Using a Cognitive Architecture to Specify and Test Process Models of Decision Making

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Theoretical Background

Imagine you are asked which city is larger, York or Stockport. About York you recently read an article in the newspaper. You remember that it had some mentionable industry, but no international airport and also no premier league soccer team. Of the city of Stockport you have never heard before. Which city will you answer to be the larger one? According to the recognition heuristic (Goldstein, Gigerenzer, 2002), if you recognize one of the alternatives, but not the other, you should infer that the recognized one to is larger. Your answer would be York. As an alternative to the recognition heuristic, you may rely on a strategy that uses your knowledge about the city's attributes as cues. Following corresponding compensatory models of decision-making, (e.g. unit-weight linear strategy), you might conclude that the absence of an airport and a premier league soccer team speak against York being a large city. Consequently, you might infer Stockport to be larger.

The example illustrates a debate that has received much attention in the decision-making literature. Are decisions better described by non-compensatory simple heuristics, or by complex compensatory decision strategies? A large amount of evidence has been gathered in support of as well as against both positions – for support of the recognition heuristic (e.g. Gigerenzer et al., 2008; Pachur, 2010; Volz et al., 2006), and for challenges of the heuristic: (e.g. Beaman et al., 2010; Dougherty et al., 2008; Oppenheimer, 2003). However, non-compensatory and compensatory processes are broad categories that subsume a number of different strategies. For instance, compensatory strategies propose that knowledge about the alternatives is used in some way; however, they do not agree on how this is done. Constraint satisfaction models, for example, assume that all available information is integrated at once, in a parallel, automatic fashion (Glöckner, Betsch, 2008). Evidence accumulation models, on the other hand, assume that evidence for the alternatives is accumulated sequentially until a decision boundary is reached (e.g. Lee, Cummins, 2004).

In assessing different proposed strategies against each other, research has encountered various problems. First, theories are often specified at varying levels of detail, making it difficult to directly compare them. Second, they are often formulated at a verbally qualitative level and are therefore underspecified relative to the empirical data against which they are tested. Consider the city size example again. Based on the different theories, one might generate predictions about decision times, i.e., the time participants need to decide which of the two cities is larger. However, participants' decision times will not only depend on the decision strategy itself, but also on other factors, like the time it takes to read the names of the cities, to retrieve information from memory, and to enter a response. Consequently, the contribution of the decision strategies themselves might be drowned out by these additional factors.

In the project we report here, we try to tackle both of these issues. First, we implement different strategies that have been proposed for decisions from memory into one cognitive modeling framework. This results in directly comparable quantitative predictions of the strategies. Second, by using a cognitive architecture for this implementation, we take into account the contribution of and interaction with additional components of cognition, like reading, memory retrieval and giving a motor response. This allows us to assess the contribution of different decision strategies in a more detailed way and to directly compare them against empirical data.

Methods: Empirical Data

To test different decision strategies against each other, we reanalyzed data from Pachur et al. (2008), which has been argued to provide evidence for both the recognition heuristic and compensatory strategies (Gigerenzer et al., 2010). Pachur et al. presented their participants with choices between cities, as in the introductory example: a recognized city with three associated cues and an unrecognized city about which nothing was known. The cues were industry, airport and soccer and they could be either positive (speaking for a city being large) or negative (speaking against a city being large). The cities varied in the pattern of associated cues, with three, two, or one of the cues being negative as shown in Table 1. The participants' task was to decide which of the two cities was larger. Decisions and decision times were assessed.

Tab.1 Cues Patterns associated to the recognized cities in Pachur et al. (2008) (+ = positive cue value; - = negative cue value).

	City					
Cue	Aberdeen	Bristol	Nottingham	Sheffield	Brighton	York
Industry	+	+	+	+	+	+
Airport	+	+	–	–	–	–
Soccer	+	+	+	+	–	–

Cognitive Model

The models were implemented in the cognitive architecture ACT-R (Anderson et al., 2004), which takes into account both sub-symbolic and symbolic components of cognition as well as perceptional and motor processes.

