P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

CHAPTER 17

Situating Rationality

Ecologically Rational Decision Making with Simple Heuristics

Henry Brighton and Peter M. Todd

1. Introduction

Many within cognitive science believe that rational principles rooted in probability theory and logic provide valuable insight into the cognitive systems of humans and animals. More than this, some say that rational principles, such as Bayesianism, algorithmic information theory, and logic, not only provide elegant and formally well understood frameworks for thinking about cognition but also are the very principles governing thought itself, guiding inferences and decisions about the world (e.g., Chater, 2002; Feldman, 2003). It is not difficult to see why ascribing such principles to the cognitive system is a tempting and desirable goal: if correct, these principles would provide universal normative laws governing the cognitive system. Even faced with the diversity of tasks and environments handled by the cognitive system, a valid universal principle would have the advantage of providing a theoretical handle with which to grasp the range of cognition in a unified manner. In contrast, situated theories of cognition take the specific and concrete details of the interaction between mind and environment to matter significantly, so much so that seeking universal principles of rationality is seen as one of the primary wrong turns in the path of traditional approaches to understanding cognition (e.g., Smith, 1999).

Other approaches to cognition find similar fault with the search for universal mechanisms or all-powerful inferential machinery. The recently developed view of ecological rationality places a strong focus on the structural properties of environments, and takes a structure-specific, and, as we will show in this chapter, situated approach to the study of cognitive processes. Ecological rationality emerges when simple cognitively plausible heuristic processes exploit specific environmental characteristics to make adaptive choices in particular circumstances (Gigerenzer, Todd, & ABC Research Group, 1999). Adaptive choices are those that help an organism function successfully in its environment. Rather than view the mind as a general purpose processor endowed with

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

the considerable computational resources demanded by classical notions of rational inference, we instead explore the possibility that the mind is more like a mixed bag of cognitive processes, each working within the limitations of the cognitive system, and each tuned to specific structures occurring in natural environments. We term this mixed bag of simple heuristics the *adaptive toolbox* (e.g., Gigerenzer & Selten, 2001). In section 3 we firm up this metaphor by providing examples of simple heuristics, and we discuss work that demonstrates, through computational modeling and experimental studies, that these heuristics are both plausible and often more effective than traditional models of inference.

In section 4 we address our main concern: situating rationality in such a way that the specific, concrete, engaged, and located nature of human cognition is given due significance. We argue that classical visions of rationality fail to consider the computational limitations of the cognitive system and the importance of the role of cognitive exploitation of environment structure. On this view, normative theories derived from classical notions of rationality prove limited in their ability to capture the specific nature of how the cognitive system interacts adaptively with the environment in inference and decision-making tasks. Although systems of logic, for example, can be tailored to specific tasks and environmental contexts (e.g., Stenning & van Lambalgen, 2004), the issue of how the cognitive system might plausibly process information to achieve logical consistency, and whether such a task is computationally feasible, remains unclear. In contrast, we argue that ecological rationality bounds rationality to the world by considering both ecological context and constraints on cognitive processing (Todd & Gigerenzer, 2003). This view of rationality is closely allied with the situated cognition movement, and in section 5 we clarify the ways in which ecological rationality can be understood in terms of the key dimensions of situated approaches proposed by Smith (1999).

2. Mind and Environment: The Terms of the Relationship

In what ways does the environment influence the contents of the mind? A wide range of possibilities exists. For some aspects of the cognitive system it could be that the environment plays an insignificant role in influencing the contents of the mind. The human language faculty, for instance, is thought by some researchers to be shaped not by the environment but by boundary conditions internal to the mind in the sense that the linguistic system is an optimal solution for meeting the requirements of transforming thought between the conceptual-intentional system and the articulatory-motor system (Chomsky, 1995). According to this view, if we want to understand the language faculty, then it pays not to consider the environment at all, either over evolutionary or ontogenetic timescales. But for many aspects of the cognitive system we cannot ignore the important impact of the environment, and several possible forms of relationship between mind and environment need to be considered. Within psychology, the ecological approach to cognition seeks to understand the terms of such relationships. We begin by considering three metaphors (Todd & Gigerenzer, 2001) that aim to capture some key relationships.

2.1. *Three Kinds of Relationships*

To understand the contents of the mind, we should consider the environment in which it acts and in which it has evolved. This ecological, situated perspective has been promoted within cognitive psychology in particular by Roger Shepard's work (see, e.g., Shepard, 2001, and other papers in the special issue of *Behavior and Brain Sciences* on Shepard's research and related efforts it has inspired), focusing on a particular vision of how the external world shapes our mental mechanisms. For Shepard (2001), much of perception and cognition is done with mirrors: key aspects of the environment are internalized in the brain "by natural selection

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

specifically to provide a veridical representation of significant objects and events in the external world" (p. 2). In particular, Shepard considers how the cognitive system reflects features of the world, or laws, which support, for example, tracking the movement of objects in Euclidean space. These abstract principles are based "as much (or possibly more) in geometry, probability, and group theory, as in specific, physical facts about concrete, material objects" (Shepard, 2001, p. 601). Thus, the cognitive system possesses deeply internalized, abstract, and universal reflections of physical reality. Shepard's work can be viewed as ecological in that an understanding of mind is taken to be fundamentally dependent on identifying the important properties of the physical world. Yet this view also turns on the contentious issue of the mind representing properties of the world, albeit at very abstract level. Without entering into arguments over the need for representations of any sort (for a discussion of the key issues, see, e.g., Brooks, 1991; Markman & Dietrich, 2000), we can still question whether assumed representations should be veridical, constructed to accurately reflect the world, or instead be useful in an adaptive sense. In short, whatever the functional role of such representations, this mirrorlike relationship characterizes those properties of mind that are present as a result of an internalization of universal laws governing physical environments.

A less exacting view of internalization can be seen in the work of Egon Brunswik (1955), who proposed a lens model that reconstructs a representation of a distal stimulus on the basis of the current proximal cues (whose availability could vary from one decision situation to the next) along with stored knowledge of the environmental relationships between those perceived cues and the stimulus. These relationships were later usually conceived of as correlations in the field of social judgment theory that followed from Brunswik's work (see Hammond & Stewart, 2001). For Brunswik, the mind models and projects the world more than reflects it (or, as he also put it, mind and world accommodate each other like husband and wife).

Herbert Simon (1990) expressed a still looser coupling between mind and environment: bounded rationality, he said, was shaped by a pair of scissors whose two blades are the characteristics of the task environment and the computational capabilities of the decision maker. Here, computational capabilities refer to sensory, neural, and other mental characteristics that may impose cognitive limitations on, for example, memory and processing. Crucially, these capabilities, when coupled with certain characteristics of the environment, can complement one another. Rather than the mind reflecting or projecting properties of the environment, Simon's scissor metaphor highlights a very different kind of relationship in which properties of mind are viewed as fitting properties of environments in an exploitative and complementary relationship. From this perspective, it is less clear how meaningfully one can characterize the relationship between mind and environment in terms of internalization or representation, as some properties of the mind can be only implicitly related to the environment rather than more directly, as suggested by metaphors of mirror images or projections. Considering this kind of exploitative relationship led Simon (1956) to consider, in the context of decision making, "how simple a set of choice mechanisms we can postulate and still obtain the gross features of observed adaptive choice behavior" (p. 129). This question highlights how an exploitative relationship between mind and environment has implications for kind of cognitive machinery used by the mind: as Simon and others have since shown, simple, boundedly rational decision mechanisms coupled with the right environmental context can yield adaptive choice behavior that is typically attributed to more complex and information-hungry mechanisms.

2.2. *Appropriate Metaphors for Higher-Level Cognition*

We expect that the mind draws on mechanisms akin to all three tools, mirrors, lenses, and scissors, from its adaptive toolbox

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

(Gigerenzer & Todd, 1999). The question now becomes, Where can each be used, or where does each different view of situated cognition best apply? In perception, using Shepard's mirror or Brunswik's lens may often be the right way to look at things, but there are also examples in which these tools are inappropriate. Consider the problem of a fielder trying to catch a ball coming down in front of her. The final destination of the ball will be complexly determined by its initial velocity, its spin, the effects of wind all along its path, and other causal factors. But rather than perceive all these characteristics, reflect or model the world, and compute an interception point to aim at, the fielder can use a simple heuristic: fixate on the ball and adjust her speed while running toward it so that her angle of gaze – the angle between the ball and the ground from her eye – remains constant (McLeod & Dienes, 1996). By using this simple gaze heuristic, the fielder will catch the ball while running. No veridical representations or models of the world are needed – just a mechanism that fits to and exploits the relevant structure of the environment; namely, the single cue of gaze angle. How widely such scissorslike heuristics can be found in perception remains to be seen, but some (e.g., Ramachandran, 1990) expect that perception is a bag of tricks like this rather than a box of mirrors.

When we come to higher-order cognition and decision making, our main concern in this chapter, Simon's cutting perspective seems the most appropriate way to extend Shepard's and Brunswik's ecological views. Consider a simple decision rule that has been proposed as a model of human choice: the Take the Best heuristic (Gigerenzer & Goldstein, 1996). To choose between two options on the basis of several cues known about each option, this heuristic says to consider one cue at a time in order of the ecological validity of each (i.e., how often each cue makes correct decisions), and to stop this cue search with the first one that distinguishes between the options and make the final decision using only that cue (we will explain this heuristic in more detail later in the chapter). This "fast and frugal" heuristic makes decisions about as well as multiple regression in many environments (Czerlinski, Gigerenzer, & Goldstein, 1999) but usually uses far less information (cues) in reaching a decision. It does not incorporate enough knowledge to reasonably be said to reflect the environment, nor even to model it in Brunswik's sense (because it only knows cue order, not exact validities), but it can certainly match and exploit environment structure: when cue importance is distributed in something like an exponentially decreasing manner (as is the case in some environments), Take the Best performs about as well on training data sets as multiple regression or any other linear decision rule (Martignon & Hoffrage, 1999) and generalizes to new data sets even better.

