An Analytical Reasoning Framework for Visual Analytics Representation

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Abstract. Analytical Reasoning is the foundation of visual analytics, assisted via interactive and dynamic visualization representation. The main concern of visual analytics is the analytics process itself, it is important to facilitate the human mental space during the analysis process by embedding the analytical reasoning in the visual analytics representation. This paper aims to introduce and describe the essential analytical reasoning features within visual analytics representation. The framework describes analytical reasoning features from three parts of visual analytics representation which are higher-level structure, interconnection and lower-level structure. For higher-level structure, we proposed the features of big picture, analytics goal and insights through storytelling to ensure the analytics output becomes knowledge and applicable to facilitate the business decision. For interconnection, the features of trend, pattern and relevancy induce a relationship between higher and lower-level structures. Finally, analytical reasoning features for lower-level structure are quite straightforward which are benchmarking, ranking, decluttering, clueing and filtering. It is hoped that this framework could help to shed some light in terms of understanding analytical reasoning features that can facilitate the business decision.

Keywords: Analytical reasoning · Visual analytics · Visualization · Representation

1 Introduction

Visual analytics is an outgrowth of the fields of information visualization and data visualization that focuses on analytical reasoning facilitated by interactive visual representation. [1] Describe visual analytics as a discovery technology that incorporates automated analysis with interactive visualization representation. Hence, [2] highlighted the importance of visual analytics to enhance the effective and competent decision making. It consists of the combination of visualization techniques, statistical methods and the analytics process to extract usable data from a larger set of raw data to become meaningful and able to facilitate business decisions. Furthermore, visual analytics also can

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be described as an interactive knowledge discovery system which purpose is to guide the user for critical insights via data exploration and understanding [3]. Visual analytics is to make the tools visually enabled, coupling visualization-analytical reasoning and interaction with human understanding and judgement.

The seminal visual analytics researches are describing analytical reasoning at a high level and yet lack detailed discussion on it. As such, [4] has identified five spaces within visual analytics structure which namely as information, computer, representation, interaction and mental spaces. This categorization is at a high level and numerous sub-spaces are yet to be identified at different levels of granularity. As representation is one of the essential spaces in visual analytics, it influences how users perceive the information and analytics output. This is because representation space will facilitate cognitive activities and the partnership is formed between internal mental processes and external representation which provides a number of benefits to perform analytical activities. In consequence to the visual analytics building model from [1, 5] also describes the visual analytics building model by explaining the reality, computer and human parts. It highlighted the importance of visualization to represent data and how it can improve the knowledge and model schemata of users. Furthermore, the model argues that the main goal of doing visual analytics is to build a mental and/or formal model of a certain piece of reality reflected in the data. As to complement the visual analytics building model [5] and visual analytics space, we found the essential of analytical reasoning for visualization representation to be put inside the visual analytics framework as a whole. Therefore, this research will enrich analytical reasoning within the visualization representation space as shown in the visual structure in Fig. 1.

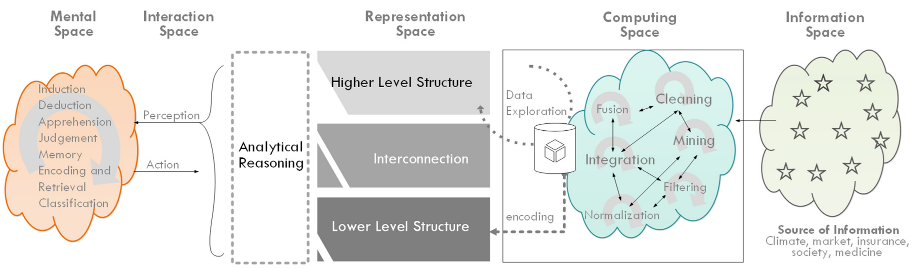

Fig. 1. Five spaces of visual analytics.

