Temporal Visualization of Social Network Dynamics: Prototypes for Nation of Neighbors

Jae-wook Ahn[1,2], Meirav Taieb-Maimon[2,3], Awalin Sopan[1,2], Catherine Plaisant[2], and Ben Shneiderman[1,2]

[1] Department of Computer Science
[2] Human-Computer Interaction Lab, University of Maryland, College Park, MD, USA
{jahn,awalin,plaisant,ben}@cs.umd.edu
[3] Ben-Gurion University of the Negev, Beer-Sheva, Israel
meiravta@bgu.ac.il

Abstract. Information visualization is a powerful tool for analyzing the dynamic nature of social communities. Using Nation of Neighbors community network as a testbed, we propose five principles of implementing temporal visualizations for social networks and present two research prototypes: NodeXL and TempoVis. Three different states are defined in order to visualize the temporal changes of social networks. We designed the prototypes to show the benefits of the proposed ideas by letting users interactively explore temporal changes of social networks.

Keywords: Social Network Analysis, Information Visualization, Social Dynamics, User Interface, Temporal Evolution.

1 Introduction

Information visualization is a powerful tool for analyzing complex social networks so as to provide users with actionable insights even against large amount of data. Numerous social network analysis (SNA) methods have been coupled with visualization to uncover influential actors, find helpful bridging people, and identify destructive spammers. There are many research tools and a growing number of commercial software packages, some designed for innovative large scale data analysis, while others deal with common business intelligence needs. However, few approaches or tools sufficiently address the problem of how to analyze the social dynamics of change over time visually. Communities are not static. Like living organisms, they evolve because of cultural, environmental, economic, or political trends, external interventions, or unexpected events [4]. Technological developments have also had strong impacts on social changes, a phenomenon that has become influential with the arrival of mobile communications devices and social networking services.

Nation of Neighbors (http://www.nationofneighbors.com) (NoN) is a new web-based community network that enables neighbors to share local crime, suspicious activity, and other community concerns in real time. The NoN developers

J. Salerno et al. (Eds.): SBP 2011, LNCS 6589, pp. 309–316, 2011.

have achieved an admirable success with "Watch Jefferson County" that empowers community members to maintain the security in their local neighborhoods. It began in Jefferson County, WV, but the NoN team is expanding their efforts across the U.S. in many communities. We are collaborating with them to provide appropriate tools that can help community managers explore and analyze the social dynamics embedded in their social networks.

This paper introduces our first efforts to visualize the temporal social dynamics on top of the NoN testbed. Due to the nature of the social dynamics, we need a method to interactively *compare* the time slices of social networks. In previous attempts, we combined statistics and the visualization [12] for interactive network analysis and to support multiple network comparisons using tabular representations [3]. The current work integrates the best of these two approaches by using the graphical representations and statistics to enable researchers and community managers to compare networks over time.

2 Related Studies

The importance of capturing the network change over time has been the origin of previous attempts of temporal network visualizations. Two common approaches were used. The first approach plots network summary statistics as line graphs over time (e.g. [1,7]). Due to its advantage in detecting the increase and decrease of certain statistics, many systems adopted this idea. In the VAST 2008 mini challenge 3:"Cell Phone Calls" [8] various teams (e.g. SocialDynamicsVis and Prajna teams) used similar approaches such as line graphs to characterize changes of the cell phone call social network over ten days. SocialAction integrated a time-based interactive stacked graph to display a network property such as degree. Each stack represented a node and the thickness of each stack on a given day represented its degree. The interactive visualization facilitated the exploration of the change in the degree of each node over time.

The second approach is to examine separate images of the network at each point in time. Powell et al. [13] used such a snapshot approach to show network changes over time. They distinguished new arrivals with triangles and incumbent with circles. They also used size encoding for degree; a shortcoming of such size and shape encoding might be that the new arrivals having small degree are very small and sometimes the triangles and circles are too small to be distinguishable. Furthermore, in snapshot view we cannot compare a network easily in two timeslots as the layout algorithms can dynamically change the node positions. Durant et al. [2] presented a method for assessing responses and identifying the evolution stages of an online discussion board. Their snapshot-based network visualizations could show different node positions between time.

