

# Exploratory choices reveal human sensitivity to the temporal structure of changes

## Introduction

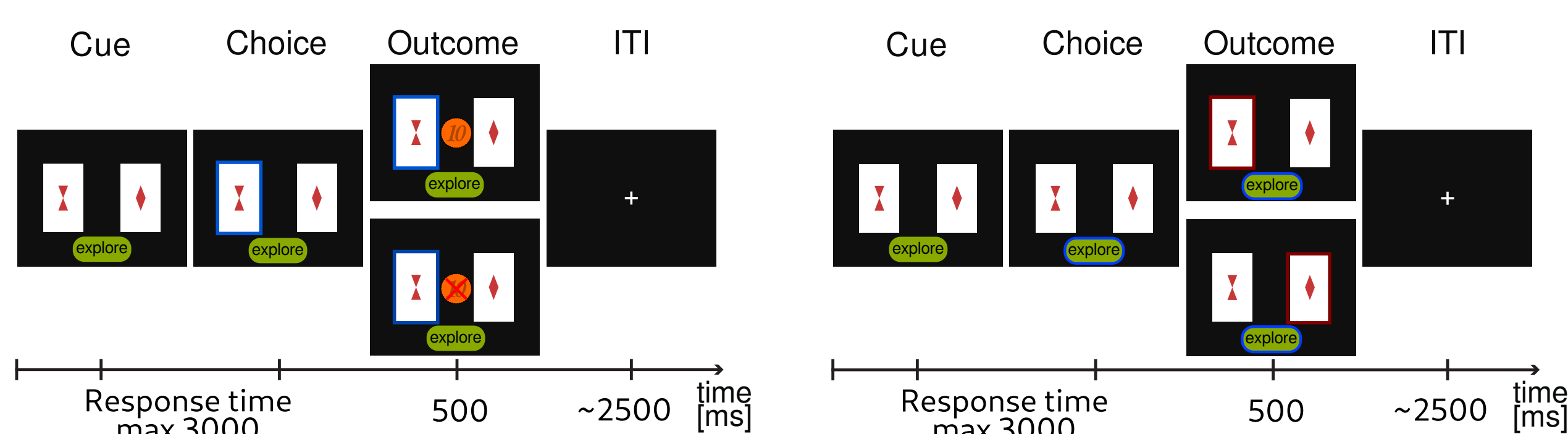
Understanding how the brain represents temporal structure over multiple time scales [1] and uses these representations for making decisions [2] is essential for understanding human adaptive behaviour and the functional role of involved brain networks. Here we investigate if beliefs about hidden temporal structure of changes in the environment are reflected in exploratory behaviour.

Using a modified reversal learning task [3] that includes exploratory (epistemic) choices we can demonstrate that priming subjects to a specific temporal structure of reversals influences the statistics of both exploitative and exploratory choices on a group level.

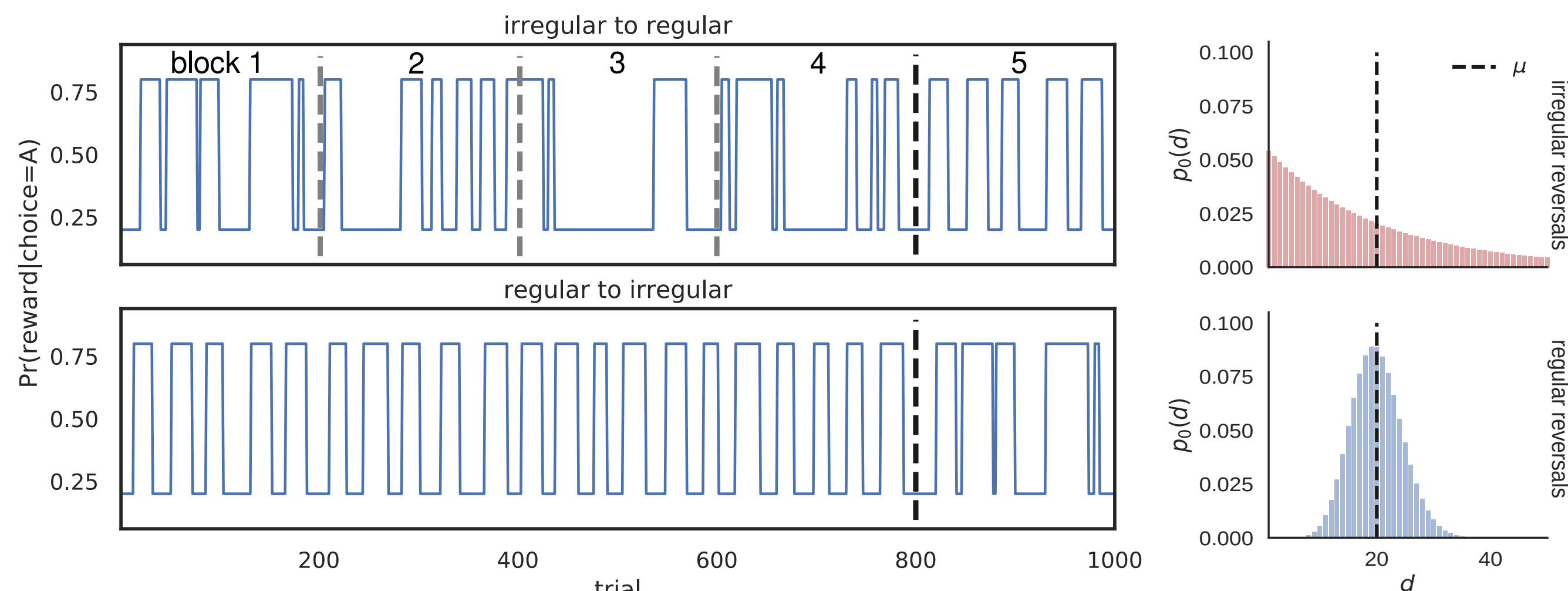
A model-based analysis illustrates that the group specific exploratory behaviour can be replicated with an active inference model [4] informed about the true temporal structure of reversals [2], hence revealing computational principles that underpin the evolution of uncertainty in the presence of temporal regularities.

