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The beauty of simple models: Themes in recognition heuristic research

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Abstract

The advantage of models that do not use flexible parameters is that one can precisely show to what degree they predict behavior, and in what situations. In three issues of this journal, the recognition heuristic has been examined carefully from many points of view. We comment here on four themes, the use of optimization models to understand the rationality of heuristics, the generalization of the recognition input beyond a binary judgment, new conditions for less-is-more effects, and the importance of specifying boundary conditions for cognitive heuristics.

Keywords: recognition heuristic, less-is-more, memory, model comparison.

1 Introduction

Galileo formalized the movement of objects in his law of falling bodies, S. S. Stevens (1957) described sensation as stimulus intensity raised to a power, and the behaviorists (e.g., Hull, 1935) formulated laws of learning with equations no more complex than those encountered in high school physics. Simple models, from physics to psychology, have driven much of progress in science. Yet no model, simple or complex, can explain all behavior. The beauty of simple models is that one can easily discover their limits, that is, their boundary conditions, which in turn fosters clarity and progress. The law of falling bodies does not hold generally; it works for situations in which the object starts in rest, there is no air resistance, and the gravitational force g does not change over the distance of the fall.[1] Similarly, the laws of learning do not hold in every situation, as illustrated by the concept of "biological preparedness": the fact that certain CS–UCS (conditional stimulus – unconditional stimulus) associations are learned rapidly but not others (Garcia, Ervin, & Koelling, 1966). Evolved organisms work with multiple tools, not one general principle. The concept of an adaptive toolbox assumes that an individual, culture, or species can be characterized by a set of heuristics for surviving in an uncertain world. These heuristics exploit evolved and learned core capacities, and are simple in order to be robust, fast, and efficient. The recognition heuristic is one of these tools in the adaptive toolbox of humans (and other animal species) and exploits recognition memory. This journal has devoted three special issues to elaborating, generalizing, and testing the model we proposed a decade ago (Goldstein & Gigerenzer 1999, 2002). We have reviewed the progress made in the first decade before (Gigerenzer & Goldstein, 2011); here we would like to comment on some of the theoretical insights put forward by the contributions to these issues.

1.1 Use Optimization Models to Understand Heuristics

One of the central questions in the research on the adaptive toolbox is, "how can a decision maker know in which situation a given heuristic is efficient?" One methodological approach to answer this question is to choose an optimization model whose structure is well understood and try to map the building blocks of a heuristics into this structure. Signal detection theory is such an optimization model that has been used to understand the nature of fast-and-frugal trees (Luan, Schooler, & Gigerenzer, 2011) and the effect of false alarms and misses on the recognition heuristic (Pleskac, 2007). Davis-Stober, Dana, and Budescu (2010) mapped the recognition heuristic into a different class of optimization models, the framework of linear models. They compared its weighting scheme (place all weight on one predictor, recognition, and none on the rest) to multiple regression's scheme on the dimension of minimizing maximal risk. (A weighting scheme minimizes maximal risk when it is, on average, closest to an optimal set of weights.) The recognition heuristic can be shown under plausibly common conditions to approximate a mini-max weighting scheme which is optimal on this prevalent criterion. While decision makers do not have access to the correlations that would let them assess whether "overweighting" recognition is a promising weighting strategy in a given domain and thus can-

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[1] A person jumping headfirst from an airplane will never exceed a speed of about 200 km/h (120 mph), due to air resistance.

not be said to be optimizing from the information given, users of the recognition heuristic are effectively betting that the environment will have the structure that Davis-Stober, Dana, and Budescu describe. When these bets are correct, inferences will be close to optimal despite having arisen without learning cue values or weighing multiple sources of information. An appealing future direction for this work would be to manipulate the costs to the decision maker of erring on the basis of risk, as opposed to other statistical benchmarks, and to observe whether such incentives cause decision strategies to fall more or less in line with the predictions of the recognition heuristic and minimax weighting.

1.2 Beyond Binary Recognition

Whereas the Davis-Stober, Dana, and Budescu paper connects the recognition heuristic to broader analytical results on cue weighting, the Erdfelder, Küpper-Tetzel, and Mattern (2011) article connects definitions within the recognition heuristic model to theories of recognition memory, meeting the call of other memory researchers in the field (Tomlinson, Marewski, & Dougherty, 2011; Dougherty, Franco-Watkins, & Thomas, 2008). Recall that the recognition heuristic takes the output of recognition memory as its input, but does not provide a model of the underlying recognition memory process (Goldstein & Gigerenzer, 2002). Erdfelder et al.'s memory state heuristic (MSH) builds upon the recognition heuristic as well as the *two-high threshold* model of recognition (Bröder & Schütz, 2009; Snodgrass & Corwin, 1988), positing three natural states of memory—recognition certainty, memory uncertainty, and rejection certainty—rather than the two in our original model (Goldstein & Gigerenzer, 2002). The MSH model subsumes the recognition heuristic as a special case and nicely resolves a number of observed phenomena. These include (1) the negative correlation between adherence and recognition latency (e.g., Marewski & Schooler, 2011; Hertwig, Herzog, Schooler, & Reimer, 2008; Newell & Fernandez, 2006), (2) the difference in accordance for pairs in which the recognition heuristic is normatively correct or incorrect (e.g., Hilbig & Pohl, 2008), and (3) the difference in accordance on pairs in which the recognized object is merely recognized or associated with further knowledge (e.g., Marewski & Schooler, 2011; Marewski, Gaissmaier, Schooler, Goldstein, & Gigerenzer, 2010; Hilbig & Pohl, 2008; Hilbig, Pohl, & Bröder, 2009). Extending the number of recognition states from two to three is a sufficient condition for these phenomena. These results show, for instance, that it is not valid to conclude that accordance differences between normatively correct and incorrect pairs would imply the use of additional cue information besides recognition, as has been claimed before. For instance, Glöckner and Bröder (2011) conclude that measuring such a difference (the "discrimination index") is "a very clever way to prove the use of additional cue information" (p. 24).

