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Psychology into Economics: Fast and Frugal Heuristics

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Abstract

The present essay focuses on the fast and frugal heuristics program set forth by Gerd Gigerenzer and his fellows. In particular, it examines the contribution of Gigerenzer and Goldstein (1996) 'Reasoning the Fast and Frugal Way: Models of Bounded Rationality'. This essay, following the theoretical framework and the empirical evidence of Gigerenzer and Goldstein, points out that simple cognitive mechanisms such as fast and frugal heuristics can be capable of successful performance in real world, without the need of satisfying the classical norms of rational inference.

Keywords: behavioral economics; heuristics; biases; fast and frugal heuristics.
Jel Classification: D0; D10; D80.

1. Introduction

In this contribution, we examine the fast and frugal heuristics approach. This approach is based on the pioneering work of Herbert Simon (1956; 1972; 1982). His *bounded rationality* theory gave start to an approach based on heuristics, that are interpreted as a trade-off between the limits of the human mind and the computing performance required by complex problems. Gerd Gigerenzer proposed a psychological approach based on fast and frugal heuristics to examine simple alternatives to a full rationality analysis as a mechanism for decision making. He argued that simple heuristics frequently lead to better decisions than the theoretically optimal procedure. Fast and frugal heuristics are rules of thumb for decision making; they refer to simple, task-specific decision strategies that are part of a decision maker's repertoire of cognitive strategies for solving judgment and decision tasks.

The fast and frugal heuristics approach, derived from Simon's work, has become the fast and frugal heuristics program (Gigerenzer and Goldstein, 1996; Todd and Gigerenzer, 2003; Gigerenzer *et al*., 2011). It emphasizes the need for formal models of heuristics and the analysis under conditions of uncertainty as opposed to risk. Models of fast and frugal heuristics describe not only the outcome of the decision-making process but also the process itself.

Thus, this essay, following the theoretical framework and the empirical evidence of Gigerenzer and Goldstein (1996), points out that cognitive mechanisms such as fast and frugal heuristics can be capable of successful performance in real world, without the need of satisfying the classical norms of rational inference.

2. Fast and Frugal Heuristics Program

The present essay focuses on the fast and frugal heuristics program set forth by Gerd Gigerenzer and his fellows. They try to answer the question whether reasoning can be rational and psychological at the same time. Fast and frugal heuristics meet the criteria set forth in Goldstein and Gigerenzer (2002). Fast and frugal heuristics are: ecologically rational (that is, they exploit structures of information in the environment); founded in evolved psychological capacities such as memory and the perceptual system; fast, frugal, and simple enough to operate effectively when time, knowledge, and computational might are limited; precise enough to be modeled computationally; powerful enough to model both good and poor reasoning.

The study of heuristics has three goals. The first is descriptive and looks at the question of which heuristics people use. Answering it requires analysis of the "adaptive toolbox" (collection of heuristics) that individuals have at their disposal, including how the heuristics in the toolbox are learned and applied. The second goal is prescriptive and concerns the question of when one should use which heuristic. The examination of this latter problem is known as the study of the ecological rationality of heuristics. The final goal is one of engineering, called "intuitive design," that is, the design of heuristic tools and/or environments that improve decision making (Gigerenzer *et al.*, 2011).

In short, studies on fast and frugal heuristics include:

(a) the use of analytical methods and simulation studies to explore when and why heuristics perform well; and

(b) experimental and observational studies to explore whether and when people actually use fast and frugal heuristics.

Gigerenzer and Goldstein, in 'Reasoning the Fast and Frugal Way: Models of Bounded Rationality'[1], following Simon's notion of *satisficing*[2], aim at identifying something positive that could replace the unrealistic view of the mind call the *Laplacean Demon* view, which treats the mind as if it was equipped with unlimited knowledge and time, and computational might. Thus, they propose a family of algorithms based on simple psychological mechanism: one-reason decision making. These fast and frugal algorithms violate fundamental tenets of classical rationality.

