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Toward flexible visual analytics augmented through smooth display transitions

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Visualizing big and complex multivariate data is challenging. To address this challenge, we propose *flexible visual analytics* (FVA) with the aim to mitigate visual complexity and interaction complexity challenges in visual analytics, while maintaining the strengths of multiple perspectives on the studied data. At the heart of our proposed approach are transitions that fluidly transform data between user-relevant views to offer various perspectives and insights into the data. While smooth display transitions have been already proposed, there has not yet been an interdisciplinary discussion to systematically conceptualize and formalize these ideas. As a call to further action, we argue that future research is necessary to develop a conceptual framework for flexible visual analytics. We discuss preliminary ideas for prioritizing multi-aspect visual representations and multi-aspect transitions between them, and consider the display user for whom such depictions are produced and made available for visual analytics. With this contribution we aim to further facilitate visual analytics on complex data sets for varying data exploration tasks and purposes based on different user characteristics and data use contexts.

1. Introduction

Analyzing multi-faceted big data is challenging (Kehrer and Hauser, 2013; Hadlak et al., 2015). To support a comprehensive understanding of this kind of data, different views and perspectives must be made available to the user during the visual data exploration and analysis.

A common example for multivariate data offering multiple perspectives is spatio-temporal data. Such data consist of a set of entities and measured attributes that have been observed at different points in time and at different locations in space. From a visualization perspective, widely-used visualization approaches exist to display a single aspect of such data. Three examples are shown in Fig. 1. A spiral may visualize cyclic temporal patterns (Aigner et al., 2011), a choropleth map can show spatial areal relationships (Dykes et al., 2005), and a node-link diagram may expose the structural connections between data entities (Tamassia, 2013). When multiple perspectives on the same data set are depicted in different views, understanding of the interplay of these different data characteristics may be hindered. However, once multiple data aspects are channeled into separate and distinct views, understanding the interplay of these aspects becomes a non-trivial task. Mechanisms like view coordination (Tominski et al., 2009), brushing & linking (Chen, 2004), or dynamically embedded visual links (Collins and Carpendale, 2007) are frequently deployed to enable users to develop an overall understanding of patterns and relationships existing in the data shown in separate views.

One alternative to linked views (Roberts, 2007) is to integrate multiple data characteristics into one single visualization. An

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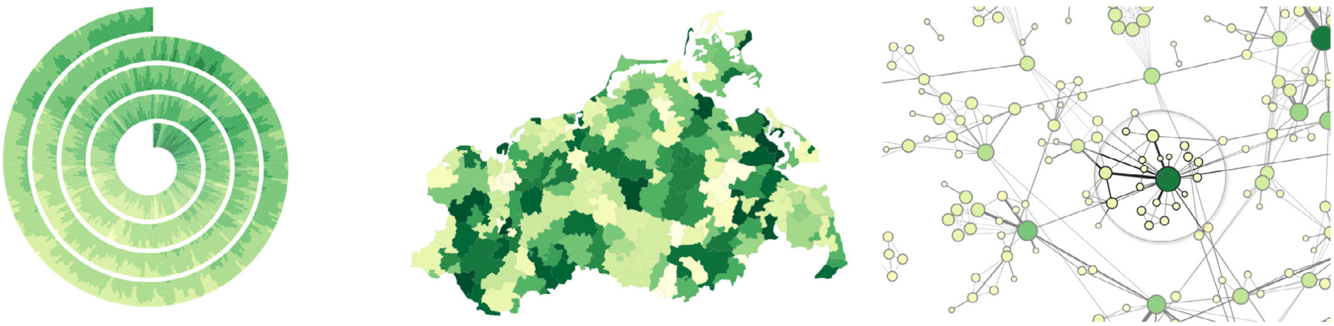

(a) Time spiral. (b) Choropleth map. (c) Node-link diagram.

Fig. 1. Visualizing time, space, and structural connections in separate views.

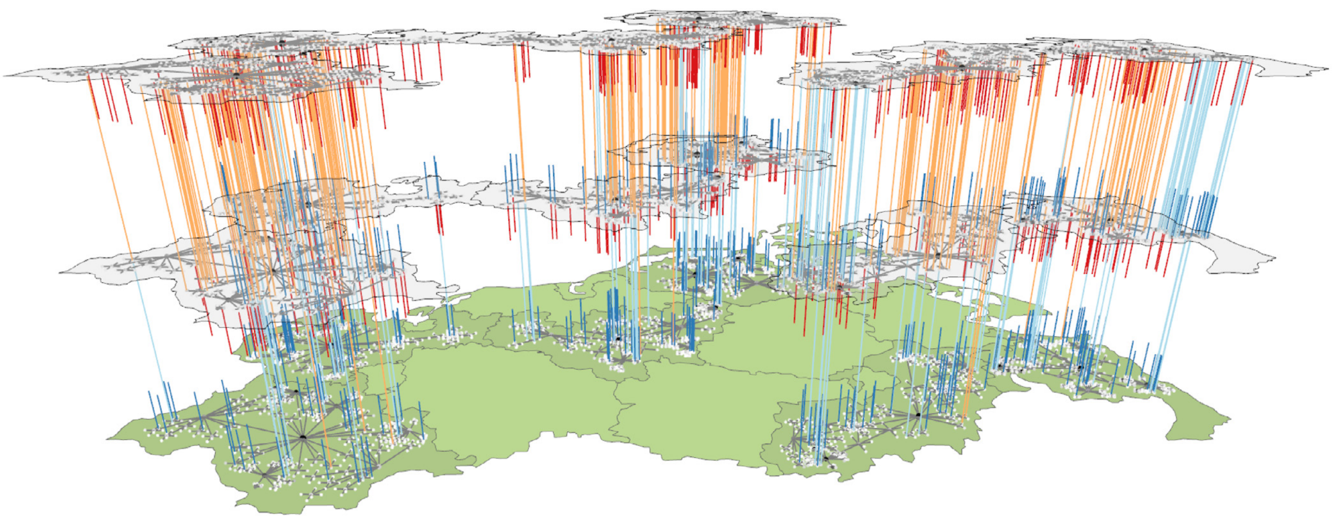

Fig. 2. Time, space, and structural connections integrated in a single visual representation.

