# Towards sustainable entrepreneurship via fairness in recommender systems

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## Abstract

This paper demonstrates a provider-side fairness extension of Fairness Maximal Marginal Relevance (FMMR) technique described by Karako and Manggala (2018). This extension is demonstrated by a case study where, based on the geographic location of various item providers, the objective is to bolster local businesses in small countries competing against larger providers in a global online marketplace. Competitiveness is measured as the exposure of item providers in recommendations. It is shown that standard relevance-based recommendations often provide more exposure to providers that are larger in size with more user interactions. FMMR is used as a post-processing technique to tune the interplay between standard relevance-based recommender systems and fairness of item provider exposure. Using contextual embeddings to represent item providers, we show that FMMR is able to mitigate the large differences in provider exposures that standard recommenders most often do not account for.

## 1 Introduction

The evolution of the internet has arguably impacted businesses both in the developed and developing world, opening doors to entrepreneurs to access the global market [Zhu et al. (2006)]. Such businesses in developing countries are considered an important segment of the labour force who can provide sustainable effects on the country's long-term development [Rahayu and Day (2015)].

With the internet becoming more accessible, there is a clear trend towards the emergence of online businesses from developing countries. Often such businesses work in close partnership with global internet companies creating an ecosystem of actors that collectively work towards meeting customers' needs.

A common technique by internet companies, especially in the e-commerce sector, is to use recommender systems to provide the most relevant content and services from their partners to their downstream customer. A common critique of recommenders is that they often suffer from popularity bias, where long-tail items (content and services) are less likely to gain exposure in user recommendations [Steck (2011), Sürer et al. (2018)].

In this paper we discuss the notion of provider side fairness in which providers may be unfairly represented when being exposed to downstream users via recommendations, giving them an unfair market share relative to bigger providers. We demonstrate that companies may be able to mitigate this issue by using a simple postprocessing technique in recommenders.

## 2 Fairness in Recommender Systems

Burke (2017) distinguishes *consumers* (C) and *providers* (P), as the two main stakeholders of a multistakeholder recommender system [Abdollahpouri et al. (2017)]. Consumers are individuals who receive the recommendations, whereas providers are entities that supply or otherwise stand behind the recommended objects, and gain from the consumer's choice.

Burke (2017) argues that fairness in recommendations follows a similarly multi-sided pattern, in which fair outcomes can be determined by considering the various sensitive groups in the multistakeholder environment. Based on the two stakeholder groups, he defines two notions of fairness: *C-fairness* and *P-fairness*.

Kiva.org, an online micro-finance site, is a good example for P-fairness. Kiva offers small donations from people all around the world to help entrepreneurs' loan requests in local communities in developing countries. In Kiva's example, providers are the suppliers of the loan requests, where a recommendation example could be to help match donors with the loan seekers. In this example, P-fairness refers to fairness in the distribution of how capital is allocated across different loan seekers.

P-fairness may also be of interest for an internet company that wants to ensure market diversity by avoiding monopoly domination by its various value provider partners. This is especially important for online marketplaces like Etsy, Amazon or Shopify, that work in close partnership with other value providers that naturally have different resources, size, customer base, and customer exposure.

Focusing on the example of marketshare fairness, our hypothesis is that using simple postprocessing techniques, we can induce recommendations with fairness with respect to providers' demographic characteristics as measured by their country of origin.

# 3 Methodology

In typical recommender systems, we speak of users (consumers) and items (content and services from providers). To obtain relevance scores of items that users have not interacted with in the past, we can use simple linear techniques like Sparse Linear Methods [Ning and Karypis (2011)].

After obtaining the user-item relevance scores, we use Fairness Maximal Marginal Relevance (FMMR) from Karako and Manggala (2018) to incorporate fairness into user-item recommendations via a post reranking approach.

Let our sensitive demographic characteristics be defined as the providers' country of origin. For each item, first we create a vector embedding from items' descriptions [1]. Next, we define one pivot vector per demographic group, that is constructed by averaging the item embeddings of items that were provided by the given demographic group.