It is well known that classical decision theory is designed for situations under risk such as monetary gambles and lotteries, where probability theory suffices for making decisions. In situations of risk, all possible alternatives are known, as are all possible consequences and their probabilities.

In the '70s, Tversky and Kahneman (1974) with their "heuristics and biases program" attacked the view that probability theory and human reasoning are two sides of the same coin. They postulated that the mind has to resort to so-called heuristics, or rules-of-thumbs, that afford useful proxies most of the time.

"These heuristics [that are usually employed in making judgments under uncertainty] are highly economical and usually effective, but they lead to systematic and predictable errors" [in certain task situations]. (Tversky and Kahneman, 1974, p. 1131).

The heuristics and biases program concluded that human inference is systematically biased and error prone, suggesting that the laws of inference are quick heuristics and not the laws of probability. However, the heuristics and biases program retained the normative kernel of the classical view (Kahneman, Slovic, and Tversky, 1982). Both views (Subjective Utility theory and heuristics and biases program) accept the laws of probability and statistics as normative, but they disagree about whether humans can stand up to these norms. Many experiments have been conducted to test the validity of these two views. But real-world situations are complex and computationally intractable, at least for ordinary human minds. These situations make neither of the two views look promising.

The fast and frugal heuristics program is clearly in contrast to the theoretical position of Tversky and Kahneman and the theoretical strands of behavioral economics (Schilirò, 2016).

In fact, according to Gigerenzer and Goldstein (1996), there is a third way to look at inference, focusing on the psychological and ecological rather than on logic and probability theory. This view questions classical rationality, as a universal norm, and the heuristics and biases view. Herbert Simon, who inspired this third view, proposed looking for models of bounded rationality instead of classical rationality (Schilirò, 2012). Bounded rationality depends – according to Simon (1972), on the limits of attentive and computational capacity. Simon (1956; 1982) argued that information-processing systems typically need to satisfice rather than optimize. Simon's notion of bounded rationality has two sides, one cognitive and one ecological. The two go in tandem:

"Human rational behavior 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).

For the most part, however, theories of human inference have focused exclusively on the cognitive side, equating the notion of bounded rationality with the statement that humans are limited information processors.

Gigerenzer and Goldstein (1996) propose, instead, a class of models that exhibit bounded rationality in both of Simon's senses. This latter is showing the distortions of judgment and choice defined as cognitive biases, highlighting the negative effects and the errors that these heuristics lead in the behavior and choices of individuals. These satisficing algorithms operate with simple psychological principles that satisfy the constraints of limited time, knowledge, and computational might, rather than those of classical rationality. At the same time, they are designed to be fast and frugal without a significant loss of inferential accuracy, because the algorithms can exploit the structure of environments.

By using computer simulation, Gigerenzer and Goldstein (1996) show that the satisficing 'Take-The-Best' algorithm matched or outperformed various "rational" inference procedures (e.g., multiple regression) in inferential speed and accuracy. This result is an existence proof that cognitive mechanisms capable of successful performance in the real world do not need to satisfy the classical norms of rational inference.

2.1 The task

Gigerenzer and Goldstein begin by describing the task the cognitive algorithms are designed to address. They deal with inferential tasks in which a choice must be made between two alternatives on a quantitative dimension.

[1] Gigerenzer and Goldstein (1996).

[2] *Satisficing* is the blend of *sufficing and satisfying*. A term that Simon uses to characterize algorithms that successfully deal with conditions of limited time, knowledge, or computational capacities.

They propose to consider the following example based on two - alternative - choice tasks that occur in various contexts in which inferences need to be made with limited time and knowledge (Gigerenzer and Goldstein, 1996, p. 651):
Which city has a larger population? (a) Hamburg or (b) Cologne.
More specifically, Gigerenzer and Goldstein study two – alternative - choice tasks in situations where a person has to make an inference based solely on knowledge retrieved from memory. They refer to this as *inference from memory* as opposed to *inference from givens*[3]. The satisficing algorithms proposed by Gigerenzer and Goldstein (1996) perform inference from memory. These algorithms use limited knowledge as input, and they can actually profit from a lack of knowledge (*ibid.* p.652).
In short, the problem can be summarized as follows: "assume that a person does not know or cannot deduce the answer to the Hamburg-Cologne question but needs to make an inductive inference from related real-world knowledge. How is this inference derived? How can we predict choice (Hamburg-Cologne) from a person's state of knowledge?" (*ibid.* p.652).

