Analyzing (Social Media) Networks with NodeXL

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ABSTRACT

We present NodeXL, an extendible toolkit for network overview, discovery and exploration implemented as an add-in to the Microsoft Excel 2007 spreadsheet software. We demonstrate NodeXL data analysis and visualization features with a social media data sample drawn from an enterprise intranet social network. A sequence of NodeXL operations from data import to computation of network statistics and refinement of network visualization through sorting, filtering, and clustering functions is described. These operations reveal sociologically relevant differences in the patterns of interconnection among employee participants in the social media space. The tool and method can be broadly applied.

Categories and Subject Descriptors

H.4.1 [**Information Systems Applications**]: Office Automation – *spreadsheets*; H.5.2 [**Information Interfaces and Presentation**]: User Interfaces – *Graphical user interfaces (GUI)*; E.1 [**Data Structures**]: Data Structures – *Graphs and networks.*

General Terms

Design, Measurement

Keywords

NodeXL, Network Analysis, Visualization

1. INTRODUCTION

We describe a tool and a set of operations for analysis of networks in general and in particular of the social networks created when employees use an enterprise social network service. The NodeXL tool adds "network graph" as a chart type to the nearly ubiquitous Excel spreadsheet. We intend the tool to make network analysis tasks easier to perform for novices and experts. In the following we describe a set of procedures for processing social networks commonly found in social media systems. We generate illustrations of the density of the company's internal connections, the presence of key people in the network and relationships between network and job role attributes. We suggest these steps can be applied to similar data sets and describe future directions for developing tools for the analysis of social media and networks.

Social media applications enable the collective creation and sharing of digital artifacts. The use of these tools inherently creates network data. These networks represent the connections between content creators as they view, reply, annotate or explicitly link to one another's content. The many forms of computer-mediated social interaction, including many common communication tools like SMS messages on mobile phones, email and email lists, discussion groups, blogs, wikis, photo and video sharing systems, chat rooms, and "social network services", all create digital records of social relationships. Almost all actions in a social media system leave a trace of a tie between users and other users and objects.

These networks have academic and practical value: they offer detailed data about previously elusive social processes and can be leveraged to highlight important content and contributors. Social media systems are at an inflection point. Authoring tools for creating shared media are maturing but analysis tools for understanding the resulting collections have lagged. As large scale adoption of authoring tools for social media is now no longer in doubt, focus is shifting to the analysis of social media repositories, from public discussions and media sharing systems to personal email stores. Hosts, managers, and various users of these systems have a range of interests in improving the visibility of the structure and dynamics of these collections.

We imagine one network analysis scenario for NodeXL will be to analyze social media network data sets. Many users now encounter Internet social network services as well as stores of personal communications like email, instant message and chat logs, and shared files. Analysis of social media populations and artifacts can create a picture of the aggregate structure of a user's social world. Network analysis tools can answer questions like: What patterns are created by the aggregate of interactions in a social media space? How are participants connected to one another? What social roles exist and who plays critical roles like connector, answer person, discussion starter, or content caretaker? What discussions, pages, or files have attracted the most interest from different kinds of participants? How do network structures correlate with the contributions people make within the social media space?

There are many network analysis and visualization software tools. Researchers have created toolkits from sets of network analysis components not limited to R and the SNA library, JUNG, Guess, and Prefuse [[2], [12], [15]]. So why create another network analysis toolkit? Our goal is to create a tool that avoids the use of a programming language for the simplest forms of data manipulation and visualization, to open network analysis to a wider population of users, and to simplify the analysis of social media networks. While many network analysis programming languages are "simple" they still represent a significant overhead for domain experts who need to acquire technical skills and experience in order to explore data in their specific field. As network science spreads to less computational and algorithmically

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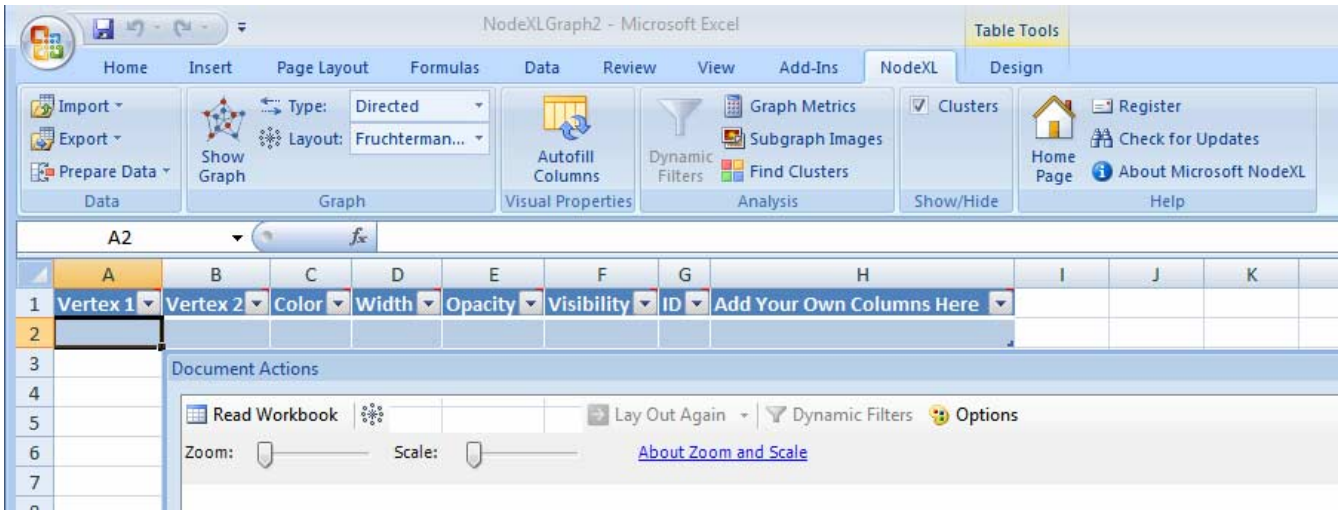


