

UNIVERSITY OF CALGARY

Design and Discussion of Visualizations in Pairs

by

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Abstract

There are many commercial information visualization tools that enable domain experts to create visualizations on their own. However, when the data and the domain is complex, the visualization design task is delegated to a visualization designer. In this case, the visualization designer works in close collaboration with domain experts and their knowledge of the domain evolves through prototyping visualizations. The visualization prototypes are designed programmatically or on paper. Therefore, we propose that visualization designers and domain experts should create visualizations together using a visualization tool. These visualization design activities can lead to discussion and criticism on existing representations and serve as important usability criteria for more useful designs.

We designed PairedVis, a tool to support both experts, the visualization designer and the domain expert in creating visualizations together. We conducted a study to investigate whether PairedVis supports the two experts in sharing knowledge and discussing representations.

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I would like to dedicate this thesis to my husband and children for their comfort and smiles which kept me going. I also dedicate this thesis to my parents, who made me into what I am today. I love you all.

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Epigraph

Graphical excellence is that which gives to the viewer the greatest number of ideas in the shortest time with the least ink in the smallest space.

Edward R. Tufte, *The Visual Display of Quantitative Information*.

Chapter One: **Introduction**

A visualization is a representation of data as an image made up of visual elements such as shapes, position, text, and colors. The intention is to design this image so that it makes effective use of our human visual capabilities of recognizing patterns and outliers. The interpretation of this image should result in amplified cognition, insight generation, and decision making [1] [2]. Interest in visual representations of the data spread from graph theory, sociology, and scientific communities to all major fields such as Humanities, Art, and Chemistry. This is not just due to its inherent qualities of providing quick and effective interpretation of large amounts of data, but also due to availability of commercial tools and open source toolkits that enable any user to quickly transform data into not just simple, but also complex visualization designs and interactions. Wider interest in information visualization has been encouraged by open source datasets and visualization sites like Many Eyes and Gap minder [3], where communities can share and discuss visualizations. However, there still exists the traditional scenario where the domain and the tasks are complex and the domain experts require a custom visualization to assist in their work related problems. As a result, visualization designers are brought on board to understand the problem, gather requirements from the domain experts and then design and create visualizations to be tested by the domain experts. My research interest is in enabling a domain expert to actively participate in the design of a visualization in collaboration with a visualization designer.

“A graphic is no longer ‘drawn’ once and for all: it is ‘constructed’ and reconstructed manipulated until all the relationships which lie within it have been perceived...a graphic is never an end in itself: it is a moment in the process of decision making.” (Bertin [1])

As Bertin said, while creating data representations you learn more about the data and relationships within the data. With the help of this new understanding about the data you can improve the design of your visualizations. Domain experts have stronger and deeper knowledge about the data and its relationships than the visualization designers. Therefore, we propose that the domain experts should always be involved in the design of a visualization.

I have provided above a brief introduction to this thesis. Section 1.1, describes the visualization design process, the scenario in which a visualization designer is hired by domain expert(s) for creating visualizations and the limitations of this process. Section 1.2, provides the motivation behind our research. The research challenges and objectives are outlined in Section 1.3. Section 1.4 provides a brief overview of this thesis.

1.1 Visualization Design Process

To understand collaboration between the domain expert and visualization designer, we first need to understand how visualizations are designed to facilitate domain experts in their work related activities. In a real-world setting, while conducting design studies, Sedlmair et al. [4], have outlined the design study process, suggesting nine activities carried out by a visualization designer, as illustrated in Figure 1.1

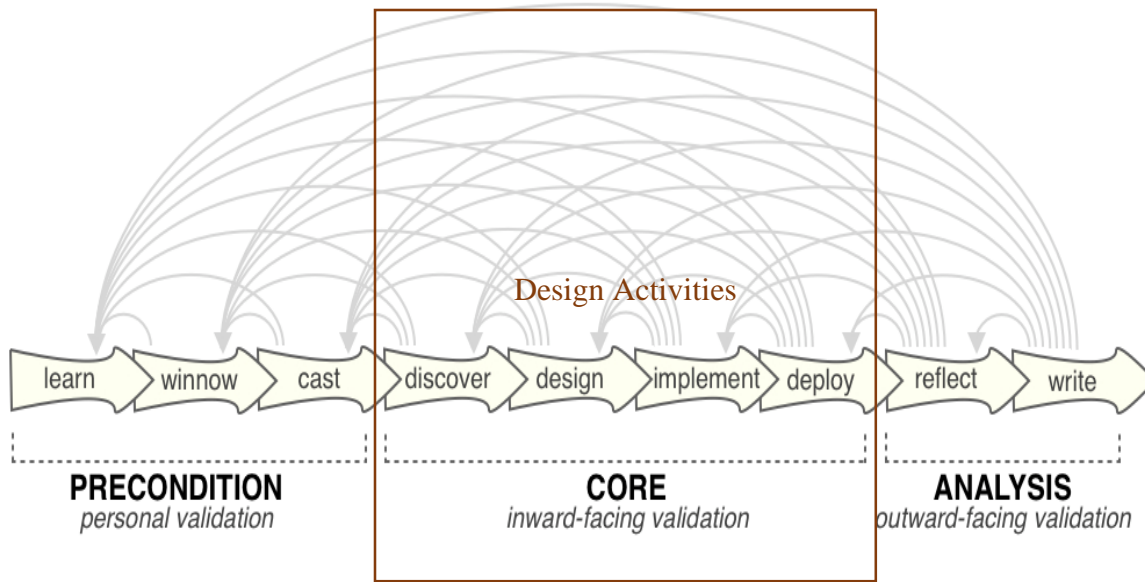


Figure 1.1: The nine stage Design Study Methodology Framework. Modified from Sedlmair et al. [4]. Illustrates activities carried out by the visualization designer while conducting a design study.

In this nine stage process, the precondition stage explains the tasks necessary to ensure that the data, the task and the collaborators, will result in a successful design study for the visualization designer. These tasks include Learn, Winnow, and Cast. However, the next phase, the Core phase consists of the visualization design activities; Discover, Design, Implement, and Deploy. *Discover*—the first step involves the visualization designer’s developing understanding of the domain, the users, and the problem, using user-centered design approaches, such as, observational studies, contextual enquiries, and interviews [5]. The second step in the Core Phase, *Design*—requires the Visualization designer to create low-fidelity paper or programmatic prototypes. The steps performed by the visualization designer are; data collection & abstraction, mapping data to visual encodings and visual representation & interaction, also known as the Reference Model, Card et al [2]. The role of the domain expert(s) at this stage is to review the

prototype designs and select the most useful. The third step in the Core Phase, *Implement* — requires a visualization designer to implement the selected prototype and test it using HCI usability evaluation techniques and modify the tool to overcome usability issues. Finally, the last step in the Core Phase, *Implement and Deploy* — requires the domain expert to test the visualization in their day to day work activities and provide usability feedback to the visualization designer. According to this process, visualization designer handles the responsibility of understanding the domain, the requirements, and designing a useful visualization tool whereas the domain expert's role in the process is to provide input in the form of requirements, review, and feedback.

1.2 Motivation

According to the existing process of visualization design in the field, domain experts do not actively participate in the design of visualizations. Moreover, the domain experts and the visualization designers work asynchronously, with communication points for sharing information and feedback. This led to our first research question:

- 1. Can we better support collaboration between the domain expert and the visualization designer during visualization design activities?*

Van Wijk [6], has noticed discomfort between the visualization designer and the domain expert during data collection and requirement analysis activities. He believes that a knowledge gap exists between a domain expert and a visualization designer. By knowledge gap the researcher means that they have diverse areas of expertise and use different terms and terminology to express themselves, which can result in confusion and frustration. The researcher suggests that this gap can be filled by educating domain experts to define visualizations. Lloyd and Dykes [7],

have tried to bridge this gap while performing a long-term case study. They educated the domain experts on a comprehensive set of possible visualization designs and interactions by giving them a lecture. Then they asked them to sketch possible designs for their data and tasks. The researchers were able to identify important design and interaction requirements from the sketches. It is evident from their research that teaching information visualization to domain experts and taking design requirements from them is useful. However, in this case study, the visualization designers did not assist the domain experts in creating the sketched paper prototypes.

Grammel et al. [8] conducted a study to learn whether users with limited knowledge of visualization design like domain experts have skills to design effective visualizations on their own. According to their findings, such users face difficulties in all three stages of visualization pipeline [2] and also during visual analysis. Another important finding of this research is that participants repeated visualization design activities with different representations till a useful visualization was found. The researchers inform us that these iterative visualization design activities support learning in three ways: understanding the data with different representations, finding the accurate representation, and gaining experience in visualization design [8]. These learning benefits gained from iterative design is an important research interest of this thesis. This idea is also used in educating design to students and is known as learning by design or problem-based learning [9]. This is a very effective practice in supporting collaborative designs in a classroom setting and helps students create better designs based on their own learning through problem-solving and critique from their peers. Therefore, we want visualization designers to create visualizations in collaboration with domain experts using existing visualization templates. We propose that collaborative construction and discussion on the constructed visualizations can

support knowledge sharing between the two experts and can contribute to better design of visualizations.

This lead to our second research question:

2. *Can we support collaborative design activities with visualization templates so that the two experts can discuss existing representations and see how they fit the needs of the data and the needs of the domain experts?*

Pretorius and Van Wijk [10] with evidence from their experiences in design studies, have highlighted that information about the data and the tasks evolves through prototyping in close collaboration with domain experts. “Rather than trying to fine-tune a single technique”, the researchers suggest “an exploratory approach where a number of prototypes are developed in close collaboration with users” and “when a promising idea is uncovered, it is then possible to nurture it to a mature solution.” [10]. Besides developing paper or programmatic prototypes, we want to support visualization designers in mapping data interactively to adjustable templates in collaboration with domain experts. These collaborative visualization design and discussion activities can help in learning about the data and the domain expert’s requirements.

1.2.1 Collaboration in Information Visualization

The field of computer-supported cooperative work or CSCW was introduced by Greif and Cashman [11]. The objective was to investigate and support groups of people with different skills, environments, and needs to coordinate and communicate with the help of technology or techniques. In recent years there is an increase interest in using CSCW research to support collaborative work in information visualization. Ever increasing size of data and its complexity has given rise to collaborative analysis of information visualizations on large displays [12] [13].

Collaborative analysis was even more encouraged by the results of an empirical study conducted by Mark et al. [14]. The results from the study clearly suggest “that given the right visualization system, groups do better than individuals in finding more accurate results.” [14]. As a result, Collaborative Visualization is sprouting into a new area of interest under information visualization. Isenberg et al. [15] have defined Collaborative Visualization as:

“Collaborative visualization is the shared use of computer-supported (interactive), visual representations of data by more than one person with the common goal of contribution to joint information processing activities.” [15]

This definition and the current overviews [16] [15] [17] in this area convey that the focus of collaborative visualization is in enabling teams to collaborate during data analysis activities. A recent study on how novices in information visualization construct visualizations [8] shed some light into design activities, however not into how a team of experts design visualizations.

1.2.2 Pair Programming and Pair Analytics

Under software development methodologies a well-known concept of collaboration is Pair programming. Pair programming comes from agile methodologies. Pair programming is the scenario when two programmers work together on the same machine. One programmer, the driver writes code, while the other, the navigator, reviews and helps the driver. The two programmers exchange roles frequently. According to a survey on pair programming [18], there is evidence that pair programming improves design quality, reduces defects, and improves team communication. Arias-Hernandez et al. [19] used this concept to study visual analysis. They paired a domain expert and a visualization designer to study visual data analysis activities and referred to it as “Pair Analytics”. The researchers found that Pair Analytics provided them with a more natural means of capturing analytic reasoning rather than “think aloud protocol”. Think-

aloud is a usability analysis method that requires participants to talk about their thinking while performing tasks. However, we wanted paired domain experts and visualization designers to create visualizations in collaboration and not just use this pair as an approach for conducting studies.

1.3 Research Challenges

As discussed in Section 1.1, according to the Visualization Design Process [4] the task of visualization design is performed by the visualization designer. We propose a modification to the Core Phase of the Visualization Design study Methodology, illustrated in Figure 1.1. We want to facilitate close collaborative design activities between the domain expert and the visualization designer as suggested by [10]. Our suggestion to the existing Visualization Design Process is illustrated in Figure 1.2.

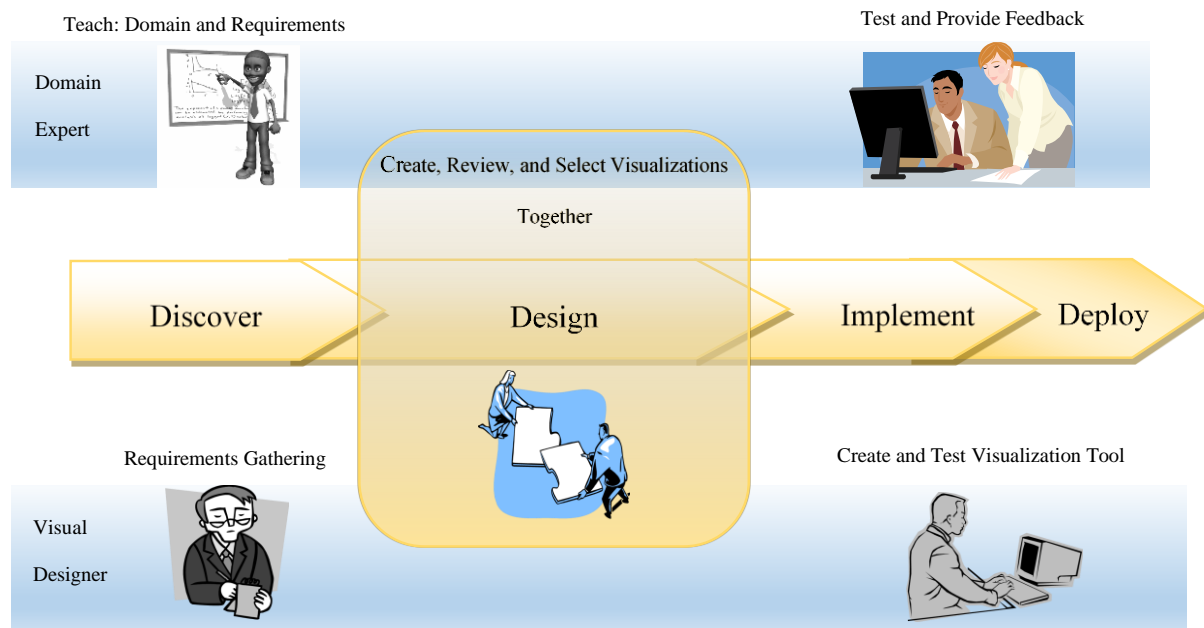


Figure 1.2: Proposed Visualization Design Activities during the Core Phase. Modified from Sedlmair et al. [4]. Illustrates activities carried out by the Visualization Designer while conducting a design study.

Our research objective is to facilitate a domain expert and a visualization designer to create visualizations and perform data analysis tasks to determine, how well existing representations satisfy the data, the tasks, and the domain expert. To facilitate this scenario of collaborative design, we faced the following challenges:

1. ***Two Expert Challenge***: We need a tool that can facilitate communication between two experts with differences in knowledge and skills.
2. ***Iterative Design Challenge***: We need to provide an interface that facilitates quick and interactive means of mapping data to different templates, to help support communication during visualization design.

These research challenges formed the basis of our research objectives described as follows:

1. *We need to explore existing tools, literature, and processes that support visualization design and collaboration.*

After looking into current literature, we found that researchers have investigated how a team of experts conduct visualization analysis [20]. However, no one has investigated how a team of experts with different expertise conduct visualization design activities.

We assessed commercial visualization tools and found current tools do not facilitate discussion on the data and visualizations to better support communication between the two experts, discussed in Chapter 3. As a result, we decided to design a visualization tool to specifically support a visualization designer and a domain expert in discussing data and visualizations. This led to the formulation of our second research objective.

2. *Can we design a tool to support both the experts in sharing their knowledge and expertise during visualization design?*

Based on our knowledge of the current research and experience with existing visualization tools, we designed and implemented a tool, PairedVis which can support two experts in design and discussion of visualizations. This lead to our third research objective:

- 3. Can we provide evidence that facilitating collaboration between a domain expert and a visualization designer leads to discussion on the limitations of current designs in satisfying data and user requirements.*

We designed a study to investigate that when a domain expert and a visualization designer create visualizations together, they share their knowledge and discuss limitations of current representations in satisfying the requirements of the domain and the domain experts.

In this chapter, we have discussed the research questions that motivated our efforts in learning and exploring how to enable collaboration between a domain expert and a visualization designer.

The following section provides a brief description on the rest of the chapters in this thesis.

1.4 Thesis Overview

The following chapters describe various parts of our research:

Chapter2 – A Background in Visualization Design:

In this chapter we describe current literature on visualization design and tool design, which was required to design our visualization tool, PairedVis.

Chapter3 – Paired Visualization Requirements:

In this chapter we devised requirements to satisfy the needs of both our experts, the visualization designer and the domain expert in creating visualizations together. Then we accessed whether existing visualization tools satisfy our two experts in creating and discussing visualizations.

Chapter4 – PairedVis:

This chapter describes how we designed PairedVis based on the functional requirements elicited in Chapter3, to support collaboration between a domain expert and a visualization designer in creating and discussing visualizations together.

Chapter5 – Evaluation:

This chapter explains the study conducted to investigate the collaboration between a domain experts and a visualization designer and investigate whether they share their knowledge and discuss the limitations of existing representations in satisfying the data and the tasks. It also provides details on the approach taken to conduct the study and its results.

Chapter6 – Conclusion and Future Work:

This chapter provides the conclusion and guidelines for future work in this area.

Chapter Two: A Background on Visualization Design

Information Visualization as defined by Card et al. [2] is:

“The use of computer-supported, interactive, visual representations of abstract data to amplify cognition.”

A visual representation is made up of both a structure and interactions that enable a user to explore the data and gain more insight. Information visualization experts have inherited visual representations from Data Graphics and Scientific Visualization communities, and have also invented new representations based on the needs of the data. Looking at the world around us, we can understand that the design possibilities are limitless. Take snowflakes for example, it is difficult to find two similar in design at the same time. We can understand the basic structure of a snowflake and reconstruct the various forms it can possibly take. Similarly, in order to create new or customized designs we need to understand the basic components of visualizations.

2.1 Components of Visualization Structures

Bertin [21] [22] provides us with the basic components of visual design that have helped him in drawing data graphics on paper. To understand them, we first must learn about the surface on which a design is represented also referred to as the Plane and in our case the Screen. On a screen we can represent data with a Mark. A mark can take any of the three forms; Point, Line, Area.

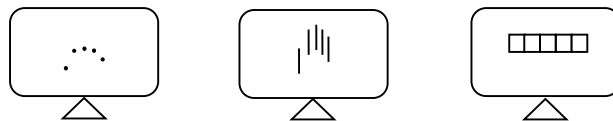


Figure 2.1: Three Forms that can represent data a) Point, b) Line, and c) Area.

Figure 2.1 illustrates three representation with four marks (or data values) in each. Marks can also take up the shape of surfaces and volumes, Carpendale [23].

2.1.1 Visual Variables

After selecting a suitable mark to represent the data, we can represent the characteristics of the data using any of the following Visual Variables [21] [22]. In another words, visual variables are visual characteristics of a Mark that can be varied in Position, Size, Shape, Value, Color, Orientation, and Texture. Position constitutes of two visual variables, because when we use a two dimensional plane a mark can vary in position in the x-axis as well as the y-axis. Similarly, in a three dimensional surface, data can be encoded to three variables, x, y, and z axis [23].

Figure 2.2 illustrates the seven visual variables presented by Bertin [21] taken from [23].







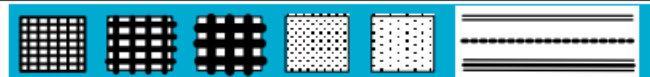
Bertin's Original Visual Variables	
Position changes in the x, y location	
Size change in length, area or repetition	
Shape infinite number of shapes	
Value changes from light to dark	
Colour changes in hue at a given value	
Orientation changes in alignment	
Texture variation in 'grain'	

Figure 2.2: Visual Variables. Taken from Carpendale [23].

Carpendale [23] added Motion to the list because with the support of computers the position of the Mark can be changed on run time. Moreover, the researcher renamed Bertin's Texture visual variable to Grain, to clarify that when Bertin means marks on marks to show low or high density

he is actually referring to the granularity of the mark. Carpendale uses Texture for its original meaning in order to represent composition or surface of a mark. As a result, we now have Bertin seven visual variables plus motion and grain, totalling nine visual variables assuming position as one variable, illustrated in Table 2.1.

Bertin [22] and Carpendale [23] have also presented us with the most effective and useful ways of using these visual variables in order to provide accurate interpretation. The appropriate use of a visual variable can be measured based on the following criteria.

2.1.1.1 Selective

A visual variable is selective when its application to a mark distinguishes it from other marks. For example, a square is distinguishing from a circle. As a result, shape is selective.

2.1.1.2 Associative

A visual variable is associative when its application to a group of marks can help the human brain perceive them as a group. For example, two circles and a square positioned closely at a corner of a chart will be perceived as a group. As a result, position is associative. Within this association the two circles can be considered a subgroup because shape is associative.

2.1.1.3 Quantitative

A visual variable is quantitative if it can represent numerical data visually and can be still perceived by the human mind as numerical. For example, profits can be mapped to position of a mark on the y-axis. The highest mark will be perceived as higher in quantity. As a result, position is quantitative.

2.1.1.4 Order

A visual variable is ordered if it can represent ordinal data visually and can be perceived by the human mind as ordinal. For example, ratings on the web can be mapped to shades of grey. As a result, value is ordered.

2.1.1.5 Length

The length is the maximum variations of a visual variable that can be easily distinguished even at a distance. There is a difference between what we can distinguish, when two items are adjacent or across the screen from each other. For example, consider shades of grey to represent a rating scale. If two items touch each other, our eyes are very sensitive and will recognize small differences in shades of grey. However, if the two things are across the screen from each other, it becomes much more difficult to tell if they are the same shade of grey or different. Carpendale [23] suggests that when using value to represent data, 7 shades of grey is a good guideline for the number of variations that can be used to represent the data. The suggested length of the visual variables in Table 2.1 are a safe estimate for what can be used.

Table 2.1 displays the visual variables and their most useful characteristics. Carpendale [23] suggests shape is sometimes associative and selective when there is a small number of variations in shapes and the amount of Marks. Similarly, orientation is associative and selective with non-perspective displays and only with more linear Marks. Orientation can be used for showing order, however human minds are not sensitive to recognizing order with orientation [23]. Color is ordered if it is paired with value. The visual variables that more effective in certain conditions are shaded grey in Table 2.1. Motion is an important visual variable, not included to Table 2.1 because researchers are currently investigating and formulizing motion codes to support awareness while reducing distraction and irritation caused by motion [24].


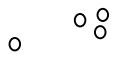
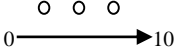
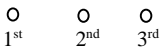
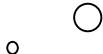
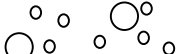















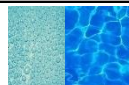

	Selective	Associative	Quantitative	Order	Length
Position					Limited to Screen Resolution and Size
Size					5
Value					7
Grain					5
Color					7
Orientation					4
Shape					Infinite
Texture					Infinite

Table 2.1: Modified from Bertin [22] and Carpendale [23]. Rows represent the visual variables and the columns represent the suggested characteristics supported by them. We are unable to show Motion in this table.

It is clear from above table that Position, Size and Value enable us to represent more data variables. Quantitative data can be converted to ordered sets to be supported with value, grain, or color.

2.1.2 Effective Use of Visual Variables

Cleveland and McGill's [25] conducted a study to understand the effectiveness of the visual variables with quantitative data and the results of the study are presented in Figure 2.3.

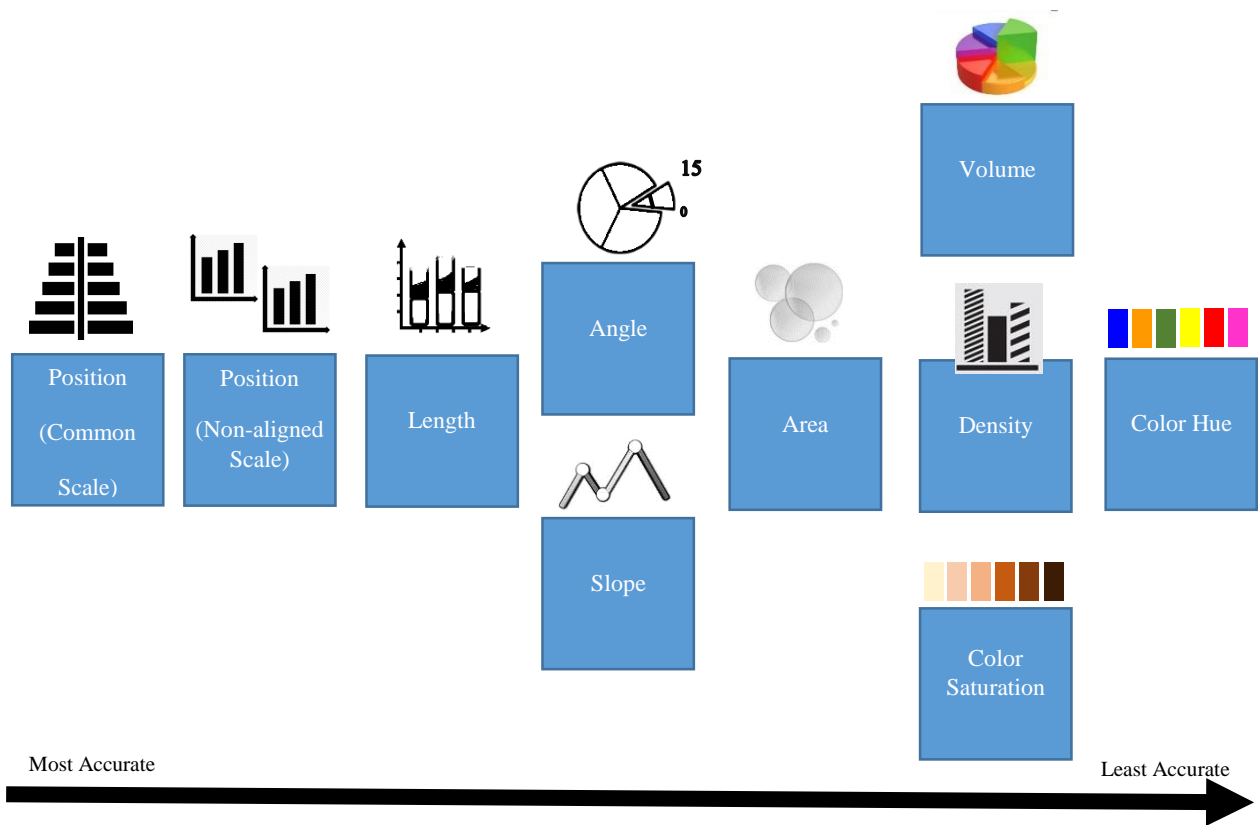


Figure 2.3: Accuracy of Visual Variables for Quantitative Data. Presented by Cleveland and McGill [26].

Figure 2.3, illustrates the most effective visual variables starting from left to right. Position of a point or a shape on a common axis being the most effective visual variable and colour hue being the least accurate method of mapping quantitative data.

Mackinlay [2] provided an extended observation to include all the three types of data, Nominal, Ordinal, and Quantitative, as shown in Figure 2.4.

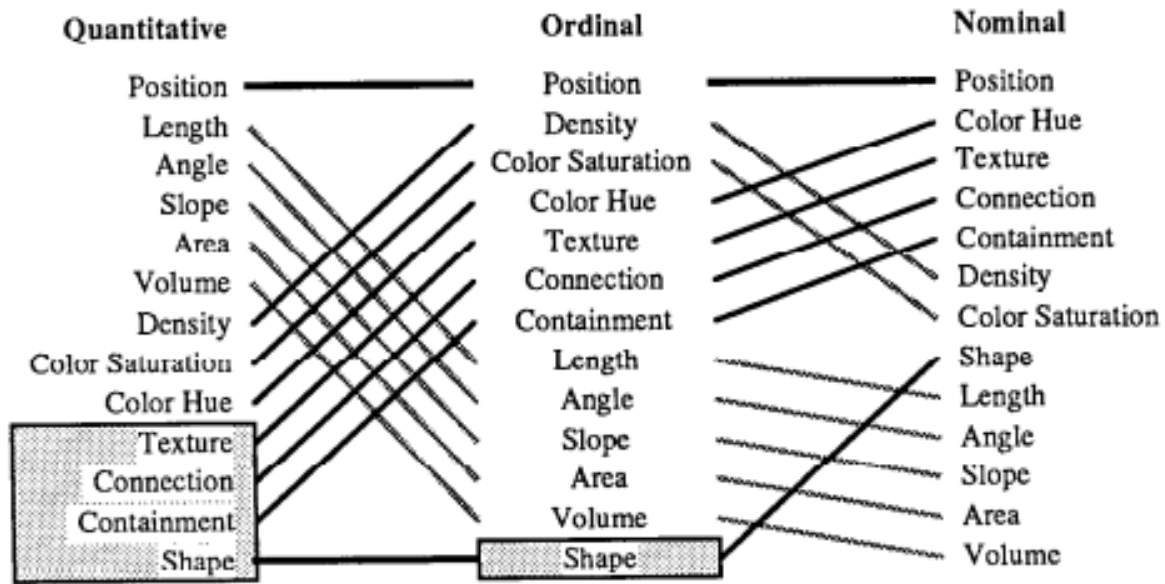


Figure 2.4: Accuracy of Visual Variables for different types of data. Taken from Mackinlay [26].

In Figure 2.4, the researchers list the most effective visual variables for a specific type of data at the top and the least effective at the bottom. The visual variables that should not be used for a specific set of data are shaded grey.

Mackinlay [2] made use of these observations to select appropriate representations. For example, to represent a country's expenditure on health and warfare, we need to select a representation that can best support relationship between two quantitative variables. One possibility is the use of a scatter plot that offers x and y position to encode the two variables. Since, position is the best possible visual variable for quantitative data, we can hypothesize that the scatter plot is a good choice.

In this section, we discussed the Visual Variables, in other words the basic components that can help us build effective representations. Visual variables are not enough to represent values, but we need structure to also represent relationships between variables. For example, in the use of a scatter plot, we place variables on the orthogonal axis and view the relationship in the area

between the axis. As a result, the scatter plot provides structure for placing the data points. In the following section we will discuss structural contribution to the visualization community in addition to the visual variables.

2.1.3 Visual Representations

Structure is an organized placement of Marks. For example, organization of marks in a row results in a linear structure. Bertin [22] has also classified visual structures into four types from which we are excluding Symbols and Maps because they belong to the field of Info graphics and Cartography respectively. The other two classifications of structure are:

- Diagrams or Charts that support relationship between two or more data variables.
- Relational Structures or networks that support relationships within a data variable.

2.1.3.1 Diagrams or Charts

The most common structures, such as Bar charts, line Charts, and scatterplots fall under this category. A Chart can support up to three data variables with the use of three axis. However, we can also represent more characteristics of the data using visual variables. For example, a scatterplot can represent information about the average price of houses on the x -axis and average crime rate on the y axis, for major communities in a city, as shown in Figure 2.5.

