Unravelling the computational mechanisms underlying choice history biases

Robin Vloeberghs (robin.vloeberghs@kuleuven.be)
KU Leuven (Belgium)

Anne E Urai (a.e.urai@fsw.leidenuniv.nl)
Leiden University (Netherlands)

Kobe Desender (kobe.desender@kuleuven.be)
KU Leuven (Belgium)

Abstract

A fundamental feature of decision making is the influence of experimental history. In two independent datasets we show that previous responses and stimuli can shape subsequent decision making, a process that depends on decision confidence. In the drift diffusion model these effects were explained by a bias on the evidence accumulation process. Simulations suggest that this bias could be caused by either via sensory adaptation and reinforcement learning, or a via a randomly fluctuating decision criterion. By directly estimating these fluctuations in decision criterion from behavioral data, it will be possible to dissociate between both mechanisms.

Keywords: decision making; history effects; drift diffusion model; signal detection theory

Introduction

Decision making is typically studied in isolation, with the assumption that subsequent decisions are independent. However, a decision is not only based on the current sensory input, but also influenced by experimental history. First, decisions are biased towards the previous decision (e.g., Bosch et al., 2020; Urai et al., 2019; Urai & Donner, 2022). This attractive effect, the so-called choice history bias, is modulated by decision confidence with an increased repetition tendency following high confidence trials (e.g., Bosch et al., 2020; Braun et al., 2018). Second, decisions are biased away from the previous stimulus direction, with a stronger effect for increasing stimulus strength (Bosch et al., 2020). Whereas these history effects are well described at the behavioral level, a mechanistic explanation on how they exert their influence on decision making is still missing. In the current work, we used a drift diffusion model, which assumes that decision making is based on accumulating noisy information over time until a threshold is reached. In this model, history effects are captured by a bias on the evidence accumulation process. Two processes that could underlie this bias are discussed.

Methods

We analyzed data from two perceptual decision making tasks. In the first dataset (N = 81) participants had to respond from which location, either left or right, a series of dots was sampled from (Figure 1a). In the second dataset (N = 58) participants had to determine whether the average color of eight briefly shown shapes was more red or blue (Figure 1b). In both datasets, participants had to indicate decision confidence after giving a response.

A hierarchical drift diffusion model was fitted with the starting point and drift bias allowed to vary in function of previous trial variables such as the response, confidence, and stimulus (Wiecki et al., 2013). The code for the simulations was custom-built.

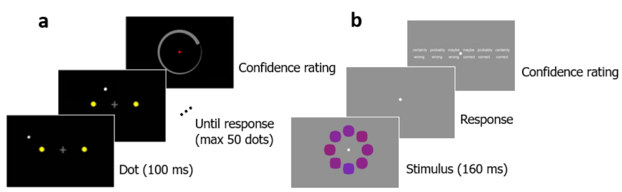

Figure 1. Paradigms (a) Participants determine whether the generative mean of a series of dots is left or right and indicate decision confidence on a continuous scale. **(b)** Participants respond whether the average color of the eight shapes is more red or blue and indicate decision confidence on a six-point scale.

Results

Replicating previous studies, we found that the previous response following high confidence trials produced an attractive effect (Figure 2a), while previous stimulus direction produced a repulsive effect that increased with stimulus strength (Figure 2b). Different from previous research, in our experiments participants had the possibility to indicate awareness of having committed an error. By virtue of this scale, we observed a novel effect (Figure 2a): a repulsive effect of previous response following trials on which participants thought they committed an error.

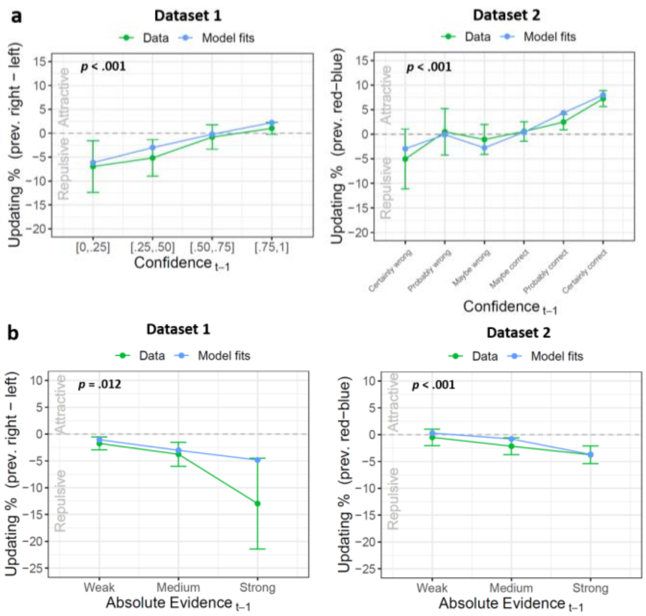

Figure 2. History effects in human decision making (a) Attractive effect of previous response following high confidence trials, repulsive effect of previous response following perceived error trials **(b)** A repulsive effect of previous stimulus direction that grows with stimulus strength.

