Chapter 8
Conclusion

> All the pieces are there – huge amounts of information, a great need to clearly and accurately portray them, and the physical means for doing so. What has been lacking is a broad understanding of how best to do it.
>
> Wainer (1997, p. 112)

This book has dealt with concepts and methods for visualizing time and time-oriented data. This chapter will briefly summarize the key aspects that have been discussed in the previous chapters and shed some light on practical concerns when applying the described solutions to real-world data analysis problems. We will also consider going one step further from visualization to visual analytics of time-oriented data, for which we outline a basic framework. We conclude with a list of research opportunities for future work.

8.1 Book Summary

Computational analysis and visualization often deal with data that are anchored in space and time. Depicting a spatial frame of reference and the data within it are topics of cartography and geo-visualization, which are independent disciplines with their own books and scientific communities. As there are no such independent disciplines for the temporal frame of reference, this book focused deliberately on the visualization of time-oriented data. In fact, visual depictions of time have a long and venerable history, which has been illustrated by means of several classic examples from the pre-computer era in Chapter 2.

In order to design appropriate visual representations for time-oriented data, one needs to consider the characteristics of time and of the data that are related to time. In Chapter 3, we introduced what these characteristics are and how they can be categorized. A discussion of the issue of data quality provided some insight into

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what problems one might have to deal with before any reasonable data visualization can take place.

General principles of how time and time-oriented data can be visualized were presented in Chapter 4. Yet, to apply the principles successfully, it is necessary to understand why a visualization is needed, that is, to understand the users' tasks. In terms of user tasks, we distinguished the goals to be achieved, the analytical questions involved, the targets being relevant, and the means to be applied to actually accomplish a task. In terms of general visualization principles for time-oriented data, two basic strategies were introduced: mapping time to space and mapping time to time, which result in static and dynamic visual representations, respectively. On top of these basic strategies, we explained various examples of concrete visualization designs addressing specific aspects of the data, the task, and the presentation itself.

Visual exploration and analysis of time-oriented data also require interaction methods allowing users to manipulate the visual representation in a variety of ways, including navigation of time and data, adjustment of the visual encoding and the spatial arrangement, selection of data of interest, filtering out irrelevant data, and many more. Chapter 5 provided a compact overview of such interaction concepts and techniques.

Moreover, analytical methods have to be provided for supporting the generation of expressive visual representations. Among other purposes, analytical methods are useful for computing data abstractions that may serve to cope with large volumes of data or to enable visual analysis at different levels of granularity. Chapter 6 was dedicated to the aspect of analytical support.

As diverse and varied as time and data characteristics and the choice of visualization design, interaction concepts, and analysis methods are, as diverse is the range of visualization techniques for time and time-oriented data. In Chapter 7, we categorized many state-of-the-art techniques according to six major criteria and proposed some ideas to guide the process of selecting appropriate visualization solutions via an easy-to-use interactive tool, the TimeViz Browser. For reference, brief descriptions and illustrations of all techniques listed in the TimeViz Browser are given in Appendix A.

In conclusion, this book suggests that time is indeed an important dimension that deserves special treatment in visualization with appropriate support for interaction and analytical computation. In the next sections, we will take a look at selected issues that are worth considering further but could not be discussed in this book.

8.2 Practical Concerns

A main concern from an application perspective is the gap between the development of powerful visualization methods on the one hand, and their integration into the real-life data analysis workflows in different application scenarios on the other hand. Bridging this gap requires addressing a variety of software-related and user-related aspects.

Software systems and research prototypes There are a variety of commercial and open source visualization systems, for instance, Tableau,[1] Spotfire,[2] Qlik Sense,[3] Redash,[4] or vtk.[5] Many available systems provide excellent support for visual exploration and analysis of multivariate data. However, the specifics of time are not always considered comprehensively. Quite contrary, support for the wide range of characteristics that are relevant when dealing with time (e.g., support for cyclic time or for different time primitives) is often lacking. Consequently, it can be difficult or actually not feasible for users to apply existing visualization systems. As a result, users may have to design and implement custom solutions that emphasize the dimension of time as necessary for the task at hand.

