SUSTAINABLE DEVELOPMENT GOALS

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Supporting MSMEs by Strengthening Socially Driven MFIs through Crowdfunded Microfinancing

Aviles | Mamangun | Reguyal | Vergara

14 Dec 2023

Capstone Project

WHAT ARE MSMEs?

Micro, Small, and **Medium** Enterprises

Latest data shows that...

Of all business in the PH are MSMEs

99%

**Philippine Department of Trade and Industry (DTI)*

Economic Impact of PH MSMEs

36%
Gross Value Added as of 2022

25%
Of all exports made in 2022

63%
Of Total Employment in the PH

Philippine Department of Trade and Industry (DTI)

MSME Day, June 27, 2023

“Micro-, Small and Medium-sized Enterprises Are Key to an Inclusive and Sustainable Future”

Pamela Coke-Hamilton
Executive Director,
International Trade Centre (ITC), UNCTAD

ONE OF THEIR BIGGEST ISSUES:

ACCESS TO CREDIT

Percentage of MSMEs in emerging economies that **lack access to credit.***

70%

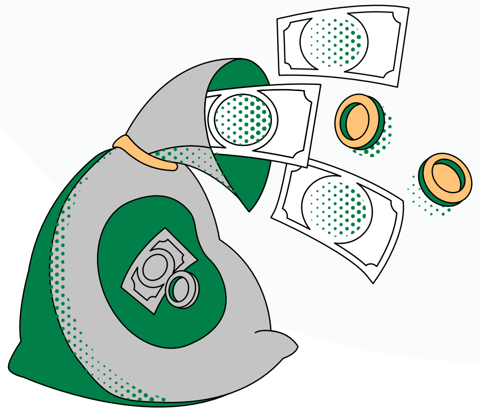
Clark Ke Liu, UN Policy Brief

Common reasons why MSMEs lack access to credit.

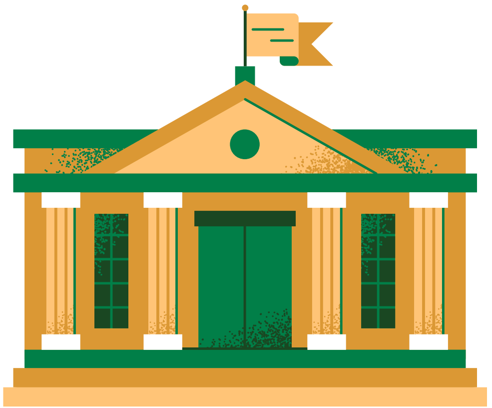
- Poor credit history
- Insufficient collateral
- Considered high-risk borrowers
- Unable to bear high-interest rates at short terms

Where do MSMEs get their financing?

Personal Financing



Informal Lending



Traditional Microfinancing

Crowdfunded Microfinancing

Non-traditional Approach

Traditional Microfinancing

"Often backed by **large banks**, has **rigid structures** and has been criticized for veering toward **profit-seeking**"

Crowdfunded Microfinancing

Non-traditional Approach

"Offers flexibility through small investors, expediting funding and catering to diverse MSME needs"

Make a loan, change a life.

Crowdfunding on kiva

Asunta wants to borrow $1,950 to expand her textile business

How does kiva work?

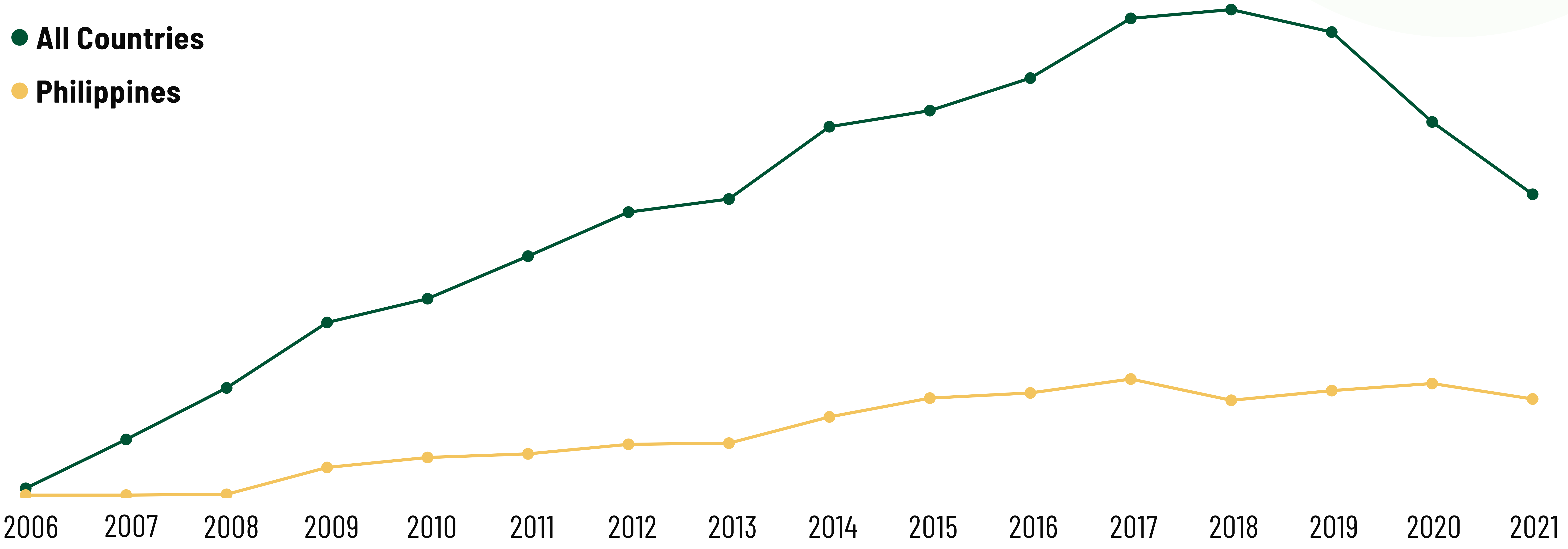
Five investors from the US want to help fund the loan!

How does kiva work?

