# Visualizing Time-Oriented Data – A Systematic View

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**Abstract**

The analysis of time-oriented data is an important task in many application scenarios. In recent years, a variety of techniques for visualizing such data have been published. This variety makes it difficult for prospective users to select methods or tools that are useful for their particular task at hand.

In this article, we develop and discuss a systematic view on the diversity of methods for visualizing time-oriented data. With the proposed categorization we try to untangle the visualization of time-oriented data, which is such an important concern in Visual Analytics. The categorization is not only helpful for users, but also for researchers to identify future tasks in Visual Analytics.

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## 1 Introduction

Time is an outstanding dimension. For ages, scientists have been thinking about meaning and implications of time. Understanding temporal relations enables us to learn from the past to predict, plan, and build the future. This rationale can be found throughout sciences. Hence, it is no surprise that time is also a key concern in Visual Analytics, where the goal is to support the

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knowledge crystallization process with appropriate analytical and visual methods (1).

Visualizing time-oriented data, which is the focus of this paper, is not an easy business. Even though many approaches to this task have been published in recent years, most of them are specific to only a particular analysis problem. The reason why most methods are highly customized is simple: It is enormously difficult to consider all aspects involved when visualizing time-oriented data. Time itself has many theoretical and practical aspects. For instance, time points and time intervals use different sets of temporal relations. It also matters if we interpret time as a linearly ordered set of temporal primitives, or if we assume the temporal primitives to recur cyclically. The data that tie to the time axis are another decisive concern. Do we have a single variable per temporal primitive or are there multiple variables we have to consider? Moreover, data can be abstract or can be bound to a spatial frame of reference. Many more data-related questions have to be thought of when designing visual analysis methods. Only if the characteristics of the data are taken into account is it possible to generate expressive visual representations. Finally, visual representations themselves imply the need of thinking about representational and perceptual issues.

All these aspects are important when applying or developing visual methods for analyzing data that are connected to time. The problem is that the diversity of the involved aspects makes it difficult for practitioners to find appropriate solutions for their task at hand, and difficult for researchers to identify directions for future work to bring forward the visualization of time-oriented data.

In this paper, we develop a systematic view on the visualization of time-oriented data. We are aware that this is not an easy endeavor. Our categorization must be specific to be useful for others. A too general view would not be of much help in alleviating the addressed problem. A very fine-grain categorization is not desirable because categories would hardly be distinctive. What we aim for with this article is to initiate categorization of visual concepts for analyzing time-oriented data.

In Section 2, we will explain the basics of visualizing time-oriented data. We describe why time is important and what makes time worth special consideration in the context of visual analysis methods. Our attempt to categorize approaches for visualizing time-oriented data is presented in Section 3. The categorization will be illustrated with examples from visualization literature; it is not our intent to provide a comprehensive state-of-the art overview. A discussion of the proposed categorization and its implication is provided in Section 4. Our paper summarizes the made statements and gives an outlook on future work in Section 5.

## 2 Basic Considerations

When analyzing time-oriented data, users are commonly interested in the evolution of their data over time. To achieve this goal, the users' primary task is to compare data located at different positions of the time axis. Detecting trends and pattern are second order goals that lead to insight, and to understanding the data. In giving this coarse description of analysis goals we do not neglect that there is certainly an interplay of further basic visualization tasks (e.g., as described in (2; 3): check for existence of data elements, locate data elements in time, determine rates of change).

Many different types of data are related to time. One can think of stock exchange data, census data, simulation data, and much more. But also news articles, photo collections, or project plans can contain temporal information. From a theoretical point of view, all these data are time-oriented and should be representable with one and the same approach. From a practical point of view, each of these types of data requires a dedicated visualization. For instance, stock exchange data can be visualized with Flocking Boids (4), census data can be represented as described in (5), SimVis (6) is efficient for visualizing simulation data. News articles (or contained keywords) can be analyzed with ThemeRiver (7), photo collections can be mapped via MyLifeBits (8), and project plans can be made comprehensible with PlanningLines (9). Apparently, this list of techniques is not exhaustive. The aforementioned approaches are examples out of many that recognize the special role of the dimension time.

