Human Factors and Multilayer Networks

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ABSTRACT

Analysts of specific application domains, such as experts in systems biology or social scientists, are often interested to visually analyze a number of different network structures in conjunction, for example by using various visual structures of so-called multilayer networks. From the perspective of the human analyst, a sufficient perception and, consequently, a good understanding of those visual representations of multilayer networks is a non-trivial and often challenging task. Despite this practical importance and the clearly interesting visualization challenges, only few evaluation studies exist that investigate usability and cognitive issues of complex networks or, more specifically, multilayer networks. In this position paper, we address two main goals. On the one hand, we discuss existing studies from the fields of human-computer interaction and cognitive psychology that could inform the designers of multilayer network visualization in the future. On the other hand, we formulate first tentative recommendations for the design of multilayer networks, identify open issues in this context, and clarify possible future directions of research.

Index Terms: Human-centered computing—Visualization—Visualization techniques—Graph drawings; Human-centered computing—Visualization—Visualization design and evaluation methods Human-centered computing—Visualization—Empirical studies in visualization

1 INTRODUCTION

In many application domains, such as biology or sociology, analysts are not only interested in the visualization of a single network consisting of nodes and edges which show the relationship between the nodes. In practice, many different networks need to be considered and visually analyzed together. For instance in systems biology, networks are used to structure and combine data. Typically, they can be arranged within a hierarchy of different levels (or layers), such as to represent molecular-biological relationships or to show the interaction of proteins within cells. A biologist might then be interested in to get an idea how the different network elements in this set of networks are connected with each other. Other real-world application examples encompass scholarly networks in social sciences—e.g., citation networks or collaboration networks of authors and their affiliations—or static/dynamic structures of software artifacts in software engineering, see Schreiber et al. [16] for a more detailed description of these examples.

From the user's point of view, the understanding of the visual display of such *Multilayer Networks* is a challenging task. Multilayer networks are very complex resulting in a significant amount of cognitive load on the users. It is an open question how to visually design such complex networks so that users can derive useful insights from such visualizations.

The goal of this position paper is twofold. First, we want to show that results from evaluation studies and cognitive psychology can be applied or re-used to improve the visual design of multilayer networks. For this, we highlight existing evaluation examples and relevant psychological research in Sections 3 and 4. Note that our aim in this work is not to provide a comprehensive overview of this topic, but to discuss a few study examples to indicate the validity of our position. Second, based on such previous research, we derive some first tentative recommendations and also identify open issues that need to be addressed in future research to clarify how multilayer networks should be visually represented (Section 5). Our goals are also relevant from a methodological point of view, because a theoretical framework based on previous research allows for a more rigorous design of experiments. Moreover, a theoretical framework enables researchers to conduct experiments more systematically and to generalize their results beyond a single evaluation study.

2 BACKGROUND OF MULTILAYER NETWORKS

Before we discuss related work on evaluation studies and cognitive psychology, we have to briefly introduce the used terminology in context of multilayer networks and their visualization without providing too much detail. There is a number of ways how the relationship between the elements of multilayer networks can be defined, and consequently, there is an even larger number of terms that are used to describe the networks depending on those definitions. The term *multilayer networks* seems to have developed to a kind of generally accepted umbrella term at least within the visualization community [12]. However, there are many other terms that are usually used within different research communities and subjects, such as *multiplex networks* (also called *multirelational networks*) that are networks with multiple edge types. Those networks can be considered as one single holistic network, but also as a network consisting of many layers, one for each edge type. Other related terms are *multinetworks*, *multislice networks*, *composite networks*, etc. In 2014, Kivelä et al. [10] try to unify the different terminology in the existing work, show the differences, and propose a general framework for multilayer networks.

Figure 1 (upper part) shows a conceptional view on the data structure of a multilayer network with each layer consisting of a different network type. More precisely, the diagram shows three different layers (e.g., metabolic networks, protein-protein interaction networks, regulatory networks), and each layer might consist of 2-3 networks types (metabolic network I, metabolic network II, etc.). There are relationships (links) between nodes in different networks within the same layers (*intra-links*) and relationships between the nodes of networks within different layers (*inter-links*). This complexity of the data structure is one reason why the visualization of such multilayer networks is challenging. Other reasons are additional multivariate attributes that might be attached to the nodes/edges [16] and the broad diversity of user tasks during the analysis, ranging from crosslayer entity connectivity, layer manipulation & reconfiguration, to layer comparison based on topological patterns, cf. McGee et al. [12] for a detailed survey on these characteristics.

