Computational principles underlying the learning of sensorimotor repertoires

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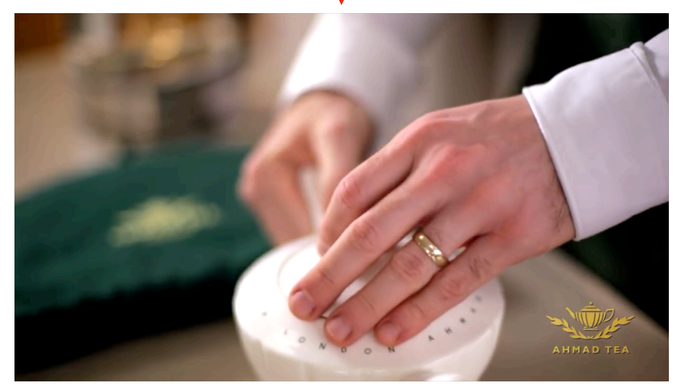
Contexts

States



- Rules for motor memories in sensorimotor learning
- COIN (COntextual INference) model of motor repertoire learning
  - Memory creation, expression and updating
  - Experimental tests of the model on new and existing data

Type of Motor Learning

strategy learning

skill learning/
variability reduction

sequence learning

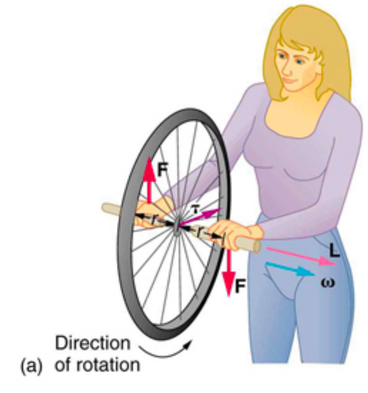
adaptation

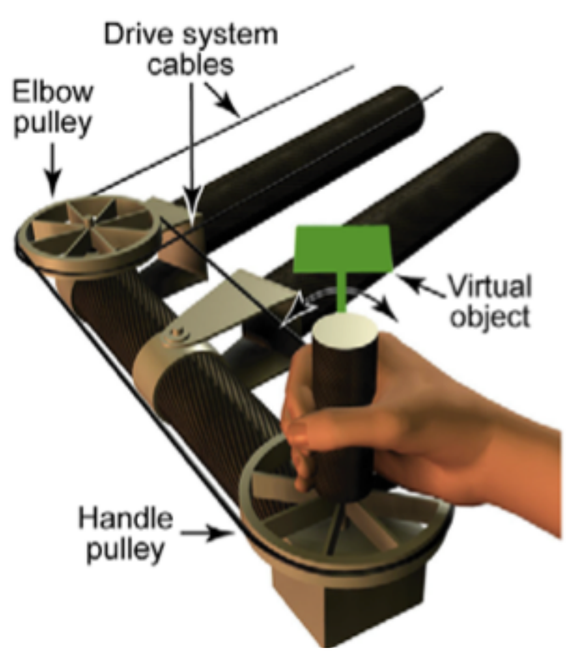
optimization

Reaching, manipulation, walking, balance, speech, eye movements etc.

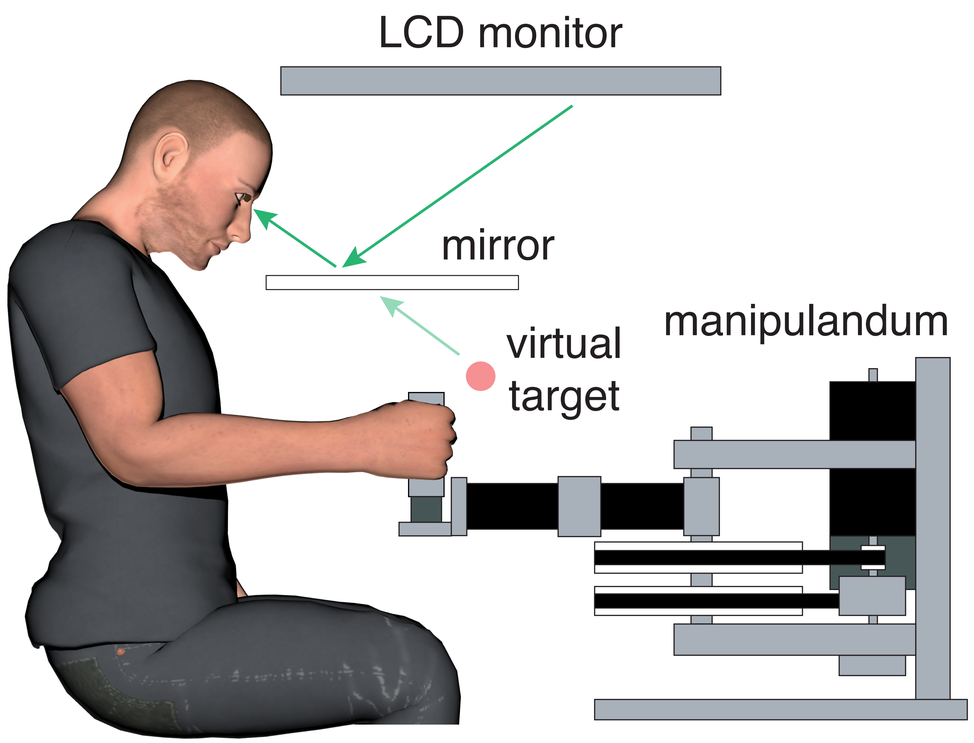
Adaptation to novel dynamics

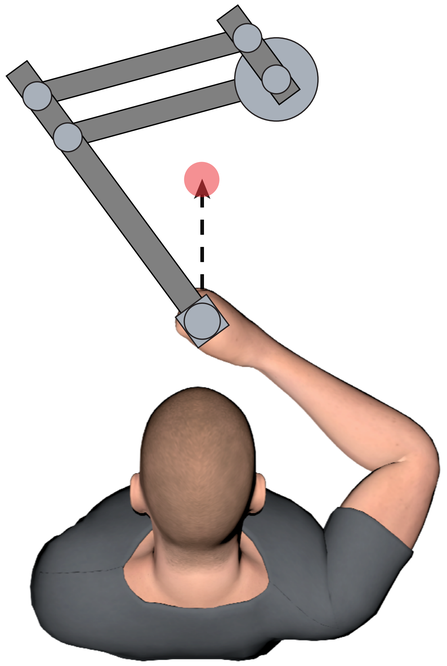
Reaching when changing relation between motor command and consequences by applying forces





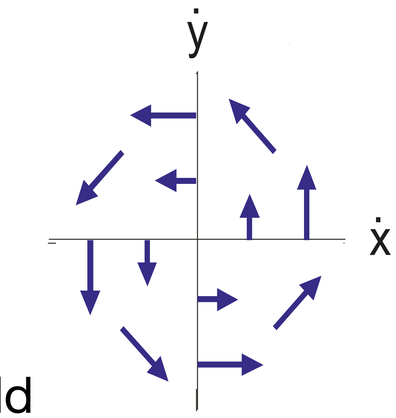
Robotic manipulandum and VR system

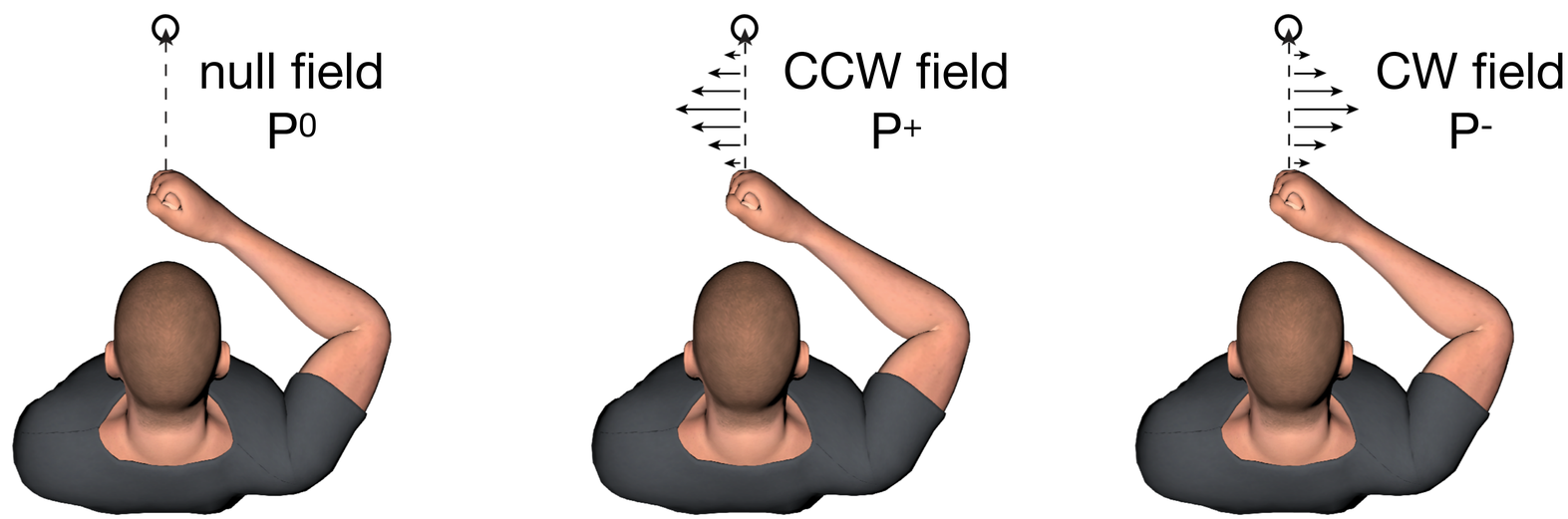


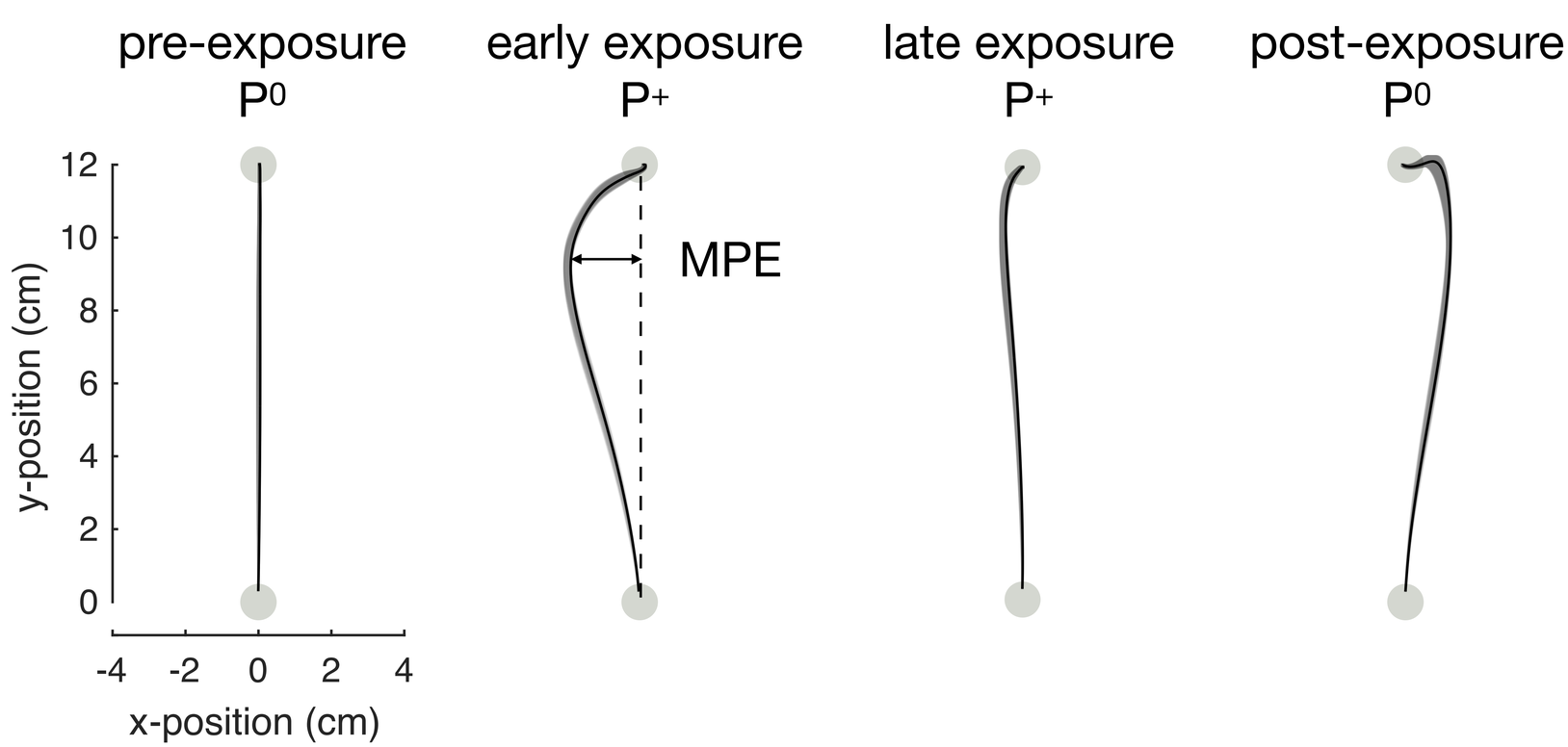


Motor learning of novel dynamics

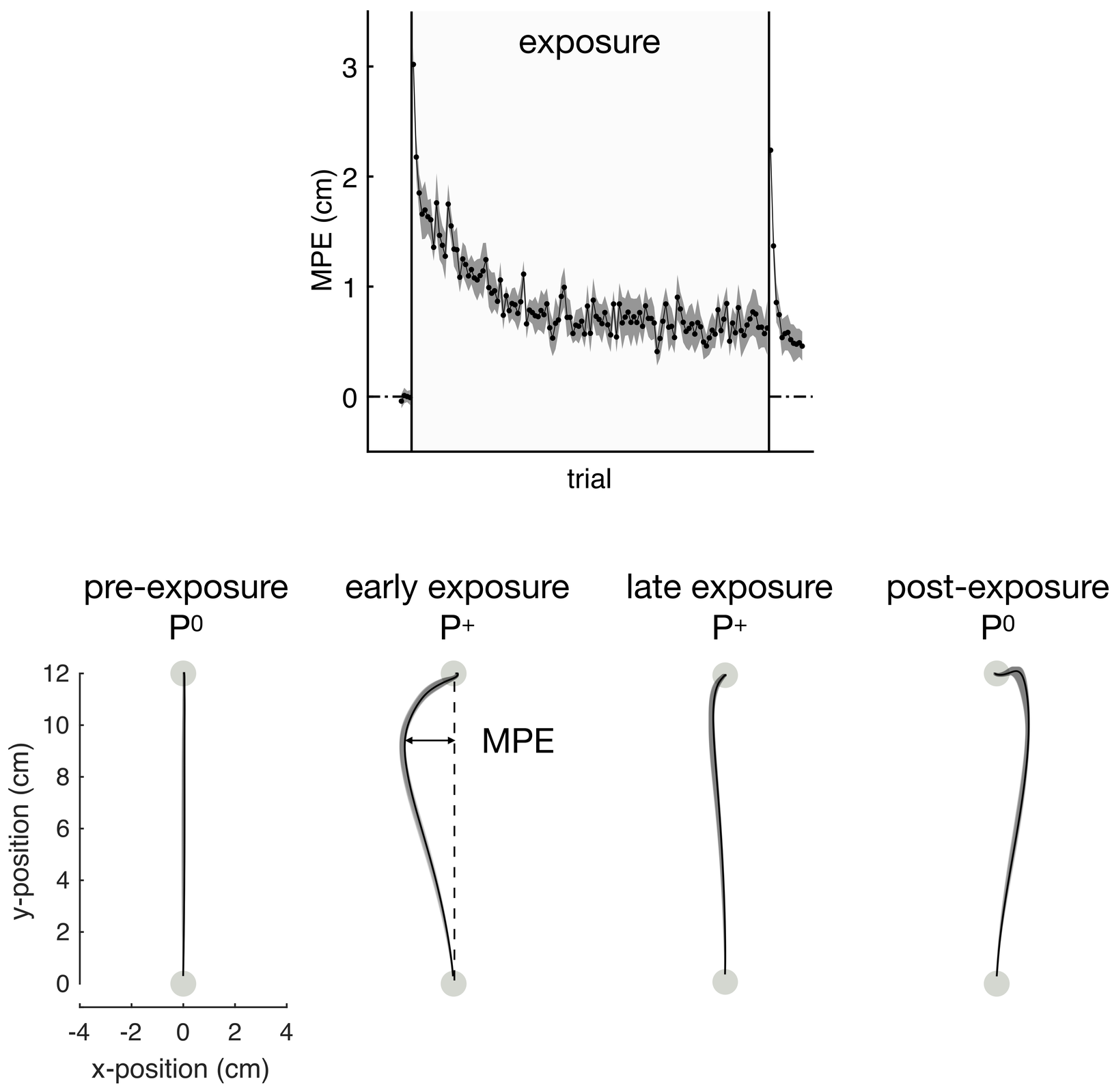
$$\begin{pmatrix} F_x \\ F_y \end{pmatrix} = \pm k \begin{pmatrix} 0 & -1 \\ +1 & 0 \end{pmatrix} \begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix}$$



