The Analysis of Sub-Communities Behavior in Social Networks

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Abstract—Clique relations are useful in understanding the dynamics of a wide range of social interactions. One application of studying clique relations involves studying how such "detection of abnormal cliques' behaviors" can be used to detect sub-communities' behaviors based on information from Online Social Networks (OSNs).
In social networks, a clique represents a sub-group of the larger group in which every member in the clique is directly associated with every other member in the clique. Those cliques often possess a containment relation with each other where large cliques can contain small size cliques. Thus, finding the extent of the clique, or the maximum clique is an important research questions. In our approach, we evaluated adding the weight factor and integrating graph theory to clique algorithm in order to derive more data about the clique. In this regard clique activities are not like those in group discussions where an activity is posted by one user and is visible by all others. Our algorithm calculates the overall weight of the clique based on individual edges. Users post frequent activities. Their clique members, just like other entities, may or may not interact with all those activities.

Index Terms—OSN groups detection; Weighted cliques; Groups collaboration; Graph Theory and Social Media

I. Introduction

There are a diverse array of applications for tracking and measuring relationships in Online Social Networks (OSN's) (Stieglitz, et al., 2015; Papadopoulos, Kompatsiaris, Vakali, & Spyridonos, 2012). Marketing is a common application of social network analysis (Soares, et al., 2012). Another application is to study the influence of emotionally charged information such as social or political memes (Kramer, Guillory, & Hancock, 2014). However, social network relationships are also important for investigative applications (Duijn & Klerks, 2014). Whether the investigating agency is a law enforcement agency or an intelligence gathering agency the needs for an investigative application are identical. Counterterrorism is one area of investigation in which analysis of social media interactions can be very important and produce significant, actionable intelligence (Choudhary & Singh, 2015; Ishengoma, 2014; Kirby, 2007; Leistedt, 2013).

There are diverse approaches to analyzing social media interactions, regardless of the investigative intent (Alhajj & Rokne, 2014; Scott, 2017). Analytical approaches can be formulated based on diverse foundations. In some case large scale data scraping and mining is the preferred approach. This can be coupled with statistical analysis of the interactions. Graph theory provides a modality for studying a wide range of interactions (Easttom, 2018). Thus, it is appropriate to apply graph theory to analyzing social network relationships (Mitrou, Kandias, Stavrou, & Gritzalis, 2014; Zafarani, Abbasi, & Liu, 2014).

The approach we used in this current study was to focus on cliques in social media, and to apply graph theory to analyze those relationships. In the social sciences a clique is defined as a sub-group that has intergroup interaction coupled with some common interest (Scott, 2017). The specific nature of that interest does not affect the analytical approach. The extraction of clique relations in social networks can reveal information related the group those members belong to. In one pending application, we are showing how such "detection of abnormal cliques' behaviors" can be possibly used to detect terrorists' attacks based on information from OSNs.

In social networks, a clique is defined as a group of elements (people or subgroups) where every member in the clique is a friend with every other member in the clique. Several recent contributions tried have attempted to extract knowledge related to cliques in OSNs (e.g. Cotterell 2013, Comandur et al 2014, Hao et al 2014, Acemoglu et al 2014, Basuchowdhuri et al 2014, Hunter et al 2015, Hao et al 2016). The fact of so much research focused on this problem, is indicative of the importance of the problem.

II. Maximum Cliques, Weighted Cliques and Maximum Weighted Cliques

Clique analysis is effectively accomplished by the application of graph theory. A clique, C, (in an undirected graph G of (V, E), is a subset of the vertices where between each two vertices, there is an edge (i.e. a

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relation). In the scope of groups collaborations, ω(G), is the size of a largest clique or maximal clique of G. For an arbitrary graph the clique can be defined as per the formula in figure 1.

$$\omega(G) \geq \sum_{i=1}^{n} \frac{1}{n - d_i},$$

Figure 1: Maximal cliques
where di is the degree of a graph vertex i

Several papers have indicated that maximum cliques' problem is an NP-complete problem (e.g. Butman et al 2007, Francis et al 2015, Paulusma et al 2016, Bart and Jansen 2016, etc.).

