Implicit learning of successor representations is related to backward replay in visual cortex

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BACKGROUND

The **successor representation (SR) is a predictive map** that reflects the expected visitations of future events & explains behavioral and neural decision-making data [1]

Replay: Fast, sequential reactivation of neural patterns reflecting experience [2]

Replay during short on-task pauses might reflect **sampling from previously experienced transition structure** for learning, planning and decision-making [3]

Q1: Does SR learning occur on-task in a non-rewarded task domain?

Q2: Is SR learning linked to on-task replay?

Q3: Do SR learning and on-task replay link to conscious task knowledge?

METHODS

Participants

n = 39 healthy young adults (mean age = 24.3 years, SD = 4.24 years, 23 female)

MRI data acquisition

3T, TR = 1.25 s, TE = 25 ms, multiband factor 4, 2 mm³ voxels, +20° tilt from AC-PC

fMRI data preprocessing

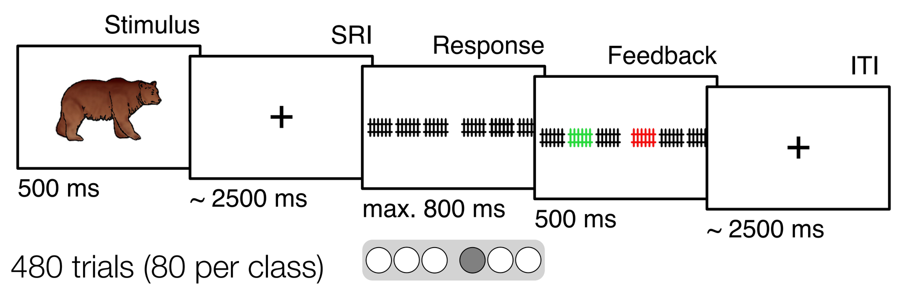
Standard preprocessing using fMRIPrep [4] (incl. slice timing correction, realignment, distortion correction, coregistration, etc.), 4 mm smoothing, detrending, z-scoring

Study procedure

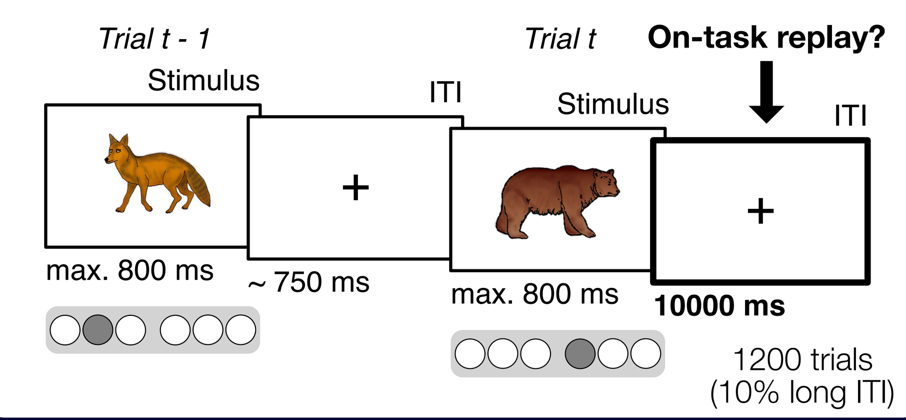
Two 90-mins. fMRI sessions (Day 1: Localizer task, Day 2: Main task)

