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STORYTELLING WITH SPATIOTEMPORAL DATA: ARE VISUAL CLUES THAT IMPORTANT?

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Resumo

No caso específico de dados espácio-temporais, há uma infinidade de conjuntos de dados possíveis, todos com uma panóplia de tipos de variáveis, angariadas de várias fontes, o que resulta num processo de análise difícil. Devido à complexidade dos dados em questão, existe uma maior dificuldade no que toca a ligar, relacionar e fazer sentido de um conjunto de dados espácio-temporais.

Analisar este tipo de informação é de importância elevada para o progresso do estado da arte atual e dos avanços científicos. No entanto, devido à complexidade das variáveis em questão, as observações e resultados em primeira mão tendem a ser difíceis de interpretar ou confusos, principalmente para quem não possui algum tipo de conhecimento avançado neste tópico de investigação.

Muitas dessas tentativas de visualização tentam exportar muitos dados de um conjunto de informação dentro de uma única tela, pelo que não são então facilmente compreendidas sem conhecimento avançado dos atuais métodos de visualização.
Este trabalho revê as técnicas de visualização de dados espaço-temporais, apresenta um resumo e classificação das técnicas de visualização mais utilizadas dentro deste espectro. Este trabalho visa também a identificação, relato e classificação das pistas visuais que são utilizadas nas técnicas analisadas e, posteriormente, quais as variáveis e canais visuais utilizados, na tentativa de comunicar os dados de forma mais eficiente ao observador.

Com base nas taxonomias revistas existentes para estruturas de dados, tarefas e pistas visuais, este trabalho realiza uma sugestão de integrar essas taxonomias de maneira a alcançar uma nova taxonomia ainda mais abrangente que, para pistas visuais, classifica, de acordo com sua natureza, como são usadas, para que finalidade, e tenta identificar o seu nível de eficácia. Para testar esta taxonomia, este trabalho abrangerá um estudo que visa estabilizar o desempenho da taxonomia e fornecer um relatório sobre as pistas visuais mais promissoras por meio de uma experimentação qualitativa e quantitativa com os participantes.
Ao realizar o trabalho referido, é esperado que a principal questão de pesquisa “Serão as pistas visuais importantes para a compreensão dos dados espaço-temporais?” seja respondida. Um dos resultados deste trabalho é uma tabela de taxonomia combinada, que resulta da classificação das técnicas revistas. Outro resultado é um estudo de usabilidade sobre as pistas visuais levantadas mais promissoras e boas práticas para o uso efetivo de uma variável visual, com base nos resultados do questionário a ser realizado.

Palavras-Chave: Visualização de Informação; Dados Espácio-temporais; Metáforas Visuais; Pistas Visuais; Storytelling; Experiência de Utilizador; Taxonomia

Abstract

In the specific case of spatio-temporal data, all these possible data sets are immense, as they include many dynamic types of variables, from many different sources, which in turn result in a harder time to link, relate and find sense within the whole data collection.

Analyzing and mining such kind of information is of incredible significance for progressing the current state-of-the-art and scientific advances. However, due to the complexity of the variables at stake, first-hand observations and results tend to be difficult to interpret or confusing, especially for those who don't have some kind of expertise in the researched domain.

Many of these attempts of visualization try to export much data of an information set inside a single canvas, which cannot be easily understood without advanced knowledge of the visualization methods.

This work reviews visualization techniques regarding spatiotemporal data and presents a summary and classification of the most used visualization techniques within the spatiotemporal data spectrum. This work also aims at the identification, report and classification of visual clues that are used in the reviewed techniques, and subsequently what visual variables and channels are used, in an attempt to communicate the data more efficiently to the observer.

Based on the existing reviewed taxonomies for data structures, tasks and visual clues, this study performs an attempt to integrate these taxonomies to achieve a wider taxonomy that, for visual clues, classifies, according to their nature, how they are used, for what purpose, and tries to identify their effectiveness. To test this aggregated taxonomy, this work will encompass a study aimed to stabilize the taxonomy's performance and to provide a report on the most promising visual clues through a qualitative and quantitative experimentation with participants.

By performing said work, we expect that the main research question "are visual clues important for the understanding of spatiotemporal datavis?" would be answered. One outcome of this work is a combined taxonomy table that results from the classification of reviewed techniques according to the proposed taxonomy. Another outcome is a usability study regarding the most promising reviewed visual clues and good practices for an effective visual variable use, based on the results from the questionnaire to be performed.

Keywords: Information Visualization; Spatiotemporal Data; Visual Metaphors; Visual Clues; Storytelling; User Experience; Taxonomy

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I want to express gratitude to my significant other and to all my friends, for I am deeply thankful for their kindhearted motivation, always being there, and reminding me what this is all for.

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To everyone who participated in the questionnaire - I may not know all of you personally but know you have made a great contribution towards scientific research for the information visualization community.

And last, but certainly not least, to all my family, from the bottom of my heart, for all the opportunities given to me, for trusting me, and always bringing out the best part of me.

To all of you, thank you.

Diogo Fernandes

"The impediment to action, advances action.
What stands in the way, becomes the way."

Marcus Aurelius

Index

Lista de Figuras

Abbreviations

ST	Spatiotemporal
GIS	Geographic Information System
InfoVis	IEEE Conference on Information Visualization
VAST	IEEE Conference on Visual Analytics Science & Technology
EuroVis	Eurographics/IEEE VGTC Conference on Visualization
PacificVis	IEEE Pacific Visualization Symposium
LDAV	IEEE Symposium on Large Data Analysis and Visualization
TVCG	IEEE Transactions on Visualization & Computer Graphics
AT	Aggregated Taxonomy (for Spatiotemporal Visual Clues)
SUS	System Usability Scale

1. Introduction

This chapter introduces the current work, starting by providing context, in Section 1.1, regarding data visualization, more importantly in the spatiotemporal (ST) domain, and the motivation behind the work. Afterwards, the problems with current spatiotemporal visualization frameworks are identified in Section 1.2. Subsequently, in Section 1.3, the objectives aimed to be accomplished with this work are listed. Finally, in Section 1.4, an outline of the document structure is provided, briefly explaining the contents of each chapter.

1.1 Context and Motivation

Alongside the evolution of science and technology, people have access to large amounts of data regarding spatiotemporal phenomena. However, having more data does not necessarily ease the perception, communication or analysis of a phenomenon's evolution (Marques et al., 2020).

When it comes to visualizing spatial information, most techniques rely on maps. As for visualizing data related to time, most techniques often use timelines or time frames. But despite that, when combining these two types of data, hence having spatio-temporal phenomena, there are no standard techniques that simultaneously reveal both aspects of the data equally.

This happens because spatiotemporal data heavily relies on context.

While some visualization techniques apply for more general cases, like road traffic or pandemic growth analysis, others tend to display data belonging to a more niche situation. Some examples include visual systems created for colonial seabirds (Palleschi & Crielesi, 2019), attenuation and accumulation maps for generalized crime analysis (Albino et al., 2017), or even systems that cluster event collections such as a whole overview of Mexican history (Craig et al., 2014).

While there is currently a lot of work and articles exploring all types of niches within the spatiotemporal spectrum of data (see chapter 2), it was clear that there wasn't much investigation made regarding the actual visualization techniques themselves yet. This means that there are still plenty of experiment opportunities regarding how this specific type of data is best meant to be analysed, and how important the concept of storytelling can be for the analyst. Be it consciously to the user or not, the overall visual narrative through a visualization interface plays an important role in gathering all the information and showing it to the viewer in an engaging and intuitive way.

Therefore, the motivation behind this work consists of studying how user experience aspects can be improved and tailored according to the task, facilitating the data visualization process and allowing the end-users to retrieve more valuable knowledge regarding the spatiotemporal phenomenon. Furthermore, this work also contributes to the spatiotemporal visualization spectrum, more specifically towards a review and summarization of current state-of-the-art methods regarding each respective adopted visual clues.

1.2 Problem Definition

As spatiotemporal data is a very broad and complex term, and every dataset is different from the other, choosing the right visualization technique can be a difficult job, which also is related to the tasks that are related to the visualization. Each visualization method available adopts many different "visual clues" in order to visually represent certain data characteristics such as outliers, trends and correlations, in a simpler and faster way: some use growth ring techniques on top of maps, others approach data in a more abstract way with three-dimensional glyphs, icons, etc.

There are a wide number of methods and possible visual clues for visualizations - but which ones may be considered more used or suitable for a task? What is the most efficient way to display a specific type of spatiotemporal data? And most importantly, what are the most promising types of visual clues and what are they more useful for? What visual channels are being used to communicate, and what is their intended purpose? Do they convey the correct information to the user?

1.3 Hypothesis

The presented work addresses these questions in a broader research question - Are visual clues important for the understanding of spatiotemporal data visualization? The proposed hypothesis is that, undoubtedly, the effective use of proper visual clues provides a better understanding of complex data such as ST data.

To explore this question, user experience and visual narratives will be intertwined, within the ST spectrum of data visualization, to observe how semiotics and visual communication can play a crucial role in understanding information correctly.

1.4 Objectives

The starting goal of this work is to assess the current situation on spatiotemporal visualization techniques. For each work regarding the literature, to analyse and categorize the adopted visual clues and their role in the storytelling and visual narrative process and how they convey the intended information. Based on the previous literature review and on previous taxonomies the current work expects to further contribute to classification systems, in which future ST data visualization methods can be classified regarding their visual clues and purpose. From the previous work we also expect to develop a prototype and perform user tests to study a subset of visual clues and their level of efficiency regarding particular tasks. The work can be summarized as follows:

- review literature on visualization techniques for ST data / Obtain an exhaustive list of state-of-the-art spatiotemporal techniques

- review literature on taxonomies for (spatiotemporal) information visualization

- develop a summarized taxonomy integrating previous reviewed techniques / Have an extensive knowledge on data visualization and ST data techniques and know how they are linked

- classify reviewed literature on visualization techniques according to the summarized taxonomy and draw a summary (table and description) / Categorize main visualization techniques based on visual metaphors, clues used and main purpose

- for a subset of the most promising visual clues used in spatiotemporal data visualization, to conduct a user-centered design process, tests and measurements of the expressiveness of these visual clues.

- evaluate the results achieved from the previous tests, based on user tests and interviews, draw conclusions and relate to the proposed research questions and hypothesis.

1.5 Work Plan

To guarantee an organized workflow and to successfully go through all the objectives specified on chapter 1.4, a work plan has been developed according to the expected key milestones. The table below visually demonstrates this, starting from january until june 2022:

	JAN	FEV	MAR	APR	MAY	JUN
Spatiotemporal Techniques Research	**X**	**X**	**X**			
Development and Refinement of taxonomy regarding ST technique classification based on visual clues		**X**	**X**			
Classification of ST Techniques using proposed taxonomy		**X**	**X**			
ST technique selection for experiments				**X**		
Construction of test units				**X**		
Experiment with participants				**X**	**X**	
Experiment Analysis + relate to research questions / hypothesis					**X**	
Dissertation Writing	**X**	**X**	**X**	**X**	**X**	**X**

Firstly, the main step is to obtain an exhaustive list of state-of-the-art spatiotemporal techniques. At the same time, current taxonomies will be studied. Right after and based on this literature review on all ST visualizations, a new taxonomy will be researched, developed and proposed - this new classification is built upon previous iterations made by many different authors and will focus specifically on categorizing ST techniques based on their visual clues and used visual variables.

While the taxonomy is being developed, it will also be continuously refined and used to classify studied ST techniques to test its reliability, stability and validity. Once the most relevant techniques have been classified in context of this proposed taxonomy, its most promising visual clues will be identified and chosen for the next stage: testing.

For one or more selected test data sets, the most promising visual clues will be tested on different environments with various types of participants, to find out what their main purposes are, in what contexts the visual clues are most effective on, and how important this storytelling aspect of design, semiotics and user experience impacts the understanding of a visualization, more specifically on the spatiotemporal spectrum.

1.6 Document Structure

This dissertation is structured as follows. Chapter 2 introduces spatiotemporal (ST) information visualization and general concepts such as visual channels, visual clues etc. Next, it addresses visual analytics and visual narratives with spatiotemporal data. Following that, in the same chapter, a literature review is presented regarding techniques for spatiotemporal data visualization, going in depth regarding the perspective of adopted visual clues for storytelling purposes. This chapter concludes with a description of the reviewed taxonomies for spatiotemporal techniques and methods and with a classification of review visualization techniques.

Chapter 3 presents a new proposed classification system that includes the previous taxonomies and, while doing so, classifies techniques with regard to the adopted visual clues.

Chapter 4 details the experiment done to test the taxonomy and, at the same time, find out the most adopted visual clues used, along with their intended purpose. The experiment will measure their effectiveness through a test that encompasses the usage of the aggregated taxonomy and running user tests through it by questionnaires.

Chapter 5 presents the results achieved as well as an analysis and discussion of the results about the research questions presented in this chapter.

Finally, chapter 6 presents the conclusions and outcomes from the current work and relates them to this thesis hypothesis. This chapter also presents lessons learned and possibilities regarding future work.

2. Literature Review

This chapter reviews the related work of each of the different areas that the current work regards. The initial subsections address the most relevant concepts around data and information visualization. These include visual analytics, followed by a deeper dive on visualization of phenomena involving space and time, an overview on visual narratives, storytelling and their juxtaposition regarding techniques for spatiotemporal data visualization.

Moreover, a review of the current state of the art is presented in terms of prototyping and user testing, as part of the dissertation will later explore this topic. The last section will identify the available tools and technology that will enable said visualization, prototyping and testing mentioned earlier in the document.

2.1 Information Visualization

2.1.1 Definitions and concepts

Visualization is one important part of information communication using graphical representations, like icons or other glyphs. Pictures have been used as a mechanism for communication even before the formalization of written language (Ward et al., 2015). A single picture can contain a wealth of information and can be processed much more quickly than a comparable page of words. This is because image interpretation is performed in parallel within the human perceptual system, while the speed of text analysis is limited by the sequential process of reading combined with context (Healey & Enns, 2012). Pictures can also be independent of local language, as a graph or a map may be understood by a group of people with no common language (Ward et al., 2015).

Information Visualization is a wide research field, capable of branching towards various directions and domains. Generally, it can be referred to the domain of theories and techniques that use interactive visual computing and representations to amplify human cognition with abstract information (Card et al., 1999). DeFanti et al. (1989) specifically define the term "visualization" as the set of methods that allow the transformation of abstractionism into geometrism. This "...enables researchers to augment their process of scientific discovery", thus allowing an efficient mean to display a structure of information, as well as potentially exploring new interpretations of abstract sets of data through the practice of visual analytics. Moreover, Card et al. (1999) also introduce a relevant term, scientific visualization, in which the data, as opposed to information visualization, is physically-based, rather than assuming a more abstract form. An example of a scientific visualization would be any type of geographic data originating from real world observations.

2.1.2 Visualization Pipeline

There are many ways of creating visual representations of data. However, Tominski (2006) states each transformation is created following four main steps - data analysis, filtering, mapping and, finally, rendering. This whole process can be referred to as the visualization pipeline, a concept first approached by Campo et al. (1997). In 2000, Chi also offered a similar perspective regarding a reference model for data visualization, later to be refined by dos Santos & Brodlie, in 2004, having all previous work in mind. Figure 1 summarizes this process, and visually describes what each chapter goes through in order to progress through the pipeline.

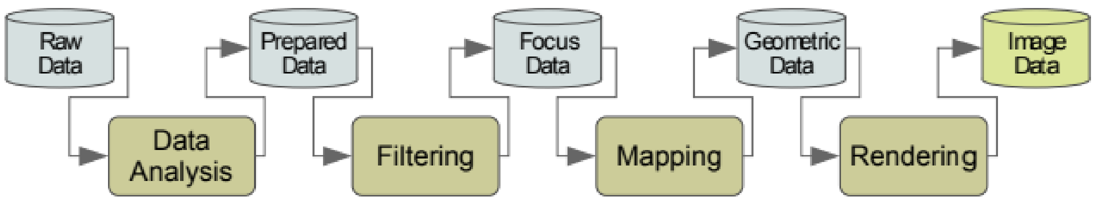

Figure 1: The visualization pipeline (Santos et al.,2004)

According to Tominski's (2006) interpretation, the dataset is firstly prepared, from a computer-centered perspective, to be visualized. This includes any interpolation of faulty values or incorrect measurements. Subsequently, the data is filtered, tailored to focus on only a specific section of the information. Since this filter is chosen by and for the user, this chapter can be seen as a user-centered step. However, there can sometimes be an edge case where the filtering is done by the computer itself. In the mapping part of the pipeline, the data set goes through what can be considered the core meaning of information visualization - it is transformed from an abstract piece of data to a logical and geometric representation for the user. These geometric primitives, which can be shown as points, lines, or other types of glyphs, differentiate themselves by presenting different graphical attributes, such as form, size, brightness, pattern, etc. (Tominski, 2006). This combination of geometric primitive along with its graphical aspects can be referred to as a visual clue. By carefully designing and mapping many visual clues, each having a unique identity when it comes to their visual channels, a visual metaphor is created. As Tominski (2006) emphasizes in his work, "*... this mapping step is the most critical one for achieving expressiveness and effectiveness, and is, therefore, the most interesting one to visualization designers.*"

Once mapped, the data is then converted into geometric data, which is rendered to an image to finally be properly visualized. When the source data through the whole visualization pipeline process, it is ready to be viewed, explored and analysed, allowing users to interactively browse through it, discovering behaviors, trends, outliers, thus being able to make decisions such as the validation or refutation of hypotheses (dos Santos & Brodlie, 2004).

Semmo et al. (2015), as seen in Figure 2, has also extended the previous pipeline to include a more thorough taxonomy tailored to cartography-based visualization, which not only integrates the general guidelines of the original reference model but also includes additional classifications regarding user interactions. These include categorizations on psychological and physiological perception aspects, cartography modeling forms, various types of filtering aspects, variables of rendering techniques, and most importantly, in terms of relevancy to the current work, mapping aspects based on graphical variants, how they turn into visual elements (visual clues and metaphors) and the respective tridimensional mechanisms involved.

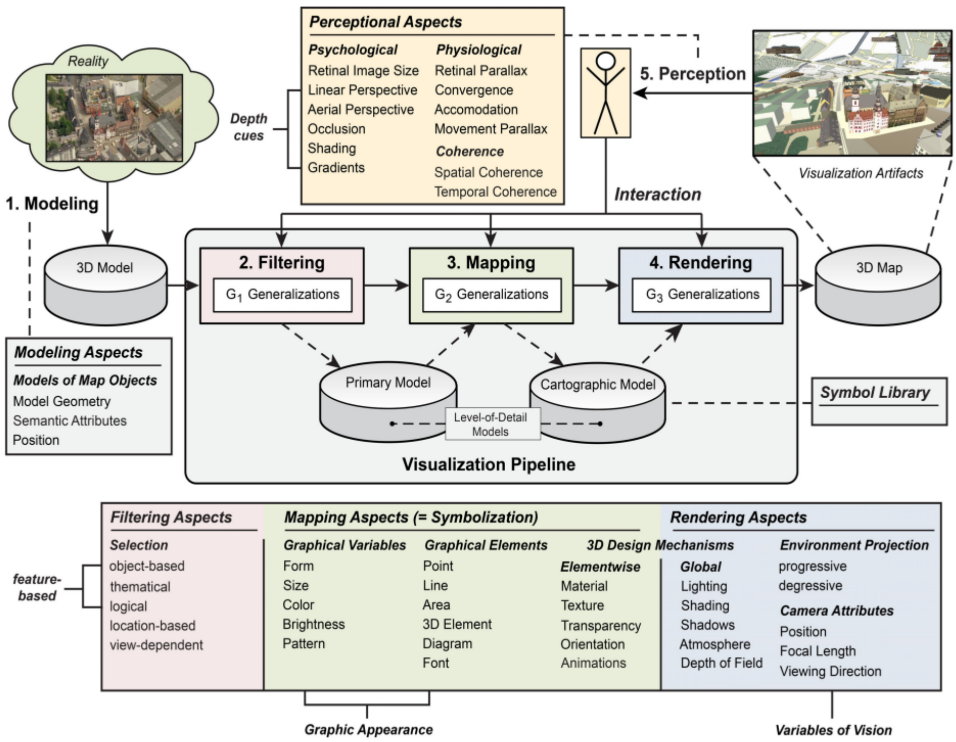

Figure 2: Extended 3D semiotic model by Semmo et al. (2015)

2.1.3 Visual Analytics

Visual analytics (VA) is the science and practice of analytical reasoning by combining computational processing with visualization (Andrienko et al., 2020). VA intertwine the strength of data gathering that computers have, with the abstract reasoning and interpretation of human analysis. Through VA users can identify new types of relationships, patterns or groups between data subsets that may be hidden to the machines' "binary eye".

Overall, VA systems help users navigate from small to large and complex datasets. However, in the situation of a larger and more extensive dataset, there is often too much information or too many dimensions to display in one single view, requiring VA researchers to study systems that summarize available data through either a set of interlinked visualizations or summary visualizations. Sarikaya et al. (2018) have identified trends in how designers use these factors to provide a basis for a more structured design of a visualization, known as *summary visualizations*.

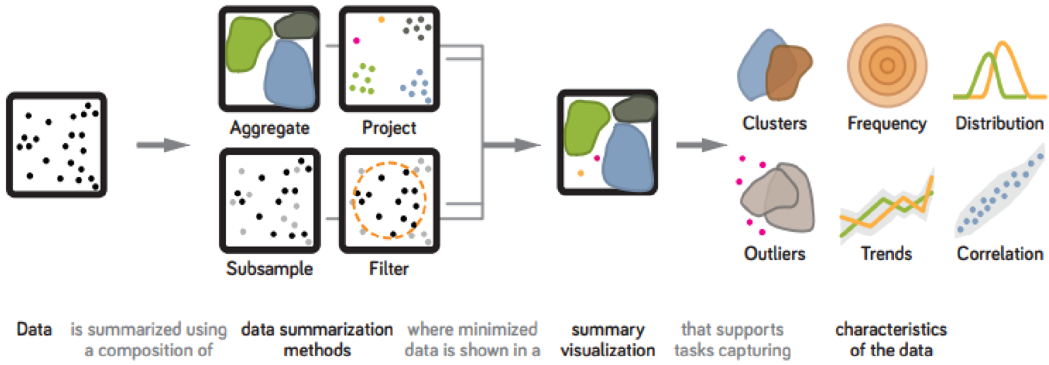

Figure 3: Generalized schematic of summary visualizations for data (Sarikaya et al.,2018)

As described in **figure 3**, summary visualizations help the user to capture certain data characteristics such as outliers, trends and correlations, in a simpler and faster way. This taxonomy, according to its authors, sufficiently captures the most common strategies for data summarization and helps to identify trade-offs between summary approaches.

2.1.4 Visual Clues and Metaphors

The mapping stage of the visualization pipeline, (chapter 2.1.2), is the most related to the concepts of visual metaphors and how they are built with the rendered image data. In a simple and summarized way, and for the purpose of context for this work, it can be said that visual metaphors are built with a group of visual clues (image data, as seen on the visualization pipeline), which in turn are made of various visual channel properties.

As presented in said section, the mapping and rendering stages of the visualization pipeline encompass the decisions of the graphical representation of the data in question and the rendering of that representation, respectively. Every visualization technique has its own way of processing and showing image data, but generally speaking these last two stages always convert the raw/processed data into abstract/scientific visualization objects to be perceived and analysed by the user.

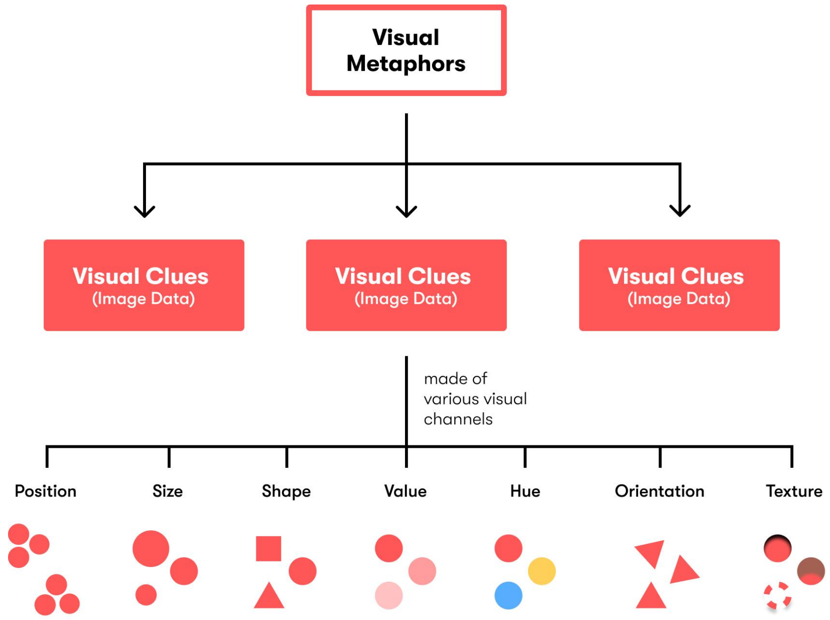

Figure 4: Visual Metaphors are made of Visual Clues (also known as Image Data), which include many visual properties on different channels

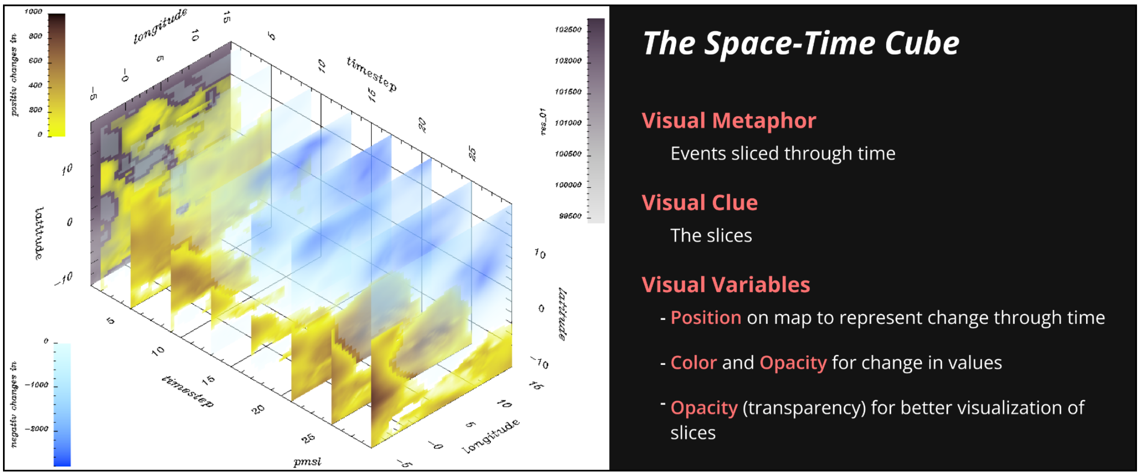

Figure 4.1: Analysis of the metaphors on the Space-Time Cube, as an example of the logic displayed in figure 4.

The obtained image data (also referred to as "visual clues" in this work) can then be dissected into various properties and characteristics according to the used visual channels (Figure 4). Formally, image data can show visual metaphors, which are visual representations of metaphorical concepts (Refaie, 2003). In terms of spatiotemporal visualization, this is essential to facilitate the knowledge that the raw data encompasses. However, it is also not without its difficulties and it can raise some very complex questions in cognitive terms, such as the context of how and where the visual metaphor is shown and how this can affect the understanding of the overall visualization (Refaie, 2003). The components of a visual metaphor are referred to as visual variables (Bertin, 2010). Additionally, the author identifies seven types of variables, each of them having an associated level of organization: planar dimensions (position), size, value (brightness of the color), texture, color (hue), orientation and shape (Figure 5).

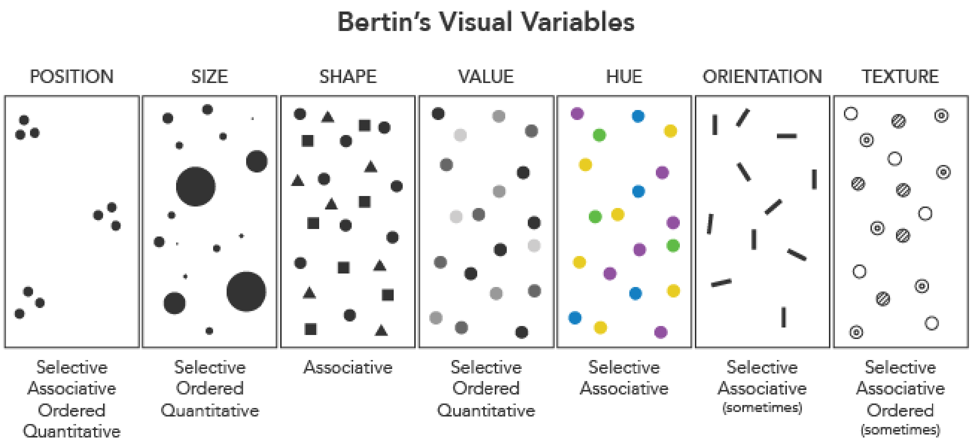

Figure 5: Jacques Bertin's Visual Variables, adapted from *AxisMaps* (2022)

Later, Morrison (1975) expands the original set and adds color saturation and arrangement as new visual variables. Furthermore, MacEachren (1995) introduces the concepts of crispness, resolution and transparency as properties that have important influence in their use for map symbols and visual metaphors.

As summarized by Marques et al. (2020), Jacques Bertin points out that each of these visual variables have a certain level of how they are perceived:

- **Associative perception** — the assessment of equality of a variation or category classification (i.e., the perception of two instances of the visual variable representing the same category or value);

- **Selective perception** — the ability to instantly isolate all the elements of a category (i.e., being able to answer the question "Where is a given category?");

- **Ordered perception** — the instantaneous estimation of relative order between the elements (i.e., being able to order the categories without consulting the legend);

- **Quantitative perception** — the immediate perception of the numerical ratio between two elements (e.g., understanding when a sign represents the double of another).

Position

In a spatiotemporal visualization, it is crucial to know the absolute position of the data entries for later comparison. Typically, the **position** property of data can be easily identified as spatiotemporal data tends to be presented on top of some sort of cartographic visualization. Since locations in maps are predetermined by geography, Bertin separates this property from other visual variables by classifying this as an “imposition variable”, as opposed to a regular retinal variable.

Size

The size property of a visual variable refers to how much space a glyph or image data occupies. Be it an area, perimeter or thickness increase, size is easily perceivable making it a strong and consistent variable for conveying information. However, there can be drawbacks in using such property, as it has been reported that there is an extensive amount of people who cannot properly differentiate or compare two-dimensional sizes (The Pennsylvania State University, 2017). This problem is related to the Ebbinghaus and Delboeuf illusions (Figure 6), similar situations in which two identical circles can appear to be different sizes, depending on the symbols that surround the central circles (Roberts et al., 2005).

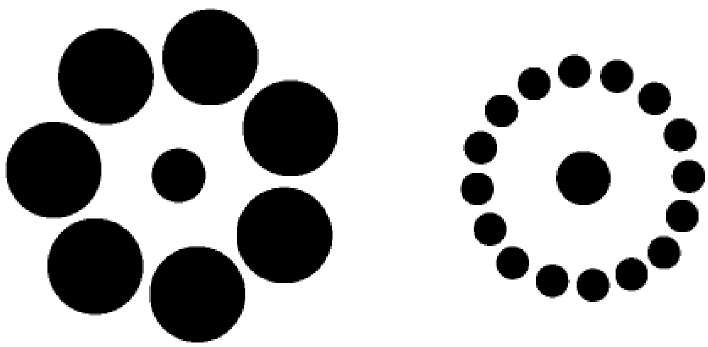

Figure 6: The Ebbinghaus and Delboeuf visual illusions.
Source: (The Pennsylvania State University, 2017)

As a mean to eliminate this visual conflict from visualizations, Flannery (1971) developed a scaling factor in an attempt to "correct" the sizes of circles so that map readers would correctly estimate values from symbols.

Shape

According to ESRI, an international supplier of geographic information system (GIS) software, web GIS and geodatabase management applications, a shape is a simple design that is used to symbolize an attribute on a map[1]. The shape property is a group of characteristics or visible forms of a geographic object as represented on a map. A GIS uses points, lines, and polygons to represent the shapes of geographic objects[2].

Hue

Hue is the main property of a color. It is described as "the degree to which a stimulus can be described as similar to or different from stimuli that are described as red, orange, yellow, green, blue, violet,..." by Fairchild of RIT Munsell Color Science Laboratory[3] (Fairchild, 2011). Within a two-dimensional setting, the whole aspects of color may not help in understanding an object's shape, its layout in an environment, or stereoscopic depth, but it can certainly be perceived as an attribute of an object, which suggests an important role in visualization: labeling and categorization (Ware, 2004). The author also introduces a group of *perceptual factors* to be raised when considering using hue, saturation, or any other color property as a label for image data in visualizations: distinctiveness, unique hues, contrast, color blindness, number, field size and conventions. As compared later in this chapter, these perceptual observations will have an impact alongside the Gestalt Principles.

The next list outlines the most important aspects of each factors (Marques et al., 2020):

- **Distinctiveness** — the degree of perceived difference between colors placed close together;
- **Unique Hues** — suggests that for each category there should be one color, sufficiently separated from the others in the color space;
- **Contrast with Background** — the background color can drastically alter the perception of a color. One could either place a black border around the object or ensure a significant difference in luminance between both colors;

[1] Definition sourced from https://support.esri.com/en/other-resources/gis-dictionary/term/9fe8e022-872d-442e-8f0d-a08229167823

[2] Definition sourced from https://support.esri.com/en/other-resources/gis-dictionary/term/9fe8e022-872d-442e-8f0d-a08229167823

[3] Definition sourced from https://docplayer.net/140632-Color-appearance-models-ciecam02-and-beyond-outline.html

- **Color Blindness** — take in consideration that there is a portion of the viewers which cannot distinguish between some colors;
- **Number** — limit the number of colors to a range of five or ten;
- **Field Size** — the realization that very small color-coded objects are difficult to distinguish. Smaller objects should have highly saturated colours to increase discrimination, while larger objects the colours should have lower saturation, differing only slightly between each other;
- **Conventions** — to consider common color conventions, like using red for high temperatures or for dangerous objects, without disregarding cultural differences (death can be depicted using black in most European countries but in China the same phenomenon is symbolized by the green color).

