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What Makes a Good Decision? Robust Satisficing as a Normative Standard of Rational Decision Making

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In the thirty years or so since it began, the field of behavioral decision making, or behavioral economics, has developed an ever-growing catalogue of the mistakes human beings are susceptible to when they use a variety of heuristics and biases to evaluate information, make decisions, and then evaluate the results of those decisions. In assessing probability, people seem to interpret "how likely is this event to happen?" as "how typical is this of the class of events of which it is a member?" People treat the vividness of an event in memory as an indication of how frequently the event occurred in the past. People make risk averse choices when choosing among possible gains and risk seeking choices when choosing among possible losses. This is not, in itself, a problem, but it becomes a problem when variations in the language of description can induce people to treat the identical choice situation as one involving gains or as one involving losses. People organize inflows and outputs of money into a variety of mental accounts, which helps explain why they are willing to treat themselves to a luxury when they have a windfall, but otherwise not. This also helps explain why people will make deposits into savings accounts that pay 3% interest while at the same time making minimal payments to reduce credit card debt at 18% interest. Peoples' assessments of the value of a good at a given price are dependent on surrounding other goods that provide "anchors" (eg., a $600 suit may be a "steal" on a rack of $1000 suits, but an extravagance on a rack of $300 suits). Phenomena like these have grown out of the research program on heuristics and biases launched by Daniel Kahneman and Amos Tversky (e.g., Gilovich, Griffin, & Kahneman, 2002; Kahneman, 2003; Kahneman & Tversky, 1984, 2000). And they have led to a kind of "two-process" theory of judgment and decision making. One process, which is rapid, automatic, and inaccessible to consciousness, delivers results to consciousness that are produced by these heuristics. Afterwards, the second, slower process, which is conscious and rule-governed, goes to work with logic, probability theory, and other formal systems. A decision maker need not accept the results of the automatic system as competent or definitive, but the automatic system delivers answers upon which consciousness acts. The results of the operation of the heuristics and biases of the automatic system do not always lead to mistaken judgments and bad decisions. Indeed much of the time, they serve us well (see, e.g., Gigerenzer, 2007). Nonetheless, thirty years of research documents that sometimes, they can lead to serious errors.

In all the research on how heuristics and biases can lead people into bad decisions, the normative standard for comparison has rarely been called into question. However, in this paper, we will argue that many decisions we face cannot be handled by the formal systems that are taken for granted as normatively appropriate. Specifically, the world is a radically uncertain place. This uncertainty makes calculations of expected utility virtually meaningless, even for people who know how to do the calculations. We will illustrate some of the limitations of formal systems designed to maximize utility, and suggest an approach to decision making that handles radical uncertainty—information gaps—more adequately. The arguments below will be normative in intent. They will suggest that "robust satisficing," not utility maximizing, is often the best decision strategy, not because of the psychological, information processing limitations of human beings (see Simon, 1955, 1956, 1957), but because of the epistemic, information limitations offered by the world in which decisions must be made.

We begin by discussing an example that illustrates severe uncertainty. The decision maker faces substantial gaps between what is known and what needs to be known in order to evaluate the quality of each option. This information gap precludes the evaluation of the options in terms of both value and probability. Expected utility theory and its extensions, such as rank-dependent expected utility (Quiggin, 1993), cannot be implemented by the decision maker given the information gap that we consider. An alternative normative approach (Ben-Haim, 2006) that enables decision makers to calculate robustness to uncertainty of satisfactory outcomes—what we call "robust satisficing"—is suggested.

We then discuss two issues regarding the domain over which our normative concerns extend. First, we try to specify what counts as "radical uncertainty," by discussing various approaches to the meaning of statements of probability. Second, we argue that robust satisficing really is a different normative standard for making decisions and not just a prescriptive alternative to utility maximizing that acknowledges human information-processing limitations.

CHOOSING A COLLEGE

Suppose you've been fortunate enough to be admitted to a half-dozen colleges. Now, you sit down to decide which one to attend. How should you go about this process? It is generally agreed that the best approach is to do a multi-attribute utility analysis (Keeney & Raiffa, 1993) First, put together a big spreadsheet.

Then, list all the things that matter to you about college (e.g., size, location, reputation, quality of its program in field biology, social life, music department, housing, etc.) Then, attach a weight to each attribute, to reflect its importance to you. If you are devoted to field biology, it may get a weight of 1.0, while other dimensions get fractions of that weight. Next, evaluate each school on each dimension; give it a score, say from 1–10. Finally, multiply scores by weights, and do some addition. Choose the school with the highest score.