The potentially large design space of suitable visual representation and interaction techniques has a direct influence on how visualizations of multilayer networks are perceived by humans. In consequence, different visualizations may lead to discrepancies with respect to cognition. Figure 1 (lower part) conceptualizes three potential ways to visualize a multilayer network by using stacking in

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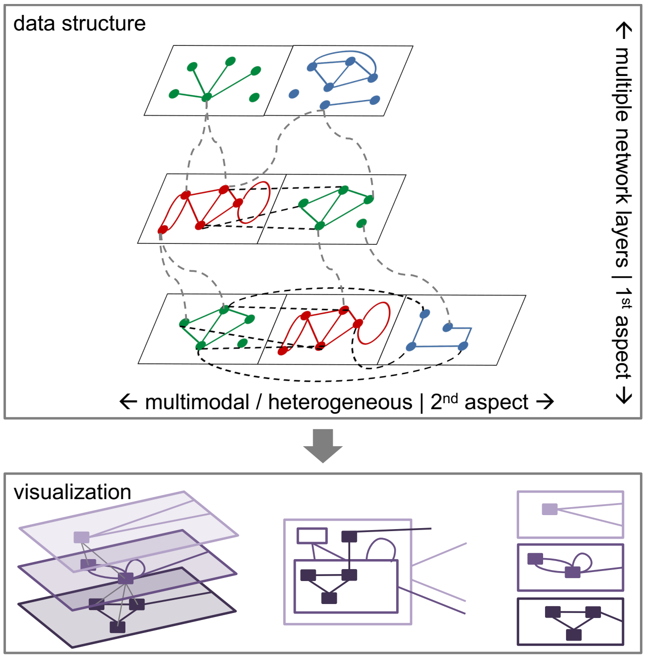

Figure 1: An example multilayer network. Colors in the upper part are used to separate different graphs types within individual layers; colors in the bottom part separate different layers instead. Taken and adapted from [16].

2.5D/3D, 2D nesting of layers, and 2D alignment (e.g., by juxtaposition) [16]. Of specific importance is the visual representation of the intra- and inter-links of a multilayer network [12]. If the network becomes larger, the differentiation of the edge types causes additional clutter beyond the usual clutter that we have when visualizing large networks in general [9]. In addition, navigating across intra- and inter-links to adjacent nodes within the same or different layers may be difficult for the user. Interaction techniques may help to reduce this navigation complexity. Examples are Bring&Go [13], which moves adjacent nodes into the current view, close to the actual selected node, or Hub2Go [24], which supports heterogeneous network exploration by automatic camera movements in multiple network views to facilitate the navigation from and to nodes across interconnected networks. Due to space constraints and the overall focus of this position paper, we do not introduce concrete visualization techniques and approaches for displaying networks, such as layouts of node-link diagrams or matrix-based approaches. Instead, we refer to the graph drawing and network visualization literature or corresponding surveys/textbooks [2, 6, 8, 9, 19, 20].

3 Overview of Existing Evaluation Studies on Multilayer Networks or Other Complex Networks

There are still very few studies doing evaluations of multilayer networks. In this context, it might be useful to look at studies of other complex networks (see e.g. [22]) and try to transfer the results of these studies to multilayer networks. The results of such studies can inform the design of multilayer networks.

Yoghourdjian et al. [22] provide a comprehensive overview of research on large and complex networks with a focus on evaluation studies. They point out that it is still an open question how to define large or complex graphs, but that most visualization studies were done with smaller graphs, and only very few with graphs with more than 1,000 nodes. They mention that other measures than number of nodes could also be used (number of edges, density), but these numbers are reported less often in the literature. They also found that there is a relationship between tasks, interactions and application areas and basic measures of size of node-link diagrams. Large node-link diagrams are mainly used for overview tasks, as opposed to smaller node-link diagrams. Interaction techniques appropriate for larger, more complex node-link diagrams are different than the ones for smaller node-link diagrams in that in larger node-link diagrams interaction techniques requiring less effort are predominantly used. The authors argue that more detailed knowledge about cognitive scalability would be beneficial for the design of usable large and complex node-link diagrams.

Yoghourdjian et al. [22] also point out that there are different possibilities to simplify sensemaking processes with large graphs. One possibility is to use *aggregation*, and the other is to offer appropriate *interaction* possibilities to the users. While interaction is an important approach to ease the cognitive load of the users, Hegarty points out that interaction also has a cost because it puts the burden of choosing the specific appearance of the visualization (choice of variables shown, choice of segment of the visualization shown, etc.) on the users [5]. This requires some degree of meta-knowledge that not all users possess. In the following paragraphs, we briefly discuss contributions addressing the issue of aggregation and interaction.