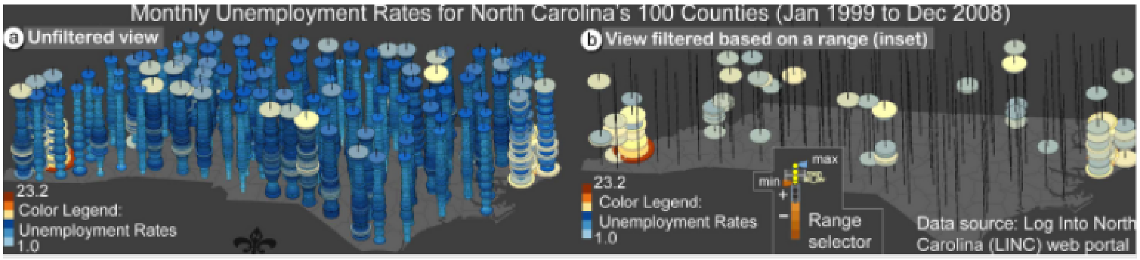

Figure 7: A spatiotemporal visualization technique, *DataVases*, using color-based visual channels to create a metaphor - a vase that expands in width based on value and vertically as time progresses. (Thakur & Rhyne, 2009)

Alongside the stated color properties, spatiotemporal visualizations take advantage of *pseudocoloring*, a technique that continuously represents varying map values using a sequence of colors (Ware, 2004)**.** Figure 7 demonstrates a ST technique using color-based visual metaphors and figure 8 exemplifies a use of pseudocoloring on a choropleth map to represent the magnitude variance of an earthquake on a non-specified region.

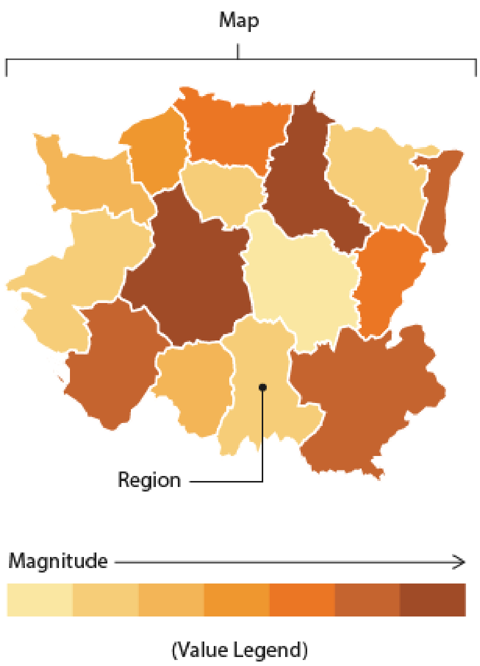

Figure 8: A choropleth map that uses pseudocoloring to signify value change from region to region. Source: datavizcatalogue.com[4]

Orientation

Orientation is another property of visual clues. The term refers to the direction labels, symbols and other glyphs are facing on a map (Ware, 2004). As this is a more context-specific property, it is not as commonly used as other variables. However, it is especially useful in visualizations that encompass the notions of movement and direction, such as wind or storm tracking, or even road and traffic analysis.

Figure 9 demonstrates the spatiotemporal technique, "Trajectory Wall" (Tominski et al., 2012), that shows temporal, spatial, and attribute aspects of movement data as a hybrid 2D/3D visual representation. The movement patterns displayed are regarding the maximum velocity cars reach in everyday traffic around the whole continent of Africa. Within each line, speed is represented with hue variations and the concept of pseudocoloring, as well as an embedded arrow indicating the orientation of the traffic. As time progresses, the two-dimensional line rises its position on the y-axis, on top of the cartographic map.

[4] Sourced from https://datavizcatalogue.com/methods/choropleth.html

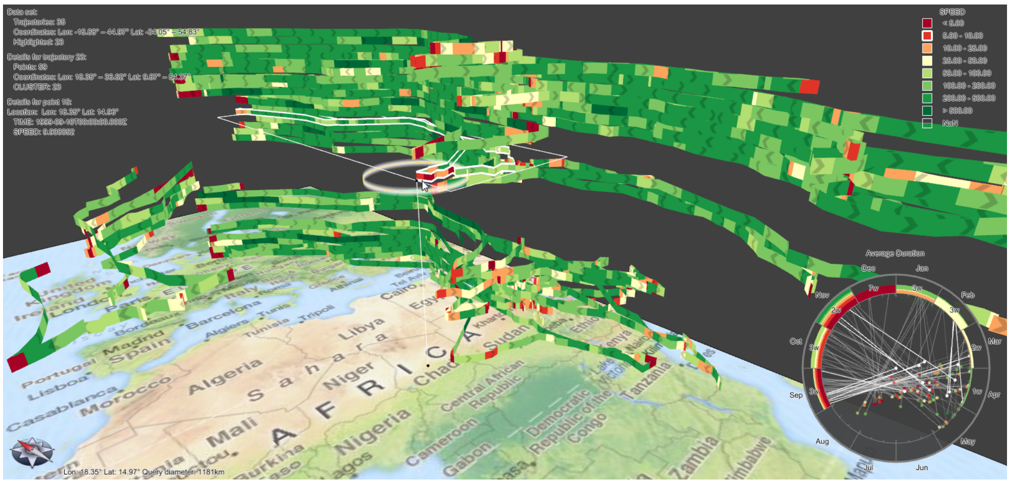

Figure 9: Spatiotemporal technique, Trajectory Wall, using color, position and orientation channels to effectively display its data (Tominski et al., 2012)

Texture

Although terminology for this property still varies somewhat today, texture or pattern in this context generally refers to an aggregate symbol composed of recurring sub-symbols. Figure 10 is an example of how this can be beneficial - the spatiotemporal technique *Contour Line Stylization* displays multiple views, some of them containing the same region and information but with a different texture, in order to show various types of data (albedo, soil moisture, pressure and temperature).

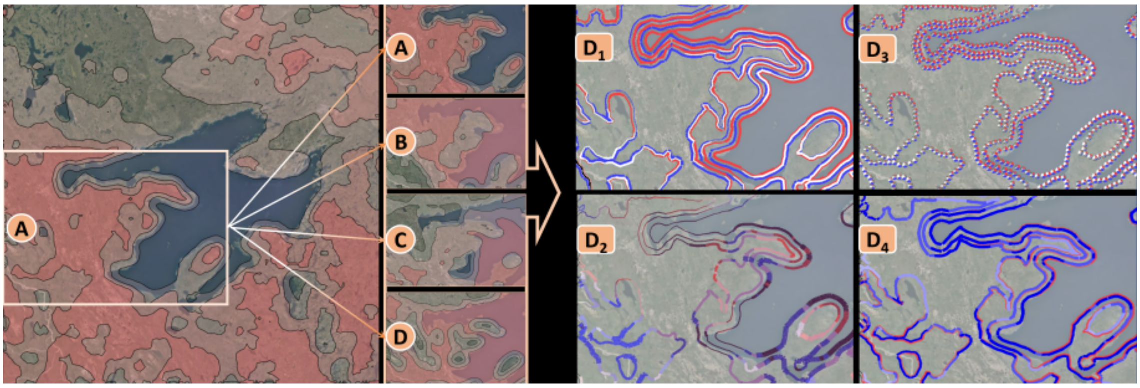

Figure 10: Spatiotemporal technique called Contour Line Stylization, using texture in multiple views (Zahan et al., 2021)

All of Bertin’s visual variables and respective combinations form an image data capable of representing a visual metaphor (Refaie, 2003). An image data with its own visual variables can also be referred to as a visual clue. So, consequently, it can be said that a visual metaphor is made of visual clues, which in turn, are made of one or more visual variables.

When it comes to identifying which elements in our visuals are signals (the information we want to communicate) and which might be noise (visually distracting clutter), the **Gestalt Principles of Visual Perception** are to be considered (Knaflic, 2015). **Gestalt principles** have been outlined as the “laws” of perceptual organization which may vary in different studies, but the following ten are generally accepted (Peterson and Berryhill, 2013):

- **Proximity** — Elements that are close together appear to be more related than things that are spaced farther apart.
- **Similarity** — When visual elements appear to be similar between them, they subconsciously get grouped together. Furthermore, users tend to think they have the same function.
- **Common Region** — Objects which are physically enclosed together are perceived to be part of a group;
- **Symmetry**— To perceive symmetrical elements as part of a unified group
- **Continuity** — The eyes seek the smoothest path and naturally create continuity in what is seen even where it may not explicitly exist;
- **Connection** — If elements are physically connected (e.g., through a line), people tend to understand that they are paired together
- **Figure/Ground -** To seek solid, stable image data. The brain dislikes uncertainty, so it distinguishes between the objects it considers to be in the foreground and the background of an image;
- **Closure -** Simple parts are combined to create a whole image, even if that information is not explicitly displayed
- **Common Fate** - Elements moving in the same direction are more related than elements that are static or moving in different directions
- **Past Experience -** Experiences we have with a cognitive trigger such as an image, music, smell, etc. For example, the hard disk icon on a UI reminds of the “save” action for a digital file

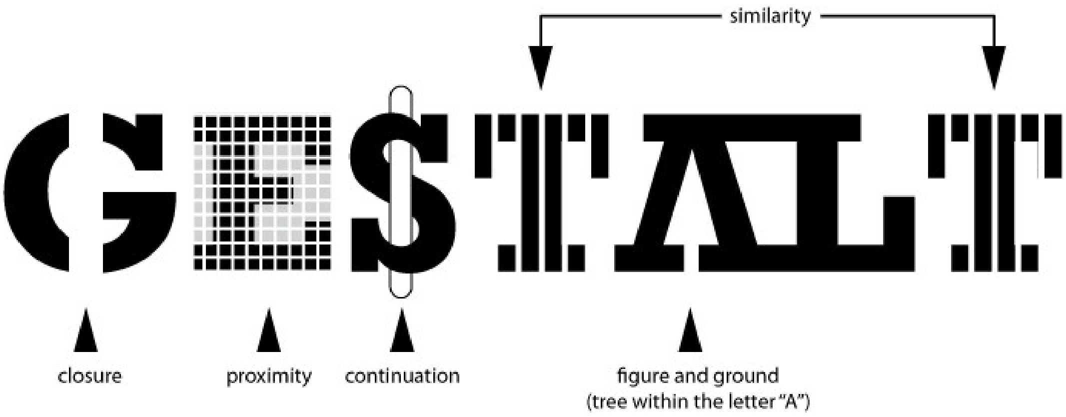

Figure 11: Some examples of the Gestalt Principles.

Source: Medium Blog Post[5]

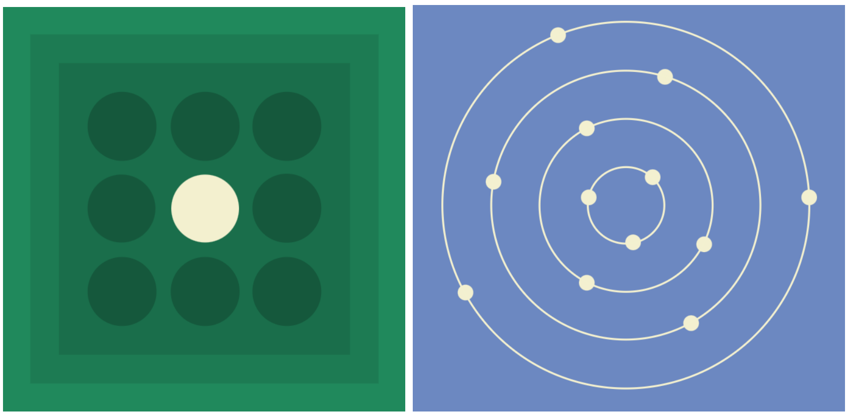

Figure 12: The Law of Common Region (left) and Connection (right). Respectively, one states that elements within the same boundaries get grouped together, and the other groups elements together if they are visually connected. Source: Laws of UX[6]

As human perception plays an important role in correct visualization (Healey & Enns, 2012), a deep understanding of the topic can significantly improve both the quality and the quantity of information being displayed (Ware, 2004). Yablonski (2020) also shares this vision, by stating *"...understanding of psychology—specifically the psychology behind how users behave and interact with digital interfaces—is perhaps the single most valuable non-design skill a designer can have. The most elegant design can fail if it forces users to conform to the design*

[5] Sourced from https://medium.com/ringcentral-ux/gestalt-principles-learn-how-to-influence-perception-83112932d0bc

[6] Sourced from https://lawsofux.com

rather than working within the "blueprint" of how humans perceive and process the world around them". In addition, the book *Laws of UX,* by the same author, goes around exposing how, exactly, aesthetically pleasing design creates positive responses. Furthermore, it also demonstrates how the cognitive and psychological principles of Gestalt and heuristics can be applied to any type of design - information visualizations included.

2.1.5 Categorizing Phenomena Involving Space and Time

Data can assume many different forms. These, as said in previous chapters, can go from an abstract to a more specific frame of reference, have just one or multiple variables, be displayed in a 2D or 3D manner, or even be presented in a dynamic or static way. Spatiotemporal phenomena is a term that describes objects that exist or occur in space and the transformations that occur to their multidimensional attributes over time (Andrienko et al., 2011).

An example of a spatiotemporal phenomenon is the COVID-19 pandemic spread. The virus (the object) spreads from person to person, country to country (geospatial variable), through time. A dataset describing COVID-19 pandemic spread could then be explored to identify possible origins, potential spread locations and to discover new variants.

In an attempt to classify this phenomena in a simpler, more general way, N. Andrienko et al.(2020) states there are three major forms of spatiotemporal data structure: spatial events, spatial time series, and trajectories. Spatial events are considered to be the elemental component of ST data - it's an event happening in a geospatial location. Spatial time series, as the authors say, "*consist of attribute values specified at multiple different spatial locations and different times*". As for trajectories, they're considered as movement data, meaning they can be used to identify changes of spatial positions of moving entities.

Aigner et al. (2011) propose a taxonomy for time-oriented data in which each category has been purposefully created to answer the three fundamental questions of where ("where is it?"), when ("when is it?) and what ("what is it?"), inspired by the *pyramid framework,* first acknowledged by Mennis et al. (2000). **Figure 13** gives a summarized view on the three main categories created, as well as their respective subclassifications.

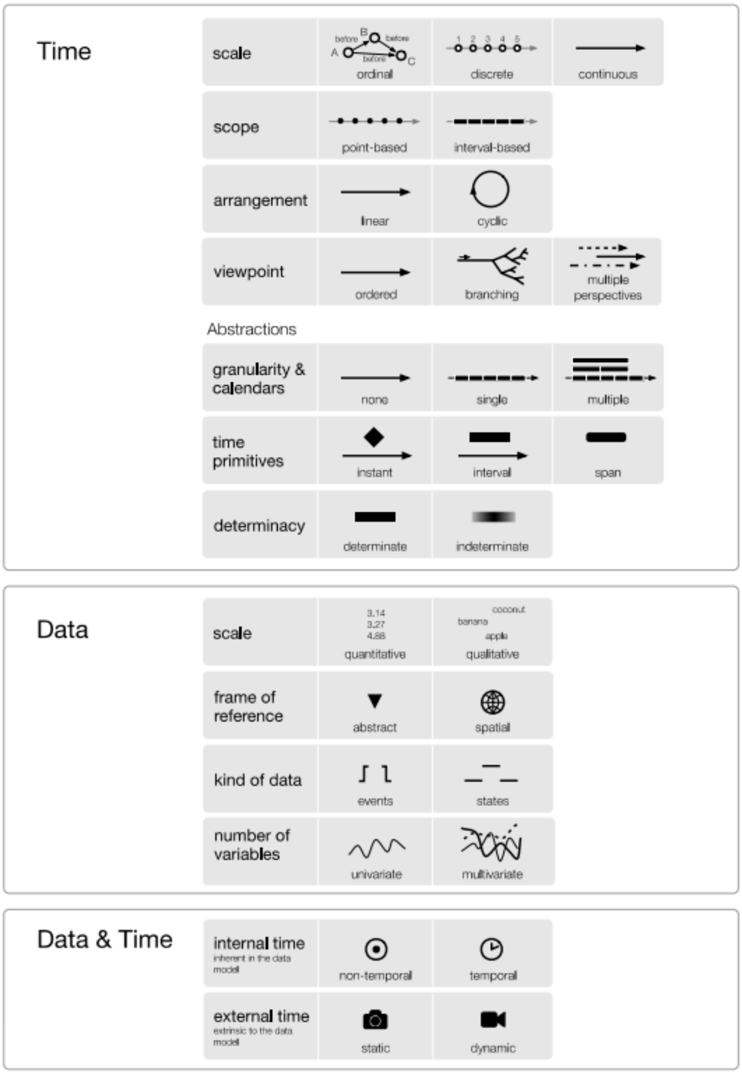

Figure 13: Taxonomy for time-oriented data proposed by Aigner et al. (2011)

Alternatively, Zhu et al. (2021) presented a categorization for space-and-time data with the intent of creating an easy-to-understand low-level grammar to describe visualization techniques (Figure 14). This taxonomy is based on four dimensions: spatial data visualization, temporal data visualization, spatial-temporal synchronization, and structure. As described by the creators, “*Each dimension is further divided into lower-level visualization attributes. Our survey shows that a small set of visualization elements can describe a wide variety of spatial-temporal data visualization techniques. This work is the first step towards creating a grammar for spatial-temporal data visualization.*”.

III. TAXONOMY

A. Overview

Our taxonomy tree for spatial-temporal data visualization is as follows.

- Spatial data visualization
  - Chart type
    - Cartographic map
    - Scatter plot
    - Circular chart
    - Other map
  - Visual variable
    - Color
    - Position
    - Orientation
    - Text
- Temporal data visualization
  - Chart type
    - Time curve
    - Timeline
    - Time frames
    - Time circle
    - Time table
  - Visual variable
    - Color
    - Position
    - Orientation
    - Text
- Spatial-temporal synchronization
  - Interaction
  - Coordinate system (regular or polar coordinates)
  - Layer
  - Animation
  - Separation
  - Visual
- Structure
  - Dimension
    - 2D
    - 3D
    - 4D
  - View
    - Single view
    - Multiple views

Figure 14: Taxonomy tree for spatio-temporal visualization (Zhu et al., 2021)

As this type of data is very complex, there is a need to have increasingly more typologies based on specific topics, rather than having an extensive one that attempts to describe every possible outcome of a spatiotemporal event. Such is the case of interaction classifications. Figueiras (2015), as seen in figure 15, contributes to this topic by exploring a new categorization set for interactions on data visualization techniques. Additionally, inspired by this last work, a new iteration has been developed by Rodrigues and Figueiras (2020), based on user testing and new classification suggestions made specifically for data involving space and time.

ST	1	filtering	*theme*	Display only items with the properties in which I am interested.
			time	Display only time points or intervals in which I am interested.
			space	Display only locations in which I am interested.
	2	selecting	*theme*	Mark or track items with the properties in which I am interested.
			time	Mark or track time points or intervals in which I am interested.
			space	Mark or track (a) location(s) in which I am interested.
	3a	zooming	*time*	Vary the level of abstraction on a time interval.
			space	Zoom in or out on an area.
	5	connect / relate	*theme*	Relate two or more items from different themes.
			time	Relate two or more time points or intervals.
			space	Relate two or more locations.
	6	reconfigure	*theme*	Give me a different arrangement of the data.
			time	Give me a different arrangement of the temporal structure.
			space	Give me a different arrangement of the locations.
	7	encode	*theme*	Give me a different visual code for the thematic components.
			time	Give me a different visual code for the temporal structure.
			space	Give me a different visual code for the geographical components.
	4	overview	*first*	Give me an overview of all the occurrences first.
			last	Give me an overview of all the occurrences last.
			on-demand	Give me an overview of all the occurrences anytime.
Generic	3b	details-on-demand	*theme*	Show me details on a specific item on demand.
	3c	linking	*theme*	Take me to complementary information.
	8	history	-	Allow me to retrace the steps I take in the exploration.
	9	extraction of features	*theme*	Allow me to extract data in which I am interested.
	10	participation / collaboration	*theme*	Allow to contribute with data.
	11	gamification	*theme*	Show me the data in a more playful way.

Figure 15: Novel interaction taxonomy for spatiotemporal data by Rodrigues & Figueiras (2020)

There are other classifications regarding ST data, though not as relevant to the dissertation topic as the taxonomies specified above. However, they have been reviewed, studied and acknowledged. Having this in mind, they will be listed below:

- Boria (2010) classified the visualization of time on maps into the following categories: moments, duration, structured time, time as distance, and space as clock.
- Bach et al. (2017) developed a detailed taxonomy for temporal data visualization on space-time cubes as well as an interactive UI for their survey.
- N. Andrienko et al. (2003) proposed a task-centric classification that consists of three dimensions: search target, search level, and cognitive operation. The search level is divided into two levels: elementary and general. The cognitive operation dimension contains two main tasks: identify and compare. They classified many research papers based on the different combinations of sub-categories within each dimension. The types of visualizations classified in this survey include map iteration, map overlay,

change map, map animation, static trajectory, animated trajectory, linked displays, and space-time cube.

- Persson (2020) proposed a data-centric classification of spatial temporal data visualizations on cartographic maps. The author classifies visualization techniques into four groups: event data, movement data, raster data, and point reference data. There are several other high-level classifications.
- Zhong et al. (2012) classified spatial-temporal data visualizations into five groups: timestamps and time labels, baselines, image series, space-time cube, and real-time rendering of dynamic 3D scenes.
- The classification by Kjellin et al. (2008) includes three groups: 2D maps, animation, and 3D space-time cube.
- The classification by Mayr et al. (2018) includes four groups: color coding, animation, space-time cube, and coordinated multiple views. These high-level classifications do not provide a comprehensive breakdown of visualization techniques into elementary visualization elements.

In conclusion, multiple authors provided very different perspectives for the classification of ST data visualization and despite some of these perspectives being complementary, there is not yet a unique encompassing and exhaustive classification system.

2.1.6 Representation of time

The concept of time has been a topic of interest in many disciplines. Be it in philosophy, mathematics, or any other major area, it can go by various definitions. The observations made by Aigner et al. (2011) and Frank (1998) are one of the most relevant, when it comes to spatiotemporal information visualization - time is not seen as a physical dimension, but more of a frame of context to situate and correlate the various states of data. Therefore, as it relies on context and how a visualization is meant to be analysed, there are infinite ways to classify the concept of time. Frank (1998) points out this exact fact - there is no correct or definitive taxonomy of time, as every information system is modeled differently and has many applications that depend on the problem they're trying to solve. So, having this in mind, many attempts of time models have been created, each to their own specific purpose.

Work regarding time-oriented systems by Aigner et al. (2011) explores and summarizes the main findings of previous time taxonomies, namely the instances of Frank (1998), Goralwalla et al (2006) and Furia et al (2008). The most relevant touch points to have in mind to effectively design a good visualization of time needs to consider the following features: the scale of time, its scope and the arrangement and the viewpoint.

According to Aigner et al. (2010), in terms of scale, time can be classified as ordinal, discrete or continuous. When it comes to ordinal time, Aigner et al. points out that "... only order relations are present (e.g., before, after).". Inspired by Aigner's work, an example of ordinal time would be a statement such as "Lucas went shopping after his dad left for work." With the given information, it is not possible to know when Lucas came back home, or if it was before or after his dad came back from work (see Figure 16).

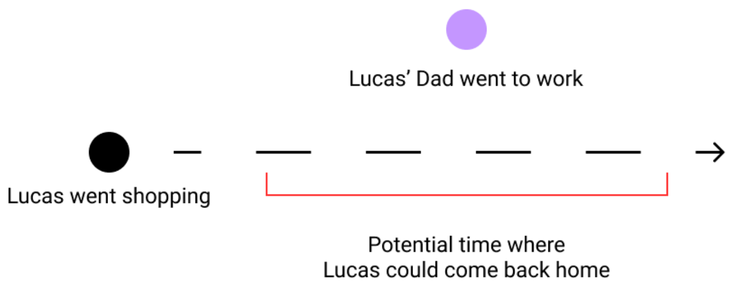

Figure 16: Ordinal scale of time. It is impossible to know if Lucas came back home before or after his dad.

When it comes to the discrete scale of time, Aigner *et al*. state the time domains can be included, and are mostly based on a small unit, such as seconds or milliseconds (Figure 17).

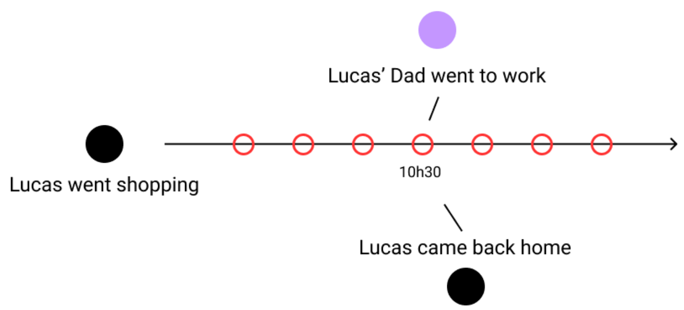

Figure 17: Discrete scale of time. Although Lucas comes back home at the same time instance as his dad goes to work, it's impossible to know the exact sequential order of both events due to the granularity of the time scale.

Finally, as the author refers, the continuous scale of time is "*...characterized by a possible mapping to real numbers, i.e., between any two points in time, another point in time exists.*" In other words, this means that it is possible to map the events in a sequential order, as time is always being monitored. Figure 18 gives an example of a continuous time scale.

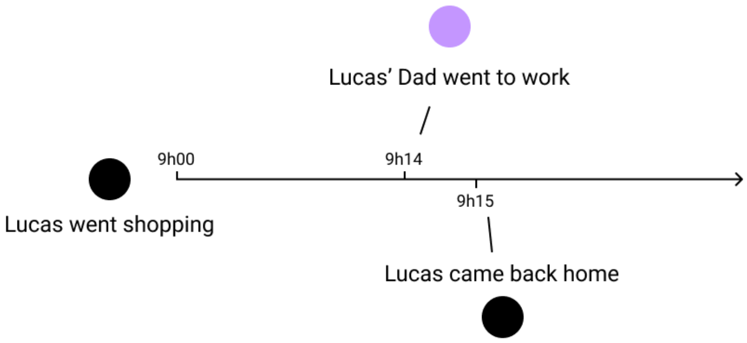

Figure 18: Continuous scale of time. It is possible to timestamp and order every event.

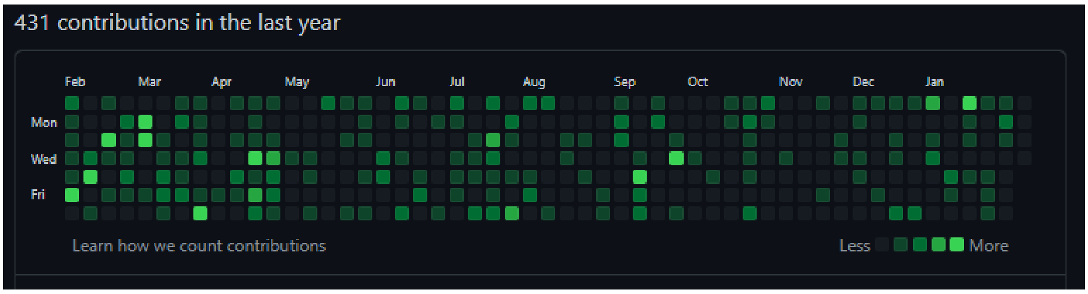

Figure 19: A practical example of a discrete time scale made with tile maps.

Source: github.com

Aigner et al. refer, in terms of scope, that time can be either point-based (Figure 20) or interval-based (Figure 21). A point-based scope consists only of static "checkpoints". In other words, on visualizations with this typology, time is seen as a single instance rather than a whole spectrum that has relations and similarities between its subsections. This particular concept happens in interval-based domains, where every time frame is related to the ones before and after.

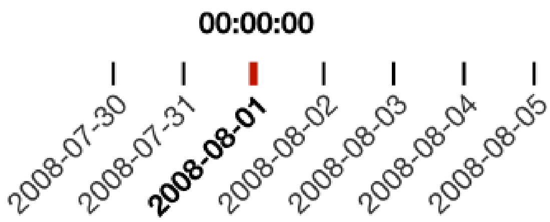

Figure 20: An example of a point-based time scope, created by Aigner et al.

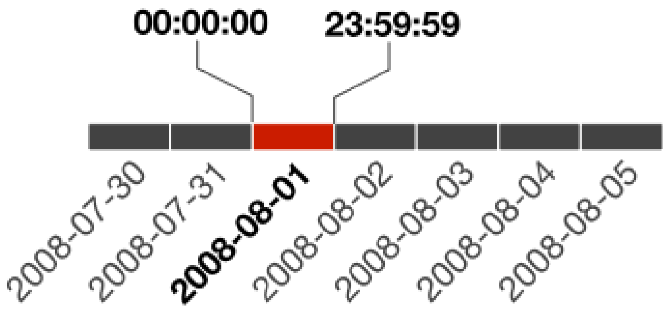

Figure 21: Interval-based time domain. Each time instance is identified by when it started and its end, in a spectrum-like representation. Source: Aigner et al.

The next main feature is called arrangement, and it seeks to explain how time is displayed and organized for the user. As time is relative to every visualization, so is the way it is represented. According to the author, time can either be linear or cyclic. A linear time arrangement (Figure 22) is directly proportional to our real-life concept of time - it's possible to identify every time instance as a past, present, and future action. As spatiotemporal data tends to focus on a specific time frame, the concept of periodicity is usually introduced to organize data into, for example, seasonal variations or weekly, monthly, and yearly averages.

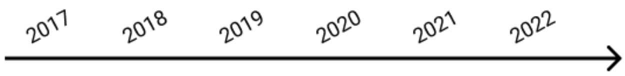

Figure 22: A linear time domain, going from the year 2017 to 2022

When it comes to cyclical time (Figure 23), the domain is infinitely interconnected within a loop, meaning that the included time values are always recurring one after the other.

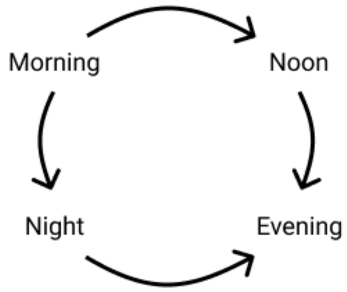

Figure 23: A cyclical time frame, looping around the various phases of the day.

Finally, on the perspective of viewpoint, Aigner et al. claims that the concept of time can be classified into an ordered view, a more branching visualization, or it can have multiple perspectives.

Frank (1998) also adds in his work, that with ordered views, events happen one after the other. Opposed to this linear concept, a branching state of time (Figure 24) represents multiple instances and events that would happen within the same time frame, but with different journeys. In other words, time is split apart into various possibilities of actions, consequently supporting decision-making processes where only one of the possible courses of actions will happen in reality. Similarly to this, a multiple-perspective viewpoint also analyses simultaneous actions, but with the difference that both actions are valid and actually happen, but within a different context. An example of this would be, as Aigner et al. explains on figure 25**,** the birth of a person (Vincent). Realistically, Vincent was born on August 8 of 2006, but his registration only went through on August 10 of 2006, two days later - so both events are factual.

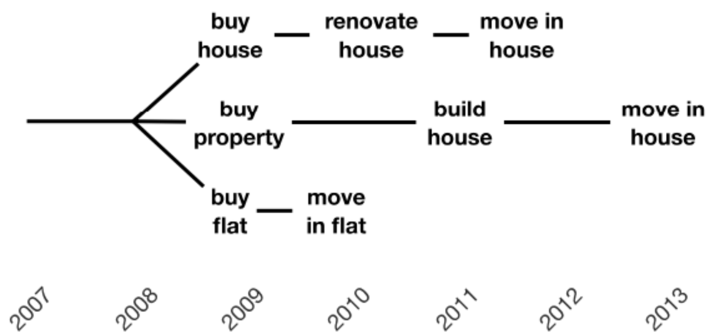

Figure 24: A branching viewpoint example by Aigner et al.

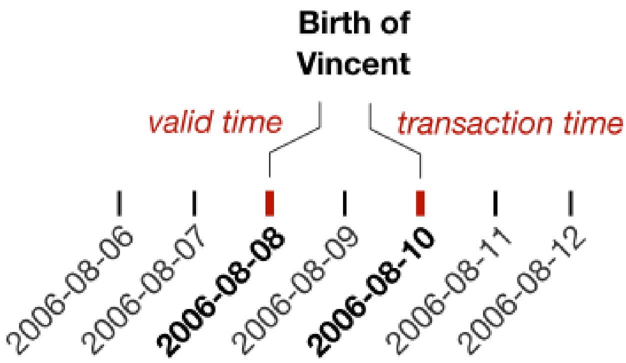

Figure 25: Multiple-perspective view of time regarding the birth of a human, by Aigner et al.

2.1.6.1 Time Primitives

To understand changes in time, we must also understand the fact that there are human abstractions to it. According to (Kerren et al., 2014), these abstractions are considered granularities. In essence, their purpose is to convert the concept of time into a much easier topic to handle in everyday life. Granularities include human-made simplifications such as days, weeks, months and years.

All of these different simplifications of time rely on a concept called time primitives, in which time is split into anchored (absolute) and unanchored (relative) primitives (Kerren et al., 2014).

As Aigner et al. (2011) states, this first group belongs to instant and interval-based time frames (situated on a fixed position alongside the time domain), as opposed to the span primitive, that has no absolute position in time.

In a summarized way, absolute primitives are portions of time that can be represented by one or more instances, hence insinuating that there is a beginning and an end to the event. In contrast, the span primitive has no absolute position in time, meaning that it merely represents a duration of intervals without a fixed position. The exact length of a span is not known precisely (Aigner et al., 2011).

2.2 Spatiotemporal information visualization and analysis

In this chapter, the definitions and concepts of spatiotemporal information visualization (ST InfoViz) will be first introduced in a more general way and in-depth in later sections. As ST InfoViz considers variables that change through space and time, it is important to also understand the different representations of time, the human abstractions and granularities to it, and how these are applied in the visualizations. Furthermore, the storytelling and visual narrative aspects of visualization are brought into consideration, as well as their relation to the world of user experience, to heighten the possibility that immersiveness and effective storytelling positively influence the user's perception of image data and ST visualizations.

2.2.1 Definition and concepts

The widespread use of Geographical Information Systems (GIS) has significantly increased the demand for knowledge about spatial analytical techniques across a range of disciplines. As growing numbers of researchers realized they are dealing with spatial data, the demand for specialized statistical and mathematical methods designed to deal with spatial data has been undergoing a rapid increase since the early 2000s (Fotheringham & Rogerson, 2008). The authors stress that the selection of said methods heavily depend on the focus of the analysis in question, hence geographers and researchers need to distinguish their visualizations between the following aspects:

- Physical structure of the spatial context (*morphogenetic analysis*);
- Symbolic meaning of space (*symbolic analysis*);
- Image data and representations of space (*cognitive maps or mental maps*);
- The purpose of the space used (*functional analysis*)
- The way people act, interact or are distributed within a spatial unit (*social analysis*)
- How the dimensions of analysis interact (Heineberg, 2006)

As Fotheringham & Rogerson (2008) observe, all these approaches take advantage of a map or some sort of cartographic data as a focal point of analysis.
However, the definition of GIS may depend on the perspective which GIS is being defined (A. M. B. V. de Carvalho, 2009). For example, Cowen (1990) writes that there are four distinct perspectives to GIS, namely a process-oriented, function-oriented, domain-oriented, tool-set or database-oriented perspectives. Clarke (1986) identifies GIS as an automated set of functions that provides professionals with advanced capabilities for storage, retrieval, manipulation and

display of geographically located data. Later, GIS is also defined as an active object or set of interrelated objects that process representations of geo-referenced entities, activities and phenomena through the use of spatial coordinate systems (Oliveira, 2008). The overall objective of a GIS is essentially said to be the management of spatial information and the appropriate support for exploratory data analysis and decision making (A. M. B. V. de Carvalho, 2009). More recently, Zhong et al. (2012) consider GIS to be based on a two-dimensional or tri-dimensional system that has the goal of answering questions such as where and when changes occur, what change patterns may be observed, and what may be the underlying causes of such changes.

