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CHAPTER 15

Mechanisms of ecological rationality: heuristics and environments that make us smart

Peter M. Todd and Gerd Gigerenzer

15.1. Introduction: making quick decisions well

A high fly ball comes down towards centre field. Wind is blowing, the ball is spinning, and gravity exerts its parabolic pull, but still the fielder smoothly runs to make the catch. A diner confronts two dishes at a new restaurant, ignores the extensive menu descriptions and offer of input from the waiter, and quickly decides to go with the one she recognizes. A doctor just starting a rotation in a different city assesses a man brought to the emergency room, checks two vital signs without consulting the banks of sophisticated test machinery available, and makes a fast assignment of the patient to the operating room, saving a life.

Most of the decisions we make spring relatively effortlessly from our minds. We make snap judgments, jump to conclusions, choose quickly—indeed, if a decision takes more than minimal time and effort, it becomes worthy of comment (and possibly aversive). And yet, our frequent fast decisions end up working out more often than not—the fielder catches the ball, the diner chooses an acceptable meal, the doctor saves her patient. We do not typically need to gather a great amount of information and process it extensively, as traditional maxims of rationality would instruct us to do, before successfully making up our minds. How are we able to make adaptive choices in our more limited fashion?

The answer is that we can often draw on a collection of simple 'fast and frugal' heuristics for inference and choice that enable us to make quick and accurate decisions using little information (making them frugal) and little mental computation (making them fast). These and other mechanisms filling the mind's *adaptive toolbox* (Gigerenzer *et al.*, 1999) can accomplish their trick of good performance without high information and processing demands because of three main features. First, they are built on evolved capacities that synthesize multiple environmental features into single cues for decision making, and simple building blocks that limit how many cues are considered. Second, they exploit the structure of information patterns in the environment to let the world do some of their work, allowing the internal mechanisms to be simpler and quicker. Third, their use of less information enables heuristics to avoid overfitting meaningless noise in the environment and leads to better generalization to new situations.

Thus, the fielder is able to catch balls without stopping to account for wind speed, drag, spin, and the like by using a *gaze heuristic* that capitalizes on our underlying evolved ability to track moving objects and uses the angle of gaze between ball and horizon as the only piece of information to guide where to run (Raab and Gigerenzer, 2005). The diner exploits only her pattern of systematic recognition of some foods and not others to reason with the *recognition heuristic* and conclude that those dishes she recognizes are known to her because they are more often talked about and hence probably tastier (Todd, 2000). And the doctor uses the *'Take The Best' heuristic* or decision tree to check only those cues necessary to make a quick diagnosis, focusing on the most valid pieces of information and ignoring the other possible tests that may not generalize well from her previous experience in another city (Gigerenzer *et al.*, 1999).

In this chapter, we describe some of these simple heuristics that we believe the human mind has evolved to use in particular circumstances, and the pressures on decision making that may have shaped the contents of the mind's adaptive toolbox. We begin by considering the notion of bounded rationality—the assumption that human cognition is constrained by limits of some sort—and just which types of bounds have been most important in cognitive evolution. We then look at the components that our decision mechanisms are built up from and examine how they enable simple and fast choices to be made. Next, we present four main classes of simple heuristics that have been explored in depth: ignorance-based heuristics, one-reason decision mechanisms, elimination strategies, and satisficing search methods. Finally, we consider some of the challenges facing the understanding of simple heuristics and why they can work so well.

15.2. From bounded rationality to ecological rationality

Traditional notions of *unbounded rationality* have posited that the appropriate way to make decisions is to gather all of the available information, weight each piece appropriately according to its importance for the current decision, and combine all this weighted information in an optimal fashion to find the option with the greatest utility (Edwards and Fasolo, 2001); furthermore, it is commonly assumed that people behave as if they are maximizing their utility in this way. But to make choices in most common everyday contexts, real decision makers must employ limited search for information and limited processing of what they find, because they have only a finite amount of time, knowledge, attention, or money to spend on a particular decision (Todd, 2001). As such, people are usually acting in accordance with what Herbert Simon called *bounded rationality*—making decisions within the bounds of time, information, and computational ability that the task environment and human cognitive capacities impose on us (Simon, 1990). The notion of unbounded rationality, following the tenets of logic and probability theory, is a convenient fiction for constructing mathematical models of behaviour, but to understand real human behaviour, we must consider the actual bounded psychological processes that guide our decision making.

