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Heuristics

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ABSTRACT

For many legal problems, finding the absolutely best solution to a problem (i.e., optimization) is out of reach. The problem is too complex, information is scarce and contradictory, too many players are involved with dissimilar goals, or time is pressing and the world uncertain. Yet experts and laypeople are not paralyzed in such circumstances; they find solutions by using what is often called intuition, habit, or rules of thumb. The science of heuristics explicates the processes underlying intuition and habit. These heuristics are often unconscious, and their systematic study can help to improve decision making. Heuristics are not good or bad per se. Instead, their rationality is ecological; that is, they are successful in the environments (institutions) to which they are adapted. The study of the structure of environments, and their systematic change, is thus a necessary part of efforts to improve decision making under uncertainty.

INTRODUCTION

There are two views on the nature of heuristics. In the first, heuristics are seen as the solution to a problem. This view is common in mathematics, where heuristic methods are indispensable for problems that analysis cannot solve. Finding a proof, as opposed to checking its steps, is one example. Here, a heuristic is not a mental shortcut or a second-best solution: It is *the* way to find a solution. Similarly, in artificial intelligence and machine learning, heuristics provide solutions when optimization is out of reach. Optimization—as opposed to the use of heuristics—means finding the absolutely best strategy for a given problem. An example of this is calculating the maximum of a function. However, we do not know the optimal strategy for the majority of interesting problems, including well-defined problems such as chess, ill-defined problems with ambiguous pay-off structures or multiple goals, and social interactions whose present rules may change in the future. Heuristics are essential when the optimal strategy cannot be computed by mind or machine (as in chess), or when optimization is too costly, slow, and dangerous (as in intensive care unit decisions). According to this first view, heuristics are indispensable, because optimization can only solve a small class of problems in the real world.

In the second view, heuristics are the problem itself. This approach assumes that we can find the optimal strategy for a given problem and considers heuristics to be second-best strategies. The use of heuristics is attributed to people's cognitive limitations rather than to the nature of the problem. These limitations are, in turn, seen as the source of various cognitive illusions or biases. The terms *heuristics* and *biases* are often used interchangeably, since both are seen as creating the problem, even though the one term describes a process and the other an outcome. This second view is widespread in social psychology and behavioral economics and has, accordingly, shaped behavioral law and economics.

If the first view is true, heuristics are indispensable for lawyers, lawmakers, judges, legal institutions, and their clients; the only question that remains is which heuristics should be used in which situations. If the second view is true, these legal agents fare better without heuristics by relying on logic, probability theory, or optimization. In this chapter, I will sketch the foundations of a science of heuristics that resolves the tension between these two views. I begin with some widespread misconceptions about the nature of heuristics.

SIX MISCONCEPTIONS

1. *People use heuristics only because they have limited cognitive capacities.* This much-repeated phrase incorrectly locates the reason for heuristics exclusively inside the human mind, which is seen as an impoverished instrument.[1] However, as mentioned before, external reasons (e.g., that a problem is computationally intractable, the future is uncertain, and the goals are ambiguous) are sufficient for minds and computers to rely on heuristics. For instance, when former chess world champion Kasparov played against the IBM chess program Deep Blue, both had to rely on heuristics. The reason is not simply because people or computers have limited cognitive capacities, but because the problem is computationally intractable. Its solution is not computable for even the most brilliant minds and the fastest machines. Limits of attention, memory, and reasoning can, of course, contribute to the use of simple heuristics, but external reasons are sufficient.

2. *Limited cognitive capacities are always bad.* This phrase is often implied but rarely stated, perhaps because it seems so obvious. Yet limited capacities can in fact enable cognitive functions, not only constrain them (Hertwig and Todd 2003). For instance, large memory capacities can prevent language acquisition in children as well as in neural networks, whereas starting small (limited capacity) and with simple sentences (baby talk) enables learning (Elman 1993). Luria's (1968) famous mnemonist with almost unlimited

[1] For example, "Employing simplifying heuristics is a rational approach to decision making only *because* of our cognitive limitations" (Korobkin 2003, pp. 1292–1293).

memory could perfectly recite pages of text, but his memory was flooded by detail, so that he had problems summarizing the gist of the text and thinking on an abstract level. The short-term memory capacity limit of "seven plus/minus two"seems to enable us to detect covariation of events better than with higher (or lower) capacities (Kareev 2000). Zero-intelligence traders make as much profit as intelligent people do in experimental markets (Gode and Sunder 1993). Last but not least, satisficers are reported to be more optimistic and have higher self-esteem and life satisfaction, whereas maximizers excel in depression, perfectionism, regret, and self-blame (Schwartz et al. 2002). Limited capacities can have a function.

3. *Heuristics lead to second-best outcomes whereas optimizing leads to best outcomes.* If the optimal strategy is not known, or too slow, heuristics cannot be the second-best solution. They may be the only one. For this reason, the science of heuristics is both *positive* (what heuristics do people use?) and *normative* (what heuristics should be used in what situations?). Moreover, every optimization model is optimal only relative to a set of mathematically convenient assumptions. To the degree that these assumptions do not hold in the real world, the outcome of optimization can be disappointing. In these cases, optimizing theories are second best (Bookstaber and Langsam 1985). Thus, it is important to separate the terms *optimization* and *heuristics*, which refer to the internal process of decision making, from external evaluations such as *optimal*, *good*, and *bad results*, which refer to the outcome of decision making.

4. *Labels such as availability and representativeness "explain" behavior.* To explain and predict behavior, we need models of heuristics, not mere labels. A model of a heuristic is a rule that specifies a *process* anchored in mind and environment. For instance, *Tit-for-Tat* specifies the process "cooperate in the first move, keep a memory of size one, and then imitate the other player's move." This process exploits evolved abilities such as reciprocal altruism—the ability to cooperate with genetically unrelated members of the same species, which is almost uniquely human (as a consequence, there is little evidence that animals use Tit-for-Tat; see Hammerstein 2003). It also exploits structures of environments such as the rules of the prisoner's dilemma; when this environment changes, its seminal performance can deteriorate. The task of the science of heuristics is to understand and modify behavior based on the triad of heuristics, evolved abilities, and environmental structures. In contrast, commonsense labels such as availability neither specify a process rule nor the situations where a heuristic succeeds or fails. Labeling allows almost every phenomenon to be accounted for *post hoc*, inviting just-so story telling.[2] Explanations of behavior such as "actor A uses Tit-

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2 The seductive plausibility of labeling is a problem both in psychological studies and legal applications. For instance, a frequently cited study reported that people estimated that there are more

for-Tat in a class S of social situations" can be falsified, as they have been (Hammerstein 2003), whereas mere labels cannot be disproved, proved, or improved. Without precise models, one is left with the vague phrase that "heuristics are sometimes good and sometimes bad." To make this phrase informative, one needs to specify what the "sometimes"refers to, that is, to study the *ecological rationality* of a heuristic (see below). This task, however, cannot be accomplished until there are precise models rather than mere labels.

5. *Everything except optimization and logic is a heuristic.* Not every proposed explanation of behavior is a heuristic. A heuristic is a process model, that is, a type of strategy rather than a state. Long-term states, such as traits and attitudes, and short-term states, such as moods and affects, are possible explanations of behavior, but not heuristics. Strategies exist that are not fast and frugal, nor do they involve optimizing; endless committee meetings are one example. A fast and frugal heuristic is a strategy that ignores part of the information and enables fast decisions.

