Popularity Bias in Ranking and Recommendation

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ABSTRACT

Many recommender systems suffer from popularity bias: popular items are recommended frequently while less popular, niche products, are recommended rarely or not at all. However, recommending the ignored products in the "long tail" is critical for businesses as they are less likely to be discovered. Popularity bias is also against social justice where the entities need to have a fair chance of being served and represented. In this work, I investigate the problem of popularity bias in recommender systems and develop algorithms to address this problem.

CCS CONCEPTS

• **Information systems → Recommender systems**; • **Computing methodologies → Ranking**; *Machine learning*; *Learning to rank*.

KEYWORDS

Ranking; Recommender systems; Information retrieval; Popularity bias

ACM Reference Format:
Himan Abdollahpouri. 2019. Popularity Bias in Ranking and Recommendation. In *AAAI/ACM Conference on AI, Ethics, and Society (AIES '19), January 27–28, 2019, Honolulu, HI, USA.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3306618.3314309

1 INTRODUCTION

Recommender systems (RS) have an important role in e-commerce and information sites, helping users find new items. Like many other machine learning systems, RS can have certain types of biases [10, 11]. In this work, I investigate the popularity bias in ranking and recommendation and provide algorithmic solutions to address this problem. One of the main biases in recommender systems is the problem of popularity bias[5]: collaborative filtering recommenders typically emphasize popular items (those with more ratings) over other "long-tail", less popular ones [8] that may only be popular among small groups of users.

Although popular items are often good recommendations, they are also likely to be well-known. So delivering only popular items will not enhance new item discovery and will ignore the interests of users with niche tastes. It also may be unfair to the producers of less popular or newer items since they are rated by fewer users.

AIES '19, January 27–28, 2019, Honolulu, HI, USA

ACM ISBN 978-1-4503-6324-2/19/01.
https://doi.org/10.1145/3306618.3314309

Furthermore, long-tail recommendation can also be understood as a social good. A market that suffers from popularity bias will lack opportunities to discover more obscure products and will be, by definition, dominated by a few large brands or well-known artists [6]. Such a market will be more homogeneous and offer fewer opportunities for innovation and creativity.

Long-tail items are also important for generating a fuller understanding of users' preferences. Systems that use active learning to explore each user's profile will typically need to present more long tail items because these are the ones that the user is less likely to know about, and where user's preferences are more likely to be diverse [7, 9].

In addition, bias in recommender systems could have even societal consequences–in social media websites like Facebook,for example, everything a user sees in his/her feed is generated by recommender systems. Just imagine how these recommendations are affecting how people think, feel and even behave in a society. The same example could be given in News websites where someone could affect the holistic ideology of a group or even a society by tuning the recommender system to recommend certain types of News which could potentially benefit a certain political party or viewpoint. A system with popularity bias will impose a narrow ideology to the large population of the society.

And finally, as I discuss in [3], we can think of recommender systems and many other ranking systems as *multi-stakeholder environments* in which the needs and interests of different stakeholders should be taken into account instead of solely focusing on the end users. Popularity bias can lead to certain stakeholders (popular ones) achieving very high utility values while other stakeholders (less popular ones) to be ignored. Multi-stakeholder recommendation is also related to the concept of *fairness* in social sciences and *equity* in economics.

2 WORK I HAVE DONE SO FAR

So far, I have approached the popularity bias in recommender systems in two different ways:

- **Model-based treatment**: In this approach, I have modified the underlying ranking model that generates the recommendations such that less popular items also have a fair chance of being recommended. In other words, the model has been modified so the final recommendations are more balanced in terms of giving fair chance of exposure to less popular items. A more detailed description of this approach and the experiments I conducted to test it can be found in [2] which was published at the $12th$ ACM conference on recommender systems.
- **Re-ranking treatment**: In this approach, I assume there is a base recommender system which generates an initial list of

items to be recommended along with their predicted ratings. The idea is to keep existing algorithms untouched and add an extra level of selection as an add-on to those algorithms to control popularity bias. This initial list is generally much larger than the final list and it serves as a candidate pool of items to select from for the final list. Now, using this initial list and taking into account the fair representation of less popular items and maintaining an acceptable level of accuracy, the modified algorithm tries to give a boost to the predicted ratings of less popular ones so they have a higher chance of being recommended at the end. It is worth noting that I also take users' tolerance for less popular items into account in my model so users with no interest in less popular items will not be bothered by getting those recommendations. A more detailed description of this approach can be found in [4].

3 FUTURE PLAN

As the next steps for this work, I'm planning to do the followings:

- **Investigating theoretical reasons behind popularity bias in recommender systems:** I would like to see how different algorithms differ in the way they create popularity bias in the recommendations. This could be considered as a diagnosis strategy because different algorithms might vary in the way they create popularity bias and, therefore, it is important to find out what aspect of each algorithm is causing the popularity bias so we could find better solutions for that particular algorithm or class of algorithms.
- **Generalizing to other biases in recommender systems:** I will also extend those two aforementioned approaches I discussed to combat popularity bias in recommender systems to be applicable to other biases such as gender bias, age bias etc.

- **Temporal treatment of popularity bias:** Another possibility for future work is to look at long-tail promotion as a temporal process. Almost all the works on long-tail promotion have done the optimization on individual's recommendation lists hoping this will lead to an overall optimization within the entire user base. However, optimizing individual users' list will not necessarily result in the overall optimization [1]. Therefore, we need to approach this problem as a temporal process such that, at any given time T, the recommender system optimizes the objective function by also looking at what the outcome for optimization was at previous times. Figure 1 shows a schematic view of what a temporal optimization looks like. $R_{i,j}$ is the recommended item j to user i

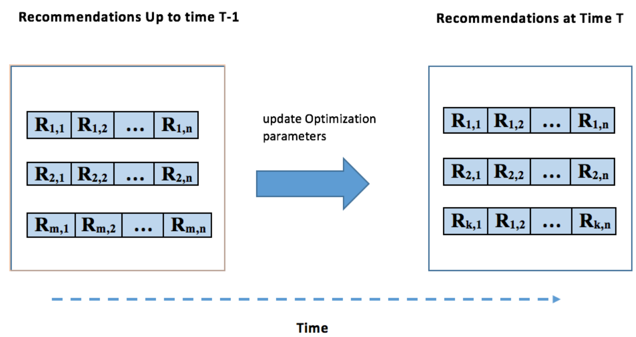

Figure 1: Dynamic optimization of the recommendations over time

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