On modularity-based fair community detection

Keywords: network fairness, algorithmic fairness, community detection, social network analysis, modularity

Extended Abstract

The increasing reliance of contemporary decision-making systems on automation has led to algorithmic fairness becoming a critical field of study [1]. More recently, attention has turned to algorithmic fairness within the context of social network analysis, with recent studies showing that use of fairness-oblivious methods can reinforce latent biases in the data [2–4]. As a result, algorithmic fairness in social network science has emerged as a nascent field of study, where the aim is to design methods that mitigate network inequalities, ensuring outcomes do not disproportionately favor any particular groups [5].

One area where algorithmic fairness can have an important societal impact is community detection, due to its usage in grouping together similar users and providing similar recommendations in very large platforms, including online social media and retail systems. However, using standard community detection algorithms can often exacerbate biases present in the data by reinforcing homophily and demographic imbalances, resulting in homogeneous communities that can amplify echo chambers and undermine diversity in information exposure. Thus, we need community detection methods that are not only based on sub-graph density, but also are able to maintain a diverse demographic representation in the identified communities (cf. Fig. 1).

Recent studies have started to explore fairness outcomes in community detection methods [6–8], and adapt modularity-based methods to consider fairness constraints [9, 10]. These contributions, albeit important, remain restricted in scope: current methods often only handle binary sensitive attributes, do not account for imbalanced group sizes, and provide limited control over the trade-off between fairness and community quality. Simultaneously, these works highlight several open challenges: how can we extend fairness metrics beyond two sensitive demographic groups, or consider multiple demographics and their intersections? How can fairness constraints be integrated to community detection without sacrificing partition quality?

This work reviews the state of modularity-based, fairness-aware community detection, illustrating the current capabilities and limitations in the field. Specifically, we compare the aforementioned fair community detection methods, examining their ability to offer a trade-off between modularity and fairness outcomes, their ability to support multiple sensitive attributes, as well as their scalability to large networks. Drawing from these empirical results, we also highlight the current challenges in the field, and discuss extending such methods to still more complex network structures, such as multilayer networks.

References

[1] Dana Pessach and Erez Shmueli. “Algorithmic Fairness”. In: *Machine Learning for Data Science Handbook: Data Mining and Knowledge Discovery Handbook*. Ed. by Lior Rokach, Oded Maimon, and Erez Shmueli. Cham: Springer International Publishing, 2023, pp. 867–886. DOI: 10.1007/978-3-031-24628-9_37.

[2] Farzan Masrour et al. "Bursting the Filter Bubble: Fairness-Aware Network Link Prediction". In: *Proceedings of the AAAI Conference on Artificial Intelligence* 34.01 (2020). Number: 01, pp. 841–848. DOI: 10.1609/aaai.v34i01.5429.

[3] Lisette Espín-Noboa et al. "Inequality and inequity in network-based ranking and recommendation algorithms". In: *Scientific Reports* 12.1 (2022). Publisher: Nature Publishing Group, p. 2012. DOI: 10.1038/s41598-022-05434-1.

[4] Vedran Sekara et al. *Detecting and Mitigating Bias in Algorithms Used to Disseminate Information in Social Networks*. arXiv:2405.12764 [cs]. 2024. DOI: 10.48550/arXiv.2405.12764.

[5] Akrati Saxena, George Fletcher, and Mykola Pechenizkiy. "FairSNA: Algorithmic Fairness in Social Network Analysis". In: *ACM Comput. Surv.* 56.8 (2024), 213:1–213:45. DOI: 10.1145/3653711.

[6] Konstantinos Manolis and Evaggelia Pitoura. "Modularity-Based Fairness in Community Detection". In: *Proceedings of the International Conference on Advances in Social Networks Analysis and Mining*. Kusadasi Turkiye: ACM, 2023, pp. 126–130. DOI: 10.1145/3625007.3627518.

[7] Elze de Vink and Akrati Saxena. "Group Fairness Metrics for Community Detection Methods in Social Networks". In: *Complex Networks & Their Applications XIII*. Ed. by Hocine Cherifi et al. Cham: Springer Nature Switzerland, 2025, pp. 43–56. DOI: 10.1007/978-3-031-82435-7_4.

[8] Georgios Panayiotou, Matteo Magnani, and Ece Calikus. "Towards intersectional fairness in community detection". In: *Workshop Proceedings of the 19th International AAAI Conference on Web and Social Media* 2025 (2025), p. 40. DOI: 10.36190/2025.40.

[9] Georgios Panayiotou and Matteo Magnani. "Fair-mod: Fair Modular Community Detection". In: *Complex Networks & Their Applications XIII*. Ed. by Hocine Cherifi et al. Cham: Springer Nature Switzerland, 2025, pp. 91–102. DOI: 10.1007/978-3-031-82435-7_8.

[10] Christos Gkartzios, Evaggelia Pitoura, and Panayiotis Tsaparas. "Fair Network Communities through Group Modularity". In: *Proceedings of the ACM on Web Conference 2025*. New York, NY, USA: Association for Computing Machinery, 2025, pp. 506–517.

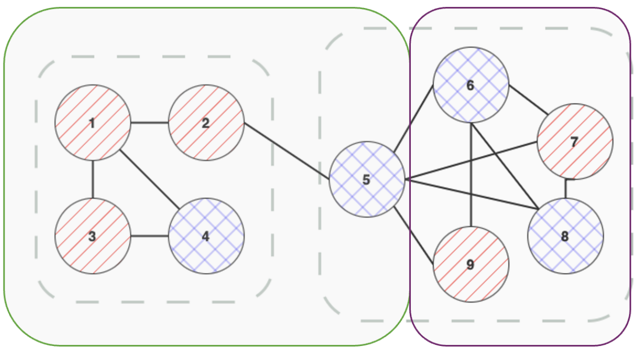

Figure 1: **Example of group balance-aware community detection.** Two clusterings of the same network. Dashed lines: two highly modular communities identified using traditional methods. Solid lines: two more balanced communities, still highly modular.