TASK

Localizer task: Simple stimulus-response learning

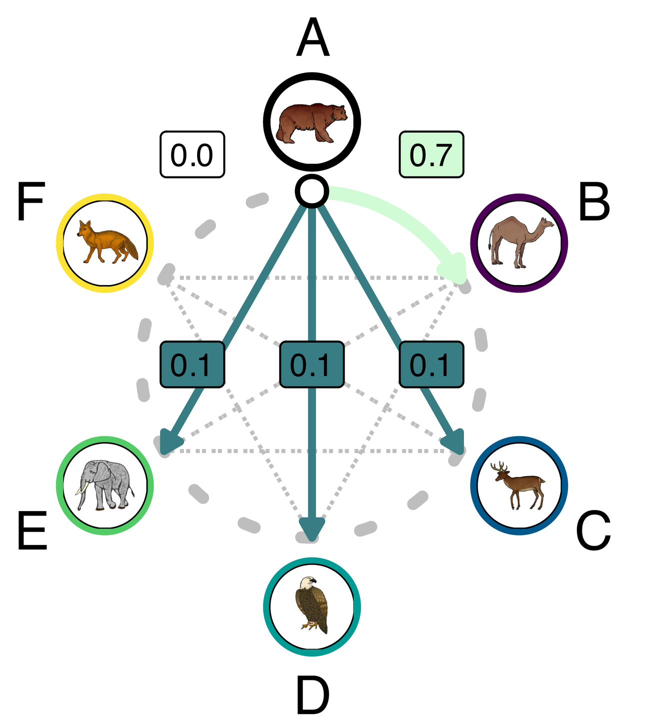


Main task: Incidental sequential stimulus learning



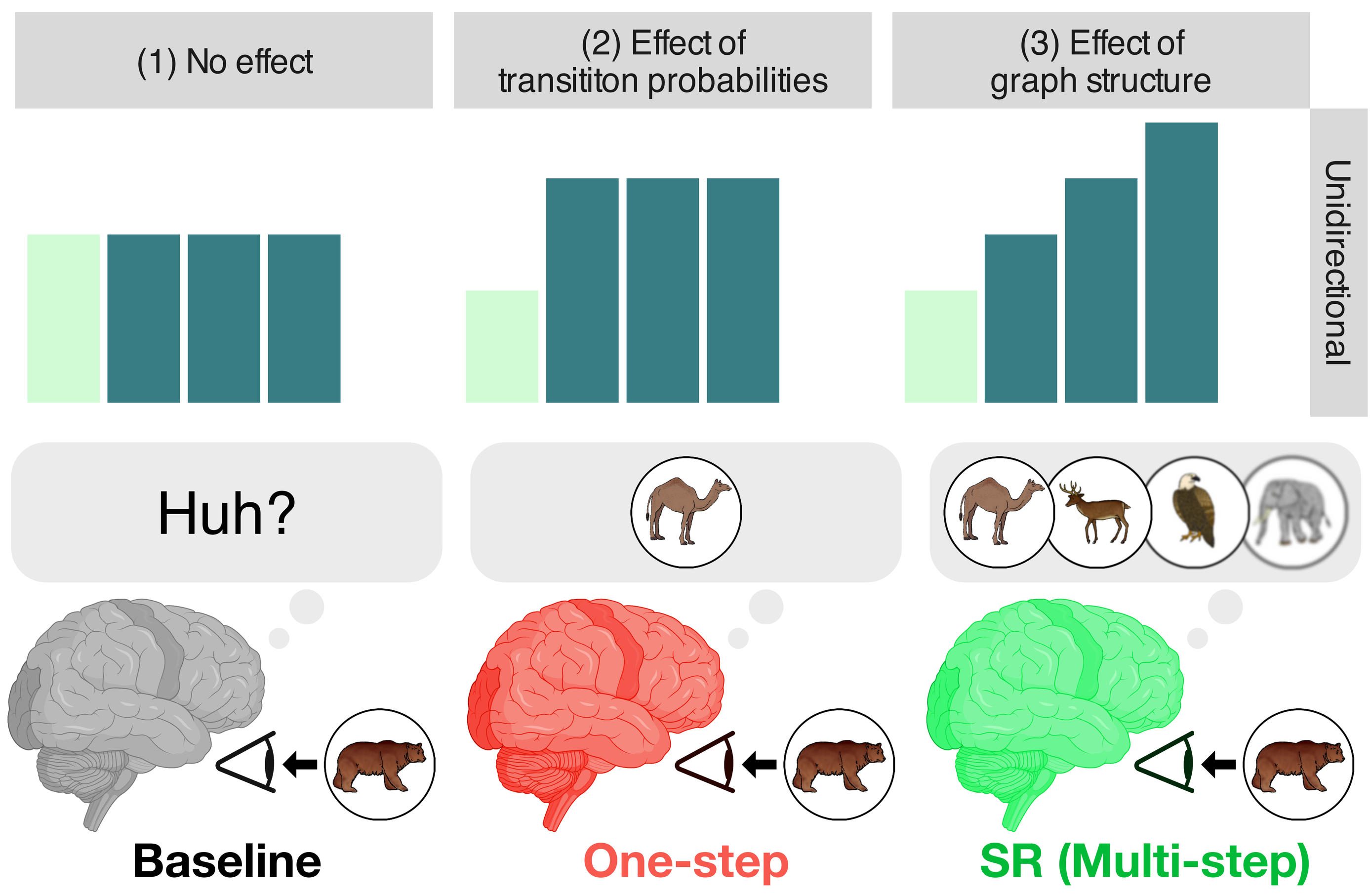
EXPERIMENTAL DESIGN & HYPOTHESES

Main idea: **Only multi-step knowledge differentiates low probability transitions**



