Using Visual Representations of Data to Enhance Sensemaking in Data Exploration Tasks*

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Abstract

This paper explains how visual representations of data enable individual sensemaking in data exploration tasks. We build upon theories of human perception and cognition, including Cognitive Fit Theory, to explain what aspects of visual representations facilitate sensemaking for the viewer. We make three primary contributions. First, we give a general characterization of visual representations that would be used for data exploration tasks. These representations consist of a scene, objects within the scene, and the characteristics of those objects. Second, we extend Cognitive Fit Theory into the data exploration task domain. We explain that the data exploration task has a number of spatial subtasks including observing data points, looking for patterns or outliers, making inferences, comparing observed facts or patterns to one's own knowledge, generating hypotheses about the data, and drawing analogies from the context being observed to another context. Third, we offer a set of theoretical propositions about how visual representations of data can serve the sensemaking goal. Specifically, visual representations best facilitate sensemaking in data exploration tasks when they (1) support the four basic human visual perceptual approaches of association, differentiation, ordered perception, and quantitative perception, (2) have strong Gestalt properties, (3) are consistent with the viewer's stored knowledge, and (4) support analogical reasoning. We propose that visual representations should possess several of these four aspects to make them well-suited for the task of data exploration.

Keywords: *Information visualization, visual representation, perception, decision making support, data mining, analogy, business intelligence, sensemaking*

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1. Introduction

The need for effective information visualization is as great as it has ever been. Managers and knowledge workers have a persistent and long-recognized need to make sense of their organizations and the environments in which they operate. The amount of data available to meet this need increases continually with the expansion of data storage, the gains in computer processing capacity, the growth of enterprise-wide database access, and the evolution of Internet search engines. People have more data than ever available from their own desktops, their organizations' applications, and global web servers. The development of tools to analyze and distill valuable insights from this data is imperative if information overload is to be avoided. Not surprisingly, IT toolsmiths continue to create more tools for the access, organization, and analysis of data. These tools are often used to generate visual representations of data (Card et al., 1999). This situation suggests a possible benefit to be gained from research on human perception and processing of visual representations in the context of making sense of new and complex data.

The purpose of this paper is to explain how visual representations of data can enable individual sensemaking during data exploration tasks. By visual representations of data, we mean spatial representations that are derived from symbolic data (e.g., words or numbers), such as are found in database tables (Card et al., 1999). By sensemaking, we mean the ability to comprehend complex information, assimilate it, create order from it, and develop a mental model of the situation as a precursor to responding to the situation (Anderson, 1983, Gentner and Stevens, 1983, Klein, 1993)[1].

We take sensemaking as the primary goal of data exploration tasks. Data exploration tasks are those of examining data without having an *a priori* understanding of what patterns, information, or knowledge it might contain (Grinstein and Ward, 1997, Tukey, 1977, Tukey, 1980). Exploratory tasks include observing specific data points, looking for patterns or outliers, making inferences, comparing observed facts or patterns to one's own prior knowledge, generating hypotheses about the data, and drawing analogies from the context being observed to another context (Grinstein and Ward, 1997, Tufte, 1990, Tufte, 1997, Tufte, 2001, Tukey, 1977, Tukey, 1980). Exploratory tasks are generally contrasted with confirmatory and presentation tasks (Grinstein and Ward, 1997, Tukey, 1977, Tukey, 1980).

Our work builds on a long stream of research that explains how users perceptually and cognitively process visual representations of data. The earliest MIS research studies on visual representations of data are collectively known as "the Minnesota Experiments." These studies conclude that graphical displays of information can in some cases lead to faster and more accurate decision making, that summarized data can enable decision makers to make faster and more accurate decisions, and that the relationship between the decision, decision-maker, and the information system used to present the data should continue to be investigated (Dickson et al., 1977). Related research in psychology shows that problem representation type matters (Hayes and Simon, 1977, Kotovsky et al., 1985) and that diagrams can offer significant advantages over informationally equivalent text (Larkin and Simon, 1987). The "tables vs. graphs" literature in MIS (Benbasat and Dexter, 1985, Benbasat and Dexter, 1986, Benbasat et al., 1986, DeSanctis, 1984, Ives, 1982, Jarvenpaa, 1989, Jarvenpaa and Dickson, 1988) provides a basis for the theoretical synthesis that is Cognitive Fit Theory (Vessey, 1991, Vessey and Galletta, 1991). The Theory of Cognitive Fit explains that when the data presentation format matches the task type, cognitive fit can be achieved, and both decision making accuracy and decision-making speed can be enhanced. Researchers continue to build on Cognitive Fit Theory as they investigate such areas as GIS (Dennis and Carte, 1998, Khatri et al., 2006), spreadsheet error correction (Goswami et al., 2008), and virtual reality (Suh and Lee, 2005).

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[1] Our definition of sensemaking retains some of the flavor of the work of Karl Weick (Weick, 1993, Weick, 1995, Weick et al., 2005). While Weick focuses on factors that lead to both individual and organizational sensemaking, we focus exclusively on sensemaking at the individual level and focus on those cognitive aspects that are relevant to sensemaking from a visual representation of data.

We make three primary contributions to this line of research. First, we extend Cognitive Fit Theory as we elaborate on spatial representations by characterizing (spatial) visual representations as consisting of scenes, objects within the scene, and characteristics of those objects. We use this characterization as we consider how various aspects of visual representations affect perception during data exploration tasks. Second, we further extend Cognitive Fit Theory as we link it to the data exploration task domain and that domain's goal of sensemaking. We explain that the data exploration task domain has a number of spatial subtasks including observing data points, looking for patterns or outliers, making inferences, comparing observed facts or patterns to one's own knowledge, generating hypotheses about the data, and drawing analogies from the context being observed to another context. We explain that each of these spatial subtasks has sensemaking as its primary goal. Third, we offer a set of theoretical propositions about how visual representations of data can serve the sensemaking goal. Specifically, visual representations best facilitate sensemaking in data exploration tasks when they (1) support the four basic human visual perceptual approaches of association, differentiation, ordered perception, and quantitative perception, (2) have strong Gestalt properties, (3) are consistent with the viewer's stored knowledge, and (4) support analogical reasoning.

Our model explains why various types of visual representations, such as map-based representations, have been well-received; why some, such as Chernoff faces, have yielded mixed results; and why still others, such as traditional graphs, work well in some tasks, but poorly in others. Our paper contributes to the literature by building upon theories of human perception and cognition to describe the aspects of visual representations that facilitate sensemaking for the viewer.

The paper proceeds as follows. First, we describe the building blocks for our model of visual representations that facilitate sensemaking, reviewing work in information visualization and visual perception. We also explain the relationship of our work to extant literature on the Theory of Cognitive Fit. Second, we explain how visual representations can facilitate sensemaking as we present a conceptual model of the sensemaking experience in data exploration tasks. Third, we present a research agenda to test the theoretical propositions we develop in this paper. We conclude by noting the contributions of our paper and summarizing our arguments.

2. Characterization of Visual Representations

Human information systems, similar to computerized information systems, have often been understood as systems for the input, processing (along with associated retrieval and storage in memory), and output of information (Hogarth, 1980, Newell and Simon, 1972). We observe that in many prior studies, predictions about how visual representations affect decision outcomes are derived by examining how the human viewer's processing and memory interact in the execution of decision strategies. These strategies determine which information is sought from the visual representation, in what sequence, and how that information is used to construct a decision or problem solution (Benbasat and Dexter, 1985, Benbasat and Dexter, 1986, Benbasat et al., 1986, Dickson et al., 1977, Jarvenpaa, 1989, Jones et al., 2006, Kumar and Benbasat, 2004, Vessey, 1991, Vessey and Galletta, 1991). That is, the vast majority of prior research examining visual representations has focused on the processing and outputs of the human information processing system, with only a secondary focus on perception.

In contrast, this paper focuses primarily on the human perception of visual representations and only secondarily on the processing and output of information. This change of focus from the prior literature enables us to view human perception in detail and to investigate the specific components of perception that might be associated with large classes of strategies or subtasks in the data exploration task domain. That is, we anticipate that a visual representation will be more useful to its human viewer for individual sensemaking if the individual components of the representation are relatively straightforward and facilitate the acquisition of information that could become building blocks for processing, decision making, and other types of output.

Perception is defined as "the process of interpreting and recognizing sensory information" (Ashcraft, 1998, p. 428). Cognition is defined as "the collection of mental processes and activities used in

perceiving, learning, remembering, thinking, and understanding, and the act of using those processes" (Ashcraft, 1998, p. 5). This definition is similar to Neisser's classic definition of cognition: all processes by which sensory input is transformed, reduced, elaborated, stored, recovered, and used (Neisser, 1967). Thus, cognition is a more comprehensive term that encompasses not only perception, but also the post-perceptual processing, storage, retrieval, and use of information for decision making and to generate other responses and output. Throughout the remainder of this paper, we use the term "cognition" when we mean to incorporate post-perceptual processing of information.

2.1. Perception of Visual Representations

The term *information* (or *data*) *visualization* is used most often in literature to describe the process of creating a visual representation of data, but is also used to describe the output of that process (Card et al., 1999, p. 7, 17). To avoid confusion, we use the terms "information visualization" and "visualization" to refer to the *process* (often computer-supported) of creating a visual representation of data. We use the terms "visual representation of data" and "visual representation" to refer to the *product(s)* of the process of information visualization. We take it that these visual representations are spatial representations, meaning that "they present spatially related information. According to Larkin and Simon (1987), a diagram (and therefore a graph) 'preserves explicitly information about the topological and geometric relations among the components of the problem,' i.e., they *emphasize information about relationships in the data*" (Vessey and Galletta, 1991, p. 67). We do not distinguish between "data" and "information" in this paper and, thus, will treat them as synonyms.

