Visualization of Uncertainty and Reasoning

Torre Zuk and Sheelagh Carpendale

University of Calgary
{zuk,sheelagh}@cpsc.ucalgary.ca

Abstract. This article gathers and consolidates the issues involved in uncertainty relating to reasoning and analyzes how uncertainty visualizations can support cognitive and meta-cognitive processes. Uncertainty in data is paralleled by uncertainty in reasoning processes, and while uncertainty in data is starting to get some of the visualization research attention it deserves, the uncertainty in the reasoning process is thus far often overlooked. While concurring with the importance of incorporating data uncertainty visualizations, we suggest also developing closely integrated visualizations that provide support for uncertainty in reasoning.

1 Introduction

Uncertainty and its complement certainty are fundamental parts of any analytic or reasoning process and relate to important cognitive constraints in using any visualization. To inform the design process we review and coalesce many important aspects of reasoning under uncertainty and discuss these with regard to implications for visualization. For each of these aspects we consider reasoning and representational requirements and assess the potential for exploiting visual support. Based on our analysis of the impact of uncertainty in the reasoning processes, we propose that these receive increased consideration in the design of visualization systems. For instance, when appropriate this could include an additional visual component focusing on reasoning uncertainty and support for introspection. For this reasoning support we contribute design considerations and describe an example system for medical diagnosis.

In the analytic reasoning process, often choosing the visual representation drives the exploration for an iteration of searching, comprehension building, or hypothesis testing. The inability to transform or change this representation is the representational primacy that Amar and Stasko consider a limitation of many current visualizations [1]. In addition to options for alternate representations, it is important to augment a representation with uncertainty in order to allow potential interpretations of the data to be considered. Hepting has described an analogous process for visual interfaces as “begin with an incomplete articulation of a context and allow the user to interactively develop and refine it” [16]. Leaving uncertainty out of a data visualization promotes assumptions that lead to more uncertainty in the reasoning process and the viewer may not be aware of this uncertainty. With insight problems (e.g. the 9-dot problem [30]) searching representation space may be key and Gestalt may even hinder the process [30]. Thus providing cues about uncertainty in representation may promote consideration of other representations and help further the exploration. Based on and extending the impact of data uncertainty visualization, we suggest that representing the reasoning process may aid

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in determining both the next reasoning step, and the assessment of the solution. Further this visual representation specifically designed to support the reasoning process should also incorporate uncertainty to provide transparency of confidence.

Given that both knowledge and representation are coupled to uncertainty, we will present arguments to illustrate that uncertainty of reasoning as well as uncertainty in data should be visualized and if possible integrated in a manner that supports the reasoning process. Even well-defined problems such as proving a premise using predicate logic usually requires an external aid (visualization, such as hand drawn sketches) due to the limits of working memory. When adding the complexity of uncertain data or actions, one would expect Bayesian reasoning or some form of satisficing [37] would also benefit from visualization support.

2 Cognition, Uncertainty, and Visualization

In this section we have gathered together the central components of several discussions of reasoning and cognition and discuss them in light of uncertainty visualization. For our discussion we define reasoning very loosely and consider how *knowledge constructs, heuristics and biases*, and *temporal constraints* impact reasoning and discuss the potential for uncertainty visualization. We close this section by delineating types of reasoning uncertainty.

2.1 Knowledge Constructs

Thomas and Cook describe three higher order knowledge constructs: *arguments*, *causality*, and *models of estimation* [38]. Arguments are "logical inferences linking evidence and other reasoning artifacts into defensible judgments of greater knowledge value" [38]. Causality is an understanding of the action-reaction relationship. Models of estimation provide for the use of powerful abstractions in interpreting the data and providing estimates of solutions. We will discuss these three constructs in terms of their relationship to visualization.