2 Working Background

Visualization has been recognized to facilitate the information overload in the Information Communication and Technology (ICT) world. Since the 1980's, the field of data visualization has been evolving dramatically from information graphics to Information Visualization, Knowledge Visualization and Visual Analytics. In the big data era, data visualization has become more significant in representing the 5Vs of data which are identified by volume, velocity, variety, veracity and value. This concurs with knowledge transformation and technology growth that has accelerated the evolution of data arena

[6]. There are a large number of complex, noisy and heterogeneous mass data sets in the big data. Therefore, data visualization is now an important research task for numerous areas that includes various questions relating to data storage, query and indexing [7]. Data visualization is the collection of techniques for easy comprehension and visual impact that transform information from its numerical to graphical presentations. The analytics demand for data visualization is increasing due to the awareness of its benefit to the business, organization and community. One of the current demands is to visualize the analytics results effectively to the end users. In precedent time, most of the analytics are used for scientific data and have been presented for expert users. Today, data analytics has been demanded by business and in needs for organizational data. Therefore, the way to develop the visualization for data analytics and to be easily understood by the end users need to be revised extensively. Hence, the field of visual analytics has emerged within the data visualization.

When using visual analytics, facilitating the reasoning is critical during data and information analyzing stage. Usually, visual analytics are used for complex cognitive activities such as decision making, problem solving and sensemaking which are higher-level thinking and require the facilitation of reasoning (why knowledge). Thus, guiding and supporting the reasoning will improve the capabilities of users when using visual analytics. Analytical reasoning is about the ability to analyze the situation, explore in a step-by-step approach to reason all the alternatives and find the best logical conclusions or solutions for the problem in hand. The process of analytical reasoning is important to be inferred because it facilitates the users to look and identify the problem within the situation. Usually, analytical reasoning will break the situation into smaller problems and reasons it out in a multi-dimensional way. Within each of the smaller problems, analytical reasoning will break down information and find a discern pattern or trends from the information. Analytical reasoning can be viewed as a process to understand, perceive and reason in regards to the dynamic and complicated data as to gather evidence for judgement in the decision making.

Sensemaking as one of the complex cognitive activities happened when using visual analytics. Through interacting with the visualization within visual analytics, the users are able to explore possible connections, gain insight and match the goal. It composes from the divergence and convergence part. sensemaking composes from divergence to convergence which are mentioned as foraging and synthesis. Foraging refers to the stages of the process to collect and filter the relevant and interesting information. While synthesis describes stages of the process where users create and test hypotheses about how foraged information may relate. In general, foraging lends itself to more computational support, while synthesis leverages human intuition for establishing relationships between information. Thus, the goal of visual analytics is to develop visualizations that are tightly coupled with mathematical models to provide computational support for the user – integrating foraging and synthesis. In this kind of process, the coupling between the system and human cognitive is important for sensemaking. The analytical reasoning is being produced during this dynamic coupling process. Throughout the tightly coupling cognition [8] engages in a process known as analytical discourse, where several, iterative dialogues with information available are conducted [1]. Sets of information are sought and processed, preferably from various sources, assert and test key assumptions.

Knowledge structures are then constructed using a series of reasoning to integrate new information into existing knowledge in possession.

Analytical reasoning is rarely a straightforward process to be handled in direct ways. Mainly because it is often intensified by time pressure, high uncertainty, high stakes and multiple tasks to be done and various information to be connected at the same time. Oftentimes, users work with information that is incomplete, dynamic, evolving and often deceptive. Hence, any attempt to find insights using this information involves dissecting the data into components, analyzing the patterns to expose evidence, gathering and connecting evidence, and compiling and synchronizing multiple varieties of insights from separate observations. Visual analytics representation (after this, the paper will use the term visualization) will be able to facilitate analytical reasoning of human cognition. Visualization in which as a tool will not only be linked together to the human cognition but also dependent upon each other. The visualization within visual analytics can be designed through the production of reasoning framework which is known as the science of analytical reasoning, as mentioned by [9]. This paradigm emphasizes the significance of visualization to facilitate human analytical reasoning in the process of integrating data to facilitate decision making and judgment.

3 An Analytical Reasoning Framework

The research extends an analytical reasoning framework based on the systemic visual structure developed by [23]. The visual structure used systemic approach as a basis for the visualization framework to synthesize the analytics outcomes. The framework only focuses on representation space because it is the most explicit and quite straightforward to be embedded with the analytical features. The concept of systemic is closely related to understanding interconnection and providing the big picture in the sense of holism. For this reason, the framework theorizes the use of synthesis visual structure by extending the overview concept towards the systemic view. Then using General System Theory, the research proposed the systemic view by embedding the underlying structure to underpin the concept of the synthesis visual structure. Moreover, the cycle of formation will help to strengthen the needs for higher-level and lower-level of multiple view visual structure as to support synthesis as higher-level thinking as shown in Fig. 2. There are three levels of the representation framework, each will be explained in the following paragraph.