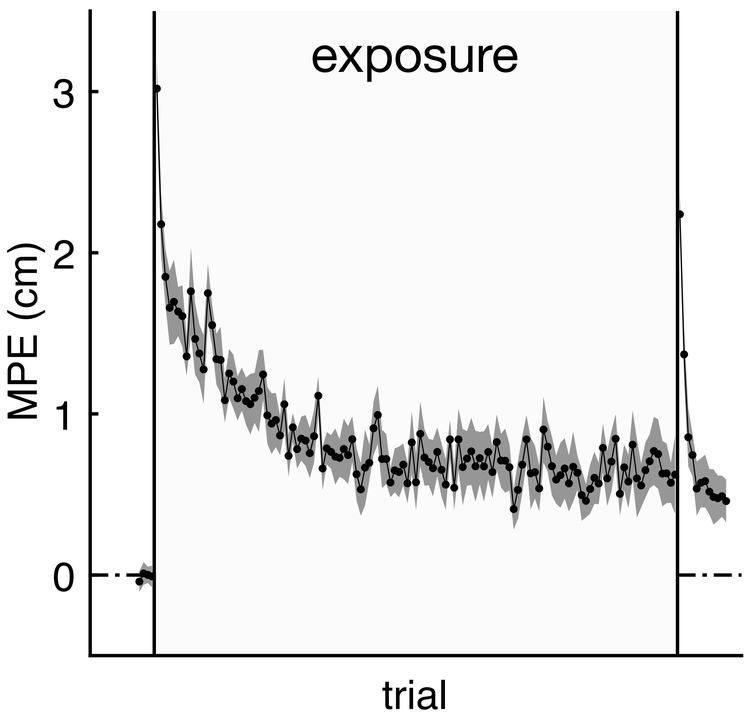


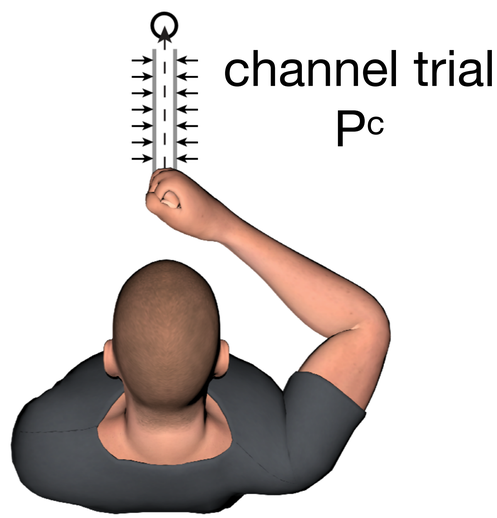


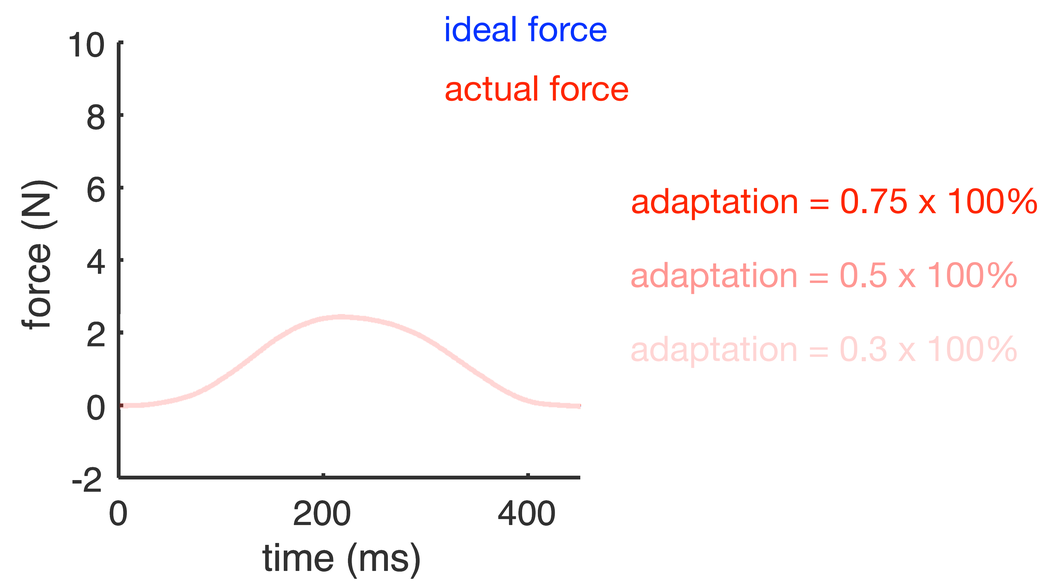
Motor learning of novel dynamics

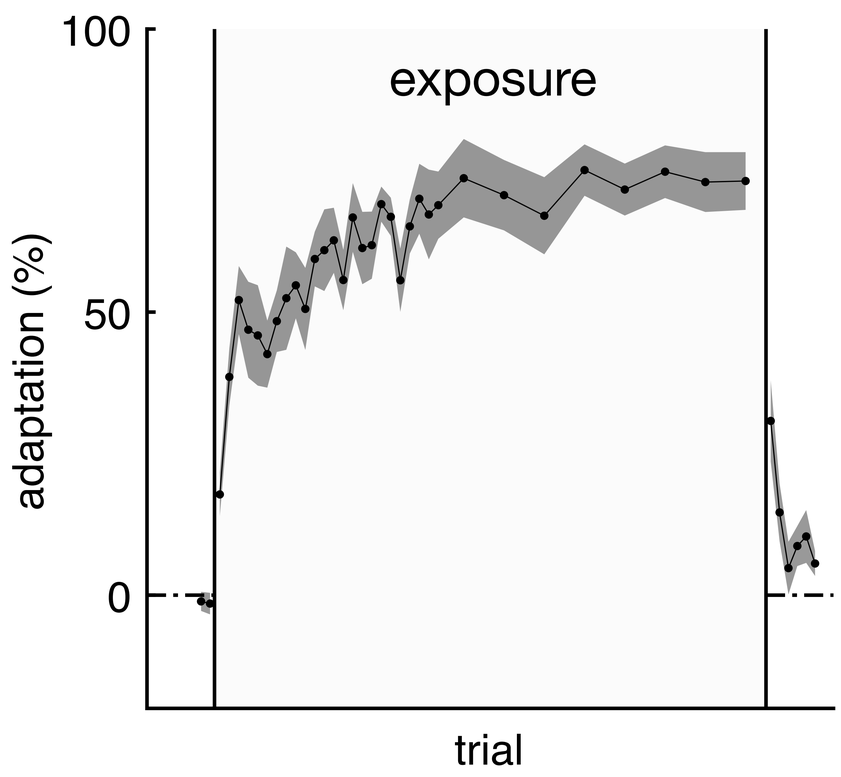


Measuring adaptation

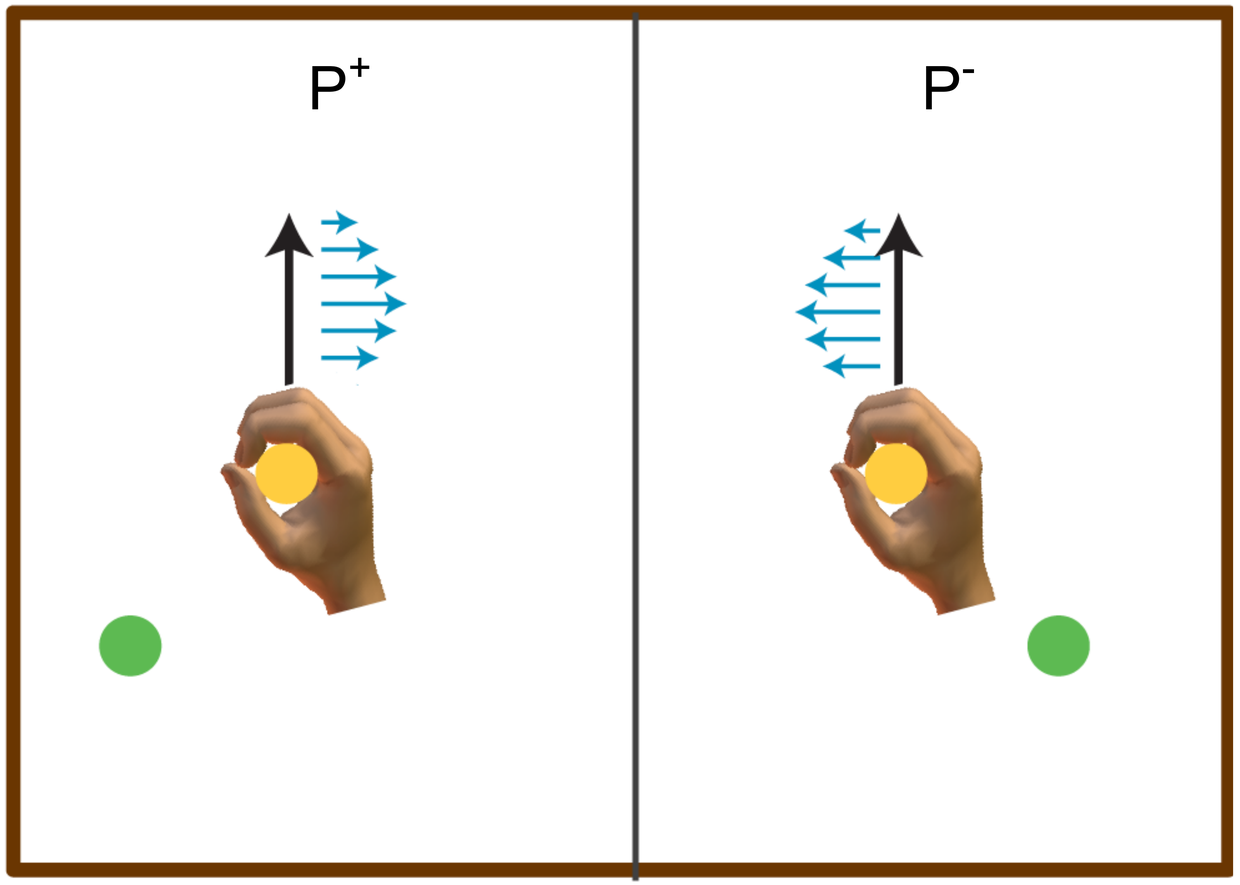


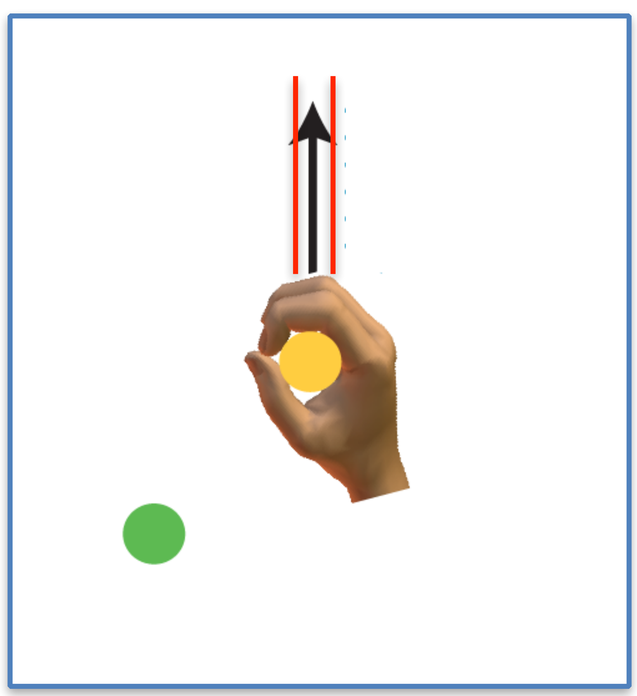


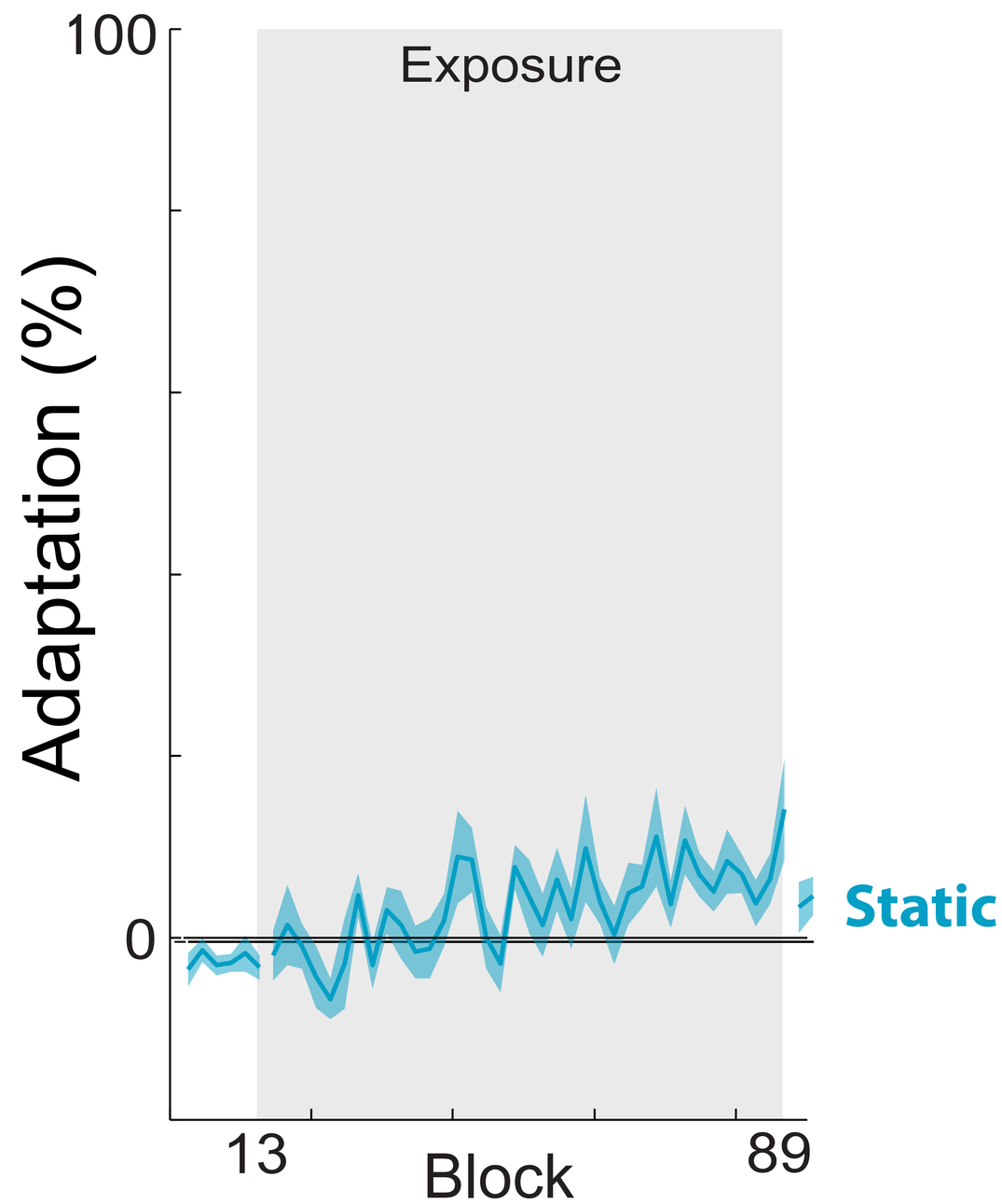




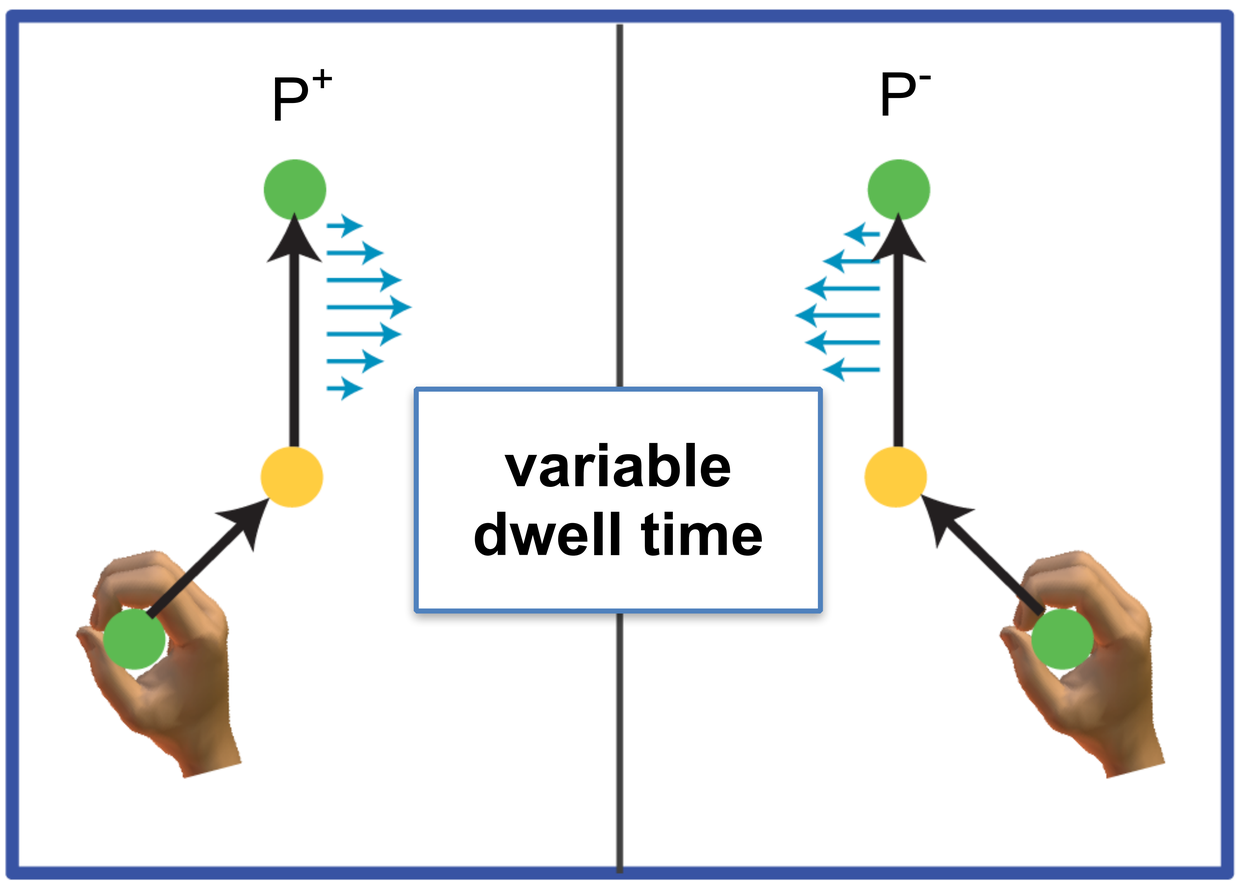
Contextual cues: static visual

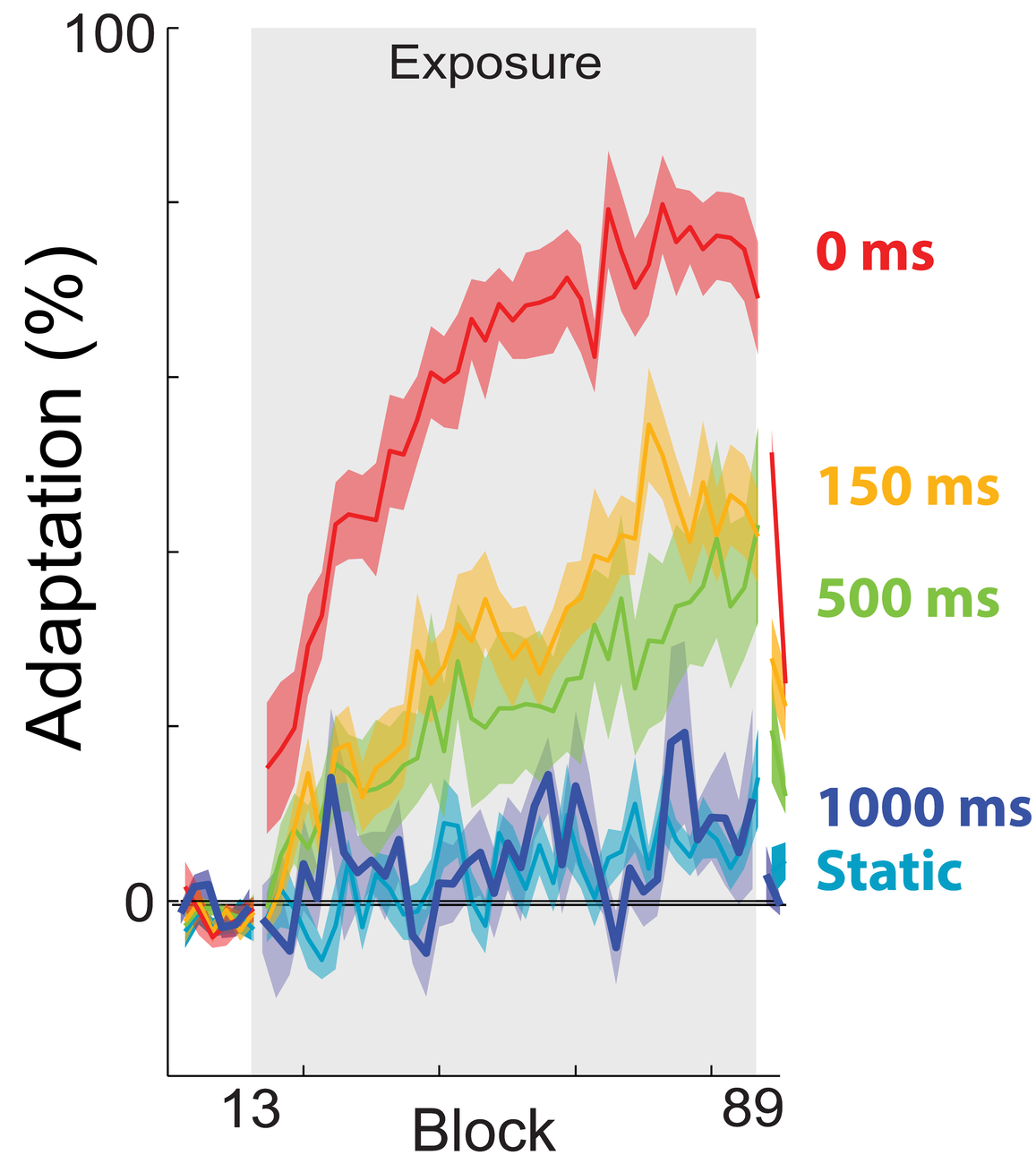






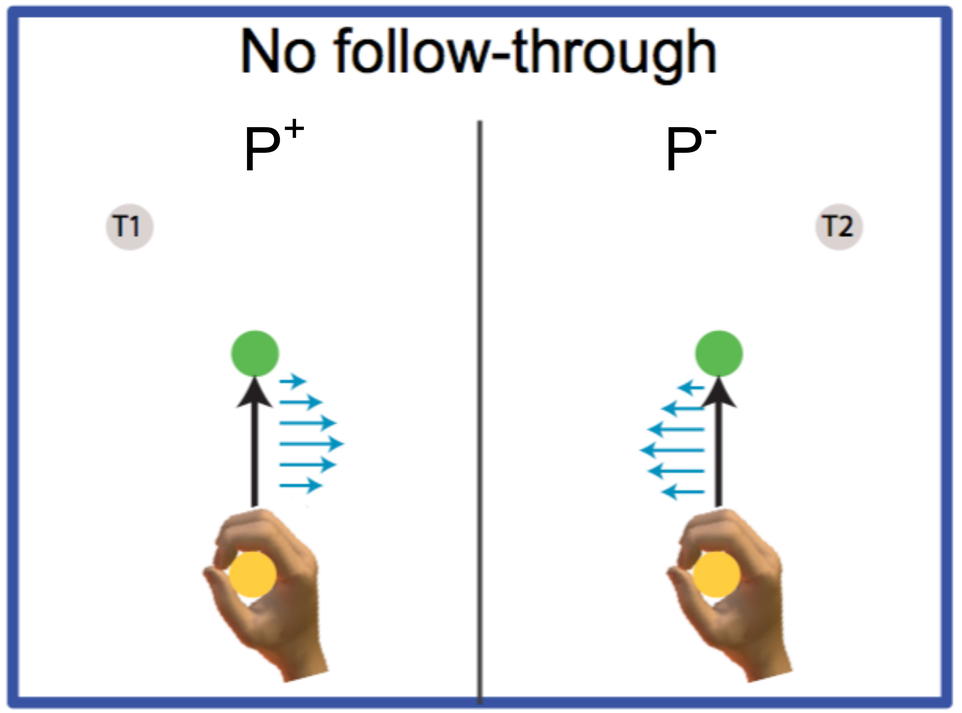
Sequential action with variable dwell time

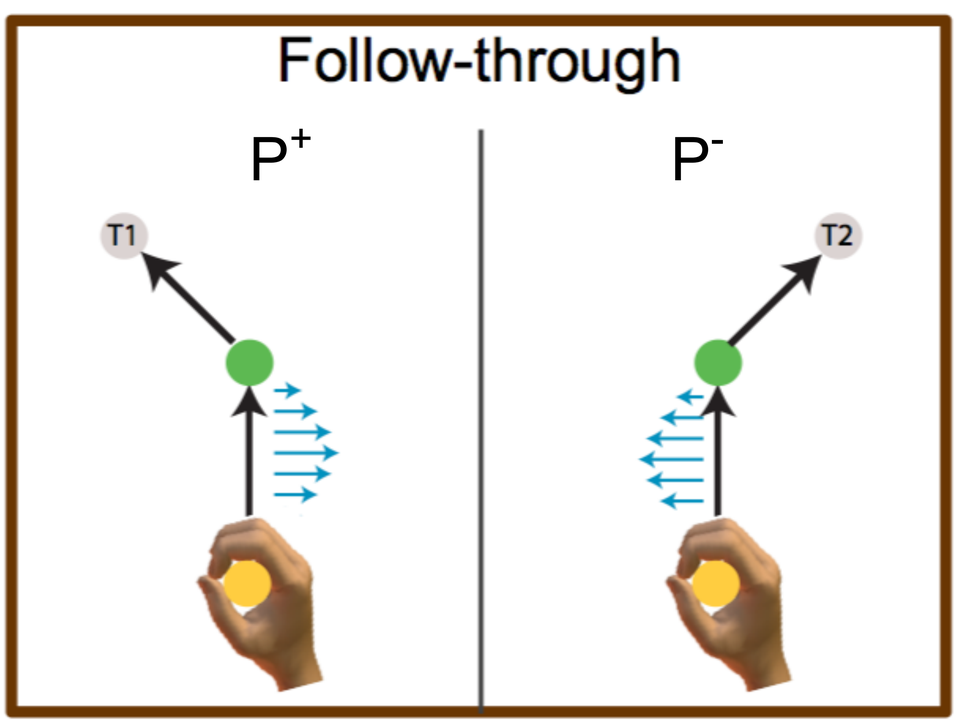


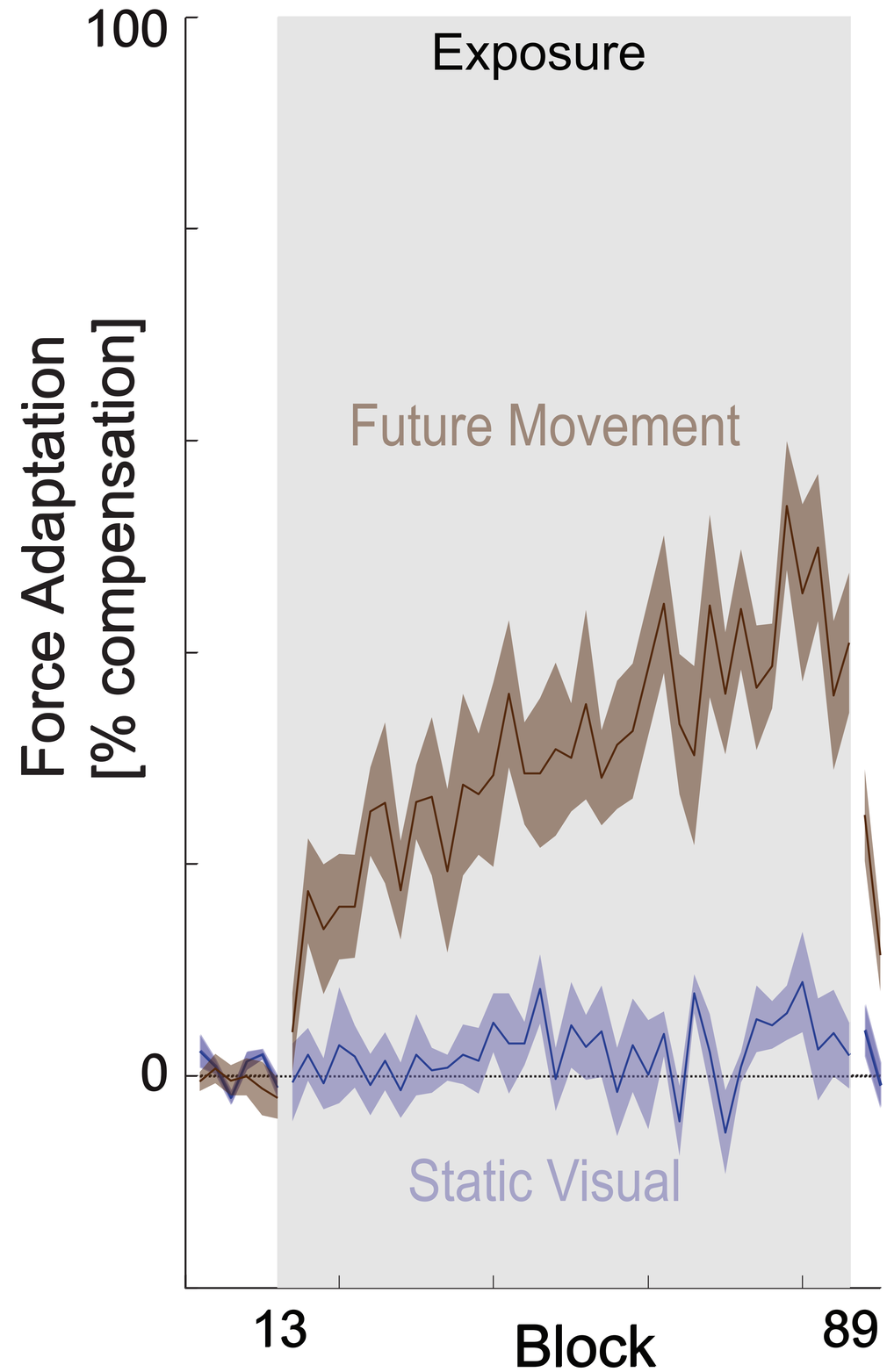


(Howard et al, J. Neurosci., 2012)

