2009 International Conference on Computational Science and Engineering

First Steps to NetViz Nirvana: Evaluating Social Network Analysis with NodeXL

Elizabeth M. Bonsignore*§, Cody Dunne *†, Dana Rotman*§, Marc Smith¶,
Tony Capone‖, Derek L. Hansen*‡, & Ben Shneiderman*†
* University of Maryland, College Park, MD 20742
§ Center for Advanced Study of Communities & College of Information Studies {drotman, ebonsign}@umd.edu
†Human-Computer Interaction Lab & Department of Computer Science {ben, cdunne}@cs.umd.edu
¶Telligent Systems Corporation marc.smith@telligent.com
‖Microsoft Corporation v-tonyc@microsoft.com
‡ dlhansen@umd.edu 301-405-7622 2118C Hornbake Library

***Abstract*—Social Network Analysis (SNA) has evolved as a popular, standard method for modeling meaningful, often hidden structural relationships in communities. Existing SNA tools often involve extensive pre-processing or intensive programming skills that can challenge practitioners and students alike. NodeXL, an open-source template for Microsoft Excel, integrates a library of common network metrics and graph layout algorithms within the familiar spreadsheet format, offering a potentially low-barrier-to-entry framework for teaching and learning SNA. We present the preliminary findings of 2 user studies of 21 graduate students who engaged in SNA using NodeXL. The majority of students, while information professionals, had little technical background or experience with SNA techniques. Six of the participants had more technical backgrounds and were chosen specifically for their experience with graph drawing and information visualization. Our primary objectives were (1) to evaluate NodeXL as an SNA tool for a broad base of users and (2) to explore methods for teaching SNA. Our complementary dual case-study format demonstrates the usability of NodeXL for a diverse set of users, and significantly, the power of a tightly integrated metrics/visualization tool to spark insight and facilitate sense-making for students of SNA.**

I. Introduction

The booming popularity of social networking is reflected in recent statistics from the Pew Internet & American Life Project [1]: the number of adult internet users who have a profile on an online social network site has more than quadrupled in the past four years, rising from 8% in early 2005, 16% in 2006, to 35% in December 2008. Over half of those adults maintain more than two online profiles, generally on different sites. They blog: 54% of college students read blogs and 33% write them; overall, 36% of adults read blogs and 13% write them, and almost 20% remix content into their own inventions to be shared online [2]. The widespread use of social networking applications has precipitated a greater need by more diverse users to understand how their online communities evolve and thrive. SNA tools are not just for scientists anymore. Moderators, administrators and other community experts also have a stake in learning more about the structural dynamics of their interactions. The emergent challenge for designers and educators is to build easy to learn interfaces that enable these users to discover community patterns and individual roles they might not otherwise see.

This paper relates the process and early results of 2 user studies, in which graduate students of information science (IS) and computer science (CS) learned SNA concepts and techniques while using NodeXL. Our aim is to focus on the unique features that made NodeXL learnable and usable. First, we provide an overview of the NodeXL tool. We also describe an emergent research method called Multi-dimensional In-depth Long-term Case studies (MILCs), an ethnography-based approach that seems well-suited to enabling more effective evaluations of complex visual analytics tools ([3-7]). Next, we discuss our methodology and present visualizations produced by the students. We also describe *NetViz Nirvana*, layout principles that can increase the readability and interpretative power of social network visualizations [3]. As a set of criteria aspired to by most of the students, we feel it is useful for the future design of SNA tools in general and NodeXL in particular. Finally, we offer lessons learned for educators, researchers, and developers of SNA tools such as NodeXL. We report on the process of learning SNA techniques to study online communities in [4].

A. NodeXL Overview

NodeXL (Network Overview for Discovery and Exploration in Excel) is an open-source SNA plug-in for Microsoft Excel 2007 (http://www.codeplex.com/NodeXL). NodeXL is intended to be easy to adopt for existing users of Excel, taking advantage of common spreadsheet capabilities such as sorting, filtering, and creating formulas. NodeXL extends the spreadsheet into a network analysis and visualization tool by incorporating a library of basic network metrics (e.g., degree, centrality measures, elementary clustering) and graph visualization features. Data can be entered or imported into the NodeXL template and quickly displayed as a graph. It is uniquely positioned to support the growing number of community analysts who have neither the time nor desire to step through static visualizations or to learn complex programming interfaces. Because it is an evolving open source project, users with programming skills can also access NodeXL components [5].