This process can obviously be taxing and time consuming, but the situation is even more complex. When you assign scores for each school on each dimension, you're making guesses or predictions. Your assessment of the music department, the field biology program, and the social life may be wrong. So to acknowledge uncertainty, you will need to assign probabilities to the values in each cell of the spreadsheet. Since this process is not like flipping a coin, it is also hard to judge the accuracy of your probability estimates, which themselves may be wrong. And the situation is more complex still. You may be wrong about how important field biology, social life, and location are to you. You're only seventeen, after all, and people change. So the weights you attach to dimensions also need probabilities, and these probability estimates are also subject to error. There is an additional complexity. Even if your estimates of importance and quality are correct, you don't know how it will actually feel to experience being a student at a school that has the qualities of the one you choose. You are making a prediction about a future subjective state, and as Daniel Gilbert, Timothy Wilson, and their various collaborators have amply documented, (e.g., Gilbert, 2006; Wilson & Gilbert, 2005), such predictions are notoriously inaccurate. And there is one final matter. There are some influences on your satisfaction with college that just can't be predicted. Will you get along with your roommate? Will the best professor in the biology department leave? Will you form a romantic attachment? These kinds of factors can play a major role in determining your college experience, and they are inherently uncertain. You can't even pretend to attach probabilities to them, or even to identify all of them. Making this decision is tough. You could easily be wrong. Nonetheless, you do the best you can, and that seems to be multi-attribute utility calculation. It's your best strategy.

Or is it? Suppose you know that all that really matters to you is field biology; everything else is window dressing. In that case, your decision-making process is easier. You can rate the schools strictly in terms of their offerings in field biology, and choose the school that finishes first. You use other features only to break ties. This process, sometimes called "lexicographic preference," essentially gives infinite weight in your consideration to one dimension. Gigerenzer (e.g., 2007) refers to strategies like this as "one-reason decision making." Of course, you can still be wrong, both in your assessment of the various schools or in your assessment of your commitment to field biology. But this process makes decision making considerably simpler. Though multi-attribute utility analysis and lexicographic preference are different (and see Baron, 2008, for a discussion of these and several other decision-making strategies), they have one important feature in common—the goal of maximizing utility. The idea is to use the best information you have in order to choose the best school for you, and the question is, what is the best way to do it.

But now, imagine a different goal. Given the multiple sources of uncertainty that are a part of the process, suppose your goal is to choose the school that is likely to be satisfactory, even if your estimates of its quality on various dimensions are wrong. Instead of maximizing utility if everything goes well, you are trying to maximize confidence in an acceptable outcome, even if you suffer the slings and arrows of outrageous fortune. We call such a goal "robust satisficing." You are still trying to maximize something, but what you're trying to maximize is your confidence of a good enough outcome even if things go poorly. There is no particular reason to assume that the school that is best in your utility calculation is also the school that is most robust to error in the data underlying that calculation.

RADICAL UNCERTAINTY

What this scenario, and countless others (e.g., buying a car, choosing a place to go on vacation; choosing a job; choosing a treatment plan for a serious medical condition; choosing investments for your retirement), have in common is that you are faced with a decision that has multiple dimensions, with outcomes that are uncertain and influenced by factors that are difficult to evaluate or even identify. And they are not merely uncertain in a probabilistic sense. In many cases, you cannot even attach probabilities in a meaningful way. Your uncertainty is more radical than the uncertainty you face when rolling dice. Knight (1921) distinguished between probabilistic risk, which can be insured against, and non-probabilistic "true uncertainty," as he called it, which is the source of entrepreneurial profit (and loss) in a competitive market. Ellsberg (1961) famously pointed out this distinction when he contrasted an urn with 50 red and 50 black balls with an urn that has 100 balls, some of which are red and some black. If their task is to pick a red ball, people typically prefer the first urn to the second, preferring (probabilistic) uncertainty to what Ellsberg termed "ambiguity." The thrust of our advocacy of robust satisficing as a decision criterion is this:

1. Most of the decisions people face in life involve Knightian uncertainty or ambiguity at least as much as they involve probabilistic uncertainty. This is especially true when a key feature of a decision is the person's estimation of how it will feel to have one outcome rather than another. For example, having a side effect (e.g., impotence) of prostate cancer surgery is one thing; estimating the subjective consequence of this side effect, before the fact, is quite another.

2. In conditions of radical uncertainty, utility maximization as a strategy is unreliable. Indeed, it may even be self-deceptive, in that it involves assigning probabilities to outcomes in a context in which probabilities can not be specified.
3. There is a quite reasonable alternative to utility maximization. It is maximizing the robustness to uncertainty of a satisfactory outcome, or robust satisficing. Robust satisficing is particularly apt when probabilities are not known, or are known imprecisely. The maximizer of utility seeks the answer to a single question: which option provides the highest subjective expected utility. The robust satisficer answers *two* questions: first, what will be a "good enough" or satisfactory outcome; and second, of the options that will produce a good enough outcome, which one will do so under the widest range of possible future states of the world.
4. This alternative has been formalized as "info-gap decision theory" (Ben-Haim, 2006). Though we will not discuss it here, it has been used effectively as a decision-making framework in an extremely wide variety of domains, though none of them, to date, are psychological.