Time-oriented data can also be visualized using generic approaches. Since time is mostly seen as a quantitative dimension (or at least can be mapped to a quantitative domain), common visualization frameworks like the XmdvTool (10) or Visage (11), standard visualization techniques like Parallel Coordinates[1] (13), or more or less sophisticated diagrams and charts (14) have their eligibility for visualizing time-oriented data. For simple data and basic analysis tasks, these approaches outperform specialized techniques, because they are easy to learn and understand (e.g., common time diagram). However, in many cases, time is treated as one quantitative variable among many others, as for instance in Parallel Coordinates – not more, not less. Therefore, generic approaches usually do not support establishing a direct visual connection between multiple variables and the time axis, and they are limited in their capabilities to enable direct interactive exploration and browsing of time-oriented data, which is essential for a successful visual analysis.

[1] Interestingly, the class *ParallelCoordinatesVisualization* of the InfoVis Toolkit (12) derives from a super class *TimeSeriesVisualization*, which gives evidence of the importance of time in a visualization environment.

Interaction is indeed crucial for the analysis process. To allow users to explore their data, direct manipulation (as already suggested in (15)) and brushing are the means of choice in many interactive visualization tools (e.g., (16; 17; 18)). Particularly, browsing the time axis and switching between different levels of temporal aggregation (e.g., daily, weekly, or monthly data) are important. Such interactions are rather uncommon for other quantitative variables, and hence, are uncommon in generic visualization frameworks.

The bottom line is that time must be especially considered in Visual Analytics. Different types of time-oriented data need to be visualized with dedicated methods. Additionally, visualization tools must provide a high degree of interactivity. As the cited examples suggest, a variety of concepts for analyzing time-oriented data are known in literature (19; 20; 21). This variety makes it difficult to assess the current state of the art in visualization of time-oriented data. What is required is a systematic view. In the next section, we will present a categorization schema that is intended to help in untangling this important subarea of Information Visualization and Visual Analytics.

## 3 Categorization of Techniques for Visualizing Time-Oriented Data

As indicated earlier, devising a categorization that is broadly applicable is not an easy task. We decided to develop a systematic view that is geared to three practical questions, so that prospective users and researchers find an easy entry to the ideas behind it:

(1) What are the characteristics of the time axis?
(2) What is analyzed?
(3) How is it represented?

These three questions correspond to the categorization criteria: *time*, *data*, and *representation*. The criterion time addresses the time axis itself. Question (2) considers the data that tie to the time axis. How the data are represented is covered by the third criterion. The following sections will provide detailed explanations of each criterion, including sub-criteria and respective categories.

### *3.1 Criterion: Time*

Self-evidently, the temporal dimension itself is an interesting aspect for any approach to temporal Visual Analytics. It is virtually impossible to design effective analysis methods, without knowledge about the characteristics of the time axis. From a theoretical perspective, different models and algorithmic representations of time have been studied well in literature (22). However, we adhere to a more practical categorization of different types of time as presented in (23). From Frank's taxonomy, the following two sub-criteria are worth discussing.

**Temporal primitives: time points vs. time intervals**

This first differentiation addresses the temporal primitives that make up the time axis. A time axis can be composed of time points or of time intervals. A *time point* can be considered an instant in time. In contrast to that, a *time interval* is a temporal primitive with an extent. It can be specified by two time points or by a time point plus a duration.

When reasoning about time, the question of whether time points or time intervals are considered is decisive. As described in (22), different relations are possible among time points and among time intervals (see Fig. 1). Accordingly, different analysis tasks or goals can be accomplished depending on the addressed temporal primitives.

One might think that the distinction between time points and time intervals is of minor relevance for visualization. However, when considering the validity of data, which is an important concern in Visual Analytics, it becomes clear that this is not true. If data are given on a time axis that is composed of time points, then particular data values are valid only at certain points in time; there is nothing said about how the data look like between adjacent time points. This fact should be reflected in the visual representation to avoid misinterpretations. On the other hand, it is necessary to visualize the range in which interval-based data are valid.

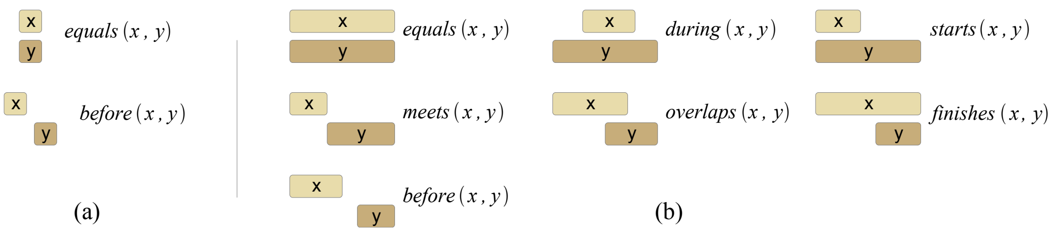


Fig. 1. Temporal relations: (a) Relations between time points; (b) Relations between time intervals (24); respective inverse relations are possible as well.