Figure 1 shows that the world is abstracted as data, which is then used to create a visual representation that can be viewed by a human viewer. The human is viewing the representation, but she is trying to learn something about either the data or the world it represents. Most of the following discussion refers to visual representations and the data from which a visual representation is derived rather than the world. Nevertheless, we acknowledge that most viewers try to make sense of data only because it could tell them something about the world. For example, stock traders might look at visual representations derived from stock transaction data, but they have little interest in making sense of this data unless it represents assets actually changing hands in real-world stock trades.
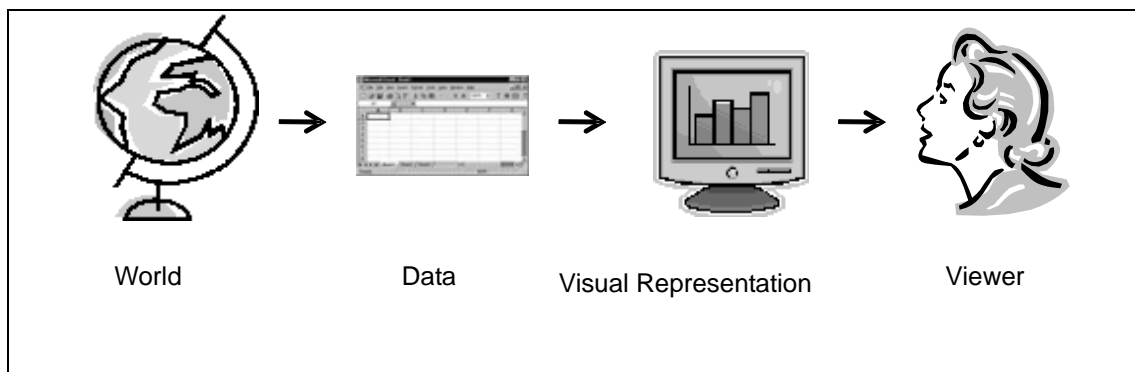

World   Data   Visual Representation   Viewer

Figure 1. Sensemaking Using Data Visualization

2.2. Features of Visual Representations

At the most basic level, a visual representation consists of only three types of features that are perceived by the human viewer: a scene, objects within the scene, and characteristics of the objects. The **scene** is defined as "*a semantically coherent (and often name-able) view of a real-world environment comprising background elements and multiple discrete objects arranged in a spatially licensed manner. Background elements are taken to be larger-scale, immovable surfaces and structures such as ground, walls, floors,...*" (Henderson and Hollingworth, 1999, p. 244). A simple example of a scene is the well-known X-Y graph (see Figure 2a). In this figure, the X and Y axes as well as the coordinate field are the scene.

Figure 2. Objects, Scenes, and Characteristics
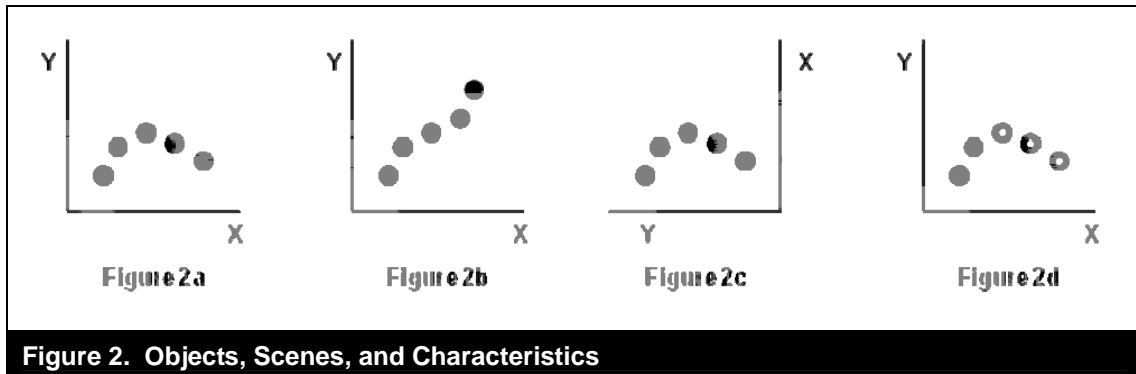
Objects are defined as "*small-scale discrete entities that are manipulable (e.g. can be moved) within the scene*" (Henderson and Hollingworth, 1999, p. 244). Restated, objects are related to scenes in that scenes are understood to be background elements that cannot be moved or altered, while objects are entities that may appear in different locations in the scene.

The essence of the scene-object idea is that most visual representations have some type of background (a scene) within which some point, line, or other visual element (an object) is displayed. In the simple example of the X-Y graph (Figure 2a), we see the points (objects) in the coordinate plane of the graph (scene). In Figure 2b, we see the points (objects) on the graph (scene), but the points are in locations different from where they were in Figure 2a. The points move, or, using the terminology of Henderson and Hollingworth (1999), they are "manipulable" within the scene of the X-Y graph. Viewers understand that the points (objects) may appear in various locations in the scene. The scene, in contrast, never moves. Under no circumstances would a viewer expect to see the X and Y axes in different locations as in Figure 2c. Thus, objects move (or are "manipulable") within the scene, but the scene itself is immovable.

Other examples of scenes and objects are as follows. If a bar graph is understood to be a scene, the bars on that graph are objects; and if a line graph is understood to be a scene, the lines on the graph are objects. In more sophisticated environments such as medical images, the human body can be understood to be a scene on which an object such as a tumor appears. Research suggests that scene and object identification are supported by separate areas of the brain (Henderson and Hollingworth, 1999).

We expand the Henderson and Hollingworth characterization of visual representations by noting that objects possess **characteristics**, *attributes of objects that allow qualities of the objects to be observed or allow objects to be compared to one another*. In Figure 2d, the X-Y graph (scene) contains points (objects) that can be distinguished by being black or white-filled (characteristic). A graph such as the one shown here might be constructed with points that have two different fill colors to indicate that the data points represent data from, for instance, two different firms. Any value beyond the *x* and *y* values can be represented by an additional characteristic such as shading. Other characteristics of objects include their size, texture, orientation, shape, and other sources of differentiation.

These features of scene, object, and characteristic appear elsewhere with slightly different terminology. For instance, graphs, one type of visual representation, have been described as having a framework and labels (scene) as well as content on the graph (objects and characteristics) (Kosslyn, 2006). Based on this similar description, we propose that the Henderson and Hollingworth's theory of high-level scene perception, which was initially developed and tested with pictures of concrete real-world scenes, is also able to explain the perception of more abstract, computer-generated scenes and objects. We interpret the concept of scene to include abstract environments such as traditional graphs as well as real-world environments such as maps and three-dimensional virtual reality renderings such as medical images. Our review of numerous visual

representations (Fayyad et al., 2002, Tufte, 1990, Tufte, 1997, Tufte, 2001), as well as the examples included in this paper, leads us to believe that the scene/object/characteristic description of visual representations has broad applicability. Nonetheless, we consider the theoretical constructs and arguments presented herein to be limited to those visual representations that are perceived as consisting of a scene, objects, and those objects' associated characteristics.

A visual representation has one scene and one or more objects (Henderson and Hollingworth, 1999); objects have one or more characteristics. This presents a finite, albeit potentially large, set of sources that offer information. Information is derived from:

- the scene alone
- the object(s) within the scene
- the characteristic(s) of an object
- the scene and its relationship to objects
- the relationship of an object to another object (vis-à-vis their respective characteristics).

The scene offers constraints on the objects, subject to the availability of stored knowledge possessed by the human viewer about the scene type (Henderson and Hollingworth, 1999). The scene conveys information to help the viewer interpret the placement of objects in the scene. Nonetheless, scenes are informative even if they contain no objects because they can trigger the human viewer to retrieve certain knowledge from memory and cause the human to impose certain constraints due to the elicited knowledge. Moreover, the scene sets up in the mind of the human viewer an expectation about the types and placement of objects that might be encountered in the scene.

Objects are introduced into the scene, and information is then derived from the relationship of the objects to the scene. For example, if the scene is an X-Y graph, as has been described above, a point (object) still contains x and y values (characteristics) that are derived from the placement of the object within the scene. If we introduce another object to the scene, the viewer is able to infer x and y values of the second object relative to the first. Indeed, Bertin (1983) has identified four basic human visual perceptual approaches that can be used by the viewer to acquire information from the visual representation.[2] As more objects are added to a scene, a viewer might infer trends or patterns among these objects.

Characteristics of an object allow the viewer to derive additional information from the features of the object itself. For example, if we shade the object in increments from light to dark, we add a third characteristic to the object. Now, two objects differ from each other on three characteristics (x, y, and shading). It is possible to continue to add characteristics to the objects to represent additional values up to some point. In addition to location in the plane, Bertin identified size, value, texture, color, orientation, and shape as distinguishing characteristics (Bertin, 1983).

2.3. Cognitive Fit Between Visual Representation and Task

The Theory of Cognitive Fit was introduced to synthesize the results of the numerous studies on the effects of information presentation using graphs and tables (Vessey, 1991, Vessey and Galletta, 1991). The theory's earliest experimental application investigated what type of visual representation was best suited to spatial tasks, and what type of visual representation was best suited to symbolic tasks. Symbolic tasks involve extracting discrete values from a set of data. Spatial tasks, on the other hand, involve assessing the data as a whole, rather than as discrete data values (Vessey and Galletta, 1991). Symbolic representations present discrete numeric values contained in a dataset; numerical tables are one example of this type of representation. Spatial representations present images and words based on data; graphs are one example of this representation type (Vessey and Galletta, 1991).

These researchers concluded that (1) when a problem solver has a spatial task, problem solving will be more efficient and effective when a spatial representation is presented, and (2) when a problem

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[2] We will describe these four perceptual approaches in greater detail in the next section of the paper.

solver has a symbolic task, problem solving will be more efficient and effective when a symbolic representation is presented. Thus, the Theory of Cognitive Fit explains that when the problem representation matches the task type, cognitive fit can be achieved and decision making performance will improve. These explanations have been echoed in related fields, where researchers study the relationships between external problem representation, internal problem representation, and processing (Scaife and Rogers, 1996), and where others have noted that "effective diagrams depict information the same way that our internal mental representations do" (Chabris and Kosslyn, 2005, p. 40).

This theory has also been presented as a fundamental part of a theory of general problem solving, and it was clear from its inception that Cognitive Fit Theory would be applicable in a wide variety of problem solving domains (Vessey, 2006). Vessey stated that the Theory of Cognitive Fit rests on cost benefit theory as a framework, according to which decision makers trade off the effort required to make a decision vis-à-vis the accuracy of the outcome (Beach and Mitchell, 1978, Payne et al., 1993). In general, increasing task demands encourage users to shift to perceptual processes, which are better supported by visual representations, and away from analytical processes, which are better supported by tables of words and numbers.

More recent research has addressed other dimensions of cognitive fit. For example, it has been described that the type of spatial representation could be matched to task type (Hubona et al., 1998) and that Cognitive Fit Theory applies in the domains of GIS (Dennis and Carte, 1998, Khatri et al., 2006), spreadsheet error correction (Goswami et al., 2008), software development and maintenance (Shaft and Vessey, 2006), and virtual reality (Suh and Lee, 2005) These studies show that not only can the presence of a visual representation expedite problem solving, but that various aspects of the visual representation vary in their degree of match to the task. For a more detailed explanation of such cognitive processes and strategies, and for a review of the literature on the variety of studies that have applied Cognitive Fit Theory, see Vessey (2006).

