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Images of time

Visual representations of time-oriented data

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Time is a special dimension with much more to it than a simple linear succession of consecutive moments. Time-oriented data, that is data collected over or related to time, are a rich source of multifaceted information. Visual representations are often used as an aid helping us to untangle the complexities of the data and to understand the essential information they contain. Expressive depictions of time-oriented data can only be designed by taking into account the special nature of time.

We discuss principal design aspects for conceptualizing time and time-oriented data, and based on that, fundamental ways of visualizing time-oriented data will be explained. Examples of implemented visualization techniques illustrate the diversity of possible solutions. To assist practitioners and researchers in finding relevant techniques amidst this diversity, we developed the TimeViz Browser, an interactive visual survey of visualization for time-oriented data. The TimeViz Browser categorizes more than 100 visualization techniques with respect to the nature of the dimension of time, the character of the data, and the properties of the visual representation.

Today, we live in a world full of data. Our daily life depends to a large degree on our ability to efficiently work with the information contained in these data. However, technological advances have led to a situation where we collect far more data than we can make sense of. This problem has become known as information overload.

As early as the 1980s, visualization pioneers recognized the enormous potential that modern computers would offer to address the information overload. Considering analytic power, graphics output, and interactive manipulation, they formulated the key idea behind visualization as follows:

> Visualization is a method of computing. It transforms the symbolic into the geometric, enabling researchers to observe their simulations and computations. Visualization offers a method for seeing the unseen. It enriches the process of scientific discovery and fosters profound and unexpected insights. (McCormick, DeFanti, and Brown 1987, 3)

Gaining insight into and understanding time-oriented data are challenges of continued relevance. Learning from the past, comprehending the present, and predicting the future are key themes in many fields with wide applications in business, science, politics, and humanities.

In this chapter, we lay out the fundamentals of the dimension of time and discuss different models of how data can be connected to time. We outline basic strategies for designing visual representations of time and time-oriented data and illustrate how these basic strategies are implemented in different ways by existing visualization techniques. With the goal of providing an overview of the wealth of available solutions, we designed the TimeViz Browser as a publicly available interactive website. It is based on a visual bibliography that currently contains brief descriptions and thumbnails of more than 100 different visualization techniques for time-oriented data. To enable users to find the techniques relevant to them, the TimeViz Browser supports dynamic filtering according to various delineating criteria. These criteria were derived from an analysis of the properties of time and time-oriented data.

Conceptualizing time and time-oriented data

In this section, we discuss the particularities of time and the characteristics of data as key factors influencing the design of visual representations for time-oriented data. Here, we consider time to be the key reference with respect to which the data are given.

Time is one of the most deeply entrenched phenomena for mankind. Perceivable by the succession of day and night and the seasons of the year, it influences literally every aspect of living creatures on earth. Considering that, it comes with no surprise that some of the earliest known artefacts of humans are bone engravings used as calendars (Lenz 2005). In many branches of science such as philosophy, physics, astronomy, or biology, time has been a central theme for centuries. Two of the most influential theories on time are Newton's concepts of absolute vs. relative time and Einstein's four-dimensional spacetime. Further information on the concept and history of time can be found in Gerald James Whitrow's *What is time?* (2003).

The dimension of time

Time is a universal concept. No one can escape the steady progress of time. Yet, there is more to time than a seemingly linear progression. Upon a closer look, time reveals several facets, each of which play an important role in understanding time-dependent phenomena. The key facets to look at are:

- time primitives (instants and intervals)
- time arrangement (linear and cyclic)

When working with time, we usually create anchors that allow us to pinpoint certain events in the time continuum. An example is to agree on a specific time to meet for lunch. In this case, the anchor is a time primitive in the form of an *instant,* a single point in time (see Figure 1). Time

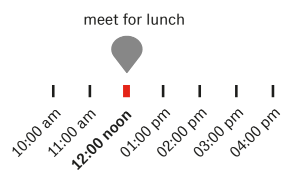

Figure 1
Instant. A single point in time, e.g. 12.00 noon.

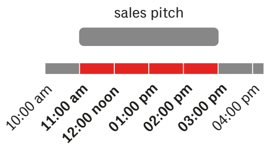

Figure 2
Interval. Portion of time with a duration, e.g. 11.00 a.m. to 3.00 p.m.

instants can be used to construct time *intervals*, which allow us to expand our view of time from simple events to phenomena that exhibit duration. For example, when we enter a meeting in our electronic calendar, we do not only have a single point in time but usually reserve a stretch of time delimited by a beginning and an end or a beginning and a duration, respectively (see Figure 2).

Moreover, we also need to take a look at the underlying time dimension that these time primitives are tied to. When thinking about time, two main metaphors are used. The first conceptualizes time as a *linear* progression from past to present and future (see Figure 3). The second emphasizes the *cyclic* nature of time based on natural phenomena such as the rhythms of night and day and the seasons, as well as human creations such as semesters or fiscal years (see Figure 4). These two metaphors are of fundamental importance to the visualization of time-oriented data. Depending on the nature of the problem and the goals of the user, it can be beneficial to emphasize one point of view or the other, but both can also exist in parallel.

Figure 3
Linear arrangement of time. Time progresses from past to present and future.

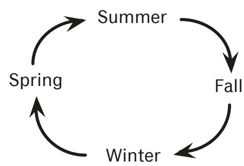

Figure 4
Cyclic arrangement of time. Set of recurring time values, such as seasons of the year.

Despite the fact that the key facets mentioned are the most important ones to consider, they can only cover parts of the complexity of the time dimension. On a more detailed level, there are further design aspects when modelling time, such as the scale of time (ordinal vs. discrete vs. continuous) and viewpoints on time (ordered vs. branching vs. multiple perspectives). Moreover, the granularity of time and corresponding calendar systems are a complex topic. There are many issues to be taken into account, including irregularities in days of months and leap years, different time zones, and calendars in different cultures. Last but not least, uncertainty is another important topic of time, specifically when dealing with future planning. For further details, we would like to refer to Aigner et al. (2011), where the dimension of time is dissected in full detail.

