

# **It's About Time:**

User-centered Evaluation of Visual  
Representations for Temporal Data

**Kahin Akram Hassan**





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IT'S ABOUT TIME: USER-CENTERED EVALUATION OF  
VISUAL REPRESENTATIONS FOR TEMPORAL DATA

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Norrköping, March 2021



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*I promise to achieve the life dreams you couldn't because you were too busy ensuring we would survive. To my dearest parents, thank you both for all your sacrifices.*



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Finally, there are soooo many series and characters to thank. I could go on and on about how much time I have “wasted” getting lost in fictional stories. But who are we to say anything when time just is a big ball of wibbly-wobbly, timey-wimey ... stuff.

---

Norrköping, February 2021

Kahin Akram



# Abstract

The primary goal for collecting and analyzing temporal data differs between individuals and their domain of expertise e.g., forecasting might be the goal in meteorology, anomaly detection might be the goal in finance. While the goal differs, one common denominator is the need for exploratory analysis of the temporal data, as this can aid the search for useful information. However, as temporal data can be challenging to understand and visualize, selecting appropriate visual representations for the domain and data at hand becomes a challenge. Moreover, many visual representations can show a single variable that changes over time, displaying multiple variables in a clear and easily accessible way is much harder, and inference-making and pattern recognition often require visualization of multiple variables. Additionally, as visualization aims to gain insight, it becomes crucial to investigate whether the representations used help users gain this insight. Furthermore, to create effective and efficient visual analysis tools, it is vital to understand the structure of the data, how this data can be represented, and have a clear understanding of the user needs. Developing useful visual representations can be challenging, but through close collaboration and involvement of end-users in the entire process, useful results can be accomplished.

This thesis aims to investigate the usability of different visual representations for different types of multivariate temporal data, users, and tasks. Five user studies have been conducted to investigate different representation spaces, layouts, and interaction methods for investigating representations' ability to facilitate users when analyzing and exploring such temporal datasets. The first study investigated and evaluated the experience of different radial design ideas for finding and comparison tasks when presenting hourly data based on an analog clock metaphor. The second study investigated 2D and 3D parallel coordinates for pattern finding. In the third study, the usability of three linear visual representations for presenting indoor climate data was investigated with domain experts. The fourth study continued on the third study and developed and evaluated a visual analytics tool with different visual representations and interaction techniques with domain experts. Finally, in the fifth study, another visual analytics tool presenting visual representations of temporal data was developed and evaluated with domain experts working and conducting experiments in Antarctica.

The research conducted within the scope of this thesis concludes that it is vital to understand the characteristics of the temporal data and user needs for selecting the optimal representations. Without this knowledge, it becomes much harder to choose visual representations to help users gain insight from the data. It is also crucial to evaluate the perception and usability of the chosen visual representations.



# Populärvetenskaplig sammanfattning

Det primära syftet för att samla in och analysera tidsdata skiljer sig mellan individer och deras kompetensområde, t.ex. prognoser kan vara syftet i meteorologi medan detektering av avvikelser kan vara syftet i ekonomi. Även om syftet skiljer sig åt, är behovet av utforskande analys av tidsdata gemensamt då det förenklar sökandet efter användbar information. Tidsdata kan vara utmanande att förstå och visualisera, därför blir det en utmaning att välja lämpliga visuella representationer för datan. Många visuella representationer kan visa en enda variabel som förändras över tiden, men det är mycket svårare att visualisera flera variabler på ett tydligt och lättillgängligt sätt, och för att dra slutsatser eller känna igen mönster i data krävs ofta visualisering av flera variabler. Eftersom syftet med visualisering är att hjälpa användaren att nå insikt, är det avgörande att undersöka om representationerna faktiskt hjälper användaren att nå denna insikt. För att utveckla effektiva och användbara visuella analysverktyg behövs också förståelse av datastrukturen och hur dessa data kan representeras, samt en god insikt i användarens behov. Att utveckla användbara visuella representationer är utmanande, men genom nära samarbete med och involvering av slutanvändare i hela processen kan användbara resultat uppnås.

Denna avhandling syftar till att undersöka användbarheten av olika visuella representationer för olika typer av multivariata tidsdata, användare och uppgifter. Fem användarstudier har genomförts för att undersöka olika visualiseringsprinciper, layouter och interaktionsmetoder för att undersöka visuella representationers förmåga att underlätta analys och utforskning av tidsdata. Den första studien undersökte och utvärderade användbarheten av presentation av timdata i olika radiella designidéer baserade på en analog klockmetafor, genom olika uppgifter som att hitta och jämföra värden. Den andra studien undersökte 2D- och 3D-parallella koordinater för mönsterigenkänning. I den tredje studien undersöktes lämpligheten hos tre visuella representationer för att presentera inomhusklimatdata med domänexperter. Den fjärde studien var en fortsättning på den tredje studien, och utvecklade samt utvärderade ett visuellt analysverktyg med olika visuella representationer och interaktionstekniker med domänexperter. Slutligen, i den femte studien, utvecklades och utvärderades ett annat visuellt analysverktyg med olika visuella representationer av tidsdata för domänexperter som arbetar och utför experiment i Antarktis.

Forskningen inom ramen för denna avhandling har visat att det är viktigt att förstå egenskaperna hos tidsdata och användarens behov för att välja de optimala visuella representationerna. Utan denna kunskap blir det svårt att välja representationer som hjälper användare att få insikt från data. Det är lika viktigt att utvärdera användbarheten av de valda visuella representationerna.





# Publications

The following list of publications have been included in this thesis:

- Paper A:** K. Akram Hassan, L. Besançon, J. Johansson, A. Ynnerman, and N. Rönnerberg. Investigation of radial methods based on the clock metaphor for visualization of cyclic data. Submitted to *IEEE Transactions on Visualization and Computer Graphics*, 2021
- Paper B:** K. Akram Hassan, N. Rönnerberg, C. Forsell, M. Cooper, and J. Johansson. A study on 2d and 3d parallel coordinates for pattern identification in temporal multivariate data. In *2019 23rd International Conference Information Visualisation (IV)*, pages 145–150, 2019
- Paper C:** K. Akram Hassan, Y. Liu, L. Besançon, J. Johansson, and N. Rönnerberg. A study on visual representations for active plant wall data analysis. *Data*, 4(2), 2019
- Paper D:** K. Akram Hassan, Y. Liu, L. Besançon, J. Johansson, and N. Rönnerberg. Timeplant: A tool for monitoring indoor climate and controlling active plant walls. Submitted to *IEEE Computer Graphics and Applications*, 2021
- Paper E:** Z. Orémuš, K. Akram Hassan, J. Chmelík, M. Kňázková, J. Byška, R. G. Raidou, and B. Kozlíková. Pingu: Principles of interactive navigation for geospatial understanding. In *2020 IEEE Pacific Visualization Symposium (PacificVis)*, pages 216–225, 2020



# Contributions

## **Paper A: Investigation of Radial Methods Based on the Clock Metaphor for Visualization of Cyclic Data**

This work presents a quantitative user study split into three experiments investigating radial visualization techniques inspired by the metaphor of an analog clock. Four 12-hour and two 24-hour representations were investigated using four different hourly collected real-world datasets. The evaluation measured completion time and accuracy on four different analysis tasks. Subjective ratings were collected regarding the usability of the radial designs. This work has been submitted to *IEEE Transactions on Visualization and Computer Graphics*, February, 2021.

## **Paper B: A Study on 2D and 3D Parallel Coordinates for Pattern Identification in Temporal Multivariate Data**

A quantitative study evaluating the usability of multiple axes, 2D and 3D parallel coordinates, for a pattern identification task in multivariate temporal data. The study measured effectiveness (accuracy) and efficiency (faster response time) but also subjective ratings regarding the usability of the representations. This work was presented at *the 23rd International Conference Information Visualization (IV)*, pages 145–150, 2019.

## **Paper C: A Study on Visual Representations for Active Plant Wall Data Analysis**

This work presents a qualitative user study with domain experts working with active plant walls. It evaluates different linear representations, both shared- and split-space, of multivariate temporal data collected via sensors integrated with plant walls. Based on this, the paper offers a categorization of the identified user responses linked to analysis tasks and discusses them in comparison to previous findings. This work was published at *Data*, 4(2) under Multidisciplinary Digital Publishing Institute (MDPI), 2019.

## **Paper D: TimePlant: A Tool for Monitoring Indoor Climate and Controlling Active Plant Walls**

This work is based on the findings from Paper C and presents TimePlant, a visual analytics tool developed with close collaboration with domain experts working with plant walls. TimePlant consists of different linear representations, line graph, silhouette graph, and horizon graph, for analyzing indoor climate data. The usability of TimePlant was qualitatively evaluated with domain experts. This work has been submitted to *IEEE Computer Graphics and Applications*, February, 2021.

**Paper E: PINGU: Principles of Interactive Navigation for Geospatial Understanding**

This work present a visual analytics tool for extraction and interactive exploration of temporal measurements collected in the periglacial areas of Antarctica. The visual analytics tool is used for interactive exploration of multivariate temporal data using multiple views with different visual representations. The tool was qualitatively evaluated with domain experts. This work was presented at *2020 IEEE Pacific Visualization Symposium (PacificVis)*, pages 216–225, 2020.

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# Introduction

I love humans, always seeing patterns in things that are not there.

---

—*The Eighth Doctor, Doctor Who (Paul McGann)*

The rapid advances in computer technology during the past decades have opened up possibilities for many domains to collect and store information regularly. This information is often referred to as *Data* and can be collected in many types. Ben Shneiderman [86] distinguished between seven data types: one-, two-, three-, and multi-dimensional, tree, network, and temporal data. The work presented in this thesis has focused on *temporal data*. This type of data is centered around time, a unique quantitative dimension containing a hierarchical structure of granularities, such as seconds, minutes, hours, etc. [1]. Apart from such data often being large, it also is complex due to the time dimension. Like any other data type, temporal data is difficult to understand without visual analysis. Visually displaying data is not a new phenomenon, it has been used throughout the years to analyze, explore, communicate, and present information [1, 85]. However, it is still not entirely clear how to best visualize temporal data.