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words beginning with the letter "r" in English than words having "r" as their third letter. In fact, words beginning with "r" are far less numerous. The proposed explanation for this bias was that people judge "frequency by availability, that is, by an assessment of the ease with which instances could be brought to mind" (Tversky and Kahneman 1982, p. 166). This sounds plausible, but note that there was no definition or independent measure of "ease" in that study (or elsewhere; no replication seems to exist). When Sedlmeier et al. (1998) measured "availability" independently as the time it takes a person to recall the first word ("ease"), or alternatively as the number of words that a person can produce within a fixed time ("number"), it was found that neither of these two measures actually predicted people's frequency judgments of words with "r" or other letters. Thus, there was in fact no evidence for "availability," defined as "ease" or as "number." One could conjecture that there might be different ways to define availability, which might actually predict frequency judgments, but this possibility is the very problem. Vague labels such as availability and representativeness explain at once too little and too much. Too little, because we do not know when and how these heuristics work; too much because, *post hoc*, one of them seems to "explain" almost any experimental result (Gigerenzer 2000).

The same problem arises in legal writings, where the term *availability* has been used to "explain" many phenomena, from residents worrying about the health effects of Love Canal to their fear of nuclear accidents. However, the meaning of the term is constantly being changed; here are some illustrations. People judge the frequency of events, we are told, (a) by the *actual ease of retrieval* ("people tend to think that risks are more serious when an incident is readily called to mind or 'available' "; Sunstein 2000, p. 5); (b) by its *imagined ease* ("the frequency of some event is estimated by judging how easy it is to recall other instances of this type [how 'available' such instances are]"; Jolls et al. 1998, p. 1477), (c) by the *number of instances that come to mind* ("a person may overestimate the incidence of AIDS simply because many of his acquaintances have the disease and he can easily think of AIDS cases"; Kuran and Sunstein 2000, p. 381), (d) by the *recency of witnessing one instance* ("People tend to conclude, for example, that the probability of an event [such as a car accident] is greater if they have recently witnessed an occurrence of that event than if they have not"; Jolls et al. 1998, p. 1477), and (e) by the *salience of instances* (" 'availability,' after all, is in many respects just another name for the 'salience' of standard political theory"; Noll and Krier 2000, p. 353). Ease, imagined ease, number, recency, and salience are, however, not the same thing and may not even be correlated (Sedlmeier et al. 1998).

6. *More information is always better.* In most models of rationality, it is taken for granted that the quality of the decision (or prediction) always improves—or at least cannot diminish—with increasing amounts of information. However, this assumption is incorrect; the relation between amount of information and quality of prediction is often an inversely U-shaped curve (Gigerenzer et al. 1999). One reason for this is that part of the information we have today does not generalize to tomorrow; by ignoring information, heuristics can lead to better predictions than can strategies that use all relevant information. Specifically, when uncertainty is high, one needs to ignore part of the information to make *robust* predictions (see below). The important distinction here is between *data fitting* and *prediction*. To fit the parameters of a model to a body of data that is already known is called data fitting; here and in other situations where one simply explains what has already happened, more information (and more free parameters) is almost always better. To test whether a model with fixed parameters can predict future or unknown events is called prediction. In an uncertain world that is not perfectly predictable, the belief that more information is always better is no longer true. For instance, based on the limited knowledge of semi-ignorant people, the recognition heuristic (Goldstein and Gigerenzer 2002) predicted the outcomes of the Wimbledon tennis matches more accurately than the "official"predictions based on the ATP world rank lists and the seedings of the Wimbledon experts did (Frings and Serwe, submitted). The Tit-for-Tat heuristic, which only keeps a memory of length one, has repeatedly made more money than have strategies using more information and computation. As for every strategy, its success depends on the structure of the environment (the rules of the institution and the strategies of the other players). Experts base judgments on surprisingly few pieces of information (Shanteau 1992), and professional golfers and handball players tend to make better decisions when they have less time (Beilock et al. 2002; Johnson and Raab 2003). Less information, time, and knowledge can be more.

Why are these misunderstandings entrenched in the literature? For one, heuristics are evaluated against divine ideals, which makes them appear to be all-too-human failures. I refer to three ideals: *omniscience, optimization*, and *universality*. Omniscience is the ideal of full knowledge, which is often (at least approximately) assumed in theories of human rationality; its modest sister is the ideal that more information is always better, or cannot hurt. Optimization is the ideal that a best solution for each problem exists and that we know how to find it. Universality is the ideal that this best strategy, such as maximizing expected utility, is universally the same for all problems. Heuristics run counter to these ideals, in that they assume limited knowledge rather than omniscience. Their goal is to find a good solution without the fiction of an optimal one. There is no universal heuristic, but an *adaptive toolbox* with many building blocks from which new heuristics can be constructed.

WHAT IS BOUNDED RATIONALITY?

Paradoxically, three distinct and partially contradicting interpretations of bounded rationality exist. Proponents of law and economics tend to think of bounded rationality as *optimization under constraints*, such as information costs. Here, the omniscience of unbounded rationality is no longer assumed, but the assumption is made that people stop search when the marginal benefits of search equal its costs. The result is "a research program to build models populated by agents who behave like working economists or econometricians" (Sargent 1993, p. 22). In personal conversation, Herbert Simon once remarked with a mixture of humor and anger that he had considered suing those authors who misuse this term of bounded rationality to construct ever more psychologically unrealistic theories (Gigerenzer 2004). Optimization under constraints is silent about the heuristics people use. Proponents of behavioral law and economics tend instead to think of bounded rationality as the study of *cognitive illusions*. These two interpretations are like fire and water: the first emphasizes rationality, the second irrationality. Jolls et al. (1998, p. 1477) wrote, "Bounded rationality, an idea first introduced by Herbert Simon, refers to the obvious fact that human cognitive abilities are not infinite. We have limited computational skills and seriously flawed memories." This second interpretation provides a role for heuristics, but mainly as a problem. Simon's bounded rationality is neither the study of optimization under constraints nor a supplement of mental biases added to rational choice theory. Although the cognitive illusions program seems to be the very opposite of the optimization program, both essentially share the same norms. These (mostly logical norms) are used to define human judgment as an error.

There is a third view of bounded rationality—one that Simon actually put forward (Simon 1956, 1990) upon which others have elaborated (e.g., Gigerenzer et al. 1999; Gigerenzer and Selten 2001; Payne et al. 1993). This interactive view concerns the adaptation of mind and environment. Simon's (1990) ecological conception is best illustrated by his analogy between bounded rationality and a pair of scissors: "Human rational behavior is shaped by a scissors whose blades are the structure of task environments and the computational capabilities of the actor" (p. 7). Just as one cannot understand how scissors cut by looking only at one blade, one cannot understand human behavior by studying cognition or the environment alone. As a consequence, what looks like irrational behavior from a logical point of view can often be understood as intelligent behavior from an ecological point of view (e.g., as a response to a social environment or a legal institution).[3] Furthermore, many remaining true errors can be eliminated by

[3] For instance, the argument for paternalism (or for anti-anti-paternalism, in Sunstein's terms) is based, in part, on pointing out logical errors in ordinary people's reasoning. The problem with this argument is that any discrepancy between human judgment and the laws of logic is taken as indicating human irrationality, rather than the limits of logic, or an inappropriate normative use

improving the environment rather than people's minds. Consider, for instance, the well-documented problem: many judges, jurors, and law students are confused when they hear the conditional probabilities in a murder trial with DNA evidence (Koehler 1997). Classical decision theory would advise these legal actors to take a course in Bayesian statistics—the problem and its solution are assumed to be internal; that is, people's cognitive virtues need to be improved. There is, however, a much faster and more efficient external solution: to present the evidence in natural frequencies rather than conditional probabilities. For instance, only 10% of professional lawyers understood the implications of DNA evidence when it was presented in the form of conditional probabilities. This number increased to about 70% with natural frequencies, and guilty verdicts decreased (Hoffrage et al. 2000; Lindsey et al. 2003).