Future states

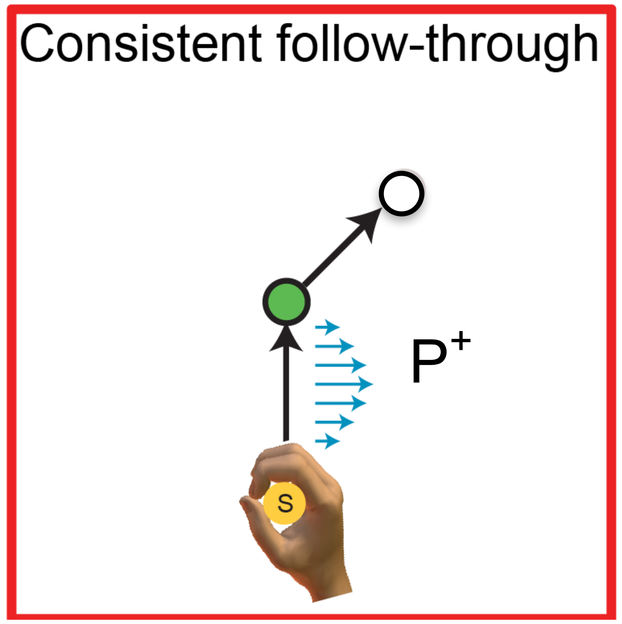


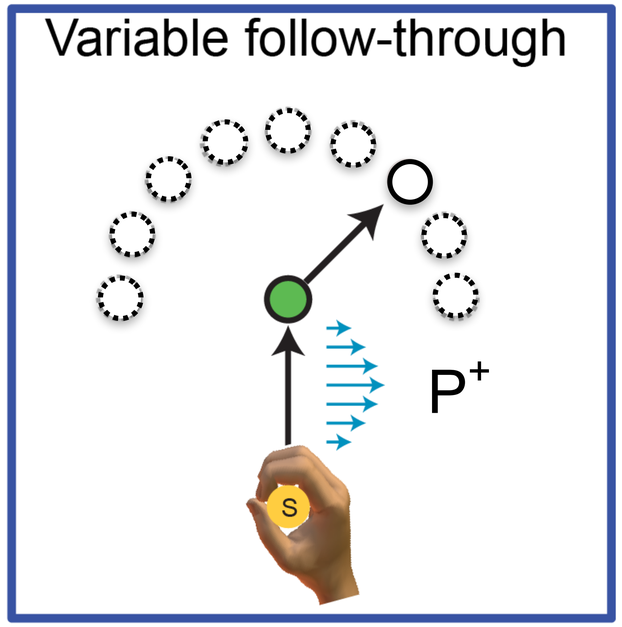


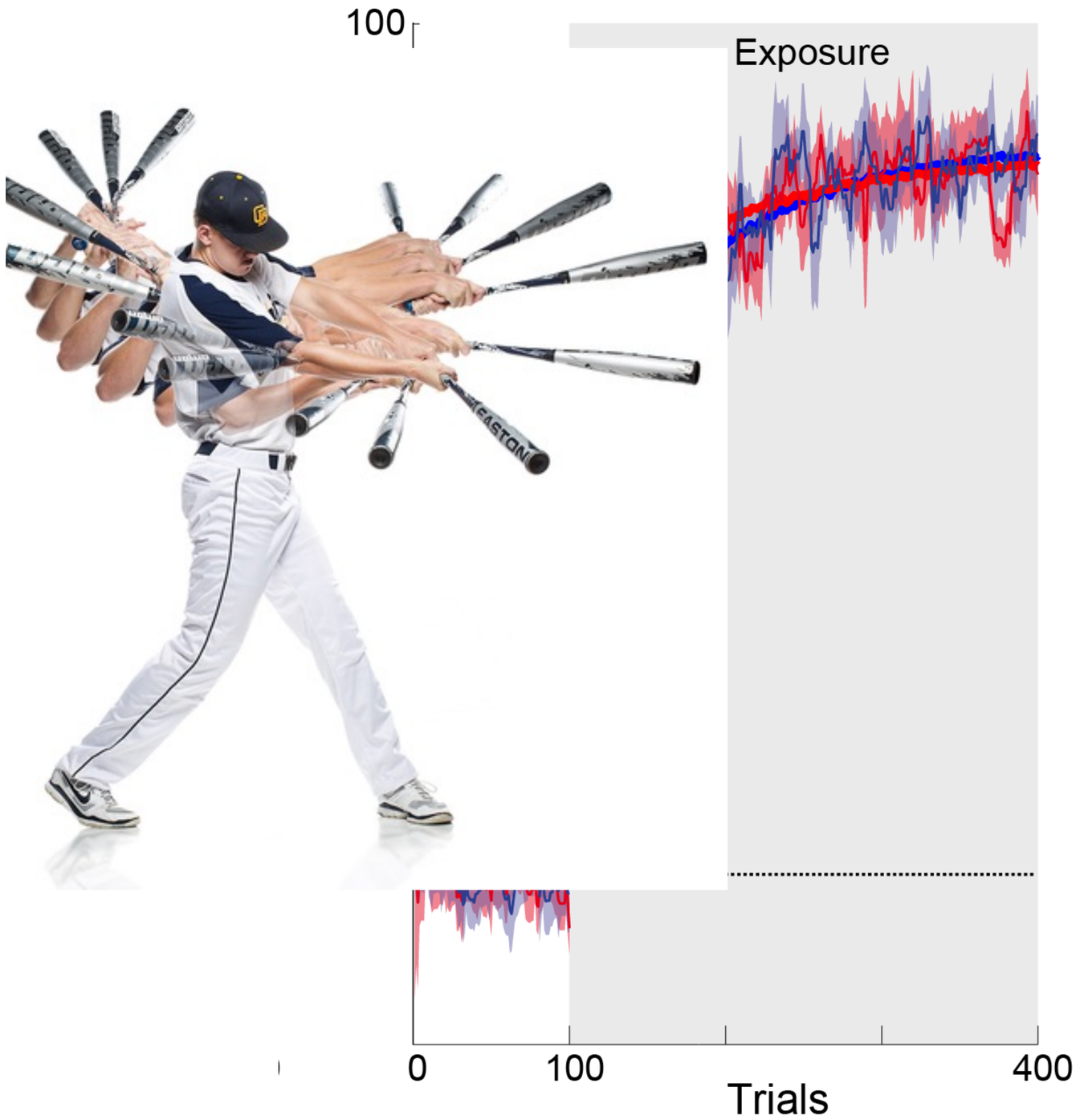


(Howard et al, Curr. Biol., 2015)

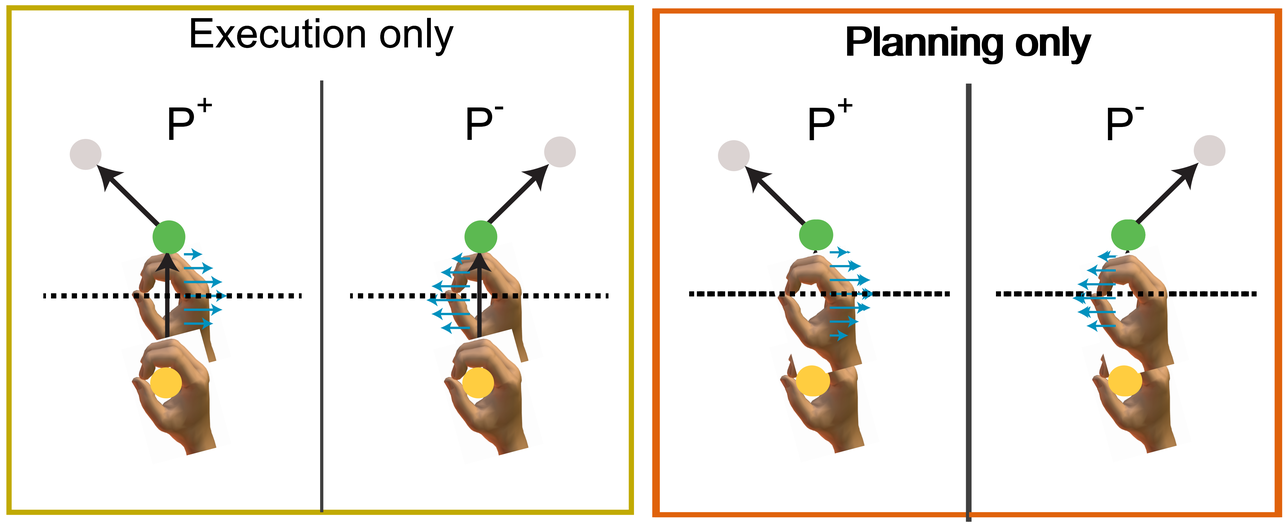
Consistent vs. Variable Future

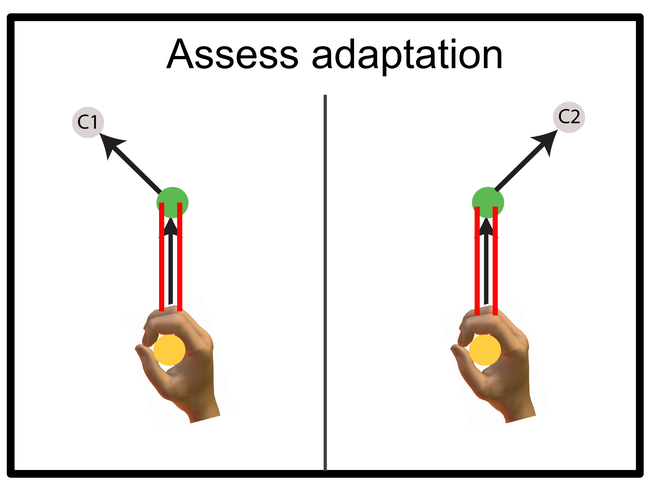


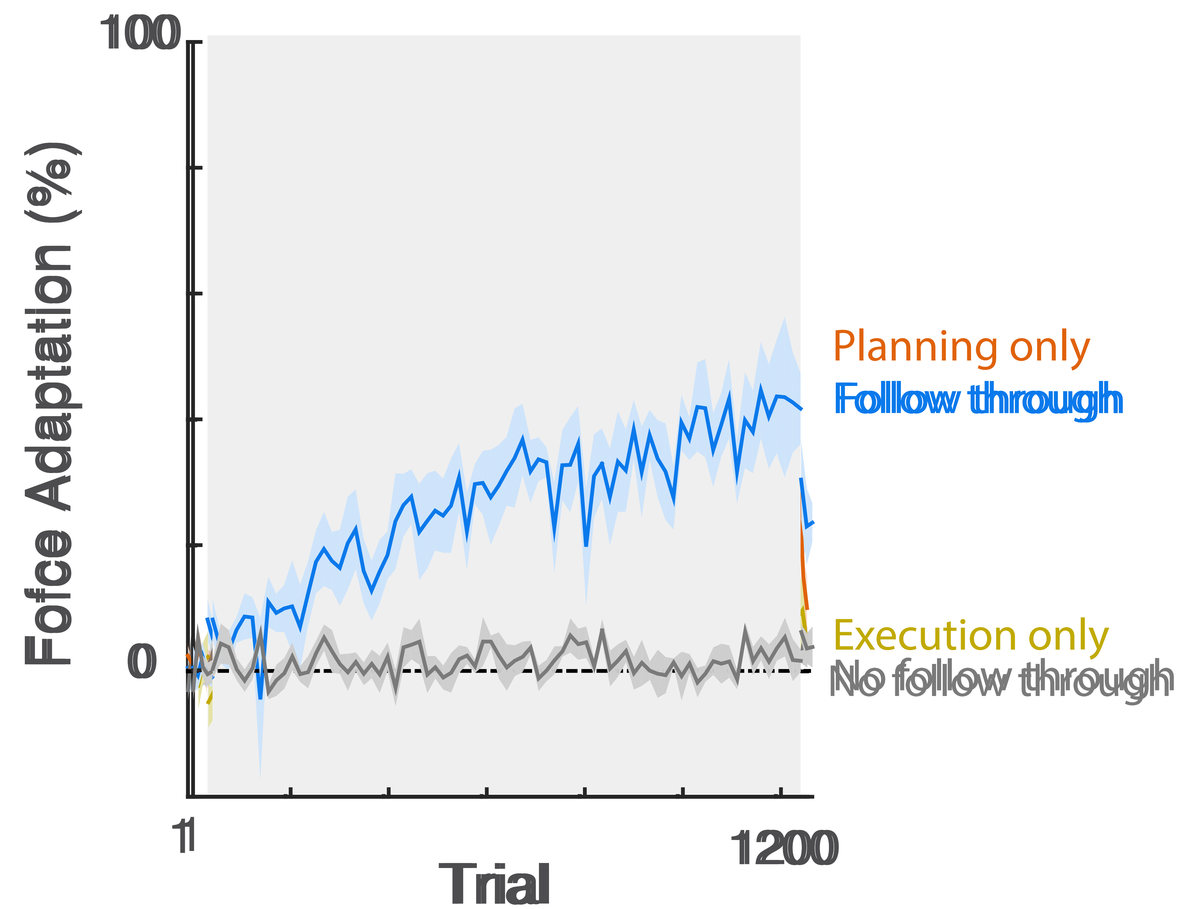




Planning vs. execution







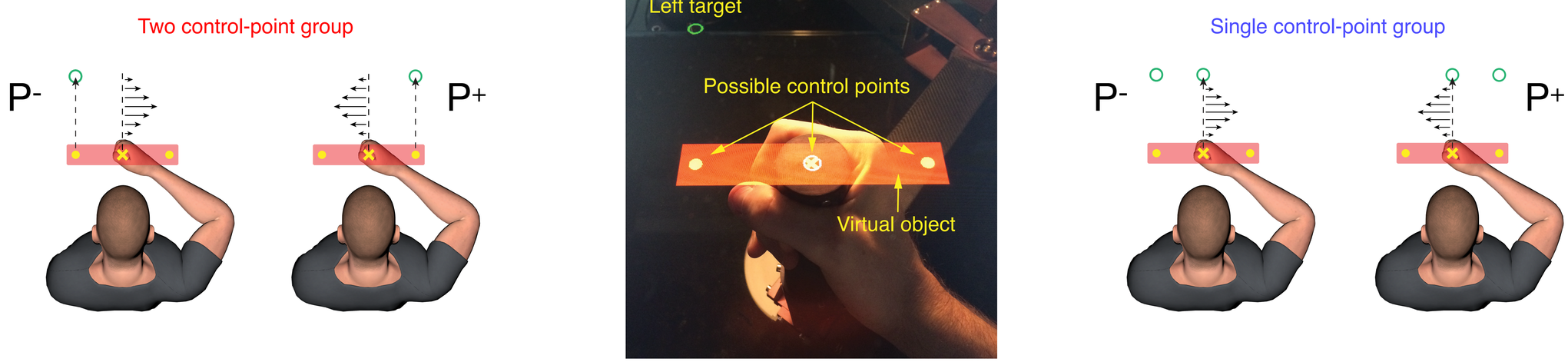
(Sheahan et al. Neuron 2016)

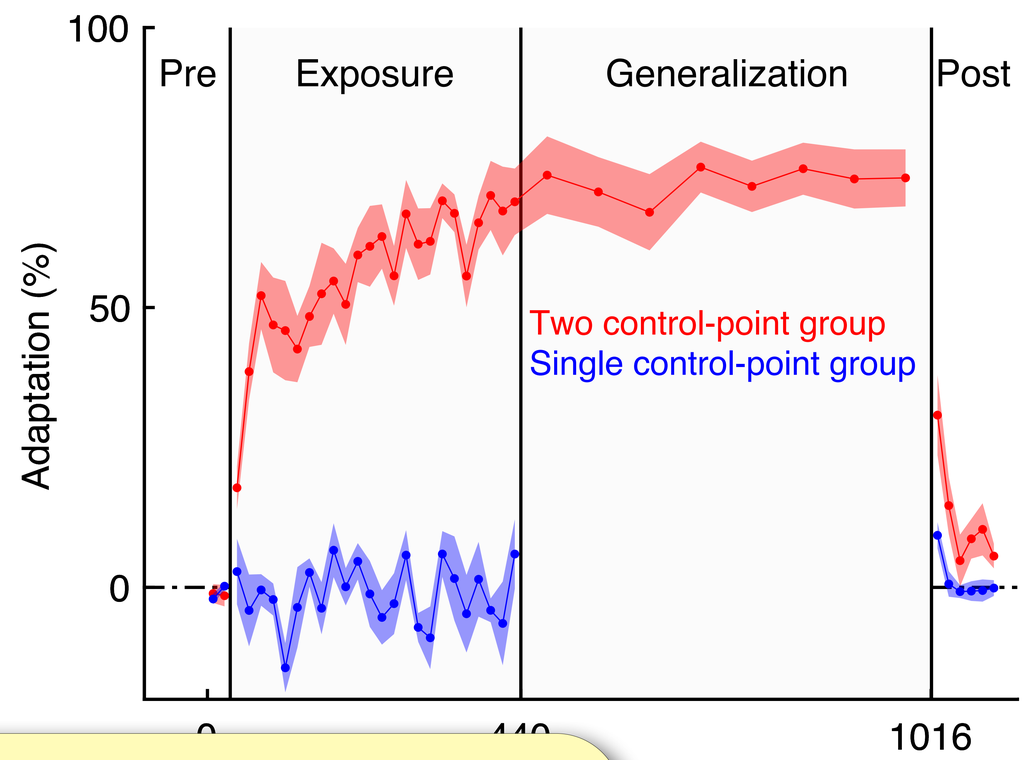
Recent past and future actions determine current motor memory: planning more important than execution

Tool use

Control points on an object

Sensory cues: control points on an object

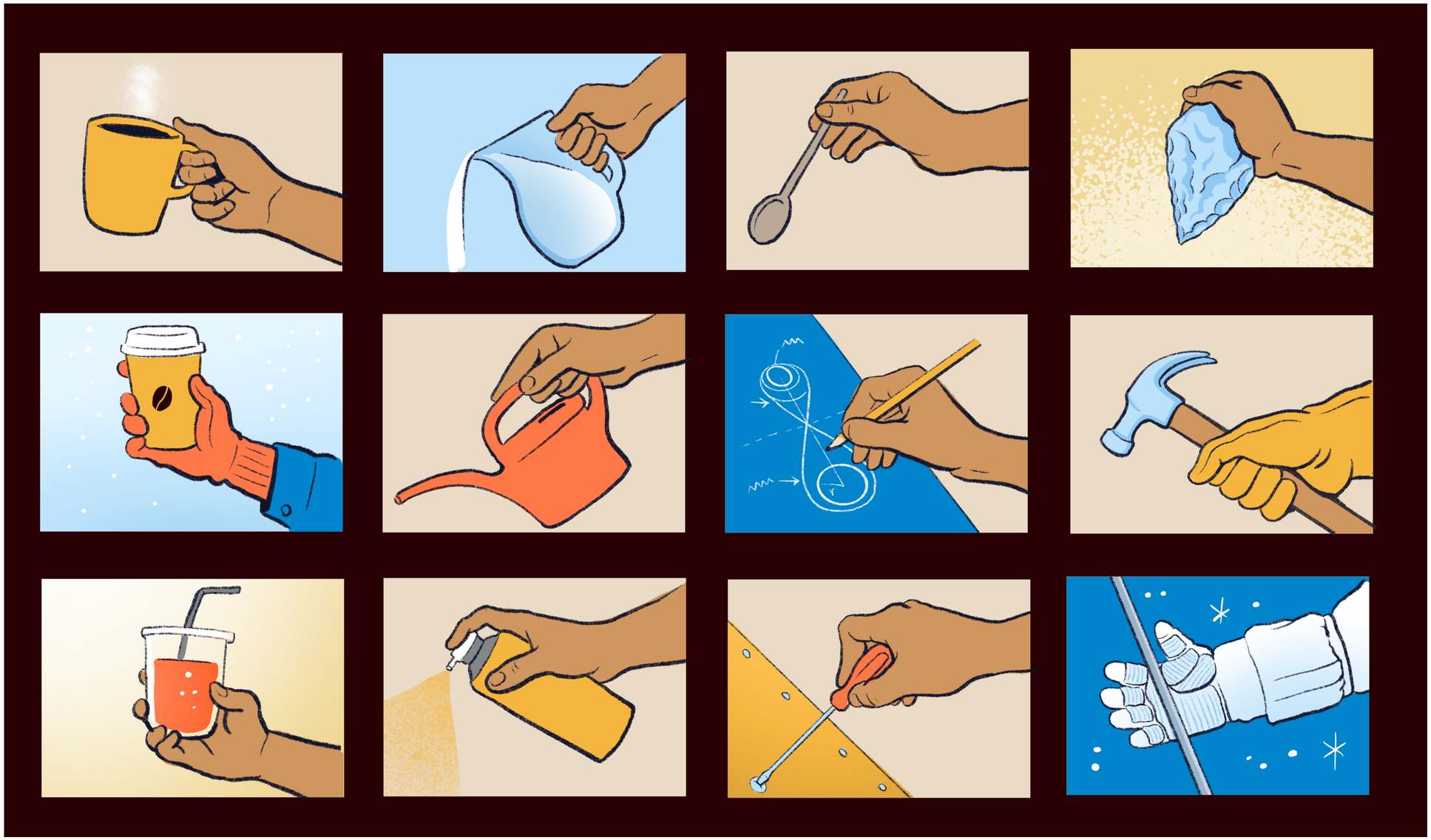




Control points on an object can be associated with different dynamics for the same movement = sensory cue

(Heald et al., *Nature Human Behaviour*, 2018)

Repertoire learning



Artwork by Matteo Farinella (Columbia University)

Develop a model as a simplified, abstract model of motor adaptation

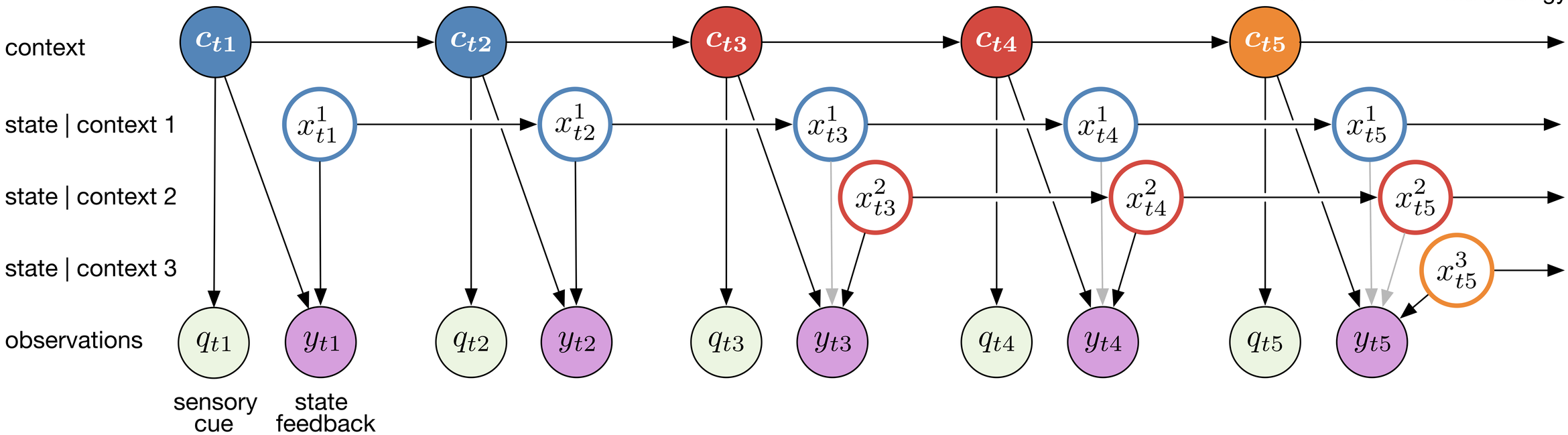
- scalar states, observation and action variables
- trial-level model
- core computational problem identified applicable to more complex models of motor learning

