

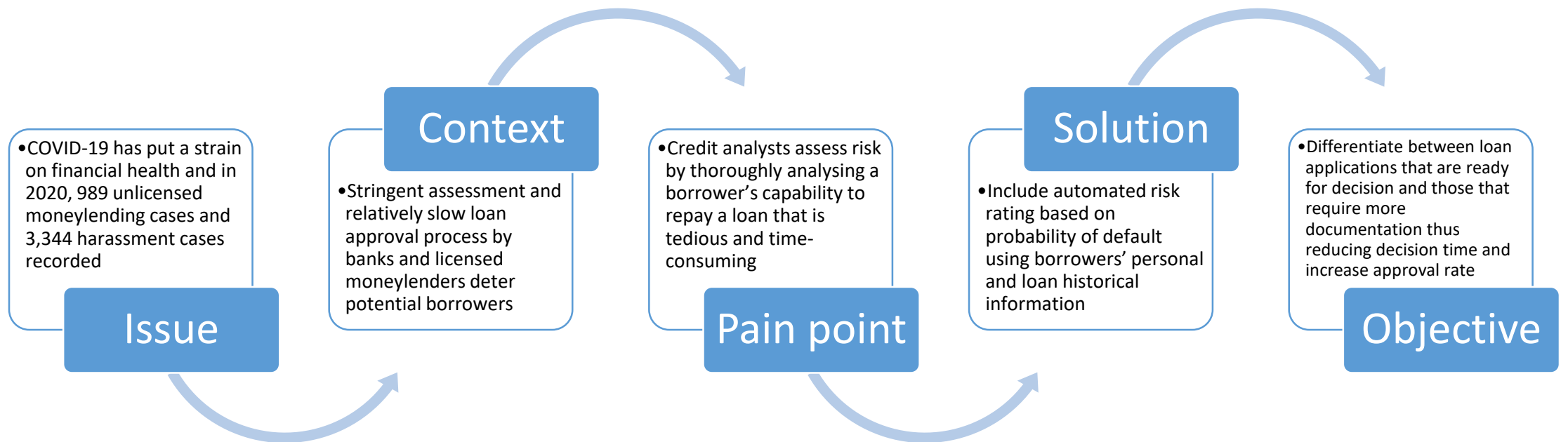


# Improving Over Indebtedness in Singapore

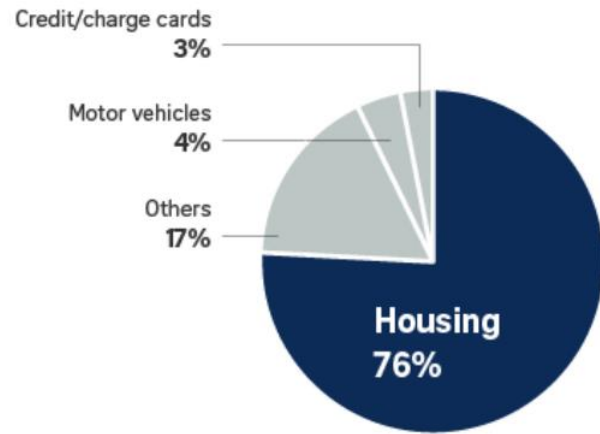
Borrowers Exploitation by Unlicensed Moneylender



# Executive Summary



# Families could face difficulty with home loan payments



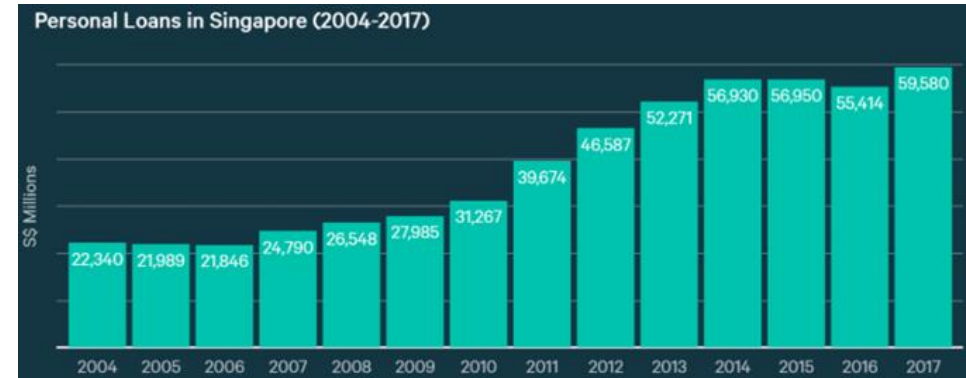
**Credit card charge-off rate rose from 5.9% to 9.1% from last year**

Breakdown of Outstanding Household Debt

- COVID-19 has put a strain on financial health, impacting families' ability to pay their housing loans
- Credit card charge-off rate measures bad debt written off during the year against the average rollover balance, and is a leading indicator for the credit quality of housing loans
- A borrower is likely to miss payments for their credit card bills in the initial period of financial distress

