EVENT SCHEMAS: LEARNING AND USE IN HUMANS AND RECURRENT NETWORKS

Andre Beukers, Cathy Chen, Qihong Lu, Christopher Baldassano, Uri Hasson, Kenneth Norman

Schemas

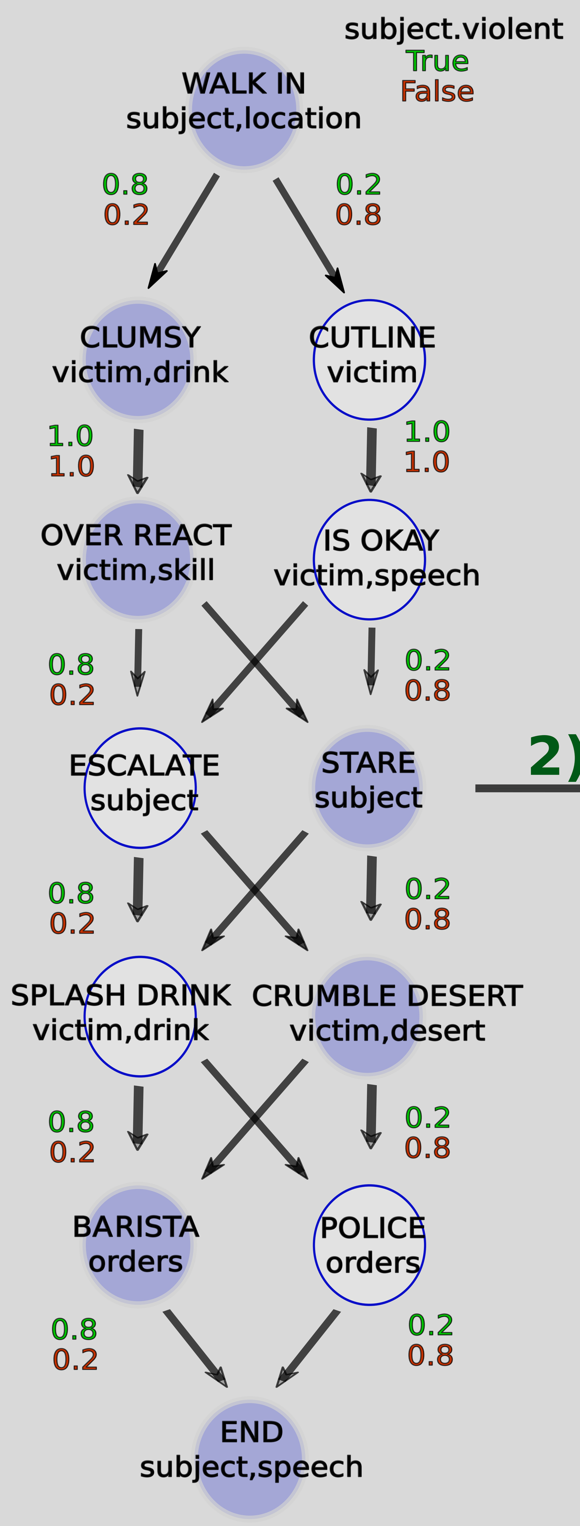
* scaffolding of memory
* constructed from episodes
* supports generalization
* aids encoding
* how are they learned and used?

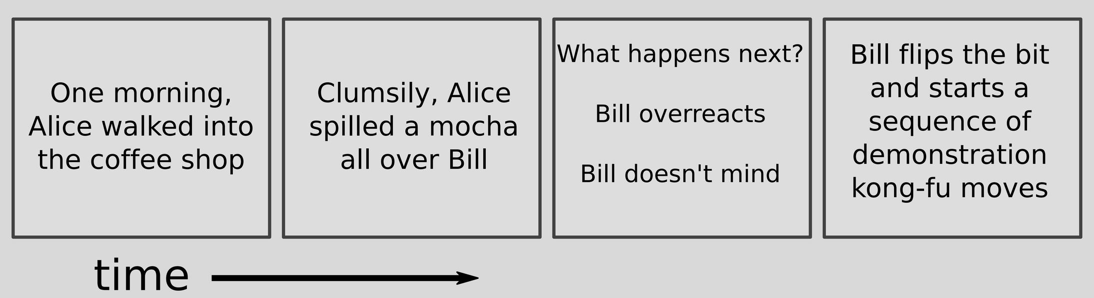
Approach:

* algorithmically generate narratives with:
  - long range probabilistic dependencies
  - filler dependent transition

1) sample fillers:

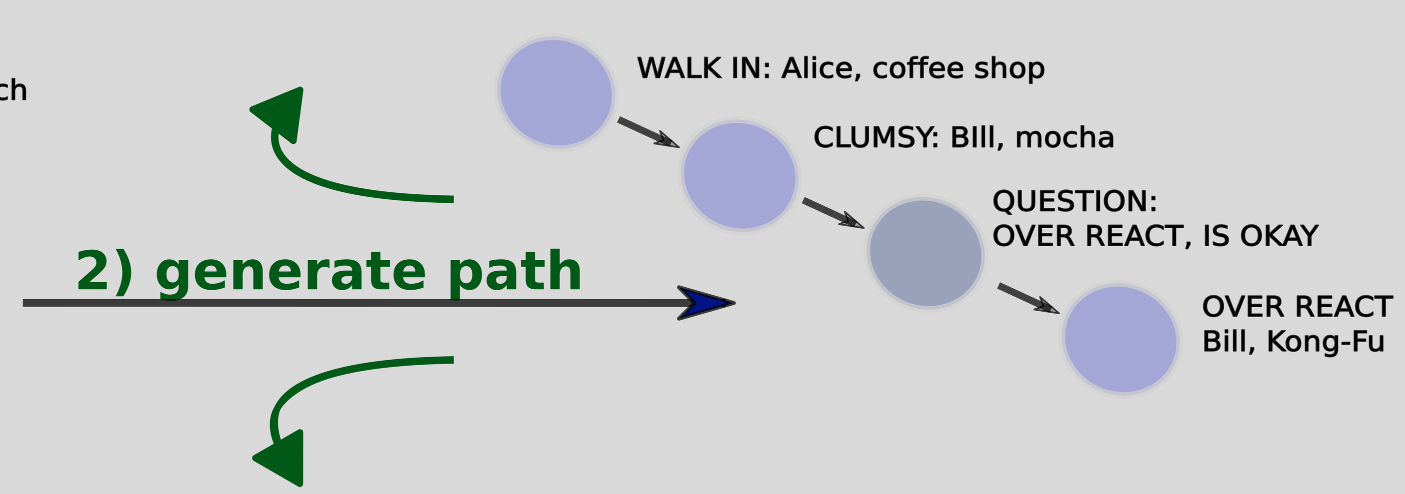
fix probabilities



