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Netzwerke in Zeit und Raum

Visuelle Analyse dynamischer Netzwerkdarstellungen

DISSERTATION

zur Erlangung des akademischen Grades

Doktor der Technischen Wissenschaften

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Networks in Time and Space

Visual Analytics of Dynamic Network Representations

DISSERTATION

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Velitchko Filipov

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Kurzfassung

Netzwerke sind abstrakte und flexible Datenstrukturen, die im Wesentlichen eine Vielzahl von Objekten und ihre Beziehungen untereinander modellieren. Netzwerkvisualisierung bezieht sich auf eine Sammlung von Methoden, die speziell für die Erzeugung ästhetischer und skalierbarer Layouts solcher Daten entworfen wurden. In der Praxis ändern sich die Daten jedoch im zeitlichen Ablauf, und es ist oft von Interesse, diese Entwicklungen zu untersuchen und zu analysieren, weshalb man sich mit der dynamischen Netzwerkvisualisierung beschäftigt. Die dynamische Netzwerkvisualisierung erforscht, wie die Entwicklung von Netzwerken und ihre strukturellen Veränderungen angemessen und effektiv dargestellt werden können. Das übergreifende Ziel ist es, Darstellungen zu konstruieren, die sowohl die strukturelle als auch die zeitliche Information in einer lesbaren Art und Weise darstellen. Dies ist eine anspruchsvolle Aufgabe, und aktuelle Ansätze optimieren häufig Standardnetzwerkdarstellungen wie Knoten-und-Kanten-Diagramme, um gleichzeitig die Topologie und die Dynamik des Netzwerks mittels Animation darzustellen. Alternative Visualisierungsmodalitäten werden nur selten erforscht, was eine interessante Forschungsrichtung darstellt. Da Netzwerkkonnektivität schwer zu visualisieren sein kann, nutzen viele Methoden den Raum, um die Lesbarkeit zu verbessern und ästhetische Kriterien zu implementieren, was oft Einschränkungen hinsichtlich der Skalierbarkeit mit sich bringt. Diese Einschränkungen haben mehrere interessante Forschungsfragen hervorgebracht, die in dieser Dissertation untersucht werden. Wie können die Standardtechniken der Netzwerkvisualisierung verbessert werden, um dynamische Informationen zu vermitteln? Welche Techniken sind geeignet, effektiv und vermeiden eine Informationsüberflutung? Wir tragen zum aktuellen Wissensstand im Bereich der Visualisierung dynamischer Netzwerke bei, indem wir den Designraum formal evaluieren und neuartige Visualisierungsmetaphern für die Darstellung dynamischer Netzwerke untersuchen. Unsere Ergebnisse zeigen, dass alternative Visualisierungsmodalitäten vielversprechend sind, und unsere Evaluierung struktureller und zeitlicher Kodierungen zeigt die Nützlichkeit von Kombinationen auf, die in der einschlägigen Literatur selten untersucht werden. Darüber hinaus werden offene Forschungsfragen diskutiert, die interessante Möglichkeiten für zukünftige Entwicklungen eröffnen, und es werden Vorschläge zur Unterstützung von Forscher*innen bei der Entwicklung von Methoden zur Visualisierung dynamischer Netzwerke vorgestellt.

Abstract

Networks are abstract and flexible data structures that broadly model a set of entities and the relationships between them. Network visualization refers to a set of techniques, specifically, designed to produce aesthetic and scalable layouts of such data. However, in real-world applications data changes over time and it is often of interest to investigate and analyze these dynamics, motivating the study of dynamic network visualization. Dynamic network visualization explores how the evolution of networks and their structural changes can be appropriately and effectively conveyed. The overarching goal is to construct representations that depict both the structural and temporal information in a readable manner. This is a challenging task and current approaches often optimize standard network representations, such as node-link diagrams, to simultaneously portray the network's topology and dynamics using animation. Alternative visualization modalities are seldom explored and this presents an interesting research direction. As network connectivity can be cumbersome to visualize, many approaches make use of space to improve readability and implement aesthetic criteria, which often presents scalability concerns and limitations. These limitations exposed several interesting research questions that are investigated in this dissertation. Namely, how can we augment standard network visualization techniques to convey dynamic information, which techniques are appropriate, effective, and avoid causing information overload, as well as investigate alternative visualization metaphors for dynamic networks? We contribute to the body of knowledge on dynamic network visualization by formally evaluating the design space and investigating novel visualization metaphors for the depiction of dynamic networks. Our results show promise for alternative visualization modalities and our evaluation of structural and temporal encodings highlights the usefulness of combinations that are under-investigated in related literature. Furthermore, we outline open research challenges that present promising opportunities for future work and provide recommendations to better support researchers in the development of dynamic network visualization approaches.

Contents

CHAPTER 1

Introduction

In the following chapter, we present the motivation behind this dissertation and contextualize our work based on the application domain of the Digital Humanities. We introduce networks as data structures and provide a brief preface to the historical development of the field of network visualization, its usefulness, and its adoption in diverse research disciplines. We demonstrate the advancement of the field and the necessity to consider the dynamics and complexity of real-world network data. Furthermore, we present our research questions, outline the research methodology, and provide an outline of this dissertation.

1.1 Motivation

Networks are abstract and ubiquitous data structures that are used to model a broad set of phenomena and problems in many domains. In their simplest form, they are defined as a set of data points and the relationships between them. This data is typically modeled as entities, also referred to as nodes and their connections or relationships, also referred to as links[1]. The study of networks historically developed as a method of analyzing complex relational data in diverse domains of research and application. One of the earliest known applications of network visualization and analysis was developed and presented by Jacob Moreno, a psychologist, who presented a sociogram representing the social structure of elementary school students [Mor53] (see Figure 1.1). His work was a critical moment in the further development of social network analysis and since then research in this field has increasingly gained interest mostly focusing on statistical tool-kits and models, with the visualization and visual exploration of networks falling behind. This resulted in a wealth of statistical modeling techniques and approaches to synthesize and simulate social network data including dynamics and evolution [BC96; Car99] that introduced novel challenges involving visualizing, communicating information, and extracting insights from such networks [BM06].

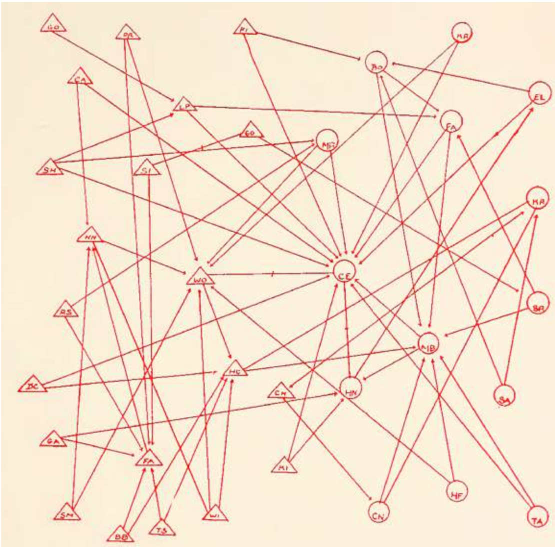

Figure 1.1: An example of a sociogram developed by Moreno [Mor53] encoding the social attraction between students. In this example, the nodes depicted by triangles are boys and the circles are girls. The links are directed and the arrowheads represent the direction of the attraction. Links with a centered line on them mean that the attraction is mutual.

This type of data and the outlined challenges presented the motivation for the further development of the field of network visualization. Research on network visualization is concerned with providing meaningful and effective representations of network data, supporting researchers and

[1]In mathematical graph theory a network is referred to as a graph, nodes are vertices, and links are edges. In the context of this thesis, we use these terms interchangeably.

analysts in understanding connections, gathering insights about the network's structure, and detecting and identifying unexpected patterns or behaviors [Bez+10]. In real-world scenarios, data is seldom static and for most applications and domains it is essential to visualize and analyze the evolution of such networks. However, for the sake of simplicity, the temporal dimension in such data sets is often ignored due to its complexity [Bec+17]. Time itself is a particular characteristic of dynamic data requiring carefully chosen visual and analytical approaches to effectively explore and analyze [MA14]. The perceived importance of time is increasingly considered in diverse branches of visualization in the visual analytics community. There is increasing scientific interest in the topic of *dynamic network visualization* that is concerned with visualizing dynamic relational data in order to detect trends and patterns, re-occurrences, peaks and valleys, and the growth and contraction of such networks [APS14]. Furthermore, the discipline of multi-variate network visualization has evolved to address challenges related to networks enriched with multiple attributes, aiming to identify nodes or links with specific attribute values, detect similarities or differences in attribute distributions among entities in a network, and discover outliers within the network [Nob+19].

Domain: To contextualize this dissertation in the following, we present and discuss the application domain of Digital Humanities. Our contributions are centered on dynamic network visualization and analysis within this domain. Digital Humanities is a broad domain, including academic disciplines, such as linguistics, archeology, musicology, and art history. Experts in these disciplines are interested in using visual analytics solutions that enable them to explore and analyze their data from new and diverse perspectives. Such digital computational methodologies are increasingly used in a variety of research disciplines. However, the humanities often conduct their research in archives gathering material sources. Their research questions and methodologies stem from a different epistemological standing compared to technical fields [Hin+17]. New technologies are quickly changing the landscape of this domain by making research materials widely accessible and enabling scholars to explore their data, find patterns, and present their work. The data in Digital Humanities can be seen as rich, interpretable data [Lam+18] with relational, spatial, and temporal characteristics that can be represented as a network [Sch+19]. Network visualization and analysis support scholars in numerous tasks. For example, identifying and understanding relationships between actors, highlighting central or similar objects, or observing how the underlying structure of the network changes over time to reveal expected or unexpected behavior.

In the following, we briefly describe each of the projects, elaborate on the characteristics of the data, and outline the research questions that were investigated.

Interactive Music Mapping Vienna[2]: This project presents an interdisciplinary collaboration with the Music and Arts University with the goal of mapping the history of public festivities in Vienna during the Second Republic (from 1945 to the present day), exposing narratives that contributed to the construction of the city's musical identity and the connection to historical events. The project aims to highlight and communicate the potential of music as a tool for urban identification, exploring its interaction with urban elements such as identity, political symbolism,

[2] `https://www.cvast.tuwien.ac.at/projects/immv` Accessed: 03/01/2024

mental determination, and imagination. Through the integration of network visualization and interactive Visual Analytic technologies, the aim is to make this interaction accessible to both academic and general audiences, providing a comprehensive understanding of the dynamic relationship between music and urban elements. The data in this project is an event-based network that relates entities and embeds them in space and time. The dataset consists of six different types of entities (and their respective counts): Events (1243), Historic Events (78), People/Organizations (1538), Themes (61), Locations (180), and Sources (1279) with a total of 15,866 links between them.

PolyCube[3]: In this project we collaborated with the Danube University Krems on the topic of visualizing cultural heritage data by constructing space-time cube representations that display the spatial distributions as well as the temporal developments in multiple coordinated views focusing on spatial, temporal, categorical, and relational aspects of the data. The aim of the project was to investigate how to maximize the connections between the multiple coordinated views and how they can better help in constructing a mental model to explore the data and understand the relationships. The data in this project are cultural artifacts with locations (spatial), dates (temporal), keywords (categorical), and short descriptions. Furthermore, we additionally computed relationships between the cultural objects based on keyword and description similarity.

ArtVis[4]: This project is an ongoing research project where we have established a transdisciplinary collaboration with the University of Vienna. The project aims to address significant challenges in Digital Art History, specifically focusing on comprehending the intricate interactions among the components of the art system, including persons, objects, places, institutions, and events, and how these interactions evolve over time. To tackle this complexity, we employ an event-based network model encompassing multiple types of entities. Dynamic network visualization is used to visualize and explore the rich and dynamic nature of the data in this domain, emphasizing its complex aspects and dynamics. The dataset in this project is based on the Database of Modern Exhibitions (DoME[5]) and it was translated into a graph database that contains the following entities (and their respective counts): Artists (13999), Exhibitions (1492), Hosts (446), Items (961), Catalogues (1170), and Catalogue Entries (210707) with a total of 8,287,482 relationships between them.

1.2 Research Questions

In our research questions the term "structural encoding" refers to the underlying representation of the network's topology, whereas the "temporal encoding" describes how time and, consequently, the network's dynamics are depicted [KKC14]. Dynamic network visualization approaches can make use of the structural encoding in order to depict relationships between entities and represent other data properties.

In exploratory data analysis [AA06], the concept of structural encoding is referred to as "frame of reference" and has a two-fold categorization: (i) *abstract*: abstract data are not explicitly

[3] `https://www.cvast.tuwien.ac.at/projects/polycube` Accessed: 03/01/2024
[4] `https://www.cvast.tuwien.ac.at/projects/artvis` Accessed: 03/01/2024
[5] `https://exhibitions.univie.ac.at/` Accessed: 03/01/2024

connected to a spatial location (visualizing this type of data requires designers to find an expressive layout such that the temporal domain is exposed), (ii) *spatial*: spatial data are associated with an inherent spatial position (visualizing this type of data requires spatial information to be used to find a suitable layout).

To align the frame of reference from exploratory data analysis with (dynamic) network visualization, we can translate the categorization for the structural encoding as: (i) *abstract*: the elements of a network (nodes and links) are abstract, contain no inherent spatial positioning, and are laid out according to a set of rules optimizing certain constraints (often referred to as aesthetic criteria [Ben+07]), (ii) *spatial*: the elements of a network are augmented with external properties, multiple data facets [HSS15] and time-varying changes [Bec+17] and can be laid out according to these (e.g., attribute-based layouts [Nob+19] and geo-spatial networks [Sch+21]).

The main goal of this dissertation is to investigate, develop, and evaluate visual analytical techniques to support gathering insights and extracting knowledge from dynamic networks. To this end, the overarching research question of this dissertation is as follows:

How do different structural and temporal representations of dynamic network data facilitate effective visual analytics for different task abstractions?

For practical research purposes, we further subdivide this general question into the following sub-questions:

- **RQ1:** How can we modify the structural encoding of dynamic network representations to encode further data properties about the nodes and/or links?
- **RQ2:** Which combinations of structural and temporal representations for dynamic networks are effective, appropriate, and avoid causing information overload?
- **RQ3:** What can we recommend to dynamic network visualization designers and developers to support users depending on the granularity and applications of network analysis?

We aim to investigate both the structural and temporal encoding categories when representing dynamic networks and to achieve this we design and develop multiple coordinated view approaches, novel network visualization metaphors, and integrated techniques that encode properties and attributes directly in the network's representation.

1.3 Contributions

Our work has been published in peer-reviewed scientific journals and the results and findings have been presented at conferences, where the main focus and scope is visual analytics or network visualization. In the following, we outline the main venues we have submitted and presented our work to:

Conferences: IEEE Visualization Conference (VIS), Eurographics Conference on Visualization (EuroVis), Graph Drawing and Network Visualization Symposium (GD), IEEE Pacific Visualization Symposium (PacificVis)

Journals: Computer Graphics Forum (CGF) by Wiley, Transactions on Visualization and Computer Graphics (TVCG) by IEEE, Visual Informatics (VI) by Elsevier.

In this dissertation, we present three publications focusing on answering the aforementioned research questions and applying dynamic network visualization to different domains and application contexts. Each of these publications is peer-reviewed and presents an evaluation of the approach, an outline of the results, a discussion of the limitations, and concluding remarks for future work. The main contributions of our work are:

- Exploring the design space of network visualization to depict the evolving dynamics of networks, encompassing both their topological and temporal aspects utilizing novel network visualization approaches and metaphors;
- Conducting comparative evaluations of state-of-the-art network visualization approaches with respect to the structural representation and temporal dimension;
- Investigating the relationship between the granularity of network analysis (i.e., temporal [APS14] and graph-based tasks [Lee+06]) and the visual encoding of the network, leading to recommendations for developing dynamic network visualization approaches;
- Summarizing our results, presenting the limitations and lessons learned from existing approaches, and reflecting on directions for future research.

The contributions of this dissertation are centered around the following three publications that are part of this cumulative dissertation. The articles are described in greater detail in their respective chapters (see Chapters 3, 4, 5). The following list is an overview of the publications along with the individual contributions following the CRediT authorship statement [AOK19].

- Velitchko Filipov, Alessio Arleo, Paolo Federico, and Silvia Miksch: *CV3: Visual Exploration, Assessment, and Comparison of CVs*, (Presented at EuroVis 2019, Published in Computer Graphics Forum 38, 3 (2019), 107–118) [Fil+19a]
  - Contributing with Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing (Original Draft & Review & Editing), and Visualization.
  - Published in the context of the Interactive Music Mapping Vienna and PolyCube projects.
- Velitchko Filipov, Victor Schetinger, Kathrin Raminger, Nathalie Soursos, Susana Zapke, and Silvia Miksch: *Gone full circle: A radial approach to visualize event-based networks in Digital Humanities*, (Published in Visual Informatics 5, 1 (2021), 45–60) [Fil+21]
  - Contributing with Conceptualization, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing (Original Draft & Review & Editing), and Visualization.

  - Published in the context of the Interactive Music Mapping Vienna project.

- Velitchko Filipov, Alessio Arleo, Markus Bögl, and Silvia Miksch: *On Graph Structural and Temporal Encodings: A Space and Time Odyssey*, (Published in IEEE TVCG (2023)) [Fil+23b]
  - Contributing with Conceptualization, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing (Original Draft & Review & Editing), and Visualization.
  - Published in the context of the ArtVis project.

The following are further articles that are published in the scope of this dissertation, where we contributed to the problem of effectively representing dynamic networks in different domains of application and analyzing the results:

- Florian Windhager, **Velitchko Filipov**, Saminu Salisu, Eva Mayr, *Visualizing Uncertainty in Cultural Heritage Collections*, (Presented at EuroVis, EuroRV3 Workshop (2018), 7-11) [Win+18]
- **Velitchko Filipov**, Davide Ceneda, Michael Koller, Alessio Arleo, and Silvia Miksch, *The Circle Of Thrones: Conveying the Story of Game of Thrones Using Radial Infographics*, (Presented at IEEE VIS, VISCOMM, (2018)) [Fil+18]
- **Velitchko Filipov**, Paolo Federico, and Silvia Miksch, *CV3: Visual Exploration, Assessment, and Comparison of CVs*, (Presented at EuroVis Posters (2018)) [FFM18]
- Eva Mayr, Saminu Salisu, **Velitchko Filipov**, Günther Schreder, Roger Leite, Silvia Miksch, and Florian Windhager, *Visualizing Biographical Trajectories by Historical Artifacts: A Case Study based on the Photography Collection of Charles W. Cushman*, (Presented at Biographical Data in a Digital World (2019), Published in CEUR vol. 3152, 49–56) [May+19]
- **Velitchko Filipov**, Nathalie Soursos, Victor Schetinger, Susana Zapke, and Silvia Miksch, *Exiled but not forgotten: Investigating commemoration of musicians in Vienna after 1945 through Visual Analytics*, (Presented at Biographical Data in a Digital World (2019), Published in CEUR vol. 3152, 57–65) [Fil+19b]
- **Velitchko Filipov**, Alessio Arleo, Davide Ceneda, and Silvia Miksch, *The Fabric of Heroes: an Infographic about Marvel Cinematic Universe*, (Graph Drawing and Network Visualization Symposium, Graph Drawing Contest (2019)) [Fil+19c], **Third Place**
- Saminu Salisu, Eva Mayr, **Velitchko Filipov**, Roger Leite, Silvia Miksch, and Florian Windhager, *Shapes of Time: Visualizing Set Changes Over Time in Cultural Heritage Collections*, (EuroVis Posters (2019)) [Sal+19b]

- Saminu Salisu, Eva Mayr, **Velitchko Filipov**, Florian Windhager, Roger Leite, and Silvia Miksch, *Shapes of Time: Visualizing Set Changes Over Time*, (IEEE VIS, SetVis Workshop (2019)) [Sal+19a]

- Victor Schetinger, Kathrin Raminger, **Velitchko Filipov**, Nathalie Soursos, Susana Zapke, and Silvia Miksch, *Bridging the Gap between Visual Analytics and Digital Humanities: Beyond the Data-Users-Tasks Design Triangle*, (IEEE VIS, Vis4DH Workshop (2019)) [Sch+19], **Best Paper**

- Florian Windhager, Saminu Salisu, Roger Leite, **Velitchko Filipov**, Silvia Miksch, Günther Schreder, and Eva Mayr, *Many Views Are Not Enough: Designing for Synoptic Insights in Cultural Collections*, (IEEE Computer Graphics and Applications 40, 3 (2020), 58–71) [Win+20]

- **Velitchko Filipov**, Alessio Arleo, and Silvia Miksch, *Exploratory User Study on Graph Temporal Encodings*, (IEEE Pacific Visualization Symposium, Pacific Vis (2021), 131–135) [FAM21]

- **Velitchko Filipov**, Alessio Arleo, Markus Bögl, and Silvia Miksch, *On Time And Space: An Experimental Study on Graph Structural and Temporal Encodings*, (Presented at Graph Drawing and Network Visualization Symposium (2022), Published in Springer LNCS 0302-9743 (2023), 271–288) [Fil+22].

- **Velitchko Filipov**, Alessio Arleo, and Silvia Miksch, *Are We There Yet? A Road Map of Network Visualization from Surveys to Task Taxonomies*, (Computer Graphics Forum 2023, Invited to present at EuroVis 2023) [FAM23]

- **Velitchko Filipov**, Davide Ceneda, Daniel Archambault, and Alessio Arleo, *TimeLighting: Guidance-enhanced exploration of 2D Projections of Temporal Graphs*, (Graph Drawing and Network Visualization Symposium, 2023, Accepted) [Fil+23c]

- **Velitchko Filipov**, Daniel Archambault, Tatiana von Landesberger, and Alessio Arleo, *Back to the Graphs: Collection of Datasets and Quality Criteria for Temporal Networks Layout and Visualization*, (IEEE VIS 2023, Posters, Accepted) [Fil+23a]

1.4 Research Methodology

In our research, we employ the nested model proposed by Munzner [Mun09] as our overarching methodological framework for design and validation. The nested model is comprised of four layers, each serving as input or a starting point for the next one (see Figure 1.2). Each level in this model has a different set of threats to validity and requires a different approach to validation that we will discuss.

It is important to note that while the entirety of this dissertation follows the nested model as its guiding methodology, the individual publications within it each delineate their specific methodologies. For instance, Chapter 3 is an application paper, Chapter 4 is a design study, and Chapter 5 is an evaluation paper.

In the following, we will present the individual layers of the nested model and discuss supplementing methodologies for each.

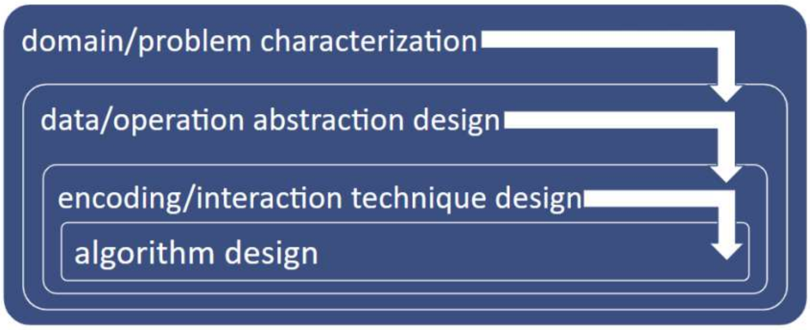

Figure 1.2: Nested Model proposed by Muzner [Mun09] depicting how each layer serves as an input for the following ones.

Problem Domain Characterization: This is the first level of the nested model and the main objective here is to characterize the problem domain by learning about the tasks and data that the intended (target) users of the system have in their daily work. For this level, we characterize the problem domain by utilizing the design triangle framework by Miksch and Aigner [MA14] (see Figure 1.3).

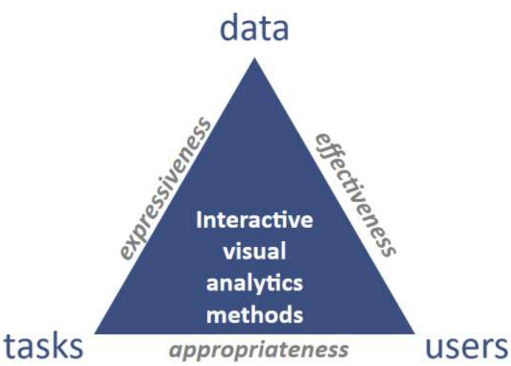

Figure 1.3: Data-Users-Tasks triangle represents the main aspects to consider when designing and developing interactive visual analytics solutions [MA14].

The design triangle methodology puts the focus on developing effective, expressive, and appropriate visual analytical techniques by posing the following three questions:

- **Data:** What kind of data are the users working with?

- **Users:** Who are the intended users of the visual analytical solution?
- **Tasks:** What are the tasks of these users?

Validation: We validate this level by conducting systematic literature research on the topic(s) at hand and investigating the problem domain as well as the data, users, and their tasks by periodically organizing workshops where we reassess and validate the proposed problem domain characterization.

Data/Operation Abstraction Design: The second layer in the nested model is centered around the idea of translating domain-specific data and problems from the vocabulary of the problem domain to a more abstract and generic description of tasks and data in the vocabulary of visual analytics. To achieve this we consider the design by immersion methodology to tackle problem-driven visualizations by Hall et al. [Hal+20]. The main goal here is to dissolve the barriers between fields and individuals, creating a common grounding and understanding that allows both sides to feel comfortable in the target domain. This is achieved by so-called immersion activities, such as organizing collaborative design workshops and cross-literature studies.

Validation: Validating this level of the nested model is achieved through immersion activities, workshops, and cross-literature studies. In order to guarantee that both the domain experts and visual analytics experts have created a common ground it is essential for either side to immerse themselves in the other and understand their methodology, research, and literature.

Encoding/Interaction Technique Design: The third layer of the nested model focuses on the topic of designing the visual encoding and interaction techniques that will be available in the visual analytics solution. The visualization modality (i.e., encoding of data points and interaction techniques) is mainly defined by the outcome of the previous level, where the data and operations are abstracted. We conduct further systematic literature review [Sny19] in this layer on the topic of task taxonomies as well as state-of-the-art reports to ensure that no guidelines or recommendations are violated with our proposed encoding and interaction techniques.

Validation: To validate the developed designs and interaction techniques at this level we conduct both qualitative and quantitative user studies and heuristic evaluations. Through usability studies, we assess potential issues, ambiguous or unclear encodings, and missing interaction techniques.

Algorithm Design: The last level in the nested model is concerned with the development and design of algorithmic solutions in order to carry out the encodings, interactions, as well as analytics automatically. In order to efficiently and effectively design these algorithms we use rapid application development [Mar91], an agile strategy commonly employed in software engineering. This approach puts an emphasis on quick and iterative development cycles that focus on solving atomic problems using minimal feature sets.

Validation: There are two potential threats to this level, specifically, the algorithm performance and its correctness. To investigate performance and issues concerning memory and responsiveness we analyze the algorithm's computational complexity in order to discover bottlenecks and resolve these. To address the algorithms' correctness we present the results of the algorithms to the target audience in order to verify that it meets the specifications identified from the problem domain characterization.

1.5 Outline

In the following section, we outline the structure of this dissertation as a flow diagram (see Figure 1.4). We relate our contributions and publications to the research questions (presented in Section 1.2).

How do different structural and temporal representations of dynamic network data facilitate effective visual analytics for different task abstractions?

- **RQ1:** How can we modify the structural encoding of dynamic network representations to encode further data properties about the nodes and/or links?
- **RQ2:** Which combinations of structural and temporal representations for dynamic networks are effective, appropriate, and avoid causing information overload?
- **RQ3:** What can we recommend to dynamic network visualization designers and developers to support users depending on the granularity and applications of network analysis?

A consistent theme throughout this dissertation is the exploration and visualization of relationships within biographical data modeled as event-based networks. In Chapter 3, we develop an interactive environment for comparing resumes and facilitating the creation of networks based on shared skills, experiences, and mobility. Chapter 4 introduces a dynamic network visualization metaphor for event-based networks, emphasizing connections between people in the Interactive Music Mapping Vienna project. In Chapter 5, while evaluating dynamic network visualization designs, we leverage a publicly available co-authorship dataset [Ise+17], seamlessly integrating it into our exploration and evaluation of dynamic network visualization techniques. Despite diverse applications, the overarching theme unifies these chapters, collectively addressing research questions and contributing to dynamic network visualization. This common thread underscores the versatility of the methodologies explored, enhancing our understanding of effective visual analytics for diverse network analysis scenarios.

The remainder of this dissertation is structured as follows.

In Chapter 2 we provide an extensive overview of the field of network visualization, focusing on defining dynamic network visualization and discussing how it is related to different branches of network visualization. Additionally, we provide a taxonomy of consolidated terms that are used throughout different publications to categorize a broad set of network visualization approaches. We further outline the current state-of-the-art as well as open challenges and promising directions for future research.

In Chapter 3 we present a novel interactive exploration environment for exploring, comparing, and assessing multiple résumés. The users, in this case hiring managers and recruiters, are able

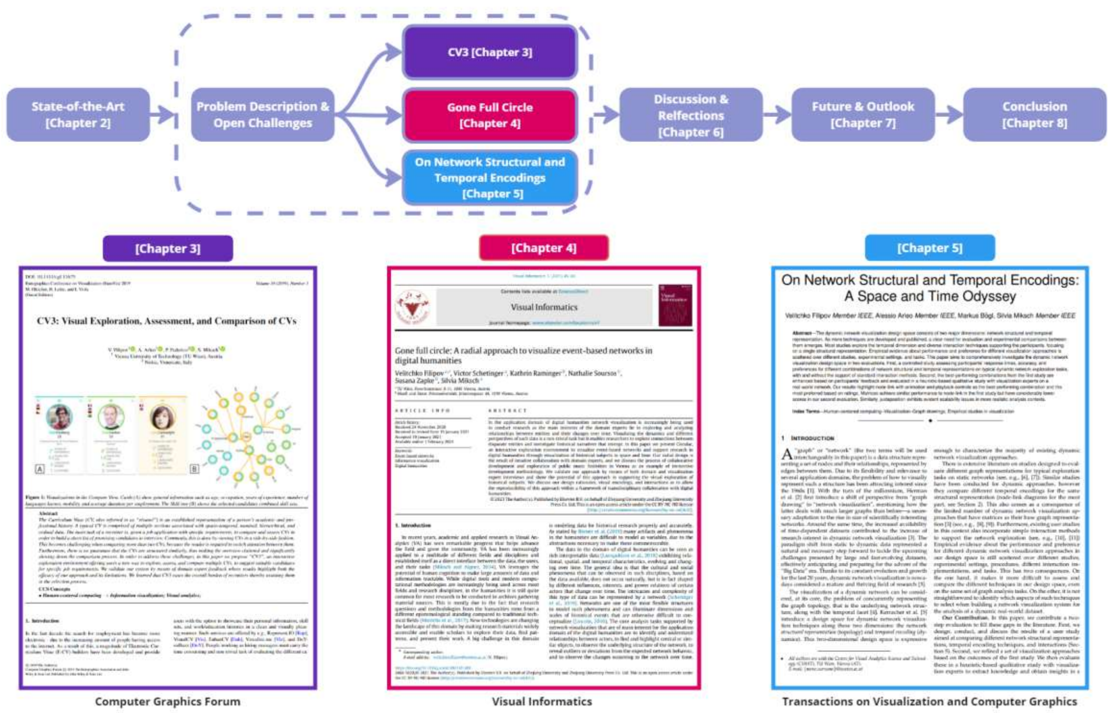

Figure 1.4: A visual overview of the outline of this dissertation along with the three publications that address the research questions presented in Section 1.2 [Fil+19a; Fil+21; Fil+23b].

to select and build a network of multiple applicants that are all related to each other based on common skills and experiences and competitively rank them. We explore their common skills, mobility networks, as well as different metrics we use to rank the candidates. In this chapter, we evaluated our ranking metrics, visualization design, and interaction techniques by conducting a task-based user study with domain experts.

In Chapter 4 we explore a novel dynamic network visualization metaphor in the context of the Interactive Music Mapping Vienna project that focuses on representing event-based networks. Our approach utilizes a radial layout and tightly integrates the temporal and event-based nature of the network into its representation. The context of our work was in the application domain of Digital Humanities and a big emphasis was put on aesthetic appeal and presentation. Our approach was validated with domain experts with a focus on engagement, immersion, and the ability to extract insights from the visualization.

In Chapter 5 we explore the design space of dynamic network visualization and evaluate different combinations of network structural encoding and network temporal encoding. In this chapter, we focus on the effects that the structural encoding and temporal encoding have on the performance of network evolution tasks as well as in an exploratory analysis scenario focusing on insight generation. To evaluate the techniques we conducted both a quantitative user study with hypothesis testing as well as a qualitative heuristic evaluation [Wal+19] with domain experts and report on the results as well as limitations.

In Chapter 6 we reflect on and discuss the results of our work, summarize the key takeaways and contributions, and answer our research questions. Furthermore, from our work and research questions, we derive recommendations for the design and development of dynamic network visualization techniques. We also discuss the scalability and generalizability of our proposed approaches, as well as the implications of our contributions beyond the domain of visualization and visual analytics.

Chapter 7 provides a summarizing discussion, outlining the lessons learned, and highlighting notable directions for future work.

Finally, Chapter 8 concludes this dissertation and summarizes the main research questions and contributions.

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CHAPTER 2

Background

In the following chapter, we will present an overview of the field of network visualization, specifically focusing on the representation and analysis of its dynamics.

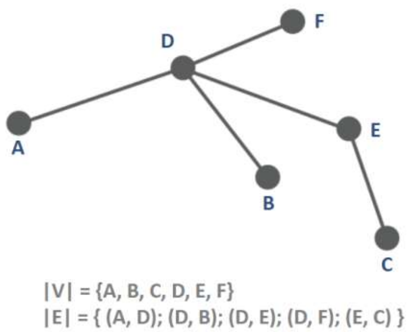

Figure 2.1: An example of a node-link representation of a network $G = (V, E)$. Where V is the set of vertices (nodes) and E is the set of edges (links).

Network visualization is a research field concerned with providing effective and aesthetic representations of graphs. A graph $G = (V, E)$ is a data structure composed of a set of vertices $V = \{v_1, ..., v_n\}$ (nodes) and a set of edges that are (un-)ordered pairs of vertices $e = (v_i, v_j) \in E \subseteq V \times V$ (see Figure 2.1) representing their relationships (links). The majority of research in network visualization focuses on techniques that tackle the problem of producing layouts for the graph [Beh+16; CS20], improving visual scalability of the edges [Zho+13], graph drawing aesthetic criteria [Ben+07], and visualization of trees [GK10]. However, over time graphs are becoming increasingly more complex with different application domains and researchers needing to visualize multiple facets, properties of nodes and edges, and the changes of these over time. In the following, we explore how network visualization has evolved to tackle multiple data facets [HSS15], multiple variables [Nob+19], and time-varying structures [Bec+17].

2.1 Network Visualization

A network is an abstract and ubiquitous data structure, defined, in its simplest form, as the combination of a set of data points and the relationships between them. Due to its simple yet flexible nature, it found its way to a wide range of applications in diverse problem domains. Network visualization is a research field concerned with providing meaningful representations of network data, supporting researchers in understanding the connections, gathering insights, and detecting unexpected patterns [Bez+10].

Over the last two decades, the field of network visualization has been building up momentum and developing rapidly, focusing its research on increasingly challenging disciplines, such as the visualization of dynamic, multi-variate, and complex network data. The variety and diversity of this research represent an obstacle for researchers and practitioners surveying the domain, and, more specifically, when building a comprehensive overview of the literature in the field. To address this problem, numerous surveys have been published on these different disciplines of network visualization, i.e., large network visualization [Lan+11], dynamic network visualization [Bec+17], multi-variate network visualization [Nob+19], and others [SSK14; HSS15; VBW17; McG+19; Sch+21]. While immensely helpful in systematically exploring and categorizing research in their own disciplines, similar approaches and techniques have been classified by multiple surveys in different ways and under diverse names, ultimately resulting in a lack of clarification and uniformity between the terminology used. For example, the concept of *juxtaposition* has been referred to as “small multiples”, “static flipbooks”, or “[visualization of] multiple timeslices” in the context of dynamic network visualization. This requires further effort when mapping and categorizing the plethora of different visualization techniques and approaches.

We provide an overview of the larger field of network visualization that we refer to as a roadmap (see Figure 2.2) [FAM23]. To obtain our roadmap metaphor, we group surveys and task taxonomies into non-overlapping sets that we label as disciplines (illustrated as large nodes with a heading and gray border in Figure 2.2). Disciplines represent individual branches of network visualization that deal with specific data *types*. The disciplines refer to branches of network visualization that deal with specific data types. While the network nature of the data is common among all disciplines, each one is enriched with other attributes and dimensions, such as time (dynamic/temporal network visualization), geographic information (geospatial network visualization), facets, multiple layers, and multiple attributes. Each branch of network visualization has matured enough to be referred to as a network visualization discipline. A multitude of specific techniques were developed within each discipline to the point that it warranted the writing of one or more surveys, categorizing the corresponding approaches and summarizing the advancements and open challenges in literature. Different disciplines can build upon a common theoretical ground in diverging directions or one can be a specialization of another. We model these relationships as directed inheritance relationships depicting how the different disciplines are connected. In our roadmap metaphor, these can be seen as roads that lead from one network visualization discipline to the other. The green road signs indicate how data changes (i.e., with new features and, therefore, with added complexity) when traveling from one discipline to the other (see Figure 2.2).

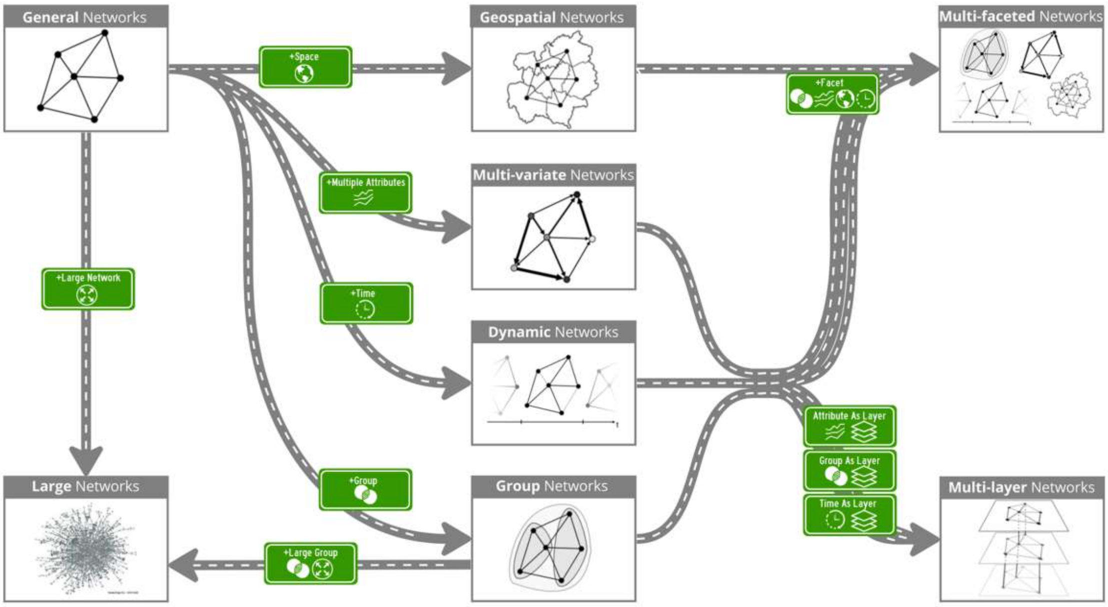

Figure 2.2: The roadmap metaphor we propose depicts network visualization disciplines grouped into non-overlapping sets as nodes with a title and gray border, and the relationships between them as labeled roads connecting them. The direction of the links represents inheritance between disciplines. A source discipline can be extended to the target by considering extensions to the data type, depicted by the green road signs. This structure was extracted from surveys published on each of the disciplines. We refer to our work for a more elaborate description [FAM23].

In the context of our work, we use the terms **network** and **graph**, **nodes** and **vertices**, and **links** and **edges** interchangeably. While there is a semantic difference between the terms graph and network (i.e., graphs are mathematical concepts, whereas networks are more general, often referring to real-world systems), in visualization literature, these two terms are used interchangeably and the keywords associated with the publications reflect this.

In the following we narrow down the larger field of network visualization to the disciplines that are most relevant to the scope of this dissertation, namely, **multi-faceted**, **dynamic**, and **multi-variate** network visualization.

To provide some background on how the time-oriented and multi-variate aspects of data in networks can be considered we introduce the notion of a facet and multi-faceted network visualization as described by Hadlak et al. [HSS15]. The temporal as well as multi-variate aspects of data are considered facets in this work and we discuss how they can be represented along with the structural dimension of the network. Examples of popular techniques to encode the structural dimension of networks are presented in Figure 2.3, whereas for time-oriented data different approaches can be considered (see Figure 2.4). A subset of these combinations can be utilized to depict multi-variate data in networks by adapting the temporal encoding to represent multiple attributes rather than the temporal dimension. We then further discuss, specifically, dynamic and multi-variate network visualization which are the main scope of this dissertation. We present a

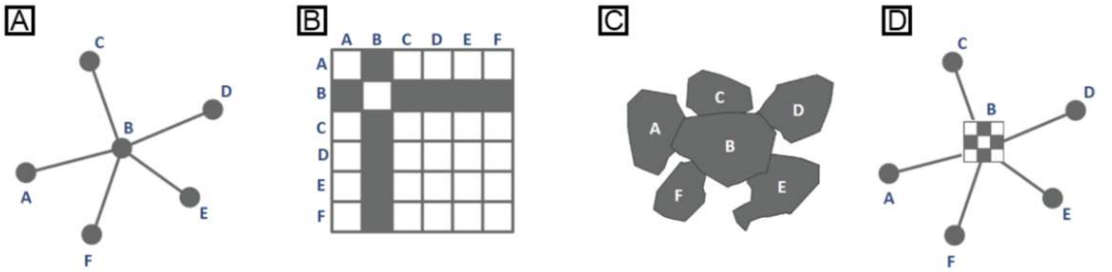

Figure 2.3: Examples of popular network structural encoding techniques. From left to right: (A) Node-Link Diagram, (B) Adjacency Matrix, (C) Contact Map, and (D) Hybrid Representation.

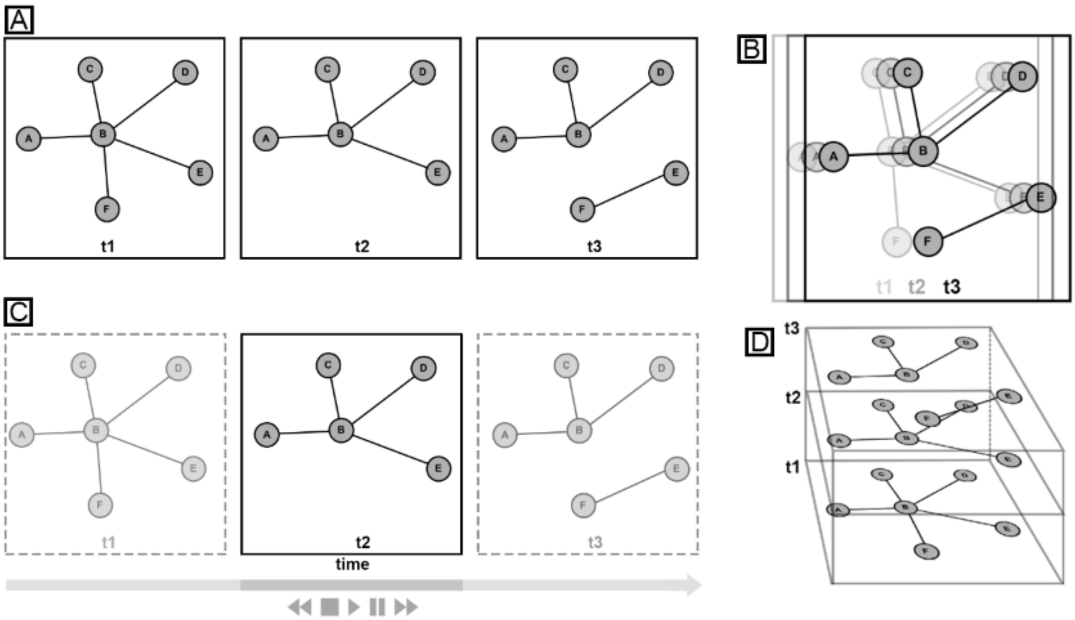

Figure 2.4: Examples of popular network temporal encoding techniques. From left to right: (A) Juxtaposition, (B) Superimposition, (C) Animation with Controls, and (D) Space-Time Cube.

categorization of visualization techniques, gaps in the surveyed literature, and outline the current challenges and directions for future research. For a more extensive overview of the field of network visualization we refer to the recent state-of-the-art report by Filipov et al. [FAM23].

Multi-faceted Network Visualization: Kehrer and Hauser [KH12] introduce the concept of multi-faceted scientific data, where a facet is considered an aspect of the data at hand (e.g., spatio-temporal, multi-variate, multi-modal, etc.). Data often comes with different aspects, whose interplay might provide useful insights during the visual exploration process. Multi-faceted network visualization introduces specialized techniques for scenarios where one or more facets need to be displayed concurrently with the graph's topology, incorporating together data aspects that are commonly considered distinct and non-overlapping in other network visualization

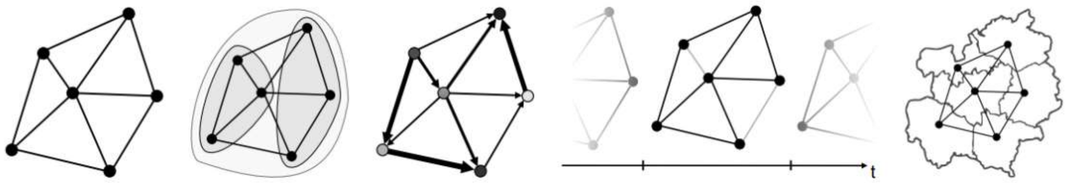

Figure 2.5: Illustrative examples of multi-faceted network visualization. From left to right networks from the following network visualization disciplines: general, group structures, multi-variate, dynamic, and geospatial. Figure courtesy of Hadlak et al. [HSS15].

