HOME CREDIT DEFAULT RISK

A Machine Learning Approach

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Github repository: https://github.com/HebaAladdin/Kaggle-home-credit-risk

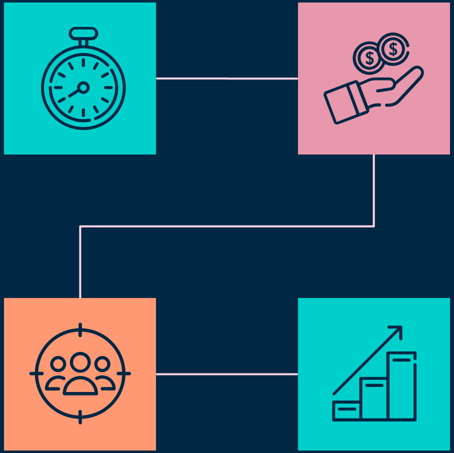
BUSINESS PROBLEM

HOME CREDIT

Default risk is the chance that companies or individuals will be unable to make the required payments on their debt obligations. In other words, credit default risk is the probability that if you lend money, there is a chance that they won't be able to give the money back on time.

Lenders and investors are exposed to default risk in virtually all forms of credit extensions. To mitigate the impact of default risk, lenders often impose charges that correspond to the debtor's level of default risk. A higher level of risk leads to a higher required return

VALUE PROPOSITION



FASTER PROCESS

Shorter lending process

DECREASE EXPOSURE

Decrease exposure that leanders are exposed to

INCREASE BORROWER BASE

Trust more applicants and unbanked population

INCREASE PROFIT

Lend more gain more

APPROACH

01

DATA ANALYSIS & EDA

Exploaring the dataset to find patterns and business insights

02

FEATURE ENGINEERING & FEATURE SELECTION

03

MODELING

Training machine learning models

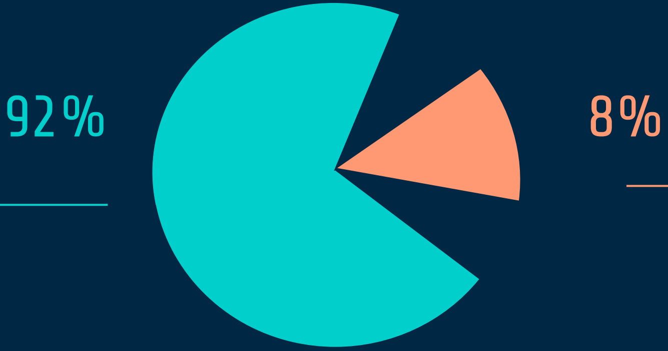
UNDERSTANDING THE PROBLEM

REPAY

Applicants with no payment delays on their first few installments.
TARGET = 0

DEFAULT

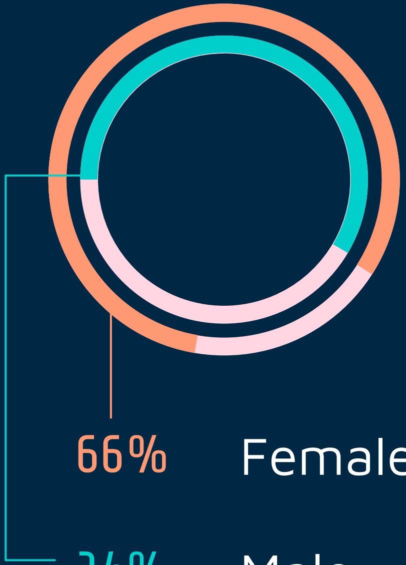
Applicants with payment difficulties on their first few installments.
TARGET = 1



