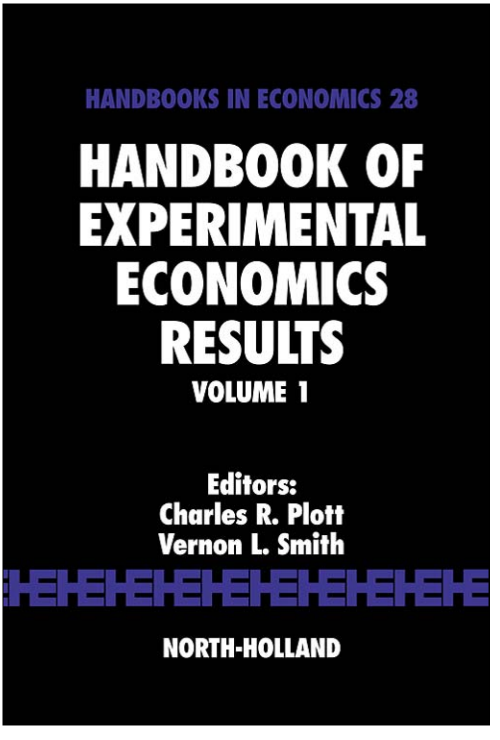

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Chapter 106

THE RECOGNITION HEURISTIC AND THE LESS-IS-MORE EFFECT

DANIEL G. GOLDSTEIN
London Business School

GERD GIGERENZER
Max Planck Institute for Human Development, Berlin

Missing data are often considered an annoyance. However, a fast and frugal heuristic can turn missing knowledge into predictive information. Consider the outcomes of the following two cross-cultural experiments. We asked Americans and Germans, "Which city has a larger population: Milwaukee or Detroit?" Forty percent of Americans correctly responded that Detroit is larger. Compared to the Americans, the Germans knew very little about Detroit, and many had not even heard of Milwaukee. Yet 90% of the Germans answered the question correctly. In another study, Turkish students and British students made forecasts for all 32 English F.A. Cup third round soccer matches (Ayton and Önkal, 1997). The Turkish participants had very little knowledge about English soccer teams while the British participants knew quite a bit. Nevertheless, the Turkish predictions were nearly as accurate as the English ones (63% versus 66% correct).

Can a lack of knowledge be useful for making accurate inferences? It can be when using the recognition heuristic, a simple rule that exploits not abundant information, but rather a lack of knowledge (Goldstein and Gigerenzer, 1999, 2002; Gigerenzer and Goldstein, 1996). Following the heuristic, a person who has heard of Detroit but not Milwaukee would infer that Detroit is larger. For inferring which of two objects is greater on some criterion, the recognition heuristic is simply stated:

If only one of a pair of objects is recognized, then infer that the recognized object has the higher value on the criterion.

As opposed to an all-purpose tool like a linear model, the recognition heuristic is domain specific. Instead of being unboundedly rational, it is ecologically rational, that is, reasonable with respect to some environments but not others. There are domains in which the recognition heuristic will not work. A wise organism will only apply the rule in domains where recognition is strongly correlated with the criterion. (If this correlation is negative, then the rule should be reversed, and the unrecognized object should be chosen.) There are situations in which the recognition heuristic cannot be applied, for instance, when all objects are recognized. There are domains in which people will not apply it, for example, when they suspect that they are being asked a trick question. And there will be individual differences: different people use different heuristics at different times. Nonetheless, the very simple rule can make very accurate predictions from very little information, as we shall see.

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1. Accuracy of the Recognition Heuristic

Here we derive the proportion of correct answers one would expect to achieve using the recognition heuristic on two-alternative inference tasks (Goldstein and Gigerenzer, 1999, 2002). Suppose there is a reference class of N objects and a test consisting of pairs of randomly-drawn objects. When randomly drawing pairs of objects, there are three ways they can turn out: one recognized and one unrecognized, both unrecognized, or both recognized. Suppose there are n recognized objects and thus $N-n$ unrecognized objects in the reference class. This means that there are $n(N-n)$ pairs in which one object is recognized and the other is unrecognized. A similar calculation shows that there are $(N-n)(N-n-1)/2$ pairs in which neither object is recognized. Finally, there are $n(n-1)/2$ pairs in which both objects are recognized. To transform each of these absolute numbers into a proportion of cases, it is necessary to divide each of them by the total number of possible pairs, $N(N-1)/2$.