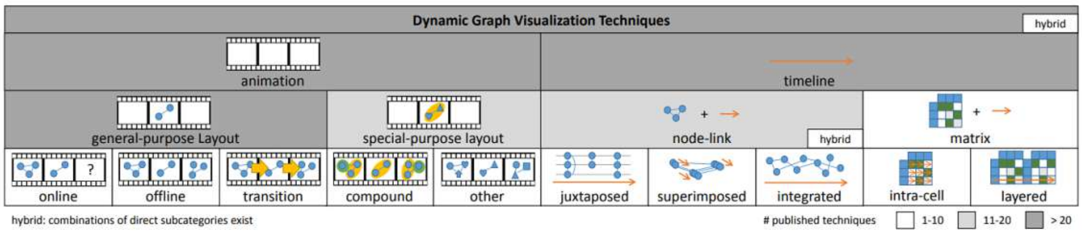

Figure 2.6: The design space of dynamic network visualization broadly categorizes approaches as “time-to-time” (animation) or “time-to-space” (timeline). As the brightness of the table background encodes the number of techniques, it is possible to evaluate at a glance more or less saturated categories. Courtesy of Beck et al. [Bec+17]

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disciplines. Hadlak et al. [HSS15] present a state-of-the-art on multi-faceted network visualization (see Figure 2.5). Considering the great amount of research in this field, the survey is compiled following three principles: (i) focus on the final visual result (rather than on the algorithmic means to obtain it), (ii) separate the base representation of the graph from the overlying facets and discuss their composition instead, (iii) describe a few representative examples of each composition in detail rather than providing an exhaustive list of approaches. The proposed categorization separates the base representation (i.e., the primary graph facet that governs the central aspects of the composed visualization) from the composition modality (in space or time), which instead denotes how these different facets are combined together. With this categorization, the survey presents approaches for graph representation with (i) one facet, (ii) multiple facets, and (iii) multiple instances of the same facet. The survey also discusses cases of balanced representation, i.e., with no clearly defined base representation. When only one facet is shown along with the graph structure, several of the discussed approaches can be mapped to techniques discussed in other surveys, like dynamic network visualization for the temporal facet and multi-variate network visualization for the attributes facet.

Dynamic Network Visualization: This discipline investigates the visualization of networks that change over time. Traditionally, dynamic networks are described as a series of timeslices, i.e., the graph evolution is portrayed as a sequence of graph snapshots, one for each time unit [Bec+17]. Moody et al. [MMB05] survey graph and visualization principles, in the context of temporal representations of social networks. The goal of the paper is to investigate how to reflect the change and temporal development of a network in its graphical representation. Specifically, the paper addresses theoretical questions about the temporal representation of social networks and how to present its changes to the user. The authors categorize papers based on the representation of time, either as (i) discrete or (ii) continuous. In discrete time analysts can focus on identifying changes from one network state to the other. To visualize continuous network data the authors characterize a network by using a time window that spans an interval aggregating events within it, which can either be overlapping (i.e., a moving average) or non-overlapping (i.e., time windows are separate or distinct). Based on the encoding of time, the authors survey graph layout algorithms categorizing them into two classes, namely, static flipbooks and dynamic network movies.

Kerracher et al. [KKC14] map the design space of temporal graph visualization in a different way and consider more representations of the time-oriented information. The proposed design space presents a wider look at visual techniques involved in the visualization of temporal graph data, considering the conceptual tasks required to make sense of graph changes over time. The survey identifies two independent dimensions for temporal graph visualization: (i) the graph structural and (ii) temporal encoding. The former describes how to represent the graph structure, with the most common options being space-filling, node-link, and matrix. Based on Javed and Elmqvist's [JE12] design patterns and Gleicher et al.'s [Gle+11] comparative designs, this survey identifies seven temporal encoding strategies, including (i) sequential views, (ii) juxtaposition, (iii) additional spatial dimension, (iv) superimposition, (v) merged views, (vi) nested views, and (vii) time as a node in the graph.

Beck et al. [Bec+17] present one of the most influential and comprehensive characterizations of the dynamic network visualization discipline. With the increased availability of time-varying network data, dynamic network visualization quickly became a mature and thriving research field. As more and more techniques were presented, a clear need for a comprehensive review emerged, a gap in literature this paper aims to fill. The authors collected and tagged 162 publications, categorizing them by the type of publication, the visual representation of time, the visualization paradigm, the type of evaluation that was conducted, and the target application domain. This multi-level taxonomy has become the standard way to categorize technique papers related to this discipline (see Figure 2.6). It divides the design space into (i) animation- (time-to-time mapping) and (ii) timeline-based (time-to-space mapping) techniques. Only very few of the surveyed approaches (e.g., Animatrix [RM14]), adopt a matrix-based representation of the network. A section of the survey categorizes evaluation papers, dividing them into evaluation frameworks, algorithmic evaluations, and user studies. Specifically, in the first category, task taxonomies and papers related to aesthetic criteria are discussed, as they are the foundations for fair and reproducible user and experimental studies.

Multi-variate Network Visualization: Kerren et al. [KPW14] define multi-variate network visualization as the representation of an underlying graph G plus n additional attributes attached to the nodes and/or edges. The main challenge in visualizing multi-variate networks is showing both the network's topology and its associated attributes at the same time [Nob+19].

Nobre et al. [Nob+19] survey papers on multi-variate network visualization. Most real-world networks have attributes that characterize their nodes or edges. When the topology of the network has to be displayed alongside these extra attributes, several challenges arise. The developed

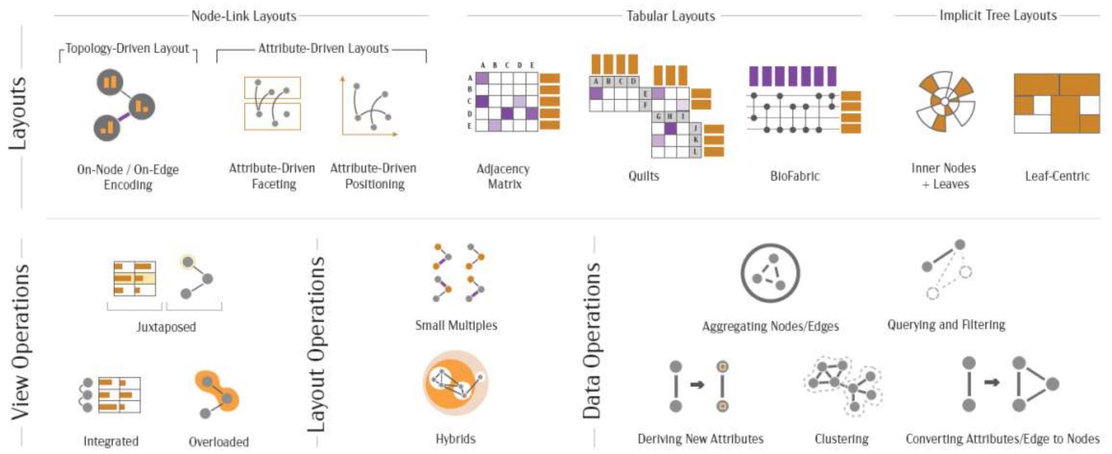

Figure 2.7: Typology of layouts and operations in multi-variate network visualization as presented by Nobre et al. [Nob+19]. Approaches are classified according to the layout and operations supporting the views, layout, or data. Courtesy of Nobre et al. [Nob+19].

techniques tackle these differently: the paper introduces new typologies for multi-variate network tasks and visualization methods, surveying related literature and classifying these accordingly. The survey includes 210 publications on multi-variate network visualization and reports a typology of tasks, visualization techniques, and evaluation methods for multi-variate network visualization. The presented typology of tasks inherits and simplifies the one from Pretorius et al. [PPS14], and its purpose in the scope of the survey is to characterize and recommend techniques based on their suitability for specific tasks. The paper categorizes the surveyed techniques by layout (further divided into node-link, tabular, and implicit) and by the supported operations, specifically, if they act on the views, layout, or data (such as aggregation or querying) (see Figure 2.7). The survey also provides explicit guidelines and recommendations for the usage of each technique, considering the network and attribute types. The evaluation methods used throughout the corpus of surveyed papers are discussed, outlining that the majority of techniques were evaluated through use cases (i.e., informal evaluations without any quantitative measure of the tool's validity), followed by controlled experiments, and user and usability studies.

2.2 Discussion & Challenges

In the following section, we discuss and summarize the major open points and challenges we identified from the surveys reported in Section 2.1, with a specific focus on problems that crosscut and affect different disciplines. We also outline, whenever possible, their progression over time, i.e., if they were tackled or solved or if they still represent an open and unsolved challenge. In the following, we provide a comprehensive overview of the major takeaways from our literature survey.

Exploring the disciplines' design spaces beyond node-link layouts is a recurring point that comes up in multiple surveys and we consider this to be a cross-cutting challenge identified in dynamic [KKC14; Bec+17] and multi-variate [Nob+19] networks. These surveys outline and suggest exploring new combinations of visualization techniques as well as some of the under-investigated categories from their respective design spaces.

Evaluating the cognitive load on the user during the insight-generation process is an open challenge that is reported in dynamic network visualization [Bec+17]. However, it has been recently investigated mostly in this context [Bre+20; Lin+21], evaluating animation-based and small multiples approaches. Alternative ways to represent a graph's temporal dynamics other than discrete time, such as **continuous or event-based** representations, also play a major role in this intersection as performing traditional time-slicing may hide or obscure significant behaviors and patterns that occur in the network or any of its attributes. This research direction has been formulated in the context of dynamic network visualization [Bec+17] and received increased attention recently [SAK18; AMA22]. This topic can still be explored in more detail considering how these changes can be represented in other facets of the network. Finally, it has been suggested that visualization of dynamic graphs might move towards a **confirmatory analytical modeling** stage, with the use of statistical models of network change [MMB05]. Change centrality [Fed+12] is proposed as a statistical model to perform a pairwise comparison between subsequent states of an evolving network in the discrete-time domain for dynamic network visualization, however, more research can be conducted on this problem targeting continuous networks and intersections of different disciplines exhibiting multiple facets of the network (i.e., multi-variate changes over time).

The problem of visualizing **multiple dynamic data dimensions** presents a bridge between dynamic and multi-variate network visualization [Arc+14; Bec+17]. These have been tackled through research on attribute-based layouts [GFV13; Nob+19], which exploit the underlying node and/or edge variables (or characteristics) to produce a layout of the network. Another cross-cutting challenge between these disciplines focuses on the topic of detecting and conveying **patterns in networks**. Such patterns can be captured and depicted in matrix-based approaches by applying reordering algorithms. Reordering the rows and columns of matrix-based representations to highlight such structures, either automatically using algorithms or leveraging interaction and human knowledge, to detect and convey these patterns is discussed as an open challenge [Beh+16]. This same problem is also presented as a future research direction in the context of multi-variate network visualization [Arc+14], however, the focus here is more on node-link representations and patterns or network motifs concerning the network's topology and its node or edge attributes.

Over time, visualization techniques specialized for **new graph types**, as well as combinations of these, were introduced, a topic that is still frequently discussed in many disciplines [SS06; Lan+11; HSS15; Bec+17; Sch+21]. Approaches for **hypergraphs and compound dynamic graphs** are still considered as an under-investigated open topic [Lan+11; Che+19]. This concept is generalized in the context of multi-faceted network visualization [HSS15]. In this case, the network can exhibit one or more facets simultaneously and the composition of the structural aspect along with the facets in order to effectively convey this information is considered a nontrivial problem. For multi-faceted network visualization, specifically, a direction for future research is that some facets are still under-investigated in literature with no dedicated approaches to representing this type of data, such as **text, uncertainty, and provenance** [HSS15].

In the following, we summarize the more notable challenges that represent promising opportunities for further research. For a comprehensive list, we refer to our state-of-the-art report [FAM23].

Potential of Matrices. Several surveys point out how tabular techniques present an interesting yet underdeveloped potential for network visualization. As matrix-based representations of networks present several advantages compared to the more popular node-link approaches, they have been highlighted as promising future research directions for the visualization of dynamic and multi-variate networks [KKC14; Bec+17; Nob+19]. The use and value of this representation has still not been comprehensively evaluated in the network visualization disciplines relevant to this dissertation (see Table 2.1), leaving several future work opportunities, especially considering the use of existing reordering techniques.

Hybrid and Alternative Approaches for Complex Data. The size, heterogeneity, and dimensionality of network data are on the rise. However, this complexity also presents opportunities for novel contributions, specifically, hybrid and alternate representations for such complex network data should be investigated, to overcome the limitations of standard approaches (e.g., scalability). Research on alternate visualization methods also renewed the drive and motivation for recent developments in immersive network analytics [FP19]. Innovative metaphors to visualize network data have been pointed out by selected surveys as an interesting direction for future research [SHS10; Bec+17; McG+19]. Furthermore, the approaches that we have identified from the surveys and grouped together as alternative (see Table 2.1) are not an exhaustive list, meaning that the design space of hybrid and alternative network representations has not been explored to its full potential.

Evaluations. Our literature research shows that there are a number of open challenges related to evaluating the readability and aesthetic criteria associated with network visualization approaches not only in terms of execution time and correctness but also considering other metrics to determine their effectiveness. Filling these gaps would facilitate the formal evaluation and comparison of network visualization techniques. Specifically, as network visualization systems become more complex, several surveys push for surpassing the traditional performance metrics (time and accuracy) and instead focus on the evaluation of cognitive aspects, perception issues, and user engagement [HMM00; Rod05; GK10; Zho+13; LHT17; Bec+17].

Interaction Techniques. Approaches to facilitate navigation, exploration, and interaction with the network and its elements are highlighted by a number of reports as a promising direction for future work [Lan+11; Pie+15; Bec+17; McG+19]. They are a central point of discussion in dynamic network visualization [Bec+17] Additionally, human-assisted approaches to combine the knowledge of domain experts with automated analysis and visualization of network data are considered to be an increasingly important yet under-investigated research direction [Beh+16; VBW17]. We believe this still to be an open and unresolved issue with great potential for future work, as there is no well-defined taxonomy or survey on interactions for network visualization with few exceptions, such as the work by Wybrow et al. [Wyb+14] on interactions on multi-variate networks. These play a very important role in collaborative network analysis, a topic that has been recently gaining traction [LAN20].

Restructuring and Unifying. Our literature research shows the significant breadth of concepts, terminology, and research related to network visualization. Several concepts span multiple disciplines and we also experienced how small changes (or overlaps) of terminology might confuse and mislead. With this large body of knowledge, we believe we have reached a point in network visualization research, where we should consider taking a step back and reassessing the problem from a broader perspective. As this field begins to face the challenges offered by machine learning and immersive analytics, "de-fragmenting" and unifying the existing research would increase the awareness and knowledge of the available technologies and theory. Our state-of-the-art report is a first step in this direction [FAM23].

2.3 Taxonomy

The boundaries between the different disciplines of network visualization are becoming blurred, which poses a challenge to provide an overarching and comprehensive overview of the field. The same techniques have been categorized over and over from surveys investigating different disciplines, often using different terminology and potentially generating confusion. We aim to mitigate this effect by consolidating the terminology used in the surveyed literature and establishing a common dictionary of the field. We consolidate the terminology by classifying tags and keywords from each of the surveys discussed and grouping these into several categories. We look for terms referring to *similar* concepts (e.g., the terms *static flip books*, *small multiples*, refer to *juxtaposition* techniques) and the use of different wording that refers to the same concept (e.g., *network movies* to refer to *animation* techniques). We further group the categories and identify six higher-level groups. In Table 2.1 we map each survey to the consolidated terms, effectively providing a *heatmap* of the most (and least) discussed concepts in recent visualization research. In the following, we present the consolidations and define the inconsistent terms present throughout the related literature. To simplify the discussion, we focus on visualization-related concepts only, not including operations on the data (e.g., filtering) and terminology related to interaction and tasks (e.g., pan, zoom, etc.).

Consolidation

Entity Encoding. In this category, we consolidate the terminology about the visual encodings of the network entities (i.e., node, edges, etc.). We first discuss the encodings of network entities at different granularities, from individual nodes and edges to clusters, partitions, sub-graphs, and the entire network.

Nodes (Vertices) are one of the fundamental entities in network structures. From the literature we reviewed, we identified different options to encode nodes and their related facet information, including *explicit*, *implicit*, *aggregated*, *abstract*, *leaf-centric*, and *inner node* (the last two concern representation of trees).

Links (Edges) are the other fundamental entity in network data. There exist different encoding possibilities for links, such as *explicit*, *implicit*, *aggregated*, and *abstract*. To improve readability, edges can be aggregated together, this form of encoding is also referred to as *bundling* [Zho+13;

Terminology		Multi-faceted	Dynamic	Multi-variate
Facet Composition	Superimposition	[HSS15]	[KKC14], [Bec+17], [Bac+17]	
	Juxtaposition	[HSS15]	[MMB05], [KKC14], [Bec+17], [Bac+17]	[Arc+14], [Nob+19]
	Animation	[HSS15]	[MMB05], [KKC14], [SL17], [Bec+17], [Bac+17]	[Arc+14]
	Timeline	[HSS15]	[SL17], [Bec+17], [Bac+17]	[Arc+14]
	Integration		[SL17], [Bec+17]	[KPW14], [Nob+19]
	Nesting	[HSS15]	[KKC14]	
	Embedding		[KKC14]	
	Overloading	[HSS15]	[KKC14]	[Nob+19]
	Multiple Views	[HSS15]		[KPW14], [Arc+14], [Nob+19]
Network Representation	Node-Link	[HSS15]	[MMB05], [KKC14], [SL17], [Bec+17], [Bac+17]	[KPW14], [Arc+14], [Nob+19]
	Matrix	[HSS15]	[KKC14], [SL17], [Bec+17], [Bac+17]	[Arc+14], [Nob+19]
	List		[SL17], [Bec+17]	
	Space-filling	[HSS15]	[KKC14]	[Nob+19]
	Hybrid	[HSS15]	[KKC14], [Bec+17]	[KPW14], [Nob+19]
	Alternative		[KKC14], [Bac+17]	[Arc+14], [Nob+19]
Entity Encoding	Node	[HSS15]	[KKC14], [Bec+17], [Bac+17]	[KPW14], [Nob+19]
	Link	[HSS15]	[KKC14], [Bec+17], [Bac+17]	[Nob+19]
	Network	[HSS15]	[MMB05], [KKC14], [Bec+17], [Bac+17]	[Nob+19]
Dimensionality	1D		[VBW17]	
	2D	[HSS15]	[MMB05], [KKC14], [SL17], [Bec+17]	[KPW14], [Arc+14], [Nob+19]
	2.5D	[HSS15]	[KKC14], [Bec+17]	
	3D	[HSS15]	[KKC14], [Bec+17], [Bac+17]	[Arc+14]
Layout	Energy-based	[HSS15]	[MMB05], [SL17], [Bec+17]	[Arc+14], [Nob+19]
	Heuristic			[Arc+14]
	Embedding (DR)			[Arc+14]
	Tabular			
	Geometrical	[HSS15]	[SL17], [Bec+17]	[Nob+19]
	Special-purpose	[HSS15]	[MMB05], [SL17], [Bec+17]	[Arc+14], [Nob+19]
Aesthetic Criteria	Nodes		[Bec+17]	
	Links		[Bec+17]	
	Mental Map		[MMB05], [KKC14], [Bec+17], [Bac+17]	[Arc+14]
	Network		[Bec+17]	

Table 2.1: Our proposed terminology consolidation. In each cell, we group references to surveys that present concepts of the consolidated terminology (rows) applied to each discipline (columns). Cells colors encode the number of papers for each discipline and term (from yellow to orange). Gray denotes empty cells, which means that none of the surveys discuss that combination of terminology/discipline.

LHT17]. Edges' representation can further be categorized as *undirected* or *directed* and this property also has an impact on the resulting link encoding.

Network encodings are designed to support the identification of patterns throughout the entire network and are useful for overview and exploration tasks. Encodings include *axis-oriented* or *radial* methods (*circular representations*) along which the elements of the network are positioned, *free*, *styled*, or *fixed* approaches that define the positioning of the elements and network encoding. A further distinction between the encodings can be made based on methods to *implicitly* or *explicitly* visualize the network.

Network Representation. In the following we consolidate the terminology about network representation, outlining six categories.

Node-Link diagrams visualize a network using circles for the nodes, with line segments connecting them representing the edges. In the majority of the surveys, the drawing is laid out on a two-dimensional plane and with straight edges. They are extremely common, widely studied, and employed, but are not ideal for all types of tasks and suffer from visual scalability issues [Lan+11]. In our literature survey, we discovered no major inconsistencies when referring to this type of representation.

Matrix approaches visualize a graph as a $n \times n$ matrix, where n is the number of vertices. A non-zero value in cells indicates that there exists an edge between the nodes (i.e., adjacency matrices). Vertex ordering in rows/columns can be arbitrary or computed [Beh+16]. Matrices can encode facet information in their cells and do not suffer from visual clutter, however, they are not as effective on some tasks compared to node-link representations (e.g., path following). In the surveys we reviewed, we found a few different terms used to refer to this concept, including *matrix-based visualization*, *tensor representation* [Kiv+14], *adjacency matrix*, and *supra adjacency matrix* [Kiv+14].

List, also referred to as an adjacency list, is a structure used to represent a network as a list of edges. During our review of related literature and surveys, we did not find many references to this technique or any different terminology.

Space-Filling techniques make use of the entire drawing area and implicitly encode relationships between entities by employing the principle of enclosure and proximity. These techniques are designed to visualize networks presenting a non-overlapping hierarchy between their nodes. This type of network visualization offers benefits similar to matrix or list representations, in that, by design there is no overlap or visual clutter in the resulting visualization. However, this approach is also very limited to the display of hierarchical data. From the surveys, we discovered the following terms describing this concept and have grouped them under the term *space-filling*: *space-filling diagram*, *icicle plots*, *compound*, *hierarchical/hierarchy representations*, and *treemaps*.

Hybrid approaches are defined as the mixing of techniques, combining the strengths of multiple network representations to mitigate weaknesses associated with the individual approaches [Lan+11; Bec+17]. Combinations, such as *Nodetrix* (node-link with matrix) [HFM07], group-in-a-box layouts (node-link with treemap) [ZMC05], and matrix and tree visualization [Shi+19] are quite popular. A number of surveys categorize these approaches as hybrid. In our reviewed literature, we discovered the following terms that refer to the concept of hybrid network representations: *hybrid approaches*, *matrix with links*, *combination of node-link and matrix*, and *hierarchical matrix*. We consolidate all these terms from related literature as *hybrid* representations.

Alternative representations are other approaches that do not fall into the categories we outlined before to visually depict network data. Approaches in this category are usually very custom implementations of network visualization techniques typically designed with specific analytical tasks, datasets, or user groups in mind. In the surveys, we reviewed we found a wide range of techniques that fall into this type of representation, including terms and techniques such as *hypergraph*, *trail sets* [LHT17], *flow maps/diagrams*, *quilts* [Nob+19], *biofabric* [Nob+19], *parallel coordinate plots*, *self-organizing maps*, *alternative representations*, and *other*. We have consolidated all these terms under the concept of *alternative* network representations.

Dimensionality. The dimensionality of the resulting visualization is also a point of interest for many researchers. From our literature search, we identified four classes depending on the number of dimensions used in the representation.

1-D techniques arrange nodes on a single axis or on a circumference. Nodes are linearly ordered and edges are typically represented as arcs between the nodes.

2-D approaches are the most common network visualization techniques. Nodes are placed into a 2-D space. Edges are displayed using straight, bent, or curved lines. 2-D techniques represent the bulk of research conducted in the field of network visualization, with widespread and mature libraries that make developing such approaches very accessible.

2.5-D representations refer to the use of parallel planes to convey different facets of the network [HSS15]. It can be considered as a stack of 2-D planes with interdependent layouts and, in comparison to 3-D approaches, the axes are not interchangeable as the use of the third dimension has a fundamentally different semantic [BDS04; Lan+11]. The challenges associated with 2.5-D approaches are linking the planes together in an effective and comprehensible manner and providing interactions to mitigate perspective distortion and occlusion.

3-D approaches commonly depict different points in time in dynamic networks [Bec+17] or group nodes together according to their partition or layer information [McG+19]. 3-D visualization techniques need to provide some form of navigation to enable the viewers to see the data from different perspectives, as well as a way to mitigate occlusion and distortion.

Facet Composition. The notion of a facet is introduced by Kehrer and Hauser [KH12] to refer to data that can have different aspects to it. Terms included in this category relate to how each of these aspects have been composed and represented in the final visualization [HSS15].

Superimposition is an approach, where two or more visual representations of the network's facets are overlaid on top of each other [JE12]. The resulting visualization is a combination of each of the facets, often needing a form of explicit encoding to distinguish between them [Gle+11] (i.e., the use of color, transparency, or other visual variables). We have found superimposition being referred to as *superimposed*, *superposition*, and *superimposition*. We also discovered the use of the term *merged* to refer to the same principle of overlaying multiple facets together in the same display space [KKC14].

Juxtaposition is the most popular approach to depict multiple facets of network data (e.g., temporal or multi-variate). With juxtaposition, each of the values of a facet is dedicated to its own display space and the multiple visualizations are then arranged in a side-by-side manner, possibly ordered according to some criteria (i.e., time). In our research, we discovered a lot of diverse terms referring to this concept. Terms, such as *small multiples* [Bec+17], *static flip books* [MMB05], *multiple timeslices* (in the case of dynamic networks [KKC14]), *attached juxtaposition* [VBW17], and variations of the word, i.e., *juxtaposed* or *juxtaposition*.

Animation is a dynamic representation that utilizes the physical dimension of time to convey the time-oriented nature of the data [Aig+23]. This approach is also referred to as a time-to-time (*dynamic*) mapping where the temporal facet of the data is mapped to simulated (*animation*) time [Bec+17]. Animation can be effective in conveying an overview of the evolution of a network and facilitating high-level behavior and pattern identification [BBL12]. We identified diverse terms referring to the concept of *animation* and have grouped these accordingly, including *dynamic movies*, *network movies*, *sequences*, *sequential views*, and *transitions*.

Timeline is a representation that visualizes the time-oriented nature of network data in still images [Aig+23]. Timelines utilize space to convey changes occurring to the data and are a form of time-to-space mapping [Bec+17] that depicts the entire evolution of a network in one or more still images [TMB02]. Surveys that referred to the concept of timelines have used different terms, such as *timeline-based*, *static temporal plots* [Arc+14], and *intra-cell timelines* (specifically, for matrix representations [Bec+17]).

Integration is defined as placing visualizations of the different facets of a network in the same view and visually linking the elements of these together [JE12]. This approach is quite similar to juxtaposition, with the exception that for integration the elements in each of the visualizations are explicitly linked together relating the data items from the different facets (e.g., in the form of graphical lines connecting the entities). We did not find many uses of this composition technique in our literature survey and related literature used different terms to refer to this concept. Terms such as *integration* and *integrated approaches* were pretty straightforward to group together. An exception being the *time as node* [KKC14], *separated juxtaposition* [VBW17], *agglomeration* [GK10], and *semantic substrates* [AS07; HSS15] terms that were used to refer to the concept of integration.

Nesting is a composition where the contents of a visual representation of a facet are nested inside another visualization [JE12] (also referred to as client and host visualizations). *NodeTrix* [HFM07] is an example of this approach, where the dense communities' topology, represented as an adjacency matrix, is nested into the node-link visualization representing the inter-community relationships. We discovered several terms associated with this concept of *nesting*, such as *including*, *embedding*, *layering*, and *intra-cell* [Bec+17] (for matrix visualizations) compositions.

Overloading is a form of nested visualization where a client visualization is rendered inside of a host visualization using the same spatial mapping as the host [JE12]. The client is laid over the host, as in superimposition, but there is no one-to-one spatial linking between the two visualizations. We identified the following terms used to refer to the concept of *overloading*: *overloaded*, *overloaded views*, and *additional spatial dimension*. The term *additional spatial* *dimension* [KKC14] refers to the use of an additional visual cue to depict the time-oriented nature of a network either as a separate layer or stacking them on top of each other without flattening them (as would be the case in superimposition). In this context, the underlying host visualization is overlaid with an additional spatial dimension (client) depicting another facet of the network and its entities utilizing the same display space as the host.

Multiple Views refers to a composition modality describing the use of multiple (coordinated) views [Rob07]. Each window is dedicated to depicting (with its own visual representation and encoding) a specific facet of the network. Typically, this term broadly applies to multiple coordinated views, where interacting with one view would also provoke changes in other views during exploratory analysis. We have found some uses of this composition modality in network visualization and these are often referred to in a consistent manner, using terms such as *multi-view*, *multiple coordinated views*, and *coordinated multiple views*.

Layout. In this section, we group and consolidate all the different terms that were used throughout the surveys to describe the algorithms and techniques behind the process of laying out a network. We identified six different categories with the most prominent ones being exclusively targeted for node-link representations.

Energy-based layouts refer to algorithms that minimize an energy function in order to draw the network in an aesthetically pleasing fashion. The intricacies of the layout algorithms falling into this category vary widely, most notably in their implementation of what the energy function to be minimized is. Energy-based approaches encompass *(classical) force-directed*, *spring layout*, *spring embedder*, *spring electrical*, *energy function minimization*, *hybrid force-directed*, *accumulated force-directed*, *multi-level force-directed*, and *multi-dimensional scaling force-directed*.

Heuristic approaches for network layout involve approaches that use a number of measurements to improve the current candidate solution (often optimizing certain aesthetic criteria) [CS20]. Such approaches query the solution space iteratively and evaluate the results of the graph layout problem optimizing for certain constraints. We have identified a number of approaches in the surveyed literature referring to layout techniques matching this concept, including *hill climbing*, *mixed integer programming*, *ink minimization*, *cost-based*, and *combinatorial model* techniques. Furthermore, algorithms, such as genetic algorithms, simulated annealing, and evolutionary algorithms (e.g., differential evolution [CS20]) would fall into this category of graph layout techniques.

Embedding/Dimensionality Reduction includes techniques where a high-dimensional embedding of the network is projected into a lower-dimensional space. In this class of layout techniques, the surveyed literature referred to this concept in a consistent manner, referring to techniques such as *linear dimension reduction*, *dimensionality reduction*, and *multi-dimensional scaling*.

Tabular layouts are primarily intended for matrix network visualizations and concern the problem of finding an ordering of the rows/columns to highlight specific patterns in the data [Beh+16]. The approaches we identified from our literature survey that refer to the concept of *tabular* layout techniques are: *spectral*, *Robinsonian*, *bi-clustering*, *image-based*, *graph-theoretic*, and *spectral* reordering techniques.

Geometrical approaches refer to techniques whose network representations satisfy specific geometrical constraints. Such techniques are tightly coupled with the structure and properties of the network data and elicit visual representations of the graph emphasizing a certain topology (i.e., planar graphs, trees, or hierarchies [SSK14]). In our survey of literature, we include the following terms in this category: *grid layout*, *Tutte layout*, *planar layout*, *topology-driven layout*, *Sugiyama layout*, *hyperbolic drawing*, *orthogonal layout*, *hierarchical layout*, *hierarchical graph drawing*, *(implicit) tree layout*, and *traditional layout*. *Topology-driven layout* is a term from the survey by Nobre et al. [Nob+19] to describe force-directed, orthogonal, and spectral layouts.

Special-Purpose visualization techniques have been applied to different types of networks to support specific tasks, e.g., represent time in a dynamic graph [SL17; Bec+17] or represent the value of an attribute of the node [Nob+19]. Terms that fall under this category include: *layout of a clustered graph*, *attribute-driven layout*, *anchoring* (in the context of temporal and/or geospatial networks), *node-attributes for layout*, *constraint-based layout*, *clustering-based attribute layout*, and *dynamic graph layout*. *Constraint-based layout* techniques define the placement of the nodes by taking into consideration one or more specific properties of the data (i.e., multi-variate attribute-driven positioning) or user-defined constraints on a selection of the nodes or the entire graph.

Aesthetic Criteria. In the context of graph drawing, aesthetic criteria are a set of heuristics that have been proposed (and evaluated) under the assumption that these improve readability and understanding in node-link layouts [Ben+07]. From our survey of related literature, we have identified aesthetics related to the nodes, the links, the network as a whole, and, recently, aesthetic criteria for dynamic graph representations have been proposed as well.

Nodes. We include in this category all nodes' positioning criteria we found in the surveyed literature, specifically, *clustering similar nodes*, *maximizing node orthogonality*, *keeping nodes apart from edges*, *avoiding node overlap*, and *distributing nodes evenly*.

Links need to be drawn with careful consideration in order to improve the resulting visualization's readability. There are a number of (sometimes conflicting) criteria for laying out the links between nodes that we have identified in our literature search, including, *using directional indicators*, *minimizing edge crossings*, *minimizing edge bends*, *keeping edge length uniform*, *joining inheritance edges*, *maximizing edge orthogonality*, *minimizing edge length*, *keeping edge bends uniform*, *maximizing edge minimal angles*, and *avoiding separate arrow on edges*.

Network aesthetics concerns the overall layout and play a major role in determining the final representation of the graph [Ben+07]. They all relate to node-link representations and include *minimizing the drawing area*, *maximizing global and local symmetries*, *preserving correct aspect ratio*, *maximizing convex faces*, and *ensuring a consistent overall flow direction*.

Mental map preservation is an aesthetic criterion primarily associated with dynamic network visualization and is concerned with preserving the viewers underlying understanding of the relational information in a dynamic context [DG02; PHG06] (i.e., changing and evolving network topology). The mental map preservation criterion is also considered in other disciplines of network visualization, e.g., in multi-variate network visualization when the attribute-based layout is changed to depict another attribute. In related literature, we identified the following terms used to refer to this concept *mental model*, *cognitive map*, and *mental map preservation*.

2.4 Reflections

Table 2.1 provides insights into the research landscape in the field of network visualization as a high-level indicator of the most researched concepts in literature according to the surveys included in this dissertation. If a survey is present in our table, it discusses papers that describe terms coinciding with our own categorization. In turn, grey cells *do not* represent a lack of research in that direction, but rather indicate that in the surveys there are no terms that fall into that category.

A quick, visual analysis of the table shows that the discipline of general network visualization, which is also the most dated, comprises the majority of the available research, considering the included surveys. Within this discipline, 2-D node-link representations, drawn using an energy-based algorithm appear to be the most discussed topics. Conversely, few papers discuss facet composition, which is expected as general network visualization does not encompass the representation of further dimensions.

Dynamic network visualization is the second discipline, in terms of the number of surveys. The majority of research focuses on the temporal facet composition, specifically on techniques ranging from superimposition to animation. Other methods have been explored in the survey by Kerracher [KKC14], but multiple views have not been considered in these publications for integration of the time facets. Concerning the network representation, there is more balance between node-link and matrix representations. In terms of layout, energy-based is still the most popular, possibly due to the fact that many techniques extend visualization approaches for static graphs. We also note that the *mental map* category is also the most researched aesthetic criterion in this field.

Another observation that we can make, based on the surveyed research, is that network visualization disciplines tend to experiment with different facet composition methods. This can be seen by the non-uniform distribution of grey cells within the facet composition category across different disciplines (see Table 2.1). It is also clear that very little research is done on aesthetic criteria in the multi-faceted and multi-variate disciplines. We argue this to be due to the fact that research on disciplines other than general network visualization is more application-oriented, and therefore, can be harder to extract concepts that can be generalized in terms of readability and human perception.

Limitations

Although we provide a detailed overview of the available surveys on the network visualization disciplines relevant to the scope of this dissertation, there are also inherent limitations of this work that must be considered. The number of surveys is relatively small, especially when compared to McNabb and Laramee meta-survey [ML17]. However, that work surveyed the much broader field of Information Visualization, while we have a specific focus on networks only. In our literature research, we excluded algorithmic and theoretical contributions which would require a survey on their own. Graph theory is a huge topic and our focus is on visualization-specific aspects allowed us to provide a descriptive overview of the aspects of the field that we believe to be of the most interest to the visualization community.

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CHAPTER 3

On Time, Space, and Multiple Attributes

This paper first appeared in Computer Graphics Forum (**38**, 3, pp.107–118), 2019. Computer Graphics Forum 2019 ©. Reused with permission (see [Fil+19]).

Title: CV3: Visual Exploration, Assessment, and Comparison of CVs

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Context: In the following publication, we explored how to dynamically construct networks of interrelated résumés by offering interactions, querying, and ranking functionality to the users to select applicants based on their expert requirements.

We explored, how to effectively and appropriately model the time-oriented and geospatial data that is present in such résumés (e.g., education, training, and employment history). Moreover, we also generate and visualize a hierarchical tree structure that describes the combined and overlapping skill sets of each of the applicants additionally encoding their expertise. Our approach was validated by a domain expert interview determining the appropriateness of the visualization techniques, the usability of our approach as well as the transparency and interpretability of our scoring and ranking system.

In the context of network visualization, a few different networks are mined, modeled, and visualized based on the data available (i.e., curriculum vitae). First, we model a network of interrelated applicants that all have some attributes in common, as defined by the domain experts, resulting in a social network of applicants, each having a set of categorical and multi-variate properties along with event-based (temporal & geospatial) data. Second, we use a hierarchical organization of the skill sets of the individual résumés. We use single trees to model and visualize these for a single applicant, which are combined into a skill "forest" in order to showcase and outline the overlaps as well as individual skills the applicants possess alongside their expertise. Finally, we also have the mobility networks of the applicants that we model as an event-based

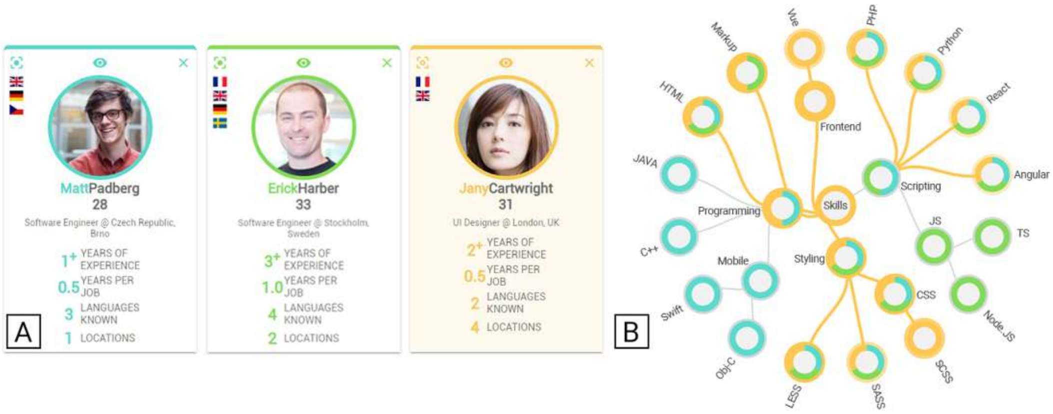

Figure 3.1: Visualizations in the Compare View. Cards (A) show general information such as age, occupation, years of experience, number of languages known, mobility, and average duration per employment. The Skill tree (B) shows the selected candidate's combined skill sets.

network, showcasing their movement and development over time and space according to their professional employment history, education, training, and other qualifications obtained.

3.1 Abstract

The *Curriculum Vitae* (CV, also referred to as "*résumé*") is an established representation of a person's academic and professional history. A typical CV is comprised of multiple sections associated with spatio-temporal, nominal, hierarchical, and ordinal data. The main task of a recruiter is, given a job application with specific requirements, to compare and assess CVs in order to build a short list of promising candidates to interview. Commonly, this is done by viewing CVs in a side-by-side fashion. This becomes challenging when comparing more than two CVs because the reader is required to switch attention between them. Furthermore, there is no guarantee that the CVs are structured similarly, thus making the overview cluttered and significantly slowing down the comparison process. In order to address these challenges, in this paper we propose "CV3", an interactive exploration environment offering users a new way to explore, assess, and compare multiple CVs, to suggest suitable candidates for specific job requirements. We validate our system by means of domain expert feedback whose results highlight both the efficacy of our approach and its limitations. We learned that CV3 eases the overall burden of recruiters thereby assisting them in the selection process.

3.2 Introduction

In the last decade, the search for employment has become more electronic - due to the increasing amount of people having access to the internet. As a result of this, a magnitude of Electronic Curriculum Vitae (E-CV) builders have been developed and provide users with the option to showcase their personal information, skill sets, and work/education histories in a clean and visually pleasing manner. Such services are offered by e.g., Represent.IO [Rep], VisualCV [Vis], EnhanCV [Enh], Vizualize.me [Viz], and DoYouBuzz [DoY]. People working as hiring managers must carry the time-consuming and non-trivial task of evaluating the different careers of candidates or employees. This includes reading through their work and education experience, assessing their skill sets and language proficiency, and understanding their career choices; all of this while extracting strengths and weaknesses out of each experience. Hiring managers can quickly navigate through and extract relevant information from a single CV, due to the fact that they are accustomed to standard résumé formats, such as EuroPass [Eur]. Once the evaluation has been done, recruiters must compare the careers of the candidates in order to build a short list of people who appear to have all the necessary skills required for the job. The most common and intuitive way to do so is to compare the CVs side-by-side and go through each of the sections individually. However, since the advent of the new E-CV trend, more employers accept CVs online via e-mail or other mediums. This inevitably led to an increased number of applicants for each position. As the number of candidates grows, recruiters need to read through and make sense of a rapidly increasing amount of résumés. As a result of this, it is more difficult to maintain a comprehensive overview. Furthermore, it is cumbersome and inefficient to compare the events across multiple CVs by navigating back and forth between them. It becomes obvious that this technique does not scale very well, thus justifying research for a new approach. To the best of our knowledge, no other system attempted to competitively rank the candidates for a specific job application: most of them just show a list based on a user-based recommendation (see Section 3.3). To tackle this problem, we present CV3: an interactive environment supporting users in their tasks of exploring, comparing, ranking, and analyzing multiple instances of CVs using Information Visualization (IV) and Visual Analytics (VA) techniques. CV3 manages a collection of résumés and suggests the best ones to include in the shortlist for a job application by combining well-established visualization and interaction techniques with novel modeling approaches in the application domain of Human Resources (HR) and recruitment. The main contributions of our paper are:

- A unified model that incorporates all relevant data in a CV, including skills, education, work experience, awards, etc;
- The "Skill Forest" and the "Skill Tree": two novel approaches to the modeling and visualization of the candidate's knowledge and skills;
- A two-dimensional scoring system for CVs computed against specific job requirements (in terms of skills) that also portrays the overall knowledge of the candidate in the field;
- A prototype that allows users to interactively explore, compare, and analyze multiple instances of CVs in an interactive exploration environment;
- The results of the evaluation of our solution by means of a user study by professional recruiters;
- The discussion of the lessons learned and exploration of open challenges for future research.

The remainder of this paper is organized as follows: in Section 3.3 we discuss the related work; in Section 3.4 we present our methodology; we describe and validate CV3 design respectively in Sections 3.5 and 3.6; Section 3.7 concludes the paper.

3.3 Related Work

Our primary focus is dedicated to the visualization, comparison, and analysis of the hierarchical and spatio-temporal data contained in CVs in an interactive exploration environment. Such data are present in certain sections of a CV, like the candidate's skills or work and education history.

In Section 3.3.1, we first illustrate previous work about the interactive exploration and comparison of CVs. In CVs the entries in the work and education history sections can be seen as events. Events have a temporal dimension - start and end date, a spatial dimension - a location associated with the event, and other possible metadata, such as title, description, media, etc. If the end date is not specified we can assume that it is an ongoing event.

In Section 3.3.2 we discuss and establish the State-of-the-Art techniques for visualizing time- and spatially-oriented data in CVs. In Section 3.3.3 we will discuss the established visualization approaches of hierarchical data. In CVs, candidate competencies are generally organized following a (shallow) hierarchical structure. Europass [Eur] divides them into "Digital skills", "Communication skills" etc.; Linkedin professional social network [Lin], automatically assigns a skill to a group following a built-in ontology, with each one belonging to a single category (inclusion).

3.3.1 Visual Comparison of CVs

Résumé analysis and comparison have been used in several application domains to evaluate career mobility and progress patterns [GR04; SCM06]. Lately, massive publicly accessible résumés have emerged on the internet. To tackle the problem of providing a quick and unmanned tool to categorize CVs, Zhang et al. presented *ResumeVIS* [ZWW17; Wan+17]. ResumeVIS is able to parse data from semi-structured résumés, focusing on career progress patterns, social relationships, and mobility (type of organizations previously served, such as government, non-profit, etc.) of the candidates. The main view allows to select a candidate, whose career trend and interpersonal relationships are represented respectively with a line chart (named "career trajectory chart") and a node-link graph visualization (star-shaped, with the candidate in the center). Statistics about all the parsed CVs are visualized using a histogram, while the mobility information is displayed using a quadrant diagram. While effective for categorizing and browsing large amounts of semi-structured CVs, the system is specifically tailored for the Chinese labor market and does not provide a scoring system. Moreover, the system does not support any geographical information, and the authors state this to be an open challenge worth exploring. Jafar et al. [JWB17] present an ontology-based visual analytics approach to get insights from CVs. The ontology comes from the ACM Computer Science Curricula Report [Joi13] that describes a taxonomy of terms that follow the "KA-KU-LO" model: Knowledge Area, Knowledge Unit, Learning Objective. To improve the expressive power of the existing model, it has been extended to also include “competencies”: each one of them is associated with Knowledge, Skills, and Dispositions. The authors gather data from a survey by Longenecker et al. [LFC13] and map them to the ontology. Finally, the results are visualized using heatmaps, stacked bar charts, and wordclouds, consequently moving the scope of their research to CV categorization rather than ranking/comparison. Existing commercial solutions for the assessment and comparison of candidates include *Applicant Tracking Systems (ATS)* [MBB14]. ATSs are built to better assist the management of résumés, applicant information, and help companies in the task of recommending candidates that best match a given position’s requirements. They are well suited for typical tasks such as talent acquisition and evaluation. These applications are based on a statistical analysis of keywords, skills, former employers, and years of experience and only identify specific attributes in a CV. However, each CV needs to be manually analyzed, compared with others, and evaluated to find the best applicant. These systems do not take into account the career paths of the individuals, which are a key factor in identifying successful candidates, nor do they provide an intuitive way of comparing multiple candidates simultaneously.

3.3.2 Spatial and Temporal Data

The most common and intuitive visualization technique for representing time-oriented data is the use of timelines. Timelines typically display a sequence of events on a horizontal axis depicting time. This visualization method provides the user with a quick and clear overview of the temporal dimension of the data represented in the work and education sections of a CV. LifeLines by Plaisant et al. [Pla+96] is a well-known approach for visualizing temporal data using timelines. Lifelines provide a general visualization environment primarily focused on multiple personal histories. A comprehensive survey and analysis of the design space of timeline visualization techniques is available from Brehmer et al. [Bre+17]. One of the main drawbacks of using timelines in non-interactive (static) environments is that only a small subset of the event’s information can be displayed - we can see the start and end date, along with the title of an event but the description, location, the type of event, and other metadata are not visible. Furthermore, timelines do not account for the spatial information associated with the event. These issues limit the usage of this approach in the HR application domain.

To incorporate both the spatial and temporal aspects of events into a single visualization we can use multiple coordinated views [Rob07] or isosurface [Lor95] approaches. In spatio-temporal visualization, multiple coordinated views refer to a visualization technique that presents the temporal and spatial data in two separate views (e.g., timeline + maps). The same data is shared across both views with each presenting a different perspective enabling interactive discovery, analysis, and comparison of the data. In contrast to multiple coordinated views, isosurfaces take on a different approach, namely incorporating both the spatial and temporal aspects of the data in a single visualization. This is done in a three-dimensional space, where the horizontal axes (X and Y axis) represent the spatial data (e.g., a map of the underlying geography) and the vertical axis (Z axis) depicts the variation in time. These techniques are based on Hägerstrand’s time geography [Häg89] - the study of space-time behavior of human individuals. Since CV3 follows a multiple coordinated views approach, we will focus on the techniques that are categorized as such.