To further complement this, Zhong et al. (2012) states that a spatiotemporal model can be identified as a data model that not only efficiently organizes and manages information revolving around spatial attributes (similar to a GIS), but also temporal semantics. And due to the complex nature of this group of data, there was then a need to develop a specific set of methods and techniques that transform raw information into visually readable and interpretable visualizations, each one being adapted to its specific situation - called spatiotemporal techniques.

The challenges of ST visualization emerge from different areas. First, because of the size of data accumulating changes in both space and time, spatiotemporal visualizations may require considerable computing capacity that may not be easily accessible to everyone. Secondly, this type of data can be presented through various forms and views, from 2D maps to 3D layered models, to four-dimensional and multidimensional models. The problem with an extensive visualization variety is that it requires a deep understanding of the context and technology being used. The understanding of the displayed image data is now more dependent on human cognitive principles (Zhong et al., 2012). Finally, the author points out the common problem that variables from different sources have: they are often complementary but not well combined. And for that to happen, both space and time variables need to be properly understood.

2.2.2 Spatiotemporal Information Base Concepts

How to visualize spatiotemporal data has been researched for a long time and is still a very relevant subject to expand on today. A very extensive number of approaches have been explored, but as different types and combinations of data exist, it’s important to determine which data type is going to be visualized, since it determines the problem formulation and different types lead to different formulations (Persson, 2020). As explored in the previous chapter, there are many valid but different taxonomies. However, this does not eliminate the fact that there are guidelines, in a very broad way, that most spatiotemporal information visualizations follow. With the purpose of demonstrating such techniques and their behaviors, the work of Atluri et al. (2018) will be taken into consideration.

As pointed out previously, the authors state that there are four common types of spatiotemporal information:

- **Event Data** - Data that's defined by an event occurring at a specific location in a specific time

- **Movement data** - Trajectories, considered a type of movement, are the path traveled by objects in space over time. Flight data and taxi data are common types of trajectory data. The smaller the time difference between these timestamps the greater the accuracy of the trajectory.

- **Point reference data** - Point reference data is data collected from a group of moving reference points. Say for instance data collected by weather balloons floating in space or sensors recording the surface temperature of a water body.

- **Raster data** - Raster data is defined as data measured in continuous or discrete fields with fixed points in space and time. Similar to point reference data but instead of moving, the reference points are static.

Event data, also known as **spatial events**, are described to be "Physical or abstract entities, such as lightning strikes or mobile phone calls, which occur at some time moments at particular locations and have limited existence times" (N. Andrienko et al., 2015).

In a two-dimensional scenario, this type of data can be represented as points or icons on top of a cartographic reference. One of the most popular general techniques to display such data are event maps. Event maps have icons spread out on the map representing an event. In an event map, these icons are directly related to the spatial position of the event. Many ST visualization techniques take advantage of this base-concept, as seen on figure 26, which shows the technique Icons on Maps (Fuchs & Schumann, 2004).

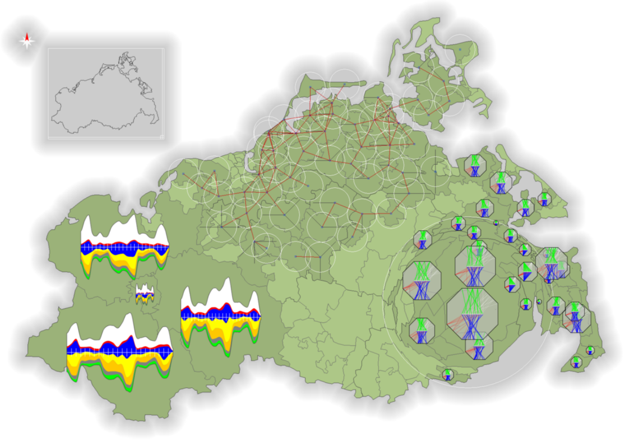

Figure 26: Icons on Maps, referenced by Fuchs & Schumann (2004)[7]

In case of tri-dimensional visualizations, (Persson, 2020) denotes that the most used techniques are the space-time cube (Figure 27) and one of its iterations - GeoTime.

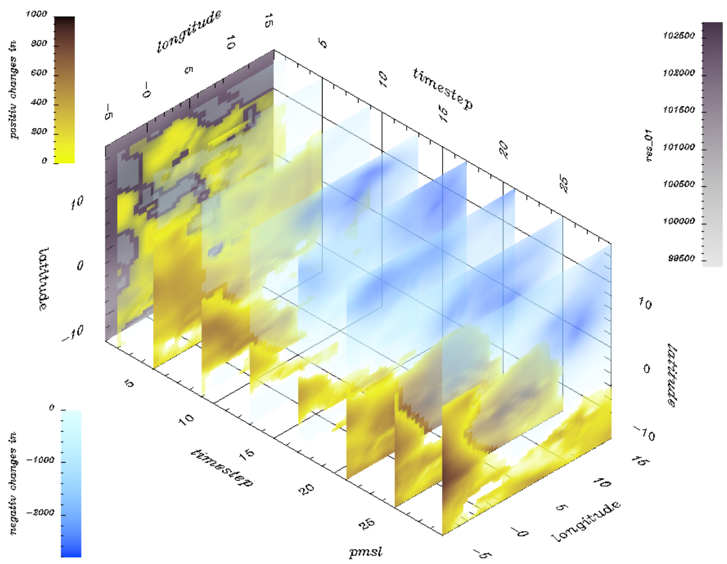

Figure 27: The Space-Time Cube, pioneered by Hägerstraand (1970)

Firstly introduced in 1970, this classic concept combines visualization of space and time in a tri-dimensional cube. The basic idea is to map two spatial dimensions to two axes of a cube-shaped object and to use the third axis for the mapping of time (Hägerstraand, 1970). One can place graphical objects in the cube to mark points of interest, or one can construct trajectories that illustrate paths of objects (Aigner et al., 2011). As the authors note,

[7] Illustration sourced from The TimeViz Browser: http://vcg.informatik.uni-rostock.de/~ct/timeviz/timeviz.html?goto=Icons%20on%20Maps

“Space-time cubes usually rely on appropriate interaction to allow users to view the data from different perspectives”.

After its first conceptualization, many researchers took the space-time cube’s core aspects and iterated them into more advanced and interactive techniques. One of the main examples is called GeoTime (Figure 28). Kapler & Wright (2005) describe GeoTime as a system to visualize data items (e.g., objects, events, transactions, flows) in their spatial and temporal context. It provides a dynamic, interactive version of the space-time cube concept, where a map plane illustrates the spatial context and time is mapped vertically along the third display dimension.

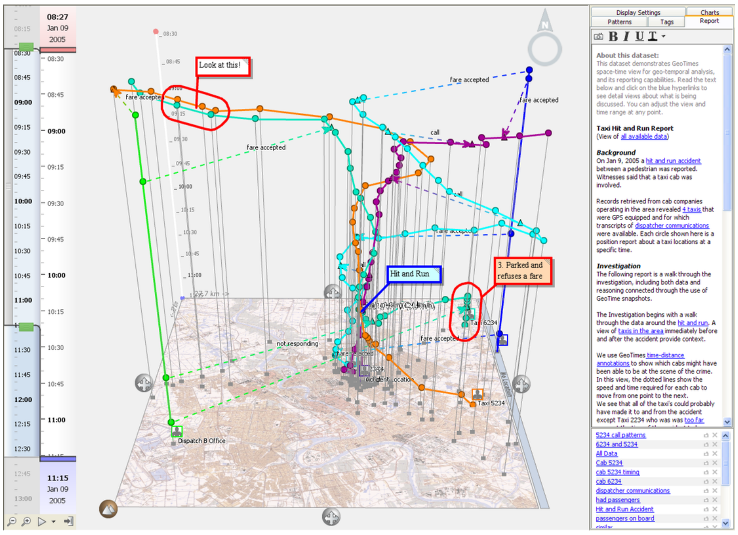

Figure 28: An example of the GeoTime interface[8]

The main purpose of GeoTime is to display all the information and data available in a single view, with the need of having multiple instances or screens. As the tri-dimensional object is fully interactive, users can rotate, zoom in and out to observe data with higher detail (Eccles et al., 2008).

Similarly to GeoTime, other techniques have been developed thanks to the Space-Time Cube. These include *Space-Time Path* (Kraak, 2008), in which a space-time cube is placed on top of a cartographic reference and path data is visualized through a line draw moving vertically as time progresses, *Spatio-Temporal Event Visualization* (Gatalsky et al., 2004), where objects differentiated by visual channels are placed inside the cube, *Time-Varying Hierarchies on Maps* (G. Andrienko et al., 2010), a technique based on hierarchical layers, as well as the Helix and

[8] Illustration sourced from The TimeViz Browser: http://vcg.informatik.uni-rostock.de/~ct/timeviz/timeviz.html?goto=GeoTime

Pencil Icons (Tominski et al., 2005) that possibilitate the view of multivariate spatio-temporal data on top of a map or other cartographic context.

Movement Data

When it comes to spatiotemporal information that are considered to be movement data, Atluri et al. (2018) consider a different approach. Movement data is considered by the authors to be a broad term that encompasses the movement progression of one or more objects. The main data gatherers for this situation are GPS-tracking devices, but information can also be observed through geo-referenced images such as social media posts or any picture containing relevant EXIF (Exchangeable Image File Format) metadata.

Movement data can be translated into trajectory-based visualizations, flow maps, density trajectory maps or tri-dimensional trajectories models (Atluri et al., 2018).

As the author indicated, trajectory tracking is especially useful for crisis or human-concentrated situations, much like concerts, traffic jams or weather disasters. Since this data is placed on top of a cartographic reference, a map, overplotting - when the data overlaps itself, making it confusing and unintelligible - may be a concern, as seen in figure 29. Relating this to Bertin's visual channels, and the concept of visual clues in general, the figure below takes advantage of the hue and value channels to accentuate the difference between data clusters (color spectrum from yellow to dark blue).

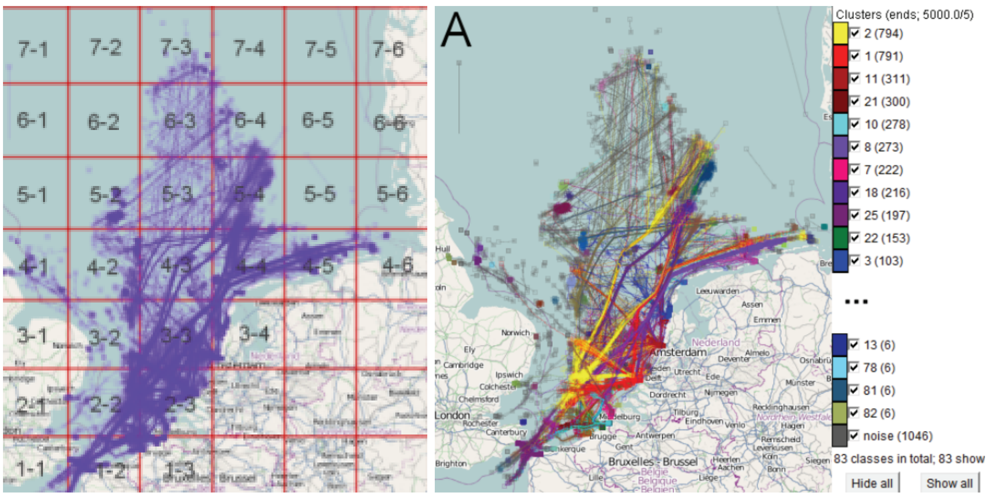

Figure 29: Overplotting on trajectory maps. Source: (G. Andrienko et al., 2013)

Another way to visualize movement data is by flow maps. With flow maps, the focus is not so much on each iteration of the trajectory, but more on the general flow and direction of the overall aggregated moves (Persson, 2020). Here, one of the main observed visual clues used is the orientation visual channel along with the Gestalt principles of connectedness. Thanks to these visual aids, and with each data iteration being separated with different values on hue, opacity, orientation and texture, overplotting is no longer a big concern as the main objective of the displayed data is to expose correlations, trends or outliers in clusters. Additionally, in order to further reduce possible clutter, the visualization could show the flows only when the number of trajectory segments are above a fitting threshold.

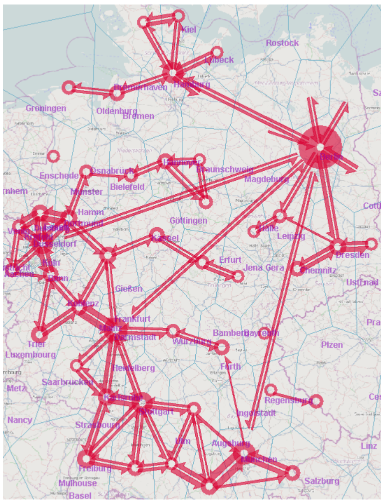

Figure 30: Flow map, showing change of positions over time, rather than a change of data values. Source: The TimeViz Browser[9]

Usually, such movements form directed (optionally segmented) trajectories connecting the starting point of a movement and its end point (Aigner et al., 2011). The most recognizable example of a flow map is the iconic representation of Napoleon Bonaparte's army through Russia in 1812 by Charles Minard. The map, shown below, features multivariate data, including both temporal and spatial information and is considered the "best statistical graphic ever drawn" by visualization expert Edward Tufte (Tufte, 2001).

[9] Sourced from http://vcg.informatik.uni-rostock.de/~ct/timeviz/timeviz.html?goto=Flow%20Map

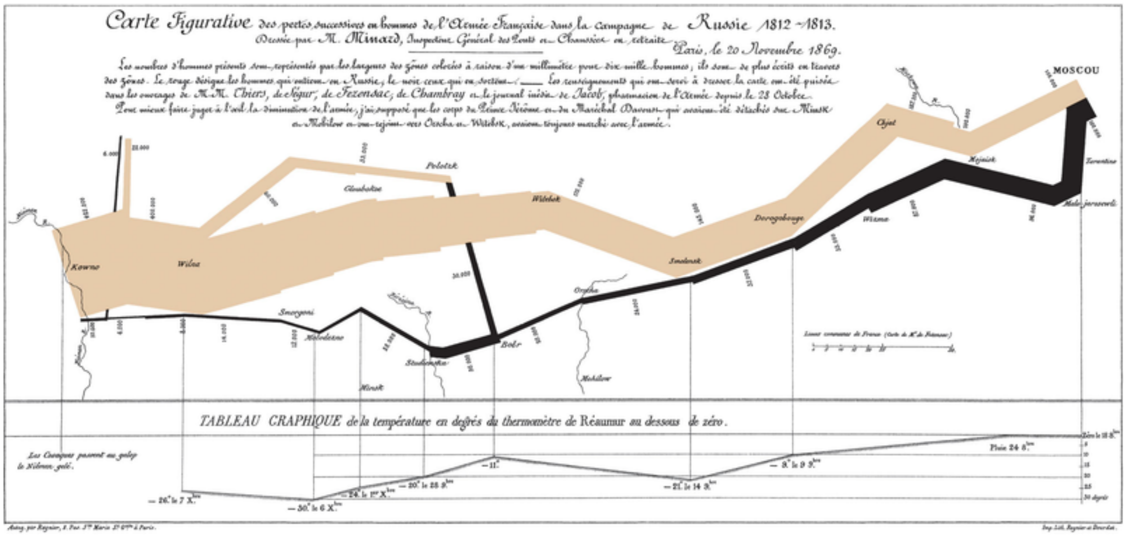

Figure 31: Charles Minard's flow map on the Napoleon's army 1812 French invasion[10]

In such a small frame, Minard's chart shows six types of information: geography, time, temperature, the course and direction of the army's movement, and the number of troops remaining. Joyce (2008) thoroughly analyzes this minimalistic yet complex graph, but efficiently summarizes: "The widths of the gold (outward) and black (returning) paths represent the size of the force, one millimeter to 10,000 men. Geographical features and major battles are marked and named, and plummeting temperatures on the return journey are shown along the bottom".

A flow map is considered to be efficiently made if it follows three aspects: merging of the edges that share the same goal, smart distortion of positions and good routing of the edges (Sagl et al., 2012). It is also not uncommon for flow maps to present various directions in terms of orientation or trajectory - the next figure demonstrates such an event, with a visualization on the export of softwood lumber from British Columbia in 2014.

[10] Sourced from https://www.nationalgeographic.com/culture/article/charles-minard-cartography-infographics-history

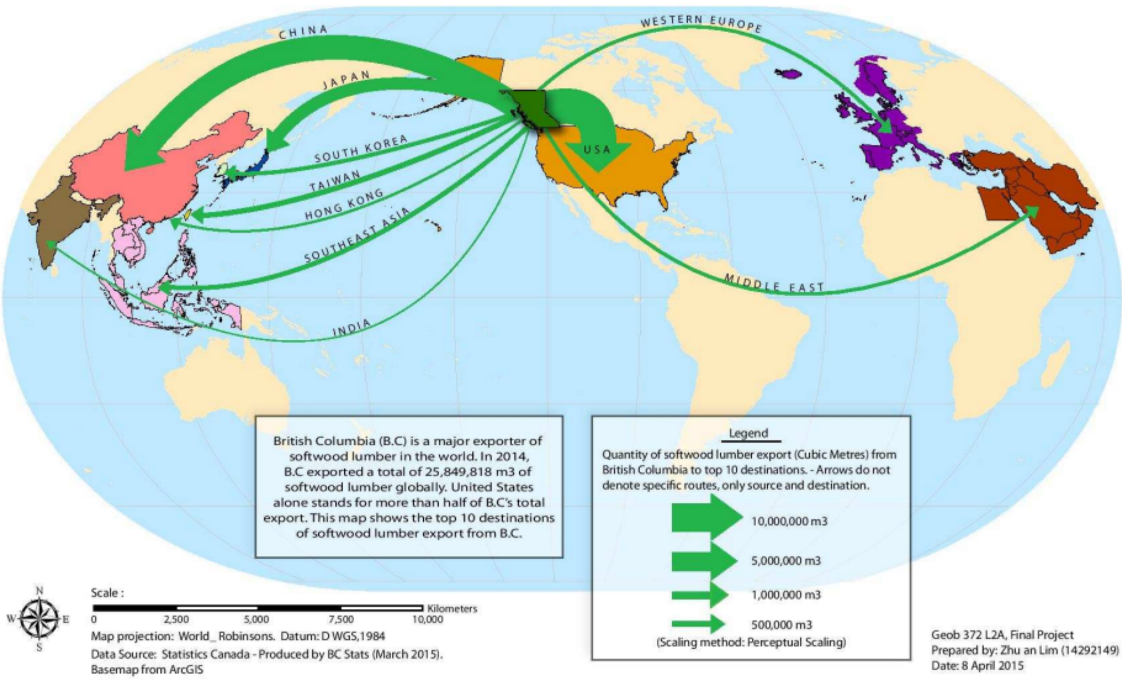

Figure 32: Different directions on a flow map. Source: (Persson, 2020)

A more niche use-case for movement data include **density trajectory maps**. A density map is a visual aggregation using kernel density estimation to generalize the behavior of multiple trajectories (Scheepens et al., 2011). They are quite similar to regular trajectory maps, but are more focused on single attributes rather than the whole movement data (Persson, 2020). In essence, density fields are shown as illuminated height maps - and as such, they take high influence from the texture and hue value (color) visual channels. With said visual clues, the created visual metaphor has the same logic as raised-relief maps, as seen in figure 33 and 34.

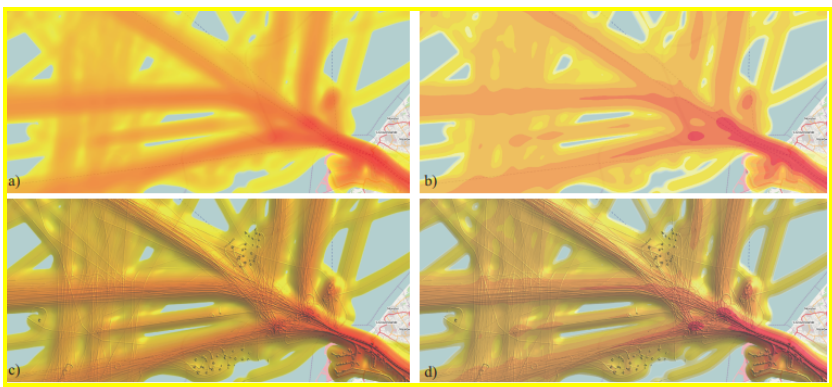

Figure 33: A portion of a density trajectory map to represent vessel movements in Rotterdam. Source: (Willems et al., 2011)

Figure 34: A raised-relief map, also known as terrain models.[11]

Density maps are often utilized in analyses of anomaly detection and risk analysis but are however quite limited and not suitable for many types of data (Scheepens et al., 2011).

In terms of tri-dimensional visualizations, the most common techniques to follow are the space-time path (iteration of the space-time cube), tubes / ribbons and other stack-based trajectory paths.

The space-time path (Kraak, 2008) uses the same logic as the space-time cube - the trajectory instances move along a 2D axis while correlated to a map, and at the same time, the instances move in a vertical direction as time progresses. Charles Minard's flow map of the french invasion has once been adapted and transformed with this technique, proving how two-dimensional information can be transposed into a 3D render.

As for the other stack-based techniques, visual channels like hue, saturation and orientation take great part in creating visual clues for the intended metaphor. This method helps with the overplotting problem, as each data instance is stacked on top of each other (Persson, 2020).

[11] Sourced from https://en.wikipedia.org/wiki/File:Tatry_Mapa_Plastyczna.JPG

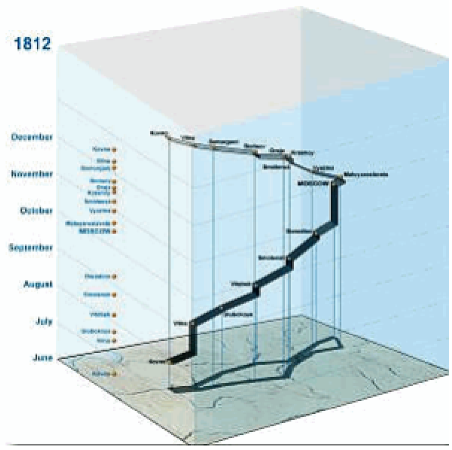

Figure 35: Minard's map adapted to the space-time path technique (Gatalsky et al., 2004)

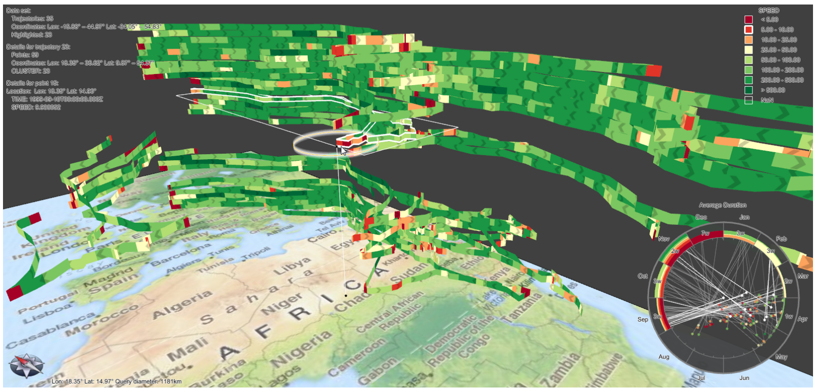

Figure 36: ST Technique called *Trajectory Wall* is a perfect example of stack-based trajectories (Tominski et al., 2012)

Raster Data

Raster maps are represented by a grid-system displaying the pattern of the spatiotemporal data (Persson, 2020). Raster data is made up as a matrix of pixels, also referred to as cells (in much the same way as you might find when working within a spreadsheet (Rushton, 2020). The visual clues in raster maps are mostly color-based, as the visualization of hue gradients may vastly improve the context and the overall visual metaphor the graphic intends to convey.

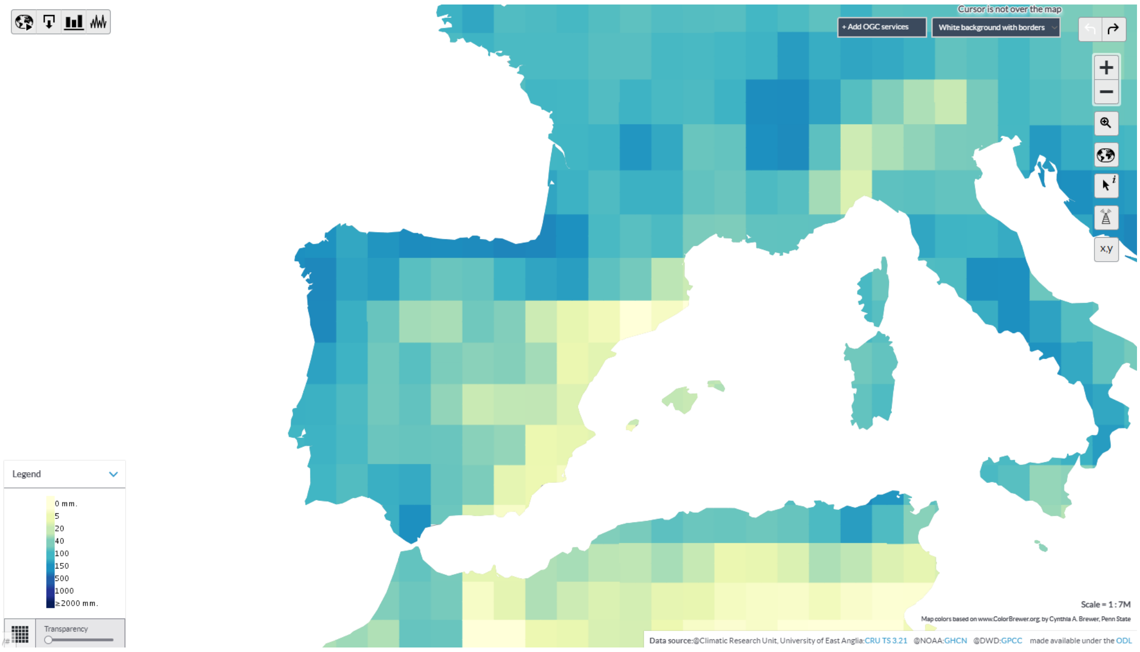

Figure 37: A raster map demonstrating monthly rainfall on december 2021 in southern-europe. Source: globalclimatemonitor.org[12]

As the figure shows, the map uses stronger color values for regions that have been affected with heavier rainfall between the specified time-frame. With this “gradient” visual metaphor, the user can easily perceive the data and observe that, for example, Italy had a higher index of rain than Spain in december of 2021.

Spatiotemporal raster data can also be shown with isarithmic maps (also known as contour maps), heat maps, origin-destination maps and point-reference maps. Each one of these maps have a high use of color-based visual channels (Persson, 2020). In addition, the author points out that these types of maps are especially useful for showing continuous and gradual change over space, which can be seen in figures 38 and 39. As for the time spectrum, it can either be a fixed view or changed with a slider (Persson, 2020).

[12] Sourced from https://www.globalclimatemonitor.org

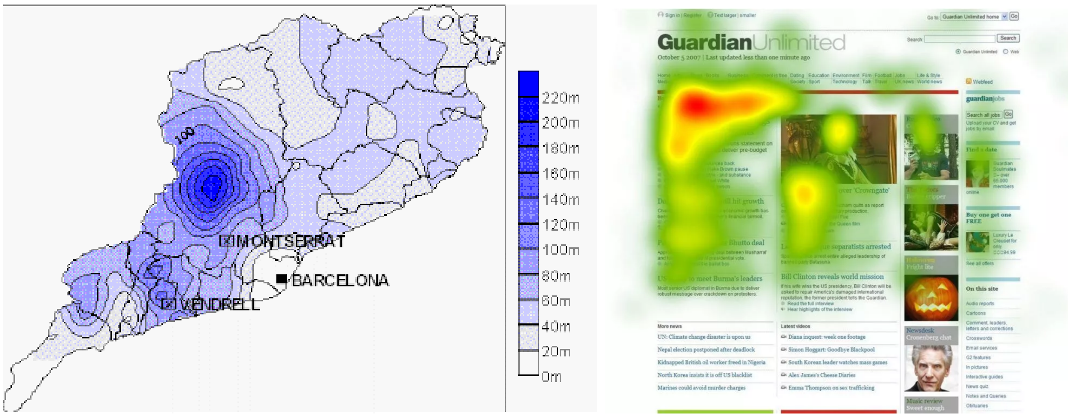

Figure 38: An isopleth map (right) gradually showing precipitation values in a spanish region. On the left, a heatmap on top of a website page, showing the main clicked areas

Source: geographyfieldwork.com[13] and talkroute.com[14]

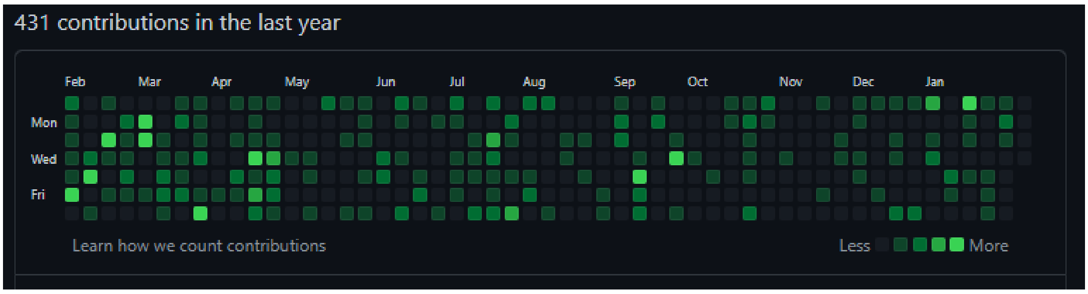

Figure 39: Origin-destination maps avoid overplotting

Source: github.com

Multi-purpose visualizations

Even though most of the situations can be covered within the classifications discussed above, proposed by Persson (2020), there are certain types of visualization techniques that apply to many cases, making it harder to categorize them into a single specific data type (Persson, 2020). These go from dot maps, to diagram maps, choropleth maps, dasymetric and ring maps.

Dot maps (Figures 40 and 41) are said to be visualizations that represent some numeric amount of data , in which an area with a higher number of dots indicates a higher concentration of values (Persson, 2020). Dot maps are used to visualize distributions and densities of a big number of discrete distributed single objects (GITTA, n.d.).

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[13] Sourced from https://geographyfieldwork.com/DataPresentationMappingTechniques.htm

[14] Sourced from https://talkroute.com/heat-maps-worth-every-penny-or-a-waste-of-time/

Visual clues are mainly made thanks not only to color-based visual channels but size and grouping channels as well. Furthermore, the Gestalt principles of connectedness may also play an important role.

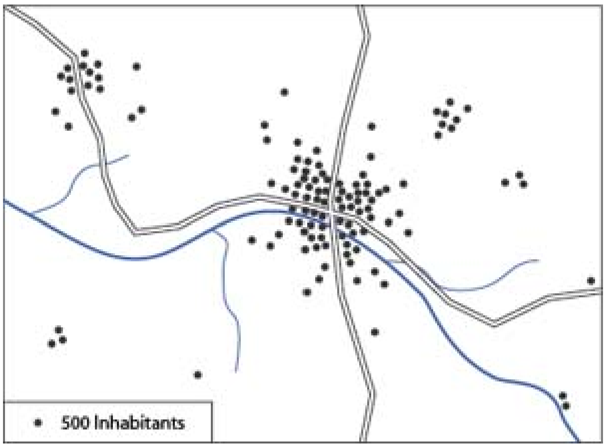


Figure 40: Generic Dot Map, showing uniformized population density (GITTA, n.d.).

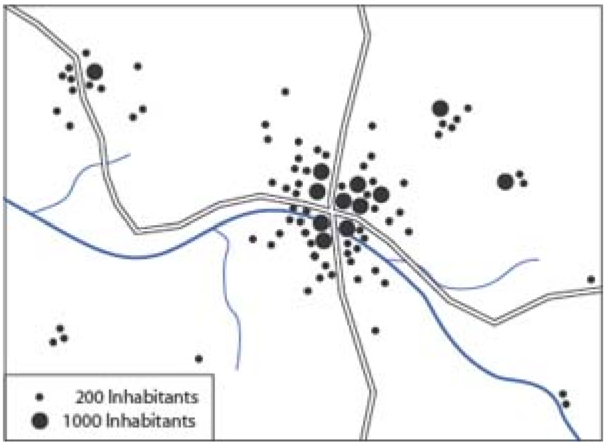


Figure 41: Dot Map showing population density with different instance values (GITTA, n.d.).

Diagram maps are another type of multi-purpose visualization. Essentially, N. Andrienko & Andrienko (2004) state that these are geographical maps which have been divided into areas which have diagrams on them that represent the image data. An example of this is the ST technique *Icons On Maps* or *Value Flow Maps* (N. Andrienko & Andrienko, 2004) - On top of a cartographic reference that has been split into regions or other types of section, data instances are displayed as glyphs. Specifically for figure below, demonstrating *Value Flow Maps*, the glyphs layered on top of the map use miniature silhouette graphs, paired with color hue differences to symbolize positive or negative deviation from the context given.

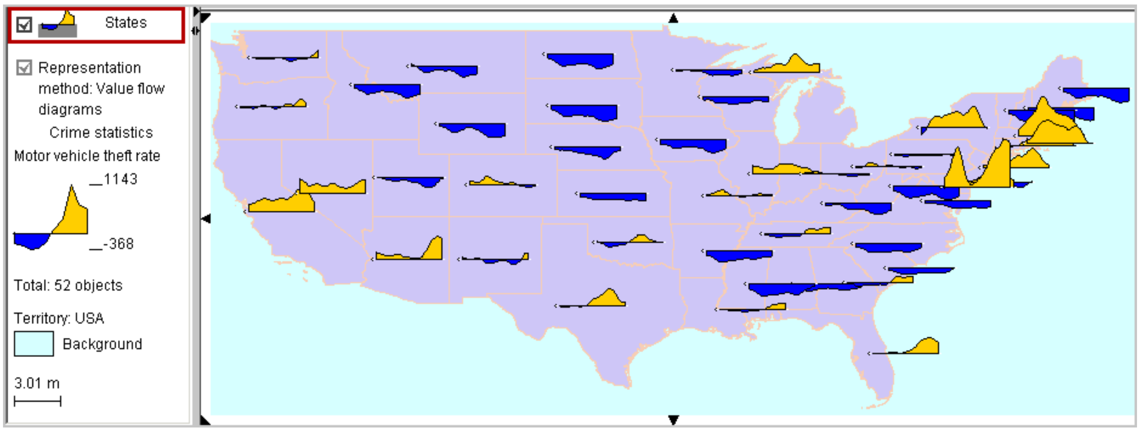


Figure 42: Value Flow Maps using silhouette graphs to display vehicle theft data in the USA. (N. Andrienko & Andrienko, 2004)

Choropleth maps (Figure 43) are one of the most common visual representations of spatial data and can be used to describe both event data and raster data (Persson, 2020). Choropleth Maps display divided geographical areas or regions that are coloured, shaded or patterned in relation to a data variable (Ribecca, 2017). This provides a way to visualize values over a geographical area, which can show variation or patterns across the displayed location.

