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Framework for Analysis of Dynamic Social Networks Evolution

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Abstract

Recent years have seen an explosive growth of various online communities. The processes by which communities come together, attract new members, and develop over time is a central research issue in the social sciences—political movements, professional organizations, and religious denominations all provide fundamental examples of such communities. In the digital domain, on-line groups are becoming increasingly prominent due to the growth of community and social networking sites such as MySpace, Twitter. However, the challenge of collecting and analyzing large-scale time resolved data on social groups and communities has left most basic questions about the evolution of such groups largely unresolved: what are the structural features that influence whether individuals will join communities, which communities will grow rapidly, and how do the overlaps among pairs of communities change over time? So considering these, in this paper we present a framework for modeling and detecting community evolution in social networks. This framework allows tracking of events related to communities as well as events related to individual nodes. These events can be considered as building blocks for pattern detection in networks with evolving communities. This framework can be formalized by applying it to a real dataset consisting of emails.

Keywords – Event based Framework, Group formation, Network Evolution, SNA (Social Network Analysis).

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I. Introduction

The tendency of people to come together and form groups is inherent in the structure of society; and the ways in which such groups take shape and evolve over time is a theme that runs through large parts of social science research [9]. The study of groups and communities is also fundamental in the mining and analysis of phenomena based on sociological data—for example, the evolution of informal close-knit groups within a large organization can provide insight into the organization's global decision-making behavior; the dynamics of certain subpopulations susceptible to a disease can be crucial in tracking the early stages of an epidemic; and the discussions within an Internet-based forum can be used to follow the emergence and popularity of new ideas and technologies. The digital domain has seen a significant growth in the scale and richness of on-line communities and social media, through the rise of social networking sites beginning with Friendster and its relatives, and continuing to more recent systems including MySpace, Facebook, and LiveJournal, as well as media-sharing sites such as Flickr.

While abstract descriptions such as this — of groups growing concurrently and organically in a large network —are clearly suggestive, the fact is that it has been very hard to make concrete empirical statements about these types of processes. Much of the challenge arises from the difficulty in identifying and

working with appropriate datasets: one needs a large, realistic social network containing a significant collection of explicitly identified groups, and with sufficient time-resolution that one can track their growth and evolution at the level of individual nodes.

II. The Present Work: Analyzing Group Formation And Evolution:

In this paper we seek to address these challenges, exploring the principles by which groups develop and evolve in large-scale social networks. We consider a number of broad principles about the formation of social groups, concerning the ways in which they grow and evolve.

We consider three main types of questions.

- **Membership.** What are the structural features that influence whether a given individual will join a particular group?
- **Growth.** What are the structural features that influence whether a given group will grow significantly (i.e. gain a large net number of new members) over time?

• **Change.** A given group generally exists for one or more purposes at any point in time; in our datasets, for example,
groups are focused on particular "topics of interest." How do such foci change over time, and how are these changes correlated with changes in the underlying set of group members?

Conventional data is typically a set of observations, which are considered independent of one another and identically distributed. In reality, data could be highly dependent, with observations relating to one other in a variety of relationships. The analysis, visualizing, and interpreting of such relational data is known as social network analysis (SNA).

Network input format is common to other SNA tools, using a simple pair of vertices to indicate an edge. The Network file can optionally include explicit lists of vertices, edge or vertex properties, and timeframe labels for dynamic networks. Meerkat's functionality can be divided into four general categories: (1) interactive network visualization and network metrics; (2) filtering and extraction; (3) community mining; and (4) event analysis. These features allow researchers to discover the importance of entities in their domain networks, and make inferences about algorithmically discovered communities. Being able to track entities and communities over time, observing community evolution, and performing analysis at different hierarchical granularities allows for better leverage in network exploration.

This idea of analysis over time, or dynamic network analysis, is the final pillar on which Meerkat is built. Social networks in many domains are subject to entities dropping in and out of interactions and thus migrating across communities. To promote and facilitate community mining across time, Meerkat offers event analysis functionality.

We propose an event-based framework to categorize and track how communities evolve in social networks. Our framework takes the detected communities at consecutive snapshots as an input and provides a mapping of how each community evolved at each snapshot. It also allows one to follow the events pertaining to individual nodes across each snapshot.