I refer to this third interpretation of bounded rationality as the *science of heuristics*. It has three goals:

1. *Adaptive toolbox.* What are the heuristics and their building blocks in the adaptive toolbox?
2. *Ecological rationality.* In which environments (institutions) will a given heuristic succeed or fail; that is, when is it ecologically rational?
3. *Design.* How can heuristics be designed for given problems (environments), and how can environments be designed to improve human problem solving?

The first question is descriptive, the second normative, and the third concerns human engineering. In my view, the rationality of a heuristic is external or "ecological" (i.e., how well a heuristic performs in a real-world environment) and not internal. External criteria include predictive accuracy, frugality, speed, and transparency. For instance, bail decisions aim to predict the trustworthiness of defendants accurately; frugality is at issue when one asks whether a court should admit all of the 112 defense witnesses, or whether 12 jurors are better than 0; speed is reflected in the doctrine that "only swift justice is good justice" (Dittrich et al. 1998); and transparency is a goal for those who aim at fewer and simpler tax laws, with the hope of increasing public trust and compliance (Epstein 1995). The internal criteria of rational choice theory, such as transitivity,

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of logic. Sunstein (2005), for illustration, presents Tversky and Kahneman's (1983) Linda problem and calls people's modal response "an obvious mistake, a conjunction error." The issue, however, is far from obvious; there is disagreement whether the fallacy is in people's minds or rather in the researchers' logical norm. Logicians and philosophers such as Hintikka (2004) argue that the problem is in the proposed norm rather than in the human mind, as do linguists and psychologists (e.g., Hilton 1995; Moldoveanu and Langer 2002; Sweetser 1990). Hertwig and Gigerenzer (1999) argue that the majority response arises from social intelligence (which helps to infer what the English terms *probable* and *and* mean in a given pragmatic context) and show how to make the "conjunction fallacy" largely or completely disappear. Apparent "logical errors" that most likely reflect social intelligence (unnoticed by social scientists) are not good arguments for paternalism.

consistency, and additivity of probabilities, are important insofar as they contribute to improving the external criteria.

The science of heuristics has its origins in the work of Nobel laureates Herbert Simon and Reinhard Selten. Early work on heuristics in decision making focused on preferences, not inferences, that is, on problems where no external criterion of success exists (Payne et al. 1993; Tversky 1972). Therefore, the ecological rationality of a heuristic—the conditions in which a heuristic does and does not work—could not be systematically studied. Rather, internal criteria such as dominance or a linear weighting and adding strategy were used as an a priori gold standard and, compared to these standards, heuristics were by definition always second best. Only after studying real-world situations with external criteria for accuracy was it discovered that heuristics were in fact often more accurate than the "normative" weighting and adding strategy (e.g., Czerlinski et al. 1999; Dawes 1979). An introduction to specific models of heuristics and their ecological rationality can be found in Gigerenzer et al. (1999) and Gigerenzer and Selten (2001). Explicit reference to bounded rationality is relatively new in the law. For instance, Engel (1994) reported that he did not know of any German administrative lawyer who had ever referred to bounded rationality. I will now introduce heuristic problem solving with three situations where optimal strategies are unknown.

IF OPTIMIZATION IS IMPOSSIBLE, HOW DO PEOPLE MAKE DECISIONS?

Coronary Care Unit Decisions

A patient with severe chest pains is rushed to the emergency department in a hospital. The physicians need to make a decision, and quickly: Should the patient be assigned to the coronary care unit or to a regular nursing bed with ECG telemetry? In two Michigan hospitals, emergency physicians sent 90% of all patients to the care unit. This "defensive" decision making led to overcrowding, decrease in quality of care, and greater health risks for the patient. Researchers from the University of Michigan were called in to teach the physicians how to use the Heart Disease Predictive Instrument, an expert system (Green and Mehr 1997). This consists of a chart with some 50 probabilities and a logistic formula with which the physician, aided by a pocket calculator, can compute the probability of requiring the coronary care unit for each patient. If the probability is higher than a certain value, then the patient is sent to the care unit, otherwise not. A quick glance at the chart makes it clear why the physicians are not happy using this and similar systems. To them, the calculations are nontransparent; they do not understand the system, as it does not conform to their intuitive thinking, and hence they avoid using it.

The researchers tried a third procedure: a heuristic that has the structure of physicians' intuitions, but is based on empirical evidence. This *fast and frugal*

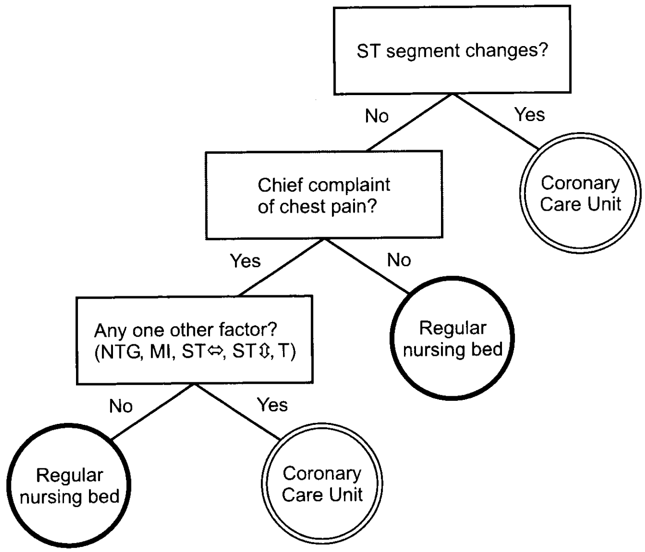

Figure 2.1 A fast and frugal decision tree for coronary care unit allocation (adapted from Green and Mehr 1997).

tree (Figure 2.1) poses only a few yes/no questions. If a patient has a certain anomaly in his electrocardiogram (the so-called ST segment), he is immediately admitted to the coronary care unit; no other information is required. If this is not the case, a second cue is considered: whether the patient's primary complaint was chest pain. If this is not the case, he is immediately assigned to a regular nursing bed. No further information is sought. If the answer is yes, then a third question is asked to classify the patient.

This heuristic violates the ideal of omniscience: It ignores all 50 probabilities, uses only one or a few predictors, and ignores the rest. It also does not combine (i.e., weight and add) the predictors. For instance, an anomaly in the ST segment cannot be compensated for by any of the other predictors. This noncompensatory heuristic allows the physician to stop search for information and make a decision after each question. It is quick, frugal, transparent, and easy to understand, so that physicians are willing to use it. But how accurate is it? Note that every diagnostic technique can make two kinds of errors, which are called *false alarms* (or Type-I errors) and *misses* (or Type-II errors)—a distinction courts rarely make when they talk about *the* rate of error (Faigman and Monahan 2005). Figure 2.2 shows the results of the study, with the false alarm rate on the abscissa and the complement of the miss rate on the ordinate. An ideal diagnostic procedure allocates all of those to the coronary care unit who should be there (who suffer an heart attack) and none of those who should not be there (who do not suffer an heart attack). Thus, the ideal strategy has a miss rate and a false alarm rate of zero, and is located in the upper left corner of Figure 2.2. Still, no perfect strategy is known; the problem of predicting infarctions is too difficult.