As another example, the QuickEst heuristic for estimating quantities (Hertwig, Hoffrage, & Martignon, 1999) is similarly designed to use only those cues necessary to reach a reasonable inference. QuickEst makes accurate estimates with a minimum of information when the criteria of the objects it operates on follow a J-shaped (power law) distribution, such as the sizes of cities or the number of publications per psychologist. Again this crucial aspect of environment structure is nowhere built into the decision mechanism, but by processing the most important cues in an appropriate order, QuickEst can exploit that structure to great advantage. Neither of these heuristics (which we will describe in more detail in the next section) embodies logical rationality – they do not even consider all the available information – but rather they demonstrate ecological rationality, making adaptive decisions by relying on the structure of the environment.

Why might it be that Simon's scissors could help us understand cognitive mechanisms more than Shepard's mirror? We (and others) suspect that humans often use simple decision-making mechanisms that are built on (and receive their inputs from) much more complex lower-level perceptual mechanisms. For instance, the recognition heuristic, an elementary mechanism for deciding between two options on the basis of

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

which of them are merely recognized, simply uses the binary cue of recognized versus not recognized; however, the computational machinery involved in the lower-level assessment of whether a voice, or face, or name actually is recognized involves considerable complexity (Todd, 1999). If these decision heuristics achieve their simplicity in part by minimizing the amount of information they use, then they are less likely to reflect the external world and more likely to exploit just the important, useful aspects of it, as calculated and distilled by the perceptual system (which may well base its computations on a more reflective representation).

Thus, in extending the search for the imprint of the world on the mind from perception to higher-order cognition, we should probably look less for reflections and more for complementary pairings à la Simon's two scissors blades. This approach to studying environmentally situated decision mechanisms is just what we shall introduce in this chapter. While Simon studied bounded rationality, we use the term *ecological rationality* to emphasize the importance of the match between the structure of information in the environment and the structure of information processing in the mind. In the next section, we introduce the notion of the adaptive toolbox and describe how its contents can be studied, before expanding on some examples of its contents by describing simple ecologically rational decision heuristics. In section 4 we develop further the concept of ecological rationality by discussing how it contrasts with traditional notions of rationality, and why, in the context of the study of mind, ecological rationality is a more appropriate notion when considering aspects of high-level cognition. In section 5 we relate these discussions to the study situated cognition by framing ecological rationality as a form of situated cognition.

3. The Adaptive Toolbox and Its Contents

It is certainly the case that not all of human behavior is ecologically rational, as defined here. For instance, people can (if given the luxury of sufficient time and training) use more general methods of reasoning according to traditional norms of rationality, such as the tools of logic or probability theory, to come to decisions with little concern for adapting their reasoning to the specific structure of the current task environment. Or people may use simple decision heuristics that try to exploit some features of the environment to allow for cognitive shortcuts, but in the wrong environment, so that biased decision making arises (as studied in the heuristics and biases research tradition; see, e.g., Kahneman, Slovic, & Tversky, 1982). But we propose that much of human decision making is ecologically rational, guided by typically simple decision heuristics that exploit the available structure of the environment to make good choices. Given the right environmental circumstances, these simple methods perform adequately for many tasks and sometimes better than more complex mechanisms. One consequence of this theory is that a single all-purpose decision-making system is no longer the appropriate unit of study, as different tasks call for different simple mechanisms. The idea of the adaptive toolbox leads us to consider a collection of simple mechanisms drawn on by the cognitive system. We view these mechanisms as structure specific rather than domain specific. In contrast to the concept of domain specificity, structure specificity is the ability of a process to deal effectively with informational structures found in environments that may or may not be encountered in multiple domains (e.g., a systematic correlation between recognition knowledge and some criterion of interest, which we discuss herein). These mechanisms are built from basic, cognitively primitive building blocks for information search, stopping the search, and making a decision based on the search's results. How heuristics are constructed using these building blocks, when and why one heuristic is used over another, and how and how well they work in different situations are all key issues confronting this research program. In this section, we give a taste

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

of how these issues are addressed and discuss how this approach can be a productive route to understanding the cognitive system in terms of simple process models tuned to environment structures.

A number of steps are involved in studying the contents of the adaptive toolbox. First, after identifying a particular ecologically important decision domain, we must determine the structure of information available to people in that domain. As Shepard (2001) indicated, this involves discovering the "general properties that characterize the environments in which organisms with advanced visual and locomotor capabilities are likely to survive and reproduce" (p. 581) – these might include power laws governing scale invariance (Bak, 1996; Chater & Brown, 1999) or costs of time and energy in seeking information (Todd, 2001). Shepard (1987) considers only the longest-applying physical laws as stable parts of the environment, avoiding discussion of the biological and social realms that he feels have not been around as long and so will not have exerted as much pressure on our and other animals' evolved cognition. However, we have certainly evolved adaptive responses to these realms of challenges as well, and so we should extend the study of environmentally matched decision heuristics to biological and social domains (as is done within evolutionary psychology; e.g., Barkow, Cosmides, & Tooby, 1992; Buss, 2005). This means we should look for environmental-information regularities that may be internalized to guide our cognition when situated in different evolutionarily important domains, such as predator risk (e.g., Barrett, 2005), knowledge of infection and disease transmission (e.g., Rozin & Fallon, 1987), understanding genetic dynamics (e.g., kin selection; Hamilton, 1996), and social interactions of various types (e.g., on the dynamics of signaling between agents with conflicting interests, see Zahavi & Zahavi, 1997; on mate choice, social exchange, and dominance hierarchies, see Buss, 2005).

With these characteristic environment structures in mind as one half of Simon's scissors, we can look more effectively for the decision mechanisms that form the other matching half. This can involve a further set of steps, as follows:

1. Investigating, through simulation, candidate models of cognitive processes built from elementary processing abilities such as search and recognition; to achieve this, a model selection criterion is required (e.g., performance criteria such as predictive accuracy, frugality of information use). These yardsticks set the scene for comparisons with other models.
2. Identifying if and when these heuristics perform well in certain environments, and what the characteristics of these environments are, often using analytic methods. Is it possible to give precise environment-structure conditions for good or poor performance of the heuristics? Do these conditions match those of typical environments inhabited by humans?
3. With an understanding of how the model and the environment (or task) structure match, carrying out empirical studies to see if humans use these processes in appropriate situations.

The use of elementary processing abilities to guide the construction of candidate models reflects a commitment to bottom-up design. One consequence of this approach is that it leads to simple and testable models with few parameters and therefore makes for a more transparent relation between theory and data. Another consequence, which affects a core concern for the study of ecological rationality, is that the resultant cognitive models, by virtue of their simplicity and close reliance on fundamental processing abilities, are more likely to be cognitively plausible. This approach adopts the view that functioning cognitive models can be built with nontrivial consequences without needing to be monolithic, generally applicable, and computationally complex. In short, robust cognitive processing is achieved with simple and ecologically targeted mental heuristics. The concept of

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

ecological rationality and the adaptive toolbox, in some respects, is close in spirit to Anderson's rational analysis, where a consideration of the structure of the environment constrains the development of cognitive models, and a focus on the plausibility of the cognitive models then steers future development (Anderson, 1990; Oaksford & Chater, 1998). However, rational analysis, in contrast to the approach explored here, places less of an emphasis on bottom-up design. One consequence of this difference is that the adaptive toolbox leads to a consideration of multiple simple models rather than fewer, more complex models.

What is in the adaptive toolbox? Several classes of simple heuristics for making different types of decisions in a variety of domains have been investigated (see, e.g., Gigerenzer et al., 1999; Kahneman et al., 1982; Payne, Bettman, & Johnson, 1993; Simon, 1990), including ignorance-based heuristics that make decisions based on a systematic lack of information, one-reason heuristics that make a choice as soon as a single reason is found on which to based that choice, elimination heuristics that whittle down a set of choices using as few pieces of information as possible until a single choice is determined, and satisficing heuristics that search through a sequence of options until a good-enough possibility is found. Other tools are also present, and more await discovery. Here we present three examples of the heuristic tools in the toolbox.

3.1. *Paired Comparison Using the Recognition Heuristic*

The capacity for recognition is common to many species. The most basic cognitive heuristic we will focus on exploits this capacity to make inductive inferences. Given the task of deciding which of two objects in the world scores higher on some criterion of interest, the recognition heuristic can provide a quick and robust decision procedure by exploiting a lack of knowledge. If one of the objects being considered is recognized and the other is not, then the recognition heuristic tells us to judge the recognized object as scoring higher on the criterion. For example, given the names of two tennis players, the recognition heuristic simplifies the task of deciding which of these two tennis players is most likely to win the next grand-slam tournament: if we only recognize one of the players and not the other, then the recognition heuristic tells us to pick the player we have heard of (Pachur & Biele, 2007). Similarly, given the task of choosing which of two cities has a higher population, the recognition heuristic tells us to pick the city we have heard of over the one we have not (Goldstein & Gigerenzer, 1999, 2002). Clearly, the appropriate use of this heuristic depends on (a) applicability, because to apply the recognition heuristic certain conditions must be met, and (b) validity, because the ability to apply the heuristic does not necessarily imply that it will lead to accurate inferences. Specifically, the recognition heuristic is applicable only when the decision maker has an intermediate amount of (recognition) knowledge, not complete or completely lacking knowledge (which would render the recognition heuristic unusable). And this heuristic is only valid when the partial recognition knowledge is systematic; that is, correlated with the criterion on which the decision is being made – for example, given that winning tennis players are talked about in person and in media more than second-rate ones, more people will recognize the best players, meaning that recognition is correlated with past success, and hence, presumably, with future chances as well. Both these conditions place restrictions on the kinds of environments in which the recognition heuristic will perform well, and defining such environments and determining how the heuristic operates in them are precisely the sorts of questions addressed and explored by the study of ecological rationality.

