Choice-confirmation bias in favorable vs. adverse environments

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1 Introduction

Among the heuristics humans use in their everyday reasoning, "positivity-oriented" biases have been highlighted by psychologists for decades: the confirmation bias, whereby an individual tends to take into account evidence that is compatible with her beliefs, and to discount the rest (Del Vicario *et al.*, [1]; Nickerson, [2]); unrealistic optimism, which involves underestimating the probability of encountering future negative events, and overestimating the probability of encountering future positive ones (Hoorens & Buunk, [3]; Sharot & Garrett, [4]); or the superiority illusion, whereby an individual believes she is better than other people (Sharot & Garrett, [4]). Disruptions of these positivity biases in mental disorders such as depression suggest that they are adaptive and necessary for mental health (Garrett *et al.*, [5]).

In parallel, similar biases have been discovered at the lower level of reinforcement learning; in particular, research has shown that individuals learn faster from positive than from negative outcomes, by updating related prediction errors differentially (Lefebvre *et al.*, [6]; Palminteri *et al.*, [7]). This suggests that positivity biases do not only occur at the abstract level of beliefs and reasoning, but also influences the very mechanisms of decision-making. Ultimately, this calls into question traditional models of reinforcement learning, that assume a neutral, unbiased update of information (Chambon *et al.*, [8]).

However, it seems that this positivity bias depends on agents' freedom of choice. Recent research (Chambon *et al.*, [8]) has revealed a "choice-confirmation bias" (participants were shown to give more weight to positive outcomes compared to negative ones) which appeared only when participants were free to choose. When they were forced to select a given option, however, their learning rates were equal for both positive and negative outcomes.

Interestingly, Chambon *et al.* showed that this choice-confirmation bias occurred at the decisional level, as opposed to the predictions of cognitive dissonance theories, according to which actions themselves introduce a bias by shaping preferences. Following these theories, then, choices that involve refraining from action should induce no bias. Using a Go/No-Go paradigm, Chambon *et al.* disconfirmed these hypotheses by showing that the same biased pattern of learning rates emerged in tasks where participants refrained from acting.

However, if the confirmation bias occurs at the decisional level, forced-choice trials should not induce a neutral pattern of learning rates. Indeed, information provided by forced-choice trials still confirms or disconfirms what participants *would have done*, independently of the occurrence of a subsequent action. Thus, it is expected that, when forced-choice trials do not align with what participants would have done, negative outcomes will weigh more than positive ones, since they are choice-confirming. A reversed pattern should be found when forced-choice trials align with what participants would have done. In this project, we will test this hypothesis by designing and implementing an experimental task in which free-choice trials will be compared to two types of forced-choice trials: 1. "congruent" forced-choice trials, where the computer selects the option the participant would have selected had she been free to choose, and 2. "incongruent" forced-choice trials, in which the computer's choice is not aligned with what the subject would have chosen. Our specific research question is: does a choice-confirmation bias appear when the agent is forced to choose something that she would have (freely) chosen anyway? We hypothesize that, if forced-choice trials' outcomes are mostly aligned with what participants would have done, then participants will learn faster from positive outcomes than from negative ones; and if forced-choice trials' outcomes are mostly opposed to participants' choices, then the reverse pattern will appear.

2 Methods

Participants

24 participants will be recruited to take part to the experimental task. Only participants older than 18, with no history of neurological or psychiatric disorders, and with normal or corrected-to-normal vision, will be included. The sample size and exclusion criteria are based on Chambon *et al.*'s study (Chambon *et al.*, [8]).

Procedure and stimuli

Participants will be presented with twelve pairs of different symbols, each one being stochastically associated with two different outcomes—i.e., "+1 pt" and "-1 pt". Regarding the procedure, the experimental task will contain 800 trials, divided in 12 blocks according to the following conditions:

- 4 blocks of 40 free-choice trials each, where participants choose one of the two stimuli and are then showed the outcome;
- 8 blocks of 80 "intermixed" trials each—i.e., 40 free-choice trials and 40 forced-choice trials, pseudo-randomly presented within the block. These 8 blocks will be further divided into 2×4 blocks:
  - 4 blocks where forced-choice trials will obey a congruency condition—i.e., in 75% of the trials, the computer will force participants to choose the stimulus they would have chosen had they been in a free-choice trial (participants' last free choice will be considered a reliable indicator of what they would have chosen in a free-choice condition);
  - 4 blocks where forced-choice trials will be incongruent—i.e., in 75% of the trials, the computer will force participants to choose the stimulus they would *not* have chosen had they been in a free-choice trial.

