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Visual Analytics as a Translational Cognitive Science

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Abstract

Visual analytics is a new interdisciplinary field of study that calls for a more structured scientific approach to understanding the effects of interaction with complex graphical displays on human cognitive processes. Its primary goal is to support the design and evaluation of graphical information systems that better support cognitive processes in areas as diverse as scientific research and emergency management. The methodologies that make up this new field are as yet ill-defined. This paper proposes a pathway for development of visual analytics as a translational cognitive science that bridges fundamental research in human/computer cognitive systems and design and evaluation of information systems in situ. Achieving this goal will require the development of enhanced field methods for conceptual decomposition of human/computer cognitive systems that maps onto laboratory studies, and improved methods for conducting laboratory investigations that might better map onto real-world cognitive processes in technology-rich environments.

Keywords: Visualization; Human-computer interaction; Visual analytics; Information systems; Translational research; Cognitive systems; Visually-enabled reasoning; Augmented cognition

1. Introduction to visual analytics

1.1. Origins

Visual analytics was defined as ''the science of analytical reasoning facilitated by interactive visual interfaces'' (Thomas & Cook, 2005) and its initial structure established by a 2
panel of researchers drawn largely from the computer science visualization community. Under the auspices of the U.S. Department of Homeland Security's National Visualization and Analytics Centre, this group was assembled at Battelle's Pacific Northwest National Laboratory and asked to define a research agenda for a new interdisciplinary effort to design and evaluate technologies for strategic and operational decision making. As with other

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proposed visual analytics application areas, these domains are characterized by information that is incomplete, contradictory, uncertain, or changing over time. From the perspective of the decision-maker, they frequently pose ''wicked problems'' (Rittel & Webber, 1973) that resist computational solutions due to constraints on time and resources for computation and poorly defined criteria for solutions. After analyzing the problems associated with understanding threats posed by terrorism and natural disasters, the visual analytics research agenda panel proposed a broad interdisciplinary effort to design, develop, and evaluate technologies to make advanced computational techniques available to human analysts through the use of interactive visualization. Their conclusions were reported in ''Illuminating the Path: A National Research Agenda in Visual Analytics'' (Thomas & Cook, 2005). This paper builds upon that document, discussing the evolution of parallel tracks of visual analytics research—as an engineering discipline, as a ''science of the artificial,'' and as a translational cognitive science.

1.2. Visual analytics as an engineering discipline

Given the challenge of automatic computational analysis of complex data, much recent effort in the analytics community has focused on the design of interactive graphical representations of information that might better support the human ability to perceive and to construct meaningful patterns from data. Some of the goals for the analytic process, for example, ''to detect the expected and discover the unexpected,'' (Thomas & Cook, 2005, p. 22) further complicate the situation—while some form of automatic pattern recognition might ''detect the expected,'' ''discovering the unexpected'' necessarily relies on the ability of human analysts, perhaps in partnership with intelligent systems, to generate novel insights about information sets by discovering new patterns. From the perspective of engineering design, interfaces that must support human analysts' interaction with information as a primary design specification ought to be informed by design guidelines and formative and summative evaluation criteria that incorporate what we know about human perceptual and cognitive capabilities. These design constraints must be integrated with more conventional specifications such as specifications for computational processing of data and generation of the graphical algorithms required to build visualizations in software engineering practice.

In this view, visual analytics can be thought of as a cognitive science-aware engineering discipline whose goal is to apply findings from research in human cognitive performance to the design and evaluation of technologies for presenting and interacting with information. Success for this effort would be measured by improved effectiveness of new information and communication technologies for enabling analysts to work with multiple and complex datasets that may contain uncertainty, for example, uncertainty in fact, relevance to the problem, or time and location of events.

The visual analytics as an approach to system design can be distinguished from earlier visualization approaches by its stronger focus on human cognitive processing of display information. From this perspective, the scientific study of human cognition may exist to a great extent at arms-length from system design so long as it manages to shed light on perceptual and cognitive processes commonly found in technology-rich environments. The results of those studies should provide design guidelines, formative measures for evaluation of aspects of designs prior to their implementation in full systems, and summative measures for evaluation of operational systems with regard to the primary goal of the effort, enhanced cognitive processing.

1.3. Visual analytics as cognitive ''science of the artificial''

A more integrative approach to the interplay of science and technology in visual analytics would build new scientific methods for developing and empirically evaluating theories of human-computer ''mixed-initiative'' cognitive processing. This cognitive systems approach to the design of visual analytic interaction echoes Herbert Simon's proposal for intellectual foundations for design, which he referred as the ''sciences of the artificial'' (Simon, 1996). Following Simon, this cognitive ''sciences of the artificial'' approach to visual analytics would seek to adapt scientific methods to better address designers' need for guidance from the cognitive sciences, such as support for ''satisficing,'' means-end analyses, and models of nearly decomposable systems (Simon, 1996).

