Optimal Timing for Episodic Retrieval and Encoding for Event Understanding

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Summary

- A neural network model that learns to use episodic memory for event prediction.
- The learned memory-retrieval policy show a speed-accuracy trade off, adaptive to the cost of incorrect prediction.
- Models that encode at event boundaries had less subsequent retrieval errors.
- Collectively, this model provides insights about why empirical episodic retrieval seems to be sensitive to prediction demand and uncertainty [1]; and episodic encoding seem to happen exclusively at event boundaries [3, 4].

Model

Cortex is a recurrent neural network (LSTM) that predicts the upcoming state.
Hippocampus represent memories as a set of evidence accumulators with lateral competition. Each memory is a cell state vector. **Retrieval** is a evidence-accumulation process that decides which memory to retrieve. The feed-forward weights and the level of lateral competition is set by the **retrieval control** layer. **Encoding** a new memory corresponds to adding a new node.
The model is trained with reinforcement learning. The reward is positive/negative if the prediction is correct/incorrect. The model can say "don't know", then the reward is zero.

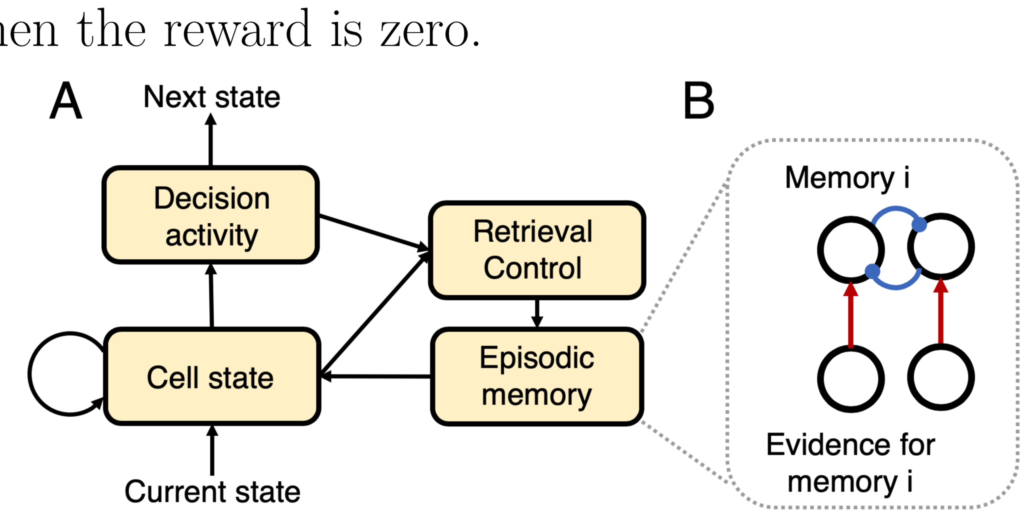

Figure 1: A) The model architecture; B) Memories are represented as a set of mutually competing evidence accumulators. The input weights (red) and the level of competition (blue) is controlled by the neural network.

Task

An **event sequence** is a sample path from a event schema conditioned on a situation (fig 2). A **event schema** is a graph. Each transition on the graph is controlled by a particular feature of the situation 2 A). Thus, knowing the feature of the situation is useful for predicting upcoming events.

