Credit Risk Analysis

Background – Credit Risk Analysis

CredX gives credit cards to thousands of people every year, of which **approx. 4% default**. The defaulters form the largest fraction of the portfolio's loss (credit loss).

The objectives of the analysis are to:

- Identify the most important variables affecting likelihood of default
- Build an application scorecard to identify the likely defaulters at the application stage using predictive models
- Estimate the potential financial benefits of using the models for auto-approval of credit cards

Credit Risk Analysis - Flow of Topics

The analysis is divided into 5 parts:

- **Data Understanding** – Demographic and Credit bureau information
- **Identifying important variables using** Exploratory Data Analysis
- **Predictive modelling**
    - Modelling on demographic data only
    - Modelling on combined data of demographic and credit bureau variables
- **Application scorecard**
    - Identifying the optimal score for rejecting the applicant
- **Financial Benefits**
    - Assessing the potential benefits of using predictive models for auto-approval

- **Data Understanding**
- Identifying important variables
- Predictive modelling
- Application scorecard
- Financial Benefits

Data Understanding - Demographic and Credit Bureau Data

Demographic Data

Provided by applicants at the time of credit card application.

Application Information*
Age
Income
Gender
Marital Status
Education

Credit Bureau Data

Provided by credit bureau agency of every individual. The data contains Information related to applicants' previous loans, credit cards etc.

Credit Bureau Information**
Outstanding balance
Past due 30,60,90 DPD
Total trades
Number of inquiries
Presence of home loan

* Demographic Data contains 12 attributes. Only few are shown in the table

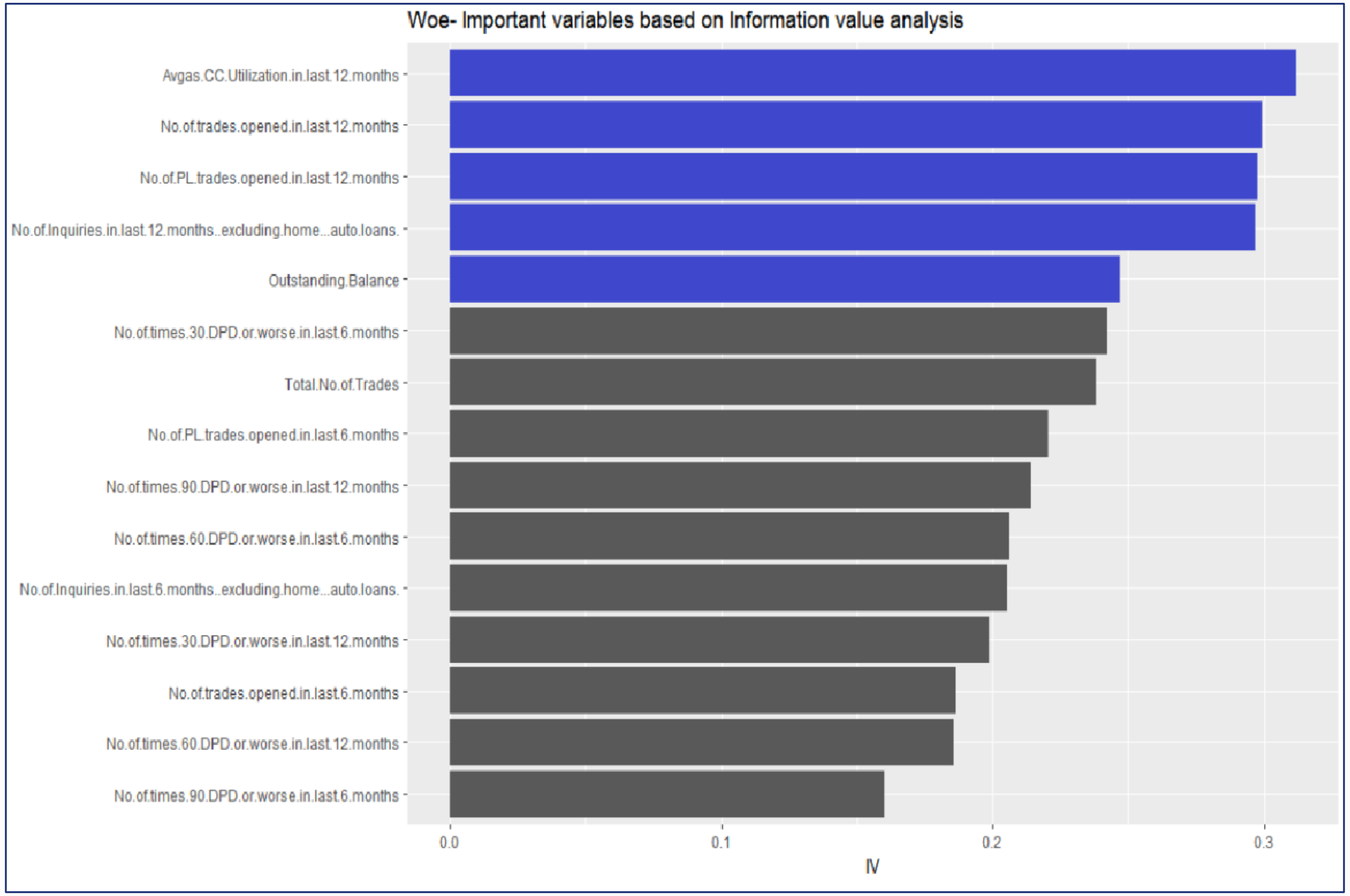
** Credit Bureau Data contains 19 attributes. Only few are shown in the table