Aggregation

Rossi and Magnani [15] discuss design considerations for multiplex networks of social actors. They argue that special designs for the visualization of multiplex networks are necessary. While their paper does not present an evaluation, it addresses important design issues. They argue that one possibility to achieve an improvement of multiplex network visualization is by adding analytical measures (e.g., degree distribution). They discuss several different possibilities to ease the cognitive load on the user, e.g., by slicing the node-link diagram into layers with similar edges and showing them as small multiples (either with the same or with different layout). The solution they find most promising is to show only edges conforming to a relevance measure. In this way, they try to identify hidden clusters in social networks.

Simplification of large and complex node-link diagrams has been discussed to some extent in the scientific literature. Dunne and Shneiderman [3] propose to achieve this simplification through abstraction with glyphs. They argue that in some application areas (e.g., social networks) certain motifs are meaningful ways to represent the underlying structure of networks. They suggest to use fans (nodes with a single neighbor), connectors (linking a set of nodes) and cliques (completely connected nodes) as motifs. In a user study, they could show that these abstractions are helpful for many types of tasks. They also provide guidelines for the design of the glyphs. Nevertheless, the authors point out that these motifs have to be learned and therefore increase the cognitive load. In addition, it is not yet clear whether there are other glyphs which might be more appropriate for other domains.

Archambault et al. [1] investigated path-preserving clustering of graphs resulting in opaque meta-nodes. Their results were not entirely unambiguous. Nevertheless, they state that their results imply that path-preserving clusters can lead to an improved performance on global tasks.

Yoghourdjian et al. [23] introduce the notion of thumbnails: small icon-like visualizations representing high-level structures of graphs. Thumbnails are presented as small multiples to allow users to compare these high-level structures. The authors point out that there has been some research to investigate detailed comparison of individual changes, while their research addresses comparison of more general characteristics of graphs. They investigated in detail the possible design alternatives for thumbnails and came up with circular structures that also allow to include annotations of the visualization. In general, thumbnails were more effective than either node-link diagrams or matrices for overview comparison of large graphs.

Interaction Another possibility to support the users sensemaking processes is to offer interaction features. Ware and Bobrow [21] use highlighting to enable users to get meaningful insights from node-link diagrams of varying sizes (from 32 nodes up to 3,200 nodes). The results indicate that highlighting is a fairly efficient interaction method, especially for large networks. The authors state that without highlighting error rates were rather high even for the smallest network. They also show that search times were rather high for the largest network even with highlighting. This is an indication that large graphs are a form of visualization posing specific challenges.

Nekrasovski et al. [14] compared pan and zoom interfaces with a rubber sheet navigation (as an example for focus and context methods). They found out that, contrary to their expectation, pan and zoom interfaces were significantly faster than rubber sheet navigation. Added overviews did not contribute to the success of the participants, but the participants subjectively appreciated the overviews nevertheless.

Marner et al. [11] developed an interaction technique for graph representations on large screens. They used animation to support users in the processes of rearranging nodes on the screen. They found that animation can be helpful to support users in this activity. They also point out that the results of evaluation studies for small graphs cannot always be transferred easily to the design of large graphs.

4 Overview of psychological research relevant for the evaluation of multilayer networks

There are several areas in psychology that might be relevant for evaluation studies of multilayer networks, especially in the area of cognitive load [7]. In general, it is necessary to take cognitive issues into account and use cognitive models as a foundation for the design of visualizations [5].

Cognitive Load As mentioned above, increased cognitive load is probably the most serious challenge facing designers of multilayer network interfaces. It has been argued that restricting investigations of visualizations to simple tasks can be misleading. Cognitive load theory can form a theoretical foundation for getting a more comprehensive picture of cognitive processes users engage in when interacting with complex visualizations.

Cognitive load theory has been developed to describe cognitive processes learners engage in when interacting with educational material [17, 18]. Sweller distinguishes between *intrinsic* and *extrinsic* cognitive load [17]. Intrinsic cognitive load results from the nature of the material presented to learners; extrinsic cognitive load results from the manner in which the material is presented. Both types add up to the total cognitive load. If this exceeds the working memory resources, the learners will not be able to process the information presented to them. Sweller and his collaborators have also described various effects based on cognitive load theory that can be used as a framework for an improved design of educational material [18].

