Original Article

Science of analytical reasoning

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Abstract There has been progress in the science of analytical reasoning and in meeting the recommendations for future research that were laid out when the field of visual analytics was established. Researchers have also developed a group of visual analytics tools and methods that embody visual analytics principles and attack important and challenging real-world problems. However, these efforts are only the beginning and much study remains to be done. This article examines the state of the art in visual analytics methods and reasoning and gives examples of current tools and capabilities. It shows that the science of visual analytics needs interdisciplinary efforts, indicates some of the disciplines that should be involved and presents an approach to how they might work together. Finally, the article describes some gaps, opportunities and future directions in developing new theories and models that can be enacted in methods and design principles and applied to significant and complex practical problems and data.
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Introduction

The science of analytical reasoning is an essential part of visual analytics, as discussed in the introduction to this special issue and in *Illuminating the Path*.[1] To attack complex, exploratory, insight discovery and knowledge-building problems, visual analytics requires a foundation in the science and theory of analytical reasoning. Little in terms of controlled observations and practical results exists for higher-level reasoning processes in perceptually rich environments, not even in the field of cognitive science. Thus, it has been hard to build such a science. Visual analytics offers the promise of providing the practical basis where theories can be tested and (cognitive) analytics must be applied in order to have any hope of successfully solving very important, but quite challenging, real-world problems. Although analytical reasoning is an essential part of visual analytics, there are other essential components (computation, interactive visual representations and analytic methods). All of these must eventually be brought together to provide an overarching science of visual analytics. Some approaches to bringing these elements together are discussed in other articles in this special issue.

Initial recommendations and assessments

Chapter 2 of *Illuminating the Path* dealt with the science of analytical reasoning and laid out eight recommendations for future research. We do not have space in this article to address all these recommendations individually. Instead, we will present and discuss a couple of combined recommendations that cover the main points of the full set. (For a discussion of the complete set of recommendations, see Chapter 2 of *Illuminating the Path*.)

This article is a product of a workshop on the Future of Visual Analytics, held in Washington, DC on 4 March 2009. Workshop attendees included representatives from the visual analytics research community across government, industry and academia. The goal of the workshop, and the resulting articles, was to reflect on the first 5 years of the visual analytics enterprise and propose research challenges for the next 5 years. The article incorporates input from workshop attendees as well as from its authors.

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Recommendation

Build upon theoretical foundations of reasoning, sense-making, cognition and perception to create visually enabled tools to support collaborative analytic reasoning about complex and dynamic problems.

Over a period of many years, there has been a large amount of research in reasoning, cognition and perception that can be applied to the visual analytics framework and to the complex and dynamic problems that it must address. Although this work has clear implications for visual analytics, it is essential that it must also be focused on areas that are critical for the design and evaluation of systems that aid human cognitive processing. The relative lack of this study so far in the visual analytics community may be due to the lack of communication between visualization researchers and cognitive scientists whose methods could be used to shed light on analytic cognition in visually complex environments. Much of this study might be adapted from the existing literature; however, progress in this area could be considerably improved by a higher level of communication. In addition, the focus of visual analytics is to make the tools visually enabled, coupling visualizations and interactions with the human visual/understanding channel for maximum throughput integrated with human understanding and judgment. Interaction is the mechanism of coupling, and thus interaction should be considered from the standpoint of coupling human reasoning and analytic processes with computer-based processes. Collaboration should be considered in two senses: collaboration between the human and the computer; and collaboration among humans to provide enhanced perspective, more effective generation of new ideas and hypotheses and diverse viewpoints. Scalability in problem solving must be supported in both types of collaboration.

Recommendation

Conduct research to address the challenges and seize the opportunities posed by the scale of the analytic problem. The issues of scale are manifested in many ways, including the complexity and urgency of the analytical task, the massive volume of diverse and dynamic data involved in the analysis and challenges of collaborating among groups of people involved in analysis, prevention and response efforts.

A main realization among leaders in the visual analytic community is that the most challenging applications are not just large scale in terms of, say, the data that must be analyzed or even in terms of the dimensionality of the data; they are also complex in terms of the analysis task, and this task involves reasoning, inference building, hypothesis creation and testing and decision making. The sensemaking model of Pirolli and Card[2] was the most comprehensive existing model addressing these issues from the standpoint of investigative analysis. It shows that the investigation must be iterative with data foraging, evidence building, hypothesis creation and testing and decision making, overlapping one another. This general operational model is relevant for all types of investigation. However, it does not say much about what is inside each of the steps or how they should be connected. Understanding these steps in terms of reasoning and argument building and connecting them through interactive interfaces is a main province of visual analytics. Beyond this, dynamic data, changing conditions and new insights require an exploratory, adjustable approach to problem solving. Such an approach is really not explicitly addressed in models, such as sensemaking. There are many aspects to dynamic problem solving. Dynamic data require their own structure and analytical approach. In this regard, analyzing and organizing data in terms of temporal events is an important and, it seems, general approach, as tools such as EventRiver,[3] STAB[4] and GeoTime[5] show. Also, general models that explicitly consider dynamic behavior and temporal sequencing must be developed and integrated into visual analytics approaches. An illustration of this requirement is the need to incorporate flow models and explicit temporal sequence in routing for large-scale emergencies.[6] Efficient evacuation of a very large building or evacuation routing in a city requires not just one shortest path route, but a series of routes that can be used in alternating fashion so that no route becomes gridlocked. These must be available in a situation-aware context that is dynamic in order to be usable.