Arguments and Visualization: Visualizing an argument formalizes it for introspection and collaboration. *Arguments* are one of the reasoning steps of problem solving, and the presence of uncertainty is what creates an ill-structured problem. Paraphrasing van Bruggen [44], an ill-structured problem has: an ambiguous and incomplete problem specification, a lack of clear stopping criteria, multiple information sets and representations with no clear indication of relevance, and incomplete knowledge of operations or solution path. Solving ill-structured problems often requires non-linear progression, partial solutions, and representational refinement [44], for which extra cognitive support will be beneficial.

Complex problems and arguments are also more likely to require external assessment or benefit from collaborative refinement. Without a representation of the current uncertainty in different analytic strategies resource management is difficult. By visualizing which areas have uncertainty and are making the problem ill-structured, users may more easily monitor progress and decide to divert resources to reduce the most significant uncertainty.

Causality and Visualization: More causality may be perceived than your visualization intends. *Causality* is often perceptually linked to temporality. Michotte [27] found that with the movement of patches of light, the relative timing of motion could create the strong perception of causal relationships. Likewise with less abstract occurrences people will often assume causality based on temporal relationships. Due to this perception, animation may enhance the communication of causality and should be used carefully if causality is not to be inferred.

Reasoning about causality under uncertainty may also utilize heuristics that are prone to error and bias. Tversky and Kahneman found that if one event (C) was naturally viewed as a cause of another (E), then even if they had equal probabilities their participants would be biased in favor of causal inferences over diagnostic inferences (i.e. believe $P(E|C) > P(C|E)$ even though $P(C) = P(E) \Rightarrow P(E|C) = P(C|E)$) [43]. Furthermore they found that people were biased toward weighing evidence for causal impact in the future versus diagnostic reasoning about the past. Kahneman and Miller hypothesize that alternatives to the effect are more available to the mind than alternatives to the cause [20], and so leading the user to consider more causes could reduce this bias. When there is an effect with an uncertain cause this might be visually induced by showing additional dangling links back from the effect.

Models of Estimation and Visualization: A visualization is a model which adds its own uncertainty. Applying any *models of estimation* requires a jump from the concrete to the abstract. This may likely increase uncertainty by requiring assumptions, introducing translation errors, or adding in the stochastic variability of a model. Any uncertainty this abstraction process introduces should be visualized to keep under consideration when interpreting the model results. The propagation of errors is also important to consider when using models as the input uncertainty will often be increased, potentially by something as simple as the addition of variables.

2.2 Reasoning Heuristics and Biases

An exemplar of reasoning heuristics and biases may be found from user prediction calibration. Griffin and Tversky [14] state in the assessment of evidence that overconfidence often resulted when the evidence strength (extremeness) was high and weight (predictive validity) low. For example, there may be a bias toward rejecting the null hypothesis when the means are very different even when there are large standard deviations. Under-confidence often resulted when the strength of evidence was low but the weight high (i.e. a moderate impression based on extensive data) [14]. An example may be the failure to confidently communicate the need to address climate change. One might help address these biases by showing the merged strength-weight visually.

For information systems Turpin and Plooy [42] review the decision-making heuristics and biases: *representativeness*, *availability*, *adjustment and anchoring*, *problem or decision framing*, and *automation*. Their literature review found real world examples providing some evidence for each of these types. They touch on the role of how information systems may elicit biases as well as aid in debiasing, and also suggest innovative representations and decision process support may reduce bias. They conclude by calling for more field research to better quantify the effects of these biases in relation to other problems such as data quality. The debate continues as to how frequently these heuristics and biases occur outside the laboratory [14], but they are certainly relevant to design when considering user constraints.

We provide a subset of these heuristics and biases, most from the foundational collections on the subject [14, 19], and others as cited. We have organized these into three categories based on visualization strategies that may potentially mitigate them. The categories are: *associations*, *ignorance of rules*, and *application of rules*. Mental associations have a conscious and subconscious influence on reasoning. Rules encompass the simple cognitive constructs for inferring information (e.g. a theorem) all the way up to methods for forming arguments. We will describe each in turn along with visualization strategies that may be beneficial.

