In R. Bibace, J. D. Laird, K. L. Noller & J. Valsiner (Eds.). (2005). *Science and medicine in dialogue* (pp. 3–15). Westport, CT: Praeger.

Chapter 1

FAST AND FRUGAL HEURISTICS IN MEDICAL DECISION MAKING

Gerd Gigerenzer and Stephanie Kurzenhäuser

How do doctors solve the challenging task to make treatment decisions under time pressure? Consider the following situation: A man is rushed to the hospital with serious chest pains. The doctors suspect acute ischemic heart disease and need to make a decision, and they need to make it quickly: Should the patient be assigned to the coronary care unit or to a regular nursing bed for monitoring? The decision to admit a patient to a coronary care unit has serious medical and financial consequences. How do doctors make such decisions, and how *should* they?

One way to do it is to rely on experience and intuition. For instance, in a rural Michigan hospital, doctors sent some 90 percent of the patients to the coronary care unit. This behavior can be understood as defensive decision making—physicians fear malpractice suits if they do not send a patient into the care unit, and he subsequently has a heart attack, but less so if they send a patient into the unit unnecessarily, and he dies of an infection. This indiscriminate use of the coronary care unit causes unnecessary costs (too many people in the coronary care unit, which results in high per-day costs), decreases the quality of care, and adds additional health risks (such as serious secondary infections) to patients who should not be in the unit. Only 25 percent of the patients admitted to the coronary care unit did actually have a myocardial infarction (Green & Mehr, 1997; Green & Smith, 1988). Similar rates were found at larger hospitals (ranging from 12% to 42%).

Researchers at the University of Michigan Hospital tried to solve this overcrowding problem by training the physicians to use a decision-support tool based on logistic regression, rather than relying on their intuitive judgment (Green & Mehr, 1997).

Physicians were trained to use the Heart Disease Predictive Instrument (Pozen, D'Agostino, Selker, Sytkowski, & Hood, 1984), which is a

Figure 1.1
The Heart Disease Predictive Instrument (HDPI), a decision-support tool, in the form of a pocket-sized, plastic-laminated card. The reverse side of the card gives the following definitions:

Chest Pain = Chief Complaint
EKG (ST, T wave Δ's)

History	ST&T Ø	ST⇔	T⇑⇓	ST⇔	ST⇔&T⇑⇓	ST⇑⇓&T⇑⇓
No MI& No NTG	19%	35%	42%	54%	62%	78%
MI or NTG	27%	46%	53%	64%	73%	85%
MI and NTG	37%	58%	65%	75%	80%	90%

Chest Pain, NOT Chief Complaint
EKG (ST, T wave Δ's)

History	ST&T Ø	ST⇔	T⇑⇓	ST⇔	ST⇔&T⇑⇓	ST⇑⇓&T⇑⇓
No MI& No NTG	10%	21%	26%	36%	45%	64%
MI or NTG	16%	29%	36%	48%	56%	74%
MI and NTG	22%	40%	47%	59%	67%	82%

No Chest Pain
EKG (ST, T wave Δ's)

History	ST&T Ø	ST⇔	T⇑⇓	ST⇔	ST⇔&T⇑⇓	ST⇑⇓&T⇑⇓
No MI& No NTG	4%	9%	12%	17%	23%	39%
MI or NTG	6%	14%	17%	25%	32%	51%
MI and NTG	10%	20%	25%	35%	43%	62%

Chest pain: Patient reports chest or left arm pressure or pain.

Chief complaint: Patient reports chest/left arm discomfort is most important symptom.

NTG: Patient reports a history of PRN use of nitroglycerin for relief of chest pain. Not necessary to have used NTG for this episode.

MI: Patient reports a history of definite myocardial infarction.

ST⇐⇒: Initial EKG shows ST segment "barring," "straightening," or "flattening" in a least two leads excluding aVR.

ST⇑⇓: Initial EKG shows ST segment elevation or depression of at least 1 mm in at least two leads excluding avR.

T⇑⇓: Initial EKG shows T waves that are "hyperacute" (at least 50% of R-wave amplitude) or inverted at least 1 mm in at least two leads excluding aVR.