The VA system 'VAiRoma' presented by Cho et al. [Cho+16] attempts to couple State-of-the-Art text analysis with an intuitive visual interface to assist users in exploring and analyzing events, trends, places, times, and the relationships between them in the context of Roman history. The VAiRoma interface is composed of three primary views - timeline view, geographic view, and topic view. The timeline view uses a stacked graph approach to visualize trends and topics over time, where each point in time represents the number of articles related to a certain topic. The geographic view utilizes three different layers to visualize the spatial data - heatmap layer, points layer, and pin layer. Furthermore, VAiRoma offers a topic view, which utilizes multiple visualization techniques for displaying topic hierarchies, content, and topic weights. Each of the views utilizes different visualization techniques that are interlinked to allow users to gain insights through analyzing and exploring large amounts of historical data from different perspectives. Although this specific system is primarily suited for analyzing and exploring historical data, we believe some components can be adapted for the comparison and visualization of multiple instances of CVs.

Jänicke et al. [JFS16] propose the development of an interactive visual profiling system for musicians, which utilizes IV and VA techniques to support users in determining similar musicians. The interface consists of various columns for visualizing the multifaceted data of a musician's CV attributes. The different columns represent metadata related to a musician's professions, where they worked, and their denominations. Consistent color-coding is used throughout the interface to provide intuitive means of visually distinguishing different musicians. The relationship graph illustrates a musician's social network, where the edge length maps the strength of the relationship. The map of the visual profiling system displays all places of activity for the selected musicians. The idea behind this visualization technique is to provide an intuitive means of displaying and interpreting the information associated with an activity region and to support users in the discovery, exploration, and comparison of different activity regions.

For the sake of completeness, we suggest the paper by Aigner et al. [Aig+23] for a comprehensive survey of time-oriented data visualization techniques. A systematic overview of approaches, techniques, and methods for exploring and visualizing spatial and temporal data is presented by Adrienko et al. [AA06].

3.3.3 Hierarchical Data

A hierarchy can be represented as a set of elements and a set of recursive inclusion relationships between them that depict the structure of the hierarchy, starting from a single element, a "root". Such structures can be easily represented as "rooted tree" graphs, mapping the elements as vertices and the inclusion relationships as edges. The importance of rooted trees in representing simple relationships is recognized [Bat+98], with extensive research carried out on how to draw such graphs. A very well-known approach is the "Layered tree drawing", which yields a downward planar layout. In this approach, vertices at a distance i from the root are placed on layer L_i, with the root on layer L_0. Each subtree is drawn independently in a recursive fashion and then appended to the root following a divide-and-conquer philosophy. Another approach is the radial drawing algorithm. It still follows the principle of the layered layout but in this case, the root of the tree serves as the origin of concentric circles where the layers are arranged expanding outwards. For a more in-depth analysis of rooted tree layout algorithms please refer to the book by Di Battista et al. [Bat+98]. Balloon trees [LY+07; HMM00] are a visualization technique for trees in which each subtree is enclosed in a circle centered in its root. The radius of such a circle depends on the number of nodes belonging to the subtree, and Lin et al. present an algorithm to obtain a balloon tree visualization with optimized angular resolution [LY+07]. Hyperbolic trees are a focus+context approach for visualizing large hierarchies [LRP95; LR96]. The hierarchy is laid out on a hyperbolic plane which is then projected to a 2D drawing. This approach proved to be effective and many related papers and applications followed [Mun98; Du+17], making also its way to the exploration of data in immersive 3D environments [Zha+17; Kwo+16]. Other visualization approaches that leverage 3D graphics include Cone Trees [RMC91] and "botanical" visualizations such as the one by Kleiberg et al. [KDV01].

An alternative to node-link visualizations are space-filling techniques. The hierarchical information is encoded by containment rather than with straight lines. Containment shows the complete information about the hierarchical structure, whereas edges only show pairwise relationships [Mun14]. Treemap layouts are a prime example of this technique [Shn92]. In this approach, the elements of the hierarchy are represented as squares or rectangles, with their descendants enclosed in the area allocated to their ancestors. By relaxing the constraint of only having rectangular shapes, we obtain Voronoi diagrams [BDL05]. This class of treemap layouts is based on arbitrary polygons and presents an improved aspect ratio and present advantages in the identification of boundaries between and within the hierarchy levels. Alternatively, circular shapes can be used [Wet], however, while aesthetically appealing, they suffer from reduced space efficiency.

3.4 Problem Domain Characterization and Abstraction

We employ the nested model approach by Munzner [Mun09] as our main design and validation methodology. At the first level, we characterize the problem domain by utilizing the design triangle framework proposed by Miksch et al. [MA14]. The first step towards designing and developing a solution is to answer the following questions:

- What kind of data are the users working with?
- Who are the users?
- What are the tasks of the users?

To validate our approach against domain threats [Mun09] and fully understand the problem domain, we conducted a preliminary user-centered design study in the format of semi-structured interviews [Woo97]. The interviews lasted between 20 and 30 minutes and the main objective was to get acquainted with the participants' individual responsibilities, workflow, and the hiring process as a whole. In our user study, we had six participants employed in HR departments of various companies. The participants had different positions and responsibilities in the department, including two interns in smaller companies, one hiring manager in a larger company, and three recruiters with experience in talent acquisition. By listening to their experience, we were able to derive and formalize the data model and the tasks that representatives of the HR department face in the process of compiling the short list of candidates for an open job position. In the following sections, we focus on each one of those aspects, describing the insights that steered the development of CV3. In Section 3.4.1 we formally describe the data model of a CV; in Section 3.4.2 we discuss the users that were considered when designing the system; in Section 3.4.3 we illustrate the tasks.

3.4.1 Data

CVs are semi-structured documents and are an encapsulation of a candidate's personal information, background, and skills. To identify the data types and model, we have analyzed several résumés, collected from various sources, and abstracted the information into a generalized model for CVs which we outline in the following:

- **Contact Information**: name; address; e-mail; telephone.
- **Skill set self-evaluation**: recursive hierarchy of topics; knowledge level (Basic to Expert).
- **Employment history**: traineeships; work history; academic positions.
- **Education and training**: high school; university; graduate school; post-doctoral training; publications.
- **Professional qualifications**: certifications; awards; languages.
- **Personal Information**: birthplace and date, gender, personal summary, profile picture (for the purpose of the system all this information is optional).
- **Other information**: interests; hobbies; references.

Nowadays, it is common for large companies to ask candidates to fill out a form during the job application with the data organized similarly as above, in addition to uploading their CVs, for quick categorization. From the structure of a typical CV, we can identify several sections, each having a different type of data associated with it. There are four major data types that can be distinguished from this model:

- **Nominal data**: general, personal, and contact information, etc.
- **Hierarchical data**: professional skills and competencies.
- **Ordinal data**: social skills and languages.
- **Spatio-temporal data**: professional and academic history

3.4.2 Users

The HR department of an organization oversees numerous aspects of employment, including recruitment, talent acquisition, and performance management. From our interviews, we could classify the users into two distinct user groups: non-expert "novice" users (interns and hiring managers), and experts (the recruiters). Novice users have experience in the general process of hiring and interviewing candidates, are acquainted with the responsibilities of employees in an HR department, and know the characteristics of good and bad CVs. The expert users share the same knowledge as non-experts and have experience in talent acquisition and CV comparison possibly using an ATS. Additionally, they possess domain knowledge and can offer us insights regarding the limitations of such systems. In our approach, we aim to provide a tool that can accommodate the needs of both user groups, as opposed to ATSs, which in our experience are only known to an expert audience.

3.4.3 Tasks

The purpose of this section is to outline the users' needs and provide support for the successful execution of their tasks. To understand the problem domain, the hiring process, current challenges, and identify potential bottlenecks and unsupported tasks in the tools that are in use, we asked the participants of our preliminary design study a series of questions on the following topics:

- Responsibilities as a hiring manager and the recruitment process.
- Characteristics of good and bad CVs.
- Relevant data to quickly assess the quality of CVs.
- Comparison and assessment of CVs.
- Time spent on searching, comparing, and assessing candidates.
- Tools used in the HR department and features that are potentially missing.

As a result of the interviews we had a clearer overview of the hiring and talent acquisition process, gained deeper insights regarding the data and tasks, and received a better understanding of what tools and systems are in use. The tasks along with a short description are provided in the following list:

- **T1: Explore** - The proposed solution should provide a straightforward and effective interface to access the applicant's information. The importance of this feature is twofold: in the first place, it should allow users to view a specific candidate and explore the sections of her/his CV in more detail; moreover, it should allow the user to have an overall view of the entire CV database.

- **T2: Assess and Evaluate** - The solution should provide effective visualizations for the CV data, with the goal of assessing their quality at-a-glance, also highlighting patterns that would be difficult to see on paper. The system should visually convey to the recruiter information about a candidate's skill set, in order to evaluate the candidate's overall and specialized knowledge about a particular domain of expertise. Additionally, the system should provide an effective way to visualize the time-oriented and geospatial data, encapsulated as events, in CVs. This includes gaps between employment (in terms of time elapsed), concurrent jobs, correspondence between skills and employment history, and mobility (in terms of experience abroad). Those are considered relevant factors in assessing the résumés and determining which candidates are to be included in the shortlist.

- **T3: Compare** - Our approach should provide the recruiter with a scoring system, capable of suggesting a subset of candidates who are the most knowledgeable against a specific set of skills required by a job application. Furthermore, recruiters also need to consider the general experience of the candidate in the specified field, with this being one of the most difficult tasks to carry out with a manual comparison of paper CVs. For this reason, the system should model the skills accordingly, and include a ranking function that takes this specific need into account. Once a short list of candidates has been compiled, the solution should allow an in-depth comparison between several candidates, using effective visualizations of common skills, work experience, education, and job mobility. The visualizations should further assist the recruiters in determining patterns, commonalities, and outliers in terms of career development.

3.5 CV3's Design

In the following Section, we describe the design of CV3 and discuss how the system supports the tasks presented in Section 3.4.3. In Section 3.5.1, we describe how we modeled the candidates' skills; we present the scoring system in Section 3.5.2; we conclude with Section 3.5.3 where we discuss the design of the views included in the system. CV3 is an open-source web application: the code and a live demo can be found at `https://github.com/velitchko/cvthree`.

3.5.1 Skill Forest

Our observations (see Section 3.4.1) suggest that the skills can be represented as a hierarchy. We propose a modeling approach in which each individual skill is modeled after a rooted tree. It depicts the hierarchy of a specific skill (i.e., "JavaScript") or a category (i.e., "Programming"), which represents nodes in the tree. A skill node comes with a name and a corresponding expertise level (which can either be "Basic", "Novice", "Intermediate", "Advanced", or "Expert" [Nat]); a category node cannot be a leaf and is not associated with a skill level. Therefore, the knowledge of the candidate is represented as a "Skill Forest". When we visualize it, a common faux root node is created and connected to the roots of all the individual trees, thus creating a "Skill Tree" (see Fig. 3.1(B)). Skill trees have been used extensively in video games (the "Diablo" series made it famous back in 1996) as a visual way to track the player progression in the character's abilities: research on knowledge representation investigated their use to allow students of "Massive Open Online Courses" (MOOCs) to easily keep track of the new skill acquired with each new lecture [Ant+17]. With this grounding and our observations, we decided to explore the use of skill trees to represent the knowledge of each individual candidate (**T2**): they are familiar, flexible, and can be easily adapted to support new tasks. The parent-child and sibling relationships in a tree can be used to understand which skills are respectively specializations and branches of others: we exploited this information to conceive a score that goes both vertical (Specialization) and horizontal (Diversification) in the tree. To the best of our knowledge, this is the first time that this modeling approach has been used in the domain of HR and recruitment.

3.5.2 "Specialization" and "Diversification" Scores

In order to suggest the best candidates given a specific set of skills (**T3**), we designed a two-dimensional scoring function that we use to competitively rank the candidates. This information is then used to create appropriate and meaningful visualizations supporting the user on the assess and compare tasks (**T2** and **T3**). The input of the function includes the "query", an array of skills with corresponding knowledge requirements (among the 5 possibilities shown in Section 3.5.1) and the candidate's Skill Tree. The knowledge requirements defined in the query are mapped to numerical values in the range $[0.2, 1]$ and act as skill-weighting factors. In turn, the knowledge "levels" defined in the candidate's Skill Tree are mapped in the range $[1, 5]$. The first dimension of our ranking function is called "Specialization" score and its values can lie in the range $[0, 10]$. It is more focused on precision and provides a relevance measure of a candidate's CV according to specific job requirements defined in the query. For each candidate, the Specialization score is computed using the following procedure:

1. For each skill in the query, find matches in the Skill Tree;
2. For every matching skill, increment the score by multiplying the skill weighting factor and the candidate's knowledge level;
3. As a final step, average the obtained score by the sum of the skill weighting factors (for both matching and not matching skills) and scale it so that it falls into the range $[0, 10]$.

The second ranking function is called "Diversification" score. It expresses the candidate's knowledge about skills related to the ones in the query. It is intended as a way to contextualize the Specialization score by giving a measure of how much a candidate knows about a specific field, rather than about specific skills. The score is computed using the following procedure: once a matching skill has been found (as in the Specialization score), if its node has children, the score is incremented by the number of children; otherwise by the number of siblings. The final output of our scoring system is a pair of coordinates, that can be plotted on a scatter-plot (see Fig. 3.2), easily providing a visual way to compare the candidates. We exclude candidates scoring $(0, 0)$ from the results. While the rationale behind the Specialization score is straightforward, the Diversification score design is inspired by the Skill Tree structure itself. On the one hand, if a matched node has children, it means that the candidate also has more specialized knowledge than requested. On the other hand, the presence of siblings of the matched skill, reveals a broader scope of knowledge in the field of interest. We count the number of children/siblings regardless of their knowledge level: the Diversification score has the purpose of contextualizing the knowledge of the candidate immediately "around" specific required skills, with an orthogonal semantic than the one behind the Specialization score. If both cases occur (the matched node has children and siblings), we give precedence to the descendance relationship, this choice was made considering the feedback obtained in the preliminary interview. We wanted the Specialization and Diversification scores to complement each other and provide a well-structured overview of the candidate's skills in the scope of fulfilling **T3**.

3.5.3 Views design

CV3 is composed of four views: (1) the List View, (2) the Compare View, (3) the Profile View, and (4) the Add/Edit View. In the following Section, we describe the first two in detail and give a short description of the others, along with an explanation of our design choices,

List View

The List View supports the recruiter in: (i) consulting the CV database (**T1**), (ii) accessing single profiles (**T1** and **T2**), (iii) querying the database for eligible candidates given a set of skills, and (iv) selecting a set of candidates for in-depth comparison (**T3**). At the top of the view, we placed a form for filtering the candidates and querying the database. The form has two functions: (i) it is intended to filter the candidates according to occupation, location, and language(s); (ii) it allows to define a set of skills, with the corresponding requested knowledge level, which will be used to rank the candidates according to the scoring function. Only the CVs that fulfill the filtering conditions (in an OR fashion) will be ranked. Proceeding downwards, we show the candidates "cards" (see Fig. 3.1 (A)) with the portrait of the candidate, name, age, full details of current job (position, company, city, and state), icons for spoken languages, the average job duration, years of experience, and the number of unique locations where s/he had work experiences. The "deck" can be sorted in several ways, including age, years of experience, and many more, using a select box at the top left corner of the cards. By combining the design of the cards and the sorting tools, we present the recruiter with a concise but comprehensive visualization of the whole database. The choice of the information to show on the cards was made by picking up the data that the recruiters search for first in a CV according to our interviews. A click on any card accesses the Profile View (see paragraph below) of the corresponding candidate.

Once one or more skills are selected, the search can be performed. The results are displayed in a scatterplot (see Fig. 3.2). On the x-axis, we plot the Diversification score, while on the y-axis we show the Specialization score. The points in the scatterplot display the candidates' profile picture (if present). In case of overlapping coordinates, we show a single point, depicting the number of overlapping elements; on mouseover, a tooltip appears, displaying details about which candidates share the same score. We are aware that the scatterplot can become very dense with many applicants: the grouping of overlapping candidates attempts to improve both the scalability and clarity of the visualization. We chose a scatterplot to display our ranking due to its efficacy in providing an overview and finding extreme values and outliers [Mun14]. In this case, we overview the approximate knowledge of several individual CVs at the same time, significantly accelerating

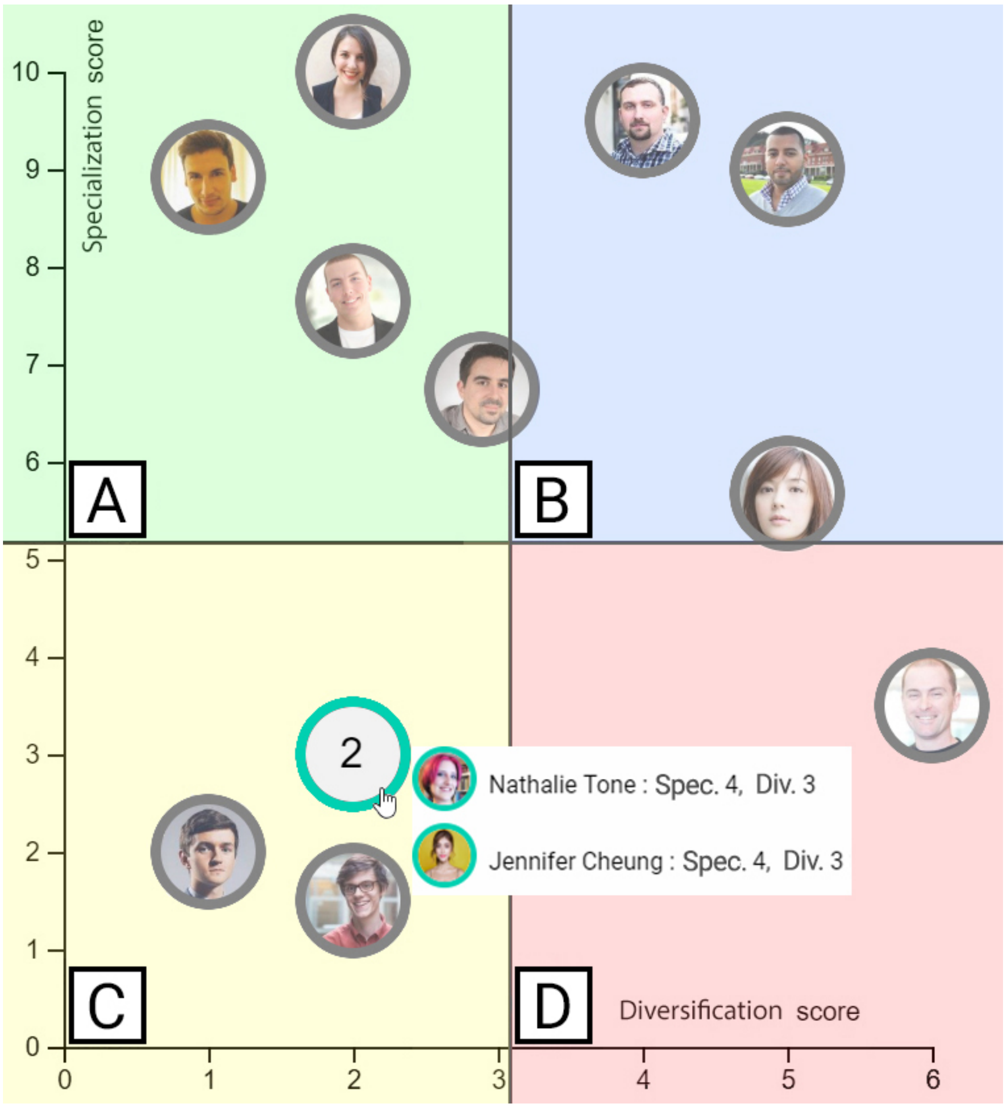

Figure 3.2: Scatterplot showing the score of the candidates. The different sectors convey a different level of knowledge.

the task of building a short list for evaluation. The area of the scatterplot splits into four quadrants (see Fig 3.2): in the first quadrant (top-left A) we find people with a high Specialization score but with a lower Diversification score. In the second quadrant (top-right B) we find the candidates who are both proficient in the requested skills and possess high overall knowledge in the field, thus being the most interesting for a specific application and likely to be included in the shortlist. In the third quadrant (bottom-left C) there are people with low Specialization and Diversification scores. Finally, in the fourth quadrant (bottom-right D) we find people with moderate expertise in the requested skills but with significant overall knowledge. Interaction is made by brushing: the recruiter draws a rectangular shape on the scatterplot area and the points falling into the rectangle

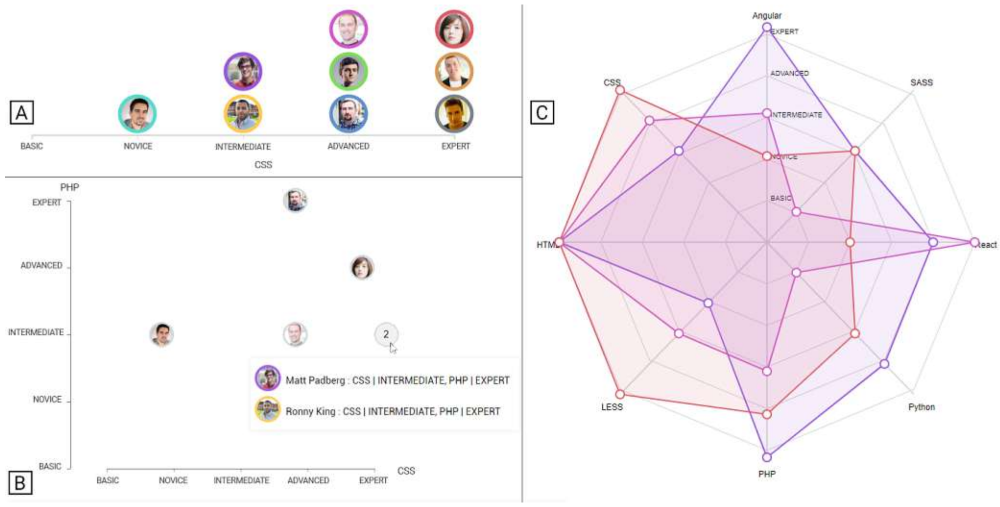

Figure 3.3: Common skills visualization. According to the number of common scores, we use different techniques. For a single skill, we use a bar chart with the candidates' portraits stacked depending on their knowledge (A). For two common skills, we display the candidates' expertise in a scatterplot where we plot the common skills on the x- and y-axis (B). For three or more matched skills we construct a radar-chart where each axis is a unique common skill (C).

will be added for comparison; the rectangle can be moved around the area and re-sized. It is also possible to add/remove résumés to/from the comparison by clicking the appropriate button on the cards or by selecting the points in the scatterplot. By clicking on the "Compare" button the view is switched accordingly.

Compare View

The Compare View is used to compare the candidates who made it to the shortlist. To avoid excessive clutter, we have set an upper bound of 15 candidates that can be concurrently compared. This design choice sets a limit to the size of the shortlist: we overcome this constraint with interactivity, by allowing the recruiter to easily add or remove candidates from the view (as we will describe in this paragraph). The goal is to provide a comparison of the salient sections of the candidates' careers, experience, and skills (**T3**). Here we opted for a multiple coordinated views approach. In Fig. 3.1(A), we arranged the cards of the selected candidates to provide a quick side-to-side comparison. On top of each card, there are three switches (left to right): the first permanently highlights the candidate's features across all views; the middle one hides the candidate, and the last one removes the candidate from the comparison altogether. Below the cards, we placed the "Skills" section. Here we directly compare both the skills the candidates have in common (see Fig. 3.3) and the combined Skill Tree of all the candidates (see Fig. 3.1(B)). This specific design choice was made to fulfill both **T2** and **T3**, and follows a focus+context approach. The "focus" is on the common skills: it makes more sense to directly compare the knowledge level on those only, considering it is more than likely that the ones required by the job application will appear here. To do so, different visualizations are suggested depending on the

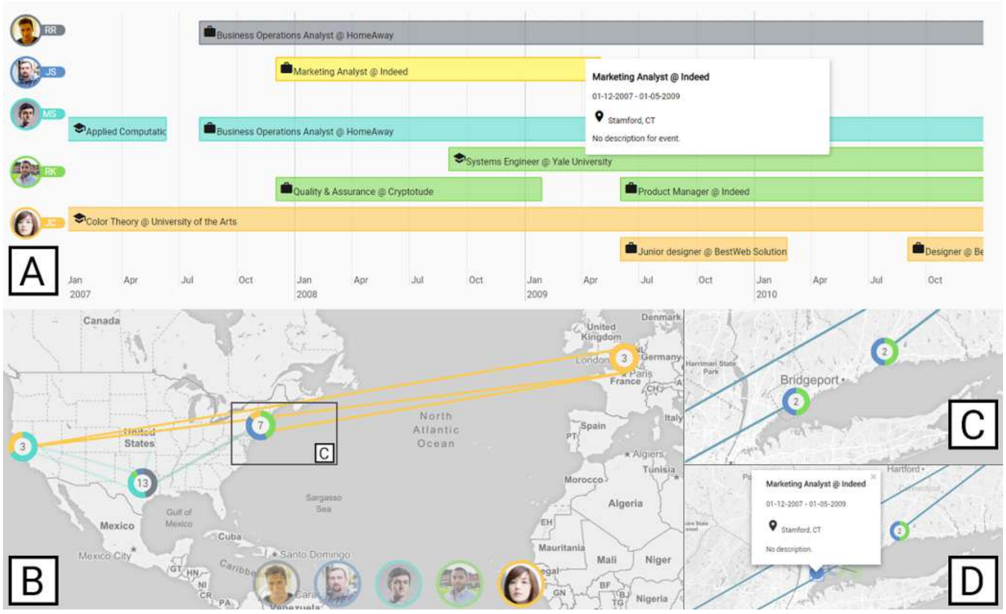

Figure 3.4: Timeline (A) and Map (B-D), the linked views of the candidates' events. In case of overlapping markers, these are clustered together (C). Each event in the timeline is associated with a tooltip where we display detailed information related to the event (D).

dimensionality of the data, which depends on how many skills the selected candidates have in common. If only one is matched, we show a bar chart, with the skill level plotted on the x-axis and the portraits of the candidates stacked on top of the corresponding level (see Fig. 3.3(A); if two are matched, we visualize a scatterplot, with a skill on each of the two axes (see Fig. 3.3(B)). Finally, if three or more skills are matched, a radar-chart (also known as spider-chart) is shown, with each skill plotted on a different axis, which creates a polygon for each candidate filled with her/his color (see Fig. 3.3 (C)). The radar-chart is an appropriate choice because it allows for easy recognition of outliers and commonalities [Cha+83].

The context information is given by merging together the Skill Forest of each candidate into a single result tree (see Fig. 3.1(B)). At first, the result tree contains a faux root node. We then append every tree of each forest to this node. We do not allow duplicates in the result tree, therefore, in the case of shared skills, we retain the information about the candidates possessing them along with the corresponding knowledge level. The matching is performed by case-insensitive string comparison of the skills' names. By construction, the result tree is a representation of the combined knowledge. On each node, the outer ring is split uniformly into sections depending on the amount of people that share the given skill and each section is colored according to the candidates who own that skill. Hovering with the mouse on each node shows a tooltip with the names of candidates and their corresponding expertise. In this case, we also encode the expertise as the opacity of the border (higher opaqueness corresponds to higher expertise) but also show this information in a tooltip on demand. We choose a radial tree layout over a layered one because of its better aspect ratio and area efficiency as the number of nodes to display grows, aiming at achieving better scalability. We also considered using a treemap, but intermediate nodes are relevant for both interaction and visualization, so a node-link visualization is better suited for our goal. Furthermore, pathfinding tasks such as highlighting the Skill Tree of an individual candidate are not supported in a treemap visualization [GFC04].

Below the skills area, we put the "Timeline" (see Fig 3.4(A)) and "Map" (see Fig. 3.4(B-D)). With these last two visualizations, we aim at completely fulfilling **T2** and **T3**. The timeline shows the aggregated temporal data about the candidates' career developments. As already mentioned in Section 3.3, events have a temporal and spatial dimension along with possible other metadata. Furthermore, they can be associated with a category (i.e. education, work, awards, etc.), which is depicted by a specific icon. The timeline is searchable by location or by category: in this way, it is possible to compare the different careers from several points of view, looking at gaps in employment, concurrent jobs, and job variety. It is possible to have extra information about each event by hovering over it. A legend shows which category each event belongs to. The temporal data about the candidates' career development is additionally reflected in a spatial context to support recruiters in assessing their mobility in the map below. Here we plot the geographical data associated with each event in the CVs. We allow the recruiter to evaluate the mobility of the candidate and compare it with the others. The events are represented as points on the world map, colored as the candidate and connected by a line. By clicking on them, a tooltip shows a summary and the timeline re-orients itself to focus and highlight the corresponding event. If considering the zoom level, two or more points are geographically close, they are grouped together in a single marker that bears a number representing the number of events. The outer ring is split proportionally to the number of events belonging to each candidate. By clicking on such marker(s), it "blooms" and shows the single points, which are now interactive.

Profile View and Add View

With the Profile View and Add/Edit View we fulfill **T1** and **T2**. In the Profile View, we show all available information about the candidate, including the proficiency in the spoken languages according to the "Common European Framework of Reference for Languages" [Cou], the candidate's Skill Forest, and timeline. In the Add/Edit View, candidates can add or edit their information using a form.

3.6 Validation

In this Section, we describe how we validated the proposed system. In Section 3.6.1 we describe the procedure we followed, in Section 3.6.2 we discuss the results of our interviews, and in Section 3.6.3 we summarize our findings and highlight the lessons learned.

3.6.1 Domain Expert Validation Procedure

We conducted the evaluation of CV3 by means of a small-scale user study with domain experts. We conducted our study as a task-based evaluation: we asked the participants to think aloud while using CV3 to perform tasks so that we could gain insights into how they interacted with the system. Our hypotheses are as follows:

- **H1:** CV3 does not need extra training for recruiters and managers, since it fits the current process of selecting candidates without introducing new steps or changing the work methodology;
- **H2:** CV3's scoring system (Specialization + Diversification) and result visualization assists the recruiters in assessing multiple candidates' capabilities on a specific query;
- **H3:** CV3 skills modeling and visualization approach is a suitable representation of the candidates' knowledge.

We conducted the user study with four participants: two of them are managers of medium-large enterprises and are responsible for interviewing and selecting candidates for hiring. One is responsible for recruitment in a medium-sized company and the last one has experience evaluating CVs in an academic environment. We chose the experts to test how CV3 would perform in various environments with different foci and users with diverse expertise. Each interview lasted between 60 and 90 minutes. The sessions were structured as follows: (i) introduction to the system, (ii) hands-on testing, (iii) task-based evaluation, and (iv) general feedback and opinions. Since there were no publicly available datasets that fit our data model, we merged information from real CVs and online identity generators to create 15 different realistic résumés. We tailored the résumés for software/web development careers, with varying ages, skills, education, and work experience. The tasks focused on providing answers to our hypotheses. We chose the tasks to determine the efficacy of each visualization on its specific focus and how they worked together:

- **VT1:** Select the candidates with the highest knowledge for a given query (this selected pool will be used for the other tasks);
- **VT2:** Assess the geographical data of the selected CVs in terms of proximity (to the recruiter) and job mobility (in terms of geographical movement);
- **VT3:** Compare the education, work experience, and other events of a candidate to all the others in order to find outliers and assess their potential;
- **VT4:** Evaluate the expertise of the candidates based on their common skills and overall knowledge.

With the tasks completed, we asked the experts for their feedback about the overall experience; we asked for their opinion about the ranking system, and, more generally, insights into how they would use CV3 in a real scenario.

3.6.2 Discussion

In this Section, we will discuss how each participant solved the given set of tasks and whether we can confirm or deny the associated hypotheses. We start with **VT1**. All experts quickly completed the task by using the skill search form in the List View and the resulting scatterplot (see Section 3.5.3). The experts agreed that the two-dimensional score visualization was insightful and gave a quick but reliable impression of the candidates' skill background. With different wording according to their own experience, all the experts agreed on the usefulness of the Diversification score, stating that it would most likely allow people usually overlooked to have better chances to be part of the shortlist. However, they pointed out the lack of transparency on how the query is constructed: the skills are queried in an "OR" fashion, and while the experts mostly agreed that this is a reasonable approach, they suggested that providing the option to customize the query construction could cover more possible usage scenarios. All experts suggested implementing a more guided input on the query form, such as auto-complete on each field.

With **VT2** we want to understand how the geographical data is conveyed to the users. The experts agreed that mobility is useful in providing contextual information about the candidates' careers, with some of them pointing it as being "relevant" in the selection process. According to the different experiences of the experts, mobility, and proximity had varying impacts on the selection process: people who moved more might be more willing to relocate as opposed to those who did not. All the experts completed the task using the information on the cards, the timeline, and the map. The map was praised for its clarity and all the experts could easily identify the mobility patterns of the candidates. However, they pointed out the lack of temporal information on the map, which made the task of finding the closest candidate(s) harder. The linking with the timeline partially helped in coupling the temporal with the geographical data.

VT3 task is conceived to assess the usefulness of the timeline in visualizing the career experience of the candidates. We asked the experts to assess and compare the careers of the candidates over time. They used the information on the cards to have a quick reference of the people with the most working years and job duration. The experts then verified and better contextualized this information using the timeline. A couple of them found the timeline confusing at the beginning (especially with many events) but it was mostly helpful when completing the corresponding tasks. Filtering played a major role, especially in the assessment and comparison of education. Furthermore, the experts could quickly find the gaps between different and concurring events, which is information they considered relevant. The interactions were useful with some minor complaints about the timeline interacting with the mouse wheel. One of the experts pointed out that one of the most interesting aspects of the timeline was the automatic calculations of the years of experience: in this way, rounding and bias (human error) are avoided. Finally, the concurrent (but filterable) display of all the different categories was praised: however, all the experts reported difficulty in interpreting the icons due to the lack of a legend (that was later included).

VT4 focuses on determining the skill set visualization of the selected candidates. Our intention is twofold: we want to evaluate how the experts use the common skills chart and the Skill Tree to perform tasks that involve the candidates' knowledge.

Among the other views in the system, this is the one that required the most clarification to be completely understood. The experts found it too colorful and confusing at the beginning. However, after the design rationale was explained, all the tasks referring to this view were solved by the experts with minimum to no assistance. In particular, the experts praised the interactions between the two views, with highlighting playing a major role in keeping track of the candidate's profile in larger skill trees. Highlighting was also useful in path-finding tasks, i.e. finding a specific candidate's set of skills (subtree). The coloring of the tree nodes was very efficient in depicting the most (and least) common knowledge between the selected candidates. In the Compare View, experts used the tree to find the subset of candidates that shared the most skills and then used the corresponding radar-chart for direct comparison. Experts did not understand why the common skills visualization changed according to the number of common skills, asking for a more detailed explanation about why the radar-chart was swapped with other completely different visualizations.

The general feedback was mostly positive, with all the experts praising the idea of the Diversification score: one of them explicitly stated that in a software development company, given the high amount of different technologies/skills needed for every project, it is hard to find a profile that fits perfectly. For this reason, a more inclusive ranking would be useful in this application domain. The scatterplot for candidate selection in the List View was appreciated as an easy, visual, and interactive solution to quickly categorize the CVs. However, what really caught the attention of the experts was the Skill Tree: they praised both the Skill Forest idea and how it was implemented in the Compare View, effectively conveying the overview of the skills of all the selected candidates at the same time. Moreover, we noticed that the experts were generally faster in completing the tasks involving the use of the Skill Tree. Even if one expert found it confusing at the beginning, afterward they agreed about its usefulness in a real-life situation. The common skill visualization needed the most explanation, compared to the other views. Constructive criticism included improvable user experience on the timeline and on the map, and, in general, the experts preferred to have a more informative interface, especially when making queries.

3.6.3 Lessons Learned and System Limitations

According to our experience and the results of the expert interviews, the findings seem to confirm our hypotheses. Based on the general feedback and the results of expert interactions on **VT2** and **VT3**, it appears that CV3 would fit in the existing workflow of a HR department, thus confirming **H1**. Feedback on **VT1** seems to support **H2**: the proposed scoring and visualization fulfilled their purpose in providing an overview of each candidate's competence in a specific set of skills. Moreover, the experts praised our two-dimensional scoring and the idea of evaluating the overall knowledge in a succinct way (Diversification score). They explicitly stated that they were likely to include more people in the shortlist based on the Diversification score provided. Finally, the experts agreed on the choice of modeling the skills of an individual after a tree, and used it proficiently on **VT4**, to compare and evaluate the knowledge of several CVs. This suggests that the experts found our knowledge representation straightforward and stated that it could support their assessment process (**H3**). Overall, based on our findings in the evaluation, CV3 can indeed support the exploration and comparison of multiple instances of CVs and can assist users, that work in a HR department, with their tasks in a meaningful way. Concerning CV3 limitations, we currently match the skills of the candidates to a query using a string-based approach, thus being prone to false negatives (such as “Development” and “Programming”). However, this tends to happen much less with skills in specific technologies (e.g., CSS, JS, etc.). An additional limitation of the system is that it does not account for missing data. The system does not penalize candidates with missing data by design, however, it also assumes that the information being processed is complete and valid, thus candidates with incomplete information could be excluded from the results. Currently, as already stated, the skills in a query are searched for in an “OR” fashion, this means that it is possible to get candidates that partially match the requirements. Some experts found this confusing, but they also found it a reasonable approach, preferring less selective querying. Therefore, the system should also allow the user to select different options for the query construction (including “AND”-ing the constraints). On a closing note, CV3 presents known scalability limitations: we integrated some remediation measures for the List View, but we still decided to limit the maximum amount of people to include in the Compare View. Finally, the experts suggested including the possibility of automatic résumé parsing to ease the process of entering data into the system.

3.7 Conclusions and Future Work

In this paper, we presented CV3, a VA approach for résumé comparison and visualization. CV3 offers multiple visualizations for the data represented in CVs, provides a scoring system to suggest the best candidates for a specific application, and allows for interactive exploration, assessment, and comparison of multiple CVs. We have evaluated our solution by conducting a small-scale expert study and have presented it to colleagues and visualization experts for valuable feedback and future work directions. To the best of our knowledge, CV3 applies modeling, interaction, and visualization techniques unprecedented in this application domain. We believe this approach is a step forward toward applying IV and VA techniques in the area of recruitment and HR. Other than tackling the current CV3 limitations, interesting future work includes investigating ontology-based Skill Tree matching/comparison techniques. Moving from a simple string matching to a more *fuzzy* approach would possibly provide more meaningful and accurate results. Additionally, this extension would allow the system to recommend candidates based on more flexible similarity metrics. Another interesting improvement would be the introduction of an age-aligned timeline: events would be arranged according to the candidate’s age to compare each person’s achievements at specific stages of their life.

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CHAPTER 4

On Alternative Network Representations

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Title: Gone full circle: A radial approach to visualize event-based networks in digital humanities

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Context: In the following publication, we conduct a design study resulting in a novel network visualization metaphor focusing on depicting the temporal, spatial, and categorical aspects of an event-based network representing the lifespan of musicians and their events in the public space of Vienna during the Second Republic, starting with 1945 up to the present day. Our approach presented in this paper aligns with the broader field of event-based and dynamic network visualization in digital humanities. We utilize a radial design and emphasize aesthetics, engagement, and compactness considering our domain experts and application field.

We evaluated our proposed approach by a task-based domain expert evaluation where we focused on the engagement, immersion, as well as ability of our visualization to support insight generation and extraction. The evaluation was conducted in the spirit of a history exam and we recorded both the response times and difficulty as well as the correctness of the answers.

In the context of network visualization, we depict an event-based network that relates entities embedded in both space and time. There are two different kinds of networks that we focus on in our approach, the first one is a social network of musicians that are all related based on common events they have participated in and other user-defined criteria (e.g., exiled musicians during World War II). The second one is a similar network, where we depict the relationships between locations in the City of Vienna based on their overarching theme and the events that took place there. This shows how the importance and popularity of these locations changed over time. Our approach provides numerous interactions to see the data from different perspectives, filtering, grouping, and reordering the network as well as diving into the details of individual entities and their properties, an important aspect for the domain experts.

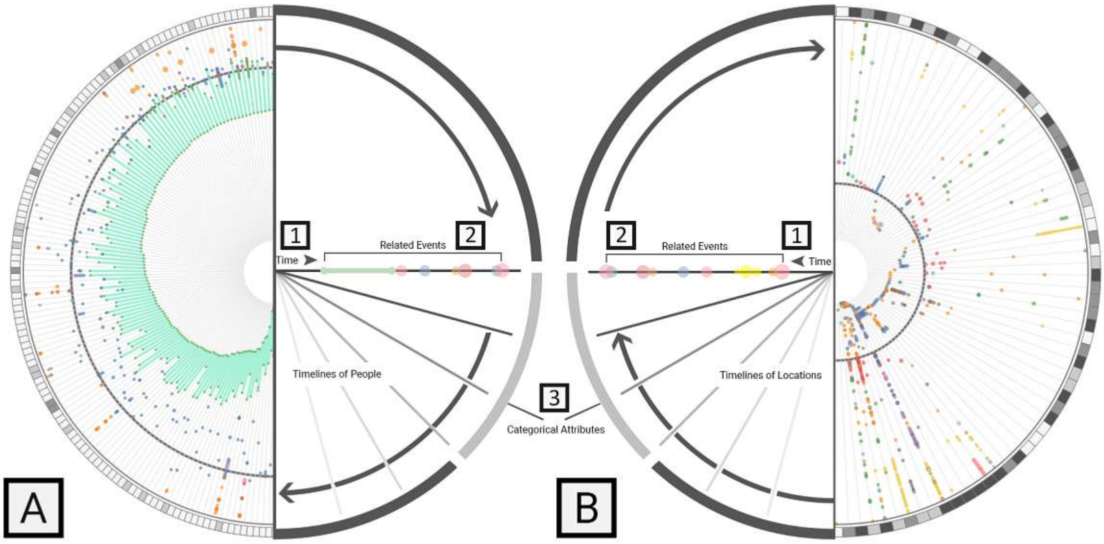

Figure 4.1: Circular depicting two networks from our data (A and B). The persistent entities and their temporal developments are encoded as rays along the circle (1), whereas their related events are represented by dots superimposed on the respective rays and are color-coded according to their association to different themes (2). On the exterior of the circle we encode categorical attributes that can be user selected (3). (A) depicts people, their related events, and the themes associated with those events. The rays are ordered according to user selected criteria, in this case by date of birth. The people of interest in this dataset have a large amount of events related to them occurring after their death. (B) shows important locations in Vienna alongside events that have been organized there and the themes associated with those events. In this dataset we can observe the change of popularity for certain locations over time and their shift in motifs.

4.1 Abstract

In the application domain of digital humanities network visualization is increasingly being used to conduct research as the main interests of the domain experts lie in exploring and analyzing relationships between entities and their changes over time. Visualizing the dynamics and different perspectives of such data is a non-trivial task but it enables researchers to explore connections between disparate entities and investigate historical narratives that emerge. In this paper, we present Circular, an interactive exploration environment to visualize event-based networks and support research in digital humanities through visualization of historical subjects in space and time. Our radial design is the result of iterative collaboration with domain experts, and we discuss the process of collaborative development and exploration of public music festivities in Vienna as an example of immersive development methodology. We validate our approach by means

of both domain and visualization expert interviews and show the potential of this approach in supporting the visual exploration of historical subjects. We discuss our design rationales, visual encodings, and interactions as to allow the reproducibility of this approach within a framework of transdisciplinary collaboration with digital humanities.

4.2 Introduction

In recent years, academic and applied research in Visual Analytics (VA) has seen remarkable progress that helps advance the field and grow the community. VA has been increasingly applied to a multitude of different fields and disciplines and established itself as a direct interface between the data, the users, and their tasks [MA14]. VA leverages the potential of human cognition to make large amounts of data and information tractable. While digital tools and modern computational methodologies are increasingly being used across most fields and research disciplines, in the humanities it is still quite common for most research to be conducted in archives gathering material sources. This is mostly due to the fact that research questions and methodologies from the humanities stem from a different epistemological standing compared to traditional technical fields [Hin+17]. New technologies are changing the landscape of this domain by making research materials widely accessible and enabling scholars to explore their data, find patterns, and present their work. A big challenge in this domain is modeling data for historical research properly and accurately. As stated by Börner et al. [Bör+19] many artifacts and phenomena in the humanities are difficult to model as variables, due to the abstractions necessary to make these commensurable.

The data in the domain of digital humanities can be seen as rich interpretable data [Lam+18] exhibiting relational, spatial, and temporal characteristics, evolving and changing over time. The general idea is that the cultural and social phenomena that can be observed in such disciplines, based on the data available, do not occur naturally, but are in fact shaped by different influences, interests, and power relations of certain actors that change over time. The intricacies and complexity of this type of data can be represented by a network [Sch+19]. Networks are one of the most flexible structures to model such phenomena and can illuminate dimensions and scales of historical events that are otherwise difficult to conceptualize [Lin16]. The core analysis tasks supported by network visualization that are of main interest for the application domain of the digital humanities are to identify and understand relationships between actors, to find and highlight central or similar objects, to observe the underlying structure of the network, to reveal outliers or deviations from the expected network behavior, and to observe the changes occurring to the network over time. Network visualization has proven to be a successful tool to model data and phenomena for such tasks, yet most modern solutions do not account for the dynamic nature of the data. Real-world data is rarely static and for most applications and problems it is of essence to model and visualize the evolution or change in the network, its actors, their relationships, and movement over time. The dynamics of such a network can be expressed by event-based network visualization and we consider the challenge of visualizing this type of data for historical research.

This paper presents the results of interdisciplinary collaboration in the project Interactive Music Mapping Vienna (IMMV [1]). The project aims to map the history of public festivities in Vienna

[1] `http://www.musicmapping.at/` (accessed Oct. 8, 2020)

during the Second Republic (from 1945 to the present day), exposing narratives that contributed to the construction of the city's musical identity and the connection to historical events. It stands in the domain of musicology, a field in which aesthetics play an important role in motivating research questions, and is conducted mainly by historians, who prime for critical analysis of events and their representations. As VA researchers our challenge was to provide efficient and effective means for the humanists to explore their subjects with the desired level of rigor and artistic inquiry.

We present a circular visualization that is flexible and transparent to the underlying subject. It uses event-based networks as inputs, considering the existence of a small set of entities in space and time: people, places, events, and themes. This ontologically minimal model is powerful enough to represent many facets of historical subjects and explore trends and narratives mainly through their temporal and spatial developments, serving as VA support to humanists. Our solution was developed through an iterative process of immersive collaboration [Hal+20] that was shaped by the continuous research of material sources and the construction of the data. The evaluation was designed by the humanities domain experts with the methodological aid of VA researchers. Our main contributions in this paper are:

- Characterizing the problem domain of musicology and musical history, along with the data and tasks the domain experts have for conducting their research.
- Exploring the design space of radial visualizations, the conceptualization, and prototypical development of Circular - a radial visualization of event-based networks.
- Elaborating the evaluation results of our user study along with feedback and insights that were gained with Circular from both domain and visualization experts.