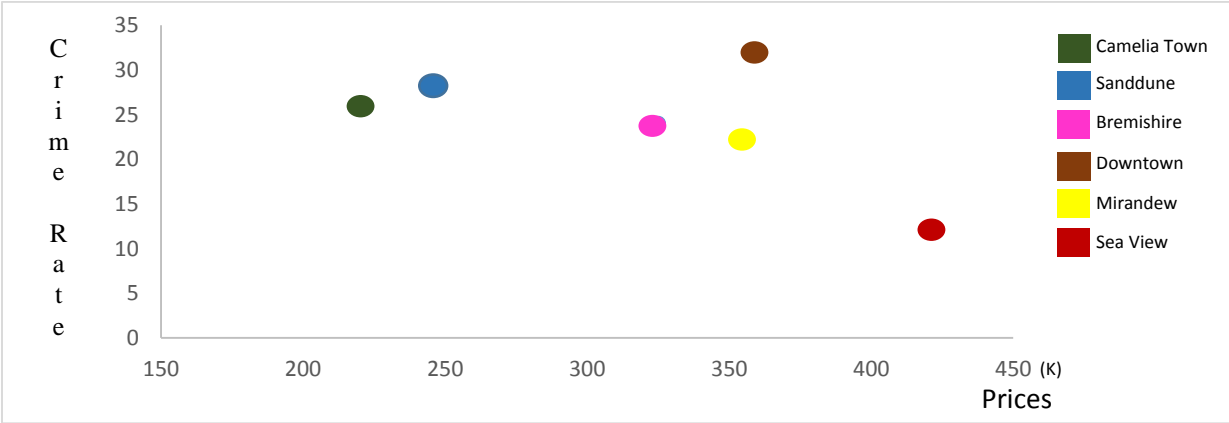


Figure 2.5: Scatterplot: Crime rate and average price of houses for six communities.

Charts either use a single axis, two opposed axis, or parallel axis. Opposed axis are used when all the points in one data variable corresponds to all the points in another data variable. For example, in Figure 2.5 for each community we have a house price and a corresponding crime rate. With the use of this representation we can study the relationship between the two data variables. Parallel Co-ordinates is a very useful design in which each data variable is represented on an axis and these axis are positioned in parallel to each other, as shown in Figure 2.6. In this representation, we can analyze two data variables that are adjacent to each other. Therefore, this representation enables users to move axis of interest next to each other.

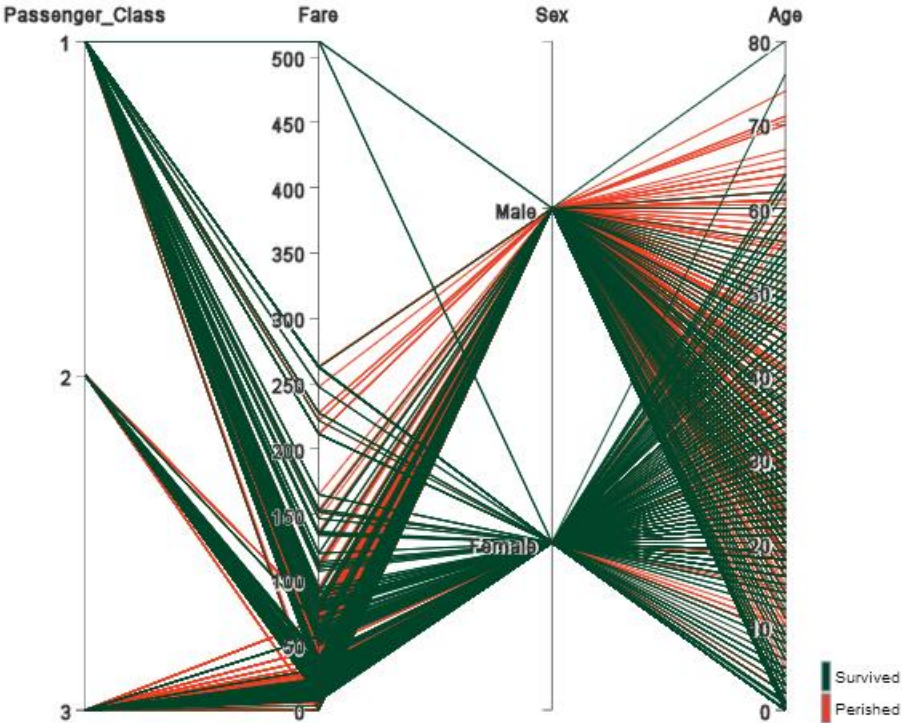


Figure 2.6: Parallel Coordinates representing the data about passengers on Titanic.

2.1.3.2 Relational Structures

There are five types of relational structures that support relationships within a data variable:

rectilinear, circular, ordered patterns, unordered patterns and stereograms [22] as shown in Figure

2.7.

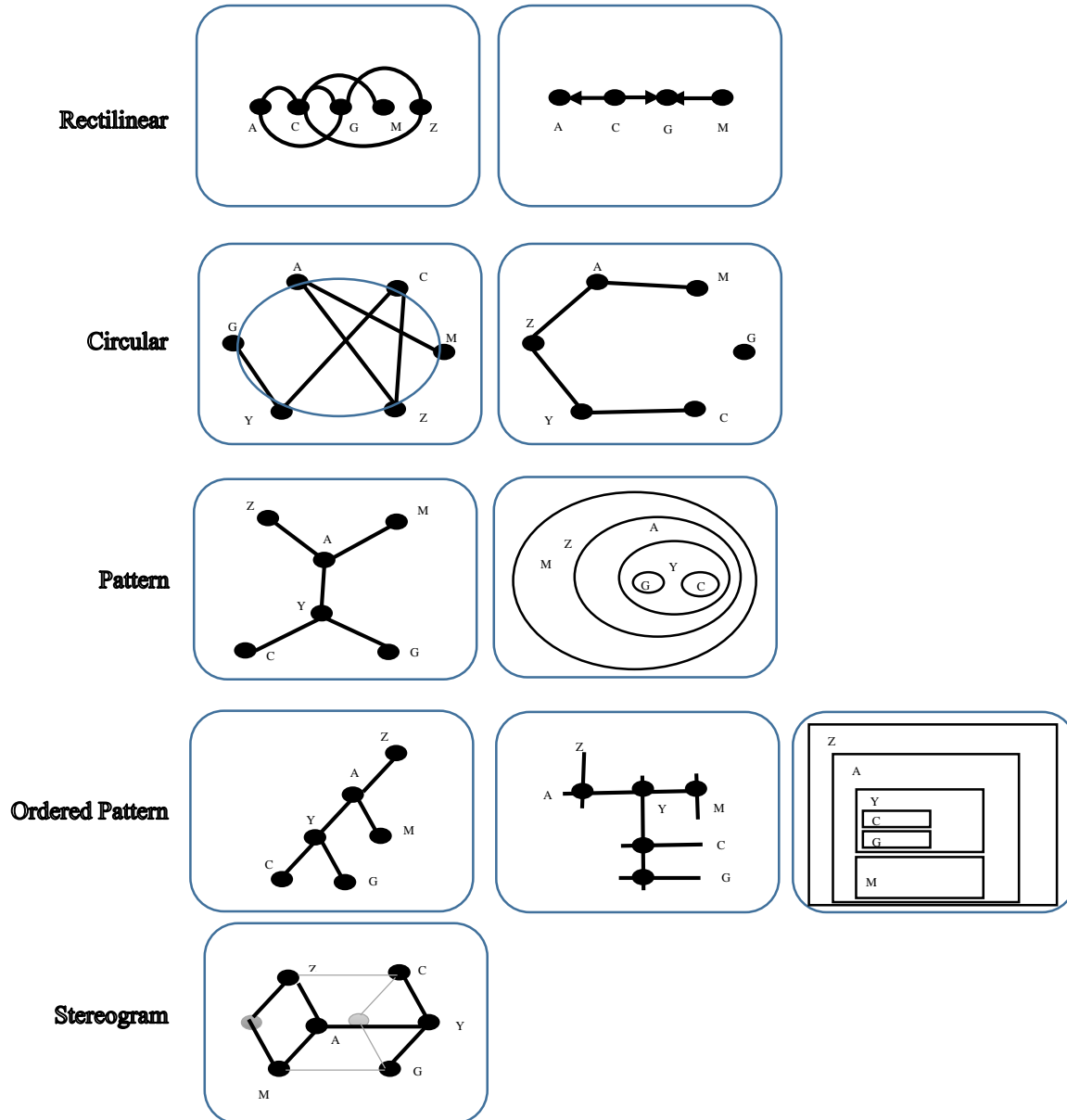


Figure 2.7: Five Basic Structures for visualizing relationships. Bertin [22].

Rectilinear representations help represent data values in a linear fashion and lines are used to represent relationships between them.

Circular Representations represent data values on circumference of circles and lines are used to represent relationships.

Ordered patterns represent hierarchical relationships using a repeated pattern, for example a tree structure.

Unordered patterns: organize data based on the relationships but the relationships do not follow a set pattern, such as a graph structure.

Stereograms make use of 3d shapes to place data values and use the shape's structure to represent the relationship.

Mackinlay [2] explained that there also exist composite representations that make use or more than one method of placing data, as shown in Figure 2.8.

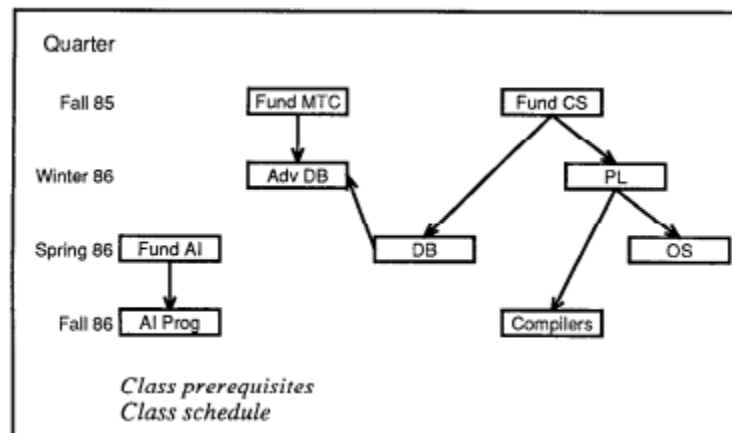


Figure 2.8: A composite representation: A graph structure with node placement based on y-axis. Mackinlay [27].

In Figure 2.8, rectangular nodes represent courses. The y position of the node is based on the semester they belong. The diagram is rectilinear, however the nodes are linked to represent the prerequisite relationship between the nodes (courses), resulting in a graph.

In this section, we discussed the Visual Structure, in other words the techniques in which we can place marks in an organized way. With the help of visual variables and structures we can build many representations. In the following section, we will discuss the process of transforming data to a representation and an interactive interface that facilitates data analysis.

2.2 Transforming Data to a Visual Representation

We know now the various methods of representing data, however data to visual transformation requires three steps, also known as the Data State Reference Model [2] [28] or Visualization pipeline. Most current visualization tools facilitate this process, as shown in Figure 2.9.

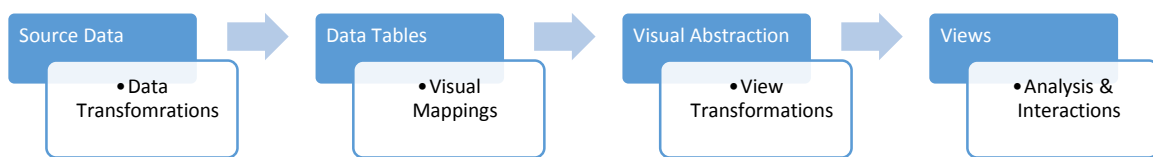


Figure 2.9: Data State Reference Model. Adapted from [2].

2.2.1 Data Transformations

The data source can be a set of books, an email account or web navigation activities of multiple users. The first step in visualization design in general involves transforming the data into a set of tables that have a clean and true subset of the data. It is common to represent data in a table, as most types of data can be represented in tabular form. At this stage data variables are classified as Nominal, Ordinal, or Quantitative. This classification or other specific information about the data is referred to as the Metadata. For example, two columns can identify the date and time of an event.

At this stage various operations can be performed on the data to make it more useful for representing visually. For example, let us consider that we have aeroplane flight information between cities in two columns. One column represents the departure city and the other column

represents the destination. We will extract all the cities from the two columns to create a new column called nodes. This is an example of a data transformation operation. There are in total four types of transformations provided by Tweedie [29] and are described below:

Values to Derived Values is the operation of generating more values from existing, such as adding two columns to generate a total.

Structure to Derived Structure is the operation of changing the data variables. For example, if we have population based on two data variables, region and country, we can aggregate all the country's data based on their region. This type of operation is specifically named class [2]. Sort [2] is another operation in which data variables are sorted based on values.

Structure to Derived Values is the process of changing data variables to values. For example, if we have two variables positive mood and negative mood, we can create one variable mood and represent positive mood by one, negative mood by zero, and in case of both true we represent it by two.

Values to Derived Structure is the transformation of values to data variables and distributing the data over new data variables. For example, consider that we have data about children in a class with their ages. We want a consolidated representation of the amount of children in a certain age group. We will structure the age column into multiple columns representation certain age groups, 2-5, 6-9, 10-13. Then we will count the number of children that fall under this age group.

Most visualization tools facilitate visualization users with data transformation tasks. So that they can transform the data according to their requirements before representing it in a visual form.

2.2.2 Visual Mappings

This step involves mapping of the data variables to a visual representation. A visual representation is made up of a visual structure, visual variables, and interactions to manipulate

the structure. Literature on existing representations can help a user customize, enhance, or create composite designs. Different representations can support different types of interactions.

Understanding what interactions are available can help the analyst understand the type of data explorations possible. Interactions are discussed further in Section 2.2.3.

We have categorized structures based on the type of data they support, such as networks, multi-dimensional data, and so on. We have excluded geo-spatial data from our classification, because it is a separate extensive research area.

2.2.2.1 One Dimensional Data

Dimensions in the data mean relationships between data variables and not just characteristics of the data. Lists, and text are examples of one dimensional data. Table 2.2 provides a list of student grades. Student grades can be represented with marks such as bubbles and the size of the bubble can represent the quantitative values.

Grades
3.1
1.9

Table 2.2: One Dimensional Data: One result per student

Popular representation for one-dimensional data that do not use the orthogonal axis are simple lists represented in Figure 2.10. However, researchers makes use of interactions to allow a user to explore and view data of interest.



Figure 2.10: One dimensional list with the use of lenses to view details.

In Figure 2.10, lenses are used to view details of a document. In this representation there is no information available for the documents in the overview. Representations that facilitate information both on the overview as well as more details through selection fall under the category of overview plus detail.

2.2.2.2 Two Dimensional Data

To understand two dimensional data, let us consider the previous example of student grades and add the grades for the following semester, as shown in Table 2.3. In this case, we have more than one grade per semester and more than one semester per grade.

Semester	Grade
1	3.1
1	1.9
2	3.5
2	2.3

Table 2.3 Two Dimensional Data.

As shown in Table 2.3, there are many relationships between the two variables, Semester and Grade. Two Dimensional data can be represented using the orthogonal axis, such scatterplots and bar charts. However, when the data is large, designers allow users to filter the data and see portions of the data in one view. This also leads to the difference between representation (structure) and presentation (view) as described by Carpendale and Montagnese [30]. To explain this concept, let us consider the Perspective Wall, as shown in Figure 2.11.

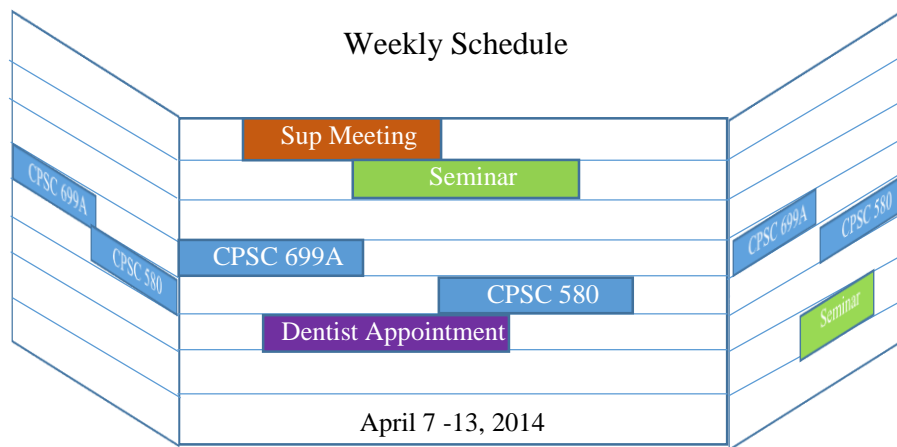


Figure 2.11: Perspective Wall. Adapted from [31].

Perspective wall makes use of the 3D surface to represent a 2D object (the wall). With the help of interaction, the data in front view can be dragged to see values of interest. In this case, the representation is a 2D table of events based on a student weekly schedule. However, the presentation space makes use of a three dimensional representation to fold the wall, in order to provide focus on the data on the front wall and still know the general context from the folding walls. This technique falls under the category of focus plus context interaction technique.

2.2.2.3 Multi-Dimensional Data

The scientific visualizations community deals with real world objects that have volume, as a result they use the 3D surface to visualize the data. We have four options to represent three dimensional data. The last three options also apply to more than three dimensional data.

- a) Use the 3D surface - x,y,z axis to represent each variable.
- b) Use a 2D visual structure with the use of a visual variable for the three or more dimensions.
- c) Use of multiple or composite structures to represent the relationship between two variables in one view.
- d) Use of interaction to change current data variables in view.

Example of an effective 2D structure that represents more than three data dimensions is parallel coordinates [32]. Another concept is the use of multiple views in the same space, such as small multiples [33] and Permutation matrices [22], as shown in Figure 2.12. Each stream chart in the small multiples visualization represents unemployment in a particular industry over ten years. In the permutation matrix visualization, each scatter plot represents relationship between two variables belonging to Car Data. Examples of such unique representations are illustrated by Heer et al. [32].

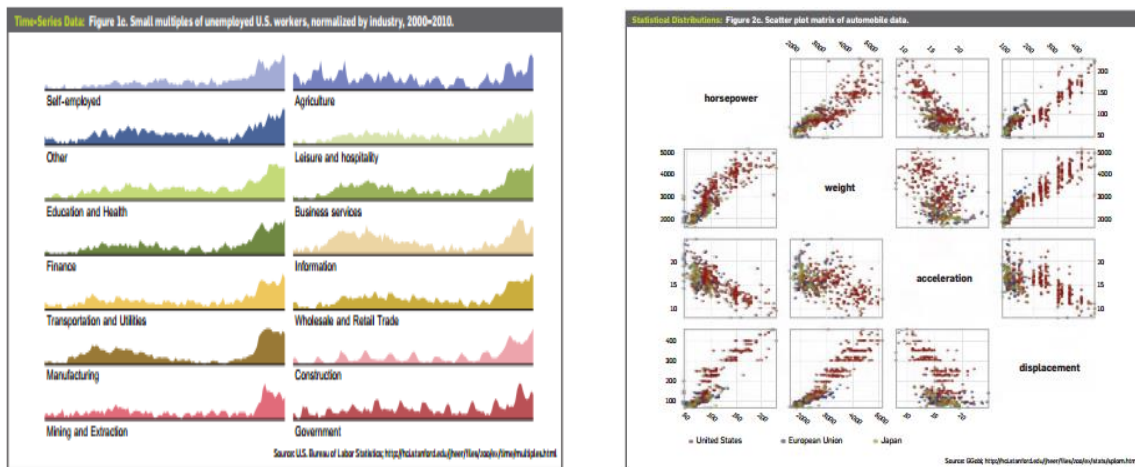


Figure 2.12: a) A small multiples visualization. b) A scatterplot matrix representation. Taken from Heer et al. [32].

The multiple view concept for multiple dimensions shown in Figure 2.12, becomes difficult to perceive as the dimensions increase. In such a case, we make use of interactions to choose variables and data that we are more interested in understanding at a certain point in time.

Trees and Graphs: Relationships between two data variables are usually stored in the form of tuples, and are more commonly represented as a tree, graph, or adjacency matrix. We are going to provide some unique representations based on the relationship classification provided by Bertin [22] illustrated earlier in Figure 2.5. Arc Diagrams is an example of a rectilinear representation and Dendograms is an example of circular and ordered structures. Nested Circles

and the reingold-tilford algorithm are pattern based and ordered structures. Space filling representations such as Treemaps, is an example of a stereogram structure. Diagrams for these representations can be found in [32].

Temporal: Temporal data consists of a series of events with their start and end time. Another property of this data is that time slots can be overlapping. Common representation is line charts and steamgraphs, shown in Figure 2.13.

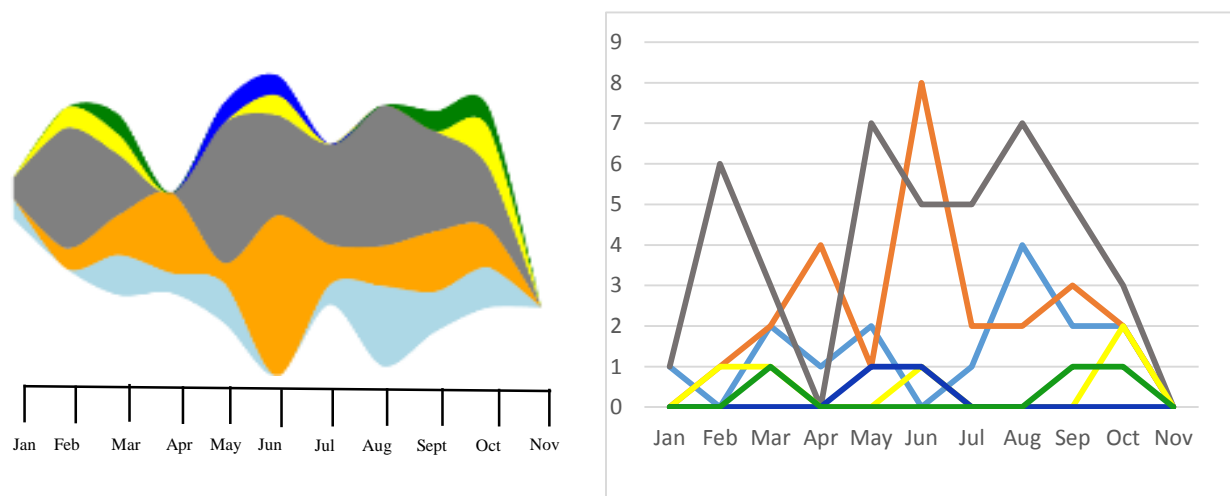


Figure 2.13 Stream graph on the left and the line chart on the right represent assault cases in six communities over the year.

In this section, we have explained a few from the vast space of visual representations provided by the visualization community. We will select a few most commonly used representations to support visualization design with PairedVis.

2.2.3 View Transformations

It is possible that data can fall under multiple data categories, such as 2 dimensional data, and times series data. In such a case, one can either use composite structures or multiple static structures. However, with the use of interactions we change the view dynamically to filter the view or change the representation. As a result, a visualization design is made up of both the

representation (structure) and the presentation (current information in view). A simple example, is the use of sliders and widgets to generate dynamic queries and filter the data on the presentation space, such as with the use of the film finder software [2]. Shneiderman [34] emphasises that we must provide an overview of all the data first and then provide details based on interactions. As a result, even with large amounts of data, all the data is represented first and details are provided based on user interactions with the visualization. A popular technique is the use of lenses to focus on a small portions of the data [30], known as the overview plus detail technique. Another commonly used technique is zooming in and out to view details, commonly used on graphs. The interaction space has also grown to facilitate coordinated views of multiple representations. Improvise [35] can help visualize multiple views of the same data and users interactions are linked across the views.

An important research contribution is from Chuah and Roth [36] . The researchers were the first to classify interactions. The operations are mainly grouped based on their effect on the data or creating and handling datasets, or changes to the visual representation, as shown in Figure 2.14.

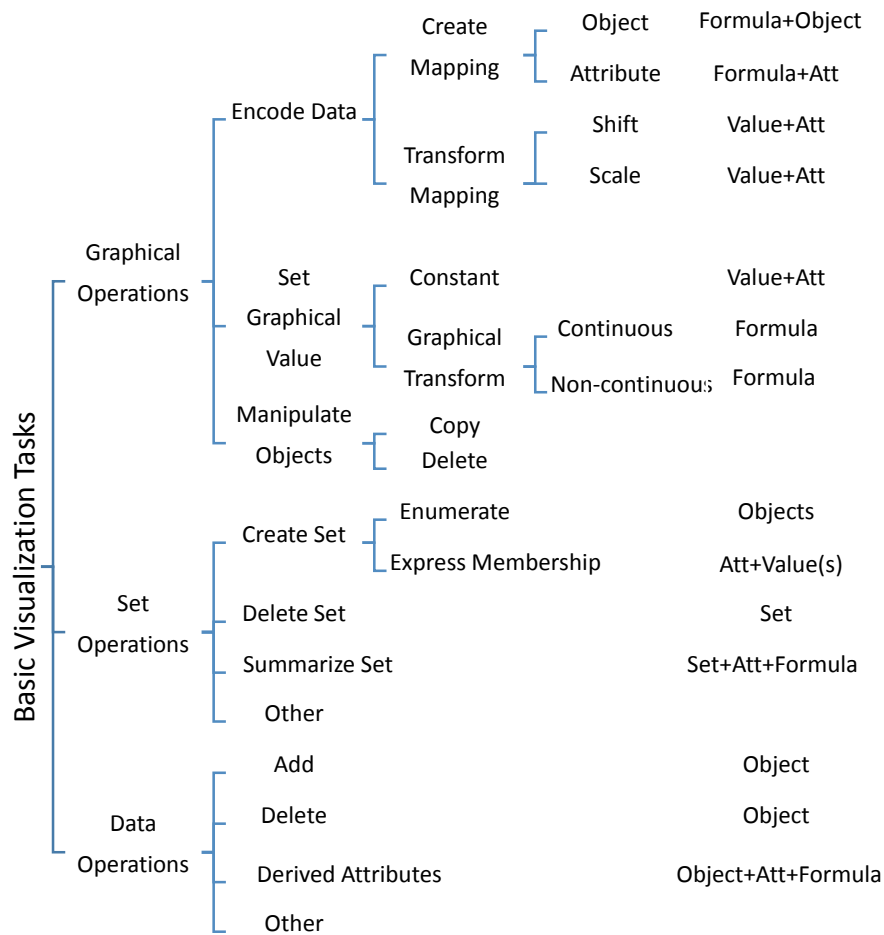


Figure 2.14: Interaction Classification Hierarchy. Taken From Chuah and Roth [36]

As shown in Figure 2.14, the operations that support mapping of data are categorized under Encode Data, whereas operations that change the view are categorized under the Set Graphical Value category, and so on. The researchers have also described whether the operations require manipulation of visual objects, visual attributes (variables), and/or require a formula to effectively support balance between the data and the visualization.

Chi and Riedl [37] have extended this classification to categorize operations based on the level of interaction in the data state reference model, as shown in Figure 2.15. According to the researchers, interactions that just change the data, are value operations and interactions that

require changes only in the visual structure and variables are view operations. Other operations can be broken down to view and value operations. The effect of the operator on the data or value depends on at which stage of the model was the interaction applied.

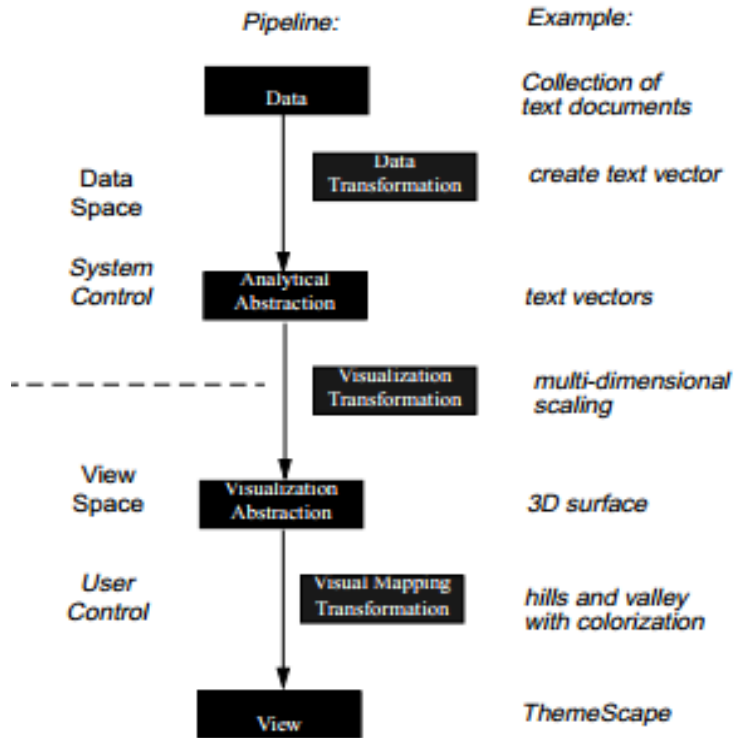


Figure 2.15: Data State Reference Model with sample operators in the view or value space. Taken from [37].

In Figure 2.15, the researchers are trying to explain that changes to the 3D surface at the Visualization Abstraction level can be considered as a view operation. However, zooming in on the 3D surface not only requires changes to the visual representation but may also require details on the specific set of data. Therefore, a value operation will be triggered. However, if the data was filtered at the data transformation level, the final representation will only provide a view of the data selected at the initial stage. Lark [38] made use of this concept to allow changes to data and the view based on the stage at which the collaborators were manipulating a view.

2.3 Conclusion

This chapter provides an overview on how to create visualizations in light of existing literature.

This information helped us in seeing the huge space of possibilities in facilitating design of visualizations. PairedVis is a research tool and the purpose of this tool is to facilitate collaborative visualization design activities between a domain expert and a visualization designer. As a result, while designing this tool we examined the literature presented in this chapter.

Chapter Three: **Paired Visualization Requirements**

Research in Information Visualization has generated considerable literature on visualization processes, designs, algorithms, and interactions, as well as frameworks to support the design of visualization tools and toolkits. Professionals have started to take an interest in information visualization due to the availability of generalized business intelligence visualization tools that support simple and interactive visual design, such as Tableau [39] and Spotfire [40]. To support all types of data, the generalized tools compromise on design and interaction space [16]. As a result, the end users are restricted to a limited set of adjustable templates. On the other hand, visualization toolkits facilitate custom, novel, and new designs, but only programmatically. New research tools like uVis Studio [41] has tried to fill this gap with more expressive formula based visual design to empower non-programmers with more expressive and custom layouts for visualizing their data. However, novice users are facing difficulties in creating appropriate encodings for even common visualizations templates [8], such as Bar Charts and also face problems performing data exploration and analysis tasks [42].

It is clear that there are different users of information visualizations and they have varying interests, skills, and demands from visualization tools. Research and industry have created a wide variety of toolkits and tools to help these users. In section3.1, we first categorize visualization users by their varying interest in visualization design and analysis. Section3.2 explains existing visualization tools and toolkits and how they facilitate the users and their different needs. In section 3.3, we provide requirements of our two experts and analyze whether existing tools and toolkits support them in creating and discussing visualizations.