On the other hand, the visualization community has developed useful research prototypes that provide dedicated support for the time aspect. A prominent example in this regard is the TimeSearcher[6] project for visual exploration of time-series data (↪ p. 290). However, the integration of such prototypes into the infrastructure of the day-to-day business is usually problematic and requires additional effort. Furthermore, research prototypes are usually not designed to cover all aspects of time, but instead address only particular cases – mostly the visualization of linear and ordered time domains.

Data interfaces Another significant problem to be solved is caused by the diversity of existing data formats and interfaces. Processes that generate or collect data and tools that manipulate or analyze the data often use specific databases and data formats that meet the requirements of the particular application scenario. Software tools for visualizing the data and interacting with them often use different formats. This circumstance requires individual and possibly complex data transformations, which can represent a substantial obstacle. To overcome this obstacle more comprehensible and simplified data interfaces need to be developed. Moreover, appropriate tools for data wrangling (see Kandel et al., 2011; Bors, 2020) can be considered to assist users in preparing time-oriented data for visual analysis.

Visualization literacy In addition to improving the technical basis of software, it is also important to take the needs of the users into account. In this regard, an important point is to improve awareness of modern visualization and interaction methods. Most of the time, people rely on traditional visualization techniques such as line plots or bar graphs. These techniques are well-established and have proven to be useful. However, new innovative visualization methods such as the line density plot (↪ p. 307) or the DimpVis (↪ p. 305) approach go beyond what is possible with classic techniques. Modern approaches often can represent a larger number of variables and data values, provide comprehensive interaction functionality, and take

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[1] https://www.tableau.com

[2] https://www.spotfire.com

[3] https://www.qlik.com/us/products/qlik-sense

[4] https://redash.io

[5] https://vtk.org

[6] https://www.cs.umd.edu/hcil/timesearcher

the specific aspects of time into account. These new possibilities can improve the data analysis and lead to new findings.

Another point to mention is that users who are experts in a specific application domain are not necessarily experts in visualization. However, to be successful in their data analysis work, the domain experts have to know which visual representation should be used for which task. If users were better supported in choosing expressive, effective, and efficient visualization techniques, the quality of information display and analysis results could greatly improve. Enabling people to browse and filter for suitable visualization techniques according to different criteria as suggested in Chapter 7 is only a first step. Visualization recommendation (see Kriglstein et al., 2014; Wongsuphasawat et al., 2016) and guidance approaches (see Ceneda et al., 2017; Ceneda et al., 2018) can offer additional support during the data analysis.

Workflow integration In many application domains, visual methods are primarily used to present previously generated analysis results. That is, the power of visualization is merely used to communicate results at the end of the analysis process. This can be a sufficient strategy, but only for those analytical problems for which a solution can be computed automatically without involving the user. However, many practically-relevant analysis problems are ill-defined and open-ended and as such require a human-in-the-loop interactive visual exploration process. In such cases, visual methods can support all stages of data analysis workflows, from data wrangling to hypothesis generation and falsification to collaborative discussion of findings, and of course, the final presentation of results.

Yet, such a comprehensive and tight workflow integration is often not achieved by existing solutions. Instead, data must be transformed and transferred manually between different analysis and visualization tools. Such extensive switching between different applications is a substantial obstacle to smooth data analysis workflows. Ideally, interactive visualization methods for time-oriented data would integrate seamlessly into existing application portals and systems. Approaching this ideal is the goal of current research on unified data analysis interfaces (see Nonnemann et al., 2021; Nonnemann et al., 2022).

To summarize, bridging the gap between research on interactive visualization methods and their application requires both imparting an awareness of the variety of possibilities and providing means to effectively use them within a given application infrastructure.

8.3 From Visualization to Visual Analytics

This book is entitled *visualization of time-oriented data*. And indeed, we focused on visualization. Interaction and computational analysis were considered as well, but merely to support the visualization. In order to optimally facilitate exploration and analysis of time-oriented data, we should strive for a tight interconnection of visual, interactive, and computational methods, effectively utilizing their strengths and compensating for their weak spots. The field of research that addresses such tight integration of visualization, interaction, and computational analysis is called *visual analytics*. At its core, visual analytics is defined as follows:

> Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces. People use visual analytics tools and techniques to synthesize information and derive insight from massive, dynamic, ambiguous, and often conflicting data; detect the expected and discover the unexpected; provide timely, defensible, and understandable assessments; and communicate assessment effectively for action.
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> Thomas and Cook (2005, p. 4)

