Fairness-Aware Loan Recommendation for Microfinance Services

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ABSTRACT

Up to date, more than 15 billion US dollars have been invested in microfinance that benefited more than 160 million people in developing countries. The Kiva organization is one of the successful examples that use a decentralized matching process to match lenders and borrowers. Interested lenders from around the world can look for cases among thousands of applicants they found promising to lend the money to. But how can loan borrowers and lenders be successfully matched up in a microfinance platform like Kiva? We argue that a sophisticate recommender not only pairs up loan lenders and borrowers in accordance to their preferences, but should also help to diversify the distribution of donations to reduce the inequality of loans is highly demanded, as altruism, like any resource, can be congestible.

In this paper, we propose a fairness-aware recommendation system based on one-class collaborative-filtering techniques for charity and micro-loan platform such as Kiva.org. Our experiments on real dataset indicates that the proposed method can largely improve the loan distribution fairness while retaining the accuracy of recommendations.

1. INTRODUCTION

Since the pioneering endeavor by Yunus and Yusus [10], microfinance has received intense attention and been widely adopted around the world. Up to date, more than 15 billion US dollars have been invested in microfinance that benefited more than 160 million people in developing countries. As a successful financial and philanthropic model, microfinance has attracted researchers from different disciplines to investigate what mechanisms underlie its success. Microfinance successfully overcomes two hurdles that prevent poor people from getting loans from the traditional financial institutions. First and foremost, the risk problem—*how can we decrease delinquency rates of loans provided to the economically disadvantaged*? Second, *how can we find willing loan providers*? Practitioners of microfinance solve the first problem in reference to social theories, using the mechanism of collective monitoring and punishment to minimize incidents of delinquency [2, 5–7]. Advocates of microfinance solve the second problem by linking microfinance to philanthropy [9], motivating loan providers to treat lending money to the poor as an act of kindness. With the two major problems being solved, it remains a question how to screen out potential loan borrowers and lenders.

Proposal. In this paper, we propose a matching algorithm for microfinance whose goal is to not only maximizing the opportunity of successful matching but also diversifying the resources of loan providers. The concepts of fairness and recommendation are, to some extent, *contradict* to each other. If one only cares about fairness, then there is no need to perform recommendation as we can simply equally divide the resources to every person in need. On the contrary, the goal of performing recommendation is indeed to break the fair situation so that some specific loan is recommended to certain lenders. Thus, a successful fairness-aware matching system needs to take such trade-off into consideration.

Since only partial binary decision labels (whether a contribution was made) of each lender to each loan is available, we formulate the problem as an one-class collaborative filtering (OCCF) problem [8], where negative (i.e. not interested) and unlabeled (i.e. not seen) examples are mixed together. To solve the one-class collaborative filtering problem, we adopt the Bayesian Personalized Ranking idea to a Matrix Factorization engine. We propose two methods take fairness into consideration: 1) Item-Based regularization method and 2) the fairness-aware BPRMF method. The first model exploits a regularization term to build the distribution of ratings to avoid skewed recommendation, but suffer the drawback of high computational cost. The second approach dynamically adjusts the learning step in the stochastic gradient descent process to achieve the goal of balancing recommendation, that is relatively efficient and yields good results.

Contribution. We propose a fairness-aware recommendation system for charity and micro-loan platform such as Kiva.org, and conduct experiments to verify the effectiveness of the system. To our knowledge, this is the first-ever loan recommendation algorithm that takes fairness into consideration.

The remainder of this paper is organized as follows. Section 2 describes related works on recommendation systems. We present an overview of the Kiva ecosystem in Section 3. In Section 4, we propose a fairness-aware loan recommender system for microloaning services and then evaluate its per-

SocialCom'14, August 04 - 07 2014, Beijing, China

ACM 978-1-4503-2888-3/14/08 ...$15.00.
http://dx.doi.org/10.1145/2639968.2640064.

formance in Section 4.2. Following that, we take a closer look of lenders' behavioral diversity in order to explore more opportunities in enhancing the proposed recommender system in Section ??. Finally, Section 5 draws our conclusion and future work.

