TieVis: Visual Analytics of Evolution of Interpersonal Ties

Category: Research

Abstract

Interpersonal ties such as strong ties and weak ties have significant impact on the formation of structure and transmission of information in networks. Tracking the dynamic changes of interpersonal ties can thus enhance our understanding of the evolution of a complex network. Nevertheless, existing studies in dynamic network visualization mostly focus on the temporal changes of nodes or structures of the network without an adequate support of analysis and exploration of the temporal changes of interpersonal ties. In this paper, we introduce a new visual analytics method that enables interactive analysis and exploration of the dynamic changes of interpersonal ties. The method integrates four well-linked visualizations, including a scatterplot, a pixelbar chart, a layered graph, and a node-link diagram, to allow for multi-perspective analysis of the evolution of interpersonal ties. The scatterplot created by multi-dimensional scaling can help reveal the clusters of ties and detect abnormal ties, while other visualizations allow users to interactively explore the clusters of ties interactively from different perspectives. Two case studies have been conducted to demonstrate the effectiveness of our approach.

Index Terms: K.6.1 [Management of Computing and Information Systems]: Project and People Management—Life Cycle; K.7.m [The Computing Profession]: Miscellaneous—Ethics

1 Introduction

Interpersonal tie is an important concept for edges from sociology, which describes the information carried by an edge in social networks [22]. It has been extensively studied in sociology and can be classified as strong ties and weak ties. A strong tie indicates that the nodes connected by the edge have a relatively large number of common neighbor nodes. On the contrary, a weak tie indicates that the nodes have only a few common neighbor nodes. The interpersonal ties can be continuously changing in an evolving network, where an edge has its own life circle. For example, it is absent from the network at the beginning, then becomes a weak tie and gradually grows to a strong tie, and it disappears from the network at the end.

The life cycles of the interpersonal ties have significant impacts on the formation of structure, such as communities, structural holes, and local bridges, and information diffusion in networks. For example, researchers revealed that novel information often spreads out through weak ties in the dynamic networks [23]. However, the information diffusion could change if the weak ties disappear or turns into strong ties. In other words, the changes in interpersonal ties could result in fundamental changes in network structure and information diffusion. Therefore, tracking and exploring the temporal changes of interpersonal ties can not only help us detect the significant structural changes in dynamic network, but also help us formulate hypotheses and seek the explanations for the changes. Nevertheless, the complexity of the network structure and dynamic and frequent conversion between strong and weak ties pose significant challenges in the analysis of the evolution of interpersonal ties.

Existing visualization methods explore and analyze a dynamic network mainly in the following ways: a) draw all the snapshots of the network along the time axis or visualize the snapshots by animation [6, 37, 33, 13]; b) stack the snapshots of the network at each time step together, then directly visualize the network in 3D or use density kernel estimation to visualize the network in 2D [5, 10, 12]; c) calculate certain metrics of the network and visualize the metrics together with the network [31, 30, 25]. These methods can visualize the dynamic network directly and support various analysis tasks for exploring the evolution of the network structure. However, they do not provide adequate support for the analysis and exploration of evolution of interpersonal ties in dynamic networks because these methods mostly focus on the dynamic changes of network structure rather than the more fundamental interpersonal ties.

In this paper, we introduce a visual analysis approach for studying interaction patterns among nodes by examining the change in strength of edges. We use strong ties and weak ties to indicate the edges of varying strength degrees. We transform each edge into a series of strength values over time, which is denoted as a feature vector for each edge. The feature vectors of these edges are then visualized in a scatterplot view using multi-dimensional scaling (MDS) to provide an overview of the interpersonal ties. The scatterplot view allows users to immediately see the clusters of the edges with similar trends of strength variation. Abnormal edges can also be easily disclosed in the scatterplot. From the overview, the users can select a group of edges and examine further their temporal changes in strength of edges in a pixelbar chart. A layered graph is introduced to enable the users to visualize the selected edges and the connected nodes over time. A node-link diagram is also presented to show the network structure for a particular time step chosen by the users.

With this work, we make the following contributions:

- A new study of the evolution of interpersonal ties for a dynamic network and their co-evolution with the network structure and information diffusion;
- An edge based analysis framework which helps users identify edges with similar trends, compare edges with different trends, and find the hidden patterns;
- An interactive visualization system that integrates four views, including a scatterplot, a pixelbar chart, a layered graph, and a node-link diagram, which allows for multi-perspective exploration and analysis.

The remainder of this paper is organized as follows. Section 2 reviews related works on dynamic network visualization and methods for analyzing time series data. In section 3 we describe the measure of edge strength and the feature vector extraction method. Section 4 presents the system design. In section 5, we report two use cases on the Enron email dataset and an MMORPG player dataset. In section 6, we conclude and discuss the future works.

