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Postscript: Vague Heuristics Revisited

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Although we continue to disagree with Gigerenzer, Hoffrage, and Goldstein (2008) on a number of points, including the interpretation of data said to be consistent with the use of Take The Best (TTB), their reply has led to considerable clarity regarding the underlying assumptions of probabilistic mental models (PMM), TTB, and the recognition heuristic. Ironically, this new found clarity has led to more questions about the functioning of their heuristics rather than fewer and has exposed PMM, TTB, and the recognition heuristic to the much more damning criticism that they are nothing more than vaguely specified process models or heuristics. Moreover, Gigerenzer et al.'s (2008) reply expounds some of the problems with the fast and frugal approach, namely that there are no constraints on how large the fast and frugal toolbox can grow. In the subsequent sections, we detail the components of PMM, TTB, and the recognition heuristic that require specification and how this lack of specification leads us to conclude that they reduce to vague heuristics of the sort Gigerenzer (1996) argued against in his critique of Kahneman and Tversky's (1996) work.

TTB Does Not Assume an Ordering Based on Ecological Validity

Gigerenzer et al. (2008) portray our belief that cue validity is the same as ecological validity as a misconception (see their Table 1). To be sure, our apparent misconception is not without basis, as there seems to be a general misuse of the term TTB in the literature. For example, Dieckmann and Todd (2004, p. 310) explicitly stated that TTB requires knowledge of ecological cue validities:

> Although TTB is a very simple heuristic to apply, the set-up of its search rule requires knowledge of the ecological validities of cues. This knowledge is probably not usually available in an explicit precomputed form in the environment, and so must be computed from stored or ongoing experience.

Likewise, Gigerenzer himself has equated TTB with use of the ecological cue orders when he stated, "We gathered 20,000 cue orders that each social rule produced until the 100th trial. Then, we classified them depending on whether they achieved a better performance than (1) the ecological cue validities order (i.e., TTB). . ." (Garcia-Retamero, Takezawa, & Gigerenzer, 2006, p. 1356). Moreover, the impressive accuracy of TTB illustrated by Gigerenzer and Goldstein (1996) and others (e.g., Todd & Dieckmann, 2005) used the ecological cue validities to determine the cue order for TTB. Finally, as an ecological model, it is natural to assume that the subjective cue validities would have some correspondence to the ecological cue validities.

However, if TTB does not assume that cue validities are ordered by ecological cue validities, what does it assume? Gigerenzer et al. (2008) are noncommittal on how cues are ordered, stating on manuscript page 7 that,

> "Take The Best algorithm assumes a subjective rank order of cues" (Gigerenzer & Goldstein, 1996, p. 653), not an order in terms of their ecological validities. Note that Take The Best needs only to order cues, not to compute quantitative values for cue validities (Table 1).

Their main argument is that individual cue learning results in a subjective cue order specific to an individual subject that need not correspond to the ecological cue validity. If we cannot assume that the cue validities are defined by the ecology, then what is the subjective rank order based on? If one's subjective rank ordering does not correspond to the best cue order (as defined by the ecology), then are they still using TTB? We are left assuming that TTB operates on ANY subjective cue order, even if it were completely idiosyncratic or, worse, negatively correlated with the ecological cue validities, so long as the decision maker uses a consistent order. Do we not need to specify what we mean by TTB for it to avoid reducing to a vague heuristic? Either the label "TTB" is tautological or it has been modified from literally TTB as defined by the ecology to TTB as defined by one's particular learning process. If the latter, then the challenge is to develop learning models that can be used to identify how an individual's cue order is derived.

Gigerenzer et al. (2008, p. 232) acknowledged that individual learning may be "practically impossible when the events are rare or feedback absent or unreliable" and appealed to social learning and evolution as alternative mechanisms by which cue orders can be constructed. Obviously, we do not dispute the possibility that people might search for cues in an order suggested by an experimenter's instructions (e.g., Rieskamp & Hoffrage, in press; Rieskamp & Otto, 2006) or social learning. We also do not dispute the possibility that evolutionary pressures might result in a preference for particular cues. However, neither of these methods for learning cues orders provides us with much insight into the cognitive processes underlying TTB. The social learning mechanism, for example, starts with the assumption that an individual has learned a cue order and then shares his or her knowledge with others.

The Frequency Processing Mechanism Need Not Be Specified

Gigerenzer et al. (2008) remained noncommittal on the precise nature of frequency encoding, suggesting that because TTB uses a subjective rank ordering of validities (not ecological validities), there is no need to specify the frequency representation on which cue validities are computed. Indeed, if we assume that the subjective rank ordering is based on social learning or evolution, then there is little need to specify a frequency process. However, if we assume that people maintain an ordering of cue validities constructed through individual learning, then one needs to specify the basis of this ordering. What type of process would allow one to learn a hierarchy of cues that retained the true statistical structure of one's environment? Gigerenzer, Hoffrage, and Kleinbölting (1991) proposed the provocative idea that the statistical relationship between cues and criteria could be inferred from a conditional probability, which they defined as cue validity (see Dougherty, Franco-Watkins, & Thomas, 2008, Equation 1). However, computation of this formula requires frequency information: Among all pairs of cities in a well-defined reference class where one city has monuments and the other does not, what is the relative frequency with which the larger of the two cities is characterized by the presence of monuments and the smaller of the two is characterized by the absence of monuments? Whether this formula is computed on almanac-like knowledge or from memory, it requires an estimate of relative frequencies. Even a subjective ordering of cue validities requires that the individual compute the quantitative values. Moreover, quantitative values are required if the cue ordering is to maintain its ecological adaptiveness, for example, when one's reference class or ecology changes. Any model that assumes that participants have a precomputed cue order, such as TTB, should be able to describe both how the cue order is derived and the underlying memory processes on which the learning of the cue order is based. For cue orders based on cue validity, this requires that one commit to specific assumptions regarding the representation of frequency information on which cue validities are computed. In the absence of understanding the basis of the frequency representation, we are left with a vaguely specified process for the computation of cue validity.

