Making Naturalistic Decision Making “Fast and Frugal”

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Abstract

The Naturalistic Decision Making (NDM) addresses how human decision makers can deal with constraints of time and information. In general, NDM theories are consistent with expert decision making but tend to be very general, referring to broad categories of cognitive processes such as recognition, pattern matching, and mental simulation, without explaining exactly how these processes are performed. The fast and frugal heuristic approach offers a computationally rigorous framework in which to explore specific decision making processes and environmental constraints. A synthesis of NDM and fast and frugal heuristic approaches is proposed as a research framework that will allow clear and precise hypotheses to be tested and serve as bases for development of support tools.

Introduction

Over the past decade or more, the Naturalistic Decision Making (NDM) approach has become a popular framework in which to study decision making in real-world settings. NDM specifically addresses the sorts of constraints of limited time, high stress, and incomplete knowledge that characterize real-world, complex environments, which has made it a useful framework in which to study military command and decision making [e.g., McMenamin, 1995; Kaempf et al., 1996; Klein, 1992]. Despite its applicability to military decision making, however, the NDM approach remains general, referring to broad categories of cognitive processes such as recognition, pattern matching, and mental simulation, without explaining exactly how people perform these processes [Todd & Gigerenzer, 2001]. One way to deal with the limitations of NDM as a scientific approach is to look to theories of bounded rationality and, in particular, an approach that makes use of “fast and frugal” heuristics [Gigerenzer & Goldstein, 1996; Gigerenzer et al., 1999]. Designed to be effective and psychologically plausible, fast and frugal heuristics offer a way to develop detailed computational models within the framework of NDM. This paper presents a review the theoretical and empirical literature pertaining to NDM and bounded rationality to address the question of whether these approaches can be synthesized in a framework for the study of decision making in the military context.

Naturalistic Decision Making

NDM is primarily a descriptive approach that seeks to explain human decision making in terms of expert performance [Klein, 1999]. No attempt is made to define normative decision rules because such normative models are generally unable to adequately explain the actions of human decision makers [Gigerenzer, 1997; Lipshitz et al., 2001]. Given the focus of NDM on actual, observable behaviors, situation constraints (e.g., time, knowledge) become key considerations in formulating specific models [Kaempf et al., 1996; Klein, 1999].

All models within the NDM framework share several basic principles. First, decisions are made by *holistic evaluation* of potential courses of action (COAs) rather than by feature-by-feature comparison of alternatives [Lipshitz et al., 2001]. Typically, the decision maker sequentially generates and evaluates potential COAs against some criterion of acceptability. The second principle is that decisions are *recognition-based* in that decision makers rely on recognition of the situation and pattern matching of COAs rather than an exhaustive generation and comparison of alternatives [Klein & Calderwood, 1991]. The third principle is that decision makers adopt a *satisficing* criterion rather than search for an optimal solution [Klein & Calderwood, 1991]. Real world problems often demand rapid responses and decision makers may have to accept a merely workable solution without considering whether a better solution exists.

NDM is perhaps best understood through the concrete example of Klein's [1997] Recognition-Primed Decision (RPD) model [see also Leedom et al., 1998]. Like all NDM models, it eschews formal, logical processes and adheres to the three main principles discussed above. RPD also incorporates additional processes meant to complement the recognition-based decision process [Klein, 1997]. According to the complex RPD model, decision makers first appraise the situation in order to classify it as familiar or not, based on experience. The assessment of familiarity can be made by matching features of the situation to prior events, recognition of a whole pattern of features that fits a familiar story or scenario, or explicit recall of an analogy from another related domain.

When the decision maker is unable to recognize a given situation, the typical reaction is to seek more information or to resolve the ambiguous situation through diagnostic processes such as "story building," by which the decision maker creates a detailed hypothesis or story that could explain the situation. Once the decision maker has diagnosed the situation, he or she can use mental simulation to form expectations about future events and test the working hypothesis. If there are too many inconsistencies between the hypothesis and the situation, the decision maker must revise his or her hypothesis. As the decision maker proceeds with mental simulation, he or she can also generate candidate COAs, which are tested by mental simulation of their likely consequences.

Studies examining the impact of constraints on decision making have suggested people act in accord with NDM because the demands of most real-life problems exceed their memory and attentional capabilities. Hutchins [1997], for example, reported that operators in representative naval threat detection scenarios had difficulty maintaining situation awareness and had little cognitive capability to accomplish other tasks. Other factors that affect how a decision can be made, including the decision maker's workload, his/her familiarity with the situation, and his/her level of experience [McMenamin, 1995; Flin et al., 1996; Pascual & Henderson, 1997; Klein, 1992]. The greater the workload, the less effort the decision maker is able to devote to conscious, deliberative reasoning processes, which make automatic processes, such as recognition and other memory-based strategies, very useful. The familiarity of the situation, however, will determine the success of these strategies. The experience of the decision maker, of course, will determine the store of memories and schemata that can be used to categorize the current situation and retrieve a workable COA.