2 Related Work

2.1 Dynamic Network Visualization

Animation has been commonly employed to visualize a dynamic network [18, 21, 6, 37, 34], such that the temporal variation of the network can be shown in an animated sequence of a certain visual representation of the network such as the node-link diagram [33, 4, 34]. Considerable research has been conducted on methods which creates stable node-link graph layouts to illustrate the continuous visual changes of the dynamic network in a smooth animation [6, 37, 34]. The animation-based scheme allows users to track and analyze dynamic networks. Nevertheless, previous research has revealed that animation based techniques are not suitable for complex analysis tasks, for example, the comparison of network structure, because of human's limited working memory [3].

Visualization of the snapshots of a dynamic network at each time step along a time axis has also been widely used to provide an overview of the dynamic network [13, 14, 35]. Edge splatting [13, 11] transforms each snapshot into a bipartite network and visualizes the bipartite networks sequentially, which provides a clear overview but lacks details. Some techniques use small multiples to represent one snapshot of the dynamic network [14, 19, 32]. Small multiples allows users to see the snapshot at each time step immediately, but do not scale well on a large dataset. The flow metaphor is another useful method to show the evolution of a network [35, 15]. By combining the flow metaphor with community information or graph metrics, the evolution of the network structure can be shown intuitively [24]. However, it is hard to show the topology information using the flow metaphor.

Adjacency matrices have also been used to visualize a dynamic network. In [5], the matrices at each time step are stacked together and visualized in a three dimensional space, but this technique can lead to increased visual clutter and overhead of interaction. In contrast, some methods [10, 12, 29] leverage a large matrix, in which each cell displays the temporal changes of a subgraph with a timeline explicitly drawn, for dynamic display. The methods can avoid the clutter problem, but they lack space efficiency.

The above methods allow users to directly see the structural changes of a dynamic network over time. However, these methods mostly put emphasis on nodes or high-level network structures. They do not provide sufficient support for the analysis of the evolution of interpersonal ties.

2.2 Network Visualization using Graph Metrics

The statistical information of edges and/or nodes statistics can be important for understanding a network [25, 26, 31]. Researchers have used different metrics to characterize the network and provide useful information such as the importance of the nodes and the edges (by using, for example, centrality) [31] or other structural properties of the network such as density, modularity, and so forth [30]. Many graph visualization systems [25, 31] provide the metrics to help analysts understand the overall structure of the network, or guide their attention to structurally significant nodes/edges through visual encoding and user interactions.

SocialAction [31] tightly integrates the statistical information with network visualization. Network statistics such as betweenness and centrality of nodes are sorted and visualized to facilitate the identification of important nodes. GraphDice [7] layouts the graph nodes based on some graph metric values. GraphPrism [26] utilizes a visual design that summarizes the structure of a graph by displaying multilevel histograms of some graph metrics such as degree, diameter, and transitivity. Panagiotidis et al. [30] have introduced Graph Metric Views, a technique that enriches the visualization of traditional node-link diagrams with the histograms of the graph metric values. CentiBiN [25] focuses on the computation and exploration of centrality in biological networks. Dwyer et al. [16] have presented 3D parallel coordinates that support orbit-based comparison and hierarchy-based comparison to explore and compare node centrality in network. Zimmer et al. have introduced ViNCent [38], a system that supports interactive visual analysis of network centralities. A set of node centralities are calculated to group similar nodes.

Compared with existing work, our work focuses on exploration and visualization of interpersonal ties through the analysis of the temporal variations of strength of edges. In particular, we aim at studying the relationship between the strong-weak tie conversion and structural changes in a network. Nevertheless, the common techniques used in existing work such as visual encoding of centrality on graph nodes are employed in our work.

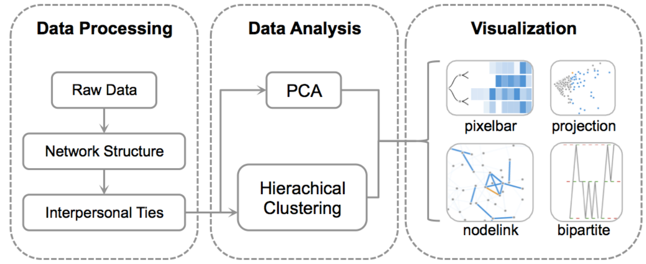

Figure 1: The pipeline of TieVis.

2.3 Sociology Studies on Interpersonal Ties

In mathematical sociology, researchers have proposed some formal models to describe and analyze social processes and social structures in social networks [9]. Interpersonal tie is one of best-known models among the models in mathematical sociology. Granovetter [23] has introduced three states of interpersonal ties, including absent, weak, and strong, in social networks. He has also discussed the importance of weak ties in spreading novel ideas or information. In [27, 8], the strength of strong ties has been extensively discussed. Friedkin [20] has described how strong ties and weak tie impact information flow in social networks.

Our work uses interpersonal ties to characterize the evolution of edges in dynamic networks. Different from the researches in mathematical sociology, our method takes the advantages of visualization and helps the user interactively analyze the temporal variations of interpersonal ties.

3 Overview

This section briefly describes the approach pipeline and user interfaces, followed by a discussion on analysis tasks for the system.

