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Personalized Fairness-aware Re-ranking for Microlending

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Motivation

- Microlending can lead to improved access to capital in impoverished countries.
- Loan recommender systems assist lenders in looking for promising borrowers. However, purely optimizing personalization may result in fairness issues.
- A desirable fairness property in microlending is to give borrowers from different demographic groups a **fair chance** of being recommended.

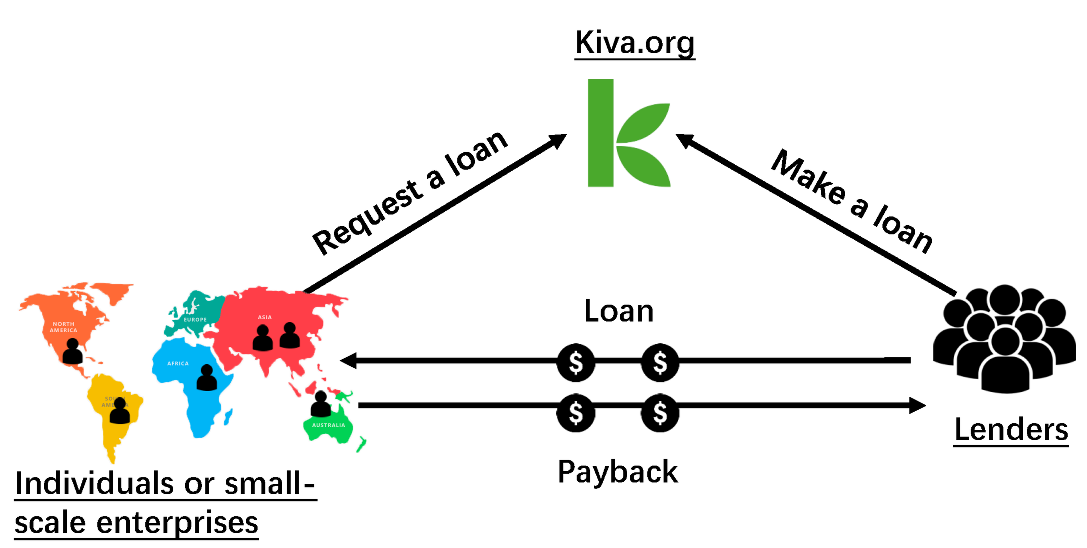

Figure 1: Kiva.org provides an intermediary service for lenders and borrowers.