Relevant visual analytics tools and results

Several tools have been developed that address aspects of analytical reasoning. There are also relevant results involving evaluations of the tools. Some main examples are given next.

Financial visual analytics

The WireVis system[7] was created in cooperation with financial analysts at the Bank of America (BoA) to address fundamental problems they had in understanding their vast flow of financial transactions. Its initial purpose was to seek and discover fraud, especially wire transfer fraud. This is a very difficult investigative analysis problem in that tools must be exploratory, because new modes of deception are tried all the time, and must help human analysts see odd patterns over time in financial transactions. The need to involve highly trained human analysts to find meaning and discover new modes of deception means that these analyses are expensive and the human part of the system does not scale very well. WireVis directly addresses the challenge of scaling-limited human resources by permitting the analyst to explore tens of thousands of transactions or more over extended time periods while still being able to dive in and look in detail at any transaction or group of transactions.

WireVis was established after extensive discussions with bank analysts and is built around the idea of *keywords*. (The keywords are a set of highly proprietary words developed by the analysts, through long-investigative experience, for flagging transactions that may be of interest. The keywords can contain names of countries or cities, types of businesses, types of transactions and so on and set the analytic context for this specialized analytic task.) WireVis has a four-window interface where each window focuses on a key aspect of the transactional analysis (frequency of keywords in a transactional cluster, temporal trends of clusters by keyword, 'search by example' for keyword and temporal patterns and keyword relation within transactions). Each window has multiple interactions, and an interaction in one window produces an update in another, which shows relationships across views.

A fast, hierarchical clustering approach is applied to the transactions, and the time window shows daily activity for all clusters over a 13-month window. One can choose certain keyword patterns for any time period and do reclustering on the fly. Thus, even for repositories of BoA's size, the analyst can start from an overview and with a few clicks get to clusters where activities of individual accounts are discriminated, all the while keeping track of longer-range temporal patterns and emerging relationships. The analysts have never had any of these capabilities before. Although WireVis was initially focused on wire fraud, its capabilities are general and appropriately extended versions are now being considered for general financial analysis including risk and customer analyses.

An evaluation of high-level reasoning processes was then undertaken with WireVis as the central application.[8] The analyst's operations were divided into strategies (overall approaches to solving a problem), methods (specific steps taken) and findings (conclusions drawn by the analyst after investigating a suspicious activity). In this study, expert analysts were subjected to multiple observational tools including video, 'talk-aloud' recording, postanalysis reports and interaction logging. However, a group of nonexpert evaluators, using only the interaction logs represented in a visualization to make it easier to organize among strategies, methods and findings, were able to recover 60% of the expert's strategies, 60% of their methods and 79% of their findings. This is an important result because it has been notoriously difficult to infer user intent and especially higher-level reasoning from interaction logs alone. The result also shows that considerable aspects of the reasoning process can be recovered without the elaborate and invasive processes of video recording, talk-aloud and post-investigation reporting. There are many cases where it is hard to impose these observational processes or where they just have not been imposed. Also, there is evidence that imposing talk-aloud or other invasive activities during an analyst's investigations can affect, often negatively, reasoning processes, such as discovery and spontaneous insight (a-ha moments).[9] Finally, talk-aloud collection will be incomplete (analysts tend to *stop* talking when they become deeply immersed) as will postinvestigation reporting (analysts forget detailed steps), so interaction log analysis provides a valuable addition permitting more complete understanding of the analyst's reasoning processes. This study also revealed that strategies of a few of the analysts were not clearly represented in the visual interface; if they had been (which would have been straightforward to do without loss of generality of WireVis), the strategic recovery would have been significantly higher. These results can be used to quickly and effectively train apprentices in the best practices of analysis, to more fully understand the analyst's craft and to uncover specific parts of the interactive interface that need improvement.

The above study raises the question of why the results from evaluation of interaction logs alone, even when undertaken by nonexperts, were as good as they were. It appears that a significant part of the answer lies with the careful preparation of the visualization tools for the reasoning tasks at hand. However, the WireVis example also shows that it is possible to do this while still keeping a strong, general aspect to the interface (although the keyword list may have to be swapped out or expanded). The WireVis outcomes are important because they suggest a generalizable approach to analytical reasoning problems. One should not just deal with cognitive tasks for a specific problem, but should always attempt to generalize to whole classes of problems. In this case, a key outcome was the development of knowledge- and strategy-laden keyword representations that were intimately coupled to other carefully chosen representations of the data. The result was an approach that could be generalized to other types of financial analytics. Further, the methods permitted deep analytical evaluation. These generalized approaches, their outcomes and evaluations provide necessary building material for the science of analytical reasoning.

Tools for investigation and reasoning

Other visual analytics tools have been developed that support reasoning and analytical processes. Jigsaw was developed to help investigators to deal with large collections of documents, in particular to support investigative analysts in sensemaking where they must understand multiple entities and their relationships within the documents.[10] Jigsaw acts like a visual index into the documents, highlighting connections between entities through multiple views, such as list, graph and timeline-based representations (see Figure 1). Jigsaw also can provide different views of the document text itself. Analysts can then follow a trail of entity connections in order to more fully understand the context of events and their detailed workings. Thus, Jigsaw helps the analyst link seemingly unconnected events together to make more complete and coherent stories across the document collection. Jigsaw has been shared with multiple investigators and agencies, who have given feedback about its capabilities. They have expressed interest in using it in some of their settings.