Taking these characteristics of time into account is crucial in order to achieve expressive visualizations. Therefore, a data and problem analysis step is necessary in every visualization design project to identify the nature of the data at hand and choose or design visual representations that fit (Munzner 2014). For example, when we would like to visualize tasks of a project plan, we need to choose a visualization technique that is capable of representing time intervals, like a Gantt chart rather than a line plot.

Time-oriented data

Time, as described in the previous section, serves as the backbone of time-oriented data. Data tuples are tied to time primitives to establish a connection between time and data. Just as there are key facets of time, there are key characteristics of data that need to be considered when designing visual representations. Two of these characteristics are:

- frame of reference (abstract and spatial)
- number of variables (univariate and multivariate)

One fundamental question is whether the data tuples additionally relate to a spatial dimension, for example, if each was measured at a different location. In such cases, we have a *spatial* frame of reference in addition to time. When this is not the case, data are said to be *abstract*, i.e. data elements do not explicitly contain a 'where' aspect and are not connected to space. The distinction between abstract and spatial data has consequences for the way the data should be visualized. With spatial data, the spatial dimension ought to be exploited to reflect the position of data elements in space in addition to time. For abstract data, there is no naturally given spatial mapping and it is up to the visualization designer to create an expressive layout of the data.

Apart from the frame of reference, the number of time-dependent variables to be represented is an important issue. In the case of *univariate* data – that is, a single variable over time – a wide range of visualization techniques exists such as line plots or bar graphs. If we have more than one data variable (*multivariate* data), things tend to get more complex and more sophisticated visual representations are needed to communicate the relationships involved. Because of that, the available palette of visualization techniques is much smaller for multivariate data than for univariate data.

In addition to the frame of reference and the number of variables, there are further facets to characterize data, such as the scale of variables (quantitative vs. qualitative) and the nature of the stored information (events vs. states).

Visualizing time-oriented data

As explained in the previous section, both time itself and data presented with respect to time can be complex and multifaceted. The enormous bandwidth of human visual perception opens up many possibilities for exploring and communicating the richness of time-oriented data. To this end, the temporal reference as well as the data must be represented visually. Haber and McNabb (1990) think of this process as a pipeline and describe it as a transformation with three steps: filtering, mapping, and rendering. The filtering is a data processing step to prepare the data for visualization. This includes data correction, interpolation, clustering, and filtering operations on the data. At the heart of the visualization pipeline is the mapping step. In this step, the prepared data are mapped to geometric primitives and associated graphical properties. The final step of the visualization pipeline is rendering the output (display or print). Here geometry and graphical properties are handed over to the graphics processor, which generates the visual representation on the output device.

As the mapping step largely decides about the expressiveness and effectiveness of the visualization, we will next take a closer look at it. We first introduce basic visual variables for the mapping and then describe the principal ways of mapping time and time-oriented data.

Visual variables

In his seminal work, *Semiology of graphics*, Jacques Bertin (1983) defines seven visual variables for representing data visually. Bertin lists position, size, value, texture, colour, orientation, and shape as variables that can encode data. For example, the position of a dot on a chart tells us where it is located in the value range associated with the chart's axes. The size of the dot and its colour can encode additional information.

Other researchers, including Cleveland and McGill (1986) and Mackinlay (1986), have largely concurred with Bertin's analysis, but made minor modifications and extensions. While the classic visual variables consider static representations, Ward, Grinstein and Keim (2015) additionally include motion as a dynamic visual variable, which is particularly relevant for time-oriented data. Figure 5 illustrates a selection of the visual variables mentioned in the literature.

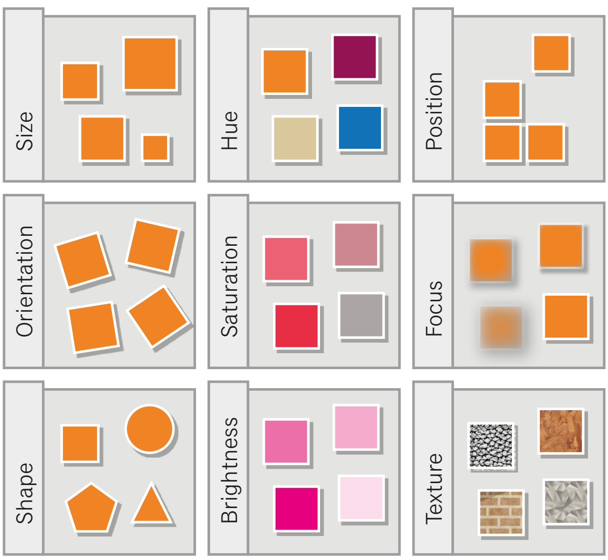

Figure 5
Illustration of visual variables for encoding data.

The question that remains is which visual variables to use. Cleveland and McGill (1986) and Mackinlay (1986) suggest that a visual variable's suitability to encode data depends on the data's scale (quantitative, ordinal, or nominal data). For example, according to Mackinlay (1986), position, length, and angle are top-ranked for quantitative data, whereas for ordinal data, position, density, and colour saturation take the lead (see Figure 6). Consequently, depending on the character of the dimension of time, different visual encodings are possible and useful.

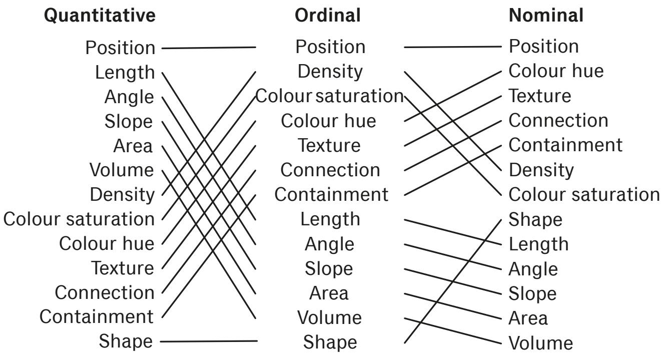

Figure 6 Ranking of visual variables by data type (Mackinlay 1986).

