History-Dependent Decision-Making across Species

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Abstract

Mice are increasingly used to study the neural circuit-level basis of behavior, often with the ultimate goal to extrapolate these insights to humans. To generalize insights about neural functioning between species, it is crucial to first ensure correspondence in behavioral and cognitive strategy. Here, we analyzed decision-making behavior in both humans and mice, and identified the same cognitive strategy of history-dependent evidence accumulation. Specifically, individual differences in choice repetition were explained by a history-dependent bias in the rate of evidence accumulation – rather than its starting point. Evidence integration over multiple temporal scales thus reflects a fundamental aspect of decision-making, conserved across mammalian species. These findings set the stage for linking the computations of decision-making to neural dynamics at the single-cell and population levels.

Keywords: evidence accumulation; sequential effects; choice history bias; cross-species comparison; neural dynamics

Introduction

Human observers' previous choices consistently bias their subsequent evidence accumulation (Urai et al., 2019). Choice history signals thus seem to bias the interpretation of current sensory input, akin to shifting endogenous attention toward (or away from) the previously selected interpretation. This decision-making strategy, which robustly captures individual differences across tasks, may be exhibited across mammalian species - thereby providing insights into the shared neural circuit mechanisms of cognition.

Recent advances in training mice to perform complex tasks, combined with powerful neural measurement tools, have positioned mice as a popular model species in cognitive neuroscience. An important assumption is that behavior and computational mechanisms are preserved across species. However, this assumption is rarely explicitly tested, creating challenges in the translatability of neuroscience findings to humans (Barron et al., 2021).

Here, we analyze choice behavior of 100 mice performing a decision task and show that these animals exhibit the same history-dependent computational strategy as humans. This sets the stage for investigating the circuit-level neural basis of choice history biases.

Methods

We analyzed data from 100 mice performing a visual decision-making task (The International Brain Laboratory et al., 2021) (Figure 1a). We selected sessions where mice had mastered the task. but before they were exposed to structured autocorrelation in stimulus sequences - ensuring that behavioral choice history biases reflected endogenous biases. Outlier RTs (< 0.1s and > 3s) were discarded.

We then fit hierarchical Drift Diffusion Models (Fengler et al., 2021; Wiecki et al., 2013) with a history-dependent starting point and drift bias, following the same fitting procedures as in our previous work on humans (Urai et al., 2019; Urai & Donner, 2022). Models with both history-dependent bias terms fit best.

After behavioral training, extracellular neural data in parietal cortex (VISa, VISam) was recorded using standardized pipelines (The International Brain Laboratory et al., 2022).

Data and code are available at github.com/anne-urai/mouse_history_ddm.

Results

Mice tended to repeat their previous choices, both after rewarded and unrewarded trials (Figure 1b).

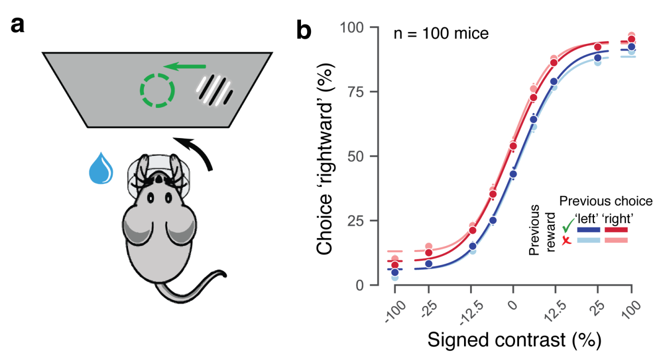

Figure 1. History bias in decision-making. **(a)** Visual decision task. **(b)** Psychometric curves shift in the direction of the previous choice, independently of the previous reward.

Computational strategies across species

Choice repetition biases were explained by the same computational principle across species: a history-dependent change in the rate of evidence accumulation, rather than its starting point (Figure 2a). Specifically, only history-dependent drift bias (not starting point) captured individual differences in repetition behavior (Figure 2b,c). While behavior can be biased by several (typically 3-5) past choices (Urai & Donner, 2022), we here use the immediately preceding choice as a proxy for such longer-timescale integration.

