

Analysis of stability of community structure across multiple hierarchical levels

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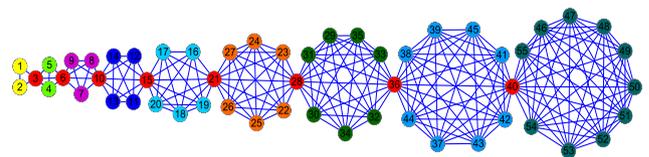
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Abstract –The analysis of stability of community structure is an important problem for scientists from many fields. Here, we propose a new framework to reveal hidden properties of community structure by quantitatively analyzing the dynamics of Potts model. Specifically we model the community structure detection Potts procedure by a Markov process, which has a clear mathematical explanation. Critical topological information regarding to multivariate spin configuration could also be inferred from the spectral significance of the Markov process. We test our framework on some example networks and find it doesn't have resolute limitation problem at all. Results show the model we proposed is able to uncover hierarchical structure in different scales effectively and efficiently.

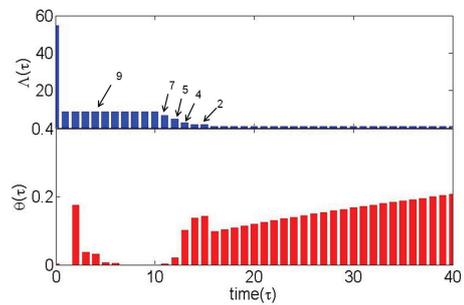
Appendix. –

Experiment on network with different modular sizes. – To illustrate the soft stability can uncover hierarchical community structures with different modular sizes, we apply the framework to a synthetic hierarchical network. The network contains 9 cliques of different sizes and we consider a line of cliques from size 3 to 11, jointed only by a common node between each other. The clique network is shown in Fig.1(a) and the common nodes are presented in red color. One can consider a specific clique is an overlapping part between the neighbor ones. So 2-8 are also reasonable numbers of modules which reveal fuzzy levels of the hierarchical structure.

The significance of such levels can be quantified by their corresponding persistent time length. The longer the time persists, the more robust the configuration is. In the upper subgraph of Fig.1(b), one can observe that 9 modules and 2 modules are the most significant community structure. However, 3-8 are also reasonable although they don't own very long persistent timescales. This is in perfect consistency with the generation mechanisms if we consider the overlapping parts of the network. Furthermore, in the lower subgraph of Fig.1(b), we plot the curve of Θ . One can



(a)



(b)

Fig. 1: (a) Structure of network contains a line of nine cliques with 3-11 nodes. The overlapping nodes are highlighted in red color. (b) The value of $\Lambda(\tau)$ and $\Theta(\tau)$ versus time τ .

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observe that Θ is an approximate parabolic shape for the timescales of a specific Λ . It can be used to estimate the modularity property of complex networks, and larger Θ indicates stronger community structure. We explore the trend of soft stability Θ and find the largest value of Θ corresponding to 9 communities with $\Gamma(9)=0.187$, much larger than 0.145 corresponding to 2 communities. The significance of community structure indicated by soft stability Θ favors finer but obvious modules. This is in keep with the network formation and reasonable for many real networks.

Experiment on real networks. – First, we tested our framework on the largest connected component of a scientific collaboration network, collected by Girvan and Newman [1]. The network illustrates the research collaborations among physicists in terms of their coauthored papers posted on the Physics E-print Archive at arxiv.org which shown in Fig.2(a). Totally, this network contains 379 nodes which color coded into 21 and 5 communities obtained by maximizing the modularity or stability measure [2]. The partitions of two different scales are corresponding to fine and coarse physical classifications. From Fig.2(b), we observe 21 and 5 communities are indeed the most significant partitions corresponding to the largest stability $\Theta(\tau)$. The result is reasonable and exactly same as [1] and [2].

Then, we apply the framework to an important biological application, i.e. finding the communities of *S.cerevisiae* proteins based on their interactions [3]. Indeed, proteins in 10 communities are shown in Fig.3(a) can be associated with either protein complexes or certain functions, as can be looked up by using the GO-Term Finder package [4] and the online tools of the Saccharomyces Genome Database (SGD) [5]. Fig.3(b) shows that 10 is indeed the optimal number of communities revealed by our framework corresponding largest stability $\Theta(\tau)$. This result shows that our framework can provide the real functional classifications of biological networks, which has broad applications in the future studies.

The comparison between modularity and our framework. – Finally, we emphasize the difference between the stability measure proposed and the modularity Q proposed by Newman [6]. Q is a well-known criterion for evaluating a specific partition scheme of a network. It is defined as “the fraction of edges that fall within communities, minus the expected value of the same quantity if edges fall at random without regard for the community structure”. Different partition schemes will get different Q values for the same network, and larger ones mean better partitions. While our Λ and Γ try to directly characterize and evaluate the structure property based on network’s spectra, rather than a specific network partition. Therefore, a network only has exactly self-deterministic Λ and Γ values regardless of how many partition schemes it would have, and the larger the Γ the stronger the network community structure. In addition, Fortunato *et al* [7] pointed

