

Personalizing Fairness-aware Re-ranking

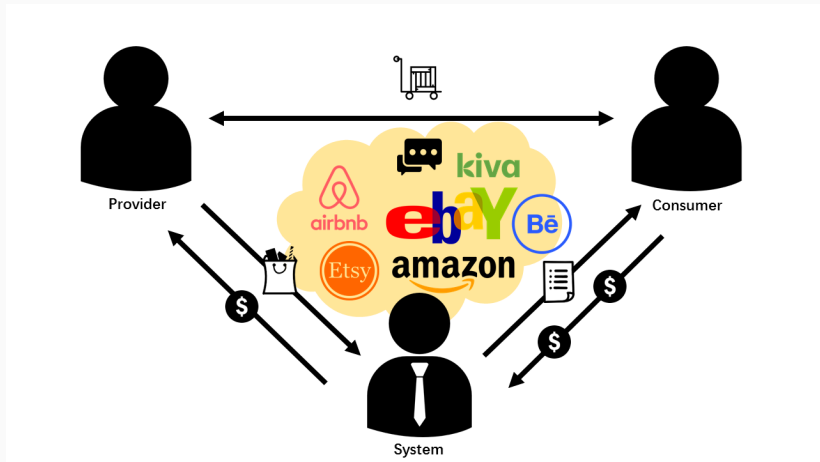
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Multi-sided Recommender Systems (MRS)

Users/Consumers are not the only stakeholder in some recommendation scenarios.



Multi-sided Recommender Systems (MRS)

Consumer: Expect personalized recommendations to meet their interests and needs.

Provider: Offer items to the system and benefit from consumer choices.

System: Receive items from providers and recommend them to the consumers.

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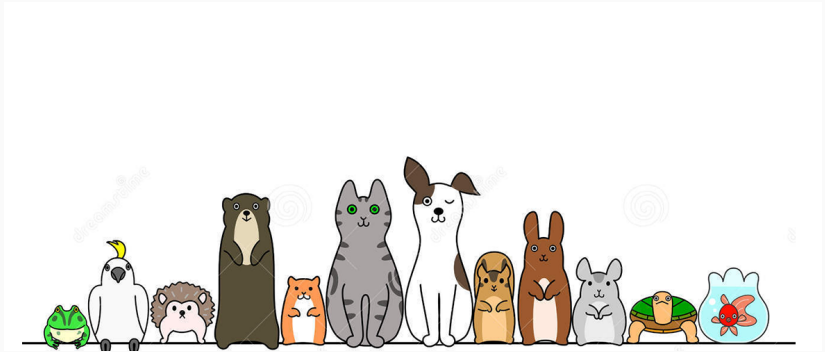
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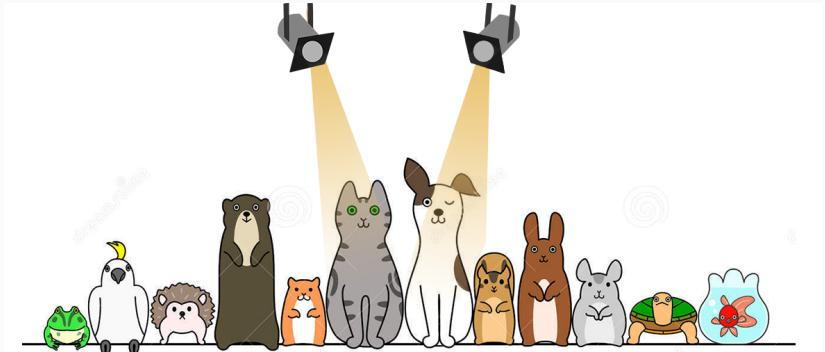
Provider-side Fairness

Twelve animals wait to become superstars



Provider-side Fairness

Only two of them get exposed...



Provider-side Fairness: Kiva.org

Kiva.org is a non-profit site for crowd-sourced micro-lending.