The overall aim for displaying the data is to gain insight into the data and extract knowledge for better decision-making [72]. Different visual representations (i.e., visualization techniques) can be used to support the user in gaining insight. While most visual representations can handle a single variable changing over time, pattern finding and inference-making often requires a visual representation that can display and support the analysis of multiple variables simultaneously. This requirement introduces the challenge of selecting adequate visual representations to display all aspects of the complex temporal data. Moreover, different representations

are useful for different situations and tasks, such as understanding how different aspects of the data effect each other over time. Therefore, knowledge about the data, the domain and domain specific problems, and user needs is required to have for selecting or creating suitable visual representations. Such knowledge can be acquired via close collaboration and evaluation studies with end-users.

The overall goal of the work presented in this thesis was to investigate how visual representations can facilitate analysis and exploration of temporal data. This goal has been explored from different approaches:

- investigation of the usability of different visual representations for different types of temporal data sources,
- exploration of representation structures for different users and different tasks,
- studying interaction as support for users performing visual analysis.

This was done by conducting five studies. **Paper A** presents an online study conducted to investigate radial representations displaying real-world hourly data for novice users solving different finding and comparison tasks. **Paper B** presents a study conducted to investigate representations using multiple axes to display synthesized multivariate temporal data for novice users performing pattern finding tasks. **Paper C** presents the findings from a qualitative study conducted with domain experts exploring the adequacy of different visual representations for identifying temporal relationships in indoor climate data. **Paper D** uses the findings from **Paper C** to develop and evaluate a visual analytics tool using different visual representations and different interaction support for domain users to analyze the displayed temporal indoor climate data. Lastly, **Paper E** presents another visual analytics tool consisting of different visual representations, developed and evaluated with different domain experts for analysis of temporal data collected on Antarctica.



## Working with Temporal Data

People assume that time is a strict progression of cause to effect but actually, from a non-linear, non-subjective point of view it is more like a big ball of wibbly-wobbly, timey-wimey ... stuff.

---

—*The Tenth Doctor, Doctor Who* (David Tennant)

To create effective and efficient visual representations, a person should analyze three aspects. They should understand the characteristics of the data represented; they should know what the visual representation will be used for; finally, they should understand how to best support the task and data with appropriate visual encoding and interaction techniques. The purpose of this chapter is to equip the reader with a general understanding of temporal data. While this chapter provides a general overview of these areas, it is not complete. The reader searching for an in-depth analysis of the field is referred to several books on the topic, such as “Visualization of Time-Oriented Data” by Aigner et al. [1] and “Visualization Analysis and Design” by Tamara Munzner [70] or this survey on available books about the topic [79].

### 2.1 Visualization as a Discipline

The visualization discipline is a result of other scientific disciplines’ curiosity to make sense of the vast quantities of data available today [63]. Although, a consensus regarding a universally accepted definition of what *Visualization* is, is still discussed. Phillips et al. [76] searched the literature dated back to 1974 and found 28 explicit definitions of the term. Many use *external factors* such as images, tables, diagrams,

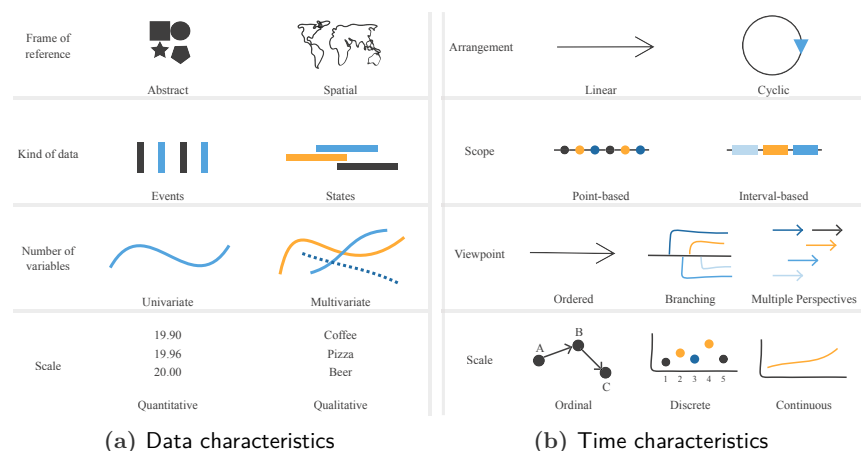


Figure 2.1: The different data and time characteristics. (a) Important data aspects about the data that can help in knowing how to visualize the data, and (b) the aspects of the time dimension that can help in knowing how to map time. (Image adopted from [1])

etc. to define the term, while other focus on *internal factors* such as the visual perception in each human observer. Nevertheless, the aim of the discipline is to combine human visual perception with the power of technology to display information expressively, effectively, and appropriately [1]. The discipline has, over time, been split into two major communities: *Information Visualization* and *Scientific Visualization*. The former focuses primarily on abstract data such as stock market observations, while the latter focuses on data with an inherent physical and spatial component, but both try to amplify cognition [22]. One challenge both these communities are facing is the investigation of which methods are optimal to use or create for different domains, data, and users. To deal with such challenges, Aigner et al. [1] suggest to ask and answer three practical and straightforward questions: *What is presented?* *Why is it presented?* and *How is it presented*. These questions are covered in the subsequent sections as knowing the data, knowing the goals, and creating visual representations for information visualization of abstract data.

## 2.2 Knowing the Data

The data to be visualized has many characteristics which are essential and dictate the choice of visual representation (see Figure 2.1). Knowing the frame of reference (abstract or spatial) can tell whether to use a representation that emphasizes precision or provides a general overview of the data. The work in this thesis has

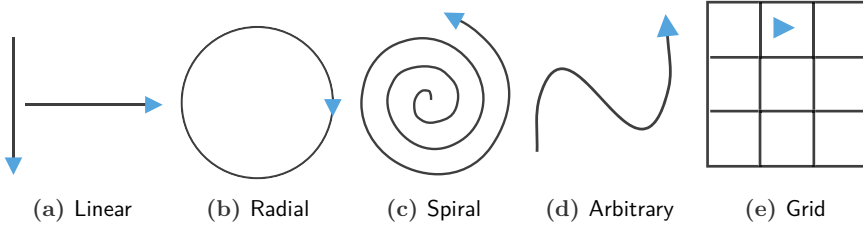


Figure 2.2: The figure shows five different layouts for mapping the time dimension. (a) standard linear (vertical and horizontal), (b-c) radial and spiral, frequently used to analyze seasonal data, (c) arbitrary, often used for storylines, and (e) grid (calendars).

mainly focused on abstract data and how it can be adequately presented for different domains and users. The kind of data is either event or states. Moreover, knowing the number of variables also simplifies the choice as different representations can handle different number of variables. However, as mentioned previously, multivariate data can be more interesting to analyze as trends and patterns often occur between the variables. Although, when visualizing many variables the representations can become visually cluttered. The collected data is either quantitative or qualitative, an important aspect to know as it tells on which type of scale the data should be displayed. A metric scale (discrete, continuous) is usually used for quantitative data, while qualitative data is either not ordered (nominal) or ordered (ordinal) (see Figure 2.1(a) for an illustration of the characteristics). For a more in-depth analysis of data characterization and modeling approaches, see [1, 68, 70, 98].

The characteristics of the time dimension are also important to know. Time can be understood as the change seen around us, such as the circular motion of the earth around the sun creating the notion of a year. While time is commonly understood as *unidirectional* that gives order to events, it can be displayed in any direction. In the visualization domain, the goal is not just to imitate the physical notion of time, but also to provide solutions that underline the importance of the dimension and simplify the analysis. Therefore, how to visualize this dimension depends on the data and situation. While the time dimension is often arranged on linear or radial layouts, there are other layouts such as spiral, arbitrary, or grid [1, 15, 31] (see Figure 2.2). The work in this thesis has mainly focused on linear and radial arrangements. Other essential time aspects include *scope*, where it tells if the time dimension is point- or interval based, *viewpoint*, is the view of the time dimension ordered, branching, or have multiple perspectives and *scale*, whether the time domain is ordered, discrete, or continuous (see Figure 2.1(b) for an illustration of the characteristics). Understanding these characteristics will simplify the design of the representations as temporal data can be complex. Once a clear understanding is acquired, the reasons and goals for visualizing the data can be defined.

## 2.3 Knowing the Goals and Tasks

The visualization discipline is inherently user-driven. Therefore, understanding *why* the data needs to be presented and what tasks could be performed when analyzing the data is vital for creating optimal representations [68]. The goal for visualizing the data usually falls under three categories: *explorative analysis*, *confirmative analysis*, and *presentation of the results* [1, 85]. The explorative analysis involves undirected search where the goal usually is to get insight into the data without any prior hypothesis. On the contrary, confirmative analysis is a directed search trying to prove or disprove a known hypothesis. The presentation category is about communicating the findings. Regardless of the goal, users are involved in the process. A user can be anyone who uses visual analysis to perform an action and normally fall under two groups: *novice*, or *expert* [108]. Novice users (also known as casual users) are people who are not trained in data analysis but use visualization for casual purposes and entertainment. Experts users (also known as domain experts) can create and consume interactive visualization to support their work but are usually not trained in data analysis either.

Moreover, seeking answers to relevant questions by interacting with the visual representation is at a basic level known as a task [1, 85]. According to Schulz et al. [85], a task can be constructed by five dimensions (goal, means, characteristics, target, and cardinality).

**Goals** define the intention with performing the task and usually falls under explore, confirm, or present results.

**Means** determines the method, navigation (i.e., searching), (re)-organization (i.e., filtering), or relation (i.e., comparing). This dimension is also known as the action of a task.

**Characteristics** of a task tells whether a task is a low-level (i.e., value look-up or identify) or a high-level (i.e., trend and pattern analysis) task.

**Target** tells which part of the data is being focused on.

**Cardinality** specifies how many instances (i.e., single, multiple, and all instances) of the target are considered by the task.