Technological support for complex cognitive processes can by guided by new methods for evaluating specific aspects of the visualization design during the development process with regard to their support for human cognitive processes. Examples of this include Po, Fisher, and Booth's (2003) examination of the two-visual systems hypothesis in gestural control for large screen interaction and Liu et al.'s (2005) study of the robustness of attentional tokens (FINSTs) over display transformations. In the case of Po et al., an analysis of gestural control of a large screen interactive display based on the ''two visual systems'' model of Trevarthan shed light on individual differences in performance commonly observed in these interaction situations. This serves as an example of the value of mapping cognitive science theory and methods to resolve an otherwise intractable interaction problem, and resulted in new metrics for evaluation of those applications. The Liu et al. (2005) study arose from concerns about the impact of shifts of point of view (i.e., changes in camera position) of a fishtank VR air traffic control display on task performance. In this case, no predictions could be made with confidence from existing work because it was not known what effect movement of a display might have on tracking targets within that space. A new set of experiments were performed that documented the surprising ability of subjects to track multiple moving targets in a moving display and provided a new evaluation task, multiple object tracking, for application developers. This second study demonstrated that in addition to design guidelines and patterns for cognitive tasks, novel summative and formative measures of cognitive performance can be generated from cognitive science methods. In addition, the question of whether limitations in multiple object tracking performance are determined by relative movement in viewer-centered or display-centered coordinates might well be considered a fundamental research question, albeit one that is more interesting because of the frequent use of moving displays in information visualization interfaces. In this more integrative view, visual analytics could be considered an ''artificial science'' that builds upon and advances fundamental research. This contrasts with a more basic applied science approach, where an application focused engineering discipline draws upon theoretically-driven scientific research findings to support the process of developing useful technologies.

Visual analytics proposes to create a science of complex interaction that can measure and predict human cognitive processes at a level of granularity sufficient to specify which aspects of a visualization might best facilitate the cognitive processes of analysis and decision-making. Achieving this combination of scientific rigor and predictive validity has proven a difficult challenge for the field. Visual analytics' emphasis on the co-development of models of cognitive processes and design of applications that support them builds upon and extends Human Computer Interaction's (HCI) focus on usability and task performance. These technology-aware models of human cognition are at an early stage of maturation (Green, Ribarsky, & Fisher, 2008). The development of these models is complicated by the need to take into account individual differences, in particular the skills and abilities acquired through extensive experience solving a particular type of problem using a given interface and dataset. Analysts in a particular knowledge domain may also share individual differences such as personality factors and institutional differences (e.g., jargon and heuristics) as part of their membership in an expert cohort (e.g., Heuer, 1999), and visual analytics models must consider this variability. We will further discuss individual differences in the next section.

Visual analytics shares much in common with some focused applications of cognitive science to specific tasks and technologies, for example, cognitive geography and educational technology. In many ways, visual analytics can be seen as the generalization of methods and findings that have emerged from a number of these focused application areas. Visual analytics itself began in the focused domain of intelligence analysis, and through collaboration with other research fields is finding application to analysis of complex information sets from medicine, education, environmental science, and banking. Variability of the form and content of data and their semantic relationships among these different application domains requires a variety of visual representations which may be used in isolation or in combination. Each representation carries with it its own form of uncertainty, which must be conveyed by framing and interaction techniques. There are many examples of this in the technology and visualization literatures, such as Correa, Chan, and Ma (2009) and Lundstrom, Ljung, Persson, and Ynnerman (2007). No choice of representation can guarantee that the analyst will be able to categorize, discover, and conclude effectively in a given situation (e.g., Boukhelifa & Duke, 2009; as well as Lee, Robertson, Czerwinski, & Parr, 2007). 3

This view of visual analytics is conveyed by its definition in Illuminating the Path. This definition places an emphasis on the development of a science, presumably a cognitive science, that addresses analytical reasoning supported by interactive visual interfaces and can support the design and evaluation of those tools. If the natural and social science of visual analytics takes as its focus the cognitive processes that take place in interactive visualization environments, it must coordinate closely with the processes that build those applications. The novel perceptual and interactive experiences generated through innovation in the design and engineering of visual analytics applications are necessary for the science as well as the technology of visual analytics to progress. In this view, the visual analytics challenge calls upon us to co-develop the cognitive science of visual analytics with its companion science of design (Simon, 1996). As with any science, the goal of a cognitive science of visual analytics should be the development of theories and models that can stand the test of empirical disconfirmation. In the case of visual analytics, this is made more difficult by the complexity of the phenomena studied. While core research in human cognitive architecture will support our ability to predict human cognitive performance in general, visual analytics asks in addition that we predict performance of a given human in dialog with a system that might be customized for his or her abilities and preference. While the general challenge for cognitive models has achieved a good deal of attention (e.g., Duric et al., 2002), visual analytics calls for an [4] expansion of these efforts, in particular with regard to modeling individual differences in analytic task performance.

