Research Paper Literature Review

Tianyi Li

1 Brief Introduction

The notion of sensemaking in the field of human-computer interaction (HCI) was framed in the early 1990s [9] as the process of forming and working with meaningful representations in order to facilitate insight and subsequent intelligent action. The sensemaking process is complicated in that it iterates on multiple intertwined stages, employs combinatorial and individually-variable reasoning heuristics, and differs according to specific goals of problem-solving. There are theories and models that seek to formalize the process. There is also increasing interest in visual analytics tools and their applications in investigative analysis.

2 Literature Review

Both humans and computers bring strength in information processing, the latter mainly assisting the former with superior working memory and lower-bias environment [3]. Crouser et al. reviewed and identified the patterns in existing affordances representative of the study of human-computer collaborative problem-solving, understanding which forms the basis of a common framework for this domain of problems. Both human and machine bring to the partnership opportunities for action, and each must be able to perceive and access these opportunities in order for them to be effectively leveraged. In the framework proposed by Russell et al, researchers should first decide if a problem would benefit from a collaborative technique, then which tasks to delegate to which party, and when. Given these two answers, different systems can then be compared to solve the same problem. Modeling human cognition and sensemaking is essential for developing computer-aided information processing and knowledge visualizations to address today's complex problems. However, the models are usually very general and do not have clear boundaries between each component, which will lead to vague or varying interpretations and applications in real-world problems.

One of the most prominent models is the Representation Construction Model (the sensemaking loop) proposed by Pirolli and Card [8]. It extends from a more basic Learning Loop Complex [9] model which summarized the activities into two iterative processes: search for representation or framework and fill in collected data. The sensemaking loop is comprised of two major sub-loops: an information-foraging loop and a synthesis loop, taking care of information discovery and knowledge building. Information processing with this model can be driven in two directions. The bottom-up processes are driven by data, from which to generate a theory. The top-down processes start from client inquiries or feedback on the theory, and trigger re-evaluation on previous intermediate analysis results or re-analysis on previous data resources. The sensemaking loop contains multiple small processes that transform data into formats described as expert mental models. However, the data formats at different stages are defined very broadly for a potentially diverse range of methods for a stage. For example, "External Data Sources", a generally defined repository that individual analyst can query in the first process “Search and Filter”, could be the Web or classified databases. The results of this process, “Shoebox”, is simply described as documents are collected into a shoebox. In addition, the methods through which this process is undertaken may depend very much on the data type and format; specifically, what to search for and by what relevance the searches are filtered should be the key concern of this step. All these features must be more clearly defined when tackling practical problems. The concept of relevance evolves as the analysis proceeds and more knowledge is learned, more questions are asked about the dataset. “Schematize” is the process that connects the foraging loop and synthesis loop, but is vaguely defined as happening in the experts mind in an informal way. This leaves open in real-world applications both the schematizing strategies and the format of output schema.

The Data-Frame Theory [6] is developed outside of HCI in the macrocognition approach of psychology, and focuses on iteratively developing meaningful representations (frames) that explain external reality (data). Building on the ample literature on frames and similar concepts, Klein et al. synthesized the concepts as a structure for accounting for the data and guiding the search for more data. The Data-Frame Theory focuses more on the dynamics between Data and Frame. It does not constrain the data type and relies on the experts mental model to frame and re-frame the data. Furthermore, by asserting that the data are inferred using the frame, and that the frame fits the data, the theory implicitly indicates that there are more than one frames in the analysis process and the previous ones influence the later ones. Such being the case, we find the data-frame model most appropriate for describing smaller stages of the sensemaking process. Building upon its other assertions that experts reason the same way as novices, but have a richer repertoire of frames and sensemaking usually ceases when the data and frame are brought into congruence, we can assign subtasks for novice analysts, with experts providing a repertoire of frames.

Prior research has also studied collaborative sensemaking and have identified several suggestions for designing collaborative visual analytics tools. Bradel et al. explored how a large, high-resolution display as a workspace in a co-located setting helps to externalize information to the display in meaningful schemas during pairwise collaboration to make sense of large text dataset [2], and addresses problems like common ground, communication, hand-offs, coordination and attention shifting in teamwork, which is shared among most, if not all collaborative work. Dispatching simpler sensemaking tasks to multiple agents may help to solve some of the problems of attention shifting and mental model interfering. By expert-driven task distribution and aggregation, the coordination can be guided thus more efficient. Expert guidance also naturally offers multiple views on the problem, given the rich pool of strategies and methodologies developed in different domains and individual experience of experts.

