DyNetVis: A system for visualization of dynamic networks

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ABSTRACT

The concept of networks has been important in the study of complex systems. In networks, links connect pairs of nodes forming complex structures. Studies have shown that networks not only contain structure but may also evolve in time. The addition of the temporal dimension adds complexity on the analysis and requests the development of innovative methods for the visualization of real-life networks. In this paper we introduce the Dynamic Network Visualization System (DyNetVis), a software tool for visualization of dynamic networks. The system provides several tools for user interaction and offers two coordinated visual layouts, named structural and temporal. Structural refers to standard network drawing techniques, in which a single snapshot of nodes and links are placed in a plane, whereas the temporal layout allows for simultaneously visualization of several temporal snapshots of the dynamic network. In addition, we also investigate two approaches for temporal layout visualization: (i) Recurrent Neighbors, a node ordering strategy that highlights frequent connections in time, and (ii) Temporal Activity Map (TAM), a layout technique with focus on nodes activity. We illustrate the applicability of the layouts and interaction functionalities provided by the system in two visual analysis case studies, demonstrating their advantages to improve the overall user experience on visualization and exploratory data analysis on dynamic networks.

CCS Concepts

•Human-centered computing → Graph drawings; Visualization systems and tools;

Keywords

Dynamic Networks; Dynamic Graph Visualization; Complex Networks; Temporal Activity Map; Recurrent Neighbors

1. INTRODUCTION

The complex interactions between the components of a system may be mapped into a network by representing these components as nodes and by linking them according to the relation they have in the respective system. This modeling framework helps to identify meaningful relations between these components at different scales and to understand how these interactions regulate the diffusion of information or other dynamic processes, such as epidemics, taking place on the network. Network science has been established as an important framework to study complex systems in various contexts and finds applications in disciplines as diverse as computer sciences, biology, linguistics and economics [7]. The popularity of network science as an analytic tool is partially explained by the increasingly availability of high quality data, for example, of contact networks between humans (collected through RFID sensors) and online social networks (web-crawlers), or communication and mobility networks, extracted from mobile phone call records or e-mail accounts [12], that reveal non-trivial patterns of interactions between the components of the system.

Network studies have traditionally focused on the structural properties of networks. Recent data however have shown that networks not only have structure but also evolve, with links and nodes appearing and disappearing over time. As a consequence, the times in which links occur have been shown to be sometimes as important as the structure of connectivity of the network. In these dynamic networks, time stamps are assigned to links to indicate the moment of link-activity. There are several dimensions that can be studied such as the geographical dimension, but as the main focus of this work is to represent connections over time, we choose to focus on the temporal dimension. The temporal dimension adds an extra level of complexity to network analysis since activation times typically do not follow regular behavior but bursts of activity, circadian cycles, causal activations, among other patterns.

State-of-the-art statistical tools are being developed to extract information and better understand the evolution of networks [10]. Nevertheless, little emphasis has been giving on solutions to represent and visualize dynamic networks beyond the standard 2D projection of a static snapshot. Network visualization is important not only to get an intuitive understanding of both spatial and temporal variations in the structure but also to identify patterns not captured by statistical methods and for interactive exploratory analysis. In fact, proper visualization is the first step to identify relevant patterns to be later detected by quantitative methods.

In this paper, we propose the *Dynamic Network Visual-*

ization System (DyNetVis), a system to assist dynamic networks visual analysis. The system incorporates strategies for visualization of time-varying networks aiming to highlight different aspects of the network evolution. We demonstrate the applicability of our tool to enhance the exploratory network analysis using two case studies that reflect specific scenarios of contact networks between humans.

The main contributions are: (i) a new node reordering method, called recurrent neighbors, that has been applied to all case studies of this work; (ii) Temporal Activity Map (TAM) method, previously used in other contexts, as for example visualization of firewall log [9], here applied to reveal node activity; (iii) the analysis of two dynamic networks in different contexts and identification of patterns not observed in previous studies; (iv) to provide a computational system, that intuitively integrates several methods that help domain experts to visualize temporal patterns on networks.

2. RELATED WORK

There are several computational tools available for quantitative and qualitative analysis of networks (e.g., Gephi [5], Cytoscape [18], DiffAni [16], among others [2]). Most of these tools, however, do not support the analysis and visualization of dynamic networks. *Gephi* and *DiffAni* implement functionalities related to dynamic network representation and visualization, but with few layout construction methods or few interaction capabilities, failing to provide an effective visual analysis experience. In *Gephi*, for example, it is possible to visualize network evolution using animation, but this visualization is limited to the structural layout (i.e., using traditional graph drawing techniques) and it accumulates links and nodes from previous times.

