Social Network Change Detection

Ian A. McCulloh and Kathleen M. Carley

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Institute for Software Research
Carnegie Mellon University
School of Computer Science
Pittsburg, PA 15213

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Abstract

Changes in observed social networks may signal an underlying change within an organization, and may even predict significant events or behaviors. The breakdown of a team's effectiveness, the emergence of informal leaders, or the preparation of an attack by a clandestine network may all be associated with changes in the patterns of interactions between group members. The ability to systematically, statistically, effectively and efficiently detect these changes has the potential to enable the anticipation of change, provide early warning of change, and enable faster response to change. By applying statistical process control techniques to social networks we can detect changes in these networks. Herein we describe this methodology and then illustrate it using three data sets. The first deals with the email communications among graduate students. The second is the perceived connections among members of al Qaeda based on open source data. The results indicate that this approach is able to detect change even with the high levels of uncertainty inherent in these data.

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1. INTRODUCTION

Organizations are not static, and over time their structure, composition, and patterns of communication may change. These changes may occur quickly, such as when a corporation restructures, but they often happen gradually, as the organization responds to environmental pressures, or individual roles expand or contract. Often, these gradual changes reflect a fundamental qualitative shift in an organization, and may precede other indicators of change. It is important to note, however, that a certain degree of change is expected in the normal course of an unchanging organization, reflecting normal day-to-day variability. The challenge of Social Network Change Detection is whether metrics can be developed to detect signals of meaningful change in social networks in a background of normal variability.

Organizations can be represented with many different networks. Relationships between people form social networks. Relationships between people and their knowledge, resources, tasks, beliefs, and other dimensions all form networks as well. The collection of these networks is referred to as a meta-network (Krackhardt and Carley, 1998). One advantage in representing organizations using meta-networks is the ability to mathematically quantify and represent complex interrelated organizational behavior. In addition, network representations of organizations can have a visual appeal that enhances insight and understanding of organizational dynamics. If we accept the notion that organizations consist of a meta-network of relationships, the data collected on the organization over time can be used to construct observed instances of the network. Due to normal fluctuations in behavior and data collection errors, it is conceivable that an observed network might differ slightly from the actual underlying network of organizational relations. How then, can we detect statistically meaningful changes in the organization, within this meta-network representation? This paper proposes an approach that is focused on social networks, but could be expanded to include other network dimensions in the future.

Social Network Analysis (SNA) is an approach to studying and analyzing groups of actors and their ties. When applied to communication networks, SNA enables us to quantitatively analyze the patterns of information flow through time and space (Monge & Contractor, 2003). These techniques can be used to characterize the roles of individuals in groups, compare subgroups with one another, or describe the informal structure of large organizations (Wasserman & Faust, 1994).

There has been a recent increase in temporal social network data (McCulloh, et.al., 2007). Unobtrusive tools now exist to extract network data from e-mail servers, from news media, from written documents within an organization. This allows an analyst to construct multiple network observations of an organization, whether it is daily, weekly, yearly, or any other temporal breakdown. With the increased emergence of observed instances of social networks over time, improved methods of detecting meaningful change are needed. Simply looking for obvious drastic changes may be insufficient for many applications.

2. BACKGROUND

Current methods of change detection in social networks are limited. Hamming distance (Hamming, 1950) is often used in binary networks to measure the distance between two networks. Euclidean distance is similarly used for weighted networks (Wasserman and Faust, 1994). While these methods may be effective at quantifying a difference in static networks, they lack an underlying statistical distribution. This prevents an analyst from identifying a statistically significant change, as opposed to normal and spurious fluctuations in the network. Social Network Change Detection significantly improves on previous attempts to detect organizational change over time by introducing a statistically sound probability space and uniformly more powerful detection methods.

Several methods for studying social networks over time have been proposed in the literature. Exponential Random Graph Models (ERGM) include structural variables to predict future graph evolution (Handcock and Morris, 2005; Goodreau, 2007; Robins, et. al., 2007). The software package SIENNA is often used to study longitudinal data (Snijders, et. al., 2007). The Network Probability Matrix (NPM) approach makes different assumptions than the ERGM and uses historic relationships to predict future networks (McCulloh, et. al. 2007). Conceptual models such as preferential attachment and fitness models have been used to predict the future behavior of network evolution through time. While it may yet be unclear which method more closely resembles the true evolution of networks, all methods provide an analyst with a means to understand a possible underlying statistical distribution for social network measures. Statistical distributions have been fit to several data sets, using the NPM and empirical approaches (McCulloh, et. al., 2007; Baller, et. al., 2008). Findings indicate that measures of average centrality, average betweenness, and density are all normally distributed for networks of greater than 30 nodes. These findings suggest that the necessary assumptions for many statistical process control charts may be satisfied for these three measures.

Social Network Change Detection is a process of monitoring networks to determine when significant changes to their organizational structure occur and what caused them. We propose that techniques from SNA, combined with those from statistical process control can be used to detect when significant changes occur in a network. In application, it requires the use of statistical process control charts to detect changes in observable network measures. By taking measures of a network over time, a control chart can be used to signal when significant changes occur in the network. We describe our technique below. First, providing an overview of the relevant SNA and statistical process control approach, then describing the impact of applying this to relational data, and which social network measures are suitable for monitoring. We follow that with demonstrations of the technique on two distinct network data sets, the emails between Army officers in a graduate program, the patterns of communication between members of Al-Qaeda.