978-0-7695-3823-5/09 $26.00 © 2009 IEEE
DOI 10.1109/CSE.2009.120

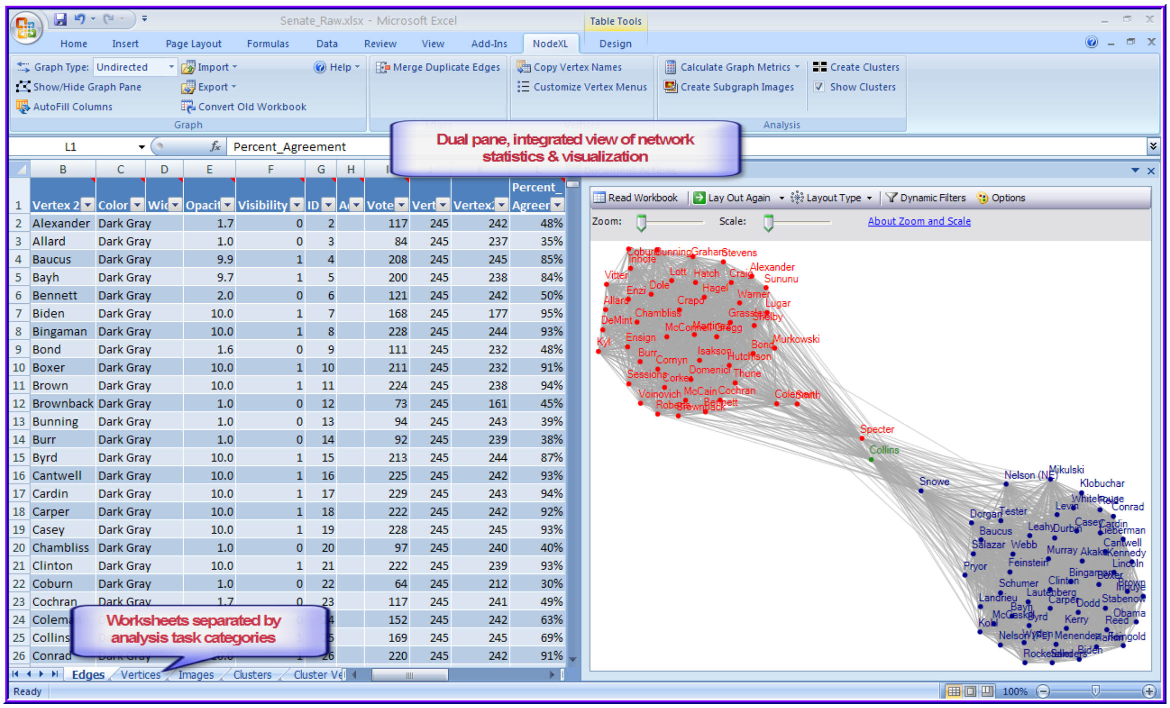

Fig. 1. **The NodeXL Workspace.** The dual pane view of network metrics (left pane) & network graph (right pane) provide an integrated snapshot of statistics & visualization, along with built-in functions & controls that support exploration & discovery. Individual worksheets separate network analysis tasks into separate categories, closely aligned with topology & attribute-based tasks outlined in [6], such as "Edges," "Vertices," "Clusters." The social network shown reflects voting patterns of U.S. senators, the analysis of which is detailed in [7] and [8].

Arguably, the most significant design model NodeXL implements is an integration of statistical measures and visualizations (see Fig. 1). As noted in [7], "SNA is a deductive task, and a user's exploratory process can be distracted by having to navigate between separate statistical and visualization packages" (p.266). In terms of interaction factors for visual analytics tools, this design feature is called the "connect" interaction [8]. This connectivity is manifest in the dynamic linkage between the data spreadsheet view and the graphic layout view. Activating one representation will cause a simultaneous change in the other [9]. For example, a node and its adjacent edges are highlighted in the graph whether a user clicks on the visual representation of the node in the layout pane or the spreadsheet row for the node in the "Vertices" tab. The simultaneous views of network statistics and network graphs combine language and visual attention modalities such that each provides "cognitive offloading" scaffolds ([9], [10]), and can trigger associative learning [11].

B. Related Work: SNA Tools' Evaluation & Education

SNA practitioners explore complex sets of relationships within social systems to discover codifiable patterns of interaction or reveal structural signatures of social roles ([5], [12]). Complex social relationships and community use of social media can become visible with SNA. Similarly, in the field of visual analytics, complex, dynamic data sets are explored for unexpected insights and synthesized into actionable information. SNA tools and techniques, then, can be situated at the intersection of social computing and visual analytics. While most SNA tasks can be classified according to a taxonomy or general workflow ([13], [6]), the actual exploratory process is dynamic, non-linear, and dependent on contextual factors such as network size, complexity and aspects of the network being investigated. Typical human-computer interaction tests conducted in controlled lab-environments cannot adequately reflect the complexity of real-world SNA tasks.

Many usability studies of visualization tools have been conducted in laboratory settings under controlled conditions ([14], [15]). Conversely, ethnographic studies of technology have allowed researchers to gain deep understanding of how users interact with technological tools ([16], [17]) in context-dependant conditions [18]. While long term qualitative studies can be difficult to sustain and may present a challenge to charting consistent usage patterns, they are more aligned with the ways users interact with complex analysis tools and engage in complex research problems. The MILCs approach is part of a growing movement in the development of visual analytic systems that argues against the use of traditional prescriptive, task-based evaluations ([14], [15], [7], [8], [19]). The original MILCs aimed to: (1) help developers design and refine information visualizations systems more effectively and (2) spark expert users to unexpected insights and discoveries.

Previous evaluations of visual analytic systems such as

SocialAction ([7], [13], [8]) and others (detailed in [20], [19]) invited domain experts to evaluate the system. The same model can be applied to the evaluation of complex visualization systems used by teachers and students. Just as exploratory efforts in scientific inquiry can be mapped to a cycle of sense-making tasks with feedback at each level [21], exploratory learning is a cycle of sense-making tasks with multiple feedback loops [11]. An early example of the MILCs paradigm in educational contexts is detailed in [22]. Of note, its non-structured observation format empowered students to explore, and in many cases reach new insights ("discovery learning," [22]). A main advantage of extending the MILCs approach to learning contexts is that it offers students the same evaluation and design affordances it holds for research with domain experts: the MILCs process reflects the real way students explore an interface as they are learning SNA concepts.

