Bottom-Up Model of Strategy Selection

Tomasz Smoleń (tsmolen@apple.phils.uj.edu.pl)
Jagiellonian University, al. Mickiewicza 3
31-120 Krakow, Poland

Szymon Wichary (swichary@swps.edu.pl)
Warsaw School of Social Psychology, ul. Chodakowska 19/31
03-815 Warsaw, Poland

Abstract

In this paper we propose a bottom-up model of decision strategy selection, We assume that working memory capacity plays a crucial role in shaping predecisional information processing. Moreover, we assume that the often postulated repertoire of choice strategies can be explained as an expression of one strategy performed with different working memory limits. A mathematical model of this process is described, together with results of computer simulations.

Keywords: decision making; strategy selection; heuristics; mathematical models;

Introduction

Decision making based on available environmental cues encounters difficulties in the form of uncertain and incomplete knowledge about the environment, partially stochastic dependency between behaviour and feedback, costs of getting information and time limitations (Simon, 1982). It is possible to distinguish two different approaches to the problem of making decisions in uncertain environment. The first is based on assumption that people are rational in their behaviour in general. The second is founded on the assumption that because of cognitive limitations, time limits and cost of information, it is rational to use faster and more frugal strategies (Simon, 1982; Gigerenzer, Todd, & ABC Research Group, 1999).

Repertoire of strategies

Within the bounded rationality framework, many strategies have been proposed to describe human cognitive processes of coping with decision making problems (Simon, 1982; Payne, Bettman, & Johnson, 1993; Gigerenzer et al., 1999). Within this framework, it is common to assume the existence of the repertoire of separate strategies, which are used contingent on the features of the task environment and cognitive characteristics of the decision maker. Two of the proposed strategies deserve a closer look: The Weighted Additive (WADD) model and Take The Best (TTB) strategy. It was shown that these two strategies are used most frequently in experiments on multiattribute choice (e.g., Rieskamp & Hoffrage, 1999; Rieskamp & Otto, 2006) These two strategies represent two different classes of strategies: rational in traditional understanding of this concept, and boundedly rational (Gigerenzer et al., 1999).

Take The Best is one of noncompensatory strategies, which do not integrate any information. Its assumptions are: 1) that the cues are ranked (from the best to the worst) based on the cue weights, 2) the cue values are binary and 3) the choice set consists of two alternatives. TTB starts the information processing with the best cue, and compares the values of alternatives on that cue. If the cue discriminates between the alternatives, then the alternative with the higher value is chosen. If the cue does not discriminate between the alternatives, then the next cue in the ranking is checked. If TTB cannot find a discriminating cue, then the choice is made at random. TTB is noncompensatory as the information of cues with higher validity cannot be compensated by cues with lower validity. In contrast, the Weighted Additive rule is a compensatory strategy, since it integrates all information. WADD chooses the alternative with the highest sum of cue values weighted by cue validities. Because of this, the low values on the most important cue can be compensated by high values on the less important cues. People seem to select WADD more often when they make decisions in an unknown environment in which they have no experience and where the costs of application of the strategy are low. In contrast, in cases with increased costs associated with information search, TTB predicts people's inferences better (Newell & Shanks, 2003).

The compensatory-noncompensatory distinction describes the decision strategy as well as the decision environment. In the context of environments, the bigger the difference between highest cue value and the next one is, the more the environment is noncompensatory. Compensatory environments are these in which advantage of first cue value over other ones is relatively small. It has been shown (Bröder, 2003) that in compensatory environments, compensatory strategies yield more accurate choices than noncompensatory ones, and vice versa — in noncompensatory environments, noncompensatory strategies are more accurate than compensatory ones.

Strategy selection

The problem of using the right strategy for a particular decision task has been framed as the strategy selection problem and several models have been proposed to account for this process. The earliest are Beach and Mitchell (1978), Christensen-Szalanski (1978) and Payne, Bettman and Johnson's models (1993), which all go under the rubric of top-down models of strategy selection. Regardless the differences, these models commonly assume that along with the repertoire of strategies, decision makers posses *a priori* knowledge of the cost and benefits of using a particular strategy, and integrating this knowledge leads to a (presumably) conscious, deliberate choice of a strategy.