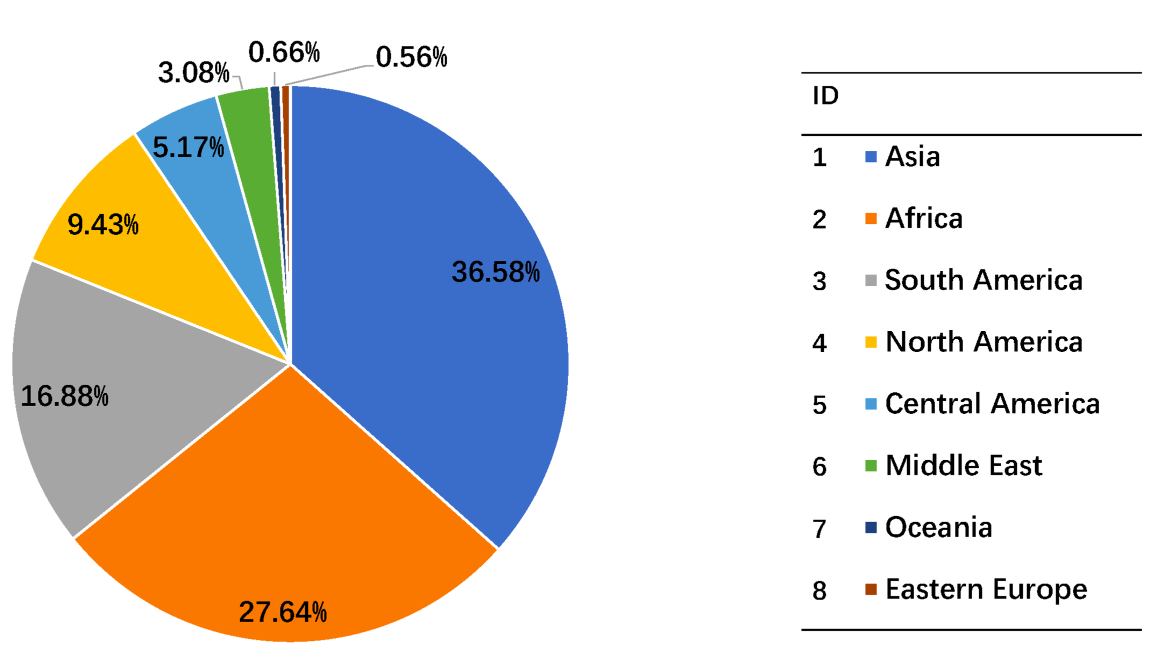

Figure 2: The issue of fairness on regions in a designed loan recommender system [1] for Kiva: the recommendation percentage for each region.

[1] Jaegul Choo, Daniel Lee, Bistra Dilkina, Hongyuan Zha, and Haesun Park. 2014. To gather together for a better world: Understanding and leveraging communities in micro-lending recommendation. *WWW*. ACM, pp. 249–260.

[2] Robin Burke. 2017. Multisided fairness for recommendation. *arXiv preprint arXiv:1707.00093* (2017).

[3] Järvelin, K. and Kekäläinen, J., 2002. Cumulated gain-based evaluation of IR techniques. *TOIS*, 20(4), pp.422-446.

Method

We propose to formulate this recommendation scenario as a Multi-sided Recommender System (MRS) [2].

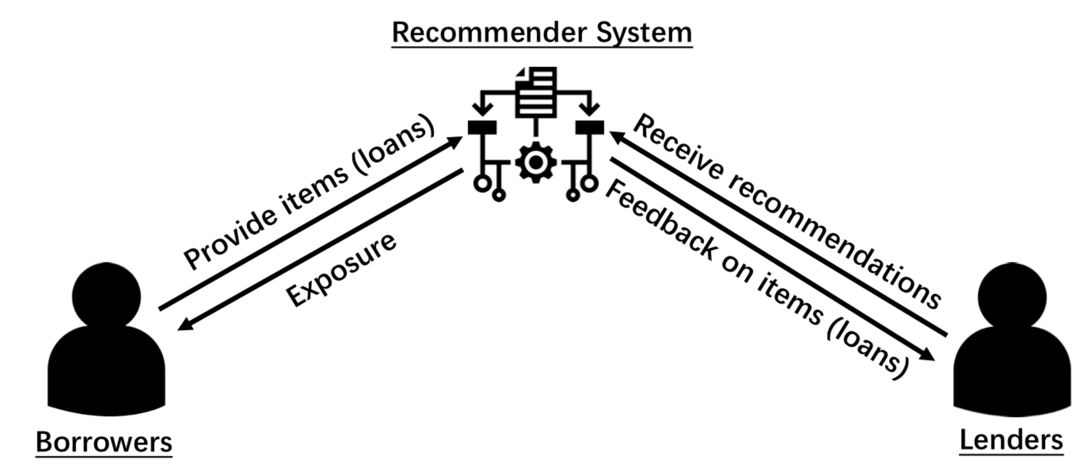

Figure 3: Multi-sided Recommender System (MRS)

- **Fairness-aware Re-ranking (FAR)**

For any user u, given the initial ranking score $P(v|u)$, we iteratively select the next item to the re-ranking list $S(u)$ by solving:

$$\max_{v} \underbrace{\lambda P(v|u)}_{\text{personalization}} + \underbrace{(1-\lambda)\sum_{c} P(\mathcal{V}_c)\mathbb{1}\{v\in\mathcal{V}_c\}\prod_{i\in S(u)}\mathbb{1}\{i\notin S(u)\}}_{\text{fairness}},$$

where λ is the hyper-parameter, and $\mathcal{V}_c$ denotes the item group with protected attribute c.