The COntextual INference (COIN) model

generative model

James Heald

Máté Lengyel

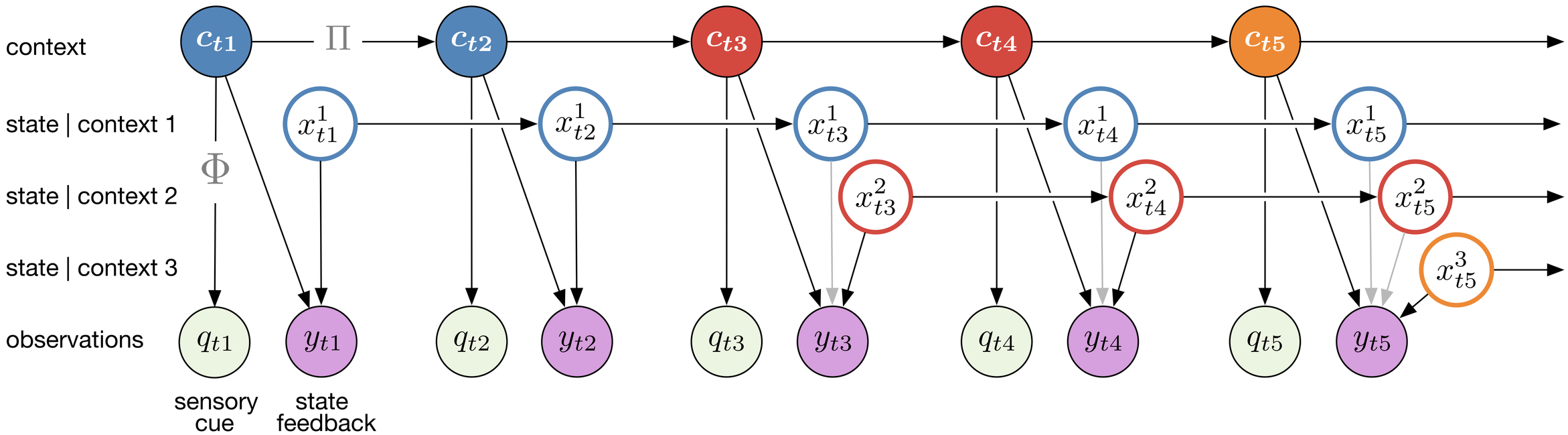


online (recursive) inference

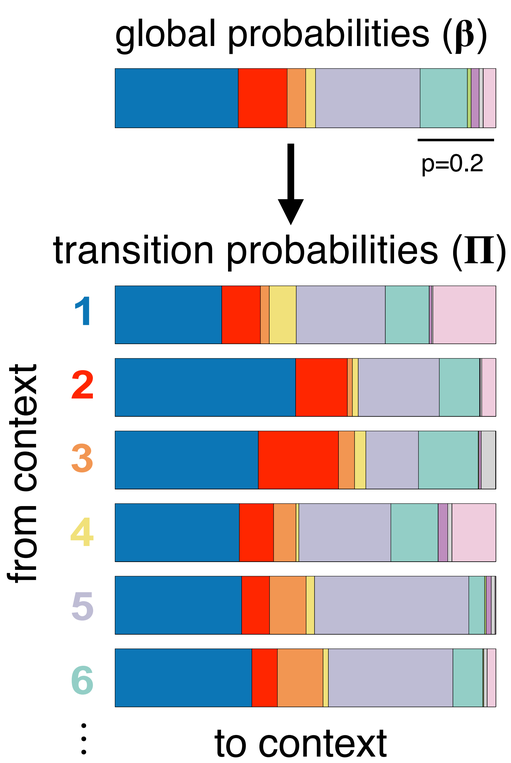
	variables	parameters
context	• current context probabilities	• number of contexts • context transition probabilities • cue emission probabilities
state	• current state (each context)	• state transition dynamics (each context)

(Heald et al, Nature, 2021)

The COntextual INference (COIN) model



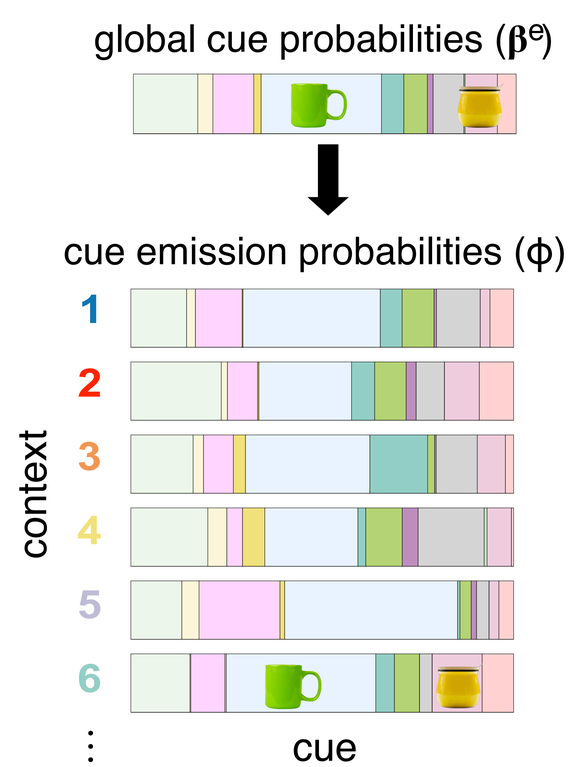
context transitions



sticky hierarchical Dirichlet process prior
(3 hyperparameters)

- non-parametric
- hierarchical

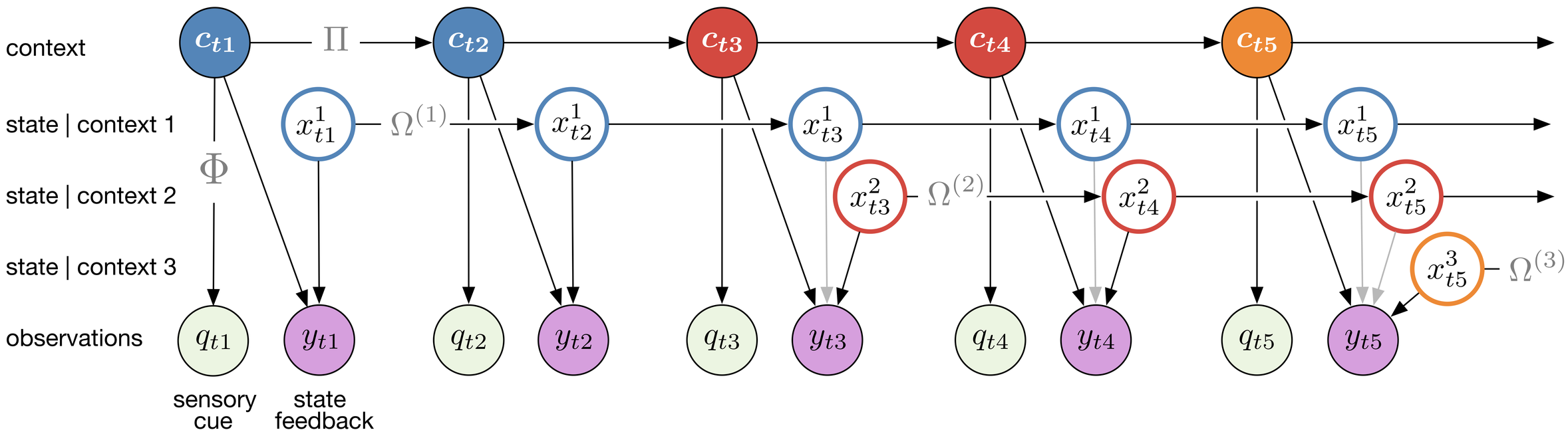
cue emissions



hierarchical Dirichlet process prior
(2 hyperparameters)

(Heald et al, Nature, 2021)

The COntextual INference (COIN) model



state transitions

$$x_t^{(j)} = a^{(j)} x_{t-1}^{(j)} + d^{(j)} + w_t$$

context j

retention state drift noise

Gaussian priors

$$\Omega^{(j)} = \left\{ a^{(j)}, d^{(j)} \right\}$$

$$a^{(j)} \sim \mathcal{TN}(\mu_a, \sigma_a^2) \quad d^{(j)} \sim \mathcal{N}(0, \sigma_{\mathrm{d}}^2)$$

state feedback observations

$$y_t = x_t^{(c_t)} + v_t$$

active context

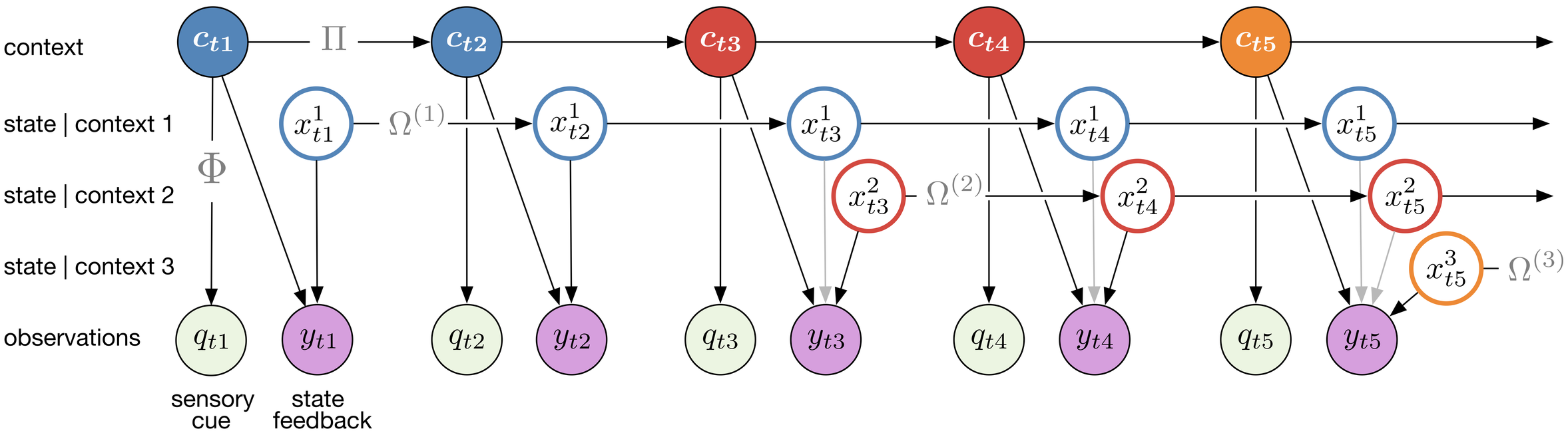
state feedback noise

number of free parameters

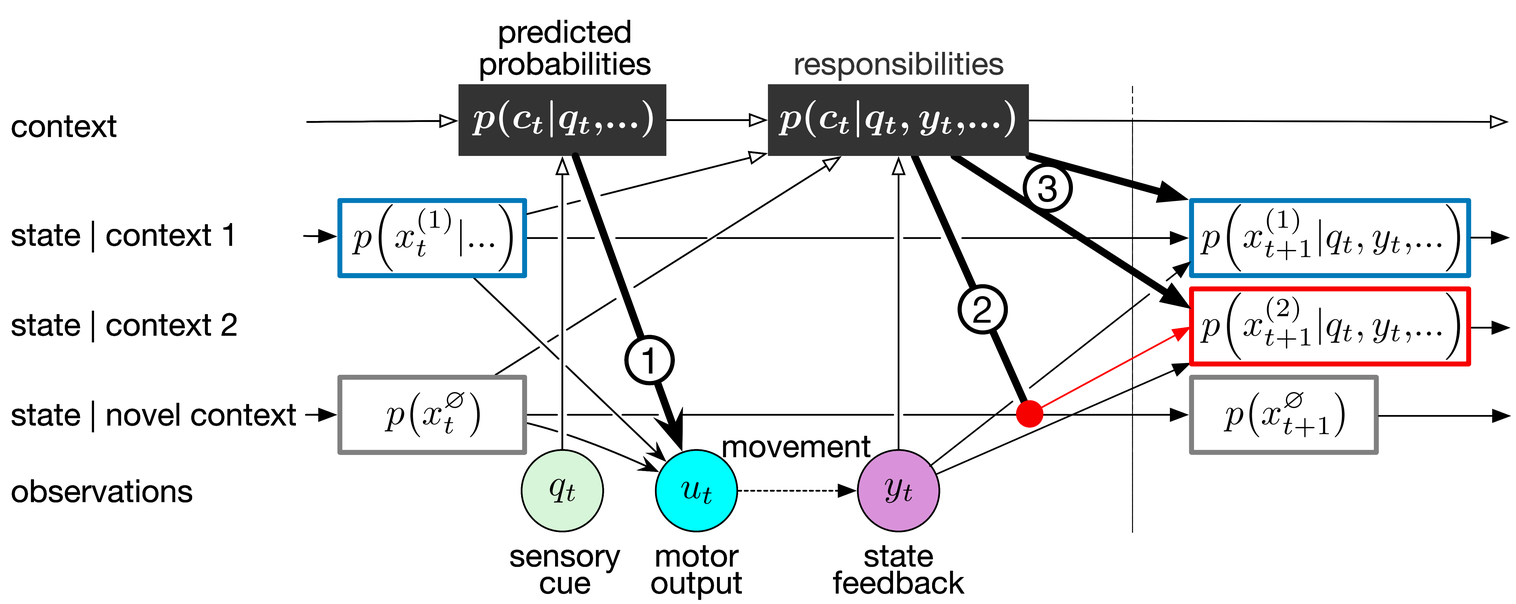
- without cues: 7
- with cues: 8

(Heald et al, Nature, 2021)

Inference

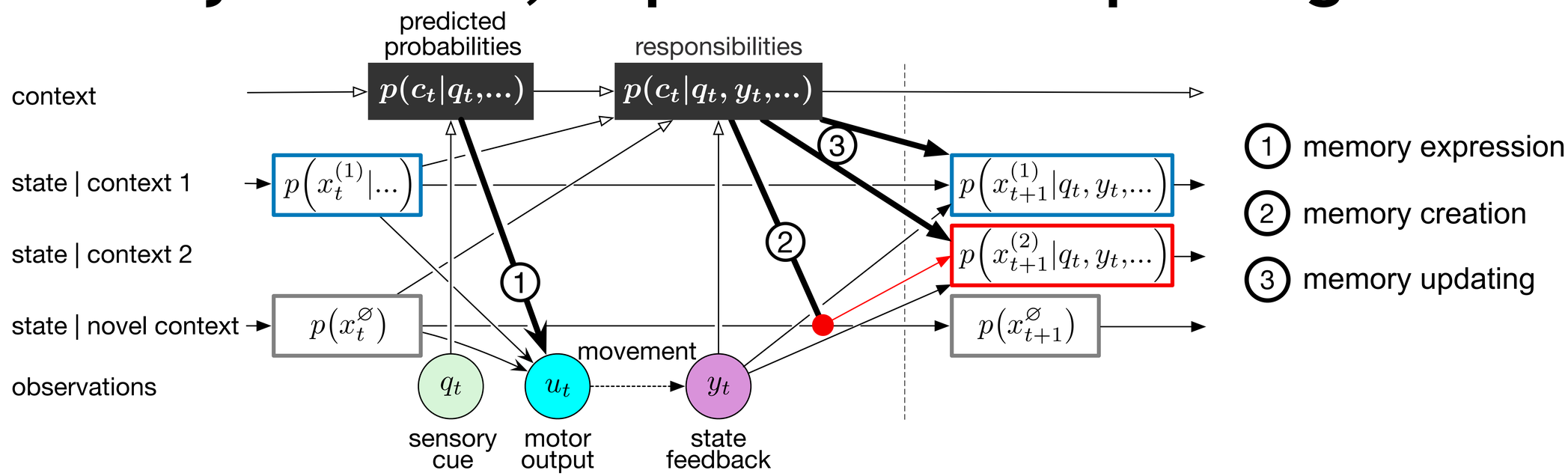


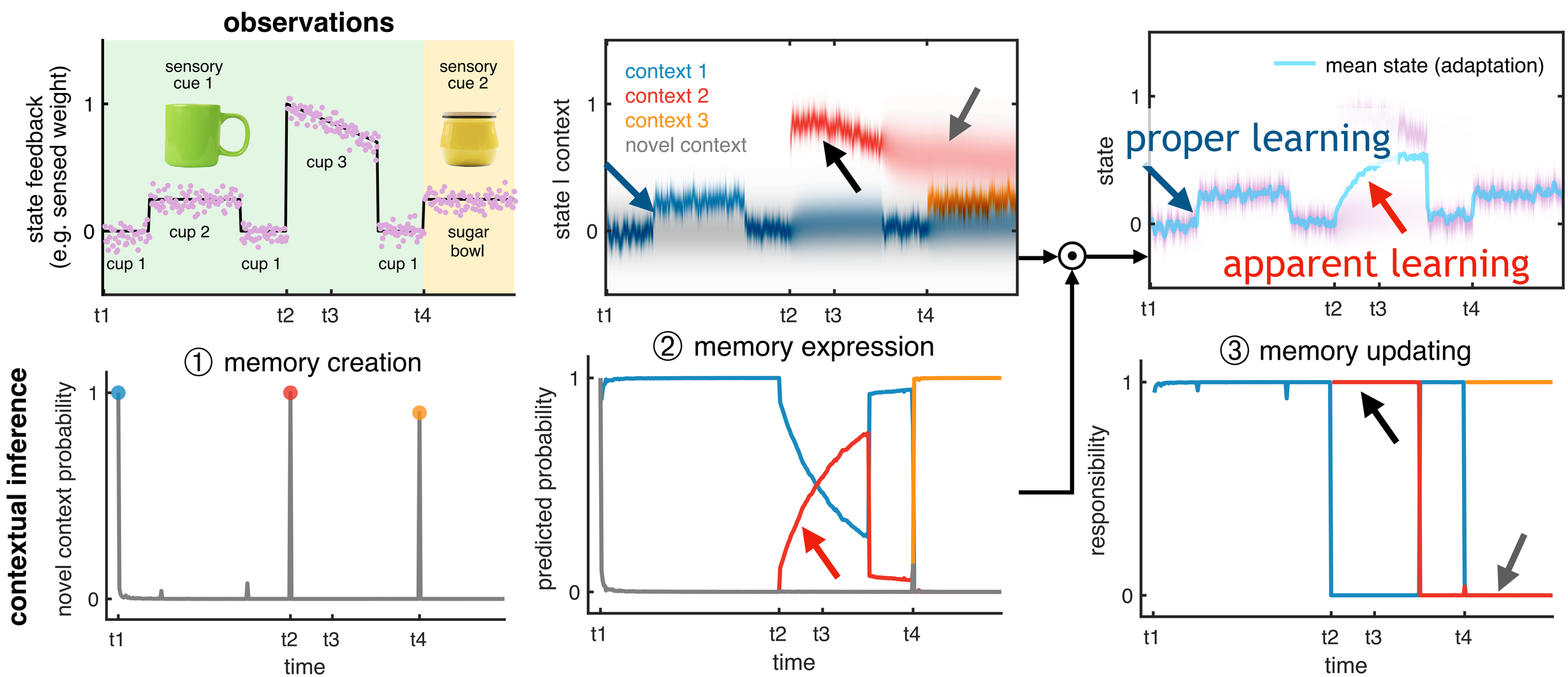
online recursive inference



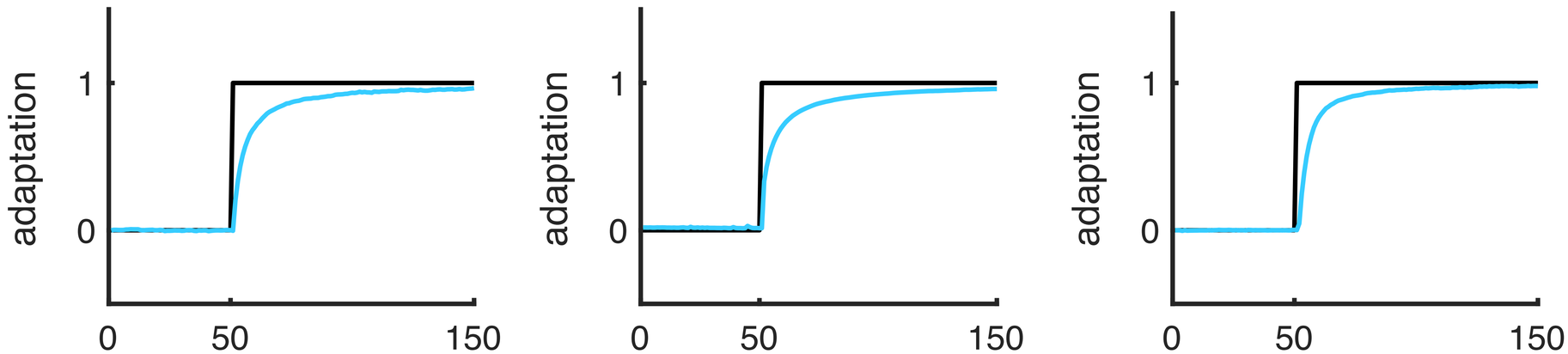
Inference performed using particle learning (Carvalho et al., *Stat. Sci.*, 2010)

Memory creation, expression and updating

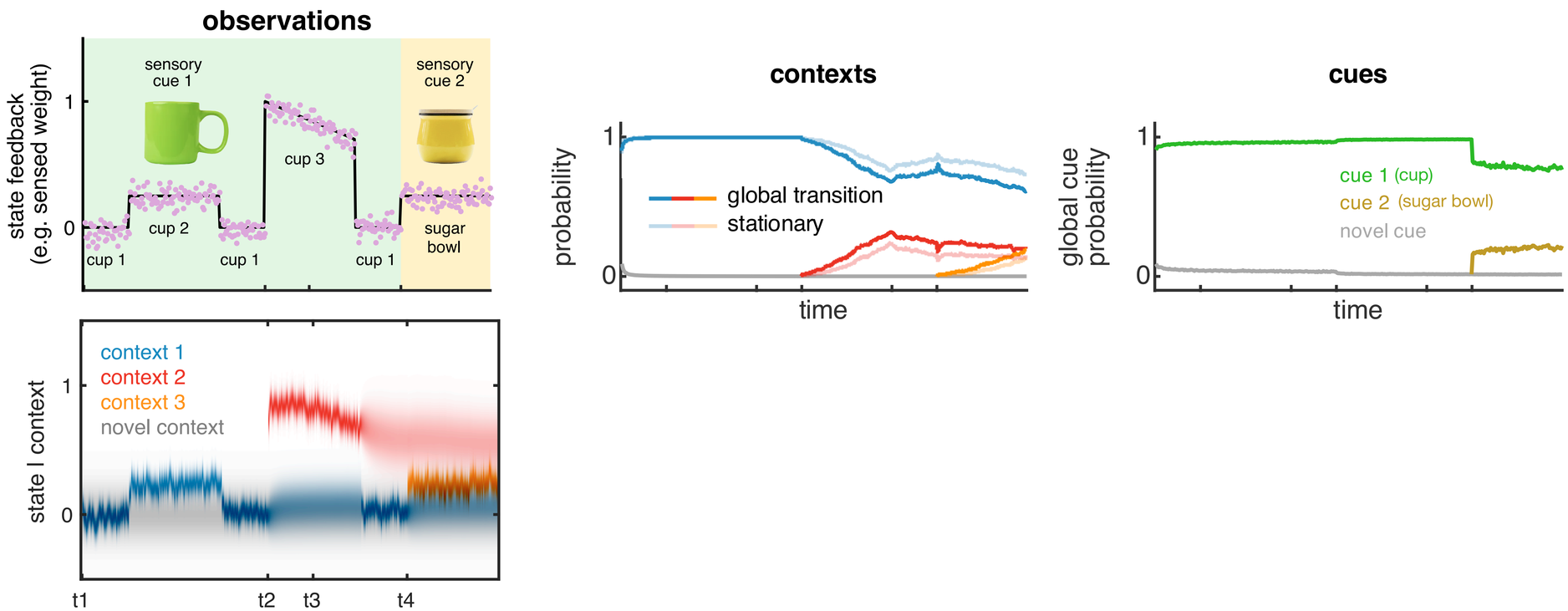




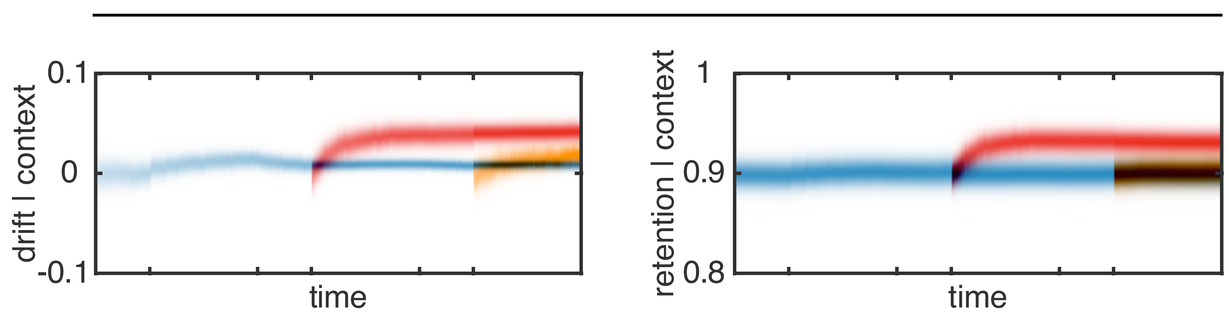
Which learning curve is proper learning?