300,000+

KEY INSIGHTS & FINDINGS

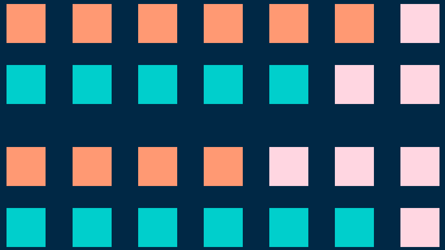
BORROWER GENDER



66% Female

34% Male

DEFAULT



Repay on time

93%

90%

Default

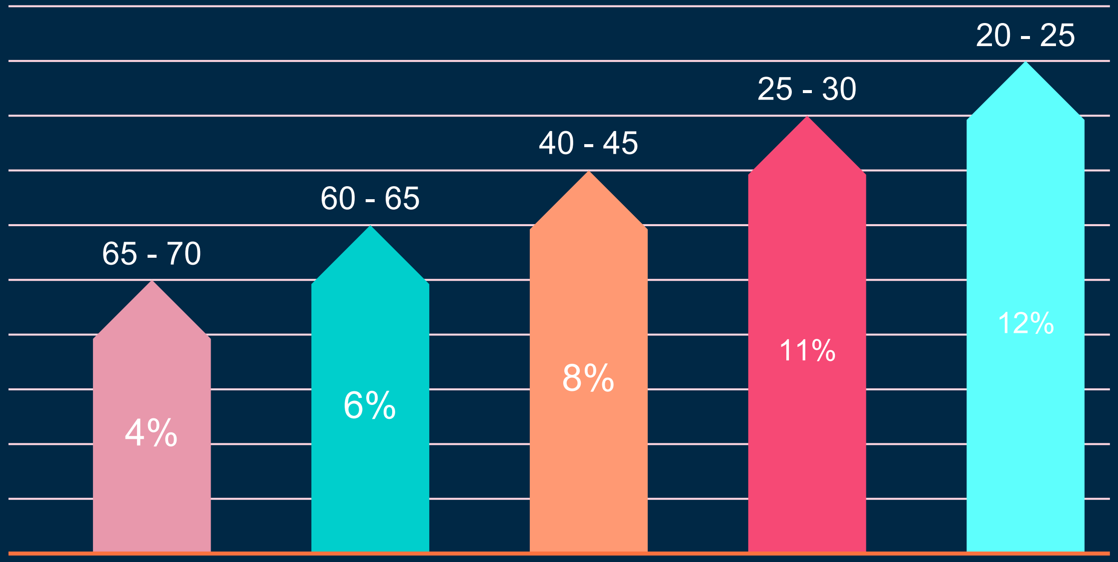
7%

10%

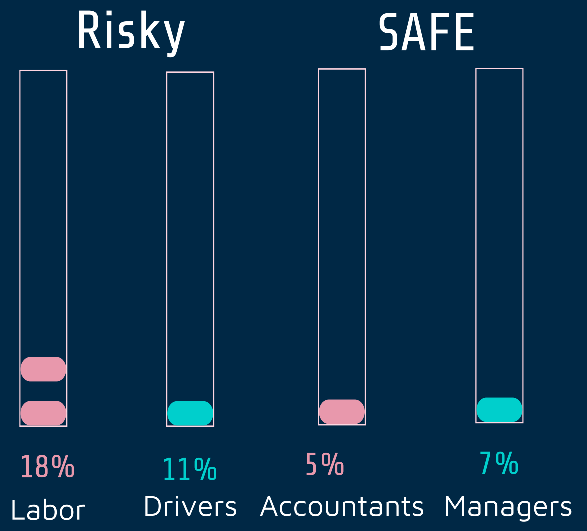
300,000+

Applicants

KEY INSIGHTS & FINDINGS



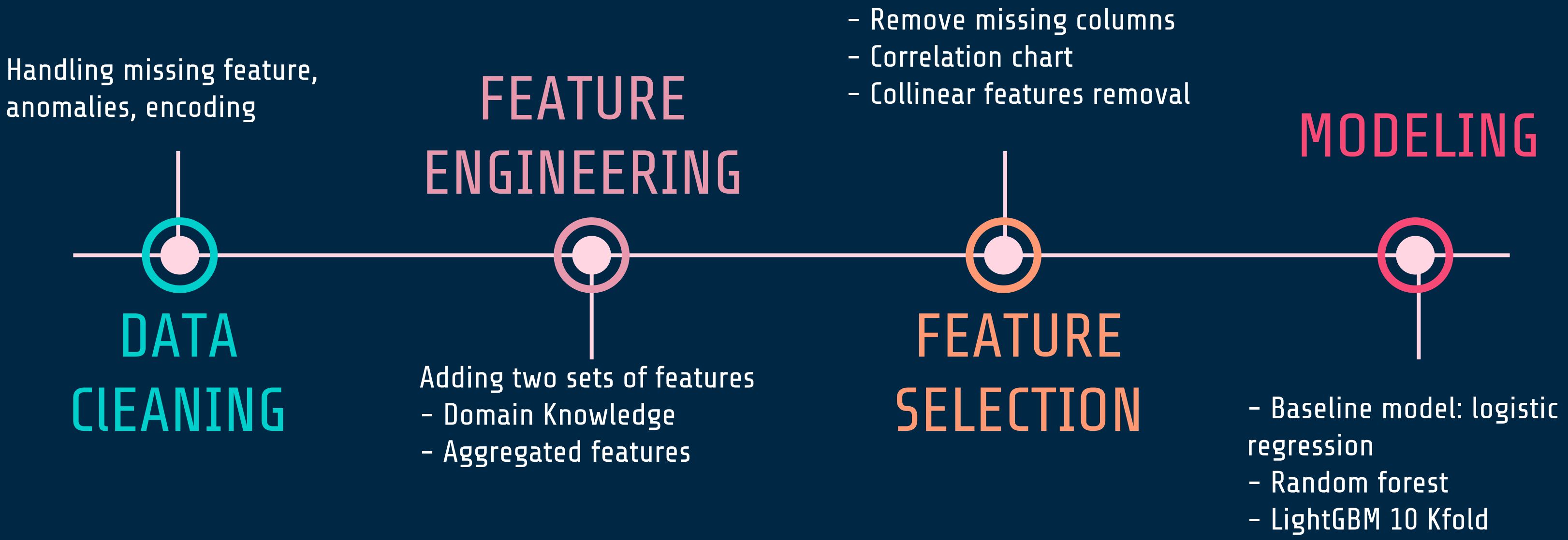
BORROWER AGE GROUP VS FAILURE TO REPAY



BORROWER JOB VS DEFAULT

For more insights check the EDA notebook

OUR PIPELINE



DATA CLEANING

Handling missing feature, anomalies, encoding

FEATURE ENGINEERING

Adding two sets of features
- Domain Knowledge
- Aggregated features

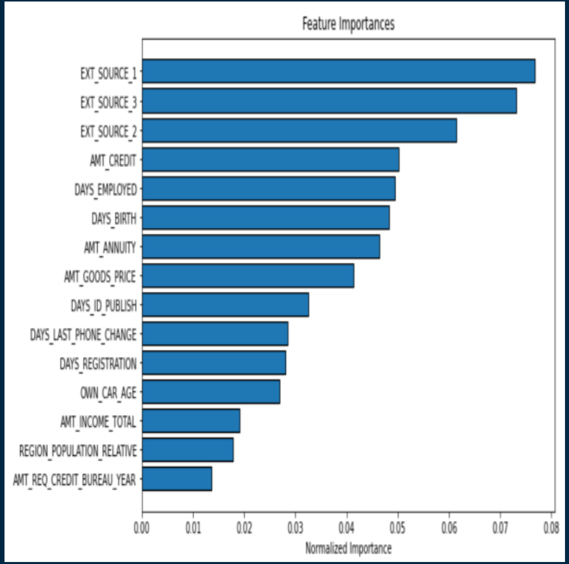
