Decision Making: Nonrational Theories

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Abstract

In a world of known risks, rational theories provide the norms for successful behavior. In a world where not all risks are known and where optimization is not feasible, 'nonrational' tools such as heuristics are needed. In comparison to optimization models, heuristics are robust and can lead to more accurate predictions, while saving time and effort. The study of heuristics addresses the descriptive question of what heuristics an individual or institution has in their 'adaptive toolbox,' as well as the normative question of their ecological rationality, i.e., which heuristics in which situations are most accurate and effective.

Nonrational theories are not theories of irrationality. Rather, they dispense with unrealistic assumptions such as omniscience and optimization in the so-called rational theories. Most important, nonrational theories apply to 'decision-making under uncertainty,' where not all alternatives, consequences, and probabilities are known or knowable (e.g., whom to marry? what job to take? where to invest?). Rational theories, in contrast, are tailored to situations where all risks are known, as in lotteries and roulette ('decision-making under risk'), and where the optimal choice can be calculated. The majority of important problems lie between the two poles of risk and uncertainty, which indicate the necessity of considering both approaches.

Nonrational theories have been denoted by various terms, including *models of bounded rationality*, *procedural rationality*, *fast-and-frugal heuristics*, and *satisficing*. Although there is as yet no consensus on the definition of *nonrational*, these theories typically differ from rational theories on several dimensions, discussed below. The term *decision-making* is used broadly here to include both conscious and unconscious preference, inference, classification, and judgment.

As mentioned, the label *nonrational* should not be confused with irrational behavior: It signifies a type of process, not a type of outcome. In other words, the fact that nonrational theories postulate agents with emotions, limited knowledge, and little time – rather than omniscient 'rational' beings – need not imply that such agents fare badly in the real, uncertain world. We will focus on the theory of heuristics, which is probably the best developed among nonrational theories that do not rely on optimization (Gigerenzer et al., 2011).

Historical Background

A few historical remarks on rational theories help to set the stage. In the mid-seventeenth century, the calculus of probability replaced the ideals of certain knowledge and demonstrative proof (as in mathematics and religion) with a more modest vision of reasonableness. What may be called the first rational theory of decision-making, the maximization of expected value, emerged at this time. According to the theory, an option's expected value is the sum of the product of the probability and the value of each of its consequences; a rational decision-maker chooses the option with the highest expected value.

The notion of defining an option's reasonableness in terms of its expected value soon ran into problems because its prescriptions conflicted in some situations (e.g., the St Petersburg problem) with educated intuition. Daniel Bernoulli therefore proposed replacing the concept of expected value with that of expected utility. For instance, the utility of a monetary gain (say, of $1000) can be defined as a logarithmic function of its dollar value and the agent's current wealth, assuming that the utility of an additional dollar diminishes as the value of the gain and current wealth increase.

The fact that rational decision-making can be defined in more than one way – for example, as maximization of expected value or expected utility – has been interpreted both as the weakness and strength of the program. This ambiguity was one of the reasons why, by 1840, most mathematicians had given up attempting to define a calculus of reasonableness (Daston, 1988). With a few exceptions, rational theories of decision-making largely disappeared until their revival in the 1950s and 1960s. Only then did the major types of rational theories, the maximization of subjective expected utility and Bayesianism, become influential in the social and behavioral sciences. At about the same time, some psychologists and economists – most notably Nobel laureates Herbert Simon and Reinhard Selten – criticized the assumptions about the human decision-maker in modern rational theories as empirically unfounded and psychologically unrealistic, calling for alternative theories.

Optimizing versus Nonoptimizing Theories

Rational theories rest on the ideal of optimization. Optimization entails the calculation of the maximum (or minimum) of some variable across a number of alternatives or values. Nonrational theories, by contrast, apply in the situations where optimization is not feasible. In many real-world situations, no optimizing strategy is known. Even in a game such as chess, whose few rules are stable and well-defined, the optimal strategy (which in fact exists) cannot be computed by a human or a machine. And even when an optimizing strategy can be calculated, it may demand unrealistic amounts of knowledge about alternatives and consequences, particularly when the problem is novel and time is scarce. Acquiring the requisite knowledge can conflict with goals such as making a decision quickly; in situations of immediate danger, attempting to optimize can actually be deadly. In social and political situations, making a decision at all can take priority over searching for the best option. Most important, for decisions made under uncertainty (i.e., most of our decisions), strategies that do not attempt to optimize (heuristics) can outperform strategies that do. In other words, the concept of an optimizing strategy needs to be distinguished from the concept of an optimal outcome. In an uncertain world, there is no guarantee that 'optimization' will result in a good or optimal outcome. An example is the problem of allocating money to N funds. While Markowitz's Nobel prize-winning mean–variance portfolio is optimal under the assumptions made, in the real world of investment a simple heuristic, 1/N ("allocate your money equally to N assets"), can lead to better performance (DeMiguel et al., 2009).