In related work on SNA education, [23] summarized the results of a course on optimizing the online communication behavior of student teams collaborating across geographic distances while studying SNA. Insofar as one-third of the course presented social network analysis concepts, its format resembled the seminar we studied. In [23]'s case, the students collaborated on course work while applying SNA principles to evaluate their own communication patterns. In contrast, our intent was to evaluate how an interface like NodeXL can be used as both an SNA tool and a means to teach SNA.

II. Methodology – Two-pronged Approach

As noted in §I-B, we used a qualitative approach, based primarily on MILCs [15]. MILCs employ multiple user analysis methods within the same case study to attain a rich evaluation of the researched tools. In order to conduct an evaluation of NodeXL sensitive to diverse categories of users (IS & CS students), we designed a two-pronged appraisal approach. For each group of users we used a core set of instruments and techniques: self-reporting pre-survey, tutorial session with NodeXL; observation/interview, and post-survey. However, the length and depth-of-focus of our evaluations were tailored to the background characteristics of each group. Because the IS users were using NodeXL as part of a semester-long course, we could follow the MILCs model with them, making in-situ observations over time and allowing them to reflect on their use of the tool as they grew more proficient. We used a more compressed but focused evaluation for the CS users, as they required significantly less time to learn NodeXL. Although the detailed methodologies employed for each group differed, we believe our two-pronged approach enabled a rich, thorough evaluation of NodeXL as a tool for a broad base of users.

A. Methodology: IS users

Over a 5 week period, 15 IS graduate students participating in a "Communities of Practice" seminar were introduced to SNA and used NodeXL to explore SNA fundamentals. While SNA was presented as a powerful set of techniques for analyzing online communities, it was considered only one of many ways students could study social interactions. This perspective situated SNA within an overall learning environment in much the same way MILCs have situated visual analytics tools within the work environments of their domain experts.

Before instruction, IS users' level of Excel and SNA literacy was assessed by a self-reporting questionnaire. Most students reported a basic competency level in Excel and almost none of them had any prior knowledge of SNA. Their first encounter with NodeXL was a tutorial session conducted in a computer lab, following the outline and examples of *Network Analysis with NodeXL: Learning by Doing*, a draft introduction to SNA text written by 3 of the authors. The tutorial tasks supported 4 of the 7 workflow steps outlined in [13], and reflected the general topology- and attribute-based tasks presented in [6]'s task taxonomy for graph analysis. During the study, participants engaged in weekly class discussions and completed 3 assignments between classes. The first assignment was based on a pre-defined dataset while follow-on assignments allowed participants to independently explore SNA-related research questions on their own datasets. The students were observed as a group during class sessions, but each also had a 1-hour one-on-one session with a researcher. The individual sessions followed a contextual inquiry protocol, in which participants 'talk-aloud' as they work, while the observer asks clarifying questions and makes note of important occurrences [24]. Self-reporting diaries are an integral part of the MILCs approach [15], and also allowed participants to capture and reflect upon their actions, emotions, and moments of insight ([25], [26]).

B. Methodology: CS users

We used similar techniques as detailed above (§II-A) for 6 CS students, compressed into a single 90 minute session for each. Two self-reporting questionnaires were given to each participant before any instruction took place: one a subset of the Excel and SNA literacy survey taken by our IS users, and the other part of the standard NodeXL network analysis survey optionally taken by new users of the tool. The latter deals more specifically with the user's experiences with other network analysis tools and their academic background. As they were more adept with both SNA tools and techniques, we favored one-on-one tutorials with the CS users in lieu of class instruction. This format also allowed them more freedom to ask questions and critique NodeXL as new features were introduced. The tutorial followed the same outline used by the IS users. In the second half, the CS users were asked to select a dataset of interest to them out of the ones we had available or their own collection and to identify and highlight three things within it:

- a unique social role within the network,
- an interesting sub-group within the larger network, and
- anything else of particular interest.

During their analysis, which lasted 30-45 minutes, we observed each participant individually in the same manner as the IS users. Their comments, along with each step they took in their analysis and any problems they encountered were

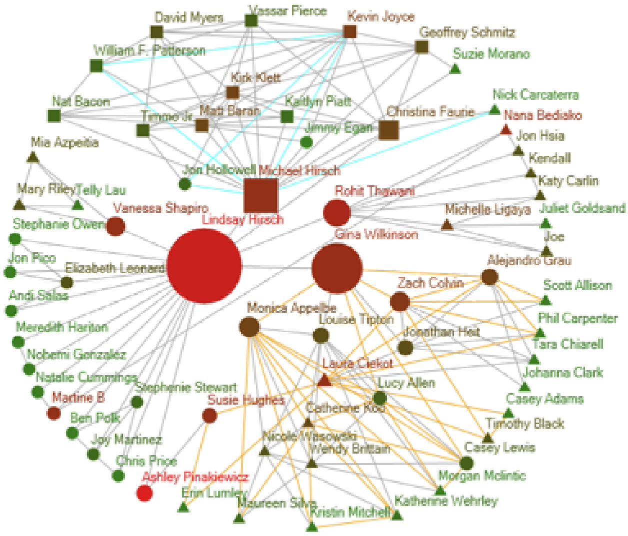

Fig. 2. Student Product: The friendship relationships of an online community. The visualization uses multiple SNA metrics to reveal structure: node color reflects clustering coefficients (identifying possible subgroups and their connectivity to the whole); edge colors reflect geographic connections. Node radius reflects betweenness centrality (i.e., bridges/boundary spanners for the community overall), and shape reflects either closeness centrality or eigenvector centrality (no nodes met both metrics at the same time). Those members with high closeness centrality are triangles; those with low closeness centrality are circles; those connected to the most popular members are squares.

noted by the observer so as to form an approximation to the self-reporting diaries used for the IS users. Personal diaries and class assignments were omitted due to the experience and technical background of the CS users, as well as the more time limited nature of the study. However, this one-on-one perspective afforded us an increase in detailed responses from each individual. At the conclusion of the second half participants completed 2 additional questionnaires: one being the remainder of the standard NodeXL survey mentioned above that deals with the user's experience with NodeXL and the other select questions from the self-reporting diaries used for the IS users.