These maps take great advantage of color-based visual clues, as the data variable uses color progression to represent itself in each region of the map (Ribecca, 2017). Typically, this can be a blending from one color to another, a single hue progression, transparent to opaque, light to dark or an entire color spectrum.

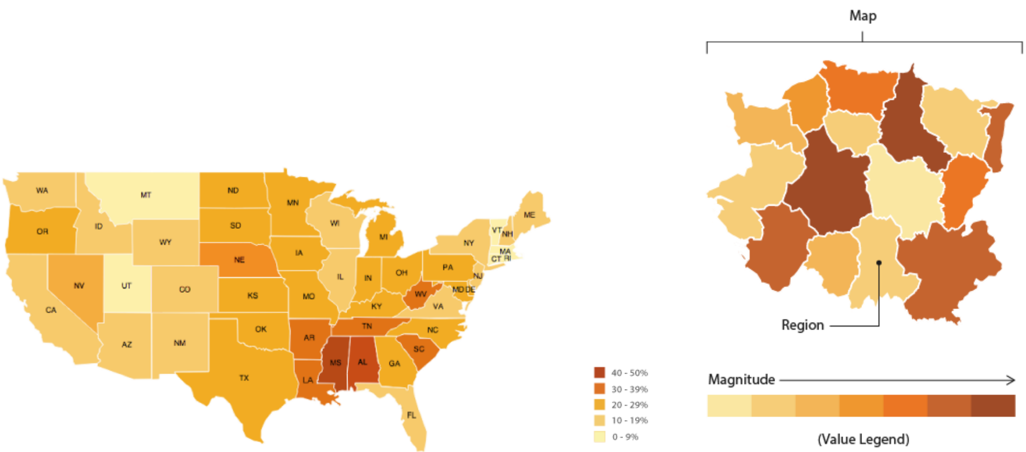


Figure 43: Choropleth Maps used in different contexts, but with the same logic - hue progression is made to signify change in data value

Source: The Dataviz Catalogue[15]

[15] Source from https://datavizcatalogue.com

In addition to standard choropleth use, a cross-classed choropleth map can also be used if there are different data values to be displayed. In the figure below, Portugal is represented by districts, each with their own color variance, depending on the age spectrum shown. The class and color division can be seen in the top left corner.

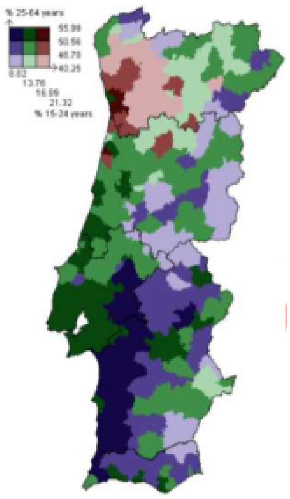


Figure 44: Cross-Classed Choropleth Maps with different color gradients dependent on the age spectrum (N. Andrienko et al., 2016).

Dasymetric maps are considered to be a mix of isopleth maps and choropleth maps (Persson, 2020). While choropleth maps have a main objective of showing data as enumeration zones, dasymetric maps tend to show the underlying data distributions. So, in a way, these maps display statistical data in meaningful spatial zones. One common type of data to visualize using dasymetric maps is population density (Eicher & Brewer, 2001).

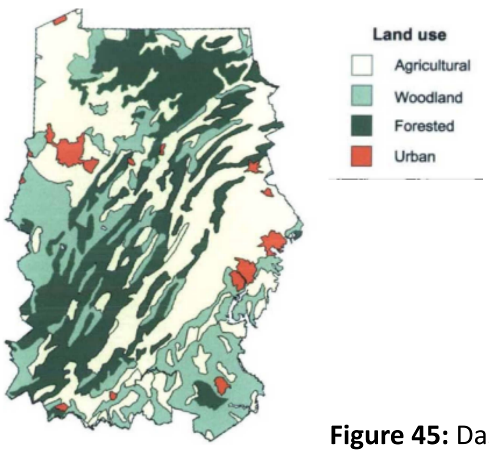


Figure 45: Dasymetric Map (Eicher & Brewer, 2001)

Finally, one of the last reported multi-purpose visualizations by Persson (2020) is the ring map. As the author specified, "Spatio-temporal data can be represented by a ring map which, in the spatio-temporal case, essentially is a choropleth map surrounded by a segmented ring, where each ring represents the temporal component of the data". Each ring of the visualization is a single instance or event that can be used to display a time series or a variable series.

Within ring maps, the position and orientation channels of the visual clues are the most relevant to transmit the visual metaphor.

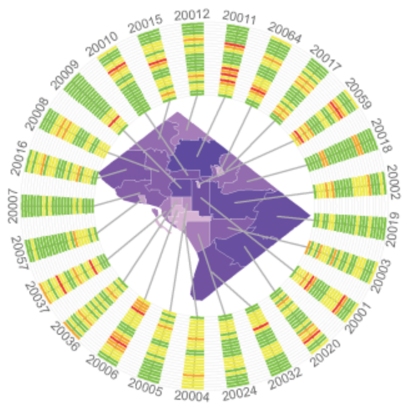


Figure 46: Ring Map displaying 24 weeks of disease alert status for each ZIP Code in the USA. Changes in status over time are much more easily discerned when displayed in this fashion (Huang et al., 2008)

2.2.3 Taxonomies for Spatiotemporal Visualization Techniques

In addition to the taxonomies discussed in chapter 2.1.5, there are more classifications tailored to the more spatiotemporal side of information visualization and their included visual clues (and visual channels).

Borgo et al. (2013) exposes various classifications and observations on the visual channel spectrum of InfoViz, by exploring modern semiotic models of glyph representations - The Dyadic Model of the Sign Notion of Ferdinand de Saussure (Saussure, 1966), the Structure of the Sign Notion (Triadic Model) of Charles Sander Peirce (Peirce, 2011), as seen in figure 47, and the visual variables by MacEachren (1995) (Figure 48).

Figure 47: The Dyadic Model of the Sign Notion and the Structure of the Sign Notion (Borgo et al., 2013)

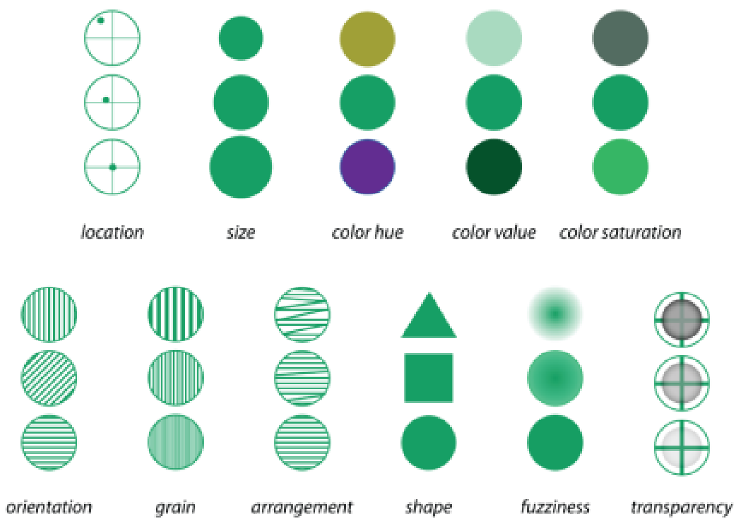


Figure 48: Visual Variables by (MacEachren, 1995)

As stated in previous chapters, the most up-to-date taxonomy for interactions in spatiotemporal data is the work done by Figueiras (2015). Another relevant work worth mentioning is the ST visualization summarization made by (Zhong et al., 2012), which was thoroughly examined in the last chapter.

There is no taxonomy or any sort of classifications made tailored specifically to categorize ST techniques regarding their used visual clues, visual metaphors and context or purpose.

2.2.4 Spatiotemporal Visualization Techniques

Throughout the whole development of this work, the most relevant types of spatiotemporal techniques will be studied and taken into consideration for testing the stability of the proposed visual-clue taxonomy, and posteriorly focusing on the most promising used visual clues.

For concepts and techniques developed and published up until 2014, the work by Aigner et al. (2011) was followed. With the author's book, *Time & Time-Oriented Data*, paired with its auxiliary web tool called *The TimeViz Browser* (Figure 49), it was possible to gather a considerable large visual survey of ST techniques and analyze the sources on how they were conceptualized, tested and implemented, in a very user-friendly way.

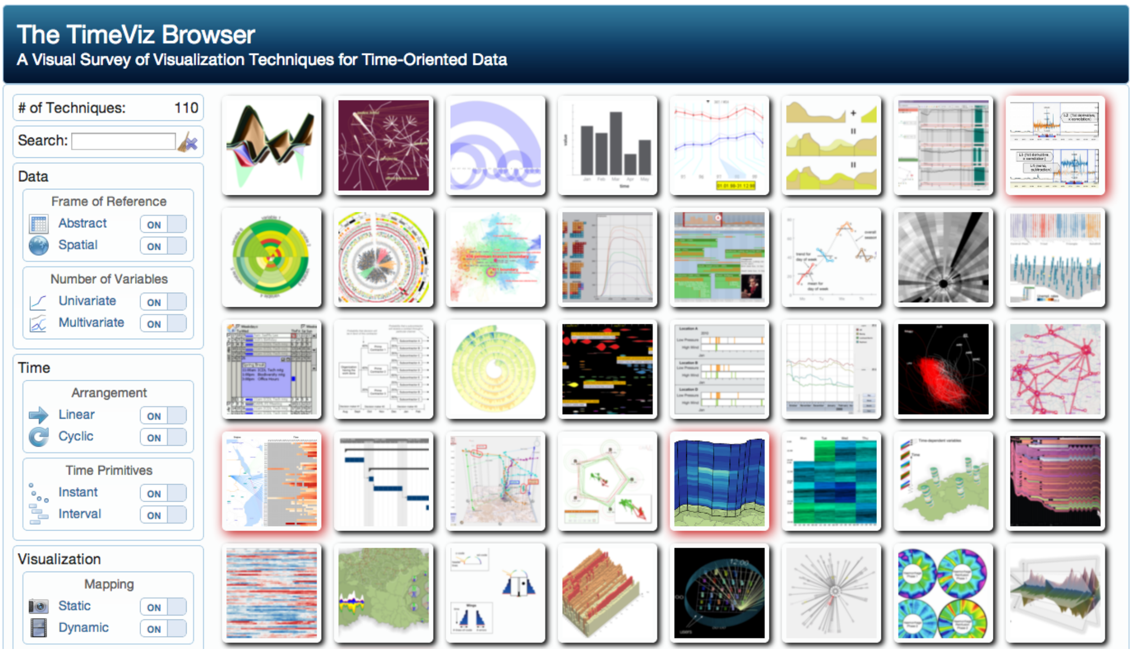


Figure 49: Screenshot of The TimeViz Browser. It is possible to filter through the techniques with the left-side menu. Filters include aspects on data, time and the visualization itself.[16]

For techniques from 2014 forward, the approach was different - there was no summarization quite like *The TimeViz Browser* included. And having in mind that spatiotemporal data can be represented in many different ways, with various contexts, objectives, and visual clues, there was a need to filter through the thousands of techniques available. Consequently, the literature review was made with a few steps in mind.

[16] Sourced from https://vcg.informatik.uni-rostock.de/~ct/timeviz/timeviz.html

The criteria followed to separate relevant-to-the-work ST techniques from less important ones, the included techniques belong only to the top and most respected journals and conferences from the Information Visualization field. These were chosen according to the acceptance percentage and criteria, number of citations per submissions and general preference from the most respected practitioners from the area. In addition, the list made by Elmqvist (2016) was taken into consideration. In summary, the reviewed scientific papers belong to:

- **IEEE Conference on Information Visualization (InfoVis)** – premier venue for InfoVis research, low acceptance rate (20-25%), single-track, proceedings published in IEEE TVCG
- **IEEE Conference on Visual Analytics Science & Technology (VAST)** – premier venue for visual analytics research: low acceptance rate (~25%), single-track, proceedings published in IEEE TVCG
- **Eurographics/IEEE VGTC Conference on Visualization (EuroVis)** – all three areas (InfoVis, VA, and SciVis); proceedings published in CGF
- **IEEE Pacific Visualization Symposium (PacificVis)** – all three areas (InfoVis, Visual Analytics, and ScientificVis)
- **IEEE Symposium on Large Data Analysis and Visualization (LDAV)**
- **IEEE Transactions on Visualization & Computer Graphics (TVCG) –** top visualization and computer graphics journal
- **Computer Graphics Forum (CGF)** – official journal for Eurographics
- **Information Visualization (IVS)** – journal dedicated to information visualization

An exhaustive research occurred, with more than a hundred techniques reviewed and studied. From this collection, there were ST techniques that stood out, because of their unique usage of visual clues, while still portraying potential regular use in most common spatiotemporal data situations. These were used as reference for the taxonomy development and the experiments, and were the following: Data Vases (Thakur & Rhyne, 2009), Growth Ring Maps (Bak et al., 2009), Temporal Focus+Context (A. Carvalho et al., 2008), and Flow Maps (Kraak & Ormeling, 2003), Space-Time Cube (Hägerstraand, 1970), Wakame (Forlines & Wittenburg, 2010), TreeRoses (Tang et al., 2019) and Great Wall of Space Time (Tominski & Schulz, 2012). A lot more techniques were studied, but not with enough relevance to be included within this work.

2.2.5 Storytelling with Spatiotemporal Visualization

Visual storytelling is a term extensively used to describe the generic sense to denote anything visually (Pimenta & Poovaiah, 2010), with the intent of narrating a story or a journey. Along with a complete list of the various types of storytelling and classification of imagery, an effort is made to precisely establish a consistent definition of what is a visual narrative, and its subcategories. Marques et al. (2020) summarizes the work done by Pimenta & Poovaiah in *"On Defining Visual Narratives"* into three critical touch points:

- **Static Visual Narratives:** The represented visual elements remain still and unchanged on the view. As the visualization is static, an active back-and-forth human-computer interaction is expected with the viewer, in an attempt for him to gather the information shown, correlate and draw conclusions on it.

- **Dynamic Visual Narratives:** The visual elements change over time. The pace of the narrative is uncontrollable, meaning that the events and how they are shown are pre-determined by the visualization pipeline. An example of a dynamic narrative would be a movie or any other cinematic media.

- **Interactive Visual Narratives**: The visual elements of the visualization are still dynamic, however, they now have the possibility of being changed interactively by the user. With the inclusion of interactivity, the viewer can decide if the narrative remains fixed (static) in a certain time frame, if it proceeds naturally according to its linear progression (dynamic) or a mix of both types. Video games can be considered interactive visual narratives, as they have a very high level of interactivity regarding how the story is unfolded.

Linked to this classification system are the models presented by Segel & Heer (2010), in which visual narratives are identified to always belong to one of three groups: the martini glass structure, an interactive slideshow, and a drill-down story (see Figure 50). Much similar to the three touch points by Pimenta & Poovaiah, this taxonomy differentiates linear storytelling from more dynamic and interactive narratives.

Starting with the interactive slideshow category, the narrative is expected to linearly progress through the expected timeline without any interruption, while still maintaining some level of interactivity, but only on the current “slide” (viewframe). This way, event order is enforced and encouraged (Marques et al., 2020), but doesn’t necessarily restrict the user’s capability of interacting with the system. The martini glass structure firstly tightens the margin of the narrative, by placing it on a fixed timeline but slowly diverges to many paths to be explored by the viewer (Segel & Heer, 2010). Lastly, the drill-down story gives the most interactive experience out of all options, as it allows the viewer to simply choose whatever part of the narrative to visualize. There is no preferred timeline or predetermined order. This structure puts more emphasis on a more user-centered approach, letting the user dictate what stories are told and when. Nevertheless, it still requires significant amounts of authoring to determine the possible types of user interaction, what potential stories to include, and the details included for each story (Segel & Heer, 2010).

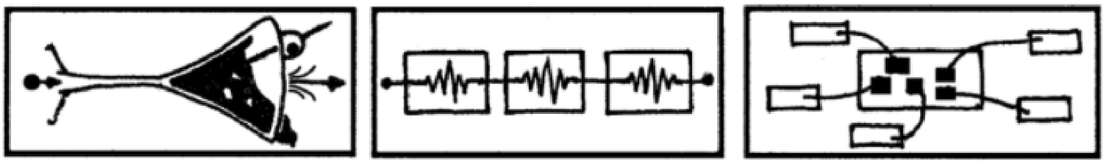


Figure 50: Visual representation of the models pointed out by Segel & Heer (2010). In order, the models are the martini glass structure, interactive slideshow and drill-down story. Source from Marques et al. (2020)

Storytelling, in the context of spatiotemporal visualization, is about telling a story on the rendered statistics data and the related analytics reasoning processes on how discovery and knowledge was obtained and shown (Lundblad & Jern, 2012).

Thanks to the visual techniques that visual narratives can offer, spatiotemporal information has the potential to be understood in a much more engaging and interactive way, enabling the users to reflect, process, and sometimes change their perspective altogether. The fact that, for example, the drill-down story method makes the user participate in the visualization, by making him an important asset, subconsciously augments the focus the viewer has regarding the shown data. Stories enable a leap in understanding (Lundblad & Jern, 2012)

2.3 Research Methods

Research methods are the tools you use to collect data or statistics (Dawson, 2019).

Before going through the various methods and procedures to effectively conduct a research of any kind, Dawson (2019) encourages the questioning of why the research is wanted, what are the main interests and objectives, and what personal characteristics does the researcher have that may impact the quality of the tests. More specifically regarding this last thought - provoking question - there are many different research methods, and some take more advantage of one's soft skills than others. Personal traits like being easy to talk to, preferring written communication or face-to-face interaction, or even being more favorable towards mathematically-driven data rather than qualitative, might help the researcher to complete its investigation in a much simpler way than expected (Dawson, 2019).

In parallel, thinking of the 5 W's strategy also comes to mind. According to Tattersall (2015), the 5 W's are a helpful starting point for identifying the key elements of a research story. This strategy is a group of questions that make the researcher think about its project in a useful and meaningful way. The questions are:

- **What?** - What is the research? What problem is there to be solved?
- **Why?** - Why does the researcher want this project? What is its purpose? (Why is there interest in this topic, is there a gap in the literature review you want to solve?)
- **Who?** - Who will be the participants? Do they need to belong to a specific group of people?
- **Where?** - Where will the research be conducted? Will there be any costs from the investigation setting?
- **When? -** When is the research going to be done? Is the schedule suitable for the participants?

Once these five questions have been answered thoroughly, the project can be considered for development (Tattersall, 2015). This is one of the most important steps of a research project as it will dictate the hypothesis, research questions and the main objectives to be achieved (Dawson, 2019).

A logical step after establishing these first steps would be to then deliberate between the various research methods.

In a general way, research methods can go from interviews, focus groups, questionnaires, participant observation, experiments, or a combination of multiple methods (Dawson, 2019).

There are three types of interviews - unstructured, semi-structured and structured interviews (Dawson, 2019). The first one, also known as life history interviews, tends to have little influence from the researcher. As the information received is of qualitative nature, the interviewer prepares a few questions and lets the interviewee delve into its own thoughts and experiences without interruption. Because of this, the researcher has very limited directional influence.

Semi-structured interviews are known as the most common type of interview used in qualitative social research (Dawson, 2019). Here, Dawson (2019) writes that the interviewer wants to know specific information that can then be compared to data retrieved in other interviews. For this purpose, the placed questions need to be the same between all participants.

Finally, for structured interviews, the researcher asks a specific set of questions to, at the end of many interviews, receive different responses to the same structure.

Focus groups are seen by many as discussion groups. Having this in mind, the group has a moderator that conducts the flow of the conversations but the interactions between participants has a certain amount of freedom. The researcher receives, at the same time, a wide range of responses during a single meeting (Dawson, 2019). With back-and-forth conversations, participants also help each other in remembering certain issues they might have forgotten, or even bring interesting topics that the researcher didn’t think of including.

Questionnaires can be close-ended to generate statistics and quantitative data, open-ended to receive qualitative information that is more broad and open to participant thoughts, or a combination of both to obtain the two types of information (qualitative and quantitative).

Finally, as for participant observations and experiments, the difference is that in one, the researcher has control of the independent variable, while in the other method it does not. In observations, the participants merely interact with the project in question, without interference from the researcher. In contrast, the experiment methods consist of various tests in which the researcher controls the interaction made by the participants, by including or altering the element being tested (Dawson, 2019).

To guarantee meaningful results without any type of bias or manipulation, a common type of study design, the balanced latin square method, as depicted in figure 51, is usually used. The American Psychological Association describes this method as “a type of study design in which multiple conditions or treatments are administered to the same participants over time”.[17] Each experiment or independent variable manipulation must occur once with each participant, each treatment must occur the same number of times for each time period or trial, and each treatment must precede and follow every other treatment an equal number of times (APA, 2022).

	Treatment Order			
	1	2	3	4
Participant 1	A	B	D	C
Participant 2	B	C	A	D
Participant 3	C	D	B	A
Participant 4	D	A	C	B

Figure 51: Balanced Latin Square Method - Four participants go through four experiments alternatively, without them being conducted at the same time (APA, 2022).

The purpose of the research will provide an indicator of the most promising methods (Lune, 2012). Furthermore, Dawson (2019) writes that they should be catered to the researcher’s personality, strengths and weaknesses, likes, and dislikes.

2.3.1 Research Methods for Information Visualization

More specifically to the InfoViz field, much like with the topic of user experience and human-computer interactions (HCI) in general, there are generally two methods to evaluate the effectiveness of visualization – heuristic evaluation and user studies (Zhu, 2007).

Heuristic evaluation is a type of evaluation in which visualization experts evaluate the visualization designs based on certain rules and principles (Craft, 2005). But what are these principles and guidelines? The work done by Zhu (2007) in *Measuring Effective Data Visualization* exposes several perspectives from respectable practitioners on this, each with their own advantages and disadvantages. However, Zhu (2007) summarizes the research and,

[17] Definition sourced from https://dictionary.apa.org/balanced-latin-square

based on the previous analysis, proposes new guidelines on how to define and measure effective visualization:

- **Principle of Accuracy -** For a visualization to be effective, the attributes of visual elements shall match the attributes of data items, and the structure of the visualization shall match the structure of the data set

- **Principle of Utility** - An effective visualization should help users achieve the goal of specific tasks.

- **Principle of Efficiency -** An effective visualization should reduce the cognitive load for a specific task over non-visual representations

The participant's thoughts and opinions behind the accuracy, utility, and efficiency of a visualization should be obtained through said research methods - be it via interviews, questionnaires or observations. Zhu (2007) adds to his by saying that "It is also important to point out that the accuracy, utility, and efficiency of visualization are greatly influenced by users domain knowledge, experience with visualization, and visual-spatial capability" - so it still remains a major challenge to correctly measure these factors without any sort of cognitive bias.

The second evaluation method is by user study. The most common measures of effectiveness here are task completion time, error rate, and user satisfaction (Zhu, 2007). It is an iterative, cyclical process in which observation identifies a problem space for which solutions are proposed (Craft, 2005). A good example for visualization experiments is the A/B testing, in which the participant is asked to choose between example A or example B. Usually paired with a SUS questionnaire and a text field for optional thoughts, the results given are of both types - qualitative and quantitative.
For context, SUS (System Usability Scale) questionnaires provide a stable and reliable method for measuring usability. It consists of 10 statements, with a scoring system from 1-to-5 ("Strongly Disagree" to "Strongly Agree"). According to usability.gov (2013) the statements are:

- I think that I would like to use this system frequently.
- I found the system unnecessarily complex.
- I thought the system was easy to use.

- I think that I would need the support of a technical person to be able to use this system.
- I found the various functions in this system were well integrated.
- I thought there was too much inconsistency in this system.
- I would imagine that most people would learn to use this system very quickly.
- I found the system very cumbersome to use.
- I felt very confident using the system.
- I needed to learn a lot of things before I could get going with this system.

Interpreting scoring can be complex. The participant's scores for each question are converted to a new number, added together and then multiplied by 2.5 to convert the original scores of 0-40 to 0-100 (usability.gov, 2013). Based on usability.gov (2013), results above a 68 would be considered above average and anything below 68 is below average.

Similarly to SUS, the NASA Task Load indeX (NASA-TLX) is a post-test questionnaire used to measure the perceived workload required by the complex, highly technical tasks of aerospace crew members. However, it is also useful for studying complex products and tasks in high consequence environments (Corno & Russis, 2019). With the same score logic as the SUS questionnaires, NASA-TLX consists of six statements around the perceived workload in terms of mental and physical demand, time pressure, perceived success, overall effort and frustration level (Corno & Russis, 2019).

2.4 Summary

The main takeaways from the literature review about spatiotemporal phenomena, information visualization as a whole, the concept of storytelling and respective research methods will be summarized in this chapter.

As presented in previous chapters, visualization can be seen as an important part of communicating an idea, thought or observation, as it can be transmitted via text, icons, or many other types of glyphs. This leads to the topic of Information Visualization (InfoViz) being considered a wide research field, capable of branching towards various directions and domains, as long as there is an interaction through visual computing and representations to amply human cognition with information (Card et al. 1999).

Though there are many methods and procedures a visualization can undergo to represent data, the visualization pipeline by Santos et al. (2004) demonstrates the main actions iterated by raw data, so that it transforms into perceivable image data. Section 2.1.3 points out possible categorizations of summary visualizations for this image data. In essence, the data can be used to capture groupings such as clusters, trends and outliers, but ultimately, they always rely on visual clues and metaphors to push for the abstract reasoning and interpretation of human analysis to correctly process the data. In other words, and so that the visualization in question is correctly analysed, many techniques take advantage of visual narratives and storytelling concepts to help users navigate from small to large and complex datasets.

In Section 2.1.4, the definitions of visual clues and metaphors are further explained. The final "image data", which was the outcome of the previously mentioned visualization pipeline, can be considered to be made of a visual metaphor. In turn, this visual metaphor can be made of many visual clues, which are made of various visual channels. The visual channels are groups of possible visual variables and were first identified by Jacques Bertin (2010). Intertwining this with the Gestalt principles (Peterson and Berryhill, 2013), data can be recognized and perceived in a more effective way.

As data can assume many different forms, and this work focuses on spatiotemporal data and its visualization, section 2.1.5 explores how the spatial and temporal spectrum can be classified, be it through existing taxonomies specifically for ST data or through classifications in a more general way. Additionally, the representation of time was researched. Time can be classified as ordinal, discrete or continuous. A relevant touch point to consider for a good visualization of time is that it generally needs to have in mind its scope, scale of time, arrangement and the viewpoint. There is always a concern of human abstractions in the concept of time, to make it a much easier topic to handle in everyday life. These are called granularities - one example of them are the concepts of days, weeks, months and years.

Section 2.2 goes through the main definitions of ST InfoViz. There are four common types of ST information: Event data, movement data, point reference data and raster data. In addition to this, this section explores the taxonomies tailored to the more spatiotemporal side of information visualization and their included characteristics. There are classifications for interactions and general summarizations, but there was no taxonomy made specifically to categorize ST techniques regarding their used visual clues, visual metaphors and context or purpose.

Concerning section 2.2.4, the most relevant types of ST techniques were studied. Initially, the conducted research was mainly through the TimeViz Browser. However, for techniques from 2014 forward, the reviewed scientific papers were found in the most respected journals and conferences from the InfoViz field. These include the InfoVis, VAST, EuroVis, PacificVis, LDAV, TVCG, CGF and IVS conferences and journals. In total, over a hundred techniques were reviewed and studied. Later on, a selection of the techniques was chosen for the proposed experiments, namely *Data Vases*, *Flow Maps, Space-Time Cube*, *Temporal Focus+Context* and *Growth Ring Maps.*

The storytelling and visual narratives section presents the main takeaways related to types of storytelling, classification of imagery, and how they can relate to ST visualization. With the visual techniques that visual narratives can offer, ST information can be understood in a much more engaging and interactive way. Subconsciously, stories have the potential to enable a leap in understanding a visualization.

Finally, the last section refers to the available research methods to collect data or statistics. It was concluded that a general good practice to start a project is to think of what the research is, why there is a need to do it, who the participants will be, where and when the research is going to be done. This is known as the five W's strategy (Tattersall, 2015). Afterwards, it was mentioned that the main research methods can go from interviews, focus groups, questionnaires, observations or a combination of multiple methods. The chosen method was a questionnaire including both close and open-ended questions (qualitative and quantitative data) and a System Usability Scale test. More specifically for InfoViz, heuristic evaluations and user studies seem to be the most effective way to conduct research (Zhu, 2007), and should focus on the principles of accuracy, utility and efficiency of the visualization.

3. Taxonomy for spatiotemporal visual clues

This chapter thoroughly describes one of the main outcomes of this work - the Aggregated Taxonomy for Spatiotemporal Visual Clues (also referenced as “AT”).

Firstly, Section 3.1 introduces the problem initially stated and its relation to the proposed taxonomy. Then, Section 3.2 links said problem statement with the research questions the work aims to answer. Afterwards, Section 3.3 defines the requirements for the proposed solution, the aggregated taxonomy, briefly followed by Section 3.4 that presents why this solution is important, within the user’s perspective, and what are its benefits. Finally, in Section 3.5, the AT is fully explained, starting with its base concepts and finishing on the final proposed taxonomy, along with possible considerations for future work.

3.1 Problem

As introduced in Chapter 1 and pointed out in the literature review, spatiotemporal data relies heavily on context. Therefore, there are a countless number of techniques and ways of showing this type of data, each with their own specific context, purpose and situation. Some visualizations rely on cartographic references, being two-dimensional, three-dimensional, or where other multivariate fields are displayed as a map of visual variables, while others opt into a more abstract representation or even a mixture of both, by displaying multiple views and bringing focus onto what the viewer selects as the main view.

Because of this, someone who wants to adopt a certain spatiotemporal visualization technique or create a new one, is suddenly met with an overwhelming amount of options, not knowing which one to choose or what seems to be the right option for the type of variables their data holds. One of the main tools in this area that help solve this problem is the TimeViz Browser[18] (Aigner et al., 2011) , which aims to be “a visual survey of visualization techniques for time-oriented data”.

The TimeViz Browser is, in essence, a compilation of the most recent and influential spatiotemporal visualization techniques, paired with a comprehensive taxonomy that enables the user to filter through the whole reviewed 115 techniques considering their usage of data, number of variables, representation of time and how it’s all visualized. Thanks to its straightforward interface, this catalog of techniques allows everyone to quickly jumpstart its spatiotemporal research and quickly scatter through the main options available, as well as gather possible inspirations for their own techniques. However, one problem of this browser and its filtering is that it does not explore how the data is displayed in a complete and exhaustive manner. The filters help the user know what techniques exist and their general concept - but not how the temporal and spatial spectrum of the data play with each other and graphically intertwine.

This time-space interaction between data tells a story, and that concept of storytelling plays an important role in representing data and engaging users with concepts of agency (Limerick et al., 2014), interactivity and flow, but is often forgotten. Alot of time and effort is usually spent in exploring and developing all types of niche techniques for one specific objective or data, when it should instead be used to think of the best way to represent it - what is the visual narrative behind it? How can the displayed data take its viewer on an engaging journey and show its variables in an intuitive way? How can the time spectrum be represented, without corrupting the spatial representation and risking less perceivability and exceeding the user’s cognitive load?

As explored in Section 2.2.3, there are some taxonomies aimed at information visualization classification, with explorations on techniques in a more general way, others specializing on available interactions and one with the objective of creating an easy-to-understand low-level grammar for spatiotemporal visualizations. However, no taxonomy has yet to explore the visual narrative side of a ST technique. There was currently no way of formally categorizing and filtering a spatiotemporal technique based on its visual channels, visual clues and attempted visual metaphor.

[18] http://vcg.informatik.uni-rostock.de/~ct/timeviz/timeviz.html

Having this in mind, there is then an opportunity and motivation to further explore this storytelling aspect and help the implementers understand how to best apply visual channels and their perceived visual metaphors to the visualization's advantage.

3.2 Research questions

With this work, there is a commitment to find answers to the following research questions:

1. Are visual clues important to the understanding of spatiotemporal data visualization?
2. What is the most efficient way to display a specific type of spatiotemporal data?
3. What are the best practices for representing data, according to their visual clues?
4. What visual channels can be used to communicate information, and with what purpose?
5. How can visual channels convey the correct information to the user?

Pairing the proposed taxonomy with its subsequent experiment, there is a higher level of certainty that the AT is stable, as it can handle most types of spatiotemporal techniques (the experiment tested the taxonomy's classification methods in various techniques encompassing a wide set of visual clues and ways of representing their visual variables) and can help anyone classify a visualization according to their visual characteristics. Thanks to this, the AT will be able to support answering the research questions.

3.3 Requirements

The requirements for the proposed solution (Aggregated taxonomy and its experiments) are as follows:

- Develop a taxonomy oriented for spatiotemporal techniques and their visual clues
- Guarantee the stability and effectiveness of the taxonomy via examples and experiments
- Explore different use cases to test in participant experiments
- Cross and analyze data with taxonomy to summarize observations and best practices

3.4 Scope

Having the requirements in mind, the main scope for this work is to first create a taxonomy tailored to the classification of a spatiotemporal technique's visual characteristics. This first step encompasses the preliminary literature review, state-of-art studies, early conceptualization and further development of the initial taxonomy. After the first version was drafted, the next goal is to test it, in order to assure its capacity of handling all types of spatiotemporal techniques - for they are complex, may encompass multiple variables and are very different from each other. This testing phase encloses both local trials (offline experiments classifying preselected ST techniques using the taxonomy) and online experiments (questionnaires for random users willing to participate in using the taxonomy). The questionnaires serve as a form to validate the taxonomy's structure, options, and to confirm the viability and popularity of certain visual variables on specific cases of visualization.

After concluding that the proposed taxonomy is valid, suitable and ready for future use, the data gathered from the questionnaires is crossed and analysed with the aim of summarizing the outcomes of the experimentation, best practices for visual variable pairing and how well certain groups of visual channels interact with each other.

From the end user's perspective, this solution is important as it serves as a steady and reliable source of classification for past, present and future ST techniques regarding their visual channel usage, and subsequently what visual clues and metaphors are being created.

3.5 Proposed Solution

In Chapter 2.2, the currently available taxonomies for spatiotemporal information visualization were explored. Among the ones mentioned, it is of utmost relevance to highlight the work done in *Design Factors for Summary Visualization in Visual Analytics* (Sarikaya et al., 2018), *Glyph-based Visualization* (Borgo et al., 2013), *A Taxonomy of Spatial-Temporal Data Visualization* (Zhu et al., 2021), *Towards the Understanding of Interaction in Information Visualization* (Figueiras, 2015), and *There and then: interacting with spatio-temporal visualization* (Rodrigues & Figueiras, 2020).