Figure 1. NodeXL Menu, Edge List Worksheet, and Graph Display Pane

focused areas, the need for non-programmatic interfaces grows. There are other network analysis tools like Pajek, UCINet, and NetDraw that provide graphical interfaces, rich libraries of metrics, and do not require coding or command line execution of features. However, we find that these tools are designed for expert practitioners, have complex data handling, and inflexible graphing and visualization features that inhibit wider adoption [[4], [5]].

Our objective is to create an extendible network analysis toolkit that encourages interactive overview, discovery and exploration through "direct" data manipulation, graphing and visualization. While relevant for all networks, the project has a special focus on social media networks and provides support for using email, Twitter and other sources of social media network data sets. NodeXL is designed to enable Excel users to easily import, clean-up, analyze and visualize network data. NodeXL extends the existing graphing features of the spreadsheet with the added chart type of "network", thus lowering the barrier for adoption of network analysis. We integrated into the Excel 2007 spreadsheet to gain access to its rich set of data analysis and charting features. Users can always create a formula, sort, filter, or simply enter data into cells in the spreadsheet containing network data. NodeXL calculates a set of basic network metrics, allowing users familiar with spreadsheet operations to apply these skills to network data analysis and visualization. Those with programming skills can access the NodeXL features as individual features in a library of network manipulation and visualization components.

In future work we report on the deployment of NodeXL and the observation of work practices with the tool across a range of users. In the following we give a brief overview of the tool, examine related work and describe key NodeXL features through an analysis of a sample network data set collected from an enterprise intranet social media application.

2. NodeXL OVERVIEW

The NodeXL—Network Overview, Discovery and Exploration add-in for Excel 2007 adds network analysis and visualization features to the spreadsheet. The NodeXL source code and executables are available at http://www.codeplex.com/NodeXL. NodeXL is easy to adopt for many existing users of Excel and has an extendable open source code base. Data entered into the NodeXL template workbook can be converted into a directed graph chart in a matter of a few clicks. The software architecture comprises three extendable layers:

Data Import Features. NodeXL stores data in a pre-defined Excel template that contains the information needed for generating network charts. Data can be imported from existing Pajek files, other spreadsheets, comma separated value (CSV) files, or incidence matrices. NodeXL also extracts networks from a small but extensible set of data sources that includes email stored in the Windows Search Index and the Twitter micro-blogging network. Email reply-to information from personal e-mail messages is extracted from the Microsoft Windows Desktop Search index. Data can also be imported about which user subscribes to one another's updates in Twitter, a micro-blogging social network system. NodeXL has a modular architecture that allows for the integration of new components to extract and import network data from additional resources, services, and applications. The open source access to the NodeXL code allows for a community of programmers to extend the code and provide interfaces to data repositories, analysis libraries, and layout methods. Spreadsheets can then be used in a uniform way to exchange network data sets by a wide community of users.

Network Analysis Module. NodeXL represents a network in the form of edge lists, i.e., pairs of vertices which are also referred to as nodes. Each vertex is a representation of an entity in the network. Each edge, or link, connecting two vertices is a representation of a relationship that exists between them. This relationship may be directed or not. Some relationships are bi-directional (like marriage); others can be uni-directional (like lending money).

An edge list is, minimally, a pair of entity names which indicate the presence of a relationship. These lists can be extended with additional columns that can contain data about the relationship. NodeXL includes a number of software routines for calculating statistics about individual vertices including in-degree, out-degree, clustering coefficient, and closeness, betweenness, and eigenvector centrality. Additional analyses features can be integrated by advanced users. The results of the network metric calculations are added to the spreadsheet as additional columns

that can be further combined and reused in Excel formula during analysis and visualization. Spreadsheet features like data sorting, calculated formulae, and filters can be applied to network data sets directly.

