

ka-a-kiva-t

Supporting MSMEs by Strengthening Socially Driven MFIs through Crowdfunded Microfinancing



WHAT ARE MSMEs?



Micro, Small, and Medium Enterprises

Latest data shows that...

Of all
business
in the PH
are MSMEs



**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

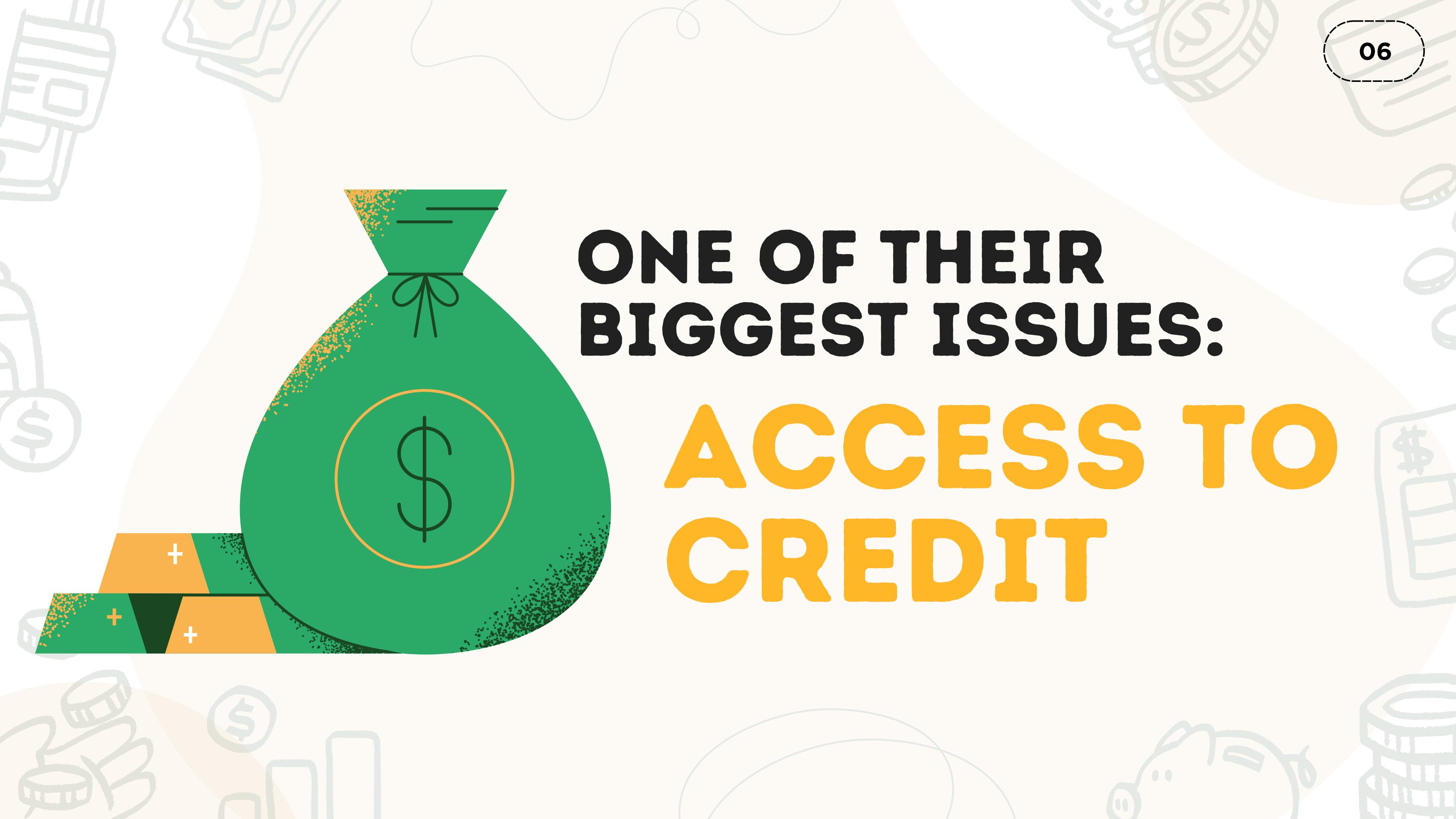
Philippine Department of
Trade and Industry (DTI)

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.*



*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?



