FastViz - Visualizing Dynamically Evolving Big Data

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ABSTRACT
Big Data Streaming visualizations convey high volumes of information in real-time. However, showing information without a precise context may lead to low effectiveness. Furthermore, when it changes, these visualizations must make the users aware of it. Our work is called FastViz, and we propose a set of transitions between different pairs of visual idioms. These may help users keep track of the information in real-time. We studied the Line chart, Heat map, and Stream graph. For each visual idiom, we defined seven transitions, most of them using animation techniques. We chose each one according to specific changes in the information structure. These changes would occur in real-time big data streaming scenarios. We designed a user study, where we showed videos with the transitions. Then we crafted online questionnaires with questions regarding those videos. Almost all techniques proved to be similar, and we concluded that animated transitions work better than no animated.

Author Keywords
Information Visualization; Big Data; Streaming; Animated Transitions; User Testing.

INTRODUCTION
Every second of evolution in the world, an enormous amount of information is produced, through multiple sources and for numerous purposes. This is largely due to the power and impact of digital globalization that the new technologies have been providing. This digitalization can be done to old records, or to new data that is received continuously and in real time, between short intervals of time. It can be produced in sensors, infrastructures or electronic devices scattered everywhere, which require large-scale monitoring, due to the proportion these data clusters acquire, when applied to large complex communication networks [10]. These volumes of data are called Big Data and one of the descriptions given is the 5V: Huge Volume, High Velocity, High Variety, Low Veracity and High Value [7].

The transmission of Big Data can be carried out continuously, without interruptions, or without the need of downloads in advance, by using streaming services. In this way, when created, the information is stored on servers and not on the devices of each user, which makes the visualization more flexible in time and place. Streaming visualization is strongly related to the time context of the information [10], as the amount of data to be presented varies according to the requirements of the applications and tasks, at the level of the relevant time intervals for the analysis [4]. The rate of new information received often exceeds the human percentile limits if the data is presented in raw formats, and can still hide important details. So by introducing real-time visual analysis in such areas of application, many benefits arise [3].

In Big Data, visualization methods are needed to enable analysts to exploit data more quickly, helping to make important decisions in time. Information visualization techniques are designed to help in this exploration, and therefore enable analysis of the information with as little effort as possible for the viewer. One of the major challenges in the visualization of data flows corresponds to the characteristics of the process of its physical sedimentation. That is, data can arise at unpredictable moments, accumulate until they are processed, and need to be kept in aggregate form, in order to show the history of contextualized information, over time [6]. The creation of this type of visualizations is not simple, as traditional techniques for visualizing information generally deal with previously known data sets of small dimensions, and are not adapted to transmit the temporal evolution of complex data sets.

Many of the studies have resulted in early attempts to understand, gain insight and make sense of this type of data, and problems of congestion, unavailability or overlapping of data have arisen. Thus, if we want to visualize ever-changing data of large dimensions and varieties, such as Big Data Streaming, we need to explore new strategies to do so. Using different visual idioms can be the solution. However, the existence of perceptible transitions between the various visual idioms becomes something essential, as the global context cannot be lost by changing from one to the other, nor the information itself. It is also fundamental to consider possible adjustments to the entire visualization, when it is divided into several temporal moments. Therefore, two important challenges arise: horizontal transitions and vertical transitions. The first ones occur between different temporal moments, and the second ones within the same temporal moment. In both, there must be a common thread to avoid loss of context and information.

The use of animations can be a solution to present the information and to move between its data in a dynamic and smooth way, being able to help in the user orientation, learning and decision making, and at the same time make user feel part of the visualization by following the changes in a close way. However, if misused, it can harm rather than benefit, since its ability to attract attention is a powerful distracting force, and the time its reproduction can take for visualization can generate loss of context, and consequently delay its understanding. Considering the specific characteristics of different data sets, and the periodicity with which their data is received, the user should always have an interface capable of keeping the display constantly updated and adapted to the changes suffered by the data over time. Thus, it is essential that a change is accompanied by a good transition.

FastViz looks for vertical transitions easy to understand, that avoid the loss of the general context or relevant information, within the same temporal time. Each transition carries out the passage between two different visual idioms that appear with the purpose of showing a given information relative to the data it represents. These data are always grouped according to the statistical measure applied in each visual idiom and the visualizations are based on the premise that the structure of information can change in real time, with smooth changes. Thus, a study of techniques and strategies for animated transitions was carried out. After its creation, videos were developed that showed significant changes in the data in a non-disruptive way, accompanied by the various transitions. These videos were used in tests with 100 participants, through questionnaires.

As such, our contributions with FastViz are: **1-** Conceptualization of a set of transition techniques and **2-** Perceptual study of the transition techniques.

BACKGROUND AND RELATED WORK

FastViz builds on research in three distinct areas of information visualization: Big data visualization, Big data streaming visualization, and animated transitions between visualizations.

Big data visualization

The information visualization aims to assist the user in the analysis of the data represented in a certain context, using graphic elements. With the progress of Big Data technology, this amount of data is increasing, so it is essential to have a good presentation of the data in order to achieve this goal. However, due to the 5V and the fact that each data domain has specific characteristics, there is no generic solution for viewing and analyzing Big Data. It is important to create presentation alternatives that were gradually directed towards total automation of the analysis process, solving the problem that a large user intervention is still required in most systems.

Time series proved to be common in Big data visualization [14, 2, 16, 5, 12], and a number of appropriate visualization techniques have been presented, such as line charts, bar charts, scatter plots, heat maps, stream graphs and pie charts. A study that stood out for its ability to represent a lot of information in a compact space and in a smooth way [5] was analyzed, allowing an easy analysis, something that passes through one of our objectives.

In terms of the V of **High Variety**, the contribution of ScrAnViz [20] is important by having a software capable of converting different types of data so that they can be visualized and understood in the desired format. In terms of **Huge Volume**, the Heat Map Scope [5] stands out for its ability to represent a large amount of information in a compact space, smoothly and easily for the analysis, by combining two popular techniques (Heat map and Stream graph). One of the main gaps found in the work explored was in relation to the V for **High Velocity**, as none of the contributions stood out in terms of speed, which may mean that although they represent large quantities, they do not do so in the most efficient way.

