The Impact of Predictability on Memory Representations

Manoj Kumar[1], Nicholas B. Turk-Browne[2], Kenneth A. Norman[1]

[1]Princeton University, [2]Yale University

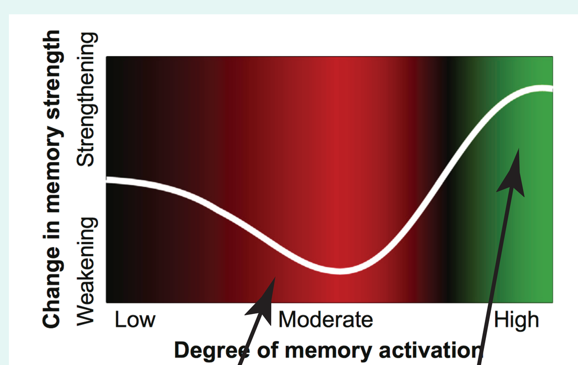
Competitor Activation: Differentiation vs. Integration

Schapiro et al. (2012) explored how predictability modulates statistical learning:

When B followed A 100% of the time, hippocampal representations of A and B became more similar (integrated)

When B followed A only 33% of the time, representations became less similar (differentiated)

Possible explanation: Non-monotonic plasticity hypothesis (NMPH; Ritvo et al., 2019)

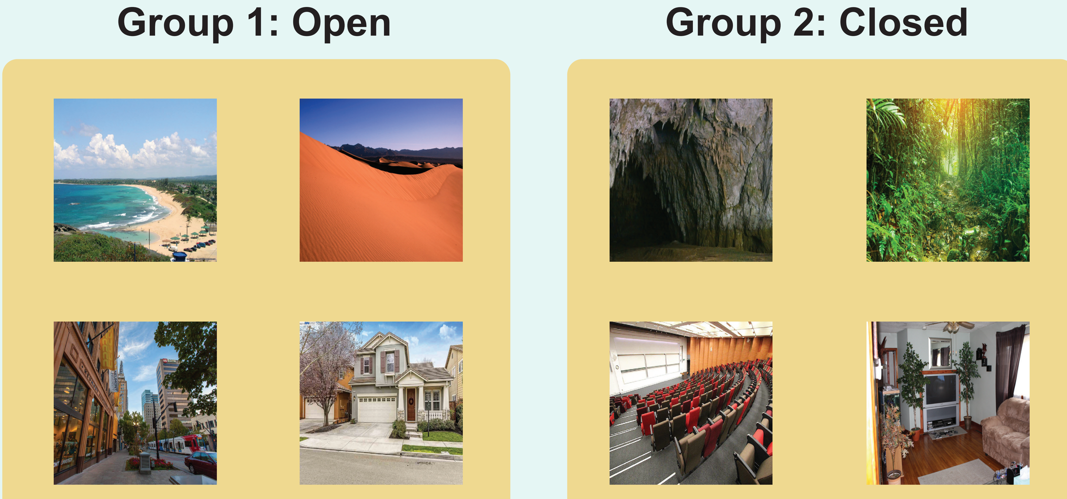


If activation of B (given A) is proportional to predictability: Possibly 33% 100%

Here, we set out to replicate and extend the above results by using a wider range of transition probability values

Hypothesis: higher activation of B in response to A for higher transition probabilities; moderate activation should lead to differentiation; strong activation should lead to integration.

Methods



A-B pairs were from the same group, but different categories

Pairs were sometimes violated with A followed by item X

X was always from the other group, facilitating detection of the prediction of B during violation trials