# Potential business lost to unlicensed moneylenders

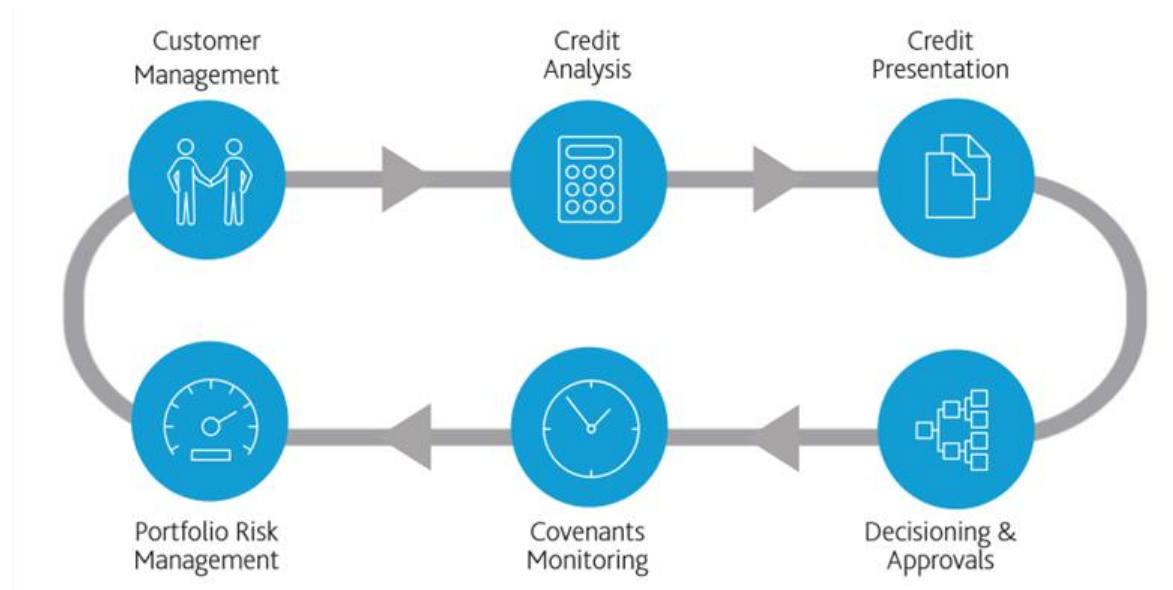
- Stringent assessment and relatively slow loan approval process by banks and licensed moneylenders deter potential borrowers
- Unlicensed moneylenders offer quick approval and hassle-free applications
- Other than house loan payments, borrowers may borrow to fund educational needs, a medical emergency or to tide over short-term cash flow challenges for a small business



Credit card debt and personal loans have been the fastest growing categories of consumer debt with potential market size of **S\$65B**

# Loan process automation for quick approval

- Credit analysis can include automated risk rating based on probability of default and give more time back to the analyst to perform their risk assessment work
- Automation of the lending process increase efficiency and reduce decision time
- Differentiate between loan applications that are ready for decision and those that require more documentation



Source: Kaggle and Department of Statistics, Singapore |  
Prepared by: Alvin Lie

# Value for all stakeholders

## Society

- Improve financial well-being of those in need
- Reduce societal issues caused by unlicensed moneylender

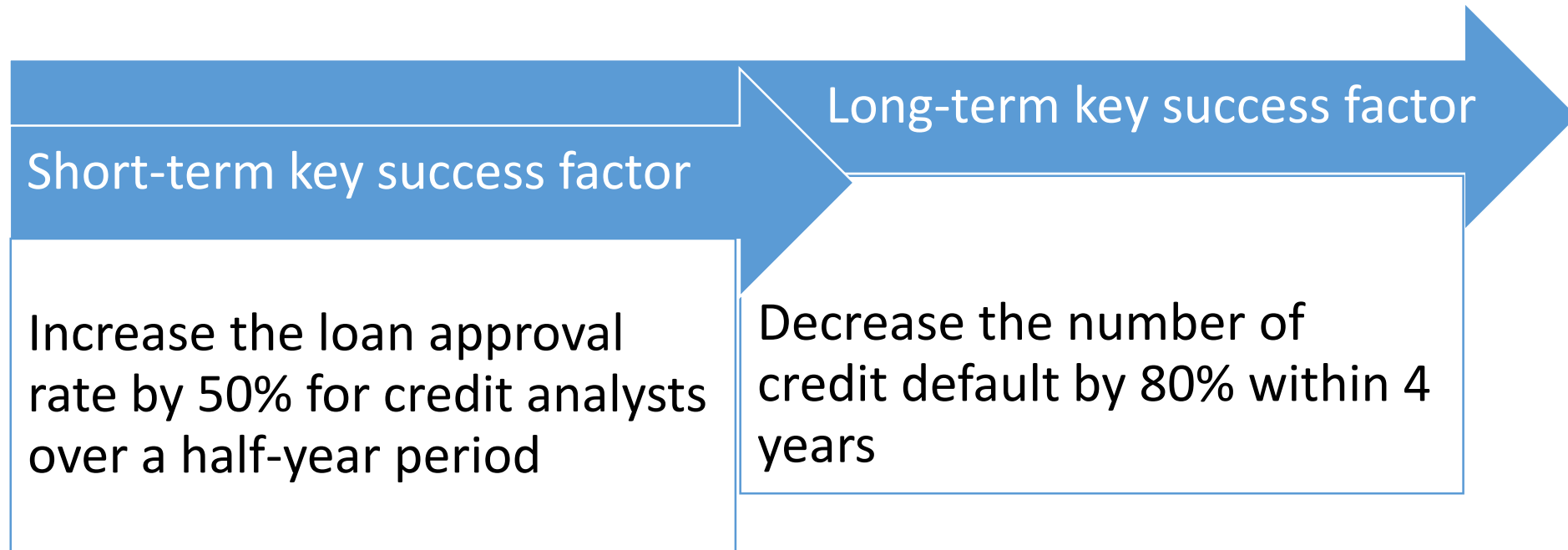
## Bank/Licensed moneylender

- Increase productivity of credit analyst
- Competitive approval process

## Borrower

- Reduced waiting time of loan process
- Better alternative to unlicensed moneylender

