A Role for Reasoning in Visual Analytics

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Abstract

Analysis supported by interactive visual interfaces is a complex process. It involves computational analytics (the visualization of both raw and derived data) and an analytical process which requires a human to extract knowledge from the data by directly interacting and manipulating both the visual and analytical components of the system. These two types of analytics are complementary and the goal of this paper is to understand interplay between the two. In this paper we discuss how a study of human reasoning and reasoning-supported cognitive processes complement the current emphasis on computational analysis and visualization. We define this process as reasoning analytics and present mechanisms by which this process may be studied.

1. Introduction

As the amount of data available for analysis and decision making has increased, researchers have begun utilizing interactive visual interfaces as a means of incorporating human reasoning into the computational analysis process. Thanks to the science of data visualization, much research has focused on methods of data analysis (referred to as computational analytics in this paper) and the visualization of those data and analyses. These tools are imperative to the analytical process, as they allow the analyst to approach and interact with the data in a meaningful way. The goal of such visual analytic tools is to enable analysts to find patterns, filter, sort, and prioritize their data, ultimately gaining knowledge and understanding. The visualization of these data and analyses also buttress a human working memory that can juggle only a handful of concepts at any one time [27].

However, the visualization and computational analysis are simply tools for the analyst to use. These tools alone cannot directly reason with the data. The analyst provides goals, motivation, and cognitive heuristics and synthesis (also known as a cognitive toolkit) that computational analytics does not have. Thus, a complete science of visual analytics requires not only a study of computational analytics, it also requires an understanding of what we will refer to in this paper as reasoning analytics: the analyses done by human reasoning. This reasoning can be an individual effort between one user and the visualization. Or it can be a collaborative effort between multiple users and multiple visualizations. In summary, it is the process of interpreting the results of the computational analyses and the data presented within the visualization.

Due to variations in the analytical process (e.g., the number of users, the complexity of the computational analytics, and the question(s) to be solved) there is variation in complexity that affects the needs and demands of the human-visualization collaborative. In this paper we will argue that visual analytics is a joint study of computational analyses resulting in visualized data coupled with the study of the human analyst and their analytical process. Because the interaction between the two sides of visual analytics – the computational analysis and the cognitive analysis is so inter-joined, we will argue that they need to be studied both separately (to understand their component parts) and together (to understand the analytical process as a whole). Furthermore, as we will soon discuss, no matter what the cognition—solving problems, making decisions, evaluating the validity of an idea or statement, or categorizing concepts—every cognitive analytical process beyond perception involves human reasoning. In this paper we will argue a need for the study of a reasoning analytics which complements a study of visualized computational analytics and broadens our study of visual analytics as a whole. The question of whether there is a reasoning analytics and whether it has a place in today’s science of visual analytics must begin with an evaluation of the current analytics, a survey of human reasoning, and whether reasoning behaviors might be quantifiable or reducible to a sufficient degree as to support a predictive or informative analytics. Further, supporting a reasoning analytics though interactive visualization depends on whether a sufficient understanding of reasoning during
interaction can be harnessed to inform interface design. We will start addressing these questions by exploring the current uses of computational analytics in visual analytics environments and then define what reasoning analytics might be, before discussing how the two types of analytics inform each other.

2. Computational Analytics

As stated previously, the amount of data available for analysis has reached unprecedented levels, such that no human alone could sort, filter and explore the data for all relevant pieces of information. Furthermore, the visual representations used to help analysts gain insight into their data are limited by the number of visual variables a human can perceive [6]. A recent approach is to utilize computational methods of dimensional reduction and clustering as a means of reducing the data to its most relevant information, and then visualizing this reduced data for the analyst to explore. Typical methods would include multi-dimensional scaling (MDS) [28], principle component analysis (PCA) [24], and k-means clustering [7]. Variations of these methods are found in many visual analytics systems as a means of classifying data. However, in order to visualize the results of computational analyses such as MDS and PCA, variables are reduced and combined, resulting in new spaces which require further reasoning by the analyst. For example, Jeong et al. [13] utilize interactive visuals as a means of explaining the results of principle component analysis to the analysts.

