RATIONALITY: JUDGMENT UNDER UNCERTAINTY

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Some things are true. Water runs downhill; bats fly and bears don't; wherever Ethan goes his head goes too. But some things arc decidedly less certain. Your children might take care of you in old age; the rain might he sufficient for a good harvest; your friend might he telling you the truth. As used by cognitive psychologists, the term **rationality** refers to our ability to make judgments and choose courses of action under conditions of uncertainty. Over the last several hundred years, mathematicians have developed the field of probability expressly for dealing with and quantifying this kind of uncertainty. There is no doubt that probability theory provides a useful formal tool for modeling uncertain causal relationships. But among cognitive psychologists there is considerable discussion about whether probability theory provides a useful model of rationality, that is, whether it reflects how people actually make judgments under uncertainty.

Bounded Versus Unbounded Rationality

Gerd Gigerenzer and Peter Todd (1999) outlined three views of rationality. An **unboundedly rational** individual has unlimited knowledge, unlimited computational ability, and unlimited time to do the calculations. Suppose you were deciding whether to marry. An unboundedly rational approach would first identify every possible outcome for both of the two alternative decisions and assign sonic probability to each, since no individual outcome is certain. Next, it would assign a "utility" (a measure of desirability, which could be either positive or negative) to each identified outcome. Then, it would multiply the probability by the utility for every possible outcome. Finally, it would total these products for the "marry" and "not marry" choices and select the choice with the higher total score. Is that how you make this kind of decision? Gigerenzer and his colleagues think not.

Trail Marker: Unbounded rationality would squander cognitive resources.

Another school of thought, whose theory of rationality is called **optimization under constraints,** has offered a possible escape from these interminable calculations. They recognize that computational resources arc limited and that **stopping rules** are needed to determine when enough possible outcomes have been evaluated. To accomplish this, they suggest that we should evaluate whether considering each successive outcome justifies the additional computational costs of doing so. Now, this is *not* a solution! It compounds the problem by adding an additional layer of computation: Not only do the outcomes have to be evaluated, but also the benefits of performing each evaluation have to be weighed. Optimization tinder constraints requires even more cognitive resources than the approach it claims to simplify, and thus it represents just another version of unbounded rationality.

Trail Marker: Optimization under constraints would be even more wasteful.

Gigerenzer and Todd's alternative to these computational nightmares is what they call **bounded rationality.** It explicitly recognizes that computational resources are limited and that speed is often critical in real-world decision situations. Thus evolution should build what Gigerenzer calls **fast and frugal heuristics** that solve real-world problems quickly with a minimum of information. A heuristic could be a simple rule Of thumb (for example, if it's bigger than a bluejay, it's probably a hawk), or it may involve a few more steps. But the computationally bulky approaches of unbounded rationality and optimization under constraints are far too complex to qualify as heuristics. We will see some examples of fast and frugal heuristics shortly.

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Heuristics and Biases

Unfortunately, there is another debate among cognitive psychologists that crosscuts the one about bounded and unbounded rationality, and we must visit it before we can fully develop the idea of fast and frugal heuristics. This debate begins with the work of Amos Tversky and Daniel Kahneman (Tversky & Kahneman, 1974; Kahneman, Slovic, & Tversky, 1982). They acknowledge that cognitive processes are based on heuristics but claim that these heuristics produce inaccurate output.

For example, try this problem. How many seven-letter words in this chapter have the form -----n- that is, how many have *n* as the next-to-last letter? Write down your estimate. Now, in contrast, how many seven-letter words in this chapter have the form ----ing? Again, write down your estimate. If you are like most people, you wrote a higher estimate for ----ing than for -----n-, but does that make sense? Every single *-ing* word also has *n* as the next-to-last letter, and quite a number of seven-letter words, such as *content, present,* and *confine,* also have *n* as their next-to-last letter without being ----ing words. So, if you estimated that there were more ----ing words than -----n- words, you were wrong. Why do people tend to make this mistake?

According to Tversky and Kahneman, we make mental errors and give biased estimates because of the heuristics our minds use. One example is the so-called **availability heuristic.** The availability heuristic leads us to overestimate the frequency of things that come easily to mind. For example, in the ----ing versus -----n-problem, ----ing words are easier to think of (are more available to memory) than are words that have *n* as the next-to-last letter (Tversky & Kahneman, 1983). The problem, as you can see, is that using the availability heuristic can give you the wrong answer. In other words, using heuristics to solve problems can produce biases.

Do Heuristics Cause Bias, and If So, How?