Analytical reasoning for real-world problem-solving usually involves the analysis of huge amounts of heterogeneous, possibly incomplete, conflicting, inconsistent, and dynamic information (see Andrienko et al., 2020). For this, human judgment is required to deal with ill-defined problems, synthesize knowledge, and make decisions based on complex data. Thus, a major tenet of visual analytics is that analytical reasoning is not a routine activity that can be automated completely (see Wegner, 1997). Instead, it depends heavily on analysts' initiative and domain experience. Thus, visual analytics aims to facilitate the collaboration of humans and machines by combining:

> [..] automated analysis techniques with interactive visualisations for an effective understanding, reasoning and decision making on the basis of very large and complex datasets.
>
> Keim et al. (2010, p. 7)

Thus, the discipline puts its focus on the information discovery process and aims to enable the exploration and understanding of large and complex datasets by combining interactive visualization, automated data analysis, and human-computer interaction. Visual analytics is an inherently multi-disciplinary field that aims to combine the findings of various research areas such as human-computer interaction (HCI), usability engineering, cognitive and perceptual science, information visualization, scientific visualization, databases, data mining, statistics, knowledge discovery, data management, and knowledge representation. Application domains benefiting from visual analytics are for example health care, biotechnology, security and disaster management, environmental science, or climate research.

The basic idea of visual analytics is the integration of the outstanding capabilities of humans in terms of visual information exploration and the enormous processing power of computers to form a powerful knowledge discovery environment. Both visual as well as automated methods are combined in an intertwined manner to fully support this process. Most importantly, the human users are not merely passive elements who interpret the outcome of visual and automated methods, but rather they are the core elements.

Visual analytics process and spaces Keim et al. (2010) propose a process-oriented view of visual analytics as illustrated in Figure 8.1. It focuses on the tight integration of visual data exploration and automated data analysis and describes the dynamic process of synthesizing knowledge from data, following the visual analytics mantra *"Analyze First – Show the Important – Zoom and Filter, and Analyze Further – Details on Demand"* as formulated by Keim et al. (2006a).

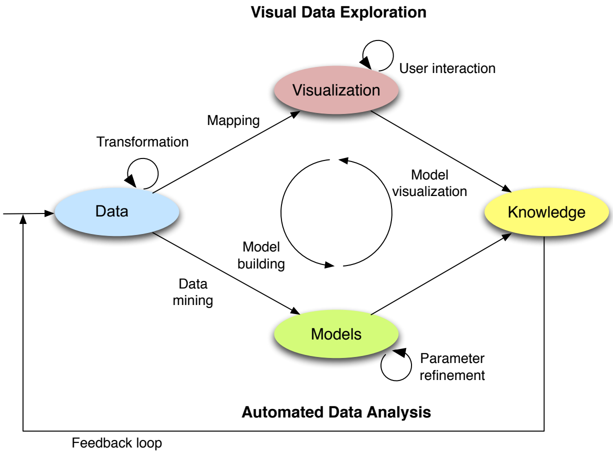

Fig. 8.1: The visual analytics process. *Adapted from Keim et al. (2010).*

Large and usually complex *data* are the basis of visual analytics systems. In many cases, these data come in forms that cannot be directly visualized or automatically analyzed. Therefore, *transformation* steps are applied to perform data cleansing, reformatting, preprocessing, and integration measures. After this initial data transformation, analysts can perform visual exploration and automated analysis. For automated data analysis, *data mining* can be applied to create *models*, which may need to be adjusted through *parameter refinement*. This involves *user interaction* with *visualizations* of the models. For visual data exploration, visual *mapping* is applied to the input data. Based on the *visualization*, *model building* can be performed via *user interactions* with the visual interface. In this sense, the interplay between automated data analysis and visual data exploration inform and support each other throughout the visual analytics process. By interacting with visualizations and models, analysts create new *knowledge* about the data and the underlying phenomena.

Visual analytics can further be conceptualized by considering the different spaces involved in the visual analytics process. Sedig et al. (2012) proposed a conceptual model that involves the five spaces shown in Figure 8.2:

- The **information space** is concerned with modeling, abstracting, and characterizing the sources of information to be studied.
- The **computing space** deals with encoding and storing internal representations of elements from the information space and includes computational operations carried out on such representations.
- The **representation space** makes the internal representations accessible to users using interactive visual representations (IVRs).
- In the **interaction space**, the dyad of action-reaction takes place and perception connects to the mental space.
- The **mental space** is concerned with internal mental events and operations of human analysts.

