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A dynamic evolutionary clustering perspective: Community detection in signed networks by reconstructing neighbor sets

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HIGHLIGHTS

- A community detection algorithm is presented for signed networks.
- The detection performance is higher than two recent community algorithms for signed networks and the runtime is reduced.
- Differential equations are proposed to imitate the constantly changing states of the nodes in signed networks.
- The main process of the evolutionary clustering algorithm is based on the reconstructed neighbor sets.
- The analytical results are verified by comparative experiments on both synthetic and real world networks.

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ABSTRACT

Community detection in social networks has been intensively studied in recent years. In this paper, a novel similarity measurement is defined according to social balance theory for signed networks. Inter-community positive links are found and deleted due to their low similarity. The positive neighbor sets are reconstructed by this method. Then, differential equations are proposed to imitate the constantly changing states of nodes. Each node will update its state based on the difference between its state and average state of its positive neighbors. Nodes in the same community will evolve together with time and nodes in the different communities will evolve far away. Communities are detected ultimately when states of nodes are stable. Experiments on real world and synthetic networks are implemented to verify detection performance. The thorough comparisons demonstrate the presented method is more efficient than two acknowledged better algorithms.

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1. Introduction

The modern science of networks is an active domain to understand complex systems. In fact, many real world complex systems can be modeled as networks, such as information systems [1], social systems [2], complex collaboration relations [3], etc. These complex relations can be represented as complex network with nodes and edges, where nodes denote individual actors and edges denote the relationships between actors. There is a lot of research work on complex network, such as dynamic behaviors [4,5], structure analysis [6–8]. Among them, community structure is one of the most important properties. Communities exist in many networked systems from biology, computer science, engineering, economics, politics, etc. A recent review about network community detection can be found in Ref. [9]. Community detection aims to find the clusters, i.e., dense connections within clusters and only sparse connections between them [10]. Community detection is

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very meaningful in the real world. For example, identifying clusters of customers with similar interests in the networks of purchase relationships between customers and products of online retailers (like, e.g. www.amazon.com) enables to set up efficient recommendation systems [9,11].

Many social relations are signed between individuals that may be positive or negative. When two individuals have like, love, respect, or trust relationship, the relationship can be thought as positive link. However, the relationship with dislike, hate, disrespect or distrust can be thought as a negative link. Such networks are called as signed networks [12], i.e., the edge weight is greater than 0, meaning a positive relationship; the edge weight is less than 0, meaning a negative relationship and the edge weight is equal to 0, meaning no relationship between these two individuals. Community detection in signed networks is quite different from the positive networks (only positive links community detection, e.g. Refs. [13–15]). Communities are defined not only by the density of the links but also by the signs of links. In signed networks, the links between communities should be sparse and negative. Meanwhile, the links inside communities should be dense and positive. Lots of negative links inside communities would improve the difficulty of community detection. A balanced signed network means that nodes in the network can be partitioned into two communities, where all the intra-cluster links are positive and all the inter-cluster links are negative [16]. The generalized concept is given in Ref. [17].

Different from the existing work, in this paper, we propose a dynamic evolutionary clustering model to imitate the changing state of nodes. It can successfully detect the community structure when state of the nodes are stable. Firstly, similarity of two nodes is defined, which can distinguish different positive links. The neighbor sets would be reconstructed by deleting the positive links with low similarity. Secondly, differential equations are presented to imitate behaviors of the individuals in networks. Finally, simulation results verify our algorithm is more efficient than two acknowledged better algorithms. The method in our paper provides a novel idea based on dynamics for signed networks.

The rest of the paper is organized as follows. Related works are introduced in Section 2. Section 3 gives the dynamic evolutionary clustering model. In Section 4, the proposed algorithm flow is shown in details. Section 5 shows the simulation results and Section 6 concludes the paper.

2. Related work

To better understood the structure of social networks, various methods have been presented from different aspects.

2.1. Related work on community detection methods

The research on community structure in signed networks has attracted a great deal of attention, and various kinds of methods have been presented.

Yang et al. presented an agent-based method to extract community structures by performing a random walk on positive links [18]. Pizzuti et al. proposed a single objective genetic algorithm, which optimized a simple but efficacious fitness function enable to identify densely connected group of nodes with sparse connections between groups [19]. Gómez et al. extended the modularity method from un-signed networks to signed networks for community detection. The new formulation of modularity that allows for the analysis of any complex network [20]. Traag et al. extended an existing Potts model to incorporate negative links as well, resulting in a method similar to the clustering of signed graphs, as dealt with in social balance theory, but more general [21]. Shen et al. presented a statistical probability model to detect the disassortative structures of signed networks with both positive and negative links [22]. Figueiredoa et al. proposed mixed integer programming formulations for clustering problems related to structural balance [23]. Cai et al. presented a discrete particle swarm optimization algorithm for identifying community structures in signed networks. In their proposed approach, the particles' position and velocity have been redefined in discrete form [24]. Anchuri et al. [25] proposed an efficient two step algorithm to detect communities in signed social networks. The objective functions that they explored are minimizing frustration and maximizing modularity. Chiang et al. [26] proposed a scalable clustering algorithm using balance normalized cut and a multilevel clustering algorithm. Amelio et al. [27] obtained network partitioning by minimizing the number of negative edges inside communities and positive edges between communities, while maximizing cluster modularity. Li et al. [28] proposed and compared two new evolutionary algorithms and two new memetic algorithms. Various experimental results show their high efficiency. Liu et al. [29] proposed a novel multiobjective algorithm, based on a new similarity to detect both separated and overlapping communities from signed social networks.

2.2. Related work on dynamic model

The evolutionary game theory is introduced, which considers a dynamic scenario. Among this scenario, the players are constantly interacting with other players and updating their strategies based on the information they obtained. In this paper, it is important to recall the original replicator dynamics equation (Ref. [30]). $N = \{1, \dots, n\}$ denotes the population set, $M = \{1, \dots, m\}$ is the strategy set. The population state can be denoted by the vector $\mathbf{x}^l = (x_{l1}, \dots, x_{lm})$, here x_{li} is the fraction of the population l that uses strategy i. Thus, $\sum_{i=1}^{m} x_{li} = 1$ and $x_{li} \geq 0$. In the replicator dynamics, x_{li} grows according

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