3.1 Pipeline

The TieVis system is designed for tracking, exploring, and analyzing temporal changes of interpersonal ties in dynamic networks. It consists of three components: a data processing module, an analysis module, and a visualization module. The workflow of our method is illustrated in 1. In the data processing module, the network structures are extracted from the raw data and each edge is transformed into a sequence of the interpersonal ties according to the network statistics. In the analysis module, the distances of the edges are calculated. Based on the distance, PCA is performed to to determine the position of edges in a 2D plane and a hierarchical clustering algorithm is applied to determine the order of edges in 1D axis. In the visualization module, interpersonal ties and network structures are visualized. The visualization enables the user analyze the evolution of dynamic networks intuitively and interactively.

3.2 User interfaces

Our interface (Figure 2) integrates five views, including a scatterplot, a pixelbar chart, a layered graph, a node-link diagram, and an information panel. It supports interactive and intuitive analysis of the evolution of interpersonal ties from multiple perspectives. In particular, the scatterplot provides an overview of all the edges in the network. The pixelbar chart visualizes the details of the temporal series of interpersonal ties. The layered graph shows the structure of the network formed by selected edges from other views at all time steps. The node-link diagram gives a snapshot of the dynamic network to show the network structure at a user-chosen time step. The information panel provides the detail information of the edges the user is interested in.

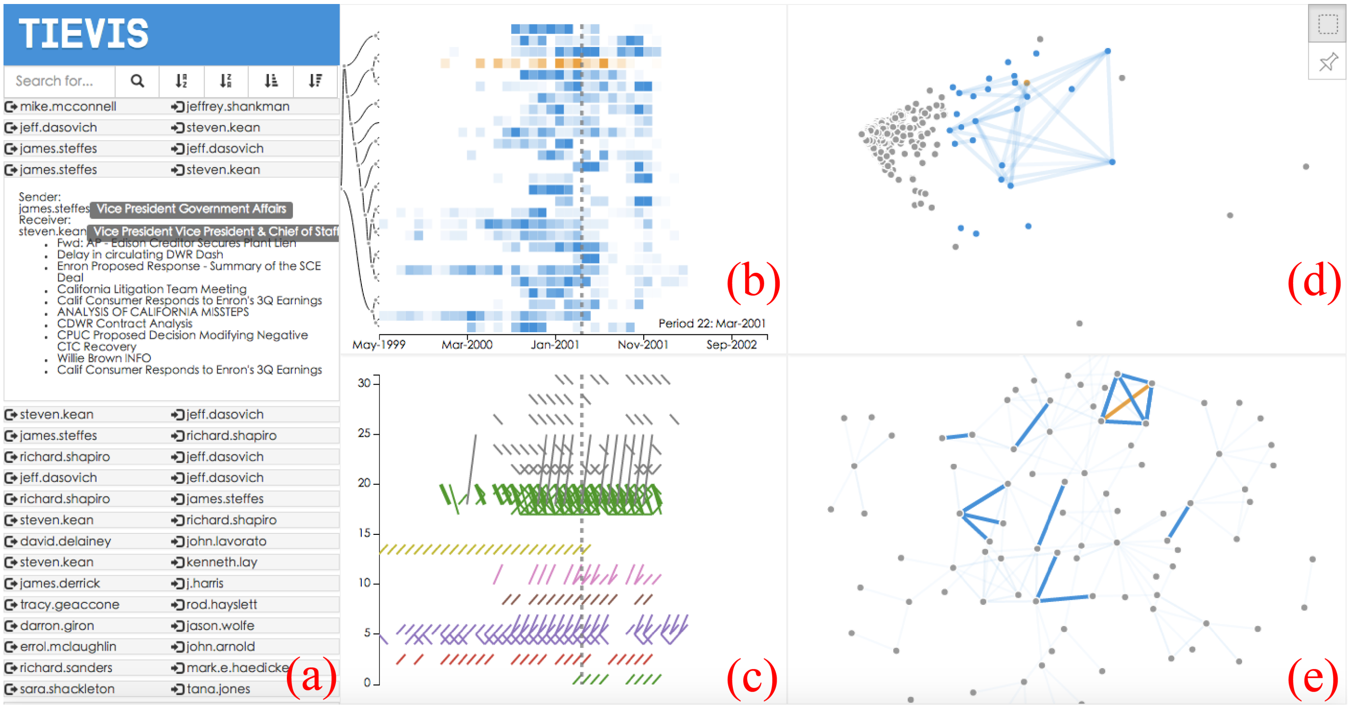

Figure 2: Our interface includes five views. (a)a information panel; (b)a pixelbar chart; (c) a layered graph (d) a scatter plot (e) a node-link diagram.

3.3 Analytical Tasks

We identify three main analysis tasks, which should be supported by our system, to enable users to explore and understand the dynamics of the interpersonal ties in a continuously changing network interactively and intuitively.

T.1 Identify the edges with similar trends in terms of the strength of the edges over time such that users can select, group, filter, or compare different groups of ties for further analysis.

