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Survey Report

Community Detection in Dynamic Social Networks: A Survey

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ABSTRACT

Social network analysis has gained much attention these days. These networks can be represented as a graph. In this graph each individual is represented as a node and the relationship between them is represented as an edge. Community detection in social networks plays a vital role. A community in social networks indicates that nodes within the group are densely connected and the connections between groups are sparse. As the activities and interaction between the entities change over time, the speed with which the network is changing is phenomenal. Because of this frequent change it has become very important to detect the community in dynamic social networks. Many methods have been proposed for the community detection in dynamic social networks. The community detection in dynamic social networks helps to understand the network structure and analyze the network properties. In this paper, various community detection methods have been studied and a comparison between them is presented.

Keywords: Social Network Analysis, Dynamic Social Networks, Graph, Community Detection.

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ABSTRACT

Social network analysis has gained much attention these days. These networks can be represented as a graph. In this graph each individual is represented as a node and the relationship between them is represented as an edge. Community detection in social networks plays a vital role. A community in social networks indicates that nodes within the group are densely connected and the connections between groups are sparse. As the activities and interaction between the entities change over time, the speed with which the network is changing is phenomenal. Because of this frequent change it has become very important to detect the community in dynamic social networks. Many methods have been proposed for the community detection in dynamic social networks. The community detection in dynamic social networks helps to understand the network structure and analyze the network properties. In this paper, various community detection methods have been studied and a comparison between them is presented.

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1. INTRODUCTION

Recent research focused much on the study of networks (a set of nodes interconnected by links) because of their suitability to represent many real world complex systems. Some of the real world networks include network of co-authorship, biological networks that includes neural networks, the World Wide Web (WWW) (e.g., a network of hyperlinks of web pages), network of friendship, food webs, technological networks (e.g., Internet), social networks, and even political elections. Many different properties in these networks have been revealed as: small world effect, power law degree distribution, network transitivity etc. An interesting feature found common in many of these networks is *community structure* which is the point of our study. A community in the network can be stated as a “sub graph such that the edge density within the sub graph is greater than the edge density between its nodes and nodes outside it”.

A **social network** is a social structure made of individuals (or organizations) called "nodes," which are tied (connected) by one or more specific types of interdependency, such as friendship, kinship, financial exchange, dislike or relationships of beliefs, knowledge or prestige. A social network is represented by a graph G = (V, E), where V is a set of vertices, called nodes and E is a set of edges, called links, that connect two elements of V. Fig. 1 shows a diagram of a simple social network with community structure.

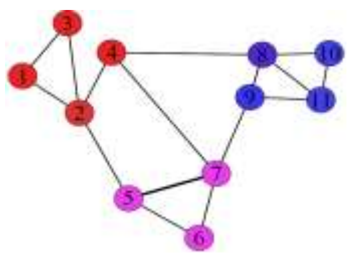

Fig 1. A schematic diagram showing a social network with three community structures. (Drawn using social network visualization tool Gephi)

Communities play a very vital role in social networks and by detecting them the illustrating features of social networks can be understood more clearly and exploit them more effectively. For example, a set of web pages on related topics can be found by identifying a community of web pages that connect to two or more web pages in the same community; with the help of this, the search engines and portals can narrow down their search by searching topically-related subsets of web pages.

Social networks are categorized as static social networks and dynamic social networks. Detecting communities in static networks is relatively a simple task. Many algorithms exist to accomplish this [11][12][13][14]. Detecting community structure in a dynamic social network has gained importance recently. Due to latest internet technologies frequent change in the size of the social network attract huge amount of people to join social networks. As the network grows in size, formation of new communities takes place and previous communities will become denser and will lead to the failure of existing static community detection methods. So, researchers are concentrating more on the dynamic aspect of social network. In this work we study the issue of community detection in dynamic social networks.

The organization of the paper is as follows. Section 2 presents the literature review. In Section 3, a preliminary concept of social network analysis is presented. In Section 4 conclusions along with future work is described.

