Defining Insight for Visual Analytics

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1 INTRODUCTION

Many have argued that providing insight is the main goal of information visualization. Card, Mackinlay, and Shneiderman declare that "*the purpose of visualization is insight* [3]," while Thomas and Cook propose in *Illuminating the Path* that the purpose of visual analytics is to enable and discover insight [10]. The idea that visualization should lead to insight seems logical, but researchers in the community have been slow to build on the concept because it is difficult to define what insight is [7, 8, 9, 11]. As Yi et al. point out [11], although a few definitions of insight exist, no commonly accepted definition has emerged in the community.

Interestingly, the visualization community is not the only one investigating insight. For the past two decades, researchers in cognitive neuroscience have been studying their own version of insight by examining neural activity. In their discipline, insight is a less ambiguous term. It specifically refers to what is commonly called an "a-ha" or "eureka" moment [5]. In fact, it is now possible to observe and identify when someone is having such a moment by examining their neural activity.

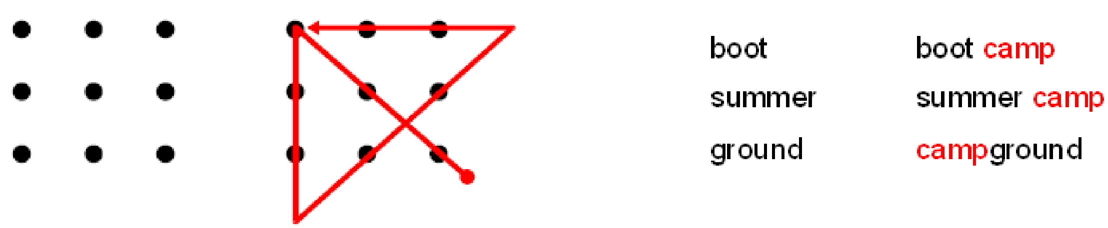
It is clear that the scope of definitions of insight in the visualization community differs from that of the cognitive community. It appears that the visualization definitions of insight are generally broader but more vague than those in cognitive science. For example, North categorizes insight to be "*complex, deep, qualitative, unexpected, and relevant*" [7], which overlaps with the neurological definition. However, he also defines insight as "*an individual observation about the data by the participant, a unit of discovery*" [9], which does not bear any clear relation to the strict "a-ha moment" of cognitive science. Instead, it implies a focus on knowledge-building not found in the cognitive definition.

We suggest that what the visualization community defines as insight actually has two parallel meanings: (1) a term equivalent to the cognitive science definition of insight as a moment of enlightenment, and (2) a broader term to mean an advance in knowledge or a piece of information. We argue that for information visualization and visual analytics to provide and enable insight, both definitions need to be considered. But we must clarify and distinguish these definitions in order to develop methods to measure insight and evaluate visualizations.

2 INSIGHT IN COGNITIVE SCIENCE

In cognitive science, the term insight has been used "*to name the process by which a problem solver suddenly moves from a state of not knowing how to solve a problem to a state of knowing how to solve it*" [6]. (To distinguish this insight from the other type of insight described by visualization researchers, we will call it spontaneous insight). In this tradition, spontaneous insight is a type of problem-solving, and differs from normal problem-solving in several key ways. First of all, unlike normal problem-solving, spontaneous insight does not appear to be facilitated by gradual learning heuristics such as bottom-up inductive reasoning. In fact, it has been observed that focused effort on normal problem-solving often inhibits spontaneous insight. It is usually when a person is in a relaxed state that a spontaneous insight takes place [4] (like taking a shower in the morning). Secondly, while gradual problem-solving requires no special inducement other than presenting someone with a problem, what precipitates spontaneous insight is still being discussed. One commonly-held theory is that spontaneous insight often occurs when a person tries to solve the problem in a habitual way, fails, momentarily becomes frustrated (perhaps due to incorrect assumptions or some other cognitive fixedness), then mentally reorganizes the pieces of the puzzle (perhaps by breaking through a failed thought paradigm), and "suddenly" sees the solution [6]. Finally, in normal problem-solving the path taken to the solution is conscious and logically clear to the problem-solver; however, participants who experience a spontaneous insight are often unable to describe the thought process that led to it [2], indicating that this insight occurs on a subconscious level and is not a process that can be directly controlled, manipulated, or repeated.

