CHAPTER 5

FRAMING OUR THOUGHTS: ECOLOGICAL RATIONALITY AS EVOLUTIONARY PSYCHOLOGY'S ANSWER TO THE FRAME PROBLEM

TIMOTHY KETELAAR
University of California at Los Angeles

PETER M. TODD
Max Planck Institute for Human Development

Abstract. Decision makers challenged by real-world adaptive problems must often select a course of action quickly, despite two computational obstacles: There is usually a vast number of possible courses of action that can be explored, and a similarly vast number of possible consequences that must be considered when evaluating these options. Thus, decision makers routinely face the frame problem: how to focus attention on adaptively relevant information and how to keep this information set small enough that the mind can actually perform the computations necessary to generate adaptive behavior. By identifying simple, effective heuristics that work within the computational and informational constraints of an organism and still result in adaptively adequate behavior, the new ecological rationality perspective within evolutionary psychology suggests how intelligent agents can overcome this frame problem. In this chapter we show how ecologically rational psychological mechanisms can address two challenges derived from the frame problem: 1) Using the example of sequential mate choice, we demonstrate that a satisficing information search strategy can lead to good decisions using only a limited amount of information; and 2) We argue that emotions can guide information search, by focusing the computational mind on precisely that information which is most useful for making decisions that lead to good outcomes over the long run.
We further describe how a bottom-up approach to studying ecological rationality, which first identifies simple heuristic decision-making components and then builds more sophisticated cognitive modules out of these components, can generate fruitful new directions for psychological scientists attempting to illuminate the structure of our evolved computational minds.

I. THE WISE BRAHMIN AND THE CHESSBOARD: HOW SEEMINGLY SIMPLE CALCULATIONS CAN REQUIRE MORE COMPUTATION THAN OUR MINDS CAN HANDLE

There is a story of an ancient rajah of India who wished to reward his royal adviser, a wise Brahmin, for inventing the game of chess (see Kasperov, 1997). When the rajah asked what he would desire for compensation, the Brahmin motioned to the grid of the 8x8 chessboard and requested that a single grain of wheat be placed on the first square of the board. He asked that the rajah’s servants then double the amount of wheat on the second square and continue doubling the amount of wheat (i.e., 4 grains on the third square, 8 on the next, etc.) until all 64 squares on the chessboard had been covered. The rajah was perplexed by the Brahmin’s seemingly simple request and asked him whether he indeed desired only grains of wheat—albeit in continuing doubled amounts on consecutive squares of the chessboard—as his compensation? The Brahmin replied, “Yes,” and the deal was set.

A day later the rajah’s senior mathematician informed him that they were having trouble granting the Brahmin’s demands. By the time his servants had arrived at the 21st square of the chessboard they required over one million (1,048,576 to be exact) grains of wheat, and by the 30th square (still not quite half finished) they needed more than 10 billion grains of wheat to satisfy the rajah’s promise to the Brahmin. According to the senior mathematician’s calculations, to continuously double the amounts of wheat across all 64 squares of the chessboard would require more wheat than the kingdom, indeed the entire world, could produce in countless millennia of bountiful harvests.

The point of this story is not that one should distrust their advisers, but rather that problems that appear quite simple and straightforward at first glance can lead to computations on humanly unmanageable scales. Many of the human capacities we most take for granted—vision, language, finding a mate, or deciding which strategy to play in a competitive bargaining game—involves problems that can potentially involve a vast number of possible inferences. In this chapter we explore what evolutionary psychology has to offer in explaining how the finite human mind can cut through this computational thicket and arrive at reasonable solutions to a variety of information processing problems that appear to involve considerably more resources than our computational minds have to offer.

The computational mind’s dilemma

Some cognitive scientists (e.g., Fodor, 1995; Haugeland, 1995; also Baumgartner & Payr, 1995) have argued that the traditional computer metaphor of the mind, instantiated in artificial intelligence (AI) in particular, runs smack into the following dilemma: How can successful decision-making be achieved under conditions of limited time and knowledge? This dilemma has come to be called the frame problem (McCarthy & Hayes, 1969; Pylyshyn, 1987; Ford & Pylyshyn, 1996). This dilemma manifests itself in many domains of human computation where the number of potentially relevant inferences that can be drawn far outpaces the human mind’s capacity to evaluate them. From the perspective of evolutionary psychology, a central information-processing dilemma concerns how to “frame” a problem with a limited set of inferences that a biologically plausible computational device (i.e., a mind) can handle. Even in cases where the mind could, in principle, generate and evaluate all possible inferences there are often severe ecological costs to attempting such computational omnipotence (see below).

Far from being a strictly conceptual puzzle for philosophers of mind, the frame problem emerges as a legitimate concern for computational modelers in a variety of real-world psychological domains. These domains include: (1) language comprehension: How do individuals actually draw appropriate inferences from the vast sea of possible interpretations of even the simplest speech acts? (see Sperber & Wilson, 1996; Chiappe & Kukla, 1996), (2) economic decision making: How do individuals actually select an appropriate strategy in a competitive bargaining game like the repeated Prisoner’s Dilemma without mapping the intractably vast decision tree of possible strategies and the infinity of possible consequences? (see Rasmussen, 1994; Samuelson, 1997), and even (3) perception: How does an individual actually determine from a single retinal image which of the incomput-
ably vast number of possible arrangements of objects in the world gave rise to this particular pattern of retinal activation? (see Pinker, 1984, 1997; Poggio, 1984). In all of these domains, drawing appropriate inferences could involve sifting through an astronomical number of relevant and irrelevant inferences. Any agent that actually attempts to locate the “optimal” conclusion in the vast haystack of alternative inferences may find itself bogged down in a sea of computation that puts it at an adaptive disadvantage compared to less omniscient, but more computationally frugal organisms. Moreover, as one philosopher notes:

unless some drastic preselection can be effected among the alternatives their evaluation could never be completed. This gives rise to what is known among cognitive scientists as the ‘Frame Problem’: in deciding among any range of possible actions, most of the consequences of each must be eliminated from consideration a priori, i.e., without any time being wasted on their consideration.... (deSousa, 1994, p. 276, emphasis in the original)

An ecologically valid description of our evolved computational architecture must account for how intelligent agents overcome this frame problem to generate adaptive cognition.

