To Gather Together for a Better World: Understanding and Leveraging Communities in Micro-lending Recommendation

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ABSTRACT

Micro-finance organizations provide non-profit lending opportunities to mitigate poverty by financially supporting impoverished, yet skilled entrepreneurs who are in desperate need of an institution that lends to them. In Kiva.org, a widely-used crowd-funded micro-financial service, a vast amount of micro-financial activities are done by lending teams, and thus, understanding their diverse characteristics is crucial in maintaining a healthy micro-finance ecosystem. As the first step for this goal, we model different lending teams by using a maximum-entropy distribution approach based on a wealthy set of heterogeneous information regarding micro-financial transactions available at Kiva. Based on this approach, we achieved a competitive performance in predicting the lending activities for the top 200 teams. Furthermore, we provide deep insight about the characteristics of lending teams by analyzing the resulting team-specific lending models. We found that lending teams are generally more careful in selecting loans by a loan's geo-location, a borrower's gender, a field partner's reliability, etc., when compared to lenders without team affiliations. In addition, we identified interesting lending behaviors of different lending teams based on lenders' background and interest such as their ethnic, religious, linguistic, educational, regional, and occupational aspects. Finally, using our proposed model, we tackled a novel problem of lending team recommendation and showed its promising performance results.

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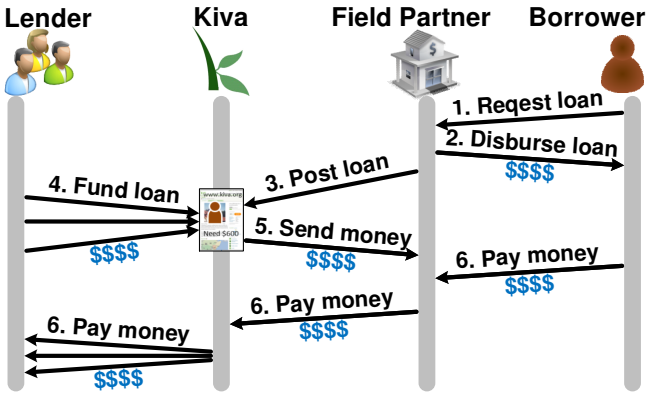


Figure 1: An overview of how Kiva works.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information filtering; I.2.6 [**Artificial Intelligence**]: Learning

Keywords

Microfinance; maximum entropy distribution; heterogeneous feature; community characteristics

1. INTRODUCTION

Micro-finance institutions lend credit to entrepreneurs who have no credit available to them in impoverished countries. Its concept was conceived when Muhammad Yunus discovered that the extreme poor barely had enough means with which to sustain themselves, only to use their business sales as repayment for the materials they loaned [33]. By loaning credit without collateral and interest, impoverished entrepreneurs are given the opportunity to overcome the vicious cycle of debt.

Kiva.org, the overall process of which is summarized in Fig. 1, takes the idea of micro-financing and pairs it with crowd-sourcing to provide easy online access for lending a small amount of money. Kiva, a non-profit organization,

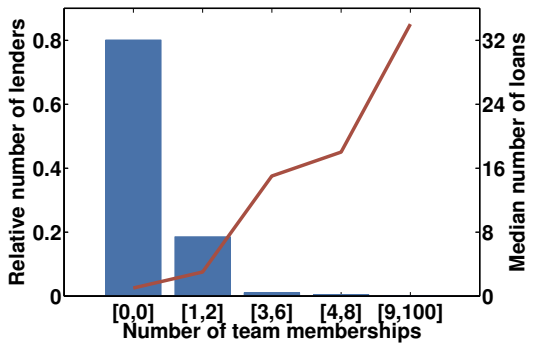


Figure 2: The degree of lending activities depending on lending team involvement.

does not collect interest but rather provides an intermediary service which pools together money from its lenders and forwards them to the field partner who then distributes it to the requesting borrower.

Kiva relies heavily on its transparency due to its core values for successful growth [10]. Kiva's transparency allows open public access to its transactional and entity data, which can be downloaded as daily snapshots or through their API. Kiva's May 2013 data snapshot contained over 1,100,000 lenders, 500,000 loans, and 150,000 journal entries for over four million transactions that resulted in 400 million US dollars of loans issued. There are a variety of data types within the Kiva data including geo-spatial, temporal, categorical, numerical, and free-text unstructured data. The size of the data set, along with its massive set of heterogeneous information makes the Kiva data set a fascinating data set for data mining and social media researchers.

Impact of lending teams. Virtual communities thrive when their users are active in their participation, and in this case, when lenders are actively lending. Particularly with Kiva, lending is synonymous with donating due to the lack of monetary gain from lending, thus keeping lenders actively and consistently involved is a critical factor in making Kiva self-sustainable. As one such way, Kiva encourages each of their lenders to join teams, called lending teams, to allow lender collaboration in locating and funding credit requests. Lending teams are primarily formed through a common interest, where one such similarity interest group could contain lenders interested in funding a particular type of business.

The Kiva data reveal that lending teams play a major role in the level of participation for lenders. As seen in Fig. 2, the median number of loans per lender increases quickly with the number of teams the lender is part of (the red line). However, about 80% of the Kiva lenders are not still affiliated with any lending teams, while most of the remaining 20% of lenders participate in only one or two lending teams. Overall, lenders affiliated with at least one lending team fulfill about 50% of the total loan activities in Kiva. These statistics suggest that matching lenders with teams can be a key driver for further increasing participation.

Overview of Our Work

Motivated by such an importance, we study the diverse characteristics of lending teams in a principled manner and show the advantage of leveraging the team information in the context of two important problems: loan recommendation as well as team recommendation for lenders.

Loan recommendation largely differs from standard recommendation problems due to two attributes: the transient nature of loans and the binary rating structure. Regarding the former, loans are only available until they are fully funded, and thus they can be seen as a consumable and limited resource. This attribute of loans makes it a difficult problem when compared to other applications such as the Netflix recommendation system in which recommendations for a movie previously liked by similar users can be recommended. Secondly, unlike other applications where the rating information is available, in loan recommendation, we know only whether a particular lender funded a loan or not. This binary structure further complicates the loan-to-lender relationship due to the fact that a lender who has not funded a loan may not have directly rejected it.