Social Network Analysis

SNA provides the basis for how networks are modeled, measured, and compared. A typical social network can be modeled on a graph with people represented as vertices and links between them as edges. (Scott, 2002; Wasserman and Faust, 1994). These edges can represent a wide variety of links including exchanged emails, shared religious beliefs, or attendance at the same university. Edges may be weighted to show the importance of the link. For example, the weight could be how many emails were sent over the data collection time period. Edges may also be directed to show who is initiating the link and who receiving it. The simplest social networks have just one edge set that is un-weighted and undirected.

There are many network measures that can be calculated from a given graph. Network measures can be calculated from the entire graph or for each individual node. Centrality network measures such as betweenness and closeness are widely used for their easily applied practical applications in determining how information spreads through a social network. For illustration this paper will use one graph level measure, density (Coleman and Moré, 1983); and two individual node measures averaged over the graph, closeness (Freeman, 1979) and betweenness (Freeman, 1977). These are chosen because they are commonly used in the literature and represent a range of the types of measures available for change detection.

Despite the practicality of these measures, several problems arise from their usage. First, these individual measures must be translated into a network picture of the entire graph. This may be as simple as averaging the measures across the entire graph and using that as the measure for each time period. An alternative method would be to use either the maximum or minimum value from nodes within the graph as the sample. Unlike in Everett and Borgatti's paper (1999) one cannot recalculate the network measure by collapsing the graph into a single node and analyzing its links with nodes outside the group because our group involves the entire graph and the result would be trivial. One must thus explore how both the individual measures and average measures are distributed and whether the average is good representation for the entire graph. A second difficulty with these measures is their normalization. In order to compare measures across different time periods, they must be normalized. For a steady sized group this should not be an issue, but in the case of an expanding or contracting group, issues arise as to whether results can be used across the different scales of group size. In other words, the network measures may change in different ways with respect to the current group size and thus provide inconsistent information about the group even absent of any changes within the group. For this research, the Organizational Risk Analyzer (ORA) developed by Kathleen Carley at the Center for Computational Analysis of Social and Organizational Systems at Carnegie Mellon University is used to compute the average network measures from all group information (Carley, 2007).

Statistical Process Control

The second component for social network change detection is Statistical Process Control (SPC). SPC is a technique used by quality engineers to monitor industrial processes. They use control charts to detect changes in the mean of the industrial process by taking periodic samples of the product and tracking the results against a control limit. Once a change has been detected, the engineers determine the most likely time the change occurred to reexamine and reset the process to avoid financial loss for the company by making substandard or wasteful product. Control charts are usually optimized for their processes to increase their sensitivity for detecting changes, while minimizing the number of false alarms – signals when no change has actually occurred in the process.

The control chart investigated for this project was the cumulative sum (CUSUM). The CUSUM control chart is a widely used control chart derived from the sequential probability ratio test (SPRT) (Page, 1961). The SPRT was derived in turn from the Neyman and Pearson (1933) most powerful test for a simple hypothesis.

The decision rule of the CUSUM chart runs off the cumulative statistic

$$C_t = \sum_{j=1}^{t} (Z_i - k)$$

where Z_i is the standardized normal of each observation,

$$Z_i = \frac{(\bar{x}_i - \mu_0)}{\sigma_{\bar{x}}}$$

and the common choice for k is 0.5 (McCulloh, 2004), which corresponds to a standardized magnitude of change of 1. The CUSUM control chart sequentially compares the statistic C_t against a control limit A' until $C_t > A'$. Since we are not interested in concluding that the network is unchanged, the cumulative statistic is

$$C_t^+ = \max\{0, Z_t - k + C_{t-1}^+\}$$

The statistic C_t^+ is compared to the constant control limit, h^+. If $C_t^+ > h^+$, then the control chart signals that an increase in a network measure has occurred. Since this rule only detects increases in the mean, a second cumulative statistic rule must be used to detect decreases in the mean.

$$C_t^- = \max\{0, -Z_t - k + C_{t-1}^-\}$$

which signals a decrease in a network measure's mean when $C_t^- > h^-$.

The CUSUM control chart was selected for two reasons. First, this chart is well suited to detecting small changes in the mean of a process over time. In terms of a social network, this is a desired quality because one would not expect a social network to change dramatically between short time periods. By casual observation, one could conclude that a person's friends generally stay the same from week to week and not expect drastic changes in that social network. In addition, drastic changes in the network are normally quite obvious, but since the CUSUM is good at detecting slight changes it may be able to provide early warning for drastic changes, or reveal when more subtle changes have occurred. A second benefit of the CUSUM control chart is its built-in change point detection. After the control chart signals, the most likely change point is found by tracing the C statistic back to the last time it was zero. This allows the time of the change in the network to be calculated quickly and easily.

