Evaluation of a novel visualization for dynamic social networks

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ABSTRACT

Adding temporal information to social network visualizations is still a challenging task despite previous research efforts. The dimension time is of great interest to analysts as it offers insights into various trends and patterns such as changing relationships between different actors or economic opportunities for businesses. Yet current approaches suffer from limitations that can be improved with the visualization design presented in this work. The visualization was developed considering aesthetic criteria and characteristics of adjacency matrices and node-link diagrams. In a formative evaluation process an artificial dataset was specifically created to examine dynamic social networks. A qualitative user study with observation and think-aloud protocols was conducted and analyzed with regard to the user's strategies, limitations of the visualization and potential additional features. The visualization appears to be suitable for all of the evaluated network tasks, however, path-related tasks were more challenging similar to the characteristics of matrix-based representations.

CCS CONCEPTS

• **Human-centered computing**; • **Visualization**; • **Empirical studies in visualization**; • **Visualization techniques**;

KEYWORDS

Spaciotemporal Visualization, Dynamic Social Networks, Communication Network, Qualitative Evaluation

1 INTRODUCTION

Social network analysis has become of great interest to researchers, businesses and individuals. It offers insight to group structure, relationships between the different actors such as friends, business partners, criminals, etc. and makes it possible to find influential actors or connecting people as Ahn et al. [1] argue.

The communication between individuals has become more and more computer-related due to the technological advances in the last decades. The various forms of digital communication, such as phone calls, SMS messages, emails, chat rooms and social networks (e.g., Facebook or Twitter), leave a digital trace that tie the individuals, groups and objects to one another, which is described by Smith et al. [16]. These digital traces can be used to depict the social network among the individuals. According to Ghoniem et al. [5] an intuitive approach to visualize relations is to use links between the actors to show who is connected to whom (e.g., a node-link diagram where nodes represent the actors). Researchers have also come up with other ways to visualize social networks and provide additional information within the visualizations. Ahn et al. [1] discuss the aspect of dynamics in social networks, as communities are rarely static. Due to a variety of reasons, such as cultural, environmental, economic or political trends or individuals changing their roles, social status or interests, relations change over time. Vehlow et al. [18] note this inherently influences the structure of the network.

The structure of the network can provide the reader with a lot of information. Liu et al. [13] compare the connected nodes of an intermediary to the ones of a professor. An intermediary may know many people which are not interconnected as they often don't know each other. Whereas professors know many students that may have many links that tie them to each other as they probably visit the same classes and are in the same social circles. As soon as these roles or professions change, the social network changes as well.

Therefore it is useful to add time as a dimension to the representation of the social network. Considering the evolution of communities can help to understand the past with its influencing circumstances at the time and to use this knowledge for predicting the future. Analyzing social networks this way can, according to Henry and Fekete [7] enable specialists to discover various trends, patterns, economic opportunities or even terrorist networks.

There has been lots of research in visualizing static networks, which can be used as a simplification of evolving networks by choosing a single point in time or by aggregating longer spans of time [3]. In comparison there has been little research on visualization approaches for dynamic social networks. These visualizations still suffer from several limitations that impair their readability such

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as edge crossings, clustering, visual clutter or the high cognitive load required to read them.

The aim of this work is to propose a novel visualization that deals with current limitations of social networks, especially the investigation of single connections over time. As our visualization approach focuses on certain characteristics it serves specific use cases and comes with its own challenges and limitations. These have been investigated in a qualitative user study leading to insights into the strategies participants used to solve network tasks as well as design implications for this visualization. For the illustrations in this work an artificial dataset of phone calls was used. The visualization was created with Tableau, which is a graphical software for creating interactive visualizations.

We conducted a user study with six participants performing a set of 15 tasks and a follow-up interview. We analyzed data from observations, think-aloud and participants ratings of confidence and difficulty for each task. The analysis emphasized three aspects: the suitability for graph visualization tasks, the usability of the visualization and possible design improvements.

We describe related work, our novel visualization approach and the qualitative user study. The results of this user study showed that the visualization appears to be suitable for all network tasks however tasks that involve finding paths were more challenging. Implications for design were derived.

2 RELATED WORK

The visualization of dynamic networks is a topic of increasing interest in the research community. Various concepts of layout, visualization and interaction techniques can be found in the literature as surveyed by Shaobo and Lingda [15].