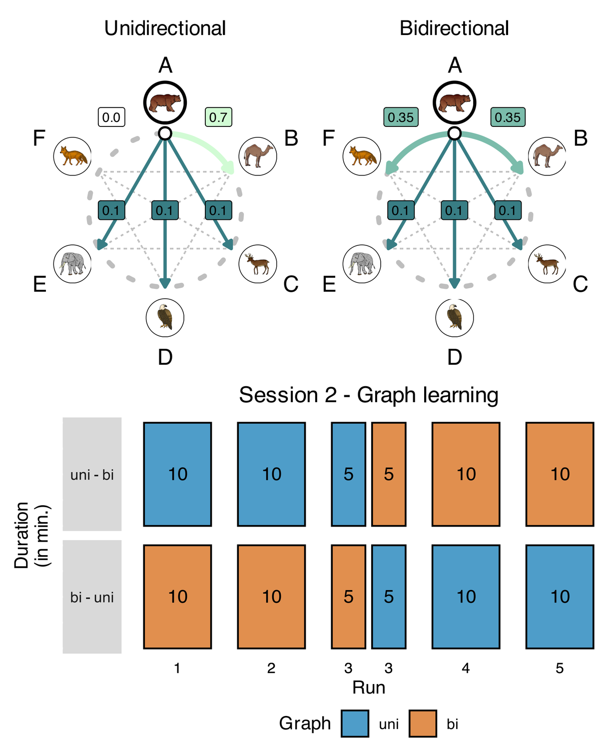
Stimulus order follow probabilistic sequence

Predictions for behavioral and neural responses to stimulus sequence



Relearning

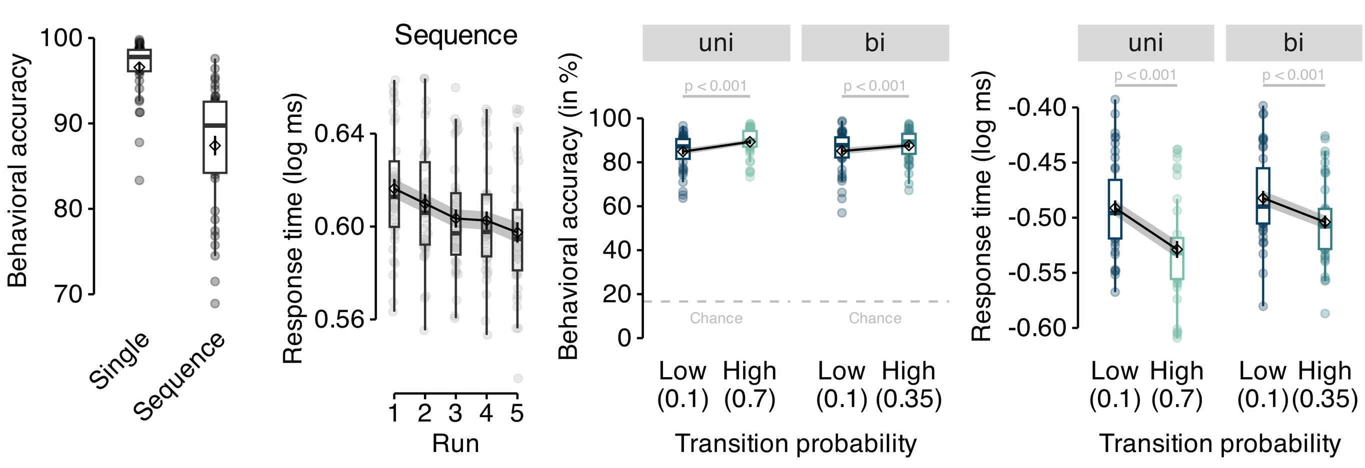
Graph structure change halfway through the task



