Credit Scorecard Model Using Logistic Regression Study Case: Home Credit

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PART ONE

01

Business Understanding

01 Business Understanding

HOME CREDIT

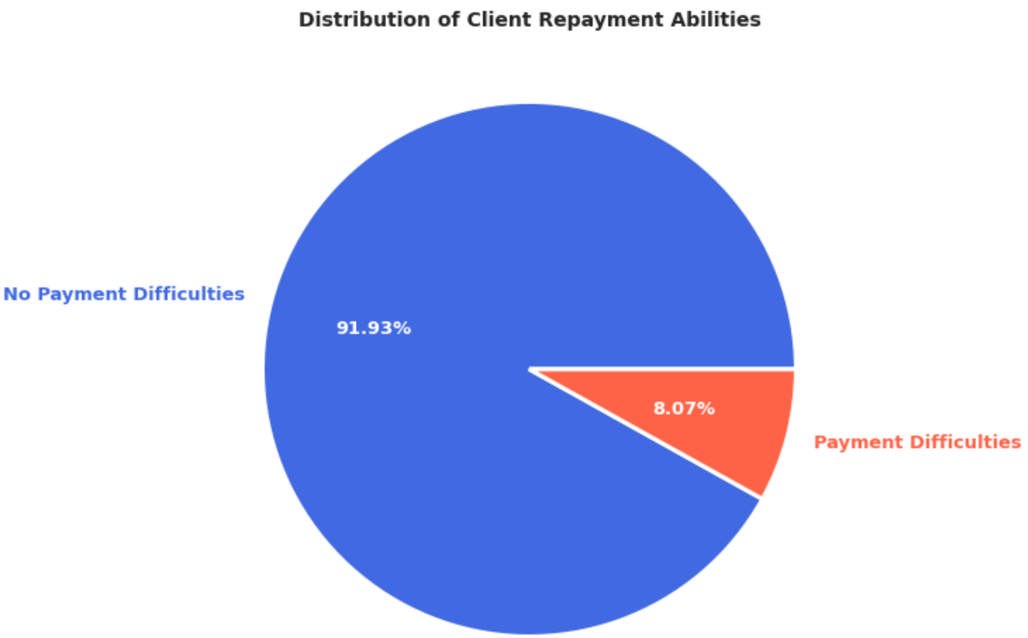
Background

Founded in 1997, Home Credit is an international consumer finance provider with operations in eight countries. Home Credit focus on responsible lending model empowers underserved customers with little or no credit history to access financing, enabling customers to borrow easily and safely, both online and offline.

01 Business Understanding

Dataset Overview

- There are about 91% (282,686 applicants) loans which indicates that client did not had any problems in repaying the loan in given time.
- While 9% of the total loans (24,825 applicants) involved the clients having problems in repaying the loan.



01 Business Understanding

HOME CREDIT

Problem Statement

A major challenge for banks and other finance lending agencies is to decide for which candidates to approve loans. In order to make sure this underserved population has a positive loan experience, Home Credit makes use of a variety of alternative data to predict their clients' repayment abilities.

Business Objectives

Create a credit scoring system where the inputs are various features describing the financial and behavioral history of the loan applicants, in order to automatically predict whether the loan will be repaid or defaulted.