**Structure of time: linear vs. cyclic vs. branching**

Now that time points and time intervals have been described as basic temporal primitives, we approach the question of the possible structure of a time axis. We will distinguish three different structures: linear, cyclic, and branching time (see Fig. 2). *Linear time* corresponds to our natural perception of time as being a (totally or partially) ordered collection of temporal primitives, i.e., time proceeds from the past to the future. A *cyclic time* axis is composed of a finite set of recurring temporal primitives (e.g., the seasons of the year). On a cyclic time axis, any temporal primitive $A$ is

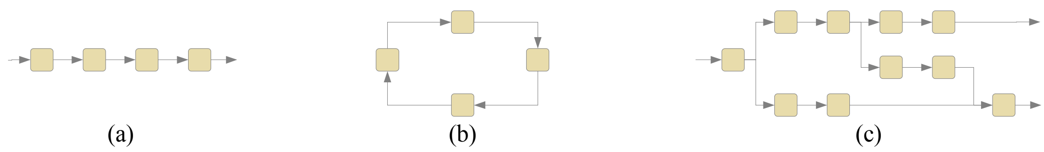


Fig. 2. Structure of time: (a) Linear time; (b) Cyclic time; (c) Branching time.

proceeded and succeeded at the same time by any other temporal primitive $B$ (e.g., winter comes before summer, but winter also succeeds summer). In practical applications it is often useful to unroll a cyclic time axis to a linear time axis. *Branching time* axes are modeled as graphs. Temporal primitives are the vertices of the graph. Directed edges describe temporal order. Vertices with more than one outgoing edge indicate a split of the time axis into alternative scenarios, which is particularly relevant for planning or prediction. Apparently, linear time and cyclic time can be seen as special cases of branching time where the graph obeys certain constraints (i.e., for linear time, every vertex has no more than one outgoing edge; for cyclic time, the graph is a circle).

Linear and cyclic time are covered well by existing visual and analytical approaches. However, methods for analyzing branching time are still rare. Here we see a potential task for future work in Visual Analytics.

The decision to which category a time-oriented dataset belongs is not always fully determined, but can depend on the interpretation of the user, on the task, or on the application. If for instance a user seeks to find a general trend in the data, a linear interpretation of the time axis makes sense. On the other hand, detecting seasonal effects in the data can be easier if a cyclic time axis is assumed. Similarly, it is a question of interpretation whether a date is considered as a time point (a day) or a time interval (a period of 24 hours or 86,400 seconds). This dependence on interpretation implies a need for highly flexible Visual Analytics methods.

We also point out that branching time is important in Visual Analytics, because data analysts commonly have to assess alternative scenarios from a whole bunch of facts from heterogenous data sources. In this context it is worth noting that Frank suggests a further category - *multiple perspectives* (23). In contrast to branching time where only one path through time will actually happen (e.g., in planning applications), multiple perspectives facilitate simultaneous (even contrary) views on time (as for instance required to structure eyewitness reports). Both branching time and multiple perspectives introduce the need for taking care of probability (or uncertainty), to convey, for instance, which path through time will most likely be taken, or which evidence is believable.

We will now take a look at the data that ties to the time axis. Like the time axis, also the data have major impact on analytical and visual approaches. As indicated in Section 2, time-oriented data can be manifold. To answer the question "What is analyzed?", we suggest categorization based on the following sub-criteria.

**Frame of reference: abstract vs. spatial**

To categorize time-oriented data, it makes sense to consider their context (or frame of reference). Without going into too much detail, we distinguish *abstract* and *spatial* data. By abstract data we mean data that have been collected in a non-spatial context, i.e., data that are not per se connected to some spatial layout. In contrast to that, spatial data contain an inherent spatial layout, which can be conditioned by natural circumstances or modeled realities.

The distinction between abstract and spatial data reflects the crystallization of different subfields of visualization research in the last decade. Information visualization, graph visualization, or software visualization are more concerned with abstract data, whereas spatial data are addressed by scientific visualization (flow visualization, volume visualization) or geographic information systems. Each field handles time-oriented data differently, despite the fact that a unified view would be more desirable.