No. of Loans

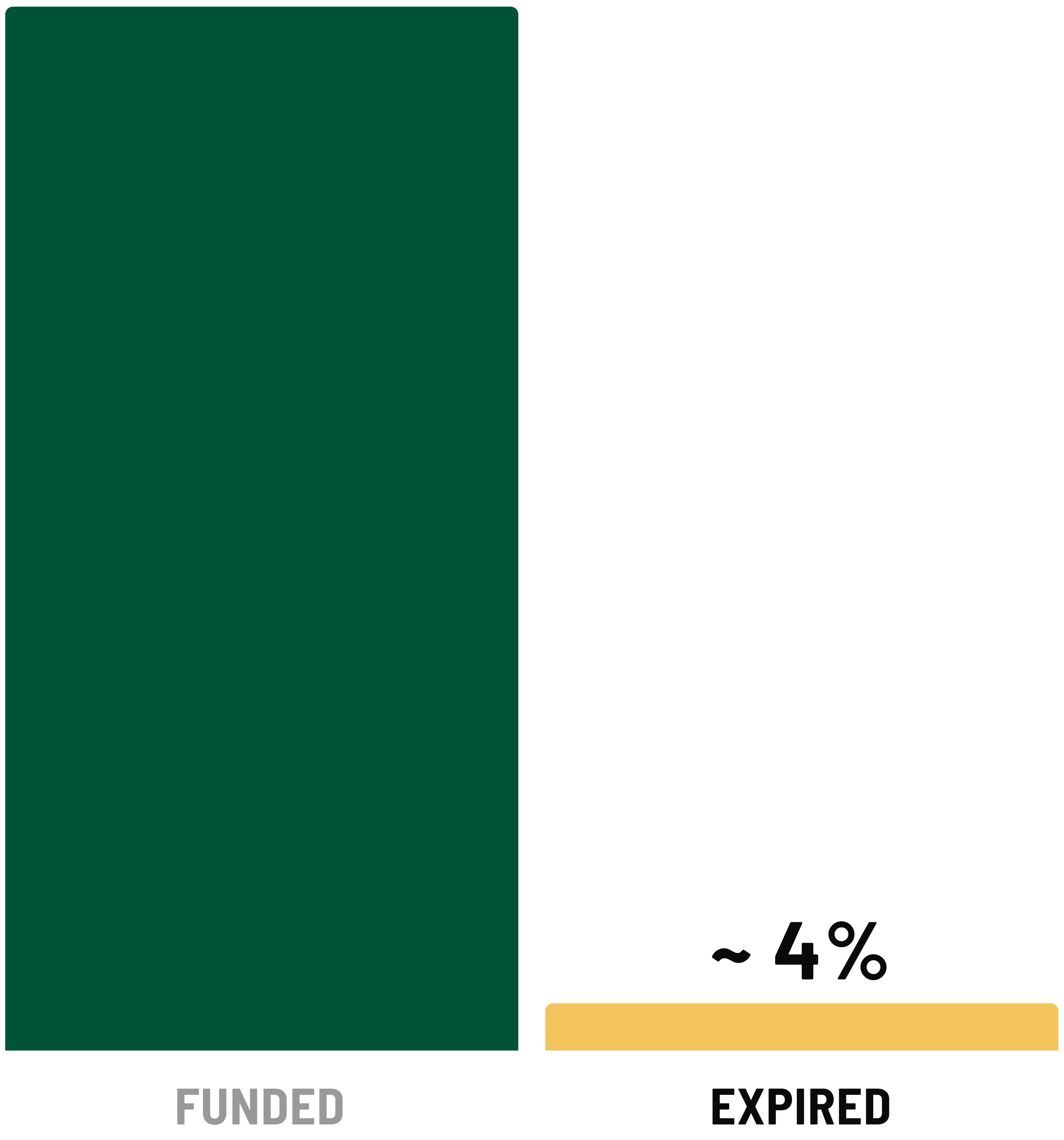
Year on year

No. of loans posted on Kiva shows a **steady increase** throughout the years.



Not all loans posted are funded.

These expired loans represent businesses that miss crucial funding opportunities.



How can we help PH loans increase their chances of getting successfully funded on Kiva?

Problem Statement

Study Objectives

01 Identify Key Features

Determine the most important features that affect whether a loan profile gets funded or not.

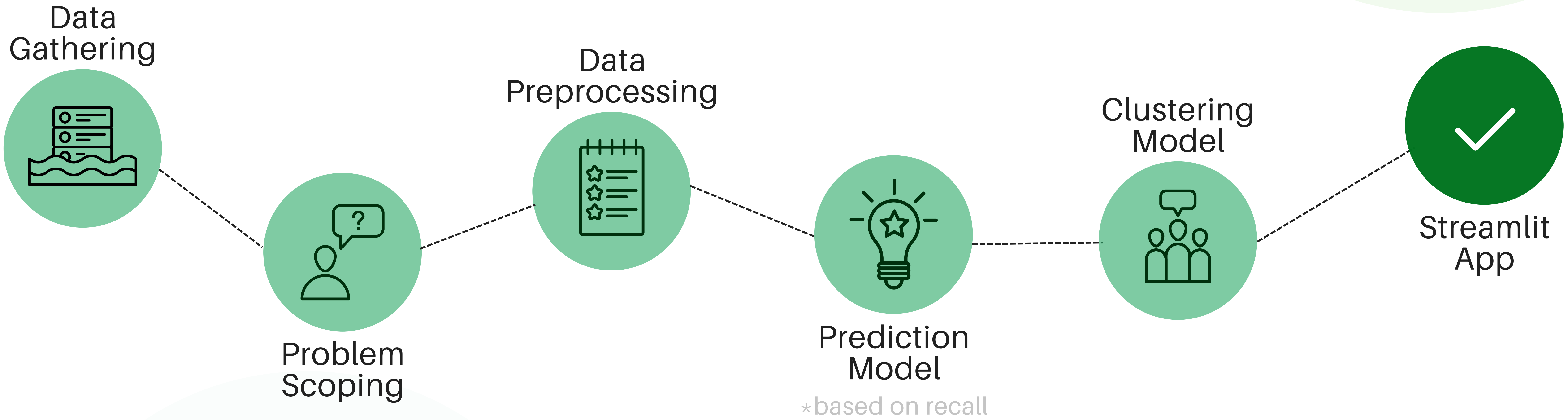
02 Select Best Prediction Model

Evaluate model performance based on recall.

03 Minimum Viable Product

Implement a Streamlit app that takes user input on key features, generate prediction, and recommend optimal loan conditions (if necessary).

METHODOLOGY



Phase 1

Data Gathering

01

Source

Dataset was conveniently downloaded from Kiva's Data Snapshots.

02

Shape

Raw data contains over **2Mn** rows across 31 columns; containing observations between 2006-2021 from 99 different countries.

