Prediction of the Applicant's Ability to Repay the Loan

Home Credit Default Risk

Yu Chun Peng, Chien-Chu Hsu, Chia-Yen Ho, Devansh Bhasin

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Abstract

HOME CREDIT

- An international non-bank financial institution
- Focuses on responsible lending to unbanked population with little or no credit history

People with insufficient credit history face...



Declined by bank



Exorbitant interest



Collateral required

Challenges for Home Credit



High risk due to lack of credit history

Time-consuming because of the scattered records



Objective

Find out the loan applicants who are capable of repaying a loan, given financial information from Home Credit and other sources.

There are 8 different sources of data

01

Application Train

The main table <u>includes</u> information about each loan application. Use this to train our models.



02

Application Test

The main table <u>excludes</u> information about each loan application. Use this to test our models.



03

Bureau Data

All applicant's previous credits provided by other financial institutions from Credit Bureau.



04

Bureau Balance Data

The monthly balances of previous credits in the Credit Bureau.



There are 8 different sources of data

05

Previous Application

Applicant's previous loan applications with Home Credit.



06

Cash Balance

Point of sales and cash loans that the applicant had with Home Credit.



07

Installments Payments

Repayment data for each installments of credit with Home Credit.



08

Credit Card Balance

Previous credit cards loans that the client applicant with Home Credit.



Data Preprocessing



Create features

The process of creating features based on our domain knowledge



Encoding the Categorical Variable

The process of converting categorical data into integer format



Imputation of Missing Value

The process of replacing missing data with substituted values

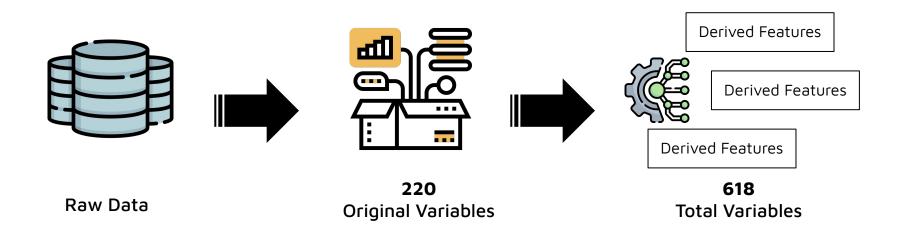


<u>Aggregation</u>

The process of aggregating data sets together using min, max, mean, and standard deviation

Feature Engineering

New features were created based on our estimate of impact of default-rate:



Methodology

Logistic Regression

is easy to implement yet provides great training efficiency in some cases. It makes no assumptions about distributions of classes in feature space.

XGBoost

is an optimized library for regularized distributed gradient boosting designed to be highly efficient, flexible and portable.

LightGBM

is a fast, distributed, high-performance gradient boosting framework that uses a tree-based learning algorithm.

Catboost

implements symmetric trees, thus helping in decreasing prediction time.

Stacking

is a model-centric ensemble model that can combine the predictions from multiple machine learning models.

Model Results

Models	AUC Score
Logistic Regression	0.71174
XGBoost	0.79111
LightGBM	0.77594
Catboost	0.78778
Stacking (XGBoost+LightGBM+Catboost)	0.79316

We use AUC Score as the metric

The predictive performance of a model can be quantified in terms of the area under the ROC curve (AUC), which lies in the <u>range [0,1]</u>. And a <u>higher</u> value of it means better accuracy.

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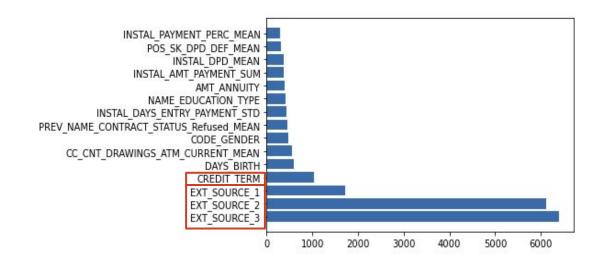
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Feature Importance

- **External Resources** are top 3 key contributors
- CREDIT_TERM also stands out. This is a feature we created using Loan annuity divided by Credit amount of the loan



Limitations



Limited Time

Didn't have enough time to explore all the variables completely before we fully understand the business domain knowledge



Missing Values

Some features used for building our model contained over 60% missing records

Future Work

- Do better at feature engineering, imputation of missing values, and handling of extreme values by <u>developing business understanding</u>
- Implement <u>advanced techniques</u>, such as Neural Network
- 3. Consider the **cost of error** when evaluating the performance of models



Thank You