Recent work offered improvements in static visualizations by applying dynamic visualization such as network "movies." Moody [11] distinguished flipbook style movies where node-positions were fixed but connectivity formation was captured and dynamic movies where node-positions changed over time. Condor (or TeCFlow) [5,6] introduced sliding time frames and animated the network changes inside a specific time frame with/without the history before that. However, approaches which use animations might be distracting for users to track changes in the network. Specifically, it might be difficult to track new nodes when the position of the nodes and edges keep changing. Human eyes can miss minute but important changes in visual spaces. For example, users can only notice the overall growth of an entire network while missing that the inclusion of a certain node is responsible for a significant change. A possible suggestion can be found in Trier's work [14] where he used node degree as a measure of inertia so the high degree nodes move less across time and made the dynamic movie less distracting. C-Group [10] visualized the affiliation of focal pairs and dynamically defined groups over time using static, dynamic layouts, or animations. It fixed the focal pair positions and could minimize distraction in the animation mode.

In the present study, we suggest an approach that keeps the nodes from earlier time slots in fixed positions but also accentuates new arriving nodes and links using color coding while using intensity as a measure of aging. This overcomes the distraction caused by dynamic fast paced network movies and also fulfills the need of identifying the deletion and addition of nodes.

3 Social Network Dynamics Visualization – Ideas

Our main concern about the temporal dynamic visualization for social networks is how to *show* and *compare* the changes over time. We established the following principles for this purpose.

1. Static (unchanged) parts of a graph should remain fixed to avoid distraction.
2. Changes should be visually manifest for easy comparisons.
3. Comparisons across time should be easily and interactively explorable.
4. Temporal change of the node and edge attributes should be discoverable.
5. Temporal change of a sub-graph and its attributes should be discoverable.

Some approaches do not fix the locations of the static elements, but since users' main interests are about what is *changing*, fixing the locations of the unchanged nodes and edges is advantageous. For the changing components, we defined three states: (1) **addition**, (2) **removal**, and (3) **aging**.

In social networks, new relationships can be added or removed to/from the entire network. At the same time, existing relationships can become inactive after they were added to the network. Especially, there are instances where the removal of the relationships is not quite clear and older activities are just becoming inactive. For example, a reference once made in a citation network cannot be removed, even though it can be less important as time passes. We tried to distinguish these three states in our network visualization. Finally, users need to easily compare the network at any pair of time points.

4 Social Network Dynamic Visualization Systems

Based on these principles, we built two example systems: (1) by using NodeXL and (2) by adopting a time-slider for temporal exploration. NodeXL [9] is an

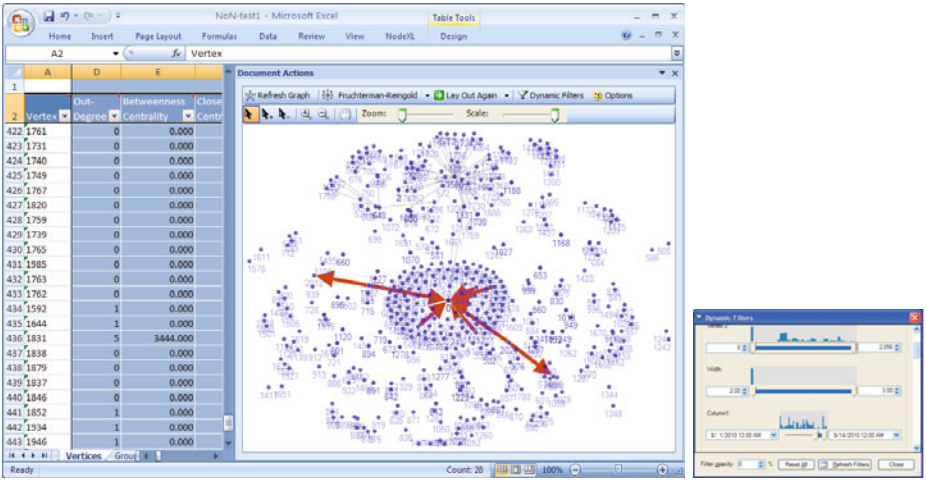

Fig. 1. Visualizing the NoN invitation network dynamics using NodeXL. Nodes and edges mean users and invitations respectively. Red edges are the ones in September 2010. Using the dynamic filter (right), it can filter out the edges before August and emphasize more recent invitations (8/1/2010 – 9/14/2010, the edges in the upper part).