**Explosive Consequences of the Frame Problem**

Philosopher and cognitive scientist Daniel Dennett (1987) describes the essence of the frame problem in a thought experiment involving a robot whose main mission in life is to survive. Suppose that its most vexing challenge at the moment is that its backup battery is in a room next door and that a time bomb is also in that room. The robot enters the room and deduces that the battery is on a wagon. It further deduces that pulling the wagon out of the room will remove the battery from the room. Although it deduces that the time bomb is also on the wagon, its limited deductive powers unfortunately prevent it from considering the further implications of pulling the wagon—along with the time bomb—out of the room and our mechanical friend is promptly blown to smithereens. Now imagine that the robot’s design engineers develop what they believe will be an obvious remedy to the robot’s limited deductive capacity: simply equip the robot with greater computational might such that it can deduce all possible implications of its alternative courses of action. Yet, this “obvious” solution, like the Brahmin’s seemingly simple request of the rajah, quickly proves to be computationally intractable. Dennett (1998) notes that the imaginary robot began its mission:

as designed, to consider the implications of such a course of action. It had just finished deducing that pulling the wagon out of the room would not change the color of the room’s walls, and was embarking on a proof of the further implications that pulling the wagon out would cause its wheels to turn more revolutions than there were wheels on the wagon—when the bomb exploded (p. 42).

Even when the robot is given the additional computational power to calculate still more possible implications, it is obvious that this strategy is doomed. What gives rise to the frame problem is that:

we need to know whether a consequence will turn out to be relevant before drawing it. If it is relevant and we have not retrieved it, we may act irrationally. But, if it is irrelevant and we have already drawn it, we have already wasted time... (deSousa, 1987, p. 194, emphasis in the original).

How can the human mind escape this quandary?

**Two aspects of the frame problem**

In Dennett’s (1987) thought experiment, the cost of the robot’s long-winded process of deducing implications far outweighed the benefits it could receive from considering those outcomes. There are simply too many implications to be considered, too much information to be computed. We identify this problem of *too much information*, as one aspect of the frame problem that confronts any computational device, be it a robot or a rabbit. So the first step that the human mind can take in overcoming the frame problem is to limit the amount of information used to make inferences—but will it still be possible to make good decisions with this limitation? We address this question in Section II of this paper.

A second important aspect of the frame problem emerges as Dennett’s robot story continues: Faced with too many possible implications for their robot to consider (the problem of *too much information*), the robot engineers resolved to “... teach it the difference between relevant implications and irrelevant implications ... and teach it to ig-
nore the irrelevant implications” (Dennett, 1987, p. 42). As straightforward as this solution appears, it too results in a combinatorial explosion of computations, followed in the story by a physical explosion of robot parts, as the robot starts churning through the virtually infinite sea of irrelevant implications trying to locate the few relevant implications it could employ to solve its task. Thus, the second challenge stemming from the frame problem is that of determining what information to attend to. In those situations where there is too much information to make use of, it is of course similarly unreasonable to decide which set of information to focus on by looking at all that is available and determining which data are relevant and which are not, i.e., this would just add another, possibly even longer, step to the already infeasible decision process. Fortunately, the human mind possesses a few built-in mechanisms that can provide shortcuts to highlighting the relevant information for different problems, as we will see in Section III.

**Simple (but effective) is sometimes better**

When AI researchers design computational algorithms to tackle specific tasks, they evaluate the performance of these mechanisms by considering not just whether they can accomplish the task, but also whether they require more or fewer resources than competing algorithms. The number of inputs required and the “worst case” and “average case” running time are often used to evaluate the performance of a computational mechanism (Cormen, Leiserson, & Rivest, 1997). Although the robot in Dennett’s thought experiment clearly fails to accomplish its mission, perhaps its greatest weakness lies not in whether it can, in principle, solve the battery/bomb problem, but in the unreasonable number of inputs and amount of running time its algorithm requires to achieve a successful solution.

The use of performance criteria such as number of inputs and running time is even more appropriate for evaluating the cognitive abilities of biologically intelligent agents. This is the case because any organism that can quickly solve an important adaptive problem, particularly by using less and only the most appropriate information, has an adaptive advantage over competing organisms employing cognitive mechanisms that require more time to reach an adequate solution. The rabbit that has successfully avoided becoming the dinner of the fox by employing several crude but fast heuristics can begin working on other important adaptive problems (e.g., the task of searching for its own dinner). By contrast, the rabbit that attempts the more mathematically elegant but time-consuming strategy of calculating the single optimal escape path by considering all possible escape trajectories (e.g., left, right, zigzagged, vertical?) may well end up doing most of its computations inside the stomach of a less elegantly calculating predator. In the grand Darwinian steeplechase of natural selection, finishing ahead of one’s competitors is more important than the mathematical elegance of one’s solution.

**Outline of this chapter**

These considerations of what kind of cognition is actually most functional and adaptively beneficial to an organism lead to the idea of *ecological rationality* (Gigerenzer, Todd, & the ABC Research Group, 1999; Todd, Fiddick, & Krauss, in press). The ecological rationality perspective focuses on identifying simple, fast, and effective heuristics that work within the computational constraints of an organism and the informational constraints of the environment and still result in adaptively adequate behavior—a perspective that meshes tightly with evolutionary psychology (Todd, 2000; Todd, Fiddick, & Krauss, in press). In the rest of this chapter we show how evolutionary psychology’s focus on ecologically rational descriptions of psychological mechanisms can provide insights into two challenges derived from the frame problem:

1. How much information do intelligent agents really need to solve important information processing problems?
2. What sort of information should an intelligent agent bother attending to, in attempting to solve important information processing problems?

We address the first question by showing that only a limited amount of information is needed to solve important adaptive questions, focusing on the example of mate search. Once we have determined that only a limited amount of information is necessary to guide some aspects of adaptive behavior in a particular context, we must of course next consider what specific information to seek out or attend to. We present an approach to this problem by describing how a simple emotion mechanism might help us surmount the frame problem inherent in strategy choice for risky choice decisions in much the same way that computer chess programs “think before they leap.”
II. HOW MUCH INFORMATION IS REALLY NEEDED TO SOLVE ADAPTIVE PROBLEMS? THE EXAMPLE OF MATE SEARCH

The ordinary chessboard referred to in our introductory story has provided a challenging set of problems for chess players and psychologists alike: how to choose the best move in a chess game, from a particular arrangement of pieces on the board. The typical solution suggested for this problem is to consider as many options as possible in the available time, focusing on the most promising ones, and then selecting the best option discovered when decision-time finally runs out (see Section III for more detail on approaches in computer chess). But many real-world decisions are rather different from this artificial setting: Some options may take a long time to assess, and some may no longer be available after they are first considered and not immediately chosen. What approach can a decision maker take in such situations outside of the chess parlor?

Consider the situation that presents itself to men and women searching for a mate in many modern Western cultures. This type of choice usually consists of a sequential search through successive potential mates, in which each one is evaluated and decided on in turn in a process that can take minutes, hours, days, or years. (Here the decision can be thought of as whether or not to settle down and have children with a particular person, though other definitions are possible.) A significant cost associated with this search is that it is often difficult, and sometimes impossible, to return to a potential mate that has been previously discarded (because they remain in the “mating pool” and will often pair up with someone else while one’s own search continues, as countless romantic tragedies attest). To further complicate matters, one does not know ahead of time what the range of potential mates may be: how can we know, during our first love, whether someone else might be able to incite still deeper passions, if only we just kept searching long enough to find them? We cannot even tell how many more potential mates we may encounter during our lifetime.