Info-gap decision theory is designed to handle situations of profound uncertainty. Since we do not know how wrong our data and models are, we evaluate a proposed decision by asking: what is the greatest horizon of uncertainty at which the decision will still yield acceptable results? How wrong can we be, in our understanding of the relevant processes and requirements, and the outcome of the decision still be acceptable? For instance, in selecting a college, you might ask: how wrong can my estimates be—estimates of the importance to me of field biology, estimates of the probability of different future emotional states, etc.—and any given school selection still be satisfactory? The answer to this question is the *robustness function*. The robustness function generates a preference ordering on the available decisions: a more robust decision is preferred over a less robust decision. Satisficing means doing well enough, or obtaining an adequate outcome. A *satisficing decision strategy* seeks a decision whose outcome is good enough, though perhaps sub-optimal. A *robust-satisficing decision strategy* maximizes the robustness to uncertainty and satisfices the outcome.

Info-gap decision theory has been applied to a wide variety of different domains. Burgman (2005) devotes a chapter to info-gap theory as a tool for biological conservation and environmental management. Regan et al. (2005) use info-gap theory to devise a preservation program for an endangered rare species. McCarthy and Lindenmayer (2007) use info-gap theory to manage commercial timber harvesting that competes with urban water requirements. Knoke (2008) uses info-gap theory in a financial model for forest management. Carmel and Ben-Haim (2005) use info-gap theory in a theoretical study of foraging behavior of animals. Ben-Haim and Jeske (2003) use info-gap theory to explain the home-bias paradox, which is the anomalously large preference for assets in investors' home countries, over more favorable foreign assets. Ben-Haim (2006) uses info-gap theory to study the equity premium puzzle (Mehra & Prescott, 1985), which is the anomalously large disparity in returns between stock and bonds, and the paradoxes of Ellsberg (1961) and Allais (see Ma-Colell, Whinston & Green, 1995). Akram et al. (2006) use info-gap theory in formulating monetary policy. Fox et al. (2007) study the choice of the size of a statistical sample when the sampling distribution is uncertain. Klir (2006) discusses the relation between info-gap models of uncertainty and a broad taxonomy of measure-theoretic models of probability, likelihood, plausibility and so on. Moffitt et al. (2005) employ info-gap theory in designing container-inspection strategies for homeland security of shipping ports. Pierce et al. (2006) use info-gap theory to design artificial neural networks for technological fault diagnosis. Kanno and Takewaki (2006a, b) use info-gap theory in the analysis and design of civil engineering structures. Pantelides and Ganzerli (1998) study the design of trusses, and Ganzerli and Pantelides (2000) study the optimization of civil engineering structures. Lindberg (1991) studies the dynamic pulse bucking of cylindrical structures with uncertain geometrical imperfections. Ben-Haim and Laufer (1998) and Regev et al. (2006) apply info-gap theory for managing uncertain task-times in projects. Ben-Haim and Hipel (2002) use info-gap theory in a game-theoretic study of conflict resolution. Thus, info-gap decision theory has been used productively to model circumstances of extreme uncertainty in a wide variety of different contexts and disciplines. But it has not been used, until now, to model the psychology of decision making.

WHAT DOES "RADICAL UNCERTAINTY" MEAN? WHEN DOES ROBUST SATISFICING APPLY?

In this section, we try to explicate the conditions under which robust satisficing applies, by explaining what we mean by "radical uncertainty." This requires a brief excursion into the foundations of probability theory. What does it mean to say that the probability of throwing a "7" with two dice is 0.17, or that the probability of developing prostate cancer is 0.03, or that the probability that the New York Yankees will win the next World Series is 0.25? Baron (2008, and see Brown, 1993) nicely summarizes three different approaches to understanding what probability statements mean. The first, we might call "logical." When the events that comprise a sample space are fully known, and their distributions can be specified, a probability statement is simply a matter of logic: in the sample space of outcomes of rolls of two dice, there are 36 equiprobable outcomes, of which six sum to "7." Thus one-sixth of possible rolls (0.17) will yield the outcome of interest. This is not an empirical matter. It is part of what it means to be throwing "fair" dice.

The second, we might call "empirical." If you follow a sample of 10,000 men between the ages of, say 40 and 75, and 300 of them develop prostate cancer, you might infer that the chances of any particular man developing prostate cancer are 300/10,000, or 0.03. You use the frequency of the event of interest in the past to infer the probability of the event with respect to any particular case in the future.