In every block, one symbol will be associated to the positive outcome with probability 0.7, and the other symbol, with probability 0.3. Before the first block, participants will undergo a training phase, composed of 60 trials where all reward probabilities will be set to 0.5, in order to make sure that participants do not expect more negative or positive outcomes in the remaining blocks. At the beginning of each new block, symbols will change, so as to force participants to learn contingencies from scratch.

In order to make sure that congruency conditions do not affect participants' learning, simulations (Matlab) will be performed before implementing the task. To this end, we will use parameters that were obtained by previous model-fitting in Chambon *et al.*'s study, and simulate the behavior of virtual agents on the task described above. These parameters are, for each subject, the inverse temperature β, and the four learning rates α^+_{forced}, α^-_{forced}, α^+_{free}, and α^-_{free}.

Equipped with these parameters, virtual agents will be simulated on the aforementioned task, and their performance on free-choice trials will be measured (see below). These simulations will allow us to determine whether different proportions of congruent vs. incongruent forced-choice trials (eg., 75%-25%, 80%-20%) affect learning. Additionally, they will enable us to check whether the number of blocks and the probabilities associated with each outcome are well-chosen and do not hinder learning, so that these parameters can be adapted if needed.

Measures

Simulations: Each virtual agent's choices and associated outcomes will be collected, in order to calculate their correct choice rate—i.e., the rate at which they chose the most rewarding symbol.

Experiment: Participants' choices and associated outcomes will be collected all along the experiment. Then, this data will be fitted with a modified Q-learning model that updates Q-values with different learning rates depending on outcome valence, type of choice, and congruency–namely, $\alpha^+_{congruent}$, $\alpha^-_{congruent}$, $\alpha^+_{incongruent}$, $\alpha^-_{incongruent}$, α^+_{free}, and α^-_{free}. Our measures will be these fitted learning rates' values.

Predictions

Simulations: We predict that congruency conditions do not affect learning—i.e., participants learn similarly from congruent and incongruent forced-choice trials.

Experiment: We predict that participants learn more from positive outcomes in the free condition and in the forced-congruent condition; and that they learn more from negative outcomes in the forced-incongruent condition. Therefore, we predict that $\alpha^+_{congruent} > \alpha^-_{congruent}$, that $\alpha^+_{incongruent} < \alpha^-_{incongruent}$, and that $\alpha^+_{free} > \alpha^-_{free}$.

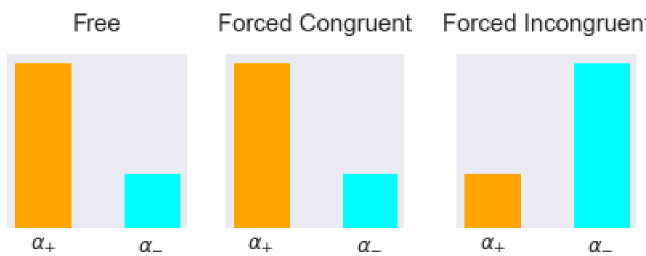

Figure 1: Predicted effects of the different conditions on learning rates

Analyses

Simulations: To make sure that congruency conditions do not affect learning, we will analyze our virtual agents' correct choice rates in free trials from intermixed blocks—i.e., blocks with both free and either congruent or incongruent forced-choice trials. A two-tailed t-test will be performed in order to check whether these correct choice rates are significantly higher than the chance-level, and whether correct choice rates in congruent forced-choice trials do not significantly differ from those in incongruent forced-choice trials.

Experiments: We will perform 2×2×2 within-subject ANOVAs on the obtained learning rates in order to investigate main effects and interaction effects of type of choice (free/forced), outcome valence (positive/negative), and congruency (congruent/incongruent). We expect a statistically significant main effect of congruency, and statistically significant interaction effects between congruency and outcome valence, and between congruency and type of choice.

Interpretation

If, after data analysis, the predicted learning-rate pattern is revealed, it means that a choice-confirmation bias can be detected in forced-choice trials. This would further confirm that the choice-confirmation bias is indeed decisional, and that participants' behavior in forced-choice trials is not due to reactance—that is, a tendency to prefer the opposite action when forced (Miron & Brehm, [9]). If it were due to reactance, indeed, learning rates in forced-choice trials would exhibit no bias.

3 Expected contributions

The internship will be supervised by Valérian Chambon (Institut Jean Nicod).

References

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