Graph Layout Engine. NodeXL provides a canvas for displaying and manipulating network charts and data. Users can apply a range of controls to convert an edge list into a useful node-link chart. These include display options that specify the appearance of individual edges and nodes as well as the overall layout of the network. The lines between nodes that represent edges can have different thickness, color, and level of transparency depending on the attributes of the data or parameters specified by the user. Similarly, each node representing a vertex can be set to have a different location, size, color, transparency, or shape. Optionally, the user can specify images to replace the node shapes.

Reliance on a spreadsheet does limit the scale of NodeXL data sets to small and medium size networks with thousands to tens of thousands of nodes. However, we see a great value of working in that spectrum of network analysis problems. First, networks with a few thousands of nodes and edges are already sufficiently challenging for visualization and interpretation and exhibit a variety of complex issues that we attempt to address in our research. Second, networks of such size are available in diverse usage scenarios, allowing us to explore a range of design choices and principles. Third, the practical scale supported by standard spreadsheets will itself also expand over time, for example, the latest version of Excel limits spreadsheet size to the limits of the computer's memory and storage resources rather than an arbitrary value. Most networks even when composed of billions of elements will ultimately need to be reduced to a limited set either by aggregation or by selectively focusing on a sub region of the larger network.

Following a brief review of related efforts in graph visualization and exploration, we offer a step-by-step guide to the creation of NodeXL visualizations and highlight analysis features of the toolkit. We conclude with the discussion of challenges and future directions for network exploration tools.

3. RELATED WORK

Over the years there have been various efforts to provide flexible, interactive, and effective exploratory interfaces for network analysis [[11], [13]]. For example, the SocialAction tool provides real-time exploration, filtering and clustering functions for small to medium sized networks by integrating statistics and visualizations [[16], [17], [18]]. An alternate approach applies semantic substrates, i.e., attribute-based layouts in which node attributes govern assignment to regions, e.g., managers in one region, employees in another, and customers in a third. Then node placement within regions is determined by other attributes

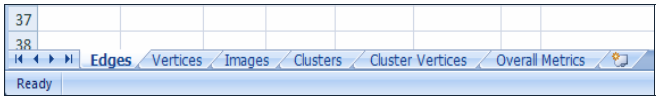


Figure 2. NodeXL template worksheets

and the user can control edge visibility to reduce clutter [[3], [20]]. The pursuit of less cluttered and more revealing visualizations has prompted further research on measures of graph layout quality [7].

The value of network visualizations for investigating social structures of computer-mediated interactions is shown in a growing number of recent papers [9]. Welser et al. [22] show that distinct connecting patterns among users are related to a variety of social roles that, in turn, form complex ecosystems in social media spaces. Social network diagrams were used to illustrate key social roles found in discussion spaces and wiki documents, including 'answer people', 'discussion people', 'discussion starters', and people who specialized in improving the formatting of wiki pages. Adamic et al. [1] illustrate the value of social network analysis for understanding the social connections within question and answer discussions in the Yahoo! Answers system. Their visualizations of different collections of messages, grouped by a common tag or category, illustrate a range of social practices and patterns, from question and answer exchanges to long debates and arguments.

4. NETWORK ANALYSIS GOALS

Network graphs can be explored along multiple dimensions, most prominently scale and time. Some research questions focus on the structure of the whole graph or large sub-graphs, other questions focus on identifying individual nodes that are of particular interest. Some analysts will want to analyze the whole graph aggregated over its entire lifetime; others will want to slice the network into units of time to explore the progression of the network's development. Attempts to enumerate the network analysis tasks that most analysts will want to perform on their data set are promoting discussion [13]. A starting point is the list from Perer and Shneiderman [17]:

1. Overall network metrics, e.g., number of nodes, number of edges, density, diameter
2. Node rankings, e.g., degree, betweenness, closeness centrality
3. Edge rankings, e.g., weight, betweenness centrality
4. Node rankings in pairs, e.g., degree vs. betweenness, plotted on a scatter gram)
5. Edge rankings in pairs
6. Cohesive subgroups, e.g., finding communities
7. Multiplexity, e.g., analyzing comparisons between different edge types, such as friends vs. enemies.

These tasks serve higher level goals for most network analysis. At its most basic level, the initial goal is to grasp basic insights into its macro structure. From an overview, the analyst can begin to seek sub-elements of the network that are of particular interest. This may involve finding sub-groups or cliques and measuring their *cohesion* in terms of the density of their internal connections.

At the micro-level, network analysts focus on individual nodes. Some nodes are notable, for example, because they have an extreme degree of connection to other nodes. For network analysts, the connection of such nodes to one another and their 'betweenness' or various forms of centrality (like degree, closeness and eigenvector centrality, among others) are common topics of interest. Some nodes play critical roles as bridges, sinks, or sources within the network. With an overview of a network in place, analysts may seek to find the gaps or holes in the network that could indicate missing data, a hidden actor, or a strategic gap that should be filled. These measures change over time and many analysts also seek to map diffusion and change over time.

We describe NodeXL features that demonstrate how to accomplish some of these basic network analysis tasks.