With the visualization of multidimensional data, the importance of searching for dimensional reduction techniques also arises, controlling the information that is being exposed, and avoiding losing the general context. Since it is fundamental that such reduction does not imply loss of relevant data, the systems try to use aggregation and simplification methods, and at the same time, methods that adapt the information to the space available to visualize it. Some of the studies analyzed have techniques to achieve this goal [9, 2, 16], however, most of them still have this gap, which is an important point to be worked on.

Big data streaming visualization

The information available for visualizing is not always based on static data, there are systems that receive it continuously over periods of time, from multiple sources, in large quantities and at high speeds. The fact that the world evolves every second, especially at the digital level, representing data in streaming is something increasingly useful and necessary. It applies to most of the industries we depend on and to many cases of Big Data, so it is essential to study good transmission systems in streaming.

For Big Data Streaming, the most popular types of data were also the time series [22, 11, 23, 21, 17]. When trying to reconcile large quantities with continuous reception, and in some cases with real time, it appears again as a priority to assess whether the systems have techniques of dimensional reduction, found in the five systems studied [22, 23, 21, 17]. Since the information is received at short intervals of time, if the type of display chosen is not the right one, it will not be able to show the data efficiently. For this reason, one of the analysis criteria has ensured focus on visualization techniques. Alternatives have emerged on the basis of the most popular ones, such as Line charts [22, 23], Bar charts [21, 17] or Scatter plots [17].

A strategy that should be taken into account to represent Big Data Streaming is Interactivity, often associated with improving and facilitating the understanding of visualization by maintaining an active relationship between the user and the visual elements [22, 23, 21, 17].

Thus, although there are some system options to handle data in streaming, the limitations that the above mentioned points may present for large amounts of data, still make it difficult to perform with Big Data, being VisMillion [17] one of the most recent contributions in that direction of efficiency.

Animated transitions between visualizations.

The animations are used to transmit illusive sensations of movement, and are generally associated with change in a visual representation over time. They can be applied in various contexts, but their main objective is to facilitate the perception of such changes, and guide a visualization in a certain direction. In the context of information visualization, animated transitions can arise between changes in states, from visualizations, to show a specific functionality, or to show trends. Animation has been a target option of many studies, namely applied to transitions between visualizations.

In animation of transitions, through linear interpolations it is possible to distort the time of an animation, which makes it easier for the user to follow it. This is a positive result, however, both the zoom [19] and other types of movements explored in this context can be quite distracting during the analysis. One of the most popular forms of motion analysis in a visualization is the use of Object Tracking. By animating object trajectories their behaviors can become more evident and easy to understand, without loss of context, if these are smooth transitions.

On the other hand, using animations can be an ineffective way of analyzing trends, but very effective in presenting them [18]. That is, if the aim is to offer the user a good interface for analyzing information, relating to data, using animation can be a risk if it is not well thought out and executed. To design any animation we can take into account a law that constitutes one of the design principles of visual animation, which Chabli et al. applied for trend analysis in real dynamic visualization scenarios, the law of Common Fate [1]. If ambiguities may arise with the type of graphics used, there is also a study that created animation designs aimed at facilitating the identification of a set of data aggregation operations, such as the minimum, mean or median [8].

In particular, we concluded that it is important to have a stronger focus on ways of illustrating all the changes in the world and how they can be analyzed, without losing context or relevant data, and avoiding dealing with sudden or distracting changes for the user. From this analysis of related work, an investigation has followed directed at the focus presented, exploring ways of making transitions between before and after information. One of the studies in particular, which dealt with animated transitions, as intended, but which only studied horizontal transitions, was continued. Above all, it was intended to facilitate the task of analyzing and understanding information in Big Data Streaming and to contribute to harnessing, or deepening, ideas from some of the studies presented here.

TRANSITIONS BETWEEN VISUAL IDIOMS

FastViz consists of a set of transitions to explore different ways of transit from the old to the new data, between data with different characteristics. For this, we developed a set of transition techniques to be applied between three different visual idioms, and prepared for visualizations with large amounts of data, transmitted in streaming, and in constant change. The goal is to facilitate the analysis and understanding of information and trends in Big Data Streaming.

Visual idioms

As representations we used three visualization techniques. Given the fact that color is an important aspect for a better recognition of the elements that make up a visualization [13], each idiom will be identified by its own color. In this way, it is also possible to make them more flexible to use and apply in different contexts, regardless of the type of transition in which they are inserted, achieving generalizable visual idioms.

Line charts unite a set of points forming a line. This idiom becomes suitable for the identification of **ascending and descending trends**, allowing the analysis of behaviour and information changes, in certain periods of time. The resulting line illustrate the means of the points in each of these time intervals that they were aggregated. Thus, it allows the analysis of the variation of behaviours with a notion of continuity.

Heat maps organize the information in a color matrix whose colors reflect relationships between the value of the data and the time interval in which they are found. Its color code will be associated with a scale of different shades, whose intensity increases with the point density it aggregates. Thus, at each time interval, it is possible to observe the different **volumes** of data and analyzing the **flow** of data. By varying the color tone of its cells according to the amount of data they aggregate, the heat map can illustrate situations where data changes value ranges. Also, it can be a good idiom to observe and analyze **patterns** within each specific value range.

Stream graphs are visual idioms in which the points are around a central baseline, rather than arranged in an axis reference. By representing the data in flow format, it gives the possibility to identify more **general patterns** of all the information. By placing the values around a central baseline, allows to observe the **dispersion/variability** of the data. Also, it limits the data between its **minimum and maximum values**, and obtains its **quartiles and median**, with the inner lines, making the observation of the dispersion of the data more reliable.

Concepts behind the transitions

The study of transition techniques focused on the creation and evaluation of Vertical Transitions with temporal context. If a visualization is composed of information belonging to different time periods, the horizontal transitions are those that deal with the passage of visual idiom from one time period to the next. On the other hand, vertical transitions happen when visual idioms change within the same time period.

In this work, the transition techniques created and studied were all vertical transitions. Vertical transitions arise when the nature of the data, or the groupings and aggregations that the data undergoes, change. They are useful when observe a new information or perform another visualization task is intended. In other words, situations in which it is necessary to change the visual idiom that was being used, to a idiom that best fits the new information or task. In order to make the change as understandable and immediate as possible for the user, a set of alternative transitions has been created. The aim is to avoid visual shocks, distractions and loss of context.