The models and theories of sensemaking are important for leveraging human involvement to improve the performance of existing computational AI systems, and facilitating the human analytical reasoning process for complex and dynamic data [7]. Parikh et al. proposed the human-debugging paradigm to explored how the human vision process could be decomposed into a pipeline in order to identify computational bottlenecks as well as opportunities where new automated techniques could make the most impact. One of the challenges they have identified is to align information available to humans with that available to the machine implementation, which requires transforming information in a manner that does not allow humans to use their prior knowledge about the world. In other words, there should be clearly defined inputs and outputs for each component in complicated big problems, that should be equivalent for both human and machine. Following this paradigm, the following research questions need to be answered in the context of text analysis: What are the information needs (inputs) and intermediate results (outputs, also serve as inputs for the following stages) at different stages of text analysis? What are the strategies to decide the sequence of analysis tasks? When should the analysis be conducted bottom-up and when top-down?

Visual analytics community straddles both foraging and sensemaking loops in its efforts to assist both individual and groups of users in investigating and hypothesizing on complex and dynamically changing information. Individual analysts can receive a rich range of assistance from evidence to hypotheses and with multiple data types with visualization tools like Jigsaw [10]. Multiple visualizations of reports and the entities within them, as well as the connections that exist in between, allows people to interact with the views and explore possible new avenues of examination. Integration of visualization with shared accessibility and discussion enhance collaborative complex problem-solving in pairs and small groups. Timelines are often used in such visual analysis tools to represent temporal relationships within the data being investigated [1]. Bier et al. identified key aspects of the design, featuring flexible, shared information structure and visualization among experts, and a notification system that finds entities of mutual interest to multiple analysts. However, synchronous collaboration among small groups is pretty much restricted to information seeking and organization up to entity-level analysis.

The crowdsourcing community has seen efforts in integrating intelligence power among bigger crowds in complex problem-solving. Knowledge Accelerator [4] applies the information foraging loop to guide crowds in searching and filtering information while gaining a sense of big picture in crowdsourced writing. They break down the process into six phases and opens up the challenges of reusing answers of each step. The system is expected be able to identify the similarity for possible answers during each information synthesis phase. This requires answering the research question that what level of granularity should be considered to form an effective system. Spatial and temporal reasoning over the existing knowledge and new information could be considered to provide context-aware and up-to-date answers. This work also provided a successful example of crowdsourcing workflow for complicated problems. Nonetheless, asynchronous and higher level analysis is still bottlenecked by communicating insights and reasoning even among few analysts. As is acknowledged in their work, the crowdsourced approach is most valuable where experts generate a lot of valuable information that is unstructured and redundant. In this paper, we take a step further to explore how crowdsourced approach can be applied to raw textual documents collected on the field that are not pre-processed by expert analysts.

3 Summary

The information explosion from modern technology has spurred increased interest in sensemaking to help people gain insights and suggest effective actions from the big data. The cognitive capability, time and expertise of individual experts are impressive but fundamentally limited, and domain experts are scarce and expensive resources by nature. Text expresses a vast, rich range of information, but encodes this information in a form that is difficult to decipher automatically [5] by modern computer technology alone, understanding and acting on the information to solve real-world problems requires human computation as well. Making sense of a large amount of text data requires understanding natural languages, which is considered AI-hard [11]. Crowdsourcing and algorithms present new opportunities for large-scale sensemaking, but we must first understand how sensemaking work can be modularized to allow powerful and diverse techniques to be used where they can contribute best. The existing models and theories of sensemaking process have been applied to various domains using different types of analysis agents including individual and groups of experts, crowd workers, and machine learning algorithms. Most of the techniques only focus on parts of sensemaking process or provide ideal inputs to non-expert agents, which requires a considerable amount of work from expert analysts. We aim to release this assumption and execute the whole sensemaking loop with non-expert agents, by modularizing different components of the process with more unified inputs and clearly defined outputs that allows combinatorial and flexible usage of them, and enabling multiple paths with a mechanism to decide where to proceed next. Such a pipeline can compare or combine different agents on each component to make full use of the complementary strength of human and computation. Having more specific goals for each component enables backtracking and re-evaluation of the analysis progress. Additionally, with multiple agents involved in the analysis process, we can overcome stereotypes, bias, and groupthink by re-examining intermediate and overall results.

References

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