Ø: None of the above ST segment or T-wave Δ's are present.

Source: (Green & Mehr, 1997).

decision-support tool that tries to weigh and combine the relevant information. The Heart Disease Predictive Instrument (HDPI) as used in the Michigan Hospital consists of a chart with some 50 probabilities (Figure 1.1). The physician has to check the presence or absence of combinations of seven symptoms and insert the relevant probabilities into a pocket calculator, which determines the probability that a patient has acute heart disease. The probability score is generated from a logistic regression formula that combines and weighs the dichotomous information on the seven symptoms. These symptoms were chosen out of 59 clinical features about which information is available to emergency room physicians (Pozen et al., 1984). However, physicians are generally not happy using this and similar systems (Corey & Merenstein, 1987; Pearson, Goldman, Garcia, Cook, & Lee, 1994). Physicians typically do not understand logistic regression, and even if they do, they are uncomfortable with being dependent on a probability chart. The dilemma the doctors in the Michigan hospital now faced was as follows: Should patients in life-and-death situations be classified by intuitions that are natural but in this case suboptimal or by complex calculations that are alien but possibly more accurate? This dilemma arises in many contexts, from financial advising to personnel recruiting: Should we rely on experts' intuition or on a fancy statistical model?

There is, however, a third alternative: smart heuristics. They correspond to natural intuitions, but they can have the accuracy of fancy statistical models. It was an unexpected observation that initially led the hospital researchers to try a heuristic model. The researchers had employed an ABAB reversal design. That is, they had let the physicians make the decision first by intuition (condition A), then given them the HDPI (condition B), then withdrew the instrument and left the physicians to their intuition once more (condition A), and so on. The researchers had expected that the quality of decision making would be relatively low in condition A and high in condition B, and would oscillate. Quality first increased from A to B, as expected, but then surprisingly stayed at this level, even when the instrument was withdrawn. Figure 1.3 shows that physicians initially had a false-positive rate of over 90 percent (condition A), which improved after they first encountered the HDPI to less than 60 percent (first condition B) and subsequently stayed at this level (all further conditions A and B). It was out of the question that the physicians could have memorized the probabilities on the chart or calculated the logistic regression in their heads. So why did the decision-support system only help the first time? The suspicion was that the probabilities and the logistic computations may have mattered little, and that physicians might have simply learned the important variables. This interpretation opened up the possibility of deliberately constructing a decision heuristic that uses only a minimum of information and computation. Green and Mehr (1997) constructed a simple decision heuristic by using three building blocks of heuristics: ordered search, a fast stopping rule, and one reason decision making (Gigerenzer, Todd, & the ABC Research Group, 1999). Before we turn to the decision heuristic of Green and Mehr, let us first consider its building blocks in more detail.

FAST AND FRUGAL HEURISTICS

There are several classes of heuristics (the term "heuristic" is of Greek origin, meaning "serving to find out or discover"). Green and Mehr (1997) based the construction of their decision heuristic on fast and frugal heuristics (Gigerenzer & Selten, 2001). These heuristics do not try to compute the maximum or minimum of some function, nor, for the most part, do they calculate probabilities. They are fast, because they do not involve much computation, and frugal because they only search for part of the information. They rely on simple building blocks for searching for information, stopping search, and finally making a decision (Gigerenzer & Goldstein, 1996; Gigerenzer, Todd, & the ABC Research Group, 1999).

Building Blocks for Guiding Search

Alternatives and cues are sought in a particular order. For instance, search for cues can be simply random or in order of cue validity.

Building Blocks for Stopping Search

Search for alternatives or cues must be stopped at some point. Fast and frugal heuristics employ stopping rules that do not try to compute an optimal cost–benefit trade-off. Rather, heuristic principles for stopping involve simple criteria that are easily ascertained, such as halting information search as soon as the first cue or reason that favors one decision alternative is found.