The final approach to probability we might call "personal" (see Savage, 1954). You are asked, in April, "will the Yankees win the World Series this year?" "I think they will," you say. "How sure are you?" "I give them a 25% chance," you say. Because each baseball season is a unique event in ways that matter to prediction, you can't really rely on frequencies in the past to infer probabilities in the future. The number you supply is merely an expression of your confidence. As Baron (2008) points out, some have argued that it makes no sense to attach probabilities to unique events. But, of course, each throw of the dice is a "unique event," and each middle-aged man is a "unique event," so distinctions among these three approaches to understanding probability statements are not so easy to make sharply. This is especially true when it comes to distinguishing frequency and personal approaches to probability. What does it mean when the weather forecaster says there is a 50% chance of rain today? Does it mean that it has rained in Philadelphia on half of the August 1sts in the history of weather records? Or does it mean that in the past, when the various atmospheric conditions thought to affect the weather that are present today have been present, it has rained half the time? Or does it mean that past weather, together with our current understanding of meteorology, makes the forecaster 50% certain there will be showers?

One could argue that on closer analysis, frequency and personal approaches to probability run together. If one uses frequency as a guide to probability, one must determine what counts as a relevant past event. This raises two questions: can relevant past events be specified objectively, and if they are, do they give us the most perspicuous purchase on what is likely to happen today? The date, April 1, is not completely irrelevant to a weather forecast (if snow rather than rain were the issue, in Philadelphia, knowing the date would tell you a lot). But we have reason to believe there are better ways to count past events as relevant than by date. On the other hand, since forecasters don't always agree on the forecast, there remains room for doubt about what is the most perspicuous set of past events. With respect to prostate cancer, gender and age can be unambiguously specified, so that a frequency approach to probability is meaningful. But as our understanding of the disease progresses, we will expect the counting of relevant past events to change. This progress may lead simultaneously to more accurate probability estimates and to more disagreements among the estimators, because not all doctors will agree on the way to construct the relevant class of past events in the way they could agree on gender and age assignment.

It is also true that even spaces that seem unambiguously characterized by the "logical" approach to probability can be characterized as "radically uncertain" (eg., Baron, 2008; Baron & Frisch, 1994; Camerer & Weber, 1992). When you throw the dice, are they "true"? Are there little irregularities on the landing surface that might affect their path? What if someone standing around the table sneezes? How is predicting the outcome of the dice throw different from predicting the outcome of the college choice? If you get molecular enough, everything is radically uncertain.

So what, then, does it mean to call an event "radically uncertain" in a way that distinguishes throwing dice from choosing a college? What makes attaching probabilities to varying degrees of satisfaction with a college's biology program different from predicting the weather? It might be that if you pushed a high school senior, she would attach a number to how likely she was to love biology at Swarthmore. But would the number mean anything? And if not, is there information available so that if she collected it assiduously, the number she attached *would* mean something? Even if the answer to this latter question is "yes," if the meaning of the number is not entirely resolved by the added information, then there is radical uncertainty.

We don't think these are easy questions to answer. It seems to us unlikely that there will ever be models of satisfaction with college that approximate the predictive power of meteorology, but that is an empirical question. There is no doubt that people can know more or less about a domain in question, so that estimates of probability from frequency can be more or less well justified. It may not mean much when a 10-year-old New Yorker tells you at the start of the baseball season that the Yankees have a 25% chance to win the World Series. It will mean more when a fanatic enthusiast of the statistical study of baseball that has come to be known as "sabrmetrics" tells you the same thing. But even the most sophisticated sabrmetrician is at the mercy of injuries or other personnel changes. The sabrmetrician can use the past to assess confidence in the future given the team, *as constituted*. But if the team changes, these estimates will change as well. The sabrmetrician could even try to estimate the likelihood of injury, which would increase his, and our, confidence in his estimates. Or he could do what we are advocating, and ask which team is likely to be the most robust to the uncertainties that each baseball season contains. In other words, in real-life decisions, we may never be confronted with the kind of uncertainty we face with Ellsberg's urn, where any number of red balls, from 0 to 100, is possible. But before we attach probabilities to outcomes, we need to assess which of Ellsberg's two urns the decision we face more closely resembles.

And one can't do a conventional utility analysis without attaching probabilities to various outcomes. Inventing probabilities in the face of serious information gaps, because you have learned that that is the normatively correct way to make decisions, can lead you astray. Info-gap robust satisficing actually provides a rational alternative to "the world is an uncertain place. Just close your eyes and pick."