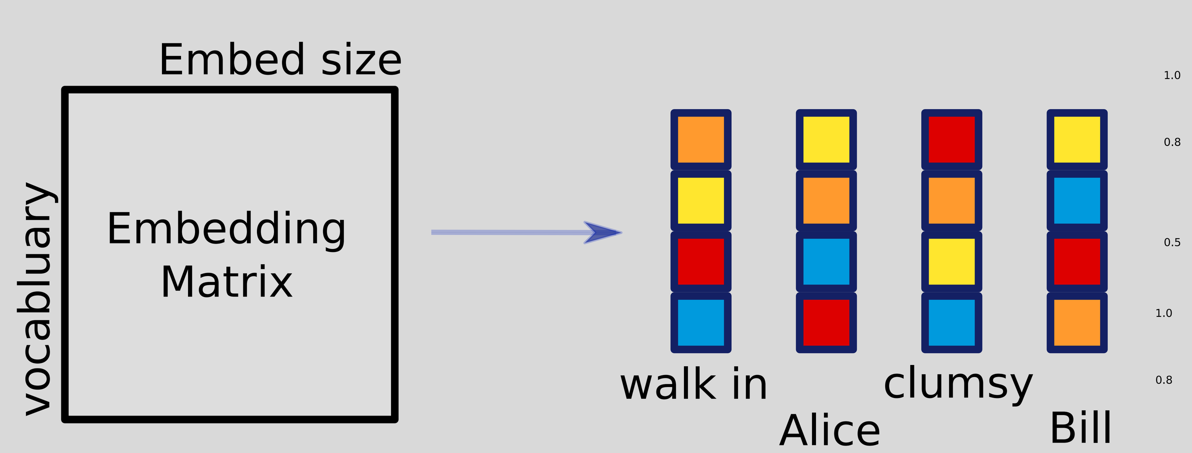


3a) Encode human task

2) generate path



3b) Encode network task

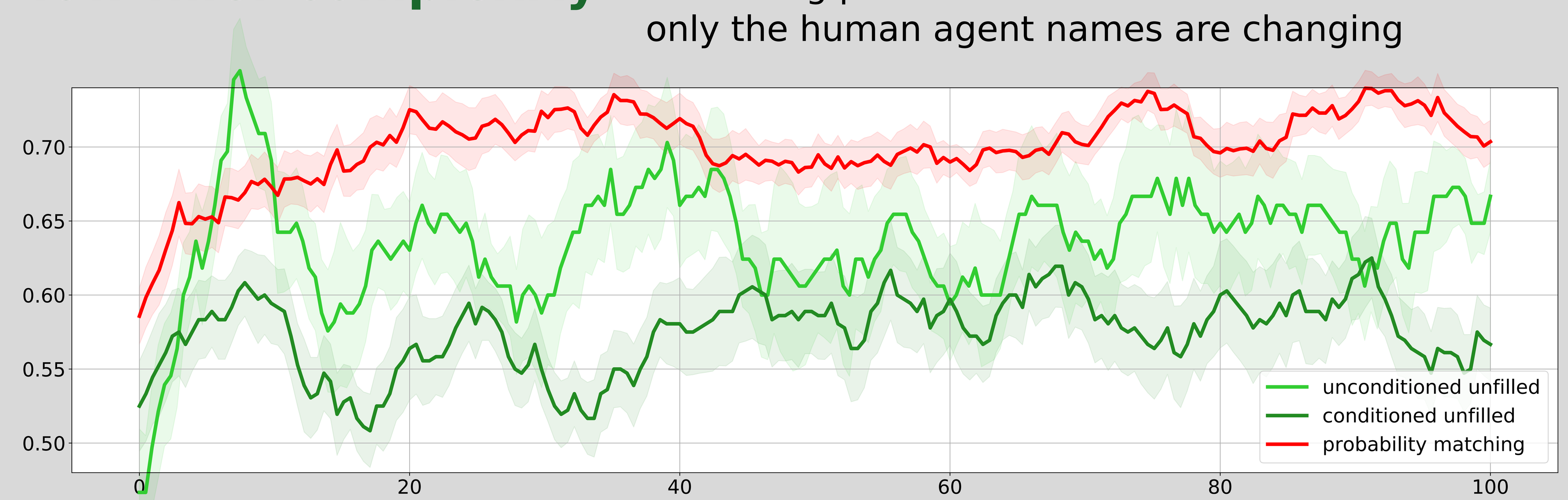


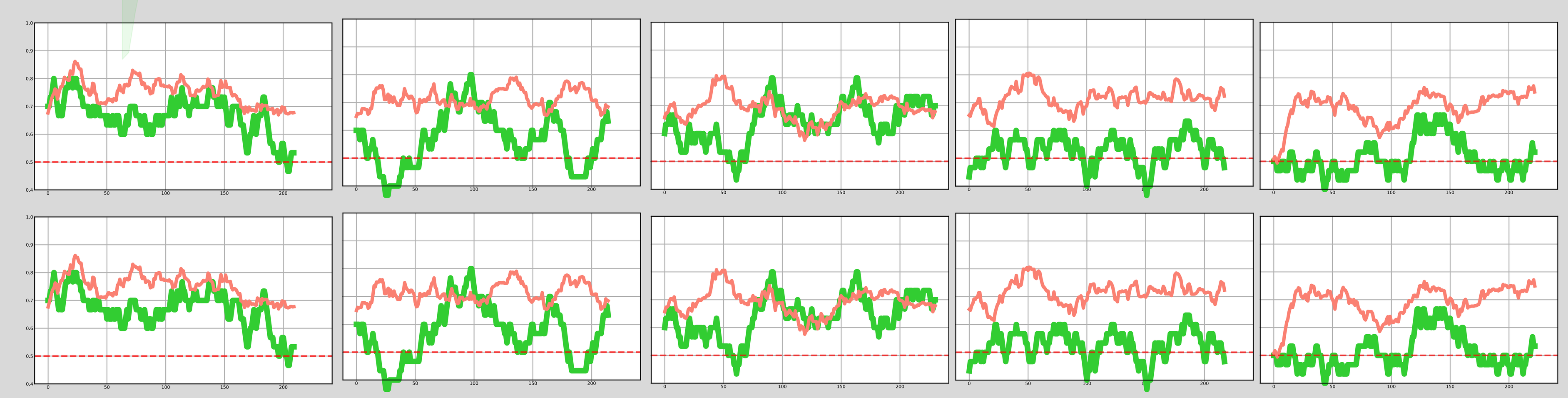