Given these constraints on the search process, how can we go about finding a mate? Certainly there is a great deal of information available about the mate values of all the possible potential mates out there—but how much of it must we gather before we can make reasonable mate choice decisions? Are we doomed to an extensive search and evaluation of all possible mates, or is there a better, faster way?

FRAMING OUR THOUGHTS

In this section, we develop a view of mate choice that we feel will be a fruitful area for future research in evolutionary psychology: exploring the role of satisficing heuristics in mating decisions.

Formalizing mate search:
How to solve the dowry problem with little information

We present the mate search problem in a more precise form that we can explore in detail, a model inspired by the dowry problem, a well-known puzzle from probability theory (Mosteller, 1987; Gilbert & Mosteller, 1966). Imagine that the Indian rajah we introduced earlier, still stinging from the enormous (and yet unmet) cost of his Brahmin’s chessboard wheat ploy, wishes to regain some measure of pride by putting this adviser to a new and deadly test. The rajah arranges to have 100 women from his territory brought before his adviser in succession, and all the Brahmin has to do to retain his post is to choose the woman with the highest dowry. If he chooses correctly, the Brahmin keeps his post, and if not, he loses his head. He can see one woman at a time and ask her dowry; then he must decide immediately if she is the one with the highest dowry out of all 100 women, or else let her pass by and go on to the next woman. He cannot return to any woman he has seen before—once he lets them pass, they are gone forever. Moreover, the adviser has no idea of the range of dowries before he starts seeing the women. What strategy can he possibly use to have the highest chance of picking the woman with the highest dowry?

The “optimal” solution: The 37 Percent rule

It turns out that the algorithm the adviser should use, to guarantee the highest chance of making the right choice, is to look at the first 37 women, letting them all pass but remembering the highest dowry from that set, and then, starting with the 38th woman, select the first candidate with a dowry larger than the maximum from the first 37. (For derivations of this procedure, see Mosteller, 1987; Gilbert & Mosteller, 1966; Ferguson, 1989). More generally, if the adviser knows that he will be presented with a succession of women from a total set of a given size, he should check the first 37% of those women, remembering the highest dowry, and then select the first one after those 37% who exceeds the previous highest value. This 37 Percent rule finds the highest value more often than any other algorithm—but it only
succeeds in finding that highest value in 37% of the times it is applied. The rest of the time, the rajah has his revenge: The adviser loses his head and the rajah gets his wheat back. Not only is this rule’s success rate limited, but it also requires a large amount of search: A minimum of 37% of the population must be checked (by definition), but then on average the adviser will end up going through 74% of the women before coming across one with a dowry that exceeds the previously-set threshold that stops his search (Todd & Miller, 1999). Clearly this is a rather exhaustive (and exhausting) approach to mate search, gathering information about three-quarters of the population of potential mates before making a decision. But as we will see, it is possible to make a successful mating decision by employing a much more frugal approach, using much less information.

Satisficing solutions using less information

Any animal searching for a mate is probably not restricted to only settling for the single “best” member of the opposite sex that can be found—other “pretty good” potential mates will often be selected instead, to save search time or energy. It may suffice for instance, in terms of having an adaptive advantage over other competing mate-seekers, to quickly locate and pair up with an individual possessing a mate value in the top 10% of the population. It turns out that to maximize the chance of finding a mate under these criteria, an individual searching through a set of 100 potential partners would only have to check 14% of them before using the highest value seen in that initial sample as the aspiration level to use for the rest of the search (see Todd & Miller, 1999). This kind of aspiration-level-guided search is an instance of what Simon (1990) calls a satisficing heuristic for guiding behavior in domains where complete information—here of the distribution of mate values—is not immediately available. This search strategy would succeed in finding a mate in the top 10% of the population over three-quarters of the time (83%, compared to the 37 Percent rule’s success rate of only 37%). If the standards are relaxed a bit further, so that a mate in the highest quartile will do, then only 7% of the population of 100 need be checked to form an aspiration level (and this will succeed 92% of the time). Finally, rather than searching for a mate in the top ranks of the population, an animal may be loss-averse, preferring only to minimize its chances of landing a mate with a value in the bottom quartile of the population. The way to achieve this goal is to use a much shorter search time, checking only 3% of

the population before setting the aspiration level. Such a loss-avoiding search strategy would select a mate from the bottom (quarter) of the barrel only 1% of the time. In contrast, following the 37 Percent rule would pick these poor mates more than 9% of the time—much worse performance by loss-averse standards.

Thus, successful mate search—defined as meeting or exceeding these biologically plausible aspiration levels—can be achieved using much less information than is required by the optimal 37 Percent rule. We do not in general know what criteria animals, including humans, may have evolved to satisfy in their mate choice, but our results show that for a broad class of possible criteria, relatively little search is necessary to gain enough information for setting an appropriate aspiration level in this one-sided search situation. But we must still ask how appropriate such a one-sided search model is—it may reasonably reflect some search situations such as buying a house (where the house does not usually search for a buyer in turn), but does it capture the realities of human mate search?

The more realistic problem of mutual mate search

In chess, the challenge and interest of the game come from playing with someone who makes moves in response to one’s own. The same is true for the mating game as well. One-sided mate search, in which the members of one sex do all the searching and make all the decisions, is not a realistic model of the problem actually faced by many species, including humans. The problem for these species is that at the same time one sex is evaluating members of the other sex as prospective mates, they are themselves being evaluated in turn. If a particular male does not meet a particular female’s standards, for instance, then no amount of proposing on the male’s part is going to win the female (in the restricted scenario we are considering, at least). Furthermore, if everyone in the population has seen one-sidedly setting their aspiration levels based on the highest mate value seen in the first few potential mates they encounter, then everyone will have a rather high aspiration for whom they will agree to mate with. The trouble is then that if an individual does not possess a high mate value (relative to the aspiration levels of others in the population), they will not be selected by anyone else as a potential mate, and will end up alone—and thus for most individuals, a one-sided search strategy in a mutual mating market will be unsuccessful.

We can explore how different mate search rules work in a mutual
search situation by constructing a more biologically plausible model. Consider a population of 100 males and 100 females, each with a distinct mate value between 0.0 and 100.0, and each with the ability to accurately assess the mate values of members of the opposite sex, but lacking knowledge of their own mate value. We give each of the 200 individuals the same search strategy, which first involves assessing some specific number of members of the opposite sex during an “adolescence period.” During this time, individuals can adjust an aspiration level, if their search rule uses one, up or down from an initial value of 50. After this adolescence period, pairs of males and females meet at random, and they can either make a proposal (an offer to mate) to their partner, or decline to do so. If both individuals in a pair make an offer to each other, then this pair is deemed mated, and the two individuals are removed from the population. Otherwise, both individuals remain in the mating pool to try again. This pairing-offering-mating cycle is repeated until every individual is mated, or until every individual has had the opportunity to assess and propose to every member of the opposite sex. We are interested in how many individuals in the population get paired up in this setting using different search rules, and how well matched the pairs end up being.