2.2 The theoretical framework

The cognitive algorithms that Gigerenzer and Goldstein propose are realizations of a framework for modeling inferences from memory. This theoretical framework is the theory of *probabilistic mental models (*PMM theory*)*[4]. The theory *of probabilistic mental models* assumes that inferences are about unknown states of the world, which are based on probability cues. The major thrust of the theory is that it replaces the canon of classical rationality with simple, plausible psychological mechanisms of inference-mechanisms that a mind can actually carry out under limited time and knowledge and that could have possibly arisen through evolution (Gigerenzer and Goldstein, 1996, p.652)[5].
Most traditional models of inference, from linear multiple regression models to Bayesian models to neural networks, try to find some optimal integration of all information available. Every bit of information is taken into account, weighted, and combined in a computationally expensive way.
The family of algorithms in PMM theory does not implement this classical ideal. Search in memory for relevant information is reduced to a minimum, and there is no integration (but rather a substitution) of pieces of information.
The fast and frugal heuristics assume that when a person cannot clearly distinguish between two alternatives, one will begin a search in order to find a cue that will provide a reason for choosing the one alternative one feels appropriate (Hardman, 2009). Therefore, these satisficing algorithms dispense with the fiction of the omniscient *Laplacean Demon*, who has all the time and knowledge to search for all relevant information, to compute the weights and covariances, and then to integrate all this information into an inference.
According to Gigerenzer and Goldstein (1996, p.652), PMMs perform intelligent guesses about unknown features of the world, based on uncertain indicators. To make an inference about which of the two objects, *a* or *b,* has a higher value, knowledge about the reference class R is searched with a, $b \in$ R. The knowledge consists of probability cues C_i (i = 1,2, …, n) and the cue values a_i and b_i of the objects for the i_{th} cue. A PMM is an inductive device that uses 'limited knowledge' to make fast inferences. 'Limited knowledge' means that the matrix of objects by cues has missing entries (i.e., objects, cues, or cue values may be unknown). People rarely know all information on which an inference could be based, that is, knowledge is limited.
Gigerenzer and Goldstein model limited knowledge in two respects: a person can have
(a) incomplete knowledge of the objects in the reference class (e.g., she recognizes only some of the cities),
(b) limited knowledge of the cue values (facts about cities), or
(c) both.
The first satisficing algorithm presented by Gigerenzer and Goldstein (1996, p.653), is called the 'Take-The-Best algorithm': It is the basic algorithm in the PMM framework because its policy is "take the best, ignore the rest".
The 'Take-The-Best' algorithm assumes a subjective rank order of cues according to their validities. The highest-ranking cue (that discriminates between the two alternatives) is known as the best cue. Gigerenzer and Goldstein (1996, p. 653) explain the 'Take-The-Best' algorithm by representing it with a flow diagram, which is made of five steps: i) The recognition principle; ii) Search for cue values; iii) Discrimination rule; iv) Cue-substitution principle; v) Maximizing rule for choice.
There is a close parallel of Gigerenzer and Goldstein's algorithm with Simon's concept of satisficing. The 'Take-The-Best' algorithm stops search after the first discriminating cue is found, just as Simon's satisficing algorithm stops search after the first option that meets an aspiration level.

[3] Studies of inference from givens involve making inferences from information presented by the experimenter.
[4] Gigerenzer (1993); Gigerenzer, Hoffrage and Kleinbölting (1991).
[5] The PMM theory accounts for choice and confidence, but Gigerenzer and Goldstein (1996) address only choice.