5. SYSTEM DESCRIPTION AND WORKFLOW

The core of NodeXL is a special Excel workbook template that structures data for network analysis and visualization. Six main worksheets currently form the template. There are worksheets for "Edges", "Vertices", and "Images" in addition to worksheets for "Clusters," mappings of nodes to clusters ("Cluster Vertices"), and a global overview of the network's metrics ("Overall Metrics").

NodeXL workflow typically moves from data import through processing, calculation and refinement before resulting in a network graph that tells a useful story (Figure 2b). These steps include:

Step 1: Import data. Network data can be imported from one or more network data sources. Users may have data in files, e.g. in text format, separated by delimiters, or stored in relational databases. Wherever the data originates, it is entered into the NodeXL template in the "Edges" worksheet in the form of pairs of names, along with any additional attributes about relationship between them. Multiple edge lists can be stored in the same spreadsheet, expressing different relationships among a set of nodes or the same relationships at different times. Relationships can be annotated with multiple additional columns, which can be used to set values for display attributes. Data about the "strength" of the relationship can be included, or edges can be annotated with the time slice or date range in which they occurred, allowing a single dataset to contain edges over multiple time periods.

Step 2: Clean the data (if required). This typically involves eliminating duplicate edges when appropriate. Data sets can often be noisy and contain redundant data. In some cases network measures cannot be calculated correctly if multiple edges between the same pair of entities exist in a single data set. In these cases redundant edges may be aggregated into a single edge with a weighting that reflects the number of original instances.

Step 3: Calculate graph metrics. A range of measurements exist that capture the size and internal connectivity of a network as well as attributes of each node. NodeXL supports a minimal set of the most crucial network measures for individual nodes: in- and out-degree, clustering coefficient, and betweenness, closeness, and eigenvector centrality. This operation also populates the Vertex worksheet with a unique list of nodes and their network measures. In some cases multiple edges between nodes are part of what is interesting in a data set and should be retained despite the fact that some metrics will be inaccurate and should be ignored. NodeXL marks these network metrics with the Excel "Bad" format if asked to calculate some metrics with duplicate edges in the data set.

Step 4: Create clusters. Network nodes may share a variety of attributes. It is often useful to group and analyze them together. NodeXL has a clustering algorithm and allows users to create clusters and map nodes to them by editing the Clusters and Cluster Vertices worksheets. Each cluster can have its own display attributes with a distinctive shape, color, size, transparency or image. Users can toggle the display of clusters so that the display features for each node is replaced by the display features for its cluster (if any).

Step 5: Create sub-graph images. Whole graph images are often too large or dense to reveal details about individual nodes or clusters. Sub-graph images produce a local network that centers on each node at a time and encompasses the nodes to which it is immediately connected. These extracted images can be useful representations of the range of variation in the local network structures of the population in the network.

Step 6: Prepare edge lists. Nodes can have a "Layout Order" value that governs the presentation of nodes in the graph display. Nodes and edges have attributes that can be used to order the data, for example, ordering nodes by their date of first appearance or rate of connection to other nodes. The value found in "Layout Order" governs the order in which nodes are laid out in the whole graph visualization.

Step 7: Expand worksheet with graphing attributes. Columns can be auto-filled to map data to display attributes. Graphical attributes of nodes and edges, their shape, color, opacity, size, label, and tooltip can be altered to convey additional information in the network visualization. Images listed in the "Images" worksheet can replace the shapes used to represent nodes. Users can insert additional numerical attributes about each node in adjacent columns. These attributes can be automatically scaled to display characteristics. For example, each node may have data about the income of the person it represents or the number of employees in an enterprise which could be mapped to the size, shape, or color of a node. Once set, these mappings apply to all networks created from that point on with NodeXL until reset. This "sticky" layout feature simplifies the creation of multiple networks while maintaining consistency of display mappings.

Step 8: Show graph. This opens or hides the graphical display pane in which NodeXL will render a visualization of the network.

At each stage of the NodeXL workflow, the toolkit provides a number of options; the workflow is not rigidly prescribed. The user can iteratively refine any stage of the analysis and visualization. This may involve operations like:

Read workbook. Load the current state of the network as stored in the spreadsheet and render it according to the selected layout.

Adjust layout. Select among a number of automated layout options that govern where each node in the network will be located. Layouts include a force-directed Fruchterman-Reingold layout [10], that attempts to dynamically find a layout that clusters tightly connected nodes near one another as well as simple geometric layouts like circles or grids.

Apply dynamic filters. Selectively hide edges and nodes, depending on the attributes of the network. For example, a filter could hide all but the most connected nodes, or show only the edges that are 'stronger' than a selected threshold. Filtering may involve "trimming" parts of the network and then recalculating network metrics and layout based on the remaining population of nodes and edges.

Re-render the graph. Redraw the network based on remaining nodes and edges and their changed display attributes.

Re-calculate network statistics. Return to the spreadsheet to sort or calculate new data. Once initial visualizations are created, the user may reorder nodes or import or calculate new data associated with each node or edge.