A slight departure from these models is Rieskamp and Otto's model, based on the concept of reinforcement learning (Rieskamp & Otto, 2006). Their Strategy Selection Learning Theory (SSL) also assumes that people possess a repertoire of strategies to solve choice problems. Moreover, it assumes that people develop subjective expectations for the strategies, based on the performance of strategies in previous choices. The performance of strategies acts as feedback for the assumed reinforcement learning. In subsequent choices, the strategies are chosen with frequencies dependent on these expectations of accuracy.

Another model is Lee & Cummins' Evidence Accumulation Model (Lee & Cummins, 2004), which assumes that both a rational decision strategy and a fast and frugal strategy are special cases of a sequential sampling decision process. Thus, it is a rather radical departure from the previous models as the assumption of the repertoire of strategies is absent in the model. Its main assumption is that fast and frugal strategy and a rational strategy can be unified within one process.

The model proposed in this paper is based on a few important assumptions related to the nature of working memory. We assume that information stored in working memory takes the form of activation of some parts of larger structure (e.g., long term memory). The parts of this structure are connected with information that is maintained in working memory, in such a way that (a) when given part of structure is activated, the content represented by it is available in mind, and (b) functional connections between parts of the structure reflect associative connections between contents of working memory. Although these assumptions concerning working memory are rather strong, they are discussed in psychology as very plausible (see Cowan's model: Cowan, 1999).

Another assumption related to working memory is that objects represented in it can be activated with various strengths and thus, available in memory to a various degree. Cowan (1999) distinguishes two parts of working memory which differ in the availability of content: activated memory and focus of attention. Contrary to this view, we assume that there is a continuum of activation of elements in working memory. In our model the number of cues represented in memory depends on current memory capacity, understood as activation allocated among representations. The processing capacity can change over time and from task to task — we call this assumption *an adaptive capacity hypothesis*.

The Bottom-Up Model of Strategy Selection

Although the proposed model concerns the problem of strategy selection, the goal of modeling this process is achieved indirectly. The proposed model has to choose the best choice alternative among several ones. As input data, the model takes 1) a set of alternatives (each represented as a vector of cue values) and 2) the order of cue weights (cue ranking). Cue values are binary (0 and 1), representing a 'low' and a 'high' quantity of a given cue. Cue values are read into the model's working memory with the order of cue weights, and the higher the weight the cue has, the stronger is its activation in memory. The model assumes that there are two properties of working memory which influence the predecisional information processing: *capacity* and *focus of attention*. Capacity determines how large is the reduction of decrease of activation between successive cue representations (compare Figure 2 and Figure 3), whereas focus determines how large is the reduction of the decrease, when moving from cues with higher validity to those with lower one (see Figure 1). The cue first in the ranking always has the activation of 'one' (it is activated on maximum level), the following cues have lower activations, in accordance with formulas shown bellow.

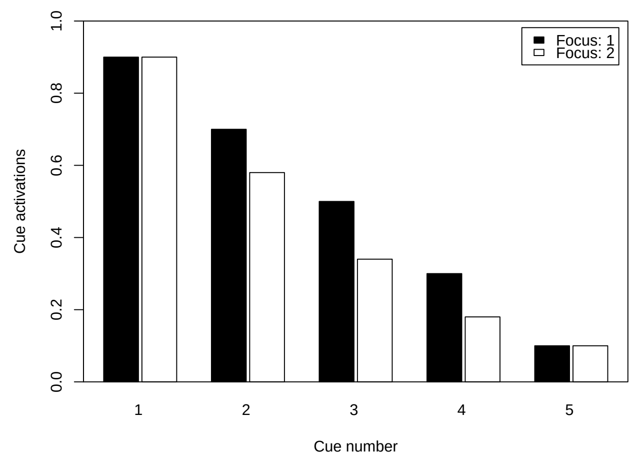

Figure 1: Relationship of cue activation, the focus and the position in weight order.

After the cues are represented in working memory with an activation computed on the basis of their place in the cue ranking and the given memory properties, all alternatives are compared with regard to their cue values multiplied by their activations. The alternative which has the highest overall value is chosen (if there is a tie, the choice is made at random).