2. RELATED WORK

From the viewpoint of fairness-aware recommendation systems, the closest works we have seen are the ones that emphasize on the *diversification* of recommendation [1, 11, 12]. The core concept of diversification is to recommend different kinds of items to improve users' satisfaction. However, it is very different from the concept of fairness where we want to diversify the matching between lenders and loan applicants.

Choo et al. [3] have focused on building personalized loan recommendation system which is based on content-based filtering techniques using specialized feature integration techniques and gradient boosting tree (GBtree). The goal is similar to ours except that fairness has not yet been taken into consideration in their design. In the authors' follow-up work [4], they continued to analyze the lending terms' behavior: How they choose which borrowers to lend money and when they would perform the next loaning? The results show that their Maxent-based model can be used to discover diverse team characteristics and predict team affiliation.

3. THE KIVA ECOSYSTEM

In this section, we describe the Kiva dataset, post-processing steps, and the user behavior of loan applicants and providers.

3.1 Data Description

On their own website, the Kiva organization provides three public datasets which contain the information about the loan applicants (i.e., borrowers), the lenders, and the connections between them. Since Kiva's launch in April 2005, till December 2013, there have been 643,495 loans coming from 80 countries, and 1,196,283 lenders registered on the website. Since each loan can be contributed by a number of lenders (each loan contribution can be ranged from $25 up to $500 USD), the lenders have in the lump made 15,355,805 contributions to the loans worldwide through the Kiva platform.

The loans on Kiva contains descriptive information such as the personal biography of the borrowers (normally their gender and marital status are included), the purpose of the needs, and the amount of money needed. The timestamps of when a loan is posted and funded, as well as its repayment schedule, are also provided. The repayment schedule can be any of three types: monthly (66.5%), irregularly (25.4%), and at end of term (7.9%). A loan can be classified into one of six statuses based on their posted and funded timestamps.

We summarize the loans on Kiva in Table 1 according their status as of December 11, 2013. The figures show that Kiva is indeed a successful microfinance platform as the proportions of expired and faulted loans are both lower than 2%. Because we will focus on the funding behavior from the lenders, we create a smaller, reduced dataset from the whole 5-year dataset with the following reduction: 1) We retain only the funding records from November 1, 2011 to October 30, 2013 where the number of loans and funding activity are relatively stable, and 2) we retain only the loans that have been fully funded, and thus loans in the fundraising and expired status are removed. This results in a reduced dataset

Table 1: Loan summary in the full and reduced datasets

Status	Full dataset		Reduced dataset	
Fundraising	5,672	(0.91%)	0	(0%)
Fully funded	280	(0.04%)	57	(0.02%)
Expired	10,594	(1.69%)	0	(0%)
Paying back	113,472	(18.14%)	99,085	(38.32%)
Paid	484,267	(77.43%)	157,407	(60.87%)
Ended with loss	11,143	(1.78%)	2,049	(0.79%)
Total	625,428	(100%)	258,598	(100%)

of 258,598 fully-funded loans, which we will analyze in more details below.

3.2 Loan Overview

On Kiva, a loan can be requested by an individual person or a group of people. Our dataset indicates that there are 541,937 (86.7%) individual loans and 83,491 (13.3%) group loans, where the number of borrowers associated with a group loan can be up to 50 persons. To help lenders find out the loans they are interested in, Kiva requires each loan to be associated with one of the 15 pre-defined sectors based on the expected usage of the loan.