Finalize the network analysis. Create final images or a data set with an optimal network layout for sharing that highlights meaningful features of the network.

NodeXL users can perform all of the operations suggested in the network analysis tasks listed in Section 4.

6. NODEXL USAGE CASE

We demonstrate the use of the NodeXL tool for finding interesting patterns in a social media data set.

6.1 Data

We extracted eight months of data from a social media application used by a medium sized corporation. The company made extensive use of an internal social networking service that allowed employees to explicitly identify other employees with whom they had a professional connection or friendship. Employees also contributed heavily to an internal discussion web board and a collection of wiki documents. There were 174 employees and other user accounts present in the data collected from April - December 2008 (Table 1).

Table 1. Network data statistics

Metric	Value
Vertices	174
Unique Edges	7,852
Graph Density	0.26

6.2 Data Visualization using NodeXL

Figure 3 displays the "raw" network of the "friend" ties that users created when they request and grant one another explicit connections in the internal social network service application. When a reciprocated tie is created, each person's profile will list the other person's name as a "friend" or colleague.

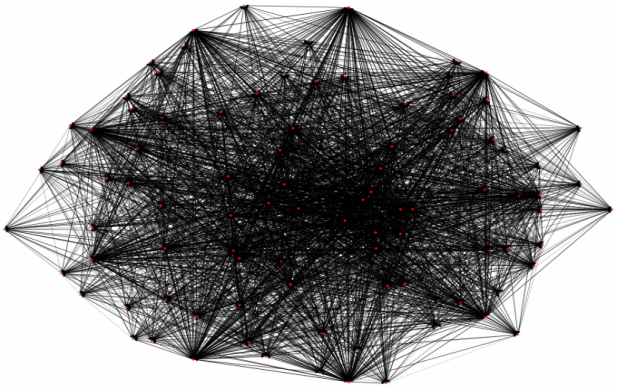


Figure 3. The unrefined whole graph visualization of the data sample comprising 174 nodes and 7,852 edges

Whole graph visualizations are often chaotic and illegible. Figure 3 is no exception, as expected given its size and the density of ties. The network density is 26% of all possible ties (Table 1). We now demonstrate several steps with NodeXL to explore and refine the graph visualization.

Node and Edge Filtering. The chart in Figure 3 does convey the high level of interconnection among members of this network but it obscures many important features like the key nodes and patterns in the network. Using NodeXL dynamic filters (Figure 4) users can hide or grey out nodes that do not meet a set of criteria and thus reveal structures among selected nodes that are otherwise obscured. In Figure 5, the nodes with the highest in-degree are highlighted while all other nodes and associated edges are grayed out. The resulting network is composed of the most connected nodes in the network.

Visual Enhancements. The network can be decorated to highlight key features with color, size, shape, transparency and images. For example, the node sizes in Figure 6 are made proportional to their in-degree, while the color is used to indicate the value of their clustering coefficient. From this display we can observe that the larger core nodes, with high degree, have relatively lower clustering coefficients because they connect to many people who are not themselves connected to one another. Nodes with high clustering coefficients typically connect to fewer people since small groups are more able to connect every member to one another.

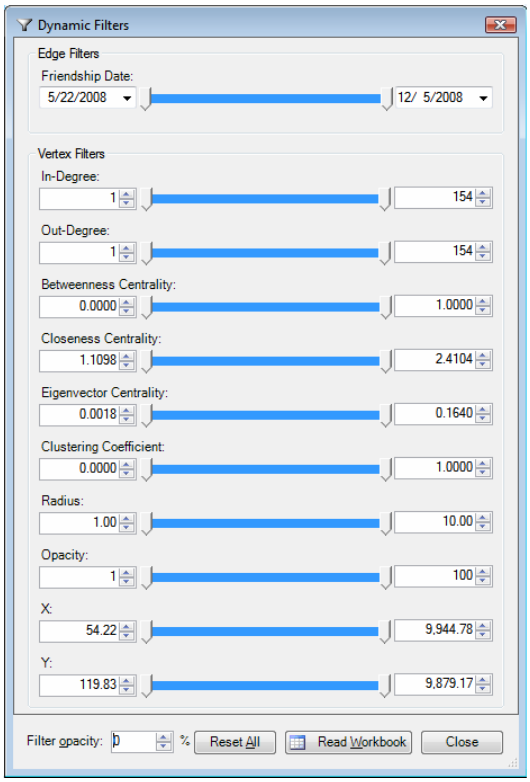


Figure 4. Dynamic filters allow edge and vertex attributes to determine what appears in the network visualization.

Analysis of Ego-centric Networks. Using the "Sub-graph Images" feature users can generate a set of thumbnail images that represent the connections around each node in the network. Users can select the number of steps away from each core node to include in the sub-graph. These ego-centric network images are inserted in-line with the other vertex data in the Vertices worksheet. This allows the images to be sorted along with the other data. Nodes can be sorted by any column using the spreadsheet sort features. In Figure 7 the nodes are sorted by decreasing clustering coefficient.

