One-hot generalized linear model for switching brain state discovery

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ICLR 2024

Introduction

- Exposing meaningful and interpretable neural interactions is critical to understanding neural circuits.
- Classical GLM is only able to find a static functional connectivity graph.
- In a long experiment, subject animals may experience different stages.
- Our new one-hot HMM-GLM can model the dynamically changing functional connectivity confined by an underlying anatomical connectome, which is more biologically plausible over the naive HMM-GLM.

One-hot HMM-GLM

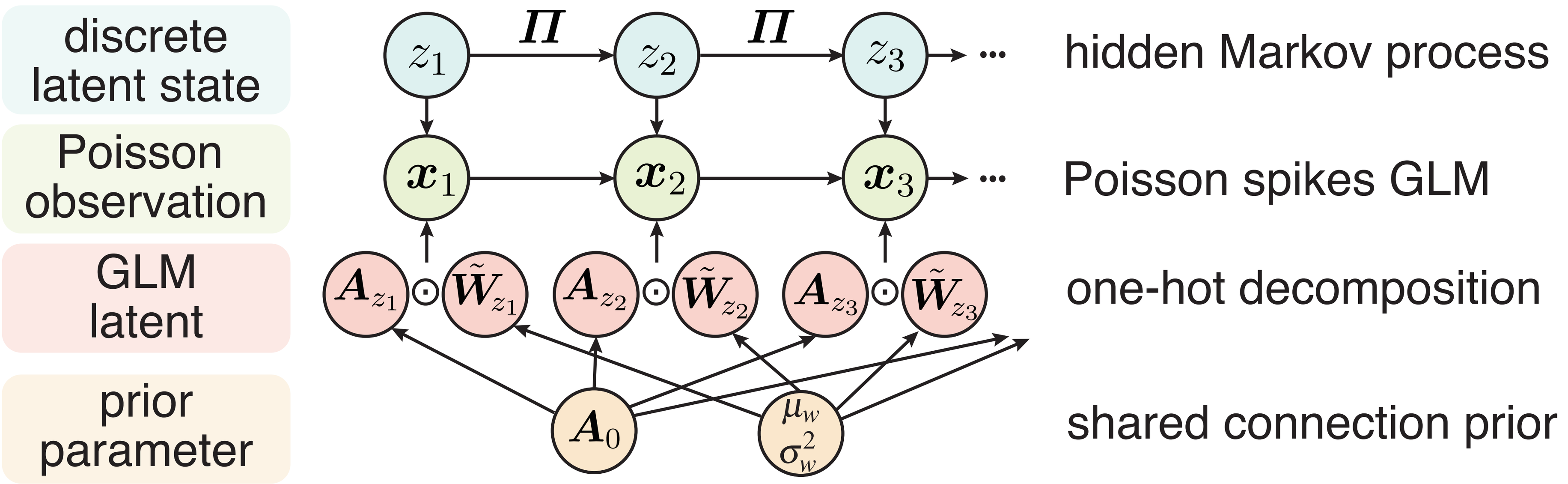
firing rate of neuron n at time t

$$f_{t,n} = \sigma\left(b_n + \sum_{n'=1}^{N} w_{z_t, n\leftarrow n'} \cdot \left(\sum_{k=1}^{K} x_{t-k,n'}\phi_k\right)\right)$$

nonlinear activation $\sigma : \mathbb{R} \to \mathbb{R}_+$ — background intensity of neuron n — weight from neuron n' to neuron n in state z_t — spiking history of neuron n' before time t

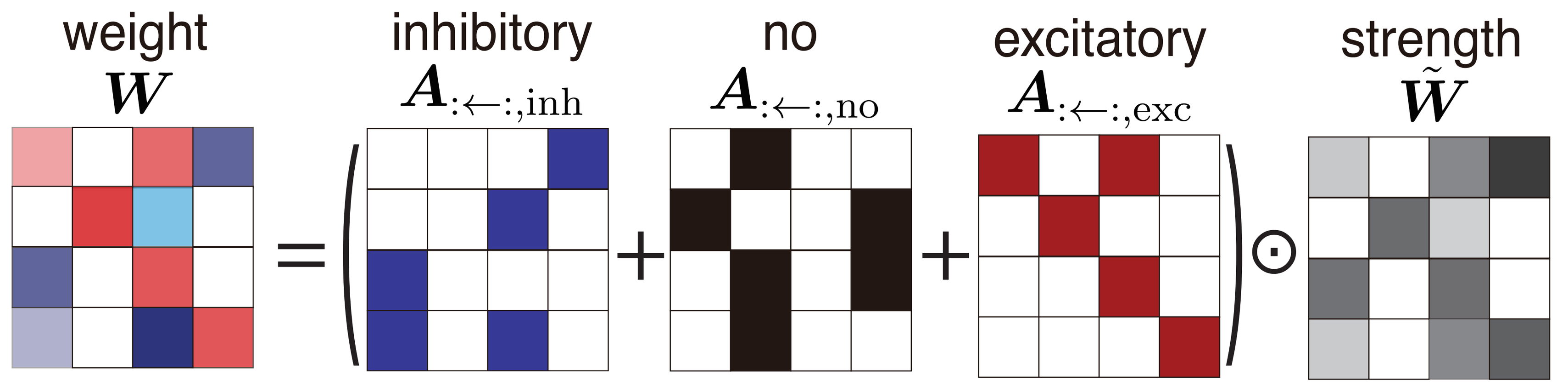
Poisson spikes $x_{t,n} \sim \mathcal{P}(f_{t,n})$