Assessing Recognition

There is evidence that, when asked to make a decision between alternatives, people will first assess the recognition of the alternatives (Pachur, Hertwig, 2006). In modeling recognition, we follow Anderson et al. (1998) and Schooler et al. (2005) in assuming that an alternative is recognized if it can be retrieved from memory. The probability and the time required for the retrieval depends on the frequency of encounters with the alternative in the past and its usefulness in the current context. The more often it was encountered and the more useful it is in the current context, the higher the chance that it will be retrieved and the faster the retrieval (see Anderson et al., 2004 for the computational details).

Assessing Cue Knowledge

We assume that the same kind of retrieval processes that enable reasoners to retrieve the alternatives themselves from memory will be used to retrieve knowledge associated to these alternatives. To reflect the fact that positive cue knowledge about alternatives seemed to be remembered more easily by the participants than negative cue knowledge, we assume that positive cues are retrieved faster than negative ones.

Decision Strategies

All models share the assumption that, when presented with alternatives on the screen, these alternatives will be read and their recognition will be assessed. The models differ in the steps that followed this initial assessment of recognition.

1. Non-Compensatory Strategies

The first group of models implements different versions of the non-compensatory recognition heuristic. They *always* decide for the recognized city. However, they differ in the amount of knowledge they retrieve from memory before this decision is made, and therefore, produce different decision time predictions.

Model 1. Implementing the simplest version of the recognition heuristic, Model-1 directly uses the outcome of the recognition assessment and responds with the recognized city.

Model 2. Implementing a more complex version of the recognition heuristic, Model-2 retrieves knowledge about the three cues of the recognized city from memory. After all cues are retrieved, the model responds with the recognized city, without using the retrieved cue knowledge.

Model-1&2. This model presents a combination of Model-1 and Model-2, in assuming a race between their strategies. After recognition is assessed, the strategies to directly decide that the recognized city is larger and to retrieve a cue race against each other. This race is repeated until the decision is made.

Model-1&2-F. This model is identical to Model-1&2, but it additionally assumes that retrieved cues will at times be forgotten. Forgetting is implemented by an additional race between retrieve-a-cue, respond-with-recognized and forgetting that starts as soon as at least two cues have been retrieved from memory.

2. Compensatory strategies

The second group of models implements versions of compensatory strategies. Depending on the cue knowledge associated to a city, they can decide for and against the recognized city. They differ in how the cue knowledge is used in this decision and they produce different decision time predictions.

Model-3. This model implements a strategy that assumes that cue knowledge is used implicitly by memory activation processes. It retrieves knowledge about the three cues of the recognized city from memory. After all cues are retrieved, the model tries to form an impression about the recognized city's size. It does this by attempting to retrieve information that indicates whether the city is large. The probability that this information can be retrieved depends on memory activation spreading from positive cues. The more positive cues a city has, the more activation is spread and the higher the chance that the city is assessed as large. If the model cannot assess the city as large, it will enter the unrecognized city.

Model-1&3. In assuming a race between the strategies of Model-1 and 3, this model implements a combination of the non-compensatory recognition heuristic and a compensatory decision strategy. After recognition is assessed, the strategies to directly decide that the recognized city is larger and to retrieve a cue race against each other. This race is repeated until the decision is made or all cues are retrieved. If all cues are retrieved and no decision has been made yet, the model can additionally try to form an impression about whether the city is large by using memory activation as implemented in Model-3.

Model-1&3-F. This model is identical to Model-1&3, but it additionally assumes that retrieved cues will at times be forgotten as in Model-1&2-F.

Model-4. This model uses cue knowledge explicitly by testing cues against a decision criterion. It retrieves knowledge about the cues for the recognized city after assessing recognition. If enough positive or negative cues are retrieved to meet its decision criterion, it responds with the recognized city (in case of positive cues) or the unrecognized city (in case of negative cues). To reflect different possible decision criteria, the model is implemented in different versions. Model-4.1, responds as soon as one positive or negative cue is retrieved. Model-4.2, needs two positive or negative cues for a decision, and Model-4.3 needs all 3 cues to be positive or negative to reach its criterion. If the model cannot retrieve enough cues to reach its criterion, it uses recognition as its best guess.

