Visual Analytics of Dynamic Networks – A Case Study

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ABSTRACT

In this paper, we present a case study of applying visual analytics methods to explore a dynamic social network. The visualization and analysis of this kind of data is challenging because of its relational and temporal nature. We illustrate a method and its prototypical implementation that integrate: the combination of three views based on node-link diagrams, a dynamic layout, the visualization of social network analysis metrics, and specific interaction techniques for tracking node trajectories and connections over time. We discuss how this integration of visual, interactive and analytical methods, driven by perceptual principles, can help users with gaining insights when examining dynamic organizational network data.

Keywords

Dynamic layout, dynamic networks, graph drawing, interaction, social network analysis, information visualization, visual analytics.

INTRODUCTION

Dynamic social networks are social networks that take into account changes over time. They not only model relations between human beings in terms of some sort of interpersonal interaction, but also consider the evolution of these relations, i.e. the way and the extent by which they change over time. In our case study, we considered the organizational network (i.e. a network consisting of the employees of an organization) of a knowledge intensive enterprise and focused on different kinds of relations, such as communication, collaboration, technical and practical advice, and spreading of new ideas. We aimed to track the evolution of these relations and of some performance indicators, considering how they relate to organizational changes: turnover, team restructuring, and other management actions. These data and tasks might be relevant, but also difficult to achieve, for enterprise managers who might not have specific expertise in social network analysis; employees also might be interested in analyzing their data to assess and improve their performance. Thus, we adopted a visual analytics approach, aiming to facilitate the interactive exploration of dynamic networks for non-expert users and the comprehension of their structures and how they change over time.

RELATED WORK

While several methods for the visualization of static networks have been proposed in Graph Drawing [5], Information Visualization [11], and Data Mining [4], the interactive visualization of dynamic networks and its integration with analytic methods is an emerging research field. Besides the choice of a visual representation for the relational data (e.g. node-link diagrams or matrix-based representation), an important issue for dynamic networks is the visual encoding of the temporal dimension. At least four different approaches exist: mapping time to time, i.e. animation [10]; mapping time to a visual variable, i.e. a superimposition view, in which different time points are distinguished by color or transparency [3]; mapping time to a space axis, i.e. a juxtaposition view, in which the diagrams are displaced side-by-side [1]; and mapping time to a space dimension, i.e. a two-and-a-half-dimensional view, in which two-dimensional graphs are arranged in a stacked pile [6]. But finding an adequate visual encoding for the time dimension does not alone solve the issue of visualizing dynamic networks. Another important aspect is to obtain a sequence of diagrams that facilitates the perception of changes, by preserving the user's mental map [7]: it must minimize unnecessary changes while emphasizing temporal trends or patterns. Moody et al. provide a common conceptual framework [12]: the dynamic stability is ensured by binding nodes to anchors, which can be fixed positions or the position of the nodes in the aggregated layout. In [8] the (dynamic) anchors are the positions of other instances of the same node in other time-slices. Several computational methods, which descend from Social Network Analysis (SNA) [14], can be integrated into the visualization. A common approach is to compute some static SNA metrics associated to nodes and edges and then encode them to a chosen visual variable or exploit them to perform dynamic filtering [13].

CASE STUDY: AN ENTERPRISE DYNAMIC NETWORK

Even though we believe that our methodology could be extended to different kinds of social networks, we confine this paper to an organizational network and present a knowledge intensive enterprise (KIE in the following) as a case study.

Data

The analysed small firm focuses on research and public communication in various areas of expertise. We gathered multi-relational network data by surveying the employees 4 times during 14 months. The questions aimed at the analysis of the organizational knowledge communication network and were asked with reference to the last 3-4 months to cover the whole time period between subsequent