## The reversal learning task

An exemplary trial sequence of the reversal learning task [4]



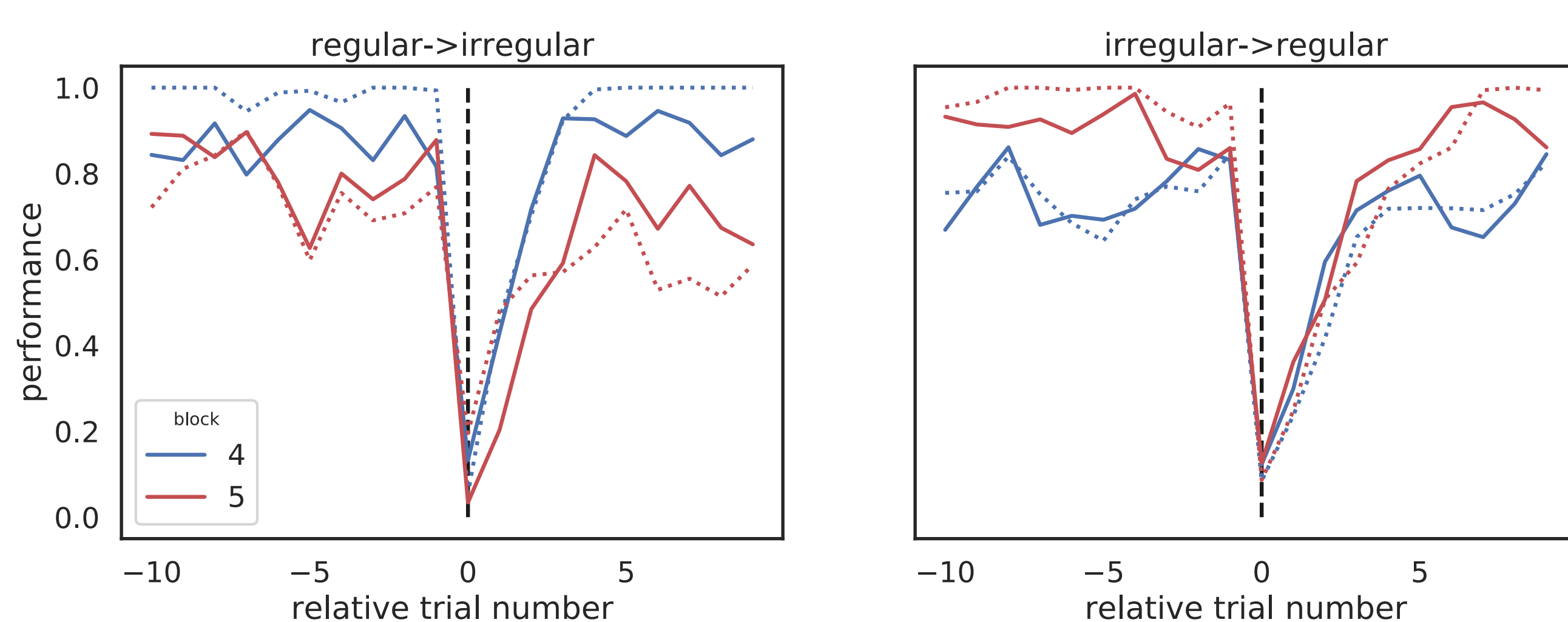
A between subject-design



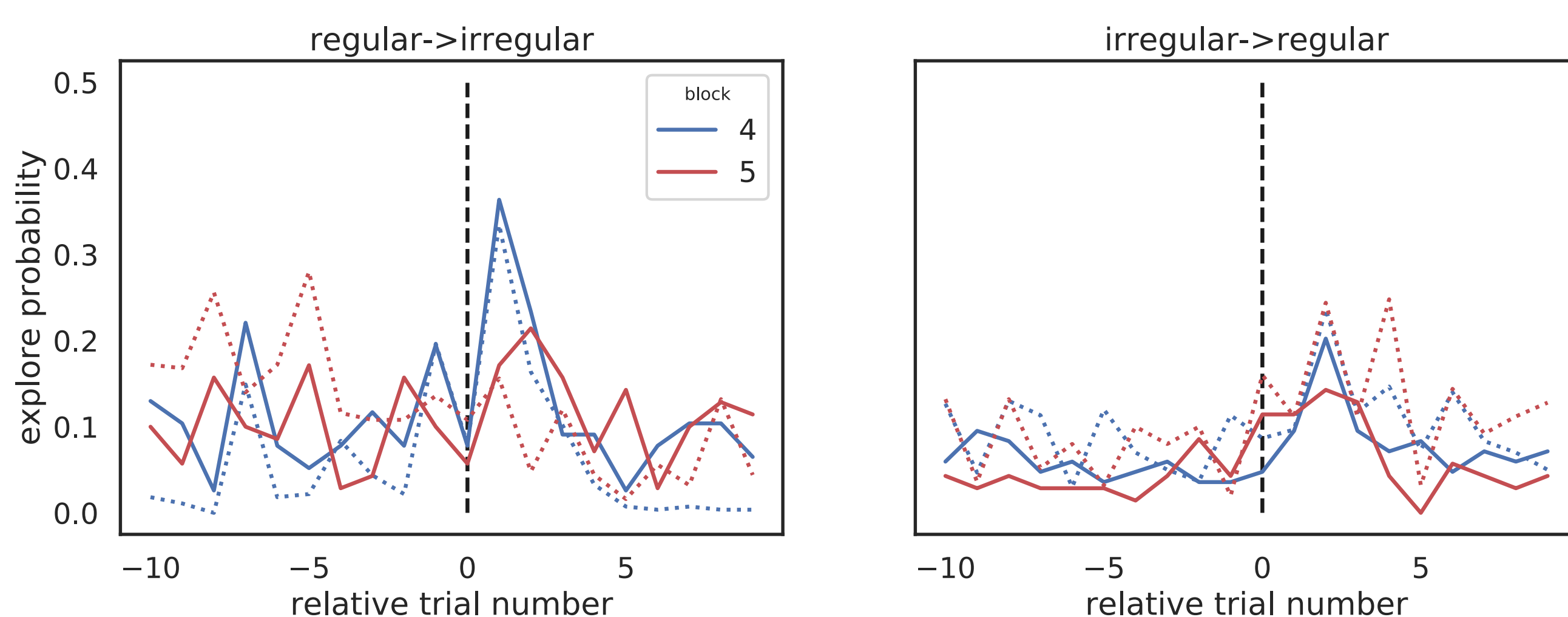
Group one: 800 trials of irregular reversals and 200 trials of regular reversals. Group two: the reversed order, 800 trials of regular reversals and 200 trials of irregular reversals. The reward probabilities of the two stimuli were always anticorrelated ( $p_B = 1 - p_A$ ).