- Data Understanding
- **Identifying important variables**
- Predictive modelling
- Application scorecard
- Financial Benefits

Identifying Important Variables: Average credit utilisation, Trades opened, Inquiries and Outstanding Balance

The most crucial variables seem to be:

- Average credit utilisation in last 12 months
- Number of trades opened in last 12 months
- Number of PL(personal loan) trades opened in last 12 months
- Number of Inquiries in last 12 months (excluding home auto loans)
- Outstanding balance



plot only contains variables with “Strong” and “Medium” IV(Information value)

- Data Understanding
- Identifying important variables
- **Predictive modelling**
- Application scorecard
- Financial Benefits

Predictive Modelling – Best Model: Random Forest*: Accuracy: 72% , Sensitivity: 75% and Specificity: 72%

- Model identifies 75% of defaulters correctly
- Captures 80% defaulters in top 4 deciles

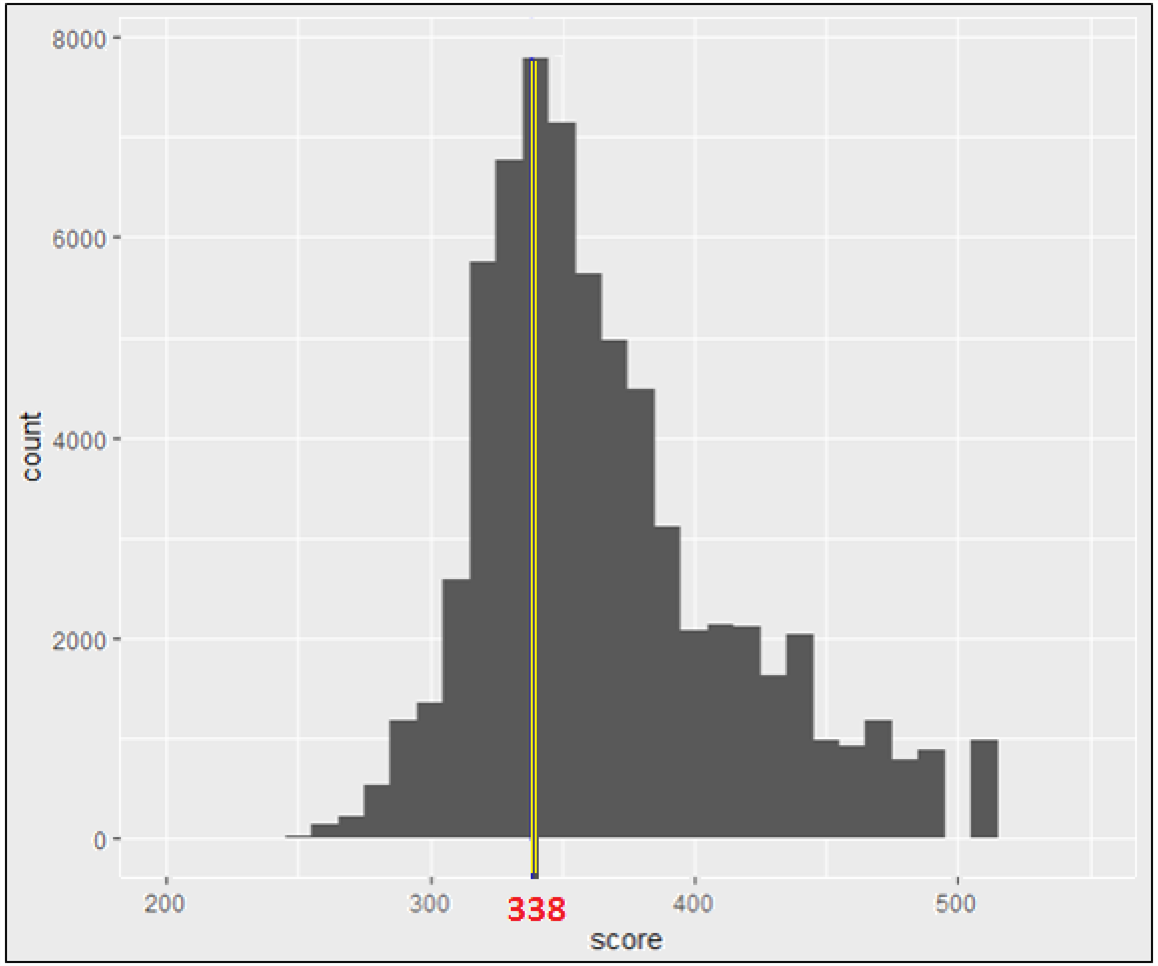
bucket	total	Total Bad	Cum- Bad	Gain	Lift
1	**6951**	**1739**	**1739**	**59.2**	**5.9**
2	**6950**	**272**	**2011**	**68.4**	**3.4**
3	**6950**	**195**	**2206**	**75.1**	**2.5**
4	**6950**	**169**	**2375**	**80.8**	**2.0**
5	6950	155	2530	86.1	1.7
6	6950	122	2652	90.3	1.5
7	6950	95	2747	93.5	1.3
8	6950	85	2832	96.4	1.2
9	6950	58	2890	98.4	1.1
10	6950	48	2938	100.0	1.0