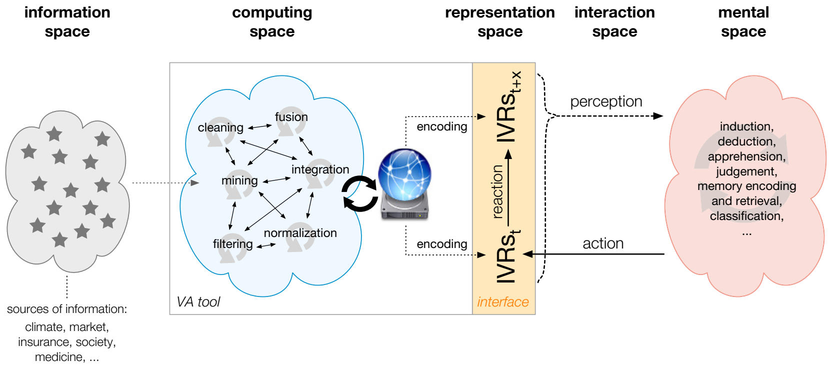

Fig. 8.2: Spaces involved in visual analytics. *The authors. Adapted from Sedig et al. (2012).*

Design issues Through the combined human and computational effort in these five spaces, visual analytics aims to amplify cognition. But simply producing images is no guarantee that complex visual representations will be understood and are useful for gaining insights. Therefore, a human-centered approach is essential and should follow four main principles:

- **Early focus on users and tasks.** Understanding the users, the tasks they perform, and the environment in which users perform these tasks is vital early in the process (see Munzner, 2009; Kerren et al., 2007).
- **Design for human perception and cognition.** Artifacts (methods, techniques, tools, and systems) need to be designed based on established knowledge of human perception and cognition, including pre-attentive processing (see Ware, 2000), Gestalt principles (see Wertheimer, 1938), and sensemaking theory (see Pirolli and Card, 2005).
- **Continuous evaluation.** Visual analytics solutions should be evaluated continuously involving studies on effectiveness, efficiency, and usability to identify measurable benefits and understand limitations (see Lam et al., 2012).
- **Iterative design and refinement.** To improve visual analytics solutions, problems found by experts and users should be corrected iteratively throughout the design and development life cycle (see Shneiderman and Plaisant, 2004).

As already indicated, implementing human-centric visual analytics solutions is challenging, and first steps have been taken to tackle this challenge. Among them are new frameworks to better understand analysis tasks (see Schulz et al., 2013a; Brehmer and Munzner, 2013), concepts to help characterize data (see Schulz et al., 2017), guidance methods to assist users during the data analysis (see Ceneda et al., 2017; Ceneda et al., 2019; Collins et al., 2018), progressive and incremental methods to cope with large amounts of data (see Stolper et al., 2014; Schulz et al., 2016), modern ways of interacting with visual representations of data (see Lee et al., 2021), and onboarding techniques allowing users to get easy access to visual analytics solutions (see Stoiber et al., 2022).

8.4 Future Research Opportunities

Despite the progress that has already been made in the context of visual analytics, there are many open questions to be addressed. In the following, we take a brief look at topics for future research. Our list of topics is aligned with the contents of this book. We will be concerned with visualization, interaction, and analytical computations. Overall, the identified research opportunities aim to advance the interactive visual exploration and analysis specifically of time and time-oriented data.

Cover the specifics of time more broadly A large diversity of powerful visualization techniques for time-oriented data are known in the literature. In Chapter 7, we outlined a corpus of 158 techniques, each of which is also detailed in Appendix A. However, still, most of them support only certain parts of the introduced time and data categorization; in the particular case of visualizing multivariate data, usually linear, point-based, and ordered time domains. Further investigations are required, including the development of techniques for interval-based time, branching time, and multiple perspectives, for simultaneously displaying raw data and data abstractions, and for showing the time-oriented data in their spatial frame of reference.