As we indicated above, trying to use a one-sided mate search rule in the two-sided setting has rather disastrous results for most of the population. For instance, if everyone checks a dozen members of the opposite sex and sets an aspiration level equal to the highest mate value seen, then only 7% of the population will end up in mutually-agreeable pairs. Furthermore, it will only be the very highest-valued individuals that end up mated. This is certainly counter to human experience, as well as that of other mutually selecting (e.g., some monogamous) species, where the majority of individuals, across a wide range of relative mate values, are able to find mates. Clearly, a different kind of search rule must be used in these cases.

**A little search of the right kind is still enough**

A much more successful two-sided mate search can be achieved by simply using *one's own mate value* as the aspiration level for deciding which members of the opposite sex to propose to. With this strategy, most of the population can succeed in finding and pairing up with mates of a similar value to their own. But there is a problem: Accurate knowledge of one’s own mate value is not necessarily an easy thing to come by. We cannot be born with it, because it is both con-

---

**What these models leave out**

These simple models certainly do not capture the full complexity and subtlety of real mate search in nature. Humans for instance can often return to previously-encountered partners for another try, and can learn about their own mate value (and those of others) through indirect observation in addition to direct (dating) experience. But such additional considerations will often serve to further shorten the search process, and thereby further strengthen our point, that mate search is a prime example of an important adaptive domain in which making good decisions does not require amassing vast amounts of information. Simple satisficing heuristics for one-sided and mutual search could be used by decision makers to learn appropriate aspiration levels after checking only a few candidates. As such, these heuristics show how considerations of ecological rationality can provide the computational mind with a way around the frame problem: the mate choice heuristics considered here use only a small portion of the available information and still yield satisfactory performance.

Adopting this ecological rationality perspective opens up a variety
of other research topics. In the domain of mate choice specifically, in addition to enhancing the realism of the search model as just described, more work is needed to understand the mechanisms that guide perception and display of appropriate (and deceptively inappropriate) traits and the process by which such perceptions are used in the assessment of mate quality (see Miller & Todd, 1998, for other research questions in mate choice). And this domain is only one among many: A variety of simple decision heuristics are being found for other decision applications, ranging from categorization and estimation to parental investment and predator intention judgment, where similar frugality of information-use nonetheless leads to reasonable decisions (Gigerenzer, Todd, & the ABC Research Group, 1999; Todd, Gigerenzer, & the ABC Research Group, in press). In all of these domains, the main questions stemming from the ecological rationality viewpoint are: What simple evolved heuristics can solve important decision-making problems in a fast and frugal manner, and how is information structured in the environment to allow these heuristics to accomplish their tasks with minimal calculation? In answering these questions, we seek to fill in the often-missing component of specific mechanisms in evolutionary psychology, while remaining faithful to the actual environments in which those mechanisms function.

At least one question, though, remains in our consideration of mate search. Any but the most dispassionate of readers is likely to wonder where love has disappeared to amidst all this rather mechanical description of mate search heuristics. Have we eliminated emotion from the process of finding a mate? Not at all—we seek to find a central place for emotions in our view of ecological rationality. This is currently another important area for further work, but at present we do have some ideas about the role that emotions can play in adaptive decision-making. In particular, emotions might help address the second aspect of the frame problem: determining which information to attend to in the first place. We turn now to the question of how emotions could guide information gathering in risky choice situations.

III. WHAT SORT OF INFORMATION SHOULD AN INTELLIGENT AGENT ATTENDING TO? EMOTIONS AND THE FRAME PROBLEM IN RISKY CHOICE DECISION-MAKING

The idea that emotions might serve an adaptive information-processing function in risky choice contexts is not a mainstream view. Indeed, emotions have traditionally been seen as impairments to decision-mak-

ing. This view is commonplace whether one considers pop culture icons of good judgment (such as Mr. Spock, the usually hyper-rational and emotionless Vulcan from Star Trek) or the scientific literature on decision-making (including social cognition research on emotional biases in information processing, see Ketelaar & Clore, 1997 for a recent review). One economist notes that:

The standard view of the relation between rationality and emotions is, of course, that emotions interfere with rationality. They are, as it were, sand in the machinery of action. Nobody would deny that this is often true. (Elster, 1995, p. 1394, emphasis added).

Most theorists consider emotions to function primarily in producing behavior, not cognition. According to this view, emotions promote adaptive behavior through the activation of so-called “action tendencies” (see Ekman & Davidson, 1994; Scherer & Ekman, 1984 for good reviews). Researchers who adopt this behaviorally oriented perspective are generally quite suspicious of any claims that emotions might function primarily to promote adaptive cognitive functioning (for a rare exception, see Demasio, 1995). However, some evolutionary psychologists have argued that such a strict focus on behavior and its adaptive consequences leap-frogs from descriptions of behavior (e.g., fear makes us run from bears) to adaptive explanations (e.g., it is fitness-promoting to avoid danger) without specifying the actual mechanisms that provide the “missing link” between these behaviors and their adaptive implications (Buss, 1995; Cosmides & Tooby, 1987). From the perspective of evolutionary psychology, decision-making behavior (i.e., enacting one’s preferences) is contingent upon the existence of cognitive (information processing) mechanisms that select information from the environment and use this information to draw appropriate inferences, which in turn, guide behavior toward the appropriate “adaptive” strategies. Might emotions play an important role in the cognitive processes underlying decision-making behavior?

In this section, we present a view of emotion that we feel will be a fruitful area for future research in evolutionary psychology: namely, the view that emotions operate, in part, as specialized cognitive (information processing) mechanisms that provide potent information about the future consequences of pursuing various strategy choices. In particular, we explore the view that emotions function to help deci-
sion-makers overcome the frame problem inherent in risky choice decisions. (Here we define risky choice decisions as situations where the individual must select one of several options—e.g., potential courses of action—under conditions of uncertainty regarding the future consequences of pursuing each option). According to this view, affective representations of the prospective utility of different strategic options—in the form of good and bad feelings generated while considering these options—may serve to focus attention on those strategies with adaptively relevant outcomes, ignoring the rest. The existence of numerous distinct emotions—each with a corresponding positive or negative affective state—suggests that we possess numerous domain-specific mechanisms that enable us to affectively represent the cost-benefit structure of a variety of distinct environmental contingencies (see also Ketelaar & Clore, 1997). In this sense, specific emotions might help solve the problem of what information to attend to in specific environmental circumstances by providing an “affective” guide to important features of the adaptive landscape.