ANALYSES & RESULTS

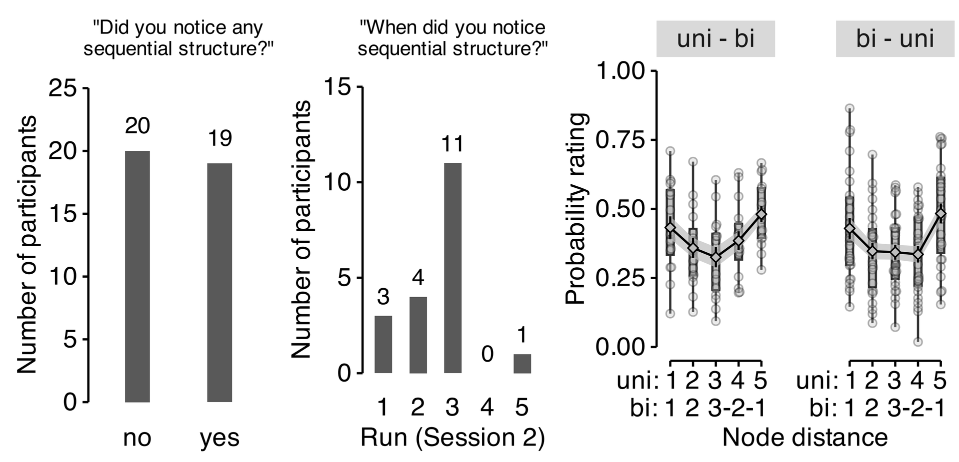
Participants learn transition probabilities expectations

Faster + more accurate after high vs. low probability transitions



Partially conscious about task structure

Graph change may trigger task knowledge



Successor representation (SR) modeling [1]

- Successor models learn **multi-step expectations**
- **Depth of learning** (horizon) depends on parameter γ
- **Learns trial-by-trial**, updates after each experience

$$\mathbf{M}_{s_t,*} = \mathbf{M}_{s_t,*} + \alpha\left[\mathbf{1}_{s_{t+1}} + \gamma\mathbf{M}_{s_{t+1},*} - \mathbf{M}_{s_t,*}\right]$$

- Model: RT when observing stimulus j in trial t is proportional to the surprise of the SR model when observing transition

Detection of stimulus (re)activation patterns

Probabilistic classifiers

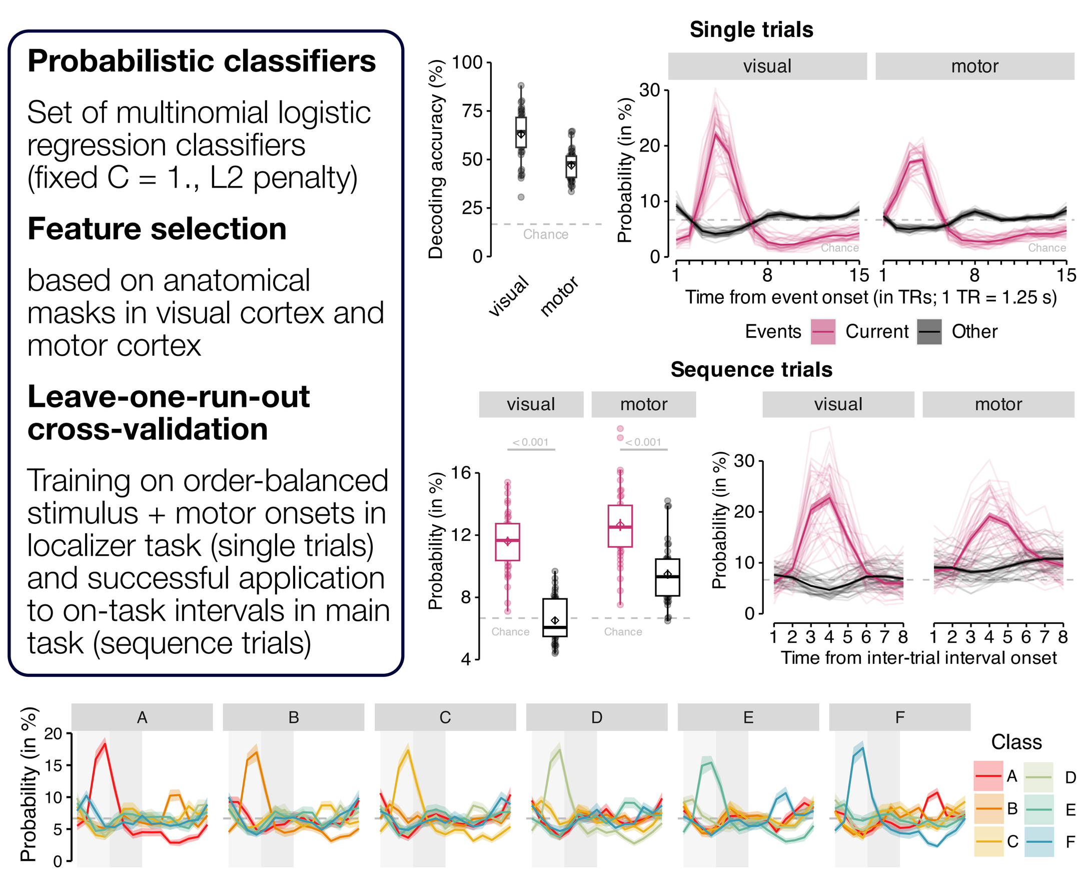
Set of multinomial logistic regression classifiers (fixed C = 1., L2 penalty)