In essence, the proposed taxonomy is a superset of previous taxonomies, intertwined with each other, to achieve a very steady and sturdy classification of visual elements on a spatiotemporal visualization. By being an aggregation of previously studied and tested taxonomies, this novel solution has already a very solid base to start with. Additionally, due to its complex and exhaustive nature, in terms of classification a visual element, this novel aggregated taxonomy provides a high amount of classification flexibility as well as a high-fidelity filtering system - which are some important aspects to have in mind for its future use.

To aid and facilitate the development process, all conceptualizations, inspirations, and state-of-art research were constantly documented within a single Figma[19] project file (See Figures 52 and 53). For context, Figma is a powerful vector-based design tool that allows collaborative and synchronized real-time cooperation.

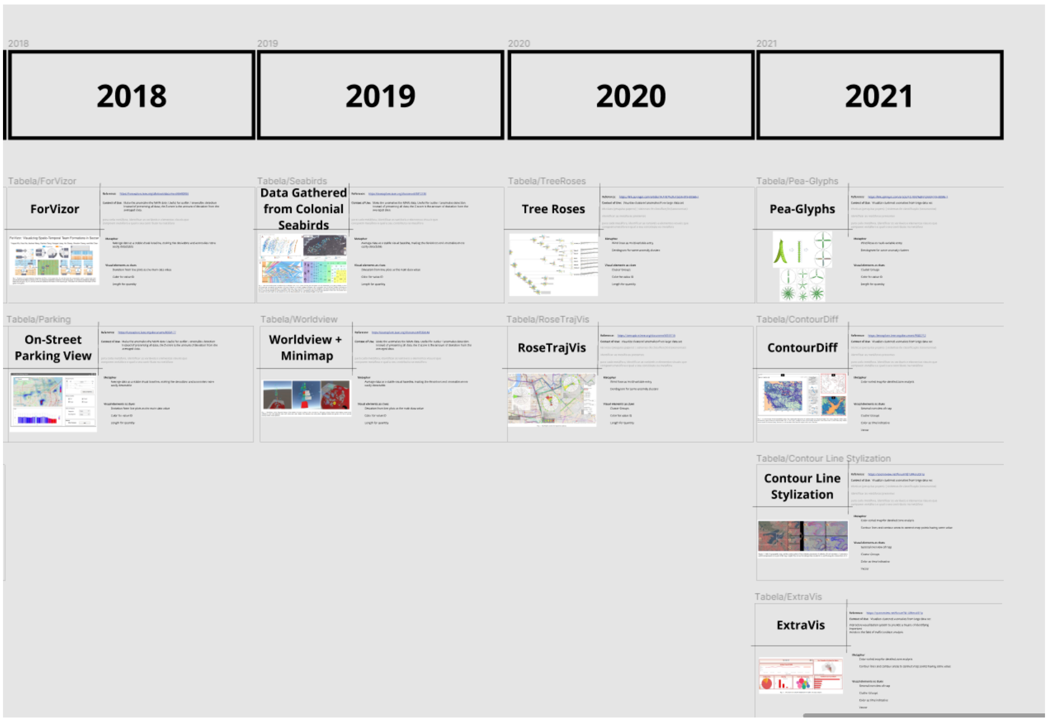


Figure 52: Snapshot of the Figma project file, showing one of the sections from the reviewed ST techniques table

[19] The Figma project file is available here - https://www.figma.com/file/Y9SWk9Xr5pQNXlikFntQ0V/Visualizing-Spatio-temporal-Data?node-id=442%3A70

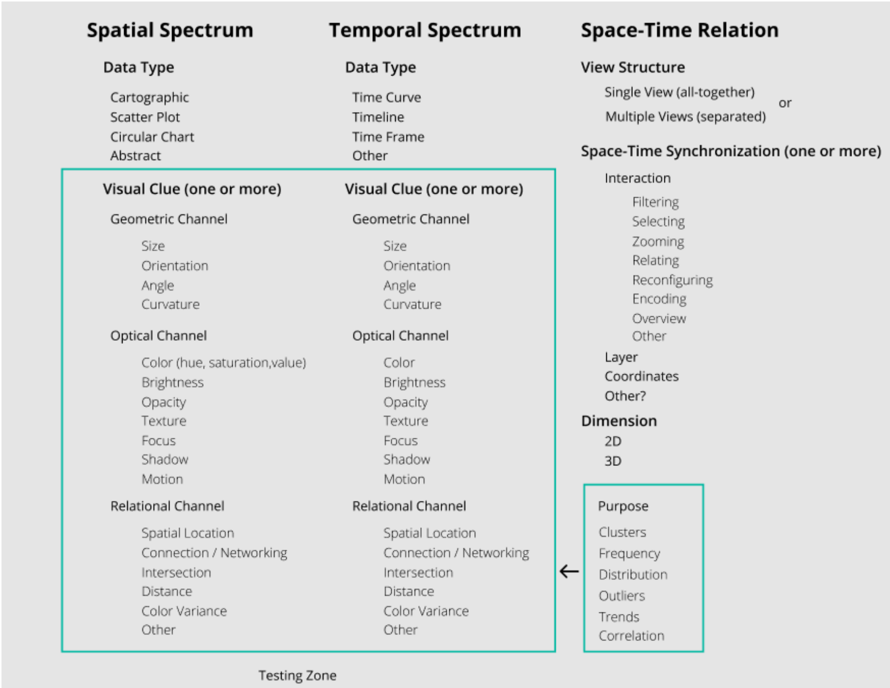


Figure 53: Snapshot of the Figma project file, demonstrating the preliminary drafts of the proposed taxonomy, along with the initial "testing zone" for the experiment

This way, the design workflow was always reliable and faster as the project files were always available online, in every type of system, without the need for a downloaded local version. Within the project file, many pages were created with the intent of documenting all work phases, from research to the user testing possibilities, aggregated taxonomy inspirations and drafts, spatiotemporal technique evaluations and respective testing for possible inclusion on the experiment.

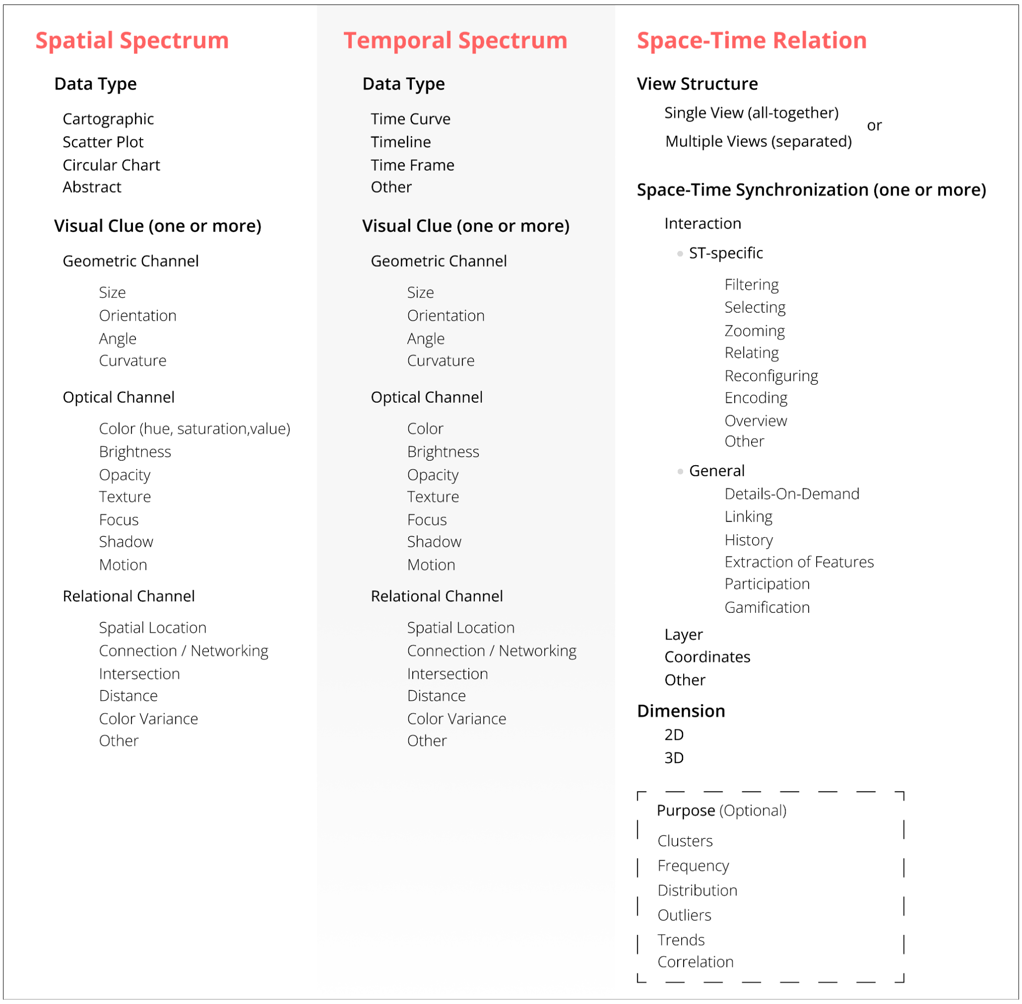


Figure 54: The proposed Aggregated Taxonomy for Spatiotemporal Visual Clues

The proposed taxonomy (see Figure 54) is made of three main columns: the spatial spectrum, temporal, and space-time relation column. This is made so that it is possible to ultimately specify what are the used visual variables to represent each and every element of a spatiotemporal visualization. The spatial spectrum column shows the visual variables available to represent space on the visualization in question. On the same level, the temporal column shows the variables that represent change in time throughout the visualization. The third column belongs to the relation between the space and time spectrums, how they intertwine and how they interact with each other.

The first two columns follow a similar pattern: both are made of two main sections - the Data Type and the respective Visual Clues. This structure is inspired by the base taxonomy architecture made in *A Taxonomy of Spatial-Temporal Data Visualization* (Zhu et al., 2021), in which the authors start by sectioning their taxonomy and splitting the space and time factors of a technique. Subsequently, these sections also have subcategories to specify how the data is represented (data type). The aggregated taxonomy adopts the data type representation for its high efficiency in categorizing such information, going from "Cartographic map", to "scatter plot", "circular chart", or a more generalized abstract representation, on the spatial spectrum column. On the temporal spectrum, the data types are simplified as the original reference had too many niche options that weren't too commonly adopted. This way, the data types available on the data spectrum are "time curve", "timeline", "time frame" or "other", giving the ability to the novel taxonomy user to further specify the less common time reference at stake.

However, the AT exhaustively expands on the visual clue classification, which is its main purpose (as contextualized in figure 55). There are no spectrum-exclusive options within the first two columns, so every option is available in both spectrums. One can choose one or multiple options, depending on the amount of visual variables being used on the visualization in order to represent a certain spectrum.

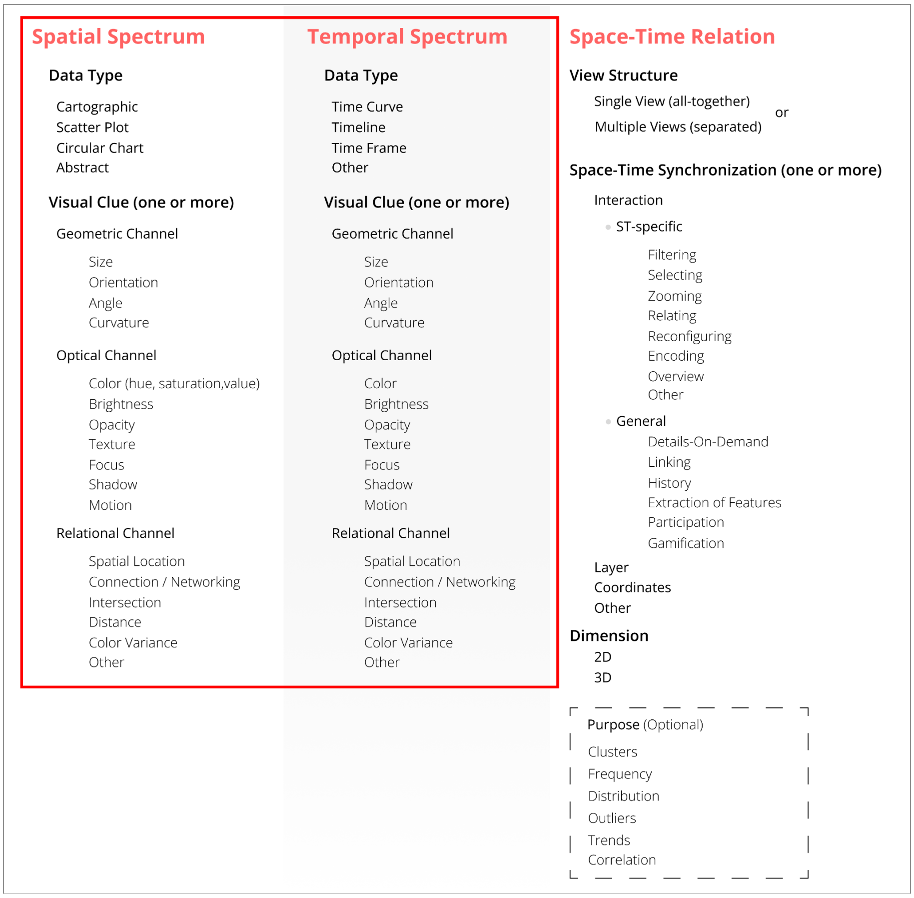


Figure 55: For context, a red rectangle surrounds the AT elements being currently explained - the Spatial and Temporal Spectrum columns

This starts the “visual clue” section of the two columns. In this section, there are three subsections: the geometric, optical and relational channels. These can be called “visual channels” and are made of many possible visual variables. In essence, linking this with the literature review research: Visual clues can be made of three visual channels - the geometric, optical and relational channels (Borgo et al., 2013). For each channel, there can be none, one or multiple visual variables at use. So, considering this, in each channel, the AT user can select one or more visual variables, according to what the spatiotemporal visualization is using on the selected spectrum. Some best practices are advised on Chapter 4 - Experiment.

These visual channels are based on the organization made by Chen and Floridi, in which the authors summarized the main ways of visually representing information and data through a simple taxonomy consisting of four categories. These categories were, namely, the geometric, optical, topological and semantic channels (Chen & Floridi, 2013). Some options were dropped off for the sake of the AT’s level of simplicity, ease of use and comprehension. As an example of this, the taxonomy by Chen & Floridi includes the geometric visual variables of size, length, width and depth to be within the same logic and framed as the same type of variable. This has an effect of simplification on the aggregated taxonomy, as that same variable is present on the AT but referenced just as “size”. While it would be a good idea to provide extra information and context on what “size” means on the AT, it would risk an overcomplication and be more cognitively loaded for the novel taxonomy user. Following this, Hick’s Law states that the more choices a person is presented with, the *longer* the person will take to reach a decision (Interaction Design Foundation, 2022). Named after psychologists William Edmund Hick and Ray Hyman, Hick’s Law finds frequent application in user experience (UX) design and all related areas—namely, to avoid overwhelming users with too many choices, thereby keeping them engaged (Interaction Design Foundation, 2022). Furthermore, one of the main objectives of this novel taxonomy was, much like the recent taxonomy by Zhu et al. (2021), to provide a low-level grammar-like vocabulary, so that the process of categorizing a spatiotemporal technique by its visual clues is a much easier process than it was until now - while encompassing more classification possibilities.

On the geometric level, the options available are size, orientation, angle and curvature. Logically, these visual variables belong to the geometrical channel of a visual clue, which act on the geometric side of a visualization.

As for the optical level, the variables proposed are color, brightness, opacity, texture, focus, shadow and motion. The ‘color’ visual variable refers to hue, saturation and value of the color represented. All the referenced variables belong to the optical channel, which act on the retinal side of a visualization. Moreover, these options are also based on a set of proposed “visual variables” capable of representing a good syntax for graphic visual representations (MacEachren, 1995).

Finally, on the relational channel, the options are “spatial location”, "connection / networking”, “intersection”, “distance” and “color variance”. Additionally, a “other” field is added as there are many possibilities of a visual clue intertwining with another, but not of enough relevance to include them in the aggregated taxonomy. Therefore, this “other” field is subject to the user’s input and open-ended. Ideally, these visual variables belong to the relational channel, which represent the possible interactions that each event has with each other.

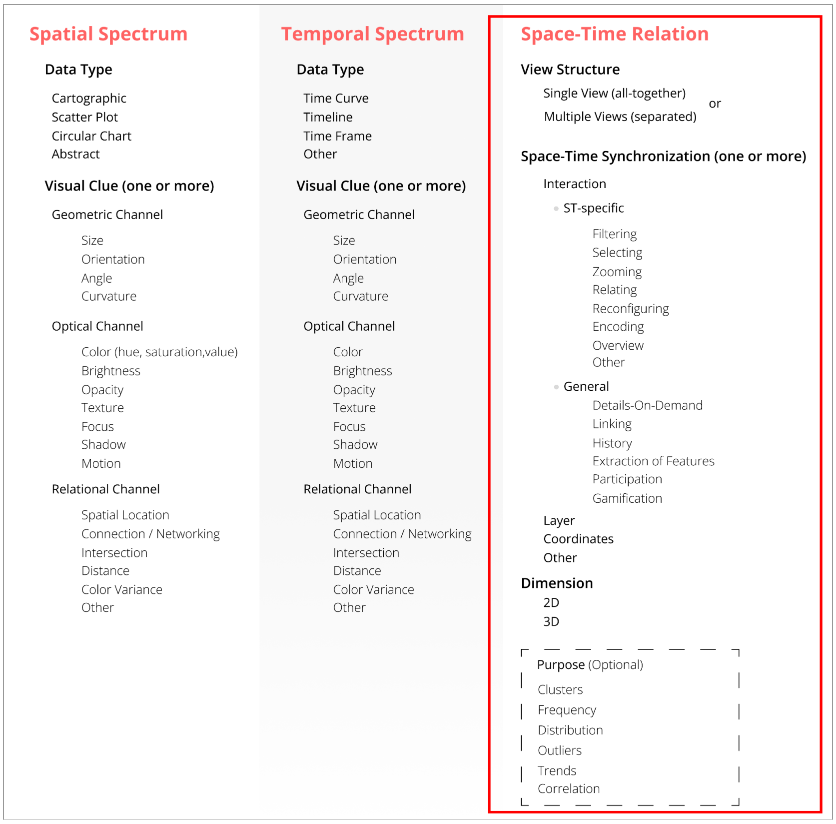


Figure 56: For context, a red rectangle surrounds the AT elements about to be explained - the Space-Time Relation column

In the last column, responsible for the space-time relation (see figure 56 for context), there are four sections: View Structure, Space-Time Synchronization, Dimension, and Purpose. The structure is inspired by the taxonomy by Zhu et al. (2021), but expands on the interaction subsections and includes a new category for classifying the main purpose of the visualization being analyzed.

Firstly, within "View Structure", a visualization can either be all displayed in a single and unique view (all the data together) or scattered through multiple views. On this last one, the data can be separated into various frames.

"Space-Time Synchronization", similarly to the referred work of Zhu et al., refers to how the spatial spectrum acts in conjunction with the temporal spectrum on a visualization. Inside this section, there are four subcategories, namely "Interaction", "Layer", "Coordinates" and "Other". Once again, the "Other" field is subjective to the user's input, in case there is a niche level of synchronization happening between the time and space references of the visualization. Specifically within "Interaction", there are possible options to choose from. Following the work done in *There and then: interacting with spatio-temporal visualization* (Rodrigues & Figueiras, 2020), the proposed taxonomy on this referenced work is embedded into the aggregated taxonomy, making it possible to categorize the interactions either by its general nature, or by a more spatiotemporal-related nature. Taking this into account, the ST-specific subsection has 9 possible interactions and the general section includes 6 options. Since it is complex to summarize a whole type of interaction by its title, Rodrigues & Figueiras succinctly explained each technique on the figure below. This way, anyone who finds it difficult to interpret any of the available options can easily search through the given table (Figure 57) and find its description.

ST	1	filtering	*theme*	Display only items with the properties in which I am interested.
			time	Display only time points or intervals in which I am interested.
			space	Display only locations in which I am interested.
	2	selecting	*theme*	Mark or track items with the properties in which I am interested.
			time	Mark or track time points or intervals in which I am interested.
			space	Mark or track (a) location(s) in which I am interested.
	3a	zooming	*time*	Vary the level of abstraction on a time interval.
			space	Zoom in or out on an area.
	5	connect / relate	*theme*	Relate two or more items from different themes.
			time	Relate two or more time points or intervals.
			space	Relate two or more locations.
	6	reconfigure	*theme*	Give me a different arrangement of the data.
			time	Give me a different arrangement of the temporal structure.
			space	Give me a different arrangement of the locations.
	7	encode	*theme*	Give me a different visual code for the thematic components.
			time	Give me a different visual code for the temporal structure.
			space	Give me a different visual code for the geographical components.
	4	overview	*first*	Give me an overview of all the occurrences first.
			last	Give me an overview of all the occurrences last.
			on-demand	Give me an overview of all the occurrences anytime.
Generic	3b	details-on-demand	*theme*	Show me details on a specific item on demand.
	3c	linking	*theme*	Take me to complementary information.
	8	history	-	Allow me to retrace the steps I take in the exploration.
	9	extraction of features	*theme*	Allow me to extract data in which I am interested.
	10	participation / collaboration	*theme*	Allow to contribute with data.
	11	gamification	*theme*	Show me the data in a more playful way.

Figure 57: Brief descriptions of each interaction technique on the taxonomy done by Rodrigues & Figueiras (2021)

The next section in the AT refers to the dimensions that the visualization uses. Out of this, there are two possible options, two-dimensional or tridimensional.

Finally, the last section of the Space-Time Relation is called “Purpose”, and is seen as an optional part of the taxonomy. This is due to the fact that it includes a very ambiguous set of options, and many of them depend on the current state of the visualization, as many spatiotemporal techniques can assume various purposes at the same time. Despite this, it is still included in the aggregated taxonomy, much due to its future work possibilities and level of relevance to the rest of the taxonomy categories and columns. The options inside this purpose category are based on the work in *Design Factors for Summary Visualization in Visual Analytics* (Sarikaya et al., 2018), which provides a more principled understanding of design practices for summary visualization and offers insight into underutilized approaches. In essence, the tasks and purpose of the visualizations, with the aggregated taxonomy, can go from cluster analysis, to frequency, distribution, outliers, correlations, and trend comparisons.

Each column of the aggregated taxonomy is orthogonal, meaning that they are independent from each other. All around, the AT attempts to comprehensively classify a spatiotemporal visualization through its visual clues and channels. Thanks to its relatively complex structure, while still maintaining ease of use, it permits high-fidelity filtering and classification, which can be useful to anyone who further researches the topic of information visualization, more specifically of spatiotemporal nature.

3.6 Summary

One of the main problems identified was the lack of more complete taxonomies and classifications available regarding spatiotemporal visualizations and how they are represented via their visual metaphors, clues, and channels. There was, then, an opportunity and motivation to further explore this visual narrative aspect of ST techniques and their visualizations. Additionally, the proposed taxonomy would help the implementers understand how to best apply visual channels and their perceived visual metaphors to the visualization’s advantage.

To aid this work, research questions were developed to better understand the work and requirements needed to reach the established goals:

- Are visual clues important to the understanding of spatiotemporal data visualization?
- What is the most efficient way to display a specific type of spatiotemporal data?

- What are the best practices for representing data, according to their visual clues?
- What visual channels can be used to communicate information, and with what purpose?
- How can visual channels convey the correct information to the user?

The research questions would then be investigated through a various number of tasks:

- Develop a taxonomy oriented for spatiotemporal techniques and their visual clues
- Guarantee the effectiveness of the taxonomy via examples and experiments
- Explore different use cases to test in participant experiments
- Cross and analyze data with taxonomy to summarize observations and possible best practices for an effective use of visual clues

One of the proposed solutions, as mentioned on the first task bullet point, was to develop a taxonomy tailored to spatiotemporal techniques and their visual clues. This resulted in what is mentioned in this work as the Aggregated Taxonomy (AT) and it was used and tested with participant experiments, as explained next, in Chapter 4. The rest of the tasks would depend on the statistical analysis of the experiment's results.

4. Experiments

This chapter aims to describe the experiment process performed to validate the aggregated taxonomy. Section 4.1 presents the methodology behind the experiment and how the questionnaires were conceptualized and implemented. Section 4.2 then addresses the tests themselves, thoroughly running through each developed page, exploring why and how each decision was made. Finally, Section 4.3 summarizes the whole chapter by considering its main takeaways and outcomes.

4.1 Methodology

To guarantee the stability of the aggregated taxonomy while still running experiments, a two-in-one test questionnaire was developed. Thus, this questionnaire tests how the novel taxonomy performs from the user's perspective, and also represents an optimal opportunity to use the AT's filtering capabilities to evaluate how the visual channels perform in a spatiotemporal technique.

Firstly, the starting point adopted for the questionnaire development was the 5 W's strategy. As described in Section 2.3, this strategy is a group of questions that make the researcher think about its project in a useful and meaningful way. The questions are:

● **What?** - What is the research? What problem is there to be solved? In this case, the work aims to know if visual clues are important for an effective visualization and spatiotemporal technique readability without requiring too much cognitive effort.

● **Why?** - Why does the researcher want this project? What is its purpose? (Why is there interest in this topic, is there a gap in the literature review you want to solve?)

As mentioned in the motivation and problem statement chapters, visual clues in general are present in every InfoViz, including in complex spatiotemporal visualizations, but the classifications of its use, context and purpose are not thoroughly explored.

● **Who?** - Who will be the participants? Do they need to belong to a specific group of people?

Participants include college students willing to participate and any type of person capable of reading spatiotemporal data.

● **Where?** - Where will the research be conducted? Will there be any costs from the investigation setting?

There will be no costs from investigation as all research was conducted online. Initial tools considered were Zoom, Google Meets, Google Forms, Prolific and UserTesting. Ultimately, Google Forms proved to be the most appropriate tool for the questionnaire, for its ease of use and familiarity.

● **When?** - When is the research going to be done? Is the schedule suitable for the participants?

The research is done when participants are available - participants sign up with google forms so it’s an asynchronous activity without the need to monitor it.

Originally, the research was envisioned to be a more engaging activity, where the participants would be presented with two prototypes, resembling possible spatiotemporal techniques that utilize different visual clues and channels to represent the same type of data. This way, in the end, it would be possible to create a scoreboard-style ranking table that would order the used visual channels in terms of efficiency and preferability towards a certain situation. However, this idea would imply a lengthy development and creation of various data sets, use cases and prototypes filled with interactivity and functionalities, potentially compromising the rest of the work, considering the time available. Furthermore, there was a risk that the created prototypes would be buggy, not correspondent to what was initially designed, and subjective to the participant’s personal opinion. This research method was briefly explored, but quickly discarded as there were too many time-consuming activities that would not be worth the effort within the time frame.

The experimentation and validation process was conducted through the form of questionnaires. This method is especially useful for this situation because it can be close-ended to generate statistics and more quantitative data, but can also include open-ended questions to receive qualitative information that is more broad and open to participant thoughts. This enables the analysis to not only be of statistical matter, but also include qualitative information such as suggestions, opinions and general observations on how the evaluation process was conducted and the questionnaire was elaborated, so that it can potentially be further explored in future work.
The questionnaire was sent via e-mail through the university’s dynamic e-mail system, shared through social media and professional workplaces, successfully reaching 50 participants.
The subjects range from young adults in universities, to middle-aged adults working in many different roles and industries. It is also of relevance to observe that the results may be influenced by sampling bias, as all participations were voluntary (voluntary response sampling) and most of them were all enrolled in the same university, University of Porto (convenience sampling). Due to ease of access and resource limitations, this sampling method was considered to be the most appropriate way to reach the maximum number of participants. Additionally, the result demographics indicate a balanced participation, having almost equal percentage of gender distribution. The gathered sample is mostly young, with the majority (66%) being 18-30. There are no Doctorate's Degree participants and the average is

college-educated. DataViz knowledge is fairly balanced, but as expected, the tendency is lower than a high level of knowledge. Having this in mind, it does not seem that demographics influences the form submissions. Summarizing, gender and education is balanced, however, 52% of participant self-assessed dataviz knowledge is more on the negative side (from 1-3, from a classification of 1 to 10).

After the specification of the 5 W's of the research, the next step was to think of what variables were about to be studied, how they would be studied and the possible outcome and expected results.

Regarding the study variables, the experiments would focus on the components of a visual clue. In other words, as a visual clue is made of one or multiple visual variables, the variables themselves would be the main element of research. This questionnaire aimed to identify what visual clues and variables were the most used, the most efficient and for what purpose spectrum are they better perceived. Furthermore, this would potentially enable the discovery of best practices and what it takes to consider a visual clue good and well applied.

These variables were studied by assigning multiple versions of the questionnaire according to what the subjects answered on a "warm up question". As Google Forms did not have an official way of distributing alternative versions of the same questionnaire, this was the best way to segment and equally distribute a very intensive form into smaller and less frustrating experiments.

To briefly summarize, the final questionnaire is made of 3 main sections:

1. **Introduction**
    a. Demographics
    b. Context and Concepts
    c. Introduction of Work
    d. Warm-Up Question
2. **Visualization Analysis** (based on warm-up question selection)
    a. Description of Event (Open-ended, qualitative data)
    b. Identification of used visual variables using aggregated taxonomy
    c. Rating of used visual variables based on effectiveness
    d. Visualization SUS Scale Test
3. **End**
    a. Time taken to analyse assigned visualization
    b. Observations and suggestions

In the end, the outcome would mainly be statistical - taking into consideration the identification of used visual variables, as well as their effectiveness rating and time taken to be analysed. Section 2.a of the questionnaire was introduced to guarantee the participant correctly understood the depicted subject on the visualization and Section 2.d was included to observe whether the selected visualization was feasible and suitable for experiment, in the sense that if the SUS scale score was below 50 points, it would not be considered a reliable asset for testing. How the spatiotemporal technique visualizations were chosen for testing is a topic to be explored in the next section.

4.2 Tests

As mentioned in the previous section, the questionnaire is composed of three distinct parts: Introduction, Visualization Analysis, and End.

4.2.1 Introduction

The first section of the questionnaire aims to introduce the participants to the work, context and motivation behind it. It is explained that the work originates from a thesis dissertation, a brief explanation of the theory behind it, the expected duration until completion (10 minutes) and a small disclaimer assuring the form complies with current data protection laws. Once the participants proceed, it means that they accept these terms and want to continue onto the next page. Afterwards, there is a small section for sociodemographic questions for statistical purposes. The data gathered from the subjects include the age group, ranging from below 18 to more than 65, their gender, highest degree of education and how knowledgeable the participants are in the data visualization field, ranging from 1 to 7. Additionally to the regular demographic questions, this last question is of special interest as it makes it possible to link the results to the subject's associated perceived knowledge ranking.

The next subsection is called Context and Concepts. Fundamentally, this page is also introductory in the sense that it succinctly describes what spatiotemporal events are, how they are complex, and details for the first time, to the user, what is a visual metaphor, their visual clues and variables. These concepts were heavily mentioned on the rest of the questions, so it made sense to introduce them right at the beginning of the form, so that the participants can read, understand them and apply them in the remainder of the questionnaire. Because of Google Forms' platform experience, all inserted media was automatically resized into a fixed aspect ratio and format. To counteract this measurement, extra links to higher resolution of each image were supplied to the participants for a better analysis and, subsequently, better understanding of the new concepts.

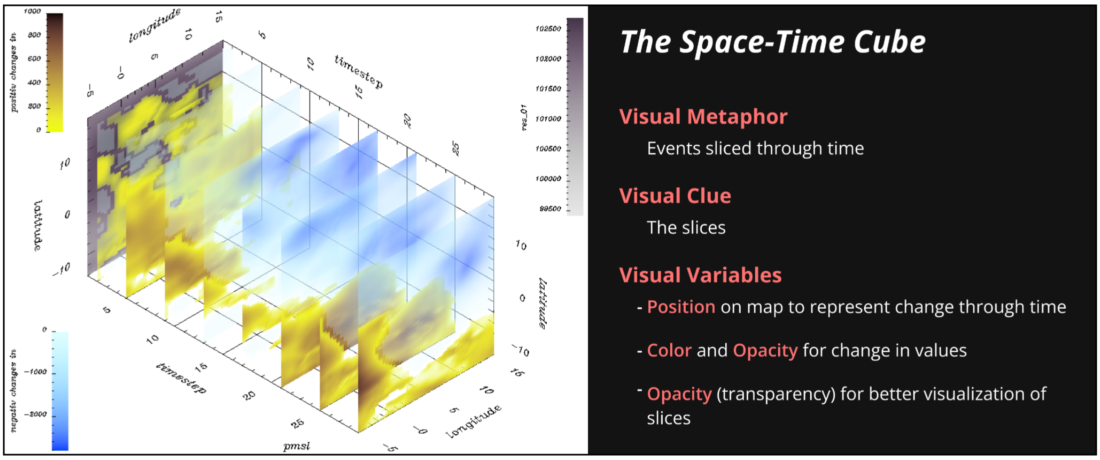


Figure 58: The illustration used to introduce the concepts of visual metaphors

Besides Figure 58, initial versions of the form also included Figure 59 as a means to further explain visual metaphors, but many subject's observations stated they learned nothing from it and found it overwhelming, distracting, or difficult to understand. Because of this, it was removed entirely after preliminary tests. The idea being attempted to pass was that visual metaphors were made of visual clues. Visual Clues are all made of various visual channels, and these go from position variables, to size, shape, and color-based elements.

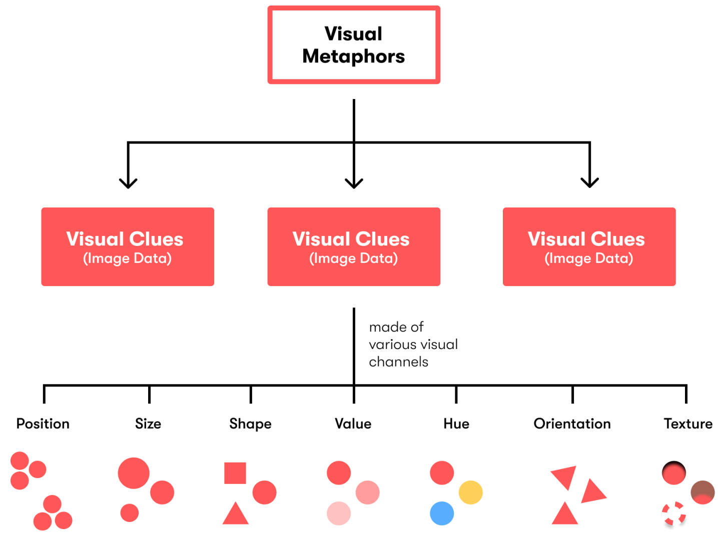


Figure 59: Illustration explaining visual metaphors, clues and variables, which was removed from the questionnaire after preliminary tests

It was encouraged to stay on this page as long as necessary to absorb the information, as the next sections would take the subject to evaluate spatiotemporal techniques using the aggregated taxonomy, which in turn uses these concepts.