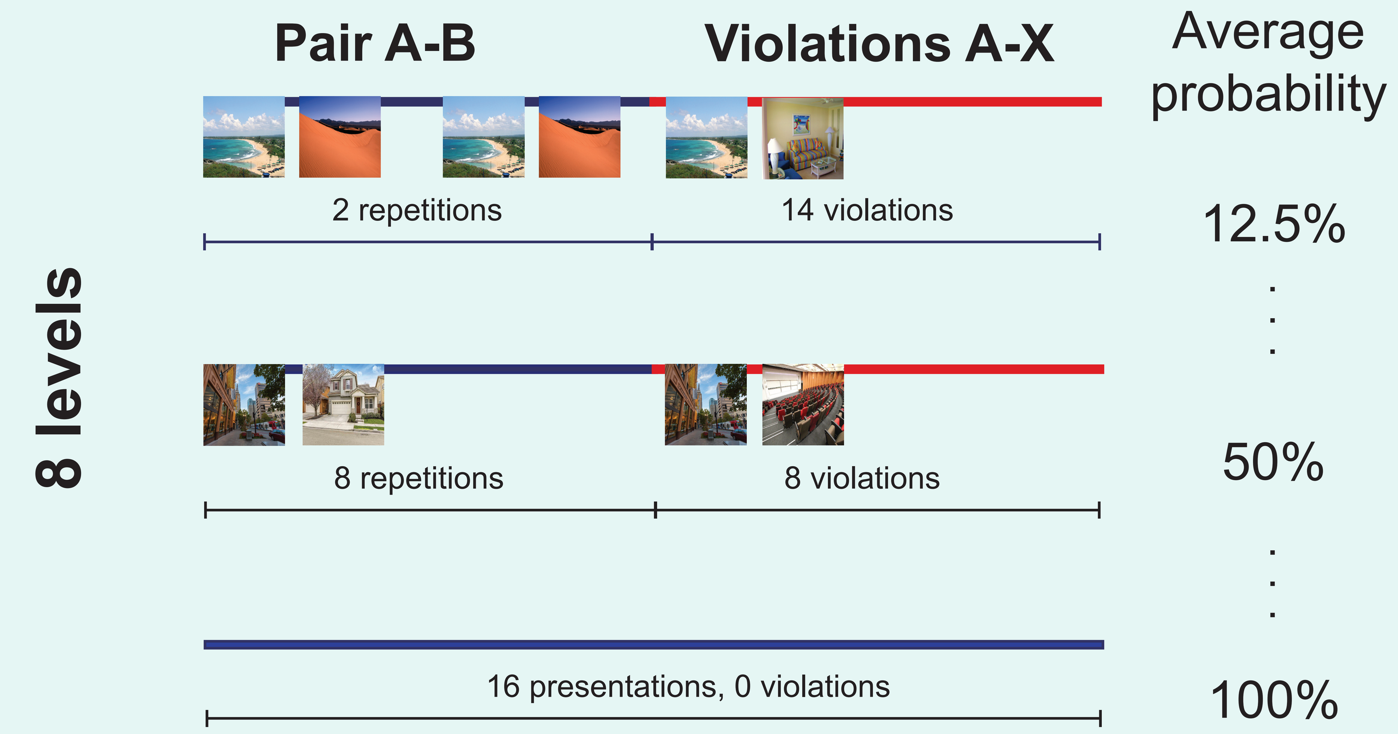
Open vs. closed distinction is optimal for decoding scenes from neural activity (Kravitz et al., 2011)