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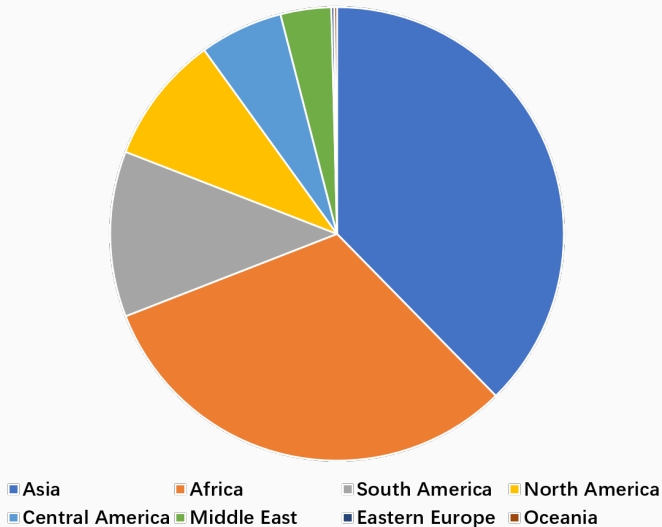


Figure 1: Number of recommendations for each region. WRMF.

Provider

- passiveness
- competitiveness
- a key role in MRS

Goal

To **balance** across different providers rather than concentrating on certain dominant ones

Problem Formulation

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- Each provider $d \in D$ owns a set of items to be recommended.
- Our task is to generate a re-ranked list S of K distinct items that is both **accurate** and **fair**.

Algorithm

We designed a re-ranking criterion:

$$\underbrace{P(v|u)}_{\text{accuracy}} + \lambda \underbrace{\sum_{d \in D} P(d) \mathbb{1}_{\{v \in d\}} \prod_{i \in S} \mathbb{1}_{\{i \notin d\}}}_{\text{fairness}},$$

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- For an item $v \in d$, if S does not cover d , then an additional positive term will be added to the estimated user preference $P(v|u) \Rightarrow$ **to balance between accuracy and fairness**
- As formulated, the criterion favors the items that belong to **multiple providers**.

Algorithm 1 Fairness-Aware Re-ranking

Input: u, R, K, λ, τ_u

Output: S

- 1: $S \leftarrow \emptyset$
 - 2: **while** $|S| < K$ **do**
 - 3: $v^* \leftarrow \arg \max_{v \in R \setminus S} P(v|u) + \lambda \sum_{d \in D} P(d) \mathbb{1}_{\{v \in d\}} \prod_{i \in S} \mathbb{1}_{\{i \neq d\}}$
 - 4: $R \leftarrow R \setminus \{v^*\}$
 - 5: $S \leftarrow S \cup \{v^*\}$
 - 6: **end while**
 - 7: **return** S
-

Diversity Tolerance

The tolerance towards **exploration or diversification in providers** varies for different consumers.



Bob

I'm open to seeing items from different providers

I only interested in certain providers



Alice

The user tolerance towards different providers τ_u is defined by

$$\tau_u = - \sum_{d \in D} I(d|u) \log I(d|u),$$

$$I(d|u) = \frac{\sum_v r(u, v) \mathbb{1}_{\{v \in d\}}}{\sum_v \sum_{d' \in D} r(u, v) \mathbb{1}_{\{v \in d'\}}},$$

$r(u, v)$ is the rating from user u to item v .

Fairness-Aware Re-ranking (FAR)

$$P(v|u) + \lambda \sum_{d \in D} P(d) \mathbb{1}_{\{v \in d\}} \prod_{i \in S} \mathbb{1}_{\{i \notin d\}},$$

Personalized Fairness-Aware Re-ranking (PFAR)

$$P(v|u) + \lambda \tau_u \sum_{d \in D} P(d) \mathbb{1}_{\{v \in d\}} \prod_{i \in S} \mathbb{1}_{\{i \notin d\}}, \quad (1)$$

- Average Provider Coverage Rate (APCR)

$$\text{APCR} = \frac{1}{|U_t|} \sum_{u \in U_t} \frac{\#recommended_provider}{\#provider}, \quad (2)$$

where U_t is the test user set.