These issues of scaling, projection and computation are even further compounded in traditional scientific visualization examples. Volumetric visualization uses a variety of computational analyses in determining how to map and render voxel data. Often times this involves the design of transfer functions [20] which project the voxel information into 1 or 2 dimensional histograms. Unfortunately, the projection of the volumetric data properties down to a 2D space will obscure features, making it difficult for users to reason about how to separate regions of interest within the volume with only a 2D transfer function. In order to overcome these difficulties, much research has focused on enhancing transfer function design through the addition of other data properties. Examples include work by Lundstrom et al. which introduced the partial range histogram [22], [23] and the α-histogram [20] as means for incorporating spatial relations into the transfer function design. More recently, Maciejewski et al. [23] utilized non-parametric clustering and density estimations to better extract data patterns and make transfer functions more effective.

Along with using computational analyses as a means of directly reducing the problem space, techniques for determining the efficacy of the data are also employed. For example, one common type of statistical analysis is user-set confidence values; these are usually set to indicate degree of uncertainty in the validity of the visualized artifact, such as in the Scalable Reasoning System [29].

Other systems directly utilize computational analyses as a means of finding anomalies within the data. For example, Maciejewski et al. [17] utilize control chart methods and spatial scan statistics to directly extract and present regions of anomalous health events to the analysts. As in all of the examples provided in this section, the analyst interacts with the data resulting from the computational analysis.

As we have seen, the topic of computational analytics covers a broad area. One thing that becomes apparent during a browsing of the literature is that the analytical technique is co-joined with how the analyses are visualized. The visualization itself is often seen as an end-product of the analysis. What the user does with the visualization is often assumed (for example, as variables of interaction used to refine the data display) or not considered (for example, how the analytical process is supported – or not – by the display) and interaction. This is where a reasoning analytics enters the picture.

3. The Makeup of a Reasoning Analytics

Generally speaking, most computational analysis is not equipped to adjust to the user; the user is expected to adapt to the visualized analysis. User interactive behavior is seen as a metaphorical, if not computational, constant; its veracity is usually not questioned. Whatever the actual state of the user (e.g., they may be completely lost within the interface and making decisions only to learn the interface by trial and error, or they may be an expert that sees something the analyses cannot see), the computational analysis often has no way to compute it. Attempts at intent analysis (see for example [38]) depend on explicit user behavior such as web histories. Subtle changes in user affect or intrinsic motivation are a black box to these analyses. In short, computational analyses assume reduction, relative certainty, and computational constancy. Ill-formed problems whose solutions are derived from large data may or may not satisfy these computational assumptions, and human analysts, with their variety of individual perspectives, cognitive variances and differential expertise almost never do.

As such, the computational solution lacks human insight and reasoning process. Computational solutions return the needle in the haystack; however, as the stacks become larger, the problem of producing a needle from a haystack becomes a problem of
producing a relevant needle from a stack of needles. Filters and computation narrow down options; they do not in and of themselves choose the relevant option. This is left to the human analyst, and for good reason. A reasoning analytics would focus on the human analyst and her ability to make sense of information, create mental models, adapt to rapid changes, generate hypotheses and defend conclusions drawn with evidence. These processes are currently outside the purview of computational analyses and can only be done by a human analyst.

Reasoning – and the processes it supports such as decision-making and problem-solving -- are all analytical processes at which human analysts are proficient, especially if the choices have been filtered to a manageable number by computational analysis and presented in a comprehensible manner through visualization. Finding associations between items, creating relationships between them, looking for evidence to support these relationships and constructing valid hypotheses or narratives that explain and motivate the relationships are all analytical processes humans do daily in a variety of settings. Each of these analytical processes involve decision making and problem solving. Decision-making, informally defined, is the choice of one option among available alternatives [19], [21]. It’s a simple definition for an involved mechanism. Defining problem-solving, however, requires defining a problem and a solution. A problem is any situation or position that differs from a desired goal. A problem's solution is the decision or series of decisions which attain the originally desired goal. When viewed this way, problem-solving could be seen as the more complex of the two analytical structures, as it utilizes decision-making throughout. You can make decisions without problem-solving but you cannot problem solve with out making decisions. Additionally, problem-solution is very flexible, and addresses a wide variety of problem states, from simple and concrete to unbelievably complex and abstract.