One example of such an effect that might be relevant for information visualization is the so-called *split-attention effect* [18]. This effect occurs when users have to attend to at least two pieces of information that are separated either in time or in space. To make sense of this information, the user has to integrate them in a meaningful way which requires a considerable cognitive effort, because some pieces of information have to be kept in short-term memory. Sweller et al. [18] suggest some ways to alleviate this problem, some of which are also relevant for the design of information visualizations. They especially point out that elements that interact with each other should be presented in an integrated way. When designing complex and large multilayer networks, it seems to be obvious to separate the single layers so that users are not overwhelmed by the information. Nevertheless, in that case users loose the information about the relationships of nodes to other layers. Designers should be aware that these relationships have to be indicated clearly, so that cognitive load to remember these relationships does not become too heavy.

Cognitive load theory has been developed for educational purposes but is also applicable in other domains. It has been applied to the design of information visualizations. Huang et al. [7] highlight that an inappropriate design of a visualization may lead to an increased extrinsic cognitive load. Changing the form of the visualization can alleviate this problem. High cognitive load occurs when many elements of the visualization have to be processed simultaneously. The authors [7] developed a cognitive load model for the evaluation of information visualizations and tested it successfully. They especially show that mental effort is an important aspect in interacting with visualizations. To a certain extent, users are able to counteract increased complexity of visualizations by exerting mental effort. In their experiment in context of network visualizations, they showed that even relatively small node-link diagrams (25 nodes and 98 edges) can impose a high cognitive load on users [7]. The authors point out that it is still not entirely clear which factors induce cognitive load. Most experiments in evaluation of visualizations have been conducted with fairly simple tasks. In realistic situations, complex tasks requiring an increased mental effort play a more important role.

Cognitive Limits Cognitive load theory implies that there are limits in cognitive resources. Franconeri [4] discusses 15 of such limits in our ability to process visual information. He distinguishes between limits on identification of objects and limits on object selection. When these limits are exceeded, response time will increase and accuracy will decrease. Franconeri [4] discusses several cases in which such phenomena will occur. In some cases, it is for example difficult to find objects among a number of distractor objects. Another example for limits in object identification is inattentional blindness (users engaging in a demanding task will miss important information right in front of their eyes). Limits on object selection also affect the sense for location of objects. Five up to eight locations can be selected at the same time. Detecting the relative spatial relationships of an object is also a very demanding task. Knowledge about such limitations have to be taken into account when designing visualizations.

5 Development of tentative recommendations for the design of multilayer networks based on the literature review

Based on the literature reviewed above, some tentative recommendations can be provided for the design of multilayer networks. Large and complex graph visualizations in general and multilayer networks in particular have not been evaluated extensively so far. Therefore, these recommendations can only be a starting point. They also indicate areas where future research is necessary as listed in the following.

Our first three recommendations are related to HCI-related issues. As described in Section 3, Yoghourdjian et al. [22] argue that tasks and interaction techniques for larger and smaller node-link diagrams differ. The authors also point out that aggregation and interaction are important techniques for supporting sensemaking processes with large node-link diagrams:

R1. *Task Evaluation:* There is some indication that large node-link diagrams support different tasks and interaction possibilities than small ones. Nevertheless, this assumption is not entirely clear, and detailed evaluations in this area have to be conducted.

R2. *Aggregation:* Different forms of aggregation are possible. Aggregation in general is helpful, especially for overview tasks and detection of the general structure. The results so far are promising, but not yet conclusive. All the suggested forms of aggregation have been developed for specific application areas, and it is an open question whether these results can be generalized.

R3. *Interaction:* Highlighting, pan and zoom, and animation have been found to be helpful for supporting sensemaking processes with large networks. It is an open question whether other forms of interaction are also useful.

Recommendation four and five are related to cognitive load theory (see Section 4). This theory addresses the issue of how to make it easier for learners or computer users to make sense of the material they encounter. In this context, Sweller et al. [18] have formulated several recommendations. We present one exemplary recommendation especially relevant for the design of multilayer networks. Huang et al. [7] also address the problem of how to investigate complex node-link diagrams which is related to our fifth and last recommendation.

R4. Cognitive load theory shows that it is especially demanding to relate facts that are presented in a disjoint way on the screen. Therefore, relationships between different layers in multilayer networks should be emphasized so that cognitive load for remembering relationships while solving tasks does not become to heavy [17]. It is still an open question how such relationships could be emphasized.

R5. So far, researchers have predominantly used simple tasks to evaluate graph visualizations. The results of such investigations are, in many cases, not valid for large and complex graph visualizations. Complex tasks should be used more often to evaluate graph visualizations.

We think that the evaluation of multilayer networks is a challenging research area. There are still many open issues that have to be solved, so that users can interact with such networks effortlessly and derive valuable insights from such networks efficiently.

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