Vol.2010-MPS-81 No.28
Vol.2010-BIO-23 No.28
2010/12/17

情報処理学会研究報告
IPSJ SIG Technical Report

Adaptive Networks: An Emerging Research Theme on State-Topology Coevolution in Complex Networks

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Adaptive networks are a particular class of dynamical networks whose topologies and states coevolve over similar time scales. Many real-world complex networks are adaptive networks, including social networks, transportation networks, neural networks and biological networks. This presentation provides a brief overview of the recent rise of research on mathematical/computational modeling and analysis of such networks and discusses current and future research directions.

The rapidly growing research on complex networks has presented a novel approach to complex systems modeling [1-3] that was not fully foreseen even in a decade ago. It addresses the self-organization of complex network structure and its implications for system behavior, which holds significant cross-disciplinary relevance to many fields of natural and social sciences, particularly in today's highly networked social/political/economical circumstances.

Interestingly, complex network research has so far addressed either "dynamics *on* networks" or "dynamics *of* networks" almost separately, without considering both at the same time. In the former, "dynamics *on* networks" approach, the focus is on the state transition of nodes on a network with a fixed topology and the trajectories of the system states in a phase space with time-invariant dimensions [4-9]. This is a natural extension of traditional dynamical systems research to a high-dimensional phase space with non-trivial interaction between state variables. On the other hand, in the latter, "dynamics *of* networks" approach, the focus is on the topological transformation of a network and their effects on statistical properties of the entire network [10-15], where a number of key concepts and techniques utilized are borrowed from statistical physics. While there are overlaps between these two areas of study, there are still unfilled gaps remaining between them, in both conceptual and technical aspects.

When looking into real-world complex biological and social networks, however, one can find many instances of networks whose states and topologies "coevolve", i.e., they interact with each other and keep changing over the same time scales due to the system's own dynamics (Table 1). In these "complex adaptive networks", state transition of each component and topological transformation of networks are deeply coupled with each other, potentially producing emergent behavior that would not be seen in other forms of networks. Modeling and predicting state-topology coevolution is now becoming well recognized as one of the most significant challenges in complex network research [12,16,17].

Table 1: Real-world examples of complex adaptive networks whose states and topologies interact with each other and change over the same time scales

Network	*Nodes*	*Links*	*Examples of node states*	*Examples of node addition or removal*	*Examples of topological changes*
Organism	Cells	Cell adhesions, intercellular communications	Gene/protein activities	Cell division, cell death	Cell migration
Ecological community	Species	Ecological relationships (predation, symbiosis, etc.)	Population, intraspecific diversities	Speciation, invasion, extinction	Changes in ecological relationships via adaptation
Epidemiological network	Individuals	Physical contacts	Pathologic states	Death, quarantine	Reduction of physical contacts
Social network	Individuals	Social relationships, conversations, collaborations	Socio-cultural states, political opinions, wealth	Entry to or withdrawal from com-munity	Establishment or renouncement of relationships

Over the last decade, several mathematical/computational models of state-topology coevolution have been developed and studied on various subjects, ranging from physical to social systems. One major research topic discussed there is the unique form of self-organization of adaptive networks. It has been demonstrated, using several different formalisms, that adaptive changes of network topology may give rise to self-organized criticality more easily than in other dynamical network models [18,19,20]. In these models,

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connections are typically modified using local rules that are based on activities and/or similarities of node dynamics.

An illustrative class of adaptive network models is that of epidemiological models. Disease propagation on social networks has been extensively studied, yet when dynamic rewiring of social ties are allowed, the model behavior changes dramatically, causing substantial changes of phase diagrams and spontaneous formation of state-homogeneous subpopulations [21,22]. These results have significant implications for real epidemiology as people tend to alter social behaviors according to epidemiological states of their neighbors.

Social games have probably been the most extensively studied topic using adaptive network models [23-32]. A typical model setting is that the strategies and payoffs of agents, represented as node states, will evolve through iterative game play over social connections, and the connections themselves will also be modified locally based on the outcomes of those games. These models have demonstrated that the nature of the game becomes fundamentally different on adaptive networks, compared to that on networks of static topologies. Moreover, application of adaptive networks to social sciences does not stop at game theoretic models. Probably the newest application area is the modeling of organizational behavior, including the evolution of organizational networks inside a corporation and information/knowledge sharing and trust formation within it [33-35].

As shown above, the body of literature on adaptive networks is rapidly growing. A more comprehensive list of relevant literature can be found online [36]. However, those models were developed using different modeling frameworks chosen for specific phenomena, making it rather difficult to generalize them and apply them to real-world data analysis across different fields. Therefore, one of the important research challenges is to establish a generalized modeling framework that can effectively describe the state-topology coevolution of complex adaptive networks, which should be suitable for not only theoretical investigation but also for more practical data-driven modeling and analysis. Historically, cellular automata and other discrete dynamical networks have played the role of common modeling tools. To meet the need of similar tools for adaptive network modeling, a graph-writing-based computational modeling framework, called *generative network automata (GNA)*, is currently under development by the author. More details of this modeling framework can be found elsewhere [37-39].

Acknowledgment This material is based upon work supported by the US National Science Foundation under Grant No. 1027752.

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