Several ways to map the time dimension to the visualization of dynamic graphs have been explored. The two most common are to either map *time to time*, which results in an animation or to map *time to space* which creates a timeline within the visualization [3]. Beck et al. [3] describe other mappings, such as time to color, saturation, glyphs, etc., are rarely applied independently and rather combined with other techniques.

Dynamic networks are present in various fields. Social networks is only one part of the field of application. Another application field for dynamic network visualization can be found in crime investigation. Seidler et al. [14] introduced a combined node-link and matrix visualization system to visualize dynamics of criminal behavior. They evaluated the technique with domain experts using think-aloud protocols with observation. They showed that using both, a node-link and a matrix visualization, strengthens the identification of harmful developments. Moreover, Gove et al. [6] designed a novel social network system which includes heat maps and matrices to support users exploring temporal changes in networks. Hlawatsch et al. [8] introduced a visualization for dynamic, weighted graphs based on adjacency lists which is timeline based and juxtaposed. They represent nodes and corresponding links separately on two horizontal axes and use colors to identify further distinguish nodes.

There are two approaches that were a significant inspiration for the design of the proposed visualization of this work. Burch et al. [4] presented a similar approach using stacked edges to show the individual connections of a graph. One of the differences is that they concentrate on weighted graphs and use colors to represent weights. Another inspiring approach was developed by Kriglstein et al. [10] who examined visualizations for group meetings. In their representations letters denote locations, numbers denote hourly intervals and colors denote different individuals. Especially their augmented matrix was an inspiration for this work. The idea to connect persons in a matrix structure via links inspired the approach of this work in that the person's row can be scanned to see who the person connects with.

3 METHODOLOGY

The visualization was created using Tableau (see 3.1) having the aesthetic criteria by Beck et al. [2] (see 3.2) in mind. For the illustrations in this work an artificial dataset of phone calls (see 3.3) was created. These components will be described in more detail in the following subsections.

3.1 Tableau

Tableau is a commercial visual analysis desktop application. We used the free student version of Tableau Desktop, version 9.3.1.

Tableau includes a graphical system that allows users to explore and analyze their own datasets in a simple, quick and uncomplicated way, as described by Wesley et al. [19]. It is based on Polaris [17] and has become a powerful addition to the technology stack of many organizations. Tableau enables users to create interactive visualizations using data from either an online data source or an offline copy of the data. The visualizations can either be saved locally offline or can be collaboratively shared on their server [19].

3.2 Aesthetic Criteria

An aesthetically pleasing design can significantly influence the usability, readability and ultimately the usage and success of a visualization or of any product for that matter.

Beck et al. [2] addressed aesthetic dimensions of dynamic graph visualizations in an effort to help designers come up with applicable new designs in practice as well as to compare and evaluate them. In their work, they attempted to translate vague aesthetic aspects into specific criteria that are directly applicable to arbitrary dynamic graph visualizations. According to them, a graph is considered readable or aesthetic when the user is both able to access detail information and to uncover general regularities and anomalies of the graph structure. Detail information may include the point in time and weights of edges, the specific nodes that are connected by an edge and paths. General regularities and anomalies could be clusters of vertices, outliers, trends, symmetries or patterns [2]. They organized these aesthetic criteria into the categories general criteria, dynamic criteria and scalability criteria.

As these criteria [2] were specifically tailored to dynamic graph visualizations and could therefore directly be applied, we chose to consider these for designing and evaluating the visualization.

3.3 Dataset

For creating the visualization we used a small artificial social network including 98 phone calls between 26 individuals during a period of 6 consecutive days. Each row represents a phone call and has an assigned intensity to reflect the length of the call in minutes.

Table 1: An exemplary excerpt of the artificial dataset with 10 phone calls out of a total of 98 calls.

Person A	Person B	Day	Intensity
Anna	Emily	1	11
Anna	Olivia	1	13
Olivia	Emily	1	8.5
Melissa	Anna	1	6
Melissa	Selina	1	5.1
Rachel	Harvey	1	7.2
Rachel	Harvey	2	12
Olivia	Tom	2	17
Anna	Emily	2	13
Anna	Olivia	2	5

However in other dataset scenarios the intensity may be used to reflect any kind of importance. The names of the 26 individuals each start with a letter from the alphabet to avoid confusing names and simplify reading the visualization. An exemplary excerpt of the dataset including 10 phone calls is shown in Table 1.

The main purpose of visualizing social networks is to be able to make sense of the social network that is represented within the data. For this reason, the dataset was created with special attention to its content in order to support storytelling, i.e., the data suggests the interpretation of circles of friends or families so that stories can unfold during the analysis.