Normative versus Descriptive Theories

Nonrational theories are descriptive, whereas rational theories are normative – this common distinction is only partly true. Indeed, theories of heuristics are concerned with psychological realism, that is, the capacities and limitations of actual humans, whereas rational theories have little concern for descriptive validity and tend to assume omniscience. But theories of heuristics are normative as well. For instance, in situations where an optimization strategy is nonexistent, unknown, or dangerous because it would impede decision-making, a simple heuristic – such as imitating the behavior of others – can be the better strategy.

Rational theories typically do not assume that agents actually perform optimization or have the knowledge needed to do so. Their purpose is not to describe the reasoning process, but to answer a normative question: What would be the best strategy for an omniscient being to adopt? In economics, psychology, and animal behavior, however, the answer to this question is sometimes used to predict actual behavior. In this way, a rational theory can be descriptive of behavioral outcomes, yet be mute about underlying processes. For instance, optimal foraging theory assumes that animals select and shift between food patches *as if* they had perfect knowledge about the distribution of food, competitors, and other relevant information, without claiming that real animals have this knowledge or perform optimizing computations. Instead, it is assumed that animal behavior has evolved to be close to optimal in specific environments. The question of what proximal mechanisms produce this behavior is a different one. These mechanisms may be simple heuristics such as 1/N and social imitation; that is, the topic of theories of nonrational decision-making.

Ecological Rationality versus Internal Consistency

A classical criterion for rational choice is internal consistency or coherence. Numerous rules of consistency have been formulated: for instance, transitivity and additivity of probabilities. Beginning with in the work of Jean Piaget and Bärbel Inhelder, these rules, which are the building blocks of rational theories, have been used to investigate the development of human thinking. Theories of heuristics, in contrast, place less weight on internal consistency; some heuristics, for instance, can violate transitivity. Instead, their emphasis is on performance in the external world, both physical and social. Measures of external performance include the accuracy, speed, frugality, transparency, and accountability of decision-making. Note that internal consistency does not guarantee that any of these external criteria are met. For instance, although the statement 'there is a 0.01 probability that cigarette smoking causes lung cancer and a 0.99 probability that it does not' is internally consistent in that the probabilities add up to 1, according to relevant research, it is not accurate.

The study of the ecological rationality of heuristics, or strategies in general, is a framework to study performance in the external world: A heuristic is ecologically rational to the degree that it is adapted to the structure of the environment. Heuristics are 'domain-specific' rather than 'domain-general'; that is, they work in a class of environments in which they are ecologically rational. Heuristics provide not a universal rational calculus but a set of domain-specific mechanisms similar to the parts of a Swiss army knife, and have been referred to collectively as the 'adaptive toolbox' (Gigerenzer and Selten, 2001). Thus, the important research question is to specify, for a given heuristic, the structures of environments in which it is faster or more accurate than other strategies in achieving a goal.

For instance, the 1/N heuristic is likely to lead to better returns than the mean–variance portfolio when (1) uncertainty is high (as in the real stock market), (2) sample size is small (typically not more than 10 years of data used by banks), and (3) N is large (because estimation error increases with N). The study of ecological rationality fleshes out Simon's scissors analogy: "Human rational behavior (and the rational behavior of all physical symbol systems) is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor" (Simon, 1990: p. 7). By looking at only one blade, cognition, it is impossible to understand why and when a behavior succeeds or fails.

Structures of Environments

While some optimization theories treat decision-making as if there were only one tool – maximization of expected utility – the study of decision-making under uncertainty shows that people rely on several tools, not just one. Simple heuristics can succeed by exploiting the structure of information in an environment. In other words, the environment itself can do part of the work for the heuristic. Environmental structures that have been identified to be important in determining the success of heuristics in comparison to other strategies include:

1. Uncertainty: how well a criterion can be predicted.
2. Sample size: number of observations (relative to number of cues).
3. Number of alternatives (N).
4. Redundancy: the correlation between cues.
5. Variability in weights: the distribution of the cue weights (e.g., skewed or uniform).

For instance, heuristics that rely on only one reason, such as *take-the-best* (see below), tend to make more accurate predictions than do strategies such as linear regression in environments with (1) moderate to high uncertainty and (2) moderate to high redundancy. The study of ecological rationality results in comparative statements of the kind "strategy X is more accurate (frugal, fast) than Y in environment E," or in quantitative relations between the performances of strategy X when the structure of an environment changes. Specific findings are introduced in Section Classes of Heuristics.