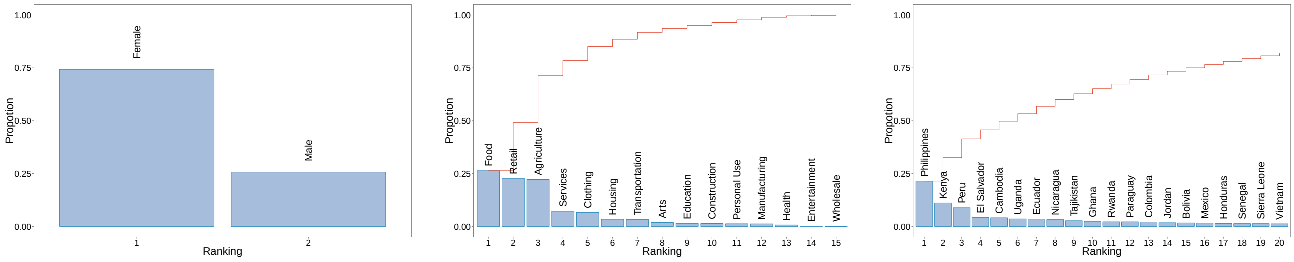
In Figure 3, we show the proportions of borrowers' gender[1] and country of origin and the sector which the loans will be used for, where the red staircase lines denote the cumulative sums of the proportions. We have made a few interesting observations. First, we observe that approximately 75% of the loans are requested by female borrowers. Second, the loans are requested for various types of purposes, among them, food (26.3%), retail (22.7%), and agriculture (22.1%) are the three main sectors the requested loans are being used for. For example, a borrower may plan to use the fund to purchase flour and baking equipments to run his own bakery or cafe (food sector); in another example, a borrower plans to buy oxen, piglets and forage for feeding the livestock (agriculture sector). Some other uses of the fund include arts, entertainment, and housing, which are much less common but not necessarily with lower desired loan amount. On the other hand, the loan applicants are from a diverse range of countries in different continents: Philippines (21.4%), Kenya (11.0%), and Peru (8.8%) together contribute 41.4% of all loans. The figures support that Kiva reaches the global needs without geographical boundaries and supports a variety of uses to improve people's lives.

4. FAIRNESS-AWARE RECOMMENDATION

The matching problem for microfinance can be modeled as a recommendation task. We want to recommend some loans to certain lenders and maximize the chances those lenders would fund the loans. In this sense, we can use the existing data to create a large matrix to represent the connections between lenders and loans. Such matrix is usually sparse as a lender is not likely to have investigated on most of the loans.

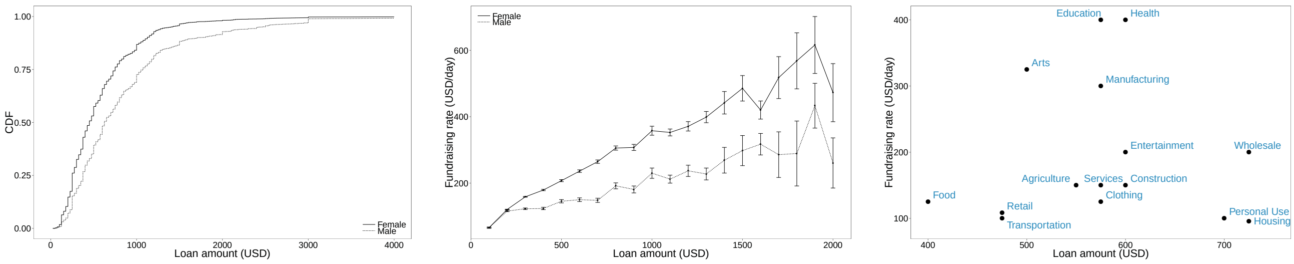
In many microfinances services such as Kiva.org, due to privacy concerns, we are only given the information about which lender has endorsed a loan, but not how much this lender contributes to the loan. Furthermore, if a lender does

[1] Only the individual loans are considered as a group loan may comprise borrowers of both genders.