4.3 Problem Domain Characterization

The main focus of the interdisciplinary research project IMMV is how music acts as a social identification instrument in the urban context and how music is functionalized to urban symbolic politics. The concrete subject of research is selected festivities in the public space of Vienna during the Second Republic, starting from 1945 up to the present day.

Our approach, Circular, is influenced by our initial attempt to analyze how the City of Vienna honored its exiled musicians [Fil+19]. This was an exploratory, open-ended task on uninvestigated data which required visualizing multiple timelines, exploring relationships between people and events, and outlining pattern formation. The core idea was to leverage adjacency between timelines to invoke gestalt effects [Wer23]. The same timelines can be reordered and regrouped according to different criteria, e.g., birth dates and honoring events, providing representations that highlight meaningful aspects for domain experts. However, this first design was a first sketch of the overall vision and was restricted to exiled musicians. In this contribution, we abstracted the conceptual design to be domain-independent and applicable to various objects (entities) in time and space, such as locations. We oriented our design according to the data, users, and tasks [MA14] as well as the nested model by Munzner [Mun09]. Consequently, this abstraction allows to utilize Circular to visually explore and analyze similar problems of different research fields, which obey the same problem characteristics.

4.3.1 Data

Our data represents a network relating disparate entities and embedding them in space and time. The data is dynamic and is shaped as new entries are added or new sources are discovered and analyzed. The main difficulties stem from the fact that most information on the subject is not easily accessible or even available as digital assets. Therefore, the construction of the data itself can be considered original research and visualizing the coverage of information to orient research efforts is a crucial task. At the time of writing, our database comprises a large amount of entities that are all related to each other through events. We model these entities as nodes in a network with the relationships between them constituting our links. Our data consists of six different types of entities (and their respective counts): Events (1,243), Historic Events (78), People/Organizations (1,538), Themes (61), Locations (180), and Sources (1,279) with a total of 15,866 links between them. In our use case and considering our application domain networks are a suitable data abstraction to model historical research and can showcase the topological structure of these highly interconnected entities, with events being the most central nodes in the network tying together different types of nodes (people, organizations, themes, locations, and sources) and embedding these in spatio-temporal frames of reference. In this specific paper, the data being depicted is only a subgraph of our entire data, representing a single theme ("Musicalization of the Topology" see Fig. 4.2-B).

Initially, our data was based on a standard model for describing digital resources and offered little flexibility to our domain experts for modeling and conducting their research. Furthermore, the initial model did not offer support for one of our main tasks, which was relating different entities. Throughout the design and development we iterated on this data model, implementing relationships and adapting entities and their properties as needed (see Fig. 4.2-A for the final model). This process concluded in six main types of entities, acting as nodes (each with its own set of specific properties and attributes), that can be related to each other through individual events, that tie these together in spatial and temporal frames of reference. An example of this could be a musical festival that was held at a specific location, organized by a group of people with different political affiliations, and sponsored by a specific organization. This festival could further be related to a multitude media sources, such as photographs, video or audio material, newspaper snippets, etc.

The data model offers significant advantages over our domain experts' previous method for modeling historical research, specifically, our approach offers flexibility to model the complex intricacies of historical narratives (i.e., by relating prominent entities to these) and enforces scope. To understand why one must realize that the main task the domain experts have is analyzing material sources and structuring these to expose historical narratives and to present the complexity of their historical research. From a single material source, many entities can be derived, e.g., from a newspaper article one can compile a set of people, an event, a location, and a date. On the other hand, from an encyclopedia one can gather a more exhaustive list of entities and their relationships. Prior to our approach, the data model did not allow us to establish and construct relationships between existing entities, and our domain experts ended up modeling an excessive amount of information from sources that did not explicitly enforce the desired subject: the role of music in an urban context as an instrument of societal identification and the question of how music is to be functionalized for constructing the image of the City of Vienna. Furthermore, our approach offers flexibility to our domain experts and enables them to easily interface with and curate the data. The data is directly tied to the visualization and can be considered an online approach, in that it allows for real-time updates. This provides better support to our domain experts in analyzing, exploring, and identifying how the overall shape and scope of the data changes between subsequent modifications, such as addition, deletion, or updates.

By using events as our central ontological objects and carefully sampling key points throughout Vienna's history, we are able to create spatio-temporal frames of reference and visualize historical contexts between people, places, organizations, and themes. A more comprehensive and detailed explanation of the data and data model can be found in our previous work [Fil+19].

Our data can be described as an event-based network. Event-based network data consists of a set of events over a period of time, each of which can relate to multiple objects [OHS05; SAK20]. Traditional dynamic networks in most cases aggregate the network to a single snapshot or multiple timeslices, often resulting in a loss of information as opposed to event-based networks that model events with real time coordinates [Du+17; Mon+13a; Mon+13b].

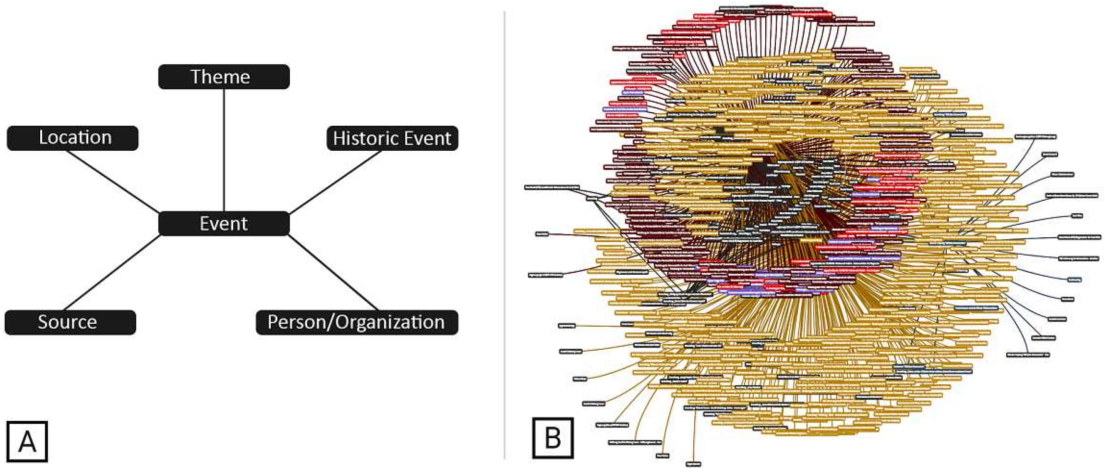

Figure 4.2: An overview of how our event-based network is modeled with real examples. Events are the most central object that can relate people, organizations, locations, sources, themes, and historic events. In (A) we present the the topology of our network and in (B) the subgraph that represents the data related to a specific theme ("Musicalization of the Topology") that is used throughout this paper is depicted as a node-link diagram.

4.3.2 Users

Our approach was designed with expert users in mind, i.e., humanists with domain knowledge who intend to perform in-depth historical research on specific narratives and topics. Domain experts in the field of digital humanities mainly conduct their research by gathering material sources from archives, analyzing collections of textual material, and structuring all this information in a comprehensive manner to establish narratives, present their work, and expose their ideas. In their research methodologies and activities, VA solutions are not common, this presents an opportunity for novel VA solutions in this domain. We intend to support them by creating VA approaches for analyzing and visualizing the data, exploring narratives or possible trends, investigating relationships between disparate entities, and conveying spatio-temporal patterns that might emerge. In our evaluation we had two groups of users participate: domain experts, with specific knowledge centered around the data and time period of interest and visualization experts, with experience in information visualization methods and VA techniques.

4.3.3 Tasks

To understand the problem domain in more detail and best provide support for our domain experts, their tasks, and current challenges, there was an extensive period of discussion about the construction of the data model, the data and scope, and their research questions. The experts suggested a lot of domain-related literature as a way to introduce us to their ongoing research and the challenges they face. Furthermore, this became a way for us to become involved in their domain, gain a better understanding of their data and requirements, and explore new domain-inspired visualization design spaces that presented interesting research challenges from a VA perspective as well but also have a contribution in the problem domain. These were necessary steps in order to immerse ourselves in the problem domain and familiarize ourselves with their research [Hal+20].

Our domain experts were interested in achieving a variety of tasks ranging from high-level to low-level as outlined in the multi-level typology of abstract visualization tasks from Brehmer and Munzner [BM13]. Starting from high-level tasks, an emphasis was put on presenting results, discovering insights, and producing narratives from the data. Some examples of these are questions posed by our domain experts that refer to how the motifs and themes of locations where events are held have changed over the course of time and how the City of Vienna treated and honored exiled musicians who returned to their homeland. Mid-level tasks included supporting the experts in free-form browsing of the data, as well as having the functionality to search for specific entities or browse for elements of interest in the visualization. Our experts were interested in being able to lookup specific people, events, and locations to find which were more important, influential, or well-connected, as well as having the ability to explore and find elements of the visualization that were pointing towards interesting periods of time, such as events related to many other events or people or people and locations with irregular event patterns throughout their lifetime. Finally, for the low-level tasks, the intent was to enable our experts to query elements of the visualization for more details on their specific characteristics or relationships with other entities. The questions our domain experts have that fall into this category include, identifying specific events, people, or locations, discovering details about them and their relationships to other entities in the dataset (the full set of questions can be seen in Table 4.1). These tasks and data of our experts became the basis for our domain problem characterization.

There has been significant work on establishing task taxonomies for visualization and graph design and analysis [TM04; AA06; Lee+06; Sch+13; Mun14; APS14], however, we found the multi-level task typology by Brehmer and Munzner [BM13] to be better suited for our specific problem domain. The authors outline that the typology allows for complex tasks to be expressed as a sequence of interdependent simpler tasks and this notion provides us with a flexible methodology for conducting our research and developing our approach. Following the nested model approach by Munzner [Mun09] we abstract these specific problems, questions, and data from their domain into a more abstract and generic description which resulted in an illustrative list of tasks in accordance with the multi-level task typology by Brehmer and Munzner [BM13]:

T1: Present - Our approach should support a straightforward, aesthetic, and engaging interface to present and gain an overview of the event-based network. Additionally, it should enable our domain experts to communicate the results of their research by telling a story with the data. The core goal of this task is for the users to work with the visualization in order to communicate information, tell a story with the data, or guide the audience through the data and visual representation. Essentially, our approach should enable users to convey the general shape of the data but also provide different interactions to slice, reshape, reorder, and view different modes of the network. The presentation and dissemination of historical research is one of the main objectives of the domain experts. Examples of questions from our domain experts that fall into this category include, e.g., *"In which locations was the First of May event celebrated in 1924?"* or *"Can you name 3 exiled musicians that do not have a street in the city named after them?"*.

T2: Compare - Our domain experts expressed their interest in comparing entities or groups of entities that exhibit similar characteristics to observe their development over time. The intent of this task category is to support them in discovering different groupings of the network based on specific properties of the entities, such as, e.g., grouping locations by district or people by their profession and supporting them in observing their similarities or differences. Some questions that our experts specifically had are, e.g., *"Which location was used most often to celebrate the First of May between 1918 and 2018, and which one was used the least?"*, or *"Are there more male or female people in the current network?"*.

T3: Explore - In addition to the presentation of research results and interactions that enable the experts to slice and compare parts of the network, our domain experts found it important to have interactions that enabled them to navigate and explore the network in more detail. This task category is concerned with the ability to search for data points with specific characteristics and investigate their properties and relationships in depth. This task starts from an overview level of the visualization, exploring a large set of data points (i.e., people or events) and includes, e.g., searching for outliers and anomalous or periodic patterns in time. This task is supported by methods for navigating, zooming, and panning. Examples of questions that motivated this task category are, e.g., *"Which events took place at the Befreiungsdenkmal? Which music was played there? Who organized the events? Which historic events are they referring to?"* or *"Can you find the location(s) attributed to Regenbogenparade in 2016?"*.

T4: Identify - As our domain experts are concerned with manually entering the data, shaping, and scoping it, being able to identify continuities and discontinuities of themes throughout the historical developments of the City of Vienna becomes an interesting topic. The experts are very detail-oriented and one of their main research challenges is to identify and summarize population-level trends and patterns that arise and decline over time. Such patterns are inherent to the data and become apparent at different granularities. Identifying these patterns and trends becomes an interesting direction for further research in the problem domain (i.e., groups of people based on their gender, profession, or people who have been exiled versus those who have not). This task differs from *T3: Explore*, in that the set of targets or data points that have been found or discovered through exploration can be further investigated and the user can drill down to their properties and relationships. In this case, the goal is to identify, for specific data points, important characteristics, and references [AA06]. Some questions that fall into this task category are, e.g., *"Which location was used most often for political stagings during the Second Republic?"* or *"In which district(s) did the least amount of events take place?"*.

T5: Verify - Finally, a task category that is not present in the multi-level typology by Brehmer and Munzner [BM13], but proved to be essential for the domain experts was the ability to verify and validate the data. It is crucial to ensure that the data being depicted is correct, as all data is entered manually and any erroneous data points, entries, or irregularities could point to entries that need to be corrected or provide interesting clues to open questions for historical research. Questions that belong to this task category are, e.g., *"When was Erich Wolfgang Korngold born / When did Erich Wolfgang Korngold die?"*, *"Which events are related to Alban Berg?"*, or *"Which exiled musicians never came back?"*.

4.4 Related Work

4.4.1 Radial Visualization

Visual representations of data that are based on circular shapes are referred to as radial visualizations [BW14]. Historically they date back to the nineteenth century, with the most famous example being the Rose charts introduced by Florence Nightingale [Nig87] and the introduction of the pie chart in 1801 by William Playfair [Pla01]. Circular designs, however, have been used consistently throughout human history across different cultures, from mandalas to navigational charts, generally associated with cyclic and periodic phenomena. Recently radial representations have seen a return in popularity [Shi+18; MM18; Cas+19], presumably due to their natural shapes, aesthetic look, and memorability [Bor+13]. Draper et al. [DLR09] provide a comprehensive survey on radial representations and present taxonomy based on seven design patterns. In their work, the authors investigate problem domains where radial visualizations are applied and typical usage domains include: hierarchical structures, relationships among disparate entities, ranking of search results, and serial periodic data. Accordingly, some examples of radial representations applied to these domains and different data types, include set-typed data [Als+13], multivariate data [Bal+07], hierarchical data [BD08], and time-oriented data [KSS04]. An interesting and widely adopted application of radial representations in the domain of genomics has been explored by Krzywinski et al. [Krz+09] where the authors present their approach, Circos, a technique utilizing a circular ideogram layout for visualizing and comparing the complexities of genome relationships.

Question	Task Categories
Q1: At which locations was the First of May celebrated in 1924?	T1
Q2: When did the first event related to “Stadtbranding” happen?	T3
Q3: Which themes are related to the events taking place at “Stadthalle”?	T1, T2, T3
Q4: When is Erich Wolfgang Korngold born / When did Erich Wolfgang Korngold die?	T5
Q5: Which events are related to Alban Berg?	T3, T5
Q6: Can you find an interesting event OR person in the timeline OR circle? Inspect it in more detail.	T1, T3
Q7: Which location was used most often for “Politische Inszenierungen” during the Second Republic?	T2, T4
Q8: Which events took place at the “Befreiungsdenkmal”? Which music was played there? Who organized the events? Which historic events are they referring to?	T1, T3, T5
Q9: Which location was most used to celebrate the First of May between 1918 and 2018, and which one was used the least?	T2, T3, T4
Q10: Can you find the location(s) attributed to “Regenbogenparade” 2016?	T3, T5
Q11: In which year(s) did the opening of the “Wiener Festwochen” NOT take place at “Rathausplatz”? Which location(s) were used instead?	T2, T3
Q12: In which district(s) did the fewest events take place?	T1, T2, T4
Q13: Which exiled musicians never came back? Name two.	T2, T3, T5
Q14: Can you name 3 exiled Musicians that do not have a street named after them?	T1, T3, T5
Q15: Are there more male or female people in the visualization?	T1, T2
Q16: Can you rank the groups by role based on the number of people in each group?	T2
Q17: Can you name the musician from each group that was born first?	T1, T2, T4
Q18: Can you find the two conferences? When did they take place and which musicians were related to them?	T2, T3, T5

Table 4.1: A table of questions along with their corresponding task category. The questions have varying degrees of difficulty that the participants performed throughout the user study. It is important to note that questions can appear in more than one task category.

Evaluations of radial visualizations have focused mainly on comparing radial and linear representations of periodic time-oriented data [Wal+19], assessing the strengths and weaknesses of radial visualizations in comparison to Cartesian representations [DBB10], and outlining the benefits and drawbacks, as well as providing guidelines for when radial visualizations are more suitable for given tasks and datasets [BW14]. Despite all the drawbacks of radial visualizations, there are also strengths in visually presenting data in a radial fashion and this is confirmed in the work of Borkin et al. [Bor+13], where they describe radial visualizations as being more aesthetic, natural, and memorable. This notion is further supported by the work of Hohman et al. [Hoh+20], where the authors elaborate that an audience that finds the content presented in an aesthetically pleasing manner is more likely to have a positive attitude towards it, engage with it, and learn from it.

Aesthetics also play an important role for us and our application domain as the main goals include fostering engagement, driving curiosity, exploring, and explaining historical narratives and connections in the data.

4.4.2 Event-based Visualization

Since the main subjects of our data are events, their dynamics, and their relationships, we also look into the related fields of event-based analytics and timeline visualization. Monroe et al. [Mon+13a] explore how an entire event-based dataset can be aggregated and transformed so that researchers and analysts can observe population-level patterns and trends. Plaisant et al. [Pla+96] propose a general technique for visualizing summaries of personal histories and other types of biographical data. The authors mention in their work that multiple facets of the data can be reflected in a single overview, using multiple timelines, with icons indicating discrete events and line color and thickness illustrating relationships between events. Cappers et al. [CW18] argue that current approaches focus only on either the temporal analysis of a single property or the structural analysis of multivariate properties. The authors propose an approach to interactively define a set of rules using multivariate regular expressions and use glyphs to encode the event sequences. Brehmer et al. [Bre+17] review related work and literature, analyzing over 200 timeline visualizations, and propose a design framework based on three main dimensions: representation, scale, and layout. This work represents the state of the art in timeline visualization and the design framework can be applied to biographical and prosopographical data visualization. Recently, Bartolomeo et al. [Di +20] have evaluated the effects and influence of different timeline shapes (radial and linear) on task performance for temporal event sequences.

4.4.3 Dynamic Network Visualization

In digital humanities it is becoming increasingly common for phenomena to be modeled as a network, as this is a flexible structure relating entities with different properties. The different entities can be represented as nodes in a network, for example, actors and events, related among each other and embedded in a spatio-temporal frame of reference. Network analysis can assist researchers in the humanities in exploring dimensions and scales of the data that are otherwise difficult to conceptualize [Lin16; Sch+14]. For this purpose, we also present related work from the field of network and graph visualization.

For a comprehensive survey on the state of the art of dynamic network visualization, we refer to the work of Beck et al. [Bec+14]. In their analysis, the authors outline open research challenges and future directions for dynamic network visualization, including visual scalability, hybrid visualizations, and new metaphors or approaches for visualizing the graph and its dynamics. In recent work [SAK20; LS15] we can see a paradigm shift in the way that time is modeled in networks: from time-slicing and aggregating the temporal dimension to representing it as an event-based network where the nodes and links can have real-valued time coordinates. With time being such an important dimension in dynamic graphs, the problem of identifying patterns and trends in the network becomes of interest. Dang et al. [DPF16] propose a novel visualization technique called TimeArcs to enable users to explore patterns in networks over time. With their approach, the authors aim to display the evolution of entities as they change over time, highlight related entities by positioning them close to each other, and reduce the amount of line crossings leading to occlusion and visual clutter. Van den Elzen et al. [Elz+14] present, Massive Sequence Views, a technique for the analysis of the temporal and structural facets of the network along with node reordering strategies to find patterns and trends in the data. As outlined in the state of the art [Bec+14] visual scalability and hybrid approaches present open research challenges, this topic has also been explored by Vehlow et al. [VBW15] in the context of visualizing group structures in graphs.

In our work, we aim to explore new metaphors for representing time in networks. We investigate how we can utilize the design space of radial visualizations and apply them to event-based network visualization. In the following, we present our approach, Circular, our design rationales and decisions, the visual encoding of our approach, and tie the features and interactions to the tasks they support.

4.5 Circular

Circular is our approach for visualizing event-based networks in the application domain of digital humanities. We discuss the design rationales leading up to the final design, the visual encoding that is used throughout the prototype, and the interactions that enable users to interface with the network and its components. Circular is an open-source web application, the implementation and a live demonstration of the approach can be found at the following URL: https://immv-app.cvast.tuwien.ac.at/biographical.

4.5.1 Design rationales

Designing for Musicological Research

During the design and conceptualization phase of our approach, we conducted workshops and meetings with our collaborators where we explored visual representations of datasets exhibiting similar properties and discussed the advantages and disadvantages of each approach. We encouraged our domain experts to find and select a few approaches they found aesthetically pleasing, engaging, and informative. The majority of the solutions we discovered were applied to the presentation of historical narratives and biographical data. The approaches were also developed with engagement and learning in mind as they were aesthetically pleasing and contained interactive and engaging visual representations of the data. We proceeded to investigate the visual encodings, layout, and interactivity of each approach and identified the tasks and requirements that were also backed by our domain experts.

An important question we needed to answer was how this data would be visually represented. As we have a large amount of event-based relational data (see Section 4.3.1), we needed to consider which aspects and properties were important for the tasks our domain experts have. We also consider how we can visually present this information in an aesthetically pleasing, but also functional, and interactive approach. Interactivity and aesthetics were important factors in guiding our design and development, as presenting the content in an aesthetically pleasing manner increases the chances that a user will have a positive attitude towards it, engage with it, and learn from it [Hoh+20]. Considering the density of our network, traditional node-link approaches do not seem suitable here, as there is a significant amount of occlusions, visual clutter, and edge crossings that arise (see Fig. 4.2-B) and further encoding the temporal dimension in such approaches presents additional difficulties. Therefore, we considered alternative representations and new metaphors for visualizing networks, such as e.g., [MKH12], where neighboring regions on the map symbolize related entities in a network. Furthermore, the proposed solution needs to offer a set of features to reshape, slice, filter, and explore the data, based on the interest(s) and task(s) of the user(s) (see Section 4.3.2 and 4.3.3). Our goal was to create an interactive visual prototype that offered users the option of re-configuring the state of the visualization to match their current interests, needs, or tasks, but also presented the data in an engaging and memorable way.

Throughout the workshops with our domain experts, we identified that a common theme amongst most visualizations developed for the digital humanities, were circular ideograms, depicting certain datasets and incorporating different ways of encoding the temporal dimension. This notion was further supported by historical examples of radial visualizations that were used to attract a broader audience as their shape and structure are more aesthetically pleasing, natural, and compact compared to their Cartesian counterparts [Nig87; Pla01]. Our final design rationale is motivated by the domain experts we collaborate with and presents an interesting opportunity to explore new domain-inspired research and design spaces.

Design Considerations

For this purpose, we explore the design space of radial layouts, how they can be applied to event-based network visualization, and consider how we can visually represent the different types of entities in our dataset, their attributes, relationships, and temporal developments. Our main focus was on representing the time-oriented nature of the data, as to enable and showcase pattern and trend formation throughout different points in Viennese history. With these considerations in mind, we investigate the related works of radial visualizations, where there are three primary ways to encode dynamic data in circular layouts (see Fig. 4.3): A) Ring-based Time; B) Space-filling Time; and C) Polar Time (for a comprehensive survey of the design space of radial visualization techniques, we refer the reader to the work of Draper et al. [DLR09]). Each of the options has certain strengths and weaknesses, in the following we discuss these and present our preferred

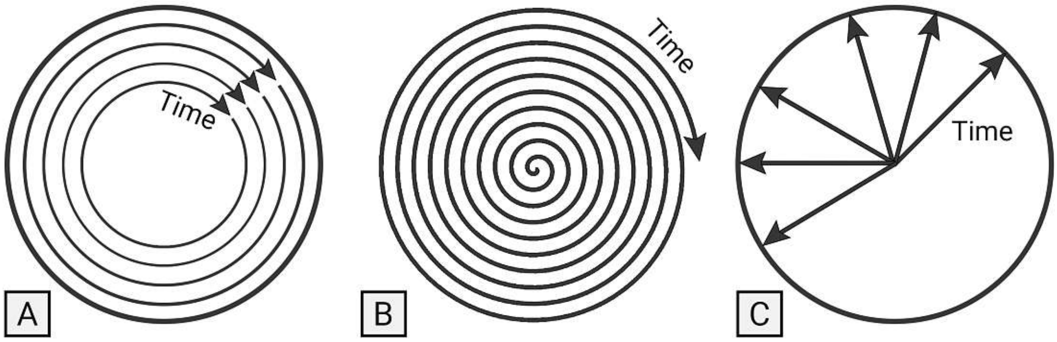

Figure 4.3: The three main representations for encoding time in radial visualizations [DLR09]. A) Ring-based Time - time is represented as progressing along the circumference; B) Space-filling - time is represented as a curve starting from the center and growing outwards; C) Polar Time - time is represented as growing outwards from the center in a ray-like fashion.

solution. We follow the categorization of the radial design space introduced by Draper et al. [DLR09].

A) Ring-based Time: This approach encodes time in a circular manner, the evolution of time is presented as going along the circumference from an arbitrary starting point (see Fig. 4.3-A). There are some drawbacks to this approach compared to the others. First, this layout relies heavily on encoding information using angle and arc length, which can not be perceived very well compared to other perceptual tasks [CM84]. Second, when attempting to visualize multiple tracks, each would need to be represented as a concentric circle, where the elements drawn closer to the circle's center would receive less drawing area compared to those drawn closer to the boundary, skewing the visualization in a way that objects represented closer to the circumference would be perceived as more important. This is true for most radial visualization techniques as the drawing area increases with the radius and elements closer to the center will receive less drawing area, but this is also true for their Cartesian representations as the drawing area is finite.

B) Space-filling Time: This fashion of encoding data is mostly utilized in visualizing serial periodic time-oriented data. The data in this encoding is visualized as a curve emanating from a point (the center), revolving around its origin as it moves further and further away (see Fig. 4.3-B). This approach, similar to the ring-based time, also has certain drawbacks, such as an inequality in the drawing areas close to the circle's center and border, but the main issue here would be encoding multiple tracks. We could, for example, have multiple spirals superimposed on each other with each depicting the properties and behavior of a single object, but this has its limitations when it comes to the upper bound on how many objects could be visualized at the same time.

C) Polar Time: For Polar Time encoding the center usually carries some special meaning and the distance between the center and a node implies some significance. In this approach time is represented as growing outwards from the circle's center to its border (see Fig. 4.3-C). The temporal information in this approach is encoded along a line, which is an improvement over the other two options that encode time along the circle, since here we are dealing with line length, a perceptual task that can be judged rather well in comparison [CM84]. Furthermore, encoding the temporal facet of the data in this manner offers us the freedom to explore what additional dimensions of the data we can encode in other parts of the circle. For example, with this design, we can represent multiple objects as neighboring lines and encode further properties on the exterior or interior of the circle (something that was not possible with the other two options). A drawback of this approach is, as previously mentioned, the limited drawing area close to the center of the circle, something we intend to address with interactivity, but we argue that this is still the most balanced approach.

The final encoding we decided on was option C) Polar Time. We believe this approach is the best-suited one for our tasks (see Section 4.3.3) and the most balanced one when comparing its benefits and drawbacks. Our design choices are further backed by the recent results of a user study evaluating the influences of timeline shapes for temporal event sequences [Di +20]. The authors conclude that linear timelines are preferred by most of the participants in their study and support reading the timelines and temporal sequences of data quicker than non-linear shapes. These claims also support our decision for selecting C) Polar Time as the temporal sequences of events in this case are depicted in a linear fashion. In the following section, we will go into more depth about how we visually represent and embed the data described in Section 4.3.1.

4.5.2 Approach

As we mentioned in the data section (see Section 4.3.1), we have historical data in the form of multiple disparate objects (people/organizations, events, locations, themes, sources, and historical events) that are related among each other and embedded in spatio-temporal frames of reference. We model our data as an event-based network [SAK20; LS15], where the nodes of the network exhibit spatial and temporal characteristics. Different types of entities are associated with a specific meaning and importance and this should also be taken into consideration when visually encoding and representing the data. An overview of the full prototype can be seen in Fig. 4.4. In the following, we will discuss the visual encodings and interactions in more detail, as well as present some interesting examples from our dataset.

4.5.3 Visual Encoding

When we look at the particular characteristics of people, organizations, and locations, we notice that these are entities that persist through time and define their own life span. These characteristics were taken into account and such objects are encoded as rays along the circle with highlighted features, such as life spans and important dates. An illustration of how we visualize a single person's or location's life line can be seen in Fig. 4.5 and 4.6, respectively. Additionally, related events are superimposed as points on the respective persistent entity's lifeline, these events have a time span of their own, defined by their start and end dates and additional properties, such as relationships to themes, sources, and historic events. If a single event is related to multiple persistent entities, this event is duplicated along the corresponding rays in the radial component (related to *T1: Present, T4: Identify, and T5: Verify*).

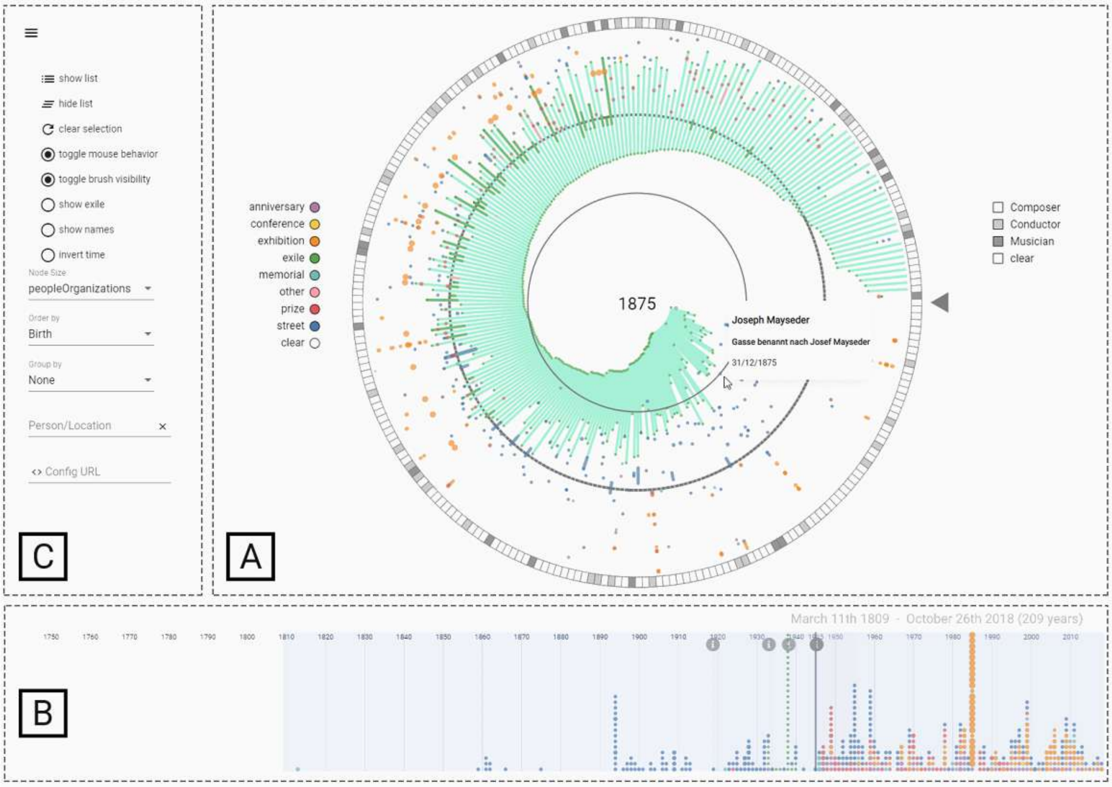

Figure 4.4: An overview of our prototype and its components. A) The main radial view where people, locations, their events, and thematic changes are visualized; B) The timeline that is used to visualize historic events and ease the users' selection of periods of time; C) A panel with settings and controls to modify the state of the visualization.

Depending on the frequency of events related to the entities, clusters can be formed. These can be seen as very busy areas superimposed on the person's or location's ray and might result in visual clutter (see Fig. 4.5-A, 4.6-A, and 4.7-A). To tackle this issue, each event is rendered with reduced opacity, which enables the user to see overlapping events, and the size of the points is used to encode the number of relationships (i.e., node degree) it has to other types of entities such as events, locations, people, organizations, sources, or themes. The nodes' size can be interactively changed based on the user's interest(s) and task(s). We provide a few options to do so, which in turn highlight events of different importance and relevance. This increases the readability of clusters and their implied network topology. The node's size guides users towards parts of the network that could be of interest to them based on their selection. For example, if a user is interested in events that are related to a lot of people, they could select the node sizing by person or organization and the changes would immediately be indicated in the visualization. This could imply that those events were considered to be fairly important in Vienna's history and with this selection, the size of the nodes would be updated to reflect that information, i.e., events with more related people would be significantly larger than events with less related people (related to

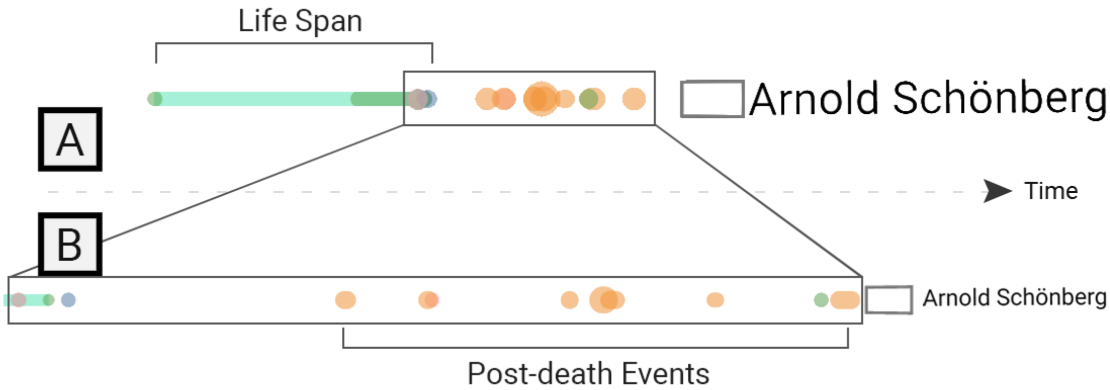

Figure 4.5: Arnold Schönberg's lifeline, along with related events and motifs. In this case, the events are color-coded according to a classification provided by the domain experts. A) Here we can see the default temporal granularity and a more scaled-up view can be seen in B). In this example, we notice Arnold Schönberg was exiled (darker green bar) close to the end of his life and the bulk of events (orange circles) honoring this person happen after his death.

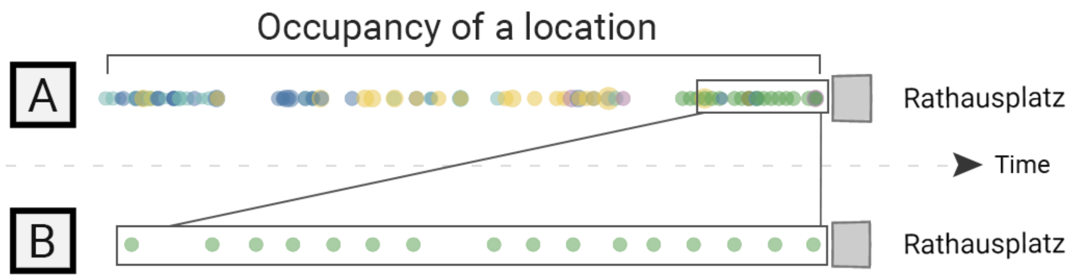

Figure 4.6: The lifeline of the Viennese Town Hall Square "Rathausplatz" along with related events and their motifs. In this case, the events are color-coded according to the classification of themes provided by the domain experts. A) We can see the default temporal granularity and a more detailed view can be seen in B). In this example, we can notice how the trends related to events happening at this location are changing over time (shift from blue to yellow to green circles).

T1: Present and T4: Identify). Further options to mitigate overlaps and clutter are to allow the user to interactively change the scale or temporal granularity so that the events are better spaced out in time to minimize overlaps (see Fig. 4.5-B, 4.6-B, and 4.7-B).

We make the relationships between events and themes explicit by exploiting the most prominent visual cue - color. Each event is color-coded according to the main theme it is related to, and this makes thematic changes over time visible as seen in Fig. 4.6, which shows that at earlier points in time this specific location was mostly used to organize events related to the blue theme, then transitioning to yellow, and being dominated by mostly green in the present day. This transition of colors reflects how the motifs of events being organized at a specific location change over time. Another example focused on people can be seen in Fig. 4.5 where after the person's death the bulk of events related to that person are linked to the orange theme. This makes sudden emergence or disruptions of patterns or trends throughout the City of Vienna's historical development visible and provides a potential narrative that encourages the viewer to examine this period of time in more detail (related to *T1: Present, T3: Explore, and T4: Identify*).

Often multiple entities are of interest and a common and important task is to compare sets of entities with common properties to identify similarities, differences, or trends. To encode persistent entities present in the network, we order them as rays along the circle (see Fig. 4.1-A for people, 4.1-B for locations). The ordering along the circle is, by default, according to the first event that happens related to each person or location (i.e., birth date). This forms a spiral pattern that implicitly shows the progression of time, as events related to every subsequent person or location happen later (related to *T2: Compare and T4: Identify*).

We experimented with different grouping and ordering strategies and supplemented the visualization with multiple options of combining these that in turn make different patterns stand out (see Fig. 4.9), each having a different impact on how the user interprets the story told by the data. Along the exterior of the circle, anchored to each ray, are rectangles that are used to encode categorical information about the persistent entities. Such categories could be, for example, the profession, gender, or period of activity of people, or the type of venue and district of locations. We can use this categorical information to group entities accordingly and outline similarities, differences, or trends within and between these groups. When a grouping option is selected the persistent entities along the circle are arranged in slices alongside others that have the same categorical information. This enables the domain experts to compare different slices of the network that are formed and explore what they have in common or how they differ. The users are free to select properties to group and order people or locations by, thus allowing them to explore the data according to their own interests (related to *T2: Compare, T3: Explore and T4: Identify*).

4.5.4 Interactions

We offer the user a set of interaction techniques to assist in selection, filtering, ordering, grouping, and inspecting the details of the network. In this section, we will present the main components and interactions of Circular.

As depicted in Fig. 4.4, the central part of our visualization is the radial representation of the event-based network (see Fig. 4.4-A). In this view, we display persistent entities (people, locations) and the events they are related to. The events also reflect relational information as they are color-coded to represent their relationship to different themes and superimposed on timelines reflecting their relationships between different people or locations. The dark gray line that is visible on the interior of the circle denotes the year 1945, which was marked by our domain experts as a baseline in history, used for comparison of the data. To the left side, we have a panel with different settings (see Fig. 4.4-C) that control the state of the visualization and enable or disable certain interaction techniques. Such controls are, for example, the direction of time (see Fig. 4.8), ordering and grouping criteria (see Fig. 4.9), and temporal zooming (see Fig. 4.7) that we will discuss in more depth.

Our decision to design and develop a radial visualization for this type of data is mainly motivated by the application domain and our domain experts. We were further interested in exploring the design space of radial visualizations for a few reasons: (i) space is utilized differently compared to rectilinear layouts and offers a more compact embedding of the data; (ii) it presents an interesting opportunity to investigate how we can visualize event-based networks in a radial layout and utilize the inner and outer parts of the circle for more features; (iii) it is important for our application domain to provide an interactive interface that offers an engaging experience in an aesthetically pleasing way and we believe a radial design supports this notion.

As discussed in the design rationales (see Section 4.5.1), there are certain drawbacks to radial visualizations, with the main concern being the limited drawing area closer to the center. For this purpose, we have looked into different ways of resolving this issue, which lead to a combination of approaches, including: temporal zoom (see Fig. 4.7), temporal inversion (see Fig. 4.8), and panning and zooming. Additionally, we have supplemented the radial component with a timeline at the bottom, which has a two-fold purpose that we will describe in more detail.

Timeline

On the bottom, just below the radial component, we have included a dot plot (timeline) of the events that occur in the network (see Fig. 4.4-B). The timeline has a two-fold purpose: (i) it is used as an interaction tool that allows users to select custom ranges of time, individual events, or periods of time defined by historical events that occur. This means users can define their own temporal granularity to inspect the data; (ii) it shows a different aspect of the data, aggregating the display of events for all related entities that persist in the network (people, locations, etc.), and showing patterns and trends that are associated with the historical development of the City of Vienna. It provides context to the data by embedding it in different historical frames of reference. Historic events are important for our application domain and expert users as they show a different perspective on the data. Historic events are represented as background areas along the timeline with darker shading and have an icon that displays a tooltip with more detailed information about it. The intent of this component is also to guide users to more interesting periods of time and enable them to explore these in more detail (related to *T1: Present, T3: Explore, and T4: Identify*).

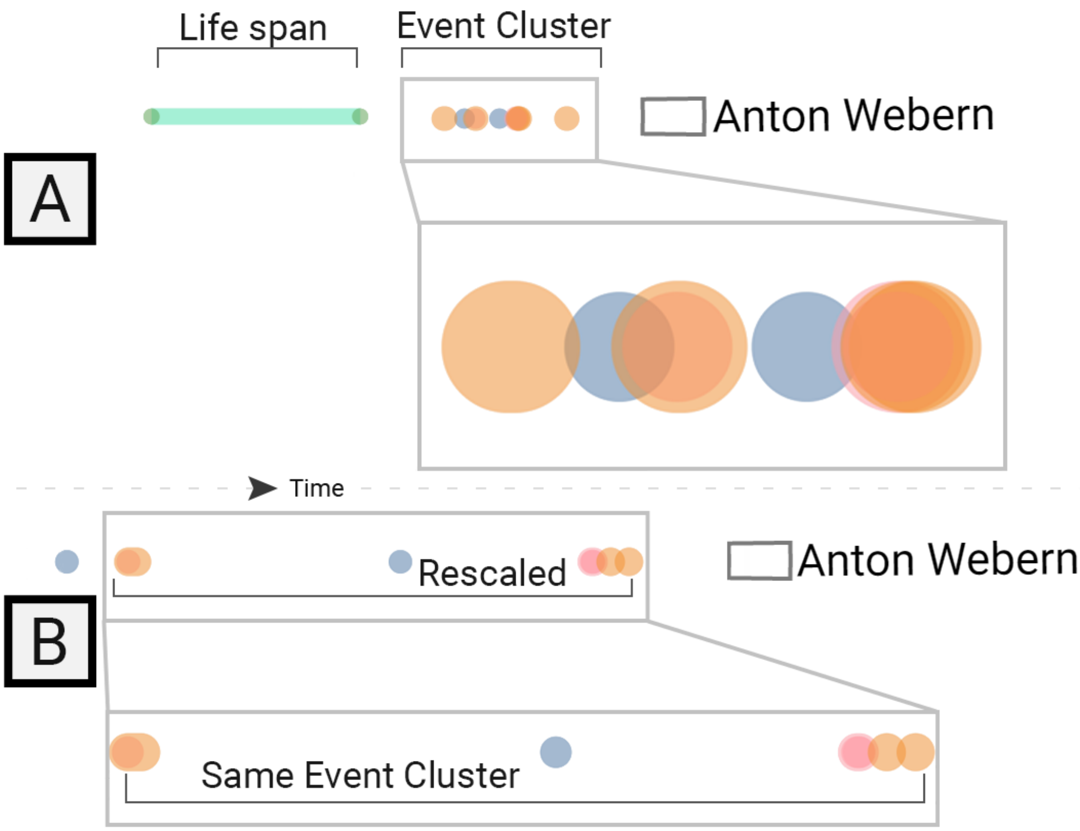

Figure 4.7: In A) we can see an event cluster happening after Anton Webern's death. These events cause clutter and overlaps. In B) we have scaled the temporal granularity up and the events are better spread out in order to mitigate dense areas and overlaps. In this example, the events are color-coded based on a classification provided by our domain experts.

Temporal Zoom

The temporal zoom interaction was conceived as a way to mitigate overlaps and very dense areas of the visualization by being able to select a span of time and have the granularity of that time span extended to the full size of the circle (see Fig. 4.4, 4.5, 4.6, and 4.7). It is also a way to support in-depth exploration and can provide different overviews depending on the selection of the user (*T1: Present* and *T3: Explore*). This interaction technique allows us to give more attention and drawing area to the selected period of time, making the data points falling into that time span spread out and declutter (related to *T3: Explore*).

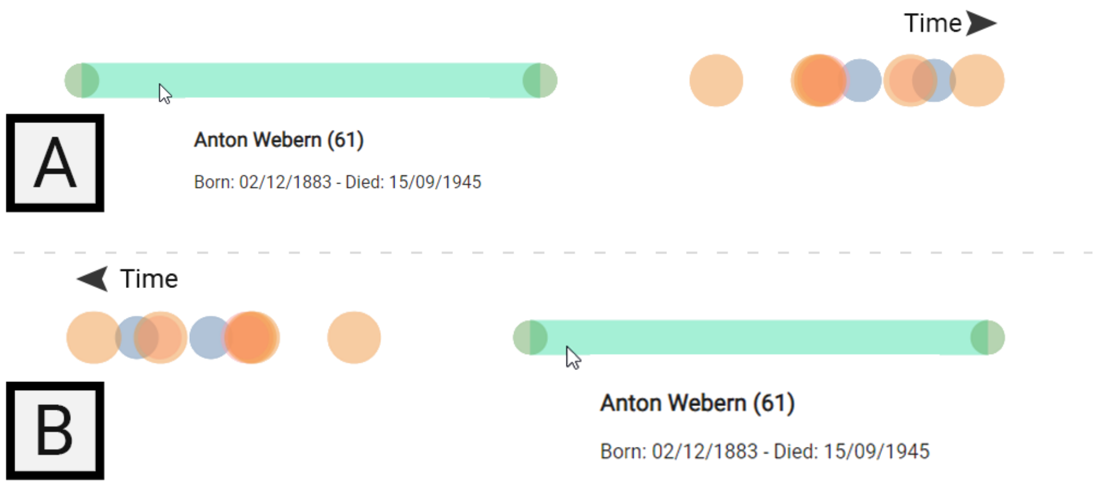

Figure 4.8: In Circular we also provide interactions to change the direction of time to resolve overlaps in dense areas close to the center of the circle. In this case, the events are color-coded based on a classification provided by our domain experts. In A) we can see the progression of time is going from the left to the right and in B) we can see that the direction of time is inverted.