T.2 Detect the edges with abnormal variations of strength quickly to allow users to make hypotheses and seek explanations. We are particularly interested in finding the abnormal patterns because the abnormal changes could significantly impact the network structure and information diffusion.

T.3 See and explore the evolution of the interpersonal ties selected by users. Major changes of the strengthen of edges can be important for understanding various phenomenons such as the formation of structural holes and small worlds.

T.4 Analyze the co-evolution relationship between the interpersonal ties and the network structures.

4 Interpersonal Ties

Our work is based on the theory of interpersonal ties from mathematical sociology. The strength of a tie characterizes a set of property of the tie, including the emotional intensity, the intimacy, time etc [23]. An edge in the network can have three different types of strength, which are absent, weak, and strong. In practice, the strength of an edge can be defined simply by counting the number of contacts between its two nodes. For example, in the telecommunication network, the strength of an edge linking user A and user B can be defined as the number of phone calls between A and B. On the other hand, it can also be computed by the Jaccard similarity between the neighbors of A and those of B, according to the hypothesis “the stronger the tie between A and B, the larger the proportion of individuals in the network to whom they will both be tied” [23].

It has been shown that there is a linear relationship between the two methods [17]. Therefore, we choose the first method for simplicity. The states of the interpersonal ties of an edge at each time step constitute an time series. Thus, the dynamic network can be transformed into a group of time series, and can be treated and studied as time series data. Principal component analysis (PCA) can then be used to analyze the similarity of the time series data.

5 Visualization

In this section, we firstly present the design goals of the system according to the analytical tasks and then introduce four views that are designed for multi-perspective analysis of interpersonal ties in details.

5.1 Design goals

G.1 Provide a visual summary of the dynamics of interpersonal ties to enable users to quickly identify the groups of edges with similar trends (**T.1**), and identify the patterns and outliers of evolution of interpersonal ties (**T.2**).

G.2 Support analysis for large dataset. The design should have high scalability to support the analysis of large dynamic network dataset (**T.1-4**).

G.3 Employ timeline-based visualization to display the temporal changes of interpersonal ties and networks (**T.3-T.4**). Timeline visualization enables users to intuitively see the temporal patterns over time, and relate the temporal patterns of interpersonal ties to those of network more intuitively.

G.4 Use multiple linked views to allow users to analyze and explore the data from multiple perspectives. Because of the high complexity of the structure of dynamic networks, the designs should support multi-perspective analysis to help the user better understand the co-evolution of the interpersonal ties and network structure (**T.4**).

5.2 The scatter plot

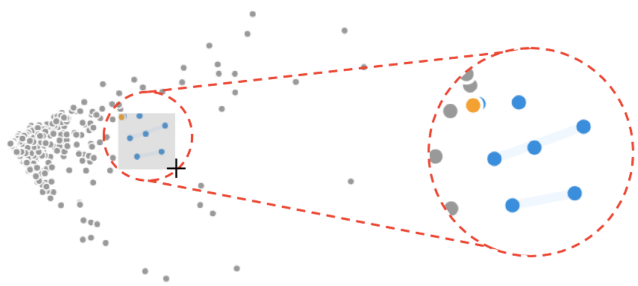

Figure 3: The visual encodings in the scatter plot.

The scatter plot view fulfills **G.1** by providing an overview of edges in the network based on the temporal similarity, see in Figure 3(a). The state of an edge at a time step is regarded as a dimension. We use Euclidean distance to measure the similarity of each pair of the high dimensional vectors, which is calculated by the following equation:

$$d(x,y) = \sqrt{\sum_{i=0}^{n} (x_i - y_i)^2}$$

where $x = \{x_0, x_1, ..., x_n\}$ and $y = \{y_0, y_1, ..., y_n\}$. Principal component analysis is then performed to reduce the high dimensional data into a 2D plane. In this way, dots that are close to each other in the plane indicate that the corresponding edges are similar.

The scatter plot supports two basic interactions, brushing and zoom, and is linked to other views by interactions. The zoom interaction enables the view to support network data with a large number of edges (**G.2**).When the user brushes a part of dots, namely the information of selected edges will be visualized in the other three views to support further analysis. Meanwhile, the linkage among the brushed edges at a certain time step will be visualized by links, as shown in Figure 3(b).

5.3 The pixelbar chart

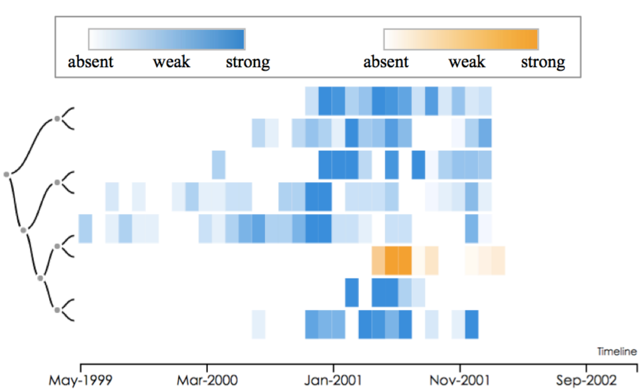

Figure 4: The visual encodings in pixelbar chart: a dendrogram is place on the left to show the hierarchical clustering results of edges

Design Rationale. Though the projection of edges gives an overview of edges, the details of the edge states are not shown. One way to visualize the time series data is the line chart. Another way is the pixelbar chart. A line chart shows the trend of time series directly but has a low scalability, while a pixelbar chart is not intuitive but has a high scalability. As the number of edges appear in the network is often large, we choose the pixelbar chart.