The goal and type of task performed when analyzing the data can help knowing which visual representation to use. The design spaces and taxonomies available in the literature can further guide the use of visual representations that effectively support users in conducting visual data exploration and analysis. Above all, when analyzing data, it is helpful to follow the Visual Information Seeking Mantra introduced by Ben Shneiderman [86]—to provide overview first, then zoom and filter, and finally details-on-demand. Over the years, the visualization community has produced a wealth of design spaces and taxonomies to define and categorize visualization tasks, see [14, 81, 85, 100]. Apart from knowing the data and the

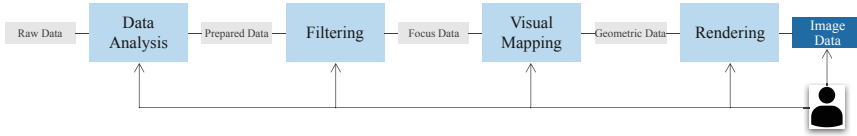


Figure 2.3: A version of the visualization pipeline with the four transformations. The raw data is moved and transformed between each step until an image is rendered. The user is then able to control each part of the pipeline, a crucial feedback loop in interactive visualization.

goals, knowledge about how to map the data to visual encoding is required to create effective and efficient representations.

## 2.4 Creating Visual Representations

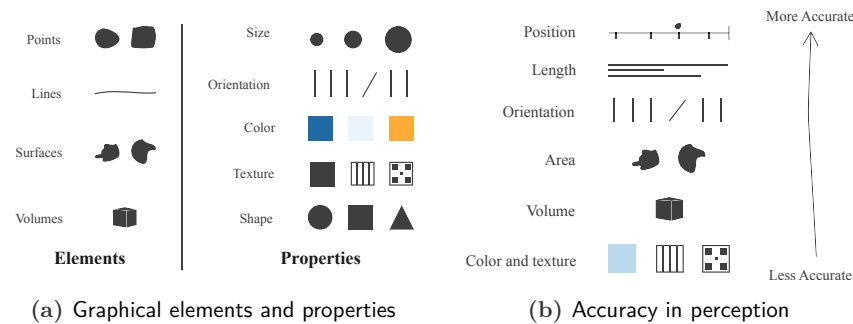
The process of transforming data into images is referred to as the *visualization pipeline*, first introduced by Haber and McNaab in 1990 [42] and later refined by Dos Santos and Brodlie in 2004 [35] (see Figure 2.3).

The raw input data goes through four transformations before it is turned into an image. First, through *Data analysis*, where re-sampling, interpolation, removal of outliers, or other actions can be applied. The prepared data is then sent to the *Filtering*, where the data is reduced concerning the specific visualization task. Often in interactive visualization, the user can filter the data on-demand. The focused data goes through the *Visual mapping* step where the variables are mapped to appropriate visual encoding, such as color, geometry, shape, texture, size, etc. Finally, the abstract visualization objects are rendered as an image for the user to view and analyze. For a complete description, please check the two original works [35, 42] or the survey introduced by Moreland [69].

### Visual Mapping

This step is the most crucial one as it largely influences the expressiveness and effectiveness of the visual representation created. A vast amount of prior research has been conducted investigating the degree to which visually encoded variables facilitate comprehension of data sets. Often the term *graphical perception* is used to denote the ability of users to interpret such visually encoded variables and thereby decode information in graphs [28]. Card et al. [22] introduced three critical structures that must be defined for creating effective representations: *spatial substrate*, *graphical elements*, and *graphical properties*.

The spatial substrate defines the representation space and/or axes placement. Depending on the data and if axes are necessary, they either use a quantitative or qualitative scale and the representation space either two-dimensional (2D) or



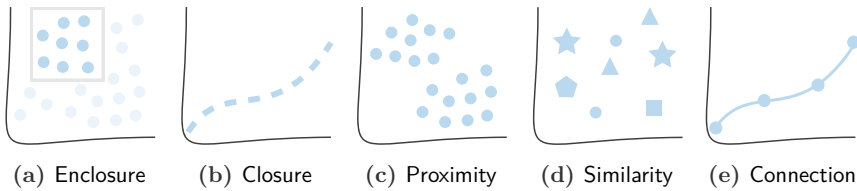
**Figure 2.4:** The figure presented in (a) shows examples of the most common graphical elements and properties used to display data, and (b) the accuracy in perception of the data displayed going from less to more. (Image adopted from [67])

three-dimensional (3D). Often the 2D representation space is following the spatial dimensions of the computer monitor and uses x and y coordinates to span the space, or the size of the object the representations is printed on. The 3D representation space uses a third axis (z-axis) to display more complex three-dimensional data. After selecting the space for the data to be displayed, graphical elements (i.e., points, lines, surfaces, volumes) are chosen to map the variables and the corresponding values (see Figure 2.4(a)). The last step is to select the element properties. The most common attributes are: size, orientation, color, texture, and shape [67] (see Figure 2.4(a)). As visual mapping is a crucial step in the visualization pipeline, mapping the proper attributes to the graphical element plays a major role in creating effective visual representations. Using the proper attributes also help in making the most important parts of the data being “popped-out” creating a clear distinguish from their surroundings. Moreover, if accuracy is important when presenting the data, then using spatial position is the alternative that best facilitates graphical perception across all data types [46, 67] (see Figure 2.4(b)). Conversely, color and texture can be used when being accurate is less important.

The color property is often used for distinguishing between the variables or encode order into the data. However, it is a unique property and needs to be used with special attention, as it can easily clutter the representation. This property also has different effects as perceiving color differences varies across element types such as points, bars, and lines [92]. For a complete description of color coding in data visualization, please check [10, 88, 112].

### Gestalt Principles of Visual Perception

Mapping the data to proper graphical elements and properties is crucial for creating adequate visual representations. However, as data visualization is about exploring



**Figure 2.5:** The figure shows five commonly used gestalt principles for influencing the perception. These principles help explain how people organize sensory information and are useful for focusing users attention.

the data visually, it is important to simplify the search and intentionally “pop-out” the essential information for the user to analyze. Such effects can also be achieved by applying the Gestalt Principles of Visual Perception [57]. The principles can be used to understand how people perceive order in their surroundings. They aim to define rules on how our visual perception tends to organize visual elements into a “unified whole” [67]. They are still accepted today and used in the development phase to identify unnecessary clutter and to simplify the visual analysis. While there exist many principles, only five relevant (enclosure, closure, proximity, similarity, and connection) are mentioned in this thesis as examples.

Enclosing elements in a box or similar object creates the notion of groups (see Figure 2.5(a)), this is often seen in brushing interaction. If the element is incomplete, our visual perception fills in the gap and creates the notion of a complete element (see Figure 2.5(b)). This principle is useful as it can help us understand what parts of the graph are unnecessary and need to be removed (i.e., to reduce clutter). The proximity principle states that elements close to each other are perceived as one group (see Figure 2.5(c)), this can simplify comparison tasks. The similarity principle uses similar shape, orientation, color, size, etc. (the properties of the elements) to create the notion of groups (see Figure 2.5(d)). Finally, the connection principle tells us which elements belong to a group by connecting them with a line (see Figure 2.5(e)).

## Interaction Support

Without interaction, the user is limited in exploring the data from different perspectives. The feedback loop in the visualization pipeline (see Figure 2.3) is important as it allows users to change parameters that best fit the needs and could help them gain insight into the data. The term *interaction* is often defined as “*the communication between a user and the system*” [109]. In general, the user is either interacting with the tool window or the representation space and the graphical elements [103]. The reasons for interacting are many. Yi et al. [109] identified several high-level reasons why users use interaction when analyzing the data. The user is either interested in *selecting* something, *reconfigure* parts of the representation

or the data, *exploring* the unknown, *encoding* the data differently, showing more or less information (*abstract/elaborate*), *filtering* data, or *connecting* items. Such interaction can be performed via different methods such as Direct manipulation, Brushing & Linking, Focus+Context, Dynamic Querying. With direct manipulation, the user can select or perform any other operation directly with the graphical elements and the representation space (i.e., zoom, dragging) [1, 56]. Brushing & linking is about interconnecting multiple views for analyzing the data from multiple perspectives [60, 65]. The focus+context method is about focusing on interesting areas while maintaining the general overview [51, 56, 60]. There is also dynamic querying, where the user can apply filtering conditions via the tool interface to focus on certain parts of the data [1]. There are many taxonomies that investigate the interaction space and categorize the techniques into levels of granularities from low-level [86] to high-level view of interaction [33, 103].

## 2.5 Summary

The short overview presented above shows how complex and challenging it can be to work with temporal data, as many aspects are needed to keep in mind. However, having a clear understanding of the data and time characteristics can help in knowing how to visualize the data for optimal use. Moreover, knowing why the data is being visualized is equally important. Throughout the years, the visualization community has suggested and studied many different visual representations with their inherent benefits and limitations concerning the data and time aspects of temporal data. Some of these representations and concepts are introduced in the next chapter.



# Visualizing Temporal Data

---

As we learn about each other, so we learn about ourselves

—*The First Doctor, Doctor Who (William Hartnell)*

Many of the common approaches used to visualize temporal data and quantitative information are based on the work of early visualization pioneers such as William Playfair [87], Johann Heinrich Lambert [1], Florence Nightingale [13, 71]. The vast number of different representations makes it challenging to know which is optimal to select for displaying temporal data. Another, equally important challenge, is to know what shape of the timeline to use, as it can affect the human ability and performance to read the displayed data accurately [31]. Often the timeline is drawn linearly with the events organized along a straight line to emphasize the chronological progression of time [15, 31]. Such linear timelines can support chronology and sequence in the temporal data, while non-linear shapes like radial, spirals, arbitrary, grids and other arrangements [15] can be effective in revealing periodic repetitions in the temporal data [15].

## 3.1 Linear Layouts

Visual representations based on a horizontal linear timeline [15, 31] used to display temporal data can be classified into two categories: *shared-space* and *split-space* [52]. In the former, variables are displayed in the same representation space, while in the latter the variables are split into equal-sized small representations with their own reduced space (see Figure 3.1).