extension to Microsoft Excel 2007/2010 that makes the SNA flexible and interactive. The node-edge connectivity data stored in Excel worksheets are directly converted to graph visualizations. Popular SNA statistics can be calculated and then be mapped to visual attributes. It is highly configurable by users through the common Excel operations and the NodeXL metrics, visual properties, clustering, and layout control panels. The second system called TempoVis was built as a standalone application prototype, in order to implement a time-based network exploration more interactively. We used two datasets provided by NoN: user invitation and forum conversation networks. The former contained information about who invited whom to the NoN service (July 2009 – September 2010). The latter showed which user created a thread and who replied to whom in the NoN forums (November 2005 – August 2010) with timestamps.

4.1 Spreadsheet-Based Approach Using NodeXL

Fig. 1 shows an example of temporal visualization using NodeXL. The worksheet stores the node (vertex) and edge information. The graph theory statistics such as centrality are calculated for each node too (for example, Vertex 1831's Betweenness Centrality=3444.0). In the right-hand side panel, the network is visualized using the well-known Fruchterman-Reingold force-directed layout algorithm (the layout was computed from the latest time point). It visualizes the invitation network of the NoN members accumulated for 14 months.

The overall network layout does not change by the dynamics of the invitation network over time. However, the temporal dynamics in the individual invitation level are represented clearly. The red edges (arrowed) in Fig. 1 indicates that they were added in a specific time point, September 2010. At the same time, the nodes and edges created earlier than a specific time (or removed) can be painted in different colors or dynamically filtered out as in Fig. 1 in order to implement the three states (Section 3). The graph elements are tightly linked to the worksheet, so that users can examine specific attributes of any nodes, edges, or subgraphs interactively while they are switching between the worksheet and the visualization. However, despite the very rich and flexible feature set that helps users to compare the data and the visual representation interactively, easy exploration across multiple time points is yet to be added to NodeXL. Even the dynamic filter requires some manual endeavors. Therefore, we built the next prototype that focused more on easier time-based exploration.

4.2 TempoVis: Adding Time-Based Interactive Exploration

TempoVis (Fig. 2) is a standalone prototype that shares the same principles but we designed it to maximize the ability to explore the time interactively. It is equipped with a time-slider with which users can navigate through different time points (months in this example). They can move the slider thumb left and right, to view the different monthly states. Users can navigate back and forth through

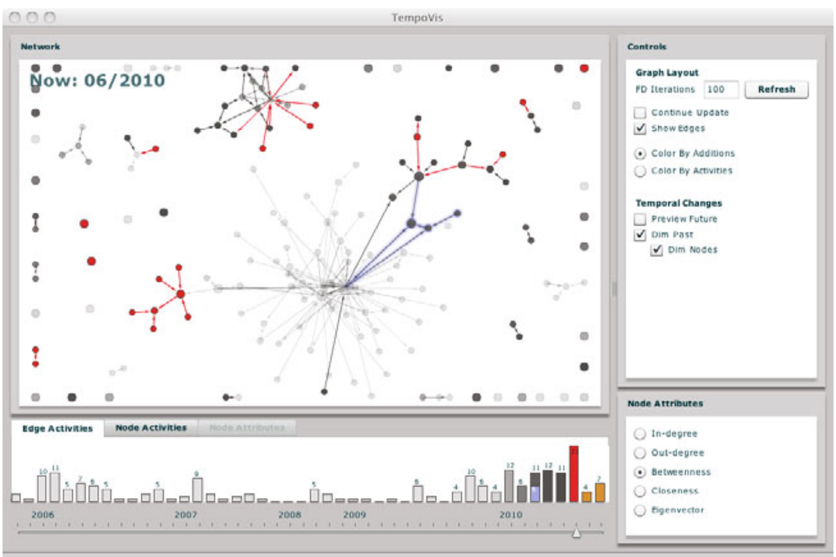

Fig. 2. TempoVis: Navigating through time using a time-slider interface (NoN conversation network). The nodes and the edges mean users and their conversations respectively. The red edges indicate the conversations of a specific month (June 2010) set by using the slider blow. The big low-intensity cluster (center below) was introduced earlier than the high intensity cluster (center top) that was added recently. Blue edges mean user selections. Node size is proportional to graph statistics dynamically calculated at each time point.

time to study the growth of the network. On top of the slider, a histogram shows the frequency of the activities. This arrangement enables users to see the overview of the activities and compare the changes over time during navigations.