3.1 Higher-Level Structure

The higher-level structure should be able to provide an overview of the visual analytics representation. For this reason, the analytical reasoning for higher-level structure should be able to synthesize the big picture, main goal and insights within the data analytics context of use. Among the benefits of applying higher-level visualization is to support logical formats and structures for users' mental model, disclosure of the existence of all information and the relationship between the key points as a whole and finally to encourage exploration of the information. Above all, the higher-level structure will govern the whole output of visual analytics. There are metaphoric phrases for higher-level structure such as "broad overview", "bird's eye view", "global overview" and "big picture". To ease the understanding, the researchers use the big picture term. This in turn describes the mental model and cognitive processes presented in Bloom's Taxonomy [11]. By gaining the big picture, the users should be able to clarify the analytics goal as the main driver while exploring visual analytics. Then, they should be able to see and draw the key points between various perspectives. The big picture also takes the lower-level structure into consideration. Based on the relationship of the data, the users should be able to find an adequate level of details or abstraction, be aware of discussing irrelevant issues and able to relate how a specific key point related to the more specific or general topic of the discussion.

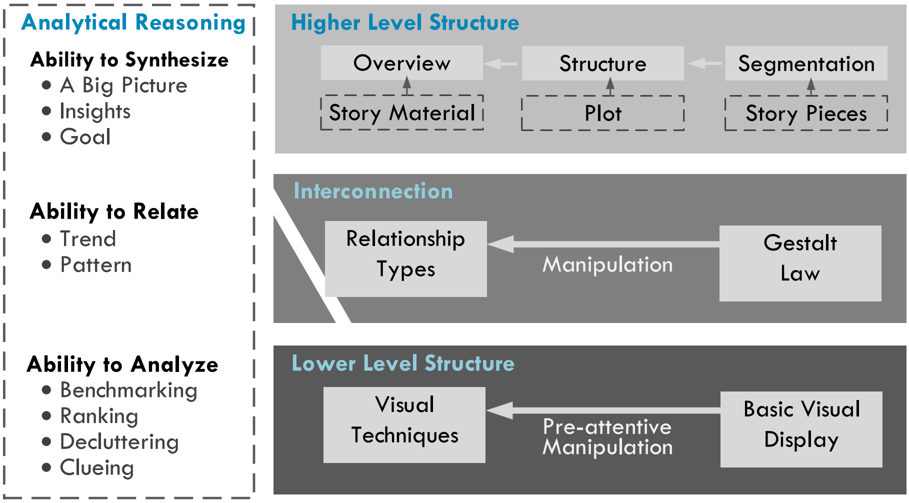

Fig. 2. Analytical reasoning framework for visual analytics representation

The framework proposed to embed visual-related analogy (e.g. similes, metaphor) as to convey meaning in addition to the straightforward reality of data. Metaphor has the capacity to link new concept and ideation with something that they are familiar with. As such, it can make sense to connect between details of analysis and application in the reality world. It also can convey an idea and emotion using literal statement which will encourage insight for non-straightforward statistics. It can be done by implying comparison that brings together two entities such as treemaps to portray containment. Finding the relevant visual-related analogy from identified storytelling can help users to refer and relate in order to emphasize on certain data. As an example, the usage of metaphor such as shrinking boats is used to indicate economic recession. While analogy such as the economy is like a coiled spring or a much straightforward related pictures of money or calculators could be used to indicate financial analysis. It is imperative for users to be able to comprehend a visualization and how its analytics will drive towards the main goal. It should be accurate and comprehensible to users in order to reduce confusion and misinterpretation [12]. Fulfilling the main goal is critical to ensure the analytics outcomes are valuable and can be used to facilitate the business decision. The visual analytics outcomes will be considered successful when the users are able to fulfill their analytics goal and become valuable to the business decision. Furthermore, business goals should be chunked into related use cases and insights. Then the visual techniques at the lower-level will be developed based on these insights. In terms of identifying the business goal, we suggest that more comprehensive elicitation of business requirement processes need to be done at the information space to ensure the business goal has been well taken care of.

