CASE STUDY: The base-rate fallacy reconsidered

Koehler (1996) reviewed findings on use of base-rate information.

Psychological research on decision making often shows that people tend to ignore base rates when estimating the likelihood of an event. This can happen when the probability of something is conditional on two events.

For example, suppose you were told that a taxi-cab was involved in a hit-and-run accident one night. Of the taxi-cabs in the city, 85% belonged to the Green company and 15% to the Blue company. You are then asked to estimate the likelihood that the hit-and-run accident involved a green taxi-cab (all else being equal). You would say that there is an 85% chance, since 85% of the cabs are green. However, suppose you were then told that an eyewitness had identified the cab as a blue cab. But when her ability to identify cabs under appropriate visibility conditions was tested, she was wrong 20% of the time. You now have to decide the probability that the taxi-cab involved in the accident was blue.

This problem was considered by Tversky and Kahneman (1982). The way to work out the answer involves the use of Bayes' theorem, a simple formula for calculating conditional probabilities.

In this example, the hypothesis that the cab was blue is H_A and the hypothesis that it was green is H_B. The prior probability for H_A is 0.15, and for H_B it is 0.85, because 15% of the cabs are blue and 85% are green. The probability of the eyewitness identifying the cab as blue when it was blue, $p(D/H_A)$, is 0.80. Finally, the probability of the eyewitness saying the cab was blue when it was green, $p(D/H_B)$, is 0.20. According to Bayes' formula:

$$\frac{p(H_A/D)}{p(H_B/D)} = \frac{p(H_A)}{p(H_B)} \times \frac{p(D/H_A)}{p(D/H_B)}$$

Therefore,

$$\frac{p(H_A/D)}{p(H_B/D)} = \frac{0.15}{0.85} \times \frac{0.80}{0.20}$$

This produces the values 0.12/0.17. Since the formula produces a ratio of probabilities, the ratio is 12:17. This means that the probability of the cab being blue is 12/(12+17), which is 12/29 – which works out to 0.41 or a 41% probability.

Most participants focused on what the eyewitness claimed, and estimated the probability as 80%. Thus, they ignored the ratio of blue cabs to green cabs in their estimation (the base rate). Note that they overestimated that the cab was blue by almost twice the actual probability.

However, in the target article, Koehler (1996) argues that it is a myth to believe that people neglect base rates in the real world. There appears to be little evidence that base rates are routinely ignored and, in fact, base rates are usually incorporated into the decisions that people make. Koehler argues that base-rate neglect emerged from the heuristics and biases paradigm that dominated decision research in the 1980s. It was generally accepted that people make errors or probability estimates because they rely on simple, but error-prone, rules of thumb.

It is not argued that Bayesian probability is logically flawed, but that most real-world problems do not easily map on to it. In other words, experiments on base rates have tended to have low ecological validity. Furthermore, many studies in which it is claimed that base rates are ignored may be exaggerating the case, since base rates were not completely ignored in those studies but less weight was attached to them. In some experimental studies that use artificial problems, it has been shown that participants readily made use of base-rate information. There are examples, too, in the real world where base-rate information is not ignored. Physicians use base-rate information of an ailment in diagnosis (Christensen-Szalanski & Bushyhead, 1981).

In the real world, base rates are learned through experience and hence may have been acquired implicitly. This makes the information more robust and more meaningful than artificially presented base-rate information provided in a single-trial experiment and made explicitly known.

According to Koehler, people may attribute less importance to base-rate information that is provided by the experiment if it is counterintuitive, appears unreal or is unlike the experiences that people have in the real world. When participants learn base-rate information over many trials, it becomes increasingly used in their judgements (e.g., Manis et al., 1980). Medin and Edelson (1988) found that base rates acquired over many trials were used in decisions, although participants had difficulty in making explicit reference to them. In addition, people may be more trusting of their own self-acquired base rates than those provided in the lab.

The evidence does not favour the view that people have a poor understanding of base rates and statistics in decision making. For example, most people know that a low-quality football team is capable of beating a high-quality football team on a given day, but they also know that the team is unlikely to repeat this over a larger number of games. Hence, they show knowledge of the law of large numbers.

Returning to the taxi-cab problem, participants might ordinarily expect not to have information about the percentage of cabs in accidents or cabs in accidents at night. They may therefore have difficulty in representing the problem without this information. When Ofir (1988) made the base rate more extreme (10% versus 90% ratio of green to blue cabs), there was strong evidence that base rates were used. It may be that when more extreme base rates are used their relevance is elevated, and in such experiments high-relevant information may dominate low-relevant information in the eyes of the participant. There is a further difficulty with the taxi-cab problem, in that most people know that if an eyewitness is aware of the ratio of green and blue cabs then that information is likely to influence their judgements in ambiguous settings.

In sum, Koehler argues that the stimuli used in such experiments, the incentives of the participants, and the way in which the responses are assessed and compared with statistical norms, are far removed from the real world, and hence it is difficult to draw sensible and useful conclusions from them.

References

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