TempoVis uses the force-directed layout and the red colored nodes/edges indicate new activities of the current month. The slider is set to June 2010 in Fig. 2 and the red edges and nodes represent the conversations added in that month. The gray items are the conversations that took place *before* June 2010. Fig. 3 (a) and (b) show how users can compare adjacent months using the time-slider and visualization. By switching (a) and (b) using the slider, they can easily discover how many new conversations (three) were added. Whereas (a) and (b) cannot give information about removed or aging conversations, Fig. 3 (b') distinguishes the current month's activities and the other older conversations by gradually decreasing the intensity as they age. We can see that the conversations added in the previous month (red in (a)) are painted in higher intensities while some far older nodes/edges are barely visible. This effect gives users information about which activities were more recent and which activities took place long before. Zhang et al. [15] used a similar approach to represent the age of the edges in an invitation network but they did not support the dynamic update of the edge intensities by navigation. A sigmoid function was used in order to implement the smooth drop of the color intensity by time.

Even though this network visualization provides users with information about the temporal change about the entire network, they may also be interested in changes in part of a graph. Therefore, we provided a marquee-selection tool that lets users select any part of the graph. For example, in Fig. 2, the user was interested in a small group of conversations (highlighted in blue by the user). S/he could marquee select them and then the information about the selected edges were dynamically overlaid on the histogram, showing that the conversations were done in March 2010 and the frequency was 9.

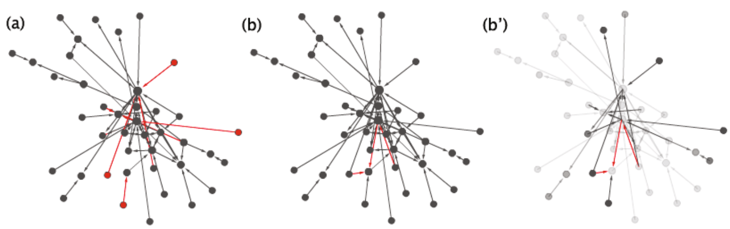

Fig. 3. Comparing February (a) and March 2007 (b and b'). Older activities can be painted in lower intensities (b') to show their age.

5 Discussions and Conclusions

This paper introduced our efforts to visualize the temporal dynamics of social networks. Five principles for implementing visualizations that support interactive exploration over time were proposed. We presented two prototypes according to these principles and showed two datasets from the Nation of Neighbors social networking service: one utilizing the NodeXL extension to Microsoft Excel and TempoVis as a standalone application. The former approach is very flexible and easy to access because it is based on the well-known spreadsheet application and highly configurable. TempoVis was aimed to test the potential of a user interface element that could facilitate temporal navigation – a time-slider. We expect the NodeXL-based idea will be preferred by the users who are proficient with the data manipulation using spread sheets. TempoVis will be useful for the tasks where more exploratory and interactive temporal comparisons are required.

In order to evaluate our prototypes and understand their usefulness from a network manager's point of view, we consulted with Art Hanson, the NoN lead designer. He said: "The temporal visualizations would help focus limited resources on community groups who could best benefit from assistance, spot emerging trends, and identify the most influential users. The tools would also help NoN visualize the network effects resulting from changes to the NoN system and achieve the desired effect quickly with each new feature or design iteration." He could easily identify which group of NoN users showed different activities at a specific time point and use that information to manage and evaluate the community service. It was achievable by combining the time and the network information of the neighbors provided by our temporal visualization tools. We are planning more extensive user studies to validate the usefulness of our five principles and its implementations in the two visualization platforms.

