Center for Adaptive Behavior and Cognition

Contents

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Introductory Overview

The Center for Adaptive Behavior and Cognition (ABC) investigates reasoning and decision making under uncertainty at the levels of both individuals and social groups. The research group consists of psychologists, mathematicians, computer scientists, evolutionary biologists, economists, and researchers from other fields. Using a range of methodologies, such as experimental methods, computer simulation, and mathematical analysis, we cooperate in solving the same problems. The ABC program combines a strong theoretical focus with practical applications, that is, the research group both develops specific models and explores their applications. Applications range from helping physicians and patients understand the statistical evidence arising from medical research; helping courts, administrators, and legislators understand the importance of heuristic thinking in the law; and improving teaching practices in statistical education by introducing transparent representation formats. The theoretical focus is on rationality and can be, albeit artificially, divided into three aspects: bounded, ecological, and social rationality.

Bounded Rationality

Models of bounded rationality attempt to answer the question of how people with limited time, knowledge, money, and other scarce resources make decisions. This program is an alternative to the dominant optimization paradigm in cognitive science, economics, and behavioral biology that poses the question of how Laplacean superintelligences or near omniscient beings would behave. We study the proximal mechanisms of bounded rationality, that is, the adaptive heuristics that enable quick and frugal decisions under uncertainty. This collection of heuristics and their building blocks is what we call the adaptive toolbox.

Ecological Rationality

Models of ecological rationality describe the structure and representation of information in actual environments and their match with mental strategies, such as boundedly rational heuristics. To the degree that such a match exists, heuristics need not trade accuracy for speed and frugality: Investing less effort can also improve accuracy. The simultaneous focus on the mind and its environment, past and present, puts research on decision making under uncertainty into an evolutionary and ecological framework, a framework that is missing in most theories of reasoning, both descriptive and normative. In short, we study the adaptation of mental and social strategies to real-world environments rather than compare human judgments to the laws of logic and probability theory.

Social Rationality

Social rationality is a variant of ecological rationality, one for which the environment is social rather than physical or technical. Models of social rationality describe the structure of social environments and their match with boundedly rational strategies that people might use. There is a variety of goals and heuristics unique to social environments. That is, in addition to the goals that define ecological rationality—to make fast, frugal, and fairly accurate decisions—social rationality is concerned with goals, such as choosing an option that one can defend with argument or moral justification, or that can create a consensus. To a much greater extent than the cognitive focus of most research on bounded rationality, socially adaptive heuristics include emotions and social norms that can act as heuristic principles for decision making.

Bounded Rationality

Humans and animals must make inferences about unknown features of their world under constraints of limited time, knowledge, and computational capacities. We do not conceive bounded rationality as optimization under constraints nor do we think of bounded rationality as the study of how people fail to meet normative ideals. Rather, bounded rationality is the key to understanding how people make decisions without utilities and probabilities. Bounded rationality consists of simple step-by-step rules that function well under the constraints of limited search, knowledge, and time—whether an optimal procedure is available or not. Just as a mechanic will pull out specific wrenches, pliers, and gap gauges to maintain an engine rather than just hit everything with a hammer, different domains of thought require different specialized tools. The notion of a toolbox full of unique single-function devices lacks the beauty of Leibniz's dream of a single all-purpose inferential power tool. Instead, it evokes the abilities of a craftsman, who can provide serviceable solutions to almost any problem with just what is at hand.

The Adaptive Toolbox

This repertoire of specialized cognitive mechanisms, which include fast and frugal heuristics, are shaped by evolution, learning, and culture for specific domains of inference and reasoning. We call this collection of mechanisms the "adaptive toolbox." We clarify the concept of an adaptive toolbox as follows:

– It refers to a specific group of rules or heuristics rather than to a general-purpose decision-making algorithm.
– These heuristics are fast, frugal, and computationally cheap rather than consistent, coherent, and general.
– These heuristics are adapted to particular environments, past or present, physical or social.
– The heuristics in the adaptive toolbox are orchestrated by some mechanism reflecting the importance of conflicting motivations and goals.

Fast and Frugal Heuristics

Fast and frugal heuristics generally consist of three building blocks: simple rules for guiding search for information (in memory or in the environment), for stopping search, and for decision making. They are effective when they exploit the structure of the information in the environment. That is, their rationality is a form of "ecological rationality" rather than one of consistency and coherence. We continue to explore fast and frugal heuristics and their importance in diverse disciplines, such as biology, economics, and cognitive psychology. In addition, we have applied our basic research in the areas of consumer behavior, medicine, and the law. In what follows, we describe some major developments in the understanding of the adaptive toolbox in the past two years.

The Mapping Heuristic: Quantitative Estimation the Fast and Frugal Way

How do people make quantitative estimations, such as estimating the selling price of a car? People typically rely on cues, information that is probabilistically related to the quantity being estimated. For instance, to estimate the selling price of a car, they could use information, such as the car's manufacturer, age, mileage, or general condition. Traditionally, linear regression models have been employed to capture the estimation process. These models assume that people weigh and integrate all available cues (attributes) to estimate a quantity. However, these models have been criticized as psychologically unrealistic. Adopting the approach of simple heuristics, von Helversen and Rieskamp (2008) developed a new cognitive theory—the mapping heuristic—for quantitative estimation. Assuming the availability of multiple binary cues, the estimation process is decomposed into a categorization phase and an estimation phase. First, objects are categorized by counting all the positive cue values the object has. Then, the heuristic estimates the object's size by using the typical (median) size within the category of objects with the same number of positive cues. This estimation strategy implies that all cues are weighted equally, avoiding the need to weight cues by their importance. Von Helversen and Rieskamp (2008) compared the mapping heuristic with a regression model in various experimental studies. Their findings showed that the mapping heuristic predicted participants' estimations well. For example, if the criterion quantity is a multiplicative function of the cues, the mapping heuristic predicted participant's behavior more accurately than the regression model. Only when the criterion quantities were determined by a linear function was the mapping heuristic less accurate than the linear regression model. Overall, the success of the mapping heuristic shows that simpler strategies can rival and exceed the ability of linear regression to describe human judgments. Furthermore, it has become clear that the cognitive processes used in quantitative estimation will often depend on the characteristics of the environment, highlighting the importance of studying the ecological rationality of cognitive processes for estimation.

Individual Differences in the Use of the Recognition Heuristic

Goldstein and Gigerenzer (2002) proposed the recognition heuristic, a strategy that uses recognition to make inferences about

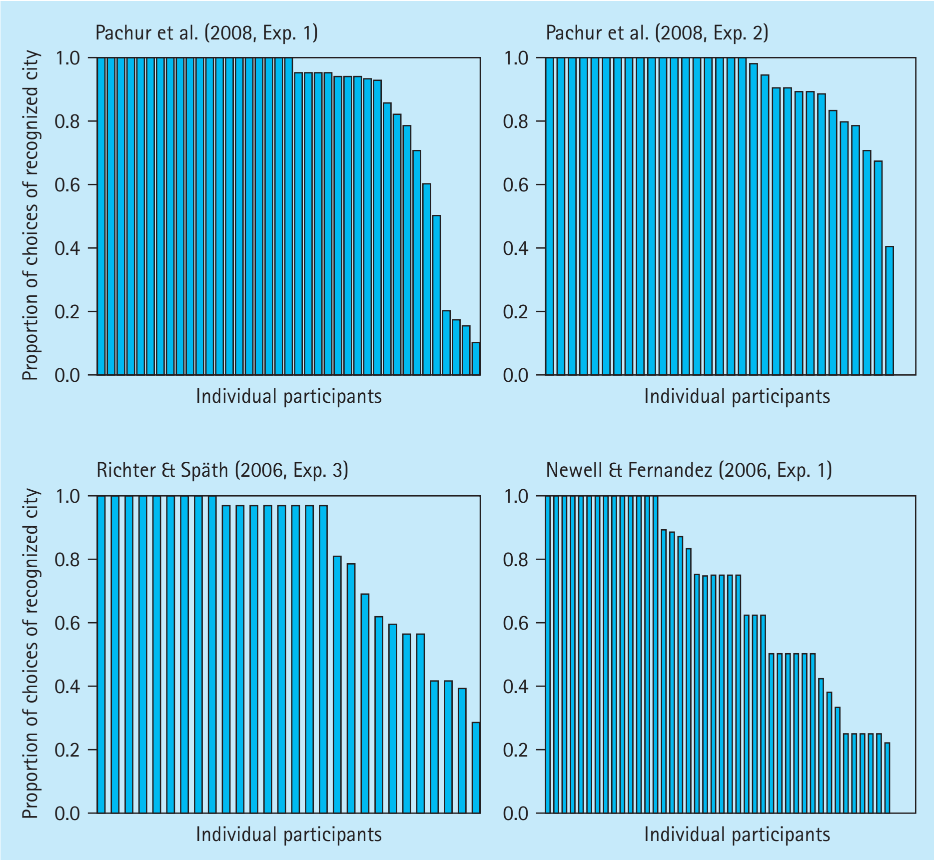

Figure 1. Regardless of contradicting cues, a large proportion of subjects consistently rely on the recognition heuristic. These four plots show the distribution of individual proportions of choices for which the recognized city was chosen. In the upper row, the result of two experiments by Pachur et al. (2008) show that, even when most additional cues suggest that the recognized city was small, the majority of subjects consistently follow the recognition heuristic. The bottom row shows a reanalysis of two experiments originally interpreted at the aggregate level, and used to suggest a lack of adherence to the recognition heuristic. However, when interpreted at the individual level, the responses of many subjects were found to be consistent with the recognition heuristic, despite the presence of conflicting cues.

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Mata, R., **Schooler, L. J.,** & **Rieskamp, J.** (2007). The aging decision maker: Cognitive aging and the adaptive selection of decision strategies. *Psychology and Aging, 22,* 796–810.

the environment. For two-alternative choice tasks, where one has to decide which of two objects scores higher on a criterion, the heuristic can be stated as follows:
If you recognize one object but not the other, then infer that the recognized object scores higher on the criterion.
The recognition heuristic piggybacks on recognition, a highly efficient cognitive ability, and exploits environmental regularities, namely, that recognition in natural environments is often systematic rather than random. In such environments, the recognition heuristic is ecologically rational, exemplifying Herbert Simon's vision of rationality as being shaped by two blades, one being the mind, the other being the environment. There has been continued progress in demonstrating the predictive power of the recognition heuristic in, for instance, soccer (Pachur & Biele, 2007) and tennis (Scheibehenne & Bröder, 2007). In addition, we have further explored its cognitive foundations, focusing on when people choose the recognized alternative and when they do not. Importantly, the recognition heuristic assumes a noncompensatory use of recognition: Even when a person could rely on knowledge about an alternative's attributes (e.g., facts about a carmaker) to complement recognition, when the heuristic is used to make inferences about that alternative, these cues are ignored. Yet, in situations of conflict, individual differences arise.
For instance, Richter and Späth (2006) ran a series of studies and—observing that fewer decisions were consistent with the recognition heuristic when knowledge that contradicted recognition were available—concluded that there was no evidence of a noncompensatory use of recognition. In contrast, Pachur, Bröder, and Marewski (2008) found strong individual differences in the use of recognition (Figure 1). Whereas approximately half of the participants chose the recognized object regardless of conflicting knowledge, the remaining participants were influenced by the additional knowledge. Furthermore, a reanalysis of Richter and Späth's data showed that the majority of participants in fact consistently followed the recognition heuristic even in the presence of conflicting evidence, whereas others switched to different (unknown) strategies (Gigerenzer & Brighton, 2009).