With a creative focus, some of the transitions have been developed based on different categories of a concept tree - Fig.1.

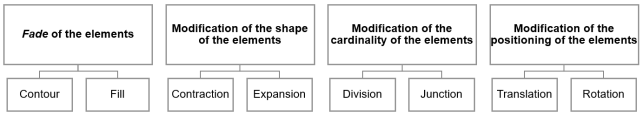


Figure 1. Concepts Tree.

In addition to the fade in the passage from one idiom to another, there is a partial fade in which the outline or the filling of the elements can be performed separately. The second concept is applied to the form of the elements, and it may be possible to contract or expand them in visualization. Cardinality was considered throughout the transitions, developing concepts of dividing and joining the initial elements in order to build new elements. Finally, it was also applied the alteration of the positioning of the elements, through translation or rotation.

Proposed Transitions

To achieve the objective of providing a continuous flow of data, we propose a set of seven transitions between pairs of visual idioms. There are two transitions common to all cases, **No Animation** (**NA**) and **Fade**. **NA** does not apply any kind of effect or animation, there is an abrupt change from one view to another, without considering aspects of color, shape, cardinality, positioning or velocity. When using the **Fade** - Fig.2 - the first idiom begins to fade away gradually at the same instant that the second idiom also begins to appear gradually. This way an approach is achieved which avoids a visual shock to the elements present on the screen.

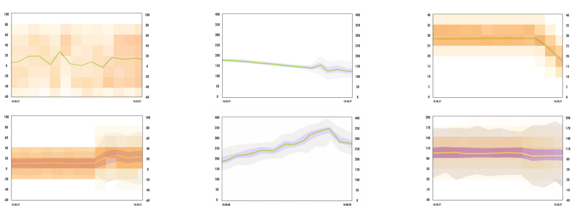


Figure 2. Fade transitions between visual idioms pairs.

Besides the **NA** and **Fade**, we created five more transitions, which apply the concept tree presented.

Line chart to Heat map

The squares on the heat map are formed according to the data density in each time interval on the line chart - Fig.8. The **Lines** transition - Fig.3 - extends the line format until the squares are formed. Because a line is an infinite set of points, the **Points** technique - Fig.4 - undoes the line into small points that will increase until they are squares. In order to agglomerate into squares, the **Squares** transition - Fig.5 - create small sections of the line chart that form overlapping squares that move to their place on the heat map. In an intermediate between points and squares, the **Rectangles** transition - Fig.6 - appears, which undoes the line in rectangles that widen to squares. The **Columns** technique - Fig.7 - allows to orient the rectangles coming out of the line chart already with the correct horizontal inclination for the heat map.

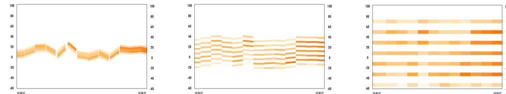


Figure 3. Transition Lines.

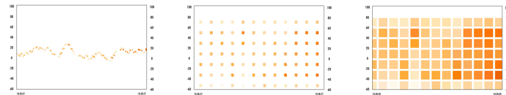


Figure 4. Transition Points.

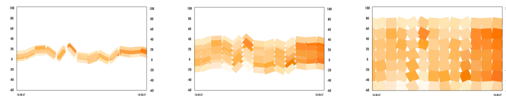


Figure 5. Transition Squares.

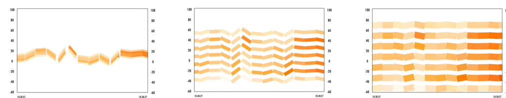


Figure 6. Transition Rectangles.

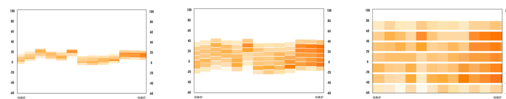


Figure 7. Transition Columns.

Figure 8. Evolution of the transitions Line chart - Heat map.

Line chart to Stream graph

The stream graph areas are delimited by five lines representing different statistical values of the data coming from the line chart, at each time interval - Fig.14. One of the options is to expand the thickness of the initial line until it reaches the full width of the stream graph, as the **Expand** technique - Fig.9 - does. As the expansion takes place, the respective areas arise. Due to the importance of the color element for a better identification of a visual idiom, this visual element was highlighted to maintain the context. The **Color** technique - Fig.10 - carries out an Expand but maintain the color of the initial line throughout the transition. As the areas of the stream graph are bypassed by lines, the **Lines** transition - Fig.11 - causes the initial line chart line to replicate on the five lines needed for the stream graph, whose space is then filled. In order for the expansion to be gradual, in terms of color of the areas, the **Fade Fill** - Fig.12 - carries out a Lines transition, but with the areas to be filled in Fade. The **Fade Total** - Fig.13 - technique applies an Expand transition, but with the entire visual idiom expanding into Fade, lines and filling areas.

Heat map to Line chart

The line chart line is formed from the points that are concentrated in the squares of the heat map, in each time interval - Fig.20. To give the user clues as to what the next visual idiom will be, the **Lines** technique - Fig.15 - makes a contraction of the squares, until they reach the thickness of a line, and overlap in a single line. Because a line is an infinite set of points, the **Points** technique - Fig.16 - reduces the heat map squares until they reach the point size, which will join together and form the line chart. In an intermediate between points and squares, the **Rectangles** transition - Fig.17 - appears, which reduces the squares to the width of a rectangle before reducing their thickness to a line. The **Squares** technique - Fig.18 - keeps the squares on the heat map longer, until they overlap to form a thick line, and reduce to the line chart line. The **Columns** - Fig.19 - applies a Squares transition, but in which the squares still overlap with the vertical alignment of the heat map, and only then rotate and reduce to line thickness.

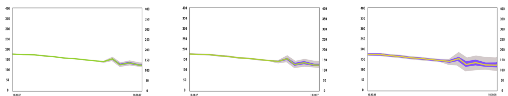


Figure 9. Transition Expand.

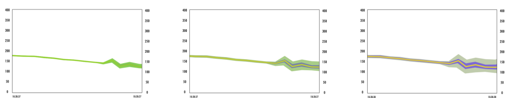


Figure 10. Transition Color.

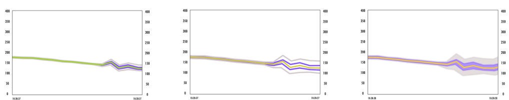


Figure 11. Transition Lines.