In network studies, small dynamic networks have been illustrated by either drawing sequences of snapshots of network structures or by presenting the history of contact events between nodes [10, 14]. For large networks, these approaches are unfeasible and then alternatives that include clustering of nodes are necessary. For example, flow maps are proposed to visualize the evolution of network community structures [15] and massive sequence views (MSV) for temporal network analysis and visualization [19]. Several aspects of MSV are explored and one of the most important is the node (lines) order changing to reduce the overlap of links (vertical lines). In one of these strategies, named circular MSV [19], the links are disposed in a circular shape and time varies from the internal to the external circles, providing a more apparent communication between two nodes if compared with the temporal layout. The limitations of this method includes a requirement for more screen space and a difficulty to compare snapshots. Other methods to enhance visual pattern detection in dynamic networks include employing 'piling' metaphors [3], adjacency lists, or representing network snapshots as high-dimensional points that are projected in two dimensions [20]. There are also strategies as Temporal Trends [4] and Heatmap Grids [9] that are used to perform visual analytics of firewall log events and dense networks in astronomy and neurology, respectively.

Previous efforts to classify the visual techniques into taxonomic categories are presented in the literature [2, 13, 6]. Nevertheless, the area still lacks systems that cover more temporal techniques. Moreover, little attention has been given to some categories as, for example, matrix related techniques. In a recent survey, the visualization of dynamic networks are categorized in animation or timeline [6]. The *animation* taxonomic category contains the node-link layout, which uses an animation to show the graph drawing, and is sub-divided in General-Purpose Layout and Special-Purpose Layout. The *timeline* taxonomic category contains all the taxonomy that uses approaches to draw the network in the time-to-space mapping (i.e., it includes a timeline in the layout). Two taxonomies are possible in the timeline, the first one, Node-Link-Based approach, contains a temporal layout in which nodes are represented by horizontal parallel lines and time is represented by a vertical axis or an interval. The second taxonomy is the Matrix-Based approach, which includes visualization of the adjacency matrix on temporal layout.

3. VISUAL LAYOUTS

A general pipeline for visualization of dynamic networks is presented in Fig. 1. In the first step, the raw dataset is converted to a tabular format, in which the entries contain connections (i.e., the links) between nodes and the time stamp of the respective connections (see Fig. 2(a)). A preprocessing step is used to filter time intervals or to change the temporal resolution of the network. Finally, visualization techniques are employed to create the desired layouts of the network. We use structural and temporal layouts that are based on the models shown in Figs. 2(b) and 2(c), respectively. Users are able to actively interact with these layouts, by selecting nodes or links, zooming in or out, scrolling in the x-y dimensions, and so on. The following sections explain the techniques used in this work together with their respective classifications according to the categories presented in [6] .

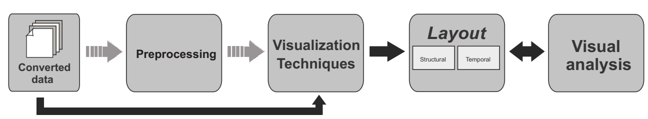

Figure 1: Dynamic networks visualization pipeline.

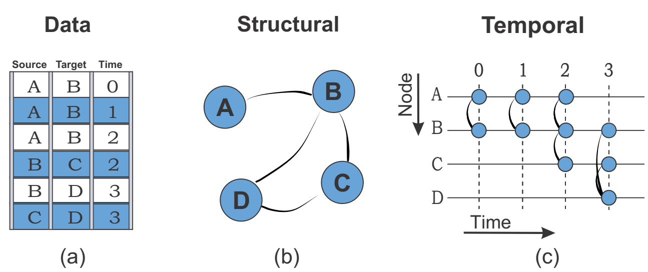

Figure 2: Structural and Temporal visualization layouts. (a) shows the tabular representation of a network. (b) shows the representation of a structural layout of the network in (a). (c) shows the temporal layout.

3.1 Structural Layout

The structural model is the standard network (or graph) static visualization, i.e., the node-link diagram in which a node is represented by a circle and the links are depicted by lines connecting the circles. There are several techniques to construct the structural layout. In the following, we look at the temporal aspects that can be captured on the structural layout and its visual properties.

The cumulative approach is good to integrate all the network history in a single layout. Several insights about the network are obtained in this view. For example, it reveals which nodes are very active and which nodes are peripheral. This is important because the node may have, for example, several connections during a short period of time or few but frequent connections in the entire time interval.

Another important aspect of network visualization is the visual features of nodes and links. This process is guided by the attribute-to-visual mapping of nodes and links [18]. In this case, nodes properties as shape, color, thickness and texture are set according to some property of the node, as for example, its degree (i.e., the total number of links connected to the node) or network centrality. The mapping of a single attribute to multiple visual properties is recommended to highlight the characteristics to be visualized, known as redundant coding [21]. This approach is classified as *Special-Purpose Layout*, because we employ the color, shape, size and positioning of nodes and edges to distinguish group of nodes and make the visualization scalable [6].

3.2 Temporal Layout

The temporal layout emphasizes the evolution of the network. The focus here is the inclusion of the connection time stamp, additionally to the connection between nodes. The **Massive Sequence View (MSV)** [19] is a temporal layout construction strategy whose underlying structure is presented in Figure 2(c). In this layout, the nodes are represented by horizontal parallel lines (one node per line), and each time snapshot is represented in the vertical axes. Connections between two nodes are represented by a vertical link connecting two horizontal lines at the respective time stamp in which the connection occurs [10, 14]. Figure 2(c) illustrates the temporal layout for the network presented in Fig. 2(a). In the taxonomy this type of temporal layout is called *juxtaposed*, more specifically the *linearized* type [6], because of the layout that has nodes in horizontal lines and each time is represented by a vertical line.