Building Blocks for Decision Making

Once search has been stopped, a decision or inference must be made. Many models of judgment and decision making ignore the search and stopping rules and focus exclusively on decision: Are predictor values combined linearly as in multiple regression, in a Bayesian way, or in some other fashion? Instead, fast and frugal heuristics use simple principles for decisions (such as one-reason decision making, see below) that avoid expensive computations and extensive knowledge by working hand in hand with equally simple search and stopping rules.

FAST AND FRUGAL DECISION TREE

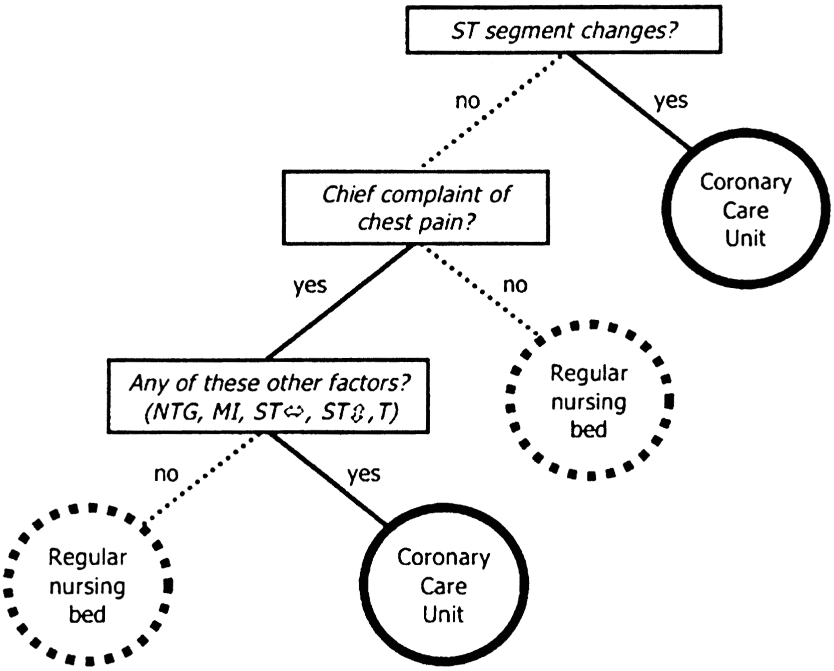
Using these building blocks, Green and Mehr (1997) constructed a simple decision heuristic for the coronary care unit allocation problem. The resulting heuristic is shown in Figure 1.2 in the form of a fast and frugal decision tree. It ignores all 50 probabilities and asks only a few yes-or-no questions. If a patient has a certain anomaly in his electrocardiogram (the so-called ST segment change), he is immediately admitted to the coronary care unit. No other information is searched for. If that is not the case, a second variable is considered: whether the patient's primary complaint is chest pain. If this is not the case, he is immediately classified as low risk and assigned to a regular nursing bed. No further information is considered. If the answer is yes, then a third and final question is asked to classify the patient.

This decision tree employs fast and frugal rules of search, stopping, and decision. First, it ranks the predictors according to a simple criterion (predictor with the highest sensitivity first, predictor with the highest specificity second, and so on). Search follows this order, similar to the Take The Best heuristic (Gigerenzer & Goldstein, 1996, 1999). Second, search can stop after each predictor; the rest is ignored. Third, the strategy does not combine—weight and add—the predictors; for instance, a change in the ST Segment sends the patient immediately into the coronary care unit, whether or not his chief complaint is chest pain, and independent of what other factors the patient has. In general terms, predictors that are lower in the tree cannot compensate for one higher up in the tree. Only one predictor determines each decision. This decision rule is an instance of *one-reason decision making.* The entire heart disease tree is a realization of a *fast and frugal tree,* which is defined as a decision tree with a small number of binary predictors that allows for a decision *at each branch* of the tree.

HOW ACCURATE IS THE FAST AND FRUGAL TREE?

The simple tree, just like the Heart Disease Predictive Instrument, can be evaluated by multiple performance criteria. Accuracy is one criterion,

Figure 1.2
Fast and frugal decision tree for coronary care unit allocation. For explanations, see Figure 1.1.