Most visual representations of data are spatial representations; therefore, our interest lies in spatial representations and spatial tasks. While the types of tasks in data exploration for sensemaking have not, to our knowledge, been specifically researched, we suggest that these tasks (or subtasks) include finding or identifying various objects, looking for patterns and relationships among the objects within a scene, making inferences about the objects or patterns noticed, comparing observed relationships among scene and objects to the viewer's prior knowledge, generating hypotheses about the data, and drawing analogies from the context being observed to another context (Grinstein and Ward, 1997, Tufte, 1990, Tufte, 1997, Tufte, 2001, Tukey, 1977, Tukey, 1980). All of these tasks can be interpreted as spatial tasks, and, if so, should have good cognitive fit with spatial representations.

A main thesis of our work, however, is that not all spatial representations are created equal. Some visual representations provide better support for sensemaking during data exploration tasks than others. In the section that follows, we explain the features of visual representations that can make them well suited for data exploration, and thus, for the goal of sensemaking.

3. Aspects of Visual Representations that Facilitate Sensemaking

A visual representation should highlight, rather than hide, patterns in the data, and, ideally, should enable the viewer's attempt to derive meaning from patterns in the data. Visual representations that require a high level of cognitive effort from viewers in order to interpret the representation are less desirable than visual representations that require relatively less effort. Figure 3 shows the aspects of a visual representation that can enhance the quality of the sensemaking experience. Each of these aspects will be discussed in turn.
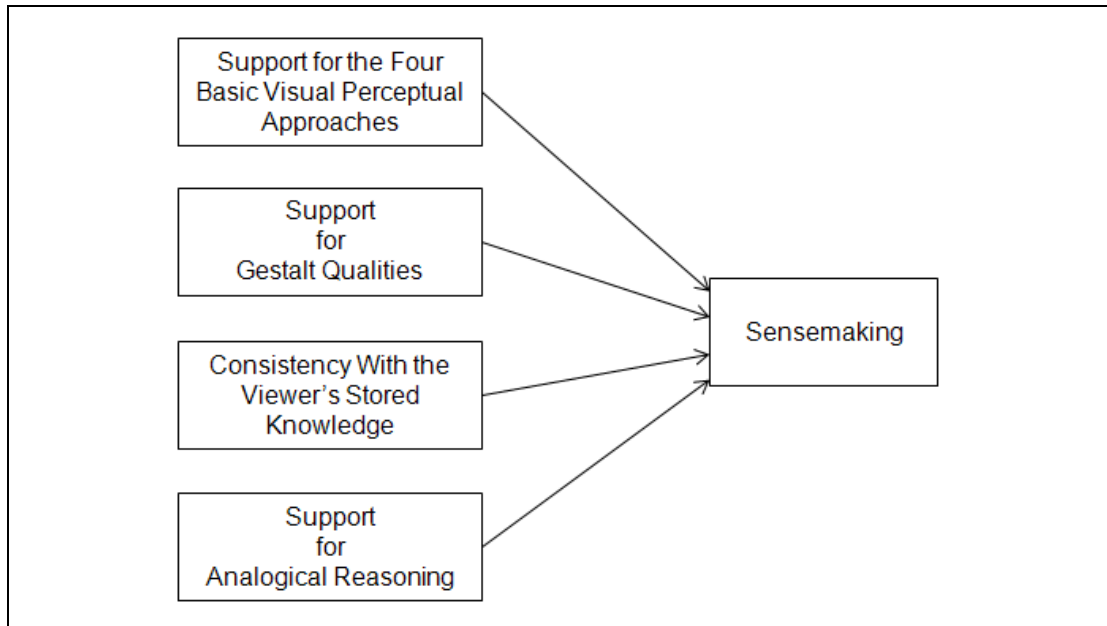
Figure 3.   Aspects of the Visual Representation that Affect Sensemaking

3.1. Support for the Four Basic Visual Perceptual Approaches

Bertin (1983) observed that there are four human visual perceptual approaches that are based on the characteristics of objects in visual representations. These are described as follows:

1. Association – The viewer notes that two (or more) objects are similar and, thus, can be grouped together.
2. Differentiation – The viewer notes that two (or more) objects are different and must be placed in different groupings.
3. Ordered Perception – The viewer notes that an object has more of a particular attribute than another item.
4. Quantitative Perception – The viewer notes that an object has some multiple of an attribute possessed by another item.

For objects in a scene to be compared, they must have characteristics that the viewer can discern. Bertin's perceptual approaches give us a way to understand such discernment. By displaying salient differences in characteristics of objects such as size, texture, color, orientation, and shape in ways that are easily discernable, cognitive burden can be lessened, and sensemaking can be facilitated. For instance, can the viewer of a visual representation R easily notice whether object point a is the same as or different from point b?   Can the viewer easily notice that point a is higher than point b; or that point a is twice as high as point b? If so, then representation R facilitates the four perceptual approaches for these particular objects and this particular characteristic. To fully facilitate the four perceptual approaches, representation R would need to support all four perceptual approaches for all characteristics on all objects. Thus, one visual representation may have greater support for these perceptual approaches than other informationally-equivalent visual representations.

Not every visual representation supports all four perceptual approaches, however. In light of this reality, we now describe how each of the four visual perceptual approaches can be linked to one or more data exploration subtasks. We describe these links to make the case for the contribution of each of the four visual perceptual approaches to the sensemaking goal. We describe these links between the four visual perceptual approaches and the various data exploration subtasks as a set of propositions.

Basic data exploration subtasks such as finding and identifying various objects, as well as subtasks

that involve pattern detection, are facilitated by a visual representation that supports association, the first of the four basic visual perceptual approaches. Similarly, basic data exploration subtasks such as identifying objects and looking for patterns and relationships (e.g., proximity of two types of objects), comparing these observed relationships with existing knowledge, and even hypothesizing about the data are facilitated by a visual representation that supports differentiation, the second of the four basic visual perceptual approaches.   These ideas are expressed in the following two propositions.

> *PROPOSITION 1A (SUPPORT FOR THE ASSOCIATION PERCEPTUAL APPROACH).   For any given set of objects in a visual representation, the greater the extent to which similar objects are perceived as belonging to a group, the better will be the viewer's sensemaking experience.*

> *PROPOSITION 1B (SUPPORT FOR THE DIFFERENTIATION PERCEPTUAL APPROACH).   For any given set of objects in a visual representation, the greater the extent to which different objects are perceived as belonging to distinctly different groups, the better will be the viewer's sensemaking experience.*

We further note that differentiation, the second of the four basic visual perceptual approaches, requires association, the first of the four basic visual perceptual approaches. For objects to be perceived as differentiated, the viewer must be able to perceive whether (or not) those objects are associated. To perceive that object *A* and object *B* are members of different groups (differentiation) implies the rejection of the conclusion that they are in the same group (association). Thus, the perception of association is foundational.

Differentiation is not, however, required to perceive association. If all objects are of the same group, the ability to easily perceive association is required by definition. The perception of differentiation is irrelevant in such a case.

We now consider additional data exploration subtasks and how they are linked to the remaining two of the four basic human visual perceptual approaches. Basic data exploration subtasks of looking for patterns and relationships, comparing these observed relationships with existing knowledge, and even hypothesizing about the data would be facilitated by a visual representation that supports ordered perception. This is expressed in the following proposition.

> *PROPOSITION 1C (SUPPORT FOR THE ORDERED PERCEPTUAL APPROACH).   For any given set of objects in a visual representation, the greater the extent to which objects ordered by some characteristic are perceived in their correct order, the better will be the viewer's sensemaking experience.*

As with the first two of the four basic visual perceptual approaches, there is a dependency relationship related to this third of the four basic visual perceptual approaches, ordered perception. The perception of order requires the perception of differentiation. That is, for object *A* to have to be perceived as having more of some characteristic than object *B*, the viewer must be able to perceive that objects *A* and *B* are differentiated.   The reverse of this relationship, namely that ordered perception is required for differentiation, is not necessary. Objects *A* and *B* may be perceived as different in a categorical sense, but not in any ordinal sense.   In such a case of categorical differentiation between objects *A* and *B*, ordered perception would not be relevant.

Finally, basic data exploration subtasks such as looking for patterns and relationships between and among objects, comparing these observed relationships with existing knowledge, and even hypothesizing about the data, would be facilitated by a visual representation that supports quantitative perception. This is expressed in the following proposition.

> *PROPOSITION 1D (SUPPORT FOR THE QUANTITATIVE PERCEPTUAL APPROACH).   For any given set of objects in a visual representation, the greater the extent to which objects*

having quantitative variation on some characteristic are correctly perceived in accordance with these relative values, the better will be the viewer's sensemaking experience.

Support for quantitative perception, the fourth and final of the basic visual perceptual approaches, is also contingent upon some of the previously-described perceptual approaches. Quantitative perception, in which the viewer discerns the relative proportions of a characteristic between two objects or among several objects, requires ordered perception. For example, to perceive that object *A* possesses twice as much of some characteristic as object *B* (quantitative perception) implies that the viewer can perceive that object *A* possesses a greater amount of the given characteristic than does object *B* (ordered perception). Again, the reverse is not true, because order can be perceived without needing to also specify quantity or degree of difference.

A well-known example of a visual representation that supports the four basic human visual perceptual approaches is the graph from the Vessey and Galletta (1991) study that had good cognitive fit with their spatial task (reproduced here as Figure 4). The scene is an X-Y graph with months on the X axis and dollar amounts on the Y axis. Objects are the data points that are plotted on the graph. Association is supported, for instance, because points indicating the amounts of monthly deposits are of similar size, shape, and shade (black). Similarly, the points indicating the amounts of monthly withdrawals are also of similar size, shape, and shade (white). Association is also supported by the black line connecting the points indicating deposits and by the lighter line connecting the points indicating withdrawals. Differentiation is supported because deposits and withdrawals are indicated with points of different shade (black or white). Ordered perception is supported because it is discernable based on the Y-value of the point when a deposit or a withdrawal is of a greater (or lesser) amount than in another month. Finally, quantitative perception is supported because it is again discernable based on the Y-value of the point how much greater (or less) a deposit or a withdrawal is than in another month.
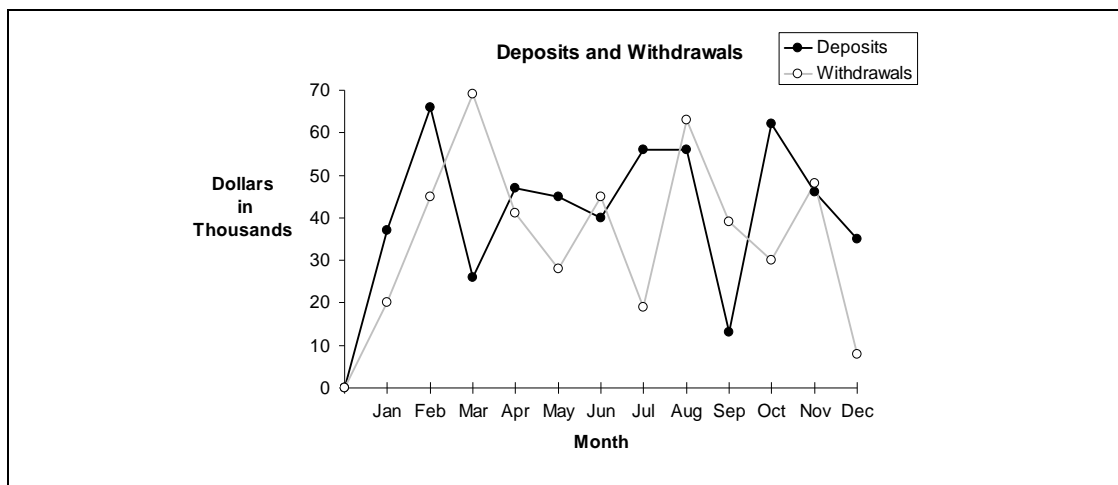
Figure 4. Traditional Graph