*Random Forest model trained on balanced data

- Data Understanding
- Identifying important variables
- Predictive modelling
- **Application scorecard**
- Financial Benefits

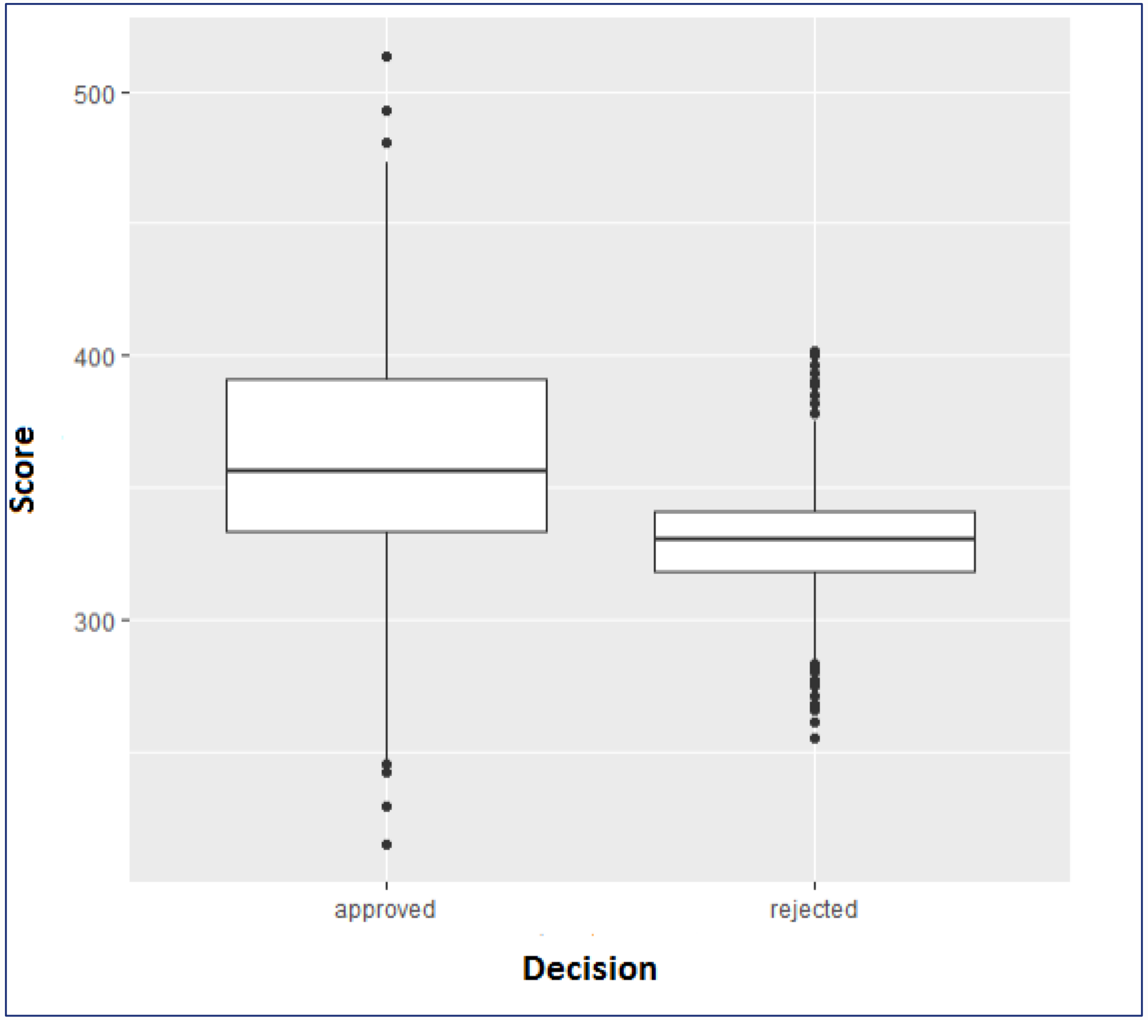
Application Scorecard (master population): Score varies between 200 to 530; Cut-off score - 338

