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Building the Theory of Ecological Rationality

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Abstract While theories of rationality and decision making typically adopt either a single-powertool perspective or a bag-of-tricks mentality, the research program of ecological rationality bridges these with a theoretically-driven account of when different heuristic decision mechanisms will work well. Here we described two ways to study how heuristics match their ecological setting: The bottom-up approach starts with psychologically plausible building blocks that are combined to create simple heuristics that fit specific environments. The top-down approach starts from the statistical problem facing the organism and a set of principles, such as the bias– variance tradeoff, that can explain when and why heuristics work in uncertain environments, and then shows how effective heuristics can be built by biasing and simplifying more complex models. We conclude with challenges these approaches face in developing a psychologically realistic perspective on human rationality.

Keywords Ecological rationality · Bounded rationality · Heuristics · Toolbox · Bias/variance dilemma · Statistical learning theory · Uncertainty · Optimality · Hedgefox

> "The fox knows many things, but the hedgehog knows one big thing."—Archilochus (Greece, c. 650 BC), as quoted by Isaiah Berlin (1953)

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Introduction

Research perspectives on rationality and decision making have often fallen near one or the other end of Archilochus's famous dichotomy between stolid, single-minded hedgehogs and crafty, inventive foxes: having one big method to address all the challenges in life, or many distinct strategies for dealing with different kinds of problems. The former hedgehogian approach corresponds to views that propose one powerful theory, such as maximizing subjective expected utility or Bayesian probability updating, to account for how people make decisions across the broad range of situations we encounter. The latter foxy approach typically manifests as a collection of decision-making strategies for a multitude of situations, such as a cognitive bag of tricks or toolbox of heuristics. Debates have raged over the merits of these two antagonistic approaches to life and thought ever since Archilochus crystalized the distinction, in the humanities (Berlin 1953), politics and economics (Tetlock 2006; Silver 2012), and psychology (Gigerenzer 2008). But as ever, the truth is likely to lie somewhere in between the two ends of this rigid dichotomy, in the realm of the hedgefox (after Loewenstein et al. 2007)—a creature that employs a range of decision-making tools, but in a way that can be predicted and explained through an overarching theoretical account.

The research program of *ecological rationality* (Todd et al. 2012a) aims to bridge these two perspectives, by providing a hedgefoxian theoretically-driven account of the variety of decision mechanisms people draw on and the environmental settings in which they will work well. It explains the effectiveness of particular decision heuristics in terms of their fit to the characteristics of the task environment. But this approach to understanding rationality risks devolving into a collection of unconnected mind-environment match-ups if the theoretical foundations predicting when different mental structures will fit with different environmental structures are not well developed. In this paper we give an overview of the current state of theorizing regarding ecological rationality, and describe ways forward. We highlight two approaches to exploring systematically the mind-environment match of the range of heuristics people employ. First, we discuss a bottom-up approach that starts with psychologically plausible building blocks that can be combined to create simple heuristics that are also fit for specific environments. Next, we outline a top-down approach that starts by considering the statistical problem facing the organism, then develops a set of statistical principles capable of explaining when and why heuristics work in uncertain environments, and finally suggests how new heuristics can be generated by biasing and simplifying—and as a result, often outperforming—more complex models. We finish with challenges that both approaches face in developing a hedgefoxian perspective on human rationality.

From Bounded Rationality to Ecological Rationality

In true hedgehogian fashion, traditional perspectives on rationality prescribe a right way to make decisions based on a single overarching principle: apply the rules of logic, apply maximization of utility, apply Bayes's rule. These perspectives typically embody a "more-is-better" philosophy toward the use of information and computation, resulting in methods that often require implausible amounts of both on the part of the decision maker (Todd and Gigerenzer 2012). More psychologically grounded models have been developed under the title *bounded rationality*: rationality that people can actually achieve given our prevailing constraints on information, cognition, memory, and time (Gigerenzer and Selten 2001).

Bounded Rationality

Within research on bounded rationality, the common view has been that people are hemmed in by purely internal constraints, such as limits on the speed with which we can process information and the amount of information we can hold in working memory (e.g., Simon 1981, chapter 3). But there are also crucial bounds that stem from the nature of the external world (Todd 2001): because the world is uncertain and changing, the mechanisms used by decisions makers need to be robust; and because the world is competitive, with other agents intent on getting the same resources and opportunities, decision making must be fast, imposing a constraint from the costs of searching for information in the world. Given these constraints, bounded rationality could be seen as the attempt to do as well as possible given the demands of the world—which is captured in the idea of optimization under constraints—or as the suboptimal outcome of the limited cognitive system—the realm of irrationality and cognitive illusions (Piattelli-Palmarini 1996).

However, there is another possibility regarding the two types of bounds, internal and external, that constrain our decision making, and what they imply for a psychologically relevant theory of rationality: rather than being separate and unrelated, the two sets of bounds may be intimately linked. As Herbert Simon put it, "Human rational behavior…is shaped by a scissors whose two blades are the structure of the task environments and the computational capabilities of the actor" (Simon 1990, p. 7). These two blades must fit together closely for the organism is to function effectively, and achieve goals in the world. While the external bounds may be more or less immutable from the decision maker's standpoint, the internal bounds comprising the capacities of the cognitive system can be shaped, for instance by evolution and development, to take advantage of the structure of the external environment (Todd 2001). From this perspective, bounded rationality can be seen as the positive outcome of the two types of bounds fitting together. Moreover, the challenges in the environment define the problems that rationality must address and the standards by which it succeeds, leading to measures of rationality based on correspondence (achieving desired ends in the world) rather than coherence (achieving internally consistent states of knowledge). To capture the importance of the environment in constraining and enabling decision making (in both humans and other species), we use the term *ecological rationality* (Gigerenzer et al. 1999; Todd et al. 2012b)—making good decisions with mental mechanisms that exploit the structure of the environment.