Source: Vessey and Galletta (1991). This is a reproduction of the "spatial representation" (p. 72) that had good cognitive fit with the spatial task instruction: "In which month is the difference between deposits and withdrawals greatest?" (p. 71)

Computer-generated visual representations are intended to give good support for the four perceptual approaches. Modern graphics software is typically programmed to present default graphs that make the characteristics easy to discern. For example, bar charts may have grid lines to make quantitative comparisons easy and direct. When shade or color is a used, the default graphs typically have highly divergent values for color or shading of different bars or pie slices to facilitate association and differentiation. Such software also allows the user to override the default settings if the original object/characteristic values are not deemed satisfactory. Thus, the level of support for the four

perceptual approaches can be improved either by altering objects so that they support a greater number of the four approaches or by altering objects so that they support any one or more of the four approaches more strongly, that is with greater salience.

3.2. Support for Gestalt Properties

While at least a modicum of support for the four basic visual perceptual approaches is necessary for the quality of the sensemaking experience, support for the four perceptual approaches is not sufficient for many data exploration tasks. While the viewer may detect differences among objects, the viewer also seeks patterns among the objects. Visual representations that have good Gestalt qualities support such pattern seeking activity. Gestalt theory explains that humans assume a simple, regular, unitary organization in the objects they perceive (Pomerantz and Kubovy, 1986, Spelke, 1990). When the natural Gestalt processes of holistic perception are allowed to operate, the viewer identifies collections of objects as units and is able to spot patterns (although not necessarily interpret them) easily. Objects that support Gestalt processing make use of the Gestalt Laws of similarity, proximity, symmetry, (near) continuity, closure, or an inference of common fate (such as all objects appearing to travel in the same direction) (Pomerantz and Kubovy, 1986, Spelke, 1990). One or more of these six laws must be present for Gestalt processing of a visual representation to occur, but it is not imperative for all six to always be present. The graph presented earlier in Figure 3 demonstrates good Gestalt properties for deposits (solid black points connected by a black line) and withdrawals (white points connected by a lighter-shaded line).

Similar ideas have been advanced by a number of researchers in cognitive science. When objects are arranged in a visual representation so that they can be perceived as a unit, they are perceived more quickly and with less effort (Wickens and Carswell, 1995). Sometimes this is achieved through proximity of the objects and at other times through so-called "emergent features" such as alignment, symmetry, and parallelism. These emergent features are not a property of any of the individual objects on the visual representation, but are a property of the objects when viewed as a whole. Emergent features allow multiple objects to be perceived as a unit and reduce the amount of effortful mental comparison of objects that viewers are required to engage in (Wickens and Carswell, 1995). Furthermore, people naturally group objects in visual representations into units, which they then attend to and remember (Kosslyn, 2006). Thus, visual representations that incorporate Gestalt or Gestalt-like features facilitate sensemaking because they make use of viewers' predispositions to perceive related objects as a unit.

The potential benefit of Gestalt properties for sensemaking is exemplified by comparing the traditional graph (Figure 4) to a collection of Chernoff Faces (Figure 5). Chernoff (1973), on noting that people can apparently perceive massive amounts of information when they look at human faces, and perform such feats as recognizing numerous faces as distinct, hypothesized that if information is represented as the components of faces, then this information could be very quickly perceived by human viewers. With Chernoff faces, the length of the nose, the width of the mouth, the size of the eyes, and so forth, all represent the values of different variables, and present a compact representation of multidimensional data. Thus, properly constructed Chernoff faces can support their viewers' holistic rapid integration of data from each face (Umanath and Vessey, 1994) and can, therefore, support quick overall assessment of each of several faces.

Furthermore, the collection of Chernoff faces in Figure 5 can be said to support the four visual perceptions of Bertin because the objects, including the eyes, nose, mouth, ears, and so forth, are distinct from one another. The viewer can observe, for instance, when the size of the eyes on one face is similar to the size of the eyes on another face (association), when the slant of the eyebrows on one is different from the slant of the eyebrows on another face (differentiation), when the mouth of one face is more curved than the mouth on another face (ordered perception), or when the nose on one face is twice as long as the nose on another face (quantitative perception).

On the other hand, it is a demanding task for the viewer to quickly spot all faces with identical, medium-sized eyes. Such task would be better supported by, for example, each size eye having a

distinct color, which would be consistent with good Gestalt principles. Then a viewer of the entire collection of faces could instantly perceive the group of red-eyed Chernoff faces.
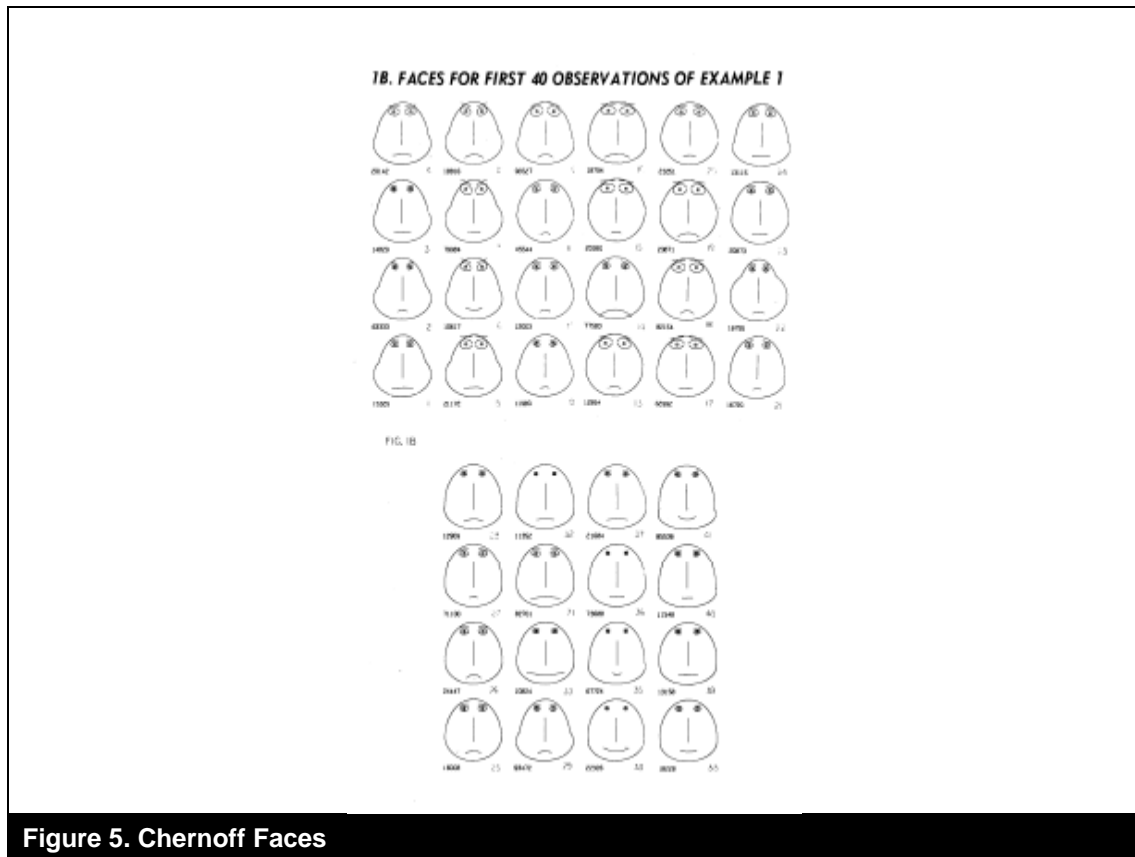

Figure 5. Chernoff Faces

Source: (Chernoff, 1973)

An important aspect of sensemaking is the ability of viewers to modify their knowledge schemas as they process the patterns supported by Gestalt. For example, the viewer of a map containing salient objects for police presence and crime rates might notice a positive relationship between police presence and crime rates. The viewer initially thinks that this seems counterintuitive, because police are supposed to prevent crime, which implies a negative relationship between police presence and crime. Then, that viewer infers that the situation might be that police are actually assigned to locations with the most criminals, which explains the positive relationship. In other words, the human viewer is beginning to integrate the pattern he or she has detected with his or her existing knowledge. For a visual representation to support the viewer's making sense of patterns, it must have enabled the detection of such patterns, but it necessarily involves cognitive processing and memory retrieval and storage, because sensemaking entails a modification of knowledge structures in the viewer. In other words, patterns in data are made salient by good Gestalt properties. The detection of, and thinking about, patterns can improve the viewer's knowledge. This relationship is summarized in the following:

> PROPOSITION 2. *The better a visual representation's Gestalt properties, the better will be its viewer's sensemaking experience.*

3.3. Consistency with the Viewer's Stored Knowledge

Visual representations that take advantage of the knowledge that exists in the viewer's memory can also enhance the sensemaking experience. When a visual representation has high consistency with the viewer's knowledge, it avoids imposing an unnecessarily high cognitive cost for the translation

from object/characteristic to its meaning (Hutchins et al., 1986, Kotovsky et al., 1985). For example, typical weather maps that show temperature ranges from high to low as ranging from red to blue impose low translation costs because people generally associate red with warmth, blue with cold, and can easily order colors. Thus, there is no mental translation required to get from the color (red) to its meaning (hot). Other patterns, say from green (hot) to pink (cold) would still support ordered differentiation of characteristics as well as pattern detection (i.e., all areas in pink are in the same temperature range) but not facilitate sensemaking because of the inconsistency with the viewers' stored knowledge. Hutchins et al. (1986) refer to the amount of effort for translation as "directness," with visual representations that do not impose this barrier being more direct than those that impose high translation costs.