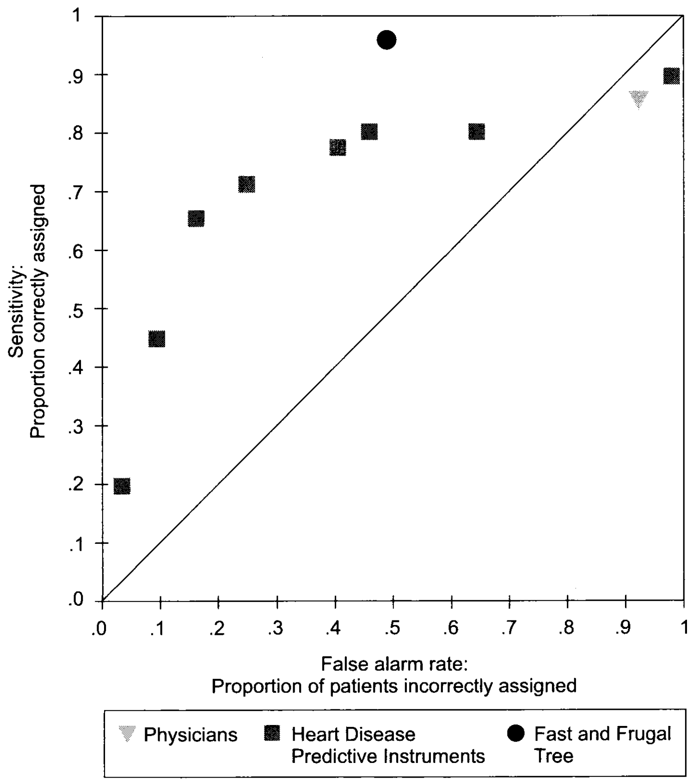

Figure 2.2 Coronary care unit decisions by physicians, the Heart Disease Predictive Instrument (a logistic regression), and the fast and frugal tree (adapted from Green and Mehr 1997). Accuracy is measured by the proportion of patients correctly assigned to the coronary care unit ("sensitivity" = "1 – miss rate"), and the proportion of patients incorrectly sent to the unit ("false alarm rate"). Correct assignment is measured by the occurrence of myocardial infarction. The diagonal represents chance performance.

How do the three methods used to make the coronary care unit decision compare in terms of accuracy? The average accuracy of physicians' intuitive decisions was slightly below (!) chance level (the diagonal). The Heart Disease Predictive Instrument is represented by a series of points; its accuracy was substantially better than chance. The reason why there is more than one point is that one can adjust the criteria, which represent various trade-offs between the two possible errors. The fast and frugal tree was more accurate in classifying actual heart attack patients than were the expert system and physicians. Note that the expert system contained all of the information that the heuristic had, as well as more. Simplicity can pay off.

Yet how can less information be better than more? The study of the ecological rationality of the heuristic specifies the conditions in which this is the case, and in which it is not. Several conditions are known and have been formalized

(Martignon and Hoffrage 1999, 2002; Katsikopoulos and Martignon 2006). Here I summarize two of these. In data fitting, a fast and frugal tree that ignores information will be as accurate as a logistic regression that uses all available information if the weights of the cues are heavily skewed (e.g., regression weights such as 1, 1/2, 1/4, 1/8, ...). If there is substantial unpredictability involved (and heart attacks are highly unpredictable, as Figure 2.2 illustrates), the heuristic is likely to be more accurate than the logistic regression because its simplicity tends to make it more robust. In other words, to make good decisions under high uncertainty, one needs to ignore part of the relevant information.

Do physicians who rely on the heuristic and ignore information run the danger of being sued for malpractice? For illustration purposes, consider a patient who showed no ST segment change and whose primary complaint was not chest pain. Relying on the coronary care heuristic, he was sent to a regular bed. Two days later, he died from heart disease. His relatives sued the hospital for malpractice after they found out that the doctors only checked two variables and ignored all others. Does the hospital have a chance of winning? Time pressure, coronary care unit space, and cost-benefit calculations might count. The answer depends, however, on the standard court practice, which varies across countries. Still, two elements are commonly found: reliance on formal rules of consent and on the state-of-the-art treatment (Engel 2000). Note, however, that the state-of-the-art treatment, at least in the two Michigan hospitals, was the intuitive, holistic decision making by physicians. Its accuracy, which does not seem to have been tested before, was only at chance level (Figure 2.2). Intuitive decisions, whose rationale is not made transparent to the public, and which physicians themselves may not be aware of, seem to protect primarily the physician, not the patient.

Medical malpractice suits are often assumed to increase the costs of negligence and therewith the amount of care that physicians take. However, as the present case illustrates, the threat of malpractice can also backfire and lead to defensive decision making, which decreases the quality of care. In addition, it seems to produce a medical "split brain." In personal conversation, many physicians have told me that they use only a few cues to make a diagnosis or treatment allocation, and are unsure about the accuracy of this procedure. In public, however, they claim to have processed all information and found the optimal treatment (Gigerenzer 2002). The physicians at the two Michigan hospitals, for instance, seem to have relied on the wrong ("pseudodiagnostic") cues, according to the dismal quality of their intuitive decisions (Green and Yates 1995). Once physicians' intuitive heuristics are made public and tested, one can progress to the next step of improving these by better, empirically informed heuristics.

The potentials of fast and frugal heuristics are currently being discussed in medicine. According to Naylor (2001, p. 523), they can lead to "understanding the cognitive processes of those master clinicians who consistently make superb decisions without obvious recourse to the canon of evidence-based medicine." Good experts ignore more information than do novices, but the defensive character of much of present-day health care is an institutional straightjacket that hinders young physicians from learning the art of heuristics.

Due Process

One of the initial decisions of the legal system is whether to bail the defendant unconditionally or to react punitively by bailing with conditions such as curfew or imprisonment. In the English system, magistrates are responsible for making this decision. About 99.9% of English magistrates are members of the local community without legal training. The system is based on the ideal that local justice be served by local people. In England and Wales, magistrates make decisions on some two million defendants every year. They sit in court for half a day every one or two weeks and make bail decisions as a bench of two or three. The law says that magistrates should heed the nature and seriousness of the offense; the character, community ties, and bail record of the defendant; as well as the strength of the prosecution case; the likely sentence if convicted; and any other factor that appears to be relevant.[4] Yet the law is silent on how magistrates should weigh and integrate these pieces of information, and the legal institutions do not provide feedback as to whether their decisions were in fact appropriate or not. The magistrates are left to their own intuitions.

How do magistrates actually make these millions of decisions? To answer this question, several hundreds of trials were observed in two London courts over a 4-month period (Dhami 2003). The average time a bench spent with each case was between 6 and 10 minutes. The analysis of the actual bail decisions revealed a fast and frugal heuristic that fitted 95% of all bail decisions in Court A (predictive accuracy = 92%; Figure 2.3, left). When the prosecution requested conditional bail, the magistrates also made a punitive decision. If not, or if no information was available, a second reason then came into play. If a previous court had already imposed conditions or remand in custody, then the magistrates also made a punitive decision. If not, or if no information was available, they followed the action of the police.

The magistrates in Court B used a heuristic with the same structure, except that one of the reasons differed (Figure 2.3, right). The first two reasons had the same "pass-the-buck" rationale as those in Court A. Both heuristics had the same structure as the coronary care unit heuristic: a *fast and frugal tree* (see below).

The self-presentation of the magistrates in interviews or questionnaires, however, was strikingly different. When magistrates were asked how they made bail decisions, they generally responded that they thoroughly examined all the evidence in order to treat individuals fairly and without bias. For instance, one explained that the situation "depends on an enormous weight of balancing information, together with our experience and training" (Dhami and Ayton 2001,

[4] The Bail Act 1976 and its subsequent revisions; see Dhami and Ayton (2001).