Weighting is commonly applied in graph theory in order to better model the phenomena being graphed. A weighted clique is the total weight of weighted maximum clique (Kumlander 2004). Based on this definition, calculating weighted clique takes two consecutive steps:

1. For a particular graph, calculate maximum clique in that graph, and then:
2. For that particular clique, calculate the overall weight of the edges in the clique.

In this formula, while for a particular graph, the maximum clique is dynamic and may change from one time to another, however, the weighted clique will always be tied to the maximum clique.

subset with 3 cliques (1,2,4,5,7,11), (1,5,6,8), and (3,9,10). In this graph and edges-weights shown in the right:

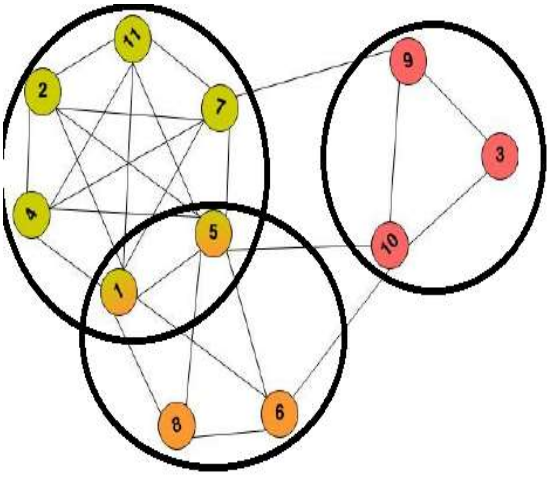
- Maximum clique is (1,2,4,5,7,11).
- Weighted clique is 2.84.

- Maximum weighted clique is 5.4 (for a clique that is not a maximum clique).

A couple of observations on our definition of: maximum weighted clique:

- This is a direct graph where edges are directional and for example value of edge-weight 1-5 is 0.1 and is different from the value of edge 5-1, (0.05). This is particularly true for relations in Online Social Networks (OSNs) where relations and not symmetric. A typical example is between a fanatic and their celebrity, edge will be very high only from one direction (which indicates high interactions from the fanatic side with celebrity activities).
- In our hypothetic example, that may look odd but true, a small size clique may have an overall stronger weighted clique than a larger clique.
- If we consider relations dynamics, maximum cliques can vary dynamically as so their maximum weighted cliques. We hypothesize that a significant increase of maximum weighted clique for a particular clique beyond their historical norms can be used to predict "abnormal behaviors).

Using this method detection of some "detection avoidance methods" is possible. For example, a clique may suddenly



Edge	Weight	Edge	Weight	Edge	Weight	Edge	Weight
1--2	0.01	4--5	0.01	7--1	0.01	6--8	0.15
1--5	0.1	4--7	0.1	11-1	0.1	6--5	0.04
1--7	0.03	4--1	0.03	11-2	0.03	6--1	0.05
1--11	0.05	5--1	0.05	11-4	0.05	6--8	0.15
1--4	0.12	5--2	0.12	11-5	0.12	8--1	0.23
2--1	0.13	5--4	0.13	11-7	0.13	8--5	0.04
2--5	0.2	5--7	0.2	1--6	0.2	8--6	0.05
2--7	0.09	5--11	0.09	1--8	0.09	9--3	0.9
2--11	0.15	7--1	0.15	5--6	0.15	9--10	0.88
2--4	0.23	7--2	0.23	5--8	0.23	3--9	0.95
4--1	0.04	7--4	0.04	6--5	0.04	3--10	0.78
4--2	0.05	7--5	0.05	6--1	0.05	10--9	0.97
						10--3	0.92
	Clique 1	2.84	Clique 2	1.38	Clique 3	5.4	

Figure 2: Three hypothetical cliques and their maximum weighted cliques

We introduced (Maximum weighted clique) to be always dynamic and not tied to the maximum clique. This means that for a particular graph, the maximum clique and the maximum weighted clique may refer to different subsets in the same graph. In order to show the difference, assume Figure 2 below indicates a hypothetical graph

delete an edge to avoid detection. However, as we

evaluated directed-edges, a single edge removal will not change the structure of the clique and will only cause that edge value to be zero.

