Modeling Complex High Level Interactions in the Process of Visual Mining

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ABSTRACT

Modeling complex high level interactions in the process of visual mining

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Visual Mining refers to the human analytical process that uses visual representations of raw data and makes suitable inferences. During this analytical process, users are engaged in complex cognitive activities such as decision making, problem solving, analytical reasoning and learning. Now a days, users typically use interactive visualization tools, which we call as visual mining support tools (VMSTs), to mediate their interactions with the information present in visual representations of raw data and also to support their complex cognitive activities when performing visual mining.

VMSTs have two main components: visual representation and interaction. Even though, these two components are fundamental aspects of VMSTs, the research on visual representation has received the most attention. It is still unclear how to design interactions which can properly support users in performing complex cognitive activities during the visual mining process. Although some fundamental concepts and techniques regarding interaction design have been in place for a while, many established researchers are of the opinion that we do not yet have a generalized, principled, and systematic understanding of interaction components

of these VMSTs, and how interactions should be analyzed, designed, and integrated to support complex cognitive activities. Many researchers have recommended that one way to address this problem is through appropriate characterization of interactions in the visual mining process. Models that provide classifications of interactions have indeed been proposed in the visualization research community. While these models are important contributions for the visualization research community, they often characterize interactions at lower levels of human information interaction and high level interactions are not well addressed. In addition, some of these models are not designed to model user activity; rather they are most applicable for representing a system's response to user activity and not the user activity itself.

In this thesis, we address this problem through characterization of the interaction space of visual mining at the appropriate level. Our main contribution in this research is the discovery of a small set of classification criteria which can comprehensively characterize the interaction space of visual mining involving interactions with VMSTs for performing complex cognitive activities. These complex cognitive activities are modeled through visual mining episodes, a coherent set of activities consisting of visual mining strategies (VMSs). Using the classification criteria, VMSs are simply described as combinations of different values of these criteria. By considering all combinations, we can comprehensively cover the interaction space of visual mining. Our *VMS interaction space model* is unique in identifying the activity tier, a granularity of interactions (high level) which supports performance of complex cognitive activities through interactions with visual information using VMSTs.

As further demonstration of the utility of this VMS interaction space model, we describe the formulation of an inspection framework which can provide quantitative measures for the support provided by VMSTs for complex cognitive activities in visual mining. This inspection framework, which has enabled us to produce a new simpler evaluation method for VMSTs in comparison to existing evaluation methods, is based soundly on existing theories and models. Both the VMS interaction space model and the inspection framework present many interesting avenues for further research.

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Finally, I would like to dedicate my thesis to my Mother Ghamar Afiati who passed away nine months before the submission of the thesis. Her everlasting spirit has guided me through my difficult times.

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ABBREVIATIONS

Abbreviations	Description
AVS/ Express	Advanced Visual systems/Express
CW	Cognitive Walkthrough
HE	Heuristic Evaluation
GOMS	Goals, Operations, Methods, and Selection rules
UEM	Usability Evaluation Method
Vapor	Visualization and Analysis Platform for Ocean, Atmosphere, and Solar Researchers
VM	Visual Mining
VMS	Visual Mining Strategy
VMST	Visual Mining Support Tool

Chapter 1 : Introduction

In the last decade, technological changes in large data acquisition, management, analysis, and dissemination have increased rapidly (Keim, 2002). Fields as diverse as bioinformatics, geophysics, astronomy, medicine, engineering, meteorology and particle physics are faced with the problems of dealing with exponentially increasing volumes of available data (Mann et al., 2002). Therefore, one of our greatest challenges is to take advantage of this flood of raw data and turn it into understandable information. As stated in the US National Science Foundation's (NSF) report on challenges in visualization research, "our primary problem is no longer acquiring sufficient information, but rather making use of it" (Johnson et al., 2006). Therefore, visualization tools are recommended to facilitate the transformation of raw data into understandable information, typically visual representations which help in the identification of relationships and patterns that are not evident in the raw data.

Over the years, a large number of interactive visualization tools have been developed, all claiming to help users analyze, understand and gain insight into the large quantity of available data through appropriate transformations of the raw data into visual representations. In the literature, many different terms are used to denote this process of turning raw data into visual representations and their analysis by human analysts – *data visualization*, *information visualization*, *visual exploration*, *visual analytics*, *visual mining*, etc. Figure 1.1 below shows screen shots of three popular tools used in different domains. More details of these tools will be discussed in Chapter 5 later. In this thesis, we shall use a single term, the Visual Mining (VM) process, to refer to the human analytical process that uses such visual representations of raw data and makes suitable inferences. It is that process which uses the visual medium (through visual representations) and contributes to the discovery of patterns and relationships, which then form the knowledge required for informed decision making.

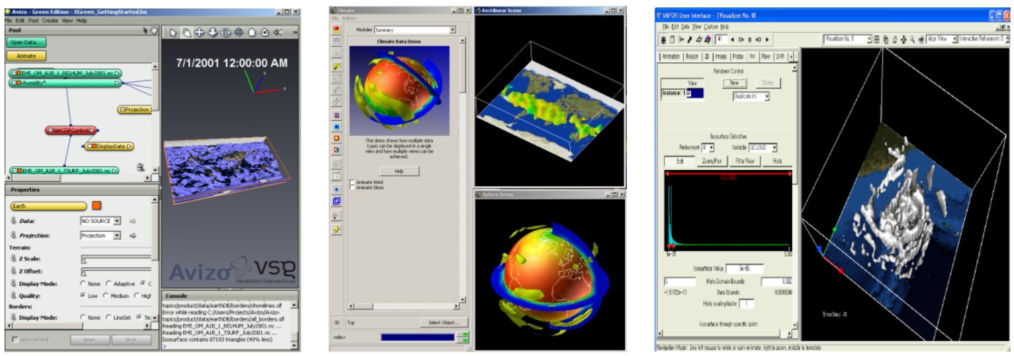


Figure 1.1: Screen shots of three commercially available Visual mining tools (Left to right : Avizo, AVS/Express and Vapor)

During this analytical process, users are engaged in complex cognitive activities (Sternberg et al., 2001) such as decision making, planning, problem solving, analytical reasoning and learning. In the performance of complex cognitive activities, users are actively involved in goal-directed information processing (Funke, 2010). This information processing is comprised of users using and working with some existing information to derive new information (Knauff et al., 2010). These days, users typically use interactive visualization tools such as those shown in Figure 1.1 to mediate their interaction with the information present in visual representations of raw data and to support their complex cognitive activities when performing visual mining. Specifically, users interact with the information present in the visual representations to support their information-intensive thinking processes (Parson et al., 2012).

Different terms are used to refer to the tools which are meant to provide support in the human analyst's information- intensive thinking processes, such as *cognitive technologies*, *decision support systems*, *knowledge support systems*, *cognitive tools*, *learning support tools* and *mind tools* (e.g., Markus et al., 2002; Fischer et al., 1998; Kim et al., 2007; Bhargava et al., 2007; Sedig et al., 2008). All of these invariably resort to presenting of information through visual representations to facilitate analysis activities. As our focus is on tools that mediate and enable visual mining activities, we unify all of them into one term and refer to all such tools as visual mining support tools (VMSTs). In this context, the term "support" suggests that VMSTs can partner, augment, guide, cognize with, and, transform human activities and human thinking to perform visual mining for the information which exists in visual representations of raw data.

While interacting with visual representations using VMSTs, users engage in behaviors (activities) stimulated by their desire to manage a problem, resolve a problematic situation or resolve an anomalous state of knowledge. A single episode of visual mining consists of a coherent set of activities with a specific purpose, say, browsing through visual representations to keep up-to-date, searching for some specific information, and so on. There is clearly a variety of such activities leading to a wide range of visual mining episodes. We consider visual mining episodes as consisting of visual mining strategies (VMSs), a term inspired by related work in library and information science[1]. It is important to note that, despite the wide range of forms that VMSs take, they are all interactions with visual representations. By interaction, we mean that, in such activities, people are not just passive recipients of information, but rather active seekers of information through visual representations, and active constructors of meaning from them. They look for potentially interesting information items, make judgments about the usefulness or interest of information items presented in visual representations by engaging with them and interpret them in order to understand them. Thus, their engagement with visual representations and their interpretations are central to their ability to use the information in these visual representations to reach their analysis goals.

Based on the above, we see that the core of visual mining is user interaction with information present in the visual representations of raw data. This visual mining interaction space has the following three important aspects: 1) visual mining is inherently an interactive process, and that process is characterized by the general features of people's interactions with visual representations, 2) the interaction takes place through visual mining episodes (coherent set of user activities/behaviours) which we have termed as visual mining strategies (VMSs), and 3) the goal of VMSTs is to support the range of VMSs.

[1] In the field of library and information sciences, similar activities are called as information behaviors, defined as the totality of human behavior in relation to sources and channels of information (Wilson, 2000; Belkin et al., 1983; Dervin, 1983; Wersig, 1979; Schutz et al., 1973) and information seeking episodes are defined in terms of Information Seeking Strategies.

As we shall see next, appropriate characterization of the visual mining interaction space is essential to be able to address various issues concerning the design and evaluation of VMSTs based on the support provided for such interactions.

1.1. Motivation

Although some fundamental concepts and techniques regarding interaction design have been in place for a while (Bertin, 1983; Beynon et al., 2001; Lohse et al., 1994; Shneiderman, 1991; Tufte, 1983; Yi et al., 2007), many are of the opinion that we do not yet have a generalized, principled, and systematic understanding of interaction components of these VMSTs, and how interactions should be analyzed, designed, and integrated to support complex cognitive activities (Sedigh et al., 2013-a). Many established researchers have recently endorsed this problem as can be seen from the following statements made in their publications:

- The process of stimulating and enabling human reasoning with the aid of interactive visualization tools is still a highly unexplored field. (Meyer et al., 2010, p. 227);
- There is hardly ever an explanation of what these benefits [of interaction] actually are as well as how and why they work. (Aigner, 2011, p. 18);
- With all of this research, there is still a lack of precedent on how to conduct research into visually enabled reasoning. It is not at all clear how one might evaluate interfaces with respect to their ability to scaffold higher-order cognitive tasks. (Green et al., 2010, p. 45); and,

- We have barely scratched the surface of this exciting new line of research [regarding interaction], and much work remains to be done. (Elmqvist et al., 2011, p. 337).

What manifests from an extensive survey of available literature is that more research is needed as there is no comprehensive model which can support researchers and practitioners in terms of understanding how visual representations of information and interactions relate in the context of performing complex cognitive activities.

The interactions that take place between a user and a VMST can be characterized at multiple levels of granularity (Sedigh et al., 2013-b; Gotz et al., 2008; Yi et al., 2007) as follows. Interactions at a high level are often complex and open-ended (e.g., problem solving, decision making, and forecasting) which are usually termed as activities. Tasks, at the next level, are goal-oriented behaviors that occur during the performance of activities (e.g., categorizing, identifying, ranking, etc.). Tasks are performed using interface features (tool-driven-actions performed on the visual representations, such as, navigation in the visual space, selection of a specific visual, filtering through visuals, and so on). Interface features are provided by the VMST that is being used for visual mining and form the third level, and are performed as a sequence of moves. Moves occur at the lowest level and are performed using the VMSTs interface; they can be mental or physical (e.g., mouse clicks, keyboard presses). While VMSTs are designed to provide support at the "feature" and "move" level, what is required is really support at the "task:" and "activity" levels. Thus, the understanding and representation of activities that a user performs are essential for effective design and evaluation of VMSTs.

Many researchers have recommended that one way to address this problem is through appropriate characterization of interactions in the visual mining process. Characterization takes the form of the interaction space being modeled by classification criteria (dimensions of the space) with different values along each of the criteria. For example, Thomas and Cook have claimed that "the grand challenge" of interaction is to develop a taxonomy to describe and clarify the interaction design space (Thomas et al., 2005). Some other researchers have suggested that not only do we need the knowledge of what actions are available, but we also require knowledge of how interactions facilitate visual mining activities such as problem solving and decision making (Keim et al., 2008; Liu et al., 2008). Models that provide classifications of interactions have indeed been proposed in the visualization community (e.g. Amar et al., 2005; Keim, 2002; Shneiderman, 1996; Zhou et al., 1998). While these models are important contributions for the visualization research community, they often characterize interactions at lower levels of human information interaction (Sedigh et al., 2012; Scholtz, 2006) and high level interactions are not well addressed. In addition, some of these models are not designed to model user activity; rather they are most applicable for representing a system's response to user activity and not the user activity itself (Gotz et al. 2008). Further details about these models will be provided in Chapter 2.

1.2. Problem Statement

Our primary problem is motivated by the fact that characterization of the interaction space of visual mining, particularly the space which includes complex cognitive activities, has not been adequately addressed so far. The problem is articulated in the following two research questions:

1) Are there generic classification criteria that can be used to comprehensively characterize the interaction space of visual mining so as to enable systematic thinking about user interactions with visual mining support tools which are intended to support complex cognitive (high level) activities? If so, what are they and how are they discovered in a trustworthy manner?
2) A related problem is the one raised in the following question: how do we demonstrate that a model developed for characterization of the interaction space of visual mining can indeed be used in the evaluation of support provided by any VMST for performing the complex cognitive activities required in visual mining?

1.3. Methodology

Our research methodology is composed of the following stages:

Qualitative research was chosen as the primary approach for determining appropriate classification criteria for interactive activities in visual mining. For this, in the first stage, we developed a complete work-flow description of the visual mining process to enable us to identify all the analysis activities and information interactions which take place during visual mining. The workflow was developed as follows: A first version was created based on descriptions in the literature. Subsequent refinement of this workflow was based on reviews of the workflow by experts who have used interactive visualization tools for visual mining.

The second stage was discovery of a comprehensive set of criteria and their use in the formulation of visual mining strategies. This was done through qualitative content analysis of a comprehensive list of publications reporting case studies concerned with visual mining activities in different domains as follows:

For our content analysis, we first identified and classified all human information interactions using the visual mining workflow created in the first stage. This gave us an initial set of classification criteria, which we shall term as the initial coding scheme for human information interaction. The aim of the qualitative content analysis is to finalize the set of classification criteria such that the finalized criteria are necessary and comprehensively model the interaction space. Each criterion could take on multiple values. Next, we chose around sixty published papers primarily concerned with reports on effective use of visualization for analysis and mining of large datasets. The chosen papers were from four different domains, namely, medicine, bioinformatics, epidemiology and geosciences. Each paper was studied and those which did not report actual case studies by experts were excluded from further consideration. Every one of the remaining papers was analyzed and used in the human-information interaction coding process.

Refinement of the initial coding with the help of publications took place in multiple iterations over time. Iterations involving reading and coding of each publication, along with constant comparison with previous publications and coding, resulting in refinement of the initial coding scheme throughout the coding process.

Throughout the coding process, dynamic models illustrating relationships among various criteria/values were used to explore and view connections and patterns in extracted codes. This process led us to formulate an interaction space model consisting of a comprehensive set of criteria and their possible values which characterizes the space of interactions in the visual mining process.

Lastly, VMSs are simply derived in this interaction space model as combinations of values of these different criteria. By considering all possible combinations we believe that the resulting VMSs comprehensively cover the interaction space of visual mining and provide us with a compact interaction space model for reasoning with interactions involved in complex cognitive activities in visual mining.

In the second stage, we designed an inspection framework that combines the proposed interaction space model and existing interaction models at the lower task/move levels in a way that enables us to produce quantitative estimates of the strengths and weaknesses in any given VMST. The framework enables us to estimate, for a given VMST, the support provided for performing user tasks, the support provided by interface features of the VMST, and the support for complex cognitive activities or visual mining strategies (VMSs).

In the final stage, in order to demonstrate the applicability of this framework, we used it to evaluate the three comprehensive visualization tools used in the community for visual mining (shown in Figure 1.1). The estimates we obtained using this framework were consistent with our own feel for the support provided by these tools, as we experimented with these tools for the purpose of evaluation.

1.4. Research Contributions

Our principal contribution is the discovery of a small set of classification criteria which can comprehensively characterize the interaction space of visual mining involving interactions with visual mining support tools for performing complex cognitive activities. These complex cognitive activities are modeled through visual mining episodes, a coherent set of activities consisting of visual mining strategies (VMSs). Using the classification criteria developed, VMSs are simply described as combinations of different values of these criteria. By considering all combinations we can comprehensively cover the interaction space of visual mining. We call this as the VMS interaction space model.

This model has the following four important characteristics, which position it extremely well to address existing research challenges in modelling the interaction space and to make a significant contribution to the existing literature:

a) ***Syncretic***: bringing together a number of previously disconnected ideas (some of the ideas are adapted from the field of library and information science; and they will be discussed in more detail in Chapters 2 and 4);

b) ***General***: operating at a level of abstraction that is applicable to all kinds of classes of visual mining activities, users and visual representations;

c) ***Comprehensive***: identifying patterns that cover an extensive range of complex cognitive activities; and,

d) ***Generative***: the ability to motivate design and evaluation as well as to encourage further theoretical and applied research.

We do recognise that no model or theoretical paradigm can address all possible activities, tasks and situations (Purchase et al., 2008; Thomas et al., 2005). Accordingly, we do not claim that the proposed criteria are exhaustive (necessary and sufficient), but on the basis of describing typical real-world visual mining scenarios which will be discussed in more detail in Chapter 4, we will show that they are necessary, if not sufficient, given the nature of the domain of "complex cognitive activities". Further, we firmly believe that they represent at least a valuable starting point for characterizing user interactions with visual representations for performing complex cognitive activities in visual mining.

Our other important contribution is the formulation of an inspection framework for comparative evaluation of VMSTs based on the above model. This framework is built upon principles for drawing relationships between different VMSs and design features of VMSTs intended for supporting the VMSs. This inspection framework, which has further enabled us to produce a new simpler evaluation method for VMSTs, is based soundly on existing theories and models. The research approach taken to develop this inspection framework is similar to development of other, now established methods for developing an evaluation framework. Although there is no single established approach on how to build such an evaluation framework, there are several examples that we have followed. It includes the following phases: theory identification, development, application, validation, extension and further validation repeated as many times as needed (Wilson et al., 2009-a). For example, Peterson (2000), went through these stages in the development of the multi-point scale for questionnaires. Similarly, O'Brien and Toms (2008) report that they too progressed through similar stages while developing a framework to evaluate user engagement with software. The GOMS approach (John et al., 1985) was built using the theoretical model of human information processing (Card et al., 1983). It was however validated only after 2 years with an example study (John et al., 1987). Then, after a further 3 years, it was extended (John, 1990). In fact, the GOMS model has been extended and revalidated several more times afterwards by other researchers (Gray et al., 1992; Gong et al., 1994). Likewise, initial validation of the Cognitive Walkthrough method was performed by Lewis et al., (1990) and modifications were proposed in 1992 (Rowley et al., 1992). The modifications weren't applied until 8 years later (Spencer, 2000). Remarkably Blandford et al. (2008) explained a 10 year plan for designing and validating a method called PUM.

In our work too, we have performed several of these key steps including theory identification, framework development, application and an initial attempt at validation. Chapter 5 describes the advances through these key steps in greater detail.

1.5. Structure of the thesis

The rest of this thesis is organized as follows:

Chapter 2: This chapter first draws attention to the importance of interaction in visualization research. While existing research in the area often focuses on presentation, in this chapter we highlight the overshadowed, but very important interaction component and strongly argue that it provides a way to overcome the limits of presentation and augment a user's cognition. We discuss how VMSTs mediate and supplement human cognition to enable complex cognitive activities. In addition, we review and classify existing prominent models of interaction related to visualization. We clearly bring out the much felt need for providing high level characterization of interactions that can guide the analysis, evaluation and design space of interaction in VMSTs in order to provide better support for complex cognitive activities. This chapter also provides an overview of usability evaluation methods, background knowledge which is needed to understand our developments reported in Chapter 5.

Chapter 3: This chapter first provides an overview of background concepts and terms about qualitative directed-content analysis which are necessary for understanding the methods we have used for deriving classification criteria for the interaction space of visual mining reported in Chapter 4. It provides a detailed description of human analysis activities in visual mining, in order to identify analysis activities and user interaction with visual representation in the process. Then building upon this description of the analytical process, we create a visual mining work-flow which identifies all human–information interaction activities. Later in chapter 4, we will use this workflow to formulate our initial set of classification criteria that get appropriately refined by methods of qualitative directed-content analysis.