But what are the most critical bounds on our cognitive mechanisms? The usual assumption is that human cognitive abilities are bounded by the hard mental constraints of our limited memory and information-processing power. However, given sufficient adaptive pressure to succeed in complex tasks, evolution could build complex information-processing structures to handle those tasks. That is, cognitive limitations on memory and processing could be circumvented over the course of evolution, if the benefit outweighs the cost. For instance, our ability to store and retrieve information from memory could be much greater, as the skills of mnemonists attest (Luria, 1968). The amount of information that can be held and processed in working memory can be greatly increased through practice (Ericsson and Kintsch, 1995). And the processing of information itself could be more rapid and sophisticated, as evidenced both by the great processing power that the visual system already possesses, and by the ability of some individuals to solve complex problems rapidly that most of us would find impossible (e.g. chess masters, or horse-race experts—see Ceci and Liker, 1986). Thus, human cognitive boundaries could have been extended, if that had been adaptive for our ancestors. What then *did* lead to our highly constrained decision mechanisms in so many situations?

This typical assumption, that the constraints bounding our rationality are internal ones such as limited memory and computational power, leaves out most of the picture—namely, the external world and the constraints that it imposes on decision makers. There are two particularly important classes of constraints that stem from the nature of the world. First, because the external world is uncertain—we never face exactly the same situation twice—our mental mechanisms must be robust, that is, they must generalize well from old instances to new ones. One of the best ways to be robust is to be simple, for instance, by employing a mechanism containing few parameters. As a consequence, external uncertainty can impose a bound of simplicity on our mental mechanisms.

Second, because the world is competitive and time is short, our decision mechanisms must generally be fast. The more time we spend on a given decision, the less time we have available for other activities, and the less likely we are to outcompete our rivals in the endless arms race of life. Because it takes time to find and assess the informative cues or choice alternatives (external in the world or internal in memory) we need to make a decision; there is pressure to base decisions on fewer cues. And even if the search for more information could be accomplished quickly, it might not do the decision maker much good: cues are often highly intercorrelated (Brunswik, 1943), so that searching for additional cues provides rapidly diminishing returns in terms of useful data. Thus, to be fast, we must minimize the information or alternatives we search for in making our decisions. In other words, the external world also constrains us to be frugal in what we search for.

But the external world does not just impose the bounds of simplicity, speed, and frugality on us—it also provides the means for staying within these bounds. A decision mechanism can stay simple and robust by relying on some of its work being done by the external world—that is, by counting on the presence of certain useful patterns of information in the environment. Some observable cues are useful indicators of particular aspects of the world, such as red colour usually indicating ripe fruit. Our minds are built to exploit such patterns and thereby reduce the need for gathering and processing extra information. As we will show in the following sections, heuristics that use just a little of the patterned information and process it in simple ways can make decisions that are fast, accurate, and adaptive. However, as research in both evolutionary psychology and the heuristics-and-biases programme has demonstrated, the reliance on particular expected information patterns can lead us astray if we are presented with environments that violate our expectations (such as environments where fatty foods are readily obtained, or where the representativeness of the choices we encounter in a laboratory setting are made to violate distributions familiar from daily life). Adaptive behaviour emerges just when the mechanisms of the mind are properly matched to the (information) structures of the environment—producing what we call *ecological rationality*.

The importance of looking at the world to understand the mind has long been appreciated, though not very widely. Charles Darwin held that environmental forces had shaped human behaviour through natural selection, leading to the modern call by evolutionary psychologists to look to our ancestral world for the problems our mind is designed to solve. Egon Brunswik, half a century ago, urged studying the array of noisy cues available in the environment and how the mind adjusts its use of them, like a husband and wife coming to mutual agreement; Roger Shepard spoke of the mind more as a mirror, reflecting long-standing physical aspects of the world such as the 24-hour light–dark cycle (Brunswik, 1943; Shepard, 2001). Herbert Simon (1990) proposed the metaphor of the mind and world fitting together like the blades of a pair of scissors—the two must be well-matched for effective behaviour to be produced. In each case, looking for structure in the world will help us find corresponding structure in the mind, and considering the latter without the former, like a solitary husband or single scissor-blade, can lead to much misapplied effort.

Research on ecological rationality builds on these foundations to create a framework for understanding how patterns of information in the world can be exploited by decision mechanisms in the head to produce adaptive behaviour (Gigerenzer *et al.*, 1999; Todd *et al.*, in press). Rather than studying how the mind may employ or deviate from unbounded logical rationality via domain-general, normatively optimal reasoning systems, bounded ecological rationality explores how the mind uses simple, domain-specific decision heuristics that expect the world to do some of the work in providing useful structure for making choices. The fact that there is structure to be relied on in the world implies that the mind can get away with using less extensive, though more problem-specific, computations, leading to an emphasis on studying simple, psychologically plausible heuristics. In this view, a decision mechanism cannot be deemed good or bad on its own—it is only the match between a mechanism and an environment in which it is employed that can be assessed as yielding good or bad performance. This notion of mind–world match is missing from most logical and mathematical principles of rationality and their corresponding theories of cognition, which posit what is correct behaviour independent of any application domain.

