Application of Graph Neural Networks to Mitigate Popularity Bias in Content Recommendations

In this project, we explore the use of Graph Neural Networks (GNNs) to address the issue of popularity bias in content recommendations. Popularity bias issue leads to the over-representation of popular items, thereby reducing the visibility of less popular but potentially relevant content. By considering the ability of GNNs to capture complex user-item interactions, we aim to develop a graph-based approach that provides fair exposure to all items regardless of their popularity.

1 Introduction

Table 1 presents a comparative analysis of GNN-based approaches aimed at mitigating popularity bias in content recommendations. The table summarizes the strengths and weaknesses of various methods, highlighting the need for a novel solution.

Table 1: Comparative analysis of recent approaches to mitigate popularity bias in content recommendations.

Solution	Strengths	Weakness
BiGNN: A Bilateral-Branch Graph Neural Network [1]	Leverages a bilateral-branch framework to handle both long-tail and popular items, improving fairness	Requires complex optimization and may not generalize well to all recommendation tasks
MixGCF: Graph Neural Network-based Recommender Systems [2]	Improves GNN-based training by combining graph convolution with user-item interactions, reducing bias	High computational cost and may overfit on sparse or imbalanced data
XSimGCL: Simple Graph Contrastive Learning for Recommendation [3]	Utilizes a very simple contrastive learning approach that significantly reduces model complexity	Decreases performance on more complex and larger datasets due to its simplicity

The section references contain the full list, collected for this project.

References

[1] Yingshuai Kou, Neng Gao, Yifei Zhang, Chenyang Tu, and Cunqing Ma. Bignn: A bilateral-branch graph neural network to solve popularity bias in recommendation. In *2022 IEEE 34th International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 840–847. IEEE, October 2022.

[2] Tinglin Huang, Yuxiao Dong, Ming Ding, Zhen Yang, Wenzheng Feng, Xinyu Wang, and Jie Tang. Mixgcf: An improved training method for graph neural network-based recommender systems. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery; Data Mining*, KDD '21. ACM, August 2021.

[3] Junliang Yu, Xin Xia, Tong Chen, Lizhen Cui, Nguyen Quoc Viet Hung, and Hongzhi Yin. Xsimgcl: Towards extremely simple graph contrastive learning for recommendation. *IEEE Transactions on Knowledge and Data Engineering*, pages 1–14, 2023.

[4] Cheng Liu, Chenhuan Yu, Ning Gui, Zhiwu Yu, and Songgaojun Deng. Simgcl: graph contrastive learning by finding homophily in heterophily. *Knowledge and Information Systems*, 66(3):2089–2114, November 2023.

[5] Kibeom Lee and Kyogu Lee. Escaping your comfort zone: A graph-based recommender system for finding novel recommendations among relevant items. *Expert Systems with Applications*, 42(10):4851–4858, June 2015.

[6] Xueqi Li, Guoqing Xiao, Yuedan Chen, Zhuo Tang, Wenjun Jiang, and Kenli Li. An explicitly weighted gcn aggregator based on temporal and popularity features for recommendation. *ACM Transactions on Recommender Systems*, 1(2):1–23, April 2023.

[7] Anastasiia Klimashevskaia, Mehdi Elahi, and Christoph Trattner. Addressing popularity bias in recommender systems: An exploration of self-supervised learning models. In *Adjunct Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization*, UMAP '23, pages 7–11. ACM, June 2023.

[8] Shiwen Wu, Fei Sun, Wentao Zhang, Xu Xie, and Bin Cui. Graph neural networks in recommender systems: A survey, 2020.

[9] Anastasiia Klimashevskaia, Dietmar Jannach, Mehdi Elahi, and Christoph Trattner. A survey on popularity bias in recommender systems. *User Modeling and User-Adapted Interaction*, 34(5):1777–1834, July 2024.