The problem may be well-defined, with clearly outlined boundaries and solved algorithmically. Well-formed problems are the type that may be solved with a computational approach; following the algorithm will arrive at the goal state. Ill-formed problems, however, such as those tackled by visual analytics, lack clear problem definition and can involve daunting complexity. There are no clear paths to these solutions. But the solution is likely to employ a wide variety of reasoning methods including trial and error, means-end analysis [34], and analogy [9]. Some problems require analogical and abstract reasoning to reorganize before acquiring a solution; the solution for some of these problems is so “impossible” that research still has not been able to explain how or why the participant was able to find the solution [39]. Humans can restructure problems by rearranging information in ways that computational analysis quite literally could never imagine. The way a human does this reorganization is not completely understood, even by the human analyst, and can vary from a Gestalt organization to the unpredictable a-ha! moment [39],[18].

As previously stated, problem-solving depends on decision-making. Decision-making can be algorithmic, and is computable enough to have become the basis of several artificial intelligence systems [14],[32]. The central normative theory of decision-making in psychological study is Expected Utility Theory (EUT) [44],[15]). EUT uses smaller decisions about the weight (expected value) of each possible option, combined with probability logic, to make a decision about which option is preferred. However, humans do not always make decisions in a normative (or best practices) fashion, and so other theorists have focused on the differences between normative decision-making and how humans are observed to have made the decision[15]. Whatever the decision-making domain, decision-making is empowered by multiple reasoning heuristics and systems. Heuristics such as satisficing [34] and elimination-by-aspects [14] are used, as are more complicated reasoning systems such as analytical reasoning and mental model creation [21]. Decision-making directly informs and interacts with reasoning [15] and either directly or through decision-making, interacts with problem-solving. While some argument may be made as to where reasoning ends and decision-making and/or problem-solving begin, it is fair to assume there would be little higher cognition without reasoning; reasoning is the glue that holds the whole analytic process together. Further, many of the decision-making processes have been studied to the point of understanding how and why decisions were made as they were [14]. This is not necessarily true of reasoning; unlike decision-making, there are no computable models of reasoning. In seeking comprehension of the analytical process, understanding and predicting reasoning completes the narrative. Therefore, in our exploration of a reasoning analytics, reasoning is a logical place to focus.

4. Reasoning

As we have seen, humans who use visual interfaces manipulate concepts and ideas through reasoning. Human reasoning as a construct, however, is rarely wholly defined on its own. Any general definition is subject to tweak and critique from a variety of scholarly disciplines such as philosophy, psychology, and the computational sciences (in the case of formal logic). Thus, every definition tends to be narrowed to a specific perspective or to a particular type of reasoning (abductive, moral, etc.). In our discussion of a
reasoning analytics, we will focus predominantly on the perspectives of psychology and cognitive sciences, which define human reasoning based on the task and human behavior involved.

The Terms for the Two Systems Used by a Variety of Theorists and the Properties of a Dual-Process Theories of Reasoning