Bayesian decision theory attempts to deal with a decision maker's objective and subjective (personal) uncertainty about contingencies and outcomes. Bayesian tools are suitable when the decision maker feels confident that a probability distribution reliably or realistically represents likelihoods or degrees of belief. We are concerned, however, with situations in which uncertainties are not confidently represented by probabilities. For instance, an individual may have no personal experience with the outcomes of prostate therapy, and yet still have to choose a therapy. In such a situation the individual may reasonably be unable to make probability statements about utilities or disutilities resulting from the outcomes of therapy. The individual may have some anticipations about utilities, but have no idea how wrong those anticipations are, and even less understanding about how likely different subjective feelings will be. A Bayesian analysis is difficult to operationalize in such a situation.

DOES ROBUST SATISFICING AVOID PROBABILITY ESTIMATES?

It might be argued that robust satisficing does not really offer an alternative to utility maximizing that avoids estimating probabilities in a radically uncertain decision space. After all, if we want the alternative that is the *most* robust to uncertainty, doesn't that require attaching probabilities to various future states of the world? To say that, for example, Brown is more robust to uncertainty than Swarthmore, both when it comes to field biology and when it comes to estimating the prospective student's future interest in field biology, don't we need to estimate how likely it is that current assessments of both program quality and student interest will be wrong? Or is it enough to say that Brown has three relevant biologists and Swarthmore only has one, so that if one of Brown's biologists leaves, the student will have recourse? Is it enough to say that Brown also has wonderful programs in music and molecular biology, so that if the student's interests change, there will be recourse? The short answer is Yes, as we can understand from the meaning of robustness. The robustness of a decision (e.g. choose Brown) is the greatest amount by which Brown and the student can change, and the choice is still acceptable. Choosing Brown is more robust than choosing Swarthmore if more profs can leave Brown than Swarthmore, and if the student's interests can change more widely and still be satisfied within Brown's biology dept but not Swarthmore's. No probability judgments are involved in these assessments, but uncertainty is handled in both the student's interests and the schools' characteristics.

But there is more to be said about the relation between utility maximizing and robust satisficing. Utility assessment entails the judgment of value: what is useful or valuable to the decision maker as an outcome of the decision. These values are personal or organizational or social values of the "goods" and "bads" that may result from a decision. The confidence (e.g. robustness) with which we anticipate the value of the outcome of our decision is not itself an outcome; it is an assessment made before the outcome. For instance, the financial return that we need from an investment is different from the confidence with which we make the investment; you can deposit cash in the bank, but not confidence.

Of course, sometimes we do include measures of risk (or confidence) in our utility functions. So, a critic might claim that by incorporating robustness in the utility function, and then optimizing this extended utility function, we have reformulated the robust satisficing procedure as a utility maximization procedure, in effect attaching probabilities to the various possible outcomes. Such incorporation of robustness or related quantities (such as variance) into a utility function is common. But in any such case, one could (and should) still apply the info-gap critique and propose a robust satisficing response. The critique is that the augmented utility function is based on best-model estimates (e.g. of the variance), and these best models are probably wrong in ways that we do not know. The response is to satisfice the augmented utility and maximize the robustness against error in the best models.

Does this cause an infinite regress? No, with one caveat. One has "best models," whatever they might be (e.g., models of statistical variance), and one has unknown info-gaps on those best models. One builds the best utility function available, assessing variance or other risks if desired. One then evaluates the robustness to info-gaps. End of process; no regress. The caveat is this: we must be willing to make judgments about what we know and what we don't know. Philosopher John Locke (1706/1997, I.i.5, p. 57) says it nicely: "If we will disbelieve everything, because we cannot certainly know all things; we shall do muchwhat as wisely as he, who would not use his legs, but sit still and perish, because he had no wings to fly."

What is challenging about the above account is that for many, there is no way to think about uncertainty aside from using probability. So to say that the field biology teacher *might* leave Swarthmore is just to say that there is some probability of departure, even if we don't, and can't, know what that probability is. But in fact, info-gap models are non-probabilistic (for technical details see Ben-Haim, 2006). They entail no assumptions about or choice of a probability distribution. They do not even entail the presumption that a probability distribution exists. For instance, one might say that the best information indicates a future sea-level rise of 1 cm per decade, and that we don't know how wrong this estimate is. The sea level might rise more, or it might fall. We just don't know how to evaluate errors in the underlying data and models. We are not asserting anything about probabilities (maybe we could, but we aren't). A robust satisficing decision (perhaps about pollution abatement) is one whose outcome is acceptable for the widest range of possible errors in the best estimate. No probability is presumed or employed.

ROBUST SATISFICING: NORMATIVE OR PRESCRIPTIVE?

