The Impact of Predictability on Memory Representations

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**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**

- **Group 1: Open**
- **Group 2: Closed**

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 (Krawitz et al., 2011)

Subjects made a natural vs. man-made task judgement from neural activity (Kravitz et al., 2011)

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

**Using Probabilistic Transitions to Manipulate Memory Activations**

**Design**

<table>
<thead>
<tr>
<th>Pair A-B</th>
<th>Violations A-X</th>
<th>Average probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 repetitions</td>
<td>14 violations</td>
<td>12.5%</td>
</tr>
<tr>
<td>8 repetitions</td>
<td>8 violations</td>
<td>50%</td>
</tr>
<tr>
<td>16 presentations, 5-violations</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

**Day 1 Pre-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:

- Evidence for B = Similarity to item B
- Baseline similarity to other items

Overall representational change

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: 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**


**Acknowledgements**

This project was funded by NIH Grant R01MH095495 to N.B.T.-B. and K.A.N.

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

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