The concept of ecological rationality should not be confused with the biological concept of adaptation: A match between a heuristic and an environmental structure does not imply that the heuristic evolved because of that environment. Nor does ecological rationality mean that the mental representation mirrors the world: A heuristic is functional, not a veridical copy of the world.

Robustness

A second reason why a simple heuristic can make accurate predictions is robustness. To understand this point, it is necessary to distinguish between data fitting (i.e., determining the best-fitting parameter values for a model given a specific body of data) and prediction (i.e., using these parameter values to predict new data). For data fitting, it generally holds that the more parameters a model has, the better the fit, whereas for prediction there can be a point where less is more. For instance, when recording the air temperature on all 365 days of a year, one can fit the resulting jagged curve increasingly well by adding more free parameters to the model. However, for predicting the daily temperature in the year thereafter, the model that best fits the past data may be less accurate in predicting than a simpler model with fewer parameters and a worse fit. More generally, in noisy environments only part of the available information generalizes to the future. The art of building a good model is to find this part and to ignore the rest. The more noise in the environment, the more models with many free parameters tend to overfit, that is, reflect the noise in a specific sample. Overfitting can become a problem when overly powerful mathematical models, such as neural networks with numerous hidden units and multiple regression with many predictors, are used to fit and then predict behavioral data. Simplicity can reduce overfitting and thereby produce robust decision strategies. A general formulation for when and why one should simplify is the bias–variance dilemma (Geman et al., 1992).

In much research on reasoning, a *bias* typically refers to ignoring part of the information, as in the base-rate fallacy. This can be captured by the equation:

$$\text{Error} = \text{bias} + \varepsilon \qquad [1]$$

where ε is an irreducible random error. In this view, if the bias is eliminated, good inferences are obtained. In statistical theory, however, there are three sources of errors:

$$\text{Error} = \text{bias}^2 + \text{variance} + \varepsilon \qquad [2]$$

where *bias* refers to a systematic deviation between a model and the true state, as in eqn [1]. To define the meaning of *variance*, consider 100 people who rely on the same strategy but have different samples of observations from the same population. Because of sampling error, the 100 predictions may not be the same. Across samples, variance is the expected squared deviation around their mean, while bias is the difference between the mean prediction and the true state of nature.

Consider the problem many companies face in predicting which of their thousands of customers will continue to be active, that is, make purchases in the future. To do so, the Pareto/negative binomial distribution (NBD) model relies on complicated math to estimate its four free parameters from previous data. In contrast, the hiatus heuristic used by experienced managers classifies customers as active only if they have made a purchase within the last 9 months (the hiatus). It was shown to predict customer purchases more accurately than the Pareto/NBD model, despite using less information (Wübben and von Wangenheim, 2008). The bias–variance dilemma provides an explanation for this less-is-more effect. Because the hiatus heuristic does not need to estimate any parameters, it has zero variance, although it probably has a strong bias. In contrast, the Pareto/NBD model likely has a smaller bias but, nevertheless, a larger overall error because it additionally suffers from variance.

Variance decreases with increasing sample size, but also with simpler strategies that have fewer free parameters (and less flexible functional forms; Pitt et al., 2002). Thus, a cognitive system needs to draw a balance between being biased and flexible (variance), rather than simply trying to eliminate bias. Heuristics can be fast, frugal, and accurate by exploiting the structure of information in environments, by being robust, and by striking a good balance between bias and variance. This bias–variance dilemma helps to understand the rationality of simple heuristics and why less can be more (Brighton and Gigerenzer, 2008).

Classes of Heuristics

A heuristic is a strategy that ignores part of the information, with the goal of making decisions more accurately, quickly, and frugally (i.e., with fewer pieces of information) compared to more complex methods. Heuristics are defined by common *building blocks* from which the various heuristics are constructed as an organizing principle. This allows the larger number of heuristics to be reduced to a smaller number of components, similar to how the chemical elements in the periodic table are built from a small number of particles. Three building blocks have been proposed:

1. *Search rules* specify in what direction search extends in the search space.
2. *Stopping rules* specify when search is stopped.
3. *Decision rules* specify how the final decision is reached.

Different classes of heuristics have been specified, all of which can be described in terms of these building blocks. Fast-and-frugal heuristics model decision-making as a dynamic process in which cues or reasons are sequentially searched for – in memory or in the outside world – and inferences are determined by simple stopping and decision rules. The challenge is to understand what the class of heuristics is, how a heuristic is selected, and in which environments it is successful. The following summary is based on Gigerenzer and Gaissmaier (2011), where further references can be found.