Another aspect to be considered originates from the multi-scale nature of time. New visualization techniques are required to allow analysts to combine different levels of data and time and to switch between the levels. How this can be done with a basic line plot of linear time series was indicated in Section 5.4.3. But it remains unclear how multi-scale data exploration can be carried out with other visual representations for different categories of time-oriented data.

In light of a diversity of dedicated visual representations for time-oriented data, there is also the question of how a more comprehensive picture of the data can be drawn by combining multiple views. Classically, multi-view approaches work with side-by-side arrangement of views. A promising alternative is to consider smooth transitions between views as suggested by Tominski et al. (2021). Exploring the design space for transitioning between multiple non-trivial representations of time-oriented data while at the same time considering the human capabilities in perceiving and comprehending such transitions seems a formidable research challenge.

Consider more data aspects Throughout this book, we considered time-oriented data, either as abstract data or as data with a spatial frame of reference. However, while being important, space is not the only additional aspect that might be relevant in analyzing time-oriented data.

On top of temporal and spatial dependencies in the data, as a third data aspect, there can be semantic relationships between data items, typically modeled as edges between nodes in a graph. When these relationships change over time, we are dealing with dynamic graphs or temporal networks (see Holme and Saramäki, 2012). Beck et al. (2017) provide a comprehensive overview of visualization techniques for dynamic graphs. However, these techniques primarily represent changes in the graph topology (i.e., creation and removal of edges) rather than communicating the time-oriented data being associated with a graph's nodes and edges. Hence, Beck et al. (2017)

identified the consideration of multiple (dynamic) data dimensions as an open issue, which remains an open topic even today.

Parameter dependency and analytic provenance are two closely related and relevant data aspects that should also be considered. These aspects help users understand how obtained analysis results are influenced by the choice of parameters and how the involved choices were developed. General concepts for visually analyzing parameter spaces (see Sedlmair et al., 2014) and incorporating provenance information (see Xu et al., 2020a) have already been established. There are also techniques specifically developed in the context of time-oriented data (see Eichner et al., 2020). However, existing approaches still have difficulties in dealing with multi-scale dependencies of multiple data variables depending multiple parameters.

Finally, data quality and uncertainty are further important data aspects. We briefly discussed them in Section 3.4 and Section 6.3.2, respectively. Integrating these data aspects more tightly into the visual analysis process of time-oriented data is the goal of ongoing research. For example, Gschwandtner et al. (2016) study different visual representations for temporal uncertainty. How such representations can be employed to support the analysis of time-series segmentations was described by Bors et al. (2020). While these works illustrate the benefit of integrating data quality and related uncertainties into the visualization, we still do not know how to do this generally for different applications and different visualization techniques. This is where future work can improve the expressiveness of visual representations and also strengthen the user's confidence in the obtained findings by considering the aforementioned additional data aspects more broadly.

Communicate on more channels Apart from the numerous options for visualizing time-oriented data, other forms of communication are possible. The data could for example be communicated via sound or haptic sensations (e.g., with braille interfaces). Smell and flavor might also be candidates for alternative communication channels. Despite the fact that these mappings are in principle imaginable, their feasibility and usefulness have to be investigated.

Speeth (1961) already showed how seismographic data can be presented in an auditory display. Another example of attempts in this direction is a system for data sonification by Zhao et al. (2008a) to explore spatial data for users with visual impairments. It seems there are several similarities between the methods and design theories of visualization and sonification (e.g., perceptually encoding data attributes). However, comparatively little is known about combining auditory and visual representations for data analysis. First theoretical underpinnings were proposed by Enge et al. (2021), who conceptualize space as substrate for visualization marks and time as a substrate for auditory marks. Later, Enge et al. (2022) could instantiate their theoretical approach in an exploratory data analysis tool for multivariate data. However, further research is needed to explore these communication channels, particularly for time-oriented data.

Support a broader range of interactions Similar to using perceptual channels more broadly, it would also be interesting to study different ways of interacting with time-oriented data. Our Chapter 5 on interaction already hinted at new interaction modalities such as touch and tangible interaction. These are but two examples of modern approaches to interacting with data; there are more to be explored.

An interesting question is how to better support the interaction on the different scales of time-oriented data. New interaction techniques could address the combination of fine-grained and precise interaction on a local level with coarser, but also faster interaction on a global level. This would also include providing users the option to effortlessly switch between different scales of time or even work on multiple temporal scales simultaneously.