The algorithm is hardly a standard statistical tool for inductive inference. It does not use all available information, it is non-compensatory and nonlinear, and variants of it can violate transitivity. Thus, it differs from standard linear tools for inference such as multiple regression, as well as from nonlinear neural networks that are compensatory in nature.
"Despite their flagrant violation of the traditional standards of rationality, the 'Take-The-Best' algorithm and other models from the framework of PMM theory have been successful in integrating various striking phenomena in inference from memory and predicting novel phenomena, such as the confidence-frequency effect (Gigerenzer, Hoffrage and Kleinbölting, 1991), and the 'less-is-more effect'[6]." (Gigerenzer and Goldstein, 1996, p. 654).
The theory of *probabilistic mental models* seems to be the only existing process theory of the overconfidence bias that successfully predicts conditions under which overestimation occurs, disappears, and inverts to underestimation[7]. The 'Take-The-Best' algorithm explains also why the popular confirmation-bias explanation of the overconfidence bias is not supported by experimental data[8].

2.3 The tests and the empirical results

Gigerenzer and Goldstein tested the performance of the 'Take-The-Best' algorithm on how accurately it made inferences about a real-world environment. The environment was the set of all cities in Germany with more than 100,000 inhabitants (83 cities after the German reunification), with a population as the target variable.

"The model of the environment consisted of 9 binary ecological cues and the actual 9 x 83 cue values…. Each cue has an associated validity, which is indicative of its predictive power. The *ecological validity* of a cue is the relative frequency with which the cue correctly predicts the target, defined with respect to the reference class (e.g. all German cities with more than 100,000 inhabitants)" (Gigerenzer and Goldstein, 1996, p.654).

Thus, Gigerenzer and Goldstein assume that the model is descriptively valid and investigate how accurate this satisficing algorithm is in drawing inferences about unknown aspects of a real-world environment.
Among the evidence for the empirical validity of the 'Take-The-Best' algorithm are the tests of a bold prediction, the less-is-more effect, which postulates conditions under which people with little knowledge make better inferences than those who know more.

Gigerenzer and Goldstein test how well simple satisficing algorithms perform compared with standard integration algorithms, which require more knowledge, time, and computational power.

The authors test in particular how well individuals using the 'Take-The-Best' algorithm did at answering real-world questions such as:
Which city has more inhabitants: (a) Heidelberg or (b) Bonn?

The results of the tests are[9]:
The 'Take-The-Best' algorithm is designed to enable quick decision making. Gigerenzer and Goldstein show the amount of cue values retrieved from memory by the 'Take-The-Best' algorithm for various levels of limited knowledge. The 'Take-The-Best' algorithm reduces search in memory considerably. The 'Take-The-Best' algorithm, even with a limited amount of information, is very accurate. The 'Take-The-Best' algorithm drew as many correct inferences about unknown features of a real-world environment as any of the integration algorithms, and more than some of them. In fact, the satisficing 'Take-The-Best' algorithm produced a surprisingly high proportion of correct inferences, compared with more computationally expensive integration algorithm (Gigerenzer and Goldstein, 1996, p.660). In addition, it is also the fastest. Therefore, the competition goes to the 'Take-The-Best' algorithm as the highest performing, overall.

Such a result is an existence proof that cognitive algorithms capable of successful performance in a real-world environment do not need to satisfy the classical norms of rational inference.

The final consideration by Gigerenzer and Goldstein concerning these results is that the classical norms may be sufficient but are not necessary for good inference in real environments.
In addition, Gigerenzer and Goldstein considered and tested two further simplifications of the algorithm: the 'Take-The-Last' algorithm, which replaces knowledge about the rank orders of cue validities by a memory of the discrimination history of cues, and the 'Minimalist algorithm'.
"These latter algorithms showed a comparatively small loss in correct inferences, and only when knowledge about cue values was high" (*ibid.*, p. 662).