Ecological Rationality

The idea of ecological rationality leads to the foxy prediction of multiple inference mechanisms, driven by a hedgehogian vision of the fit between mental and environmental structure that tells us what kind of mechanisms to expect people will use in what kinds of settings. Specifically, to produce adaptive, effective decision-making behavior that achieves our desired ends in the world, we make decisions within our bounds by using a collection of simple mechanisms. That is, people draw on an *adaptive toolbox* of decision mechanisms that include fast and frugal heuristics, quick shortcuts, and rough rules of thumb (Gigerenzer and Todd 1999). Some of these tools are pre-wired for us by evolution, and some are learned through individual experience or through cultural inheritance. Many are applicable to specific decision tasks and in particular domains—different tools for different tasks, as a consequence of the biases they embody that enable their fit to particular environmental situations. These biases mean that the simple heuristics are tuned to certain environmental contexts at the expense of others. And this in turn means that they often require little information, and little processing of that information, to yield ecological rationality—adaptive behavior fit to various settings.

Having multiple task-specific tools in the mind's adaptive toolbox is akin to having multiple domain-specific modules as proposed in evolutionary psychology (e.g., Cosmides and Tooby 1994) in what is sometimes called the Swiss army knife metaphor of the mind. The extent of the collection of tools studied in ecological rationality remains to be determined, though it may not be as large as implied by discussions of *massive* modularity in evolutionary psychology (Barrett and Kurzban 2006). This is because the adaptive toolbox is not arranged by ancestral adaptive domains, such as mate choice, foraging, and parental investment, as done in evolutionary psychology, but rather by underlying environmental structures that the tools are fit to, such as statistical patterns among cues in the environment. In some cases, adaptive domains and environmental structures will be correlated, but in other cases, the same environmental structure may be found in multiple adaptive domains, implying that the same kind of tool could be used across those domains. Discovering these relationships between ancestral adaptive domains (or new modern tasks), environmental structures, and the tools that fit them is one of the goals of the study of ecological rationality.

Distinguishing Unbounded, Bounded, and Ecological Rationality

Taking the hedgehog stance, traditional unbounded rationality postulates one big powerful means of making proper decisions. Bounded rationality has traditionally been studied in two main species (Gigerenzer 2008): a hedgehogian application of the similarly all-encompassing idea of optimization under constraints, and a foxy collection of fallible, error-prone heuristics, shortcuts, and rules of thumb (Kahneman et al. 1982). The former retains the goal of optimality, and the latter threatens to proliferate in an endless list of ad-hoc decision mechanisms and biases (e.g., see the list of over 150 cognitive biases on Wikipedia). Ecological rationality takes the hybrid hedgefoxian approach of seeking to discover and explain the variety of simple heuristics people employ in their adaptive toolbox through the lens of overarching predictive theory. Before examining the study of ecological rationality in more detail, the major distinctions between unbounded, bounded and ecological rationality are worth clarifying.

Notions of rationality are not inherently valid or invalid but provide varying degrees of insight depending on the problem being addressed. Ecological rationality is a response to the problem of understanding how biologically constrained organisms function under the uncertainty of the natural world. This uncertainty will typically preclude knowledge of all relevant states, actions, and consequences, and most importantly, preclude probabilistic quantification of the various uncertainties facing the organism. This perspective on uncertainty undermines the objective of optimality. Rather than focus on problems with optimal solutions, the study of ecological rationality focuses on the analysis of the relative ability of competing models to confer function under uncertainty, and when the optimal response is indeterminable. As we discuss further in "A Top-Down Statistical Approach to Studying Ecological Rationality" section, this statistical approach to understanding the function conferred by models is distinct from (a) the optimization under constraints approach to studying bounded rationality, and (b), classical notions of unbounded rationality. Specifically, on finding that a heuristic outperforms some set of competing models, the conclusion need not be that the heuristic is optimal, nor that it approximates an optimal response, but that it is effective relative to the currently entertained alternatives. To state that the heuristic, or any other model, is optimal requires one to probabilistically quantify the relevant uncertainties.

Thus, the study of ecological rationality is not a response to our failure to live up to unbounded rationality, but a response to the fact that "it is sometimes more rational to admit that one does not have sufficient information for probabilistic beliefs than to pretend that one does" (Gilboa et al. 2012, p. 28). In the following, then, it is imperative to keep in mind that the study of ecological rationality examines how, when, and why organisms manage to function so effectively despite (1) environmental constraints that render optimal responses indeterminable, and (2) internal cognitive and biological constraints that restrict the processing of information. As such, ecological rationality does not supplant classical notions of rationality, nor can it be reduced to classical notions of rationality. Rather, it addresses a fundamentally different problem to those considered by the study of optimization under constraints and the study of unbounded rationality.

The Components of Ecological Rationality

Studies of human rationality often start with the question "How good are people at making decisions?" With such a broad question, one can find (or construct) examples that lead to answers ranging from "optimal" to "not so bad" to "really quite awful", leaving the inquiry in a muddle. The problem is that starting with the wrong question will lead to wrong (or useless) answers. The study of ecological rationality aims to alleviate this problem by asking more precise questions to which we can provide useful answers.

Ecological rationality is the answer to a different question: How do minds "fit" their environments? Or, to restate the typical rationality question more precisely, what tools do people use to make decisions in the situations that matter to us, and how well do they work? It is not enough just to ask how well different tools perform particular actions in general. The setting—the structure of the environment—is crucial. A homebuilder would be unlikely to walk into a hardware store, pick up a plausible blade, and ask, "How well does this saw cut?"—unless she would be happy with answers all over the place, from "quick and smooth" from the guy in the plumbing department who is thinking about how fast it will get through a PVC pipe, to "don't even bother" from the lumberjack passing down the aisle who is thinking about how long it would take to get through a redwood. While the tool could conceivably be applied to cutting tasks in a variety of settings, there are some for which it was meant, and some for which it was not, and we will only get sensible answers to our questions about its operation if we ask about its effectiveness in the settings where it is used. We must be similarly specific when we ask about the mental tools—decision mechanisms—that people employ in particular environmental settings in order to learn about mind-environment matches and mismatches.

