Using a human cognition model in the creation of collaborative knowledge visualizations

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ABSTRACT

This paper explores the basis and usefulness of a predictive model for the architecture of data and knowledge visualizations based on human higher-cognition, including human tendencies in reasoning heuristics and cognitive biases. The strengths and weakness of would-be human and computer collaborators are explored, and a model framework is outlined and discussed.

Keywords: cognitive modeling, cognitive processes, visual analytics, intelligence analysis, knowledge visualization

1. INTRODUCTION

One purpose of interactive knowledge visualizations is to facilitate the efficient human-computer interaction in the presentation and manipulation of knowledge. Yet up to this point, these knowledge visualizations have been passive, displaying information and waiting on the human to intitate everything else. We have developed a model framework that utilizes what is known of the human's cognitive processes and use it to create a more active, intuitive collaboration between human and computer, focusing on the strengths of both. Such a framework is important to study because there are a growing number of complex reasoning and analysis problems that must also handle very large amounts of data. These problems cannot be handled automatically, by the computer alone, or by the human alone. Rather a highly interactive collaboration must occur between the human and computer. In order to construct the best interactive visual interfaces for these problems, it is most useful to understand better what is the province of the computer and what is the province of the human.

In this paper, we discuss the complementary strengths that humans and computers would bring as collaborators to an interactive visualization, and we apply a model framwork to interactive knowledge visualization tasks, showing how the model could be used to establish criteria and design guidelines that could maximize the effectiveness of the collaboration for reasoning, discovery, and decision-making. Additionally, we will highlight task areas in which the model would be particularly useful in intelligence analysis.

2. HUMAN REASONING STRENGTHS

2.1 Superior accommodation

The human reasoning process is of a different order than computer-based reasoning. In attempting to construct a higher-cognition model that would guide computer interface development, it is essential to capture the unique aspects of human thinking while also accounting for the aspects that are best handled by the computer. A cursory evaluation of both thinking systems quickly reveals complimentary strengths, which are tabulated in Figure I. For example, humans, at present, are vastly superior reasoners to computers. One reason for this superiority is that humans are also equipped to accommodate the presentation of novel information[1]. As a problem is being worked through, new information is sometimes uncovered that seems different or contradictory from what has been considered up to that point. While this would stymie any artificial reasoner which has not been carefully programmed to handle specific instantiations of novel data, humans are very capable of taking new information, fitting it to the current paradigm, altering the boundaries of the paradigm to include it, or, if necessary, even creating a new paradigm. By the time humans are adults, they have vast experience accommodation, evaluating sensory and semantic data and incorporating new data into knowledge schemata, often almost effortlessly. These skills are foundational for reasoning and decision making.

Adaptation and accommodation would be nearly impossible without the human capacity to categorize new stimuli “instantly.” Recognition of concepts or objects that are closely similar to what has been added to the knowledge schemata in the past is almost instantaneous. This ability is used so often, that, to humans, it seems subconscious. And unlike the computer, which currently identifies concepts and visual observations somewhat rigidly, humans are capable of plasticity when categorizing what they have not observed before. For example, humans might categorize a newly-observed animal as “dog-like,” placing a temporary marker in the schemata in which the definition for dog sits, until more information is available[2]. This ability to partially-categorize the unfamiliar allows humans to move forward, while the computer, in a similar situation, might sit stymied or abort the process.

2.2 Superior reasoning and decision-making

In addition to categorization and accommodation, humans have a battery of predictable, descriptive heuristics which they can apply singly or in congress to solve a problem or draw a conclusion. These tools would include elimination by aspects, satisficing, reasoning rules, and use of mental modeling.

Elimination by aspects[3] is a serial heuristic which allows the reasoner to decide at first only which attribute of a problem or decision is most important or of highest priority, and then eliminate all choices that do not grade well on that single attribute. Then, within the smaller pool of available choices, the possibilities are again evaluated with a second attribute, which has been deemed the next most important. And once again, all choices that do not meet attribute criteria are purged. This process iterates until there is only one choice left, and the human, with surprisingly little cognitive outlay, has made a choice that meets a need or solves a problem.