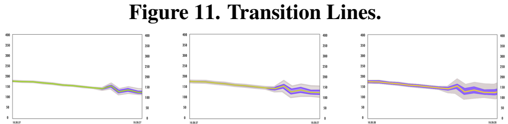


Figure 12. Transition Fade Fill.

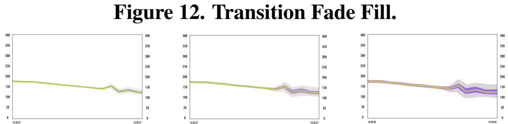


Figure 13. Transition Fade Total.

Figure 14. Evolution of the transitions Line chart - Stream graph.

Heat map to Stream graph

The stream graph boundary lines represent different statistical values of the data that are concentrated in the squares of the heat map, in each time interval - Fig.26. The squares may shrink in lines, which will be the five boundaries of the stream graph. With the **Lines** technique - Fig.21 - after the they appear, the areas are filled with the respective colors. For the transformation not to be so fast, instead of lines, the contours of the areas can first consist of rectangles, with the **Rectangles** technique - Fig.22. Due to the importance of the color for a better identification of a visual idiom, we highlighted to maintain the context. The **Rectangles Color** technique - Fig.23 - carries out a Rectangles transition, but quickly changes all the elements to the final colors of the stream graph, throughout the transition. To keep the heat map present longer, instead of the squares moving to lines or rectangles, they can keep as squares, taking advantage of their areas for the stream graph areas. This is what the **Squares** technique - Fig.24 - does, having also the **Squares Color** variant - Fig.25.

Stream graph to Line chart

The line chart line is formed from the lines that delimit the areas of the stream graph - Fig.32. One of the options is to contract the thickness of the initial line until it reaches the width of the line chart, as the **Contract** technique - Fig.27 - does. As the contraction takes place, the respective areas disappears. Due to the importance of the color element for a better identification of a visual idiom, this visual element was highlighted and the entire stream graph gradually changes to the line chart color. The **Color** technique - Fig.28 - carries out a Contract but with the color of the future line throughout the transition. As the areas of the stream graph are bypassed by lines, the **Lines** transition - Fig.29 - makes the filling disappear and the contraction is made only in terms of lines that bypassed the areas, which will overlap and form the line chart. In order for the contraction to be gradual, in terms of color of the areas, the **Fade Fill** - Fig.30 - carries out a Lines transition, but with the areas disappearing in Fade. The **Fade Total** - Fig.31 - technique applies a Contract transition, but with the entire visual idiom contracting into Fade, lines and filling areas.

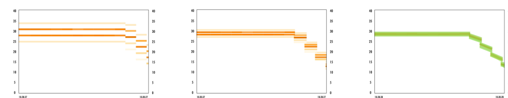


Figure 15. Transition Lines.

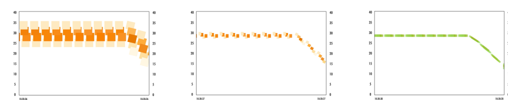


Figure 16. Transition Points.

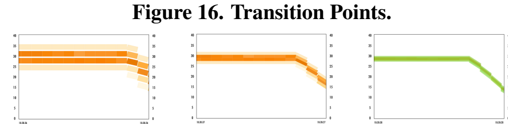


Figure 17. Transition Rectangles.

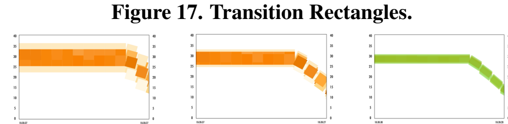


Figure 18. Transition Squares.

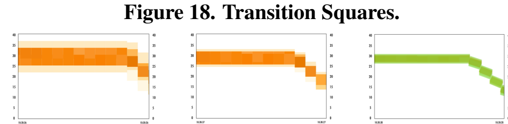
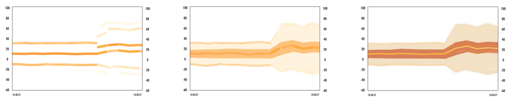


Figure 19. Transition Columns.

Figure 20. Evolution of the transitions Heat map - Line chart.

Stream graph to Heat map

The squares of the heat map are formed according to the data density in each time interval of the stream graph - Fig.38. The stream graph can lose the filling of its areas and leave only its contours, which with the **Lines** technique - Fig.33 - will then thicken until they form squares. This technique can be applied but with the emphasis given to color, **Lines Color** - Fig.34 - immediately changes the outlines for the heat map colors, before the lines form squares. For the transformation not to be so fast, instead of lines, the contours of the areas can first consist of rectangles, by increasing the size to rectangles, before they reach squares, with the **Rectangles** technique - Fig.35. The Stream graph can also by itself expand to the area occupied by the heat map, without first dividing into different elements. In the **Expand** transition - Fig.36 - the



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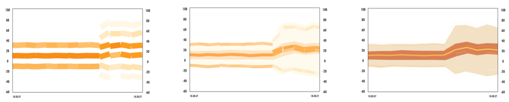

Figure 22. Transition Rectangles.

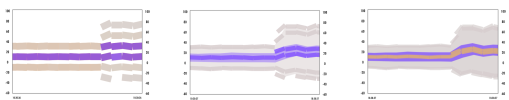

Figure 23. Transition Rectangles Color.

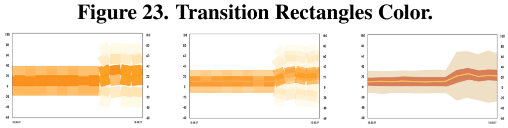

Figure 24. Transition Squares.

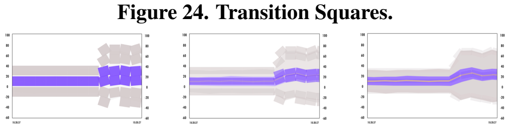

Figure 25. Transition Squares Color.

Figure 26. Evolution of the transitions Heat map - Stream graph.

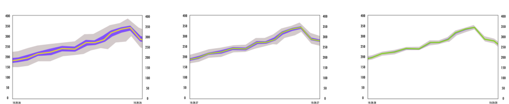

Figure 27. Transition Contract.