Mapping time and data

In order to visualize time-oriented data, we first have to think about how to map the dimension of time. There are two principal representations:

- *static*: time is mapped spatially
- *dynamic*: time is mapped temporally

Mapping time spatially means that a visual representation of the dimension of time is embedded directly into the display space. Typically such visual representations do not change while the viewer observes them, which is why we call such visualizations of time-oriented data *static*. On the other hand, one can use physical time (i.e. the real time whose passage we experience) to encode the temporal dynamics of data. In such cases, the visual representation changes as it is viewed as an animation, and hence, we call them *dynamic*. Both static and dynamic approaches have advantages and disadvantages, as we will see in the next paragraphs.

Static representations

In static representations, time, or more precisely an interval of time, has a spatial embodiment on the screen or on paper. The most common approach is to use the horizontal display dimension (the x-axis) to represent time. There are, though, examples where two or more display dimensions are used in conjunction for mapping time. Using more display dimensions allows us to construct more elaborate representations of the dimension of time, for example, as two-dimensional spirals or three-dimensional helices, which are capable of emphasizing cyclic patterns in the data.

The actual time-oriented data can be visualized in many different ways. When time is shown along the horizontal x-axis, classic charts or plots typically show a time-dependent data variable along the vertical y-axis. For example, point plots, line plots, and bar graphs represent data values by varying the distance of a graphic element from the time axis. When two or more display dimensions are already occupied for mapping time (e.g. with a spiral or a helix), visual variables other than position and size must be used. In such cases, colour is a good choice. That means assigning to each point or interval on the time axis a specific colour that represents the relevant data value. The choice of the colours to use is not trivial and depends on the characteristics of the data and the visualization task. The ColorBrewer (<http://www.colorbrewer2.org>) is a helpful tool in assisting the selection of appropriate colour scales for visualization purposes.

As an alternative to using basic visual variables to encode time-dependent data, one can follow an approach called *small multiples* by Tufte (1983). Small multiples are visual snapshots of the data. A snapshot is devoted to showing an elaborate depiction of the data at a particular time. Only in a second step are several snapshots arranged in a temporally meaningful fashion (see Figure 7). The advantage is that individual snapshots may be more sophisticated than a basic visual encoding. On the other hand, the number of snapshots (and so the number of time primitives) that can be shown simultaneously is limited and their size is restricted.

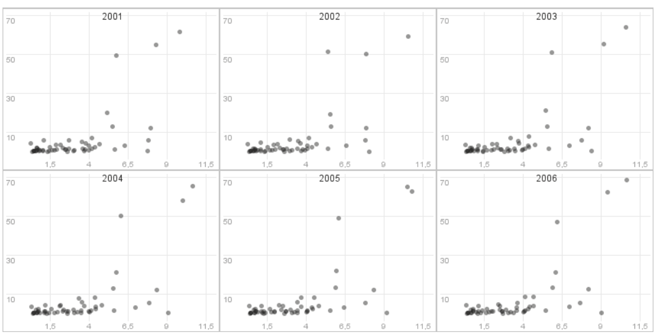

Figure 7 Small multiples.

Dynamic representations

In contrast to static representations, dynamic representations change over time in order to represent changes in the time-oriented data. For each time primitive in the data, an individual visual representation is generated (also called *frames*). So each frame encodes the data of a particular time point or interval, where visual variables are employed as needed. Once generated, the frames are rendered successively one after the other, which leads to an animation that represents the dynamics in the data as dynamic changes of the display. Theoretically, one could think of a one-to-one mapping of time steps and frames, so that the dynamic visualization represents time authentically. In practice, however, there is typically a need to interpolate intermediate results in cases where only a few time steps are present, or to aggregate or sample the data to reduce the size of an animation when too many time steps exist.

The speed with which dynamic representations are presented to the user should match the underlying data. For data with a large number of observations of highly dynamic processes, animations with 15 to 25 frames per second are suitable. In contrast, data consisting of only a few measurements of the underlying phenomenon should preferably be represented at a slower pace. To avoid creating a false impression of seamless change, a new frame can be shown every 2 to 4 seconds. Irregularly sampled data should be represented using an adaptive mapping.

The distinction between static and dynamic representations is important, because they suit different visualization tasks and goals. Dynamic representations are good for communicating general dynamics and major trends in a data set. Yet, they have also been criticized (Tversky, Morrison, and Bétrancourt 2002; Simons and Rensink 2005). For example, in dynamic representations of a complex multivariate time series, users may have difficulty following all of the changes; the flood of information may be indigestible. It is smart to pair dynamic approaches with interactive controls that allow the user to go through the data in slow motion or fast forward and rewind to interesting points in time.

In contrast to animations, which show only one time primitive at a time, static representations typically show many if not all time primitives simultaneously. Thus, static representations have the advantage of providing a single-frame overview of the time domain and the associated data. This suits tasks such as trend detection or finding temporal patterns, which typically involve visual comparison of the data from several points in time. On the other hand, it is clear that integrating many time primitives and their associated data in a single image can lead to an overcrowded representation that is difficult to interpret. In such cases, it makes sense to use automated data analysis methods to extract meaningful features prior to the visualization and to enhance the visualization with interaction techniques that support the navigation in time.

In general, the visualization designer has to find a good balance of how much of the dimension of time and how much of the data can be communicated with a visual representation.