Chapter 4: This chapter describes the method we have used for discovering and finalizing the set of classification criteria and their values which can characterize the interaction space of the visual mining process. As already mentioned, we use qualitative directed-content analysis methods to reveal the visual mining activities of scientists from a large number of case studies reported in scientific publications. These publications in general, clearly record the behavior of experts while being engaged in visual mining activity. The finalized classification criteria make up our model for the interaction space for visual mining comprehensively encompassing, in our opinion, all visual mining episodes reported in these publications. The model thus helps us to define the full set of visual mining strategies. Lastly, we discuss the steps we have taken to address trustworthiness of the qualitative content analysis methods we have used.

Chapter 5: This chapter demonstrates one use of the interaction space model created in the previous chapter by developing an inspection framework for evaluating the support provided by VMSTs for performing complex cognitive activities in visual mining. This inspection framework combines the interaction space model with previous lower level interaction models at the task/move levels in a way that can provide quantitative estimates of the strengths and weaknesses in any given VMST. It illustrates the application of this framework in a sample evaluation exercise for three commercially available and popular VMSTs. By applying this evaluation, it provides quantitative estimates of the strengths and weaknesses in supporting user tasks, the support provided by interface features, and the support for visual mining activities.

Chapter 6: This Chapter summarizes the work, major research contributions that have resulted, research benefits that can be reaped from our proposed activity model and inspection framework, and future avenues for research in this area.

There are also two Appendices as follows:

Appendix A lists all the publications which have been used for content analysis.

Appendix B shows examples of coding of publications in analysis process leading to the derivation of the final classification criteria.

Chapter 2 : Background and Related Work

Visual Mining Support Tools (VMSTs) are software environments which are designed for users to explore information spaces. They present information in the form of visual representations and enable users to perform complex cognitive activities during visual mining process. A VMST acts as a partner in performing complex cognitive activities, enabling users to explore, investigate, deconstruct, decode, analyze, evaluate and generate information (Sedig et al., 2008). In particular, because they can share and distribute the cognitive processing load of users, VMSTs are touted for their abilities to transform the way in which complex cognitive activities are performed (Jonassen, 2000; Lajoie, 2000; Beynon et al., 2001; Liang, 2009). In general, VMSTs do not provide any explicit instructions to users on what/how to carry out the investigation. Rather, users are provided with only the means to plan and realize their own investigative approach to reach their visual mining goals. That is, users are encouraged to formulate and test their hypotheses, analyze their findings, interpret their results, and draw their own conclusions which are all activities which need to be carried out in a dynamic fashion.

VMSTs have two main components: visual representation and interaction (Sedigh et al, 2013-a; Yi et al., 2007). The visual representation is concerned with the mapping of data to visuals and how best the information present in the data should be encoded and displayed. The interaction component is concerned with the discourse between the user and visual representation. Although they are discussed as two separate components, visual representation and interaction clearly are not mutually exclusive. Users can restructure and modify the form and amount of visually represented information through interaction.

Even though, these two components are fundamental aspects of VMSTs of equal importance, the visual representation has received the vast majority of attention in visualization research as pointed out by a number of researchers (Liang et al., 2009, Yi et al., 2007). For example, in a major review of advances in visual analytics, Thomas and Cook (2005, p. 73) point out that, ''researchers tend to focus on visual representations of data,'' and that the interaction design aspect of such tools ''is not given equal priority.'' They suggest that what is needed is to develop ''a deep understanding of the different forms of interaction and their respective benefits''. There are many other researchers who have expressed the same concern (e.g. Tory et al., 2004; Kosara et al., 2003; Dix et al., 1998; Tweedie, 1997; Buja et al., 1991). As we explained in Chapter 1, it is still unclear how to design interactions which can properly support users in performing complex cognitive activities during visual mining process (Thomas et al., 2005; Sedig et al., 2006-a; Keim et al., 2008; Liu et al., 2008). Many researchers have been recommending that one way to address this problem is through characterization of the interaction space of visual mining at the appropriate levels (Yi et al., 2007; Thomas et al., 2005). However, the characterization of the interaction space of visual mining, particularly concerning the higher level of complex cognitive activities, has not been adequately addressed so far (we will discuss this further in Section 2.2). In this research, our main goal is to provide a better understanding of the interaction space of visual mining by developing an appropriate model of visual mining activities at the higher levels. This model should comprehensively characterize the interaction space and enable the evaluation of VMSTs which are intended to support complex cognitive activities.

The remainder of this chapter is organized as follows. Section 2.1, explains the importance of interactive visual representations in the performance of complex cognitive activities. Section 2.2, provides a review of prior research about interaction in visualization research, examines how other researchers have characterized interactions, identifies some of their shortcomings and explains how they are going to be addressed in this thesis. Section 2.3 presents related research on different usability evaluation methods (UEMs) that have been proposed that could be used for human-information interaction evaluation. First a categorization of the different types of UEMs, such as user studies and expert methods, is presented. This categorisation provides context for the aims of different UEMs, which are each briefly described. This categorisation of UEMs is later used in Chapter 5 to explain how our proposed inspection framework relates to other methods.

2.1. The Importance of Interacting with Visuals

Visual representations are defined as a collection of graphical symbols organized to emphasize the functional, structural and semantic properties, and the relationships among the represented information (Glasgow et al., 1995; Peterson, 1996; Anderson et al., 2002; Cheng, 2002; Spence, 2007). They give perceptual access to an underlying information space in such a way that there is a unity of meaning between the visual representation and the information (Parsons et al., 2013). In other words, from the perspective of the user interactions, the visual representation is the information to interact with (Cole et al., 2005; Peterson, 1996; Zhang et al., 1994).

Visual representations make use of the human visual channel (the most powerful information processing channel), to enhance the exploration of the represented information. During exploration, they support the perceptual abilities of users, allowing users to offload some lower-level cognitive processes (e.g., memory, attention) onto the visual form, and, as a result, free up resources to conduct other higher level cognitive activities. Therefore, visual representations constitute a particularly powerful aiding tool for supporting human information exploration as they provide many cognitive benefits (Card et al., 1999; Spence, 2007; Tufte, 1990; Chen, 2004; Ware, 2004). In short, visual representations, through emphasis on visual inference, can dramatically increase user capacities to understand large amounts of information; investigate complex patterns and structures in the data; discover hidden and unexpected trends; observe inconsistencies and outliers; find solutions to problems, make appropriate decisions; construct mental models and create new knowledge (Norman, 1993; Card et al., 1999; Tufte, 2000; Ware, 2004; Fast & Sedig, 2005; Thomas et al., 2005; Sedig et al., 2006-b; Liang, 2009).

Regardless of their numerous benefits, visual representations in just their static form will be very difficult to explore. As the data set that they represent grows larger with more variables, their usefulness becomes even more limited in the static form. It is by adding interactions to them that some of these limitations can be overcome.

Interaction refers to the dual process of a user acting upon the visual representation through the intermediary of a human-computer interface, and the responses given back to these actions (Sedig et al., 2006-a). Therefore, interaction can be viewed as a communication loop (Kirsh, 1997), through which users can have conversation and have discourse with the visual representations (Perez-Quinones et al., 1996; Dix et al., 2004; Thomas et al., 2005).

In VMSTs, when using visual representations to assist with cognitive activities, cognition capabilities of the user are engaged (Scaife et al., 1996).The partnership that is formed between internal mental processes of the user and the visual forms presented by the VMST provides many benefits for performing complex cognitive activities. It should be noted that complex cognitive activities take place over a span of time, where internal mental processes (e.g., categorizations, abstractions, memory encodings, and comparisons) are dynamic and involve constant adjustment and reorganization of information. Static representations do not support this dynamic and temporal processing of information. Users have to put in a great deal of mental effort in order to reason and think about the information. Thus, use of static visual representations alone could put in more of the processing load onto internal mental processes. This creates a gap between the mental process of the users and the visual representation. However, by adding interaction to visual representations, this gap can be bridged. If interaction is designed properly, a strong coupling forms between the mental processes of a user and a VMST (Figure 2.1). This coupling provides support for performing complex cognitive activities (Brey, 2005; Clark, 1998; Hoc, 2005; Kirsh, 1997, 2005, 2010; Sedig et al., 2013-c).

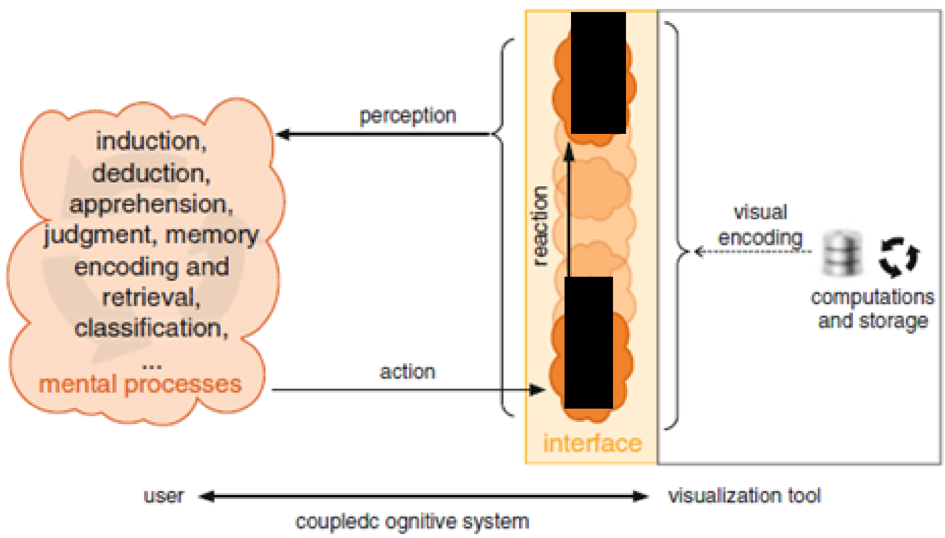


Figure 2.1: The coupling that is formed between a user and a VMST (based on Parson et al., 2013)

In VMSTs which support interaction with visual representations, users can dynamically adapt visual representations to adjust them to their needs. As a visual representation typically encodes only a part of information present in the entire dataset, static visual representations can force users to put in a great deal of mental effort to bring hidden and implicit information to a more observable level (Kirsh, 2003). But, when using interactive visual representations, users can easily and repeatedly act upon visual representations and adapt the visual representations according to their needs (Kirsh et al., 1994; Neth et al., 2002; Schwan, 2002). Dix and Ellis (1998, p. 133) suggest that the ‘‘most important thing about computer visualization is interaction.’’ Interaction can extend the communicative power of static visual representations (Sedig et al., 2006-b).

In this thesis, interaction is thought of as a communication loop (Kirsh, 1997), through which users can have discourse with visual representations (Thomas et al., 2005) to support performance of complex cognitive activities.

In the next section we shall review prior research on interaction modeling in the visualization research community and examine how other researchers have attempted to define and characterize interactions with visual representations.

2.2. Overview and Classification of Interaction Models

As it was mentioned earlier, appropriate characterization of human-information interaction is essential to achieve a better understanding of the space of interactions supported by a VMST and enable its evaluation and design. A number of models have been developed which do characterize the interactions with information, visual or textual. Table 2.1 summarizes prominent existing models. A few of these models have been developed in the field of information and library science; however they have found use within the visualization research community, especially for visual information retrieval (Becks, 2001;

Morse, 1999). These models fall into two distinct groups: system-oriented and user-oriented. Each of these is discussed in more detail below.

System-oriented models focus on characterizing/describing visualization or data operations. They characterize system actions which are provided to help users reach their goals. For example, Chuah and Roth (1996) define a set of operations, called *basic visualization interactions (BVIs)*, describing various data and visual interaction operations (e.g., *set-graphical-value*). These models are most applicable for representing a system's response to user actions.

In contrast, user-oriented models typically characterize user's cognitive visual behaviours (Gotz, 2008; Bavoil, 2005). For example, Amar et al. (2005) have come up with ten basic task types describing various user needs in interactive information analysis.

Table 2.1 : Units of Some prominent interaction models

Publications	**Units modeled**
System-oriented models	
Shneiderman (1996)	Overview, zoom, filter, details-on-demand, relate, history, and extract
Buja et al. (1996)	Focusing (choice of [projection, aspect ratio, zoom, pan], choice of [variable, order, scale, scale aspect ratio, animation, and 3-D rotation]), linking (brushing as conditioning / sectioning / database query), and arranging views (scatter plot matrix and conditional plot)

Chuah and Roth (1996)	Basic visualization interaction (BVI) operations: graphical operations (encode data, set graphical value, manipulate objects), set operations (create set, delete set, summarize set, other), and data operations (add, delete, derived attributes, other)
Dix and Ellis (1998)	Highlighting and focus, accessing extra information – drill down and hyperlinks, overview and context, same representation / changing parameters, same data / changing representation, linking representation – temporal fusion
Keim (2002)	Dynamic projections, interactive filtering, interactive zooming, interactive distortion, interactive linking and brushing
Wilkinson (2005)	Filtering (categorical/continuous/multiple/fast filtering), navigating (zooming/panning/lens), manipulating (node dragging/categorical reordering), brushing and linking (brush shapes/brush logic/fast brushing), animating (frame animation), rotating, transforming (specification/assembly/display/tap/2 taps/3 taps)
Tweedie (1997)	Interaction types (manual, mechanized, instructable, steerable, and automatic) and directness (direct and indirect manipulation)
Spence (2007)	Interaction modes (continuous, stepped, passive, and composite interaction)
User-oriented models	
Belkin et al. (1993)	Method of interaction (scan vs. search), goal of interaction (learn vs. select), mode of retrieval (recognize vs. specify), resource considered (information vs. meta-information)

Bates (1989)	Footnote chasing, citation searching, journal run, area scanning, subject search in bibliographies and abstracting and indexing service, author searching
Marchionini (1992)	Define the problem, select the source, articulate the problem, examine the results, extract information
Zhou et al. (1998)	Visual grouping, visual attention, visual sequence, visual composition, structuring, encoding, modification, transition
Amar et al. (2005)	Retrieve value, filter, compute derived value, find extremum, sort, determine range, characterize distribution, find anomalies, cluster, and correlate
Valiati et al. (2006)	Identify, Determine, Visualize, Compare, Infer, Configure and Locate

While the units used in the different models are all about interaction, actual units in individual models may vary in their granularity (see Table 2.1). Some models try to categorize low-level interaction techniques (Wilkinson, 2005; Keim, 2002; Dix et al., 1998; Buja et al., 1996; Chuah et al., 1996; Shneiderman, 1996). Some other models provide classification criterion to describe interaction techniques (Spence, 2007; Tweedie, 1997). Similarly, some other models focus on tasks and activities or their classification criteria (Valiati et al., 2006; Amar et al., 2005, Zhou et al., 1998, Belkin et al., 1993; Marchionini, 1992; Bates, 1989). It is interesting to note that this divergence in the units of modeling corresponds rather well to Norman's action cycle (Norman, 2002). Norman's action cycle describes interaction between a user and the world in several steps (forming the goal, forming the intention, specifying an action, executing the action, perceiving the state of the world, interpreting the state of the world, and evaluating the outcome).

In summary, a modeled unit can be a) *low level interaction technique* which is in fact a representation of a system action, b) *class of interaction techniques* which forms a dimension along which one can describe interaction techniques, c) *user task* which is a representation of user actions and d) *class of user tasks* which also forms a dimension along which one can describe user actions.

A model of interaction can be *domain-dependent* or *domain-independent*. Domain-dependent models can be further classified depending on their degree of domain-dependence (e.g. task models for text retrieval in general or task models for retrieving bibliographic data). Domain-independent models of interaction are generalized descriptions of interactions. They can be considered as meta-models from which domain-dependent models can be derived (Becks, 2001).

Another criterion of distinguishing models of interaction is the *type of relationship* between units. Examples for possible relationships are a set, a logical sequence or a hierarchy of tasks.

This categorization of existing interaction models is shown in Table 2.2.

Table 2.2: Unit-based categorization of prominent interaction models

Publications	**Modeled unit**	**Domain**	**Type of relationship**
Shneiderman (1996)	low level interaction techniques	domain-independent	set of interactions
Buja et al. (1996)	low level interaction techniques	domain-independent	set of interactions
Chuah and Roth (1996)	low level interaction techniques	domain-independent	set of interactions

Dix and Ellis (1998)	low level interaction techniques	domain-independent	set of interactions
Keim (2002)	low level interaction techniques	domain-independent	set of interactions
Wilkinson (2005)	low level interaction techniques	domain-independent	set of interactions
Tweedie (1997)	interaction technique	domain-independent	classes of interactions
Spence (2007)	interaction technique	domain-independent	classes of interactions
Belkin et al. (1993)	user activity	domain-independent	classes of user tasks
Bates (1989)	user tasks	literature retrieval	set of tasks
Marchionini (1992)	user tasks	retrieval and browsing	sequence of tasks
Zhou and Feiner (1998)	user tasks	domain-independent	hierarchy of tasks
Amar et al. (2005)	user tasks	domain-independent	set of tasks
Valiati et al. (2006)	user tasks	domain-independent	set of tasks

From the units of modeling, it is clear that these models are useful in providing us an understanding of the interaction space of VMSTs at the lower levels (interface features and tasks). But, they are still lacking in a number of aspects important to visual mining, particularly concerning activities at the higher levels. We discuss below as to why the above mentioned models are not able to comprehensively characterize the interaction space of visual mining in a way that they can enable systematic thinking about user interactions with VMSTs which are intended to support complex cognitive activities.

- The models included in the first set in Table 2.1, are system-oriented. They are representing system's response to user activities (Gotz et al., 2008).
- Marchionini's approach is strongly related to goal-directed and query-driven processes instead of allowing the description of complex cognitive activities in visual mining (Becks, 2001; Morse, 1999, Wilson, 1999).
- The Bates model (Bates, 1989) is primarily designed for describing published literature, and oriented mainly to the discipline of library and information science, (Becks, 2001; Morse, 1999, Wilson, 1999).
- The models by Zhou et al. (1998), Amar et al. (2005) and Valiati et al. (2006) characterize interactions at lower levels of human-information interaction (Sedigh et al., 2012, Scholtz, 2006). The high level interactions which are representative of complex cognitive activities are not addressed in these models. Their work is significant from the point of view of classification of the user tasks that users can perform in VMSTs. But they cannot provide explicit classification of complex cognitive activities carried out by analyst users. However, their work is important to us in this research, as we believe that it provides the substrate of user tasks performed to support different complex cognitive activities in visual mining. Hence, as we shall see later, the user tasks which are proposed in the models developed by Valiati et al. (2006) are used by us to provide

appropriate support for complex cognitive activities in the proposed inspection framework proposed as part of our research (this will be discussed in more detail in Chapter 5).

- The model of Belkin et al. (1993) was noted by the authors themselves, that it is limited and in need of possible elaboration and empirical support. In addition it is quite strictly limited to interactions with information aimed explicitly at information seeking (Cool et al., 2002).
- Finally, measuring the effectiveness of a model is difficult itself. This issue is discussed by Beaudouin- Lafon (2004) who proposes three dimensions to evaluate interaction models:
  1) descriptive power, “the ability to describe a significant range of existing interface”;
  2) evaluative power: “the ability to help assess multiple design alternatives”; and
  3) generative power: “the ability to help designers create new designs”.

Based on the above points, none of the models listed above appear to address modeling of interaction space of visual mining at the higher level concerned with support for complex cognitive activities.

For our work, we found the model proposed by Belkin et al., (1993) as being the best suited as a basis to develop an interaction space model whose primary concern is the modeling of complex cognitive activities in visual mining. This is because, as compared to the other user centered models mentioned above, Belkin’s model is unique in identifying the activity tier, a granularity of interactions (high level) which supports information seeking in the information retrieval domain. This model suggests a view of the total process as a kind of user interaction with text, more generally user interaction with information. They attempted to characterize the variety of information interactions in the information seeking process in a way that would be useful for the evaluation and design of the systems to support user information seeking activities.

In Chapter 3, through presentation of the visual mining work-flow, it can be seen that all of the major analysis activities in the visual mining process are also in the form of information interactions, to be specific, interactions with visual representations. Following the same approach as Belkin et al., (1993) we too would like that the information interactions in the visual mining process are characterized through a small set of classification criteria. Goals and intentions leading to different interactions should be identified and visual mining episodes should be comprehensively characterized according to the chosen set of classification criteria. Such a classification scheme would lead us to an interaction space model for visual mining that will largely address the primary research problem mentioned earlier in this thesis. As already mentioned in Chapter 1, the use of such an interaction space model should be demonstrated through its application towards evaluating the specific interaction space instance of any given VMST. In the next section, we provide a review of existing evaluation methods for interaction spaces of VMSTs.