FEATURE SELECTION

- Remove missing columns
- Correlation chart
- Collinear features removal

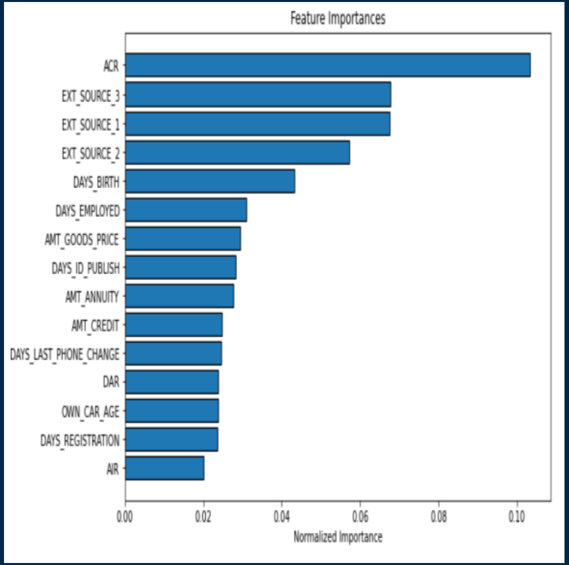
MODELING

- Baseline model: logistic regression
- Random forest
- LightGBM 10 Kfold

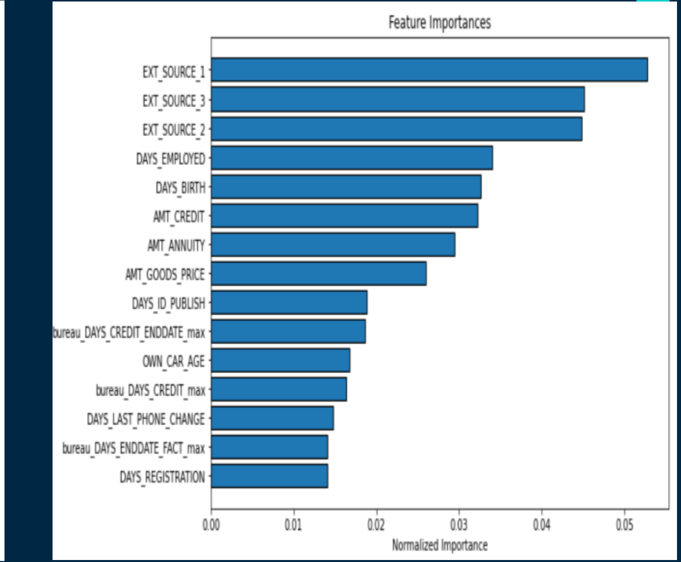
MODELING



LightGBM on raw Data



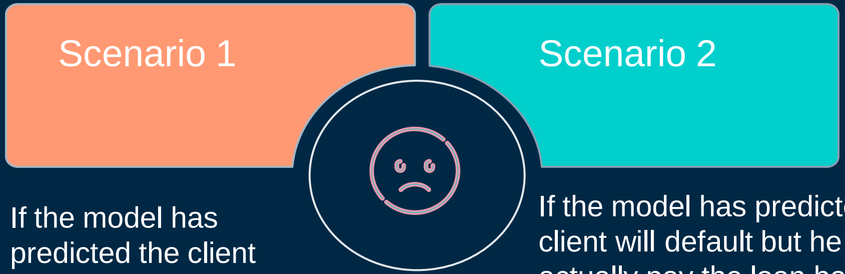
LightGBM with Domain knowladge features



LightGBM with Aggregated features

RESULTS

- The metric we choose to evaluate our models is Receiver Operating Characteristic Area Under the Curve (ROC AUC, also sometimes called AUROC) due to the high unbalanced labels.
