Supplementary Material for Group Fairness for Content Creators: the Role of Human and Algorithmic Biases under Popularity-based Recommendations

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CCS Concepts: • **Human-centered computing → Collaborative and social computing theory, concepts and paradigms**; **Social network analysis**.

Additional Key Words and Phrases: algorithmic fairness, agent-based modeling, network formation

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The present document contains additional information for the paper titled "Group Fairness for Content Creators: the Role of Human and Algorithmic Biases under Popularity-based Recommendations" and published in the Seventeenth ACM Conference on Recommender Systems (RecSys '23). We include visual representations to provide an overview of the model and additional sensitivity analysis. Please note that in this supplementary material, we use "recommendation biases" instead of "visibility allocation (VAS) biases".

A OVERVIEW OF THE MODEL

Figure 1 provides a visual representation of our model. On the left, it shows the network structure. The right part is reserved for the two phases of each iteration. The top part illustrates the three recommendation processes which govern how visibility is allocated between CCs when the recommendation are not biased (for an illustration of how biases affect the Uniform Random recommendation process, see Figure 2 instead). Lower, we show how seekers with homophilic biases make decisions using two alternative situations: on the left, the seeker is recommended a matching type CC with quality $q_C = 1$, and, on the right, a non-matching type CC with quality $q_{C'} = 3$. After computing the respective evaluations and after comparing them with that of the current followees, the seeker ends up following the matching type CC (in the first case), but not following the non-matching type CC (in the second case). This shows how homophilic biases can affect the decision-making process of seekers.

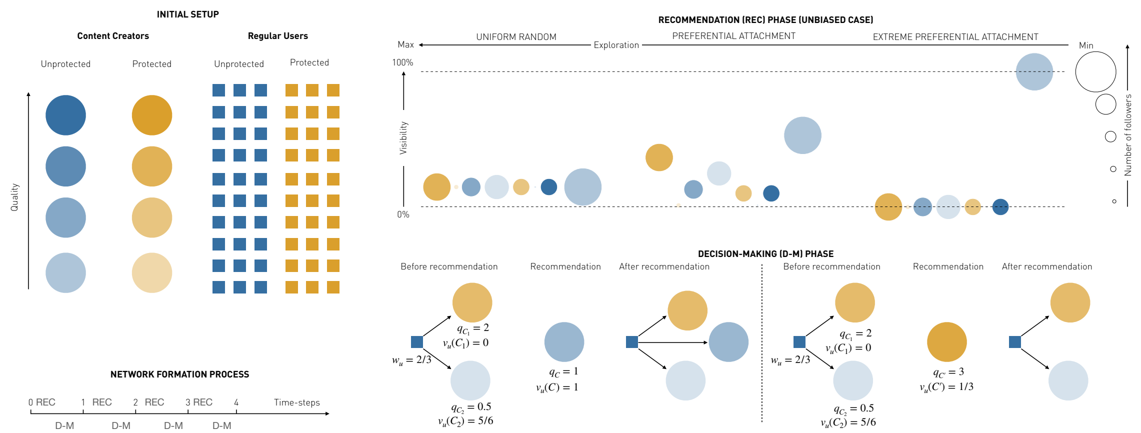

Fig. 1. The diagram shows the network formation model. On the top-left, we start with an empty network with content creators (CCs) and seekers. They each have a specific matching attribute, denoted with a different color. CCs also have a quality attribute (darker shades are used for better-quality CCs). On the bottom-left, we show how each timestep is composed of two phases: recommendation (REC) and decision-making (D-M). On the top-right (REC), each CC is assigned a given visibility depending on the recommendation process and on their number of followers (and eventually on the protected attribute if recommendations are biased). On the bottom right (DM), the seeker follows the new recommended CC if the corresponding evaluation is higher than that of the seeker's current followees. In the numerical example, this is the case only when the recommended CC is of a matching type.