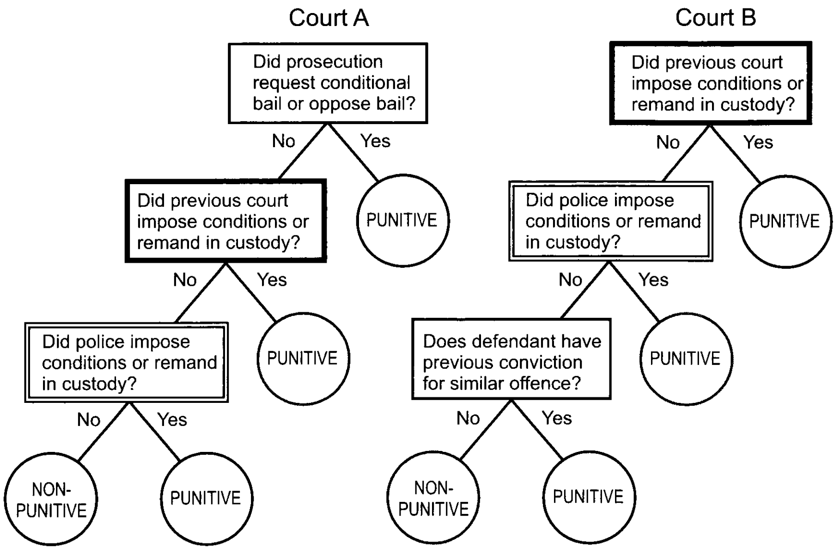

Figure 2.3 The heuristics underlying magistrates' bail decisions in two London courts. The heuristics predict about 92% of 342 actual bail decisions. Adapted from Dhami (2003).

p. 163). Another said that "the decisions of magistrates are indeed complex, each case is an 'individual case' " (Dhami 2001, p. 255). Contrary to the magistrates' self-perception, their heuristic seemed to involve no complex weighing and balancing of pros and cons.

These heuristics raise two issues: *due process* and *defensive decision making*. Both bail heuristics violate the ideal of due process, according to which the number of innocent defendants who are treated punitively—the false alarm rate—should be minimized. However, each bench based a punitive decision on just one reason, such as whether the police had imposed conditions or imprisonment. One could argue that relying on the police or a previous court might be a "short-cut" toward due process and, as we know from the coronary care study, a fast and frugal process need not be less accurate than a due process. However, in the present case, these "short-cut" reasons were not even correlated with the nature and seriousness of the offense. Moreover, nobody knows the accuracy of the bail decisions, because the British institutions seem to collect no information about their quality. Note that like physicians, magistrates can make two kinds of errors: *misses* and *false alarms*: They can bail a person who subsequently does not appear in court, threatens a witness, or commits another crime (a miss), or imprison a person who would not have committed a crime if he or she had been bailed (a false alarm). Even if statistics were kept about the number of misses, no information about false alarms would be available. One cannot find out whether an imprisoned person would have committed a crime if he or she had been bailed. That is, the magistrates operate in an institution in which only one of the two possible errors can be determined (unlike in the clinical institution of the care unit, where both can be measured; see Figure 2.2), but no data for errors is collected. In such an institution, it is difficult to learn how to solve the problem of protecting defendants. But magistrates can solve a different problem, namely of protecting themselves by "passing the buck."

The magistrates' situation shows that the design of institutions can transform the problem that the agents try to solve. Institutions that foster the self-protection of their professionals over the protection of their clients are prone to support forms of self-deception. If magistrates were fully aware of their heuristics, they would come into conflict with the ideal of due process. Thus, the bail heuristics are a solution, but not necessarily to the problem the magistrates are supposed to solve.

Discrimination

In 1985, the Equal Employment Opportunity Commission brought suit against a small Chicago company that offered cleaning and janitorial services. The firm, whose annual sales were only $400,000, went through seven years of federal litigation at outrageous expense for a company of that size.[5] The owner was a Korean immigrant, as were most of its employees. The suit charged that the firm discriminated in favor of persons of Korean origin. For instance, in the first quarter of 1987, 73% of applicants and 81% of those hired were Korean, whereas less than 1% of the national work force and at most 3% of the janitorial and cleaner work force were Korean. This statistical disparity provided the evidence against the firm.

The company owner had previously advertised in Chicago newspapers to hire workers, but these attempts were unsuccessful. The owner then switched to a more frugal method of recruitment, *word of mouth*: *Hire persons whom your employees recommend.*

This heuristic is the cheapest one and seems ecologically rational in the environment of the Korean immigrant community. Employees can inform an applicant more openly and accurately about the job than a newspaper advertisement or an employment agency can, which results in a higher probability of a good match. Furthermore, an employee who recommends someone may get into trouble if the new employee is a dud, so the employer can assume that employees screen new applicants conscientiously. Applying this heuristic in an environment of Korean immigrants provides these benefits without spending a cent, but has the consequence that those hired are mostly Korean. Members of these communities tend to socialize and work with each other rather than with people in

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5 *Equal Employment Opportunity Commission v. Consolidated Service Systems.* United States Court of Appeals for the Seventh Circuit; 989 F.2d 233; 1993 U.S. App. LEXIS 4102; 61 Fair Empl. Prac. Cas. (BNA) 327; 61 Empl. Prac. Dec. (CCH) P42, 086.

the larger community. Note that this heuristic, like every heuristic, would not work equally well in any environment.

The Seventh United States Court of Appeals affirmed an earlier decision of a district judge that this word of mouth policy was not discrimination, or certainly not intentional discrimination. It was the cheapest and most effective way to recruit.

THE SCIENCE OF HEURISTICS

If people cannot optimize—as in treatment allocation, bail decisions, hiring, and many other real-world situations—how do they make decisions? We say that people rely on routines, habits, intuition, and rules of thumb. The science of heuristics explicates these routines and intuitions, and the resulting models of heuristics provide answers to the normative question as to in what environment a heuristic is successful and where it fails. Consider the decision between coronary care unit and a nursing bed. The optimal solution to this treatment allocation problem is not known, because there are more than 50 valid predictors, and a complete decision tree would have more than 2^{50} branches if the predictors were binary. The exponential increase makes optimization computationally intractable; moreover, there is never sufficient data for all branches. This is why nonoptimizing, yet sophisticated methods, such as logistic regression (the Heart Disease Predictive Instrument), were used. Assume that the instrument was very good (recall that we cannot know whether it was optimal) for the six New England hospitals where it was developed. This alone, however, does not tell us how well it performed in the Michigan hospitals. The patient sample in the Michigan hospitals differs in unknown ways from that in New England, and we have no reason to believe that both samples are random samples from the same population. Even if they were, one has to face the problem of robustness, that is, the limited robustness (generalizability) of a strategy validated in one random sample to another one. The method to improve robustness is to simplify the strategy. In the world of hospitals and patients, where samples come from different populations rather than the same ones, the problem of robustness is further amplified. The solution is the same: to simplify even more. This is exactly what the coronary care unit heuristic does.

The British magistrates' task is similar to that of the emergency physician: There are numerous predictors for the trustworthiness of a defendant, and the optimal solution is unknown. However, it is also more difficult because, as mentioned, the legal institutions do not provide feedback whether or not the magistrates' decisions were correct, and there seems to be no feedback possible for false alarms. Unlike physicians, who could collect data for both error rates (although this is typically not done), the magistrates have no systematic opportunity to learn.

Note the similarity between the care unit heuristic and the bail heuristics. This kind of heuristic is called a *fast and frugal tree* (Katsikopoulos and

Martignon 2006). For n cues (predictors), a complete tree has 2^n branches, whereas a fast and frugal tree has only $n + 1$ branches. This simple decision tree enables a decision to be made after each cue. The cue value that allows for an immediate decision is called a positive value. For three cues, the general structure of a fast and frugal tree consists of three building blocks:

- *Search rule:* Look up top cue.
- *Stopping rule:* Stop search if cue value is positive. Otherwise go back to search rule and look up next cue.
- *Decision rule:* Choose the action that the positive cue value specifies.