2.3. Related Work on Evaluation of Interactions Supported by a VMST

In this section, previous related efforts in the field of visualization evaluation are examined. It discusses previous research closely related to the inspection framework proposed in this thesis in some detail so as to provide a perspective on how our approach compares.

2.3.1. Existing Visualization Evaluation Methods

A large number of evaluations have been conducted measuring the effectiveness of VMSTs using the following methods:

1. Controlled experiments: This is a short-term evaluation, which consists of several different controlled experiments conducted over a short period of time. These experiments usually measure the time to perform the task and quality of the performed task (Espinosa, 2000). The study subjects are asked to perform a list of tasks and the evaluator observes and records the performance time. The dependent variables are usually accuracy and efficiency measures. Accuracy measures include precision, the average number of incorrect answers and error rate. Efficiency measures typically include the average time to complete the tasks (Chen et al., 2000).

We give two examples of controlled experiments as follows: (1) interface and data architecture for query preview in networked information systems evaluation (Plaisant et al., 1999), and (2) spatial ability and visual navigation evaluation (Chen et al., 1997). The strength of this method is that it can accurately measure the accuracy, efficiency, and other properties of a tool. Evaluation using controlled experiments has helped researchers to compare a new tool with an existing tool, which is considered to be the standard tool or a cutting edge technology tool (Plaisant et al., 2002; Wiss et al., 1998).

2. Usability: This approach is also a short term approach. Usability is the most common evaluation method along with controlled experiments (Chen et al, 2000). It typically focuses on usability issues concerning the tool interfaces. A Usability evaluation method usually involves a usability survey or a "think aloud" protocol as an evaluator observes participants performing tasks with a tool or just simply using a tool. It identifies problems encountered while performing tasks, provides feedback on those problems, and helps to provide a new solution. In these evaluations, the study subjects are important because a lot of the outcome depends on the ability of the participants. Some examples of usability evaluations are tree visualization systems (Kosba, 2004) and usability evaluations of Bifocal Browser (Freitas, 2002). The strength of usability evaluation method is that it gives value to user opinions.

3. Comparing two or more tools: This is another short-term evaluation. Although there are cases reported where such comparative evaluations have been conducted with methods such as usability evaluation (Kobsa, 2004), a controlled experiment is the most common method used. This is because results of controlled experiments are easy to compare. The approach typically compares a number of tools and their particular features and design elements. Most of the time, the evaluation compares a new tool with another standard or cutting edge tool. Some examples include: comparison of SpaceTree with Microsoft explorer and hyperbolic tree browser (Plaisant et al., 2002) and comparison of different three dimensional information visualization designs (Wiss et al., 1998). The strength of this approach is that the evaluation method can highlight the improvements and the differences of the multiple tools being compared.

4. Inspection: These methods are possible through the involvement of expert evaluators, who inspect the user interface and provide judgments based on their knowledge. For example heuristic evaluation method focuses on finding usability problems in a user interface design by comparing interface design with several recognized usability principles by expert users (Nielsen et al., 1990). Another method in this group is known as cognitive walk through, where experts step through scenarios of use repeatedly asking questions regarding the intuitiveness of the interface design. The strength of these methods is that it values expert view of usability and it effectively and efficiently evaluates interaction mechanism aspects of a tool. Also, like other short-term evaluation, it is time efficient.

5. Insight-based: This is a newly introduced evaluation approach by Saraiya (Saraiya et al., 2005; Saraiya et al, 2004). An empirical study measures insight. This method allows evaluators to quantify insight using different characteristics.

6. Field/longitudinal studies: Field studies are different from the other evaluation methods because they are conducted in natural settings. Their goal is to understand what users do naturally and how technology impacts on them. They are useful for discovering the effectiveness, problems, and actual use of a tool in a real daily work environment over a longer period of time. Their use is beneficial when dealing with complex data, such as biology data which need a longer period of time to analyze and evaluation results may not be accurate if short-term evaluation methods are used (Plaisant, 2004). Short-term methods, such as controlled evaluation, are limited in a sense that they are conducted under controlled environments under a given period of time. Since insight may have to be gained by analyzing visual representation from different perspectives over a long period of time, a short-term evaluation cannot address this aspect of the tool (Park, 2008).

2.3.2. Major Challenges in Evaluation of VMSTs

In practice, most of the evaluations in the field of visualization are oriented towards usability evaluation and controlled experiments (empirical methods) in which evaluation is done through user participation (Thomas et al., 2005; Feritas et al., 2014; Carpendale, 2008; Tory et al., 2004). There are many challenges in evaluating a VMST. Most of them are common to all empirical research. The major challenges are discussed further below.

Focus, Questions and Methodology

In all empirical research it is difficult to choose the right focus and to ask the right questions. Given interesting questions, it is difficult to choose the right methodology and to be sufficiently rigorous in procedure and data collection. In addition, appropriate data analysis is difficult and the most difficult of all is relating a new set of results to previous research and to existing theory (Carpendale, 2008).

Time Availability of Appropriate Experts

Obtaining an appropriate sample of participants is always difficult. Usually VMSTs are intended for domain experts and it can be hard to obtain the required amounts of their time for evaluation (Plaisant, 2004).

The Need for Large Number of Participants

Results of empirical evaluations with users depend on the background knowledge, experience, and ability of participants. Therefore a large number of participants are preferred for producing reliable results from the experiment, which makes it expensive and time consuming.

Difficulty in Including Complex High Level Tasks During Evaluation

Empirical evaluations of human information interaction generally include only simple tasks such as locate, identify, etc. Other tasks such as requiring users to compare, associate, distinguish, categorize or etc are rarely covered (Komlodi, 2004). Visual mining with VMSTs also involves performance of variety of complex high-level tasks (complex cognitive activities) which are challenging to test empirically in short time. Many complex cognitive activities can require weeks or months to complete.

Dependence of Results on Choice of Test Data

The test data used in empirical evaluations significantly affects the end result. As discussed by Plaisant (2004), there are two approaches: 1) to use real data gathered from real-world instances; 2) to use synthetically generated data. While use of real data may enhance external validity of the evaluation it may not be possible to determine ground truth and therefore to generate useful performance metrics. The real datasets can be interpreted in multiple ways, leading to ambiguous test results. Synthetic data provides an opportunity to insert known data that provides ground truth. However the validity of an experiment with synthetic data may not be applicable to real-world situations. Synthetic data may not reflect the operational environment.

Unbiased Comparison of Different VMSTs

In the case of ***comparing two or more VMSTs***, a major problem is that they often report overall performance for a combined set of tasks. The composition of a set of tasks can favor one tool or another when measuring overall performance, therefore introducing a bias (Plaisant, 2004). Also it is likely that participants may be much more familiar with the existing software and that this may skew the results. The other weaknesses of the method are that it requires having the "standard" tool to compare against.

Subjectivity Introduced by Participant Knowledge and Expertise

The weakness of using ***inspection methods*** are that results may be subjective and influenced by the knowledge of the expert performing the evaluation. According to Nielsen et al. (1990), the result can be varied by an evaluator's ability to find problems. In addition, performing inspection methods with VMSTs are challenging. Because these techniques are (for the most part) designed for traditional user interface testing, it is not clear how well they will be able to evaluate the interaction space VMSTs. For example, walking through a complex cognitive task is very different from walking through a well-defined interface manipulation task (Tory et al., 2004). Also, heuristic evaluations can be challenging because few guidelines exist specific to user interaction while performing in visual environment (Feritas et al., 2014).

Insight is Hard to Measure

In the case of ***insight based approach***, usually what exactly insight is varies from person to person and instance to instance therefore it is hard to define and consequently hard to measure it. Plaisant (2004) describes this challenge as "answering questions you didn't know you had." While it is possible to ask participants what they have learned about a dataset after use of a given VMST, the answer strongly depends on the participants' motivation, their previous knowledge about the domain, and their interest in the dataset (Carpendale, 2008; North, 2006; Saraiya et al., 2005). Development of insight is difficult to measure because in a realistic work setting it is not always possible to trace whether a successful discovery was made through the use of a VMST. This is because many factors might have played a role in the discovery. Insight is also temporally elusive in that, insight triggered by a given VMST may take place hours, days, or even weeks after the actual interaction with the VMST.

In practice, only short-term insight evaluations have been performed. Authors of this evaluation approach explicitly explained their need for conducting a longitudinal study over a longer period of time to obtain valuable conclusions (Saraiya et al., 2005).

Field Evaluations are Lengthy and Expensive

The challenge of ***field studies/longitudinal studies*** is that they are time consuming to conduct, and results may not be replicable or generalizable (Plaisant, 2004). In addition, evaluating usability in the field is difficult, due to the complexity of the environment and the activities to be observed, and to the large amount of data to be analysed (Pascoe et al., 2000). Overall, this approach is lengthy and expensive.

Table 2.3 provides a summary of disadvantages of above mentioned evaluation methods.

Table 2.3: Summary of challenges in current evaluation methods

Method	Challenges
Controlled experiments evaluation	-absence of realistic data sets reduces validity. -difficulty in obtaining sufficient number of participants. - requires large number of participants. -expensive and time consuming.
Usability evaluation	-difficulty in obtaining sufficient number of participants. - results may be subjective based on the background. knowledge, experience, and ability of experiment participants. - requires large number of participants. expensive and time consuming.
Comparing two or more tools	-it requires having the "standard" tool -difficulty in obtaining sufficient number of participants - requires large number of participants.
Inspection methods evaluation	-results may be subjective. -usually designed for traditional user interfaces.
Insight-based evaluation	-it is hard to measure. -requires long term studies. -in practice, only a short-term study has been performed to measure insight.
Field studies/longitudinal studies	-often lengthy and expensive. -different backgrounds and experience of experiment. participants leads to wide variation in performance.

In summary, most of existing evaluation methods, from the traditional controlled experiments and usability evaluation to more recent ones such as quantifiable insights, are inherently biased towards the outcomes of using VMSTs by users

(Liu et al., 2010). In addition, the big downside of controlled experiments and usability evaluation which form the backbone of evaluations today (Chen et al., 2000) is the uncertainty of actual integration of the VMST into the real work setting (Park, 2008). They are conducted in a laboratory environment with limited number of low level tasks and often unrelated field data sets. The absence of realistic data sets and high level cognitive activities reduces the effectiveness of these evaluations in terms of the appropriateness of the tool for a given domain. As it can be seen from Table 2.3, most of the methods are subjective and/or lengthy and expensive, hard to measure considering the complex nature of visualization and need large number of participants. In this thesis we provide a new inspection framework based on our proposed model of interaction space of visual mining. This inspection framework tries to address many of the challenges presented by existing evaluation methods. The inspection framework and its benefits will be described in more detail later in Chapter 5.

2.4. Summary

In this chapter we first drew attention to the importance of interaction in visualization research. While existing research in the area often focuses much more on transformation of raw data into visual representations and their presentation, this chapter highlights the overshadowed, but very important interaction component. In this chapter we strongly argue that it is primarily interaction which provides a way to overcome the limits of representation and to suitably augment a user's cognition. We have discussed how VMSTs mediate and supplement human cognition to enable complex cognitive activities. Due to their interactive nature, VMSTs allow users to perform actions on visual representations that facilitate mental information processing. This creates a strong coupling between the user and a VMST and allows the VMST to become an active participant in the user's cognitive processes. When using a VMST, to perform complex cognitive activities, users engage in an interaction cycle in which they perceive visual representations, interpret them and perform other mental operations, act upon them and so on to reach their goal. Next, we bring out the importance of having interaction space models which appropriately characterize complex cognitive activities which humans perform during visual mining. Such a model can help us in the evaluation of the support provided by existing VMSTs for such activities and can also help us in the process of designing the interaction space of VMSTs.

We have reviewed and classified existing prominent models of interaction related to visualization. We have brought out the short-comings of existing models and clearly noted the need for providing high level characterization of interactions that can guide the analysis, evaluation and design of interactions supported by VMSTs in ways that provide better support for complex cognitive activities. Lastly, we have reviewed different methods of evaluating visual mining interactions using a VMST and the major challenges in using these evaluation methods.

Chapter 3 : The Visual Mining Workflow

Belkin et al., (1993) model the interaction space of information seeking with the help of classification criteria which characterize complex cognitive activities in information seeking and allow us to define information seeking strategies covering the interaction space. Each classification criterion can take different values. As was previously mentioned, we wish to use this model as our basis and define visual mining strategies which will cover the interaction space of visual mining. For this we need to discover the classification criteria for visual mining activities. This will be done through *qualitative directed-content analysis* of a comprehensive list of publications reporting case studies concerned with visual mining activities in different domains. The initial set of criteria will be defined by identifying all the interactions which have taken place in visual mining, as gathered from many different case studies.

In the first part of this chapter, we will provide some background on qualitative content analysis techniques. This background is necessary for understanding the specific methods we have adopted and described in Chapter 4 for discovery of classification criteria for visual mining. In the second part, we will develop a comprehensive work-flow description of the visual mining process. This visual mining workflow includes all the analysis activities and information interactions, described at a high level, which take place during the process of visual mining. Using this visual workflow we will be to identify a comprehensive set of interactions which take place in visual mining. This comprehensive set of interactions will be used in Chapter 4 to create the initial set of criteria, which get refined by qualitative directed-content analysis.

3.1. Content Analysis

Content analysis refers to a research technique which is used to analyse written, verbal or visual communication messages (Cole, 1988). As a research method, it is a systematic and objective way of describing and quantifying phenomena (Krippendorff, 2004; Sandelowski, 1995; Downe-Wamboldt, 1992). It is also known as a method of analysing documents (Elo et al., 2008).

Through content analysis, researchers can test theoretical issues to enhance understanding of the data. It makes it possible to condense words into fewer content related categories with the assumption that when classified into the same categories, words, phrases, or even bigger text chunks share the same meaning (Cavanagh, 1997). Like other techniques, it is essential to be able to provide defensible inference based on valid and reliable data collection (Lewis-Beck, 1995).

There are two types of content analysis: qualitative and quantitative (Hsieh et al., 2005, Krippendorff, 2004). In the beginning, content analysis was used as a quantitative research method, with text data coded into explicit categories and then described using statistics. Later on, the potential of content analysis as a method of qualitative analysis was recognized which further led to its increased application and popularity (Nandy et al., 1997). Qualitative content analysis has been defined as “a research method for the subjective interpretation of the content of text data through the systematic classification process of coding and identifying themes or patterns” (Hsieh et al, 2005, p.1278).

The quantitative content analysis approach is deductive and is used to test hypotheses or address questions generated from theories. By contrast, qualitative content analysis is inductive and attempts to generate theory. Since the qualitative content analysis approach is used in this research, quantitative content analysis will not be discussed further. More details of the qualitative content analysis process will be given in the following subsections.

3.1.1. Qualitative Content Analysis Approach

The qualitative content analysis process uses inductive reasoning to condense raw data into categories or themes based on valid inference and interpretation. In inductive reasoning, themes and categories emerge from the data through careful examination and constant comparison by the researcher (Zhang et al., 2009). Hsieh and Shannon (2005) introduced three approaches to qualitative content analysis based upon the degree of involvement of inductive reasoning:

- Conventional qualitative content analysis: in this approach, coding categories are derived directly and inductively from the raw data. The purpose of this approach is usually to develop a grounded theory.
- Directed-content analysis: in this approach, initial coding starts with a theory or relevant research findings. Then, during data analysis, the

researchers immerse themselves in the data and allow themes to emerge from the data. The approach is normally used to validate or extend a conceptual framework or theory.

- Summative content analysis: this approach starts with the counting of words then extends the analysis to include hidden themes and meanings. It looks quantitative in the early stages, but its goal is to investigate the usage of the words, phrases or chunks in an inductive manner.

The analysis approach that is used in this research falls into the second category which is directed-content analysis. The initial classification criteria are extracted (a procedure termed as coding) from a comprehensive workflow representation of visual mining process. The workflow description is provided in a later section in this chapter. These initial criteria are continuously refined and finalized after coding a large number of published articles describing actual case studies of visual mining activities carried out by experts in different application domains (more details are given in Chapter 4).

3.1.2. The Process of Qualitative Content Analysis

A key feature of content analysis is that the many words of the text are classified into much smaller set of content categories (Weber, 1990; Burnard, 1996). Qualitative content analysis involves a set of systematic procedures for processing data to support valid and reliable inferences. Some of the steps overlap with the quantitative content analysis procedures (Tesch, 1990), while others are unique to the qualitative content analysis.

3.1.2.1. Preparation

The preparation phase starts by selecting the unit of analysis (McCain, 1988; Cavanagh, 1997; Guthrie et al., 2004). The unit of analysis is the basic unit of text to be classified during content analysis. Unit of analysis can be a word or a theme (Polit et al., 2004). Qualitative content analysis usually uses individual themes as the unit for analysis, rather than the physical linguistic units (e.g., word, sentence, or paragraph) which are most often used in quantitative content analysis. An instance of a theme might be expressed in a single word, a phrase, a sentence, a paragraph, or an entire document (Zhang et al., 2009).

Themes primarily are expressions of an idea therefore a code might be assigned to a text chunk of any size as long as that chunk represents a single theme or issue relevant to the research question (Minichiello et al., 1990).

3.1.2.2. Inductive Analysis

In this phase researchers organize the data. It includes open coding, creating categories and abstraction. During open coding, notes and headings are written in the text while reading it. The written material is read again. As many headings as necessary are identified and written down again to describe all aspects of the content (Burnard, 1991, 1996; Hsieh et al., 2005). The headings are transferred to coding sheets (Cole, 1988; Downe-Wamboldt, 1992; Dey 1993) and categories are generated at this stage (Burnard, 1991).

After open coding, the lists of categories are grouped under higher order headings (McCain, 1988; Burnard, 1991). The aim of grouping categories is to reduce the number of categories by putting similar ones into broader higher order categories (Burnard, 1991; Downe-Wamboldt, 1992; Dey, 1993). In this stage, constant comparison method is highly recommended (Glaser et al., 1967), because it is not only able to emerge new insights, but is also able to make differences between categories clear. The constant comparison method is based on (1) the comparison of each text assigned to a category with each of those already assigned to that category, in order to fully understand the theoretical properties of the category; and (2) integrating categories and their properties through the development of interpretive memos (Zhang et al., 2009).

After creating categories, the content analysis researcher formulates a general description of the research topic through generation of categories (Robson, 1993; Burnard, 1996; Polit et al., 2004). Each category is named. Similar subcategories are grouped together as categories, categories are grouped as main categories, and so on (Dey, 1993; Robson, 1993; Kyngas et al., 1999). The abstraction process continues as far as possible.

This step involves making sense of the themes or categories identified, and their properties. At this stage, the content analysis researcher will make inferences and present their reconstructions of meanings derived from the data. This usually involves the researcher exploring the properties and dimensions of categories, identifying relationships between categories, uncovering patterns, and testing categories against the full range of data (Bradley, 1993).

Let us recall that the categories we are interested in are those which will help us characterize complex cognitive activities in visual mining which are performed in the form of interactions with visual representations of raw data. These are at the conceptual/theme level and may be present in the published papers either as phrases, sentences or larger chunks of text. Coding of the content of these publications has to be done by keeping this in mind.

3.1.2.3. Report Methods and Findings

For the study to be replicable, the analytical procedures and processes should be reported completely and truthfully as possible (Patton, 2002). In addition, the decisions about the coding processes, decisions and methods used to establish the trustworthiness of study (discussed below) should be described.

Presenting research findings of qualitative content analysis is challenging because it does not produce counts and statistical significance. Instead, it discovers patterns, themes, and categories important to a social reality.

In the past it was a common practice to use a typical quotation to justify conclusions which is prone to mistakes and bias (Schilling, 2006). Miles and Huberman (1994) recommended other options for data display, including matrices, graphs, charts, and conceptual networks. The form of reporting finally depends on the research questions and goals (Patton, 2002).

It is recommended that in the reports, there should be a balance between description and interpretation. Description gives readers background and context therefore it should be rich and thick (Denzin, 1989). Interpretation represents researcher personal and theoretical understanding of the phenomenon under study. An interesting and readable report "provides sufficient description to allow the reader to understand the basis for an interpretation, and sufficient interpretation to allow the reader to understand the description" (Patton, 2002).