Non-traditional Approach



Traditional
Microfinancing

“

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

Non-traditional Approach

”



Non-traditional Approach

“

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

”



Asunta

A loan of \$1,950 helps to increase production by hiring more artisans for her workshop.

Make a loan, change a life.

Crowdfunding on

kiva

How does kiva work?



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

**kiva**

A loan profile for Asunta on the Kiva platform. It includes a small photo of a woman smiling, a larger photo of her working in a workshop, and the name "Asunta". Below the name is a brief description: "A loan of \$1,950 helps to increase production by hiring more artisans for her workshop."

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

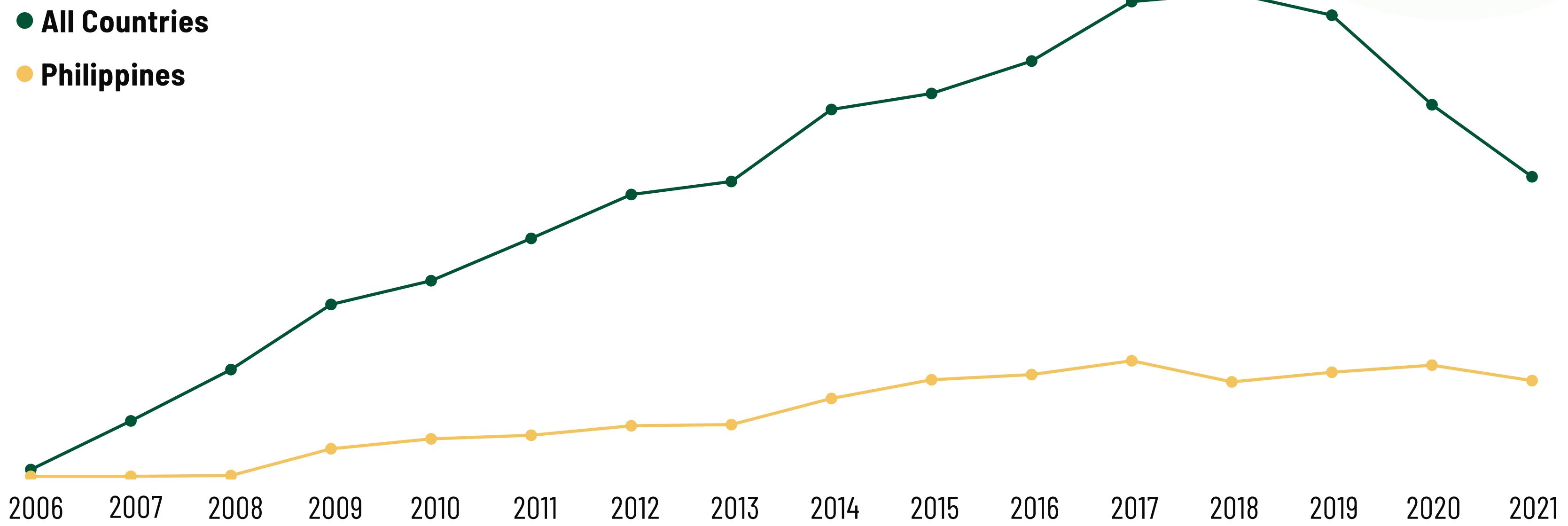


How does kiva work?

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.