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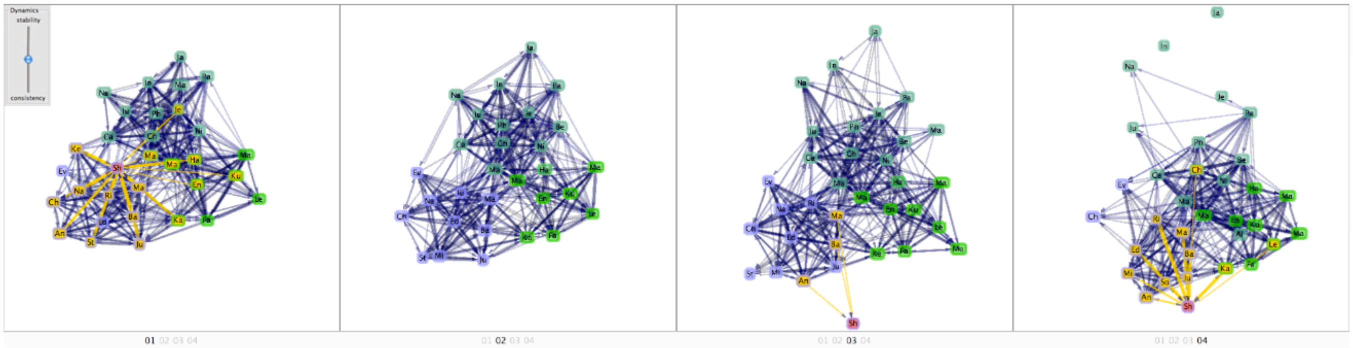

Figure 1. Identifying network's structure and its evolution in a juxtaposition view; node colored according to organizational units; selected node highlighted in red and its connections in yellow.

surveys. Due to generally high response rates, relational data of all relevant and active actors could be collected at each survey. We disregarded probabilistic aspects and multi-modality, by considering only employees as nodes and disregarding skills, tasks and any other organizational data. At first the enterprise was structured into three organizational units, while a restructuring process was altering the initial compartmentalisation at the end of the surveys. The number of the enterprise staff varied between 33 and 34, with a total of 38 persons considering the turnover. To preserve the privacy of the employer and of the employees, we rendered both anonymous.

Users

After having defined the context and the features of data, we conducted preliminary interviews with users to outline their needs and collect a list of requested features. We chose subjects to be interviewed from two groups: business users with a managing function (i.e. non-experts with reference to network analysis), who are our main potential users, and network experts as reference group. We questioned 11 persons by the means of a semi-structured method; then we analyzed the resulting audio recordings, each lasting between one and two hours, and processed them into a list of requirements.

Tasks

As a result of the user interviews, we elicited a list of tasks, both general (at network level) and specific (at node level), all focused to dynamic aspects. A general task is to understand the structure of the entire network and its evolution over time, for example by identifying large clusters of employees with tighter relationships and observing how they change over time. Examples of tasks at the node level are the identification of: any occurrence of hires, leaves and resignations; increasing or decreasing levels of involvement; and the presence of key players and their evolution.

ANALYSIS AND DISCUSSION

A visual analytics approach

Given a rough sketch of data, users and tasks, we engaged in the design of our visual analytics prototype [9], whose main features are:

- Three views for visualizing network's dynamics, and animated smooth transitions between them.
- A dynamic interactive layout that enables the user to tune the balance between stability and consistency according to her/his task and data.
- The integration of automatically computed SNA metrics into the interactive visualization.
- A specific interaction technique to highlight a given node and its connections.
- The visualization of node trajectories by which users can focus on specific nodes and track their evolution.

In the following, we discuss how these features can help us with analyzing the KIE data, accomplishing the aforementioned tasks and gaining insights.

Network Structure

The first task consists of identifying the structure of the network and following its evolution. In more detail, we are interested in finding clusters, putting them in relation with organizational units, and observing if and how they vary over time. Several features of our prototype can support this task. The visualization is based on node-link diagrams (which scale properly for networks in our size range). The identification of clusters is ensured by the dynamic layout algorithm, which also is one of the benefits of the integration between visual and computational techniques. We adopted a continuously running force-directed layout, computed by the Barnes-Hut algorithm [2]. The preservation of the mental map is assured by a mechanism similar to the one used in [8], but in our implementation the user can interactively control the stability/consistency trade-off: a simple GUI slider allows her/him to select stability or consistency and to pass from one to the other through stepwise transitions. Looking at the KIE dataset, we have found that an intermediate value lets the positions of nodes vary over time according to their connections, while it preserves the positions of clusters (corresponding to organizational units, which remained unchanged until time point 3, when they faced major organizational changes). These clusters and their evolution can be seen in Fig.1 and Fig.2. The former shows a juxtaposition view, which applies the principle of small multiples and allows the reader to compare the time-slices and find commonalities and differences. Coordinated zooming & panning and coordinated highlighting further facilitate comparison. The latter (Fig.2) shows a superimposition view, obtained by superimposing the node-link diagrams.