3.1 Concerns and Interests of Information Visualization Users

Information visualization users can be professionals that use business intelligence visualization tools to help them in making business decisions. Information visualization users also belong to the mainstream population that is interested in visualizing and sharing community specific data, such as number of schools and crime statistics in the neighbourhood. Users can be domain experts that require custom designs to help them explore their complex domain. Users are also visualization experts that design and develop custom and new visualization designs for complex data and domains. Therefore, information visualization users have different visualization design and analysis skills, unique data and domain requirements, and a role to play in visualization design and analysis. As a result, current tools and toolkits need to support these differences. The requirements of information visualization users differs based on the following factors:

- User skill and knowledge of visualization design and analysis.
- User's role in visualisation design and analysis.
- Visualization Design Requirement: Exploratory vs Explanatory Design.
- Number of Users: single or collaborative visualization design and analysis.

3.1.1 User Skills and Knowledge

Heer et al. [16] categorize visualization users into three major categories based on their skill level in information visualization and programming, Novice Users, Savvy Users, and Experts Users. By Expert users he means users that have expert knowledge in visualization design and creation [16]. Expert visualization designers fall in this category. Their designs are usually implemented programmatically. The second type of users that researchers discuss are novice users or end users, people with limited knowledge of information visualization design [16]. Novice users include domain experts that require visualizations to support them in their tasks and

also mainstream users that require visualizations for personal or casual interests (in newspapers or on the web). The researchers also emphasize that there exists an untargeted third type of user the, savvy user that has medium visualization design skills. The researchers state that most users that have an interest in information visualization fall under this category but there are no tools designed for these users. Pantazos and Lauesen [43] made a comparison between thirteen information visualization tools and toolkits based on their own experience with using these tools, they comply with Heer et al. [16] that there is a need for tools to support expert and savvy users with simple and interactive design of visualizations, but should also facilitate programmatic or formula based customizations of these designs in order to extend existing layouts or explore new designs. However, Pantazos and Lauesen [43] believe that the uVis toolkit in support with a development environment, the uVis Studio, is a good combination to support savvy and expert users to create designs quickly and extend these designs by using the uVis toolkit.

3.1.2 User's Role in Visualization Design and Analysis

As described in detail in Chapter1, according to the Visualization Design Process, a visualization designer takes up the role of the designer, creating sample visualization designs for critique and selection by the domain expert. Then the visualization designer or a team of programmers implement the selected designs using existing tools or toolkits. Sedlmair et al. [4] have explained that custom designs are necessary when task clarity is low or domain scope is huge and complex. When the data and the tasks are simple, visualization experts can use existing visualization tools with customizable templates to satisfy the requirements of the domain experts. When the tasks are complex or the scope of the domain is huge, visualization designers create new designs that are implemented using graphic or visualization toolkits. In such cases, the metadata information is partially in the head of the domain expert [4]. The visualization designers need to create new

visualization prototypes in close collaboration with domain experts [10]. We propose that the visualization designer can make use of an interactive tool to learn about the data, domain, and domain expert's requirements.

In this scenario, the domain expert and the visualization designers both participate in visualization design to understand and discuss the data and the requirements. However, these experts have different skills in visualization design. Graphical toolkits, such as OpenGL [45] and Processing [46] facilitate visualization designers or their team to create new and custom visualization designs from scratch. Whereas, information visualization toolkits, such as Prefuse [46] and D3 [47] facilitate visual design based on components of existing visualization layouts. However, none of these toolkits are supported with an integrated development environment (IDE) that can support visualization design with drag and drop features. As a result, visualization experts cannot create quick visualizations in the presence of domain experts using visualization toolkits.

There are some tools designed for savvy users that facilitate quick and interactive means of creating visualizations with adjustable templates, such as uVis Studio. However, this tool suffers from the abstraction barrier and is not suitable for novice users [16]. By abstraction barrier the researchers mean that the users have to know all the possible methods of constructing and customizing representations before being able to create a visualization.

There are tools that have the purpose of supporting novice users and provide visualization design and analysis with interactions, such as Spotfire [40], Jigsaw [49], and Tableau [39]. Though they are powerful visualization tools, studies [8] [42] indicate that novices with limited knowledge in visualization design and analysis face difficulties in using visualization tools. Kobsa [49], found that Spotfire has a higher cognitive cost and requires a more direct and simple method of

selecting and configuring a visualization. We need to support communication between a domain expert and visualization designer so that they can discuss visual representations of the data. As result, we do not want to use a tool that will require a visualization designer to spend time in explaining the tool. Therefore, a tool is required that enables visualization design and analysis with quick and simple interactions, so that the domain expert can also understand the design of a visualization.

3.1.3 Visualization Design Requirement: Exploratory vs Explanatory Design:

Visualization design is also dependant on the purpose of the visualization, whether it is for exploratory data analysis or explanatory data analysis [16] [50].

Exploratory Data Analysis: Visualizations are in some cases created to understand the data, when little or limited knowledge is known about it. In this case, users create designs that represent all the data in greater granularity, in other words, abstract representations of the data are avoided. For example, to view sales data over the past five years, a bar chart can be created to represent sales per year. This representation will be abstract because it does not show the sales data per month or per sale. Data exploration can be achieved with the use of interactions or shifting to a different representation. In our case, we want visualization designers and domain experts to construct different representations of the data. Each representation organizes data differently and can inherently emphasise a relationship that may not be easily readable in another representation [52]. Therefore, while constructing visualizations we want the experts to explore the data with different representations.

Explanatory Data Analysis: Visualizations are also created to answer a specific set of questions and are used for reaching a greater set of audience and inform them of something a visual creator already knows about [50]. Heer et al. [16] refer to it as communicative visualization. To make

the communication more effective, designers remove irrelevant data and make the visualization abstract and the insights more prominent.

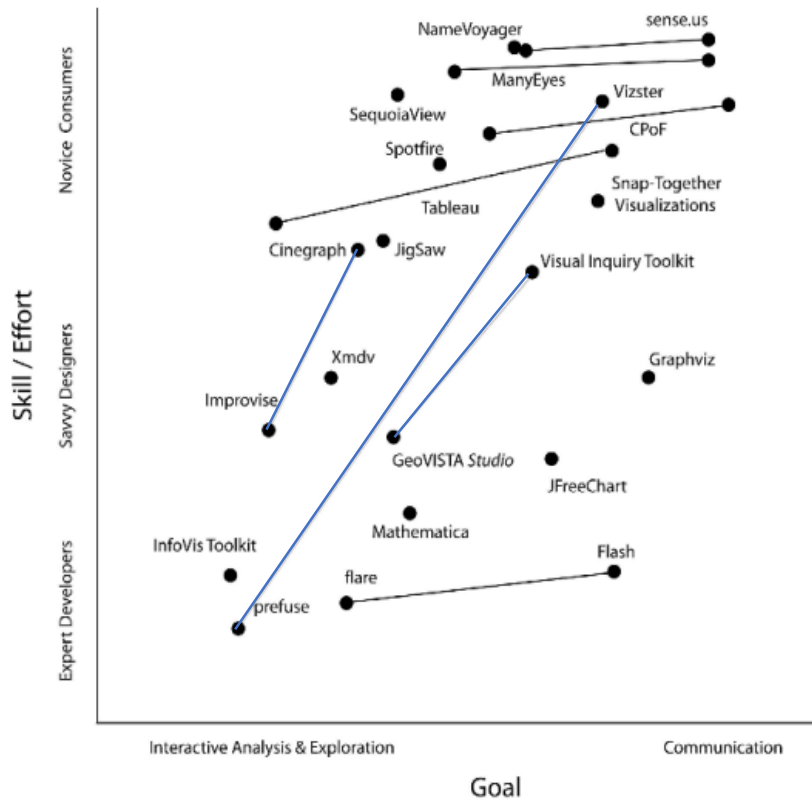


Figure 3.1: Existing Tools and Toolkits based on two dimensions: User Skills and Visualization Design Type, taken from Heer et al. [16]. Blue lines represent toolkits to visualizations tools created with them and dark lines represents systems that facilitate a wider range of users or goals.

Heer et al. [16], believe that only experts in visual design can create deep exploratory visualizations. The researchers compared existing visualization tools and toolkits based on two dimensions, user's skill and visualization design type referred to as visualization goal, as shown in Figure 3.1. This analysis informs us that current user tools do facilitate deep exploratory tasks [16]. However, novices are known to struggle with creation of visualizations [8]. In case of our scenario, whether the intended visualization is exploratory or explanatory in nature, the visualization designer always performs exploratory tasks to find appropriate possible designs and

determine whether they satisfy the required data analysis tasks. Moreover, finding the appropriate representation requires repetitive design of prototypes [10]. As a result, our tool should facilitate iterative design with existing templates to support exploration of useful representations.

3.1.4 Number of Users: Single or Collaborative Visualization Design and Analysis

It is natural for a group of people to work together in accomplishing huge or complex tasks in an everyday work environment. Research to support collaborative work in computer science falls under the field of Computer-supported cooperative work (CSCW). As data increases in size and complexity, researchers feel the need to support multiple users to perform collaborative data analysis tasks on visualizations [14]. Researchers that want to facilitate collaboration in visualization analysis are using techniques, methods, and technology from CSCW. Heer et al. [16], Stusak [17], and Isenberg et al. [15] provide an overview on this interdisciplinary research area between Information visualization and CSCW.

Under the field of CSCW, the first step towards facilitating collaboration, is to envision the context in which a group will collaborate over space and time, as shown in Figure 3.2. The first context is; when people get together at the same time and at the same location to collaborate, like a meeting room. The second context, also in a co-located environment is; when people coordinate asynchronously with each other at different points in time, such as night shift staff can leave annotations for the morning shift staff in a shared workspace. The third context is about distributed collaboration at the same time. A common example is the use of Skype for online meetings between individuals separated by distance. The fourth context involves the study of collaboration in a distributed and asynchronous setting, such as discussions on blogs.

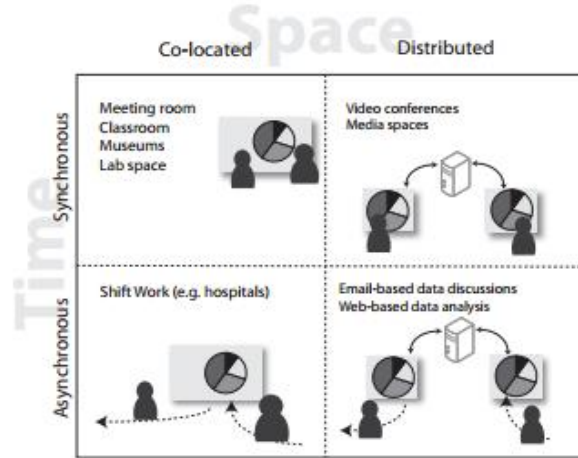


Figure 3.2: Space-Time Matrix, taken from Isenberg et al. [15].

According to the space-time matrix shown in Figure 3.2, we are currently interested in the first context of co-located synchronous collaboration between two experts. Existing research and commercial visualization tools have not investigated how to support collaboration between two experts with different skills. In our case, we want to support the domain expert with functionality to explain the data and the requirements using the tool. We also want to support the visualization designer with quick and interactive means of mapping and explaining visualizations.

3.2 Existing Approaches to Facilitate Visualization Needs

Pantazos and Lauesen [43], have made a comparison between thirteen information visualization toolkits and tools based on their own experience as users of these tools. The results of their comparative analysis point out that existing efforts in the industry and academia can be easily segregated into two categories:

- **Toolkits** that facilitate novel designs but require programming or expression based programming skills, such as Infovis [52], Prefuse [46], Protovis [53], Flare [52], Piccolo [54], Processing^[2,29], Improvise [35], and uVis [55].

- **Tools** that facilitate drag and drop interactions to facilitate novice users, such as Tableau [39], Spotfire [40], Visokio (Omniscope) [56], and Many Eyes [57]. These tools facilitate visualization design with templates.

In addition, we add a third category of tools to this classification which includes tools that support collaborative design and analysis. However, current collaborative efforts only support visualization analysis.

- **Collaborative Tools** that have been presented by academia to study and facilitate collaboration during visualization analysis.

In the following section, we classify existing tools and toolkits based on the above mentioned categories.

3.2.1 Toolkit support for Expert Programmers

The Infovis toolkit [52] is one of the first efforts from academia that targeted programmers with little knowledge of graphic design but a growing interest in visualization design. It facilitated programmers to quickly develop existing visualization designs with less programming effort than graphical toolkits like Processing. The toolkit supports three types of data structures, tables, trees, and graphs. Each type of data structure can be mapped to specific visualization designs. For example, a tree structure can be mapped to node-link diagrams and treemaps only. It requires knowledge of the java programming language.

The Prefuse [46], toolkit went a step further into facilitating mainstream programmers with novel visualization designs. The designs were based on basic building blocks of visualizations. The researchers used the Data State Reference Model^[3.1] to develop the tool. As a result, the visual design was divided into three steps; data abstraction, mapping data to an intermediate visual representation and then encoding it to a final visual presentation. The intermediate form is a

graph structure that supported entities as nodes, relationships as edges, and aggregates as aggregate groups. The intermediate form can be mapped to existing visualization designs, such as circular, tree map, and grid-based. A significant contribution of this work is that users could build a novel design from using components of existing layouts.

The Data Driven Documents, D3 [47] and its predecessor Protovis [53] are web-based toolkits, that make use of the Document Object Model (DOM) to create visualizations. The toolkits availability on the web makes it easier to access on any device that has a web browser such as, Google Chrome, enabling users to share and discuss visualizations. Its similarity with web programming technologies, such as Javascript and CSS, have initiated a wide spread interest in the toolkit by web developers. Similar to Prefuse, D3 enables design of custom visualizations using components of existing visualization templates. However, like any other graphical toolkit, it enables users to create new visualization designs and node placement algorithms with considerable effort [16].

Improvise [35] enables programmers to create multiple coordinated views of the data to support data exploration. Data abstractions and encoding is supported by expressions based on the relational database model. Though the tool allows creation of highly coordinated custom visualization views, the expression building requires high cognitive effort [16].

The uVis studio [41] is a recent addition to visualization tools and is developed on top of the uVis toolkit [55]. The toolkit targets savvy or expert programmers to create visualizations using formulas. The uVis Studio, enables them to drag and drop visual objects in the Design Panel, bind data to visual objects with the use of formulas. The results of the binding and setting properties are immediately shown in the Design panel, and the users can interact with the

visualization like an end user. The uVis studio facilitates custom visualization designs using expressions.

Mohammed et al. [58] made a comparative analysis between toolkits; Prefuse, Improvise [35], Protovis, and Uvis. According to their findings, Prefuse is more successful in providing a larger design space than the other three, however suffers from the abstraction barrier. By abstraction barrier the researchers mean, having knowledge of all the encapsulations to ensure a more customized design. On the other hand, Improvise suffers from system transparency, as it forces the users to customize the design using multiple dialogs. Protovis, facilitates a customized visualization by allowing direct manipulation of the primitive visual objects, however has a small abstraction barrier. Out of the four tools, the researchers are more drawn towards uVis studio because it facilitates customized design with the use of simple formulas and with relatively few abstractions.

3.2.2 Tool support for Novice Users

Visokio [56], Spotfire [40], and Tableau [39] are few among many commercial visualization tools. We have chosen to discuss these because they have been used in studies [49] [8]. Though they lack custom visualization designs, they provide an easy and interactive means of creating visualizations. They are facilitating end users to create visualizations on their own and share them on the web by providing a free public version for viewing and discussing visualizations. However, these tools do not explore how to support communication between domain experts and visualization designers.

Many Eyes [57] is a public web-site that empowers the general public to upload data, create, and share visualizations. The intent of the website is to generate discussions on a large scale about

the data and the visualizations. It provides a step by step means of creating visualizations through web based menus.

Kobsa [49] performed a study in 2001 to find usability issues faced by users of visualization tools. He compared Spotfire, Eureka, and Infozoom. The participants in the study had difficulties in answering questions involving correlations and selecting appropriate visualization templates. The researchers had noticed that once a visualization template had been chosen, the participants had difficulty going back and setting up another visualization layout. System transparency is a very important usability factor which the researchers noticed was low in Spotfire. The researchers believed that Spotfire needed a direct and simple method of selecting and configuring a visualization. As a result, it is important for end users to quickly choose visualization templates and test and reselect another template, if the first did not satisfy their query.

All the tools described above are intended for visualization design by a domain expert. Many Eyes and Tableau do facilitate multi-user asynchronous annotations for collaborative analysis.

3.2.3 Collaborative Visualization Tools

As discussed section 2.1, teamwork can be facilitated in any four contexts of collaboration in space and time. We will only focus on research efforts to support co-located synchronous collaborative efforts in information visualization. Tang et al. [59] conducted a study to understand the trade-offs between allowing individual or joint work in a collaborative setting. When a team is solely supported by a single shared view, team members cannot divide work to perform activities in parallel. Whereas, independent work on individual screens may lead to insufficient group communication and coordination. Visualization tools have tried to facilitate users with both individual and shared screens.

The first effort to support collaborative visualization is the tree comparison visualization [60]. This tool was supported on a tabletop and enabled two simultaneous inputs. Each team member could work with their individual representation and resize, rotate, or translate their views for personal or collaborative analysis. Another such effort is Cambiera [61], a tool that facilitates brushing and linking of data to make team members aware of each other's document exploration activities and analysis. Brushing and linking is used in multiple representations of the data, and when data points are selected in one representation, they are highlighted across all other representations. The tool linked all the views from each team member, to support awareness of each other's exploration areas. The tool enabled sharing of views and exchanging of artifacts to support discussion and collaborative analysis. Lark [38] is another collocated collaborative tool that allowed a team to segregate work from any stage of the Data State Reference Model [2]. The interface presented the four stages of the data in a visual form; Analytic Abstraction, Spatial Layout, Presentation, and View. A team member can start work at the Data Abstraction stage of the pipeline. Filtering data at this initial stage is a value operation. As a result, changes propagate in all the views sprouting from that data. Two team members can start work at the presentation stage and perform filters on their separate views. However, view operations performed at the presentation stage can explicitly change all the views that generate from it. The main contribution of this work was to enable a team to make their view and value operations explicit to others, in order to share insights.

DTlens [13], is an attempt to facilitate multiple lenses for individual work during group analysis of spatial data on a shared surface. Forlines et al. [62] and Forlines and Linen [63] used multiple surfaces to support collaborative work with multiple coordinated views of the same data.

These are some examples of how to support collaboration on visualizations.

3.3 Paired Visualization Requirements

In section 3.1 we defined a tool design criteria in order to understand how we can facilitate the needs of information visualization users:

- User skill and knowledge of visualization design and analysis.
- User's Role in visualisation design and analysis.
- Visualization Design Requirement: Exploratory vs Explanatory Design.
- Number of Users: single or collaborative visualization design and analysis.

With this criteria we can investigate the needs of our two experts whom we are trying to support to satisfy our research objectives.

- We need to facilitate both a visualization designer and a domain expert with different skills in visualization design. This complies with our first research challenge, the *Two Expert Challenge*, defined in Chapter1.
- Their role in this scenario is to design and analyze visualizations together.
- The intended goal is exploratory in nature and requires them to repeat visualization design and analysis activities with existing templates until useful representations are found. This complies with our second research challenge, *Iterative Design Challenge*, defined in Chapter1.
- Finally, we want to provide a collocated synchronous environment to perform visualization design activities in collaboration.

Based on the needs of our users and the recommendations from existing literature on how to support domain experts [16] [8] [42], we elicited functional requirements for a tool that can support both the domain expert and the visualization designer in creating and exploring

visualizations together. We will use these requirements to examine existing tools and see whether they fits the needs of our users and our research objectives.

3.3.1 Functional Requirements

R1. *Support Two Experts with Different Visualization Skills*: The tool should provide interactive means of creating visualizations. This requirement will facilitate a domain expert with novice understanding in visualization design [16]. On the other hand, we also need to support a visualization designer. Therefore, we need to provide functionality for customization of representations programmatically, so that a visualization designer or his team can enhance an existing template into a functional prototype.

R2. *Provide an interface for discussing data and discussing visualizations*: There are underlying relationships in the data that are in the mind of the domain expert [4], which the visualization designer needs to know to create useful representations [10]. Therefore, we want to provide an interface to the domain expert to share their knowledge about the data and the relationships between the data variables. Similarly, we need to support a visualization designer with interactions for explaining existing templates and how to perceive them.

R3. *Support Iterative Visualization Design and Exploration*: Grammel et al. [8] found that domain experts keep creating representations until a useful representation is found. As a result, the tool should support quick and interactive means of selecting and switching templates and mapping variables [8]. This requirement complies with our second research challenge, *Iterative design challenge*, defined in Chapter 1.

R4. *Support Synchronous Collocated Collaboration*: To support this collaboration, we require tightly coupled work between a visualization designer and the domain expert in a collocated environment [10].

These are the major requirements of a tool that can facilitate collaboration between the domain expert and the visualization designer in creating and exploring visualizations together.

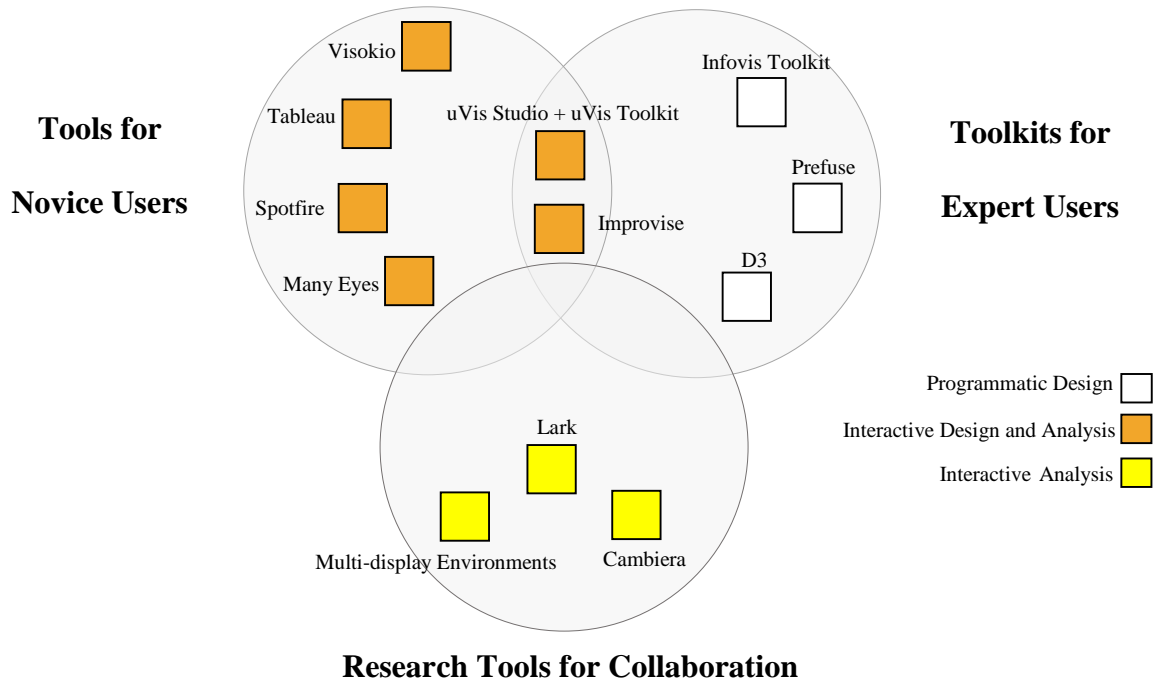


Figure 3.3: Visualization Design Tools and Toolkits categorized based on how they support visualization users.

In Figure 3.3, we described various tools and toolkits provided by the industry and academia to support visualization users. Based on existing literature and our own experience with visualization tools, we know that existing tools do facilitate some of the above requirements, but not all. According to our first requirement (R1), we need a tool that can facilitates interactive means of creating visualizations, as well as enable programmatic means of enhancing the visualization designs. uVis studio [41] satisfies this requirement and provides both interactive means of visualizing data, as well as programmatic changes through the underlying toolkit [55]. However, uVis Studio is designed for savvy users [16]. Tableau [39] and other novice user tools

described in this chapter provide interactive means of creating visualizations, but do not facilitate programmatic means of enhancing designs into functional prototypes. On the other hand, visualization toolkits, such as D3 [47] are not supported with drag and drop development environments to create visualizations interactively. Whereas, collaborative tools only support interactive analysis and not visualization design.

None of the tools and toolkits satisfy all of our requirements. Therefore, we decided to develop a tool specifically to support a visualization designer and a domain expert to create and explore visualizations together.

Chapter Four: **Design of PairedVis**

We wanted to study whether it was beneficial to provide synchronous collaboration between a domain expert and a visualization designer during visualization design and exploration activities. To facilitate this scenario, we elicited functional requirements for a tool, in chapter3 and found that existing tools do not satisfy these requirements. As a result we decided to design a tool based on these functional requirements:

R1. *Support Two Experts with Different Visualization Skills*: The tool should provide interactive means of creating visualizations. This requirement will facilitate a domain expert with novice understanding in visualization design [16]. On the other hand, we also need to support a visualization designer. Therefore, we need to provide functionality for customization of representations programmatically, so that a visualization designer or his team can enhance an existing template into a functional prototype.

R2. *Provide an interface for discussing data and discussing visualizations*: There are underlying relationships in the data that are in the mind of the domain expert [4], which the visualization designer needs to know to create useful representations [10]. Therefore, we want to provide an interface to the domain expert to share their knowledge about the data and the relationships between the data variables. Similarly, we need to support a visualization designer with interactions for explaining existing templates and how to perceive them.

R3. *Support Iterative Visualization Design and Exploration*: Grammel et al. [8] found that domain experts repeat designing representations until a useful representation is found. As a result, the researchers suggest that this process should be supported with quick and interactive means of selecting templates and mapping variables. This requirement complies with our second research challenge, *Interactive Design challenge*, defined in chapter1.

R4. *Support Synchronous Collocated Collaboration*: To support this collaboration we require tightly coupled work between visualization designer and the domain expert in a collocated environment [10].

In the following sections we are going to discuss how we addressed these requirements in the design of PairedVis.

4.1 Designing PairedVis

The major goal of the tool is facilitate visualization design. As a result, we had to design an interface that can enable the experts to transform the data to a visual representation, the data state reference model [2]. As a result, we have designed our interface on this model. The interface has four panels; the data panel, the data transformation panel, the view transformation panel, and the code panel. The main interface design is shown as an abstract representation in Figure 4.1. The screen can show two panels at a time. Arrows can be used to flow back and forth between the panels at any time.

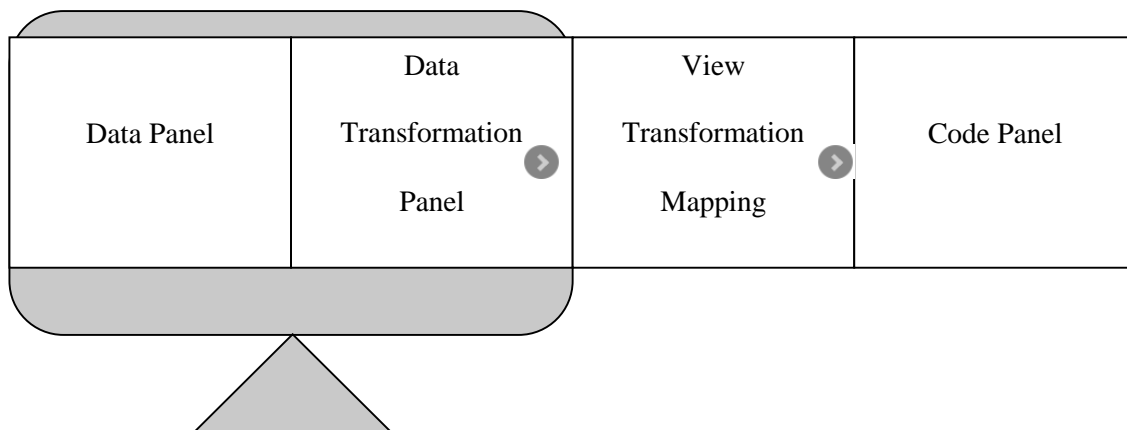


Figure 4.1: PairedVis interface with four panels. The screen showing two panels at a time.

The first panel the Data Panel, holds the dataset in a table format. The second panel, the Data Transformation panel, can be used to create relationships between the data columns. The third

panel enables mapping of data to visual representations, therefore it is called the View Transformation panel. The Code panel provides the code behind the visualization for sharing or customization.

4.1.1 Discussing Data

“When team members meet initially to start work on a problem, they must first develop a shared problem frame” [63]. In this scenario, a domain expert and a visualization designer need to have a shared understanding of the data and the requirements. We have designed PairedVis to support discussion on the data and the relationships between data variables with an interactive interface. This satisfies the first part of our requirement; [R2] *Provide an interface for discussing data and discussing visualizations*. Our approach to providing discussion on the data is inspired by concept mapping [65], Class Diagrams from UML in software engineering, and entity-relationship diagrams in database modeling. A concept map is a visual representation of concepts to give a meaningful structure to our knowledge. Relationships between concepts are represented with the use of links. More important concepts are organized at the top. UML diagrams are an extension of concept maps. They are created to structure software requirements and designs as a visual representation. Similarly, entity-relationship diagrams are visual representation of relationships between different tables based on data variables.

The tool allows the paired users to upload the data and select data variables of interest, as shown in Figure 4.2.



Figure 4.2: Left panel for uploading data and selecting data variables. Right panel for describing relationships between the data variables.

As shown in Figure 4.2, we represent the data variable as a bubble (circle). The domain expert can use the Data Transformation panel on the right to explain the relationships between the data. In concept mapping all relationships are represented with links. Relationships in UML diagrams are defined based on how one object makes use of another, such as dependency, aggregation, composition, inheritance, and realization. We are inspired by relationships based on database modeling with the use of entity-relationship diagrams. In database modeling there are two major types of relationships, parent-child relationships and associative relationships. We have used these two relationships to represent our metadata:

Hierarchical: This relationship includes grouping and inheritance. We needed one interaction for both, because the nesting operation is required to facilitate both grouping and hierarchy of data to visual representation. Lets assume that the domain expert is interested in visualizing disastrous

events that occurred in Canada. He/she can explain that events can be grouped based on event types and event types can be grouped based on event groups. This relationship can be represented using a bubble inside a bubble, as shown in figure 4.3.