Feature selection

based on anatomical masks in visual cortex and motor cortex

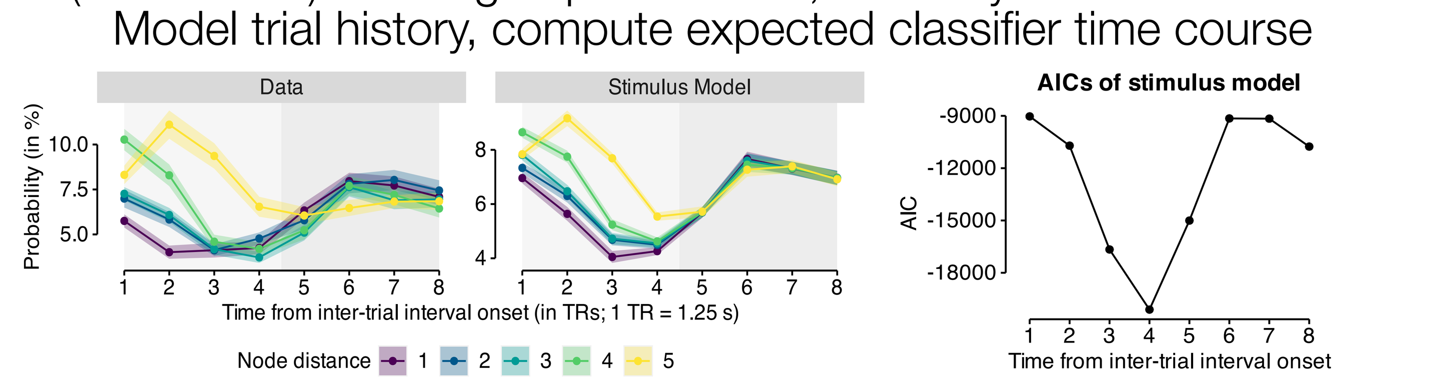
Leave-one-run-out cross-validation

Training on order-balanced stimulus + motor onsets in localizer task (single trials) and successful application to on-task intervals in main task (sequence trials)