# Success is defined by 2 measurable factors



# The dataset will be used to predict credit default risk

- 32,581 borrowers' personal and loan information as 12 indicators

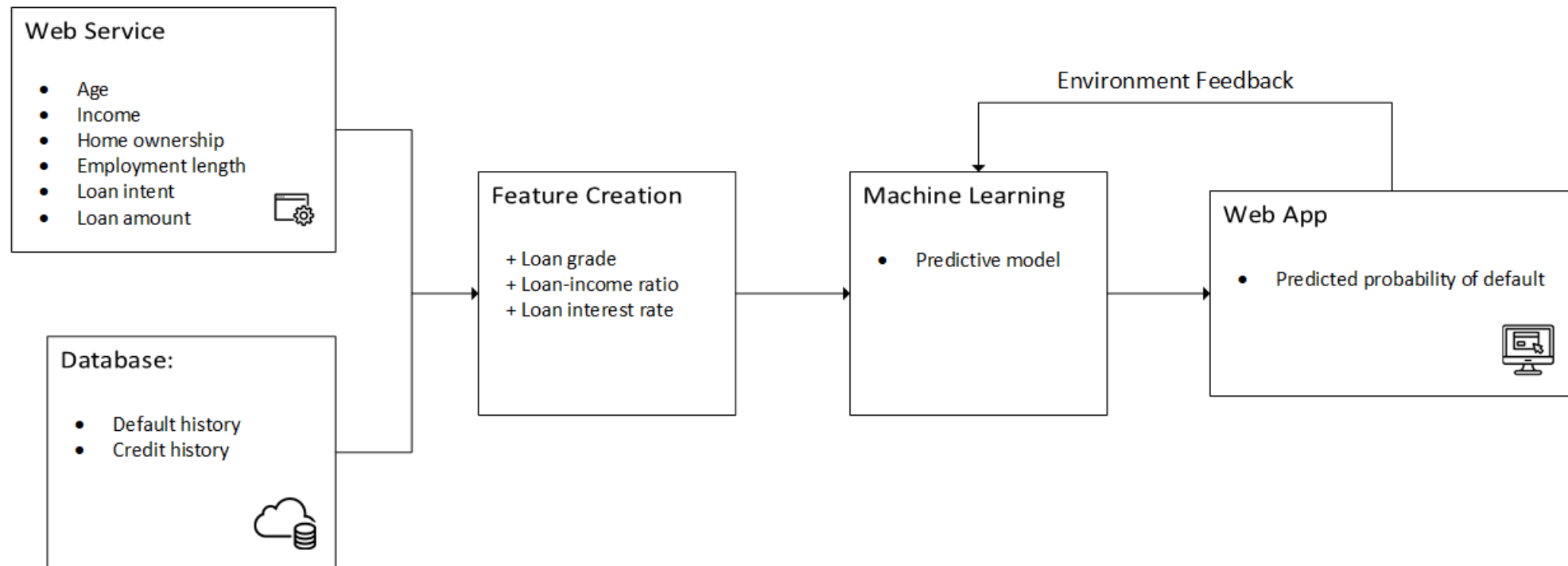
|             | Age   | Income                   | Loan Amount                   | Interest Rate                       | Loan Grade   | Credit History                               | Default History                                     | Loan Status                            |
|-------------|---|--------------------------|-------------------------------|-------------------------------------|--|--|---|--|
| Description | Age of the borrower in years                                  | Annual income in dollars | Amount of loan in dollars     | Interest rate of loan in percentage | A function of variables to grade the loan from 'A' to 'G'  | The number of years since the loan was taken | 'Y' for defaulted before or 'N' for never defaulted | '0' for non-default or '1' for default |
|             | Home Ownership  |                          | Employment Length             |                                     | Loan Intent  |  | Loan-Income Ratio                                   |  |
| Description | Current status of home ownership: 'own', 'rent' or 'mortgage' |                          | Number of years in employment |                                     | Intended use for loan: 'education', 'medical', 'venture', 'home improvement', 'personal' or 'debt consolidation' |  | Ratio of loan to annual income                      |  |



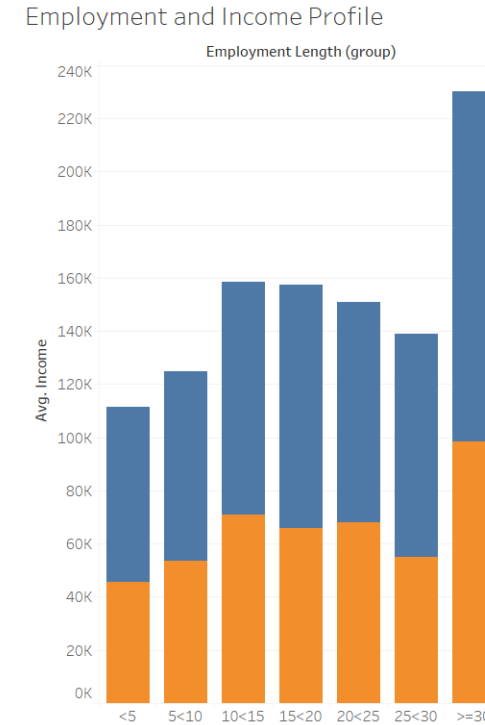
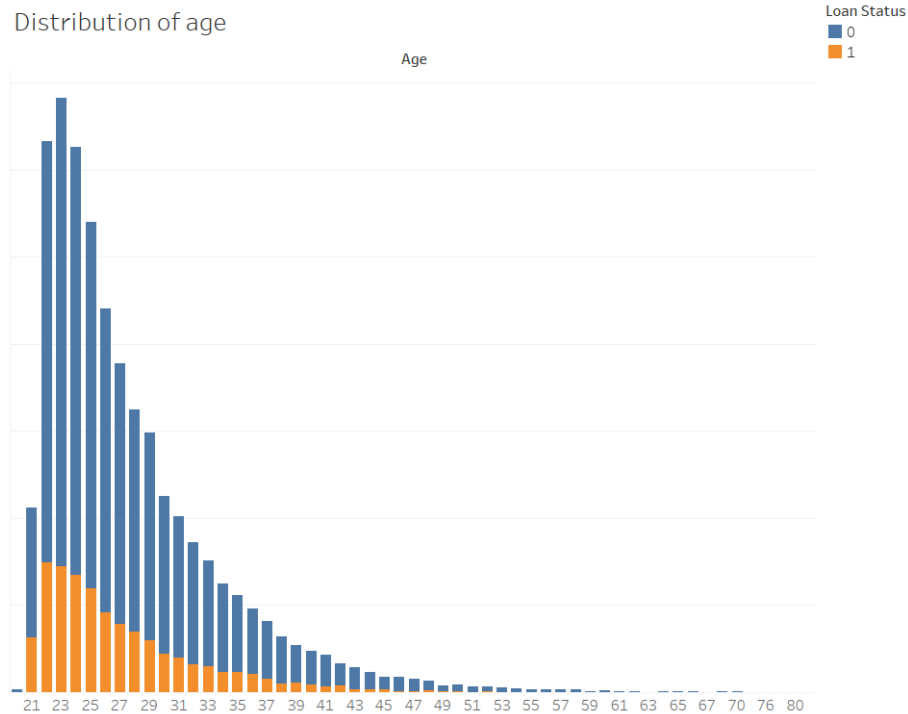
# Interpretation of the indicators