How is ecological rationality possible? That is, how can fast and frugal heuristics work as well as they do and escape the trade-offs between different real-world criteria including speed and accuracy? The main reason for their success is that they make a trade-off on another dimension: that of generality versus specificity. While internal criteria for the coherence of decisions are very general—logical consistency, for instance, can be applied to any domain—the correspondence criteria that measure a heuristic's performance against the real world require much more domain-specific solutions. What works to make quick and accurate inferences in one domain may well not work in another. Thus, different environments can have different specific fast and frugal heuristics that exploit their particular information structure to make adaptive decisions. But specificity can also be a danger: if a different heuristic were required for every slightly different decision-making environment, we would need an unworkable multitude of heuristics to reason with, and we would not be able to generalize to previously unencountered environments. Fast and frugal heuristics can avoid this trap by their very simplicity, which allows them to be robust in the face of environmental change and enables them to generalize well to new situations.

Robustness goes hand in hand with speed, accuracy, and especially information frugality. Simple heuristics can reduce overfitting (focusing too much on the specific details in a particular data set) by ignoring the noise inherent in many cues and looking instead for the 'swamping forces' reflected in the most important cues. Thus, simply using only one or a few of the most useful cues can automatically yield robustness—more information, like more processing, is not necessarily better (Hertwig and Todd, 2003). Furthermore, important cues are likely to remain important. The informative relationships in the environment are likely to hold true when the environment changes. Because of this pattern, fast and frugal heuristics that pay attention to systematic informative cues while overlooking more variable uninformative cues can ride out environmental change without suffering much decrement in performance.

The study of ecological rationality thus requires analysing the structure of environments, the structure of heuristics, and the match between them. The research programme proposed by Gigerenzer *et al.* (1999) for studying the simple ecologically rational heuristics that humans and animals use involves (i) proposing and specifying computational models of candidate simple heuristics, (ii) analysing the environmental structures in which they perform well, (iii) testing their performance in real-world environments (often via computer simulation), and (iv) determining whether and when people really use these heuristics (both experimentally in the laboratory and empirically in the field). This process is similar to that proposed for studying the Darwinian algorithms of evolutionary psychology (Cosmides and Tooby, 1987). We now turn to the first step in this process, exploring the components that go into a proposed heuristic model, before considering some specific heuristics and the ways they have been tested in the further steps of this research programme.

15.3. Creating simple heuristics from capacities and building blocks

To study particular heuristics in detail, computational models must be developed that specify the precise steps of information gathering and processing that are involved in generating a decision, allowing the heuristic to be instantiated as a computer program. In particular, simple fast and frugal heuristics are made up of building blocks that guide the search for alternatives, information, or both, stop that search, and make a decision. But 'below' these building blocks comes a foundation of evolved capacities that provides many of the cues that the building blocks (and heuristics) process. This evolved foundation distinguishes human and other animal minds from artificial computational models that focus on abstract information-processing abilities.

15.3.1. Evolved capacities

The various simple heuristics that are built up from building blocks and other nested heuristics can all be thought of as making up part of the adaptive toolbox: the collection of specialized cognitive mechanisms that evolution has built into the human mind for specific domains of inference and reasoning (Gigerenzer *et al.*, 1999; see also Cosmides and Tooby, 1992; Payne *et al.*, 1993). The adaptive toolbox contains all manner of psychological (as opposed to morphological or physiological) adaptations. These include so-called 'lower-order' perceptual and memory processes that can be fairly automatic, such as depth perception, auditory scene analysis, and face recognition, as well as 'higher-order' processes that are based on the 'lower' processes and can be at least partly accessible to consciousness. Within the class of higher-order mental processes fall fast and frugal heuristics for decision making, which themselves often call upon lower-order processes of cue perception and memory.