The scalable reasoning system (SRS)[11,12] is focused more on structured argumentation and provides a web-based diagrammatic reasoning interface that allows the

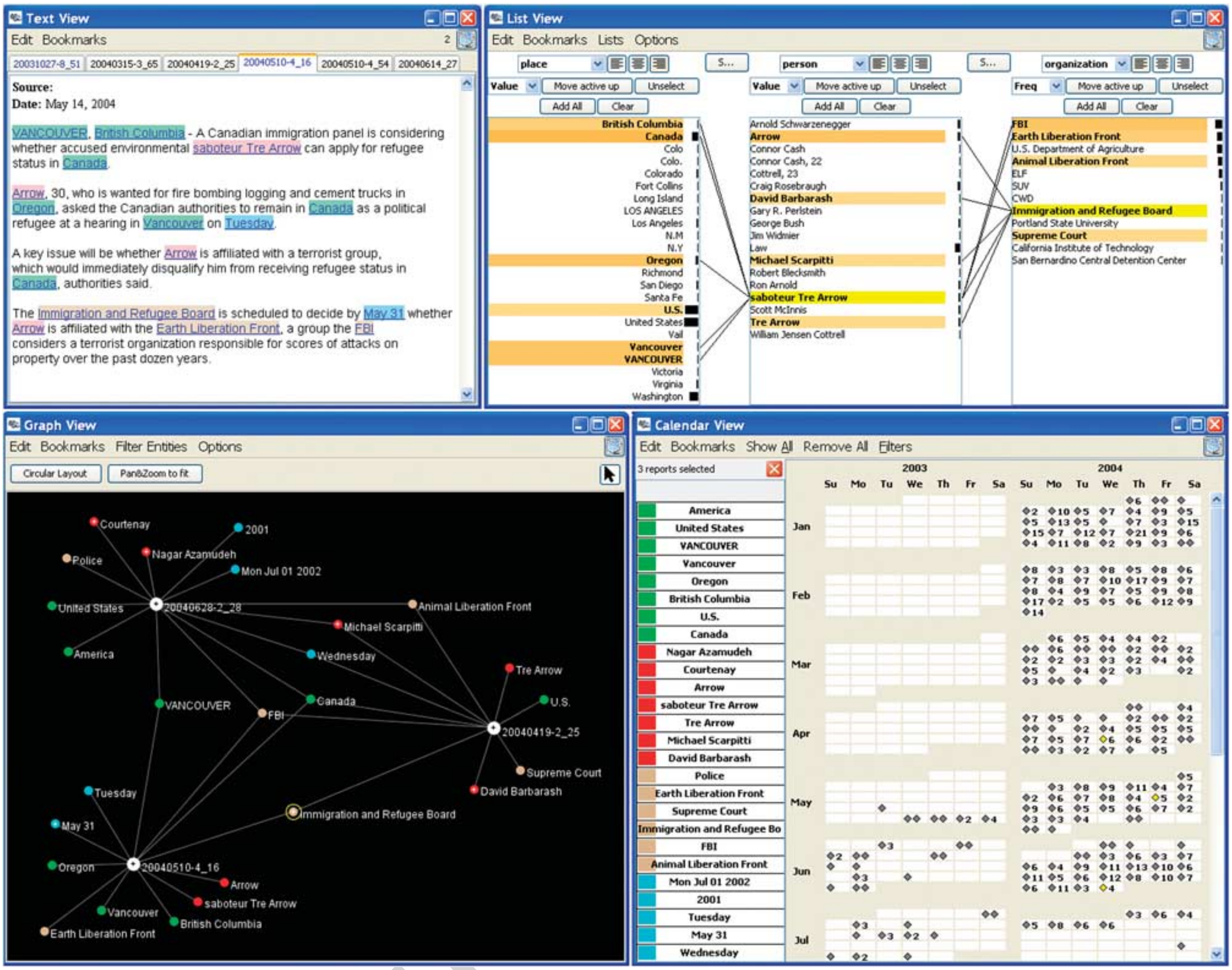

Figure 1: Jigsaw multi-window interface.[10] The document view is in the upper left, the list view is in the upper right, the calendar view is to the lower left, and the graph view is to the lower right.

users to record the structure of their arguments and hypotheses. Data brought in from other applications and from the web are represented as 'sticky notes'; the contents of these notes can be visualized using data clustering, timeline and map-based displays. Using the idea of 'reasoning artifacts' from structured argumentation, SRS tags these notes with reasoning roles, such as evidence, assumption or hypothesis. Reasoning artifacts can be turned into edges that describe relationships between notes, and users can record confidence assessments for each artifact and the attached note. This provides an explicit knowledge structure for the argument. SRS uses Dempster–Shafer belief theory to compute likelihood scores for each artifact, allowing users to see quickly the sum of likelihood and uncertainty for each component of their reasoning structures. By tracking the development of their hypotheses graphically, SRS can help users reflect on knowledge that might otherwise be kept tacit.