The fact that frequentist approaches to probability bleed into personal approaches, and that well-justified personal approaches bleed into what we are calling radical uncertainty, raises another issue for discussion—one that has been central to the field of judgment and decision making. There are three kinds of accounts one can offer of decision making: descriptive, normative, and prescriptive. Descriptive accounts are strictly empirical: they answer the question "how *do* people decide?" Normative accounts, in contrast, provide standards. They answer the question "how *should* people decide?" In between are prescriptive accounts. They compare the processes by which people *do* decide to the normative standards, and ask whether, given human limitations of time, information, and information processing capacity, there are procedures people can follow that, while not up to the normative standard, do a better job than what people currently do. Are there things people can do, in other words, to diminish some of the unfortunate consequences of the heuristics and biases that decision-making researchers have been documenting for years (see Baron, 2004; 2008; Over, 2004 for discussions of the distinctions between normative and prescriptive theories). Much of Gigerenzer's work on "fast and frugal heuristics" (eg., 2004, 2007) is intended to spell out what some prescriptive decision making procedures might be.

Robust satisficing is certainly not a description of what decision makers typically do—at least not yet. But is it normative or prescriptive? We believe it is normative. When Simon (1955, 1956, 1957) first introduced the term "satisficing," he was making a prescriptive argument. The alternative to satisficing—utility maximizing—was not feasible, given the limits of human cognition and the complexity of the environment. An "ideal" human, with unlimited capacity, should maximize, but for an actual human, it would usually be a foolhardy undertaking. It is important to emphasize here that whereas Simon's formulations were focused on the processing limitations of organisms, our discussion is focused on epistemic uncertainties inherent in the environment in which decisions get made. No amount of information-processing capacity will overcome a decision space in which probabilities—whether of outcomes, or of people's subjective responses to outcomes—cannot be specified.

If what we are calling radical uncertainty is not an epistemic problem but a psychological one, then robust satisficing becomes a prescriptive alternative to utility maximizing. Satisficing is the thing to do if collecting and analyzing all the data isn't worth the time and trouble, especially if getting a "good-enough" outcome is critical. But what if the problem is epistemic? What if no amount of time and trouble can enable a high school senior to pick the best college? Under these conditions, it is our view that maximizing robustness to uncertainty of a good enough outcome is the appropriate norm. Maximizing expected utility is not, not least because one can't really compute expected utilities.

Suppose you face a decision about how to invest your retirement contributions. You can try to answer one of these questions:

1. Which investment strategy maximizes expected value?
2. What are the risk/reward ratios of different strategies?

3. What is the trade-off between risk and value?
4. I want $1 million when I retire. What investment strategy will get me that million under the widest range of conditions?

Robust satisficing is what provides the answer to Question 4. And that might be the right question to be answering, even when you know more about the "urn" than that it has 100 balls. This is not to suggest that robust satisficing makes the investment decision simple. By no means. Nor is it to suggest that it guarantees success. But an investment strategy that aims to get you a million dollars under the widest set of circumstances is likely to be very different from one that aims to maximize the current estimate of future return on investment. Managers of major financial institutions were often accused of bad risk management in the events leading to the financial collapse of the last few years. No doubt, their risk management was bad. But this may have been less the result of underestimating the likelihood of very low probability events, as Taleb (2007) has argued, and more the result of pretending that certain consequential events could even have probabilities meaningfully attached to them. Furthermore, many sub-prime collateralized debt obligations were sold as high quality assets by assuming that defaults were uncorrelated, when in fact the correlations were simply unknown (Ben-Haim, 2011). A business operating with an eye toward robust satisficing asks not, "How can we maximize return on investment in the coming year?" It asks, instead, "What kind of return do we want in the coming year, say, in order to compare favorably with the competition? And what strategy will get us that return under the widest array of circumstances?"

The same obviously applies to choosing a college. If you want an acceptably good college experience, you are asking Question 4. And if the uncertainties you face are not meaningfully quantifiable, Question 4 is the question you should be asking, as a *normative* matter.

Robust satisficing may even be the right normative strategy in at least some situations in which probabilities *can* be specified. Consider what von Winterfeldt and Edwards (1986) called the "principle of the flat maximum." The principle asserts that in many situations involving uncertainty (and college choice is certainly such a situation), the likely outcomes of many choices are effectively equivalent, or perhaps more accurately, the degree of uncertainty surrounding the decision makes it impossible to know which excellent school will be better than which other excellent school. Said another way, there are many "right" choices. Uncertainty of outcomes makes the hair-splitting to distinguish among excellent schools a waste of time and effort. There is more uncertainty about the quality of the student/school match than there is variation among schools—at least within the set of excellent, selective schools (this qualification is important; it is the principle of the flat *maximum*, after all). So once a set of "good enough schools" has been identified, it probably doesn't matter very much which one is chosen; or if it does matter, there is no way to know in advance (because of the inherent uncertainty) what the right choice is. On the other hand, schools that are all at the "flat maximum," and thus essentially indistinguishable, may be substantially different in their robustness to uncertainty—in how good they will be if things go wrong. Schwartz (2005) has made this argument, and suggested that it applies as well to schools deciding which excellent students to admit as it does to students deciding which excellent school to attend.