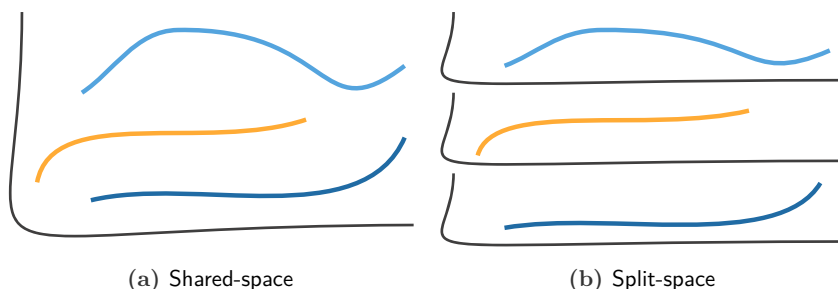


Figure 3.1: Two different visual representation spaces, (a) shared-space where the data variables are visualized on the same representation space, and (b) split-space, where each data variables is rendered with its own small space and superimposed.

### Shared-space

Shared-space representations (see Figure 3.1(a)) uses the same space to display all variables and an early example of such representation is the tenth-century illustration of the inclinations of planetary orbits as a function of time [1, 99] (See Figure 3.2(a)). It took a long time for similar representation to appear again in the scientific literature [99]. Joseph Priestley (1733–1804) created a shared-space representation with linear timeline showing the life span of famous historical people (see Figure 3.2(b)). Using such linear layout to present quantitative information only become popular when William Playfair (1759–1823) frequently used them to display statistical data. Today, he is known as the greatest inventor of modern graphical designs [99]. He invented the modern line graph we all know and frequently use to display temporal data, and also the bar graphs, the area graphs, and the silhouette graphs. The line graph uses position encoding for both the time dimension and the variable values. The variables are overlaid on the shared-space which facilitates comparison between the variables. However, such shared-space representation can only support a limited number of variables (more than four introduces visual clutter [52]).

While the possible number of variables that could be displayed in a shared-space is limited by screen size and resolution, displaying multiple variables is often necessary for finding patterns and drawing useful conclusions. William Playfair filled the area under the line in a line graph for emphasizing the values (see Figure 3.3(a)). Using this approach to visualize multiple variables creates a so-called stacked area graph (see Figure 3.3(b)). Variables are stacked on top of each other on a straight bottom baseline creating a visual summation of variable values providing an aggregate view formed by the individual variables [93]. However, stacking areas cause maximal distortion for the variables positioned at the top causing illusions and difficulties for the viewer [93]. Moreover, changing the variable order also

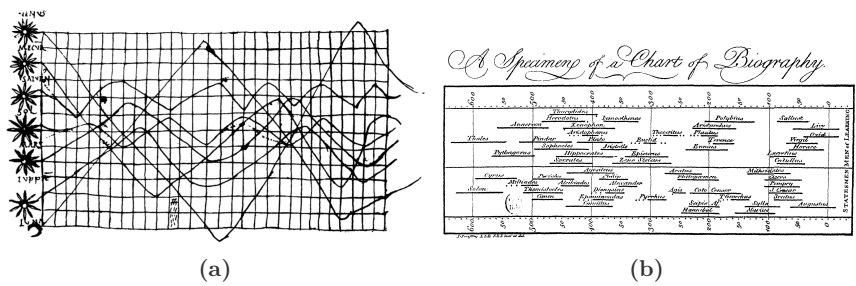


Figure 3.2: (a) A line graph from the 10th century depicting planetary orbits, (b) Joseph Priestley's 1765 timeline chart of famous historical peoples life spans.

Source a: commons.wikimedia.org: Retrieved Feb. 2021 Source b: commons.wikimedia.org: Retrieved Feb. 2021

changes the shape of the representation, which also creates challenges and can mislead the viewer [3].

To minimize this distortion and make the representation more aesthetically pleasing new versions have been introduced. The ThemeRiver [44] organizes the variables in a symmetrical fashion around a horizontal axis, and StreamGraphs [21] further reduces the distortion and creates asymmetrical outer shapes. Minimizing illusion effects between the different variables (layers) has been investigated and shown to improve readability of StreamGraphs [18]. Thudt et al. [93] investigated the readability of these three representations and found that each representation is useful for different types of tasks. Distinguishing between the layers in such area-based representations is important for finding patterns and trends. This can be achieved with the color property (see Figure 3.3(b)), however, interpreting the representation becomes a challenge when multiple variables are displayed in such representations. While strong distinctive colors might necessary for noticing local contrasts, they could be visually distracting and make the representation hard to read [21]. Therefore, the color scheme chosen highly depends on the underlying

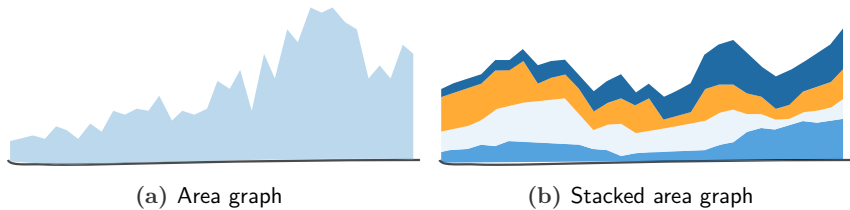


Figure 3.3: The figure shows two examples of shared-space representation, (a) simple area graph, and (b) more complex stacked area graph.

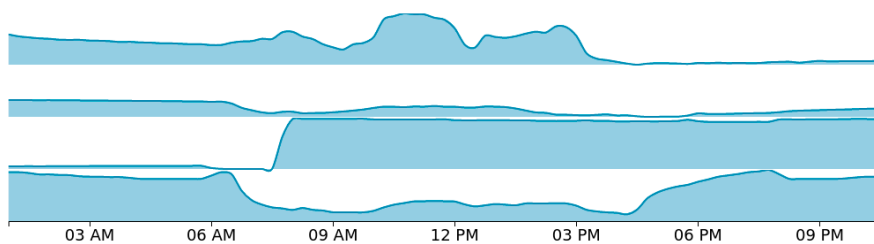


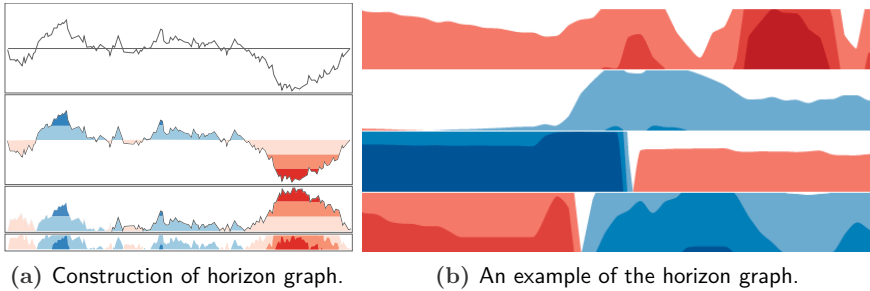
Figure 3.4: An example of the silhouette graph using the split-space concept with a common x-axis and each variable visualized with its own space and superimposed.

data displayed [21]. Apart from this issue, color itself might be a challenging visual property. It can easily be affected by environmental factors, display settings, and graphical element properties, which inhibits the viewer's ability to distinguish the colors in the representation [92].

### Split-space

The split-space concept, sometimes known as *small multiples* [99], is a popular alternative to overcome the above-mentioned challenges with shared-space representations, such as visual clutter. Each variable is displayed with its own representation, reduced space, and is superimposed for saving vertical screen space (see Figure 3.1(b)). This approach minimizes visual clutter and aids the comparison of variables for pattern and trend finding. A popular representation using this concept is the silhouette graph [1, 43] (see Figure 3.4). The time dimension is displayed on a shared x-axis, while each small representation has its own y-axis to present the value of the variables. Superimposing these small graphs makes the representation space-efficient and reduces visual clutter. The representation provides an overview and can emphasize the visual impression of long temporal data, making it easier to compare multiple variables [1, 43]. While a monochrome color channel is commonly used, different color hues can be used for each small graph to facilitate variable separation [52].

To reduce the vertical space even more, a horizon graph can be used (see Figure 3.5). This representation also takes advantage of the split-space concept and can display many variables. The representation was first introduced by Saito et al. [83] as two-tone pseudo-coloring, and further developed by Reijner [80]. A standard line graph with its mean as a baseline is split into  $N$  uniformly-sized bands (see Figure 3.5(a)). Values above and below the baseline are colored differently and saturated based on the distance from the baseline. Then the values below the baseline are horizontally mirrored which wraps the variable into a single space-efficient graph (see [1, 3, 52] for more details). By cutting the y-axis into bands as described above, the representation becomes even more space-efficient than the standard line graph and the silhouette



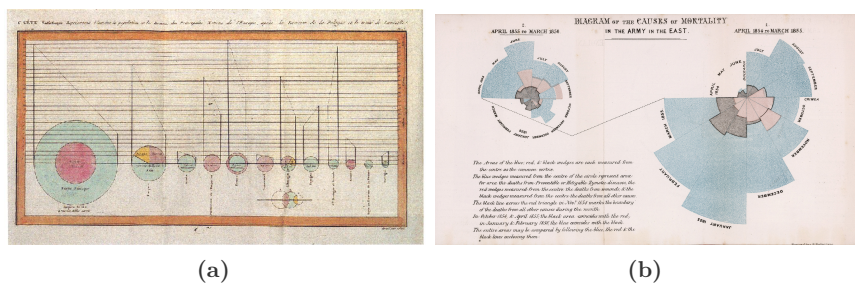
**Figure 3.5:** The figure shows (a) how horizon graphs are constructed and (b) an example of the horizon graph representation. (Image (a) adopted from [52])

graph. However, the abstraction level of the horizon graph limits the representation to only show an overview of the data, show trends and patterns with the help of the color property. Interactively moving the baseline vertically could support in better visual analysis of the displayed temporal data [74].

## 3.2 Radial Layouts

The linear layouts pose the issue of continuity, starting and ending at arbitrary points. This issue could be addressed by using a radial layouts, where a true zero of a starting point is non-existing [64]. Using the radial layout is said to simplify the readability of cyclic data (i.e., seasonal variations) as the strictly linear progression from past to future is neglected [1, 19]. They are also said to simplify comparisons of the periodic behavior as they are good for displaying data distribution and can increase users chronological orientation, and are useful for detecting temporal locations [19, 39].