3.1.2.3.1. Trustworthiness

Credibility, dependability, confirmability, and transferability are the established trustworthiness criteria for qualitative research (Erlandson et al., 1993; Lincoln et al., 1985; Patton, 1990).

Credibility is guaranteed truthfulness of the research report (Erlandson et al., 1993; Lincoln et al., 1985; Patton, 1990). Lincoln and Guba (1985) recommended a number of methods that would help improve the credibility of the research results: prolonged engagement in the field, persistent observation, triangulation, negative case analysis, checking interpretations against raw data, peer debriefing, and member checking. To improve the credibility of qualitative content analysis, researchers not only need to design data collection strategies that are able to adequately solicit the representations, but also to design transparent processes for coding and drawing conclusions from the raw data.

Coders' knowledge and experience have significant impact on the credibility of research results. It is necessary to provide coders precise coding definitions and clear coding procedures. It is also helpful to prepare coders through a comprehensive training program (Weber, 1990).

Transferability refers to external validity. It depends on the extent to which the working hypothesis of the researcher can be applied to another context.

It is not the researcher's job to provide an index of transferability. However, the researcher is responsible for providing rich data sets and descriptions which makes it possible for other researchers to be able to apply the researcher's findings to other contexts.

Dependability refers to the criterion of consistency (Lincoln et al., 1985). Bradley (1993) defines it as "the coherence of the internal process and the way the researcher accounts for changing conditions in the phenomena".

Confirmability depends upon the degree to which the findings result from data and not from researcher bias. It is supported through an audit trail (Lincoln et al., 1985), which is a major technique for establishing confirmability. It is done by checking the internal coherence of the research products i.e. the data, the findings, the interpretations, and the recommendations. The materials that could be used in these audits include raw data, field notes, theoretical notes and memos, coding manuals, process notes, and so on (Zhang et al., 2009).

3.1.3. Computer Support for Qualitative Content Analysis

Qualitative content analysis is usually supported by software tools such as NVivo 9 and ATLAS.ti. The objective of using these software tools is to assist researchers in organizing, managing, and coding qualitative data more efficiently. The main functions that are usually supported are: text editing, note and memo taking, coding, text retrieval, and node/category manipulation. The visual presentation module of these software tools provides good support for researchers to see the relationships between categories and to discover patterns in data. Some programs even record a coding history to allow researchers to keep track of the evolution of their interpretations. In our research, we used NVivo 9 software for performing qualitative content analysis. This is explained in more detail in Chapter 4.

3.2. Visual Mining Workflow

As it was explained in Chapter 1, visual mining refers to the human analytical process that uses visual representations of raw data and makes suitable inferences. It is the process which uses the visual medium (through visual representations) and contributes to the discovery of patterns and relationships, which then form the knowledge required for informed decision making.

In this process, users interact directly with visual representation, analyze, gain insight and perhaps even formulate a new hypothesis. Later on, the user can evaluate the best possible hypotheses and make a judgment based upon it. In fact, this visual information exploration process helps to form the knowledge for informed decision making.

In this process, the user creates a mental picture and speaks of the mind's eye, when saying "I see" to indicate understanding and to express the connection among vision, visualization, and reasoning. It involves the user in analytical reasoning. As stated by Thomas and Cook (2005): "Analytical reasoning is central to the analyst's task of applying human judgments to reach conclusions from a combination of evidence and assumptions". By applying analytical reasoning, hypotheses about the data can be generated, confirmed and discarded. This eventually leads to a better understanding of the data and supports the analysts in their task to gain insight (Keim et al., 2008).

In order to identify analysis activities and user interactions with visual representations in visual mining, we first have a detailed look at how the human analysis process works.

The analytical process itself is both structured and disciplined. Usually, analysts are asked to perform several different types of tasks such as assessing, forecasting and developing options (Thomas et al., 2005). Assessing requires the analyst to describe their understanding of the present world around them and explain the past. Forecasting requires that they estimate future capabilities, threats, vulnerabilities, and opportunities. Finally, options are developed in order to establish different possible reactions to potential events and to assess their effectiveness and implications.

The analytical process begins with planning. The analysts must determine when and how to address the issue, what resources to use, and how to allocate time to various parts of the process. Then, they must gather relevant information and evidence in order to relate them to their existing knowledge. Next, they are required to generate multiple candidate explanations in the form of hypotheses. Then, they evaluate these hypotheses based on the evidence and assumptions to reach a judgment about which hypothesis is the most likely. Once conclusions have been reached, the analysts broaden their way of thinking to include other explanations that were not previously considered and provide a summary of the judgments they had made (Thomas et al., 2005).

Building upon the above description of the analytical process, we have created the visual mining workflow with all its activities as shown in Figure 3.1.

From this work-flow, it can be seen that all complex cognitive activities are in the form of interactions with information which cover the four primary areas of peoples' interaction with interaction: a) interact; b) find; c) interpret and d) use (Albers, 2008).

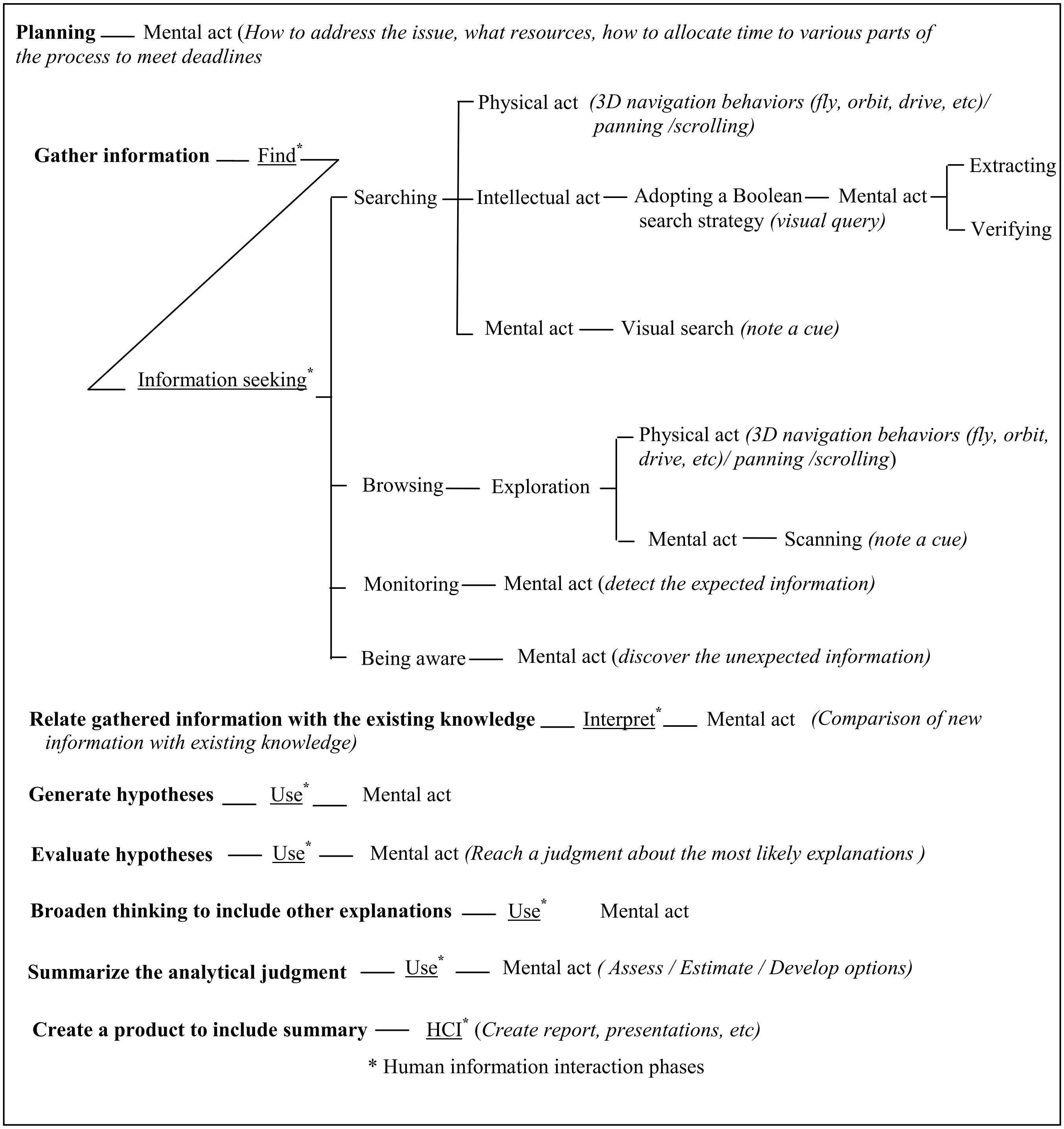


Figure 3.1: Work-flow of the visual mining process

Interaction itself is defined by Marchionini (2008) as being a special kind of action that involves two or more entities and a set of reciprocities which effect changes to each entity. In order to characterize an interaction, it is necessary to specify the entities and the nature of each action. In the case of human information interaction, quite naturally he considers humans and information as the entities. Furthermore, he categorizes actions as mental and physical. Using this categorization, the various components of the visual mining work-flow are shown in Figure 3.1 and described in further detail next.

The sequence of events used by the analyst in the above work-flow chart is as follows:

a) The analyst initiates the visual mining process by planning which issue(s), and when and how to address it (them), what resources to use and how to allocate time to various parts of the process to meet deadlines. The next step is to gather all relevant information by seeking information through searching, browsing, monitoring and generally being aware (Bates, 2002).

b) Searching refers to active attempts to answer questions, look for a specific item or develop understanding around a question or topic area. During the searching process, the analyst is involved in physical, intellectual and mental acts. Physical acts are at the level of human computer interaction and involve clicking on a link, panning and scrolling, etc. In a 3D virtual environment, there also could be more elaborate navigation behavior exhibited such as drive, fly, and orbit that involve using a pointing device (digital stylus or mouse) or gestures to control the view platform. At the intellectual level, the analyst may adopt a Boolean search strategy which also involves mental acts such as extracting and verifying the relevance of information retrieved. Also, sometimes searching itself involves mental acts. For example in the case of a visual search, the analyst may note a cue.

c) Browsing is an active yet undirected form of behavior. For example, when performing physical acts such as 3D navigation or panning and scrolling, the analyst has no special information need or interest, but becomes actively exposed to possible new information. From this mental act, patterns may be discovered and any useful cue would be noted.

d) Monitoring is a passive but directed behavior. In this mental act, the analyst does not feel such a pressing need to engage in an active effort to gather interested information but may be motivated to take note of any expected information as it goes by. Also, when the analyst has a question in mind, and may not be specifically acting to find an answer, they would take note of any relevant information that appears.

e) Being aware is a passive undirected behavior and is similar to browsing in a way that an analyst may find information that they need to know. It is a mental act of detecting unexpected information.

f) The next step in the VM process is to relate the findings with the knowledge in the expert's mind. In this mental act, the analyst interprets information based on their experience and knowledge.

g) Based on the findings, the analyst then generates multiple candidate explanations in the form of hypotheses. Again this is a mental act. By applying analytical reasoning the analyst can use their prerogative to either confirm or reject any hypothesis and formulate a judgment about which ones are the most relevant.

h) Once conclusions have been reached, the analyst will be engaged in the mental act of broadening their thinking to include other possible explanations that were not previously considered. Then the analyst summarizes the analytical judgment either as assessment, estimation or evaluation of options depending on the goal.

i) As the concluding step, the analyst usually creates a product to include the analytical judgment in the form of reports, presentations or whatever other form of communication is deemed appropriate.

3.3. Summary

In this chapter we provided an overview of background concepts and terms about qualitative directed-content analysis which are necessary for understanding the methods used and described in the next chapter. We also provide a detailed description of human analysis process, in order to identify analysis activities and user interaction with visual representations in visual mining. Then building upon the description of the analytical process, the visual mining workflow was created which includes all complex cognitive activities in the visual mining process. In the next chapter we will identify all the interactive activities from this visual mining workflow and develop the initial classification criteria.

Chapter 4 : Visual Mining Strategies Model

In this chapter we describe the process which has resulted in the discovery of the set of classification criteria that characterize the interaction space of visual mining. Qualitative directed-content analysis methods have been used to reveal the visual mining activities carried out by human analysts and reported in scientific publications as visual mining case studies. The publications chosen, in general, clearly record the behavior of experts while being engaged in visual mining activities. We also describe how the naturalistic methods recommended by Lincoln and Guba are applied to ensure that the content analysis is credible, transferable, dependable and confirmable. Furthermore, using examples in four different domains (medical, geographical, bioinformatics and epidemiology) we demonstrate that the proposed interaction space model can comprehensively capture visual mining activities.

4.1. Discovery of Classification Criteria

Surveys and interviews are the most common research methods for studying user interactions with information (McKechine et al., 2002). As we know, in a typical user study or survey, the user's motivation, knowledge and expertise considerably influence user performance and, thus, the final conclusions. Of course, using domain experts provides more realistic results (Plaisant, 2004). However, it is not easy to employ adequate number of participants (domain experts) for interviews and surveys in this type of study, nor is it possible to have access to them for any extended period of time because most of the experts work in many different institutions that are widely dispersed geographically. Therefore we have turned to scientific publications which, in general, clearly record the behavior of expert analysts while being engaged in visual mining activities and, equally importantly, are also peer reviewed. By adopting qualitative directed-content analysis methods (Kyngas et al., 1999), we will reveal the visual mining activities of expert analysts from case studies reported in such publications. As we have mentioned in the preceding chapter, qualitative content analysis is an unobtrusive method which uses nonliving form of data, generally categorized as texts, of which, one kind that can be used for qualitative data inquiry in content analysis is official publications (Patton, 2002; Bhowmick et al., 2007). The three main advantages of working with prior published works are:

1) The data are stable and non-changing,
2) The data exists in the world regardless of any research that is currently being undertaken (Hesse-Biber, 2006), and further is independent of the research itself because the data is not influenced through the researcher's interaction as is the case with interviews, and:
3) They provide information about procedures and past decisions carried out by visualization and domain experts, possibly over long periods of intense study, which could not have been observed by usability researchers in a short usability study (Patton, 1990).

Through analysis of end-results of visual mining activities as they were described in published scientific literature, we obtained the information on work practices. The naturalistic methods recommended by Lincoln and Guba were applied to ensure that the content analysis was (to the extent possible) credible, transferable, dependable and confirmable.

4.1.1. Brief Description of Chosen Content

For our content-matter, we initially chose around sixty published papers primarily concerned with reports on effective use of visualization for analysis and mining of large datasets. The chosen papers were from four different domains, namely, medicine, bioinformatics, epidemiology and geoscience. Each paper was studied and those which did not report actual case studies by expert analysts were excluded from further consideration. The final numbers of papers which contained case studies that described expert analyst's interaction with visual information in each domain are given in Table 4.1. Every one of these papers was analyzed and used in the information interaction coding process described next. Table A.1 in Appendix A includes the list of publications which have been used.

Table 4.1: Numbers of papers analyzed in each domain for qualitative content analysis

Domain	**Number of papers initially chosen**	**Number of papers excluded from further analysis**	**Final numbers of papers analyzed**
Medical	19	10	8
Geoscience	19	8	11
Bioinformatics	13	5	8
Epidemiology	10	7	2

4.1.2. The Coding of Visual Information Interactions

As mentioned above, use was made of naturalistic inquiry analyses which is inductive and often uses the constant comparison method (Glaser et al., 1967; Lincoln et al., 1985). Restating from Glaser and Strauss (1967), constant comparison can be simply described as follows: "while coding an incident for a category, compare it with the previous incidents in the same category". Coding is the label provided by qualitative theorists to the process of data conceptualization. It is a transcript containing an idea which the researcher recognizes as belonging to a significant concept and labels the material to specify a link between data and concept (Foster, 2003). In this study, any interaction between user (expert analyst) and visual information is coded. Coding took place via three main iterations over an extended period of time. The coding of concepts in each paper began with manual annotation of papers during the process of close reading of case studies in papers to highlight each concept (visual information interaction) and label it. This process exactly corresponds to the unitization or open coding process. Subsequent iterations of reading and coding of concepts in each paper was constantly compared with previous papers.

The development of coding, including the renaming and definition of categories was facilitated by using NVivo 9 software, which was used to manage the coding process.

NVivo 9 is very useful when one is working with unstructured information such as documents, surveys, audio, video and pictures in order to assist in better decision-making (QSR International website, 2014). NVivo 9 allowed us to code relevant user interactions with visual information extracted from the articles and to assign them to nodes which can be hierarchical (tree nodes) or non-hierarchical (free nodes) as desired. In our case, the relevant visualization related interactions were first coded as free nodes. Then, after analyzing a number of articles and comparing the interaction nodes with previous ones, they were either modified to tree nodes, renamed or deleted as required. We found that coding with NVivo 9 was convenient since it allowed adding, renaming, deleting or merging of codes as required but it did not, however, automate the coding process. The coding in NVivo 9 took place in multiple stages as described next.

(1) The work-flow of visual mining was used to develop the initial coding scheme (Kyngas et al., 1999). Figure 4.1 shows a static model of coding during this first stage. As analysis proceeded, additional codes were developed and this initial coding scheme was revised and got refined.

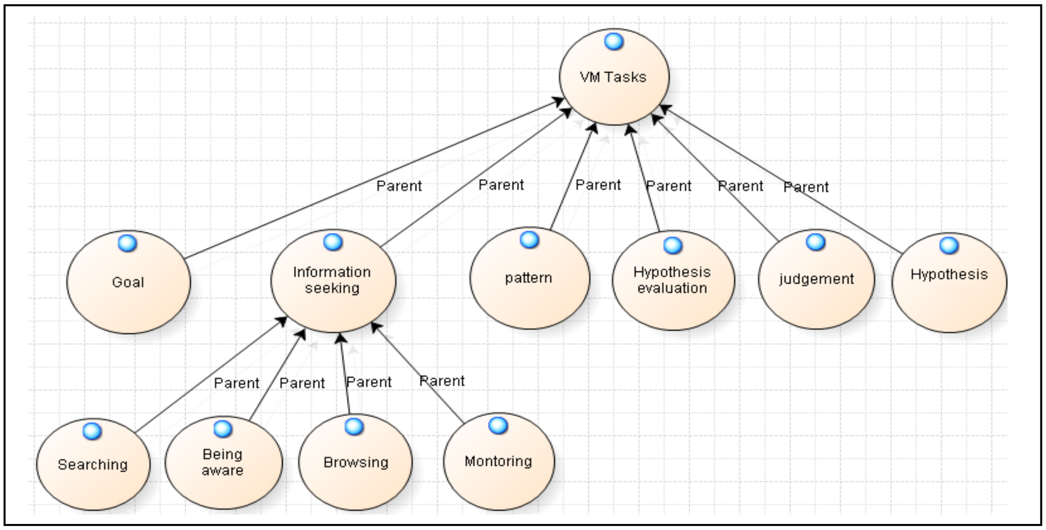


Figure 4.1: NVivo model corresponding to first iteration of coding

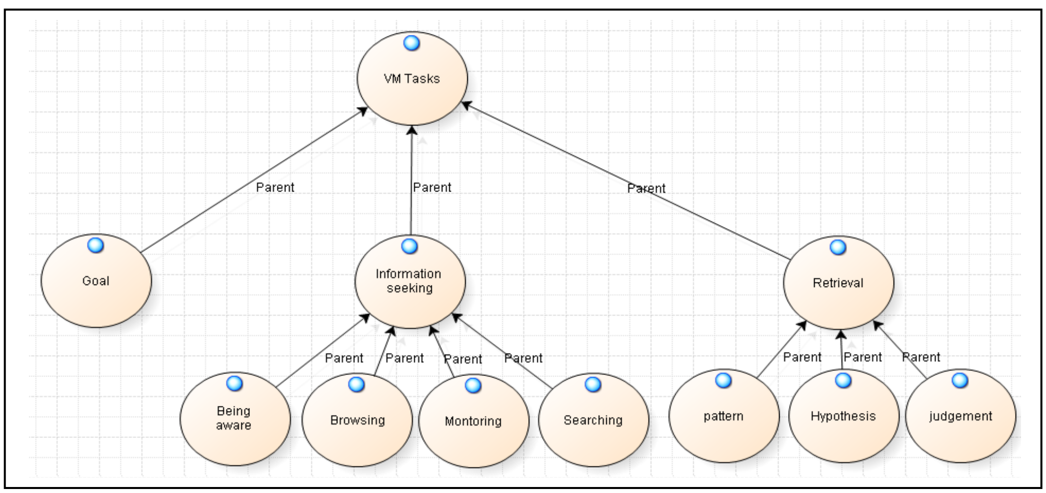


Figure 4.2: NVivo model corresponding to second iteration of coding

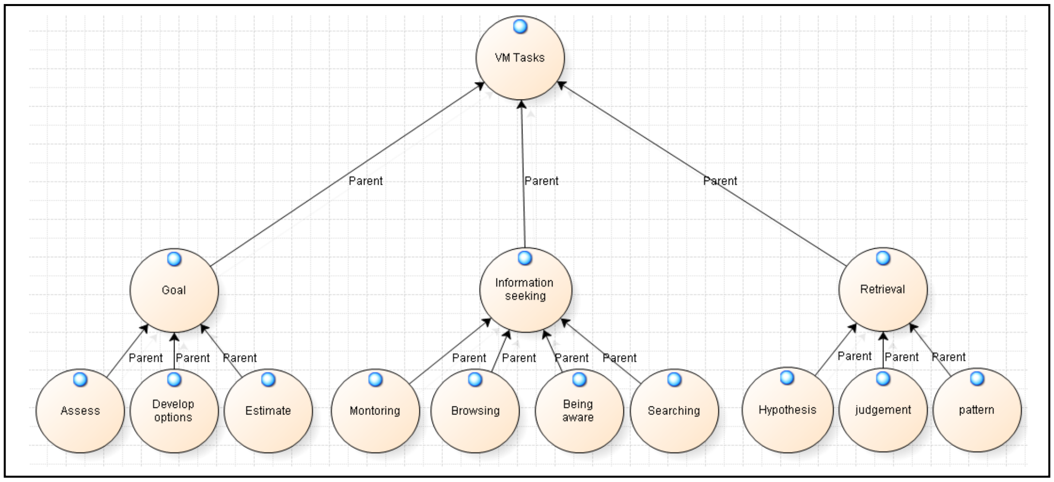


Figure 4.3: NVivo model corresponding to third iteration of coding

(2) One additional coder was recruited. She was a PhD student and had background knowledge about using VMSTs for data analysis. She was required to carefully read the initial coding scheme. The questions about the initial coding scheme raised by the coder were answered. The two coders separately coded the 10 sample papers. They discussed the major inconsistent results and agreed on new coding rules. In the second stage they coded 10 more papers and again checked for inconsistencies and agreed on new coding. In the final stage, they repeated the same process with remaining papers.