In the pixelbar view, each edge is represented by a series of pixelbars (**G.3**). The strength of the edge is encoded by color. Light grey indicates that the edge has the lowest strength, i.e., the weakest tie, the dark grey indicates that the edge has the highest strength, i.e., strongest tie, and white indicates that the edge is absent. The color map is shown in Figure 4.

The nearest-neighbor chain algorithm [28] is used to layout the pixelbars, of which the pseudo code is shown in Algorithm 1. The algorithm guarantees closer pixel bands are more similar. A dendrogram is presented in the left of the view to show the structure of a hierarchical clustering tree (Figure 4). When the number of pixelbars is large, the space is not adequate to visualize all the bars. An adaptive algorithm is applied when the total space of the pixelbars exceeds the view height. To decrease the number of pixelbars, we merge pixelbars within one cluster into a larger one which is their average. The merge result is the average of merged pixelbars. The pseudo code is shown in Algorithm 2. By the merging operation and the dendrogram, the pixelbar chart can visualize a large number of edges and has a high scalability (**G.2**)

Algorithm 1 Nearest-neighbor Chain Algorithm

Input: $P = \{p_0, p_1, ..., p_n\}$: point set;
Output: Hierarchical cluster C

initial $Cluster = [[p_0], [p_1], ..., [p_n]], Stack = []$;
while $Size(Cluster) > 1$ **do**
    if $Size(Stack) = 0$ **then**
        push a random cluster in *Cluster* into *Stack*
    end if
    Let c be the top of the *Stack*
    Find nearest cluster d to c in *Cluster*
    if $d \in Stack$ **then**
        Pop c and d from *Stack*
        Merge c and d to e
        Push e into *Cluster*
    else
        Push d into Stack
    end if
end while

Algorithm 2 Merge Tree

Input: *node*: node of hierarchical clustering tree; *goal*: the number of node to be decrease;
Output: node after merging

Let lc be the left children of the node
Let rc be the right children of the node
if The number of leaf nodes in $lc \leq goal$ **then**
    Merge leaf nodes in lc into one node
    $goal = goal - size(lc) + 1$
else
    Merge Tree(lc)
end if
if The number of leaf nodes in $rc \leq goal$ **then**
    Merge leaf nodes in rc into one node
    $goal = goal - size(rc) + 1$
else
    Merge Tree(rc)
end if

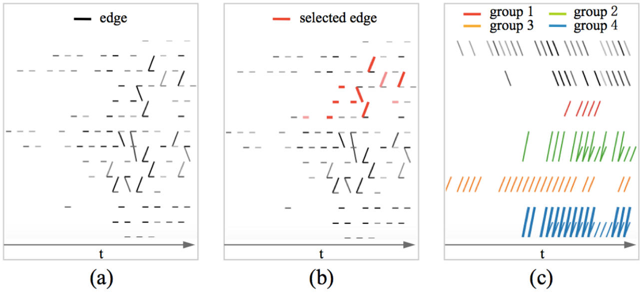

Figure 5: The layered graph visualizes the structure of selected edges by a sequence of bi-partite network. (a) DAG layout before time selection. (b) Mouse hovers on an edge. (c) Layout is optimized according to the group information after time selection.

5.4 The layered graph

Design Rationale. As the structure of a dynamic network is constantly evolving, it is necessary to show the structure information of the edges in which the user interested. However, the life cycles of the edges are not the same, therefore the structure of the network formed by the edges are also evolving. There are three designs we have considered, including an animated node-link diagram, sequential adjacency matrix, and a modified layered graph. The animated node-link diagram is a straightforward and intuitive design, but it can not show the complete evolution process in a glance. The sequential adjacency matrix is a better choice, because it compactly visualizes both temporal and topological information. However, the modified layered graph can visualize both the temporal and topological information of the selected edges more intuitively.

In the layered graph view, the temporal information is encoded horizontally, as shown in Figure 5(a). The snapshot at each time step is visualized as a bipartite network by representing source nodes and target nodes on two axes. The left axe encodes the source vertices of the edges, and the right one encodes the target vertices. Each edge is visually encoded as a link between the left axe and the right one. Then snapshots are arranged end-to-end according to the temporal sequence. Note that two adjacent snapshots shares the same node order on the shared node axis. A modified Sugiyama-style graph drawing algorithm [36] is applied to optimize the node order on the axes to minimize the visual clutter within an adequately short time interval (**G.3**). When the mouse is hovering on an edge in the view, the edge will be highlighted, see in Figure 5(b).