Associations and Visualization: A visualization is impacted both positively and negatively by associations it triggers. *Associations* may bias the reasoning process in various ways. One major type is the *affect* or reliance on the associated "good" or "bad" response to a stimulus [36], which Norman has recently discussed in relation to its impact on design [29]. *Availability* of instances in the mind for estimating probability form another type: retrievability of instances is important when the size of a set is estimated by availability of instances [19]; if instances are not available, the ease of imagining them will act as availability [19]; *illusory correlation* when the frequency of co-occurrence may be estimated based on strength of association [19], and a *recency bias* results in the overweighting of recent events [41].

Visualizations can provide access to huge amounts of data and thereby reduce the biases of one's own limited associations. By providing high density visual queries that can be quickly modified one may be influenced less by expectations and let the data provide its own associations. Using a computer to analyze the data and make a visualization based on a fixed set of rules inherently reduces these types of biases.

Ignorance of Rules and Visualization: If a visualization does not convey to the viewer the meanings of its representation(s) the user may fail to form the correct interpretations and arguments. *Ignorance of rules* (often statistical) can also lead to poor reasoning and the *representativeness* heuristics [19]. These include: insensitivity to prior probabilities (e.g. Bayes' rule not applied); small sample expected to be as representative of population as a larger sample; failure to consider regression to the mean; misconceptions of chance (e.g. representativeness of a random process as a whole expected in short sequences); irrelevant data may be used as a predictor; and the *illusion of validity* where redundancy in inputs reduces accuracy but increases confidence.

While visual representations themselves may not promote statistical ignorance, they rarely go the one step further to aid statistical interpretation. Even the basic box and whisker plots tailored for hypothesis testing are in rare use. Visualizations have the potential to alleviate these issues by integrating realizations of other potential outcomes and integrating statistical information with drill downs.

Application of Rules and Visualization: Direct visual support for reasoning may assist with the application of rules. Any given strategy or *application of rules* may provide an inferior result, as is possible with the *adjustment and anchoring* set of heuristics. A selection of these are: insufficient adjustment when an initial estimate is weighted too strongly during subsequent revisions (and may be based on irrelevant data) [6, 19]; adjustment from single event probability produces overestimate of conjunctions and underestimate of disjunctions [19]; a tendency to be overconfident in decisions or estimates [8, 17]; *automation* or technology dependency leading to errors of omission and commission [4, 33, 42]; and overestimated confidence in the ability of a priori predicting past events (i.e. hindsight is 20:20) [8]. Similar to the application of rules category, the use of heuristics in software programs dealing with complex problems is also common-place and they need to be understood by the user to avoid introducing interpretation errors.

Many visualizations do not include visual explanations of the mapping of data, algorithms and uncertainty, but this is crucial for avoiding these types of biases. This class of reasoning shortfalls will be greatly aided by a visualization of the reasoning process itself. Any reasoning visualization may provide grounds for review, analysis, and collaboration; thereby opening up what might be a hidden and flawed decision process. Just as MacEachren noted for visualization errors [23], we can group reasoning errors into Type I, reaching conclusions that are not supported, and Type II, failure to reach conclusions that are supported.

When these biases or heuristics are likely to manifest in a user's reasoning, we can make attempts to debias or provide alternative heuristics (or algorithms). Fischhoff reviewed some of these attempts for *overconfidence* and *hindsight* bias, and found only partial success [8]. The review was organized around three categories: faulty tasks (attempts such as raise stakes, clarify instructions, ...), faulty judges (warn of problem, train extensively, ...), and mismatch between judge and task (make knowledge explicit, search for discrepant information, ...). There is greater potential for cognitive support with visualization systems as the offloaded tasks may use algorithms that do not suffer from these issues, and may dynamically attempt debiasing, but the danger of the *automation* heuristic also needs to be considered.