example is shown in Fig. 2, where data entities (white dots) and their structural connections (gray lines) are embedded within selected geographic regions of a perspective 3D map display (Hadlak et al., 2010). For each time step in the data, there is a map layer stacked along the vertical axis. Additionally, blue and red spikes between the layers indicate where data entities start or cease to exist across time. While this visual representation integrates time, space, and structural connections, it is also rather complex and requires some training to decipher and some interaction to explore.

Typically, integrating a large number of data characteristics into a single visual representation is not feasible, because the resulting image would be visually too dense and thus too difficult to interpret. On the other hand, with many separate single-aspect views, the user needs to visually integrate findings made in one view with patterns of different data characteristics shown in other views. In summary, both integration and separation of data characteristics may require considerable cognitive and perceptual load or view interaction effort by the user. In short, separate linked data views and integrated multivariate views have their strength and weaknesses. For this, we propose flexible visual analytics to combine the strengths of both data visualization approaches, as we discuss next.

2. Flexible visual analytics

We introduce an alternative approach situated at the interface of integration and separation, which we call *flexible visual analytics* (FVA). Our working definition of the term is as follows:

> "Flexible visual analytics is an approach to support the comprehensive visual exploration and analysis of multi-faceted data via several smoothly integrated elastic multivariate views".

The goal of FVA is to mitigate the challenges associated with visual complexity and interaction complexity in visual analytics, while maintaining the strengths of multiple perspectives on the studied data. Essentially, FVA is based on the effective blending of different data views. The main ingredient of FVA are thus *transitions* that are designed to smoothly transform one view into other data views. Conceptually, transitions are a visual and computational means to transform between different data views, such as visual encodings, visualization techniques, view types, parameterizations, data query results, or the results of different analytical computations. Transitions may reduce interaction complexity and allow users to fluidly and seamlessly study different perspectives of the data. The start and end points of transitions are user-selected views that highlight a particularly relevant or interesting perspective on the data based on a user's task or interest. These *prioritized views* are designed with maximal expressiveness for that chosen data perspective, while other data characteristics are compressed or omitted. The prioritized views are assumed to be balanced in terms of their visual complexity.

FVA, according to our definition, has been used in the literature before, however, as we contend, without fundamental conceptualization in its own right. For example, Yuan et al. blend parallel coordinates and scatter plots (Yuan et al., 2009). Their approach smoothly pushes two parallel axes apart to make space for embedding scattered data points. Flexibly blending time series plots with parallel coordinates is possible as well (Gruendl et al., 2016). Tominski et al. blend 2D and 3D representations of movement trajectories (Tominski et al., 2012). Starting from a 2D overview of the entire movement data the user can smoothly transition to a 3D view that reveals details about individual movement trajectories. Schulz and Hadlak study transitions in the design space of implicit tree representations (Schulz and Hadlak, 2015). This allows visualization designers to explore new potentially useful designs for particular data analysis tasks. Brosz et al. developed an approach for transforming visual representations via skeleton-based image deformations (Brosz et al., 2013). Being pixel-based, the approach can be applied to any visualization, but is oblivious to its geometric model and the underlying data facets. Previous work also studied morphing between visualization techniques for educational purposes (Ruchikachorn and Mueller, 2015). In the context of digital humanities, the PolyCube approach utilizes space–time cube transformations to switch between different perspectives on complex cultural data collections (Windhager et al., 2020).

All these examples have in common that they involve smooth transitions between views that focus on different aspects of the studied data within a given application context or part of a visualization system innovation. For several years, smooth animated transitions have been a topic of research in visualization, for example, for data graphics (Heer and Robertson, 2007), data navigation (Pulo, 2007), or data aggregation (Kim et al., 2019). Several approaches have been developed to enhance animated transitions, for example, by bundling trajectories (Du et al., 2015), by grouping (Zheng et al., 2018), or via a grammar for authoring (Kim and Heer, 2021). A design space for animated transitions has recently been published (Thompson et al., 2020).

Our goal for this paper and future similar research is to review, build upon, and extend transition research in a way that transitions are not only possible for elementary visualizations or charts, but for complex, multivariate visual depictions of big and complex data. Eventually, FVA's aim is to be able to systematically transition between several different views, and not only between two simple visual representations. Such a research endeavor can also be informed by research on animated transitions for user interfaces, which arguably, are already more complex than basic charts (Dessart et al., 2012; Vanderdonckt, 2012; Chevalier et al., 2016).

Smooth transitions are well known for animated data graphics such as the popular Gapminder project (Gapminder Foundation, 2021). Yet, for this current definition of FVA, we do not consider views that change along a time line, but what cartographers have called re-expression or non-temporal animation that is using any numeric data dimension other than time (Harrower and Fabrikant, 2008). Nonetheless, research on animation is certainly related to what we discuss here.

While past and current animation research and authoring systems contain smooth transitions between static scenes out of the box, there are many open research issues: From a conceptual perspective, we do not have a clear understanding of the requirements and principles of FVA, specifically for complex multivariate views. What does the design space look like? It is further unclear which data dimensions or facets can be combined with which visual mappings. Are there general principles that can help us find such suitable combinations? We are also lacking a thorough understanding of how much integration, separation, and transitioning are appropriate in the context of a specific data domain, application type, and visualization user. Where is the sweet spot satisfying those contextual requirements; does such an optimal solution even exist?