- Age of borrower: a productive age range is to be identified as it affects their income
- Income: a higher income increases the probability of repayment of the loan
- Loan amount: the loan amount affects the interest rate charged to the borrower
- Interest rate: higher interest rate indicates higher risk of the loan
- Loan grade: grade is determined by a number of factors such as loan amount and interest rate
- Credit history: higher number of years since loan was taken indicates better repayment history
- Default history: borrower that has defaulted before may increase the probability of credit default
- Loan status: current status of their loan will be used to predict the probability of default for future loans
- Home ownership: whether they own, rent or mortgage their home shows their financial liability
- Employment length: length of employment may indicate the stability of their income
- Loan intent: the intention of their loan may affect future income and determines the loan's risk
- Loan-income ratio: higher ratio indicates over-borrowing and increases credit default risk

# Data Flow Diagram



# Exploration of the indicators



- The age distribution of our dataset is right-skewed with the majority of the borrowers in their 20s. Borrowers in their 20s have a higher percentage of defaulters compared to older age groups
- Despite earning higher average income, borrowers that have been employed for 30 years or more have higher number of defaulters

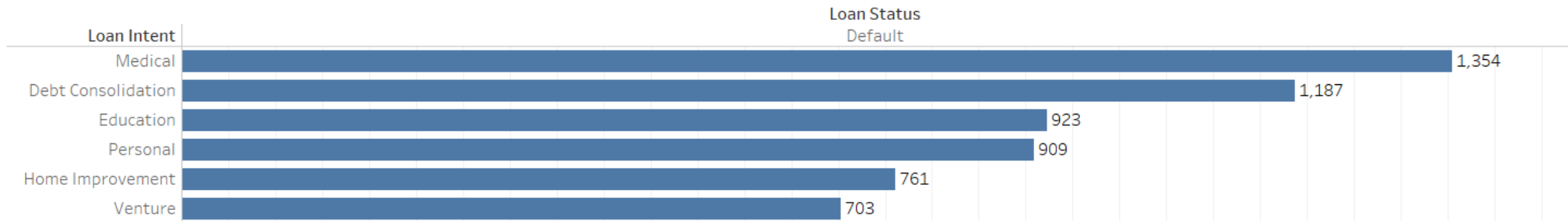
# Exploration of the indicators

## Home Ownership



- Borrowers that rent or mortgage their homes are more likely to default

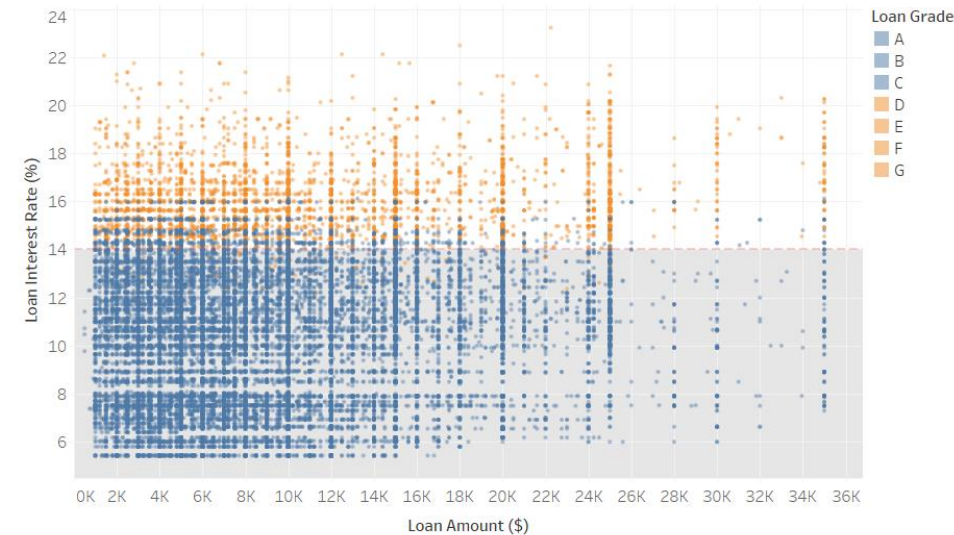
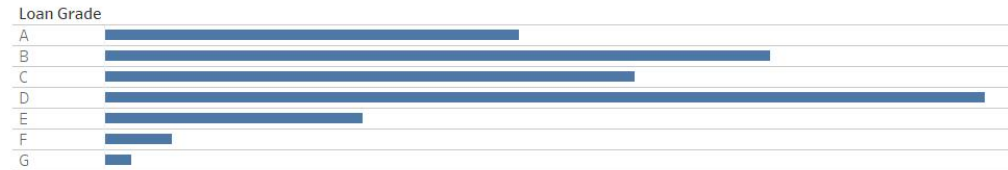
## Defaulted Loan Intent