In sum, to compute an outcome the model performs the following operations:

1. Gathering data to be processed (i.e., alternatives, cue values and cue weights).
2. Sorting the cues according to their weights.
3. Computing activation of the cues based on the place of a cue in the ranking and the current amount of processing capacity, on the basis of formula (1).
4. Executing the Weighted Additive strategy on the given cue values and cue activations used as cue weights. This pro-

cess chooses the alternative which has the highest overall value computed from the formula (2).

Parameters and formulas

As it was said above, there are two main parameters of the model: memory capacity and focus of attention. Memory capacity is an overall amount of activation which can be divided among different cue representations; it is denoted as M. Focus is the kind of mapping between the place of a cue in the ranking based on the weights and the amount of memory allocated to that cue (in the proposed model it can be either linear or polynomial, decreasing in both cases) and will be represented as S. Formula (1) shows the relation between the amount of the activation (a) ascribed to nth cue on one hand and focus parameters on the other.

$$a_n = max\left(\left(\frac{-nl}{M}+1\right)^S, 0\right) + \varepsilon \tag{1}$$

In the formula (1) ε is the activation noise, l stands for the number of choice alternatives and *max* denotes the function which returns larger of its arguments. The negative values of a, if they occurred, are not taken into consideration — they were treated as zeros. Note that the smaller the n is, the more activation is given to the cue. The model chooses the alternative for which the value v is the highest, where value (v) is computed from the formula (2) based on the Weighted Additive rule.

$$v = \sum_{n=1}^{k} a_n c_n \tag{2}$$

The k stands for the number of cues, a_n is the activation of nth cue, and c_n is the value of the nth cue. Note that all variables except capacity and focus (i.e., values of the cues, number of the cues and number of alternatives) are not brought into the simulation as parameters, but they are features of the environment.

Figure 2 shows the hypothetical levels of cue activation in a situation when relatively large memory capacity is available. In this example all cues are represented in working memory, and all activations are relatively similar (compare figure 3).

Figure 3 shows the hypothetical levels of cue activation in a situation of relatively small memory capacity. Only the four first cues are activated in memory and there are big differences between levels of activation.

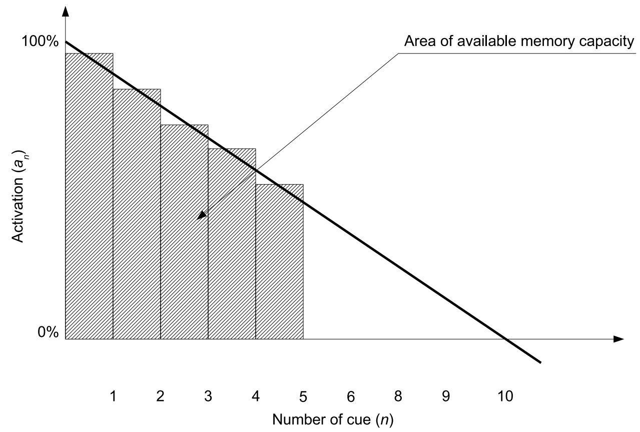

Figure 2: Cue activations given by the model with large memory capacity.

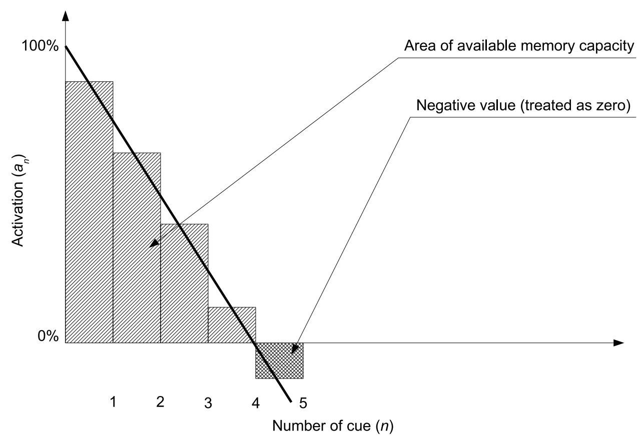

Figure 3: Cue activations given by the model with small memory capacity.