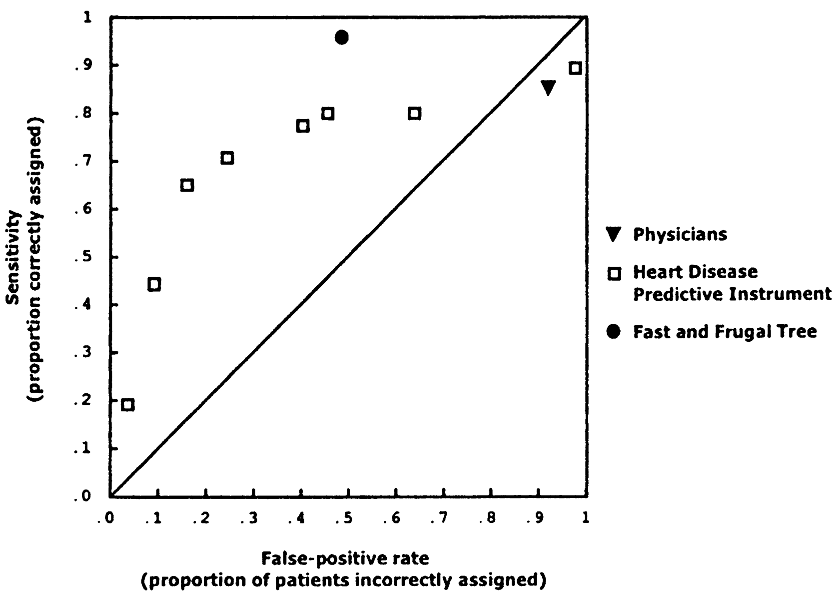
Source: Based on Green & Mehr, 1997.

which includes two aspects: The decision strategy should have (a) a high sensitivity, that is, it should send most of the patients who will actually have a serious heart problem into the coronary care room; and (b) high specificity, that is, it should send few patients into the care unit unnecessarily. Being able to make a decision fast is a second criterion, which is essential in situations where slow decision making can cost a life. A third criterion is frugality, that is, the ability to make a good decision with only limited information. The second and third criteria are not independent, and the fast and frugal tree is, by design, superior in both of these aspects to the HDPI decision-support system, as may be physicians' intuition. A fourth criterion is the transparency of a decision system. An accurate system is worth little when it is not accepted. Unlike logistic regression, the steps of the fast and frugal tree are transparent and easy to teach. But how accurate is one-reason decision making? Would you want to be classified by a few yes-or-no questions in a situation with such high stakes? Or would you rather be evaluated by the HDPI, or perhaps by physicians' intuition?

Figure 1.3 shows the performance of the three forms of decision making. On the *Y* axis is the proportion of patients correctly assigned to the coronary care unit, as measured by a subsequent heart attack. On the *X* axis is the proportion of patients incorrectly assigned. The diagonal line represents chance performance. A perfect strategy would be represented by a point in the upper left-hand corner, but nothing like that exists in an uncertain world.

As one can see from the triangle, the physicians' initial performance turns out to be at the chance level, even slightly below. The HDPI did

Figure 1.3
Coronary care unit decisions by physicians, the Heart Disease Predictive Instrument (HDPI), and the fast and frugal tree. Accuracy is measured by the proportion of patients correctly assigned to the coronary care unit and the proportion of patients incorrectly sent to the unit. Correct assignment is measured by the occurrence of myocardial infarction. Physicians' initial performance is represented by the right point, and their performance after they encountered the HDPI for the first time is represented by the left data point, which shows a smaller false-positive rate. An ideal diagnostic instrument would be represented by a point in the upper left-hand corner, but in the real world, no such performance exists.



Source: Based on Green & Mehr, 1997.

much better than the physicians' intuition. Its performance is shown by the open squares, which represent various trade-offs between the two possible errors.

How did the fast and frugal tree perform? The counterintuitive result is that the fast and frugal tree was more accurate in classifying actual heart attack patients than both the physicians' intuition and the HDPI. It correctly assigned the largest proportion of patients who subsequently had a myocardial infarction into the coronary care unit. At the same time, it had a comparatively low false-alarm rate. Note that the expert system had more information than the smart heuristic and could make use of sophisticated statistical calculations. Nevertheless, in this complex situation, less is more.