This layout has been thoroughly investigated in the visualization community [19, 32, 36, 40]. William Playfair used such radial layouts to invent his last major graphical invention—the *Pie Chart* [87, 90, 99] (see Figure 3.6(a)). The pie chart displays percentages as “part-to-whole” by using the angle, area, and arc length [58]. It has been shown that the area is the best visual cue to use when displaying data with such representations [58, 59]. Moreover, the center of the pie chart can be removed (turning it into a Donut chart) without affecting the readability of the values [89]. While such representations could be useful for displaying variable amount in the data, they are limited in displaying temporal data, and minimal research has been conducted investigating this challenge [66, 110]. Although, Florence Nightingale (1820-1910) invented an extension of the pie chart, the *Polar Area Chart* (also known as a “Rose Diagram” or “Coxcombs”) (see Figure 3.6(b)). With this representation, Nightingale displayed the number of deaths caused by



**Figure 3.6:** (a) The pie chart figures display statistical data for European countries in 1801 (The Statistical Breviary), (b) Rose diagram consists of circularly arranged wedges that convey quantitative data. Florence Nightingale (1858) tediously recorded mortality data for two years and created a novel diagram to communicate her findings.

Source a: [commons.wikimedia.org](https://commons.wikimedia.org/); Retrieved Feb. 2021. Source b: [commons.wikimedia.org](https://commons.wikimedia.org/); Retrieved Feb. 2021

preventable diseases, results of wounds from the Crimean war, and other causes during the same time period. Radial layouts are often used among practitioners to display temporal data in creative ways (e.g., climate change over a long period of time [45], interactive storytelling and movie analysis [104], and personal data [12]).

In radial layouts, the time dimension is often mapped to the representation space. Waldner et al. [102] investigated such radial layouts resembling the metaphor of an analog clock with daily pattern data for standard viewing displays. Their study showed that using two separate radial representations for displaying values for AM and PM is not recommended. Moreover, visualizing ranges over time-series on small displays (e.g., smartphone) has also been investigated with radial representations [16]. The study focused on identifying limitations in terms of how many ranges could feasibly be displayed on such small screens. Furthermore, using radial layout to visualize time-series has also been investigated in small multiples [39]. Also, other approaches have been taken to facilitate pattern exploration (i.e., splitting a circle into colored segments to present temporal data [7, 55]).

Carlis et al. [23] introduced multiple examples on how to present serial periodic data on spiral timelines, presenting time growing outwards from the center. They presented the data on the spiral time dimension arrangement by using points, lines, bars, and color. They also looked into such representation in 3D. However, temporal univariate data might be more suitable with such spiral timelines due to space restrictions and visual cluttering. Additionally, values rendered in the center representing past time are displayed smaller creating the illusion of smaller values. Others have also investigated how to map temporal data on spiral layouts using different graphical elements and properties can be used to visualize the variables (e.g., lines, area, color) [25, 95, 105].

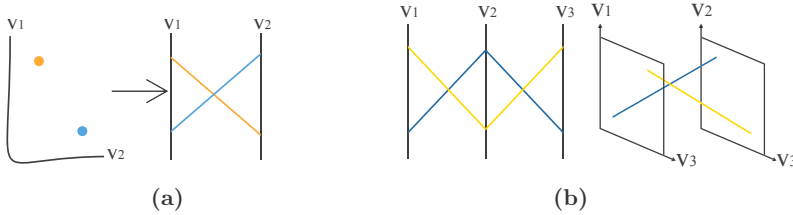


Figure 3.7: Illustrations of how (a) Cartesian coordinate systems with two variables ( $v_1, v_2$ ) can be transformed into 2D Parallel coordinates with two axes and (b) 2D Parallel coordinates with three axes into 3D parallel coordinates.

### 3.3 Multiple Axes

Adjusting the graphical elements and properties can help visualize many variables, however, the representation might become visually cluttered. Another approach is to increase the number of axes in the representation [27, 96], and a common representation that can display many axes is the parallel coordinates (see Figure 3.7). This representation was originally invented by d'Ocagne [34] but introduced to the visualization community by Inselberg [48] and Wegman [107].

The representation is commonly used to analyze multivariate data, however, few have investigated their usability for displaying temporal multivariate data. Often a temporal-slider is augmented onto the representation to filter and explore the data as well as the temporal dimension [11, 30]. Some have investigated different graphical elements, such as polygons with blending methods instead of standard polylines to capture time-varying dynamics in datasets [54], while others investigated temporal multivariate data with three dimensional parallel coordinates, originally proposed by Wegenkittl et. al [106] to investigate higher dimensional data. The time dimension in such representation is either displayed on one of the axes or as the fourth dimension where users can investigate the three-dimensional data changing over time. Investigating temporal datasets with parallel coordinates in the three-dimensional space, where the time dimension is mapped to one of the axes, is common [2, 41, 94, 111]. Although, the visualization community has long discussed whether the use of a three-dimensional space makes sense to present and explore two-dimensional abstract data [22]. Studies have shown that 3D representation could help shift the viewing process from being a cognitive task to being a perception task [91]. However, if two axes are sufficient to present the two-dimensional abstract data, using a third axis will often mislead the viewer in their analysis [91, 99].

## 3.4 Summary

Using representations based on linear timelines have been used for a long time. However, little can be found how such representation using shared- or split-space help domain experts in understanding the temporal data and solve their tasks. Moreover, radial representations have been investigated to a great deal, yet there is still a lot to explore. The effectiveness of presenting hourly data with one radial representation needs to be explored further. As for representations using multiple axes, little research has been conducted investigating the well-known parallel coordinates technique for their usability to display temporal data. To investigate such challenges and ensure usability of different types of visual representations, user evaluations should be conducted.



# Evaluating Visualization

There's always something to look at if you open your eyes!

---

—*The Fifth Doctor, Doctor Who (Peter Davison)*

It is important to know the type of data visualized, the reasons for visualizing it, and using what type of representations. It is equally important to understand the usability of the representations and tools. The term *Usability* can be defined as—“*the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use.*”(ISO9241-11 (1998)) [9]. Effectiveness is measured as to what extent users achieve their objective (i.e., solving the task or not), while efficiency can be measured as the amount of effort users put into the task (i.e., the time spent solving the task or the cognitive load). Satisfaction is often measuring subjective opinions, attitudes, and preferences through standardized questionnaires [8, 17, 37]. Often these measurements are done via evaluation studies. The findings from the studies could potentially provide a basis for future developers to know what to build with confidence and what to do better [38]. Evaluation is today a research field of its own with many methods available [50, 61]; therefore, it becomes a challenging task to know which method to select for investigating the tools and representations [77].

## 4.1 Choosing an Approach

Many of the evaluation methodologies that could be used to conduct user studies are borrowed from Human-Computer Interaction [24, 38, 97]. Among these methodologies, the visualization community often implement *empirical methods*, which

involve studies with users to find verifiable evidence to arrive at a good research outcome. The empirical methods are often divided into two categories: *Quantitative*, *Qualitative*.

### **Quantitative approach**

These types of studies are better known as experiments conducted under controlled environments and include hypothesis development, identification and control of independent variables, and observation and measurement of dependent variables [24, 67, 97]. These studies are often used to compare multiple ideas by measuring accuracy (effectiveness) and completion time (efficiency), which are analyzed with appropriate statistical methods for producing evidence that could be used to demonstrate that the ideas investigated are useful [38, 78].

Despite the long and effective usage across many different scientific fields, these experimental approaches are still challenging to conduct [24]. There is always the issue of reliability and validity of the results. The former concerns consistency and reproducibility (i.e., Are we measuring what we intended to measure?), and the latter concerns soundness and quality (i.e., How well does the measured phenomenon correspond to reality?). Additionally, there is also ecological validity discussing the degree to which the experimental situation reflects the type of environment in which the results will be applied. On top of all, every study has a trade-off between building generalizable and domain-specific tools [97].

### **Qualitative approach**

In qualitative methods the goal is often to seek meaning and gather contextual information that may include subjective experience [49]. There exists a wealth of methods that could be used for collecting rich information regarding the visualization tools and user experience. These methods are often grounded in realistic settings and can be used as part of the design process, but also complement quantitative methods or any other type of study [24, 49]. Both objective and subjective data can be collected during the investigation and is often done via Think-Aloud protocol [62], semi-structured interviews, video and audio recordings, computer logs, artifacts (e.g., drawings, sketches, diagrams), and questionnaires.

A well-known challenge is that qualitative research methods are labor intensive [24]. They often take a long time to plan, conduct, and transcribe and analyze the collected data. Another issue is the sample size, a recurring discussion in the community regarding what appropriate number is needed to draw useful conclusions. However, as qualitative methods are not concerned with making statistically significant statements [24], the number of participants used in qualitative studies can vary greatly depending on the scope of the research and domain. Nevertheless, recruiting too many participants will result in a large amount of data needed to be transcribed and analyzed, a time-consuming and tedious task. Besides, the transcribed data quality depends on the investigators' experience in performing such analysis [24]. Above all, the aim is often to produce results that support *trans-*

*ferability* rather than *generalizability*, as it is more difficult to produce generalizable results [24].

## 4.2 Summary

Often the two above-mentioned approaches are combined together, such studies are referred to as mixed-method studies. These combine two or more evaluation methods drawing on quantitative and qualitative data collection and analysis [84]. Similar to any other study, mixed-method research requires advanced planning. These studies could be challenging as the study administrator has to know both quantitative and qualitative study methodology. Nevertheless, when mixed-method studies are implemented correctly, rigorous results can be produced. Mixed-methods can often be used to add further insight, explanation, and new questions to the investigation [24]. Moreover, it could be beneficial to combine quantitative and qualitative methods to collect objective and subjective methods as there might not always be a correlation between these two. Although, participants can perceive time passing by more quickly when engaged in a task [26, 29, 82]. This phenomenon could explain the discrepancy between subjective experience and objective measures concerning response times. Therefore, knowing participants' subjective preferences in combination with quantitative measurements could show whether the correct visual representation has been used. Often quantitative approaches are used to understand objective results, while qualitative approaches are used to understand subjective feedback. However, using mix-methods is in most cases a good idea and can produce robust results.