1.4. Individual differences in a cognitive science of visual analytics

Because visual analytics proposes to find commonalities in analytical cognition across a range of specific application domains, the innate differences, learned proclivities, self-beliefs and reasoning biases of different populations of analysts must be taken into account. Individual differences have been observed to impact task performance during visual perception (Colombo, Mitchell, Coldren, & Freeseman, 1991), skill acquisition (Ackerman, 1987), and reasoning (O'Keefe, 1988; Stanovich, 1999; Stanovich & West, 2000), to name only a few. Studies of performance differences of individual analysts during interaction with visual analytic tools confirm that individual differences are also a factor in visual analytics. These differences include perceptual and attentional abilities and bottlenecks as well as cognitive factors such as memory and processing capacity and schemas and scripts. Some of these differences may come about as a result of experience with interactive visualization environments, and so an understanding of the development of perceptual, attentive, and cognitive expertise is important. Thus, one of the goals of a natural science of visual analytics might well be the complement of an understanding of human cognitive architecture: The creation of methods that can parameterize aspects of a general cognitive architecture for a given individual's characteristic abilities and limitations. This ''personal equation of interaction'' builds upon foundational work in human perception (the ''personal equation'') conducted in the early 19th century by Friedrich Bessel (Brooks & Brooks, 1979). While Bessel's goals were to reduce the impact of individual differences in astronomical observations, a ''personal equation of interaction'' (Fisher, Fels, MacLean, Munzner, & Rensink, 2004; Green, Jeong, & Fisher, 2010) could someday support not only technological compensation for limitations (e.g., color or stereo blindness) but also more effective utilization of individual abilities and skills developed through experience with interactive visualization systems.

Individual differences are important to the study of human-computer cognitive systems in visual analytics whether the intent is interface customization or building theories of individual differences and the acquisition and impact of expertise in human-information interaction. Human cognition is not standardized, but humans do tend to be habitual (see e.g., Norman, 1994) and, as discussed earlier, expert visualization users or analysts in a specific domain might well share similar training effects and innate characteristics. If an expert domain can be profiled, the interface can be roughly tailored for the group. Profiling subpopulations of users also begins the process of approximation of a personal equation of interaction for a given individual.

While human perception, cognition, and communication can be explored by methods common to the natural and social sciences, many of the requirements for a cognitive science of interactive visual interfaces relate to the fact that they are necessarily the product of human design. This mutual dependence of science and technology complicates the process of transferring knowledge from basic studies of human perception, cognition, and action in these environments to the designers of those environments. In consequence, a cognitive science for visual analytics has to be also a traveling science between the natural and the artificial world, between pure scientific knowledge and design. We refer to this kind of science as translational science.

2. Towards visual analytics as translational science

In this section, we will define translational science and we will review the working model of translational science in medicine with an emphasis on processes that can be applied to visual analytics. We will also explore the characteristics of visual analytics as a translational science, illustrating technology development with examples of visual analytics applications.

Translational science is science that bridges centers of production of knowledge and applications where knowledge is put to use. This kind of science works in ''trading zones,'' where complimentary epistemic and practice communities meet to exchange and transform knowledge and other artifacts that would help them achieve better their own particular epistemic and pragmatic goals (Galison, 1997). These trading zones can be found in industry-academy consortia or research agendas, multidisciplinary or transdisciplinary journals and conferences, or more informal social interactions among scientists and other professionals. The work of translating science consists in making scientific production mobile and in facilitating the traveling of scientific facts and artifacts back and forth between the worlds of scientists and non-scientists.

2.1. Translational research in medicine

Perhaps the closest complement to this tight linking of science and application can be found in the health sciences. The concept of a ''translational science'' (Marincola, 2003) began as a response to the perceived gaps in the transfer of knowledge between basic laboratory science and clinical practice in medicine. Translational research plays a significant role in the 2004 U.S. National Institute of Health Roadmap. It has earned a place in journals of general medicine (e.g., JAMA) and has given rise to its own journal, *Translational Research*.

The key innovation in translational research was the emphasis on research methods whose primary goal is the transfer of knowledge between clinical practice and laboratory research and their associated methodologies. The three primary phases of this process cycle can work in two directions, either ''bench to bedside'' or ''bedside to bench'' (Marincola, 2003). This allows for a flexibility of discovery, and moves beyond the distinctions usually associated in the pure versus applied research approaches (Stokes, 1997).

The three phases of translational research in medicine are as follows:

- Phase 1 translational research examines the impact of laboratory findings on patient outcomes in controlled clinical trials to establish overall effectiveness of a given treatment and to observe how different patients respond. Individual patient reactions (e.g., side effects) are of particular interest.
- Phase 2 translational research examines the incorporation of new treatments in the health care system. Aspects like patient compliance, interaction with medication etc. play a role here. In effect this level of translational research examines the interaction of a novel treatment variable with more familiar variables that characterize patient care in the medical system.
- Phase 3 translational research examines the interaction of new evidence-based medical practices and health care policies. Aspects like cost, impact on resources, and need for policy changes are addressed. This phase draws much less upon the laboratory work, and typically uses techniques from the social sciences and policy analysis.