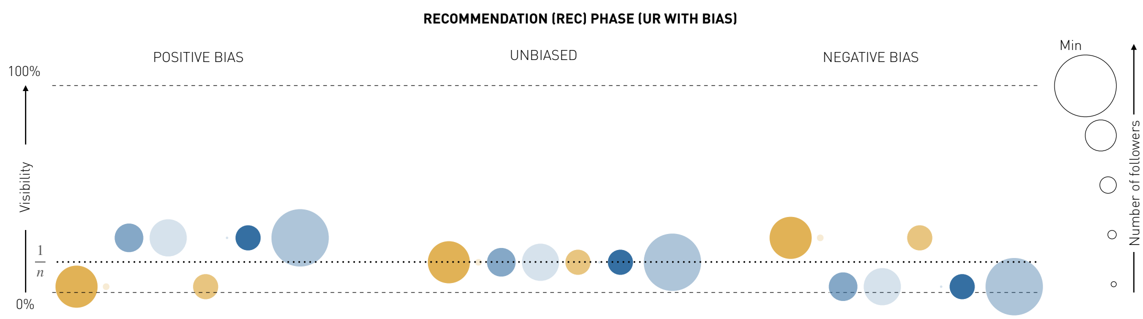

Fig. 2. The diagram shows the effect of a positive, neutral, or negative bias on the Uniform Random recommendation process. The effect on Preferential Attachment and Extreme Preferential Attachment are analogous.

B SENSITIVITY ANALYSIS: SIMULATION RESULTS FOR OTHER METRICS AND PARAMETERS

B.1 Recommendation and moderation biases have a higher impact than seeker biases for all three metrics of CC-unfairness

Takeaways. Figure 3 show the conclusions of the first paragraph within results are similar even when considering the other two metrics of unfairness. First, we note that reducing the share of biased seekers is only beneficial when the recommendation process is not biased; otherwise, it can actually increase the level of unfairness. Second, increasing the biases of recommendation processes always increases the unfairness. Third, recommendation biases have the highest impact for PA; moving to more explorative recommendation processes almost always reduces unfairness. Last, biases of recommendations have a higher impact on unfairness than homophilic biases in the seeker population.

