In Proceedings of the Sixth International Conference on Cognitive Modeling, 384-385.
Mahwah, NJ: Lawrence Earlbaum.

How Forgetting Fosters Heuristic Inference

Lael J. Schooler (schooler@mpib-berlin.mpg.de)
Max Planck Institute for Human Development
Lentzeallee 94, 14195 Berlin Germany

Ralph Hertwig (Ralph.Hertwig@unibas.ch)
Institut für Psychologie
Universität Basel, Missionsstraße 60/62
CH-4055 Basel Switzerland

Functions of Forgetting

The notion that forgetting serves an adaptive function has repeatedly been put forth in the history of the analysis of human memory. Bjork and Bjork (1996), for instance, have argued that it prevents obsolete information from interfering with the recall of more current information. Here we explore functions that forgetting may play in memory-based inference strategies. To this end, we bring together two research programs—the program on fast and frugal heuristics (Gigerenzer, Todd, & the ABC research group, 1999) and the ACT-R research program (Anderson & Lebiere, 1998). Specifically, we implement in ACT-R the *recognition heuristic* (RH) (Goldstein & Gigerenzer, 2002), and the *fluency heuristic* (FH), each of which exploit fundamental memory retrieval processes.

The Recognition Heuristic

Consider one of the simplest decisions that can be made: selecting one option from two possibilities, according to some criterion on which the two can be compared. How this decision is made depends on the available information. If the only information at hand is whether or not the decision maker recognizes one of the alternatives, and she suspects that recognition is positively correlated with the criterion, then she can do little better than rely on her own partial ignorance, choosing recognized options over unrecognized ones. This kind of "ignorance-based reasoning" is embodied in the *recognition heuristic* (RH) (Goldstein & Gigerenzer, 2002), which for two–alternative choice tasks can be stated as follows:

***If** one of two objects is recognized and the other is not,*
***then** infer that the recognized object has the higher value with respect to the criterion.*

This minimal strategy may not sound like much for a decision maker to go on, but there is often information implicit in the failure to recognize something, and this failure can be exploited by the heuristic.

Goldstein & Gigerenzer (2002) conducted studies to find out whether people actually use the recognition heuristic. For instance, they presented U.S. students with pairs of U.S. cities and with pairs of German cities. The task was to infer which city in each pair had the most inhabitants. The students performed about equally well on both types of cities. This result is counterintuitive: The students had accumulated a lifetime of facts about U.S. cities that could be useful for inferring population, but they knew little or nothing about the German cities beyond merely recognizing about half of them. According to Goldstein and Gigerenzer (2002), the latter fact is just what allowed them to employ the recognition heuristic to infer that the German cities that they recognized were larger than those they did not. The students could not use this heuristic when comparing US cities, because they recognized all of them and thus had to rely on other methods for making their decisions. In short, the RH works because our lack of recognition knowledge is often not random, but systematic and exploitable.

Recognition Heuristic Exploits Correlations

According to Goldstein and Gigerenzer (2002) the recognition heuristic works, because there is a chain of correlations, linking the criteria (e.g., city population), environmental frequencies (e.g., how often a city is mentioned) and recognition. ACT-R's activation tracks just such environmental regularities. Therefore activation differences reflect, in part, these frequency differences. Thus, it appears that inferences could be based on activation values read off the chunks. However, it has been a long-standing policy in ACT-R that sub-symbolic quantities, such as activation, cannot be accessed directly. We propose, nevertheless, that the system could still capitalize on activation differences associated with various objects by gauging how it responds to them. Two such responses that correlate with activation are (1) whether a chunk associated to a specific object can be retrieved and (2) how quickly it can be retrieved. The first response is key to our implementation of the RH and the second to the FH.

Fluency Heuristic

The use of fluency of reprocessing as a cue in inferential judgment has been termed the *fluency heuristic* (e.g., Jacoby & Dallas, 1981). We adopt this name but define the heuristic in the context of a two-alternative choice task in which the objective is to select one option from two possibilities, according to some criterion on which the two can be compared. According to the fluency heuristic:

***If** one of two objects is more fluently reprocessed,*
***then** infer that this object has the higher value with respect to the criterion.*

To see how this might work, let us assume that American students are sensitive to differences in recognition times. That is, they are attuned to, for instance, being able to recognize instantaneously "Berlin", but taking a moment to recognize "Stuttgart". We suggest that these differences in recognition time reflect, in part, retrieval time differences, which, in turn, reflect the base level activations of the corresponding memory chunks, which correlates with environmental frequency, and finally with city size. Further, rather than assuming that the system can discriminate between minute differences in any two retrieval times, we allow for limits on the system's ability to do this. Thus, if the retrieval times of the two alternatives are within a j.n.d. of , say, 100 ms., then the system must guess.