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Phase 2

Scope and Limitations

01

Timeline

Dataset only covers loans posted between 2014 - 2021

02

Only Philippine Loans

Due to time and computational constraints, the team has decided to only focus on loans in the Philippines

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Phase 3

Data Preprocessing

01

Data Cleaning

Empirical approach on the imputation of nulls in partner_covers_currency_loss.

02

Feature Engineering

Engineer features based on name, loan amount, and repayment term.

03

Dimensionality Reduction

Retain only features that exhibit the most association and correlation wrt target.

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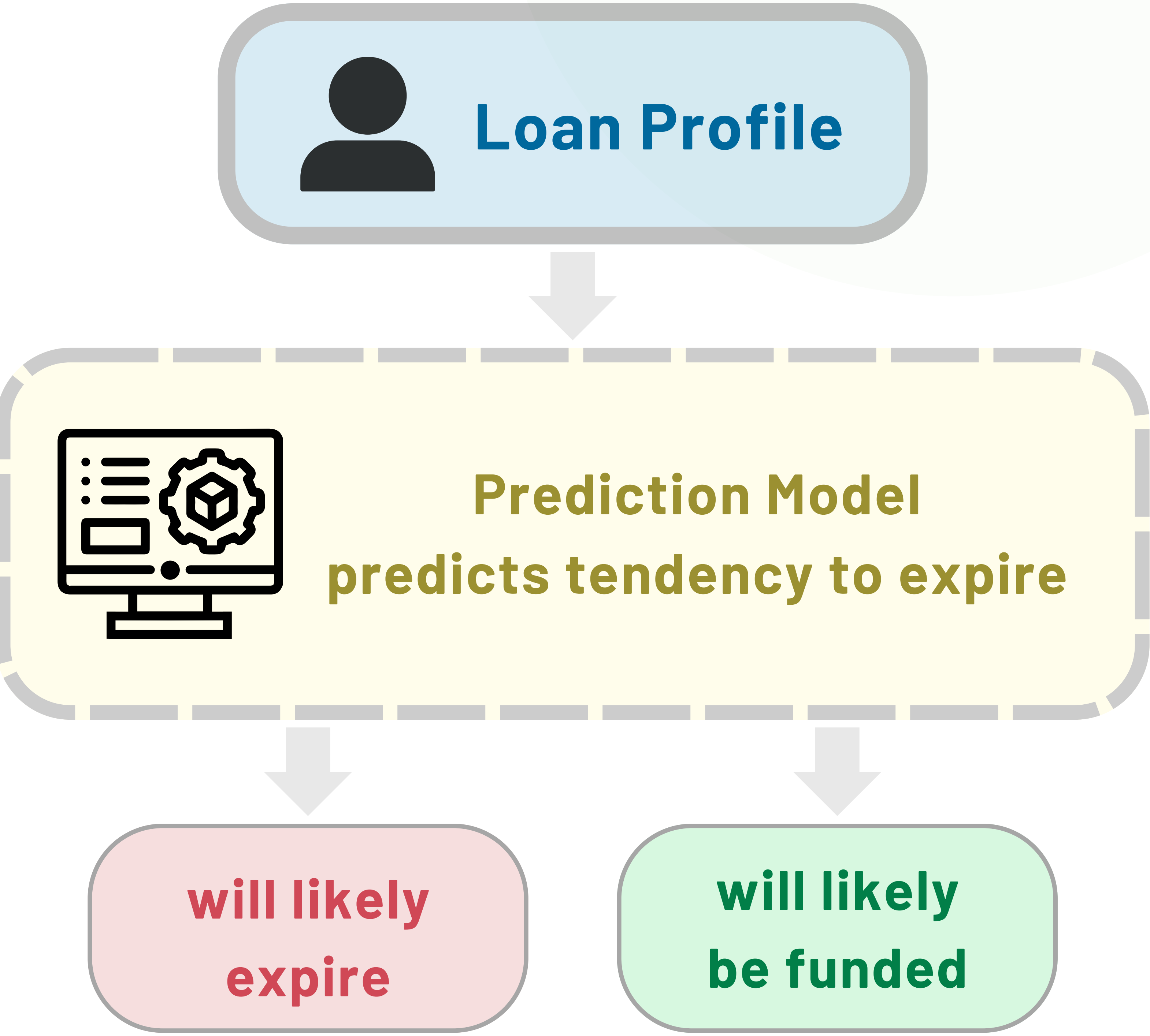
FEATURES		TARGET
Raw	~378k rows 30 columns	is_expired
Raw + Engineered *drop original columns on which the engineered features are based	17 columns	
Raw + Engineered + One-Hot-Encoded Categorical Features *drop identifiers	32 columns	
Key Features *retain only features that exhibit the most association and correlation with target	16 columns	

KEY FEATURES

- Loan Amount
- Repayment Term
- Partner covers Currency Loss
- Profile with Image
- Profile with Video
- Repayment Interval
- Sector Name