2. LITERATURE REVIEW

The initial and early research in this area [15] mainly focused on the static properties of the stated networks, avoiding the fact that most real-world communication networks are dynamic in nature. In practical life, many of the stated networks constantly evolve over time, with the addition and deletion of edges and nodes representing changes in the interactions among the modeled entities. Identifying the portions of the network which are changing, characterizing the type of transformation, predicting future events (e.g., link prediction), and developing generic models for evolving networks are challenges that need to be addressed.

For example, the speedy growth of online communities has dictated the need for analyzing large amounts of temporal data to reveal community structure, dynamics and evolution
[15].

The community detection methods are broadly classified into two main types: *Static Methods* and *Dynamic Methods*. The static community mining algorithms can be classified into two main categories: *optimization based algorithms* and *heuristic based algorithms*. A thorough and meticulous survey conducted on this literature, is presented in the following topological form.

Optimization based algorithms solves a community mining problem by transforming it into an optimization problem and trying to find an optimal solution with respect to a pre-defined objective function, such as various cut criteria adopted by spectral methods [23][31][32], the evaluation function introduced by the Kernighan-Lin algorithm [25], the network modularity employed in several algorithms [2][3][4][33] and others [34].

On the contrary, heuristic algorithms do not explicitly state optimization objectives, and they solve a community mining problem based on certain intuitive assumptions or heuristic rules. . For example, the heuristic rule used in the maximum flow community (MFC) algorithm [14] is based on the assumption that “flows” through inter-community links should be larger than those of intra-community links. Similarly, the heuristic rule employed by the GN algorithm [2] is that the “edge betweenness” of inter-community links should be larger than that of intra-community links. Others such as the Wu-Huberman algorithm [28], the HITS algorithm [13], the CPM [29], and the FEC [30] have adopted different assumptions.

Besides the above two main categories, there exist some other algorithms for solving community detection problems. For example, a network can be clustered through a bottom-up approach by repetitively joining pairs of current groups based on their similarities, such as correlation coefficients [21] and random walk similarities [40], which are defined in terms of their linkage relation.

Real-world social networks, however, are not always static. In fact, most popular social sites in reality (such as Facebook, Twitter and LinkedIn) evolve heavily and witness a rapid expansion in terms of size and space over time. As a result, they lend themselves naturally to the field of dynamic

networks, in which resources and controls are not only decentralized but also updated frequently.
In such a case, we need find a way to solve a more challenging network community mining problem.
Many researchers are working in this domain to solve challenges like Growing size of the network, Dynamic evolution of a network, and various performance issues.

Sitaram Asur, Srinivasan Parthasarathy, and Duygu Ucar in the 2009 have proposed a framework which was based on the events for the characterization of evolutionary behavior of interaction graphs [43]. The framework is based on the use of certain critical events that facilitate our ability to compute and reason about novel behavior oriented measures, which can offer new and interesting insights for the

