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# Social Graph Dynamism from Community Perspective

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**Abstract – Social network analysis has emerged as a set of methods for the analysis of social structures and uncovering the patterning of interactions among the entities. In the past, social network analysis was mainly a static investigation by considering independent graphs at different snapshots or one aggregated graph over the time period. However, for the dynamic social networks that change over time, the static analysis misses the opportunity to capture evolutionary patterns. A community is one of these patterns, and it is affected by changes in the underlying population in the dynamic social networks. In the literature there has been a considerable amount of work done to detect communities in social networks. However, the communities are independently detected at each snapshot regardless of the structural relationship between consecutive snapshots. In this paper we present a viewpoint based on communities through which dynamism in the network can be seen. Communities detected at different snapshots if put together, reflect significant pattern of evolution. If the pattern of evolution is identified then dynamism can be predictive. Several distinguished researchers provided solutions to this with significant challenges in tackling dynamism. Those challenges are discussed and a future scope is presented to handle them.**

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## 1. INTRODUCTION

Social networks are defined as collection of individuals interconnected among each other arbitrarily, generally represented by graphs. The interactions between individuals or entities can be depicted through social graph. In these networks, each individual is represented by a node in the network, and there is an edge between two nodes if an interaction has occurred, or a relationship exists, between the two individuals during the observation time. For instance, co-authorship, the exchange of ideas, information, and experiences between people in the web can be modelled as a social network [1].

Increased popularity of Online Social Networks (OSNs) has come up with several diverse and prominent areas of research interest such as sociology [2], epidemiology [3], recommendation systems [4], email communication [5], criminology [6], etc. The need to identify communities, which are densely connected subset of individuals that are loosely connected to others [7], has recently driven significant attention in the research community. The analysis of communities can help determine the structural properties of the networks as well as facilitate applications such as targeted marketing and advertising [8], and finding influential individuals [9].

Most networks, such as social media, blogs, and co-authorship networks, are dynamic as they tend to evolve gradually, due to frequent changes in the activity and interaction of their individuals [10]. Furthermore, the communities inside a dynamic network could grow or shrink, and the community membership of the individuals shifts regularly [11, 12]. In these dynamic networks, researchers may be interested in the evolution of communities and membership of individuals such as author communities in the blogosphere [13], the analysis of mobile subscriber networks [14], and evolution of research communities [15]. However, past community detection analyses of social networks modelled the dynamic network as a static graph by discarding the temporal information. This static representation misses the opportunity to detect the evolutionary behavior of the network

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and the communities. One way to model the structural changes in dynamic networks is to convert an evolving network into static graphs at different snapshots [16]. Such dynamic analysis of social network, especially assessing the evolution of communities, provides various insights into: 1) understanding the structures of the complex networks; 2) detecting a drastic change in the interaction patterns; 3) making predictions on the future trends of the network, etc. The evolution of communities in dynamic social networks can be tracked by identifying critical events that characterize the changes in a community over time [15, 17-20].

Another significant challenge for SNA is gigantic size of social network that puts pattern identification in dynamic social network at its worst [1]. Sampling is seen as rescue to the problem [21]. Sample is a sub-graph collected through crawling of huge social graph. Sample is considered to be representative of the network and ought to exhibit similar characteristics [21]. Sampling has attracted researchers to handle big OSNs. Correctness of results derived from analysing sample depends on the representativeness of the sample, which is highly affected if sampling algorithm suffers from biasing [6].

Dynamic behaviour of social graphs is a significant challenge in order to derive valid inferences. The validity of inferences can be sustained if evolution pattern of the graph is known. User interactions on the network are extremely volatile and change over time thereby migration of the user from one community to another is achieved. Evolution pattern of the network is proportional to migration extent of the users. This paper presents in-depth study of various community detection algorithms to go along with the dynamic social web.

## 2. COMMUNITIES IN SOCIAL WEB

An important tool in network analysis is the detection of mesoscopic structures known as communities (or cohesive groups), which are defined intuitively as groups of nodes that are more tightly connected to each other than they are to the rest of the network. One way to quantify communities is by a quality function that counts intra-community edges compared to what one would expect at random. Given the network adjacency matrix A, where the component $A_{ij}$ details a direct connection between nodes i and j, one can construct a quality function Q for the partitioning of nodes into communities as $Q = \sum_{ij}[A_{ij} - P_{ij}]\delta(g_i, g_j)$, where $\delta(g_i, g_j) = 1$ if the community assignments $g_i$ and $g_j$ of nodes i and j are the same and 0 otherwise, and $P_{ij}$ is the expected weight of the edge (Generally this weight is 0, that means each interaction has same weight).