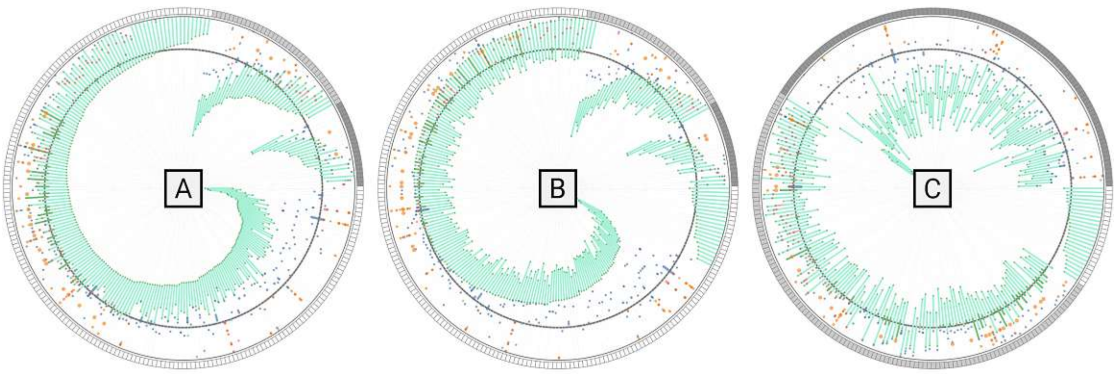

Figure 4.9: Three different patterns of people are visualized, each using a different combination of ordering and grouping criteria. A) People are ordered by their birth date and grouped by their role (composer, conductor, musician). A spiral forms growing outward, which is complementary to that of B), where people are ordered by their death date and grouped by role and completely different to C) where people are ordered by their honoring time and grouped by their role to highlight musicians that were honored early on by the City of Vienna.

Temporal inversion

Similarly, we have also explored how different approaches could be combined together to mitigate very dense areas, and overlaps created by busy periods of time. This is an issue with radial visualizations as points closer to the center of the circle receive less drawing area compared to those that are placed at the boundary of the circle. This could potentially affect the perceived importance of objects and lead the users to wrong insights and hypotheses or skew the importance of entities in an unintended way. We experimented with inverting the direction of time and allowing the user to interactively change this setting depending on the period of time that is of interest (see Fig. 4.8) (related to *T1: Present and T3: Explore*).

Ordering & Grouping

Combinations of ordering and grouping can be used to detect similarities, differences, or patterns in event-based networks. Grouping can be used to position persistent entities, such as people, organizations, or locations, with similar properties in the same sector and can be further combined with ordering criteria that would reorder the rays in each sector according to some metric or criteria. Ordering and grouping can be used separately or combined to explore and investigate patterns that emerge under certain configurations or to explore if different groupings exhibit more similarities or more differences (related to *T2: Compare and T4: Identify*).

Fig. 4.9-A, B, and C show three different ways to order and group people, and how they affect the visual subject. In each case, different trends stand out. In Fig. 4.9-A people are ordered by their birth date and grouped by their role (composer, conductor, musician). A spiral forms growing outward, which is complementary to that of Fig. 4.9-B, where they are ordered by their death date and grouped by role. In the latter, the spiral signifies a ceiling, the limit of one's life. It is much easier to identify people who are alive in the second case, as all people who are still alive will form a contiguous arc. From these groupings and orderings, we can see the average period of activity for the different roles and when this is put into historical context it can show shifts in musical motifs and trends. Additionally, the year 1945 (denoted by the dark gray circle) is used by our domain experts as a baseline for comparison to separate the data and we can see the difference between the types of events and their frequency before and after the end of World War II. Another insight that can be gained from this kind of grouping and ordering is that earlier on the bulk of the events related to people happened after their death as opposed to later periods of time. This implies that after the end of World War II the City of Vienna started honoring musicians during their lifetime as opposed to after their death in a pursuit of developing its public image as a “Music City”. It is important to note that the data remains the same in all cases. By re-ordering and grouping them according to different criteria it is possible to obtain unique patterns that can tell us something about the underlying behavior of the data. This can also be used for other entities, for example, users can also explore the subject of locations, their occupancy, and the change of their thematic nature over time by using different grouping and ordering options. Another use case could be exploring organizations and what different events they have contributed to over the course of time relative to their political affiliation.

Details

As mentioned in Section 4.3.3, we also would like to facilitate in-depth exploration and support verification of data points (people, locations, events, etc.). In our approach, we achieve that by providing detail panels, where the users can explore the particularities of different entities, lookup their characteristics, and their relationships to other objects in the data. Our main objective with the detail panels was to engage users in learning new things and was meant as a way of answering questions that arose during the exploration and validation of the data. At the same time, we wanted the detail panel to provide an informative and descriptive interface for users to access the details of objects and explore related entities, including aspects of the data that are not visualized, such as descriptive texts and material sources (related to *T3: Explore and T5: Verify*). When an object is selected the detail panel opens up and the radial visualization is reconfigured to focus and highlight the current selection, which enables the exploration of the temporal context and provides details.

4.6 Evaluation

In this section we describe the methodology employed in the evaluation of our approach, we present the procedure we followed, discuss the results of our interviews, and summarize our findings highlighting the lessons learned along the way.

4.6.1 Procedure: Evaluation Setting

Our evaluation was designed mainly by domain experts in the spirit of a history exam, to be performed with the aid of Circular. In this regard, we would like to remark that the majority of tasks are phrased as questions rather than tasks in the traditional sense of VA research. Essentially, the participants were asked to present their answers to different questions by using our approach and to compare, explore, and identify particular elements of the visualization that were the focal point of the user study.

We conducted a small-scale user study with both domain experts and VA experts, that was structured as a task-based evaluation. Throughout the study, we encouraged the participants to think aloud [Lew82] as they performed tasks and to voice their thoughts and reasoning process along with feedback about interacting with our prototype.

We conducted the user study with six participants. Three of the participants were domain experts with little experience using visualizations to solve tasks, but possessing domain-specific knowledge about the data. The other half of the participants were visualization experts with a more technical background but lacked knowledge in this specific application domain and the data itself. The sessions lasted around 60 minutes and were structured as follows: (i) onboarding and introduction to our approach; (ii) letting the users interact with and get used to our approach by performing some exploratory tasks; (iii) task-based evaluation; (iv) general feedback. There were a total of 18 different tasks belonging to five task categories (see Section 4.3.3 for more information and examples on the tasks).

As our approach is situated at the intersection of multiple disciplines, it is not trivial to formally evaluate it. Due to the fact that most of the tasks are not analytical, it becomes even more difficult to decide on an evaluation methodology as tasks are not a well-defined subject [Sch+19]. Common metrics that are used to formally evaluate and prove the efficacy of approaches in well-established and defined disciplines are difficult to apply to domains such as digital humanities. We believe that metrics, such as measuring error rates or time per task are not relevant for determining the usefulness of such approaches. Furthermore, our intent was not to conduct a comparative evaluation with other representations of the same data (i.e., rectilinear timeline visualizations or other traditional network layout representations) as these were not in line with our evaluation interests. Our main aim was to investigate the capability of radial representations for representing event-based networks and to assess how domain and visualization experts perceive it in order to identify the benefits and drawbacks of our approach. For this purpose, we investigated alternative evaluation methodologies, including the work of Klein et al. on sense-making models [KMH06a; KMH06b] and arrived at the conclusion that we would like to evaluate how well our approach supports the tasks outlined in Section 4.3.3.

In our evaluation, we used a simple qualitative ranking to identify issues that made it difficult for users to perform their tasks. We encoded each of the participants' answers as easy (E), medium (M), or hard (H). If the answering process was straightforward and the user could translate the question into a set of interactions, perform them, and identify the answer, this counts as an easy (E) answer. If the user had to try different approaches to reach the goal or there was something that caused confusion or was unclear, it counts as medium (M). If the user was stuck and the evaluators had to intervene and provide guidance, it is counted as hard (H). The encoding of the answers was done during each session by two visualization experts. After each session, there was a short discussion about the results of the participant to reach a final decision on the encoding. Additionally, we had a domain expert verify the correctness of the participants' answers and clarify any misconceptions about the data. There was little ambiguity observed when deciding between which of the categories to register, and the gathered results showed consistency among the different questions.

4.6.2 Discussion

In this section, we will discuss how each of the tasks was solved in the user-study along with the participants' feedback and personal opinions. We consider both the results of the domain experts and visualization experts. A general overview of how our approach performed for the different task categories can be seen in Fig. 4.10.

T1: Present: For the most part our approach provides a good overview of the data and allows for different ways to present the historical narratives, data, and specific details about different entities. In this task category we noticed that most participants managed to answer the questions with little to no difficulties, apart from two questions that were outliers, so we inspected these in more detail (*Q3 - Which themes are related to the events taking place at Stadthalle?* and *Q12 - In which district(s) did fewest Events take place?*) to determine the cause of the issues (see Fig. 4.10-T1). We expected the participants to present their answers to the questions in this task category by interacting with different components of our approach, specifically, the operations to filter, order and group data points. Through navigation methods, such as zooming, panning, and triggering on-demand detail views, we expected the participants to present the elements of interest in the visualization. We anticipated that the answers to the questions would become evident in the radial and timeline components of our approach. For the first question (Q3) the participants needed to identify the themes related to events happening at a specific location and then enumerate these. We observed that this turned out to be difficult for most users due to a usability issue. When selecting a location, the visualization is reconfigured to highlight the events taking place at that

Figure 4.10: The results of the user study. The bars represent the level of difficulty the participants experienced for each task category as a percentage (0-100%). The categories E (easy); M (medium); H (hard) represent a qualitative ranking of the performance of the participants for the questions from our evaluation. For the different tasks in the evaluation we can observe that our approach supports most tasks well (E), with some minor issues (M), and severe difficulties (H) were very rarely encountered.

location and hides interface elements, this in turn made it difficult for our users to identify exactly which themes were related to the events, some users attempted to access this information from the detail panel of each event and keep track of this information whereas some answered the question by listing the colors they observed along the ray of this location. The second question (Q12) involved altering the state of the visualization to display a different aspect of the data, specifically, grouping locations by district and then quantifying the number of events taking place in each grouping in order to gain an overview of which district had the most events organized.

Our findings are that these two questions were fairly complex as they involved keeping track of multiple details and associations throughout different views and states, which led some participants to confusion and affected their performance at this task. Overall, the evaluation results lead us to believe that our approach supports *T1: Present* because the majority of the questions were answered with ease. An additional observation we made is that some tasks were easier for our domain experts to accomplish because they had the advantage of possessing more in-depth domain knowledge so they could easily identify this information in the visualization and confirm what they already knew. Furthermore, we noticed that the domain experts spent more time exploring the different options and settings that Circular offers to reconfigure the visualization and got acquainted with it quite quickly.

T2: Compare: For the second task category the results of the evaluation lead us to believe that our approach performs better at compare tasks than present tasks (see Fig. 4.10-T2). Overall, the participants answered most questions with ease apart from some difficulties that we investigated more carefully. Our findings are that the main problem stems from the same two questions as the previous task (Q3 and Q12), where the goal is to compare quantitative information of groupings and identify the details of thematic changes over time and list these. The issues identified here were related to elements of the user interface being hidden during the selections of data points and the unfamiliarity with the set of options for grouping and ordering criteria we offer. This caused the participants to have to keep track of many details throughout the tasks in this category and increased their cognitive load. The domain experts did perform overall better and managed to answer the questions with no difficulty due to the fact that they invested more time, initially, to explore the different options and settings that are used to reconfigure the state of the visualization. We expected the participants to answer the questions in this task category by interacting with the different options in our approach for grouping and ordering data and also combining these to modify the state of the visualization. The use of different arrangement methods to reorganize elements of the visualization spatially should support the users in the comparison task. The aim of the participants is to configure the radial component in such a way as to better outline differences between categories of the data in order to detect changes that occur over time and compare these. In the general case, we discovered some limitations that impacted how users performed at questions including counting and grouping tasks. Overall, the results of our evaluation for task *T2: Compare* show that identifying objects of similar characteristics and comparing them is supported in Circular and users are able to successfully complete these tasks. The difficulties we discovered in the evaluation were related to counting and comparing the quantitative information of different groups of entities as this information had to be manually acquired by the participants, but the relative sizes of the sectors managed to convey a sense of this to the participants. As an improvement, we believe it would be best to either encode the result of the groupings and count of specific properties straight into the visualization itself (e.g., by having the numbers and percentages displayed in each grouping) or offer an additional view dedicated to the display of such information.

T3: Explore: The intent of this task was to provide support for accessing the details of each object, including any material sources that are related to it. These sources were gathered by our domain experts and were used to shape and structure the data. For our domain experts, it was very important to be able to see and explore the sources and various details that were associated with each object, including related entities. In our approach we provide a few different ways to explore the details of the data: (i) a detail panel that opens up when an object is selected and is configurable for multiple object types as they have different properties associated with different importance; (ii) a list view that users can use to explore a different perspective that depicts a more high-level representation of the data. For this task category, we expected the participants of the study to find the answers to the respective questions by filtering according to categorical attributes and navigating to the detail view in order to access and explore further information, including material sources (video and photographic material, audio recordings, and textual resources). By selecting elements of the visualization or by brushing specific periods of time to explore, the users should be able to explore the properties and relationships of elements and discover anomalous behavior (e.g., discontinuity of periodic events). We also expected more participants would make use of the list view that provides a high-level overview of the data that is currently selected, but this was not the case as most participants preferred using the radial component and detail panel to answer the questions.

For this category the results of our evaluation and user feedback show that our approach supports the *T3: Explore* task very well and that the participants felt that the solution provides suitable interactions for examining the details and intricacies of the complex historical data we are depicting. The difficulties (M) that can be seen in our findings (see Fig. 4.10-T3) stem from the fact that in our implementation when selecting individual data points, the visualization is reconfigured to highlight the selected data and the rest of the information fades away, which was a bit confusing for most participants. While, initially, we felt this was a playful interaction made to capture the participants' attention and interest, it seemed to be counter-intuitive for most. Overall, we observed that there were very few difficulties encountered in the questions belonging to this task category and most of them could be performed in a straightforward fashion.

T4: Identify: One of the major requirements (see Section 4.3.3) when designing and developing our approach was to enable users to see patterns and trends throughout the City of Vienna's history, including continuities and discontinuities of certain themes over time and how they are related to different people and/or locations. For the majority of questions in this task category, the participants managed to provide answers with little to no difficulties and this is also reflected in the results of our study (see Fig. 4.10-T4). We expected the participants to identify the persistent entities of interest (people or locations) by using different combinations of grouping and ordering options and observing their temporal developments (related events and themes over time). The goal for this task category is for the participants to identify targets or sets of targets that are to be further investigated to drill down to their properties and relationships. Identifying outliers or data points that exhibited interesting temporal developments is also important in this context and we anticipated this to be visible under certain configurations of the visualization. We expected the answer to each question in this task category to be evident in the radial component of our approach. The issues that the participants had with the tasks in this category were related to the questions, that were also associated with difficulties in the other task categories. The reason for these difficulties arose from the interactions to access the details of specific data points. These interactions enable the detail panel and hide legends and other parts of the visualization that are not part of the current selection, but provide additional information that is necessary to answer the questions. The participants expressed some frustration about the disappearing elements and this can be also observed with the increase in difficulty of the questions in this category (increase in the M and H categories relative to other tasks, see Fig. 4.10-T4).

Overall, the results from the evaluation indicate that our approach supports this task category fairly well despite some usability issues. Most questions were easily answered, but there were some difficulties with the more complex questions, requiring a longer path of interactions and keeping track of interim details to provide an answer. We believe that by improving some of the usability issues and making certain details more explicit we could achieve better support for the tasks in this category.

T5: Verify: The data that we used in our approach is modeled as an event-based network, shaped and scoped by our domain experts. The domain experts continuously modify data points and entities to better frame the data and their perspectives. Our dataset is the result of historical research conducted by experts, sampling key points and important figures, establishing narratives, and identifying the most prominent themes in the City of Vienna's history. For this purpose, it was very important to also provide support for validating and verifying the data that was entered and visualized. For our domain experts, this can be a cumbersome process as the data is manually entered and curated. Since most database solutions usually require a level of technical expertise and knowledge, validating the data and finding errors becomes a bit of a challenge. Furthermore, most database solutions generally do not provide any visual means to gain an overview and contextualize the data. Whereas when presenting the data in a visual manner to our domain experts the erroneous data became immediately obvious to them and supported them in resolving the inaccuracies and inconsistencies of the data. In this task category, we expected the participants to query the visualization for particular persistent entities based on their characteristics and utilize the radial and detail components of our approach to provide answers related to specific properties of those entities (i.e., dates, names, and relationships). We constructed the questions in this task category as a way to validate and verify the correctness of the data that is being depicted in the visualization. From the results of the evaluation and feedback from the domain experts, we can also conclude that Circular provides support for the tasks associated with *T5: Verify*. Any issues with the data immediately become obvious in the visualization and through the use of detail panels and interactions we offer users multiple views to identify and correct this information. In Fig. 4.10-T5 we notice that there were no difficulties encountered throughout the tasks in this category by the participants, but during the sessions we observed that there were some attempts at trying different approaches and paths to reach the answer for the same question and confirm the validity of the data being inspected, which is expected.

The tasks presented in this evaluation are low-level tasks, but we also consider the different ways that they can be combined together to form more complex paths of interaction and to support higher-level tasks as well. In this regard, we would like to draw parallels to the synoptic vs. elementary tasks introduced by Adrienko et al. [AA06]. This notion is further supported by the multi-level task typology we employ in our research, in that sensemaking is built upon combinations of such low-level tasks [BM13].

4.6.3 Feedback

All participants agreed that this was an interesting approach to explore linked historical data and offered an engaging interface to delve into the details of events, people, locations, and themes seeking changes over time. Specific attention was brought to the radial component as the participants stated that this was an aesthetically pleasing, compact, and interesting way of encoding this type of information. These statements also align with our initial assumptions that a radial visualization would be an engaging interface, which is also backed by existing literature [Bor+13; Hoh+20] (see Section 4.5.1). One of the domain experts mentioned that radial visualizations were something new to them and they were an interesting way of representing data. The interaction techniques that we designed and implemented were appreciated and fostered user engagement and drove the participants' curiosity to explore the data in more detail and discover new information. We observed that even after the evaluation session had concluded some participants spent additional time exploring the data and discussing topics that were of interest to them. Overall, the results of our evaluation lead us to believe that our approach achieves an interesting way of engaging users who would like to explore linked historical data and discover new insights.

According to the participants our solution provides a nice and compact overview of historical data. The general consensus is that it succeeds at representing both the relational and temporal information between disparate entities using appropriate metaphors and it enabled for exploration in multiple dimensions.

The participants also commented on the ability of our approach to show the progression and evolution of themes and patterns over space and time. One of the visualization experts who participated stated that our node-sizing could be considered a double-edged blade as increasing a node's size that is positioned closer to the circle's center would presumably cause even more overlaps, but it was also appreciated and considered interesting as the user could interactively change it based on their interests and explore events that are more connected to themes, material sources, people, or other types of entities.

There were also some drawbacks to our approach, including that it has a bit of a learning curve and some onboarding [Sto+19] or guidance [Cen+17] would be useful to get the participants better acquainted with the visualization and guide them towards interesting points in history. Furthermore, we identified minor usability issues throughout the evaluation, which made some of the questions in the study difficult to answer. In the current state of our approach interface elements are hidden when selecting data points to explore their details, which in turn caused difficulties for the participants of our study. Initially, this was intended as an engaging way to keep the focus of the users on their selection, but according to the results and feedback of the evaluation, this was not considered helpful or useful. The most notable functionality that was missing was the ability to navigate back and forth between different selections in the detail view alongside a history of interactions so that users could easily go to previous states of the visualization. Additionally, the participants suggested that we provide the ability to lock the temporal selection of the user when interacting with the different components and display a list of the events that are happening within that selection along with the people, locations, and themes they are related to. These features would be relevant for future work as quite some participants expressed that it would increase the usability of our approach and improve the ability to navigate the data. There were also a few comments about the data quality, completeness, and uncertainty, but these are out of the scope of our evaluation.

4.7 Conclusion and Future Work

In this paper, we presented our approach, Circular, for visualizing event-based networks in the domain of digital humanities. It is an interactive exploration environment that utilizes a radial layout to represent a large amount of linked historical research modeled as an event-based network that is embedded in spatial and temporal frames of reference. In Circular we put the spotlight on the temporal and relational aspects of the data and visualize event-based networks in a compact, aesthetic, and engaging manner. We provide users with multiple ways to slice the network based on their tasks and interests and also explore how grouping and ordering combinations change the network's topology along with what insights can be extracted from the visualization. We have evaluated our approach by conducting a small-scale user study with both domain experts and visualization experts that highlights the usefulness and uniqueness of our approach but also its limitations and drawbacks. For future work, other than improving upon the current limitations and usability issues that were identified, we would like to augment the topology of the network with more information, such as historic events and sources that add an additional layer of complexity to the network but also provide more context and narrative to the data. Additionally, we believe implementing semantic zooming would be an interesting approach to control the information density based on the granularity specified by the user and offer a solution to the clutter and overlaps close to the circle's center.

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CHAPTER 5

On Evaluating Structural and Temporal Graph Encodings

This paper first appeared in the Proceedings of the International Symposium on Graph Drawing and Network Visualization, 2022 (see [Fil+22a]) and was invited for publication in Transactions of Visualization and Computer Graphics, 2023. IEEE TVCG 2023 ©. Reused with permission (see [Fil+23]).

Title: On Network Structural and Temporal Encodings: A Space and Time Odyssey

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Context: In the following publication, we explore the design space of dynamic network visualization both in terms of the graph structural encodings as well as the graph temporal encodings.

We evaluate the differences between the visual representations by conducting a two-fold evaluation. The first is a quantitative user study, where we employ statistical analysis and hypothesis testing. In the second study, we applied a qualitative heuristic evaluation using domain experts, where the focus is on the ability of the visual representations to support insight generation.

We summarize the benefits and drawbacks of each combination of techniques and contextualize these based on the qualitative feedback of both studies considering the participants' preferences, confidence, response times, accuracy, and insights. We summarize the limitations of our studies as well as outline the lessons learned and propose recommendations for dynamic network visualization techniques.

In terms of network visualization both the studies used different datasets with a strong focus on the dynamic nature of the elements. In the first study, we artificially generated small-scale random networks exhibiting properties common to real-world (social) networks. We augment each of these with four time slices and model the dynamics as edge removal and addition. In the second study, we used a larger real-world co-publication network [Ise+17] with 8 time slices, where both the nodes and edges varied through time in terms of appearance and disappearance.

5.1 Abstract

The dynamic network visualization design space consists of two major dimensions: network structural and temporal representation. As more techniques are developed and published, a clear need for evaluation and experimental comparisons between them emerges. Most studies explore the temporal dimension and diverse interaction techniques supporting the participants, focusing on a single structural representation. Empirical evidence about performance and preference for different visualization approaches is scattered over different studies, experimental settings, and tasks. This paper aims to comprehensively investigate the dynamic network visualization design space in two evaluations. First, a controlled study assessing participants' response times, accuracy, and preferences for different combinations of network structural and temporal representations on typical dynamic network exploration tasks, with and without the support of standard interaction methods. Second, the best-performing combinations from the first study are enhanced based on participants' feedback and evaluated in a heuristic-based qualitative study with visualization experts on a real-world network. Our results highlight node-link with animation and playback controls as the best-performing combination and the most preferred based on ratings. Matrices achieve similar performance to node-link in the first study but have considerably lower scores in our second evaluation. Similarly, juxtaposition exhibits evident scalability issues in more realistic analysis contexts.

5.2 Introduction

A "graph" or "network" (the two terms will be used interchangeably in this paper) is a data structure representing a set of nodes and their relationships, represented by edges between them. Due to its flexibility and relevance to several application domains, the problem of how to visually represent such a structure has been attracting interest since the 1960s [Tut63]. With the turn of the millennium, Herman et al. [HMM00] first introduce a shift of perspective from "graph drawing" to "network visualization", mentioning how the latter deals with much larger graphs than before—a necessary adaptation to the rise in size of scientifically interesting networks. Around the same time, the increased availability of time-dependent datasets contributed to the increase of research interest in dynamic network visualization [Bec+17]. The paradigm shift from static to dynamic data represented a natural and necessary step forward to tackle the upcoming challenges presented by large and fast-evolving datasets, effectively anticipating and preparing for the advent of the "Big Data" era. Thanks to its constant evolution and growth for the last 20 years, dynamic network visualization is nowadays considered a mature and thriving field of research [Bec+17].

The visualization of a dynamic network can be considered, at its core, the problem of concurrently representing the graph topology, that is the underlying network structure, along with the temporal facet [HSS15]. Kerracher et al. [KKC14] introduce a design space for dynamic network visualization techniques along these two dimensions: the network *structural representation* (topology) and *temporal encoding* (dynamics). This two-dimensional design space is expressive enough to characterize the majority of existing dynamic network visualization approaches.

There is extensive literature on studies designed to evaluate different graph representations for typical exploration tasks on static networks (see, e.g., [KEC06; OJK19]). Similar studies have been conducted for dynamic approaches, however, they compare different temporal encodings for the same structural representation (node-link diagrams for the most part, see Section 5.3). This also comes as a consequence of the limited number of dynamic network visualization approaches that have matrices as their base graph representation [Bec+17] (see, e.g., [HF07; RM14]). Furthermore, existing user studies in this context also incorporate simple interaction methods to support the network exploration (see, e.g., [AP13a; OJK18]) Empirical evidence about the performance and preference for different dynamic network visualization approaches in our design space is still scattered over different studies, experimental settings, procedures, different interaction implementations, and tasks. This has two consequences. On the one hand, it makes it more difficult to assess and compare the different techniques in our design space, even on the same set of graph analysis tasks. On the other, it is not straightforward to identify which aspects of such techniques to select when building a network visualization system for the analysis of a dynamic real-world dataset.

Our Contribution. In this paper, we contribute a two-step evaluation to fill these gaps in the literature. First, we design, conduct, and discuss the results of a user study aimed at comparing different network structural representations, temporal encoding techniques, and interactions (Section 5.6). Second, we refined a set of visualization approaches based on the outcomes of the first study. We then evaluate these in a heuristic-based qualitative study with visualization experts to extract knowledge and obtain insights in a realistic analysis scenario (Section 5.7). Finally, we discuss the findings and takeaways across both evaluations (Section 5.8) and derive an overall conclusion (Section 5.9). We outline the following contributions resulting from our two-step evaluation:

- We assessed the accuracy, response times, and preference of node-link diagrams and adjacency matrices for dynamic graph tasks and concluded that the former performs better for high-level tasks (overview, estimation, higher-level structures), whereas the latter was more accurate for low-level tasks (identifying nodes, edges, and timeslices).
- Our study shows the influence that interaction techniques have on response times and accuracy regardless of the network's structural representation. Providing interactions significantly increases the response times, however, at the same time it increases the accuracy of the responses.
- The study results suggest that animation and animation with playback significantly outperformed the other techniques in our design space consistently.
- Our results show that node-link diagrams are the most preferred structural representation, as well as the one associated with the highest accuracy and lowest response times from both studies.

A preliminary version of this research has been presented at the International Symposium on Graph Drawing and Network Visualization (GD) 2022, selected by the Program Chairs and invited for publication in TVCG. This extended journal version contains a revised writing and experiment description, a new qualitative evaluation, and a discussion of takeaways from both studies.

5.3 Related Work

We outline recent related studies conducted along the two dimensions of the design space introduced by Kerracher et al. [KKC14].

Structural Representations. In graph drawing literature, several studies assess the readability, task performance, and effects of aesthetic criteria on human cognition of different graph structural encodings (e.g., [Ben+07; Gia+22; Ren+19; GFC04; OJK18; OJK19; Pur98; PCA02]). Okoe et al. [OJK18; OJK19] conduct comparative evaluations between node-link and matrix representations on a large scale ($\sim$ 800 participants). Their results show that node-link diagrams better support memorability and connectivity tasks. Matrices have quicker and more accurate results for tasks that involve finding common neighbors and group tasks (i.e., involving clusters). Concurrently, Ren et al. [Ren+19] conduct a large-scale study ($\sim$ 600 participants) comparing the readability of node-link diagrams against two different sorting variants of matrix representations on small to medium social networks ($\sim$ 50 nodes). Their findings do not differ significantly from the ones by Okoe et al. [OJK18], suggesting that node-link provided a better implicit understanding of the network, with lower response times and higher accuracy than matrices. However, the gap between the two tended to reduce as the size of the graph increased. Abdelaal et al. [Abd+23] conduct a crowd-sourced study ($\sim$ 150 participants) where bipartite layouts are compared with node-link and matrix-based representations on their performance on overview tasks for large graphs ($\sim$ 500 nodes) and detail task for smaller ones. Their findings suggest that matrices are the most reliable across all tasks, also providing evidence of the positive effect of bipartite networks in exposing the network structure.

Temporal Encodings. One of the most studied problems concerning dynamic network visualization, is the ability of participants to retain a “mental map” of the graph while investigating its evolution [APP11; AP13b; AP13a; AP16; PHG06]. Archambault and Purchase investigate the effect of drawing stability on the node-link graph representation coupled with animation and small multiples [AP13a; AP16]. Drawing stability proved to have a positive effect on task performance, with animation able to improve over the timeline in low-stability scenarios. Ghani et al. [GEY12] investigate the perception of different visual graph metrics on animated node-link diagrams. Results suggest that animation speed and target separation have the most impact on performance for event sequencing tasks. Linhares et al. [Lin+21] compare four different approaches for visualization of dynamic networks, namely the Massive Sequence View [Elz+13] (timeline-based), the Temporal Activity Map [Lin+17], and animated node-link and matrix diagrams. While all techniques reached satisfactory results, the animated node-link was the favorite choice of the participants. Even though matrix-based approaches are included in this study, it does not exhaustively cover all the possible combinations of our design space. Filipov et al. [FAM21] conduct an exploratory study comparing different combinations of structural and temporal representations. The results suggest that tasks with matrices were completed quicker and

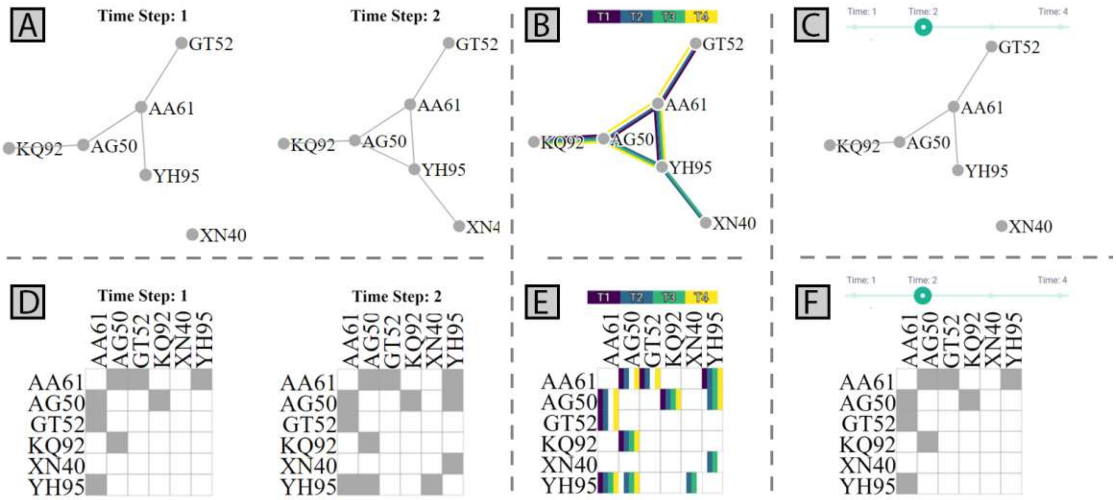

Figure 5.1: Network structural and temporal encodings: Juxtaposition (A,D), Superimposition(B,E), and Animation with Playback Controls (C,F)

more accurately, the participants preferred matrices with superimposition, and juxtaposition was among the least preferred approaches. However, these results comparing matrix-based approaches with node-link diagrams and their temporal encodings require further confirmation and formal statistical analysis. Overall, related literature shows that the perception of different temporal encodings has been mainly investigated on node-link diagrams, with few papers focusing on the other combinations of structural and temporal encodings. In this sense, our paper constitutes an effort in understanding whether the differences between node-link and matrix representations still hold in a dynamic scenario, what is the efficacy of the temporal representations, and how effective (and how important) is it to include interactions when designing such approaches.

5.4 Dynamic Graph Visualization

We refer to a dynamic graph Γ as a sequence of individual graphs each one representing its state at a specific point in time: $\Gamma = (G_1, G_2, ..., G_k)$; we denote the individual G_x as a dynamic graph *timeslice*. We now briefly describe the different structural and temporal encodings, detailing their implementation in our experiments.

5.4.1 Network Structural Representations

The structural dimension focuses on the challenges of laying out a graph to visually present the relationships between elements in an understandable, accurate, and usable manner [KKC14].

Node-Link (NL) diagrams present the relational structure of the graph using lines to connect the entities that are depicted using circles, whose coordinates on the plane are computed using specialized algorithms. In our study, we compute the NL layouts using the force-directed implementation of *d3js* [BOH11] by aggregating all the available timeslices into one graph for which a drawing is computed. This process of *aggregation* [BM11] is simple to implement and provides a stable layout throughout the sequence of timeslices, at the expense of the quality of individual layouts. In this paper, we assume to have the complete time sequence available, therefore the drawing can be computed based on both *past* and *future* timeslices (an *offline* drawing approach [DG02]). This is opposed to an *online* scenario where the layout can be computed only based on *past* timeslices (e.g., when dealing with streaming data). We refer to the following for a broader discussion on dynamic network layout algorithms [AMA22; Bau+01; Bec+17; BC03; Col+03; CCM17; Ert+03; Ert+04; SAK18].

Adjacency Matrices (M) visualize the network as an $n \times n$ table. A non-zero value in the cell indicates the presence of an edge between the nodes identified by the corresponding row and column. In our study, we order the rows and columns lexicographically according to the node's label. This ordering would appear immediately familiar to the user without the need for further onboarding and has been used in previous studies [GFC04]. More advanced reordering methods exist [Beh+16], however, matrix reordering is still under-investigated in a dynamic context and we include this aspect in our secondary study design.

5.4.2 Network Temporal Encodings

In dynamic networks, the temporal dimension plays an important role in the analysis process and requires special attention to enable effective exploration and a better understanding of the behavior of the network [MA14].

Superimposition (SI) encodes the temporal dimension of the network in the same screen space by overlaying the timeslices (see, e.g., [BC03; Ert+04]) or making use of explicit encoding (see., e.g., [Gle+11; JE12]). In our study, we represent the temporal information in SI using colorblind-friendly color palettes [Gar+]. In NL, we generate multiple parallel edges between the nodes, one for each timeslice where the edge is present, and color-code them individually. In M we subdivide each cell uniformly into rectangles, each representing the existence of that edge during that timeslice, which is colored similarly (see Figure 5.1 B-E).

Juxtaposition (JP) represents the graph's temporal dynamics as distinct layouts, each with dedicated screen space, similar to the small multiples approach by Tufte [Tuf83] (see Figure 5.1A,D). In our study, we generate one diagram per timeslice and arrange them adjacent to each other.

Animation with Playback Control (ANC) uses a time slider to control the state of the animation and move to any of the available timeslices in no particular order (see Figure 5.1-C,F). The transition always happens between the start and end time slice that is selected, intermediate ones are not considered. This enables a more fine and controlled exploration and analysis compared to animation, where speed and time progression are typically fixed.

Auto Animation (AN) depicts the change of the graph over time as smooth transitions between subsequent timeslices. Differently from ANC, with AN it is not possible to skip forward or navigate backward in time and it automatically goes over each of the timeslices in a sequence.

5.5 Evaluation Process

In order to understand the effect on performance and preference that different combinations of network structural and temporal encoding have on graph temporal tasks, we construct a two-step evaluation process.

In our first study (see Section 5.6), we opt for a controlled user study which would exhaust all possible combinations of our design space on the same predefined set of tasks. We also evaluate the impact of simple interactions by introducing their presence as a study condition. We perform a complete statistical analysis of the quantitative results of the study (i.e., response times and error rates), which we use to test our research hypotheses.

In the second study (see Section 5.7), we move beyond low-level benchmarks for predefined tasks and investigate how our proposed visualizations can be used to gain insights about a real-world dataset [SND05], also addressing some of the most important limitations that we identified in our first user study. We aim to explore the capabilities of the techniques in the understanding of data and insight generation, by performing a heuristic evaluation meant to determine and compare the "value" of each visualization following the methodology proposed by Wall et al. [Wal+19]. We refine our initial selection of techniques by considering the results of the statistical tests as well as other qualitative information from the previous study (i.e., users' feedback and preferences) narrowing them down to two temporal encodings for both structural representations in our design space, for a total of four techniques (out of the initial 16). Moreover, we consider the feedback to enhance the interactions available for each of the techniques, simulating the use of more advanced visualization tools in the context of a real analysis scenario.

In the following sections, we present both studies in detail, discussing the study design, results, and limitations. We summarize the lessons learned in Section 5.8.

5.6 Study 1: User Evaluation

In this section we present the structure of our first study, and describe the study design, including our tasks, research hypotheses, stimuli, and procedure.

Tasks. The tasks used in our experiment are available in Table 5.1. We picked one task for each category of temporal feature in the taxonomy proposed by Ahn et al. [APS14], namely, *Individual Temporal Features* (**T1**), *Rate of changes* (**T2**), and *Shape of changes* (**T3**). We selected the most common tasks referenced in the taxonomy and included in our experiment these tasks for both low- (nodes and edges) and higher-level (cliques) entities.

Research Hypotheses. We base our research hypotheses on the proposed tasks and we report them in Table 5.2. The research hypotheses **H1**, **H2**, **H4**, and **H5** are derived from the observations and results of our previous exploratory study [FAM21] (see also Section 5.3). While the focus of this experiment is centered around the *visual* encoding combinations within our design space, **H3** is intended to investigate the effects of common interaction techniques in this context. We conjecture that these increase response times over visual inspection alone without a significant impact on accuracy. This research hypothesis is determined empirically from previous work [FAM21] where

T#	Low-level	High-level
T1	At which time step is the relationship between `{source}` and `{target}` introduced for the first time?	At which time step does the clique between `{nodes}` appear for the first time?
T2	Sum up the changes (additions and removals) of `{node}`'s degree across all time steps.	Calculate the change of the clique's size between `{nodes}` across all time steps.
T3	At which time step does the node `{node}` have its highest degree?	Consider the set of nodes `{nodes}`. Find the size of the largest maximal clique across all the time steps between the given nodes.

Table 5.1: The test questions (trials), per task (rows) and entity type (columns).

participants performed tasks on dynamic network visualizations within a similar design space as the one in this paper *without* the support of interaction methods. We assume that providing interactivity would have an impact on the response times, due to the time needed for the users to accept and then adopt it. Similarly, based on prior observations, we also assume that the benefit of providing interactions will not be associated with a significant increase in the accuracy of the tasks. In **H4** we conjecture that following the evolution of a cluster or clique is more difficult with M compared to NL. This assumption is derived from the results of our previous study where participants focused on low-level tasks (i.e., individual nodes and their temporal features [APS14]). Since in this study, the participants must track several elements at once, we expect this would be easier to achieve with NL as the nodes are drawn closer together, compared to M.

5.6.1 Interactions

The interactions we implement are meant to support network exploration. The following apply regardless of the temporal encoding: (i) zooming and panning (both for M and NL); (ii) hovering over a M cell highlights its corresponding row (from the left) and column (from the top); (iii) in NL, nodes can be moved by dragging in order to de-clutter some denser areas of the drawing. Moreover, for AN only and regardless of the structural representation, the time between consecutive timeslices can be increased (7 sec maximum) or decreased (1 sec minimum). This selection should not favor any specific combination of structural and temporal encoding techniques over the others. Zooming, panning, and node rearrangement are commonly available in graph exploration software, like *Gephi* [BHJ09]. M mouse-over was also used by Okoe et al. [OJK18].

H #	Research Hypothesis
H1	M have lower response times and higher accuracy for all tasks compared to NL diagrams, regardless of the temporal encoding.
H2	From all temporal encoding techniques, SI has the lowest response times and highest accuracy, regardless of the structural representation.
H3	Providing interaction techniques increases the response times but not the accuracy.
H4	M have lower response times and higher accuracy for tasks on low-level entities and NL diagrams have lower response times and higher accuracy for tasks on higher-level entities, regardless of the temporal encoding.
H5	The combination M+SI results in the lowest response times and highest accuracy compared to other combinations of network structural and temporal encoding.

Table 5.2: The research hypotheses that were evaluated in our experiments.

AN speed could also be manipulated in the study by Archambault and Purchase [AP13b].

5.6.2 Experiment Setting

Stimuli. We generated 24 different scale-free random [Bol+03] graphs ($35 \leq |V| \leq 45, 46 \leq |E| \leq 71$) with the *NetworkX* python library [HSS08; HC20]. We chose this category of networks as they resemble real-world data examples of scientific interest (e.g., the worldwide web, authors' co-citation networks [AB02]). We augmented each graph with 4 timeslices as follows. A single timeslice was created from the input graph by randomly deleting edges; the process is repeated for each of the 4 required. Then, they are arranged to form a sequence (in no particular order), so that we simulate the temporal dynamics of edge addition/removal. Finally, we split the datasets into two different types: 12 graphs with cliques and 12 without. As the input graphs did not naturally include cliques, they were introduced artificially when necessary. 5 random nodes in each graph were randomly selected, and then new edges were added to form the clique in one or more random timeslices (simulating the clique forming and breaking). The size of the graphs is comparable with the majority of empirical studies on graph visualization [Ren+19; Yog+18].

Trials. Each of the tasks is applied to all combinations of structural and temporal encodings of interest in our study (see Section 5.4) resulting in 48 unique trials: $3(task\ types) \times 2(entity\ types) \times 2(network\ encodings) \times 4(temporal\ encodings)$. The entity types refer to either low-level (node or link) or high-level (cliques or clusters) components of the network [APS14]. The order of the trials during the study is randomized in order to mitigate learning effects. The participants take part in the online experiment by completing the trials prepared using SurveyJS [Sur].

Study Design. Our experiment follows a between-subject arrangement: all participants complete the same entire set of 48 trials on the same graphs but are exposed to one of two conditions, either *without* (Group *A*) or *with* (Group *B*) the support of the interactions discussed in Section 5.6.1. Participants were randomly assigned to the two groups, with the majority (75%) in Group *B*. This subdivision is justified by the fact that only one of our research hypotheses (**H3**) requires participants *not* to take advantage of interactions. Therefore, we designed the experiment to have a higher number of participants with interaction support. We estimated a split of 25% over the expected number of participants, as a sufficient size for Group **A** to obtain statistically significant results, see Sections 5.6.3 and 5.6.4 for further details. For each trial, we ask the participant to provide a confidence score of their answer using a 5-point Likert scale (1 least confident - 5 most confident). At the end of the experiment, the participants express their thoughts in a text field (i.e., "Please enter any personal comments") about the encoding combinations they encountered and rank them on a 5-point Likert scale (1 least preferred - 5 most preferred).

Participants. For our study, we enrolled students who were part of a graduate course on information visualization design. To ensure that participants had a sufficient level of knowledge on the topic, we gave an online introductory lecture about the visualizations and the experiment modalities. Participation was optional and its performance did not impact the final grade of the students. The online setting was necessary to guarantee a sufficient number of participants while ensuring a safe social-distancing protocol. However, this also meant giving up control of the experiment environment (i.e., no control over the participants' setup, devices used, and resolution).

5.6.3 Analysis Approach

We received a total of 76 submissions from as many participants, of which we removed 8 that either recorded anomalous response times (way too quick or long) or incorrect answers to control questions, suggesting participants trying to "game" the study. This resulted in a final set of 68 valid submissions that were used as the basis of our analysis. We provide further details as supplemental material.

For each question of our study, we collected the participants' answers, their corresponding response times, and confidence values. We ignored the group subdivision (Group *A* and *B*) for research hypotheses that did not focus on the presence of interactions in the visualizations (all except **H3**, see Section 5.6), as ANOVA tables do not show a statistically significant interaction effect between the independent variables for **H1**, **H2**, **H4**, **H5** (for more information we refer to [Fil+22b]).

We conduct our analysis as follows, supported by Python libraries for statistical analysis [Har+20; Val18; Vir+20]. We consider the structural and temporal encoding, the task type, entity type, and the groups (Group *A* and *B*) as *independent variables*, the response times and accuracy are taken as *dependent variables*. As the group subdivision is not even (25-75), we choose methods that are robust against these unbalanced designs [BEW15; Bor13; HS16; WW05]. For each of the

H#	Groups	MWU	T-Test	Binomial
H1	*(NL T1) vs (M T1)*	0.0104*^{b}	<0.001***^{b}	0.0013*^{b}
	(NL T2) vs (M T2)	0.1579	<0.001***^{b}	0.9313
	(NL T3) vs (M T3)	<0.001***^{b}	<0.001***^{b}	0.0022**^{b}
H2	*(SI) vs (JP)*	<0.001***^{b}	0.1065	0.166
	(SI) vs (ANC)	0.8662	0.1429	0.0883
	(SI) vs (AN)	0.2766	0.7751	<0.001***^{b}
H3	*(Grp A) vs (Grp B)*	<0.001***	<0.001***	<0.001***
H4	*(M Low) vs (NL Low)*	<0.001***^{b}	0.1392	<0.001***^{b}
	(M High) vs (NL High)	<0.001***^{b}	<0.001***^{b}	0.4321
H5	*(M+SI) vs (M+JP)*	0.0056**	0.2567	0.2424
	(M+SI) vs (M+ANC)	0.6301	0.2989	0.0261
	(M+SI) vs (M+AN)	0.2766	0.6328	0.0646
	(M+SI) vs (NL+SI)	0.0038**^{b}	<0.001***^{b}	0.449
	(M+SI) vs (NL+JP)	<0.001***^{b}	<0.001***^{b}	0.1389
	(M+SI) vs (NL+ANC)	0.0088	<0.001***^{b}	<0.001***^{b}
	(M+SI) vs (NL+AN)	0.0331	<0.001***^{b}	<0.001***^{b}

Table 5.3: The results of the statistical test (p-values) for each research hypothesis. We mark the cells with * if $p < 0.05$, ** if $p < 0.01$, *** if $p < 0.001$. If multiple comparisons are performed, ^{b} indicates the Bonferroni correction [Bon36].

research hypotheses, we decomposed them into simpler hypotheses and executed multiple null hypotheses tests (see groups in Table 5.3) to find evidence for or against our research hypotheses. For multiple group comparisons, we took countermeasures by using the Bonferroni corrected alpha significance levels [Bon36]. For the analysis, we consider and visually inspect response times and accuracy (number of correct answers ÷ total number of answers). To remove outliers from the data before the analysis we employ the inter-quantile range (IQR) [RC93]. We set the IQR lower ($q_1 - 1.5 \cdot \text{IQR}$) and upper ($q_2 + 1.5 \cdot \text{IQR}$) bounds at $q_1 = 0.25$ and $q_2 = 0.75$ as the outlier cut-off boundaries. This resulted in 116 trials (or 3.43%) being detected as outliers and omitted from the analysis.