Recognition-Based Decision-Making

The recognition memory literature indicates that a sense of recognition (often called *familiarity*) appears more quickly than recollection in consciousness. This core capacity is exploited by the first class of heuristics. The goal is to make inferences about a criterion that is not directly accessible to the decision-maker, based on recognition retrieved from memory. Prominent heuristics in this class are the recognition heuristic and the fluency heuristic.

Recognition Heuristic

If one of two alternatives is recognized and the other is not, infer that the recognized alternative has the higher value with respect to the criterion (Goldstein and Gigerenzer, 2002). This heuristic is ecologically rational in an environment (reference class) R to the degree the recognition of alternatives a, b ∈ R positively correlates with their criterion value. If the correlation between recognition and the criterion is sufficiently large, a counterintuitive result is observed: Knowing fewer alternatives can lead to more accurate predictions than knowing more alternatives because people who recognize both alternatives cannot use the heuristic.

The recognition heuristic is a model that relies on recognition only and assumes that people will ignore strong, contradicting cues (the so-called noncompensatory inferences). Much research in the past decade was devoted to investigating to what degree people actually rely on the recognition heuristic in such a noncompensatory fashion, and what the boundary conditions are. Additionally, research has identified several environments in which, from a prescriptive perspective, the recognition heuristic is ecologically rational and can compete with well-established forecasting instruments. These environments include the prediction of sports results such as Wimbledon or soccer, election outcomes, university rankings, and geographical properties such as the size of cities or mountains (for a recent overview of the discussion, see Marewski et al., 2011).

Fluency Heuristic

If both alternatives are recognized but one is recognized faster, then infer that this alternative has the higher value with respect to the criterion (Schooler and Hertwig, 2005).

The fluency heuristic is ecologically rational if the speed of recognition is correlated with the criterion, that is, the fluency validity >0.5. Fluency has been shown to predict the performance of stocks, sales figures, and wealth. The validity of fluency is typically lower than that of recognition, but above chance. Fluency also plays a role when alternatives are not given (as in two-alternative choice) but need to be generated from memory. Johnson and Raab (2003) showed, for instance, that experienced handball players can successfully rely on the first alternative that comes to mind when deciding which move to make in a game (a strategy they called *take-the-first*).

One-Reason Decision-Making

While the recognition and fluency heuristics base decisions on recognition information, other heuristics rely on recall. One class looks for only one 'clever' cue and bases its decision on that cue alone, as in the hiatus heuristic (see above). A second class involves sequential search through a number of cues but also bases its decision on just one. Examples include lexicographic rules and elimination-by-aspect (Tversky, 1972). These heuristics were originally developed for preferences; here, the focus is on models of inferences.

One-Clever-Cue Heuristics

What this class of heuristics has in common is that a decision is based on one specific cue only. Many animal species appear to rely on one cue for locating food, nest sites, or mates. For instance, to catch a fly ball high in the air, baseball players rely on the gaze heuristic "*fixate your eye on the ball, start running, and adjust the running speed so that the angle of gaze remains constant.*" Variants of this heuristic that rely only on the optical angle have been observed in bats, birds, and fish when pursuing a prey or a mate. Similarly, to choose a mate, peahens have been reported to investigate only three or four of the peacocks displaying in a lek and choose the one with the largest number of eyespots (Petrie and Halliday, 1994). The ecological rationality of one-clever-cue heuristics is not entirely clear at this point in time, but candidates are environments where the variability of cue weights and redundancy is moderate to high and sample size is small (Hogarth and Karelaia, 2007).

Take-the-Best Heuristic

This heuristic is a model of how to infer which of two alternatives has a higher value on a criterion, based on binary cue values retrieved from memory: *Search through cues by their validities, and stop search when the first cue is found that allows for a decision.* A striking discovery was that take-the-best's predictions can be more accurate than those of linear multiple regression models (Czerlinski et al., 1999) and complex nonlinear strategies such as an exemplar-based model (nearest-neighbor classifier), Quinlan's decision-tree induction algorithm C4.5, and classification and regression trees (CART) (Brighton and Gigerenzer, 2008). Research on the ecological rationality of take-the-best suggests two structures of environments it can exploit: moderate to high cue redundancy and moderate to high variability in cue weights (Hogarth and Karelaia, 2007). And it is precisely these features that determine when people's inferences can best be predicted by take-the-best and when they cannot, indicating adaptive strategy use (Bröder, 2012). Variants of take-the-best have been successfully applied to model consumer choice and improve literature search.