In order to find a balance between visual quality and performance, we finally decide to do the optimization hierarchically. The related vertices are grouped, and the vertices in the same group are aligned together.

The grouping is performed according to the connectivity of the vertices in the selected time step. The vertices of the edges connected together are regarded as in the same group. By mentioning the selected time step here, it is important to point out that the alignments are identical for distinct time steps. If the alignments are distinct for multiple time steps, it would be difficult for the analyzer to find the pattern. If edges of all time steps are considered, the connected subsets may be too large to minimize the visual clutter quickly. We optimize the alignment of the vertices in the groups by Algorithm 3 and optimize the alignment of these groups by Algorithm 4. Group information is encoded by color as categorical data (Figure 5(c))

5.5 The node-Link diagram

The network structure is visualized in the node-link diagram. It helps the user locate the brushed edges in the network. Before a time step is selected by the user, the node-link diagram shows the network merged by networks at every time step, which shows an overview of the network dataset (Figure 6 (a)). After a time step is selected, the node-link diagram shows the snapshot of the dynamic network at the time step, as shown in Figure 6 (b).

Algorithm 3 Inner-group Alignment Algorithm

Input: $G = \{e_0, e_1, ..., e_{n-1}\}$: edges in the group G;
Output: $G' = \{e_{k_0}, e_{k_1}, ..., e_{k_{n-1}}\}$: optimized alignment G;

if $n < 2$ **then**
  $G' = G$
else
  $minCross$ = maximum number
  $perms$ = all permutations of G
  for $perm$ in $perms$ **do**
    $cross = 0$
    for $i = 0; i < n-1; i = i+1$ **do**
      for $j = i+1; j < n; j = j+1$ **do**
        if $e_i.source \neq e_j.source$ and $e_i.target \neq e_j.target$ **then**
          ps = position of $e_i.source$ in $perm$ > position of $e_j.source$ in $perm$
          pt = position of $e_i.target$ in $perm$ > position of $e_j.target$ in $perm$
          if $ps \neq pt$ **then**
            $cross = cross + 1$
          end if
        end if
      end for
    end for
    if $cross < minCross$ **then**
      if $cross = 0$ **then**
        break;
      end if
      $G' = perm$
      $minCross = cross$
    end if
  end for
end if

As the four views show the evolution of interpersonal ties from different aspects, including overview of similarity of ties (the projection view), temporal changes of the values (the pixelbar chart), temporal changes of structure (the layered graph view), and structural details at each time step (the node-link view), and they are highly connected by interactions, the system fulfills **G.4**.

6 Case Studies

In this section, we present two case studies on two datasets to demonstrate the usability and effectiveness of our method.

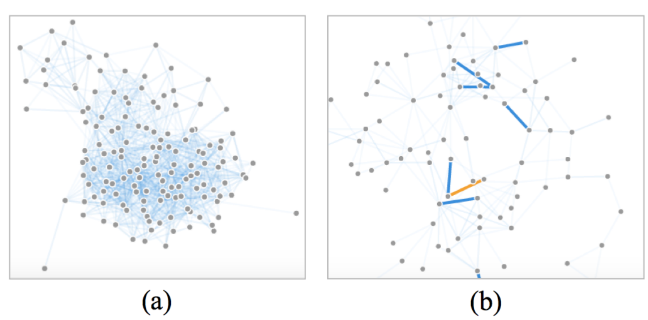

Figure 6: The visual encodings of node-link diagram

Algorithm 4 Inter-group Alignment Algorithm

Input: $S = \{G_0, G_1, ..., G_{n-1}, H\}$: A set of edge groups G_i and a group of other edges H;
$E = e_0, e_1, \ldots, e_{w-1}$: the set of all edges

Output: $S' = \{e_{k_0}, e_{k_1}, ..., e_{k_{n-1}}, H\}$: optimized alignment S;

```
if n < 2 then
    S' = S
else
    transGroup = []
    relatedGroups = {}
    for e in E do
        ps = the group contains e.source
        pt = the group contains e.target
        if ps = pt then
            continue
        end if
        if ps is not in relatedGroups then
            add ps into relatedGroups
        end if
        if pt is not in relatedGroups then
            add pt into relatedGroups
        end if
        transGroup[ps, pt] += number of times Edge e exists
    end for
    frontPart = G − relatedGroups − {H}
    middlePart = relatedGroups − {H}
    minCrossValue = maximum number
    perms = all permutations of middlePart
    for perm in perms do
        crossValue = 0
        perm = frontPart + perm + H
        for i = 0; i < n; i = i + 1 do
            for j = i + 1; j < n + 1; j = j + 1 do
                crossValue+ = transGroup[perm[i], perm[j]] · (j − i)
            end for
        end for
        if crossValue < minCrossValue then
            G' = perm
            minCrossValue = crossValue
        end if
    end for
end if
```

6.1 Data Description

The first dataset is extracted from the Enron Email Dataset. The original dataset includes all the mails sent and received by 184 employees in the network. In [1], the occupations of the employees are given. We extracted 25370 emails sent among these employees from May 1999 to Dec. 2002.