The storytelling is the main feature to govern the visual analytics representation. The storytelling aims to create stories to tell data narrative, supply context and provide how the business decision can be facilitated using the outcomes from visual analytics. In representing visualization, storytelling may include text and images but essentially must be based on data. According to [13], in visual analytics, storytelling is a sort of controlled presentation of information that must relate to human emotion and analytics. It can be with or without a predefined temporal or narrative structure. It is always made up of components that form the story (structures, elements and concepts) and the telling part of storytelling (people, tools and channels). We proposed the development of storytelling concepts based on the structure and elements of analytics data that need to be presented to the users. The theme of story material will be proposed based on the overall business requirements, goals and its context of use. Then the overview concept will be segmentized into a few story pieces. Bear in mind, the structure of storytelling is the key elements to give flow to the story based on the overall concept. It can be done by following the concept of typical storytelling narration such as conflict-resolution and adding the element of surprise, emotions and punchline. The framework suggests at least each of the story pieces must contain at least a story point so it is easier for lower-level structure to provide detail explanation, justification and depth on it. It will become meaningful based on the story point for each of them. Each of the story pieces will be further developed using visualization techniques at the lower-level structure. Finally, all of the story pieces will be plotted and arranged according to the structure identified in the story material.

3.2 Interconnection

Interconnection is a relationship between two or more things within the representation data. In terms of analytical reasoning, this level should be able to relate data by identifying trend, pattern and relevancy. Contextual representation must at least show the interconnection between higher-levels of the information space (abstraction, key points, and perspectives) and lower-levels (concrete details). It is important to handle the analytical and synthetical process and furthermore the divergence to the convergence phase. This is because the users develop abstractions of the higher-levels by accessing and manipulating the lower-level details. Therefore, the relationship between these lower and higher-level elements is important to facilitate the reasoning process. To support the process, the cycle of formation can strengthen the main relationship between the higher and lower-level of visual structures.

We propose the interconnection as an organization of representation structure from an assumption of going from divergence to convergence – from lower-level details to the higher-level structure. The lower part is to encourage discussion of lower details, and is meant to help the understanding of the 'state of the art' of each of the elements, perspectives or departments. The upper level has been placed to guide the analysis process towards the synthesis of the cognitive process so that convergence of ideas can take place over time. As a whole, the users are able to view the higher and lower-level at the same time. They can view, relate and refer to the details during the reasoning for higher-level abstraction. Moreover, through the organization of representation, our emphasis is on guiding the users to discuss details according to any of their particular needs. The whole representation structure will act as explicit guidelines to be shared across several mental models so that there would be shared understanding among the users. By knowing what to do through the representation structure, it makes the process more focused on relevant elements. Nevertheless, since the research is about the complex domain, the interconnection between elements is not limited between the higher and lower-level visual structures. For this reason, the relationship can also be formed either between the elements in the same key component, between different key components or lower-level details.

Previous research from [14] has further identified and classified visualization techniques based on the six types of relationship which are correlation, comparison, distribution, differences and relationship outliers. From these six relationships of visualization, it is applied to fit into all dataset in the organizations to be used in visualizing their data for further decision making. Nowadays, due to varieties of visualization tools, methods and requirements, multiple observations and parameters of the data have to be combined in a single image in order to identify a meaningful relationship within the representation. Meaningful relationship means the users are able to identify the pattern, trend and relevancy of the data. This identification is the most important part of analytical reasoning within the interconnection of the representation level.

Trend is a general direction of elements over a period of time. It is a specific type of pattern distinguished by continuous gradational transition from one data point to another which is usually influenced by a driver parameter, such as time, process stage, etc. [15]. Generally, there are three basic concepts of trend. The first being uptrend that shows the overall elements direction in ascending manner. Then, there is the downtrend which displays the overall of elements direction in the form of descending. Lastly, is the sideway that demonstrate stagnant or nonmoving direction of the overall element. Pattern is a repeated form by a series of data in a recognizable way. Our brains are built to see structure and patterns in order for us to better understand the environment that we are living in. We visually and psychologically attempt to make order out of chaos, to create harmony or structure from seemingly disconnected bits of information [16]. Analytical reasoning is the ability to recognize and determine the meaning of patterns in a variety of information. As mentioned before, it refers to the ability to look at information, be it qualitative or quantitative in nature, and discern patterns within the information. At the same time, getting historical data is of importance in order to demonstrate patterns of classification, clustering, regression and outlier analysis. Classification is a form of supervised learning by relating the data with class labels. Meanwhile, clustering is a type of unsupervised learning by a group data without pre-labeled classes. In addition to that, regression is categorized under supervised learning for continuous data type. Lastly, outlier analysis is use to identify and reveal anomaly from the data. Relevancy is the quality and condition of the relationship between data. It can become a strong supportive evidence for visual analytics by showing the level of relevancy, consistency, clarity and similarity depending on the scenario in use. One dimensional view from a single source should be avoided while data source accuracy and dynamism of varying data perspective is highly essential.