Using simple heuristics can also lead to surprising outcomes, which the ecological rationality framework can predict and explain. For example, when knowledge about and recognition of the objects in the environment (e.g., cities) is positively correlated with the criterion of interest (e.g.,

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

population), then the recognition heuristic can lead an individual with less knowledge to make more reliable decisions than a person with more knowledge. This less-is-more effect has been confirmed in simulations and demonstrated in experiments involving individuals (Goldstein & Gigerenzer, 1999, 2002) and groups of subjects (Reimer & Katsikopoulos, 2005). This example is striking because it shows how a simple mechanism built on a basic cognitive capacity, here recognition memory, when used in the right environmental setting, can enable the cognitive system to exploit environmental structure and subsequently make good decisions with little information or processing.

3.2. *Paired Comparisons Using Take the Best*

If only one object in a paired comparison task is recognized, then there is little choice but to apply the recognition heuristic. But when both objects are recognized, and knowledge of several cues about each object is available to aid the decision, then many possible decision processes exist. For example, the paired comparison task is a special case of the general task of learning to categorize from labeled examples, which is explored thoroughly in machine learning research (Mitchell, 1997). In that field, a litany of potential processes exist, typically complex algorithms designed from an engineering perspective to approximate a general solution to the problem of learning from examples, which leads these methods to veer from considerations of cognitive plausibility. In contrast, the study of ecological rationality from the perspective of the adaptive toolbox takes the issues of cognitive plausibility and the specific nature of the task as fundamental. These emphases are reflected in a bottom-up approach in which simple processes are built from elementary building blocks chosen to match a particular task environment. In particular, as mentioned earlier, Gigerenzer and colleagues (1999) have explored the following types of building blocks for processing cues representing features of objects encountered in the world:

1. Search rules, which define how information in the form of cues is searched for. For example, one possible search rule is to look through cues in an order that reflects how useful these cues have been in the past.
2. Stopping rules, which define when cue search is to be terminated. For example, given the task of comparing two objects in terms of their cue values, search can be terminated when a stopping criterion of different cue values for the two objects is met.
3. Decision rules, which define how the information found by the first two building blocks is used to make a decision. For example, given information about a cue that differs in value for two objects, the object with the higher cue value could be chosen.

Take the Best is a simple heuristic built from three such building blocks where (a) cues are searched in order of their ecological validity, (b) search stops at the first discriminating cue (i.e., the first cue that has a different value for each object, and hence discriminates between the two objects), and (c) the object selected is the one indicated by the discriminating cue. Ecological validity is a property of a cue, which indicates how frequently in the past the discriminating cue picked out the object with the higher criterion value. (Discrimination rate is another important property of cues, indicating how often a given cue discriminates between pairs of objects in some environment.) For example, Take the Best could decide which of two tennis players is more likely to win an upcoming competition by first considering the most valid cue, say, "Has this player won a grand-slam competition in the past?" If this cue discriminates – that is, it is true for one player and not the other – then Take the Best will stop information search and select the previous-winning player over the other. If the first cue does not discriminate, then further cues are considered in

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

order of ecological validity until one is found that does discriminate and is then used by itself to determine the decision.

Unlike many other models of decision making, which typically take all cues into consideration and combine them somehow to yield a decision, Take the Best is frugal in its use of information. The decision is made only on the basis of the first discriminating cue, and all other information is ignored. In this sense, Take the Best employs one-reason decision making. But does Take the Best suffer, in terms of performance, by ignoring so much of the available information? No – Take the Best often performs just as well as other less frugal and more computationally intensive models such as multiple linear regression, even though it uses only a fraction of the available information. But even more surprising is the fact that in a considerable number of decision environments examined so far, Take the Best can outperform rival models of decision making when generalizing to new decisions (Czerlinski et al., 1999). Furthermore, recent work demonstrates that Take the Best can even beat the key models of inductive inference used in machine learning research on connectionist, rule-based, and exemplar-based approaches – as long as the environment has a particular information structure (Brighton, 2006; Chater, Oaksford, Nakisa, & Redington, 2003). Thus, this work has shown in principle that decision processes built from simple cognitively plausible building blocks that use little processing and little information in ways that are matched to the task environments in which they are situated can outperform some of the most widely used and studied models of induction that take a domain-general, environment-agnostic approach.

But in practice, do people use such simple, fast-and-frugal heuristics to make decisions? A growing body of experimental and empirical work is demonstrating that people do use one-reason decision heuristics in appropriately structured environments, such as where cues act individually to signal the correct response (Rieskamp & Otto, 2005) or where information is costly or time consuming to acquire (Bröder, 2000; Bröder & Schiffer, 2003; Newell & Shanks, 2003; Rieskamp & Hoffrage, 1999). People also make socially and culturally influenced decisions based on a single reason through imitation (e.g., in food choice; Ariely & Levav, 2000), norm following, and employing protected values (e.g., moral codes that admit no compromise, such as never taking an action that results in human death; see Tanner & Medin, 2004).

3.3. *Estimation Using QuickEst*

Not all choices in life are presented to us as convenient pairs of options, of course. Often we must choose between several alternatives, such as which restaurant to go to or which habitat to settle in. In situations where each available cue dimension has fewer values than the number of available alternatives, one-reason decision making will usually not suffice, because a single cue will be unable to distinguish among all of the alternatives. For instance, knowing whether each of fifteen cities has a river is not enough information to decide which city is most habitable. But this does not doom the fast-and-frugal reasoner to a long process of cue search and combination in these situations. Again, a simple stopping rule can work to limit information search: seek cues (in an order specified by the search rule) only until enough is known to make a decision. But now a different type of decision rule is needed instead of relying on one reason. One way to select a single option from among multiple alternatives is to follow the simple principle of elimination (Tversky, 1972): successive cues are used to eliminate more and more alternatives and thereby reduce the set of remaining options, until a single option can be decided on.

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. The estimates are constrained to map onto certain round numbers (e.g., when estimating city population sizes, QuickEst can return values of 100,000, 150,000, 200,000, 300,000, and other similarly round numbers), so this heuristic can be seen as choosing one value from several possibilities. The elimination-based estimation process operates like a coal sorter, in which chunks of coal of various sizes first roll over a small slit, through which the smallest pieces fall into a bin for fine-grained coal; the bigger pieces that remain then roll over a wider slit that captures medium-sized pieces of coal into a medium bin; and finally the biggest chunks roll into a large coal bin. In the case of QuickEst applied to city population estimates, the coal chunks are cities of different population sizes; the bins are the rounded-number size estimates; and the slots are cues associated with city size, ordered according to the average size of the cities without that cue (e.g., because most small cities do not have a professional sports team, this could be one of the first cues checked – i.e., one of the first slots that the cities roll past). To estimate a city's size, the QuickEst heuristic looks through the cues or features in order until it comes to the first one that the city does not possess, at which point it stops searching for any further information (e.g., if a city possesses the first several features in order but lacks a convention center, the city falls into that bin and search will stop on that cue). QuickEst then gives the rounded mean criterion value associated with the absence of that cue as its final estimate (e.g., the mean size of all entries in the bin for cities without an exposition site). Thus, in effect, QuickEst uses features that are present to eliminate all smaller criterion categories, and absent features to eliminate all larger criterion categories, so that only one criterion estimate remains. No cue combination is necessary, and no adjustment from further cues is possible.

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, where the *J* is seen on its side). Such distributions characterize a variety of naturally occurring phenomena including many formed by accretionary growth. This growth pattern applies to cities (Makse, Havlin, & Stanley, 1995), and indeed big cities are much less common than small ones. As a consequence, when applied to a data set of cities, QuickEst is able to estimate rapidly the small sizes that most of them have.

4. Rationality in the Real World: From the Classical to the Ecological

The heuristics introduced in the previous section are tools for making inductive inferences. Induction is the task of using the past to predict and make decisions about the future. Without being able to look into the future, we can never answer with certainty questions such as, say, which tennis player will next win Wimbledon. We instead have to make an inductive inference, a prediction about the future, based on observations and knowledge we have acquired in the past. Clearly, by using prior experience we can often make better than chance predictions about future events in the world. This would not be possible if the world were unstructured and behaved randomly. Fortunately, most environments we face are highly structured, so that principled decision making serves us well. But what principles should guide our decision making? Many theories take what we will term *classical rationality* as a source of answers. This is to say that for the task of reasoning under uncertainty, clear normative principles such as Bayesian inference and variants of Occam's razor based on algorithmic information theory tell us what the rational course of action is (e.g., Chater, 1999; Hutter, 2005; Pearl, 1988). Yet humans often deviate from the classically rational: we make errors in a sometimes-systematic fashion and appear to only partially adhere to normative ideals. This view of occasionally error-prone human behavior is most forcefully argued within the heuristics-and-biases tradition, which proposes that people rely on a limited number of heuristic principles that reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations. In general, these heuristics are quite useful, but

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

sometimes they lead to severe and systematic errors (Tversky, 1974, p. 1124).

In this section we develop and justify why the classical view of rationality, when adopted as a concept with which to understand human decision making and inference, fails to capture significant aspects of the inference task. We will contrast classical rationality with ecological rationality and argue that the latter offers a far more productive concept with which to understand human decision making, as it bounds rationality to the world rather than treats the two as fundamentally separate (Todd & Gigerenzer, 2003). Thus, the ecological approach differs significantly from both classical rationality and the heuristics-and-biases tradition, and it offers what we consider another way of thinking about rationality:

> *There is a third way to look at inference, focusing on the psychological and ecological rather than on logic and probability theory. This view questions classical rationality as a universal norm and thereby questions the very definition of good reasoning on which both the enlightenment and heuristics-and-biases views were built. (Gigerenzer & Goldstein, 1996, p. 651)*

But in what sense does ecological rationality differ from classical rationality? The apparent strength of rational principles of inference stem from their generality and their formal justification by way of probability theory, and ultimately information theory (Li & Vitányi, 1997). For example, Occam's razor tells us to prefer simpler explanations over complex ones, and this principle proves productive when fitting a polynomial to a set of data points, choosing between scientific theories, or describing the behavior of human visual perception (Sober, 1975). That such principles hold across diverse tasks that are seemingly unrelated in their formulation, their physical characteristics, and importantly, the environmental context is seen as evidence of their strength.