<table>
<thead>
<tr>
<th>Dual Process Theories:</th>
<th>System 1</th>
<th>System 2</th>
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<tbody>
<tr>
<td>Sloman (1996)</td>
<td>associative system</td>
<td>rule-based system</td>
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<tr>
<td>Evans (1984, 1989)</td>
<td>heuristic processing</td>
<td>analytic processing</td>
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<tr>
<td>Evans &amp; Over (1996)</td>
<td>tacit thought processes</td>
<td>explicit thought processes</td>
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<tr>
<td>Reber (1993)</td>
<td>implicit cognition</td>
<td>explicit cognition</td>
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<tr>
<td>Levinson (1995)</td>
<td>interactional intelligence</td>
<td>analytical intelligence</td>
</tr>
<tr>
<td>Epstein (1994)</td>
<td>experiential system</td>
<td>rational system</td>
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<tr>
<td>Pollock (1991)</td>
<td>quick &amp; inflexible modules</td>
<td>Intelllection</td>
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<tr>
<td>Hammond (1996)</td>
<td>intuitive cognition</td>
<td>analytic cognition</td>
</tr>
<tr>
<td>Klein (1998)</td>
<td>recognition-primed decisions</td>
<td>rational choice strategy</td>
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Figure 1. Nine theorists and their dual system theories. Adapted from [36], pg 145.

Visual analytics is the science of analytical reasoning supported by visual interfaces [37]. Analytical reasoning can be defined in a variety of ways. In addition to the Kantian idea of analytical reasoning as an evaluation of the validity or virtue of the proposition itself, we will consider analytical reasoning also as a determination about the value of given associations between concepts or statements. Notice that other than determinations about validity, there are no other required outcomes for analytical reasoning. This is important because it highlights a core characteristic: reasoning has little or no explicit observable behavior. Reasoning is usually not defined as the outcome; it is defined as how the outcome is made possible. This may not be explicitly stated, but it is a common assumption in the psychology of reasoning literature. Because reasoning and the cognitive processes it informs are so closely interrelated, they are often studied together. Decision-making and problem-solving both have explicit behavioral outcomes, and reasoning is often studied through evaluation of the decision made and solutions created through reasoning. For example, Johnson-Laird (e.g. [41]) studies mental models through the decisions that participants make about formal syllogisms through deductive reasoning. His research demonstrates that these models are used to make decisions and solve problems, but a model or a system of mental models can be used to make a variety of decisions or create multiple problem solutions. That is to say, that model is not the decision or problem solution; it is how the decision or solution is reached. Johnson-Laird postulated this himself, arguing that reasoning and decision-making inform each other, but the two are separate cognitive processes [15]. He goes on to argue that there are computational models of decision-making, but no counterparts exist for reasoning, largely because reasoning has little to no observable behavior. Reasoning must be studied indirectly through the output of other cognitive processes.

Another example of how reasoning is not the outcome but the method of reaching the outcome is Gigerenzer & Goldstein’s Fast and Frugal reasoning [10]. This is a short series of “one-decision” reasoning heuristics, or decisions made through simple but strong elimination reasoning.

These heuristics can be used for a variety of decisions (most notably about comparisons between ideas), but the heuristics themselves are not the decisions. This type of reasoning is also called “bounded rationality.” Bounded rationality refers to a reasoning and/or decision-making process that is bounded by limited information [35].

Human reasoning is a complicated proposition. For every type of reasoning defined (deductive, inferential, sentinel, etc.) there is a frame or context in which the reasoning defined and studied. In real-life usage however, the different reasonings tend to run together and inform each other with little or no noticeable transition. In addition to types, there are also reasoning systems. The most common type of system is the dual process theory. There are at least nine published dual process theories ([36], pg. 145), and each theory shares characteristics with the others. (See Figure 1.) The first process, or System 1, tends to be a quicker and/or more superficial reasoning. It is heuristic [12], or based on recognition, such as Klein’s priming [19]. This “first” system is quick, and as a result tends to be rather inflexible. It tends to be heavily dependent on rules, clear boundaries or other devices for quick elimination. Bounded
rationality is a System 1 reasoning. The first system can be used to make superficial decisions, or to “narrow down the field” in the case of more difficult tasks. It can reduce a blindingly cluttered field of choices to a more manageable number.