(a) Borrower gender (b) Loan sector (c) Borrower country

Figure 1: Distributions of major loan attributes



(a) Loan amount distribution (b) Fundraising rate for female- and male-loans (c) Fundraising rate for loans in different sectors

Figure 2: Summary of loan amount and fundraising rate

not endorse a loan, it is not possible to know whether it is because this lender has not yet reviewed this loan, or simply does not like it. Researchers have proposed the *one-class collaborative filtering* (OCCF) framework to design recommenders for such scenario. It is called one-class since only positive endorsement, where the negative and unseen behaviors are indistinguishable. Our proposed method will be developed based on BPRMF, the Bayesian Personalized Ranking (BPR) optimization criterion coupled with matrix factorization (MF), to achieve satisfactory results. Thus, we will call our method as Fairness-Aware BPRMF method.

4.1 Fairness-Aware BPRMF

Since that we need the tuples (u, i, j) for training the model in SGD. For a given lender u and the positive loan i, we find a negative sample j from I_u^- and perform updating. Normally each (u, i, j) tuple is treated as equally important during updating. Our idea is that to achieve fairness, maybe we should treat the tuple with "popular" j more seriously than those with less popular j. The intuitive behind is that if j has been a popular loan liked by many lenders, it is preferable to update our model more toward a direction to reduce lenders' interests in this loan for fairness purpose. Therefore during the SGD process, we do not assign equal step size for each instance tuple, but larger step to the situation where a popular tuple has been assigned the "negative" weight adjustment. Given this idea, the next question would be how to evaluate the "popularity" of a loan j during training. Our idea is to use the model learned up to date (i.e. most recent P and Q) to predict the ratings of both i and j on all users, and the popularity of a loan j with respect to an update (u, i, j) is defined as the probability that a user likes j more than i. This popularity then becomes a weight to adjust the step size of SGD.

The detailed process goes as: first we random sample a negative example j, and then sample N_{ref} reference lenders $u_1, u_2, \cdots, u_{N_{\text{ref}}}$, based on which we can generate the popularity of j, proportional to which we can determine the step size of SGD during updating:

$$\text{popularity}(j) := 2\sum_{n=1}^{N_{\text{ref}}} [\![P_{u_n} Q_j^T > P_{u_n} Q_i^T]\!] / N_{\text{ref}} \qquad (1)$$

$$\begin{aligned} P_{uk} &\leftarrow P_{uk} - \alpha \left(\text{popularity}(j) \cdot \frac{\partial \text{Error}}{\partial P_{uk}} \right) \\ Q_{ik} &\leftarrow Q_{ik} - \alpha \left(\text{popularity}(j) \cdot \frac{\partial \text{Error}}{\partial Q_{ik}} \right) \qquad (2) \\ Q_{jk} &\leftarrow Q_{ik} - \alpha \left(\text{popularity}(j) \cdot \frac{\partial \text{Error}}{\partial Q_{jk}} \right). \end{aligned}$$

Note that our modification mainly focuses on the learning rate of SGD (Stochastic Gradient Descent), which means it can not only be applied to BPRMF, but also other BPR models that exploit SGD for updating.

4.2 Evaluation

Up to date, we have not yet seen any recommendation model that considers fairness as a key factor. Thus in the evaluation we focus on comparing the proposed item-based regularized BPRMF method and fairness-aware BPRMF approach against the original BPRMF as a baseline. Note that the goal here is not about beating the competitors in the prediction accuracy, rather we want to test whether the goal of achieving fairness can be achieved without sacrificing too much accuracy in rating prediction.