By exploring how minds fit environments, researchers studying ecological rationality aim to specify three things: the structure of information-processing mechanisms operating in minds, the structure of information available to those minds in the environments they inhabit, and the way the two structures—mental and environmental—fit together. Specifying particular aspects of the decision maker's environment allows us to get specific about questions regarding the mind. This key insight has been repeatedly discovered, forgotten, and revived through the history of scientific inquiry into animal and human behavior, from Charles Darwin to Herbert Simon (e.g., Todd and Gigerenzer 2007).

To look more specifically ecological rationality's central issue of how minds fit environments, we need to unpack what we mean by each of the three components: minds, environments, and their fit. First, *minds* guide agents' behavior to achieve certain goals in particular settings. In doing this, they are influenced by those settings. We can think of minds as processing information about those settings (e.g., stimuli or input from the current situation) along with information about past experiences and current goals to come up with decisions about what to do next. Because the natural world is uncertain, organisms need to make inductive inferences. The models studied under the rubric of ecological rationality tend to address inference problems, and mechanisms that respond to these problems can be separated into two processing "stages". First, after observing the environment, an organism may attempt to second-guess what regularities govern these observations. For example, when exposed to a series of products, one might infer that size is good predictor of price. Second, and based on such subjective knowledge (which may or may not have gleaned from observations), decision making is the process of categorizing, estimating, or predicting events of interest. For example, one might estimate the price of new product on the basis of its size. Broadly speaking, inductive inference is the problem of inferring hypotheses from observations, and decision making is the problem of using hypotheses to make decisions.

As mentioned earlier, the mind uses different information-processing mechanisms for different decision tasks, drawing on an adaptive toolbox if not a whole hardware store. While some of these mechanisms may be general-purpose and able to tackle multiple jobs more or less broadly, many are specific, simple, and effective heuristics. A heuristic is an information-processing mechanism that ignores information. More precisely, it ignores much of the available information, and instead focuses on just a few key pieces of data to make its decisions. Estimating the value of a product using only a single cue such as size, and ignoring all other cues, is an example of ignoring information.

The root of the word "heuristic" refers to guided search, which is just what a heuristic does, guiding search for crucial information and the good decisions it can lead to. So-called fast and frugal heuristics (Gigerenzer and Goldstein 1996) process the little information they find in a quick and simple way—they are frugal in the information they seek, and fast in the processing they do with it. Consider the very fast and very frugal recognition heuristic (Goldstein and Gigerenzer 2002), which for instance can be used to decide which of two stocks to invest in based solely on whether the decision maker has heard of one and not the other: it seeks only information about recognition, and makes its decision based solely on the binary values of that information, that is, whether each stock is recognized or not. And yet, like other heuristics it can make very effective decisions, when used in appropriate environments to which it fits (Borges et al. 1999; Boyd 2001). This "when" is the question of the heuristic's ecological rationality.

An *environment* is what an agent acts in and upon. The environment also influences the agent's actions in multiple ways, by determining the goals that the agent aims to fulfill, shaping the tools that the agent has for reaching those goals, and providing the inputs processed by the agent to guide its decisions and behavior. We can think of the environment as a set of structural and statistical properties. Note, however, that the relevant conception of the environment for some decision-making task is not something independent outside the mind, but rather is defined in terms of what the agent can perceive or be influenced by. This subjective aspect of the environment does not however mean that correspondence criteria cannot be used to assess ecological rationality—evolution builds sensory systems that make the subjective perceptions of the environment that an agent bases its decisions on reflect the objective structures in the environment sufficiently for the agent to achieve its goals. Moreover, the environment of interest is not a fixed and stable pattern of information, but a dynamic system that the agent can actively influence and change its perception of—cognition and environment co-mingle and co-evolve. The relevant environment can be made up of patterns among physical objects, such as landscapes, but also among other organisms such as predators and prey, and other conspecifics such as social partners, family members, and cultural institutions. We often refer to ecological rationality in environments of the latter types as *social rationality* (Hertwig et al. 2013).

The *fit* between a decision mechanism and a particular environment is some measure of how well adapted that mechanism is to performing its task given the specific information structures available in the environment. This fit is typically measured in two ways: by testing how well a heuristic can be trained to perform in a given environment, and by testing how well a heuristic that is trained in one environment generalizes to a new one. For training, we can collect a set of decisions from the environment for which we know the correct answers—inferences, such as which of two companies made more money last year, or which of two islands had more rainfall—and let the heuristic or other mechanism in question learn about the relationships between the answers and the available information or cues—such as how latitude relates to rainfall. Then we test how accurate the heuristic is at producing the correct answers given some cues. (We can also look at preferences—e.g., the choices that people make according to their own tastes—and test how good particular heuristics are at reproducing or predicting those in particular information environments—Fasolo et al. 2007.) This kind of performance tells us something about the comparative ability of different inference mechanisms to exploit information patterns to reach good decisions, and we can also see how much information and how much computational resources they need in order to function. But we are often interested in the second measure of a mechanism's fit to an environment: How well it can function beyond the training situation and generalize to decisions in new settings, for instance about new items that it has never previously encountered—such as newly-formed companies whose profits for the next year must be estimated. This generalization ability or *robustness* in the face of changing questions or environments is crucial for agents dealing with the dynamic world (Brighton and Gigerenzer 2012a; Hogarth 2012).