The structural properties of the simple trees reflect the motivation of their users. For instance, a tree that promotes professional self-defense (as opposed to diagnostic accuracy) has the same action associated with each cue. For instance, Court A's bail heuristic allows for a punitive action after each cue was looked up, but for bail only after the last cue; that is, after one is sure that none of the three relevant institutions has suggested otherwise. Similarly, a fast and frugal tree for physicians whose primary motivation is self-defense would have "care unit" at all branches, which would minimize the number of cases where physicians can expect to be sued, such as when a patient dies after being sent to a nursing bed. Thus, the same heuristic can be used in different types of problems, and its structural properties can tell us about the underlying motivation.

The Adaptive Toolbox

The contents of the adaptive toolbox are threefold: heuristics, building blocks, and abilities. The coronary care heuristic and the bail heuristics illustrate sequential search heuristics with three building blocks: a search rule (in what order to search cues), a stopping rule (when to stop search), and a decision rule (where to send the client). The two bail heuristics illustrate how slightly different heuristics can be built by changing one building block, in their case the search rule.

Heuristics can be very specific, but the building blocks are more general. I now illustrate how the same building blocks can apply to quite different problems, namely violations of expected utility (EU) theory. Consider Allais's paradox, where one has a choice between alternatives A and B:

A: 100 Million for sure. [*]
B: 500 Million with probability .98, otherwise nothing.

Most people choose A, which is indicated by the star in brackets. Now consider a second choice:

C: 100 Million with probability .01.
D: 500 Million with probability .0098. [*]

Because alternatives C and D are the same as A and B except that the probabilities were multiplied by a common factor of 1/100, EU theory implies that if A is chosen from {A, B} then C is chosen from {C, D}. However, most people now prefer D, which has been called a "paradox." The common reaction to this and other violations has been to retain the EU framework and to add repairs such as nonlinear functions for probabilities, as in prospect theory (there have also been other reactions, such as disregard, or the hope that markets will take care of these violations). In his Nobel acceptance speech, Reinhard Selten called this common reaction the "repair program." The science of heuristics offers a fresh alternative to the EU framework, not another repair. Consider the *priority heuristic*, which has the same sequential process as the coronary care heuristic and the bail heuristics. For positive prospects (all outcomes positive or zero), the heuristic consists of the following steps:

- *Priority rule*: Go through reasons in the order: minimum gain, probability of minimum gain, maximum gain.
- *Stopping rule*: Stop examination if the minimum gains differ by 1/10 (or more) of the maximum gain; otherwise, stop examination if probabilities differ by 1/10 (or more) of the probability scale.
- *Decision rule*: Choose the gamble with the more attractive gain (probability).

The term *attractive* refers to the gamble with the higher (minimum or maximum) gain and the lower probability of the minimum gain. This process is called the *priority heuristic* because it is motivated by first priorities, such as to avoid ending up with the worst of the two minimum outcomes (Brandstätter et al. 2006). EU theory makes conditional predictions of the type "if *A* is chosen over *B*, then it follows that *C* is chosen over *D*." The priority heuristic, in contrast, makes stronger predictions: It predicts whether *A* or *B* is chosen, and whether *C* or *D* is chosen. Consider the choice between *A* and *B*. The maximum payoff is 500 million, and therefore the aspiration level is 50 million; 100 million and 0 represent the minimum gains of the choice problem. Because the difference (100 million) exceeds the aspiration level of 50 million, the minimum gain of 100 million is considered good enough and people are predicted to select gamble *A*. In fact, the heuristic predicts the majority choice correctly.

In the second choice problem, the minimum gains (0 and 0) do not differ. Hence, the probabilities of the minimum gains are attended to, $p = .01$ and .0098, a difference that does not reach the aspiration level. Thus, the higher maximum gain (500 million vs. 100 million) decides choice, and the prediction is that people will select gamble *D*. Again, this prediction is consistent with the choice of the majority. Together, the two predictions amount to Allais's paradox.

The priority heuristic captures the Allais paradox by assuming the principles of order, a stopping rule with a 1/10 aspiration level, and one-reason decision making. For negative prospects, the heuristic is identical except that "gain" is replaced by "loss." The priority heuristic is based on the sequential structure of the Take The Best heuristic (Gigerenzer and Goldstein 1996) combined with aspiration levels (Simon 1990). The aspiration level is not arbitrary; it reflects one order of magnitude in our cultural base-10 system. Unlike cumulative prospect theory, the heuristic does not introduce five adjustable parameters for decision weights and utilities to improve its fit. Yet despite its simplicity, the priority heuristic predicts many deviations of human judgment from EU theory. Consider Rachlinski's (1996) copyright litigation problem:

- *The plaintiff can either accept a $200,000 settlement [*] or face a trial with a 0.5 probability of winning $400,000, otherwise nothing.*
- *The defendant can either pay a $200,000 settlement to the plaintiff, or face a trial with a 0.5 probability of losing $400,000, otherwise nothing [*].*

The stars in brackets indicate which alternative the majority of law students chose, depending on whether they were in the role of the plaintiff or the defendant. Note that the choices of the two groups were diametrical, creating conflict. What does the priority heuristic predict? Plaintiffs who use the priority heuristic first consider the minimum gains, which are $200,000 and $0. This difference is larger than the aspiration level (1/10 of the maximum gain); therefore search is stopped, and all other pieces of information are ignored. The decision is to take the more attractive minimum gain, that is, the settlement. Defendants who use the priority heuristic consider first the minimum losses, which are $200,000 and $0, the difference of which again is larger than the aspiration level. Search is stopped, and the alternative with the more attractive minimum loss is chosen, that is, to opt for trial. In both cases, the heuristic predicts what the majority of participants in Rachlinski's (1996) study chose.

Now consider Guthrie's (2003) frivolous litigation case, where the probabilities of winning are low:

- *The plaintiff can either accept a $50 settlement or face a trial with a .01 probability of winning $5,000, otherwise nothing [*].*
- *The defendant can either pay a $50 settlement to the plaintiff [*], or face a trial with a .01 probability of paying $5,000, otherwise nothing.*

Plaintiffs who use the priority heuristic consider first the minimum gains, which are $50 and $0, a difference that does not exceed the aspiration level ($500). They then turn to the probabilities of the minimum gains, which are 1.0 and 0.99, a difference that again does not exceed the aspiration level (1/10). Thus, the maximum gain decides, and the plaintiff goes for the trial. In the same way, one can deduce that the defendant will not opt for the trial but rather for the settlement. In both cases, the heuristic predicts the response of the majority of the law students as reported by Guthrie (2003). Note that the response of the students in the copyright litigation problem is consistent with the idea that people are risk averse with gains but risk seeking with losses, whereas in the frivolous litigation case, this pattern reverses.

This simple heuristic predicts a wide range of behavior inconsistent with EU theory, including (a) risk aversion for gains if probabilities are high, (b) risk seeking for gains if probabilities are low (e.g., lottery tickets), (c) risk aversion for losses if probabilities are low (e.g., buying insurance), (d) risk seeking for losses if probabilities are high, (e) the certainty effect, (f) the possibility effect, and (g) intransitivities in choice. Thus, sequential search heuristics can predict phenomena that cumulative prospect theory can also predict, as well as many others that prospect theory cannot, such as conditions in which hindsight bias does and does not occur (Hoffrage et al. 2000); how long people search for information; when they ignore information; and how classifications of objects, estimations of quantities, and other inferences with limited time and knowledge are made (Gigerenzer et al. 1999; Gigerenzer and Selten 2001). On the other hand, prospect theory is likely to predict phenomena that fast and frugal heuristics cannot; the overlap and the differences between these two frameworks have not yet been sufficiently analyzed.

