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Editorial

Advances in dynamic temporal networks: Understanding the temporal dynamics of complex adaptive networks

Peter M.A. Sloot[1,2,3,a], George Kampis[4,6,7,b], and László Gulyás[4,5,6,c]

[1] University of Amsterdam, The Netherlands
[2] Research Institute ITMO, St. Petersburg, Russian Federation
[3] Complexity Program, Nanyang Technological University, Singapore
[4] Lorand Eötvös University, Budapest, Hungary
[5] Aitia International, Inc., Budapest, Hungary
[6] PetaByte Research Ltd., Budapest, Hungary
[7] DFKI (German Research Insitute for Artificial Intelligence), Trippstadter Strasse 122, 67663 Kaiserslautern, Germany

Abstract. Complex networks have been extensively studied in the past 15 years and with increasing details. However, research on the temporal dynamics of complex networks is largely a new territory yet to map out. The present volume presents a collection of papers dealing with various aspects of the problem and this editorial introduces the field as well as the papers.

1 Introduction

Over the past few years we have come to realize that networks are all around us. Even we are ourselves, as individuals, the units of a network of social relationships of different kinds and, as biological systems, the delicate result of a network of biochemical reactions. Networks can be tangible objects in the Euclidean space, such as electric power grids, the Internet, highways or subway systems, and neural networks. Or they can be entities defined in an abstract space, such as networks of collaborations between individuals.

2 The theory of complex networks

The development of the theory of complex networks (including social networks and systems from other domains) has been in the foreground of interest in the past decade.

[a] e-mail: `p.m.a.sloot@uva.nl`

[b] e-mail: `gk@hps.elte.hu`

[c] e-mail: `gulyas@petabyte-research.org`

Many network characteristics were identified and several network models introduced. However, the overwhelming majority of these have dealt with networks understood as static objects, unchanging in time.

For example, the various well-known measures describing important structural properties of the network, such as diameter (largest distance between two nodes of the network), path length (average distance between the nodes), or the various forms of centrality (i.e., node importance) are all defined on invariant, and by that virtue, static networks. Similarly, the study of the most important statistical properties such as degree distributions (characterizing the number of neighbors nodes have) assume the same form. Real world networks are, however, inherently dynamic, as virtually no natural network pops up instantaneously and in full form. A few issues of network generation have been dealt with by network growth models (e.g. [2,3,32]), but the aim of these now-classical works was to characterize properties of the resulting network (i.e. the envelope), and not the dynamic temporal process itself. Also, in real networks the changes often occur for endogenous, network-internal reasons that are more complicated than can be grasped by a simple growth rule. For instance, the change of a node's internal attributes can imply changes in its connectivity, and so on. (In an epidemic network, the recovered patient does not infect any more, so no more infection links can be formed from this node.) Interests of this kind put the questions of the interrelated dynamics of and on networks (e.g. [19,24,26,33]) into a new focus of investigation. Several important problems ranging from virology [4], to contact networks [34,35] and ecological theory [23] similarly invite a treatment of dynamic temporal networks on their own. A list of early works is given in [10].

3 Towards dynamic networks

Partly as a response to these current challenges, several approaches and tools were introduced more recently [18,25,40]. These are mostly isolated works, however, focusing on special problems. Only a few aim at developing general methodology. The SONIA project of Stanford [5] promises the visualization of longitudinal network data, but also raises some of the most important methodological questions for general dynamic networks. New problems include that of slicing, i.e. the use of thin or thick time slices or windows, and the implied question of how a flexible binning (the grouping of raw data into varying time slices) is achievable to obtain relevant network properties at a zero width snapshot the network properties, at a full time window, the dynamics is lost [31]. SONIA is built on the assumption that time stamped and -sliced data will grow in significance. Yet public longitudinal network data are still rare (a comprehensive list is [37]).

Dynamic Network Analysis (DNA, [9]) is the name of a prolific approach to various Social Network Analysis problems (the general name is slightly misleading, as DNA is more about modeling and decision support; also, DNA considers special nodes which, just like human agents, can learn). DNA uses the meta-matrix concept [9] to grasp multi-mode, multiplex, dynamic networks with multiple node attributes (such as a person's relation to events, organizations, resources, and other people). Some radically new network measures such as the notion of "cognitive load" were introduced – this is the amount of information that an agent has to handle in order to maintain its position in the network, and translates to connection intensity in a multi-net. DNA also endeavored to develop an interoperable dynamic network toolkit [11]. All in all, this is an interesting endeavor based on the recognition of the entirely new kinds of problems encountered in the dynamic domain, but it does not alone change the status of the field.