Subjects made a natural vs. man-made task judgement

Neural patterns extracted 4.5 s after stimulus onset

Using Probabilistic Transitions to Manipulate Memory Activations

Design



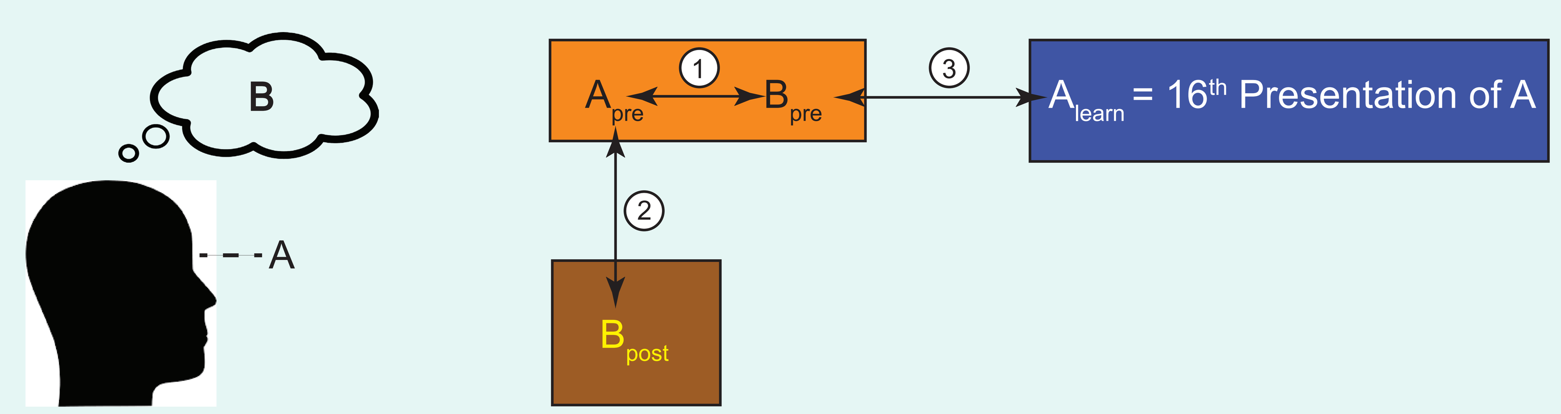
Day 1 Pre-learning | **Learning**

4 runs: A, B random sequence

Day 2 Post-learning

1 run: All B items

Analyses



Online prediction of item B when item A is presented:

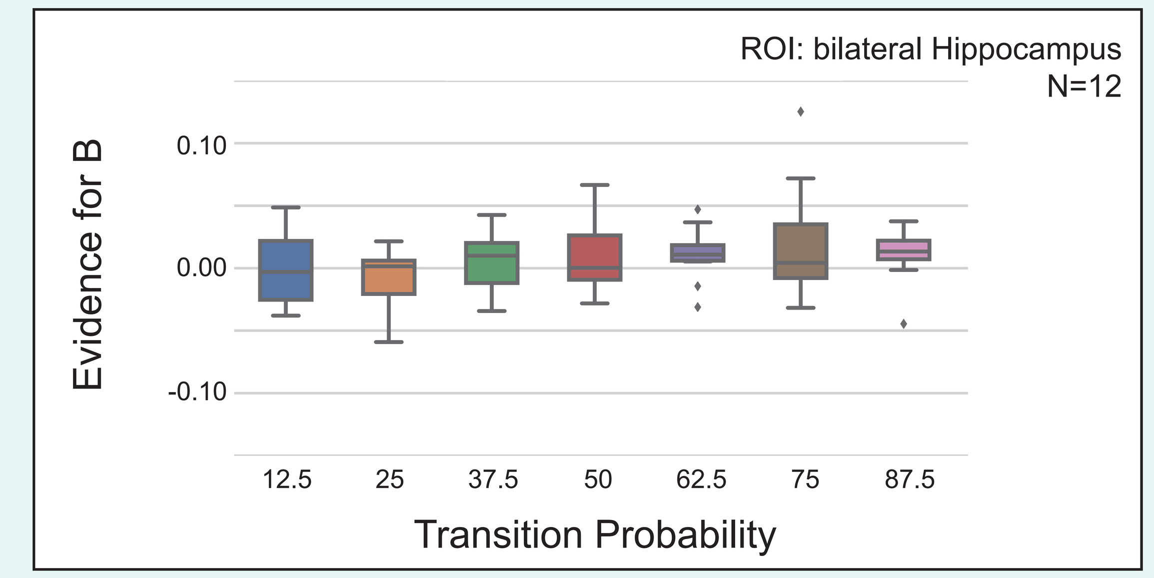
$$\text{Evidence for B} = \underbrace{\text{Corr}(A_{learn}, B_{pre})}_{\text{Similarity to item B } ③} - \underbrace{\text{Corr}(A_{learn}, B_{other})}_{\text{Baseline similarity to other items}}$$

$$\text{Overall representational change} = \underbrace{\text{Corr}(A_{pre}, B_{post})}_{②} - \underbrace{\text{Corr}(A_{pre}, B_{pre})}_{①}$$

