Perceptual Control Theory Model of the "Beads in the jar" task

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Introduction

Perceptual Control Theory (hereafter PCT) has been successfully employed in modelling skilled performance (Marken, 2001) and prescribing errors (Marken, 2003). Here we model the draws-to-decision (DTD) behaviour of participants on the "beads-in-the-jar" task (see Fine *et al.*, 2007).

PCT is a control theory approach to explaining human behaviour, derived from negative-feedback loops used in engineering and developed for the application to Psychology since the latter half of the last century (Powers, 1973). The theory states that all behaviour is purposeful and is intended to control specific environmental variables. A system of hierarchical control directs behaviour through interconnected control systems at multiple levels. Higher level systems set reference values for immediately subservient systems and these systems also feedback information regarding their current state. First order systems act on, perceive and feedback the state of the controlled variable to the system hierarchy.

"Beads in the jar task"

Participants were told there were two jars, (*jar R* 60:40 red to green and *jar G* 60:40 green to red beads) and that up to 20 beads would be drawn randomly from one of the jars, with a 50% chance of either jar being chosen. The task required subjects to choose after the first draw and on every subsequent draw either which jar the beads were coming from or to draw another bead. They were instructed only to decide when they were sure which jar the beads were coming from. The number of draws participants chose before deciding was the draws-to-decision (DTD) measure.

Method

Behavioural data was collected from 39 participants in the "beads-in-the-jar" task under three conditions: *High Cost Condition* (*HCC*) where participants could win £4 by deciding the correct jar on the first draw, and then lost 20p for every subsequent draw; *Low Cost Condition* (*LCC*) initial winnings £2 on the first draw and then 10p lost for every draw; and the *No Cost Condition* (*NCC*) where no winnings or drawing costs were applied.

Participants' mean DTD was significantly lower in the *HCC* than in the two other conditions, and significantly lower in the *LCC* than the *NCC* (figure 1).
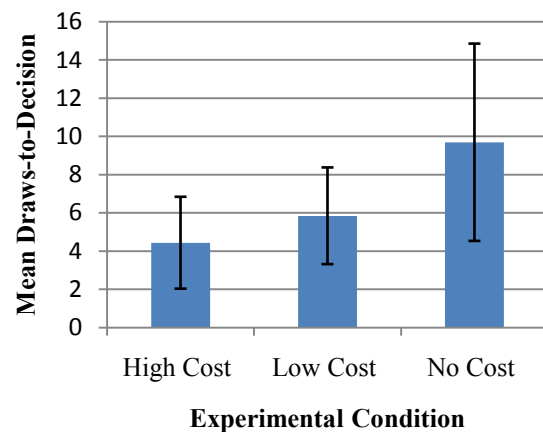

Figure 1: Mean conditional DTDs and associated standard error. Significant differences found between all conditions.

Model

Our PCT model of the DTD behaviour employed two competing control systems at the same level: 1) participants were controlling for how much drawing was costing, 2) participants perceived how sure they were of which jar the beads were being drawn from. This fed into a comparator that outputted a decision when they were surer of it being *jar R* or *jar G* than how much they perceived it cost them to draw another bead. We modelled these using winnings versus the perceived likelihood of the jars (exp. 1) and perceived total cost versus jar uncertainties (exp. 2).

Results

Experiment.1

We accounted for all possible DTD results in the *HCC* and the 18/20 *LCC* using a perceived likelihood measure based on red and green bead counts and optimising the gain on the winnings only using a deterministic linear optimisation for each DTD value (equations.1-3).

$$Red\ Count = No.Red\ Beads - No.Green\ Beads \tag{1}$$

$$Green\ Count = No.Green\ Beads - No.Red\ Beads \tag{2}$$

$$Perceived\ Winnings \\ = \{Total\ Winnings\ [f(condition)] \\ - Cost\ per\ Draw\ [f(condition)]\} * Gain \tag{3}$$