## Included Work

In 900 years of time and space, I've never met anyone who wasn't important.

---

—*The Eleventh Doctor, Doctor Who (Matt Smith)*

The included work in this thesis has explored different type of data, evaluating different type of visual representations and presentation structures as well as different approaches to interaction support. All work has included a user-evaluation, both novice users as well as domain experts, to assess the usability of the visual representations.

The order of the included work is based on target users and divided into two sections: investigation with novice users (Paper A and Paper B) and investigation with domain experts (Paper C, Paper D, and Paper E). **Paper A** investigated six radial representations for displaying hourly data. The representations are implemented with different graphical elements (e.g., area, position) and low-level tasks are used in a quantitative online study with novice users. **Paper B** investigated two versions (2D and 3D) of the well-known parallel coordinates. The nature of the representations required their own interaction which were used to solve high-level tasks (i.e., pattern identification) in a quantitative study with novice users. **Paper C, Paper D** investigated multiple visual representations based on a linear timeline for domain experts. The representations were qualitatively evaluated with ecological tasks and domain experts are involved in all the steps of the development process. Lastly, **Paper E** investigated multiple visual representations presented with a multiple view concept for geologist to analyze weather data collected on Antarctica via different sources.

## 5.1 Paper A

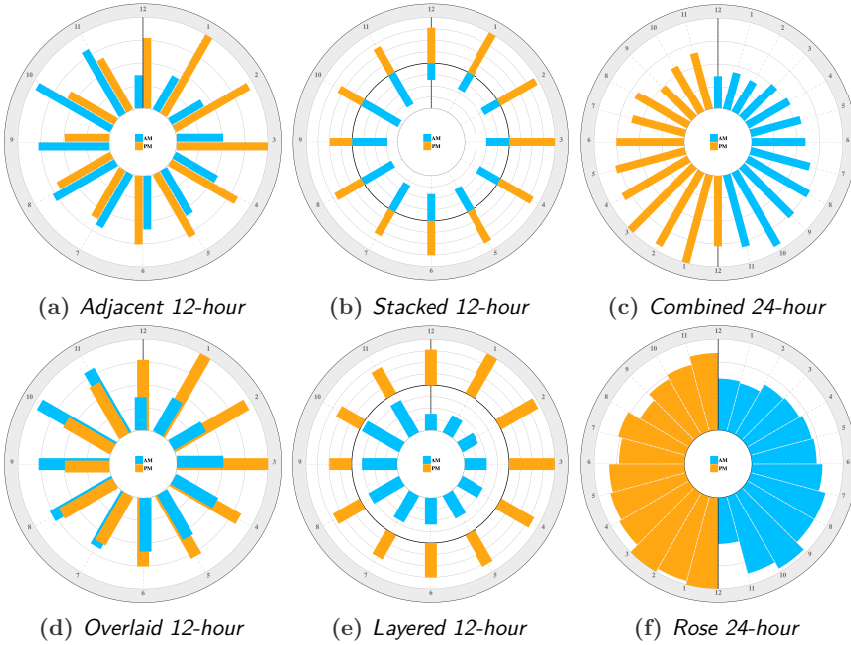
The aim of this work was to investigate how to best present hourly data with one shared-space radial representation. Previous research has shown that radial representations are useful to display temporal data and perform comparison tasks [16]. They have also been found effective for reading values at specific temporal locations [39]. While different layouts (12-hour cycle mimicking the display of an analog clock and full 24-hour cycle) have been used to display such data, little research has been found in the literature on comparing the layouts. Moreover, Waldner et al. [102] found that displaying hourly data with two separate representations (one for AM and one for PM) is not useful for detection of salient features [102].

### Method

A quantitative user study split into three experiments was conducted to investigate six radial representations for their usability to present hourly data (see Figure 5.1). Completion time and accuracy were measured on four commonly used tasks (locate time, locate min/max, compare values, and compare ranges) for each radial design. The first experiment investigated the *Adjacent and Stacked 12-hour* (Figure 5.1(a), Figure 5.1(b)), and *Combined 24-hour* (Figure 5.1(c)). The findings were then used in a second experiment investigating three new designs *Overlaid and Layered 12-hour* (Figure 5.1(d), Figure 5.1(e)) and *Rose 24-hour* (Figure 5.1(f)). Finally, the representation where users performed best with were compared in the third experiment (Adjacent, Overlaid and Layered).

### Results and Lessons Learned

The results showed that radial representations were useful for displaying hourly data. It was also found that radial representations might not be optimal for comparison tasks, when proximity between visual elements are important. Such tasks often require users to combine multiple element properties (e.g., value location, color, height) to search for the answers, making comparison tasks hard. This was especially difficult in 24-hour design as users were required to compare non-neighboring visual elements, which forced them to move their eyes over longer distances in the graph while simultaneously memorizing the element properties. Another challenge with proximity arose due to interruptions between elements for the compare range tasks, making the range a continuous area or detached elements depending on the radial design. Moreover, the color property was used for distinguishing between the elements (i.e., AM and PM), an important aspect, however, using multiple baselines (as in Figure 5.1(b) and Figure 5.1(e)) will confuse the viewers. It is easy to misunderstand such radial representations, if not carefully designed. The 24-hour design was more plausible to misunderstand as the placement of the wedges (before or after the hour) might have been affected by cultural and linguistic factors.

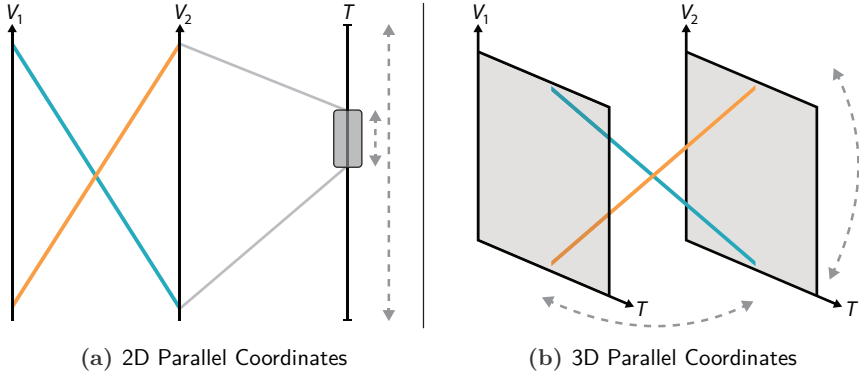


**Figure 5.1:** The six radial representations (four 12-hour and two 24-hour) investigated in Paper A. The bar elements placed (a) adjacent with the zero baseline starting from the inner circle, (b) stacked, where the zero baseline starts from the middle circle, (c) combined, where the values are separated into each side, (d) overlaid, where the bar elements are close, (e) layered, where the direction of the bars is the same, and (f) rose, where wedges are used to present the data values. (Images taken from [5], used with permission.)

Radial representations are useful for presenting a low number of variables, but the representation have some limitations. While they are useful for displaying hourly data (i.e., up to 24 hours), they might not be able to handle more variables without introducing visual clutter. Using color is crucial to use for distinguishing the variables and the gestalt principles of visual perception play a major role (e.g., proximity, enclosure, similarity).

## 5.2 Paper B

The aim of this work was to investigate the usability, through efficiency, effectiveness and satisfaction, of parallel coordinates for displaying temporal datasets (see Figure 5.2). The parallel coordinates representation is a well-established approach and used for presenting and analyzing non-temporal multivariate data [47, 53]. The



**Figure 5.2:** The two version of the parallel coordinates representation investigated in Paper B, (a) standard 2D version where the rightmost axis presents the time dimension with the brush interaction, and (b) the 3D version with rotation interaction and the time dimension displayed on one of the three axes. (Image taken from [4] ©2019 IEEE, used with permission.)

representation has been improved in many ways to handle such data in different settings [53]. However, little investigation has been discussed in the literature regarding their potential value for the analysis of temporal datasets.

## Method

The study was designed with one within-subject factor: visual representation (2D, 3D) investigated with synthetic temporal data. The representation investigated in this work were both kept simple using transparent and semi-opaque with additive blending monochrome line elements to render the patterns between the axes. Filtering and brushing the data simultaneously was implemented in 2D parallel coordinates (see Figure 5.2(a)), while rotation with a restriction of  $\pm 45^\circ$  around pitch (i.e. horizontal axis) and yaw (i.e. vertical axis) was implemented for the 3D parallel coordinates to restrict users rotating the representation into a 2D view (see Figure 5.2(b)). The participants were required to solve pattern recognition tasks. For each participant, efficiency was measured through completion time (response time in seconds) while effectiveness was measured through the terms of achieved goal (accuracy). Between each condition, the participants filled in a questionnaire regarding their subjective preference (satisfaction) with the tested representation.



## Results and Lessons Learned

The result showed that using 3D parallel coordinates was easier than using standard 2D parallel coordinates for pattern finding in temporal data. One reason was that the rotation interaction in 3D was found natural to work with when analyzing the data. While in 2D, participants had to brush and filter out the data values thus losing overview, and making the pattern identification task harder. Additionally, the type of interaction used in 3D helped the viewing process to be a perception task (finding and matching patterns) rather than a cognitive task (thinking about how the variables evolve to conclude the patterns). Therefore, when working with such high-level tasks, it is necessary to display all the data and to avoid losing overview and cohesion. This study investigated these specific versions of parallel coordinates, further research is needed for fully understanding how parallel coordinates and other multiple axes representations might be used for displaying temporal datasets.

### 5.3 Paper C

The aim of this work was to investigate different visual representations based on a linear timeline, by using shared-space and split-space concept, that would be relevant to use for such domain and the challenges faced. The indoor climate is affected by a number of factors such as temperature, ventilation, humidity, CO<sub>2</sub> levels etc. One way to improve the indoor climate is by placing active plant walls in the environment (see Figure 5.3). These plant walls can help improve the indoor climate via evaporation, air purification, and water retention [3]. Sensors attached on the plant walls collect information about the environment as well as the well-being of the plant wall. The collected data is updated in real-time and consists of many dimensions which makes it difficult to understand. Therefore, presenting the data visually could help in understanding it better and aid domain experts in decision making regarding the indoor climate quality and well-being of the plant walls.

