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Simple Heuristics in a Complex Social World

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We have all had the experience. Agonizing over a difficult decision—be it a matter of the heart, a moral predicament, a risky financial proposition, or a grave medical decision—we have on occasion wished for ourselves a sage *consigliere* who would simply tell us the right thing to do. When Joseph Priestley, an eminent 18th-century scientist and discoverer of oxygen, faced a particularly difficult choice, he had no need to dream up a wise man—he knew one. It was Benjamin Franklin, 27 years his senior, one of the Founding Fathers of the United States, and a noted polymath. Asked for his counsel, Franklin did not tell Priestley what to do. Franklin (1772/1987) gave him a potentially even more precious piece of advice—a versatile decision tool that can be employed to decide which of two options to choose, whatever the options may be:

> In the Affair of so much Importance to you, wherein you ask my Advice, I cannot for want of sufficient Premises, advise you what to determine, but if you please I will tell you how. ... My Way is, to divide half a Sheet of Paper by a Line into two Columns, writing over the one *Pro*, and over the other *Con*. Then during three or four Days Consideration I put down under the different Heads short Hints of the different Motives that at different Times occur to me for or against the Measure. When I have thus got them all together in one View, I endeavour to estimate their respective Weights; and where I find two, one on each side, that seem equal, I strike them both out: If I find a Reason *pro* equal to some two Reasons *con*, I strike out the three. If I judge some two Reasons con equal to some three Reasons pro, I strike out the five; and thus proceeding I find at length where the Ballance lies; and if after a Day or two of farther Consideration nothing new that is of Importance occurs on either side, I come to a Determination accordingly. And tho' the Weight of Reasons cannot be taken with the Precision of Algebraic Quantities, yet when each is

> thus considered separately and comparatively, and the whole lies before me, I think I can judge better, and am less likely to take a rash Step; and in fact I have found great Advantage from this kind of Equation, in what may be called *Moral or Prudential* Algebra. (p. 878)

Franklin's decision tool is to search for all considerations, positive or negative, weight them with care, and tot them up to find out where the balance lies. Franklin's tool embodies "two commandments that are often taken as characteristic of rational judgment" (Gigerenzer & Goldstein, 1999, p. 83), namely, complete search and compensation. The first stipulates that all the available information should be found (or if not possible that search should be terminated when the cost of further search exceeds the search's benefit). The second stipulates that all pieces of information should be combined in one judgment. Modern descendants of Franklin's tool, also embodying the commandments of complete search and compensation, are, for instance, multiple linear regression and nonlinear Bayesian networks.

We pursue a different vision of rationality, one that challenges the commandments of complete search and compensation. Instead, the vision of bounded rationality proposes that in navigating a world full of uncertainty under the constraints of limited time and knowledge, people cannot help but resort to fast and frugal decision making (Gigerenzer, Todd, & the ABC Research Group, 1999). Counterintuitively, this kind of decision making of mere mortals can be as accurate as strategies that use all available information (complete search) and expensive computation (compensation).

The research program on fast and frugal heuristics (henceforth also referred to as simple heuristics) has instigated a considerable amount of debate over the past decade (see, for example, the commentaries and the reply following Todd & Gigerenzer, 2000, or Gigerenzer, Hertwig, & Pachur, 2011). Moreover, it has stimulated research that has focused on two key aspects. The first aspect is the *ecological rationality* of simple heuristics, and the second is their potential also to account for judgments and decisions in the social world. Some of the research concerned with ecological rationality is featured in Todd, Gigerenzer, and the ABC Research Group (in press), whereas some of the research investigating the use of simple heuristics in a social world is featured in Hertwig, Hoffrage, and the ABC Research Group (in press), and in Hertwig and Herzog (2009).

The present chapter reflects the major themes of the aforementioned three volumes on simple heuristics. First, we will explain how simple heuristics can be understood as models of bounded rationality. Second, we will introduce the notion of ecological rationality and explain when and why simple heuristics perform so well, both to describe the environment and to model behavior. Third, we will show how this research program can be extended to the social world; specifically, we will provide illustrations of heuristics that can be used in what Hertwig and Hoffrage (in press) have called *games against nature* and *social games*, and we will describe how research on simple heuristics investigates the *structures of social ecologies*.