If the network is scanned frequently at certain intervals then an evolution of communities can be seen in different snaps of social network. This is due to dynamic behaviour of social networks. Individuals in the network tend to change their orientation and thereby may change their affiliation from one denser portion of the network to another denser portion of the network. In deriving an optimization formulation of community identification, we make the following explicit assumptions about the behavior of individuals:

1. In each time step, every group is a representative of a distinct community. If two groups are present at the same time, there is a reason they are separate and, thus, represent distinct communities.
2. An individual is a member of exactly one community at any one time. While the individual can change community affiliation over time, it is affiliated with only one community at any given moment. Notice that this does not preclude an individual from belonging to multiple communities over the course of the observation. It requires that the individual, in each time step, determines “which hat to wear today”.
3. An individual tends not to change its community affiliation very frequently.
4. If an individual does change its community affiliation several times, it will usually be an oscillation among a small number of communities, rather than promiscuity among many. In other words, if an individual keeps changing its affiliations among many different communities, then it is not a true member of any of those communities.

An individual is frequently present in the group representing the community with which it is affiliated. It rarely misses being with its community’s group, and rarely is with other community’s groups. That is, individuals within a community interact more than those in different communities.

## 3. COMMUNITIES DETECTION AND EVOLUTION PATTERN RECOGNITION

In the literature there has been a considerable amount of work done to detect communities in social networks, such as modularity methods [23-25], spectral clustering methods [26], stochastic methods [27-29], and heterogeneous clustering methods [30, 31]. A common issue in the previous work is that the analysis of social networks was mainly a static investigation of the aggregated graph of the network across multiple snapshots. Hence, in the noticeable effect of time was neglected. However, a large number of social networks are continuously changing over time, thus they require a dynamic analysis.

Recently, the temporal evolution of social networks has attracted many researchers. White et al. [32] is the first proposed approach for finding community structure applied to network observed over time as well as over different relations. Leskovec et al. [33] study the patterns of growth for large social networks based on the properties of large networks, such as the degree of distribution and the small-world phenomena. They also propose a graph generation model to produce networks satisfying the discovered patterns. Backstrom et al. [34] approximate the probability of an individual joining two explicitly defined communities based on defining critical factors and then analyze the evolution of these communities. Kumar et al. [35] provide the properties of two real-world networks and then analyze the evolution of structure in these networks. However, in these cases the properties on the graph level are studied while the properties on the level of communities are not observed.

Falkowski et al. [36] transfer the basic concepts of DBSCAN [37] and its incremental variation Incremental DBSCAN [38] algorithms to graph mining by first defining proximity for graph nodes. DBSCAN stands for "Density-Based Spatial Clustering of Applications with Noise". For DBSCAN, a cluster is a continuous area of arbitrary shape that is denser than its surroundings. To capture this into a cluster, DBSCAN scans the data points in the dataset and computes neighbourhoods. A neighbourhood has a given radius (ε) and must contain a minimum number of points (η). A data point that has such a neighbourhood around it is termed a core point. A data point that has no such neighbourhood is a noise point, unless it is itself located in the neighbourhood of a core point; then, it is a border point. The two thresholds ε, η ensure that neighbourhoods are dense areas. Incremental DBSCAN considers insertions (new records arrive) and deletions (old records are forgotten) and identifies neighbourhoods that are affected by these updates. DBSCAN and Incremental DBSCAN have been mainly designed for spatial data. Falkowski et al. [36] proposed an incremental graph mining algorithm DENGRAPH that transfers the idea of density-based incremental clustering to social network (graph) structures. The intention of DENGRAPH is to cluster actors into communities. Traditionally, clustering is based on proximity of the objects to be clustered.