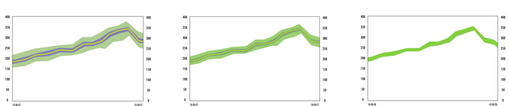

Figure 28. Transition Color.

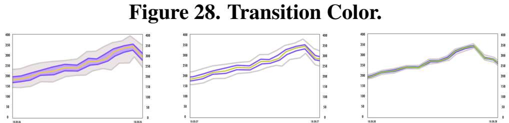

Figure 29. Transition Lines.

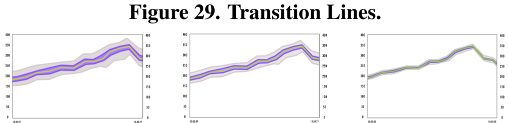

Figure 30. Transition Fade Fill.

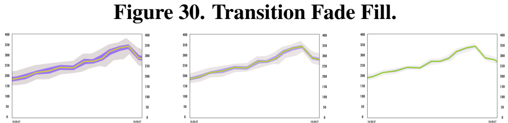

Figure 31. Transition Fade Total.

Figure 32. Evolution of the transitions Stream graph - Line chart.

squares are created as a result of the stain created by the heat map expansion. This technique has also been developed with a focus on color, where the spot expands while maintaining the color of the stream graph, by applying the **Expand Color** transition - Fig.37.

Figure 33. Transition Lines.

Figure 34. Transition Lines Color.

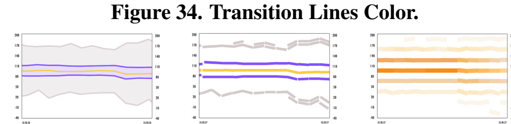

Figure 35. Transition Rectangles.

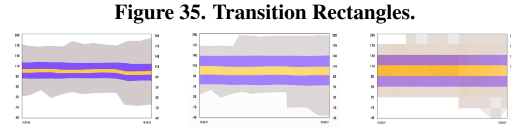

Figure 36. Transition Expand.

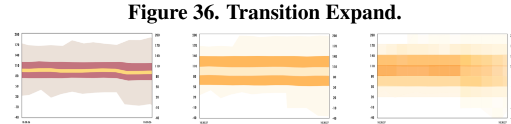

Figure 37. Transition Expand Color.

Figure 38. Evolution of the transitions Stream graph - Heat map.

USER EVALUATION

After the development of the transition techniques, studies with real users were carried out to understand which ones worked best for each of the cases under study. The study process consisted of three moments: preparation, implementation and analysis of results.

Method

The main objective of these studies was to compare the sets of transitions, to find those that ensured that the viewing context was not lost and that the task to be performed was successfully completed, preferably in a short space of time. By using different transition alternatives for the same moment of visualization, and for the same task of analysis, we intended to understand the results produced by each one of them, assessing the differences in user responses to the same question, for different transition strategies. The preparation of the studies consisted in the development of a set of videos, of short duration, that would make possible the visualization of each transition, as well as a set of questions associated with them.

The combination of the videos and the questions resulted in questionnaires to be answered by a group of participants, to show which of the transitions proved best for a certain simple visual analysis task, and also to know their preferences. Recognizing the importance of remote testing in terms of the amount of feedback, and at the same time circumventing the limitations of not being able to conduct face-to-face testing, a set of public online links to the questionnaires were distributed.

Data sets

Each video used a different date set, with characteristics favorable to what each transition was intended to evaluate. For this purpose, they were obtained through a time series generator, ensuring that incoming data values increased, decreased, oscillated or remained with the same initial trend, according to our objective for each transition. We sought to create drastic changes in the characteristics that each idiom best represented, trying to give emphasis to its variation.

Questions

Regarding the the **visualization elements**, in terms of data sets, visual idioms, and the data information, we asked users if both graphs showed the same data set (**Q1**) and if the information transmitted by them was the same (**Q2**). This could lead to the conclusion whether the transition conveyed the idea that the data changed with the change of graph, or whether the users considered that all visual idioms allowed to obtain all the information concerning the data. At each transition presented, the user had the main task of evaluating the behaviour of information relative to the data, possible to observe in the displayed visualization. They were asked to observe how **information trends** varied such as **mean** (**Q3**), **median** (**Q4**), **dispersion** (**Q5**), **minimum** (**Q6**), **maximum** (**Q7**) and data **flow/volume** (**Q8**), according to a set of given options. The "I don't know" option allowed to understand if the user was able to identify the cases in which certain information could not be observed in each visualization, and to avoid random answers.

To understand which of the transitions best met the objective of **facilitating and helping** in the analysis of the information present in the various graphs, we asked three different questions. (**Q10**): Did the transition help to understand the change from the first to the second chart?; (**Q11**): Did the transition interrupt the analysis that was taking place of the data in the first graph? and (**Q12**): Is the transition of adequate duration?

In order to assess the **workload of visualization and analysis** felt by the participant, when responding to what was requested, three questions, at different levels, were presented: **Mental demand** (**Q13**): What was the degree of difficulty you felt?; **Time demand** (**Q15**): How do you rate the duration of the transition? **Overall effort** (**Q14**): How many times have you played the video?. For the evaluation of their **individual characteristics**, users rated the appealing level of each transition (**Q9**). In the end, we asked them to classify each technique globally (**Q16**), and to sort all the techniques for each visual idiom pair according to **preference** (**Q17**).

Participants

The questionnaires were answered by 100 participants, distributed electronically in a balanced way across seven different versions. Among the participants, 39 are male and 61 are female and their ages range mostly from 18 to 26 years (69%) and 45 to 62 years (24%). At least 81% of the participants have a degree. In terms of frequency of analysis of data graphs, only 4% say they analyze every day, while 22% say they do so at least once a week and 27% at least once a month. 54 people say they have never analyzed data in real time. The visual idiom most recognized by the participants was the Line chart, with 99%, and the least recognized was the Box plot, with 47%. The Heat map was recognised by 67% of participants.

Line chart to Heat map

Lines was the best for understanding the mean variation (**Q3**). When all transitions were ordered, No Animation was considered worse than Fade, Lines, Rectangles and Columns. Also, Fade was better classified than Points, Rectangles and Squares. Lines was more preferred than Points, which was less preferred than Rectangles (**Q17**). **Summary:** All techniques were similar for the identification of the other trends, as well as for their characteristics and their visualization/analysis workload.