- **Personalized Fairness-aware Re-ranking (PFAR)**

We further take into consideration that lenders may differ in their receptivity to the diversification of recommended loans and develop a Personalized Fairness-Aware Re-ranking (PFAR):

$$\max_{v} \underbrace{\lambda P(v|u)}_{\text{personalization}} + \underbrace{(1-\lambda)\boldsymbol{\tau_u}\sum_{c} P(\mathcal{V}_c)\mathbb{1}\{v\in\mathcal{V}_c\}\prod_{i\in S(u)}\mathbb{1}\{i\notin S(u)\}}_{\text{personalized fairness}}.$$

We use the information entropy to identify the lender diversity tolerance:

$$\tau_u \triangleq \sum_{c} P(\mathcal{V}_c|u)\log P(\mathcal{V}_c|u).$$

Experiment

We define Average Coverage Rate (ACR) and use nDCG [3] to measure accuracy and fairness respectively, where

$$\mathrm{ACR} = \frac{\sum_{u\in U_t} N_{S(u)}}{N_{bg}|U_t|}.$$

test lender set.
the number of borrower groups covered in the list $S(u)$.
the total number of borrower groups.
the number of lenders in the test set.

We apply our proposed re-ranking algorithms on four representative recommenders. Experimental results show that our proposed algorithms can achieve a balance between accuracy and fairness.