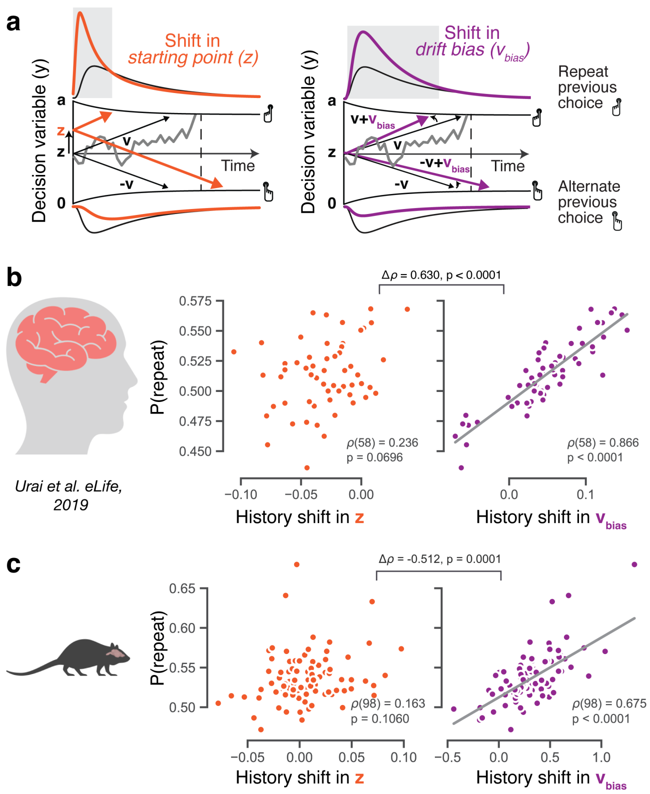

Figure 2. Mice and humans use the same decision-making strategy. **(a)** In the DDM, noisy sensory evidence is accumulated over time until the resulting decision variable reaches one of two bounds. Repeating this process over many trials yields RT distributions. Orange (left): bias in starting point. Purple (right): bias in drift. **(b)** In humans, choice history bias reflects a change in drift bias (Urai et al., 2019). **(c)** In mice, choice history bias reflects a change in drift bias.

Neural dynamics of history coding

We analyzed extracellular recordings in posterior parietal cortex (PPC; VISa, VISam), acquired using standardized pipelines (The International Brain Laboratory et al., 2022) (Figure 3b,c). Note that during recording sessions, animals performed a task that includes biased stimulus blocks (The International Brain Laboratory et al., 2021, 2022) and were no longer naïve to the existence of this task structure. Here, we use only the first 90 trials with a 50:50 stimulus prior.

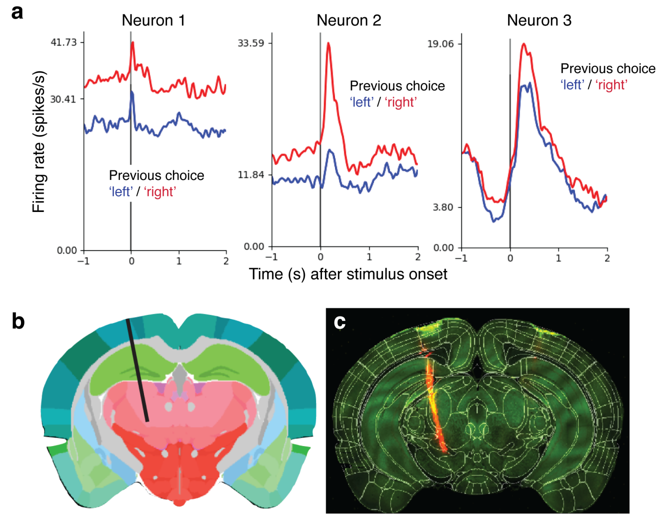

Figure 3. Preliminary neural recordings. **(a)** Example neurons in left parietal cortex (VISa/VISam) encode the animal's previous choice. **(b)** Targeted recording using Neuropixels probes, shown on a coronal view of the mouse Allen Atlas (Wang et al., 2020). This recording path goes through cortex, hippocampus and thalamus. **(c)** Anatomical reconstruction of the probe tract, indicated by red dye.

Neurons in PPC encoded animals' previous choice, as previously reported in mice (Hwang et al., 2017), rats (Akrami et al., 2018) and humans (Urai & Donner, 2022). Interestingly, there is a variety of ways in which neurons encode previous choices (Figure 3a): some neurons show sustained previous choice coding throughout the trial (e.g. neuron 1), while others mostly alter their sensory response (e.g. neuron 3), or a combination of the two (e.g. neuron 2). This variety of neural response profiles likely plays a role in the circuit-level mechanisms by which choice history is integrated into the next decision.

Conclusion

Evidence accumulation over multiple temporal scales reflect a fundamental aspect of decision-making, conserved across mammalian species. Future work will explicitly link neural activity at the single-cell and population levels to trial-by-trial variations in drift bias. We also aim to further explore the effects of slow drifts in decision criterion (Gupta & Brody, 2022) and engagement states (Ashwood et al., 2022) on choice history biases and their neural correlates.

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