Simulations

Method

First, like Goldstein and Gigerenzer (2002) we assume that the frequency with which a city is mentioned in the newspaper mirrors its overall environmental frequency. Based on this assumption, we constructed environments such that the probability of encountering a city name on any given day was proportional to its relative frequency in the Chicago Tribune. Second, the model learned about the environment by strengthening memory chunks associated with each city according to ACT-R's base level activation equation. Third, the model's recognition rates were determined by fitting the activation strengths of the city records to the recognition rates of Goldstein and Gigerenzer's (2002) students. These recognition rates, in turn, determine how well the recognition and fluency heuristics perform on the city comparison task.

Results

Figure 1 shows how the performance of the heuristics depends on how quickly chunk activation decays (i.e., ACT-R's parameter *d*); both heuristics peak at intermediate decay rates. In the case of the recognition heuristic, intermediate levels of forgetting maintain a distribution of recognition rates that are highly correlated with the criterion. In the case of the fluency heuristic, intermediate amounts of forgetting increase the chances that differences in the retrieval times of two chunks will be detected. To see why, consider Figure 2 that shows the exponential function that relates a chunk's activation to its retrieval time. Forgetting lowers the range of activations to levels that correspond to retrieval times that can be more easily discriminated. In other words, a given difference in activation at a lower range results in a larger, more easily detected, difference in retrieval time than the same difference at a higher range

Conclusion

The recognition and fluency heuristics can be understood as means to indirectly tap the environmental frequency information locked in the activations. These heuristics will be effective to the extent that the chain of correlations, linking the criteria, environmental frequencies, activations and responses, is strong. Forgetting functions to foster the performance of these heuristics by strengthening this chain.

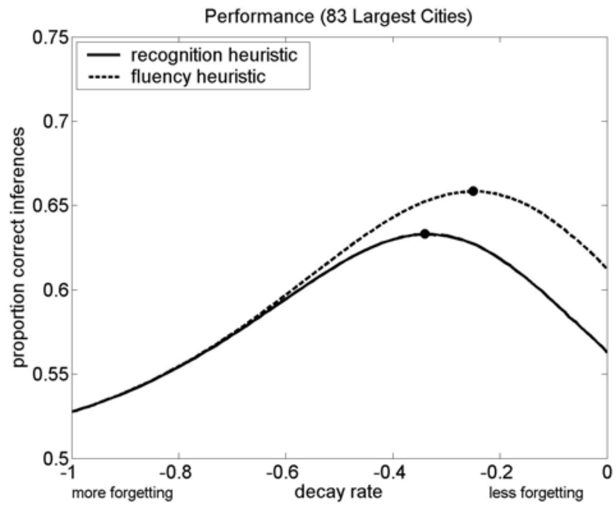

Figure 1. Performance varies with decay rate.

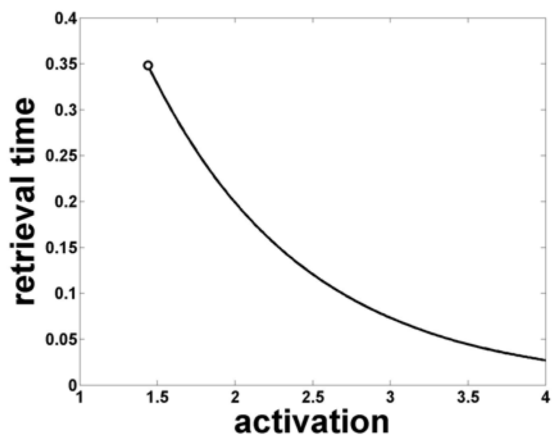

Figure 2. A chunk's activation determines its retrieval time.

References

Anderson, J. R., Lebiere, C. (1998). *The atomic components of thought*. Mahwah, NJ: Lawrence Erlbaum Associates.

Bjork, E. L., & Bjork, R. A. (1988) On the adaptive aspects of retrieval failure in autobiographical memory. In M. M. Gruneberg, P. E. Morris, & R. N. Sykes (Eds.). *Practical Aspects of Memory II*, London: Wiley, 1988.

Gigerenzer, G., Todd, P. M. & the ABC Research Group (1999). *Simple heuristics that make us smart*. New York: Oxford University Press.

Goldstein, D. G. & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review*, *109*, 75-90.

Jacoby, L. L., & Dallas, M. (1981). On the relationship between autobiographical memory and perceptual learning. *Journal of Experimental Psychology: General*, *110*, 306-340.