4 VISUALIZATION APPROACH

The newly developed visualization for a dynamic social network is a timeline-based approach. It has characteristics of node-link diagrams and matrix-based representations. The visualization of this work was created with Tableau, using an artificially constructed phone call dataset consisting of 26 individuals and six points in time. Figure 1 shows the visualization with an extract of the dataset.

The representation depicts each conversation on a daily basis, i.e., it shows precisely who talked to whom on which day and for how long. Figure 1 lists the names of the 26 individuals on the left. Vertical, blue lines symbolize a connection between two persons which are indicated by the connected dots along the horizontal line to their name on the y-axis. Additionally, the names of the pair are shown along the vertical connection line to facilitate identifying the connected individuals. To overview the connections of one person the horizontal auxiliary lines, which are kept in a light grey tone, can be followed. The phone calls are consecutively numbered for identification (ID 1-51), which are additionally shown on the x-axis next to the days and intensities. With these IDs users can refer to a specific connection, which can be helpful when different users are analyzing the visualization and talk about their findings.

In this visualization the representations of the different points in time are positioned next to each other, i.e., they are juxtaposed. The intensities can be seen below each connection. The longest (most intense) calls are shown on the left of each day. This is in accordance with the most common reading direction (left to right) and thereby meant to put emphasis at the connections with the highest intensity, which might be most important. The visualization is in its early stages and interactivity is limited to zooming, scrolling and displaying additional information when hovering on connections.

5 USER STUDY

We conducted a small user study with a qualitative methods approach to test the usability of the visualization with regards to social network tasks and receive first feedback for improvements. Lam et al. [11] was taken as a basis for forming the research questions as well as for designing the study. In their work seven evaluation scenarios are introduced that were divided into two categories: process and visualizations. These allow the analysts to draw their focus on analyzing the visualization itself for example testing its usability and making design decisions as well as the process and role of the visualization. As the primary goal of the study is to see how the visualization is accepted by users, the tasks were based on the two scenarios for evaluating user performance and user experience by Lam et al. [11]. Our research questions were:

RQ1 **Suitability for graph visualization tasks:** How well does the visualization's performance meet the tasks for which it was designed?

RQ2 **Usability:** Which usability issues can be identified?

RQ3 **Design Improvements:** What design improvements can be made to increase the visualizations usability?

5.1 Tasks

The tasks for the user study were created by taking generic tasks from Ghoniem et al. [5] and task taxonomies of Lee et al. [12] and Kerracher et al. [9] as starting points. The tasks should represent actions that a user would typically carry out with the visualization. The choice of tasks assured to keep a balance of tasks from different categories. In order to keep the testing sessions in an appropriate time frame, the data set and task set were balanced to meet the goals of this study. Therefore the original data set was limited to 20 actors and 56 phone calls within seven days, attempting to maintain a realistic network. A total of 17 tasks, grouped into the seven generic network task types (TT) by Ghoniem et al. [5], were developed to investigate the research questions:

TT1 **Counting the nodes as *nodeCount*:**

Task 1 How many persons can you identify in the network?

TT2 **Counting the edges as *edgeCount*:**

Task 2 How many phone calls can you identify in the network?

TT3 **Finding the most connected node as *mostConnected*:**

Task 15 Find a day where people had more than 2 phone calls?

Task 16 Who has the most contact people? How many contact people does she/he have?

Task 17 Who has the most phone calls over the time?

TT4 **Finding a given node as *findNode* and**

TT5 **Finding a link between two nodes as *findLink*:**

The two task types were combined as *findLink* implies *findNode*. In general, at first the two given nodes must be found to then find a connection between them. Tasks for temporal graphs by Kerracher et al. [9] were also incorporated into the following task definitions. These include: direct look-up, inverse look-up, direct comparison, inverse comparison and relation seeking.

Task 3 To whom was Daniel talking to on Day 2?