We suggest that developers utilize and manipulate all the visualization techniques that are currently available. However, to induce analytical reasoning of pattern, trend and relevancy, the visual analytics developers must understand the manipulation of Gestalt Law. By understanding it, the developer will know why and how to show and emphasize pattern, trend or relevancy within the relationship types. Gestalt means pattern and it offers nine principles of grouping to facilitate visual perception based on the capacity of human brain to see structure, logic, and patterns. It is a natural human ability that helps make sense of the world. According to [16], Gestalt Law is about the theory around how people perceive the world around them and focused on how people interpret the world. It offers a principle of grouping to facilitate visual perception. This is because human visual working memory has limited storage, by using Gestalt, the human brain can reduce the amounts of items that need to be stored. There are six individual principles commonly associated with Gestalt theory: similarity, continuation, closure, proximity, continuity, connectedness, figure/ground, pragnanz and symmetry & order. There are also some additional, newer principles sometimes associated with Gestalt, such as common fate. In the simplest terms, Gestalt theory is based on the idea that the human brain will attempt to simplify and organize complex images or designs that consist of many elements, by subconsciously arranging the parts into an organized system that creates a whole, rather than just a series of disparate elements [17]. This approach facilitates the maintenance and retrieval of information in the visual working memory.

3.3 Lower-Level Structure

Lower-level structure is the details of analytics information within the visual analytics representation. It provides in depth analytics for each aspect of the data. As a result, users would be able to view complex information in smaller segments. Each of these segments will be understood in detail, in order find evidence and reason to support the business decision. It is quite straightforward and much of the visualization research is focused on developing this component. We suggest that developers utilize and manipulate all the visualization techniques that are currently available. However, to facilitate analytical reasoning that is able to justify decision making in a more convincing and less cluttering manner, developers must first master the visual concept mapping. By understanding it, the developer will know why and how to provide analytical reasoning in the representation. The framework proposed that lower-level structure should be able to facilitate analytical reasoning via benchmarking, ranking, decluttering, clueing and filtering.

The concept of visual mapping (encoding) is the most important part in lower-level structure. There are three important parts in visual concept mapping which are basic visual display, pre-attentive manipulation and the visual techniques. Basic visual display is the basic element in the visualization field. Using multiple terms such as graphical display, visual glyph/form and visual representation [18], basic visual display is a simple elementary thing that is visible in the visual analytics representation. There are four types of basic visual display which are point, line, spatial position and colors with comprised of attributes such as position, length, color, orientation and shape can be manipulated to amplify cognition using pre-attentive elements. Simple visual attributes can be processed extremely fast in parallel and high volume by using pre-attentive elements without any conscious effort by the iconic memory. The visual analytics representation should be made to prioritize on important data to be manipulated by the pre-attentive element that could catch the users' attention. Based on data selected from computer space, the lower-level structure will encode the information (from data/attributes) to be presented as basic visual display (e.g., form, line, picture etc.). Hence, the visual technique can be developed by composing a few elements of basic visual display and manipulating some of pre-attentive elements.

The framework suggests that lower-level details to be based on the insights identified to fulfill the business goals. The selection of the key components and the development of visual techniques will then rely on the priority business requirements and analytics goal – either depending on its function, tasks or knowledge in the context of use. Indirectly, this condition will complement the overall theme of visual analytics context of use. The categorization of lower-level structure will be governed by the overall story material and segmentation that has been identified from the higher-level structure. The lower-level structure can develop multiple visualization techniques for each story piece based on severity and depth of its analytics. Usually, for important and critical story points – multiple and in-depth visualization techniques need to be developed to provide rich insights and more potential exploration for that particular story point and how it implicates others.