- Loans taken for medical and debt consolidation purposes are likely to default

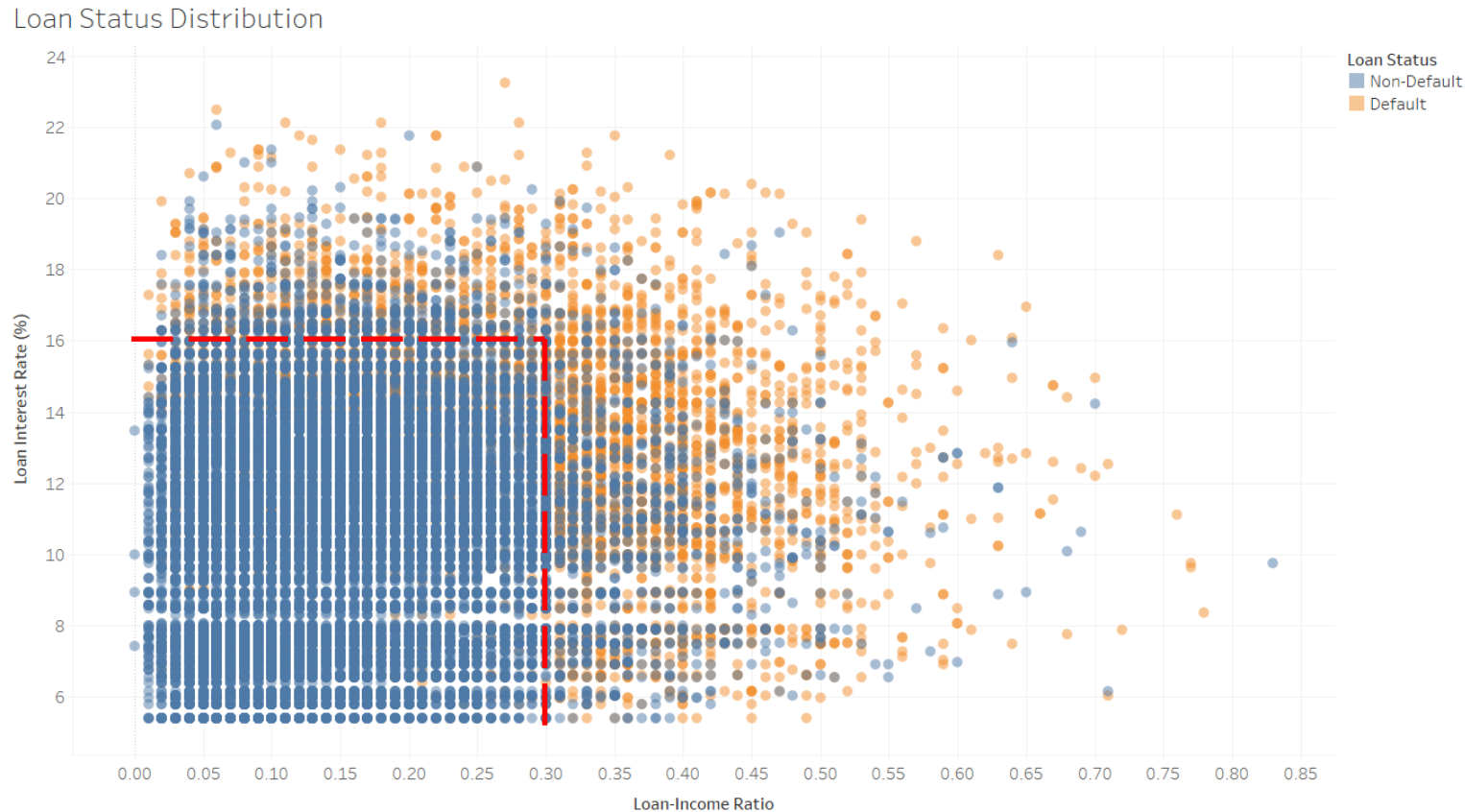
# Exploration of the indicators

Loan Grade Performance



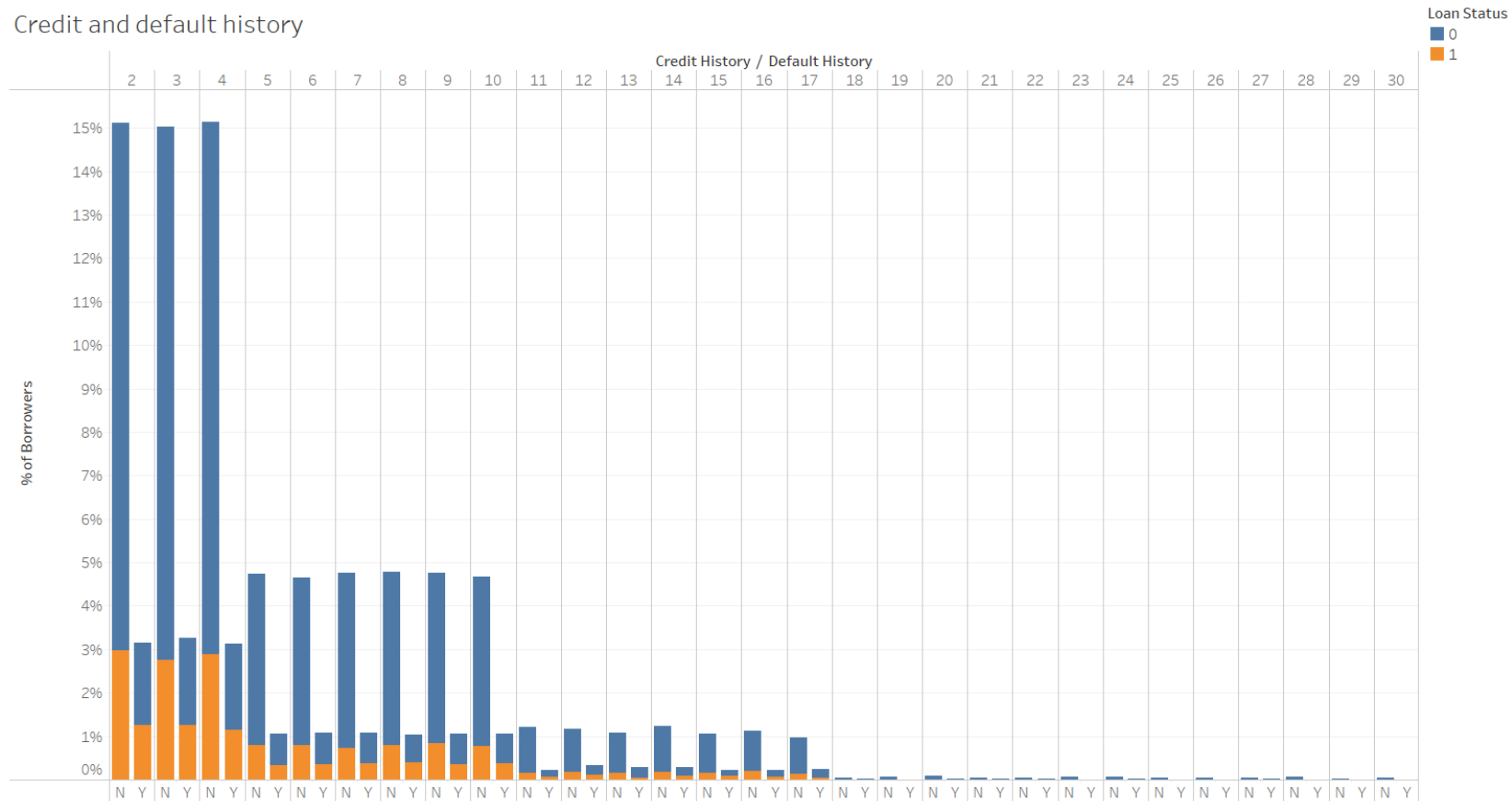
- Loan grade 'D' is the lowest performing loans with highest number of defaults. Loans with interest rate higher than 14% are graded 'D to G' indicating higher risk of defaulting

# Exploration of the indicators



- Borrowers with loans that have interest rate higher