FUNDED

~ 4%

EXPIRED

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

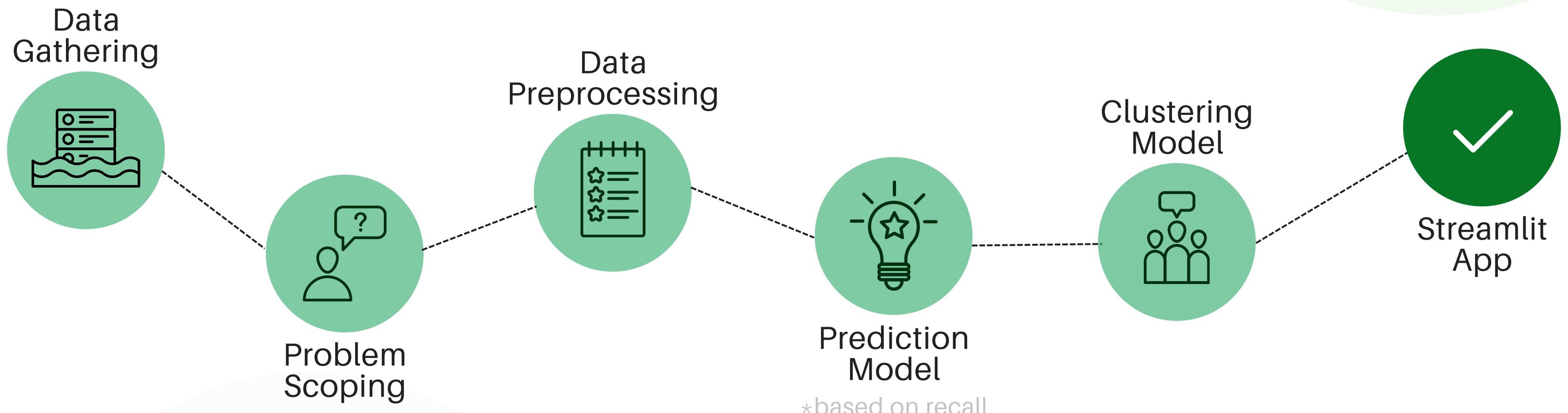
Evaluate model performance based on recall.

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.

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

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.

