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FairSNA: Algorithmic Fairness in Social Network Analysis

Algorithmic Fairness, Social Network Analysis, Structural Bias, Inequalities, FairSNA

Extended Abstract

In recent years, designing fairness-aware methods has received much attention in various domains, including machine learning, natural language processing, and information retrieval. However, understanding structural bias and inequalities in social networks and designing fairness-aware methods for various research problems in social network analysis (SNA) have not received much attention. In recent years, we observed that a very few works have considered fairness and bias while proposing solutions; even these works are mainly focused on some research topics, such as link prediction [1, 2, 3], influence maximization [4, 5], and PageRank[6]. However, fairness has not yet been addressed for other research topics, such as influence blocking and community detection. In Fig. 1, we show a small example of unfairness in link prediction using the Dutch School social network [7] that has 26 nodes (17 girls and 9 boys), and 63 edges. The homophily value of the network is 0.7 [8]. In Fig. 1 (a), the network is shown, and the nodes are divided into two groups based on gender; blue nodes represent girls and pink nodes represent boys. Next, we remove around 10% of intra-community and inter-community edges uniformly at random, and the missing links are shown using dashed lines in Fig. 1 (b). Now, we compute the similarity scores for predicting the missing links using two heuristics methods, (i) Jaccard Coefficient [9], and (ii) Adamic Adar Index [10]; and similarity scores are shown corresponding to the missing links in Fig. 1 (c) and (d), respectively. We can observe that the value of similarity scores for inter-community links is lower than the intra-community links. Besides this, similarity scores are lower for small and sparse communities. For example, in Fig. 1 (d), Adamic Adar coefficient values for the links from the pink community are smaller than the blue community. However, in fair link prediction, the aim is to efficiently predict all kinds of links with high accuracy, irrespective of users' attributes, their communities, or community sizes.

In this talk, we will highlight how the structural bias of social networks impacts the fairness of different computing methods. We will further discuss fairness aspects that should be considered while proposing solutions for various research problems to understand social interactions using online social networks, such as link prediction, influence maximization, centrality ranking, and community detection. Finally, we will highlight various open research directions that require researchers' attention to bridge the gap between fairness and SNA.

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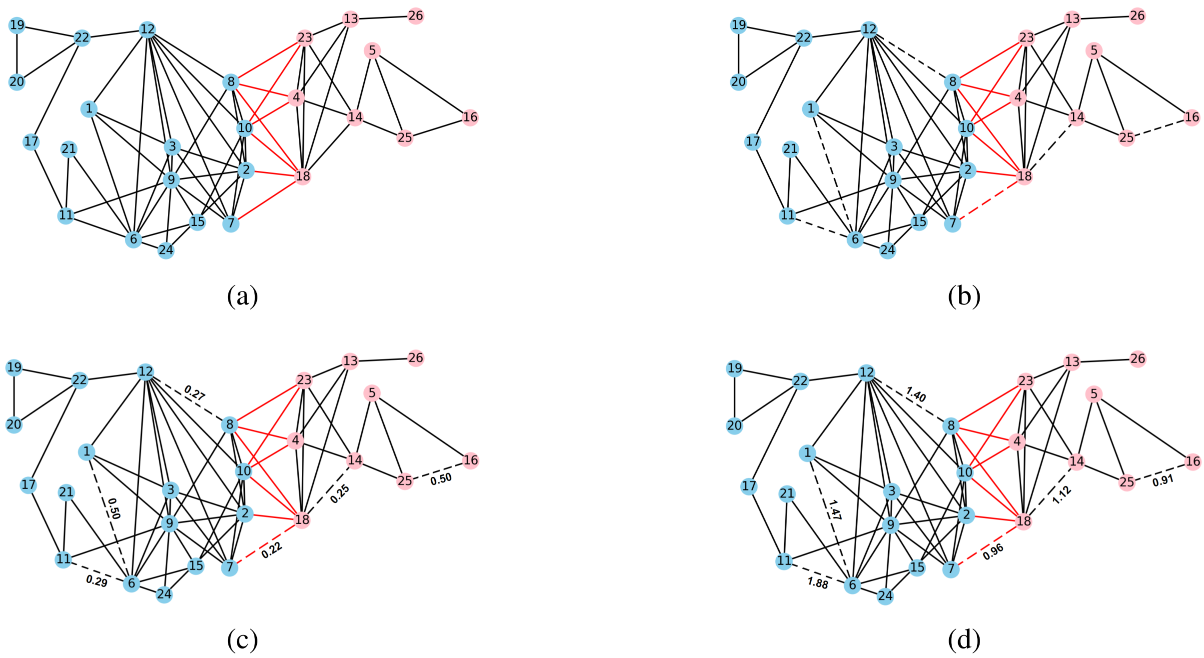

Figure 1: (a). Dutch School Social network having two groups where blue nodes represent girls and pink nodes represent boys, (b). Dashed lines represent around 10% u.a.r. removed links from the network, (c). and (d). Values corresponding to dashed lines show the Jaccard coefficient and Adamic Adar scores for predicting the missing links, respectively.

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