As ''bench to bedside'' translational medicine matured, the need for a complementary ''bedside to bench'' approach became apparent. The goal of this research is to identify aspects of patient care and outcomes that might give rise to research questions that can best be addressed in laboratory studies. For example, observations of a common side effect of a new drug in patients might give rise to laboratory investigation of its impact on a particular biological system, which may in turn give rise to new pharmaceuticals.

As defined by the health care community, translational research is compatible with the belief that research that is fundamental (e.g., basic or ''pure'' research) may well have practical applications, and that fundamental research questions may arise from applied settings. This extends the Stokes (1997) critique of the pure versus applied distinction in science funding policy to the practice of science itself, and so provides an example of a way in which scientists might reconcile the goal of building fundamental understanding of natural phenomena with practical utility.

2.2. Visual analytics as translational science

Because the science of visual analytics takes as its focus the cognitive processes that take place in interactive visualization environments, it must coordinate closely with the processes that build those applications. Innovation in the design and engineering of visual analytic applications is necessary for the science as well as the technology to progress. The theories that are built and tested using the scientific method should be powerful enough to make specific predictions to guide the design and evaluation of interactive visualization technologies with regard to their ultimate goal of aiding human cognitive processing. We should also expect those findings to impact the human side of the equation in a complementary manner—producing not only generalizable insights into human perceptual, cognitive, and motor processes in rich sensory environments but also recommendations and metrics for evaluation of human capabilities, training methods, organizational structures and methods for collaboration.

A translational science approach to visual analytics (see Fig. 1) would avoid the pure versus applied research distinction by proposing a more structured two-way translation of knowledge. An evolution towards this model can be observed and evaluated using a three-phase model based on the translational science model used in medicine:

- Phase 1: Research findings from the cognitive, perceptual, and social sciences can inform the development and evaluation of interactive visualization environments so as to enhance their support for cognitive performance on real-world tasks and data. This is to say that Phase 1, ''lab-to-design practice'' translational research, is productive in advancing visual analytics system engineering. Additionally, new visualization techniques and metaphors are created in Phase 1, usually triggered by system-development discoveries in Phase 2; when no available technique can reasonably abstract the large datasets visual analytics often uses, or the interaction methodology is subpar for the available task or hardware, new techniques and metaphors are often created in response.
- Phase 2: The interpretation of novel visualization environments is not necessarily straightforward. It is possible that variables associated with choice of visualization, interaction method etc. may interact with more familiar cognitive, perceptual, and social factors. It may also be the case that considering these variables together might be scientifically progressive (Larva, 1998) in the sense of generating novel theories that explain the nature of the interaction of display and cognitive factors. If this is the case, then Phase 2 translational research might support a well-formed cognitive ''science of analogical reasoning facilitated by interactive visual interfaces'' as posited in Thomas and Cook (2005). For this to be the case, observations of the use of interactive visualization in the field must be able to generate research questions that can be explored in the laboratory and that contribute to cognitive science in some fundamental sense, albeit one that focuses on reasoning that is facilitated by use of interactive visualization.

This list of desiderata omits the policy dimension of the third phase of translational research discussed above, which in the case of medicine leads to changes in health care policy. This is not due to any concerns about the importance or achievability of this phase of translational science, but simply a matter of the scope of the current paper. Phase 3 translational-science ought to take place within the mission agency or other organization that has a

Fig. 1. ???????.

voice in policy decisions. In the case of mission agencies responsible for current visual analytics research, it forms a substantial part of the efforts of the U.S. DHS Center of Excellence in Command, Control, and Interoperability that includes the DHS visual analytics research program.

3. Visual analytics translational research

In this section, we will discuss the emergence of visual analytics as a translational science and illustrate core translational components through brief consideration of the contribution of selected visual analytics applications.

3.1. Introduction

Visual analytics is a translational science ''in the works.'' It offers a potential trading zone between cognitive science and the design of interactive-data visualizations. However, this trading zone is still incipient. Cognitive science has produced valuable knowledge on human perception of visual displays (Oliva & Torralba, 2006; Pylyshyn, 1989, 2001; Rensink, 2000; Triesman & Gormican, 1998), and analytical reasoning in interactions with [5] complex visualizations (Trafton et al., 2000; Trickett & Trafton, 2007). However, it is not [6] evident that this knowledge has been effectively translated into the world of designers of visual analytic tools. In addition, it is questionable to what extent the majority of studies of the use of visual analytic attempt to confirm or refute cognitive theories that might in turn generate those design principles. Therefore, it is not clear to what extent the ''trading zone'' for cognitive studies of visual analytics and design of visual analytic tools is developing as an effective mechanism for coordination of these research streams. Lacking a mechanism for translation of knowledge between these two research domains it is difficult to see how visual analytics technologies will avoid cognitive overload, underuse of innate cognitive abilities and interrupted analytic flow.