The potentials of fast and frugal decision making are currently being discussed in the medical literature, and some medical researchers see in it a powerful alternative to the prescriptions of classical decision theory for patient care (Elwyn, Edwards, Eccles, & Rovner, 2001). The crucial question is, when does simplicity pay and when does it not?

WHEN LESS IS MORE

How can it be that a heuristic that ignores information and forgoes computation can be not only faster, more frugal, and transparent but also more accurate? A comparison between the logistic regression (HDPI) and the fast and frugal tree can help to understand the secret of less is more.

Consider the error-free case in which a decision strategy can classify all objects correctly, that is, where a point in the upper left-hand corner of Figure 1.3 exists. In an error-free world, what is the relation between a fast and frugal tree and a logistic regression? The answer is: If an error-free fast and frugal tree exists in an environment, then an error-free logistic regression always exists as well (Forster, Martignon, Masanori, Vitouch, & Gigerenzer, 2002; Martignon, Vitouch, Takezawa, & Forster, 2003). But can one prove the converse, that for each logistic regression there exists a fast and frugal tree that is error-free, or equally accurate? This is not the case. Thus, although this analysis shows that in the error-free case, some fast and frugal trees can be as accurate as logistic regression, it cannot explain *why* they are more accurate. For this, we need to look at more realistic situations in which error-free decision making is impossible.

ROBUSTNESS

In situations where decisions are liable to error, the twin concept of robustness and overfitting can predict situations in which less is more. Robustness is the ability to generalize well to new environments, specifically those whose structure is not known in advance. The important distinction here is between data fitting and prediction. In the first case, one fits a model to the empirical data, that is, the training set is the same as the test set. In prediction, the model is based on a training set but is tested on new data. A good fit to the new data may be deceptive because of overfitting. In general, a model A overfits the training data if there exists an alternative model B, such that A has higher or equal accuracy than B in the training set but lower accuracy in the test set. Consider two diagnostic systems, one with more adjustable parameters (e.g., predictors) and one with only a subset of these, that is, with fewer adjustable parameters. Both systems fit a given body of data (e.g., a sample of patients) equally well. When making predictions about a new sample, the general result is that the simpler system will make more accurate predictions than the system with more parameters. This form of less-is-more has been mathematically proven for specific situations (Akaike, 1973; Forster & Sober, 1994; Geman, Bienenstock, & Doursat, 1992). With a sufficient number of parameters, one can always force a model to fit a sample of observations. However, part of this fit involves overfitting, that is, explaining noise and idiosyncrasies that do not generalize to a new sample, such as new patients. In an uncertain world, only part of the information available today will generalize to new situations; therefore, good decision making implies ignoring part of the information. The more unpredictable the situation is, the more information should be ignored. The art of good decision making is to focus on that part of the information that generalizes and to ignore the rest.

Predicting heart attacks is far from error-free. In the original sample of several thousands of patients on which the HDPI was validated (Pozen et al., 1984), the latter may very well have provided a better fit than a fast and frugal tree. But it was subsequently applied in different hospitals to new groups of patients who deviated in unknown ways from the original sample. As a result, the model that was best in the original population was no longer guaranteed to be the best in those new situations; it may suffer from overfitting. A fast and frugal heuristic that focuses only on the key variables is likely to be more robust, and it has a chance of performing better than the system that used more information. As Figure

1.3 amply illustrates, assigning heart disease patients is one of these difficult tasks.