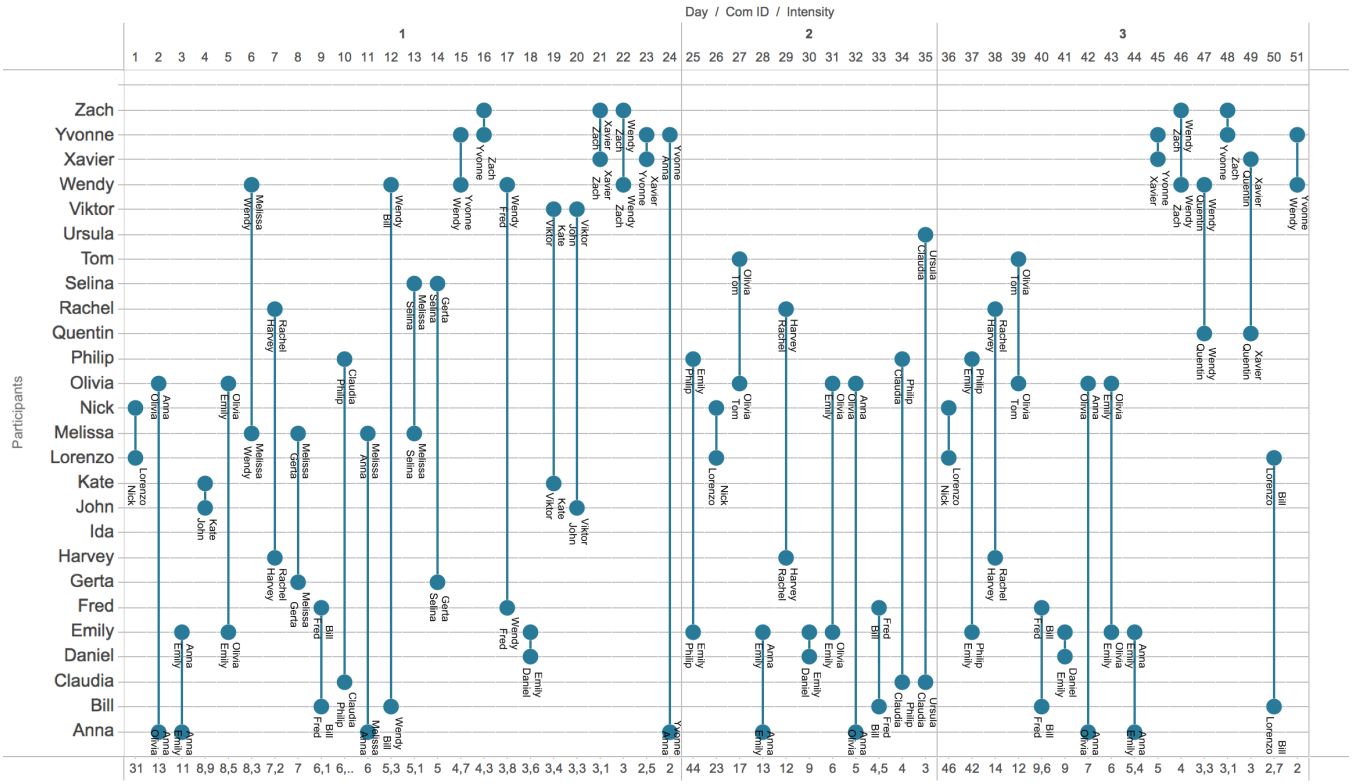


Figure 1: The novel visualization approach showing 51 phone call connections between 26 actors. The x-axis shows the days and communication IDs at the top and intensities of the calls in descending order on the bottom. On the y-axis the names of the participants are given. The names of the pair of a call are additionally labelled alongside each connection.

Task 4 When did Claudia and Tom have the most intense phone call?

Task 5 With whom was Quentin's most intense relationship over the time period?

Task 6 Compare the relationship between Bill and Fred with Selina and Fred. What do you notice?

Task 7 Find a person who left the network. When did the person leave?

TT6 Finding a common node as *findNeighbor*:

Task 8 Are Anna and Daniel friends? If not, which persons connect them both?

Task 9 Which common friends do John and Philip have?

Task 10 Are Emily and Claudia directly connected? If not, which persons connect them both?

TT7 Finding a path between two nodes as *findPath*:

Task 11 Find a valid path from Nick to Gerta.

Task 12 Is there a valid path from Nick to Gerta? If yes, where is the path?

Task 13 Is the following a valid path: Ida-Bill-Gerta-Harvey?

Task 14 Which persons connect Selina and Olivia?

5.2 Procedure

The study followed a qualitative methods approach using think-aloud protocols combined with observations and field notes. Each participant was asked to speak their thoughts out loud and was observed while performing a set of predefined tasks. The field notes include the observed user's interaction techniques, problems and quotes or comments related to the research questions. Each session was audio and screen recorded. Additionally, a follow-up interview was conducted. Each session took approximately 45 - 60 minutes.

The combination of think-aloud, observation and an interview provided insights on the participants' opinion of the visualization, their strategies for each task, as well as frustrations and considerations encountered while using the visualization. Two pilot studies were conducted to assure the tasks are defined clearly and are solvable within a reasonable time.