The NoN team suggested to add the ability to distinguish node types (e.g. post and report) to the visualizations and to add the community group or location/distance information, so that they could link the temporal dynamics to community group activities or communications types. At the same time, we will also investigate how to locate sub-graphs and analyze their temporal dynamics. While fixing the locations of stable nodes/edges (principle 1) is useful, we are also planning to add a user option to dynamically redraw the graph layouts. The tasks such as observing large growth and change of clusters will require this feature. We are also considering to adopt multiple network views of user-selected time points in order to let users directly compare multiple time points. Enriching the visualization with additional attributes such as discussion topics will help differentiate various activities too. After more evaluation with community managers and network analysts we will embed the most valuable features into the NodeXL platform, while continuing to explore novel features in TempoVis.

Better understanding of network dynamics is necessary so that community managers can discover the triggers for growth, decay, active use, or malicious activities. Then they can develop strategies to promote growth and prevent decay and destructive interference. Social media have great potential for benefits in key domains such as community safety, disaster response, health/wellness, and energy sustainability. Better understanding of how to manage them effectively raises the potential for more successful outcomes.

Acknowledgements. We appreciate the support of Microsoft External Research for the development of the free, open source NodeXL (`http://www.codeplex.com/nodexl`) and for National Science Foundation grant IIS0968521, Supporting a Nation of Neighbors with Community Analysis Visualization Environments, plus National Science Foundation-Computing Research Association Computing Innovation Fellow, Postdoctoral Research Grant for Jae-wook Ahn. We appreciate the assistance of Art Hanson and the NodeXL team.

References

1. Doreian, P., Kapuscinski, R., Krackhardt, D., Szczypula, J.: A brief history of balance through time. The Journal of Mathematical Sociology 21(1), 113–131 (1996)
2. Durant, K., McCray, A., Safran, C.: Modeling the temporal evolution of an online cancer forum. In: 1st ACM International Health Informatics Symposium (IHI 2010), pp. 356–365 (November 2010)
3. Freire, M., Plaisant, C., Shneiderman, B., Golbeck, J.: Manynets: an interface for multiple network analysis and visualization. In: Proceeding of the 28th Annual SIGCHI Conference on Human Factors in Computing Systems, pp. 213–222 (2010)
4. Giddens, A.: Sociology. Polity, Cambridge (2006)
5. Gloor, P., Laubacher, R., Zhao, Y., Dynes, S.: Temporal visualization and analysis of social networks. In: NAACSOS Conference, June, pp. 27–29 (2004)
6. Gloor, P., Zhao, Y.: Analyzing actors and their discussion topics by semantic social network analysis. In: Tenth International Conference on Information Visualization, IV 2006, pp. 130–135. IEEE, Los Alamitos (2006)
7. Gould, R.: The origins of status hierarchies: A formal theory and empirical test. American Journal of Sociology 107(5), 1143–1178 (2002)
8. Grinstein, G., Plaisant, C., Laskowski, S., O'connell, T., Scholtz, J., Whiting, M.: VAST 2008 Challenge: Introducing mini-challenges. In: IEEE Symposium on Visual Analytics Science and Technology, VAST 2008, pp. 195–196. IEEE, Los Alamitos (2008)
9. Hansen, D.L., Shneiderman, B., Smith, M.A.: Analyzing Social Media Networks with NodeXL: Insights from a Connected World. Morgan Kaufmann, San Francisco (2010)
10. Kang, H., Getoor, L., Singh, L.: Visual analysis of dynamic group membership in temporal social networks. ACM SIGKDD Explorations Newsletter – Special Issue on Visual Analytics 9(2), 13–21 (2007)
11. Moody, J., McFarland, D., Bender-deMoll, S.: Dynamic network visualization. American Journal of Sociology 110(4), 1206–1241 (2005)
12. Perer, A., Shneiderman, B.: Integrating statistics and visualization: case studies of gaining clarity during exploratory data analysis. In: Proceeding of the 26th Annual SIGCHI Conference on Human Factors in Computing Systems, pp. 265–274 (2008)
13. Powell, W., White, D., Koput, K., Owen-Smith, J.: Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences. American Journal of Sociology 110(4), 1132–1205 (2005)
14. Trier, M.: Towards dynamic visualization for understanding evolution of digital communication networks. Information Systems Research 19(3), 335–350 (2008)
15. Zhang, J., Qu, Y., Hansen, D.: Modeling user acceptance of internal microblogging at work. In: CHI 2010 Workshop on Microblogging (2010)