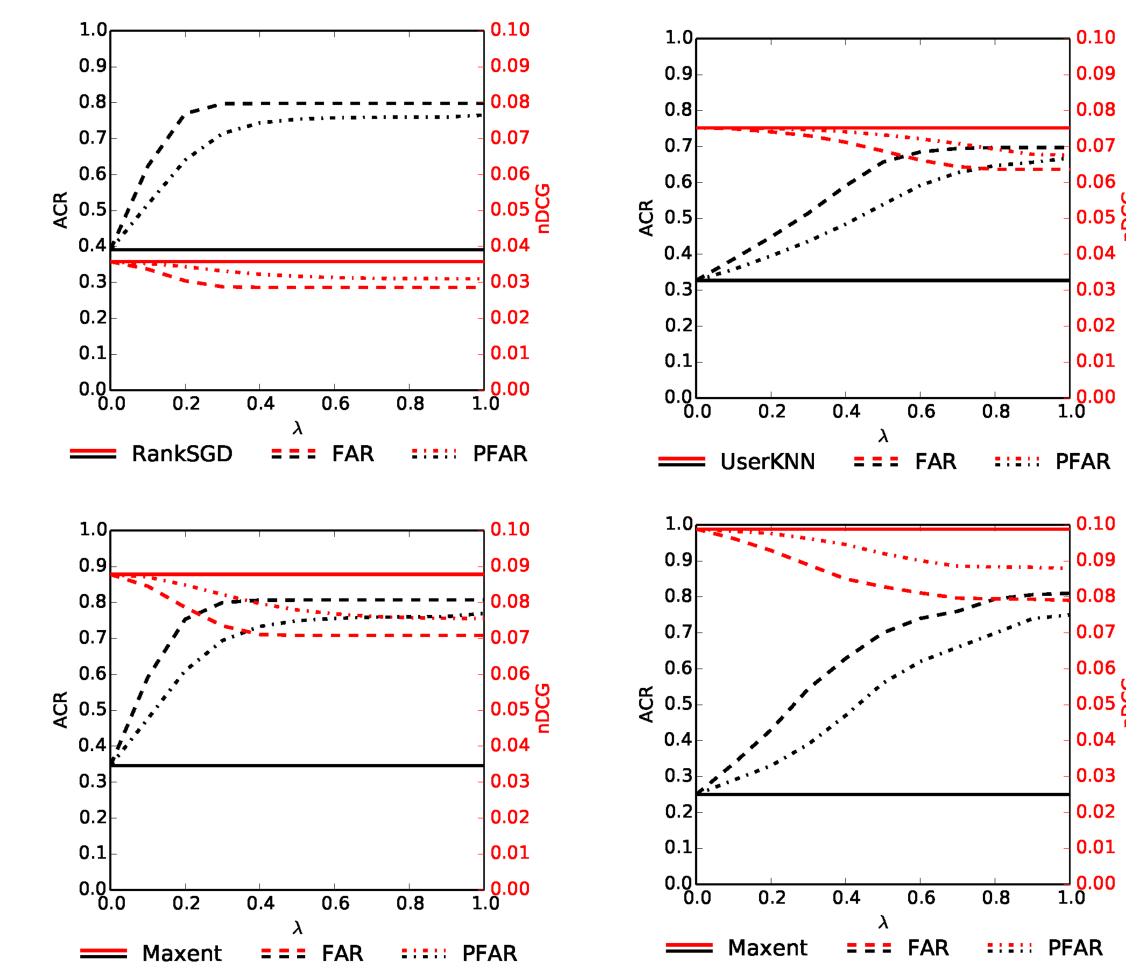

Figure 4: Tendencies of ACR and nDCG with increasing λ.

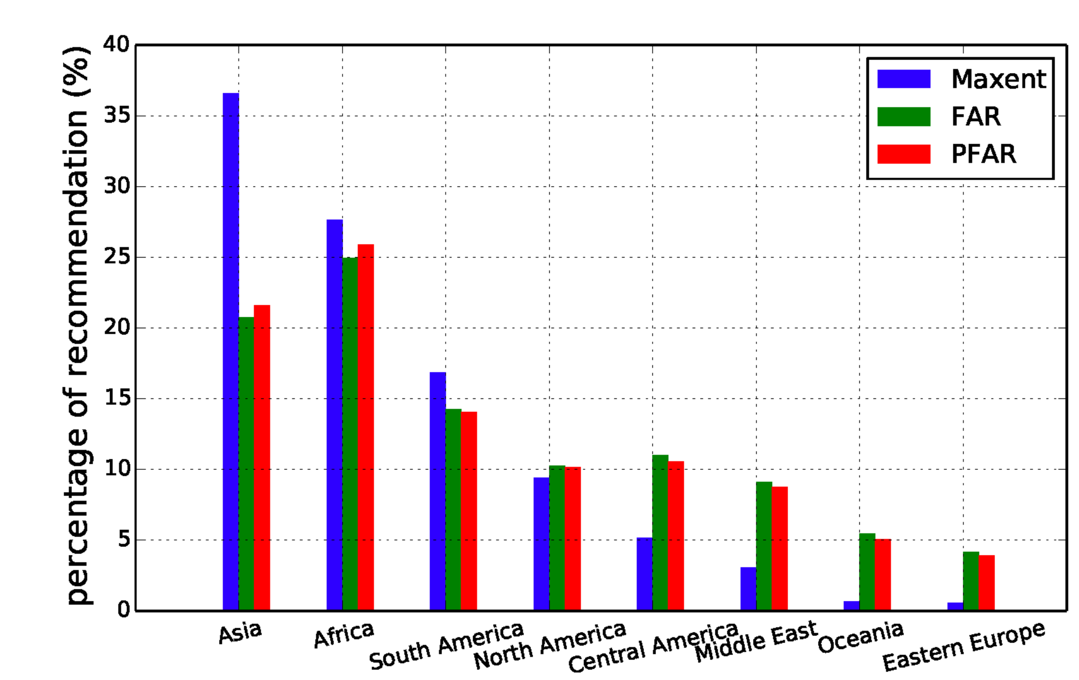

Figure 5: Recommendation percentage of each region.