However, if our concern is the study of human and animal cognition, then there are good reasons to view these apparent strengths as weaknesses. Neither humans nor animals uniformly adhere to overarching principles because, as we will argue, such principles make cognitive demands that cannot always be met. Furthermore, the generality of rational principles is in large part due to abstractions away from specific aspects of the task. Sometimes specific considerations, such as response time, are significant and may outweigh more general considerations such as predictive accuracy. We suspect that no single and universal measurement can characterize what is functional for an organism for all tasks, and in this sense we should be weary of proposals that collapse the problem characterizing rational choice down to a single yardstick. The concept of ecological rationality accepts the deep problems that arise with universal and abstract principles of rationality and works with them.

First of all, an important distinction to consider is that rational principles of inference are normative vehicles for judging inductive inferences. As such, they are inert with respect to how, in processing terms, organisms should arrive at inferences. Herbert Simon (1990, chap. 2) made the distinction between substantive and procedural rationality. Although some formulations of rational behavior consider procedural rationality, rational theories of inductive inference are typically claims about substantive rationality. Substantive rational principles are yardsticks for judging inferences; they do not tell us, in mechanistic terms, how to arrive at inductive inferences. It is useful, therefore, to distinguish between the substantive problem of induction and the procedural problem of induction. This distinction is essential when we come to consider fundamental computational limits that make realizing rational norms in processing terms often intractable, if not provably uncomputable. Note that this problem – the dichotomy between what is rational and what is computationally achievable – extends beyond the particular details of the cognitive system. It is an issue for all computational processes carrying out inductive inferences. We mention the processing issue here because, if what is deemed rational is

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

fundamentally unobtainable by organisms, then perhaps our motives for adopting such a concept of rationality should be questioned.

Another distinction we will draw contrasts the substantive problem of induction and the cognitive-ecological problem of induction. This distinction will lead us to consider how behaving rationally in the classical sense (the substantive problem) and behaving adaptively (a species specific cognitive-ecological problem) are not necessarily the same endeavor. For instance, the inference suggested by the most probable prediction (and therefore the most rational one) may require expending considerable time, memory, and processing resources compared with an inference arrived at quickly and on the basis of a cognitively undemanding decision process requiring minimal information; moreover, the latter may be only marginally inferior in probabilistic terms. Adaptive behavior, that which fits the functional requirements of an organism, is unlikely to be characterized using probability theory and logic given that "people satisfice – look for good enough solutions – instead of hopelessly searching for the best" (Simon, 1990, p. 17). Put differently, the payoff function with which we measure the efficacy of a decision maker is not simply how accurate inferences are; it also must consider ecological factors that take into account the structure of the task, the criticality of response time, and factors contributing to cognitive effort. Now, in this section the question we ask is, Does one rationality fit all tasks?

4.1. *Living Up to Expectation: From Substantive to Procedural Rationality*

Substantive rationality refers to rational principles such as Bayesian inference or Occam's razor. Procedural rationality, in contrast, considers what can be accomplished when one takes into account the processing steps required to arrive at an inference. Once an inference has been made, the role of substantive rationality is clear: it provides a criterion with which to judge this inference against others. By considering the problem of procedural rationality, we are taking one step toward situating the task of human decision making. Constraints on realization can transform the nature of the problem, or, as Herbert Simon (1990) put it: "at each step toward realism, the problem gradually changes from choosing the right course of action (substantive rationality) to finding a way of calculating, very approximately, where a good choice of action lies (procedural rationality)" (pp. 26–27). In stressing this difference between substantive and procedural rationality in this way, we do not want give the impression that substantive theories of rationality are wrong. The issue is how appropriately a given notion of rationality fits the question at hand. Simon's point, and the point we are developing here, is that, for the task of understanding cognition, procedural rationality is more appropriate than substantive rationality. Again, this does not imply that substantive theories of rationality, such as Bayesianism, are the wrong tool for studying cognition, but rather that such principles are inherently limited because they neglect the fact that organisms are constrained in their ability to process information.

Some tasks, because of their inherent difficulty, lack a clear notion of substantive rationality. For example, choosing which of two candidate moves in chess is most likely to lead to a win can, in the general case, be only an estimate. Unsurprisingly, this inherent difficulty makes the procedural problem of playing chess even harder. In other words, if we lack a clear formulation of rational choice in the first place, then we cannot expect that procedural solutions conform to this rational expectation. Although chess is a supremely unenlightening example of human inference that, at best, may tell us about the fringes of human cognition (Chomsky, 2000, p. 161), there are many other common human decisions that are similarly difficult – or impossible – to rationally analyze fully, such as deciding which of two potential mates to woo (Gigerenzer & Todd, 1999). Furthermore, there are tasks for which we do have a clear notion of

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

substantive rationality, yet procedural rationality still forces us to rethink what is achievable from the perspective of the organism. This is the issue we will focus on.

Consider the modern formulation of Occam's razor: hypotheses that recode observations in such a way to minimize encoding length should be chosen over others (Grunwald, 2005; Hutter, 2005; Li & Vitányi, 1997; Rissanen, 1989). Such a formulation has been proposed as a unifying principle of the cognitive system (Chater & Vitányi, 2003; see also Feldman, 2003) and "suggests a possible (although of course partial) account of the remarkable success of the cognitive system in prediction, understanding, and acting in an uncertain and complex environment: that cognitive processes search for simplicity" (Chater, 1999, p. 283). Yet paradoxically, adherence to simplicity principles can be so complex in processing terms that it "will not be possible in general" (Chater, 1999, p. 283). As another example of the substantive-procedural gap, in both perception and action it is proposed that a "striking observation . . . is the myriad ways in which human observers act as optimal Bayesian observers" (Knill & Pouget, 2004, p. 712). Once again, however, it is acknowledged that, "owing to the complexity of the task, unconstrained Bayesian inference is not a viable solution for computation in the brain" (Knill & Pouget, 2004, p. 718). Here we see the struggle between the desire to find concise universal laws of rational behavior and the processing difficulties that accompany these principles. To see why this problem occurs, and how the concept of ecological rationality can help to clarify issues, we will consider the cognitive task of categorization. Categorization requires making inductive inferences, it is a ubiquitous ability of humans and other animals, and it offers a useful example for illustrating the dichotomy between procedural and substantive rationality.

For the categorization task, Bayesian inference and modern castings of Occam's razor provide well-defined and precise rational criteria with which to compare one potential category judgment against another. Given a series of observations, these criteria tell us, for any two candidate category explanations, which is the "best" category description. Stepping back from any specific solutions that the cognitive system may employ, it will prove useful to consider first the more general class of computational procedures for performing inductive inferences. Machine learning is the study of procedural solutions to inference problems (Mitchell, 1997), and therefore offers a useful source of insight into the relationship between substantive and procedural rationality (which is sometimes termed *approximate rationality* within artificial intelligence; see Russell & Norvig, 1995). Like economic and psychological research, artificial intelligence and, in particular, machine learning often appeal to classical notions of rational behavior (Goodie, Ortmann, Davis, Bullock, & Werner, 1999). For example, using algorithmic information theory to fix a universal (i.e., both problem independent, parameterless, and rationally motivated by way of Occam's razor), prior probability distribution on the hypothesis space (Solomonoff, 1964), Bayesian-inspired models of inductive reasoning have led some to explore "a theory for rational agents acting optimally in any environment" (Hutter, 2005, p. 24). Unfortunately, when realized in procedural terms, such theories partly assume the "availability of unlimited computational resources" (Hutter, 2005, p. v). Even with extremely liberal constraints on resources, universally applicable laws of rationality, in processing terms, are difficult or even impossible to achieve.

In practice, machine-learning research places more conservative bounds on what is considered practical by often narrowing its interests to the class of computationally tractable algorithms. Computationally tractable algorithms are those that place computational demands on time and storage space resources that grow as polynomial function of the size of the problem (e.g., sorting a series of n numbers into ascending order is deemed tractable because it can be achieved by an algorithm requiring time and space polynomial in n). Under these

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

constraints, a widespread realization, and arguably an axiom within machine learning, is that procedural adherence to rational expectation breaks down. One useful concept in thinking about ad hoc adherence to the rational ideal is inductive bias, which refers to any basis on which one explanation is chosen over another, beyond simple adherence to the observations (Gordon & Desjardins, 1995; Mitchell, 1997).[1] An appropriately formalized Occam's-razor principle is a bias, for example, but typically bias occurs as a result of restrictions on the representational power of the hypothesis space (the set of explanations the algorithm can consider) and how thoroughly the hypothesis space can be searched (the manner in which the search for the optimal hypothesis is approximated).

