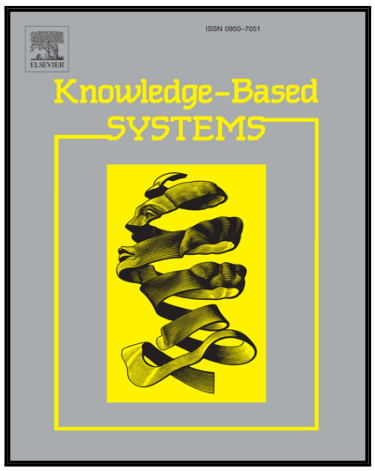

A local dynamic method for tracking communities and their evolution in dynamic networks

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A local dynamic method for tracking communities and their evolution in dynamic networks

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Abstract The analysis of communities and their evolutionary behaviors in dynamic networks is a challenging topic. Although a growing body of work on this topic is emerging, there are few methods which can reveal and track meaningful communities over time and can also deal with large networks efficiently. In this paper, we propose a method to track dynamic communities and their evolutionary behaviors. The main idea behind our method is to discover dynamic communities by exploring the local views of nodes that change. Moreover, based on the discovered dynamic communities, the global community structure can be derived by updating the historical community structure and the evolutionary behaviors of communities can also be tracked. To discover the dynamic communities, we apply the technique of approximate personalized PageRank vector; to track the evolutionary behaviors of the communities, we introduce a partial evolutionary graph. We compare the proposed method with several existing methods by performing experiments on nine synthetic networks and one real network. The experimental results show that the proposed method performs well on discovering communities as well as tracking their evolution in dynamic networks, and spends much less running time than the existing methods.

Keyword: community evolution; community detection; dynamic networks; dynamic communities; local structure

1 Introduction

Many systems such as World Wide Web, bloggers, co-author relationships and social relationships are represented as networks where nodes indicate individuals, e.g., web pages, bloggers and authors, and edges indicate the interactions among individuals, e.g., hyperlinks in web pages, co-authorships and friendships. These networks often present a fundamental structure, i.e., community structure. In the community structure, nodes in the same group are densely connected while nodes between groups are sparsely connected (Girvan and Newman 2002; Wang et al. 2015). These groups of nodes are referred to as communities[1]. The analysis of these communities, i.e., discovering communities (revealing the members and the structure of communities) and tracking their temporal dynamics (Lin et al. 2009), is an important research topic.

Although a large body of work on communities has been done, much progress on the analysis of communities has mostly been based on the assumption that the network is static (Fortunato 2010; Wang et al. 2015; Yang and Leskovec 2014; Yang and Leskovec 2015). In this case, the network is derived from the aggregation of nodes and their associated interactions with respect to total time, or it is taken as a single snapshot at a particular time (Lin et al. 2009). However, considering networks as static ignores the dynamic property of networks and omits the temporal evolution of communities, which is a key feature of many networks such as online social networks and co-authorship networks (Sun

[1] In this paper, we follow the most widely-used definition of community, i.e., a community is a subnetwork within which the nodes are densely connected while having sparser links to other parts, and we do not consider the definitions of other dense subgraphs such as k-clique (Bron and Kerbosch 1973; Xiang et al 2013), k-truss (Cohen 2008; Wang and Cheng 2012; Shao et al. 2014), k-core (Cheng et al. 2011), k-plex (Balasundaram et al. 2011) and k-component (Makino 1988; Jaberi 2015).