SIMPLE HEURISTICS AS MODELS OF BOUNDED RATIONALITY

Our premise is that much of human reasoning and decision making in the physical and social world can be modeled by *simple heuristics* that enable organisms to make inferences and decisions under conditions of limited time, knowledge and computational capacity. They are models of *bounded rationality* (Simon, 1956, 1982). In contrast to strategies that aim at finding the optimal solution to a problem at hand, models of bounded rationality take human constraints into account when specifying the (cognitive) processes that lead to a *satisficing* solution to a given problem; that is, to a solution that is both *satis*fying and su*fficing* (Gigerenzer et al., 1999, 2011). Moreover, boundedly rational strategies are the only alternative when real-world problems become computationally intractable; their solutions cannot be computed, neither by the most brilliant minds nor by the fastest computers. Unlike models of classic rationality such as probability theory, rational choice theory, or logic, heuristics are task specific, designed to solve a particular task (e.g., choice, estimation, categorization, cooperation, resource allocation). They cannot, however, solve tasks that they are not designed for. A hammer is perfect for driving a nail into the wall but try cutting wood with it. Indeed, the premise of task specificity is fundamental to the notion of the *adaptive toolbox* (Gigerenzer & Selten, 2001), the collection of heuristics that has evolved through phylogenetic, cultural, social, and individual learning, and that can be used by the human mind.

Although simple heuristics differ with respect to the problems they have been designed to solve, their architecture has common properties. In particular, they are composed of *building blocks*, which specify how information, be it stored in memory or externally presented, is searched for (*search rule*); when information search is stopped (*stopping rule*); and how a decision is made based on the information acquired (*decision rule*). Thus, unlike models that assume all information is already known to the decision maker and that are merely used to predict the outcome of the decision-making process, simple heuristics specify the cognitive processes, including those involved in information acquisition (for related programs that explicitly include information search, see Busemeyer & Townsend, 1993, and Payne, Bettman, & Johnson, 1993).

Heuristics can be fast for two reasons. First, they do not integrate the acquired information (e.g., probabilistic cues, reasons) in a complex and time-consuming way. In this respect, many heuristics of the adaptive toolbox are extremely simple because they do not combine pieces of information at all; instead, they search for only a single cue (*one-reason decision making*). Examples are the recognition and the fluency heuristics (Goldstein & Gigerenzer, 2002; Hertwig, Herzog, Schooler, & Reimer, 2008; Schooler & Hertwig, 2005). Second, they can be fast as a consequence of being frugal, that is, they stop searching for further information early in the process of information acquisition. Examples are the take-the-best heuristic (Gigerenzer & Goldstein, 1996), the elimination-by-aspects model (Tversky, 1972), and the priority heuristic (Brandstätter, Gigerenzer, & Hertwig, 2006).

Research on simple heuristics endorses a methodological pluralism. Across investigations researchers employ (a) computer simulations to explore the performance of the heuristics in a given environment, in particular in real-world environments (for example, Czerlinski, Gigerenzer, & Goldstein, 1999); (b) mathematical and analytical methods to explore when and why they fare well or poorly (for example, Martignon & Hoffrage, 2002); and (c) experimental and observational studies to explore whether and when people actually use these heuristics (for example, Bröder, in press; Rieskamp & Hoffrage, 2008). The most important finding from these studies is that simple heuristics can perform well, both as prescriptive models when predicting the environment and as descriptive models when fitting behavioral data (for example, Gigerenzer et al., 2011; Goldstein & Gigerenzer, 2002).