The important point here is that the inductive bias of an algorithm typically reflects concrete issues of realization such as the particular characteristics and assumptions imposed by the implementation of the algorithm (e.g., the nature of hypothesis space) rather than a rationally motivated normative bias, such as Occam's razor. Consequently, and as a result of tractability and computability constraints, the procedural problem of induction has a different character from that suggested by the rational problem. The combination of considering nontrivial tasks in conjunction with tractability constraints limits researchers to a vaguer adherence to rational expectations, where algorithms "should process the finite sample to obtain a hypothesis with good generalization ability under a reasonably large set of circumstances" (Kearns, 1999, p. 159). For machine learning, this breakdown in adherence to the rational, or optimal, outcome is simply a well-established fact. Algorithmic solutions are, to varying degrees, focused rather than general, and their performance is adequate rather than normative:

> *Induction is not unbridled or unconstrained. Indeed, decades of work in machine learning makes abundantly clear that there is no such thing as a general purpose learning algorithm that works equally well across domains. Induction may be the name of the game, but constraints are the rules that we play by. (Elman, 2003, from ms.)*

Because uniform adherence to a normative criterion is taken as a goal, alleviating the discrepancy between this goal and what can be achieved in practice can partially be overcome through the selective choice of learning algorithms, dependent on the task structure. For example, given knowledge of the tasks for which some learning algorithm A performs better any other algorithm, then A could be chosen over all others when such a task is encountered. This problem is known as the selective superiority problem. It remains largely unexplored, and only limited practical progress has been made in addressing it (e.g., Kalousis, Gama, & Hilario, 2004). Unfortunately, for anything other than trivial tasks, machine learning tells us that there is a gap between substantive and procedural rationality. This gap exists because tractable algorithms tend to focus their performance on some problems at the expense of others. Crucially, most tasks are not trivial in the sense we mean here and require the expenditure of considerable computational effort to find good, let alone optimal, solutions. For example, the apparently trivial task of recognizing a face is extremely difficult from a computational standpoint: a full integration of the many facial properties that need to be considered is computationally intractable. In the study of artificial intelligence, which seeks engineering solutions for tasks like these, optimal solutions are almost always unobtainable (for discussion, see Reddy, 1988). Likewise, the study of cognition rarely reduces to the study of computationally trivial problems.

This brief discussion of machine learning provides us with some conceptual tools with which to consider the cognitive problem. The cognitive problem of induction is a particular instance of the procedural problem of achieving rationality, and one that is subject to hard biological/cognitive constraints rather than the more abstract notion of

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

computational tractability encountered previously. As for machine learning's algorithmic rationality problem, the general human cognitive problem is also broken down into tasks with particular characteristics. For instance, tasks spanning low-level aspects of the visual system and high-level tasks such as concept learning and categorization are commonly viewed as inductive tasks (e.g., Chater & Vitányi, 2003; Sober, 1975). However, unlike a general constraint such as computational tractability, these cognitive tasks are likely to work within very different and more stringent constraints, such as the physical limitations of the underlying biological machinery; constraints imposed by other cognitive systems also using resources in the mind; and limits on attention, working memory, and the like. Thus, different cognitive tasks are likely to yield to processing solutions of different forms.

4.2. *Situating Decision Making: Confronting the Cognitive-Ecological Problem*

Processing makes demands on computational resources. Placing constraints on these resources limits the degree to which rational expectations can be met, and in particular, processes tend to be focused on some instances of the task with respect to their ability to adhere to the demands set by substantive rationality. Specific kinds of constraint impose specific kinds of focus and, as Simon argued (1990, 1996), a full consideration of cognitive limitations leads us to consider boundedly rational processes. On the one hand, constraints beyond those of an abstract computational nature would appear to limit even further the degree to which rational expectations are likely to be met, and, as a result, the human cognitive system needs to pull a neat trick if it is to measure up to the demands of rationality under these terms. On the other hand, we will argue that there are good reasons to view cognitive limitations not as barriers but as enablers of robust inference. Limitations can be viewed as adaptive constraints in the sense that they may lead an agent to exploit informational structures present in the environment (Hertwig & Todd, 2003; Todd, Billari, & Simão, 2005). In this sense, the cognitive system does pull a neat trick: its limitations can become enablers once we consider the ecological side of problem.

Until now we have focused on internal aspects of the organism. The previous section highlighted how by coupling limitations in cognitive structure to environment structure, simple mechanisms can match or exceed the performance of more complex mechanisms. For instance, the simplicity of Take the Best can be interpreted as an inability to consider intercue correlations because Take the Best is restricted to acting on conditionally independent ecological cue measurements. For some environments, this inability actually acts as an enabler, as conditional information can be highly misleading and unstable. In fact, among twenty natural environments tested by Brighton (2005), over half reveal this property within the paired comparison task. In the same study, these characteristics of the environment posed serious problems for five classic machine-learning algorithms because they all carry out complex computations that consider conditional cue dependencies. As a result of their reliance on noisy cue relationships, they performed worse than Take the Best. Constraints that act as enablers illustrate how the adaptive-toolbox metaphor exploits the strengths of simplicity. This trick is worth considering in more depth.

For a specific task, the environment can be viewed as set of structures to be exploited by multiple simple processes. This perspective differs from the more traditional view, where a single task is often seen in terms of a single-process solution that is assumed to possess a general competence on a diverse range of environmental structures. Decomposing the problem space into structurally distinct subproblems, according to this view, is not the principle objective because we assume the competence of a single process to be sufficient for all relevant problems. For example, the paired comparison task addressed by the Take the Best heuristic can be viewed as a special case of the

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

categorization task. Within this task, Take the Best is one process among several possible candidates tuned to particular instances of this problem. In contrast, both in machine learning and in psychological modeling, the categorization task is often viewed from the perspective of a single process, applied independently of the precise nature of the task environment. For example, PROBEX is presented as "a model of probabilistic inference and probability judgments based on generic knowledge" (Juslin & Persson, 2002, p. 563), yet such a claim cannot be sustained in any meaningful sense, as the inductive bias of PROBEX, like any other process, will lead to good performance on some instances of the problem at the expense of others. Such single-process approaches often neglect the structure of the environment, and therefore the models are general only in the sense that no clear understanding of their focus exists.

Simple heuristics can work extremely well because they are focused and tailor their inductive bias to match specific information structures in the environment. To support this view, our experiments show that in comparisons across twenty different natural environments, Take the Best more often than not outperforms all competitors drawn from a collection of neural networks, exemplar models, and decision-tree induction models (Brighton, 2005).

These simulation results strengthen the claim that, when faced with a varied set of environments, one approach toward achieving adaptive behavior is to rely on an adaptive toolbox, from which ecologically rational heuristics are selected contingent on the task and the ecological context. This notion of contingent application is the crucial difference between the adaptive-toolbox metaphor and the more widespread approach of focusing on a single general-purpose processing system. Thus, the performance of heuristics must always be considered conditional on the task, and in the study of adaptive behavior, understanding environmental context is just as important as understanding processing mechanisms. To be more precise, we say that a mechanism M is ecologically rational in environment E in comparison to some other mechanism M′ when M outperforms M′ on some criterion, or currency, of comparison. There are two components to statements such as these. First, such statements are comparative rather than absolute: heuristics must be judged in comparison to other models. For example, Take the Best is ecologically rational compared to other models of inference (Brighton, 2005; Czerlinski et al., 1999), and the recognition heuristic is ecologically rational compared to those models that do not consider, and therefore cannot exploit, recognition information (Goldstein & Gigerenzer, 2002). Second, statements about the ecological rationality of a heuristic appeal to some criterion of comparison. For instance, models of inference are often compared using cross-validation, which considers the criterion of zero-one loss predictive accuracy (e.g., Browne, 2000), or using a criterion that measures the degree to which a heuristic compresses the observations (Grünwald, 2005).

For some, performance measures such as these call into question the concept of ecological rationality due to an ultimate appeal to rational criteria, which in the final analysis are used to justify and explain the performance of heuristics (Chater et al., 2003). But this argument misses a fundamental dimension of the concept of ecological rationality that we mentioned briefly at the start if this section. Given some criterion, the rational course of action is defined as the one that maximizes the criterion. Cross-validation tells us to prefer the model that yields the highest predictive accuracy, and Occam's razor tells us to prefer the model that compresses the observations most succinctly. Both these rational criteria consider only a single perspective, which we might dub "raw inductive performance," as they constitute perhaps the most basic and assumption-free rational criterion. For this reason their use is widespread in the comparison of machine-learning algorithms (Kearns, Mansour, Ng, & Ron, 1997) and between models of cognition (Pitt, Myung, & Zhang, 2002). However, these criteria ignore crucial aspects of the ecological problem. Mechanisms that

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

blindly maximize the rational criteria may ignore marginally less predictive solutions that can be found using, for example, less information search and fewer processing steps. Thus, it is apparent that general and universal measures can abstract the problem away from significant factors influencing the adaptive function of the mechanism. Put differently, the appropriate payoff function with which to assess human decision making is likely to be both multidimensional and task specific. Rational criteria, because of their generality, necessarily sidestep this ecological aspect of the problem. Although rational criteria widely used to judge inductive performance are often also used to compare heuristics, their use in statements about ecological rationality is more a matter of practical factors than a reflection of conceptual necessity. For this reason, heuristics are often additionally compared using multiple criteria, such as cross-validation and frugality of information use (Czerlinski et al., 1999). Although substantive theories of rationality could, in principle, be elaborated to consider further costs and more complex payoff functions, issues of processing must, at some point, be considered. In the limit, such a refined notion of substantive rationality could become procedural rationality, the approach that we are advocating here. Thus, there are varying degrees of abstraction when formulating a rational theory, and ecological rationality is a form of rationality tailored to understanding cognitive processing in its ecological context.

4.3. *Ecological Rationality as a Form of Situated Cognition*

Ecological rationality depends on intelligent agents deploying their various decision strategies in particular situations, sensitive to the structure of the environment in which they are embedded. This sounds like cognition situated in specific settings – but can we say more precisely in what way the study of ecological rationality is related to the situated movement in cognitive science? In broad terms, and to varying degrees, situated-cognition approaches view "intelligent human behavior as engaged, socially and materially embodied activity, arising within the specific concrete details of particular (natural) settings, rather than as an abstract, detached, general-purpose process of logical or formal ratiocination" (Smith, 1999, p. 769). As we argued in the previous section, the concept of ecological rationality is called for precisely because formal and generally applicable visions of rational behavior fail to consider significant aspects of human decision making. These aspects range from the algorithmic constraints on what can plausibly be achieved by the cognitive system to ecological considerations that affect the potential difference between adaptive (and ecologically rational) decisions and classically rational decisions. Thus, the concept of ecological rationality bears some of the hallmarks that characterize situated approaches.

