COMMENTARY

Rich gets simpler

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Network science plays a central role in the study of complex systems, offering a range of computational tools and, importantly, a common language to represent systems as diverse as the World Wide Web, the human brain, and social networks (1). Within the framework of network science, a system is modeled as a set of nodes, representing the individual units of the system, and a set of links, representing the dyadic relationships between these units. Many networks have been shown to exhibit a complex organization and yet can often be comprehended by simple and universal mechanisms. However, to properly capture the complexity of real-world interacting systems, standard network models are sometimes not sufficient. For this reason, different attempts have been made to enrich the network language in recent years. Important examples include multiplex or multilayer networks (2), where different types of interactions are accounted for, higher-order networks (3–5), focusing on pathways instead of dyadic interactions, and temporal networks (6, 7), where nodes and links become dynamical entities. In PNAS, Sekara et al. (8) make two important contributions to the latter approach, first by studying a longitudinal, high-resolution dataset on human interactions over an extended time window and second by showing that significant structural patterns naturally emerge from the system when considered at an appropriate time scale (Fig. 1).

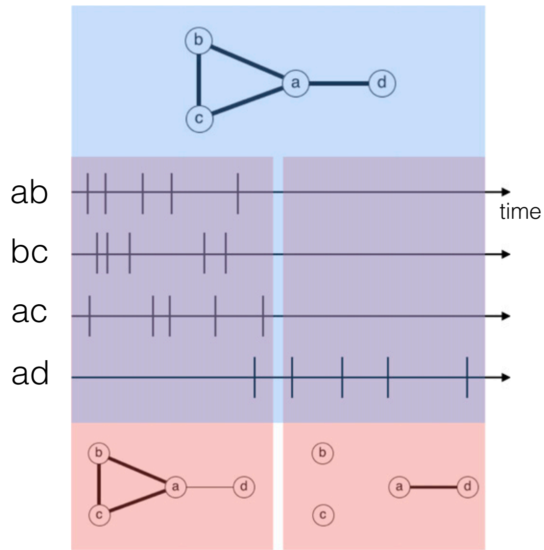

Fig. 1. In temporal networks, the time series of link activations (e.g., when *a* calls *b* in a communication network) may present complex temporal patterns. An aggregation of the time series into a static network (blue) may hide the inner structure of the system. When aggregated at an appropriate time scale, however, the system exhibits groups of nodes synchronized in time, associated to its overlapping community structure (red). In this simplified example, *a* belongs to two groups.

The study of temporal networks starts from the observation that real-world interacting systems exhibit nontrivial temporal patterns. Nodes and links are often dynamical entities that may emerge and disappear in the course of time. Take a social network, for instance, and the timings at which two individuals communicate via emails or phone calls. The resulting time series exhibit patterns at different scales, from minute-by-minute variations to yearly reorganizations. In particular, their rate of interaction is time-dependent due to obvious circadian and weekly rhythms (9), and their interevent times are broadly distributed because of self-exciting, multiplicative processes (10), possibly leading to a cascade of responses. In general, temporal networks are much more complex objects than static ones, and their study requires new computational and mathematical tools, combining structural and dynamical complexity. Temporality alters even the most basic concepts of network science, such as the path between two nodes (11). Nonetheless, as Sekara et al. (8) show, temporality may also help in uncovering information in networks when properly incorporated.

Interest in temporal networks has been fueled by the increasing availability of time-stamped interaction data in social systems. Important examples include communication patterns on Twitter (12) or mobile phones (13). Although they are routinely collected by network providers and online services, these data suffer from some important limitations due to their proprietary nature: Strict confidentiality agreements

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often hamper the scientific reproducibility of the results obtained. Furthermore, because the precise collection procedure cannot be controlled, this often leads to datasets with limited quality (e.g., due to biased or too-sparse sampling). For instance, locations captured by call detail records are known to provide a sparse and heterogeneous sampling of human trajectories with a fairly poor spatial resolution, which is not sufficient to estimate face-to-face interactions. To overcome these limitations, several attempts have been made to deploy large-scale data collection experiments. Such studies are typically based on handing mobile devices to a limited number of users or distributing software, typically downloadable applications, to track the social behavior of users. For instance, in the seminal reality mining study (14), data from 100 mobile phones were collected over a 9-mo period. In a similar vein, the work of Sekara et al. (8) builds upon an ambitious data collection program, the Copenhagen Networks Study (15), which takes this type of experiment to an unprecedented size and resolution. The study aims at measuring human interactions across a variety of communication channels with high temporal resolution and spanning multiple years. Using state-of-the-art smartphones as social sensors, collected data include face-to-face interactions, communication, social network information, and geographical location as well as background information for a population of approximately 1,000 students at a large European university.

With richer data come new computational challenges, discoveries but also at times simplifications. The unique quality of the dataset, combining high temporal resolution and long observation windows, has enabled Sekara et al. (8) to investigate the detailed evolution of networks over different time scales, leading to interesting insights on community detection (16). Community detection has been an active field of research for the past decade, aiming at automatically finding cohesive groups of nodes in large networks. Although a range of computationally efficient methods exists to uncover nonoverlapping communities (17), the study of overlapping communities, where each node can belong to more than one group, is less developed. It is, however, well documented that social networks can be pervasively overlapping (18), with each individual participating in multiple communities. In the case of temporal communities, which may undergo several morphological changes over time (e.g., birth, death, merging, etc.), finding and tracking communities is still a challenge (19, 20). Sekara et al. (8) address both problems by carefully exploring the impact of the temporal resolution of the data on the representation of the system. They observe that the participation of nodes in different groups clearly emerges when the data are aggregated over an appropriate time window, whereas this pervasive overlap is blurred when the resolution is not properly tuned. In a static framework, where the data are aggregated over long periods of time, this effect leads to no apparent modular structure. However, at adequate temporal resolutions, Sekara et al. (8) demonstrate that the system naturally splits into synchronized groups, akin to temporal network motifs, which makes the problem of overlapping community detection straightforward. Beyond this contribution, the work of Sekara et al. (8) opens further research perspectives by its identification of statistical regularities in the dynamical properties of social groups and its emphasis on the importance of structural and temporal scales to find patterns in networks. Overall, it raises important questions on finding the right representation of complex temporal data and constitutes a step toward a truly unified framework of structure and dynamics for networked systems.

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