- $\text{APCR@NDCG}_{5\%}$

The increased APCR value obtained when we allow a 5% decrease in nDCG .

Experiment: Synthetic Data

Table 1: Movielens: $\text{APCR@NDCG}_{5\%}$ on the data sets (%), providers assigned at random.

	PFAR		FAR	
	λ	$\text{APCR@NDCG}_{5\%}$	λ	$\text{APCR@NDCG}_{5\%}$
itemKNN	2.45	77.47 (+70.24)	1.62	78.33 (+72.14)
userKNN	0.15	67.89 (+57.94)	0.10	68.98 (+60.48)
rankALS	0.29	72.81 (+59.01)	0.22	74.43 (+62.57)
WRMF	0.24	70.45 (+58.79)	0.16	72.10 (+62.50)

Experiment: Kiva.org

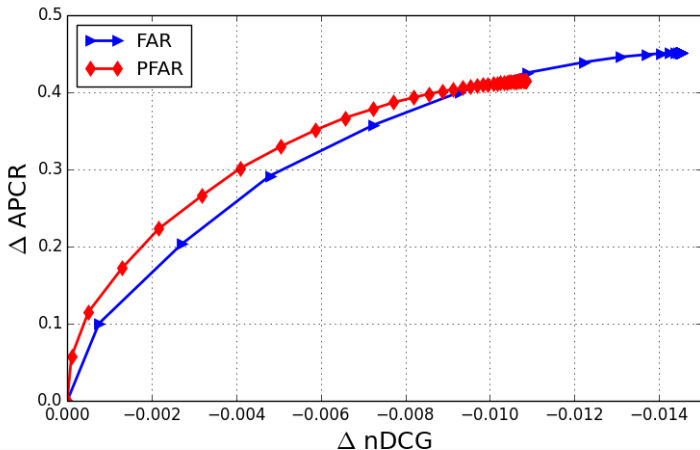


Figure 2: Change in nDCG and APCR with increasing λ (range 0 to 2.0 in steps of 0.05).

Experiment: Kiva.org

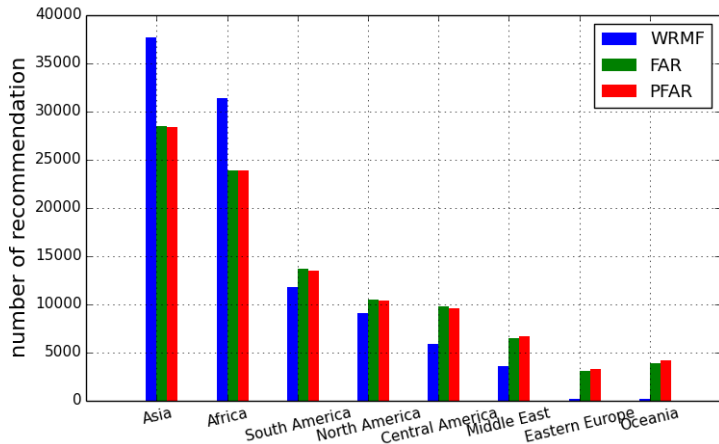


Figure 3: Number of recommendations for each region.

Conclusion

- We formulate a recommendation scenario in a **multi-sided recommender system** and define the fairness requirement for providers.
- We design a re-ranking algorithm to **balance** between **personalization and fairness**, and propose the incorporation of diversity tolerance of individuals.
- We show the results of experiments conducted on synthetic and real-world data to validate the effectiveness of our proposed algorithm.

Future Work

- Explore different methods for computing personalized diversity tolerance factors, e.g to solve the cold start problem
- Examine variants of the re-ranking algorithm to take into account **the size of each providers' inventory**.
- Adjust the accuracy/coverage tradeoff **in a dynamic way** as items are ranked, valuing accuracy more at the top of the list and provider coverage more at the bottom of the list.
- Explore the **online** fairness algorithm.