than 16% and loan-income ratio of more than 0.3 are more likely to default

# Exploration of the indicators



- Borrowers with credit history of 2-4 years make up the bulk of the borrowers and show higher percentages of defaulters. History of default does not seem to be a good indicator of defaulting

# Predictive model success metrics

Recall

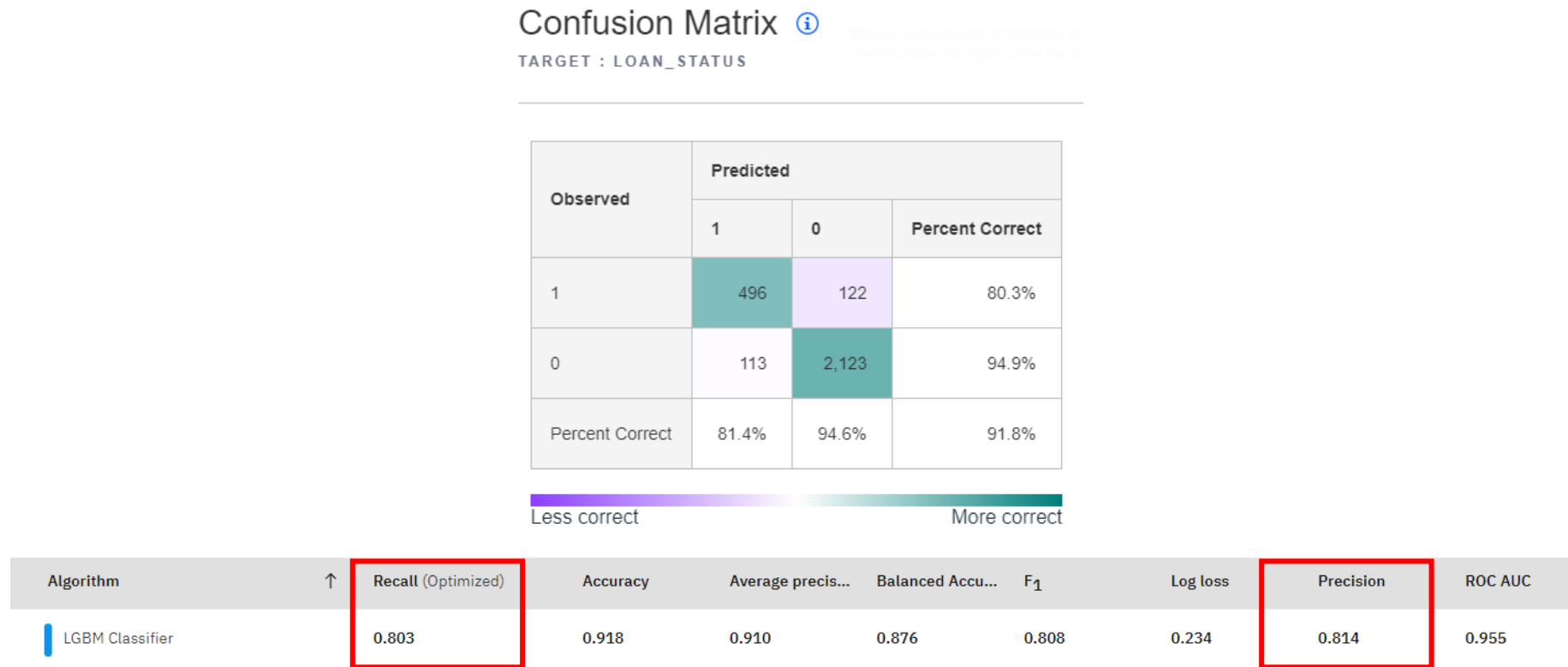
- Effect of false non-default is costly to the bank because defaulters are classified as non-defaulters