Maximum-entropy distribution modeling (Section 4). To address these difficulties of our domain, we treat the lending activity data as presence-only data or one-class data and apply a maximum-entropy distribution approach (**maxent**). Maxent has been successfully used in various applications such as species distribution modeling [24, 26] and natural language processing [4]. Based on the maxent approach, we build team-specific models by fully incorporating a wealthy set of heterogeneous information reflecting the lending behavior of each team. Furthermore, using the team-specific lending models, we propose an ensemble model based on a weighted-stacking approach [32].

Loan recommendation (Section 5). We discuss how we built up the feature vectors and constructed the proposed ensemble model in detail. We also demonstrate the evaluation of our method, which shows that the ensemble approach performs significantly better than individual team-specific models as well as an aggregate lending model in which the team diversity is ignored.

In-depth analysis about team behaviors (Section 6). We utilize our team-specific lending models to gain valuable insights into the team characteristics. We point out that lending teams generally have specific preferences in selecting loans with respect to a loan's geo-location, a borrower's gender, a field partner's reliability, and other loan aspects when compared to lenders without team affiliations. We identify various interesting lending behaviors of different lending teams based on lenders' background and interest such as their ethnic, religious, linguistic, educational, regional, and occupational characteristics.

Team recommendation (Section 7). To increase lending activities via community building such as lending teams, we propose a team-to-lender recommendation model that leverages our team-specific lending models. For a given lender, we rank potential teams based on how likely his first few loans are under the team-specific model. We show that our approach outperforms two baseline approaches.

2. RELATED WORK

In this section we discuss related work in terms of (1) opinion-based recommender systems and (2) micro-finance analysis.

Opinion-based recommender systems. Sinha and Searingen [29] showed that users' friends consistently gave higher quality recommendations than those from a recommender system due to the friends' intimate knowledge of their tastes. The idea is that individuals with similar tastes

will form connections and develop a sense of trust within the communities. The following literature on the relation between connections based on shared interests, trust, and agents' decisions justify the importance of lending teams for member participation in Kiva.

Abdul-Rahman and Hailes [1] claimed this very idea and proposed a trust model for recommender systems that in part showed that agents within a similar context, e.g. professional communities, trusted the opinions of agents with similar profiles of interest. In virtual communities, trust can be seen as a derivative of both the ability and the combined benevolence and integrity of the agent to be trusted [27]. Ridings et al. [27] hypothesized that this gained trust is positively related to their willingness to give and receive information from within their network. In essence, recommendations from those with similar interests have significant impacts on an agent's decision because of the strong correlation between trust and interest similarity [34], and furthermore, agents find themselves less vulnerable to risk and are even encouraged to collaborate when trust is present within their network [22]. That is why it is not surprising to see that recommender systems which have incorporated trust models have gained much attention due to their favorable properties for social filtering [23, 19, 13].

In our system, we felt that there were two major dimensions that encouraged participation in a network: interest similarity and civic responsibility. We believe that having like-minded individuals who want to address similar issues of public concern within a team will help foster an environment that is conducive to peer encouragement. Specifically for Kiva, if lending teams are developed around mutual interests, due to the non-profit nature of Kiva participation, lenders are highly likely to trust in the general direction of their lending team network.

Micro-financial activity analysis. Technological advancements have reshaped the structure of micro-financing as seen by the effects of the internet on micro-financing [6] and by the transformation of lending transaction behavior caused by peer-to-peer technologies [3]. Studies on microfinance lending patterns have discovered that lenders choose opportunities based on similarity of interests, emotional responses, and other social biases. Lenders tend to choose borrowers who share similarities to their personal or professional interests, e.g. artists will loan to other artists, and/or trigger an emotional response [2, 11]. Findings specific to Kiva have claimed patterns that show bias within the lending decision process. In particular, women and more physically attractive individuals have a higher probability of receiving support from first-time lenders and lesser-active lenders [16]. Other studies on Kiva have observed the nature of lending behaviors by correlating the impact of group dynamics to lending participation [14, 21].

Surprisingly, even with Kiva's openly available data set, only a handful of research work has used advanced statistical analysis approaches in studying micro-financing. In one study, researchers manually defined a set of categories about the motivation of lending and applied machine learning techniques to train automatic text classifiers using a lender's *loan_because* field [21]. Their work only used several simple features such as the loan count and team affiliations to perform regression on lending frequency and amount. They revealed various interesting knowledge about lending behaviors, but the used information and techniques are relatively limited compared to our work.

To the best of our knowledge, *our work is the first in-depth study to directly tackle the loan and the lender recommendation problems by actively incorporating the lending team information available from Kiva.* As seen in Section 5, *we achieve performance viable for practical application and reveal significant finding about lending behavior of teams that has not been discussed in any previous other work.*

3. OVERVIEW OF KIVA DATA

The Kiva data set[1] contains a massive set of heterogeneous information about the following types of entities:

- a lender or kiva user u (1,174,383 in total),
- a lending team t (25,481 in total),
- a loan l (564,177 in total),
- a field partner p (254 in total), and
- a borrower b (1,099,997 in total).

Entities of each type contain various information involving both unstructured data, such as image, video, and text, and structured data, such as geo-spatial, numerical, categorical, and ordinal data. For example, a lender entity is represented in terms of its essential web profile data, e.g., a profile image, a registration timestamp, a geo-location, a lending count, an occupation, and other fields. A lending team entity also has its own information including a name, a team category (e.g., religious, common interest, etc.), a brief description, and a webpage URL. Finally, a loan entity , which has the most rich set of information, are characterized by a textual description, an industry category (e.g., agriculture, food, retail, etc.), a list of borrowers requesting the loan, a field partner, a geo-location, a loan amount, and posted/funded/paid timestamps. A borrower entity, which has the least amount of information, contains a gender and a name.[2]

In addition, a complex set of many-to-many relationships are available in the data set. For example, a loan is funded by multiple lenders while a lender can contribute to multiple loans. A lender may concurrently participate in more than one lending team. A field partner manages loans within their local region while a loan can be requested by multiple borrowers. These relationships can be represented as graphs between different entities, and the following two important graphs are directly available from the data set:

- a graph between lenders and loans, which indicates funding activities (12,355,814 edges in total), and
- a graph between lenders and lending teams, which indicates the team membership of lenders (313,040 edges in total).