There are also tools that tackle the mixed-initiative aspects of the investigative process. Mixed-initiative systems are those where the human and computer work together, although sometimes independently, in intimate partnership, each doing what it does best. A mixed-initiative approach is necessary because the most challenging (and often most important) visual analytics problems require the insertion of the human ability to attach meaning or to create or extend hypotheses, yet the data are too large, the dimensions too high and the ramifications of a change or decision too many for a human to handle unaided. These last areas are the province of the computer. In the sensemaking approach, the investigative process is divided into two main overlapping loops: the foraging loop and the sensemaking loop, the latter entailing higher-order hypothesis creation, comparison and evaluation. RESIN has been developed to support the first loop, except that it is extended to a foraging/analysis loop to make explicit the integrated analysis that occurs in visual analytics. RESIN provides an automated framework for the reasoning and analytical process, concentrating in particular on data selection and

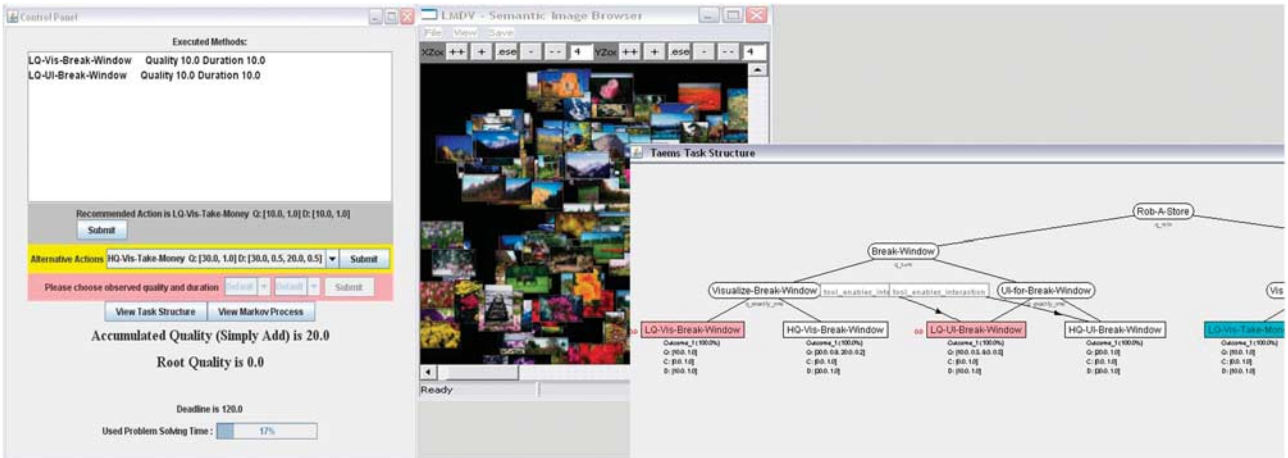

Figure 2: RESIN[27] interface for image browsing and analysis application. The control panel on the left is set for a task with a tight deadline. It sets the scale of imagery to be browsed in the center tool. The panel on the right updates information on real-time execution of subtasks so that the user can allocate time appropriately for completing the end-to-end task.

choosing the proper visual analytics tools for analyses[13] (see Figure 2). It relies on an artificial intelligence (AI) blackboard-based[14] software agent that employs interactive visualization, mixed-initiative problem-solving and time-series analyses to support predictive analyses from a particular viewpoint. (The blackboard architecture was developed to handle complex, ill-defined problems. In this case, a hierarchical system is developed with several agent-based knowledge sources for specific problem aspects. The blackboard is iteratively updated by the knowledge agent when its internal specifications match the current blackboard state.) The RESIN system enables analysts to explore large amounts of data in order to generate, track and validate multiple hypotheses in an uncertain environment. This general approach has been applied to some specific problems. For example, in terrorism event analysis, RESIN uses information from the National Consortium for the Study of Terrorism and Responses to Terrorism (START) Center's Global Terrorism Database[15] to match an event with a likely group or groups and to determine the threat level in a region in the near future based on past behavior of the group. RESIN is now being extended to also analyze sociocultural factors that could be significant in predicting behavior trends.

To attack the sensemaking loop, STAB has been developed. STAB is based on the human proclivity to make sense of complex information or processes by constructing stories that causally connect events, ascribe intentions to actors and make predictions about the world. Humans also use stories to communicate goals, hypotheses, explanations and conclusions to one another. However, humans also have cognitive limitations and biases in constructing stories, including biases in collecting, interpreting and using information. The aim of the STAB project is to develop an interactive approach that uses the structures and processes of story construction to support and guide information visualizations for complex problems.[4,16] The STAB system provides an interactive story editor for entering specific stories as well as generic story plots. STAB uses its library of story plots to interpret input streams of events, generate multiple stories that provide causal explanations for sequences of events and calculate confidence values for the generated stories. Current study on STAB investigates how the entities occurring in a story may focus information visualizations of input data streams. Also under investigation is how predictions made by a generated story may focus data foraging, analyses and visualizations. This study connects STAB closely with RESIN, and activity is underway to combine the two to provide an overall mixed-initiative approach to sensemaking. The combined system could be embedded within RESIN, which already has a structure for considering end-to-end reasoning and decision-making processes.