- Cut-off: 338 is the baseline for providing credit card to the customers



Application Scorecard (rejected population) : 70% of defaulters correctly identified

- Average score of rejected population is less than the average score of approved* population
- Total rejected applications by bank: **1423**
- Identified correctly at cut-off score by model: **1006**



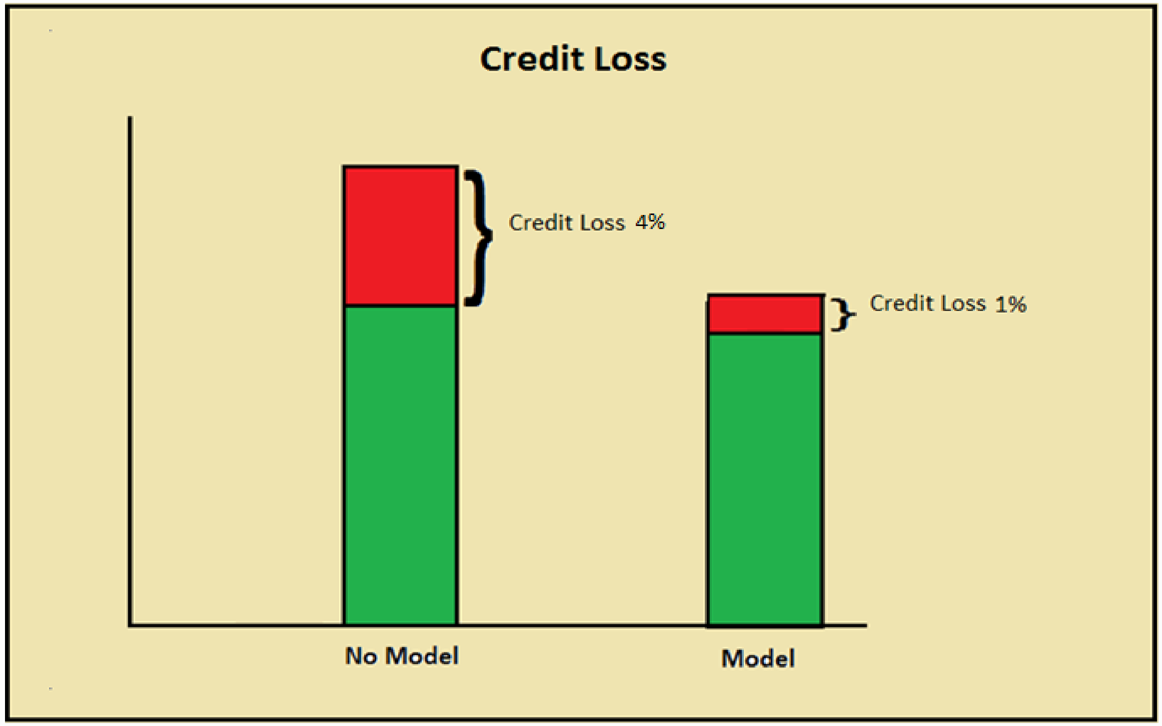
*Approved population (master data) is a population for which the application is accepted by bank