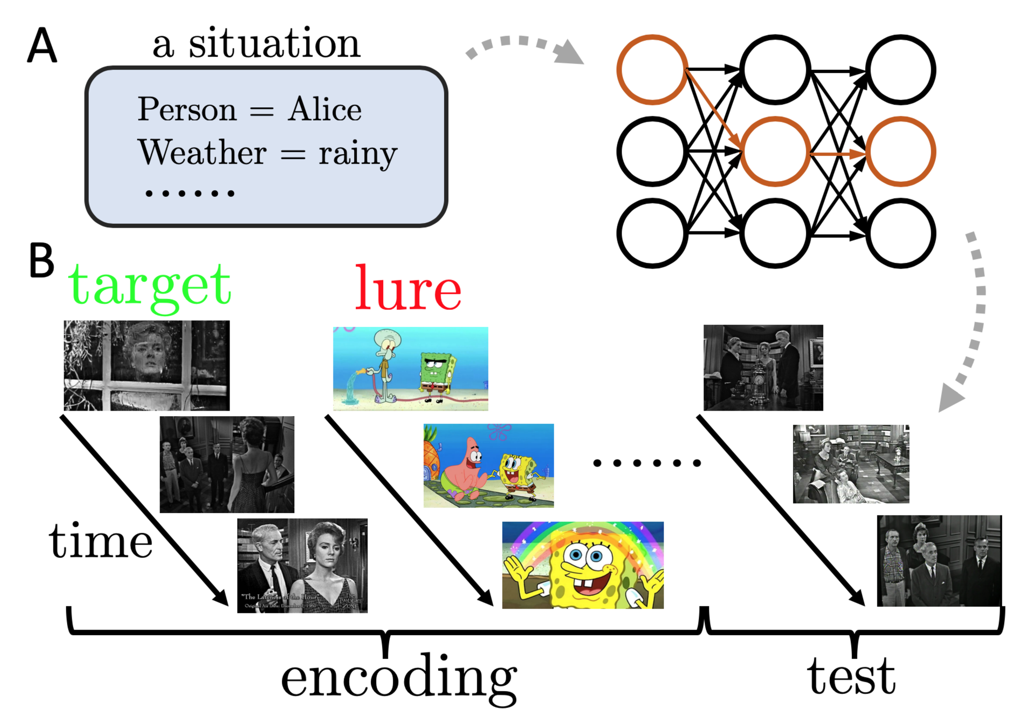

Figure 2: A) Sample an event sequence from the schema; B) An example trial.

Event prediction

Three conditions: ongoing situation is recently observed (RM); observed in distant past (DM); new (NM). The model can recall memory to support event prediction. When penalty is high, the model delays recall and flexibly expresses uncertainty. This design mimics Chen et al. (2016) [1].

