Why Heuristics Work

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ABSTRACT—*The* adaptive toolbox *is a Darwinian-inspired theory that conceives of the mind as a modular system that is composed of heuristics, their building blocks, and evolved capacities. The study of the adaptive toolbox is descriptive and analyzes the selection and structure of heuristics in social and physical environments. The study of ecological rationality is prescriptive and identifies the structure of environments in which specific heuristics either succeed or fail. Results have been used for designing heuristics and environments to improve professional decision making in the real world.*

Logic, probability, and heuristics are three central ideas in the intellectual history of the mind. For Aristotle, logic was a theory of ideal human reasoning and inference. Probability theory emerged only late in the mid-17th century, replacing logical certainty with a more modest theory of rationality acknowledging the fundamental uncertainty of human conduct (Daston, 1988). From its inception to the mid-19th century, probability theory was regarded as being, in Laplace's (1814/1951, p. 196) famous phrase, "only common sense reduced to a calculus." Mathematical probability and human thinking were originally seen as two sides of the same coin, and in his famous treatise *An Investigation of The Laws of Thought*, George Boole (1854/1958) set out to derive the laws of logic and probability from the psychological laws of thinking. Probability theory has since transformed science and everyday life, from statistical mechanics to experimentation to DNA statistics. We christened this process the *probabilistic revolution* (Gigerenzer et al., 1989; Krüger, Gigerenzer, & Morgan, 1987). Yet only the 20th century saw the beginnings of a systematic study of cognitive heuristics, promoted by biologists such as Niko Tinbergen, who described the rules of thumb animals use for choosing mates, food, and nest sites; by Gestalt psychologists such as Karl Duncker, who described heuristic methods for restructuring and insight; and by the mathematician George Pólya, who introduced Herbert Simon to heuristics. Heuristics are frugal—that is, they ignore part of the information. Unlike statistical optimization procedures,

heuristics do not try to optimize (i.e., find the best solution), but rather satisfice (i.e., find a good-enough solution). Calculating the maximum of a function is a form of optimizing; choosing the first option that exceeds an aspiration level is a form of satisficing.

Each of the three systems pictures the goals of human behavior in its own way. Logic focuses on truth preservation. Consequently, mental logic, mental models (in the sense of Johnson-Laird, 1983), and other logic-inspired systems investigate cognition in terms of its ability to solve syllogisms, maintain consistency between beliefs, and follow truth table logic. Logic makes us see the mind as an intuitive logician, as in Piaget's operational stage of development. The relevance of the logical and the psychological has been discussed since the very beginnings of psychology as a discipline. For instance, Wundt (1912/1973) rejected both the descriptive and normative usefulness of logic: "We can in fact say of such attempts, that measured by the results they have been absolutely fruitless. They have disregarded the psychological processes themselves." Probability theory depicts the mind as solving a broader set of goals, performing inductive rather than deductive inference, dealing with samples of information involving error rather than full information that is error-free, and making risky "bets" on the world rather than deducing true consequences from assumptions. Yet it played only a limited role in cognitive theories before 1950 and was vehemently rejected by leading psychologists of the time, including Stanley Stevens, Edwin Boring, and David Krech (Gigerenzer & Murray, 1987). Probability theory suggest that the mind is an intuitive statistician, as in signal detection theory modeled after Neyman-Pearson theory or in causal attribution theory modeled after Fisher's analysis of variance (Gigerenzer, 1991). Models of heuristic cognition, in contrast, focus on situations in which people need to act fast (rarely a concern for logical models of mind), the probabilities or utilities are unknown, and multiple goals and ill-defined problems prevent logic or probability theory from finding the optimal solution. In this view, the mind resembles an adaptive toolbox with various heuristics tailored for specific classes of problems—much like the hammers and screwdrivers in a handyman's toolbox.