- Data Understanding
- Identifying important variables
- Predictive modelling
- Application scorecard
- **Financial Benefits**

Credit Loss*: Reduced credit loss from 4% customers to 1%customers

- Credit loss no model = **4%**
- Credit loss with model =**1%**

Credit Loss Saved: 3%



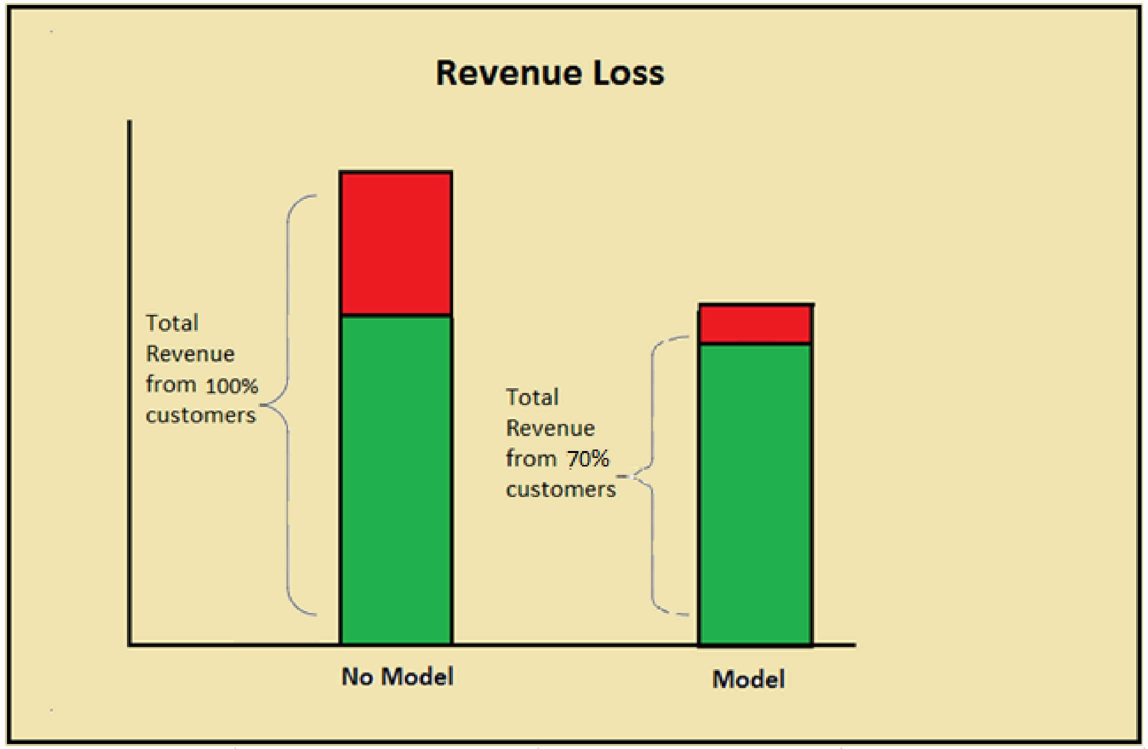
Confusion Matrix		Actual Defaults	
		Good Customers(0)	Bad Customers(1)
Predicted Defaults	Good Customers(0)	47938	732
	Bad Customers (1)	18625	2206

* The loss occurred from the bad customers

Revenue Loss*: Reducing 30% revenue (Auto-approval)

- Revenue no model = **100%**
- Revenue with model = **70%**

Revenue Loss : 30%



Confusion Matrix		Actual Defaults	
		Good Customers(0)	Bad Customers(1)
Predicted Defaults	Good Customers(0)	47938	732
	Bad Customers (1)	18625	2206

* The revenue loss is occurred by wrongly identified "bad" to the good customers