3. METHOD

Social network change detection algorithms are implemented in much the same way a control chart is implemented in a manufacturing process. The average graph measures for density, closeness, and betweenness centrality are calculated for several consecutive time-periods of the social network. When these measures appear to have stabilized over time, the "in-control" mean and variance for the measures of the network are calculated by taking a sample average and sample variance of the stabilized measures. The subsequent, successive social network measures are then used to calculate the CUSUM's C^+ and C^- statistics. These were then compared to a control limit to determine when or if the control chart signals a change in the mean of the monitored network measure. Upon receiving a signal, the change point is calculated by tracing the signaling C^+ or C^- statistic back to the last time period it was zero. In order to continue running the control chart after a signal, the in-control mean and variance are recalculated after the network measures have stabilized following the change.

The suspected time periods when the network appears to be significantly changing can be estimated using the CUSUM statistic. The network can then be studied in depth across these time periods in the wide variety of network measures to determine the extent of changes to the network structure. Further study can also be directed towards determining changes in the environment in which the network operates during those time-periods.

4. DATA

Two data sets are used to demonstrate the efficacy of the social network change detection approach. The first data set is email traffic from a group of 24 Army officers in a one year graduate program at Columbia University. This program is known as the Tactical Officer Education Program. The second data set is an open source Al-Qaeda social network. Details of these data sets are provided.

Tactical Officer Education Program e-mail Network

The Tactical Officer Education Program (TOEP) is a one-year graduate program run as a joint effort by the United States Military Academy (USMA) and Columbia University. Each year, twenty-four Army officers (referred to in this study as TOEPs 1 through 24) enter the program to earn a Master's degree in Social-Organizational Psychology with a concentration in Leadership and to prepare for service as mentors for West Point's cadet companies during the following two years. Social network data on email communication was collected for 24 weeks. Details regarding the data collection and network properties are described in McCulloh, et. al. (2007).

The data were pre-processed before any social network change detection algorithms were performed. The first step of processing the raw data was to remove all emails sent outside of the TOEP network. The primary concern of the study was to examine how email communication changed within the exclusive group of TOEP students. This required that records of emails sent to non-TOEPs and email addresses of non-TOEPs in messages that were sent to mixed parties were deleted. Thus, all subsequent network pictures would only involve the email communication among the 24 TOEPs. Despite our best efforts though, the network information can only be viewed as "near" complete as emails sent using Webmail are not collected because of limitations of the data collection software (McCulloh, et. al. 2007).

The data were then separated it into weekly time periods. Too much variance existed in the data set if it were to be divided into monthly time periods (McCulloh, et. al. 2007). This variance was due to communication patterns that changed between months of schoolwork (e.g., October and February) and those of long break periods (e.g., December and March). These large changes in communication patterns would prevent unbiased calculation of the baseline measurements with which to calibrate the control chart. Dividing the data based on days provided too much resolution and was also unacceptable as network communication patterns change dramatically from weekdays to weekends.

The network measures of interest were selected because they should theoretically follow or approximate a normal distribution due to the central limit theorem. For veracity, the measures' distributions were verified so that usage of the CUSUM Control Chart could be justified. Each of the network measures were fit with five continuous distributions: normal, uniform, gamma, exponential, and chi-squared. Least Squares was used to determine the best overall distribution for each measure. The distribution with the best fit for betweenness and density network measures was the Gamma Distribution. This invalidated further usage of the CUSUM Control Chart to detect changes in these network measures over time.

Observing that the average network measures followed a distribution other than the normal distribution, violates the central limit theorem and warranted further investigation. Upon deeper exploration of the data, it was found that certain subjects stopped sending email at some point in the study and did not send email again. The principal investigator interviewed these subjects and found that they had experienced technical problems during the study and had reformatted their hard drive, thereby erasing the collection patch. Other subjects began to rely on webmail, which bypassed the collection patch. Therefore, the communication data collected was incomplete and not identically distributed. Subjects, whose data collection was incomplete, were eliminated from further study. Average network measures calculated on the reduced data set did follow a normal distribution. A communication network for the reduced data set is shown in Figure 1 for the week of 29 October 2007.