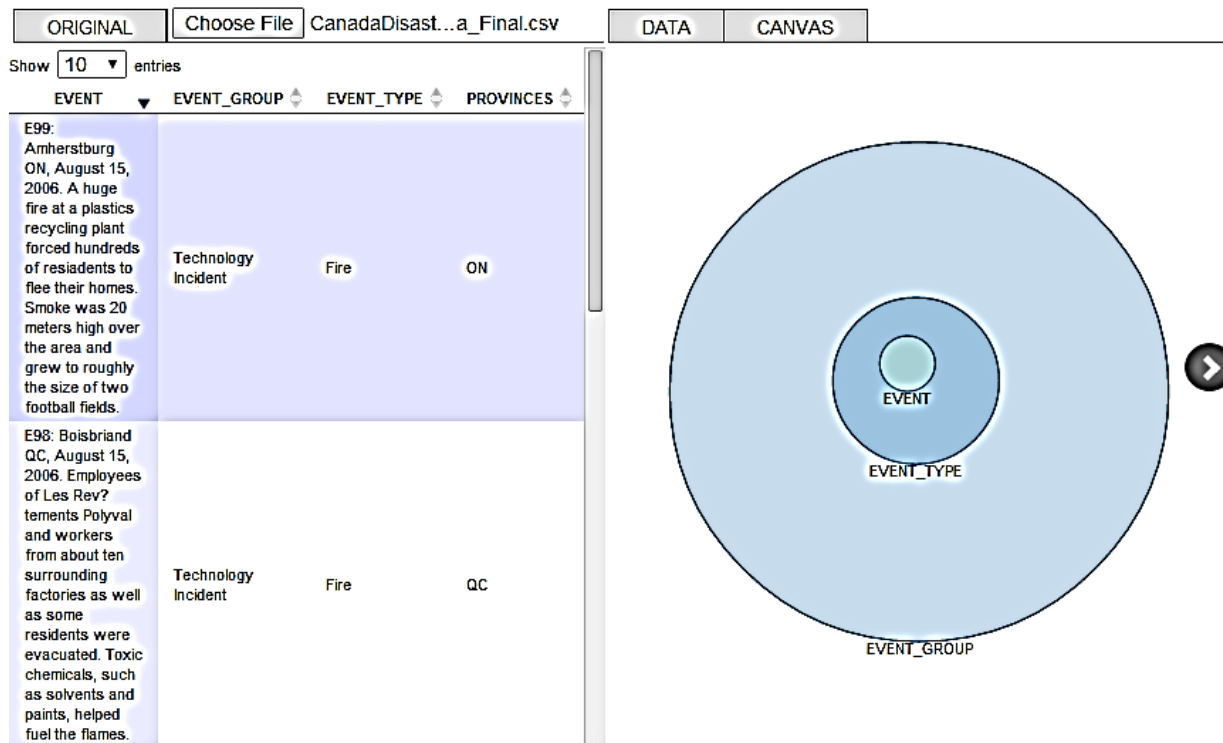


Figure4.3: Data Transformation Panel on the right showing a grouped relationship.

Lets consider another example of the use of this relationship by the domain expert to explain requirements. He can push events inside the province bubble and inform the visualization designer that he want to visualize events per province. This is an example of grouping events based on the province in which they occurred.

Causal or Associative Relationship: This relationship is used when one data variable is associated or dependant on the other but cannot be categorized as inheritance. Both these relationships have the same effect on the six visual representations used in PairedVis, therefore we used the same interaction to represent these relationships. For example, a domain expert

might want to explain that for each event he has information about the number of injuries, evacuees, and fatalities. This relationship can be represented with the use of links between the bubbles, as shown in figure 4.4.

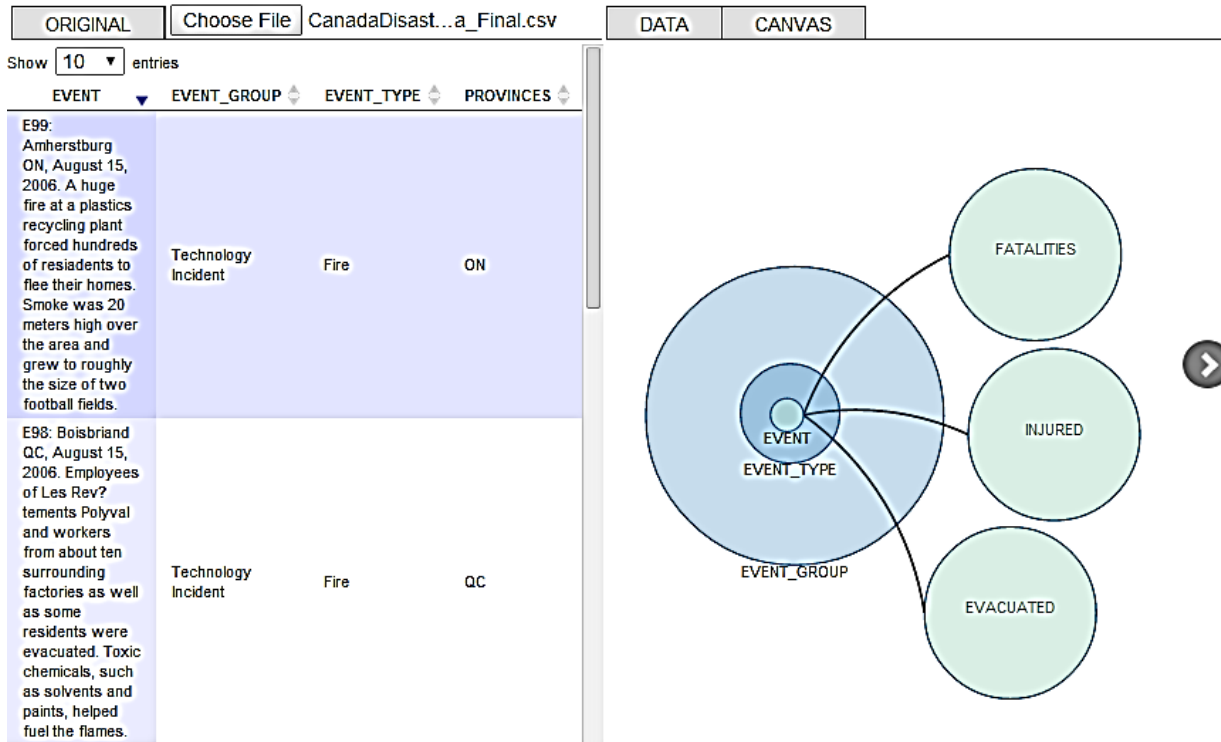


Figure4.4: Data Transformation Panel on the right showing an associative relationship.

The use of these two relationships results in a graph structure. Prefuse [46], made use of a graph structure between the data and the visualization, to facilitate data transformation operations. The difference in our tool is that we have provided a visual form for representing data and have provided interactions to show relationships between the data variables in visual form.

4.1.2 Discussing Visualization Design

After understanding the data and the requirements, the visualization designer can suggest appropriate visual representations for the data. We have presented sample visualization

representations in a sliding thumbnail bar at the top of the view transformation panel, shown in Figure 4.5.

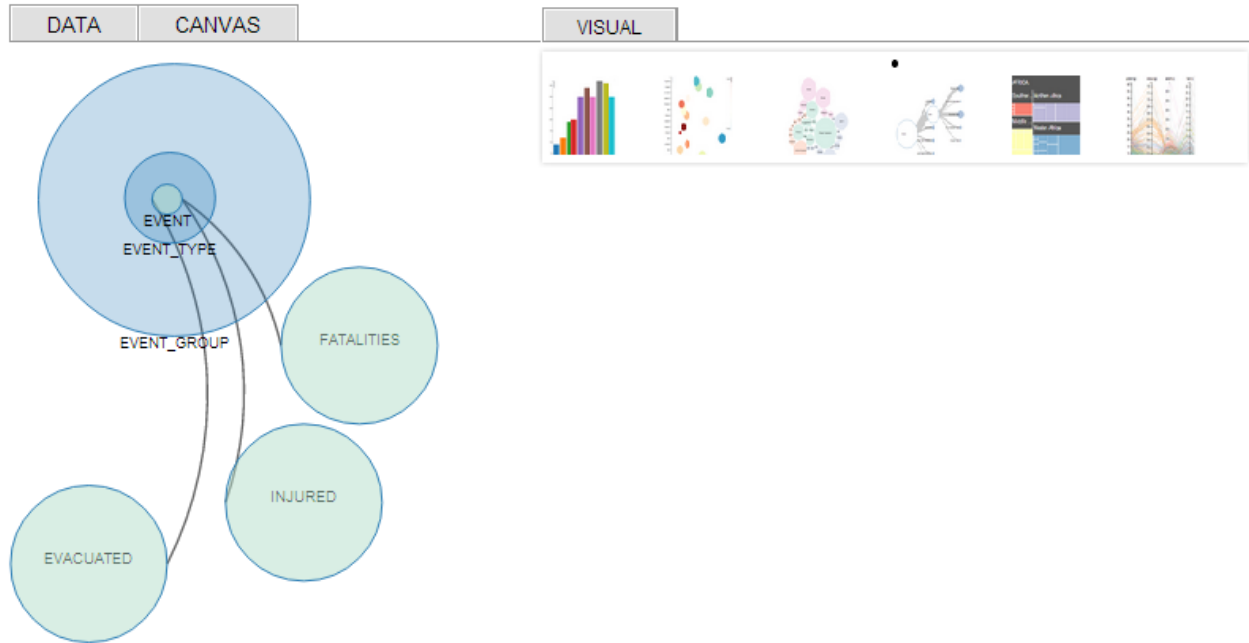


Figure4.5: View Transformation Panel on the right showing sample visualization templates.

The view transformation panel represents six representations; bar chart, scatterplot, bubble chart, Reingold tree layout, treemap, and parallel coordinates. Each of these representations are mapped to sample datasets to help explain the structures and the interactions that can be performed with them. The interactions are discussed more in detail in section 4.1.3.3. This functionality satisfies second part of our requirement: [R2] *Provide an interface for discussing data and discussing visualizations.*

To see or switch to a representation the user can simply tap on the representation in the thumbnail bar. For example, consider that the domain expert inquires whether they can see events based on the number of fatalities, evacuees, and injuries. In reply, the visualization designer can suggest a scatterplot view of the events. One of them will tap on the scatterplot in

the thumbnail bar and the scatterplot will appear below, as shown in Figure 4.6. The scatterplot is mapped to the data about immigrants to Canada based on country of birth. The bubbles represent the country of birth and the bubble size represents the total immigrants from the country. The x-axis represents the employed, whereas the y-axis represents the unemployed.

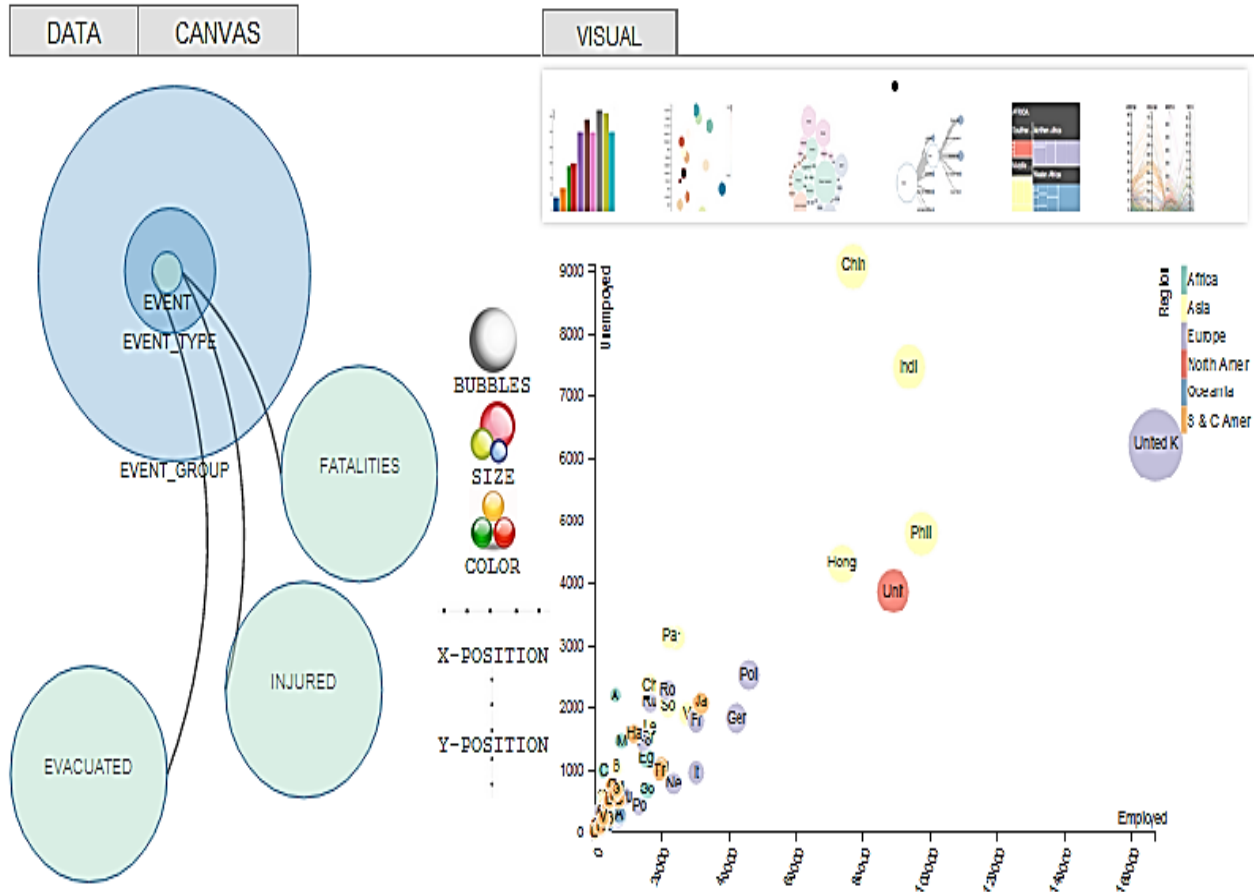


Figure 4.6: View Transformation Panel on the right showing sample data mapped to a Scatterplot. The sample data is about Immigrants to Canada based on Country of Birth.

The visual variables supported by the visualization template are represented in between the data transformation and view transformation panel. In case of the scatterplot, the visualization can support, Bubbles as the Marks, Size, Color, X-position, and Y-position as visual variables, shown in Figure 4.6.

Grammel et al. [8] and Kwon et al. [42] have both suggested that tools should provide explanations of what is displayed in the visualizations, because domain experts have difficulties in mapping data to variables of a visualization. Because of the presence of an expert we do not require automated suggestions from the tool to support the domain expert. However, we believe that a breakdown of visualizations into their basic components can help explain visual mappings. For example, showing one variable at a time in the visualization. This can serve as a simple beginning for domain experts to understand some of the complex visualizations developed by the community. As ink on the visualization grows, the visualization becomes difficult to analyze, Tufte [33]. As a result, by displaying one or two data variables at a time, we can “*draw the viewer’s attention to the sense and substance of the data*” [33]. This adding of variables to the view one or two at a time is supported by animation in our tool.

Using our tool, the visualization designer can break the visualizations into their basic visual components by clicking on the component. For example let us consider the scatter plot representation in Figure 4.6. To view the marks only in this Figure, we can tap the Bubbles icon in the middle of the data transformation and visual transformation panel. As a result, of this action the bubbles become equal in size and we can only view the countries represented by bubbles in Figure 4.7(a). Similarly, clicking on the y-axis will place the bubbles based on unemployed immigrants for that country, as shown in Figure 4.7(b).

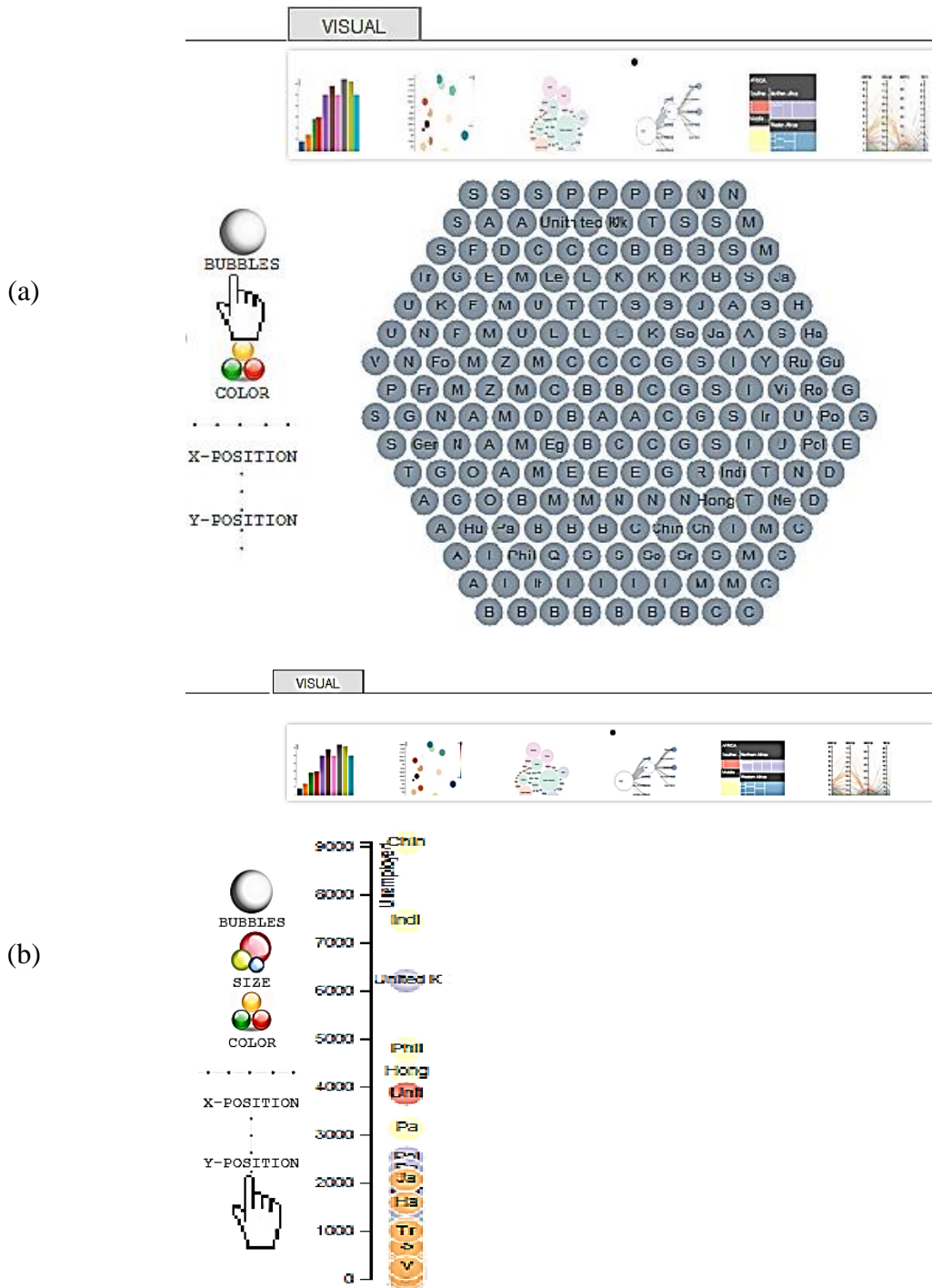


Figure 4.7: (a) Clicking on bubbles displays just the marks, in this case countries. (b). Clicking on the Y-position displays the data based on unemployed immigrants for that country mapped to the Y-axis.

In this section, we have described how our tool supports the collaboration between the domain expert and the visualization designer. In the following section, we are going to discuss the interactions provided to support quick and simple visualization design to support iterative design of visualizations.

4.1.3 Creating Visualizations

We have designed PairedVis to facilitate quick and interactive means of creating visualizations.

Reducing the cost of creating a representation can help the experts to switch between representations and concentrate on understanding the data and uncover underlying relationships [10] [1]. We want to facilitate iterative design activities so that visualization designers and domain experts can discuss how existing templates support a certain task. This functionality complies with our requirement [R3]. *Support Iterative Visualization Design and Exploration.*

PairedVis enables the paired experts to create visualizations with simple drag and drop of visual components on to the data variables of interest. For example, let us consider that the domain expert wants to view Canada's disastrous events in a bubble chart. To do this, one of the experts will tap the Bubble Chart template in the thumbnail slider. Then the Bubble Chart and its visual variables will appear in the view transformation panel. The user has to first map the Mark in any of the visualization templates. In case of the bubble chart, the Marks are the *Bubbles*. For each visualization, the Marks are predefined and cannot be modified. To map the Marks, the user drags and drops on the data column, for example *Bubbles* in the scatterplot can be dropped on Events. The Marks and the text will represent the selected data column. Drag and drop of *Size* to *Fatalities* will result in mapping of the numeric range to a range of bubble sizes. Drag and drop of *Color* on *Injured* will map the numeric range to an ordinal range of colors, as shown in Figure 4.8.

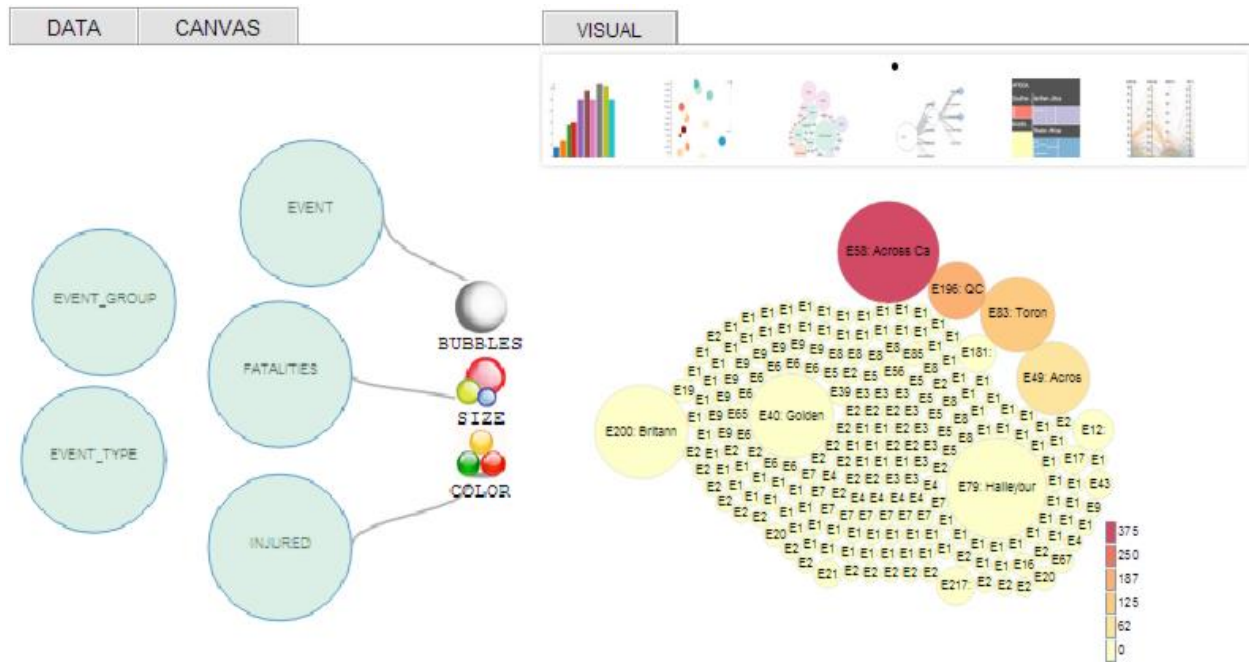


Figure 4.8: Drag and drop of visual variables on data variables.

When a visual variable is dropped on the data variable, it moves back into position, however a link is created between the two and is represented in grey. This link clearly informs the other paired participant about which data variable is affecting which visual component. As a result, it supports understanding of visualization design.

We wanted to facilitate interactions for mapping, as well as exploring data. We categorized interactions based on their relevance to the data state reference model:

- 1) Operations that facilitate Data transformations
- 2) Operations that facilitate data to Visual Component Mapping
- 3) Design of interactions on the visualization to support Data Analysis

4.1.3.1 Data Transformation Operations

The Data Transformation panel was first used by the domain expert for concept mapping, but it is also used for data transformation operations. Since, this is an initial functional prototype of the

tool. We were only able to support some structure to derived structure operations. For example, if the domain expert needed to see events based on provinces, he would have pushed the *Event* bubble inside the *Province* bubble to represent the relationship. Now when this relationship is mapped to the Bar chart, a grouped Bar chart is represented to show the events per province (a group for each province) as shown in Figure 4.9.

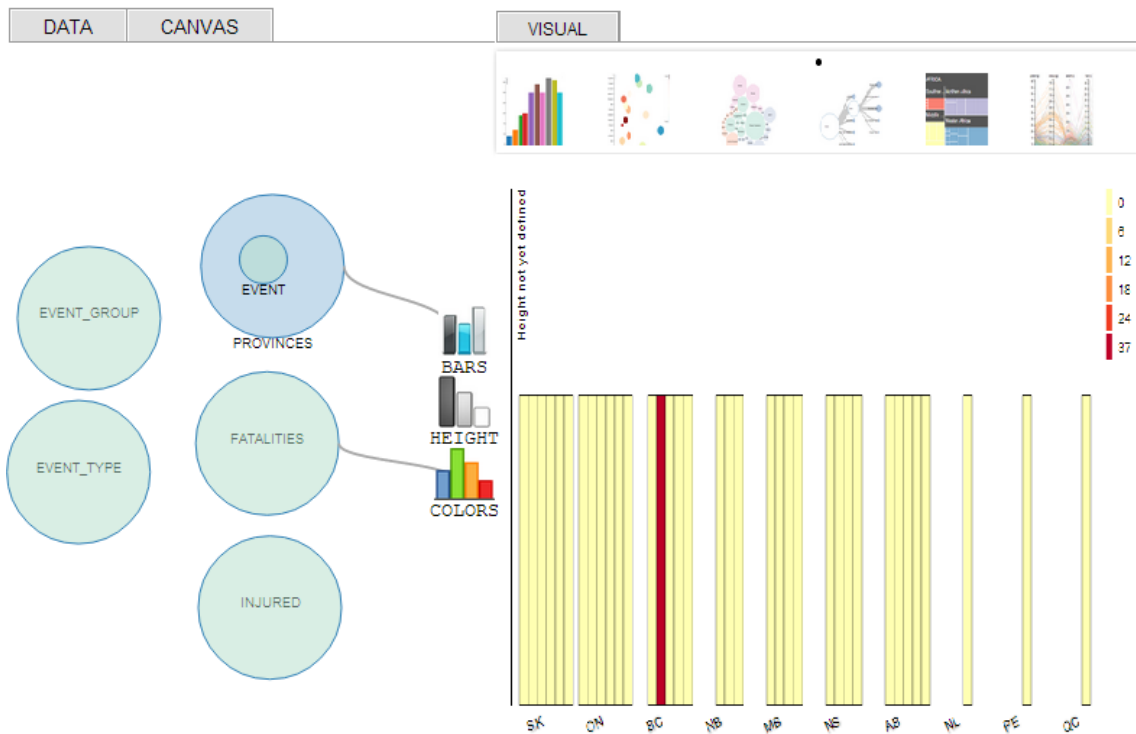


Figure 4.9: Grouped Bar Chart based on the relationship created in the Data Transformation panel.

Lets assume that the domain expert is not satisfied with this representation and wants to see events based events types and within each event type the province in which the events occurred. To support this relationship visualization designers will push *Events* inside *Provinces* and *Provinces* inside *Event type*. Then this relationship is mapped to a treemap, the tool will perform the necessary nesting to represent the data in a hierarchical layout, shown in Figure 4.10.

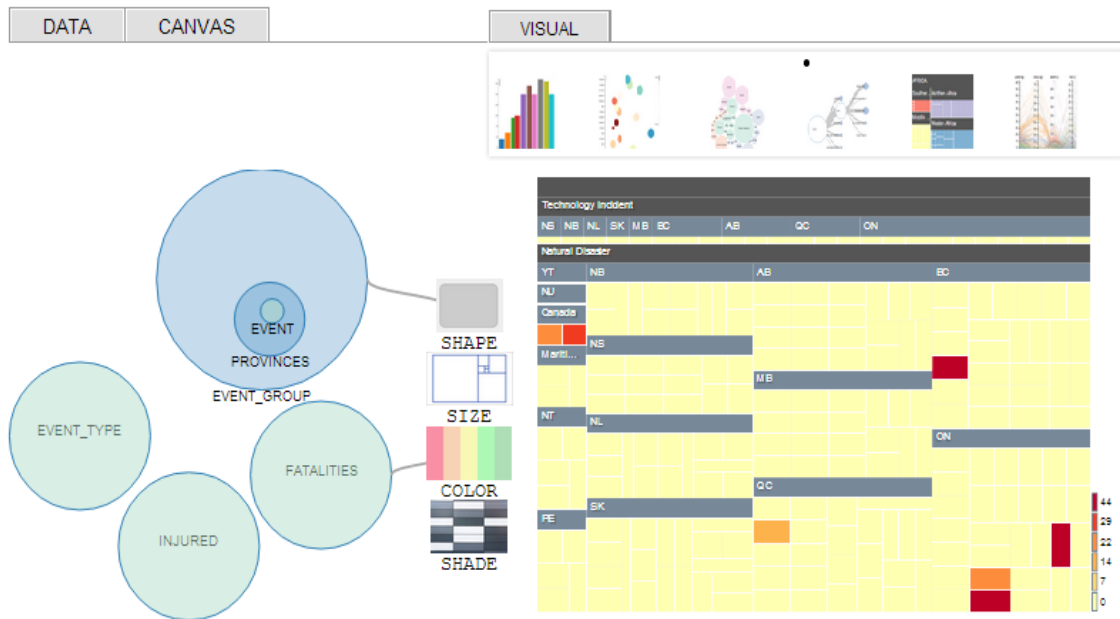


Figure 4.10: Treemap based on the relationship created in the Data Transformation panel. This operation is classified under structure to derived structure operations.

4.1.3.2 Visual Mapping Operations

Operations that map visual variables of the selected template to data variables fall under this category. These operations depend on the type of data variable. PairedVis can automatically detect quantitative data, if the variable contains numeric values. Otherwise, PairedVis considers the data to be nominal. However, when creating visualizations we need to differentiate between nominal, ordinal, and numeric values. Nominal values are qualitative values that don't have a natural order, for example student names, gender, and sport they play. Ordinal values have a natural order can be qualitative or quantitative. Example of a qualitative ordinal data is in the use of Likert scales: disagree, neutral, agree. Example of quantitative ordinal values can be 1st, 2nd, and 3rd. In certain cases quantitative data can actually be nominal data, for example, Sim Card numbers. As a result, in future versions we can provide an interactive interface to the user to change this automatic recognition of data types manually, whenever required.

Quantitative Data: The Scatter Plot and the Parallel coordinates support the use of axis. Axis in both the scatter plot and parallel coordinates can be mapped to both quantitative and nominal data. Size is used to represent quantitative data in the Bar Chart, Scatter Plot, Bubble Chart, Treemaps, and Reingold Tree layout. These Charts allow mapping of quantitative data to a linear scale. For example, PairedVis parses the data and finds the highest value in the data variable. By default PairedVis considers the lowest value as zero. We map this range to a linear scale starting from zero to the maximum size the chart can reasonably represent, so our maximum value is height of the screen divided by fifteen. For example, consider that the data variable is ages of a population and the oldest person is 90. In this case, our range will be 0-90. This range is mapped to a linear scale of 0 to height of screen/15. As a result, lets assume that when this linear scale is given the value 80, it returns the size 30, which will be the radius of the bubble on the bubble chart. However, the Treemap algorithm automatically calculates the size of the rectangles based on the numeric data variable using a space filling algorithm.