(3) The issue of consistent coding was addressed by performing several iterations of coding spread over a period of about a year.

(4) Coding changes were maintained for future reference and ideas, discussions, interpretations and decisions were recorded in the memos during analysis in

order to keep track of the development. NVivo also allowed an audit trail to be maintained.

(5) Throughout the process, the dynamic models illustrating code relationships were used to visualize, explore and present connections and patterns in the data. As we mentioned, they were converted to static models and were maintained in the software in different stages of analysis.

(6) Some of the changes that occurred through the coding process can be seen by comparing Figure 4.1 and Figure 4.2. As analysis of papers continued, we realized that the generation and evaluation of a hypothesis are basically repeated processes of information seeking and finding patterns from which a hypotheses or a final judgment is retrieved. Because information seeking, pattern and judgment already existed in the coding, we added a new code named retrieval and renamed hypothesis generation to hypothesis evaluation. Retrieval was created as a parent node and Judgment, Pattern and Hypothesis were considered as children nodes (Figure 4.3).

(7) Again, by reviewing and coding several more papers, and by continuing to compare them, we noted that the goals of the visual mining process can be classified as being able to assess, estimate and develop options. Therefore, under the Goal node, we added three new children nodes named Assess, Estimate and Develop options. This is shown in Figure 4.3.

4.1.3. Trustworthiness of the Results from Our Coding Process

As was described earlier in Chapter 3, credibility, dependability, confirmability, and transferability are the established trustworthiness criteria for qualitative research (Erlandson et al., 1993; Lincoln et al., 1985; Patton, 1990). The following section briefly describes these concepts and the approach we have used to address them in our analysis.

Credibility is guaranteed truthfulness of the research report (Erlandson et al., 1993; Lincoln et al., 1985; Patton, 1990). One method to establish credibility is member checking. According to Lincoln and Guba, member checking is one of the most important criteria when making a naturalistic inquiry. In our case this was conducted to test the result of analysis with that of a geographer and a research fellow in biomedical engineering. They confirmed the results and verified the interpretations. Yet another technique that we used to build credibility was peer-debriefing. This is used to confirm interpretations and coding decisions. Our peer-debriefer, an observer, but not a participant in our project, analyzed the research materials and questioned the data, meaning, and interpretation. She was a colleague and has a PhD in Computer Science but was in no way involved in the study although she has knowledge about qualitative research and the phenomenon under investigation. The interactions between researcher and the peer-debriefer also included the audit trail in which she later performed the role of an auditor.

Dependability refers to the criterion of consistency (Lincoln et al., 1985). An auditor was invited to conduct a dependability study by reviewing notes from the document review and reflexive journal which was kept by us. It consists of information about the implementation of the research, reasons for methodological decisions made throughout the research, and insights recorded during research implementation.

Confirmability depends upon the degree to which the findings result from data and not from researcher bias. It is again supported through an audit trail (Lincoln et al., 1985). The auditor tracked findings to data by reviewing journals and documents to make sure that the interpretations made were consistent with the data.

Transferability refers to external validity and depends, in large part, on the extent to which readers are able to apply findings of the research to other contexts. It is supported by a thick description (Lincoln et al., 1985) which brings readers into the setting of the study and allows them to determine if the findings can be transferred (Merriam, 2001). To support transferability, a thick description has been created in the form of final report which would allow readers to make constructive decisions.

4.1.4. The Result: Classification Criteria

The above mentioned process enabled us to discover a set of classification criteria which characterizes the space of interactions in visual mining. Table 4.2 presents these criteria and the different values which each criterion can take.

Table 4.2: Classification criteria for modeling interaction space in visual mining

Criteria	Values
Goal	Assess (A), Estimate (E), Develop Options (DO)
Information seeking	Searching (S), Browsing (B), Monitoring (M), Being Aware (BA)
Retrieval	Pattern (P), Hypothesis (H), Judgment (J)

The above criteria for characterizing the interaction space in visual mining can be paraphrased in continuous text as follows. The user's *goal* of visual mining requires an understanding of the current situation and explaining the past (*assess*), estimating future capabilities (*estimate*) and developing different possible options (*develop options*). In order to accomplish these goals, the user must gather relevant information and evidence through active or passive *information-seeking* activities which, as already described, are classified as *searching*, *browsing*, *monitoring* and *being aware*. The retrieved item(s) during these activities (*retrieval*) can be a *pattern*, *hypothesis* or final analytical *judgment*.

4.1.4.1 Comprehensiveness of Classification Criteria

In the last stage of our qualitative analysis process, in order to further validate the classification criteria for visual mining, typical real-world visual mining activities were extracted and listed from the reviewed literature. All extracted activities were re-described using these criteria in order to validate their ***necessity***. Finally to ensure that further refinement is not needed (to ensure **sufficiency**, to the extent possible), visual mining activities were extracted from ten new papers all containing reports of visualization case studies. We then confirmed that in the process of describing these visual mining activities using the classification criteria, every value of every criterion was indeed needed. Further all these visual mining activities were comprehensively described by these criteria. This process was repeated again with an additional five papers. Since no changes were required in the set of classification criteria, we concluded that our refined set of criteria was stable and no further refinements seem to be needed. We do not claim that these criteria are exhaustive, but on the basis of describing typical real-world visual mining activities, they appear to be necessary if not sufficient, and represent at least a valuable starting point for characterizing the interaction space of visual mining.

4.2. Visual Mining Strategies (VMS) Model

A complex visual mining activity is characterized by the relevant values of the three criteria, namely: Information seeking, Goal and Retrieval. We call each distinct combination of values as a Visual Mining Strategy (VMS). Table 4.3 lists all thirty-six possible strategies, and is called as the Visual Mining Strategy Model or VMS model for short. As formulated, since all admissible combinations of criteria values have included, collectively these VMSs span the entire interaction space in visual mining.

Several VMSs would be adopted in the course of a visual mining episode. Consider the example of visually mining from a large medical dataset with the goal of diagnosing a certain disease. The different strategies which the users could adopt are: searching for some specific side effect of the disease, browsing to find some interesting information about the disease, identifying some unexpected information (such as changes in DNA sequence), finding expected information (such as fatigue), providing several candidate diagnoses in the form of hypotheses, diagnosing the disease which is making a judgment and so on. It is easy to see that the above strategies are actually differentiable according to their values on the chosen set of criteria in our VMS model. For example, searching for some specific side-effect of the disease is a classic example of a well-defined search to identify a pattern in data whereas exploring the visual representation to find something interesting about the disease is an example of typical browsing to identify an as yet unknown pattern in the data. Along the same lines, providing candidate diagnosis is one example of developing a hypothesis about the data that can be done by browsing, searching, being aware or monitoring. And, diagnosing the disease is an example of making a judgment about the most likely hypothesis.

Table 4.3: Visual Mining Strategies (VMSs)

Strategy	S*	B*	M*	BA*	A*	E*	DO*	P*	H*	J*
VMS1	×				×			×		
VMS2	×				×				×	
VMS3	×				×					×
VMS4	×					×		×		
VMS5	×					×			×	
VMS6	×					×				×
VMS7	×						×	×		
VMS8	×						×		×	
VMS9	×						×			×
VMS10		×			×			×		
VMS11		×			×				×	
VMS12		×			×					×
VMS13		×				×		×		
VMS14		×				×			×	
VMS15		×				×				×
VMS16		×					×	×		
VMS17		×					×		×	
VMS18		×					×			×
VMS19			×		×			×		
VMS20			×		×				×	
VMS21			×		×					×

VMS22			×			×		×		
VMS23			×			×			×	
VMS24			×			×				×
VMS25			×				×	×		
VMS26			×				×		×	
VMS27			×				×			×
VMS28				×	×			×		
VMS29				×	×				×	
VMS30				×	×					×
VMS31				×		×		×		
VMS32				×		×			×	
VMS33				×		×				×
VMS34				×			×	×		
VMS35				×			×		×	
VMS36				×			×			×

* Refer to Table 4.2 for full nomenclature

Our VMS model has many different applications. For example, it can be used to support requirements analysis in system engineering of VMSTs where understanding actual user needs are an important step in system modeling. From a user-centered view, studying and assessing different user activities which occur in visual mining could be undertaken using this model. However, because it provides a system-independent classification scheme of interaction space of visual mining, it can also be used for evaluating and classifying existing VMSTs based on what they support (Morse, 1999). Since interaction is such an important aspect of VMSTs, this classification scheme should make a significant contribution to the improvement of functionality and interface design of newer systems.

4.2.1. Examples: Visual Mining Scenarios Using the VMS Model

In this section, we give four examples of describing a user's high level interactions with visual representation using the VMS model. The examples are from case studies in the list of papers used in our qualitative content analysis.

Example 1 (Medical domain): We take up a visual mining scenario known from a case study concerned with interactive blood damage analysis (Hentschel et al., 2008). The goal is blood damage assessment (Goal: assess). The scientist starts the interactive analysis with a first look at the animated particle traces (Information seeking: browsing). The traces were colored by the cumulative hemolysis value. They observe a surprising fact: while the hemolysis level stayed low throughout most of the impeller, it quickly rose after leaving the impeller (Retrieval: pattern) (VMS10). Then, they investigate selected particles with high rates of hemolysis in more detail using the static view. In this view, they use the temporal browsing facility to quickly jump to both key positions (Information seeking: searching) and analyze the particle's motion in these regions more closely. They then make an interesting follow-up observation: some particles did not directly pass the diffuser. Instead, after passing halfway through, they were drawn back and floated around in the gap between impeller and diffuser eventually heading towards the outlet through another section of the diffuser. This observation led to the hypothesis that the high rates of hemolysis might somehow correlate with this backflow (Retrieval: hypothesis) (VMS2). Backflow or recirculation is not easily detectable in a general setting. They investigate this using function plots (Information seeking: searching). The plot clearly reveals the following two facts: First, it confirms the existence of backflow areas in the transition region between the end of the impeller and diffuser. Negative z-velocity values can be predominantly found in that region. Second, the range of the z-velocity values is widest there, i.e., both large positive and large negative values are revealed at the diffuser's entrance. Based on their previous knowledge and observations, they summarize that the transition region between impeller and diffuser has been identified as being a high-shear region leading to high hemolysis rates at the exit of the diffuser (Retrieval: judgment).

Example 2 (Geographical domain): Here we take up a visual mining scenario concerned with analyzing the history of visits to a hotel (Weaver et al., 2007). The goal is to determine weather and climatic effects on hotel visits (Goal: assess). While visualizing the data, the analysts notice the regular pattern of Friday visits by one of the guests named A. M. Sheats (Information seeking: browsing, Retrieval: pattern) (VMS-10). This pattern prompts them to look for deviations from this routine (Information seeking: searching). By setting the view to a fourteen-day cycle then scrolling to earlier dates, the analysts are able to determine that there were two periods when his scheduled visits were not on Fridays. These two Fridays were during winter months (Retrieval: pattern) (VMS-1). This leads the analysts to believe that the weather may have had something to do with these variations (Retrieval: hypothesis) (VMS2). While the exact reason for these deviations has not yet been determined, they examine historical climate data to test this hypothesis. Such records indicate that on February 5–14, 1899, there occurred the coldest period of weather in the United States meteorological records (Information seeking: search, Retrieval: pattern) (VMS1). Further visualization also reveals how the time of year strongly correlates with the overall number of visits, possibly due to seasonal variations in climate that affect travel. (Information seeking: browsing, Retrieval: pattern) (VMS10). In addition, in the vertical histogram, the total number of visits is highest during the summer and lowest during the winter, with the exception of major holidays which confirms the hypothesis (Information seeking: search, Retrieval: judgment) (VMS3).

Example 3 (Bioinformatics domain): In this example we take up a visual mining scenario from a case study concerned with finding the leftmost and rightmost protein alignment (Smoot et al., 2005) (Goal: assess). The analysts visualize the set of all near-optimal alignments in the path graph. Then they attempt to find candidate alignments by animating pathgraphs and filtering (Information seeking: searching). The successive application of tighter and tighter filters helps them to find evidences that the Left and Right output might not have been correct (Retrieval: pattern) (VMS1, VMS2). The software allows them to create new alignments manually using an alignment editor, path graph display, and a dual display from which they suppose that the new alignments are correct (Retrieval: hypothesis) (VMS2). To verify the hypothesis, they view the new alignments in the path graph with the rest of the set. To see the exact two alignments, they apply the filters and quickly find the new alignments and highlight them (Information seeking: search). They see that proper boundary edges of the path graph were highlighted. Therefore, they conclude that the boundaries are correct (Retrieval: judgment) (VMS3).

Example 4 (Epidemiology domain): This visual mining scenario is concerned with analyzing distribution, determinants, and potential impacts of the avian flu outbreak (Proulx et al., 2006) (Goal: estimate). By visualizing data, the analysts find that Asia is a hotspot for disease activity (Information seeking: search, retrieval: pattern) (VMS4). They decide to investigate this region more closely (Information seeking: search). They notice that the concentration of three different strains in the specific geographic area is apparent (Retrieval: pattern) (VMS4). Through visualizing and information seeking (Information seeking: browsing, search), they can find many patterns such as: disease events in Asia occur in clusters by location, the absence of the disease from nearby countries like Laos and Korea, Indonesia is not connected to mainland Asia. However, somehow disease events later occur there. These patterns suggests avian flu was somehow brought over from the mainland, perhaps due to bird migration or poultry exports (Retrieval: hypothesis) (VMS5). By continuing information seeking, finding patterns and relating them to their existing knowledge, they can generate possible hypothesis, evaluate them and reach the final judgment.

4.3. Summary

This chapter presented the formulation of our VMS model which comprehensively characterizes the interaction space of visual mining. This will enable systematic thinking about user interactions with VMSTs which are intended to support complex cognitive activities. By using trustworthy qualitative directed-content analysis methods and using content from published papers reporting interactions with visual representation, it was discovered that user activities in this context, termed as visual mining strategies, can be differentiated along a small set of three criteria to make up a domain independent activity model, the VMS model. Furthermore, it is demonstrated through four examples in different domains (medical, geographical, bioinformatics and epidemiology) that the proposed VMS model can comprehensively capture visual mining activities in a tool independent fashion.

In Chapter 5 we will develop a framework which uses this tool independent VMS model to design an inspection framework that can compare the strengths and weaknesses of a given VMST. For a demonstration of the capability of this inspection framework, we have applied this to three existing commercially available VMSTs. The goal is to estimate the strengths and weaknesses of a VMST when providing support for user operations, the support provided by interface features, and the support for all the strategies in the VMS model.

Chapter 5 : An Inspection Framework for Evaluation of Visual Mining Software Tools

In this chapter, we develop an inspection framework which enables evaluation of the support provided by a VMST for performing complex cognitive activities required in visual mining without the need for extensive expert involvement. The evaluation metrics defined consider, in a comprehensive manner, various levels of visual mining interaction. The framework considers interactions at four levels of granularity: activities, tasks, interface features and moves. As we explained in Chapter 1, interactions at a high level are often complex and open-ended (e.g., problem solving, decision making, and forecasting), and are usually termed as activities. Tasks, at the next level, are specific goal-oriented behaviors that occur at the next lower level during the performance of activities (e.g., categorizing, identifying, and ranking). Interface features occur at an even lower level and involve tool driven actions that are performed upon visuals (e.g., selecting and filtering). Moves occur at the lowest level and are performed using the VMSTs interface; they can be mental or physical (e.g., mouse clicks, keyboard presses). In fact with different levels of interactions, this framework views interactions in a VMST as hierarchical, embedded, and emergent. That is, each level of the interaction hierarchy is embedded within the level above and each level has emergent characteristics that result from the relationships occurring within the levels below (Figure 5.1).

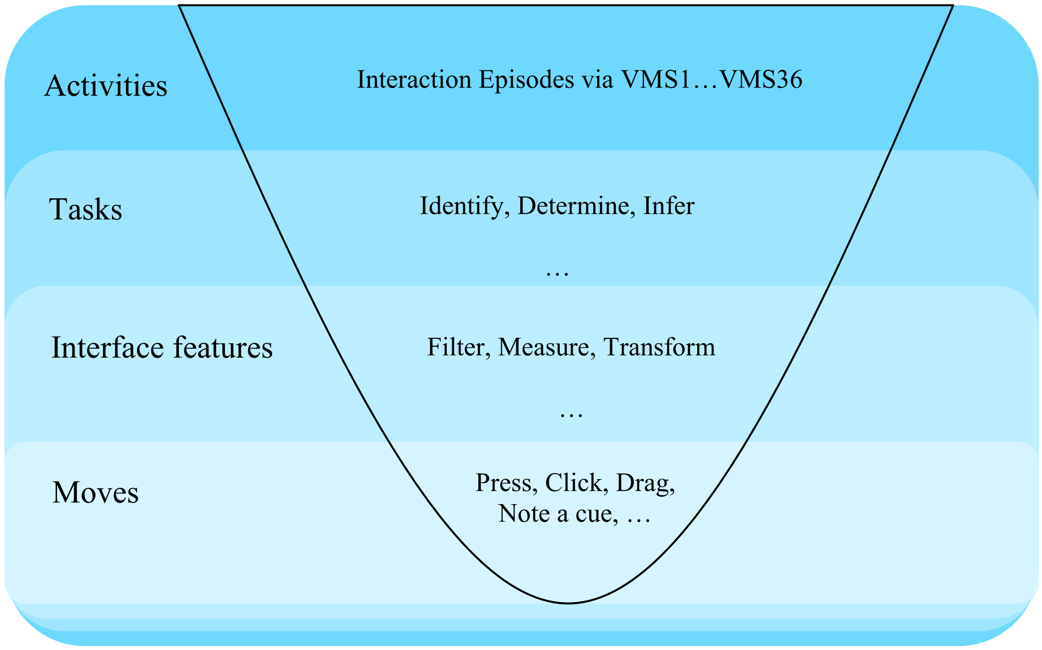


Figure 5.1: Levels of interactions in visual mining

Our proposed inspection framework integrates the VMS interaction space model, analyst-user tasks, (we use tasks proposed by Valiati et al. (2006)), and VMST interface features and moves to define new metrics. The evaluation is done through quantification of the strengths and weaknesses of a VMST in supporting analyst-user tasks and activities. The framework provides three types of analyses: 1) analysis of the interface features of a VMST , such as spatial navigations or documentation, to identify how they contribute to the overall support provided by a VMST, 2) analysis of the support provided for analyst-user tasks such as identify and compare and 3) analysis of the support provided for 36 visual mining strategies, which as per our interaction space model, comprehensively represent the complex cognitive activities in visual mining process. We demonstrate the value of our framework by using it to quantitatively measure the support for visual mining provided by three widely used VMSTs.