Human cognitive model (HCM)

In order to organize the above and other studies in a meaningful way and use it to establish design principles for visual analytics tool development, it is necessary to create an HCM. Such a model is also necessary to treat the mixed-initiative aspects of the visual analytics process. However, even in cognitive science, higher-order reasoning processes associated with attaching meaning to results, developing and evaluating models or hypotheses and making decisions are in a sense black boxes, and no general, practical model exists. Visual analytics can give a fresh perspective to this problem, and researchers have begun to develop a prototype HCM.[17] The model uses the cognitive science literature to clearly state and differentiate the strengths of the human and computer components of the mixed-initiative system. Thus, we have a basis for determining when a human should intercede (for example, to attach meaning at a key point in the analysis and reasoning process) and what the computer should do to best prepare for this moment. A significant part of the computer's role is to keep track of pertinent information, including analysis processes and outcomes. We see one approach to keeping track of analyses and outcomes in the RESIN/STAB study above. These systems, plus tools, such as SRS, can also keep track of competing hypotheses and the evidence for each, helping to remove the natural human bias to prefer one hypothesis over another, even when, in many cases, substantial counterevidence is available. The computer also can use its vastly superior 'working memory' to keep information available and accessible via highly interactive, exploratory visualization tools. Finally, of course, the computer has an ever more powerful ability to carry out computations and perform computation-based analysis. All of this provides the opportunity for the computer to augment human discovery by computer-aided discovery. One approach is for the computer to observe what interests the human; the computer then suggests information that is semantically related, but not yet considered, or does computations to create new relevant information. The human is then free to explore or to ignore these suggestions.

The HCM leads to design principles for visual analytics tools.[18] For example, semantically rich and complex reasoning applications often require multiple windows, each focusing efficiently on one aspect of the problem. This need is established in WireVis, Jigsaw, SRS and a number of other visual analytics tools. To minimize the human attentional overhead of dealing with multiple windows, each window must be efficiently focused on a task and obey the principal of 'balanced interaction'. Balanced interaction goes beyond brushing and linking from information visualization in that it requires that an interaction in one window not only cause an update in another window but also be available, in a general way, in all windows. With balanced interaction, reasoning and interaction become merged for the user, and the attentional and cognitive switches required for handling different visualizations or different focuses among the windows tend to subside. This aspect is part of a general consideration of cognitive flow within the HCM. One goal of intuitive, exploratory visualization should be that the visualization should not hamper the rhythm of reasoning until the human chooses to refocus resources elsewhere. This sense of being 'in the zone' allows the human collaborator to reason without encountering unnecessary attentional or cognitive impediments. In cases where task complexity exceeds the user's ability to process information, or a cognitive impasse is reached for some other reason, the computer can provide a scaffolding of support by presenting the information within relevant context, suggesting what may have been overlooked, and keeping relevant information present. These considerations result in a series of design choices in terms of interaction. In particular, interaction should be, as much as possible, direct and intimate. Direct interaction ensures that one deals directly with the artifacts of the reasoning/analysis process rather than with indirect representations that require cognitive shifts (for example, Boolean inputs or pull-down menus where selections or queries must be entered). Intimate interaction ensures that the interaction is so translucent to the human that it appears natural and obvious, thus maintaining the intimate collaboration between human and computer. A key method for maintaining direct, intimate interaction is through 'search-by-example' where one merely indicates the pattern or relationship one is interested in (rather than, for example, having to construct an elaborate Boolean query). Prominent instances of search-by-example are selecting a keyword distribution or transaction pattern over time from an account of interest and then finding accounts with similar patterns (as in WireVis), searching for images similar to (or dissimilar from) a selected group of images, searching for video patterns similar to a selected one or various text body search techniques. To fully achieve search-by-example requires a full-fledged visual analytics approach with a true marriage of visualization and analysis. Imposing the design principles described here does not just lead to improved exploration and knowledge building for problem solving, it may also lead to discoveries and insights that one would not find otherwise. There is evidence that spontaneous insights (a-ha moments) can actually be suppressed if a tool is not flexible enough to permit the user's mind to roam freely.[9]

This treatment of interaction in terms of cognition and cognitive flow offers a broadened perspective on the development of an interaction theory discussed in another article in this special issue.[18] The interaction theory needs to take into account these issues of cognitive flow, higher-level reasoning and human cognitive modeling. The principles described here and others that may follow from further theoretical development should be part of the theory's outcomes. Much remains to be done with the HCM before a more complete, working theory can be developed, as discussed in the next section.

Establishing a Science, Future Directions and Opportunities

If we are to build a science of analytical reasoning, we must think about what this entails. A common definition of science is, 'The intellectual and practical activity encompassing the systematic study of the structure and behavior of the physical and natural world through observation and experiment'. This definition extends to psychology and the cognitive sciences when we remember that mental processes are embodied in physical beings and must be studied that way. The science must have observations and undertake experiments that can be reproduced independently and that work to constrain or disprove theories. A usual way to build the science is to lay down basic, general principles that define its scope and withstand testing and then build theories, models or hypotheses that are themselves subject to observational and experimental confirmations. To pursue these issues, we must apply the scientific method, defined as a method of procedure consisting in systematic observation, measurement and experiment, and the formulation, testing and modification of hypotheses. As researchers in analytical reasoning build up a body of study that addresses all these aspects, we will have a science.

We must also identify who should be involved in this new science. Certainly visualization scientists, cognitive scientists and psychologists should be and already are involved. Because analytics and reasoning can have a social component, other social scientists should be involved as well. Because this new science of analytical reasoning should be part of the broader science of visual analytics, developers of analysis methods (statistical, database, AI and so on.) may also take part. Although this intrinsically interdisciplinary science requires substantial effort, we should also keep in mind its benefits. As Bordon has pointed out, most advances in science come when a person for one reason or another is forced to change fields.

