Choice History Biases Subsequent Evidence Accumulation

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Abstract

Perceptual choices depend not only on the current sensory input, but also on the behavioral context. An important contextual factor is the history of one's own choices. Choice history often strongly biases perceptual decisions, and leaves traces in the activity of brain regions involved in decision processing. Yet, it remains unknown how such history signals shape the dynamics of later decision formation. Models of perceptual choice construe decision formation as the accumulation of sensory evidence towards decision bounds. In this framework, it is commonly assumed that choice history signals shift the starting point of accumulation towards the bound reflecting the previous choice. We here present results that challenge this idea. We fit a bounded accumulation ('drift diffusion') decision model to behavioral data from multiple perceptual choice tasks and sensory modalities, and estimated bias terms that dependent on observers' previous choices. Individual history biases in behavior were consistently explained by a history-dependent change in the evidence accumulation, rather than in its starting point. Choice history signals thus seem to affect the interpretation of current sensory input, akin to shifting endogenous attention towards (or away from) the previously selected interpretation.

Keywords: choice history bias; bounded accumulation models

Introduction

Decisions are not isolated events but are embedded in a sequence of choices. Preceding choices can exert a large influence even on low-level perceptual judgments (Fernberger, 1920). Computational theory (Gao, Wong-Lin, Holmes, Simen, & Cohen, 2009; Glaze, Kable, & Gold, 2015) and psychophysical data (Braun, Urai, & Donner, 2018; Kim, Kabir, & Gold, 2017) indicate that choice history biases result from the accumulation of internal decision variables across trials, with a timescale governed by the decision-makers' internal model of the correlation structure of their environment.

Bias in the DDM

Current models of perceptual decision-making posit the accumulation of noise-corrupted sensory evidence over time, resulting in an internal decision variable that grows with time (Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; Ratcliff & McKoon, 2008). When this decision variable reaches one of two decision bounds, a choice is made and the corresponding motor response is initiated. In this framework, a bias can be brought about in two ways: (i) by shifting the starting point of accumulation towards one of the two bounds, or (ii) by selectively changing the rate at which evidence for one versus the other choice alternative is accumulated (Figure 1). The former can be conceptualized as adding an offset to that 'perceptual interpretation signal' during the generation of the response, whereas the latter as altering the perceptual interpretation of the current sensory input.

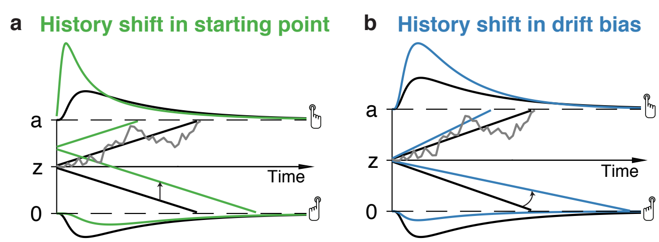

Figure 1. *Two biasing mechanisms within the drift diffusion model. (**a**) Choice history-dependent shift in starting point. Gray line: example trajectory of decision variable from single trial. Black lines: mean drift and resulting RT distributions under unbiased conditions. Green lines: mean drift and RT distributions under biased starting point. (**b**) As (**a**), but for choice history-dependent shift in drift bias. Blue lines: mean drift and RT distributions under biased drift. Both mechanisms differentially affect the shape of RT distributions.*

A shift in starting point would be most prevalent early on in the decision process: it would affect the leading edge of the RT distribution, shifting its mode. It predicts that the majority of history-dependent choice biases occur on trials with fast reaction times. A shift in the drift bias instead grows with time. Therefore, it would affect the trailing edge of the distribution with little effect on the mode. In contrast to starting point bias, drift bias alters choice fractions across the whole range of reaction times, well into the tail of the RT distribution.

While many current models of choice history bias posit that a history-dependent starting point can explain choice patterns (Gao et al., 2009; Yu & Cohen, 2008), is unknown which effect best captured psychophysical data. We addressed this issue by fitting a computational decision model to human behavioral data from five studies of human perceptual decision-making, covering a variety of task protocols and sensory modalities.

History-dependent shifts in drift bias explain individual choice behavior

We used five existing datasets, four of which were previously published (de Gee et al., 2017; de Gee, Knapen, & Donner, 2014; Murphy, Vandekerckhove, & Nieuwenhuis, 2014; Urai, Braun, & Donner, 2017). These covered a range of task protocols and sensory modalities commonly used in the study perceptual decision-making: two alternative forced-choice, two interval forced-choice, as well as yes-no (simple forced choice) tasks; RT as well as so-called fixed duration tasks; visual motion direction and coherence discrimination; and visual contrast and auditory detection. As found in previous work, observers exhibited a wide range of idiosyncratic choice history biases across all experiments.

