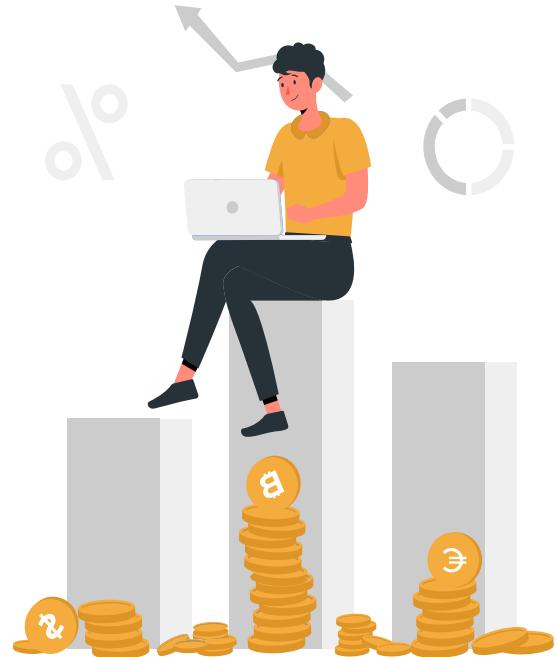


HOME CREDIT

Default Risk Assessment

Yuri Croci

Personal Project



Project Overview

Context & Challenge:

- Home Credit provides loans to customers with limited or no credit history, typically rejected by traditional banks.
- Traditional credit scoring is insufficient, making it difficult to identify creditworthy applicants and manage default risk.

Project Objective:

- Build a predictive model to assess loan default risk and inform lending decision.
- Segment customers by risk level to enable differentiated lending strategy.

Data Overview

Dataset:

- 307,511 loan applications containing application details and applicant profile characteristics.
- Additional data from external sources including credit bureau history and previous Home Credit applications, decisions, and transactions.

Key characteristics:

- Highly unbalanced class with 8% defaulted application over the 92% repaid.
- High data sparsity with complex missing value patterns where some missing information carries predictive signal.
- Mixed data types including categorical, numerical, and binary variables.