SIMPLE HEURISTICS AS MODELS OF ECOLOGICAL RATIONALITY

Tools, be they physical or cognitive, work well in one domain but may not work in others. A corollary of this general law is that different environments can give rise to different simple heuristics that succeed in exploiting their particular information structure. To the degree that a match between heuristics and informational structures exists, heuristics need not trade accuracy for speed and frugality. The importance of considering the environment when studying the human mind is best illustrated in Simon's analogy of a pair of scissors, with the mind and environment as the two blades: "Human rational behavior is shaped by a scissors whose blades are the structure of task environments and the computational capabilities of the actor" (Simon, 1990, p. 7). By restricting one's attention to one blade at the expense of the other, researchers will fail to fully understand how the mind works, and also how simple heuristics can perform surprisingly well by co-opting the environment as an ally. In other words, the study of bounded rationality is also the study of ecological rationality (Todd et al., in press).

For illustration, consider Woike, Hoffrage, and Petty's (2011) investigation of venture capitalists. The authors used computer simulations to determine the performance of various strategies that venture capitalists may use to sequentially decide whether to invest in a series of business plans. Highlighting the importance of ecological rationality, the authors found that the profit the decision strategies accrued depended on the cue importance structure in the environment. When all cues were equally predictive, a simple equal-weighing strategy (Dawes, 1979) achieved highest profits (even higher than those by logistic regression). In contrast, when the distribution of the cues' predictive power was highly skewed, a fast and frugal decision tree (ordering cues lexicographically) achieved the best results and even outperformed logistic regression.

Another important ecological property that is relevant for the performance of simple cue-based inference heuristics and complex inference strategies is the ratio of structure and noise. Robustness is the ability of an inference model only to extract relevant information from the past, and to disregard irrelevant information, which will not generalize to the future (Gigerenzer & Brighton, 2009). Fitting, in contrast, refers to the ability to explain or describe the past (i.e., data that are already known).

An excellent fit can be indicative of overfitting, that is, lack of robustness (for example, Mitchell, 1997; Myung, 2000; Roberts & Pashler, 2000). A strategy is said to overfit relative to another strategy if it is more accurate in fitting known data (hindsight) but less accurate in predicting new data (foresight). One can intuitively understand overfitting from the fact that past experience can be separated into two classes: the structure class comprises those aspects of the past that are relevant for predicting the future; the noise class includes those aspects that are vacuous with regard to the future. Everything else being equal, the more difficult a criterion is to predict (that is, the higher its uncertainty), the more noise exists in past information and needs to be ignored. An adaptive cognitive system operating in an uncertain world thus needs to ignore part of the information. Robustness can be enhanced by ignoring information and by exploiting evolved capacities such as the ability to forget (Schooler & Hertwig, 2005). The art is to ignore the right information. Heuristics embodying simplicity, such as one-reason decision making, have a good chance of focusing on the information that generalizes because they are—due to their simplicity—more "immune" to noise than complex strategies built to combine plenty of information. Heuristics are less likely to be "fooled by randomness," seeing "faces in the clouds" when there is no robust pattern. Complex strategies, in contrast, are more prone to overfitting due to their greater flexibility in fitting data, and—as an unavoidable byproduct—noise.

In sum, the research program on simple heuristics (Gigerenzer et al., 1999; Hertwig et al., in press; Todd et al., in press) rests on Simon's (1956, 1982) notion of bounded rationality. Strongly emphasizing and elaborating on the ecological intelligence of heuristics, it has proposed models of heuristics across a wide range of tasks and domains. A model of a heuristic encompasses search, stopping and decision rules, and aims to describe the actual process—not merely the outcome—of decision making. By taking advantage of environmental structures, they can achieve as high or even higher accuracy than much more complex models (Gigerenzer & Brighton, 2009). Due to their simplicity and frugality, they are less likely to fall prey to the risk of overfitting, relative to complex models. We now show by means of examples how the framework of simple heuristics can be extended to a social world.