FEATURES

TARGET

Raw

**~378k rows
30 columns**

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

is_expired

KEY FEATURES

Loan Amount

Repayment Term

Partner covers Currency Loss

Profile with Image

Profile with Video

Repayment Interval

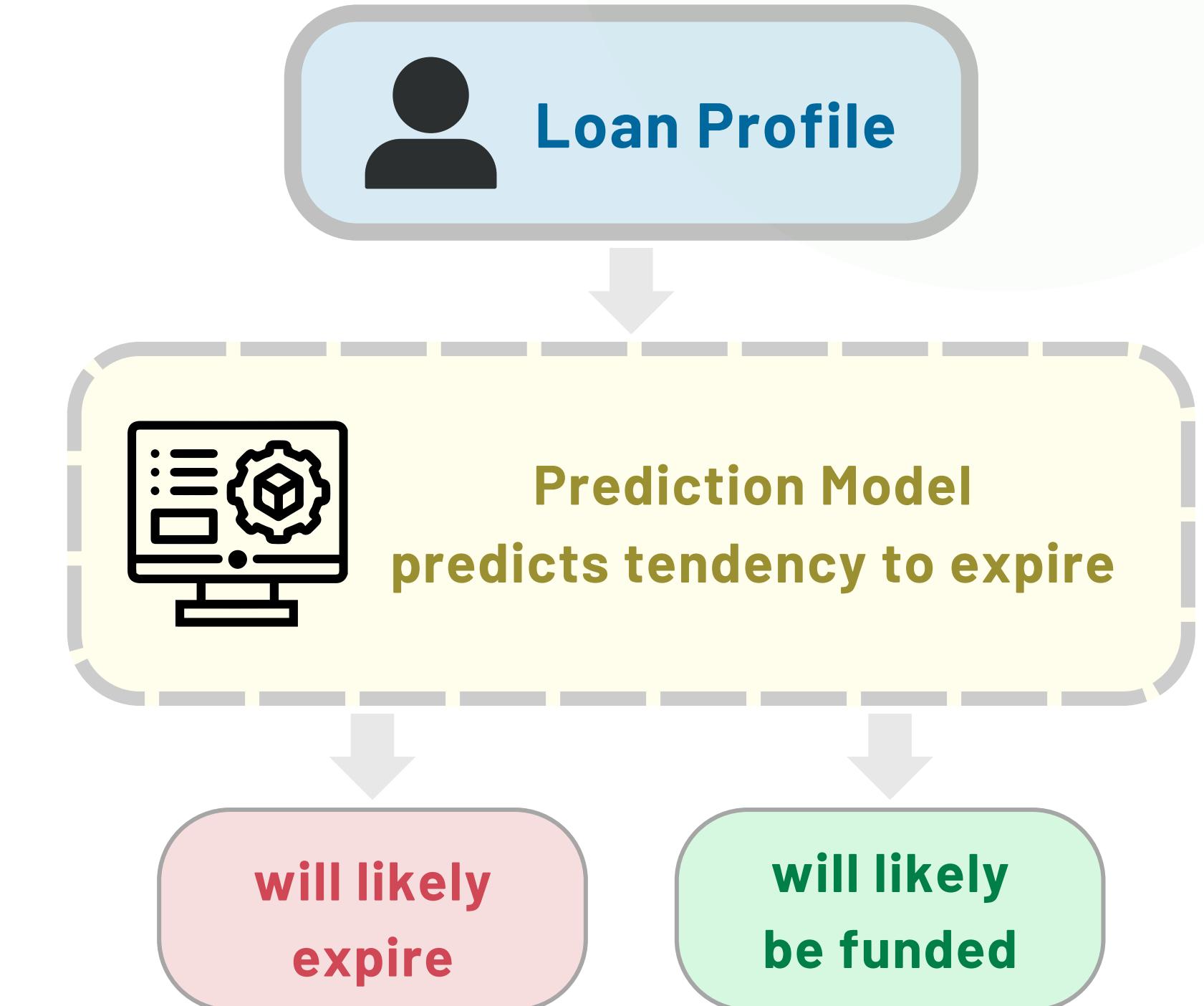
Sector Name

Phase 4

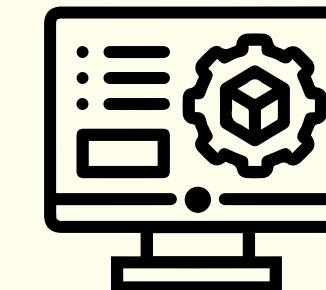
Prediction Generation

SUSTAINABLE DEVELOPMENT GOALS

kiva



Loan Profile



Prediction Model
predicts tendency to expire

will likely
expire

will likely
be funded

Phase 5

Recommend Optimizations

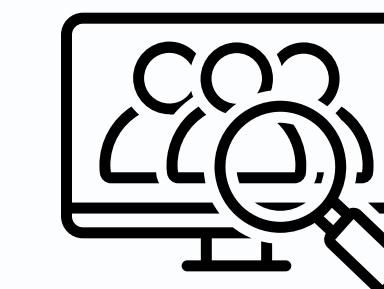
SUSTAINABLE
DEVELOPMENT GOALS

kiva

if the model predicts...