But for more difficult decisions, or when System 1 reasoning can no longer tackle the complexity, such as those propositions which involve abstract thinking, dual process theorists purport a System 2. Analytical reasoning is a System 2 process [31]. System 2 reasoning is powerful and flexible; it allows the reasoner to modify mental models and wrestle with complicated concepts. It can make the implicit explicit. System 2 can be more difficult to study; the concepts are more complicated; it is informed by System 1 processes and the transitions are not always clear. All of the referenced theorists purport that the 2 systems do interact; System 1 is usually seen as the first step to tackling the current task, but System 2 processes also inform System 1 as the reasoning evolves through the task.

Reasoning could be seen as the Swiss Army knife of human cognition. Humans reason early and often. It is arguable that reasoning gets involved as early in the process as image understanding, in which an object is perceived and identified, and during which semantic meaning begins to be attached. Biederman suggests this identification is done by reducing the larger visual scene to smaller recognizable components, and then using that decomposition to “understand” the visual image. This understanding persists even if the edges of the component are broken or missing[4]. Category learning is usually accomplished by inferencing or information integration, both of which are reasoning processes; information integration is the more System 2 of the two. Categorization feeds mental model creation, which, as has already been discussed, is a deductive reasoning process. The beginning of categorization, is a form of reasoning inference[11]. Hypothesis generation and insight creation, both identified as integral cognitive tasks in visual analytics [11] are reasoning processes that start with reasoning in image understanding and end with mental models and analytical reasoning. Each decision or problem solution requires reasoning to acquire. No matter how advanced the computational analysis, it is arguable that there is no visual analytics without human cognition, and that human cognition depends reasoning.

Because visual analytics problems are so complex, the visualization itself cannot derive the conclusions or generate the hypotheses on its own. This is slowly becoming a more common focus in visual analytics [42]. However, the study of “reasoning analytics” has a much shallower literature than computational analytics. Much of the reason for that is that reasoning is hard to study, difficult to evaluate, and to date, nearly impossible to quantify. If it is to have a role similar to its counterpart computational analytics, more effort needs to be invested in understanding how analytical cognition impacts and is impacted by its computational analytics, within the context of the interactive visualization.

5. How to Study a Reasoning Analytics

If we are to pursue a reasoning analytics, we need to understand reasoning and the roles it plays in visual analytics. In order to build that understanding, it would seem appropriate to build on the research that has been reported in the behavioral sciences. Reasoning in the behavioral sciences is studied almost exclusively by evaluating the decision made using reasoning, and, if possible, the methods or heuristics used to reach those decisions. As has previously been discussed, it can be quite difficult to discern between the decision-making and the reasoning used to reach that decision. However, with a focus on describing the narrative of reasoning and then aggregating the behaviors observed to understand the analytical structure of the reasoning process, we can begin to describe the analytics.

At the same time, studying reasoning through the study of decision-making and problem-solving also allows a continuing study on how decisions are made during interface interaction. As the task changes, how the human analyst uses the visualization changes; the available interactions and the changes in the view are variables that can impact cognition, with some techniques being better than others depending on the goal. We have already seen these differences in Ware, Neufield, & Bartram’s analysis of the best techniques for visualizing a causal association[42]. Understanding these cognitive transitions will add to the understanding of reasoning analytics as well. An interactive visualization is not the typical artifact, and it is important also to evaluate how reasoning may or may not be influenced by an artifact that is at once virtual and tactile and conceptual. For example, the interaction metaphors chosen for the interface may impact reasoning. Ashby, Eh, and Walron found in their study of learning behaviors that participant learning performance changed when the input method changed [50]. These are just a handful of variables that could impact reasoning analytics, and to date they have only been studied in piecemeal fashion, if they have been studied at all. Unlike computational analytics however, the analytical machine that is the human analyst cannot be easily
modularized or even compartmentalized. Each aspect of cognition is present and influencing the analytical process as a whole. Therefore, “reasoning analytics” must be reduced into pieces small enough to study, and then allowed to inform the study of the other pieces. This has already been done in a small way through evaluations of “sensemaking,” which involved a study of analysts solving a particular kind of task was evaluated not only for the holistic process but for the decomposable subprocesses [33].