Results of simulations

There are two interesting predictions of the model. The first concerns differences between the fit of different strategies (TTB and WADD) in environments with specific characteristics. We expect that agents with memory features that determine the use of a simple noncompensatory strategy (i.e., low capacity, high focus) will be more accurate in the noncompensatory environment, and analogously, opposite memory features (high capacity, low focus) will result in higher agents' accuracy in a compensatory environment.

Another prediction relates to the correspondence between decisions given by our model and the WADD or Take The Best strategies. We expect that responses given by the agent with memory characteristic favouring the use of a compensatory (high capacity, low focus) strategy will be consistent with WADD responses, whereas the agent with memory features favouring the use of a noncompensatory strategy (low capacity, high focus) will give responses consistent with Take The Best.

To verify the assumptions of the model, we conducted computer simulations of its performance on two different data sets. The simulations were programmed in Lisp. The data sets we used for the simulations were provided by Joerg Rieskamp and had been used in his studies (Rieskamp & Otto, 2006). The two environments used for the simulation were a compensatory and a noncompensatory one. In each of the environments, there were two choice alternatives, described by six cues; the cue values were binary (0 and 1). In the compensatory environment, the cue validities were 0.71, 0.66, 0.65, 0.61, 0.55, 0.53, and for the noncompensatory environment they were 0.78, 0.7, 0.65, 0.61, 0.56, 0.53.

In this paper, we present the results concerning only one parameter — the memory capacity. We set the model's parameter *M* to two values: low (2) and high (6) and tested the performance of these two versions in the two different environments. The model's processing capacity indeed interacted with the environment structure. In the compensatory environment, there was no difference in the accuracy of choices made by the high and low capacity versions of the model. However, in the noncompensatory environment, the low capacity version of the model, surprisingly made better choices than the high capacity version of the model (see Figure 4).

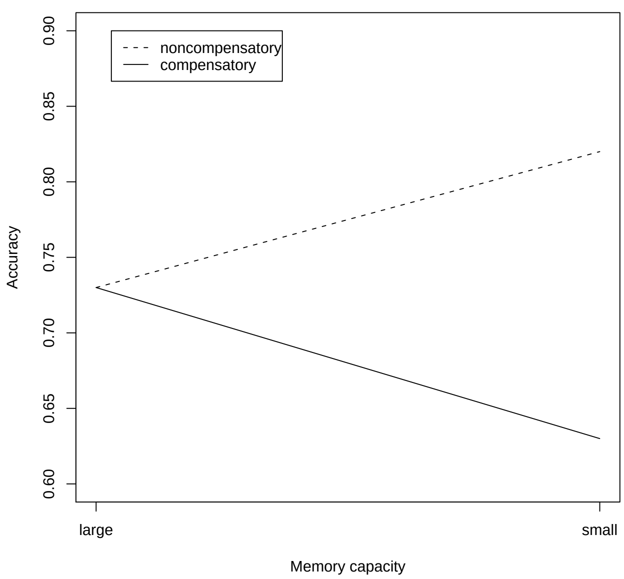

Figure 4: Simulation results: interaction between working memory capacity and the type of environment.

Second, we present the results concerning the match in choices between our model and the strategies we used for comparison, namely TTB and WADD. The question we ask here is whether our model is a good approximation of these two strategies. First, we manipulated the parameter *M* of the model, which describes the processing capacity to be divided among all cues. Again, we set this parameter to two values: high (6) and low (2). We assumed that with the high processing capacity our model will accurately recreate the choices made by WADD strategy. The actual percent of overlapping choices between our model and WADD is 70% for the compensatory environment and 56% for the noncompensatory environment. Similarly, we assumed that with the low processing capacity the model will accurately recreate the choices of the TTB strategy. In fact, the match between our model and TTB was quite high — 80% for the compensatory environment and 96% of choices in the noncompensatory environment (Figure 5).