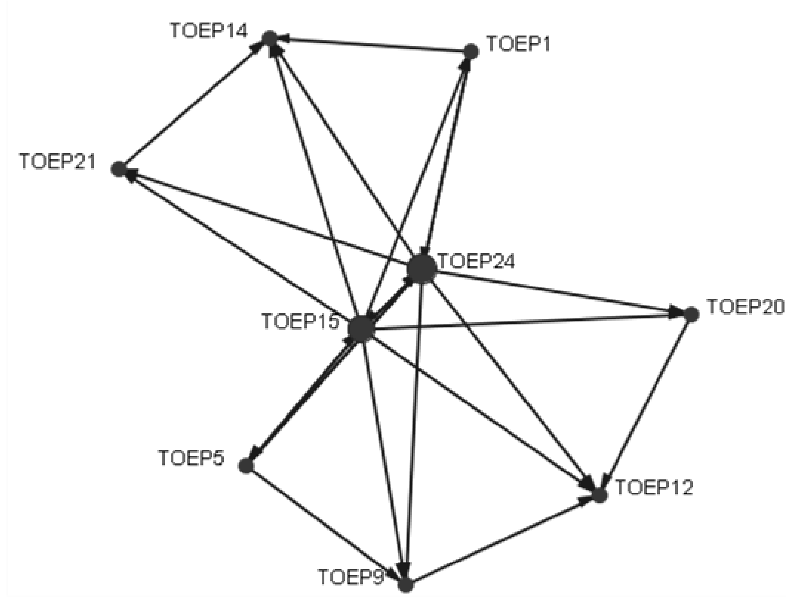

Figure 1 Email Network of Active TOEPs During Week of 29 October 2007

Using this much smaller, but complete network, the three network measures of interest were all found to be normally distributed. Determining baseline values, however, was still not possible because the network contained too much variance. There was no stable network measure behavior. In order to account for the variance caused by differing schedules week to week, we examined a copy of the TOEP planning calendar for the entire year. The calendar combined with interviews with participants allowed investigators to determine the number of significant events from a variety of categories that occurred each week. The significant events based on qualitative assessments by the participants were Academic Requirements, the Next Week's Academic Requirements, Administrative Events (such as a class trip or cancelled class), Group Projects, Social Gatherings, and Days Off.

Using MINITAB Statistical Software, analysis of variance (ANOVA) tests were run on predictors to determine if they were statistically significant factors in determining network measures. Days Off was the most significant factor, due to Christmas break in the middle of the 24 week study, however once these weeks were removed from the study, Days Off was no longer a significant factor in any model. The best linear regression model obtained from first semester (12 weeks) data for closeness based on the number of group projects, the number of social gatherings, and the number of emails sent each week found in Table 1 was,

$$\text{Closeness} = 0.18 - 0.11(\text{Group Projects}) + 0.11(\text{Social Gatherings}) + 0.0074(\text{Number of Emails})$$

Table 1 *ANOVA Table for Closeness Predictors*

Predictor	Coefficient	SE Coefficient	T	P	VIF
Constant	0.18	0.034	5.4	0	

Group Projects	-0.11	0.05	-2.1	0.05	1.3
Social	0.11	0.04	2.89	0.01	1.3
Number of Emails	0.0074	0.00084	8.77	0	1

This model has an adjusted R^2 value of 79.8%, accounting for a large majority of the variance in the network measure and a predictive R^2 value of 70.9%. Slightly surprising from this model is the effect of group projects on closeness. An increase in group project work was correlated with a decrease in communication. This might be due to the fact that as a group project comes due, the subjects may communicate more with their immediate team of group members, and communicate more face-to-face, but overall they decrease communication outside of their working groups and through email in order to focus on the project. The positive effects of Social Gatherings and more emails sent over the week had the foreseen effect of improving group closeness.

The model created from the first semester was used to predict the average closeness value for the second semester. The CUSUM control chart was applied to the residual error between the prediction and the actual second semester data. This allowed the investigators to conduct real-time monitoring of a social group for change.

Al Qaeda Communications Network

The Center for Computational Analysis of Social and Organizational Systems (CASOS) at Carnegie Mellon University created snapshots of the annual communication between members of the al Qaeda organization from its founding in 1988 until 2004 from open source data (Carley, 2006). The data is limited in that we do not know the type, frequency, or substance of the communication and all links are non-directional, meaning we do not know who initiated communication with whom. Finally, the completeness of the data is uncertain since it only contains information available from open sources. The data is unique in that it provides a network picture of a robust network over standard time-periods of one year.