Precision

- Effect of false default is missed business opportunity because non-defaulters are classified as defaulters



# Predictive model performance



- The preliminary predictive model shows promising results with Recall and Precision of at least 80%

# High-probability default example

## ~80% probability to default

### Borrower's indicators:

- Age - 40 years old
- Income - \$60,000
- Home ownership - OWN
- Employment length - 15 years
- Loan intent - MEDICAL
- Loan amount - \$45,000
- Loan interest rate - 20%
- Loan-income ratio - 0.75
- Default history - Yes
- Credit history - 5 Years

### Result

```
0 {  
1   "predictions": [  
2     {  
3       "fields": [  
4         "prediction",  
5         "probability"  
6       ],  
7       "values": [  
8         [  
9           1,  
10          [  
11            0.19565150275634302,  
12            0.804348497243657  
13          ]  
14        ]  
15      }  
16    ]  
17  }
```

# Low-probability default example

## ~10% probability to default

### Borrower's indicators:

- Age - 25 years old
- Income - \$40,000
- Home ownership - RENT
- Employment length - 1 year
- Loan intent - EDUCATION
- Loan amount - \$10,000
- Loan interest rate - 10%
- Loan-income ratio - 0.25
- Default history - No
- Credit history - 1 year

### Result

```
0 {  
1   "predictions": [  
2     {  
3       "fields": [  
4         "prediction",  
5         "probability"  
6       ],  
7       "values": [  
8         [  
9           0,  
10          [  
11            0.9030697225889706,  
12            0.09693027741102946  
13          ]  
14        ]  
15      }  
16    ]  
17  }
```

# Prototype

## A2Z BANK

[Home](#) [Origination Configuration](#) [Contacts](#) [Accounts](#) [Quick Quotes](#) **Applications** [Reports](#) [Dashboards](#) [+](#)

[Loan Dashboard](#) [Application](#) [Parties](#) [Credit](#) [Bank Transactions](#) [Scorecard](#) [Pricing](#) [Deal Room](#) [Documents](#) [Financial Information](#) [Amortization](#) [Assets & Liabilities](#) [Collaterals](#) [LOI](#) [Funding](#)

Overall Status

[Reject Application](#) [Submit To Next Department](#) [Create Exception Task](#) [Convert To Marketplace](#) [Convert to CL Loan](#) [Generate Loan Agreement](#)

Being Processed By Processing Department

[Save](#) [Cancel](#)

Application Details

|                             |                         |                     |                             |
|-----------------------------|-------------------------|---------------------|-----------------------------|
| Account                     | Biltmore Investors Bank | Loan Product        | Real Estate Commercial Loan |
| Contact                     | Carlos Testcase         | Primary Collateral  |                             |
| Loan Amount                 | 7,000.00                | CL Purpose          |                             |
| Term                        | 36                      | Days Convention     | 365/365                     |
| Interest Rate               | 10.0000                 | Status              | NEW - ENTERED               |
| Expected Start Date         | 1/2/2016                | CL Product          | PRO-00000003                |
| Expected First Payment Date | 2/22/2016               | Payment Frequency   | MONTHLY                     |
| Status                      |                         | Lending Product     | Simple Loan Product         |
|                             |                         | CL Contract         |                             |
| Loan Summary                |                         |                     |                             |
|                             |                         | Default Probability | 20%                         |

Departments and Tasks

[Save](#)