Thus, when the future outcome of various courses of action cannot be objectively “calculated,” often because there are simply too many plausible consequences to consider (i.e., the frame problem), it may pay to “let your emotions be your guide” in selecting which course of action to pursue. This view of “affective information processing” is consistent with a more general view of emotion endorsed by some economists (Frank, 1988; Hirshleifer, 1987) and evolutionary psychologists (Nesse, 1990; Nesse & Williams, 1994; Tooby & Cosmides, 1990) who contend that emotions function, in part, to focus attention on information about the future cost-benefit structure of one’s environment. In this sense, emotions are seen as evolved software packages designed to alert an intelligent agent to the most propitious courses of action among one’s current options (Nesse, 1990).

**Affective representations of value:**

**A guide to strategic decision-making?**

If evolutionary psychologists focus attention on “real world” asymmetries in the prospective utility of gains and losses, emotional representations of value might provide a better guide to strategy choice than more “objective” valuations, even though emotional decisions often override lots of seemingly “rational” information. One promis-

**Framing Our Thoughts**

...ing view of emotion would be to explore whether affective representations of the cost-benefit structure of the environment are: 1) more salient than objective, “cold” calculations of costs and benefits (thereby provoking individuals to attend more to their emotional perceptions when making decisions), and 2) a more accurate guide to the long-term consequences of pursuing various strategy choices (thereby provoking individuals who make “emotional” decisions to perform better over the long-run than their “emotion-less” counterparts).

**Affective feelings are an immediately salient source of information**

Emotions are typically seen as having both a cognitive structure and an accompanying affective (e.g., good-bad) feeling component (Ortony, Clore, & Collins, 1988). Experiencing a pleasant or unpleasant feeling state is, by definition, a large part of what it means to have an emotional experience; as such, these affective feelings can be seen as a necessary, but not sufficient component of emotion (Clore, 1992). Perhaps emotions so often intrude in our most important decisions precisely because the affective feeling component accompanying an emotion is so immediately salient and unable to be ignored. One can’t help but attend to one’s affective feelings while one is experiencing them. This is the case because feeling states, as opposed to other types of cognitive states, are by definition, states of awareness. Thus, it makes little sense to say that “I feel really bad right now, but I’m not aware of it,” or that “I feel really good right now, but I am not aware that I do.” Indeed, there is ample evidence that affective feeling states, including those that accompany specific emotions, intrude on a wide variety of seemingly “purely cognitive” judgments and decisions (see Clore, Schwarz, & Conway 1994; Ketelaar & Clore, 1997 for reviews). This robust finding has been labeled the “Affect-as-information” model because individuals appear to consult their affective reactions as one source of information when evaluating objects and events (see Schwarz & Clore, 1983, 1988).

**But is affective feeling an accurate indicator of long-term consequences?**

The question remains, is the information conveyed by affective feeling states actually useful in decision-making? In the rest of this sec-
tion we focus on the idea that specific emotions may help solve the problem of what information to attend to in specific environmental circumstances, by virtue of their accompanying affective feeling states. According to this view, the affective feeling state that accompanies a specific emotion can function as a strategic information state—in the form of an “affective” decision weight—that accurately represents the prospective utilities corresponding to the specific set of circumstances in which the emotion arose. We now explore how the affective feeling component of emotion might help us surmount the frame problem inherent in risky choice decisions in much the same way that computer chess programs operate, by focusing attention on a limited number of strategic options and making the future consequences of those options accurately and powerfully salient.

The Frame Problem in risky choice decision-making: A computer chess analogy

Although forecasting the future consequences of alternative courses of action (to help select the best strategy) is an important adaptive problem, it also presents considerable computational obstacles. Strategy choice in a risky choice context entails a version of the frame problem, resulting from the exponential explosion of potential outcomes that one must consider when calculating the future consequences of pursuing each of the possible alternative strategies at one’s disposal. Considering an analogy between risky choice decisions and chess can readily highlight this point.

The frame problem occurs whenever constructing the decision tree of possible alternative courses of actions and inferring their likely future consequences becomes computationally intractable (remember the robot in Dennett’s though experiment). The game of chess also involves considering a large number of strategies and their future consequences. For example, performing at a reasonable level of skill in chess requires more than simply selecting the one move that will generate the best immediate outcome (say, capturing your opponent’s queen). Instead, a better strategy is to look ahead several consecutive moves to consider the likely outcomes of various alternative sequences of moves (known in chess parlance as continuations). If one could simply map out the entire decision tree of all possible continuations and their final consequences, chess would become equivalent to tic-tac-toe where the sure-fire winning (or perpetually tying) strategies are well documented. Yet, any computational device that attempts to select its next move in the game of chess by considering all possible legal moves and all possible future consequences of such moves will soon find itself tangled in a decision tree of immeasurable complexity. The number of possible sequences of moves that can be played from the start of a game to the end is astronomically large. It is literally impossible to generate the entire decision tree of possible sequences of consecutive chess moves (see Newborn, 1996 for an accessible overview of computer chess). Therein lies the rub, and the frame problem. Could AI’s solution to the problem: of selecting the “best” chess move suggest a workable analogy for how emotions might surmount the frame problem inherent in risky choice contexts?

A fast and frugal answer to the frame problem in chess: Limited search with an evaluation function

In light of the computational difficulties inherent in selecting the “best” chess move, AI researchers had to find an alternative to mapping out the entire decision tree of chess continuations. Today the very best computer chess programs rely on an alternative strategy outlined by the grandfather of computer chess, Claude Shannon (see Newborn, 1996). Shannon (1950) proposed that the goal of mapping the entire decision tree of chess moves be abandoned in favor of a simpler strategy in which a move “evaluation function” played a central role. Successful chess playing computers, such as Deep Blue, employ this relatively simple strategy and map only a minuscule portion of the decision tree when selecting their next move. In one variant of this approach, known as the “fixed depth” search, a move is selected by:

exploring all lines of play to some fixed depth and then assigning a score to the position at the end of each continuation. The score assigned to the position by a “scoring function” is a measure of how good the position is for the side on the move (Newborn, 1996, p. 9, emphasis added).

This “scoring function” or “evaluation function” considers a number of factors including relative material (piece) advantage, the mobility of one’s pieces, et cetera. This simple strategy can be summarized as follows: 1) look ahead a limited number of moves, 2) assign a score to the terminal position at the end of each continuation, and then 3) select a move that guarantees progress toward the terminal position with the highest score.
Although hardly omnipotent, strategy has performed quite well in competition. In the most recent encounter with arguably the best human chess player ever, Grand Master Gary Kasparov, Deep Blue’s successor (Deeper Blue) employed this method to achieve the first-ever computer victory over a human world champion (see King, 1997). Thus, Shannon’s (1950) strategy of searching a limited portion of the decision tree with an appropriate evaluation function not only appears to overcome the frame problem (as it is manifest in this chess example), but equally important, is able to perform at (or above) par with the best human chess players. How similar is this to how human reasoners use emotions to help select future courses of action?