To see these components in action, consider a vital investment problem that many people face in some form or other, such as saving for one's retirement: How to invest money in *N* available assets? A commonly used heuristic is: *Allocate your money equally to each of the N options.* This heuristic is known as the *1/N rule*. It is bounded in that it ignores all information about the previous performance of the *N* assets, making it frugal and fast. It stands in sharp contrast to optimal asset allocation models, such as the mean–variance model of Nobel Prize winner Harry Markowitz, which seek to maximize the gain (mean) and to minimize the risk (variance) of the portfolio by applying heavy computation to all the performance information available. The environment in which the heuristic is applied can be characterized in terms of the number *N* of assets, the uncertainty of the market, and the amount of performance data available (e.g., in number of years). And the fit between the heuristic and the environment can be assessed by how much money it makes when applied to the particular market environment for some period of time. (In this case, the 1/*N* rule is not trained on a particular set of data, so there is no distinct generalization performance to assess, though there can be for the optimizing models.)

The psychology–ecology fit that is at the center of ecological rationality comes about through the coadaptation of minds and their environments. The mind's internal bounds (sensory abilities, memory limits, cognitive power) can be shaped by evolution, learning, and development, to take advantage of the structure of the external environment (Todd 2001). Likewise, the environment's external bounds, stemming from the structure of available information, can be shaped by the effects of minds making decisions in the world, including most notably in humans the process of cultural evolution (Boyd and Richerson 1985, 2005). This coadaptation results in decision mechanisms that are fit to particular environments, and to the particular adaptive goals that humans (or other species) have in those environments. This perspective also illuminates what is meant by the "adaptive" toolbox—capturing the notion of adaptive tools both in the sense of being *well-adapted* to the environment, emphasizing the fit between the mind and environment structures and how the mind is able to achieve its goals (as measured by correspondence criteria), and in the sense of *adapting* to the environment, by learning the appropriate heuristics, features, and patterns to use in current environmental settings (through those processes of development, individual learning, social copying, or cultural inheritance).

With these three components more clearly defined, the ecological rationality of a decision mechanism, such as a heuristic, can be specified in a particular environment in terms of how accurate or robust it is. We will often also be interested in comparative statements that assess how much better or worse one heuristic performs compared to other mechanisms in some environment: insights of the kind that mechanism *A* performs better than *B* in environment *E*. Here we get to a most important point: Heuristics (like all inference mechanisms) are not good or bad per se, but only relative to the structure of the environment (and each other). Consider the 1/*N* investment heuristic again. Markowitz's optimization model is not always better than this heuristic, nor does the opposite hold; it depends on the environment. Specifically, if *N* is large (which is typical for an investor), the predictability of the performance of the funds is low (which is typical for the stock market), and the window of available data is rather small, then the 1/*N* rule has an advantage in predictive accuracy over the optimization method. The smaller *N*, the higher the predictability, and the larger the window of data, the more that complex optimization methods will have an advantage (DeMiguel et al. 2009). Different decision mechanisms are ecologically rational in different environments. This is the key notion of ecological rationality: that adaptive behavior is determined by the interaction of particular decision mechanisms in particular environments. It cannot be assessed in terms of cognitive processes alone (as would be implied by relying on coherence criteria to evaluate their performance).

Finally, and crucially from an empirical and psychological perspective, we are interested in not just how ecologically rational specific heuristics are in specific environments, but also how ecologically rational humans and other agents are in their environments—do people rely on heuristics fit to the tasks in environments they face? Because the human mind has been shaped by the adaptive processes of evolution, learning, and culture, we predict that people will tend to be ecologically rational themselves, often using simple decision heuristics that can offer the twin advantages of speed and accuracy in appropriate environments. This prediction has been supported in numerous studies (see Bröder 2012, for an overview); for instance, people employ fast and frugal heuristics when information is costly or takes time to find—situations in which it is advantageous to limit information search. Moreover, people are sensitive to the statistical properties of cues in an environment, appropriately applying different mechanisms depending on which will be more accurate (Rieskamp and Otto 2006). We will return to this question of selecting what decision mechanism to apply at the end of this paper.

How to Study Ecological Rationality

Recall that the ecological rationality perspective posits a foxy collection of decision mechanisms that make up the mind's adaptive toolbox. But to avoid being an atheoretical exercise in mere stamp collecting, of which the heuristics-and-biases approach to studying bounded rationality has sometimes been accused, ecological rationality seeks to unify the study of the adaptive toolbox via a hedgehogian application of overarching theory—yielding the hybrid hedgefoxian approach to predicting the existence and efficacy of heuristics for different environments. Two theoretical perspectives have been consistently applied to the study of ecological rationality: evolutionary theory and the formal study heuristics using statistical (machine) learning and mathematical analysis. Each produces a somewhat different method for exploring the contents of the adaptive toolbox, as we discuss below: a bottom-up approach starting from evolved capacities and building blocks that combine to form heuristics in the former case, and a top-down approach that examines statistical tricks that explain why existing heuristics work as well as suggesting new ones. But both approaches follow the same basic outline, as follows.

The study of ecologically rational mechanisms begins with identifying important decision tasks (e.g., on psychological or evolutionary grounds) and specifying the structure of information in the environment that can be exploited in making those decisions. Next, models of candidate heuristics are proposed—this is the step that differs between the two methods. In both approaches, the models are specified in computational terms as information-processing algorithms. These proposed heuristics are analyzed using computer simulation and mathematical modeling to understand when and how they work, and then via empirical experimentation or observation to see when people (or other animals) actually use them to make decisions. The whole process is iterated as needed to narrow in on credible explanations of the decision mechanisms people (or other animals) use to solve their goals in the environments under consideration. This research method differs from that of the heuristics-and-biases program, in emphasizing explicit computational models of heuristics: 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. We now go into more detail about the bottom-up and top-down approaches to specifying those heuristic algorithms.