The rest of the paper is organized as follows. First in Section 2, we discuss related work. In Section 3, we describe our event-based framework in detail. Expected experimental results on sample email datasets are discussed in Section 4. Finally in Section 5, we discuss the conclusion and future work.

III. RELATED WORK

In the literature there has been a considerable amount of work done to detect communities in social networks [1, 4]. 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 there has been some work on analyzing communities and their evolutions in dynamic social networks. Leskovec et al. [5] studied the patterns of growth for graphs based on various topological properties, such as the degree of distribution and small-world properties of large networks. They also proposed a graph generation model, called the Forest Fire model, to produce graphs exhibiting the discovered patterns. Backstrom et al. [6] proposed using structural features of communities and individuals and then applying decision-trees to approximate the probability of an individual joining a community. They also tried to identify communities that are more likely to grow over time and predicted the movements between communities based on the same features. Tantipathananandh et al. [7] presented frameworks and algorithms to determine the evolution of communities in social networks. Although they assumed all groups are disjoint and explicitly defined, they tried to identify the notion of a community over all snapshots based on the changes in those groups. They focused mostly on tracking the membership of an individual across all snapshots. Asur et al. [8] analyzed the behavior of interaction graphs by defining critical events and computing them in an efficient manner. They also introduced novel behavioral measures such as stability, sociability, influence and popularity for nodes and an incremental way to calculate them over time. Falkowski et al. [9] analyzed the evolution of communities and studied their stability and fluctuation by defining similarity between them. Moreover, in order to identify persistent communities, they applied standard statistical measures. The use of on-line social networking sites for data mining applications has been the subject of a number of recent papers; see [13,14] for two recent examples. These recent papers have focused on different questions, and have not directly exploited the structure of the user-defined communities embedded in these systems. Studies of the relationship between different newsgroups on Usenet [16,15] has taken advantage of the self-identified nature of these online communities, although again the specific questions are quite different.

According to Jiyang Chen et al. [4], Meerkat's community mining abilities are meant to synergize with its other features. Although an analyst might come to understand their networks through exploration of entities and through patterns visible through a particular layout, having automated community detection can give insight that is otherwise difficult to achieve. Given high quality community groupings based on edge connections, a researcher may be able to alter social policies in government, advise marketing plans in telecommunications, or understand what groups of proteins function together. To facilitate this, Meerkat offers both existing and novel community mining algorithms. This includes several central algorithms, and slight variations of them, including Fast Modularity , Max-Min Modularity [12], TopLeaders , Clique Percolation , Local Mining with or without hubs and overlap [11].

The results of these algorithms are visualized by colouring or labeling the nodes that belong to each community, as well as listing community membership in tabular form as shown in Fig.1. After identifying communities, Meerkat can compute common statistics such as density, diameter, and cohesion for each community.

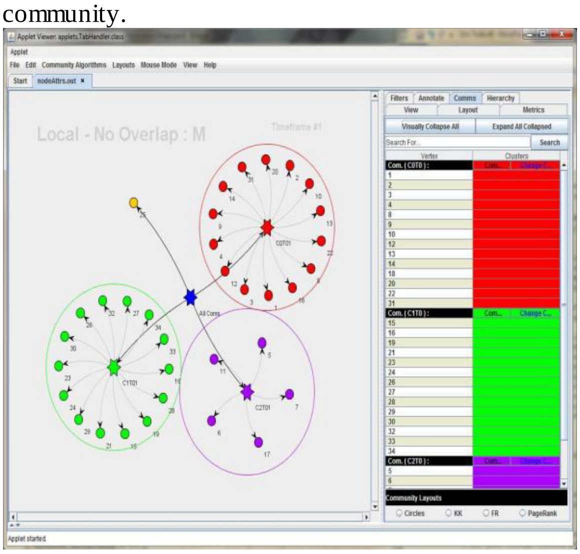

Figure 1.. Meerkat's hierarchy layout. The small coloured circles are the nodes, and the edges depict an 'owner' relationship in the hierarchy. Nodes within the larger coloured circles belong to the community indicated by its colour. The star-shaped objects represent a community, with the grey objects being a community made up of other communities and the blue object being the top-level super community. The community panel displayed on the right indicates which nodes belong to which communities