#### Method

A line graph, a stacked area graph, and a horizon graph (see Figure 5.4) were qualitatively evaluated with the domain experts. The stacked area graph used a shared-space design while the line graph and the horizon graph used a split-space design. Interaction was not implemented as the focus was on the static benefits and limitations of the representations.

The goal was to understand domain experts' subjective experience and preference for the different visual representations when exploring the data. Relevant tasks were used to evaluate the three visual representations with five domain experts.



Figure 5.3: An example of an active plant wall hanging on the wall in a local company.

(Image taken from [3] ©2019 MDPI/Data, used with permission.)

They were asked to find correlations between variables and Think-Aloud protocol was used to collect their feedback. This feedback was transcribed to develop an understanding of how the experts reasoned when working with the representation. Additionally, a semi-structured interview was conducted after each experiment for collecting further feedback regarding their preference. Thematic content analysis [20] was used to derive useful findings from the audio recordings, and answers from the semi-structured interviews were open-coded [20].

## Results and Lessons Learned

Based on the study findings and complemented by previous research [21, 93], stacked area graphs were not well suited for temporal multivariate data. Overall, when end-users with little visualization knowledge need to analyze data, it is vital to use simple and intuitive representations. The simplicity of the representations will effect the learnability, with simpler representations being more helpful in work tasks. For this domain, a line graph, was found useful, but a shared-space might be more optimal to use. Moreover, a horizon graph was also recommended for analyzing such data, even though further research needs to be conducted to assess the usability of these representations further.

The indoor climate data analyzed is often large and multivariate. Therefore, when displaying such variables, it is important to keep in mind that the visual representation can quickly become visually cluttered. Using a split-based representation could potentially decrease the visual clutter. However, with such approach some variables will be rendered far apart, which might be challenging for certain tasks, such as comparison tasks. Ordering the variables might be necessary for finding hidden patterns, especially so for improving usability of stacked area graphs.

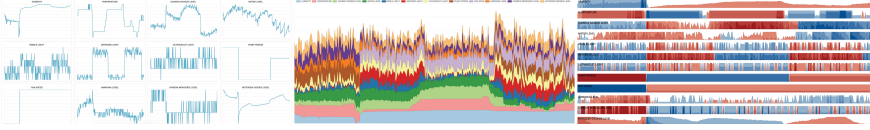


Figure 5.4: Examples of how the three representations were implemented for displaying the temporal indoor climate data in Paper C. From left, a line graph using split-space concept, a stacked area graph using a shared-space concept, and a horizon graph using a split-space concept. (Image taken from [3] ©2019 MDPI/Data, used with permission.)

## 5.4 Paper D

The aim of this study was to further develop and evaluate the findings from Paper C, and present a tailor-made visual analytics tool—*TimePlant* for monitoring indoor climate as well as controlling the plant walls (see Figure 5.5). A tailored solution was necessary as existing solutions that use visualization were either not useful, too expensive, or not tailored to the domain needs. Today, service personnel have to physically visit each plant wall for maintenance, which becomes a time-consuming and expensive activity. With the tool, the service personnel can keep track of the plant walls’ health and system functions as well as remotely controlling them. Moreover, real-time and historical indoor climate data can be monitored, analyzed and improved via the tool. Involving domain experts in the development process ensures that tailor-made solutions are implemented that best fit their requirements. It also created a clear communication channel which minimizes knowledge and interest gaps between the domain experts and the visualization researchers [101].

### Method

The tool was developed in close collaboration with one domain expert in two workshops, where the domain challenges, tool requirements and graphical interface were discussed in workshop one before a prototype was developed and shown to the domain expert in workshop two. The line graph and horizon graph were added based on the findings from Paper C while a third representation (a silhouette graph) was added based on the discussions from the two workshops. Furthermore, the feedback provided in the workshops hinted on two types of interaction (Brush and Zoom), which were implemented to be investigated with the tool. The tool was qualitatively evaluated with six other domain experts who were not part of the development process.

Tasks relevant for the domain experts (locate, compare, explore) were used to investigate the experts’ understanding of the visual representations, the interaction techniques and the usability of the tool. The study was audio and screen recorded, and the Think-Aloud protocol was used to collect subjective feedback. After the



Figure 5.5: The TimePlant tool showing the analytical view. To the left, the user can filter by dynamic querying the data, selecting the representations and the variables. To the right are the actuators displayed using an eventViewer [1], the selected representation, and the interaction using Focus+Context [60]. (Image taken from [6], used with permission.)

study a semi-structured interview commenced. Thematic content analysis [20] was used to derive useful findings from the audio and screen recordings, and answers from the semi-structured interviews were open-coded [20].

## Results and Lessons Learned

The shared-space concept evaluated in this work was found useful but sometimes difficult as it could quickly become visually cluttered. In this study, the line graph was using shared-space, as it was suggested from the previous study conducted with domain experts. The visual clutter was caused by the color property used for each variable and the number of variables displayed. Therefore, a low number of variables was experienced as useful for this representation, a similar result also found by [52]. The other two representations investigated used a split-space concept. The silhouette graph was more preferred by the domain experts, while the horizon graph needed more time to work with before understanding and being experienced as useful. Although, the horizon graph was mentioned to be easy for getting an overview of the data as it used to colors only. The investigation also showed that using an interaction technique based on focus+context with zoom navigation was more intuitive than a brush navigation for such domains and tasks. The domain experts easily lost the overview of the data with the brush navigation. While the three representation had different strengths and weaknesses, they were all experienced as useful for solving different tasks, such as horizon graph providing a easy overview of trends while the line graph provided a more detailed view. This

shows the importance to chose visual representation based on the user needs and reasons to use visualization. Therefore, all three representations were kept in the final version of the tool with the zoom navigation.

## 5.5 Paper E

The aim of this work was, with the power of visualization, to help domain experts working with temporal data collected in the periglacial areas of Antarctica to interactively explore and discover temporal patterns, trends and gain further insight into the data. Today, this information is often analyzed with standard tabular representations, and tools to explore the data are seldom available or are not tailored to the domain experts' needs. While these tabular representations might be useful to draw general conclusions, temporal patterns and trends are usually difficult to find using such representations. Furthermore, the collected data is often incomplete and involves uncertainty, a challenge difficult to notice without visualization.

### Method

As domain experts usually lack visualization knowledge, close collaboration is necessary to achieve successful results. The domain experts in this collaboration desired a visual analytics tool as one software to display datasets collected from multiple sources simultaneously for faster analysis (see Figure 5.6). Temporal data, air temperature, wind speed, and soil temperature at 5cm and 15cm depth, are every 30 minutes measured and stored. To measure and collect the snow level, multiple cameras around boulders of interests are, every three hours, taking photos of bamboo stick marked with uniformly black labels indicating snow height in centimeters.

Multiple informal sessions with one domain expert were conducted to understand and set the tool requirements. A prototype was then developed and tested in a pilot study with two domain experts, and the feedback was used to improve it further. Finally, the tool was evaluated in a qualitative user study with five additional domain experts. The evaluation was focused on measuring the usability of the tool. The domain experts solved multiple tasks regarding value, range, and correlation finding. Each session was audio and screen recorded, and thematic content analysis was used to analyze the data [20]. The feedback collected from the transcribed data was incorporated into the final version to improve the tool one final time and discussed with two experts in an informal interview before deploying it.



## Discussions and Reflections

There's something that doesn't make sense. Let's go and poke it with a stick.

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—*Dr Who (Steven Moffat)*

The goal of the work presented in this thesis was to investigate how visual representations can facilitate analysis and exploration of temporal data. This was done by investigating usability of different visual representations, exploring different representation structures, and studying how interaction supports users when analyzing the data. Even though the work has focused on a few visual representations for displaying temporal data, the findings and impact should be applicable to a broader range of visual representations used in the field. In this chapter, the combined knowledge and limitations from all studies are discussed and reflected upon, and possible future directions are suggested. The main contributions can be summarized as follows:

- investigations of different representation spaces based on shared-space, split-space, multiple axes, and 3D for visualizing multivariate temporal data,
- investigations of different representation layouts based on linear and radial timelines for visualizing multivariate temporal data,
- explorations of multiple interaction methods for analyzing and exploring such data, and
- five user evaluations of visual representations with different types of data sources and user tasks.

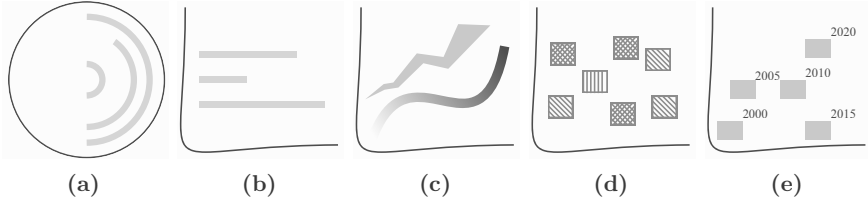


Figure 6.1: Possible static alternatives to map time, (a) angles and slopes, (b) line length, (c) line width and color brightness, (d) texture, and (e) text label. (Image adopted from [1].)

### Mapping Time

The representations investigated in this thesis were all static and implemented using a time-to-space mapping. That is, mapping the time dimension to one of the visual axes in the spatial space, while the data value occupied the other spatial dimension and mapped to visual encoding (e.g., height of the bars). There are other timeline shapes, such as spiral, arbitrary and grid, to investigate with temporal data. However, such ways of presenting the time dimension might limit the possibilities of encoding the data depending on time. Another approach is to map the time dimension to the graphical elements and properties instead, such as angles, and slopes, line width, line length, brightness, texture, labels (see Figure 6.1). Perin et al. [75] investigated how some of these visual encodings can be used to map time and speed on 2D+time trajectories. Their study showed that using color brightness was found less useful for such mapping, while using line length was found useful for mapping time and speed. However, further research is required for knowing whether these types of mapping of the time dimension would be useful for domains, data, users, and tasks similar to those explored within this thesis. Such investigations could also be conducted on different display sizes, as small devices are common nowadays.

