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A memetic algorithm for computing and transforming structural balance in signed networks

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A B S T R A C T

Structural balance enables a comprehensive understanding of the potential tensions and conflicts of signed networks, and its computation and transformation have attracted increasing attention in recent years. The balance computation aims at evaluating the distance from an unbalanced network to a balanced one, and the balance transformation is to convert an unbalanced network into a balanced one. In this paper, firstly, we model the balance computation of signed networks as the optimization of an energy function. Secondly, we model the balance transformation as the optimization of a more general energy function incorporated with transformation cost. Finally, a multilevel learning based memetic algorithm, which incorporates network-specific knowledge such as the neighborhoods of node, cluster and partition, is proposed to solve the modeled optimization problems. Systematical experiments in real-world social networks demonstrate the superior performance of the proposed algorithm compared with the state-of-the-art algorithms on the computation and transformation of structural balance. The results also show that our method can resolve the potential conflicts of signed networks with the minimum cost.

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1. Introduction

Social interaction involves friendly and hostile relationships in many complex systems, including multi-player online games, Wikipedia, Web 2.0, online communities and information recommendation systems [1–3]. In these systems, the entities with friendly relationships are friends, cooperators, alliances or memberships in a group, while those with hostile relationships are enemies, competitors, opponents or memberships in different groups. These systems can be represented as signed networks in which nodes represent social entities and positive/negative edges correspond to friendly/hostile relationships.

Structural balance, one of the most popular properties in ensembles of signed networks, reflects the origin of tensions and conflicts, and its computation and transformation have received much attention from physicist, sociologist, economist, ecologist, ecologist and mathematician [4–10]. The structural balance theory introduced by Heider states that the relations "the friend of my friend is my enemy" and "the enemy of my enemy is my enemy" are unbalanced in the strong definition, which is based on the statistical analysis of the balance of signed triads from the perspective of social psychology [11]. There are broad applications of the computation of structural balance, due to the ubiquity of the multi-relational organization of modern systems in a variety of disciplines. Furthermore, the pursuit of balance is desirable in many real-world signed systems. For instance, the pursuit of balance in international relationship networks can reduce military, economic and culture conflicts. The pursuit of balance in information systems can improve the authenticity of collected information and accelerate opinion diffusion [12–14].

The computation of structural balance aims at calculating the least imbalances of signed networks [7]. There are mainly two issues in the computation of structural balance: (i) how to verify imbalances and (ii) how to compute the least imbalances. There have been recent efforts in addressing these issues. The frustration index [5] evaluates the imbalances of signed networks as the number of negative cycles which have an odd number of negative links. The energy function proposed by Facchetti et al. [7,15] measures the imbalances as the number of unbalanced links in signed networks, and both the gauge transformation [7,15] and memetic algorithms [16] are utilized to minimize the energy function. Besides, some studies evaluate the imbalances as the sum of the positive links across two different communities and the negative

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links within the same community [15,17], and thereafter they adopt the classical community detection algorithms, such as Infomap [18], FEC [19] and MODPSO [20], to identify the communities in signed networks. Note that, in many cases these studies are constraint to the strong definition of structural balance, and they are worth to be applied to the weak definition of structural balance. In the weak definition, "the friend of my friend is my enemy" is unbalanced while "the enemy of my enemy is my enemy" is balanced.

The transformation of structural balance focuses on how to convert an unbalanced network into a balanced one. Classical transformation models are divided into two categories: discrete-time dynamic models and continuous-time dynamic models [21]. Local triad dynamic and constrained triad dynamic are two representative discrete-time models [22,23]. With these models, an unbalanced network is finally evolved towards a balanced or a jammed state by changing signs of edges [5]. Another classical discrete-time model is based on transforming the least number of unbalanced links in signed networks [24,25]. Differential dynamic presented by Kulakowski et al. [26] is a classical continuous-time model, and it exhibits the evolutionary process from an unbalanced network to a balanced one. In this model, the final evolutionary state (i.e., conflict or harmony) of social networks is determined by the total amount of positive links [8]. These models can effectively transform an unbalanced network into a balanced one, and they are worth improving if they take into account the cost of balance transformation.

Recent studies have demonstrated that the computation and transformation of structural balance in signed networks are non-deterministic polynomial-time hard (NP-hard) problems [7,27]. This is of particular concern since the solution space increases with the size of a signed network exponentially. Memetic algorithms (MAs) as hybrid global–local search methodologies are widely adopted to solve NP-hard problems [28]. In general, a global search benefits explorations while a local search facilitates exploitations [28]. MAs synthesize the complementary advantages of global and local search methodologies [28–31], which makes it possible to solve large-scale NP-hard optimization problems. MAs have been applied into some large-scale networks optimizations, including balance computation [16], community detection [32,33], network resource allocation [34], neural network design [35], network robustness improvement [36] and network prediction [37–39].