Because there is room for disagreement about whether a given domain is properly characterized as radically uncertain or not, there will also be disagreement about whether robust satisficing is a normative or a prescriptive alternative to utility maximization (too much time and trouble to find out makes it prescriptive; not possible to find out makes it normative). The norm of expected utility maximization is so entrenched that it might seem to behoove us to collect more and more information in an effort to eliminate radical uncertainty. But we should be wary. As Gigerenzer (2004; 2007; Todd & Gigerenzer, 2003) points out, one can account for increasing amounts of the variance in a data set by adding variables to a regression model. A point may be reached at which, with many variables in the model, one captures almost all the variance. The regression model now provides an excellent description of what came before. However, it is quite possible that this model will be less good as a predictor of future events than a model with fewer variables, because at least some of the variables that have been added to the model are essentially capturing randomness. As a general matter, Gigerenzer's argument is that the best *descriptive* model will often not be the best *predictive* model. Not all efforts to reduce uncertainty will make for better predictions.

ROBUST SATISFICING AND STRATEGIC DECISIONS

There is a common class of decisions people face in life to which utility maximizing as a norm arguably does not apply. There are decisions that involve the simultaneous decisions of others—what might be called "strategic" decisions. Strategic decisions, often modeled by formalisms from game theory, involve two or more participants, with differing, often competing objectives. There is radical uncertainty in that the right thing for Player 1 to do will depend on what the other players decide to do, and attaching probabilities to the moves of other players is often difficult, and sometimes impossible. Will the manager of the other team change pitchers if I put in a pinch hitter? Will Walmart come to the community if I build a big-box store on the outskirts of town? Will Amazon start a price war if I lower what I charge for best sellers? Will China or Russia become more aggressive internationally if I reduce the U.S.'s nuclear arsenal? Sometimes it is possible to assign educated guesses about probabilities to the various moves open to the other players, especially in situations that have had similar occurrences in the past (eg., "Walmart almost always comes to town when competition appears";

"the manager almost never lets the upcoming left-handed batter bat against a left-handed pitcher." In cases like these, probability estimates (based on past frequencies) may be helpful. But in many such strategic interactions, there is no past history that is obviously relevant, so that probability estimates are as likely to be inventions as they are to be informed assessments. What, then, is one to do in such situations? And does robust satisficing apply?

Various suggestions have been proposed for making decisions in competitive strategic games. A common one is what is called the "minimax" strategy: choose the option with which you do as well as you can if the worst happens. Though you can't specify how likely it is that the worst will happen, adopting this strategy is a kind of insurance policy against total disaster. Minimax is a kind of cousin to robust satisficing, but it is not the same. First, at least sometimes, you can't even specify what the worst possible outcome can bring. In such situations, a minimax strategy is unhelpful. Second, and more important, robust satisficing is a way to manage uncertainty, not a way to manage bad outcomes. In choosing Brown over Swarthmore, you are not insuring a tolerable outcome if the worst happens. You are acting to produce a good-enough outcome if any of a large number of things happen. There are certainly situations in which minimax strategies make sense. But there are also strategic situations in which robust satisficing makes sense (see Ben-Haim & Hipel, 2002 for a discussion of the Cuban missile crisis; and Davidovitch & Ben-Haim, in press, for a discussion of the strategic decisions of voters).

EPISTEMIC SATISFICING AND PSYCHOLOGICAL SATISFICING

The foregoing has been an argument that robust satisficing is the normatively appropriate goal when people are operating within the epistemic limits of a radically uncertain world. Schwartz (2004; Schwartz et al., 2002; Iyengar, Wells & Schwartz, 2006) has argued that satisficing also has psychological benefits, even in decision spaces that might permit maximizing. Satisficers may obtain less good outcomes than maximizers, but satisficers tend to be more satisfied with their decisions, and happier in general. Psychological satisficing is encouraged by mechanisms such as regret, disappointment, missed opportunities, social comparison, and raised expectations, all of which are more pronounced in maximizers than in satisficers, and all of which contribute to reduced satisfaction with decisions (Iyengar, Wells, & Schwartz, 2006; Schwartz, 2004).