The lower-order processes are typically evolved capacities that operate quickly and effortlessly to distill multiple pieces of information from the environment or from memory into more compact representations, often even single cues, that can be used in further decision making. There are many of these capacities; here we list just a few for illustration, grouping them into rough classes. Among search capacities are exploring (quasi-random search for information), tracking (following a specific moving object), and observing other people (vicarious search). Memory capacities include recognition (noticing that one has seen/heard/smelled an object before), recall (when knowledge beyond mere recognition comes to mind about an encountered object), and forgetting (losing information from memory). Learning capacities cover, among other things, Pavlovian and operant conditioning (e.g. learning to avoid unpleasant stimuli), preparedness (enabling one-trial learning of evolutionarily important stimulus–reaction associations), and imitation (copying the behaviour of others). And basic evolved social capacities, while perhaps not being lower-order in the same sense (and themselves being built on other primitives such as face recognition and memory for features of individuals), may include reciprocal altruism and ability to trust (cooperating with non-related others to achieve a common goal), reputation memory (ability to recall an individual's relative score or rank on a socially important trait), and group identification (aligning one's values and identity to that of a group).

Lower-order perceptual and memory processes such as these are complex and difficult to unravel, in part because they may make use of massively parallel computations. No one has yet managed to build a machine that recognizes faces as well as a 2-year-old child. Now consider a higher-order decision mechanism that makes inferences based on these processes, the recognition heuristic mentioned earlier. This fast and frugal heuristic uses recognition to make rapid inferences about unknown aspects of the world: for instance, food whose taste one recognizes is probably safer than unrecognized food, and a university whose name one has heard of probably provides a more prestigious education than one whose name is unfamiliar. Although the mechanisms of recognition memory may be intricate and complex, the recognition heuristic can be described as an algorithm just a few steps long. We do not need to know precisely how recognition memory works to describe a heuristic that relies on recognition. This example illustrates an apparently paradoxical thesis: higher-order cognitive mechanisms can often be modelled by simpler algorithms than can lower-order mechanisms. This thesis is not new, having been proposed in various forms over the past century (e.g. by proponents of the Würzburg school of psychology in the early 1900s—see Kusch, 1999). But it is central to the discussion of when we should postulate simple versus complex decision mechanisms in the adaptive toolbox.

15.3.2. Building blocks

Our evolved capacities provide our decision mechanisms with inputs distilled and compiled from multiple environmental features. The decision mechanisms in the adaptive toolbox, including simple heuristics, process those information inputs through a series of steps that can be characterized in many instances as three types of building blocks: for guiding information search, stopping that search, and making the decision on the basis of the search results.

15.3.2.1. Building blocks for guiding search

Decisions must be made between alternatives, and based on information about those alternatives. In different situations, those alternatives and pieces of information may need to be found through active search. The building blocks for guiding search, whether across alternatives or information, are what give search its direction (if it has one). For instance, search for cues can be simply random, or in the order of some precomputed criterion related to their usefulness, or based on a recollection about which cues worked previously when making the same decision. Search for alternatives can similarly be random or ordered. Fast and frugal search-guiding principles do not use extensive computations or knowledge to figure out where to look next.

15.3.2.2. Building blocks for stopping search

To fit within the temporal limitations of the human mind, search for alternatives or information must be terminated at some point. Moreover, owing to the computational limitations of boundedly rational agents, the method for determining when to stop search should not be overly complicated. For example, one simple stopping rule is to cease searching for information and make a decision as soon as the first cue or reason that favours one alternative is found (as embodied in one-reason decision making, described below). This and other cue-based stopping rules do not need to compute an optimal cost–benefit trade-off for determining when enough information has been found; in fact, they need not compute any costs or benefits at all. For search among alternatives, simple aspiration-level stopping rules can be used (see Section 15.4.4 below on satisficing search).

15.3.2.3. Building blocks for decision making

Once search has been guided to find the appropriate alternatives or information and has then been stopped, a final type of building block can be called upon to make the decision or inference based on the results of the search. These components can also be very simple and computationally bounded. For instance, a decision or inference can be based on only one cue or reason, whatever the total number of cues found during search (as in the ignorance-based and one-reason decision mechanisms). Such single-cue decision making does not need to weight or combine cues, and so no common currency between cues need be determined. Decisions can also be made through a simple elimination process, in which alternatives are thrown out by successive cues until only one final choice remains (see Section 15.4.3 on elimination heuristics).

15.3.3. Heuristics

These building blocks can be put together to form a variety of fast and frugal heuristics. Given that the mind is a biological rather than a purely logical entity, formed through a process of successive accrual, borrowing, and refinement of components, it seems reasonable to assume that new heuristics are built from the parts of old ones, rather than from scratch (Pinker, 1998). Following this assumption, two main methods can be used to construct computational models of fast and frugal heuristics: combining building blocks and nesting existing heuristics. Building blocks can be combined in multiple ways, though not arbitrarily: for instance, a fast and frugal heuristic for two-alternative choice that stops information search at the first cue on which the alternatives differ must also use a decision principle based on one-reason decision making. Whole fast and frugal heuristics can themselves be combined by nesting one inside another. As an example, the recognition heuristic can also serve as the first step of one-reason decision heuristics that draw on other capacities beyond recognition, such as recall memory. Recognition memory develops earlier than recall memory both ontogenetically and evolutionarily, and the nesting of heuristics can similarly be seen as analogous to the addition of a new adaptation on top of an existing one.