People Can Infer Missing Information

Gigerenzer et al. (2008) made a cogent argument for how people might be able to encode missing information. They pointed out that the absence of a cue may well be noticed within a particular context (e.g., no pepper in a chili recipe). However, in many cases, the reference class (i.e., the context) is not defined in such a way to draw attention to noticing the absence of potentially relevant cues. Does one encode all cities with respect to presence or absence of national sports teams, presence and absence of monuments, and presence and absence of Ferris wheels? No. Yet this would be necessary for the cue to work when called on. Without explicitly looking for absent information, Gigerenzer et al. asserted that people can infer its absence. However, just like the inference processes of TTB and recognition, we are left without a specification of how this inference process works. How do people infer missing information? Gigerenzer et al. argued that in cue-based inferences, "the absence of highly associated information would be registered" (Gigerenzer et al., 2008, p. 232, manuscript p. 9). Such a process requires that we have a way of defining the context (or reference class) over which the missing cue can be inferred and a process for operationalizing what we mean by "highly associated." If we were to accept Gigerenzer et al.'s conjecture that people can infer missing information, do we not need a model of (probabilistic) cue inference to avoid cue inference being reduced to a vague process?

The Recognition Heuristic Is Not a Model of Memory

Goldstein and Gigerenzer (2002, p. 77) stated that, "the recognition heuristic does not address comparisons between items in memory, but rather the difference between items in and out of memory," and that, "Experiments that use nonwords or never-seen-before photographs capture the distinction of interest here: that between the truly novel and the previously experienced." Nevertheless, Gigerenzer et al. (2008) have clarified that the true functioning of the recognition heuristic operates on a yes–no recognition judgment and not on the binary status of items in and out of memory. Obviously, we do not dispute the idea that the recognition heuristic operates on a yes–no recognition judgment. However, if the recognition heuristic merely operates on the output of the memory system, without specifying the process details of that system, then it reduces to a vague heuristic: To derive predictions based on the recognition heuristic, one needs to instantiate it at the level of a recognition memory model, as has been done by Pleskac (2007) and Schooler and Hertwig (2005). In fact, as was eloquently illustrated by Pleskac's analysis, the predictions of the recognition heuristic become crucially dependent on the particular model chosen, the parameters of the model, and/or the distribution of the underlying memory activations. Without being instantiated within the context of a memory model, the recognition heuristic reduces to a vague heuristic of the sort Gigerenzer (1996) argued against.

As Gigerenzer et al. (2008) pointed out in their reply, our original critique was aimed primarily at the TTB and recognition heuristics. However, it is important to note that these heuristics are both the most widely studied and the most widely cited of their proposed heuristics (see Gigerenzer, Todd, & The ABC Group, 1999). Moreover, TTB and recognition serve as illustrative examples of the two main philosophical points on which we and Gigerenzer et al. (2008) disagree. First, we disagree on whether the assumptions embodied by PMM, TTB, and the recognition heuristic are well specified enough to constitute testable theories. Second, we disagree on whether the best approach to modeling decision making involves assuming a small number of domain-general processes or a large number of specialized heuristics. Our approach has been to build models of judgment and decision making grounded in memory theory, assuming that the memory system places constraints on judgment processes (Dougherty, 2001; Dougherty, Gettys, & Ogden, 1999; Dougherty & Hunter, 2003a, 2003b; Dougherty & Sprenger, 2006; Thomas, Dougherty, Sprenger, & Harbison, 2008). Of importance, our assumption is that the memory system is an ecologically adaptive system that retains the statistical structure inherent in the environment. In contrast, the fast and frugal program has approached the study of judgment and decision making by proposing a set of domain-specific heuristics, each adapted to an ecology through learning and/or evolution. The problem with this approach is exemplified by the statement, "If recognition does not discriminate, then an inference could be made by the fluency heuristic, TTB, or another heuristic, as the constraints of the environment dictate" (Gigerenzer et al., 2008, p. 235). Further, Gigerenzer et al. (2008) suggested that we consider the familiarity model as a member of the fast-and-frugal toolkit. These statements expound the problems we see with the fast and frugal program. Not only do the statements suggest a high degree of redundancy among the heuristics (e.g., recognition, fluency, and familiarity are all based on an underlying memory variable), but they also imply that there are few constraints on how large the tool box can be aside from whatever constraints are present in the environment.

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