The second dataset [2] is a game player chatting dataset which is collected from a massively multiplayer online role playing game (MMORPG). We use the chat log of the game players on Jan. 10 2014, which is aggregated by hour. The network in each hour contains a number of connected subgraphs. We ordered the subgraphs by the number of nodes and take top-k networks to do our test. There are 508 nodes and 1265 edges in total.

6.2 Case 1: The Enron Mail Dataset

The Enron Corporation used to be one of the biggest energy, commodities, and services company in the world. It went bankrupt on December 2, 2001. In this case study, the analyst explores and analyzes the evolution of interpersonal ties in Enron in the period around its bankruptcy.

The analyst firstly find that the uneven distribution of density of the edges. He explores the evolution of interpersonal ties in different areas of the view and finds out that the evolution patterns are different, as shown in Figure 7(a),(b).

He checks the edges on the lower right of the view by brushing these edges (T.1). The evolution of interpersonal ties of these edges is shown in the pixelbar chart. The pixelbars shows that the first six edges appear in almost the same period and have similar trend of interpersonal ties (T.3). By checking the node information of these edges in the info panel by hovering mouse on the pixel bars, he finds out that the employees linked by these edges are executives and vice presidents of Enron. He checks the occupations of the nodes and finds out the occupations include "Employee Government Relation Executive", "Vice President Government Affairs", "Vice President Regulatory Affairs", and "Vice President Vice President & Chief of Staff" (Figure 7(b)). The occupations indicate that the employees deal business with government, therefore the edges between them show high strength from September to November as they contact frequently during the government investigation and the bankrupt procedure.

He notices that the interpersonal tie between james.steffes and jeff.dasovich is evolving regularly. To explore the relationship between the evolution of interpersonal tie and the evolution of structure evolution, he brushes many edges in the projection view. He first selects the time May-2001 when the edge is a strong tie and he notices that in the bipartite view. There is some edges missing at the next time step (June-2001) and the edge turns into a weak tie at the next time step, see in Figure 7(d). He therefore clicks on the next time step to further explore the difference of the network structure. He finds out that there are some edges disappear in the group, including the edges that link jeff.dasovich and steven.kean, richard shepiro and james.steffes (T.4), which reveals the relationship between the network structure around james.steffes and jeff.dasovich between the interpersonal ties of the edge (in Figure 7(e)).

6.3 The MMORPG Player Dataset

The analyst first brushes different areas in the projection view. The pixelbar chart shows that the behaviors of the users are different: palyers in Figure 8 mainly talk to each other after 12 am and the interpersonal ties between them is strong; players in Figure 8 talk to each other after 12.pm more and the strengths of ties decrease in the period from 12 pm to 12 am; players in Figure 8 talk to each other almost the all day, but the strengths of the ties are weak (T.1). This is mainly caused by the different log on time of the players. Besides, the personality of players may also affect the interpersonal ties, which interprets the different strength of ties of the players at the same time step.

7 Discussion and Future Work

In this paper, we presented a new, interactive approach for analysis and exploration of dynamic interpersonal ties. The scatter plots together with the other four views provide an overview to detail analysis scheme, which makes it much easier for users to find interesting patterns. We demonstrated the effectiveness of our method with case studies on two datasets.

One of the limitations is that the current approach supports only small dataset analysis. Although we design the visualizations with the ability of scaling to large datasets, we don't test large datasets in our system. Another limitation is that visual comparison and visual query is not well supported in the system, which makes the analysis of pattern not very convenient.

As future works, we intend to further explore more scalable visual encodings for large-scale dataset and add visual comparison and visual query into the system.