HOME CREDIT

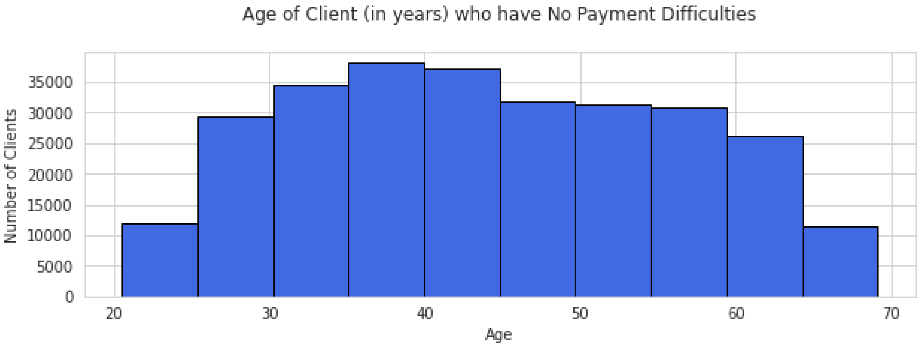
PART TWO

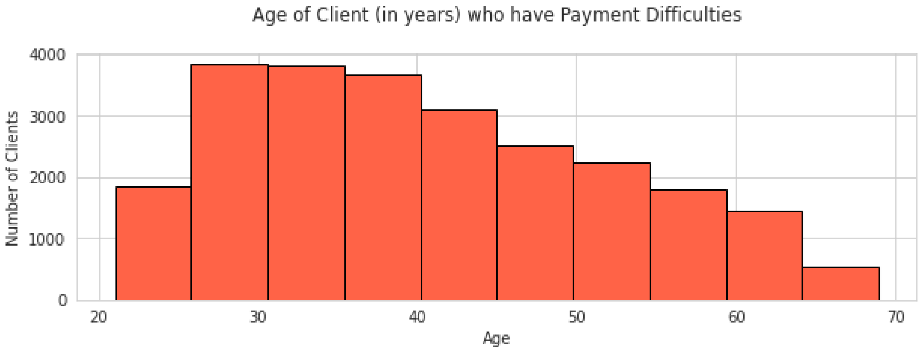
02

Business Insights

02 Business Insights

HOME CREDIT

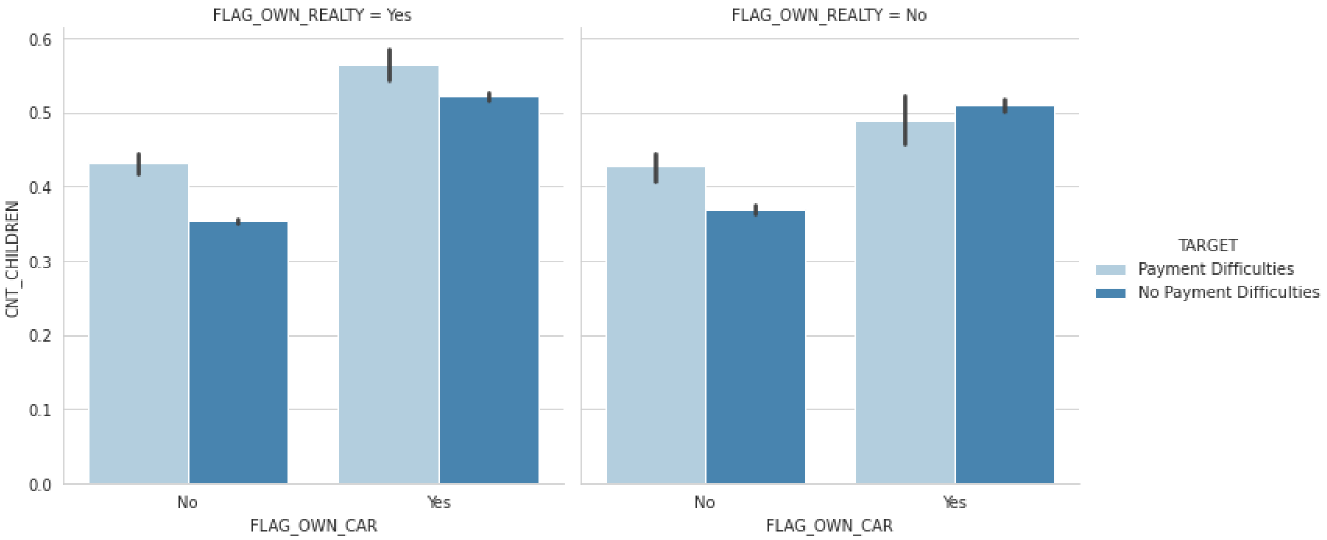




Clients who have no payment difficulties are client in the range of 35-45 years. While clients who have payment difficulties are client in the range of 25-35 years.

