Analyzing the Correlation of Classical and Community-aware Centrality Measures in Complex Networks

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Extended Abstract

Identifying influential nodes in social networks is a fundamental issue. Indeed, it has many applications, such as inhibiting epidemic spreading, accelerating information diffusion, preventing terrorist attacks, and much more. Classically, centrality measures quantify the node's importance based on various topological properties of the network, such as Degree and Betweenness. Nonetheless, these measures are agnostic of the community structure, although it is a ubiquitous characteristic encountered in many real-world networks. To overcome this drawback, there is a growing trend to design so-called community-aware centrality measures. Although several works investigate the relationship between various classical centrality measures [1-3], the interplay between classical and community-aware centrality measures is still unexplored. This work presents an extensive investigation aimed at a better understanding of the relationship between community-aware centrality measures, classical centrality measures, and network topology.

Artificial and real-world networks are used in the experiments. The Kendall's Tau correlation quantifies the interaction between ten classical and twenty-eight community-aware centrality measures. The community-aware centrality measures are divided into three groups. The first group's ten measures are based on the intra-community links of a node (local measures). The second group's twelve measures are based on the inter-community links of a node (global measures). Finally, the six measures of the third group consider both types of links (mixed measures). The LFR algorithm generates artificial networks with controlled properties. Indeed, the community structure strength (μ), the exponent of the degree distribution (γ), and the community size distribution (θ) can be specified. The experiments show that the community structure strength is the main feature governing the correlation between classical and community-aware centrality measures. The heatmap on the left of Figure 1 represents the correlation in an artificial network with a strong community structure. The global community-aware centrality measures exhibit a low correlation with classical centrality measures, while local community-aware centrality measures show a high correlation. The results are inverted when the network has a weak community structure. Differences are more subtle for mixed community-aware measures. One can also notice that results are relatively insensitive to variation of the degree and community size distributions' exponents.

Fifty real-world networks originating from various domains are also investigated. Linear regression is performed considering six macroscopic (Density, Transitivity, Assortativity, Average Distance, Diameter, Efficiency) and nine mesoscopic topological features (Mixing

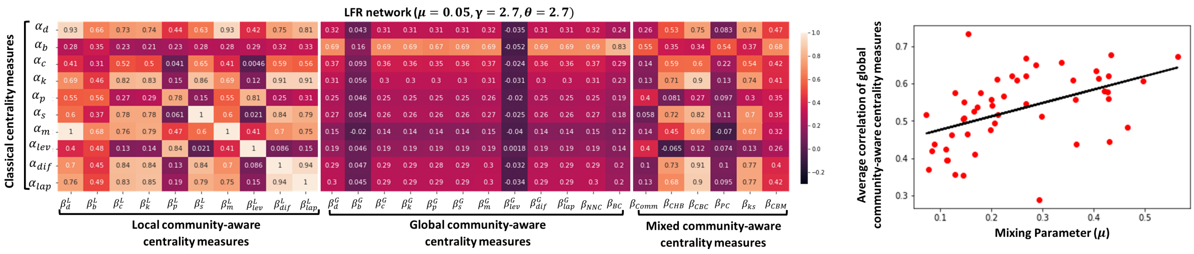

Figure 1: Left figure: Heatmap of Kendall's Tau correlation of the various combinations of classical (α_i) and community-aware (β_j) centrality measures. The classical centrality measures are: α_d = Degree, α_b = Betweenness, α_c = Closeness, α_k = Katz, α_p = PageRank, α_s = Subgraph, α_m = Maximum Neighborhood Component, α_{lev} = Leverage, α_{dif} = Diffusion, α_{lap} = Laplacian. The local community-aware centrality measures are: (β_d^L, β_b^L, β_c^L, β_k^L ,β_p^L, β_s^L, β_m^L, β_{lev}^L, β_{dif}^L, β_{lap}^L) = the local component of the classical centrality measures based on modular centrality. The global community-aware centrality measures are: (β_d^G, β_b^G, β_c^G, β_k^G ,β_p^G, β_s^G, β_m^G, β_{lev}^G, β_{dif}^G, β_{lap}^G) = the global component of the classical centrality measures based on modular centrality, β_{NNC} = Number of Neighboring Communities centrality, β_{BC} = Bridging centrality. The mixed community-aware centrality measures are: β_{Comm} = Comm centrality, β_{CHB} = Community Hub-Bridge centrality, β_{CBC} = Community-based centrality, β_{PC} = Participation Coefficient, β_{ks} = K-shell with Community centrality, β_{CBM} = Community-based Mediator centrality. Right figure: Relationship between the mean correlation of classical and global community-aware centrality measures with respect to the mixing parameter for 50 real-world networks.

Parameter, Modularity, Internal Distance, Internal Density, Max-ODF, Average-ODF, Flake-ODF, Embeddedness, and Hub Dominance). These are the dependent variables. The independent variables are the mean values of the correlation values between classical and local/global community-aware centrality measures. Results show that transitivity and the mixing parameter are the most significant features ($p \leq 0.01$). As transitivity increases, the correlation between global community-aware and classical centrality measures decreases. The opposite is true for local community-aware centrality measures. As the mixing parameter increases (i.e., weaker community structure strength), the correlation between global community-aware and classical centrality measures grows. The opposite is true for local community-aware centrality measures. This work sheds light on how network topology influences the relationship between classical and community-aware centrality measures. It shows that the stronger the community structure and the higher the transitivity, the more different classical and community-aware centrality measures. Besides, results open new directions to design community-aware centrality measures incorporating additional network topology information.

References

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