

Modeling cognitive parsimony with a demand selection task

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awareness of it, thus making the DST an interesting task to evaluate implicit behaviour.

Introduction

The law of less work (Hull, 1943) is our natural tendency given two alternatives with equal incentives to pick the less demanding one. This notion also appears in the field of judgment and decision making (Gigerenzer & Goldstein, 1996; Tversky & Kahneman, 1974), it is referred to as internal cost of effort. Cognitive parsimony is our tendency to favour low-effort strategies that help us to decide faster and simple strategies to approach a complex problem. An experimental paradigm for this phenomenon has been developed by Kool, McGuire, Rosen, & Botvinick (2010) and referred to as the demand selection task. In this poster, we present a model of this task developed in the ACT-R architecture (Anderson, 2007), which offers an hypothesis as to which cognitive mechanisms might participate in this phenomenon.

Demand Selection Task

In the demand selection task (Kool et al., 2010), two decks of cards are placed symmetrically left and right of the center of the screen. The keyboard is used to select one of the decks and uncover the card upon which a digit, between 1 and 9, will be displayed. According to the color of the number, the subject has to perform a different type of judgement. Blue calls for a magnitude judgment: if the number is less than five, subjects should say yes, otherwise no. Yellow calls for a parity judgment: if the number is even, subjects should say yes, otherwise, no. Unbeknownst to the participants, one deck leads to a low demand task and the other deck to a high demand task. Participants are instructed to 'Feel free to move from one deck to the other whenever you choose' and 'if one deck begins to seem preferable, feel free to chose that deck the more often'. In the low demand task, the color of each numeral matches the previous color on 90% of trials, whereas in the high demand task, the color of each numeral matches the previous color on 10% of trials. Overall, response times (RT) and error rates showed that task switching was cognitively costly, and that subjects mostly choose to pick the less cognitively demanding deck. While some subjects demonstrated their awareness of this effect, the effect did not depend on their

Experimental procedure

We reproduced Experiment 1 from Kool et al's paper (2010). The simulation included 50 runs of 500 trials of the Demand Selection Task (DST). The task was self-paced with a maximum limit of time of 1h (which was never reached by the model or the participants). Subjects had to pick between two decks, by pressing a key ("F" for left, "J" for right). According to the color of the number (yellow or blue), participants had to either produce a parity judgment (even or odd) or a magnitude judgment (less or greater than five) on the number. Depending on the deck selected, the color of the number switched with a probability of 0.9 (making it a higher demand task) or 0.1 (making it a lower demand task) at each trial.

Model

The model¹ was built in the computational cognitive architecture and theory of human cognition ACT-R (Adaptive Control of Thought - Rational) (Anderson, 1990; 2007). In ACT-R, different modules, including two memory modules (procedural and declarative) interact to complete a cognitive task. The modules are accessed via their associated buffers. ACT-R has been used to model several tasks. Declarative memory stores facts about the environment (know what). The procedural memory, through procedural rules (know how), allows for action selection. ACT-R is a hybrid cognitive architecture composed of symbolic and subsymbolic components: the retrieval of a fact (symbol) from declarative memory depends on subsymbolic retrieval equations (pondering the context and history of retrieval of the fact), and, the selection of a rule (symbol) depends on utility subsymbolic equations (which computes costs and benefits associated to the rule). The memory elements (chunks) are reinforced through patterns of occurrence within the environment. Learning processes act at both subsymbolic and symbolic levels.