SIMPLE HEURISTICS IN A SOCIAL WORLD

Should simple heuristics be expected to excel in the social world? One reason to believe that they may fail is complexity. The social world has been characterized as more complex, unpredictable, or challenging than nonsocial ones (for example, Byrne & Whiten, 1988), and people, the key agents in the social world, have been described as "unavoidably complex as targets of cognition" (Fiske & Taylor, 1984, p. 18). Humphrey (1976/1988, p. 19), for instance, argued that social systems have given rise to "calculating beings," who "must be able to calculate the consequence of their own behaviour, to calculate the likely behaviour of others, to calculate the balance of advantages and loss." He concluded that "here at last the intellectual faculties required are of the highest order" (p. 19). Similarly, the neuroscientists Seymour and Dolan (2008) argued that "choice in social interaction harbors a level of complexity that makes it unique among natural decision-making problems" and that renders "many social decision-making problems computationally intractable" (p. 667).

The argument that navigating complex social systems requires and has given rise to complex intellectual operations echoes the commandments of complete search and compensation. Indeed, many scholars of rationality believe that the more complex a problem is, the more complex the cognitive machinery of a successful problem solver needs to be (see Hertwig & Todd, 2003). The world's complexity thus licenses—in fact, even calls for—models of unbounded rationality.

This argument, however, overlooks the importance of robustness—the aforementioned key ability of successful strategies. If social environments are indeed more complex than nonsocial environments, robustness will prove to be even more important in the former and will give a competitive edge to those simple strategies that successfully generalize to the unknown by ignoring irrelevant information. In addition, the problems of intractability (Reddy, 1988) and multitude of goals and criteria in social environments collude and put optimization out of reach, probably even more so than in nonsocial environments. Optimization requires a single criterion to be maximized. One cannot maximize several criteria simultaneously, unless one combines them by, say, a linear function (which, in turn, calls for a justifiable rationale for how to weight those criteria). Social environments are notorious for their multitude of conflicting criteria and goals, including speed, accuracy, loyalty, accountability, transparency, trust, fairness, dependability, control, freedom, autonomy, honor, pride, face-saving, consent, equity, equality, and self-interest.

To the extent that the same selective forces that are likely to favor the evolution of simple strategies in nonsocial environments—such as the need for generalizable (robust), fast, and informationally modest (frugal) solutions—are also likely to be at work in social environments (Todd, Hertwig, & Hoffrage, 2005), there is good reason to assume that evolution also selects for simple heuristics in a social world. This does not mean, however, that there is no difference between simple heuristics in a nonsocial and in a social world. Just like simple heuristics in a nonsocial world, those used in a social world may consist of some of the same building blocks (e.g., ordered search, one-reason decision making, or aspiration levels), but they may also include genuinely social building blocks such as emotions and social norms.

When considering the applications of simple heuristics in a social world, it is useful to distinguish between two broad domains. We refer to them as games against nature and social games (Hertwig & Hoffrage, in press). Games against nature refer to situations in which one person needs to predict, infer, or outwit nature in order to achieve his or her ends (e.g., predicting the temperature to inform agricultural decisions). The person's outcome is determined jointly by his or her decision(s) and by the state of nature. A person can engage in games against nature using purely nonsocial information, but can also call upon social information (e.g., what most other people are doing or what the most successful people are doing), thus possibly fostering performance. In contrast, social games refer to situations involving social exchanges, in which other people create the most important aspects of an agent's "reactive" environment (Byrne & Whiten, 1988, p. 5). Simple heuristics enable the protagonists in these interactions to make adaptive decisions regarding, for instance, the allocation of tangible and intangible resources, the choice of allies and mates, and the deduction of others' intentions to name but a few of those decisions involving others.

Games Against Nature

When making inferences about states of the world, people may not only rely on physical cues but also use social information, that is, their knowledge of other's behaviors, attributes, intentions, and preferences. Consider, for instance, the task of predicting the magnitude of risks in one's environment (for example, Hertwig, Pachur, & Kurzenhäuser, 2005). Following the September 11, 2001, terrorist attacks, many people considered alternatives to flying and worried about the safety of various means of long-distance transportation. Lacking official statistics, one way to gauge which of two means of transportation, say, taking the train or taking a cross-country bus, involves a higher risk is to collect information distributed in one's social environment. One hypothesis about how people search for such information is the *social-circle heuristic* (Pachur, Hertwig, & Rieskamp, in press; Pachur, Rieskamp, & Hertwig, 2005). It embodies sequential search and one-reason decision making, but rather than retrieving probabilistic cues, it samples instances of the target events in question. The heuristic proceeds as follows:

Search rule—Search through social circles in order of their proximity to the decision maker, beginning with the "self" circle, followed by the "family," "friends," and "acquaintances" circles. Look up the instances of the class of events in question (e.g., experienced accidents involving trains versus cross-country buses) in the most proximate circle first, and tally them.