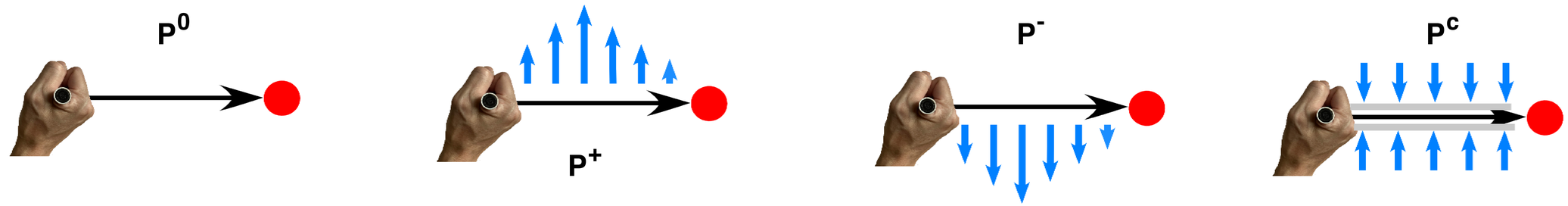
Parameter learning in the COIN model

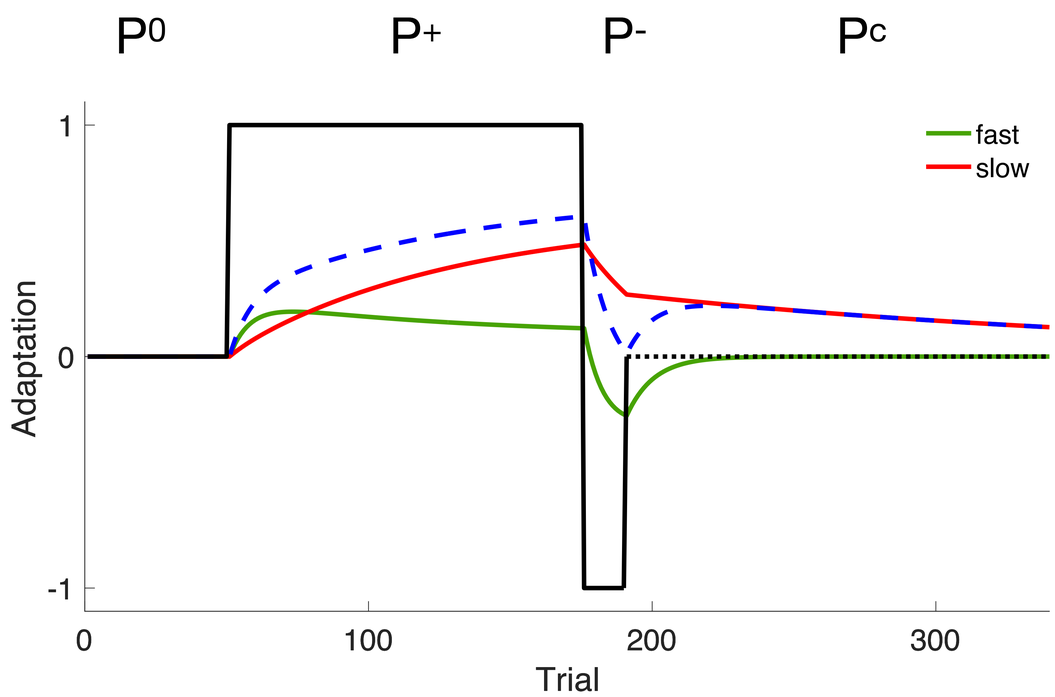


hierarchy supports generalisation across contexts via the inferred global probabilities



Spontaneous recovery (Smith et al. Plos Biol, 2006)





Dual-rate model

$$\theta^{\mathrm{S}}_{t+1} = \beta^{\mathrm{S}}\,\theta^{\mathrm{S}}_{t} + \alpha^{\mathrm{S}}\,(x - \hat{x})$$

$$\theta^{\mathrm{F}}_{t+1} = \beta^{\mathrm{F}}\,\theta^{\mathrm{F}}_{t} + \alpha^{\mathrm{F}}\,(x - \hat{x})$$

$$\hat{x} = \theta^{\mathrm{S}}_{t} + \theta^{\mathrm{F}}_{t}$$

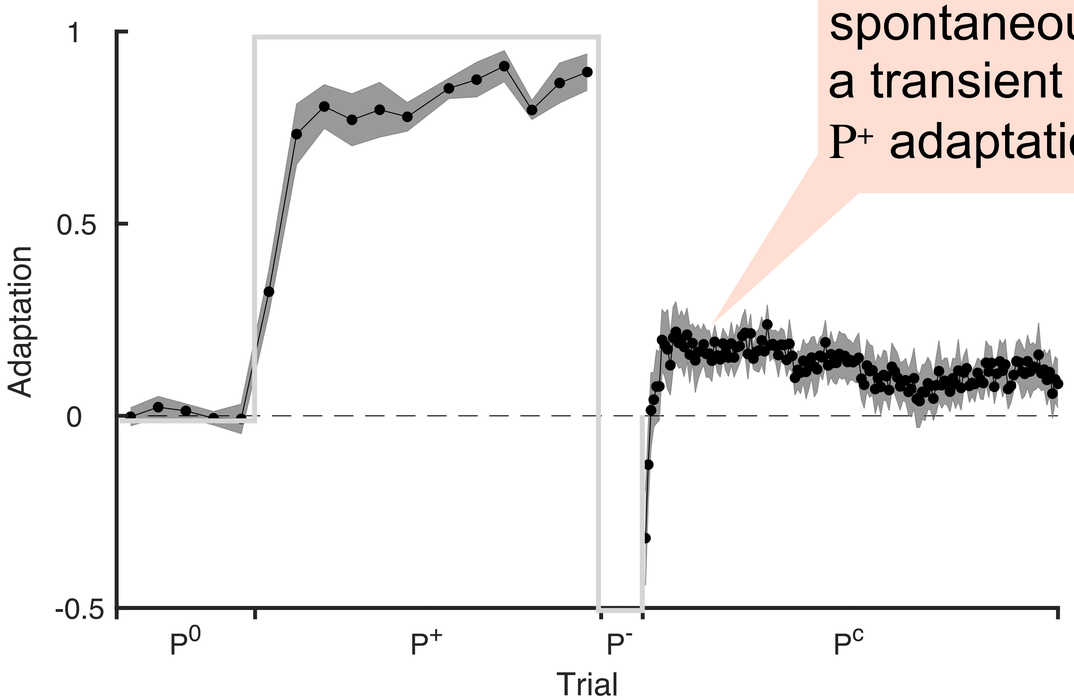
slow process

fast process

output

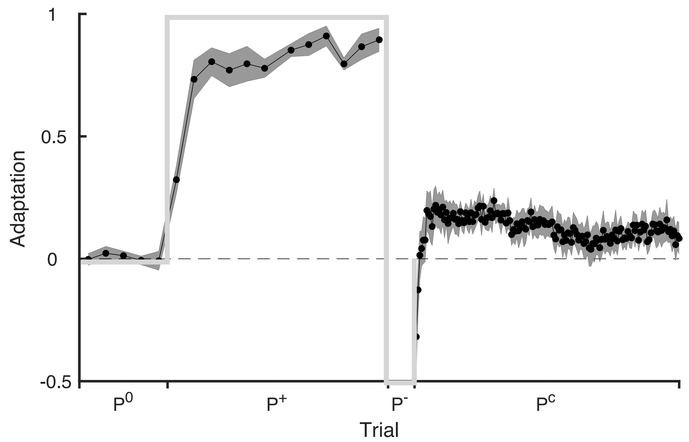
$\alpha^{\mathrm{S}} < \alpha^{\mathrm{F}}$

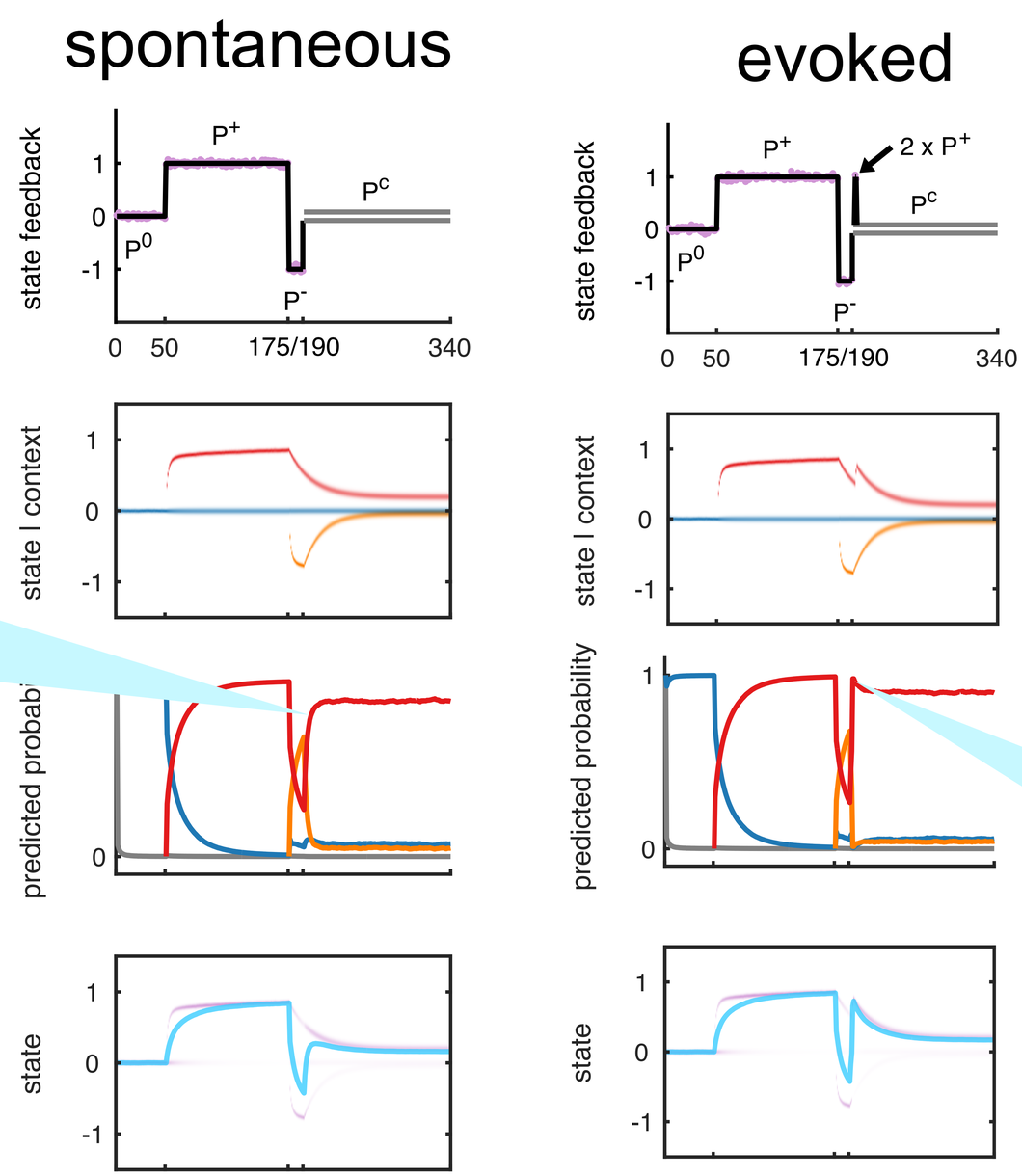
$\beta^{\mathrm{S}} > \beta^{\mathrm{F}}$



spontaneous recovery:
a transient re-expression of
P^{+} adaptation

COIN model: Spontaneous and evoked recovery





COIN model
changes in motor output can occur without changes in the internal state → apparent learning

dual-rate model
changes in motor output can *only* occur with changes in the internal state → proper learning

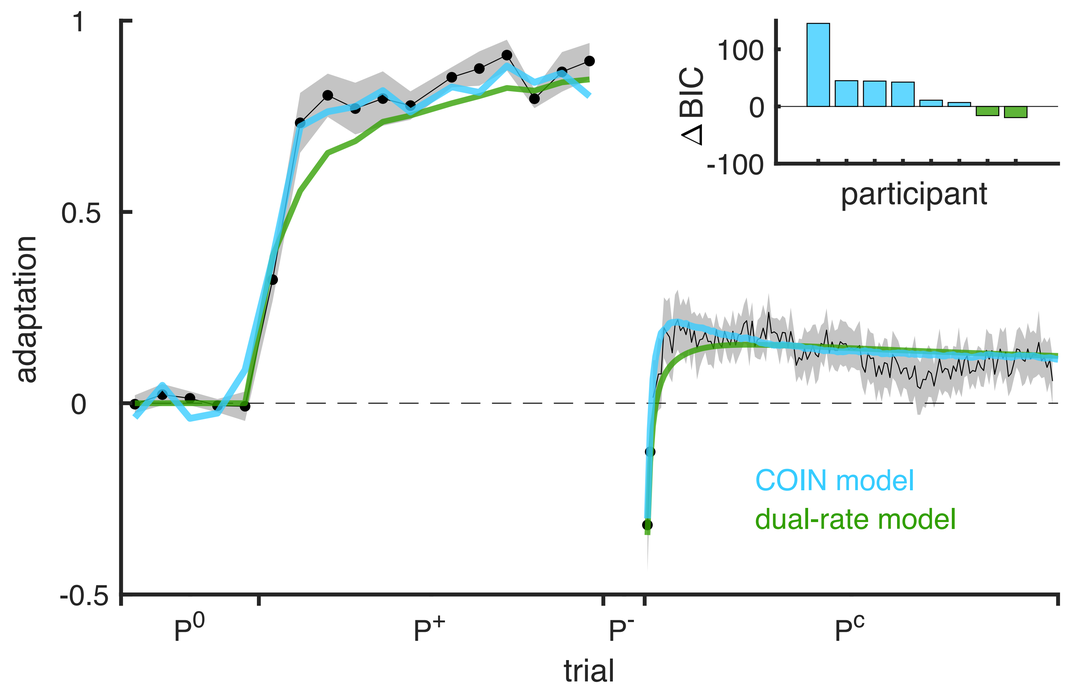
COIN model
rapid changes from re-expression of a memory

Spontaneous recovery (n=8)

COntextual INference model (BioRxiv tiny.cc/co-in)

COIN: Bayesian model: with 7 parameters

Dual rate model: with 5 parameters



Δ group-level BIC = 302.6

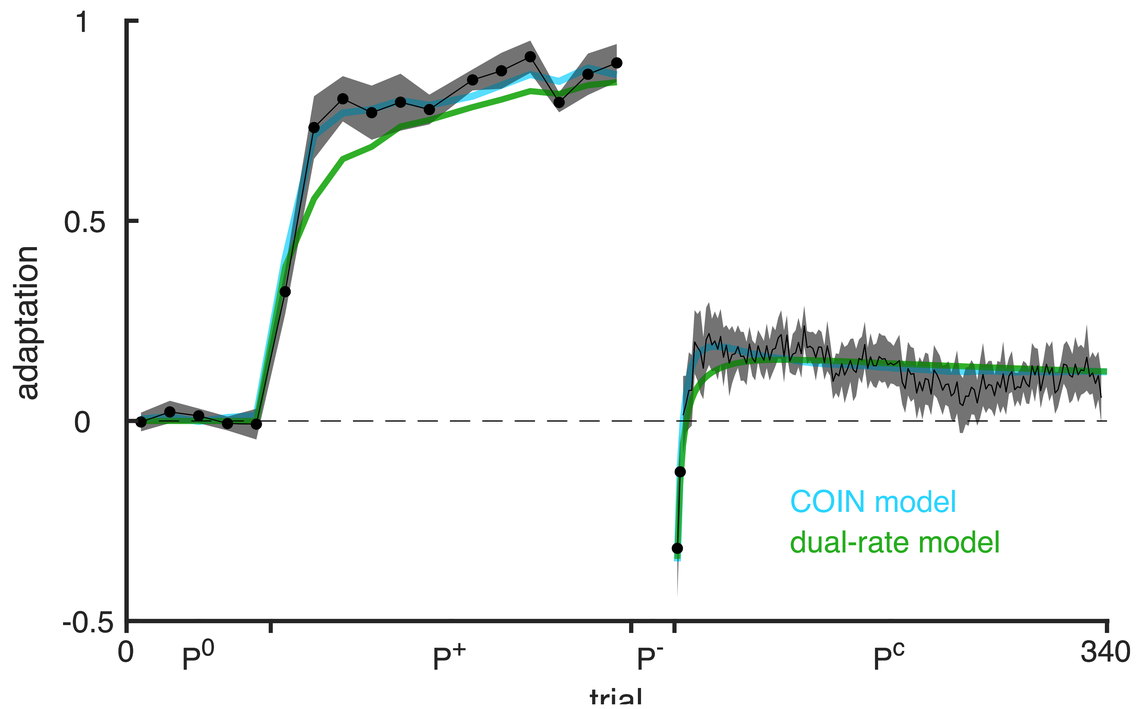
$$\mathrm{BIC} = k\ln(n) - 2\ln(\widehat{L})$$

DOF datapoints likelihood

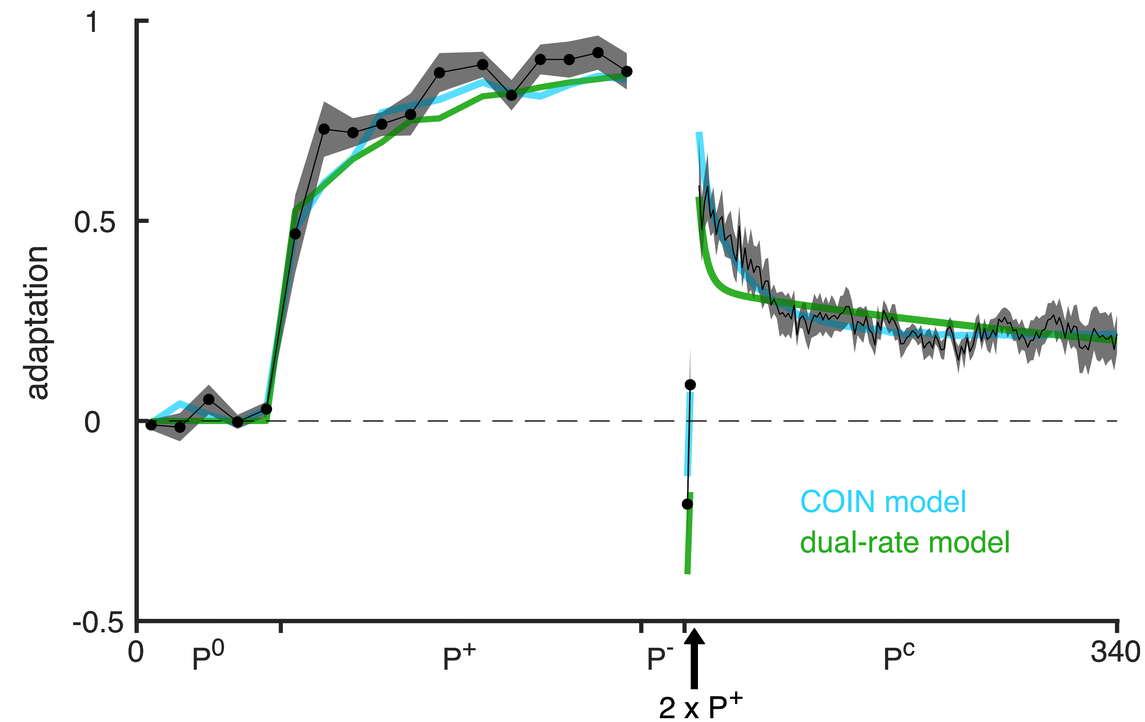
8. Why should you not yet be convinced that COIN is the better model?

Spontaneous and evoked recovery

spontaneous (n = 8)



evoked (n = 8)



$$\mathrm{BIC} = k\ln(n) - 2\ln(\widehat{L})$$

DOF datapoints likelihood

Δ group-level BIC = 302.6

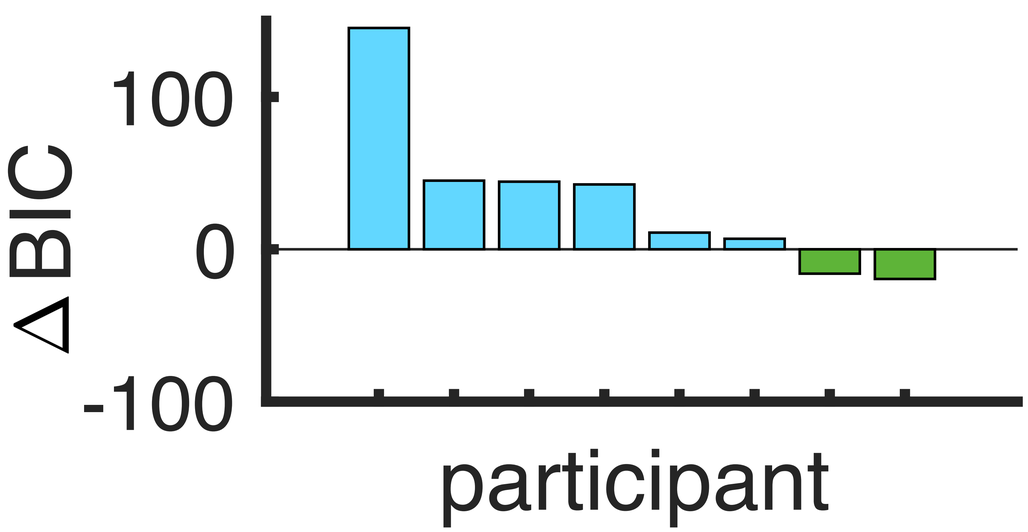
Δ group-level BIC = 394.1

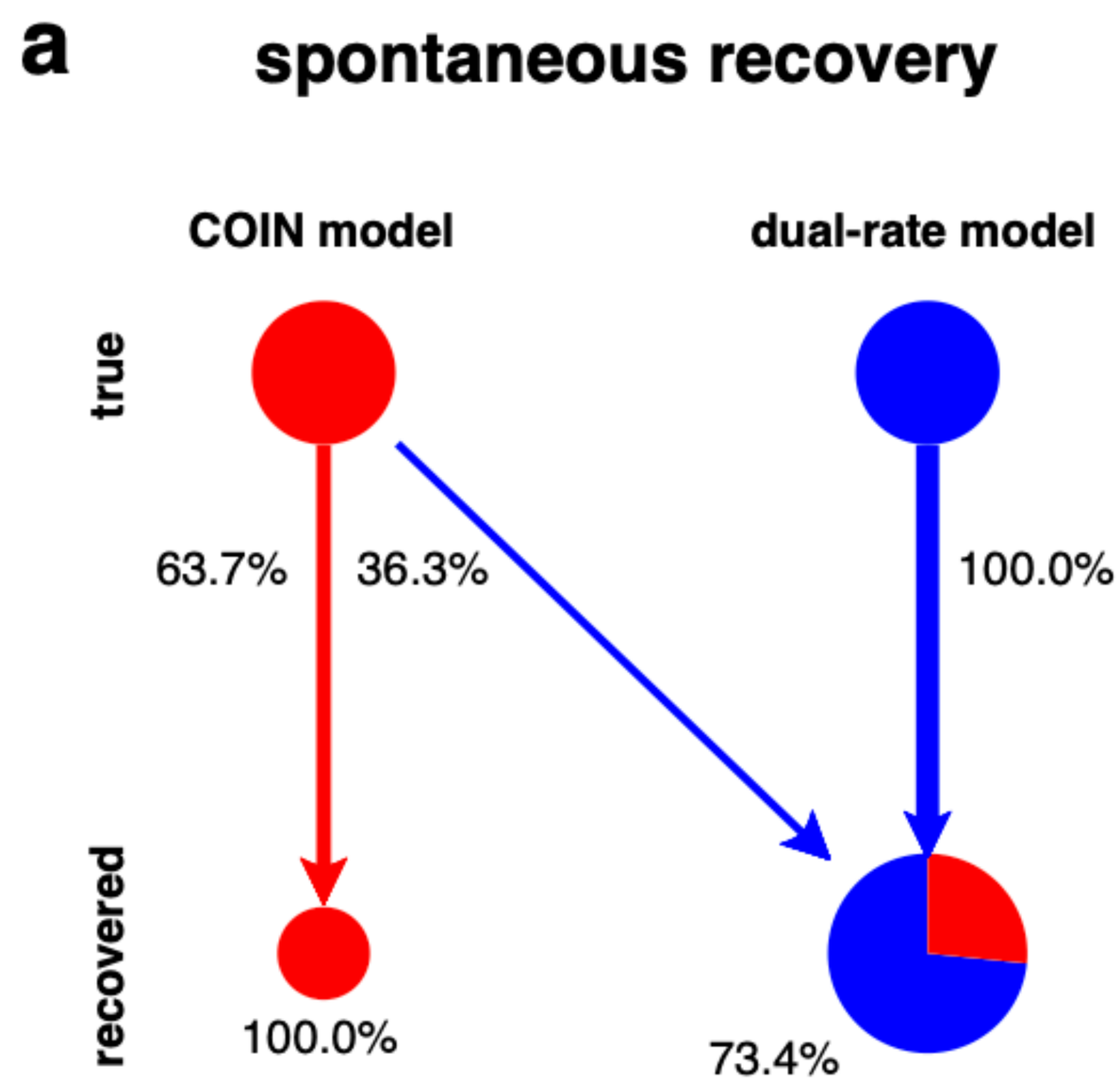
context estimation controls memory creation and expression in spontaneous and evoked recovery

Why should you not yet be convinced that COIN is the better model?

