How Robust are Communities in Temporal Networks? A Comparative Analysis using Community Detection Algorithms

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Abstract

Communities often represent structural and functional clusters in networked systems. Communities have been found to be essential building blocks for understanding the robustness of critical infrastructures and the diffusion of information in online social networks. Previous work in community robustness analysis has focused on studying changes in the community structure of networks as a response of edge rewiring and node/edge removal. However, many real networked systems are constantly evolving and increasing their connectivity. Thus, there is a growing need to understand the limits of the robustness of communities with respect to expanding density. We hypothesize that the choice of algorithm used for detecting communities has an effect on the robustness of the associated community structure. Here we use state-of-the-art community detection algorithms (i.e., Infomap, Label propagation, Leiden, and Louvain) to understand their effect when studying the robustness of community structures in temporal networks. We test this hypothesis in both synthetic LFR benchmark networks under random addition of edges and on email networks with increasing edges over time. Our preliminary results indicate that the robustness of communities is heavily dependent on the chosen community detection algorithm. We suggest that for understanding the robustness of communities in temporal networks, a careful selection of the community detection algorithm is imperative.

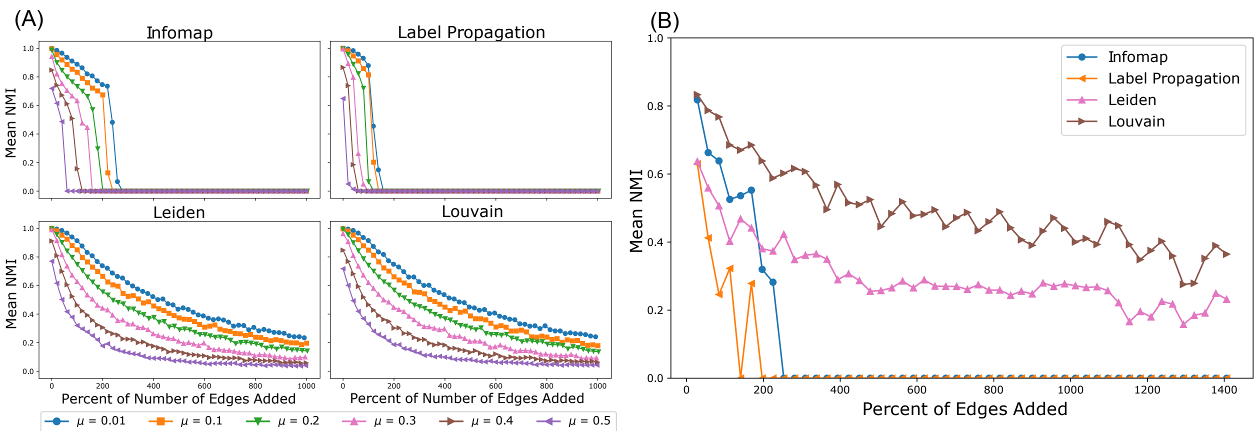

Figure 1: **Mean Normalized Mutual Information(NMI) over percentage of edges added.** We compute the similarity between community partitions using NMI. (A) **LFR benchmarks** with 1000 nodes, average degree 10 and six different mixing parameters μ. We cluster them using Infomap, Label propagation, Leiden and Louvain. We add up to 10 times the original number of edges over 50 independent steps. Edges added uniformly at random without producing multi-edges. For each algorithm, we average NMI between the ground truth partition and new partitions of the perturbed network over 10 independent runs at each step. (B) **Sub-network from ia-radoslaw-email network with** 74 **nodes**. We use fast consensus [1] to get 20 initial community partitions. We add up to 14 times the initial number of edges over 50 steps following timestamps from the dataset. We report results on average NMI over all pairs of the initial consensus partitions and the partitions from 10 independent realizations at each time step.

[1] Aditya Tandon, Aiiad Albeshri, Vijey Thayananthan, Wadee Alhalabi and Santo Fortunato: "Fast consensus clustering in complex networks", **Phys. Rev. E.**; 2019

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