Stopping rule—If one class of events has a higher value (i.e., more instances) than the other, then stop search and proceed to the next step. Otherwise search the next circle. If the least proximate circle does not discriminate, guess.

One-reason decision making—Predict that the event with the higher tally has the higher value on the criterion (e.g., is more risky).

The social-circle heuristic suggests that the external hierarchical structure of a person's social network, measured in terms of degree of kin relationship (oneself, family; Hamilton, 1964) and reciprocal relationship (friends, acquaintances), guides the order of search for social information in the person's cognitive space. Such a search policy is adaptive because the individuals probed by the social-circle heuristic tend to be those about whom we have the most extensive, accessible, reliable, and veridical knowledge.

Like the availability heuristic (Tversky & Kahneman, 1973), the social-circle heuristic samples instances; unlike the former, however, this heuristic does so in a sequential and ordered way. The assumption that search starts with one's own experiences is consistent with the argument that the self acts as a superordinate schema facilitating encoding and subsequent retrieval of information (cf. Alicke, Dunning, & Krueger, 2005). There are now several studies that have analyzed the performance of the heuristic, relative to other heuristics and complex search models, and the conditions under which people use the social-circle heuristic (Pachur et al., 2005, in press).

Others not only provide useful information for our judgments or decisions, they can also help us to learn information that boosts the performance of our simple

heuristics used for making inferences, predictions, and decisions. One example is the learning of good cue orderings, a problem considered notoriously difficult by many researchers (see Katsikopoulos, Schooler, & Hertwig, 2010). Cues on which people base inductive inferences are typically uncertain, and the individual learning of cue validities (i.e., the relative frequency with which they correctly predict the criterion), apart from being computationally taxing (Juslin & Persson, 2002), can be dangerous (Boyd & Richerson, 2005). Indeed, people are not very efficient learners of cue validities (for example, Todd & Dieckmann, in press; but see Katsikopoulos et al., 2010). However, when individual learners are allowed to actively exchange information about their experience, they learn good cue orderings faster and perform better than individuals prohibited from coopting their social environment (Garcia-Retamero, Takezawa, & Gigerenzer, 2009). In other words, social exchange can enable individuals to efficiently and quickly learn the information that fosters the performance of their heuristics.

There is still another way that can help individuals to perform better in games against nature. The heuristic of imitating the behavior of others allows individuals to learn about the environment without engaging in potentially hazardous learning trials or wasting a large amount of time and energy on exploration (for example, Henrich & McElreath, 2003; Laland, 2001; Todd, Place, & Bowers, this volume, Chapter 11). The imitation heuristic, a prime example of social intelligence, is particularly versatile in that it can be more nuanced than an unconditional "do-what-others-do" heuristic. Depending on situational cues and opportunities, the behavior copied may be that exhibited by the majority (Boyd & Richerson, 2005; for example, of two similar restaurants, patrons tend to choose the one with the longer waiting queue; Raz & Ert, 2008), by the most successful individuals (as in the earlier example; Boyd & Richerson, 2005), or by the nearest individual. The crucial point is that using any variant of imitation (or even simpler forms of social learning; see Noble & Todd, 2002) can speed up and foster decision making by reducing the need for direct experience and information gathering.

Another route through which social learning can occur is by actively seeking the advice of others (rather than by just probing socially distributed information, for instance, as the social-circle heuristic does) and by interpreting institutional arrangements as implicit recommendations (for example, policy defaults; McKenzie, Liersch, & Finkelstein, 2006; Thaler & Sunstein, 2008). Advice taking can be seen as an adaptive social decision-support system that compensates for an individual's blind spots (Yaniv & Milyavsky, 2007).