Let $\mathcal{I}$ represent the set of items $i$, $k$ be the size of the desired result set, $\lambda$ be a convex combination parameter , $f$ be the vector transformation function, and finally let $\mathcal{I}_{\text{rep}}$ represent the set of pivot vectors. In the next steps, our objective is to populate $S_k^*$, the set of recommended items, while looping through each not yet chosen item $j$ in $k$. Formally, we solve the following objective function

$$
\begin{aligned}
i_j =_{i \in \mathcal{I} \setminus S^*_{j-1}} & \Big( \lambda \text{rel}(i) - (1-\lambda) \\
& \times \max_{i' \in S^*_{j-1}} \sum_{v \in \mathcal{I}_{\text{rep}}} - \left| d(f(i'), v) - d(f(i), v) \right| \Big) \\
S_j^* = S^*_{j-1} & \cup \{i_j\}
\end{aligned}
$$

where $d$ computes the Euclidean distance between two vectors from the same space as the fairness representations.

# 4 Case study and Discussion

We conduct a case study on an internal dataset containing 5,013 users' interactions with 429 services that are provided by individuals that we group into four segments based on their country of origin

[1] These embeddings were constructed using the document classifier described in Xiong and Manggala (2018)

Table 1: Item provision and user-item distributions across the chosen target countries

| Country | Number of recommendations | Number of items |
|---|---|---|
| United States | 203,485 | 355 |
| India | 28,982 | 69 |
| Mexico | 1,514 | 6 |
| Malaysia | 1,783 | 7 |

Number of recommendations is calculated based on the number of users that were recommended an item in the top 100 recommendations where the item was provided by the target country.

[2]. The dataset is summarized in Table 1. It is clearly visible that value providers in this dataset are heavily skewed towards the United States, while the other countries are much less represented in the overall item set [3].

The final reranked recommendations are evaluated on 100 users, using the four best values of the $\lambda$ hyperparameter, after hyperparameter search. We use the difference in entropies as a measure of gain in fairness, as discussed in Venkatasubramanian et al. (2015), and evaluate relevance based on the percentage of the most relevant item categories that were both in the original and the reranked recommendations over those that were in the original recommendations. [4].

Summarized in Table 2, we see that as $\lambda$ changes from 1.0, from our baseline relevance based model, we notice an increase in fairness gains with respect to the recommended items' country of origin. We achieve the best result for $\lambda$ = 0.9995, where we see a 10% average decrease in the top most relevant items' categories, for a fairness gain of 0.022.

## 5 Conclusion

In this paper, we argued that incorporating fairness into recommendations can be an important tool in marketplace-like businesses to ensure a fair market share to content and services providers. In particular, we focused our discussion on doing so as way of empowering individuals and small businesses from the developing world. We discussed a case study on leveraging a simple postprocessing technique, FMMR, to induce recommendations with provider fairness, and demonstrated that we are able to achieve gains in fairness with respect to our country specific demographic groups. In future work, it would be insightful to conduct a user-study on the true impact of this technique in practice.


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[2]To obtain this dataset, we use a candidate selection process in which we first filter items based on our four chosen target countries, and then filter items whose ranked relevance were beyond 100.

[3]Due to the sensitivity of this data, unfortunately, we cannot share more details on the characteristics of users and items

[4]Category labels are additional metadata that exist for all items used in the experiments and that were used to measure relevance.

Table 2: Experiment results summarized

| $\lambda$ | relevance | fairness |
|---|---|---|
| 1.0 | 1.000 $\pm$0.0 | 0.000 $\pm$0.0 |
| 0.9999 | 0.947 $\pm$0.028 | 0.007 $\pm$0.037 |
| 0.9995 | **0.907** $\pm$0.029 | **0.022** $\pm$0.059 |
| 0.0 | 0.915 $\pm$0.026 | 0.018 $\pm$0.067 |

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