A brief history of visual representations for time-oriented data

Visual methods for understanding data over time have a long and venerable history. The earliest known visualization has been found in a monastery school and dates back to the tenth century (Funkhouser 1936). It depicts planetary movements over time using line plots along a horizontal time axis. In his *Chart of biography*, Joseph Priestley depicted the lifetimes of a number of historic figures in 1765 (see Figure 8). He came up with the concept of using horizontal lines that span from the beginning to the end

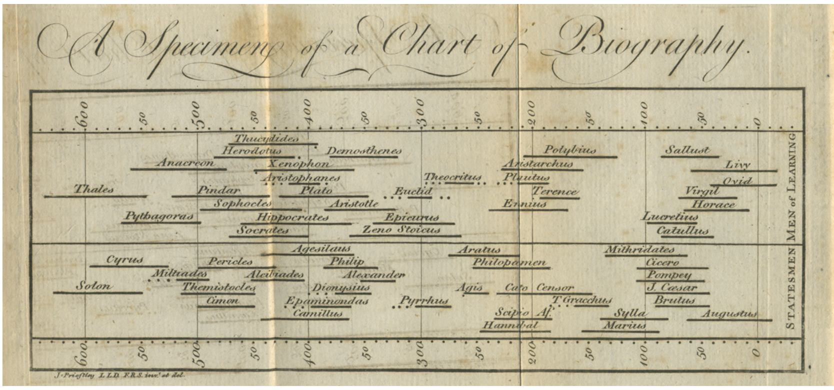

Figure 8
A very small specimen extract of Joseph Priestley's extensive *Chart of biography* (1765).
Photograph Stephen Boyd Davis.

of a time interval (*timelines*). Interestingly, he even used special symbols to denote temporal uncertainties in cases where the exact dates of birth or death were not known exactly. As intuitive as using a horizontal line to denote an interval might seem for us today, it was certainly different in Priestley's days, as he spent four pages of text to explain how the visual representation is to be read.

The probably single most influential individual for data visualization was William Playfair (1759–1823). He single-handedly invented the majority of business charts still in use today such as line plots, bar graphs, pie charts, or silhouette graphs (see Figure 9 for an example).

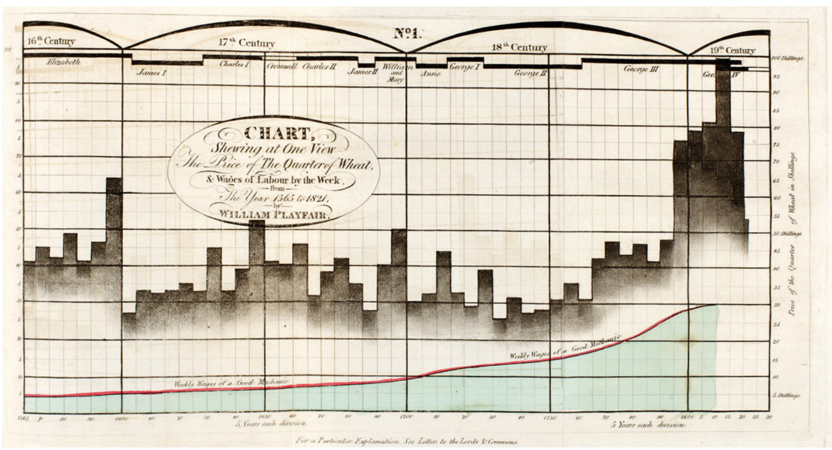

Figure 9
Chart by William Playfair (1821) depicting wages (line plot), prices of wheat (bar graph), and historical context (timelines).
A letter on our agricultural distresses (1821), chart no. 1. Princeton University Library.

Further, two of the most well-known historical representations of time-oriented data were created in the nineteenth century. First, Florence Nightingale's rose charts (1858) that show causes of death of soldiers in the Crimean war using polar area charts (see Figure 10, overleaf), and second, a flow map that depicts Napoleon's deadly Russian campaign across space and time by Charles Joseph Minard in 1869 (see Figure 11, overleaf).

As we have seen in this brief section, the topic of visualizing time-

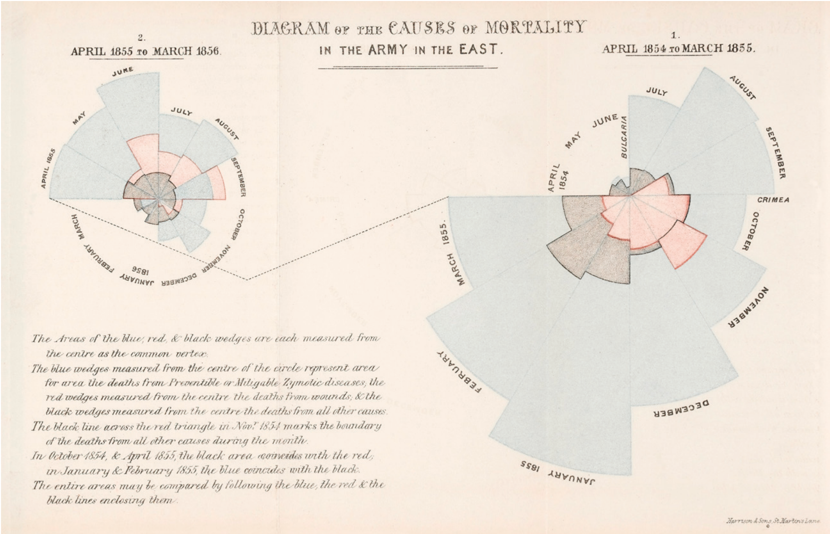

Figure 10
Rose charts showing causes of death in the Crimean War by Florence Nightingale.
Notes on matters affecting the health, efficiency, and hospital administration of the British Army: founded chiefly on the experience of the late war (1858). Wellcome Library, London, CC-BY-4.0.