Kiva provides a recent snapshot of this data set in JSON and XML formats.[3] In this work, we used a 2.9 GB JSON snapshot collected on 5/31/2013. We preprocessed it to obtain

[1]The processed data is available at `http://fodava.gatech.edu/kiva-data-set-preprocessed`.

[2]The loan history of a particular borrower is not available since the data set do not contain his/her unique identifier information.

[3]`http://build.kiva.org/docs/data/snapshots`

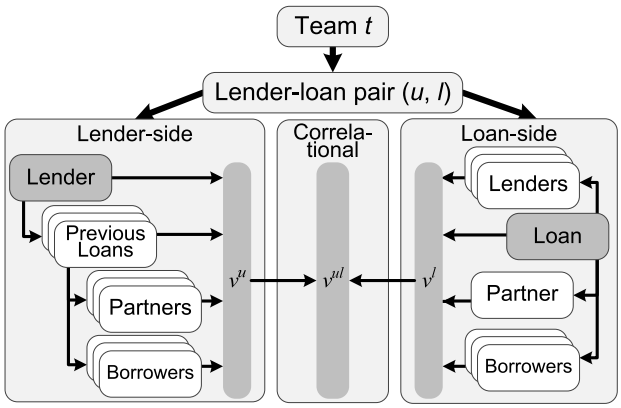


Figure 3: A feature integration framework for modeling lending activities in a team

the numerical representations of each available field. For temporal data, such as a loan's *posting date* and a lender's *sign-up date*, we converted them to a serial date number using Matlab's *datenum* function. In the case of categorical data, such as a loan's *country code* and a team's *category*, a dummy coding scheme was used to convert an n-categorical variable to an n-dimensional binary vector indicating the associated categories. Each textual field was encoded as a set of bag-of-words vectors with its own vocabulary set. We then reduced the dimensionality of each textual field to 100 using nonnegative matrix factorization[4] [20, 18] for memory efficiency.

4. TEAM-BASED MODELING

In this section, we describe the process of modeling lending teams in terms of their lending activities in Kiva.

4.1 Feature Representation of Lending Activities

As we briefly highlighted in Section 1, although lending activities are usually performed at an individual lender level, a significant amount of them are driven by lending teams that lenders are affiliated with. Furthermore, different lending teams may have different characteristics in their lending behaviors. Due to these reasons, we intend to model each lending team separately as follows.

We represent each lending team as a set of its lending activities. Each lending activity of a lending team t is described as a pair (u, l) of a lender u belonging to a team t and a loan l. As depicted in Fig. 3, we first obtain various entities to which a lender u and a loan l have links to. For a lender u, we obtain his/her previously funded loans as well as their associated partners and borrowers. For a loan l, we obtain its associated partner, borrowers, and other lenders who funded loan l.[5]

Lender- and loan-related features. By incorporating the information from these linked entities, we form two feature sets for lenders and loans, v^l and v^u, respectively. Note that all these features are numerically represented as described in the basic preprocessing steps in Section. 3.

In order to have the same number of dimensions for v^u (or v^l) against a different number of linked entities across different lender-loan pairs, we treat multiple entities of the same type as a single averaged entity. For instance, if a lender has funded multiple loans in the past, the feature vectors generated from them are averaged into a single vector. Similarly, features about multiple borrowers associated with a single loan, such as their genders, are also averaged. However, in this process, information about the total number of previous loans or the total number of borrowers is lost. To compensate, we encode any potentially lost information as additional features.

Lender-loan correlation features. The lender- and loan-related feature sets, v^u and v^l, are now represented in the same-dimensional space. That is, both lenders and loans have all the feature sets for borrowers, field partners, loans, and lenders. If lenders prefer to fund a particular type of loan, then these two counterparts would have similar values. To directly take into account such correlation information, we compute an element-wise multiplication of a lender-and a loan-related feature vectors, i.e.,

$$v^{ul} = v^u \circ v^l,$$

and include it as an additional feature set (Fig. 3).

Temporal features. Each loan contains temporal information such as its *posted_date*, *funded_date*, and *paid_date*. We assume that the relative time difference between two consecutive lending activities could be an important factor for a particular lender, and thus we encode such information as our features. That is, we generate all the temporal features in the form of $t_a - t_b$ where t_a is one of *posted_date* and *funded_date* of a loan of interest and t_b is one of *posted_date*, *funded_date*, and *paid_date* of a lender's most recent loan. Additionally, we encode the time taken for a lender to fund the loan since it has been posted.[6]

Finally, by including all the features encoded in the above-mentioned manner, we construct an m-dimensional feature vector $f(u, l) = \begin{bmatrix} f_1(u, l) & \cdots & f_m(u, l) \end{bmatrix}^\mathsf{T}$ representing a lender-loan pair (u, l)

4.2 Maximum-Entropy Distribution Model

Due to the nature of lending activities, lenders who have not chosen to fund a loan have not necessarily opted against funding it. It is often the case that the lender never knew about it. This type of data is known as presence-only or one-class data. In order to properly address this issue, we propose to apply a maximum-entropy distribution model (**maxent**) to a lending team's lending activity data.

Formulation. To model the lending activity, we want to use maxent to estimate the density $\pi^t(u, l)$, which indicates how likely a lender u will fund a loan l as a member of a lending team t. The goal of maxent is to maximize the entropy, or *uncertainty*, of an estimated density $\hat{\pi}^t(u, l)$, subject to the constraint that the expected value of each feature $f_i(u, l)$ under $\hat{\pi}^t(u, l)$ should be the same as that of $f_i(u, l)$ under the empirical distribution $\tilde{\pi}^t(u, l)$. The main idea of maxent is, given presence-only data, to estimate the

[4]We used the code available at `http://www.cc.gatech.edu/~hpark/nmfsoftware.php`

[5]Information about when individual lenders funded a particular loan is not available in the data set. Therefore, we randomly selected five other lenders in our experiment.

[6]Due to the lack of the temporal information about individual lenders' activities, we assume all lenders funded a particular loan at the same time as a loan's *funded_date*.