✓ Origination Department

⊙ Processing Department

☒ (\*) Review Entity docs and confirm entity validity / Good Standing

☒ (\*) Review Identification

☒ (\*) Review loan application to ensure it is completed, signed and dated

⊙ Underwriting Department

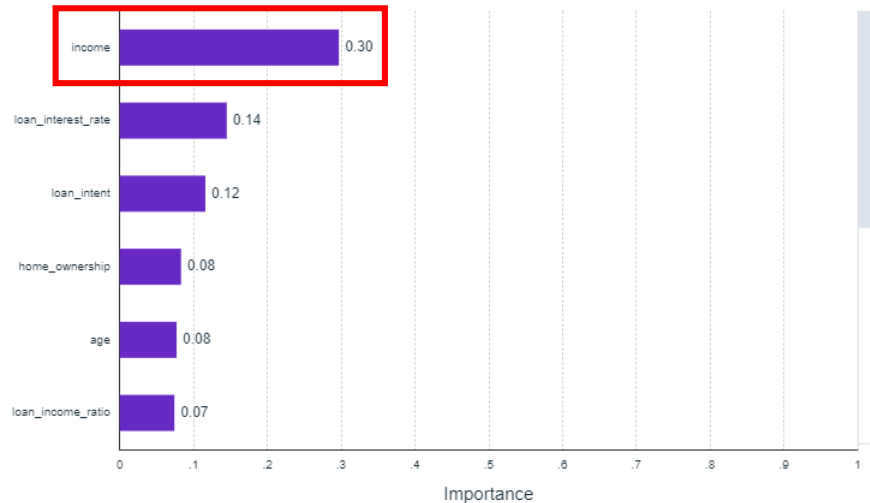
⊙ Closing Department

⊙ Exception Tasks

# Importance of the indicators

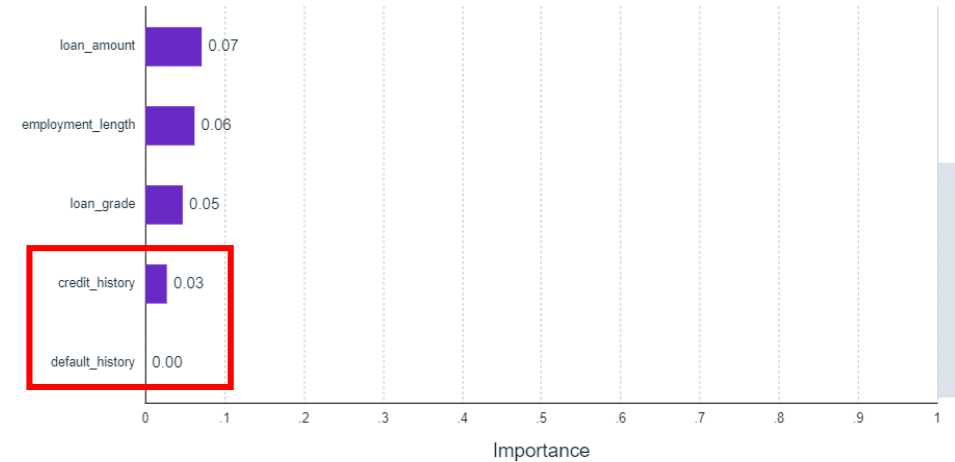
## Feature Importance ⓘ

TARGET : LOAN\_STATUS



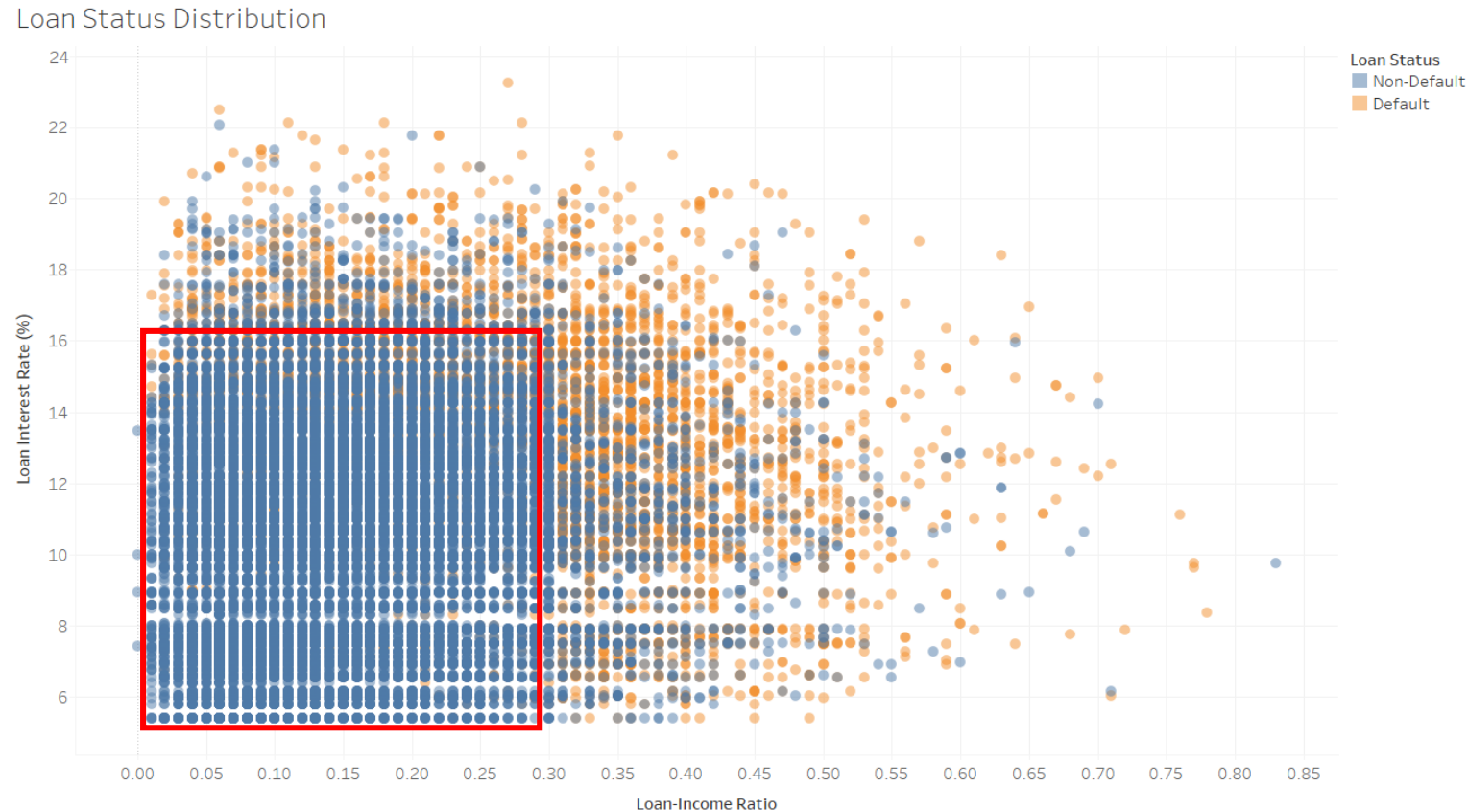
## Feature Importance ⓘ

TARGET : LOAN\_STATUS



- The applicant's income has the highest importance in predicting the likelihood of a default
- Credit and default history are of low importance in predicting default, thus the predictive model will work just as well for new loan applicants


# Recommendation




- To reduce loan defaults it is recommended to limit loan amount up to \$35,000, charge loan interest rate of not more than 16% and ensures borrowers' loan-income ratio is less than 30%

# Action plan

Create a loan product with amount up to \$35,000 and interest rate of not more than 16%



Probability of default generated by the predictive model to aid the credit analysts in their decision when considering loan approval



These actions will achieve the objectives of reducing loan defaults through having more quality borrowers and increasing the approval rate of loans by credit analyst