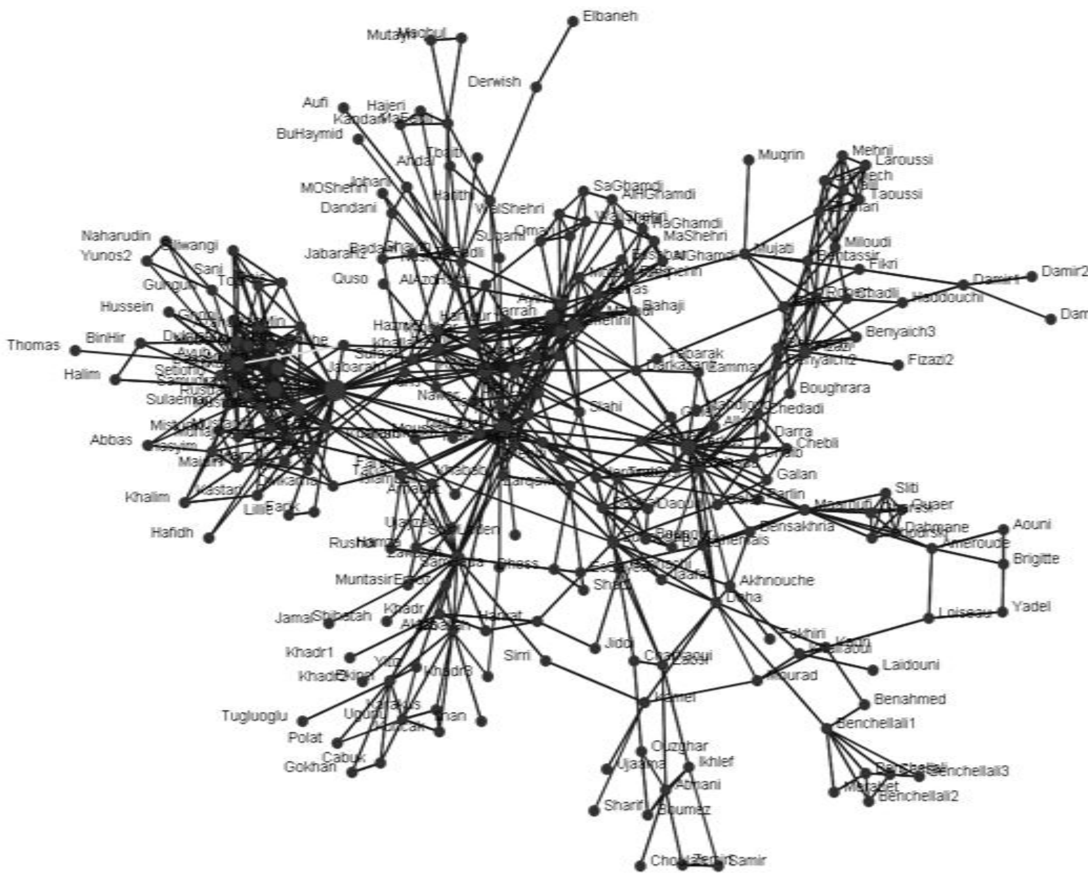

Figure 2 Monitored al Qaeda Communication Network for Year 2001

Using the network snapshots for each year time-period, the average social network measures were calculated and plotted for betweenness, closeness, and density. Each of these measures increased from 1988 until 1994, and then leveled off. There are many possible reasons for this burn-in period, such as the quality of our intelligence gathering on al Qaeda and the rapid development and reorganization of a fast growing organization. In al Qaeda's early years, access to the infant organization may have been limited, as well as the resources devoted to tracking a small, new, and relatively unaccomplished terrorist network. The organization itself may have also been changing drastically during its first years by actively recruiting new members, and shifting its structure to accommodate new resources and infrastructure. For this reason, the averages for each measure and standard deviation were calculated over the five years that follow the burn-in period that ended in 1994. The CUSUM control chart was then used to monitor the three measures above from 1994 to 2004. Figure 3 displays the plot of each average social network measure in the Al-Qaeda network. The general trends for each of these measures are the same throughout the entire time period.

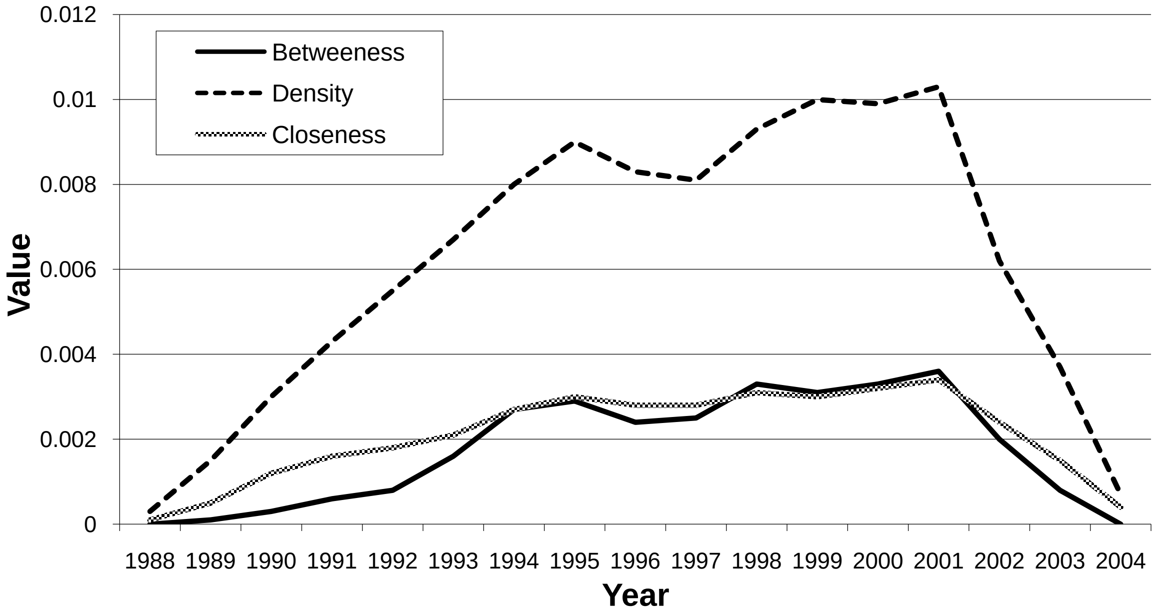

Figure 3 Plot of Selected Network Measures of al Qaeda Organization

5. RESULTS

The approach proposed in this paper was found to be successful at predicting the most significant events in both data sets. Although the approach varied slightly between the two data sets, we have been able to show that statistical process control is effective at identifying organizational change in these two social groups. For the TOEP data set, there were relatively few nodes and many time periods. Therefore, variance effects were much stronger. It was necessary to control for this effect by constructing a statistical model and conducting statistical process control on the model residuals. With the al Qaeda data set, however, we were able to conduct statistical process control directly on the network measures, due the greater stability of the network measures.