The general methodological lesson is: If a subset of participants does not follow the predictions of the recognition heuristic, this does not imply that this subset uses a compensatory strategy. Yet all three phenomena above have been repeatedly interpreted as evidence for compensatory strategies. If Erdfelder et al.'s generalization of the recognition heuristic applies, the conclusion is that there may be a subset of participants who distinguish between three recognition states and apply the generalized recognition heuristic to these.

1.3 Conditions For Less-Is-More

In 1996, we showed that less-is-more effects can result both from the recognition heuristic (Figure 4, Gigerenzer & Goldstein, 1996) as well as from compensatory processing of recognition, such as tallying and regression (Figure 6, Gigerenzer & Goldstein, 1996). That is, observing a less-is-more effect does not imply that the recognition heuristic was used. The logic goes the other way around: If certain conditions hold ($\alpha > \beta$; α, β independent of n; Goldstein & Gigerenzer, 2002), this implies an inversely u-shaped function between accuracy and n, that is, a less-is-more effect. Beaman, Smith, Frosch, & McCloy (2010) extend this argument and investigate the conditions behind less-is-more effects beyond the recognition heuristic. Katsikopoulos (2010) provides new insights into how less-is-more effects depend on false alarm rates and miss rates, and derives conditions for a below-chance less-is-more effect. Smithson (2010) provides further conditions for less-is-more effects. Taken together, these three papers show a number of conditions that lead to less-is-more effects that were previously unknown. The challenge is to integrate these into a common theoretical framework.

1.4 Boundary Conditions

In the introduction, we mentioned the importance of specifying the boundary conditions of a strategy, heuristic or otherwise. Figure 1 (from Gigerenzer & Goldstein, 1996) illustrates one boundary condition: the recognition heuristic, like take-the-best, was formulated for inferences from memory, as opposed to inferences from givens (Gigerenzer & Goldstein, 2011). If an object is not recognized (object D in Figure 1), no cue values can be recalled from memory (these missing values are represented with question marks). In contrast, in inferences from givens—such as when one looks up the cue values of recognized and unrecognized products online—this restriction does not hold. In inferences from mem-

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Figure 1: Recognition states of four objects A through D. Cue values are positive ("$-$"), negative ("$-$"), or missing ("?"). When an object such as D is unrecognized, all cue values are unknown. Adapted from Gigerenzer & Goldstein, 1996, p. 652.

		Objects: A	B	C	D
Recognition		+	+	+	−
Cues:	Cue 1	+	−	?	?
	Cue 2	?	+	−	?
	Cue 3	−	+	?	?
	Cue 4	?	−	−	?
	Cue 5	?	?	+	?

ory, one has to search for cues in memory, and search in memory appears to elicit more noncompensatory processes (Bröder & Schiffer, 2006). However, Glöckner and Bröder (2011) neglect this boundary condition and present inferences from givens as a test of the recognition heuristic (or the "enhanced recognition heuristic"), placing detailed information about "unrecognized" objects before the participants' eyes while they make decisions. Similarly, Ayton, Önkal, & McReynolds (2011) provide cue values about unrecognized objects. Their results indicate that, in inferences from givens, the model of the recognition heuristic predicts less well than in inferences from memory. Yet the authors do not present their result in this way, but claim that in our original article (Goldstein & Gigerenzer, 2002), we also would have tested "information from givens". Yet in none of our studies did we provide cue values for unknown objects. As illustrated by Figure 1, "Inferences from memory are logically different from inferences based on external information. If one has not heard of an object, its cue values cannot be recalled from memory" (Gigerenzer & Goldstein, 2011, p. 108). One can test the use of the recognition heuristic outside its boundary conditions to understand the boundary conditions themselves, but one should not suggest this as test of the recognition heuristic per se.

Situations in which no cue values are known about unrecognized objects are fairly common. Statistical models deal with such missing values through a process called imputation, and the recognition heuristic is a proposal of how the mind addresses, and in some sense exploits, the missing value problem. At the margin, the name of an unrecognized object itself may suggest cue values (e.g., the name of a product may reveal some attribute values), and there are on occasion cases in which a cue value can be deduced (e.g., someone who can name all the G-20 countries can deduce that Norway is not among them). But unlike in Figure 1, these cue values are inferred, not recalled from memory.

1.5 Beauty and Benefits of Simple Models

Complex problems often demand simple solutions, particularly in an uncertain world (Goldstein & Gigerenzer, 2009). The beauty of simple models lies in their transparency. One can measure how often and in what situations models predict behavior and when they fail. The benefits are in their robustness: the ability of a strategy to work well in new situations. A complex model with many adjustable parameters is more prone to overfitting than a simple model (Czerlinki, Gigerenzer, & Goldstein, 1999). The resulting error can be measured in a quantitaive way using the bias-variance framework (e.g., Gigerenzer & Brighton, 2009).

Future research should steer away from testing the recognition heuristic as a null hypothesis, without the specification of an alternative model. A competitive testing approach for models of recognition-based inference was introduced by Marewski et al. (2010), who tested several compensatory strategies and reported that none could predict judgments better than the recognition heuristic. Besides competitive testing, a promising future research strategy is to test whether models can predict multiple phenomena, such as choice and process data (Tomlinson, et al. 2011). It should become standard to measure the performance of models by prediction, such as out-of-sample prediction, not by data fitting.

In closing, we would like to thank the contributors to the three special issues of the journal. You helped us to better understand the strengths and limits of the recognition heuristic.

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