How Time Pressure Influences Strategy Selection

Do the inference strategies people select depend on time pressure? Rieskamp and Hoffrage (2008) addressed this question in a study in which participants made inferences after having searched for information on a computerized information board. In a series of experiments, time pressure was induced indirectly by imposing opportunity costs for being slow, a form of time pressure that is common in daily life but that has rarely been examined in the literature, or directly by limiting the time for each choice. Regardless of how time pressure was induced, under high time pressure, the inferences participants made could be best predicted with a simple fast and frugal heuristic, whereas under low time pressure, a weighted linear model that integrates all available information predicted their inferences best. These results show that people select strategies adaptively depending on characteristics of the situation.

The Aging Decision Maker: Individual Differences in Strategy Use Induced by Limited Cognitive Resources

Rieskamp and Hoffrage (2008) argued that people rely on simple heuristics when they lack the time to execute a complex information-intense strategy. Analogously, Mata, Schooler, and Rieskamp (2007) examined whether individuals with limited cognitive resources might rely more frequently on a simple heuristic in comparison to individuals with more cognitive resources. Two populations that differ in their cognitive recourses are the elderly and young adults. Therefore, one might predict that the elderly use simple heuristics more frequently than young adults. This prediction was tested by Mata et al. (2007). In their experiment, participants made decisions in an environment that favored the use of information-intensive strategies and in an environment favoring the use of simple information-frugal strategies. The

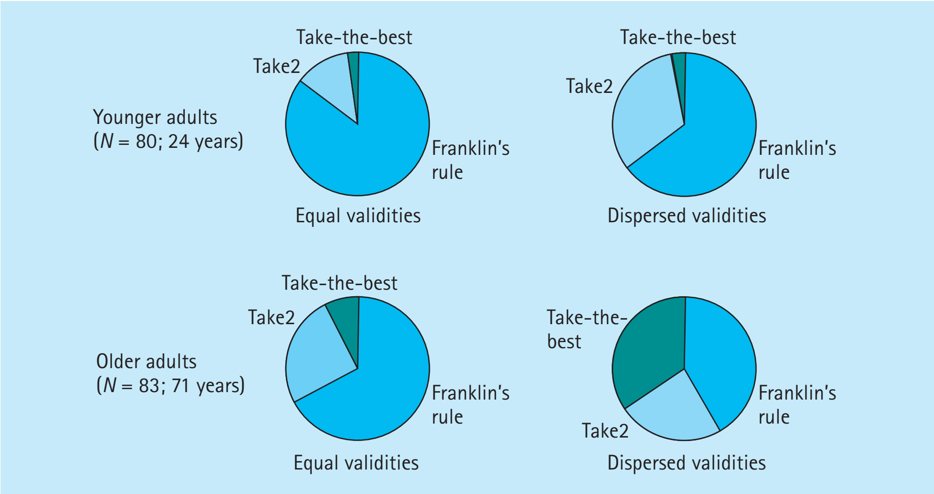

Figure 2. Older subjects use strategies adaptively: Mata et al. (2007) conducted an experiment in which the participants had to infer which of two diamonds was more expensive. When making their inferences, participants were able to look up attributes (e. g., size, cut) about each diamond. In the equal validities condition, the attributes were equally predictive of price. In the dispersed validities condition, some attributes were more predictive than others. Using simple heuristics, Take2 and take-the-best, would yield the higher payoff in the dispersed validities condition. Franklin's Rule, which weights the attribute values based on how well they predict, would yield the higher payoff in the equal validities environment. Participants were classified according to which strategy or heuristic described their decisions best. In general, the older participants had a stronger preference for selecting a simple heuristic than the younger participants. Moreover, both younger and older participants were sensitive to the environment characteristics; that is, they were more likely to use the simple heuristics in the dispersed validities environment.

results (shown in Figure 2) indicated that both younger and older adults seem to be adaptive decision makers, adjusting their information search and strategy selection as a function of environment structure. Crucially, however, old adults tended to look up less information and relied more on simpler less cognitively demanding strategies compared to young adults. In accordance with the idea that age-related cognitive decline leads to reliance on simpler strategies, measures of fluid intelligence explained age-related differences in information search and strategy selection.

How the Misperception of Randomness Facilitates the Detection of Patterns

"Clarice, does this random scattering of sites seem overdone to you? Doesn't it seem desperately random? Random past all possible convenience? Does it suggest to you the elaborations of a bad liar?" (Harris, T. [1988]. *The silence of the lambs* [p. 293]. New York: St. Martin's Press).

In Thomas Harris' "The Silence of the Lambs," the imprisoned cannibal Dr. Hannibal Lecter helps FBI agent Starling hunt a serial killer. The killer tries to hide his whereabouts among seemingly random crime scenes, but by trying too hard to give the impression of randomness, he unintentionally helps agent Starling discover an important pattern which ultimately results in his location being revealed. This example illustrates that people have trouble mimicking randomness, and that they are very good in detecting patterns. Both may be two sides of the same coin: The well-documented misperception of randomness may facilitate the detection of patterns. Sometimes, however, people detect patterns where there are none.

Probability matching, a classic choice anomaly, could be a further consequence of hunting for patterns. In a typical experiment, people have to predict which of two events, with different probabilities of occurring, will take place. For example, event $E1$ could occur with a probability of $p(E1) = .67$, while event $E2$ occurs with $p(E2) = 1 - p(E1) = .33$. Given that the sequence of events is random, the best strategy would be always to predict the more

Key Reference

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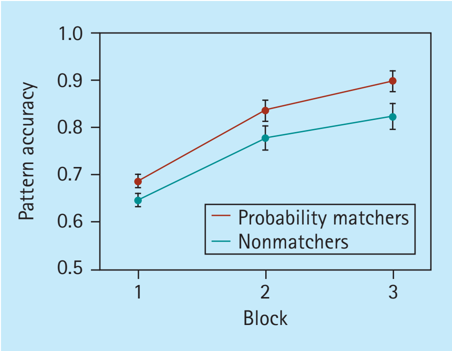

Figure 3. Are probability matchers irrational? A smart strategy underlies this classic choice anomaly: When a systematic pattern is present, probability matchers outperform everyone else. Mean accuracy when systematic sequence pattern is present (± standard error of the mean) for probability matchers and nonmatchers as classified by their tendency to probability match in the absence of a systematic pattern. The data is depicted for three blocks of trials (adapted from Gaissmaier & Schooler, 2008).

frequent event, *E1*. This strategy is called maximizing and would yield an average accuracy of 67 %. However, probability matching is often observed, which means predicting the events in proportion to their probability of occurrence. In the example, this would mean predicting *E1* in 67 % of the trials and *E2* in 33 % of the trials. Probability matching is considered suboptimal because it would yield an accuracy of only 55.78 % on average (67 % × 67 % + 33 % × 33 %). Does this mean that people are not smart enough to solve this simple task? Not necessarily. Rather, one could say that people are too smart. They do not believe that consistently predicting *E1* is the best policy, but try to improve their accuracy by looking for other patterns in the sequence. Any plausible pattern a person might try tends to match the probabilities, which is why searching for patterns leads to probability matching at the outcome level.

Supporting the hypothesis that probability matching is the result of pattern searching, Gaissmaier and Schooler (2008) showed that those people who fall prey to the probability matching choice anomaly, looking irrational in the absence of patterns, were better in detecting patterns when they were there to be found. This finding, shown in Figure 3, illustrates how important it is to consider the structure of the environment when evaluating behavior. From this perspective, pattern search is not a suboptimal policy. Outside casinos and psychology laboratories, there are few natural environments where one can safely assume that events occur at random. Thus, suboptimal probability matching in these few cases could well be a price worth paying for being better at detecting patterns in everyday settings.

Ecological Rationality

The structure of the environment will often play a crucial role in determining the performance of cognitive processes for reasoning and decision making. The study of ecological rationality examines this relationship by considering the structural properties of natural environments, precise quantitative models of heuristics and other cognitive models, and how the two interact to yield functional outcomes, such as fast, frugal, and accurate inferences about the world. We employ a variety of methods to examine these issues, including computer simulation and mathematical analysis. Our recent research has led to considerable advances in our understanding of the interplay between environmental conditions and heuristic performance.

Fast and Frugal Trees

In everyday cognition, categorization tasks typically involve limits on time and the availability of information. These decision-making problems often have significant consequences, need to be made under pressure, and involve high stakes. Models of categorization, and professional decision making more generally, have been studied in fields spanning biology, education, engineering, law, and medicine. For example, a patient who is rushed to the hospital with intense chest pain has to be categorized quickly and accurately as being at a high or low risk of suffering from ischemic heart disease. Can heuristics rival the accuracy of the decisions made using the standard methods found in fields such as medicine and engineering? If so, under which ecological conditions are simple heuristics likely to perform well in comparison?

Categorization methods used in engineering applications typically integrate all available cues, compute sophisticated statistical measures of similarity and informativeness, and consider potentially complex dependencies between cues. Fast and frugal trees, in contrast, process cues sequentially and use simple descriptive statistics that ignore cue dependencies. A fast and frugal tree of depth n is unbalanced and has only $n + 1$ exits, whereas a full binary decision tree of depth n is balanced and has 2^n exits. When using a fast and frugal tree, cues are considered in sequence, and the final categorization decision can be made at any point during this process. A fast and frugal tree for the heart disease problem is shown in Figure 4.

For 30 real-world problems, Martignon, Katsikopoulos, and Woike (2008) compared the performance of fast and frugal trees with the performance of two commonly used categorization methods: classification and regression trees (CART), and logistic regression (LR). Two kinds of fast and frugal tree were considered, both of which ignore cue dependencies, but differ in how they order cues. The accuracy of all four methods was evaluated in four settings: data fitting and three measures of predictive accuracy. In the data fitting case, all data was used to estimate the parameters of each method, and the models were then evaluated on their ability to describe this data accurately. For the case of predictive accuracy, each method had access to 15 %, 50 %, and 90 % of the objects in the data set, and their parameters were fitted to data samples of these sizes. The models were then evaluated on their ability to make correct categorization decisions for novel objects from the same data set, those which were not

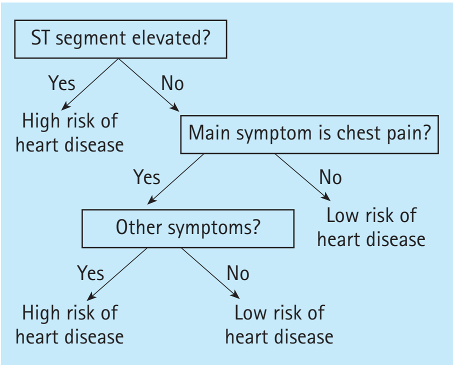

Figure 4. A fast and frugal tree for categorizing patients as having a high or low risk of heart disease. Rather than requiring consideration of all three pieces of information, a fast and frugal tree can lead to a decision being made at any point during the sequential consideration of this information.