The Bottom-Up Evolutionary Approach to Specifying Heuristics

The bottom-up approach to specifying heuristics in the adaptive toolbox starts with evolved capacities and information-processing building blocks and combines them in psychologically plausible ways (see Hammerstein and Stevens 2012 for a broad perspective on studying *Darwinian Decision Theory*). This differs from the closely related approach taken in studying modules in evolutionary psychology in that it also considers how adaptive (learning) processes can yield heuristics that fit modern task environments as well as ancestral ones. At the same time, the coverage of current task environments makes the approach similar to the method of rational task analysis (Anderson 1990; see also Neth et al. this issue), which also emphasizes analyzing the structure of task environments—including those constructed in laboratory experiments—and assessing how mental mechanisms with particular constraints can process the information available to them to come to appropriate decisions.

The bottom-up evolutionary perspective draws attention to how environment structure has an impact on behavior and hence ecological rationality in three important ways: by defining the goals that agents must meet, by shaping the capacities and processes that they have for meeting those goals, and by providing the information needed to make the ongoing decisions that guide behavior toward the goals. We can think of these influences more specifically for our (and other species') evolved minds as operating at three levels (Wilke and Todd 2012): first, the demands of life in our general terrestrial environment determined the adaptive goals that much of decision making is aimed at reaching (the specific domains that evolutionary psychology focuses on). Second, the ancestral environment determined through its interaction with evolution those cognitive capacities that an organism can bring to bear in making adaptive decisions. And third, the particular task environment determines what environmental structures are available to an organism's evolved decision mechanisms for making particular choices.

Adaptive Goals

Evolutionary biology distinguishes between a species' proximal and ultimate goals. The ultimate goal driving evolution is reproduction; survival is important insofar as it leads to increased reproduction (of oneself and one's kin). Beyond this ultimate goal, there are many typically shorter-term proximal ones, and often subgoals of each of those (e.g., Buss 2011; Kenrick et al. 2009). Some proximal goals are more closely related to survival, such as finding food, avoiding predators, and taking care of one's injuries; others are more associated with reproduction, such as finding mates. For organisms that care for their offspring and live in social groups, such as humans, there are additional basic proximal goals, including protecting offspring, forming coalitions, and achieving status. The adaptive toolbox of a social species contains a repertoire of social heuristics for solving these kinds of proximal goals (Hertwig et al. 2013); imitation heuristics, for instance, such as copying the behavior of successful group members, can enable learning how to provision one's family as well as how to achieve status (Boyd and Richerson 2005). Again, each of these proximal goals can be split up into sub-goals, such as reading the behaviors of others to infer what their intentions are. Many of the behavioral mechanisms in the adaptive toolbox have evolved to achieve some proximal (sub)goal, though it can be difficult to determine which, for instance whether language serves a goal of conveying survival-relevant information, or attracting mates, or both (Miller 2000). And even if a tool evolved for one goal originally, it could be exapted (through further evolution) or adopted (through culture and learning) for use in a new context with similar environmental structure.

Evolved Capacities and Heuristics

Given particular proximal goals, organisms will have means of meeting them, including decision heuristics and the cognitive capacities and building blocks from which they are constructed (Todd and Gigerenzer 2012). Some of these will be evolved and essentially "built-in", while others will be learned, either through individual experience or from other individuals or one's culture (but all via learning mechanisms that are themselves ultimately evolved). The underlying evolved cognitive capacities, which can be important for a range of applications, include search processes for food or other resources (e.g., controlling attention and balancing exploration/exploitation—Todd et al. 2012), learning (e.g., conditioning, preparedness, and imitation—Davey 1989), storage and retrieval of information (e.g., recognition, recall memory, and adaptive forgetting—Schooler and Hertwig 2005), and use of social cues (e.g., reputation, trust, and in-group/out-group distinctions—Hertwig et al. 2013). These capacities will differ across species, and some, such as reputation and trust, may be found only in the adaptive toolbox of Homo sapiens and perhaps a few other social organisms. Knowing what cognitive capacities a particular species has is helpful for uncovering what heuristics and other behavioral mechanisms it may be able to use.

The building blocks of heuristics draw on an organism's evolved capacities: for instance, "search for recognition knowledge" is a building block of the recognition heuristic that employs the capacity to recognize objects encountered in the past. Heuristic building blocks include three main types: those that guide the search for information or alternatives (or both), those that stop this search process, and those that make a decision based on the results of the search. The first type give search its direction (if it has one): for instance, search for informative cues can be simply random, or ordered by some measure of their usefulness (e.g., validity). The second type of building blocks keep decision making within the temporal constraints imposed by the environment by terminating the search for alternatives or information in some simple manner: for example, stop searching for information as soon as the first cue or reason is found that favors one alternative—a building block that underlies one-reason decision making. This and other related stopping rules do not need to compute an optimal cost–benefit trade-off for how long to search; in fact, they need not compute any costs or benefits at all. For search among alternatives, simple aspiration-level stopping rules can be used (Simon 1990; Hutchinson et al. 2012). Finally, once search has been guided to find the appropriate alternatives or information and then been stopped, the third type of building block can be called upon to make an inference (or choice) based on the results of the search: for instance, use only one cue or reason, whatever the total number of cues found during search (Bröder 2012). Such single-cue decision making does not need to weight or combine cues, and so no common currency between cues need be determined. Different building blocks, like the heuristics they compose, will perform better or worse in particular environments (see e.g. Gigerenzer et al. 2012, for a discussion of search and stopping building blocks and their fit to different information structures).