Heuristics are the most flexible of the contents of the adaptive toolbox. This is because the heuristics, not the evolved capacities or building blocks, act directly on the environment and hence need to be adaptive and adapted. The flexibility of a given heuristic seems to be linked with the way it has entered into the adaptive toolbox. Evolution leads to the most inflexible heuristics, as the unconscious inferences of the gaze heuristic and other perceptual heuristics illustrate. Social and cultural learning leads to more flexible use of heuristics, applying them in different domains according to what others have found to be useful. Finally, individual learning, such as reinforcement learning, seems to lead to the most context-sensitive and rapidly adjusted use of heuristics (Rieskamp and Otto, 2006), which is highly dependent on the specific circumstances of the learned task environment.

15.4. Four families of simple heuristics

The decision-making building blocks just described can be put together to form classes or families of heuristics whose members are related by the particular search, stop, or decision rules they use. In this section we briefly introduce four such families of heuristics (out of many possible) covering decision situations that vary in the amount of information available, the number of options to choose between, and the distribution of options in time or space. These algorithmic models are intended to capture how real minds make decisions under constraints of limited time and knowledge.

15.4.1. Ignorance-based decision mechanisms

One of the simplest forms of decision that can be made is to select one option from two possibilities, according to some criterion on which the two can be compared. What simple cognitive mechanisms can be used to make this type of decision? This will depend on the amount and type of information that is available in the environment. If the only information available is whether or not each possibility has ever been encountered before, then the decision maker can do little better than rely on his or her own partial ignorance, choosing either recognized options or unrecognized ones. For heuristics applicable to such situations, their information-search building block merely specifies that recognition should be assessed for the alternatives being compared; the search-stopping building block limits consideration to this recognition information alone; and the decision building block indicates exactly how recognition information determines the final choice. This 'ignorance-based reasoning' is embodied in the recognition heuristic (Goldstein and Gigerenzer, 1999, 2002), which uses the following decision rule: when choosing between two objects (according to some criterion), if one is recognized and the other is not, then select the former. For instance, Norway rats have evolved to behave according to a rule of this type, preferring to eat things they recognize through past experience with other rats (e.g. items they have smelled on the breath of others) over novel items (Galef, 1987).

Following the recognition heuristic will be ecologically rational—that is, will yield correct responses more often than would random choice—in those decision environments in which exposure to different possibilities is positively correlated with their ranking along the decision criterion being used. Thus, the rats' food preference copying presumably evolved because the things that other rats have eaten (i.e. recognized items) are more often palatable than are random (unrecognized) items sampled from the environment. Such useable correlations are likely to be present for species with social information exchange where important environmental objects are communicated and unimportant ones are ignored, as well as for species in environments where important environmental objects are simply encountered more often or earlier in life.

People have been shown to make decisions in accordance with the recognition heuristic in domains such as choosing the larger of two cities, the deadlier of two diseases, or the more successful of two sports teams (Goldstein and Gigerenzer, 2002), where socially transmitted information is indeed typically about items at one end of the criterion range (large cities or successful teams). Recent research has also shown that people put considerable stock in the value of recognition information for making decisions, even being swayed more in a group decision setting by colleagues who only recognize one available option (and choose that option on the basis of their recognition) than by those who have more information and recognize all available options (Reimer and Katsikopoulos, 2004). Situations in which the recognition heuristic can be applied arise in daily life as well: companies vie for name recognition among consumers in the hope that this will guide their purchase decisions (Borges *et al.*, 1999). In fact, in the modern environment, our recognition memory has become rather easily manipulable by the steady stream of media we are exposed to. Whereas in ancestral environments, we would only recognize people whom we had actually encountered in person, television shows and movies can now trick us into thinking the faces we recognize belong to people we actually know (Kanazawa, 2002). As a consequence, using the recognition heuristic may no longer be ecologically rational in some settings, particularly those where other agents aim to influence what we recognize.

15.4.2. One-reason decision mechanisms

Of course, we often have more information than just recognition available for making our decisions. What kinds of fast and frugal heuristics are appropriate in situations like the following? Imagine trying to decide between two restaurants for taking a guest to dinner. The traditional and normatively prescribed method would be to collect all the information or cues that you know or could find out about each restaurant, such as the average meal cost, distance from home, and amount of garlic in the dishes; then weight each of these cues by its importance for this decision; and finally combine all the weighted values for each alternative to come up with a final total criterion value for each. Whichever restaurant has the higher final criterion value is the one to go to, according to this weighted-additive approach to computing the expected utility of the two choices (Edwards and Fasolo, 2001).

