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Abstract

In this paper we propose several human-machine strategies for decision support, the central thesis being relying on purely human ability or blindly on decision support mechanisms results in ineffective and inefficient decisions in most situations. The need for strategies that effectively and efficiently combine human decision ability with those of computer systems is of pivotal concern. A suggested research program is outlined.

Keywords Decision, decision support, decision support systems, management models, entropy, human-computer interaction

Introduction

Understanding weaknesses of humans' and decision support systems (DSS') in decision-making serves the purposes of reducing the impacts of these weaknesses. Human and DSS' weaknesses can be addressed in isolation, however, a better solution is to combine human decision makers with a DSS so that they can compensate each other's weaknesses with their distinct strengths.

This paper examines common human decision making errors and weaknesses in the design of traditional decision support systems. Building on these limitations, we then propose how to incorporate human-machine strategies for effective and efficient decision support.

Shortcomings in Human Decisions

Over the last few decades, psychologists have discovered a number of systematic biases we are subject to as humans (George et al. 2000). Included below is an examination of a few common biases that may be encountered in the decision making process, specifically those that a DSS would likely not be subjected to.

- **Anchoring Trap:** gives disproportionate weight to the first information received. Initial impressions, estimates, or data anchor subsequent thoughts and judgments.
- **Sunk-Cost Trap:** inclines the decision maker to perpetuate the mistakes of the past in an attempt to justify past choices.
- **Confirming-Evidence Trap:** leads the decision maker to seek out information supporting an existing predilection and to discount opposing information.
- **Overconfidence Trap:** occurs when the decision maker overestimates the accuracy of their own forecasts, even though they are subjective and error prone.

- **Prudence Trap**: occurs when the decision maker is overcautious when making estimates about uncertain events; this is a natural response to high stakes.

- **Recallability Trap**: leads the decision maker to give undue weight to recent, dramatic events.

Typically decision makers cannot eradicate the distortions noted above. The best option is to build tests and disciplines into the decision making process that can uncover errors in thinking before they become errors in judgment (Hammond et al. 1998). These tests and disciplines can be built into a DSS as warnings to the user, and as an explanation as to why a DSS solution may differ greatly from the user's identified solution.

Shortcomings in Decision Support System Design

Much has been written about how decision support systems should be calibrated, but one component, *entropy*, is not accounted for. "Entropy in a signal is inversely proportional to compressibility: the greater the entropy, the smaller the factor by which the data can be compressed" (Shannon and Warren 1949). Entropy measures *uncertainty* in a system. Failure to acknowledge the effects of entropy on any system is a mistake, which may degrade the value of the information provided because it may serve as the basis for decisions grounded in incomplete information.

Traditional DSS approaches focus solely on the summarization, compression, and the reduction of data. Below we examine some of the shortcomings of DSS in the context of entropy with respect to these three dimensions.

Summarization

A component of the DSS process involves the ability to summarize, reduce and compress original data into meaningful chunks (Desouza 2002; Marakas 1998). Many DSS are designed on the presumption that executives want a snapshot of the big picture. This approach increases the overall efficiency required in the decision process, as the executive is not overloaded with details. But, it does little toward improving the effectiveness of the decision or decision-making process since hiding details can lead to poor decisions as the fine-grained signals are missed.

Including a concern for entropy in the design of a DSS model may provide the solution in this instance. Summarization should occur *only* for information with low value or uncertainty (entropy). Hiding important signals such as outliers through summarization will prevent a manager from attacking a problem early on.

Ranking Mechanisms

A common facility in most DSS processes involves a search and retrieval engine to help practitioners filter through large databases in order to retrieve useful information, similar to Internet search engines like Google. Most ranking mechanisms are based on criterion such as relevance and popularity. These mechanisms help in increasing the overall efficiency of a decision process by enabling for quick searches; which comes at the cost of effectiveness of the process. Moreover, a *popular* document is not the same as a *precise* document.

An understanding of the concept of entropy may provide some remedial measures in this instance. First, a change in how ranking algorithms are devised is in order. The relevance portion of the mechanism is still needed regarding *adequacy*. *Adequacy* addresses the notion that the mechanism is capable of handling the task at hand and nothing more. Instead of ranking documents solely based on one-dimensional characteristics, documents must be *indexed* in anticipation of entropy. This would call for ranking documents based on elements of the requestor's certainty as they seek for new information on which they are uncertain.