The main issue of the temporal layout is that links overlap in each time stamp. A high degree of overlapping may pollute the layout and consequently hamper user analysis. In order to minimize this overlapping, several node reordering strategies were proposed. In this work we discuss two techniques [19]: time of first appearance and accumulated node degree. In addition, we propose a third ordering strategy named **recurrent neighbors**. These three strategies are discussed as follows.

3.2.1 First appearance

Nodes are ascendantly ordered by the first time they have a connection on the network (Fig. 3(a)). In this view, it is possible to visualize how nodes are introduced in the network, for example, the time elapsed from first to last introduced nodes. It also helps to verify if the first nodes that appeared on the network remain active over time or concentrate their activity on specific time periods.

3.2.2 Node degree

Nodes are ascendantly ordered by their accumulated degree. In Figure 3(b), node E, with the lowest accumulated degree (4), is placed in the first row, whereas node B, with the highest accumulated degree (8), is placed in the last row. This strategy is useful to compare activities of nodes with similar degree, as they are gathered in neighboring lines. For instance, two nodes with same degree will be positioned in adjacent positions. These nodes may have significant different connection patterns over time – the first can concentrate its connections in a specific time period whereas the other can interact along the entire time period.

3.2.3 Recurrent neighbors

Nodes whose connections are recurrent in time are maintained spatially closer. The idea is to approximate nodes with more connections with each other, highlighting node clusters and the connection distribution inside these clusters. This strategy minimizes the size of links in the temporal layout, reduces the number of long edges and consequently the visual clutter.

The reordering process is as follows: the node (reference node) with the highest accumulated degree of the network is positioned in the central row on the layout. The two nodes (K and L) with the highest number of connections with the reference node are then selected and placed on the rows above and below the reference node. A similar procedure is repeated for each of the nodes K and L, but now only one new node is selected for K and one for L. The new node M with the highest number of connections with node K (similar for node N in respect to node L) is positioned just above (below) it. This process is repeated until all nodes are exhausted. If there are unselected nodes in the network, the process starts over again. For example, in Figure 3(c) the node with the highest degree is node B. This node is placed in the central line of the layout. Note that node B connects with nodes A (four times), C (one time) and D (two times). The algorithm then selects nodes A and D to be placed above and below node B, respectively. Next, node C is placed above node A, as node C is the only neighbor of node A which has not yet being selected. The same occurs with node E, which is finally placed below D.

3.3 Temporal Activity Map

We implemented a layout named **Temporal Activity Map (TAM)** to emphasize the node activity based on the number of connections that each node forms at each time stamp in respect to all connections in the network. The same strategy was presented by Temporal Trends [4] and Heatmap Grids [9], but now it is applied in a different context. In the TAM layout, the node degree at each time stamp is computed for all nodes at all times and the highest degree is taken as the maximum value of the activity range, that is used to map the color of nodes. The node placement strategies are the same as for the previous cases but we draw rectangles instead of circles to represent the nodes. We also remove the links between them. An example of a layout constructed using TAM is shown in Figure 4. The rectangular shape gives a better sense of continuity [21] and the absence of links decreases the amount of elements in the layout, highlighting the node activity. TAM can be taxonomy classified as *intra-cell timelines*, more specifically *pixel-based* technique, where each cell can be represented as a point in time [6].

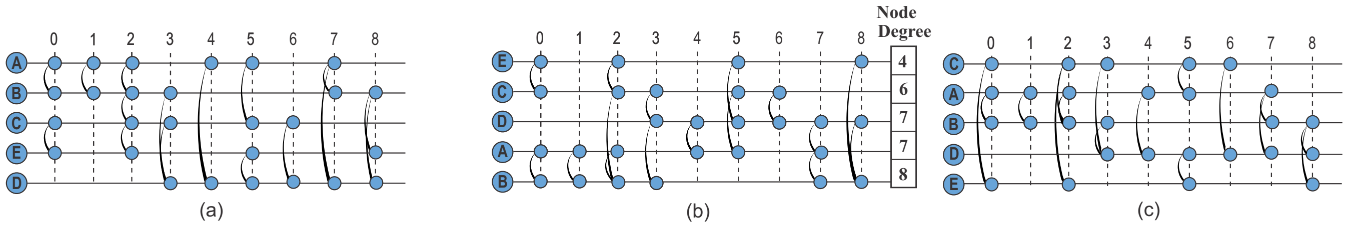

Figure 3: Temporal layout reordering strategies. (a) First appearance. (b) Node degree. (c) Recurrent neighbors.