In this case, a visual variable must be employed to differentiate between time-slices: we used transparency, so that more recent elements are more opaque. This view has also the advantage, with reference to juxtaposition, of reducing the eye movement from one slice to the other during comparison, and preserves the context. In both views we see that the dark-green cluster at the top (which also faced the major organizational changes) moves away from other nodes.

Hires, leaves and resignations

Passing from overall tasks at the network level to more specific tasks at the node level, the first thing we are interested in is identifying any occurrence of hires, leaves, and registrations. The combination of our dynamic layout algorithm with two interaction techniques supports us with this task. One interaction is the simple highlighting of adjacent nodes. The other consists of showing the node trajectory as a polygonal chain, which connects instances of a given node in subsequent time slices. In the juxtaposition view (Fig. 1) the node corresponding to Sharon (Sh) is highlighted in red: we observe a leave at time point 2, and a gradual reintroduction at 3 and 4, when she reestablished most of the relations she had. In the superimposition view (Fig. 2), we allow users to alternatively visualize edges and trajectories, or to visualize them only on demand, to reduce the visual clutter. Trajectories of all nodes are visualized as gray directed polygonal chains. The mouse-hovered node Jack (Ja) is highlighted in red, while its neighbors are highlighted in yellow. The most recent instances are opaque, previous ones are increasingly transparent. Jack has been loosing connections, so he moves from the center to the periphery. Also Nadine (Na) and Ines (In), in the upper left, move from to center to the periphery (and in the case of Nadine this corresponds to a resignation). Sharon (Sh), in the bottom, moves the other way round, since she is coming back to work after a leave.

The trend of individual performance

Another node-level task is to monitor the trend of individual performance, in the sense of social involvement in the communication/collaboration network. To illustrate how our prototype supports it, we introduce two additional features: a two-and-a-half-dimensional (2.5D) view and the integration with SNA computational methods. We

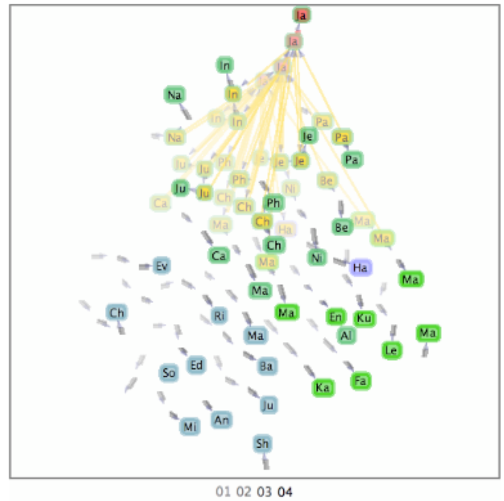

Figure 2. Node trajectories in a superimposition view; links shown (yellow) for the selected node (red) only.

considered metrics for static (i.e. non-temporal) and single-relational networks, like for examples node centralities [14]. In this way the user can interactively select a certain metric to be computed for a certain type of relation; the entire temporal multi-relational network is partitioned into as many static single-relational networks as time-slices are and the requested metric is computed for each of them. Then the resulting values are encoded to visual variables within the visualization (color, size, shape) for each time-slice. We obtained a 2.5D view (Fig. 3) by mapping time to an additional spatial dimension. In such a view, we draw diagrams for each time-slice on separate transparent planes, stacked along the horizontal time axis. It combines some of the advantages of the two aforementioned views. 3D zooming, rotating and panning controls allow the user to set the best viewpoint. In this view, trajectories run along the spatial dimension dedicated to time. We shade different colors along the trajectory of a given node to show how its values for a certain metric vary over time. In this way, the results of analytics methods are integrated directly into the main visualization of the network, enabling the user to examine its relational and temporal aspects simultaneously without any additional diagram. In the KIE organizational network, we observe that Paul (Pa) has constantly middle importance (bluish trajectory) while Jeff (Je), holding a