For many problems, heuristics can provide fast and accurate enough approximations for the task at hand. Gigerenzer et al. compared some satisficing methods (fast and frugal heuristics) against some "optimal" algorithms (e.g. Bayesian networks) representing unbounded rationality [13]. With complete knowledge and across 20 real-world scenarios some simple heuristic strategies (*minimalist* and *take the best*) were found to perform comparably to the algorithms [13]. If specific heuristics are accepted for use as standard operating procedures we may look at providing visualization support to enhance them further or to reveal when they can not be trusted.

Arnott [2] has provided a taxonomy of biases and proposed a general decision support design methodology utilizing these theories. Watkins [45] also reviewed many cognitive heuristics and biases and believed that they are worth considering for uncertainty visualization. While we agree that they are an important design consideration, especially when providing a decision support tool, we should be wary of their potential impact on the analysis and discovery process, and so should perform research on their role in visualization in general.

If we assume two cognitive models of reasoning: associative and rule-based [34], then some issues may be more related to one system. The associative system may be directly affected by Gestalt and a visualizations' ability to convey the required uncertainty for immediate processing and consideration. There may be the flexibility in rule-based reasoning to use methods that avoid the drawbacks of potential heuristics and biases.

With the more general rule-based reasoning we have the potential to learn and utilize problem solving "programs" that have been validated to some extent, but perhaps at the cost of sacrificing creativity and imagination (associative). A graphical or visualization system should try to provide assistance to both systems but avoid leading users to the *automation* heuristic.

2.3 Uncertainty and Reasoning Time-Frames

One fundamental constraint on the reasoning process is time. Time stress and other situational attributes can distort our perception leading directly to biases [25]. This distortion adds uncertainty, confounding the uncertainty that may have led to the time stress. Strategies will vary based on the amount of time resources available. At a high level it may be similar to game strategies in which search space (e.g. minimax tree) is pruned based on the time allowed. Cognitive models such as Cohen et al.'s Metarecognition [3] have been proposed for time limited decision-making. In these cognitive models visualizations may illustrate uncertainty of the data, but visual support of meta-reasoning may be the area where they can contribute the most.

Watkins created and analyzed an uncertainty glyph to depict three types of uncertainty and their sum in a decision support system [45]. One interesting finding was that all analyst participants agreed somewhat or stronger that in general "uncertainty visualization would degrade the ability of most analysts and decision-makers to respond to or 'interpret a scenario' in a timely manner". The majority thought, however, it would not overload decision-makers in less time-constrained situations, and were not comfortable adding data with associated uncertainty to a knowledge base without an uncertainty visualization.

Delay is also Lipshitz and Strauss' first conceptual proposition: uncertainty in the context of action is a sense of doubt that blocks or delays action [22]. They cite Dewey's statement that problem solving is triggered by a sense of doubt that stops routine action [5], but dropped the important aspect that uncertainty triggers problem solving that necessitates neither blocking or much delay. One should note that changes in uncertainty may trigger action, and that delay can be the optimal "action". An example of this may be the space shuttle Challenger disaster, for which the criticality of data quality has been discussed by Fisher and Kingma [9]. Tufte has also analyzed the space shuttle Challenger and Columbia disasters from a visualization point of view [40, 41], and one may argue the most significant uncertainty was not in the data but in the reasoning.

2.4 Types of Reasoning Uncertainty

There are many taxonomies of uncertainty to be found in different domains. Lipshitz and Strauss found in a study of military decision makers that they distinguished between *inadequate understanding*, *incomplete information*, and *undifferentiated alternatives* [22]. Different strategies were employed based on these types of uncertainty. Thus task considerations may dictate the types of uncertainty that are significant. Hence we would suggest a user and task centered approach be taken with uncertainty issues.