One way to study reasoning as part of the narrative of cognition is to use more holistic methods of evaluation, such as field studies, case studies, ethnographies or other types of in situ protocols. See Figure 5. The strength of in situ is the context it provides, not only on reasoning at every stage of analysis, but of the analytical process as a whole. This allows the researcher to see how reasoning interacts with visualization, and how reasoning informs decision-making and problem-solving. It also provides context for computational and reasoning analytics interact within the visualization. It is arguable that in situ studies could not replace carefully constructed laboratory tasks; neither method answers all the questions that inform a reasoning analytics. Depending on the topic of inquiry, both methods should be employed at some point in the investigation.

Placing reasoning inside the architecture of cognition is another way to study the narrative of a reasoning analytics. Several cognitive architectures have been used to model cognition and test extant reasoning theories. It is probably safe to assume that no current cognitive architecture could capture the complexity of a reasoning analytics, but a brief survey of one or two provide an idea of how useful they can be in the study of complex cognition in visual analytic

ACT-R is a hierarchical cognitive architecture which modularizes cognition into modules, buffers and production systems [1]. The production system evaluates the state of the each of the modules and their respective buffers. There are two primary modules: perceptual-motor and memory (See Figure 2.) These modules execute as directed by the production system. Also part of the basic architecture is the pattern matcher, which looks for a in-process production which matches the current state, as only one production may fire at a time.

ACT-R demonstrates how the cognitive processes interact and feed each other. Many of the simpler cognitive processes, including some forms of categorization, have been modeled with ACT-R (see http://act-r.psy.cmu.edu/ for more). But the architecture is still too limited to allow for the complexity of visual analytics cognition: one production at a time is no where near enough; sequential processing is not adequate when working solutions to ill-formed problems.

Soar is a non-hierarchical cognitive architecture. The core of the architecture consists of a long-term memory and a short term memory. The long-term memory is shared with the short-term memory, which stores the information as in a graph of associations and relations between information. See Figure 3. The
decision structure uses these associations to decide which rules apply to the decision, and all rules which apply fire at the same time. This decision procedure more closely mimics human reasoning, which can certainly handle more than one variable at a time.

Further, Soar handles fuzzy logic in its basic architecture, which makes it a better representation of how humans would handle ambiguity. Soar has been used to model some learning and problem-solving behaviors (see http://sitemaker.umich.edu/soar/home for more.) Its flexibility is preferable to ACT-R, but once again, it is limited in modeling problem-solving and more complicated decision processes. However, as a way of modeling aspects of visual analytics cognition as an attempt to describe how computational and reasoning analytics interact, it is useful.

Lastly, one way to view the interaction between computational and reasoning analytics is to consider a metaphor within reasoning itself. Much like dual process theories of reasoning, visual analytics has a dual process mechanism. (See Figure 4.) Computational methods could be seen as a semblance of a System 1; they are powerful but cognitively (although not computationally) simple methods, rather inflexible. Their objective is to narrow down or filter the data in a meaningful way. They can be used over and over again, in part because, thanks to the speed of today’s hardware, they are quick and easy to execute. And, in an appropriately-written interactive interface, their variables are simple to manipulate and change. And finally, much like with System 1 reasoning, they are rarely sufficient to complete the analytic process in and of themselves.

### Complementary Strengths of Computational and Reasoning Analytics

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<thead>
<tr>
<th><strong>Computational Analytics</strong></th>
<th><strong>Reasonable Analytics</strong></th>
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<tbody>
<tr>
<td>Narrows the field of available choices</td>
<td>Make holistic sense of data</td>
</tr>
<tr>
<td>Juggle many variables</td>
<td>Develop mental models of analytic concepts</td>
</tr>
<tr>
<td>Make simple decisions</td>
<td>Rapid adaptation and accommodation of new information</td>
</tr>
<tr>
<td>Rationalize without bias</td>
<td>Categorization with ambiguous rules</td>
</tr>
<tr>
<td>Simplification of noisy data scenes</td>
<td>Superior problem reorganization</td>
</tr>
<tr>
<td>Support human memory (though visualization)</td>
<td>Abstract reasoning</td>
</tr>
<tr>
<td>Hypothesis generation and analysis</td>
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Figure 4. The strengths of a complementary analytics.