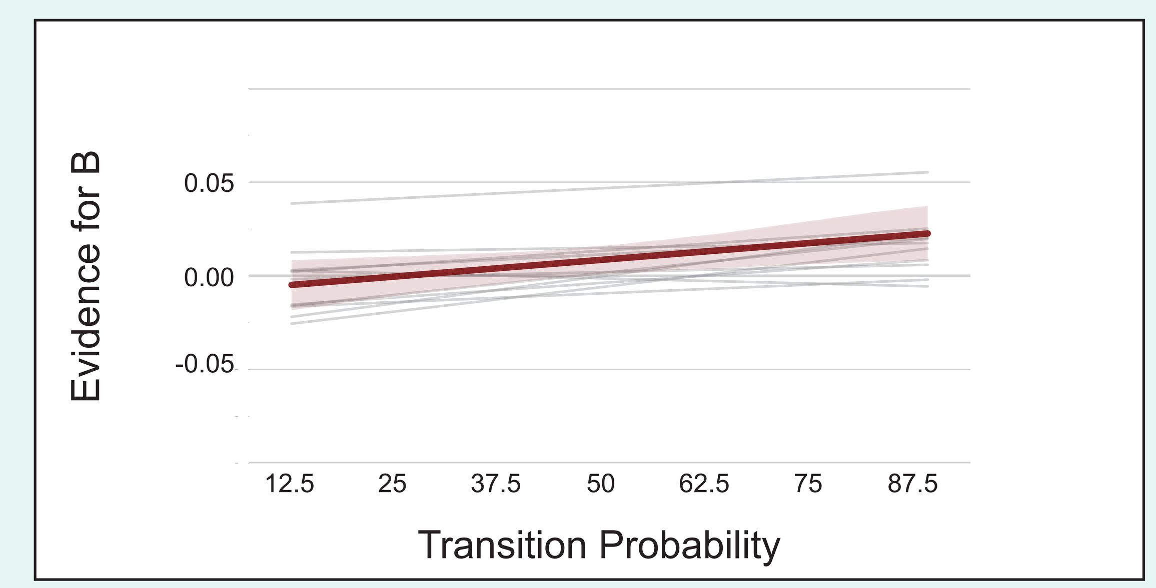
Use Probabilistic Curve Induction and Testing (P-CIT) toolbox (Detre et al., 2013) to continuously map between B activation to representational change

Prediction Strength vs. Transition Probability

Prediction strength within each transition probability level

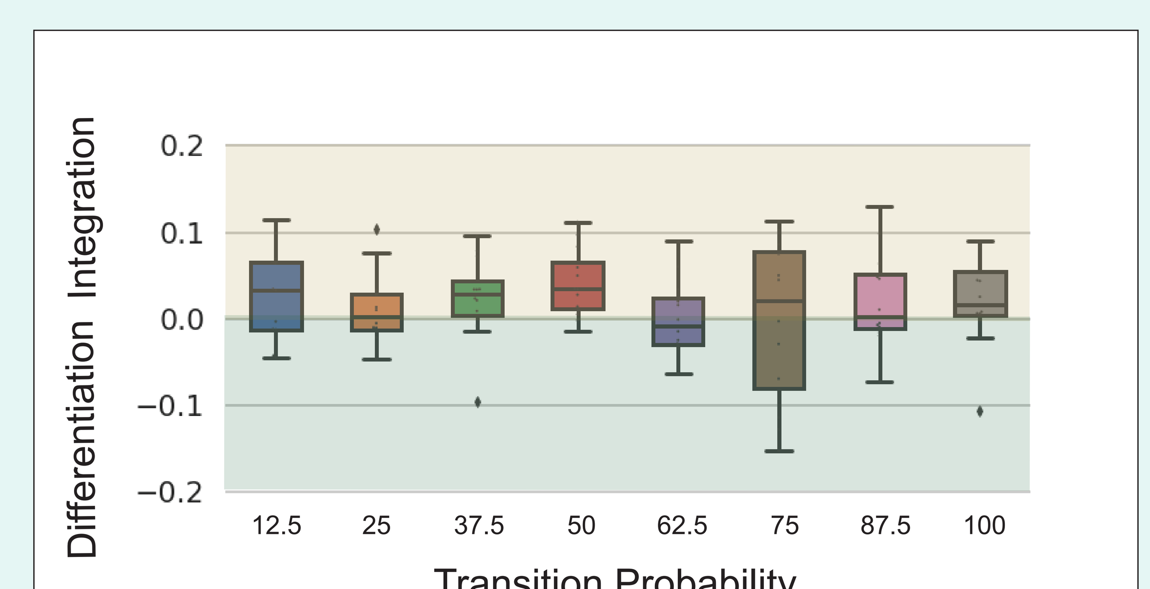


Overall slope (maroon) and individual subject slopes (grey), maroon band denotes 95% CI