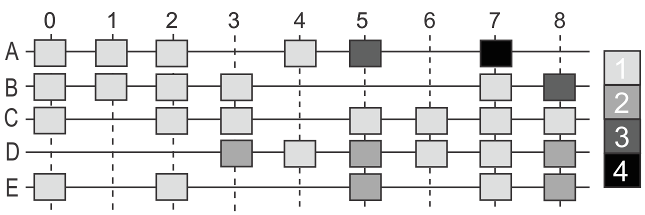

Figure 4: Temporal Activity Map (TAM). The nodes are represented by rectangles. This layout provides information on the node activity that is represented by the color of the rectangles.

3.4 Temporal Resolution

An important interaction in the dynamic network analysis is the ability to change the temporal resolution of the network being analysed. This procedure rearranges the data in the temporal dimension, grouping connections from subsequent time stamps. Eq. 1 represents the change in the temporal resolution, in which t'_{new} is the new time stamp, t_{ori} is the time stamp in the original resolution, t_{s} is the first time stamp and δ is the resolution factor, i.e. the scale in which the time will be modified. For instance, if $\delta = 2$, the new resolution will be double of the original and the network will have half of time stamps when compared to the original.

$$t'_{\text{new}} = \left\lfloor \frac{t_{\text{ori}} - t_{\text{s}}}{\delta} \right\rfloor \delta + t_{\text{s}} \tag{1}$$

Figure 5 shows the layout before and after change in the temporal resolution, using $\delta = 2$. Node connections with different time stamps are grouped together in a single time. Changing the resolution of dynamic networks may facilitate the analysis when the network is temporally sparse, favoring the identification of patterns that can be difficult to identify using the original resolution.

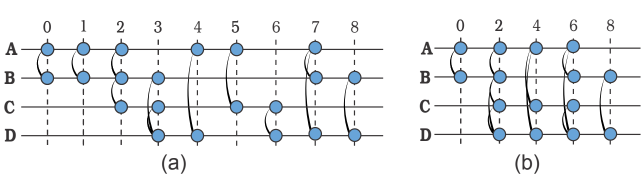

Figure 5: Changes in the temporal resolution. (a) Original resolution. (b) Change of resolution ($\delta = 2$). For example, nodes at time steps 2 and 3 in the original version are grouped in time 2 if using the new resolution.

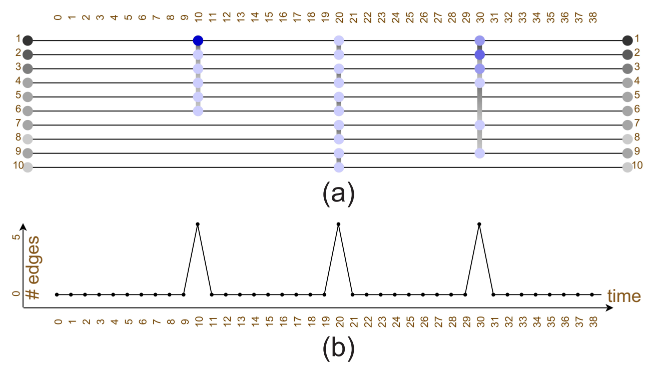

Figure 6: Comparison between temporal layout and line graph. (a) Temporal layout reveals three different connection patterns between the nodes at times $t = 10, 20, 30$. (b) Line graph representing the same temporal pattern. The corresponding timestamps are indistinguishable.

3.5 Line graph

Line graph is a common way of representing data based on statistical models [17]. In temporal networks, it can be used to show the evolution of the number of connections over time. It provides an overview of nodes activity, allowing the user to promptly identify times (represented by line peaks) for further analysis. Despite representing a potential analytic tool, its utilization alone may hide relevant patterns or fail to distinguish important events during the time interval under analysis. Figure 6 shows a situation in which three different activity patterns are equally represented by a line graph: In time $t = 10$, one node connects to various different nodes, in $t = 20$ pairs of nodes connect between themselves, and in $t = 30$ there is a dispersed connection between some nodes.

Figure 7 illustrates another situation using two different time periods obtained from a real dataset. In the first time period (Fig. 7(a,b)) line graph (bottom) does not reveal any pattern, while in the second time period (Fig. 7(c,d)) a significant change is observed in the middle of the layout. Figure 7(a) shows a temporal layout in which instances are ordered by appearance, and Figure 7(b) employs the proposed recurrent neighbors ordering. In this situation, line graph and the appearance ordering layout were both unable to reveal any relevant patterns. Only recurrent neighbors reveal a pattern in the node connections. On the other hand, Fig. 7(c) shows an example in which the temporal layout using order of appearance do not reveal any significant changes in the connection pattern but the line graph