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used to estimate the parameters of the models. Put simply, fitting refers to describing the past, while prediction refers to the tougher test of second-guessing the future.
The results of this study are shown in Figure 5, which illustrates that the performance of each method depends in large part on the environmental conditions, such as the amount of data available. In the data fitting case, where all data is available, the more sophisticated methods, such as classification and regression trees and logistic regression, are more accurate. In the prediction case, which considers more realistic settings in which small amounts of data are available (15 % prediction), the fast and frugal trees were almost as accurate as the more complex methods. However, the fast and frugal trees were more robust in the sense of losing less of their accuracy when moving from the fitting problem to the prediction problem. Given that fast and frugal trees also require less time, information, and computation than the more computationally complex methods, they represent a particularly attractive option when categorization decisions need to be made quickly and with limited resources. This

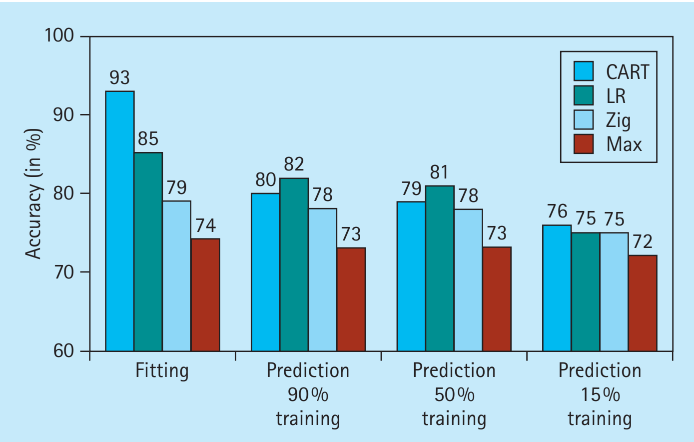

Figure 5. A comparison of the predictive accuracies of two kinds of fast and frugal tree, with two standard and more resource intensive methods: classification and regression trees (CART) and logistic regression (LR). Two kinds of fast and frugal tree, Max and Zig, were tested. Max considers cues in decreasing order of their validity. Zig is similar, but alternates between using left and right exits at each level of the tree. The results reported are the mean accuracies achieved by each method over 30 real-world data sets. For example, one data set considers the problem of deciding where a postoperative recovery patient should be sent next, using cues such as body temperature and blood pressure.

first example shows how the performance of heuristics and other decision rules will depend on environmental conditions, such as sample size. But can we understand this dependence in more detail?

The Bias-Variance Dilemma in Inductive Inference

How and when can fast and frugal heuristics achieve higher predictive accuracy than linear regression, classification and regression trees, and several other resource-intensive statistical methods? In previous work, we have shown how the simple heuristic take-the-best can often outperform such methods. Take-the-best models the process of inferring which of two options scores higher on some criterion of interest, such as price. These findings, which surprised many experts, were made when evaluating the performance of several methods on real-world problems. Previously, we have shown how mathematical analyses can go some way to explaining these results and provide pointers to the precise environment conditions under which they will occur. More recently, however, we have taken a statistical approach to the problem of understanding when and why heuristics work. Brighton and Gigerenzer (2008) examined the ecological rationality of take-the-best using a statistical decomposition of prediction error into bias and variance. For illustrative purposes, consider the problem of finding a predictive pattern for the mean daily temperature in London. Figure 6 plots temperature data for the year 2000 as well as showing two polynomial models (one of degree 3 and one of degree 12) superimposed on this data. These two models attempt to capture a systematic predictive pattern in the data. In general, the more parameters a model has, the better the fit to the data it can achieve. However, there is a point at which using too many parameters begins to damage the predictive accuracy of a model. This point is illustrated in Figure 7, which plots the error in both fitting and predicting temperature data for polynomial models, ranging from degree 1 to 12. A model with an intermediate number of parameters (in this case, a degree 4 polynomial with 5 parameters) predicts best. The reason why

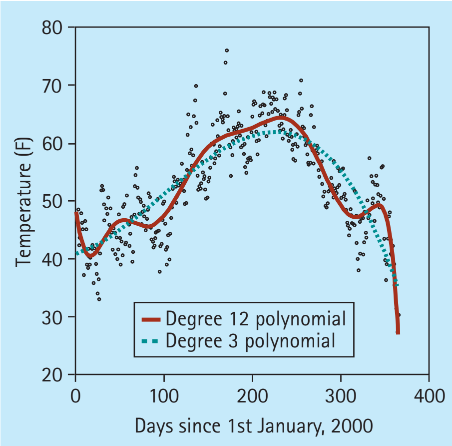

Figure 6. When fitting data, complex models are more accurate. For example, consider London's mean daily temperature on each day of 2000: Two polynomial models attempting to capture a systematic pattern (one of degree 3, the other degree 12) are superimposed on this data. The models were fitted to the data using the least squares method.

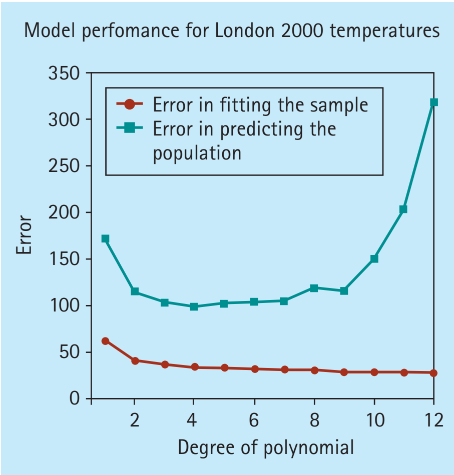

Figure 7. When predicting data in an uncertain world, complex models are often less accurate: As the degree of the polynomial model increases, the more parameters it has, and the lower the error it incurs when fitting samples of observations of London's mean daily temperature (circles). For the same models and samples, the error in predicting the temperature (squares) follows a U-shaped pattern: Too many parameters damage the predictive ability of the model, and the best predicting model is of degree 4. Models of degree 5 and higher become unstable and suffer from high variance. Notice that a degree 2 polynomial model (which is biased) incurs less prediction error than a degree 10 polynomial model (which is unbiased). It achieves this by incurring low variance in error.

this occurs can be explained by considering the statistical problem known as the bias-variance dilemma. Here, bias and variance, along with noise, additively contribute to the total prediction error as follows:

Total error = (bias)^2 *+ variance + noise.*

The bias of a method is its error when given an infinitely large sample of observations with which to estimate its parameters. The variance is the additional error this method incurs when only a finite sample of observations are available, and reflects how sensitive the method is to the particular content of samples.

Returning to our temperature example, polynomial models of degree 1 to degree 3 suffer from bias: They lack the flexibility to adequately describe what is systematic in the data. Overly complex models, those of degree 5 and higher, have zero bias, but suffer from high variance: They become unstable, model noise and accidental patterns in the data, and predict poorly. In exactly the same way, heuristics and other cognitive models of decision making suffer from bias and variance. Brighton and Gigerenzer (2008) used this fact to show that heuristics outperform alternative approaches exclusively as a result of reducing variance. This means that heuristics are often more stable in the face of noise and small samples. In the inaugural issue of the *Cognitive Science Society's* new journal, *Topics in Cognitive Science,* Gigerenzer and Brighton (2009) use these findings to make a general point: Minds rely on heuristics in order to combat the uncertainty arising from limited observations of our world. Although heuristics can suffer from bias, they can also have very low variance, and this allows them to outperform more resource intensive

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unbiased methods. Statistical bias can be a positive force in an uncertain world.

These first two examples of our recent research into ecological rationality have a prescriptive flavor. That is, they help answer the question of what heuristics people should use in order to increase their accuracy. Taking a prescriptive stance was possible because the tasks we considered had a correct answer (e. g., a patient either suffers from heart disease or not). Importantly, the approach to studying the predictions of a method in relation to the environment also proves insightful for tasks where there is no correct answer.

In this next example of our recent research, we examine the descriptive question: What heuristics do people use?

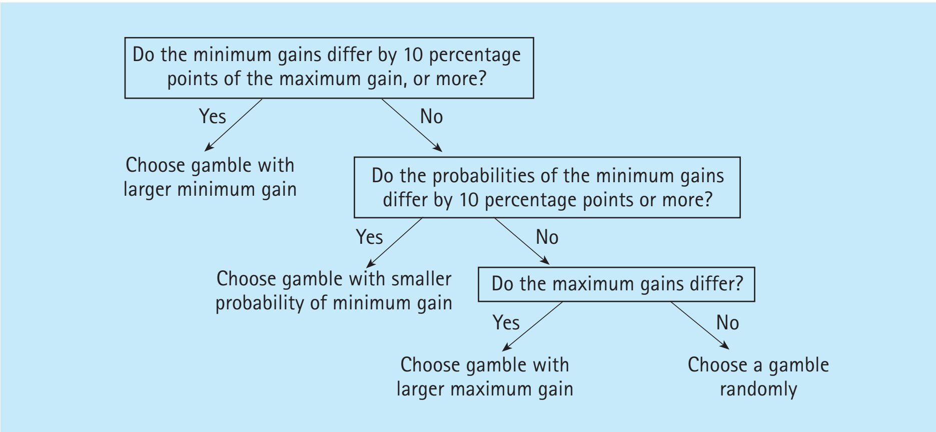
A Novel Approach to Explaining Violations of Expected Utility Theory

Expected utility theory has been the dominant theory in the social and behavioral sciences for explaining how people make choices under risk. In a risky choice, choosing an option does not always lead to the same outcome. For example, a participant may be asked to choose between the following two options. The first option is a gamble where there is a 50 % chance of receiving 1,000 Euro and a 50 % chance of receiving nothing. In the second option, 500 Euro is received with certainty. Expected utility theory tells us that, for each option, people add the worth or utility of each possible outcome, weighted by its probability, to calculate the expected utility of the option. Then, so the theory goes, people choose the option with the highest expected utility.

In the choice between a sure gain of 500 Euro and a fifty-fifty chance of 1,000 Euro or nothing, most of us choose the sure gain of 500 Euro. In this case, we are risk averse. Expected utility theory predicts that a person's attitude toward risk does not change as the outcomes or probabilities change. But people are not risk averse when the gambles involve losses. For example, very few people choose a sure loss of 500 Euro over a gamble in which there is a 50 % chance of losing 1,000 Euro and a 50 % chance of losing nothing. That is, people are risk averse for gains and risk seeking for losses. But this view conflicts with the fact that people buy lottery tickets (i. e., are risk seeking for gains) while, at the same time, buy insurance (i. e., they are risk avoiding for losses). That is, when the probability of the gain is relatively small (e. g., ≤ 5 %, as in lotteries) people are risk seeking; also, when the probability of the loss is relatively small (again ≤ 5 %), people are risk averse (and buy insurance). This pattern of behavior is called the four-fold pattern of risk attitude. This four-fold pattern is not predicted by expected utility theory.

The four-fold pattern is an empirical puzzle that needs to be modeled quantitatively and accounted for theoretically. If one wishes to stay within the expected utility approach, it has to be assumed that the probabilities entering the utility calculation are weighted. Furthermore, in order to account for the four-fold pattern, it has to be assumed that

Figure 8. Conflict resolution without trade-offs. The priority heuristic for a choice between two gambles when all outcomes are gains. This simple heuristic implies the Allias paradox, the four-fold pattern, and other violations of expected utility theory (Katsikopoulos & Gigerenzer, 2008).



small probabilities are overweighted and large probabilities are underweighted. For example, a participant could perceive a probability of 5 % as 7.5 % and a probability of 95 % as 92.5 %. In recent years, some researchers have elevated probability weighting from a modeling assumption to the status of an empirical phenomenon, but there is no direct empirical evidence that people weight probabilities when making risky choices. Crucially, this claim is only necessary when one views human behavior through the lens of expected utility theory.