Chernoff Faces may also at times run into this problem of inconsistency with real world knowledge. The potential for sensemaking, which might exist to a high degree for someone interpreting expressions on real humans' faces, can be either high or low in Chernoff faces. Chernoff faces facilitate sensemaking when realistic emotions are depicted. When a Chernoff face's objects and characteristics do not combine to form a known facial expression, the face is not consistent with the viewer's stored knowledge. When a common facial expression is not recognized, a greater amount of cognitive effort is required to apprehend the meaning of the face (Umanath and Vessey, 1994).

For an example of a visual representation that does capitalize on the viewer's real world knowledge, we offer the Napoleon's March pictorial created by Minard in 1861 (see Figure 6). This visual representation does a particularly good job with the first three aspects of representations that facilitate sensemaking. Indeed, Tufte (1983), in his classic book on the principles of graphical design, referred to this pictorial by stating, "It may well be the best statistical graphic ever drawn (p. 40)." This visual representation facilitates sensemaking by enabling the four basic visual perceptual approaches, allowing Gestalt processing, and accessing viewers' stored knowledge.
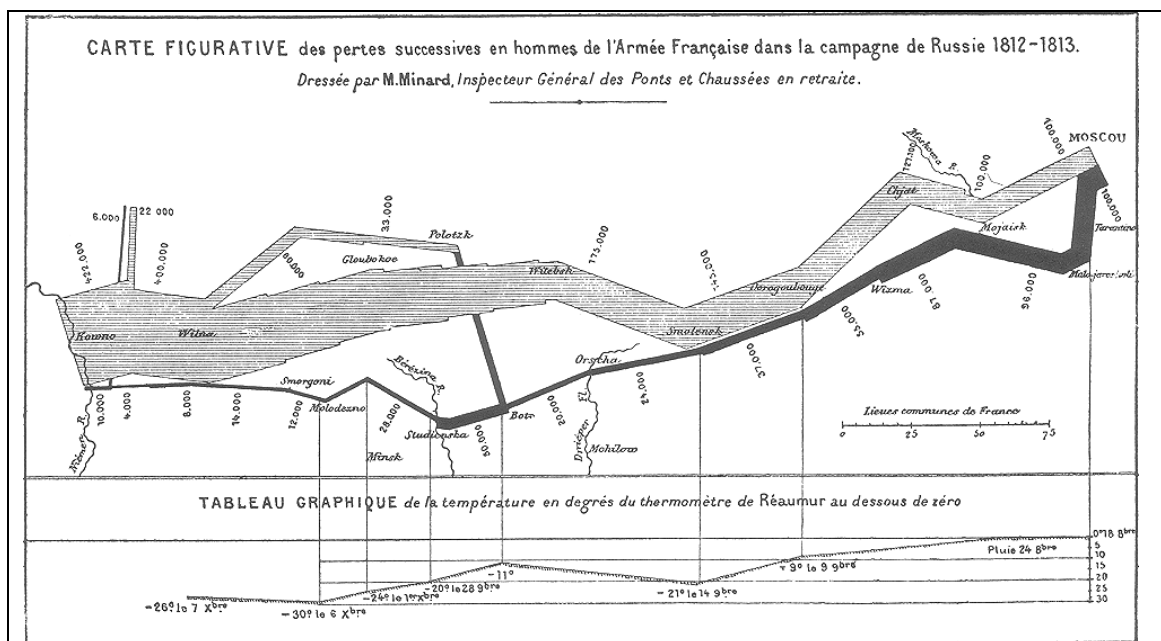
Figure 6. Representation Using a Geographical Map: Napoleon's March
Source: Tufte (2001)

This figure conveys information about Napoleon's disastrous march on Moscow from the Polish-Russian border and shows the direction of the army (lighter shade is invading, darker is retreating), the size of the army (width of the path, with occasional numbers attached), some geographic features (the scene is a map, with relevant rivers and cities), the freezing temperatures encountered by the

army during the winter (with months and temperatures indicated on the graph at the bottom, with vertical lines connecting the temperature points to points on the return march. The scene gives some very distinct and direct information cues, by showing the destination ("Moscou") and various rivers that have to be crossed by the army. The main object of interest, the march of the army, has a high level of directness since it is shown as a path, with the width (size) being easy to see at any point in the march, with size also shown (indicating that the initial army size is 422,000 but the returning army size is only 10,000). One aspect of the directness of the army's path is that it is easy to detect when the army was split into two groups, and when the groups were rejoined. The figure incorporates a traditional graph showing the temperatures and dates during the return trip at the bottom of the figure, but the translation effort required to use this graph is relatively low since the temperatures are tied (via vertical lines) to points on the march, and the labeling is shown directly on the graph at the appropriate location to remind the viewer what each point represents.

This figure facilitates sensemaking for the viewer because it triggers ties to knowledge of the viewer about such things as armies, marches, terrain (i.e., river crossings), that an army could split with one group directed at a secondary military target while the main group marches on to the primary target, cold winter weather in Russia, and European history, to name a few. An indication of this figure's directness is that all text is in French, yet non-French speaking viewers can typically get much information from the graphic once they know its basic purpose. The Napoleon's March figure demonstrates the advantage to human perception of using a scene, objects, and their characteristics that are consistent with the viewer's real-world knowledge. This is expressed in the following proposition.

> PROPOSITION *3. The more consistent a visual representation's features are with the viewer's knowledge, the better will be its viewer's sensemaking experience.*

One point to be emphasized here is that not all viewers have the same stored knowledge. Many visual representations are designed for wide viewership, such as in newspapers, and in such cases there is an assumption that the viewers have knowledge typical of their readers. Other visual representations may require specialized knowledge and were created for a smaller audience of specialists. In certain cases, the visual representation itself might have been part of the viewer's education, as in the case of data flow diagrams in the education of MIS specialists.

Obtaining the advantages of the Napoleon's March figure was surely a labor-intensive undertaking for its creator, Minard. Modern GIS software, however, makes creation of such maps feasible for non-professionals. GIS outputs have been found to expedite problem solving in a variety of tasks and difficulty levels (Smelcer and Carmel, 1997). These tasks included several spatial tasks such as we discuss here. GIS systems are capable of displaying data on maps using a variety of conventions such as color, icons, and features (having the appearance of 3-D). Such systems store maps for the user. Objects representing data are shown as "layers" that can be added to a map based on location coordinates. The underlying data for layers are typically in tabular format.

Map-based visual representations appear to serve their human viewers very well for the four basic visual perceptual approaches, for pattern detection, and for interacting with most viewers' knowledge. If all data were geographically or otherwise physically based, then the search for excellent visual representations for spatial tasks might be declared over (Card et al., 1999). Not all data, however, are geographically or physically based. In the following, we discuss one additional way that a visual representation can support its viewers' efforts at sensemaking.

3.4. Support for Analogical Reasoning

Up to now, our focus has been on aspects of a visual representation that would make it easy for someone trying to acquire the information explicitly displayed by the representation. Learning occurs as the viewer observes information that is present, and the point has been to reduce barriers to this observation. In the following, we discuss how visual representations that support analogical reasoning can help the viewer discover additional information that might remain hidden in

representations that support the four basic perceptual approaches, Gestalt processing, and consistency with real world knowledge, but not analogical reasoning.

Analogical Thinking

An analogy is a mapping process that allows for the understanding of one situation in terms of a more familiar situation (Gentner, 1983). Four steps exist in analogical thinking (Hummel and Holyoak, 2001):

1. The relevant terms are accessed from long-term memory.
2. The source is mapped to the target to identify correspondences.
3. Analogical inferences are made about the target, creating new knowledge.
4. Learning occurs when new links in memory are created (Hummel and Holyoak, 2001).

The source analog is a familiar model or situation that is used to make inferences about an unfamiliar model or situation. The target analog is the unfamiliar model or situation that is to be comprehended by inference from the source analog. The process of aligning the two different analogs and projecting inferences from one to the other is known as mapping. Ideally, there should be a one-to-one correspondence between the mapped elements in the source analog and the elements in the target analog; when this one-to-one correspondence occurs, the analogs are said to be structurally consistent (Gentner, 1983).

A classic example of structurally consistent analogs is found in the representation of electricity as water (Figure 7). In the electricity/water analogy, the properties of water flow (the source analog) are used as to aid in the understanding of electrical flow (the target analog). A water reservoir maps to the electrical ground, a water pump maps to a battery, and a pipe restriction maps to an electrical resistor. Not only are the elements between the base and target structurally consistent, but this particular analogy allows for the mapping of inferences that range from that of pressure to voltage, current to flow rate, and even the equivalency of Poiseulle's law to Ohm's law. The electricity/water analogy works well as a visual representation. This particular analogy is serendipitous in that there is near-perfect correspondence between the base and target elements. It is advantageous for teaching principles of electricity to those who already understand water from their real world experiences, but it has the drawback that it could only have been created by someone who thoroughly understood both systems and the mapping between them.
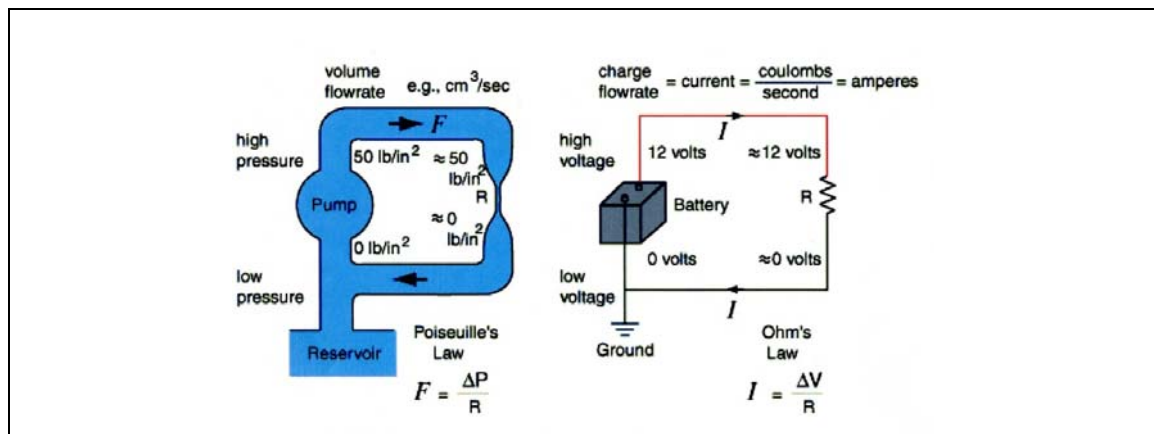
Figure 7. Electricity Modeled as Water

Source: R. Neve, from http://hyperphysics.phy-astr.gsu.edu/hbase/electric/watcir.html

Analogical thinking enables users to counteract the limitations of human processing capacity and short-term memory by modifying the mental models used to process data so that the application of previous knowledge is facilitated and the need for new information is minimized (Rasmussen, 1986). When a problem-solver reaches a state for which there are no adequate problem-solving operators, the problem solver searches for an example of a similar problem-solving state and tries to solve the

problem by analogy to that example (Anderson, 1993). Analogy allows users to apply knowledge, models, rules, and strategies from previous experience and similar situations to a potentially novel problem domain in order to generate a solution (Rasmussen, 1986).