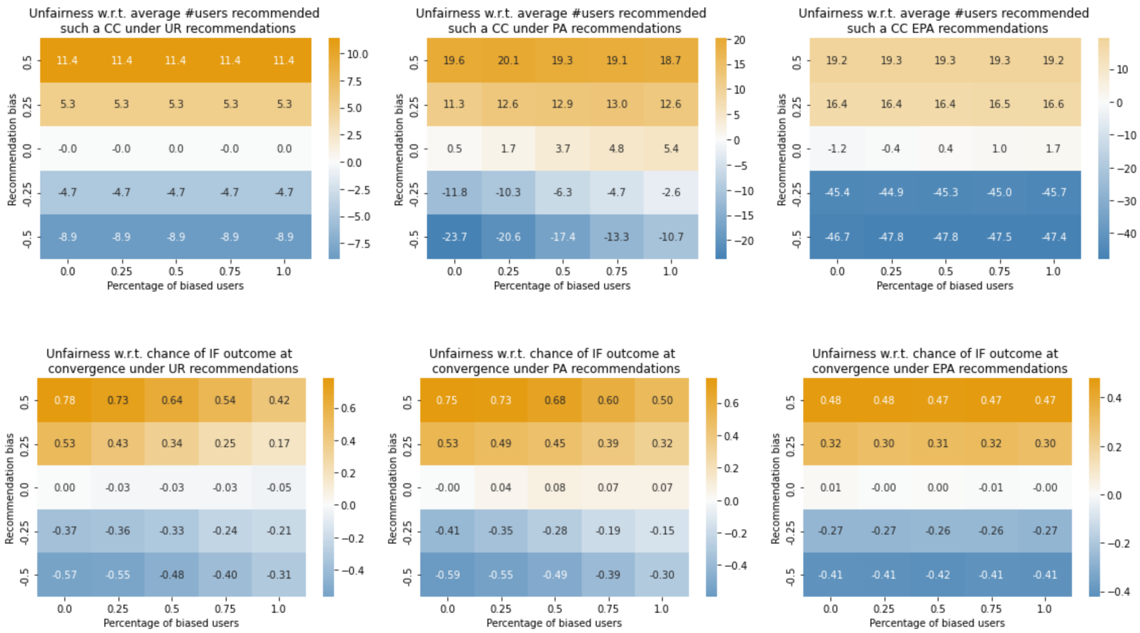

Fig. 3. Figure showing the average unfairness with respect to (top row) the average number of seekers recommended a CC of the respective type and (bottom row) the average chance of achieving an individually fair outcome. We plot this for different levels of biases in the recommendation process and different shares of homophilic-biased seekers. We show the results for the three different recommendation processes in decreasing order of exploration. Biased seekers have a 50% level of bias.

B.2 Recommendation and moderation biases have a higher impact than seeker biases even when seekers have higher levels of biases

Takeaways. Figure 4 shows that the conclusions of the first paragraph within the Results section continue to hold even when biased seekers have higher levels of biases. Overall, trends remain the same; the level of seeker biases only affects the amount of change. In general, increasing the level of bias of seekers leads to slightly more fair results for protected CCs. The reason for this perhaps surprising behavior is the same as the one described in the aforementioned paragraph: protected viewers who are biased at higher levels come to follow only protected CCs quicker. This decreases the gap in follower count between protected and unprotected CCs.

B.3 Boosting the visibility of protected CCs always increases their average number of followers at convergence

Takeaways. Figure 5 shows the effect of boosting the visibility of protected CCs for different fractions of biased seekers. Even when more seekers are biased, this intervention proves effective in reducing inequalities. However, as the share of biased seekers increases, higher visibility boosts are needed. For example, as noted in the main text, under PA recommendations and when 75% of seekers are biased, the average number of followers of protected and unprotected CCs is expected to be the same. However, when all seekers are biased, the same level of compensation still leads to unfair outcomes.

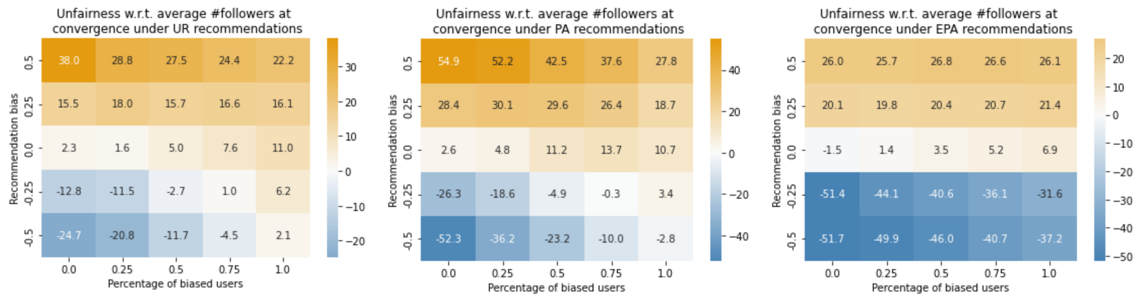

Fig. 4. Figure showing the average unfairness with respect to the average number of followers at convergence. We plot this for different levels of bias in the recommendation process and different shares of biased seekers. We show the results for the three different recommendation processes in decreasing order of exploration. Biased seekers have a 99% level of bias.