A ready example of elimination by aspects is the common dilemma of where to eat dinner. The human may decide that he would prefer pizza to other food choices, and thus eliminates the nearby steak house and hamburger joint. In the second round of elimination, all pizzerias that are not close by are eliminated, and then perhaps the pizzerias that do not serve New York style pizza. When all criteria have been met, there is often only one possibility left standing. Using elimination by aspects is limited as a sole means of decision making. For while it makes quick work of temporal decisions, it cannot successfully juggle multiple attributes, and risks eliminating viable possibilities for the lack of a single attribute.

Satisficing[4] is another elimination heuristic. An attribute of the desired goal is labeled the most important. The very first presented possibility that possesses the important attribute is immediately selected and no other choices are considered. Obviously, using satificing will eliminate an unknown number of viable possibilities. But the decision is made quickly and with minimal effort. These heuristics do not require formulae, and yet allow the decision maker to break down the decision into small, manageable chunks, avoiding cognitive overload.

Yet when the information to be considered is novel or complex, the elimination by aspects or satisficing methods are too myopic to consider multiple, semantically-rich variables with perhaps rich correlations. Beyond the determination of a single decision, the human reasoner must intuitively manipulate multiple strands of thought. These patterns of information are often described as reasoning mental models and rules-of-thumb. There are multiple theories of rules and models, several of which focus on the use of predictable rules to accommodate new information[5], and others that discuss the use of schemata using implicit rules only observable by the human’s behavior[6,7].

A better approach than using one formula to approximate this complexity would perhaps be a reasoning “mechanization,” utilizing a two-stage approach. The first stage is model creation, during which the reasoner creates a mental conception of the new idea. This requires an initially large proffering of information. For example, in order to paint a picture, an artist would need to see the object from many angles, and in various lighting conditions. Providing more information instead of less allows the human collaborator to create a robust mental model which would less likely be tainted by invalid assumptions and more resilient to situations in which context effects would be common.

The second stage is the creation of a rules-based heuristic. The creation of rules could also be called the “creation of predictable short-cuts.” Referencing a mental model with each initiation of the problem would cause a human to cognitively overload, draining resources such as working memory. Instead, the human reasoning process looks patterns upon which it can predict future behavior or base a reasonably reliable assumption about the concept. This short-cut will then also be applied to any future idea that bears remarkable similarity to the mental model. Additionally, the transition from model-creation to short-cut or rule-creation can happen very rapidly, sometimes in a matter of seconds, saving valuable cognitive resources.[8]

By way of example, let’s consider a human who is presented with a new idea: a new name in a database. The computer provides as much information about the relationships it has connected with this name. From this the human starts to draw a mental picture of this name, connecting previous knowledge with new. For example, the human learns that this name was attached to a symbol – a red triangle – and that this red triangle appeared on traffic lights in Boston before the last blizzard. Depending on the context of this learning, from this point forward during her investigation, the human might associate all future visualized red triangles with traffic lights, Boston, and/or perhaps an urge to check the weather forecast.

Regardless of which model or theory is applied, what seems apparent is that humans possess an inherent ability to take a pattern of information, look for similar pattern structures in memory, and draw conclusions about the novel information based on what is already known. While a computer may be able to conditionally reason through a set of situations, it is difficult if not impossible for any computer to approximate the ease with which humans evaluate data, construct mental models, apply available rules, and draw conclusions which, on average, are sound and workable, if not ideal. That ease of reasoning, in addition to a human’s intuition and “gut,” make the human an integral and invaluable partner in any analytical process of knowledge creation.

3. COMPUTER REASONING STRENGTHS

3.1 Superior “working memory”

Even for humans, using an arsenal of heuristics and effectively employing fuzzy logic to categorize, sense-make, and reason involves an enormous amount of processing power. Yet the human reasoning system does not make available similar capacity for its working memory. So while the human system has unsurpassed ability for deep semantic reasoning, it becomes easily overloaded if asked to juggle multiple concepts simultaneously. The commonly-given mantra that human working memory can manage “7 ± 2” chunks of information is only partially correct. A human might be able to manage the 7 digits in a phone number. But the more complex the concepts that are being managed, the fewer concepts that can be effectively manipulated[9].