Visualization

A picture is equal to a thousand words and DSS models seek to take advantage of this notion with pictorial representations in the forms of graphs, charts, etc (Tufte 1982). Pictures are effective at showing the "big picture" but are sometimes used to deliberately hide the details.

Visualizations are potentially problematic in that they are a static representation of a dynamic environment. In order to understand their meaning in relation to entropy affects, they should be dissected and subjected to empirical analysis. We would thus urge designers to look at three-dimensional live models. Models such as these are very similar to the traditional OLAP cube found in data warehousing applications (Desouza 2002; Gray and Watson 1998), with the added dimensionality of an *event tracer*. Thus, besides the traditional capabilities of drill-down, the event-tracer functionality allows a manager to see how a certain signal can propagate and traverse within the model and cause cascading effects.

Human-Machine Strategies

Both humans and machines are completely error prone however; they both offer distinct strengths. The distinct strength of a DSS includes not being subject to physical and emotional effects and being capable of complex computations. The distinct strength of human decision makers includes creativity, flexibility, domain knowledge (Bruggen et al. 2001), and qualitative evaluation (Blattberg and Hoch 1990).

Combination of human experts' judgment/intuition with DSS has been repeatedly shown to be superior to either human experts or DSS alone. For example, Ganzach et al. (2000) showed that a mathematical model's prediction accuracy can be significantly increased by adding a human experts' judgment as another predicting variable into the mathematical model. In another study with very different settings, Blattberg and Hoch (1990) showed that a combination of human experts' and a regression model's predictions is more accurate than either human experts' or the regression models' predictions alone. Hoch and Schkade (1996) found that the superiority of human experts and mathematical model combination is moderated by degree of difficulty of the problem. That is, the combination superiority is more significant when problems are more difficult.

Contextualization of Human-Machine Integration Strategies

Integrating human decision makers with a DSS itself is not a new idea. However, most research on this topic focuses on a specific decision making context, such as clinical diagnosis, or business prediction (Einhorn 1972; Little 1970; Blattberg and Hoch 1990). Although different strategies of integrating human decision makers and DSS (human-machine strategies) were proposed in these studies, the question of when and where these strategies should be used is not answered. In other words, there is a lack of contextualization of human-machine integration strategies in current literature. The section that follows aims to fill this blank through classification and context analysis of human-machine integration strategies.

According to direction of knowledge flow, human-machine integration strategies can be classified into two major categories: integrating human experts' knowledge into DSS, and integrating DSS knowledge into human decision makers' decisions. The first category of strategies is more applicable to DSS design and implementation. And the second category of strategies is more applicable to final decision making by human decision makers. Both categories should be used in intermediary decision-making where human decision makers and DSS should engage in frequent knowledge exchange.

According to knowledge type, strategies of integrating human experts' knowledge into DSS can be further classified into two categories: informational and procedural. In informational strategies, human experts' thinking outcomes, such as judgment, are integrated into DSS. In procedural strategies, human experts' thinking strategies, such as pattern matching, are integrated into DSS. An example of informational strategies is involvement of domain experts in the practice of data mining (Hirji 2001). One of the major roles that domain experts play is to select data that will be mined, and in so doing, their knowledge is transformed into data selection criteria, which are reflected in the data that is selected. While the data that will be mined itself is not domain experts' thinking outcome, it captures their thinking outcomes.

Informational strategies have been shown to be effective in increasing decision-making performance (Einhorn 1972). Einhorn studied an informational strategy called "expert measurement + mechanical combination". The idea of this strategy is to decompose a highly qualitative problem into multiple underlying dimensions, which are still qualitative. Human experts then evaluate these dimensions and their evaluations are fed into a mathematical model that assigns different weights to each dimension so as to produce a final score. Einhorn's results showed that "expert measurement + mechanical combination" is indeed superior to experts alone.

Although modern computers carry enormous computation power, they are often incompetent or inefficient in the face of complex problems, such as voice and image recognition. Meanwhile, human beings have very limited computation ability but are very competent in certain complex problems. This implies that human beings employ very different thinking strategies than computers. The ideal would be to integrate human beings thinking strategies into a DSS. Decision calculus (Little 1970) represents an effort in such a direction. Decision calculus' idea is to extract domain experts' problem solving strategies and represent them by formulas, so that the formulas can replace domain experts to solve similar problems in the future. Besides the benefits of increased computation ability, formulas are more stable and consistent than practitioners. Unlike informational strategies that might be applied in both DSS design and DSS usage, procedural strategies are mainly applied in DSS design.