Being able to predict the closeness of the TOEPs communication network was essential in explaining much of the variance in the network. The control chart could then be used to determine when the network changed away from the model. In effect, when is the model no longer providing a good prediction? Using the closeness model developed from data obtained during the first semester of the TOEP graduate program, predicted values were calculated for each week of the second semester using the number of social gatherings and group projects from the TOEP calendar and the number of emails sent by observation. These were compared with the observed network measures. The residuals were verified as normally distributed to meet the prerequisites of the CUSUM Control Chart. The C^+ and C^- statistics were calculated for each week using a k value of 0.5 and a control limit of 3. By running a Monte Carlo simulation with these settings, we were able to predict that the CUSUM would have a false alarm rate of once out of every 59 observations or practically once every year. A graph of the CUSUM statistic is in Figure 4.

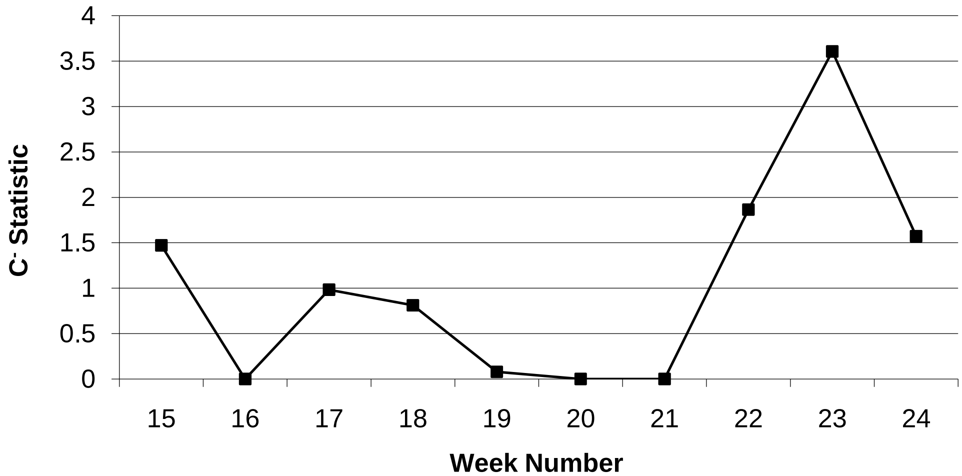

Figure 4 Plot of closeness CUSUM statistic for nine active TOEPs

Figure 4 indicates that the control chart signals on Week 23 (see Table 2). Week 23 was the week that the TOEPs took the comprehensive exam for their graduate program. It was the most significant academic event of the year. Tracing the C^- statistic back to the last time it was zero, the most likely change point was during Week 21. Upon first examination, Week 21 looks like it should be a typical academic week, with no unusual events or graded projects. However, based on interviews conducted with TOEPs after the signal was detected, it was discovered that Week 21 was a critical preparation week prior to the comprehensive exam when the study questions for the exam were sent to the students. Thus, the CUSUM control chart signals on Week 23 as it represents a significant departure from the value predicted by the model.

Table 2 *CUSUM Statistic Values for Closeness Network Measure*

Week	Closeness	Model	Z	C+	C-
15	0.3332	0.4712	-1.9714	0.0000	1.4714
16	0.5134	0.3798	1.9086	1.4086	0.0000
17	0.2760	0.3798	-1.4829	0.0000	0.9829
18	0.3332	0.3562	-0.3286	0.0000	0.8114
19	0.5406	0.5243	0.2329	0.0000	0.0786
20	0.6536	0.5745	1.1300	0.6300	0.0000
21	0.4977	0.3916	1.5157	1.6457	0.0000
22	0.1258	0.2913	-2.3643	0.0000	1.8643
23	0.2646	0.4215	-2.2414	0.0000	3.6057
24	0.5226	0.4152	1.5343	1.0343	1.5714

The CUSUM control chart implemented on the residuals of a communication model proved to be effective at detecting organizational change in the TOEP program. It is also interesting to note, that a decrease in communication can indicate that a major event is about to occur, as the subjects rely less on email and more on face-to-face communication and study groups.

The success of social network change detection on the TOEP data set warranted further investigation. The al Qaeda data set offered data with more nodes, that were aggregated over a much larger time period. At the same time, we were able to identify at least one major event in al Qaeda's history. The question was asked, "can we identify September 11 from the social network?" Perhaps more importantly, "can we identify the point in time when the organization changed into such a threatening menace?"

The reference value, *k*, and the control limit, *h*, were set at 0.5 and 4 respectively for all of the social network control charts based on no other reason than widely used industry standards (McCulloh, 2004). This would correspond to a false alarm once every 168 years. Figure 5 shows the CUSUM statistic for the average closeness that is plotted in Figure 4. It can be seen that the CUSUM statistic in Figure 5 is a more dramatic indication of network change than simply monitoring the network measure in Figure 4. This is a result of the CUSUM statistic taking into account previous observations and deviations from the mean in the network measure. A single observation of a network measure that is slightly higher than normal may not indicate a change in the network; however multiple observations that are slightly higher than normal may indicate a shift in the mean of the measure.