None of these three systems is always the best to use in any situation. This insight corrects several misunderstanding concerning heuristics: that heuristics are always second-best

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TABLE 1

Six Common but Erroneous Beliefs About Heuristics

Six common misconceptions	Clarifications
1. Heuristics produce second-best results; optimization is always better.	In many situations, optimization is impossible (e.g., computationally intractable) or less accurate because of estimation errors (i.e., less robust; see investment example).
2. Our minds rely on heuristics only because of our cognitive limitations.	Characteristics of the environment (e.g., computational intractability) and of the mind make us rely on heuristics.
3. People rely on heuristics only in routine decisions of little importance.	People rely on heuristics for decisions of both low and high importance. See investment and organ donation examples.
4. People with higher cognitive capacities employ complex weighting and integration of information; those with lesser capacities use simple heuristics (related to Misconception 1).	Not supported by experimental evidence (e.g., Bröder, 2003). Cognitive capacities seem to be linked to the adaptive selection of heuristics and seem less linked to the execution of a heuristic. See also the Markowitz example in this article.
5. Affect, availability, causality, and representativeness are models of heuristics.	These terms are mere labels, not formal models of heuristics. A model makes precise predictions and can be tested, such as in computer simulations.
6. More information and computation is always better.	Good decisions in a partly uncertain world require ignoring part of the available information (e.g., to foster robustness). See the investment example in this article.

strategies, that we use them only because of our cognitive limitations, and that logic or probability is always the best way to solve a problem (see the six misconceptions in Table 1). If we take a broader view and include some principles of logic and probability as tools in the adaptive toolbox, a new task emerges: defining the class of problems where a given strategy of logic, statistical inference, or heuristic works. This is the question of a strategy's ecological rationality (see below).

Although formal systems of logic and probability have been developed over centuries, nothing comparable yet exists for cognitive heuristics. In this article, I will focus on the formal system being developed by my research group at the Max Planck Institute for Human Development, based on earlier work by Nobel laureates Herbert Simon and Reinhard Selten and the work of others (e.g., Payne, Bettman, & Johnson, 1993; Thorngate, 1980; Tversky, 1972). This brief article cannot do justice to the experimental, simulation, and analytic results that have been gathered in the last 10 years. I begin with five principles of models of heuristics, followed by concrete examples.

MODELS OF HEURISTICS

Computational Models

The first goal is to design computational models of heuristics that make precise predictions and can be tested experimentally and by computer simulation. Formalization enhances transparency and testability and facilitates comparing heuristics with logical and probabilistic models of mind in terms of accuracy or other criteria. Yet much of the research on heuristics previously relied on labels such as *representativeness*, *availability*, and *affect heuristics*. The problem is that without a formal definition, common-sense labels can account for almost everything. Heuristics are sometimes subsumed into a "System 1" that is supposedly responsible for associations and making errors and is

contrasted with a "System 2" that embodies the laws of logic and probability, again without specifying models of the processes in either system. In contrast, I believe that such process models can promote theoretical progress (Gigerenzer & Regier, 1996). For instance, without computational models we would not know that situations exist in which a simple heuristic makes more accurate predictions than multiple regression or Bayesian models do (see below; Brighton, 2006; Czerlinski, Gigerenzer, & Goldstein, 1999). They are essential in overcoming the misunderstandings listed in Table 1—for instance, that heuristic cognition is always second-best to complex information integration. Formal models help to identify the class of problems in which more information and processing pays or those in which ignoring or forgetting information is successful.

Tractability

Another misunderstanding is that we use heuristics only because of our cognitive limitations. Yet the reasons for using them also lie in the very nature of the problem the mind has to solve. Two of the reasons the mind reaches for heuristics are tractability and robustness. Many real-world problems are computationally intractable (or *NP-hard*), which means that no machine or mind can find the best (optimal) strategy, even if one exists. For instance, determining the best strategy may be tractable in the children's game tic-tac-toe but not in the more complex game of chess. Probabilistic inferences using Bayesian belief networks are NP-hard (Cooper, 1990), as are approximate inferences (Dagum & Luby, 1993). In fact, almost every interesting problem in artificial intelligence is computationally intractable (Reddy, 1988), as are computer games with well-defined rules such as Tetris and Minesweeper. In addition, ill-defined problems, such as "finding a spouse," are by definition beyond the reach of optimization. Intractable problems defy

optimizing and make satisficing solutions necessary for both mind and machine.

Robustness

Humans and other animals need to predict the future and not merely rely on hindsight to analyze the past. A complex cognitive strategy is said to *overfit* relative to a simpler one if it is more accurate in fitting known data (hindsight) but less accurate in predicting new data (foresight). One can intuitively understand overfitting from the fact that information from all past experience can be divided into two groups: information that is relevant for the future and irrelevant information (or "noise"). Everything else being equal, the more difficult a criterion is to predict (i.e., the higher its uncertainty), the more noise exists in past information that needs to be ignored. An adaptive cognitive system that operates in an uncertain world thus needs to ignore part of the information. The problem is determining which part to ignore. Heuristics that order cues by importance and employ limited search are means towards that end. A cognitive heuristic that can reduce the chance of fitting noise is called *robust*. Robustness can be enhanced by ignoring information and by cognitive limitations such as forgetting. These are not simply regrettable deficiencies, and they can enable cognitive development (Turkewitz & Kenny, 1982) and functioning in an uncertain world (Hertwig & Todd, 2003).