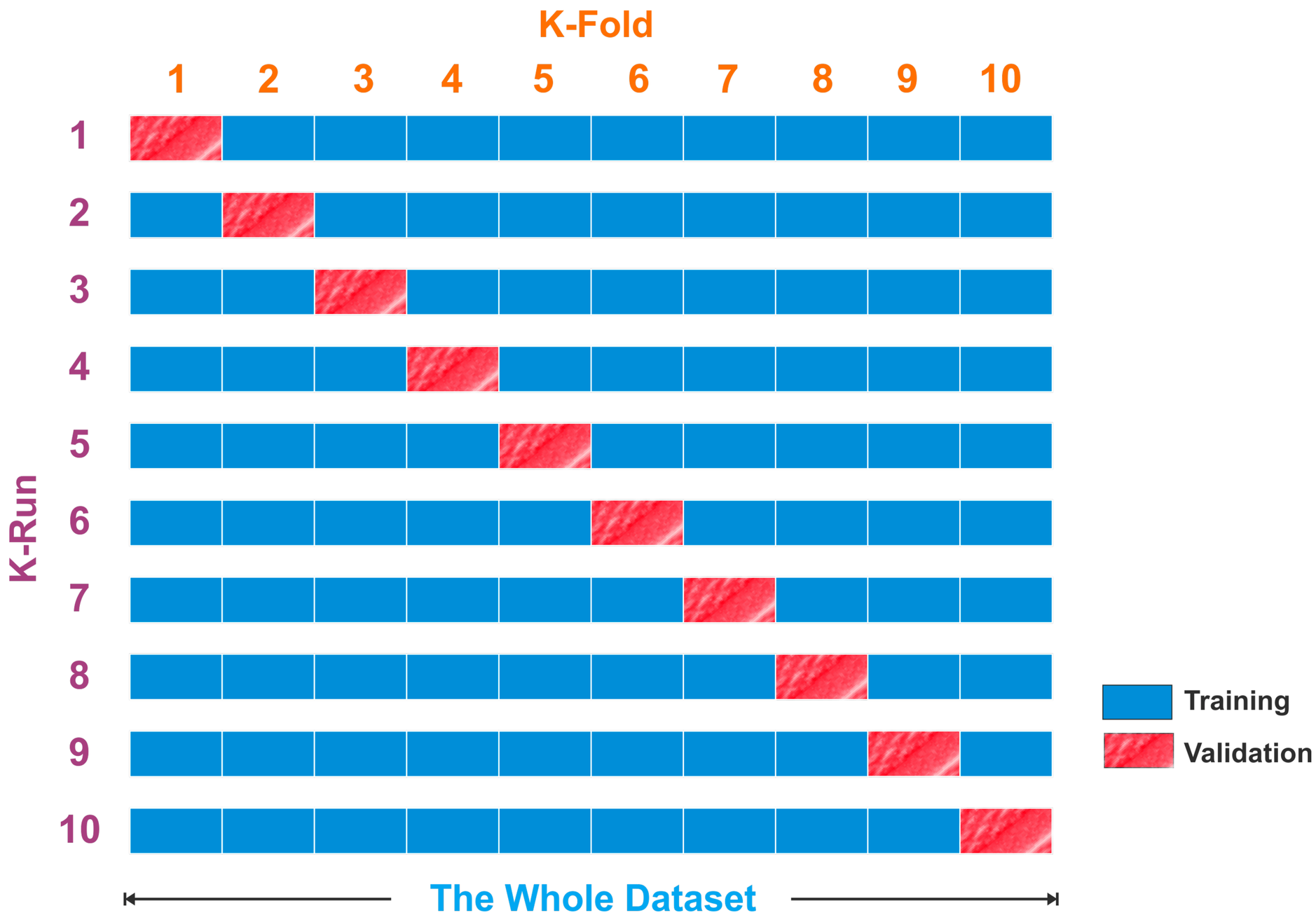
(Heald et al, Nature, 2021)

1. Model class recovery



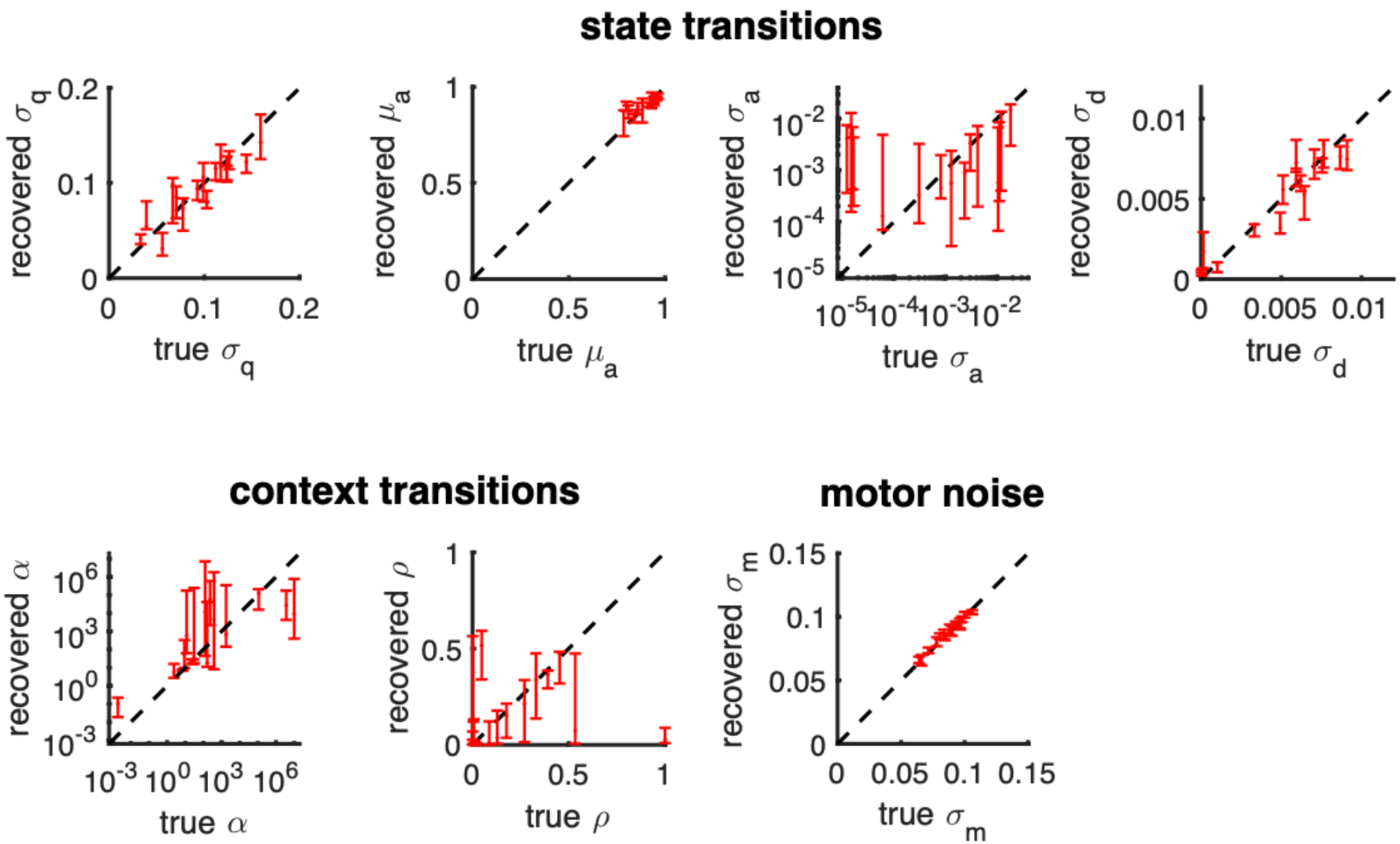


2. cross-validated log likelihood

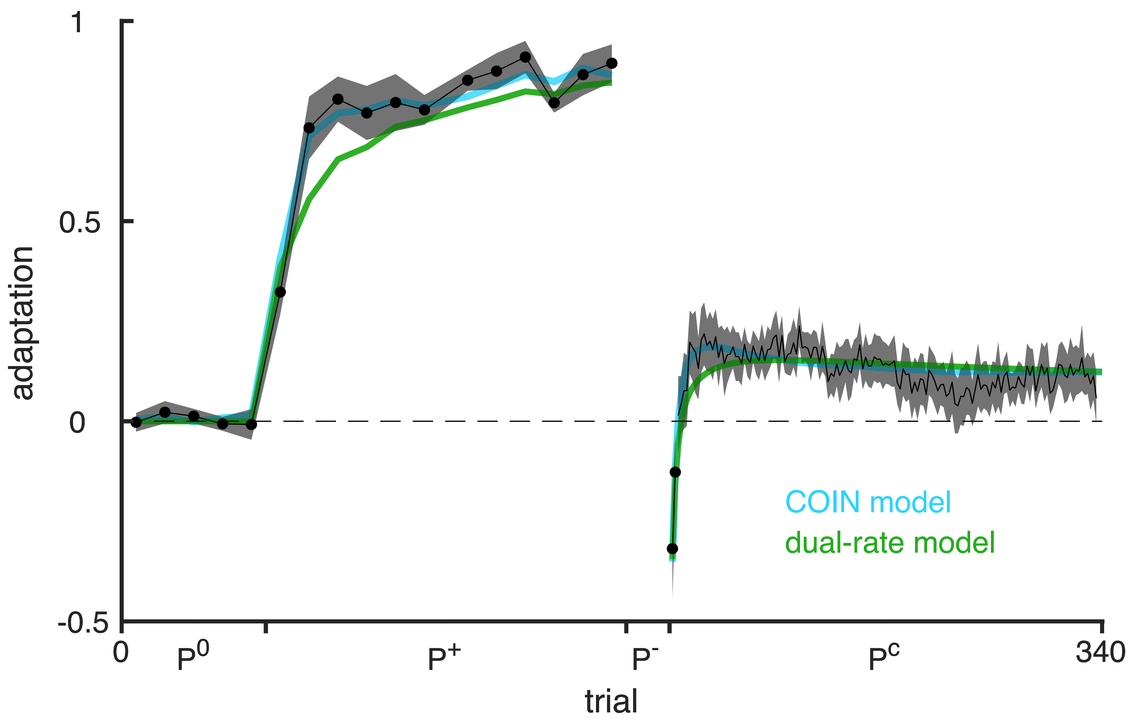


3. Model fitting and parameter recovery: COIN model

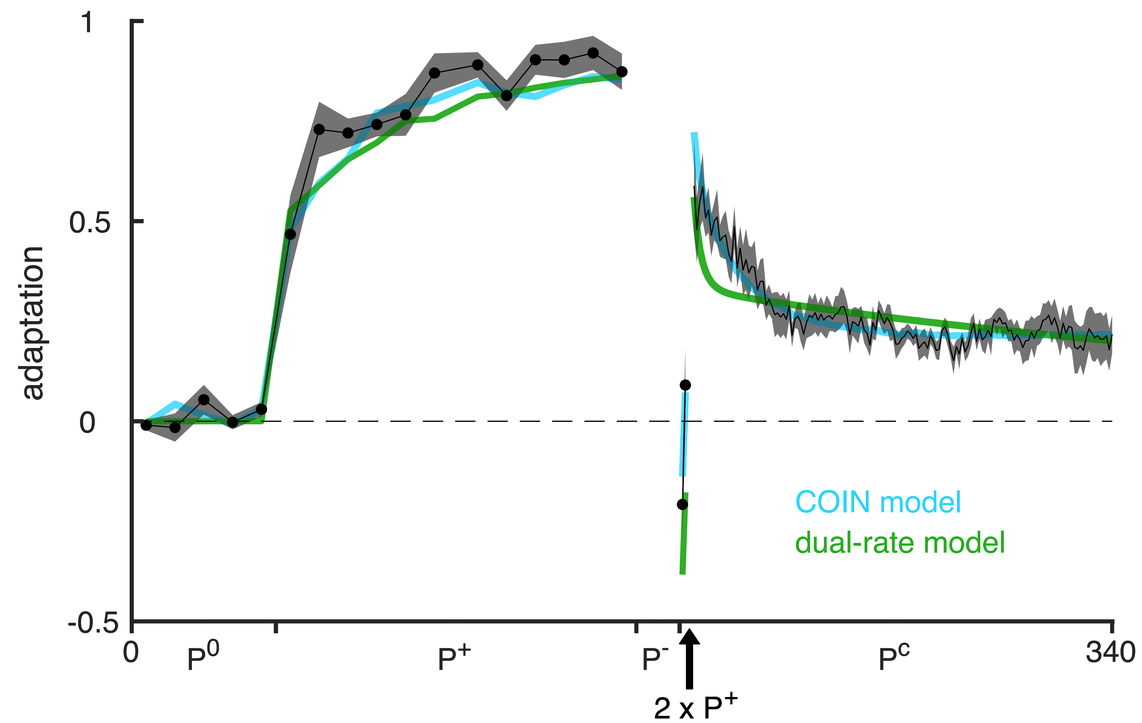
If claims are made about parameters are they recoverable from synthetic data?



Spontaneous and evoked recovery



Δ group-level BIC = 302.6



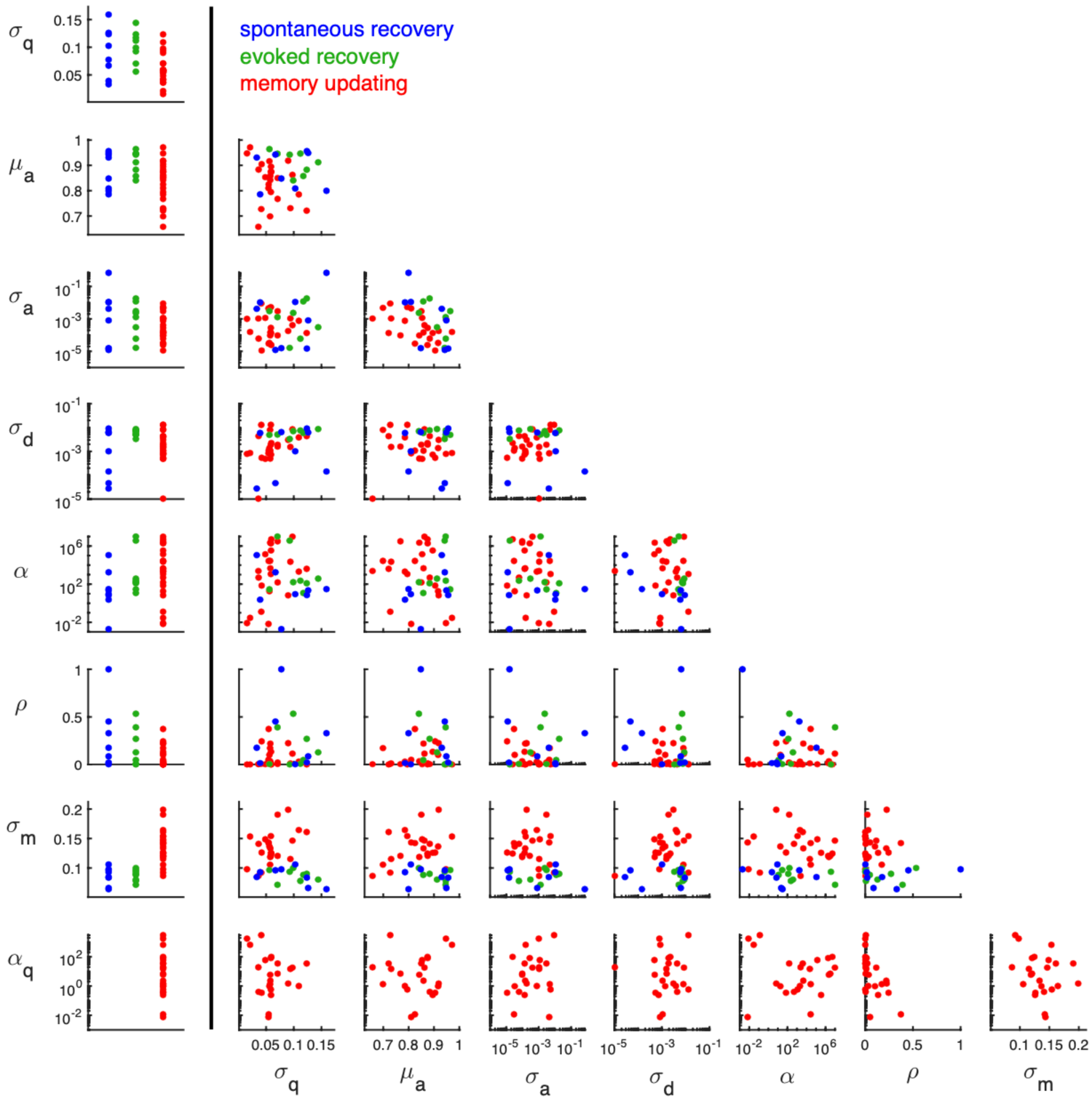
Δ group-level BIC = 394.1

context estimation controls memory creation and expression in spontaneous and evoked recovery

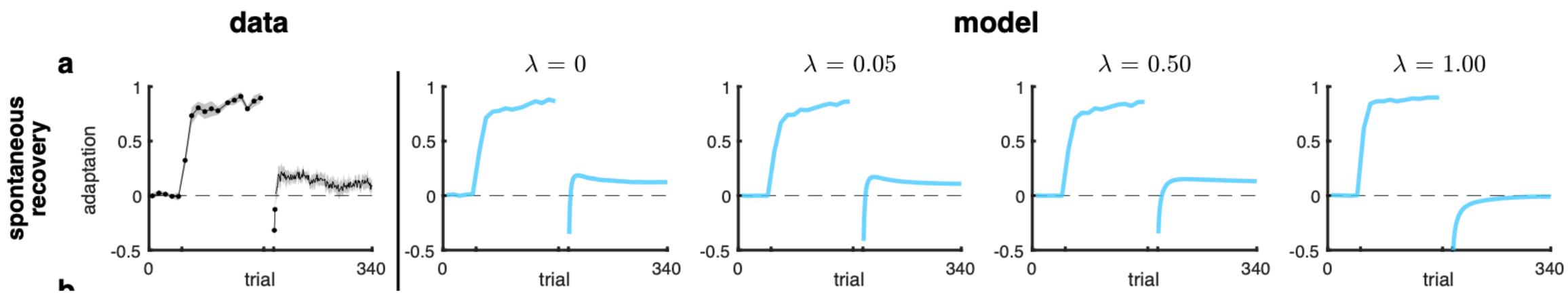
We can fit two datasets well.
What more might you need to be convinced that COIN is the better model?