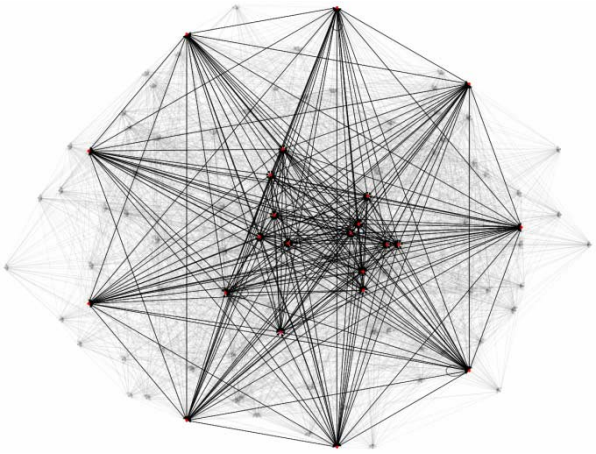


Figure 5. Filtered network, highlighting the most connected employees and their connections to one another.

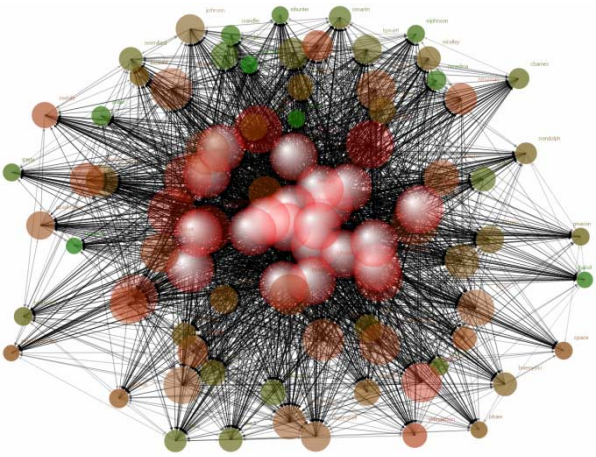
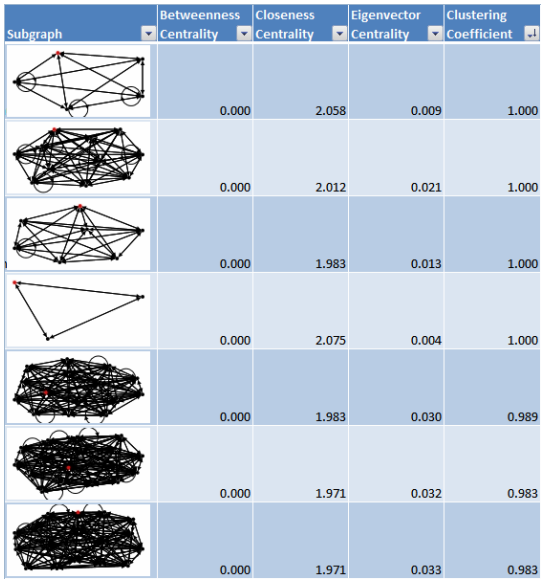


Figure 6. NodeXL graph with node size proportional to node in-degree statistics and node color mapped to the value of the clustering coefficient: low values are indicated in red, high values indicated by shades of green.

This combination of visual data representation and statistical analysis support additional non-trivial observations about the data. For example, sub-graph images illustrate how the same clustering coefficient can refer to very different local network sizes: a triad (row 4) has the same clustering coefficient of "1" as a complete graph (or strong "clique") among a larger group (row 1). Sorting nodes by various attributes can help correlate network structures and other attributes of the nodes.

Visualization through Alternative Layouts. Additional alternative layouts may be useful for some data analysis and visualization. For example, in Figure 8 the network is laid out in a grid. Nodes are ordered by the date on which they first connected with another employee, laid out from left to right and top to bottom, where the top-left node was the first joiner and the right bottom one was the last joiner. This is roughly an indication of their hire date since most employees quickly used the company intranet social network tool and began to link to other employees in the company shortly after being hired (many existing employees started using the



Subgraph	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	Clustering Coefficient
	0.000	2.058	0.009	1.000
	0.000	2.012	0.021	1.000
	0.000	1.983	0.013	1.000
	0.000	2.075	0.004	1.000
	0.000	1.983	0.030	0.989
	0.000	1.971	0.032	0.983
	0.000	1.971	0.033	0.983

Figure 7. NodeXL Vertex worksheet showing the list of nodes, (employees), with sub-graph images indicating the node-networks (personal networks of colleagues) and selected related metrics.

system in a large wave of "friending" when the system was first installed and made operational).