Humans

stop and ask 2AFC
what happens next?

low filler complexity

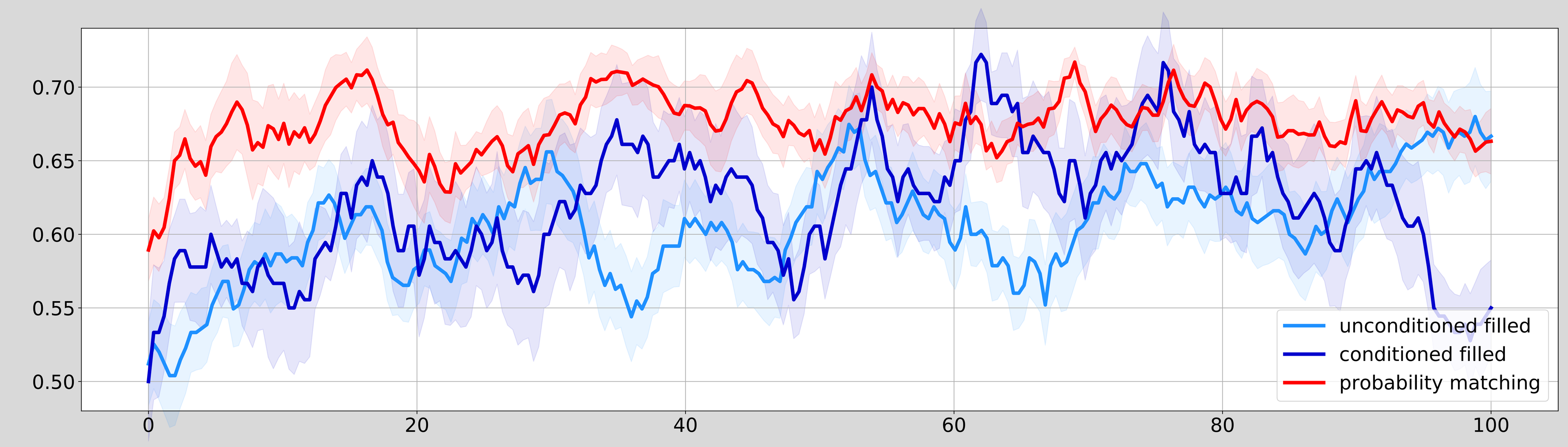
is learning possible in our task?
only the human agent names are changing