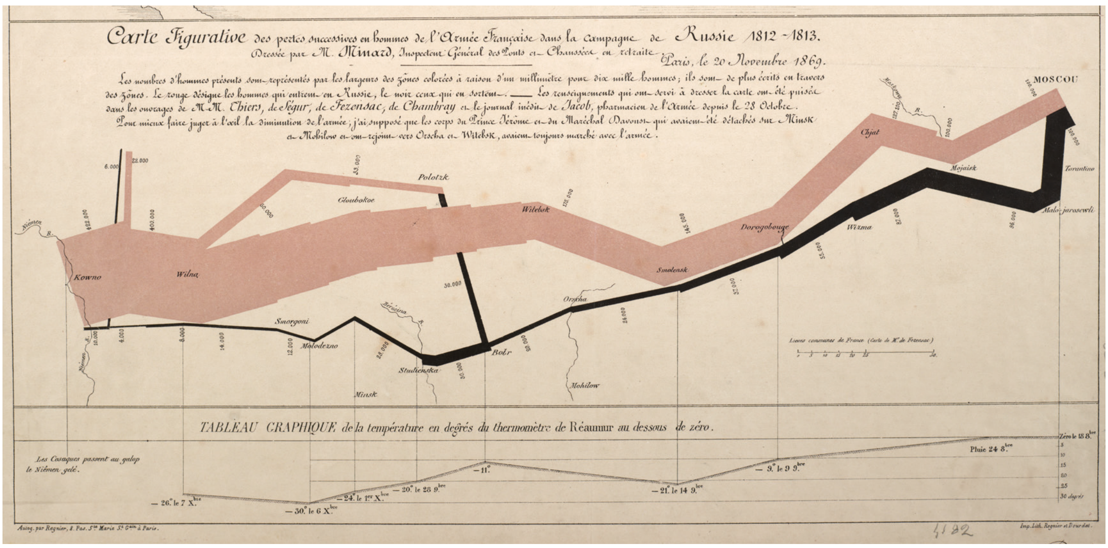

Figure 11
Napoleon's Russian campaign of 1812 by Charles Joseph Minard (1869).
Bibliothèque nationale de France. GE DON-4182.

oriented data has a very long and rich history. Apart from the mentioned direct ancestors, also different areas of the arts such as cubism, comics, or music and dance notations have dealt deeply with the notion of time and can serve as fruitful sources of inspiration for visualization designers today. Interested readers can find more information about historical representations of time-oriented data in Boyd Davis (2012), Boyd Davis (2016, chapter in this volume), Rosenberg and Grafton (2010), as well as in Brinton (1914, 1939), Tufte (1983, 2006), and Wainer (2005).

The historical examples already illustrate the communicative power of visual representations of time-oriented data. While historically created by hand, today we can use the power and flexibility of computers to quickly generate expressive depictions of large amounts of data. In the recent decades a large variety of visualization techniques have been developed particularly for time-oriented data. A selection of interesting examples will be presented in the following paragraphs.

Contemporary visualization techniques for time-oriented data

This section illustrates how the characteristics of the dimension of time and the associated data can be considered when visualizing time-oriented data. We present several examples that individually emphasize different aspects of the topics discussed so far: time instants vs. intervals; linear vs. cyclic time; abstract vs. spatial frame of reference; univariate vs. multivariate data; and static vs. dynamic representation.

Probably the oldest and surely the most well-known representation for time-series are line plots where time is usually mapped to the horizontal axis and a quantitative variable is mapped on the vertical axis of a plot (Tufte 1983). A common problem when displaying real-world data is to find ways to deal with multivariate data when the number of time-oriented variables is large. Two principal ways are to show all variables in the same space (superimposition) or to partition the available space and show each variable in a separate part (juxtaposition). In both cases, the number of variables that can be displayed while retaining reading precision and avoiding clutter is severely limited. For example, when stacking many line plots on top of each other, the individual plots become thin stripes, which no longer provide the same precision as a full-frame line plot. To mitigate these problems, *horizon graphs* have been developed by Reijner (2008).

As shown in Figure 12, the basic idea of horizon graphs is the slicing and layering of line plots using a technique called two-tone pseudo colouring (Saito et al. 2005). In a first step, areas under the curve of the plot are divided into equally sized bands. Second, these bands are coloured using different hues to distinguish areas below and above zero (e.g. blue above

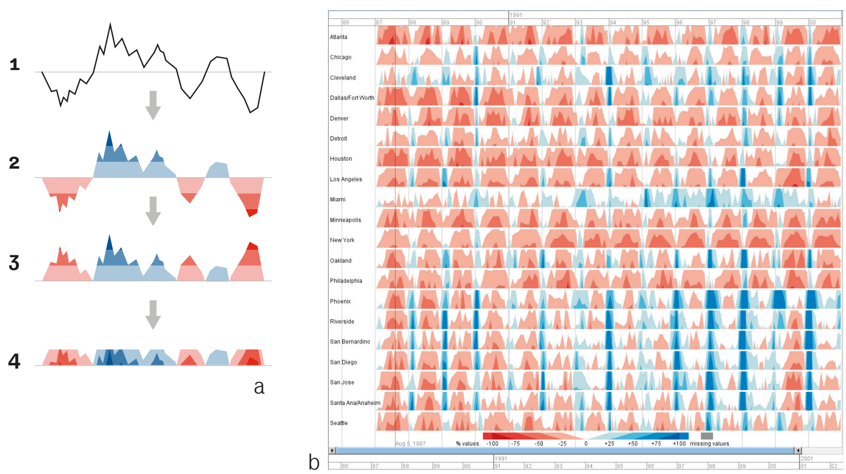

Figure 12
Horizon Graphs (Reijner 2008).
a. Construction of a horizon graph.
b. Due to their space efficiency, a large number of time-dependent variables can be compared on a single screen effectively.

zero and red below zero) as well as variations in brightness to represent different magnitudes (e.g. darker colours for high values and lighter colours for low values). Optionally, the parts below zero are mirrored to even better make use of the available screen space. Finally, the individual bands are moved on top of each other. In this way, the virtual information resolution of the display is increased (Lam, Munzner, and Kincaid 2007) and a much richer and more precise representation of a large number of time series plots becomes possible. User studies by Heer, Kong, and Agrawala (2009) show that mirroring does not have negative effects and that layered bands are more effective than the standard line for small-sized charts. A further development of the horizon graphs concept by Federico et al. (2014) combines qualitative abstractions of data with the quantitative data values into so-called *qualizon graphs*.

Sparklines (Tufte 2006) are an allied technique that also compresses data into a small horizontal space. Sparklines are small, word-sized graphics meant to be integrated directly into text, such as this: . The main idea of this technique is to more tightly integrate text with data visualization by interweaving them instead of laying them out separately. Sparklines can be integrated seamlessly into paragraphs of text, can be laid out as tables, or can be used for information dashboards (see Figure 13). Different subtypes of sparklines display data in various ways such as lines and bars . Sparklines are usually miniaturized versions of well-known chart types.