Once the participant proceeds, a warm-up question is displayed - it is asked to choose one prime number out of four randomized options. As Google Forms does not have an official way to create different versions of the same questionnaire, this was the closest solution within the platform - Each of the possible prime numbers transfer the participants to a different section, where they analyse and test one spatiotemporal visualization. In total, there were four prime numbers, so there were four possible ST visualization configurations to be tested, as seen in Figure 60. The original form aimed to test all four options in a sequential manner, but after consideration, it was concluded that it would take too long for the participants to finish them, while also risking the flow of the questionnaire and overwhelming the users with too many tasks. This change made the average form submission time drop from 40 minutes to just over 10 minutes.

Figure 60: Participant's questionnaire journey

4.2.2 Visualization Analysis

Starting from this section of the questionnaire onward, the participants are forwarded to one of four possible options, based on their warm-up question choice.

The selected visualizations chosen for analysis were previously reviewed in the state-of-art research phase of this work. Out of hundreds of possible choices and combinations, this group of visualizations were seen to be the most probable, in terms of chance of usage in a realistic setting, and the most diverse in terms of visual channels used for their clues and metaphors. This way, it would be possible to gather a steady set of conclusions with the minimal amount of time and effort from the participants, avoiding them losing their flow and focus on the questionnaire.

The spatiotemporal visualization techniques chosen were Data Vases (Thakur & Rhyne, 2009), Growth Ring Maps (Bak et al., 2009), Temporal Focus+Context (A. Carvalho et al., 2008), and Flow Maps (Kraak & Ormeling, 2003). For each of these and for every candidate technique (before this selection was decided), a classification using the aggregated taxonomy was made, so that it would be possible to know if the visualizations would be well perceived, not very difficult to categorize, and well diversed visual-channel-wise.

All techniques are different and serve different purposes - And because so, there are certain spatiotemporal techniques that are better for a data set than others. Therefore, in order to mitigate this and so that the questionnaire focuses purely on the performance of visual channels (and not on the performance of the techniques themselves), the logic approached when selecting the four techniques would consist of them being the least niche as possible, or in other words, more adapted to a real-world situation, while still maintaining uniqueness on their visual metaphors. Additionally, the chosen set of techniques all have different purposes and there was an effort made for them to also be of different data types on the spatial and temporal spectrum. However, due to time constraints and to gather the most amount of participations as fast as possible, it was not possible to explore all data types, leaving behind the "abstract" data type of the AT and experimenting with 2D or 3D cartographic-referenced techniques.

The runner-up candidates for the experiment included Contour Line Stylization (Zahan et al., 2021), Contour Diff (Ahmed et al., 2021), Trajectory Wall (Tominski et al., 2012), and, on the abstract side, TreeRoses (Tang et al., 2019) and Circos (Krzywinski et al., 2009). Due to their multiple usage of views, lack of context, predicted time spent on classifying them, and overall complex nature, their selections were scrapped.

On the questionnaire, the user is met with its corresponding visualization, based on the warm-up question. Visualization #1 demonstrates Data Vases, and the remaining, respectively visualizations number 2, 3 and 4, show Growth Ring Maps, Temporal Focus+Context and Flow Maps to be analysed. The first question is open-ended, asking the participants to describe the event displayed in the visualization. This is merely meant to guarantee that the images are, at first glance, giving good context and showing understandable information. Users are free to either briefly comment on what they see, or thoroughly describe every detail provided, from visual metaphors to clues, visual channels used, what data is shown and to what extent. Afterwards, once the participant proceeds, the user is met with subsection 2.b - Identification of used visual variables using aggregated taxonomy (see Figure 61). Located below the displayed image, is a small text box confirming the context of the visualization given, in case the subject is unsure. It is then asked to classify the visualization based on what visual variables are depicted.

The possible options are separated by what visual channels they belong to: it is asked to choose variables from the geometric channel, the optical channel and the relational channel. It is not made aware for the participants, but these separations are part of the novel aggregated taxonomy and their sole purpose is to make the subjects classify the visualizations using it.

Because the subjects lack this context, they may not know what certain variables mean or what are the differences between one another. Having this in mind, there was always an option to declare there was no visual variable at use, and an extra option called "Other", in which the user could type their own variable suggestions, in case they don't fit the descriptions of the other available options.

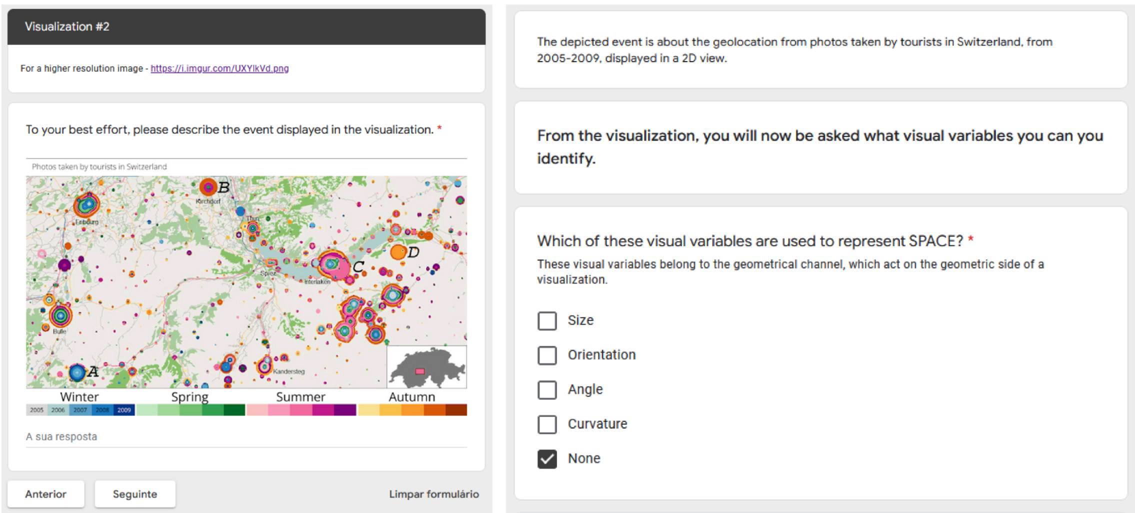


Figure 61: Section 2.a and a brief part of Section 2.b of the questionnaire

As previously mentioned, these participant actions made the subjects put the visual metaphor theory into practice, making them further understand the explained concepts, and also made it possible to test the stability of the aggregated taxonomy in four different situations and visualizations. The essential objective, taxonomy-wise, was to seek if the available visual variables were enough, distinctive and pertinent, hence making the AT a classification capable of handling many different types of spatiotemporal techniques.

The next section, 2.c (Figure 58), involved the rating of used visual variables based on effectiveness. Following the previous section 2.b, where the subjects classificated the visualizations based on the taxonomy, section 2.c shows the correct choices on each spectrum (spatial and temporal) and on each channel.

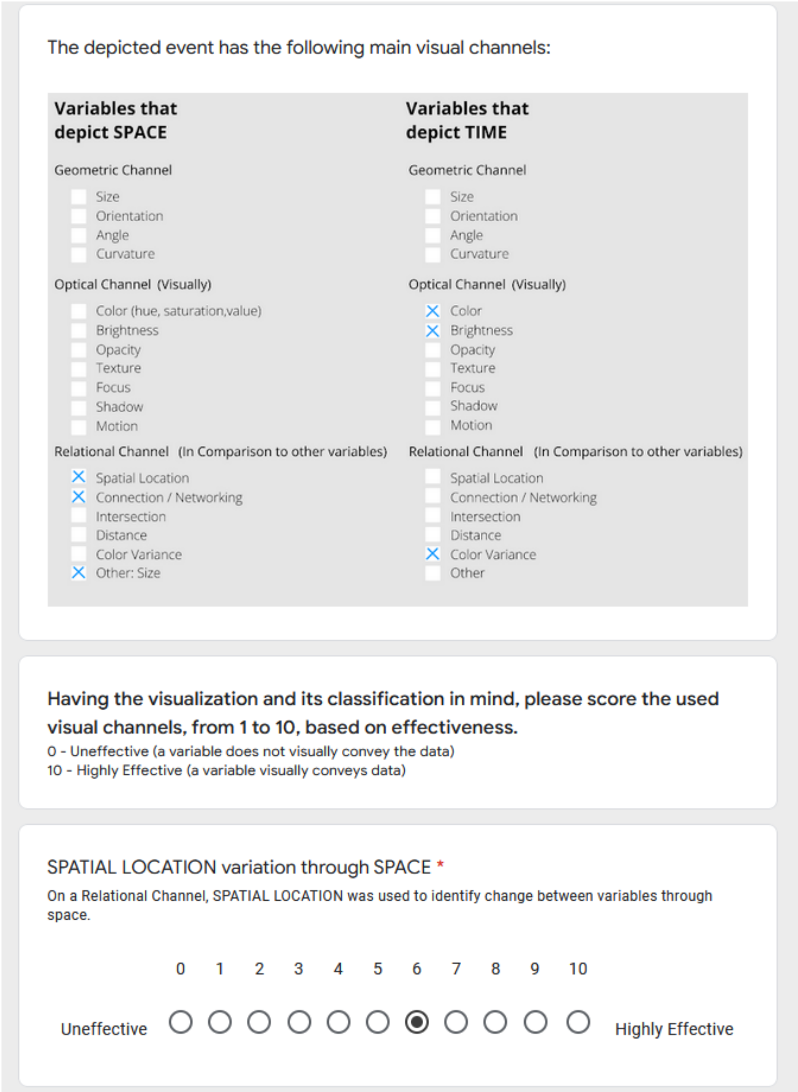


Figure 62: Initial part of Section 2.c

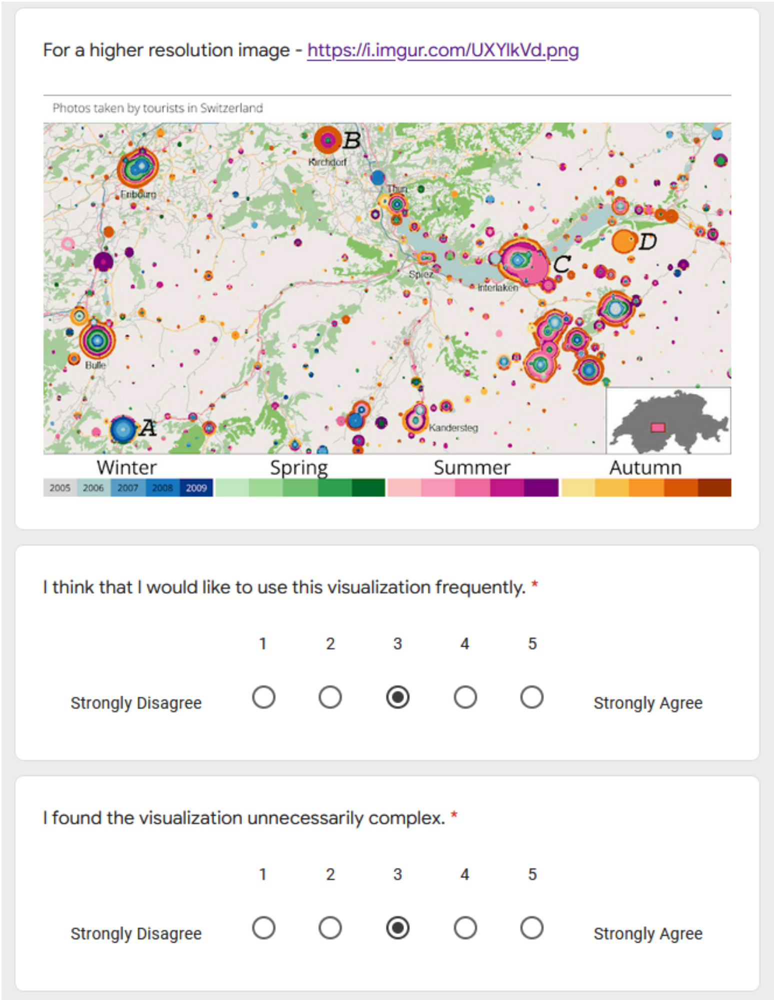
It is then asked to score the used visual variables, from 1 (uneffective) to 7 (highly effective), to see how each variable is perceived and how it conveyed the intended information. On each evaluation, a small descriptive text is shown to further explain the rationale behind this question. For example, in figure 62, it is clarified that the participant must score the visual variable “Spatial Location” based on how well it identifies change throughout the space spectrum of the visualization.

This logic is iterated through all the visual variables identified at the top of the section, making it possible to statistically analyse the results at the end of all participations.

Section 2.d aims to score the selected visualizations through a System Usability Scale test to assure their viability for testing. The SUS test is a standardized questionnaire for measuring perceived usability (Lewis & Sauro, 2017). It is originally designed as a 10-question form, where users agree or disagree with certain statements regarding a specific website, application, or system. Based on the user's response, the SUS score would determine if the system in question would be of very poor perceived usability, with a score of 0, to excellent perceived usability, up to a score of 100.

In the context of this work, there is no goal or necessity of a very high score. A medium score is merely needed, as the System Usability Scale here is being purely used to evaluate the perceived usability of a mockup screenshot of a fictional event in a spatiotemporal technique. In a way, there isn't a system available to be used by the participant, and the screenshot doesn't offer the same operability and interactivity of an actual high-fidelity prototype, so the SUS score is bound to reveal that. The System Usability Scale will not count towards the concluding remarks or statistical analysis, as it was more of a tool to test if the selected spatiotemporal techniques were viable for this experiment, rather than a contribution to the actual research.

The original SUS items refer to "system" in their statements, but substituting the word to "website" or "product," or using the actual website or product name seems to have no effect on the resulting scores (Lewis & Sauro, 2017). So, according to this, the SUS for this work will replace the word "system" with "visualization" for context purposes on the questionnaire. Moreover, one of the SUS statements is "I found the various functions in this visualization were well integrated." This is not relevant to this work, as the scale is scoring a screenshot and not an actual visualization. As stated by Lewis & Sauro (2017), it was found that removing one question from the SUS does not have a significant impact on the final results. It is recommended to keep all ten questions, but if necessary, it is possible to remove one. It is of importance to have a score deviation of +-1 because of it, and to make an appropriate adjustment to the score calculation - to multiply the sum of the adjusted item scores by 100/36 instead of the standard 100/40, or 2.5, to compensate for the dropped item (Lewis & Sauro, 2017). So, having this research in consideration, it was best to remove the mentioned item from the SUS, having only 9 questions counting towards the score. Figure 63 exemplifies how the SUS test looked like, from the user's perspective.


For a higher resolution image - https://i.imgur.com/UXYlkVd.png

Photos taken by tourists in Switzerland

Winter Spring Summer Autumn

2005 2006 2007 2008 2009

I think that I would like to use this visualization frequently. *

1 2 3 4 5

Strongly Disagree Strongly Agree

I found the visualization unnecessarily complex. *

1 2 3 4 5

Strongly Disagree Strongly Agree

Figure 63: Initial part of Section 2.d

Finally, in section 3, the questionnaire displays the closing remarks to the participants before submission. It is asked how long it took to analyse the visualization, to possibly cross with other data and reveal if any visual variables or channels tend to carry a heavier cognitive load than others. An extra area for observations is given, so that the participants can suggest or comment on any part of the questionnaire, as well as an e-mail slot in case the users want to know the results of this work.

4.3 Summary

The methodology behind the experiments was based on the five W's. By knowing what the research is, why it is going to be conducted, who the participants would be, where and when the research would be done, there would be a solid base to start the research with.

In the end, the final questionnaire, to be run through Google Forms, would test the aggregated taxonomy for its stability and would also test the visual variables themselves in terms of performance and perceived effectiveness. The questionnaire is made of 3 main sections: introduction, visualization analytics and the end observations (see section 4.1).

The outcome is mainly statistical and provides a good starting point of knowledge to know what visual channels are there to display information, how they can function together, the most used visual variables and best variables for what context.

5. Results

This chapter reports the results from the testing stage, along with its analysis and further discussion about the outcome, lessons learned, and important observations. All results from the questionnaire were exported to a spreadsheet, where draft conclusions and comments were made with the purpose of later crossing all information and drawing key remarks.

5.1 Results

5.1.1 General overview and sociodemographics

The first section of the questionnaire served as an introduction to the current work and gathers commonly asked personal details, such as age, gender and the current degree of education. Additionally, it was asked how knowledgeable the participants were in the data visualization field, in order to see if the obtained results would portray truthful information to the most common and probable type of persona to be in an information visualization setting.

There were a total of 50 participants. It consisted of a balanced participation, having almost equal percentage of gender distribution: 46% of subjects identified as female, 52% as male and 2% preferred not to reveal their gender. The gathered sample is mostly made of young adults, with the majority (66%) being 18-30. 30% stated to be within the 31-50 age group. There are no Doctorate's Degree participants, but over 78% are college-educated. As for data visualization knowledge, as predicted, it is fairly balanced, but the tendency is lower than a high level of knowledge.

Overall, and as expected, it does not seem that demographics influenced the form submissions. Gender and education is balanced, however, 52% of dataviz knowledge classifications are more on the negative side (from 1-3, out of a 1-10 classification), as evidenced in Figure 64.

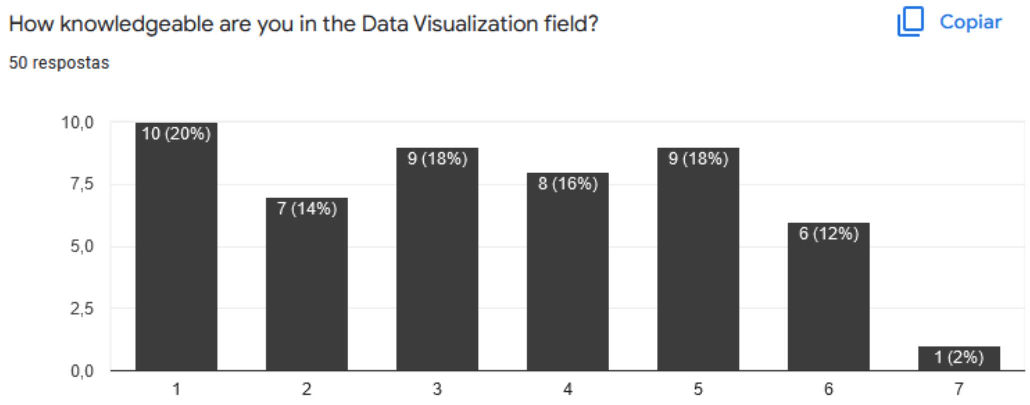


Figure 64: Results from the data visualization knowledge question

5.1.2 Visualization #1 - Data Vases

The results shown below are part of section 4 of the questionnaire. Remembering the format, 4.a starts by asking for a brief description of the event in the visualization given the image in Figure 65, 4.b regards the identification of used visual variables using the AT, 4.c is about rating the visual variables at use based on effectiveness, and 4.d is the visualization System Usability Scale test.

Regarding this last subsection, the SUS test for the Data Vases visualization scored 61.8 +-1. This deviation is necessary because, as referred in earlier chapters, one statement was removed from the SUS test, changing the logic behind the final score calculations. It has been reported that the deviation is needed and the statement removal does not greatly affect any other aspect of the research.

On the SUS score rating scale, C- is acceptable ("Ok"). This score means that the visualization was mostly hard to analyse and therefore, difficult to identify visual variables in action. As such, effectiveness scores made by the participants on this visualization may not be as truthful as in other settings, ST techniques or environments. With a low sample size of 10 answers, the score tends to be lower, as each "opinion" has a higher value and is more susceptible to deviation and noise. The SUS was more as a means to know if the visualization technique was viable to be analysed instead of its actual usability, so in terms of analysis, the score is not important, as long as it isn't below 50, as it then portrays a negative usability score.

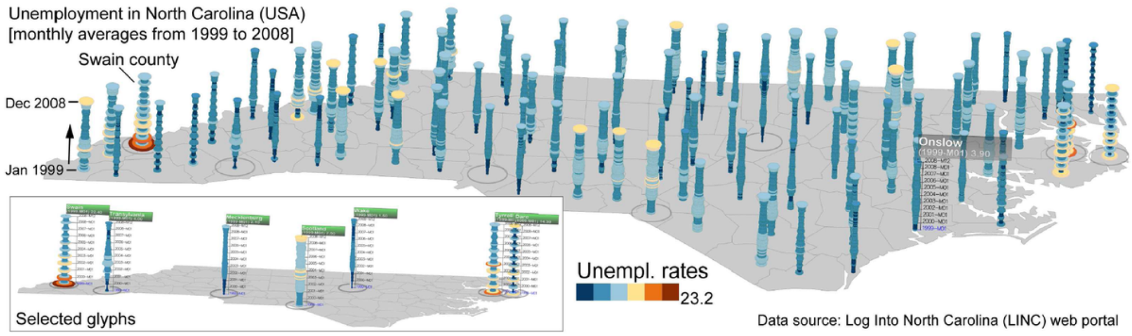
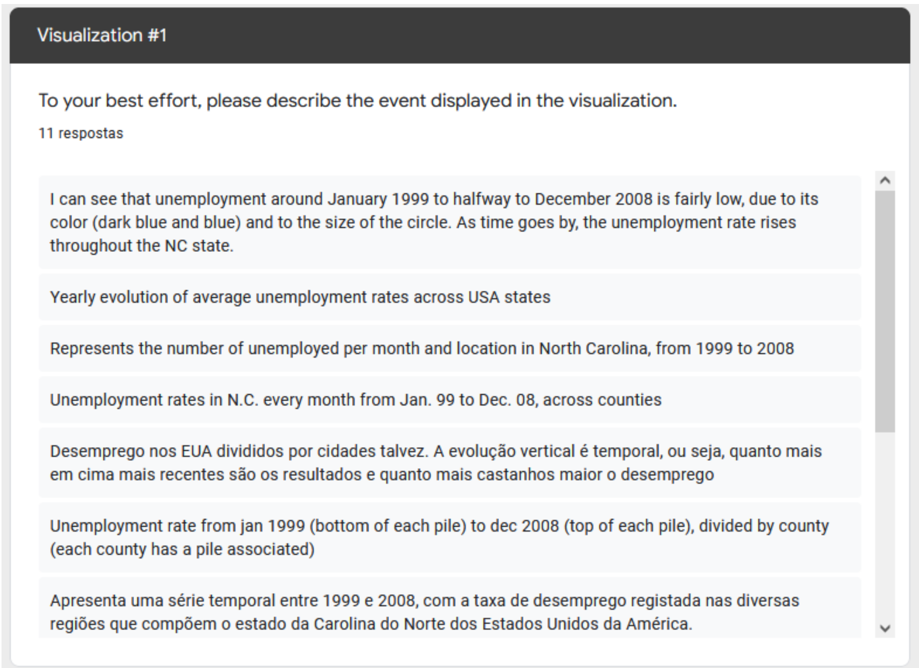


Figure 65: Visualization #1 of the questionnaire - Data Vases

On section 4.a of the questionnaire, all 11 descriptions were correct, demonstrating that the visualization is, at first glance, giving good context. A correct interpretation would have to mention the fact that the depicted event is about the unemployment rate in North Carolina, USA, 1999-2008, displayed in a 3D view. Figure 62 demonstrates some of the answers given.



Visualization #1

To your best effort, please describe the event displayed in the visualization.

11 respostas

I can see that unemployment around January 1999 to halfway to December 2008 is fairly low, due to its color (dark blue and blue) and to the size of the circle. As time goes by, the unemployment rate rises throughout the NC state.

Yearly evolution of average unemployment rates across USA states

Represents the number of unemployed per month and location in North Carolina, from 1999 to 2008

Unemployment rates in N.C. every month from Jan. 99 to Dec. 08, across counties

Desemprego nos EUA divididos por cidades talvez. A evolução vertical é temporal, ou seja, quanto mais em cima mais recentes são os resultados e quanto mais castanhos maior o desemprego

Unemployment rate from jan 1999 (bottom of each pile) to dec 2008 (top of each pile), divided by county (each county has a pile associated)

Apresenta uma série temporal entre 1999 e 2008, com a taxa de desemprego registada nas diversas regiões que compõem o estado da Carolina do Norte dos Estados Unidos da América.

Figure 62: Screenshot of some of the descriptions for Viz #1

Section 4.b asks the users to classify the visualization using the variables available through the aggregated taxonomy. For context, Figure 66 shows the main visual variables used on this visualization. This was also the same figure shown in section 4.c to the participants, so that they scored the checked visual variables based on effectiveness.

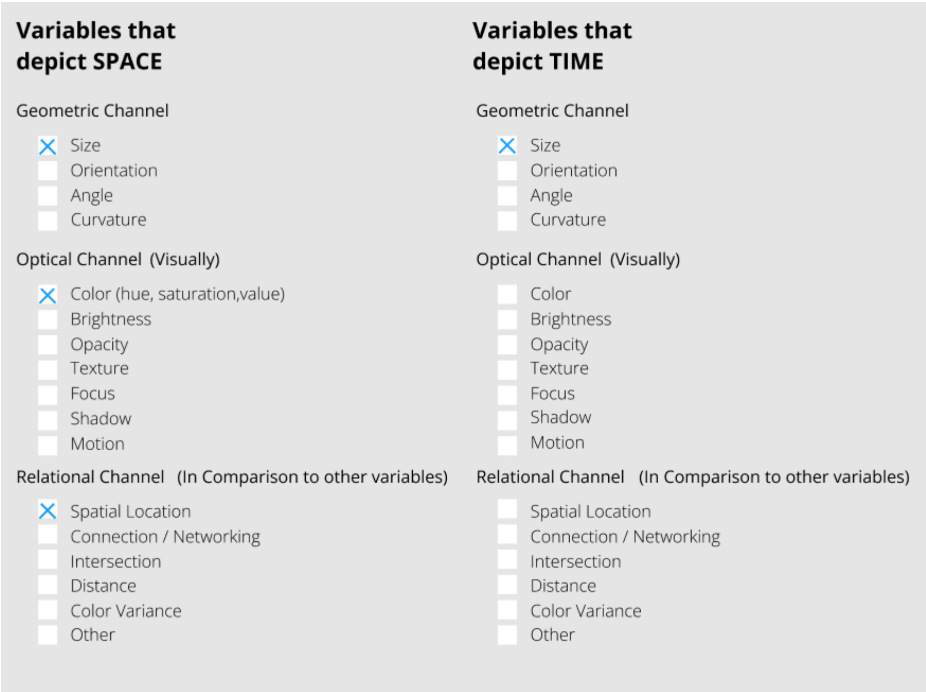


Figure 66: Visualization #1 evaluated using the Aggregated Taxonomy

Regarding the results from Section 4.b, on the spatial spectrum, “size” is correctly observed, most of the time (54.5% of votes included size as a variable in use). Other choices were selected but were not correct, albeit "understandable" as people did not have much context on what the variables directly meant to portrait

On the optical channel, spatial spectrum-wise, about 50% of the people identified the usage of color for spatial representation, and the other 50% did not observe any optical channel usage. Brightness and opacity selections were also made (27.3%), but as mentioned, are understandable, as people did not have much context on what the variables directly meant to portray. Focus was not meant to be detectable through the given image but would also be a correct choice, as 27.3% of votes selected the variable. This variable was not supposed to be identified, so it will not count towards the analysis on this visualization.

On the relational channel of spatial representation, the variable “Spatial Location” was well identified, with 81.8% of the answers selecting it. With this considerable amount of selections, it means the spatial location variable correctly signifies and represents space in the visualization. It is seen as an effective and clear visual variable.

When it comes to the temporal spectrum side of section 4.b, and more specifically on the geometrical side, about 50% of participants voted on the combination of size and orientation. At the time of development, it made sense to just include “Size” as a variable that is representing time in the visualization. However, it can be argued that, in essence, the selected combination of size and orientation can assimilate the same logic as the "spatial location" variable on the relational channel. Therefore, while not considered correct at the time, these selections may count as eligible as "spatial location" votes, hence making it possible to consider it a well identified variable in action for time depiction.

On the optical side, 82% of participant votes correctly identified there were no optical channels being used for temporal representation.

When it comes to the relational channel, 27.3% identified spatial location as a variable representing time change, as well as the distance and color variance variables. At the time of the questionnaire, spatial location was not seen as a visual variable representing the temporal spectrum. However, after reviewing the taxonomy, it was concluded that there was indeed a representation of time in each data vase, in the sense that the bottom of the vase initiated the time frame, and the top of the vase meant the end of the time reference. Linking this to the geometrical channel observations, it can be said that spatial location was correctly identified, though it was not specified so on the questionnaire. The lack of context the participants had resulted in a problem when choosing visual variables, as sometimes, the subjects did not know the difference between a certain variable when compared to another.

Section 4.c went through the visual variables that were considered correct at the time, and asked participants to rate them based on effectiveness, from 1 to 10. Firstly, the visual variables on the spatial spectrum were scored, and only afterwards was the temporal spectrum score done.

80% of the participants agreed that size variable, on a geometric perspective, positively depicted space in this 3D, cartographic-referenced environment (see Figure 67).

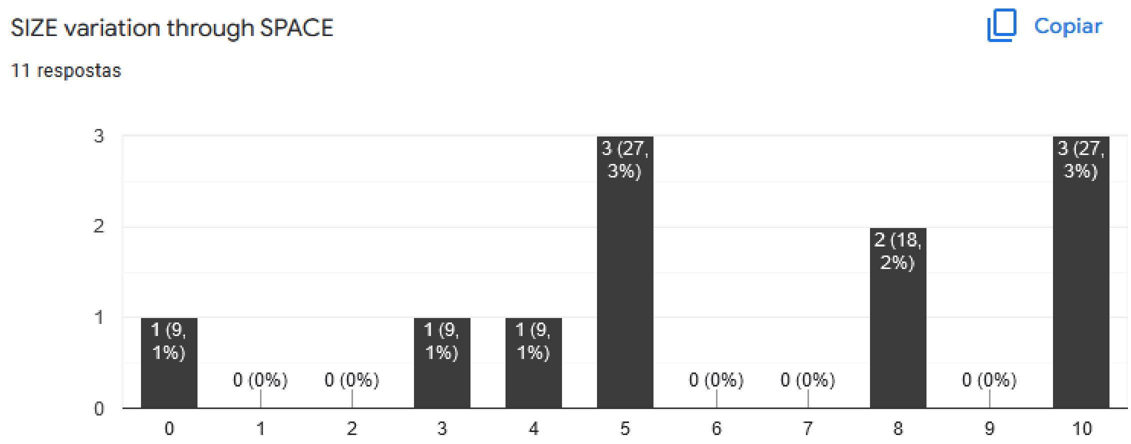


Figure 67: Snippet of section 4.c results regarding size on the spatial spectrum

63% of participants positively observed color, from the optical channel, for the representation of space. One relevant observation is that, while mixed, the most voted selection gathered 27.3% of the participants and corresponded to a score of 9 out of 10 (see Figure 68).

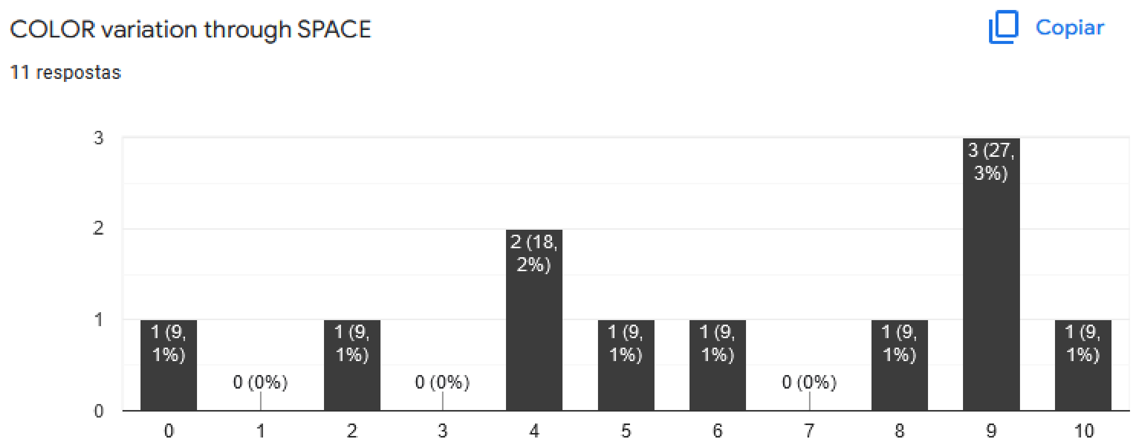


Figure 68: Snippet of section 4.c results regarding color on the spatial spectrum

Spatial Location was nearly perfectly identified on the spatial spectrum, with 90.9% of votes being positive, remarking it as a very effective way to represent spatial change on this visualization. Using this variable in conjunction with a cartographic reference, it is almost certain that the variable effectively transmits its conveyed information correctly.

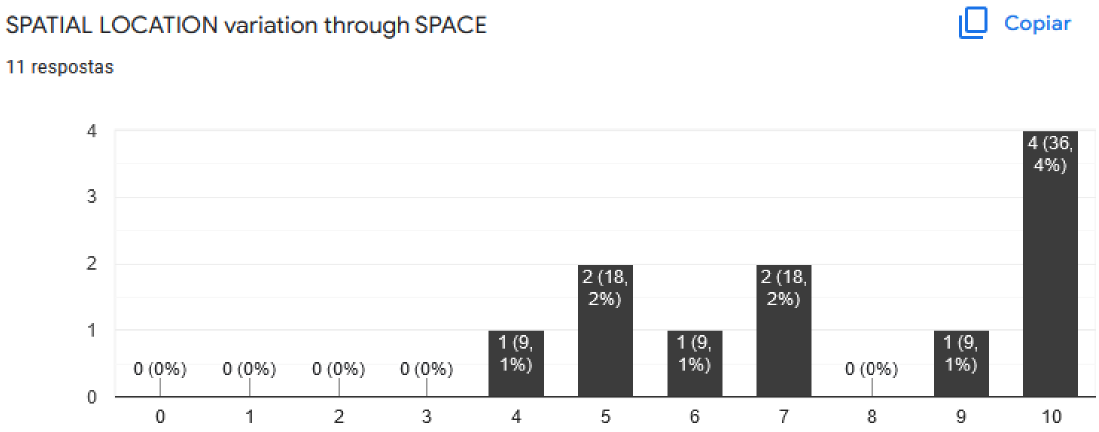


Figure 69: Snippet of section 4.c results regarding spatial location on the spatial spectrum

On the temporal spectrum, the only evaluated variable was size. As mentioned previously, after consideration, size was not a correct variable in action for time so this may be considered irrelevant at first. However, 63% understood some form of size variation was in play to represent the time reference. This is because, in turn, spatial location was being used on each data vase to represent the evolution of time.

5.1.2 Visualization #2 - Growth Ring Maps

Visualization #2 is named Growth Ring Maps (shown in Figure 70). On the SUS test, the visualization scored 64.52 +-1, which according to the score table, is classified as “Ok”. This score means, much like visualization #1, there was a certain difficulty to identify visual variables in action on both spectrums. As such, effectiveness scores made by the participants on this visualization may also not be as expected or reflective of reality.