Critical to setting forth an interdisciplinary science are the ways in which disparities in the research questions, methods, data and arguments can be reconciled between fields. One approach, taken by cognitive science, attempts to bridge component disciplines of psychology, AI, philosophy, neuroscience, linguistics and anthropology using the concept of a 'trading zone'[19,20] formed in part by methods that cross-cut the various disciplines. Thagard[19] points out that computational models of cognition (for example, SOAR, ACT-R) serve to draw out the unforeseen empirical consequences of cognitive theories and display their limitations. One can argue that a similar role could be played for computational models of cognitive systems in visual analytics. One can further argue that a trading zone should be set up for the partners in developing the science of analytical reasoning.

A parallel approach to interdisciplinarity, translational science[21] avoids the 'pure' *vs* 'applied' science distinction, focusing instead on building application-driven basic research paradigms.[22] The idea of a scientific discipline that spans exploration of underlying phenomena and complexities of real-world practice originated in the health sciences. Health sciences' need for effective 'evidence-based medicine' required the scientists to more closely coordinate clinical studies and research in underlying physiological, biochemical and biophysical phenomena. For a translational science of visual analytics, we emphasize the reciprocal flow of knowledge between studies of real-world practices; this flow of knowledge generates laboratory research directions and the results of laboratory studies, which are directed by field work to more effectively address technology designers' 'need to know' about analytical cognitive processing. As in the health sciences, translational research methods will require a coevolution of field and lab approaches.[23] This blurring of the somewhat arbitrary distinction between pure and applied science is especially appropriate and useful for visual analytics. It is quite evident that the challenges and problems that visual analytics was established to face are deep and thus require new, deep basic research and methods, even in the core areas of visualization science, data analysis and knowledge acquisition and other areas.

Beyond these general considerations, much specific work must be done to build the science of analytical reasoning. Perry *et al.*[24] propose an approach based on the core idea that an interactive analysis system can use data from user interactions to infer high-level knowledge of the analyst's state within a sensemaking process, and then use this high-level knowledge to provide feedback that encourages a maximally effective route through the sensemaking process.[2] In other words, the software should know enough about what the user is doing to be able to support a sensemaking profile that provides high efficiency and minimizes errors due to known human cognitive limits.

One can see how this higher-level knowledge might be obtained through machine learning, say, by having a sensemaking expert together with an analyst go over the user interaction sequence and manually label sensemaking states and then train an HMM or Markov Net to predict where transitions occur. However, experience in machine learning shows that this would produce too large a number of parameters to learn without a huge amount of training data, and the model would likely be too sensitive to variations in users' investigative styles. With such a setup, we would be unlikely to learn much useful knowledge about the sensemaking process.

Another, perhaps better, way to gain high-level knowledge is to encode more detailed knowledge of the elements of the sensemaking, from the level of raw user interactions up to the higher-level abstractions of the model. This is in line with the general observation above about the need to 'get inside' the sensemaking steps; the studies already done developing and evaluating visual analytics tools for reasoning tasks could also be used to develop this detailed knowledge.[7,8,12,13] In representing the sensemaking model, there are three primary classes of objects: Stages, Artifacts and Data Tasks. The dependency structure of these classes can be encoded in a description language. The sensemaking stages and artifacts are represented as classes, and the relationships between them can be encoded in the class properties. This will produce a set of hierarchical relationships that shows the sensemaking tasks at the highest layer of abstraction, the artifacts at the next lower layer and the data tasks at the lowest layer. The data tasks can be recorded directly from the user interface, where recording them corresponds to instantiation of objects of the classes of the sensemaking ontology.

The structure of this ontology immediately suggests how the sensemaking tasks can be inferred from the data tasks. In addition, this ontological model of the process can be analyzed to find entailments that provide limits to the set of sensemaking stages that are logically possible given a history of data tasks performed and access to artifacts, thus limiting the scope and complexity of the learning problem. However, if we make the relationships in the ontology such that the current sensemaking state is always a matter of strict necessity, we would have a model that required a much too restrictive user interface and workflow. Thus, we see the need of learning from actual analysts rather than specifying the entailments of the model too strictly. In addition, the ontological structure itself may have to be loosened so that, for instance, categories of general knowledge can be included rather than just task-specific knowledge and so that the ontology can be dynamic.

Much study remains to be done with dynamic data and the temporal structure of data, especially with streaming data and with data that accumulate into long histories. This is not just a problem of data representation and transformation, although certainly the approaches described in the article in this issue by Kasik *et al.*[25] are essential. Dynamic data must be also considered from the standpoint of reasoning and analytical processes. Here, the event-based approaches mentioned above[3,5] are a start in the right direction, but much more remains to be done. Beyond this, modeling approaches that fit, in a mixed-initiative sense, into a human/computer system must be developed. For large-scale emergencies, fixed plans are often quickly invalidated by events. (Large-scale emergencies are just one example where these approaches to dynamic data and temporal processes are needed.) One needs, rather, a *dynamic* model-based plan that can be updated and responds to unexpected events in the current situation. Otherwise, even expert decision makers can be overwhelmed. The responses to hurricanes Katrina and Rita give ample evidence of this issue. Although incompetence and failure to respond quickly were major factors in the Katrina disaster, it is questionable whether the best decisions would have been made even if responders and officials had been much better at doing their jobs once the levees started failing and the situation changed completely. A general model that could take the new situation into account running within a visual analytics system so that it was readily available to decision makers would have been a great help. In the case of Rita, previously established evacuation routing plans failed completely because people did not act as expected; because Katrina was fresh in their minds, people tried to leave all at once. One aspect that must immediately be faced if evacuation, critical infrastructure and other models are to be integrated into visual analytics systems is to make the models fast and interactive; otherwise, they will not be compatible with either the visual analytics interactive interfaces or the need to respond to a disaster as it unfolds. Trade-offs must be made among accuracy and speed and, more generally, with not having complete resources (for example, lots of data could be missing). Systems, such as RESIN,[26] are looking at this problem, but much more remains to be done. In addition, the models must be placed into the analytical reasoning environment in such a way that they fit the human reasoning and decision-making process. The HCM[17] and cognitive analyses are starting to provide some direction here, but, again, much more must be done.