This framework operates by assessing the ease of performing user tasks as a measure of support provided for visual mining. These measures may then be used for redesign and improvement of the VMST interface.

5.1. Characteristics of an Evaluation

Judging whether a VMST is effective requires answering the question: effective for what? Therefore, the evaluation methodology has to take into account, to the extent possible, the different kinds of complex cognitive activities and how they are performed through the mediation of VMSTs.

In order to address this, the proposed inspection framework considers all the four levels of interactions in VMSTs. Then for developing the evaluation metric we define a mapping between these different levels of interactions.

Similar attempts have been made in the field of library and information science by Wilson et al (2009-b). They have developed a framework to evaluate the support provided by different interfaces specifically for the activity of searching for information using the interface of a browser. This is done through the quantification of the strengths and weaknesses of the interfaces in supporting user tactics and information seeking strategies. Their framework also combines established models of information seeking. Specifically, they employ aspects of two models: the information seeking strategies from the interaction model of information seeking (Belkin et al., 1993) and the levels of search strategies (i.e., moves, tactics) presented by Bates (1990) in her strategic model. In particular, the "moves" in Bates model are used to speculatively quantify the "tactics". As previously mentioned, a "move" is a single action performed by users, either physically or mentally. They combined the information seeking strategies with metrics (the values produced by quantifying the tactics) to predict the support provided by different VMSTs.

Following these ideas, we also develop a similar inspection framework which combines appropriate interaction models, but for the domain of visual mining. As per the VMS interaction space model, in the visual mining process, every activity of any visual mining episode can be categorized as belonging to one of the 36 VMSs. For identifying the tasks performed in any activity, as mentioned earlier, we use the interaction model proposed by Valiati et al. (2006) (this model is explained in more detail in Section 5.1.1). Users perform these tasks using the interactive features provided by the VMST interface which in turn comprise of mental and physical acts.

As in Wilson's framework, Bates moves (Bates, 1990) are used. Bates moves enable quantification of the support provided by each interface feature of the visualization tool for user tasks. Lastly, the measures obtained for each of the tasks are appropriately combined, so that the support for each activity can be calculated (See Figure 5.2). More details are given in Section 5.2.

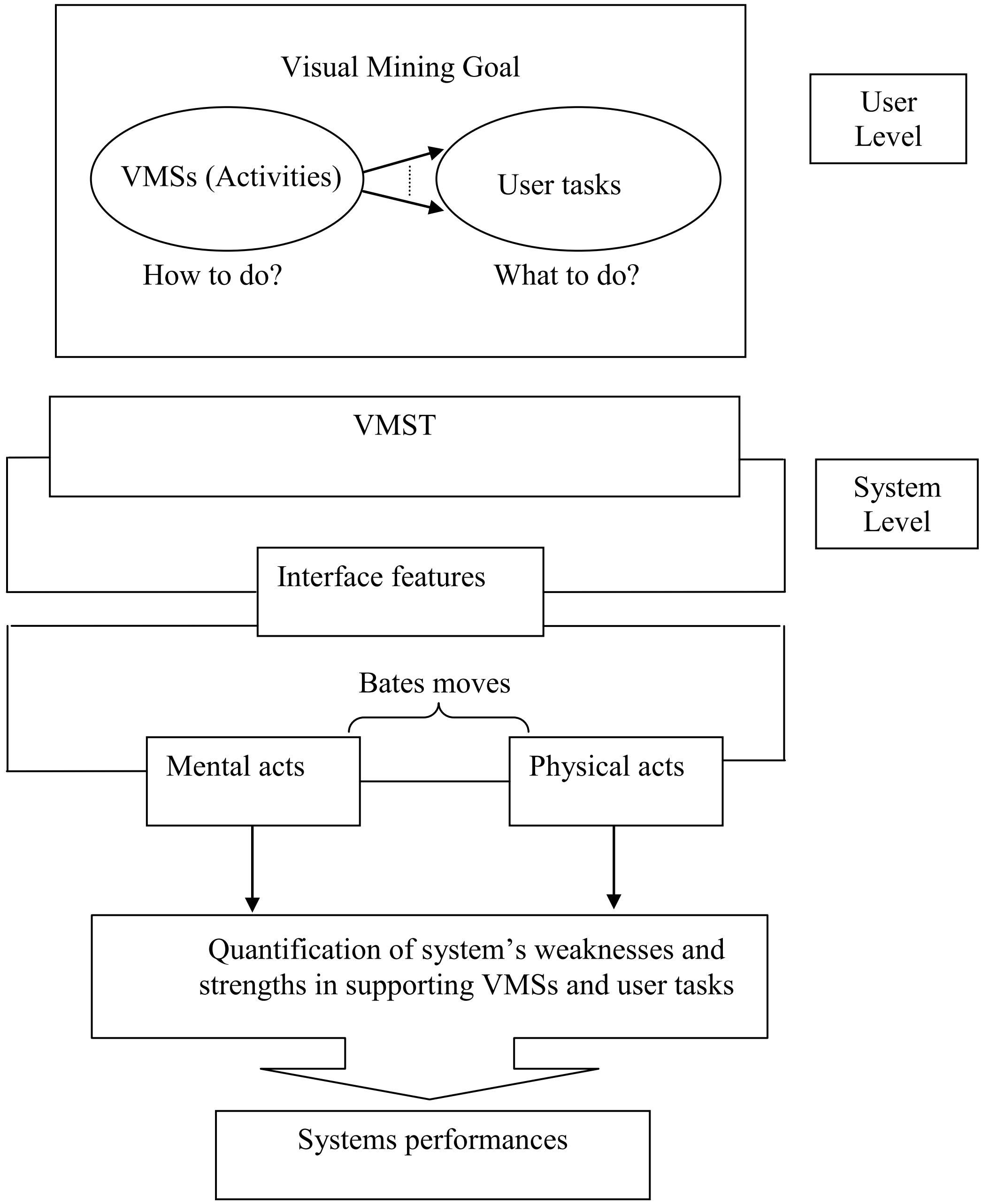


Figure 5.2: Evaluation environment for visual mining

5.1.1. User Tasks

The interaction model by Valiati et al. (2006) is among the most recent interaction models for multidimensional visualizations. It is also called taxonomy of tasks in literature. This model focuses on the process of exploring the information in a large dataset. This work is based on many existing interaction models (Zhou et al., 1998, Wehrend et al., 1990). It integrates existing interaction models with new exploratory tasks in a multidimensional dataset. Valiati et al. (2006) have pointed out that a clear understanding and precise representation of tasks that a user performs while carrying out data analysis are essential for effective evaluation of information visualization tools. They have identified tasks that a user might need to execute to analyze data as follows:

Identify: Refers to any action of finding, discovering or visually estimating the value of some piece of information in the data. It begins each time the user begins a new activity with the goal of finding, discovering or estimating the value of some new information regarding the data.

Determine: Corresponds to any action of calculating, defining or precisely indicating values such as mean, distance etc. This task begins each time a user needs to calculate a specific value.

Visualize: Represent graphically desired dimensions or data items.

Compare: The user can compare identified, visualized, determined or located data by analyzing dimensions, properties, proportions, locations, distances, visual characteristics, etc.

Infer: After identifying, determining or comparing information, the user is able to infer knowledge from the information and define hypotheses.

Configure. For visualizing the data space, the user usually has to configure the visual representation. This task is related to the possible actions available to change visual characteristics used to represent data items or attributes.

Locate. This task is related to the actions of searching and finding precisely in the display, the information previously visualized, identified or determined.

5.2. The Proposed Inspection Framework

The user interaction space is vast, since an analyst user can perform any combination of moves any number of times. Hence it is important to be able to delimit the space to those regions in which most analyst user activities would belong. In the proposed framework, the analyst-user looks at the user interface (UI) (Figure 5.3) from the viewpoint of 1 of the 36 VMSs (Table 4.3).They see each VMS in terms of the tasks they can perform. The VMSs and the tasks act as filters. They delimit the space of possible interactions with the VMST interface. The VMST interface can be seen by each task, in terms of how easy it is to perform that task using its interactive features. As already mentioned, Bates moves (Bates, 1990) are used as a metric. Therefore, each user task can be assigned a total score indicative of how easily it can be performed using the VMST's user interface features.

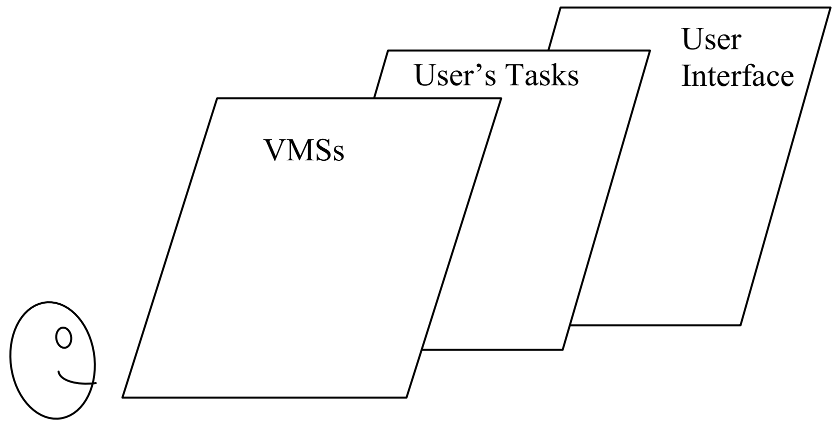


Figure 5.3: Three layers of the inspection framework

5.2.1. Internal Working of the Framework

The inspection framework comprises of the following four stages:

Stage 1: Feature Identification:

For each VMST, user interface features are identified.

Stage 2: Measuring Support for user tasks

For each interface feature used in performing a user task, a count of the number of moves involved is recorded. Figure 5.4 illustrates the steps of measuring support in the proposed framework, by counting moves which consist of three loops: each VMST interface (L1), each interactive feature (L2), each user task (L3).

L1. For each VMST interface

L2. For each interactive feature in VMST interface

L3. For each user task defined by Valiati

Count the number of moves the user must make to achieve the current user task with the current feature

L3. Next user task

L2. Next feature

L1. Next interface

Figure 5.4: The steps of measuring support by counting moves

As we mentioned before, to calculate the support for each user task, by each interactive feature, of each VMST interface, the notion of a move from Bates' model is used. When using an interactive feature to locate some specific information in visual representation, for example, a user might press the right mouse button (move 1 - physical), drag the mouse (move 2 - physical), scan through visual representation (move 3- Mental) and note a cue (move 4 - Mental). Several existing models and analytical methods include the notion of mental moves. For instance, in the Keystroke Level Model, mental moves, which Card et al. (1983) call 'Operators', can include actions, such as choosing a query, retrieving information from long term memory, reading, or scanning through a list of options.

By following the procedure described in Figure 5.4 and recording number of moves, for each VMST a table is generated. In this table, the tasks are listed across the top and the features down the side. The entry in each cell of this table is the count of moves. An example table is shown in Table 5.1. As further explanation, let us consider the Trackball interface feature. Two tasks, identify and configure would require to make use of the Trackball feature and the number of moves required each time is 3.

Table 5.1: An example table

Interface features	Identify	Determine	Compare	Configure	…	Total for interface feature
Trackball	3			3		6
Measure		4				4
…	…	…	…	…	…	…
Totals for user task						

Stage 3: Data Processing

A well designed interface feature obtains a low score while a poorly designed feature obtains a high score. No support for an interface feature is represented by a blank entry. Before summarizing the result, the scores, except for blanks are inverted. Therefore better designs receive a higher score which approaches 1 and poor designs receive a lower score approaching zero. In this way, the graphs that are later produced have the intuitively correct feeling that a taller bar, or a higher value, represents stronger support. These inverted values can then be summed by interface features and by user tasks. This calculates the support provided by an interface feature for all tasks and the support provided for a user task across all features.

Stage 4: Visual Analysis

To support analysis of results, various graphs can be produced to represent the results visually. We consider the following three graphs:

1) Support for interface features: This graph includes the summed values for each interface feature in a tool. Strong interface features will produce tall bars, and a comparison of user effort within and among VMSTs can indicate a strong feature in the UI design.

2) Support for user tasks: A second graph includes the summed values for each user task in a tool. Again, tall bars indicate strong support for a user task. This sort of comparison may help identify which user tasks require improved support through redesign in a given tool.

3) Support for VMSs: The third graph shows the difference in support for different VMSs. Each user task is part of one or more of the 36 VMSs. For example, locate, a task typically used by the analyst-user to search for special information is part of a number of VMSs. Table 5.2 shows the 36 VMSs and the tasks that are included in each of them. In the following sections, more details will be given about the user-driven process adopted for assigning tasks to VMSs.

Table 5.2: The user tasks assigned to each VMS

VMSs	**Tasks that support this VMS**
VMS1	locate, visualize, configure, identify, compare, determine
VMS2	locate, visualize, configure, Infer
VMS3	locate, visualize, configure, determine
VMS4	locate, visualize, configure, identify, compare, determine
VMS5	locate, visualize, configure, Infer
VMS6	locate, visualize, configure, determine
VMS7	locate, visualize, configure, identify, compare, determine
VMS8	locate, visualize, configure, Infer
VMS9	locate, visualize, configure, determine
VMS10	identify, visualize, configure, compare, determine
VMS11	identify, visualize, configure, Infer
VMS12	identify , visualize, configure, determine
VMS13	identify , visualize, configure, identify, compare, determine
VMS14	identify , visualize, configure, Infer
VMS15	identify , visualize, configure, determine
VMS16	identify, visualize, configure, identify, compare, determine
VMS17	identify, visualize, configure, Infer
VMS18	identify, visualize, configure, determine

VMS19	visualize, identify, locate, configure, compare, determine
VMS20	visualize, identify, locate, configure, Infer
VMS21	visualize, identify, locate, configure, determine
VMS22	visualize, identify, locate, configure, compare, determine
VMS23	visualize, identify, locate, configure, Infer
VMS24	visualize, identify, locate, configure, determine
VMS25	visualize, identify, locate, configure, compare, determine
VMS26	visualize, identify, locate, configure, Infer
VMS27	visualize, identify, locate, configure, determine
VMS28	visualize, identify, locate, configure, compare, determine
VMS29	visualize, identify, locate, configure, Infer
VMS30	visualize, identify, locate, configure, determine
VMS31	visualize, identify, locate, configure, compare, determine
VMS32	visualize, identify, locate, configure, Infer
VMS33	visualize, identify, locate, configure, determine
VMS34	visualize, identify, locate, configure, compare, determine
VMS35	visualize, identify, locate, configure, Infer
VMS36	visualize, identify, locate, configure, determine

In the above table we can see the following. Locate is assigned to the VMSs in which their information seeking attribute is *search*. Visualize and configure are assigned to *search* and *browsing* because they are active information seeking activities. The infer task is assigned to VMSs in which their retrieval attribute is *hypothesis*. Determine is assigned to VMSs in which their retrieval is *judgment*. Compare is assigned to VMSs in which their retrieval is either *pattern* or *judgment*. For each of the 36 VMSs, the sum of the total support values can be calculated and displayed as a graph.

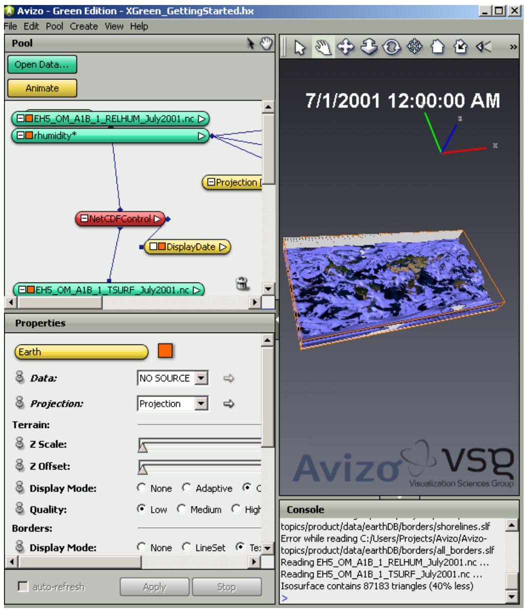
5.2.2. Example Analysis

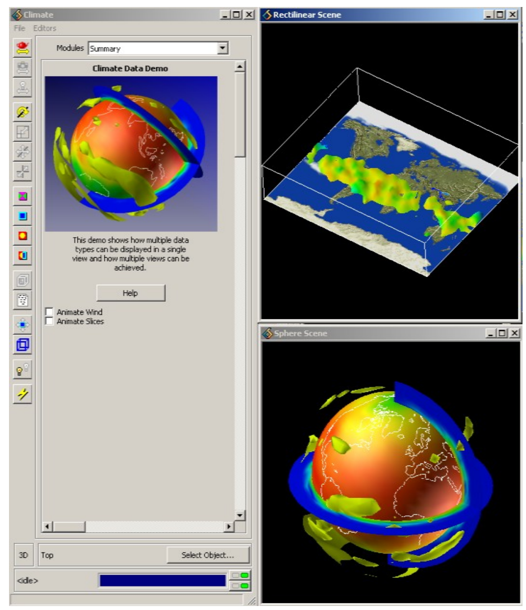
In order to demonstrate the evaluation capability of the proposed approach, we used this framework to compare and analyze the three VMSTs shown in Figure 1.1. As a result three graphs are produced which provide a deep and rich insight into the strengths and weaknesses of each VMST in terms of support provided by the features of each VMST, support provided for 7 user tasks by each VMST and support provided for 32 VMSs. The three VMSTs that we used are as follows: 1) Avizo, 2) Advanced Visual systems/Express (AVS/ Express) and 3) Visualization and Analysis Platform for Ocean, Atmosphere, and Solar Researchers (Vapor).

Avizo (see Figure 5.5(a)) is 3D visualization software intended for visualizing, manipulating, and understanding scientific and industrial data (AVizo website, 2014).

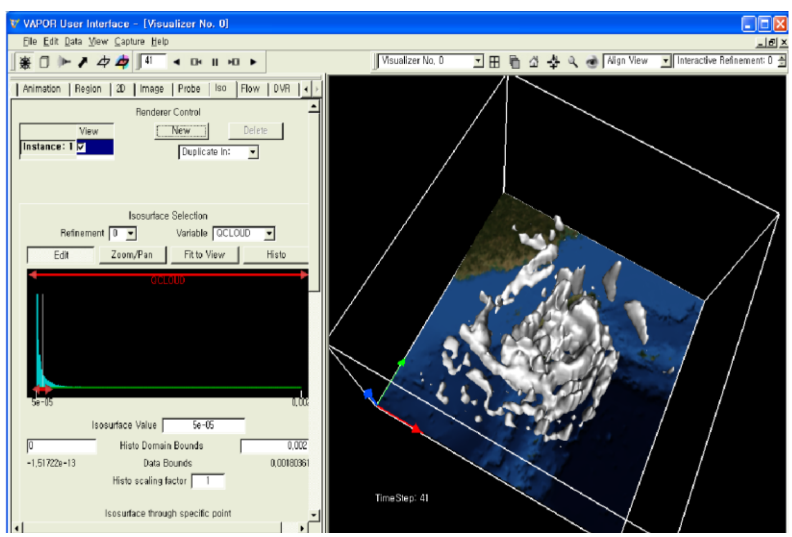
AVS/ Express (see Figure 5.5(b)) an interactive data visualization software provides visualization methods for problems in a vast range of fields, including science, business, engineering, medicine, telecommunications and environmental research (AVS website, 2014).