The task response times in our experiment are not normally distributed. To mitigate this, we perform a Box-Cox transformation [BC64]. Visual inspection of the quantile-quantile (Q-Q) plots confirmed a normal distribution of the transformed data. This allows us to run parametric tests, specifically, ANOVA (see [Fil+22b] for further information about the ANOVA tables) and T-tests [BEW15; Bor13; HS16; WW05]. The standard ANOVA and T-tests are robust against such skewed distributions [Bon60; Pos84; Sch+10], therefore, we rely on them for our analysis as they

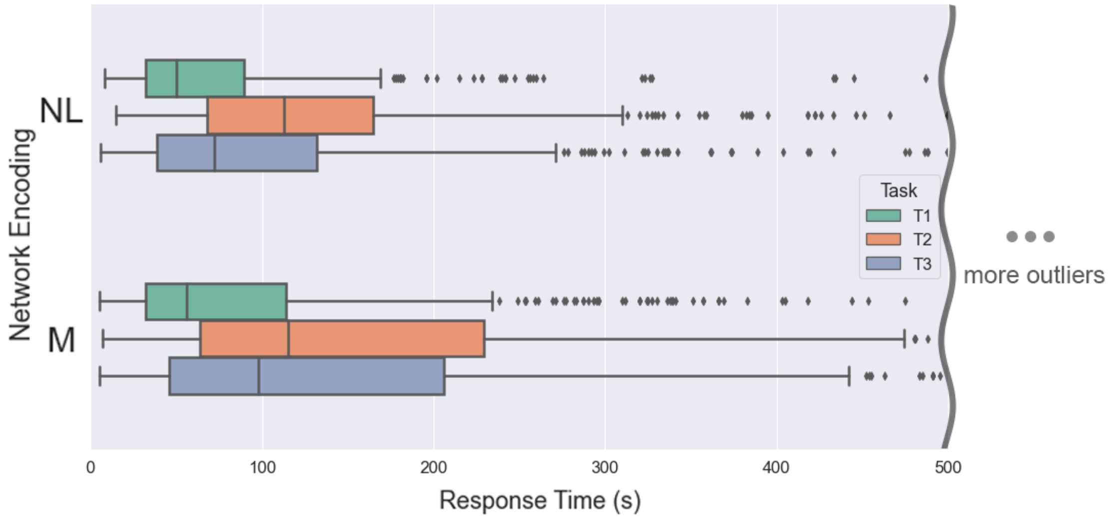

Figure 5.2: **H1:** Box plot of response times for NL and M per task.

both have more statistical power than non-parametric tests and detect significant effects if they truly exist. In the presence of a statistically significant difference (p-value < 0.05), we check, with T- and Mann-Whitney-U (MWU) tests, whether the significance held and visually explored the corresponding box plots to come to a conclusion. To evaluate our research hypotheses on accuracy, we also perform Binomial tests to detect statistical significance between the distributions.

5.6.4 Quantitative Results

H1. We presume, based on previous work [FAM21], that M would perform better overall compared to NL for all tasks. Figure 5.2 depicts differences in response times between M and NL diagrams per task type. The results (see Table 5.3) indicate that NL is generally faster and more accurate than M. However, when looking at their differences per task we discover for **T1** that NL is significantly faster than M (NL: 73.49s, M: 97.93s), whereas M proves to be more accurate (NL: 74.9%, M: 80.7%). For **T2** the T-Test detects a significant difference in response times between NL and M (NL: 133.41s, M: 194.20s), however, in terms of accuracy they both perform similarly (NL: 52.5%, M: 52.7%). For **T3** NL representations significantly outperform M in terms of response times (NL: 107.32s, M: 175.92s) as well as accuracy (NL: 65.7%, M: 59.4%). In summary, the results suggest NL generally has the lowest response times and higher accuracy compared to M for the proposed tasks. Thus, our results do not support H1.

H2. We assume SI to have the lowest response times and highest accuracy out of all the temporal encoding techniques. In our analysis, however, we do not detect any statistical significance in the comparisons shown in Table 5.3, with the only exception being JP, which has considerably lower response times than SI (see Figure 5.3). Concerning response times, JP has the lowest (118.32s), followed by AN (127.76s), SI (129.69s), and ANC (141.35s). We also ran a paired T-Test comparing the temporal encoding approaches to check for statistical significance between pairs out of our initial research hypothesis and detect a significant difference between JP and ANC.

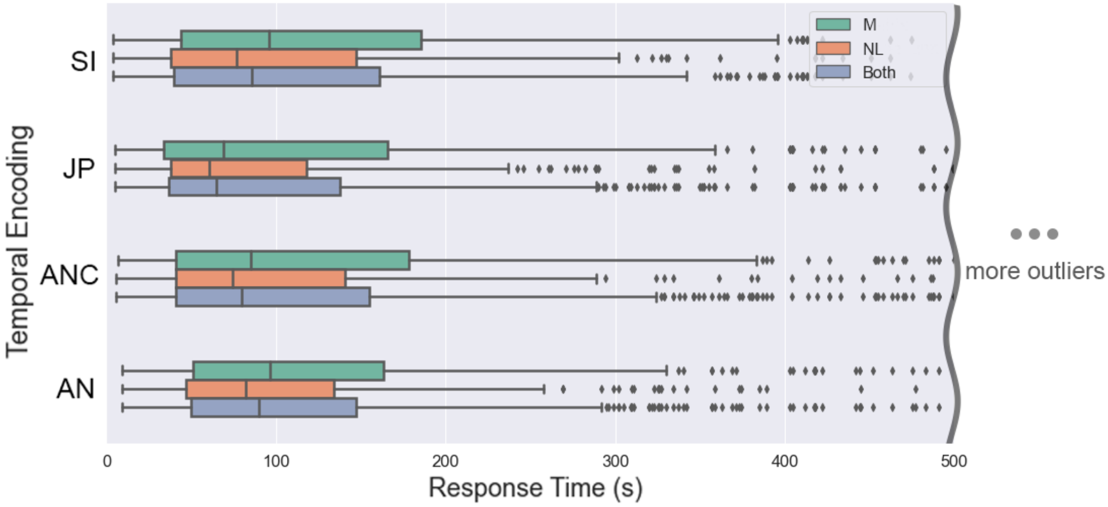

Figure 5.3: **H2:** Box plot of response times for temporal and network representations.

In terms of accuracy, we discover a significant difference between SI (62.1%) and AN (68.6%). Whereas, between SI and JP (64.45%) or ANC (59.13%) there is no significant difference. We conjecture these results to be due to the graph's size and limited number of structural changes over time, which might favor AN as it is possible for participants to follow all changes during animation. Our analysis shows no evidence to support H2.

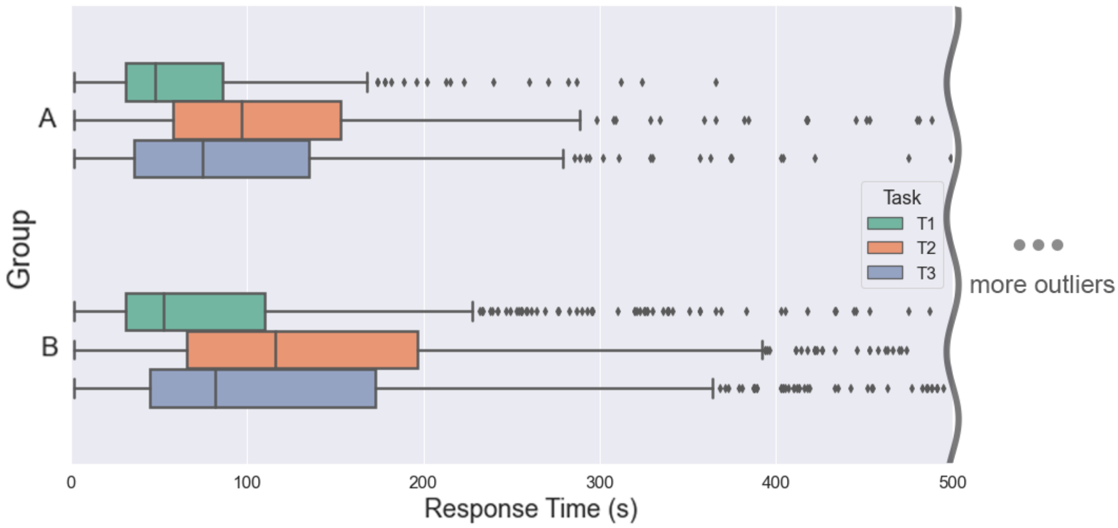

Figure 5.4: **H3:** Box plot of response times for interaction groups per task.

H3. We conjecture that providing interactions influences the response times but not the accuracy. Our tests detect a significant difference (see Table 5.3) in the response times between group A (no interactions; 114.76s) and B (interactions; 163.83s). As we initially assume, the group

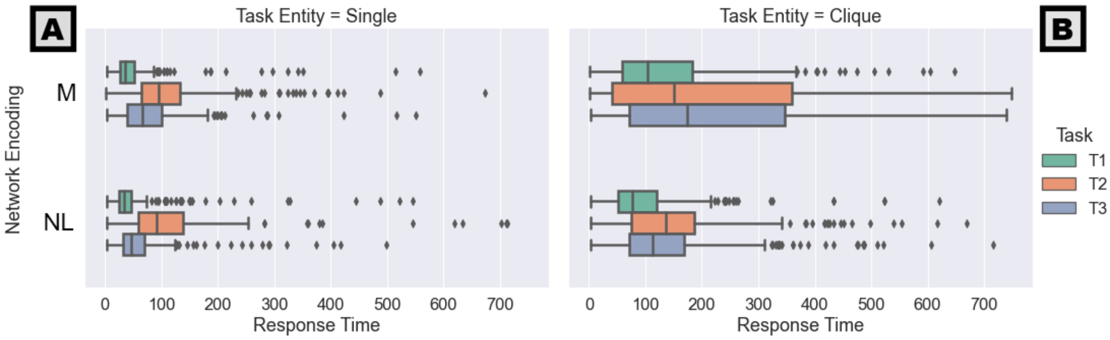

Figure 5.5: **H4:** Box plot of response times for (A) single entities and (B) cliques.

with interactions is much slower in completing tasks than the group with no interactions (see Figure 5.4), however, the difference in accuracy is unexpected. The group with interactions is significantly more accurate than the one without (group A: 58%, group B: 65%). This suggests that interactions indeed increase response times, but at the same time provide the participants with a much better understanding of the visualized graphs and corresponding network dynamics regardless of the temporal encoding, therefore, leading to more accurate responses. The analysis shows that our results support H3 in terms of response times, but not accuracy.

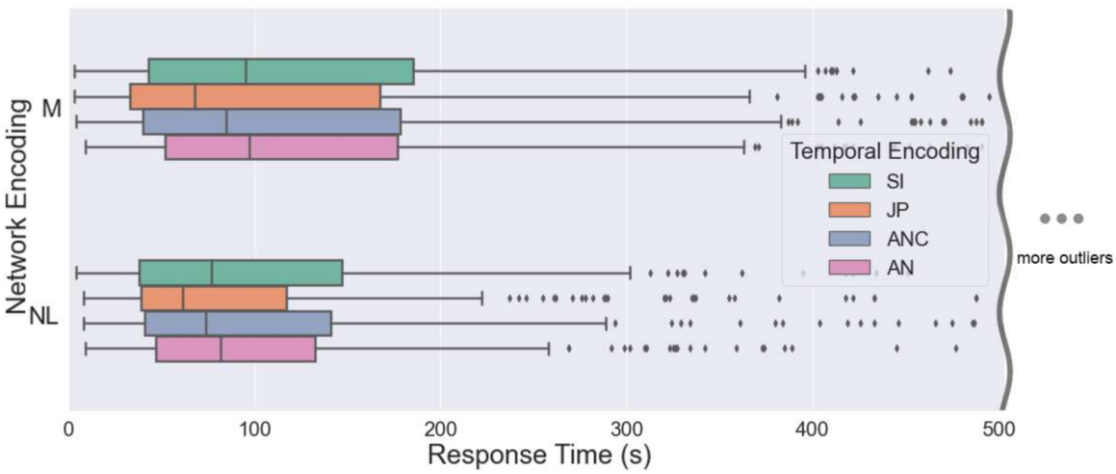

Figure 5.6: **H5:** Box plot of response times for temporal and network representations.

H4. We formulate this research hypothesis to evaluate whether the response times and accuracy of M and NL representations are affected by the type of target entity in a dynamic context (*low-level* - individual nodes and edges; or *higher-level* - cliques), regardless of the temporal representation. For low-level entities, we do not detect any significant differences in the response times between network representations (see Table 5.3), both NL and M diagrams perform similarly. The results (see Figure 5.5) for tasks on low-level entities indicate that M has lower response times (NL: 97.08s, M: 90.24s), whereas for higher-level entities NL has significantly lower response times (NL: 146.66s, M: 245.2s). However, in terms of accuracy M is significantly better than

NL for lower-level entities (NL: 82.1%, M: 86.4%). For the higher-level entities, NL and M representations perform quite similarly in terms of accuracy (NL: 42.1%, M: 41.3%) Based on these findings, the results suggest that H4 is partially supported.

H5. Finally, we want to assess the response times and accuracy for all possible combinations of network structural and temporal encodings. Our assumption is that M representations with SI temporal encoding have the lowest response times and highest accuracy. We compare M+SI to all other combinations of network structural and temporal encodings (see Figure 5.6). The results of the statistical tests yield significant differences in response times when comparing M+SI (154.53s) with M+JP (140.13s), NL+SI (105.25s), NL+JP (99.54s), NL+AN (108.8s), and NL+ANC (110.97s). Between M+SI (154.53s) and M+ANC (168.87s) and M+AN (160.62s) there is no significant difference in response times (see Table 5.3). In terms of accuracy, we detect statistically significant differences between M+SI (61.1%) and NL+ANC (51.8%) and NL+AN (71.4%). Whereas, the other combinations do not differ enough to warrant significance: M+JP (64%), M+ANC (66.4%), M+AN (65.5%), NL+JP (64.6%), and NL+SI (62.9%). From these results, the most balanced combination in terms of response times and accuracy is NL+AN followed by NL+JP. Therefore, we find no evidence supporting H5.

5.6.5 User Ratings and Feedback

We collect the participants' ratings per combination of network structural and temporal encoding along with textual feedback pertaining to their preferences and experience during the experiment (see Figure 5.7). There are no major differences in the preferences between the SI and JP encodings; ANC is the most preferred temporal encoding when coupled with an NL base representation. The NL representation is generally the most preferred approach, regardless of the temporal encoding. In terms of the participants' confidence, we observe that most participants seemed to be fairly confident in their answers across all approaches (see Figure 5.8). Most notably, the participants were most confident with NL+JP, followed by M+ANC, NL+ANC, and M+JP. There is general consensus that NL+SI was a very cluttered combination, whereas for M it performed a lot better and was easier to understand ("*SI was really confusing for some of the NL tasks but really useful for many of the M tasks*"). This is presumably due to the clutter generated by parallel edges crossings that occur in NL diagrams, which does not affect M. As in previous tudies [FAM21], the feedback on JP outlines that it requires participants to split their attention between multiple views in order to compare the temporal information. The ANC approach was preferred by the study participants for its flexibility due to the additional controls (i.e., time slider). AN was not considered to be a very good temporal encoding technique with the feedback being consistent across structural representations. Some participants commented that they needed to "*screenshot every timestamp to look at the different connections between the nodes*" and wait to watch the whole animation from the beginning. NL+AN, therefore, appears to be the least practical of the approaches, however, it also provides the best results. We conjecture this to be due to the size of the graphs and the number of structural changes occurring. M+AN is the lowest rated by the participants. The general consensus for AN is that it was difficult to keep track of the changes occurring between the nodes, requiring the viewer to memorize node positions and labels incurring a high cognitive effort to complete the tasks. Despite the aforementioned drawbacks,

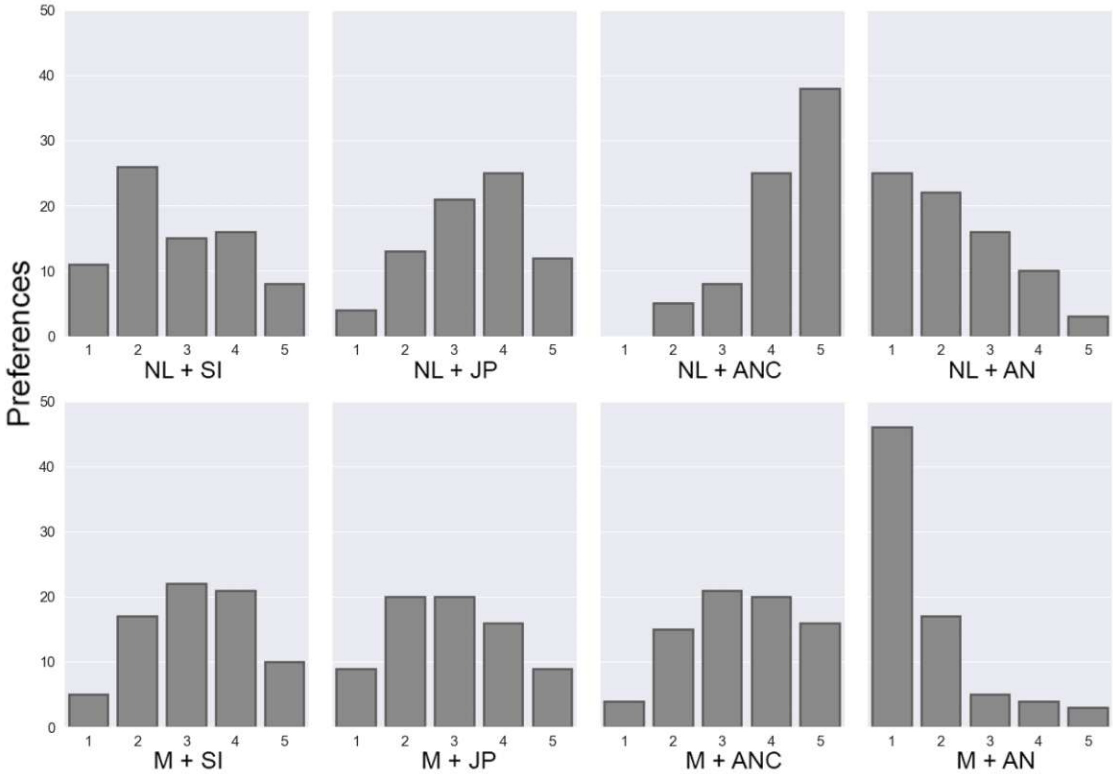

Figure 5.7: Preferences per network and temporal encoding on a Likert scale (1-5).

AN scales better to a larger amount of timeslices compared to SI and JP. Finally, the group with interactions had a better experience overall compared to the group without. The majority of the members of this group explicitly requested interactions to be implemented, supporting our findings concerning H3.

5.6.6 Limitations

In this experiment, the **size** of the graph was not considered when preparing the stimuli. Small graphs were chosen, both in the number of nodes/links and timeslices. M scales better to larger graphs than NL, while AN and ANC support a greater number of timeslices compared to SI and JP. Second, we chose simple, custom implementations for our structural and temporal encodings, disregarding more advanced solutions in literature (see Section 5.4). While this was done with the intention of testing the fundamental principles of the techniques in our design space, evaluating more sophisticated approaches might have significantly impacted the results. Finally, we focus on a selection of tasks from a taxonomy on network evolution analysis [APS14], other graph-based taxonomies could present relevant benchmarks for the proposed techniques.

In contrast to our previous exploratory study [FAM21], the analysis of the results in this paper show that M-based approaches do not perform well in terms of response times and accuracy compared to NL diagrams. Our results also confirm the outcomes of similar studies evaluating the

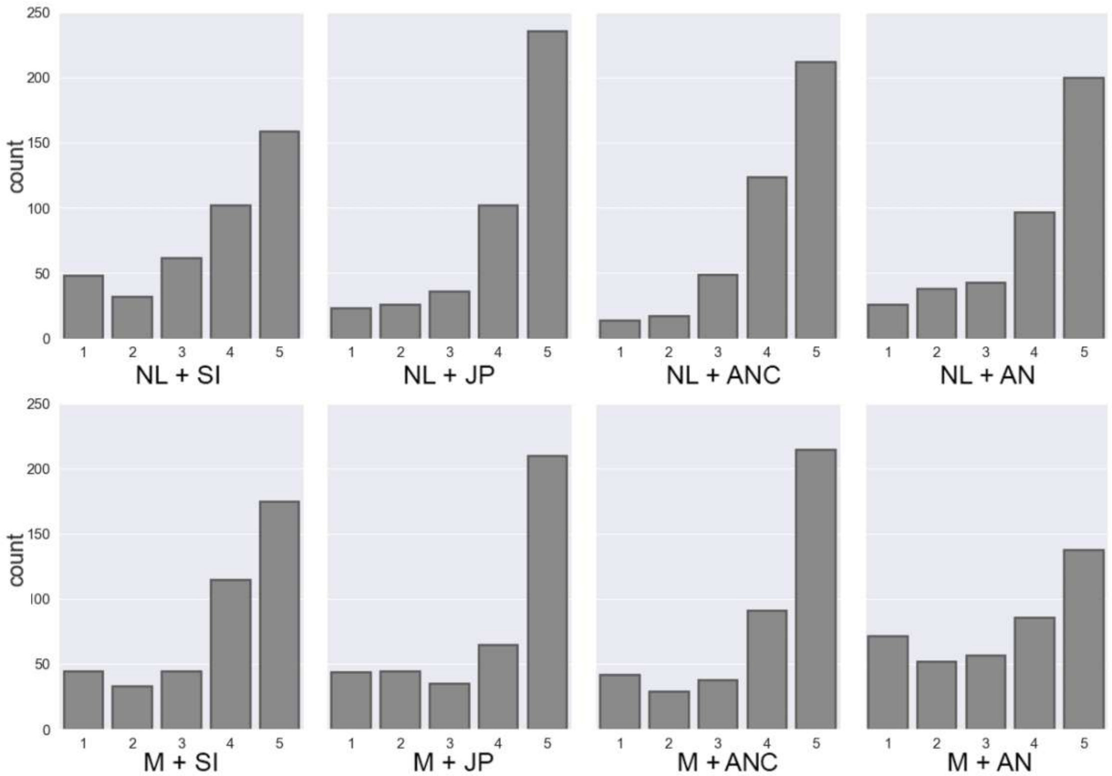

Figure 5.8: Confidence per network and temporal encoding on a Likert scale (1-5).

differences between structural representations in a static environment [OJK19; OJK18]. Many of our research hypotheses are not supported and this challenges our opinions about the usefulness of M-based representations in a dynamic context. Therefore, building on the outcomes of this study, we conduct a further evaluation with the goal of investigating how well the techniques support extracting insights and gaining knowledge about the network's dynamics. We describe the experiment setting and results in our follow-up study (see Section 5.7), where we also aim to overcome the limitations we identified.

5.7 Study 2: Heuristic Evaluation

In this section, we describe the structure of our second study, discuss the design, present our dataset, stimuli, and the evaluation procedure we follow.

Complementary to the previous study, we evaluate the techniques based on their potential to gain insights about the depicted dataset. For this purpose, we follow the heuristic evaluation methodology ICE-T by Wall et al. [Wal+19]. The goal of this evaluation is to determine the value of the best-performing visualizations from the first study: the value of visualization is defined as its capability to respond to data-driven questions, generating insights, and inspiring confidence in the potential results of the analysis [Wal+19].

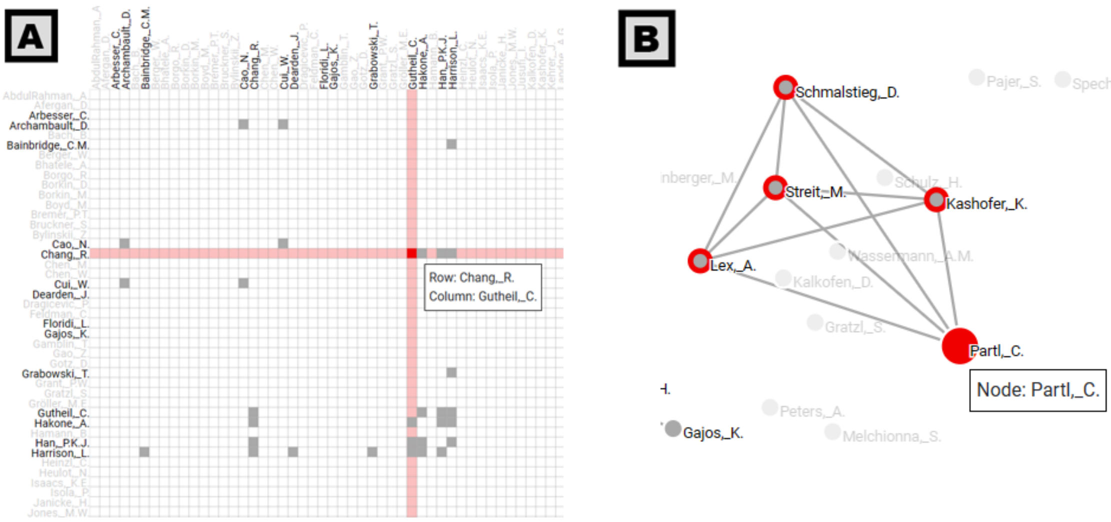

Figure 5.9: Highlighting in the visualizations: (A) both the columns and rows of the selected cell in M-based representations are highlighted; (B) the selected node and its adjacent neighbors are highlighted for NL diagrams.

5.7.1 Tested Techniques and New Interactions

We selected four combinations from our design space for this evaluation as the overall best performing from our first study (see Section 5.6). These are: NL+JP, NL+ANC, M+JP, M+ANC. Based on the user feedback, we modified the visualizations from the first study.

In terms of visualization, we improved the highlighting for both M and NL (see Figure 5.9). In NL diagrams hovering with the mouse over a node highlights it as well as its adjacent nodes. With M we highlight the entire column and row of the currently selected cell, providing the participants with a better view of intersecting cells. We depict the inactive nodes (i.e., not present at the current timeslice) in gray. Furthermore, we added tooltips for both structural representations showing the viewer the label(s) of the currently selected node or cell.

In terms of improved interaction techniques, for NL diagrams we implemented sticky nodes as a way for the participants to reorganize the layout of the network mitigating edge crossings in denser areas: each time a node is dragged around, its position becomes fixed and is not changed by the layout algorithm. For M-based representations, we included reordering algorithms, that are part of the ReorderJS library [Fek15] (Leaf Order, Reverse Cuthill-McKee, Spectral, and Barycentric), with the aim of outlining structural patterns. Users can switch between the different reordering techniques at any point in the exploration. We also improved interaction with the temporal encodings as follows. For ANC we updated the animation to include both auto-animation as well as a time slider providing more interactive control. For JP we updated the layout to accommodate 8 timeslices so that all of these are visible on a single screen.

5.7.2 Experiment Setting

Stimuli. For this evaluation we used a real-world dataset describing co-authorships between authors in the Information Visualization community from 2008 to 2016, with 8 timeslices (compared to 4 in the first study) each spanning 1 year, obtained from a co-citation network [Cit]. We aimed at obtaining a graph about twice the size as the ones from the first study. We filtered the original input graph as follows: first, we stacked and ordered the graph nodes by descending degree; second, we popped the stack and included that node and its neighborhood in the filtered graph. This process continued until we reached a predefined threshold of 80 nodes, which we increased to 107 to avoid breaking any existing clique. This resulted in a total of 469 individual edge occurrences (avg. 58,6 per timeslice). In order to evaluate the capabilities of the visualizations to highlight invalid, unusual, or unexpected data cases [Wal+19], we inserted an additional 194 random edge occurrences, that brought up the average to 82,8 edges per timeslice. This is well within the typical scale of the graphs used in other evaluations [Yog+18].

Trials. In this study, we apply the heuristic evaluation by Wall et al. [Wal+19] aimed at evaluating the value of a visualization. This evaluation protocol entails an open-ended exploration of the data, where participants identify their own data-driven questions and find the corresponding answers. To initiate the analysis, we encouraged the participants to perform free-form exploration and browsing of the network and the timeslices, pointing out interesting insights they found (e.g., highly connected nodes, changes in relationships, reoccurrences, cliques or clusters that are formed, more interesting timeslices).

Study Design. We conducted the experiment as individual expert interviews remotely using a video conferencing platform (Zoom [Zoo]) that lasted 60 minutes on average, preceded by a 10-minute introduction to the scope of our evaluation. Our visualizations were implemented using Angular [Ang] and d3.js [d3] and hosted on a web server accessible to our participants from their own devices. The participants shared their screen content, which allowed us to record their activities and interactions as well as audio recordings. We kept a protocol of notes for each interview as well as reviewed the recordings after the evaluation sessions. Each participant spent about 15 minutes per visualization technique, exploring and interacting with the data, gaining insights, and voicing their thoughts about what they were doing, searching for, finding, or expecting to see. In the end, we asked them about their opinions on each visualization technique and to fill out one ICE-T survey [Wal+19] for each technique at their own convenience. We provided the surveys as online forms, where we would collect the results and calculate the overall score for each visualization technique afterward. Additionally, we added a field where the participants could explicitly provide any textual feedback pertaining to the visualization or interaction techniques, what they found useful, and what could be further improved (i.e., "Feel free to add any comments and feedback here."). Interviews were done in an uncontrolled setting. Participants used their own devices to complete the study by accessing the experiment online.

Participants. We recruited five participants, which is considered an appropriate number for an ICE-T survey stated by Wall et al. [Wal+19]. All participants are experts and have experience in both visual analytics and network visualization with a prominent publication track record in these fields. To ensure that they were all informed about the different modalities of our study we introduced the visualization and interaction techniques, dataset, and provided a brief explanation of patterns that might occur in M-based representations prior to the evaluation.

5.7.3 Analysis Approach

The ICE-T evaluation methodology used in this study [Wal+19] is structured hierarchically into 4 aspects relevant to visualizations (components), which are Insight, Time, Essence, and Confidence. Each component contains two to three visualization guidelines (intermediate level), with each encapsulating one to three heuristics. Heuristics represent how the visualization guidelines can be achieved (e.g., "*The visualization provides a big picture perspective of the data*"). These 21 heuristics are formulated as rateable statements asked directly to the participants (e.g., "*The visualization presents the data by providing a meaningful visual schema*"). Each participant provided a response to each one of the 21 heuristics in the questionnaire.

Heuristics are rated on a 7-point Likert scale with 1 being "Strongly Disagree" and 7 being "Strongly Agree". Additionally, there is a "Not Applicable" answer in case any of the participants thought the question does not apply (and excludes the answer from the score calculation). Scores are then averaged per component, whose average value is the visualization's overall score (or value). According to this methodology [Wal+19], a valuable visualization should obtain an overall average score of at least 5. To make the reported scores more transparent, we included the standard deviation of the ratings in our results together with the average scores (see Table 5.4). We include in the supplemental material the complete questionnaire and a detailed breakdown (including the individual responses) of the results we obtained. For more details about the ICE-T methodology, we refer to Wall et al. [Wal+19].

We report the quantitative results of this evaluation in Section 5.7.4. In addition, to the heuristic evaluation, we collected the participants' qualitative feedback and discussed it in Section 5.7.5.

	Component	**Insight**		**Time**		**Essence**		**Confidence**		**Total**	
Technique	**Score**	**AVG**	**STD**	**AVG**	**STD**	**AVG**	**STD**	**AVG**	**STD**	**AVG**	**STD**
	M+ANC	4.65	1.22	4.25	1.84	3.93	1.44	4.73	1.73	4.46	1.53
	M+JP	4.33	1.46	3.85	2.06	4.36	1.91	4.53	1.96	4.26	1.78
	NL+ANC	6.22	0.82	6.00	0.84	6.14	0.83	6.13	1.02	6.15	0.87
	NL+JP	6.10	0.80	5.65	1.19	5.93	0.96	6.00	0.97	5.96	0.97

Table 5.4: Results of the ICE-T heuristic evaluation. The rows are the individual combinations of structural and temporal graph encodings that were evaluated. The columns are grouped per component and within each we calculate the mean and standard deviation of the participants' ratings. The right-most column shows the total for each technique.

5.7.4 Quantitative Results

The results of the evaluation (see Figure 5.10) indicate a clear preference of the participants for NL representations compared to M. This result is also consistent and confirms the findings of our first study, especially the ones concerning participants' preferences (see Sections 5.6.4 and 5.6.5). NL+ANC obtained a score of 6.15, whereas NL+JP was 5.96, while M did not get past 4.26.

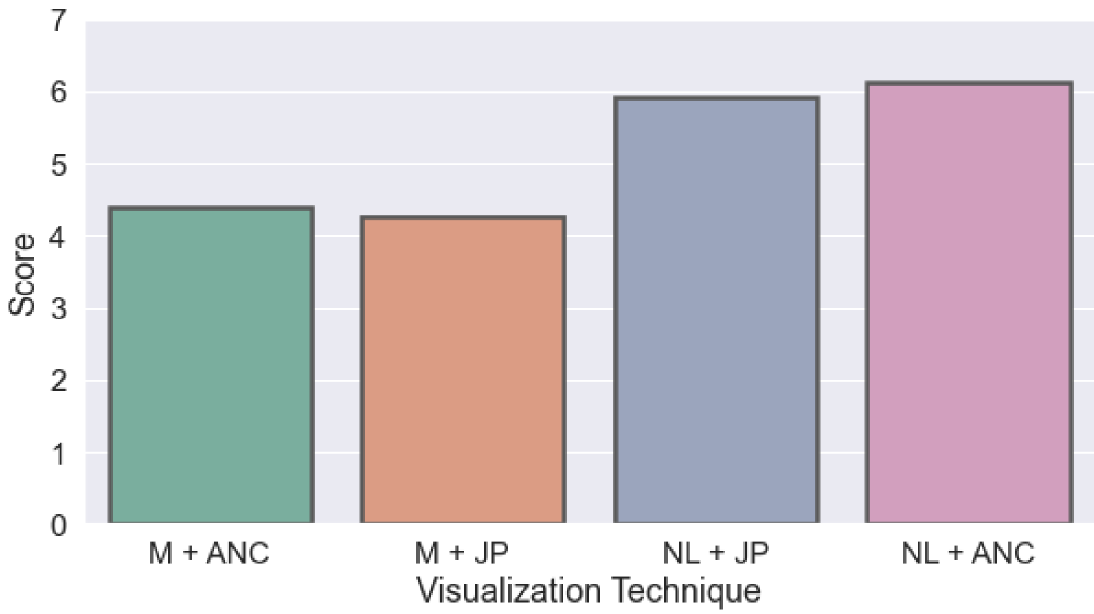

Figure 5.10: Results of the ICE-T heuristic evaluation. This figure shows the average scores of each of the combinations of structural and temporal encodings evaluated in the study. The scores vary from 1 (Strongly Disagree) to 7 (Strongly Agree).

Unsurprisingly, study participants found NL visualizations to provide a more natural and intuitive representation of the topology of the network, being more capable of highlighting structural patterns thus supporting insight generation and knowledge extraction. In turn, when using M representations a viewer must first decode the visualization in order to make sense of the relational data and structure, which takes more time and cognitive effort compared to NL.

When comparing the temporal encoding, a reoccurring trend from the first study (see Section 5.6), is that ANC is consistently preferred to JP. We presume this to be due to the nature of JP, which requires the viewer to continuously switch attention between the individual timeslices in order to trace an individual node, edge, and/or cell, and to observe its behavior over time. However, differently from JP, with ANC is not possible to compare distant (non-adjacent) timeslices.

We additionally inspected the scores of each visualization technique on a per-component basis (see Figure 5.11). The scores are mostly consistent throughout the four components, following the same trend as in Figure 5.10) with the exception of M+JP and M+ANC for the "Essence" (i.e., "*Live view or summarization of the dataset*" [Wal+19]), where M+JP scores better (4.36) than M+ANC (3.93). This may also come as a consequence of the divided opinion on M-based representations in a dynamic context, which is indicated by the high variance of both ANC and JP (see Figure 5.11). While the participants were interacting with the M-based representations, overall they favored ANC over JP, however, their opinions were somewhat divided if they found M useful for such analysis tasks or not.

The NL-based network visualization results indicate that across all components the ANC temporal encoding is consistently preferred to JP (see Figure 5.11). Furthermore, the participants' opinions and scores on NL diagrams are more consistent and in agreement compared to M representations as seen in Figure 5.11 (low variance for all NL techniques).

Overall, the best-performing combination of techniques (as well as the highest valued one), indicated by these results is NL+ANC (6.15), followed by NL+JP (5.96), M+ANC (4.46), and, finally, M+JP (4.26) (see Figure 5.10).

5.7.5 Qualitative Results

According to the study participants, with ANC it was easier to track changes occurring to a specific part of the graph (local changes), whereas for JP it was easier to observe more global changes happening over all the available timeslices and the entire graph regardless of the structural representation. With the support of our linked interaction techniques in JP, it was easier to compare distant timeslices compared to ANC, which most participants expressed being only useful to compare up to two neighboring timeslices. Thus, we believe the choice of temporal encoding, in this case, depends heavily on the granularity of the network analysis that participants are interested in (i.e., local vs. global behavior, distant vs. neighboring timeslices). Generally, the participants observed how ANC offered a lot more screenspace compared to JP for each timeslice, which is common for time-to-time vs. time-to-space visualization techniques [Aig+23].

Our decision to favor layout stability to preserve the viewers' mental map both in NL and M was generally received favorably by the study participants. However, they also remarked that a balance between the layout stability and quality on a per-time slice basis may improve graph readability and insight generation - despite the cognitive impact on the users' mental map. In support of this claim, several participants argued that the existing reordering algorithms available for M representations were not able to emphasize topological patterns existing on individual timeslices as reordering was applied on the matrix representing the aggregated graph. Due to the nature of the publication dataset, where local neighborhoods can change drastically across adjacent timeslices, it was a challenging task to observe the global behavior of the network in M-based representations, regardless of their temporal encoding. This is also indicated in the results of M-based representations in the "Total" column of Table 5.4, where the standard deviation of the participants' ratings is significantly higher than those for the NL representations. Based on these results and our observations during the evaluation sessions this illustrates the diverging opinions and preferences that the participants had about M-based representations. Based on the interview videos, we also observed that all participants managed to identify smaller-scale structures and important or central nodes with the aid of matrix reordering algorithms. Using the M+ANC combination was more useful for detecting local changes compared to JP, which is consistent with the participants' general feedback about the temporal encodings. Based on the comments of the participants it became clear to us that M-based representations possess a steep learning curve in order to be decoded properly. However, when asked about the usefulness of M-based representations, there was also agreement there is potential to improve these by including more sophisticated interaction techniques, visual encodings, and reordering algorithms ("*M seems a bit nerfed*").

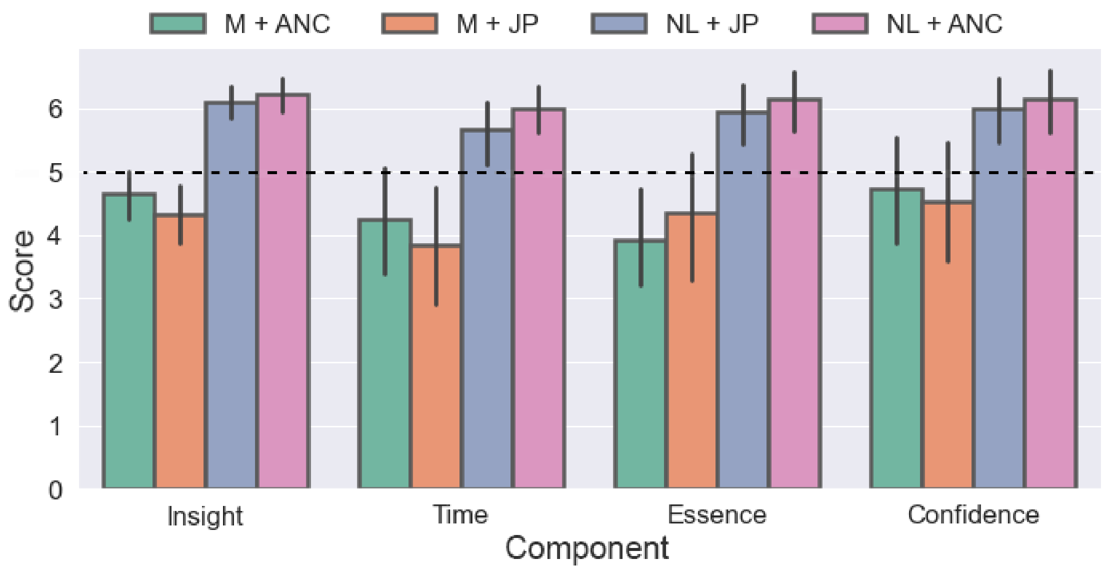

Figure 5.11: Results for each of the ICE-T heuristics. The bars each represent one of the techniques being evaluated. The scores vary from 1 (Strongly Disagree) to 7 (Strongly Agree). The dashed line indicates a score of 5, which is considered the minimum .

For NL+JP all participants expressed that the linked interactions and adjacency highlighting were extremely useful in order to observe changes occurring to a node and its neighbors over time. From the evaluation sessions, we observed that NL+JP was regarded by most participants as providing a better view of the network and being effective at supporting cluster/clique identification, as well as, central (or bridge) nodes. However, there was consensus among participants on NL+ANC being the most intuitive approach contrary to their initial expectations. Prior to experimenting with the approaches, the participants assumed that NL+JP would be the most efficient technique for extracting insights. NL+ANC made it easier to identify persistent nodes and how clusters/cliques appear, disappear, or evolve over time due to the natural time-to-time encoding. These results are also visible in the scores of the ICE-T questionnaire [Wal+19], where NL+JP and NL+ANC are quite closely ranked in terms of *Essence*, that is the capability of the visualization of communicating both overview and context of the data (see Figure 5.10 and Table 5.4)

5.7.6 Limitations

In our second study, we explored how the scale of the graph (in terms of the number of nodes and edges as well as timeslices) affected the ability of the participants to extract insights and generate knowledge from a real-world dataset. We had to face space issues with JP, as beyond 8 timeslices there is not nearly enough screen space to depict the graph in its entirety in all timeslices while keeping a sufficient zoom level to keep labels and nodes readable.

While the results of the evaluation are clear in showing the participants' preference, two elements might have negatively affected M-based representations leading to a lower score. These should be considered when elaborating on the study results, and, therefore, we discuss them as limitations.

First, M visualizations appeared to be sparse ("[There was] *lots of whitespace*"). Co-authorship networks appear as rapidly changing cliques and we picked the biggest cliques in order to have a sufficient amount of nodes and edges. However, we soon hit an upper bound on the number of nodes, as space requirements for M are particularly demanding to accommodate node labels. While it is commonly accepted that sparse graphs are better visualized as NL diagrams, we were not testing task performance, but rather the expressive power of combinations of structural and temporal encodings in a dynamic scenario. Nonetheless, it remains untested whether M-based approaches would provide improved task performance compared to NL in a dynamic scenario with larger, denser graphs.

Second, one participant observed that there could be some negative bias towards M-based approaches as NL are more common. We did not measure or counteract bias effects.

Finally, we remark that this study provides empirical evidence of the expressive power and preference of different dynamic network visualizations in a more realistic scenario, which includes larger graphs and more nuanced interactions. However, we can't conclude whether the findings of the first study apply to larger graphs, which would require further studies in this direction.

5.8 Takeaways

Our results suggest that, within the aforementioned limitations, the selection of NL as a structural representation leads to better performance, and participants generally prefer NL over M. In our first experiment, M was closer to NL regarding performance and preference, considering the simple interactions and few timeslices. In the second study, a broader gap in preference appeared between the two. Existing research proved the potential of M over NL representations for specific tasks in a static context (see, e.g., [GFC04; OJK18]). Despite offering interactions and reordering techniques for M-based representations, these need to be adapted and extended for a dynamic context in order to emphasize the topological structures that exist and change over time. This has two interpretations.

First, there is an intrinsic difficulty in reporting the dynamics of a graph using matrices: as all the rows/columns are visible simultaneously, choices have to be made on whether to hide the currently inactive ones. To help maintain the mental map, we chose to show all rows and columns for all timeslices. This enabled the participants to orient themselves but simultaneously created clutter that played against them rather than providing a more comprehensive view of the dataset and its temporal evolution. The first study's results could also support this: M could provide a similar performance to NL as only edges were added/removed.

Second, M representations are undoubtedly oriented towards a more expert audience of users. In the first study, some participants (students, see Section 5.6) commented that they needed to redraw the M representation as a NL diagram. Whereas in the second study, even expert participants admitted a potential bias as they were used to interacting with NL diagrams compared to M representations in their daily work.

Within the context of our two studies and the basic implementations of the graph representations, temporal encodings, and available interactions these results appear in contrast to the ones we obtained in our exploratory study [FAM21]. We would like to remark that our previous work was intended as an *exploratory* study to gather empirical evidence about the problem to be further evaluated in this work. In fact, we focused on a significantly reduced set of tasks, used smaller graphs (both the number of nodes/edge and timeslices), did not consider mental map preservation, and neither presented a statistical analysis of the results. Therefore, we believe that the *combination* of the findings of the two studies can support users in making the best-informed decisions for the task at hand. The insights, quotes, and results of our exploratory study [FAM21] should be mediated with the results of both experiments in this work.

The results of both studies highlight that it is easier for users to transition to a dynamic network exploration scenario with NL representations. At the same time, for M there are still open, underinvestigated problems related to the presentation of the temporal dynamics. Furthermore, when considering the use of M for dynamic networks, the target user groups' expertise should be considered.

Concerning the temporal encodings, we found AN, ANC, and JP to be the best performing and most preferred across our two experiments. In the first study, AN generally had lower response times and higher accuracy than JP. AN was closely followed by ANC, which was the most preferred due to the presence of the manual time slider. JP showed evident limitations when we scaled up the number of timeslices, but it is still the encoding of choice for overview tasks. Participants remarked that the eye needed to travel some distance and locate the same position within the graph to focus on it before they could see what was happening to an individual node or edge. This hints that JP may not be as well suited for low-level tasks as ANC but was regarded as a suitable approach for getting an overview of the entire network and how it changes across all timeslices. Nonetheless, the space requirements of JP should be carefully considered when designing a dynamic network visualization system.

5.9 Conclusion

In this paper, we investigated the design space of dynamic network visualization along its two major dimensions, structural representation and temporal encoding, considering the effects of simpler and more advanced interaction techniques. We presented two studies: Firstly, we conducted a user study, assessing response times, accuracy, and preferences. We evaluated the results against our research hypotheses through a complete statistical analysis. Secondly, based on these results, we selected the best-performing structural and temporal encodings and improved interactions according to participants' feedback. The resulting visualizations were compared in a heuristic evaluation [Wal+19] aimed at investigating to which extent they support conducting exploratory analysis and insight generation.

In accordance with the results of the first study, participants favored NL over M for the structural encoding and preferred ANC over JP for the temporal encoding. We condensed our results into a series of takeaways and discussed the limitations of our studies, which opened several interesting future research directions. First, we believe the tradeoff between layout quality and stability [BM11] should be further investigated in this context for both NL and M. Second, while both ANC and JP had high scores for NL diagrams, it would be interesting to see if and how both approaches could be combined interactively to provide an overall better experience for network exploration and analysis. Finally, we believe that the staged animation technique proposed by Bach et al. [BPF14] could be applied to both NL and M helping users orient when transitioning from one timeslice to the other, with visual cues indicating the location and type of change (appearance or disappearance).