Fast-and-Frugal Trees

One way to model classification is in terms of trees. For instance, for m binary cues or attributes, Bayes' rule can be represented as a tree with 2^m leaves. In contrast, a fast-and-frugal tree is defined as a tree with $m+1$ exits only, with exits at each cue: *Search sequentially through cues, and stop search as soon as a cue leads to an exit* (Martignon et al., 2003). When the number of cues grows, a Bayesian tree becomes computationally intractable or fraught with estimation error because one typically has too few data points for the thousands of 'leaves' of such a gigantic tree. In contrast, a fast-and-frugal tree needs to estimate fewer parameters and is likely more robust. Fast-and-frugal trees are used by experts in many fields, from emergency medicine to bail decisions.

Trade-off Heuristics

Unlike recognition-based and one-reason decisions, the third class of heuristics weights cues or alternatives equally and thus makes trade-offs (compensatory strategies).

Tallying

Whereas take-the-best ignores cues (but includes a simple form of weighting cues by ordering them), tallying ignores weights and simply counts the number of cues favoring one alternative to others. Dawes (1979) showed that tallying was about as accurate as multiple regression in its predictions and sometimes even better. In a more extensive test across 20 environments, Czerlinski et al. (1999) demonstrated that tallying had, on average, a higher predictive accuracy. The challenge is to figure out *when* this is the case. Einhorn and Hogarth (1975) found that unit-weight models were more successful than multiple regression when the ratio of alternatives to cues was 10 or smaller, the linear predictability of the criterion was small ($R^2 \leq 0.5$), and cues were highly redundant. Successful applications of variants of tallying include predicting strokes with simple bedside rules (which actually outperformed magnetic resonance imaging (MRI) in this regard) and avoiding avalanches.

Mapping Model

How do people arrive at quantitative estimates based on cues? The mapping model assumes that people tally the number of relevant cues with an object's positive values (von Helversen and Rieskamp, 2008). The estimate is the median criterion value of objects with the same number of positive cues. People's judgments were better captured by this model than by a linear regression and an exemplar model when the criterion values followed a skewed distribution, and it was successfully applied to predict sentencing decisions.

1/N Heuristic

Another variant of the equal weighting principle is the 1/N heuristic (also known as the *equality heuristic*), which is a simple rule for the allocation of resources (time, money) to N alternatives. Use of this heuristic has been reported for financial investment (see above), parental investment, and as a tool for fair allocation of money in experimental games.

Aspiration Level Theories

Simon (e.g., 1956, 1982) proposed a heuristic known as *satisficing*, which allows an agent to make a decision without evaluating or even knowing all the alternatives: *Set an aspiration level, search through alternatives sequentially, and stop search as soon as an alternative is found that satisfies the level.* An aspiration level is either a value on a goal variable (e.g., profit or market share) or, in the case of multiple goals, a vector of goal values that is satisfactory to the agent. For instance, agents might set a lower limit on the price at which they would be willing to sell their shares in a company (the aspiration level). In this satisficing model, the agent makes no attempt to calculate an optimal stopping point (here, the best day on which to sell). The aspiration level need not be fixed but can be dynamically adjusted to feedback. For instance, if the investors observe that the share price is monotonically increasing rather than fluctuating over time, they might conclude that there is some stable trend and adjust the limit upward. Thus, aspiration level theories model decision-making as a dynamic process in which alternatives are encountered sequentially and aspiration levels stop search. The challenge is to understand where aspiration levels come from in the first place (Selten, 1998; Simon, 1982).

Summary

In a world of known risks, rational theories provide the norms for successful behavior. In a world where not all risks are known, statistics and logic are not sufficient – additional tools, such as heuristics, are needed. Although heuristics are often classified as nonrational, there is nothing irrational about them. The study of the adaptive toolbox analyzes the heuristics that an individual, a profession, or society relies on to deal with an uncertain world. While this analysis is descriptive, the study of the ecological rationality addresses the normative questions of what heuristic to rely on in what situation. The emerging science of heuristics shows when and why complex problems do not need complex solutions, and why less information can be more.

See also: Apprenticeship and School Learning: Lessons from Germany; Control Behavior: Psychological Perspectives; Health Self-Regulation, Motivational and Volitional Aspects of; Personal Projects; School Achievement: Motivational Determinants and Processes; Self-Regulation in Adulthood; Successful Aging in Western Societies: The 'Selection, Optimization, and Compensation' Model; Vocational Interests, Values, and Preferences, Psychology of.

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