In light of these open issues, we do see the need for developing a systematic view of FVA in order to gain a better understanding of the potentials and limitations of augmenting visual data analysis by means of transitions between discrete visual states. Such a systematic view would allow us to comparatively evaluate different approaches, match them to tasks and contexts, and identify the potential for not yet existing techniques to be developed in the future.

We thus aim to position this contribution as a call to action for more research on FVA. We propose some conceptual considerations that identify key aspects of FVA in terms of views and transitions between them. Moreover, we discuss implications of FVA from the perspective of human perception and cognition. Finally, we identify open research questions to spark further research in the context of FVA contributing to the overall goal of making big and complex multivariate data analysis not only a fluid and seamless, but also a fruitful experience with less cognitive load and fewer required interactions.

3. A technical perspective on FVA

As indicated earlier, FVA builds upon the idea of (i) relevant views and (ii) smooth transitions between these views. Next, we focus our discussion on the technical aspects involved in FVA.

3.1. Relevant multivariate views

We first need to clarify what we mean by relevant multivariate views and what they are supposed to show. In the first place, the data attributes A are of interest. The data attributes may be embedded in a temporal T and spatial S frame of reference. Moreover, structural relations R may exist between data entities. The different data aspects A, T, S, and R lead to several common data classes (Tominski and Schumann, 2020): multivariate data (A), time-oriented data ($T \rightarrow A$), spatio-temporal data ($T \times S \rightarrow A$), or dynamic graphs ($T \rightarrow R$). One can imagine further data aspects of interest such as uncertainty (Bonneau et al., 2014) or set affiliation (Alsallakh et al., 2016).

Multivariate data offer several analysis opportunities. For example, they may be analyzed with respect to outliers, correlations, or clusters. For spatio-temporal data, the analyst may want to study how data values develop over time or where certain values are located in space. For a dynamic graph, one may ask which of its parts form stable communities over time. More generally, many data facets imply that there are many questions one may ask about the data, which in turn lead to a more complex data exploration and analysis process (Kehrer and Hauser, 2013).

In light of this multitude of issues, it is a truism that there is no one optimal view that will suffice. As a starting point for FVA, we propose relevant, that is, prioritized views that emphasize one or two selected aspects of the data while potentially hinting at or omitting other aspects of the data.

The visualization literature is quite clear about the fact that particular types of data require dedicated visual representations (Hanrahan, 2009; Tominski and Schumann, 2020). Yet, designing visual representations for multiple aspects of high-dimensional and multivariate data remains challenging.

One example of a prioritized multi-aspect visualization is described by Dübel et al. (2017), who balance the visualization of terrain, collected geo-spatial data, and their uncertainty. When the terrain is prioritized, it is rendered using sophisticated lighting algorithms, whereas the geo-spatial data are represented only in an aggregated fashion. On the other hand, when the geo-spatial data are prioritized, they are shown in full detail, while the terrain is visualized only by means of contours. As this example illustrates, the prioritization can be implemented by varying the

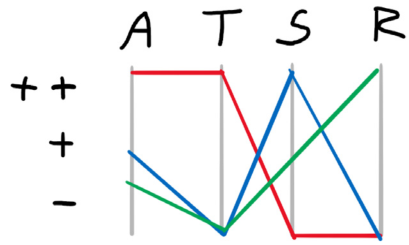

Fig. 3. Prioritized views (red, green, blue) communicate data aspects (A, T, S, R) at different levels of detail (++, + , −).

data's degree of abstraction (e.g., aggregated vs. exact values) and the degree of visual abstraction (e.g., detailed relief shading vs. contours only).

In the context of visual analytics, one may also consider approximate, heuristic data analysis methods in contrast to exact and precise computational steps. Prioritization may also be achieved by changing the amount of data items through selective sampling or changing data components through dimensionality reduction. Although selected questions of multi-aspect views have already been studied (Kehrer and Hauser, 2013; Hadlak et al., 2015), no comprehensive design-space for prioritizing data aspects in visual analytics has been described in the literature.

Prioritized views as described before form the basis for FVA. An individual view can be characterized conceptually as illustrated in Fig. 3. The different aspects (A, T, S, R) a view might contain are depicted as vertical axes. For each of the aspects, we define a continuum of the level of detail from full detail (++), to reduced detail (+), to omitted (−). Full detail is provided for aspects that are prioritized, reduced detail is sufficient to provide context, omitted data aspects are not included in the visualization. In order to be able to develop a comprehensive understanding of the data, an analyst would need a whole set of views, each with a different prioritization of the relevant data aspects and dimensions. The figure shows the characteristics of three hypothetical views as polylines in red, green, and blue. The red line corresponds to a view that emphasizes the temporal dependencies of the data, but does neither include space nor structural relations (e.g., a spiral display). The green line stands for a view that focuses on the relations, but shows space and data attributes only to a lower degree, leaving out time completely (e.g., a node-link diagram overlaid on a 3D globe). Finally, the blue view emphasizes the spatial aspect and includes aggregated data attributes, but does not convey aspects of time and relations (e.g., a choropleth map). A challenge for FVA is to systematically research and find concrete views that are suitable for different applications and use contexts. The set of views should comprehensively accommodate all data aspects, but also strive to be minimal to reduce cognitive load.

3.2. Smooth multivariate transitions

Conceptually, FVA is about flexibly transitioning between relevant multivariate views. In a sense, FVA is a kind of navigation between views, where transitions exist to make the navigation smooth rather than abrupt. Robert Spence argues (Spence, 1999) (p. 938):

> "If change has to occur it is immensely helpful, as far as minimizing the cognitive load associated with the maintenance of a good internal model is concerned, if the external representation can change smoothly".