A simpler and faster method is the following. Consider a single cue for the two alternatives, such as meal cost. Does this cue distinguish between the restaurants? If it does, then stop and choose the restaurant pointed to by the cue (e.g. the cheaper one, or the more expensive one, depending on if you want to conserve your resources or impress the guest). If the first cue does not distinguish between the alternatives, then consider a second cue, such as distance. If that cue distinguishes, then stop at this point and go with the indicated choice (e.g. the nearer restaurant). If not, consider a third cue, and so on, stopping this search for cues at the first distinguishing one found and using that cue alone to make the final decision. Mechanisms that operate in this way are called 'one-reason decision heuristics', because their final decision is made on the basis of a single cue or reason alone (Gigerenzer and Goldstein, 1999). A one-reason decision heuristic works as follows.

1. Select a cue dimension using some search building block and look for the corresponding cue values of each option.
2. Compare the two options on their values for that cue dimension.
3. If they differ, then stop (this is the stop-search building block) and choose the option with the cue value indicating a greater value on the choice criterion (the decision building block).
4. If the options do not differ, then return to the beginning of this loop (Step 1) to look for another cue dimension.

Such a heuristic will often have to look up more than one cue before making a decision, but the simple stopping rule (in Step 3) ensures that as few cues as possible will be sought, minimizing the time needed for information search. Furthermore, ultimately only a single cue will be used to determine the choice, minimizing the amount of computation that must be done.

To finish specifying a particular simple heuristic of this type, we must also determine exactly how cue dimensions are 'looked for' in Step 1—that is, we must choose a specific information search building block. For instance, the Take The Best heuristic searches for cues in the order of their validity—that is, their correlation with the decision criterion, while the Minimalist heuristic selects cues in a random order (Gigerenzer and Goldstein, 1996, 1999). Again, both stop their information search as soon as a cue is found that allows a decision to be made between the two options. Particular cue orders will influence just how quickly and how accurately a decision can be made. (The open question of determining which cues and cue order to use will be considered below.)

Despite (or often because of) their simplicity and disregard for most of the available information, these two fast and frugal heuristics can make very accurate choices. A set of 20 environments was collected to test the performance of these heuristics, varying in number of objects and number of available cues, and ranging in content from the German cities data set mentioned earlier to fish fertility to high-school drop-out rates (Czerlinski *et al.*, 1999). The decision accuracies of Take The Best and Minimalist were compared with those of two more traditional decision mechanisms that use all available information and combine it in more or less sophisticated ways: multiple regression, which weights and sums all cues in an optimal linear fashion, and Dawes's Rule, which counts up the positive and negative cues and subtracts the latter from the former. The two fast and frugal heuristics always came close to, and often exceeded, the performance of the traditional algorithms when all were tested on the data they were trained on (data fitting). This surprising performance on the part of Take The Best and Minimalist was achieved even though they only looked through a third of the cues on average (and only decided using one of them), while multiple regression and Dawes's Rule used them all.

The advantages of simplicity grew in the more behaviourally important test of generalization performance, where the decision mechanisms were assessed on a portion of each data set that they had not seen during training; in that case, Take The Best outperformed all three other algorithms by a clear margin. Thus, making good decisions need not rely on the standard rational approach of collecting all available information and combining it according to the relative importance of each cue—simply betting on one good reason, even one selected at random, can provide a competitive level of accuracy in a range of environments. Just what environments allow one-reason decision mechanisms to excel—that is, what conditions lead them to be ecologically rational—is still being explored, but some are known: Take The Best, for instance, seems to do well in environments where cue validities are distributed in a highly skewed fashion, with some cues being much more useful than others (Martignon and Hoffrage, 2002), and where learning samples are small.

Not only are simple one-reason decision mechanisms accurate and robust, they also correspond to how people (and other animals) make decisions in a variety of circumstances. People use these fast and frugal algorithms in environments that have the appropriate structure, even when they must first learn how the environment is structured (Rieskamp and Otto, 2006). Heuristics such as Take The Best are also particularly used where information is costly or time consuming to acquire (Rieskamp and Hoffrage, 1999; Bröder, 2000; Newell and Shanks, 2003), whether the costs come from searching for cues in the environment or from searching in memory (Bröder and Schiffer, 2003).