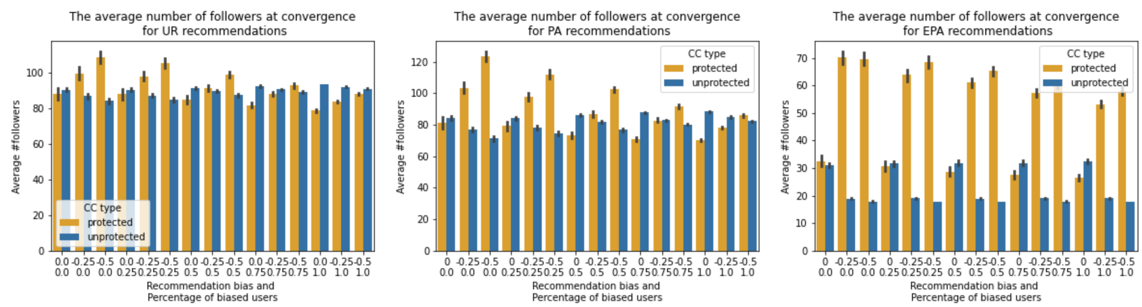

Fig. 5. Figure showing the effectiveness of boosting the visibility of protected CCs in order to overcome homophilic biases of seekers. We show this for different fractions of biased seekers and different recommendation processes. The first line of the x axis shows the level of bias in recommendations, while the second line shows the percentage of biased seekers. Biased seekers have a 50% level of bias.

B.4 Biases lead to seeker-unfairness even when seekers have higher levels of homophily

Takeaways. As shown in Figure 6, when seekers are biased at higher levels, they also generally suffer from higher absolute levels of unfairness. However, differences remain small and general trends persist.

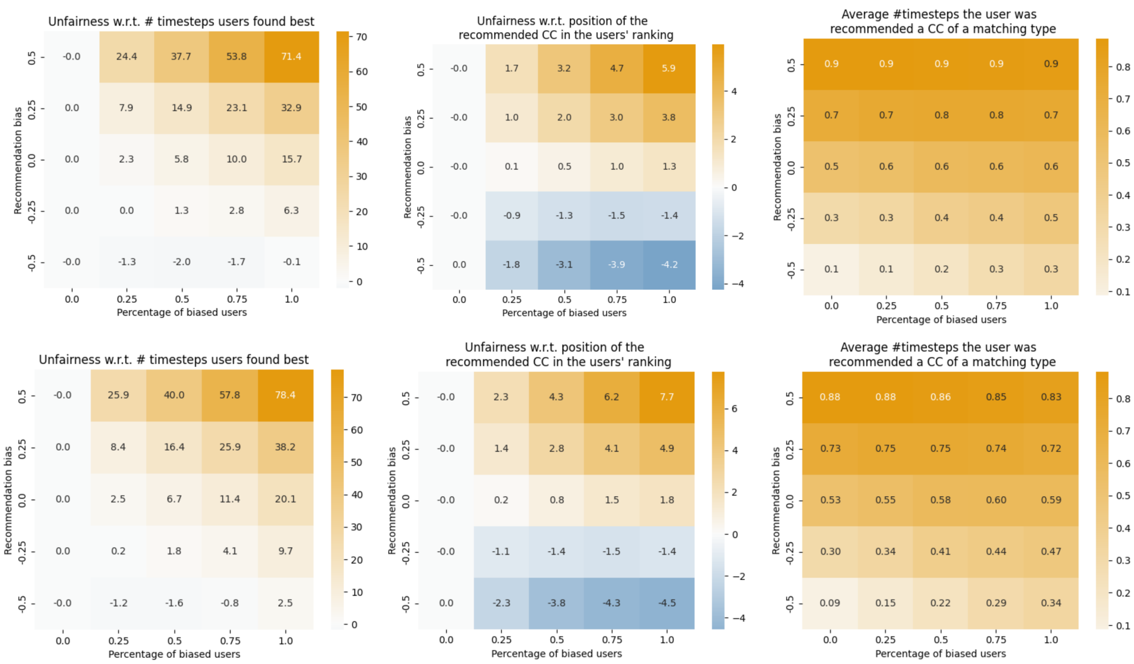

Fig. 6. Figure showing the unfairness for seekers when they are biased at (top row) a 50% level and (bottom row) a 99% level. We plot this for different levels of recommendation biases and different shares of biased seekers. All plots are for PA.