Abstract

Many recommendation systems rank items based on popularity, assuming that higher user engagement signals higher quality. In this paper, we examine whether this approach can lead to unequal exposure purely through feedback loops. Using a simple simulation, we model repeated recommendation rounds in which an item's popularity affects its future visibility. Our findings show that even small initial differences in popularity can grow over time, resulting in consistent exposure disparities between groups of items. These results underscore the importance of incorporating fairness-aware and causal perspectives into the design of recommendation systems.

Feedback Loops & Exposure Bias in Recommender Systems

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1. Introduction

Recommendation systems shape user attention at scale. While popularity-based ranking is widely used due to its simplicity and effectiveness, it can unintentionally create feedback loops that amplify exposure inequality. This paper investigates how such dynamics emerge even in the absence of explicit preference bias.

2. Related Work

Prior research has explored popularity bias, filter bubbles, and fairness in recommender systems. However, many real-world systems remain difficult to study due to data and access limitations. Simulation-based approaches provide a controlled environment to analyze these effects.

3. Problem Formulation

We study a recommendation system that ranks items based on historical popularity. Users interact with the top-ranked items, and these interactions are fed back into future ranking decisions. We examine whether this process leads to systematic exposure disparities between item groups.

4. Methodology

We construct a simulated environment consisting of users and items divided into two groups. At each round, items are ranked by popularity score, users interact with the top-K items, and popularity is updated accordingly. Exposure counts are tracked over multiple rounds to observe long-term dynamics.

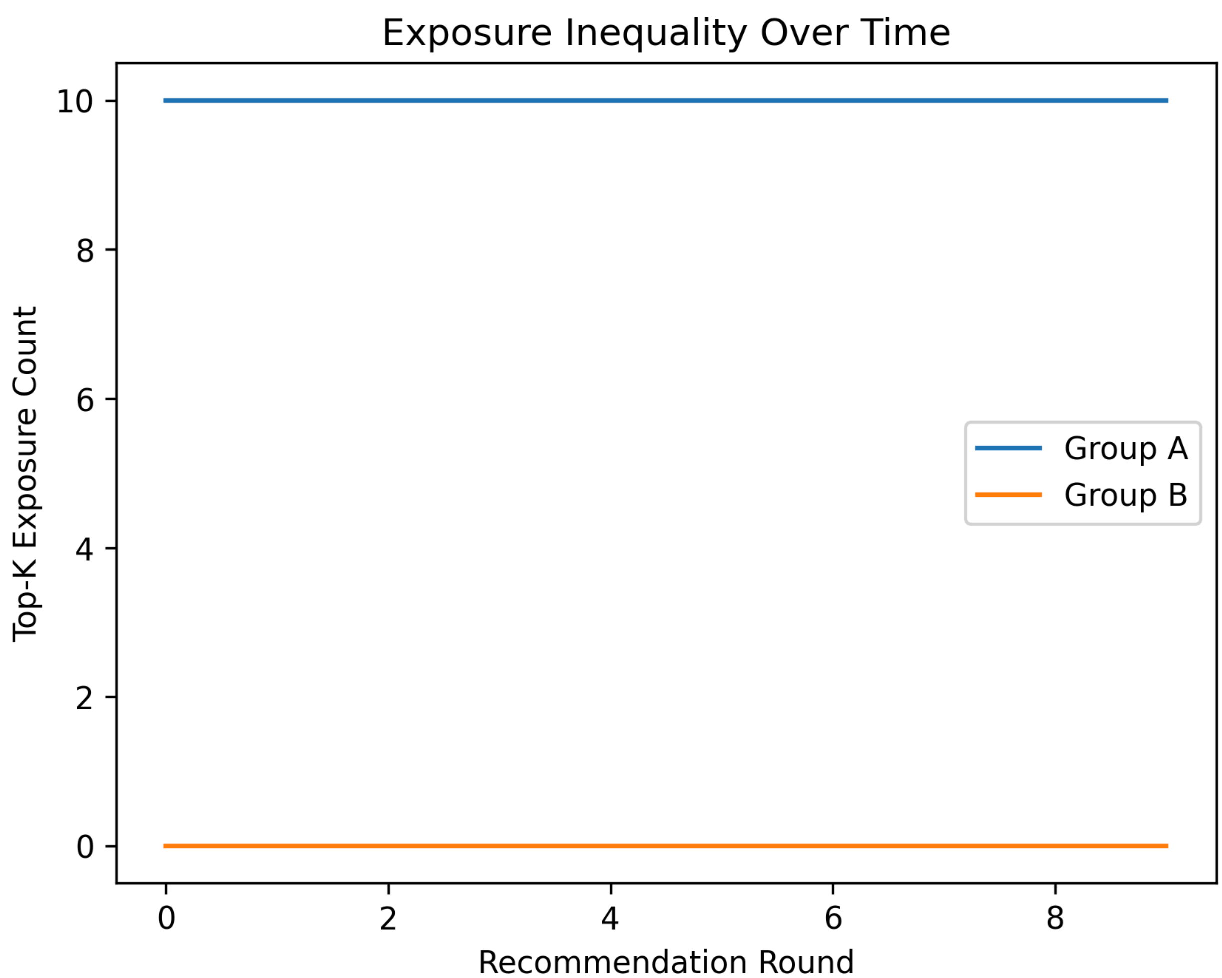
5. Experiments

We run multiple recommendation rounds under identical initial conditions. Exposure levels for each item group are recorded after every round to measure how ranking decisions evolve over time.

6. Results

Our results show that small initial popularity differences grow over time, resulting in increasing exposure inequality between item groups. The exposure gap widens consistently across rounds, indicating a self-reinforcing feedback loop.
We quantify exposure bias as the difference in cumulative top-K exposure between item groups across rounds.

Figure : Exposure inequality between item groups over recommendation rounds.



Above figure shows how exposure diverges between item groups over time, despite neutral user behavior, indicating the presence of a feedback loop driven by popularity-based ranking.

7. Discussion

These findings suggest that popularity-based recommenders can introduce systemic bias without explicit discriminatory signals. Such effects raise concerns for fairness and diversity in real-world systems.

8. Limitations and Future Work

This study uses a simplified simulation and does not model real user behavior or complex recommendation architectures. The goal was to isolate algorithmic feedback effects rather than achieve realism.

Future work could include incorporating public datasets, modeling heterogeneous user preferences, or testing fairness-aware ranking strategies.

9. Conclusion

We demonstrate that feedback loops in recommendation systems can significantly amplify exposure bias. Future work should explore causal and fairness-aware ranking mechanisms to mitigate these effects.

10. References

[1] Pariser, E. (2011). The Filter Bubble. Penguin Press.

[2] Burke, R. (2017). Multisided fairness for recommendation. FATREC Workshop.

[3] Narayanan, A. (2018). Translating fairness to practice. FAT* Conference.

11. Author Statement

This project was conducted as an independent learning and research exercise.
The author is an undergraduate student exploring algorithmic fairness and recommendation systems.