Transitions may form bridges on different conceptual levels. They can link views with different *analytical abstractions*, for example, between the results of different time-series forecast methods (Wang and Hornbæk, 2020). However, transitions will more commonly involve different *visual representations*, for example, between a 2D and a corresponding 3D representation, or between a geographic projection and a multi-dimensional projection. Note that transitions are not only for communication-oriented purposes (e.g., storytelling, onboarding), but are also supposed to be a vehicle for data exploration.

No matter the specifics of what is being connected by a transition, it leads from one prioritized view to another one. From there, another view and yet another view may be reached, forming a chain of connected views. Alternatively, there may be a central view from which several other views can be reached, but no lateral transitions are available between these other views. This would form a star-shaped topology.

In general, transitions between views may thus form different topologies, some are illustrated in Fig. 4. However, we do not yet know the potential impact that a particular topology may have on the analysis and on the generation of insights involving complex data. More research is necessary to investigate which specific types of topologies may be suitable under which circumstances.

For the transition itself, we define two key requirements: A transition should be (i) smooth and (ii) controllable. Smoothness is required to support users in understanding how one visual representation transforms into another. Achieving smoothness typically involves some form of interpolation. A transition should also be controllable to allow users to reverse or replay it, or to watch it at a different speed. An appropriate user interface can offer these operations.

An elementary transition is concerned with an atomic visual change. An example would be to change the position of a single dot. A transition from one visual representation to another typically involves a whole series of elementary transitions. For example, collapsing a set of dots might involve the temporary display of their convex hull, which is then folded into a single meta dot replacing the original set.

From a conceptual perspective, a transition can be based on the underlying data model or on the view's graphical model. On the side of the data model, a transition can involve data attributes, derived statistics, or parameters of any step along the visual analytics pipeline. Transitions on the graphical side work on a geometrical scene definition or the plain pixel array. Consequently, three different strategies for implementing transitions exist:

1. Interpolate data model,
2. Interpolate geometry model, or
3. Interpolate pixel model.

The decision on which strategy to use must be made depending on the intended visual outcome for the transition. The reason is that different strategies can lead to different outputs. Consider, for example, the illustration in Fig. 5. Let us assume an analytical computation is parameterized with two different values $p = v_T$ and $p = v_S$ to convey either temporal or spatial aspects of the data. The two resulting views show the data as a black dot at different positions. When interpolating the dot position (geometry model), the visual outcome is a linear trajectory. On the other hand, when interpolating the parameter values between v_T and v_S directly (data model), the trajectory of the dot might be totally different, as indicated by the curve in our example. When interpolating between images (pixel model), for example, by means of alpha-blending, no trajectory appears at all. Therefore, the interpolation strategy to be employed must be chosen carefully.

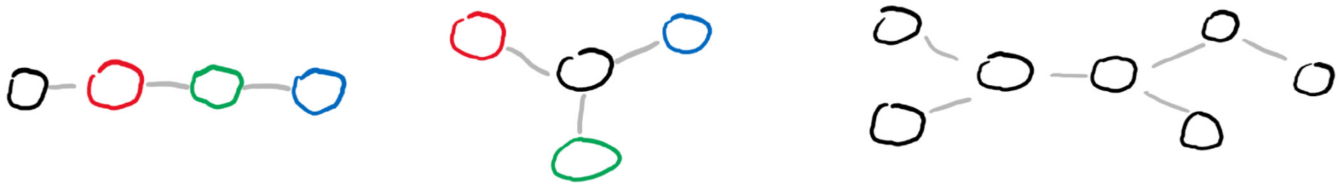

Fig. 4. Transitions between views may form different topologies.

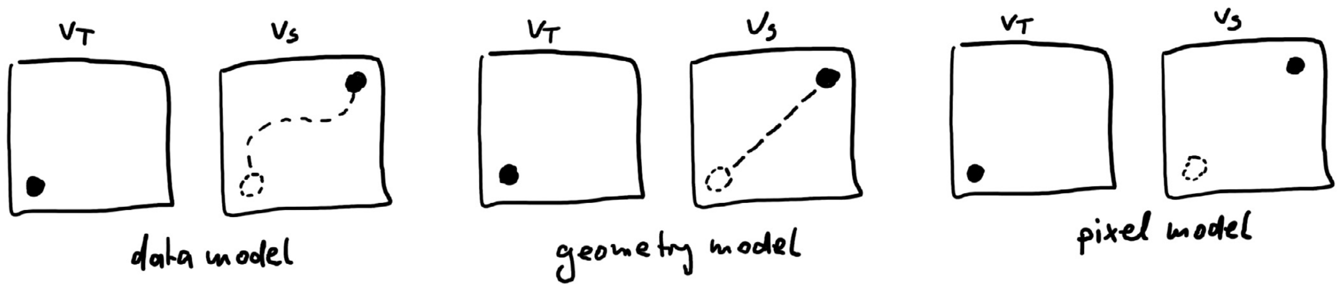

Fig. 5. Different visual outcome of interpolation in data space and visual space.

