Individual Fairness in Community Detection: Metrics and Insights

Keywords: Community Detection, Algorithmic Fairness, Individual Bias, Social Network Analysis, Structural Inequalities

Extended Abstract

Community detection is an important task in network science, providing insights into the modular structure of complex systems such as social, technological, information, and biological networks [1, 2]. While numerous methods exist for identifying communities, fairness considerations have been largely overlooked, particularly at the *individual* level. Prior studies mainly focus on group fairness [3, 4], leaving a gap in evaluating how fairly algorithms treat each node. This work introduces novel metrics to quantify *individual fairness* in community detection, agnostic of the detection method. We propose **Individual Bias (IB)** to measure node-level fairness by comparing the context change in predicted and ground-truth communities using cosine distance on community co-occurrence (CC) matrices. Further, we introduce **Graph Individual Bias (IB_g)**, which aggregates node-level biases to evaluate how uniformly a community detection algorithm treats all nodes and compute the bias at the graph level. We apply the proposed metrics to a diverse set of 30 community detection algorithms falling under optimization, spectral, random-walk, information-flow, and statistical approaches [3, 5].

Experiments are conducted on synthetic networks generated with the ABCD benchmark model [6] having varying ξ (mixing parameter), and real-world networks. Figure 1 illustrates the relationship between the modularity and graph-level bias (IB_g) for varying mixing coefficients (ξ). The scatter plots confirm that as communities become harder to detect, IB_g values converge, implying that algorithms tend to treat all nodes equally unfairly in near-random settings. Results show that no class of algorithms is consistently fairer. Community detection methods which maintain relatively stable fairness across different levels of network noise include Paris, Head Tail, and MCODE, whereas algorithms like Spinglass and Significance communities display high unfairness at individual level. This work provides the first systematic approach to measuring *individual fairness* in community detection. By addressing disparities at the node level, our proposed framework lays the foundation for fairness-aware algorithms and more accountable applications of community detection in social network analysis [7]. In this presentation, we will discuss the motivation for fair community detection, introduce our proposed individual bias metrics, present results on both synthetic and real-world networks, highlight methods that perform comparatively well, and outline future directions as well as ongoing work in our group on developing fairness-aware community detection approaches.

Ethical Considerations. In this study, we used publicly available datasets. Our work highlights that unfair community detection can reinforce structural inequalities, marginalize individuals, and distort access to information. By introducing individual fairness metrics, we lay the groundwork to develop fair community detection methods. We aim to foster more equitable and accountable network analyses as identified communities are used to deploy fairness in various network analysis methods, including link prediction, influence maximization, influence blocking, and so on.

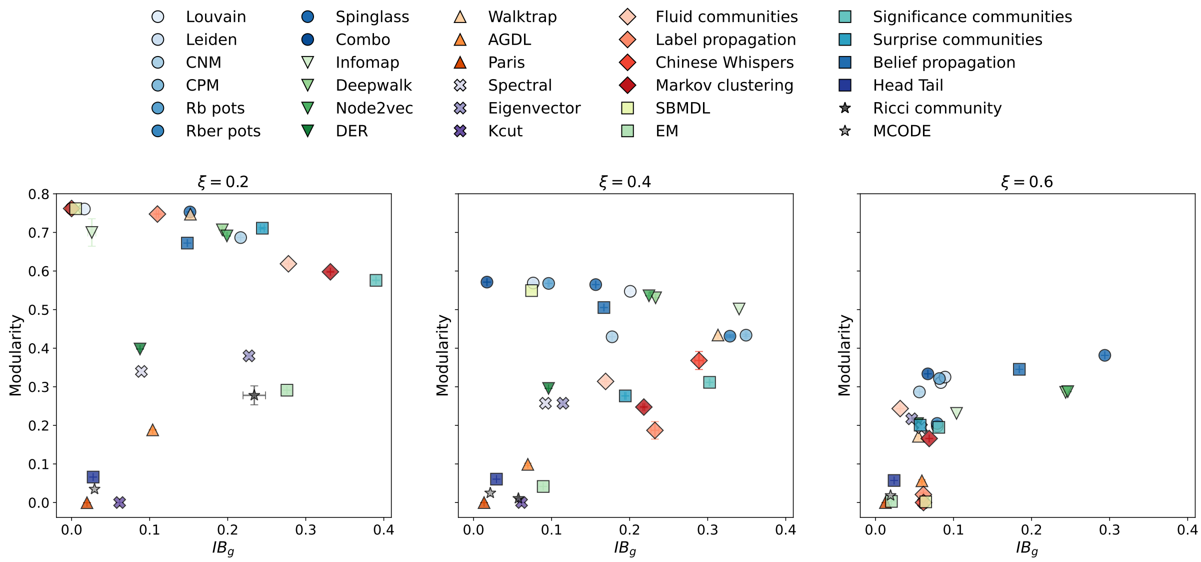

Figure 1: Modularity versus Graph Individual Bias (IB_G) on ABCD networks with $\xi = 0.2$, $\xi = 0.4$, and $\xi = 0.6$, evaluated across 30 community detection methods. Each point represents the mean result over 10 graphs generated with identical parameters, with error bars indicating variance.

References

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