Let G(V, E) be the graph of interactions and let p,q∈ V be two vertices/actors. Let $\mathrm{Intensity}(p,q) = \min(I_{p,q}, I_{q,p})$ be the "intensity" of the interaction between them. Their "proximity" prox( p, q) is defined as:

$$\mathrm{prox}(p,q) = \begin{cases} 1 & p = q \\ 1 - 1/\mathrm{Intensity}(p,q) & \exists(p,q) \in E \\ \text{undefined} & \text{not}\exists(p,q) \in E \end{cases}$$

To build a cluster, DENGRAPH traverses the graph and places all density-connected points it encounters to the same cluster. If a vertex is not density-connected to the vertices seen thus far, it is assigned to the next cluster candidate. Not each vertex becomes member of a cluster: If a vertex does not have an adequately dense neighbourhood w.r.t. ε, η and is not density connected to any other vertex, then it is termed a noise vertex and its cluster candidate is dropped.

In the dynamic scenario, the interactions arrive as a stream: new edges are added, old edges are forgotten. The DENGRAPH algorithm is extended to adapt the clusters incrementally. The "forgetting" of old edges reflects the intuitive observation that a community is characterized better by recent interactions rather than from past activities. It is modelled with an ageing function which decreases the weights of the interactions seen thus far. An edge is deleted when its weight becomes zero.

Takaffoli et al. [39] present a framework for modelling and detecting community evolution in social networks. The framework allows tracking of events related to communities as well as events related to individual nodes. In order to define events which cover all possible transitions of a community, a new term called the community flag is defined that shows characterization of the community and its members. For example, members gather physically, or virtually, to share an idea or to discuss about a topic. One can assume an independent identity for a community based on the interests that members share with each other. This identity is called community flag.

The life cycle of a community is defined as follows. A community forms in a snapshot: Flag has been raised. It may be stable from a snapshot to another: Flag is still there. It could attract new members or lose some members: Flag is waving. It may incorporate another community: Dominant flag takes control. It may divide into two or more smaller communities, with each new part having its own independence: The most significant part carries the flag with itself. Finally it can break apart into pieces while no piece preserves the identity of the community: Flag has been vanished. The identity of a community is defined by a significant portion of that community. However, this portion could be different in various contexts thus event definitions are parametric based on this portion, denoted by k.

The social network is first converted into a time series graph, where the static graph at each time captures the information at that specific moment. Then, based on a community mining algorithm, the communities in each snapshot are obtained independently. Finally the transition of the communities between two consecutive snapshots will be obtained by the critical events defined in the framework. A snapshot $S_i = (V_i, E_i)$ of G = (V, E) represents a graph only with the set of individuals and interactions at a particular time interval i. Each snapshot $S_i$ contains $k_i$ communities $C_i = \{C_i^1, C_i^2, \ldots, C_i^{k_i}\}$ where the community $C_i^j$ is also a graph denoted by $(V_i^j, V_i^j)$. For each two consecutive snapshots a total of 11 events are defined with four involving individuals in the network and seven events involving communities - k-form, k-dissolve, k-continue, n-k-merge, n-k-split, k-shrink and k-reform.

Takaffoli et al. in their further endeavour [40] reduce the problem of detecting the transition and evolution of communities to identify meta-communities and also the events characterizing the changes of the communities across the time of observation. The communities at any snapshot can be the result of any static community mining algorithm. A community contains individuals that are densely connected to each other at a particular time snapshot. On the other hand, a meta-community is a series of similar communities at different time snapshots and represents the evolution of its constituent communities ordered by time of the snapshots. To capture the changes that are likely to occur for a community, five events are considered including split, survive, dissolve, merge, and form. Any of these could be evident in successive snapshots of social network. Formal definitions of these events are as follows:

FORM: In a later snapshot of the network a new community may be formed that did not exist in the previous snapshots of the same network. This may happen if members of other communities leave their old communities and form a new community.

DISSOLVE: In a later snapshot of the network a community existing in previous snapshot may get vanished. If the community that existed in previous snapshots could not be traced in the later one then the community is assumed dissolved.

SURVIVE: A community survives if in later snapshots a match can be found in the communities of previous snapshots. The match can be verified against some tolerable extent set experimentally.

SPLIT: A community is said to have split into several communities if in the later snapshot no match is found for the community that has split and also no match is found for the newly created communities in previous snapshots. That means if the community that existed in previous snapshots, in a later snapshot gets dissolved and form new communities then it is said to have split.

MERGE: Several communities in previous snapshots may get merged together to form a new community in later snapshot. That means the communities existing in previous snapshot must get dissolved and a new community is formed in later snapshot.