In this study, we propose a fast memetic algorithm, referred to as MLMSB, to compute and transform structural balance of signed networks. First, we extend the energy function criterion [7] to the weak definition of structural balance, and model the computation of structural balance as the optimization of the extended energy function H. Second, by introducing a cost coefficient parameter, we present a more general energy function H_w to evaluate the balance transformation cost, and model the transformation of structural balance as the optimization of H_w. Finally, a multilevel learning based local search is integrated into a population-based genetic algorithm (GA) to solve the modeled optimization problems. For the proposed MLMSB algorithm to converge fast, we make full use of the network-specific knowledge such as the interactions of nodes, clusters and partitions. Experimental results on five real-world networks demonstrate that MLMSB outperforms the classical algorithms that compute and transform the structural imbalance of signed network. Furthermore, the results also illustrate that MLMSB can identify and resolve potential conflicts with the minimum transformation cost.

The rest of this paper is organized as follows. Section 2 briefly introduces ground knowledge about structural balance of signed networks. The optimization models and our method MLMSB are detailed in Section 3, followed by systematical empirical results in Section 4. The conclusions are summarized in Section 5.

2. Related backgrounds

A signed network with N nodes can be represented as an adjacency matrix J, with each item J_{ij} defined as follows.

$$J_{ij} = \begin{cases} +1 & \text{if nodes } v_i \text{ and } v_j \text{ are positively linked,} \\ -1 & \text{if nodes } v_i \text{ and } v_j \text{ are negatively linked,} \\ 0 & \text{if nodes } v_i \text{ and } v_j \text{ have no link.} \end{cases} \quad (1)$$

2.1. Structural balance

Structure balance theory investigates the balance of three interconnected individuals. Assuming that an edge labeled $+$ ($-$) indicates a friendly (hostile) relationship between the corresponding two individuals, there are the following four types of social relations [11]:

- $+++$: "the friend of my friend is my friend";
- $++-$: "the friend of my friend is my enemy";
- $--+$: "the enemy of my enemy is my friend";
- $---$: "the enemy of my enemy is my enemy".

Structural balance theory in its strong definition claims that the social relations $+++$ and $--+$ are balanced while the relations $++-$ and $---$ are unbalanced. Structural balance theory in its weak definition illustrates that the social relations $+++$, $--+$ and $---$ are balanced while the relation $++-$ is unbalanced. Fig. 1 illustrates the differences between the strong and the weak definitions of structural balance.

Structural balance theory states that a complete signed network is balanced if and only if all its signed triads are balanced. For a non-complete signed network, it is balanced if it can be filled into a complete network by adding edges in such a way that the resulting complete network is balanced [1]. Wasserman gives an equivalent theorem from the perspective of clustering as follows [40].

The strong (weak) definition of structural balance: "A signed network G is completely balanced, if and only if its nodes can be divided into $k = 2$ ($k \geqslant 2$) clusters such that the nodes are positively linked within each cluster whereas negatively linked between the clusters" [40].

According to the equivalent balance theorem, the social relation $---$ is unbalanced (balanced) when its individuals are divided into $k = 2$ ($k = 3$) clusters.

2.2. Energy function

The energy function [7] measures the imbalances of signed networks as the number of unbalanced links, and it is computed as follows.

$$h = \sum_{(i,j)} \frac{(1 - J_{ij} x_i x_j)}{2}, \quad (2)$$

where $J_{ij} \in \{+1, -1\}$ represents the sign of the edge between nodes v_i and v_j: $+1$ denotes a positive link, whereas -1 indicates a negative link; $x_i \in \{+1, -1\}$ is the identifier of cluster s_i. It is noteworthy that if two friendly nodes are assigned to different clusters, $(1 - J_{ij} x_i x_j)/2 = 1$, and $(1 - J_{ij} x_i x_j)/2 = 0$ otherwise. If two hostile nodes are assigned to different clusters, $(1 - J_{ij} x_i x_j)/2 = 0$, and $(1 - J_{ij} x_i x_j)/2 = 1$ otherwise. In other words, the link between nodes v_i and v_j is unbalanced when its corresponding $(1 - J_{ij} x_i x_j)/2$ value

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