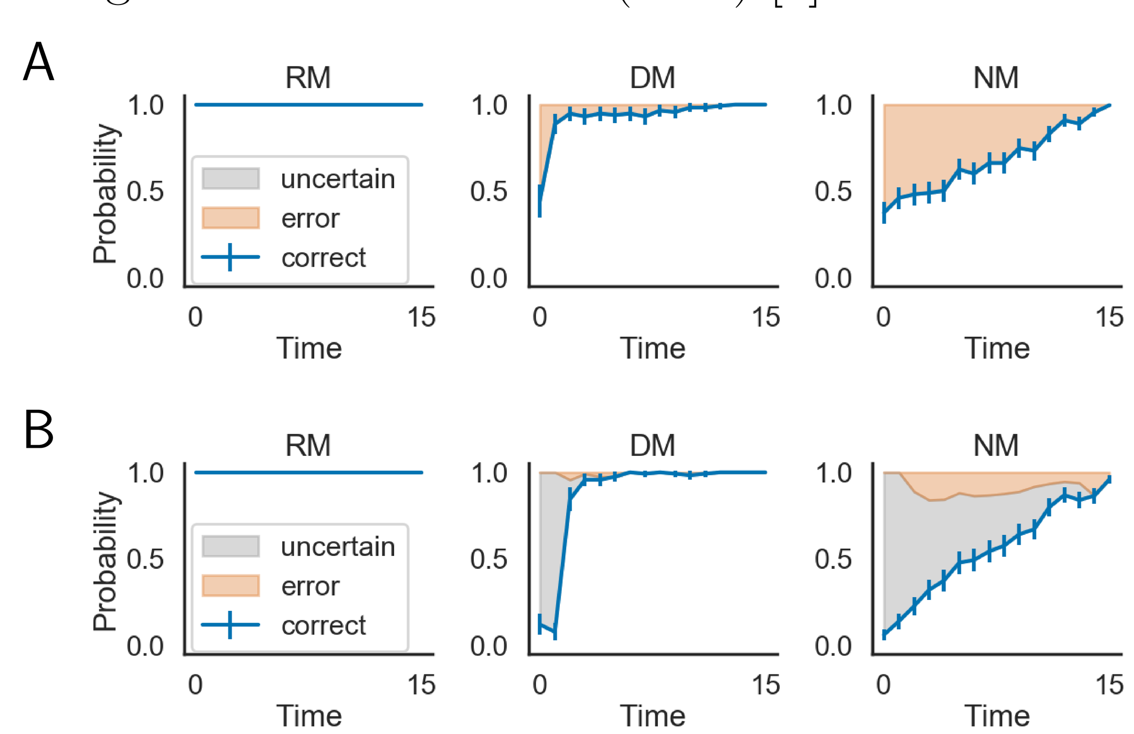

Figure 3: Prediction accuracy in the A) low; and B) high penalty environment;

The learned recall policy

Recall is sensitive to prediction demand and uncertainty (fig 4; fig 6). When penalty is high, recall is delayed (fig 4 A vs. B); and it learn to set a higher recall threshold (fig 5), similar to a well-established model of hippocampus [2].

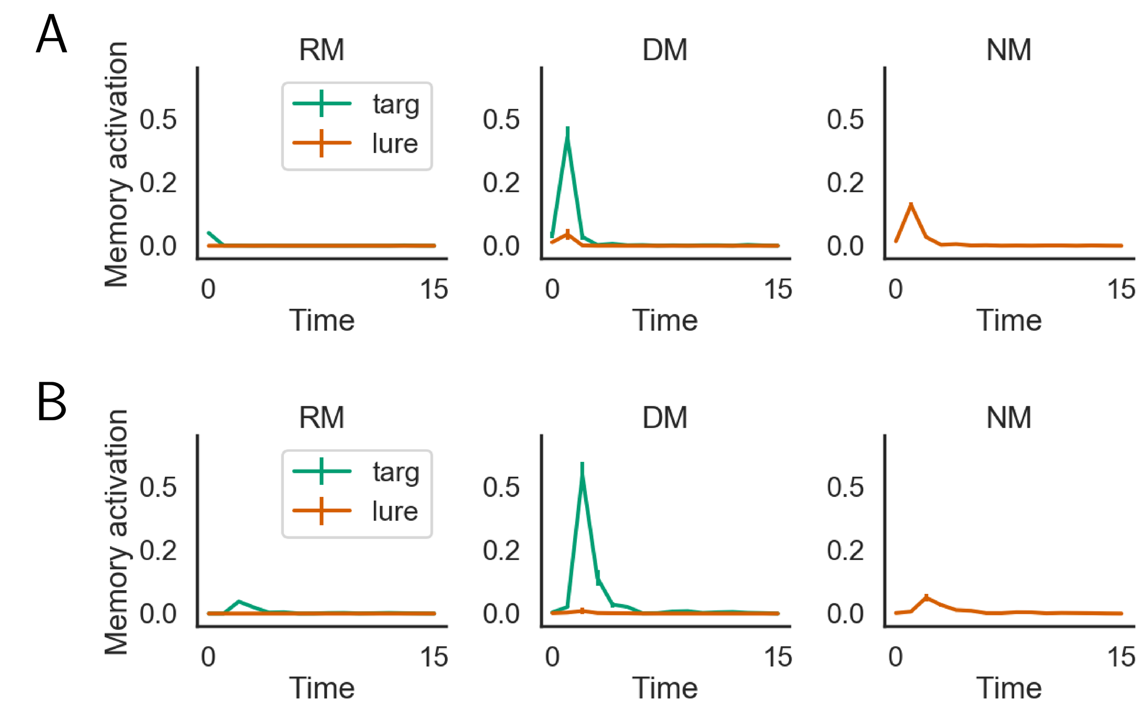

Figure 4: Memory activation in the A) low; and B) high penalty environment.