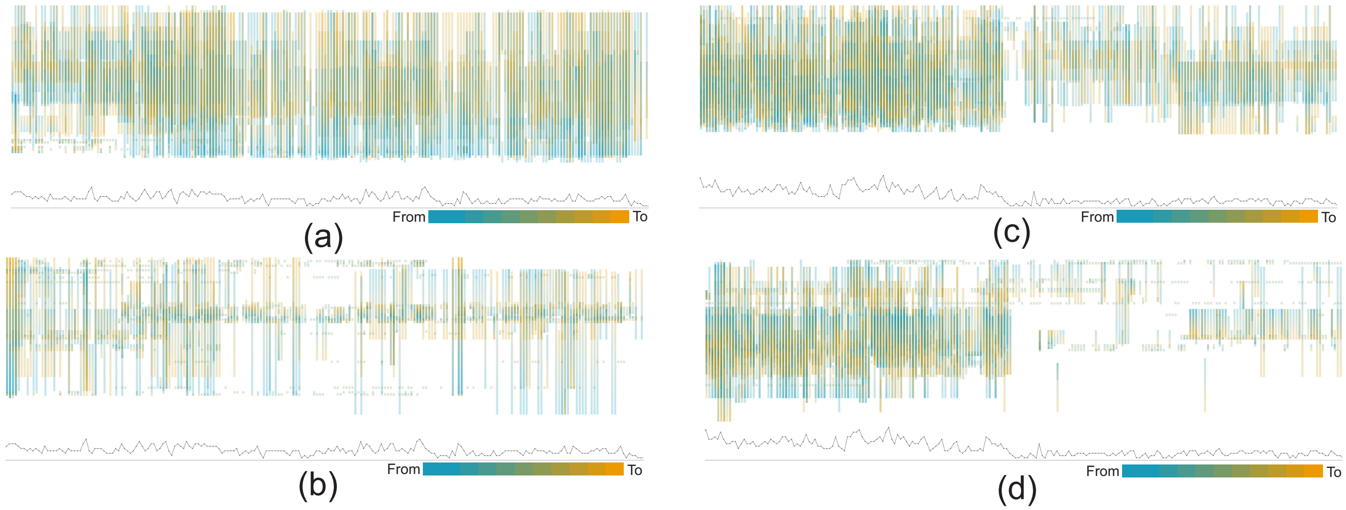

Figure 7: Temporal visualization of two distinct time periods of a real network. (a) First time period with nodes ordered using first appearance; (b) First time period with recurrent neighbors; (c) Second time period using first appearance; and (d) Second time period using recurrent neighbors.

suggests that changes in the density of connections occurs from about half time towards the end. Recurrent neighbor ordering (Fig. 7(d)) is able to show this change.

4. DYNAMIC NETWORK VISUALIZATION SYSTEM

We have developed the **Dynamic Network Visualization System (DyNetVis)** that implements the visual strategies discussed in the previous sections. The system aims to support the analysis of dynamic networks and provides both the structural and temporal layouts, as well as a set of interactive tools to allow data exploratory analysis. DyNetVis is freely available on http://tinyurl.com/zpgsk26

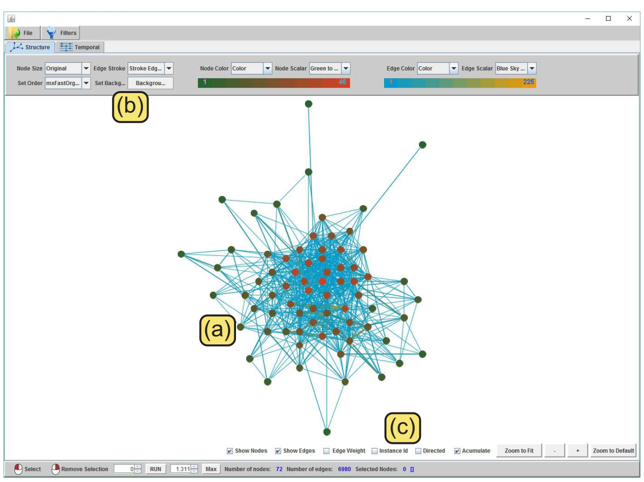

Figure 8: DyNetVis structural layout. (a) The layout. (b) and (c) Visualization options.

Figures 8 and 9 show the main screens of the system, presenting the structural and temporal layouts, respectively. Users are able to load networks from text files containing a list of connections (source node, destination node and time

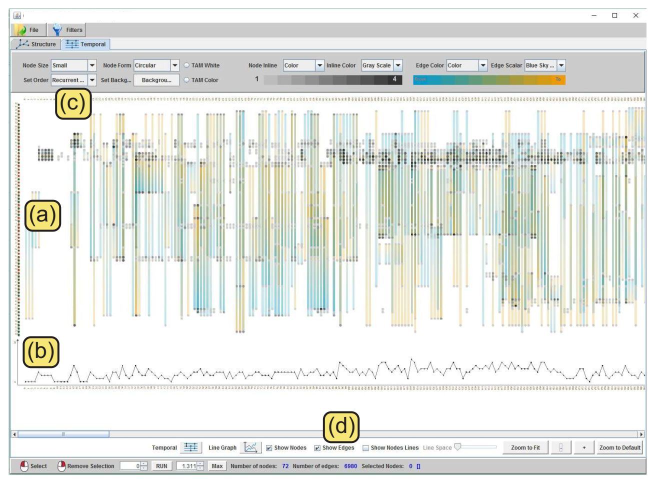

Figure 9: Temporal layout of the DyNetVis. (a) Temporal layout. (b) Line graph. (c) Temporal customizations – e.g., change size and color of nodes and edges, change node ordering, use TAM templates. (d) Zoom in and out and options to show or hide edges and nodes.

stamp, as shown in Figure 2(a)). It is possible to select the time interval and the temporal resolution to avoid loading the entire network in case of large data sets. It is also possible to change the color, shape, and size of nodes and links, as well as to select different background colors for TAM layout (Fig. 9(c)).