Emotional Gambits: Affect, risky choice, and the computer chess evaluation function

We can cross the bridge from computer chess programs to more day-to-day risky choice decision making through the example of a strategy game known as the repeated Prisoner’s Dilemma. This is a popular if somewhat overused example of the common problem of having to select one of multiple courses of action (e.g., some pattern of cooperating or defecting in social encounters) with incomplete knowledge of the long-term consequences of one’s decision. In the single-shot, no-future version of this game, each player encounters the other only once, and the immediate consequences of either cooperating or defecting are obvious: Defection yields the higher expected utility. However, in the repeated version of this game where players encounter each other multiple times, this strategy choice (i.e., always defecting) must contend with several alternative strategies (e.g., tit-for-tat, generous tit-for-tat, GRIM, mutual cooperation, etc.) that can lead to a higher long-term payoff (see Axelrod, 1984; Samuelson, 1997). If the number of iterations to be played is large or unknown (as it often is in real life), trying to search the whole decision tree of strategies and counter-strategies is no longer computationally feasible for determining one’s best next move. Just as in the game of chess, the number of possible strategies and their ultimate consequences that can be considered soon becomes mind-boggling. How else then can one determine which strategy to play in a repeated Prisoner’s Dilemma game where the number of iterations to be played is large or unknown? One view is that the affective component of emotion can play a functional role in evaluating alternative courses of action in situations such as these (see also Frank, 1988).

This is not a particularly popular notion. As in other domains of judgment and decision-making, emotions are more commonly viewed as impairing, rather than improving, rational judgment. Kahneman (1999), for example, has found that when individuals evaluate the quality of an experience extended over time, their affective reactions lead them to assign a disproportionate weight to how the experience ends. Kahneman (1999) argues that the normative “correct” strategy for evaluating the quality of episodes extended over time is to calculate the temporal integral across all momentary affective (good-bad) sensations experienced during these episodes. Rather than integrating the hedonic values (affective reactions to the task) across all momentary instants, individuals instead appear to judge the utility of the entire episode in terms of its peak and how it ends. Accordingly, this judgment strategy has been labeled the “peak-end” rule (Kahneman, 1999). In several experiments participants have provided real-time recordings of their hedonic experiences during an episode, after which they were asked to provide global evaluations of the entire episode. Time and time again, it is revealed that individuals judge experiences as being worse if the peak amount of negative affect occurs later, rather than earlier in the episode (see Kahneman, 1999 for an overview). This leads to the paradoxical finding that individuals sometimes prefer episodes with more (rather than less) overall summed pain. In one study, individuals undergoing an uncomfortable medical procedure (colonoscopy) were shown to evaluate the entire episode as being less painful overall if the intensity of the pain was made to drop off slowly rather than quickly (a modification that does not involve changing the peak height, but does move its location from the end of the procedure to the middle) even though the former strategy results in more overall pain than the latter strategy (Redelmeier & Kahneman, 1996). If one assumes that one should utilize all available information in judging the overall quality of an outcome stretched over time, then this consistent focus on the affective representation of only “the peak and the end” of the episode has the appearance of a crude and irrational heuristic (see Kahneman, 1999). But is the “peak-end” rule really so irrational?

Consider our chess-playing computer again. It is interesting to note that both computers and humans appear to assign a disproportionate weight to the endings of events when considering possible courses of action (see Kahneman, 1999; Newborn, 1996). In chess, it is the score at the final or “end” positions of the decision tree of possible continuations that matters most. If an initially attractive line of play concludes with a high negative score at the end of the limited series of moves
being considered, it will be appropriately seen as a dubious long-term strategy, despite its initial attraction. By contrast, if a particular line of play exhibits a high negative score early on in that particular sequence of moves, this does not necessarily portend a significant blunder. It may be the case that the course of action that exhibits its “peak” negative value early on in the sequence of moves merely reflects that one has employed a strategic gambit. A gambit is a strategic sacrifice, often made very early in the game, where one incurs a significant immediate loss in exchange for a long-term strategic advantage. The economist Robert Frank (1988) proposes that emotions operate in this same way, as devices for provoking strategic gambits in the game of life.

**Affective gambits**

The default information state of most organisms appears to be one where the environment is represented in terms of its immediate consequences (e.g., that piece of cake looks good right now, see Frank, 1988, p. 76-80). However, just as in the game of chess, relying on immediate outcomes for strategy choice can have dubious consequences for the long-term strategist. What if an initially attractive strategy (such as defection in the Prisoner's Dilemma) actually leads to a large negative score (e.g., a very low payoff) at the end of a limited series of moves? Because decision-makers are not clairvoyant, the final “negative” consequences of an initially attractive strategy cannot be directly perceived. Moreover, even if one could imagine all possible future scenarios in order to “simulate” their outcomes, by calculating the ultimate consequences of adopting a particular strategy and comparing it to the ultimate consequences of all possible alternative strategies (in order to select the best strategy), we run headlong into the frame problem. Just like chess-playing computers, human decision-makers need some means of focusing attention on a limited set of adaptively relevant strategic options.

Frank (1988) argues that one’s affective reactions while considering various options can “inform” the individual of the future consequences of pursuing each option. Analogous to the “evaluation function” of a chess-playing computer, the emotions aroused during the process of making important decisions might aid individuals in strategy choice by shifting attention away from certain dubious long-range strategies that initially appear quite attractive, and toward other strategies that fare better over the long haul. For example, an individual may experience the emotion of guilt while considering the initially attractive strategy of defection in the repeated Prisoner’s Dilemma. Because the affective feeling state that accompanies guilt is aversive, the individual might be provoked to select an alternative, less aversive, course of action. One interpretation of Frank’s (1988) model is that emotions such as guilt function to move the future costs of actions such as defection into the current situation, in the form of a powerful and salient feeling state such as the negative affect associated with guilt (see Ketelaar & Clore, 1997). In a similar fashion, the consideration of alternative strategies (mutual cooperation, tit-for-tat, etc.) might evoke positive affective reactions, suggesting that their prospective future utilities are considerably higher, even if their immediate consequences (lower payoffs) are less attractive. These affective states can thus serve as psychological “stand-ins” for the imperceptible future consequences of pursuing particular courses of action. In this way, emotions are analogous to the “evaluation function” of chess-playing computers in that they assign disproportionate weight to the final outcome of the strategy choice that one is considering.