Does the simple priority heuristic or the computationally complex modifications of EU theory better predict people's actual choices? Or do they all perform similarly well? The first direct contest (Brandstätter et al. 2006) involved the predictions of the empirical results in 260 choice tasks (four sets, taken from Kahneman and Tversky 1979; Tversky and Kahneman 1992; Lopes and Oden 1999; I. Erev et al., unpublished). Note that three of the four test sets were constructed by proponents of EU modification theories; the fourth was a random sample. The heuristic used only about half of the information that the EU modifications used (Brandstätter et al. 2006). The priority heuristic predicted people's choices most accurately (87%), compared to Tversky and Kahneman's (1992) cumulative prospect theory (77%), Lopes and Oden's (1999) security-potential/aspiration theory (79%), and Birnbaum and Chavez's (1997) transfer of attention exchange model (67%).

Thus, models of fast and frugal heuristics can predict not only people's inferences, but also their preferences. These models are simple and transparent. One can see the conditions in which they fail to predict people's choices, which is difficult for highly parameterized modifications of EU theory. For instance, the priority heuristic has its limits when the expected values of two gambles are highly discrepant, which is when the choice becomes trivial.

Environmental Structures and Institutions

Heuristics do not simply develop in the mind but are equally the product of its past and present environments. Human institutions, not geological or meteorological conditions, are the most important environmental structures for the law. These environmental structures include the signal-to-noise ratio, that is, what proportion of the information transmission in an institution is reliable rather than irrelevant; the framing of information, that is, whether information is transmitted in a confusing form (e.g., expert witnesses often present DNA evidence in "random match probabilities," which tend to confuse jurors and judges) or in a transparent form (such as natural frequencies; see Gigerenzer 2002); the goals of other agents; and the rules of the institution.

For instance, consider the coronary care unit decisions. Emergency physicians make these life-and-death decisions in institutions that tend to punish misses (not sending a patient into the care unit who should be there) substantially more heavily than false alarms (sending patients to the care unit who should not be there). If the patient dies as a consequence of a miss, the physician is likely to be sued for malpractice; if the patient dies as a consequence of being sent to the care unit (because he picked up one of the dangerous viruses that circulate in care units, or the unit was overcrowded because the physicians sent too many patients there), the physician is unlikely to be sued. Such an institution invites defensive decision making; physicians first protect themselves rather than their patients. Not all institutions are designed in that way. One counterexample is commercial aviation, where if the passenger dies in a crash, the pilot will usually die as well. In the patient–physician relationship, however, the risks are decoupled. Furthermore, aviation keeps records of "near misses" whereas in medical institutions, there is no system of reporting errors without punishing the individual physician, and little systematic feedback about the quality of physicians' decisions in the first place. These are some of the environmental structures responsible for the disturbing fact that in U.S. hospitals, an estimated 44,000 to 98,000 patients die every year from (recorded) preventable medical errors, whereas in 2004, only about 500 people died in commercial aviation worldwide. The study of the environmental structure is essential for understanding what heuristics people use: heuristics are "selected" by institutions.

Ecological Rationality

Consider the dots on the left-hand side of Figure 2.4. They appear concave, that is, they recede into the surface, away from the observer. The dots on the right side, however, appear convex—they project up from the surface, extending toward the observer. When you turn the page upside down, the concave dots will turn into convex dots, and vice versa. Why do we see the dots this way or the other?

The answer is that our brain does not have sufficient information to know for certain what is out there, but it is not paralyzed by uncertainty. It makes a good bet, based on the structure of its environment, or what it assumes is its structure. The brain assumes a three-dimensional world and uses the shaded parts of the dots to guess in what direction of the third dimension they extend. The relevant environmental regularity is that light comes from above. This was true in human

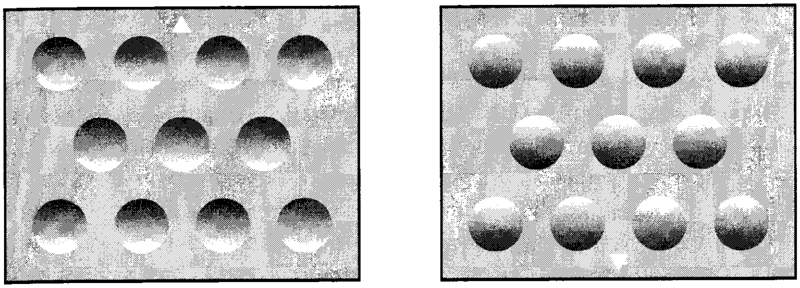

Figure 2.4 Unconscious inferences. The mind infers that the dots in the left picture are curved inward, that is, away from the observer, and those on the right picture are curved outwards, that is, toward the observer. If you turn the book around, the inward dots will pop out and vice versa. The right picture is identical to the left rotated by 180 degrees.

history where sun and moon were the major sources of light, and still holds true for most artificial light that is typically placed above us, such as streetlamps (although there are exceptions, such as car lights). The perceptual heuristic adapted to this regularity is:

> *If the shade is in the upper part, then the dots are concave; if the shade is in the lower part, then the dots are convex.*

For instance, the dots in the right-hand picture are shaded in the lower part. Thus, the brain's unconscious inference is that the dots extend toward the observer because then the light would hit the upper part, which looks bright, and less light would hit the lower part. The heuristic process is not conscious and has been called an unconscious inference (Helmholtz 1856–1866/1962). The heuristic is ecologically rational in three-dimensional environments where light comes from above, but not in other environments such as the two-dimensional pictures in Figure 2.4.

Heuristics for decision making "bet" on environments in a similar way to perceptual heuristics, but are more flexible and can be modified by feedback. The study of the ecological rationality of a heuristic answers the question as to in which environments the heuristic will be successful. It examines the institutions that make heuristic bets correct.

Consider now a fast and frugal tree, as in the coronary care heuristic or in the bail heuristic. These trees base their decision on one reason alone, although they may search through a few. When is one reason as good as many reasons? We know of several structures, including the following condition for data fitting (Martignon and Hoffrage 1999, 2002): Consider a situation with five binary cues, as in Figure 2.5, where the weights correspond to the order of the cues in a fast and frugal tree.

Figure 2.5 (left) shows an environmental structure in which one reason is as good as five (or more). Here, a fast and frugal tree is as accurate as any linear

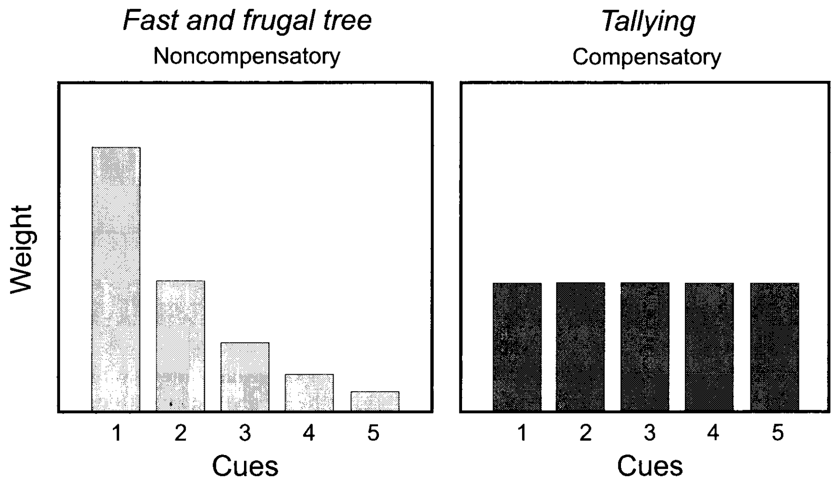

Figure 2.5 Ecological rationality. Left: An environmental structure where a fast and frugal tree (as in the coronary care heuristic or in the bail heuristic) is as accurate as any linear (weighting and adding) combination of all cues. The weights of the cues are 1, 1/2, 1/4, and so on. In other words, one reason is as good as many. Right: An environmental structure where a tallying heuristic (which discards information about weights and treats all cues equal) is as accurate as any linear weighted strategy. Here, cues have equal weights.