To compute the proportion correct on such a test, it is necessary to know the probability of a correct answer for each type of pair. Let the recognition validity α be the probability of getting a correct answer when one object is recognized and the other is not. The probability of getting a correct answer when neither object is recognized (and a guess must be made) is .5. Finally, let β be the knowledge validity, the probability of getting a correct answer when both objects are recognized. We shall make the simplifying assumption that α and β stay constant as n varies. Combining all these terms together, the expected proportion of correct inferences, $f(n)$, on an exhaustive pairing of objects is:

$$f(n) = 2\left(\frac{n}{N}\right)\left(\frac{N-n}{N-1}\right)\alpha + \left(\frac{N-n}{N}\right)\left(\frac{N-n-1}{N-1}\right)\frac{1}{2} + \left(\frac{n}{N}\right)\left(\frac{n-1}{N-1}\right)\beta. \tag{1}$$

The right side of the equation breaks into three parts: the leftmost term equals the proportion of correct inferences made by the recognition heuristic; the middle term equals the proportion of correct inferences resulting from guessing; and the rightmost term equals the proportion of correct inferences made when knowledge beyond mere recognition can be used. Inspecting this equation, we see that if the number of objects recognized, n, is 0, then all questions will lead to guesses and the proportion correct will be .5. If $n = N$, then the leftmost two terms become zero and the proportion correct will be β. We can see that the recognition heuristic will come into play most when an organism is operating under "partial ignorance." Based on the recognition validity α, the knowledge validity β, and the degree of ignorance, that is, n compared to N, Equation (1) specifies the proportion of correct inferences made by the recognition heuristic.

2. The Less-is-More Effect

Equation (1) lets us make exact predictions, for instance, about how accurate American students should be making inferences about cities in Germany. We surveyed University

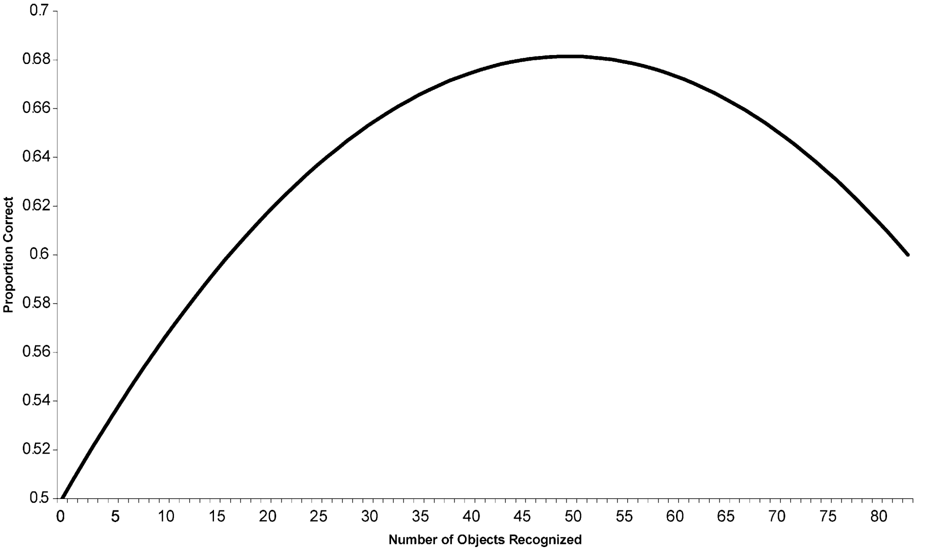

Figure 1. Plot showing how use of the recognition heuristic can lead to a less-is-more effect. The recognition validity α is 80%, the knowledge validity β is 60%, the total number N of objects is 83, and the number n of objects recognized varies. When over 50 objects are recognized, learning to recognize more only causes inferential accuracy to decrease. When all objects are recognized, accuracy equals the knowledge validity. Figure adapted from Goldstein and Gigerenzer (1999).

of Chicago students on all cities in Germany with more than 100,000 inhabitants (83 cities in 1994). We found that the cities they recognized had larger populations than those they did not recognize in about 80% of all possible pairs. This figure corresponds to a recognition validity α of .8. Interestingly, this value of 80% seemed largely independent of the number of cities recognized, giving support to the assumption that α is constant. Americans differ greatly on the knowledge validity β. Assume for illustration that it is around .6. Inserting these two values into Equation (1) we see the relationship between the accuracy and the number of objects recognized in Figure 1 (Goldstein and Gigerenzer, 1999, 2002).