IV. FRAMEWORK ELABORATION:

3.1. Event-based framework to detect evolutions in social Networks:

Detecting the evolution of communities by monitoring when they form, dissolve, and reform can provide great insight into a dynamic social network. Asur et al. [8] proposed an event-based framework to capture and identify events on communities and individuals. Based on these events, the behavioural patterns of communities over time can be characterized. Although they formulate the critical events for communities, and propose behavioural measures for individuals, the presented events are too restricted to cover all of the changes that a community may experience.

In this paper we present a framework for modeling 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 that cover all possible transitions of a community, a new term called the community flag is defined. Base on this concept, we propose event definitions that cover all possible transitions of a community.

Naturally, individuals in a community have mutual common interests and interact with each other around those interests. For example, members gather physically, or virtually, to share an idea or to discuss about a topic. This is exactly what identifies members from non-members. Although this is more sensible for human communities, artificial communities have the same patterns in their structure. Thus one can assume an independent identity for a community based on the interests that members share with each other. We call this identity the c*ommunity flag*, which shows characterization of the community and its members. A community flag is unique and cannot be divided or cloned.

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 our new event definitions are parametric based on this portion, denoted by *k*. In order to use our proposed framework, the social network should first be 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.

In the following, $G = (V, E)$ denotes a dynamic social network where V and E are the total individuals and total interactions respectively. A snapshot $Si = (V_i , E_i)$ of G represents a graph only with the set of individuals and interactions at a particular time interval i. Each snapshot Si contains k_i communities $C_i = \{C^1_i , C^2_i , ..., C^k_{ii}\}$ where the community C_{ji} is also a graph denoted by (V_{ji} , E_{ji}). For each two consecutive snapshots a total of 11 events are defined with seven events involving communities and four
other involving individuals in the network.

3.2 Events involving communities:

In order to categorize the changes of communities that evolve over time, we consider seven events including form, dissolve, continue, split, merge, shrink, and reform. These events are based on the relationship between communities and are parameterized based on the portion k.

A community splits if it fractures into more than one community and one of these communities carry the flag of the former community. In the case where it fractures into more that one community but none of these communities carry the flag, a dissolve event is occurred. A community continues if there exists a community in the future that contains all the nodes of the former community. A community may shrink or reform when it loses a portion of its members but this portion is not significant enough to be detected as a split. In the case where new individuals join to the community, the community is marked as reformed, while it shrinks when no one has joined to it. Two or more communities are marked as merge if a major portion of at least one of these communities involve in the merge. Furthermore at any snapshot there may be newly formed community that does not carry the flag of any community at previous time.

For two consecutive snapshots Si and Si+1 where Ci and Ci+1 denoting the set of their communities respectively, the formal definitions of the seven events involving communities are as follows:

k-form: A new cluster Cki+1 is marked as formed if at least k% of its nodes have not been a member of the same community at the previous time. Thus Cki+1 is formed if

$$\nexists C_i^k \; such \quad that \qquad \frac{\left|V_{i+1}^k \cap V_i^j\right|}{\max\left(\left|V_i^j\right|,\left|V_{i+1}^k\right|\right)} \ge k\%$$

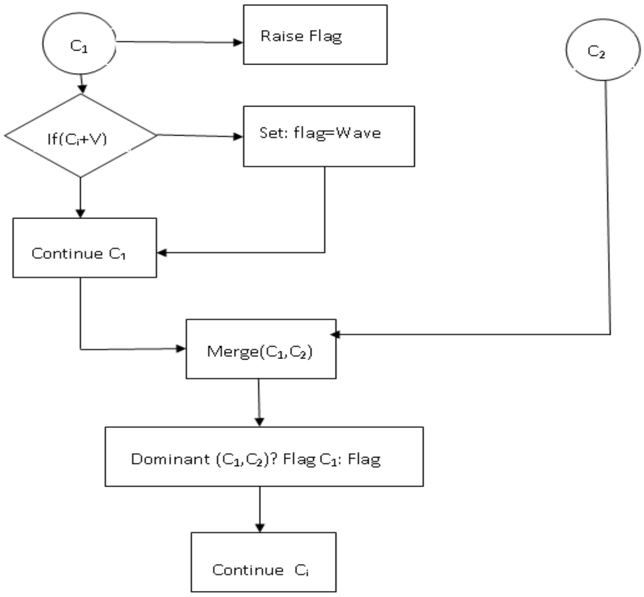

Figure 2. Community formation, merge and continue.