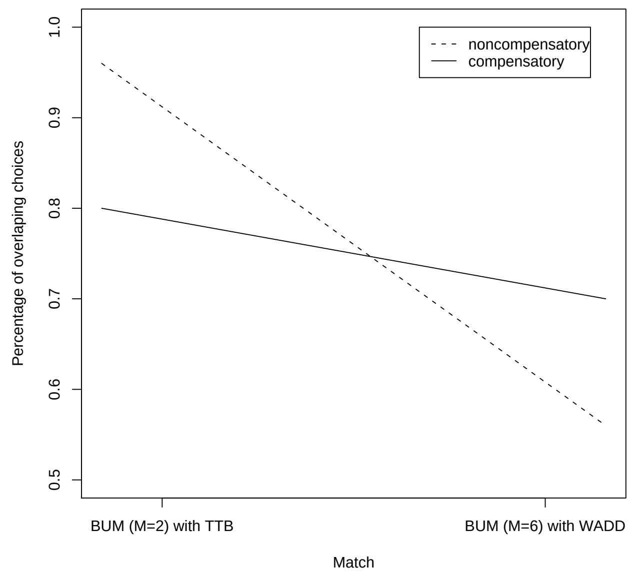

Figure 5: Simulation results: match in choices between the versions of the Bottom-Up Model and WADD and TTB strategies in different type of environments.

Discussion

The model proposed above is based on two novel ideas which can help explain the process of strategy selection during decision making. The first idea is that there are no separate strategies chosen and used on the basis of either deliberation or earlier learning, but all strategies are various expressions of one process which depends on some cognitive characteristics, which can vary intra- and interindividually.

In this perspective, our model shares some features with Lee & Cummins (2004) unifying model of strategy selection. The most important one is the assumption that the selection of strategy is not a real choice, but is only seen as such from the observer's third-person perspective. Both models establish that some decision maker's internal property (conviction about strength of evidence in Lee and Cummins' model, and working memory allocation in our model) can be changed and thus result in apparent use of different strategies.

The second idea that distinguishes the Bottom-Up Model of Strategy Selection from the majority of the models proposed so far, lies in the emphasis of the importance of working memory in decision making. It is claimed here that such memory operating characteristics like capacity and attention focus are essential for the process of decision strategy selection. It is also an important feature distinguishing the present model from Lee and Cummins' model. As our model employs an idea that is central to cognitive psychology (namely, working memory), it thus seems to be better prepared to corroborate other models of performance on complex cognitive tasks.

Further tests of the model are based on fitting people's choices in decision task with different characteristics. We expect that after appropriate setting of the model's parameters the model's outcomes will recreate real choices of people with different working memory characteristics. The model should be also able to capture the intraindividual variation in choices resulting from changing working memory characteristics. To this end, it seems reasonable to manipulate people's working memory characteristics and expect that this will result in decision strategy shifts and in different decision outcomes. For the results see (Wichary & Smoleń, in prep.).

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References

Beach, L. R., & Mitchell, T. R. (1978). A Contingency Model for the Selection of Decision Strategies. *The Academy of Management Review*, *3*, 439–449.

Bröder, A. (2003). Decision Making With the "Adaptive Toolbox": Influence of Environmental Structure, Intelligence, and Working Memory Load. *Journal of Experimental Psychology*, *29*, 611–625.

Christensen-Szalanski, J. J. J. (1978). Problem Solving Strategies: A Selection Mechanism, Some Implications, and Some Data. *Organisational Behavior and Human Performance*, *22*, 307–323.

Cowan, N. (1999). An Embedded-Process Model of Working Memory. In A. Miyake & P. Shah (Eds.), *Models of working memory.* Cambridge, MA: Cambridge University Press.

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

Lee, M. D., & Cummins, T. D. R. (2004). Evidence accumulation in decision making: Unifying the "take the best" and the "rational" models. *Psychonomic Bulletin & Review*, *11*(2), 343–352.

Newell, B. R., & Shanks, D. R. (2003). Take the best or look at the rest? Factors influencing "one-reason" decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*, 53–65.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The Adaptive Decision Maker*. Cambridge, UK: Cambridge University Press.

Rieskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics and how can we tell? In G. Gigerenzer, P. Todd, & the ABC Research Group (Eds.), *Simple Heuristics that Make Us Smart.* Oxford: Oxford University Press.

Rieskamp, J., & Otto, P. E. (2006). SSL: A theory of how people learn to select strategies. *Journal of Experimental Psychology: General*, *135*, 207–236.

Simon, H. A. (1982). *Models of bounded rationality*. Cambridge, MA: MIT Press.

Wichary, S., & Smoleń, T. (in prep.). *A simple, bottom-up mechanism of decision strategy selection.*