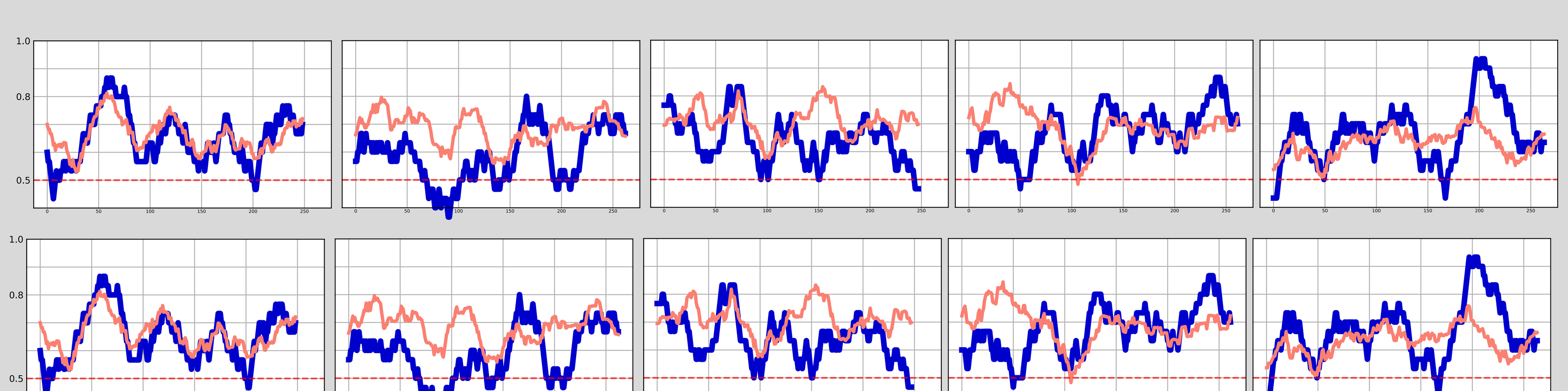




high filler complexity

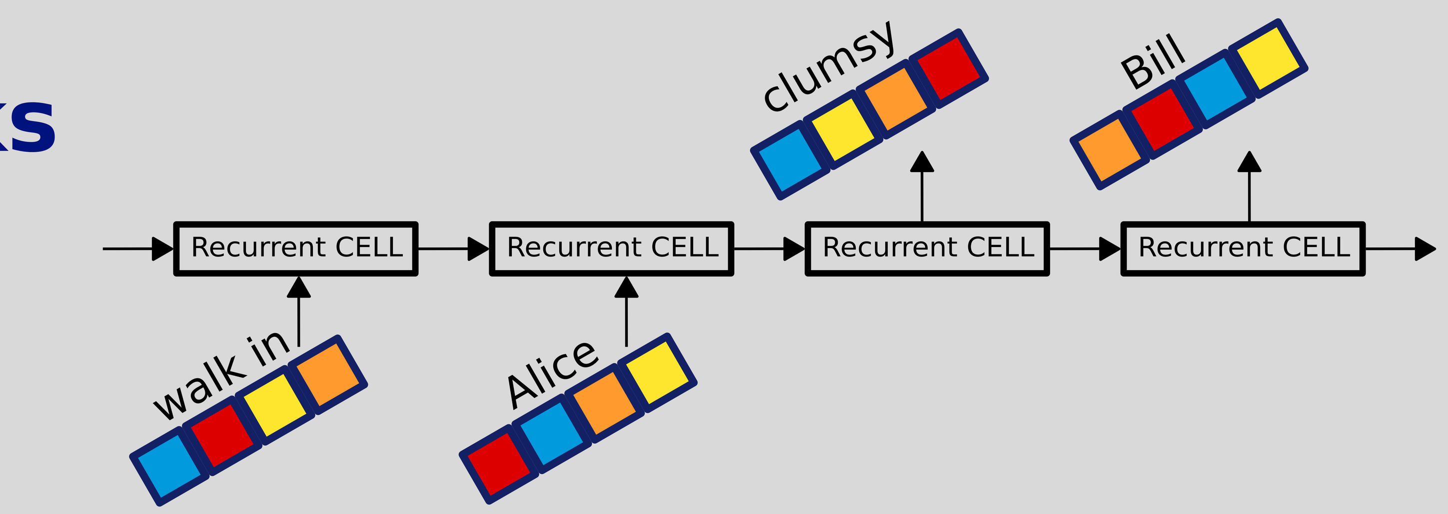
does surface complexity help or hinder learning?
4096 possible different combinations of objects