Working memory also depends on the human’s ability to pay attention. The more a human is distracted by new information, the more likely that new information will interfere with what was trying to be remembered before[10]. When working memory becomes overloaded in this way, information is lost, concepts are poorly formed, incorrect conclusions are drawn, and the human system as a whole suffers. But as our model framework demonstrates, the collaboration with an intuitive computer interface can easily mitigate the suffering. With a “working memory” limited only by available hardware, the computer can theoretically “keep present” an infinite number of concepts before the human.

Additionally, the computer keeps pertinent information visible within a larger context, preventing human cognitive overload or the tendency to become "lost" in the data audit trail, performing requested manipulations and keeping accurate records. And because the computer never tires, it is always there, remembering. This augmentation of human memory is valuable to the deeper levels of processing that depend upon it. With the computer as collaborator, the human can reason and problem-solve with all of the pertinent information, not just what is recalled in human memory.

3.2 Lack of reasoning bias.

The computer remembers well. And it can remember without bias. Due perhaps to a need to filter the overwhelming input of stimuli, or the need to see patterns in everything, humans often tilt or distort the evidence for their conclusions. For example, humans demonstrate confirmation bias[11] and/or believability effect[12] when they look for information that "confirms" what they already believe or only seek out information that reinforces a previously-held assumption. The human actually hunts for information that confirms what he/she intuitively believes or "has a hunch" about. All other information tends to be ignored, no matter its possible relevance.

Aside from the propagation of urban myths and old wives tales, these biases can be dangerous. In intelligence analysis, it is imperative that the conclusions drawn are those that best fit the data, not those that best fit the bias of the human analyst. But, as these biases are often subconscious and often unrecognized, a computer collaborator that faithfully presents the analyst with all pertinent information in a relevant context can aid the human reasoner by encouraging exploration of information that the analyst may not have thought to seek out.

The presentation of data within relevant context is an essential for any human-computer collaboration. For, in addition to other biases, humans are susceptive to framing effects, wherein the conclusion drawn is based heavily on the way the problem is presented, or framed [13]. Retail marketing takes advantage of this effect frequently, offering "deals" for cash and carry or encouraging the purchase of one alternative over another. Human perception of a problem can be shaped merely by the way it is described. A careful presentation of data in context will help prevent unintentional framing effects, as well as discourage those that might be brought to the collaboration by a framed description of the problem to be analyzed. or the biased wording of a question.

But before the computer can provide these valuable services, it must "think" more like a human, so it understands where the human is coming from and where the human is likely to need assistance. For this reason, our cognition model framework is based on human cognition, with the intention of using the strengths of both collaborators to effectively utilize what is already known to create new knowledge.

	Strength	Weakness
Human collaborator	• Superior accommodation • Superior reasoning and decision-making	• Limited working memory • Use of cognitive biases and effects
Computer collaborator	• Superior working memory • Use of information without inherent bias	• Incomplete categorization and accommodation • Limited reasoning ability

Figure I. Complementary strengths of human and computer collaborators in the creation and analysis of

4. HUMAN COGNITION MODELING IN KNOWLEDGE VISUALIZATION DEVELOPMENT

The human cognition model (HCM), pictured in Figure II, is a framework built on these and other strengths of both human and computer collaborators, as described in the research literature, in the creation of a collaborative model which uses human cognition as a guide. The HCM framework has been focused by the goal of visual analytics in intelligence analysis, which has been stated as the facilitation of “high quality human judgment with a limited investment of the analysts’ time.” [14] With that in mind, the intention of the HCM is the development of an interactive knowledge visualization interface that harnesses the cognitive strengths of both the human and the computer, that creates a space where knowledge is robust and interactive, and that offers a richly-semantic visualization which is more intuitive and thus more efficient and easier to use.

4.1 Definition of knowledge visualization

Knowledge visualization interfaces are a subset of information visualizations. Information visualizations present information to the human in a graphical or pictorial manner, expressing patterns inherently and allowing the user to interact directly with the data through the use of a mouse or other controller.