III. NodeXL & SNA Sense Making

As noted in [3], Euclid established that a point is that which has position but no magnitude. He also defined a line as that which has position and length, but no breadth [27]. While these axioms are applicable in plane geometry and algorithms historically used to display graphs [3], nodes and edges in social networks must convey the same attributes as the people and relations they represent. Practitioners who wish to explore community member characteristics such as number of contributions, gender, or degree (i.e., number of friends) may want to represent them visually via multiple node and edge attributes such as shape, size and color. The ability to apply a variety of visual features to SNA data elements based on various individual and community metrics was a NodeXL feature that all students used and enjoyed.

However, a tool that enables unrestricted manipulation of these attributes can serve as a double-edged sword. While it allows users to create complex visualizations of multi-dimensional data, over-use of multiple display options can quickly reduce the graph's readability and obscure potentially significant perspectives. To ensure that students maintained a high awareness of the importance of producing readable graphs that accurately reflect the community relationships they hoped to convey, the students read and discussed the readability metrics (RMs) outlined in [3]. They were enjoined to aspire to the four principles of *NetViz Nirvana* [3]:

- Every node is visible
- Every node's degree is countable
- Every edge can be followed from source to destination
- Clusters and outliers are identifiable

In-class and online discussions about *NetViz Nirvana*, coupled with NodeXL's tight integration of statistics views and graph layouts empowered the students to produce relatively sophisticated SNA graphs in a short period of time. Most students took full advantage of the ease with which NodeXL can map individual and collective metrics to the shape, size, and color attributes of visual graph objects. A sample of student products, along with captions detailing their layout choices, are shown in Figures 2–5. In each case, the way NodeXL supports thoughtful use of shape and color, as well as selective labeling of nodes of interest, helps direct attention to important relationships.

The student who created Fig. 2 used multiple SNA metrics to reveal her community's structure (see caption for details). The layout she chose also follows many *NetViz Nirvana* design principles, as larger, more connected nodes are pulled into the layout's center. The student who created Fig. 3 focused on identifying the relationship between 3 community forums. Like the Fig. 2 author, this student also mapped metrics (degree & tie strength) to visual properties (diameter & edge thickness), using her graph results to identify boundary spanners in the community and highlight a close connection between two sub-groups. Again, the use of shapes and color were used to draw attention to important individuals, supported by the ability to label only select nodes. Another student applied a simple NodeXL "skip" filter to model a complex community management dilemma: how to find the best candidate to replace a departing administrator (Fig. 4 & 5). He hypothesized that his admin and experienced community members would have higher eigenvector and betweenness centrality measures, and reflected these metrics in visual properties. Using NodeXL's "skip" filter to remove the existing admin, he was quickly able to model and "see" which member possessed the best network values to take over (see captions for details).

IV. Aspects of NodeXL Usability

Of our 6 CS users, 5 had a course background in network visualization, and 4 also had general information visualization course experience. Only one participant lacked both. Three of the participants had studied SNA as part of a course, and one has presented network analysis findings in both academic

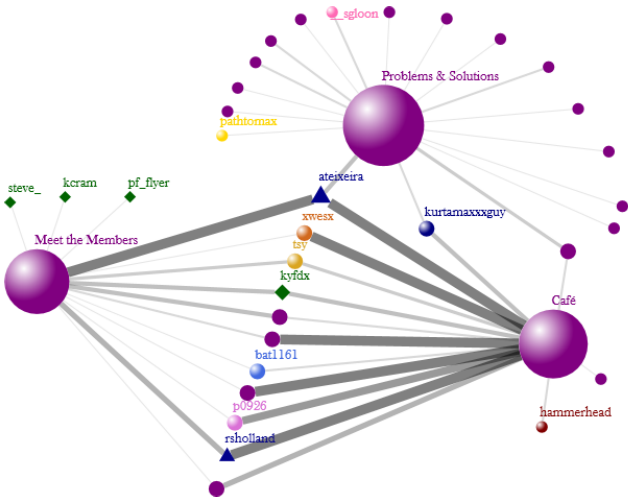

Fig. 3. Student Product: This graphic helped the student identify key boundary spanners (e.g., ateixeira), recognize the close connection between 2 different forums, and the lack of significant activity by the official community leaders. Blue triangles are community leaders; green diamonds are hosts. She could also easily label nodes selectively. However, she did have to manually create a separate legend to explain these roles and relationships.

and business settings. Thus, with CS users, an emphasis was made on specific usability aspects of the tool. However, these aspects were also correlated against IS users' feedback. We categorized the CS user surveys and comments according to the tutorial outline described in §II-B, with additional areas added as needed for comments that defied classification. Overall, we found 16 unique acclamations of NodeXL across 10 aspects of the tool, 5 of which were were outside the scope of the tutorial document. Moreover, we found 96 unique criticisms and feature requests across 37 areas, which were substantially more specific than the acclamations. 17 of the 37 areas were mentioned during the IS users' tool exploration, not instruction. Of the 16 acclamations, 3 were made by 2 or more of the participants.