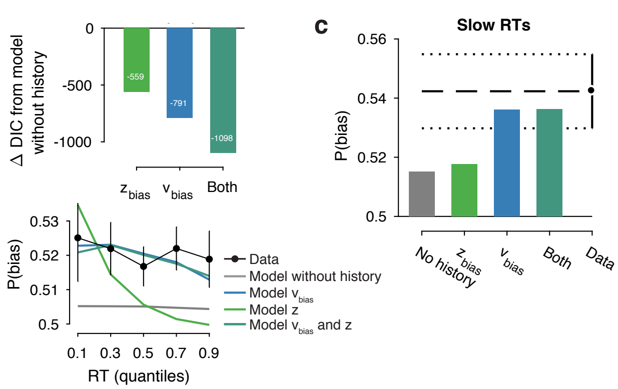

Figure 2*. *Model comparison and simulations. *(**a**) We used the Deviance Information Criterion (DIC) as a measure of model fit, and took the model without history dependence as a baseline for each data set. Lower DIC values indicate a model that is better able to explain the data, after taking into account the model complexity; a DIC of 10 is generally taken as a threshold for considering one model a sufficiently better fit. (**b**) Conditional bias functions. For each of four simulated models, as well as the observed data, we divided all trials into quantiles of the RT distribution. For each quantile, the fraction of choices biased towards each individual's history bias (repetition or alternation) indicates the degree to which behavior is biased, within that range of RTs (White & Poldrack, 2014). (**c**) Choice bias on slow response trials (last three quantiles of the RT distribution) can be captured only by models that include history-dependent drift bias. Black error bars indicate mean ± 95% confidence interval across all data sets, bars indicate the predicted fraction of choices in late RT quantiles.*

We fit the drift diffusion model (Wiecki, Sofer, & Frank, 2013) to behavioral data (choices and reaction times, RT) from a total of 162 human participants across these 5 tasks. We allowed starting point, drift bias, or both to vary as a function of the observer's choice on the previous trial. The model with both history-dependent starting point and drift bias provided the best fit to the data (Figure 2a). We further examined the ability of each model to explain the diagnostic features in the data that distinguished starting point from drift bias. In particular, the biased choices on slow RTs could only be captured by models that included a history-dependent shift in drift (Figure 2b,c).

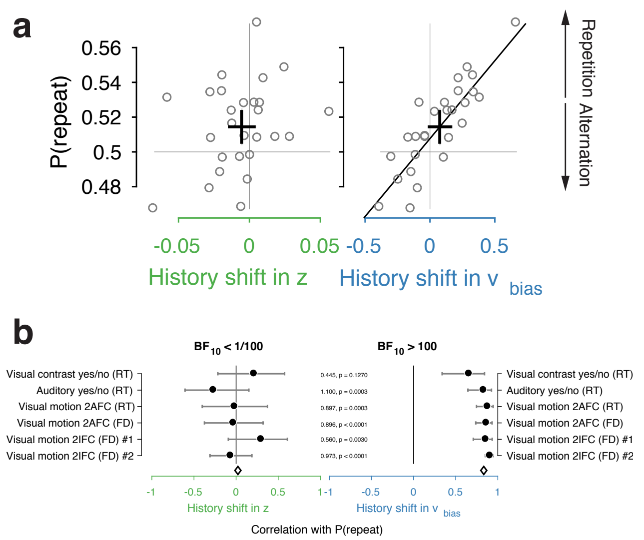

Figure 3. Individual choice history biases are explained by history-dependent changes in drift bias, not starting point. *(**a**) Correlations between individual choice repetition probabilities, P(repeat), and history shift in starting point (left column, green) and drift (right column, blue). Parameter estimates were obtained from a model in which both bias terms were allowed to vary with previous choice. Horizontal and vertical lines, unbiased references. Thick black crosses, group mean ± s.e.m. in both directions. Black lines best fit of a linear regression (only plotted for significant correlations). (**b**) Summary of the correlations between individual choice repetition probability and the history shifts in starting point*

(green; left) and drift bias (blue; right). Error bars indicate the 95% confidence interval of the correlation coefficient. Δr quantifies the extent to which the two DDM parameters are differentially able to predict individual choice repetition probability, p-values from Steiger's test. The black diamond indicates the mean correlation coefficient across data sets. The Bayes factor (BF_{10}) quantifies the relative evidence for the alternative over the null hypothesis.

We then used the parameter estimates obtained from the full model (with both history-dependent starting point and drift bias) to investigate how the choice history-dependent variations in starting point and drift bias related to each *individual's* tendency to repeat their previous choices (Figure 3a). We call each bias parameter's dependence on the previous choice its 'history shift'. Across all five data sets, the history shift in drift bias, but not the history shift in starting point, was robustly correlated to the individual probability of choice repetition (Figure 3b).

Conclusion

We found that across five data sets, history biases evident in observers' overt choice behavior were explained by a history-dependent change in the accumulation bias rather than the starting point. This result calls for a revision of current models of history biases (Yu & Cohen, 2008) and indicates that the interaction between choice history signals and decision formation is more complex than previously thought. Choices may act like an endogenous cue for selective attention that biases evidence accumulation towards (or away from) the previous chosen perceptual interpretation of the sensory input.

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