How helpful is advice, and what if the wisdom of others widely diverges from or conflicts with one's own opinion? Consider a fund manager trying to predict the profitability of an investment tool (a game against nature). After asking each of her colleagues for a profitability estimate, she ends up with a heterogeneous set of numbers. How should she make use of them? From a prescriptive viewpoint, averaging the estimates from different people (and even one's own; Herzog & Hertwig, 2009) taps into the "wisdom of crowds" (Surowiecki, 2004) and is an efficient heuristic that exploits the principle of error cancelation and works very well under a wide range of situations (for example, Armstrong, 2001; Clemen, 1989; Larrick, Mannes, & Soll, this volume, Chapter 3; Soll & Larrick, 2009; Yaniv, 2004).

Social Games

We now turn to social games, that is, to exchanges between two or more agents. As with games against nature, we suggest that much of the decision-making processes in social games can be described in terms of simple heuristics. We illustrate this thesis with two examples: the equity heuristic, and fast and frugal trees in the ultimatum game.

Equity Heuristic

The equity heuristic (sometimes called *1/N* rule) is an example to support the conjecture that the cognitive processes of social intelligence may not be qualitatively different from the processes of nonsocial intelligence. This heuristic has been proposed to describe how people invest their resources in *N* options, with the options referring to either social (e.g., children) or nonsocial entities (e.g., saving options for retirement). Although dismissed by some behavioral economists as naïve (for example, Benartzi & Thaler, 2001), the heuristic competes well with optimizing strategies in environments with high uncertainty, a large number of assets, or with small learning samples. Such environmental properties impose a unique risk on complex strategies: Given environmental noise, complex strategies tend to overfit the data, which results in a lack of robustness (i.e., reduced accuracy) in predicting new data. DeMiguel, Garlappi, and Uppal (2009) compared the performance of the *1/N* allocation heuristic with the performance of optimizing mean variance, and various Bayesian and non-Bayesian models. The striking result was that with 10 years of investment data, none of the optimization models could consistently beat the simple *1/N* rule.

The equity heuristic also provides a model of how contemporary parents may allocate limited resources to their children (Hertwig, Davis, & Sulloway, 2002). Parental resources such as affection, time, and money (e.g., for education) are notoriously limited, and parents with more than one child need to constantly decide how to allocate their resources among their *N* children. Consistent with parents' expressed values in egalitarian societies, the heuristic predicts that parents attempt to split resources equally among all *N* children at any given investment period. This simple heuristic has several interesting properties. By implementing an equal ("fair") allocation of resources, it takes into account parents' inequality aversion (for example, Bolton & Ockenfels, 2000; Fehr & Schmidt, 1999; Hertwig et al., 2002). In addition, it permits parents to justify their allocation decisions to the "stakeholders" in the family: quarreling children and observant grandparents. Finally, it allows parents to (sometimes) hand over the actual implementation of the allocation to their children and invite them to make use of the time-honored heuristic, "I cut, you choose," in which one sibling divides the cake (or a chore) in two parts that she likes equally well, and the other one gets to pick the piece he prefers.[1] Yet, the equity heuristic is not a panacea. Although each single allocation decision is fair, the equity heuristic predicts inequalities on higher levels of aggregation.

As an illustration of how the equity heuristic works in the home, consider the allocation of parental time. Although the heuristic guarantees an equal distribution of parental time for any given period, the *cumulative* distribution will be unequal. Middleborns will receive less time than either first- and lastborns. Unlike their siblings, middleborns never enjoy a period of exclusive attention in the family. Such

inequalities in resource distribution—although smaller in size—will continue to exist even if parents attempt to find a reasonable compromise between equity and children's age-specific needs (Hertwig et al., 2002, p. 741).