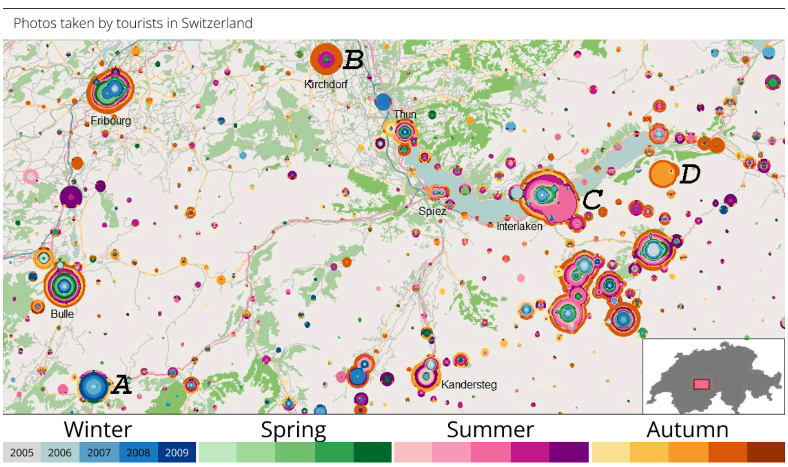
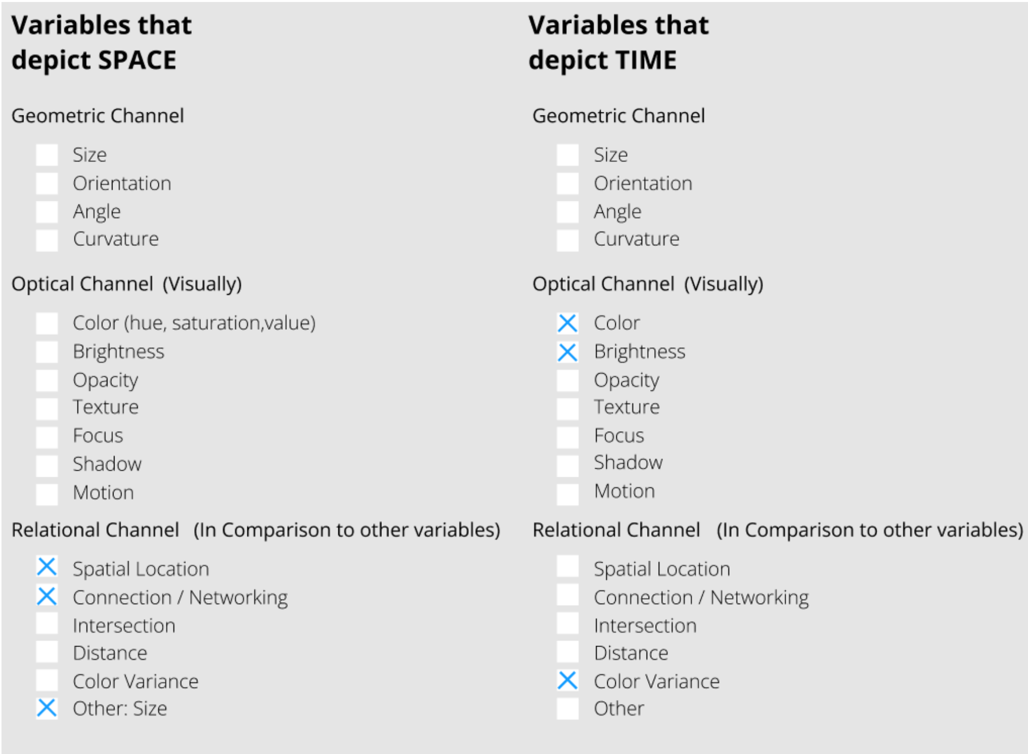


Figure 70: Visualization #2 - Growth Ring Maps

The comments from the participants in Section 4.a accurately described the event depicted on the provided visualization. The observations must have had to specify the geolocation from photos taken by tourists in Switzerland, from 2005-2009, displayed in a 2D view.

For context on later result analysis, Figure 71 shows the Growth Ring Maps visualization assessed by the aggregated taxonomy.


Variables that depict SPACE

Geometric Channel

- [ ] Size
- [ ] Orientation
- [ ] Angle
- [ ] Curvature

Optical Channel (Visually)

- [ ] Color (hue, saturation,value)
- [ ] Brightness
- [ ] Opacity
- [ ] Texture
- [ ] Focus
- [ ] Shadow
- [ ] Motion

Relational Channel (In Comparison to other variables)

- [x] Spatial Location
- [x] Connection / Networking
- [ ] Intersection
- [ ] Distance
- [ ] Color Variance
- [x] Other: Size

Variables that depict TIME

Geometric Channel

- [ ] Size
- [ ] Orientation
- [ ] Angle
- [ ] Curvature

Optical Channel (Visually)

- [x] Color
- [x] Brightness
- [ ] Opacity
- [ ] Texture
- [ ] Focus
- [ ] Shadow
- [ ] Motion

Relational Channel (In Comparison to other variables)

- [ ] Spatial Location
- [ ] Connection / Networking
- [ ] Intersection
- [ ] Distance
- [x] Color Variance
- [ ] Other

Figure 71: Visualization #2 evaluated using the Aggregated Taxonomy

On section 4.b, on the spatial spectrum (see Figure 72), over 57% of participants agreed there was no representation of space on the geometric channel. 28.6% chose the orientation variable as a possible way to represent space. Having Figure 65 as a reference, it is possible that the participants mistook the cluster assimilation of the growth rings as orientation, as a means to indicate the direction the trend of photos taken by tourists was heading to, as time passed by. However, this interpretation is incorrect. The correct logic behind the growth ring maps is that a pixel represents a certain amount of photos taken by tourists. The more photos are taken in an area, the more pixels that area will have, hence creating a cluster that sometimes may appear deformed due to the area of concentrations being irregular.

71.4% of participant votes observed that no optical channel was in use for space representation. 28% of votes stated to see optical variance through color and opacity, which is not a correct interpretation. This potentially means that, in turn, color and optical variables may be a confusing way to depict time as they can be easily mistaken or misinterpreted.

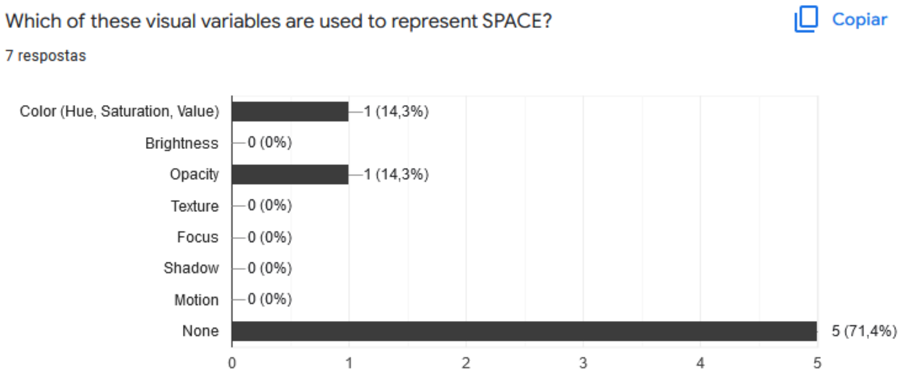


Figure 72: Snippet of section 4.b from visualization #2

Regarding the relational channel, and as in other tests, the spatial location variable on top of a cartographic reference is a very effective way of representing space. This minimizes the data-to-ink ratio and keeps the visualization simple to analyse. 100% of the participants succeeded in choosing spatial location as a variable that represents change within the space spectrum.

On the temporal spectrum side, participants correctly identified there was no variable geometric-wise for time representation.

In the optical channel, color was correctly identified for temporal change. This leads to deliberate if a potential best practice for ST techniques is to think of ways that depict either space or time by only including variables from a single channel. In other words, to not mix visual channels in each spectrum)

When it comes to the relational channel, 85.7% correctly selected color variance as an option, as Figure 73 shows. This can be linked to the optical channel results: As a single relational variable is being used, it is easier for it to be detected. Nevertheless, this does not mean "the less the better". Multiple relational channel variables can be a possibility but they need to be able to harmonize between each other and also with the variables from other channels.

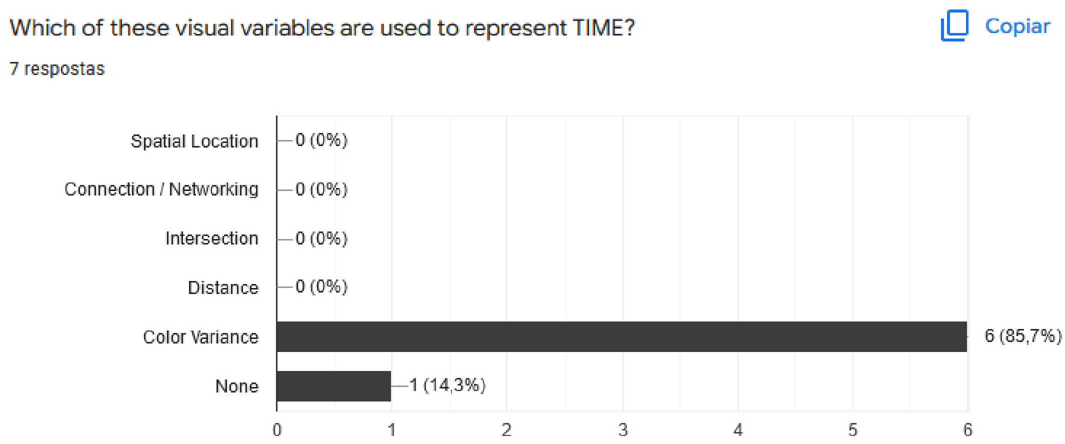


Figure 73: Snippet #2 of section 4.b from visualization #2

With section 4.c, it was possible to observe that 100% of the participant votes saw the spatial location variable as a very highly effective way of representing space. More specifically, 57.1% voted a 10 out of 10, and the remainder selected 8 out of 10. Spatial Location is, then, seen as a very effective variable in this situation.

However, as for the connection variable for space representation, 57.2% of the votes were on the negative side. This means that the connection / networking relationship between variables is not that clear, unless mentioned or previously explained.

85% of votes were positive on color variation to represent time. Participants concluded that it was well displayed and explained, which leads to a potential good practice: each channel that is being used on each spectrum must be briefly explained or captioned in some way, in order for it to be understood.

Brightness, when paired with color value variation to represent time, is not as detectable or perceivable - hence receiving mixed opinions. Although, the color variance variable is well explicit and captioned, so it had a very positive effect and feedback - 85% rated its effectiveness a score of 7 or higher.

5.1.2 Visualization #3 - Temporal Focus+Context

Visualization #3 is named Temporal Focus+Context (Figure 74). On the SUS test, the visualization scored 67.72 +-1, which according to the score table, is classified as “Ok”. It had a total of 19 participants and all sector 2.a comments were accurate. The acceptance criteria for this sector was that it had to mention the depicted event was about the evolution of a building construction, displayed in 3D, through its various stages from january to june 2014.

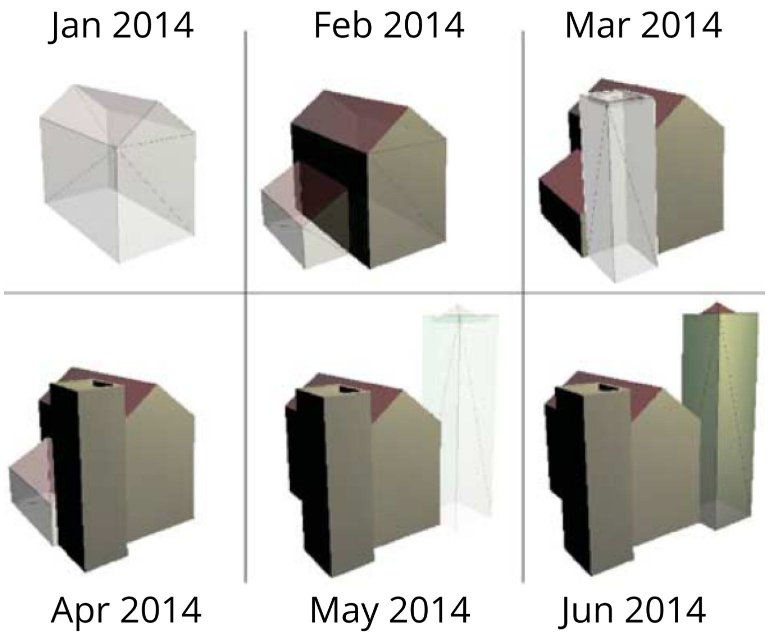


Figure 74: Visualization #3 - Temporal Focus+Context

Variables that depict SPACE

Geometric Channel

- [ ] Size
- [ ] Orientation
- [ ] Angle
- [ ] Curvature

Optical Channel (Visually)

- [x] Color (hue, saturation,value)
- [ ] Brightness
- [ ] Opacity
- [ ] Texture
- [ ] Focus
- [ ] Shadow
- [ ] Motion

Relational Channel (In Comparison to other variables)

- [ ] Spatial Location
- [ ] Connection / Networking
- [ ] Intersection
- [ ] Distance
- [ ] Color Variance
- [ ] Other

Variables that depict TIME

Geometric Channel

- [ ] Size
- [ ] Orientation
- [ ] Angle
- [ ] Curvature

Optical Channel (Visually)

- [ ] Color
- [ ] Brightness
- [x] Opacity
- [x] Texture
- [x] Focus
- [ ] Shadow
- [ ] Motion

Relational Channel (In Comparison to other variables)

- [ ] Spatial Location
- [ ] Connection / Networking
- [ ] Intersection
- [ ] Distance
- [x] Color Variance
- [ ] Other

Figure 75: Visualization #3 evaluated using the Aggregated Taxonomy

In section 4.b, through the spatial spectrum, participants stated to have seen geometric channel usage to represent space. Hence, 84.2% have selected size as a variable in use. While this visualization is of easy comprehension, its use of visual clues is more complex than expected. Here, the size variable was mistaken by color, of the optical channel. Size is not used as a means to represent space. But it can be argued that "shape" is used geometrically to differentiate a tower variable from a house variable. Furthermore, over 50% of votes also saw a usage of orientation and angle for spatial representation. While this is true in the actual technique itself, as it is a tridimensional representation that can then be manipulated and interacted with, by dragging it and exploring the various angles, it was not meant to be detected or evaluated within this visualization.

Because of this mistaken observation on the geometrical channel, the choices made on the optical channel for spatial representation were also impacted. From Figure 76, it can be seen that there was a mixed set of opinions and votes, from which it is not possible to gather any steady conclusions from such a low and mixed sample.

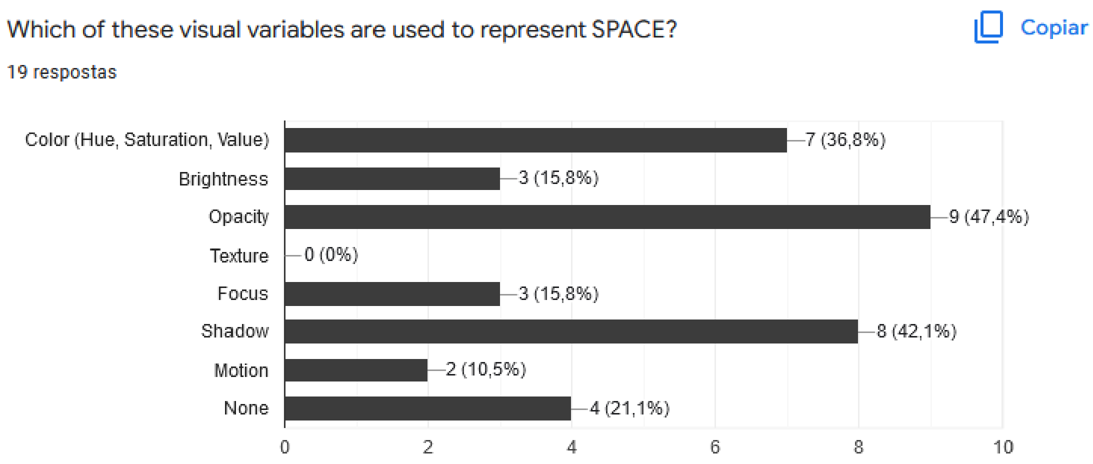


Figure 76: Snippet #1 of section 4.b from visualization #3

Once again, on the relational channel, the spatial location variable proved to be a valuable and easily identifiable asset, even on an abstract spatial representation, with the absence of a cartographic reference. At the time of the experiment, the spatial location variable was not identified to be in use in this visualization, but after considering it, it is correct to say it is. Color variance had less recognition, but 52% of votes remained to correctly identify it (see Figure 77 for full context).

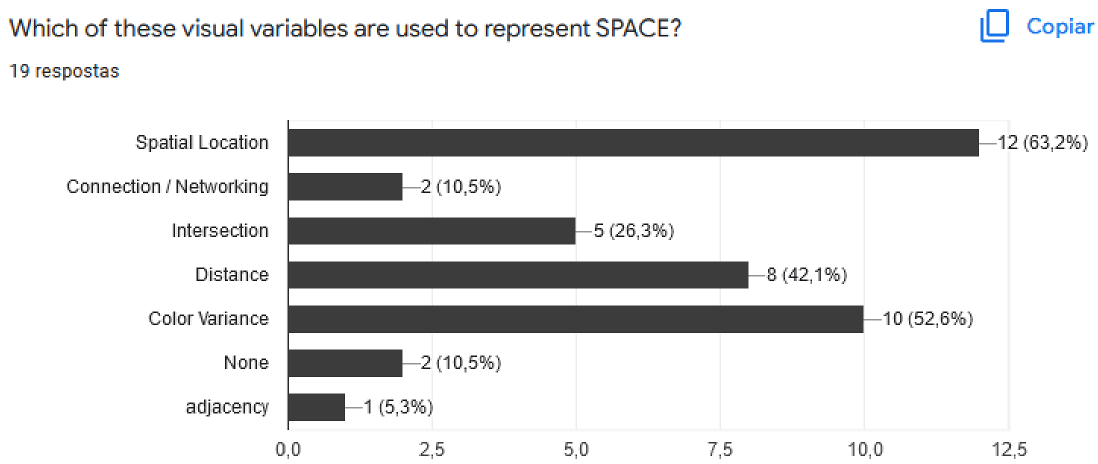


Figure 77: Snippet #2 of section 4.b from visualization #3

Regarding the temporal spectrum visual variable identifications, on the geometric side, 84.2% of subjects stated there were no variables in action.

On the optical channel, the same problem occurs as the one on the spatial spectrum. There are many different and mixed opinions, which makes it difficult to gather a steady conclusion, other than the same visual channels cannot be used simultaneously for the Spatial and Temporal spectrum, or it risks being confusing to the user at first glance.

Interestingly, on the relational channel of the temporal spectrum, 15% stated there was no common variable at use, but that the only reference of time were the captions provided alongside each time-frame in the visualization. For this effect, participants opted to choose the “Other” variable and type their own variable stating said observation.

As for section 4.c, subjects scored the color variable on spatial representation to be very positive. 84.1% scored it positively, from 5 to 10.

On the same line, Opacity as a means to represent time was said to effectively transmit its idea when used in conjunction with other optical variables - 89.6% rated opacity as a very effective variable in this visualization (from a score of 5 and upwards)

The focus and texture variables failed to be seen as effective, much due to the fact that they are being used alongside other optical channel variables. As their concepts are very similar, they can often be confused and, because of that, not easily detectable. Most users (68.4%) failed to detect texture and focus (58%) as a way to represent change in time.

5.1.2 Visualization #4 - Flow Maps

Visualization #4 is named Flow Maps (see Figure 78). On the SUS test, the visualization scored 69.08 +-1, which according to the score table, is classified as “Ok”. It had a total of 13 participants and all sector 2.a comments were accurate. The acceptance criteria for this sector was that it had to mention the depicted event was about the road traffic on 27th January 2005 in Germany. Main traffic areas are pointed out with bigger circles and traffic trajectory is indicated with an arrow.

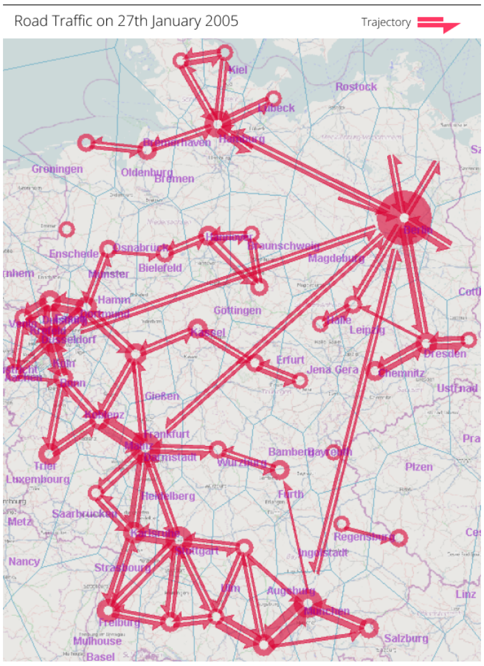
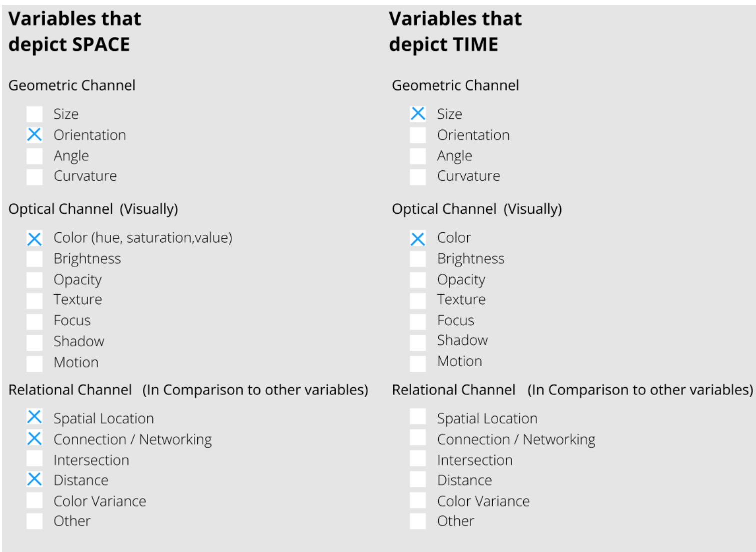


Figure 78: Visualization #4 - Flow Maps



Variables that depict SPACE	Variables that depict TIME
Geometric Channel	**Geometric Channel**
☐ Size	☒ Size
☒ Orientation	☐ Orientation
☐ Angle	☐ Angle
☐ Curvature	☐ Curvature
Optical Channel (Visually)	**Optical Channel (Visually)**
☒ Color (hue, saturation,value)	☒ Color
☐ Brightness	☐ Brightness
☐ Opacity	☐ Opacity
☐ Texture	☐ Texture
☐ Focus	☐ Focus
☐ Shadow	☐ Shadow
☐ Motion	☐ Motion
Relational Channel (In Comparison to other variables)	**Relational Channel (In Comparison to other variables)**
☒ Spatial Location	☐ Spatial Location
☒ Connection / Networking	☐ Connection / Networking
☐ Intersection	☐ Intersection
☒ Distance	☐ Distance
☐ Color Variance	☐ Color Variance
☐ Other	☐ Other

Figure 79: Visualization #4 evaluated using the Aggregated Taxonomy

On Sector 4.b, on the spatial spectrum, size was mistaken as a representation for space instead of time. But orientation, the correct choice, about 50% got it right.

On the optical channel, on the other hand, and as seen in Figure 80, the color variable was correctly identified. Brightness and opacity can usually be mistaken with color, as they are very similar optical variables, and this can be confirmed by the figure below, showing said results.

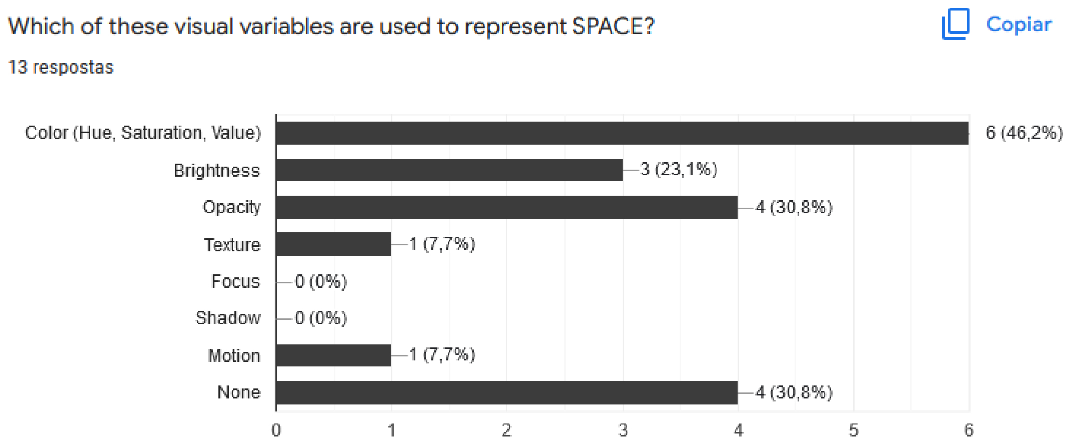


Figure 80: Snippet #1 of section 4.b from visualization #4

The relational channel was expected to have mixed results, as there were several visual relational variables being used, but the participant votes correctly identified most of them. About 50% of the participants identified the spatial location and distance variables. Nevertheless, only 38.5% reported to see the connection and networking aspect of the visualization.

On the temporal spectrum, and as a result of size being mistaken as a representation of space rather than time, 53% failed to correctly choose size and instead selected “None” as for geometrical channel variables.

In a certain way, on the optical channel, color is used to portray the effect of time passing. This can be seen on the visualization, as the stronger the color gets, it means that the road traffic was more intense in that area for a longer period of time. Therefore, color, more specifically its hue, became stronger with the more time passed on that certain spot. Because of this logic demanding a higher cognitive process than other variables, it is normal for participants with lower level knowledge of data visualization to effectively understand this with low effort. This can be confirmed, as only 30.8% successfully detected color as a time variant, and 38.5% didn’t select any optical variable.

There is no relational channel variable at use in the visualization, and over 50% of the participants recognized that.

Based on section 4.c, which is briefly represented in Figures 81, 82 and 83, the orientation variable for spatial representation was correctly identified with near 100% positive effectiveness.

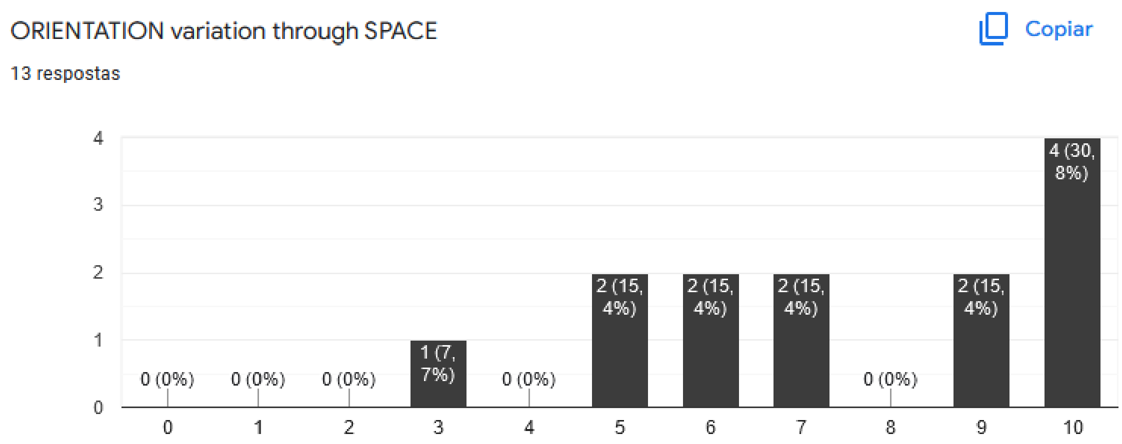


Figure 81: Snippet #1 of section 4.c from visualization #4

Color was used in both spatial and temporal spectrums. Because of this, there were mixed reactions in terms of rating the variable for effectiveness. 30.8% rated it positively effective, 15.4% considered it neutral, and 46.2% found it more on the uneffective side.

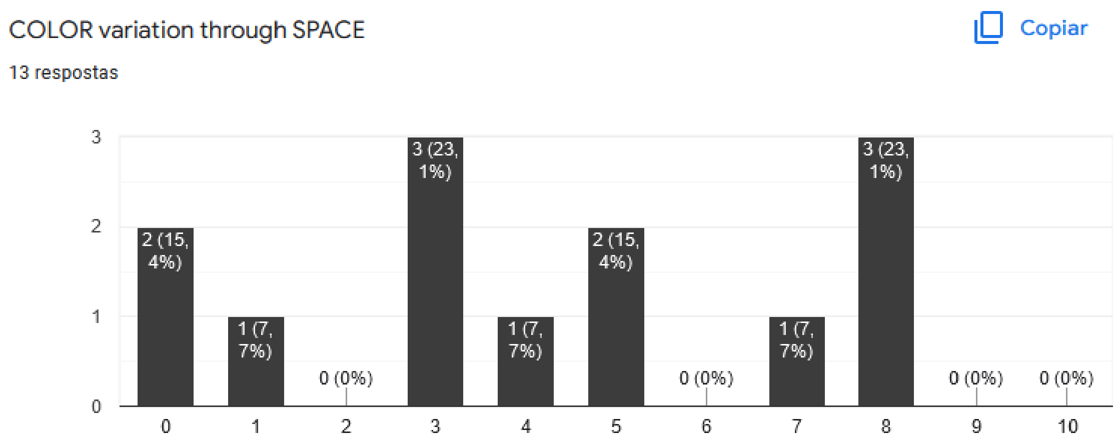


Figure 82: Snippet #2 of section 4.c from visualization #4

Regarding spatial location representing space, 92.7% considered it to be highly effective, from scores ranging from 7 to 10. The spatial location variable proves to be a valuable option for any type of spatiotemporal representation.

The connection / networking and distance variables for space representation were correctly identified and seen as a highly effective method in this visualization. The majority of votes were positive, with little to no negative selections.

Finally, the size variation variable, despite being one of the only variables representing time, is not being well perceived. Its score results are mixed, leaving the possibility that further exploration of this testing format could be researched, as it seems the questionnaire would benefit with a larger sample. With this low number of entries and participants, it is more subjective to answers and statistics that are not depicting the reality and thoughts from the majority of regular dataviz users.

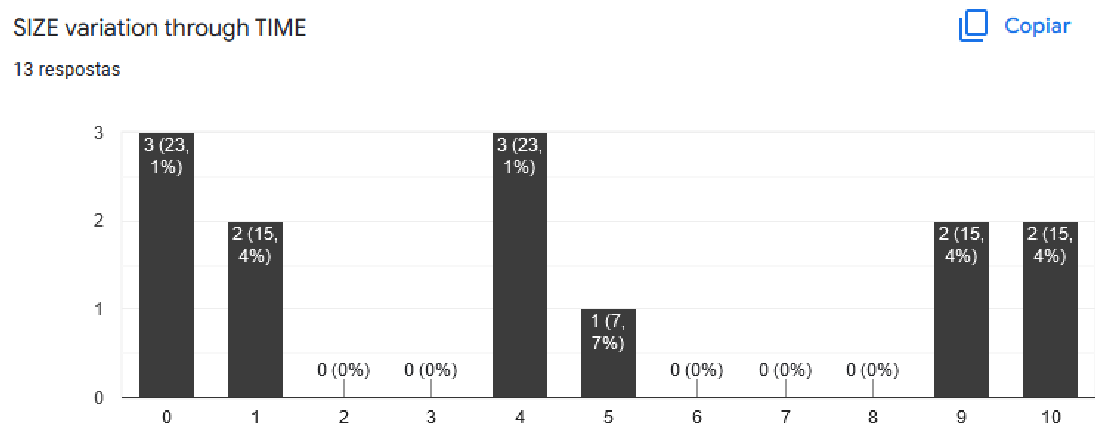


Figure 83: Snippet #3 of section 4.c from visualization #4

5.2 Discussion

Overall, and as expected, it does not seem that demographics influenced the form submissions. Gender and education levels are balanced, though 52% of dataviz knowledge classifications are more on the negative side. This had a slight effect on the results, as it seems the questionnaire would benefit with a larger sample. With this low number of entries and participants, the form was more subjective to answers and statistics that are not depicting the reality and thoughts from the majority of regular dataviz users. However, some key points can be made about the conducted research.

In general, good spatiotemporal visual clue best practices include being aware of how many visual channels are being used on a single spectrum, and if they potentially clash. From the test results, it's possible to point out this when certain visualizations used a combination of optical variables, such as the color variable simultaneously with brightness and opacity. Because of their similar nature, paired with lack of further explanation of what each variable means, it was difficult for the participants to process their differences and what they meant in the visualizations. This too leads to assume that for every visual channel and, if possible, visual variable, some type of description, caption or keyline is needed, in order to aid the user on the visualization analysis and to lessen the perceived cognitive load.

It is also advised that the same visual channel cannot be used simultaneously for the spatial and temporal spectrum, or it risks being confusing to the user at first glance.

On the other hand, mainly thanks to the results gathered from visualization #2, a good practice for ST techniques is to think of ways that depict either space or time by only including variables from a single channel or as few channels as possible. In other words, it is advised to avoid mixing channels within each and between spectrums. On the same line, and as mentioned in previous chapters, this does not mean "the less visual glyphs and variables, the better". Multiple channel variables can be a possibility but they need to be able to carefully harmonize between each other. A bad cooperation of variables would be the brightness and opacity combinations, as seen above. However, a good harmonization observed would be the size variable, on the geometric channel, paired with the spatial location and distance relational variables. This is particularly evidenced in the Data Vases visualization.

All in all, basing off the gathered data, the most effective visual channel on both spectrums was the relational channel. The way it conveys information and relates the displayed visual clues with each other, facilitates the user's understanding of the visualization, making it make sense in a more engaging and comprehensive way, as the visual clues start having a storytelling effect. This aspect promotes focus to the user, creating an implicit visual narrative and immersing the user.

Specifically regarding the spatial location and color variance variables, they proved to be important relational channel variables, with a high level of adaptability and of easy understanding with a relatively low effort. Thus, it can be observed that these variables could be a valuable asset in future spatiotemporal visualizations, because of their level of efficiency, especially in a setting where geographic context is given through a map or some type of cartographic reference.

On the geometric channel, within all spatiotemporal techniques reviewed (not just the ones selected for the questionnaire) size was the most used visual variable to represent both spatial and temporal spectrums and, on the optical channel, color was predominantly chosen as the main variable. Statistically, from the questionnaire, about 58.08% of the respondents scored the size variable as positively effective and 65.22% viewed the color variable as effective.

The data pulled from the questionnaire suggested that the color variable was not a good way of representing the time spectrum, as it received many mixed scores, most of them being negative, on visualization #4 (Flow Maps). However, this conclusion is to be taken lightly, as the low amount of participation on this visualization meant that each result was more subjective to answers not depicting the reality and thoughts from the majority of regular dataviz users.

