A SYNTHESIS OF DESCRIPTIVE AND PRESCRIPTIVE MODELS FOR DECISION MAKING

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INTRODUCTION

Experimental psychology has uncovered many instances where decision makers consistently and persistently violate the postulates of classical normative theories. This paper reviews the main results of this literature, its implications for prescriptive approaches and resulting demands on decision aiding tools. Finally, it reviews artificial intelligence techniques that may help in meeting some of these demands.

The focus of this paper is on individual decision makers in an organizational environment who do not and should not have the liberty of violating normative rules out of personal preference or as a consequence of cognitive limitations but who, usually unknowingly, still are subject to these influences. The goal of the paper is to lay a foundation for the development of flexible decision aids that will apply in such situations.

DESCRIPTIVE MODELS -- BEHAVIORAL DECISION MAKING

The descriptive study of human decision processes originated some 35 years ago when psychologists discovered that newly developed or formalized normative theories of judgment and choice (e.g., expected utility theory or Bayesian probability revision) did not describe human performance in these situations (Edwards, 1954). The field subsequently developed as a dialectic between behavioral and normative theories, a fact that has been deplored by some (Lopes, 1986), but accepted as fruitful and productive by most (March, 1978). There are many ways in which to classify the large body of empirical results [see reviews by Edwards, 1954, 1961; Rapoport & Wallsten, 1972; Slovic, Fischhoff, & Lichtenstein, 1977; Einhorn & Hogarth, 1981; Pitz & Sachs, 1984). For this paper we will discuss the following: (i) Cognitive limitations of human information processing; (ii) Restructuring of the problem representation by the decision maker; (iii) Use of heuristics or simplifying processing algorithms; and (iv) Instability of preference structures.

Cognitive Limitations of Human Information Processing

Several limitation on human information processing capacity can be distinguished (Hogarth, 1987). Because humans cannot process the multitude of incoming information,

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perception of information is selective. Processing usually occurs in a sequential manner or using simple procedures designed to reduce mental effort which may not always produce optimal results. The final limitation is on memory capacity. Unlike computers which can access all stored information in its original form, much of human memory works by a (less reliable) process of reconstruction. The realization of human information acquisition and processing costs and constraints underlies Simon's advocacy of "bounded rationality" (March, 1978; Simon, 1955). The next two phenomena to be reviewed, namely restructuring of the problem space and the use of heuristics, can be seen as procedures people develop over time and with experience to deal with their cognitive limitations. While adaptive and "boundedly rational" in the context of intuitive judgments, these processing styles can become so habitual or automatic that they will be applied even in important and formal decision situations where they can lead to serious biases.

Restructuring of Problem Representation

One of the basic assumptions of the classical economic model of rational choice (e.g., expected utility theory) is the requirement that choice alternatives be evaluated in terms of their effects on final assets. That is, the outcomes of choice alternatives should be combined with current assets and that alternative should be selected which provides the most desirable final asset position. Continuously updating current asset levels and integrating those with the outcomes of every new choice set requires a significant amount of cognitive effort. Therefore it is perhaps not surprising that people do not encode outcome information in this way, but instead in terms of gains or losses from the status quo or some other reference point. This is one of the central assumptions of Kahneman and Tversky's (1979) prospect theory which (in conjunction with a value function that is concave for gains, convex for losses, and steeper for losses than for gains) accounts for a wide variety of decision behavior that no version of expected utility theory can explain. The reference point used to encode a particular outcome as a gain or a loss can be manipulated by normatively irrelevant changes in context or wording, often leading to reversals of preference between two choice alternatives. These "framing effects" are striking and robust, occur in natural environments, and for experts as well as naive decision makers (McNeil, Pauker, Sox, & Tversky, 1982; Tversky & Kahneman, 1981).

Use of Heuristics

The use of heuristics (i.e., simplified processing rules that provide the correct answer most but not all of the time) has been found extensively in people's judgments of the likelihood of uncertain events (Tversky & Kahneman, 1974). In making such judgments, people over time and experience learn certain regularities in their environment. One such regularity is the fact that similarity is an index of class membership. Estimating the probability that object A belongs to class B on the basis of A's similarity to B is an application of the representative heuristic. Another regularity is the fact that more probable events occur more frequently and thus produce more memories. Estimating the probability of an event by the ease with which instances or occurrences can be brought to mind is an example of the availability heuristic. These heuristics often lead to biased probability judgments because representativeness and availability are diagnostic but not exclusive determinants of probability. Use of the representative heuristic, for example, can lead to the neglect of baserates or prior probabilities. Use of the availability heuristic can lead to overestimation of easily imagined events and to the perception of illusory correlations.