Each session started with a short introduction of the aim of this work. Afterwards an explanation of the visualization was given personally to the participant. It was emphasized that the visualization itself is in the focus of the evaluation and not the behavior of the participant. Therefore, participants were allowed to ask any questions during the test and go on to the next task if a task was unresolved. Also zooming and scrolling the visualization was allowed. Using a 4-point Likert scale, respondents rated (a) the difficulty level (ranging from "very easy to very difficult") and (b) the confidence level (ranging from "very confident to very unconfident") of each task. These questions were proposed after finishing a task.

At the end of each session, a follow-up interview collected the subjective opinion regarding efficiency, usefulness and user satisfaction with the visualization. The following questions were asked:

- What was easy for you? What was difficult for you?
- What did you like about the visualization?
- What did you not like about the visualization?
- What would help you to solve the tasks?

5.3 Participants and Setting

For this qualitative user study, six participants (three males, three females) with a mean age of 23 years were recruited. Four of six participants were engineering students, the remaining two were students for landscape architecture. Three of them stated that they had experiences working with information visualizations. We aimed to qualitatively investigate whether differences could be noted depending on the participants' previous knowledge, however did not find notable insights in this small population. As this is a small explorative study, the validity of results is limited and could further be investigated in a larger scaled user study.

The visualization was shown on a 15" Retina Display. In order to have a better understanding on specific interaction techniques with the visualization, all participants were asked to use the mousepad when solving the tasks. We conducted audio and screen recording using QuickTime Player 1. The task answers were surveyed using Google Forms which was presented on a tablet computer during the session. The participants could submit their answers directly.

6 RESULTS

The data of the user study was gathered from the usability evaluation and the follow-up interviews. As a qualitative approach thematic analysis was chosen to make sense of the data. For this, 434 quotes were extracted from the evaluation. Afterwards, these quotes were categorized into four themes: user's strategies while solving the tasks, challenges, additional features and general user preferences and other comments. Each of these four themes was analyzed individually and is summed up in the following paragraphs.

6.1 Users' task-solving strategies

Using the observations, screen captures and categorized think-aloud quotes it was attempted to derive strategies participants used to solve the tasks. The strategies are presented for each task type (**TT1-TT7**). The error rates of each task and the level of difficulty and confidence which were estimated by the participants are shown in Figure 2.

6.1.1 TT1: nodeCount . In this task the amount of individuals in the network was asked. All participants answered correctly and found the task very easy. Also five of six participants were very confident with their solution.

Two different patterns could be identified among the participants. Half of the participants counted the names on the y-axis. Those mentioned that they would find it helpful if there was a value that can be read from the visualization directly and they would expect this information on the right side of y-axis. The other half of the participants retrieved the number of individuals in the network from the y-axis on the right side. However, there were two participants who noticed the axis information, but were uncertain about what the values meant.

6.1.2 TT2: edgeCount. The task for edgeCount was to find how many phone calls are in the network. All participants answered correctly and perceived the task as easy. Five of 6 participants were very confident with their solution.

As expected, almost all participants solved this task by reading the information that was displayed on the top axis. There was only one participant who counted the encountered edges in the visualization. The reason for this was that the test person was unsure about the communication ID and the day as both information was displayed on the top axis.

6.1.3 TT3: mostConnected. There were three tasks for this task group: finding a day where people had more than two phone calls, finding the node with the most contact partners and finally finding the node with the most phone calls throughout the whole visualization. The latter two were answered correctly by all participants. The first task could not be answered correctly by two participants and one participant rated the task as difficult.

In this group of tasks all participants used similar techniques: By going through each person's horizontal line, either the number of nodes was precisely counted or a rough estimation was made. The latter was achieved by scanning through the lines quickly. Two of six participants were able to tell at a glance which individuals in the visualization have fewer connections than others and could therefore exclude these quickly.

6.1.4 TT4: findNode. This task type occurs in almost every task. From the analysis of tasks 3-7 various strategies to find a node could be identified. Finding specific nodes, i.e., names, was rated as very easy. Tasks including temporal aspects were rated more difficult; the combination of finding an unspecific node with a temporal criteria (task 7) was rated less easy and two participants rated it as rather and very difficult, however the error rate was 0%. All participants were very or rather confident.