However, the main reason for a distinction between abstract and spatial data is the way of how data are processed in Visual Analytics. For spatial data, the inherent spatial information can be exploited to find a suitable mapping of data to screen. The representation of time has to be incorporated into that mapping, where it is not always easy to achieve an emphasis of the time domain. For abstract data, no a priori spatial mapping is given. On the one hand, that implies, it is first of all necessary to contrive an expressive spatial layout. This requires creative thinking and experience. On the other hand, screen dimensions can be used almost exclusively to expose the time domain.

**Number of variables: univariate vs. multivariate**

The second data-related categorization criterion concerns the number of time-dependent variables. When speaking of variables, we do not limit our consideration to basic data types like integers, real numbers, or categorical enumerations. We also consider a vector, a matrix, or a news article as possible data variables if this is required by the application at hand. Obviously, it makes a difference if we have to represent data where each temporal primitive is associated with a single data value (i.e., *univariate data*) or if multiple data values (i.e., *multivariate data*) must be considered. With the latter case, an additional visualization goal – the detection of correlations – is introduced.

Approaches for single-valued data have been around for a long time. There are also various techniques that allow the visualization of two or three data values (which are literally already multivariate). However, the big challenge in Visual Analytics is to handle larger numbers of variables. This is where analytical methods come into play. Usually, it is necessary to apply dimension reduction methods (e.g., principle component analysis) to derive major temporal trends.

**Level of abstraction: data vs. data abstractions**

"Above all else, show the data" is what Tufte claims in (25). The majority of visual methods follow that claim. Visualizing *data* is useful in many application scenarios. However, if larger data sets must be analyzed, Tufte's postulation is hard to fulfill without introducing new problems like overcrowded and cluttered displays. In such cases, it makes sense to melt down the data to condensed form, i.e., to derive *data abstractions* (see (26) for a survey) that reflect interests and needs of users. Calculating aggregated data values (27) is one example for deriving abstractions, which is particularly useful to drive overview+detail interfaces (28). Feature visualization also follows the idea of computing data abstractions. *Features* are data portions that obey certain user-defined constraints (29). In the context of time-oriented data a third derivable information unit must be mentioned – *events*. Events are special situations in the development of time-oriented data. Events can be user-defined or found by methods of Artificial Intelligence. Focusing on events lifts the data analysis to yet a higher level of abstraction (30; 31; 32). The essence of this categorization criterion is that visually driven analysis of time-oriented data should not be limited to a mere representation of data. Visual Analytics methods have to consider task- and user-centered higher order data abstractions specifically designed for time-oriented data. To communicate such data abstractions efficiently, a better integration of analytical and visual methods is required (1).

These three criteria for data-centric aspects are intentionally settled at a quite high level of abstraction. We are aware that the data aspect is certainly worth further discussion. However, we do not want to overemphasize data aspects, but refer the interested reader to Shneiderman's "Task by Data Type Taxonomy" (28) and Wilkinson's "The Grammar of Graphics" (33), which are widely accepted references already available in literature.

### *3.3 Criterion: Representation*

Finally, this last criterion addresses the visual representation of time-oriented data. We do not try to investigate subtle details of the variety of visual approaches available, but concentrate on two fundamental sub-criteria that concern the time dependency and the dimensionality of the presentation space.

**Time dependency: static vs. dynamic**

*Static* representations visualize time-oriented data in still images (i.e., representations that do not change automatically over time). In contrast to that, *dynamic* representations utilize the physical dimension time to convey the time dependency of the data (i.e., representations that change automatically over time such as slide shows or animations). The presence or absences of interaction facilities has no influence on whether a visualization approach is categorized as static or dynamic.

Distinguishing between static and dynamic representations is crucial for Visual Analytics, because different tasks and goals are supported. Dynamic representations are well suited to convey the general development of the analyzed data over time. However, there are also critical voices on animation (e.g., (34; 35)). Especially when longer multivariate time series have to be visualized, animation-based approaches reach their limits. Users simply cannot follow all changes in the visual representation and the animation takes too long for the user to remember its course. Static representations show all information on one screen, which is advantageous to fully concentrate on the data and to compare different parts of the time axis. However, in contrast to animations, static representations require screen real estate to represent the time axis itself. Therefore, it is challenging to develop representations that avoid visual clutter. Again larger data sets aggravate this problem.