Empirical evidence strongly supports the NDM approach for decision making in the military domain. Serfaty et al. [1997], for example, observed that naval officers followed a three-stage process of matching the situation to a schematic memory representation of a general case, gathering information to elaborate the remembered case, and then recognizing a plan for action to perform simulated anti-submarine warfare scenarios. Other studies [e.g., Cannon-Bowers & Bell, 1997; Kaempf et al., 1996; Klein et al., 1995] have demonstrated that decision makers focus on recognizing the situation in making naval command decisions. Both Leedom et al. [1998] and Serfaty et al. [1997] have also reported findings that support the use of recognition-based decision making by Army commanders in performing simulated missions.

The Fast and Frugal Approach

Whereas the NDM approach produces a fairly general description of decision making processes, the fast and frugal heuristic approach emphasizes formal modeling [Todd & Gigerenzer, 2001]. The approach is based on a reconceptualization of rationality in which behaviour is evaluated in terms of its adaptivity within the limits of time and knowledge imposed by the situation and the computational power and the decision maker [Tietz, 1992; Todd, 2001; Todd & Gigerenzer, 2000]. To behave adaptively is to act in ways that promote survival and reproduction, whether the actions are consistent with normative rules or not and cognitive mechanisms are considered rational to the extent that they support such behavior. Todd and Gigerenzer [2000] define this concept of *ecological rationality* as “adaptive behavior resulting from the fit between the mind’s mechanism and the structure of the environment in which it operates.”

The basic premise of the fast and frugal heuristic approach is that much of human decision making and reasoning can be explained in terms of simple heuristics that operate within the limits of time, knowledge, and computation imposed on the individual [Todd & Gigerenzer, 2000]. Fast and frugal heuristics do not compute quantitative probabilities or utilities, as in classical decision making models, because these values require too much computation to serve as practical bases for decision making and often require knowledge (e.g., costs, benefits, precise outcomes) that is unavailable in real-world tasks [Todd & Gigerenzer, 2000]. The aim of the fast and frugal heuristic approach is to develop models of cognition that are simultaneously plausible on psychological and ecological grounds, as well as being computationally specific [see Slegers, Brake, & Doherty, 2000].

Fast and frugal heuristics are implemented as step-by-step procedures, which can be unambiguously stated and computationally modeled [Gigerenzer, 1997]. Each heuristic is different, depending on the task for which it is designed and the precise steps involved, but three basic features characterize all fast and frugal heuristics: the search rule, the stopping rule, and the heuristic principles for making the decision [Gigerenzer & Selten, 2001; Todd & Gigerenzer, 2000]. The *search rule* defines the principle by which the heuristic directs its search for alternative choices and for information to be used in evaluating the alternatives. The search rule must not involve extensive observation or computation. The *stopping rule* comprises the principles that specify when and how the search procedure should be stopped. The stopping rule is the basis for satisficing processes [Richardson, 1998], and thus must operate within the time limits imposed by the task environment. To be robust, a stopping rule is simple and relies on relatively little knowledge and information, which may be scarce in the task environment. The *heuristic principles for decision making* comprise the procedures used to choose among decision alternatives that have either been presented by the task or generated by the decision maker.

These are computationally simple, requiring little combination or elaboration of the information obtained through search.

Different Types of Fast and Frugal Heuristics

The specificity of fast and frugal heuristics implies that one must need many different heuristics for different purposes [Gigerenzer et al., 1999, pp. 29-31]. Individual heuristics can be categorized in terms of three factors, a) the number of options presented in the decision, b) the number of options that can be chosen, and c) the number and kinds of cues available [Todd & Gigerenzer, 2000]. Although the study of fast and frugal heuristics is relatively new, this approach has been applied to a range of basic problem types and yielded a corresponding range of heuristics designed to solve these problems (see Figure 1).

1. Ignorance-Based Decision Making
2. One-Reason Decision Making
3. Elimination Heuristics
4. Satisficing Heuristics

Figure 1. Some Kinds of Fast and Frugal Heuristics

Ignorance-based decision making heuristics are designed for a very simple kind of problem in which the decision maker must select one option from just two possibilities [Goldstein & Gigerenzer, 2002]. Examples of this kind of problem range from the trivial – deciding whether to use the escalator or stairs in a mall – to the critical – designating a radar contact as hostile or not. Ignorance-based heuristics use only the decision maker's knowledge or lack of knowledge of the options to make a choice [Goldstein & Gigerenzer, 2002; Gigerenzer et al., 1999, Ch. 2]. An example is the Recognition Heuristic, which Todd and Gigerenzer [2000] define as follows, "when choosing between two objects (according to some criterion), if one is recognized and the other is not, then select the former." For example, when choosing between two kinds of wine offered by a friend, you might select the vintage that you recognize (either from past experience or reviews of others) as the wine that will taste best. In this case, the sole basis for rejecting the alternative is that you do not recognize it. Although in cases where both or neither object is recognized the heuristic leads only to random choice, the heuristic can yield good choices when only one object is familiar *and* one's familiarity with objects is correlated with their ranking along the judgment criterion [Gigerenzer et al., 1999, pp. 41-43]; i.e. high quality wines actually do receive better reviews and/or are more likely to be sampled at restaurants, etc.