Drift diffusion model

In the drift diffusion model, biases can arise by two mechanisms: a change in the starting point of the accumulation process or a bias on the evidence accumulation process, the so-called drift bias (Figure 3). History biases were captured by a drift bias (Figure 4). This bias acts as a stimulus-independent component steering the evidence accumulation process towards one of the response boundaries (Ratcliff & McKoon, 2008; Urai et al., 2019). The starting point, however, was not dependent on history effects (Figure 4)

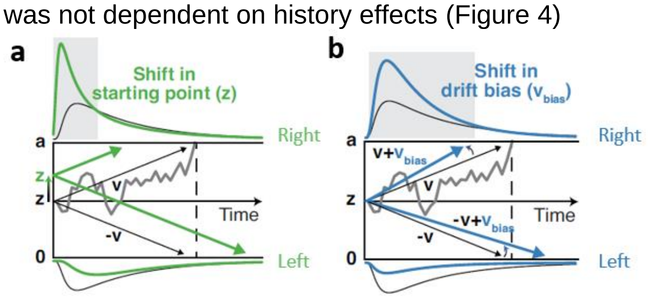

Figure 3. Two mechanisms by which a drift diffusion model can capture biases. Influence on the evidence accumulation process and reaction time distributions is shown. Figure adapted with permission from Urai et al. (2019). **(a)** Shift in starting point. **(b)** Shift in drift bias.

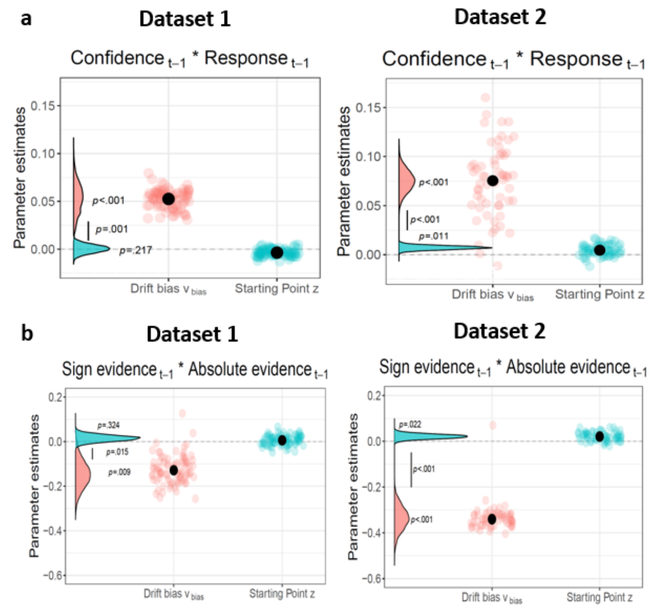

Figure 4. History effects map onto drift bias in drift diffusion model (a) Effect of previous response and the modulation of previous confidence **(b)** The effect of previous stimulus.

Conceptual interpretation

The descriptive nature of the drift diffusion model findings raise a new question: what process underlies the biased evidence accumulation? To shed more light on this issue we developed a process model. A model that implements sensory adaptation and a reinforcement learning process based on decision confidence could reproduce the attractive and repulsive history effects. However, an alternative explanation can be found in the signal detection theory framework (SDT). Using simulations we show that merely allowing the decision criterion in SDT to randomly fluctuate over time, is sufficient to generate history effects, even in absence of an actual causal role of previous response or stimulus. To quantify these latent shifts in decision criterion, or *slow drifts*, we are currently developing a hierarchical linear dynamical system (hLDS), which will allow to disentangle the two mechanistic explanations.

Conclusion

In this study we show that previous decisions and stimuli have a significant impact on subsequent decision making, and these effects can be captured by the drift diffusion model. Further research using a hierarchical linear dynamical system will enable us to disentangle the mechanisms underlying this biased evidence accumulation and gain a deeper understanding of the computational and neural processes underlying perceptual decision making.

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