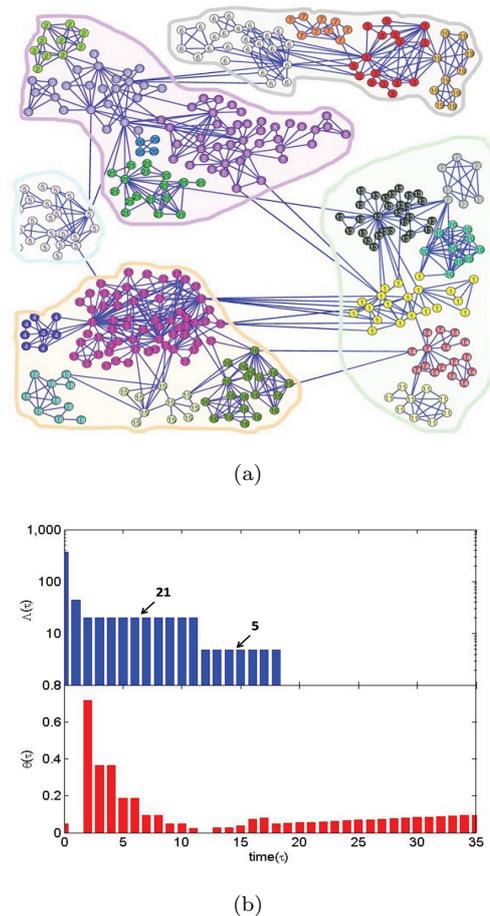


Fig. 2: (a) The largest connected component of scientific collaboration network science. The nodes corresponding to 379 researchers which color coded into 21 and 5 partitions obtained by maximizing the stability [2] at $\tau = 1$ (or equivalently, modularity). The researcher are grouped mainly based on the physical classifications. (b) The value of $\Lambda(\tau)$ and $\Theta(\tau)$ versus time τ .

out the resolution limit problem of the modularity Q , that is, there exists an intrinsic scale beyond which small qualified communities cannot be detected by maximizing the modularity. As shown in Fig.4, when a clique ring contains cliques with different scales (i.e., the heterogeneous community size), the intrinsic community structure can be exactly revealed by Λ . With Λ and Γ , we can quantitatively compare the modularity structure of different types of complex networks.

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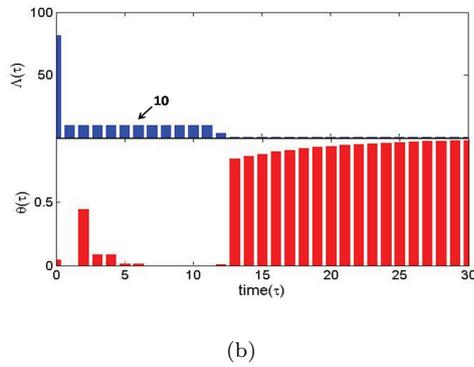
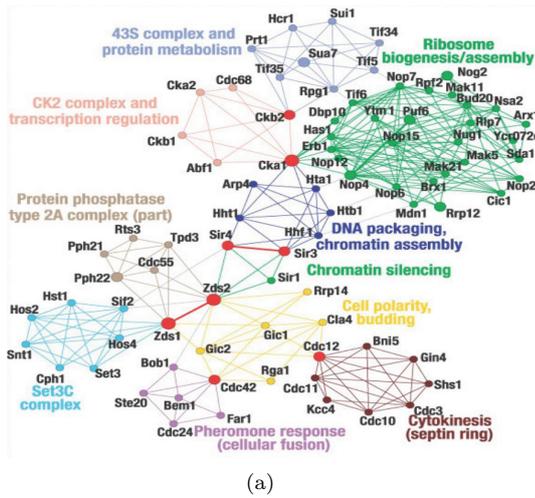


Fig. 3: (a) The protein–protein interactions network of *S.cerevisiae* containing 10 communities [3]. Different communities are described by different colors and the biological functions are annotated beside correspondingly. (b) The value of $\Lambda(\tau)$ and $\Theta(\tau)$ versus time τ .

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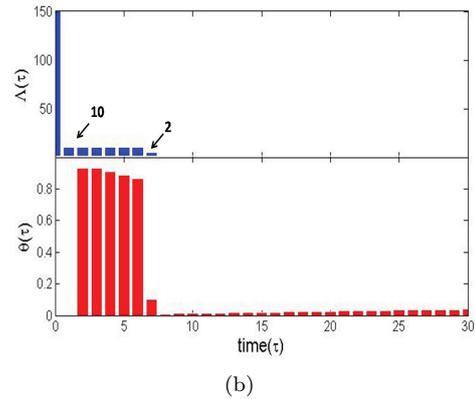
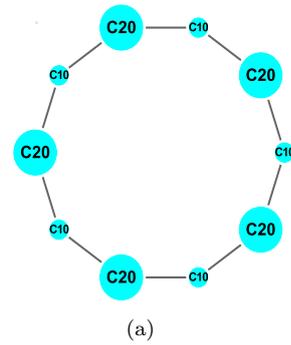


Fig. 4: (a) Ring of clique network as a schematic example. Each circle corresponds to a clique, whose size is marked by its label C20 (contains 20 nodes) or C10 (contains 10 nodes). (b) The value of $\Lambda(\tau)$ and $\Theta(\tau)$ versus time τ .