There is a problem, though, in applying one-reason decision strategies: how can we tell what cues a heuristic should use, and in what order? Take The Best's validity-ordered cue search does considerably better than Minimalist's random search—but how do we come to know a more-or-less validity-ordered set of cues? In evolutionarily important decision contexts like choosing a mate or selecting something to eat, we might have some built-in knowledge of valid cues to use, such as facial symmetry or sweet taste. But we are unlikely to have innately specified cues to use, for instance, in deciding between restaurants. For decisions like this in modern environments, people must learn what cues are most useful or valid. This can be done through individual experience using simple learning rules, for instance, keeping an ordered list of possible cues and moving a cue up in the list every time it leads to a correct decision and down in the list every time it fails (Dieckmann and Todd, 2004). While such learning could happen relatively quickly (i.e. with few learning trials), in some cases people can arrive at a good cue order more quickly by learning it socially from other decision makers, or through culturally transmitted rules.

15.4.3. Heuristics for multiple-option choices

When there are more than two options to choose from, then more than a single binary cue must typically be used to determine a single choice. But here, too, in these situations of multi-attribute decision making it is possible to reach quick decisions using a minimal amount of information, rather than gathering and combining a large number of cues or attributes. A fast and frugal approach to these decision situations is to use the process of elimination, as incorporated by Tversky (1972) in his Elimination By Aspects (or EBA) choice mechanism. For instance, if there are several restaurants to be decided among, first select a cue (or aspect) dimension somehow, and a way of using that cue to discard some of the available options. In the case of EBA, the cues are selected probabilistically, and a threshold is set for determining which options are eliminated from further consideration, such as discarding all restaurants that are more than 10 kilometres away. If there are still multiple options left to be considered, then select another cue and use it to eliminate some more possibilities—such as all restaurants not serving fish tonight. Proceed in this way, using successive cues to whittle down the set of remaining options, until only a single one remains, which is the final choice. Tversky found that this process describes well what people do in these types of preferential choice tasks.

A similar elimination process can be used to categorize objects or stimuli, where the task can be conceived of as deciding which of several possible categories the object best fits into (Berretty *et al.*, 1999). When information may be difficult to come by, and decisions should be made quickly, a fast and frugal categorization process can be adaptive. Consider the situation of trying to decide about another's intentions as that person approaches. Does this person want to greet me, dance with me, or take my wallet? How can one judge this, especially if the person is a stranger and is not announcing any aims verbally or facially? One way is to come to a quick first guess on the basis of how the person is moving, that is, using motion cues alone and an elimination process to limit the number of cues considered, to make a rapid yet accurate categorization (Blythe *et al.*, 1999; Barrett *et al.*, 2005).

Estimation is another related task that can also be performed accurately with few cues by a simple algorithm that exploits environments with a particular structure. The QuickEst heuristic (Hertwig *et al.*, 1999) is designed to estimate the values of objects along some criterion while using as little information as possible. To estimate the criterion value of a particular object, the heuristic looks through the available cues or features in a criterion-determined order, until it comes to the first one that the object does not possess. At this point, QuickEst stops searching for any further information and produces an estimate based on criterion values associated with the absence of the last cue. QuickEst proves to be fast and frugal, as well as accurate, in environments characterized by a distribution of criterion values in which small values are common and big values are rare (a so-called 'J-shaped' distribution). Such distributions characterize a variety of naturally occurring phenomena including many formed by accretionary growth (e.g. cities, some businesses, etc.).

15.4.4. Satisficing heuristics for sequential choices

The heuristics presented so far assume that all of the possible options to be chosen between are presently available to the decision maker. But a different strategy is called for when alternatives (as opposed to information about the alternatives) take time to find, appearing sequentially over an extended period. This is an important type of decision to study, because sequential search is ubiquitous, occurring whenever resources being sought are distributed in time or space and so cannot be considered (or at least not encountered) simultaneously. Searching for mates or friends, houses or habitats, jobs, parking spaces, shopping bargains, or restaurants to eat at all involve sequential decisions of this sort. The problem is that, whatever option you currently have available—for instance, the restaurant that you are standing in front of—another possibly better option could become available in the future, so how can you decide when to stop searching and stick with the current (or some previous) option?

In this type of choice task, a fast and frugal reasoner need not (only) limit information search, but (also) must have a stopping rule for ending the search for alternatives themselves. Here, Herbert Simon's (1955, 1990) notion of a satisficing heuristic is applicable: an aspiration level is set for the selection criterion being used, and the search for alternatives is stopped as soon as the aspiration is met. Simple mechanisms can be used to set the aspiration level in the first place, such as checking the first few alternatives and taking the best value seen in that set as the level to beat in further search (Todd and Miller, 1999). The trick here is to balance the desire for a short, fast and frugal search on the one hand (achieved by checking as few initial alternatives as possible), against the need for enough information about the potential alternatives to set an appropriate aspiration level on the other hand (achieved by checking as many initial alternatives as possible). People seem relatively adept at striking this kind of balance (Seale and Rapoport, 1997; Dudey and Todd, 2002).