02 Business Insights

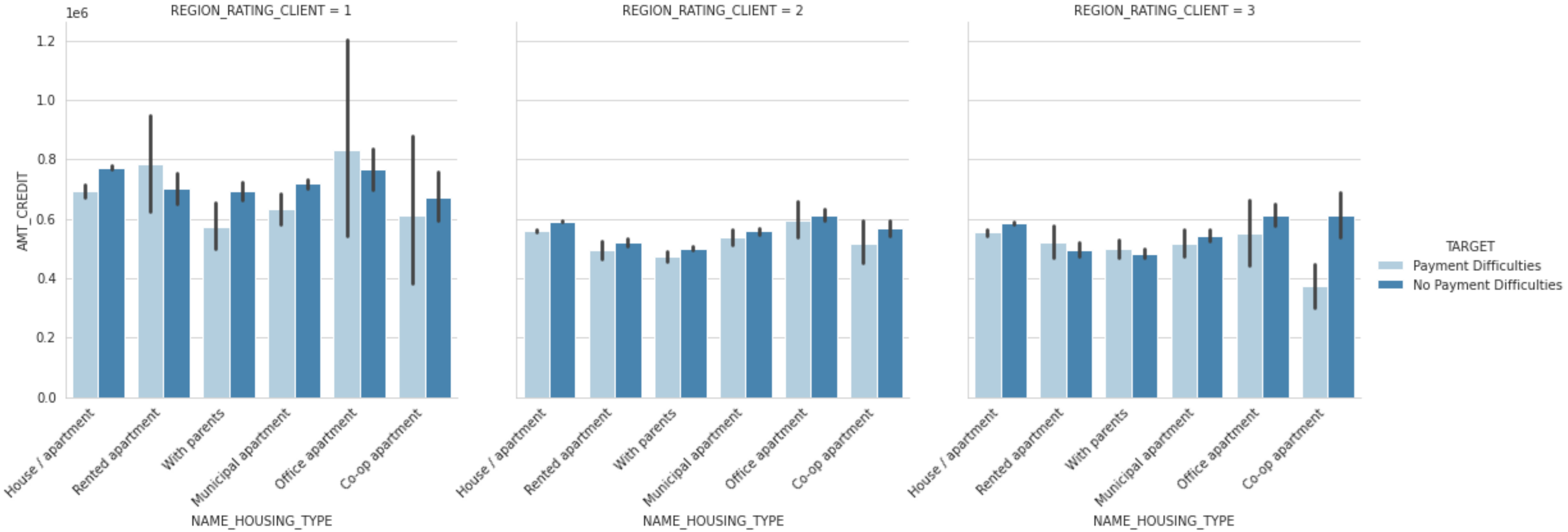
HOME CREDIT



Clients who own a car and a house/flat have a problem repaying the loans for a high number of children compared to clients who do not own houses/flat

02 Business Insights

HOME CREDIT



Clients who lives in rented apartment and office apartment and their region have a rating of 1, have a problem repaying the loans compared to client in region with rating of 2 or 3.

PART THREE

03

Data Processing

HOME CREDIT

03 Data Processing

Data Cleansing

Check Data Duplicates

Check Missing Values

Drop Feature

Simple Imputer Median.

Feature Selection

Data Splitting (80:20)

Categorical Data (Chi-Square)

Numerical Data (ANOVA)

Feature Engineering

Information Value (IV)

Weight of Evidence Binning

Weight of Evidence Transform

Modeling and Evaluation

Logistic Regression

Class Weight = Balanced

AUROC

PR Curve

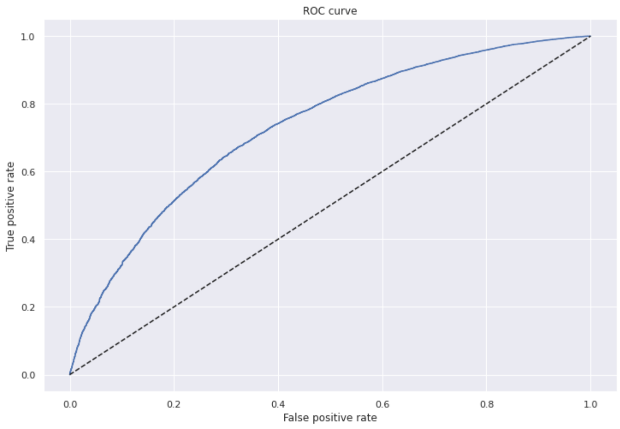
KS Statistics

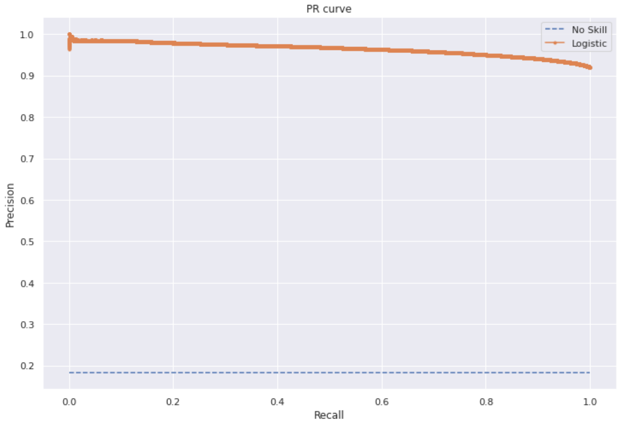
PART FOUR

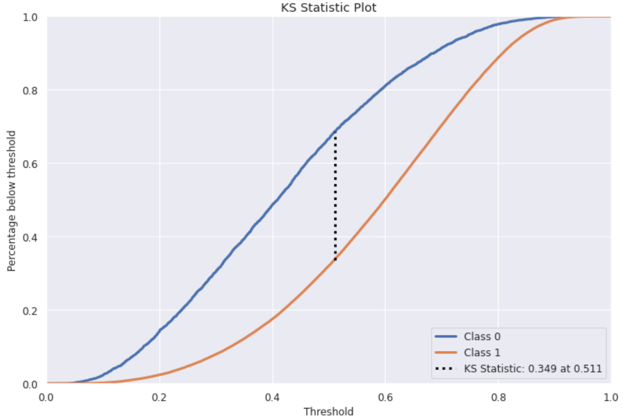
04

Data Modeling

04 Data Modeling







Model Result

Models	MEAN AUROC	GINI
Random Forest	0.6578	0.3155
Decision Tree	0.5351	0.0702
Logistic Regression	**0.7310**	**0.4620**

Based on AUROC score 0.7310, PR AUC score 0.9642, and, KS score 0.349, the Logistic Regression model is considered as a good performance model.