[6] Goldstein (1994).
[7] Gigerenzer (1993); Gigerenzer, Hoffrage and Kleinbölting (1991); Juslin (1993;1994); Juslin, Winman and Persson (1995).
[8] Gigerenzer, Hoffrage and Kleinbölting (1991).
[9] The authors considered 500 simulated individuals and the exhaustive set of 3,403 city pairs. However, we do not enter in the details of the tests contained in Gigerenzer and Goldstein (1996, pp.656-658).

2.4 Cognitive algorithms that satisfice

After carrying the tests, Gigerenzer and Goldstein discuss the fundamental psychological mechanism postulated by the PMM family of algorithms: one reason decision making. They examine how this mechanism exploits the structure of environments in making fast inferences that differ from those arising from standard models of rational reasoning.

What Gigerenzer and Goldstein call 'one-reason decision making' is a specific form of satisficing. These are the features of one-reason decision making:

i) The inference, or decision, is based on a single, good reason.

ii) There is no compensation between cues.

iii) One-reason decision making is probably the most challenging feature of the PMM family of algorithms.

One-reason decision making means that each choice is based exclusively on one reason (i.e., cue), but this reason may be different from decision to decision. This allows for highly context-sensitive modeling of choice.

One-reason decision making is not compensatory. Compensation is, after all, the cornerstone of classical rationality, assuming that all commodities can be compared and everything has its price. Compensation assumes commensurability. However, human minds do not trade everything, some things are supposed to be without a price[10].

The discussion of the mechanism postulated by the PMM family of algorithms touch several aspects (Gigerenzer and Goldstein, 1996, pp.663-664):

- *Recognition principle* **(**a version of one-reason decision making that exploits a lack of knowledge).
- *Limited Search* (both one-reason decision making and the recognition principle realize limited search by defining stopping points[11]).
- *Nonlinearity* ('Take-The-Best' algorithm and its variants belong to the family of nonlinear models). One advantage of simple nonlinear models is transparency[12].
- *Intransitivity* (transitivity is a cornerstone of classical rationality. It is one of the few tenets that school of Ramsey and Savage shares with the competing school of Allais).

The PMM family of algorithms includes algorithms that do not violate transitivity (such as the 'Take-The-Best' algorithm), and others that do (e.g., the Minimalist algorithm).

"The Take-The-Last and the Minimalist algorithms involve essentially no estimation (except for the sign of the cues). The fact that there is no estimation problem has an important consequence: an organism can use as many cues as it has experienced, without being concerned about whether the size of the sample experienced is sufficiently large to generate reliable estimates of weights" (Gigerenzer and Goldstein, 1996, p. 665) .

Gigerenzer and Goldstein think that in future it is possible generalize the present satisficing algorithm from two-alternative-choice tasks to other inferential tasks, such as classification and estimation and that nonlinear satisficing algorithms have a greater power for understanding the structure of real-world environment than traditional proposal as linear correlations.

Finally, facing the question: can reasoning be rational and psychological? Gigerenzer and Goldstein firmly believe that "after 40 years of toying with the notion of bounded rationality, it is time to overcome the opposition between the rational and the psychological and to reunite the two. The PMM family of cognitive algorithms provides precise models that attempt to do so" (*ibid*., p.666).

The authors conclude stating that the single most important result in this article is that simple psychological mechanisms can yield about as many (or more) correct inferences in less time than standard statistical linear models that embody classical properties of rational inference. The demonstration that a fast and frugal satisficing algorithm won the competition defeats the widespread view that only "rational" algorithms can be accurate (Gigerenzer and Goldstein, 1996, p.666).

CONCLUSION

This essay pointed out the relevance of cognitive mechanisms such as fast and frugal heuristics and how such heuristics can be capable of successful performance in real world. The analysis of fast and frugal heuristics approach set forth by Gigerenzer and Goldstein and other fellows can be summarized as follows: fast-and-frugal heuristics are useful in situations of uncertainty. The study of ecological rationality is prescriptive, investigating the environments which heuristics exploit to reduce effort and increase accuracy. More information and computation is not always better. Decision aids based on heuristics (as opposed to complex algorithms) can be intuitively understood and effectively used. Models of inference do not have to forsake accuracy for

[10] For instance, true friendship, military honors, and doctorates are supposed to be without a price.