On the technical side, different interaction modalities (Lee et al., 2021) could be investigated for their usefulness in the context of analyzing time-oriented data. For example, to address the limited precision of touch interaction, it would make sense to consider more precise pen-based interaction to support navigation in time or to define temporal queries. Natural language interaction also seems a promising research direction. It allows users to formulate temporal queries via spoken commands, which would significantly reduce interaction costs.

Finally, interaction for collaborative data analysis is a hot research topic. Large high-resolution displays combined with small mobile displays appear to be particularly suited for collaboration (see Horak et al., 2018). Large displays naturally lend themselves to interactively exploring large time-oriented data. Small mobile displays can be used for detailed inspection of data subsets. However, interacting at large scale (e.g., via gaze or physical navigation) and small scale (e.g., via touch or wrist gestures) requires dedicated interaction designs. According to Brehmer et al. (2021), supporting a seamless interaction experience in such cross-device scenarios is a challenge for future work.

Better support for computational analysis Computational analysis plays an important role in understanding large time-oriented data. However, many analytical methods that are applied to time-oriented data treat time as a flat, ordered sequence of events. Thus, these methods are lacking information about the time intervals between events or the reoccurrence of particular temporal patterns. Only few existing analytical methods, like for example the seasonally adjusted autoregressive integrated moving average (SARIMA), model cyclic temporal behavior adequately. As a consequence, better support for dealing with the hierarchical and cyclical structures of time is needed.

Moreover, analytical methods usually behave like black boxes. They accept some input data and generate some analytic result as output, but it often remains unclear to users what happens inside the black box. Yet, as already mentioned, understanding the involved computations and how they are influenced by parameters is essential to appropriately configure analytical methods with regard to the given data and tasks. Therefore, Mühlbacher et al. (2014) demand that black boxes be opened to make computational methods more transparent and steerable for users. This typically involves parameter space analysis to facilitate understanding and progressive algorithms to make analytical computations steerable.

General challenges with respect to parameter space analysis were already identified by Sedlmair et al. (2014). But the particular problems associated with time-oriented data were not yet sufficiently addressed. In a recent survey, Piccolotto et al. (2023) investigate the visual parameter space exploration for spatial and temporal data in particular. They come to the conclusion that spatial and temporal parameters received comparably little attention in the literature and therefore recommend studying these types of parameters in particular in the future.

To make analytical computations steerable, long-running calculations must be split into smaller pieces. This can be achieved via progressive and incremental methods (see Stolper et al., 2014; Schulz et al., 2016). Given the typically large size of time-oriented data, such methods could greatly improve the analysis. However, it is still a task for future work to either develop new temporal analysis methods that are inherently progressive or to revise and adapt existing methods to give them progressive capabilities where possible.

Focus more on user needs While advancing individual visualization, interaction, and computational analysis methods and techniques, it is decisive to take the needs of users into account. Only if the users' data analysis workflows are sufficiently understood can appropriate solutions be developed in a user-centered manner.

In the field of software engineering, it is generally acknowledged that the first step in developing tools and user interfaces should be a sound requirements analysis of the given problem domain (see Hackos and Redish, 1998; Courage and Baxter, 2005). The same applies to designing visualization solutions, where a couple of design recommendations were introduced, general ones by Munzner (2014) and ones specifically for time-oriented data by Miksch and Aigner (2014). In the first place, it is necessary to appropriately characterize the visualization problem, which in the case of visually analyzing time-oriented data includes (1) the characteristics of time and time-oriented data, (2) the characteristics of users, and (3) the intentions and tasks of users. Federico et al. (2017) suggest that providing means to appropriately describe, store, and utilize this knowledge can help in automating the selection or the development of visualization solutions that suit the users, the data, and the tasks.

Approaches for automatic visualization design have been studied for decades already (see Mackinlay, 1986; Senay and Ignatius, 1994; Wills and Wilkinson, 2010; Moritz et al., 2019). In this book, we described the TimeViz Browser as a tool for selecting visualization techniques based on data characteristics. However, a selection based on analysis tasks is not yet possible, not to mention a selection based on user characteristics. These would require an easy-to-use way of specifying tasks and users, and also studies to determine which techniques are suitable for which specification. Both these aspects bear great potential for future research.