In the structural layout, one may select: (i) network type (directed or undirected); (ii) network drawing algorithm, employing techniques available in jgraphx library [1], such as random, force-directed or hierarchical placement (Fig. 8(b)); (iii) animated visualization of the network dynamics over time, for both transient and accumulated views (Fig. 8(c)); (iv) nodes and links to drag-and-drop; (v) accumulated or transient structural visualization (Fig. 8(c)).

In the temporal layout, the following tools are available: (i) time interval selection (Fig. 9(a)); (ii) links exhibition – for better visualization of large networks (Fig. 9(d)); (iii) node line spacing modification (Fig. 9(d)); (iv) node ordering method (Fig. 9(c)); (v) zooming in and out – for better visualization of specific regions of the network, as well as the entire time interval (Fig. 9(d)). Along with the temporal layout, a line graph is shown, representing the amount of connections for each time stamp (Fig. 9(b)).

5. CASE STUDIES

In order to demonstrate the application of DyNetVis and the proposed visualization strategies, we present results of the of two dynamic networks representing real scenarios. The **Museum** network represents contacts between people visiting the Science Gallery in Dublin, Ireland [11], during one day, and is composed of 72 nodes and 6,980 links. This network has the sampling resolution of 20 seconds, i.e., the proximity between two individuals was collected every 20 seconds using radio-frequency badges worn by each person. The nodes represent the individuals while the links represent interactions among them in a specific time stamp. The **Enron** network, is derived from an email dataset from Enron, a bankrupt energy company involved in a scandal of accounting fraud in 2011 [12, 19]. After removal of duplicate emails and spam, we have obtained a network composed of 148 nodes and 24,667 links, considering a time resolution of 1 day. The nodes represent the employees while the links represent email exchanges between them. This network was already employed in a previous visual analysis task [19].

5.1 Visual Analysis

5.1.1 Museum

Figure 10 shows an overview of the museum network using the temporal layout and recurrent neighbors ordering. It is possible to identify regions of denser and sparser concentration of nodes activities. This higher concentration may correspond to groups of individuals touring the museum altogether since visits are organized into time slots [11]. This information may help the administration of the museum to better plan the work schedule of employees.

Figure 11 illustrates a short time interval of the museum network using the first appearance and recurrent neighbors ordering strategies. Figure 11(a) shows an intense activity which is not noticeable when using the recurrent neighbors strategy (Fig. 11(b)). These differences demonstrate the influence of the node ordering on the analysis. Different visualization methods may lead to different interpretations of the network characteristics. As the recurrent neighbors reordering strategy tends to reduce edge intersection due to closeness of interconnected nodes, it produces a clearer layout whereas the appearance ordering can lead to misinterpretation of the data, as edge intersection may result in a dense visualization. Recurrent Neighbors can also highlight regions with high activities, as shown in the last time intervals of Figure 11(b).

Figure 12 shows two TAM layouts for the initial time periods using first appearance node ordering. Three node groups with intense activity can be identified. One can notice a significant difference when using a white background (Fig. 12(a)) in which all nodes of all time stamps are visible, and using a blue background, an activity related color (Fig. 12(b)), in which nodes with low activity tend to disappear. The latter option highlights the most active network nodes, and this type of visualization can thus be useful for identification of bursts of activity.

Figure 13 shows the coordination between the structural layout and two distinct periods of time in the temporal layout, in which the colors of the nodes represent their degrees. The thickness and color of the links are proportional to the number of connections between the respective nodes. In Figure. 13(a) two nodes with high activity in the central region of the structural layout were selected. When analyzing the color of these nodes and the thickness of the corresponding links, one may conclude that these two nodes have intense interaction over time but not identify in which time stamps these interactions occur. By exploiting the coordination of the views, the same nodes are selected in the temporal layout. Figures 13(b-c) depict two different time periods for the two nodes. Figure 13(b) shows that these nodes are very active with other nodes but not between them. In Figure 13(c) however the visual pattern shows an intense activity between them. These patterns may indicate that these two visitors had several interactions with other visitors and the interactions between them were concentrated only in a specific time period.

5.1.2 Enron

Figures 14 and 15 show the temporal and TAM layouts using the recurrent neighbor for the Enron network, respectively. The temporal resolution is modified to represent two days in each snapshot. The time span covered by the network is approximately four years. This time period includes several important events that occurred in the company, as the promotion of a new CEO and its resignation, followed by the beginning of fraud investigation and bankruptcy. The days of occurrence of these events are marked in the figures.

By analyzing the layout of Figure 14, one may identify seven potential communities before the new CEO mark. The communities are characterized by node clusters over time. These clusters are formed due to the recurrent neighbors ordering process, in which nodes that interact with each other tend to be positioned close together in the layout. After the 'new CEO' mark and shortly before the 'Resignation' mark, the communities are still noticeable but with aggregation of other nodes.