There is also much study to do with respect to mixed-initiative approaches and human cognitive modeling. Although there are some promising initial results, the surface of this broad and deep area has just been scratched. For HCM, many experiments and evaluations should be done to validate the precepts of the model and to see how they apply to specific tools and tasks. Although the initial modeling is founded on principles from cognitive science and related areas that already have some validation and evaluation, the cognitive analyses that we must attack with visual analytics tools are more complex, larger and deeper than what have been considered before. If nothing else, the required HCM must be more comprehensive, and it will be necessary to see how precepts that may have some independent validity work together.

Some visual analytics tools have been used collaboratively[27,28] and some studies have been done on design considerations,[29] but not much work has been done that studies collaboration in a more fundamental way with respect to analysis and reasoning. Certainly, tools such as Jigsaw, SRS and others have capabilities that lend themselves to collaboration because they enact knowledge structures and track reasoning processes that can then be shared. From the standpoint of the scope of this article, sharing knowledge through a knowledge structure and sharing aspects of the reasoning/argument-building processes are essential to meaningful collaboration. However, a basic approach is needed that investigates the form that collaboration should take, what artifacts should be shared, in what form and at what stage of the reasoning process. This approach would help us determine the design and functionality of the interactive visual analytics tools. At least three types of collaboration might come into play. The first is collaboration within a group of people with equal status who may have different tasks, say a group of analysts. The second is collaboration across groups, say between analysts and professionals in charge of emergency planning. The third is vertical collaboration within a hierarchy between, say, analysts and their managers.

The HCM must also be made predictive and practical. To be practical, the model must have several diverse instances of application so that one can clearly see how its precepts can be applied and can get a concrete sense of the success and effectiveness of the application. To be truly powerful, the HCM must be predictive so that one has an operational approach for not only designing but *optimizing* visual analytics tools for complex reasoning applications. At the core of the predictive model is the goal that actions taken by the computer – presentation of new data, modification of existing data, computation and analysis of patterns of data and so on – should be done in such a way that they do not interfere with the human's train of thought or flow of reasoning. Indeed, the temporal constraints of human memory, perception and cognitive processing are such that optimizing the sequence of computational operation to match those constraints is likely to enhance the depth of analysis that the user is capable of. 'In the zone' is the term often used to indicate the state of heightened cognitive efficiency and insightful thinking that can be achieved. In the predictive HCM, one would want to predict both qualitatively and quantitatively what being in the zone means, how it can be achieved, and such things as what certain types of distractions cost, how cognitive efficiency can be measured and how (especially interaction) techniques can be ranked. One could then imagine having a cost/benefit model, such as van Wijk's,[26] but much more detailed and predictive, with which to determine the value of a particular visual analytics approach. This study is complicated, however, by the fact that research in neuroscience[30] and other areas indicates that the focus required, for example, to complete certain types of cognitive tasks more quickly may significantly impede the human's ability to have a flash of insight or an important new idea.[9] An environment that supports more free association and less focus is superior for this. Thus, there is the tension of trying to balance contradictory characteristics, both of which may be needed.