Katsikopoulos and Gigerenzer (2008) proved that the four-fold pattern of risk attitude is logically implied by the priority heuristic, which does not assume probability weighting. This explanation rests on the mathematical analysis of a simple parameter-free sequential heuristic for making risky choices between two gambles. In the case of gambles with gains, the priority heuristic is depicted on Figure 8. The objective values of probabilities, not any weighted probabilities, can be used to stop information search and make a choice. The priority heuristic has the same building blocks as both fast and frugal trees and take-the-best: a search rule, stopping rule, and a decision rule. Katsikopoulos and Gigerenzer (2008) showed analytically that users of the priority heuristic would also exhibit the four-fold pattern of risk attitude. The result delineates the conditions under which risk averse and risk-seeking behaviors are predicted to occur. For example, if the probability of a gain is larger than 10 %, a priority heuristic user will be risk averse, while if the probability of a gain is smaller than 10 %, a priority heuristic user will be risk seeking. Because the priority heuristic has no free parameters, it *implies* the four-fold pattern rather than merely being consistent with it for one particular parameter setting.

To summarize, this work shows how major violations of expected utility theory can be explained without appealing to probability weighting, but are implied by a heuristic which relies on limited search, a stopping rule, and aspiration levels.

Social Rationality

Social rationality is a specific form of ecological rationality, capturing the fact that social species need to make decisions in an environment that may be constructed by the actions of others. By studying social rationality, we attempt to understand the cues and heuristics that underlie cooperation and group decision making, and to uncover the role of emotions in social heuristics. These social heuristics represent adaptive solutions to recurring social problems faced by humans during their phylogenetic and ontogenetic development.

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Biele, G., Rieskamp, J., & Czienskowski, U. (2008). A model of reciprocity: Explaining cooperation in groups. *Organizational Behavior and Human Decision Processes, 106,* 89–105.

How Can Cooperation Be Maintained When Contributing to Public Goods?
Contributing to public goods (PG) often presents a social dilemma: If nobody contributes, everyone is worse off than if everyone had contributed, but each individual group member benefits most from not contributing. Consequently, it is difficult to maintain cooperation in PG situations. Biele, Rieskamp and Czienskowski (2008) examined whether reciprocal strategies can predict people's behavior better than alternative learning models. In past research, it has been showed that reciprocal strategies, such as tit-for-tat, can outperform alternative noncooperative strategies in repeated social interactions. Biele et al. (2008) argue that, compared to PG games, cooperation is more easily maintained in two-person interactions, such as the prisoner's dilemma, because in the latter individuals can reciprocate directly, whereas in the former they must react uniformly to the heterogeneous group. If people reciprocate cooperation in iterated PG games, then cooperation should increase when the PG can be divided among the group members, thus strengthening dyadic interdependencies. To test this prediction, Biele et al. (2008) compared cooperation in a standard PG game with a social dilemma network (SDN) game. In the SDN game, the public project is split into multiple public projects, such that every individual can cooperate simultaneously in several two-person public projects (see Figure 9).

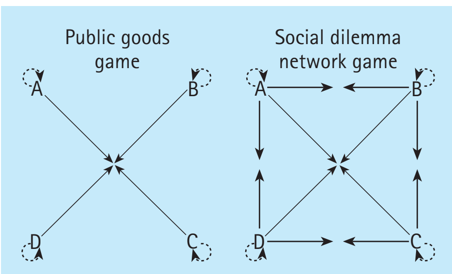

Figure 9. Public goods game and the social dilemma network game. Solid lines represent possible contributions to public projects. Dotted lines represent the possibility to keep resources for oneself.

In the experiment, one group of participants played the SDN game. Every point invested into the joint projects was multiplied by 1.5 and divided equally among two members of the project. Two other groups of participants played a standard iterated PG game with four members. Again, every invested point was multiplied by a constant. The two groups differed only by the incentive given for cooperation, so that points that were invested to the PG were increased by different magnitudes. In one group, the incentive to cooperate had the same magnitude as in the SDN game, whereas in the second group it was twice as high. Therefore, if incentives for cooperation matter, then cooperation should have been highest in the high incentive PG group, whereas if reciprocity principles underlie cooperation in groups, then the highest cooperation should be observed in the SDN game.
The results were clear cut: The median contributions in the SDN game were about 50 % higher than in the two standard PG games (with similar contribution levels). To predict participants' decisions Biele et al. (2008) compared the prediction of a reciprocity model with two other learning models. The reciprocity model and one of the two learning models described the decisions equally well. However, only the reciprocity model was also able to predict participants' information search preceding their decisions. The information search was recorded using an information board paradigm: Information about the behavior of other players, and their own payoffs and decisions, had to be acquired by clicking on information boxes. In line with the reciprocity model, participants focused their information search on the contribution of the

other players instead of accessing information about their own payoffs, as predicted by learning models. In particular, in the SDN game, 80 % of the participants were classified as searching for information as predicted by the reciprocity model. In sum, Biele et al. (2008) showed that cooperative decisions in groups are best predicted by a reciprocity model, which also predicts that cooperation increases when the opportunity for dyadic interactions are given.

How Does Advice Influence Learning?
In many real-life situations, people make their decision on the basis of past experience, on the basis of social information, such as the advice of others, or on the combination of both. Biele, Rieskamp, and Gonzalez (in press) examined how social information can be incorporated into individual learning models to predict how people's learning processes are influenced by advice. The learning processes were examined using the Iowa Gambling Task (IGT), where participants try to obtain high rewards by repeatedly choosing the best out of four choice options. Participants receive feedback about the outcomes of their choices and learn which options provide the highest average payoff. The challenge of the IGT is that the good options with positive average payoffs are associated with only moderate gains and small occasional losses. In contrast, the bad options with (on average) negative payoffs are associated with high gains, but even higher losses. In the experiment, participants had to solve the IGT after they had received advice about which option leads to the highest payoff. The results of the experiment showed that advice improved performance: Participants who had received advice received a higher payoff in comparison to participants who did not receive any advice. Participants who received advice also chose the recommended deck more frequently than the corresponding deck with the same expected payoff. However, examining the choices of advice receivers over time showed that receivers did not follow the advice blindly. Instead, they first followed the advice, then explored other options, and finally returned to choosing the advised option.

To examine the underlying learning mechanisms, Biele et al. (in press) compared one individual and four social learning models. The individual learning model assumed that each option has an expectancy which changes with received feedback and that choices are made probabilistically as an increasing function of the options' expectancies. The influence of advice was examined by modifying the different submechanisms of individual learning, such as initial expectations, evaluation of outcomes, and the updating of expectations. All social learning models predicted the actual learning process better than the pure individual learning model. The best social learning model—the outcome-bonus model—assumed that advice results in the outcome of recommended options being evaluated more positively. This advantage was clearly demonstrated in a second experiment, where all options led, on average, to negative payoffs. In such a situation, the social learning model that assumes slower forgetting for advised options predicts that people will choose nonrecommended options quickly. In contrast, the other social learning models still predict a preference for the recommended options. As predicted by the outcome-bonus model, advice receivers in the second experiment chose the recommended deck more frequently than the corresponding deck with the same expected payoff. Only the outcome-bonus model correctly predicted receivers' adherence to advice and predicted more adherence to good than to bad advice (see Figure 10). These experimental studies show that people *combine* individual reinforcements and the advice of others to make good decisions. Only a minority of participants relied exclusively on advice, and nobody relied exclusively on individual learning. The results also indicate that a one-time recommendation has a long-lasting influence on behavior. Thus, generalizing from our findings, repeated advice seems not to be necessary to guide behavior in a particular direction. Therefore, successful advice could focus on a single convincing recommendation. People neither ignore nor blindly follow advice, rather, they integrate advice to accelerate the individual learning process and arrive at solutions quicker.

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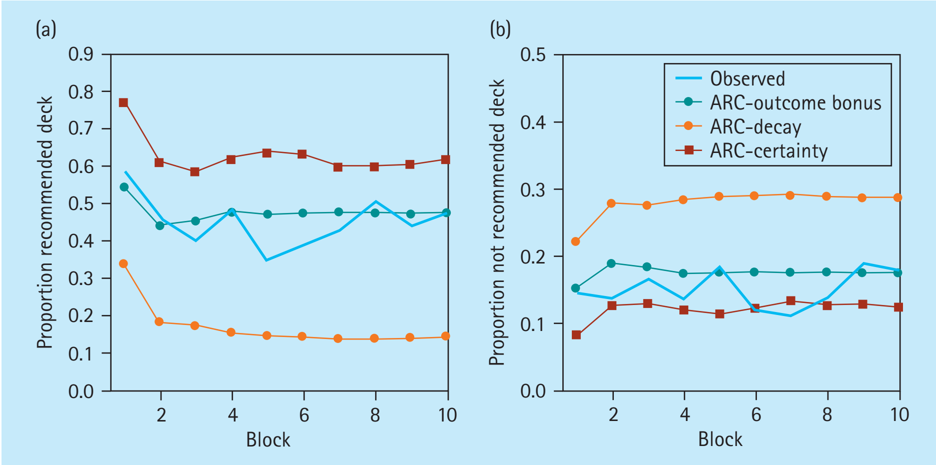

Figure 10. Can the effect of advice on decision making be predicted? These two plots examine the performance of the outcome bonus model of Biele et al. (2008). Receivers' observed and predicted choice proportions in Experiment 2 (described in the main text) for (a) the recommended deck or (b) the corresponding deck with the same average payoff. Only the outcome-bonus model predicts choices well, whereas the decay model overestimates the preference for the not-recommended deck and adaptive reinforcement combination. The certainty model overestimates the preference for the recommended deck.

Are the Chinese More Generous Than Germans?

How do differences in age and cultural background impact on group decision making? In a series of studies, we used game theory as a paradigm to examine this question in relation to cooperation. This is an interdisciplinary approach which integrates economics and moral developmental psychology. We explored children's and adolescents' sharing of resources in the context of two experimental games (Gummerum, Keller, Takezawa, & Mata, 2008; Keller & Canz, 2007), allowing us to examine individual and cooperative decision making in a group context. We were interested both in the decision heuristics used, and the arguments given, by people of different ages and cultural backgrounds.

Following up on experiments described in the previous report on individual and group decision-making processes when sharing, we studied children and adolescents in China and in Great Britain (Leman, Keller, Takezawa, & Gummerum, in press). About 15 groups of children and adolescents of ages 9, 12, 14, and 17 years played two experimental games: In the *dictator game,* one group (proposer) had to decide unilaterally whether and how to share a sum of money (20 coins of different value, overall 2, 4, 4, 6 Euros) with another anonymous group (responder) who could only accept the offer. In the *ultimatum game,* the responder group has the power to accept or to reject the offer of the proposer group. If the responders accept the offer, the money is distributed according to the suggestion of the proposers. In the case of rejection, neither of the groups receive any money.

Game theory predicts that a rational actor will allocate nothing to the other group in the dictator game, and give only one coin in the ultimatum game. Empirical research with adults has refuted these predictions, but little is known about children and adolescents. Our research with German pupils

Figure 11. Chinese children participating in the group dictator game.