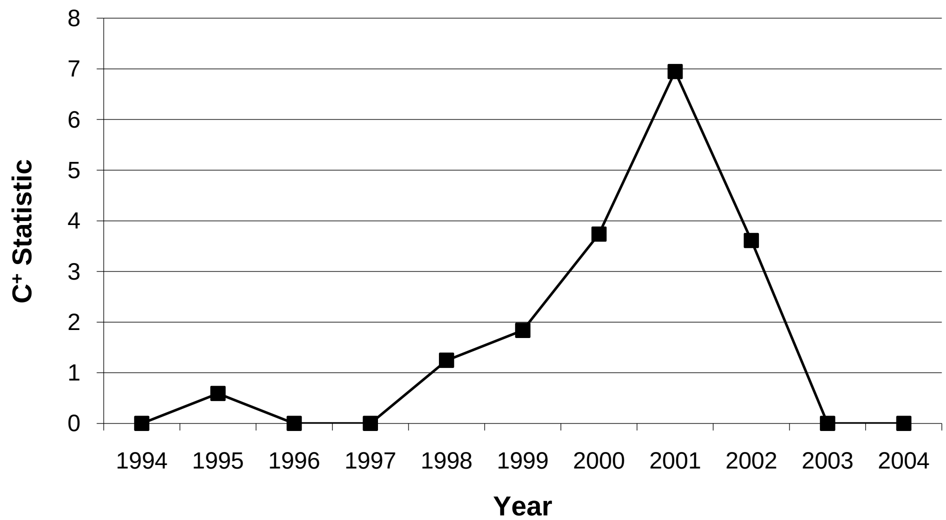

Figure 2 Plot of Closeness CUSUM Statistic of al Qaeda

Recall that the CUSUM will detect either increases or decreases in a measure, but not both. Therefore, two control charts must be run for each social network measure monitored. One chart is used to detect increases and the other chart for decreases. Table 3 displays the CUSUM statistic values for closeness measure. The trends in the data for the closeness measure are the same as the betweenness and density measures.

Table 3 *CUSUM Statistic Values for Closeness Network Measure*

Time	Closeness	Z	C^+	C^-
1994	0.0027	-0.8729	0.0000	0.3729
1995	0.0030	1.0911	0.5911	0.0000
1996	0.0028	-0.2182	0.0000	0.0000
1997	0.0028	-0.2182	0.0000	0.0000
1998	0.0031	1.7457	1.2457	0.0000
1999	0.0030	1.0911	1.8368	0.0000
2000	0.0032	2.4004	3.7372	0.0000
2001	0.0034	3.7097	6.9469	0.0000
2002	0.0024	-2.8368	3.6101	2.3368
2003	0.0015	-8.7287	0.0000	10.5655
2004	0.0004	-15.9300	0.0000	25.9955

It can be seen in Table 3 that the CUSUM statistic exceeds the control limit of 4 and signals that there might be a significant change in the al Qaeda network between the years 2000 and 2001. Therefore, an analyst monitoring al Qaeda would be alerted to a critical, yet subtle change in the network prior to the September 11 terrorist attacks.

The CUSUM control chart also has a built in feature for determining the most likely time that the change occurred. This time is identified as the last point in time when the CUSUM statistic is equal to zero. For all measures, this point in time is 1997. To understand the cause of the change in the al Qaeda network, an analyst should look at the events occurring in al Qaeda's internal organization and external operating environment in 1997.

Several very interesting events related to al Qaeda and Islamic extremism occurred in 1997. Six Islamic militants massacred 58 foreign tourists and at least four Egyptians in Luxor, Egypt (Jehl, 1997). United States and coalition forces deployed to Egypt in 1997 for a bi-annual training exercise were repeatedly attacked by Islamic militants. The coalition suffered numerous casualties and shortened their deployment. In early 1998, Zawahiri and Bin Laden were publicly reunited, although based on press release timing, they must have been working throughout 1997 planning future terrorist operations. In February of 1998, an Arab newspaper introduced the "International Islamic Front for Combating Crusaders and Jews." This organization established in 1997, was founded by Bin Laden, Zawahiri, leaders of the Egyptian Islamic Group, the Jamiat-ul-Ulema-e-Pakistan, and the Jihad Movement in Bangladesh, among others. The Front condemned the sins of American foreign policy and called on every Muslim to comply with God's order to kill the Americans and plunder their money. Six months later the US embassies in Tanzania and Kenya were bombed by al Qaeda. Thus, 1997 was possibly the most critical year in uniting Islamic militants and organizing al Qaeda for offensive terrorist attacks against the United States.

6. CONCLUSION

Control charts are a critical quality-engineering tool that assist manufacturing firms in maintaining profitability (Montgomery, 1991; Ryan, 2000). The TOEP and al Qaeda examples demonstrate that social network monitoring could enable analysts to detect important changes in the monitored communication of both command and control networks as well as terrorist networks. Furthermore, the most likely time that the change occurred can also be determined. This allows one to allocate minimal resources to tracking the general patterns of a network and then shift to full resources when changes are determined[1].