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References

1 Thomas, J.J. and Cook, K.A. (2005) *Illuminating the Path: The Research and Development Agenda for Visual Analytics*. IEEE Computer Society Press.
2 Pirolli, P. and Card, S. (2005) *The Sensemaking Process and Leverage Points for Analyst Technology as Identified Through Cognitive Task Analysis*; 2–4 May, McLean, VA: Mitre, pp. 2–4.
3 Luo, D., Yang, J., Fan, J., Ribarsky, W. and Luo, H. (2009) EventRiver: Interactive Visual Explorations of Streaming Text, Charlotte, NC: The Charlotte visualization Center. VisCenter Technical Report CVC-UNCC-09-05.
4 Adams, S. and Goel, A. (2007) Making sense of VAST data. Proceedings of the IEEE Intelligence and Security Informatics; 23–24 May, New Brunswick, NJ. Los Alamitos, CA: IEEE Computer Society Press, pp. 270–273.
5 Eccles, R., Kapler, T., Harper, R. and Wright, W. (2008) Stories in geo time. *Information Visualization* 7(1): 3–17.
6 Kim, S., Shekhar, S. and Min, M. (2008) Contraflow transportation network reconfiguration for evacuation route planning. *Transactions on Knowledge and Data Engineering (TKDE)* 20(8): 1115–1129.
7 Chang, R. *et al*. (2007) WireVis: Visualization of categorical, time-varying data from financial transactions. In: W. Ribarsky and O. Keim (eds.) Proceedings of the IEEE VAST '07; 30 October–1 November. Sacramento, CA. Los Alamitos, CA: IEEE Computer Society Press, pp. 155–162.
8 Dou, W. *et al*. (forthcoming). Recovering the reasoning process from user interactions. *IEEE Computer Graphics & Applications* (in press).
9 Chang, R., Ziemkiewicz, C., Green, T.M. and Ribarsky, W. (2009) Defining insight for visual analytics. *IEEE Computer Graphics and Applications* 29(2): 14–17.
10 Stasko, J., Gorg, C. and Liu, Z. (2008) Jigsaw: Supporting investigative analysis through interactive visualization. *Information Visualization* 7(2): 118–132.
11 Pike, W., May, R. and Turner, A. (2007) Supporting knowledge transfer through decomposable reasoning artifacts. In: R.H. Sprague (ed.) Proceedings of Hawaii 40th Annual Hawaii International Conference on System Sciences (HICCS 2007); 3–6 January, Waikoloa, HI. Los Alamitos, CA: IEEE Computer Society Press, p. 204c, doi.ieeecomputersociety.org/10.1109/HICSS.2007.508.
12 Pike, W.A. *et al*. (2008) The scalable reasoning system: lightweight visualization for distributed analytics. In: D. Ebert, and T. Ertl (eds.) IEEE Symposium on Visual Analytics Science and Technology: VAST '08; 21–23 October, Columbus, OH. Los Alamitos, CA: IEEE Computer Society Press, pp. 131–138.
13 Yue, J., Raja, A., Liu, D., Wang, X. and Ribarsky, W. (2009). A blackboard-based approach towards predictive analytics. Proceedings of AAAI Spring Symposium on Technosocial Predictive Analytics; 23–25 March. Stanford, CA. Menlo Park, CA: Association for the Advancement of Artificial Intelligence, Stanford University, pp. 154–161.
14 Corkill, D. (1991) Blackboard systems. *AI Expert* 6(9): 40–47.
15 LaFree, G. and Dugan, L. (2007). *Global Terrorism Database*, 1970–1997. College Park, MD: University of Maryland. Ann Arbor, MI: Inter-University Consortium for Political and Social Research. Study Number ICPSR04586-v1, doi: 10.3886/ICPSR04586.
16 Goel, A.K., Adams, S., Cutshaw, N. and Sugandh, N. (2009). Playing Detective: Using AI for Sensemaking in Investigative Analysis. Georgia Tech GVU Technical Report no. GIT-GVU-09-03.
17 Green, T., Ribarsky, W. and Fisher, B. (2008) Visual analytics for complex concepts using a human cognition model. In: D. Ebert and T. Ertl (eds.) IEEE Symposium on Visual Analytics Science and Technology: VAST '08; 21–23 October. Columbus, OH. Los Alamitos, CA: IEEE Computer Society Press, pp. 91–98.
18 Pike, W.A., Stasko, J., Chang, R. and O'Connell, T.A. (2009) The Science of interaction. *Information Visualization* 8(4): 263–274.
19 Thagard, P. (2005) Being interdisciplinary: Trading zones in cognitive science. In: S.J. Derry, C.D. Schunn, and M.A. Gernsbacher (eds.) *Interdisciplinary Collaboration: An Emerging Cognitive Science* Mahwah NJ: LEA.
20 Gallison, P. (1997) *Image & Logic: A Material Culture of Microphysics*. Chicago, IL: University of Chicago Press.
21 Woolf, S.H. (2008) The meaning of translational research and why it matters. *The Journal of the American Medical Association* 299(2): 211–213.
22 Stokes, D.E. (1997) *Pasteur's Quadrant: Basic Science and Technological Innovation*. Washington DC: Brookings Institution Press.
23 Fisher, B. (forthcoming) Science and smart graphics. *Information Technology* (in press).
24 Perry, J.M., Janneck, C.D. and Pottenger, W.M. (2009) Supporting Cognitive Models of Sensemaking in Analytics Software Systems. Rutgers University, DIMACS Research Report 2009-12.
25 Kasik, D., Ebert, D., Lebanon, G., Park, H. and Pottenger, W.M. (2009) Data transformations and representations for computation and visualization. *Information Visualization* 8(4): 275–285.
26 van Wijk, J.J. (2005). The value of visualization. In: C.T. Silva, E. Groller and H.E. Rushmeier (eds.) IEEE Visualization, Vis '05; 23–28 October. Minneapolis, MN. Piscataway, NJ: IEEE, pp. 79–86.
27 Isenberg, P. and Fisher, D. (2008) Collaborative brushing and linking for co-located visual analytics of document collections. *Computer Graphics Forum* 28(3): 1031–1038.
28 Robinson, A. (2008) Collaborative synthesis of visualization analytics results. In: D. Ebert and T. Ertl (eds.) IEEE Symposium on Visual Analytics Science and Technology: *VAST '08*; 21–23 October. Columbus, OH. Los Alamitos, CA: IEEE Computer Society Press, pp. 67–74.
29 Heer, J. and Agrawala, M. (2008) Design considerations for collaborative visual analytics. In: W. Ribarsky and O. Keim (eds.) *IEEE Symposium on Visual Analytics Science and Technology: VAST '07*; 30 October–1 November. Sacramento, CA. Los Alamitos, CA, pp 49–62.
30 Wilson, T.D. and Schooler, J.W. (1991) Thinking too much: Introspection can reduce the quality of preferences and decisions. *Journal of Personality and Social Psychology* 60(2): 181–192.