Phase 4

Prediction Generation



Phase 5

Recommend Optimizations

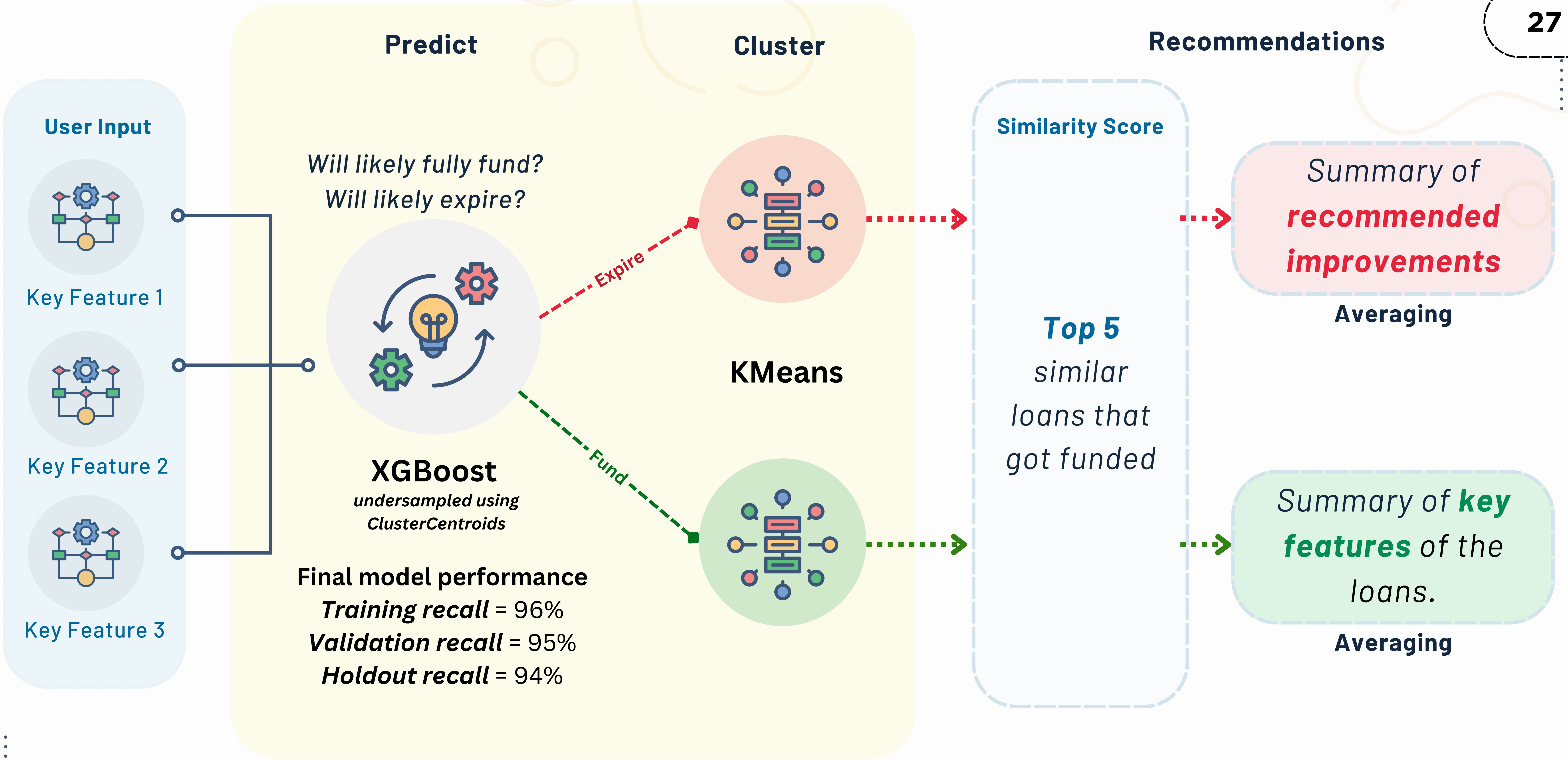
if the model predicts...

will likely expire

will likely be funded

Recommender Model recommends similar profiles

show **similar fully funded loans** that the borrower can **adapt**



Modelling pipeline

Phase 6

App Demo

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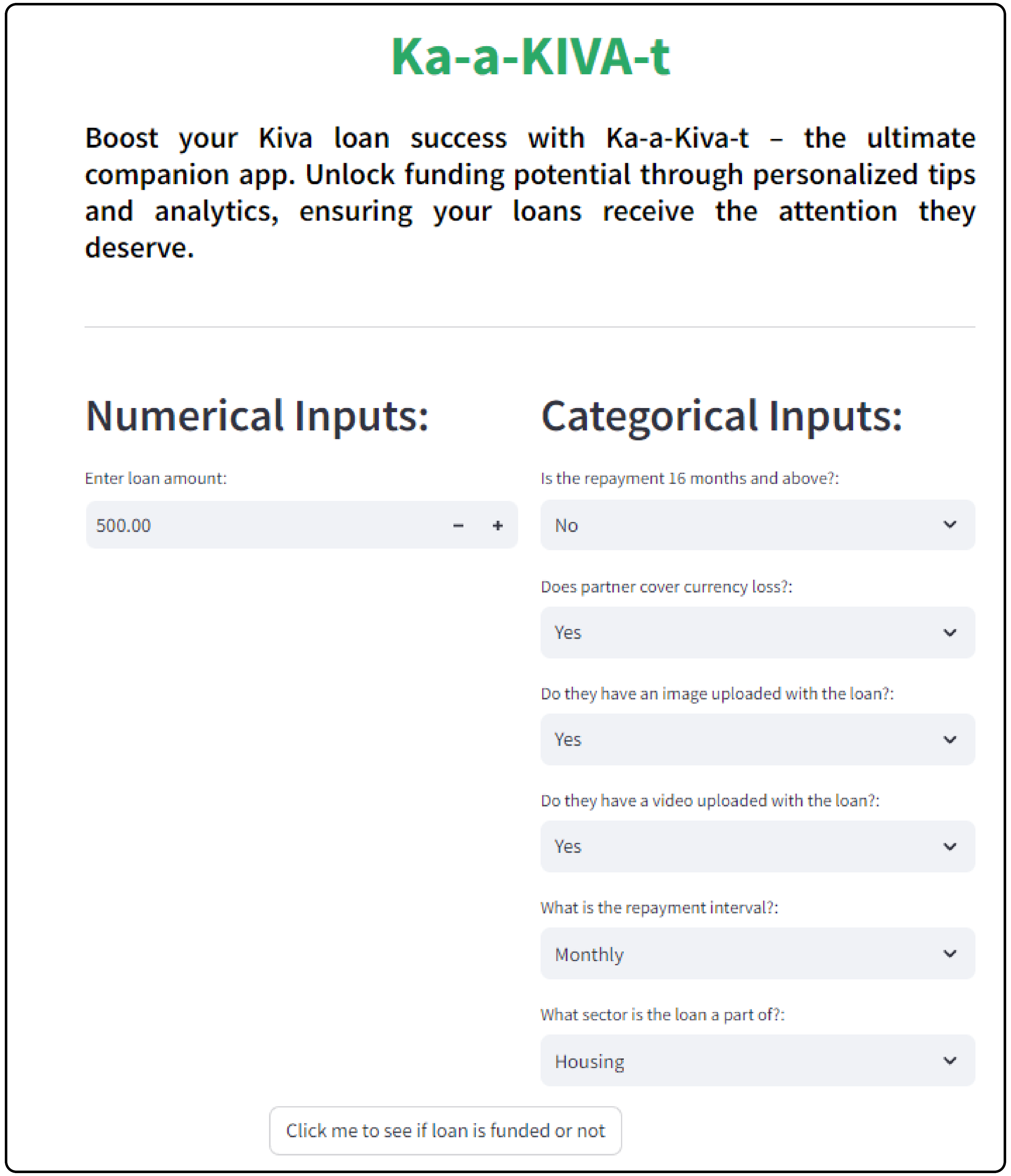

- User can input different loan characteristics, as seen on the left
- The user can click a button to predict whether the loan is approved or not

Result: The loan is funded

Here are 5 similar loans that were funded given the loan characteristics input:

	loan_id	group_loan	with_image	with_video	posted_time	loan_amount	loan_amc
0	1,774,650	0	1	0	2019-06-05 13:08:16+00:00	500	(450.0, 90
1	1,523,784	0	1	0	2018-05-08 02:33:39+00:00	500	(450.0, 90
2	1,390,571	0	1	0	2017-10-05 02:11:22+00:00	500	(450.0, 90
3	1,482,926	0	1	0	2018-03-07 01:58:33+00:00	500	(450.0, 90
4	1,784,083	0	1	0	2019-06-20 03:40:05+00:00	500	(450.0, 90

- The app will show whether the loan is funded or not.
- The app will also show similar loans that are funded, so the user can compare characteristics.