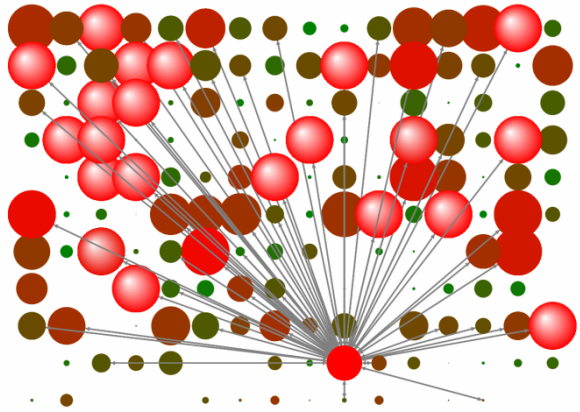


Figure 8. A grid layout ordered by first connection date (from left to right and top to bottom), sized by in-degree, and colored by clustering coefficient. A recently hired employee's network is selected. High clustering coefficients are shown as green.

A grid layout shows some aspects of the network more clearly than one that clusters nodes tightly. As before, the size of each node is proportional to the in-degree of that employee while its color reflects the clustering coefficient of that person's network. Greener nodes are employees whose connections are all connected to one another. Red nodes are those with lower clustering coefficients, which indicate people who connect to people who are not themselves densely connected to one another.

While edges can be displayed in this layout, it is possible to remove the clutter of the underlying edges. In this time-sorted grid, it is possible to see that the more recently hired employees have been connected to by fewer other employees. One employee is selected and that node's edges or relationship connections is displayed.

Nodes can also be located on the grid based on other attributes or projected into any two dimensional space with the use of the "X" and "Y" data columns in the Vertex worksheet. For example they can be plotted in a coordinate space defined by their clustering coefficient and 'betweenness' centrality. Figure 9 shows a scatter-plot of these two statistics for the nodes in the graph.

Interactive Exploration of Graphs. NodeXL enables users to display and hide connectivity data interactively, as shown in Figure 8. This particular graph highlights a recently hired employee who is more connected to other employees than others among the latest hires in the data set.

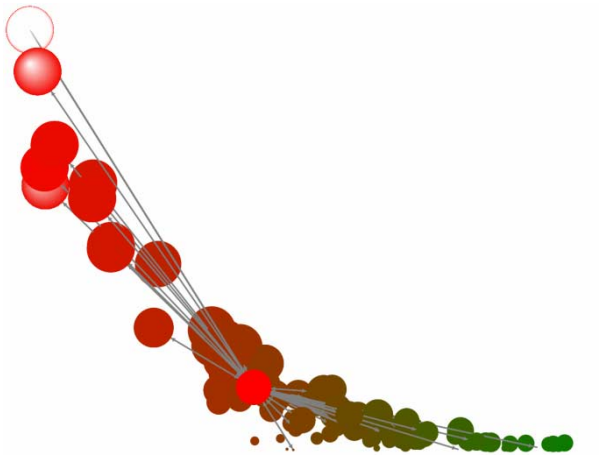


Figure 9. Scatter plot of employees based on their betweenness centrality (y) and clustering coefficient (x) highlighting the same employee as Figure 8.Figure Size represents in-degree, Red maps to high clustering coefficient.

We note that highly connected employees, represented with large circles, tend to be red, indicating low clustering coefficient, i.e., the people they connect to are less well connected to one another. This is in contrast with employees with smaller in-degrees who are designated with smaller size but often greener color, i.e., with higher clustering coefficients.

7. DISCUSSION

NodeXL is intended to simplify the process of network data analysis, making it easier to convert edge lists and incidence matrices into useful visualizations that accelerate discovery. Adding networks as a chart supported by a spreadsheet reduces the barriers to network data analysis and manipulation. Since network visualizations are not always immediately comprehensible, simpler charts featuring a subset of network attributes can be appealing during analysis. For instance, scatter plots of nodes led to insights into outliers and gaps when larger network visualizations were visually muddled in SocialAction [18].

The use of a spreadsheet to host network data does not resolve many of other long standing challenges facing network analysis in general and network visualization in particular. Network visualizations can easily become unintelligible or convey limited information. Edge and node occlusion limit the number of nodes and edges that can be distinctly displayed. Layout algorithms often fail to find optimal arrangements of lines and nodes in order to maximize the comprehension of the structure of the network. Clusters of nodes are difficult to identify and represent, particularly when a node participates in more than one cluster. Large scale data sets remain hard to display.

NodeXL has not directly addressed these and many other of the hard problems in graph layout and network visualization. Nonetheless, the integration of network visualizations in a spreadsheet continues to yield surprising payoffs that point to improvements in some areas of the network analysis workflow.

In many cases, a spreadsheet is the existing home of much network data, reducing data migration and pipeline issues. For those who can code, the spreadsheet offers a rich and deep programming language. For those who do not code, creating a spreadsheet formula may be a more accessible while still powerful way to manipulate data. NodeXL shows that a significant level of flexibility can be achieved with nothing more than a few spreadsheet formulae.

Flexible slicing of data. One of the strategies for increasing the comprehensibility of network presentation is filtering and slicing the network. Spreadsheet features provide useful support for data manipulations related to collections of edges from multiple time periods.