Conversely, if methods can be found to support this translation, it may be possible for sound scientific principles to more effectively inform design principles for visual analytic tools while at the same time visual analytics design and use can inform progress in the cognitive sciences. This convergence will produce better designs that make the most out of human innate capabilities and computer-based interactive visualizations. Also, analyses of successful and unsuccessful designs as well as user studies will provide opportunities to prove, disprove, and generate new scientific questions.

3.2. Examples of translational science in extant visual analytics research

What follows is a brief illustration of visual analytics as a translational science through two visual analytics tools and a discussion of VA evaluation. Throughout, we discuss translational science as it has been previously defined in the section ''visual analytics as translational science'' (see Fig. 1).

3.2.1. Jigsaw

Jigsaw is a text analysis tool developed by Stasko, Gorg, and Liu (2008b) at the Georgia Institute of Technology. It was developed in response to a known problem in text analysis: There is too much to read (see Fig. 2). Several factors served as motivation and/or Phase 1 translations. Work by Norman (1994) in visual representational aids, as well as by Card, Mackinlay, and Shneiderman (1999) in ''external cognition aids,'' are cited as previous related work. Another Phase 1 translation was previous work by the authors, which generated process-derived insights on approaches text analysis (Gorg, Liu, Parekh, Singhal, & Stasko, 2007; Stasko, Gorg, & Liu, 2008a). 7 8

In a Phase 2 translation, the development of Jigsaw utilized Pirolli & Card's (2005) evaluation of task analysis as well as the resulting sensemaking loop in its tool design. The sensemaking loop elucidates some of the search and filtering processes involved in abduction and/or induction. Another Phase 2 translation was the incorporation of the 9

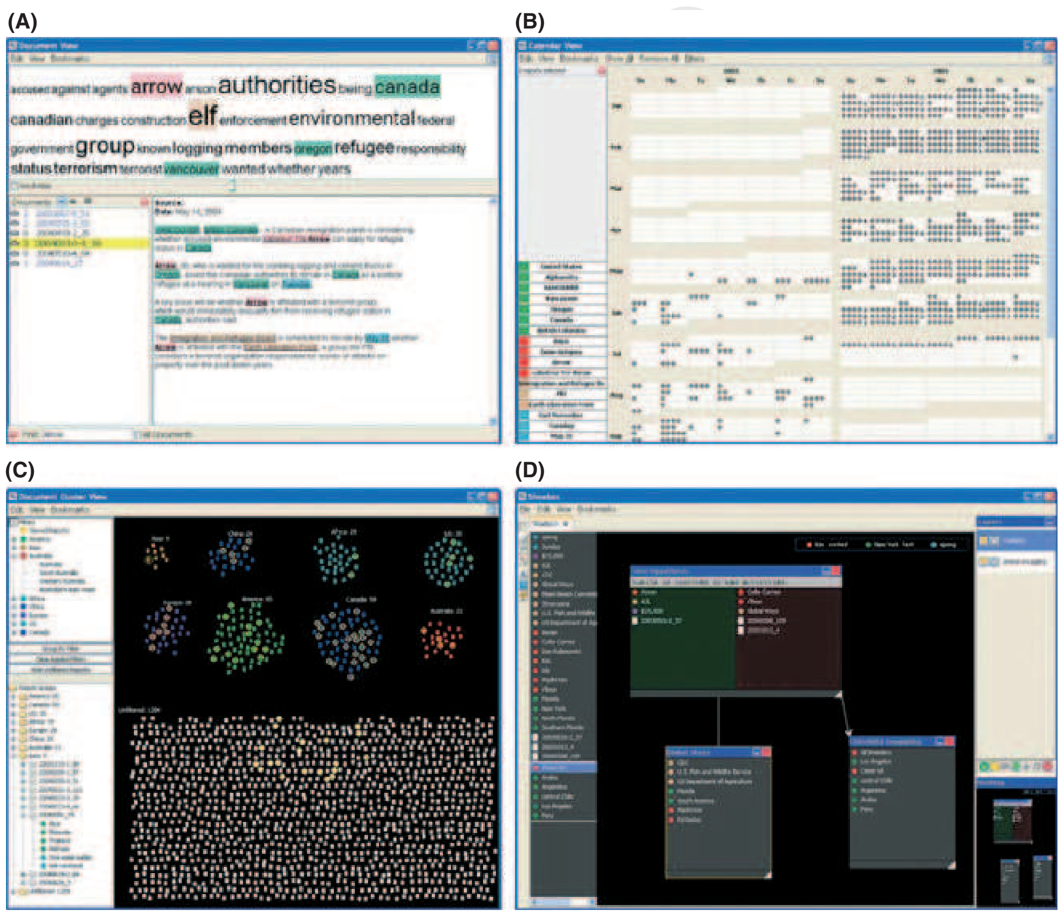

Fig. 2. ???????. 19

ANNIE lexical processing software package to identify linguistic ''entities,'' which can be the name of a person, a date, a place, or any other data item of interest. Jigsaw's design requires that the human user be able to identify and highlight entities and the relationships between those entities in order to find the relationships.