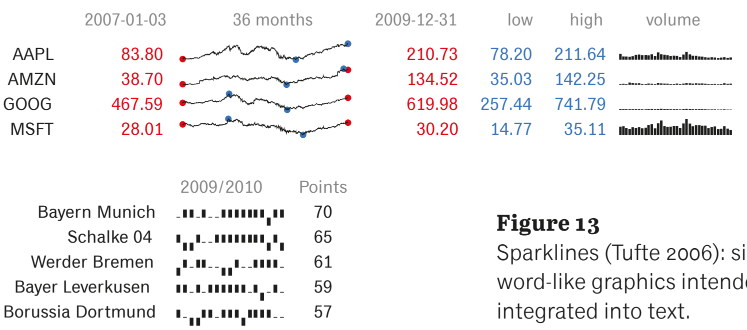

Figure 13
Sparklines (Tufte 2006): simple, word-like graphics intended to be integrated into text.

Our third example is a visualization method suitable for representing time cyclically. *Cycle plots* by Cleveland (1993) are used to emphasize both linear trends and cyclic patterns in a data set (see Figure 14). On the left chart, the seven coloured lines represent data for the same day of the week over four successive weeks. For comparison, the chart at right shows the same data day by day. With the cycle plot, it is easy to spot trends (such as increasing sales on Mondays) that might not be visible on a standard linear plot. At the same time, the linear plot emphasizes the cycles in the data.

Visual representations can show whether cycles are present in the data and what the lengths of the cycles are. With the *Enhanced Interactive*

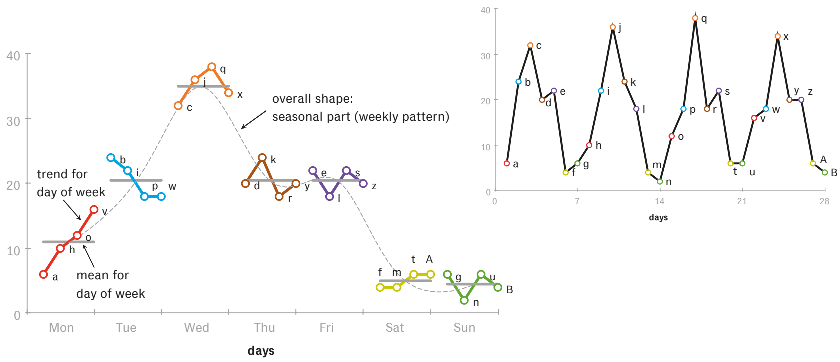

Figure 14 Cycle plots (Cleveland 1993) allow for showing both, seasonal and trend components of a time series (*left*), which is hardly possible when using standard line plots (*right*).

Spiral technique presented by Tominski and Schumann (2008) this can be done interactively. The technique combines the idea of two-tone pseudo-colouring (similar to horizon graphs) with a spiral layout of the data as shown in Figure 15. By interactively adjusting how much time one 360° cycle represents, different cycle lengths can be brought into focus. The existence of a cyclic feature can be easily detected by the emergence of a regular pattern which is perceived instantly by human visual perception.

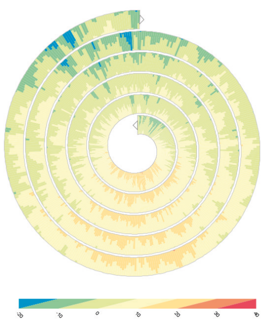

Figure 15 Enhanced Interactive Spiral (Tominski et al. 2008). Time series data are drawn along a spiral for showing and detecting cycles in the data.

The techniques so far have been appropriate for data that relate to instants (points in time). Other techniques are appropriate for data that relate to intervals of time. *Gantt charts* are a well-known and widely used representation technique for project planning (Gantt 1913). Tasks in a project plan are represented as bars along a time scale and tasks that need to be processed in a certain order are connected by arrows. When planning for the future, temporal uncertainties are unavoidable and need to be considered. For example, it might not be known for sure how long a certain task will take or when exactly it can start. To model and represent such uncertainties, Aigner et al. (2005) developed *PlanningLines* (see Figure 16). These can be thought of as bars that are held by caps on both ends. The glyph represents a complex set of time attributes in an integrated manner (earliest start and latest start by the extent of the left cap, earliest finish and latest finish by the right cap, and minimum and maximum duration by the two bars in the centre).

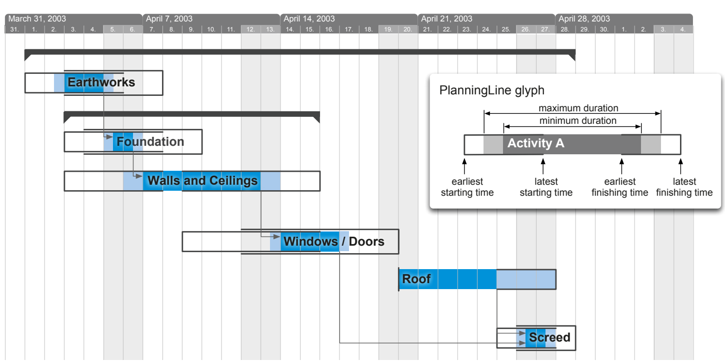

Figure 16 PlanningLines (Aigner et al. 2005) allow the depiction of interval data with temporal uncertainties.

Also applicable for future event data, but with different goals is the *SpiraClock* technique by Dragicevic and Huot (2002). SpiraClock's aim is to fill the gap between classical calendar applications and pop-up alerts for calendar events. It shows future event data as bars along a spiral layout that resembles a clock's face (see Figure 17). The amount of time shown in the future, i.e. number of hours or cycles, can be adjusted interactively. In contrast to the techniques presented so far, SpiraClock is a dynamic technique that updates automatically based on the current time and upcoming event data.

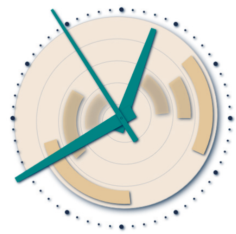

Figure 17 SpiraClock (Dragicevic and Huot 2002). Future appointments are aligned along a spiral on the clock face.