An Example

Several examples of visual representations that support analogical reasoning such as we describe exist. One of the first to be developed was the Spatial Paradigm for Information Retrieval and Exploration (SPIRE) text visualization system that was developed by the US government to help in the analysis of the multitude of documents collected by intelligence agencies (Wise, 1999). The SPIRE system is intended to reduce "information processing load and to improve productivity" (Wise, 1999, p. 1,224). This text-mining system generates ecological visual representations of relationships among terms in the documents analyzed.

SPIRE was originally used to analyze word and theme patterns in a set of documents (such as e-mails, memos, and communiqués intercepted by an intelligence agency) and display the documents as a three-dimensional relief map of natural terrain referred to as a "ThemeScape" visual representation. Mountains indicate dominant themes; small hills indicate weak themes. Additionally, the topography, such as broad mesas or sharp summits, indicates the prominence of themes across the set of all documents analyzed. Broad mesas indicate themes common in many documents; sharp summits indicate significant themes that are not widely dispersed across documents. Additionally, themes with similar, closely related content are placed in proximity to each other in the ThemeScape topography (see Figure 8[3]).
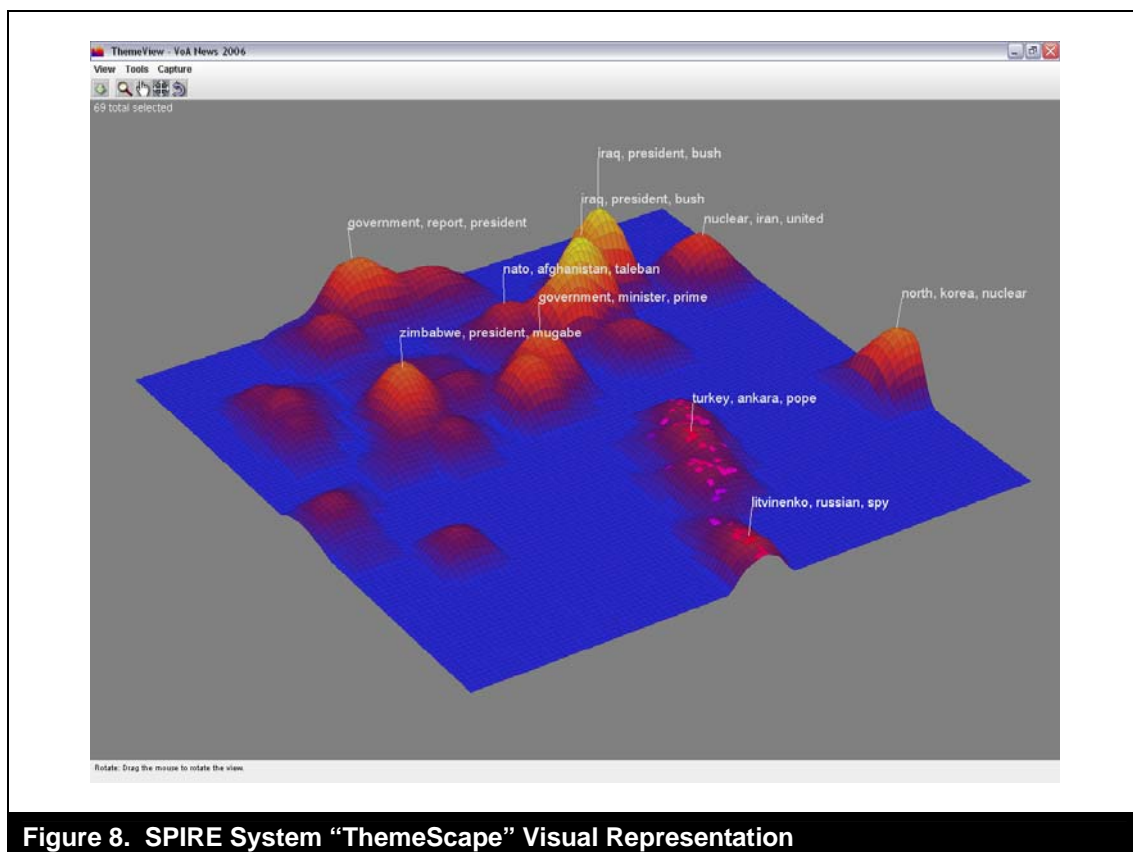
Figure 8. SPIRE System "ThemeScape" Visual Representation

[3] The visual representation generated here was created from a database of news stories gathered from the Voice of America news service in late 2006. Themes include the US-Iraq war (top center), nuclear weapons in North Korea (far right), elections in Zimbabwe (left center), and the poisoning of former Russian spy Alexander Litvinenko (bottom, right of center). Readers should note that this graphic is best viewed in color.

Here, the three-dimensional relief map is the scene, the mountains are objects, and the sharpness of mountain peaks, the depth of valleys between the peaks, and the broadness of mesas are characteristics of the objects. By mapping from the familiar source analog of topography to a target analog where identification and interpretation of patterns is perceptually challenging (a vast number of possibly unrelated documents), the cognitive burden of interpretation is lessened. Users are able to interpret the target analog of the document dataset with minimal cognitive burden. Following the logic of the foregoing discussion about the potential advantages of analogical reasoning, we are in the position to express our final proposition.

> PROPOSITION 4. *The greater a visual representation's support for analogical reasoning, the better will be its viewer's sensemaking experience.*

In sum, we argue that visual representations that facilitate sensemaking: (1) enable relatively easy processing of the four basic visual perceptual approaches: association, differentiation, ordered perception, and quantitative perception, (2) support Gestalt processing, (3) display information in a way that is consistent with the viewer's existing knowledge, and (4) support appropriately the viewer's attempts at analogical reasoning.

3.5. General vs. Strong Approaches in Data Exploration

We now consider the extent to which each of the four aspects of visual representations that facilitate data exploration might be generalizable across a wide variety of data exploration tasks for sensemaking. We are guided by Newell's discussion of strong and weak approaches for solving ill-structured problems (Newell, 1969). According to Newell, a method or approach for problem solving is considered more general to the extent it is applicable to a larger set of problems. On the other hand, a method is considered stronger for a particular problem if it gives a better, or more accurate, answer. Newell observed an inverse relationship between generality and power of methods: The most general methods are weak, while the strongest methods usually apply only to a narrow class of problems.

Our characterization of visual representations suggests a large class of problems that can be represented by them, namely, those representable as scenes, objects, and their characteristics. According to our interpretation, the way to consider generalizability in light of our four aspects of visualization is to consider the approaches to data exploration that could be executed on the visual representation. The first aspect, Bertin's perceptual approaches (association, differentiation, ordered perception and quantitative perception), is the most atomic and foundational of our four aspects. Bertin's perceptual approaches serve as the basic signals about information contained in the scene, objects, and characteristics, and we predict that they will be relevant to the efficiency and effectiveness of any data exploration task based on a scene, objects, and their characteristics. The second aspect, support for Gestalt qualities, is only relevant for those data explorations that would benefit from finding unitary constructs comprising multiple objects or characteristics. Thus, Gestalt qualities may serve a smaller number of tasks, but data exploration approaches that incorporate the unitary constructs of Gestalt might be stronger in some respect for the pattern detection or inference-making tasks, which might contribute significantly to the goal of sensemaking. The third aspect, consistency with stored knowledge, also delimits the number of data exploration approaches to those about which the viewer has knowledge, but such approaches might contribute significantly to the modification of knowledge structures or the building of mental models in the viewer. Therefore, visual representations that are consistent with stored knowledge may facilitate data exploration approaches that are stronger but less general. Finally, the fourth aspect, support for analogical reasoning, is the most restrictive in terms of approaches but may make feasible for the viewer some of the strongest approaches to data exploration that would not otherwise be possible. Nonetheless, a visual representation's support for certain analogies, by making certain strong approaches salient to the viewer, might bias the viewer against noticing patterns or making associations that are not suggested by the analogy but are present in the underlying data.

4. Research Agenda

We now present a brief outline of how each of our research propositions might be tested experimentally. These potential experimental tasks are not an attempt to define a final and comprehensive set of tasks to evaluate our propositions, but are a demonstration that our propositions are, indeed, testable. While only one task for each experimental proposition is described here, it is likely that rigorous experiments would involve a larger series of tasks, with multiple tasks used to test each proposition. Also, we wish to note here that we have chosen to use real-world visual representations of data to demonstrate how our propositions might be tested, but more abstract or hypothetical visual representations could be used as well. Real-world examples have the advantage of face validity (precisely because they are from the real world), but have the disadvantage that experimental subjects' prior knowledge may allow them to answer the question without reference to the visual representation. Hypothetical examples mitigate the risk of prior knowledge biasing experimental results, but are subject to the criticism that the task is "contrived" and intended only to support the proposition, not to be applicable to the real world. In any case, future experimental work will likely include tasks utilizing both real-world visualizations and hypothetical visualizations.

4.1. Quantifying the Dependent Variable

The constructs in the propositions given above are, by intention, widely encompassing. There are, however, a number of ways that each of our propositions might be tested. Our first concern is to develop a way to quantify the dependent variable, the quality of the viewer's sensemaking experience. This quantification could include objective measures about the data exploration performance. For example, viewers could be asked to tell what patterns or relationships they noticed during a quick (timed) opportunity to view a visual representation, and the experimenter could count these patterns or relationships. Similarly, the experimenter could observe whether viewers noticed some important anomaly. Also, time-related measures of the sensemaking experience could be used, such as time to complete a sensemaking exercise, number of facts discovered per unit of time, and rate of slowdown in idea discovery. More sophisticated measures could include number or quality of hypotheses generated by exploring the data. Experimenters could observe whether opportunities for analogical reasoning were exploited. They could also observe whether subjects gained understanding about information that was contained in the representation. More subjective measures could include the viewer's satisfaction or confidence with using the visual representation. Now, we turn our attention to a series of concrete tasks that might be included in future empirical research.

4.2. Experimental Tasks

Our first set of propositions, which collectively state that *for any given set of objects in a visual representation, the greater the objects' level of support for the four basic visual perceptual approaches, the better will be its viewer's sensemaking experience,* could be examined in the following experimental task. Two different visual representations could be presented to experimental subjects that have been randomly assigned to a control group and a treatment group. The experimental group would receive a visual representation that supports the four basic visual perceptual approaches, and the control group would receive a visual representation that does not support them. The experimental group's representation shows the price of oil over time where price is displayed on a line graph (see Figure 9a); the control group's representation contains the same information in a less-conventional graphic, where price is displayed in a modified type of bar graph (see Figure 9b). Both sets of viewers would be given the same experimental task, "Estimate the percentage increase in the price of oil from 1973 to 1979."