The Jigsaw system is a compilation of tools (or visualization views) that were designed to fit together like pieces of a puzzle (Stasko et al., 2008b). One of these tools is the List View, which displays a list of the sets of entities, as well as their relationships by the use of lines or edges between related entities. These lists can be sorted and related entities are highlighted for easy identification. Another tool is the Graph View; whole documents and entities of interest are displayed as nodes or clusters of nodes, with relationships denoted by lines or edges. And in the Scatter Plot View, the same entities are displayed as points on a 2D scatterplot, with the entities on the X and Y positions. These views and others like it are designed to allow the analyst to view and sort through entity relationships with a minimum of text reading, at least until the field of interest has been narrowed. Jigsaw tools and methods informed work in a substantial number of related projects including CZSaw (Kadivar et al., 2009). This project takes the Phase 2 translational approach a step further, building design support for cognitive operations such as chunking, scripts, and schemata, and providing a platform for investigating the impact of those design decisions on users' mental models of the problem space.

3.2.2. Scalable reasoning system

The Scalable Reasoning System (SRS) was designed to tackle another variety of analysis task: hypothesis generation and analysis. SRS is a web-based, visual analytics application suite developed by the Pacific Northwest National Laboratory. The ''scalable'' dimension of SRS refers to its support for scalability across diverse computational platforms/devices and distributed users (Pike et al., 2008). See Fig. 3. The ''reasoning'' dimension refers to its support for the analytical reasoning process (Pike et al., 2008) and it is in this aspect that we consider SRS to be an example of translational visual analytics. Two key instances of knowledge generated in cognitive sciences and applied in the design of SRS will illustrate this.

The first effective Phase 2 translation corresponds to the general conceptualization of the tool to support the analytical process. Pike et al. describe the functionality of SRS in terms of supporting three states in a recursive analytic process that allows analysts to identify high-value information: explore, enrich, and exploit (Pike et al., 2008, p. 131). This analytic process was first described in cognitive science research (Patterson, Roth, & Woods, 2001) and used later in ''Illuminating the Path'' as a model to represent user strategies for sense-making (Thomas & Cook, 2005, p. 45).

Patterson et al. conducted an investigation for studying inference-making under data overload and time-pressure in the domain of intelligence analysis, using data generated in Phase 1 research in the generation of new methodologies to accommodate the findings of the research. The researchers observed the analysts in a simulated setting and they documented and conceptualized in detail their analytic process. Their findings showed that analysts tended to sample from a big pool of potentially relevant data by progressively

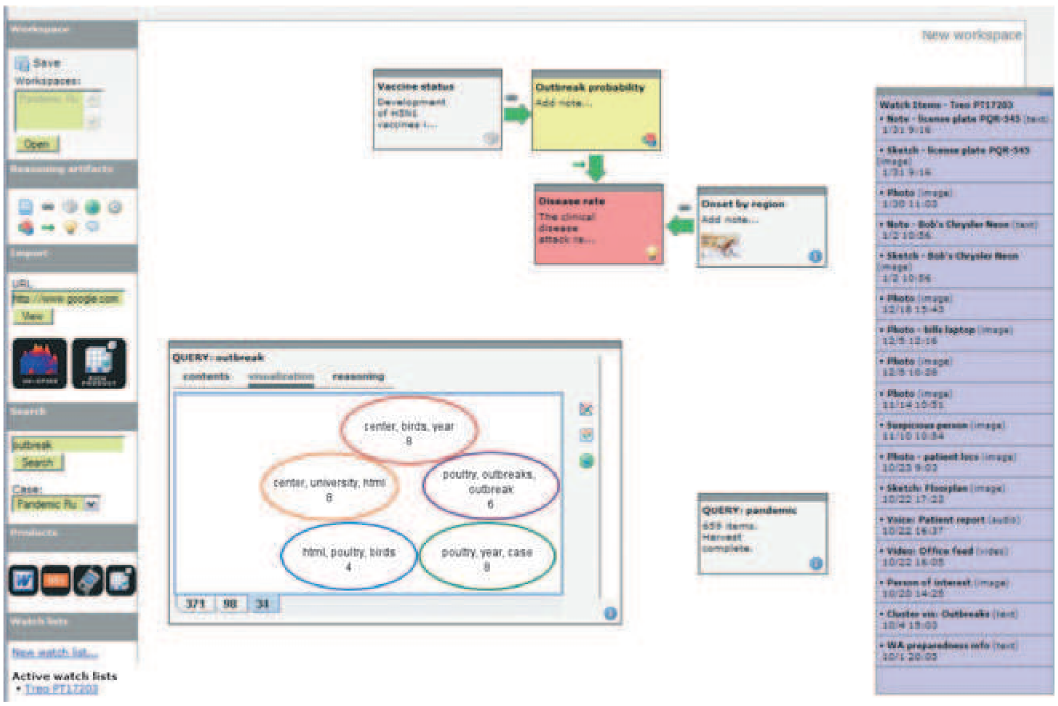

Fig. 3. ???????.