One-reason decision making, as the term implies, includes heuristics in which the choice of an option is based exclusively on just one cue (or reason) [Gigerenzer & Goldstein, 1996]. A one-reason heuristic begins with the selection of a dimension along which to compare options, followed by inspection of the cue values of the options, and comparison of the options on those values [Gigerenzer et al., 1999, pp. 77-81]. If the options differ on their cue values, then the process is stopped and the option with greater value is selected. If the options do not differ (or, more realistically, do not differ to a sufficient degree), then the entire procedure is repeated for a new cue dimension until a choice can be made. One-reason decision making involves inspecting, potentially, more cues than simply whether the options are familiar but these heuristics are still fast and frugal because cues are used in a non-compensatory fashion (i.e. the choice is made on the basis of a single cue and there is no computation of weighted sums or averages involved).

Many problems do not feature a simple choice between just two alternatives; many require the decision maker to choose from multiple options, not all of which are necessarily explicitly presented by the problem environment. Elimination heuristics apply simple search and stopping rules to select from multiple options by using successive cues to eliminate more and more alternatives until a single option is left [Gigerenzer et al., 1999, Ch. 11]. The Categorization by Elimination heuristic, for example, works well for problems in which the decision maker must infer the category of an object. It does this by successively consulting cues and comparing the object's value on this cue to a criterion set by the categories under consideration.

Satisficing heuristics are quite similar to NDM models in that they involve setting a criterion, or aspiration level, for some dimension along which decision alternatives are to be evaluated [Gigerenzer, 1997; Gigerenzer et al., 1999, pp. 12-14]. Various options are evaluated one at a time until one is found that exceeds the aspiration level and the search stopped. Satisficing heuristics are similar in form to one-reason decision making heuristics, except that rather than successively comparing cue values of options, satisficing involves successively comparing each option to a fixed criterion value.

Empirical Evidence

Fast and frugal heuristics have a number of attractive qualities that recommend them as models of human decision making but the viability of this approach hinges on two questions. The first is whether there is any evidence to indicate that such simple heuristics can actually solve the kinds of problems for which they are designed. Evidence with respect to this question comes from analyses of the effectiveness of the heuristical procedures relative to other more complex procedures in making correct decisions for representative classes of decision tasks [e.g., Holte, 1993]. A second question is whether people actually use fast and frugal heuristics, or cognitive processes like them, to make decisions. Evidence with respect to this question comes from empirical studies in which peoples' behaviors are compared to predictions of a fast and frugal heuristic model and alternative models.

Gigerenzer and Goldstein's [1996] test of the "Take the Best" heuristic serves as a good illustration of the kind of research done to assess the effectiveness of fast and frugal heuristics. The Take the Best heuristic works for tasks involving the choice of one of two alternatives based on a single criterion. In their research, for example, Gigerenzer and Goldstein's task was to indicate which of two German cities had the larger population. To make a choice, one would have to either know the city populations of the choices or rely on various cues correlated with city population, such as whether the city possessed a professional soccer team. In the latter case, the Take the Best heuristic dictates that cues are searched sequentially in the order of their validity or predictiveness until a single cue is found to discriminate the two choices. To test whether the Take the Best heuristic is a viable strategy for solving the city population problem, Gigerenzer and Goldstein applied it and several linear strategies, including a linear regression model, to the task. Assuming various levels of knowledge of the populations of cities, each procedure was trained on a subset of city pairs then tested on a different subset. The results indicated that the Take the Best heuristic made choices as accurately, or nearly as accurately, as more computationally intensive linear strategies across all levels of assumed knowledge.

The finding that the Take the Best heuristic performs comparably in terms of accuracy to linear regression and other compensatory procedures has been replicated with 19 other data sets drawn from psychology, economics, and other fields [Gigerenzer et al., 1999, Ch. 5]. Despite achieving comparable accuracy, however, the Take the Best heuristic exhibited a clear advantage over linear procedures in terms of frugality. The Table the Best heuristic, on average, consulted fewer cues and performed fewer computations than did the linear procedures. Similar simulation studies have confirmed that other fast and frugal heuristics, such as Categorization by Elimination, can perform roughly as accurately as more complex statistical models while using much less information and fewer computational steps [Todd & Gigerenzer, 2000].