In real-world situations, it is difficult to predict when spontaneous insight will be used instead of traditional problem-solving. For this reason, much of the spontaneous insight research in cognitive science has utilized carefully crafted laboratory problems that are more likely to be solved with a sudden breakthrough. One such problem is the "nine dot problem," which asks the participant to use four lines to connect 9 dots that are arranged in a 3x3 matrix, without pulling the pen off the paper (Figure 1 left). Participants often fail at first by assuming their lines cannot extend outside the boundaries of the matrix [6]. They seem to succeed when they relax their paradigms and try a different heuristic.



(left) (right)

Figure 1: Left: an example of the nine dot problem. To solve the problem, participants must relax their paradigms and allow lines to extend outside the boundaries of the matrix. Right: an example of the compound remote associate (CRA) problem. In this example, the participant finds that the word "camp" can either precede or follow each of the stimulus words.

Similarly, Bowden and Jung-Beeman [2] have developed a set of "compound remote associate," or CRA, problems for use in studies of spontaneous insight. These present a list of three words to a participant, who then has to come up with another word that makes a compound phrase when placed at either the beginning or end of each of the stimulus words. For example, the problem words *boot*, *summer*, and *ground* lead to the solution camp (Figure 1 right). This kind of problem can be solved through normal trial-and-error problem solving, by systematically coming up with potential solutions that work for one of the problem words and testing them against the other two. However, about 50% of the time, participants report that they identify the solution in a flash after several failed attempts [4].

With the help of electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI), researchers can now observe the neural activities of the participants during experiments such as the nine-dot or the CRA problems [2]. Two distinct patterns are observed that correspond to the two modes of problem solving, normal and insight-based. In both cases, frontal lobes, which are associated with working memory and executive processes, and temporal lobes, which hold long-term memory and semantic information, both show a high amount of activity.

However, in normal problem solving, the activity in the temporal lobe is continuous and mostly localized in the left hemisphere, which is thought to encode more detailed information in tightly related semantic networks. This indicates that normal problem solving involves a narrow but continuous focus on information that is highly relevant to the problem at hand. In contrast, when participants solve a problem with spontaneous insight, the right temporal lobe shows a sharp burst of activity, specifically in an area known as the superior temporal gyrus [2]. Unlike the left temporal lobe, the right temporal lobe is thought to encode information in coarse, loosely associated semantic networks. This suggests that spontaneous insight occurs through sudden activation of less clearly relevant information through weak semantic networks, which corresponds to a participant's paradigm shift following an impasse.

These findings suggest that spontaneous insight is qualitatively different from everyday problem-solving. It involves a unique pattern of neural activity that corresponds with the unique sensation of the "a-ha moment" that participants report. However, while cognitive scientists have successfully identified the neural patterns of the spontaneous insight phenomenon and can now observe and measure the insight process, there has been little success in understanding why spontaneous insight occurs in normal situations. More importantly, aside from laboratory experiments using artificially designed simple problems, cognitive scientists do not understand how to promote spontaneous insight for solving complex real-world problems like the ones the visualization community encounters on a regular basis.

3 INSIGHT AS KNOWLEDGE AND INFORMATION

In a recent visualization publication, Yi et al. [11] provide a comprehensive survey of literature in information visualization that have considered insight as a goal or a measurement. Yi et al. base their hypothesis on sensemaking theories and conclude that according to the literature, there are four distinct but intertwined processes in interaction with a visualization that can lead to insight, which they identify as *Provide overview*, *Adjust*, *Detect patterns*, and *Match mental model*. While these processes can in some cases result in an "a-ha moment," it is clear that in the work by Yi et al. as well as the literature used in their survey, insight is considered to be more or less units of knowledge. (For the purposes of this discussion, we call this type of knowledge-building or model-confirming insight as, simply, *insight*.)