The Structure of the Environment

The information that heuristics process to make inferences can arise from a variety of environmental processes, including physical, biological, social, and cultural sources (Todd and Gigerenzer 2007, 2012). Despite this variety, certain structural and probabilistic environmental characteristics recur, and are observed across otherwise distinct sources of information (Czerlinski et al. 1999; Martignon and Hoffrage 1999; Şimşek 2013). Many of these characteristics describe the ability of cues to make accurate inferences, such as their validities (how often a cue leads to a correct inference when it can be used) and their discrimination rates (how often a particular cue distinguishes between alternatives, regardless of its accuracy), and how these cues are related. Relationship between cues that prove critical to heuristic functioning include redundancies (i.e., inter-cue correlations; Dieckmann and Rieskamp 2007), whether cue validities have high variance (Martignon and Hoffrage 1999; Katsikopoulos and Martignon 2006), and how the cues determine patterns of dominance between the decision alternatives (Hogarth and Karelaia 2006; see Katsikopoulos 2011, for a review). Furthermore, the spatiotemporal patterns of items and events can be exploited, such as whether they are common or rare (McKenzie and Chase 2012), or how they are spread across patches such as fruits clustered on bushes (Hutchinson et al. 2008). Structures in and from social environments are also crucial for social species (Hertwig et al. 2013): for instance, because people and the media tend to discuss noteworthy items, such as the tallest buildings, biggest cities, richest people, and winningest teams, patterns of recognition in individual memory that are generated through social spread of knowledge can be successfully exploited by the recognition heuristic mentioned earlier (Pachur et al. 2012).

Other forms of structure can emerge through the social interactions of many individual decision makers, as when drivers seeking a parking space by using a particular search heuristic create a pattern of available spots that becomes the environment for future drivers to search through (Hutchinson et al. 2012). Some environment structures are also specifically created by cultures or institutions to influence the behavior of individuals. Sometimes this is felicitous, as when governments figure out how to get citizens to donate organs by default, or design traffic laws for intersection right-of-way in a hierarchical manner that matches our one-reason decision mechanisms (Bennis et al. 2012). But it can also be detrimental if institutions create environment structures that do not fit well with people's decision mechanisms, and instead cloud minds and lead to poor choices: for instance, when information about medical treatments is represented in misleading ways (Kurzenhäuser and Hoffrage 2012). Figuring out ways to fix such poor designs and make new ones that people can readily find their way through is an important applied goal of studying ecological rationality (Gigerenzer and Todd 2012).

A Top-Down Statistical Approach to Studying Ecological Rationality

A contrasting, but complimentary approach to studying ecological rationality sets out to establish a theoretical setting from a different, statistical, perspective in which both the study of specific models and the philosophical outlook of ecological rationality have a single coherent foundation. It uses a top-down approach that holds the promise of explaining the ecological rationality of larger families of heuristics all at once. It also explores how the functional implications of heuristics can be studied without appealing to optimality principles or conventional rationality paradigms such as Bayesian rationality. Recall that the study of ecological rationality not only concerns itself with constraints internal to the decision maker but also constraints arising from the environment. Uncertainty is a key constraint, and if one considers the statistical "goal" of decision making under environmental uncertainty then, for many cognitive scientists and philosophers, Bayesian rationality provides the ideal framework for formalizing the problem. In such top-down analyses a model of the problem and its optimal solution are used to guide the development of specific cognitive models. For instance, the Bayesian paradigm tends to stress the role of optimal solutions, generating distributions, state-spaces, and utility functions both when constructing the problem and when analyzing potential solutions. In short, the statistical outlook one chooses to adopt will likely have a strong influence on subsequent model development, interpretation, and analysis. Now, the goal of this second approach is to work toward an answer to the following question: Can the study of ecological rationality proceed in a statistical, top-down fashion yet (a) abstain from making the assumptions required to define optimal responses, and (b) retain its "foxy" focus on multiple decision making strategies?

A common assumption is that heuristics provide approximations to optimal solutions. Ultimately, this means viewing ecological rationality as being subservient to conventional rationality principles, and merely contributing a source of quick and dirty approximate shortcuts to more complex, optimal calculations. Another option is to reconsider the statistical framework used to construct the question, and view ecological rationality as addressing a related, but different problem. This second option promises to unite the foxy aspects of ecological rationality with the hedgehogian demand for a deeper formal, and in this case statistical, foundation. Unlike the preceding approaches to studying ecological rationality, this second approach looks to statistics, rather than the cognitive or biological sciences, for inspiration. Indeed, several statisticians have questioned the objective of defining an optimal solution relative to a hypothesized probabilistic model of the environment. For example, Brieman's (2001) algorithmic modeling, Rissanen's (2007) minimum description length principle, and Geisser's (1993) approach to predictive inference all reject the idea of an optimal solution. Instead, they argue that the uncertainty of the natural world more frequently poses problems that require search, prediction, and ultimately, an understanding of the relative ability of multiple models to reduce, rather than resolve, uncertainty. These views have much in common with the study of ecological rationality. For instance, many of the findings that drive the study of ecological rationality rest on demonstrating that heuristics can achieve higher predictive accuracy than more familiar cognitive and statistical models in environments where the optimal solution is not known, or may not meaningfully exist. By specifying the statistical assumptions of the ecological rationality program in this way, it becomes clear that the approach not only provides an alternative view on cognitive processing, but also an alternative view on the statistical problem facing the organism (Brighton and Gigerenzer 2012b).