The striking aspect of the accuracy curve is its non-monotonicity. Accuracy increases until a certain point (around 50 objects recognized), after which learning to recognize objects causes accuracy to decrease. This state of affairs, where less recognition knowledge leads to greater inferential accuracy, is what we call the less-is-more effect.

When will the less-is-more effect appear? A proof shows that, under assumptions, Equation (1) leads to a non-monotonic curve whenever $\alpha > \beta$ (Goldstein and Gigerenzer, 1999, 2002). The intuition for this is simple. When all objects are recognized, accuracy is equal to β. When just one object is unrecognized, accuracy equals some combination of α and β. If $\alpha > \beta$ this combination will be greater than β alone, and the condition for a less-is-more effect is met.

The surprising results cited at the beginning of this paper could be due to less-is-more effects resulting from the recognition heuristic. In addition to predicting people's inferences, recognition even helped out in forecasting the outcomes of soccer matches. Often, the name of an English soccer team includes a city name within it, such as "Manchester United." It happens that teams from well-recognized cities tend to be good ones. The Turkish students could use city-name or team-name recognition to inform their forecasts. In cases where the Turkish students rated one team as unfamiliar and the other as familiar to some degree, they chose the more-familiar team in 627 out of 662 (95%) of the forecasts (Ayton and Önkal, 1997). In the sections that follow, we present experiments that test whether people apply the recognition heuristic in their judgments, and if we can evoke a less-is-more effect in the laboratory.

3. Do People Use the Recognition Heuristic?

This simple test asks how often unprompted people will use the recognition heuristic (Goldstein and Gigerenzer, 1999, 2002). We quizzed people on pairs of cities drawn from the largest in Germany and asked them to choose the more populous city in each case. We had the participants check off from a list which of these cities they recognized either before or after the test. From this recognition information, we could calculate how often participants had an opportunity to choose in accordance with the recognition heuristic, and compare it to how often they actually did. Figure 2 shows the results for 22 individual participants.

For each participant, two bars are shown. The left-hand bars show how many opportunities the person had to apply the recognition heuristic, and the right-hand bars show how often their judgments agreed with the heuristic. For example, the person represented by the leftmost pair of bars had 156 opportunities to choose according to the recognition heuristic, and did so every time. The next person did so 216 out of 221 times, and so on. The proportions of recognition heuristic adherence ranged between 100% and 73%. The median proportion of inferences following the recognition heuristic was 93% (mean 90%).

People may follow the recognition heuristic when they have no better strategy to rely on. But what about those who have access to more reliable information? In a companion experiment, we taught Americans facts about which German cities have major league soccer teams (Goldstein and Gigerenzer, 1999, 2002). The presence of a major league team is an excellent predictor of city population in Germany. We wanted to see which they would choose as larger: a city they had never heard of before, or one that they recognized but just learned, has *no* soccer team. The result was that they chose the recognized cities as often as in the previous experiment, despite the knowledge that these recognized cities are likely to be small (that is, that they lack soccer teams).