Evolved Capacities

Some models of cognition stem from statistical methods that were projected onto the mind (Gigerenzer, 1991). Heuristics, in contrast, can exploit evolved capacities naturally available to humans to find different solutions for a problem than a statistical calculus would. Recognition memory is one such evolved capacity that is exploited by the recognition heuristic and the fluency heuristic. The important point here is that these capacities need not be unlimited. In fact, a certain degree of systematic forgetting is beneficial for the recognition and fluency heuristics to operate (Schooler & Hertwig, 2005).

Social Environments

Simon once compared mind and environment with the two blades of a pair of scissors: to understand behavior, one must look at both and at how they fit. Studying only one blade will not reveal why scissors cut so well. Similarly, studying only the mind can mislead researchers into confusing adaptive heuristics with a cognitive deficits. Yet ecological perspectives are still rare in cognitive science aside from a few exceptions, such as the perspectives of Brunswik, Gibson, Shepard, and Anderson and Schooler. Most theories are about mental processes only: neural networks, production rules, Bayesian calculations, or dual-systems notions. An ecological theory defines human rationality by correspondence (how cognition succeeds in the world) rather than by coherence (its match with the laws of logic or probability). An evolutionary view broadens this ecological view from present to past environments and helps researchers understand that behavior adapted to the past may fail when environments change quickly (Cosmides & Tooby, 1992). The link between mind and environments is the topic of the study of ecological rationality: In which environment does a given heuristic perform well and where will it fail?

EXAMPLES OF HEURISTICS

Let me illustrate these principles with two examples of heuristics.

Investment Behavior

In 1990, Harry Markowitz received a Nobel Prize in Economics for his theoretical work on optimal asset allocation. He addressed a vital investment problem that everyone faces in some form or other, be it saving for retirement or earning money on the stock market: How to invest your money in N assets? Markowitz proved that there is an optimal portfolio that maximizes the return and minimizes the risk. Nevertheless, for his own retirement investments, he did not use his award-winning optimization technique but relied instead on a simple heuristic, the $1/N$ rule, which states, "Allocate your money equally to each of N funds."

There is considerable empirical evidence for this heuristic: about 50% of people studied intuitively rely on it, and most consider only three or four funds to invest in. Researchers in behavioral finance criticized this behavior as simple and silly. But how much better is optimizing than the $1/N$ rule? A recent study compared the results of 12 optimal asset allocation policies with the results of the $1/N$ rule in seven allocation problems, such as allocating one's money to 10 American industry portfolios. The 12 policies included Bayesian and non-Bayesian models of optimal choice. Despite their complexity, none of the 12 policies could beat the $1/N$ heuristic on various financial measures (DeMiguel, Garlappi, & Uppal, 2006).

How can a heuristic strategy be better than an optimizing one? At issue is not computational intractability, but robustness. The optimization models performed better at data fitting (adjusting their parameters to the data of the past 10 years) than the simple heuristic did, but they performed worse at predicting the future. Thus, they overfitted the past data. In contrast, the $1/N$ heuristic, which does not estimate any parameter, cannot overfit.

Note that $1/N$ is not generally superior to optimization or vice versa. The important question of when, in fact, it does better predict the future can be answered by studying the ecological rationality of a heuristic. Three relevant environmental features for the performance of $1/N$ are known: the predictive uncertainty of the problem, the number (N) of assets, and the size of the learning sample.

Typically, the larger the uncertainty and the number of assets and the smaller the learning sample, the greater the advantage of 1/N. When would the optimization models begin to outperform the heuristic? As the uncertainty of funds is large and cannot be changed, we focus on the learning sample, which was comprised of 10 years of data in DeMiguel et al.'s (2006) study. The authors report that with 50 assets to allocate one's wealth to, the optimization policies would need a window of 500 years before they eventually outperformed the 1/N rule.