The first technique all participants applied was to find the node on the left side of the y-axis. This was particularly the case with inverse look-up tasks. Subjects went through the list from top to bottom until the name sought after was found. 5 of 6 participants did not realize that the names are sorted alphabetically in descending order. Therefore, search effort was required. Instead of scrolling to the left side, participants looked for a specific node in the visualization area. This pattern occurred when participants zoomed in the visualization and thus only a part of it was visible. Moreover, participants used this technique when a certain point in time as additional parameter was provided.

6.1.5 TT5: findLink. FindLink was also an essential part of tasks 3-7. The most intuitive way of finding a connection between two nodes was to focus on one row and the corresponding dots. People read the names next to the colored dots as they represent the information of a link. In contrast, a less frequently used technique to find a link was to first look for the names on the y-axis and check if they have connecting lines.

		CONFIDENCY						DIFFICULTY						ERROR RATE
Task 1	How many persons can you identify in the network?	1	1	1	1	1	2	1	1	1	1	1	1	0 %
Task 2	How many phone cals can you identify in the network?	1	1	1	1	1	2	1	1	1	1	1	1	0 %
Task 3	TO whom was Daniel talking to on Day 2?	1	1	1	1	1	2	1	1	1	1	1	2	17 %
Task 4	When did Claudia and Tom have the most intense phone call?	1	1	1	1	1	2	1	2	2	2	2	2	17 %
Task 5	With whom had Quentin the most intense relationship over the time period?	1	1	1	1	1	1	1	1	2	2	2	3	0 %
Task 6	Compare the relationship between Bill and Fred with Selina and Fred.	1	1	1	1	2	2	1	1	2	2	2	2	0 %
Task 7	Find a person who left the network. When did the person leave?	1	1	1	1	2	2	2	2	2	2	3	4	0 %
Task 8	Are Anna and Daniel friends? If not, which persons connect them both?	1	1	1	1	2	2	1	1	1	1	2	2	0 %
Task 9	Which common friends do John and Philip have?	1	1	2	2	2	3	1	1	2	2	3	3	33 %
Task 10	Are Emily and Claudia directly connected? If not, which persons connect them both?	1	1	2	2	2	2	2	2	2	3	3	3	0 %
Task 11	Find a valid path from Nick to Gerta.	1	1	1	1	2	3	2	2	3	3	3	4	0 %
Task 12	Is the following a valid path: Ida-Bill-Gerta-Harvey?	1	1	1	1	1	3	1	1	2	2	2	2	0 %
Task 13	Is there a valid path from Ida to Melissa?	1	1	2	4	4	4	1	4	4	4	4	4	67 %
Task 14	Which person connect Selina and Olivia?	1	1	1	1	1	3	2	2	2	3	4	4	33 %
Task 15	Find a day where person had more than 2 phone calls?	1	1	1	1	1	2	1	1	2	2	2	3	33 %
Task 16	Who has the most friends?	1	1	1	1	1	1	1	1	1	2	2	3	0 %
Task 17	Who has the most phone calls?	1	1	1	1	1	2	2	2	2	2	3	3	0 %

Figure 2: Overview of participants' estimated confidence level, difficulty level and error rates for each task.

6.1.6 TT6: findNeighbor. Three tasks belong to this category. Two tasks were solved with a 0% error rate. The difficulty level, however, was rated as more difficult in, e.g., task 10 by half of the participants. Two participants failed to answer task 9 correctly, one participant reported lower confidence.

Participants applied three techniques in order to find common friends of two given nodes. The first approach involves taking one node and seeing all relations for one node. They followed the auxiliary line and kept the relations in mind. Afterwards, the second node was focused and revisions were carried out as to whether connections exist between the second node and the adjacent nodes to the first node. Another technique is quite similar to the previous technique. Participants only looked at the connections from one node. They took the first encountered edge and checked whether the second node also has a direct connection with the focused node. If this was not the case, participants kept repeating the action until they found a node that is adjacent to both given nodes. The last technique was only used once: one participant took both nodes and followed the lines in order to see if a common friend appeared on both lines.

6.1.7 TT7: findPath. Finding a path in the evaluated visualization can be achieved by applying the technique for finding a neighbor repeatedly. We used four path-related tasks in this study (tasks 11-14), one of which was to validate a given path. Participants struggled most with this type of task and the highest error rate (67%) could be observed. One participant was not confident in any of the tasks and overall all participants found the tasks more difficult.