Visual analytics’ reasoning analytics could be seen as System 2 analysis. Much like System 2 reasoning, reasoning analytics are flexible, adaptable, and sometimes enigmatic. They are often complex methods which can take considerable time, effort, and perhaps collaboration with other involved parties and artifacts, including interactive visualization. They also tend to be more holistic and/or systemic in their approach to the problem. They are harder to study and predict. They are harder to study and predict, and, thus, they are often poorly understood. When viewed in this way, the interaction between computational and reasoning analytics becomes clearer. As a System 1 process, computational analytics narrows down choices and (hopefully) simplifies the problem set. Reasoning analytics as a System 2 process makes sense of and manipulates the results of System 1. System 1 feeds and informs System 2 and System 2 refers back to System 1 whenever further narrowing of the choices or reference to the computation analyses is useful. This is a somewhat imperfect metaphor, as humans are affected by a limited working memory, which a computer with gigabytes of RAM is not. Another advantage is that computational analyses can operate without cognitive biases. These biases can impact human analytical processes as early as System 1 reasoning, influencing which data are considered. This can mean relevant data is overlooked or irrelevant data being considered important. A computational analysis is immune to cognitive bias, unless, of course, it is programmed to have one.
Methods for Studying a Reasoning Analytics

1. Laboratory tests of decision-making and problem-solving
   a. Design the tasks carefully so the heuristics or reasoning methods being utilized become apparent.
   b. Compare performance in laboratory tasks of decision-making and problem-solving with performance using more traditional artifacts (pencil/paper, spreadsheets, etc.)

2. Ethnographic and field studies which place reasoning in a narrative of the analytical process.

3. Place what is learned from laboratory and field studies within the context of a cognitive architecture

Figure 5. Methods for studying a reasoning analytics.

6. Conclusion

Visual analytics requires both a computational analytics and a reasoning analytics working together. Interactive visualization supports reasoning analytics currently by providing tools that augment the “reasoning analytics” process. The large data commonly associated with “wicked” problems are overwhelming stimuli even for the superior reasoning capacities of the human analyst. The computational analytics applied to large data narrow the field of what has to be visually considered by the human. It also frames the problem and primes the reasoning process to see the analysis in a particular way. This can be a strength of the visualization or it can be a weakness. When the computational analysis detects patterns and visualizes them, it also does so without apparent bias. In an effort to narrow the data to be considered, it is not uncommon for humans to bias their elimination heuristics in an attempt to make the process easier [8]. This is an area where computational analytics can support reasoning analytics. By not over-weighting its analyses, humans can work with all pertinent data and not overlook what might be pertinent.

Further, human reasoning depends on human working memory, which is easily overwhelmed and can be effected supported by the visual representation that an interactive visualization provides. It is not uncommon for humans to use artifacts to remember pertinent information which overwhelms Miller’s 7+-chunks of information [26], which is yet another way that interactive visualization supports reasoning analytics. In addition to supporting the need for bias-free filtering of large data, a visualization provides a way to remember the many data that need to be remembered and considered in the generation of a hypothesis or considered in a decision. It can also provide a place where human analysts can work collaboratively, providing a shared artifact [12] and supporting asynchronous human to human interaction.

In conclusion, computational analytics and reasoning analytics are different but equally necessary parts of visual analytics. Without the statistical analyses, the human reasoner would have an overwhelming task that would likely prove impossible. And without reasoning analytics, the visualization of computational analytics produces pretty pictures of questionable relevance. Further, both types of analytics have much to learn from each other. Each informs the other, and supports the other, as the strengths of each are complementary. (See Figure 4 & 6.) While more difficult to study, a reasoning analytics is imperative to the study of a successful visual analytics system.
7. References