But many sequential choice problems involve an added complication: they are two-sided, which means the searchers are being searched by others at the same time, and choice must therefore be mutual. Job applicants must select their employer and be selected in return; men and women on the marriage market must both decide to take the plunge together. This additional challenge can be solved by the searchers learning their own value or rank position within their pool of fellow searchers and using this self-knowledge to determine how high they should aim their search aspirations (Kalick and Hamilton, 1986), rather than merely setting an aspiration level based on the values of a small sample of available options, as in the one-sided approaches covered above. Todd and Miller (1999) presented a range of simple heuristics that do just this, for instance, heuristics for learning one's mate value through the acceptances and rejections encountered during an adolescent dating period or more generally a phase 1 search period. These heuristics, like the one-sided mechanisms already mentioned, can perform well with little search, quickly learning appropriate aspiration levels based on the searcher's own quality. Evidence for their use can be obtained both via population-level demographic measures (Todd *et al.*, 2005a) and in laboratory experiments of sequential dating.

15.5. **The challenge ahead for ecological rationality**

Studying ecological rationality as the fit between structures in information-processing mechanisms in the mind and structures in information in the world gives us three things to focus on: the mind (decision heuristics), the world (information patterns), and how they can match. As we have shown in this chapter, the heuristics that have been studied so far cover a wide range of possible types of choice tasks that people face, such as choosing one option from two or more, or finding a good option from a sequence of alternatives. However, another way to think of the organization of the adaptive toolbox is in terms of content domains, such as heuristics for finding food or for choosing mates (Todd, 2000). Some of the same sorts of heuristics (e.g., satisficing mechanisms for sequential search) are, as indicated earlier, likely applied in multiple domains (e.g., in mate search and habitat search), so it will be beneficial to explore the adaptive toolbox from both the decision task and the content domain perspectives, combining cognitive psychology approaches with evolutionary psychology (Todd *et al.*, 2005).

To discover more about the tools in the mind's toolbox, we should also proceed in two additional directions. Delving downward, we need to expand our understanding of the set of building blocks and deeper evolved abilities (e.g., the capacity for recognition or for trust) that can combine to create decision mechanisms. Connecting upward, we must consider how the adaptive toolbox of heuristics for inference and preference ties in with other cognitive, memory, perceptual, and motor systems to produce adaptive behaviour (as has been done in implementing the recognition heuristic within a broader cognitive modelling framework, ACT-R—see Schooler and Hertwig, 2005).

As indicated in earlier examples, researchers have also started to put together a vocabulary for describing environment structures, for instance, in terms of cue validities and distributions of objects. But this effort is still largely incomplete and disconnected. Useful ways to describe psychologically relevant aspects of spatial structure, temporal patterns, and social environments must still be developed, or imported from other disciplines. And the different sources of environment structure—long-term physical and biological aspects of our world, social environments composed of other people, cultural and institutional structures created by others to influence us, and emergent patterns arising from the interactions of populations of individuals each following their own decision heuristics—must all be mapped out and placed in a coherent framework so that their commonalities and differences can be made evident.

The greatest challenge remains in tying the two types of structure, mental and environmental, together. Heuristics often lead to correct answers, but sometimes lead to errors, as emphasized in the heuristics-and-biases research tradition (Kahneman *et al.*, 1982); the work ahead needs to focus on when, where and why they succeed or fail—their ecological rationality. This is only possible if we have precise models of these heuristics, as in terms of the building blocks described earlier. Uncovering the ecological rationality of particular decision mechanisms can be a matter of predicting their performance based on how well their specific building blocks fit to certain information patterns, and then testing them via experimentation, simulation, or mathematical analysis in different environments. However, explaining *why* a heuristic matches some environments and not others largely remains a conundrum at the centre of ongoing research (Todd *et al.*, in press).

The adaptive processes of evolution, learning, and culture have shaped human minds to be ecologically rational, relying on simple decision heuristics that confer the twin advantages of speed and accuracy in particular environments bearing exploitable patterns of information. Individuals can certainly be led to use heuristics in inappropriate environments and consequently make errors in reasoning, but this serves to show the boundaries of a mechanism's ecological rationality, rather than its irrationality. When mind and world fit together, the evolved capacities, building blocks, and simple heuristics in our adaptive toolbox can guide us to make good choices in a fast and frugal manner.

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