At this point we lay down what we take to be some key characteristic features of situated approaches to studying cognition and how they apply to ecological rationality. The dimensions we consider are taken from Smith's (1999) characterization of situated approaches in terms of six key dimensions: located, concrete, engaged, specific, embodied, and social.

4.4. *Located*

The significance of being located arises when we adopt the view that "context-dependence is a central and enabling feature of human endeavor" (Smith, 1999, p. 769). Using Simon's metaphor of the scissors, context dependence is the environmental blade. In particular, Simon (1956) makes the point that "we might hope to discover, by a careful examination of some of the fundamental structural characteristics of the environment, some further clues as to the nature of the approximating mechanisms used in decision making" (p. 130). As we have shown, characteristics of the environment indeed represent a central and enabling feature when we consider their role in supporting cognitively simple heuristics. For example, some environmental contexts

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

"enable" frugality in information use: in noncompensatory environments, where the best cues outweigh the combined strength of all other cues, there is no reason to consider any but the first discriminating cue found, which is just the strategy adopted by lexicographic decision strategies like Take the Best. It is the precise context that the environment presents that provides the traction enabling simple cognitive heuristics to perform so well. In these terms, location is everything when considering ecological rationality. Without the enabling aspects of each precise context, ecological rationality cannot get off the ground.

4.5. *Concrete*

The issue of concreteness refers to the view that "constraints of realization and circumstance are viewed as of the utmost importance" (Smith, 1999, p. 769). Constraints on realization, again using Simon's metaphor of the scissors, correspond to the cognitive blade. There are two degrees of concreteness we have considered. First, at a purely computational level, there are hard constraints on what can be achieved by computationally tractable processes (e.g., problems that cannot be solved in polynomial time). Second, moving from an abstract consideration of issues of computability to the more concrete issue of cognitive limitations, there are constraints arising from the cognitive system as a biologically realized computing device that further limit what can be achieved. The vagaries of the human memory system, for example, form a set of cognitive constraints that influence how information is processed. Yet constraints can also be important because they can enable some capabilities – continuing the memory example, the role of forgetting can be seen as an enabler for heuristic inference, as it affects the capacity for name recognition and therefore the ability to use the recognition heuristic (Schooler & Hertwig, 2005). In a nutshell, the details of the concrete realization of cognitive mechanisms matter because certain constraints enable the exploitation of context.

4.6. *Engaged*

The property of engagement considers how "ongoing interaction with the surrounding environment is recognized as primary" (Smith, 1999, p. 769). Because heuristics are specialized – tuned to specific environmental contexts – the adjustment of the decision mechanism contingent on the structure of the task environment demands that a decision maker consider the inference task as an ongoing rather than a static activity. Furthermore, because most of the heuristics in the adaptive toolbox involve search for information in the environment, these mechanisms are of necessity engaged in a process of environmental interaction. This can happen on a moment-to-moment basis, as when a consumer deciding which good to buy checks the packaging for information until he or she finds enough to make a choice or when a fielder trying to catch a ball adjusts her running speed so as to maintain a constant gaze angle (McLeod & Dienes, 1996), or at longer time spans, as when a person encountering different decision tasks or environments must choose or adapt the decision mechanism he or she is using. Precisely how decision makers react to environments is the subject of ongoing research. For example, Todd and Dieckmann (2005) describe a process by which individuals may learn an order in which to use cues with Take the Best, and they show how this learned order itself influences the decisions made and the subsequent learning that an individual can perform. Strong path dependencies – a hallmark of an engaged process – emerge in the application of this learning mechanism as it is intertwined with ongoing decision making. Rieskamp and Otto (2005), in contrast, explore the changing use of particular fixed, simple heuristics in a reinforcement-learning scenario. Here, a balance between exploration and exploitation is struck by integrating feedback from the decision-making process, which in turn allows the agent to learn when to apply which strategy. This line of research is particularly promising, as there are potential connections with other psychological

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

research into strategy selection (Erev & Barron, 2005; Gonzalez, Lerch, & Lebiere, 2003) and with attempts within machine learning to use human problem solving as inspiration for systems that learn to learn, where the relationship between multiple tasks is considered an enabling feature of human inductive performance (Thrun & Pratt, 1998).

4.7. *Specific*

Considerations of specificity refer to the fact that "what people do is seen as varying, dramatically, depending on contingent facts about their circumstances" (Smith, 1999, p. 769). For ecologically rational inference, the particular circumstances a decision maker faces are paramount. The discussion earlier of the importance of being located highlights how circumstance can act as an enabling feature in decision making. We take specificity to capture a slightly different set of contingencies of the tasks that people face, such as are evident from experimental studies of when people use heuristics. For example, circumstances in which subjects are required to act under time pressure show how the choice of decision strategy changes as a result, with subjects showing a strong tendency to prefer simple sequential, cue-based decision mechanisms (Edland, 1994; Payne et al., 1993). The costs of information search also have a strong bearing on which strategy is used. For instance, when subjects are required to search for information from memory, rather than on screen, they are far more likely to use fast-and-frugal decision strategies like Take the Best (Bröder & Shiffer, 2003). If subjects are required to estimate the values of associated with different choices, rather than simply make a choice, different decision strategies are, again, likely to be used (Westenberg & Koele, 1992). These studies not only highlight how subtleties in the specific nature of the task (in contrast to the statistical structure of the environment) can lead to quite different cognitive tools being used but also reveal that individual differences are often at play. Information processing, from the perspective of the adaptive toolbox, is highly dependent on both the specific nature of the task and the particularities of the individual cognitive system.

4.8. *Embodied*

The importance of embodiment refers to the fact that "material aspects of agents' bodies are taken to be both pragmatically and theoretically significant" (Smith, 1999, p. 769). In other words, the particular physical instantiation of the agent's body is taken to have a strong impact on how the problem is both conceived of and solved. The gaze heuristic for ball catching mentioned earlier, for example, is a process that relies on a particular morphology: an eye and a bipedal locomotion system. Embodiment is important, as an agent with a different morphological design may solve the problem of catching the ball using quite different processes: being equipped with wings and echolocation would open up entirely different ball-catching solutions. Ecological rationality has, to date, been studied in an embodied form mostly in the field of behavior-based robotics (e.g., Brooks, 1991; for a discussion, see Goodie et al., 1999), where simple heuristics are used to help physically embodied agents navigate through environments and solve different (usually rather simple) tasks. Despite these low-level investigations of embodied ecological rationality so far, we nevertheless take issues of embodiment to have significant impact on high-level cognition. In particular, these issues are important for considering the sensory and proprioceptive origins of the cues going into the decision process, as well as the bodily and motor-system consequences of the decisions being made.

4.9. *Social*

Being social means "being located in humanly constructed settings among human communities" (Smith, 1999, p. 769). In studying ecological rationality, we must acknowledge that a significant part of environment structure will often be made up of other individuals and the results of

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

their actions, whether in choosing a mate (Todd et al., 2005), selecting a parking space (Hutchinson, Fanselow, & Todd, forthcoming), negotiating a fair division of resources (Takezawa, 2004), reaching a group decision (Reimer & Hoffrage, 2005; Reimer & Katsikopoulos, 2004), deciding how to communicate important information (Kürzenhäuser & Hoffrage, 2002), and many other situations. The social rationality called for in all of these cases is a special form of ecological rationality specifically dealing with social environments.

4.10. *Summary: The Role of Situatedness in High-level Cognition*

It is clear that the concept of ecological rationality is closely allied and in strong agreement with the six defining characteristics of situated approaches to understanding cognition proposed by Smith (1999). However, it is worth pointing out that the approach we advocate here is conservative in comparison with other more radical situated positions. As the preceding sections have demonstrated, ecologically rational heuristics are uniformly described in terms of symbolic process models operating on representations. These processes draw on the classical notions of search, satisficing, and decision rules. In contrast to more radical positions, the concept of ecological rationality is agnostic with respect to, for example, issues of antirepresentationalism (Slezak, 1999; Varela, Thompson, & Rosch, 1991), dynamic systems theory (van Gelder, 1995), or more philosophical rethinkings of the nature of cognition (Winograd & Flores, 1996). These issues are certainly significant dimensions of some theories of situatedness, but we take the concept of ecological rationality to be orthogonal to, for example, what level and in what terms one describes processes (for a related discussion, see Vera & Simon, 1993). To be clear on this point, we could note that simple heuristics could be implemented just as well using connectionist networks or cognitive architectures such as ACT-R (Anderson & Lebeire, 1998; for an example, see Schooler & Hertwig, 2005), but we do not see this as the key issue at stake in this discussion. In short, we should sound a note of caution. As Clancey (1997, p. 345) points out, it is often tempting and all too easy to present an either-or message. In our case, this would amount to claiming that existing principles of rationality are irrelevant to the study of human cognition. However, this is not the point we wish to make. When it comes to theorizing about situated cognition, we view ecological rationality as "adding new tools to cognitive science's tool kit" (Clark, 1997, p. 175) rather than replacing the existing ones (see also Vera & Simon, 1993).

Ecological rationality speaks to the relationship between mechanisms and environments and, in particular, how simple and cognitively plausible mechanisms that exploit the environment provide a productive basis on which to explore human decision making. Thus, the adaptive-toolbox vision of decision making has less to do with what Smith (1999) terms "situatedness with a vengeance" (p. 770) and more to do with recasting, rethinking, and adding to familiar concepts of cognition and situatedness. Mental representations, for instance, are not abandoned, but the fact that simple processing solutions exploit structure in the environment does suggest the possibility of a weaker reliance on internal models of the world. In Brooks's (1991) terms, we are sympathetic to the view that it is "better to use the world as its own model" (p. 139). Furthermore, in contrast to other frameworks with a focus on the relationship between rational principles and the role of the environment, such as Anderson's (1990) rational analysis (see also Oaksford & Chater, 1998), ecological rationality – realized through the adaptive toolbox – has a strong bottom-up orientation to model construction reminiscent of Brooks's subsumption architecture for behavior-based robotics (Brooks, 1991). In this sense, ecological rationality draws on concepts that are more often associated with situated approaches to lower-level aspects of cognition and demonstrates their productivity in studying higher-level aspects of human decision making and inference.