The speed and frugality of heuristics such as Take the Best derive from their non-compensatory nature [Todd & Gigerenzer, 2000]. By definition, fast and frugal heuristics employ search rules that limit the number of cues consulted and stopping rules that make choices as soon as sufficient evidence has been obtained. In contrast, most statistical and probabilistic models are compensatory and consult all available cues and make choices only after comparison of multiple options. Fast and frugal heuristics perform accurately because they take advantage of the structure and regularities of information in a particular task environment [Gigerenzer et al., 1999, pp. 113-114]. Thus, the Take the Best heuristic will perform well when the task environment is structured in a non-compensatory way; i.e. when the validity or importance of cues falls off dramatically in a particular pattern [Gigerenzer et al., 1999, pp. 120-124]. In this environment, the best cue is likely as reliable an indicator of the correct choice as the weighted average of all available cues because the sum of all other cues will not compensate for the value one cue used.

Although fast and frugal heuristics can perform accurately for certain kinds of tasks, do people actually make decisions by applying such heuristics? One way to address this question is to compare the performance of human decision makers to the level of performance predicted by a heuristic [Todd, 2001; Todd & Gigerenzer, 2000]. Unfortunately, if people's decision performance is roughly that predicted by a heuristic, we cannot conclude that they necessarily employ that heuristic in making their decisions [Todd, 2001]. Fast and frugal heuristics often perform at levels indistinguishable from complex statistical methods, making the human decision maker's behavior consistent with any number of potential models [Todd & Gigerenzer, 2000]. One can examine the specific choice behavior of subjects for each individual decision to determine when the subject's decision is consistent with the decision predicted by the heuristic. This kind of evidence is even more compelling in cases in which a fast and frugal heuristic makes different predictions than a complex, compensatory model [Todd, 2001]. Finally, researchers can determine whether a particular heuristic predicts an overall pattern of choice behavior different than that predicted by other models of decision making [Todd, 2001].

Despite the difficulties in unambiguously assessing the use of fast and frugal heuristics, researchers have obtained some empirical evidence to support this approach. Goldstein and Gigerenzer [2002], for example, directly tested the Recognition Heuristic for a two-alternative choice task. Although the Recognition Heuristic predicts overall levels of performance similar to those predicted by more complex inference procedures, it also makes a novel prediction that the accuracy of inferences will be related to the level of recognition memory one possess for the objects in the category under consideration [Goldstein & Gigerenzer, 2002]. At low levels of recognition, neither of the two objects under consideration will be recognized much of the time, resulting in guessing and chance inference performance, thus lowering overall performance. Likewise, when recognition is high, both alternatives will be recognized in many pairs, leading to guessing and chance performance on a significant proportion of decisions. It is in the middle range of recognition that a greater proportion of pairs will be discriminated on the basis of recognition, which will lead to above-chance performance.[1] Goldstein and Gigerenzer [2002] have termed this the "less-is-more" effect because it predicts that judgment accuracy is an inverse-U shaped function of the proportion of objects recognized.

Goldstein and Gigerenzer [2002] tested this hypothesis by examining German and American subjects' performance on the city population task described earlier. To manipulate recognition levels of the reference set, they had subjects judge the larger of two cities for sets of both German and American cities. Obviously, German subjects were less familiar with American cities than the American subjects, and vice versa. Goldstein and Gigerenzer [2002] found that both the German and American groups made systematically less accurate inferences for the cities of their own nation, for which they had better recognition memory. Another group of German participants were given training on the sizes of American cities and tested both early and late in the process. These participants made a greater proportion of correct inferences early in training, when they were much less knowledgeable, than later.

Border [2000] has observed the use of the Take-the-Best heuristic in a series of experiments in which subjects learned to distinguish two different kinds of alien creatures on the basis of configurations of certain cues. Subjects were tested by asking them to infer the type of alien for a set of novel items drawn from the same underlying population. This task is exactly like the city population task, except that subjects learned an artificial reference class and cue values. A strong prediction that all people always employ the Take-the-Best heuristic to make choices in this kind of task was disconfirmed. A weaker prediction, however, that some people, in some cases, employ the Take-the-Best heuristic received support [Broder, 2000].[2] Using a statistical procedure to classify the patterns of choices of individual subjects, Broder found that 28% of subjects' choice behaviors could be classified as consistent with the Take-the-Best heuristic. The remaining subjects were classified as using some other strategy that was probably compensatory, although not equivalent to a formal equal weighted linear model.

In a subsequent experiment, Broder manipulated the procedure slightly, requiring subjects to "purchase" cues by expending some amount of resources to uncover cue values. This had a large effect on subjects' choice behavior, with 40% of subjects classified as using the Take-the-Best heuristic when the cost of cue information was relatively low and 60% classified as using the Take-the-Best heuristic when the cost of cue information was relatively high. Thus, the Take-the-Best heuristic seems to be a viable model of inferential choice if viewed as a procedure *available* to the decision maker but the particular task conditions, especially the costs associated with obtaining information, seem to affect whether a fast and frugal heuristic is.