Thomson et al. have constructed a typology for visualizing uncertainty in geospatially referenced data [39]. They considered Pang et al.'s low-level classification [31]

Table 1. Extending Thomson et al.'s typology of uncertainty [39] to reasoning

Uncertainty Category	Reasoning Definition
Currency/Timing	temporal gaps between assumptions and reasoning steps
Credibility	heuristic accuracy & bias of analyst
Lineage	conduit of assumptions, reasoning, revision, and presentation
Subjectivity	amount of private knowledge or heuristics utilized
Accuracy/Error	difference between heuristic & algorithm (e.g. Bayesian)
Precision	variability of heuristics and strategies
Consistency	extent to which heuristic assessments agree
Interrelatedness	heuristic & analyst independence
Completeness	extent to which knowledge is complete

and Gershon's high-level taxonomy [10] and provide a typology to be instantiated based on task, giving examples from intelligence analysis. They advise a hierarchical approach for instantiating this typology across multiple domains or tasks. We extend the definitions of their typology to the reasoning process in Table 1, demonstrating how their typology is useful at the level of reasoning as well. Considering how this typology applies to reasoning can extend its intended purpose of guiding the development of visual representations for uncertainties.

Dynamic data is the main reason why *currency / timing* is tied to uncertainty. Thereby the error between prior observations and the current state generally increases over time. In some cases the duration of observation allows for a trade-off between uncertainties in attributes (e.g. Heisenberg's Uncertainty Principle). Temporal constraints are a major reason why completeness of knowledge can not be fully attained. Past decisions, assumptions, and arguments often form the a priori knowledge base. Visualizing the impact time constraints had on this prior information can greatly influence its usage. Opacity is often used for temporal encoding where data fades out over time as it becomes dated.

For *credibility*, *lineage*, and *subjectivity*, all levels from data gatherers to decision-makers should be considered in the reasoning instantiation of the framework. When the decision processes span multiple levels of management or government these aspects are especially important to consider. One example was when the director of the NASA Goddard Institute for Space Science (a climatologist) had the qualitative certainty and causality in his report on climate change strongly diluted by the U.S. White House Council on Environmental Quality [18] (See Figure 1). In this case the reader would

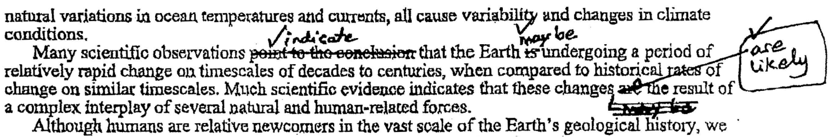
natural variations in ocean temperatures and currents, all cause variability and changes in climate conditions.
Many scientific observations ~~point to the conclusion~~ indicate that the Earth ~~is~~ may be undergoing a period of relatively rapid change on timescales of decades to centuries, when compared to historical ~~rates~~ of change on similar timescales. Much scientific evidence indicates that these changes ~~are~~ are likely the result of a complex interplay of several natural and human-related forces.
Although humans are relative newcomers in the vast scale of the Earth's geological history, we

Fig. 1. Draft copy showing hand editing of scientific confidence. Changing of definite wording "is" to speculative "may be" among the 3 revisions in the paragraph shown.

assume the credibility and subjectivity of the scientist authors, with no way of knowing that a non-scientist had revised the scientific judgment. The final decision makers (U.S. Congress) would benefit from visualizing the uncertainty in credibility, lineage, and subjectivity of reasoning. Ignorance of any of these types of uncertainties may directly impact the ability of decision-makers to make good decisions, and therefore guidelines mandating the visualization of such uncertainty should be considered.

To visualize *accuracy / error* one must consider the effects of potential heuristics and biases, as discussed in Section 2.2. The visualization of reasoning accuracy will likely not be possible unless tools are used for the reasoning in which heuristics and strategies are made explicit. Error itself is not usually known a priori and so would be visualized as a post mortem task. Visualizing *consistency* and *precision* in heuristics or strategies is important for decision confidence. Precision of a single heuristic may be difficult to assess as cognitive strategies themselves may not be precisely defined. The same visualization of reasoning heuristics that provides an estimate of precision, could likely reveal inter-heuristic consistency.