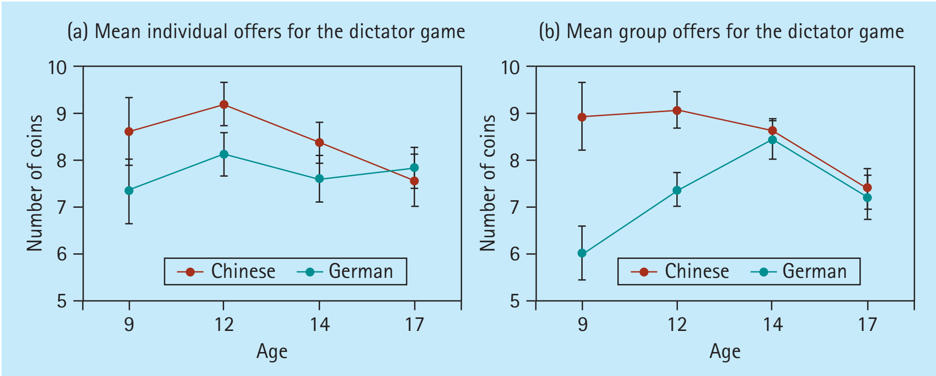

Figure 12. In the dictator game, younger German children are less generous than Chinese children, both individually and as groups. These plots show the individual (a) and group offers (b) made by Chinese and German children in the dictator game. The total sum to be divided was 20 coins.

demonstrated that children and adolescents offered more than adults in the dictator game (on average 35 % compared to 25 % of the stake). It also revealed a preference for using an equal split heuristic, resulting in sharing across all age groups, both with respect to individual and group offers. The analysis of the arguments given during negotiations revealed that reference to the fairness norm and the ascription of positive characteristics to the other group supported higher offers, while selfishness and negative group stereotypes served to lower offers (Gummerum, Keller et al., 2008).

Drawing on the distinction between individualistic Western and collectivistic Asian societies, we hypothesized that participants from Great Britain would be similar to the German sample, while Chinese children should offer more than their Western counterparts. For the dictator game, the findings in the three cultural settings showed that the offers of children and adolescents were more generous than those found for adults, and the equal split heuristic was dominant across all age groups and cultures (Leman et al., in press). Figure 12 shows the comparisons between the age groups in China and Germany for the dictator game.

Overall, in individual offers, Chinese participants offered more than Germans with the exception of the 17-year-olds. As for group offers, Chinese participants offered significantly more than Germans, with the difference in large part being due to the offers of the 9- and 12-year-olds, while the offers of the 14- and 17-year-olds did not differ.

In the ultimatum game, the equal split heuristic described the typical offer for all ages, in both countries, in individual and group settings. This was consistent with previous findings relating to adults. Contrary to the hypothesis that Chinese share more than Germans, no overall effect was found for culture. However, an age-specific comparison of individual offers revealed a systematic pattern: Younger Germans gave less than the younger Chinese, while the reverse was true for the 17-year-olds (Figure 13). Age-specific comparisons revealed an opposite cross-over

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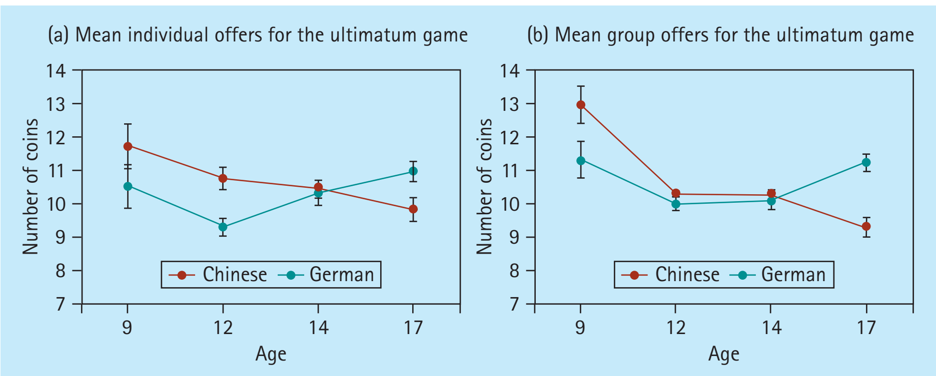

Figure 13. In the ultimatum game, younger German children are less generous than Chinese children, both individually and as groups. These plots show the individual (a) and group (b) offers made by Chinese and German children in ultimatum game. The total sum to be divided was 20 coins.

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pattern for group offers: Younger German groups offered less than younger Chinese groups, while, by age 17, this pattern was reversed as Germans become more generous. A first analysis of the arguments provided during the group discussions for the dictator game revealed that, in both Chinese and German participants, fairness was the most frequently mentioned type of argument across all age groups. The German children in the youngest group used selfish arguments much more frequently while the Chinese children were more concerned with psychological characteristics of the other group. The 12-year-old German children were more concerned with reciprocity (e.g., how much the others would give them) than their Chinese counterparts. This helps to explain why German children in these two age groups offered less than German children in the dictator game group discussions. Overall, the results reveal similarity across cultures concerning the dominance of the equal split as a simple heuristic of sharing. But there exists also an interaction of culture and age which will have to be further explored.

Happy Victimizers, Unhappy Moralists

Moral emotions, such as guilt and shame, which are associated with the consequences of moral transgressions, are important cues for the motivational acceptance of moral norms. In our previous research, we examined the "happy victimizer" phenomenon in young children (e.g., attributing positive feelings to a moral-rule violator in spite of moral knowledge that the violation is not right) by exploring emotions of violator and victim in a situation of contract violation. More recently, Barrett, Keller, Takezawa, and Wichary (2007) followed up on a finding that contract violation in parent-child relationship was accompanied less frequently with feelings of guilt than in peer relationships. Based on evolutionary considerations, we controlled the relevant parameters by using the same contract and controlled for relatedness and nonrelatedness. We could not replicate the previous finding, which suggests that emotions to contract violation are not specific to any particular type of relationship.

In addition, we studied moral emotions using the moral dilemma-approach, which enabled us to study both moral emotions of guilt due to violating an obligation and positive moral feelings of pride due to acting in accordance with obligations. Keller, Brandt, and Sigurdardottir (in press) had proposed different types of emotion patterns beyond the "happy victimizer." Keller and Malti (in press) analyzed these types in four age groups of 7-, 9-, 12-, and 15-year-old Icelandic and Chinese participants, where the task was to reason about a moral dilemma of self interest, altruism, and friendship loyalty. The results revealed that the "happy victimizer" phenomenon was highly infrequent because even the youngest children mostly understood the consequences of violating a promise to the best friend. Typically, Icelandic children were "unhappy victimizers" when giving precedence to self-interest over friendship. On the other hand, some younger Icelandic children were "unhappy moralists" by showing selfish regret over keeping the promise, but missing a good opportunity. In contrast, most Chinese children and adolescents were "unhappy moralists" who felt guilty whatever choice they made because they interpreted the conflict as either violating obligations of friendship or altruism toward the third child. This research demonstrates that emotions are dependent on the interpretation of the situation, which is itself dependent on development and culture.

Evolutionary and Comparative Psychology

An evolutionary approach lies at the heart of many research projects undertaken by the ABC Research Group and motivates the central concepts we work on. In this section, we focus on use of evolutionary principles and models to understand human behavior (evolutionary psychology) and study decision making in other animal species (comparative psychology). First, we focus on recent empirical studies of foraging decisions both in the external world and inside the mind. Second, we outline work exploring how comparative psychological studies of other animals can inform our notion of ecological rationality.

Foraging Decisions

When should we move on to greener pastures? Humans and other animals face decisions of this type in a variety of common domains. Whenever resources are distributed in space or time, it is important to decide when one could do better by switching to a different source. People searching for blackberries must assess whether there are enough ripe berries on the current plant, or if it would be better to move on to the next plant. Optimal foraging theory has proposed the optimal solution to the problem. The classic theory is the marginal value theorem, which states that you should leave a patch when the current rate of return is less than the mean rate in the environment under the optimal strategy. Finding the optimal policy requires complicated computations, but biologists do not assume that animals solve differential equations. Instead, they assume that natural selection has endowed individuals with simple heuristics (sometimes referred to as "rules of thumb" by biologists) that approximate the optimal outcomes. A number of these decision rules for foraging have been tested in a variety of animal species, shown in Figure 14.
Hutchinson, Wilke, and Todd (2008) examined the decision rules used by humans when foraging in a computer game environment. Participants were given the task of fishing at a succession of ponds and earned money by catching fish (Figure 15). Brief glimpses of fish in the pond were shown to the participants. The appearance of fish was stochastic, at a rate proportional to how many fish remained in the pond. Participants could move to a new pond any point, but doing so cost them time. From the perspective of ecological rationality, some decision rules will perform better than others, depending on the properties of the environment. Foraging decision rules are no exception, and Hutchinson et al. (2008) tested their participants in three environments, with an even, random, or aggregated distribution of fish across ponds.
Like other animals tested in patch-foraging situations, the human participants stayed

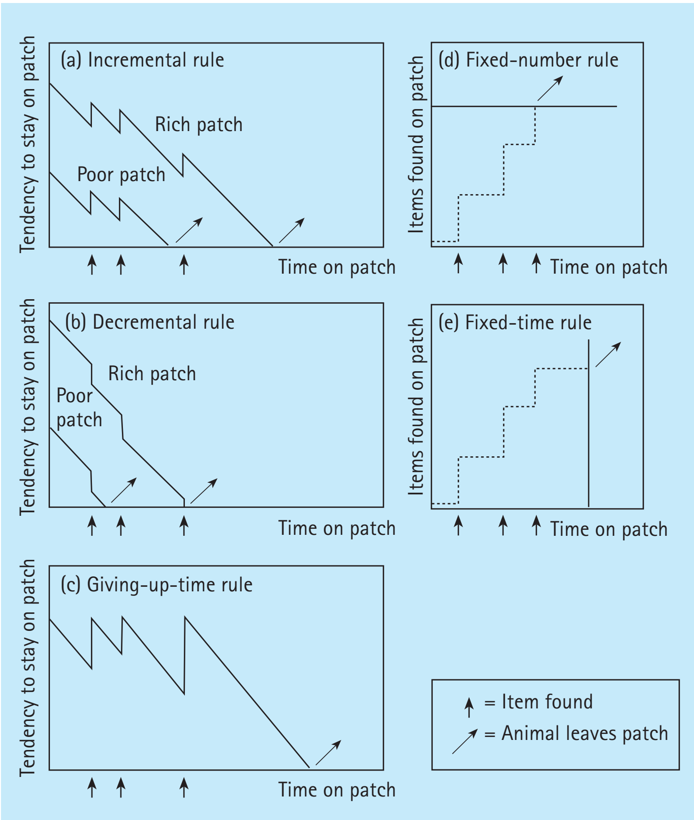

Figure 14. Biologists have tested a number of patch-leaving rules. (a) With an incremental rule for deciding when to leave a patch, each resource capture (indicated by small arrows) increases the probability of staying in a patch. (b) With a decremental rule, each resource capture reduces the probability of staying. (c) With a giving-up time rule, the tendency to stay in the patch declines with unsuccessful search and is reset to a maximum with each resource found. (d) With a fixed-number rule, a patch is left after a fixed number of items have been found. (e) With a fixed-time rule, the patch is left independent of the number of food items found.

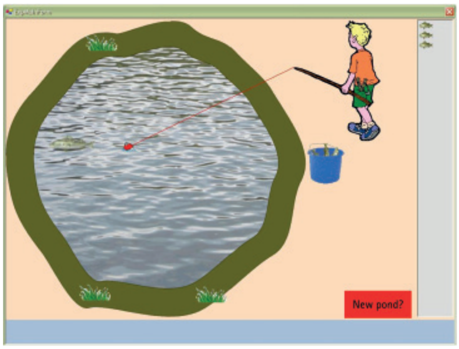

Figure 15. Participants had to decide how long to stay at a pond to catch fish.