The interaction between the workbook and the graph pane in NodeXL was quite appealing to the CS users, as they wanted to maintain a separation of data and visualization while enabling connections through brushing and linking. One user especially liked the ability to use cell referencing within the worksheets to define tunable constants for their vertex attribute formulas, something he had not been able to do in other tools. Of the criticisms and feature requests, 11 were brought up by at least 2 participants and 2 were mentioned by at least 3 of them. The foremost concern our CS users had was the lack of responsive controls at all times during their analysis. While running the layout algorithms, 3 users requested a progress indicator with stop or pause buttons, even though the graph pane is updated after every iteration. Moreover, the brushing and linking between the workbook and visualization slowed down 2 users who worked with large datasets, as selecting many vertices in either caused a substantial update in the other. One participant even requested the ability to disable real-time updating, instead preferring to make all the data modifications beforehand and visualizing the data only as a final step.

Conversely, this real-time updating was the most appealing aspect to 3 of our users, who also requested that "autofill columns" immediately update the graph pane with the results instead of only placing them in the workbook. This feature, as well as the optional disabling of real-time updating, has been added to NodeXL. Though it would further increase the response time, 2 users also asked that the autofilled columns to optionally stay in sync with their source data.

Another key complaint is the desire for increased usability. Our participants expected many operations to be available directly from the context menu of the graph pane, including fixing vertex placement, deletion of vertices and edges, and skipping filtered out vertices and edges after using dynamic filters. Further, users found the NodeXL ribbon tab to be confusing and too detailed, instead requesting simpler, larger icons that give precedence to frequently used features. The latest version of NodeXL has implemented part of an interface overhaul designed to address these issues, with basic features exposed in the ribbon tab and grouped in a more orderly fashion while advanced ones are moved to pop-up dialog boxes. CS users also requested shortcuts for many existing functions, some of which we have already implemented.

For some datasets, users hit the limits of edge aggregation within NodeXL. Two of our users requested more expressive aggregation techniques than only a count of the number of aggregated items, instead preferring the option of selecting a measure such as sum, median, or mean for the weight column. Another user wanted a way to easily merge vertices while aggregating the data columns.

Finally, when our participants wanted to output the results of their analysis they found the existing image export features of NodeXL lacking. Specifically, many requested vector graphic formats such as SVG, EPS, and WMF to output publishable images. We added an XPS export to satisfy this need. To improve text legibility and reduce file size they suggested a compressed, lossless format like PNG replace NodeXL's default image export options (JPEG/lossy and BMP/uncompressed).

All participants rated their satisfaction with NodeXL higher than current network analysis software except for one, who rated NodeXL equivalent to current software. This participant had the weakest background in Excel, SNA techniques, and alternative SNA tools among those studied.

V. Lessons Learned from Various Perspectives

The process of evaluating visual analytics tools involves the intersection of learning a new, complex system, learning the language of complex SNA concepts, and applying these components to abstract goals. How do you learn to explore and interpret patterns of interaction in online communities to reveal latent social structures or signature roles? [12] Our study provides a first look at the impact a tool like NodeXL may have on the teaching and learning of fundamental SNA concepts, and the benefits of using MILCs as an evaluation method for the learning process. Our two-pronged methodology for

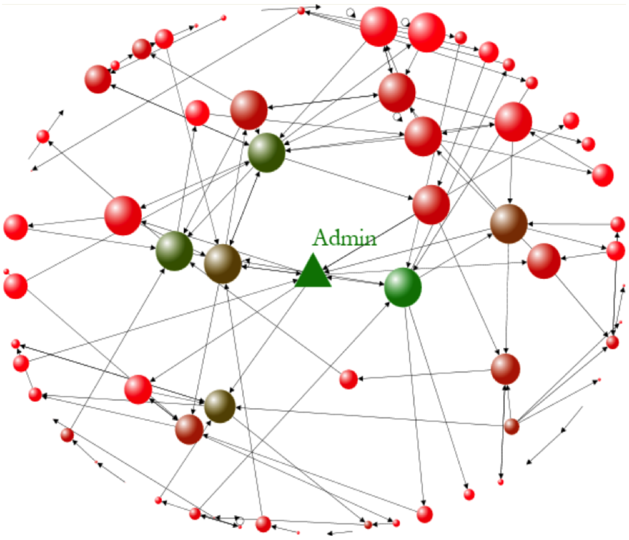

Fig. 4. Student Product: The student confirms a hypothesis that the community administrator and more experienced members will have high eigenvector centrality (connectedness, represented by node radius) and betweenness centrality (bridging, represented by node color). He takes this idea one step further in Fig. 5.