HEURISTICS CAN BE FRUGAL BY EXPLOITING STRUCTURES OF ENVIRONMENTS

A second reason why heuristics that ignore information can nevertheless be accurate is their ecological rationality. A heuristic is ecologically rational to the degree it is adapted to the structure of information in an environment, whether the environment is physical or social. Heuristics that employ one-reason decision making can exploit environments in which the importance (e.g., beta weights in regression) of the cues available are exponentially decreasing, that is, noncompensatory. An example are binary cues with weights 1, 1/2, 1/4, 1/8, and so on. If this is the case, one can prove that a simple heuristic called Take The Best can perform as well as any optimal linear combination of binary cues (Martignon & Hoffrage, 1999). Similarly, the fast and frugal tree can exploit noncompensatory environments. If the environment, in contrast, has a compensatory structure, tallying heuristics can exploit this type of information. A tallying heuristic has the following structure: If you find n ($n \geq 2$, say 3) positive indicators of a heart disease, then stop search and send the patient into the care unit; otherwise, into the nursing bed (Forster et al., 2002). In contrast to the fast and frugal tree, tallying does not employ one-reason decision making: It uses more than one cue, but its simplicity is in the fact that it uses only few cues and does not order or weight them, and it can search for cues in any order.

To summarize, the reasonableness of fast and frugal heuristics derives from their ecological rationality, not from following the classical definitions of rationality in terms of coherence or internal consistency of choices. Indeed, some of the fast and frugal heuristics can produce intransitive inferences in direct violation of standard rationality norms, but they still can be quite accurate (Gigerenzer, Czerlinski, & Martignon, 1999).

THE UNAPPRECIATED VIRTUES OF SIMPLICITY

Consider a physician who uses the fast and frugal tree in Figure 1.2 to allocate patients. She makes more accurate decisions than her colleagues who rely on intuition and defensive decision making do, and ones that are as good as or better than with the logistic regression classification. However, one of the patients whom she sent into a nursing bed had a heart attack and died. The relatives ask why the patient wasn't in the care unit, and their lawyer finds out that the doctor had only checked two predictors (the two predictors in Figure 1.2), ignoring the rest. The relatives sue the doctor for malpractice. Do physicians want to run this risk?

The irony in this situation is that physicians often feel pressed to hide how their decisions were actually made and to pretend they have made them on the basis of something different. The virtue of less-is-more is not yet fully understood. As a consequence, the quality of treatment can suffer by the covert and uneducated use of heuristics. For instance, Figure 1.3 shows that whatever intuitive heuristics physicians used before they encountered the researchers, their performance was dismal.

There is growing empirical evidence that physicians rely on fast and frugal heuristics when they make treatment decisions. For instance, a recent study on decisions of British general practitioners to prescribe lipid-lowering drugs suggests that doctors do indeed use only very few cues for their decisions (Dhami & Harries, 2001). But in private conversations, physicians indicate that they often cannot risk admitting to using heuristics. At the same time, there is growing evidence that heuristics can be powerful tools for clinical judgments under uncertainty (Fischer et al., 2002; Forster et al., 2002). Medical researchers have begun discussing fast and frugal decision making as an alternative to classical decision making (Elwyn et al., 2001). The systematic study of fast and frugal decision making can help to bridge the worlds of intuitive heuristics and classical decision making. Furthermore, it can teach physicians what heuristics to use, as well as when and how to improve the decisions they make.

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EDITORIAL COMMENTARY

The word "heuristic" is not commonly used in medical circles in the United States. However, the concept of "triage" and the use of algorithms are well-accepted and used every day. "Fast and frugal heuristics" are a bit—but only a bit—different from these. It was battlefield medicine that first gave us the concept of triage. In that setting, nearly instantaneous decisions regarding a combatant's ability to survive needed to be made based on very little information.

The typical algorithm uses some data reference set, often based on complex mathematical models. While some are useful, others are so complex and take so much time to go through the various branches that they become cumbersome and are often ignored. Such overfitting should be avoided—a point made well by the authors—whenever clinical algorithms are developed.

—Kenneth L. Noller

Simplicity is nice, but it needs to be substantive. What we see in this chapter is an argument in favor of the fast and frugal heuristics—in comparison with probability calculations. Yet it seems to replace one black box with another—we still do not know the precise ways in which these fast and frugal heuristics work. We do know that (a) they do work, and (b) they work quickly and relatively efficiently (compared to others). However, unless the actual mechanisms that operate—frugally and fastly—are clarified, we only have a demonstration of effectiveness and not of the reasons for such effectiveness.

—Jaan Valsiner