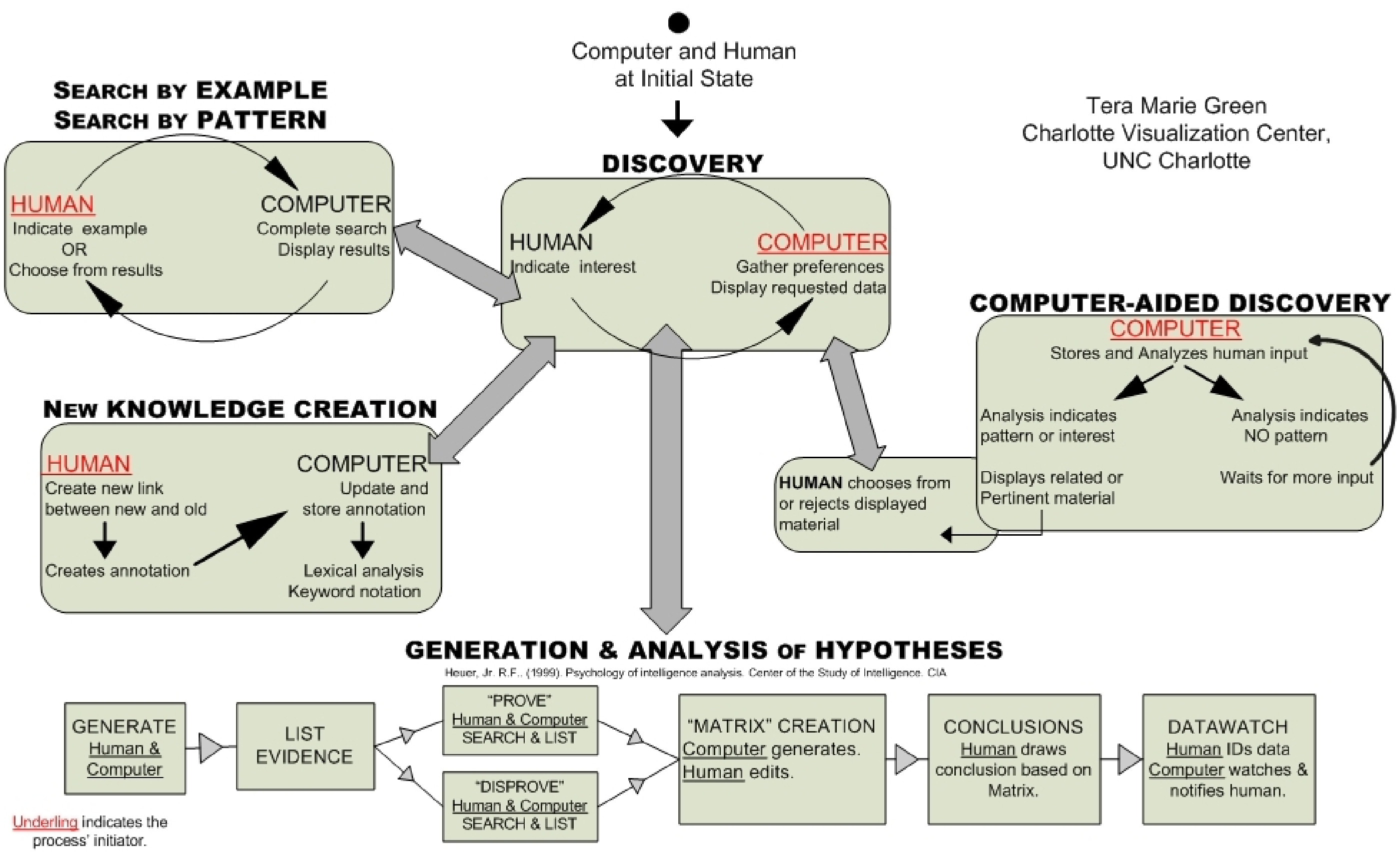

Figure II. Human Cognition Model, showing subprocesses including Analysis of Competing Hypotheses

Knowledge visualizations differ from information visualizations in that, by design, they are developed to encourage the creation of new knowledge by a) using an underlying knowledge structure to decide what information is most valuable to express at a given point in the process or for a given task, b) presenting information within an appropriate context to maximize collaborative insight, and c) allowing the user to create new relationships between concepts, which then go into the knowledge structure so that each human builds on the knowledge of the humans that used the visualization in the past.

Currently, both information and knowledge visualizations are passive, waiting for the human to initiate action. With the use of a human cognition model as a guide, it would be possible to create an interface that would not only be reactive, but proactive, as we will soon discuss.