From one point of view, this emotional focus on “how things end” seems irrational (Kahneman, 1999). By contrast, an evolutionary perspective argues that, far from being maladaptive, emotions such as guilt can actually evoke an individual to pursue emotional gambits that, while incurring an immediate cost, lead to higher payoffs over the long haul (Frank, 1988). These emotional gambits provoke the individual to experience the peak amount of pain (a lower initial payoff) in the earlier stages of the decision-making episode in order to avoid selecting a strategy where the peak amount of pain is incurred at the end of the series of moves. An evolutionary psychological interpretation of this model suggests that the affective component of emotion functions as a sort of evolved decision weight where the perceived positivity or negativity of one’s mental state while considering a particular strategic option reflects the future “adaptive” utility of pursuing that option. In circumstances where the future consequences of different strategy choices cannot be directly perceived, it may make sense to “let your emotions be your guide” in strategy selection. This can be the case if affective representations of value reflect the long-term evolutionary history of the particular cost-benefit calculations one is considering. While a mortal individual cannot look into the future to determine the ultimate consequences of pursuing a particular strategy, by using the “affective weights” attached to that option the individual may be able to “look back into the past” evolutionary his-
tory of similar scenarios to assign appropriate weights according to the likely fitness consequences of pursuing that strategy (see Tooby & Cosmides, 1990 for a similar view). We now describe preliminary research aimed at testing these ideas, which is producing promising support (Ketelaar & Au, 2001).

To examine whether this functional information-processing model of emotion is valid, one could examine the effects of so-called "emotional gambits" on strategic behavior in repeated social bargaining games such as the Prisoner's Dilemma. One could examine whether individuals who experience an aversive affective state (e.g., guilt) while considering "defection" are more likely to incur an immediate cost (i.e., lower payoff) by forgoing this initially attractive strategy in favor of adopting an alternative, "more cooperative," strategy. Specifically, one could compare individuals who experience guilt to those who do not, to determine who is more likely to display higher levels of cooperation indicative of adopting the better long-run strategies (see Axelrod, 1984, Frank, 1988). This is exactly the direction being pursued in an ongoing set of studies.

In one experiment college students were randomly assigned to guilty mood and neutral mood inductions and asked to play an indefinite number of iterations of the Prisoner's Dilemma on a computer (see Ketelaar & Au, 2000). Players in the guilt condition displayed higher levels of cooperation (53 per cent cooperative responses) compared to players in the control condition (39 per cent cooperation). Similar findings were observed in a repeated ultimatum game where participants had to negotiate how to divide a sum of money with a partner twice over a two-week period. Of primary interest was whether individuals who felt guilty after proposing a selfish division of the money at Time 1 would be more likely to propose a more generous split of the money when they repeated this negotiation (with the same partner) one week later (at Time 2). The idea here is that experiencing guilty feelings after proposing a selfish offer may serve to alert the individual that continued selfishness is a dubious long-term strategy in a repeated social bargaining game. Thus, one predicts that only those selfish individuals who felt guilty about their behavior at Time 1 will reverse their offers (in a "tit-for-tat" fashion consistent with reciprocal altruism), and propose a more generous split of the money one week later (at Time 2). The differences in responses at Time 2 as a function of guilt at Time 1 were quite large: 91% of the individuals who felt guilty after making a selfish offer at Time 1 proposed a generous offer at Time 2, compared to only 22% of the individuals who felt no guilt after a selfish offer. These preliminary findings are consistent with Frank's (1988) view that emotions (here we considered guilt) can provoke strategic gambits in repeated social bargaining games, leading individuals to incur an immediate cost (e.g., a lower payoff) by forgoing an initially attractive strategy option in order to reap a long-term strategic advantage.

Emotions, the "peak-end" rule, and the frame problem

The philosopher Ronald deSousa (1987, p. 195) has argued that emotions limit "the range of information that the organism will take into account, the inferences actually drawn from a potential infinity, and the set of live options among which it will choose." This view is consistent with our claim that emotions function, in part, to overcome the frame problem by both: 1) focusing attention on a limited number of strategic options and 2) making the future consequences of those options immediately salient. It would appear that under ecological conditions where future outcomes are uncertain and the frame problem runs rampant (as illustrated by the artificial example of chess-playing computers), the attention-limiting focus provoked by emotions that adhere to something like the "peak-end" rule makes good adaptive sense as an alternative to evaluating all possible strategy options (remember the vast decision tree of chess continuations). Under ecological conditions where strategic gambits need to be taken into consideration (as in the game of chess), endings really do matter more than earlier moments. Rather than viewing emotions as impairments to decision-making, this alternative model describes emotions as adaptively designed information processing mechanisms that provide information—via affective decision weights—about the future consequences of pursuing various strategy choices. In some circumstances, an affective focus on peaks and ends may not be so irrational after all.

In this manner, emotions may thus be crucial in generating intelligent behavior, one hallmark of which is the capacity to "look before you leap," by considering the consequences of actions before embarking upon them:

Sophisticated—or just risk-averse—creatures avail themselves of systems of temporally distal anticipation. They use their brains to produce more far-ranging versions of the relevant future. So far as I can see, this is really just an extension of letting the
world warn you. It attempts to build less direct, more devious sorts of warnings out of the masses of individually unthreatening tidbits of information gleaned from the passing show, which it fabricates into internal alarm systems. (Dennett, 1996, pp. 2-3, emphasis in the original)

Emotions, we suggest, can perform the role of these internal alarm systems, alerting us to adaptive dangers and benefits by inferring the distal future from one’s current circumstances and strategy choices. In this way, emotions can help the computationally limited human mind to circumvent the pitfalls of the frame problem by determining which information to attend to in the first place.

**IV. CONCLUSIONS—A FAST AND FRUGAL APPROACH TO STUDYING ECOLOGICAL RATIONALITY**

For any given problem that faces us in the real world, the number of ways we can think about solving the problem, and the number of consequences that follow from any particular course of action, are limitless. Considering all possibilities is clearly impossible. To function effectively and behave adaptively, we must have some way of cutting the possibilities down, putting a very narrow frame around any given problem we face and staying within it. As we have shown in this chapter, an ecological view of how an organism can behave rationally makes it clear that even a narrow frame—even taking only a small amount of information into account—can still allow for reasonable performance in important adaptive domains. Furthermore, we have argued that emotions can guide where this narrow frame is placed, by focusing the computational mind on just that information that will be most useful in making adaptive decisions with appropriate long-term outcomes.

But there is also a frame problem lurking for researchers trying to understand the nature of human cognition. There are too many possible mechanisms that could produce human behavior, so how do we search for appropriate ones? Even a progressive meta-theory like evolutionary psychology vastly underdetermines the scope of psychological mechanisms that could have arisen, evolutionarily speaking, to solve a particular information-processing problem (Ketelaar & Ellis, 2000). Ecological rationality gives us a way forward within this larger frame problem, by suggesting a bottom-up research approach of first identifying and exploring simple heuristic decision-making components, and then building more sophisticated cognitive modules out of these simpler components. We now briefly sketch this research methodology and how it contrasts with that inspired by the more traditional view of rationality.