Another apparent regularity of our natural environment is some dependence between the desirability of events and their frequency. Truly wonderful and truly awful events happen rarely, whereas regularly occurring events seem ordinary almost by definition. Thus it is perhaps not surprising that people violate the independence assumption underlying expected utility theory. Violations of the axioms of expected utility theory are extensive and have been reviewed elsewhere (Schoemaker, 1982; Slovic & Tversky, 1974; Keller, 1985). A large and steadily growing literature of alternative models of choice under uncertainty attempts to describe such choice behavior (Weber & Camerer; 1987). Some of these models re-specify the expected utility problem as a multiattribute case with another evaluative dimension such as "regret" (Bell, 1982) or "risk" (Coombs, 1975) in addition to the outcomes' utility. Others weaken one or more of the (subjective) expected utility axioms (Kamarkar, 1978; Machina, 1982). Several of these models explicitly introduce dependencies between subjective probabilities and utilities. In Luce's (1989) rank-dependent subjective expected utility theory, the most general model to yield an interval-scaled utility function, the subjective probability weight functions depend on the rank-order of outcomes. In Becker and Sarin's (1987) lottery-dependent utility theory, the utility function of outcomes depends on the lottery, i.e., on the probability distribution with which the outcomes occur.

Instability of Preference Structures

Another assumption of the classical economic model of rational choice is that of procedure invariance, especially with respect to the elicitation of a decision maker's preference space. That is, his or her preference order for a set of outcomes or alternatives should not depend on the particular method by which it is assessed. However, empirical evidence is beginning to accumulate which suggests that people often do not have stable and well-defined preferences (Fischhoff, Slovic, & Lichtenstein, 1980; Grether & Plott, 1979; Shafer & Tversky, 1985). In such situations, judged or revealed preference is not a reflection of the "true" internal preference structure, but is actually constructed during the elicitation process. Different elicitation procedures highlight different aspects of decision alternatives and may suggest different heuristics or different decision frames, thus giving rise to inconsistent responses (Tversky, Sattath, & Slovic, 1988).

PRESCRIPTIVE MODELS AND TECHNIQUES -- DECISION AIDING

Prescriptive techniques (e.g., decision trees or linear programming) employed in decision aiding are based on normative theories of decision making. Psychological research has raised profound questions about the validity of these normative theories, hence calling "... the foundations of choice theory and decision analysis into question" (Tversky, Sattath, & Slovic, 1988). In particular, a decision aid is developed based on three normative assumptions: Given a decision problem, the decision maker should (a) be able to articulate his preference structure in order to evaluate relative merits of alternative solutions or choice alternatives, (b) be able to assess the probabilities of uncertain events using his or her problem domain knowledge, and (c) select the choice alternative that maximizes (subjective) expected utility. The bad news is that, as reviewed in the previous section, empirical studies of decision making have uncovered human heuristics, biases, and limitation that violate every one of these normative assumption.

Experimental results demonstrating systematic and persistent deviations of human behavior from normative standards have created much controversy (Schoemaker, 1982). From the prescriptive perspective the results are, at one extreme, sharply rejected as "... unwarranted generalizations from unrepresentative experiments" (Phillips, 1983, p. 537), and, at the other extreme, simply ignored (Keeney, 1982). For practioners developing decision aids, there seem to be two relevant points of view. One is that human cognitive limitations and biases, even if they exist outside of the laboratory, do not have any significant effect on the quality of decisions (Christensen-Szalanski, 1986). Little empirical evidence is provided for this position, and the instances cited seem to refer to circumstances with a flat criterion maximum.

In contrast, the other viewpoint acknowledges potential errors and inconsistencies in decision makers and advises the analyst to deal with them prudently (von Winterfeldt &

Edwards, 1986; Watson & Buede, 1987). For example, von Winterfeldt and Edwards view the decision maker's errors and inconsistencies as "... an asset rather than a liability [which] forces both the analyst and the client to think hard and provides them with an opportunity to gain insights into the decision problem" (1986, p. 385). Furthermore, they perceive some non-normative behavior as "creative stress" between the demands of a decision model and human intuition.