Home Credit Overview



Loan Performance Overview

Overview

Model

Risk Segment

8.07%

Default Rate

\$599.0K

Average Loan Amount

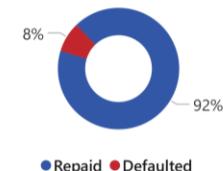
307.51K

Number of Loans

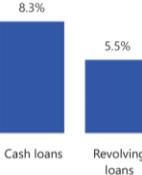
\$184.2bn

Total Loan Volume

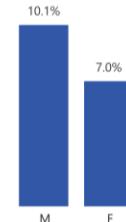
Default Status Distribution



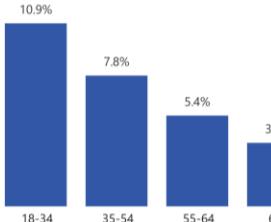
Default % by Contract Type



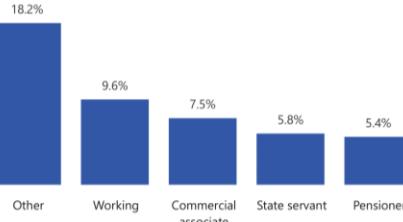
Default % by Gender



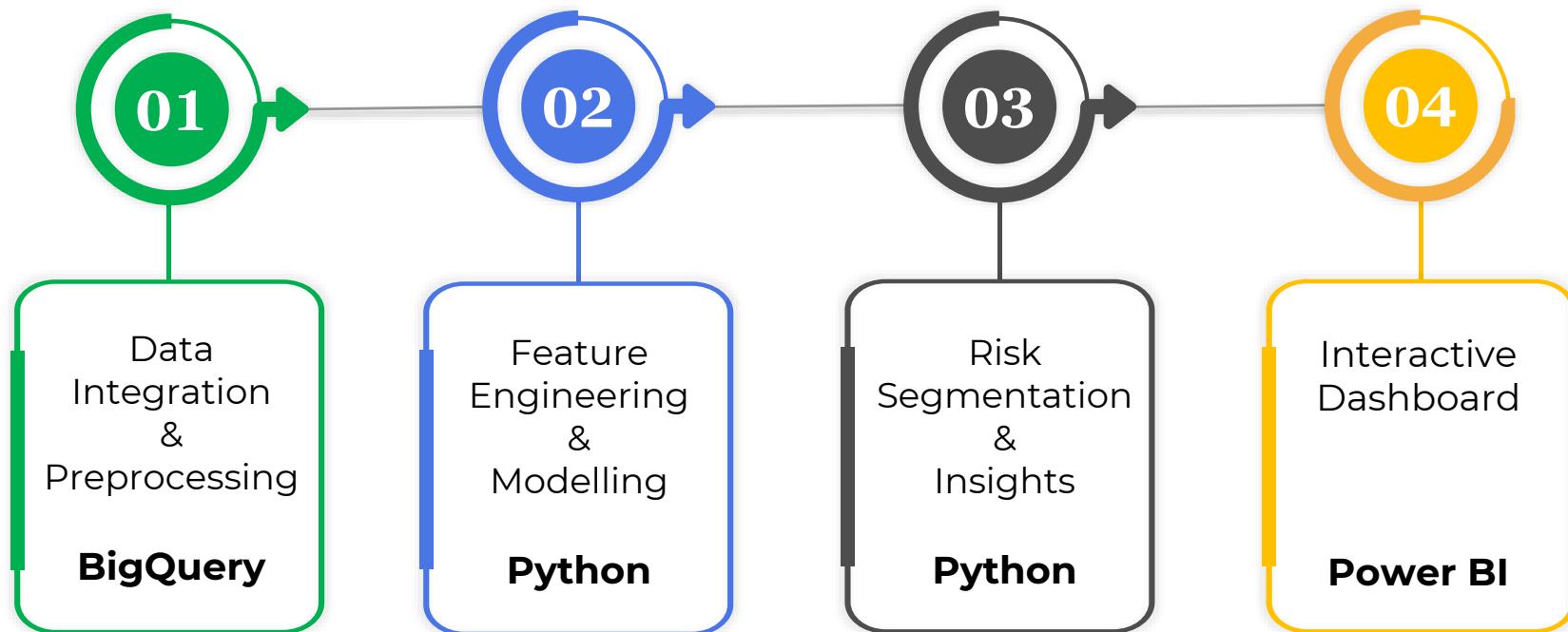
Default % by Age Group



Default % by Income Type



Methodology Overview



Data Preparation & Feature Engineering

Data Preparation:

- Data cleaning including outlier treatment, sentinel value normalization, and category consolidation.
- Missing value handling with informative flags, temporal feature transformation, and data type conversions.

Feature Engineering:

- Multi-table integration aggregating bureau and previous application data to construct historical credit behavior profiles.
- Feature selection using phi-k correlation for mixed variable types followed by multicollinearity analysis, reducing from 100+ to 36 relevant features.

Modelling Development

Modelling Setup:

- 80/20 stratified split with cross-validation for hyperparameter tuning to ensure robust performance estimates.
- Baseline logistic regression compared against LightGBM for native handling of missing values and mixed data types.

Model Selection:

- Threshold optimization via cross-validation folds to prevent data leakage.
- Evaluation prioritizing recall and AUC given asymmetric costs of misclassification in default prediction.
- LightGBM selected for improved performance and computational efficiency.

Model Performance

HOME CREDIT Model Performance

Overview Model Risk Segment

Model: LightGBM (Gradient Boosted Trees)
Task: Binary Classification
Target: Loan Default Prediction

75.69%
Recall

17.94%
Precision

0.76
AUC

Decision Threshold
0.077

70.09%
Accuracy

29.01%
F1 Score

ROC Curve

The ROC Curve plot shows the relationship between the True Positive Rate (Y-axis) and the False Positive Rate (X-axis). The X-axis ranges from 0.0 to 1.0, and the Y-axis ranges from 0.0 to 1.0. A solid black curve represents the ROC Curve, starting at (0,0) and ending at (1,1). A dashed diagonal line represents the Random Classifier. A blue circle marks the CV Threshold at a False Positive Rate of approximately 0.077, corresponding to a True Positive Rate of approximately 0.82.

Dataset Split

train	80.0%
test	20.0%

Loan Decision Volume

Approved	203K
Rejected	105K

Key Predictive Features

Rank	Feature
1	ORGANIZATION_TYPE
2	EXT_SOURCE_1
3	EXT_SOURCE_3
4	EXT_SOURCE_2
5	AMT_CREDIT
6	YEARS_BIRTH
7	AMT_ANNUITY
8	OCCUPATION_TYPE
9	YEARS_EMPLOYED
10	YEARS_REGISTRATION

Risk Segmentation

Segmentation Approach:

- Four-tier risk classification with Very Low (<5%), Low (5-10%), Medium (10-20%), and High ($\geq 20\%$) based on model predicted probabilities of default.
- Feature profiling of the risk segment across demographic, employment, and credit dimensions.

Key Findings:

- Increasing average default rates across segments validating risk separation.
- Negative correlation between age, employment tenure, education level, and default risk.
- Positive correlation with prior loan refusals and multiple active bureau loans.

Risk Segment Analysis



Risk Segment Analysis

[Overview](#)[Model](#)[Risk Segment](#)

Risk segmentation by **predicted default probability**.
Decision threshold: 0.077 based on CV.

Segment definitions:

- **Very Low Risk:** < 5%
- **Low Risk:** 5-10%
- **Medium Risk:** 10-20%
- **High Risk:** ≥ 20%

8.07%

Default Rate

\$599.0K

Average Loan Amount

6.53

Years in Current Job

\$184.2bn

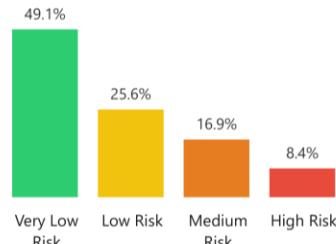
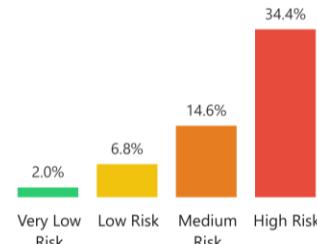
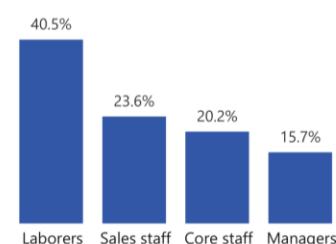
Total Loan Volume

43.94

Age

1.76

Bureau Active Loan

Risk Segment Distribution**Default Rate by Risk Segment****Organization Type Distribution**

Recommendations

1. **Streamline approval process** through automation for the Very Low Risk segment (49% of applications, 2.0% default rate) while concentrating manual screening resources on Medium and High Risk tiers requiring deeper evaluation.
2. **Implement risk-based pricing strategy** with differentiated interest rates and flexible repayment schedules across segments to enable approvals for higher-risk segments through appropriate risk compensation.
3. **Enhance credit evaluation workflows** by integrating insights on feature-risk relationships to support decision-making in borderline or uncertain application cases.