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

5. Conclusion

Ecological approaches to understanding the mind focus on the relationship between mind and environment. We have explored one form of this relationship, in which simple mental mechanisms can make adaptive decisions by exploiting the characteristics of environments. As such, the concept of ecological rationality proves closely tied with the key dimensions that characterize situated approaches to understanding the mind. To examine this connection, we began by considering three metaphors that have been used to characterize the relationship between mind and environment: mirrors, lenses, and scissors. Mirrors reflect fundamental features of the world such that aspects of mind are shaped by the external environment. Here, minds represent useful and ubiquitous properties of the world, and these properties help the mind to function in environments. A lens projects rather than reflects, and reconstructs a representation of a distal stimulus on the basis of the current proximal cues. Again, by projecting aspects of the environment into the mind, the environment can be acted on by processing this information. Scissors are different. The scissors metaphor captures a relationship in which properties of the environment are exploited by, rather than represented by, the capabilities of the agent. It is only in circumstances in which mind and environment fit together like the blades of a pair of scissors that this relationship works. We have argued that the scissors metaphor is often appropriate when considering high-level cognitive processing tasks such as decision making and inference. The concept of ecological rationality, realized using an adaptive toolbox of simple mechanisms, builds on this scissors metaphor.

Simple decision heuristics that exploit features of natural environments perform very well and sometimes better than more conventional and complex models of inference. Mechanisms such as these are termed *ecologically rational*, and we have argued that the concept of ecological rationality is far more productive than conventional notions of rationality when seeking to understand decision making and inference in humans. First of all, ecological rationality treats the cognitive task as both located and concrete in the sense that the particular structure making up the task environment can be exploited by the concrete limited structure of the processor. This relationship, the match between cognitive limitations and environment structure, is the core concept behind ecological rationality. Conventional notions of rationality consider neither aspect and instead seek universally applicable principles that are independent of both the capabilities of the actor and the structure of the task. Part of the motivation for considering ecological rationality, as we have discussed, is that the cognitive system needs to solve the procedural problem of arriving at inferences. This task is notoriously difficult, and we drew on machine-learning research to show how conventional notions of rationality cannot be universally adhered to. Faced with a fundamental dichotomy between procedural and classical visions of rationality, we question how appropriate these classical visions of rationality are when seeking to understand the cognitive system.

The approach of ecological rationality also turns on the engaged and specific nature of cognition. The use of simple heuristics changes over time and as a reaction to changes in the environment. Although few cognitive theories would deny such a state of affairs, this reactive aspect of cognition is far more pivotal when considering a toolbox of ecologically rational heuristics, because of their highly situation-specific nature. Ecological rationality also treats as highly significant the social and (to a lesser extent) embodied aspects of cognition. Humans inhabit environments constructed and occupied by other humans, and social heuristics exploit the structure of environments constructed by the behavior of other humans. Similarly, the concrete details of sensor and muscle morphology are likely to be significant in defining how simple heuristics exploit body-environment interactions.

Despite the widespread adoption of rational principles as normative laws governing

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

the cognitive system, we have argued that there are solid grounds for questioning this assumption. Rather than being rooted in probability theory, information theory, and logic, the concept of ecological rationality provides an alternative vision of rationality rooted in the concrete constraints of the cognitive system and the structure of natural environments. Behaving in line with classical rational principles and behaving adaptively, as we have argued, are not necessarily the same endeavor. Ecological rationality, by taking a situated perspective, provides a vision of rationality bounded to the world in such a way that the limitations of the cognitive system and the specific context of cognition are viewed as significant and enabling features of adaptive cognition. If we are to understand the adaptive nature of high-level cognition, then the cognitive system needs to be viewed more as an ecologically rational bag of tricks and less in terms of formally motivated calculating device adhering to general principles of classically rational inference.

Note

1 The use of the term *inductive bias* differs both from (a) the term *bias* in the heuristics and biases literature and (b) the term *estimation bias* in statistics (although inductive bias is connected to the later; see Mitchell, 1997).

References

Anderson, J. R. (1990). *The adaptive character of thought*. Hillsdale, NJ: Lawrence Erlbaum.
Anderson, J. R., & Lebeire, C. (1998). *The atomic components of thought*. Mahwah, NJ: Lawrence Erlbaum.
Ariely, D., & Levav, J. (2000). Sequential choice in group settings: Taking the road less traveled and less enjoyed. *Journal of Consumer Research*, 27(3), 279–290.
Bak, P. (1996). *How nature works*. New York: Springer-Verlag.
Barkow, J. H., Cosmides, L., & Tooby, J. (Eds.). (1992). *The adapted mind: Evolutionary psychology and the generation of culture*. New York: Oxford University Press.
Barrett, H. C. (2005). Adaptations to predators and prey. In D. M. Buss (Ed.). *The handbook of evolutionary psychology* (pp. 200–223). Hoboken, NJ: Wiley.
Brighton, H. (2006). Robust inference with simple cognitive models. In: *Between a Rock and a Hard Place: Cognitive Science Principles Meet AI-Hard Problems*, pp. 17–22. Papers from the AAAI Spring Symposium (AAAI Technical Report SS-06-03), eds. C. Lebiere and B. Wray, Menlo Park, CA: AAAI Press.
Bröder, A. (2000). Assessing the empirical validity of the "Take The Best" heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 26, 1332–1346.
Bröder, A., & Schiffer, S. (2003). "Take The Best" versus simultaneous feature matching: Probabilistic inferences from memory and effects of representation format. *Journal of Experimental Psychology: General*, 132(2), 277–293.
Brooks, R. A. (1991). Intelligence without representation. *Artificial Intelligence*, 47, 139–160.
Browne, M. W. (2000). Cross-validation methods. *Journal of Mathematical Psychology*, 44, 108–132.
Brunswik, E. (1955). Representative design and probabilistic theory in a functional psychology. *Psychological Review*, 62, 193–217.
Chater, N. (1999). The search for simplicity: A fundamental cognitive principle? *Quarterly Journal of Experimental Psychology*, *52A*(2), 273–302.
Chater, N., & Brown, G. D. A. (1999). Scale invariance as a unifying psychological principle. *Cognition*, 69, B17–B24.
Chater, N., Oaksford, M., Nakisa, R., & Redington, M. (2003). Fast, frugal and rational: How rational norms explain behavior. *Organizational Behavior and Human Decision Processes*, 90, 63–86.
Chater, N., & Vitányi, P. (2003). Simplicity: A unifying principle in cognitive science? *Trends in Cognitive Sciences*, 7, 19–22.
Chomsky, N. (1995). *The minimalist program*. Cambridge, MA: MIT Press.
Chomsky, N. (2000). *New horizons in the study of language and mind*. Cambridge: Cambridge University Press.
Clancey, W. J. (1997). *Situated cognition: On human knowledge and computer representations*. Cambridge: Cambridge University Press.

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

Clark, A. (1997). *Being there: Putting brain, body, and world together again*. Cambridge, MA: MIT Press.

Czerlinski, J., Gigerenzer, G., & Goldstein, D. G. (1999). How good are simple heuristics? In G. Gigerenzer, P. M. Todd, & The ABC Research Group, *Simple heuristics that make us smart* (pp. 97–118). New York: Oxford University Press.

Edland, A. (1994). Time pressure and the applications of decision rules: Choices and judgements among multiattribute alternatives. *Scandinavian Journal of Psychology*, 35, 281–291.

Elman, J. L. (2003). Generalization from sparse input. In *Proceedings of the 38th annual meeting of the Chicago Linguistic Society*. Chicago: Chicago Linguistic Society.

Erev, I., & Barron, G. (2005). On adaptation, maximization, and reinforcement learning among cognitive strategies. *Psychological Review*, *112*(4), 912–931.

Feldman, J. (2003). The simplicity principle in human concept learning. *Current Directions in Psychological Science*, *12*(6), 227–232.

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*, 650–669.

Gigerenzer, G., & Selten, R. (Eds.). (2001). *Bounded rationality: The adaptive toolbox*. Cambridge, MA: MIT Press.

Gigerenzer, G., & Todd, P. M. (1999). Fast and frugal heuristics: The adaptive toolbox. In G. Gigerenzer, P. M. Todd, & The ABC Research Group, *Simple heuristics that make us smart* (pp. 3–34). New York: Oxford University Press.

Gigerenzer, G., Todd, P. M., & ABC Research Group. (1999). *Simple heuristics that make us smart*. New York: Oxford University Press.

Goldstein, D. G., & Gigerenzer, G. (1999). The recognition heuristic: How ignorance makes us smart. In G. Gigerenzer, P. M. Todd, & The ABC Research Group, *Simple heuristics that make us smart* (pp. 37–58). New York: Oxford University Press.

Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review*, *109*, 75–90.

Gonzalez, C., Lerch, J. F., & Lebiere, C. (2003). Instance-based learning in dynamic decision making. *Cognitive Science*, *27*, 591–635.

Goodie, A. S., Ortmann, A., Davis, J., Bullock, S., & Werner, G. M. (1999). Demons versus heuristics in artificial intelligence, behavioral ecology, and economics. In G. Gigerenzer, P. M. Todd, & ABC Research Group, *Simple heuristics that make us smart* (pp. 327–355). New York: Oxford University Press.

Gordon, D. F., & Desjardins, M. (1995). Evaluation and selection of biases in machine learning. *Machine Learning*, *20*, 5–22

Grünwald, P. (2005). Minimum description length tutorial. In P. Grünwald, I. J. Myung, & M. A. Pitt (Eds.), *Advances in minimum description length* (pp. 23–79). Cambridge, MA: MIT Press.

Hamilton, W. D. (1996). *Narrow roads of gene land: Evolution of social behaviour* (Vol. 1). Oxford: Oxford University Press.