This viewpoint seems overly idealistic. It is neither fair nor realistic to expect an analyst to have the expertise and experience that Edwards and von Winterfeldt have in dealing with such conflicting situations without the support of some operational rules from a sound theory. Indeed, the authors of this paper have observed analysts in practice performing blatantly erroneous analyses in order to release the "creative stress" through oversimplistic approaches rather than "thinking hard." After all, practioners, despite their professional training and ethics, operate under their own limitations, biases, and utilities. It has been suggested that decision analysis is a clinical skill even under normal circumstances and one that should only be practiced after an internship with an expert (Brown, Kahr, & Peterson, 1974). Moreover, even if decision makers and analysts judiciously and prudently think hard, how can they detect the violation of, for example, the independence axiom of EU? If they do, how should they proceed? These, and a host of other questions necessitate the development of sound theoretical principles and methodological tools.

Implications of non-normative behavior

What then is the impact of non-normative behavior of a decision maker on decision aiding tools? A prescriptive approach to decision aiding goes through four principal stages: (i) problem formulation, (ii) solution, (iii) post-solution analysis (e.g., sensitivity analysis, reiteration, etc.), and (iv) implementation (i.e., actual execution of the solution). The formulation stage takes into consideration the nature of the problem and may lead to a representation of the problem in form of a decision tree or a linear program. Formulation can further be subdivided into the following three components: identifying the variables, options, parameters, and objectives; establishing the relationships between them (e.g., constraints in a linear program, consequences of options and their probabilities in a decision tree); and determining the preference (value) structure of the decision maker (i.e., the objective function, composed of a multiattribute utility function, to be maximized). Potentially, all of these steps in the prescriptive procedure can be affected by non-normative behavior. Elicitation of probabilities and utility assessment, for example, can be affected by certainty and framing effects (among others). The certainty effect, in turn, violates the independence principle and hence the solution procedure of folding back the decision tree. This suggests two, complementary, approaches to solving the problem: the first one is to change the non-normative behavior and the second to modify the decision tools.

Rectifying non-normative behavior

The key factors in rectifying any non-normative behavior are (a) to anticipate the occurrence of such behavior, (b) to detect it, and (c) to make it explicit to the decision maker and others concerned. In order to appreciate the need for such procedures, one should recognize that an individual operating within an organizational setting cannot knowingly violate rules that are normative from the organizational perspective. For example (adapted from Tversky & Kahneman, 1981), a public health official may choose an immunization program that guarantees to save a particular number of lives in a population at risk over another program that offers some less than certain chance at saving an even larger number of lives in this population when the effects of the two immunization programs are presented in terms of lives saved, but may reverse his or her preference when the identical programs are described in terms of lives lost. From a public policy perspective, such inconsistency is unacceptable, and the only criterion to decide between the two immunization programs (all other things being equal) probably should be the expected number of lifes saved (i.e., the final asset position) which is identical under the two formulations. In their personal choices, decision makers may or may not want to represent alternatives in terms of their final asset position. However, in dealing with an organization's assets they should not have this latitude. In such situations, decision makers need to be reminded and encouraged to use a final results perspective. (Machiavellian decision analysts, aware of the power and mechanisms of "framing effects," can of course also employ decision frames in such a way that the public official or employee will make decisions in line with the policies of his or her organization.)

Cases where a decision maker insists on violating a normative principle knowingly raise the question of whether some important factor has been overlooked in the formulation of the problem. For example, a quality control engineer may find a particular part out of tolerance after the machining operation. The part may not necessarily be defective, but its defectiveness will be revealed only in the actual assembly process. Should the engineer accept the part and send it to the assembly line, taking the risk of an expensive revelation of the defect should one exist, or should she scrap the part? The normative answer would, of course, depend on the probability that a part registering out of tolerance is actually defective as well as on the cost of revealing the defect on the assembly line. However, the quality control engineer will most likely insist on scrapping the part even in situations where this decision has smaller expected utility than the other alternative. Situations where a retained part turns out to be defective are not only costly, but also constitute an identifiable and visible error on her part. Regret theory or some other multi-attribute representation that incorporates the cost of making a wrong decision or accountability could perhaps explain the decision of the quality control engineer. However, the goal may not be to predict or justify her decision by some formal model, but to guide the decisions towards some organizationally acceptable standards. Hence, a decision tool should, in addition to traditionally desired qualities, be able to remove any contextual biasing effects or to make them explicitly known to all concerned if the decision maker insists on his or her non-normative behavior. The latter case may, in fact, reveal a factor not considered in the original problem formulation which is of sufficient normative appeal to be included in future versions of the prescriptive model.

Similar arguments can be made for decision tools designed to elicit probability judgments. Awareness, understanding, and anticipation of the heuristics used to make such judgments and the conditions under which these heuristics will lead to biases, can actually help prevent their occurrence by suggesting effective countermeasures. Thus it has been shown, for example, that base rate neglect as a function of use of the representative heuristic can be significantly reduced by explicitly emphasizing the causal connections between events (Bar-Hillel, 1980).