Line chart to Stream graph

Fade, Expand, Color and Fade Fill were more appealing than No Animation (**Q9**). Fade, Color and Fade Total proved to be more helpful in comprehension than No Animation (**Q10**). The duration of transitions Fade, Expand, Color, Fade Fill and Fade Total were more appropriate than the duration of the transition No Animation (**Q12**). Fade, Color, Fade Fill and Fade Total were globally better ranked than No Animation (**Q16**). When all transitions were ordered, No Animation was less preferred than that all other transitions, and Fade was the second worst. Expand was considered more preferred than the transition Color (**Q17**). **Summary:** All techniques were similar for the identification of trends. For their characteristics and their visualization/analysis workload, there were only statistically significant differences for the level of appeal, help in comprehension, adequacy of duration and overall rating.

Heat map to Line chart

Columns was the most preferred when all transitions were ordered (**Q17**). **Summary:** All techniques were similar for the identification of trends, as well as for their characteristics and their visualization/ analysis workload, but the Columns was the most preferred of the participants.

Heat map to Stream graph

No Animation was considered shorter than Lines, Rectangles, Rectangles Color and Squares transitions (**Q15**). When all transitions were ordered, No Animation was considered less preferred than the Fade, Lines, Rectangles Color, Squares and Squares Color transitions, and Rectangles was less preferred than Fade, Lines, Rectangles Color, Squares and Squares Color. Also, the Fade transition was more preferred than Lines and Rectangles, and the Lines was more preferred than Rectangles. (**Q17**). **Summary:** All techniques were similar for the identification of trends. For their characteristics and their visualization/analysis workload, there were only statistically significant differences for the classification of duration.

Stream graph to Line chart

No Animation was less appealing than all the others transitions (**Q9**). Contract, Lines, Fade Fill and Fade Total proved to help significantly more than the transition No Animation

(**Q10**). No Animation was pointed out as having a less adequate duration than all the other transitions (**Q12**). In terms of overall rating, No Animation was significantly worse ranked globally than all the other transitions (**Q16**). All transitions were more preferred than No Animation. Contract and Color were more preferred than the Fade transition, and the Contract transition was more preferred than the Lines transition (**Q17**). **Summary:** All techniques were similar for the identification of trends. For their characteristics and their visualization/analysis workload, there were only statistically significant differences for the level of appeal, help in comprehension, adequacy of duration and overall rating.

Stream graph to Heat map

Fade, Rectangles, Expand and Expand Color were more appealing than No Animation (**Q9**). No Animation presented the shortest duration (**Q15**). When all transitions were ordered, No Animation was less preferred than all the others, and Expand was more preferred than the Lines Color. (**Q17**). **Summary:** All techniques were similar for the identification of trends. For their characteristics and their visualization/analysis workload, there were only statistically significant differences for the level of appeal and classification of duration.

Discussion

After a detailed analysis of the results obtained for all the transitions, using some statistical tests, we concluded that there were some transitions that stood out for positive and negative in each topic being evaluated. However, for most of them, the results were not statistically significant, which made it somewhat difficult to create a clear distinction and to formulate a certainty of which transitions worked better or worse, as the rankings were similar. Thus, for these cases, only the success rates were considered and analyzed.

We noticed that the non-animated transitions were the ones that were worst rated, in most of the topics under evaluation. This result met one of our expectations and objectives, which was to demonstrate that animation is a useful tool for presenting and stimulating the understanding of the transition between different representations of data, in a visualization [15]. However, the fact that the animation allows the user to follow each change more closely and spontaneously, can on the one hand improve its orientation between the data and, consequently, the analysis of the different information, and on the other hand distract the user. In cases where the non-animated transition was better rated, animated transitions may had some source of distraction, generating a loss of attention or context [18], preventing the user from being able to perceive the behaviour of the data and analyze the information requested.

With regard to the analysis of data information (mean, median, dispersion, minimum, maximum and flow/volume), most of the responses obtained were not aligned with what the visualizations showed, and the results of the statistical tests did not allow conclusions to be drawn from statistically significant differences. Only the identification of the **mean** in one of the visual idioms pairs (Line chart-Heat map) obtained clear results to define a better transition for this purpose, which means that, in general, the transitions proved to be similar in the way they passed on information to users. The identification of the **flow/volume** behaviour and the **dispersion** of the data were those statistical measures that showed the lowest percentages of correct responses. A limiting factor for this may have been the participants' unfamiliarity with the statistical measures, with the visual idioms in which the measures are analyzed, or with the dynamics of the visualization itself, which may not be a result directly related to the transitions themselves. Through the analysis of the profile of the participants, we observed that more than 50 percent of the participants said they had never

Table 1. Summary of the statistical analysis. Showing χ^2 and p values for Chi-Square Test of Homogeneity (Q3), Kruskal-Wallis (Q9-Q12 and Q15-Q16) and Friedman's (Q17) tests; count values for Multiple z-test of two proportions post hoc (Q3); p values for Kruskal-Wallis's post hoc with corrections of Holm-Bonferroni (Q9-Q12 and Q15-Q16) test; Z and p values for Wilcoxon's signed-rank post hoc test (Q17); success rate (Q1-Q8), median and interquartile range (Q9-Q17) for the techniques in each test. Only statistically significant results are reported