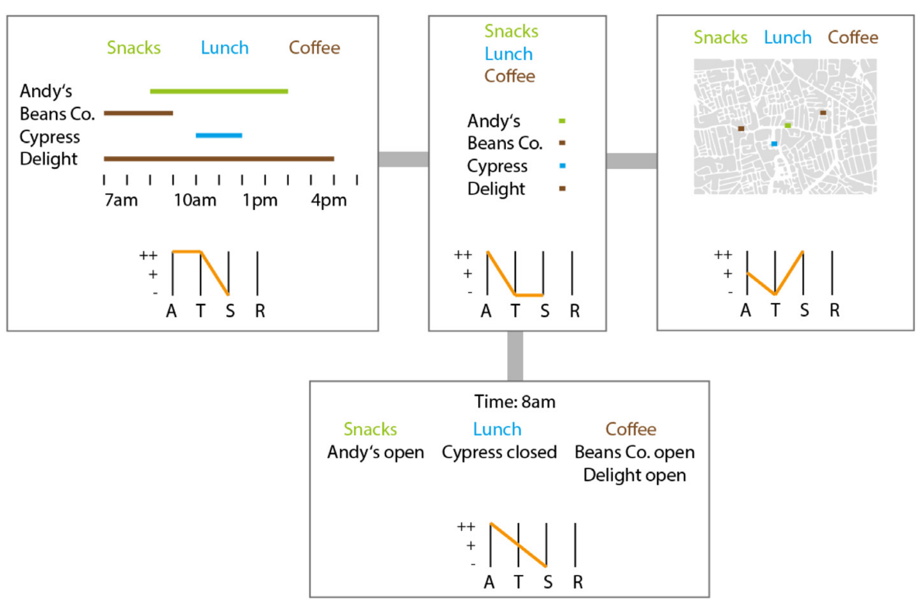

Fig. 6. Four differently prioritized views of the food stall example data from Table 1. Left: Attributes and time are shown in full detail, space is omitted. Middle top: Attributes in full detail, time and space are omitted. Right: A map showing the location and type of the food stalls but not their labels (attribute with reduced detail, time omitted). Middle bottom: Time is fixed (reduced detail) and attributes shown, space omitted.

In our example, p is a numeric parameter that is suitable for interpolation between v_T and v_S. However, what if a transition needs to convey the change of a categorical parameter, for which no interpolation of the parameter value is possible by definition. In such cases, graphical interpolation is the only choice we have for a smooth transition. Yet, the intermediate views being created during the transition do not have a corresponding state in the data/parameter space. It is important to make viewers of such transitions aware of this fact. How this can be done is an open research question.

The previous example was concerned only with an elementary transition of a single dot. The situation gets more complex when considering transitions between elaborate visual representations such as those mentioned earlier—balancing the visualization of terrain, geo-spatial data, and their uncertainty. While there are previous works on animated transition for data graphics, we do not yet know how these translate to more complex multivariate views. Which aspects need to be transitioned via interpolation in the data space, which aspects are safe to be transitioned in the visual space? How to best group and stage individual atomic transitions to generate an overall comprehensible and helpful view transition? The literature does not yet provide guidelines in this regard, which calls for more research on FVA.

3.3. Examples

In this section, we discuss examples illustrating how smooth display transitions might connect different visual representations better. In doing so, we also demonstrate that FVA is indeed a concept for multi-faceted data, including attributes, time, space, and structural relationships.

An example with a simple fictional food stall data set shall illustrate options for different prioritized views of the same data and how those views might be chained using transitions. Table 1 shows the example data set with four different food stalls. Each

Table 1
Simple food stall data set to be visualized with different prioritized views in Fig. 6.

Name (A)	Type of food (A)	Open (T)	Location (S)	...
Andy's	Snacks	09 am–03 pm	X_A, Y_A	...
Beans Co.	Coffee	07 am–10 am	X_B, Y_B	...
Cypress	Lunch	11 am–01 pm	X_C, Y_C	...
Delight	Coffee	07 am–05 pm	X_D, Y_D	...
...	...	...	...	...

stall has a name, sells a type of food, is open at certain times, and is located somewhere. Fig. 6 shows four different prioritized views. The parallel coordinate plots at the bottom of each frame indicate which aspect of the data is prioritized, shown with reduced detail, or omitted (as illustrated earlier in Fig. 3). The thick gray lines between the frames indicate options for transitions. We hypothesize that to transition smoothly between prioritized views it may be useful to stage the transition and to increase or decrease data details along the axes of data aspects consecutively. For example, to go from the time view (Fig. 6, left) to the map view (Fig. 6, right), one might first collapse the timeline to a point (decrease details of time T from full to omitted, as shown in Fig. 6, middle top) and then move the points to their location on the map (increase space S from omitted to full detail). The colors for food stall type information are kept during the transition, while the name of the food stall is removed (reduced detail for attributes A).

Our second example comes from previous work on combining the advantages of node-link diagrams and matrix representations in a technique called NodeTrix (Henry et al., 2007). Node-link representations and matrices are visually quite different, and therefore, a smooth transition between them requires several stages. Fig. 7 shows an example with five stages. Starting with a node-link representation (1), the edges are bent (2), nodes are rearranged (3), and edges are blended to become the cells (4) of the final matrix representation (5). Stages (2) and (3) operate in the geometry space, whereas stage (4) is in pixel space. This illustrates that transitions between complex visual representations might require combining interpolation in different spaces.

Finally, Fig. 8 shows screenshots from an exemplary transition between a 3D and a 2D categorical representation (Windhager et al., 2020; Salisu et al., 2019). The 3D view (left) clusters the data points in eight time layers and uses a 'hull' to show their flow over time. The 2D view (right) uses color to encode time on a more fine-grained level. The transition consists of several steps: First, the reference cube is broken up to individual time layers and the new color coding is introduced. Then, in a smooth animation, the layers are superimposed until the representation arrives at the final 2D view.

4. A human perspective on FVA

From a human perspective, making sense of a visualization—be it in a more data exploratory or in a more information communicative setting—requires the interplay of different perceptual (e.g., visual search, object tracking, pattern detection) and cognitive processes (e.g., build up a mental model, integrate insights into an existing knowledge structure). These perceptual and cognitive processes are bound to be more demanding and challenging for users, when they wish to make sense of big and complex multivariate data. User studies show that extracting multivariate spatiotemporal patterns is more difficult in separated views than in integrated ones (Andrienko et al., 2010; Windhager et al., 2020). Prior empirical research suggests different constraints of the human information processing system that may explain this effect: (1) split attention (especially with animated views) (Opach et al., 2014; Maggi et al., 2016), (2) inattentional blindness (Shipley et al., 2013), (3) change blindness (Rensink, 2002; Fabrikant, 2005), (4) cognitive load (Sweller, 1988; Sweller et al., 2011), and (5) generally the lack of support for incremental construction of mental models, missing gradual augmentation of users' conceptual models (Fabrikant et al., 2008; Ceneda et al., 2017; Windhager et al., 2018).