How can problems that lack optimal solutions be studied? As we have stressed, the study of heuristics usually involves comparing the abilities of multiple models to predict unseen, novel events in the environment given only limited experience. Predictive accuracy is usually estimated using cross-validation, where each model is first trained on some subset of the observations, and its predictive accuracy is then measured relative to the remaining observations. One can then explain the functional success of models within such a framework without conjecturing optimal responses, or an underlying probabilistic model of the environment. Specifically, recent research into ecological rationality has recruited the concepts of bias, variance, and the bias/variance dilemma from statistical learning theory (Geman et al. 1992) to further understand when and why heuristics can outperform more familiar models, but also how a more refined statistical explanation of the success of heuristics might lead the way to developing new models (Gigerenzer and Brighton 2009). Considerations of bias and variance become critical when a learning algorithm, such as a heuristic, first infers a statistical model from observations of the environment and then uses this model to make predictions. In general, the prediction of error of a learning algorithm can be decomposed into three terms:

$$\text{total error} = (\text{bias})^2 + \text{variance} + \text{noise}$$

We decompose prediction error in this way because we are typically interested in the behaviorally-crucial question of how well an algorithm predicts outcomes in new situations based on different samples drawn from the same population, rather than the performance of the algorithm at learning to fit (i.e., explain post-hoc) a specific sample of observations. Bias and variance refer to two distinct sources of error when predicting from different samples drawn from the same population. Here, different samples could represent different "replays" of an organism's experience of the environment. After all, if the tape of experience had been played from a slightly different starting position, then the organism would have likely experienced a different set of observations even though they were generated by the same environmental processes. More precisely, the bias component of prediction error measures the difference between the mean model (defined with respect to all potential sets of experience) and the "true" model of the environment. The variance component of prediction error measures to what extent the predictions made after observing each specific sample will vary about this mean. For example, a model may on average perform very well but the prediction error incurred for each specific set of experiences could show a high variance around that generally well-fitting mean. On the other hand, the model could be systematically biased, with average performance that is consistently different from observed data, yet it could achieve lower mean prediction error than an unbiased method because it incurs lower variance. Possibilities such as these highlight that a bias/variance dilemma exists in statistical inference: under uncertainty, achieving low prediction error requires striking a balance between achieving low bias and low variance. A dilemma arises because techniques for achieving low bias (such as using highly flexible models with many parameters) tend to increase variance, and techniques for achieving low variance (such as using simple models with few parameters) tend to increase bias.

What insights can considerations of bias and variance provide, particularly in conjunction with a statistical perspective that disavows the existence of optimal solutions? One source of insight is to deepen our understanding of existing models. For instance, Gigerenzer and Brighton (2009) showed how the performance of the take-the-best heuristic—both in environments where it outperforms other models, and in environments where take-the-best performs poorly in comparison to the same models—is explainable almost exclusively in terms of variance. This means that the sensitivity (or robustness) of take-the-best versus other models to small changes in the observations drives the observed performance differences, rather than the relative ability of the different models to accurately represent predictive regularities in the observations. Findings such as this can refine our understanding of when and why heuristics perform well by refocusing the question, to ask: Which features of the environment determine take-the-best's ability to incur low variance? Another source of insight is to clarify, from a statistical standpoint, the substantive differences between the ecological rationality program and alternative notions of rationality. Although a clear and complete picture is yet to be established, the following four distinctions outline some key differences:

Relative Function Rather than Optimal Function

The bias/variance perspective stresses the view that learning and decision mechanisms incur greater or lesser degrees of error rather than optimal or sub-optimal degrees of error. Notice that "bias" in decision making is often regarded as present or absent, as well as having a largely negative connotation in the popular imagination and in the scientific literature (e.g. in the heuristics-and-biases research program following from Tversky and Kahneman 1974). But bias, in the statistical sense that we use the term here, is an omnipresent feature of learning and decision mechanisms: these mechanisms should not be described as biased or unbiased, but rather as incurring greater or lesser degrees of bias relative to alternative mechanisms in conjunction with the structure of the environment. Similarly, mechanisms will incur greater or lesser degrees of variance relative to each other, rather than zero or some optimal degree of variance. In short, the bias/variance perspective invokes a less idealized picture of the statistical problem facing the organism, and allows us to understand the functioning of cognitive models without assuming that optimality is a meaningful objective.

Prediction Rather than Explanation

The bias/variance perspective stresses the predictive ability of models rather than their ability to accurately represent nature's data-generating processes. For example, a successful simple heuristic should not be interpreted as evidence that the world is simple, but rather as evidence that the world is uncertain and that reducing prediction error can often be achieved by ignoring information (as a heuristic does) so as to decrease variance. The study of rational models of cognition, and particularly Bayesian models of cognition, will often begin with the goal of modeling nature's generating processes with a view to defining optimal responses relative to this model. This distinction between ecological rationality and traditional rationality is a statistical one, and reflects two related but different objectives: prediction versus explanation (Shmueli 2010). Those who view optimal behavior as an essential aim of rationality will tend to stress the goal of explanation, while those who study the ecological rationality of good-enough behavior will tend to stress the goal of prediction.

Less Rather than More Information

How can making a decision by using less information or performing less processing on it lead to more accurate inferences? Rather than reducing bias, ignoring information tends to reduce variance. This helps us to understand the benefits of ignoring information, but also suggests a way of generating new heuristics by taking familiar statistical models and "hobbling" them in such a way as to improve their performance. To generate heuristics in this way, we can begin from, say, an "optimal" multiple regression model that is trained to decide which of two cities is larger based on a set of cues (e.g., Gigerenzer and Goldstein 1996, 1999). This model will use all of the available cues, weighted appropriately by their association with the city-size decision criterion, and taking the intercorrelations between cues into account. We can then introduce particular sources of bias by creating heuristics that ignore some of the cues, cue weights, interactions between cues, or some combination of these factors. The tally heuristic, for example, uses all the cues, but ignores their weights and interactions. Take-the-best, which checks cues in order of their validity until the first discriminating cue is found and then uses only that cue to make its decision, ignores most of the cues and all of their interactions, but does calculate the validities of the cues and weight them by those values. And the minimalist heuristic, which searches cues in random order until the first discriminating cue is found, ignores most cues, all interactions, and all weights. In short, one way of generating new heuristics is to bias familiar statistical and cognitive models by introducing simplifying shortcuts and leaving out some information. This method thus fills in the heuristic-specifying steps of the overall research plan described earlier by starting with some well-understood statistical decision strategy appropriate for the task under consideration, and then adding particular biases and constraints to that strategy to shape it into a psychologically plausible mechanism that a person could use. In this way it is similar to the research approach of behavioral ecology, which starts with general optimal models (e.g., optimal foraging theory) and proceeds to add simplifying constraints to make them fit the specifics of the animal and its environment. Understanding when, why, and how these simplifications, for humans and other animals, lead to improved decision performance is key to the study of ecological rationality.