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longer than predicted by the optimal policy. Furthermore, regardless of the distribution of prey, they spent longer at ponds where they had found more items. This suggests that participants did not simply use the total number of fish caught or the total time spent fishing when deciding to switch. Instead, they appear to be using a very rough version of a giving-up time rule (illustrated in Figure 14 [c]), where the time since the last capture and the interval between the previous two captures play a prominent role in determining when to leave. Although in an aggregated environment this type of rule performs well, in even and random environments it performs poorly relative to the optimal policy. Despite this, the participants typically used the same rules equally in the three environments: Humans did not appear to switch strategies as expected, but tended to use a single strategy.

Foraging in the Mind

In addition to foraging in patchy environments in the external world, humans spend much of their time seeking information resources internally, from memory. Like animals maximizing their rate of energy intake, optimal information foragers might maximize the long-term rate of valuable information gained per unit time. Wilke, Hutchinson, Todd, and Czienskowski (2009) examined this issue by studying the mechanisms people use for moving through a succession of cognitive information-foraging tasks: The problem of seeking anagrams in a "patch" of letters. For example, which words can you find in the sequence LGIRNAHEM? Perhaps RING, NAME, ANGEL, and LAGER come to mind quickly. Yet, as with the feeding-patch paradigm, reward rate declines with time spent in each patch, so that at some point it is better to switch to the next patch of letters. Do people use similar rules when rewards are produced by thinking and searching in internal memory, rather than by exploring the external environment? As in the fishing task, Wilke et al. (2009) provided subjects with different environments: either an even environment with roughly the same number of words per patch, or an aggregated environment in which patches contained either many or few words.

The results for this internal foraging task closely matched those for the external foraging task. Among the most important cues used when switching patches were the time since finding the previous solution and the interval between finding the previous two solutions. Again, whether the participants experienced the even or aggregated environment had little influence on their performance or the cues that predicted switching behavior. Thus, there are striking similarities between human foraging in the outside environment and in the mind. Importantly, the cues used to make these foraging decisions do not differ according to variation in the distribution of items in the environment.

If the brain uses domain-specific decision rules, why does it not respond to the different environments confronted in these two foraging tasks? One possibility is that most environments that we experience (and that our ancestors experienced) are aggregated, not evenly dispersed. In addition, the costs of treating an aggregated environment as evenly dispersed are higher than costs of treating an evenly dispersed environment as aggregated. For these reasons, decision rules that bet on aggregation may perform well on average. In both the fishing and word-puzzle tasks, people seem to use rules and cues that perform well in aggregated environments. To explore this issue further, Wilke and Barrett (in press) measured people's predictions of how dispersed certain objects were in the environment. For instance, if you found a fruit, are you likely to find another fruit nearby? Would you expect the same pattern after finding a bird's nest? Despite receiving feedback suggesting that finding or not finding another fruit was equally likely, participants demonstrated a preference toward predicting that more fruit would be found following a previous find. Thus, the participants showed a preference toward assuming that the items were distributed in patches when, in fact, they were randomly distributed. Additionally, this preference was found for objects that are dispersed rather than patchy in the real world (e. g., bird nests and bus stops). These results were found for both UCLA undergraduates and members of the Shuar—a group of hunter-horticulturists from Amazonian Ecuador—suggesting that we may see the world as patchy, and, if we find a resource in one place, there will likely be more resources around. Wilke and Barrett suggest that this may account for the "hot hand" phenomenon described in the judgment and decision-making literature. People often perceive streaks or repetitions in data when they do not exist. From an evolutionary perspective, this may prove adaptive in a world which is largely patchy.

Ecological Rationality in Other Animals

An important tool in the evolutionary biologists' toolbox is the comparative method. By comparing species that differ in specific aspects of their world, we can test hypotheses about the selective pressures particular environments place on organisms. For instance, the snow cover of the arctic tundra favors white fur and feathers: Camouflage is important both when hunting and when avoiding being hunted. Similarly, cognitive and behavioral traits of animals are selected to fit their environments. This then suggests an evolutionary aspect to the definition of ecological rationality: Adaptive behavior results from the fit between the mind's mechanisms and the structure of the environment in which it *evolves* (Stevens, 2008).

The notion of adaptive specialization in cognition is common (although not uncontroversial) in the animal cognition literature. For instance, primates that forage for fruits have been shown to have larger brains than those that forage for leaves, with the explanation that tracking the temporal and spatial variations in the distribution of fruit in the environment requires more complicated cognition than tracking the more stable distribution of leaves. This provides only a weak test of ecological rationality. More direct tests have explored how chimpanzees and bonobos respond to delayed or risky outcomes. These two species provide a unique opportunity to test questions about ecological rationality because, in addition to being our closest living relatives, they share many morphological and behavioral characteristics; however, they differ markedly in their foraging behavior. Bonobos rely more heavily than chimpanzees on plant material, such as stems and leaves, whereas chimpanzees hunt for meat more often than bonobos. This is an interesting difference because hunting requires waiting until food is captured and entails risk associated with an unsuccessful hunt. Foraging on plants, in contrast, requires neither waiting nor risk because the plants are plentiful in the environment. Thus, an ecological rationality perspective would predict that chimpanzees should be more patient and risk seeking than bonobos because the time delays and risks associated with hunting are higher than those associated with foraging for plants.

Rosati, Stevens, Hare, and Hauser (2007) tested the ecological rationality of intertemporal choice in chimpanzees and bonobos in a laboratory task. Here, subjects chose between two grapes available immediately and six grapes available after a time delay (Figure 16). The time delay in receiving the six grapes was increased gradually until each subject chose the two immediate grapes and the six delayed grapes equally. This offered a point

Figure 16. Chimpanzees and bonobos chose between two grapes available immediately or six grapes for which they had to wait.

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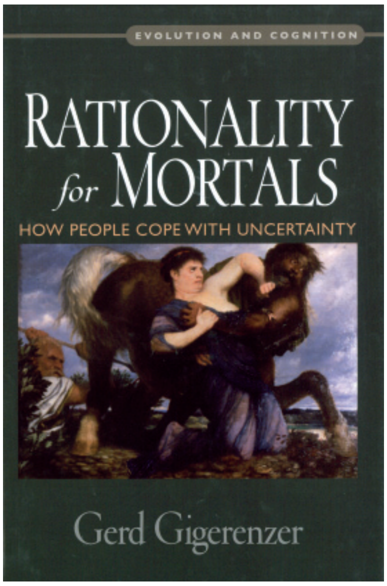
Figure 17. Chimpanzees and bonobos chose between safe and risky rewards hidden under bowls. The blue bowl contains four grapes, whereas the yellow bowl contains either one grape or seven grapes with equal probability.

at which subjects were indifferent between the two options and gave a measure of how they valued future rewards. As predicted by the ecological rationality hypothesis, the chimpanzees tolerated longer delays than the bonobos: when given a choice, two grapes immediately or six grapes after a delay, bonobos waited about one minute (mean 74.4 s, SE = ±8.5 s) whereas chimpanzees waited about two minutes (mean 122.6 s, SE = ±15.9 s). The hunters waited longer than the gatherers. Hunting involves not only waiting but also the risk associated with an unsuccessful attempt at capturing prey. Heilbronner, Rosati, Stevens, Hare, and Hauser (2008) applied the same logic as Rosati et al. (2007) to questions of risk instead of delay. In this experiment, chimpanzees and bonobos chose between a "safe" option of always receiving four grapes and a "risky" option of receiving either one grape or seven grapes with equal probability (Figure 17). The bowls offered the same payoff on average, so any preference for one option over the other indicates sensitivity to risk. In this task, five out of five bonobos preferred the safe option whereas four out of five chimpanzees preferred the risky option. Like the time delay results, these findings support the ecological rationality hypothesis: That the risks chimpanzees face in hunting have molded their risk preferences more generally.

Both intertemporal and risky choices in chimpanzees and bonobos match the time delays and risks seen in the species in the wild. Similar findings in two monkey species, tamarins and marmosets, further support the importance of feeding ecology on intertemporal and risky choice. Thus, it seems likely that ecological circumstances have strong influences on the decision mechanisms dealing with time and risk. These types of comparative studies offer valuable insights into ecological rationality because we can test how key aspects of a species' ecology influence their decision making.

Decision Making in the Wild

As we have shown, the study of bounded, ecological, and social rationality conceives of behavior as the result of an interaction between cognition and environment. This approach implies two ways of improving decision making: first, changing the environment so that people can better understand and act in a successful way and, second, changing people's heuristic strategies so that they can better handle a given environmental task. Our work on decision making in the wild includes improving police hunches in locating criminals (Gigerenzer & Brighton, 2007), and facilitating financial investments (Ortmann, Gigerenzer, Borges, & Goldstein, 2008). We will focus here, however, on our work in health care and energy choice.



What is the nature of human wisdom? For many, the ideal image of rationality is a heavenly one: an omniscient God, a Laplacean demon, a super computer, or a fully consistent logical system. Gerd Gigerenzer argues, in contrast, that there are more efficient tools in our minds than logic; he calls them fast and frugal heuristics. These adaptive tools work in a world where the present is only partially known and the future is uncertain. Here, rationality is not logical, but ecological, and *Rationality for Mortals* (published in 2008 by Oxford University Press) shows how this insight can help remedy even the widespread problem of statistical innumeracy.

Helping Doctors and Patients to Make Sense of Health Statistics

In Gigerenzer, Gaissmaier, Kurz-Milcke, Schwartz, and Woloshin (2007), we—a team of psychologists and physicians—describe a societal problem that we call *collective statistical illiteracy.* The qualifier *collective* signals that lack of understanding is not limited to patients with little education; many physicians, journalists, and politicians do not understand health statistics either. We provide evidence that statistical illiteracy is: (1) a widespread phenomenon; (2) created by nontransparent framing of information that is sometimes an unintentional result of a lack of understanding but can also be a result of intentional efforts to manipulate or persuade people; and (3) a problem which can have serious consequences for health. In what follows, we illustrate this ethical and societal problem with several cases and studies.

Higher Survival Rates Do Not Mean a Longer Life

In a 2007 campaign advertisement, former New York City mayor Rudy Giuliani said: "I had prostate cancer, five, six years ago. My chance of surviving prostate cancer—and thank God, I was cured of it—in the United States? Eighty-two percent. My chance of surviving prostate cancer in England? Only 44 percent under socialized medicine."

For Giuliani, these health statistics mean that he was lucky to be living in New York and not in York, since his chances of surviving prostate cancer appear to be twice as high. This was big news. It was also a big mistake. High-profile politicians are not the only ones who do not understand health statistics or misuse them.