***k*-dissolve:** A community C^k_i is marked as dissolved if at least *k*% of its nodes will not be a member of the same community in the next snapshot as depicted in Fig 3. Thus, the conditions for the dissolved is

$$\nexists C_{i+1}^k \; such \quad that \qquad \frac{\left|V_{i+1}^j \cap V_i^k\right|}{\max\left(\left|V_i^k\right|,\left|V_{i+1}^j\right|\right)} \ge k\%$$

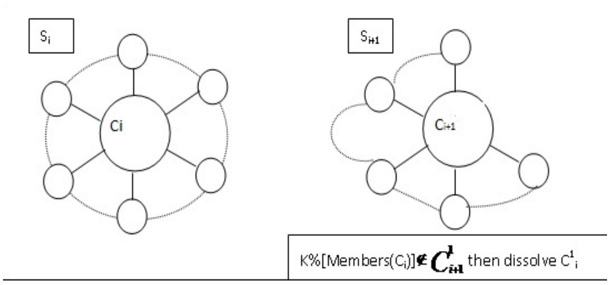

Figure 3. Community Dissolve

***k*-continue:** A community C^k_i is marked as continued if there exists a community

$$\exists C_{i+1}^j \; such \quad that$$

C^j_{i+1} that contains all the nodes of C^k_i and at least k% of its nodes are belonging to C^k_i. In other words, the two conditions for continue are as follows:

1. $\boldsymbol{V}^k_i \subseteq \boldsymbol{V}^j_{i+1}$
2. $\dfrac{\left|\boldsymbol{V}^k_i\right|}{\left|\boldsymbol{V}^j_{i+1}\right|} \geq k\%$

***n-k*-merge:** A set of communities *{ C^1_i , C^2_i …, C^n_i}* are marked as merged if there exists a community C^j_{i+1} in the next snapshot that for any community C^k_i, the following conditions are held:

$$\frac{|(V^k_i \cup V^m_i) \cap V^j_{i+1}|}{Max(|V^k_i \cup V^m_i|, |V^j_{i+1}|)} \geq k\%$$

$$\frac{|V^k_i \cap V^j_{i+1}|}{|V^k_i|} \geq k\% \quad \text{The flag of } C^k_i \text{ has been moved into } C^j_{i+1}$$

$$\frac{|V^m_i \cap V^j_{i+1}|}{|V^m_i|} \geq k\% \quad \text{The flag of } C^m_i \text{ has been moved into } C^j_{i+1}$$

The flag of C^m_i has been moved into C^j_{i+1}

Also at least one flag in C^j_{i+1} has to be dominant in order to distinguish this case and the case that a new community has been formed from small pieces of some other communities as shown in Fig 2. Thus the following condition should be held for *{C^1_i , C^2_i …, C^n_i }*:

$$\exists\, C^m_i \text{ such that } \frac{|V^m_i \cap V^j_{i+1}|}{|V^j_{i+1}|} \geq k\%$$

***n-k*-split:** A community C^j_i is marked as split (Fig 4)if there is a set of communities *{ C^1_{i+1} , C^2_{i+1} …, C^n_{i+1}}* in the next snapshot that for any community C^k_{i+1} the following conditions are held:

$$\exists\, C^m_{i+1} \text{ such that}$$

$$\frac{|(V^k_{i+1} \cup V^m_{i+1}) \cap V^j_i|}{Max(|V^k_{i+1} \cup V^m_{i+1}|, |V^j_i|)} \geq k\%$$

$$\frac{|V^k_{i+1} \cap V^j_i|}{|V^k_{i+1}|} \geq k\% \quad \text{There is a potential of raising the flag of } C^j_i \text{ in } C^k_{i+1}$$

$$\frac{|V^m_{i+1} \cap V^j_i|}{|V^m_{i+1}|} \geq k\% \quad \text{There is a potential of raising the flag of } C^j_i \text{ in } C^m_{i+1}$$