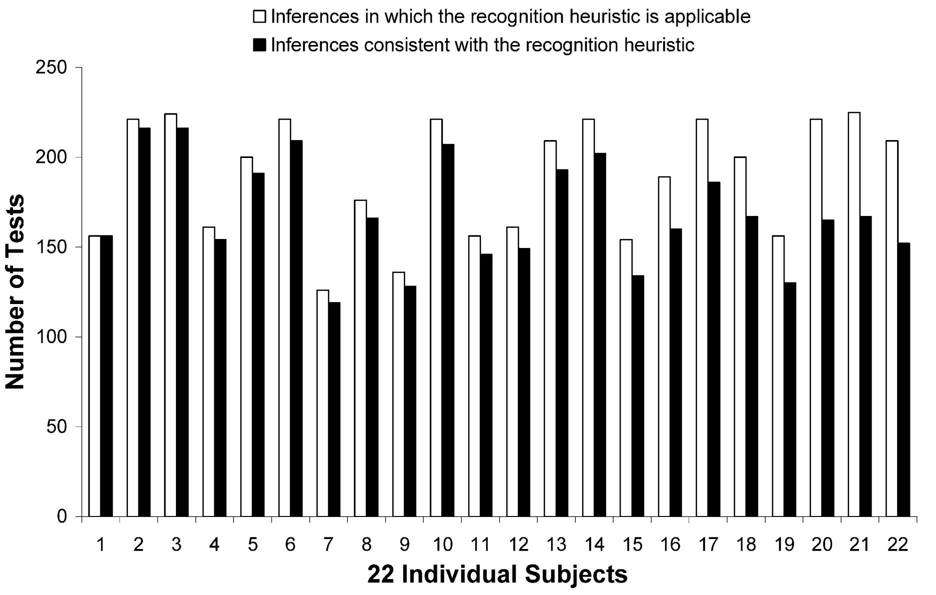

Figure 2. American participants were given pairs of German cities and asked to choose the larger in each case. Before or after this task, they were asked which cities they had heard of before the experiment. The left-hand bars show for each subject how many pairs they were presented in which one city was recognized and the other not. The right-hand bars show in how many of these cases the recognized city was chosen. Figure adapted from Goldstein and Gigerenzer (1999).

4. Does the Less-is-More Effect Occur in Human Reasoning?

We asked 52 University of Chicago students to take two tests each. One was on the 22 largest cities in the United States. The other was on the 22 largest cities in Germany: cities about which they knew little or nothing beyond mere recognition (Goldstein and Gigerenzer, 1999, 2002). Each question consisted of two randomly drawn cities, and the participants' task was to pick the larger. One would expect participants in this experiment to score somewhat higher on the American cities than the German ones. For instance, many Americans can name the three largest American cities in order, and this alone would give them the correct answer in 26% of all possible questions. For those who know the top five cities in order, this figure climbs up to a definite 41% correct.

When tested on their own cities, the Americans scored a median 71% (mean 71.1%) correct. On the German cities, the median was 73% (mean 71.4%) correct – roughly the same accuracy despite great differences in knowledge. For half of the subjects, we kept track of which German cities they recognized. In this group, the mean proportion of inferences in accordance with the recognition heuristic was 88.5% (median 90.5%). Participants recognized a mean of 12 cities, roughly half of the total, which would allow them to apply the rule about as often as possible. In a study that is somewhat the reverse of this one, the less-is-more effect was demonstrated with German and Austrian students who scored more accurate inferences on American cities than on German ones (Hoffrage, 1995; see also Gigerenzer, 1993).

5. The Underpinnings of the Recognition Heuristic

Name recognition can be a good predictor, as it is often correlated with wealth, resources, quality, and power. This correlation can arise from people being interested in, and thus talking and publishing about, highly-ranking people, places, and things. Top athletes and star lawyers make the headlines more than average ones do. If people prefer recognized products, these preferences can be manipulated by advertisers paying great sums for a place in the recognition memory of potential customers.

Much modeling of choice uses linear models that can be applied to domains from meterology to marketing. In contrast, the recognition heuristic is rooted in a fundamental and well-studied part of the cognitive architecture: recognition memory. It proves capable of making accurate inferences in the real world where recognition is often correlated with various important criteria. This heuristic exploits a quantity that is readily available to all organisms: missing knowledge.

References

Ayton, P., Önkal, D. (1997). “Forecasting futball fixtures: Confidence and judged proportion correct”. Unpublished manuscript, City University, London.

Gigerenzer, G. (1993). “The bounded rationality of probabilistic mental models”. In: Manktelow, K.I., Over, D.E. (Eds.), Rationality: Psychological and Philosophical Perspectives. Routledge, London.

Gigerenzer, G., Goldstein, D.G. (1996). “Reasoning the fast and frugal way: Models of bounded rationality”. Psychological Review 104, 650–669.

Goldstein, D.G., Gigerenzer, G. (1999). “The recognition heuristic: How ignorance makes us smart”. In: Gigerenzer, G., Todd, P.M., the ABC Group (Eds.), Simple Heuristics that Make Us Smart. Oxford University Press, New York, pp. 37–58.

Goldstein, D.G., Gigerenzer, G. (2002). “Models of ecological rationality: The recognition heuristic”. Psychological Review 109, 75–90.

Hoffrage, U. (1995). “The adequacy of subjective confidence judgments: Studies concerning the theory of probabilistic mental models”. Doctoral thesis, University of Salzburg.