Visualizing *interrelatedness* may allow results from analysts working in teams to be collectively considered. It may be useful for the interrelatedness of many data points to be visualized using preattentively processed visual cues. For example, connectedness (from Gestalt theory) may allow one to consider linked reasoning artifacts holistically, potentially reducing the risk of over weighting redundant findings. As *completeness* includes comprehension (ignorance) some aspects are dependent on all the other types of uncertainty being visualized. Similar to error, in advance it will usually only be estimated. A good example of the cost of unvisualized uncertainty is the wasted resources in duplicated research caused by the lack of publishing on scientific failures.

3 Visual Support for Uncertainty in Reasoning

Numerous methods have been proposed integrating uncertainty into data for visualization [31], and some have been evaluated for specific tasks [15, 26]. However there has been less research into how well these provide decision support. How best to provide reasoning and meta-reasoning support that incorporates uncertainty is an open question.

3.1 Problem Solving

Newell and Simon [28] provided a high level organization of a problem solver for a generic information processing system. We have used this organization to highlight aspects of uncertainty in the process of reasoning in general as shown in Figure 2. While uncertainty likely exists in some form in all aspects of the organization, the method selection process is important (shown in bold red in the figure) in that it is affected by both data and problem representational uncertainties as well as potential ambiguity in the relationship of methods to goals. Our looser interpretation of their general problem solver allows the method selection to require problem solving (a recursive invocation) and methods would include all heuristics and strategies (top-down, bottom-up, etc.). Visual aids for the method selection process would likely be beneficial as this complex

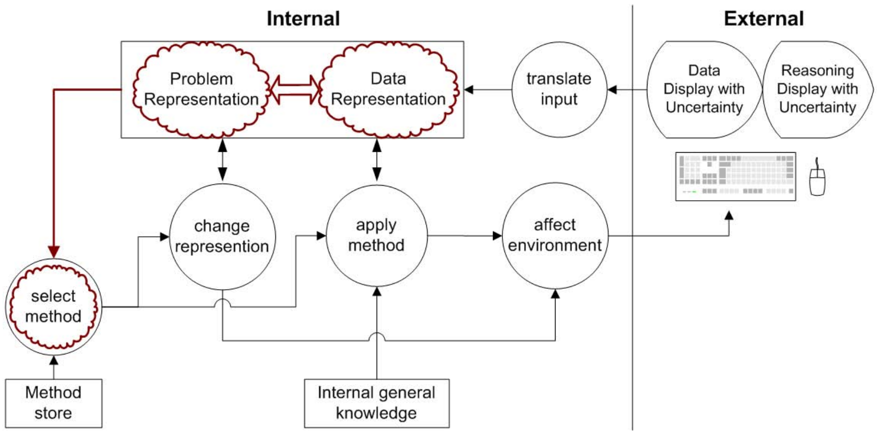

Fig. 2. Organization of problem solving with uncertainty. Revision of Newell and Simon's general organization of a problem solver [28] highlighting where uncertainties likely exist.

"phase" requires the consideration of sub-goals and the actions related to them, while still considering their context in the overall problem. There is the potential for change in both internal and external representations of the problem and of the data [32].

While traditional graphics and HCI research has focused on the external part, more considerations need to be made for the internal part. The visualization system should also produce the artifacts that may assist introspection on the cognitive process. As these processes are tightly coupled, the ability to monitor and aid the reasoning process will add additional requirements to the visualization. Visualizations may need to be modified in order to allow parallel support both data and reasoning process visualization, which might be useful to think of as a larger task context. This support could tie both direct visual artifacts in with meta-data artifacts recording a history of exploration and the discovery processes that were used.

3.2 Analytic Processes

Amar and Stasko's [1] precepts for design and evaluation of information visualizations provide a set of principles on how visualizations can better support the analytic process. The three main weaknesses of current systems were stated as: limited affordances, predetermined representations, and the decline of determinism in decision-making. These weaknesses or gaps in the analytic process were to be addressed by the Rationale Precepts: expose uncertainty, concretize relationships, and expose cause and effect; as well as the Worldview Precepts.