We could observe the following pattern for finding paths. The participants started with one node and looked for its relations. When a given node had only one connected actor, they kept looking for the relations of the actors node. When a node had more than one unique connection then the first relation found was considered. After that, it was compared with the second given node in order to find out whether there is a link. When two nodes are given, participants started with one node and looked for its relations. Then they worked with the neighbor nodes and continued looking for other relations until a path was found.

Another common pattern that was identified is that people tend to start with the node with fewer cinnections. In that case participants used the find "mostConnected" technique, compare 6.1.3.

6.2 Challenges

Four main challenges were identified in the observations and participant's statements during the evaluation and follow-up interviews:

Remembering things The study demonstrates that for finding paths, comparing more than three nodes was difficult. Participants complained that "it's exhausting" and "it's becoming difficult". Four of six participants mentioned that they often feel confused by persons that have several different relations. A main issue for them was that a lot of information had to be remembered and compared during the tasks. One participant also suggested: "... for finding a path another visualization would probably be better".

Finding maximum of intensity of given couple In some tasks the intensity was relevant. The meaning of intensity information did not seem to be a problem. When two individuals in the network have a higher intensity, participants interpreted this as they are having a strong friendship or close relationship. However, finding the connection with the maximum intensity between two nodes over the time led to confusion at several points. In 2 of 6 interviews it was mentioned that they were unsure whether there is a need to compare the intensity values or only the position of a conversation within a day is sufficient. For example when a certain

conversation is at the front within a day, then it must not be the call with the maximum intensity over the time. Therefore some comparison work had to be done in this case.

Layout This sub-theme summarizes all feedback gathered regarding the layout of graph data. An unanimous opinion emerged from the evaluation. Essential information such as number of calls or names of individuals can be clearly seen in the visualization. Nevertheless, the communication ID and the day were often confused, likely because both information were located in close proximity.

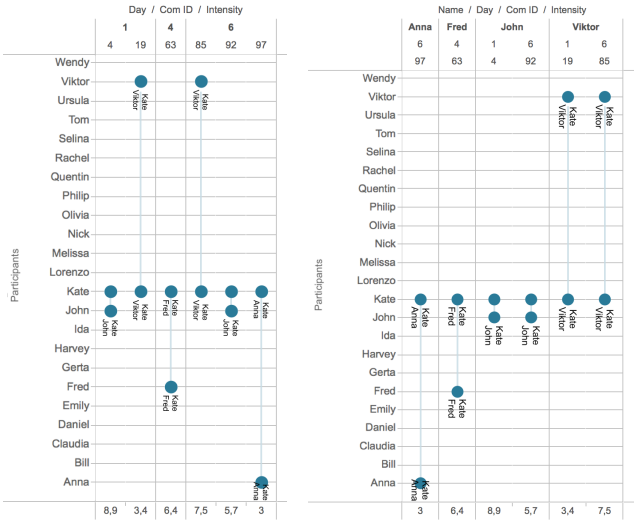
Another problem was the text orientation of the names next to the dots. Two participants found it hard to read the names because of their vertical orientation. According to the observations during two of the evaluation sessions the participants had to turn their head to be able to read the names correctly. Regarding the names on the left side of the y-axis, there were no complaints, but one participant mentioned that it would be easier to find the name in the list when the names are sorted alphabetically in ascending order to scan the list from the top to bottom.

Navigation and orientation Participants used the horizontal lines and the vertical lines as well to navigate through the visualization. On the one hand they were seen as useful as one participant stated "Lines make sense now when having so many names". On the other hand one participant mentioned that following the horizontal line from one end to the other is not always possible. Especially when users want to zoom in and out, it can happen that they slide into the wrong line. People found it challenging to do comparison tasks. When they had to jump from a point to another or jump between the lines, they lost the thread easily.

6.3 Features

In the follow-up interview the participants were asked which additional features would have helped to solve the social network tasks. Their answers are grouped into three sub-themes.

Filtering Participants would like to filter by days, certain relations, individuals or intensities so they can reduce the number of phone calls in the representation to only those of interest. They want to be in full control of the information that is hidden or additional information being shown. Figure 3a and 3b illustrate two filtered views of *Kate's* communications. Figure 3a uses the standard visualization characteristics removing the calls where Kate is not part of, which means results are ordered by day and intensity. The idea in this approach is to support the constructed mental map from the overview by changing as little as possible in the new view. Figure 3b, on the other hand, groups the calls by partners instead of days. In this way, relationships and common history between pairs can be investigated easier. The first view (Figure 3a) has the advantage to easily observe specific patterns that are related to time, for example, that Kate always communicates with John and Viktor on the same days, and never with just one of them. The same information is evident in the second view (Figure 3b) as well, but it might not be detectable as easily. On the other hand, this view can help to make sense of the different relationships the person has and how intense these relationships are. It is immediately recognizable, for example, if the person communicates every day with one person but only every other day with another person due to significantly different column widths per person.