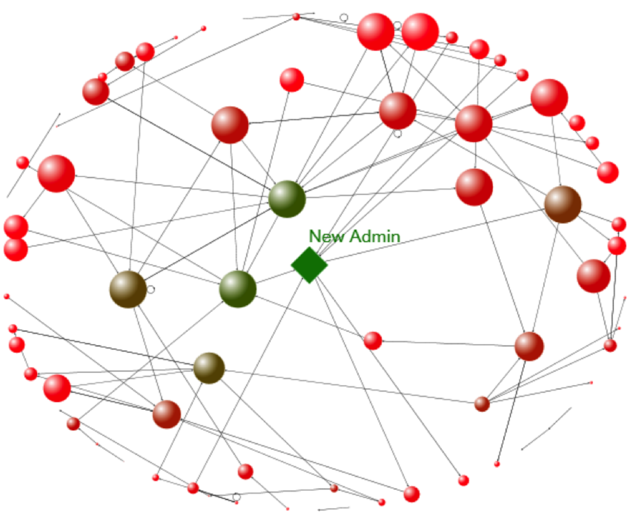

Fig. 5. Student Product: Modeling which node would be the next-best candidate to serve as community administrator. To simulate this management dilemma, statistical data about the current admin was 'skipped' via NodeXL filtering functions, & the next best "node" pops up in his visualization.

studying different types of users has also enabled us to offer a robust evaluation of NodeXL as a visual analytics tool. The guidelines for interaction design proposed by Ji Soon Yi (cited in [8]), such as "connect," "encode," "filter" and "explore" serve as our evaluation criteria, as described in the following lessons learned.

A. Lessons Learned for Designers

Connect: The "dual-front approach," or "connect" interaction design [8] that combines statistics and visualizations into one integrated visual analytics tool was effective in empowering new users of SNA tools to create quite sophisticated, meaningful social network diagrams. Most students took advantage of the close coupling between spreadsheet metrics and the visualization to manually manipulate their layouts, moving fluidly between 1) finding a node in the spreadsheet to maneuver it on the graph pane, and 2) selecting a node in the graph to review statistics for it from the spreadsheet. This interaction was cited by the CS users as a key feature of NodeXL. The Communities of Practice instructor found it useful during teaching to highlight SNA concepts as they were presented on the classroom projector. However, the "connect" interaction paradigm designed into NodeXL did not extend to the automatic creation of labels or legends for visualizations created by users – a feature that is standard in chart features found within Excel. Most students had to create their own legends for nodes (see Fig. 3). This failing has been addressed in an upcoming release.

Filter: NodeXL's suite of "filter" interactions seems to be missing a classic "details-on-demand" feature. Several students commented that in order to make side-by-side comparisons of columns of interest in the worksheets, they had to scroll back and forth constantly. At times, their efforts to cut-and-paste user-created columns near built-in columns to simplify comparisons caused unexpected results (either human error in the "cut-n-paste," or a lack of awareness about the inability to mix certain types of columns in NodeXL). Based on informal feedback with NodeXL developers, such straightforward comparisons are possible, but require multiple steps. A macro could be created as a shortcut, following the familiar "cut-n-paste" paradigm. Or, in some cases, the "freeze panes" feature could be used more effectively.

Encode: The "encode" interaction, or the ability to apply shapes, size, labels, orientations by encoding data elements with attributes of interest, is the most popular way in which students chose to represent their communities. NodeXL offers an impressive array of visual attributes to represent SNA metrics. Variations in node/edge color, size and shape were used extensively by students to improve the interpretive and expressive power of their visualizations. Most students used relatively simple metrics like degree for nodes and tie-strength for edges. Five of the 12 IS users felt their use of extensive metrics was limited due to the structure of the data they collected – many of the students chose to collect data about community member's connections to community artifacts, such as contributions to various forums (see Fig. 3), and in one case, time-stamps. In such cases, metrics are not easily interpreted or may not apply.

Explore: The students enjoyed using attribute rankings to try to make their graphs more readable. However, in their effort to reach *NetViz Nirvana*, they still had to invest in a great deal of manual manipulation. As noted in [3], automated layout algorithms are not sufficient to effectively represent the range of attributes and often localized structures that most SNA experts and students would like to highlight. Based on the exploration process followed by many of the users, we believe the addition of specific RM interactions into the design of SNA tools would be of great value. Specifically, node RMs such as node occlusion and node size, shape, and color variance constraints should be the highest priority (a potentially positive side effect of incorporating these node RMs is they may reduce the risk of edge tunnels). An interactive edge RM for reducing edge crossings would also be of immediate value, as many students used edge thickness to reflect tie-strength. Both IS and CS users alike had difficulty using labels effectively, underscoring the potential benefits of node RM research efforts.

The ability to help users track their exploration process, or navigate through a history of their actions is also a component of the "Explore" interaction. Currently, NodeXL does not contain any supports for "undo" or traceable histories of exploration or annotation paths. Students were quite frustrated with the interruptions they faced when the tool crashed, and often, "had to start over." SocialAction is one SNA tool that can serve as an example in adding these features to the design queue [13]. An "Undo/Redo" function would appear to be especially useful in beta-testing contexts, when users who experience multiple system crashes are supported by some means for reverting back to a recent "safe" mode. (Note: a few users successfully used Excel's crash recovery feature to resume analysis.)

B. Lessons Learned for Educators/Tutorial Designers

NodeXL was found to be a relatively easy to learn tool. Excel experience and familiarity with graphs and networks appear to be baseline skills for effective use of NodeXL. Lack of in-depth knowledge of Excel proved to be the primary barrier to the learning process for IS users. Three of the CS users and 5 of the IS users felt their Excel experience was useful, while 8 of the IS users felt their inexperience with Excel, especially a lack of expertise in creating Excel formulas, prevented their rapid adoption of the full features of NodeXL.