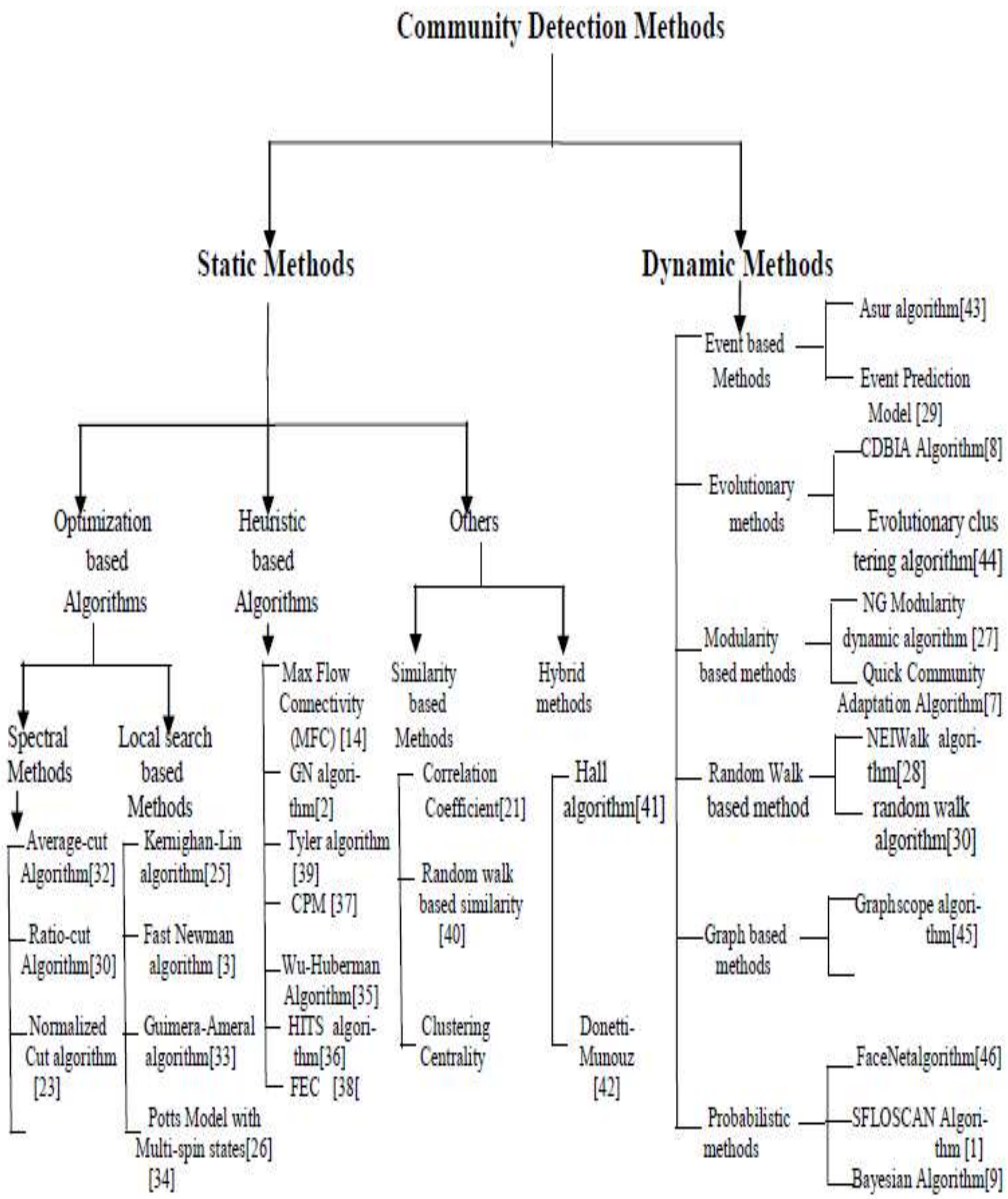

Fig. 2 Classification chart of the existing community detection algorithms in social networks.

Characterization of dynamic behavior of such interaction graphs. The author has demonstrated how measures for Sociability, Stability, Influence and Popularity can be compiled. Deepayan Chakrabarti, Ravi Kumar and Andrew Tomkins in 2006 [44] solved the problem of clustering data over time. They proposed an evolutionary clustering framework. This framework requires that the clustering at any point in time should be of high quality while ensuring that the clustering does not change dramatically from one time step to the next. They presented two instantiations of this framework: k-means and agglomerative hierarchical clustering. The experiments on Flickr tags showed that these algorithms have the desired properties — obtaining a solution that balances both the current and historical behavior of data.

Chang-Dong Wang, Jian-Huang Lai and Philip S. Yu had proposed a method named NEIWalk [28] which supports community discovery in dynamic content-based network. This paper proposes a novel transformation of content-based network into a Node-Edge Interaction (NEI) network where linkage structure, node content and edge content are embedded seamlessly. The content-based network is first transformed into the NEI network, which is a multi-mode network comprising two types of nodes and three types of edges. In the NEI network, the two types of nodes correspond to the nodes and the edges of the original content based network, which are respectively termed as n-node and e-node.

On the other hand, the three types of edges respectively characterize the structural similarity, node content similarity and edge content similarity. A differential activity based approach is proposed to incrementally maintain the NEI network as the content-based network evolves. Then heterogeneous random walk is applied in the NEI network to discover latent communities.

Jimeng Sun, Spiros Papadimitriou, Philip S. Yu, Christos Faloutsos in 2007 proposed a method GraphScope [45]. This framework is based on one form of the Minimum Description Length (MDL) principle and employs a lossless encoding scheme for a graph stream. The goal of GraphScope is to find the appropriate number and position of change points, and the number and membership of source and destination partitions so that the cost is minimized.