The view of ecological rationality we have presented stems from illuminating simple adaptive heuristics that can solve the information-processing problems recurrently faced by our ancestors in their natural environment. As we have indicated, this stands in sharp contrast to traditional views of rationality that often presuppose a complex, content-free apparatus of logical or probabilistic reasoning instantiated in people’s heads. This contrast does more than just draw argumentative lines in the sand between two camps—it has deep implications for how one believes the reasoning mechanisms of people and animals should be explored. If reasoning is to be logically and mathematically sound, then it makes sense to start looking for psychological reasoning mechanisms by finding the mathematically optimal solution to some particular behavioral challenge or problem, and then whittling that down through successive simplifications—all mathematically derivable and testable—until finally a psychologically plausible mechanism is found. Note that this “top-down” approach to deriving human psychology from lofty optimal heights presents several challenges, the foremost being that one must first construct an optimal solution to the problem being considered. In many cases, this will simply be impossible; no optima exist for a wide class of realistic behavioral challenges (Simon, 1990). In those cases where it is still possible, deciding on the appropriate steps of successive derivation and simplification to bring the optimal solution down to the psychological level of human computation presents a further challenge, again one of deciding which of many possible approaches to a problem is the best to take. In the end, if this approach succeeds, we will have gained a model of human behavior that is mathematically guaranteed and logically sound (without undesired intrastabilities, etc.). This strategy also promises a clear paper trail of derivations leading back to the optimal solution, so that direct comparisons can be made in terms of performance on various criteria, range of applicability, mechanisms of operation, etc. But the path down the mountain can be arduous, and even finding the peak in the first place, let alone an appropriate descending path out of the multitude of possible derivations, presents a search problem all too familiar from our earlier discussions of the frame problem.
But there is an ecologically rational way around this problem as well. We start instead with the view that reasoning heuristics evolved because they performed well for people living and behaving in certain types of environments. With this perspective, it is reasonable to begin our search for mental mechanisms not empty-handed, but rather with some adaptive building blocks that people actually use—like emotions, or aspiration levels—and see how these can be combined into strategies that achieve sufficient levels of performance. This bottom-up approach to the construction of fast and frugal heuristics starts with psychological plausibility and ends with adaptive behavior in a particular problem domain. Determining the initial set of building blocks to work with should be simpler than finding an optimal solution in the top-down approach. Finding suitable combinations of fast and frugal building blocks for a particular problem may often prove challenging—we do not yet know how to specify this (re)search process—but trial-and-error methods (including heuristic-guided search) and exploratory shuffling will work here in a way that is impossible with the mathematical derivations required by the top-down method.

We hasten to point out that much work still has to be done once a fast and frugal heuristic is put forth for testing. The ecological rationality approach demands a demonstration of how a putative adaptive heuristic performs in different environments and an explanation for why it acts the way it does. Without the mathematical derivation pedigree of heuristics found by the top-down whittling away of optimal solutions, these questions must be answered instead by empirical observation, computer simulation, or even new mathematical analysis. Both the top-down derivation and bottom-up exploration approaches can yield the same results or, a particular problem, identifying the same heuristic in the end. However, we expect that the bottom-up approach will illuminate plausible mechanisms faster, and with fewer false starts (e.g., those caused by the impossibility of specifying an optimal solution in the first approach). More important, because the bottom-up approach can discover mental mechanisms that do not lie within traditional mathematical or logical bounds—for instance, heuristics that violate transitivity—we expect this research plan to identify a broader range of psychologically plausible but potentially irrational (by traditional standards) fast and frugal heuristics.

By looking for specific heuristic solutions to particular environmental challenges, an ecological rationality perspective on evolutionary psychology aims to reveal a domain-specific collection of well-adapted tools. In this chapter we illustrated how an ecological rationality perspective on decision-making, even in domains that have traditionally been viewed as non-cognitive—such as finding a mate and thinking while under the influence of emotion—can generate fruitful new directions for psychological research by shining the spotlight of the Darwinian approach inside the framework of the computational mind.

FOOTNOTES

1 In approaches to decision-making such as game theory, equilibrium solutions to social bargaining games are sometimes determined by introducing assumptions such as mutual knowledge or perfect information states (e.g., "I know the rules of the game, you know the rules of the game, I know that you know the rules of the game, you know that I know that you know the rules of the game," ad infinitum). An equilibrium solution is the strategy that—in the case of a two-person game, for example—yields the mutually "best" strategy in the sense that each agent's strategy is optimal given the strategy of the other agent (see Rasmussen, 1994; Samuelson, 1997). Although such methods of equilibrium selection work in the abstract, they typically cannot be considered biologically plausible explanations of human decision-making because, in many cases, obtaining a "perfect information state" and "mutual knowledge" would entail versions of the frame problem: The mind is incapable of spinning through an infinity of recursive information states to locate an equilibrium solution.

2 One could claim, of course, that they were experiencing an emotion, but were unaware that they were experiencing it at the time. This perception is quite common. The point here is that there is little empirical evidence to support anecdotal claims that individuals can experience full-blown affective "feelings" without awareness of these feelings. There is some evidence, however, that individuals can have valenced, affective reactions to stimuli without awareness (see Winkielman, Zajonc, & Schwarz, 1997 and Bargh, 1997 for one view of unconscious attitudes).

3 These decision weights are referred to as "prospective" utilities to distinguish them from evaluations of the current worth of an option (e.g., strictly in terms of its immediate benefits). From an evolutionary standpoint, what is important is not just the current value of an option, but rather its future or "prospective" value. Drinking salt water might be just as effective in the short-run for decreasing current feelings of thirst as drinking fresh water, but the long-term consequences of these two options may differ. The use of the term "prospective" is meant to convey the idea that organisms can benefit from using decision weights that somehow represent the future (as opposed to the immediate) value of an option (see Frank, 1988 for a similar view).

4 Although some definitions of the frame problem exclude domains such as chess (see Raamgartner & Payz, 1995, p. 314) because they are "well de-
fined." we include the game here as a clear example of a problem where the optimal solution involves an incomputable search and reasonable solutions require intelligent compromises to frame the search appropriately. Selecting the best possible move in a game of chess entails specifying the decision-tree of all possible continuations from the current position. The task of constructing and searching through this tree is beyond the scope of any computational device yet known. For example, the average midgame scenario has around 30-40 possible valid moves that can be played, over 1000 possible two-move continuations to ponder, over 1 million three-move continuations to consider, over 1 billion possible four-move continuations to think over, and the number grows exponentially as one looks further ahead (see Newborn, 1996). Not even computers such as Deep Blue (which can consider some 250 million moves per second) can make a dent in the complete search. Thus, selecting a move in chess requires addressing a version of the frame problem, deciding which options and consequences to explore and which possibilities to leave out.

REFERENCES