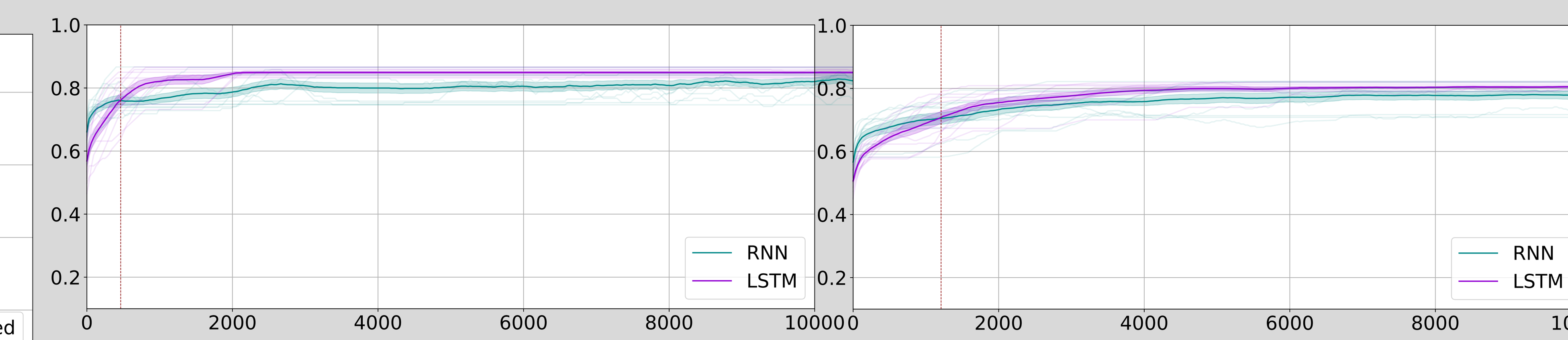


Networks

RNN vs LSTM

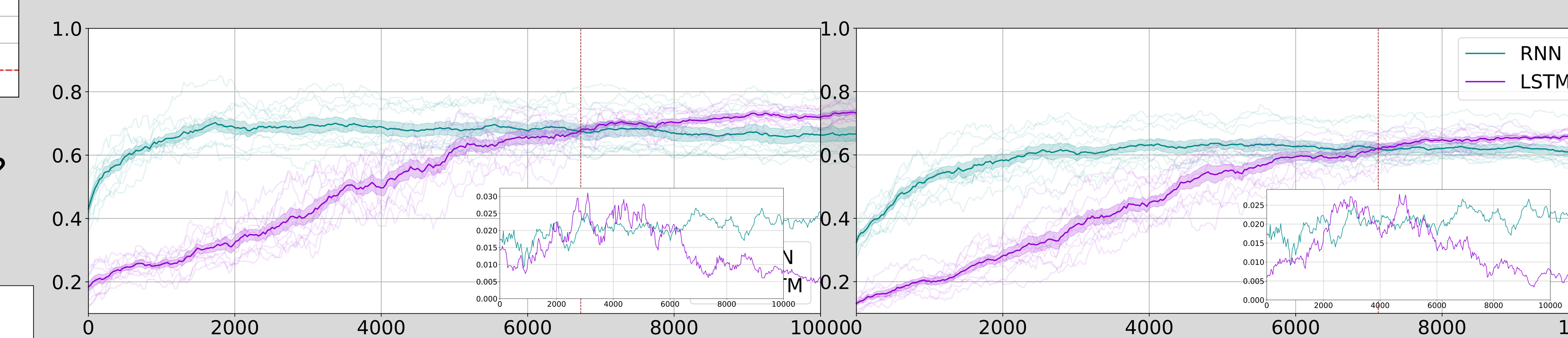


Unconditioned **Conditioned**



* nb diffences in learning dynamics: while RNN kept being perturbed by incorrect responses, LSTM quickly settled into rational performance this evinces different solutions settled onto by different architectures.

Future Directions



* generalization task: similar to before, but now filler vectors were random.
* ~~nb non-monotonicity of second derivative of LSTM learning curves. do different dynamics reflect differences in the structure of hidden representations?~~

* we have begun to investigate the impact of different learning regimes: blocked versus interleaved learning, and curriculum learning. how do these influence learning dynamics, task solutions and latent representations?

Take home

* validation of new task for studying schemas
* naturalistic complexity helps learning
* different mnemonic architectures have different learning dynamics, task solutions ~~and possibly hidden representations~~ (tradeoff?)