The Markowitz case illustrates that an optimization model does not guarantee an optimal outcome. Both heuristic and optimization models can lead to good or bad outcomes, depending on the structure of the environment, including the three features specified above.

Moral Behavior

Since 1995, an estimated 50,000 Americans have died waiting in vain for an organ donor. As a consequence, a black market in kidneys and other organs has emerged as an illegal alternative. Why are only 28% of Americans potential organ donors in comparison with a striking 99.9% of the French? Do the French have a higher moral consciousness, or are Americans perhaps less informed about the shortage? The answer, however, cannot be found by examining differences in national personality traits or knowledge. Rather, the majority of Americans and French seem to employ the same *default heuristic*, which states, "If there is a default, do nothing about it." But how would that heuristic explain why there are too few organ donors in the U.S., whereas France has plenty? Recall Simon's two blades: mind and the environment. In the United States, the legal default is that nobody is a donor without registering to be one. You need to opt in.[1] In France, everyone is a potential donor unless they opt out. Behavior is a consequence of the default heuristic and of the legal environment, leading to the striking contrasts between countries (Johnson & Goldstein, 2003). Knowing the cognitive process has policy implications. For instance, it explains why the various expensive information campaigns in the opt-in countries have failed to increase participation: the issue is not lack of information. If most citizens in the U.S. rely on the same default heuristic that the citizens of France use, the solution for the donor problem is to change the legal default.

TOWARD A SCIENCE OF HEURISTICS

1/N and the default heuristic are instances of fast and frugal heuristics. These are fast in execution and frugal in the information used. Note that 1/N is not an investment heuristic, nor is the default heuristic a moral heuristic. Their range is broader. For instance, 1/N is used to achieve fairness in sharing goods between friends, where it is known as the equality rule, and

insurance policy buyers rely on the default heuristic when choosing between several policies. Heuristics are neither particular nor general, but they have some intermediate range of applicability. The study of heuristics serves three goals, the first descriptive, the second prescriptive, and the third one of design (Gigerenzer & Selten, 2001; Gigerenzer, Todd, & the ABC Research Group, 1999).

1. *The adaptive toolbox.* The goal is to analyze the adaptive toolbox—that is, the heuristics, their building blocks, and the evolved capacities exploited by the building blocks. This analysis includes phylogenetic, ontogenetic, and cultural development.
2. *Ecological rationality.* The goal is to determine the environmental structures in which a given heuristic is successful—that is, the match between mind and environment. This analysis includes the coevolution of heuristics and environments.
3. *Design.* The goal is to use the results of (1) and (2) to design heuristics and/or environments that teach and improve decision making in fields such as health care, law, and politics.

As in the natural sciences, attempts to understand the mind are structured by scientific themata (Holton, 1988). I already introduced one themata for modeling mental processes: optimizing versus satisficing. Heuristics aim at satisficing solutions (i.e., results that are good enough), which can be found even when optimizing is unfeasible. A second themata is universality versus modularity. When he was young, the philosopher Leibniz dreamt of formulating the universal calculus that settles all scientific debates and personal quarrels by simple calculation. Leibniz never realized his beautiful dream. Yet the vision of a universal calculus of reason persists in the form of surrogates—the expected utility calculus, logic, and Bayesian statistics have all at one time or another been interpreted this way. The study of the adaptive toolbox, in contrast, implies a modular view of the mind. Rather than one universal calculus, there are many heuristics, organized into building blocks by the evolved capacities they exploit.

THE ADAPTIVE TOOLBOX

With no claim to completeness, Table 2 lists 10 heuristics that, according to empirical evidence, are likely to be in the adaptive toolbox of humans and are used in an adaptive way (e.g., Bergert & Nosofsky, 2007; Bröder & Schiffer, 2003; Rieskamp & Otto, 2006). Each of these heuristics can be used with and without awareness. In the latter case, each provides a potential mechanism of intuition. An intuition is defined as a judgment that is fast in consciousness, whose underlying mechanism is unconscious, yet is nevertheless strong enough to act upon (Gigerenzer, 2007).

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[1] In some U.S. states, citizens are forced to make a choice.