Dhami and Ayton [2001] have also obtained evidence supporting the use of the Take the Best heuristic in the real-world decision making task of British magistrates determining whether to grant bail to criminal suspects. Although instructed to weigh all evidence to reach their decisions, anecdotal evidence, as well as the severe time constraints under which they work, suggested that magistrates might actually rely on heuristical procedures. Dhami and Ayton [2001] had magistrates evaluate a set of realistic cases, then compared the decisions made by magistrates to two weighted linear models that integrated all cues and to a version of the Take the Best heuristic that searched cues in the order of their relative importance until finding a cue

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[1] Assuming that the underlying task environment is such that recognition is positively correlated with the criterion dimension.

[2] Indeed, the Adaptive Toolbox framework would suggest that this is more likely than all people using the same heuristic in all cases [e.g., Todd & Gigerenzer, 2000].

that indicated the suspect should be denied bail (if no such cue was found, then bail was granted). Results indicated that the decisions of roughly 32% of magistrates best matched the heuristic, with the remainder better matched by either the two linear rules under consideration or some combination of these rules and the heuristic.

Military Applications of the Fast and Frugal Heuristic Approach

Almost no work has been done so far on applying the fast and frugal heuristic approach to military decision making. This does not reflect any fundamental inconsistency between the approach and military issues but rather the relative newness of the fast and frugal heuristic approach has not afforded time for it to make an impact on researchers in the military field. Nevertheless, one study has examined the potential benefits of designing military decision support systems from the perspective of bounded rationality. Blackmond Laskey et al. [2000] proposed that, although exclusive reliance on simple heuristics may not be possible in the high risk domain of military operations, there is still a role for such heuristics in dealing with the massive amounts of data that can be collected through sensors and other sources. In particular, they argue that fast and frugal heuristics can serve as excellent tools for performing "reactive" decision processes; i.e. decision processes that transform sensor data directly into some output or action. In their view, the speed with which fast and frugal heuristics can operate is a clear advantage in cases where decisions can be made by assessing the situation and applying a rule or pre-programmed response. According to Blackmond et al. [2000], however, more deliberative decisions, which involve extensive computation and problem solving, are less amenable to a fast and frugal solution.

Forging a Research Framework

Both NDM and fast and frugal heuristics are intended to address the same issues in real-world decision making, namely limitations of computational power, knowledge, and time. NDM models, however, have not been formally modeled in terms of ecologically rational heuristical procedures. As research on fast and frugal heuristics has shown, when the decision problem, environment, and available resources can be thoroughly described, it is possible to develop computational models that can be simulated and objectively tested [Gigerenzer, 1997]. Thus, decision making processes that are currently described vaguely in NDM models can be specified more precisely by examining the nature of decision tasks and the environments in which they are performed. In this section, I will discuss how the NDM and fast and frugal heuristic approaches can be synthesized and how this might lead to specific research objectives for the support of military decision making.

Similarities and Differences in Approach

The ways in which the NDM and fast and frugal heuristics approaches differ and are alike will determine whether a workable synthesis can be achieved. The key characteristics on which to compare the approaches are those that pertain to the explanatory power of the models they can produce. These characteristics reflect the ways in which testable hypotheses are drawn within the assumptions, or "theoretical language," of NDM and fast and frugal heuristics.

Figure 2 indicates several points of commonality between the NDM and fast and frugal heuristics approaches. They both emphasize the adaptiveness of decision making models with respect to the environment in which decisions must be made. Rejecting classical decision theory's search for universal rules, both approaches consider a wide range of possible mechanisms by which decision makers can deal with different tasks. Because both approaches consider environmental constraints, they both reject traditionally normative compensatory processes that would require extensive and time-consuming computation. Thus, both approaches favour the use of primarily satisficing criteria in decision making. Neither NDM methods nor fast and frugal heuristics seek optimal answers; instead they balance accuracy, speed, and knowledge requirements in evaluating the quality of the decision making process. Finally, both approaches are highly sensitive to the situation, which not only defines constraints but what kinds of decision processes can work for a given task and environment.