### Representations Spaces

When using shared-space representations, such as a line graph or a stacked area graph, as explored within the work of this thesis, the number of variables possible to visualize without introducing visual clutter and distraction is limited. The visual clutter is often caused by the color property used to distinguish between different elements representing the data variables. Using a qualitative color scheme is common as the colors are perceptually easy to distinguish. Shared-space representations have been found useful for locating values only when a low number of variables are displayed [52]. This was found for stacked area graph used in Paper C and the line graph in Paper D. Therefore, if a shared-space representation must be used, a low number of variables should be displayed with pleasant and intuitive colors. Another way to overcome the clutter issue is by rendering each variable



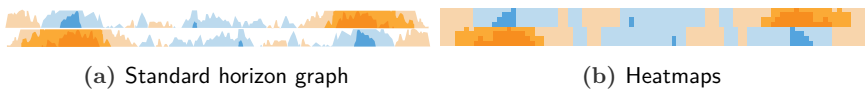


Figure 6.2: A Possible future investigation of horizon graph and pixel-based representations (e.g., heatmaps) Investigate horizon graphs with pixel based horizon

with its own representation space, often called split-space or small multiples. The advantage with such approach is that visual clutter is less possible, even if each variable is rendered with its own color. Although, comparing variables becomes challenging as they might be far apart. Furthermore, as each representation is rendered on a small space, it might become difficult to read exact values in the representation. Therefore, such representations, i.e., horizon graphs, are often useful for providing an overview of the data rather than value reading. One interesting question left to answer is how many variables can be superimposed in a horizon graph, displayed on a standard computer monitor, before the values become too difficult and a pixel-based representation must be used (i.e., see the illustration in Figure 6.2). Moreover, exploring how heat-maps representation would perform with a split-spaced concept would be another idea to investigate further. Nevertheless, interaction, i.e., grouping, filtering, zooming, hovering, etc. is crucial for exploration of temporal data with such implementations.

Moving on, split-space concepts are not always the most useful option. Previous research has found that displaying hourly data (AM and PM) with two separate radial representations is not recommended [102] as it make the analysis more difficult. Therefore, the work in Paper A investigated multiple radial designs based on shared-space concept for displaying hourly data. Minimal difference was found between using a 12-hour and 24-hour design, and using the metaphor of an analog clock did not improve the analysis. Moreover, as only two variables were displayed, the use of color did not clutter the representation but was necessary for

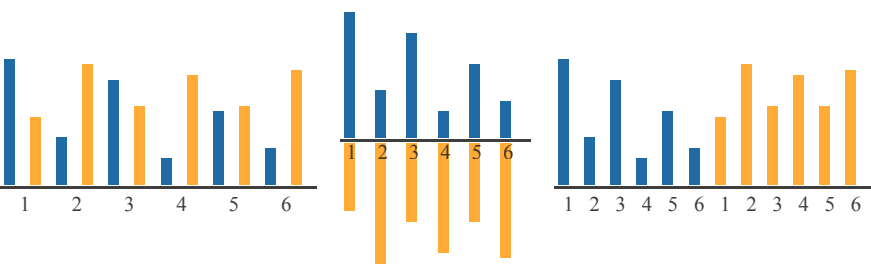


Figure 6.3: The radial representation used in Paper A could potentially be compared with a standard bar graph, stacked bar graph, and a bar graph with hour values presented on each side.

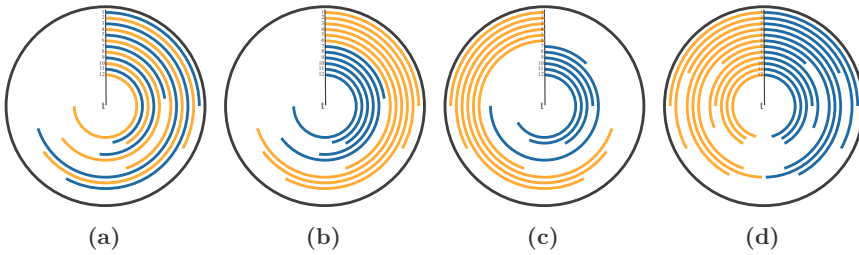


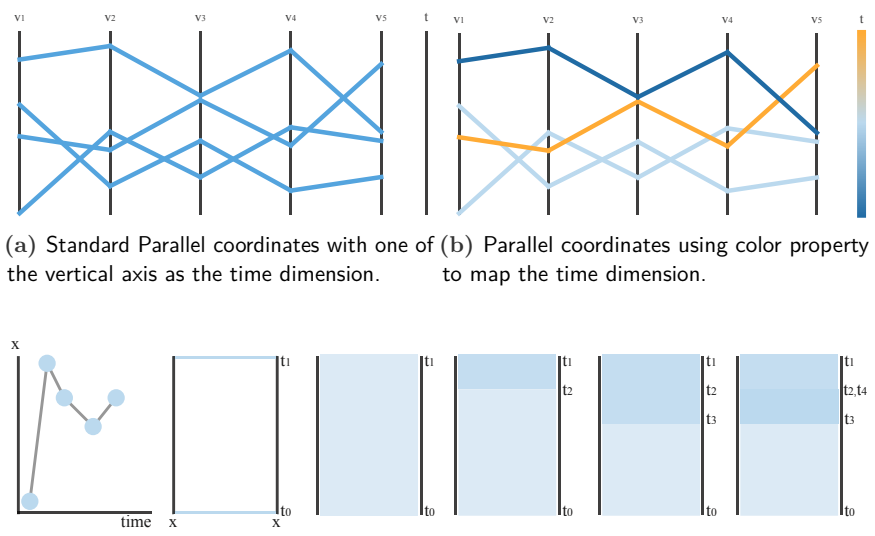
Figure 6.4: Other possible layouts that could be used to visualize hourly data, (a) radial bar graph with AM and PM hour values next to each other, (b) hour values for AM first, then values for PM, (c-d) AM and PM hour values presented on each side.

distinguishing between AM and PM. Even though a shared-space concept was used with the elements close, comparing the variables was found challenging, especially with a 24-hour design as users had to move their eyes over longer distances while simultaneously memorizing the element properties. The radial design investigated within the scope of this thesis could potentially be compared with different linear-based representations for visualizing hourly data (see Figure 6.3) or investigate other approaches to visualize hourly data with radial designs (see Figure 6.4).

### Multiple Axes

Representations that use multiple axes, e.g., parallel coordinates as used within the work of this thesis, for displaying multivariate data can be useful for revealing correlations and patterns between many variables. The work conducted in Paper B investigated whether they would be able to handle pattern finding in temporal multivariate data. The results showed that using a 3D might be more optimal for displaying temporal data and for such comparison tasks. One possible explanation for this was the type of interaction used. The Brush interaction used to filter the data in the 2D version introduced a loss of overview of the data. In contrast, the rotation in 3D did not filter out data but helped users analyze the data from different perspectives. What was not investigated in the scope of this thesis is how to use other graphical elements and properties, such as line width, color, brightness, texture, labels, to map the time dimension. One possible future investigation is to compare three approaches on how to map time in parallel coordinates, e.g., map time to one of the vertical axes, use color, or area and color (see Figure 6.5).

For advancing the visualization field, it is necessary to both design new methods and visualization concepts as well as ensuring the usability of these visual representations in other domains. When working with end-users, there are often two gaps between visualization researchers and users that need to be addressed, the knowledge gap and the interest gap [101]. This was also found in Paper C, Paper D, and Paper E. The experts taking part in the visualization research were focused on a final product that could help them solve their problems fast. However, as a user-centered approach



(a) Standard Parallel coordinates with one of the vertical axis as the time dimension. (b) Parallel coordinates using color property to map the time dimension.

(c) Parallel coordinates using area element to map the time dimension going outward from the screen. (Image adopted from [54])

**Figure 6.5:** Possible investigation of which alternative to map the time dimension in parallel coordinates would be most useful and easily understood.

was taken where the domain experts were involved in all development steps, such as an issue was mitigated, and joint agreements were possible. Therefore, a crucial aspect to remember is that selecting the optimal representations is challenging and often requires involving the end-users in each stage of the design process where their needs, wants, and limitations are given extensive attention.

While the purpose of visualization is to gain insight [72], the path to reach this insight might be different depending on the user. Users are different with different levels of knowledge and with interest in different aspects of a dataset. This level of difference creates a challenge for the visualization researcher in knowing and understanding which visual representation to use for helping users to gain insight. One user might find the line graph the best representation for exploring the data, solve a task and gain insight into the data, while others might find radial representations easier. Such challenges were to a certain degree addressed in Paper D, but further research needs to be conducted.



## Concluding Thoughts

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We're all stories in the end. Just make it a good one, eh?

—*The Eleventh Doctor, Doctor Who (Matt Smith)*

There are many different perspectives to investigate the visualization of temporal data. The five studies conducted within the scope of this thesis investigated various visual representations for different domains, users, and tasks. Visualizing multivariate temporal data is challenging. We need to know and understand the data and the time dimension, the need to visualize the data, and how to visualize the complex data adequately. Because of these challenges and thanks to people's curiosity, the visualization community can frequently introduce new ideas, tools, and approaches to display, analyze, and explore multivariate temporal data. A challenge that will remain in the field for many years is the usability assessment of the methods introduced for analyzing and exploring multivariate temporal data. Visually analyzing data is something users have to learn and get familiar with before mastering it, as the information is presented through abstract graphical elements and properties. Therefore, I hope the work presented in this thesis will inspire and encourage further investigations of how temporal data can be displayed, explored, and understood. It is not by chance that a line graph is easy to use; it has been around for more than two centuries and is most often made by easy to understand graphical elements. If visualization researchers and practitioners have such simplicity in mind when creating new methods, some of them might become the new line graph, and **It is About Time!**

*Kahin Akram*



*“Run, you clever boy ... and be a Doctor”*

Clara Oswin Oswald





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# Papers

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