A relevant pattern change occurs after the 'resignation' mark, represented by an increase in the communication between the employees, that decreases after the 'bankruptcy' mark. This pattern is revealed by denser connections between the nodes in the temporal layout and by a peak in the line graph.

The analysis of Enron TAM layout (Fig. 15) reveals the same evolution of communities observed in the temporal layout. In addition, after the 'resignation' mark, high activity in specific time stamps, represented by darker color regions, is observed. This pattern is probably related to the impact caused by the resignation process and drives the attention for further investigations of the involved employees.

Our findings on Enron network corroborate the results report by Elzen et al. [19] for the same case study. They also reported the existence of gaps (related to less email traffic) before announce of the new CEO and after bankruptcy. The gaps are better seen in our temporal layout using recurrent

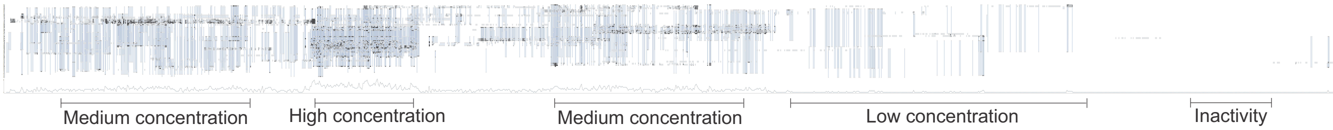

Figure 10: Temporal layout for the museum network. Annotated visualization. Different patterns can be observed from this view, specially when considering the concentration of edges between nodes, categorized here as low, medium and high. A period of inactivity can be identified as well.

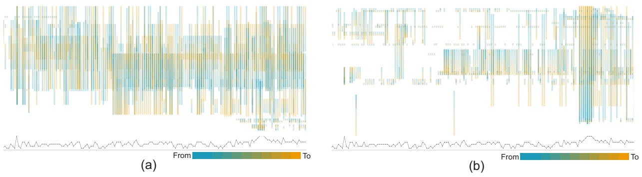

Figure 11: Reordering strategies for museum network. (a) Order of appearance; and (b) Recurrent neighbors. The strategy employed in (a) can lead to misinterpretation of the data, as it seems the network has an intense activity during this time interval, when in fact only part of the nodes are active in this interval (see (b)). Tthis time interval corresponds to the second time interval labeled as *medium concentration* in Figure 10.

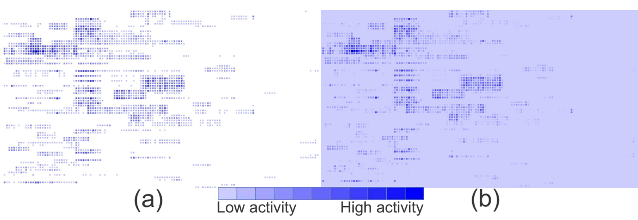

Figure 12: TAM layout for the museum network. Order of appearance reordering. using (a) white and (b) blue backgrounds, corresponding to the color of the node with lowest activity.

neighbor ordering and the line graph (Fig. 14).

6. SCALABILITY

The algorithm of recurrent neighbors has better time performance than other reordering methods as for example the simulated annealing [19]. In DyNetVis, for the networks presented in this work, all the interaction process (reordering, changing color, selecting, zooming) lasts 1 second maximum each, on the computer Intel(R) Core(TM) i5-3330 CPU @ 3.00GHz, 8 GB RAM, video card AMD Radeon HD 7870 2GB and Windows 10.

7. CONCLUSION AND FUTURE WORK

This paper describes a computational system for visual analysis of dynamic networks. The system allows the visualization of structural and temporal network layouts and implements a set of known and innovative visual strategies. The system also provides the coordination between structural and temporal layouts, as well as several interactive tools to allow the exploration and understanding of the patterns in the studied networks. We have also investigated two strategies to improve temporal network visualization: recurrent neighbors, a node reordering strategy, and Temporal Activity Map, a layout that emphasizes the activity of the nodes in time.

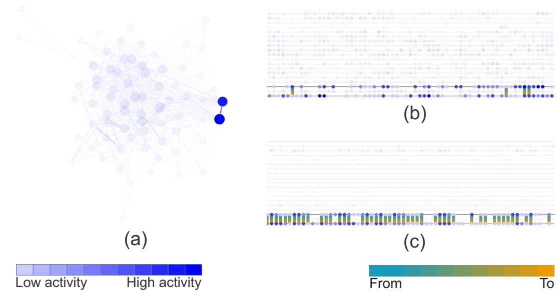

Figure 13: Example of coordination between layouts and different pattern of connections in temporal layout for the museum network. (a) Structural layout, with intense connection rate between two selected nodes; (b) Temporal layout showing that, at a specific time interval, the same nodes are active in the network but with little communication between them; (c) Another time interval, also visualized using temporal layout, showing an intense interaction between the same pair of nodes.

Figure 14: Temporal layout (with links) representing the Enron network. Some important events – new CEO, resignation, investigation and bankruptcy – are tagged in order to help on understanding the network.