III. METHODS AND APPROACHES

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The focus of this study is on how to analyze information gathered from online social networks. The process of acquiring that information is not part of this study. There are a range of tools and techniques available for acquiring such data. One such tool that has been applied in many areas of social medial data gathering, is BuzzSumo (Dicerto , 2018). This tool has been used to analyze fake news and its relation to medical data (Waszak, Kasprzycka-Waszak, & Kubanek, 2018). ViralWoot is another tool that can be used to gather data from social media (Simmhan, 2017). The specific tool or technique for gathering the data is not relevant to this current study. Our focus is on analyzing the data once it has been collected.

For investigative purposes, particularly in intelligence gathering, the primary focus is on any deviation from established norms. For example, terrorists' networks will often have an increase in interactions prior to an operation. Therefore, we focused on an approach that identified such anomalous social interactions. We propose a method to detect "abnormal" clique behaviors through OSNs. We will collect cliques' networks from major OSNs such as: Facebook, Twitter and LinkedIn. We will use a weighted clique metric that we developed to be as a baseline for estimating average interactions between any OSN clique members. This weighted clique metric will be periodically (e.g. once a week), assessed and updated. A separate monitoring system will frequently (e.g. once every 8 hours) read the current weighted clique metric. The early alert will be triggered if this instance metrics is significantly (e.g. > 25%) higher than average weighted clique.

For example, say, for a Facebook clique of 6 individuals, weighted clique reading (as of the last month) is 13. While reading most recent weighted clique, if it shows a weighted clique of 20 (which is more than 25% increase from 13), an alert will be triggered to investigate the increase.

The usage of Cliques is popular in graph based analysis areas (e.g. social networks, bioinformatics, etc.) in order to understand connections and trust relations between graph node members.
As an algorithm, Clique calculates the maximum number of nodes in the graph in which every node in the Clique is a friend to all other nodes in the Clique.
Here are the major tasks toward this goal:

- We introduced a new "weighted clique" algorithm. We showed also how this algorithm can be used to extract different types or aspects of knowledge in Bioinformatics or OSNs. This was the first task to accomplish in this goal.
- As we acknowledged that different OSNs have different "models" of interactions between the different individuals, we plan to create several concrete models, based on the availability of time and resources for one or more of the following OSNs: Facebook, Twitter and LinkedIn.
- A major task, in terms of time and resources, in this goal is data collection and analysis for cliques' interactions. We started collecting data, based on our model from Facebook and Twitter. We need to extend the collection and analysis process to collect a "significantly" large enough dataset.

In this research we introduced the following three intuitive concepts:

1. Weighted edges (i.e. strength of bonds between nodes that interact with each other). Typically, such relation is considered only from a binary perspective (i.e. exist:1 or does not exist: zero). We showed that the mere existence of the relation can be misleading in some cases and a significant amount of information is needed to know the weight of level of such relation, if exists.
2. Weighted Friendships: Based on each node or user (e.g. in OSNs) edges or connections, weighted friendship can calculate a friendship value based on the overall values of weighted edges. We showed in our paper, some applications for such value.
3. Weighted Cliques: As described earlier the mere existence of relation between either one or a group of nodes, may not be enough to understand social interactions. Based on weighted edges, we introduced the concept of weighted cliques to show the strength of bond between clique members. Figure 3 shows the different between normal cliques count and our proposed weighted or normalized or weighted clique.

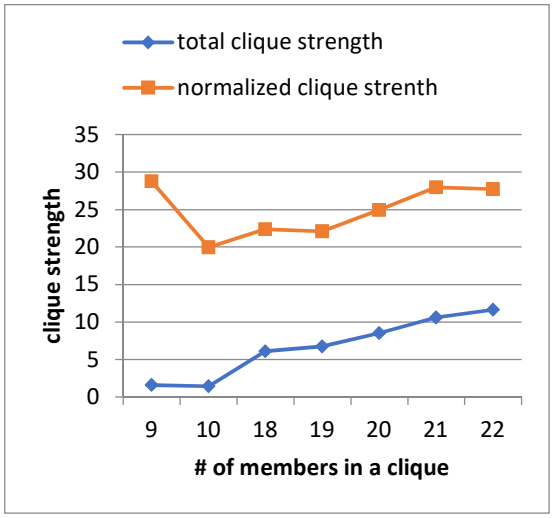


Figure 3: The comparison between total and normalized/weighted clique strengths

The extraction of clique relations in social networks can show information related to groups and how those groups are formed or interact with each other. In social networks, a clique represents a group of people where every member in the clique is a friend with every other member in the clique. Those cliques can have containment relation with

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each other where large cliques can contain small size cliques. This is why most algorithms in this scope focus on finding the maximum clique. In our approach, we evaluated adding the weight factor to clique algorithm to show more insights about the level of involvement of users in the clique. In this regard clique activities are not like those in group discussions where an activity is posted by one user and is visible by all others. Our algorithm calculates the overall weight of the clique based on individual edges. Users post frequent activities. Their clique members just like other friends, may or may not interact with all those activities.