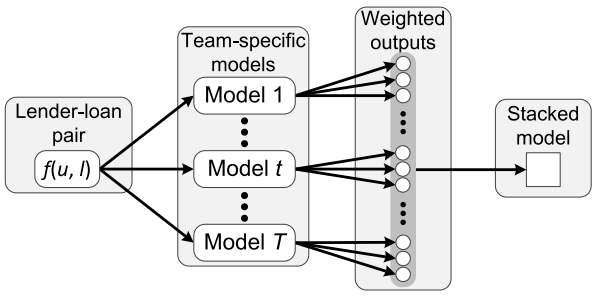


Figure 4: An ensemble model framework based on weighted stacking. Weight values are defined by considering various similarities between a lender-loan pair and each team.

target density as uniform as possible by assigning the most probability evenly to unseen parts of the space while keeping the same expected values of individual features as those from the observed data.

It has been shown that a problem of solving the maxent distribution can be converted to that of solving a maximum likelihood of $\hat{\pi}^t(u, l)$ in the form of a Gibbs distribution [9, 26], i.e.,

$$\hat{\pi}^t(u, l) = q_{\lambda^t}(u, l) \propto \exp\left(\sum_{j=1}^{m} \lambda_j^t f_j(u, l)\right),$$

whose probability is represented as a log-linear model in terms of an m-dimensional feature vector. With relaxation on the above constraints, the maxent distribution is solved by maximizing a penalized log-likelihood of these presence data, i.e.,

$$\max_{\lambda^t} \sum_{i=1}^{n^t} \log q_{\lambda^t}(u_i, l_i) - \sum_{j=1}^{m} \beta_j \left|\lambda_j^t\right|,$$

where a lender-loan pair (u_i, l_i) is the i-th lending activity (n^t activities in total) in team t, and β_j's are regularization parameters.[7] Similar to many other approaches such as the lasso in least squares [31], the l_1-norm regularization on λ_j^t's gives a sparse representation, which is robust against overfitting and deals with potential multi-colinearity among different features.

The algorithm for solving this formulation follows a coordinate-descent procedure, and in our work, we used the implementation available at `http://www.cs.princeton.edu/~schapire/maxent/`. In this implementation, in order to overcome the limitation of the original log-linear model, various additional features derived from original features, such as quadratic, threshold, and hinge features, are internally generated and used so that it can handle nonlinear responses of original features.

4.3 Ensemble Model based on Team-Specific Models

In Kiva, all the lending activities are still done at an individual lender level instead of a team level. Thus, even if a lender is affiliated with lending teams, such activities may not necessarily reflect his/her teams' characteristics. Nonetheless, the team-specific maxent models based on such team membership information can still be a versatile component that maintains coherent lending characteristics within each team as well as diverse characteristics between different teams. Based on this idea, we propose an ensemble approach that carefully combines team-specific models to model individual lending activities.

Specifically, we employ a weighted-stacking approach [32, 28], as summarized in Fig. 4. Suppose we obtained T team-specific models $\hat{\pi}^t(u, l)$'s for $t = 1, \cdots, T$. Now, we consider a similarity between a lender-loan pair (u, l) and a team t. Such similarity can be defined in multiple ways, e.g., the numbers of loans in terms of common geo-spatial location, industry, and field partner. In this manner, we compute K different similarity values $S_k((u, l), t)$'s for $k = 1, \cdots, K$. These similarity values act as weighting factors for the outputs from the team-specific models, and we collect all these values, $S_k((u, l), t)\,\hat{\pi}^t(u, l)$ for all the possible $t = 1, \cdots, T$ and $k = 1, \cdots, K$, as another feature vector. These feature vectors are then used to train another learner for better modeling lending activities.

5. LOAN RECOMMENDATION

5.1 Experimental Setup

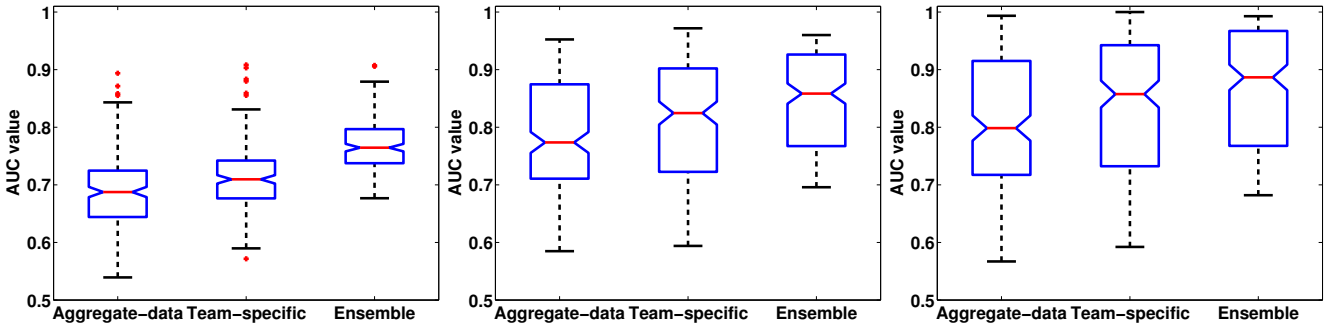
Data selection for lending teams. To begin, we chose the top 200 lending teams with the highest number of lending activities, totaling 70% of the total lending amount made by teams. From each of these lending teams, we randomly selected 5,000 lender-loan pairs in which the funding occurred. Additionally, maxent requires background or pseudo-negative data instances that properly reflect the overall distribution of the data instances. Therefore, we also randomly selected 5,000 lender-loan pairs where the funding did not occur.

On the other hand, we prepared for another set of lender-loan data purely from lenders who had no affiliations with lending teams. We then constructed an additional maxent model using this data set, which we refer to as the *no-team* model. Finally, we have 201 team-specific maxent models.

Feature groups. Each lender-loan pair (u, l) generated in this manner (10,000 in total for each team) is then encoded as a feature vector, as presented in Section 4.1. The constructed features can be categorized as follows:

1. Textual information (600 dimensions): reduced-dimensional textual features from a lender's *loan_because* and a loan's *loan_description*.
2. Loan sector (45 dimensions): features about the industry of a loan, e.g., agriculture, food, retail, etc.
3. Geo-location (228 dimensions): features about the country of a loan and/or a lender.
4. Loan delinquency (13 dimensions): features indicating how many loans previously funded by a lender u have been defaulted or delinquent.
5. Partner (33 dimensions): features about field partners in terms of their loan amount, rating, delinquency rate, etc.
6. Borrower (12 dimensions): features about borrowers, e.g., a borrower's gender and whether he/she has a picture.

