ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Animated Society of Temporary Electricity Network Trace

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Abstract:

Community formation analysis of dynamic networks has been a hot topic in data mining which has attracted much attention. Recently, there are many studies which focus on discovering communities successively from consecutive snapshots by considering both the current and historical information. However, these methods cannot provide us with much historical or successive information related to the detected communities. Different from previous studies which focus on community detection in dynamic networks, we define a new problem of tracking the progression of the community strength - a novel measure that reflects the community robustness and coherence throughout the entire observation period. To achieve this goal, we propose a novel framework which formulates the problem as an optimization task. The proposed community strength analysis also provides foundation for a wide variety of related applications such as discovering how the strength of each detected community changes over the entire observation period. To demonstrate that the proposed method provides precise and meaningful evolutionary patterns of communities which are not directly obtainable from traditional methods, we perform extensive experimental studies on one synthetic and five real datasets: social evolution, tweetinginteraction, actor relationships, bibliography and biological datasets. Experimental results show that the proposed approach is highly effective in discovering the progression of community strengths and detecting interesting communities.

Index Terms:
Dynamic Networks, Community Analysis, Community Strength.

I.INTRODUCTION:

In recent years, there has been a growing interest in modeling and mining various kinds of dynamic networks whose structures evolve over time, such as biological networks, social networks, co-authorship networks and co-starring networks.

Specifically, people have investigated community analysis in dynamic networks [1]–[4]. The focus is on detecting communities successively from consecutive snapshots by considering the historical information [5]–[7]. Although these methods can give us quite reasonable and robust communities by considering the temporal smoothness, few historical and successive information related to these communities are provided. Thus we do not know when these communities were assembled or when they are going to disband. Aiming to answer these questions, we propose a novel measure called community strength, which can reflect a community's temporal community robustness and coherence throughout the entire observation period. In this paper, we define that a community is with high strength if it has relatively stronger internal interactions connecting its members than the external interactions with the members to the rest of the world. Dense internal interactions and weak external interactions guarantee that the community is under a low risk of member change (current members leaving or/and new members joining).Intuitively, a friend community is "strong" if its members tie together closely and   nore the temptation from the outside world. On the contrary, a friend community is regarded as a"weak" community if it is likely to confront a member alteration situation. To illustrate this concept, Fig. 1(a) shows a toy example, where the nodes represented by the same geometric shape belong to the same community, solid lines represent internal interactions and dash lines represent external interactions. The circle community (i.e. nodes A, B, C and D) is considered to be stronger than the rectangle community (i.e. nodes E, F, G and H), due to the weaker external attractions. On the other hand, node H has a close relationship with the diamond community (i.e. nodes I, J and K), which makes the rectangle community in the risk of losing its members. In other words, the higher strength score a community obtains, the less possible member alternation occurs in it. It is worth noticing that community strength is a measure which synthetically considers both the community cohesion (i.e. how close the members are in a community) and separation (i.e. how distinct a cluster is from the

ISSN No: 2348-4845
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other clusters). Furthermore, community strength should be a temporal measure whose value may change as the network evolves. Here's an example in the real world. A set of authors have collaborated closely from 2000 to 2006. During this period, they cooperated frequently among themselves and barely with others outside the community. However, after 2006, because of interest changes, some authors' attentions have been attracted to some other fields. Thus the internal cooperation decreased and the external cooperation increased. In this case, this author community's strength is high and stable during 2000-2006, but begins to decrease after 2006. As a toy example, in Fig. 1(b) (i.e. the network in the 2ndsnapshot.

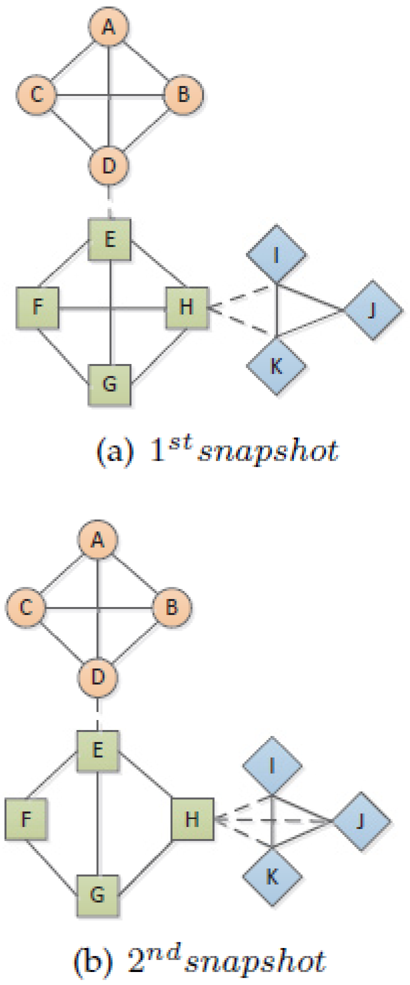

Fig.1:A Toy Example Illustrating Community Strength

II.PROBLEM SETTING:

In this section, we first introduce the definition of community strength and related notations, and then formally define the problem. Before proceeding further, we introduce the notation that will Be used in the following discussion: Let a matrix be represented with uppercase letter (e.g. D), dij denotes the ij-th entry in D, and di: and d:j denote vectors of i-th row and j-th column of D, respectively. Now, let us start by introducing the definition of the community strength. Community strength: Given a network G = (N;E;W) where N is the set of nodes in this network, E is the set of edges connecting the nodes, and W is a symmetric weight matrix representing the weights on edges. There have been some existing work on measuring the strength of community by considering its internal compactness or identifying outlier data with probability model [10]. In this paper, we propose the measurement for the community strength which very well fits our problem in real scenarios. The community strength of a community z can be defined as:

$$Strength(z) = \sum_{i \in N} \sum_{j \in N} w_{ij} * \sum_{k \in z} \sum_{l \in z} w_{kl} - \left(\sum_{k \in z} \sum_{v \in N} w_{kv} \right)^2$$

III.METHODOLOGY:

In this section, we present our method for solving the problem of temporal community strength analysis. We begin by introducing the method of partitioning the network from each snapshot into communities.

A.COMMUNITY DETECTION AT EACH SNAPSHOT:

Given a series of temporal networks Gt = (V;Et;Wt) (1 _ t _ T), we first partition each network independently into Kt communities at each timestamp t. Due to the change of network, the value of Kt may not be the same across different snapshots. Then we store all the detected communities from all the snapshots in a community pool. To detect communities from each temporal network, we use Non-negative Matrix Factorization (NMF) technique [12]. There are two major reasons to choose NMF: First, it can be easily applied to both hard clustering (i.e. each object belongs to exactly one community) and soft clustering (i.e. each object can belong to multiple communities). The property of soft clustering very well fits many real social scenarios.

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For instance, each user in social network usually participates in more than one discussion group, as he may have a variety of interested topics. Second, it could uncover the underlying intercommunity relationships quite accurately, that can be utilized for other related tasks like progression analysis - refer Section 4.1. The details of these advantages are discussed further in the following discussion of the method. Please note that we believe one can opt to use other evolutionary clustering algorithm so long as it provides a mechanism for soft clustering and also the ability to identify inter-community relationships. In this paper, we mainly focus on the undirected network, where the matrix W is symmetric, the clustering to the rows and columns should be identical. Hence we propose to symmetrically factorize each temporal network as follows:

$$\min_{C^t \geq 0, S^t \geq 0} \left\| W^t - C^t S^t C^{t^{Trans}} \right\|^2, \ s.t.\ C^{t^{Trans}} C^t = I$$

B.TEMPORAL COMMUNITY STRENGTH ANALYSIS:

Now, we propose an integrated optimization framework that conducts community strength estimation across snapshots. A naive approach for this task is to calculate the strength of each community individually at each snapshot and track the evolution. However, this approach does not take historical information into account when deriving community strengths and the communities derived across snapshots are not easily comparable. In contrast, we propose the following framework based on the smoothness assumption in which both current and historical networks contribute to the community strength detection. Moreover, in the proposed framework,communities across snapshots are brought into alignment so that we can easily compare them.Based on Eq. 1, the strength of community z can be further reformulated in terms of the community pool matrix ~ C as follows:

$$\begin{aligned} Strength(z) &= \sum_{i,j=1}^{n} w_{ij} \sum_{i,j=1}^{n} w_{ij}\tilde{c}_{iz}\tilde{c}_{jz} - \left(\sum_{i,j=1}^{n} w_{ij}\tilde{c}_{iz}\right)^2 \\ &= sum(W)\tilde{c}_{z.}^{Trans} W \tilde{c}_{z.} - (\sum_{i=1}^{n} d_i \tilde{c}_{iz})^2 \\ &= \tilde{c}_{z.}^{Trans}(\tilde{W} - D)\tilde{c}_{z.}, \end{aligned}$$

C.TEMPORAL SMOOTHNESS:

In many real-world dynamic network applications, networks are expected to change gradually and stably. Examples include geometric networks [15] and gene networks [16].As a consequence, we expect a certain level of temporal smoothness between community strengths in successive snapshots. The temporal community strength should depend on the current network, and it should not deviate too dramatically from the previous snapshot's network. Actually, temporal smoothness assumption has been adopted in many previous evolutionary clustering work [6], [7], [17]. However, instead of applying the smoothness among the clusters detectedin adjacent timestamps as previous work did, we have applied it on the temporal community strength. The overall cost of the objective function is represented as the linear combination of the cost of community strength fitting to the current snapshot and the cost of community strength fitting to the previous snapshot. Thus _ (0 _ _ _ 1) is a predefined parameter to reflect users' emphasis on the smoothness assumption. Usually, _ could be assigned a relatively large valuewhen the networks are stable and evolve slowly (e.g., social networks). _ should be assigned a relatively small value when the target networks include noise and are likely to evolve swiftly.

D.PACS ALGORITHM PROCEDURE:

Now, we derive the solution for the community strength scores azt for objective function below. Using the method of Lagrangian Multipliers, we can rewrite below as follows:

$$\begin{aligned} \min_{a_{.t}} J(a_{.t}) = \alpha \sum_{z=1}^{K} \log(\frac{1}{a_{zt}}) \left[\tilde{c}_{z.}^{Trans}(\tilde{W}^t - D^t)\tilde{c}_{z.}\right] \\ +(1-\alpha)\sum_{z=1}^{K} \log(\frac{1}{a_{zt}}) \left[\tilde{c}_{z.}^{Trans}(\tilde{W}^{t-1} - D^{t-1})\tilde{c}_{z.}\right] \\ +\gamma\left(\sum_{z=1}^{K} a_{zt} - \mu_t\right), \end{aligned}$$

E.COMMUNITY STRENGTH PROGRESSION NET:

The output of Algorithm 1 provides information on how all the communities' strength evolve over time. In addition to that, we also want to know how the communities from immediate preceding snapshots (i.e. Ct1 and Ct) influence the strength of each other. To illustrate these relationships, we construct a bipartite network that represents the relationship between communities detected at snapshot t-1 and communities detected at snapshot t.

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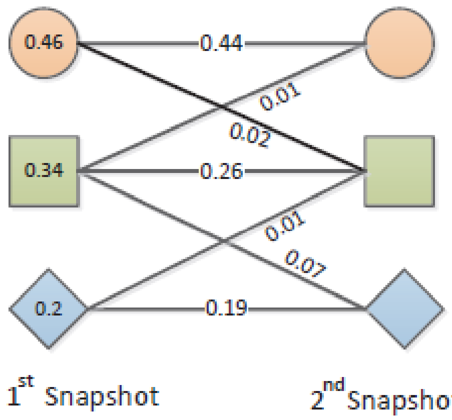
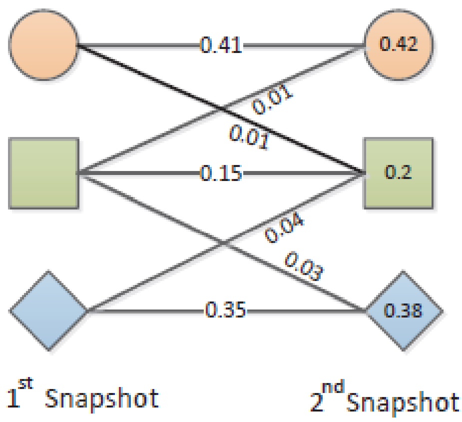
In such a network, the nodes on the left represent the communities detected at previous timestamp, the nodes on the right represent the communities detected at the current timestamp and the edges connecting the nodes denote the influence transmission between the communities.



(a) Strength Transmission Net



(b) Strength Reception Net

Fig. 2: Strength Progression Nets of the Toy Example.

IV.CONCLUSIONS:

In this paper, we introduced a new problem of analyzing the progression of community strengths. Community strength is a temporal measure which represents the probability that a particular community has a stable membership at the current snapshot. To solve this problem, we propose a framework that provides reliable and consistent community strength scores which are not only insensitive to short-term noise in the current network but also adaptive to long-term network evolution.

The results of community strength analysis can be also used to find the top-K strongest or weakest communities and track the change of strengths via constructing the community strength progression net. Extensive experimental analysis demonstrated that the proposed method is very effective on both synthetic and real dynamic datasets. Case studies on three real datasets showed that interesting and meaningful communities can be revealed by community strength detection.

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