Statistical Physics of Complex Dynamics Group at APCTP

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INTRODUCTION

Many real-world systems are complex not only because they consist of a huge number of constituents, but also because a collection of interaction between those constituents could lead to the emergence of macroscopic patterns. Macroscopic patterns in physical, biological, and social phenomena have been described by long-range spatiotemporal correlations and heavy-tailed distributions of observables [1]. These scaling behaviors are often characterized simply by scaling or power-law exponents. Although complex systems intrinsically have a number of factors, not every factor is relevant to macroscopic or scaling behaviors. Consequently, systems having very different origins might show surprisingly similar macroscopic patterns or *universality* if they have common relevant factors. Each combination of relevant factors can lead to the corresponding universality class, i.e., equivalence class in terms of scaling behavior. Therefore, by identifying and classifying universality classes one can show which factors are (ir)relevant to macroscopic patterns. Then, irrelevant factors can be filtered out to considerably reduce the complexity of systems, which would enable us to better understand the connection between microscopic and macroscopic properties of complex systems, namely, *micro-macro link*.

Prominent examples of complex systems include epidemic outbreaks of diseases and bursty diffusion of information in a population. For understanding the structure and dynamics of such systems it is crucial to properly characterize the interaction structure. For this, we adopt the well-known concept of a *graph or network*, where nodes and links represent constituents and interactions between them, respectively [2]. In many cases, the topological properties of interaction networks already can tell, e.g., which properties can account for the emergent collective dynamics on such networks. More recently, the temporal information of interactions has been analyzed for more detailed understanding of the collective dynamics in complex systems. Thus, for considering both topological and dynamical aspects simultaneously, we take the emerging framework of *temporal networks*, in which a link between nodes is considered existent only at the moment of interaction [3]. See Fig. 1 for a schematic diagram.

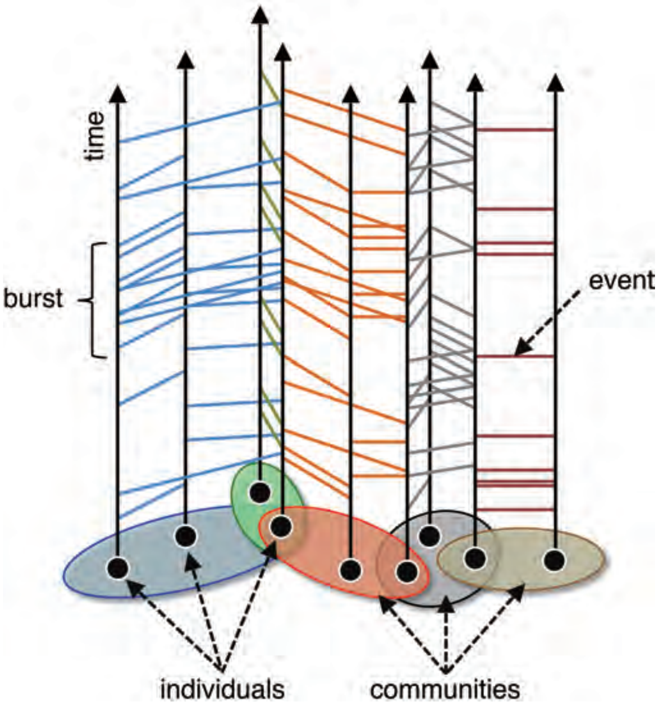

Fig. 1: Schematic diagram for the interaction structure of a complex system with overlapping communities and bursty temporal patterns.

COMPLEX INTERACTION STRUCTURE

Topological structure

Recent empirical analyses of large-scale datasets on networks have revealed several common features or *stylized facts*, such as broad distributions of network quantities, existence of communities, assortative mixing, and weight-topology correlations. As for the mesoscopic picture, real-world networks have a rich community structure. Communities are groups of nodes with high link density within groups and low link density between groups [4]. It has been observed that the activity on the link, or link weight, is correlated to the topology. However, as each individual may belong to multiple communities, communities are not necessarily separated but overlapping. This implies that the global structure of networks can be better described by *a continuum of overlapping communities*. To test this hypothesis, more work needs to be done with larger datasets.

Dynamical structure

The link weight plays a crucial role in understanding the effects of weight-topology correlations. It has been defined as the frequency of interaction events between nodes. The temporal information encoded in the exact timings of events enables us to study temporal inhomogeneities or *bursts* that are rapidly occurring events within short time-periods alternating with long periods of low activity [5]. Thus bursts have been characterized in terms of heavy-tailed or power-law distributions of inter-event times, where the inter-event time is the time interval between consecutive events. Examples for bursts include a unified scaling law for the inter-occurrence time of earthquakes, 1/f frequency scaling for inter-spike interval distributions in neuronal activities, and heavy-tailed inter-event time distributions in human communication patterns.

In order to understand the origin of these dynamical scaling behaviors, a number of empirical datasets have been analyzed using various measures like inter-event time distribution, burstiness parameter, bursty train size distribution, and autocorrelation function. In particular, the strong interdependency between consecutive inter-event times is called correlated bursts. In addition, if information about the contexts of events is available, the contextual bursts can be defined and studied. However, the origin of dynamical scaling behaviors in natural and social phenomena is not yet fully understood, despite its crucial importance, e.g., for preventing disease spreading and for the efficient design of infrastructure for the society.

Interplay between topological and dynamical structures and their effects on dynamical processes

Communities and bursts are key features for characterizing the temporal networks, which are closely entangled to each other. For deeper understanding of the interplay between communities and bursts, a simple model was studied by extending well-known link formation mechanisms into the temporal dimension. Based on this, one can better characterize dynamical processes on such temporal networks. Recently, much effort has been devoted to clarify how individual bursty dynamics influences the spreading speed of infectious disease in a population. There were conflicting results for the role of burstiness on the initial spreading speed. We analytically studied the Susceptible-Infected spreading dynamics to find that individual bursts speed up spreading in an early stage [6]. As a future work, we aim to study the correlated and contextual bursts and their effects, when combined with the overlapping community structure, on various dynamical processes in complex systems.

References

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