[7] For the information about how to set the regularization parameters, we refer readers to [25].



(a) Loan-related features only (b) Loan- and lender-related features (c) Loan-side, lender-side, and their correlation features

Figure 5: The AUC values for the aggregate-data, the team-specific, and the ensemble models across different lending teams, depending on various feature sets used.

7. Temporal information (7 dimensions): Relative time differences between a loan l and a lender's most recently funded loan as well as the time taken for a lender u to fund a loan l since it has been posted (Section 4.1).

Eventually, the overall feature vector $f(u, l)$ is represented as a 938-dimensional vector.

5.2 Compared Methods

To utilize and evaluate our proposed team-specific models, we compared between the following three models:

Aggregate-data model. In this approach, we aggregate all the data instances from different teams into a single data set and train a single maxent model $\hat{\pi^a}(u, l, t)$ on these aggregated data. To make the comparison fair, we still incorporate team information in this case, such as a team's loan amount, member count, and category (e.g., common interest, religious, etc.), associated with the lender-loan pairs as additional 60-dimensional features into the aggregated model, as seen as its new input argument t in $\hat{\pi^a}(u, l, t)$. In this manner, our baseline method still uses the same amount of information as in the proposed team-specific models but does not distinguish between the lending characteristics from different lending teams. That is, the distinction is only made at a feature level, but not at a model level.

Team-specific model. Based on the information about the team t from where a given lender-loan pair (u, l) was chosen, this approach uses a single team-specific model $\hat{\pi^t}(u, l)$ corresponding to this team as a final output.

Ensemble model. This ensemble model is the one discussed in Section 4.3. The similarity functions $S_k((u, l), t)$'s are computed as cosine similarities in terms of the above-described seven feature groups, respectively, between a target test vector for a lender-loan pair (u, l) and an averaged vector of lender-loan pairs within each team. Such diverse similarity values provide a means to take into account the outputs from team-specific models at different levels depending on the respective feature characteristics. As an additional learner for stacking, we used l_1-regularized logistic regression, but any other advanced learning model could also be used.

5.3 Recommendation Performance

Evaluation measure. For lender-loan pairs obtained from each team, we performed 5-fold cross-validation.[8] As our performance measure, we report an averaged area under the receiver operating characteristic curve (AUC) value,[9] which measures how well the data samples with funding are ranked higher than background samples.

Performance comparison. For the three compared methods, Fig. 5 shows the AUC values of 201 teams when using either (1) loan-related features only, (2) loan- and lender-related features, and (3) lone-related, lender-related, and their correlation features. In all cases, the team-specific model shows better performances than the aggregate-data model, indicating that the diversity of lending behaviors across different teams is indeed substantial and that it cannot be fully handled at a feature level. Furthermore, our ensemble model works even better than the team-specific model. It is also shown that the overall performance variance across different teams is reduced compared to the other two models, which indicates that the ensemble model is helpful for those teams of which the lending activities are difficult to predict.

Starting with the information about loans of interest, as we incorporate additional features discussed in Section 4.1, the performance is shown to improve significantly. It indicates that the information about lenders and their past lending activities is critical in predicting his/her next loan activities. In particular, the fact that such performance increase due to involving lender information is significant even for our team-specific models implies that the diversity within each lending team is also existent.

Overall, the highest AUC value we could achieve by using all the proposed features under team-specific model was 0.88 on average across teams, which seems to be reasonable for use in practice in loan recommendation.

6. EXPLORATORY ANALYSIS

In this section, by analyzing the team-specific maxent models, we present our in-depth analysis on diverse behaviors among different lending teams.

[8]Note that the lending activities of the same lender were not included in both training and test sets.

[9]The AUC value is computed using the trapezoidal approximation [5].

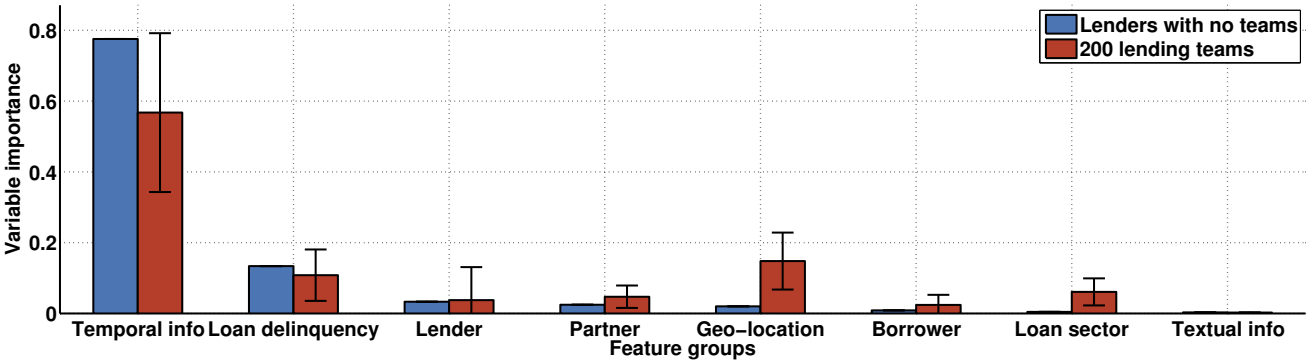


Figure 6: The variable importance scores of different feature groups. The values are sorted in a decreasing order with respect to those in the *no-team* model.

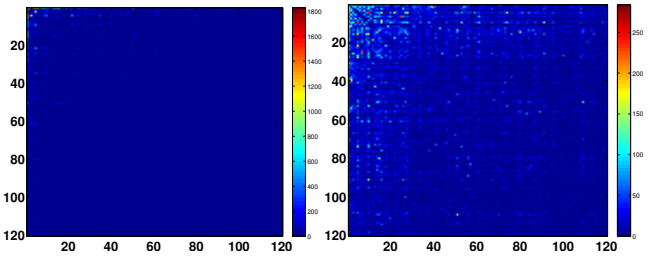
Interpretation of maxent models. Our strategy to analyze each team's lending behaviors is to compute the variable importance scores in its maxent model. As a way to compute these scores, we chose to use the permutation importance score, often used in various machine learning methods [30]. The importance score of each variable is determined by randomly permuting the values of that variable among the training data items and measuring the resulting decrease in the AUC value. A large decrease in the AUC value indicates that the model depends heavily on that variable. After computing the permutation importance score of each variable, these scores are normalized to give relative percentage values among the entire variables.