The key concept for the detection of the events, and also the meta-community, is the concept of similarity between communities at different times. Two communities that are discovered at different snapshots are similar if a certain percentage, $k \in [0, 1]$, of their members are mutual. The similarity threshold k captures the tolerance to member fluctuation, and can be set based on the characteristic of the underlying network. This framework encompasses community matching algorithm and also an event detection model to capture all of the possible events that occur for communities. This includes tracing the formation, survival and dissolution of communities as well as identifying meta-communities, series of similar communities at different snapshots, for any dynamic social network.

Huang et al present a multi-agent based decentralized algorithm, in which a group of autonomous agents work together to mine a network through a proposed self-aggregation and self-organization mechanism. A network can be modelled as a graph G = (V, E), where V is the set of nodes and E is the set of links. It is assumed that the network is non-directed graph. A k-way partition of graph G is defined as $P = \{C_1, C_2, \ldots, C_k\}$, where components $C_1, C_2, \ldots, C_k$ satisfy $\bigcup_{1\le i\le k} C_i = G$ and $\bigcap_{1\le i\le k} C_i = \emptyset$. P is said to be a community structure if the number of edges within components is much greater than that between components.

Let A be the adjacency matrix of G containing n nodes, and P be a k-way partition of G. The evaluation function in terms of P is defined as:

$$F(P) = \sum_{1\le i,j\le n} (1 - A_{ij}) g_{ij}$$

$$\text{Where, } g_{ij} = \begin{cases} 1, & v_i \text{ and } v_i \text{ belong to same component of P} \\ 0, & \text{otherwise} \end{cases}$$

For a component of the network, its corresponding F -value is actually the number of newly added edges in order to change it into a clique. So, if a component is a community in which links are very dense, its F -value should be very small. Otherwise, it will be very large. The partition which can minimize F is the best network community structure. Now the network community mining problem can be transformed into an optimization problem as follows:

$$P^* = \arg\min_p F(P)$$

Where $P^*$ is the desired network community structure.

A basic multi-agent system is composed of three main components: an environment, a predefined system objective and a group of autonomous agents. Now we introduce the concept of ''complementary graph'' to model the environment of agents. Let $A = 1 - \bar{A}$, where 1 denotes the matrix in which all entries are equal to one and A is the adjacency matrix of graph G = (V, E). This problem is same as the graph colouring problem. So, to cluster a network is to actually color its complementary counterpart so that the adjacent nodes in the complementary network are assigned distinct colors as possible as they can. In the colored complementary graph, the nodes with the same color will be clustered together. Multiple agents are activated in this environment. Each agent in this multi-agent model is a mobile agent, which can freely move from one node to another along the links between them. When an agent gets to a node, it will take actions to update the color of the node. Then, it will select its next stop and move there. Each agent maintains a variable, hops, which records the total moving steps it has done so far. An agent will die after its total hops attain a predefined constant. This method is suitable for clustering distributed networks. All agents can run concurrently and asynchronously without any synchronization mechanisms. The proposed method has some limitations. For example, instead of setting same lifetime for all entities, they can be dynamically generated and removed according to their history performance. Another key issue is how to get rid of k from the basic algorithm.

## 4. CONCLUSION AND FUTURE ASPECTS

Above mentioned research works are a few significant endeavours carried out by distinguished researchers in order to handle and identify dynamic behaviour of social networks. Dynamism if captured properly can revolutionise SNA. It has been evident that social graph dynamism is strictly random and hardly sticks to some pattern. Patterns discovered so far in various datasets by researchers are not very crisp but vague. Mere identification of pattern followed by any social graph in the past is not enough but prediction is also a crucial aspect. In this regard community identification has come up as a promising door to enter in jungle of social graph dynamism. Generally, social graphs follow power law and are randomly distributed. Actors in social graphs are clustered that implicates that the whole network is actually a collection of clusters. These clusters can be seen as communities which are volatile in nature. Different types of social networks exhibit different patterns of this volatile behaviour and therefore the strategy to tackle them must be designed as per the behaviour of actors in the network.

Two aspects can be concluded as future aspect of this study – (1) actors are distributed in the social graph in clusters. The may choose to retain their cluster or may opt to join other totally depends on their behaviour. (2) Patterns of migration of actors from one cluster to another is related to the type of the network. The basic idea that has brought actors together to form a social network affects pattern of community formation and deformation.

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