## Data analysis

Average performance relative to the moment of reversal



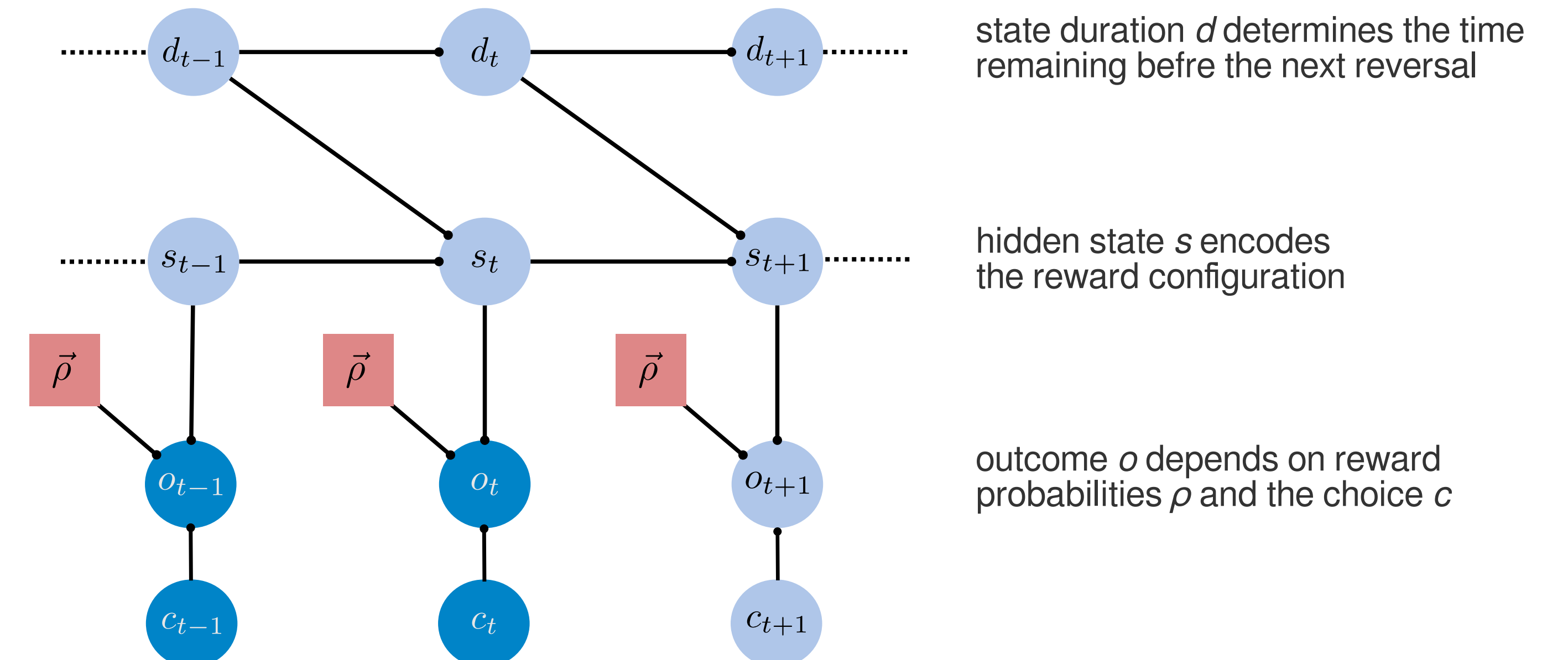
Average probability of exploratory choices



(Top) Note the differences in performance trajectories between experimental blocks. (Bottom) Note the higher explore probability just after the reversal in the group exposed to a long sequence of regular reversals. The dotted lines mark the summary statistics of simulated behavior.

## Active inference with semi-Markov models

Graphical model



$$p(d_t|d_{t-1}) = \begin{cases} \delta_{d_t, d_{t-1}-1}, & \text{if } d_{t-1} > 1 \\ p_0(d_t), & \text{if } d_{t-1} = 1 \end{cases} \quad p(s_t|s_{t-1}, d_{t-1}) = \begin{cases} I_2, & \text{if } d_{t-1} > 1 \\ J_2 - I_2, & \text{if } d_{t-1} = 1 \end{cases}$$