Pacing issues, both in the tutorial task flow, lab sessions, and assignments, were of paramount concern to the IS users, who were asked to learn the language of SNA, common statistical and graph-based approaches, and a new tool in a relatively short amount of time. Users had less than 2 weeks to learn the basics of NodeXL and relevant SNA metrics, then to interpret their first set of graphs, starting with a pre-defined data set that did not reflect their communities of interest. Nine of 12 IS users noted that the tutorial and first assignment made too steep and quick a transition from small networks of relatively low graph density to large networks of high graph density. Similarly, our CS users emphasized the importance of a series of small tasks with predefined goals, especially when the users do not have a vested interest in the dataset [28].

Promoting user awareness of layout considerations such as *NetViz Nirvana* resulted in a high level of reflective thought and effort put forth by IS users in their analyses. Thus, incorporating *NetViz Nirvana* functions such as real-time RM interactions may support educational goals for SNA. NodeXL's semi-automatic "Calculate Metrics" function, a powerful library of basic techniques, often hid some of the instructional power of statistics from the students. Interaction functions to allow metric tweaking and graph response, along with interactive RM layout functions could enable "teachable moments" that make SNA metrics explicit, guide the user through recommended steps required to attain *NetViz Nirvana*, and allow further opportunities for experimentation and exploration to reach novel insights.

Tutorial tasks did not take advantage of the "reconfigure" interaction design [8], i.e., offering different perspectives on the same data. NodeXL is embedded within Excel, which is equipped with multiple existing charts that can be exploited to display data through different lenses (e.g., scatterplot, histograms). Emphasis was placed on creating and analyzing network views or sorting the tabular spreadsheet to find interesting patterns. Time constraints within the course, along with student lack of in-depth familiarity with Excel's features reduced opportunities to experiment with and learn from a greater variety of perspectives.

The ability to keep track of actions is a scaffolding support that enhances learning, confidence and enables extensive freedom to explore. As noted in §V-A, an "undo" feature for adjustments made to either the spreadsheet view or the layout of nodes should be added. A work-around several students developed for lack of this function was to keep track of multiple saved versions of their work, or maintain various simultaneous Excel spreadsheets that reflected their workflow status. These additional files required explicit tracking, which may have increased the cognitive load the students experienced.

C. Lessons Learned for Researchers

MILCs are indeed difficult to execute and analyze [28], due to amounts of data collected, and the amount of time invested by both participants and researchers. However, they provide more accurate representations of the processes experts and learners follow while exploring complex data sets, and can result in more meaningful evaluation measures and recommendations for improvement in design and teaching approaches. Exploratory learning can be described, fundamentally, as a cycle of exploration, insight (learned concept), and deeper exploration. Consequently, it is difficult to shoe-horn into specific tasks – much like the exploratory analysis processes followed by experts. MILCs are thus an effective, rich information source for visual analytics usage and learning. Overall, this study not only adds to the growing body of research establishing MILCs as an effective evaluation method for visual analytics tools, but also extends it as a valid approach for evaluating systems designed for exploratory learning, specifically those designed for a wide range of learners.

Previous MILCs and a field study on exploratory learning ([19], [26]) captured moments of insight via "Eureka" reports. In these early studies, users not only recorded the analysis steps they followed, along with times-on-task for major activities, but also reflected upon key insights they experienced. In future research applying MILCs to teaching/learning contexts, explicitly capturing similar "Eureka" reports may prove of value.

VI. Future Work and Conclusions

In their post-session survey, CS users prioritized pending NodeXL development tasks in the following order: (1) better automated layout algorithms, (2) clustering algorithms or additional means to group nodes, and (3) additional metric algorithms to measure networks. Other options were more evenly tied, though, interestingly, all of our CS users ranked 3D layouts last on their list. IS users were also interested in improved layout algorithms and struggled with a need for better support of grouping nodes.

The top design suggestion made in addition to specific survey responses was the ability to use NodeXL outside of Excel 2007. Both CS and IS students requested a means to use NodeXL outside of Excel 2007. Several users desired a port to OSX, while another requested a completely open source implementation. NodeXL is released under the Microsoft Public License, and a Silverlight implementation may allow for broader adoption. Much of the other users feedback not mentioned here has already been included in the current release.

Our findings demonstrate the power of the complementary methodologies we used to evaluate NodeXL as a tool for SNA experts and teaching:

- our user pool represented both diversity & depth from a research methods perspective;
- our IS users' feedback showcased NodeXL's power as a teaching/learning tool for SNA;
- our CS users' feedback enabled us to compare NodeXL to existing tools & enabled us to rapidly implement requested features & fixes during the study & beyond.

Our findings suggest that NodeXL enabled sharp, but non-technical students to interpret and create meaningful representations of complex social structures in a fairly short timeframe. Their success was based on the tool's close coupling of spreadsheet and graph visualization, as well as the range of ways it allows metrics and attributes to be mapped onto graphs. As a result, nearly all of our users found NodeXL to be more usable and learnable than existing SNA tools.

Acknowledgments

We thank the University of Maryland participants who offered improvements for NodeXL. Natasa Milic-Frayling provided helpful suggestions and support. Microsoft External Research provided partial support for this project.

References

[1] A. Lenhart, "Adults and social network websites," Pew Internet and American Life Project, Tech. Rep., Jan 14, 2009 2009.

[2] L. Rainie, "The new news media-scape," Feb 17 2009.

[3] C. Dunne and B. Shneiderman, "Improving graph drawing readability by incorporating readability metrics: A software tool for network analysts," University of Maryland, HCIL Tech Report HCIL-2009-13, May 2009.