6. Conclusions

6.1 Final Remarks

In a time where vast volumes of data are collected, the current research confirmed the necessity of information visualization investigation in data analysis, as it greatly improves the user's experience behind all the related tasks and processes. Specifically for spatiotemporal data, it was concluded that there was a lack of tools available regarding how to classify the various types of visual glyphs and other graphical representations used in visualizations. Hence, there was an opportunity to further explore the storytelling and visual narrative aspect of a visualization, in an attempt to make it easier to classify multiple orthogonal perspectives and therefore to understand, reduce its data-ink ratio and increase its effectiveness in passing the intended information to the user. There were a few options with the aim of categorizing spatiotemporal interaction levels and other taxonomies regarding what visual variables there are, but none specifically targeted the spatiotemporal spectrum and their complex nature.

Spatiotemporal visualizations are of complex nature. While some visualization techniques apply for more general cases, others tend to display data belonging to a more niche situation.

There is a lot of work and articles exploring all types of niches within the spatiotemporal spectrum of data, but little has been researched about the actual visualization techniques themselves. This means that there were still plenty of experiment opportunities regarding how this specific type of data is best meant to be analysed, and how important the concept of storytelling can be for the analyst. Be it consciously to the user or not, the overall visual narrative through a visualization interface plays an important role in gathering all the information and showing it to the viewer in an engaging and intuitive way.

Therefore, the motivation behind this work consisted of studying how user experience aspects can be improved and tailored according to the task, facilitating the data visualization process and allowing the end-users to retrieve more valuable knowledge regarding the spatiotemporal phenomenon. Furthermore, this work also contributed to the spatiotemporal visualization spectrum, more specifically towards a review and summarization of current state-of-the-art methods regarding each respective adopted visual clues.

From the literature review, the initial concepts of information visualization were explored. Here, visual metaphors, clues and variables were introduced for the first time. As a means to introduce the complex temporal spectrum, the various representations of time were also researched, going through the definitions of granularity, the many definitions of time and time primitives. Additionally, the visualization pipeline was presented, which is of great relevance to this work, as it was the main focus area of research. Towards the spatiotemporal side of information visualization, all main definitions were presented, as well as the previous and most recent taxonomies made in an effort to contribute to this dataviz topic. The most relevant spatiotemporal techniques were also reviewed, by analysing all main conferences, journals and magazines regarding information visualization. This included more than a hundred of revised techniques, some of which (the referenced ones) revealed to be of great relevance towards the development of the work, as a taxonomy was developed with the objective of categorizing these techniques effectively based on their visual clues. Besides this, the storytelling aspect of spatiotemporal visualization was also explored, though there was not much research available for this topic, at the time.

In a more general note, many techniques suggested by other authors were also researched, so that it would be possible to gather a very diverse collection of ST visualizations. Further down the work, some of the gathered techniques would be chosen to develop the experiments.

At the end, the state-of-the-art research, which included information visualization, time, visual narrative, and all sorts of spatiotemporal aspects of data visualization, enabled the authors of the current work to later design and assess a proper taxonomy suited for spatiotemporal visual clues and its corresponding testing.

One of the proposed solutions, as mentioned above, was to develop a taxonomy tailored to spatiotemporal techniques and their visual clues. This resulted in what is mentioned in this work as the Aggregated Taxonomy (AT), and it was used and tested with participant experiments, as exposed in Chapter 4. In the end of the experiment, which ran through Google Forms, the aggregated taxonomy was successfully run for its capacity of handling visual channel classifications and the visual variables themselves were assessed in terms of identification of use and perceived effectiveness. Within section 5.2 of this work, the results were analyzed and discussed, bringing potential good practices when it comes to visual variable and channel usage. In addition, statistical conclusions, such as the most used visual variable and the most effective visual variable in each spectrum, were drawn.

With the development of the Aggregated Taxonomy, along with its testing and result analysis, leading to good practical suggestions, there was a significant scientific contribution to the spatiotemporal information visualization community.

Thanks to these outcomes, it is now possible to answer the initially proposed research questions:

- **What is the most efficient way to display spatiotemporal data?** Ultimately, the most efficient way to display spatiotemporal information depends on what technique is being used, along with its visualization and interactions available. However, from the experiment statistics, the most efficient visual variable in both spectrums proved to be the spatial location variable, on the relational channel, when displayed preferably on top of a cartographic reference. In terms of raising the efficiency of a visualization, it is recommended that for every visual channel used, a caption or brief description is used, on the side, to clarify its usage. This leads to less cognitive load from the viewer and an easier information understanding of the visualization and its data.

- **What are the best practices for representing data, according to their visual clues?** General good practices include ensuring all used visual variables act in conjunction with each other, as in, they don't overlap or repeat the same type of information. Being aware of how many visual channels are being used on a single spectrum, keeping in mind that some repetitive combinations can potentially clash and confuse the user (see chapter 5.2 for examples). Because of their similar nature, variables within the same visual channel need to be explained and given context through captions or a brief introductory text. Any type of keyline is accepted, as long as it aids the user in knowing what the visual clue at stake is, so that the perceived cognitive load is lessened. Furthermore, it is advised to avoid mixing channels within each and between spectrums. However, multiple channel usage can be advantageous in certain occasions, but most of the time it results in a bad cooperation between variables, thus compromising the effectiveness of a visualization. Good cooperation comes to mind, for example, when the size geometrical variable is paired with the spatial location relational variable on a spatiotemporal visualization that is displayed on top of a cartographic reference, be it abstract or a map. Figure 84 exemplifies this observation.

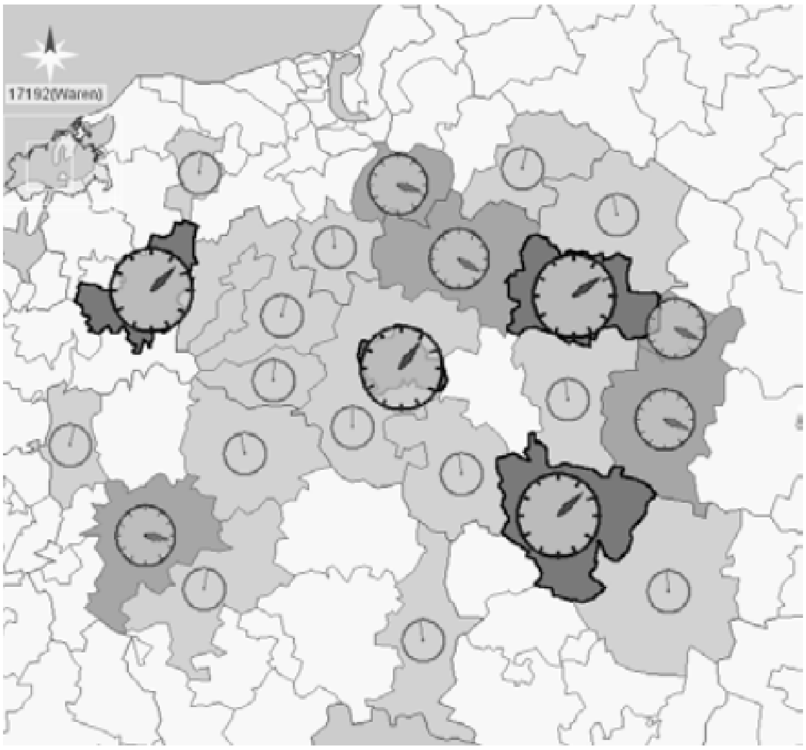


Figure 84: Icons on Maps as an example of a good relationship between the size geometrical variable and the spatial location relational variable, displayed on top of a map

- **What visual channels can be used to communicate information, and for what purpose?** According to the research done and the developed aggregated taxonomy, the visual channels available on the spatial and temporal spectrum include the geometric, optical and relational channels. Each has their own characteristics and their own set of visual variables, which range from size to color values, texture variations and things such as spatial location interactions between variables, which is further described with the aggregated taxonomy. Visual channels don't have a specific purpose, but their spatiotemporal visualizations do. Having this in mind, the main purposes that visualizations can have range from clusterization, to frequency, distribution, outliers, trend and correlation identification.

- **How can visual channels convey the correct information to the user?** In light of the mentioned best practices, from the data pulled from the experiment, it is advised to use as few visual channels as possible, with them being mainly used on a single spectrum. There are a few exceptions where multiple channel variables work well with each other, but in general, keeping as few channels as possible is the safest approach. For each variable that is in use, a caption, keyline or signpost providing context is recommended.

The hypothesis, which states that, undoubtedly, the effective use of proper visual clues provides a better understanding of complex data such as ST data., can be corroborated with the previous research questions. Assuming that each visual variable carries a certain amount of information essential to the visualization, which can be more effective in a different setting than others, it is possible to assume that yes, visual clues are indeed important to properly understand all types of spatiotemporal data visualizations. This can be further proved by the experiments conducted, where various visual variables and channels scored differently in terms of utility, perceivability and effectiveness, leading to understand that, in the end, the usage of the correct visual clues is very important to properly acknowledge all the information that a spatiotemporal visualization carries.

To conclude, the hypothesis is validated.

6.2 Future Work

Although the hypothesis is validated and the research questions were answered, this does not mean that this work is complete to its full extent. This work can be seen as the stepping stone of a further study:

a) It explored the existing spatiotemporal techniques, their visual clues, developed a taxonomy for its classification and suggested how to properly use visual channels and variables.

However, there is potential future work to be done, so that the topic of storytelling can have an increasingly steadier impact on future sets of information visualization.

b) Due to time restrictions, the aggregated taxonomy was tested for its first two columns, the spatial and temporal spectrums. The space-time relation column, catering more towards the types of interaction each spectrum has with one another, was left untested, much like the optional "Purpose" field. This leads to a good opportunity to further test these groupings and provide a much more solid foundation on this aspect.

c) Due to time constraints and failure in spreading the questionnaire, the experiments only reached 50 participants. At first, this seemed like a good number of subjects and potential answers, but when the analysis process began, it was quickly observed that some answers were not as truthful or meaningful as it would have been if the questionnaire counted with a much larger sample size. Furthermore, as the participants were mostly university students with low data visualization knowledge, the results did not fully represent the expected results from a set of participants that would be most likely to use the taxonomy and be in an information visualization setting. This means that possible future research can be done, with the intent of not only also exploring the space-time relation column, but also utilizing a larger sample size of participants, to analyse a larger set of experimentation results. Specifically on the "purpose" group, while it can be a subjective classification, it would be interesting to discover new combinations and options, so that the aggregated taxonomy can describe a spatiotemporal visualization in an even more detailed manner.

On the same line, while a few good practice guidelines were provided for effective visual clue usage on spatiotemporal visualizations, further research with a higher number of participants could be conducted to extend these best practices, and to create a set of rules that would benefit from a larger experimentation

d) In the beginning chapters of the literature review, the concept of visual metaphors is mentioned. This is highly relevant to this work, but was not properly addressed. In addition to the purpose group of the AT, it would potentially be of scientific interest to explore if the introduction of an extra "visual metaphor" optional group made sense, if it conflicts with other classification dimensions, with the aim of it being of open contribution by the taxonomy users. This meant that this field would be subjective, highly open-ended and catered towards each specific spatiotemporal visualization. All visual metaphors are very different from each other and impossible to broadly categorize. So, in a way, this would not be a mandatory taxonomy field, but can be seen more as a brief introductory text, a sort of abstract, describing the visual metaphor happening in the visualization. For inspiration, the TimeViz Browser[20] explores a

[20] http://vcg.informatik.uni-rostock.de/~ct/timeviz/timeviz.html

similar logic - when you click on a certain ST technique, it opens a small window quickly describing what the technique is about, who created it and references for it.

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A - Aggregated Taxonomy

Spatial Spectrum

Data Type

Cartographic
Scatter Plot
Circular Chart
Abstract

Visual Clue (one or more)

Geometric Channel

- Size
- Orientation
- Angle
- Curvature

Optical Channel

- Color (hue, saturation,value)
- Brightness
- Opacity
- Texture
- Focus
- Shadow
- Motion

Relational Channel

- Spatial Location
- Connection / Networking
- Intersection
- Distance
- Color Variance
- Other

Temporal Spectrum

Data Type

Time Curve
Timeline
Time Frame
Other

Visual Clue (one or more)

Geometric Channel

- Size
- Orientation
- Angle
- Curvature

Optical Channel

- Color
- Brightness
- Opacity
- Texture
- Focus
- Shadow
- Motion

Relational Channel

- Spatial Location
- Connection / Networking
- Intersection
- Distance
- Color Variance
- Other

Space-Time Relation

View Structure

Single View (all-together) or
Multiple Views (separated)

Space-Time Synchronization (one or more)

Interaction

- ST-specific
  - Filtering
  - Selecting
  - Zooming
  - Relating
  - Reconfiguring
  - Encoding
  - Overview
  - Other
- General
  - Details-On-Demand
  - Linking
  - History
  - Extraction of Features
  - Participation
  - Gamification

Layer
Coordinates
Other

Dimension

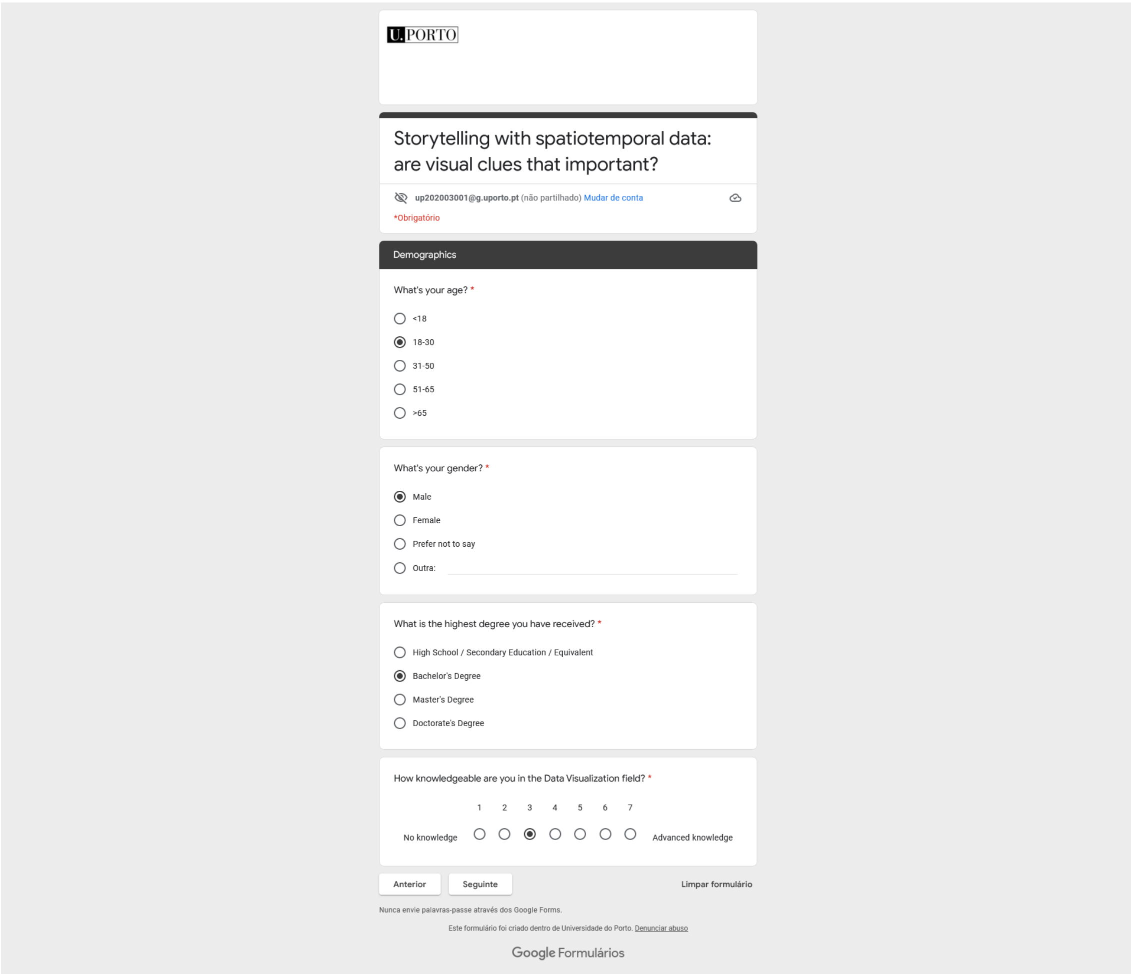
2D
3D

Purpose (Optional)

- Clusters
- Frequency
- Distribution
- Outliers
- Trends
- Correlation

B - Experiment

Questionnaire available at https://forms.gle/jA1FVdDL8wm49jfc8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Storytelling with spatiotemporal data: are visual clues that important?

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Demographics

What's your age? *

- <18
- 18-30
- 31-50
- 51-65
- >65

What's your gender? *

- Male
- Female
- Prefer not to say
- Outra:

What is the highest degree you have received? *

- High School / Secondary Education / Equivalent
- Bachelor's Degree
- Master's Degree
- Doctorate's Degree

How knowledgeable are you in the Data Visualization field? *

No knowledge 1 2 3 4 5 6 7 Advanced knowledge

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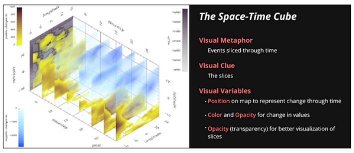
Context and concepts

The data collection on spatiotemporal events (such as icebergs, storms, fires, traffic, etc.) makes it possible to study these phenomena in real time or a posteriori. However, given the huge amount of data being collected, it is sometimes challenging to extract meaning from the collected data.
Currently, there are many strategies to overcome this challenge, often recurring to the usage of different "VISUAL VARIABLES" to create "VISUAL METAPHORS".

The figure below demonstrates a VISUAL METAPHOR being created in order to pass complex information to the viewer in a much simpler way.
The visual metaphor here is data being shown inside a tri-dimensional cube that is cut into various slices. Each slice indicates the same event, but in a different time instance.

Thanks to the visual variables of color and opacity of each slice, it is possible to observe that the data changes through time, as you can see more yellow terrain in each slice.

Higher resolution image - https://i.imgur.com/Wa9dmQx.png



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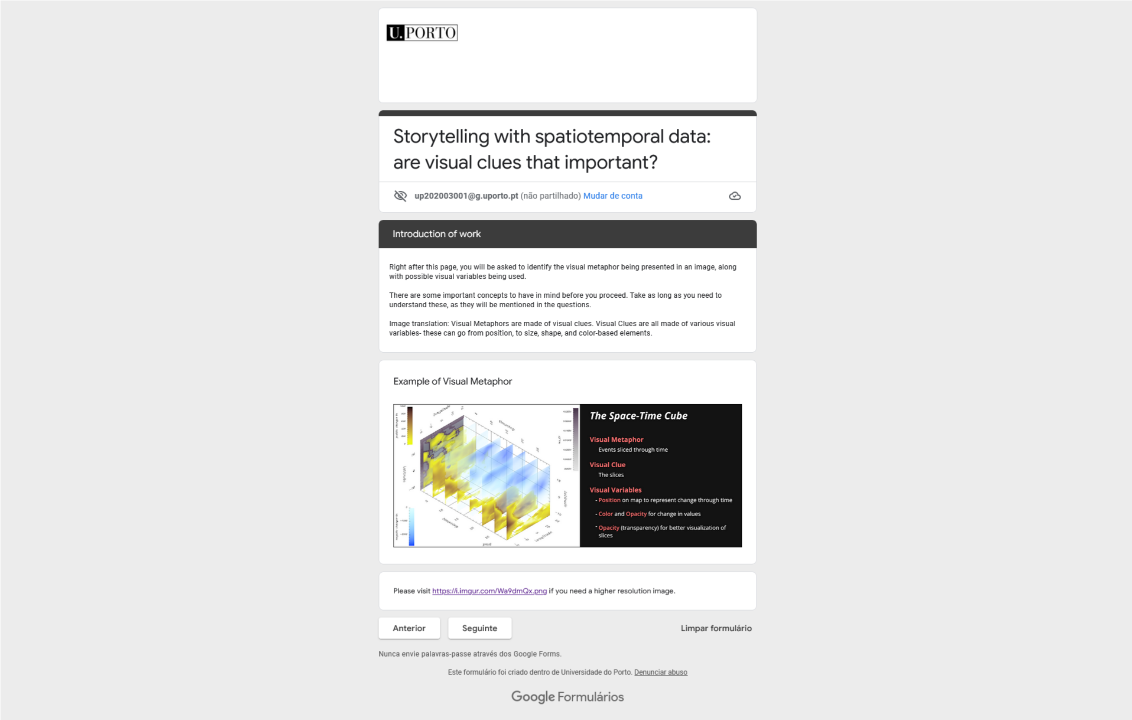

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Introduction of work

Right after this page, you will be asked to identify the visual metaphor being presented in an image, along with possible visual variables being used.

There are some important concepts to have in mind before you proceed. Take as long as you need to understand these, as they will be mentioned in the questions.

Image translation: Visual Metaphors are made of visual clues. Visual Clues are all made of various visual variables- these can go from position, to size, shape, and color-based elements.

Example of Visual Metaphor

The Space-Time Cube

Visual Metaphor
Events sliced through time

Visual Clue
The slices

Visual Variables
- Position on map to represent change through time
- Color and Opacity for change in values
- Opacity (transparency) for better visualization of slices

Please visit https://i.imgur.com/Wa9dmQx.png if you need a higher resolution image.

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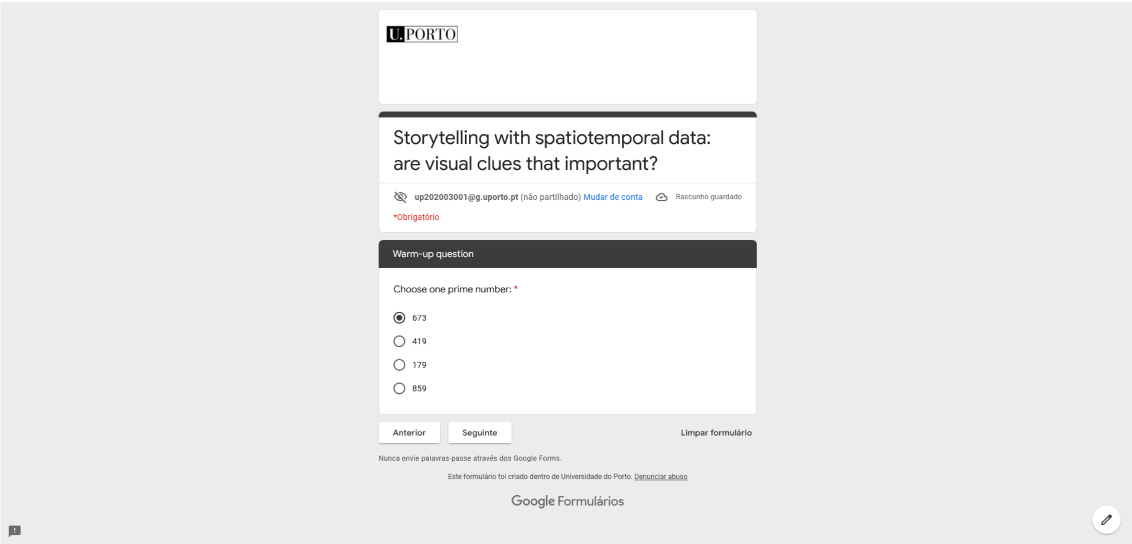

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Warm-up question

Choose one prime number: *

- (●) 673
- ( ) 419
- ( ) 179
- ( ) 859

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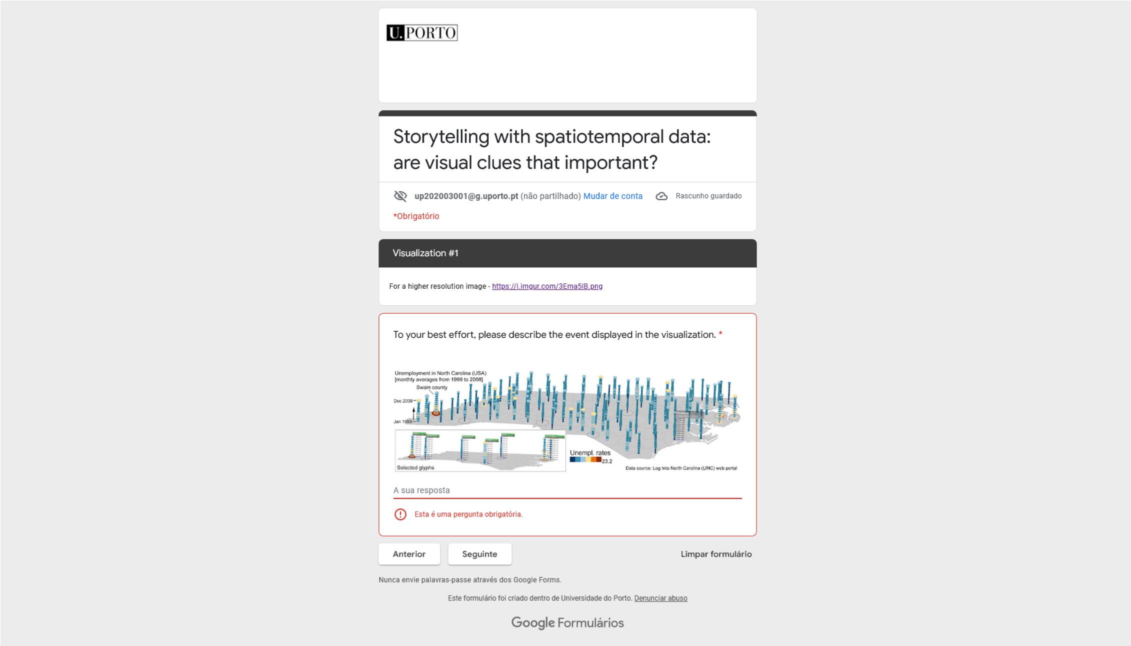
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*Obrigatório

Visualization #1

For a higher resolution image - https://i.imgur.com/3Ema5lB.png

To your best effort, please describe the event displayed in the visualization. *

A sua resposta

Esta é uma pergunta obrigatória.

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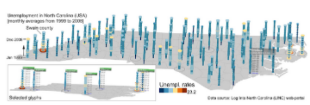
Visualization #1.2

For a higher resolution image - https://i.imgur.com/3Ema5I0.png



The depicted event is about the unemployment rate in North Carolina, USA, 1999-2008, displayed in a 3D view.

From the visualization, you will now be asked what visual variables you can you identify.

Which of these visual variables are used to represent SPACE? *

These visual variables belong to the geometrical channel, which act on the geometric side of a visualization.

- [x] Size
- [ ] Orientation
- [ ] Angle
- [ ] Curvature
- [ ] None

Which of these visual variables are used to represent SPACE? *

These visual variables belong to the optical channel, which act on the retinal side of a visualization.

- [x] Color (Hue, Saturation, Value)
- [x] Brightness
- [ ] Opacity
- [ ] Texture
- [ ] Focus
- [ ] Shadow
- [ ] Motion
- [ ] None

Which of these visual variables are used to represent SPACE? *

These visual variables belong to the relational channel, which represent the possible interactions that each event has with each other.

- [ ] Spatial Location
- [ ] Connection / Networking
- [ ] Intersection
- [x] Distance
- [ ] Color Variance
- [ ] None
- [ ] Outra:

Which of these visual variables are used to represent TIME? *

These visual variables belong to the geometrical channel, which act on the geometric side of a visualization.

- [ ] Size
- [ ] Orientation
- [ ] Angle
- [ ] Curvature
- [x] None

Which of these visual variables are used to represent TIME? *

These visual variables belong to the optical channel, which act on the retinal side of a visualization.

- [ ] Color (Hue, Saturation, Value)
- [ ] Brightness
- [ ] Opacity
- [ ] Texture
- [ ] Focus
- [ ] Shadow
- [ ] Motion
- [x] None

Which of these visual variables are used to represent TIME? *

These visual variables belong to the relational channel, which represent the possible interactions that each event has with each other.

- [x] Spatial Location
- [ ] Connection / Networking
- [ ] Intersection
- [ ] Distance
- [ ] Color Variance
- [ ] None
- [ ] Outra:

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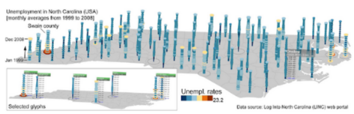
Visualization #1.3

For a higher resolution image - https://i.imgur.com/3Ema5IB.png



The depicted event has the following main visual channels:

Variables that depict SPACE

Geometric Channel

- [x] Size
- [ ] Orientation
- [ ] Angle
- [ ] Curvature

Optical Channel (Visually)

- [x] Color (hue, saturation,value)
- [ ] Brightness
- [ ] Opacity
- [ ] Texture
- [ ] Focus
- [ ] Shadow
- [ ] Motion

Relational Channel (In Comparison to other variables)

- [x] Spatial Location
- [ ] Connection / Networking
- [ ] Intersection
- [ ] Distance
- [ ] Color Variance
- [ ] Other

Variables that depict TIME

Geometric Channel

- [x] Size
- [ ] Orientation
- [ ] Angle
- [ ] Curvature

Optical Channel (Visually)

- [ ] Color
- [ ] Brightness
- [ ] Opacity
- [ ] Texture
- [ ] Focus
- [ ] Shadow
- [ ] Motion

Relational Channel (In Comparison to other variables)

- [ ] Spatial Location
- [ ] Connection / Networking
- [ ] Intersection
- [ ] Distance
- [ ] Color Variance
- [ ] Other

Having the visualization and its classification in mind, please score the used visual channels, from 1 to 10, based on effectiveness.

0 - Uneffective (a variable does not visually convey the data)
10 - Highly Effective (a variable visually conveys data)

SIZE variation through SPACE *

On a Geometric Channel, SIZE was used to identify change through space.

	0	1	2	3	4	5	6	7	8	9	10	
Uneffective	○	○	○	○	○	◉	○	○	○	○	○	Highly Effective

COLOR variation through SPACE *

On a Optical Channel, COLOR was used to identify change through space.

	0	1	2	3	4	5	6	7	8	9	10	
Uneffective	○	○	○	○	○	◉	○	○	○	○	○	Highly Effective

SPATIAL LOCATION variation through SPACE *

On a Relational Channel, SPATIAL LOCATION was used to identify change between variables through space.

	0	1	2	3	4	5	6	7	8	9	10	
Uneffective	○	○	○	○	○	◉	○	○	○	○	○	Highly Effective

SIZE variation through TIME *

On a Geometrical Channel, SIZE was used to identify change through time.

	0	1	2	3	4	5	6	7	8	9	10	
Uneffective	○	○	○	○	○	◉	○	○	○	○	○	Highly Effective

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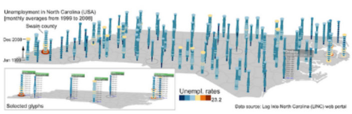
Visualization #1.4

Regarding the visualization and its visual clues

For a higher resolution image - https://i.imgur.com/3Ema5IB.png



I think that I would like to use this visualization frequently. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I found the visualization unnecessarily complex. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I think the visualization would be easy to use. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I think that I would need the support of a technical person to use this visualization. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I thought there was too much inconsistency in this visualization. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I would imagine that most people would learn to use this visualization very quickly. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I would find the visualization very awkward to use. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I would feel very confident using the visualization. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

I would need to learn a lot of things before I could get going with this visualization. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

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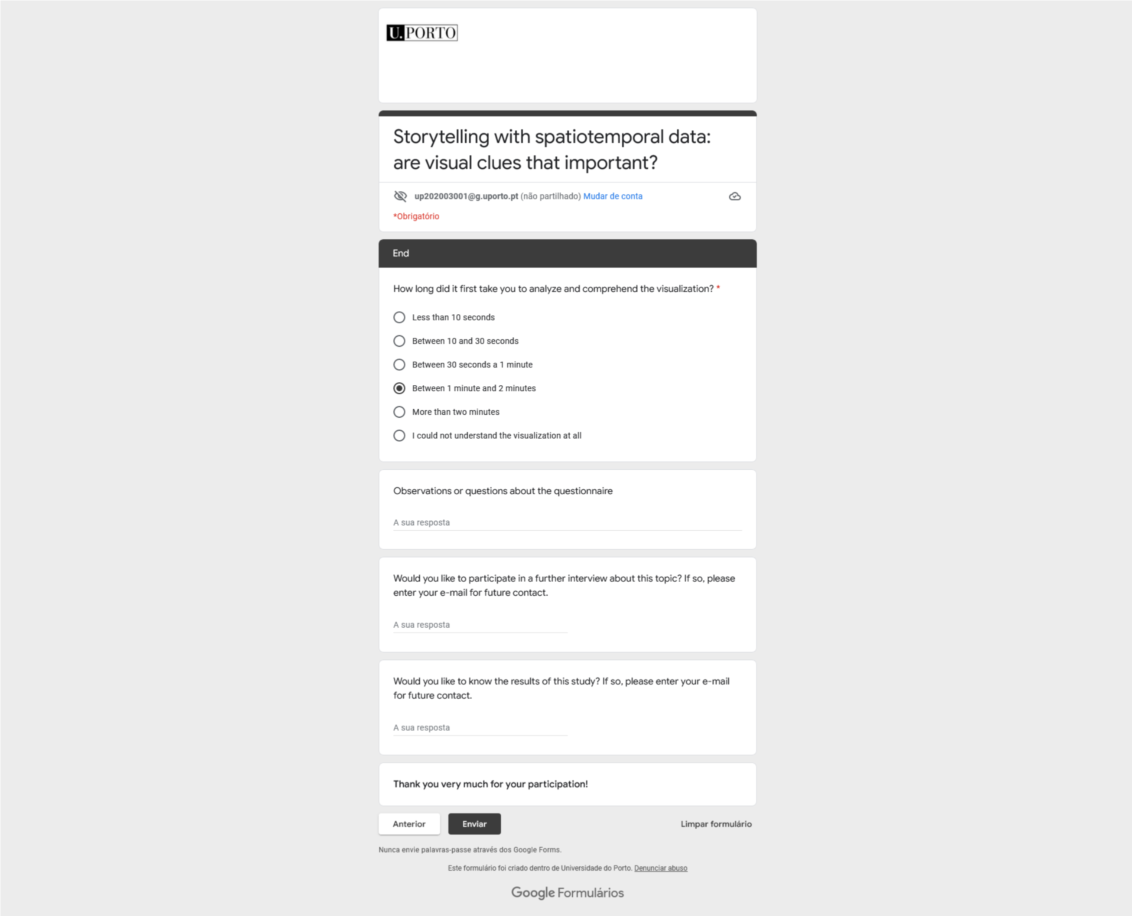

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*Obrigatório

End

How long did it first take you to analyze and comprehend the visualization? *

- Less than 10 seconds
- Between 10 and 30 seconds
- Between 30 seconds a 1 minute
- Between 1 minute and 2 minutes
- More than two minutes
- I could not understand the visualization at all

Observations or questions about the questionnaire

A sua resposta

Would you like to participate in a further interview about this topic? If so, please enter your e-mail for future contact.

A sua resposta

Would you like to know the results of this study? If so, please enter your e-mail for future contact.

A sua resposta

Thank you very much for your participation!

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C - Experiment Results

Due to its large size, the experiment results are split into two files and are available online through this link - https://drive.google.com/drive/folders/1Guac4XvriFdAu_ySIJpZlWwcPW5y7QQd?usp=sharing