For mapping color to a quantitative variable, we map a range starting by default from zero to a maximum value in the data variable. This range is mapped to a quantile scale or ordinal sets of three or six colors, depending on the maximum value in the data variable, as shown in figure 4.11 (a). For example, let us consider again that we have ages of a population and the oldest person is 90. We can map the range 0-90 to a scale of three color sets. 1 – 30, 31-60, and 61- 90. These three sets will be mapped to three colors. The color range uses an analogous color scheme, however the tint in the first few colors is kept low and in the others high, enabling a natural ordinal feel to the colors, taken from color brewer [65].

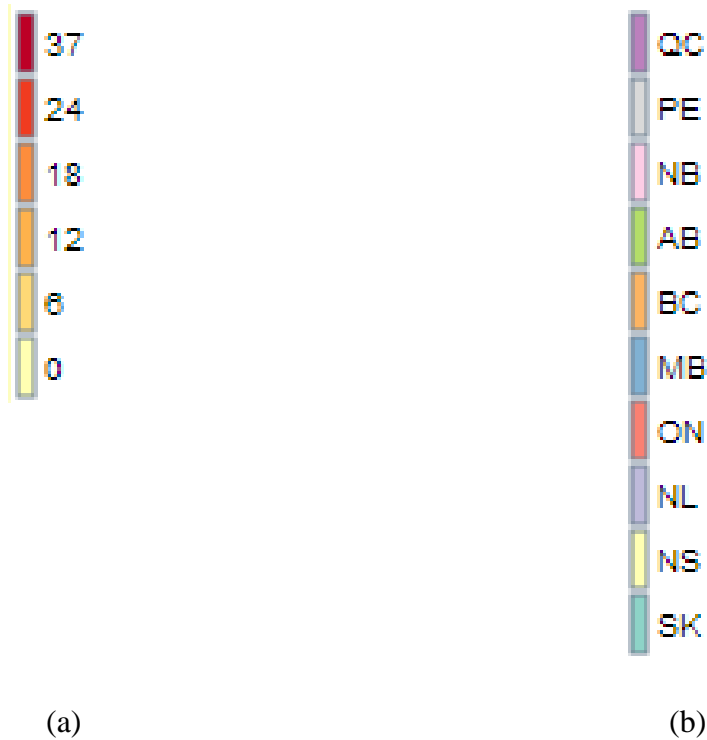


Figure 4.11: (a) Ordinal Color Sets for Quantitative Data. (b) Color Range for nominal data.

Nominal Data: Both the Axis in the Scatter plot and the Parallel Coordinates can be mapped to nominal data. However, the height of the Bars in the Bar Chart is not considered a nominal axis and cannot be mapped to nominal data, but is considered as the size of the Bar and can represent qualitative data. In the parallel coordinates, if values in the nominal data variable exceed 200, then the data is categorized based on the first letter of the data, resulting in 27 letters of the alphabet on the axis. Otherwise, the screen is over crowded with the labels of the nominal data. Color is another useful attribute for mapping nominal data. Though there are many colors to represent the data, the human eye can only perceive a few [30]. PairedVis automatically maps nominal data to fifteen complementary colors taken from Color Brewer [65] and cannot be modified manually, shown in figure 4.11(b).

4.1.3.3 View Transformation Operations

After a data variable is mapped to a visual component, the visualization transforms to accommodate the visual variable mapped to the data variable. The elements in view change in position or size based on the new values. This change is represented with the use of animation. The users can view how the mapping of the data variable changes the visual components in view. Each template facilitates interactions that support data exploration activities. For example, the treemap template facilitates zooming in and out a specific parent to only view the children that belong to it. Similarly, the parallel coordinates allows filtering the axis to view data points of interest and reordering the axis to bring two data variables of interest together.

4.1.4 Customizing Representations

We have provided quick and interactive means of creating and exploring visualizations, however we also wanted to support the visualization designer to enhance or customize existing representations. Therefore, PairedVis provides a panel, the Code Panel, which consists of the code. After mapping a template, a visualization designer can simple go to the code panel and copy paste the code in any text file for customization. This text file can be given an html extension and can be shared easily over the web as a functional prototype. As a result, we have satisfied our requirement [R1] *Support Two Experts with Different Visualization Skills*.

4.1.5 Collaborative Support

Research in collaborative environments encourage the use of large displays to support collaborative work [12] [59]. However, the shared display should also provide personal views to allow individuals to work independently [60]. Since this two expert scenario requires tightly coupled work, we propose the use of a shared display without personal views. This collaborative support will force the paired experts to work together. This idea is inspired by pair programming

practice in agile methodologies [32]. In pair programming, two programmers work together on the same machine. One programmer, the driver writes code, while the other, navigator reviews and helps the driver. The two programmers exchange roles frequently. “An effective pair will be constantly discussing alternative approaches and solutions to the problem” [67]. This natural method of exploring new venues is an important aspect in design. “Pair programming improves design quality and reduces defects, and improves team communication” [18]. As a result, we decided that providing a pair programming environment to collaborative visualization design will enable useful exchange of information. Pair programming is effective in distributing knowledge throughout the team [32]. As a result, we adapted this idea to support exchange of information between the two experts on a shared display without personal views. As a result, we have satisfied our requirement [R4] *Support Synchronous Collocated Collaboration*.

4.1.6 System Architecture

Like most visualization tools discussed in Chapter3, we wanted our visualization tool to facilitate data exploration with predefined visualization templates and interactions for exploring data. Moreover, we wanted the tool to be easily accessible on the web. Therefore, PairedVis is designed with html5 and javascript to make it platform independent. The visualizations are created using the javascript based toolkit, D3 [47]. D3 is an open source JavaScript library and there are many open source templates designed by the community that do not just provide data representations but also interactions to support data exploration. For example, we used the treemap template that facilitates zooming in on a parent to view only the children that belong to it. We however, made small modifications to the interactions provided by default with these templates to facilitate details with touch interactions.

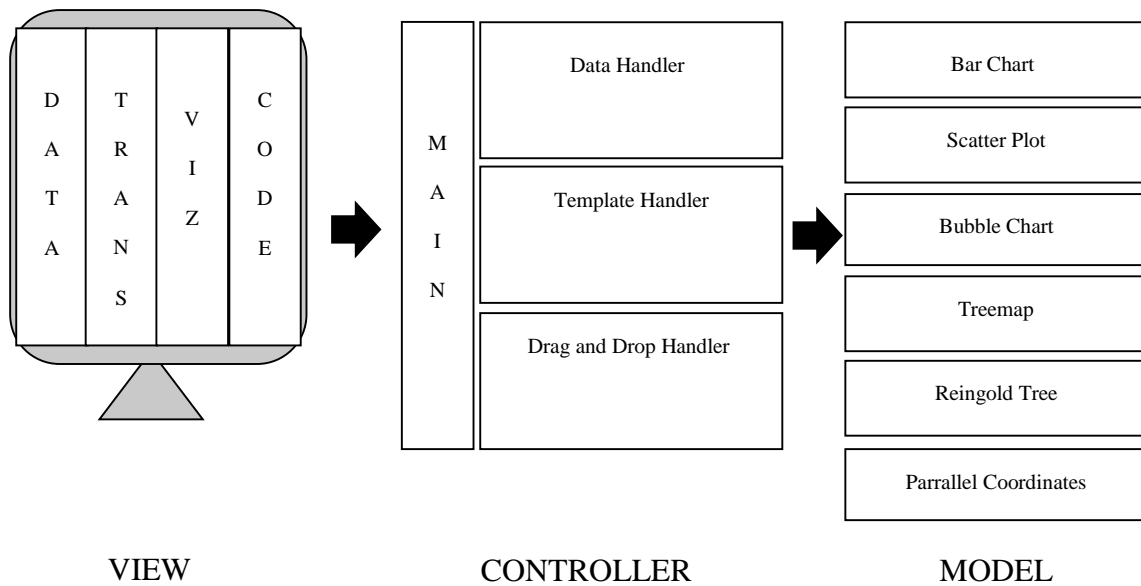


Figure 4.12: System Architecture based on MVC.

To implement the system we used ASP.net as the development environment. The system architecture was based on the Model View Controller principles [68], as shown in Figure 4.12. The view consists of a single ASP page with four panels to facilitate different stages of visualization design, illustrated earlier in Figure 4.1. The PairedVis interface also consists of a main controller that delegates works to other controllers to handle interactions separately. For example, there are separate controllers for data selection, data abstraction and selecting templates. The controllers and the templates exist in JavaScript files and are included in the main ASP page. Each template presents its visualization in the view panel of the ASP page and handles view operations delegated by the Template Controller.

4.2 Summary

In chapter3, we described how existing tools do not support the scenario of a domain expert and a visualization designer in creating and exploring visualizations together. As a result, we had elicited requirements for a tool that can support this scenario.

This chapter described how we satisfied these requirements with the design of PairedVis.

PairedVis satisfies, R1. *Support Two Experts with Different Visualization Skills*, by providing interactive means of creating visualizations and programmatic means of customizing and enhancing existing representations into a functional prototype.

PairedVis has satisfied, R2. *Provide an interface for discussing data and discussing visualizations*. PairedVis provides an interface to the domain expert to discuss the data and the relationships in the data, with an idea similar to concept mapping. Moreover, PairedVis facilitates visualization templates mapped to sample datasets, so that visualization designers can explain visualization layouts by breaking them down to individual visual components.

With quick and interactive means of switching to different representations, PairedVis has satisfied, R3. *Support Iterative Visualization Design and Exploration*:

We have satisfied R4. *Support Synchronous Collocated Collaboration* by providing these design activities on one shared screen to only facilitate tightly coupled work.

As a result, PairedVis is designed specifically to facilitate collaborative visualization design activities with paired participants, a domain expert and a visualization designer.

Chapter Five: **Evaluation of PairedVis**

This chapter describes the initial laboratory study we conducted as a first step towards evaluating PairedVis. We had designed PairedVis to support collaboration between a domain expert and a visualization designer. As a result, it would have been natural to study this collaboration in a real world setting. However, PairedVis is in the early stages of development and is currently a functional prototype. Therefore, we decided to get initial feedback in a laboratory setting.

5.1 Study Goals

We have designed PairedVis to support both the domain expert and the visualization designer in sharing their knowledge. The interface of PairedVis enables a domain expert to share his knowledge of the data and the visualization designer to share his knowledge of visualizations. Moreover, PairedVis interface was made simple to ensure that domain experts can also understand how to map data and analyze representations. As a result, we had designed PairedVis specifically to support our second research objectives defined in Chapter1.

“Can we design a tool to support both the experts in sharing their knowledge and expertise during visualization design?”

Therefore, our first study goal was to investigate whether any knowledge sharing activities occur during visualization design with PairedVis. We wanted to provide evidence that PairedVis supports teamwork as well as task work.

The key focus of our research was to facilitate collaboration between a domain expert and the visualization designer during visualization design activities to uncover important data and domain expert’s requirements [10]. Therefore, we wanted to satisfy our research objective:

“Can we provide evidence that facilitating collaboration between a domain expert and a visualization designer leads to discussion on the limitations of current designs in satisfying data and user requirements.”

We had designed PairedVis to provide quick and interactive means of creating visualizations and switching to different representations to support iterative design activities. Our second study goal is to investigate whether iterative design activities with paired experts’ leads to discussion on existing representations and their limitations.

5.2 Study Methodology

To satisfy our evaluation goals, we conducted the study in a laboratory environment. We decided to use a fresh pair of participants, a domain expert and a visualization designer in each experiment. We took a qualitative approach to investigating the impact of PairedVis in both questions; how it supports the participants in sharing their knowledge and experience and how this collaboration provides discussion on existing representations and their limitations with respect to data and user requirements. We did not make use of two controlled groups, one controlled group with paired Visualization Designers and Domain Experts and the other with one expert. The second control group, with one expert working individually will naturally result in no communication. The major goal of the study was to investigate whether PairedVis supports communication, therefore there was no requirement for a second controlled group.

5.2.1 Participants

Twelve university students were recruited for this study through mailing lists and word of mouth. Two participants worked together as a pair resulting in six experiments that took place in one week. Participants with two or more years of experience in visualization design were given the role of a visualization designer and were paired with a participant with no experience in

visualization design, who took up the role of a domain expert. We could not recruit actual domain experts and visualization designers. However, in the first 20 minutes of the study, we motivated them to take up the role of a domain expert or the visualization designer. The domain expert was provided some time to get familiar with the data, while the visualization designer was given some time to learn how to create visualizations with PairedVis.

5.2.2 Setup

The study environment consisted of two labs in close proximity, Lab A and Lab B. Lab A was setup with a touch-enabled tabletop connected to a keyboard and a mouse. PairedVis was running in the browser on the tabletop before the experiment. A camera was positioned on top of the table top to capture participants' activities on the tabletop and record the conversation between the participants. Lab B was setup with data and tasks on paper, as well as on an electronic tablet, to facilitate data and tasks on both mediums.

5.2.3 Procedure

The study required two researchers, one to assist each participant in the two Labs, A and B. The visualization designer was invited to Lab A, whereas the domain expert was invited to Lab B. The study consisted of three parts. Part 1, took 20 minutes of the study and during this time the participants were given the information necessary to take up their respective roles. Part 2, took 30 minutes during which the domain expert and the visualization designer created visualizations together using PairedVis. During Part 3, the participants shared their experiences in a follow-up interview separately. In the following sections, we describe in detail the activities carried out during each part of the study.

Study Part 1: Training (20 minutes)

The participants were informed about the voluntary nature of the experiment and were asked to sign their consent on a form.

Domain Expert: As the study did not use a real domain expert, the training was used to familiarize the study subject with the domain. The researcher working with the domain expert explained that the purpose of the study was to visualize data in collaboration with a visualization designer. The participant was told that he will be playing the role of the domain/data expert in this study. The participant was provided with a dataset on paper as well as on a tablet, to choose whichever medium they were comfortable with. The dataset was about Disastrous events that occurred in Canada from 2010 [68]. The dataset is explained in more detail in the TASKS section. The research explained each field in the dataset. Then the domain expert was asked to look at the task sheet and list down the data columns that were necessary to investigate each task. The domain expert was told that during the study he could ask any question related to the data and task for clarity.

Visualization Designer: In this training session, the visualization designer was provided with a demo of PairedVis. The researcher guided the visualization designer to the tabletop with PairedVis already open in the browser. The researcher explained that the purpose of the study was to visualize data in collaboration with a domain expert. The participant was also told, that he will be playing the role of the visualization designer. A common and simple dataset was chosen for demonstrating the tool to the visualization designer. The sample dataset was about Canada and Great Britain medals won in Olympics in 2000 [69]. The functionality provided by each panel in PairedVis was demonstrated in the first twenty minutes of the study. The visualization designer was told that he could ask any question regarding PairedVis during this training session.

Study Part 2: Visualization Design and Discussion (30 minutes)

After the first twenty minutes of the study were over, the domain expert was guided to Lab A, where the visualization designer was sitting in front of the tabletop. The data was uploaded and the domain expert was asked to explain the data and the requirements to the visualization designer and the visualization designer was requested to help analyze this data with visualizations. The researchers seated themselves back in the laboratory, so that they do not affect the collaboration and only observed the conversation and took notes.

Study Part 3: Follow-up Interviews

For the follow up interviews the domain experts were taken back to Lab B, while the visualization designer's interview took place in Lab A. The follow-up interviews were used to gain more insight into the experience of the participants in the study.

5.2.4 Tasks

We used a simple dataset that provides details about the disastrous events that occurred in Canada [68]. The events were described in ten columns, consisting of the Event_Group, Event_Type, Provinces, Fatalities, Injured, Evacuated, Days, Cost, Year, and Month. 0 provides a sample of the data. The domain experts were provided with a task sheet on paper, consisting of six tasks, as shown in Table 5.1.

	Data Analysis Tasks	Expected Results
T1	List two most significant disastrous events that occurred in Canada with respect to fatalities?	Participants were expected to use the bar chart and the bubble chart to find the results.
T2	What type of events have effects for larger no of days.	Participants were expected to aggregate events based on event type by pushing bubbles inside bubbles and using a grouped bar chart or a treemap or a reingold tree layout.
T3	What type of events cause more fatalities and injuries?	Participants were expected to aggregate events based on event type and use a treemap or a reingold tree layout.
T4	List two type of events that are most disastrous?	Exploratory question. Domain experts were asked to list the data columns that they thought were most disastrous. As a result, we were expecting that the participants will choose the parallel coordinates for this visualization.
T5	Which provinces are most effected by the major types of events identified in Q4?	Participants were expected to answer this with the previous visualization or a new one.
T6	Is there any event types reoccurring in the same season?	Participants were expected to use the parallel coordinates for seeing data based on years and months.

Table 5.1: Tasks and the expected results of these tasks.

In Table 5.1, the Data Analysis Task column, lists each task and the Expected Results column enlists, what we had expected that the participants will select to accomplish each task. The expected visualizations are also provided in Appendix D: The tasks were designed with different levels of complexity. Bertin [21] has provided us with three types of insights that we can gain from a representation: Read Fact, Read Comparison, and Read Pattern. Task 1, 2, and 5 are simple tasks that require the participants to find data points, therefore fall under the read fact category. Tasks 3 and 4 are tasks that require participants to compare variables, as a result they fall under the Read Comparison category. In task 3, we had provided the variables that needed to be analyzed. However, Task4 was an exploratory task and we wanted the data variables for this task to be based on the understanding of the domain expert. As a result, the visualization selection would have depended on the domain expert's choice of the number of variables he considered as disastrous. There are in total ten data variables in this dataset, so the selection

could not exceed ten. The last Task 6 was designed towards making the participants look for recurring pattern of an event based on the date and time.

5.2.5 Data Collection

We had observed and videotaped the participants during the second part of the study, while they were creating visualizations in collaboration. We did not consider how much time was taken to complete the tasks or how many tasks were completed in each study. We had told the participants before the visualization design and discussion session that we were not concerned with how many tasks are completed. We are trying to learn about the process. After the study, we took interviews to gain more insight into the experience of the participants. We had determined a few questions to guide us through these open ended interviews.

5.2.6 Data Analysis Methods

We took a qualitative approach to analyzing the data. The basis of our analysis were the video recordings that were taken during Part 2 of the study. These helped us in determining how the participants visualized the data and discussed the limitations of the representations. We transcribed the video based on the major activities carried out during visualization design. These activities were repeated in a cycle for each task and can be described based on the Data State Reference Model [2]; data abstraction, visual representation selection, visual mappings, and visual analysis. This is a similar approach to [15]. As a result, a visualization design cycle starts when a task is read and ends what the task result is written in the task sheet. During the second parse of the video recordings we closely observed discussions while these tasks were performed and found other important activities, such as task and data clarifications, representation explanations, and critique. We used the trial version of Inqscribe [70], to synchronize our manual

transcriptions with the video recording. After analyzing the video recordings, we transcribed the interviews to gain more insight into the experiences of the participants.

5.3 Qualitative Results

We had intended to conduct ten experiments. However, with the first six experiments we found that system errors and touch interaction issues were hampering the smooth execution of the study. These errors had not surfaced before because the system had only passed functionality tests. As a result, we stopped further studies and decided to analyze the data collected from the six experiments before taking further steps.

Two studies were excluded from our analysis. While transcribing the video data in Experiment 2, we noticed that the visualization designer had very little experience with visualizing data and had more experience with writing algorithms for analyzing social networks. As a result, visualizations created during this experiment were based on incorrect mappings. Therefore, Experiment 2 was excluded from the analysis. Experiment 4 was also excluded, because the domain expert had experience using PairedVis and he took over the design process and the actual visualization designer's role was compromised.

In the first parse of the video recordings we analyzed the data based on the activities performed while trying to accomplish each task. In the second parse, we analyzed the discussion that took place while the participants performed data analysis. The analysis of the discussion provided us with evidence that visualization designers and domain experts discuss limitations in current representations in satisfying data and task requirements. Secondly, we were able to uncover important usability issues faced by the participants in the study. In this section, we first provide how the visualization design activities were carried out by the participants and then provide the usability issues faced by the participants.

5.3.1 Visualization Design Activities

This study is different from other studies [12] [8] [42], because we have looked at how a domain expert and a visualization designer create and analyze visualizations together using PairedVis.

This section provides you detailed information on how PairedVis supports discussion on the data, on choosing templates, and discussing representations during design activities.

5.3.1.1 Data Abstraction

In all the studies the domain experts would start with dictating the task and the data. In certain cases, the visualization designer would ask clarification questions to understand the task or ensure that the selected data was correct. For example, in experiment1, the visualization designer asked, “Do we need to select the country as well?” and the domain expert replied, “The dataset is only from Canada”.

The visualization designer selected the appropriate data variables for the tasks and moved towards visualizing the data. The participants would come back to the data panel to get data for the next task. In two cases, they came back to select a variable they had missed. In one case, the visualization designer suggested selecting all the data variables for the tasks, so that they do not have to come back to the data panel.

5.3.1.2 Visual Representation Selection

After selecting the data, visualization designers moved to the View Transformation panel and looked at the thumbnail bar for representations. A visualization designer commented in the interview, “It is really nice to see a bunch of different prototypes.” Similarly, a domain expert commented, “I like the sample data that was in there. It sort of helped to understand some stuff.”

In all four experiments, the visualization designers started with selecting the Bar Chart for the first task. One activity not mentioned in existing framework for visual information analysis [12]

is explanations on representations, because these studies only studied domain experts and did not include visualization designers. However, in this study, if the visualization designer had selected a representation for the first time, they would explain it to the domain expert. In experiment 3 and experiment 4, the visualization designers made use of the animations to break down the representation into its' individual components. In some cases, the visualization designer would explain why they selected the particular representation. For example, in experiment 1 the visualization designer explained “as the dimensions go more than two it is better to use these new charts” and starts pointing to the scatterplot and moved the finger towards the parallel coordinates.

5.3.1.3 Visual Mappings

After selecting a representation, the visualization designers mapped the data to the available visual variables and in most cases explained what was being mapped. The domain experts linked the links between the visual variables and the data variables. One of them commented in the interview, “The easy thing to understand was, oh you make a connection from color to a certain column. That is very explicit.” Another domain expert liked how the visualization changed when each visual variable was mapped. ‘I also like the feature that your visualization changed dynamically, you see the visual variable you mapped to, so if I made a mistake, I just cancel it, put another.’”

The visualization designers encountered many problems in understanding what kind of data transformations can they achieve with the interactions explained during the training session. The major problem was creating hierarchies or grouping. Only in experiment 3, was the visualization designer able to create the appropriate grouping and hierarchy and used the bar chart and the treemap respectively, to represent these transformations. Even in this case, the domain expert

could not trust his visual analysis, because he did not believe that using of size of rectangles in the treemap was a good visual variable for analyzing quantitative data. As mentioned in [10], representations not only need to satisfy the data but also the user.

5.3.1.4 Visual Analysis

In most cases the visualization designers did not explain how to perform interactions with the mapped representation. Only in case of the parallel coordinates, all visualization designers explained how to understand and analyze the visualization, after the data was mapped. It could be due to the fact that most representations selected were very simple or sometimes they were explained before the data was mapped. In experiment 3, after the visualization designer had mapped the data to the treemap and was analyzing the data, the domain expert asked what each rectangle meant, and the visualization designer explained.

5.3.1.5 Iterative Design and Discussion

PairedVis had facilitated the two experts with quick and simple interactions in order to map data to different representations. A domain expert had noticed this and said, “.. you can instantly try out different charts, usually for excel if you pick one chart, trying to change it to other things for same data takes time but this one switching between charts, its design to actually for people to use different charts.”

An important activity during data analysis is Critique, discussion on limitations of current representations. When analyzing the data, the domain experts would view the visualizations and explained how else they wanted to see the data. For example, in experiment 4 while performing task 3, the domain expert said that I would like to group fatalities and injuries together. As a result of such discussions, the visualization designer would look over the thumbnail bar for representations and think before choosing a more useful one. Then the data was mapped again

and the analysis was performed with the new representation. These steps would iterate until both of them were satisfied with the visual representation and the results of the analysis. As a result, in our experiments we noticed iterative design activities to satisfy a task.

5.3.1.6 Data Transformation Interactions

We had represented data as visual bubbles and data transformations can be performed by pushing bubbles inside bubbles. A domain expert really liked the idea of the data being represented as visual objects, “basically everything is visualized from the beginning, you see the columns, you drag them out.”

We had facilitated grouping of data with an interaction that is pushing bubbles inside bubbles. For example, pushing events inside event types, results in the grouping of events based on event types. However, all the visualization designers during task 2, expected the tool to aggregate data based on event types. PairedVis facilitates the grouping to be mapped to a Grouped Bar Chart, Treemap, and the Reingold Tree layout. However, in these representations the data is not aggregated, it is only grouped together. We wanted the participants to use visual grouping to analyze the data as a whole. In experiment 3, the visualization designer created the grouping accurately and mapped them to appropriate representations. However, later in the interview the visualization designer said that, “it looks like you are aggregating but you are not, confuses it even more.”

The reason that the other three visualization designers could not create appropriate mappings could be due to lack of experience with the tool. A visualization designer said, “the way to do it was not quite explicit”. It is important to note that this visualization expert has had experience in designing with visualization tools, such as Tableau.

It was very obvious from the experiments that the users mental model of pushing bubbles inside bubbles complied with aggregation but not grouping and hierarchy. In two studies, the participants pushed fatalities and injuries inside another bubble and mapped it to size. Hoping that the size of the mark will split, to represent the respective proportions of fatalities and injuries. Though we had investigated such interactions, we have not yet implemented them in the tool. Lack of aggregation with Bar Chart in task 2 and 3, led to the selection of different representations. As a result, the participants used 3 to 4 representations before coming to a decision.

5.3.2 Discussion

In general, we agree with [19], that using paired participants results in a natural continuous conversation between the participants and is a useful data collection technique. Visualization templates in PairedVis are mapped to sample datasets. All four visualization designers made use of these to explain visualization templates to the domain experts, and in two cases also used the animations that show one visual variable at a time. The domain experts understood how visualizations were mapped and in certain cases also suggested a mapping between a visual variable and data variable. As a result, we were able to support our first study goal:

“Does the design of PairedVis support both, the domain expert and the visualization designer in sharing their areas of expertise?”

We had designed PairedVis to facilitate quick and interactive means of performing iterative design activities. With the presence of both the experts in creating and analyzing visualizations, we found that they discussed limitations of a representation in satisfying a task requirement. The domain experts were very enthusiastic in viewing the data according to their requirements and discussed how certain representations did not satisfy their conceptual model. While conducting

the above activities, the visualization designers took a very supportive role and continuously tried to satisfy the domain expert's requirements. Especially for Task3, visualization designers switched to at least 3 different representations. As a result, this study also supports that visualization design activities between a domain expert and a visualization designer results in a discussion of whether a representation satisfies the data and user requirements.

In an interview, when a visualization designer was asked, whether the presence of the domain expert was helpful? She replied: "Yes definitely, just being able to talk him through the problem and seeing certain types of things that he would like to be able to do further with the system is very helpful." As a result, we are able to support our second research objective:

"Can we provide evidence that facilitating collaboration between a domain expert and a visualization designer leads to discussion on the limitations of current designs in satisfying data and user requirements."

5.4 Usability Issues

Analysis of the discussion also showed us that the participants faced usability issues in creating visualizations with PairedVis. As a result, we also analyzed these discussions to understand usability issues with the tool.

Difficulty in Viewing Details: The first usability issue was difficulty to view details when bars in the Bar Chart are too thin. For the first task, all visualization designers selected the Bar Chart. When the visualization designers tapped on the bars to view the details, they would not show because the bars were too thin. As a result, two visualization designers selected the Scatter plot, and the third chose the Bubble chart. They were able to get the details with the use of these charts.

Marks: Another usability issue was that the tool could not map the visual variables until the marks of the visualization was mapped. In studies 3 and 4, the visualization designers tried to map the visual variables before choosing the marks. For example, in one case the x and y positions in the scatter plot were being mapped before the bubbles. We need to change PairedVis to allow mapping of visual variables before the marks are selected. This is not possible in a treemap or the Reingold tree but possible with the representations that facilitate axis.

Bugs in the tool: The most significant problems faced by the participants were system errors in PairedVis and touch problems with the tabletop. During the study, participants' activities were hampered by these errors. For example, in two studies the tool would not allow the creation of a new bubble to support the parallel coordinates. These bugs affected the thought process of the visualization designers and have affected the study results.

5.5 Study limitations

In this section, we provide various limitations in the design of study. Some of these limitations could have led to the problems faced by the participants of the study.

Limited Number of Experiments: Our study analysis is based on four experiments consisting of 8 participants. These are limited number of results to support our research objectives. Therefore, this study can only be considered as a pilot study.

Lack of Field Expertise: Currently, PairedVis is a functional prototype, as result we evaluated it in a laboratory setting. Moreover, the participants of the study were not visualization designers and domain experts from the industry. For further experiments we need participants that truly represent domain experts.

Lack of Training on PairedVis: Though the Visualization Designers were given twenty minutes of training on the PairedVis, they were not given the time to familiarize themselves with the tool

and explore its capabilities before being able to explain it to others. As a result, they will perform tasks differently than explained. For example, the mixed the use of bubbles inside bubbles for aggregation rather than grouping. Two visualization designers mentioned in the interview that they needed more time to explore the tool before visualizing the data.

Tabletop Issues: There were many problems faced by the users with the interactions on the tabletop. In two studies, the domain experts placed the task sheets on the tabletop that interfered with the visualization designer's selection of the data in task 1. After realizing their mistake they removed it. In certain cases, use of the mouse and touch simultaneously resulted in a system error, with PairedVis. Another problem was when a visualization designer has to reach to the other end in the data panel, her arm covered the tabletop and the tabletop stopped responding to touches. As result, to conduct this study again, the use of a vertical display will be more appropriate.

5.6 Conclusion

Overall the participants liked the interface of PairedVis and two visualization designers described the experience as enjoyable, despite the problems they faced. The domain experts easily understood how to create representations. One domain experts said, "it was pretty straightforward". The Analysis of our study support that PairedVis enables both the experts, a domain expert and a visualization designer in sharing their knowledge. The results of study also support that when domain experts and visualization designers create visualizations, they gain more insight into the data and this problem solving activity can lead to choosing more useful representations.

Chapter Six: **Conclusion and Future Work**

The main aim of our research was to better support collaboration between a visualization designer and a domain expert during visualization design activities. Our overview on current literature in information visualization processes and tools led us to think that domain specific visualization designs are either created on paper or programmatically by visualization designers. In this case, domain experts are limited to reviewing and providing feedback on these designs. However, when the domain is simple, commercial business intelligence tools help domain experts in creating visualizations on their own. When the domain is complex, we proposed that they can create visualization designs in collaboration with visualization experts. Pretorius and Van Wijk [10] have suggested an exploratory approach to creating prototypes in close collaboration with domain experts. However, we propose the use of adjustable templates in order to explore and discuss representations.

In Chapter1, we have provided our research questions, challenges, and objectives which formed the basis of our research. The following section describes, how we addressed them during our research.

