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Predicting Loan Default Risk for Home Credit

MSBA Practice Capstone | Fall 2025

AGENDA

- 01 Problem Overview
- 02 Modeling Approach
- 03 Key Drivers of Default
- 04 Bringing the Model to Life (Personas)
- 05 Business Impact/Implementation

Problem Overview

Home Credit wants to extend loans to underbanked customers

Challenge: Many applicants **lack traditional credit histories** → high uncertainty → financial risk

Goal: Build a model that predicts default risk to guide smarter approvals

The logo for Home Credit, featuring the words "HOME" and "CREDIT" in a bold, red, sans-serif font, stacked vertically. The logo is centered within a white square, which is itself centered on a magenta background.

Modeling Approach

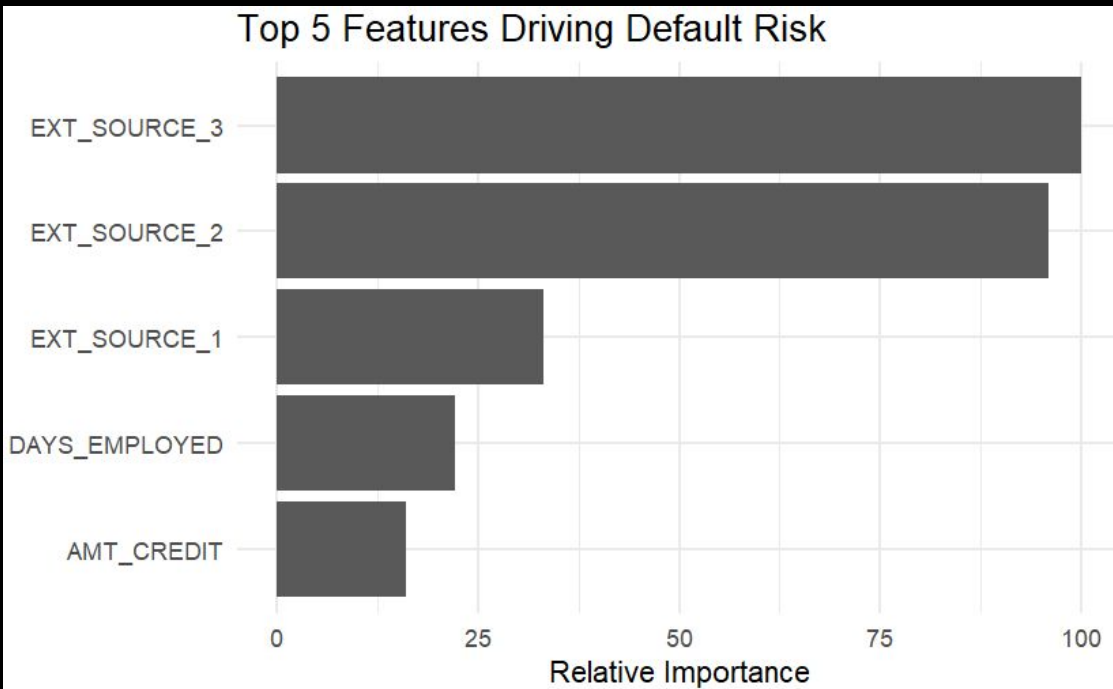
Model	Description	AUC
Logistic Regression (Baseline)	Benchmark	0.709
Regularized Logistic	LASSO/Ridge tuned	0.721
<u>Random Forest</u>	<u>Nonlinear ensemble</u>	<u>0.73399</u>
Neural Network	Basic feedforward	0.730
Logistic + CV	Cross-validated tuned version	0.722

Best model:
Random Forest
– strong
balance of
accuracy and
interpretability.