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CHAPTER 6

Discussion and Reflections

In the following chapter, we revisit the research questions outlined in Section 1.2 and discuss how we answer them based on our publications. We start by discussing how we address each of the individual sub-questions leading to a conclusive answer for the overarching research question of this dissertation. We further reflect on our work by discussing how VA techniques can be effectively applied to our application domain of Digital Humanities and consider how we can address common concerns about the scalability and generalizability of the proposed approaches.

6.1 Research Questions

RQ1: How can we modify the structural encoding of dynamic network representations to encode further data properties about the nodes and/or links?

The design space of dynamic network visualization can be broadly categorized into structural and temporal encodings [KKC15]. The structural encoding encompasses techniques that are specialized in representing the topology of the network (i.e., node-link diagrams and matrices), whereas the temporal encoding depicts the time-oriented nature of the data (i.e., timeline and animation). To address this sub-question and answer it we investigate both these dimensions in our work. In the following, we discuss how the publications from the previous chapters match the scope of this question and subsequently present our answer.

In CV3 [Fil+19] (see Chapter 3), we explored how we can represent an event-based mobility network of applicants from their résumés by using linked views. Furthermore, we experimented with standard tree visualization techniques and modified these to account for other attributes in the context of CVs, such as skill sets and expertise. The central goal of this work is to enable both novice and expert users to gain insights and competitively rank applicants at a glance in order to determine which should fall into their shortlist to further investigate and compare. We achieved this by data mining and constructing networks of applicants based on common skillsets (hierarchical and categorical), mobility (spatio-temporal), and other metadata (ordinal and categorical). The outcome of our domain expert evaluation confirmed the appropriateness and efficacy of the proposed visualization techniques. The linked views and interactions were greatly appreciated and immensely helpful to the participants in answering their questions and deciding on applicants to include in their shortlist.

In our second publication, “Gone Full Circle” (see Chapter 4), we explore a novel visualization metaphor for event-based dynamic network visualization as well as interaction techniques supporting the users in reshaping the layout via grouping and ordering methods based on their interests and questions. We investigated radial visualizations and how we can utilize the design space, adapting it for event-based dynamic network visualization. We validated our design and interaction techniques by conducting a domain and visualization expert evaluation, with participants expressing a general agreement on the appropriateness of the visualization metaphor, specifically outlining how it was aesthetically pleasing, compact, and an interesting way of encoding event-based dynamic network data.

In our third publication “On Network Structural and Temporal Encodings” (see Chapter 5), we investigated how we can adapt common structural encodings of the network (i.e., node-link diagrams and adjacency matrices) to convey the temporal information associated with appearance and disappearance of nodes and relationships. In this case, we conducted two evaluations with a common goal: to determine the best-performing combination of structural and temporal encoding for dynamic network visualization tasks [APS14]. In our first study, we focused on quantitatively evaluating the response times, accuracy, and preferences of participants for these different combinations and ranked these according to their performance. In the second study, we conducted a qualitative evaluation using the ICE-T heuristic evaluation methodology [Wal+19] with network visualization experts using improved versions of the techniques from the previous study. The results show that the combination of a node-link structural representation with animation and playback controls is the best performing for the study tasks as well as being the participant’s most preferred one. Matrix-based approaches achieve similar performance in the first study but have considerably lower scores in our second evaluation.

In conclusion, we can modify and augment the structural encoding of standard network encodings to encode further data properties and aspects of the nodes and/or links. In cases when the network’s topology is needed for specific analytical tasks along with the temporal and multivariate aspects of the data, this could be achieved by using multiple views, integration, nesting, and overloading (see Section 2.3 for definitions) as well as leveraging constraint-based (attribute-based [Nob+19]) or special-purpose layouts. In situations where only the network’s topology along with the time-oriented information is necessary, we can make use of superimposition, juxtaposition, animation with playback controls, or explore alternative approaches to visualize the network and its dynamics (see Section 2.3 for definitions). The chosen approach to modify the visual representation of the network depends highly on the data facets to be represented, their importance, the analysis tasks and goals as well as the necessary granularity of the analysis (high-level or low-level, i.e., network behavior or node connectivity, respectively). In our research, we have determined that for high-level tasks related to the network’s topology and change node-link diagrams with animation and controls seem to be the most preferred and best-performing approach, whereas if there are many facets that need to be depicted simultaneously multiple linked views or alternative visualization metaphors are more appropriate. For low-level tasks related to identifying the existence of relationships over time or the value of specific attributes matrices were quite competitive and even better in some tasks compared to node-link diagrams utilizing both multiple linked views and animation and controls. Both approaches can be adapted to convey multiple attributes/facets and their usefulness in this case depends heavily on the granularity of analysis and types of tasks that need to be performed.

RQ2: Which combinations of structural and temporal representations for dynamic networks are effective, appropriate, and avoid causing information overload?

In “Gone Full Circle” (see Chapter 4), we developed an alternative representation for an event-based dynamic network focusing on a compact visualization with aesthetic appeal. In this publication, our main goal was to appropriately depict the event-based nature of the network without causing information overload or incurring the “hairball effect” that happens with dense networks. The “hairball effect” occurs with large and dense networks with many relationships between the sets of nodes where standard network visualization approaches depicting this network do not result in any useful representation. We validated our proposed visual representation, its readability, and usefulness in the context of an expert evaluation with three domain experts and three visualization experts performing tasks in the spirit of a history exam. The outcome of the evaluation confirms our initial assumption that compactness and aesthetics play a major role in how the visualization is used and interpreted, as well as how alternative approaches to visualize dense event-based networks can greatly improve their readability and support insight generation, thus avoiding information overload and “hairball”-like effects. Our proposed approach has since been used by the domain experts to present their research and the identified historical narratives in multiple conferences and has contributed to engaging the audience, generating discussions, and piquing the interest of other experts in the field.

In “On Network Structural and Temporal Encodings” (see Chapter 5), we evaluated a large design space of both structural and temporal encoding techniques on both typical dynamic network analysis tasks [APS14] as well as insight-driven and information extraction tasks [SND05]. In order to determine which combinations of structural and temporal representations are effective and appropriate for dynamic network visualization we conducted a two-fold evaluation, performing both statistical analysis and hypothesis testing and a qualitative evaluation using the ICE-T heuristics [Wal+19]. In our first evaluation, we had a large number of participants (68) and presented them with network analysis tasks on 8 different combinations of structural (node-link and matrices) and temporal encodings (juxtaposition, superimposition, auto-animation, and animation with controls). We analyzed the results and tested hypotheses we had regarding both the performance and accuracy of specific structural and temporal encoding techniques. The results show that node-link was most preferred with matrices being a secondary choice. As for the temporal encoding, the best-performing approach was auto-animation with the participants expressing a strong preference for animation with controls. In our second evaluation, we conducted a qualitative evaluation with network experts (5) using the ICE-T heuristics [Wal+19]. In this case, we narrowed down the design space and improved the temporal and structural encodings according to the feedback from the previous evaluation. The experts all expressed strong preferences for node-link diagrams in supporting knowledge extraction and insight generation tasks.

In terms of temporal encoding animation with controls was the most preferred one due to its compactness, interactivity, and time-to-time encoding approach. The participants also remarked that matrices may be more useful for different kinds of tasks as well as that juxtaposition seems to be better at conveying an overview of the network and its changes and subsequently using animation with controls to explore it in more detail.

To answer this sub-question we compared combinations of standard structural and temporal encodings for dynamic network visualization as well as evaluated an alternative network visualization approach focused on event-based network data. In terms of the standard available approaches, node-link diagrams combined with animation and controls performed best (both in terms of performance and preference) in both studies we conducted on comparing combinations of structural and temporal encodings. Furthermore, we also explored how alternative network representations for event-based network data are perceived by domain experts in the domain of digital humanities. In their research, it is common for them to conduct exploratory analysis tasks in order to extract narratives and insights from the data as well as to present and disseminate the results of their work. Our evaluation of the proposed approach demonstrates its appropriateness and efficacy in depicting this type of data. Concluding, we can state that based on our research alternative network representations developed specifically for a set of predefined tasks and data characteristics are an appropriate and effective network visualization method and avoid causing information overload. Moreover, if the tasks are more generic and the visualization approach should support a wider range of data characteristics the results of our studies indicate that node-link diagrams combined with animation and controls are an effective and appropriate method of depicting this type of data.

RQ3: What can we recommend to dynamic network visualization designers and developers to support users depending on the granularity and applications of network analysis?

In "Gone Full Circle" (see Chapter 4), we developed a flexible alternative visualization approach for event-based networks that can be reconfigured based on the interests and tasks of the users. In this case, we had experts in the domain of digital humanities and used a flexible task typology [BM13] to model their analysis and exploration tasks. The result was a set of tasks, ranging from high- to low-level, that could also be chained together to form more complex tasks and analysis paths. In order to support this wide range of tasks, we developed a lot of interaction techniques that support these as well as different ways of slicing, grouping and reordering, and modifying the state of the visualization to surface similarities, differences, or patterns that emerge. The expert evaluation we conducted with three domain experts and three visualization experts shows that these interaction techniques indeed supported the participants in the wide range of tasks that we had initially modeled. Furthermore, the alternative visualization approach of this type of data offered the domain experts a more playful, compact, and aesthetically pleasing representation. Even after the evaluation sessions had concluded, the participants kept exploring the dataset and used the interaction techniques to reshape the visualization and see it from different perspectives, gaining deeper insights into the data being depicted.

In "On Network Structural and Temporal Encodings" (see Chapter 5), we explored how different combinations of structural and temporal encodings performed for a wide range of tasks based on a two-fold evaluation. In our first study, we included well-defined network evolution tasks [APS14] ranging from low-level (centered around individual nodes and links) to high-level (cliques, groups, and clusters). There were three task categories that we considered based on [APS14], namely: (i) individual temporal features, (ii) rate of changes, and (iii) shape of changes. We had a large number of participants split into two different groups, one with the support of common interaction techniques and one without. This division was intended so we could evaluate the effect that interaction techniques have on the accuracy and response times of the tasks as well as their necessity and usefulness. In the second study, we focused on an evaluation using the ICE-T heuristics [Wal+19]. In this case, we had fewer participants with expertise in network visualization and did not focus on response times and accuracy, but rather on determining the value of the best-performing combinations of structural and temporal encodings from the first evaluation. The value of a visualization is defined as its capability of responding to data-driven questions, generating insights, and inspiring confidence in the potential results of the analysis [Wal+19].

As for recommendations for dynamic network visualization designers and developers, based on our research, we have identified the following concepts that are important to consider:

Well-defined Tasks: In order to develop effective and appropriate visualization approaches for dynamic networks, prior to their design and development the supported tasks need to be identified. It is a major step in the process of developing appropriate and effective visualizations that are suitable for the users' workflow. In our research, we have used several methodologies in order to properly model and infer the tasks of the domain experts [Mun09; MA14; Hal+20]. We would recommend as a first step to investigate the problem domain and understand the typical workflow of the target audience in order to design and develop appropriate and effective visual interfaces for dynamic network data.

Interaction Techniques: Providing well-established and appropriate interaction techniques to support the users in their tasks is one of the most important considerations that need to be made. The interaction techniques should be designed and implemented with the workflow of the user in mind. In our research, we have investigated the benefit of interaction techniques for well-established graph analysis tasks as well as exploratory tasks. From the results of our evaluations, we can state that they greatly improve both the user experience as well as the response times and accuracy and we would recommend investigating what interaction techniques are appropriate depending on the use cases and characteristics of the data at hand.

Flexible and Alternative Visualizations: A major consideration to make is if standard network visualization approaches will be sufficiently expressive and appropriate for the type of network data and tasks that are required. If this design space is too restrictive and not well-suited for the target users and their tasks we would recommend exploring both hybrid and alternative network visualization techniques as these may offer significant advantages over standard visualization techniques compared to traditional ones. Designing and developing flexible approaches facilitates and supports a wide range of tasks and analysis methods that can be accomplished without the need for re-designing or re-developing.

Modifying Standard Visualizations: Alternative and flexible visualization approaches are generally very tailored to specific problems and have custom implementations, supporting a more narrow selection of tasks. In cases where the approach is intended to be more generic but still encode additional facets of the data (i.e., time or other variables) we would recommend extending and augmenting standard approaches (i.e., node-link diagrams or adjacency matrices) in different ways. Different composition modalities can be considered in this case reflecting both the topological information of the network as well as one or multiple facets. These can be: (i) superimposition, (ii) juxtaposition, (iii) animation, (iv) timeline, (v) integration, (vi) nesting, (vii) embedding, (viii) overloading, and (ix) multiple views (see Section 2.3 for definitions of these terms).

Evaluations: Evaluating the proposed visualization and approach is important to ensure that it fulfills the specifications and tasks the target audience will be conducting. Evaluations in information visualization and visual analytics are shifting from standard metrics such as accuracy and response times to more qualitative, insight-based ones. As network visualization systems become more complex and surpass traditional representations, evaluating their value, effectiveness, and appropriateness becomes challenging. While performance metrics are still important and can highlight effective visualization techniques, we recommend additionally investigating the cognitive aspects, such as perception, user engagement, and the capability of the approaches to support data-driven questions, generate insights, and inspire confidence in the results of the analysis. Furthermore, in order to support reproducibility and replicability as well as foster transparent and comparative evaluations we advocate that the source code, as well as datasets, and results from the evaluations always be accompanied by the proposed publications and techniques.

Revisiting our main research question of this dissertation:

"How do different structural and temporal representations of dynamic network data facilitate effective visual analytics for different task abstractions?"

Regarding our main research question, we can formalize an answer based on our work and replies to the individual sub-questions. We can conclude that different structural and temporal encodings in dynamic network visualization can facilitate effective visual analytics. The choice of these is highly dependent on the characteristics of the data and the analysis tasks that need to be conducted. In our research we explored: (i) how modifying the structural encoding can be used to encode further characteristics of the nodes and edges augmenting the resulting approach with enriched information (RQ1); (ii) how we can evaluate the design space of structural and temporal encodings and compare their performances for insight-based and established network evolution tasks as well as proposing alternative visualization metaphors for dynamic network visualization (RQ2); and (iii) how we can summarize the outcomes of our research and lessons learned in order to recommend concepts that should be taken into account by designers and developers of dynamic network visualization approaches (RQ3).

Each use case where dynamic network visualization can be employed as an effective and appropriate solution is different and has its own set of particular requirements, data characteristics, target users, and research questions. By abstracting the characteristics of the data and mapping well-established task taxonomies to the specific problem domain, as well as the research goals of the users it is possible to generalize solutions and provide recommendations for approaches that will facilitate effective visual analytics for the given problem domain.

How can VA better facilitate research conducted in the domain of Digital Humanities?

Revisiting our application domain, we can also discuss and elaborate on how VA better supports and contributes to research in the domain of Digital Humanities. Specifically, how we can utilize concepts from dynamic and multivariate network visualization and apply these to support research in this domain. Overall, VA plays a significant role in facilitating research in the Digital Humanities, providing methodologies and techniques to explore, analyze, and extract insights from heterogeneous, relational, and complex data. A recent shift in this domain has put the focus more centered on the analysis and presentation of how networks and their properties change over time (i.e., relationships, interactions, and dynamics in historical contexts associated with different attributes). Based on our research, the most notable VA methods and techniques that can be applied to Digital Humanities with the goal of better-supporting research in this domain are:

(i) Data Exploration and Understanding: The data available and of interest in Digital Humanities research is often large and diverse associated with temporal uncertainty and data quality issues. Interactive VA techniques enable researchers to visually explore, extract insights, and identify patterns, trends, and relationships between the data points. Applying dynamic and multivariate network visualization approaches, in this case, enables an intuitive representation and interaction with this type of data. This results in a better understanding of the overall context and content as well as developing more informed decisions and refining the scope of the research questions.

(ii) Events, Influences, and Narratives: In Digital Humanities a common and important task is to discover the most well-connected and influential events or individuals in a network. These key entities usually have a significant role in the network and detecting their impact over the evolution of the network supports researchers in better understanding the network behavior. This may also result in (re-)constructing historical narratives, outlining important characters, events, and interactions between these, that shaped the network.

(iii) Multimodal Analysis: Research in this domain involves coherently analyzing and consolidating data from multiple sources. These sources usually provide data with multiple attributes that can be used to enrich the network visualization (e.g., temporal and multivariate properties), providing more context and gaining deeper insights into how these attributes interact with each other. The multivariate aspect of the network also enables us to identify clusters or communities of nodes with similar properties. Furthermore, considering these possibilities we can develop approaches to provide an attribute-driven exploration enabling a more targeted analysis as well as the possibility of uncovering hidden thematic clusters in the data (e.g., artistic movements or intellectual circles in a historical context).

(iv) Communication and Presentation: Visualization is a powerful medium that is used with the goal of communicating insights and research findings in this domain. VA can facilitate this by designing and developing compelling visual representations of the data that convey complex and intricate information in an intuitive and comprehensive manner. Unfolding the evolution of events, characters, and interactions using approaches such as storytelling can capture the viewers' attention and make the information more memorable and impactful. Furthermore, such VA approaches can provide interactive environments and be integrated into educational material, presentations, or exhibition settings as an engaging way of presenting historical research.

Scalability & Generalizability: Common questions and concerns in the visualization community are: (i) How well do the proposed approaches scale and generalize to domains besides visual analytics?; (ii) What are the implications of our contributions beyond the application domains we have considered in our work?

(i): To assess scalability we often examine the performance (computational efficiency, interpretability, and readability) of our approaches using data of varying sizes, density, and complexity. In our work, we have identified certain limitations in terms of visual scalability of the proposed approaches, testing them with varying data sizes, and often discussing options to mitigate these to some extent. These approaches were designed and developed with specific tasks and target users in mind, and, were deemed expressive and appropriate for these. However, scalability is often a concern, specifically, with the ever-increasing amount of data and complexity that needs to be depicted. We have considered and evaluated how alternative representations of networks and interactions to filter and reduce information can be used to mitigate this, resulting in overall more scalable and flexible approaches and recommend investigating such solutions moving forward.

As for generalizability, this is typically evaluated by applying the proposed approaches to different domains, considering data with distinct characteristics and structures. This notion of generalizability only has benefits for the visualization community, as we can explore how our contributions can be applied in other domains and allow us to extend our impact beyond the field of visual analytics. While most of our approaches are tightly coupled with the specific requirements of particular domains, we need to consider how transferable these underlying concepts are. To achieve this, in our work, we always use flexible and abstract methodologies that focus on defining the target users, their analysis tasks and requirements, and the characteristics of the data. The benefits of such methodologies are that they abstract core concepts and allow us to identify the fundamental design principles, interaction techniques, and analytical methodologies that are employed. By abstracting these we can enable more generalizable approaches that can be transferred and adapted to other domains.

(ii): Considering and understanding the broader implications of our contributions beyond the application domains is also an essential aspect of visualization research. Visual analytics and visualization are inherently interdisciplinary as the proposed contributions and approaches are commonly associated with particular application domains and data characteristics. Therefore, our work not only contributes to visualization research as a whole but also to the particular application domains and problems that our proposed approaches support. By developing more generalizable and flexible solutions, many other fields can benefit from these approaches. The goal is to determine the value of the visualization techniques and their applicability and impact on other domains. In our work, we have experienced how impactful approaches for interactive visualization and analysis are in domains, where these are not common methods of conducting research. The use of abstract methodologies and taxonomies to drive visualization research enables the re-use of visualization and analysis concepts in domains beyond visual analytics and extends the implications of our contributions.

> “
>
> *Instruments register only through things they’re designed to register.*
> *Space still contains infinite unknowns.*
>
> ”

Mr. Spock *in Star Trek, Season 1 Episode 4*

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CHAPTER 7

Future and Outlook

In the following, we discuss the more notable open challenges and interesting directions for future research that we identified and would like to tackle going forward.

Taxonomy of Interactions: Approaches to facilitate navigation, exploration, and interaction with the network and its elements are highlighted by a number of reports as a promising direction for future work [Beh+16; Lan+11; Pie+15; Bec+17; McG+19]. Specifically, techniques that enable interactive graph simplification and layouts have been highlighted in related literature [Lan+11; LHT17]. Moreover, there is growing interest in systems that implement novel interaction techniques for network exploration on large [LAN20] and small tactile displays (e.g. [DDI10; HL07]), including real-time collaboration during the network analysis process [Che+19]. Additionally, human-assisted approaches to combine the knowledge of domain experts with automated analysis and visualization of network data are considered to be an increasingly important yet under-investigated research direction [Beh+16; VBW17]. We believe this still to be an open and unresolved issue with great potential for future work, as there is no well-defined taxonomy or survey on interactions for network visualization with few exceptions, such as the work by Wybrow et al. [Wyb+14] on interactions on multi-variate networks.

Dynamic Analysis Metrics: It has been suggested that visualization of dynamic graphs might move towards a *confirmatory analytical modeling* stage, with the use of statistical models of network change [MMB05]. Change centrality [Fed+12] is proposed as a statistical model to perform a pairwise comparison between subsequent states of an evolving network in the discrete-time domain for dynamic network visualization, however, more research can be conducted on this problem targeting continuous networks and different properties or facets of the network (e.g., geospatial, group, and multi-variate changes over time). Event-based network analysis metrics are an under-investigated and non-trivial challenge that presents interesting opportunities for future work, considering the paradigm shift from time-sliced to continuous network representations.

Dynamics and Multiple Facets: The problem of visualizing multiple dynamic data dimensions presents an open challenge in both dynamic and multi-variate network visualization [Arc+14;

Bec+17]. A possible solution could be the use of attribute-based layouts [GFV13; Nob+19], which exploit the underlying node and/or edge variables (or characteristics) to produce a layout of the network, similar to what we proposed in our research to encode further node and/or link properties in the structural encoding of dynamic networks. Alternative ways to represent a graph's temporal dynamics other than discrete time, such as *continuous or event-based* representations, also play a major role as performing traditional time-slicing may hide or obscure significant behaviors and patterns that occur in the network or any of its attributes. This research direction has been formulated in the context of dynamic network visualization [Bec+17] and received increased attention recently [SAK18; AMA22]. This topic can still be explored in more detail considering how these changes can be represented in other facets of the network. Finally, representing multiple facets of the network simultaneously is still considered an open challenge [HSS15] and encourages designing and developing novel contributions in the field of network visualization in order to overcome the scalability limitations of more standard and state-of-the-art approaches.

Standardized Datasets for Evaluations: Our research shows that while there has been extensive work on task taxonomies, there are still several disciplines that lack a set of tasks specifically designed for them [HSS15; McG+19; Sch+21]. Filling these gaps would facilitate the formal evaluation and comparison of network visualization techniques. Specifically, as network visualization systems become more complex, representing multiple facets and alternative network encodings, several surveys push for surpassing the traditional performance metrics (time and accuracy) and instead focus on the evaluation of cognitive aspects, perception issues, and user engagement [HMM00; Rod05; GK10; Zho+13; LHT17; Bec+17]. Evaluating the cognitive load on the user during the insight-generation process is a challenge in dynamic network visualization [HMM00; Lan+11; Bec+17]. However, this has been recently investigated by evaluating animation-based and small multiples approaches [Bre+20; Lin+21]. Furthermore, there is a lack of standardized datasets that can be used in evaluation settings in order to compare different network visualization techniques. We believe that this is an important challenge that needs to be solved in future work, as standardized dynamic network datasets will allow for a more transparent evaluation process and facilitate a formal comparison of the proposed techniques with related literature and state-of-the-art approaches.

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CHAPTER 8

Conclusion

In this dissertation we introduced the state-of-the-art related to dynamic, multi-variate, and multi-faceted network visualization and proposed our own categorization of these disciplines, outlining open challenges, gaps in related literature, and opportunities for future research. This led us to formalize our research questions that were tackled in the context of three publications on the topic of dynamic network visualization in different contexts, application domains, and for different task abstractions, mostly centered around applying these to the digital humanities. We investigated how different structural and temporal representations of dynamic network data can facilitate effective visual analytics for different tasks. Specifically, we focus on different approaches to modifying structural encodings for dynamic networks and evaluating which combinations are effective and appropriate in our work. In our publications we explored how we can answer our research questions and reflected on the outcomes, leading to a set of recommendations for dynamic network visualization designers and developers. We also discuss possibilities for scaling these, generalizing them to other problem contexts as well as the implications of our contributions to other application domains.

Furthermore, from our research, we identified several interesting and novel directions for future work that we aim to pursue. Namely, we focus on the following three topics. First, we direct our attention to temporal (continuous/event-based) network visual analysis, including dynamic metrics that can be used to describe the properties of the network and its elements. We have already made some initial steps in this direction with our proposed guidance-enhanced 2D projection approach of temporal (event-based) graphs, which are traditionally visualized in a space-time cube ($2D + t$) [Fil+23b]. Second, we will investigate how to visually encode and evaluate approaches to depict multiple dynamic data dimensions and facets. Finally, we plan to address gaps in evaluation literature, specifically, the lack of standardized datasets for dynamic and temporal network visualization. In this regard, we have also started making progress with our poster, proposing a set of quality criteria and benchmark datasets for both dynamic (time-sliced) and temporal (event-based) network visualization [Fil+23a].

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Appendix A

Additional material for the paper

CV3: Visual Exploration, Assessment, and Comparison of CVs

V. Filipov [1], A. Arleo [1], P. Federico [2], and S. Miksch[1]

[1]**Vienna University of Technology (TU Wien), Austria**
[2]**Nokia, Vimercate, Italy**

The following document contains additional material for the paper "*CV3: Visual Exploration, Assessment, and Comparison of CVs*" submitted to EuroVis 2019.

Diversification and Specialization score algorithms

In this section, we provide the pseudocode for the scoring functions. In Algorithm 1 we describe the Diversification score while we illustrate the Specialization score in Algorithm 2.

Auxiliary functions

The following functions are less relevant for the score calculation itself but are included to clarify the description of the algorithm. Since they are self-explanatory and depend on the environment and data structure implementation, only the method signature is provided.

- **normalize(**s**)** - receives an integer number in the range $[1, 5]$ and normalizes its value in the range $[0.2, 1]$;
- **mapSkillToScore(**S**)** - receives a textual representation of the skill ("Basic", "Novice", "Intermediate", "Advanced","Expert") and maps it to a number in the range $[1, 5]$;
- **parent(**n**)**, **children(**n**)**, **siblings(**n**)** - the functions yield respectively the parent of the target node n, the set of n's children, and its siblings;
- **findNode(**t**,**n**)** - the function recursively searches the skill tree t for the target node n.

Algorithm 1 Diversification Score

```
Input: tree, query                              ▷ The candidate Skill Tree and the query
Output: score                                   ▷ The candidate's Diversification score
score ← 0
alreadyVisited ← query
for Skill q in query do
    if q ∈ tree then
        n ← findNode(tree, q)
        children ← children(n)
        if children ≠ ∅ then                    ▷ Check if node has children
            for c in children do
                if c ∉ alreadyVisited then
                    alreadyVisited ← c
                    score ← score + 1
                end if
            end for
        end if
    else
        siblings ← siblings(n)
        for s ∈ siblings do
            if s ∉ alreadyVisited then
                alreadyVisited ← s
                score ← score + 1
            end if
        end for
    end if
end for
```

Supplemental material for the validation section

Interviews details

In the following we report the interviews structure and the questions asked to the domain experts in order to answer to the research questions expressed in the paper.

Interview structure

- 10 minutes introduction to the system
- 10 minutes unguided hands-on
- 50 minutes task based evaluation
- 20 minutes general feedback and interview

Algorithm 2 Specialization score

Input: $tree, query$
Output: $score$ ▷ The candidate's Specialization score
$score \leftarrow 0$
$sumWeight \leftarrow 0$
for Skill s in query **do**
  $weight \leftarrow normalize(mapSkillToScore(s.level))$
  if $s \in tree$ **then**
    $q \leftarrow findNode(tree, s)$
    $score \leftarrow score + mapSkillToScore(q.level) * weight$
  end if
  $sumWeight \leftarrow sumWeight + weight$
end for
$score \leftarrow score/sumWeight$ ▷ Average by the weight
$score * 2$ ▷ Multiply to scale in the range $[0, 10]$

Interview questions

Task-based evaluation . The following questions are related to a specific task. For the convenience of the reader, we first report the tasks from the paper and afterwards the questions asked the evaluate them. The tasks are the following:

- **VT1:** Select the candidates with the highest knowledge for a given query (this selected pool will be used for the other tasks);
- **VT2:** Assess the geographical data of the selected CVs in terms of proximity (to the recruiter) and mobility (in terms of geographical movement from place to place for a specific event);
- **VT3:** Compare the education, work experience, and other events of a candidate to all the others in order to find outliers and assess their potential;
- **VT4:** Evaluate the expertise of the candidates based on their common skills and overall knowledge.

The following is the list of questions, related to each task. Some of them were asked for more than one task (indicated in brackets):

- **ALL** - Which was the view that you found most useful and why?
- **ALL** - Did the interactions (highlighting, selection, hiding candidates) help you achieve the task / gain insights / compare the candidates better?
- **VT1, VT3, VT4** - Did you find the Specialization/Diversification score that the system suggested insightful?

- **VT4** - Did the radar view assist you in comparing the common skillsets of the candidates?

General feedback . We asked the following questions to understand the opinion of the experts regarding our solution:

- Did this tool help you achieve your tasks? Would a set of normal résumés have been faster/better?
- Did the timeline/map view help you in finding/selecting the candidate(s)?
- Did the scatterplot (list/results) view recommend a candidate you would have otherwise overlooked/not selected?
- Is the way we model and visualize skills similar to what you imagine the structure of the skills to be?
- Honest personal feedback

Build and install CV3

CV3 is based on a client-server communication pattern and implemented as a Single-Page-Application (SPA). The benefit of SPAs is that they do not require page reloading and it is possible to 'remember' states when navigating to different components of the application. For the implementation of the prototype we use Angular (v6) on the client-side along with a NodeJS backend on the server-side. The code is available at `https://github.com/velitchko/cvthree`. Build instructions, sample data and live demo link can also be found there.

Appendix B

Additional material for the paper

Gone Full Circle: A radial approach to visualize event-based networks in digital humanities

V. Filipov [1], V. Schetinger [1], K. Raminger [2], N. Soursos [2], S. Zapke [2], and S. Miksch [1]

[1] Vienna University of Technology (TU Wien), Austria
[2] Musik und Kunst Privatuniversität, Austria

In this supplementary material, for review purposes, we include a larger display of the figures for our submission. Due to the constraints on margins in the review template some figures appear smaller and the annotations become illegible. In the supplementary material the figures are displayed in the same order they occur in the paper submission. Please refer to this material in cases where the original figure in the paper submission is difficult to understand. Furthermore, for an overview of all tasks we also include a table of the tasks that were performed in the evaluation.

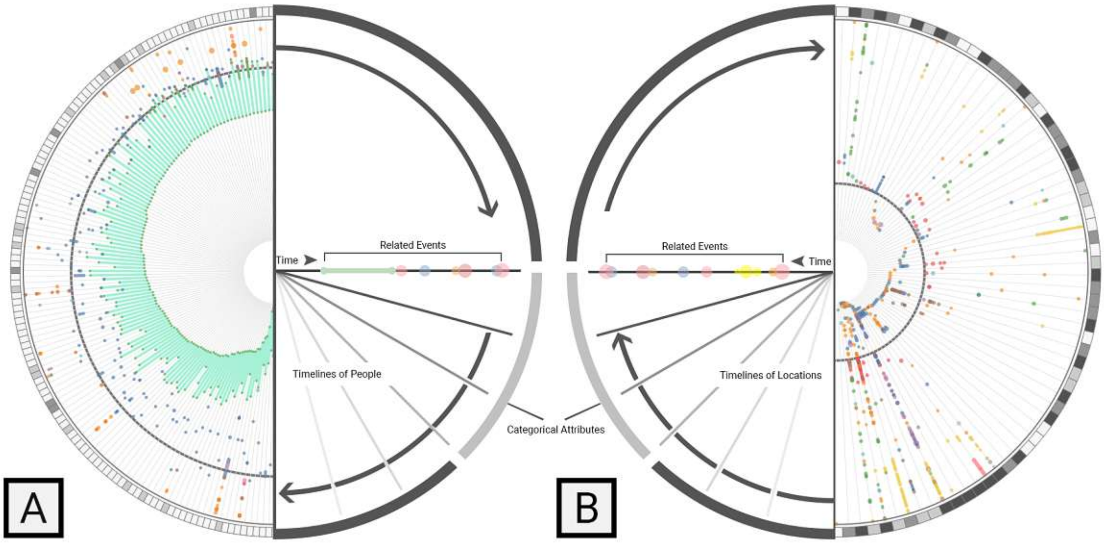


Figure 1: Our approach, Circular, depicting two different datasets. The persistent entities are depicted as rays along the circle with the line length representing their temporal development, related events are superimposed on their respective timelines and related themes are color-coded. A) Depicts people, their related events, and thematic changes over time; we can notice a spiral forming as people are ordered by their birth date and people of interest that have a large number of events occurring after their death. B) shows locations, their related events, and thematic information respectively. In this case different patterns emerge and we can observe popularity of certain locations shifting and the change of motifs over time.

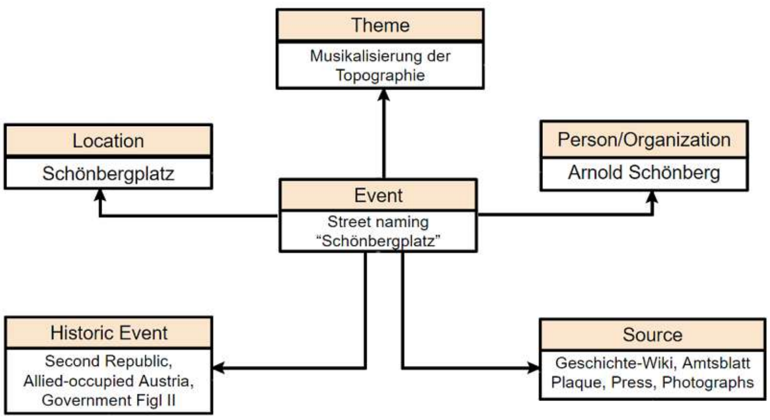


Figure 2: An example of how our event-based network is modeled. Events are the most central object that can relate people, organizations, locations, sources, themes, and historic events. In the figure you can see the topology of our network (yellow boxes) and an example of an event and its relationships (depicted by arrows) to other entities (white boxes).

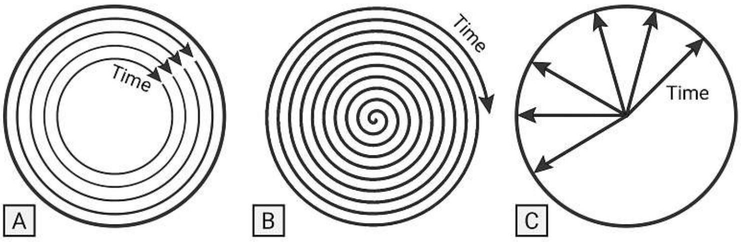


Figure 3: The three main representations for encoding time in radial visualizations [DLR09]. A) Ring-based Time - time is represented as progressing along the circumference; B) Space-filling - time is represented as a curve starting from the center and growing outwards; C) Polar Time - time is represented as growing outwards from the center in a ray-like fashion.

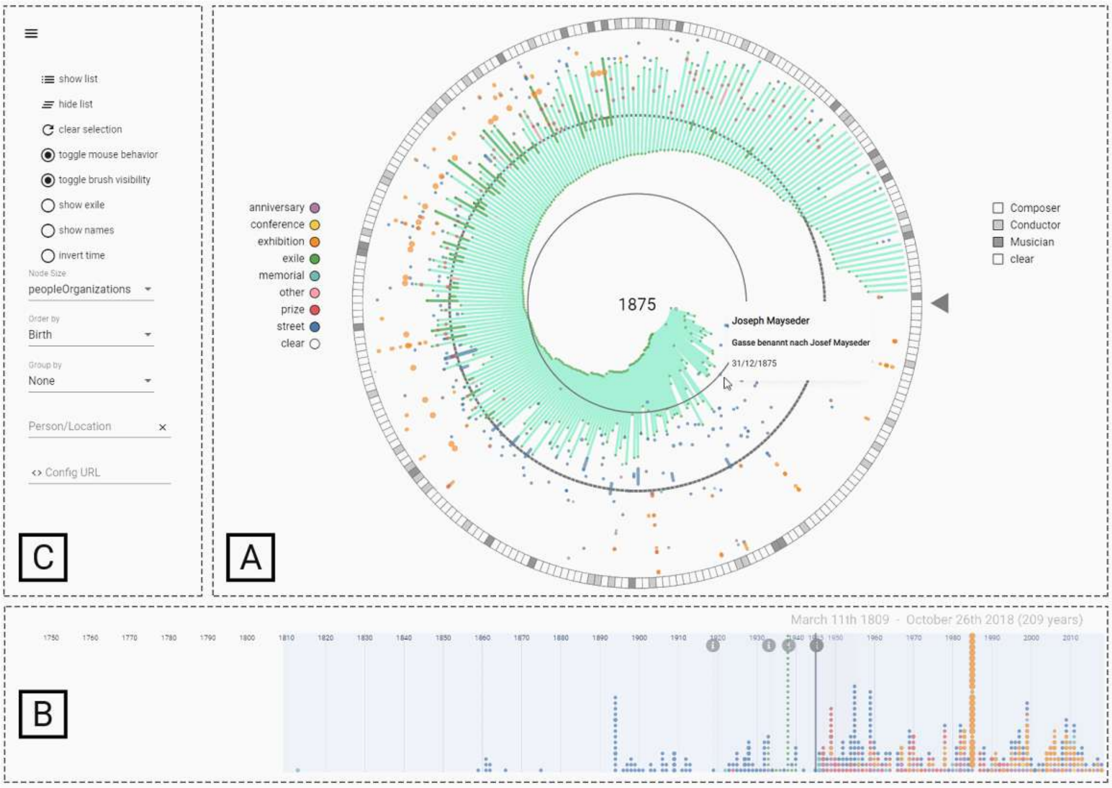


Figure 4: An overview of our prototype and its components. A) The main radial view where people, locations, their events, and thematic changes are visualized; B) The timeline that is used to visualize historic events and ease the users' selection of periods of time; C) A panel with settings and controls to modify the state of the visualization.

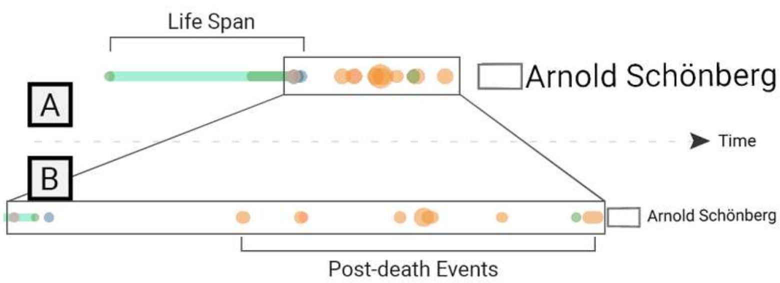


Figure 5: Arnold Schönberg's lifeline, along with related events and motifs. In this case the events are color-coded according to a classification provided by the domain experts. A) Here we can see the default temporal granularity and a more scaled up view can be seen in B). In this example we notice Arnold Schönberg was exiled (darker green bar) close to the end of his life and the bulk of events (orange circles) honoring this person happen after his death.

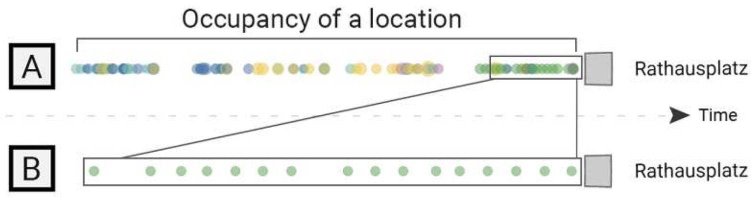


Figure 6: The lifeline of the Viennese Town Hall Square "Rathausplatz" along with related events and their motifs. In this case the events are color-coded according to the classification of themes provided by the domain experts. A) We can see the default temporal granularity and a more detailed view can be seen in B). In this example we can notice how the trends related to events happening at this location is changing over time (shift from blue to yellow to green circles).

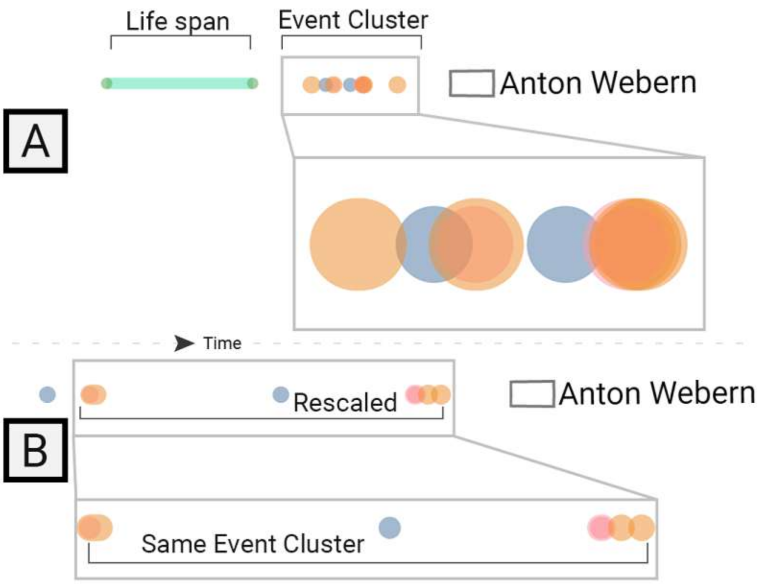


Figure 7: In A) we can see an event cluster happening after Anton Webern's death. These events cause clutter and overlaps. In B) we have scaled the temporal granularity up and the events are better spread out in order to mitigate dense areas and overlaps. In this example the events are color-coded based on a classification provided by our domain experts.

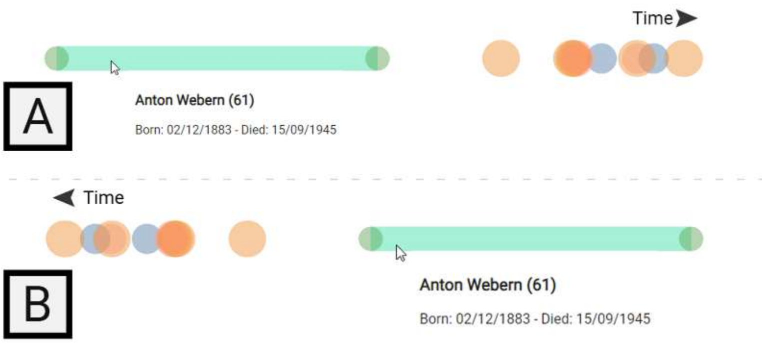


Figure 8: In Circular we also provide interactions to change the direction of time to resolve overlaps in dense areas close to the center of the circle. In this case the events are color-coded based on a classification provided by our domain experts. In A) we can see the progression of time is going from the left to the right and in B) we can see that the direction of time is inverted.

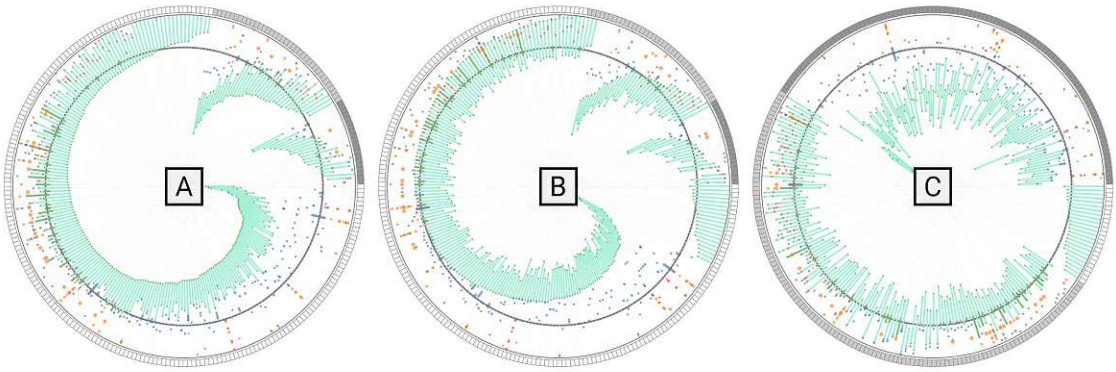


Figure 9: Three different patterns of people are visualized, each using a different combination of ordering and grouping criteria. A) People are ordered by their birth date and grouped by their role (composer, conductor, musician). A spiral forms growing outward, which is complementary to that of B), where people are ordered by their death date and grouped by role and completely different to C) where people are ordered by their honoring time and grouped by their role to highlight musicians that were honored early on by the City of Vienna.

Figure 10: The results of the user study. The bars represent the level of difficulty the participants experienced for each task category as a percentage (0-100%). The categories E (easy); M (medium); H (hard) represent a qualitative ranking of the performance of the participants for the questions from our evaluation. For the different tasks in the evaluation we can observe that our approach supports most tasks well (E), with some minor issues (M), and severe difficulties (H) were very rarely encountered.

Question	Task Categories
Q1: At which locations was the First of May celebrated in 1924?	T1
Q2: When did the first event related to “Stadtbranding” happen?	T3
Q3: Which themes are related to the events taking place at “Stadthalle”?	T1, T2, T3
Q4: When is Erich Wolfgang Korngold born / When did Erich Wolfgang Korngold die?	T5
Q5: Which events are related to Alban Berg?	T3, T5
Q6: Can you find an interesting event OR person in the timeline OR circle? Inspect it in more detail.	T1, T3
Q7: Which location was used most often for “Politische Inszenierungen” during the Second Republic?	T2, T4
Q8: Which events took place at the “Befreiungsdenkmal”? Which music was played there? Who organized the events? Which historic events are they referring to?	T1, T3, T5
Q9: Which location was most used to celebrate the First of May between 1918 and 2018, and which one was used the least?	T2, T3, T4
Q10: Can you find the location(s) attributed to “Regenbogenparade” 2016?	T3, T5
Q11: In which year(s) did the opening of the “Wiener Festwochen” NOT take place at “Rathausplatz”? Which location(s) were used instead?	T2, T3
Q12: In which district(s) did fewest events take place?	T1, T2, T4
Q13: Which exiled musicians never came back? Name two.	T2, T3, T5
Q14: Can you name 3 exiled Musicians that do not have a street named after them?	T1, T3, T5
Q15: Are there more male or female people in the visualization?	T1, T2
Q16: Can you rank the groups by role based on the number of people in each group.	T2
Q17: Can you name the musician from each group that was born first?.	T1, T2, T4
Q18: Can you find the two conferences? When did they take place and which musicians were related to them?	T2, T3, T5

Table 1: There was a total of 18 questions with varying degrees of difficulty and details required that the participants performed throughout the user study. It is important to note that questions can appear in more than one task category.

Appendix C

Additional material for the paper

On Network Structural and Temporal Encodings: A Space and Time Odyssey

V. Filipov [1], A. Arleo [1], M. Bögl [1], and S. Miksch [1]

[1]**Vienna University of Technology (TU Wien), Austria**

In this supplementary material we include additional results and information regarding both studies discussed in the paper. The aim with this material is to complement the presentation of results and discussion in the paper.