The research has identified five features that can be used to support analytical reasoning at the lower-level structure. These features are quite straightforward and yet significant to reduce the cognitive load during the analysis process. The first one is benchmarking. In general, it is a mechanism of progressive activity to attain improved results and performance as well as a basic analysis feature to clarify comparisons. It could also be used as a tool to reveal how to achieve significant performance height rather than just a way to evaluate performance measure. Benchmarking helps users to identify current performance by comparing the subject of interest and recognize the gap to fill-in. It can compare the performance, process and strategy that involves internal, competitive, functional or any generic quantitative comparison such as target, maximum, median or minimum.

The second feature is ranking. It is about giving the positions by grading the items in order to have a sense of hierarchical importance. Ranking helps to prioritize the most significant/insignificant items in the dataset, which in turn, will give a more effective view of the analysis data. Ranking is defined as one of the simplest methods in performing evaluation. It is a relationship between a set of items such that, for any two items, the first is either 'ranked higher than', 'ranked lower than' or 'ranked equal to' the second". Rankings are among universal and popular method in organizing or arranging a chaotic assortment of objects through calculating a rank for all elements according to the value of one or more of its components. This permits the prioritization of assignments or in evaluating the performance of items comparative to each other. The interpretation of ranking's visualization is not as straightforward as its visual representation. This is due to the fact that ranking only signifies the summary of a possibly more complex association among its elements and the rest of the attributes [19]. Nevertheless, ranking can also lead on the overall assessment or achievement especially in the scoreboard cases.

The third feature is decluttering. It aims to reduce messy and cluttered visualization that could improve and assist targeted audience to get at the data by significantly making the data stands out more. Evidential studies have proved the advantages of decluttering, which can be done by removing unnecessary items and properly structuring the information elements [20]. Visual clutter builds up unnecessary burden to the cognitive load which could interfere with the message communicated. By understanding the cognitive load theory and manipulating the pre-attentive elements, users will be able to boost their focus and understanding on the demanded visualization [21]. The fourth feature is clueing and it is about giving hints or cue to guide its audience to somewhere meaningful during the analysis process. There a few ways to give clue in the lower-level structure by leveraging on the effectiveness of pre-attentive attributes [21]. This is done by including annotation, providing tips and summary, adding contrast color tone to distinguish and highlight important consent, put in border to differentiate or separate certain visualization points and using color highlights to amplify and attract users to voluntarily pay more attention to what is important. Studies have shown that visual cues or clueing could act as anchors to enhance accuracy and produce positive impact (Redmond, 2019).

Finally, the fifth feature is filtering. It is the process to focus on a smaller dataset in order to have better sense of direction on attributes of interest and conceal unwanted or insignificant ones. This can be done by removing unwanted data or choosing a specific part of the dataset and using subsets for analysis. It provides flexible and adjustable environment for users over their data view. As a result, it offers additional benefits by simplifying patterns, reducing visual clutter, complexity and data congestion, which allow for a more visible correlation between data [22]. Filtering is a temporary process. It allows data to be dissected through different viewpoint or drill down to a deeper level which make for an excellent method to allow user-driven, extensive data exploration and analysis. All this, while the complete data set is kept but only part of it is utilized for analysis in current demand.

4 Conclusion

Throughout this study, a substantial review and discussion regarding analytical reasoning features was conveyed. A discernment of business and technical issues related to visual analytics were explained and a significant value of analytical reasoning was unveiled to improve the representation, interaction and communication of visualization. It is relevant due to the current demand of end-users and decision makers, in assisting them to understand the analytics outcomes. Henceforth, an analytical reasoning will be able to facilitate the business decision and stimulate the analytics outcomes to evolve into knowledge in their context of use. However, analytical reasoning in visual analytics is not easy to define, due to its implicit mental space thinking process and the usual usage within complex cognitive activities in nature. Furthermore, analytical reasoning specifically the ones in relation to visual analytics are quite new, with limited publications, most of which dating from year 2000 onwards. However, reasoning and analytical reasoning by themselves are mature subjects which came from a diverse, multi-disciplinary nature with a wide variety of application areas, such as science, philosophy, cognitive, psychology, mathematics and so forth. Hence it is challenging to find quality publications that best fit the real research intent and interest without peering into or rather adopting relevant ideas from these frontiers. In short, the visual analytics developer gave positive feedback and was able to improve the analytics output when embedding these features inside the visualization. On the other hand, through respondents' feedback, there are various improvements that could be performed in order to improve the meaning, and reasoning facilitation. Hence, we hope to expand, demonstrate and clarify these features in a more holistic detail in the future.

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