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Fairness-Aware PageRank Approximation

Keywords: Fairness-Aware PageRank, Algorithmic Fairness, Social Network Analysis, Approximation Methods, Social Network Inequalities

Extended Abstract

Real-world social networks often exhibit structural inequalities that amplify unfairness in network analysis algorithms such as link prediction, influence maximization, and centrality ranking [1]. These biases can lead to unequal distribution of social capital, disproportionately benefiting majority or well-connected groups while marginalizing minorities. Traditional centrality measures were designed without considering fairness, reinforcing existing disparities [2, 3]. Recently, fairness-aware approaches like Fairness-Sensitive PageRank [4] have been proposed to explicitly incorporate group-level constraints and mitigate these inequalities. Fairness-sensitive PageRank (FSPR) modifies the teleportation vector to enforce group-level fairness constraints but solving the associated convex optimization problem is computationally prohibitive for large networks [4]. Computing fairness-aware PageRank typically requires access to the entire network, which is often infeasible for large-scale or dynamic graphs.

In this work, we propose an approximation method to estimate fairness-aware PageRank scores without collecting the entire network and only using the local structural information. We propose an efficient approximation method for Fairness Sensitive PageRank (FSPR) based on the correlation between in-degree and PageRank [5]. Our approach partitions nodes into degree-classes within protected/unprotected groups (minority and majority), then approximates the teleportation vector using group fractions and aggregated in-degree. Subsequently, a fair mean-field approximation yields the average fair PageRank per class, significantly reducing computational cost compared to iterative optimization. We validate our approach on multiple real-world and synthetic networks, observing a strong alignment between the computed FSPR values and our mean-field approximation. In Fig. 1, we show that the approximated scores versus the actual fairness-aware PageRank on four real-world datasets, DBLP [4], LinkedIn [4], Pokec [6], and Google-Web [7]. The method consistently preserves fairness across groups achieving near-linear scalability, and yields an average correlation coefficient of $\sim$0.9 across all datasets. These results highlight the practicality of our framework for large-scale dynamic networks where exact computation is infeasible. In future work, we focus on robustness under degree correlations and extensions to multi-attribute fairness scenarios.

Ethical Considerations. In this study, we rely exclusively on publicly available datasets. This work addresses ethical concerns by mitigating structural biases in network algorithms that can otherwise reinforce social inequalities. By developing fairness-aware approximations, we aim to promote more equitable access to visibility and influence in social networks, while ensuring scalability and practical applicability.

References

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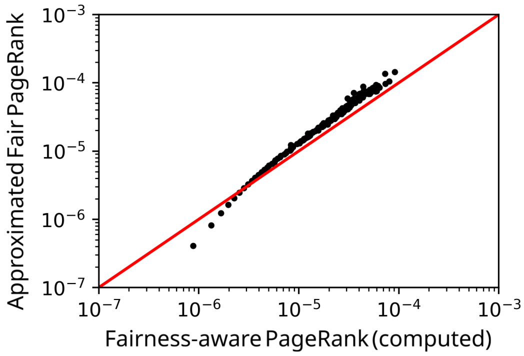
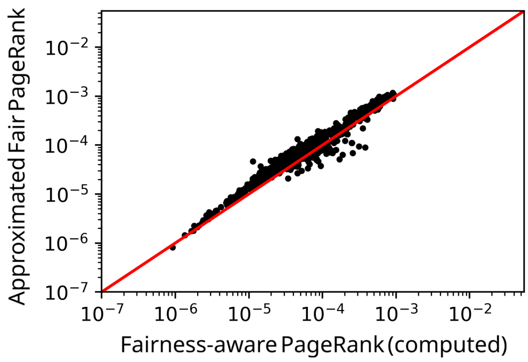
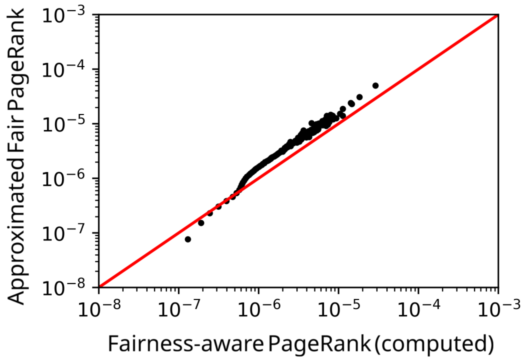


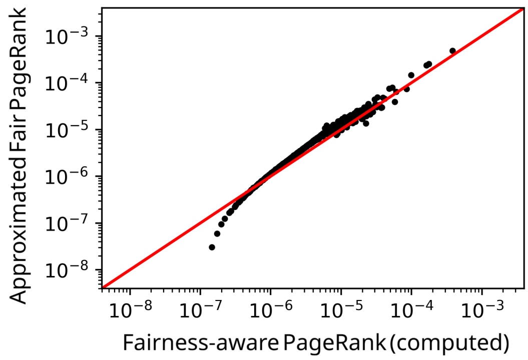
(a) DBLP



(b) Google Web



(c) LinkedIn



(d) Pokec

Figure 1: Approximated Fair PageRank values (mean-field estimate) compared with actual Fair PageRank per degree class on four real-world networks.

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