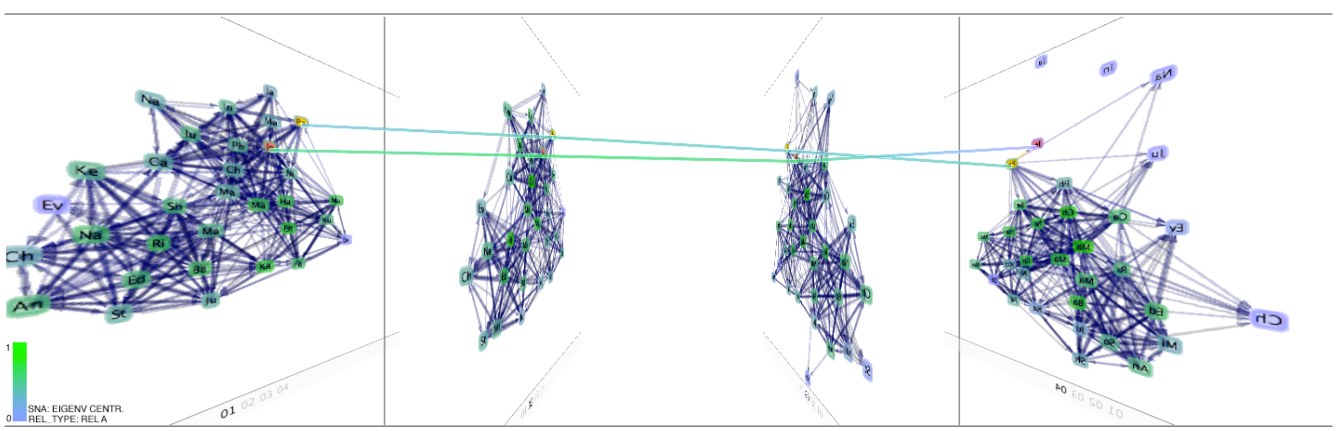

Figure 3. Analyzing the trend of individual performances in the two-and-a-half-dimensional view with trajectories.

managing function until the time point 3, had high importance at the beginning but has been loosing it (trajectory shading from green to azure).

Presence of key players and their evolution

The last task we discuss consists in identifying key players and tracking their evolution. Like the previous task, this one is supported by the combination of the SNA computation, the two-and-a-half-dimensional view and the interaction showing trajectories. In Fig.4, a zoomed and rotated 2.5D view, we observe that the betweenness associated to the top manager Hans decreased during the period 1 – 3 (green-azure trajectory), while the betweenness associated to the administrative assistants Christian (Ch) and Judith (Ju) is the highest at the time point 3 (green borders). We might correlate this observation with the managing decision to enforce inter-unit collaboration, taken at time point 1. It gave the expected result, reducing the amount of coordination efforts required to the top manager, but also resulted in a higher charge of coordination to be performed by the assistants.

CONCLUSION AND NEXT STEPS

In this paper we presented an approach to dynamic networks consisting of the integration of interactive visualizations with analytical methods (namely layout algorithms and graph-theoretical metrics), driven by basic perceptual principles. We described a prototypical implementation of our approach by discussing a case study dedicated to the analysis of a knowledge intensive organization. Our future plans comprise first of all an evaluation of our research prototype, through user studies with both experts and non-experts, in order to validate our design and implementation choices. Then we aim to explore alternative representations besides node-link diagrams and to further integrate visual and analytical methods.

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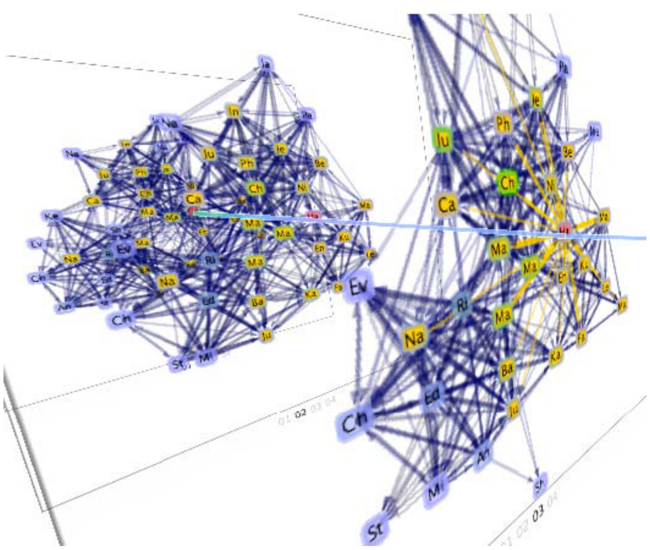

Figure 4. The evolution of a key player (red nodes).

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