TABLE 2

10 Heuristics That Are Likely in the Adaptive Toolbox

Heuristic	Definition[1]	Ecologically rational if:	Bold predictions
Recognition heuristic (Goldstein & Gigerenzer, 2002).	If one of two alternatives is recognized, infer that it has the higher value on the criterion.	Recognition validity >.5	Contradicting information about recognized object is ignored, less-is-more effect if $\alpha > \beta$, forgetting is beneficial.
Fluency heuristic (Schooler & Hertwig, 2005)	If one alternative is recognized faster than another, infer that it has the higher value on the criterion.	Fluency validity >.5	Less-is-more effect, forgetting is beneficial.
Take the best (Gigerenzer & Goldstein, 1996)	Infer which of two alternatives has the higher value by (a) searching through cues in order of validity, (b) stopping the search as soon as a cue discriminates, (c) choosing the alternative this cue favors.	Cue validities vary highly, moderate to high redundancy, scarce information (Hogarth & Karelaia, 2005, 2006; Martignon & Hoffrage, 1999, 2002).	Can predict as accurately as or more than multiple regression (Czerlinski et al. 1999), neural networks, exemplar models, and classification and regression trees (Brighton, 2006).
Tallying (unit-weight linear model; Dawes, 1979)	To estimate a criterion, do not estimate weights but simply count the number of favoring cues.	Cue validities vary little, low redundancy (Hogarth & Karelaia, 2005, 2006).	Can predict as accurately as or more than multiple regression.
Satisficing (Simon, 1955; Todd & Miller, 1999)	Search through alternatives, and choose the first one that exceeds your aspiration level.	Decreasing populations, such as those in seasonal mating pools (Dudey & Todd, 2002).	Unknown
1/N; equality heuristic (DeMiguel et al., 2006)	Allocate resources equally to each of N alternatives.	High unpredictability, small learning sample, large N.	Can outperform optimal asset allocation models.
Default heuristic (Johnson & Goldstein, 2003)	If there is a default, do nothing about it.	Values of those who set defaults match with those of decision maker, consequences of choice hard to predict.	Can predict behavior when trait and preference theories fail.
Tit-for-tat (Axelrod, 1984)	Cooperate first, keep a memory of Size 1, and then imitate your partner's last behavior.	If other players also play tit-for-tat; if the rules of the game allow only defection or cooperation, but not divorce.	Can earn more money than optimization (backward induction).
Imitate the majority (Boyd & Richerson, 2005)	Look at a majority of people in your peer group, and imitate their behavior.	Environment is not or only slowly changing, info search is costly or time-consuming.	Mass phenomena, cultural evolution.
Imitate the successful (Boyd & Richerson, 2005)	Look for the most successful person and imitate his or her behavior.	Individual learning slow, info search costly and time-consuming.	Cultural evolution.

Note. The two last columns are illustrative, not exhaustive.
[1]For formal definitions, see references.

SELECTING A HEURISTIC

How does the mind select a heuristic from the adaptive toolbox or construct a new one from its building blocks? One answer is reinforcement learning, with the unit of learning being heuristics rather than behavior. Strategy selection learning theory describes how heuristics are selected based on individual reinforcement learning (Rieskamp & Otto, 2006). In general, heuristic selection can be guided by (a) individual reinforcement learning; (b) social learning, as in medical training in which physicians are instructed on what cues to look up in what order; and (c) evolutionary learning, as with rules of thumbs for predation and mate search in animal species (Hutchinson & Gigerenzer, 2005).

Various experiments suggest that people tend to check the ecological rationality of a heuristic from trial to trial before they eventually apply it routinely. Consider the recognition heuristic (Table 2). Before it is applied, two judgments have to be made: recognition and evaluation. The recognition judgment determines whether the heuristic can be used in the situation—that is, whether one alternative is recognized but not the other. If the heuristic can be applied, an evaluation process may still inhibit its application. This process amounts to assessing the heuristic's ecological rationality for a given situation. A neuroimaging study indicates that the heuristic is the default, so to speak, but that contradicting source knowledge and criterion knowledge can deter its use (Volz et al., 2006). For instance, Oppenheimer (2003) asked members of Stanford University which city has the larger

population between Chernobyl and Heingjing and between Sausalito and "Heingjing." Heingjing was invented by the author and could not be (correctly) recognized, whereas participants knew Chernobyl because of the nuclear accident (source knowledge) and Sausalito because it was a small nearby town of 7,500 (criterion knowledge). In both cases, many participants did not follow the recognition heuristic and answered "Heingjing." They recognized a city for reasons independent from population (which invalidated the heuristic in this situation) or because they had direct knowledge about the criterion (population).