6.1 Contributions

The first contribution of this thesis is an overview of the current research space in information visualization processes and tools, described in Chapter3. With this overview we have achieved our first research objective:

- 1. We need to explore existing tools, literature, and processes that support visualization design and collaboration.*

In Chapter3, we elicited requirements for a tool that can facilitate both the domain expert and the visualization designer in creating and discussing visualizations. We also accessed existing tools

to see if they satisfy these requirements and found that none of the tools satisfy all our requirements. As a result, we decided to create our own tool. In order to design an information visualization tool, we also investigated existing literature on information visualization design. Therefore, another contribution to this thesis is in Chapter2, which provides important design guidelines for information visualization tool designers. Therefore, in light of existing literature we tried to address our second research question:

2. *Can we support collaborative design activities with a tool that can help domain experts and visualization designers discuss existing representations and see how they fit the needs of the data and the needs of the domain experts?*

The third and most important contribution of this thesis is an information visualization tool, PairedVis. PairedVis, is specifically designed to facilitate both a domain expert and a visualization designer, in creating and discussing visualizations. PairedVis is described in Chapter4 of this thesis. PairedVis satisfies our collaborative research challenges:

1. ***Two Expert Challenge:*** *We need a tool that can facilitate communication between two experts with differences in knowledge and skill.*

PairedVis provides an interface to the domain expert to explain the data and the requirements using simple interactions on visual elements. Templates in PairedVis are mapped to sample datasets, which enables visualization designers to explain representations. We also addressed our second research challenge with the design of PairedVis to support iterative design activities:

2. ***Iterative Design Challenge:*** *We need to provide an interface that facilitates quick and interactive means of mapping data to different templates, to help support communication during visualization design.*

PairedVis provides an interface that is simple and supports repetitive design activities with interactions so that the experts can communicate while designing. We conducted a study to satisfy our second research objectives:

2. Can we design a tool to support both the experts in sharing their knowledge and expertise during visualization design?

Analysis of our pilot study implies that PairedVis supports collaborative design activities and was used in sharing visualization knowledge.

The reason to develop PairedVis was to study collaborative design activities and provide evidence that when a domain expert and a visualization designer create visualizations, they uncover important data and user requirements. This is based on our third research objective:

3. Can we provide evidence that facilitating collaboration between a domain expert and a visualization designer leads to discussion on the limitations of current designs in satisfying data and user requirements.

The analysis of the pilot study, also supports that when a domain expert and a visualization designer create and analyze visualizations, it results in a discussion on the representations.

After studying existing literature, designing a tool, and conducting a study we can answer our research questions:

1. Can we better support collaboration between the domain expert and the visualization designer during visualization design activities?

We can support this research question in light of existing literature [10] [7] and our study, that we can improve the collaboration between a domain expert and a visualization designer with tools to support visualization design activities.

2. *Can we support collaborative design activities with templates so that the two experts can discuss existing representations and see how they fit the needs of the data and the needs of the domain experts?*

We can support this research question with our pilot study results that with the use of existing templates domain experts and visualization designer were able to quickly see important facts about the data. Also, the discussion and criticism on existing representations provided important requirements for a more useful design.

6.2 Future Work and Conclusion

Our short term future work involves fixing usability issues with PairedVis and rerun a study to evaluate PairedVis in a laboratory setting with more participants. Our long term goals are to enhance the functionality of PairedVis, by adding more templates, improving performance with larger amounts of data, and allowing more data transformation operations with interactions. However, we also recommend a study to investigate how mapping data to existing templates help visualization designers during prototyping.

To improve the interaction design in PairedVis, we can conduct a study to investigate more useful interactions on visual elements. There is current research that is looking into facilitating data exploration with sketch based interactions [72], similar research can guide us into finding more natural interactions for data transformations. With recent technological advancements, we can provide new ways of interacting with a device [73], for example, with the use of gestures, position of the person, tangible objects, and sound. It would be interesting to combine these interactions with tools to support paired experts.

APPENDIX A: REFERENCES

- [1] R. Spence, Information Visualization, A.Press, 2000.
- [2] Card, Stuart K., Jock D. Mackinlay, And Ben Shneiderman, "Readings In Information : Using Vision To Think," Vols. Morgan-Kaufmann: San, 1999.
- [3] Zambrano, Raul Niño, And Yuri Engelhardt., "Diagrams For The Masses: Raising Public Awareness–From Neurath To Gapminder And Google Earth.," Vol. Diagrammatic Representation And Inference. Springer Berlin Heidelberg, Pp. 282-292, 2008.
- [4] Sedlmair, Michael, Miriah Meyer, And Tamara Munzner., "Design Study Methodology: Reflections From The Trenches And The Stacks.," Vols. Visualization And Computer Graphics, Ieee Transactions On 18, No. 12, Pp. 2431-2440, 2012.
- [5] A. Dix, "Evaluation Techniques," Vols. Human-Computer Interaction. Europe, Prentice-Hall, Pp. 405-442, 1998.
- [6] Van Wijk, Jarke J., "Bridging The Gaps.," Vols. Computer Graphics And Applications, Ieee 26, No. 6., Pp. 6-9, 2006.
- [7] Lloyd, David, And Jason Dykes, "Human-Centered Approaches In Geovisualization Design: Investigating Multiple Methods Through A Long-Term Case Study," Vols. Visualization And Computer Graphics, Ieee Transactions On 17, No. 12, Pp. 2498-2507, 2011.
- [8] Grammel, Lars, Melanie Tory, And M. Storey., "How Information Visualization Novices Construct Visualizations.," Vols. Visualization And Computer Graphics, Ieee Transactions On 16.6, Pp. 943-952, 2010.

- [9] Kolodner, Janet L., David Crismond, Jackie Gray, Jennifer Holbrook, And Sadhana Puntambekar, "Learning By Design From Theory To Practice," Vol. In Proceedings Of The International Conference Of The Learning Sciences, 1998.
- [10] Pretorius, A. Johannes, And Jarke J. Van Wijk., "What Does The User Want To See? What Do The Data Want To Be?," Vols. Information Visualization 8, No. 3, Pp. 153-166, 2009.
- [11] Greif, I., And P. Cashman., Cscw: A Book Of Readings, 1988.
- [12] Isenberg, Petra, Danyel Fisher, Meredith Ringel Morris, Kori Inkpen, And Mary Czerwinski., "An Exploratory Study Of Co-Located Collaborative Visual Analytics Around A Tabletop Display.," Vols. In Visual Analytics Science And Technology (Vast), Ieee Symposium, Pp. 179-186, 2010.
- [13] Forlines, Clifton, And Chia Shen, "Dtlens: Multi-User Tabletop Spatial Data Exploration," Vol. Proceedings Of The 18th Annual Acm Symposium On User Interface Software And Technology. Acm., Pp. 119-122, 2005.
- [14] Mark, Gloria, Alfred Kobsa, And Victor Gonzalez., "Do Four Eyes See Better Than Two? Collaborative Versus Individual Discovery In Data Visualization Systems," Vol. Information Visualisation. Proceedings. Sixth International Conference On. Ieee., Pp. 249-255, 2002.
- [15] Isenberg, Petra, Niklas Elmqvist, Jean Scholtz, Daniel Cernea, Kwan-Liu Ma, And Hans Hagen., "Collaborative Visualization: Definition, Challenges, And Research Agenda," Vols. Information Visualization 10, No. 4., Pp. 310-326, 2011.

- [16] Heer, Jeffrey, Frank Van Ham, Sheelagh Carpendale, Chris Weaver, And Petra Isenberg., "Creation And Collaboration: Engaging New Audiences For Information Visualization.," Vol. In Information Visualization. Springer Berlin Heidelberg., Pp. 92-133, 2008.
- [17] S. Stusak, "Collaboration In Information Visualization," Vol. Trends In Information Visualization., P. 46, 2009.
- [18] Cockburn, Alistair, And Laurie Williams., "The Costs And Benefits Of Pair Programming.," Vol. Extreme Programming Examined, Pp. 223-247, 2000.
- [19] Arias-Hernandez, Richard, Linda T. Kaastra, Tera Marie Green, And Brian Fisher, "Pair Analytics: Capturing Reasoning Processes In Collaborative Visual Analytics.," Vols. System Sciences (Hicss), 44th Hawaii International Conference, Ieee, Pp. 1-10, 2011.
- [20] Mark, Gloria, Keri Carpenter, And Alfred Kobsa, "A Model Of Synchronous Collaborative Information Visualization.," Vols. Information Visualization, Proceedings. Seventh International Conference On. Ieee., Pp. 373-381, 2003.
- [21] J. Bertin, *Semiology Of Graphics: Diagrams, Networks, Maps*, Vols. University Of Wisconsin Press, Madison, Wi., 1983.
- [22] J. Bertin, "Graphics And Graphic Information Processing," Vols. Degruyter Press, Berlin, 1981.
- [23] M. S. T. Carpendale, "Considering Visual Variables As A Basis For Information Visualisation," Vols. Computer Science Tr# 2001-693, P. 16, 2003.
- [24] Bartram, Lyn, Colin Ware, And Tom Calvert., "Moticons: Detection, Distraction And Task.," No. International Journal Of Human-Computer Studies 58, No. 5 (2003): 515-545..

- [25] Cleveland, William S., And Robert McGill, "Graphical Perception: Theory, Experimentation, And Application To The Development Of Graphical Methods.," Vol. Journal Of The American Statistical Association 79.387, Pp. 531-554, 1984.
- [26] Cleveland, William S., And Robert McGill. , Graphical Perception: The Visual Decoding Of Quantitative Information On Graphical Displays Of Data., Journal Of The Royal Statistical Society. Series A (General) (1987): 192-229..
- [27] J. Mackinlay, Automating The Design Of Graphical Presentations Of Relational Information., Acm Transactions On Graphics (Tog) 5, No. 2 (1986): 110-141..
- [28] E. H. Chi, "A Taxonomy Of Visualization Techniques Using The Data State Reference Model," Vols. Information Visualization, 2000. Infovis 2000. Ieee Symposium On. Ieee., Pp. 69-75, 2000.
- [29] L. Tweedie, "Characterizing Interactive Externalizations," Vol. Proceedings Of The Acm Sigchi Conference On Human Factors In Computing Systems. Acm., Pp. 375-382, 1997.
- [30] Carpendale, M. Sheelagh T., And Catherine Montagnese., "A Framework For Unifying Presentation Space," Vol. Proceedings Of The 14th Annual Acm Symposium On User Interface Software And Technology. Acm., Pp. 61-70, 2001.
- [31] Mackinlay, Jock D., George G. Robertson, And Stuart K. Card., The Perspective Wall: Detail And Context Smoothly Integrated., In Proceedings Of The Sigchi Conference On Human Factors In Computing Systems, Pp. 173-176. Acm, 1991..
- [32] Heer, Jeffrey, Michael Bostock, And Vadim Ogievetsky., "A Tour Through The Visualization Zoo," Vols. Commun. Acm 53, No. 6, Pp. 59-67, 2010.

- [33] Tufte, Edward R., And P. R. Graves-Morris., *The Visual Display Of Quantitative Information*, Vols. Vol. 2. Cheshire, Ct: Graphics Press., Vol. 2. Cheshire, Ct: Graphics Press., 1983.
- [34] B. Shneiderman, "The Eyes Have It: A Task By Data Type Taxonomy For Information Visualizations," Vols. Proc. Of Ieee Symposium On Visual Languages, Los Alamos, Sept., Pp. 336-343, 1996.
- [35] C. Weaver, "Building Highly-Coordinated Visualizations In Improvise," Vols. Information Visualization, Infovis. Ieee Symposium On. Ieee., Pp. 159-166, 2004.
- [36] Chuah, Mei C., And Steven F. Roth., "On The Semantics Of Interactive Visualizations," Vols. Information Visualization'96, Proceedings Ieee Symposium On. Ieee., Pp. 29-36, 1996.
- [37] Chi, Ed Huai-Hsin, And John T. Riedl., "An Operator Interaction Framework For Visualization Systems," Vols. Information Visualization, 1998. Proceedings. Ieee Symposium On. Ieee., Pp. 63-70, 1998.
- [38] Tobiasz, Matthew, Petra Isenberg, And Sheelagh Carpendale., "Lark: Coordinating Co-located Collaboration With Information Visualization.," Vols. Visualization And Computer Graphics, Ieee Transactions On 15, No. 6., Pp. 1065-1072, 2009.
- [39] Mackinlay, Jock, Pat Hanrahan, And Chris Stolte, "Show Me: Automatic Presentation For Visual Analysis," Vols. Visualization And Computer Graphics, Ieee Transactions On 13, No. 6., Pp. 1137-1144, 2007.

- [40] " Spotfire," [Online]. Available: [Http://Www. Http://Spotfire.Tibco.Com](http://www.spotfire.tibco.com). [Accessed 20 11 2013].
- [41] Pantazos, Kostas, Mohammad A. Kuhail, Soren Lauesen, And Shangjin Xu, "Uvis Studio: An Integrated Development Environment For Visualization.," Vol. In *Is&T/Spie Electronic Imaging*. International Society For Optics And Photonics., Pp. 865401-865401, 2013.
- [42] Chul Kwon, Bum, Brian Fisher, And Ji Soo Yi., "Visual Analytic Roadblocks For Novice Investigators," Vol. *Visual Analytics Science And Technology (Vast)*. Ieee Conference On. Ieee., Pp. 3-11, 2011.
- [43] Pantazos, Kostas, And Søren Lauesen., "Constructing Visualizations With Infovis Tools- An Evaluation From A User Perspective.," Vol. *Grapp/Ivapp*, Pp. 731-736, 2012.
- [44] "Opengl," [Online]. Available: [Http://Www.Opengl.Org/](http://www.opengl.org/). [Accessed 17 03 2014].
- [45] "Processing," [Online]. Available: [Http://Processing.Org](http://processing.org/). [Accessed 17 03 2014].
- [46] Heer, Jeffrey, Stuart K. Card, And James A. Landay., "Prefuse: A Toolkit For Interactive Information Visualization.," Vol. In *Proceedings Of The Sigchi Conference On Human Factors In Computing Systems*. Acm., Pp. 421-430, 2005.
- [47] Bostock, Michael, Vadim Ogievetsky, And Jeffrey Heer, "D³ Data-Driven Documents.," Vols. *Visualization And Computer Graphics*, Ieee Transactions On 17, No. 12., Pp. 2301-2309, 2011.
- [48] "Jigsaw," [Online]. Available: [Http://Www.Salesforce.Com/Jigsaw.](http://www.salesforce.com/jigsaw/) [Accessed 17 03 2014].

- [49] A. Kobsa, "An Empirical Comparison Of Three Commercial Information Visualization Systems," Vol. Proceedings Of The Ieee Symposium On Information Visualization., P. 123, 2001.
- [50] Steele, Julie, And Noah Iliinsky., Designing Data Visualizations: Representing Informational Relationships., O'reilly Media, Inc., 2011.
- [51] Larkin, Jill H., And Herbert A. Simon., Why A Diagram Is (Sometimes) Worth Ten Thousand Words, Cognitive Science 11, No. 1 (1987): 65-100..
- [52] J. Fekete, "The Infovis Toolkit," Vol. Information Visualization. Infovis. Ieee Symposium On. Ieee., Pp. 167-174. Ieee, 2004., 2004.
- [53] Bostock, Michael, And Jeffrey Heer., "Protovis: A Graphical Toolkit For Visualization," Vols. Visualization And Computer Graphics, Ieee Transactions On 15, No. 6., Pp. 1121-1128, 2009.
- [54] "Jazz," [Online]. Available: [Http://Www.Cs.Umd.Edu/Hcil/Jazz/Learn/Index.Shtml](http://Www.Cs.Umd.Edu/Hcil/Jazz/Learn/Index.Shtml). [Accessed 2014].
- [55] Lauesen, Soren, Mohammad A. Kuhail, Kostas Pantazos, Shangjin Xu, And Mads B. Andersen, "Uvis: Visualization And Interaction With A Drag-Drop-Formula Tool.," Vol. In Is&T/Spie Electronic Imaging. International Society For Optics And Photonics., Pp. 86540I-86540I, 2013.
- [56] "Visokio," [Online]. Available: [Http://Www.Visokio.Com/Omniscope](http://Www.Visokio.Com/Omniscope), Retrieved. [Accessed 20 11 2013].

- [57] Viegas, Fernanda B., Martin Wattenberg, Frank Van Ham, Jesse Kriss, And Matt Mckeon., "Manyeyes: A Site For Visualization At Internet Scale.," Vols. Visualization And Computer Graphics, Ieee Transactions On 13, No. 6., Pp. 1121-1128, 2007.
- [58] Mohammad A. Kuhail, Soren Lauesen, Kostas Pantazos, And Xu Shangjin., "Usability Analysis Of Custom Visualization Tools," Vol. In Sigrad, Pp. 19-28, 2012.
- [59] Tang, Anthony, Melanie Tory, Barry Po, Petra Neumann, And Sheelagh Carpendale., "Collaborative Coupling Over Tabletop Displays.," Vol. In Proceedings Of The Sigchi Conference On Human Factors In Computing Systems., Pp. 1181-1190, 2006.
- [60] Isenberg, Petra, And Carpendale, Sheelagh, "Interactive Tree Comparison For Co-Located Collaborative Information Visualization," Vols. Visualization And Computer Graphics, Ieee Transactions On 13, No. 6., Pp. 1232-1239, 2007.
- [61] Isenberg, Petra, And Danyel Fisher., "Collaborative Brushing And Linking For Co-Located Visual Analytics Of Document Collections.," Vol. Computer Graphics Forum. Vol. 28. No. 3. Blackwell Publishing Ltd., Pp. 1031-1038, 2009.
- [62] Forlines, Clifton, Alan Esenther, Chia Shen, Daniel Wigdor, And Kathy Ryall, "Multi-User, Multi-Display Interaction With A Single-User, Single-Display Geospatial Application.," Vol. Proceedings Of The 19th Annual Acm Symposium On User Interface Software And Technology. Acm., Pp. 273-276, 2006.
- [63] Forlines, Clifton, And Ryan Lilien., "Adapting A Single-User, Single-Display Molecular Visualization Application For Use In A Multi-User, Multi-Display Environment.," Vol.

Proceedings Of The Working Conference On Advanced Visual Interfaces. Acm., Pp. 367-371, 2008.

[64] Jones, Jasmine, Lora Oehlberg, And Björn Hartmann., " Designing Software To Facilitate Shared Understanding In Collaborative Design Teams."

[65] Novak, Joseph D., And Alberto J. Cañas., "The Theory Underlying Concept Maps And How To Construct And Use Them.," Vols. Florida Institute For Human And Machine Cognition Pensacola Fl, Www. Ihmc. Us. , P. 284, 2008.

[66] "Color Brewer," [Online]. Available: [Http://Www.Colorbrewer2.Org](http://www.colorbrewer2.org). [Accessed 27 02 2014].

[67] L. Williams, "Pair Programming.," Vol. Encyclopedia Of Software Engineering 2., 2010.

[68] Leff, Avraham, And James T. Rayfield., "Web-Application Development Using The Model/View/Controller Design Pattern.," No. In Enterprise Distributed Object Computing Conference, 2001. Edoc'01. Proceedings. Fifth Ieee International. Ieee., Pp. 118-127, 2001.

[69] "Canada's Disaster Data," [Online]. Available: [Http://Www.Statcan.Gc.Ca/Start-Debut-Eng.Html](http://www.statcan.gc.ca/start-debut-eng.html). [Accessed 28 06 2013].

[70] "Medals Won By Olympics Athletes Data," [Online]. Available: [Https://Www.Tableausoftware.Com/Public/Community/Sample-Data-Sets](https://www.tableausoftware.com/public/community/sample-data-sets). [Accessed 28 06 2013].

[71] "Inqscribe," [Online]. Available: [Http://Www.Inqscribe.Com/](http://www.inqscribe.com/). [Accessed 03 11 2013].

[72] Browne, Jeffrey, Bongshin Lee, Sheelagh Carpendale, Nathalie Riche, And Timothy Sherwood., "Data Analysis On Interactive Whiteboards Through Sketch-Based

- Interaction.," Vol. Proceedings Of The Acm International Conference On Interactive Tabletops And Surfaces. Acm., Pp. 154-157, 2011.
- [73] Yi, Ji Soo, Youn Ah Kang, John T. Stasko, And Julie A. Jacko., "Toward A Deeper Understanding Of The Role Of Interaction In Information Visualization.," Vols. Visualization And Computer Graphics, Ieee Transactions On 13.6., Pp. 1224-1231, 2007.
- [74] "Flare," [Online]. Available:
[Http://Www.Adobe.Com/Devnet/Edu/Articles/Jeffrey_Heer.Html.](http://www.adobe.com/devnet/edu/articles/jeffrey_heer.html), [Accessed 17 03 2014].
- [75] Robertson, George G., And Jock D. Mackinlay. , The Document Lens., In Proceedings Of The 6th Annual Acm Symposium On User Interface Software And Technology, Pp. 101-108. Acm, 1993..
- [76] Heer, Jeffrey, And Maneesh Agrawala, "Design Considerations For Collaborative Visual Analytics.," Vols. Information Visualization 7, No. 1., Pp. 49-62, 2008.
- [77] Walny, Jagoda, Bongshin Lee, Paul Johns, Nathalie Henry Riche, And Sheelagh Carpendale, "Understanding Pen And Touch Interaction For Data Exploration On Interactive Whiteboards," Vols. Visualization And Computer Graphics, Ieee Transactions On 18, No. 12., Pp. 2779-2788, 2012.
- [78] Palmer, James D., And N. Ann Fields., "Computer Supported Cooperative Work," Vols. Computer 27, No. 5., Pp. 15-17, 1994.
- [79] Dork, Marian, Sheelagh Carpendale, Christopher Collins, And Carey Williamson., "Visgets: Coordinated Visualizations For Web-Based Information Exploration And

- Discovery.," Vols. Visualization And Computer Graphics, Ieee Transactions On 14.6., Pp. 1205-1212, 2008.
- [80] Mackinlay, Jock D., George G. Robertson, And Robert Deline., "Developing Calendar Visualizers For The Information Visualizer.," Vol. Proceedings Of The 7th Annual Acm Symposium On User Interface Software And Technology. Acm., Pp. 109-118, 1994.
- [81] Lohse, Gerald L., Kevin Biolsi, Neff Walker, And Henry H. Rueter., "A Classification Of Visual Representations.," Vol. Communications Of The Acm 37.12., Pp. 36-49, 1994.
- [82] Mark, Gloria, And Alfred Kobsa., "The Effects Of Collaboration And System Transparency On Cive Usage: An Empirical Study And Model.," Vols. Presence: Teleoperators And Virtual Environments 14, No. 1., Pp. 60-80, 2005.
- [83] Carl Gutwin And Saul Greenberg, "The Mechanics Of Collaboration: Developing Low Cost Usability Evaluation Methods For Shared Workspaces," No. In Enabling Technologies: Infrastructure For Collaborative Enterprises.(Wet Ice 2000). Proceedings. Ieee 9th International Workshops On. Ieee., Pp. 98-103, 2000.
- [84] R. M. Baecker, "Readings In Human-Computer Interaction: Toward The Year 2000.," Vol. Morgan Kaufmann Pub., 1995.
- [85] Neumann, Petra, Anthony Tang, And Sheelagh Carpendale., "A Framework For Visual Information Analysis.," Vols. Technical Report 2007-87123, University Of Calgary, Calgary, Ab, Canada., 2007.
- [86] Kolodner, Janet L., And Kristine Nagel., "The Design Discussion Area: A Collaborative Learning Tool In Support Of Learning From Problem-Solving And Design Activities.,"

Vols. In Proceedings Of The 1999 Conference On Computer Support For Collaborative Learning. International Society Of The Learning Sciences., P. 37, 1999.

- [87] J. Vanhanen And H. Korpi, "Experiences Of Using Pair Programming In An Agile Project," Vols. In 40th Annual Hawaii International Conference On System Sciences (Hicss), Hawaii. , Pp. 274b - 274b, 2007.
- [88] J. C. Roberts., "Multiple-View And Multiform Visualization.," Vol. Electronic Imaging. International Society For Optics And Photonics., Pp. 176-185, 2000.
- [89] Pirolli, Peter, And Stuart Card., "The Sensemaking Process And Leverage Points For Analyst Technology As Identified Through Cognitive Task Analysis.," Vol. Proceedings Of International Conference On Intelligence Analysis. Vol. 5., Pp. 2-4, 2005.
- [90] Wang Baldonado, Michelle Q., Allison Woodruff, And Allan Kuchinsky, "Guidelines For Using Multiple Views In Information Visualization.," Vol. Proceedings Of The Working Conference On Advanced Visual Interfaces. Acm., Pp. 110-119, 2000.

APPENDIX B: CANADA DISASTER DATA – FIRST FEW ROWS

EVENT	EVENT_GROUP	EVENT_TYPE	PROVINCE	FATALITIES	INJURED	EVACUATED	DAY	COS	Y E N	M	YEAR_TEXT
E12: QC, February 10, 2001. Freezing rain, heavy snow and wind caused road accidents and homelessness. Six died in weather_related motor vehicle accidents.	Natural Disaster	Winter Storm	QC	6	11	30	0	0	2 0 0	1 2	'2001'
E13: MB suffered significant losses during spring flooding. Highway infrastructures, businesses and private and public properties were extensively damaged.	Natural Disaster	Flood	MB	0	0	0	0	1671 0626	0 1	4	'2001'
E14: Peace River area BC, June 2001. The region was subjected to many intense precipitation events. Increased tributary levels combined with the spring freshet caused the over_saturation of the soil and surface runoff. This in turn triggered several landslides that cut_off highways. Property and infrastructure damage was extensive. Pink Mountain and Halfway River were both affected.	Natural Disaster	Flood	BC	0	0	0	1	2094 2391	0 1	6	'2001'
E15: Leamington ON, June 6, 2010. A strong thunderstorm cell moved over the southern portions of Essex County. It spawned 4 tornadoes and a series of damaging wind gusts along an intermittent path of damage about 40 kilometres in length. The most significant damage was done by an F2 tornado which swept through the south end of the town of Leamington, with peak winds between 180 and 240 km/h. Approximately 4,500 hydro customers were left without power, and 12 homes were deemed unsafe	Natural Disaster	Tornado	ON	0	0	0	0	1000 00	2 0	1 6	'2001'

APPENDIX C: STUDY QUESTIONS

Questions for the Domain Expert

Have you worked with the disaster data before?

Have you created charts, such as bar charts before?

Which Charts are you most comfortable with?

Have you had prior experience with using a visualization tool, such as excel or more advanced.

If yes what are they?

What do you think was different about visualizing with this tool?

Was working with the visualization designer helpful in visualizing the data?

Or do you think you could have created the visualizations on your own?

Was the tool helpful in understanding the visualizations, such as the treemap?

Was the tool helpful in creating the visualizations?

How would you describe this experience?

Questions for the Visualization designer

Have you worked with the disaster data before?

How many years of experience you have in visual design?

What are the visual design tools you have worked with?

Was this tool helpful in explaining the visualizations, such as the treemap?

Was this tool helpful in creating the visualizations?

How would you compare this tool to existing visualization tools?

Have you designed visualizations with domain experts before?

Was it helpful to have the domain expert visualize the data with you?

Was the tool helpful in understanding the data?

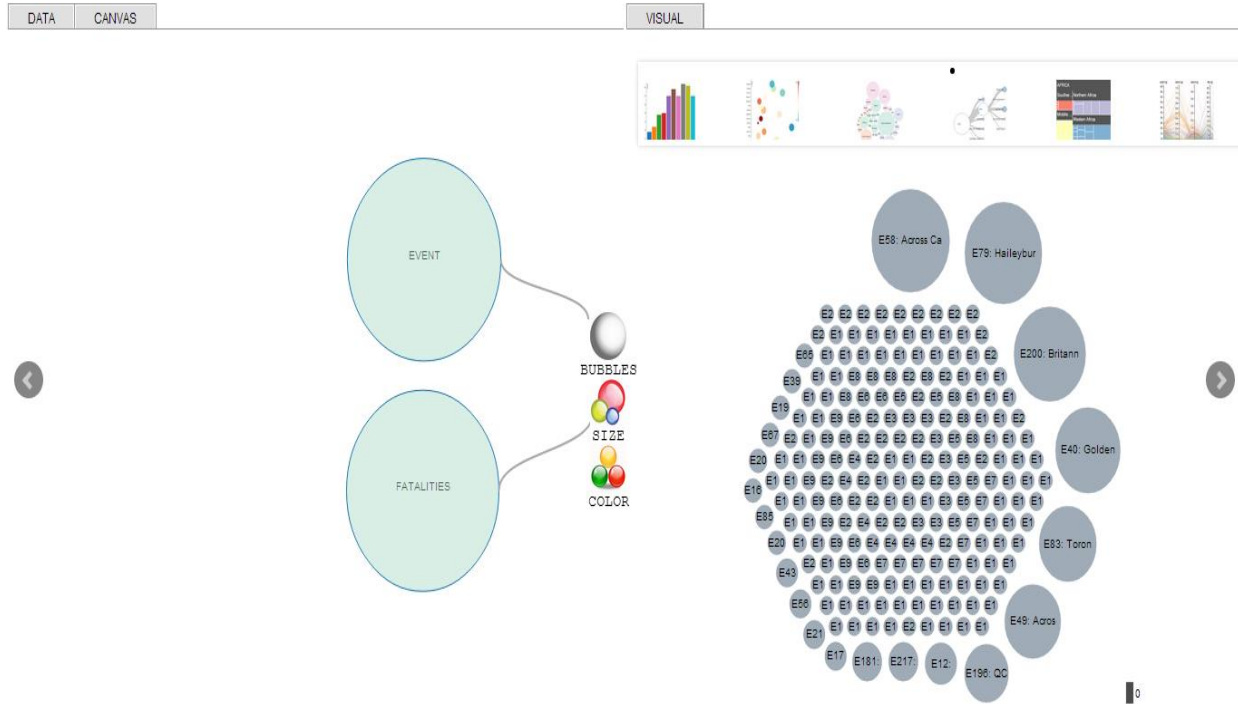
How would you describe this experience?

APPENDIX D: EXPECTED STUDY RESULTS

D.1. Task 1

List two most significant disastrous events that occurred in Canada with respect to fatalities?