The presentation to the control group (9b) does not support quantitative perception, one of the four basic visual perceptual approaches, because the graphic varies both barrel height and volume, either of which may be indicators of price. Humans are much less adept at comparing what appear to be three-dimensional volumes than they are two-dimensional quantities (Tufte, 2001). If we find that viewers in the experimental group answer the question more accurately and more quickly than those

in the control group, we would interpret this result as support for our proposition.[4]
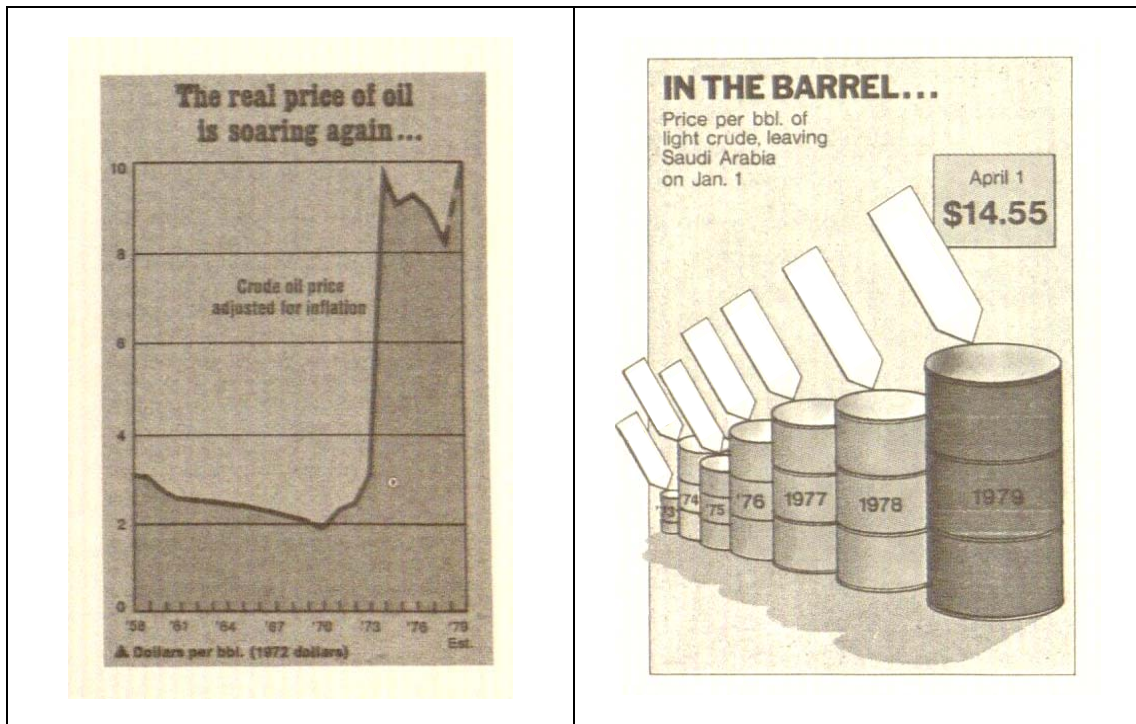
Figures 9a (left) and 9b (right). Visual Representations that Do and Do Not Support Quantitative Perception

Sources: Time, April 9, 1979, p. 57 and Business Week, April 9, 1979, p. 99, both reproduced in Tufte (2001), pp. 62, 63

Consider Figure 10a, which is a graph showing the data points and a dotted line showing the functional relationship between atomic number and atomic volume in the periodic table of elements. To examine proposition two, *the better a visual representation's Gestalt properties, the better will be its viewer's sensemaking experience*, we could present our two groups with either the scatterplot (Figure 10b) or the bar chart (Figure 10c). Viewers would then be asked, "Ignoring outliers, please sketch a graph of the basic functional relationship between atomic number and atomic volume." The visual representation given to the experimental group (figure 10c) supports Gestalt processing, because the elements in each group (column from the periodic table) are shown as unitary groups by being the same color.[5] It is relatively easy to perceive the data points in each group as a theoretically-consistent whole. In contrast, the representation given to the control group (Figure 10b) does not support the pattern recognition of Gestalt processing. It is relatively difficult to discern the pattern in the data that would be necessary to identify the basic underlying functional relationship as displayed in Figure 10a. Again, if we find that viewers in the experimental group answer the question more accurately and more quickly than those in the control group, we would interpret this result as support of our proposition.

To examine proposition three, *the more consistent a visual representation's components are with the viewer's knowledge, the better will be its viewer's sensemaking experience,* we could perform another

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[4] The answer is 454%, which is accurately depicted in Figure 9a. Figure 9b shows the increase as a percentage correctly if only height is considered, but because the size of the barrels conflate height with volume, it appears that the difference (in volume) is 4,280% (Tufte, 2001).
[5] This figure is presented in the manuscript in color. For readers to more clearly understand the nature of our experimental task, we suggest that they print or view this figure in color.
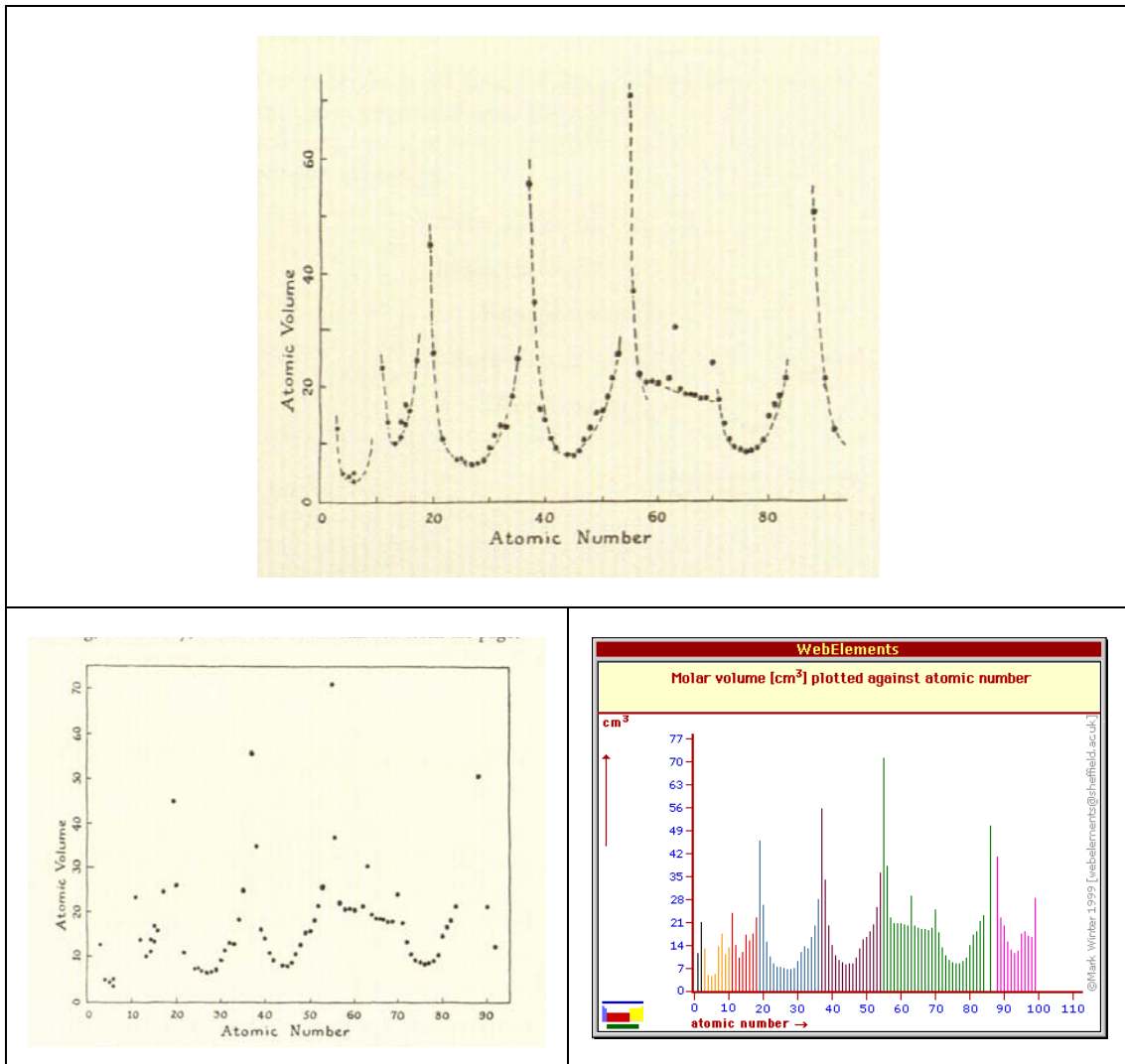
Figures 10a (top), 10b (bottom left), and 10c (bottom right). Visual Representations with Varying Support for Gestalt Qualities

Sources: Figures 10a and 10b from Linus Pauling, *General Chemistry* (Pauling, 1947, p. 64), both reproduced in Tufte (2001, pp. 103-104), Figure 10c from http://www.webelements.com
http://www.webelements.com/periodicity/molar_volume/

similar task. Figures 11a and 11b show two different landscaping diagrams.[6] Subjects would be asked, "If the city in which this home is located has an ordinance requiring that all homes have 50% or less of their yard in turf, is this home in compliance?" Information is equivalent, but Figure 11a makes use of stored knowledge (where light green represents turf; darker shades of green represent trees, shrubs, and vines; brown represents mulch; and gray represents concrete). In contrast, Figure 11b uses an informationally-equivalent coloring scheme that does not appeal to stored knowledge of landscaping. Figure 11a would be given to our experimental group and 11b would be given to our control group. Again, if our proposition holds, we expect better performance in terms of speed and accuracy from our experimental group.[7]