4.2 Knowledge discovery and creation

The central process in our model is that of knowledge discovery. Knowledge discovery is composed largely of a paired process: the computer presents information in an ontological-like, hierarchical knowledge visualization within the context of the larger user-identified related data, and the human indicates interest in a specific area of data and requests more detail. Additionally, by presenting the data in an user-defined context, the visualization keeps pertinent referential data visible, reducing cognitive overload and eliminating the feeling of being “lost.” In this way, the computer is “thinking” like a human, presenting what it knows in terms of relations meaningful to the human and keeping pertinent information for the task-at-hand visible to the human. An example of hierarchically-organized knowledge visualization is GVis, an exploratory tool for discovering genomic relations and genetic function [15].

With use of a human cognition model, the knowledge visualization could go one step further, making the visualization not just interactive, but collaborative. Aware that humans very often develop and habitually use a set of rules in the search for information of interest, the computer observes and analyzes human input during discovery. Using inductive reasoning, the computer-augmented discovery looks for trends in what areas of knowledge are explored. And by analyzing what areas of the hierarchy are being explored for patterns of interest, the computer can augment discovery by suggesting related data that have not yet been explored. The human is free to accept or reject these displayed suggestions. But by participating actively in the process, the computer helps to assure that relevant information is not overlooked in the discovery. Of course, this procedure cannot be extended too far since, as noted above, the human may veer from his/her current rule set based on intuition or discovery of a key insight. The computer cannot predict or understand this important part of the human reasoning process, so it must present its advice in such a way that it interferes minimally in the rhythm of human reasoning.

Another subprocess within the HCM is knowledge creation. When a human links what is known to what was previously considered unrelated, the data relationships are changed and the knowledge base is broadened. When the human creates a new linkage between data, and perhaps annotates the new relationships, the computer updates the knowledge structure and stores the annotation. In relationship post-processing, the computer also conducts lexical analysis, and notes the use of any possible keywords in the annotation. This post-processing provides another layer of relationships (i.e. a new layer of thought) that aids in later discovery and computer analysis. These new relationships, or knowledge, are also available to other human analysts, who can also add referential information and annotations. In this way, the computer continues to “think” along with the human, as well as facilitate collaboration between analysts.

A current example of an interface that manipulates information in a similar way is the Scalable Reasoning System (SRS), in which users can search for and create graphical representations of data concepts, create relationships between data, annotating as necessary, all of which could at least theoretically done in real time, each user building on the knowledge created by others [16]. An interface based on the HCM framework would take the SRS process one step further, remembering where each human collaborator last created new knowledge, storing that knowledge in a structure that is then used in future visualizations, and presenting the user with the context he/she was last working within.

4.3 Search by example/Search by pattern

When the desired information is not displayed in the visualization, the human collaborator may need to search for it. The most common search functionality is to enter a search parameter or expression in a text box. However, especially with subtle or more complex concepts, it is not uncommon for a user to know and be able to recognize a concept similar to the one he is looking for, but not be able to describe it for the purpose of a text search. The interactive visualization, coupled with the HCM and relevant analysis, can provide this powerful conceptual search by example. This is a general capability that the computer, within the HCM, can provide. So for example, the user might draw a box around a single data representation, an image, etc. and ask the computer to search for comparable concepts. Using a fuzzy search provides a more robust search capacity, while requiring minimal cognitive outlay from the human collaborator. This very powerful technique can be used in several ways. For example, the user can adjust the degree of similarity to the example concept or even search for patterns that are *dissimilar*. Search by example keeps the user “in the flow” so she doesn’t have to make a disruptive cognitive context switch to form traditional queries (of which more than one may be needed in order to focus correctly on the concept).

The ability to search by pattern is also important functionality, but to date, has proven far more elusive in accomplishment. Humans themselves are not fantastic analogical reasoners, but research has demonstrated that, when given a hint in the right direction, humans can reason through analogical patterns [17]. The HCM directs that the computer, with its more powerful “working” memory, provide the ability to search for similar patterns of data to the data pattern that the human collaborator indicates by, for example, drawing a bounding box around the analogical structure to be searched against. Although analogical reasoning engines do exist [18,19,20], none have gone much further than analogical reasoning with rigid propositional logic. This is far less than the HCM would dictate, as knowledge visualizations use robust ontological-like knowledge structures, and the human would likely request to search by patterns that are not delineated beforehand.