There is a potential of raising the flag of C^j_i in C^k_{i+1}

$$\exists\, C^m_{i+1} \text{ such that } \frac{|V^m_{i+1} \cap V^j_i|}{|V^j_i|} \geq k\%$$

There is a potential of raising the flag of C^j_i in C^m_{i+1} Also the flag of C^j_i has to be carried into one of *{C^1_{i+1} , C^2_{i+1} …, C^n_{i+1}}* and it has to be dominant there: If the above condition is not held, the community C^j_i undergoes the dissolve event.

A community may shrink or reform if it loses a portion of its members but this portion is not significant enough to be detected as a split. In the case where new individuals join to the community, the community is marked as reformed. On the other hand, it shrinks when no one has joined to it.

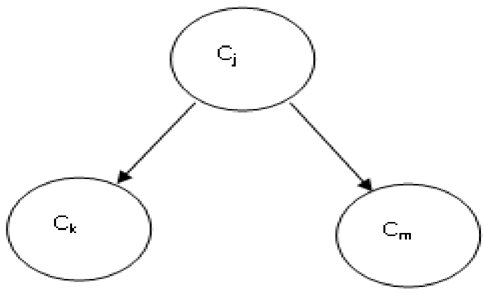

Figure 4. Community Split

$$.\ v \notin V_i \text{ and } v \in V_{i+1}\ .$$

***k*-shrink:** . A community C^k_i is marked as k-shrink(Fig 5) if there exists a community C^j_{i+1} that its set of nodes is a subset of the nodes in community C^k_i and also contains at least k% of the nodes from C^k_i . Thus the community is marked as k-shrink if

$$\exists\ C_{i+1}^{j}\ such\ that$$

$$1)\quad V_{i+1}^{j} \subseteq V_i^{k}$$

$$2)\quad \frac{|V_{i+1}^{j} \cap V_i^{k}|}{|V_i^{k}|} \geq k\%$$

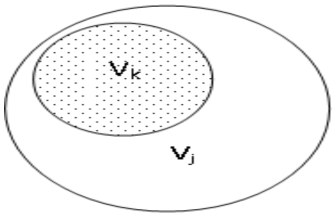

Figure 5. Community Shrink

***k*-reform:** A community C_i^k is marked as k-reform(Fig 6) if there exists a community C_{i+1}^j that at least contains k% of the nodes from C_i^k but its set of nodes is not a subset of the nodes in community C_i^k

$$\exists\ C_{i+1}^{j}\ such\ that$$

$$1)\quad V_{i+1}^{j} \not\subset V_i^{k}$$

$$2)\quad \frac{|V_{i+1}^{j} \cap V_i^{k}|}{|V_i^{k}|} \geq k\%$$

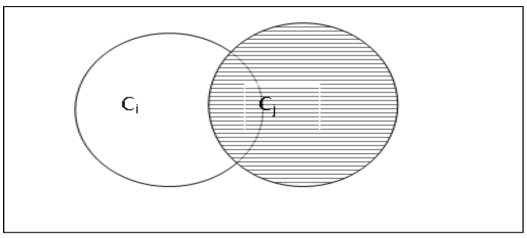

Figure 6. Community Reform

$C_j \in k\,\%[\,C_i \text{ Members}] + \text{set of nodes } \notin C_i$

$\therefore C_j$ is Reformed Community.