(Heald et al, Nature, 2021)

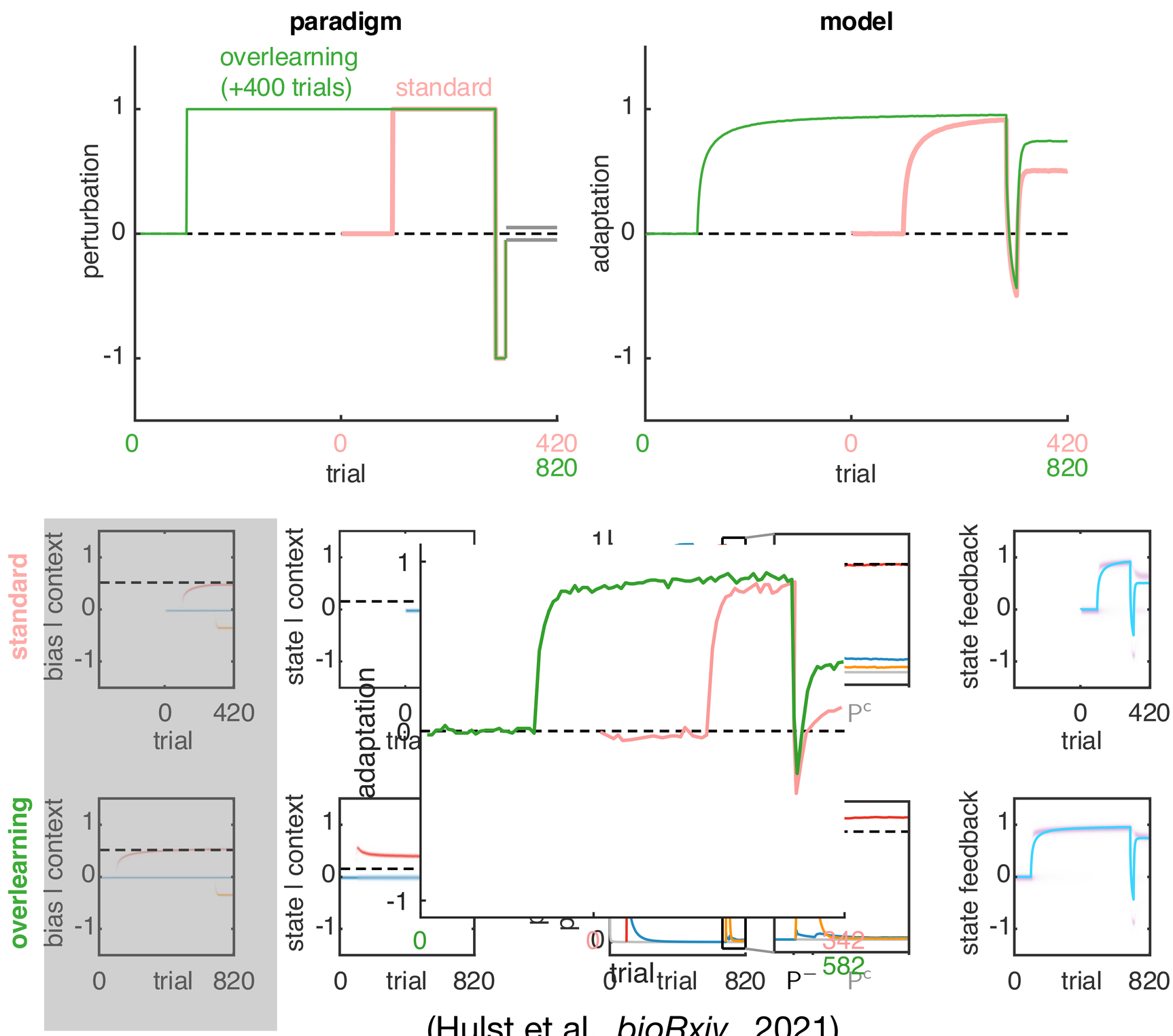
5. Parameters similar across paradigms



6. Robustness analysis



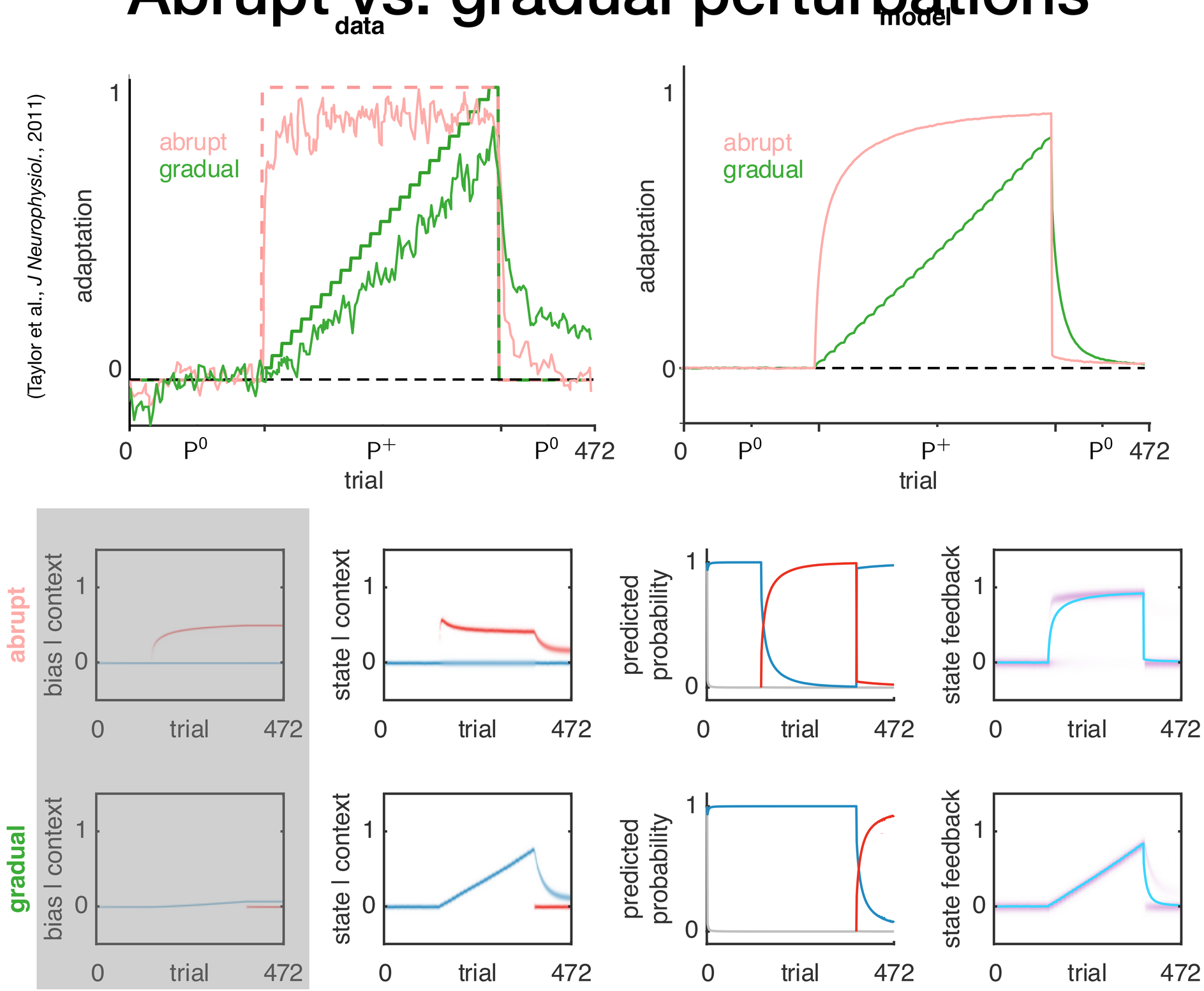
Overlearning potentiates spontaneous recovery



(Hulst et al., *bioRxiv.*, 2021)

the magnitude of spontaneous recovery is sensitive to the frequency of contexts in the environment

Abrupt vs. gradual perturbations



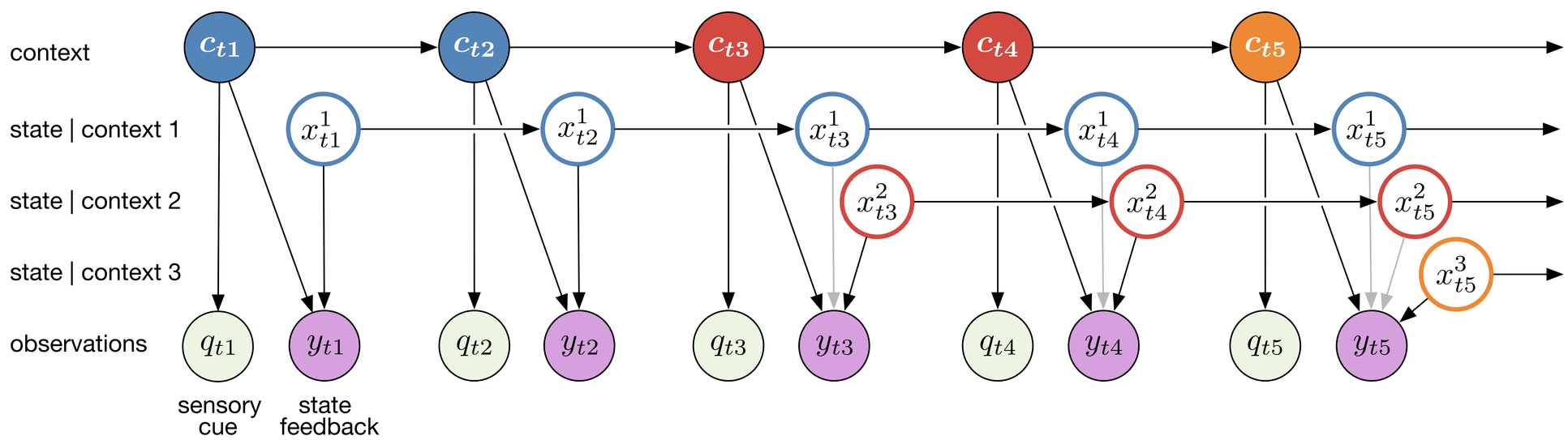
large errors are important for memory creation

Memory updating: Theory

state-space model (single context)

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + k_t e_t$$

state estimate Kalman gain error



COIN model (multiple contexts)

context *j*

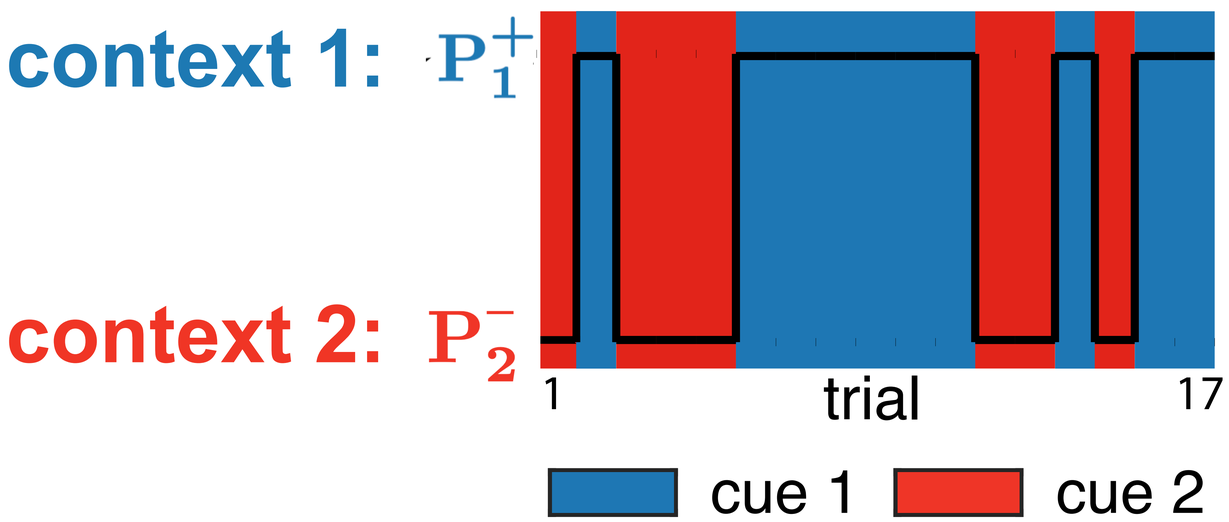
$$\hat{x}^{(j)}_{t|t} = \hat{x}^{(j)}_{t|t-1} + \gamma^{(j)}_t k^{(j)}_t e^{(j)}_t$$

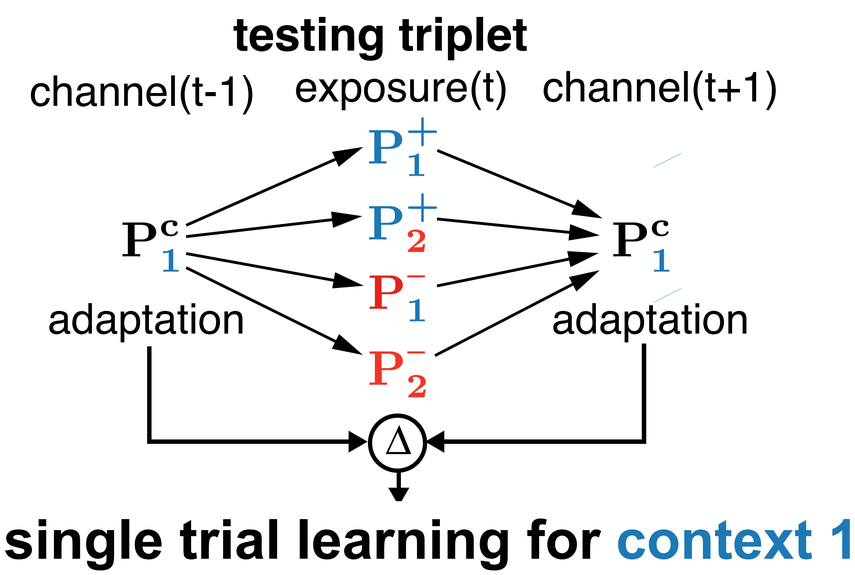
responsibility (context *j*)

each memory should be updated proportional to its responsibility

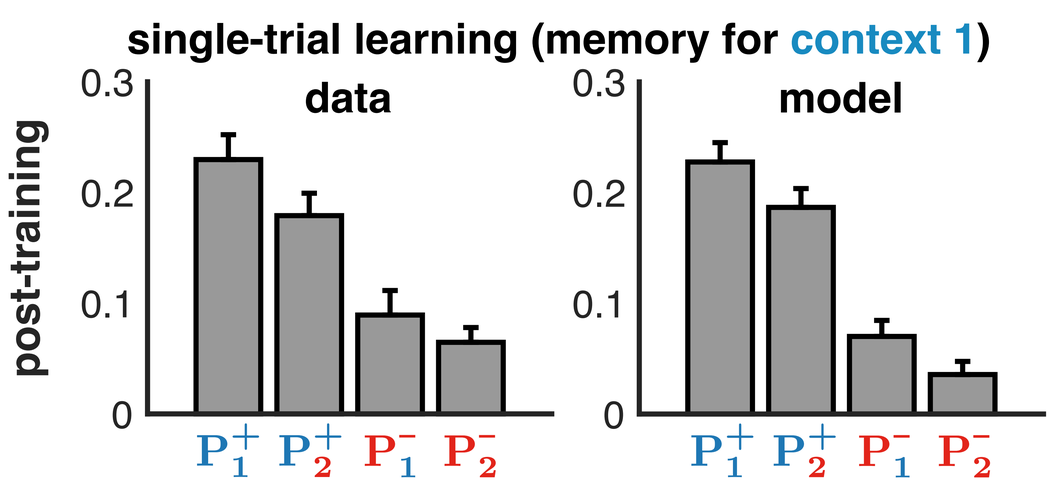
Memory updating (n=24)

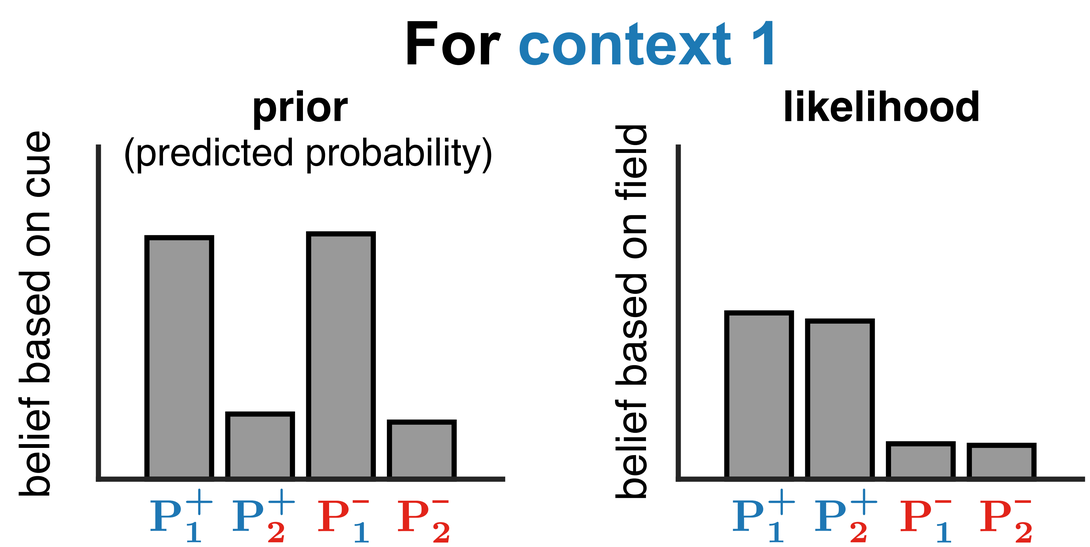
All memories should be updated proportional to their responsibility





single trial learning for context 1

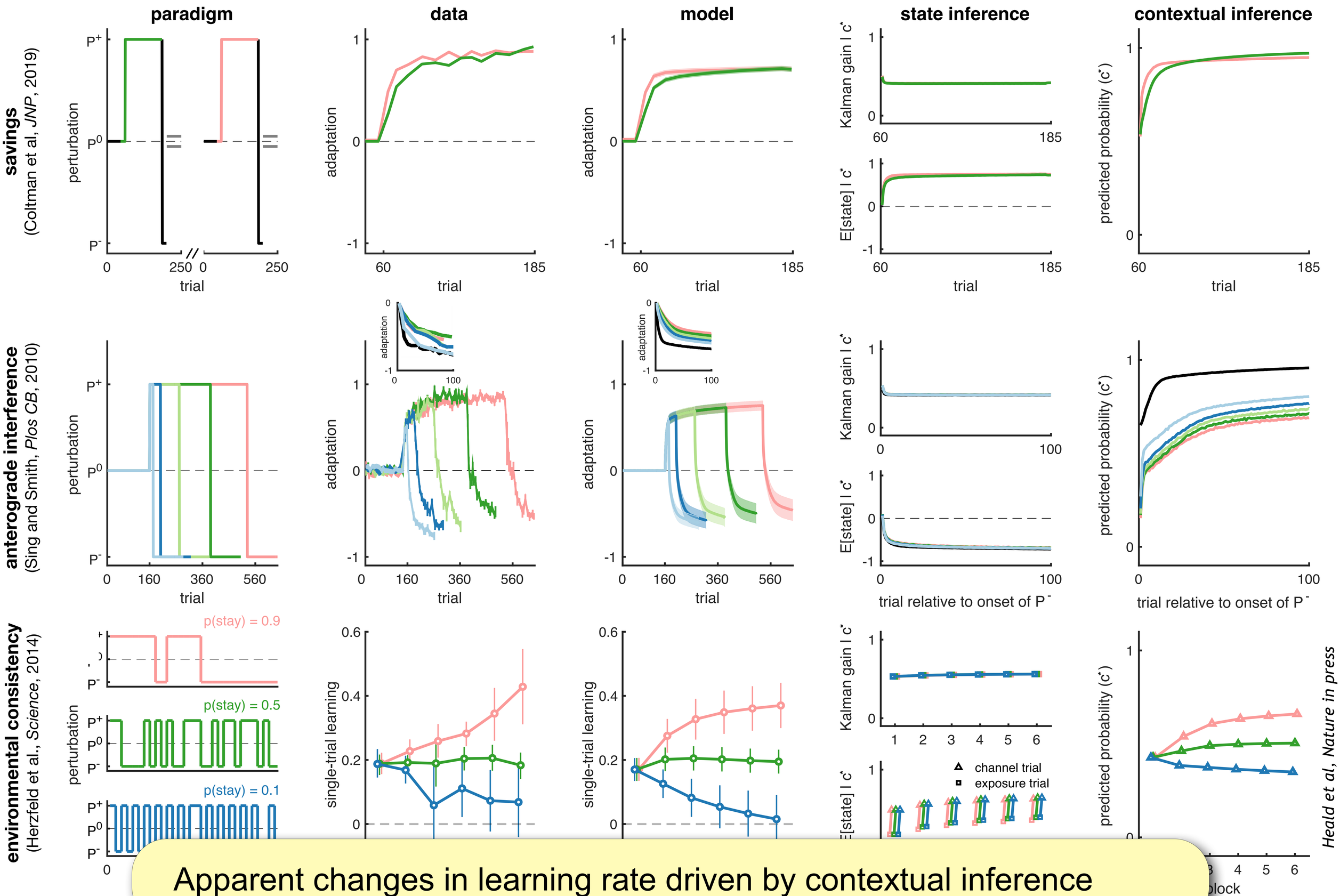




Memories updated in proportion to their responsibility

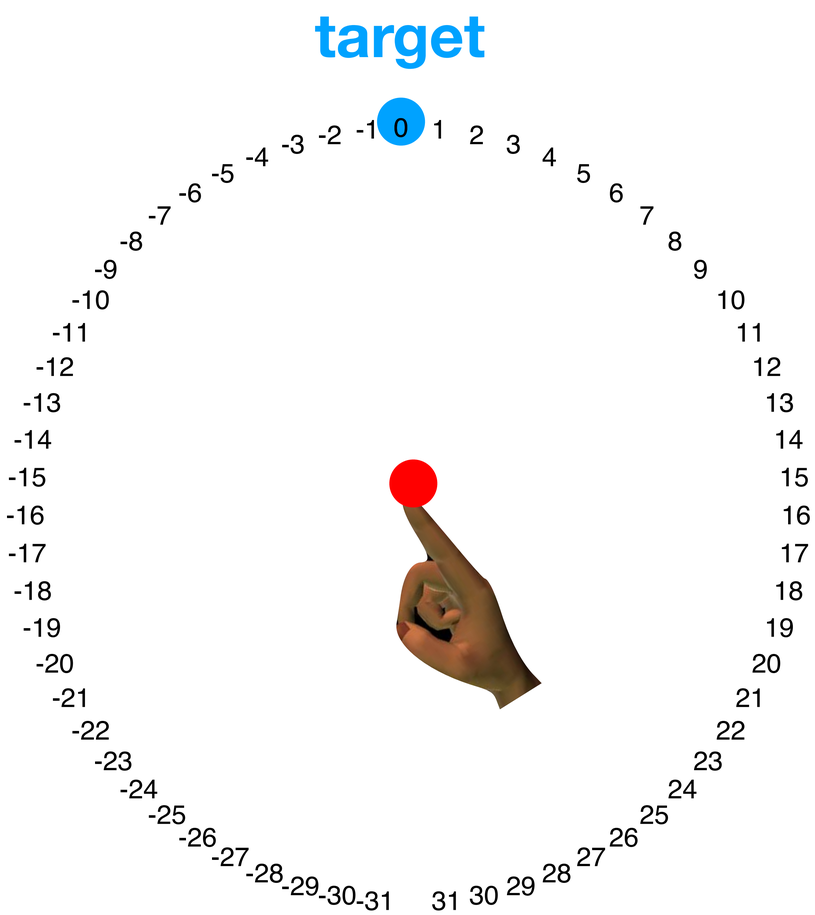
(Heald et al, Nature, 2021)

Classical paradigms as apparent learning



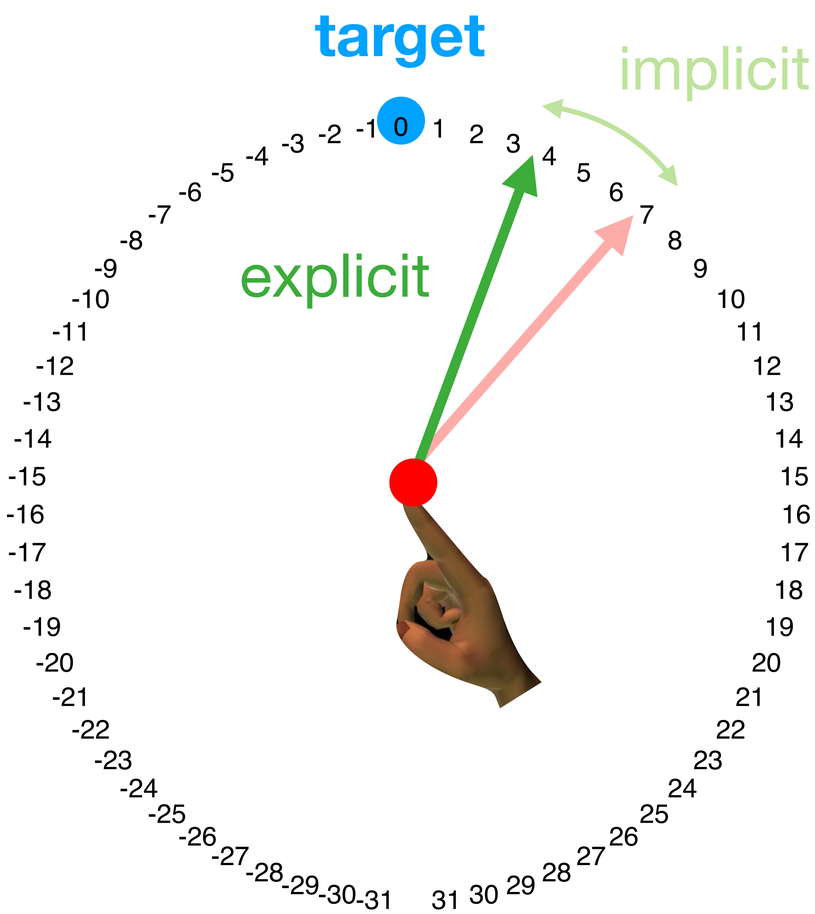
Apparent changes in learning rate driven by contextual inference