The preference of a deck over another one relies on implicit mechanisms: mainly base-level and spreading activation with the participation of utility learning. Base-level learning

¹ Model code available at: <http://psych-scholar.wright.edu/astecca/software>

determines how patterns of use affect chunk activation and decay. Spreading activation provides context to the retrieval since chunks will spread an amount of activation to other chunks in declarative memory, based on the relationship they have with other chunks. The choice between the two decks is represented by two procedures. After the model picks one deck, it perceives a number and a color, and then it retrieves the chunks associated to the color and the number. Chunks of the yellow color are associated with a ‘parity’ chunk, chunks of the ‘blue’ color are associated with a ‘magnitude’ chunk. The retrieved chunk is placed in the imaginal module. A judgement is produced based on the retrieved chunk, and an answer is vocalized. The chunk placed in the imaginal buffer will spread activation and influence the next retrieval request. A reward is backpropagated after the answer has been produced. The failure to retrieve a judgment chunk will lead to errors which are also signaled to the model by backpropagation.

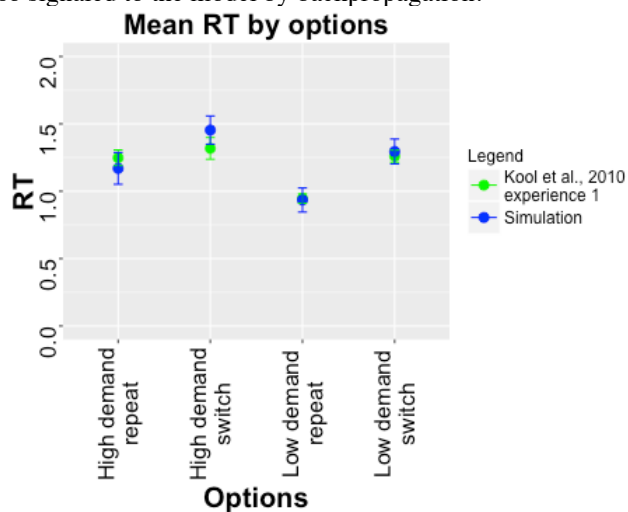


Figure 1: Mean RT by options.

Therefore, the gradual selection of the lower demanding deck occurs through two mechanisms: the retrieval of elements in the higher demanding deck (with high probability of switch) will take longer (representing the expended effort required) as activation from the previous trial will have spread less to the current trial. And, the longer this process takes, the less reward gets backpropagated to the selection of this deck (as the reward gets discounted with time). Thus, gradually, the selection of the less demanding deck is the one that is going to be reinforced the most. Errors encountered will be due to the failure of retrieval of judgment chunks.

Results

As in the original experiment, we measured the verbal RT for the two decks (low demand vs. high demand) and trial types (task switch vs. task repetition). Figure 1 shows the means of medians for each trial types and deck types. Table 1 shows the parameters used in the ACT-R model. An ANOVA indicated as in the original experiment significant

effects for trial types ($F(1,50) = 9.940$; $p < 0.002$) and deck types ($F(1,50) = 3.691$; $p < 0.05$). Average selection of the lower demanding task is 63% in our experiment (68% in the original experiment).

Table 1: Model parameters.

| Parameters | Value |
|----------------------|-------|
| :rt | -1.0 |
| :alpha | 0.1 |
| :lf | 1.5 |
| :mas | 3.0 |
| :imaginal-activation | 0.41 |
| :ans | 0.1 |
| :bll | 0.21 |

Discussion and conclusion

The demand selection task is aimed at evaluating the tendency to avoid cognitively demanding tasks. Computational cognitive models have been made of “minimal control” (Taatgen, 2007) and “least effort” (Anderson, 1990), but this is to our knowledge the first model of the DST. We were able to reproduce the results of Experiment 1 of Kool et al.’s paper (2010) with a simple ACT-R model. The performance at the DST in our explanation relies mainly on implicit mechanisms (utility learning and base-level and spreading activation), in accordance with experimental results showing that the participants did not need to be aware of the type of task (low demanding or high demanding) for the effect to be observed. The DST is interesting to correlate subjects’ individual differences with their performance at different cognitive tasks. Having a model of such a task will allow us in future work to model individual differences as captured in the DST model and as they transfer into other tasks and might affect performance there (e.g. we are currently using this task in an ongoing research studying the relationship between cognitive parsimony and vulnerability to exploitation in interpersonal transactions).

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