Yu-Ru Lin, Yun Chi and Shenghuo Hu, Hari Sundaram and Belle L. TSeng in 2009 has analyzed the communities and their evolution in dynamic social network [46]. They have termed their work as FaceNet which is a systematic framework for analyzing communities and their evolutions in dynamic networks. In FaceNet, the community structure at a given timestep t is determined both by the observed networked data at t and by the prior distribution given by historic community structures. It is the first probabilistic generative model for analyzing communities and their evolution. The proposed model solves the evolutionary clustering problem from a probabilistic (Bayesian) perspective.

Tianbao Yang , Yun Chi , Shenghuo Zhu, Yihong Gong, Rong Jin in 2010 proposed a Bayesian approach [9] for community detection and community evolution in social network. This research presents a probabilistic framework for analyzing dynamic communities in social networks. The authors has developed dynamic stochastic block model for modeling communities and their evolution in a unified probabilistic framework.

On the basis of the study carried out on various methods for community detection in dynamic social networks, a comparative study is done and shown in Table I.

Table I: Comparative Study of various algorithms for community detection in dynamic social Networks

Authors	Title of the paper	Central Idea	Weaknesses
Abdelghani Bellaachia and Anasse Bari	SFLOSCAN: A Biologically-Inspired Data Mining framework for Community Identification in Dynamic Social Networks [1]	Evaluates social interactions as they occur over time. Algorithm is based on the natural phenomena of **bird flocking**	i. No filtering of observations. ii. Included observations with low entropy.

Bing Kong, Hongmei Chen, Weiyi Liu , Lihua Zhou	A Dynamic Algorithm for Community Detection in Social Networks [27]	NG Modularity based dynamic algorithm.	i. Networks with directed and weighted edges are not considered. ii. running time grows exponentially as the no' of communities increases.
Jingyong Li, Lan Huang,Tian Bai,Zhe Wang, Hongsheng Chen	CDBIA: A dynamic community detection method based on incremental analysis [8]	Algorithm is based on the fact that communities tend to evolve gradually over time, and will not suddenly appear or disappear.	Scalability: performance decreases as the dataset size increases.
Nam P. Nguyen, Thang N. Dinh, Ying Xuan, My T. Thai	Adaptive Algorithms for Detecting Community Structure in Dynamic Social Networks [7]	Quick Community Adaptive (QCA) Algorithm	Not suitable to detect overlapping communities
Tianbao Yang , Yun Chi · Shenghuo Zhu · Yihong Gong · Rong Jin	Detecting communities and their evolutions in dynamic social networks— a Bayesian approach [9]	Dynamic stochastic block model: captures the evolution of communities by explicitly modeling the transition of community memberships for individual nodes in the network.	i. no.of communities is fixed ii. relies solely on the links to infer the community memberships of nodes in social networks. This may be insufficient when the no of links is sparse.
Chang-Dong Wang, Jian-Huang Lai and Philip S. Yu.	NEIWalk: Community Discovery in Dynamic Content-Based Networks[28]	Transformation of content-based network into a Node-Edge Interaction (NEI) network where linkage structure, node content and edge content are embedded seamlessly.	NEIWalk method gets a *bounded accuracy loss* due to the random walk sampling
Nagehan ˙Ilhan, Sule Gunduz . O	Community Event Prediction in Dynamic Social Networks[29]	an event prediction model using structural characteristics of communities has been proposed	Some of the poor performing community detection algorithms have been selected and tested.
Yu-Ru Lin, Yun Chi, Shenghuo Zhu, Hari Sundaram, and Belle L. Tseng	Facetnet: a framework for analyzing communities and their evolutions in dynamic networks[46]	Allows the participation of individuals in multiple communities at the same time and with different participation levels. Introduces new concepts such as community net, evolution net and soft modularity.	Only link information is considered, While the infor- mation of the content is necessary in some applications. The model is only used for explaining the observed data, it is not possible to predict the future behavior of the individuals of network.