Fast and Frugal Trees The ultimatum game has become a bogey for classic economists. A simple bilateral two-person strategic situation with perfect information produces robust behavior that is inconsistent with the classical economic prediction. The dominant response among those economists who accepted the reliability of the behavior was to assimilate it into the existing utility framework by modifying the utility function. Rather than retaining the universal utility calculus, however, one could heed Rubinstein's (2003) call and begin "to open the black box of decision making, and come up with some completely new and fresh modeling devices" (p. 1215). Hertwig, Fischbacher, and Bruhin (in press) did so by using the building blocks of simple heuristics to shed light on the processes in the ultimatum game. Focusing on mini-ultimatum games, in which the proposer chooses between two fixed-income distributions for both players (e.g., 3:5 versus 2:8) and the responder gets to accept or reject it, the authors modeled people's choice in terms of fast and frugal decision trees. A fast and frugal tree is defined as a tree that allows for a classification at each level of the tree (Martignon, Vitouch, Takezawa, & Forster, 2003). It consists of the same building blocks as the take-the-best heuristic: ordered search, one-reason stopping rule, and decision making on the basis of one reason.

To illustrate, the *priority tree*, one of four decision trees proposed by Hertwig et al. (in press), consists of three criteria for rejecting or accepting an allocation. The first criterion checks whether the offered allocation is larger than zero. If so, a homo economicus would accept it, regardless of its size. According to the status tree, however, a person now considers relative *status* as the second criterion. If the proposer selects the allocation in which the responder does, relative to the proposer, at least as well, the responder will accept it. No other reason enters the decision. If that is not the case (here: $2 < 8$), she does not reflexively reject. Instead, she considers a third criterion that involves a comparison between the actual and the forgone allocation, the *kindness* criterion. If the responder does at least as well as in the forgone distribution (here yes: $3 > 2$), she will accept the offered allocation. Only if the allocation also fails this test in kindness, will she reject.

Hertwig et al. (in press) described people in terms of fast and frugal trees involving one, two, three, or four criteria. Modeling responders' decisions in terms of fast and frugal trees enables tests of both decision and process. Recall that status trees assume a sequential process of examining up to three criteria. The more criteria are examined, the longer the decision will take. For instance, the status tree predicts that accepting an allocation based on the kindness criterion will take the longest. In Hertwig et al.'s study, people took significantly more time to accept allocations that failed the status test but passed the kindness test, relative to allocations that passed the status test. Explaining such differences in response times requires a process model and thus can hardly be accounted for by social preference models.

Models of heuristics are not new in studies of social games. The tit-for-tat strategy and its relatives such as "generous tit-for-tat" (Axelrod, 1984; Nowak & Sigmund, 1992), for instance, are among the famous strategies enabling and

restoring mutual cooperation in social dilemmas (see also Howard, 1988; Johnson & Smirnov, in press; Rieskamp & Todd, 2006). Another class of simple heuristics in social games is based on the emotion of anticipated regret (Hart, 2005). Regret is an emotion that may result when we relate the outcome of a previous decision to what we would have obtained had we opted for the rejected alternative. Hart's *regret-matching heuristic* suggests that a person continues with the current action if she does not anticipate any regret. If she realizes that a particular option may lead to feelings of regret, she switches to the other action with a probability proportional to the amount of regret. Hart concluded from his analytical results that "simple and far-from rational behavior in the short run [based on regret avoidance] may well lead to fully rational outcomes in the long run" (p. 1415).

Structures of Social Ecologies

Simple heuristics in the social world not only affect outcomes for the decision makers or their interactants, but they often have far-reaching social consequences. Some macro consequences simply reflect people's strategies and preferences. If many people prefer to spend their summer vacation at the beach, beaches will be overcrowded during this holiday season, and, conversely, overcrowded beaches allow us to draw inferences about where people desire to spend their vacations. However, there are interesting exceptions: Schelling (1978) observed that macrolevel patterns do not necessarily reflect microlevel intentions, desires, or goals. In his classic model on neighborhood segregation that initiated a large and influential literature, individuals with no desire to be segregated from those who belong to other social groups, nevertheless, end up clustering with their own type. Most investigations of Schelling's model and extensions thereof have replicated this result. There is an important mismatch, however, between theory and observation, that has received relatively little attention. Whereas Schelling-type models predict large degrees of segregation starting from virtually any initial condition, the empirical literature documents considerable heterogeneity in actual levels of segregation. Berg, Hoffrage, and Abramczuk (2010; see also Berg, Abramczuk, & Hoffrage, in press) introduced a mechanism that can produce significantly higher levels of integration and, therefore, brings predicted distributions of segregation more in line with real-world observation.