The FVA approach can mitigate some of these constraints by using transitions, the process in which one object (the unity of all data) is moved from one visualization reference system to another visualization reference system and thereby changes its appearance. To conceive a transition, the user needs to understand (1) how the data object in one display (in one reference system) relates to another perspective in the second reference system and (2) how the data object transforms across the reference systems.

We argue that transitions have an augmenting function for data exploration, visual search, cognitive processing, memory load, and knowledge building. Cognitive load is offloaded to the visualization system and the visual complexity is reduced by interaction. However, to fully exploit the transitions' augmenting potential, we have to take into account some cognitive and perceptual constraints in their design.

4.1. Perceptual constraints

One of the challenges of visual analytics is that the simultaneous presentation of different data aspects (e.g., spatial and temporal dependencies) raises specific problems. Using map-like representations to show developments in time leads to occlusion of relevant information (Kriglstein et al., 2016). Other solutions have to be found for the representation of spatio-temporal data. Animations could be one of these possible solutions to show spatial and temporal information in one visualization. Nevertheless, perceptual constraints have to be taken into account.

One of these constraints is change blindness and inattentional blindness (Rensink, 2002). Change blindness and inattentional blindness indicate severe limits of our visual attention that have consequences for how users will interact with visual representations of multi-faceted data. Following transitions in visual analytics requires tracking of multiple aspects on the screen simultaneously. Nevertheless, recent research on multiple object tracking indicates that human perception is better than previously assumed (Wu and Wolfe, 2018). Rensink (2002) formulated guidelines for screen design (e.g., transitions should only consist of two reference systems and one object) that take change blindness and inattentional blindness into account. These guidelines are also highly relevant when developing FVA.

4.2. Cognitive constraints

Visualizations providing complex information require a high degree of attention from the users. Cognitive load theory clarifies the cognitive processes necessary for such activities (Sweller, 1988; Sweller et al., 2011). Originally, cognitive load theory has been developed to model learning processes with educational systems. It distinguishes between intrinsic and extrinsic cognitive load. Intrinsic cognitive load is related to the complexity of the material as such, whereas extrinsic cognitive load describes the load resulting from the way the material is presented. Sweller et al. (2011) argue that intrinsic cognitive load is given, whereas extrinsic cognitive load can be reduced by appropriate ways of design. They provide several possibilities how this can be achieved.

Sweller et al. also described several effects related to cognitive load, among others the split-attention effect. This effect can be observed when two or more elements belonging together are

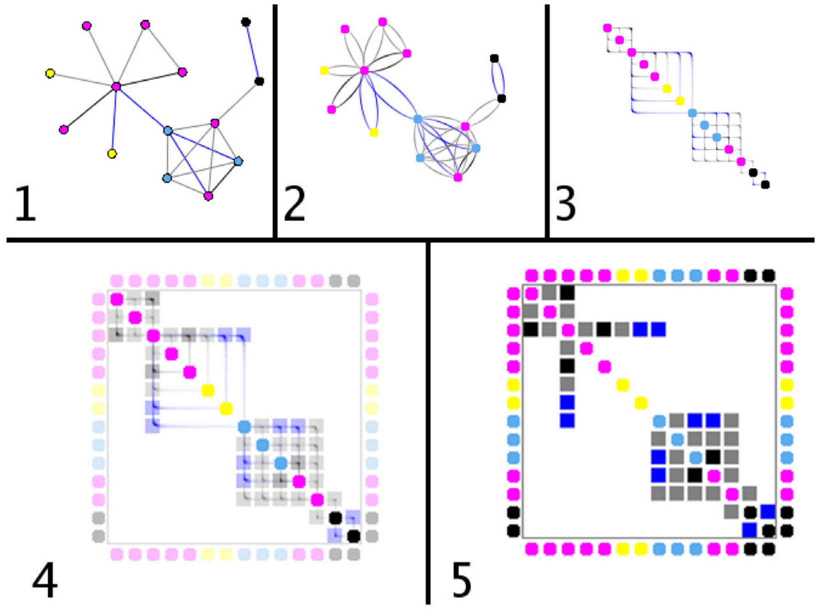

Fig. 7. Smooth transition from a node-link representation to a matrix representation.
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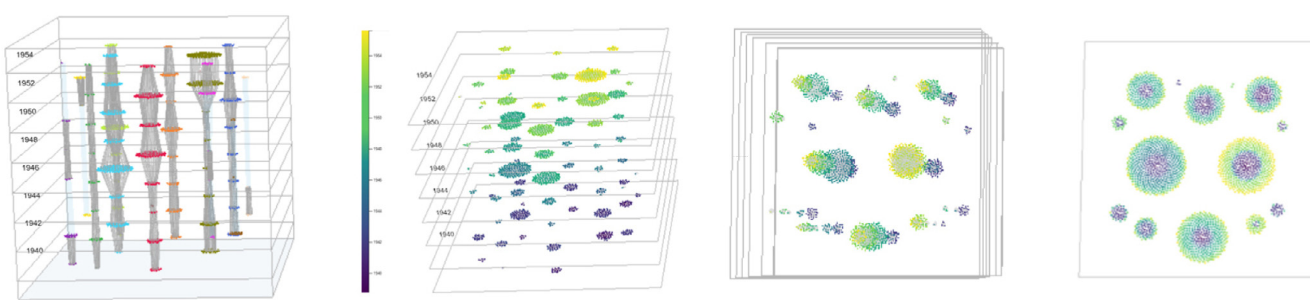