MODIFICATION OF DECISION TOOLS

Existing decision tools (e.g., procedures or algorithms such as the simplex or decision tree analysis) have at least two shortcomings: they are rigid and they are opaque. If a single data point is missing in a linear program, the program will not run. A structural sensitivity analysis on a decision requires the tedious task of restructuring the complete tree all over. Actually, in existing decision aids that employ a conventional hierarchical programming structure, even a small structural modification is rather tedious (for an example see Lehner, Probus, & Donnell, 1985, p. 471). Furthermore, most tools can not explain, let alone justify, the reasoning process which led to the decision.

If a decision tool is to be used to aid a potentially non-normative decision maker, what type of qualities must it have? The first point is a technical one. Existing decision analysis techniques can not handle the complexities (e.g., dependency between utilities and probabilities or nonlinearities) introduced by some extended utility theories which relax the substitution principle. A preliminary effort towards developing an alternative to the standard decision-tree fold-up procedure has been reported recently (Sarin, 1989). The second point is more encompassing, namely the need to increase the effectiveness of existing tools through increasing their domain of application and their range of functions. The former necessitates relaxing the rigid data and assumption requirements and the latter involves introducing reasoning and interactive explanatory capabilities (the latter providing decision makers with the information necessary to justify the decision taken). Both require a knowledge base, an inference mechanism, and a set of procedural primitives (e.g., modus ponens for symbolic manipulation, a matrix inversion algorithm for numerical computations).

Coupling Symbolic and Numerical Computation

Developing the knowledge base and inference mechanism technology as well as theory necessary for future decision tools is one goal of the field of artificial intelligence (AI). Consequently, the potentials of AI techniques have recently received much attention (von Winterfeldt & Edwards, 1986, pp. 23-25; Lehner, Probus, & Donnell, 1985; Hammond, 1987, Henrion, 1987; Keeney, 1987) amidst some cautionary remarks (Doyle, 1985; Sutherland, 1986) warning against excessive optimism.

The first author is currently developing procedures to couple the symbolic reasoning capabilities offered by AI techniques and languages with the numerical computation techniques of decision tools. Three aspects of this research are briefly discussed. To obtain anticipatory behavior (some form of "intelligence") from an artifact (e.g., a decision tool), the artifact needs to have knowledge and beliefs about its environment. Three types of knowledge can be distinguished: knowledge about the problem domain, about the algorithmic tools, and about behavioral decision theories. These types of knowledge correspond roughly to the three components of decision analysis, namely the decision problem, the decision tools, and the decision maker. The reasoning process employed in the current models is deductive reasoning (Genesereth & Nilsson, 1987). Finally, the models make use of meta-level knowledge and reasoning (Aiello, Cecchi, & Sartini, 1986; Genesereth & Nilsson, 1987, Ch. 10) with reflection capabilities (Genesereth & Nilsson, 1987, pp. 255-261), which can account for formalization of beliefs, default reasoning, inference in changing situations, and reasoning about the reasoning process.

The goal of the research is not to develop a new decision tool per se, at least not in the short run, but to investigate the capabilities of techniques currently available in AI, to create demands for new techniques, and to lay the foundation for a computational theory of decision tools which encompasses both symbolic and numerical processes.

SUMMARY AND CONCLUSIONS

Behavioral scientists have recently been providing experimental evidence on the decision behavior of individuals and have extended classical normative theories of decision making to account for such behavior. This has created a need for decision aids significantly different from existing ones. One way of bridging the gap between necessary (or desirable) and existing decision tools is to leave this task to the skill and imagination of the decision analyst. However, we are more inclined to agree with the statement by the 16th-century Italian philosopher Vico: "Certum quod factum," i.e., one is certain [only] of what one builds. Hence our desire to strengthen and extend the capabilities of existing decision tools. We have been looking for additional tools, techniques, and theories from artificial intelligence, a field currently much interested in discovering how humans deal with certain problems and what problem solution procedures can be automated.

This closes the circle between psychology, operations research, and artificial intelligence. Coordination of research in these three areas has great promise for significantly advancing the following three global research issues in the theory of decision aiding:

(i) How should a decision task been divided between the decision maker and a decision tool (Pitz, 1983)?

(ii) Where in the decision process should the decision maker be aided and how (Humphrey, 1986)?

(iii) What are the fundamentals of a computational theory for developing decision tools?

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