Results

Pachur et al. (2008) found that part of their participants always answered in accordance with the recognition heuristic, whereas other participants seemed to sometimes use their cue knowledge to decide against the recognized city.

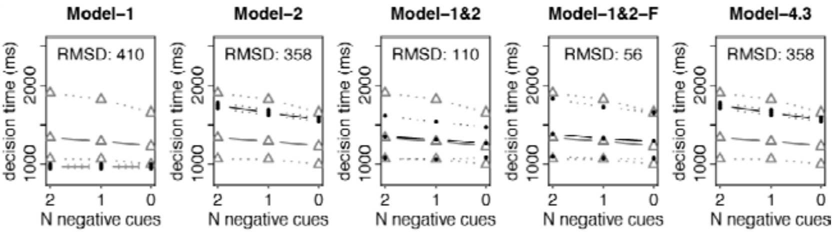

Fig. 1 Decision times (median and quartiles) for participants (grey) and models (black) that always chose the recognized city. RMSDs were calculated separately for the median and the quartiles and then averaged

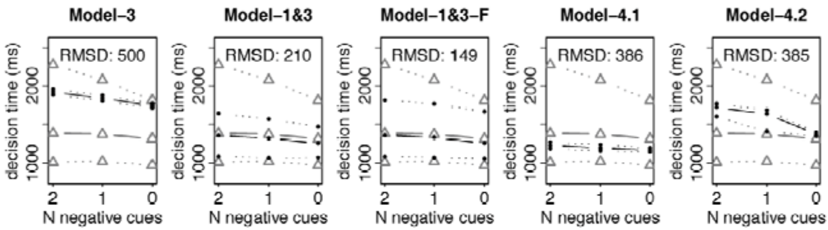

Fig. 2 Decision times (median and quartiles) for participants (grey) and models (black) that chose the unrecognized city in part of the trials. RSMDs were calculated separately for the median and the quartiles and then averaged

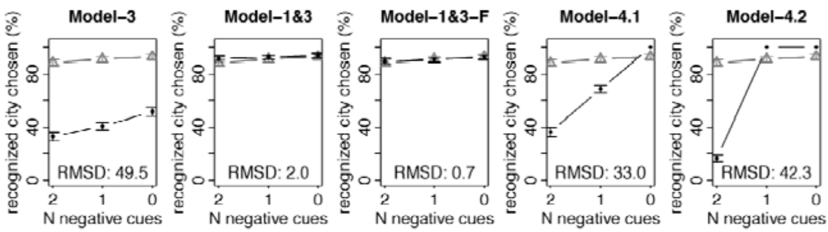

Fig. 3 Proportion of choices for the recognized city for participants (grey) and models (black) that chose the unrecognized city in part of the trials

To investigate the effect of cue knowledge, we analyzed decisions (% of choices for recognized city) and decision time distributions (medians and quartiles) separately for the different amounts of positive and negative cue-knowledge.

Recognition Group

As one would expect, the three non-compensatory models always decided for the recognized city, modeling the decisions of the recognition group. Also Model-4.3 showed this decision behavior, because it could never reach its decision criterion of three negative cues that would have been necessary to decide against the recognized city. The models largely varied in their decision time patterns (Figure 1). The empirical decision time patterns of the recognition group were best fit by Model-1&2-F, where decision times had a large spread and increased in a linear fashion with the amount of negative cues associated to a city.

Cue Group

The compensatory models (except for Model-4.3) decide for the recognized city in part of the cases, with the exact proportion depending on the amount of positive and negative cues and differing between the models (Figure 2). The decisions of the cue-group are fit best by Model-1&3-F, where the proportion of choices for the recognized city is overall high, but decreases in a linear fashion with the number of negative cues. This model also fits the decision time pattern of the cue group best (Figure 3).