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[6] These figures are presented in the manuscript in color. For readers to more clearly understand the nature of our experimental task, we suggest that they print or view these figures in color.
[7] The answer is yes. A cursory glance reveals that approximately 25% of the yard is in turf (the light-green area at the top right). Nearly all of the yard is covered in mulch (light brown)
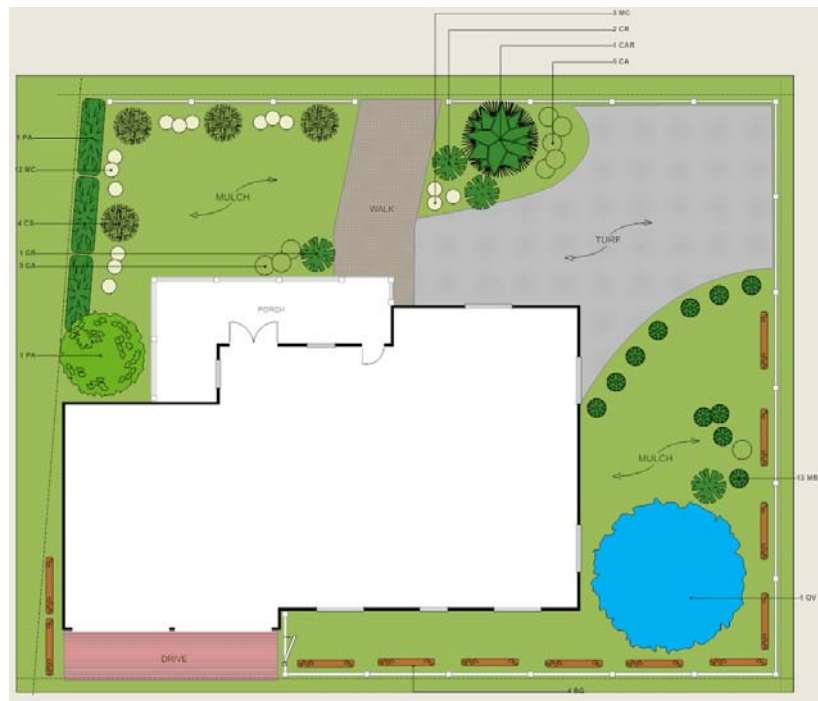
Figures 11a (top) and 11b (bottom). Visual Representations that Are and Are Not Consistent With Viewers Stored Knowledge

Source: Original drawing by authors.
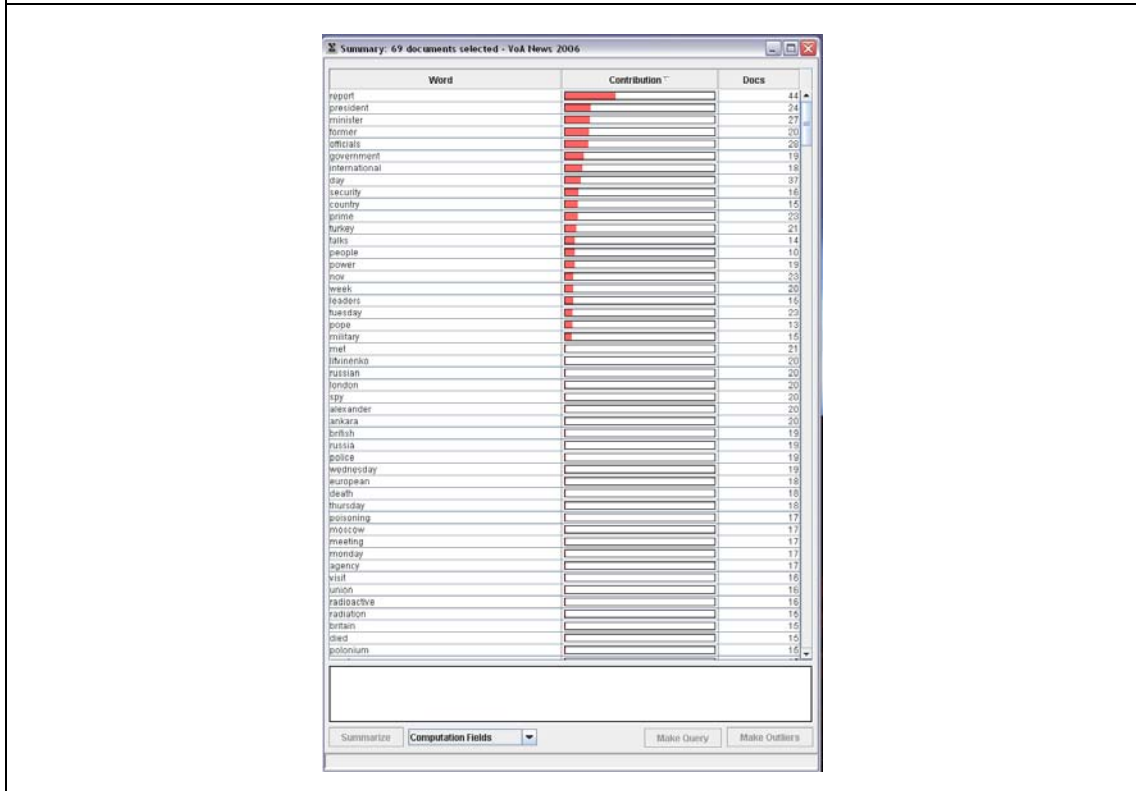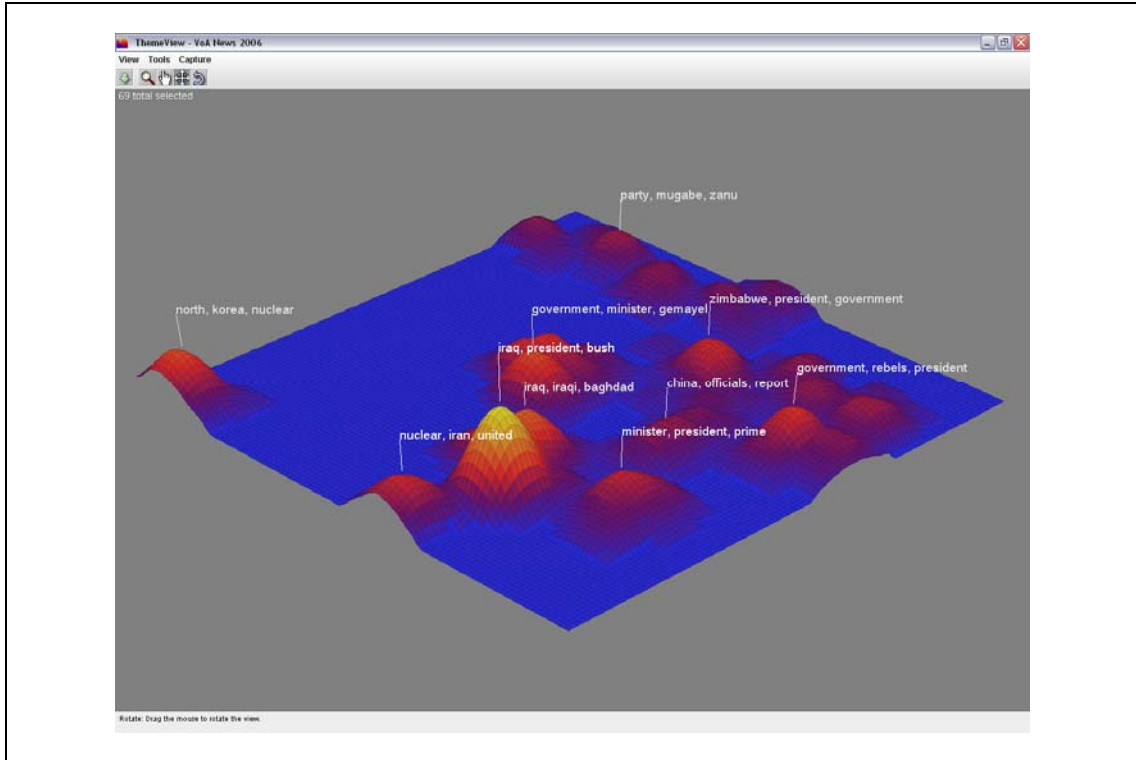
Figures 12a (top) and 12b (bottom). Visual Representations that Do and Do Not Support Analogical Reasoning
Source: Visual representations created by authors from a subset of 2006 Voice of America news stories. Both representations are created with the SPIRE software system.

Finally, a visual representation that supports analogical reasoning could be compared with an equivalent visual representation that does not enable analogical reasoning as a test of proposition four. Proposition four states that *the greater a visual representation's support for analogical reasoning, the better will be its viewer's sensemaking experience.* Using Figures 12a and 12b, our experimental and control groups could be asked, "What news topics were most prominent in late 2006?" In Figure 12b, the control group's representation that does not support analogical reasoning, this information is available by examining the bar graph of keywords from the news stories. While bar graphs are quite common and generally very useful, in this particular task, the user is forced to examine the entire bar graph and then mentally aggregate the keywords into topics. In contrast, in Figure 12a, the experimental group would only need to ascertain that the tallest "peak" on the diagram is the most prominent topic in the news. The keywords still appear, but the topography has aided the user in identifying the most prominent topic. As in our other tasks, we expect better performance in terms of speed and accuracy for our experimental group, and we will interpret such results as support for our proposition.[8]

A number of variations on the above experimental tasks could be developed. Subsequent research could investigate what factors determine whether and how a person detects a scene and objects in a visual representation, especially for abstract scenes, and to what extent these factors are universal or specific to individuals. Another interesting question has to do with the relationships among the four aspects that affect sensemaking, expressed in our propositions and displayed in our conceptual model, Figure 3. We have begun to lay out these differences by considering how the four aspects relate to approaches that would be either highly general but weak or not general but strong. Similarly, more research could give insight into how independent or related the factors are. For example, a high level of support for the four perceptual approaches might be essential for good Gestalt properties, which might be essential to exploit stored knowledge and analogical reasoning. If these additional questions were investigated and conclusively answered, both researchers and practitioners would benefit.

5. Conclusion

Our paper makes three primary contributions. First, we have extended Cognitive Fit Theory by providing a general characterization of spatial visual representations used for data exploration. These representations consist of a scene, objects, and their characteristics. In giving the scene/object/characteristic characterization to spatial representations, we have provided a framework for understanding various types of visual representations that would be used in data exploration. Furthermore, while human perception of concrete scenes and objects has been proposed and studied in psychology, our work is the first to extend these concepts to abstract visual representations such as graphics. Also, we are the first to develop the idea that objects possess characteristics, which gives us a basis for our proposition development.

Second, we have linked Cognitive Fit Theory to the data exploration task domain and that domain's goal of sensemaking. Spatial tasks, a type of task identified within Cognitive Fit theory, include a number of spatial subtasks such as observing data points, looking for patterns or outliers, making inferences, comparing observed facts or patterns to one's own knowledge, generating hypotheses about the data, and drawing analogies from the context being observed to another context. We explain that each of these subtasks has sensemaking as its primary goal.

Third, we have offered a set of theoretical propositions about how visual representations of data can serve the sensemaking goal. Specifically, visual representations that facilitate sensemaking (1) support the four basic human visual perceptual approaches, (2) have strong Gestalt properties, (3) are consistent with the viewer's knowledge, and (4) support analogical reasoning. While these factors are drawn from a long tradition of psychological research in perception and learning, we are the first to associate them with the data exploration task using a visual representation.

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[8] The answer is the US-Iraq war. The prominent peak just to the left of center is labeled, "iraq, president, bush."

Acknowledgements

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