Giuliani's numbers were survival rates that are meaningless for making comparisons across groups of people who differ dramatically in

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how they were diagnosed. In the US, most prostate cancer is detected by PSA screening, whereas, in the UK, men are screened much less frequently, with the majority diagnosed from symptoms. The bottom line is that to learn which country is performing better, we need to compare mortality rates. Imagine a group of patients all diagnosed with cancer on the same day. The proportion of these patients who are still alive 5 years later is the *5-year survival rate:*

$$\text{5-year survival rate} = \frac{\text{number of patients diagnosed with cancer still alive 5 years after diagnosis}}{\text{number of patients diagnosed with cancer}}$$

To calculate a mortality rate, imagine another group of people. Members of this group are defined as *not* having a cancer diagnosis. The proportion of people in this group who are still alive after 1 year (the typical time frame for mortality statistics) is the *mortality rate:*

$$\text{Annual mortality rate} = \frac{\text{number of people who die from cancer over 1 year}}{\text{number of all people in the group}}$$

The key difference in these two rates is the word *diagnosed,* which appears in the numerator and denominator of survival statistics. Screening profoundly biases survival in two ways: It affects (1) the timing of diagnosis and (2) the nature of diagnosis, by including people with nonprogressive cancer. The first is called the *lead time bias,* illustrated in Figure 18. Imagine a group of prostate cancer patients currently diagnosed at age 67, all of whom die at age 70. Each survived only 3 years, so their 5-year survival is 0%. Now imagine that the same group is diagnosed with prostate cancer by PSA tests 7 years earlier, at age 60. From the date of diagnosis, all have now survived 10 years, and thus their 5-year survival rate is 100%. Yet although the survival rate has risen dramatically, nothing else has changed: Whether diagnosed at age 67 or at age 60, all patients die at age 70. This simple example demonstrates how survival rates can be increased by setting the time of diagnosis earlier, even if no life is prolonged or saved.

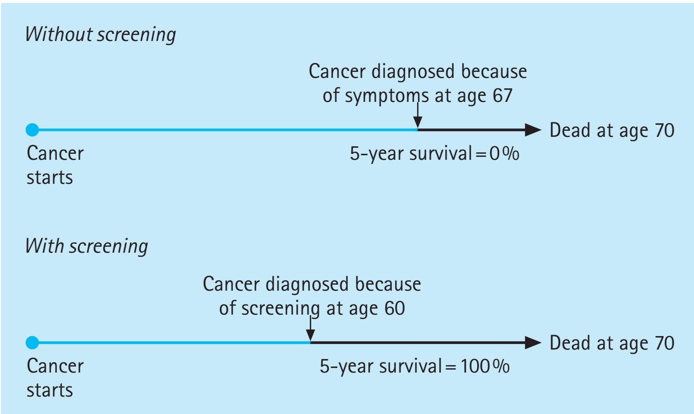

Figure 18. Why can survival rates be misleading? An illustration of the lead time bias. Even if the time of death in not changed by screening and thus no life is saved or prolonged, advancing the time of diagnosis can result in increased 5-year survival rates.

The second phenomenon that leads to spuriously high survival rates is the *overdiagnosis bias,* illustrated in Figure 19. Overdiagnosis is the detection of pseudodisease—screening-detected abnormalities that meet the pathologic definition of prostate cancer, but will never progress to cause symptoms in the patient's lifetime. These are also called nonprogressive cancers. Figure 19 (top) shows 1,000 men with progressive cancer who do not undergo screening. After 5 years, 440 are still alive, which results in a survival rate of 44%. Figure 19 (bottom) shows a population of men who participate in PSA screening; the test detects both progressive and nonprogressive cancers. Imagine that screening identifies 2,000 people with nonprogressive cancers—who by definition will not die of cancer in the following 5 years. These are now added to the 440 who survived progressive cancer, inflating the survival rate to 81%. Again, although the survival rate has increased dramatically, the number of people who die has not changed at all.

Due to the overdiagnosis bias and the lead time bias, changes in 5-year survival rates have no reliable relationship to changes in mortality. For example, consider the 20 most common solid tumors in the US over the last 50 years. A study examining the correlation coefficient relating changes in 5-year survival to changes in mortality for these cancers between 1950 and 1995 found the correlation to be $r = 0.00$! In the context of screening, survival rate is always a biased metric. In the US, screening for prostate cancer using the PSA test began in the late 1980s and spread rapidly, despite the lack of evidence that it saves lives. As a result, the number of prostate cancer diagnoses soared. In the UK, PSA testing was introduced later and is not used routinely. Consequently, prostate cancer incidence in the UK has risen only slightly. This largely explains why 5-year survival for prostate cancer is so much higher in the US. But the real story is about mortality: Are American men half as likely to die from prostate cancer than British men? The answer is no; mortality is about the same. If we take prostate cancer as a criterion for judging a health-care system, the "socialist" English system appears to win since there are fewer diagnoses, that is, less overdiagnoses, but about the same mortality rate. Many American men have been unnecessarily diagnosed (i.e., overdiagnosed) with prostate cancer and undergone unnecessary surgery and radiation treatment. This has led to between one third and two thirds of these men to suffer from lifelong incontinence or impotence.

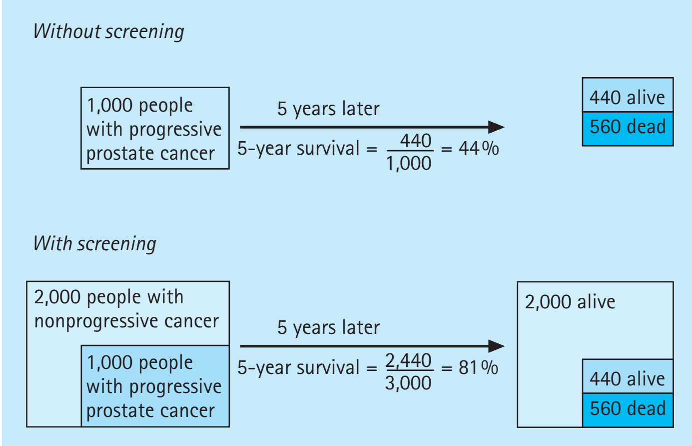

Figure 19. Why can survival rates be misleading? An illustration of the overdiagnosis bias. Even if the number of people who die is not changed by screening, and thus no life is saved or prolonged, screening-detected nonprogressive cancers can inflate the 5-year survival rates.

Are Patients Prepared to Make Informed Decisions?

In several countries, health systems are currently being reformed to provide more room for patients to choose treatments, doctors, or even health insurers. Yet we and others have shown in study after study that patients do not understand the information communicated by health organizations and do not know which questions to ask. We first need to educate the public before we can expect public policy changes to be effective. Here is an illustration taken from cancer screening, which involves people who do not have symptoms and whose responses are not likely affected by fear or any other intense emotion. In the US and the EU, the benefits of breast cancer screening using mammography are typically communicated in the following way: Screening reduces the risk of dying from breast cancer by "25%." This percentage is a *relative risk reduction,* which is a nontransparent form of communication—and like survival rates, both suggestive and misleading. For instance, we asked a representative sample of 1,000 German citizens the following question: "Early detection with mammography reduces the risk of dying from breast cancer by 25%. Assume that 1,000 women age 40 years and older participate regularly in screening. How many fewer would die of breast cancer?"

Figure 20 shows that the general public has no idea what 25% means. The estimates

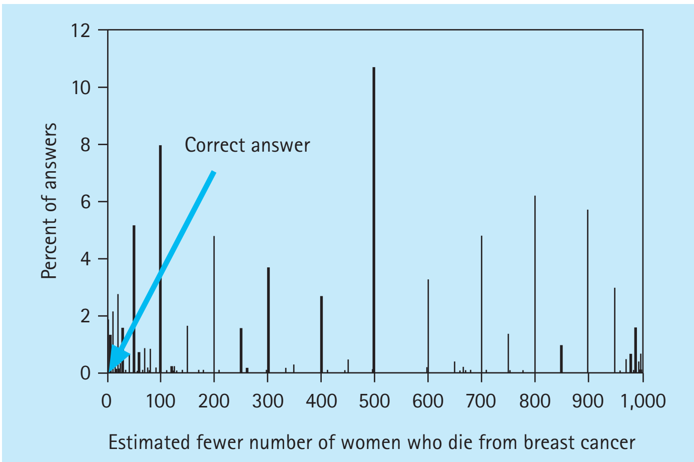

Figure 20. Illustration of statistical illiteracy among the public. A representative sample of 1,000 German citizens were asked: "Early detection with mammography reduces the risk of dying from breast cancer by 25%. Assume that 1,000 women aged 40 and older participate regularly in screening. How many fewer would die of breast cancer?"

spanned the entire spectrum, with 500 in 1,000 as the most frequent estimate. The 25% figure stems from randomized studies that found that, out of 1,000 women age 40 and older who did not participate in screening, 4 died of breast cancer within 10 years and that, out of 1,000 women who did participate, this number dropped to 3. From 4 to 3 is a 25% relative risk reduction, which is an *absolute risk reduction* of 1 in 1,000, or 0.1%. Only about 1% of the general public seems to understand this fact, and a separate analysis revealed that even less women in the age group invited for screening understood it. This study shows that the general public do not understand the benefit of screening and, thus, cannot make an informed decision about it. It also shows that the problem is not simply inside the human mind, but in the way information is framed by health-care institutions. Many institutions have a conflict of interest, pursuing the paternalistic goal of increasing the participation rates at the expense of complete and transparent information.

Do Doctors Understand Health Statistics?

According to the German Health-Care Reform of 2007, adults covered by statutory health insurance are required to visit a doctor to be instructed on the pros and cons of breast, cervical, and colon cancer screening. If they choose not to visit, and are later diagnosed with cancer, their personal expenditures are capped at 2% (otherwise 1%) of their annual income for cancer-related medical expenses. What the health-care reform did not envision was the possibility that doctors are not in a position to inform patients adequately because they have no efficient training in statistical thinking.

In 2006 and 2007, Gerd Gigerenzer trained 1,000 experienced gynecologists in risk communication as part of their mandatory further education. At the beginning of each training session, he asked the following question, designed to test the doctors' ability to explain a positive mammogram to a patient.

Assume you conduct breast cancer screening using mammography in a certain region. You know the following information about women in this region:

- The probability that a woman has breast cancer is 1% (prevalence).
- If a woman has breast cancer, the probability that she tests positive is 90% (sensitivity).
- If a woman does not have breast cancer, the probability that she nevertheless tests positive is 9% (false-positive rate).

A woman tests positive. She wants to know from you whether that means that she has breast cancer for sure, or what the chances are. What is the best answer?

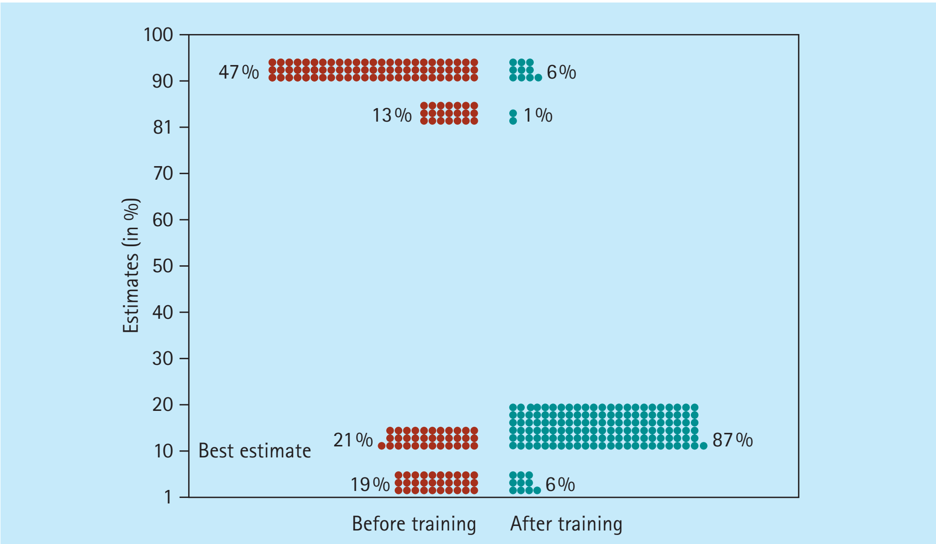

Figure 21. Illustration of statistical illiteracy among physicians. One hundred and sixty gynecologists estimated the probability that a woman has breast cancer given a positive mammogram, before and after learning how to translate conditional probabilities into natural frequencies.