[4] D. L. Hansen, D. Rotman, E. M. Bonsignore, N. Milic-Frayling, E. M. Rodrigues, M. Smith, and B. Shneiderman, "Do you know the way to SNA?: A process model for analyzing and visualizing social media data." Submitted, 2009.

[5] M. Smith, B. Shneiderman, N. Milic-Frayling, E. M. Rodrigues, V. Barash, C. Dunne, T. Capone, A. Perer, and E. Gleave, "Analyzing social (media) network data with NodeXL," in *C&T '09: International Conference on Communities and Technologies 2009*, 2009.

[6] B. Lee, C. Plaisant, C. S. Parr, J.-D. Fekete, and N. Henry, "Task taxonomy for graph visualization," in *BELIV '06: Proc. 2006 AVI workshop on BEyond time and errors: novel evaLuation methods for Information Visualization*. ACM, 2006.

[7] A. Perer and B. Shneiderman, "Integrating statistics and visualization: Case studies of gaining clarity during exploratory data analysis," in *CHI '08: Proc. 26th annual SIGCHI conference on Human Factors in Computing Systems*. ACM, 2008.

[8] ——, "Integrating statistics and visualization for exploratory power: From long-term case studies to design guidelines," *IEEE Computer Graphics & Applications*, no. May/June, pp. 24–36, 2009.

[9] K. Sedig and H.-N. Liang, "Interactivity of visual mathematical representations: Factors affecting learning and cognitive processes." *Journal of Interactive Learning Research*, vol. 17, no. 2, pp. 179–212, 2006.

[10] C. Ware, *Visual thinking for design*, ser. Morgan Kaufmann Series in Interactive Technologies. Morgan Kaufmann, 2008.

[11] S. d. Freitas and T. Neumann, "The use of 'exploratory learning' for supporting immersive learning in virtual environments," *Computers & Education*, vol. 52, no. 2, pp. 343–352, 2009.

[12] H. Welser, E. Gleave, D. Fisher, and M. Smith, "Visualizing the signatures of social roles in online discussion groups." *Journal of Social Structure*, vol. 8, 2007.

[13] A. Perer and B. Shneiderman, "Systematic yet flexible discovery: Guiding domain experts through exploratory data analysis," in *IUI '08: Proc. 13th international conference on Intelligent User Interfaces*. ACM, 2008.

[14] B. Kitchenham, L. Pickard, and S. L. Pfleeger, "Case studies for method and tool evaluation," *IEEE Software*, vol. 12, no. 4, pp. 52–62, 1995.

[15] B. Shneiderman and C. Plaisant, "Strategies for evaluating information visualization tools: multi-dimensional in-depth long-term case studies," in *BELIV '06: Proc. 2006 AVI workshop on BEyond time and errors: novel evaLuation methods for Information Visualization*. ACM, 2006.

[16] M. Tory and S. Staub-French, "Qualitative analysis of visualization: a building design field study." in *BELIV '08: Proc. 2008 conference on BEyond time and errors: novel evaLuation methods for Information Visualization*, ACM, Ed. ACM, 2008.

[17] J. Betteridge, "Answering back: The telephone, modernity and everyday life." *Media Culture Society*, vol. 19, no. 4, 1997.

[18] B. Kaplan and D. Duchon, "Combining qualitative and quantitative methods in information systems research: A case study." *MIS Quarterly*, vol. 12, no. 4, pp. 571–586, 1988.

[19] P. Saraiya, C. North, V. Lam, and K. Duca, "An insight-based longitudinal study of visual analytics," *IEEE Trans. Visualization and Computer Graphics*, vol. 12, no. 6, pp. 1511–1522, 2006.

[20] P. Saraiya, C. North, and K. Ducak, "An evaluation of microarray visualization tools for biological insight." in *INFOVIS '04: Proc. IEEE Symposium for Information Visualization*. IEEE, 2004, pp. 1–8.

[21] J. Thomas and K. Cook, *Illuminating the path: The research and development agenda for visual analytics.*, 2006.

[22] G. Marchionini and G. Crane, "Evaluating hypermedia and learning: Methods and results from the Perseus Project," *ACM Trans. Information Systems*, vol. 12, no. 1, pp. 5–34, 1994.

[23] P. A. Gloor, M. Paasivaara, D. Schoder, and P. Willems, "Finding collaborative innovation networks through correlating performance with social network structure," *International Journal of Production Research*, vol. 46, no. 5, pp. 1357–1371, 2008.

[24] K. Holtzblatt and S. Jones, *Contextual inquiry: A participatory technique for system design.* Lawrence Earlbaum, 1993.

[25] S. Carter and J. Mankoff, "When participants do the capturing: the role of media in diary studies." in *CHI '05: Proc. SIGCHI conference on Human Factors in Computing Systems*, ACM, Ed., 2005.

[26] J. Rieman, "A field study of exploratory learning strategies," *ACM Trans. Computer-Human Interaction*, vol. 3, no. 3, pp. 189–218, 1996.

[27] C. L. Dodgson, *Euclid. Books I. II*, 1882.

[28] R. A. Valiati, Eliane, C. M. D. S. Freitas, and S. Pimenta, Marcelo, "Using multi-dimensional in-depth long-term case studies for information visualization evaluation," in *BELIV '08: Proc. 2008 conference on BEyond time and errors: novel evaLuation methods for Information Visualization*. ACM, 2008.