Conclusions

A number of strategies have been proposed for how people make memory-based decisions between alternatives. In the current project, we explore how such strategies can be evaluated against each other by using the precision of a cognitive architecture. By implementing a number of decision models that have originally been defined at different levels of description into one architectural modeling framework, we make these models directly comparable to each other. By modeling not only the decision processes, but also the interplay of these processes with perceptual, memory, intentional, and motor processes, we produce quantitative predictions that can be directly compared to the empirical data. Our results suggest that models, which implement a race between competing decision strategies, best predict people's decisions and decision time distributions. This demonstrates how simplifying dichotomies that are so often used in psychological research can dissolve when using quantitative models that specify the interplay of underlying cognitive processes.

Literature

Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., Qin, Y. (2004). An Integrated Theory of the Mind. *Psychological Review, 111*(4), 1036–1060.

Anderson, J. R., Lebiere, C. (1998). *The Atomic Components of Thought*. Mahwah, NJ: Erlbaum.

Beaman, C., Smith, P., Frosch, C., McCloy, R. (2010). Less-is-more Effects without the Recognition Heuristic. *Judgment and Decision Making, 5*(4), 258–271.

Dougherty, M., Franco-Watkins, A., Thomas, R. (2008). Psychological Plausibility of the Theory of Probabilistic Mental Models and the Fast and Frugal Heuristics. *Psychological Review, 115*(1), 199.

Gigerenzer, G., Hertwig, R., Pachur, T. (2010). *Heuristics: The Foundations of Adaptive Behavior*. New York: Oxford University Press.

Gigerenzer, G., Hoffrage, U., Goldstein, D. G. (2008). Fast and Frugal Heuristics Are Plausible Models of Cognition: Reply to Dougherty, Franco-Watkins, and Thomas (2008). *Psychological Review, 115*(1), 230.

Glöckner, A., Betsch, T. (2008). Modeling Option and Strategy Choices with Connectionist Networks: Towards an Integrative Model of Automatic and Deliberate Decision Making. *Judgement and Decision Making, 3*(3), 215–228.

Glöckner, A. Bröder, A. (in press). Processing of Recognition Information and Additional Cues: A Model-Based Analysis of Choice, Confidence, and Response Time. *Judgment and Decision Making*.

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

Hertwig, R., Herzog, S., Schooler, L., Reimer, T. (2008). Fluency Heuristic: A Model of How the Mind Exploits a By-Product of Information Retrieval. *Learning, Memory, 34*(5), 1191–1206.

Lee, M., Cummins, T. (2004). Evidence Accumulation in Decision Making: Unifying the ‘Take the Best’ and the ‘Rational’ Models. *Psychonomic Bulletin & Review, 11*(2), 343.

Oppenheimer, D. (2003). Not So Fast! (and Not So Frugal!): Rethinking the Recognition Heuristic. *Cognition, 90*(1), B1-B9.

Pachur, T. (2010). Recognition-Based Inference: When Is Less More in the Real World? *Psychonomic Bulletin & Review, 17*(4), 589.

Pachur, T., Bröder A., Marewski, J. N. (2008). The Recognition Heuristic in Memory-based Inference: Is Recognition a Non-Compensatory Cue? *Journal of Behavioral Decision Making, 21*(2), 183.

Pachur, T., Hertwig, R. (2006). On the Psychology of the Recognition Heuristic: Retrieval Primacy as a Key Determinant of Its Use. *Learning, Memory, 32*(5), 983–1002.

Schooler, L., Hertwig, R. (2005). How Forgetting Aids Heuristic Inference. *Psychological Review, 112*(3), 610–628.

Volz, K. G., Schooler, L. J., Schubotz, R. I., Raab, M., Gigerenzer, G., von Cramon, D. Y. (2006). Why You Think Milan Is Larger Than Modena: Neural Correlates of the Recognition Heuristic. *Journal of Cognitive Neuroscience, 18*(11), 1924–1936.