Here is the summary of the 5 similar loans:

1. The average loan amount for the loans are 500.0.
2. The average number of days to fund the loans are 17.8.
3. The most common sector among the loans is 'Housing'.
4. The most common repayment interval is monthly.
5. Most of the loans have an image attached to them.

- The app will also show a summary of the characteristics of the 5 similar funded loans.

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Summary of Insights & Improvements

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Summary of Insights

01

Key Features

Profiles with the following conditions are likely to get fully funded on Kiva:

1. Requested loan amount within **$25 to $250**
2. Repayment term within **15mos**
3. Lending partner covers currency loss
4. Have an image
5. Video is not important
6. **Monthly** repayment interval
7. Belong to either the **retail**, **food**, or **agriculture** sector

02

Best Prediction Model

XGBoost is the best model with a holdout recall score of **94%**.

03

Minimum Viable Product

Users can use the app to get an initial prediction on their loan profiles, and get recommendations on improving their loans.

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Summary of Improvements

Text Data	In the Kiva model, lender incentives differ from traditional MFIs, **emphasizing the impact of loan stories.** Examining these factors could enhance our study.
Image & Video	Alongside these stories are also pictures. Per our study, having and image of the borrower or loan improves the chances of funding. **Further study could be done on the images themselves.**
Other Countries	Our study only focuses on PH data from 2014-2021. Although the PH represents roughly half of the population, the Kiva dataset has 99 countries in it.
Lender-Loan Match	Another avenue worth exploring is the **matchmaking process between loans and lenders.** Enhancing the recommender system to consider both lender behavior and loan characteristics could represent a valuable next step in our research.

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“

In the tapestry of knowledge, ka-a-kiva-t intricately weaves a thread of support for MSMEs, enhancing the fabric of socially driven MFIs through crowdfunded microfinancing...

”

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Supporting MSMEs by Strengthening Socially Driven MFIs through Crowdfunded Microfinancing

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Start of Appendix

Hypothesis Tests Results

Hypothesis Tests				
X	*y*	*Test*	*p-value*	*Verdict*
loan_amount_bin	is_expired	chi-square	0	associated
funded_14_days_and_above	is_expired	chi-square	0	associated
repayment_interval	is_expired	chi-square	0	associated
repayment_term_16_mos_and_above	is_expired	chi-square	0	associated
partner_covers_currency_loss	is_expired	chi-square	0	associated
personal_use	is_expired	chi-square	0	associated
sector_name	is_expired	chi-square	0	associated
with_image	is_expired	chi-square	0	associated
with_video	is_expired	chi-square	0	associated
loan_amount	is_expired	median test	0	medians are not equal
funded_amount	is_expired	median test	0	medians are not equal

Correlation Tests Results

Correlation Tests (Pearson)				
x	*y*	*r*	*p-value*	*Verdict*
loan_amount	is_expired	0.11721686	0	weak
funded_amount	is_expired	-0.02473638	2.5E-52	weak
funded_14_days_and_above	is_expired			n/a
repayment_term_16_mos_and_above	is_expired	0.06295537	0	weak
partner_covers_currency_loss	is_expired	0.02276394	1.4E-44	weak
personal_use	is_expired	-0.01315135	5.9E-16	weak
with_image	is_expired	-0.13551402	0	weak
loan_amount_bin_(24.999, 250.0]	is_expired	-0.10882476	0	weak
loan_amount_bin_(250.0, 450.0]	is_expired	0.0091543	1.8E-08	weak
loan_amount_bin_(450.0, 900.0]	is_expired	0.07850878	0	weak
loan_amount_bin_(900.0, 500000.0]	is_expired	0.13298252	0	weak
repayment_interval_bullet	is_expired	0.02246449	1.8E-43	weak
repayment_interval_irregular	is_expired	0.01505938	1.9E-20	weak
repayment_interval_monthly	is_expired	-0.02714393	1.2E-62	weak
sector_name_Agriculture	is_expired	-0.02194758	1.4E-41	weak
sector_name_Arts	is_expired	-0.01148572	1.6E-12	weak
sector_name_Clothing	is_expired	-0.00066363	0.68303	no correlation
sector_name_Construction	is_expired	-0.00448085	0.00583	weak
sector_name_Education	is_expired	-0.00455555	0.00506	weak
sector_name_Entertainment	is_expired	-0.00272071	0.09413	no correlation
sector_name_Food	is_expired	-0.00053925	0.74005	no correlation
sector_name_Health	is_expired	-0.00365407	0.02456	weak
sector_name_Housing	is_expired	-0.00596966	0.00024	weak
sector_name_Manufacturing	is_expired	-0.00983762	1.4E-09	weak
sector_name_Personal Use	is_expired	-0.01269312	5.7E-15	weak
sector_name_Retail	is_expired	0.03640514	3E-111	weak
sector_name_Services	is_expired	-0.00829212	3.4E-07	weak
sector_name_Transportation	is_expired	0.00264584	0.10353	no correlation
sector_name_Wholesale	is_expired	-0.00212572	0.1909	no correlation