As in the classic Schelling model, agents in a simulated world want to stay or move to a new location depending on the proportion of neighbors they judge to be acceptable. In contrast to the classic model, Berg et al. (2010; in press) augmented agents with memory. This allows these agents to use a very simple heuristic, the FACE-recognition heuristic, to classify their neighbors as acceptable or not. This heuristic builds on an evolved capacity, namely, recording faces into recognition memory. At the same time, the acronym FACE (for *Fast Acceptance by Common Experience*) refers to the insight that shared local experience can facilitate rapid formation of relationships that absolutely overrules the inference that would have been made by stereotyping based on group identity. The classic Schelling model appears to be a special case in the FACE-recognition model: When agents have no recognition memory, judgments about the acceptability of a prospective neighbor rely solely on his or her group type (as in the Schelling model). A very small amount

of recognition memory, however, eventually leads to different classifications that, in turn, produce dramatic macrolevel effects resulting in significantly higher levels of integration. The model is intended to contribute substantively and constructively to policy analysis with a simple message, namely, that we can, relatively cheaply, design institutions that produce modest opportunities for face-to-face encounters with members of other groups. Then, to the extent that people use a simple acceptance rule based partially on recognition, random face-to-face intergroup mixing could potentially generate large and stable levels of integration even though they are ruled out by the vast majority of simulation studies based on Schelling's model.

CONCLUSION

Simon (1990) emphasized that almost any real-world problem is far too complex and requires too much computation to be solved by present or future computers. His paradigmatic case was chess. "Playing a perfect game of chess by using the game-theoretic minimaxing algorithm is one such infeasible computation, for it calls for the examination of more chess positions than there are molecules in the universe" (pp. 5–6). If a well-defined board game, which is limited to merely six different types of "players" (pieces) with exactly prescribed strategies and a space of 64 squares, is too complicated for calculating the optimal solution, then problems in a social world, involving potentially many more players and a wider range of strategies (including deception), will be even more computationally intractable. Although we do not doubt that the social world is complex—as has been emphasized by many theorists—we do not know whether it is any more complex than the physical one. Irrespective of this relative complexity issue, one strong conclusion from the social world's complexity is unwarranted in our view: the argument that successfully navigating the social world requires complex calculations, and that simple heuristics are therefore doomed to fail in social ecologies (a view that Sterelny, 2003, appears to advocate). Simon's conclusion from his premise that nearly all real-world problems are computationally intractable was what he called "one of the most important laws of qualitative structure applying to physical symbol systems, computers and the human brain included: *Because of the limits on their computing speeds and power, intelligent systems must use approximate methods to handle most tasks. Their rationality is bounded*" (p. 6; his emphasis). Following Simon, we believe that much of human reasoning and decision making in the physical and social world proceeds on the basis of simple heuristics. Not only do they permit organisms to make inferences and decisions without overtaxing their resources, they are also the mind's ace in the hole in the many real-word situations that defy optimal solutions.

AUTHOR NOTE

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NOTE

1. According to Brams and Taylor (1996, p. 10), the origin of this heuristic goes back to antiquity: "The Greek gods, Prometheus and Zeus, had to divide a portion of meat. Prometheus began by placing the meat into two piles and Zeus selected one." Interestingly, in a simple two-person, zero-sum cake-cutting game the heuristic achieves the efficient (pareto-optimal) solution. That is, if the cutter cuts the cake as evenly as possible to minimize the maximum amount the chooser can get, thus avoiding the worst (von Neumann's, 1928, minimax theorem), there will be no allocation that is better for one person and at least as good for the other person.

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