Two case studies representing different scenarios of contact networks were discussed. The results of these analyses demonstrate the potential of the system and of the proposed techniques, for identifying patterns related to important events in different contexts, enhancing the understanding of the involved phenomena. In particular, the application of the recurrent neighbors provides the reduction of crossing edges in the temporal layout, which results in a cleaner visualization and a better comprehension of the relation between nodes.

As future work, we plan to add new attributes to compose the attribute-to-visual mapping using diverse network

Figure 15: Temporal layout (TAM) represeting the Enron network. The background color corresponds to the color mapped to the lowest activity value. Some important events – new CEO, resignation, investigation and bankruptcy – are tagged in order to help understanding the network.

quantities, such as state-of-the-art centrality measures [8]. We also plan to add relevant ordering strategies [19] and clustering algorithms [15]. A promising future direction is to further explore the temporal layout for visualizing epidemic processes on contact networks using the TAM method. In addition, in order to better explore the DyNetVis system usability, we plan to perform a formal user study to provide stronger evidence that the proposed layouts can be used for expert analysis, increasing the value of our methods.

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9. REFERENCES

[1] Jgraphx, 2012, accessed 01 January 2016.

[2] J.-w. Ahn, C. Plaisant, and B. Shneiderman. A task taxonomy for network evolution analysis. *IEEE T VIS COMPUT GR*, 2014.

[3] B. Bach, N. Henry-Riche, T. Dwyer, T. Madhyastha, J.-D. Fekete, and T. Grabowski. Small multipiles: Piling time to explore temporal patterns in dynamic networks. *Comput Graph Forum*, 2015.

[4] B. Bach, E. Pietriga, and J.-D. Fekete. Visualizing dynamic networks with matrix cubes. In *SIGCHI Conference on Human Factors in Computing Systems*, 2014.

[5] M. Bastian, S. Heymann, and M. Jacomy. Gephi: An open source software for exploring and manipulating networks. *International AAAI Conference on Weblogs and Social Media*, 2009.

[6] F. Beck, M. Burch, S. Diehl, and D. Weiskopf. A taxonomy and survey of dynamic graph visualization. In *COMPUT GRAPH FORUM*, 2016.

[7] L. d. F. Costa, O. N. Oliveira, G. Travieso, F. A. Rodrigues, P. R. Villas Boas, L. Antiqueira, M. P. Viana, and L. E. C. Rocha. Analyzing and modeling real-world phenomena with complex networks: a survey of applications. *Adv Phys*, 60:329–412, 2011.

[8] L. d. F. Costa, F. A. Rodrigues, G. Travieso, and P. R. Villas Boas. Characterization of complex networks: A survey of measurements. *Adv Phys*, 56:167–242, 2007.

[9] M. Ghoniem, G. Shurkhovetskyy, A. Bahey, and B. Otjacques. Vafle: visual analytics of firewall log events. *Proc. SPIE*, 2013.

[10] P. Holme and J. Saramäki. Temporal networks. *PHYS REP*, 519:97–125, 2011.

[11] L. Isella, J. Stehlé, A. Barrat, C. Cattuto, J.-F. Pinton, and W. Van den Broeck. What's in a crowd? analysis of face-to-face behavioral networks. *J Theor Biol*, 271(1):166–180, 2011.

[12] P. S. Keila and D. B. Skillicorn. Structure in the enron email dataset. *Comput Mqth Organ Th*, 2005.

[13] N. Kerracher, J. Kennedy, and K. Chalmers. The design space of temporal graph visualisation. In *EuroVis*, 2014.

[14] S. Lee, L. E. C. Rocha, F. Liljeros, and P. Holme. Exploiting temporal network structures of human interaction to effectively immunize populations. *PLoS ONE*, 7:e36439, 2012.

[15] M. Rosvall and C. T. Bergstrom. Mapping change in large networks. *PLoS ONE*, 5(1):e8694, 01 2010.

[16] S. Rufiange and M. J. McGuffin. Diffani: Visualizing dynamic graphs with a hybrid of difference maps and animation. *IEEE T VIS COMPUT GR*, 19(12):2556–2565, 2013.

[17] N. J. Salkind. *Statistics for People Who (Think They) Hate Statistics: Excel 2007 Edition.* Sage Publications, Inc., 2009.

[18] P. Shannon, A. Markiel, O. Ozier, N. S. Baliga, J. T. Wang, D. Ramage, N. Amin, B. Schwikowski, and T. Ideker. Cytoscape: a software environment for integrated models of biomolecular interaction networks. *Genome Res*, 13(11):2498–2504, 2003.

[19] S. van den Elzen, D. Holten, J. Blaas, and J. van Wijk. Dynamic network visualization with extended massive sequence views. *IEEE T VIS COMPUT GR*, 20:1087–1099, 2014.

[20] S. van den Elzen, D. Holten, J. Blaas, and J. J. van Wijk. Reducing snapshots to points: A visual analytics approach to dynamic network exploration. *IEEE T VIS COMPUT GR*, 2016.

[21] C. Ware. *Information Visualization: Perception for Design.* Morgan Kaufmann Publishers Inc., 2004.