Study 1

Repository GitHub Link: `https://github.com/velitchko/graph-vis-evaluation`

The study initially received 76 submissions. We introduced a control question every 12 the filter out participants trying to game the study, resulting in 8 being removed.

Protocol

We conduct a 10 min presentation explaining the scope of the study to the participants. In each question, the participants will look at a picture or at an animation and solve a simple task. We ask the participants to answer the questions and provide a confidence rating for each 1 - not confident, 5 - very confident. There are optional breaks every 12 questions that they can take. These can be skipped. At the end we ask the participants to rate each technique from 1 (least preferred) to 5 (most preferred) stars and provide comments and opinions about each.

Visualization Techniques

Matrices visualize the network as an n x n table. A non-zero value in the cell indicates the presence of an edge between the nodes identified by the corresponding row and column.

Node-Link diagrams present the relational structure of the graph using lines to connect the entities that are depicted using circles, whose coordinates on the plane are computed using specialized algorithms.

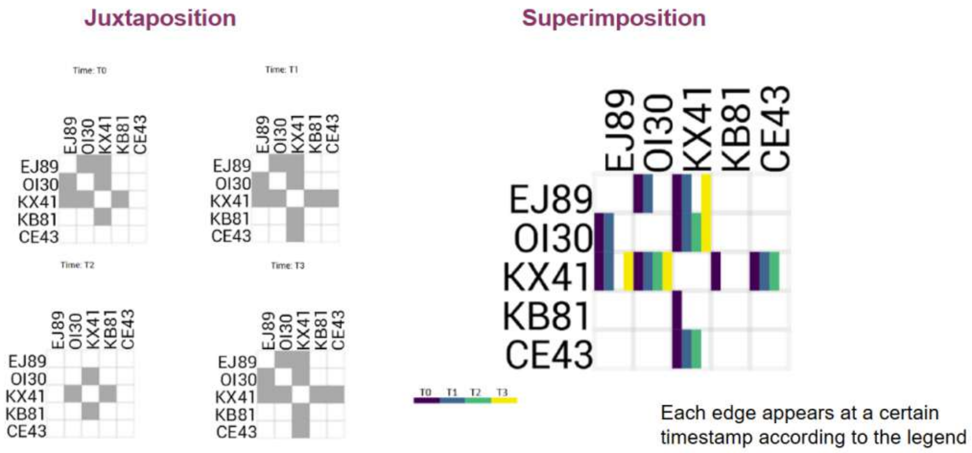


Figure 11: Matrix representations. Juxtaposition (left) creates small multiples, one for each time slice. Superimposition (right) splits each cell uniformly with each rectangle being color coded according to the time slice an edge exists in.

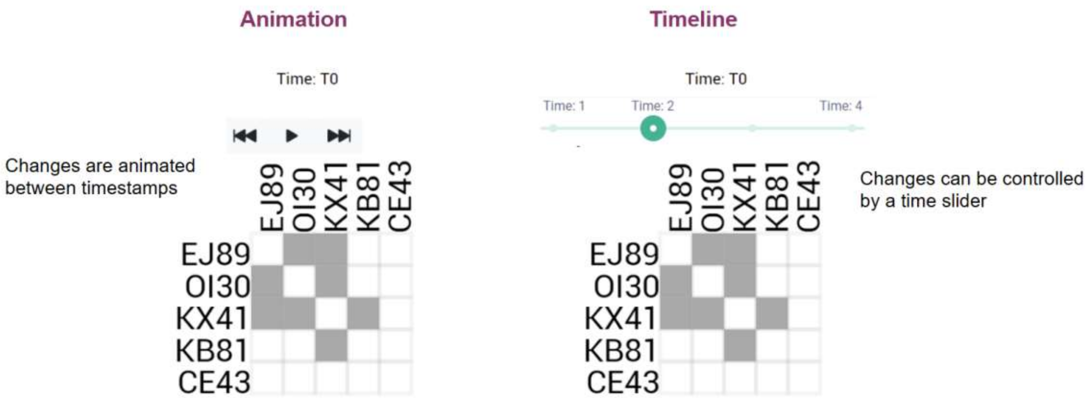


Figure 12: Matrix representations. Auto-Animation (left) where the dynamics are represented as smooth transitions between the time slices, including controls to play, speed up, or slow down the animation speed. Animation with Controls (right) where the time slider provides the option to interactively navigate to specific time slices.

Juxtaposition represents the graph's temporal dynamics as distinct layouts, each with dedicated screen space, similar to the small multiples approach (see Figures 13, 11).

Superimposition encodes the temporal dimension of the network in the same screen space by overlaying the timeslices. In node-link, we generate multiple parallel edges between the nodes,

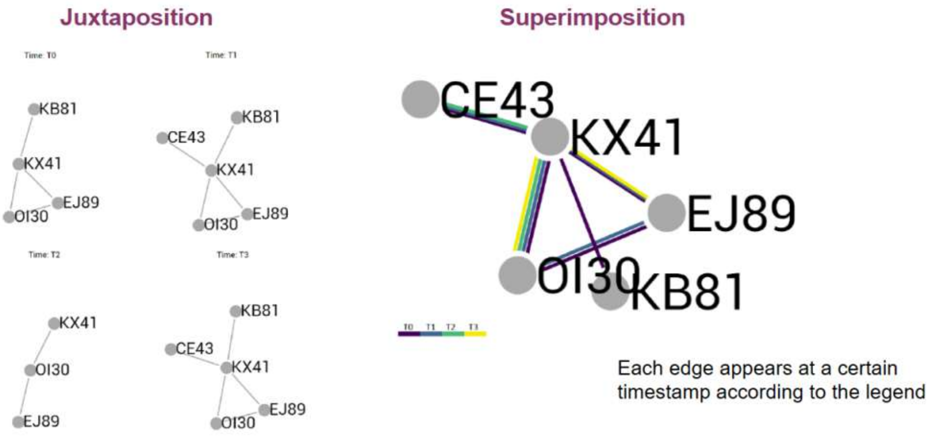


Figure 13: Node-Link representations. Juxtaposition (left) creates small multiples, one for each time slice. Superimposition (right) creates parallel edges with each being color coded according to the time slice an edge exists in.

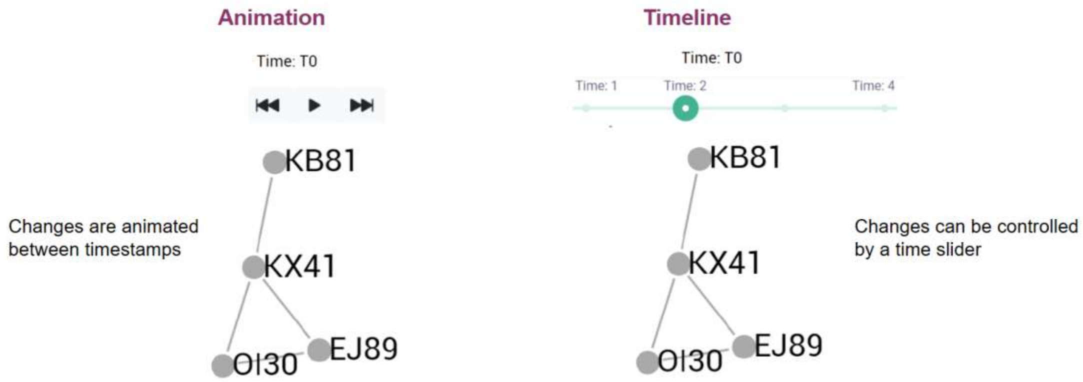


Figure 14: Node-Link representations. Auto-Animation (left) where the dynamics are represented as smooth transitions between the time slices, including controls to play, speed up, or slow down the animation speed. Animation with Controls (right) where the time slider provides the option to interactively navigate to specific time slices.

one for each timeslice where the edge is present, and color-code them individually (see Figure 13. In matrices we subdivide each cell uniformly into rectangles, each representing the existence of that edge during that timeslice, which is colored similarly (see Figure 11.

Auto Animation depicts the change of the graph over time as smooth transitions between subsequent timeslices. Differently from Animation with Controls, with Auto Animation it is not possible to skip forward or navigate backward in time and it automatically goes over each of the timeslices in a sequence (see Figures 14, 12).

Animation with Controls depicts the change of the graph over time as smooth transitions between subsequent timeslices. The controls use a time slider to control the state of the animation and move to any of the available time slices in no particular order or using play/pause buttons to automatically play through the sequence of graphs and pause at a specific time slice (see Figures 14, 12).

Interaction Techniques

Pan + Zoom Using the mouse to move around in both the node-link and matrix diagrams to focus on different areas on the network (linked panning in juxtaposition). Using the mouse scroll wheel (pinch to zoom on touchpads) in order to zoom into the node-link and matrix diagrams (linked zooming in juxtaposition). **Dragging** By holding down left mouse click on nodes in the node-link diagrams it is possible to drag nodes around to mitigate overlaps and denser areas in the network.

Highlighting By hovering the mouse cursor on the nodes (circles in the node-link diagram) or cells (rectangles in the matrix diagram) it is possible to highlight the selection in red (linked highlighting in juxtaposition).

Animation With the animation it is possible to start the animation automatically as well as to set the speed of the animation using the fast forward or rewind icons.

Time Slider With Animation with Controls it is possible to use the time slider to navigate to any of the available time slices in no particular order. Intermediate time slices are not animated, the transition only occurs between the start (current) and end (selected) time slice.

Evaluation Tasks

The tasks used in our experiment are available in Table 2. We picked one task for each category of temporal feature in the network evolution task taxonomy proposed by Ahn et al. [1], namely, *Individual Temporal Features* (**T1**), *Rate of changes* (**T2**), and *Shape of changes* (**T3**). We selected the most common tasks referenced in the taxonomy and included in our experiment these tasks for both low- (nodes and edges) and higher-level (cliques) entities.

Results & Research Hypotheses

In the following, we explain what the different columns in our results encode. The raw data is available as part of the supplementary material.

See `https://docs.google.com/spreadsheets/d/1msuE6HjceCat_M31kg1_GRdhXNhvgc0B` for the survey results and `https://docs.google.com/spreadsheets/d/1Y26d5qEHbDspH3UD5hbjrmNYmhe8gnL7G-E` `eg` for the feedback given by the participants.

- group: Indicates the assigned group. Group A - No interactions available. Group B - Interactions available.
- id: The UUID generated ID of the participant.

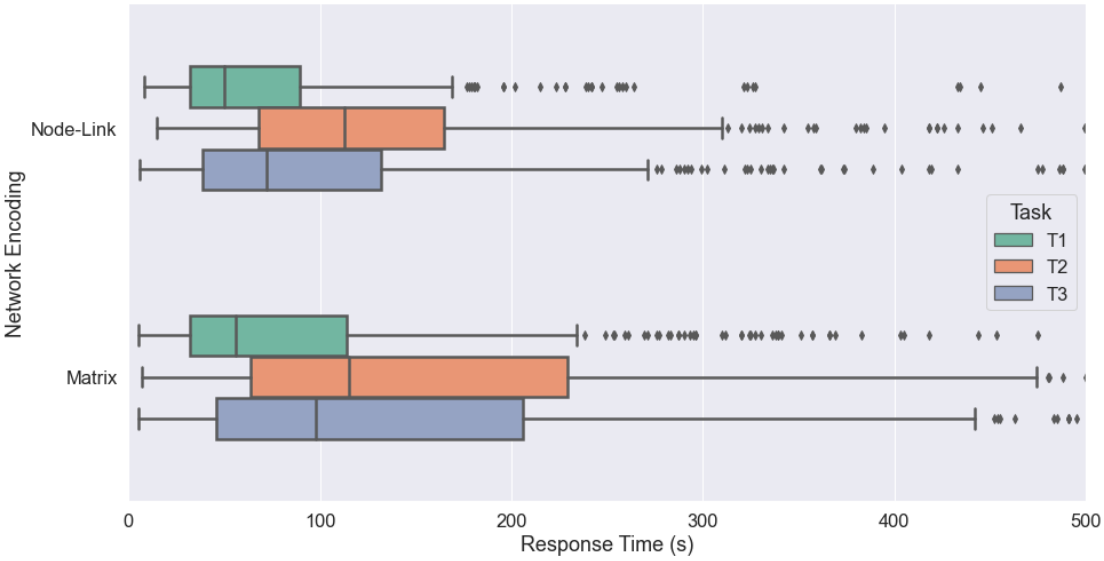
	Low-level	High-level
T1	At which time step is the relationship between {source} and {target} introduced for the first time?	At which time step does the clique between {nodes} appear for the first time?
T2	Sum up the changes (additions and removals) of {node}'s degree across all time steps.	Calculate change of the clique's size between {nodes} across all time steps.
T3	At which time step does the node {node} have its highest degree?	Consider the set of nodes {nodes}. Find the size of the largest maximal clique across all the time steps between the given nodes.

Table 2: Example questions, per task (rows) and entity type (columns). Target nodes for low-level tasks were chosen randomly during the study design; cliques were also introduced artificially as explained in Section 5.1 of the paper.

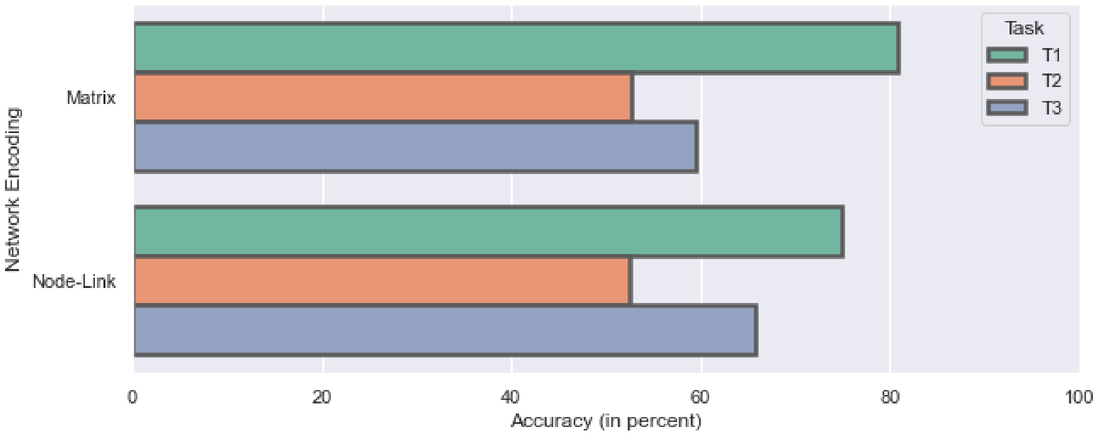
- question: The survey question short code.
- answer: The answer provided by the participant for the question.
- time: The response time (in milliseconds) of the participant.
- confidence: The confidence of the participant (1 - least confident, 5 - most confident).
- correct_answer: The correct answer for the survey question.
- correct: Boolean value (TRUE, FALSE) indicating if the participant provided the correct response for this survey question.
- zoom_timers: Array of timers for each zoom interaction that was performed (recorded in milliseconds).
- drag_timers: Array of timers for each drag interaction that was performed (recorded in milliseconds).
- highlight_timers: Array of timers for each highlight interaction that was performed (recorded in milliseconds).
- zoom_interactions: A total count of how many zoom interactions were performed.
- drag_interactions: A total count of how many drag interactions were performed.
- highlight_interactions: A total count of how many highlight interactions were performed.
- slower_interactions: A total count of how many times the participant slowed down the animation (for Auto Animation).
- faster_interactions: A total count of how many times the participant sped up the animation (for Auto Animation).

- slider_interactions: A total count of how many times the participant used the time slider (for Animation with Controls)

In the following, we provide additional figures from our statistical analysis of the research hypotheses on the response times and accuracy, as well as, the analysis of variance investigating the influence of the independent variables in the study. These figures also contain the outliers that were subsequently removed as part of the analysis using IQR outlier detection.

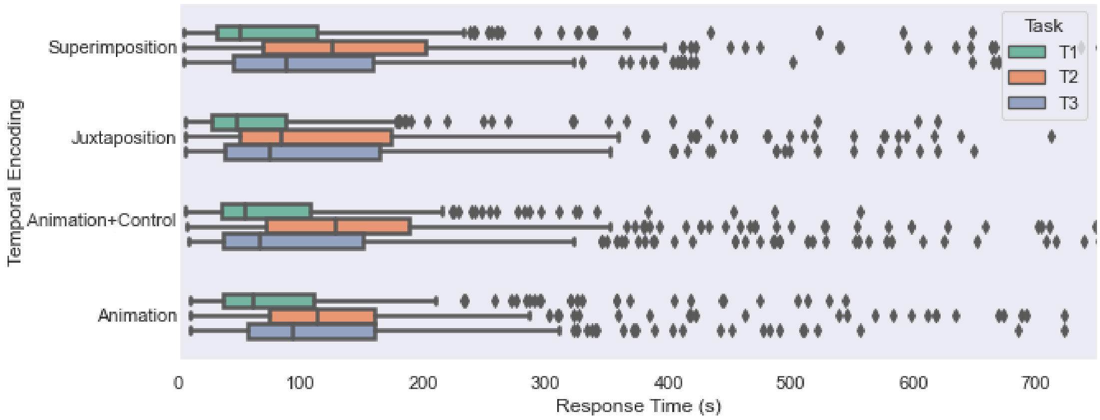


(a) Differences in response times between node-link and matrix network encodings per task.

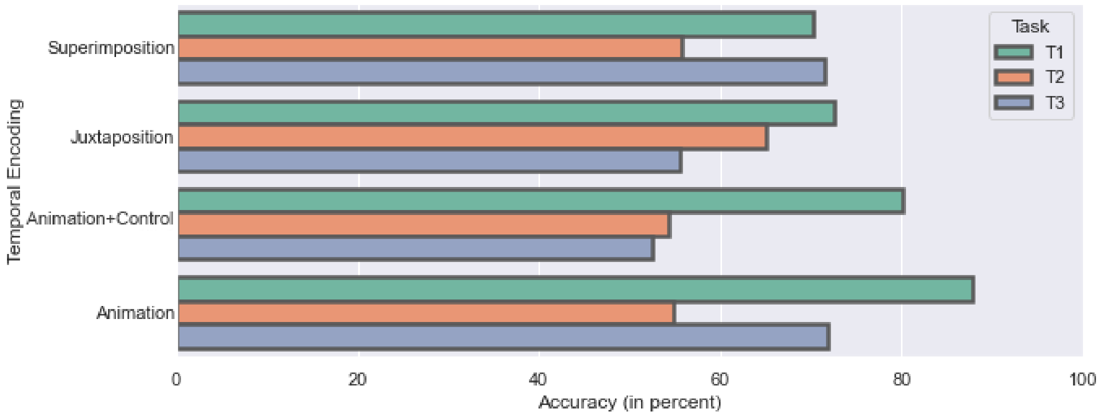


(b) Accuracy (in percent) for node-link and matrix representations per task.

Figure 15: Response times and correct responses between network encodings and tasks for **H1: Matrices have lower response times and higher accuracy for all tasks compared to node-link diagrams, regardless of the temporal encoding.**

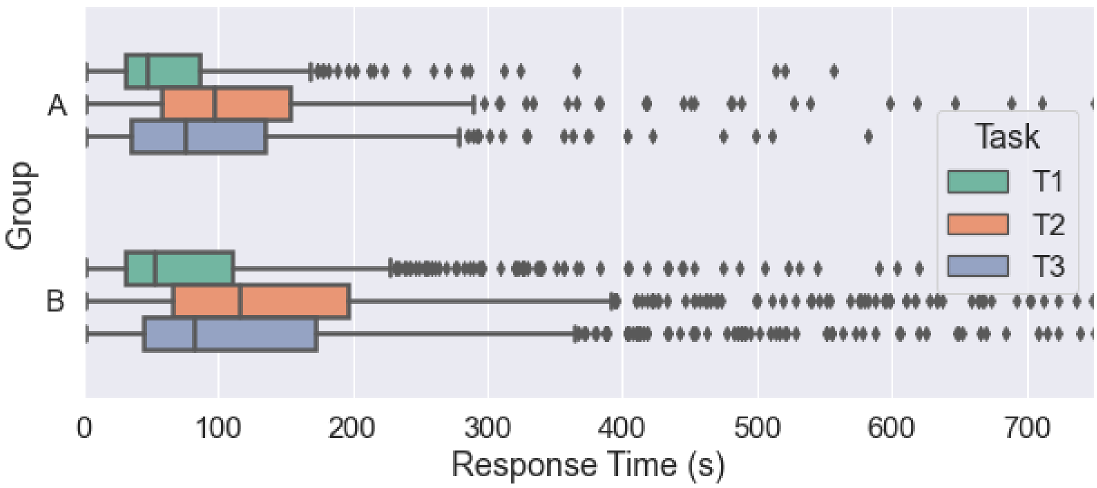


(a) Differences in response times between temporal encodings per task.

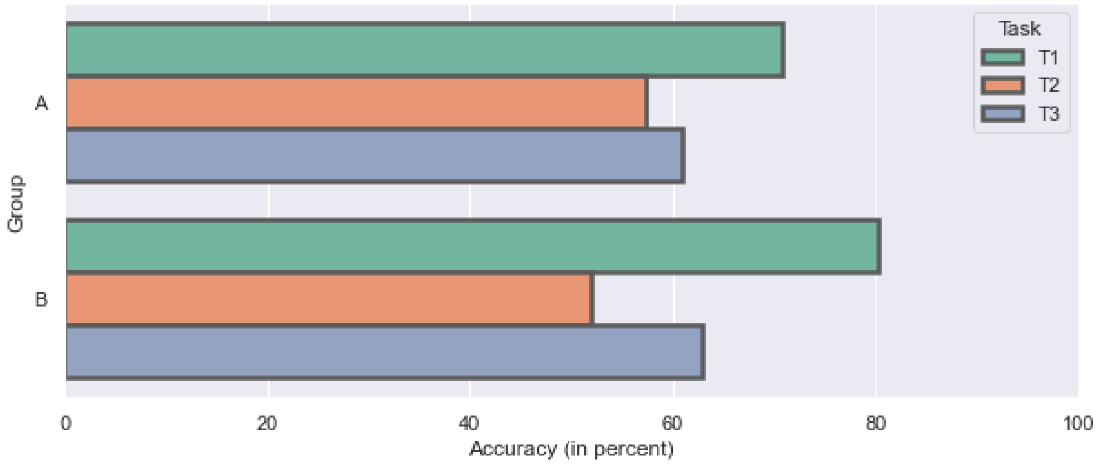


(b) Accuracy (in percent) for temporal encodings per task.

Figure 16: Response times and accuracy between network encodings and tasks for **H2: From all temporal encoding techniques, superimposition has the lowest response times and highest accuracy, regardless of the structural representation.**

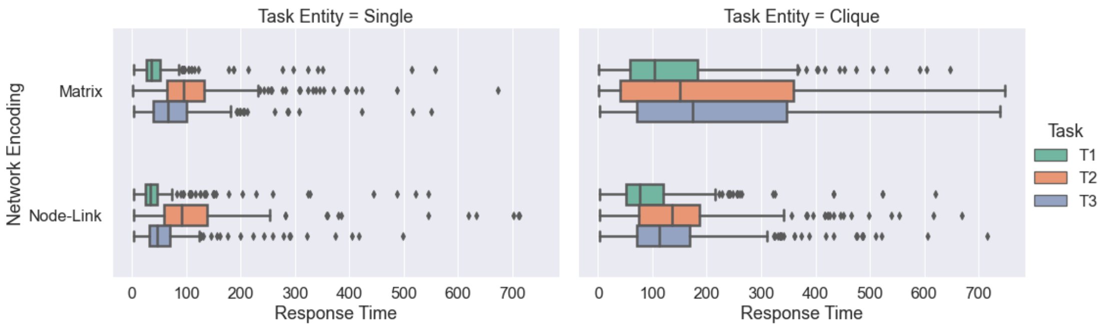


(a) Differences in response times between interaction groups per task.

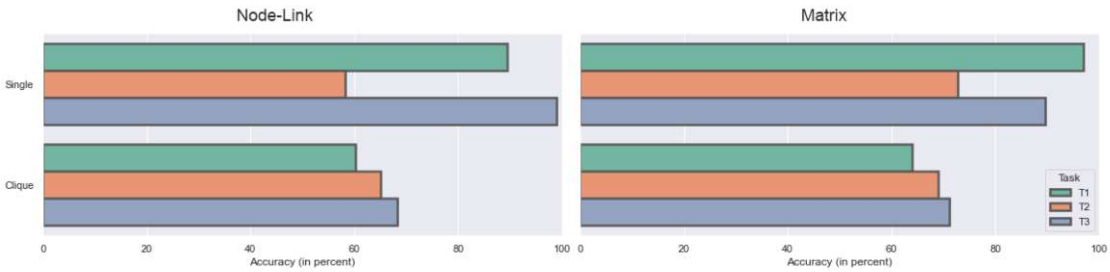


(b) Accuracy (in percent) for interaction groups per task.

Figure 17: Response times and accuracy between groups (A - no interaction; B - interaction) and tasks for **H3: Providing interaction techniques increases the response times but not the accuracy.**

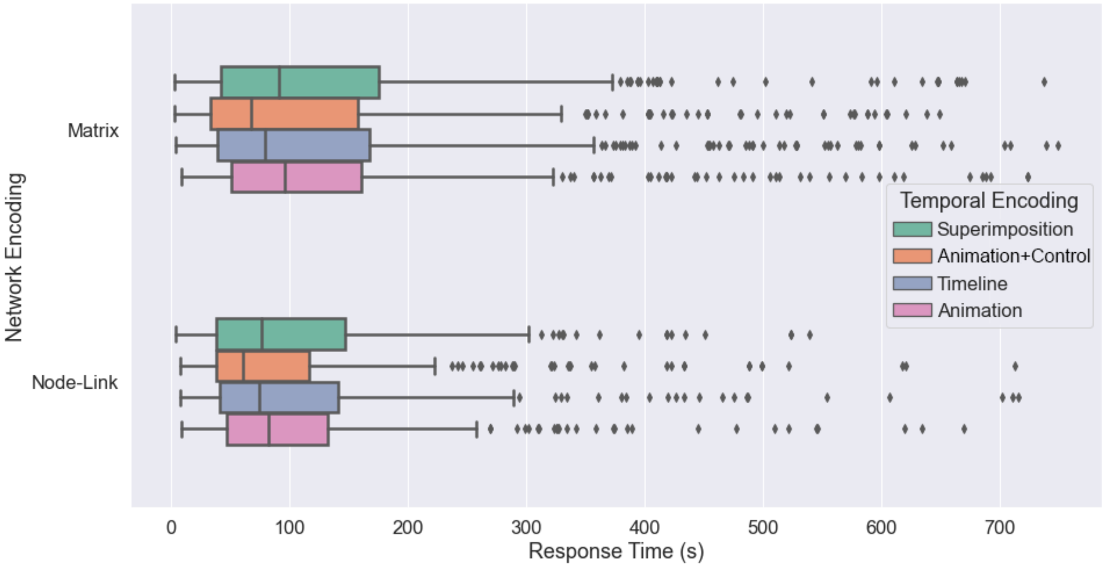


(a) Differences in response times between network encodings and entity type per task.

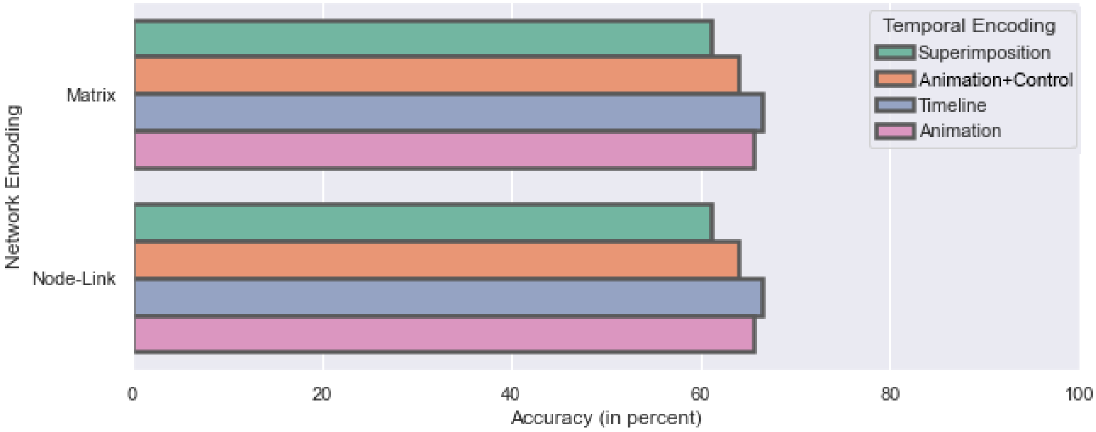


(b) Accuracy (in percent) for adjacency matrices and entity type per task.

Figure 18: Response times and accuracy between network representations and entity types (single - low-level; clique - high-level) and tasks for **H4: Matrices have lower response times and higher accuracy for tasks on low-level entities and node-link diagrams have lower response times and higher accuracy for tasks on higher-level entities, regardless of the temporal encoding.**



(a) Differences in response times between network representations and temporal encodings.



(b) Accuracy (in percent) for different combinations of network representations and temporal encodings.

Figure 19: Response times and accuracy between network representations and temporal encodings for **H5: The combination of matrices with superimposition results in the lowest response times and highest accuracy compared to other combinations of network structural and temporal encoding.**

In the following we provide the results of our Analysis of Variance (ANOVA tests for each hypothesis investigating the influence of the independent variables in our study (task type, network and temporal encoding, and group) on the dependent variable time, outlining the significance levels for each. Column "Df" refers to the degrees of freedom for the independent variable (number of levels in the variable minus 1); "Sum Sq" displays the sum of squares (a.k.a. the total variation between the group means and the overall mean); "Mean Sq" is the mean of the sum of the squares, calculated by dividing the sum of squares by the degrees of freedom for each parameter; "F Value" column is the test statistic from the F-test. It is the mean square of each independent variable divided by the mean square of the residuals: the larger the value, the more likely it is that the variation caused by the independent variable is real and not due to chance. Finally, "Pr(>F)" is the *p*-value of the F-test statistics, and the "Significance" column reports a symbol for quick visual reference about statistical significance.

Response Time	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Significance
network_enc	1	2138106	2138106	98.0501	<2.2e-16	***
task_type	2	3523697	1761849	80.7955	<2.2e-16	***
group	1	338934	338934	15.543	8.24E-05	***
network_enc:task_type	2	303223	151612	6.9527	0.0009704	***
network_enc:group	1	30489	30489	1.3982	0.2371122	
task_type:group	2	26350	13175	0.6042	0.5465832	
network_enc:task_type:group	2	9345	4672	0.2143	0.807143	
Residuals	3250	70870339	21806			
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Table 3: ANOVA table for **H1** showing the influence of the independent variables on the dependent variable "time" together with their interaction effects.

Response Time	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Significance
network_enc	1	1357060	1357060	61.7501	5.25E-15	***
task_type	3	213354	71118	3.2361	0.02134	*
group	1	346104	346104	15.7487	7.39E-05	***
network_enc:task_type	3	75322	25107	1.1425	0.33047	
network_enc:group	1	2920	2920	0.1329	0.7155	
task_type:group	3	5082	1694	0.0771	0.97239	
network_enc:task_type:group	3	36402	12134	0.5521	0.64671	
Residuals	3262	71687780	21977			
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Table 4: ANOVA table for **H2** showing the influence of the independent variables on the dependent variable "time" together with their interaction effects.

References

[1] J.-w. Ahn et al. (2014). A Task Taxonomy for Network Evolution Analysis. IEEE Transactions on Visualization and Computer Graphics, vol. 20, no. 3, p. 365–376, 10.1109/TVCG.2013.238

Response Time	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Significance
network_enc	1	867172	867172	9.1825	2.46E-03	**
task_type	3	219958	73319	0.7764	0.507051	
group	1	1537636	1537636	16.282	5.58E-05	***
network_enc:task_type	3	65818	21939	0.2323	0.873916	
network_enc:group	1	255	255	0.0027	0.958563	
task_type:group	3	44034	14678	0.1554	0.926229	
network_enc:task_type:group	3	126840	42280	0.4477	0.718939	
Residuals	3365	317783541	94438			
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

Table 5: ANOVA table for **H3** showing the influence of the independent variables on the dependent variable “time” together with their interaction effects.

Response Time	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Significance
network_enc	1	1731835	1731835	30.8822	2.95E-08	***
task_type	1	8841140	8841140	157.656	<2.2E-16	***
group	1	1036281	1036281	18.4791	1.77E-05	***
network_enc:task_type	1	2355561	2355561	42.0046	1.04E-10	***
network_enc:group	1	67782	67782	1.2087	2.72E-01	
task_type:group	1	342754	342754	6.112	0.01348	*
network_enc:task_type:group	1	15681	15681	0.2796	0.59698	
Residuals	3377	189377703	56079			
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

Table 6: ANOVA table for **H4** showing the influence of the independent variables on the dependent variable “time” together with their interaction effects.

Study 2

Protocol

In the following we include the protocol that was used to onboard to participants of the second study, detailing the different visualization modalities, interactions, and dataset.

Repository GitHub Link `https://github.com/velitchko/graph-vis-evaluation-ext`

Questionnaires that were filled out by the participants can be found here as Google Forms:

Questionnaire (per visualization) [1]

Questionnaire (combined) [2]

[1] `https://docs.google.com/forms/d/e/1FAIpQLSfTCgQALPAVswTokeBMQibD3c22PXqqsoCKa4R8aVRXnY6 viewform?usp=sf_link`

[2] `https://docs.google.com/forms/d/e/1FAIpQLSf493kQanxouJvw-931CD2ov9-R_YmGY2alrViT-NWkVbHzLg/viewform?usp=sf_link`

Response Time	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Significance
network_enc	1	1357060	1357060	61.7501	5.25E-15	***
task_type	3	213354	71118	3.2361	0.02134	*
group	1	346104	346104	15.7487	7.39E-05	***
network_enc:task_type	3	75322	25107	1.1425	3.30E-01	
network_enc:group	1	2920	2920	0.1329	7.16E-01	
task_type:group	3	5082	1694	0.0771	0.97239	
network_enc:task_type:group	3	36402	12134	0.5521	0.64671	
Residuals	3262	71687780	21977			
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Table 7: ANOVA table for **H5** showing the influence of the independent variables on the dependent variable "time" together with their interaction effects.

Visualization Techniques

Matrices visualize the network as an n x n table. A non-zero value in the cell indicates the presence of an edge between the nodes identified by the corresponding row and column.

Node-Link diagrams present the relational structure of the graph using lines to connect the entities that are depicted using circles, whose coordinates on the plane are computed using specialized algorithms.

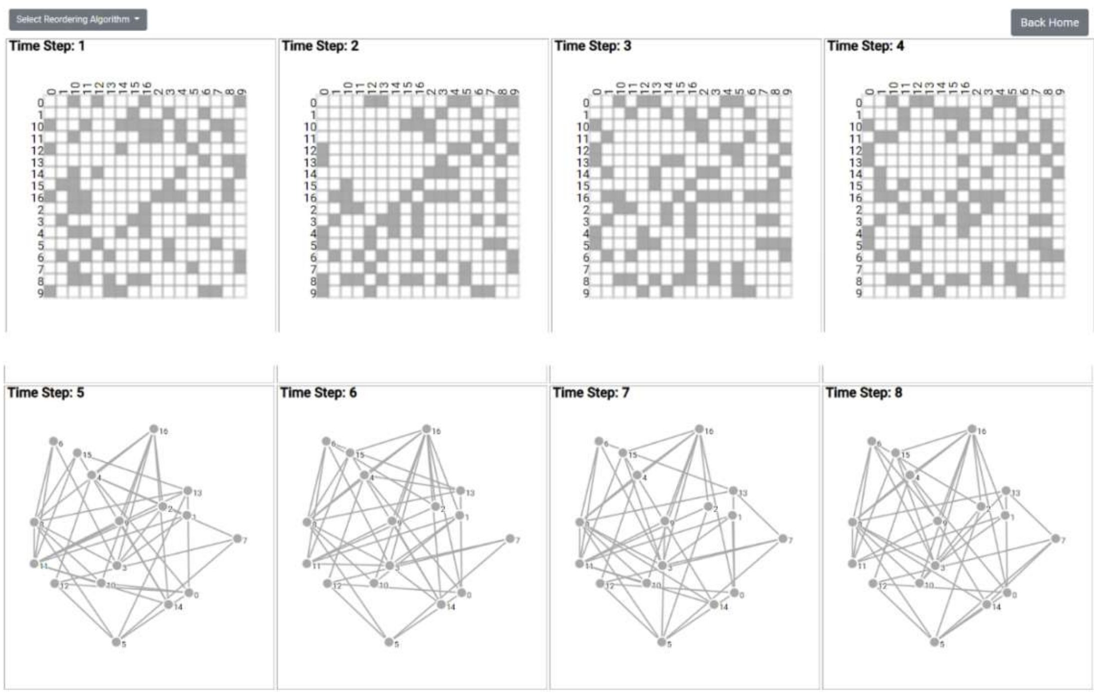


Figure 20: Example of Juxtaposition for both Node-Link and Matrix.

Juxtaposition represents the graph's temporal dynamics as distinct layouts, each with dedicated screen space, similar to the small multiples approach

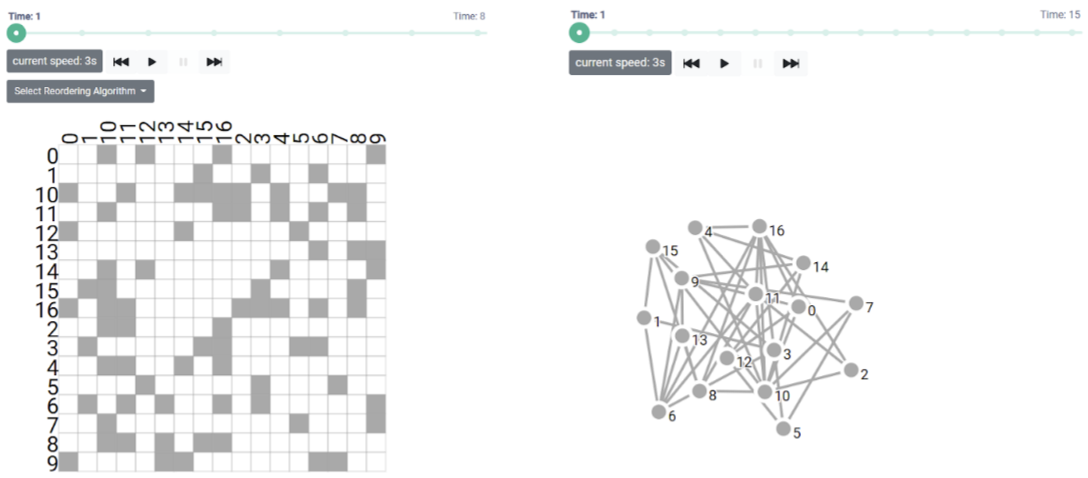


Figure 21: Example of Animation with Controls for both Node-Link and Matrix.

Animation with Controls depicts the change of the graph over time as smooth transitions between subsequent timeslices. The controls use a time slider to control the state of the animation and move to any of the available time slices in no particular order or using play/pause buttons to automatically play through the sequence of graphs and pause at a specific time slice.

Interaction Techniques

Pan + Zoom Using the mouse to move around in both the node-link and matrix diagrams to focus on different areas on the network (linked panning in juxtaposition). Using the mouse scroll wheel (pinch to zoom on touchpads) in order to zoom into the node-link and matrix diagrams (linked zooming in juxtaposition). **Dragging** By holding down left mouse click on nodes in the node-link diagrams it is possible to drag nodes around to mitigate overlaps and denser areas in the network.

Highlighting By hovering the mouse cursor on the nodes (circles in the node-link diagram) or cells (rectangles in the matrix diagram) it is possible to highlight the selection in red (linked highlighting in juxtaposition).

Animation Controls With the animation it is possible to play and pause the animation automatically as well as to set the speed of the animation using the fast forward or rewind icons. Additionally, its possible to use the time slider (which automatically pauses the animation) to navigate to any of the available time slices in no particular order.

Reordering In the matrix diagrams it is possible to reorder the rows and columns of the matrix according to a few different algorithms in order to highlight different patterns and structures that appear under these configurations. The following algorithms are available:

- **none** - the default one that sorts the rows and columns according to the alphabetical order of the labels
- **Leaforder** - Uses the optimal leaf ordering that tends to produce coherent and well-organized block-diagonal forms
- **Barycenter** - has the tendency to show clusters in the graph in the top left and bottom right corners
- **RCM (Reverse Cuthill McKey)** - Minimizes the graph bandwidth. It tends to have the matrix's nonzero elements closer to the diagonal.
- **Spectral** - Uses eigenvalues and eigenvectors to produce an ordering, i.e., each row/column is projected into the eigenspace where the distances between the eigenvectors are used to calculate the ordering.

Matrix Patterns (from Behirsch et al. [1])

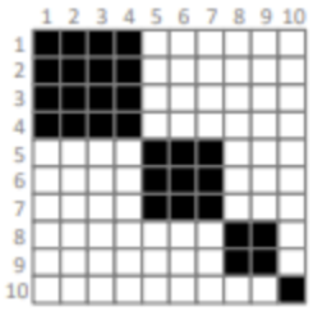


Figure 22: Block pattern.

Block Pattern "Coherent rectangular areas appear in ordered matrix plots whenever strongly connected components or cliques are present in the underlying topology. The figure shows 4 disconnected cliques (complete sub-graphs) containing 4, 3, 2, and 1 vertices."

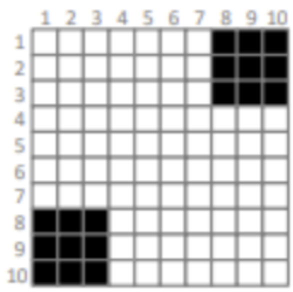


Figure 23: Off Diagonal Block Pattern.

Off Diagonal Block Pattern "Off-diagonal coherent areas correspond to either sub-patterns of a block pattern or relations in a bi-graph. In the first case, the off-diagonal pattern would be visible in addition to the previous block pattern, and show connections between cliques."

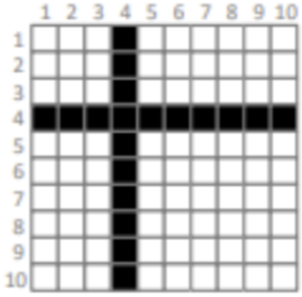


Figure 24: Line/Star Pattern

Line/Star Pattern "Continuous horizontal and vertical lines are present in matrix plots if a vertex is strongly connected to several distinct other vertices. This pattern helps the analysts to understand and reason on the general connectivity aspects within the network."

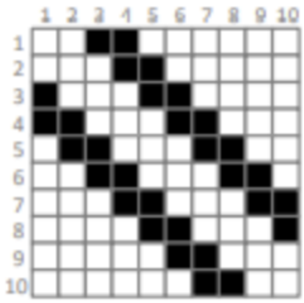


Figure 25: Band Pattern

Band Pattern “Off-diagonal continuous lines refer to paths and cycles, or meshes in a network. They represent a set of vertices with a few connections to other vertices.” Width of the band tells us how many distinct paths can be taken through the network.

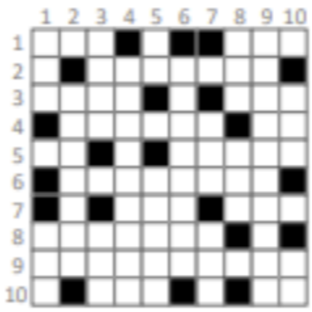


Figure 26: Noise Anti-Pattern

Noise Anti-Pattern “Noise (also called salt-and-pepper) is the classic anti-pattern for a matrix plot. It can be found whenever the row-/ column ordering is not able to reveal the underlying graph topology or if simply no structure exists.“

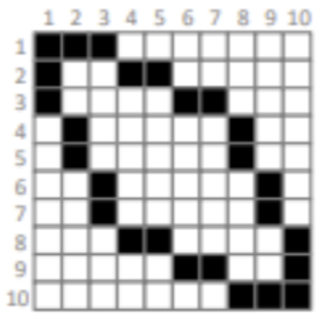


Figure 27: Band Anti-Pattern

Bandwidth Anti-Pattern “Bandwidth- or sparsity patterns visually group non-zero elements (connections) within an enclosure around the diagonal. This pattern adds little interpretation to the matrix plot if the inner part of the bandwidth enclosure reveals no structure.” Bandwidth is the maximum distance between two vertices.

Dataset

The dataset is about papers that have appeared at the IEEE Information Visualization (InfoVis) Conference from 1995 to 2018 [2]. The dataset represents a co-authorship network where the relationships indicate that two authors (nodes) published a paper together. We have extracted 80 nodes with 500 relationships between them from the dataset and aggregated them into 8 time slices.

Evaluation Tasks

Try to get a sense of the data, the relationships between the nodes, and the temporal evolution of the data. How are things changing over time? Are there interesting structures that you notice being formed?

Feel free to explore and browse, pointing out interesting insights you may find (highly connected nodes, changes in relationships, cliques or clusters that are formed, more interesting time slices).

Please voice your thoughts about what you are doing, searching for, finding, or expecting to see. Any inconsistencies, invalid or unexpected data points or relationships?

Results

The results from the ICE-T heuristic evaluation are available as part of the supplementary material.

See `https://docs.google.com/spreadsheets/d/1yfljHnlpFsSM688yj7_AJDb1mDGUFzV-` for the results of the ICE-T evaluation.

	Component	Insight		Time		Essence		Confidence		Total	
Technique	**Score**	**AVG**	**STD**	**AVG**	**STD**	**AVG**	**STD**	**AVG**	**STD**	**AVG**	**STD**
	M+ANC	4.65	1.22	4.25	1.84	3.93	1.44	4.73	1.73	4.46	1.53
	M+JP	4.33	1.46	3.85	2.06	4.36	1.91	4.53	1.96	4.26	1.78
	NL+ANC	6.22	0.82	6.00	0.84	6.14	0.83	6.13	1.02	6.15	0.87
	NL+JP	6.10	0.80	5.65	1.19	5.93	0.96	6.00	0.97	5.96	0.97

Table 8: Results of the ICE-T heuristic evaluation. The rows are the individual combinations of structural and temporal graph encodings that were evaluated. The columns are grouped per component and within each we calculate the mean and standard deviation of the participants' ratings. The right-most column shows the total for each techniques.

ICE-T Survey

The ICE-T questionnaire that was given to the study participants can be found at the following URL `https://visvalue.github.io/documents/survey.pdf`. A description of the materials provided can be found at the following URL `https://visvalue.github.io/`.

References

[1] Behrisch, Michael et al. (2016). Matrix Reordering Methods for Table and Network Visualization. Computer Graphics Forum. vol 35, no. 3, pp.693-716, 10.1111/cgf.12935.

[2] P. Isenberg et al., (2017) Vispubdata.org: A Metadata Collection About IEEE Visualization (VIS) Publications. IEEE Transactions on Visualization and Computer Graphics, vol. 23, no. 9, pp. 2199-2206, 10.1109/TVCG.2016.2615308.