What do lending teams care about? (lending teams vs. lenders with no teams)

Before exploring the characteristics at an individual team level, we tried to identify the critical factors that had the significant influence on the activities of general lending teams. To this end, we compared the variable importance scores between the 200 team-specific models and the *no-team* model, the results of which are shown in Fig. 6.

Commonalities. Temporal information is shown to be the most important feature in both cases, which is consistent with our previous findings discussed in [7]. That is, once lenders begin lending, they tend to either keep funding other loans continuously or lose interest drastically as time goes on. Next, undesirable experiences that involve a loan delinquency and default also significantly impacts the next lending activities for both cases. Information about lenders, such as the number of previous loans and their characteristics, were shown to be moderately important factors, but the importance of lender information varied highly across different teams, as shown by the relatively large error bar corresponding to the 'lender' feature group. Finally, the influence of textual information was shown to be minimal compared to other information because of the significant noise and the information sparsity in free-text data.

Contrarieties. Fig. 6 also highlights interesting distinctions of lending teams compared to lenders with no teams. Specifically, information about a loan's geo-location and the loan sector (or industry) was the two most critical factors in lending teams' activities. It indicates that *lenders in lending teams actually care more about the geo-location and the purpose of the requested loan* than lenders without team affiliations. Furthermore, it was also shown that *lending teams care who the borrowers and the associated partner are*, as shown from the relatively higher importance of the corresponding variables compared to the *no-team* model.



(a) 'Kiva Christians' (b) 'Atheists, Agnostics, Skeptics, Freethinkers, Secular Humanists and the Non-Religious'

Figure 7: Lender graphs of two lending teams. The top 120 lenders with the most number of loans have been chosen from each team. The value at each cell represents the number of common loans between two lenders within a particular team.

6.1 Individual Team Characteristics

We felt that it was important to explore deeper to discover diverse behaviors present at a team-specific level. This motivation came as a result of noticing how lending teams had such a large influence on the activity of its members. We decided to rank lending teams based on their variable importance scores for different feature groups. In doing so, we were interested in which teams cared the most (or the least) for each aspect, and in the fundamental characteristics of each team that drove these behaviors. We approached this problem from the perspective of a lender as well as a loan.

6.1.1 Lender Feature

As mentioned above, the dependency on lender information varied highly across lending teams. Although it was not reported in this paper, the most influential feature about a lender was shown to be the number of loans he/she had previously funded. As we analyzed the teams that were influenced the most (or the least) by lender features, we found out that dependency on lender information is inversely correlated with the diversity of team leaders.

For instance, Fig. 7 shows a comparison of the lender graph between two groups of teams - 'Kiva Christians' and 'Atheists, Agnostics, . . . '. The 'Kiva Christians' group was

Table 1: The top five teams influenced the most by each of the feature groups.

Features	Lending teams
Industry	'KivaFriends - Agriculture Loans', 'Ravelry.com', '101 Cookbooks', 'Give Green - Environmental Loans', 'Thailand'
Geo-location	'Para México', 'Philippines', 'Kiva Muslims', 'Kiva Detroit', 'Portugal',
Field partner	'Amici di Raffaele (Raphael's Friends)', 'Woodlands', 'Compadres', 'Lauren Avezzie', 'Kiva Jews'
Borrower	'women empowering women', 'HALF THE SKY: Empowering Women', 'Georgia Southern Alumni', 'www.idu.cc', 'Tareto Maa'

one of the teams that were influenced the most by lender features. In other words, the lending activities in 'Kiva Christians' were significantly influenced by the lender feature, mainly by the number of his/her previous loans. This observation implies that lending activities are mainly dominated by only a small number of highly active lenders. On the other hand, 'Atheists, Agnostics, . . . ' was one of the least influenced teams, indicating that lending activities are more evenly distributed over lenders with various numbers of previous loans. In the 'Kiva Christians' graph (Fig. 7(a)), one can notice that a single person, as seen in the first row/column, showed significant overlap in their lending activities with all the other members. On the contrary, in the 'Atheists, Agnostics, ...' graph (Fig. 7(b)), commonly funded loans were found amongst a large number of different lenders. It is clear from this observation that the latter case could be led by many lenders with a different degree of activities while in the former case, lending teams are mostly led by a few leading lenders.

6.1.2 Loan Feature

Now, we analyze the most influenced teams, i.e., special-focus teams, by different feature groups from a loan perspective. Table 1 presents the top five teams corresponding to each feature group.

Industry. The 'KivaFriends - Agriculture Loans' team funded 77% of its total loans to the agriculture industry, while only 21% of the entire set of loans belongs to this category. The teams '101 Cookbooks' and 'Give Green - Environmental Loans' made strong contributions to the agriculture industry while also making significant contributions to the food industry. The 'Ravelry.com' team, whose website focuses on knitting and crocheting, funded 23% of its total loans to the art industry, while only 2% of the entire set of loans belongs to this category. These interesting relationships can be expressed as *homophily*, as observed by the fact that *people tend to fund loans similar to what they like*.

Finally, although we did not find a reasonable explanation for it, we noticed that the 'Thailand' team funded 79% of its total loans to the food industry, while only 26% of the entire set of loans belongs to this category.

Geo-location. The teams 'Para México' and 'Philippines', as their team names imply, funded 49% and 91% of the total loans to Mexico and Philippines, respectively. These teams were strongly dedicated to their designated countries especially considering that the total percentage of loan requests from Mexico and Philippines were only 2% and 15%, respectively.

The 'Kiva Muslims' team made major loan contributions to Palestine (12%), Pakistan (10%), Tajikistan (8%), Lebanon (8%), and other countries where the dominant religion was Islam. The total percentages of the loans to these countries were only 6%, 2%, 3%, and 1%, respectively.