Fig. 8. Transition from a 3D categorical representation (left) to a 2D representation (right).

positioned in different areas of the screen. To interpret such a visualization correctly, users have to integrate the presented information in a meaningful way. This is difficult because users cannot observe both objects simultaneously and therefore have to keep at least one of the elements in short-term memory. A possibility to overcome this problem is to reduce the distance between elements and create a clear connection between elements belonging together. Previous work on visualizing spatio-temporal data (Tominski and Schulz, 2012) and supporting visual comparison (Tominski, 2016) have successfully applied these suggestions. Yet, the issue of split attention remains highly relevant for visual analytics, and also very challenging and difficult to solve.

Another effect identified in the context of cognitive load theory is the transient information effect (Sweller et al., 2019). This effect occurs when information is only presented briefly, and people have to retain this information in working memory. Strategies that might help to mitigate this effect are self-pacing or segmentation. These strategies can be easily supported by visualization systems.

Animation has been put forth as a strategy for integrating elements of a visualization into a coherent whole. In this sense, animation—as a core component of FVA—can overcome the split-attention effect and help us to construct relations between elements at various places on the screen. Animation has been primarily suggested as an appropriate method to represent temporal information, but other phenomena can also be represented in that way. Within the visualization community, there is a controversial discussion about the use of animation. Evaluation studies have yielded mixed results (Kriglstein et al., 2014). On the one hand, animations have advantages for tasks related to temporal developments. It has been argued that animations may convey very small changes in the data that are easily missed when using other techniques, like small multiples (Goldsberry and Battersby, 2009; Fabrikant et al., 2008; Fish et al., 2011). In addition, it can be argued that an animation conveys a more holistic picture than other visualizations. On the other hand, animations that are not well designed or inappropriately used can be confusing.

There are several factors that influence the success of an animation (Harrower, 2007). Speed can be either too fast or too slow. The possibility to control the speed of an animation is important for the users and helps them to understand the visualization in more detail. There is some empirical evidence that interactivity can help to support sensemaking processes (Amini et al., 2015). In animations, users often get overwhelmed by the sheer amount of data. Therefore, the possibility to filter the data is especially important so that users can concentrate on the crucial aspects of the visualization. Animations are also more advantageous for small datasets than for large datasets.

Bach et al. (2014) present a user study about animated transitions for dynamic networks. Their research indicates that animations decrease the error rate of study participants, but they may increase task completion time for some types of tasks. They also mention that it is difficult to track several different changes occurring in different areas of the screen.

Lowe (2014) describes a model to clarify learning and interacting with animations, the *animation processing model*. This model distinguishes between five different stages, going from more localized, detailed processing of information to the more general level of mental model consolidation. One basic idea is that decomposition of animations occurring in the first stage of the model is time-consuming and increases cognitive load of the users. Therefore, designers of animations should decompose them into meaningful units. These units are presented to the users who can, at a later stage, easily integrate them into a meaningful whole. In this way, the cognitive effort of users can be reduced considerably. Lowe and Boucheix (2016) present empirical evidence to support this notion. Lowe also argues that animations are often animated static images. He points out that, for example, methods of cueing adapted from static images (e.g., arrows) often do not work in animations, and that different methods of cueing should be adopted.

4.3. Recommendations

Several tentative recommendations can be derived from this brief overview of the literature. User studies indicate that an integrated view is better than separated views for the presentation of multivariate data (Andrienko et al., 2010; Windhager et al., 2020). So, if the number of data dimensions allows, an integrated view should be preferred. Transitions between different views can help to overcome the split-attention effect (Sweller et al., 2011; Fish et al., 2011), although these animations have to be designed carefully (Harrower, 2007; Kriglstein et al., 2014). To take change blindness and inattentional blindness into account, Rensink formulated as a design guideline that a transition should only consist of two reference systems and one object (Rensink, 2002). In general, the number of elements that are modified should be kept as small as possible (Bach et al., 2014; Fish et al., 2011). Therefore, interactivity, especially the possibility for filtering the data, is necessary (Amini et al., 2015). In addition, users should be able to control the speed of the animation (Fabrikant, 2005; Kriglstein et al., 2014; Sweller et al., 2019). Finally, segmentation and decomposition of the animation into distinct units should be possible to reduce cognitive load (Shipley et al., 2013; Lowe, 2014; Sweller et al., 2019).

5. Related work

FVA as discussed in this paper has the goal of supporting users in making sense of multiple visual representations of complex data. FVA shares this goal with existing approaches from the literature.

We already mentioned *visual linking* as a related concept (Collins and Carpendale, 2007). It is based on drawing links between different visual representations. The key advantage of visual linking is that relations between visual representations are made explicit. On the down side, visual linking requires additional visual resources for drawing the links and non-trivial measures must be taken to prevent links from occluding the visual representation (Steinberger et al., 2011). Moreover, visual linking requires the visual representations to be linked be visible at the same time. This works for classic multi-view visualizations, but not for visual representations that are dynamically embedded into parts of another visualization, as for example for Responsive Matrix Cells (Horak et al., 2021).

FVA is also related to *composite visualization* as described by Javed and Elmqvist (Javed and Elmqvist, 2012). Composite visualization is not a specific technique, but can be understood as a generalization or a design space of coordinated multiple views (Roberts, 2007). The composition can be juxtaposition, superposition, overloading, and nesting. The design space is mainly focused on the spatial arrangement of visual representations, which are shown simultaneously, but does not consider the temporal arrangement, that is, the smooth transitioning of visual representations over time across a topology. It is interesting that Javed and Elmqvist state in their paper: *"However, it is possible to envision other ways to combine two or more visualizations, for example using interaction or animation"*. This is exactly what we aim for with FVA.