In general, experimental studies indicate that people select different heuristics in different environments, intuitively evaluating their ecological rationality (as specified in Table 2). For instance, the larger the recognition validity in a study, the larger the proportion of participants who follow the recognition heuristic (Pohl, 2006), and the larger the variability of cue validities, the larger the proportion of participants who follow the take-the-best heuristic (Rieskamp & Otto, 2006). The adaptive selection is not perfect: It tends to be more successful in a new situation but seems to break down when people begin to use a heuristic habitually and when the experimenter later changes the environment (Bröder & Schiffer, 2006). Although adaptive heuristic selection has been reported in several studies, less is known about how this process works. In general, the modular organization of the adaptive toolbox reduces the size of the selection problem—some (but not all) heuristics are applicable in a given situation. My intuition is that there is no universal Bayesian algorithm that evaluates which heuristic to use but that instead there are multiple selection principles, as indicated above.

HEURISTICS AND THEIR BUILDING BLOCKS

Heuristics are typically composed of several building blocks, and by adjusting one or a few of these, they can be adapted to new situations. Consider the take-the-best heuristic, which has three building blocks (Gigerenzer & Goldstein, 1996): search rule (look up cues in order of validity), stopping rule (stop search after the first cue discriminates between alternatives), and decision rule (choose the alternative that this cue favors). Note that the building blocks are fitted to each other. The stopping rule employs extremely limited search, yet the search rule adjusts for that by ordering cues according to their validity. Validity does not guarantee the "best" ordering of cues; it ignores dependencies between cues and, despite (or because of) this, produces reasonably robust orders. Given that the problem of ordering cues is computationally intractable, it would be unrealistic to assume that minds search for the best order (Martignon & Hoffrage, 2002).

However, how do people adjust to new situations where it is difficult to learn a reasonable cue order? Experimental results suggest that people in these circumstances tend to extend search to enable more extensive cue learning (i.e., stop search after two

cues indicate the same alternative; Dieckman & Todd, 2004). This stopping rule asks for a confirming reason and is ecologically rational in situations where one is uncertain about the order of cues (Karelaia, 2006) and also in situations where the search for cue values is inexpensive. Similarly, the tit-for-tat heuristic (see Table 2) can be adjusted by changing the memory from Size 1 to Size 2, resulting in tit-for-two-tats. This prevents both tit-for-tat players from defecting after one makes a mistake.

The take-the-best heuristic is designed to help one choose between two alternatives, but its building blocks can be adjusted for classification tasks in which one object has to be assigned to one of several classes (e.g., assigning a patient to one of several treatments). The resulting classification rule, a *fast-and-frugal tree*, allows for a quick decision at each node of the tree (Fig. 1; Martignon, Vitouch, Takezawa, & Forster, 2003).

EVOLVED CAPACITIES

Heuristics exploit evolved capacities. The term *evolved* does not refer to a skill shaped by nature or nurture alone. Rather, nature provides humans a capability, and extended practice turns it into a capacity. Without the evolved capacities, heuristics could not do their job; without heuristics, the capacities alone could not do the job either. For instance, the first two heuristics in Table 2 take advantage of the evolved capacity for recognition memory, such as face, voice, and name recognition. The take-the-best, tallying, and satisficing heuristics exploit recall memory, including the ability to recall cues, cue values, and aspiration levels. Imitation heuristics take advantage of the human capacity to imitate, a capacity that no other species has evolved in this form. The tit-for-tat heuristic is probably based on the evolved capacity for reciprocal altruism, which enables the social exchange of favors and goods among unrelated conspecifics. Evidence of tit-for-tat behavior in other species apart from humans is scant and controversial. Heuristics are simple precisely because they exploit complex evolved capacities.

ECOLOGICAL RATIONALITY

Behavior is often called rational if and only if it follows the laws of logic or probability theory, and psychological research has consequently interpreted judgments that deviate from these laws as reasoning fallacies. From a Darwinian perspective, however, the goal of an organism is not to follow logic, but to pursue objectives in its environment, such as establishing alliances, finding a mate, and protecting offspring. Logic may or may not be of help. The rationality of the adaptive toolbox is not logical, but ecological; it is defined by correspondence rather than coherence.