**Dimensionality: 2D vs. 3D**

This sub-criterion simply distinguishes between 2D and 3D presentation spaces. The question of whether or not it makes sense to exploit three dimensions for visualization is discussed heavily in the community. One camp of researchers argues that two dimensions are sufficient for effective data analysis. In their thinking the third dimension involves unnecessary difficulties like occlusion and lost information on back faces. The other camp of researches see the third dimension as a possibility to encode further information. Undoubtedly, certain types of data (e.g., flow data or volume data) even require the third dimension for expressive data visualization. The mentioned disadvantages of a three dimensional presentation space are tackled with advanced interaction techniques or additional visual cues. We will not take either position, but think that both options are required depending on task and data at hand.

### *3.4 Examples*

We will now give some examples of visual methods for analyzing time-oriented data. Some of the examples stem from our own work on visualization of time-oriented data, further examples are taken from literature. This selection of techniques does not claim any completeness; a comprehensive overview can be found in (21). Our goal is to demonstrate the applicability of the developed

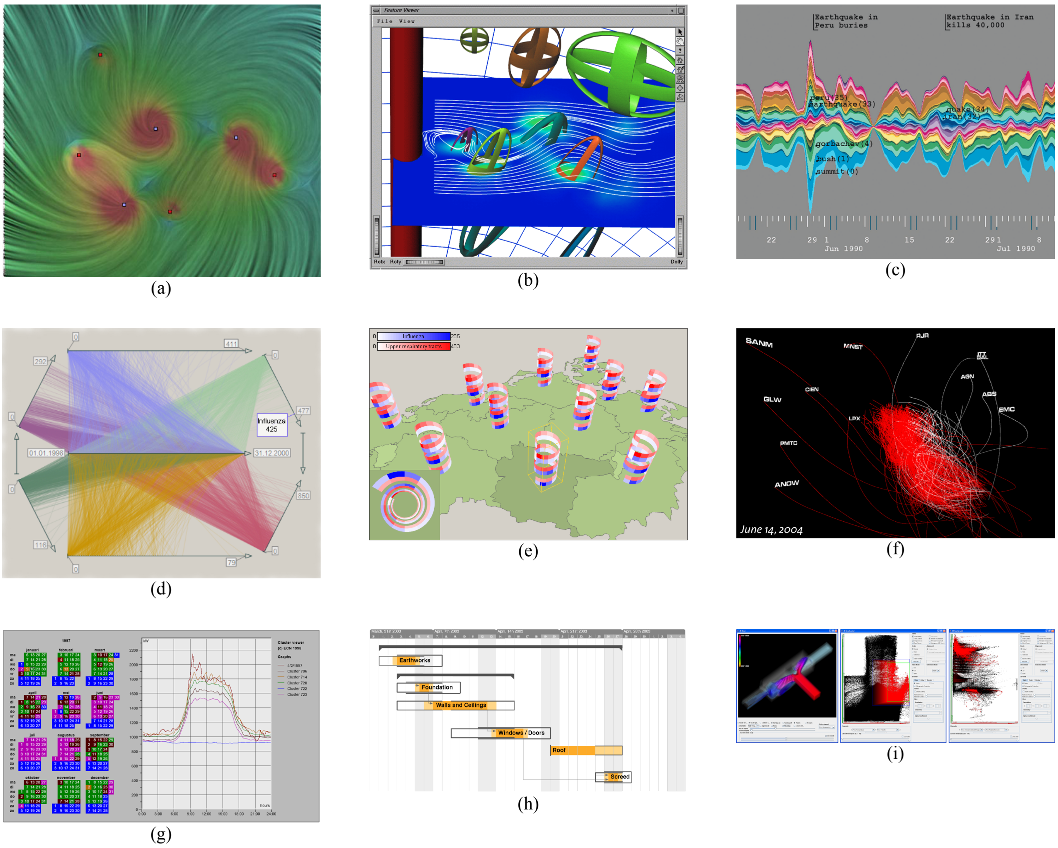


Fig. 3. Examples of techniques for visualizing time-oriented data.

classification scheme. We will not provide introductions to the examples, but refer the interested reader to the original publications for detailed explanations. Fig. 3 shows, on the one hand, the following methods and techniques:

(a) *Animated flow visualization* (36): Smooth animations created from streamline images,
(b) *Feature and event based flow visualization* (30): Animated visualization based on data abstraction and iconic representations,
(c) *ThemeRiver* (7): Static representation of thematic changes in document collections,
(d) *TimeWheel* (37): Axes-based visualization of multivariate data with focus on temporal dependencies,
(e) *Helix glyphs on maps* (38): Emphasis of cyclic patterns in spatio-temporal human health data,
(f) *Flocking boids* (4): Stock market visualization based on simulation and animation of flocking behavior,
(g) *Cluster and calendar based visualization* (39): Visualization of univariate time series on different levels of aggregation,
(h) *PlanningLines* (9): Visualization of project plans with temporal uncer-

tainty,

and, on the other hand, also screenshots of a larger visualization system:

(i) *SimVis* (6): Larger system that combines several views to facilitate flow visualization.

The systematic view along with a categorization of the aforementioned examples is presented in Table 1.

<table>
<tr><td rowspan="2">Time</td><td>Temporal primitives</td><td colspan="3">time points<br>(a) (b) (c) (d) (e) (f) (g) (i)</td><td colspan="3">time intervals<br>(g) (h)</td></tr>
<tr><td>Structure of time</td><td colspan="2">linear<br>(a) (b) (c) (d) (f) (g) (h) (i)</td><td colspan="2">cyclic<br>(e)</td><td colspan="2">branching<br>(h)</td></tr>
<tr><td rowspan="3">Data</td><td>Frame of reference</td><td colspan="3">abstract<br>(c) (d) (f) (g) (h) (i)</td><td colspan="3">spatial<br>(a) (b) (e) (i)</td></tr>
<tr><td>Number of variables</td><td colspan="3">univariate<br>(a) (b) (f) (g) (h)</td><td colspan="3">multivariate<br>(c) (d) (e) (i)</td></tr>
<tr><td>Level of abstraction</td><td colspan="3">data<br>(a) (b) (c) (d) (e) (f) (g) (h) (i)</td><td colspan="3">data abstractions<br>(b) (g) (i)</td></tr>
<tr><td rowspan="2">Representation</td><td>Time dependency</td><td colspan="3">static<br>(c) (d) (e) (g) (h) (i)</td><td colspan="3">dynamic<br>(a) (b) (f) (i)</td></tr>
<tr><td>Dimensionality</td><td colspan="3">2D<br>(a) (c) (d) (g) (h) (i)</td><td colspan="3">3D<br>(b) (e) (f) (i)</td></tr>
</table>

Table 1
Categorization schema for visual methods for analyzing time-oriented data.

## 4 Discussion

In the previous section, we have elaborated on a categorization of visual methods for analyzing time-oriented data. In this section, we will discuss findings, implications, and limitations of our systematic view. We will use them as starting point to derive open problems and future work in Visual Analytics of time-oriented data.

**Preliminary remark:** First of all, it must be mentioned that we have considered only top-level criteria. Indeed, one can easily figure out more criteria with several further categories (e.g., representation method: pixel-based, map-based, glyph-based, etc.). However, we think that such and other criteria should not be added to an initial categorization of the field by default, but only on demand. The reason is that some aspects are not relevant in certain specialized areas (e.g., distinguishing pixel-based, map-based, and glyph-based techniques makes no sense for volume visualization). Nonetheless, identifying further general categories may turn out helpful once future development in Visual Analytics yields first methodological results.

**Observation 1 – Multiple Views:** We noticed that the visual methods currently available stand separate, i.e., are suitable only for particular categories of time and data characteristics. To our knowledge, there exists no visualization framework that can handle all types of times and data, or provides a broader selection of possible representations. We think that an open framework fed with pluggable visual and analytical components for analyzing time-oriented data is useful. Such a framework will be able to support multiple analysis tasks and data characteristics, which is a goal of Visual Analytics.