3. PRELIMINARIES

3.1 Social Networks Analysis

Broadly, social network analysis conceptualizes social structure as a network with ties connecting members and channeling resources, focuses on the characteristics of ties rather than on the characteristics of the individual members and views communities as 'personal communities', that is, as networks of individual relations that people foster, maintain, and use in the course of their daily lives. There are different types of networks. Generally, network analysts differentiate the following networks:

One Mode versus Two Mode Networks. The former involve relations among a single set of similar actors, while the latter involve relations among two different sets of actors. An example of two mode networks would be the analysis of a network consisting of private, for profit organizations and their links to non-profit agencies in a community. Two mode networks are also used to investigate the relationship between a set of actors and a series of events. For example, although people may not have direct ties to each other, they may attend similar events or activities in a community and in doing so, these sets up opportunities for the formation of "weak ties".

Complete/Whole versus Ego Networks. Complete/whole or Socio-centric networks consist of the connections among members of a single, bounded community. A relational tie among all of the teachers in a high school is an example of whole network. Ego/Ego-centric or personal networks are referred to as the ties directly connecting the focal actor, or ego to others, or ego's alters in the network, plus ego's views on the ties among his or she alters. If we asked a teacher to nominate the people he/she socializes with outside of school, and then asked that teacher to indicate who in that network socializes with the others nominated, it is a typical ego network.

3.2 Metrics in social network analysis

Betweenness: The extent to which a node lies between other nodes in the network. This measure takes into account the connectivity of the node's neighbors, giving a higher value for nodes which bridge clusters. The measure reflects the number of people who a person is connecting indirectly through their direct links.

Bridge: In graph theory, a **bridge** (also known as a cut-edge or cut arc or an isthmus) is an edge whose deletion increases the number of connected components. Equivalently, an edge is a bridge if and only if it is not contained in any cycle.

An edge is said to be a bridge if deleting it would cause its endpoints to lie in different components of a graph.

Centrality: This measure gives a rough indication of the social power of a node based on how well they "connect" the network. The measures of centrality identify the most prominent actors, especially the star or the "key" players, that is, those who are extensively involved in relationships with other network members. The most important centrality Measures are: Degree centrality, centrality and Closeness centrality

Degree Centrality: Degree of a node is the number of direct connections a node has. Degree centrality is defined as the number of links incident upon a node (i.e., the number of ties that a node has). Degree centrality is the sum of all other actors who are directly connected to ego. It signifies activity or popularity. Lots of ties coming in and lots of ties coming out of an actor would increase degree centrality.

Between-ness Centrality: This type of centrality is the number of times a node connects pairs of other nodes, who otherwise would not be able to reach one another. It is a measure of the potential for control as an actor who is high in "between-ness" is able to act as a gatekeeper controlling the flow of resources (information, money, power, e.g.) between the alters that he or she connects. This measurement of centrality is purely structural measure of popularity, efficiency, and power in a network; in other words, the more connected or centralized actor is more popular, efficient, or powerful.

Closeness Centrality: Closeness centrality is based on the notion of distance. In graph theory **closeness** is a centrality measure of a vertex within a graph. Vertices that are 'shallow' to other vertices (that is, those that tend to have short geodesic distances to other vertices within the graph) have higher closeness. If a node or an actor is close to all others in the network, a distance of no more than one, then it is not dependent on any other to reach everyone in the network. Closeness measures independence or efficiency. With disconnected networks, closeness centrality must be calculated for each component.

Clique: A clique is an inclusive group of people who share interests, views, purposes, patterns of behavior, or ethnicity. A clique as a reference group can be either normative or comparative. A normative clique or reference group is often the primary source of social interaction for the members of the clique, which can affect the values and beliefs of an individual. The comparative clique or reference group is a standard of comparison in which a clique can exist in the workplace, in a community, in the classroom, in a business, or any other area of social interaction. Cliques tend to form within the boundaries of a larger group where opportunities to interact are great.

4. CONCLUSIONS AND FUTURE WORK

Social Networking now a days is considered as the most important feature as so many critical activities are depended on it. In this paper, the basic concepts of social networking and various terminologies related to social network are discussed. The study focuses on the importance of detecting communities in a dynamically changing social network. Various methods for detecting the communities in dynamic social network are discussed and a comparative study is shown which shows the central idea and weaknesses of various methods. In conclusion, we are in search of solution mechanism which gives effective detection and evolution of communities in dynamic social networks.

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