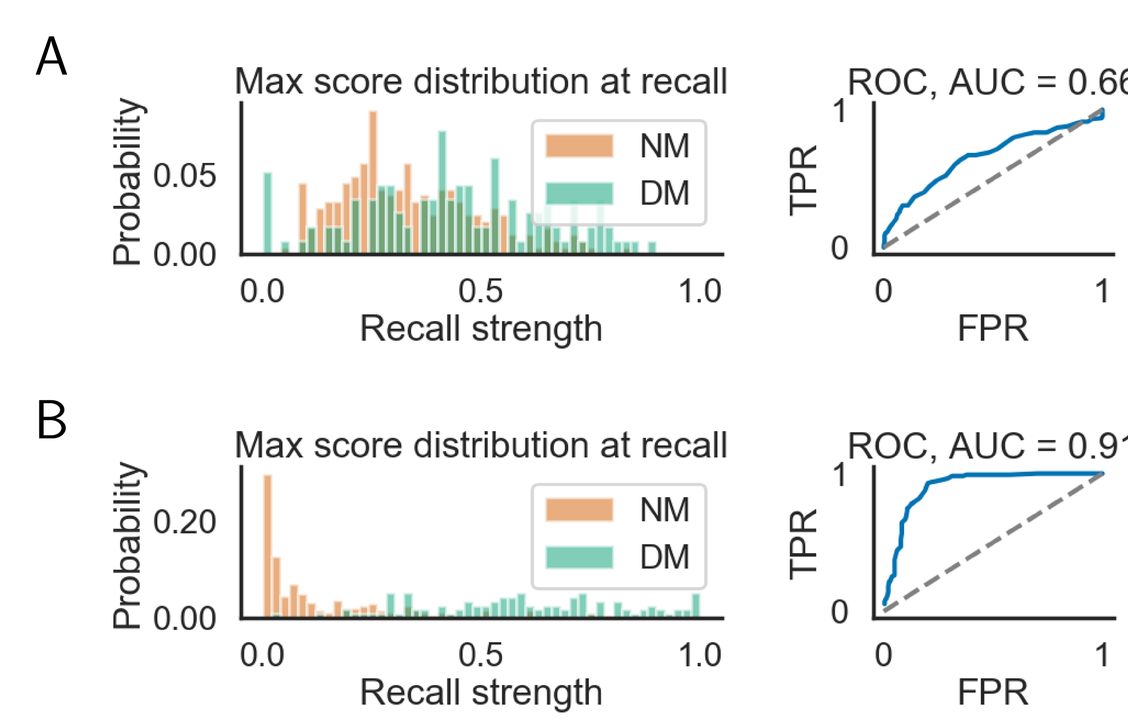

Figure 5: ROC analysis for the recall intensity in the A) low; vs. B) high penalty environment.

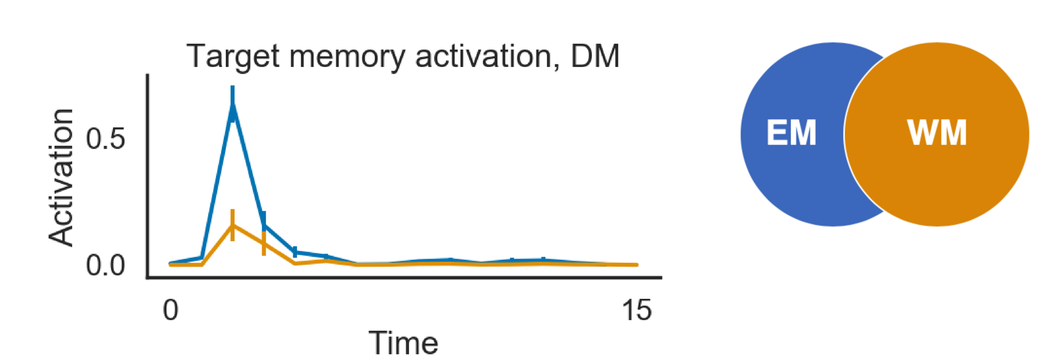

Figure 6: Recall is suppressed when the queried information is in working memory (WM; i.e. there is no uncertainty).