Vapor (see Figure 5.5(c)) is meant as a visualization and analysis platform for use by ocean, atmosphere, and solar researchers (Vapor website, 2014).





a) Avizo b) AVS/ Express



c) Vapor visualization software

Figure 5.5: Different VMSTs - Example screenshots during visual mining

Table 5.3: Summary of features in each VMST

Generic feature	VMST specific interface feature		
	Avizo	**AVS/Express**	**VAPOR**
Viewing	Display single or multiple datasets in a single or multiple viewer windows, YZ, XY and XZ Views	Display single or multiple datasets in multiple windows	Display single or multiple datasets in multiple windows
Spatial navigation	Trackball, translate, zoom, rotate, seek, home	Trackball, translate, zoom, rotate	Trackball, translate, zoom, rotate, home
Temporal navigation	Time navigation	N/A	Time navigation
Show/hide parameters	Activate/ Deactivate parameters	Activate/ Deactivate parameters	N/A
Document ation	Create snapshot, annotation	Create camera, Snapshot	Capture single image, capture sequence of images
Compute	Query the exact values, probing, measuring, counting, quantify densities, distances, areas, Min/Max.	Change the value of through sliders	Probing, change the value

Table 5.3 lists a set of generic interface features and the specifics of the implementation of those features in AVS/Express, Avizo and Vapor.

5.2.2.1. Support for User Interaction Features

For each of the three VMSTs (AVS/Express, Avizo and Vapor), similar interface features were identified. Then for each interface feature, number of moves required to perform each user task were recorded. This resulted in a table for each VMST of the type shown earlier in Table 5.1.

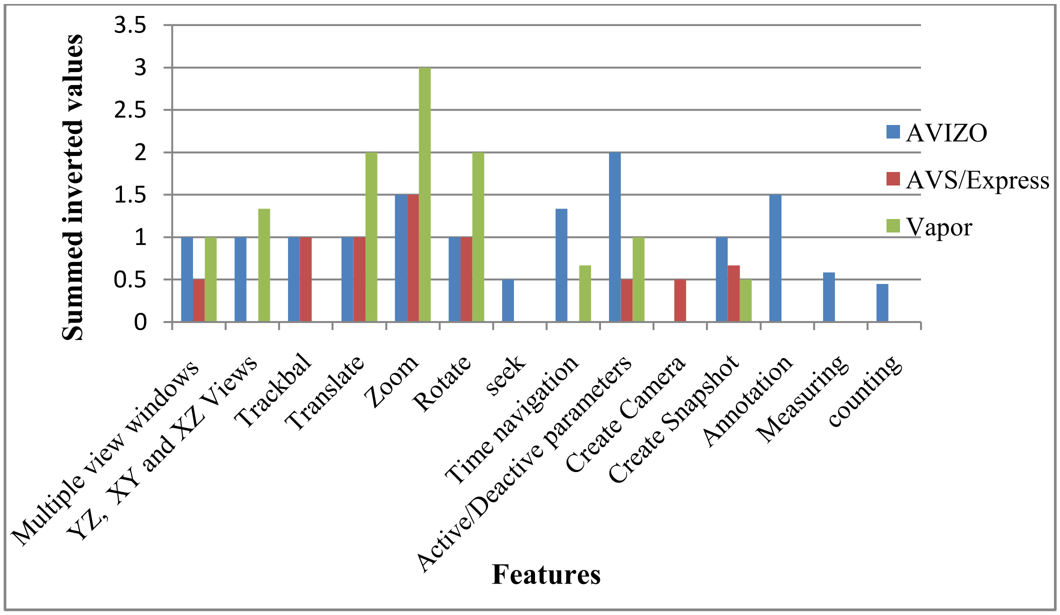


Figure 5.6: The support provided by each interface feature of the three VMSTs

Figure 5.6 shows support provided by each VMST for each of the identified interface feature. A number of observations can be drawn from this chart. The ease of using multiple view windows in Avizo and Vapor comes across clearly. In Avizo and Vapor, a user can do this by simply dividing a single window into multiple sections through a control in the main toolbar. In comparison, in AVS/

Express this requires a user to invoke a main menu and follow a more cumbersome sequence of moves. Vapor provides better support for spatial navigation because the user can translate, zoom and rotate by using different mouse buttons. Both AVS/Express and Avizo provide lesser support for spatial navigation at somewhat equal levels except for rotation which needs more moves in AVS/express because of the need to go through extra menus. AVS/Express and Vapor have no seeking function, measuring and counting features, whereas they are well supported by Avizo. This can be clearly seen in the graph. Avizo and Vapor do not provide any static camera. All of them provide a snapshot feature, though it has weaker support in AVS/Express and Vapor because the user needs to go through menus requiring more moves.

5.2.2.2. Support for User Tasks

The support provided by each tool for each of the user tasks was measured (see Figure 5.7). Vapor provides better support for "Identify" due to the higher level of support that it includes for spatial navigation as can be seen from Figure 5.6. Although AVS/Express and Avizo are similar in their level of support for spatial navigation, Avizo provides better support for "Identify" and "Locate" than AVS/Express through features like (Multiple view window, temporal navigation, seeking, XY, YZ, XZ views as was already shown in Figure (5.6). AVS/Express and Vapor do not support "determine" because they do not provide any calculation feature. Avizo provides better support for "Visualize" due to the better support that it provides for “Active/ Deactive parameters” feature. It also provides better support for compare and infer due to the extra features of “annotation”, “camera” and “snapshot”.

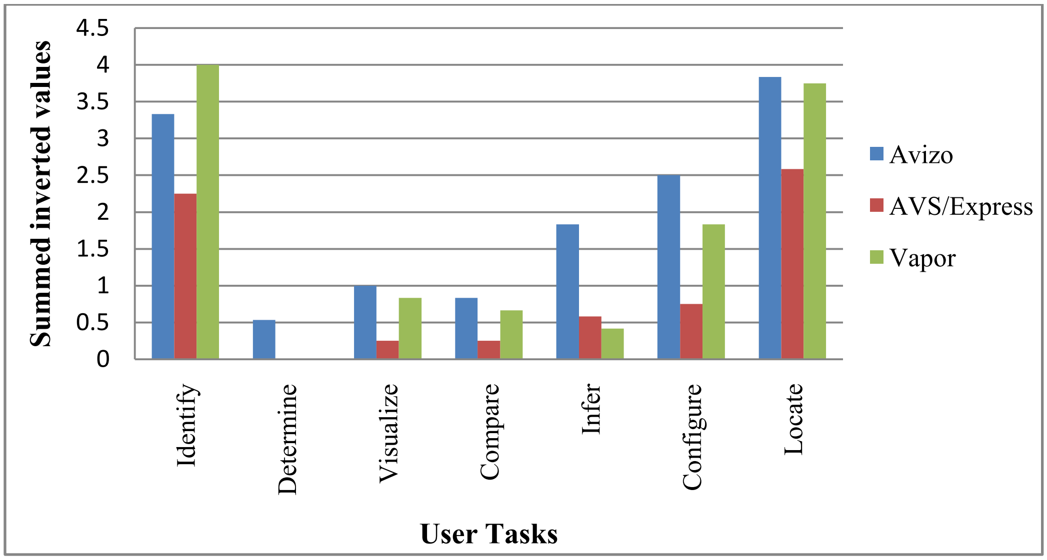


Figure 5.7: The support provided for each of user tasks by three VMSTs

5.2.2.3. Support for VMSs

The assignment of tasks to VMSs has been shown in Table 5.5. In Figure 5.8, there are three different lines in the graph which shows that Avizo provides better support for VMSs. The hidden pattern in the graph can show us under which specific criteria a visualization tool provides good support. It is important to note that in this graph the lines are just identification of trends not interpolation.

Explanation for the Sudden Rise

From the graph, we can see the *rise after first 18 VMSs*. Let us note that the first 18 VMSs constitute active information seeking criteria (searching and browsing). This is a predictable outcome as Bates (2007) explains most of the needed information is acquired in passive mode (monitoring and being aware) without requiring active efforts to acquire it.

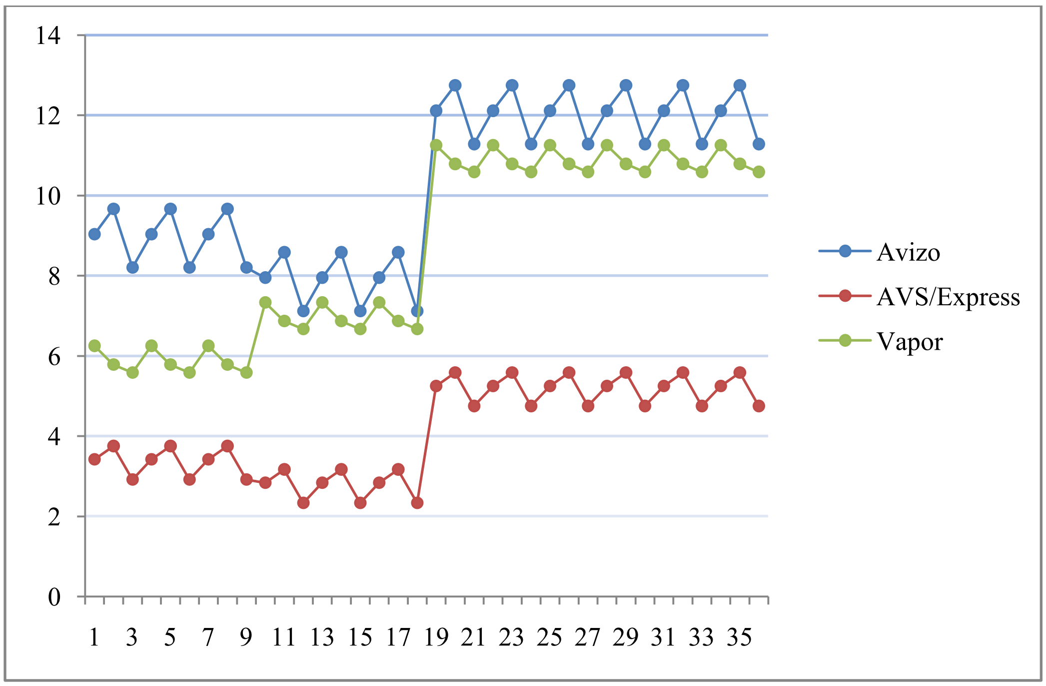


Figure 5.8: The support provided by each VMST for each VMSs

In Table 5.3 we can see that for VMSs(1-9) the information seeking value is search in contrast to VMSs(10-18) which have the information seeking value of browsing. In Figure 5.8, we can see the drop in support by VMSs(10-18) in comparison to VMSs(1-9) for both Avizo and AVS/Express. This is because they both provide higher support for users that are looking for specific information (searching) than users who are just exploring visual information (Browsing). In contrast, Vapor provides more support for users who just want to browse, as can be seen from the rise in VMSs(10-18) in comparison to VMSs(1-9).

If we compare alternating pairs (VMSs(1-3), VMSs(4-6) … VMSs(34-36)), we can see that the Avizo and AVS/Express values marginally increase where Vapor falls. For example, in Avizo and AVS/Express we can see rise from VMSs1 to VMSs2, from VMSs4 to VMSs5 and so on, however in Vapor we can see fall from VMSs1 to VMSs2, from VMSs4 to VMSs5 and so on. This denotes increasing support for hypothesis formulation in Avizo and AVS/ Express. Also, we can see that this increase is sharper in Avizo which may be due to the better support for documentation such as an extra feature for making annotation.

5.2.2.4. Discussion

In this section we summarize the strengths and weaknesses of each visualization tool interface, according to the above example inspection. The strength of Vapor lies notably in its good design for easy spatial navigation (visual exploration) which is a very important aspect in visual mining. However, it has notable absences as seen in Figure 5.6, showing that its support could be greatly improved by providing more functions such as “annotation”, “seeking”, “camera” and calculations. Also, some of the existing features such as “temporal navigation” can be further improved.

Avizo provides the broadest range of UI features which has resulted simply in the often-higher values shown in all three graphs. However, despite the broad range of features and providing good support for them, as we can see in Figure 5.7, there are only small height differences with Vapor. This is because Avizo provides less support for spatial navigation when compared with Vapor (Figure 5.6).

AVS/Express does suffer in all three graphs, given the absence of features such as "XY, XZ, YZ views", temporal navigation, annotation", "seeking" and often poor support in comparison with others in which these features exist.

5.2.3. Relationship to Similar Evaluation Methods

From the example analysis described above, we can see that our inspection framework can provide rich insights about the support for visual mining provided by different VMSTs. In this section, the relationship between our framework and other evaluation methods is discussed. The methods chosen for comparison are: Cognitive Walkthrough (CW), Heuristic Evaluation (HE), and GOMS. They have been chosen because of certain similarities with our inspection framework. Section 5.2.3.1 provides more details about these methods. Then they will be compared with our inspection framework in Section 5.2.3.2.

5.2.3.1. Similar Evaluation Methods

Cognitive Walkthroughs (Wharton et al., 1994) allow evaluators to systematically step through example scenarios (Carroll, 1995) of use, usually produced in conjunction with Personas (Cooper, 1999) and Hierarchical Task Analysis (Diaper et al., 2003). With each action, or move, required to achieve a task, four simple questions are systematically asked, including: 'does the user understand that a certain function is available?', and 'does the user receive feedback about their action?'

The aim of this method is to evaluate user interactions. The method models the experiences of first-time users of the software. The Cognitive Walkthrough can be used throughout the design process, but is designed to evaluate systems where the design, functionality, and even terminology used are well defined. This may include carefully specified paper prototypes, but is usually applied to higher-fidelity prototypes before empirical user testing. Procedurally, evaluators are expected to work separately, and then discuss their findings together. The key advantages lie in the speed and ease of use, without real users, and the drawbacks focus on the type of analysis (superficial, not functional), and the effect of evaluator skill on the results.

Heuristic Evaluations (HEs) focus on comparing an interface design with several recognized usability principles (Nielsen et al., 1990). Although often considered to be fairly informal, the process is widely used to make sure that simple usability issues, based around violation of known principles, do not hinder the design and development process. Heuristics include: consistency, feedback, providing short cuts, clear error messages, and maintaining clear and natural language. HE uses a document to understand the user's ability to use the software. HE is designed for use by a single evaluator, although multiple evaluator opinions may strengthen the analysis.

Like the Cognitive Walkthrough, HE is designed for evaluating high-fidelity prototypes, or cheaply improving finished products, but can be used with well thought-out low fidelity prototypes. Like CW, the benefits of HE are speed and ease of use, but concerns relate to the quality of the results produced.

GOMS is an HCI method that focuses on evaluating interfaces for how they support users in achieving their goals (John et al., 1996). *GOMS* stands for Goals, Operations (user actions), Methods, and Selection rules. The aim is mainly to analyze users for their specific set of goals, the operations (or functionality) available in software for achieving these goals, the methods (or task structure) used to achieve the goals, and the selection criteria for choosing different methods of achieving the same goal. GOMS requires explicit modeling of users, goals, and tasks. It also requires working software during evaluation, so that time estimates for performing certain methods can be identified. The time estimates are created using the earlier Keystroke Level Model (Card et al., 1983). GOMS was used, for example, to estimate that a new call-center workstation was less efficient, by 3%, for the tasks carried out by the staff (Gray et al., 1992). This type of analysis cannot be done through Cognitive Walkthroughs or heuristic Evaluations.

However GOMS is very complicated, does not consider different types of users (Preece et al., 2001), and does not evaluate the suitability of functionality in an interface; only the efficiency of implemented functions is evaluated. This method has received some criticism about the cost of use and the benefit it provides.

GOMS analyses the optimal actions taken by an expert user, with a specific set of functionality. Therefore it does not allow for errors or optional interactions. Further, the results provided are typically represented by a difference in seconds for a single task. Consequently, this method has been used in industry more, where designers are building systems for tasks that are repeated many times, like the call centre mentioned above. The complaint has often been that GOMS does not often fit well into working practices for activities such as visual mining.

5.2.3.2. Comparison of VMS Inspection Method to Similar Evaluation Methods

To make the relationships between our inspection framework and other evaluation methods explicit, Table 5.7 compares a few usability evaluation methods based on several criteria. These criteria have been developed by Wilson (2009-a). They are extracted from the RITE-method (Rapid Iterative Testing and Evaluation (Medlock et al., 2002)) and the types of insights provided by usability evaluation methods (Blandford et al., 2008).

From Table 5.4 one can see that in our inspection framework, the procedure is somewhat similar to the Cognitive Walkthrough; the requirements are similar to the Heuristic Evaluation and the outcomes are similar to GOMS. However, our inspection framework evaluates interfaces specifically for visual mining from multiple user perspectives while the other methods evaluate interfaces from the view of either novice or expert users. They are not specific to visual mining.

Table 5.4: Comparison of proposed inspection framework to three other similar usability evaluation methods

Criteria	**HE**	**CW**	**GOMS**	**Proposed inspection framework**
UEM category	Document based interactions model	Model-based interactions evaluation	User modeling method	Model-based interactions evaluation
Intent of method	Check the learnability of the Interface	Check the learnability of the Interface	Model the goals and tasks of users	Check for functionalities
Type of user modeled	Novice	Novice	Expert	Novice to expert
Procedure	Step through	Step through	Identify	Step through

	checklist	scenarios of use	and model scenarios of use	fixed scenarios
Prerequisites	None	Scenarios	Task Analysis	None
Scope of interfaces	Any	Any	Any	Visual mining
# of evaluators	1+	2+	2+	1+
Required time for evaluation (per UI)	2h	12h	24h	2h
Types of error	User misconceptions	User misconceptions	System-design	System-design

As we can see in the Table 5.4, our inspection framework is the only method specialized for VMSTs. Specialized usability evaluation methods, however, are not uncommon. For Example SUE is a method that is designed for Hypermedia applications (Costabile et al., 1997; De Angeli et al., 2003). SUE is a model-based evaluation technique. Also, there are many variations of the Heuristic Evaluation method such as Ambient Displays (Mankoff et al., 2003) or mobile devices (Bertini et al., 2009). The results produced by our inspection framework are similar in format to the results generated by GOMS technique. Our framework provides an overview of the entire interface, and assesses the functionality for different VMSs. While GOMS provides an analysis of how fast expert users can achieve a given task with an interface, our framework assesses how much support a user-analyst is provided with for visual mining tasks where better support is represented by the reduced effort required (shortness of the sequence of moves). When using GOMS, it is up to the evaluators, to choose which, and how many, tasks to evaluate. However, our framework by default assesses VMSTs for a comprehensive set of known VMSs. Performing an evaluation using our inspection framework, takes less time than a GOMS analysis and enables evaluators to get a broader view. Finally, instead of trying to decide which interface is fastest to use, our inspection framework provides a measure that correlates to a level of support. Therefore, our framework can easily determine that certain designs provide broader and better support for specific tasks and activities.

In summary, in a broad sense, we can say that by using our framework the kind of results produced by GOMS can be generated using a procedure in the same category as in Cognitive Walkthrough, and with the speeds and costs like those in Heuristic Evaluation.

5.3. Trustworthiness of the Framework

There are two aspects of the framework's structure that confirm the trustworthiness of its evaluation of visualization software interfaces. Firstly, let us look at the trustworthiness of the two models which were chosen from the literature for inclusion in our framework along with our VMS interaction space model. Our reasons for trust in these models are discussed in this section.

Second, a mapping is used to combine our interaction space model and the 7 tasks identified by Valiati et al (2006). This section also reports on the user-driven process followed for development of a valid mapping.

5.3.1. Trust in Models Used in the Framework

One of the first and most important steps in trusting the framework is to be confident in the models chosen to produce the analysis. As we described above, Bates' moves (Bates, 1990) are used to assess how many moves it takes to perform different user tasks using a visualization tool interface. The idea that user interactions are made up of physical and mental moves performed by users is widely accepted and included in many UEMs such as GOMS model (John, 1985) and Keystroke Level Model (Card et al., 1980). The Keystroke Level Model aims to specifically measure the time taken to perform a task, by counting: keystrokes, moving the mouse, pressing a mouse button, releasing a mouse button, moving the hand between the mouse and keyboard, waiting for system response time, and any mental act such as visual scanning. Hence we believe that use of Bates' moves is a trustworthy choice for our inspection framework.

In addition, our framework depends on the 7 user tasks suggested by Valiati et al. (2006). Two factors are considered in discussing the trustworthiness of using

Valiatis' interaction model. First, reuse and acceptance in subsequent publications within the visualization community is used to discuss how established this model has become in the research community. Second, the appropriateness of this model to be used within an evaluation procedure is discussed.