Recently, an important new area of research deals with extending the basic structural measures to dynamically changing temporal networks [21]. Our aim is to continue this new line with original contributions.

4 Complex temporal dynamics of networks

To motivate our approach, note that many relevant questions arise when studying complex networks' dynamics, such as understanding how a large ensemble of dynamical systems that interact through a complex wiring topology can behave collectively. Networks evolve over time and show a remarkable robustness and resilience to "environmental pressure". Examples are Protein-Protein Networks [15], Slime Mold Networks [1], Phylogenetic-Social Networks [41], Sexual Networks [28,29,35], "Bio" networks [22], Drug Addiction Networks [16] and Criminal Networks [17]. This robustness and resilience is often realized through dynamic modification of the network topology as well as the behavioural and functional changes of the links and nodes. Here we avoid the word "optimization" since these systems seem to function way out of equilibrium and the notion of "optimal" might not apply.

The dynamics *on* and *of* the network may emerge from a variety of causes. Yet, they seem to lead to specific classes of behavior. An important aspect seems to be the resilience with respect to uncertainty and noise. For instance it has recently been shown that stochastic resonance in the presence of noise can actually enhance information transfer in hierarchical complex social networks [14]. It seems likely that this resilience in complex networks has emerged from "evolutionary" adaptation, but little is known about that: it is an open research area.

In order to quantify, understand and even predict complex phenomena in a networked world, we need to combine the expressiveness of Individual Based Models with the structural information of Networks and quantify the way information flows through it a network [20,30,36,38].

5 Papers in this issue

This special issue on "Advances in Dynamic Temporal Networks" monitors the developments in this rapidly changing field, using 11 original invited contributions by leading experts.

The first two contributions discuss the dynamics *of* networks:

– Barrat et al. [42] studies empirical temporal networks of face to face human interactions using their original technique to apply RFID counters to register temporary human-to-human interactions in open spaces;
– Gulyás et al. [43] develop new theoretical models to understand the universal baseline dynamics of the temporal evolution of networks. This is the first systematic study of the elementary dynamics of edge addition and deletion using different classes of operators and varying aggregation windows.

The second section deals with the more classic issue of dynamics *on* the network and thus contains a single paper. The remarkable contribution of

– Czaplicka et al. [44] applies the theory of stochastic resonance to studying information flow in hierarchical networks.

The third section combines the approaches of the first two. It contains contributions tackling the combination of the two above types of network dynamics: dynamics *on* and *of* networks:

– Quax et al. [45] infers epidemiological parameters from phylogenetic information using this novel approach. On the other hand,

- Gulyás and Kampis [46] develops an agent-based model of spreading processes on dynamically changing contact networks. Finally,
- Zarrabi et al. [47] combines social and genetic network dynamics to study HIV transmission.

This is followed by an important paper developing the information theory of dynamics transmissions on networks, which served as the basis of a recent Ph.D. thesis:

- by Quax et al. [48] presenting a novel *information theory of dynamics networks.*

The volume is concluded with a chapter on applications. Four contributions use the dynamic temporal network approach in different problem domains.

- van de Vijver et al. [49] investigate the transmission of HIV in sexual networks in sub-Saharan Africa and Europe.
- Tóth et al. [50] develop novel centrality measures to grasp the dynamics of value chains in dark networks and test these new theoretical tools on classic (non-dark) empirical networks.
- The last two contributions take the volume's approach to the domain of scientometrics. Soós et al. [51] process extremely large volumes of information when performing the temporal analysis of the entire history of computer and information science using the temporal network approach.
- Apolloni et al. [52], finally, investigate the spatio-temporal relationships of scientific collaboration.

Together, elements of this collection show a variety of aspects of the current study field of dynamic, temporal networks. An essential recognition, that dynamic temporal networks behave *differently* from their static counterparts, emerges and is reiterated in several of the results. This is true for general information spreading but also for the study of infections, yielding the counter-intuitive results that preferential attachment networks are not the fastest spreaders of an infection – but also reflected in the human-to-human contact studies showing the importance of time windows over degree distributions. There is a host of future works expected along these lines and the current collection can only give a present cross-section of them. We hope that with the above contributions, the issue will inspire researchers in all fields of science to study and exploit the expressiveness of dynamic complex networks.

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