Recommender Accuracy. We choose the Area-under-ROC-curve (AUC) as the evaluation metrics for ranking ac-

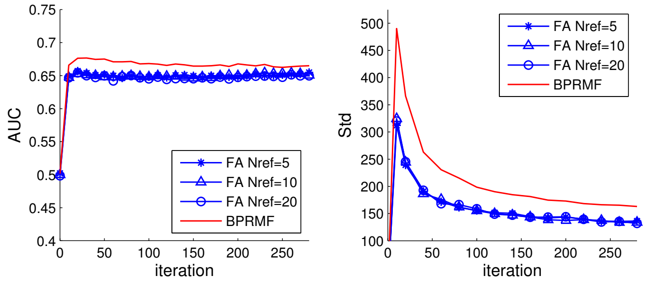


Figure 3: The AUC, Std ($N_{\text{top}} = 30$) through learning iterations

Table 2: The best AUC and the Std under such AUC for each model

Method	Best AUC	Std
BPRMF	0.678	319.16
Fairness-Aware BPRMF	0.656	131.42

curacy, as it is one of the most popular metrics to evaluate a ranking problem such as OCCF.

$$\text{AUC} := \frac{1}{N_u}\sum_{u=1}^{N_u}\frac{1}{|E(u)|}\sum_{(i,j)\in E(u)}\delta(\hat{y}_{ui} > \hat{y}_{uj}), \qquad (3)$$

where the evaluation pairs $E(u)$ per user is defined as $\left\{(i,j)|(u,i) \in I^+_{u\ \text{Validation}}, (u,j) \notin I^+_{u\ \text{Training}} \cup I^+_{u\ \text{Validation}}\right\}$.

Recommender Fairness. Here we consider whether each loan can be fairly recommended to all of the lenders. Assuming our recommendation system suggests a constant amount of N_{top} loans to each lender, which can be done easily in our model by choosing the loans of the top-N_{top}[2]. predicted ratings for each lender. Then we can gather how many times each loan is recommended to lenders and compute the standard deviation of such count to evaluate recommender fairness. Lower standard deviation indicates higher fairness since it implies all loans have the same amount of opportunity to be recommended. Note that examining this measure itself is meaningless as one can always 'enforce' fair recommendation without considering the quality of prediction. Our goal is to do so without significantly degrading the accuracy of a recommender.

In the experiments, we choose different number of reference lenders N_{ref} for Fairness-Aware BPRMF. Both methods are trained over 300 iterations, where AUC and Std are calculated over iterations for comparisons. Table 2 presents the best AUC and the Std in the iteration with the best AUC. The result shows that the Fairness-Aware BPRMF model outperforms BPRMF by reducing $\sim$ 58% in Std, while only sacrificing a small amount of AUC ($\sim$ 3.2% relative to BPRMF).

Figure 3 shows the AUC and Std metric over iterations of both models, where FA stands for Fairness-Aware BPRMF. On the graph, the three FA lines overlap with each other, which indicates that FA is insensitive to $|s_i|$ and N_{ref}. It also implies that the updating rule of Fairness-Aware BPRMF can work well even with very small samples to further improve the computational efficiency. On the other hand, higher cost in Fairness-Aware BPRMF leads to lower Std but lower AUC at the same time. To sum up, our evaluation results evidence that the proposed Fairness-Aware BPRMF algorithm provides a much higher gain in terms of fairness while merely slightly sacrifices the recommendation accuracy.

[2]We tried $N_{\text{top}} = 10, 20,$ and 30, and found that the three settings yield similar results; thus, we will only report the results with $N_{\text{top}} = 30$

5. CONCLUSION AND FUTURE WORK

In this work, we argue that a recommendation system for social welfare, optimizing accuracy and fairness altogether is more preferable, and further design a mechanism to achieve such purpose. We hope this paper can serve as an initiation to de-congest the congestible altruists using algorithms and attract more attention on designing fairness-aware recommendation systems for the good of society. On the other hand, in this paper, we merely focus on designing a CF-based recommender to achieve such purpose, while in the future we will focus on bringing the content information into consideration, as have been shown in some of our analysis that certain attributes of loans and lenders can significantly affect the acceptance rate of the proposal. By analyzing the content of the loan proposal, it is possible to gain more understanding about lenders' taste and further improve the quality of the recommendation systems.

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