5.3.1.1. The Tasks Defined by Valiati et al.

As mentioned before, the interaction model developed by Valiati et al. (2006) is among the more recent models which characterizes user tasks for visualization tools. It is based on many existing models (Wehrend et al., 1990; Zhou et al., 1998; Morse, 1999). It integrates the existing tasks in other models with new exploratory tasks in a multidimensional dataset (Park, 2008).

More importantly, Valiati et al. conducted several user studies over time to evaluate their model and to check for inconsistency and incompleteness. Their first case studies involved Computer Science students and served as a preliminary case study. In the second one, a biologist was the subject of the study. The results of these two case studies are published in Valiati et al. (2006).

They performed three other case studies later on over a one year period from September 2006 to September 2007. These studies involved one geographer, one insurance broker, one education expert and three experts on elderly people. Each case study lasted six or more weeks, ranging from a minimum of two to a maximum of four months. The results are published in (Valiati et al., 2008; Valiati et al., 2007).

There are other researchers who have used their interaction model. Boton et al. (2011) used Valiati's model in their proposed method to design coordinated multiple views based on Model-Driven Engineering. Mayr et al. (2011) used some of the tasks in this model to study problem solving processes during the exploration of information visualizations. Halin et al. (2011) used this model to present a usage-centered method that enables one to design "Adapted Visualization Services" in the field of Architecture, Engineering and Construction. Park (2008) used this model to develop intended use evaluation approach for information visualization.

Several alternative sets of tasks exist in the literature. For example, the early work of Wehrend and Lewis (Wehrend et al., 1990) proposes a set of cognitive tasks and related data types (which they call objects). Shneiderman (1996) proposes task-by-data type taxonomy including 7 data types and 7 tasks. Amar et al. (2004) have also proposed a categorization of low-level analytical tasks. Of the available task models, Valiati taxonomy explicitly includes the set of user tasks well-suited for evaluation purposes. In addition, it integrates tasks at different levels, analytic, cognitive (low-level) and operational.

However, this choice does not prevent the use of a different set of tasks, or the move to an alternative task level model in our inspection framework. An example of a somewhat similar case, the Cognitive Walkthrough method was refined by Spencer (2000), reducing the number of questions asked at every step of interaction from four to two. Any change in the interaction model representing tasks, however, will require the generation of a new mapping between the revised set of tasks and the VMSs.

Finally, in terms of scientometric impact, Valiati tasks have already been very well cited in the literature. It is a very recent model and is well cited by authors of recent papers which have reviewed models of visualization tasks (Cancino et al., 2012; Greitzer et al., 2011; Munzner (2009), Minardo, 2007). Based on all the above, we believe that Valiati's interaction model is a trustworthy choice for our inspection framework.

5.3.2. Developing the Mapping Between Models

One of the key contributions of this work which has enabled the use of three models (VMSs, Valiati's taxonomy of tasks and Bates' moves) within one UEM is the mapping used to identify which tasks are important for each of the VMSs. The integration of these models into a unified framework was not a trivial process, as it is not very obvious as to which task should be attributed to which specific VMS(s). It is important that the chosen mapping, however carefully reasoned and constructed, be user-validated. Since there is no fixed process or metric to produce the mapping, it can only be discussed with and supported by independent judges/experts.

In order to develop such a mapping, 3 visual mining experts and 3 researchers from other academic fields, with some (non expert) knowledge about visual mining were involved. The method and results of this process are discussed below.

5.3.2.1. Method

To create a proper mapping an analysis method was designed to: a) clearly present the models to multiple judges, b) collect mapping suggestions, c) identify variations in opinion, and d) create the mapping (by majority/consensus).

A special form (see Figure 5.9) was created to present the visual mining strategies (VMSs) and tasks to participating judges and to collect mapping suggestions from them. This form clearly presents each of Valiati's tasks, one at a time, along with its' description. Below each task, a description of each of our interaction space model values is shown, which are10 in total.

For every task shown one at a time, the participating judge was asked to select a dimension value that it supported. The decisions for each task, by each judge, were stored in a database. As a first step for processing the decisions provided by judges, the number of times each dimension value was selected for each task was summed and the most popular choices highlighted. This analysis provided three types of information. First, it identified parts of the mapping that were unanimously agreed upon by all judges, including expert and novice opinion. All such decisions were accepted without further discussion. Second, the process identified parts of the mapping that were in close competition. In this second case, preference was given to expert's opinion, especially if they were in agreement. Third, the process identified parts of the mapping that varied widely and required further investigation. The results of this analysis and the following discussions are presented in the next section.

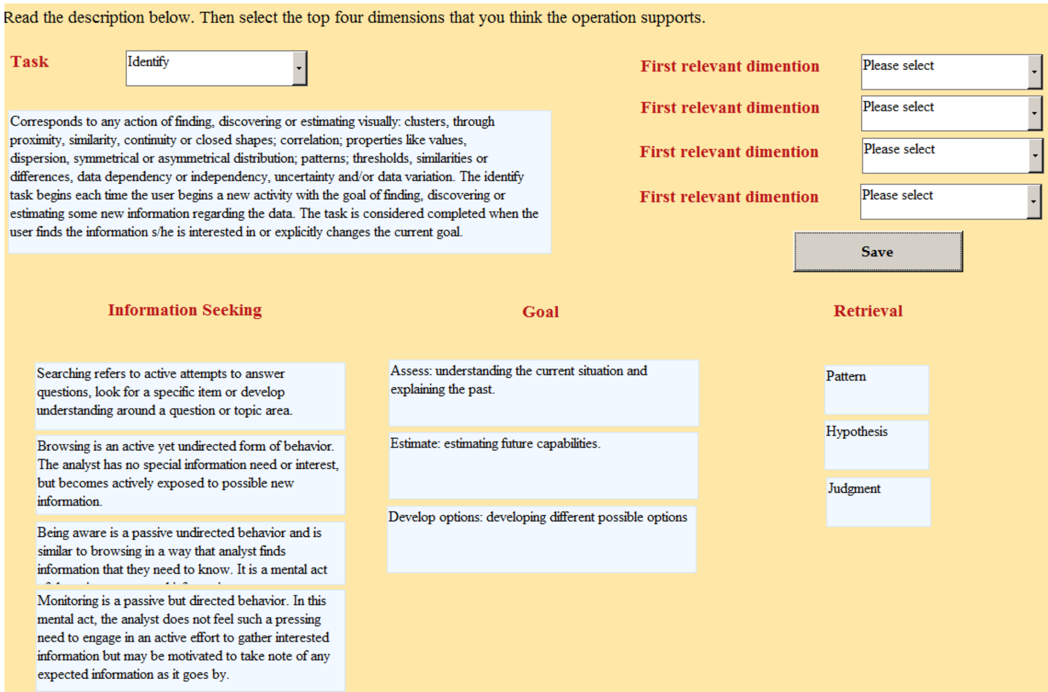


Figure 5.9: The form used to collect expert and novice judgments about mappings

5.3.2.1.1. Results of User Study for Mapping Development

For almost 43% of the tasks, the mappings were unanimously agreed upon without need for further investigation ("compare" for "*pattern*" dimension; "configure" for "*assess*", "*estimate*", "develop options"; "infer" for "*hypothesis*" development). The rest of the tasks, were investigated by either assessing the difference in expert and novice opinion, or by revisiting literature to inform the discussion. The distribution of agreement between participants is shown in Table 5.8. Another 43 % of the tasks received a high agreement. In one case the decision was taken on the side of the experts. In this case all experts and novices mapped "locate" task to "*search*" dimension which was accepted. However three experts and one novice believed that it is also associated with "*being aware*" and "*monitoring*" dimensions. Two other novices did not map it to any other dimension. In this case the decision was taken by siding with experts. The two other cases were related to "visualize" and "browsing" tasks. In this case, the highest agreement of the experts for the dimension matched the highest agreed dimension of the novices. In part of mapping, all of them associated "visualize" with the dimensions of "*assess*", "*estimate*" and "*develop options*", while "identify" was associated with "*browsing*" dimension. However two experts and two novices also mapped them to "being aware" and "*monitoring*" dimensions which have been accepted.

Finally, one of the tasks "determine" received varied opinion (14.3%). Most of the experts and novices mapped this task to "*pattern*" dimension which was accepted. In addition, one expert and one novice mapped it to "*judgment*" dimension. After further discussion with judges and referring to the definition of this task by Valiati et al. (2006) which mentions that this task can be used for hypothesis test, this mapping was also accepted.

Table 5.5: The range of agreement and disagreement for mapping between the tasks and visual mining dimensions

	Unanimous	**High Agreement**	**Varied Opinion**
# of tasks	3	3	1
Percentage	42.85%	42.85%	14.3

5.4. Summary

In this chapter we first described the design of an inspection framework that combines our VMS interaction space model and existing task models, through user validated mappings, in a way that it can be used to estimate the strengths and weaknesses of a VMST's interaction support for visual mining. Second, we demonstrated the application of this framework via a sample evaluation of three publicly available popular visualization tools. By applying this evaluation to three interfaces, it provides quantitative estimates of the strengths and weaknesses in supporting user tasks, the support provided by interface features, and the support for VMSs.

Identifying weak or even missing features can promote changes and updates in implementation to support more tasks or to reduce the user effort required to achieve each task. Finally, by summarizing and normalizing these metrics into the VMS interaction space model, it identifies particular strengths and weaknesses of VMSTs in providing support for the complex cognitive activities in visual mining.

Chapter 6 : Conclusions and Future Work

This chapter provides a brief summary of significant contributions, benefits of this research, and potential avenues for further investigation.

6.1. Summary

6.1.1. Characterizing Interaction Space Visual Mining Process

In this thesis we first drew attention to the importance of interaction in visualization research. While existing research in the area often focuses much more on transformation of raw data into visual representations and their presentation, this thesis has highlighted the overshadowed, but very important interaction component and strongly argued that it is primarily interaction which provides a way to overcome the limits of representation and to suitably augment a user's cognition. We then bring out the importance of having interaction space models which appropriately characterize complex cognitive activities which humans perform during visual mining. Such interaction models are essential for effective design and evaluation of visual mining support tools. Next we have reviewed and classified existing prominent models of interaction related to visualization. We have brought out the short-comings of existing models and clearly noted the need for providing high level characterization of interactions that can guide the analysis, evaluation and design of interactions supported by VMSTs in a way that provide better support for complex cognitive activities.

To address this need, we formulated a model which comprehensively characterizes the interaction space of visual mining. This will enable systematic thinking about user interactions with VMSTs which are intended to support complex cognitive activities. By using trustworthy qualitative directed-content analysis methods and using published papers reporting interactions with visual representations, it was discovered that user activities in this context, termed as visual mining strategies, can be differentiated along a small set of three criteria to make up a domain independent model, the VMS interaction space model. Furthermore, it is demonstrated through four examples in different domains (medical, geographical, bioinformatics and epidemiology) that the proposed VMS model can comprehensively capture visual mining activities.

6.1.2. The Inspection Framework

Further, in this thesis, as a demonstration of the utility of the VMS interaction space model, we proposed an inspection framework which uses the VMS model and can be applied to carry out a quantitative evaluation of the support provided by a VMST for performing complex cognitive activities in visual mining. We then do a comparative evaluation of three widely used VMSTs.

The inspection framework has been designed to analyse VMSTs in three ways. First, it analyses the VMST's interface features, such as spatial navigation or viewing to identify how they contribute to the overall support provided by the VMST. Second, the interface is analysed for how it supports a set of established user tasks. These tasks include identify, determine, visualize, compare, infer, configure and locate. The support for these user tasks are then summarised into user VMSs. The support for each of these VMSs is calculated by averaging the support provided for the user tasks that they will likely need. To provide these analyses, the framework is built upon the integration of interaction models at different levels, the Bates model for low level moves, Valiati model at the task level and our VMS model at the activity level. This integration is made possible by suitable mappings between the levels, which have been developed by us. One mapping establishes links between user tasks and VMSs. The mapping between user tasks and moves is via interface features. These mappings, which have enabled the combined use of different interaction models, represent another of the key contributions of the research presented in this thesis.

As an evaluation method, the inspection framework, and the analyses it provides, has the following advantages:

1) The framework focuses on functionalities of VMSTs and is dataset agnostic. Consequently, any VMST can be evaluated independent of the input domain. Similarly, VMSTs can be directly compared even if they work on different collections of input datasets.

2) Where empirical evaluations of VMSTs may tell us which design performs best for a given task, the three analyses from our inspection framework provide rich insight into the functionality provided by the VMST, and so, can be used to explain the cause of any such findings.

3) The framework analyses VMSTs from 36 different perspectives (VMSs can be seen as being representative of user profiles), whereas the tasks of any empirical user studies typically covers one to three user profiles. Thus our inspection framework can provide a more holistic view of VMST, as compared to the limited view covered by the user study conditions in empirical user studies.

4) The framework can be applied in relatively little time compared to a typical user study involving expert analyst users.

In Chapter 5 we have compared the proposed framework to other similar methods. The proposed framework provides a similar evaluation to GOMS, but with a) less constrained functional analysis, b) specific visual mining oriented focus, c) a simple procedure similar to the Cognitive Walkthrough, and d) requiring less expertise and time, like Heuristic Evaluation. In combining the benefits of these methods, the proposed inspection framework provides fast and insightful analysis of functional support for visual mining.

6.2. Contributions of This Research

- We applied directed-content analysis techniques on a large number of publications on visual mining in different domains, and were able to discover a small set of classification criteria that can be used to comprehensively characterize the interaction space of visual mining so as to enable systematic thinking about user interactions with visual mining support tools which are intended to support complex cognitive activities.

- We presented the formulation of VMSs as combinations of different values of these criteria. The interaction space of visual mining can be comprehensively covered by considering all combinations,
- We have developed an inspection framework for evaluation of VMSTs. The proposed framework incorporates the effects of supporting VMSs into measurements. It provides three contributions to the nature of academic research in evaluation of visual mining support tools:
    - The framework reuses three existing theoretical models in order to produce a metric that can be used in an evaluation. The contribution, therefore, is the approach used to convert visual mining theories into an operationalised usability evaluation method for making predictive analyses of VMSTs.
    - As mentioned above, the mappings developed to link these different models are another novel contribution. These mappings can be investigated, revised or extended by other researchers.
    - A detailed comparative analysis of three widely used VMSTs is presented, which provides some new insights into the support they each provide for visual mining at the episode level.

6.3. Future work

There are still a number of other avenues that can be explored further. These are as follows:

- To use VMSs interaction space model to develop suitable guidelines when developing or improving a visual mining support tool.
- In the inspection framework, one issue that should be considered in the future is whether or not all of the user tasks are equally important to a given user. The importance or relevance of a task may vary depending on the goal and domain. Therefore different weights could be applied to the user tasks.
- Our choice of models for the different levels was based on the current state of the art in interaction models and in user interfaces. As new interaction techniques evolve, e.g., gesture-based or full body interfaces, new models may have to be developed. Integrating these new models would be required.
- More work is needed to further validate the results produced by our proposed inspection framework against existing evaluation results.

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Appendix A: List of publications which have been used for content analysis.

Table A.1: Publications which have been used for content analysis

Paper	Context	Information Seeking	Retrieval	VM Goals
Saraiya et al., (2006)	Bioinformatics	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses, Judgment	Estimate (prediction)
Saraiya et al., (2005)	Bioinformatics	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses, Judgment	Assess (identify and understand the complex interactions among the genes and conditions)
Smoot et al., (2005)	Bioinformatics	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses, Judgment	Estimate (Prediction), Assess
Graham et al. (2005)	Bioinformatics	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses, Judgment	Assess
Kincaid et al., (2005)	Bioinformatics	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses, Judgment	Assess (Diagnosis), Estimate (Treatment)
Gehlenborg et al., (2005)	Bioinformatics	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses, Judgment	assessment, develop options
Craig et al., (2005)	Bioinformatics	Browsing, Being aware	Patterns, Hypotheses, Judgment	Assess (diagnosis), Develop options(treatment), Estimate (prevention)

Kincaid et al., (2004)	Bioinformatics	Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (correlation of gene expression with other types of relevant data such as disease classes, drug treatments)
Meyer-Spradow et al. (2008)	Medical	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (diagnosis of Coronary Artery disease)
Qian et al., (2010)	Medical	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (staging, progression and monitoring of Alzheimer's disease), estimate (prediction of Alzheimer's disease onset)
Lespinats et al., (2009)	Medical	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (breast cancer diagnosis)
Preim et al., (2009)	Medical	Searching, Browsing, Monitorin, Being aware	Patterns, Hypotheses , Judgment	Assess (ischemic stroke diagnosis, breast tumor diagnosis, diagnosis of coronary heart disease)
Hentschel et al., (2008)	Medical	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (access blood damage in ventricular assist devices)
Oeltze et al., (2007) Oeltze et al., (2010)	Medical	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (ischemic stroke diagnosis, breast tumor diagnosis, diagnosis of the coronary heart disease)
Coto et al., (2005)	Medical	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (Breast cancer diagnosis, evaluate the patient’s response to treatment)

Gresh et al., (2002)	Medical	Searching, browsing, monitoring, being aware	Patterns, Hypotheses , Judgment	Assess (variation of survival statistics)
Robinson et al., (2007)	Epidemiology	Searching, browsing, monitoring, being aware	Patterns, Hypotheses , Judgment	Assess (cancer epidemiology)
Proulx et al. (2006)	Epidemiology	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (cause of the flu propagation), Estimate (predict the flu propagation), Develop (propose options for mitigating future risks)
Jacobs et al., (2008)	GeoScience	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (earthquakes in seduction zones extend to deeper depths), Estimate (predict tsunami)
Chen et al., (2008-a)	Geoscience	Searching, Browsing, Monitorin,Being aware	Patterns, Hypotheses , Judgment	Assess (what geographical areas have similar or unusual changes in industry composition, what characterizes them)
Chen et al., (2008-b)	Geoscience	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (identification of geographic clusters of increased cervical cancer risk)
Nordvik et al. (2008)	Geoscience	Searching, Browsing, Monitorin, Being aware	Patterns, Hypotheses , Judgment	Assess (assessment of the rockslide), Estimate(rockslide prediction)
Kehrer et al., (2008)	Geoscience	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess(detect regions which react most sensitively to climate change), Estimate (predict climate change)

Que et al., (2007)	GeoScience	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess(causes of local pollution), Estimate (predict future)
Tomaszewski et al., (2007)	GeoScience	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (post-hoc analyses of real responses to disasters), Develop options (formulate hazard mitigation strategies)
Andrienko et al. (2007)	GeoScience	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (how the fire evolved in real-life), Estimate (predict the spread of a wildfire)
Weaver et al., (2007)	Geoscience	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (weather and climatic effects)
Guo et al., (2005)	Geoscience	Searching, Browsing, Monitoring, Being aware	Patterns, Hypotheses , Judgment	Assess (cancer incidence relationship to socioeconomic factors)
Giovando et al., (2003)	Geoscience	Searching	Patterns, Hypotheses , Judgment	Assess (describe changes in migration patterns over each state)

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Appendix B: An example of coding of a publication in content analysis process

NVivo permitted multiple codes to be applied to each text segment, and allowed codes and quotations to be linked quickly and easily. For example in this paragraph extracted from a case study of breast tumor diagnosis (Oeltze, 2010), the underlined text was coded to “information seeking”, the same paragraph was also coded to include “searching”. The italicised text denotes material coded as “Pattern”. As explained, in Chapter 4, in the further iterations of coding process the italicised text also coded to “retrieval”. The double underlined texts were coded to “Hypothesis” which as patterns also got coded to “retrieval” in further iterations of coding process.

“The visual analysis of the lesion in Mamma1 is illustrated by Figure 4.9. At first, a histogram of the scores of pc1 has been generated (Fig. 4.9 (b)). High scores have been brushed and the selection is visualized within the context of the entire mamma (Fig. 4.9 (c)). The tumor boundary has been derived from the segmentation mask and is indicated as dotted line. Transferring the selection in Figure 4.9 (b) to a scatterplot opposing Wash-in (xaxis) and Wash-out (y-axis), *reveals that regions exhibiting a fast CA accumulation as* well as a fast washout have been selected (Fig. 4.9(d)). This is characteristic for malignant tumors. However, the remaining parts of the lesion exhibit different enhancement characteristics ranging from *suspicious* to *benign*. “