Characteristic	**Naturalistic Decision Making**	**Fast and Frugal Heuristics**	**Same/Different?**
Adaptive Models	Yes	Yes	Same
Applicability	Complex, ill-defined problems	Simple, well-defined problems	Different
Compensatory	No	No	Same
Computational Basis	No	Yes	Different
Concept of Rationality	N/A	Ecological	Different
Criterion for Choice	Satisficing	Satisficing	Same
Derivation of Models	Expert behavior	Analysis of task/problem	Different
Formality of Models	Not formal	Formal but simple	Different
Memory-based	Yes	Can be but not necessary	Different
Role of Experience	Essential	Undefined	Different
Situational Sensitivity	High	High	Same
Testable Hypotheses	Few	Many	Different
Type of Model	Descriptive	Descriptive and Prescriptive	Different

Figure 2. Comparison of the NDM and Fast and Frugal Heuristic Approaches

Figure 2 also indicates that the two approaches differ in many respects. These differences, however, seem to make the approaches complementary rather than incompatible. One difference is the areas to which these theoretical approaches have been applied. NDM was developed to study real-world decision making in complex tasks, whereas the fast and frugal heuristic approach has explored traditional, lab-based tasks that are much simpler but easy to describe. As a result, the approaches also differ in their computational bases, fast and frugal heuristics being highly computational and NDM having no computational basis. This means that fast and frugal heuristics can be simulated and used to make quantitative predictions in ways that current NDM models cannot. Thus, one way in which the concept of fast and frugal heuristics can benefit NDM is to bring a greater level of formality to the modeling process, which opens up the possibility of more rigorous empirical testing [Todd & Gigerenzer, 2001]. Others [Lipshitz et al., 2001] have noted the problem with NDM that it is difficult to specify testable hypotheses, or at least hypotheses that are specific enough to be testable in practice. The fast and frugal heuristic approach clearly avoids this problem, as evidenced by the breadth of empirical studies already performed despite the approach's relative newness.

Although NDM is a reaction to classical decision theory, no one has developed a concept of rationality from the NDM perspective. Researchers have assumed that the ways experts solve problems defines the "right" way [e.g., Klein, 1999; Lipshitz et al., 2001], but this suggests circularity in the definitions of rationality and expertise. Gigerenzer [Gigerenzer, 1997; Gigerenzer et al., 1999, pp. 360-361], however, clearly specifies rationality in terms of ecological adaptiveness, such that any process that enhances survival or reproductive fitness in evolutionary terms is rational, whether it conforms to a particular normative model or not. Thus, NDM models are derived from expert behavior but fast and frugal heuristics from an analysis of the task or problem in its environmental context. Thus, whereas NDM models are purely descriptive, fast and frugal heuristic models can be both descriptive (i.e. psychologically plausible) and prescriptive (i.e. defining adaptive ways to solve particular problems). Perhaps because NDM models are, for the most part, created from accounts of experts, these models generally emphasize memory-based processes. Fast and frugal heuristics can make use of such processes but are not limited to them and not dependent on experience.

Synthesizing NDM and Fast and Frugal Heuristics

The NDM and fast and frugal heuristic approaches seem to share enough in common that they *can* be synthesized – most notably a focus on the environment and non-analytic processes – as well as being *different* enough to make such a synthesis worthwhile. In particular, the fast and frugal heuristic approach provides the level of scientific rigour that the NDM approach has so far lacked. The differences between the two approaches may reflect at the most fundamental level a difference in the level of the explanation provided by each approach. Military decision making in the context of command and control or planning is a complex process that is extended over time and is most often performed by a team of individuals bringing specific knowledge and expertise. Thus, at one level we must consider how decision makers build situational representations, identify problems, and select strategies to solve those problems. But these activities imply that decision makers must call upon many specific procedures to solve specific decision tasks.