Unfortunately, there is no ad hoc way of combining or linking the available methods. However, from the example of SimVis (see Fig. 3 (i)) and from current research on coordinated multiple views (e.g., (40), (41)), we see that linking several views together can extend the applicability and usefulness of visual methods. Multiple views are particularly helpful in analyzing time-oriented data. Therefore, we underline the need for a flexible system that offers various methods to support visual analysis and decision making. The goal is to provide views that are dedicated to different analysis aspects, are helpful in conveying different levels of temporal granularity and data abstraction, or are used to represent different parts of the time axis. The categorization developed in this paper can be used to identify mandatory and optional views to be developed (depending on the types of time and the data at hand). Representational preferences as well as tasks and goals of users must also be considered. For example, using an animation to analyze data can be difficult (goal: analysis), but using an animated view to present analysis results might impress the director (goal: presentation). What this example suggests is that different visual representations are needed to fully support the analysis of time-oriented data and the communication of analysis results. A similar statement was already made by Bertin in 1981, although he used different words:

"*A graphic is not drawn once and for all; it is constructed and reconstructed until it reveals all the relationships constituted by the interplay of the data.*" (42)

**Observation 2 – Interaction:** It is apparent that interaction is a must particularly for analyzing time-oriented data. All presented examples provide some level of interactivity. However, scientific papers often discuss visual representations only; interaction is not always in the focus. Navigating in time and switching between different levels of temporal granularity are prominent examples of interacting with time-oriented data. Note that such interactions are rather uncommon for abstract quantitative dimensions. Even though direct manipulation (direct interaction with the visual representation, rather than with buttons or sliders) or advanced brushing techniques are known in literature (e.g. (15; 16; 18; 43)), they are only rarely considered to drive the visual analysis of time-oriented data.

Therefore, it makes sense to put more effort in investigating the potential of interaction in Visual Analytics. We need evaluated and accepted interaction techniques that allow intuitive exploration and analysis of time-oriented data. At the same time, we have to take care not to overload the user with functionality (e.g., hold shift and control key then click and hold right mouse button and move the mouse). This means, we need not only visual methods that suit the task at hand, but also interaction that is adapted to it.

A further aspect that infers from interaction and multiple views is coordination, i.e., the propagation of interaction originated from one view to all other views (that are coordinated). To ease the use of multiple views, coordination methods are commonly applied. To facilitate reasoning about time-oriented data, coordination can be targeted in accordance with the categories of our systematic view. A particular challenge in temporal Visual Analytics is to coordinate visual *and* analytical methods that not necessarily share common parameters. For instance, how can a view that shows derived principal components be coordinated with a view that shows predicted future trends, or is it impossible to coordinate such views at all?

**Observation 3 – Analytical Methods:** When looking at our categorization, we see the following situation: Most examples visualize time-oriented data, only few of our examples support temporal data abstractions (30; 39; 6). That is, many methods focus on representing time-oriented data, and neglect the analytical component.

To fully support the knowledge discovery process, visual methods for analyzing time-oriented data should take Keim's Visual Analytics mantra into account:

"*Analyse first, Show the Important, Zoom, filter and analyse further, Details on demand.*" (44)

Keim's mantra demands for a better integration of visual and analytical methods. With ever increasing volumes of data, temporal abstractions become more and more indispensable. Only if analytical methods (e.g., segmentation, clustering, detection of events) are applied to compute expressive abstractions is it possible to analyze larger data sets efficiently. Moreover, data abstractions are necessary for interactivity to prevail.

When speaking of analytical methods, a further aspect must be taken into account: Time-oriented data often involves uncertainty (45). Analytical methods (e.g., prediction of trends) also might compute vague information. It is mandatory to notify users of this circumstance, so that they can adjust their confidence in the generated analysis results.

## 5 Conclusion

In this paper, we proposed a systematic view on methods for visually analyzing time-oriented data. Our view is based on three main criteria: *time*, *data*, and *representation*. We presented examples and discussed implications of our proposal in the context of Visual Analytics.

We see quite a lot methods available in literature (21). Most of them support only certain parts of our categorization. As a conclusion, we suggested the development of an open framework for Visual Analytics of time-oriented data. We identified the following directions for future research on this aspect:

- Multiple views for different data aspects, different levels of temporal aggregation/abstraction, and different parts of the time axis,
- Sophisticated and adaptable interaction and coordination facilities particularly suited for time-oriented data, and
- Tighter integration of visual and analytical methods.

An important issue that concerns all previous points is task-orientation. This means that Visual Analytics systems should automatically suggest and parameterize visual, analytical, and interaction methods based on the users' task at hand. Recently, an interesting analysis of possible visualization tasks has been published in (3). That list of tasks can be used as a basis for future research on task-oriented Visual Analytics. In that regard, perceptual issues must be further investigated. Empirical tests have to be conducted to judge which forms of presentation (2D or 3D, static or dynamic, etc.) are best suited for particular analysis tasks.

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