For the 'Kiva Detroit' team, the top lending country was shown to be the USA, which holds 11% of this team's total loans while the total percentage of the USA loans were minimal at 0.2%. Interestingly, we found that Kiva recently started supporting a local small business specifically in the USA under the name, Kiva City,[10] and Detroit was selected as the first Kiva City. Finally, the 'Portugal' team exhibited a unique behavior. It made 6% of their total loans to Mozambique, as compared to the percentage of the total loans to this country, 0.5%. The most probable reason is as follows. Historically, Mozambique was one of the few former colonies of Portugal in Africa, and thus the official language is still Portuguese. Looking into the languages in which the loan description was written, 92% of the loans from Mozambique were described in Portuguese while only 0.5% of the entire loans were available in Portuguese.

Field partner. Features about the field partner generally represent the reliability and credibility as represented by the total loan count/amount, a default/delinquency rate, currency exchange loss rate, etc. From a lender's and a lending team's viewpoint, choosing an appropriate partner is critical in minimizing the risk of losing money. By looking at the top ranked teams for this feature group, we found that they are mostly composed of a relatively small number of people with a large number of loans per member. For example, the teams 'Amici di Raffaele (Raphael's Friends)', 'Woodlands', 'Compadres', and 'Lauren Avezzie', each of which had 10, 45, 2, and 17 members in total, funded 305.3, 303, 2627, and 263.2 loans per member, respectively. These numbers are significantly higher than 30.5, the average number of loans per member among the entire 200 teams. This observation seems to be reasonable in that highly active lenders are likely to manage their funds carefully so that they can maintain a large volume of non-profit activities for a long period of time without losing their fund.

On the other hand, the other top ranked team, 'Kiva Jews', which had only 14.2 loans per member, did not have as many highly active lenders. Instead, our results suggest that members of this team may be more wary of the risk of lending.

Borrower. Borrower information is composed of (1) a borrower's gender and (2) a borrower's picture availability. Among the top ranked teams for borrower features, most teams were found to be mainly influenced by the gender, usually in favor of women. It is easily understood that the teams 'women empowering women' and 'HALF THE SKY: Empowering Women' funded 95% and 98% of their total loans to female borrowers, respectively. However, it is surprising that the team 'Georgia Southern Alumni' funded 98% of their total loans to female borrowers.

The two other teams 'www.idu.cc' and 'Tareto Maa' also funded 85% of their loans to female borrowers. For the for-

[10] `http://www.kiva.org/kivacity`

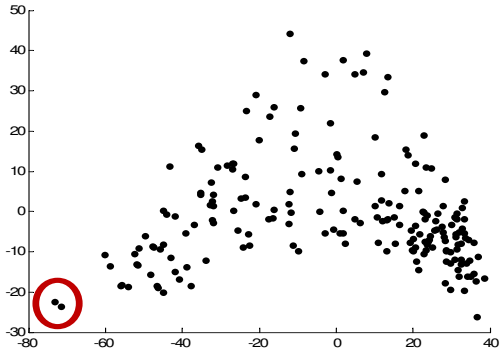


Figure 8: A PCA visualization of variable importance vectors corresponding to the 200 lending teams. The two points shown in a red ellipse correspond to the teams 'Expired Loans' and 'Late Loaning Lenders', respectively.

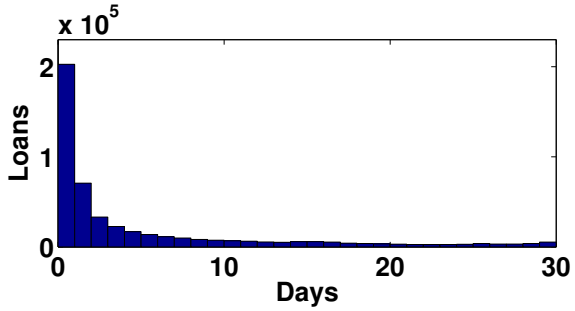


Figure 9: A distribution of the time taken for a loan to be fully funded.

mer, the variable importance about the borrower's picture availability was significantly higher than any other teams, indicating that lenders in this team are highly unlikely to fund loan requests that do not provide a borrower's picture. Finally, the team 'Tareto Maa', translated as "help for the Massai", was founded in order to eradicate the tradition of female circumcision and child marriages within the Massai people. We find this to be the most likely reason as to why they focus on female borrowers. Additionally, this team was also highly ranked as the 29th in terms of the geo-location feature group, and we found that 25% of their total loans were requested from Kenya, where the territory of the Massai is located.

6.1.3 *Outlier Teams from Visualization*

So far, we looked into various team characteristics due to each of the feature groups. However, in this approach, it may be difficult to pinpoint those lending teams that are moderately different from usual teams from a particular aspect but are significantly different when incorporating entire features altogether. For this reason, we generated the variance importance vector corresponding to the entire features for each lending team. Then, we applied principal component analysis (PCA) [17] in these vectors in order to visually represent teams in a 2D space. The visualization result shown in Fig. 8 clearly reveals two outlier teams, 'Expired Loans' and 'Late Loaning Lenders'.

Most loans in Kiva have a 30-day period of expiration for its fundraising. Fig. 9, which shows the distribution of the time taken for a particular loan to be fully funded, indicates that most loans are fully funded within a few days but some loans take much longer even possibly failing to be fully funded. These expired or soon-to-be expired loans can be thought of as relatively unpopular ones within the Kiva lending community.

These two lending teams are unique in that their mission is to fund unpopular loans in order to avoid their expiration. We found that their lending behaviors were different from other teams from many aspects. For instance, both teams funded more loan requests from males than from females, e.g., 60% and 58%, respectively. Their top lending countries included Tajikistan, Bolivia, Lebanon, Azerbaijan, Jordan, and El Salvador, all of which were not actively funded by other teams.

7. TEAM RECOMMENDATION

In this section, we utilize our team-specific maxent model for team recommendation for lenders who are not yet affiliated with any teams.