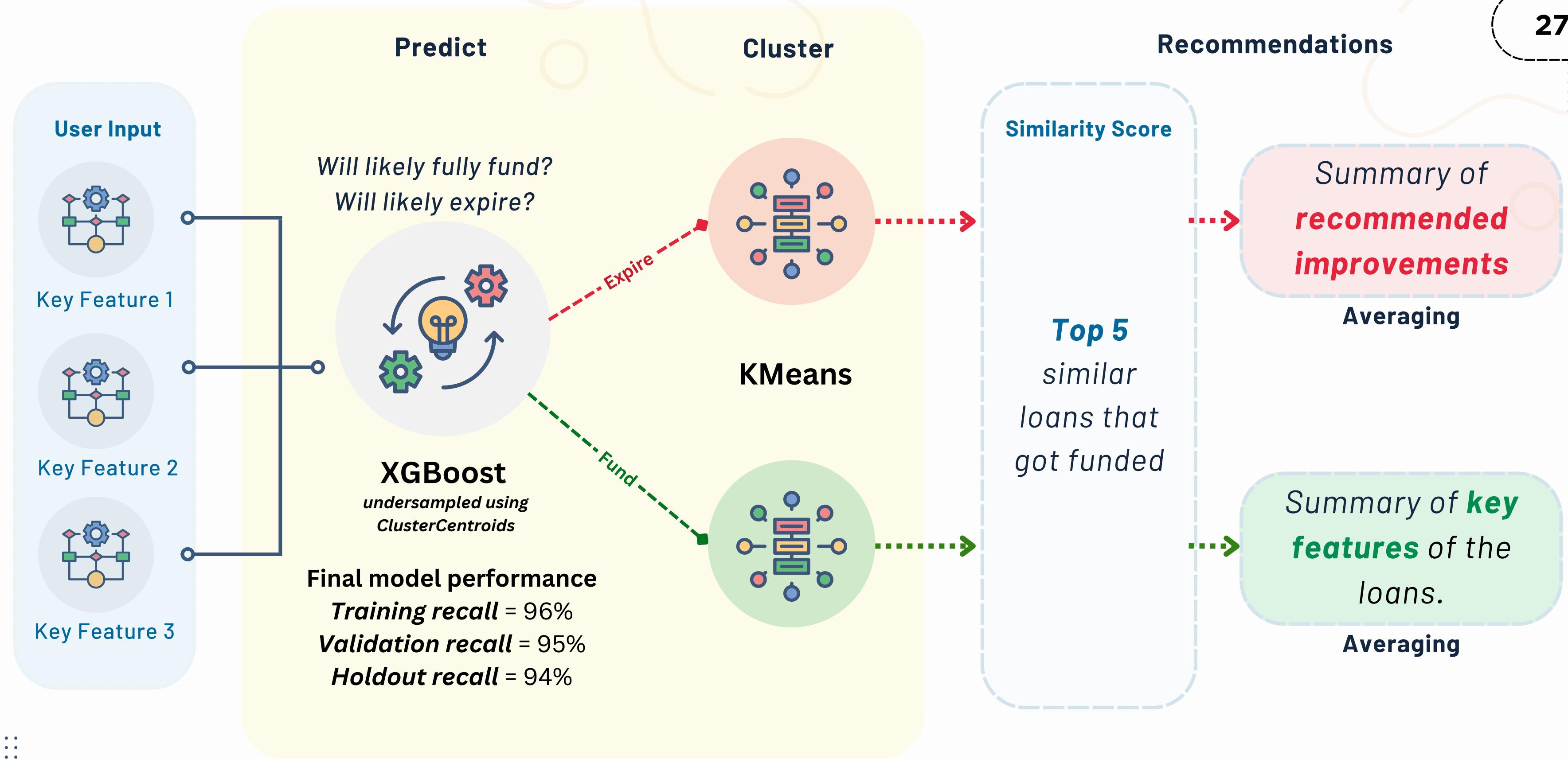
will likely
expire

will likely
be funded



Recommender Model
recommends similar profiles

show similar fully funded loans
that the borrower can adapt



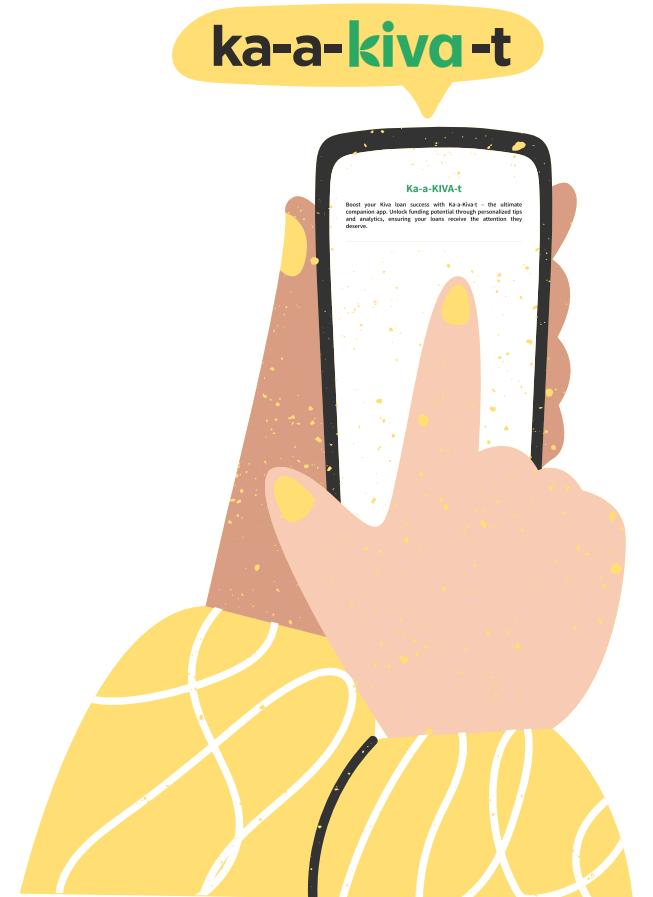
Modelling pipeline

Phase 6

App Demo

SUSTAINABLE
DEVELOPMENT GOALS

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Ka-a-KIVA-t

Boost your Kiva loan success with Ka-a-Kiva-t – the ultimate companion app. Unlock funding potential through personalized tips and analytics, ensuring your loans receive the attention they deserve.

Numerical Inputs:

Enter loan amount: - +

Categorical Inputs:

Is the repayment 16 months and above?:

Does partner cover currency loss?:

Do they have an image uploaded with the loan?:

Do they have a video uploaded with the loan?:

What is the repayment interval?:

What sector is the loan a part of?:

[Click me to see if loan is funded or not](#)

- 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

SUSTAINABLE DEVELOPMENT GOALS

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O1

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

O2

Best Prediction Model

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

O3

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

SUSTAINABLE DEVELOPMENT GOALS

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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 an 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.

“

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



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

Recall Score														
Resampler	Resample duration	Set	KNN	Logistic	Naïve Bayes	SVM	Decision Tree	Random Forest	Gradient Boosting	AdaBoos t	ExtraTrees	XGB	CatBoost	LGBM
<i>RandomUnderSampler</i>	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
<i>NearMiss</i>	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
<i>ClusterCentroids</i>	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
Execution Time														
Resampler	Section	KNN	Logistic	Naïve Bayes	SVM	Decision Tree	Random Forest	Gradient Boosting	AdaBoos t	ExtraTrees	XGB	CatBoost	LGBM	
<i>RandomUnderSampler</i>	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	
<i>NearMiss</i>	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	
<i>ClusterCentroids</i>	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.