Hammond, K. R., & Stewart, T. R. (Eds.). (2001). *The essential Brunswik: Beginnings, explications, applications*. New York: Oxford University Press.

Hertwig, R., Hoffrage, U., & Martignon, L. (1999). Quick estimation: Letting the environment do some of the work. In G. Gigerenzer, P. M. Todd, & The ABC Research Group, *Simple heuristics that make us smart* (pp. 209–234). New York: Oxford University Press.

Hertwig, R., & Todd, P. M. (2003). More is not always better: The benefits of cognitive limits. In D. Hardman & L. Macchi (Eds.), *Thinking: Psychological perspectives on reasoning, judgment and decision making* (pp. 213–231). Chichester, UK: Wiley.

Hutchinson, J., Fanselow, C., & Todd, P. M. (forthcoming). *Car parking as a game between simple heuristics*. In: P.M. Todd, G. Gigerenzer, and the ABC Research Group, *Ecological Rationality: Intelligence in the World*.

Hutter, M. (2005). *Universal artificial intelligence: Sequential decisions based on algorithmic probability*. Berlin: Springer.

Juslin, P., & Persson, M. (2002 PRObabilities from EXemplars (PROBEX): A "lazy" algorithm for probabalistic inference from generic knowledge. *Cognitive Science*, *26*(5), 563–607.

Kahneman, D., Slovic, P., & Tversky, A. (Eds.). (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge: Cambridge University Press.

Kalousis, A., Gama, J., & Hilario, M. (2004). On data and algorithms: Understanding inductive performance. *Machine Learning*, *54*, 275–312.

Kearns, M. (1999). Computational learning theory. In R. A. Wilson & F. C. Keil (Eds.), *The MIT encyclopedia of the cognitive sciences* (pp. 159–160). Cambridge, MA: MIT Press.

Kearns, M., Mansour, Y., Ng, A. Y., & Ron, D. (1997). An experimental and theoretical comparison of model selection methods. *Machine Learning*, 27, 7–50.

Knill, D. C., & Pouget, A. (2004). The Bayesian brain: The role of uncertainty in neural coding and computation. *Trends in Neurosciences*, 27(12), 712–719.

Kürzenhäuser, S., & Hoffrage, U. (2002). Teaching Bayesian reasoning: An evaluation of a classroom tutorial for medical students. *Medical Teacher*, 24(5), 516–521.

Li, M., & Vitányi, P. M. B. (1997). *An introduction to Kolmogorov complexity and its applications*. New York: Springer.

Makse, H. A., Havlin, B., & Stanley, H. E. (1995). Modeling urban growth patterns. *Nature*, 377, 608–612.

Markman, A. B., & Dietrich, E. (2000). Extending the classical view of representation. *Trends in cognitive sciences*, 4(12), 470–475.

Martignon, L., & Hoffrage, U. (1999). Why does one reason decision making work? In G. Gigerenzer, P. M. Todd, & The ABC Research Group, *Simple heuristics that make us smart* (pp. 119–140). New York: Oxford University Press.

McLeod, P., & Dienes, Z. (1996). Do fielders know where to go to catch the ball or only how to get there? *Journal of Experimental Psychology*, 22(3), 531–543.

Mitchell, T. M. (1997). *Machine learning*. New York: McGraw-Hill.

Newell, B. R., & Shanks, D. R. (2003). Take the best or look at the rest? Factors influencing "one-reason" decision-making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29, 53–65.

Oaksford, M., & Chater, N. (1998). *Rational models of cognition*. Oxford: Oxford University Press.

Pachur, T., & Biele, G. (2007). Forecasting by ignorance: The use and usefulness of recognition in lay predictions of sports events. *Acta Psychologica*, 125(1), 99–116.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. New York: Cambridge University Press.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems*. San Francisco: Morgan Kaufmann.

Pitt, M. A., Myung, I. J., & Zhang, S. (2002). Toward a method of selecting among computational models of cognition. *Psychological Review*, 109(3), 472–491.

Ramachandran, V. S. (1990). Interactions between motion, depth, color and form: The utilitarian theory of perception. In C. Blakemore (Ed.), *Vision: Coding and efficiency* (pp. 346–360). New York: Cambridge University Press.

Reddy, R. (1988, Winter). AAAI presidential address: Foundations and grand challenges for artificial intelligence. *AI Magazine*. (pp. 9–21).

Reimer, T., & Hoffrage, U. (2005). Can simple group heuristics detect hidden profiles in randomly generated environments? *Swiss Journal of Psychology*, 64(1), 21–37.

Reimer, T., & Katsikopoulos, K. V. (2004). The use of recognition in group decision-making. *Cognitive Science*, 28(6), 1009–1029.

Rieskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics and how can we tell? In G. Gigerenzer, P. M. Todd, & The ABC Research Group, *Simple heuristics that make us smart* (pp. 141–167). New York: Oxford University Press.

Rieskamp, J., & Otto, P. (2005). *SSL: A theory of how people learn to select strategies*. Manuscript submitted for publication.

Rissanen, J. J. (1989). *Stochastic complexity and statistical inquiry*. Singapore: World Scientific.

Rozin, P., & Fallon, A. E. (1987). A perspective on disgust. *Psychological Review*, 94(1), 23–41.

Russell, S., & Norvig, P. (1995). *Artificial intelligence: A modern approach*. Englewood Cliffs, NJ: Prentice Hall.

Schooler, L. J., & Hertwig, R. (2005). How forgetting aids heuristic inference. *Psychological Review*, 112, 610–628.

Shepard, R. N. (1987). Towards a universal law of generalization for psychological science. *Science*, 37(4820), 1317–1323.

Shepard, R. N. (2001). Perceptual-cognitive universals as reflections of the world. *Behavioral and Brain Sciences*, 24(4), 581–601.

Simon, H. A. (1956). Rational choice and structure of the environment. *Psychological Review*, 63, 129–138.

Simon, H. A. (1990). Invariants of human behavior. *Annual Review of Psychology*, 41, 1–19.

Simon, H. A. (1996). *The sciences of the artificial* (3rd ed.). Cambridge, MA: MIT Press.

Slezak, P. (1999). Situated cognition: Paradigm shift, empirical issue or conceptual confusion? In J. Wiles & T. Dartnall (Eds.), *Perspectives on cognitive science* (Vol. 2, pp. 69–98). Stamford, CT: Ablex.

Smith, B. C. (1999). Situatedness/embeddedness. In R. A. Wilson & F. C. Keil (Eds.), *The MIT*

P1: SQE
CUUS366-17 cuus366/Robbins ISBN: 978 0 521 84832 9 Top: 0.5in Gutter: 0.875in July 8, 2008 16:21

encyclopedia of the cognitive sciences (pp. 769–770). Cambridge, MA: MIT Press.

Sober, E. (1975). *Simplicity*. Oxford, UK: Clarendon Press.

Solomonoff, R. J. (1964). A formal theory of inductive inference, part 1 and part 2. *Information and Control*, 7(1–2), 224–254.

Stenning, K., & van Lambalgen, M. (2004). A little logic goes a long way: Basing experiment on semantic theory in the cognitive science of conditional reasoning. *Cognitive Science*, 28(4), 481–529.

Takezawa, M. (2004). Developing a new framework of adaptive concession-making strategies: An approach to behavioral game theory from psychology. Manuscript submitted for publication.

Tanner, C., & Medin, D.L. (2004). Protected values: No omission bias and no framing effects. *Psychonomic Bulletin and Review*, *11*(1), 185–191.

Thrun, S., & Pratt, L. Y. (1998). *Learning to learn*. Boston: Kluwer Academic.

Todd, P. M. (1999). Simple inference heuristics versus complex decision machines. *Minds and Machines*, 9(4), 461–477.

Todd, P. M. (2001). Fast and frugal heuristics for environmentally bounded minds. In G. Gigerenzer & R. Selten (Eds.), *Bounded rationality: The adaptive toolbox* (pp. 51–70). Cambridge, MA: MIT Press.

Todd, P. M., Billari, F. C., & Simão, J. (2005). Aggregate age-at-marriage patterns from individual mate-search heuristics. *Demography*, *42*(3), 559–574.

Todd, P. M., & Dieckmann, A. (2005). Heuristics for ordering cue search in decision making. In L. K. Saul, Y. Weiss, & L. Bottou (Eds.), *Advances in neural information processing systems 17* (pp. 1393–1400). Cambridge, MA: MIT Press.

Todd, P. M., & Gigerenzer, G. (2001). Shepard's mirrors or Simon's scissors? Commentary on R. N. Shepard: Perceptual-cognitive universals as reflections of the world. *Behavioral and Brain Sciences*, 24(4), 704–705.

Todd, P. M., & Gigerenzer, G. (2003). Bounding rationality to the world. *Journal of Economic Psychology*, 24(2), 143–165.

Todd, P. M., Hertwig, R., & Hoffrage, U. (2005). The evolutionary psychology of cognition. In D. M. Buss (Ed.), *The handbook of evolutionary psychology* (pp. 776–802). Hoboken, NJ: Wiley.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review*, 79(4), 281–299.

van Gelder, T. J. (1995). What might cognition be, if not computation? *Journal of Philosophy*, *91*, 345–381.

Varela, F., Thompson, E., & Rosch, E. (1991). *The embodied mind: Cognitive science and human experience*. Cambridge, MA: MIT Press.

Vera, A. H., & Simon, H. A. (1993). Situated action: A symbolic interpretation. *Cognitive Science*, 17, 7–48.

Westenberg, M. R. M., & Koele, P. (1992). Response modes, decision processes and decision outcomes. *Acta Psychologica*, 80, 169–184.

Winograd, T., & Flores, F. (1996). *Understanding computers and cognition: A new foundation for design*. Norwood, NJ: Ablex.

Zahavi, A., & Zahavi, A. (1997). *The handicap principle: A missing piece of Darwin's puzzle*. Oxford, UK: Oxford University Press.