Hidden Markov process of S states $z_{t+1}|z_t \sim \mathrm{Cat}(\pi_{z_t,1}, \pi_{z_t,2}, \ldots, \pi_{z_t,S})$



One-hot decomposition $\boldsymbol{a}_{s,n\leftarrow n'} \sim \mathrm{Gumbel\text{-}Softmax}(\boldsymbol{a}_{0,n\leftarrow n'}, \tau)$

$$w_{s,n\leftarrow n'} = [(-1)a_{s,n\leftarrow n',\mathrm{inh}} + (+1)a_{s,n\leftarrow n',\mathrm{exc}}] \cdot \tilde{w}_{s,n\leftarrow n'}$$



References: [1] Pillow et al., Nature, 2008. [2] Escola et al., Neural computation, 2011. [3] Jang et al., arXiv, 2016. [4] Peyrache et al, 2018. [5] Rodgers et al, Neuron, 2021.

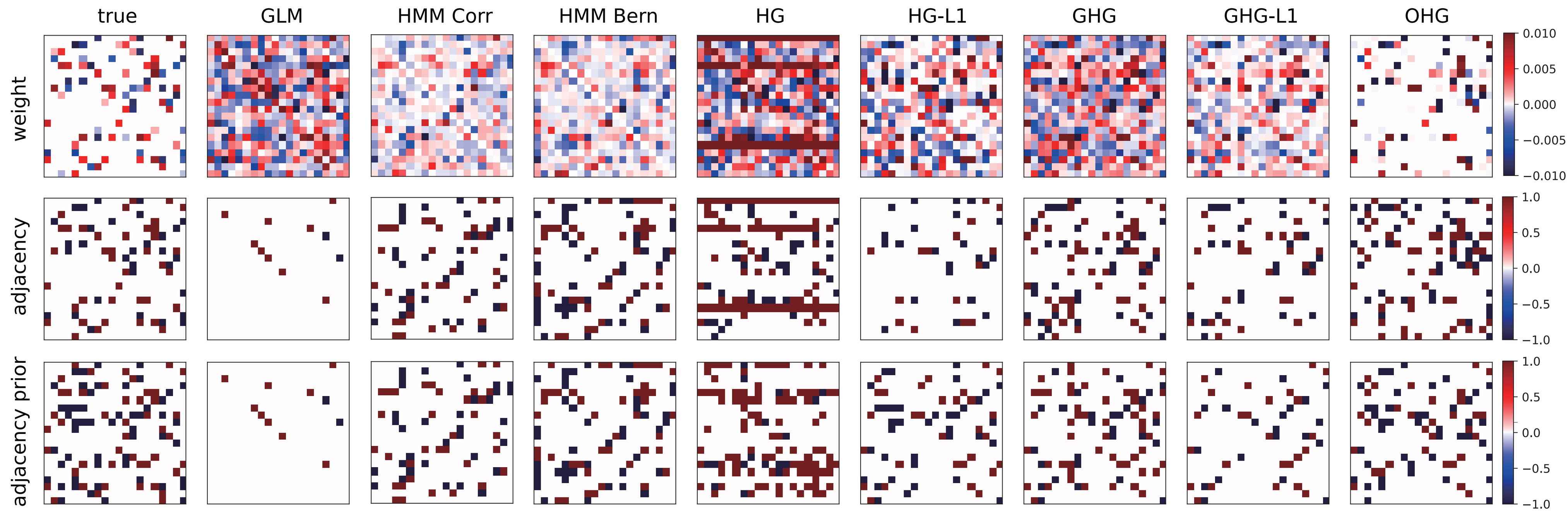
Inference

Baum-Welch (EM) algorithms. E-step: evaluate $Q(\theta, \theta^{\mathrm{old}}) = \mathbb{E}_{p(\boldsymbol{z}|\boldsymbol{X};\theta^{\mathrm{old}})} \ln p(\boldsymbol{X}, \boldsymbol{z}; \theta)$ by the forward-backward algorithm. M-step: maximize it w.r.t θ.