(a) Filter grouped by days **(b) Filter grouped by names**

Figure 3: Two filtering views

Highlighting A functionality that allows users to mark specific nodes, edges or days in order to focus on the relevant data of the highlighted component was mentioned by one participant.

Paper and Pen Two participants mentioned that it would have been helpful to have a pen and paper to write notes on relations or paths they found. This feature does not address the visualization directly, however it indicates that the mental load to remember information is quite high.

6.4 User preferences and comments

Four of six participants reported that it was easy to find whether two nodes are connected. Two participants stated that "it was exhausting" and "it took so long" to find the most connected node, however they rated those type of tasks fairly easy. In contrast people found tasks that asked for indirect relations with more than three nodes particularly hard because a lot of information had to be remembered and compared.

There were also comments on visual components like color, line, value and space. The opinions regarding the design of the nodes in the visualization varied among the participants. One participant found the size of the nodes too big. With 20 names and their corresponding lines, it became ambiguous for that participant. Another participant stated that the ratio of node size and line thickness is well chosen. Regarding the color of the nodes, the participant suggested that the colors of the node and connection line should not be the same as it seems monotonous. The participant stated that "you can loose track easily". Lastly, one participant would prefer the vertical day separator lines to be "a little bit darker" because "it can be misunderstood as the connection between two persons".

Two participants positively noted the spacing between the lines and emphasized that the horizontal lines for each person helped a lot while solving the tasks. Overall participants find that the visualization fulfills its purpose as all tasks could be solved.

7 DISCUSSION AND DESIGN IMPLICATIONS

The proposed visualization appears to be suitable for most of the described tasks. Especially *nodeCount*, *edgeCount*, *mostConnected*, *findNode* and *findLink* seem to be solvable with ease while path-related tasks such as *findNeighbor* and *findPath* become more challenging. This reflects the similarity to matrix-based representations. The compactness of a matrix gives it certain advantages such as its resistance to higher density of the visualized dataset. On the other hand the fact that the proposed visualization is less compact opens up possibilities for labeling which may facilitate reading detail information for users. The proposed visualization does not become crowded with increased density such as node-link representations do but instead grows in its horizontal size. Although only six subjects participated in the study, trends and possible usability issues were discovered. Based on these findings some design implications were drawn.

Additional View The visualization appeared to be less suitable for path-related tasks. Therefore an additional visual representation, for example a node-link representation which allows to easily find paths, could support the current visualization.

Improve visibility of day separator The day separator could be designed more prominent such as with a darker color or a thicker line as it was often overlooked.

Use color The current version of the visualization uses three colors to differentiate the components. Adding more colors could provide a better differentiation between the different elements.

Orient labels horizontally The vertically oriented text was hard to read for the participants and resulted in a poor reading performance. In order to avoid this issue, the text should be oriented horizontally which however would necessitate more spacing between the connections.

Interaction Features Interactivity of the visualization should be implemented in the next phase. Features such as filtering and highlighting were mentioned or implied three times by participants. The proposed filtering techniques therefore seem to be relevant and should be developed further.

8 CONCLUSION AND FUTURE WORK

In this work the early stage of a new visualization for social networks with an added time dimension was presented. The visualization was created using the visual analysis tool Tableau and an artificial dataset having existing aesthetic criteria and task sets in mind. The proposed visualization has characteristics of both node-link diagrams and adjacency matrices.

A qualitative user study was conducted with the aim to evaluate the suitability for graph visualization tasks, the usability and to provide improvements on design. Seven task types with a total of 15 tasks were considered. The evaluation in this work showed that the proposed visualization performs well for direct look-ups and comparisons that do not involve finding paths. Though the visualization received overall positive feedback on its visual design, some adjustments to the labeling and coloring can be made to improve the usability for certain tasks.

Further empirical studies are subject to future work in order to obtain statistically significant results and to determine the applicability in different domains, contexts and application scenarios. In future work, the visualization can also be extended to represent group calls; the visualization approach easily allows to connect multiple people by adding dots on the respective connection lines. The visualization can further be enhanced by interactivity such as filtering, sorting or highlighting. Further evaluations are necessary to explore how the visualization scales to larger datasets and how interactive views affect the performance and usability.

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