3.3 Events involving individuals

In order to analyze the behaviour of individuals in communities, four events involving individuals are defined. The taxonomy we use here is the same as Asur et al. [8]. However, unlike [8] we define the join and leave events parameterized based on the portion k. For two consecutive snapshots *Si* and *Si+1*, the events involving individuals are defined as follows:

Appear: A node *v* is marked as appeared when it is in the current snapshot but it was not in the previous snapshot *i.e*

Disappear: A node *v* is marked as disappeared when it existed in the previous snapshot but it does not exist in the current snapshot *i.e*.

$$v \in V_i\ and\ v \notin V_{i+1}.$$

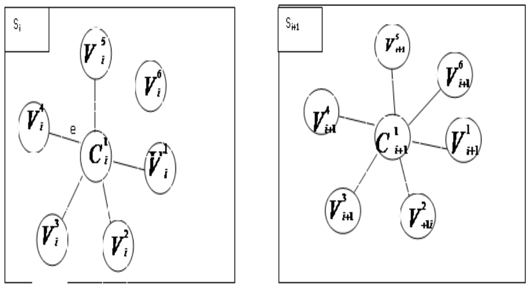

Figure 7. Individual Node Appear and Disappear

In Fig 7, C_i – Community V_i, V_{i+1} – Vertices/Nodes E – edges . S_i , S_{i+1} – snap shots(current and next respectively.)

Here V_6 – Vertex V_6 is said to be DISAPPEARED as it is present in S_i snap shot, but not in the S_{i+1} snapshot.

V_6 – Vertex V_6 is said to be APPEARED as it is present in the S_{i+1} sanp shot , which was not there in the S_i snap shot.

***k*-join:** A node *v* joined to community C^j_{i+1} if it exists in this community at snapshot *i+1* but was not in C^k_i in the previous snapshot where C^j_{i+1} carries the flag of C^k_i. Thus, the conditions for the join event are as follows:

$$\exists\ C_i^{k}\ such\ that$$

$$1)\quad \frac{|V_i^{k} \cap V_{i+1}^{j}|}{|V_i^{k}|} \geq k\%$$

$$1)\quad v \notin V_i^{k}$$

$$2)\quad v \in V_{i+1}^{j}$$

***k*-leave:** A node *v* left community C^k_i if it existed in this community at snapshot *i* but it does not exist in C^j_{i+1} in the next snapshot where C^j_{i+1} is sufficiently similar to C^k_i. In other words, the conditions for the leave event are as follows:

$$\exists\ C_{i+1}^{j}\ such\ that$$

$$2)\quad \frac{|V_i^{k} \cap V_{i+1}^{j}|}{|V_i^{k}|} > k\%$$

$$3)\quad v \in V_i^{k}$$

$$4)\quad v \notin V_{i+1}^{j}$$

V. EXPECTED EXPERIMENTAL RESULTS:

We have taken a sample dataset in order to show the feasibility of the proposed events using our framework. To visually track the evolution of communities, we have integrated our code into Meerkat [10].This tool enables us to preview the graph of each timeframe and have the communities at each timeframe marked with different colours. In fact these colours are the notion of Community Flag and they come from the results of our event-detection formulas.

Without loss of generality, we will choose only one year data set to reduce the graph size, and only considered people who had sent at least one email per day to filter out non-informative nodes. The resulting graph will b having almost 250 nodes and 1500 edges approximately. Lets set the snapshots to be 1 month each and found the communities on each month by a local community mining algorithm with no overlap between communities [4], provided in Meerkat.

In order to evaluate our framework we have also implemented the event-based framework by Asur et al. [8] which is the only framework that has an event based approach similar to our framework. Fig 8 shows the general view of communities in each snapshot. The area of each community in the figure is proportional to the number of its members.

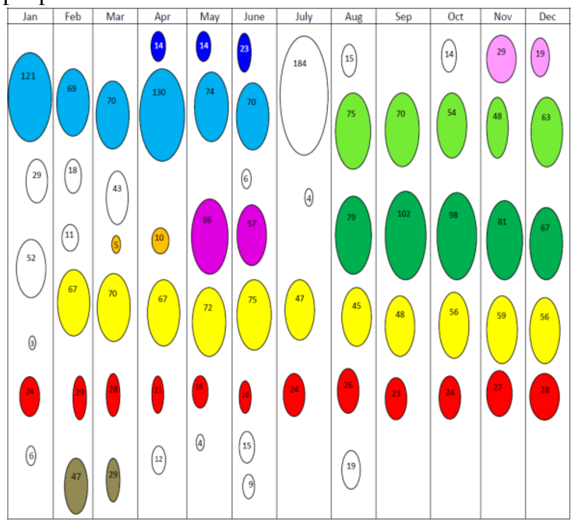

Figure 8. shows the general view of communities in each snapshot.