Time slices provide a natural and useful sampling approach as network analysts push past static graphs. The spreadsheet can easily allow for the addition of columns that represent the time periods in which edges were active. These attributes can be used to drive the "Visibility" control of each edge, allowing users to step through time slices using the dynamic filters or directly manipulating the spreadsheet data. Short time slices in which fewer modes and edges are present are often more intelligible than longer time spans in which all nodes and edges are present and displayed.

Extracting 'strong' relationships is an alternative to slicing a network by time. Users can limit complexity by constraining relationships to the strongest present in the network. "Tie strength" is a common attribute associated with an edge, a measure of how much the tie is active. The number of replies one person sends to another is an example of tie strength. A dynamic filter can hide all nodes in a graph that do not connect to another node with a frequency or strength above a threshold. Alternatively, attributes of individual nodes may be added to the spreadsheet, for example the income of people in a social network or the publication citation count of a document in a research literature can be selected to limit the number of remaining nodes and edges. All attributes of nodes and edges in columns inserted into the spreadsheet can be leveraged to control the display of the network. These features are a benefit for those exploring data sets with rich attributes.

Avoiding whole graph visualizations entirely is another approach. Instead of generating overly complex and muddy graphs with too much data, an alternative is to focus on ego-centric networks [1]. NodeXL already supports the creation of sub-graphs from a larger graph. This is a useful but often labor intensive process in which each node is visualized within its own "1.5 degree" network of

links to and among node connections. The automation of this process allows for the rapid creation of small multiples of ego-centric networks: grids of networks for each participant that support individual and group level comparisons as illustrated in Section 6.

Expanding the NodeXL layout engines. The application of multiple layouts to different parts of the data set can help call out important aspects of the network's structure. Combinations of different layouts can pull different classes of nodes into complementary shapes or patterns that highlight their interconnection. This points towards the potential benefit of implementing features to support semantic substrates and further organize nodes into more comprehensible patterns by constraining nodes to regions in the network diagram.

Presentation of analysis. NodeXL images prepared for use in print are more constrained than exploring a network structure interactively in the NodeXL application graph visualization pane. Dynamic network exploration enables users to make otherwise visually opaque graphs more comprehensible as they highlight different aspects of the network.

8. FUTURE WORK

Network visualization is so complex a field that there is no limit to the number of improvements and directions that the NodeXL effort can take. A high priority item, however, is the implementation of better support for clustering of network nodes. This feature is needed to represent how groups of entities are bound, for example, by a common membership or shared status. Furthermore, clustering is required for normalizing multiple entity identifiers that point to the same entity. For example, multiple forms of a name or email address that appear in the data would fragment a single person's representation and affect the network analysis by making what should be a single node into many.

The data structures required to support clusters are enabled in the current version of NodeXL but we still need to design and develop graphical user interfaces for creating clusters and adding and removing nodes from clusters. These operations require that the layout algorithm be altered to operate continuously as opposed to the current 'on-demand' execution of the requested layouts.

The NodeXL toolkit currently provides only a minimal set of network measures. A vast number of network measures have yet to be implemented. While key metrics are calculated in NodeXL, a more comprehensive library of network measures and transformations may be best achieved by enabling interoperability with existing libraries of network analysis algorithms. The project seeks to prioritize the highest value missing measures that would address the needs of the widest user population.

The basic layouts in the current implementation are often inadequate for rendering complex or dense graphs. Better layouts are the focus of several ongoing research efforts [8]. The modular architecture of the NodeXL system already allows other layouts to be added and, similar to the issues related to providing a comprehensive library of network analysis metrics, it points to the value of interoperability with existing libraries of layout algorithms.

Finally, providing access to additional data sources is an important direction for the project. Excel natively provides connections to database servers. Other sources of social network data include the many "Social Networking" services in popular use, such as Facebook, mySpace, and LinkedIn as well as enterprise implementations of similar services. In some cases these services are opening programmable interfaces to their data sets making connections between NodeXL and their data fairly simple to implement.

NodeXL currently supports the import of social media network data sets from the user's own personal email repository, via the Windows Search Index found on most Windows operating systems. This allows users to study the patterns of reply in their own email for any date range, set of folders, users, or keywords. The resulting maps illustrate groups and connections maintained via the exchange of email messages. NodeXL also supports extracting social network data from the Twitter micro-blogging and messaging service. Additional import connectors for social media sites are a direction for future work for the project. The goal would be to provide an extensive set of connections to widely used social media sites. The result could be a more comprehensive view of an individual's social media context.

9. CONCLUSION

Network structures are important in many disciplines and professions. Interest in these structures is growing more common as the world of social networks and computer-mediated social content becomes more main stream. NodeXL aims to make analysis and visualization of network data easier by combining the common analysis and visualization functions with the familiar spreadsheet paradigm for data handling. The tool enables essential network analysis tasks and thus supports a wide audience of users in a broad range of network analysis scenarios.

Using the tool on a sample social media network dataset we found and illustrated structural patterns like the density of connections within the enterprise, different kinds of contributors, and key network metrics. These analysis tasks can be usefully applied to a wide range of social media data sets.

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