Psychological and epistemic satisficing are different concepts, the latter applying to humans as well as to organisms very different from us (e.g. armadillos, sunfish, and fruit flies; Carmel and Ben-Haim, 2005) for whom no "psychology" in the human sense applies. One might speculate that the propensity for homo sapiens to psychologically satisfice is a behavioral trait with evolutionary selective advantage. Psychological satisficing might be a mechanism by which the individual protects against failure, analogous to the epistemic satisficing that animals seem to display in seeking essential sustenance. One might view the psychological "well-being" function in the same way as myriad other "objective functions" that are robust-satisficed in epistemic satisficing. Indeed, the very well documented phenomenon of loss aversion in human decision making (e.g., Kahneman & Tversky, 1984) has never really had a compelling functional explanation. What makes loss aversion better than symmetric assessments of gains and losses? Here is a possible answer: loss aversion pushes people in the direction of robust satisficing, which is their best chance to end up with a satisfactory outcome in a very uncertain world. It is also worth pointing out that though there are many alternatives to multi-attribute utility as decision making strategies (see Baron, 2008), what distinguishes them from one another is the amount of information processing and other cognitive work the decision maker has to do. The implicit aim in virtually all cases is utility maximization, and the various simplified strategies are all compromises of that implicit aim so that people can make some decision and also continue to live their lives. Even satisficing, as initially formulated by Simon (1955, 1956, 1957) and as discussed subsequently, is viewed as a compromise with utility maximization: give up the best, and settle for less, because it's the best you can do. In contrast, there is growing recognition that satisficing can itself be beneficial. Info-gap theory provides a quantitative framework for understanding why and when satisficing is advantageous over maximizing, and when it is not. The central concept is that there can be a trade-off between robustness and quality. We appreciate the difference between these two attributes of a decision: the estimated quality of outcome of the decision, and the sensitivity of that decision to uncertainty. Under specifiable conditions, enhancing robustness is equivalent to enhancing the probability of satisfaction, which suggests the evolutionary advantage of satisficing, as hypothesized by Todd & Gigerenzer (2003, p.161). Whatever the merit of an evolutionary argument, the fact remains that epistemic satisficing explains the usefulness of psychological satisficing. For an individual who recognizes the costliness of decision making, and who identifies adequate (as opposed to extreme) gains that must be attained, a satisficing approach will achieve those gains for the widest range of contingencies. In addition, there is some empirical evidence that satisficers may frequently make objectively better decisions than maximizers (see Bruine de Bruine, Parker, & Fischoff, 2007).

FUTURE RESEARCH

The foregoing has attempted to make the argument that as a normative matter, robust satisficing is a better strategy for decision making than utility maximizing under conditions of radical uncertainty, and that this is true whether or not the decision space overwhelms the information-processing capacities of the decision maker. Though we doubt that very many decision makers deliberately and consciously switch from maximizing to robust satisficing when they face conditions of extreme uncertainty, it would be quite interesting to know whether changes in decision strategy in fact occur when, for example, the degree of uncertainty is made salient. If so, it would be interesting to know what cues to uncertainty decision makers are responding to, and what their own understanding of their strategy shift is. It would also be of interest to know whether decision makers who seem to be pursuing a satisficing strategy interpret decision spaces as radically uncertain even when they are not. Finally, it would be of interest to know whether people we have identified as "psychological satisficers" (e.g., Schwartz, et al., 2002) are more sensitive to radical uncertainty than maximizers are.

It would also be worthwhile to explore the psychological consequences of a normative argument like the one offered here. It is possible that with utility maximizing as the norm, decision makers are reluctant to satisfice. Satisficing is just "settling" for good enough, and the decision maker can easily imagine that others are smarter, or harder working, and thus able to maximize. In other words, satisficing reflects a defect in the decision maker, compared to imagined others and accepted norms. In contrast, if the arguments in this paper came to be commonly articulated and accepted, then satisficing would become the "smart thing" to do. It would reflect thoughtfulness and analytical subtlety. People might be much more inclined to adopt a strategy that is normatively correct than one that is *merely* psychologically beneficial.

Finally, it would be of interest to know whether there are cultural differences in people's receptiveness to robust satisficing as a normative strategy. Radical uncertainty may be much more salient and tolerable in some cultures than in others. In such cultures, utility maximizing may not be entrenched as a norm, and people may engage in robust satisficing whether or not they know it and can articulate it (see Markus & Schwartz, 2010, for a discussion of profound cultural differences in decision making).

To the best of our knowledge, there are at present no data that speak to any of these issues. To some degree, this lack of research may be the result of the hegemony that utility maximizing has had as the norm for rational decision making in our culture. Despite the numerous and varied applications of info-gap robust satisficing that we referred to earlier, one rarely, if ever, sees this discussed in the popular literature. Even when risk management and its failures got enormous attention in the aftermath of the financial crisis, all the criticism was of faulty utility maximizing calculation. The possibility that utility maximization was the wrong thing to be calculating was unexplored. It is our hope that in making the normative argument we have here, we will encourage more people to think about robust satisficing as the rational strategy to be following in their own lives, and in the lives of the institutions of which they are a part.

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