PART FIVE

05

Credit Scorecard

HOME CREDIT

Using FICO Score

A FICO score is a credit score created by the Fair Isaac Corporation (FICO). Lenders use borrowers' FICO scores along with other details on borrowers' credit reports to assess credit risk and determine whether to extend credit. Most credit scores have a 300-850 score range. The higher the score, the lower the risk to lenders.

05 Credit Scorecard

HOME CREDIT

Threshold = 0.05

Accept Score	N Approved	N Rejected	Approval Rate	Rejection Rate
560.0	39840	21663	0.647773	0.352227

Best Threshold

Accept Score	N Approved	N Rejected	Approval Rate	Rejection Rate
512.0	55663	5840	0.905045	0.094955

We will choose the best threshold with accept score 512 to avoid higher rejection rate but will monitoring model's performance in production.

Setting Loan Approval Cut-offs

Base (Intercept) = 560

Min Score = 300

Max Score = 850

Threshold = 0.5

Best Threshold = 0.29682

Accept Threshold = 512

Application Test = 61503 Applicants

Model = Logistic Regression

05 Credit Scorecard

Scorecard Result

Feature	Specific Feature	Score
CODE_GENDER	Male	-10
	Female or XNA	10
NAME_EDUCATION_TYPE	Academic degree	60
	Higher education	3
	Incomplete higher	-9
	Lower secondary	-31
	Secondary / secondary special	-21
NAME_FAMILY_STATUS	Single or Unknown	-2
	Civil marriage	-4
	Married	7
	Separated	-3
	Widow	3
NAME_INCOME_TYPE	Businessman or Commercial Associate	8
	Pensioner or Maternity leave	7
	Student or Unemployed	-40
	State servant	22
	Working	3
REG_CITY_NOT_LIVE_CITY	0	7
	1	-6
FLAG_DOCUMENT_3	0	9
	1	-8

REGION_RATING_CLIENT_W_CITY	0	0
	1	18
	2	9
REGION_POPULATION_RELATIVE	<0.0147	2
	0.0147-0.0292	1
	0.0292-0.0436	-2
	0.0436-0.0581	1
	>0.0581	-1
YEAR_LAST_PHONE_CHANGE	<2	-7
	2-4	3
	4-6	2
	6-8	5
	8-10	5
	>10	0
YEAR_BIRTH	<30	-2
	30-40	-10
	40-50	-2
	50-60	6
	>60	8
AMT_CREDIT	<846000	-4
	846000-1647000	0
	1647000-2448000	9
	2448000-3249000	3
	>3249000	-7

YEAR_ID_PUBLISH	<4	-11
	4-8	-6
	8-12	-4
	12-16	4
	>16	17
YEAR_REGISTRATION	<17	-3
	17-34	0
	34-51	-3
	>51	6
EXT_SOURCE_2	<0.0855	-53
	0.0855-0.171	-35
	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	21
	0.684-0.769	38
	>0.769	59
EXT_SOURCE_3	<0.0901	-68
	0.0901-0.18	-49
	0.18-0.269	-33
	0.269-0.359	-14
	0.359-0.448	-1
	0.448-0.538	5
	0.538-0.627	26
	0.627-0.717	36
	0.717-0.806	48
	>0.806	51

05 Credit Scorecard

HOME CREDIT

Name: Novrizal Roynanda		Score Calculation
Base Score		560
CODE_GENDER	Male	-10
NAME_EDUCATION_TYPE	Academic Degree	60
NAME_FAMILY_STATUS	Single	-2
NAME_INCOME_TYPE	Working	3
REG_CITY_NOT_LIVE_CITY	0	7
FLAG_DOCUMENT_3	0	9
REGION_RATING_CLIENT_W_CITY	2	9
REGION_POPULATION_RELATIVE	0.0600	-1
YEAR_LAST_PHONE_CHANGE	7	5
YEAR_BIRTH	26	-2
AMT_CREDIT	800000	-4
YEAR_ID_PUBLISH	5	-6
YEAR_REGISTRATION	5	-3
EXT_SOURCE_2	0.420	-5
EXT_SOURCE_3	0.420	-1
Total		**619**

Simulation

- If Total Score > Accept Threshold: Approve
- If Total Score < Accept Threshold: Reject
- Novrizal's Score (619) is higher than **Accept Threshold (512)**, then his loan would be Approved

HOME CREDIT

Visit My GitHub!

You can see the entire project documentation here from my github

@novrizalrnd