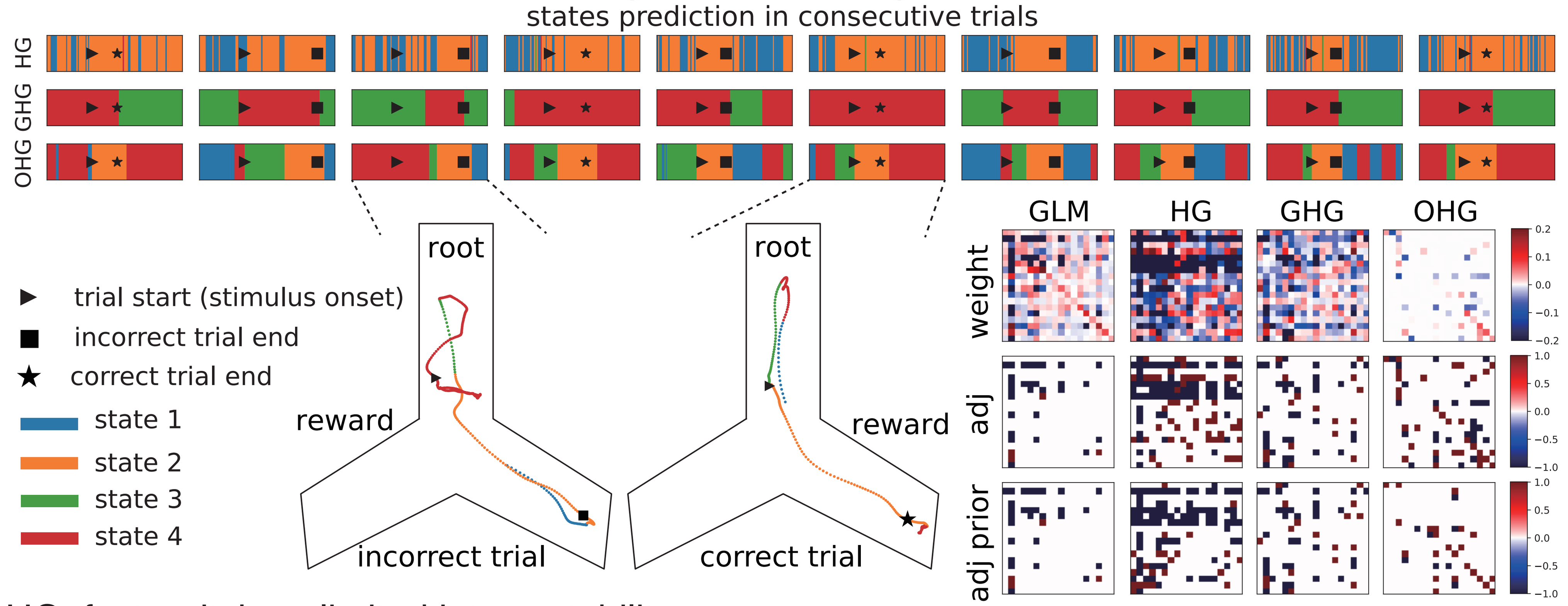
Experiments

Synthetic

method	LL ↑	state acc ↑	weight error ↓	con acc ↑	con prior acc ↑
GLM	-8.43(± 0.18)	nan(± nan)	24.71(± 0.19)	43.12(± 0.46)	44.81(± 0.61)
HMM Corr	-22.53(± 0.64)	42.84(± 1.47)	nan(± nan)	34.04(± 0.12)	15.45(± 2.49)
HMM Bern	-5.68(± 0.23)	87.95(± 0.93)	nan(± nan)	36.25(± 0.25)	40.70(± 1.53)
HG	-5.49(± 0.58)	37.73(± 2.80)	109.67(± 2.63)	34.17(± 0.08)	40.91(± 0.48)
HG-L1	9.14(± 0.18)	91.60(± 0.96)	23.14(± 0.08)	37.47(± 0.18)	48.44(± 0.57)
GHG	8.58(± 0.19)	91.80(± 0.92)	21.54(± 0.15)	42.53(± 0.22)	48.93(± 0.54)
GHG-L1	9.77(± 0.20)	92.08(± 0.89)	14.16(± 0.07)	41.08(± 0.22)	46.98(± 0.60)
OHG	**14.64**(± 0.23)	**92.75**(± 0.87)	**10.99**(± 0.21)	**73.90**(± 0.52)	**80.60**(± 0.59)