All the above precepts deal with complex issues and appear to pertain to reasoning as a whole, thus providing guidelines for reasoning visualizations and support as well as information visualizations. Bridging the analytic gaps and extending ideas in current information visualization systems to reasoning visualizations will likely require the linking of these types of tools, or developing additional integrated cognitive

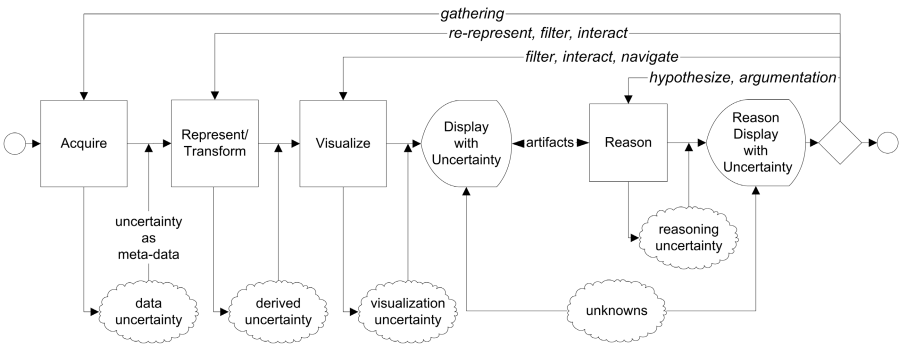

Fig. 3. Reasoning extensions to Pang et al.'s data visualization pipeline with uncertainty [31]

support, while ensuring consistent cognitive styles to avoid a huge context switch. We propose for complex problem solving that reasoning support with uncertainty should be built into the visualization pipeline. This integration could be as light-weight as virtual sticky notes for one's ideas that are colour coded based on certainty. Figure 3 shows our extension to Pang et al.'s visualization pipeline [31] to include reasoning support with uncertainty. This integration provides benefits by simplifying the backtracking (revaluation and searching) phases of the sense-making loop. Thus uncertainty in one case or hypothesis would be easily reviewable by another user. Visualizations for uncertainty in both the data and reasoning pipelines could use consistent representations and/or metaphors for the same types of uncertainty to reduce cognitive load. The complexity and constant evolution of visualization tools promotes specialized systems to handle specific sub-tasks. Therefore this pipeline may cross multiple visualization systems and so providing visual consistency will add design constraints. Independent applications will require support for restoration of data, operations, and viewing parameters.

The link between visualization and reasoning pipelines should be bidirectional to allow for feedback from the reasoning process for potential integration into the visualization tools. This could be as simple as the goal or larger context in the reasoning process that may be provided with text or graphically. It could also communicate a strategy of exploration which the data visualization tool could then dynamically facilitate. In a collaborative setting this might be valuable to provide awareness of strategy changes when one is focused on a small scale task.While this concept has been implemented to a limited extent (e.g. BAE Systems' POLESTAR), most visualizations provide little or no direct reasoning support or are not linked to one that does.

Using a participatory design approach we have developed a prototype system for evidence-based medicine diagnostic support that provides this parallel (reasoning/data) visualization approach. The parallel visualizations are in the form of multiple views, two of which are shown in Figure 4. It utilizes a decision tree as a GUI with integrated reasoning and data uncertainty. The reasoning visualization can be viewed along with other data and its uncertainty in multiple other views. This design provides transparency of the uncertainty in the Bayesian reasoning that may assist in this difficult task.