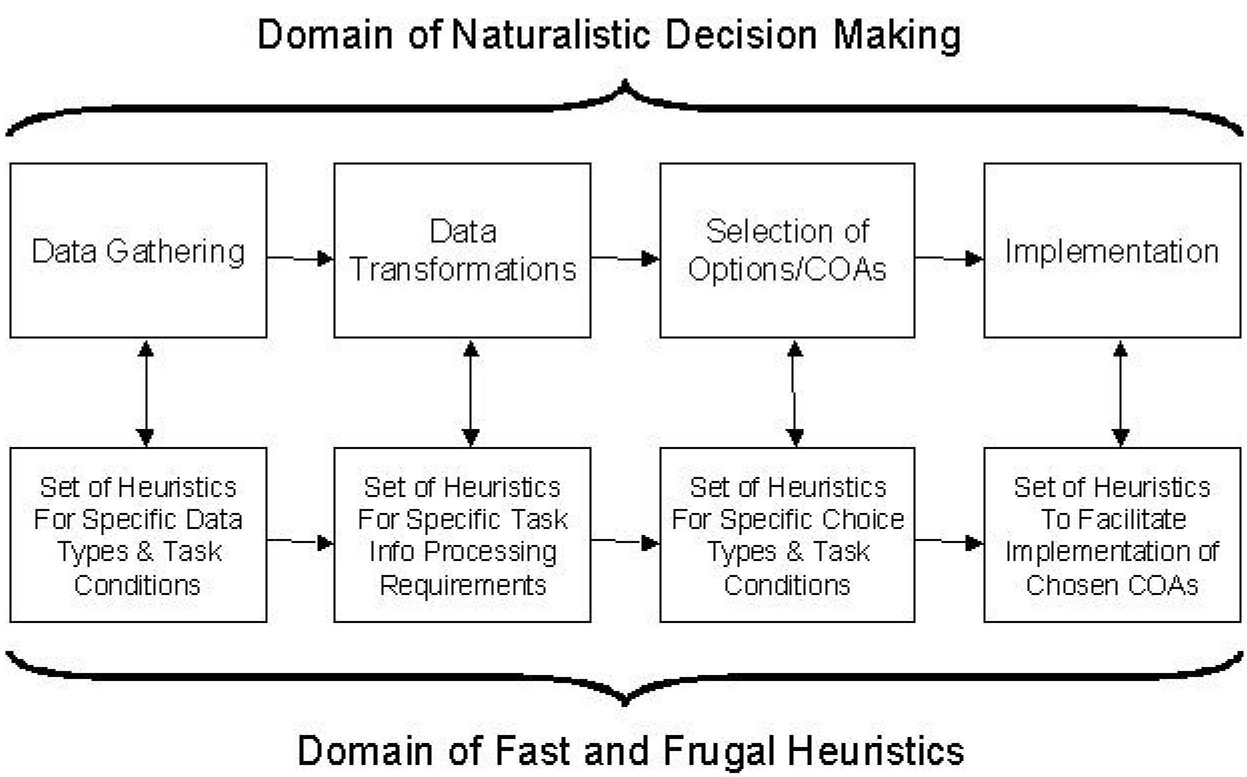

Figure 3. Synthesis of the NDM and Fast and Frugal Heuristic Approaches

Figure 3 illustrates this idea by depicting two separate streams of cognitive functions. The upper block of functions depicts, in highly simplified form, the kind of broad organizational activity in which the decision maker coordinates specific activities, such as information seeking, information interpretation, and generation of potential COAs. Underlying this organizational level are the many procedures and heuristics that an individual can draw upon to perform specific tasks dictated by the higher level. The kinds of data gathering and processing tasks to be performed will depend on the exact situational demands and constraints, which determine what choices must be made, what sensors are available, etc. The lower block of functions in Figure 3 represent the sets of presumed heuristics from which the decision maker can select appropriate means to perform tasks as required.

Rather than trying to artificially extend a single research approach to cover all aspects of complex decision making, it seems a better idea to match both approaches to the types of questions to which each is best suited. Researchers in the NDM approach have favoured process-oriented models intended to describe the cognitive processes of experts solving complex problems [e.g., Lipshitz et al., 2001]. This modeling approach has produced models that describe decision making at a high-level organizational level. It is at this level that NDM has proved itself a valuable framework. The fast and frugal heuristic approach, in contrast, has generated computational models that describe cognitive activity at a much more precise level in terms of specific cognitive operations.

In a synthesized framework, both NDM and fast and frugal heuristic approaches are used to address parts of our understanding of military decision making. The NDM approach is better suited to the deliberative, organizing flow of information among team members solving a complex problem. This level is important to the design of decision support systems, team procedures, and communications within and between units. The fast and frugal heuristic approach offers explanations of how a person performs the kinds of simple choices and decisions that are linked in complex problems. As Blackmond Laskey et al. [2000] have suggested, fast and frugal heuristics can help us understand more elementary, or reactive, decision processes, the kinds that are largely automatic and unavailable to conscious introspection but are heavily involved in all activities involving the gathering of data, its transformation, and choice and implementation of COAs.

Thus, the two approaches have complementary roles in the study of decision making, each addressing description of complex processes at different levels. Similarly, the methods generally employed by the two approaches are suited to their respective levels. Methods such as cognitive task analysis [Hoffman et al., 1998; Randel et al., 1996] favoured in NDM work well to document deliberate, sequential activities. The sorts of simulation and experimentation conducted in the fast and frugal heuristic approach are needed to identify the workings of cognitive mechanisms that are mostly hidden from our consciousness.

A Research Framework

The proposed synthesis implies the need for concurrent research paths aimed at two different levels of explanation. Each level has its own uses but exploring specific heuristical and algorithmic processes used in decision making can deepen the conception of NDM. In practice, how would this be translated into a research framework?

