Chapter 10
Dynamics and Evolutional Patterns of Social Networks

Yingzi Jin
The University of Tokyo, Japan

Yutaka Matsuo
The University of Tokyo, Japan

ABSTRACT

Previous chapters focused on the models of static networks, which consider a relational network at a given point in time. However, real-world social networks are dynamic in nature; for example, friends of friends become friends. Social network research has, in recent years, paid increasing attention to dynamic and longitudinal network analysis in order to understand network evolution, belief formation, friendship formation, and so on. This chapter focuses mainly on the dynamics and evolutional patterns of social networks. The chapter introduces real-world applications and reviews major theories and models of dynamic network mining.

INTRODUCTION

Real-world social networks are dynamic in nature; for example, friends of friends become friends. Social network research has, in recent years, paid increasing attention to dynamic and longitudinal network analysis to understand network evolution, belief formation, friendship formation, and so on. We can define a simple static network as $G = (V, E)$, where V is the finite set of vertices and E is the finite set of edges, each being an unordered pair of distinct vertices. If we let f be a function defined on the vertex set as f: $V \rightarrow N$ and g be the function defined on the edge set as g: $E \rightarrow N$, a fully weighted graph can be represented as $G = (V, E, f, g)$. Dynamic graphs, that is, graphs that change with time, include four kinds of graphs: node-dynamic graphs (in which the vertex set V varies with time—some nodes may be added or removed, and when nodes are removed, the edges or arcs incident with them are also eliminated); edge-dynamic graphs (in which the edge set E varies with time); node-weighted dynamic graphs (in

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which the node weight function *f* varies with time); and edge-weighted dynamic graphs (in which the edge weight function *g* varies with time) (Harary & Gupta, 1997). In this chapter, we first introduce data collection approaches for dynamic networks and describe real-world applications of dynamic networks; we then review the major theories and models of dynamic network mining.

DATA COLLECTION FOR DYNAMIC NETWORKS

The data for dynamic network mining have usually been collected by means of questionnaires, observations, self-reporting, and simulations. For example, Nordle and Newcomb housed together 17 University of Michigan students who were initially unknown to each other. Each person was asked to rank each of his fraternity members with regard to positive feeling. Rankings were recorded each week and continued for a period of 15 weeks (Newcomb, 1961; Nordle, 1958). Some studies generate small sets of synthetic data to validate their dynamic frameworks (Lin, Chi, Zhu, Sundaram, & Tseng, 2010; Tantipathananandh, Berger-Wolf, & Kempe, 2007). With the increasing accessibility of digitized data through electronic databases and the Internet, researchers have collected longitudinal social network data on a large scale from e-mail interaction records (Carley & Skillicorn, 2005; Freeman, 1979), Digital Bibliography and Library Project (DBLP) citation data (Huang, Zhuang, Li, & Giles, 2008), protein interaction records (Ratmann, Wiuf, & Pinney 2009; Wagner, 2001), online social networks (Falkowski, 2009; Kumar, Novak, & Tomkins, 2006), and Web blogs (Lin et al., 2010). Furthermore, some studies attempt to automatically collect dynamic networks for given entities from news articles or from the entire Web through natural language processing (NLP) and machine learning (ML) techniques (Bernstein, Clearwater, Hill, Perlich, & Provost, 2002; Hu, Xu, Shen, & Fukushima, 2009; Ma, Pant, & Sheng, 2009, Tetlock, Saar-Tsechansky, & Macskassy, 2008). For example, Bernstein et al. use name co-occurrence frequency to calculate relational strength between companies, and extract inter-company network from public news; Ma et al. observed that a company is more likely to co-occur with its competitors on Web pages than with noncompetitors; Hu et al. use publishing time in news articles to extract temporal company networks from the Web. Other description of the sample data of dynamic social networks can be found in Goldenberg, Zhang, Fienberg, and Airoldi (2009).

REAL-WORLD APPLICATIONS OF DYNAMIC NETWORK MINING

In this section, we present applications of mining in real-world dynamic networks. We introduce representative works on the evolution of collaboration networks, dynamic community identification, friendship formation networks, the evolution of organizational networks, dynamic biological networks, and so on.

Evolution of Collaboration Networks

The evolution of collaboration networks and, in particular, of scientific collaboration networks has been studied in the literature (Huang et al., 2008; Liben-Nowell & Kleinberg, 2007; Newman, 2001). Newman (2001) studied empirically the time evolution of scientific collaboration networks in physics and biology. He found that the probability of scientists collaborating increases with the number of collaborators they have in common, and that the probability of a particular scientist acquiring new collaborators increases with the number of his or her past collaborators. Liben-Nowell and Kleinberg (2007) treated the inference of the addition of edges in a future coauthorship collaboration network as a link-prediction problem, and they compared various predictors

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