narrowing the amount of data to manage at the cost of missing critical, high-profit, information. The process described by Patterson et al. of sampling by narrowing in and basing analysis on high-profit documents, inspired the ‘‘explore-enrich-exploit’’ model used in ‘‘Illuminating the path’’ (Thomas & Cook, 2005) to represent user strategies for sense-making. This three-step model makes the process described by Patterson, Roth, & Woods’ operational for design of visual analytic tools. ‘‘Explore,’’ for example, corresponds to a corrective measure to reduce the number of ‘‘high-profit’’ documents lost to the narrowing of the manageable dataset. It prompts analysts and supporting technologies to widen the search of documents in the look for ‘‘high-profit’’ documents. ‘‘Enrich’’ corresponds to the strategy described by Patterson et al. (2001) as ‘‘sampling by narrowing,’’ which focuses on sophisticated and automated search tactics, such as faceted search or query-by-example. The third step, ‘‘Exploit’’ points out to the activity of reading the documents and performing inferential analysis on them, which can be enhanced by design of VA tools that allow analysts to make inferences from read documents while keeping a link to the original sources, one of the difficulties experienced by the analysts in the Patterson, Roth, & Woods study.

The impact of using this extant model as translational knowledge used in the design of SRS is explicitly acknowledged by Pike et al.: ‘‘SRS enables analysts to efficiently explore large data spaces to identify items of potential interest; through coordinated services and displays they enrich their information collections by weeding out lower-value items;

high-value material is then exploited to discover specific events, attributes, and relationships of interest.'' (Pike et al., 2008, p. 131). The ''exploit'' phase, for example, is supported by SRS through an entity-relation view that allows users to manually create graph relations. Every time the user adds a new entity to the graph, SRS automatically updates the view by adding relations to all of the other entities and visually provide cues to quickly determine the strength of the relationships.

Another effective Phase 1 translation is the creation of a new tool to accommodate new design requirements: ''the reasoning whiteboard.'' This whiteboard uses previous Phase 1 research, described in the next paragraph, and allows analysts to structure external representations of their analytical reasoning by linking insights from the visual analysis of data within more complex reasoning constructs, such as hypotheses. The design of the whiteboard incorporates several concepts and insights from knowledge management studies that have recognized the need for technological support in visual analytics for knowledge transfer and cooperative inquiry (Pike, May, & Turner, 2007).

The whiteboard, in what is a Phase 2 translation, utilizes previous Phase 1 work by Pike et al. (2007) focused on developing a model for communication of analysis in the intelligence community, in which knowledge structures could be decomposed into the lower-level reasoning artifacts that produced them. The main idea behind this model is that collaborative analysis requires a representation of the analytical train of thought that can be made explicit, stored, and shared among analysts: ''In discovery-based applications, both efficiency and quality are served by preserving audit trails of reasoning'' (Pike et al., 2007, p. 1). Pike et al. suggested capturing this audit trail in-situ. That is, in the same applications analysts use, and associate it with the knowledge artifacts that are the object of the reasoning process. The ''reasoning whiteboard'' from SRS served as a proof-of-concept for this model. For example, Pike et al. suggests that concepts in intelligence analysis are highly context-dependant demanding constant interpretation of both the concept and the context. The researchers argue that capturing this hermeneutic process requires capturing the interpretations (concepts) and the relationships between interpretations (context) so that the reasoning process can be communicated (Pike et al., 2007). This is exactly what the reasoning whiteboard does. The analysts can graphically represent interpretations of concepts as ''sticky notes'' on the whiteboard. These representations, or ''reasoning artifacts,'' have to be classified according to a taxonomy of knowledge for intelligence analysis proposed by the authors and embedded in the design. Every feature in SRS, including views or features of views, can be brought to the whiteboard as a reasoning artifact and a link to the original feature is created to maintain the audit trail. Any reasoning artifact can then be connected to any other artifact in the whiteboard to establish logical relationships, and metrics of confidence on the data and degree of support for hypotheses can be added to every artifact to support hypothesis testing. By using the ''reasoning whiteboard'' as a proof-of-concept of their model for communication of knowledge structures Pike et al. are effectively translating scientific knowledge into visual analytics design.

Little work, to date, has amounted to Phase 3 translations of SRS, though it has been referenced as an exemplar for extant work in reasoning-supportive visual analytics (e.g., Green et al., 2008; Ribarsky, Fisher, & Pottenger, 2009).

