

# How Capable is an Applicant of Repaying a Loan?

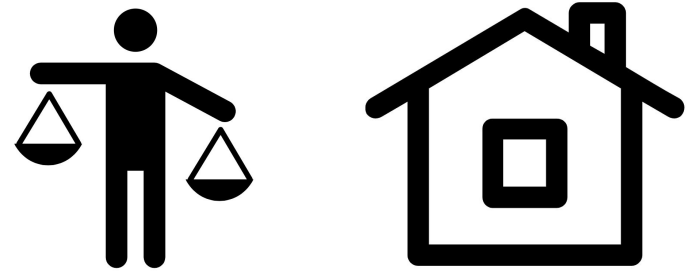
Home Credit Default Risk Results

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# Roadmap

1. Prediction Problem
  - a. Company & Customer perspectives
2. Analysis Overview
  - a. Data sources
  - b. Model results
3. Conclusion



**HOME  
CREDIT**

# How Capable is an Applicant of Repaying a Loan?



Higher risk applicants with poor credit history **adds risk to the company**

	Member can pay	Member will have difficulty paying
Model approves mortgage	\$4,548	-\$26,895
Model denies mortgage	-\$1,000	\$0

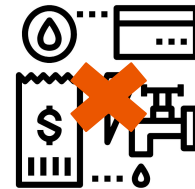
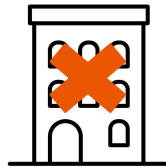
## Sources:

1. Goodman, L., & Zhu, J. (2015, February). *Loss Severity on Residential Mortgages* [PDF]. Washington, DC: Urban Institute.
2. Olick, D. (2020, September 10). Mortgage lenders just saw record profit, and expect to do better in the next quarter. Retrieved from <https://www.cnbc.com/2020/09/10/mortgage-lenders-just-saw-record-profit-and-expect-to-do-better-in-the-next-quarter.html>

# How Capable is an Applicant of Repaying a Loan?



**Individuals** with poor credit history **also** face higher risk



# Individuals face increased risk of falling to predatory lenders

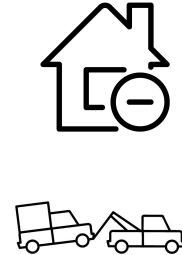
Unfair and abusive lenders profit from loan terms



High late fees



Penalty interest



Collateral



Almost 1 in 9 Americans struggle to get a home loan

26 million + 10 million = 36 million

Are credit **invisible** <sup>1</sup>

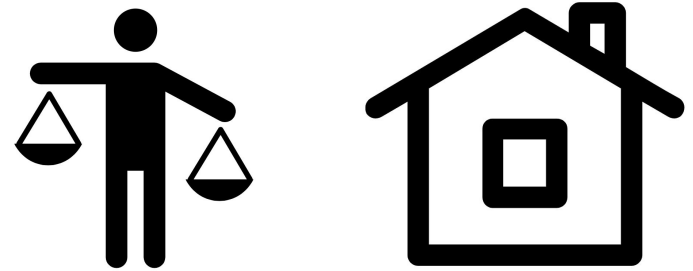
Have insufficient credit  
to get a loan <sup>1</sup>

Struggle to get a home loan



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**We use alternative data to predict repayment abilities**

# 8 datasets

## #1, 2 Application Train and Test

- Main table including the target variable (whether or not the client has payment difficulties)

## #3 Bureau Data

- Data on previous loans a client received

## #4 Bureau Balance Data

- Monthly balance of credits in the Bureau
- Gives insight into client's behavior





**We use alternative data to predict repayment abilities**

# 8 datasets

## **#5** Previous Application

→ Client's previous loan applications with Home Credit

## **#6** Cash Balance

→ Client's loan repayment history

## **#7** Instalments Payments

→ Payment data for each instalment of credit

## **#8** Credit Card Balance

→ Monthly balance of credit card loans

  
We engineer more powerful new variables

220  
Original  
Variables



Recent Monthly Credit Payments

New Credit to Income Ratio

Current Credit Down Payment

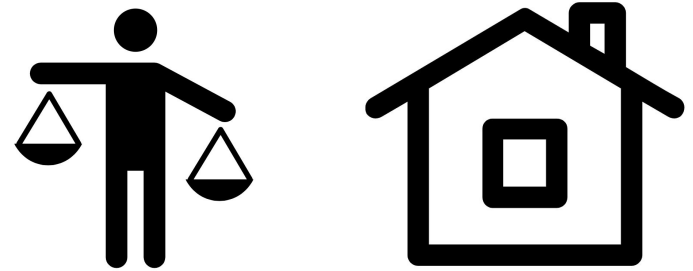
⋮

1054 additional variables



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We try various models to maximize predictive power

Algorithm	Recall
Logistic Regression	0.002
SVM	0.052
k-NN	0.062
Decision Tree	0.125
<b>LightGBM</b>	<b>0.452</b>

The best performer was:

LightGBM



## We return to the incurred risk associated with incorrect predictions

	Member can pay	Member will have difficulty paying
Model approves mortgage	\$4,548	-\$26,895
Model denies mortgage	-\$1,000	\$0



## Model Limits Cost of Mortgage Defaults

Expected  
Value =

Costs or Benefit of Outcome

\$4,548	-\$26,895
-\$1,000	\$0

X

Likelihood of Outcome

91.6%	7.7%
0.3%	0.4%



## Model Limits Cost of Mortgage Defaults

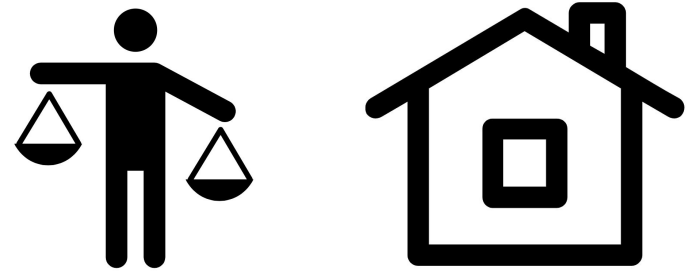
Type of Classifier	Expected Value Per Customer	Improvement with Model
Best Model	\$2,078.82	--
Give Everyone a Mortgage	\$1,990.75	4.4%

If **100,000** customers are served annually by Home Credit, the additional profit each year would be **over \$8.8 million gain**



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**We drive profit and open doors for people with less opportunity**

**\$8.8 Million**

Help people who are usually not able  
to enter the credit market do so



Thank you for your attention. Questions?



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For more technical details, check out our [GitHub](#)