- Home credit will face losses if the model prediction is wrong in two scenarios:

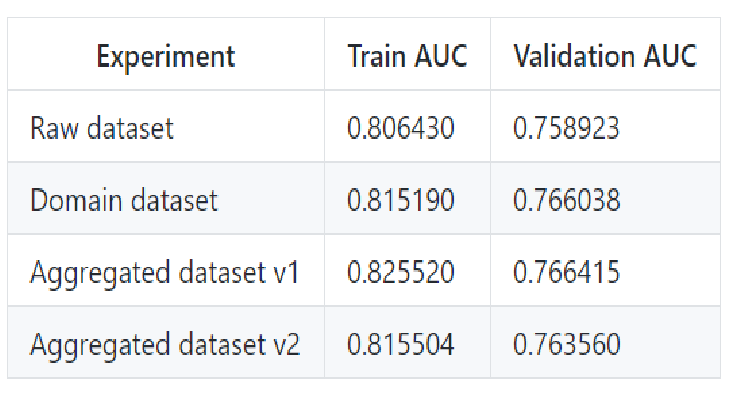


Scenario 1

Scenario 2

If the model has predicted the client will repay the loan but actually he has defaulted

If the model has predicted the client will default but he can actually pay the loan back deserving candidate not getting a loan, bank loss in return interest



Experiment	Train AUC	Validation AUC
Raw dataset	0.806430	0.758923
Domain dataset	0.815190	0.766038
Aggregated dataset v1	0.825520	0.766415
Aggregated dataset v2	0.815504	0.763560

LightGBM 10 k-fold

THANKS

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