[11] Stopping rules are crucial for modeling inference under limited time, as in Simon's examples of satisficing.

[12] "The beauty of nonlinear satisficing algorithms is that they can match the Demon's performance with less searching, less knowledge, and less computational mind" (Gigerenzer and Goldstein, 1996, p. 664)

simplicity. Therefore, fast and frugal heuristics perform successfully in real world, without the need of satisfying the classical norms of rational inference.

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REFERENCES

Gigerenzer, G. (1993). The bounded rationality of probabilistic mental models. In K. I. Manktelow and D. E. Over (eds.), *Rationality: Psychological and philosophical perspectives.* Oxford: Routledge.

Gigerenzer, G. and D. Goldstein (1996). Reasoning the Fast and Frugal Way: Models of Bounded Rationality. *Psychological Review*, 103 (4): 650–669. DOI:10.1037/0033-295X.103.4.650

Gigerenzer, G., Hoffrage, U. and H. Kleinbölting (1991). Probabilistic mental models: A Brunswikian theory of confidence. *Psychological Review*, 98 (4): 506-528.

Gigerenzer, G. and P.M. Todd (1999). *Simple Heuristics That Make Us Smart*. New York: Oxford University Press.

Gigerenzer G., Hertwig R. and T. Pachur (eds.) (2011). *Heuristics: The Foundations of Adaptive Behavior.* New York: Oxford University Press.

Goldstein, D. (1994). Why the distinction between single-event probabilities and frequencies is relevant for psychology (and vice versa). In G. Wright and P. Ayton (eds.), *Subjective probability*. Chichester, Sussex: Wiley.

Goldstein, D. and G. Gigerenzer (2002). Models of Ecological Rationality: The Recognition Heuristic. *Psychological Review*, 109(1): 75–90.

DOI: 10.1037//0033-295X.109.1.75

Hardman, D. (2009). *Judgement and Decision Making Psychological Perspectives*. Chichester, Sussex: Blackwell Publishing.

Kahneman, D., Slovic, P. and A. Tversky (eds.) (1982). *Judgment Under Uncertainty: Heuristics and Biases*. New York: Cambridge University Press.

Juslin, P. (1993). An explanation of the hard-easy effect in studies of realism of confidence in one's general knowledge. *European Journal of Cognitive Psychology,* 5(1): 55-71.

DOI: 10.1080/09541449308406514

Juslin, P. (1994). The overconfidence phenomenon as a consequence of informal experimenter-guided selection of almanac items. O*rganizational Behavior and Human Decision Processes,* 57 (2): 226-246. https://doi.org/10.1006/obhd.1994.1013

Juslin, P.**,** Winman, A. and T. Persson (1995). Can overconfidence be used as an indicator of reconstructive rather than retrieval processes? *Cognition***,** 54 (1):99-130.

Schilirò, D. (2012). Bounded Rationality And Perfect Rationality: Psychology Into Economics. *Theoretical and Practical Research in Economic Fields*, 2: 101-111.

Schilirò, D. (2016). Economics and Psychology. The Framing of Decisions*. Journal of Mathematical Economics and Finance*, Vol. II, Issue 2(3): 77-88.

Simon, H.A. (1956). Rational choice and the structure of the environment. Psychological Review, 63(2): 129-138.

Simon, H.A. (1972). Theories of bounded rationality. In McGuire, C.B. and R. Radner (eds.), *Decision and organization*. Amsterdam: North Holland.

Simon, H.A. (1982). *Models of bounded rationality. Vol.2.Behavioral economics and business organization.* Cambridge (MA): The MIT Press.

Simon, H.A. (1990). Invariants of human behavior. *Annual Review of Psychology*, 41:1-19.

DOI: 10.1146/annurev.ps.41.020190.000245

Tversky A. and D. Kahneman (1974). Judgment under uncertainty: heuristics and biases. *Science*, 185: 1124–1131.