7.1 Team Model-Based Approach

To perform this task, we assume that a lender u and his/her first c loans l_i^u's ($i = 1, \cdots, c$) are available and that a lender u did not join any teams while funding these first c loans. We then generate a feature vector for a lender-team pair (u, t) for each team as follows. First, using the team-specific model for a team t, we compute an averaged likelihood value $L(u, t)$ for the first c loans, i.e.,

$$L(u, t) = \frac{1}{c} \sum_{i=1}^{c} \hat{\pi}^t(u, l_i^u). \quad (1)$$

Second, this value is weighted respectively by K different similarity functions $S_k((u, l), t)$ introduced in Sections 4.3 and 5.2. In this manner, we obtain a K-dimensional vector corresponding to each team, where the k-th component is represented as $S_k((u, l), t) L(u, t)$.[11] Using these vectors along with the label information as to whether a lender u is affiliated with a team t or not, we learn a model, where we used l_1-regularized logistic regression.

7.2 Recommendation Performance

Baseline approaches. We introduce two different baseline approaches. As the first one, we extend the aggregate-data model $\hat{\pi^a}(u, l, t)$ described in Section 5.3. That is, we choose the most appropriate team t_u^a for a lender u as

$$t_u^a = \arg\max_t L_a(u, t) = \arg\max_t \frac{1}{c} \sum_{i=1}^{c} \hat{\pi^a}(u, l_i^u, t).$$

As the second approach, we directly use the output of the team-specific models without using the similarity functions as well as the subsequent learning process. By comparing this output values from all the 200 teams, the team recommendation for a lender u is performed as

$$t_u = \arg\max_t L_a(u, t) = \arg\max_t L(u, t).$$

Performance measure. From each team t_r, we randomly selected k lenders, e.g., $k = 500$ in our experiment, from each team along with their first five loans, i.e., $c = 5$. Then, among the values of $L(u, t)$ for 200 teams for a lender

[11] Note that any lending activities of a lender u were excluded in those of a team t.

Table 2: A comparison of the mean reciprocal rank values for team recommendation. The values represent an average value over lenders from 200 teams while those in parentheses represent the variance.

	Mean reciprocal rank
Similarity-weighted model	.1482 (.0402)
Direct team-specific model	.0851 (.0365)
Aggregate-data model	.0548 (.0210)
Random assignment	.0294

u_i, we computed the mean reciprocal rank of the correct team t_r as

$$MRR = \frac{1}{k}\sum_{i=1}^{k}\frac{1}{r(u_i,\, t_r)}$$

where $r(u_i,\, t_r)$ is the rank of $L\,(u_i,\, t_r)$ among $L\,(u_i,\, t)$'s. The maximum value of this measure is one, and a higher value of this measure indicates that the correct team ranked higher than other teams.

Comparison Result. Table 2 shows the comparison of the team recommendation results. Our approach based on the similarity-weighted model clearly shows a better performance than the two baseline methods as well as random assignment. The main reason for this performance improvement is because the differently weighted team-specific model outputs are capable of handling different aspects of a lender and a loan depending on lending teams. That is, some teams may put more emphasis on a particular aspect such as a loan's geo-location or industry while other teams do not.

8. IMPLICATIONS

Lenders are often motivated by their strong preference to address needs that they feel connected to, whether it is to a loan industry or a geographical location or even to a particular feature in the borrower, such as their gender or situation. As presented in Section 6, these preferences are often rooted in the lender's ethnic, religious, linguistic, educational, regional, and occupational background.

Our comprehensive analysis on diverse lending characteristics of teams basically reveals a meaningful yet distinct set of preferences and their connections to the underlying human factors. Based on our findings, we believe that Kiva could drastically improve their practice at both a lending team and an individual lender level.

Team-level approach. Kiva would strongly benefit from continuously guiding each team to appropriate loans. Currently, most teams have a small number of leading lenders that drive their team members' activities. Identifying the team leaders along with a deep understanding about their interest is crucial in keeping each team as active as possible by providing them with the loans they feel are within their interest. Furthermore, Kiva should also encourage each lending team to expand its interest. As discussed in Section 6.1.3, less popular loans could be easily funded with more effort at a team level. Kiva could even incentivize those teams that try to expand their interest. However, such strategies require the ability to properly identify the lending activities outside of a team's original interest, the partial clues of which we presented in this paper.

Lender-level approach. Encouraging lenders to join teams that have similar interests based on their background would allow diverse communities in Kiva to thrive. In our team recommendation task, we indirectly addressed this issue by utilizing one's previous loans, e.g., whether he/she funded loan requests from a particular gender, country, etc. However, the quality of our recommendation would significantly benefit if it also took into account a lender's background, e.g., ethnic, religious, educational, regional, and occupational information, when making team recommendations. By proactively collecting such additional information from lenders, rather than just collecting the lender's current location and occupation, Kiva would be able to accurately suggest the best lending teams to each lender, ultimately to increase the average level of participation of their lenders.

9. CONCLUSION AND FUTURE WORK

In this paper, we studied diverse characteristics of lending teams in a widely-used micro-finance service, Kiva.org. By treating lending activities as presence-only data and by fully incorporating the rich set of data available in Kiva, we modeled each lending team as a maxent distribution and achieved superior performances in loan recommendation applications using an ensemble approach based on the team-specific models from the top 200 lending teams. In addition, we discovered diverse lending behaviors by interpreting the resulting maxent models and enlightened the underlying social aspects that support these findings. Finally, we applied our team-specific models in the team recommendation application, showing promising results for matching lenders to appropriate lending teams.

The importance of our work and the information-rich nature of the Kiva data open up various future research possibilities. We describe a few of them as follows.

Social influence in lending teams. One promising direction is to further study the influence team members have on one another. As briefly seen from the lender graph in Fig. 7, most teams have a small number of key members that direct the entire team activities. Analyzing such processes in the context of peer pressure and information diffusion [12] would provide a deeper insight into how the lending team influences their nonprofit activities.

Visual analytics approach for comparison and contrast. It would be important to allow users to effectively compare and contrast the characteristics between different lending teams. Especially, one of the most challenging portions of data for analysis is unstructured text. Thus, we plan to apply an interactive visual topic modeling approach where users can dynamically explore multiple groups of textual data associated with different lending teams [8].

Evolution of lending teams. We are also interested in the process in which teams emerge and decline over time. Kiva runs a team leaderboard where they show the ten most active teams by the amount of loans and new lenders on a monthly basis. These leading teams change frequently over time, and it would be worthwhile to study the cause of their rise and fall. To this end, utilizing external data such as twitter group chats related to lending teams would also be useful [15].

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