

Reasoning the Fast and Frugal Way: Models of Bounded Rationality

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Humans and animals make inferences about the world under limited time and knowledge. In contrast, many models of rational inference treat the mind as a Laplacean Demon, equipped with un-

limited time, knowledge, and computational might. Following H. Simon's notion of satisficing, the

would suggest that the mind is a supercalculator like a Lapla- 'reasonableness' " (p. 78). They did not report such a test. We

cean Demon (Wimsatt, 1976)—carrying around the collected shall.

works of Kolmogoroff, Fisher, or Newman—and simply needs a Initially, the concept of bounded rationality was only vaguely

memory jog, like the slave in Plato's *Meno*. On the other hand, defined, often as that which is not classical economics, and one the heuristics-and-biases view of human irrationality would could "fit a lot of things into it by foresight and hindsight," as

Table 1

edge, time, and computational power. This question is impor-

Cues, Ecological Validities, and Discrimination Rates

tant for Simon's postulated link between the cognitive and the

variation between recognition of cities and city populations. Let us define the *validity* α of the recognition principle to be the

$$.8 \left[\frac{\text{var}(\text{recognition})}{\text{var}(\text{recognition}) + \text{var}(\text{populations})} \right] .8$$

predictors or cues and is commonly seen as an "optimal" way 4 cue values (that is, one fifth of all possible) are searched for.

of its tendency to compress information into an estimate (e.g., The number across all simulated participants was 6.0, which

Brunswik, 1955; Hammond, 1966). Neural networks using the less than a third of all available cue values.

delta rule determine their "optimal" weights by the same prin-

Up



Results of the Competition: Average Proportion

Here the unit-weight and weighted linear models often make

of Correct Inferences

the inference that the unrecognized object is the larger one, due

to the overwhelming negative evidence for the recognized ob-

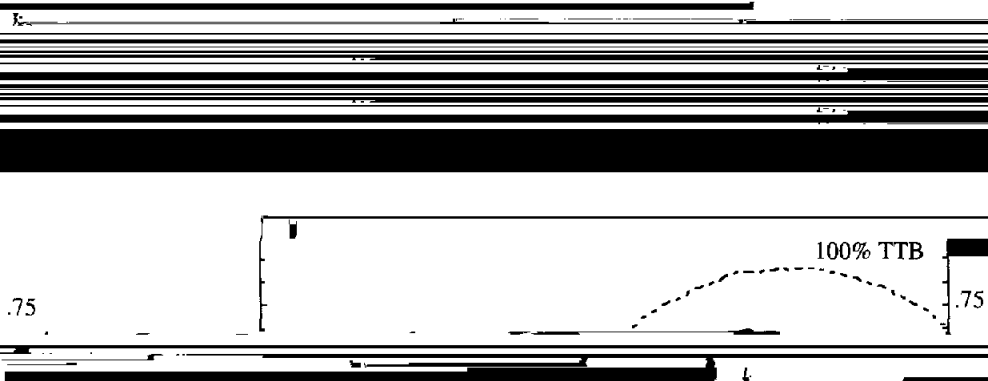
rithm then tries the cue that discriminated the time before last. smaller and smaller. The reason why the Minimalist algorithm

and so on. The algorithm differs from the Take The Best algo- looks up fewer cue values than the Take The Best algorithm is

rithm in Step 2, which is now reformulated as Step 2': that cue validities and cue discrimination rates are negatively

correlated (Table 1); therefore, randomly chosen cues tend to

Step 2': Search for the Cue Values of the have larger discrimination rates than cues chosen by cue



ative to the PMM family of satisficing algorithms is the lexico- great topic but does not recognize the name of the author, he

graphic rule. The largest evidence for lexicographic processes makes the inference that it is probably not worth buying. If,

seems to come from studies on decision under risk (for a recent after an inspection of the references, he does not recognize most

summary, see Lopes, 1995). However, despite empirical evi- of the names, he concludes the book is not even worth reading.

disjunctive algorithms (Einhorn, 1970) and highly complex

a b c

Biological systems, for instance, can exhibit systematic in- essary for the successful performance of the satisficing

ine three species: *a*, *b*, and *c*. Species *a* inhabits both water and

A New Perspective on the Lens Model

room) need to be justified (Tetlock 1992). Going with the sin- Anderson, J. R. (1990). *The adaptive character of thought*. Hillsdale

gle best reason, the strategy of the Take The Best algorithm, has NJ: Erlbaum.

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[illegible]