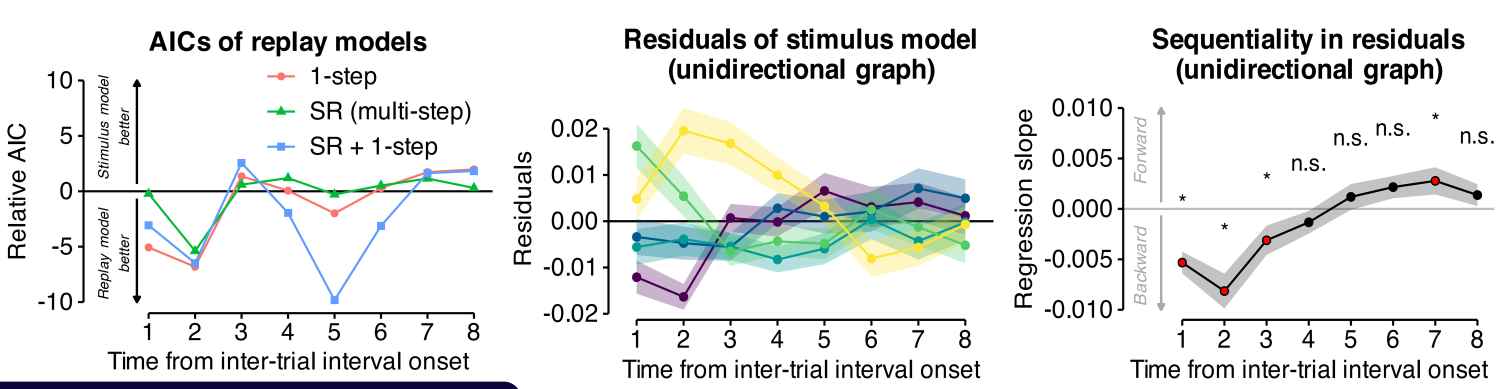


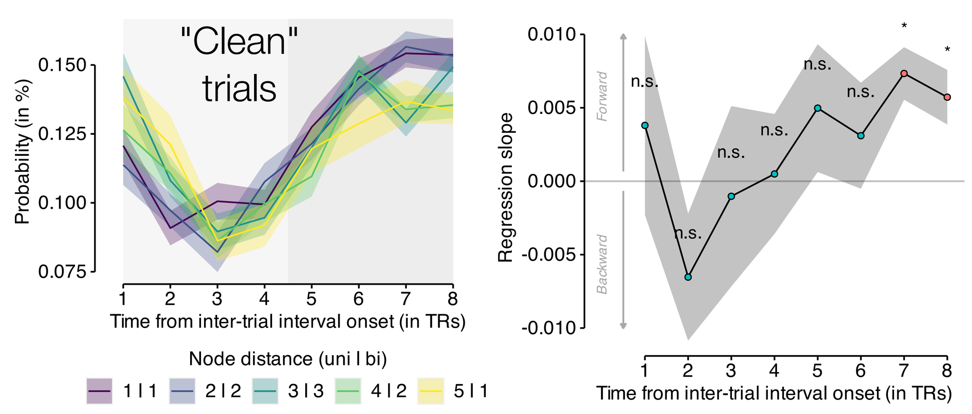
(Re)activation during on-task pauses in visual cortex

(Backwards) ordering of probabilities, but likely stimulus-driven? Model trial history, compute expected classifier time course