The overall aim is to support the users, rather than burden them with technical details. Thus, a significant shift could be realized from a technique-centered view to a user-centered view, where the user is in the focus, similar to what Shneiderman (2022) proposed for human-centered artificial intelligence.

Guide users better In addition to user-centered design, it is also of great relevance to support users during the use of visual data analysis solutions, especially in the context of visual analytics where several visualizations, interactions, and computations play in concert.

As we have seen, the special characteristics of time usually require more advanced visual representations than traditional business charts. However, Börner et al. (2016) and Börner et al. (2019) found that many people have difficulties interpreting novel visual representations and comprehending the underlying data. Limited visualization literacy skills can hamper access to valuable information and complicate problem-solving and decision-making. To mitigate this in the initial phase of the visual data analysis, visualization onboarding plays an increasingly important role. The goal of visualization onboarding is to make people familiar with unknown visual data representations and to empower them to extract the information they need. A few onboarding methods exist in the literature but further research is needed to identify effective designs of onboarding methods for time-oriented data visualization and to understand user behavior while using onboarding methods. This also involves creating flexible and adaptive approaches that take the prior knowledge of the users into account.

Even when users are familiar with a visualization solution, it can still be necessary to guide users while they are working on visual data analysis tasks. Ceneda et al. (2017) characterized guidance as a concept to support users in situations where they have difficulties making analytic progress on their own. In Section 5.4, we briefly illustrated how such guidance can look like for multi-scale exploration of large time-oriented data. But still many open questions need to be addressed to arrive at true mixed-initiative solutions wherein both the system and the user can contribute to the progress of the data analysis. The overall vision of Ceneda et al. (2020) is to make guidance effective, available, trustworthy, adaptive, controllable, and non-disruptive in the future. Yet, how to detect the point where users need assistance? How to determine an appropriate level of support and how to dynamically adjust it? How to generate guidance without actually knowing neither the elusive data analysis problem of the user nor its concrete answer, if it exists at all? While these questions are generic, the research to solve them must be tailored to the specifics of the problem domain, which in our case means time and time-oriented data.

Understand what works Finally, to be able to guide users or to suggest appropriate techniques to users based on data and tasks, we need to know which techniques are *good*. This requires evaluation. Evaluation has to be conducted in terms of the three criteria expressiveness, effectiveness, and efficiency (see Chapter 1). Expressiveness and effectiveness are related to the data level and the task level, respectively. They require testing whether the characteristics of time and data are sufficiently communicated, and whether the visual representation, interaction techniques, and analysis methods match the tasks, expectations, and cognitive capabilities of users. With the efficiency criterion, a balance of required resources (technical and human) and gained benefits in an application domain comes into play.

The literature provides a wealth of methodologies to conduct evaluation studies in general (see Lazar et al., 2017). There are also specific methods for visualization, for example, to measure effectiveness (see Zhu, 2007). However, Plaisant (2004) points out that thorough evaluation is challenging as it requires the combined consideration of multiple criteria. Addressing this challenge, Munzner (2009) introduced a nested model for design and validation where each nested level (i.e., characterization of data and tasks, abstraction into operation and data types, design of encoding and interaction, and development of algorithms) is associated with a dedicated methodology for evaluation. Lam et al. (2012) outline seven typical scenarios for empirical studies in the context of visual data analysis. However, neither Munzner's model nor Lam et al.'s scenarios consider time and time-oriented data and tasks explicitly. More research is needed to close this gap in the literature.

Even more advanced evaluation strategies are needed for understanding complex visual analysis solutions with their interplay of visual, interactive, and computational components. Adding to standard solutions more sophisticated methods such as uncertainty visualization, cross-device interaction, or user guidance can make evaluation studies extremely challenging and expensive. Therefore, it seems reasonable to investigate new evaluation strategies for their applicability to selected aspects first. For example, one could look into evaluation heuristics like ICE-T (see Wall et al., 2019) with a particular focus on guidance-enhanced visual analysis solutions for time-oriented data. Based on the results of multiple such focused evaluations one could then develop a better understanding of how to evaluate complex intertwined visual analysis solutions.

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With these ideas for future work, we close this book on *visualizing time-oriented data* hoping that the next decade of research brings us closer to *visual analytics for time-oriented data*, which then might be the title for a potential third edition – or a completely new book.

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