For example, one of the surveyed papers is a case study on visualizing evolutionary trees by Amenta and Klingner, which states that "*our tool allows the biologists to interactively visualize and explore the whole set of trees, providing insight into the overall distribution and possible conflicting hypothesis.* [1]" In this context, insight refers to knowledge about the overall distribution. Switching the word insight with knowledge does not effectively alter the meaning of the statement.

Similarly, Gonzales and Kobsa report the result of their study on adopting an information visualization system by administrative data analysts: "*the analyst determined the answers to these questions, but also came up with further insights that she shared with people from other administrative units. She used the discovered information to advise other administrators of certain previously unknown relationships in their data.*" The two sentences mirror each other and indicate that the insight shared by the analyst is in fact information of previously unknown relationships (or knowledge) in the data that she discovered.

These two examples are telling. Insight in information visualization and visual analytics not only has a different sense than in cognitive science, but is considered entirely differently. In the visualization community, researchers often talk about *discovering insight*, *gaining insight*, and *providing insight*. This implies that insight is a kind of substance, and is similar to the way knowledge and information are discussed. In the cognitive science community, on the other hand, the wording is more often *experiencing insight*, *having an insight*, or a *moment of insight*. In this context, insight is an event. The fact that the two definitions refer to entirely different kinds of concept is a major impetus to consider them separately.

4 IS THE GOAL OF VISUALIZATION INSIGHT?

With a clearer definition of insight, the statement that the goal of visualization is insight needs to be reexamined. Based on the cognitive definition of insight, this statement restricts visualization into only considering a specific mode of problem-solving that produces results that, though measurable, are not easy to track. On the other hand, when considering insight only as knowledge or information, the statement limits the potential capability of visualization to structured knowledge building and information display.

Intuitively, visualization ought to promote both types of insight. However, the differences between the two make this goal seemingly difficult. Spontaneous insight is a form of problem solving that is used to find solutions to difficult and seemingly incomprehensible problems. Knowledge-building insight, on the other hand, is a form learning that builds a relationally semantic knowledge base through a variety of problem-solving and reasoning heuristics. Additionally, spontaneous insight seems to depend on the desertion of applied paradigms and schematic structures, whereas knowledge-building insight generally depends on schematic structures (such as a mental model) to find patterns as well as to infer.

While the goals of promoting spontaneous insight and knowledge-building insight appear disparate, we propose that in fact they are related. As little as is known about the origin of spontaneous insight, it does not arise out of thin air. If spontaneous insight comes from the unexpected reconfiguration of semantic knowledge [2], then relevant knowledge about a problem must be necessary for spontaneous insight to arise. This is evident in the nine-dot and CRA experiments during which participants are often observed to experience spontaneous insight only after spending time attempting to solve the problem using normal problem-solving methods. We also can see that this is true more generally and for deeper insights: Einstein didn't come up with the Theory of Relativity out of thin air but rather based it on experiments inconsistent with existing theories and previous mathematical work. Conversely, the major paradigm shifts associated with spontaneous insight can create new structures and relationships in a user's understanding of a problem, which can then serve as the schematic structures needed for generating future knowledge-building insights.

We propose that a similar relationship between knowledge building and spontaneous insight can be found in using visualization to solve complex problems. The existence of deep, complex knowledge about a subject increases the likelihood that a novel connection can be made within that knowledge. Likewise, each major spontaneous insight opens up the possibility of new directions for knowledge-building. Together, the two types of insight support each other in a loop that allows human learning to be both flexible and scalable. Since we know more about designing systems for knowledge building than for the more elusive goal of promoting spontaneous insight, we can focus on the former and rely upon this proposed relationship to ultimately encourage both kinds of insight.