Prediction Model Results

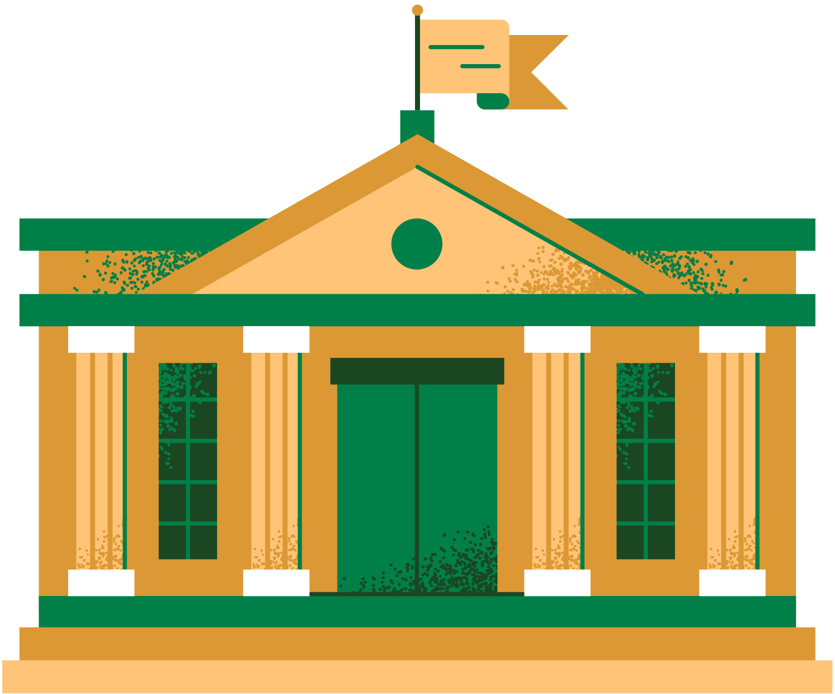
Resampler	Resample duration	Set	KNN	Logistic	Naïve Bayes	SVM	Decision Tree	Random Forest	Gradient Boosting	AdaBoost	ExtraTrees	XGB	CatBoost	LGBM
			Recall Score											
RandomUnder Sampler	0.047255	Train	0.30	0.71	0.98	0.86	0.87	0.88	0.88	0.85	0.87	0.89	0.88	0.87
		Test	0.30	0.71	0.98	0.87	0.84	0.85	0.88	0.85	0.85	0.87	0.86	0.85
NearMiss	1.316634	Train	0.25	0.58	0.24	0.60	0.73	0.75	0.72	0.66	0.73	0.73	0.70	0.74
		Test	0.24	0.60	0.26	0.62	0.71	0.74	0.72	0.68	0.72	0.72	0.70	0.72
Cluster Centroids	988.685525	Train	0.66	0.57	0.96	0.93	0.96	0.97	0.97	0.95	0.96	0.96	0.96	0.96
		Test	0.64	0.55	0.96	0.94	0.94	0.94	0.96	0.96	0.94	0.95	0.95	0.96

Resampler	Section	KNN	Logistic	Naïve Bayes	SVM	Decision Tree	Random Forest	Gradient Boosting	AdaBoost	ExtraTrees	XGB	CatBoost	LGBM
		Execution Time											
RandomUnderSampler	Fit train	0.00000	0.04625	0.00000	1.58252	0.007513	0.399108	0.344731	0.17974	0.345231	0.087506	2.92645	0.046868
	Predict train	0.45497	0.00000	0.00000	2.821056	0	0.078496	0	0.03163	0.078495	0.015621	0.015622	0.016013
	Predict test	3.87233	0.01562	0.02902	35.91992	0.015626	0.89394	0.125363	0.54873	0.956443	0.031634	0.016006	0.187848
NearMiss	Fit train	0.004006	0.051874	0	1.937958	0	0.329235	0.328619	0.171503	0.282366	0.078501	2.928321	0.052002
	Predict train	0.372081	0	0.009511	3.653296	0.013005	0.078498	0	0.031243	0.081857	0.015621	0.004	0.012001
	Predict test	3.951287	0	0.015626	45.51939	0	0.752574	0.140485	0.549119	0.830577	0.031242	0.039512	0.112013
Cluster Centroids	Fit train	0.007002	0.054491	0	1.497699	0.008013	0.500079	0.360066	0.208575	0.419311	0.088526	3.226069	0.064016
	Predict train	0.347946	0	0	2.878031	0.004001	0.080017	0.008	0.036507	0.092017	0.004001	0.004003	0.012
	Predict test	3.931863	0.006998	0.03499	35.59417	0.016001	0.929199	0.108027	0.568301	1.02816	0.052017	0.036006	0.120015

Criteria for partnership

- Display a strong commitment to serving Kiva's focus populations.
- Operate an existing lending program with portfolio quality that is in line with market context and industry standards.
- Provide a specific proposal for using Kiva's capital to fund loan products that are affordable for clients and have a high social impact.
- Be able to post at least $300,000 USD in loans in the first 12 months on the Kiva website, with the capacity to grow in subsequent years.
- Have assets or operating revenues of at least $1M USD.
- Be able to legally accept and repay debt denominated in US Dollars.
- Be legally registered, licensed, and in good standing.
- Committed to following the Cerise + SPTF universal client protection standards.

Criteria for a Lending Partner?