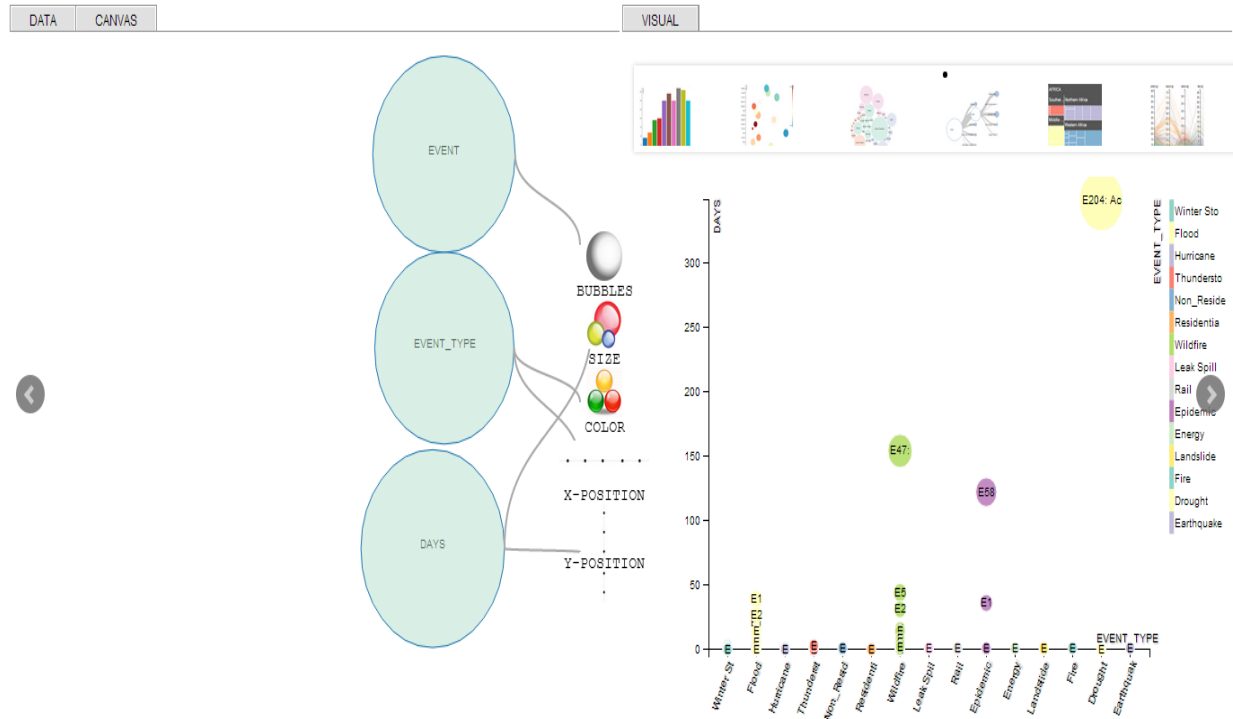
Result: E58. Across Canada



D.2. Task 2

What type of events have effects for larger no of days?

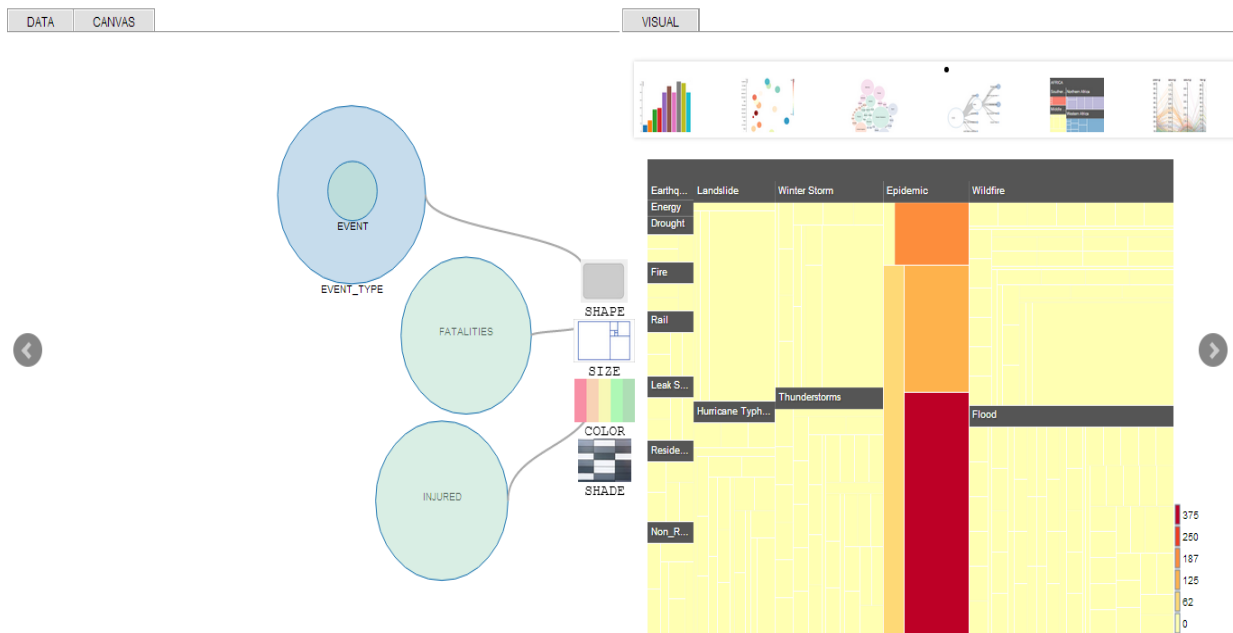
Result: Wildfire. (Green bubbles).



D.3. Task 3

What type of events cause more fatalities and injuries?

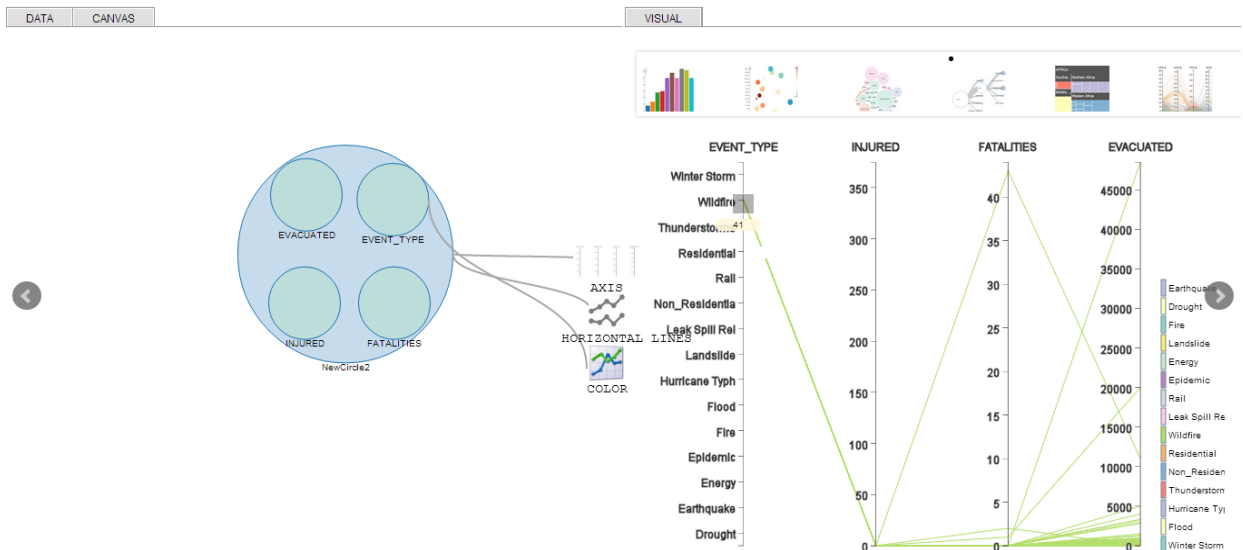
Result: Epidemic is larger in size (Fatalities) and darker in color (Injured). After Epidemic is Wildfire and Flood based on Fatalities. If you point on shape, an animation will show number of units under each category. Flood has most number of events.



D.4. Task 4

List two type of events that are most disastrous?

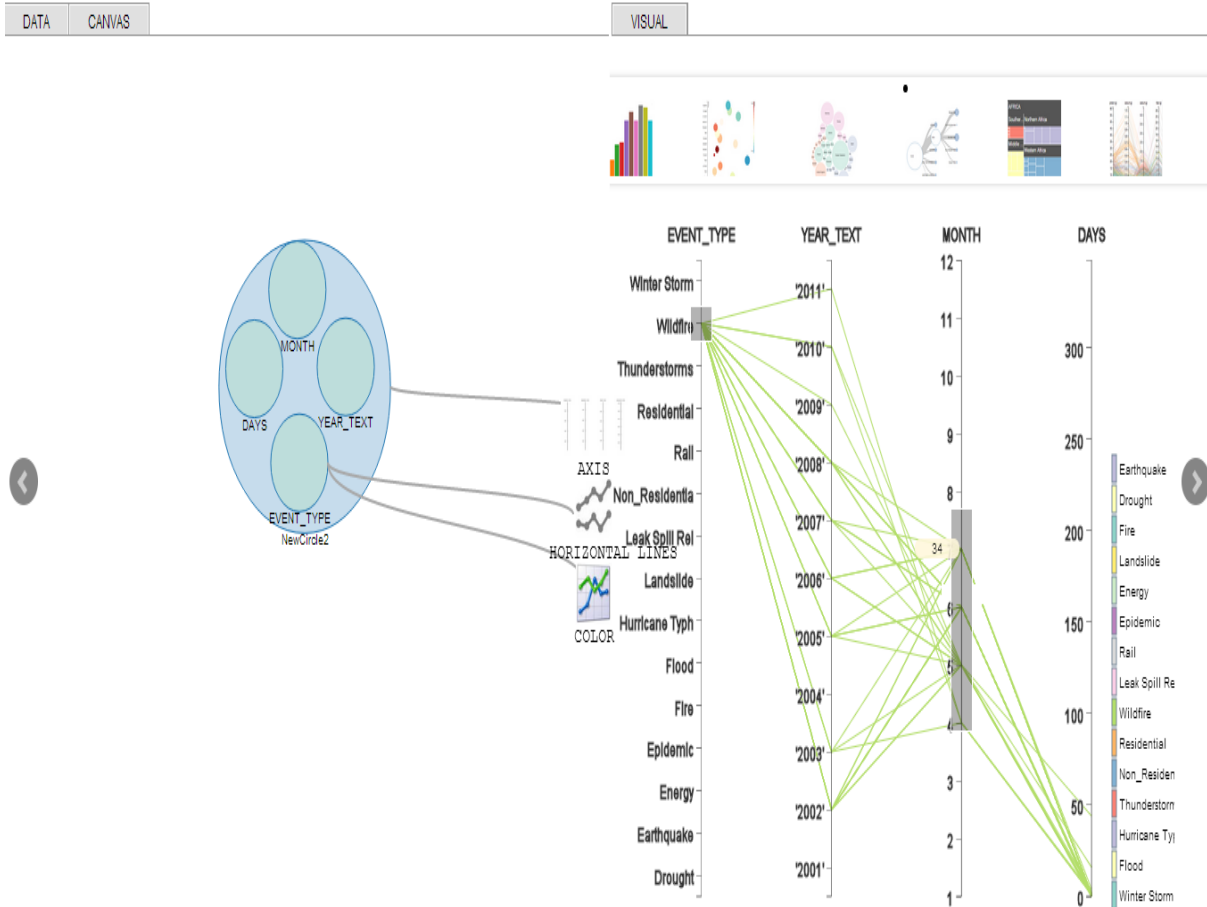
Result: We already know from Task 2 that wildfire occurs for larger number of days and Epidemic causes more fatalities and injuries. Now they can try viewing the visualization again to compare the two or find something more disastrous. A parallel coordinates, looking at one event type at a time. In the following Figure, users can move through each event type to see each event type.



D.6. Task 6

Are there any event types reoccurring in the same season?

Result: Wildfires occurred every summer more frequently between 2002 to 2008.



APPENDIX E: VIDEO TRANSCRIPTIONS FROM THE STUDY – FIRST PARSE

E.1. Experiment 1

[00:00:34.00]STARTED: DOMAIN EXPERT
[00:00:36.00]EXPLAINING DATA AND TASK
[00:00:50.00]REFERS TO FATALITIES
[00:00:52.00]VISUALIZATION DESIGNER TRIES TO DRAG FATALITIES INSTEAD OF CLICK
[00:01:12.00]DOMAIN EXPERT SAYS LETS TRY CLICKING
[00:01:22.00]DOMAIN EXPERT TAPS AND THE COLUMN APPEARS
[00:01:32.00]VISUALIZATION DESIGNER CLARIFIES IF WE NEED TO SELECT THE COUNTRY AS WELL
[00:01:42.00]DOMAIN EXPERT SAYS THIS DATASET IS ONLY FROM CANADA
[00:01:48.00]VISUALIZATION DESIGNER ANYTHING ELSE.
[00:01:50.00]DOMAIN EXPERT JUST FATALITIES FOR THIS ONE
[00:02:04.00]VISUALIZATION DESIGNER SUGGESTS THE SELECTION OF EVENTS AS WELL AFTER READING THE TASK
[00:02:10.00]
[00:02:18.00]VISUALIZATION DESIGNER SELECTING A VISUAL TEMPLATE - BAR CHART
[00:02:20.00]READS THE DOMAIN TASK AGAIN
[00:02:40.00]VISUALIZATION DESIGNER EXPLAINS THAT FATALITIES CAN BE HEAD OF THE BARS AND THE EVENTS CAN BE THE BARS.
[00:02:48.00] VISUALIZATION DESIGNER MAPS BARS TO EVENTS AND HEIGHT TO FATALITIES
[00:02:58.00]VISUALIZATION DESIGNER EXPLAINS THAT NOW WE CAN SEE WHICH ARE THE MOST SIGNIFICANT
[00:03:08.00]DOMAIN EXPERT CLICKS ON THE MOST PROMINENT BAR TO TRY TO GET THE DETAILS OF THE EVENT.
[00:03:12.00]THEY CAN NOT GET THE DETAILS BECUASE THE BAR IS TOO THIN
[00:03:16.00]DOMAIN EXPERT: "LETS TRY USING A DIFFERENT GRAPH"
[00:03:26.00]VISUALIZATION DESIGNER IS ABLE TO GET THE DETAILS FROM THE BARS
[00:03:58.00]DOMAIN EXPERT: EXLPAINS THE NEXT TASK "WHAT TYPE OF EVENTS HAVE AFFECTS FOR LARGER NUMBER OF DAYS"
[00:04:16.00]VISUALIZATION DESIGNER: REPEATS THE TASK WHILE SELECTING DAYS
[00:04:24.00]REPEATS THE TASK AGAIN
[00:04:26.00]DOMAIN EXPERT: WE NEED EVENT TYPES ASWELL AND SELECTS IT
[00:04:36.00]VISUALIZATION DESIGNER DO WE NEED ANYTHING ELSE FOR THE NEXT TASKS SO WE DONT HAVE TO COME BACK HERE
[00:04:42.00]DOMAIN EXPERT GOES THROUGH THE SECOND TASK AND SELECTS INJURIES
[00:04:46.00]VISUALIZATION DESIGNER WE ALREADY HAVE FATALITIES
[00:04:54.00]DOMAIN EXPERT READS THE THIRD TASKS
[00:05:04.00]DOMAIN EXPERT PROVIDES THE DATA OF INTEREST: FATALITIES AND COST AND SELECTS THEM
[00:05:18.00]DOMAIN EXPERT, THE FOURTH TASK
[00:05:28.00]DOMAIN EXPERT : DATA PROVINCES AND MONTH AND SELECTING IT
[00:06:00.00]VISUALIZATION DESIGNER: THE PREVIOUS TEMPLATE BAR CHART IS THERE, SO MAPPED BARS TO TYPE OF EVENT (EXPECTING THE BARS WILL AGGREGATE THE DATA BASED ON EVENT TYPE, BUT WITHOUT KNOWING WHAT TO AGGREGAETE ON)

[00:06:16.00]VISUALIZATION DESIGNER: BAR HEIGHT TO NO OF DAYS
[00:06:22.00]WHILE THE VISUALIZATION DESIGNER IS PERFORMING THE
INTERACTION TO GET THE DETAIL THE DOMAIN EXPERT TALKING ALOUD ABOUT THE
INTERACTION SAYING THAT WILD FIRE AND APEDEMIC
[00:07:00.00]DOMAIN EXPERT READING TASK 3
[00:07:08.00]VISUALIZATION DESIGNER MAPPING AND TALKING OUT LOUD. EVENT
TYPE IS ALREADY MAPPED TO THE BARS, SO THE VD MAPS FATALITIES TO HEIGHT
AND COLORS TO INJURIES
[00:07:24.00]DOMAIN EXPERT TRIES TO UNDERSTAND THAT THE MORE RED IT IS THE
MORE ...
[00:07:28.00]VISUALIZATION DESIGNER EXPLAINS
[00:07:42.00]VISUALIZATION DESIGNER LOOKS AT THE LINK THAT MAPS THE VISUAL
VARIABLE TO THE DATA COLUMN TO REASSURE WHAT IS MAPPED TO COLOR IN THE
VISUAL
[00:07:50.00]VISUALIZATION DESIGNER: EPIDEMIC IS THE MOST FATAL EVENT AND
MOST INJURIES OCCUR WITH IT
[00:07:58.00]VISUALIZATION DESIGNER: READS THE TASKS AGAIN TRIES TO MAKE
SURE THE DECISION IS RIGHT
[00:08:20.00]DOMAIN EXPERT: READ THE FOURTH TASK
[00:08:22.00]DOMAIN EXPERT: THE SAYS EVENT TYPE THAT THEY NEED TO LOOK AT
[00:08:24.00]VISUALIZATION DESIGNER: SUGGESTION FOR ANOTHER GRAPH
[00:08:36.00]DOMAIN EXPERT AGREES.
[00:08:42.00]VISUALIZATION DESIGNER SELECTS SCATTER PLOT AND EXPLAINS THAT
SHE IS USING IT BECUASE THE DIMENSIONS ARE INCREASING
[00:08:50.00]DOMAIN EXPERT: READS TASK AGAIN
[00:08:54.00]DOMAIN EXPERT: THIS TIME HE ASKS THE VISUALIZATION DESIGNER
TO MAP BUBBLES TO EVENT TYPE.
[00:08:58.00]VISUALIZATION DESIGNER MAPPING THE BUBBLES
[00:09:18.00]DOMAIN EXPERT: SUGGESTS X AND Y POSITION TO FATALITIES AND
COST
[00:09:56.00]DOMAIN EXPERT: NOT SATISFIED WITH THE REPRESENTATION BY
SAYING THIS REPRESENTS MANY'S EVENTS
[00:10:06.00]MISTAKE BY TOUCHING THE TABLE TO REDO IT.
[00:10:08.00]VISUALIZATION DESIGNER: RECTIFIES THE PROBLEM.
[00:10:16.00] VISUALIZATION DESIGNER: SELECTS THE BUBBLE CHART. BUBBLES TO
EVENT TYPE AND SIZE TO COST.
[00:10:40.00]DOMAIN EXPERT: SEES THAT THE EVENTS ARE NOT AGGREGATED BASED
ON EVENT TYPE.
[00:11:32.00]VISUALIZATION DESIGNER: TRIES TO MAP AGGREGATION TO BUBBLE
CHART.
[00:12:00.00]VISUALIZATION DESIGNER FORGOT THE QUESTION IN MAPPING
[00:12:02.00]DOMAIN EXPERT: READS THE QUESTION AGAIN
[00:12:14.00]VISUALIZATION DESIGNER COMBINING COST AND FATALITIES BY
PUSHING BUBBLES INSIDE THE BUBBLE.
[00:12:44.00]DOMAIN EXPERT TRIES TO MAP BECUASE THE VISUALIZATION DESIGNER
IS UNABLE TO.
[00:12:52.00]VISUALIZATION DESIGNER TRIES TO MAP THE EVENTS TO THE TREE
LAYOUT BUT NOT BASED ON EVENT TYPE, SO THE DATA IS TO MUCH FOR THE AREA.
[00:13:02.00]VISUALIZATION DESIGNER GETS DISCOURAGED AND MOVES BAKC TO
BUBBLE LAYOUT
[00:13:16.00]VISUALIZATION DESIGNER IS WORKING ON HER OWN, THINKING..
[00:13:36.00]DOMAIN EXPERT SUGGESTS THE BAR GRAPH

[00:13:42.00]VISUALIZATION DESIGNER GOES BACK TO THE BAR CHART
[00:13:52.00]MAPS BARS TO EVENT TYPE (NO GROUPING)
[00:14:06.00]DOMAIN EXPERT MAPS SIZE BY PUSHING BUBBLES INSIDE BUBBLES,
JUST TRYING TO SEE WHAT HAPPENS
[00:14:20.00]VISUALIZATION DESIGNER DOES NOT CONSIDER IT AN ACCURATE
REPRESENTATION AND RECTIFIES IT.
[00:14:44.00]VISUALIZATION DESIGNER WILDFIRE IS PROBABLY ONE OF THEM.
[00:14:46.00]DOMAIN EXPERT AGREES.
[00:14:52.00]DOMAIN EXPERT WRITING IN THE ANSWER
[00:15:02.00]VISUALIZATION DESIGNER EXPERIMENTING
[00:15:40.00]BOTH AGREE THAT BAR CHART IS NOT REPRESENTING THE DATA WELL
[00:15:48.00]VISUALIZATION DESIGNER DISCUSSING THE TEMPLATES IN THE TOP
BAR
[00:15:58.00]DOMAIN EXPERT: EXPLAINS THAT HE WOULD LIKE TO SEE AN
AGREGATION OF BUBBLES TO SUPPORT ONE SINGLE EVENT TYPE.
[00:16:08.00]VISUALIZATION DESIGNER MAPPING X AND Y POSITION WHILE
EXPLAINING
[00:16:46.00]CANT DO IT SO THEY GO ON TO THE NEXT TASK
[00:16:50.00]THEY FIND OUT THAT THE NEXT ONE IS DEPENDANT ON THE PREVIOUS
SO THEY
[00:16:52.00]DOMAIN EXPERT SAYS WE KNOW ONE OF THEM
[00:17:20.00]VISUALIZATION DESIGNER: MAPS EVENT TPE OF BARS AGAIN. COLOR
TO PROVINCES. UNABILITY TO GREAT GROUPED BAR CHARTS.
[00:18:10.00]DOMAIN EXPERT TRYING TO MAP BUBBLES TO EVENT TYPE IN A
SCATTER PLOT.COLOR TO PROVINCES.
[00:18:28.00]VISUALIZATION DESIGNER CLARIFYING IF WE NEED FATALITIES
ASWELL.
[00:18:34.00]DOMAIN EXPERT EXPLAINS.
[00:18:40.00]VISUALIZATION DESIGNER DISUCSSING THE DATA.
[00:18:48.00]DOMAIN EXPERT SAYS THAT WE HAVE TO PUT BUBBLES INSIDE BUBBLES
BUT BOTH DONT KNOW HOW TO MAP
[00:18:58.00]DOMAIN EXPERT AND VISUALIZATION DESIGNER MUTUALLY AGREE THAT
THEY HAVE TO PUT BUBBLES INSIDE BUBBLES.
[00:19:00.00]DOMAIN EXPERT THEN TRIES TO MAP THIS HIERARCHY USING THE
SCATTERPLOT.
[00:19:46.00]VISUALIZATION DESIGNER: AGAIN SELECTING BUBBLE CHART AND NOT
A HIERARCHY.
[00:19:58.00]VISUALIZATION DESIGNER: GOES TO PARALLEL COORDINATES.
[00:20:18.00]BUG UNABLE TO DRAW CIRCLE
[00:20:56.00]// approximately 40 secs
[00:20:58.00]VISUAL DESINER TRYING TO MAPPING TO PARALLEL COORDINATES
[00:21:42.00]DOMAIN EXPERT: READING THE TASK AGAIN
[00:21:48.00]VISUALIZATION DESIGNER WE NEED ANOTHER DIMENSION
[00:22:02.00]DOMAIN EXPERT:I DONT THINK THIS IS THE RIGHT REPRESENTATION.
THIS COULD HAVE BEEN ANSWERED WITH SELECTING A PROVINCE AND FINDING THE
DETAILS FOR EACH LINK.
[00:22:34.00]VISUALIZATION DESIGNER WHAT DO YOU MEAN BY AFFECTED
[00:22:38.00]DOMAIN EXPERT EXPLAINS ACCORDING TO HIS UNDERSTANDING.
[00:23:10.00]VISUALIZATION DESIGNER GIVES UP AND SAYS LETS TRY ANOTHER
REPRESENTATION
[00:23:26.00]VISUALIZATION DESIGNER SELECTS BUBBLE CHART AGAIN.
[00:23:28.00]VISUALIZATION DESIGNER MUMBLING AND THINKING OUT LOUD

[00:23:30.00]..approx 26 secs
[00:24:56.00]VISUALIZATION DESIGNER AGAIN TRIES TO MAP BUBBLES TO EVENT TYPES AND ASKES WHAT DOES PUSHING BUBBLES INSIDE BUBBLES DO.
[00:25:06.00]DISCUSSING THE BUBBLE CHART AND ANALYZING
[00:26:26.00]DISCUSSING AGGREGATION

E.2. Experiment 3

[00:00:00.00]SETUP FOR THE DATA
[00:00:38.00]DOMAIN EXPERT: EXPLAINING THE DATA
[00:01:26.00]VISUALIZATION DESIGNER: WHAT WOULD YOU LIKE TO SEE ABOUT THE DATA
[00:01:32.00]DOMAIN EXPERT EXPLAINING THE FIRST TASK
[00:01:46.00]DOMAIN EXPERT: WE NEED TO SORT THEM BY FATALITIES
[00:01:58.00]VISUALIZATION DESIGNER TRYING TO DRAG THE FATALITIES AND THE EVENT COLUMNS WHILE TALKING
[00:02:18.00]VISUALIZATION DESIGNER ASKS WHETHER WHEN IT OCCURED WAS IMPORTANT
[00:02:22.00]DOMAIN EXPERT AGREES
[00:02:24.00]VISUALIZATION DESIGNER SELECTS YEAR EVENT TYPE AND LOCATION
[00:02:46.00]VISUALIZATION DESIGNER ASKES WHETHER IT IS IMPORTANT TO LOOK AT HO MANY WERE INJURED
[00:02:54.00]DOMAIN EXPERT NO WE ARE ONLY LOOKING AT FATALITIES
[00:03:02.00]BUG (42 secs)
[00:04:46.00]VISUALIZATION DESIGNER: TRYING TO EXPLAIN THE BAR CHART
[00:04:48.00]MAPS BARS TO PROVINCES HOPING THAT THE EVENTS WILL BE GROUPED BASED ON PROVINCES. HOWEVER, WE KNOW THAT HE NEEDED TO PUSH EVENTS INSIDE PROVINCES.
[00:05:06.00]DOMAIN EXPERT ASKS FOR BASED ON EVENT ONLY
[00:05:20.00]VISUALIZATION DESIGNER SAYS THAT IN THIS CASE WE PROBABLY DONT NEED A BAR CHART AND SUSGGESTS AND SELECTS THE SCATTER PLOT
[00:05:34.00]VISUAL DESINER EXPLAINS THAT THE SCATTER PLOT REPRESENTATION BY BREAKING IT DOWN.
[00:05:44.00]VISUALIZATION DESIGNER TRIES TO MAP THE Y POSITION TO FATALITIES
[00:05:46.00]AND TRIES TO MAP THE X POSITION TO THE YEAR BUT HE HAD NOT MAPPED THE MARK
[00:07:22.00]VISUALIZATION DESIGNER TRIES TO ANALYZE
[00:07:52.00]DOMAIN EXPERT WANTS TO KNOW THE DETAIL
[00:07:54.00]VISUALIZATION DESIGNER CLICKS BUT THE DETAIL ARE NOT AVAILABLE ON CLICK BECUASE DATA NOT MAPPED PROPERLY
[00:08:24.00]VISUALIZATION DESIGNER SELECTS BUBBLE CHART
[00:08:44.00]VISUAL DESINER MAPS BUBBLES TO EVENTS
[00:08:48.00]DOMAIN EXPERT SUGGESTS SIZE TO FATALITIES
[00:08:50.00]VISUALIZATION DESIGNER AGREES
[00:09:08.00]VISUALIZATION DESIGNER AND DOMAIN EXPERT ANALYZING
[00:09:28.00]AGREE ON TWO BUBBLES AS THE RIGHT ANSWERS
[00:09:46.00]DOMAIN EXPERT WRITING AND VISUALIZATION DESIGNER DICTATING
[00:10:18.00]DOMAIN EXPERT PROVIDING TASK 2
[00:10:30.00]VISUALIZATION DESIGNER SELECT THE DAYS
[00:10:40.00]VISUALIZATION DESIGNER SELECTS THE BAR CHART

[00:10:44.00]VISUALIZATION DESIGNER MAPS EVENT TYPE TO BARS AND NO OF DAYS TO HEIGHT
[00:11:06.00]VISUALIZATION DESIGNER EXPLAINING THE VISUAL LAYOUT
[00:11:24.00]DOMAIN EXPERT SAYS WHETHER IT IS A SUM
[00:11:26.00]VISUALIZATION DESIGNER CLARIFIES THAT IT IS NOT A SUM BUT MULTIPLE BARS ON TOP OF EACH OTHER
[00:11:44.00]VISUALIZATION DESIGNER SUGGESTS THE SCATTER PLOT AGAIN
[00:11:50.00]HOWEVER AFTER THINKING THE VISUALIZATION DESIGNER SELECTS THE TREEMAP
[00:11:56.00]VISUALIZATION DESIGNER FIRST EXPLAINS THE TREEMAP
[00:12:10.00]MAPS RECTANGLES TO EVENT TYPE ASSUMING THAT THE EVENTS WILL BE GROUPED ON EVENT TYPE AUTOMATICALLY.
[00:12:34.00]THEY FOUND OUT THAT EVENTS ARE NOT GROUPED BASED ON EVENT TYPE
[00:12:44.00]VISUAL DESIGNER TRIES VARIOUS THINGS TO SEE WHAT WILL MAKE THE DATA CREATE A HIERARCHY.
[00:13:48.00]VISUAL DESIGNER TRIES EVENTS INSIDE EVENT TYPE THEN IT WORKS
[00:14:20.00]DOMAIN EXPERT TRIES TO UNDERSTAND THE TREEMAP AND ASKS WHETHER A CERTAIN PORTION REPRESENTS THE WILDFIRE.
[00:14:32.00]VISUAL DESIGNER TRIES TO EXPLAIN THE REPRESENTATION
[00:15:36.00] DOMAIN EXPERT WANTS TO SEE EVENTS BASED ON DAYS AND SAYS CAN WE PUSH EVENTS INSIDE DAYS.
[00:15:38.00]VISUALIZATION DESIGNER SAYS YES AND PUSHES EVENTS INSIDE DAYS, HOWEVER THE VISUALIZATION DOES NOT SEEM TO SATISFY THE TASK
[00:16:50.00]VISUALIZATION DESIGNER SAYS LETS GO TO THE BAR CHART AGAIN
[00:16:58.00]VISUALIZATION DESIGNER IS ABLE TO CREATE A GROUPED BAR CHART WITH EVENTS INSIDE EVENT TYPE
[00:17:26.00]VISUALIZATION DESIGNER CLICKS ON ONE BAR AND SAYS THAT ITS 155
[00:17:32.00]DOMAIN EXPERT HOWEVER WANTS A TOTAL OF ALL THE BARS IN WILDFIRE
[00:17:34.00]HE SAYS THAT WHAT IF COMBINED VALUES OF SMALL BARS IN ONE CAN EXCEED WILDFIRE
[00:18:00.00]AS A RESULT, VISUALIZATION DESIGNER GOES TO THE PARALLEL COORDINATES
[00:18:24.00]VISUALIZATION DESIGNER CREATES A BUBBLE AND PUSHES DAYS
[00:18:36.00]VISUALIZATION DESIGNER TRIES TO MAKE A LARGER CIRCLE, HE DOESNOT SEEM TO BE ABLE TO ENLARGE A CIRCLE
[00:18:48.00]VISUALIZATION DESIGNER STRUGGLING WITH INTERACTION
[00:19:18.00]VISUALIZATION DESIGNER PUSHING THE RELEVANT BUBBLES INSIDE THE NEW ONE
[00:20:16.00]VISUALIZATION DESIGNER REALIZES THAT ONE BUBBLE HAS GONE INSIDE ANOTHER
[00:21:08.00]VISUALIZATION DESIGNER IS TRYING TO EXPLAIN HOW TO INTERACT WITH THE PARALLEL COORDINATE
[00:21:32.00]DOMAIN EXPERT TRIES TO ANALYZE
[00:21:40.00]VISUALIZATION DESIGNER SUPPORTS THAT WILDFIRE AND EPIDEMIC
[00:22:18.00]DOMAIN EXPERT TASK 3
[00:22:40.00]VISUAL DESIGNER CONTINUES USING THE PARALLEL COORDINATES
[00:22:44.00]VISUALIZATION DESIGNER TRIES TO INTERACT TO GET THE THE RESULTS WHILE EXPLAINING
[00:22:48.00]DOMAIN EXPERT SAYS WE DO NOT NEED THE DATA IN THIS ONE