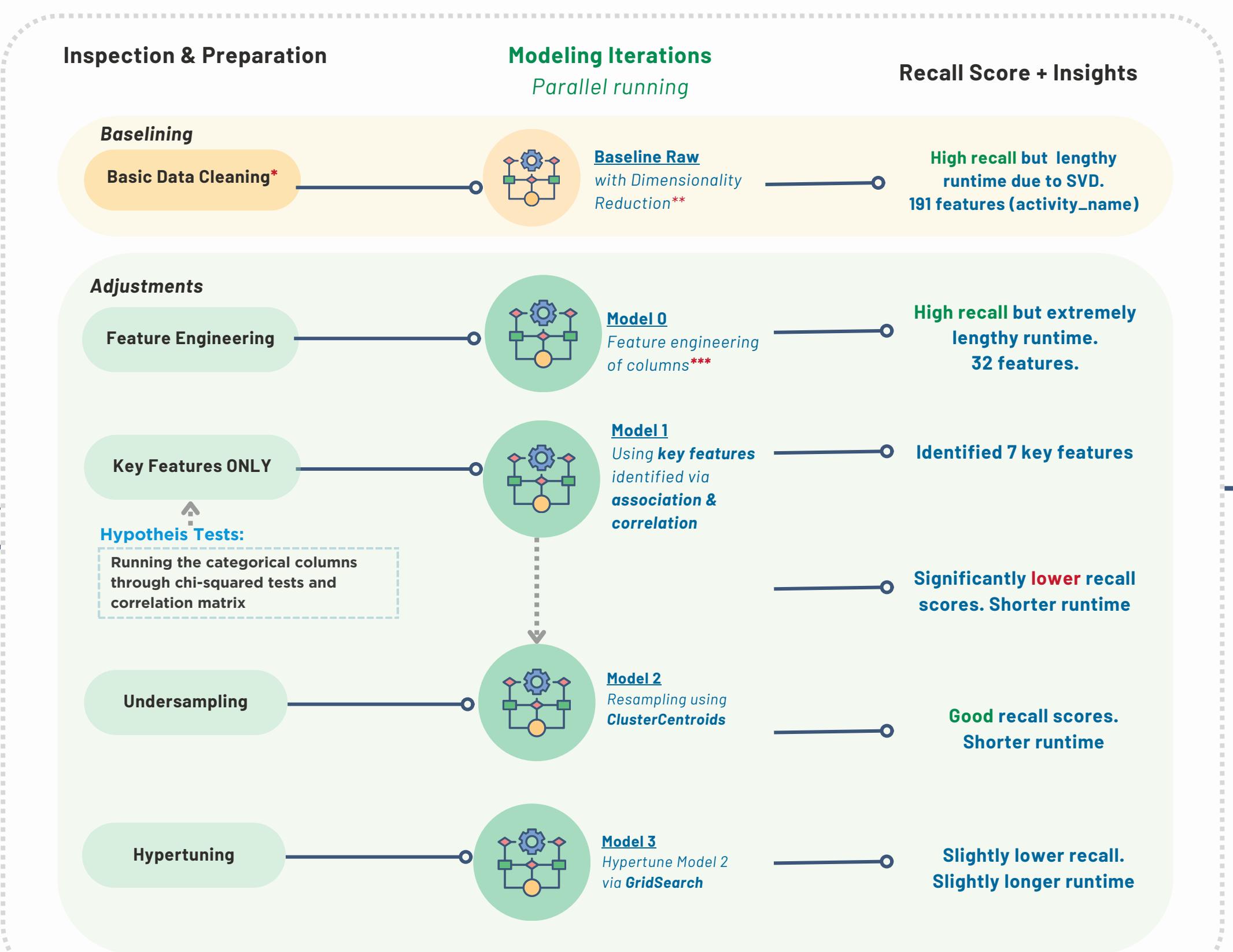
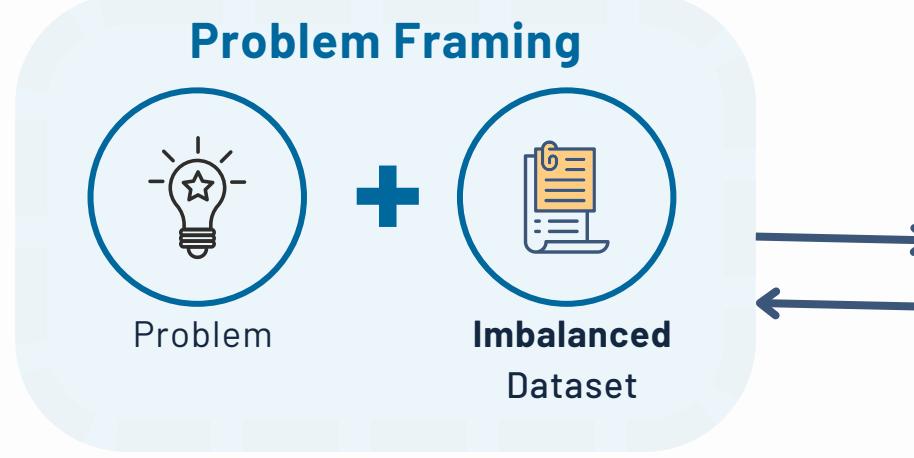


Crowdfunded Microfinancing

Non-traditional Approach

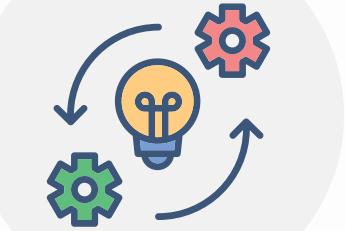
Funding Source	Individual investors who contribute smaller amounts of money to fund MSMEs, often through online platforms.
Loan Structure	More flexibility in terms of lending terms. Can be donation-based, reward-based, or peer-to-peer lending.
Process	Decisions are often influenced by the crowd, with 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