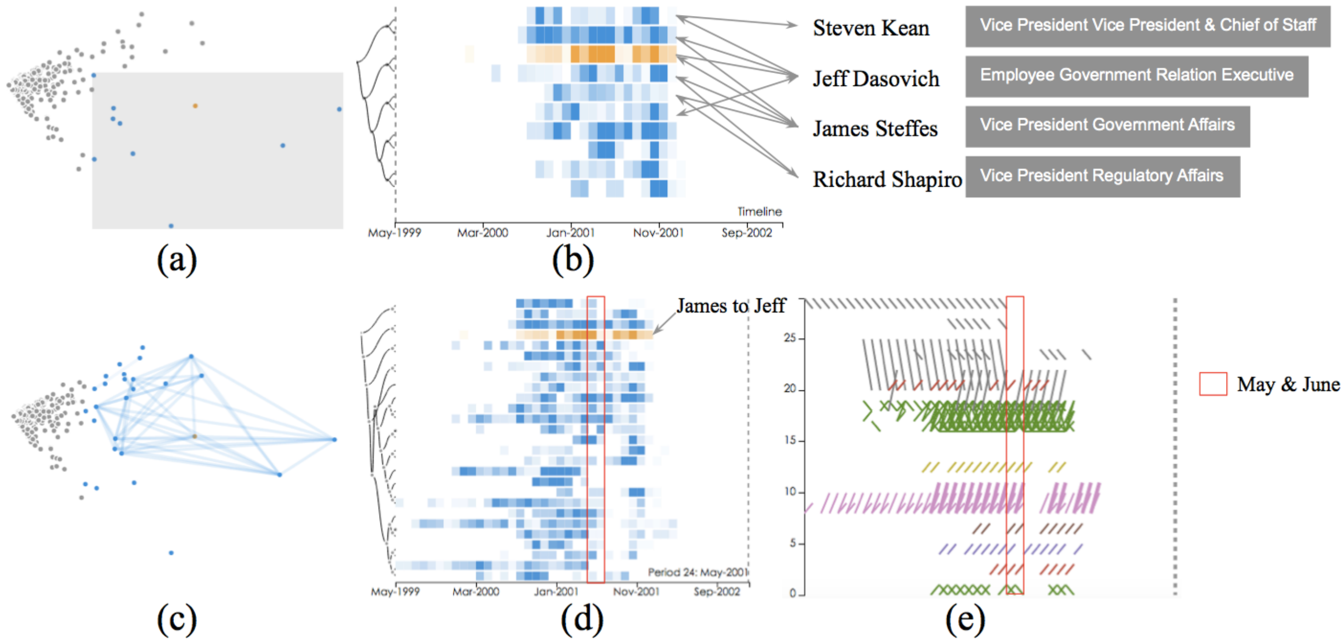

Figure 7: (a)(b) The analyst brushes edges in the scatter plot, finds that the interpersonal ties between four people evolve similar. Combing with their occupations, this is related to the government investigation and the bankrupt procedure. (c)(d)(e) The analyst notices the edge from James to Jeff is a strong tie on May but turn to a weak tie on June. He selects the two time step and observes the network structure in the scatter plot and the layered graph, finding out that some edges disappear on June.

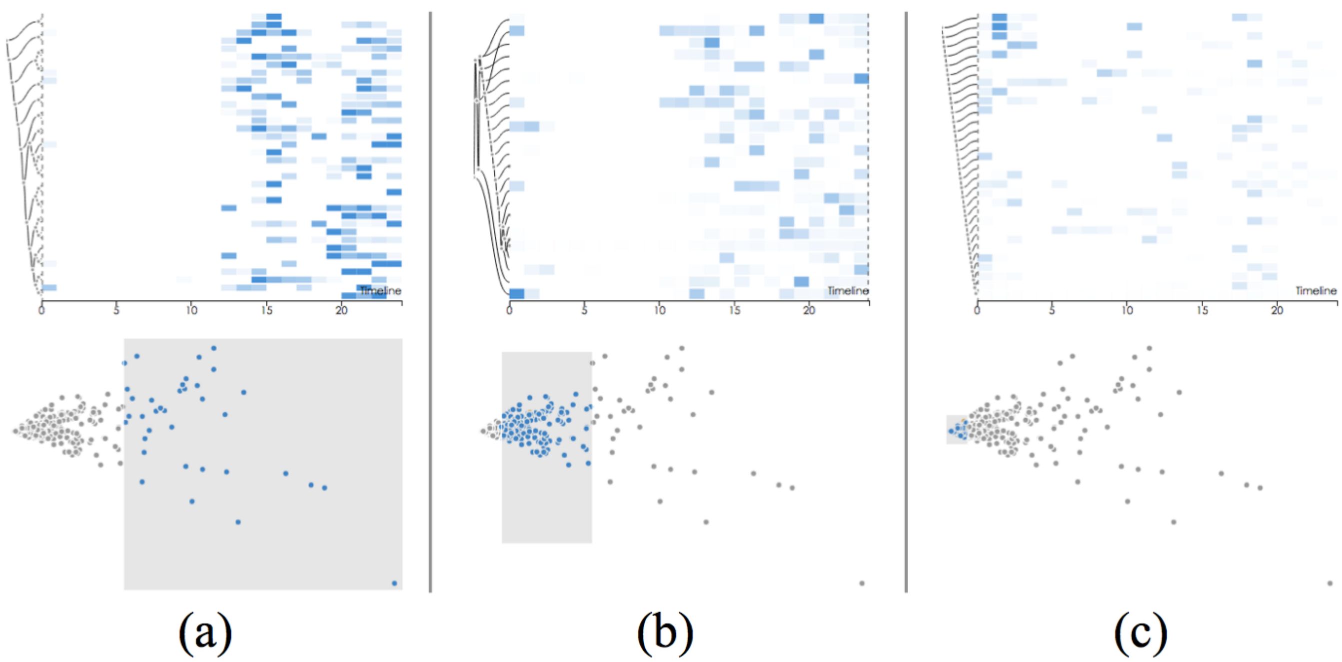

Figure 8: The analyst explores the MMORPG dataset by brushing edges in different areas in the scatter plot. (a)(b)(c) show the different evolution patterns of interpersonal ties of edges.

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