Reducing Rather than Resolving Uncertainty

When studying rationality, why investigate a toolbox of strategies rather than a single powerful statistical principle or paradigm, such as Bayesian rationality? An irony lies behind this question: the field of statistics itself calls upon a toolbox of methods and approaches for tackling problems rather than a single, unified tool (and this also holds true for Bayesian statistics). If the natural world were more certain, then perhaps a single tool would suffice. But given the uncertainty of real life, care should be taken when making the idealizations required to construct well-defined problems that a single tool can handle. Tukey (1962), for instance, vehemently opposed the use of mathematical statistics—and particularly its focus on optimality–as a sound model for approaching and making sense of real-world data. Very similar tensions underlie our distinction between the foxy and hedgehogian perspectives on rationality. Specifically, the analysis of decision mechanisms in uncertain environments need not rest on the notion of optimality (Brighton and Olsson 2009): optimality modeling is not implied by the adoption of formal, or even mathematical statistics; it merely signifies a particular way of formalizing certain kinds of problems. Optimality modelers, though, can sometimes give the impression that the problem of decision making under uncertainty is resolvable, and that ideal solutions will always exist. The study of ecological rationality, in contrast, stresses the study of the relative ability of multiple models to reduce uncertainty rather than resolve uncertainty. That a problem cannot be solved optimally does not mean that the problem is ill-defined, nor that an investigation of this problem is doomed to failure. As we have pointed out, formal frameworks such as the bias/variance dilemma allow us to formulate explanations for when and why heuristics succeed and fail in uncertain environments.

To summarize, this top-down approach to studying ecological rationality from a statistical perspective stresses the study of relative rather than optimal performance, the goal of prediction rather than explanation, the investigation of how accurate predictions can be achieved by ignoring information as well as processing information, and the framing of problems facing organisms as uncertainty reduction rather than uncertainty resolution. From this perspective, the study of ecological rationality is not a foxy mish-mash of arbitrary mechanisms, but nor does it appeal to the hedgehogian ideal of a single rational principle.

Further Challenges for Studying Ecological Rationality

These two hedgefoxian approaches to studying heuristics, the bottom-up evolutionary one and the top-down statistical one, hold promise for exploring and understanding the contents of the mind's adaptive toolbox. But both of these (and indeed any other approach) face at least three main challenges going forward: characterizing environment structure, explaining how different tools are selected from the toolbox, and accounting for individual differences in heuristic use.

In order to study and explain how particular heuristics are fit to particular environment structures, we must have the right lexicon to use in assessing and describing those structures (Martignon and Hoffrage 1999; Hogarth and Karelaia 2007; Katsikopoulos 2011; Şimşek 2013). There are a variety of structural aspects that have proven useful so far, including high-level ones such as degree of uncertainty, sample size for learning, redundancy between cues, and number of alternatives (Todd and Gigerenzer 2012), and lower-level ones such as the distribution of criterion values, cue values, and cue validities (e.g., uniform, normal, or J-shaped; see Todd et al. 2012b), as well as social attributes such as trust in information sources, configuration of social networks, and so on (Hertwig et al. 2013). But whether these or other aspects are most useful in explaining mind-environment matches (and mismatches), and whether there is a more systematic way to describe such structure, must be determined through further research.

The use of boundedly rational heuristics does not stay bounded if the way they are chosen from the adaptive toolbox is itself a psychologically implausible optimizing process. Thus, heuristic selection in the service of ecological rationality must also happen in a realistic, typically fast and frugal manner, and discovering how this is done in different environmental settings remains an active topic of study. In some cases, the agent's knowledge determines what heuristic can be used: for instance, the recognition heuristic can be used if some choice alternatives are unknown, the familiarity or fluency heuristic can be used if all items are recognized but nothing else is known about them, and one-reason heuristics like take-the-best can be used if more information is known about the alternatives (Marewski and Schooler 2011). In other cases, selecting between heuristics that can all apply to the agent's current level of knowledge can be done on the basis of past experience and learning which heuristic works best in a given situation (Rieskamp and Otto 2006). There can also be cues regarding the environment structure itself that can guide the selection of appropriate heuristics: for example, if the validity of the recognition cue is high, then the recognition heuristic can be effective, but otherwise more information should be sought (Pachur et al. 2012). These and other possibilities must still be filled out for different environment and agent conditions, in ways that do not violate the ecological rationality of the use of the mind's toolbox as a whole.

Finally, because of the variety of different tools available in the adaptive toolbox, some of which could be applied in the same situations, different people will end up using different heuristics (and different cues), and the same person may even use a different heuristic at different points in time. This individual variation is commonly observed in studies of decision strategies (e.g., Bröder 2012), and can be used to give us further insight into the range of tools in the adaptive toolbox, the ways those tools get into the toolbox (including differences in individual experience, development, and culture), and the ways they are selected for use in particular circumstances. Further developing theories about how heuristics are learned and modified will help us get a handle on what ranges of individual variation in ecologically rational heuristic use we can expect to find in specific conditions.

In sum, the ecological rationality research program leads us to ask three key questions: Given an environment, what heuristics succeed? Given a heuristic, in what environments does it succeed? And how and why do particular heuristics and environments fit together to produce good decisions? The answers help us understand the contents of the mind's adaptive toolbox and how those tools are drawn on to tackle particular problems with particular types of structure. But we need to combine the foxy approach of specifying multiple different tools for different problems with an overarching hedgehogian theory-driven ability to predict what heuristic tools are in the toolbox, whether it is a bottom-up evolutionary approach or a top-down statistical conception or a combination of these and other ideas. Enter the hedgefox.

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