Encode at event boundaries

We found models that **encode at event boundaries** performed is better for subsequent recall (fig 7), compared to models that also encode with memory within an event sequence (i.e. **cumulative encoding**) , because **encode at event boundaries** leads to a more complete memory chunk, which is less confusing at subsequent recall (fig 8).

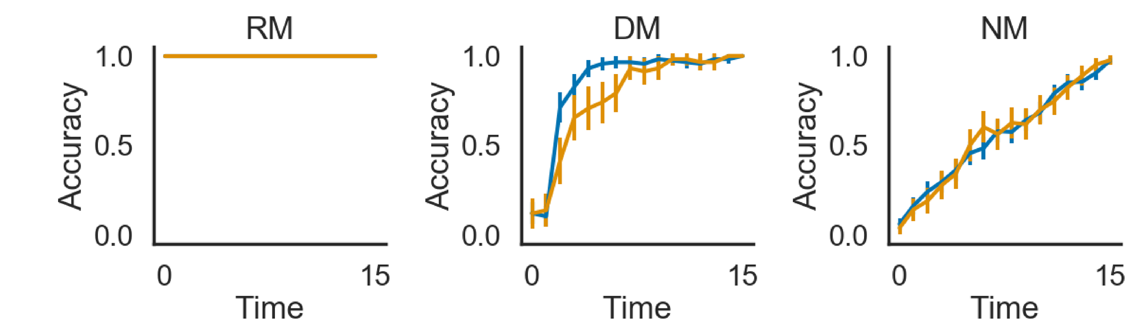

Figure 7: Event prediction accuracy for models that encode at event boundaries ; vs. models that also encode within an event sequence.

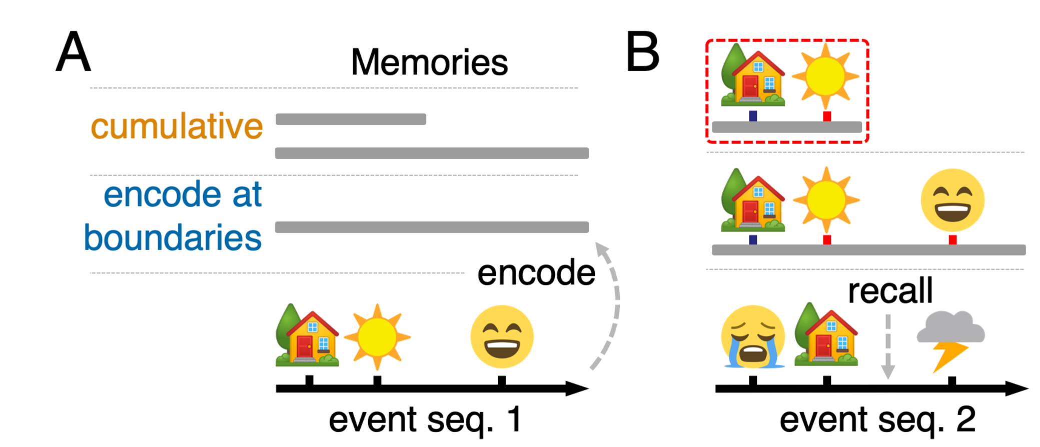

Figure 8: A) The resulting memory chunks under the two encoding regimes; B) Chunking within an event sequence might cause subsequent false recall. Connect all information make lures easier to reject.

References & Acknowledgement

[1] Chen, J. et al. (2016) Cereb Cortex.
[2] Norman, K. (2010) Hippocampus.
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[3] Ben-Yakov A., & Henson, N. (2018). J Neuro.

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