The study of ecological rationality analyzes which heuristics match with which environmental structures. Its tools are mathematical analysis and computer simulation, and its results are
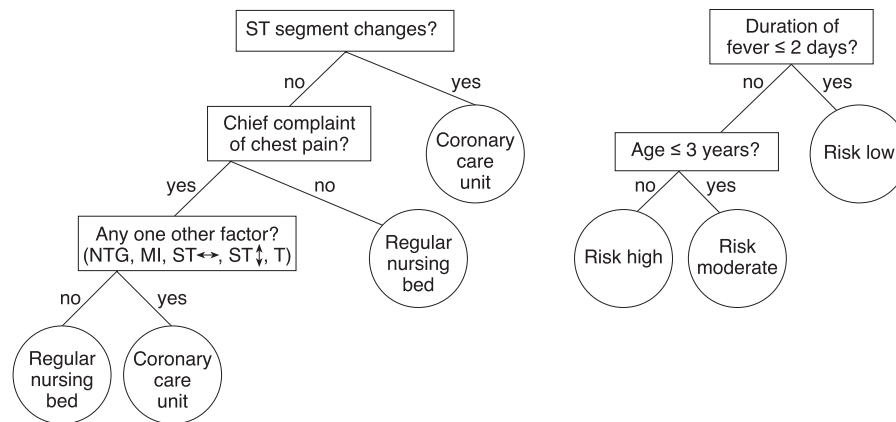
Fig. 1. Fast-and-frugal trees for coronary care unit allocation (left; based on Green & Mehr, 1997) and for macrolide prescription for children (right; based on Fischer et al. 2002). The former assists emergency unit physicians in deciding whether a patient with severe chest pain should be sent to the coronary care unit or a regular nursing bed; the latter assists pediatricians in diagnosing whether children are infected with *Mycoplasma pneumoniae* and should be treated with first-line antibiotic treatments (macrolides). A fast-and-frugal tree is a classification tree that has $M + 1$ exits (M is the number of cues) and allows for a classification after each question (cue). In contrast, the number of end nodes of a complete tree (2^M) increases exponentially, which makes complete trees computationally intractable for large numbers of cues.

statements such as "Heuristic A is more frugal or accurate than is Heuristic B in Environment X" (see the examples in Table 2). For instance, if cue validities are highly skewed (noncompensatory), no linear strategy can be more accurate in fitting than the frugal take-the-best heuristic; yet if cue validities are equal, the tallying strategy is more accurate than the take-the-best heuristic (Martignon & Hoffrage, 2002). The results can also be quantitative (rather than comparative), such as the curves for less-is-more effects (Goldstein & Gigerenzer, 2002).

The study of ecological rationality also aims to discover structures that permit more general conclusions about the match between cognitive processes and environments. One example is the degree of predictability of the criterion (e.g., stock portfolio, weather) one wants to forecast (everything else being equal), which gives rise to the following selection principle: The more unpredictable a situation, the more information needs to be ignored.

This general selection principle may at first seem counterintuitive, but its validity can in fact be easily seen. When predicting the outcome of a chance device such as a roulette wheel, all previous information can be ignored. When predicting the outcome of a completely deterministic system known in all details, all relevant information must be taken into consideration. Most human goals lie somewhere in between—for instance, selecting investment funds or predicting whether a patient with severe chest pain is suffering a heart attack. As the predictability is uncertain in both cases, but higher for heart attacks than for stocks, this principle suggests that good diagnostic systems should ignore information in both cases but should do so to a greater degree when investing in stocks.

Previous research emphasized that ignoring information is necessary because of the costs involved in acquiring it, pro-

ducing an accuracy–effort trade-off (Payne et al., 1993). This is only half of the story—the thought-provoking part is yet to come. In an uncertain world, even if the information costs nothing, cognitive processes should still ignore a proportion of it. Dawes's seminal work (1979) showed that the tallying heuristic (which does not pay attention to weights) can match and outperform multiple regression in prediction. In the late 90s, we discovered—to our own surprise—that the take-the-best heuristic (which relies on one good reason and ignores the rest) was both more frugal and more accurate than multiple regression (Gigerenzer & Goldstein, 1999). Czerlinski et al. (1999) confirmed this result for 20 real-world problems with binarized cues, which are arguably more psychologically plausible than are continuous real values. The take-the-best heuristic made, on average, more accurate predictions than did the multiple regression strategy, and it made equally accurate predictions when tested with continuous cues. Brighton (2006) showed for the first time that the take-the-best heuristic is often more accurate and frugal than are complex nonlinear algorithms, including neural networks, exemplar models, and classification and regression trees. In these situations, the trade-off between accuracy and effort disappears. This insight may be hard to grasp, but cognition seems to take advantage of this fact intuitively. An adaptive system needs to know when to ignore information, even when it is free, and cognitive theories need to model how information is ignored.