Advantage of our Framework:

1. By assigning colours to the different flags, one can easily make a map between communities through snapshots(the communities without any color are the ones that only exist for one snapshot). For example,appearance of a colour in a snapshot means a community has been formed and similarly disappearance of a colour shows the end of life for that community.
2. Also tracking the community transitions such as reformation, shrinkage, merger, and split are almost possible by looking at Table 2.

Disadvantages of Asur Framework :

1. Since there is no notion of a community identity in Asur framework, determining a map from communities in one snapshot to another is impossible.
2. There is no way to keep track of a specific community and its transitions over time when using this framework.

Thus, in order to compare the results found by the two frameworks, the number of events found by Asur and our framework are provided in Table 1 and Table 2 respectively.

Using Asur framework, most of the communities are not marked by any event. On the other hand, our framework detects exactly one of the continue, reform, shrink, split, or dissolve events.

Thus, the number of communities at each snapshot is the same as the total number of continue, reform, shrink, split, and dissolve events. From Table 2, we can observe that for the dataset, the reform and dissolve events far outnumber the other events. The high number of reform event indicates that most communities do not change greatly between two consecutive snapshots. However, the relatively high number of dissolve event denotes that most of the communities have short life cycles.

So we can conclude that in the dataset most of the communities have a short life cycle and do not change drastically.

Table 1. Number of events occurred for the dataset using Asur Framework

Month	Communities	Continue	Split	Dissolve	Merge	Appear	Disappear	Form
January	6	0	2	0	1	---	2	---
February	6	0	0	0	0	8	7	0
March	6	0	0	0	1	11	1	0
April	6	0	1	0	0	10	11	0
May	6	0	3	0	0	13	6	0
June	8	0	0	0	2	11	16	0
July	4	0	1	0	0	4	11	0
August	6	0	0	0	1	11	22	0
September	4	0	1	0	0	6	3	0
October	5	0	0	0	0	6	6	0
November	5	0	0	0	0	4	12	0
December	5	---	---	0	---	1	---	0

Table 2. Number of events occurred for the dataset using our Framework

Month	Communities	Continue	Reform	Shrink	Split	Dissolve	Merge	Appear	Disappear	Form
January	6	0	1	0	1	4	0	---	2	---
February	6	0	4	0	0	2	0	8	7	2
March	6	1	3	0	0	2	1	11	1	1
April	6	0	3	0	1	2	0	10	11	2
May	6	0	3	0	2	1	0	13	6	1
June	8	0	2	0	0	6	1	11	16	2
July	4	0	2	0	0	2	0	4	11	1
August	6	0	3	1	0	2	1	11	22	4
September	4	1	2	0	1	0	0	6	3	0
October	5	1	3	0	0	1	0	6	6	1
November	5	0	5	0	0	0	0	4	12	1
December	5	---	---	---	---	0	---	1	---	0

I. CONCLUSION AND FUTURE WORK:

VI. Conclusion:

In this paper, we presented an event-based framework to analyze different types of dynamic social networks. Defining the concept of a Community Flag allows us to capture all of the possible events among communities. This includes tracing the formation, continuation and dissolution of communities. Moreover, it detects events involving individuals in the network and tracks their behaviour. Applying our framework on the sample dataset, we visualized the Life-Cycle of all communities and the events that occurred in Corporation's final year. Our results on the dataset indicate that most of the detected communities in the sample have short life cycle while having stable members during their life.

5.2. Future Work:

Most existing community mining algorithms find separated set of communities, where every individual is a member of exactly one community. However, in social networks individuals may belong to different communities which results in highly overlapping and nested communities. One possible future research direction is to analyze the evolutions of overlapping communities based on the proposed events in a dynamic social network. Furthermore in our work, we only consider the events between two consecutive snapshots. However, it is possible to detect events for any number of contiguous timeframes. Considering more than two snapshots at a time would enable us to detect communities that are

inactive in a time frame which may reactivate again later on.

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