4.4 Analysis of competing hypotheses

An important aspect of investigative analysis is the generation of hypotheses. The HCM uses a submodel based on Heuer [21], pictured in Figure II. In hypothesis generation, both human and collaborators generate and list hypotheses. The computer contributes by asking for the topic of generation and a prioritization of relationships. It could further contribute by maintaining competing hypotheses and weighing whether evidence gathered might support the competing hypotheses or even searching for competing evidence independently. The STAB model being developed by Goel [22], for example, maintains scenarios that can be matched to similar scenarios and then used to gather or weigh evidence by a process of analogical transfer. Once the hypotheses are visible, collaborators can list evidence that attempts to disprove each hypothesis by searching for evidence and adding it to the list. In addition they can decide whether to admit the hypotheses being followed by the computer into the analysis. What follows is the creation of a confidence matrix, which the computer generates based on established relationships, and any pre-set filters or algorithms. It is the human’s task to edit this matrix, setting confidence levels for evidence and annotating where necessary.

This newly-created knowledge is then the basis for conclusions drawn by the human and displayed and stored for future reference by the computer. The last step in this process is the option for the human to flag information to be watched. When information changes, the relevant hypotheses and the associated data are flagged and displayed in any subsequent use of the knowledge visualization. By notifying the human when pertinent information changes and then showing the affected relations, the computer plays a collaborative role in the maintenance of the analysis. The human can then reevaluate drawn conclusions, and, if necessary, change confidence ratings and conclusions. The human can also return to knowledge discovery, looking for new evidence.

Why is this process necessary? As previously discussed, humans have inherent biases with respect to mental models they create to explain observed phenomena. For example, once they form an initial hypothesis, it requires more evidence against the hypothesis to change it than it was initially required to make it. Thus managing competing hypotheses and the relevant effort in an objective way is an appropriate task for the computer (as shown in the model in Figure II) although, obviously, deeper reasoning and assignment of meaning must be done by the human.

5. CONCLUSIONS

In the past, the development of an intuitive, human-centered knowledge visualization with true collaboration between human and computer was an elusive aspiration. The Human Cognition Model framework is a robust, scalable collection of sub-models that are centered in the descriptive and prescriptive heuristics of human reasoning and decision-making. This model can then be used with a model of knowledge visualization and computer action, as described in Figure I. The HCM guides the development of the visual interface and underlying analyses that should be designed into the system so that the human can reason effectively and can enter into a full collaboration with the computer.

And while not dictated by the agenda of the National Visual Analytics Center (NVAC), the model also addresses several of the agenda's recommendations for a human-computer analytical reasoning system. For example, the HCM, as the agenda recommends, defines the use of "reasoning artifacts" within the analysis process [23]. In particular, hypothesis generation and elimination is clearly outlined within the HCM, as well as methods of argument handling in knowledge relationships. The agenda also recommends the exploration and/or development of a graphically based, mixed-initiative [24] holistic analysis system [23]. And by presenting information proactively within a graphic, pertinent context, suggesting possibly pertinent information to minimize bias, and allowing the human to search for examples by delineating conceptual examples with or without search boxes, the HCM supports the richly-semantic analytical process of discovery, thinking, and learning.

The HCM is based on decades of prior research in the reasoning and decision-making processes of human cognition, as well as recent work in information visualization. Yet even with such a broad theoretical basis, there are still much to discover. For example, as mentioned previously, the ability to recognize and manipulate the analogical structure of knowledge is a significant part of intelligence analysis which humans do not always do well without help. And as yet, computer technology has yet to match a human's ability to recognize semantic categorization spontaneously.

Additionally, theories about human reasoning are occasionally contradictory and often incomplete. The pertinent research has not been generalizable; traditionally, research has focused on small subprocesses and not on human reasoning as a holistic system. And even more incomplete is the research on the interaction between human reasoning and computer manipulation; this field of research is still emerging.

And so, the HCM is still defined as a framework, and not ,as yet, as a working predictive model. We have begun to test our core assumptions with human and other research; current research addresses the learnability of a knowledge visualization. But while the details have yet to be established, what is not in doubt that a model like the HCM, which has the ability to identify key development requirements, would be an invaluable guide to the future creation of truly collaborative knowledge visualizations.

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