[00:23:12.00]DOMAIN EXPERT: EPDEMIC HAS MOST ONES
[00:23:14.00]VISUALIZATION DESIGNER AGREES
[00:23:16.00]DOMAIN EXPERT REALIZES THAT THEY ARE NOT LOOKING AT INJURIES
AND IT IS NOT PRESENT IN THE PARALLEL COORDINATES
[00:23:38.00]VISUALIZATION DESIGNER INJURIES ARE ADDED
[00:23:40.00]VISUALIZATION DESIGNER INTERACTING WITH THE VISUALIZATION
[00:24:14.00]DOMAIN EXPERT ASKS FOR THE OTHER SIGNIFICANT EVENT TYPE
[00:24:16.00]VISUALIZATION DESIGNER ANSWERS - WINTER STORM AND RESIDENTIAL
[00:24:34.00]BOTH DISUCSSING THE VISUAL DATA
[00:24:42.00]VISUALIZATION DESIGNER PERFORMING MORE INTERACTIONS TO FILTER
DATA
[00:25:22.00]DOMAIN EXPERT TASK 4
[00:25:24.00]DOMAIN SAYS THEY ALREADY DID THIS AND KNOW THE ANSWER
[00:25:26.00]VISUALIZATION DESIGNER AGREES AND INTERACTS WITH THE
VISUALIZATION TO CONFIRM

E.3. Experiment 4

[00:00:02.00]//RESEARCHER FORGOT TO UPLOAD THE DATA SET
[00:00:04.00]IN THIS CASE THE DOMAIN EXPERT IS ON LEFT AND NOT ON THE
RIGHT SIDE AND THE VISUALIZATION DESIGNER HAS TO STRECH TO CREATE THE
VISUALIZATIONS.
[00:00:32.00]//UPLOADED THE DATASET
[00:00:40.00]DOMAIN EXPERT READING TASK1
[00:00:50.00]TOUCH NOT WORKING BEACUSE THE TASK SHEET IS ON THE TABLETOP
[00:01:14.00]VISUALIZATION DESIGNER ASKS IF WE NEED DISASTORUS EVENT TYPE
[00:01:16.00]DOMAIN EXPERT SAYS WE NEED EVENTS
[00:01:26.00]TOUCH NOT WORKING AGAIN AND THE VISUALIZATION DESIGNER NEEDS
TO USE THE MOUSE
[00:01:42.00]VISUALIZATION DESGINER CHOOSES THE BAR CHART
[00:02:00.00]"SO.. SO .."VISUALIZATION DESIGNER LOOKING AT THE TASK SHEET
FOR HELP
[00:02:16.00]VISUALIZATION DESIGNER IS MAKING HEIGHT TO FATALITIES WITHOUT
CHOOSING THE MARKS.
[00:02:22.00]VISUALIZATION DESIGNER FIGURES OUT THAT THEY NEED TO MAP THE
BARS FIRST AND MAPS THE BARS
[00:02:24.00]VISUALIZATION DESIGNER: EXPLAINS TO THE DOMAIN EXPERT THAT
THE BARS REPRESENT THE EVENTS AND THEN WE CAN USE HEIGHT TO FATALITIES BY
MAPPING FATALITIES
[00:03:04.00]VISUALIZATION DESIGNER TRIES TO GET THE DETAILS FROM THE BAR
CHART BUT THE DETAILS ON MOUSE OVER NOT WORKING AND THE BARS ARE TOO THIN
FOR TO TAP AND VIEW DETAILS.
[00:03:10.00]THEY CLICK AND THE BARS START SORTING ALPHABETICALLY.
[00:03:36.00]VISUALIZATION DESIGNER: SUGGESTED THAT THEY COULD USE THE
SCATTER PLOT TO VIEW DETAILS.
[00:03:38.00] VISUALIZATIN DESIGNER: EXPLAINS MAPPING OF THE MARKS TO DATA
AND THEN THE VISUAL VARIABLES.
[00:03:48.00]VISUALIZATION DESIGNER MAPS SIZE.
[00:03:54.00]VISUALIZATION DESIGNER POINTS TO THE TWO MOST SIGNIFIANT
EVENTS.

[00:04:12.00]DOMAIN EXPERT HIGHLIGHTS A PROBLEM WITH THE DATASET. THERE ARE SOME DISASTERS MENTIONED IN THE DATASET, FOR WHICH THE PLACE OF OCCURANCE IS SOMEOTHER COUNTRY. PROBLEM WITH STUDY.

[00:04:18.00]VISUALIZATION DESIGNER GOES BAKC TO DATA TO CONFIRM

[00:04:38.00]VISUALIZATION DESIGNER MAPES THE COLOR TO EVENT TYPE

[00:04:48.00]DOMAIN EXPERT READS TASK2.

[00:04:58.00]VISUALIZATION DESIGNER: SELECTS THE BAR CHART.

[00:05:00.00] THEN MOVES BACK TO SELECTING THE APPROPRIATE DATA COLUMNS.

[00:05:02.00] DOMAIN EXPERT POINT OUT AND ASKS REMOVE THE DATA COLUMN NOT NEEDED. HE COULD DO THIS HIMSELF BUT HE RELUCTANT.

[00:05:34.00]VISUALIZATION DESIGNER EXPLAINS THE PANELS NOW THAT SHE REALIZES THAT THE DOMAIN EXPERT IS NOT PARTICIPATING ACTIVLEY.

[00:05:36.00]VISUALIZATION DESIGNER SELECTS THE BUBBLE CHART

[00:06:06.00]DOMAIN EXPERT ASKES THE VISUALIZATION DESIGNER TO MAP NO OF DAYS TO SIZE

[00:06:12.00]VISUALIZATION DESIGNER EXPLAIN THAT WE NEED TO FIRST MAP THE MARKS AND MAPS BUBBLES TO EVENT TYPE AND SIZE TO NO OF DAYS.

[00:06:28.00]VISUALIZATION DESIGNER POINTS TO THE LARGER CIRCLES AND SAYS THAT THESE ARE THE ONES

[00:06:40.00]DOMAIN EXPERT SAYS BUT THIS IS JUST EVENT TYPES REPEATED.

[00:06:48.00]VISUALIZATION DESIGNER MAPS COLOR AND SEES THAT THE COLORS ARE NOT ORGANIZED TOGETHER.

[00:07:28.00]VISUALIZATION DESIGNER NOT SATISFIED WITH JUST THE COLOR MAPPING TO DAYS AND NOT SIZE

[00:07:30.00]VISUALIZATION DESIGNER SELECTS THE PARALLEL COORDINATES

[00:07:36.00]VISUALIZATION DESIGNER EXPLAINS THE VISUALIZATION.

[00:07:46.00] ///BUG, DESIGNER CANT DRAW.(60 SECS)

[00:08:46.00]VISUALIZATION DESIGNER IS UNABLE TO EXPAND THE CIRCLE.

[00:09:40.00]VISUALIZATION DESIGNER MAPS THE AXIS AND THE EVENTS

[00:10:20.00]DOMAIN EXPERT TRYING TO ANALYZE THE DATA. AND SAYS EPIDEMIC AND WILDFIRE BUT HE WOULD LIKE TO SEE AN AGGREGATION OF THE DATA.

[00:10:26.00]VISUALIZATION DESIGNER EXPLAINS THAT SINCE THE DATA HAS INDIVIDUAL EVENTS THE MARKS DISPLAY ALL OF THEM

[00:11:06.00]SILENCE

[00:11:08.00]VISUALIZATION DESIGNER: AGREE THAT IT WOULD BE NICE TO HAVE AN AVERAGE

[00:11:50.00]DOMAIN EXPERT: TASK3

[00:12:02.00]VISUALIZATION DESIGNER SELECTS TWO DATA COLUMNS OF INTEREST.

[00:12:04.00]DOMAIN EXPERT REMINDS HER OF THE THIRD.

[00:12:10.00]//BUG (34 SECS)

[00:12:54.00]VISUALIZATION DESIGNER SELECT THE PARALLEL COORDINATES

[00:12:58.00]VISUALIZATION DESIGNER DRAWS THE CIRCLE AND ADDS THE DATA OF INTEREST

[00:13:34.00]VISUALIZATION DESIGNER MAPS THE DATA

[00:13:36.00]VISUALIZATION DESIGNER EXPLAINS THE PARALLEL COORDINATES

[00:14:00.00]DOMAIN EXPERT SAYS THIS SORT OF WORKS BECAUSE IT TALKS ABOUT INJURIES.

[00:14:18.00]DOMAIN EXPERTS WANTS THE EVENT TYPES IN THE CENTER.

[00:14:50.00]THEY BOTH AGREE THAT IT SORT OF LOOKS LIKE APPEDEMIC BUT THEY DECIDE TO LOOK FURTHER

[00:14:52.00]VISUALIZATION DESIGNER: SELECTS THE SCATTER PLOT.

[00:15:10.00]VISUALIZATION DESIGNER: EXPLAINS THE LAYOUT.

[00:15:36.00]DOMAIN EXPERT WANTS TO KNOW WHETHER THERE IS A WAY TO ADD THESE TOGETHER.

[00:15:50.00]VISUALIZATION DESIGNER THINKS YES MAYBE AND PUSHING ONE INSIDE ANOTHER TO SEE IF THAT WOULD ADD THEM TOGETHER

[00:16:00.00]AFTER MAPPING THIS THEY THINK THAT THE DATA IS ADDED IN THE REPRESENTATION.

[00:16:10.00]DOMAIN EXPERT: IF THE ANSWER WASNT OBVIOUS I WOULD HAVE LIKED TO SEE MORE.

[00:16:24.00]DOMAIN EXPERT WANTS TO GET THE DETAILS

[00:16:26.00]VISUALIZATION DESIGNER UNABLE TO DUE TO INTERACTION ISSUES WITH TOOL

[00:16:40.00]VISUALIZATION DESIGNER MAPS COLOR ASWELL.

[00:16:54.00]DOMAIN EXPERT: SUGGESTS GETTING RID OF THE X-POSITION

[00:17:00.00]VISUALIZATION DESGINER: CURRENT SYSTEM DOES NOT HAVE AN UNDO

[00:17:06.00]VISUALIZATION DESIGNER SELECTS THE SCATTER PLOT AGAIN

[00:17:08.00]MAPS DATA AGAIN

[00:17:10.00]DOMAIN EXPERT SAYS YA

[00:17:38.00]VISUALIZATION DESIGNER: NOT SO INFORMATIVE.

[00:17:48.00]MAPS COLOR

[00:17:50.00]DOMAIN EXPERT: TRIES TO GET DETAIL.

[00:17:54.00]DOMAIN EXPERT: SAYS THAT THIS NOT DOING WHAT THEY REQUIRE.

[00:18:20.00]VISUALIZATION DESIGNER TRIES HIERARCHY, BUT THINKS IT IS NOT THE BEST SOLUTION.

[00:18:30.00]VISUALIZATION DESIGNER GOES WITH A SIMPLE BAR CHART.

[00:18:48.00]VISUALIZATION DESGINER AGAIN PUSHES BUBBLES INSIDE BUBBLES AND MAPS SIZE TO IT EXPECTING THAT THE HEIGHT OF THE BAR CHART WILL SPLIT BASED ON THE MAPPING.

[00:19:00.00]DOMAIN EXPERT: NOTICES THAT THIS IS JUST INJURIES.

[00:19:14.00]VISUALIZATION DESIGNER AGREES.

[00:19:32.00]VISUALIZATION DESIGNER LOOKING AT VISUALIZATIONS.

[00:19:38.00]VISUALIZATION DESIGNER SELECTS THE BUBBLES CHART AND MAPS DATA TO IT

[00:20:14.00]VISUALIZATION DESIGNER SAYS THAT YOU CAN TELL INDIVIDUALLY FOR EACH DIMENSION WHICH IS THE GREATER BUT THE DOMAIN EXPERT DOES NOT WANT PROCESS THE DIMENSIONS SEPARATELY TO COME UP WITH AN ANSWER

[00:20:28.00]DOMAIN EXPERT: PROVIDING REQUIREMENTS "I JUST WANT TO HAVE FUNCTION WHERE I CAN MAKE THE VALUE THIS PLUS THIS."

[00:20:44.00]VISUALIZATION DESIGNER: UNFORTUNATELY THIS TOOL DOESNOT LET US DO THAT

[00:20:48.00]VISUALIZATION DESIGNER IS TRYING TO MAP DATA TO OTHER LAYOUTS.

[00:21:14.00]VISUALIZATION DESIGNER ASKS THE DOMAIN EXPERT WHETHER THIS DID THE TRICK.

[00:21:20.00]THEY DISCUSS AND ANALYZE THE DATA

[00:21:32.00]VISUALZATION DESIGNER LOOKING AT THE ANIMATIONS TO BREAK DOWN THE VISUALIZATIONS TO UNDERSTAND THEM.

[00:21:50.00]BOTH OF THEM DISCUSSING AND ANALYZING

[00:22:34.00]VISUALIZATION DESIGNER AND DOMAIN EXPERT AGREE THAT THIS SATISFIES

[00:23:10.00]DOMAIN EXOERT: TASK3

[00:23:26.00]DISCUSSING REQUIREMENTS

[00:23:50.00]VISUALIZATION DESIGNER SUGGESTS THE HIERARCHICAL FOR THIS ONE

[00:24:10.00]VISUALIZATION DESIGNER SELECT THE ATTRBIUTES OF INTEREST TO THE DOMAIN EXPERT
[00:24:30.00]VISUALIZATION DESIGNER SELECTS THE TREEMAP AND EXPLAINS THE LAYOUT AND HOW TO MAP.
[00:24:48.00]VISUALIZATION DESIGNER MAPS EVENTS TYPES TO RECTANGLES AND FINDS OUT THAT IT IS NOT SHOWING EVENTS HIERARCHIALLY
[00:24:50.00]VISUALIZATION DEIGNER TRYING TO FIGURE OUT HOW TO MAP THE DATA.
[00:25:08.00]VISUALIZATION DESIGNER MAPS SIZE TO A BUBBLE INSIDE A BUBBLE, EXPECTIG AN AGGREGATION OR SPLIT OF RECTAGLES BASED ON THIS REPRESENTATION.
[00:25:30.00]VISUALIZATION DESIGNER GOES BACK TO THE DATA TO LOOK AND SCROLL AND UNDERSTAND THE DATASET, SELECT ANOTHER DATA COL.
[00:26:26.00]DOMAIN EXPERT DISCUSSING THAT HE WANTS AN AGREEGATION
[00:26:44.00]VISUALIZATION DESIGNER STILL TRYING TO FIGURE OUT TO MAKE THE TREEMAP WORK
[00:26:54.00]VISUALIZATION DESIGNER LOOKING AT TEMPLATES THAT CAN BEST SUIT THE DATA.
[00:27:28.00]VISUALIZATION DESIGNER SELECTS THE PARALLEL COORDINATES
[00:27:30.00]CREATE THE BUBBLES TO DO THE MAPPING
[00:27:56.00]VISUALIZATION DESIGNER TRYING TO MAP THE LINES BEFORE THE AXIS
[00:28:26.00]VISUALIZATION DESIGNER EXPLAINING
[00:28:30.00]SILENCE (5 SECS)
[00:28:44.00]VISUALIZATION DESIGNER CONFIRMS WHATS THE DOMAIN EXPERT WANTED TO SEE.
[00:28:50.00]DOMAIN EXPERT EXPLAINS
[00:29:10.00]VISUALIZATION DESIGNER SELECTS THE SCATTER PLOT AFTER UNDERSTNADING.
[00:29:20.00]"DOMAIN EXPERT: THE PROBLEM WITH ALL OF THESE IS THAT IT SEEMS LIKE THEY ARE SHOWING ONE THING AT A TIME, IF I WAS DOING THIS IN EXCEL I WILL JUST ADD ANOTHER COLUMN AND USE FORMULA AND MAKE A COLUMN OF DISASTROUNOUS. YOU CAN REALLY DO MATH IN HERE."
[00:29:40.00]VISUALIZATION DESIGNER EXPLAINS.

E.4. Experiment 6

[00:00:02.00]//SETUP (2 SECS)
[00:00:06.00]DOMAIN EXPERT EXPLAINING THE DATA AND TASKS
[00:00:10.00]DOMAIN EXPERT IS POINTING TO THE COLUMNS IN THE DATA PANEL TO EXPLAIN THEM
[00:01:00.00]VISUALIZATION DESGINER ASKING QUESTIONS ABOUT THE DATA
[00:01:02.00]DOMAIN EXPERT CONTINUES EXPLAINING THE DATA
[00:01:52.00]DOMAIN EXPERT NO EXPLAINS THAT THERE ARE SIX TASKS
[00:02:18.00]VISUALIZATION DESIGNER SELECT THE REQUIRED DATA COLUMNS AFTER SPEAKING THE DATA OUT LOUD
[00:02:42.00]DOMAIN EXPERT SELECT THE DATA COLUMNS BECUASE THEY ARE OUT OF REACH FROM THE VISUALIZATION DESIGNER
[00:03:28.00]VISUALIZATION DESIGNER SELECTS THE BAR CHART AND MAPS THE BARS TO THE EVENT AND THE HEIGHT TO THE FATALITIES
[00:03:48.00]MAPS COLORS TO FATALITIES AS WELL

[00:03:56.00]MAKES THE BARS ASCENDING
[00:04:34.00]BOTH ARE TRYING TO ANALYZE
[00:04:36.00]VISUALIZATION DESIGNER TRIES TO SEE THE DETAILS BUT CAN NOT
BECAUSE THE BARS ARE THIN TO TAP AND THE MOUSE OVER DOES NOT SUPPORT
DETAILS ONLY THE NUMBER
[00:05:18.00]VISUALIZATION DESIGNER GOES BACK TO SELECTING THE EVENT
GROUP
[00:05:48.00]VISUALIZATION DESIGNER MAPS THE COLOR
[00:06:18.00]VISUALIZATION DESIGNER CLICKS ON THE BUBBLE TO FILTER THE
DATA
[00:06:22.00]HOWEVER IT CANT BE DONE SO SHE MOVES ON TO A DIFFERENT
VISUALIZATION
[00:06:26.00]VISUALIZATION DESIGNER MOVES TO A BUBBLE CHART.
[00:06:28.00]SHE MAPS EACH BUBBLE TO AN EVENT
[00:06:40.00]THEY BOTH DECIDE THIS IS CLEAR
[00:07:04.00]VISUALIZATION DESIGNER IS LOOKING AT THE DETAILS TO SEE HOW
MANY ARE DEAD IN EACH TO MAKE SURE BECAUSE THE SIZES ARE SIMILAR.
[00:07:34.00]DOMAIN EXPERT WRITES THE RESULTS
[00:07:42.00]DOMAIN EXPERT TASK2
[00:07:54.00]VISUALIZATION DESIGNER MOVES BACK TO THE DATA PANEL
[00:07:56.00]AND TRIES TO DELETE A COLUMN BECAUSE THEY DONT NEED IT
[00:07:58.00]DOMAIN EXPERT AGREE
[00:08:00.00]BOTH DISCUSS WHAT DATA IS REQUIRED.
[00:08:42.00]VISUALIZATION DESIGNER TRIES THE BAR CHART AGAIN AND MAPS
BARS TO EVENT TYPE (EXPECTING AN AGGREGATION BASED ON EVENT TYPE) AND
HEIGHT IS MAPPED TO NUMBER OF DAYS
[00:09:00.00]DOMAIN EXPERT DOES NOT UNDERSTAND THE LABELS BELOW THE BARS
AND SAYS THAT THIS IS CONFUSING
[00:09:02.00]VISUALIZATION DESIGNER TRIES TO HELP CLARIFY
[00:09:32.00]VISUALIZATION DESIGNER SEES THE PROBLEM WITH THE BAR CHART
AND TRIES THE PARALLEL COORDINATES
[00:09:44.00]VISUALIZATION DESIGNER CREATES A CIRCLE.
[00:09:46.00]DOMAIN EXPERT EXCITED "ITS COOL"
[00:09:50.00]VISUALIZATION DESIGNER TRYING TO ENLARGE IT BUT THE ARM
OVERCOMES ON THE TABLE.
[00:10:04.00]VISUALIZATION DESIGNER MAPS THE AXIS AND SHOWS THAT THE
WILDFIRE IS THE MOST.
[00:10:46.00]DOMAIN EXPERT ASKS WHETHER THE LINES IN THE PARALLEL
COORDINATES IS PROVIDING THE AVERAGE
[00:10:54.00]VISUALI DESIGNER SAYS I THINK ITS THE SUM
[00:11:06.00]DOMAIN EXPERT SAYS THAT IF IT WAS AN AVERAGE IT WOULD BE MORE
PRECISE FOR US
[00:11:08.00]VISUALIZATION DESIGNER AGREES THAT IT IS TRUE
[00:11:24.00]DOMAIN EXPERT WHAT DO WE DO NOW.
[00:11:32.00]VISUALIZATION DESIGNER THEN SAYS LET GO BACK TO BAR CHARTS
[00:11:34.00]VISUALIZATION DESIGNER MAPS BARS TO EVENT TYPES AND HEIGHT TO
DAYS
[00:11:38.00]DISCUSSING AND ANALYZING
[00:12:08.00]DOMAIN EXPERT TAKING A VISUAL AVERAGE OF THE EVENTS IN EACH
EVENT TYPE. ICORRECT REPRESENTATION BUT GOOD ANALYSIS
[00:12:14.00]AGREE THAT IT IS EPEDMIC BASED ON AVERAGE
[00:12:24.00]DOMAIN EXPERT: TASK3

[00:12:32.00]VISUALIZATION DESIGNER GOES BACK TO THE DATA PANEL TO SELECT THE DATA FOR THE TASK
[00:12:34.00]SHE DELETES THE ONES NOT REQUIRED
[00:12:46.00]SELECTS THEM AGAIN
[00:12:48.00]//BUG (180 SECS APPROX)
[00:14:54.00]VISUALIZATION DESIGNER LOOKING AT TEMPLATES TO DECIDE ON WHAT TO USE
[00:14:58.00]VISUALIZATION DESIGNER SUGGESTS THE TREEMAP
[00:15:06.00]VISUALIZATION DESIGNER EXPLAINS THAT THIS TEMPLATE SHOWS A HIERARCHY
[00:15:16.00]VISUALIZATION DESGINER USES A NEW CIRCLE AND PUSHES FATALITIES AND INJURIES IN IT TO GET A COMBINED VALUE FOR THE TWO BASED ON EVENTS. (AN AGGREGATION ON EVENTS EXPECTED BUT SEPARATELY FOR BOTH) .
[00:15:38.00]VISUALIZATION DESIGNER THEN PUSHES THEM INTO EVENT GROUP.
[00:15:50.00]THEN SHAPE IS MAPPED TO THIS RELATIONSHIP
[00:16:00.00]BECUASE THE NEW CIRCLE DOES NOT CONTAIN DATA THERE IS AN UNDEFIEND PARENT GROUPING
[00:16:12.00]VISUALIZATION DESIGNER NOW MAPS COLOR TO THE NEW CIRCLE IN HOPE THAT A DIFFERENT COLOR FOR BOTH WILL BE VISUALIZED. BUT SINCE THE PARENT COLUMN IS UNDEFINED ONE COLOR IS MAPPED TO ALL BUT GOOD MAPPING.
[00:16:28.00]VISUALIZATION DESIGNER EXPLAINS THE DOMAIN EXPERT WHAT SHE WAS EXPECTING BUT POINTS OUT THAT THIS DOES NOT WORK.
[00:16:48.00]VISUALIZATION DESIGNER MAPS SIZE TO THE NEW CIRCLE TOO, SIZE WORKS FINE
[00:16:50.00]THEY AGREE THAT THIS DOES THE AGGREGATE AND FIND THAT IT IS FLOOD BUT.
[00:17:06.00]VISUALIZATION DESIGNER FEELS THAT THEY NEED TO VISUALIZE THIS WITH ANOTHER TEMPLATE TO BE SURE
[00:17:36.00]VISUALIZATION DESIGNER CHOOSES THE REINGOLD TREE
[00:17:48.00]TOUCH NOT WORKING SO THE VISUALIZATION DESIGNER DELETES THEM ALL AND MOVE BACK TO DATA PANEL TO ADD AGAIN
[00:17:52.00]//BUGIF YOU ADD BUBBLES TO A NEW CIRCLE AND DELETE THE NEW CIRCLE THE CHILDREN CAN NOT BE ADDED AGAIN BECUASE I THINK THE SYSTEM THINKS THEY ARE STILL IN THE VIEW
[00:19:16.00]VISUALIZATION IS NOT SURE HOW TO USE THE REIGNOLD TREE
[00:19:22.00]THEY ARE LOOKING AT THE VISUAL VARIABLES AND THE SAMPLE DATA TO UNDERSTAND THE TEMPLATE
[00:19:30.00]VISUALIZATION DESIGNER IS EXPLAINING AND UNDERSTANDING THE TEMPLATE WHILE LOOKING AT THE SAMPLE DATA.
[00:19:54.00]VISUALIZATION DESGINER IS AGAIN MAKING A NEW CIRCLE INSTEAD OF CREATING A HIERARCHY WITH THE EXISTING DATA.(CONFUSION BETWEEN OPERATIONS THAT TRANSFORM THE DATA TO DERIVED STRUCTURE - PUSHING BUBBLES INSIDE BUBBLES FOR HIERARCY AND STRUCTURE TO STRUCTURE OPERATIONS - DATA CIRCLES INSIDE NEW CIRCLE TO PARALLEL COORDINATES)
[00:20:22.00]PROBLEM WITH CREATING A NEW CIRCLE, PROBLEM WITH THE CIRCLE HIGHLIGHTING FOR CONNECTIONS.
[00:20:36.00]VISUALIZATION DESIGNER GOING BACK TO PARALLEL COORDINATES BECUASE A NEW CIRCLE IS DIFFICULT TO DRAW.
[00:20:58.00]//BUG NO NEW CIRCLE DRAWING (6 SECS)
[00:21:06.00]SO THE VISUALIZATION DESGINER GOES TO USING THE SCATTER PLOT
[00:21:10.00]VISUALIZATION DESIGNER MAPS THE DATA

[00:21:40.00]VISUALIZATION DESIGNER EXPLAINS THE SCATTER PLOT WITH THE NEW DATA MAPPED
[00:22:00.00]VISUALIZATION DESIGNER EXPLAINS THAT THERE MULTIPLE BUBBLES PER EVENT AND THAT HOWEVER, WITH MORE THAN ONE BUBBLE PER EVENT BUT THEY STILL SEE ITS EPEDEMIC
[00:22:24.00]DOMAIN EXPERT AGREES AND WRITE IT DOWN
[00:22:36.00]DOMAIN EXPERT TASK 4
[00:23:00.00]VISUALIZATION DESIGNER GOES BACK TO THE DATA PANEL
[00:23:02.00]DOMAIN EXPERT IS EXPLAINING WHAT HE THINKS IS IMPORTANT
[00:23:04.00]SO EVACUATED AND COST IS CHOOSEN
[00:23:36.00]VISUALIZATION DESIGNER AFTER LOOKING AT THE TEMPLATES AND DISCUSSING THINKS THAT PARALLEL COORDINATES IS A GOOD CHOICE
[00:23:58.00]//BUG TOUCH NOT WORKING (84 SECS)
[00:26:02.00]MAPPING DATA
[00:26:58.00]VISUALIZATION DESIGNER EXPLAING THE PARALLEL COORDINATES
[00:27:38.00]DOMAIN EXPERT WANTS THE LINES IN THE PARALLEL COORDINATES HIERARCHICAL
[00:27:50.00]BOTH DISCUSSING THAT EACH LINE REPRESENTS AN EVENT AND THAT THEY NEED TO AGGREGATE THE EVENTS
[00:28:28.00]VISUALIZATION DESIGNER MAPS THE LINES TO EVENT GROUP BUT NO GROUPING HAPPENS
[00:28:36.00]VISUALIZATION DESIGNER EXPLAINS THE RATIONALE BEHIND THE DATA AND WHY AGGREGATION IS NOT HAPPENING.
[00:29:18.00]VISUALIZATION DESIGNER THINKS ABOUT FILTERING
[00:29:20.00]THEN SHE TRIES VARIOUS FILTERS
[00:29:52.00]VISUALIZATION DESIGNER HAS FOUND A GOOD FILTER AND SHE IS NOW ANALYZING
[00:30:00.00]DOMAIN EXPERT FINDS START DISCUSSING HIS ANALYSIS
[00:30:32.00]VISUALIZATION DESIGNER AGREES WITH THE DOMAIN EXPERT
[00:30:54.00]THEY AGREE WITH WILDFIRE

APPENDIX F: ETHICS APPROVAL FORM



Conjoint Faculties Research Ethics Board
Research Services Office
3rd Floor Mackimmie Library Tower (MLT 300)
2500 University Drive, NW
Calgary AB T2N 1N4
Telephone: (403) 220-3782
Fax: (403) 289-0693
cfreb@ucalgary.ca

CERTIFICATION OF INSTITUTIONAL ETHICS REVIEW

This is to certify that the Conjoint Faculties Research Ethics Board at the University of Calgary has examined the following research proposal and found the proposed research involving human participants to be in accordance with University of Calgary Guidelines and the *Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans* 2010 (TCPS 2). This form and accompanying letter constitute the Certification of Institutional Ethics Review.

Ethics ID: REB13-0983_MOD1
Principal Investigator: Frank Maurer
Co-Investigator(s): Sheelagh Carpendale
Student Co-Investigator(s): Shahbano Farooq
Alemayehu Seyed
Study Title: Software Tool Usability Evaluation - this is a generic study defining the protocol used for evaluating software tools
Sponsor (if applicable): 1026520 / Networks of Centres of Excellence
1025040 / Natural Sciences and Engineering Research Council

Effective: 11/18/2013

Expires: 11/30/2014

Restrictions:

This Certification is subject to the following conditions:

1. Approval is granted only for the project and purposes described in the application.
2. Any modification to the authorized study must be submitted to the Chair, Conjoint Faculties Research Ethics Board for approval.
3. An annual report must be submitted within 30 days prior to the expiry date of this Certification, and should provide the expected completion date for the study.
4. A final report must be sent to the Board when the project is complete or terminated.

Date:

Christopher R. Sears, PhD, Chair, CFREB

January 21, 2014

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