	Chi-Square Test of Homogeneity / Kruskal-Wallis / Friedman		Multiple z-test of two proportions / Holm-Bonferroni / Wilcoxon			
	χ^2(6)	p	Pair	Z	p	count
Line chart to heat map						
Q3	15.239	.018	Lines (64%) - Rectangles (6%)	-	-	9b - 1a
Q17	30.134	<.0005	NA (1, 2.75) - Fade (7, 1)	-3.404	.001	-
			NA (1, 2.75) - Lines (5, 2.75)	-2.263	.024	-
			NA (1, 2.75) - Rectangles (4, 2)	-2.013	.044	-
			NA (1, 2.75) - Columns (5, 3.25)	-2.183	.029	-
			Fade (7, 1) - Points (2, 1.75)	-3.091	.002	-
			Fade (7, 1) - Rectangles (4, 2)	-1.990	.047	-
			Fade (7, 1) - Squares (4, 1.75)	-2.581	.010	-
			Lines (5, 2.75) - Points (2, 1.75)	-3.143	.002	-
			Points (2, 1.75) - Rectangles (4, 2)	-2.164	.030	-
Line chart to stream graph						
Q9	16.137	.013	NA (3, 1.5) - Fade (4.5, 1)	-2.681	.028	-
			NA (3, 1.5) - Expand (5, 1)	-2.819	.025	-
			NA (3, 1.5) - Color (5, 0.25)	-3.818	<.0005	-
			NA (3, 1.5) - Fade Fill (4, 1.25)	-2.058	.040	-
Q10	14.602	.024	NA (4, 1.5) - Fade (4.5, 1)	-2.583	.040	-
			NA (4, 1.5) - Color (5, 1)	-3.189	.006	-
			NA (4, 1.5) - Fade Total (4.5, 1)	-2.769	.030	-
Q12	12.645	.049	NA (4, 1) - Fade (5, 1)	-2.782	.025	-
			NA (4, 1) - Expand (5, 1)	-2.408	.032	-
			NA (4, 1) - Color (5, 1)	-2.998	.028	-
			NA (4, 1) - Fade Fill (5, 1)	-2.499	.048	-
			NA (4, 1) - Fade Total (5, 1)	-2.499	.048	-
Q16	17.181	.009	NA (3, 2) - Fade (4, 1)	-2.897	.020	-
			NA (3, 2) - Color (5, 1)	-3.786	<.0005	-
			NA (3, 2) - Fade Fill (4, 1)	-2.705	.021	-
			NA (3, 2) - Fade Total (4, 1)	-2.897	.020	-
Q17	38.357	<.0005	NA (1, 0) - Fade (2, 1.25)	-2.590	.010	-
			NA (1, 0) - Expand (7, 3.25)	-3.108	.002	-
			NA (1, 0) - Lines (3, 3)	-3.203	.001	-
			NA (1, 0) - Color (5, 2)	-2.647	.008	-
			NA (1, 0) - Fade Fill (4, 2)	-2.486	.013	-
			NA (1, 0) - Fade Total (5, 1.50)	-3.139	.002	-
			Fade (2, 1.25) - Expand (7, 3.25)	-2.975	.003	-
			Fade (2, 1.25) - Lines (3, 3)	-2.718	.007	-
			Fade (2, 1.25) - Fade Fill (4, 2)	-1.976	.048	-
			Fade (2, 1.25) - Fade Total (5, 1.50)	-2.392	.017	-
			Expand (7, 3.25) - Color (5, 2)	-1.965	.049	-
Heat map to line chart						
Q17	37.978	<.0005	NA (1, 0) - Fade (3, 3)	-3.224	.001	-
			NA (1, 0) - Lines (3, 2.50)	-2.997	.003	-
			NA (1, 0) - Points (4, 2)	-2.603	.009	-
			NA (1, 0) - Rectangles (4, 1.50)	-3.114	.002	-
			NA (1, 0) - Squares (6, 1.50)	-3.238	.001	-
			NA (1, 0) - Columns (7, 2)	-3.239	.001	-
			Fade (3, 3) - Columns (7, 2)	-2.937	.003	-
			Lines (3, 2.50) - Rectangles (4, 1.50)	-2.303	.021	-
			Lines (3, 2.50) - Columns (7, 2)	-2.574	.010	-
			Points (4, 2) - Columns (7, 2)	-2.288	.022	-
			Rectangles (4, 1.50) - Columns (7, 2)	-2.183	.029	-
			Squares (6, 1.50) - Columns (7, 2)	-2.500	.012	-
Heat map to stream graph						
Q15	16.509	.011	NA (2,1) - Lines (3, 1)	-2.297	.044	-
			NA (2,1) - Rectangles (3, 0.25)	-2.898	.020	-
			NA (2,1) - Rectangles Color (3, 1)	-3.694	<.0005	-
			NA (2,1) - Squares (3, 0)	-2.857	.016	-
Q17	35.286	<.0005	NA (1, 0) - Fade (7,4)	-3.502	<.0005	-
			NA (1, 0) - Lines (4, 2)	-2.007	.045	-
			NA (1, 0) - Rectangles Color (5,3)	-3.195	.001	-
			NA (1, 0) - Squares (4, 3)	-2.797	.005	-
			NA (1, 0) - Squares Color (5, 3)	-2.917	.004	-
			Fade (7, 4) - Lines (4, 2)	-1.976	.048	-
			Fade (7, 4) - Rectangles (3, 2)	-2.951	.003	-
			Lines (4, 2) - Rectangles (3, 2)	-2.177	.029	-
			Rectangles (3, 2) - Rectangles Color (5, 3)	-2.823	.005	-
			Rectangles (3, 2) - Squares (4, 3)	-2.352	.019	-
			Rectangles (3, 2) - Squares Color (5, 3)	-2.926	.003	-

analyzed graphs with real time data, and that only 22 percent said they analyzed graphs with a weekly frequency.

The use of **Fade** proved to be a good option in half of the visual idioms pairs: Line chart - Stream graph, Heat map - Stream graph and Stream graph - Line chart. Something common between these three pairs is that they all include the Stream graph as one of the visual idioms. Fade can be important in this visual idiom because it consists of colored areas, which when they need to appear or disappear from the screen, make it easier for them to do so gradually. The non-animated transition (**No Animation**) has emerged as the best result for some topics of analysis of the variation of some statistical measures: median, dispersion and flow/volume. The first two are associated with Stream graph, whose concept is based on Box plots, which was the least recognized visual idiom in the participants' profile (47%). In this way, it is possible that they preferred a more visually simple transition, with fewer things happening at the same time, and that this would facilitate the analysis of the information requested.