So far, we have focused on techniques for univariate data where one variable is displayed at a time. Next, we will present two techniques that are particularly well suited for multivariate data over time. The first of these follows the idea of stacking a number of layers on top of each other (see Figure 18) and are called *stacked graphs* (Byron and Wattenberg 2008). They allow users to see both the sum of a number of variables and how the different variables contribute to the overall sum at each point in time.

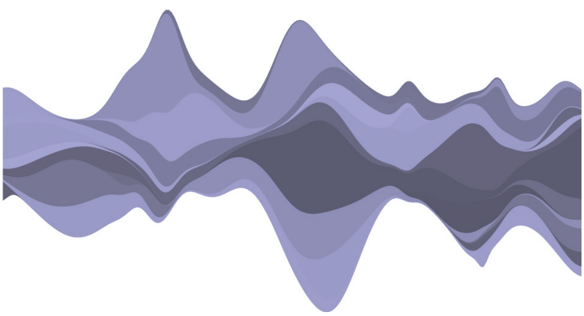

Figure 18 Stacked graph (Byron and Wattenberg 2008). Multiple graphs are stacked on top of each other.

Scatter plots are a basic and widely used visualization technique that shows the relationship between two variables as marks in a Cartesian coordinate system. One way to use this technique for time-oriented data is to animate the scatter plot to show how the relationship between the variables changes over time. Animated scatter plots received considerable attention through the Gapminder Foundation's[1] *Trendalyzer* tool and the famous TED talks by Hans Rosling,[2] who used this technique to present data on global health developments (see Figure 19 for a screenshot). Not just the x- and y-coordinates, but also the size and colour of bubbles can be used to convey data values. Moreover, one can display traces that let users see a path showing variables' developments over time. VCR-like controls are used to start, pause, skip sections, and adjust animation speed.

What we haven't covered so far are time-oriented data with a *spatial* frame of reference. Such data have an explicit relation not only to time, but also to physical space. The spatial dimensions pose additional challenges

1 <http://www.gapminder.org/world/>. Accessed December, 2015.
2 <http://www.ted.com/speakers/hans_rosling>. Accessed December, 2015.

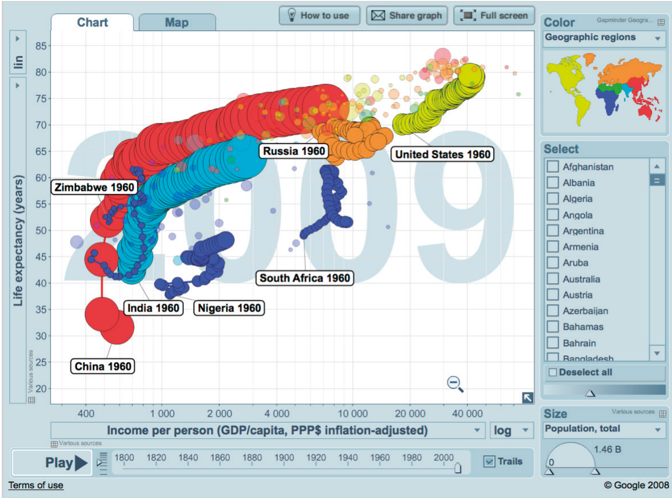

Figure 19
Trendalyzer/animated scatter plot. Two data variables are mapped to the horizontal and vertical axes, symbol size represents a third variable, and animation is used to step through time.

for the visual design. How can we integrate space, time, and data attributes in a single visual representation?

The *Trajectory Wall* by Tominski et al. (2012) is a technique that represents spatiotemporal movement trajectories on top of a map display. Individual trajectories are represented as 3D bands that are stacked above a map display. Figure 20 shows trajectories of migrating storks. A red-yellow-green colour scale visualizes the storks' speed. In this way, the map display shows *where* storks move slower (red) or faster (green). But *when* they move at which speed cannot be discerned.

This question can be answered by using an interactive spatial query (circle in the centre of the map) that is linked to an additional radial display (bottom right corner). The radial display shows a cyclic time axis, in our case the months of the year. The speed distribution per month is shown

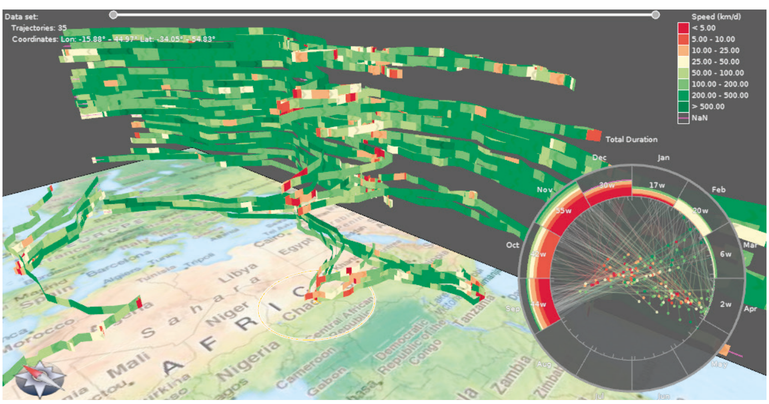

Figure 20
Trajectory Wall (Tominski et al. 2012). Movement patterns can be explored by mapping trajectories to 3D bands that are stacked above a map display.

as coloured histogram bins. When the spatial query is moved across the map, the radial display is updated to show the temporal information corresponding to the specified query region. The map display in combination with the interactive query enable users to explore data with regard to spatial and temporal dependencies.

In this section we have provided examples of visualization designs that illustrate how the conceptual issues introduced at the beginning can be addressed. Table 1 summarizes the techniques and categorizes them along the facets discussed earlier.

Table 1 Overview of presented visualization techniques

	instant	interval	linear	cyclic	abstract	spatial	univariate	multivariate	static	dynamic
Horizon Graph	■		■		■		■		■	
Sparklines	■		■		■		■		■	
Cycle plot	■			■	■		■		■	
Enhanced Interactive Spiral	■			■	■		■		■	
PlanningLines		■		■	■		■		■	
SpiraClock		■	■		■		■			■
Stacked Graphs	■		■		■			■	■	
Trendalyzer	■		■		■			■		■
Trajectory Wall	■		■	■		■		■	■	

The TimeViz Browser

The previous section gave several examples of visualization techniques for time-oriented data. Yet, these examples represent only a fraction of the rich body of existing work. As time-oriented data are common in many application areas, a great number of valuable techniques and tools for visualizing time and associated data have been developed. The problem is how to find a solution that fits a user's particular needs. As an answer to this problem, the TimeViz Browser has been designed. It enables practitioners and researchers alike to explore, investigate, and compare visualization techniques for time-oriented data.