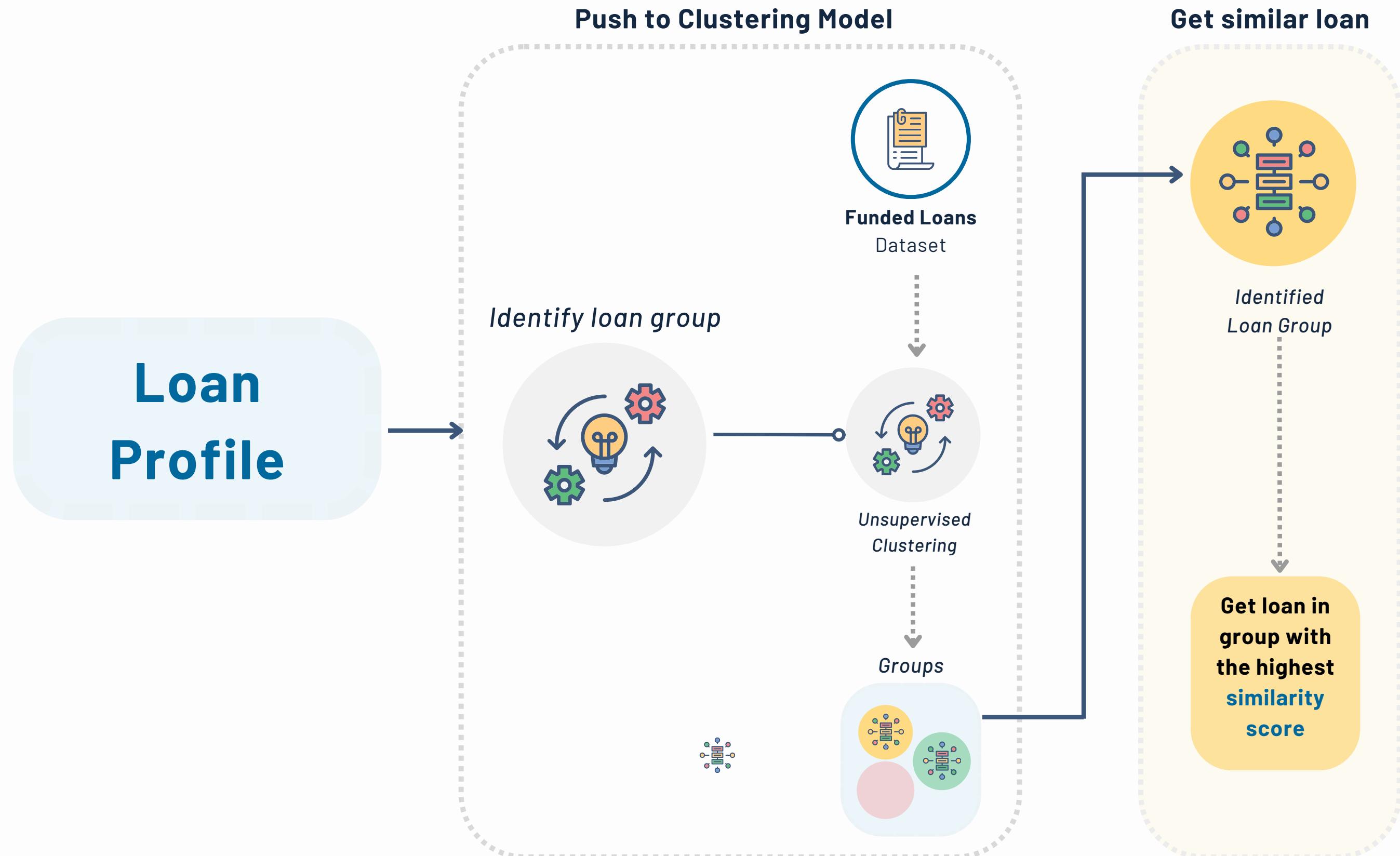


Predict

Will likely fully fund?
Will likely expire?



Clustering Model Workflow





PH Borrower has a need for a loan

The loan could be for business or personal use



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.



Field Partner posts the loan on Kiva

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



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)

How does kiva work?

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 depicts model performance

F1

- considers FPs and FNs
- vaguely depicts 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