3.3 Representations

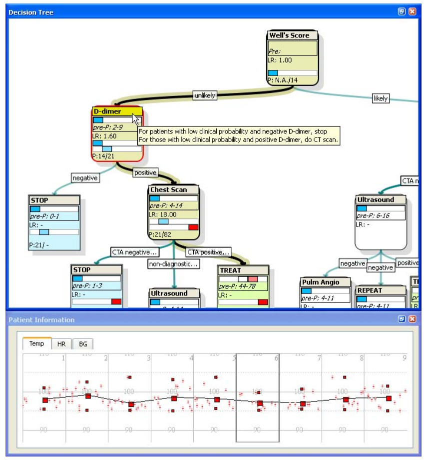

Fig. 4. Integrated data and reasoning visualizations for evidence-based medicine. Reasoning view (upper) and test data view (lower).

Visual representations of data uncertainty allow for the amplification of cognition (e.g. parallel processing, increased working memory), and when time frames allow introspection, we suggest similar benefits will acrue from visual representations of reasoning uncertainty. Kirschenbaum and Arruda [21] found an ellipse was more accurate than verbal quantification in communicating uncertainties in a spatial problem. With non-spatial uncertainty, Watkins [45] found his glyph (which distinguished: unreliability, ignorance, and analytical input) was rated well by analysts but with some qualifications. Finger and Bisantz [7] compared degraded icons (levels of blur) against the degraded icons with text probability, and full detail icons with text probability, for the task of hostile/friendly target classification with evolving target probabilities. They found for their task that the addition of text did not provide a statistical advantage, and the degraded icons without text were in general better. As the number of uncertainty levels that need to be read are task specific, this should drive the representational requirements [46].

In the field of Geographic Information Systems (GIS), which has been at the forefront of uncertainty visualization, frameworks have been put forth that recommend visual representations of the uncertainty based on the data and uncertainty types [24]. Even though their spatial considerations and constraints limit the general problem, there are still no accepted standards. For general visualization including reasoning, user and task considerations will drive the best way to create uncertainty visualizations. Some representations may be more natural for expressing uncertainty as meta-data such as opacity, fuzziness, and colour saturation [23, 24], but when distinguishing different types of uncertainty, or for integration with multivariate data, these options may not be optimal.

Representations will afford a set of methods and actions that allow one to proceed to a solution. Gigerenzer suggested that natural frequency representations may have inherent cognitive support in the brain as posing conditional probability questions in the form of natural frequencies helped more people solve the problems [11]. More recent arguments and research have indicated that it is more likely that the computational complexity, due to the transparency of the information structures, that is key to a person's ability to find the correct Bayesian solution [35]. This does not contradict the finding that natural frequencies may be a more efficient representation for promoting Bayesian reasoning [12].

Cognitive support may be given by providing uncertainty or ambiguity in representations to provide clues to potential representational transformations or new representations. User interactivity in selecting the representation, while often difficult to provide in a visualization, implicitly communicates to the viewer that there is uncertainty in the optimal representation(s). At a meta level, visualizing your own reasoning process can also reveal a bias or suggest a new strategy. Representations of the reasoning process which illustrate uncertainty will help one perform this introspection.

4 Conclusion

We have described how the cognitive issues of reasoning under uncertainty relate to various aspects of visualization and provided some guidance as to how one may address these issues. As a result of the complexity and uncertainty in the reasoning process we see potential in the integration of data and reasoning visualizations. This integration of the discovery process and sense-making loops, would provide a direct visualization of the entire analytic process, and might facilitate the exposure of analytic gaps. Without this type of cognitive support monitoring the effect of uncertainty in the data and the analytic process will be extremely difficult.

When we create new support there is a potential hazard if the external visualization does not diminish cognitive load, it may in fact raise it, thereby preventing the formation of schemata [44]. Therefore when the performance of sub-tasks require complete attention this level of integration may be more useful as an analytic context or an audit trail. Multiple views or the easy movement of reasoning artifacts between the two visualization systems could maintain this context without adding cognitive load. The visualization we briefly introduced (medical diagnostic support) illustrated that for some problem areas a reasoning component can exist as a natural and central component of the interface. As uncertainty abounds in the reasoning process we expect that visualization of the uncertainty will enhance problem-solving and decision-making.

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