Preliminary findings indicate a positive slope, prediction strength increasing as a function of transition probability

Overall representational change



Noisy results in partial sample, more data are needed

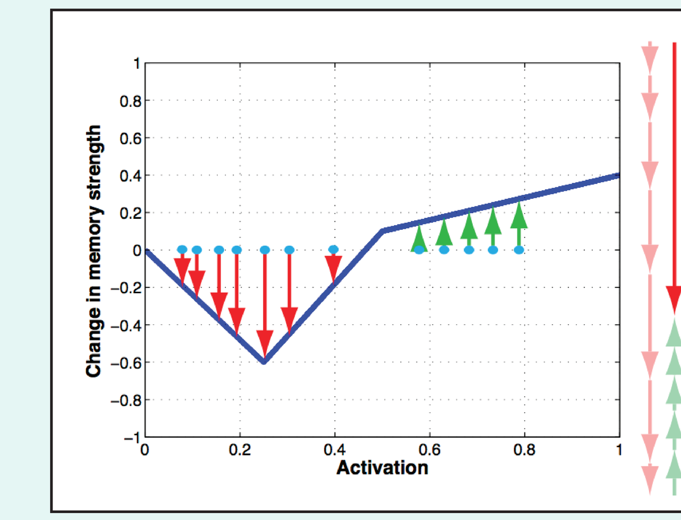
P-CIT may be more sensitive, relating actual measurements of prediction strength to differentiation/integration

P-CIT: Discrete to Continuous

Steps in P-CIT analysis (Detre et al., 2013)

1) Randomly **sample** curve (piecewise linear w/3 segments)

2) **Evaluate** curve by using it to predict learning (representational change) given measured activation values



3) Repeat procedure many times; estimated curve is weighted combination of all sampled curves

For our study, we will use all 16 trials for a given pair to measure B activation (given A), and we will relate this to representational change for that pair

Summary

These are preliminary results, data collection is in progress

Hypotheses and analysis approaches have been pre-registered

We see a trend of increasing prediction strength with increasing transition probability, as hypothesized

A P-CIT analysis will be performed to validate NMPH

References

Detre, G. J., Natarajan, A., Gershman, S. J., & Norman, K. A. (2013). Moderate levels of activation lead to forgetting in the think/no-think paradigm. Neuropsychologia, 51(12), 2371–2388. https://doi.org/10.1016/j.neuropsychologia.2013.02.017

Kravitz, D. J., Peng, C. S., & Baker, C. I. (2011). Real-World Scene Representations in High-Level Visual Cortex: It's the Spaces More Than the Places. Journal of Neuroscience, 31(20), 7322–7333. https://doi.org/10.1523/JNEUROSCI.4588-10.2011

Ritvo, V. J. H., Turk-Browne, N. B., & Norman, K. A. (2019). Nonmonotonic Plasticity: How Memory Retrieval Drives Learning. Trends in Cognitive Sciences, 23(9), 726–742. https://doi.org/10.1016/j.tics.2019.06.007

Schapiro, A. C., Kustner, L. V., & Turk-Browne, N. B. (2012). Shaping of Object Representations in the Human Medial Temporal Lobe Based on Temporal Regularities. Current Biology, 22(17), 1622–1627. https://doi.org/10.1016/j.cub.2012.06.056

Acknowledgements

This project was funded by NIH Grant R01MH069456 to N.B.T.-B. and K.A.N.

M.K. would like to thank Jordan Gunn for help with collecting stimuli; Elizabeth McDevitt and Jeff Wammes for useful discussions, and the Princeton pygers group for help with fmriprep.

email: manoj.neuron@gmail.com