DESIGN

A good theory of the mind should be useful. The study of heuristics aspires to this objective by improving strategies and/or environments to support better decisions. For instance, Green

and Mehr (1997) dealt with the problem of overcrowding in an intensive care unit in a Michigan hospital, which was caused by physicians who cautiously allocated 90% of the patients suspected of heart disease to the unit. Using the building blocks of the take-the-best heuristic, they designed a fast-and-frugal tree for coronary care unit allocation, which was more accurate in predicting heart attacks than were a complex logistic regression system and the physicians' decisions (Fig. 1). Fischer et al. (2002) designed a fast-and-frugal tree for macrolide prescription in children with community-acquired pneumonia. Heuristics offer diagnostic procedures that can be applied rapidly and with limited information. Last but not least, they are transparent. Physicians like heuristic decision tools because these correspond to their own intuitions, and the physicians at the Michigan hospital still happily use the fast-and-frugal tree. As Elwyn, Edwards, Eccles, and Rovner (2001) wrote in *Lancet*, "the next frontier will involve fast and frugal heuristics; rules for patients and clinicians alike" (p. 574).

Apart from designing strategies, one can also design human environments. Consider number representation. The Arabic number system proved superior to earlier systems in simplifying division. Unlike Roman numerals, it allows us to determine which of two numbers is larger by simply using the take-the-best heuristic. For example, consider 2,543,001 and 2,498,999. Comparing the digits from left to right and stopping after the first two differ shows that the first number is greater than the second $(5 > 4)$. Traffic rules governing right of way and the FIFA soccer world championship rules are designed in the same lexicographic way. Relying on one good reason and making no trade-offs can promote safety and perceived fairness in human interaction—consider the complaints over the American Bowl Championship Series formula that ranks college football teams by complex weighting and adding. External representations of risk that are adapted to the human mind have improved risk communication in medicine, law, and AIDS counseling and are indispensable for informed consent and shared decision making (Gigerenzer 2002; Gigerenzer & Edwards 2003; Hoffrage, Lindsey, Hertwig, & Gigerenzer, 2000). Applications in legal decision making are provided by Gigerenzer and Engel (2006) and Dhami (2003), and applications in marketing are provided by Yee, Hauser, Orlin, and Dahan (2007).

THEORY INTEGRATION

Psychological theory today is a patchwork, much like the mosaic of principalities that eventually became Italy and Germany circa 1870. A major goal for all theorists must be to integrate what exists rather than to neglect or denigrate the rest of psychology. Connecting theories conceptually exposes our mutual blind spots and can lead to new and bold insights. For instance, Schooler and Hertwig (2005) implemented the recognition and fluency heuristics in Anderson's ACT–R cognitive architecture and discovered that systematic forgetting is beneficial for heu-

ristic inference, producing counterintuitive less-is-more effects. Pleskac (2007) investigated the recognition heuristic from the perspective of signal-detection theory and derived how false recognition, such as déjà vu, influences the performance of the heuristic. Lexicographic heuristics such as the take-the-best heuristic have been used for modeling the cognitive processes underlying Allais' paradox and other violations of expected utility theory (Brandstätter, Gigerenzer, & Hertwig, 2006), confidence (Gigerenzer, Hoffrage, & Kleinbölting, 1991), and hindsight bias (Hoffrage, Hertwig, & Gigerenzer, 2000), which for the first time has enabled predictions as to whether or not hindsight occurs at an individual level. Finally, the puzzle of cognitive biases has begun to make sense from the perspective of the adaptive toolbox (Gigerenzer, 2004). In my opinion, the degree to which currently balkanized theories can be integrated will largely determine the future success of psychology as a discipline.

Why do heuristics work? They exploit evolved capacities that come for free, and thus they can provide solutions to problems that are different from strategies of logic and probability. In addition, they are tools that have been customized to solve diverse problems. By understanding the ecological rationality of a heuristic, we can predict when it fails and succeeds. The systematic study of the environments in which heuristics work is a fascinating topic and is still in its infancy. Eventually, it will clarify what models of logic, probability, and heuristics can contribute to understanding how cognition works.

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