Using 1000 random randomly generated bead sequences 60:40 in favour of red, the model was tested for robustness across all 20 DTD scores in the *HCC* and *LCC*. The mean squared error for DTD values was calculated based on the error for each novel sequence on each DTD draw (figure 2).
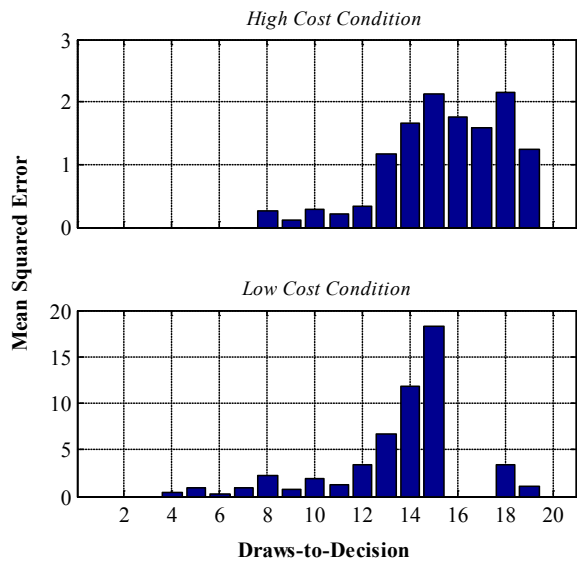

Figure 2: MSE for each DTD using 1000 random bead sequences.

Experiment.2

Here we aimed to model all participants' results in all three conditions. We optimised Gain Factors through iterations of the *HCC* and the *LCC* simultaneously and finally across all three conditions. We calculated jar "uncertainty" using a maximum bead count of 20 for each jar and taking one away each draw depending on the bead colour. We also optimised an "internal cost" value across the conditions simultaneously, for the perceived cost (equations 4-6).

$$Red\ Count = Gain \\ * (Max\ Red\ Beads \\ - No.Red\ Beads) \tag{1}$$

$$Green\ Count = Gain * (Max\ Green\ Beads \\ - No.Green\ Beads \tag{2}$$

$$Perceived\ Cost = \\ (Cost\ per\ Draw * No.of\ Draws\ ) + Internal\ Cost \tag{3}$$

The model produced: exact expected values for 12/39 participants, an error of ±1 DTD for 32/39 participants and accounted for all participants with an error margin of ±2 DTD for the *HCC* and *LCC*. When applied to all three conditions the model perfectly accounted for 2/39 participants and 35/39 with an error of ±6 DTD.

Discussion

The model was more successful in the *HCC* than the *LCC* in experiment 1, both in terms of modelling more DTD results and a lower MSE for each. This could be due to the applicability of the model to these different situations. When the winnings for a correct answer and the cost per draw are higher, participants' behaviour will be more influenced by these factors and less by other factors such as boredom with the task causing them to draw early. We therefore hypothesise that in future experiments if the initial winnings and costs per draw were even higher, then this model would be a better predictor of participants' performance.

This argument is also partially supported by the results from experiment 2: using the same gains and internal costs across conditions, the model was most successful when there was a cost for a draw: in the *HCC* and *LCC*. However when the *NCC* was introduced much larger errors resulted.

It would be unrealistic to suggest that all 39 participants were using the same mental model to compute which draw they would make a decision. However, the reliability of our model in the two cost conditions suggests that cost for drawing is an important factor for determining the DTD.

The reliable effect for delusional subjects to "jump-to-conclusions" (Fine *et al.*, 2007) may then be, to some degree, due to a higher internal cost for making extra draws in the task for these participants. This cost could be anxiety to finish the task early or an over-compensation to want to appear intelligent to the experimenter. Future studies asking participants post-experiment which factors caused them to make their decision will help to clarify this hypothesis.

The partial success of the PCT framework for this task implies its viability for modelling reasoning behaviour. Future work may consider how higher level systems interact with lower systems, and how these higher levels could serve as a regulator for which mental model participants preferentially employ for probability estimation, cost perception and other reasoning processes.

Acknowledgments

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