The idea behind the TimeViz Browser is to bring together the visualization techniques available for time-oriented data in a single place. Otherwise they would be inconveniently distributed across a variety of conference and workshop proceedings, journals, and books. To reach a wide audience, the TimeViz Browser is available as a website accessible at *browser.timeviz.net*.

The TimeViz Browser provides an overview of what is possible when visualizing time-oriented data. As the diversity of possibilities is best communicated visually, the overview is visual in nature as well, rather than a textual list of references. In this sense, the TimeViz Browser is a survey – not an ordinary survey, but a visual survey. Importantly, a searching and filtering function allows users to narrow down the scope of techniques that interest them.

The design of the TimeViz Browser is depicted in Figure 21. The main view shows thumbnail pictures to provide a compact, yet expressive visual summary of the available visualization techniques. The collection of approaches covers more than 100 exemplars. Many of them are also collected in Aigner et al. (2011). The TimeViz Browser explicitly encourages contribution of new techniques from the community.

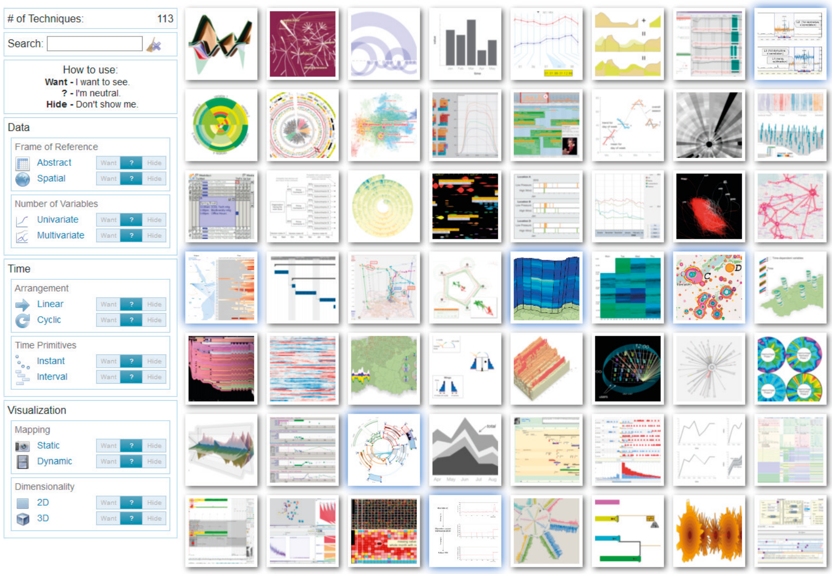

Figure 21
The TimeViz Browser provides an overview of existing visualization techniques for time-oriented data and a filter interface to search for techniques with particular characteristics.
<http://browser.timeviz.net>.

Each technique can also be explored in greater detail. Selecting a technique opens up the detail view. This view offers a brief abstract for the technique, a larger figure, and a list of relevant publications. Small icons indicate the technique's place in the categorization schema (e.g. frame of reference: abstract vs. spatial or number of variables: univariate vs. multivariate).

The filter interface (left in Figure 21) covers the data aspect (frame of reference: abstract vs. spatial; and number of variables: univariate vs. multivariate), the time aspect (arrangement: linear vs. cyclic; and time primitives: instant vs. interval), as well as the visualization aspect (mapping: static vs. dynamic; and dimensionality: 2D vs. 3D). Using these filters it is possible to narrow down the collection of thumbnails presented in the main view, for example, to techniques that use a cyclic arrangement of the time axis in 3D.

With the TimeViz Browser, we have a platform for collecting state-of-the-art techniques and methods for visualizing time-oriented data. In addition to that, the TimeViz Browser also links to other surveys, for instance, of visual representation of trees, dynamic graphs, sets, software, and text documents.

Conclusion

This chapter explored the visual world of time and time-oriented data. We briefly characterized the dimension of time and the data associated with it. We described basic ways of visualizing data in general and time-oriented data in particular. A collection of historical and contemporary visualization techniques illustrated the variety of designs already employed in existing work. A good way to explore this variety is the TimeViz Browser, which we introduced in the last part of this chapter.

Here we could only cover a fraction of the richness of the topic of visualizing time-oriented data. For more details, see the reference list, in particular the books by Aigner (2011) and Wills (2012), and the TimeViz Browser website at <http://browser.timeviz.net>.

This chapter focused on visual methods for time-oriented data. Yet, studying large amounts of time-oriented data typically requires support in the form of data analysis methods (Montgomery, Jennings, and Kulahci 2015) and interaction techniques (Tominski 2015). On a broader scope, integrating visual, interactive, and analytic methods is the objective of Visual Analytics research (Keim et al. 2010). The goal is to utilize the power of digital machinery in terms of computation and storage and multiply it with the strengths of humans in sense-making and creative problem-solving. In the light of Visual Analytics, data analysis workflows will change in the future. We will be able to look not only at the raw data, but also at features extracted analytically on the fly. Interaction techniques will provide us with the flexibility to create different perspectives on the data on demand in order to unveil patterns in subspaces and across multiple dimensions.

As this vision gradually becomes reality, a number of research challenges has to be addressed. Dealing with huge time-oriented data with many variables is a key challenge. On the one hand, technical aspects such as data management and computational efficiency are relevant topics in this regard. On the other hand, we know that human perception and cognition has strengths and also weaknesses, but we do not yet fully understand all the mechanisms involved in human sense-making processes. Developing integrated and well-balanced solutions based on automated analysis, visual representation, and interactive control is therefore still challenging. We are convinced that researching new Visual Analytics methods will make it easier for us in the future to extract valuable insight from time-oriented data.

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