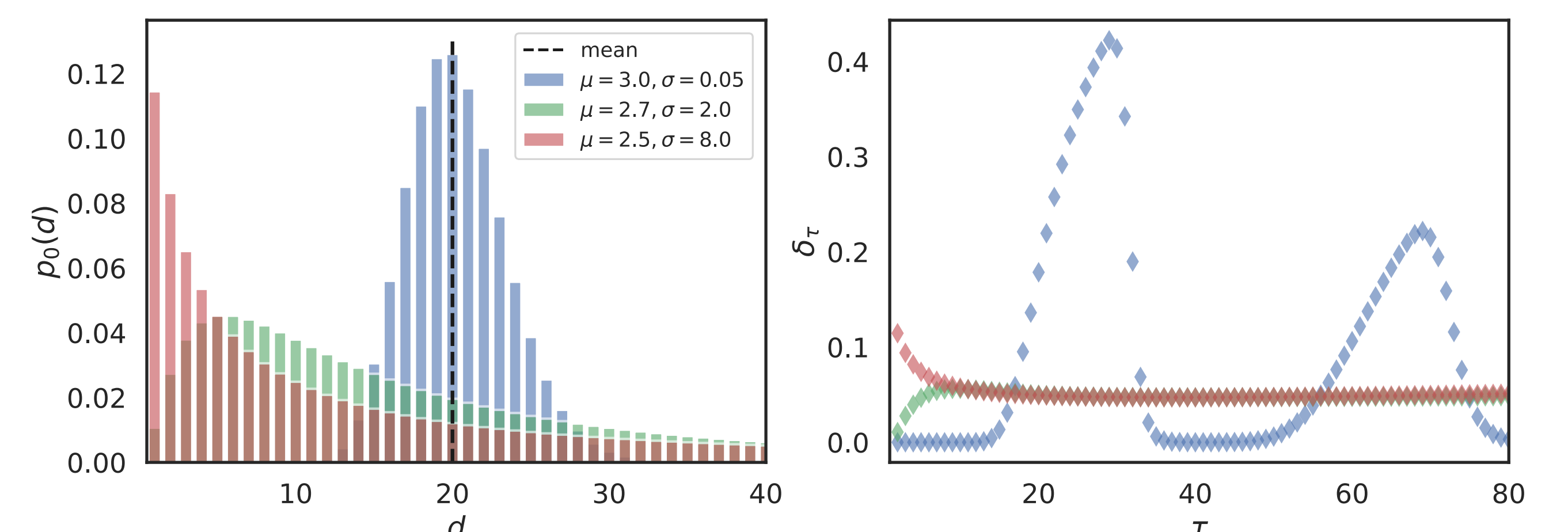
$$p(o_t|s_t, c_t) = \begin{cases} \rho_H^{(1+o_t)/2} (1 - \rho_H)^{(1-o_t)/2}, & \text{if } c_t = s_t \\ \rho_L^{(1+o_t)/2} (1 - \rho_L)^{(1-o_t)/2}, & \text{if } c_t \neq s_t, \end{cases}$$

Update of beliefs about states and durations

$$p(s_t, d_t|o_{t:1}, c_{t:1}) \propto p(o_t|s_t, c_t)p(s_t, d_t|o_{t-1:1}, c_{t-1:1})$$

$$p(s_{t+1}, d_{t+1}|o_{t:1}, c_{t:1}) = \sum_{s_t, d_t} p(s_{t+1}|s_t, d_t)p(d_{t+1}|d_t)p(s_t, d_t|o_{t:1}, c_{t:1})$$

Prior beliefs  $p_0(d)$  about the between reversal intervals



(Left) The discretised log-normal distribution captures a wide range of prior beliefs. (Right) The temporal priors shape agent's beliefs about the future moment of change.

## Action selection - minimising expected free energy

Expected utility

$$U(c) = E_{\tilde{p}(o_{t+1}|c_{t+1}=c)} [U(o_{t+1})]$$

Expected information gain

$$I(c) = E_{\tilde{p}(o_{t+1}|c_{t+1}=c)} [D_{KL}(\tilde{p}(s_{t+1}, d_{t+1}|o_{t+1}, c_{t+1}=c) | \tilde{p}(s_{t+1}, d_{t+1}))]$$

Expected free energy

$$G(c) = -U(c) - I(c)$$

Choice probability

$$\tilde{p}(c_{t+1} = c) \propto p(c) e^{-\beta G(c)}$$

$$\tilde{p}(x) = p(x|o_{t:1}, c_{t:1})$$

Both exploitative and exploratory choices are dependent on temporal beliefs. Importantly, the exploratory choices should match moments of high subjective uncertainty.

## References

- [1] Kiebel, S. J., et al. (2008). "A hierarchy of time-scales and the brain." PLoS computational biology 4(11): e1000209.
- [2] Marković, D. et al. (2019). "Predicting change: Approximate inference under explicit representation of temporal structure in changing environments." PLoS computational biology 15.1: e1006707.
- [3] Reiter, A. M. F., et al. (2017). "Impaired flexible reward-based decision-making in binge eating disorder: evidence from computational modeling and functional neuroimaging." Neuropsychopharmacology 42.3: 628.
- [4] Friston, Karl, et al. (2015). "Active inference and epistemic value." Cognitive neuroscience 6.4: 187-214.