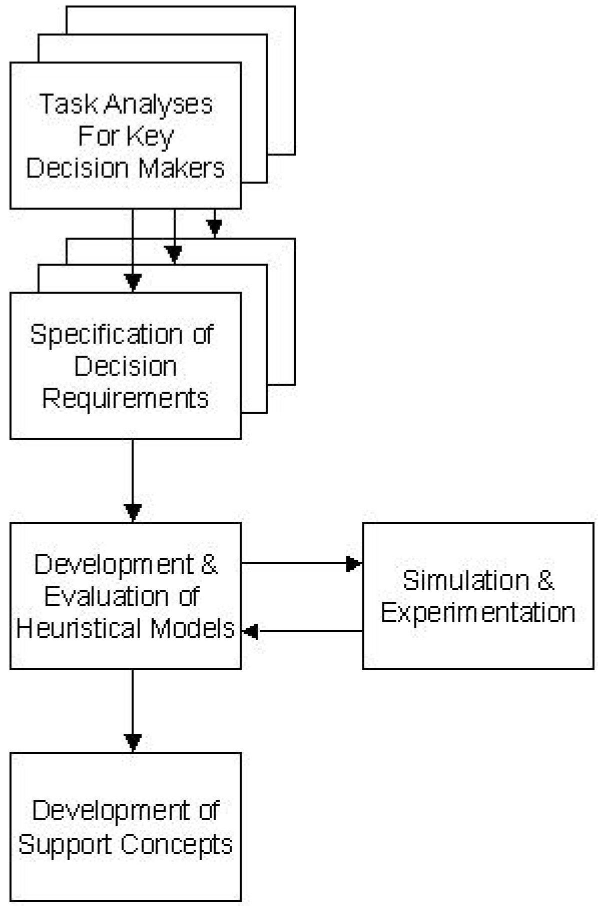

Figure 4. A Simple Research Framework

Although the “organizational” and “heuristical” levels of explanation (see Figure 3) run parallel, one must first explore decision making at the high level to set the stage for more detailed study of heuristics. Figure 4 illustrates a simple concept of how to pursue a fast and frugal heuristic approach within an overall NDM framework for military command and control. The traditional tools of NDM have been forms of task analysis and cognitive task analysis, which are sufficient to describe high-level organizational behaviour, which itself is largely deliberative. Other tools, drawn from traditional empirical research and modeling and simulation, however, are needed to describe decision making at the computational heuristical level.

The research framework presented in Figure 4 is simple and intended simply as a starting point. With that caveat in mind, I envision a framework based on four general steps or aspects of research. The first step is to perform a task analysis for the key personnel in the command and control process. Admittedly, this raises a serious issue of how many personnel can be considered given limited resources, but to understand decision making at the heuristical level requires detailed analysis of the specific decision tasks performed. Task analysis is the first step toward that goal in that it identifies the general decision making functions at the organizational level. This corresponds to creating NDM models of the deliberate strategies that govern how decision makers coordinate their activities.

The next step is to examine each general decision making function in more detail to identify elementary decision tasks for which potential heuristics can be developed. These elementary decision tasks are very specific and can be characterized in formal terms that allow procedural solutions. Examples in command and control include such decisions as determining whether a radar contact represents a real object or noise, or determining what sensors should be used given current environmental conditions. Elementary decision tasks have definable decision requirements that can be specified in terms of the task's a) goal or outcome state that completes the decision, b) constraints that comprise any environmental and cognitive factors that restrict the way in which the goal can be attained, and c) resource requirements in the form of external information and information processing mechanisms available for use in attaining the goal.

With the decision requirements specified, researchers can develop and evaluate possible mechanisms for performing the elementary decision tasks. Heuristical mechanisms are developed through analysis of the decision requirements. They are evaluated in terms of their effectiveness in solving the decision task and their psychological plausibility (i.e. fastness and frugality). To be of practical use, research at this stage must consider what kinds of decision making mechanisms are actually used by command and control personnel. Thus, the aim of this third stage is to characterize the sets of heuristics (or complex processes if plausible) available to individuals for solving particular decision tasks. This creates a description of the command and control decision making process at the heuristical level. The description does not take the form of a function-flow as at the organizational level but as a set of cognitive mechanisms (what Gigerenzer et al. [2000] term the "Adaptive Toolbox") that individuals can draw upon as needed to make the decisions underlying the broader command and control functions.

The final stage of the research process remains the development of decision support concepts. This should be dramatically enhanced by virtue of the complementary descriptions of the decision making of the personnel involved in command and control. The organizational level description, which is essentially an NDM model, provides guidance on issues pertaining to the use of sensors, control of information flow, communication within a team, etc. The more formal decision models provided at the heuristical level add to this guidance on issues pertaining to the specific use of data, procedures for making choices, and potential incompatibilities between external data processing outputs and decision makers' cognitive needs. The fast and frugal heuristic approach allows more detailed questions to be asked, which lead to insights that enhance the value of decision support. Todd and Gigerenzer [2001], for example, note that little is known about how a decision maker's criterion or aspiration level is set within the broader context of most NDM models, or how COAs might be compared to the criterion.

Conclusion

The synthesis of the NDM and fast and frugal heuristic approaches proposed here is a preliminary concept aimed at providing researchers a more sophisticated theoretical language in which to describe military decision making. The immediate requirements for advancing this concept are to look at existing task analyses [e.g., CMC Electronics Inc., 2002] to determine how well command and control roles can be decomposed into elementary decision tasks and to study the suitability of fast and frugal heuristics as psychologically plausible models for those tasks.

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