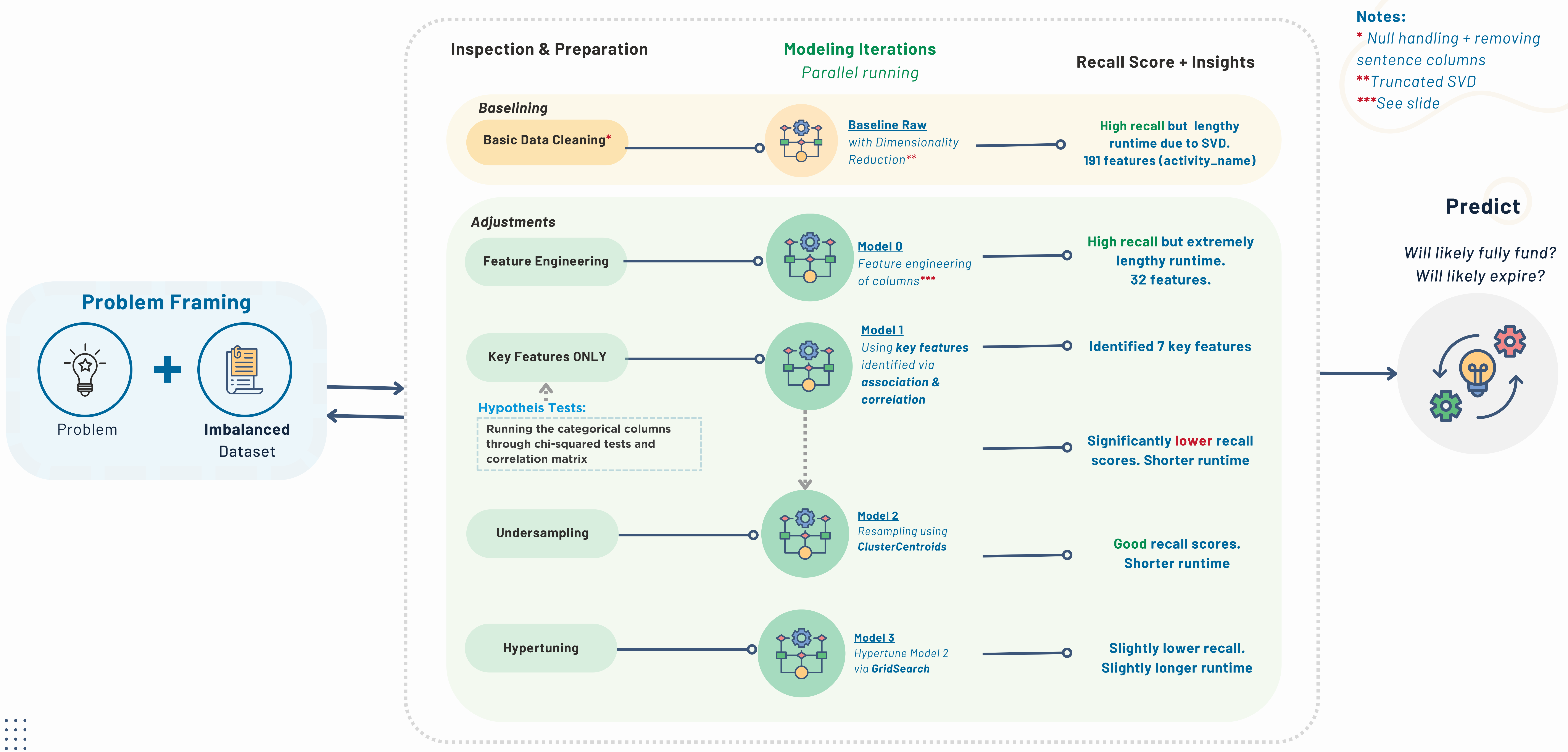
Traditional Microfinancing

Funding Source	MFIs, backed by large banks or funds
Loan Structure	Fixed interest rates, repayment schedules, and collateral requirements.
Process	Decisions are made by the lending institution
Scale	Larger sums of money provided by a single lending institution, impacting fewer MSMEs with each transaction.
Speed	Formal application and approval process, which can take time
Risk & Return	Structured risk assessment and a predefined return on investment, with the lending institution assuming the primary risk.

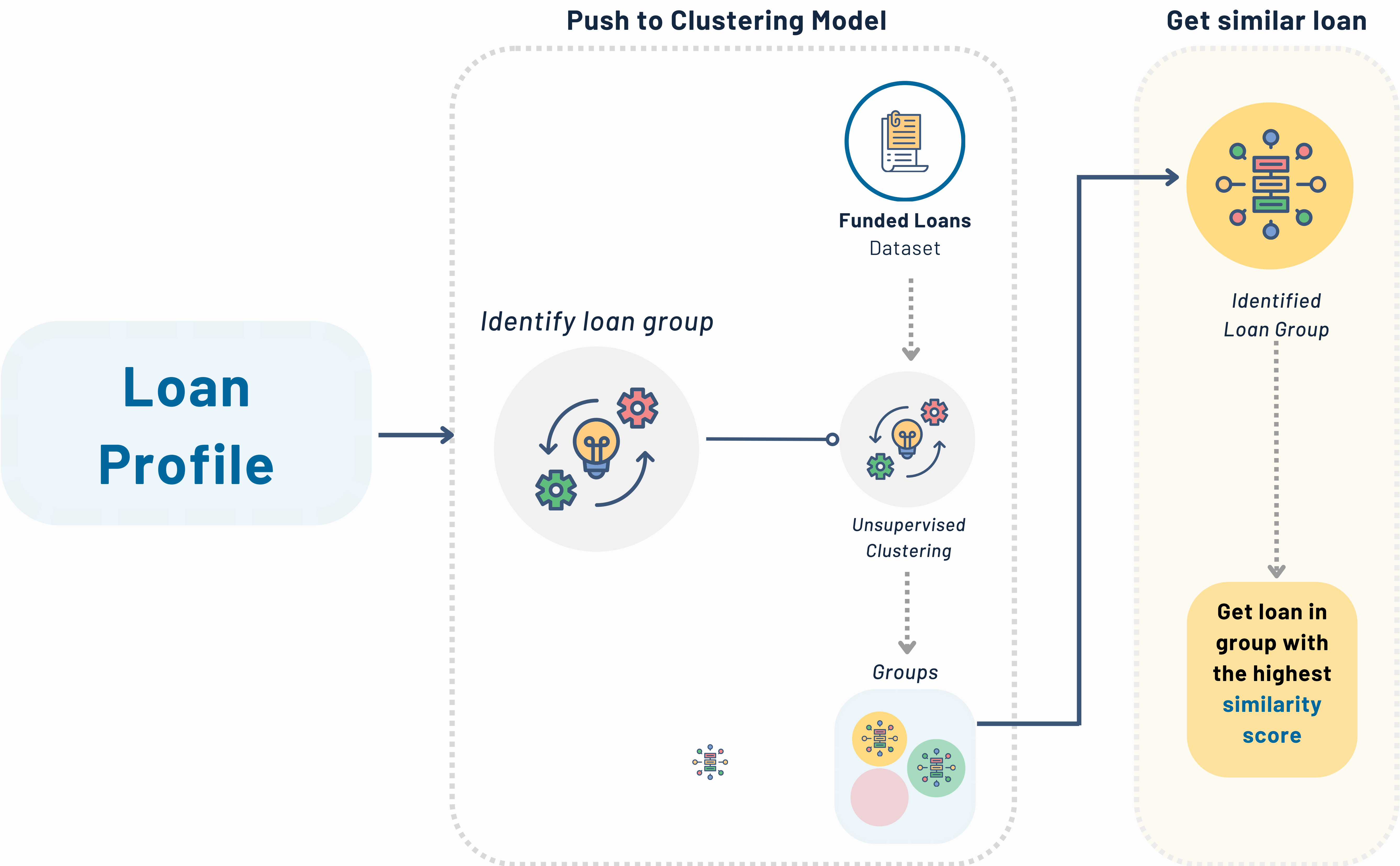
Crowdfunded Microfinancing

Non-traditional Approach

Funding Source	Individual investors who contribute smaller amounts of money to fund MSMEs, often through online platforms.
Loan Structure	More flexibility in terms of lending terms. Can be donation-based, reward-based, or peer-to-peer lending.
Process	Decisions are often influenced by the crowd, with backers choosing to support projects based on personal interest, social impact, or other factors.
Scale	Can involve numerous small contributions from a diverse pool of backers
Speed	Quicker funding process, especially for projects that resonate with a large number of backers.
Risk & Return	Backers assume a degree of risk, and returns can vary based on the success of the MSME project



Prediction Model Workflow



Clustering Model Workflow

How does kiva work?