There has been considerable debate over heuristics and the kinds of biases they supposedly cause. You learned earlier in this chapter that recall is very responsive to practice. Put in heuristic terms, more frequent events should be more available to memory. We learned also that availability depends on the retention and spacing effects. But if availability mirrors real-world patterns of occurrence (as Anderson and Schooler argue), availability should not produce biased judgments. In other words, we need to specify how the availability heuristic works. What factors (beyond practice, retention, and spacing) make one kind of memory more available than another? We do not, have answers to these questions because at present this heuristic is poorly defined. This is problematic. Poorly defined ideas are difficult to test and can actually slow scientific progress because it is hard to say exactly what experimental result would falsify them.

Trail Marker: No one has yet described how the availability heuristic works.

There is another reason why claims about mental heuristics and biases deserve careful examination. If heuristics consistently produce incorrect judgments, they are puzzling from an evolutionary perspective. If these thinking rules give us wrong answers, why have they become part of the mind's standard equipment? Perhaps heuristics produced more accurate judgment in the EEA. In other words, the tasks presently used to evaluate heuristics may be artificial in terms of what the heuristic was designed to do.

In some cases that is clearly true. Estimating the frequency of -----n- versus ----ing words is an artificial task at a number of levels. Obviously, spelling is not something that preoccupied our Pleistocene ancestors. Even in the modern literate world, normal adults do not process words letter by letter, but in larger, more meaningful chunks. In English, *ing* carries grammatical meaning (it forms the present participle of a verb), whereas *n* by itself has no meaning at all. Perhaps it is this difference in meaningfulness that explains the availability effect in the word-estimating task.

Consider a visual analogy. Computer screens and printers represent images with arrays of differently colored dots, or *pixels.* Our brain interprets the pattern of pixels as a real scene: a baby taking its first steps, an abandoned house in a sea of long grass, a coiled rattlesnake. You would probably remember these meaningful scenes, but you would not remember which one had a green pixel at sonic particular location, because all by itself, the green pixel is meaningless. The look on the baby's face, the broken windows of the house, and the snake's rattle are, like the *ing* ending, final or near-final output from complex information-processing modules. We need final output to be accessible. In contrast are we probably better off if lower levels of this processing—such as the green pixel and the n—are kept from cluttering up our consciousness, that is, if they are less available to memory.

Of course, this idea—that higher levels in the processing hierarchy are more available to memory—may be wrong, but at least it is specific enough to be testable. We mention it to illustrate the kind of refinement that must be proposed and tested in order to discover what mental processes are responsible for (any) availability effects. We cannot say whether heuristics cause bias until we can specify exactly what a proposed heuristic is doing. This is exactly the line that Gigerenzer and his associates have been pursuing in their research on fast and frugal heuristics.

Fast and Frugal Heuristics

Taking an evolutionary view, Goldstein and Gigerenzer (1999) argue that any heuristics shaped by natural selection would, on average, have to give the right answer, and they would have to do so economically in terms of time and information.

The simplest example of a fast and frugal heuristic is the **recognition heuristic.** Suppose you are asked to select which of two cites has the larger population. If you have heard of one and not the other, simply select the one you have heard of as the larger. Recognition demonstrates an important property of fast and frugal heuristics: They take advantage of the information contained in the environment itself. For example, more events take place in cities with large populations, and they have more institutions, such as museums, and stadiums. These attractions make it more likely that you will have heard of a large city than of a small one. Thus, using the very simple criterion of recognition *automatically* builds all this information into your decision.

Trail Marker: Fast and frugal heuristics exploit information contained in the environment.

Of course, the recognition heuristic will not work whenever both entities arc recognized. The **one-good-reason** class of heuristics perform well in these cases (Gigerenzer and Goldstein, 1999). These heuristics are still fast and frugal, because they consider only one factor at a time and make only same-or-different judgments. Continuing with the population size example, there are a variety of features that bigger cites arc more likely to have: universities, high crime rates, skyscrapers, professional baseball teams, and the like. Thus when both cities are recognized, the presence or absence of these features can be used as a cue to a city's size. For example, cities with a university tend to be bigger than those without one. So, if only one city has a university, select it as the larger city. If neither do, or both do, go on to another cue until you find a cue on which the two cities differ. The various one-good-reason heuristics differ in how they select cues. The minimalist heuristic picks cues in random order. Take-the-last starts with the cue that discriminated the last pair of cities. Take-the-best starts with the cue that is known to be the best predictor based on any previous experience.

Czerlinski and colleagues (1999) tested these fast and frugal heuristics alongside several other computationally more demanding algorithms, for example, the formal statistical tool of multiple regression. They did so not just for judgments about population size but for 20 different classes of judgment problems from the domains of sociology, demography, economics, health, and environmental science. Stunningly, take-the-best outperforms all competing algorithms, even though it bases its judgments on a single cue, while at least two of the competitors consider all available cues.