Key Drivers of Default

Top 5 Features:

1. EXT_SOURCE_3 – external credit score proxy
2. EXT_SOURCE_2 – external credit score proxy
3. EXT_SOURCE_1 – external credit score proxy
4. Days Employed
5. Amount of Credit



John vs. Jane

John (Rejected)

- **Income:** \$61,650
- **Credit Amount:** \$997,335
→ **Credit/Income Ratio**
= 16.18×
- **Income Type:** Pensioner
- **Education:** Secondary / secondary special
- **External Credit Score (EXT_SOURCE_3):**
Missing (no credit history)
- **Children:** 0
- **Age:** ≈ 59 years
- **Model Target: 1 → Defaulted**



Jane (Approved)

- **Income:** \$90,000
- **Credit Amount:** \$251,091
→ **Credit/Income Ratio**
= 2.79×
- **Income Type:** Pensioner
- **Education:** Secondary / secondary special
- **External Credit Score (EXT_SOURCE_3):** 0.894
(very high)
- **Children:** 0
- **Age:** ≈ 56 years
- **Model Target: 0 → Did not default**



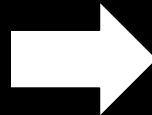
Projected Results

We want to Reject the riskiest 5% of applicants

Using a cutoff of 0.49

- Removes ~20% of defaulters
- Reduces default rate from 8% to ~6.9%
- Avoids ~\$16M in annual losses per 100k loans
- Approves 95% of applicants

Confusion matrix from our validation predictions



	Actual Default (1)	Actual Non-Default (0)
Predicted Default (1)	1022 (TP)	2054 (FP)
Predicted No Default (0)	4044 (FN)	54382 (TN)

Implementation & Monitoring

Implementation

- Integrate model in application review workflow
- Use probability threshold to approve/deny - riskiest 5% rejected (0.49 cutoff)

Monitoring

- Track AUC, drift, false positives quarterly
- Re-train every 6 months with new applicants

Evaluate performance by gender, age, and income groups

Next Steps

1



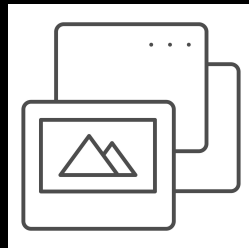
Conduct pilot
with 10K new
applicants

2



Test ensemble
stacking for
future
improvement

3



Build
dashboard to
monitor default
trends

4



Collaborate
with risk team
for operational
rollout

“Our model helps Home Credit extend loans confidently,
balancing inclusion with financial sustainability”

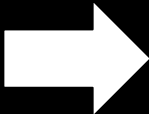
THANK YOU

Any questions?

Appendix

<u>Metric</u>	<u>Reject Top 5% (Cutoff = 0.494)</u>	<u>Reject Top 10% (Cutoff = 0.432)</u>
Applicants Rejected	5%	10%
Defaulters Removed (TPR)	~20%	~33%
Default Rate After Model	~6.9% (down from 8%)	~6.2% (down from 8%)
Approved Applicants	95%	90%
Annual Loss Avoided <i>(per 100k loans @ \$10k)</i>	~\$16M	~\$26M
False Positives (Good borrowers rejected)	~3.6%	~8%

10% Cutoff
confusion
matrix



	Actual Default (1)	Actual Non-Default (0)
Predicted Default (1)	1654 (TP)	4497 (FP)
Predicted No Default (0)	3412 (FN)	51939 (TN)

Appendix Cont.

Total defaulters: $TP+FN=1022 + 4044 = 5066$

Captured defaulters = 1022

Capture rate: $1022 / 5066 = 0.2018 \approx 20.2\%$

Rejecting the riskiest 5% removes $\sim 20\%$ of defaulters

False positives (FP): 2054

Total non-defaulters: $2054 + 54382 = 56436$

FP rate: $2054 / 56436 = 0.036 = 3.6\%$

Only $\sim 3.6\%$ of safe applicants get rejected

Approvals = Pred 0 group = $4044 + 54382 = 58426$

Defaults remaining = FN = 4044

New effective default rate: $4044 / 58426 \approx 0.0692 = 6.9\%$

Default rate goes from 8% to $\sim 6.9\%$

5% cutoff math explained

	Actual Default (1)	Actual Non-Default (0)
Predicted Default (1)	1022 (TP)	2054 (FP)
Predicted No Default (0)	4044 (FN)	54382 (TN)

Baseline loss (8% default):

$100,000 \text{ loans} \times 8\% \times \$10,000 = \$80\text{M}$

Reduction: $\approx 20\%$ of defaults removed

Loss avoided:

$80\text{M} \times 0.20 = \16M

Savings $\approx \$16\text{M}$ per 100,000 loans