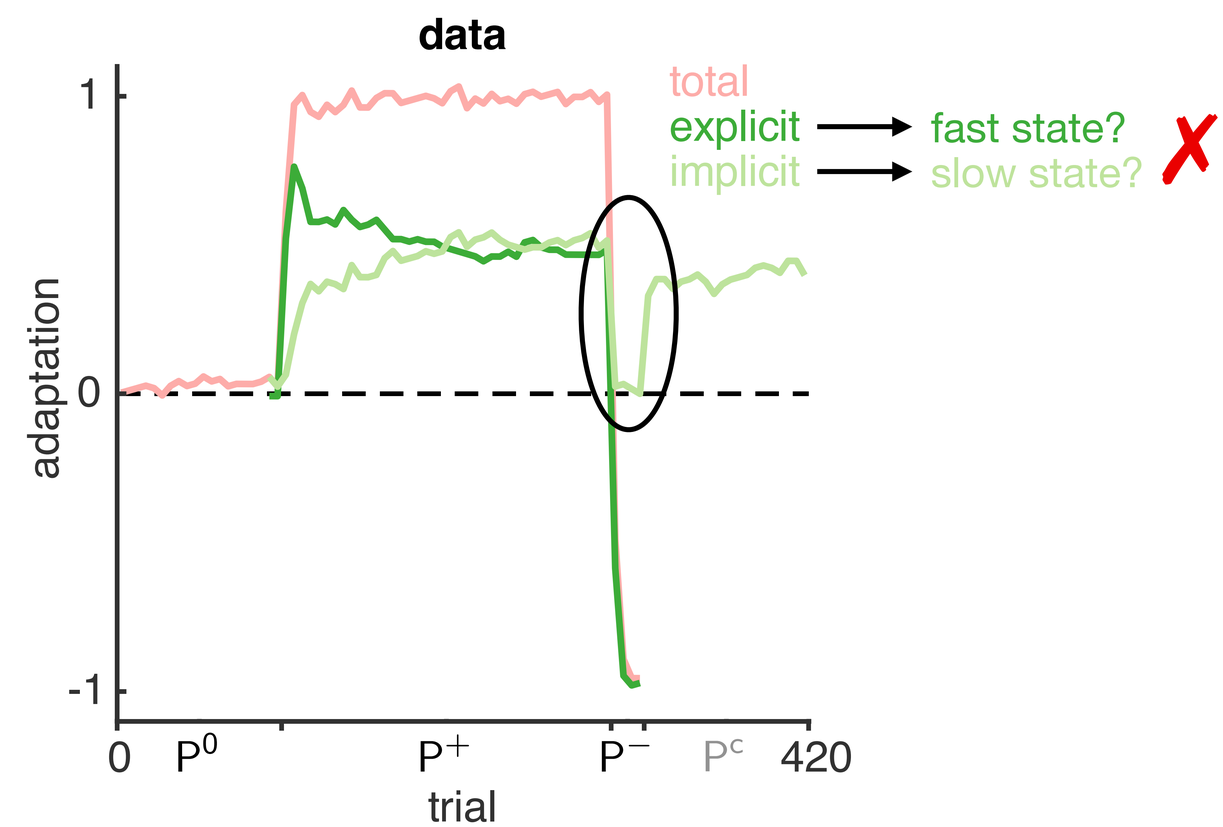
Explicit and implicit learning



(McDougle et al., *J Neurosci.*, 2015)

Explicit and implicit learning





(McDougle et al., *J Neurosci.*, 2015)

state feedback has a bias:

$$y_t = x_t^{(c_t)} + b^{(c_t)} + v_t$$

prior

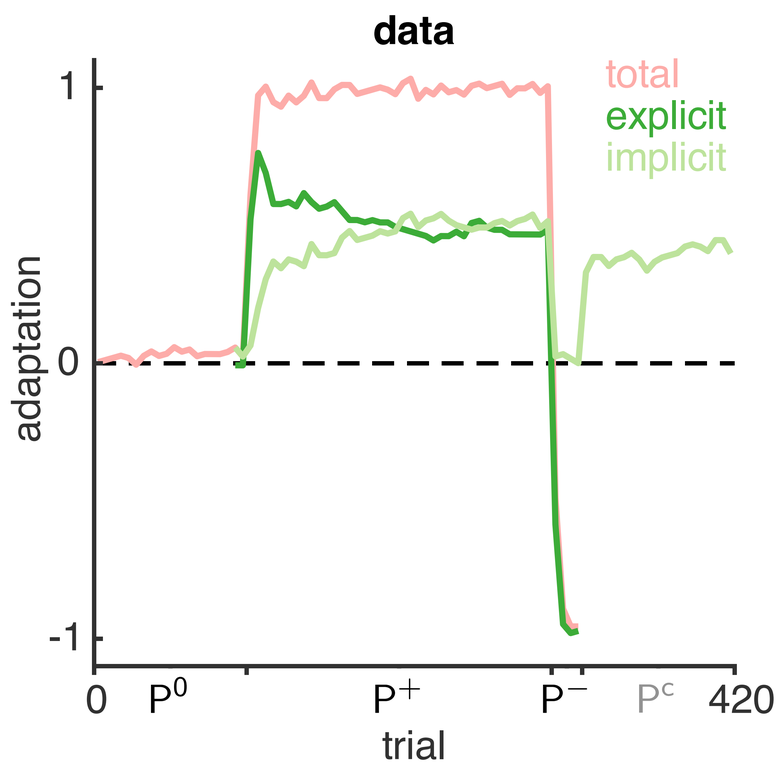
$$\mathcal{N}(0, \sigma_{\mathrm{b}}^2)$$

credit assignment problem: errors can be due to a misestimated state or sensory bias (miscalibration)

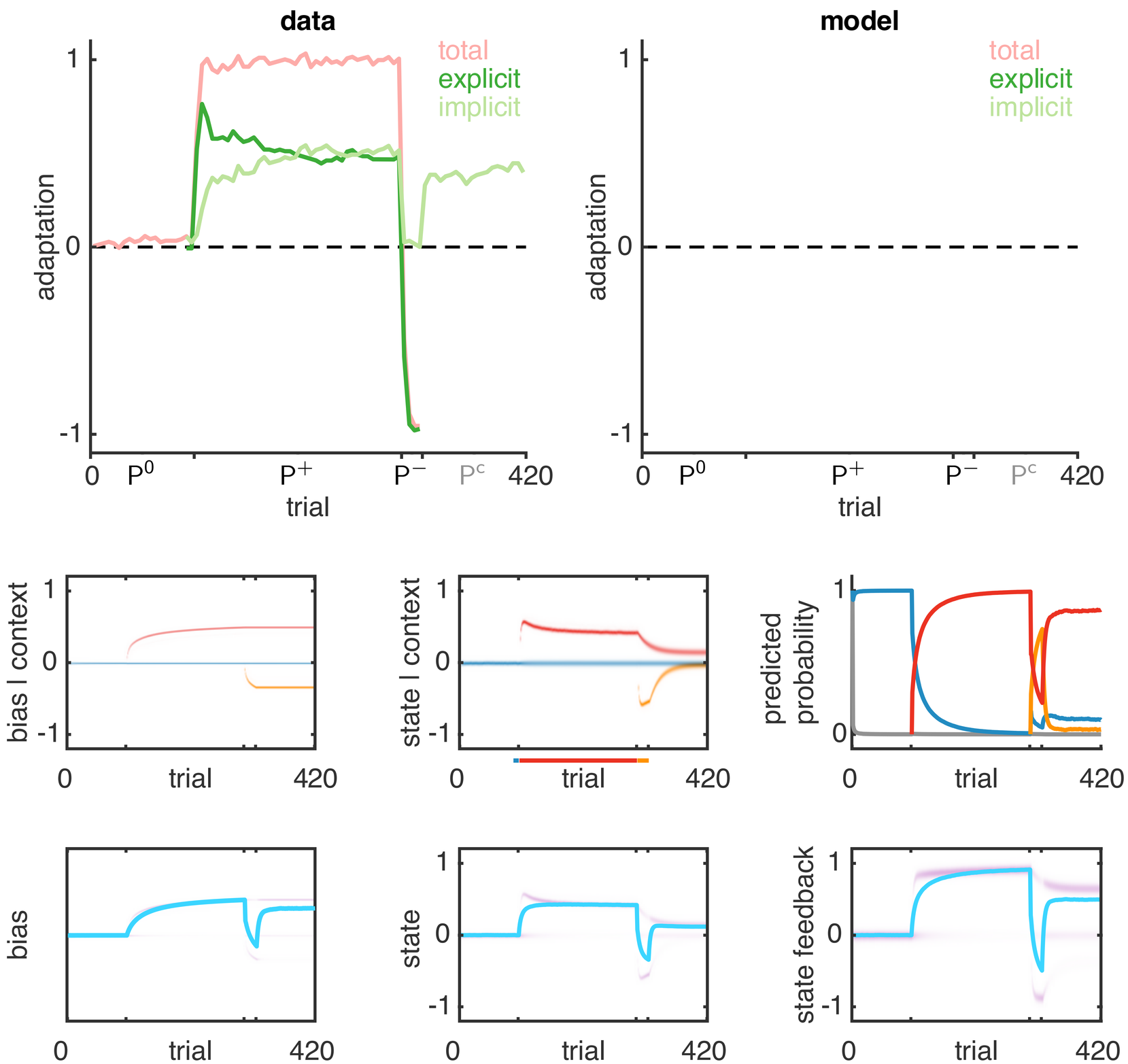
hypothesis

- implicit = sensory bias
- explicit = belief about rotation (state)

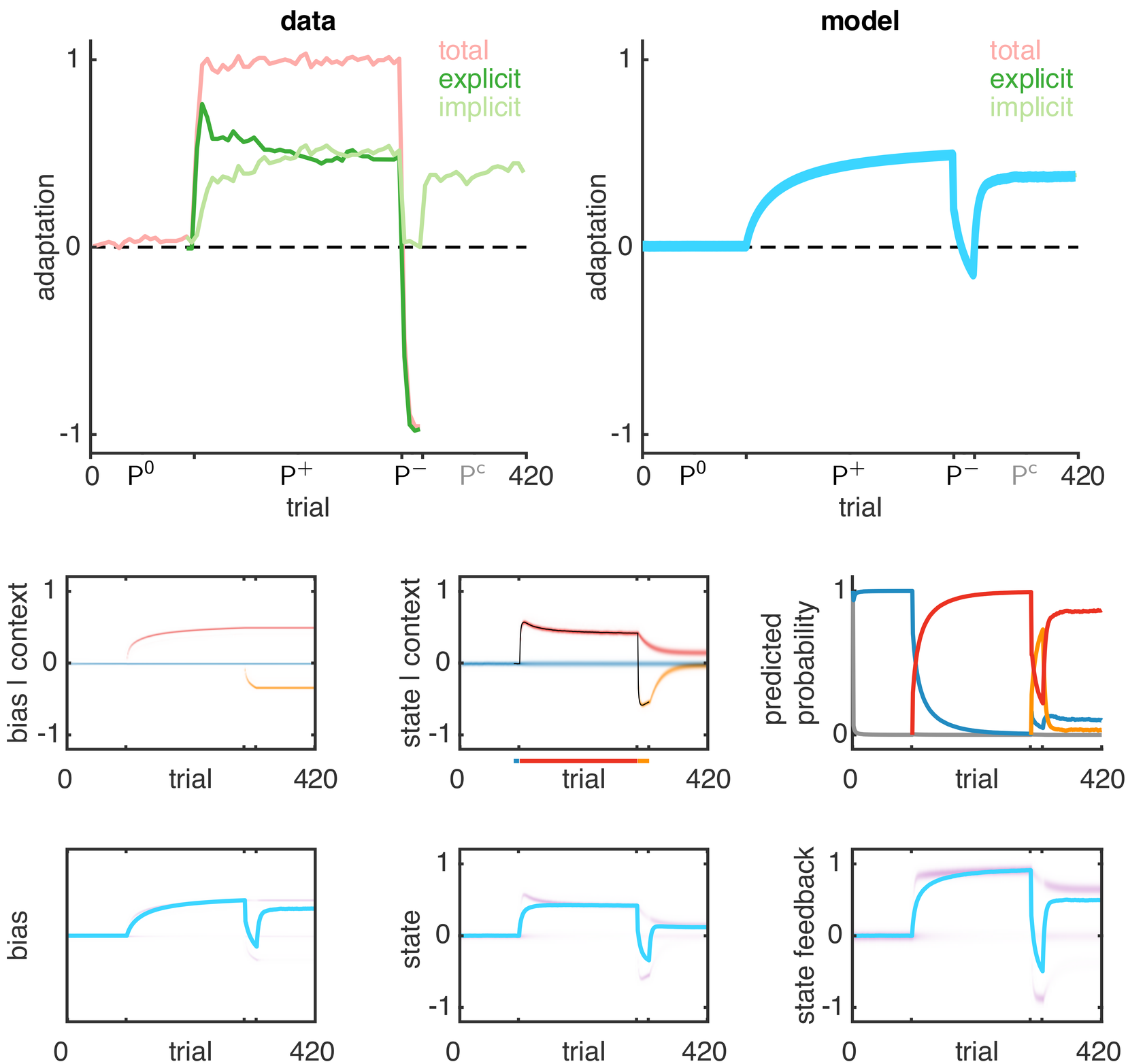
Explicit and implicit learning



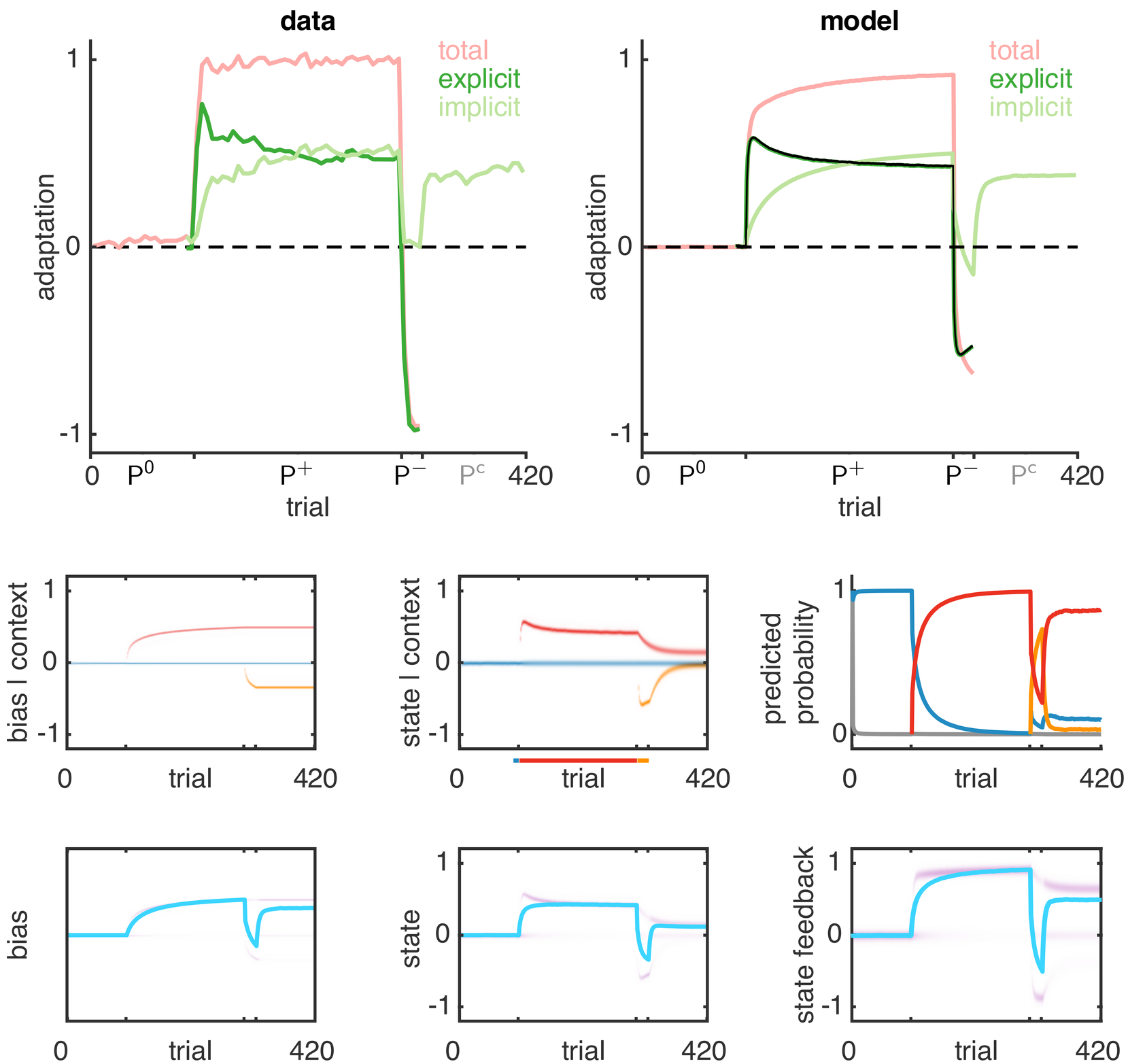
Explicit and implicit learning



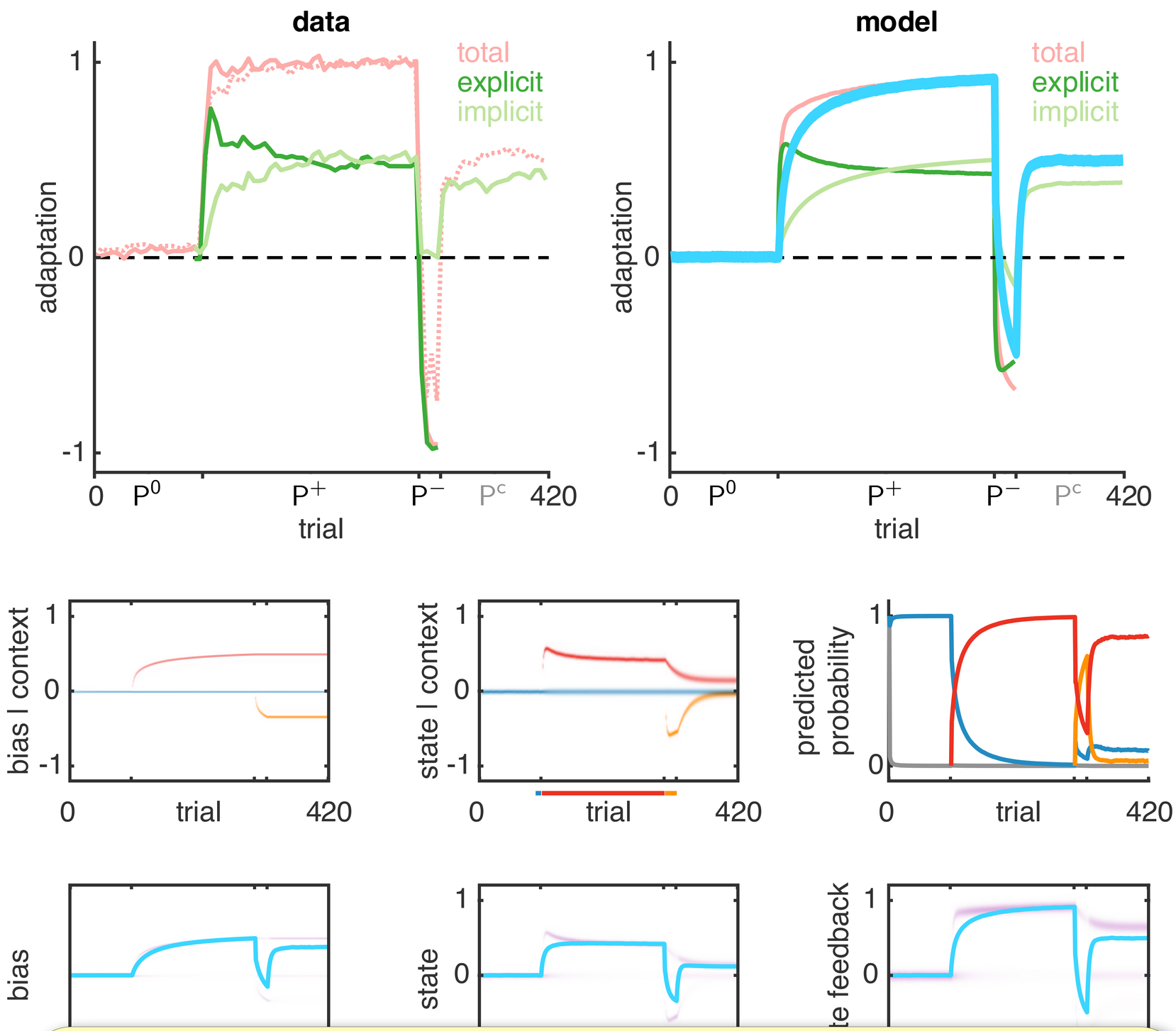
Explicit and implicit learning



Explicit and implicit learning



Explicit and implicit learning



Explicit and implicit learning may map to state and bias

Comparison with previous models

	single-context models		multiple-context models				
	dual-rate Smith et al. [3]	memory of errors Herzfeld et al. [9]	source of errors Berniker and Kording [8]	winner-take-all Oh and Schweighofer [2]	DP-KF Gershman et al. [6]	MOSAIC Haruno et al. [23]	COIN
spontaneous recovery	✓	✗ [a]	✗ [b]	✗ [b]	✗ [c]	✗ [d]	✓
evoked recovery	✗ [e]	✗ [e]	✗ [f]	✗ [f]	✗ [f]	✗ [d]	✓
memory updating	✗ [g]	✗ [g]	✗ [g]	✗ [g,h]	✗ [g,h]	✓	✓
savings after full washout	✗ [i]	✓	✓	✓	✓	✓	✓
anterograde interference	✓	✗ [a]	✗ [b]	✗ [b]	✓	✗ [j]	✓
environmental consistency	✗ [i]	✓	✗ [b]	✗ [b]	✗ [b]	✓	✓
explicit/implicit learning	✗ [l]	✗ [k]	✗ [k]	✗ [k]	✗ [k]	✗ [k]	✓

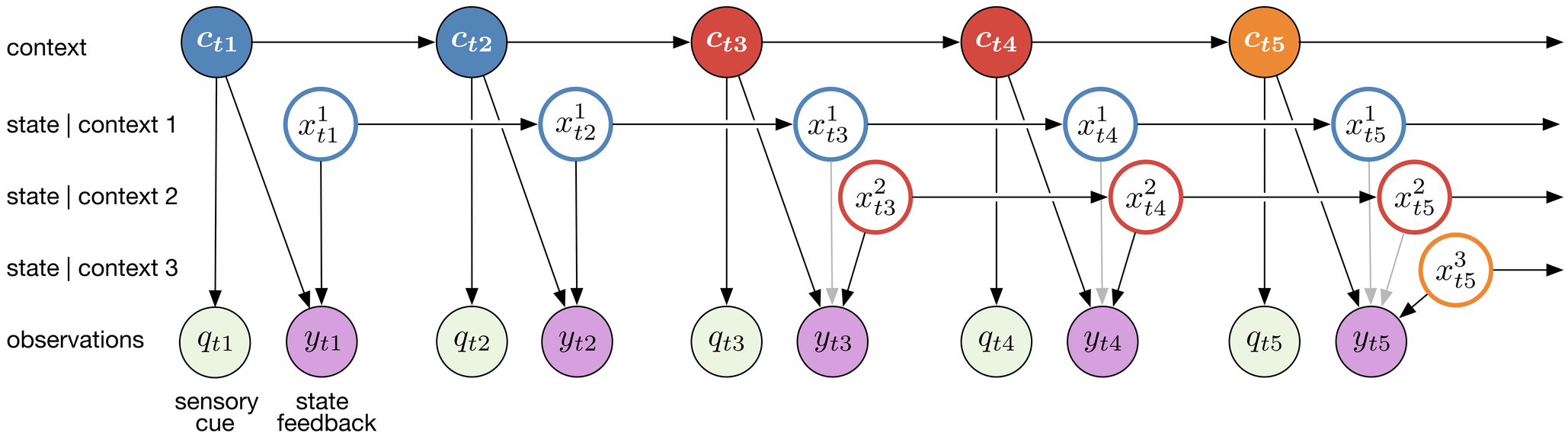
generative model

- do not model state dynamics
- do not model context transitions
- no sensory cues
- non-hierarchical
- number of contexts assumed known

inference

- only update/express a single memory
- learn no or few parameters

Summary



- Rules for motor memories in sensorimotor learning
- COntextual INference is a key computation
  - principled (Bayesian) and comprehensive
  - unifies disparate data sets
  - apparent vs. proper learning

James Heald

Máté Lengyel

James Ingram

Randy Flanagan

Hannah Sheahan

David Franklin

wellcome trust Investigator

THE ROYAL SOCIETY

NIH National Institute of Neurological Disorders and Stroke