The work by Chen et al. (2021) further explores the design space of multi-view visualization. They add to the notion of composition (frequency, diversity, correlations of view types) the notion of configuration (position and size of views). Based on hundreds of examples from the literature, numerous composition and configuration patterns are analyzed, which are utilized for a recommendation system for multi-view visualization. Yet, they also do not consider smooth transitions between visual representations.

Finally, we mention animated storytelling via Data-GIF (Shu et al., 2021) as a related approach to make data understandable. Data-GIF also utilizes animated transitions, yet these are predesigned and do not support interactive control at all. FVA is about the user taking control and traversing several multivariate views to gain insight into complex multivariate big data.

It can be concluded that (1) researchers studying the space of possible approaches to combining multiple views did not investigate flexible transitions among these approaches; (2) there are examples of the use of animated transitions but there has been no systematic general consideration of the essence of this approach; (3) the current state of research on flexible transitions does not allow valid comparisons with other approaches and creation of design guidelines for choosing a suitable approach for given data, tasks, and users.

6. Future work and conclusion

We have proposed flexible visual analytics (FVA) with the aim to mitigate visual complexity and interaction complexity challenges in visual analytics. The overall goal of our FVA approach is to make the exploration and the analysis of big and complex multivariate data a fluid and seamless process. With our work we neither propose a new approach competing with existing ones nor do we propose a specific design or software implementation. Our contribution is that we make the first attempt of systematic consideration of flexible display transitions as a general approach.

The evolving conceptual foundations of FVA offer multiple further research avenues to make FVA a useful asset in the visual analytics toolbox. Below we open several research avenues that future work might wish to address.

Prioritized multivariate views. For FVA to work, we need not only one or two prioritized data views as has been suggested before, but potentially series of displays of varied lengths for different tasks and contexts, to convey all relevant data views. Therefore, aggregating and generalizing previous literature and knowledge on multi-faceted visual analytics would be a first step for future work. A design methodology should be devised describing the necessary steps to consider for integrating across, and prioritizing different views in data exploration and visual analytics tasks. Inspiration for such a design methodology can be drawn from Munzner's nested model of visualization design (Munzner, 2009). Ideally, guidelines can describe how certain data views can be emphasized visually, what combinations of views work well, in which sequence, and where the limits of display prioritization might lie. Based on a systematic design methodology and depiction guidelines, concrete exemplars of prioritized multivariate views should be designed to form a basis for the investigation of multivariate transitions.

Multivariate transitions. More conceptual and methodological research is necessary to investigate how complex multivariate views in visual analytics can be transformed into one another. From a top-down perspective, we need to understand which aspects can be transformed from one to the other in a semantically meaningful way. Based on that, one may ask how individual transitions can be combined to form a topology of transitions that might allow for the analyst to cycle through any chosen view or series of views of the data usefully and timely. Are transitions between all possible combinations of data aspects feasible or necessary? Are there particularly compatible combinations of aspects that may serve as a generic backbone for a transition topology? What are the properties of different topologies, and how do these affect the type of knowledge generation with FVA?

From a bottom-up perspective, it is necessary to investigate how multivariate transitions can be implemented. Extending existing literature on animated transitions (Vanderdonckt, 2012; Chevalier et al., 2016; Thompson et al., 2020) strategies need to be developed for transitions between complex multivariate displays. Conceptually, we need to ask how and where transitions need to be executed—in the data model, in the geometry model, or in the pixel model? How can atomic transitions be integrated to form basic composite transitions that are information-rich and meaningful but do not overwhelm the analyst? This begs the question of how to communicate the meaningfulness of intermediate states of transitions?

Human factors of FVA. The design of flexible visualizations poses many user challenges. Human perception and cognition follow empirically established evidence that has to be taken into account in early stages of the design process. Cognitive load theory or empirical findings related to change blindness and inattentional blindness must inform future FVA investigations. Prior research on animations can serve as a useful stepping stone, but there are still open questions on how to design animations to support effective and efficient sense-making. How can we educate users to use FVA, and which level of complexity might be still graspable? How can we aggregate data into meaningful semantic hierarchies to guide users' understanding of FVA views and transitions? Which kinds of interaction mechanisms might serve users to effectively and efficiently use FVA?

In summary, we proposed the key idea of flexible visual analytics (FVA) based on user, task, and context-relevant, multivariate data views and one or more smooth transitions between them. We further considered the human dimension for developing meaningful and useful FVA approaches. With this report, we aim to put the flexible, integrated, and seamless FVA approach for visually exploring and analyzing multi-faceted data on the visual analytics research agenda. It remains to be seen how the identified research questions will lead to the development of respective solutions, empirically evaluated with actual users, that improve the visual data analysis experience when working with big and complex multivariate data.

Ethical Approval

This work does not contain any studies with human or animal subjects performed by any of the authors.

CRediT authorship contribution statement

Christian Tominski: Conceptualization, Writing - original draft, Writing - review & editing. **Gennady Andrienko:** Conceptualization, Writing - original draft, writing - review & editing. **Natalia Andrienko:** Conceptualization, Writing - original draft, Writing - review & editing. **Susanne Bleisch:** Conceptualization, Writing - original draft, Writing - review & editing. **Sara Irina Fabrikant:** Conceptualization, Writing - original draft, Writing - review & editing. **Eva Mayr:** Conceptualization, Writing - original draft, Writing - review & editing. **Silvia Miksch:** Conceptualization, Writing - original draft, Writing - review & editing. **Margit Pohl:** Conceptualization, Writing - original draft, Writing - review & editing. **André Skupin:** Conceptualization, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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