Integrating human experts' knowledge into a DSS is just one side of the human-machine integration. The other side is to integrate a DSS into human decision maker's decisions. As human decisions makers in most situations make the final decisions, integrating a DSS into human decision maker's decisions is more of a necessity than an enhancement. Strategies of integrating DSS into human decision maker's decisions include three types: compromising, total acceptance, and total rejection. Compromising applies to those problems that both DSS and human decision makers are capable of solving the problem independently. A compromise is then made between the two independent solutions with weights for each solution determined by the human based on decision contexts. For example, a human decision maker may assign more weight to his/her own solutions if a DSS has just been introduced and its effectiveness has not been well established.

Total acceptance strategies apply in situations where human decision makers are unable to reach their own conclusions due to reasons like strict time constraints or large amount of input information and occur when a human totally accepts the DSS' decision suggestions. However, human decision makers should still examine if the input data is valid and complete, if the DSS is functioning appropriately, and if the final decision makes sense. If they found any fault in any of these factors, they should totally reject DSS' suggestion. The errors should be corrected and the whole decision process should start over.

In summary, human-machine integration strategies can be categorized in terms of knowledge flow direction and knowledge type (see Figure 1).

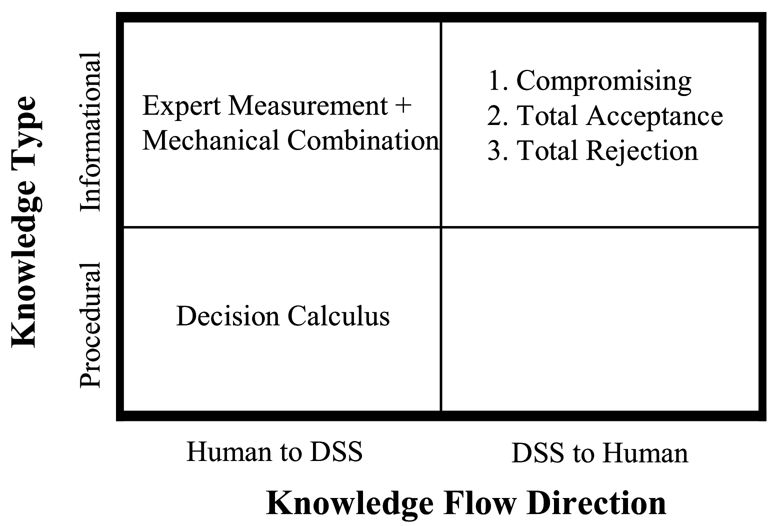

Figure 1. Categories of Human-Machine Interaction Strategies

Proposed Research Agenda

A survey can be conducted to collect data on practices of human-machine integration in the area of DSS. The survey will reveal the extent that human experts and DSS are integrated in practice. A main effect of human-machine integration is expected to be found in the data. In other words, it is expected that human-machine integration lead to better decisions than no integration. Decision quality can be measured through self-reporting, supervisor evaluation, and possible objective criteria. For example, one could compare the number and type of errors routinely made with and without human-machine integration. Effects of integration contextualization are also expected to be found in the data. As stated earlier, contextualization refers to the right selection and combination of integration strategies according to decision contexts. In general, use of a combination of multiple strategies is expected to be superior to use of a single strategy. Other effects, such as advantages of incorporating human expert's procedural knowledge into DSS rather than the opposite way (incorporating DSS' algorithms to human expert's decisions), are also expected to be found.

Conclusion

Because human experts and DSS have different shortcomings and strengths, they should be integrated so that they can compensate each other's shortcomings with strengths. Various strategies of integrating human experts and DSS have been proposed before. However, appropriate contextualization of these strategies will be as important as the strategies themselves. Knowledge can flow from human experts to a DSS or in the opposite direction depending on phase and other factors, such as experiences of human experts, in the integration. Also, information exchanged between human experts and a DSS can be informational or procedural. Appropriate selection of a combination of the integrating strategies is expected to lead to highest decision quality. This study is still at a conceptual stage. More considerations need to be taken in progressing to a full research study.

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