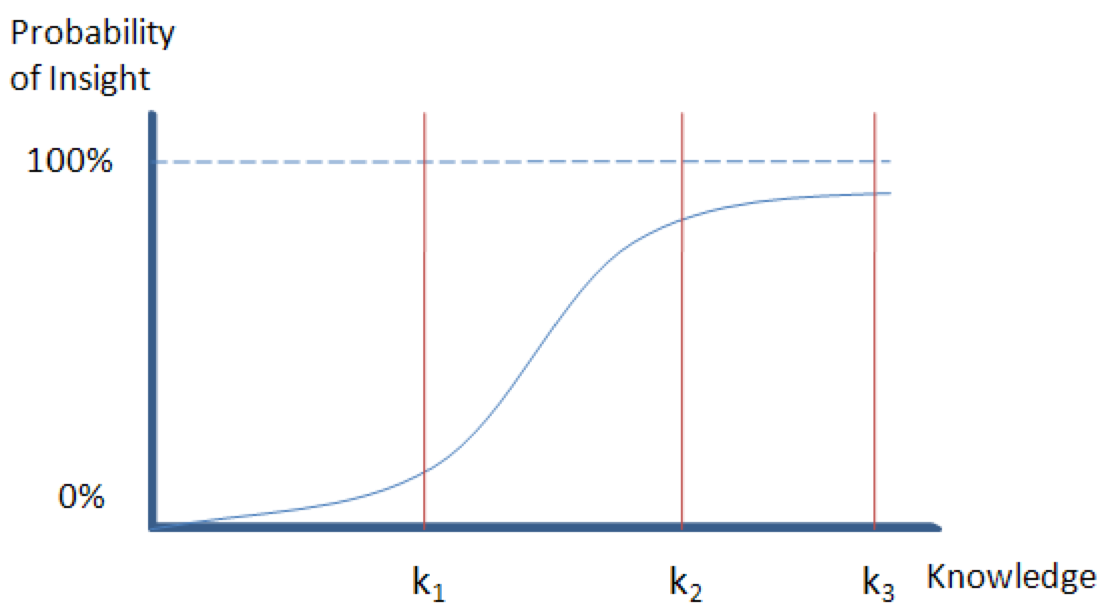


Figure 2: We hypothesize that there is a non-linear relationship between the amount of knowledge that a user gains from using a visual analytics and the probability that the user might have a spontaneous insight on the task at hand.

Figure 2 shows our hypothesis of how using an exploratory visual analytical tool to increase the user's knowledge could increase the probability of a spontaneous insight occurring. We posit that there is a general positive correlation between the two, but the relationship is not linear. As shown in Figure 2, when the user only has a limited amount of knowledge (0 to k_1), spontaneous insight is not likely to occur. As the amount of knowledge increases (k_1 to k_2), the probability of spontaneous insight increases sharply. Finally, after a certain point (k_2 to k_3), further increase of knowledge only increases the probability in a limited fashion until it is asymptotically close to a spontaneous insight occurring. On the other hand, there is undoubtedly a slowing down or even reduction in the probability of gaining a spontaneous insight, at least for a while, if the user is distracted from this freer knowledge associating.

Although this model is simple, we believe that it can provide a starting framework for more accurate insight-based evaluation of visualizations. But whatever model is chosen, our main point here is that spontaneous and knowledge-building insights should be considered as distinct because the best approaches to gain one or the other are different. In the case of spontaneous insight, we can evaluate exploratory, "pre-query" approaches that keep one "in the cognitive zone" or "in the flow", and quantitatively identify if a spontaneous insight occurs through the use of an EEG or an fMRI. For knowledge-building insight, we can evaluate detailed, knowledge gathering methods and look to appropriate user studies to measure the amount of knowledge a user gains. Using these combined approaches, not only can we more accurately determine the effectiveness of visualization tools, we can provide cognitive scientists with more complex problem-solving artifacts (they have few available) and shed light onto how the two types of insight can be promoted through visualization tools to solve real-world problems.

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