Table 2. Summary of the statistical analysis. Showing χ^2 and p values for Kruskal-Wallis (Q9-Q12 and Q15-Q16) and Friedman's (Q17) tests; p values for Kruskal-Wallis's post hoc with corrections of Holm-Bonferroni (Q9-Q12 and Q15-Q16) test; Z and p values for Wilcoxon's signed-rank post hoc test (Q17); median and interquartile range (Q9-Q17) for the techniques in each test. Only statistically significant results are reported

	Chi-Square Test of Homogeneity / Kruskal-Wallis / Friedman		Multiple z-test of two proportions / Holm-Bonferroni / Wilcoxon			
	χ^2(6)	p	Pair	Z	p	count
Stream graph to line chart						
Q9	20.960	.002	NA (3, 2) - Fade (4, 1.25)	-3.001	.009	-
			NA (3, 2) - Contract (4.5, 1)	-3.673	<.0005	-
			NA (3, 2) - Lines (4, 1.25)	-2.729	.012	-
			NA (3, 2) - Color (4, 2)	-2.226	.026	-
			NA (3, 2) - Fade Fill (5, 1)	-3.945	<.0005	-
			NA (3, 2) - Fade Total (4, 1)	-3.108	<.0005	-
Q10	15.171	.019	NA (3, 1.75) - Contract (4, 1.25)	-1.994	.046	-
			NA (3, 1.75) - Lines (4, 1)	-3.239	.006	-
			NA (3, 1.75) - Fade Fill (4, 1)	-3.239	.006	-
			NA (3, 1.75) - Fade Total (4, 1)	-2.797	.020	-
Q12	23.315	.001	NA (3, 1.75) - Fade (4, 1)	-2.949	.006	-
			NA (3, 1.75) - Contract (4, 2)	-2.693	.007	-
			NA (3, 1.75) - Lines (4.5, 1)	-3.320	.004	-
			NA (3, 1.75) - Color (5, 1.5)	-3.102	.006	-
			NA (3, 1.75) - Fade Fill (5, 1)	-4.317	<.0005	-
			NA (3, 1.75) - Fade Total (5, 1)	-3.702	<.0005	-
Q16	22.322	.001	NA (3, 1.50) - Fade (4, 0.25)	-3.035	.008	-
			NA (3, 1.50) - Contract (4, 0.25)	-3.035	.008	-
			NA (3, 1.50) - Lines (4, 0.25)	-3.035	.008	-
			NA (3, 1.50) - Color (4, 2)	-2.961	.003	-
			NA (3, 1.50) - Fade Fill (4, 1)	-4.118	<.0005	-
			NA (3, 1.50) - Fade Total (4, 1)	-3.834	<.0005	-
Q17	36.612	<.0005	NA (3, 1.50) - Fade (4, 0.25)	-3.439	.001	-
			NA (3, 1.50) - Contract (4, 0.25)	-3.310	.001	-
			NA (3, 1.50) - Lines (4, 0.25)	-3.076	.002	-
			NA (3, 1.50) - Color (4, 2)	-3.007	.003	-
			NA (3, 1.50) - Fade Fill (4, 1)	-3.075	.002	-
			NA (3, 1.50) - Fade Total (4, 1)	-3.130	.002	-
			Fade (4, 0.25) - Contract (4, 0.25)	-2.950	.003	-
			Fade (4, 0.25) - Color (4, 2)	-2.206	.027	-
			Contract (4, 0.25) - Lines (4, 0.25)	-2.093	.036	-
			Lines (4, 0.25) - Color (4, 2)	-1.963	.050	-
Stream graph to heat map						
Q9	13.893	.031	NA (2, 2) - Fade (4, 1)	-2.863	.020	-
			NA (2, 2) - Rectangles (4, 2)	-3.379	.006	-
			NA (2, 2) - Expand (4, 1)	-2.636	.032	-
			NA (2, 2) - Expand Color (3, 1.75)	-2.019	.043	-
Q15	17.278	.008	NA (2, 1) - Fade (3, 1.25)	-3.222	.006	-
			NA (2, 1) - Lines (3, 2)	-3.302	.005	-
			NA (2, 1) - Lines Color (3, 1.5)	-3.182	.004	-
			NA (2, 1) - Rectangles (3, 2)	-2.159	.031	-
			NA (2, 1) - Expand (3, 0)	-3.213	.003	-
			NA (2, 1) - Expand Color (3, 1)	-2.977	.006	-
Q17	21.765	.001	NA (1, 1.25) - Fade (4, 4.25)	-2.828	.005	-
			NA (1, 1.25) - Lines (4, 2.50)	-2.886	.004	-
			NA (1, 1.25) - Lines Color (3, 2.25)	-2.064	.039	-
			NA (1, 1.25) - Rectangles (6, 4)	-2.493	.013	-
			NA (1, 1.25) - Expand (5, 3)	-3.317	.001	-
			NA (1, 1.25) - Expand Color (5, 1.25)	-2.462	.014	-
			Lines Color (3, 2.25) - Expand (5, 3)	-2.115	.034	-

In response to the transitions with the best results, we suggest one for each pair of visual idioms, according to those that proved to be suitable for a greater number of evaluation situations, in each. If the transitions passed the data information in a similar way, we chose to consider better those that were less demanding, in terms of workload, and also those that were classified as more preferred.

The transitions suggested as best are the following:

- **Lines** to transit between **Line chart** - **Heat map**
- **Fade Total** to transit between **Line chart** - **Stream graph**
- **Rectangles** to transit between **Heat map** - **Line chart**
- **Lines** to transit between **Heat map** - **Stream graph**
- **Fade Fill** para transitar entre **Stream graph** - **Line chart**
- **Rectangles** para transitar entre **Stream graph** - **Heat map**

CONCLUSIONS AND FUTURE WORK

In this study, we explored different ways of applying transitions, in visualizations, when changes in data representation occur. Since they could not lead to visual shocks, it was necessary to understand how to smooth them, and at the same time make them suitable to help and facilitate the task of identifying data information. For this, we propose a set of transition techniques between three visual idioms, mostly using animation mechanisms. To test them, we conducted a user study with 100 participants, using short videos of the transitions created, and a set of associated questions. We realized that animated transitions worked better than non-animated ones. Also, we concluded that the transitions were similar to each other, in the way they give information to users, and so no better transition was clearly identified to analyze each statistical measure. In general, there were success percentages of responses far from ideal, given the real behaviour of the data presented.

As limitations, to make it possible to evaluate a large number of videos, a random distribution of the various transitions in seven versions was carried out, which may have prejudiced the first transitions of each random set. With the tests carried out via online, there was no opportunity to observe the users performing them, and to time the response time, or the times when they needed to pause playing the videos.

As future work, it is relevant to develop prototypes of the techniques created, with the best results, allowing them to be inserted in a Big Data Streaming data system. Also, it is important to carry out a new study, applied to data of different natures, besides quantitative data.

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