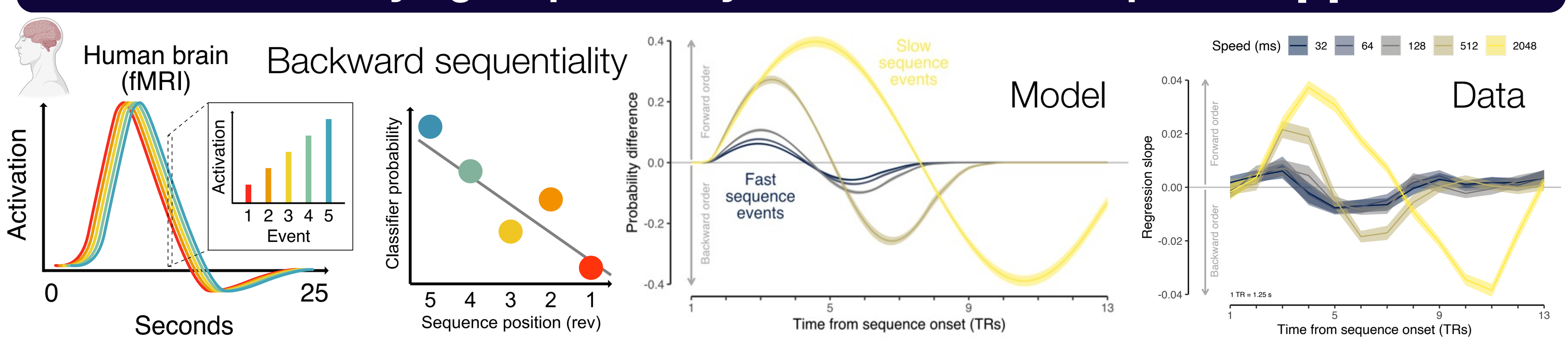


SR probabilities + 1-step activation explain neural data in on-task pauses



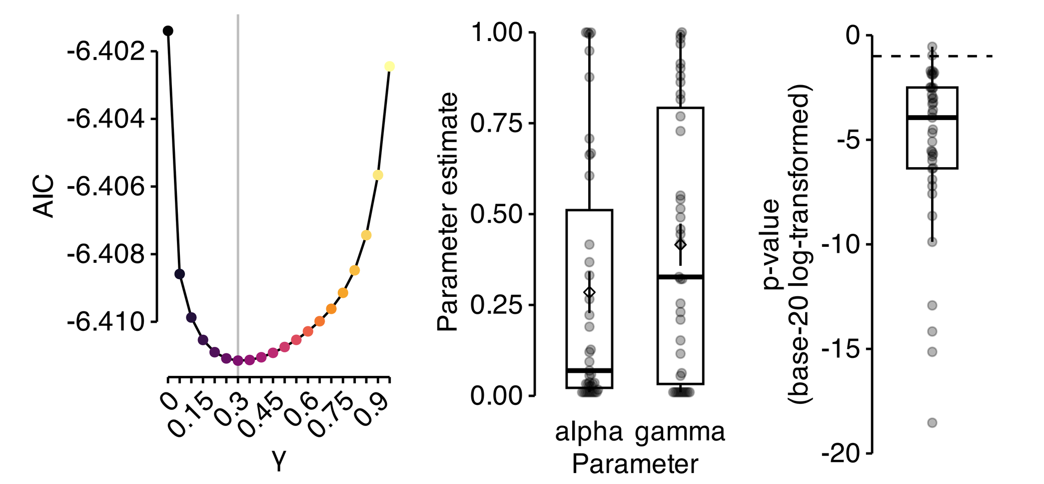


Quantifying sequentiality for multi-event sequences [4]



Response times indicate multi-step knowledge

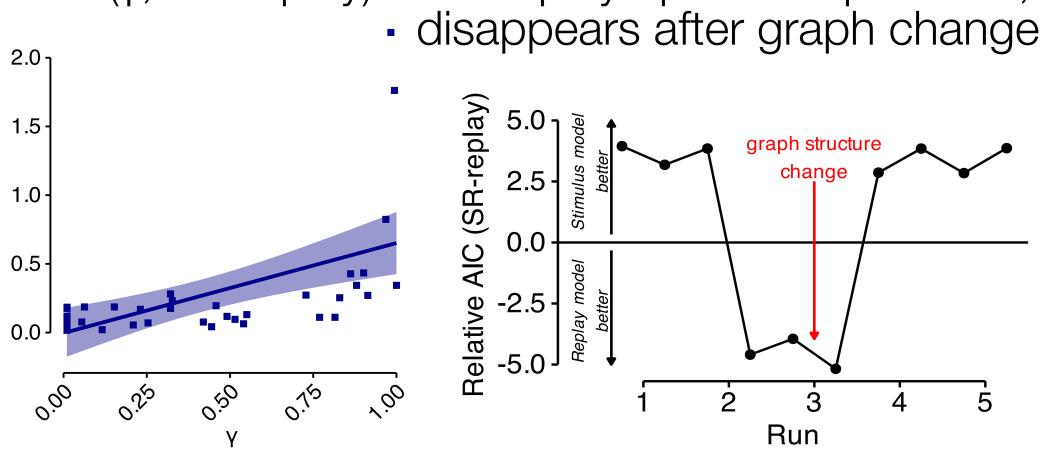
- Model fitting of RTs indicates that **non-zero gamma parameter is best** to explain behavior
- SR surprise effect **in almost all participants**



Link to behavior and time course of SR replay

corr(γ, SR replay)

SR replay up with experience, disappears after graph change



SUMMARY & CONCLUSIONS

- SRs are useful to store multi-step knowledge for prediction; can be learned online, through replay, or both
- Evidence of SR learning in an incidental sequence learning task, independent of conscious knowledge
- Evidence for on-task sequential replay: (a) replay in visual cortex, but not motor cortex or hippocampus, during brief on-task pauses, (b) replay seems to be fast-ish, (c) replay is not linked to conscious knowledge
- On-task replay and SR learning are linked; SR replay is affected by changes in task transition structure

REFERENCES

[1] see e.g., Dayan, 1993; Stachenfeld et al., 2017; Momennejad et al. 2017; Garvert et al., 2017; Russek et al., 2017
[2] see e.g., Wikenheiser & Redish, 2015; Foster, 2017; Schuck & Niv, 2019; Wittkuhn et al., 2021; Yu et al., 2021
[3] see e.g., Johnson & Redish 2007; Kurth-Nelson et al., 2016; Schuck & Niv, 2019; Eldar et al., 2020; Russek et al., 2021
[4] for details on these fMRI replay methods, see Schuck & Niv, 2019 and Wittkuhn & Schuck, 2021

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