This paper describes an algorithm for change detection, and then demonstrates its ability to detect changes in networks. No doubt other change detection methods will emerge. Our point, is that it is critical to be able to detect change in networks over time and to determine when those changes are not simply the random fluctuations of chance. The strengths of the proposed method are its statistical approach, ability to quantify the rate of false alarm, a wide range of social network metrics suitable for application, its ability to identify change points in organizational behavior, and its flexibility for various magnitudes of change. The proposed method is limited to normally distributed network measures, and a period of dynamic equilibrium must be assumed to estimate parameters of the control chart. Other limitations of the algorithm cannot yet be determined as this is the first application of statistical process control methods to the problem of social network change detection. Future research will provide much greater insight into the strengths and limitations of this approach to the problem. The remainder of this section will identify specific areas of caution when interpreting findings and identify areas for future research.

The empirical results described in this paper, such as the detection of change in the al Qaeda network should be viewed with caution. We present them here purely to illustrate the methodology. Limitations on the data make it difficult to determine the validity of the results; thus, we should simply view these results as showing the promise of this methodology. The IkeNet data is a small sample capturing only email traffic and not all communication and interaction among participants. The fact that even in this small sample of behavior we were able to systematically detect a key change suggests the value of the proposed approach.. The al Qaeda data, was based on open source information. As such it is an incomplete representation of interaction in that terror network. We cannot be sure that we have the entire communication network, or even a true picture of the observed communication network. However, the fact that our technique detects a change corresponding with the 9/11 attacks is intriguing. This work suggests that our approach may provide some ability to detect change even when there is incomplete information.

[1] Two social network change detection algorithms (Shewhart X-Bar and the Cumulative Sum) are available in the "Statistical Network Monitoring Report" in the software tool, Organizational Risk Analyzer (ORA) available through the Center for Computational Analysis of Social and Organizational Systems (CASOS), http://www.casos.cmu.edu.

That being said, it is important that future work examine the errors associated with this technique, both the false positives and false negatives. Future work should also consider the sensitivity of this approach to missing information, and to the reason why the information is missing. For example, data sets collected post-hoc that focus on activity around an event, such as the al Qaeda data are prone to errors of missing nodes and as a result links prior to the event. Whereas, data sets collected based on opportunity, such as the IkeNet data, are prone to missing links among the nodes.

In order to rectify the above shortcomings, future research should focus on near-complete datasets with high resolution. Higher resolution involves taking many snapshots of the network. This may mean, simply an increase in frequency, e..g. changes by month, or it may mean a longer time horizon, e.g., more years. The right choice will depend on the problem where we want to detect network change. More data points will provide more opportunities to detect changes while they are still small, instead of allowing them to incubate and grow as was the case for the al Qaeda data. Larger datasets will also provide near continuous network measures permitting the use of control charts for continuous data. Near complete data means that the data should cover the communication network with little or no missing information for a large contiguous period. Here one might consider simply tracking a group in general, as opposed to focusing on tracking relative to a specific event. Data such as that on the US Congress or Supreme Court that is regularly output might provide a good source of data.

Another limitation of this approach is that it assumes that network measures are normally distributed. Research on the distributions is needed. Preliminary work on these distributions suggests that the assumption of normality does not hold for small networks, extremely sparse networks, and for certain metrics (Kim and Carley, working paper). Future work should consider these factors to determine the range of networks for which this approach will work. Clearly, if the network measures are normally distributed, the CUSUM control chart can be used to monitor network change. If they are not, a different control chart must be used or a new approach at the problem made. Future work should address this issue.

Future research should also look at the sensitivity of the optimality constant, *k* and control limit values of the CUSUM Control Chart for network measure change detection. As stated earlier, these values are generally arbitrarily chosen and then optimized for the process. By using further Monte Carlo simulations, a researcher should determine which parameter value would be best in detecting certain types of changes such as sudden large changes or slow creeping shifts. Usage of control charts on comparing models and observations should also be studied to see what specific conclusions can be obtained.

Multi agent simulations would also provide valuable insight into the performance of control charts for social network change detection applications. Simulations would allow an investigator to introduce various changes into a simulated organization and evaluate the time to detect for different algorithms. Simulations provide an efficient means of evaluating change detection on social networks. More importantly, however, is the ability to create more controlled experiments, by fixing certain variables, exploring others, and using many replications to estimate error. Simulation studies will be extremely useful in exploring extensions of this methodology.

Social network change detection is important for identifying significant shifts in organizational behavior. This provides insight into policy decisions that drive the underlying change. It also shows the promise of enabling predictive analysis for social networks and providing early warning of potential problems. In the same way that manufacturing firms save millions of dollars each year by quickly responding to changes in their manufacturing process, social network change detection can allow senior leaders and military analysts to quickly respond to changes in the organizational behavior of the socially connected groups they observe. The combination of statistical process control and social network analysis is likely to produce significant insight into organizational behavior and social dynamics. Immediate applications to counter terrorism are obvious. As a scientific community we can hope to see more research in this area as network statistics continue to improve.

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