01

PH Borrower has a need for a loan

The loan could be for business or personal use

02

Socially Driven PH MFI (Field Partners)

Kiva only partners with microfinance institutions and organizations that have a social mission to serve the poor, unbanked, and underserved.

03

Field Partner posts the loan on Kiva

To hedge the risk it takes on, the PH MFI posts the loan on Kiva.

04

Global Lenders fund the loan

Once the loan is posted on Kiva, global borrowers have a set number of days to fully fund the loan

Fully funded loan is distributed to borrower

The fully-funded loan is distributed to the borrower via MFI (Kiva Field Partner)

Why Recall?

*based on false predictions we CAN'T tolerate

*target: is_expired
-> 1 (will likely expire)
-> 0 (will likely not expire)

Evaluation Metric

Accuracy

- considers FPs and FNs
- vaguely depitcs model performance

F1

- considers FPs and FNs
- vaguely depitcs model performance

Precision

- considers FPs exclusively
- we can tolerate FPs, we'll just treat them as further optimizing a would-be-funded profile

Recall

- considers FNs exclusively
- we CAN'T tolerate FNs, which is why we aim to achieve a model with high recall

MODELS CONSIDERED

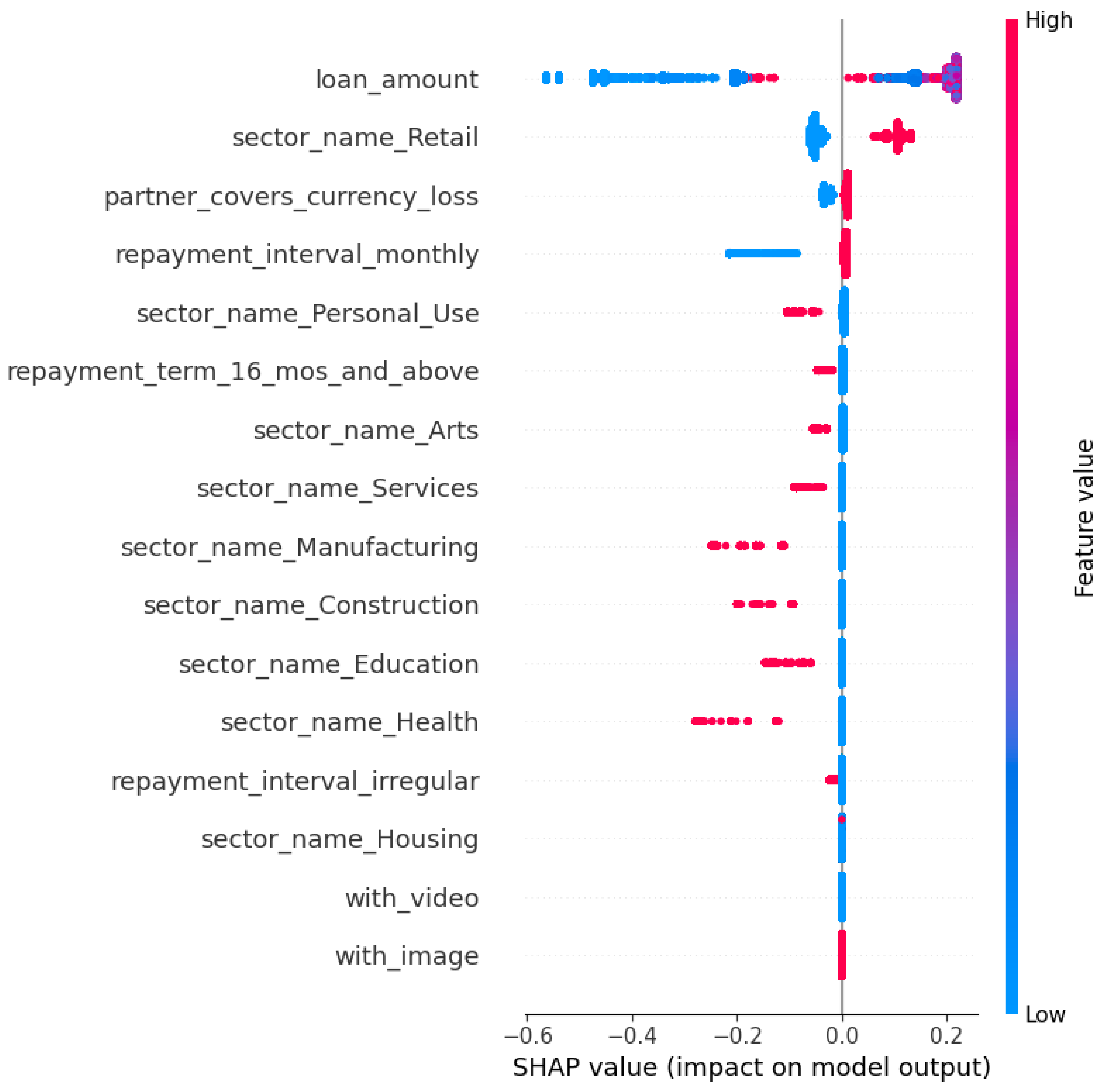
***follow the sequence when displaying the results**

1. KNeighbors
2. Logistic
3. GausianNB
4. SVC
5. DecisionTree
6. RandomForest
7. GradientBoosting
8. AdaBoost
9. ExtraTrees
10. XGBoost
11. CatBoost
12. LGBM

16 KEY FEATURES

loan_amount	sector_name_Construction
repayment_term_16mos_and_above	sector_name_Education
partner_covers_currency_loss	sector_name_Health
with_image	sector_name_Housing
with_video	sector_name_Manufacturing
repayment_interval_irregular	sector_name_Personal_Use
repayment_interval_monthly	sector_name_Retail
sector_name_Arts	sector_name_Services

SHAP


loan_amount
sector_name_Retail
partner_covers_currency_loss
repayment_interval_monthly
sector_name_Personal_Use
repayment_term_16_mos_and_above
sector_name_Arts
sector_name_Services
sector_name_Manufacturing
sector_name_Construction
sector_name_Education
sector_name_Health
repayment_interval_irregular
sector_name_Housing
with_video
with_image
−0.6
−0.4
−0.2
0.0
0.2
SHAP value (impact on model output)
High
Low
Feature value