We showed in the Table 1 the largest cliques in the dataset. The first column includes IDs of node members in the clique. The second column includes the number of members in each clique. The third column includes the clique strength as the summation of all weighted edges in the clique. The last column represents the weighted clique strength which divides the total clique by the number of edges in the clique. Normal clique strength value is constantly increasing with the number of nodes or edges in the clique. However, the weighted clique value eliminates the dependency on the number of nodes or edges. As such, we can see for example that the smallest clique in the table has the highest weighted clique.

This is not a trend however as the next highest weighted clique is the one with 20 nodes. This indicates that trust or interaction between members in the first clique is the highest. When we study social networks at a larger context, highest and lowest weighted cliques can be of special interests. We can also look at variations in clique strength over a certain period of time. For example, a clique sudden increase of the weighted clique in a certain month over a period of time can trigger further investigations of what could cause such significant sudden increase (e.g. a clique collaborative activity or event).

Table 1: Total and weighted cliques

Clique members	NO	Total clique	Weighted clique %
221, 215, 190, 187, 177, 176, 171, 151	8	1.61	28.77
221, 215, 190, 187, 177, 175, 171, 170, 151	9	1.43	19.96
221, 215, 190, 181, 177, 176, 172, 171, 169, 165, 164, 162, 157, 156, 153, 152, 151	17	6.08	22.36
221, 215, 190, 181, 177, 175, 172, 171, 170, 169, 165, 164, 162, 157, 156, 153, 152, 151	18	6.75	22.08
221, 215, 181, 177, 175, 172, 171, 170, 169, 168, 166, 165, 164, 162, 157, 156, 153, 152, 151	19	8.52	24.94
216, 209, 206, 193, 192, 191, 180, 179, 175, 169, 167, 160, 158, 151, 98, 20, 18, 9, 4, 2	20	10.62	27.96
216, 209, 193, 192, 191, 180, 179, 175, 170, 169, 167, 163, 160, 158, 151, 98, 20, 18, 9, 4, 2	21	11.64	27.73

VI: Enhancing the Methodology

It should be readily apparent that the current methodology can be easily enhanced or modified if needed. For example, the current weighting threshold is set at a specific value. It would be relatively easy to adjust the method such that the weighting is dependent on specific statistical values that can vary over time. Such statistical values could include the variance in weighting over a period in time, expressed as with the following simple formula:

$$\frac{\sum_{i=1}^{n} s^2}{\triangle \mathrm{T}}$$

This measures the change in variance in relation to a change in time (delta T). This is one example of how statistical analysis can be applied to the clique analysis to provide either more information, or more granular information.

The current methodology can also be combined with graph theory to model a given clique. The clique would be represented as vertices in the graph, with the connections being edges (or arcs). Each edge would be weighted based on the strength of the connection. That strength could be measured via frequency of connectivity, number of messages per unit of time, or any similar measurement that is pertinent to the investigation in question. Then the variation in not only activity for the clique as a whole, but also for the individual edges could be monitored. This would allow the detection in variations of sub groups within the clique. These sub groups would be represented as sub graphs of the cliques' larger graph.

V: Model Evaluation

In order to evaluate our weighted clique model in OSNs and its our ability to detect "abnormal groups dynamics", we built a historical dataset based on the initial dataset described in Himel et al 2014. The volume of interactions between the friends in the network is calculated as totals for the given period of the collection process.
Following are our general steps to construct the model dataset.

- Original Facebook dataset described in Himel et al 2014 is used is the baseline dataset.
- The number of nodes or Facebook users as well as the number of edges between the members will be frozen through our one-week historical analysis. This is an assumption to fix the overall structure of the model where no changes on the nodes or relations will occur throughout the assessment. This

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assumption is to simplify the model demonstration, but the model and algorithms do not exclude any frequent changes in the network structure.