(weighting and adding) combination of all cues, including a logistic regression. One can see this result intuitively: The sum of all cue weights to the right of a cue can never be larger than this cue's weight—they cannot compensate for the cues with higher weights. This type of environment is structured by *noncompensatory information*. Here, relying on one reason and ignoring the rest is as accurate as integrating all reasons by any linear strategy. If there is also uncertainty, as is typical in the real world, the heuristic will likely be more *robust* and will have higher predictive accuracy. One example was shown in Figure 2.2, where one-reason decision making led to more accurate predictions (for more demonstrations, see Czerlinski et al. 1999). The term *robustness* refers to the predictive accuracy of a strategy in new situations. In general, the greater the uncertainty is, the more robust simple strategies are compared to ones with a higher greed for information.

Figure 2.5 (right) shows an environmental structure in which cues have equal weights. Here, a fast and frugal tree will not be as accurate. Yet a simple tallying heuristic (which discards information about weights and simply counts positive cues) can be shown to be as accurate as any linear weighted strategy (Martignon and Hoffrage 2002). In summary, a heuristic exploits evolved and learned abilities, which make it simple, and structures of environments, which make it ecologically rational.

INSTITUTIONS SHAPE HEURISTICS

Let us call an institution an *intelligent institution* if it makes all heuristics (that apply to a given problem) ecologically rational. Do such institutions exist? They do. One example is the double auction. Major stock, commodity, currency, and many other markets are organized as double auctions. Here, buyers and sellers can freely enter limit orders (bids or asks) and accept bid requests entered by others. The crucial feature of this institution imposes a budget constraint on the trader: generating a bid (buying) above the redemption value or offering (selling) below their cost is not allowed. This protects the trader from buying or selling at a loss and not being able to settle their accounts. The market discipline imposed by its rules allows "zero intelligence" machine traders, who make random bids or offers, to perform as well as human traders do (Gode and Sunder 1993). In such a market, the choice of heuristic is no problem. In general, lawmakers are among those who decide how much intelligence is in the institution and how much in individuals. For instance, one can decrease fatal traffic accidents in two ways. One is to create safe environments or institutions—more traffic signs, enforced rules, and future car technology such as automatic safety distance control, which reduces the drivers' decisions to a minimum and enables relatively bad drivers to drive safely. The other way is to improve drivers' skills and morals. In the first case, the task-specific intelligence is shifted toward the institution, whereas in the second it is directed toward the individual.

Institutions enable and constrain heuristics, including the extreme case of the double auction described above, where institutions generate a "flat maximum" in which most or all heuristics can flourish. Typically, institutions are not "intelligent enough" to substitute for the intelligence of people, that is, to allow totally ignorant people to succeed equally well as informed ones, but they do pose some constraints. For instance, when the information structure is (approximately) noncompensatory, as shown in Figure 2.5, these institutions support basing a decision on one reason only and ignoring the rest.

A second type of institution supports what I call *split-brain agents*. These agents use a fast and frugal heuristic for decision making yet believe, or want to believe, that they make decisions following the ideals of complete information and optimization. The English bail system and the magistrates are a case in point. The magistrates seem to be largely unaware of the heuristic processes they follow. As mentioned before, when interviewed on what cues they use, they reported the cues explicitly referred to in the Bail Act 1976 (Dhami 2001). None of the magistrates in the two London courts referred to the cues on which their heuristics were actually based. Moreover, in a study with hypothetical cases, magistrates requested additional information about the case and consistently asked for information that was not part of the heuristic process, but compatible with the Bail Act. I have no reason to assume that the magistrates would knowingly waste time discussing information that will have no effect on their decisions, or deceive the interviewers. Rather, the institution of the English bail system seems to support split-brain bail decisions. The Bail Act demands attention to certain cues, so the magistrates tend to ask for these cues, spend considerable time discussing them with the other members of a bench, and believe that they have incorporated them into their decisions. In the end, however, they base their decisions on cues that protect themselves, by passing the buck.

When an institution separates the professional's risk from that of the client, and thus supports the emergence of split-brain agents, heuristic procedures are likely to emerge that protect the professional first, and the client only second. Sending 90% of the clients into the coronary care room is an example. The result is a form of protective malpractice that is tolerated by legal practice.

HEURISTICS SHAPE INSTITUTIONS

Institutions shape heuristics, but the causal arrow also points in the other direction. The heuristics in the adaptive toolbox can shape institutions. Heuristics that build on the capacities of trust and cooperation—such as word-of-mouth and Tit-for-Tat—enable institutions to be designed that do not permanently check its members, but can operate more efficiently by assuming loyalty. Heuristics can constrain the effects of legislation, and knowing the heuristics can give clues as to whether a new legislation will be effective or not. Consider the debate on bail information schemes, which gather and provide information on a defendant's community ties to the court (Dhami 2002). The argument in favor of these schemes assumes that magistrates attend to information concerning community ties. However, the magistrates' heuristics (Figure 2.3) reveal that this information plays no role in their bail decisions. Hence, if magistrates use these or similar heuristics, one can expect that legislating new bail information schemes will have no effect. Consistent with that prediction, an experiment with magistrates showed that introducing the schemes indeed had no effect on the bail decisions (Dhami 2002). The general point is that being aware of the heuristics used can help to design appropriate modifications of institutions and to avoid those that will not produce the desired consequences.

HEURISTICS AND THE LAW

Jurors, judges, and John Q. Public have to make decisions with limited time and knowledge, and under degrees of uncertainty where optimization is typically out of reach. Most politicians do not have the time to read the full text of the law they are going to vote on—many go by word of mouth, party line, or what their peers vote. Many lawyers and law professors appear to not always read the form contracts they sign (Prentice 2003). Physicians simply cannot know the side effects of some 100,000 medications on the market, nor can medical research ever hope to determine the interactions of each pair of medications. A common solution is to reduce the complexity and uncertainty to a minimum that allows optimization, and then assume that the solution in the ideal world also holds in the complex and messy world. But there is no guarantee. As the statistician John Tukey (1966) pointed out, what is optimal under ideal conditions is often dismal in a world that is less than perfect, and heuristics that fare badly in the utopian world can be highly efficient in the real world. The solution is, in my view, to start with the messy one and aim for realistic and good solutions.

The goal of the science of heuristics is to improve our understanding of the heuristics that people use, when these work, and how to improve them. These heuristics operate at different levels, in laypeople and lawyers, offenders and police officers, and in the making as well as execution of the law. Simple heuristics' attributes include transparency and predictability, two potentially important criteria by which people subject to the legal system determine the fairness of a decision. This heuristics program can inform and enrich behavioral law and economics, which began with a negative view of human rationality. The result will be a more balanced view, in which heuristics are seen both as solutions and as problems. Most important, the theoretical framework helps to organize a patchwork of experimental effects, and we are able to go beyond the phrase "heuristics are sometimes good and sometimes bad" by specifying the structures of environments, including the institutions in which heuristics are ecologically rational or not. The science of heuristics can provide the foundations of an integrative theory that explains how human behavior depends on its institutions.

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