3.3. From the field to the lab: Pair analytics 10

Most of the examples mentioned above emphasize lab-to-field translational research. Some recent efforts in our own lab work towards the development of field methods that build upon social sciences approaches (e.g., ethno methods, here used in grounded theory analyses) that can help bridge to methods and models from cognitive science such as those discussed above. The objective here is first to describe real situations of decision-making in all their complexities, and second, to target aspects that are key to analytic success and that can be addressed through laboratory study of analytical cognition. We begin by observing performance of analysis by data analysts using current computational tools, and by conducting in-depth interviews with data analysts and decision-makers. Access to skilled informants is often difficult to gain, however the strong relationships we have built with Canadian and U.S. companies and government mission agencies have given us access to data from disaster relief exercises, law enforcement, and health care management in crisis situations as well as access to those decision makers and knowledge workers.

For collaborative analytics and communication with stakeholders, we then extend those methods to bridge to the cognitive science of interpersonal communication, linking concepts from Herbert H. Clark's Joint Activity Theory (Clark, 1996) with the social science methods. We do this through the creation of ''pair analytics'' teams, loosely based on Pair Programming from Extreme Programming software development methods (Beck, 2000; Gallis, 2007; Gallis, Arisholm, & Dyba, 2003). Graduate students are trained in the use of visual analytics software created by our colleagues at Oculus, Future Point Systems, Battelle, and Tableau. The student's task is to act as the technical analyst, controlling a suite of visual analytics tools. They are paired with a subject matter expert, usually an analyst from the stakeholder organization. Based on preliminary interviews and observation, a task and data set are chosen that will be most informative about analytic challenges and opportunities faced by the company, agency, or ministry. The subject matter expert then works with our visual analyst to address the problem through the use of visual analytic applications. As in Pair Programming, the visual analyst ''drives'' the software while the topic expert directs the conceptual analysis of the problem. Discourse between the two analysts is analyzed within the framework of Joint Activity Theory. Immediate benefits for the stakeholder are insight into analytic processes and how visual analytic tools might enhance them, guidance of effective tool selection and configuration, match to task and data, and training of analysts. The technology designer benefits from a better understanding of analytic practice, potential use of their tool, errors encountered, etc.

The pairing of subject matter expert (SME) with visual analytic expert (VAE) is designed to generate a human-human dialog that will make explicit the mental models and cognitive processes of SME and VAE during their visual analysis. For example, the SME during the analytic interaction may provide expert knowledge to suggest visual comparative analysis of variables, use domain-relevant models to explain patterns and anomalies observed in the visualizations, and engage in hypothesis-making and testing. The interaction of the dyad with the VA tool also generates a human-artifact dialog in which machine-models interact with human mental models. For example, visualizations created by the dyad may result in unexpected outcomes that do not fit into existing mental models due to the way the VA tool handles the data. The analytical task and the dataset for pair analysis are selected from previous in-vivo studies of analytical work in the specific domain of expertise of the SME. Selecting a currently relevant analytical task and familiar datasets create a more naturalistic setting for controlled observations of analytical reasoning.

Currently, pair analysis is being tested in the aircraft safety and maintenance domain. Initial Phase 1 insights from the application of this research protocol have shown that the theoretical framework of Joint Action Theory proposed by Herbert Clark (1996) can be used to derive a predictive model to account for the creation and preservation of the cognitive flow in analytical discourse. Additional work is also being done to confirm that Pair Analysis is more effective than think-aloud protocols of individual analysts to capture analytical reasoning processes and mental models being used during the analysis.

From a translational perspective, the naturalistic approach for cognitive studies in visual analytics, followed in Pair Analysis, sets the scene for a translation of knowledge from ''in the wild'' studies of users of visual analytic tools to cognitive science. Previous research, using similar approaches, has demonstrated that in-vivo studies of non-interactive visual analysis can effectively translate into revised models of scientific reasoning (Trafton et al., 2000; Trickett & Trafton, 2007). If effective, work at the SCIENCE lab with Pair Analytics will also translate its in-vivo studies of interactive visual analysis into new and revised models of visual analytical reasoning and analytic interaction. This work, however, is still in the making.

4. Conclusion

We have argued that a translational science model for visual analytics is a productive approach to addressing questions of interaction in these environments. We have given some examples from visual analytics that are moving towards this goal. What remains to be determined is the extent to which these efforts are producing a well-formed scientific field of study. One measure of this is the extent to which a cognitive science of interaction might be ''progressive.'' Lakatos' view is that a progressive science is one in which the products of investigation—findings and theories—can support reasoning about novel situations and creation of strong predictions that can be tested in those situations (Larva, 1998). An extreme example of this might be Einstein's prediction of the anomalous perihelion precession of Mercury based on his theory of special relativity. The theory was developed independently of the observation, but its equations were able to predict the anomaly with a high degree of precision. As a result, many were convinced that Einstein's decision to consider gravity as a property of space-time geometry rather than a force was a valid and productive mapping of the problem onto the mathematical equations. The extent to which a translational cognitive science of interaction can be of itself a progressive science remains to be determined.

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