- In our model, we will give to the different Facebook activities the same weight in the relation (e.g. a Like, Comment, Post, etc.). This is another assumption in the model to simplify its demonstration that can be adjusted based on the different OSNs and the nature of the different activities.
- We will randomly vary volumes of activities between network users between (25% of their baseline up to 300% of their baseline). The goal is to simulate users' actual behaviors in OSN and also demo cliques' dynamics.

Figure 4 shows a small sample of our model output on some selected cliques.

We can observe the followings based on Figure 3:

N-edges	N-nodes	list-edges...	Clique	Weight									
3	3	1	2	66.88889									
6	4	1	2	4	74.72222								
10	5	1	2	1	4	61.33333							
15	6	1	2	3	2	4	44.44444						
21	7	1	2	1	6	2	7	38.63492					
28	8	1	2	2	1	4	3	7	34.30952				
38	9	1	2	1	5	2	8	3	7	34.40741			
46	10	1	2	10	1	9	2	6	4	9	33.16296		
56	11	1	2	10	4	1	5	3	11	5	9	32.39394	
67	12	1	2	10	1	8	2	10	3	11	6	9	8

N-edges	N-nodes	list-edges...	Clique	Weight									
3	3	1	2	136.3333									
6	4	1	2	4	142.8333								
10	5	1	2	1	4	106.5							
15	6	1	2	3	2	4	74.8						
21	7	1	2	1	6	2	7	67.09524					
28	8	1	2	2	1	4	3	7	60.42857				
38	9	1	2	1	5	2	8	3	7	61.58333			
46	10	1	2	10	1	9	2	6	4	9	59.31111		
56	11	1	2	10	4	1	5	3	11	5	9	57.45455	
67	12	1	2	10	1	8	2	10	3	11	6	9	8

N-edges	N-nodes	list-edges...	Clique	Weight									
3	3	1	2	114.3333									
6	4	1	2	4	102.5								
10	5	1	2	1	4	86.3							
15	6	1	2	3	2	4	63.8						
21	7	1	2	1	6	2	7						
28	8	1	2	2	1	4	3	50.53571					
38	9	1	2	1	5	2	8	7	52.33333				
46	10	1	2	10	1	9	2	4	9	50.82222			
56	11	1	2	10	4	1	5	11	5	9	46.01818		
67	12	1	2	10	1	8	2	3	11	6	9	8	10

Figure 4: A sample output of our model

- As our model uses weighted clique values rather than clique or maximum clique values, the overall strength of the clique shows at the end of each record is independent from the clique size.
- Our model shows undirect edges/relations. This means that for two-friends, we are considering only one edge-value that can reflect one-way strength of the friendship. This was just an assumption in the model to simplify its demonstration and the model can be extended to consider or assume directed-edges or the two-way strength of the relation. The total number of the edges in the clique will then be doubles (N*N-1), rather than now (N*N-1)/2. As at the end, we are considering the overall weighted strength of the clique, this will not make a significant change.
- The 3 Figure parts indicate three consecutive days in the selected network. It can be used to monitor gradual or sudden increase in the overall weighted strength of communication of the clique. This can be used to trigger further deeper focused analysis of that particular clique.
- Our model is built purely on statistics; it does not require looking at the content of communication activities between clique members. This can alleviate issues related to privacy, legal concerns and performance.

IV: CONCLUSION

In this paper, we proposed a statistical approach to detect or alert for cliques' abnormal behaviors' using Online Social Networks (OSNs). This can be part of national security alert system that does not violate users' privacies as it does not need to look into users' contents (i.e. posted activities, friends, private messages, etc.). Due to its focus only on statistical assessments, the system also balances between security issues with performance and the impact that such systems may cause to OSNs.

As was noted in this paper clique analysis can be integrated with other methodologies. For example, the weighting can be represented with graph theory. The individuals are the nodes in the graph, the connections are the edges or arcs, and the weighting can be represented in a weighted graph. It is also possible to integrate additional statistical analysis into the clique analysis, as was discussed in this paper. Both of these enhancements to the currently described clique analysis technique are avenues for further research.

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Authors' Profiles



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