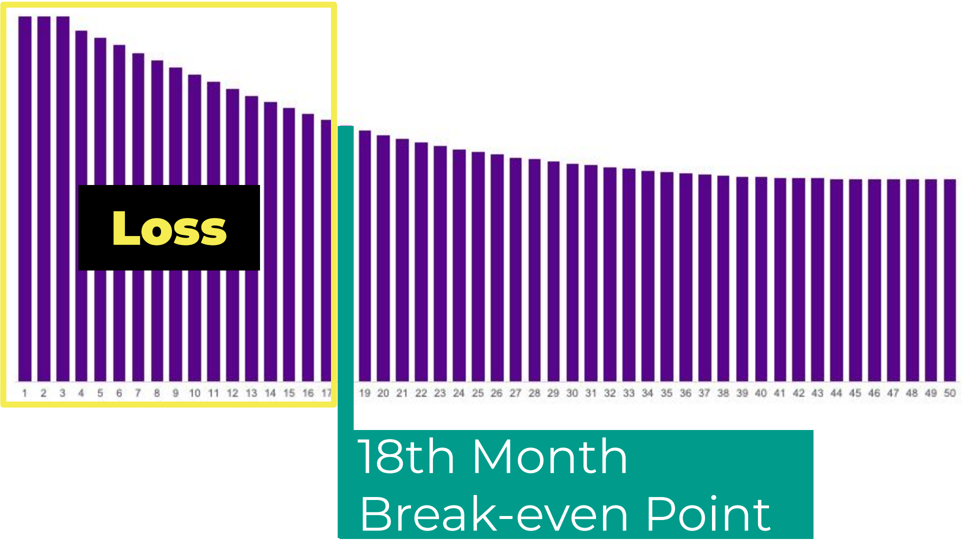
Suggestion 3 : Sell Some Loans / Seized Motorcycles

Expectations

- Turn debts to profit
- A new unit boosting revenue



Actions

Difficult-to-Collect Debts

- Sell debts to debt buying company

Seized Motorcycles

- Sell seized motorcycles
- Found a business unit

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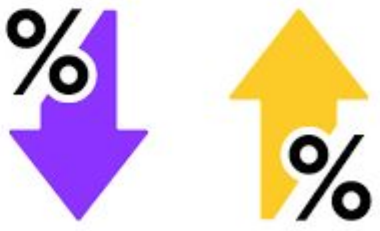
Suggestion 4 : Dynamic Interest Rate

Expectations

- More number of clients
- Sell seized motorcycles proactively



Actions

Interest Rate

- A new department for pricing
- Different type of clients, different offer

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Q&A


LET US RAISE A STANDARD TO WHICH THE WISE
AND THE HONEST CAN REPAIR THE EVENT
IS IN THE HAND OF GOD
WASHINGTON

Value Depreciation - ROI

	Standard Market Depreciation Rate	Berjaya's Depreciation Rate	Defaulted - ROI - Market	Defaulted - ROI - Berjaya
6 months	30%	35%	85	80
Year 1	30%	35%	100	95
Year 2	20%	25%	110	105
Year 3	10%	15%	120	115
Year 4	10%	15%	120	115
Year 5	10%	15%	120	115

Lost in 6 months
USD 524,272

Lost in 1 year
USD 329,373