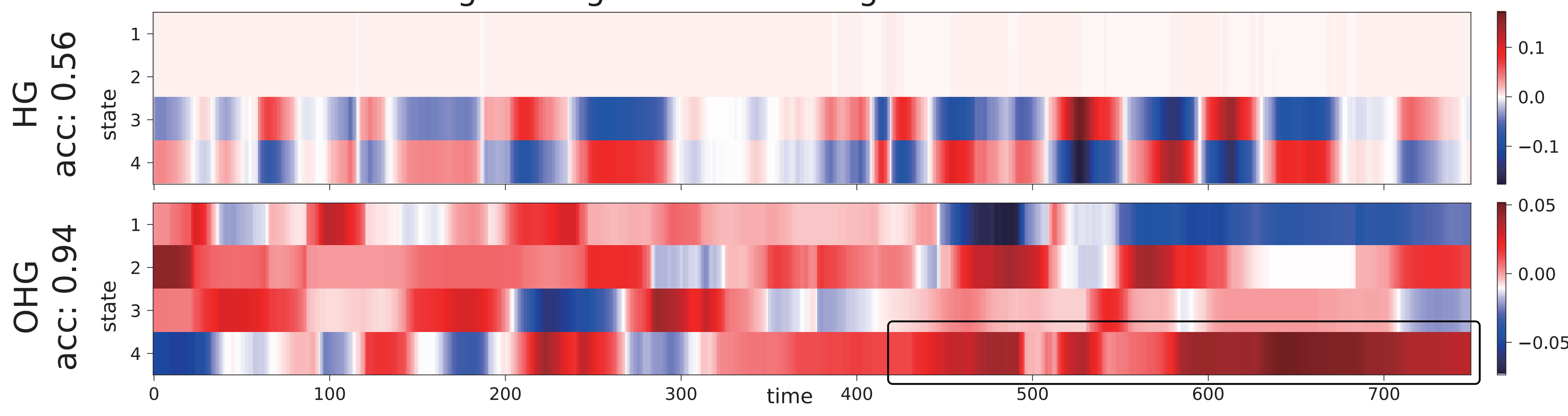


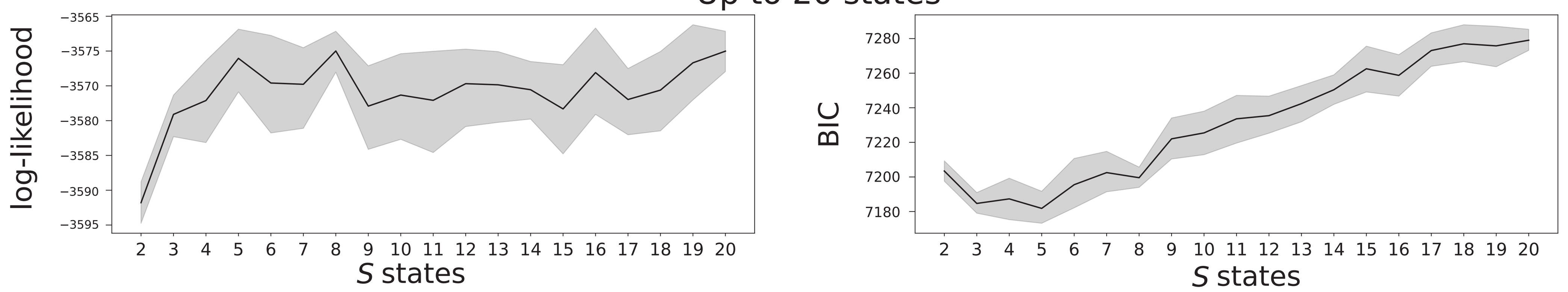
Prefrontal cortex during a contingency task



- HG: fast switches, limited interpretability.
- GHG: $S = 4$ states are assumed, but it only infers 2 effective states.
- OHG: 4 stable explainable states. Red: back to the root. Green: go to the turning point. Orange: reach a target. Incorrect trial: blue state. Correct trial: reward, red state.

method	2 states	3 states	4 states	5 states
HG	-37.30(± 0.05)	-37.61(± 0.17)	-37.22(± 0.14)	-36.98(± 0.19)
GHG	-37.17(± 0.00)	-37.11(± 0.01)	-37.12(± 0.00)	-37.11(± 0.00)
OHG	**-35.92**(± 0.02)	**-35.79**(± 0.02)	**-35.77**(± 0.03)	**-35.71**(± 0.03)





Barrel cortex during whisking