(a) The probability that she has breast cancer is about 81 %.
(b) Out of 10 women with a positive mammogram, about 9 have breast cancer.
(c) Out of 10 women with a positive mammogram, about 1 has breast cancer.
(d) The probability that she has breast cancer is about 1 %.

Gynecologists could simply recall what they should have known already or derive the answer from the health statistics provided. In either case, the answer is (c)—that only about 1 out of every 10 women who test positive in screening actually has breast cancer. The other 9 are falsely alarmed.

Figure 21 (left) shows that only 21 % of doctors knew and responded with this answer (less than chance), whereas the majority grossly overestimated the woman's probability of cancer. Another troubling result was the high variability in physicians' estimates, ranging between 1 % and 90 %. Consider what unnecessary fear doctors' innumeracy causes women who participate in screening. Again, our thesis is that there is nothing wrong with these physicians' mental capacities (although gynecologists should know this 1 in 10 figure by heart), but that the information is again framed in a confusing way. *Natural frequencies* are a transparent alternative to the *conditional probabilities* used in medical training (such as sensitivities and false-positive rates). Here is the same information in a transparent way:

- Ten out of every 1,000 women have breast cancer.
- Of these 10 women with breast cancer, 9 test positive.
- Of the 990 women without cancer, about 89 nevertheless test positive.

After a 75-minute training session, in which they learned how to translate conditional probabilities into natural frequencies, the gynecologists' confusion disappeared; 87 % understood that 1 in 10 is the best answer and only 13 % appeared to be hopeless cases (Figure 21, right). This approach to helping doctors is rooted in laboratory experiments by Gigerenzer and Hoffrage (2007), who showed that natural frequencies facilitate insight because they perform part of the Bayesian computations.

These examples illustrate the phenomenon of collective statistical illiteracy as well as techniques that can substantially reduce the problem. The major challenge is to find efficient ways to implement learning the art of understanding statistics in medical school and physicians' further education and to establish guidelines for transparency in reporting medical studies in journal articles, brochures, and the media.

To this end, David Harding, Head of the London investment firm Winton Capital Management, donated 1.5 million Euros to Gerd Gigerenzer to found a center for risk literacy, whose primary goal is to improve the public's

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"It was the outstanding research at the Max Planck Institute for Human Development in Berlin that convinced me that it would be the ideal setting for a privately financed 'Harding Center for Risk Literacy.' It is my aim to promote the proper use of statistical analysis in policy development, for the benefit of the public, and I am convinced that the excellent scientists at the institute will succeed in an area which will be of ever increasing importance for the future."

David Harding

The Harding Center for Risk Literacy

In spring 2009, the Harding Center for Risk Literacy was founded at the Max Planck Institute for Human Development, Berlin. Its mission is to help create a society of informed citizens who are competent to deal with the risks of a modern technological world. Basic and applied research will be united at the Center. In the area of basic research, questions to be investigated cover how risks can be more effectively communicated and why certain risks loom larger than others (even when they are not). The results will be applied in particular to health care and to school education in statistical thinking, with the intention of developing new and effective methods. At the same time, the Center aims at demonstrating, to a broader public, the importance of dispelling illusions of certainty and zero risk and learning to live in an uncertain world. The Center will also serve as the hub of a worldwide network of experts who are working on risk literacy, including the international Cochrane centers for evidence-based medicine, national medical associations, the Winton Chair for the Public Understanding of Risk at the University of Cambridge, and the Bank of England.

The Harding Center for Risk Literacy is headed by Gerd Gigerenzer and Wolfgang Gaissmaier and comprises a team of psychologists and physicists. The first network conference will be held in October 2009, when 40 medical researchers, medical journal editors, health economists, social scientists, and representatives of health insurances will meet for a 5-day Strüngmann Forum. It will be chaired by Gerd Gigerenzer; Sir Muir Gray, Head of the UK National Screening Program; and Günter Ollenschläger, Head of the German Agency for Medical Quality, Berlin. This conference is entitled "Better doctors, better patients, better decisions: Envisioning health-care 2020."

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understanding of risks and uncertainties, an essential skill in a modern technological world (see Box p. 55). Learning to live in an uncertain world presents an emotional challenge to relinquish the illusion of certainty, the fiction of zero risks, and the paternalism that reigns in much of health care and beyond.

"Green" Energy: A Matter of Decisions or Defaults?

Renewable energy, environmental protection, and "green" electricity are promoted by nongovernmental organizations and governments all around the world. But how do people actually decide which energy resources to purchase? One widespread view is that decisions are caused by internal factors, such as personal preferences, environmental attitudes, or knowledge states. This view only looks inside the mind for causes. The perspective of ecological rationality, in contrast, suggests that behavior is a function of heuristics and the environment. If this is correct, one cannot automatically expect that a person favoring "green" electricity will actually buy it. We report here on natural and laboratory experiments that suggest that most people's decisions on which energy resource to purchase are determined by the default heuristic and that the default is set by the environment rather than by the individual (Pichert & Katsikopoulos, 2008). This heuristic can be defined as: *If there is a default, do nothing.*
The first natural experiment occurred in Schönau, a picturesque little town in the Black Forest, with a population of 2,500.
As a reaction to the Chernobyl disaster, a citizens' group proposed to take over the local electricity grid in order to establish an environmentally friendly supply. The proposal caused so much conflict that 90 % of those eligible to vote participated in a referendum. It was accepted by a close margin of 52 % of the votes, and the initiative managed to raise enough money to buy the grid. For Schönau, the default became "green" energy generated from renewable and solar energy. Although the community was polarized, as the vote indicates, in 2006 (8 years after the default was implemented) about 99 % had remained with the default, compared to a typical value of 1 % in other German towns where "gray" energy is the default.
In the case of Schönau, opting out required some search for alternatives. In the second setting we examined, there were no search costs, since the same energy provider provided three new tariffs where previously there had been only one. In 1999, *Energiedienst GmbH* mailed 150,000 letters to private and business customers in southern Germany, offering three options: a "green" (waterpower) option, a "gray" economical option (about 8 % cheaper), and a more "expensive green" option that included a higher share of electricity generated by new facilities (23 % more expensive). The "green" option was offered as the default, that is, customers did not need to respond if they chose it. To opt out, customers only had to tick one of the two other options listed and mail off the letter. Nevertheless, the resulting behavior was close to that in Schönau: 94 % did nothing and remained with the default, 4.3 % did not follow the heuristic and switched to the "gray" option, 1 % selected the "expensive green" option, and .7 % switched to a different supplier.
We conducted two experiments to test whether energy choice follows the default heuristic, but this time under controlled laboratory conditions using hypothetical scenarios (Pichert & Katsikopoulos, 2008). Young adults ($n = 225$; 18–35 years old, mostly students) were asked to imagine that they had moved to another town. In their new apartment, they had a choice between two electricity suppliers, one advertising "clean electricity" generated from environmentally renewable sources (30 Euros per month) and the other offering an economically priced "gray" alternative (25 Euros per month). In one condition, the "green" electricity was the default, in the second the "gray," and in the third there was no default. When there was no default or a "green" default, 67 % and 68 %, respectively, stated that they would choose the "green" electricity. Yet when the default was "gray," this number sank to 41 %, that is, the majority remained with the "gray" default. Asked for the reasons behind their decisions, 71 % of the participants mentioned price and 62 %

named environmental protection, whereas only 15 % referred to reasons indicating awareness of the default heuristic.
In the second laboratory experiment, 82 participants of the same population as in the first laboratory experiment were tested in two conditions. In the *willingness to pay* (WTP) group, participants were asked whether they were willing to switch to "green" electricity if they currently had "gray" electricity, and, if so, what extra premium they were willing to pay per month. In the *willingness to accept* (WTA) condition, they were asked whether they were willing to switch to "gray" electricity if they currently had "green" electricity, and, if so, how much cheaper the "gray" electricity would have to be to make them switch. In both cases, participants were assured that there were no switching costs. Nearly half of the subjects in the WTA group refused to switch for any amount of money, emphasizing that environmental values are not for sale. Among the remaining participants, there was a substantial difference (Cohen's $d = 1.03$) between the willingness to pay a small premium for switching to "green" electricity (mean WTP = 6.59 Euro) and accepting the considerably larger compensation for giving up "green" electricity (mean WTA = 13.00 Euro).
Both the natural and laboratory results suggest that a considerable proportion of decisions about energy sources are based on the default heuristic. In the wild, where real decisions are made (or not made), more people seem to follow the default heuristic than in laboratory experiments with better control, but where little is at stake since the decision is hypothetical. Together with previous work on organ donation and on retirement plans, these results indicate that many important decisions are not made actively, but are based on defaults. This insight explains why sending mass mailings on organ donation or "green" energy has been largely ineffective and opens up a different approach to public policy, as recently popularized by Thaler and Sunstein, that installs the desired defaults while leaving open the possibility of opting out.

The ABC Research Group in October 2008

Left to right: Christian Elsner, Wolfgang Gaissmaier, Hansjörg Neth, Ana Sofia Morais, Konstantinos V. Katsikopoulos, Nadine Fleischhut, José Quesada, Jenny Volstorf, Angela Neumeyer-Gromen, Uwe Czienskowski, Monika Keller, Florian Artinger, Elke M. Kurz-Milcke, Henry Brighton, Björn Meder, Julian N. Marewski, Michel Regenwetter, Henrik Olsson, Bettina von Helversen, Jeffrey R. Stevens, Gerd Gigerenzer, Marco Monti, Özgür Simsek, Linnea Karlsson, Juliet Conlin, Mirta Galesic, Odette Wegwarth, Edward T. Cokely, Adrien Barton, Lael J. Schooler, and Fabrice Le Lec.

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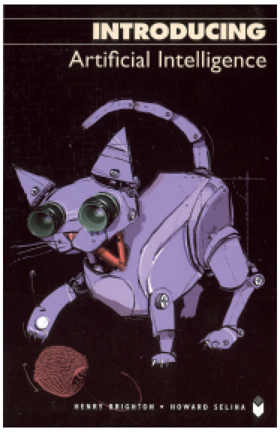

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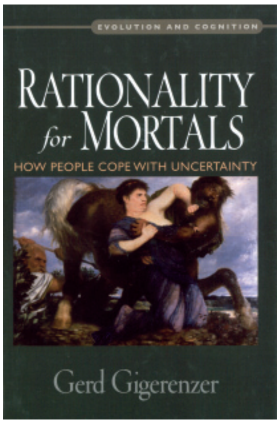

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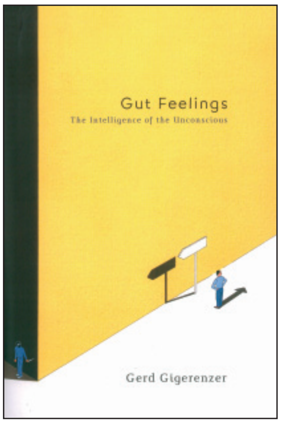

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