Hierarchical statistical learning: Behavioral, neuroimaging, and neural network modeling investigations

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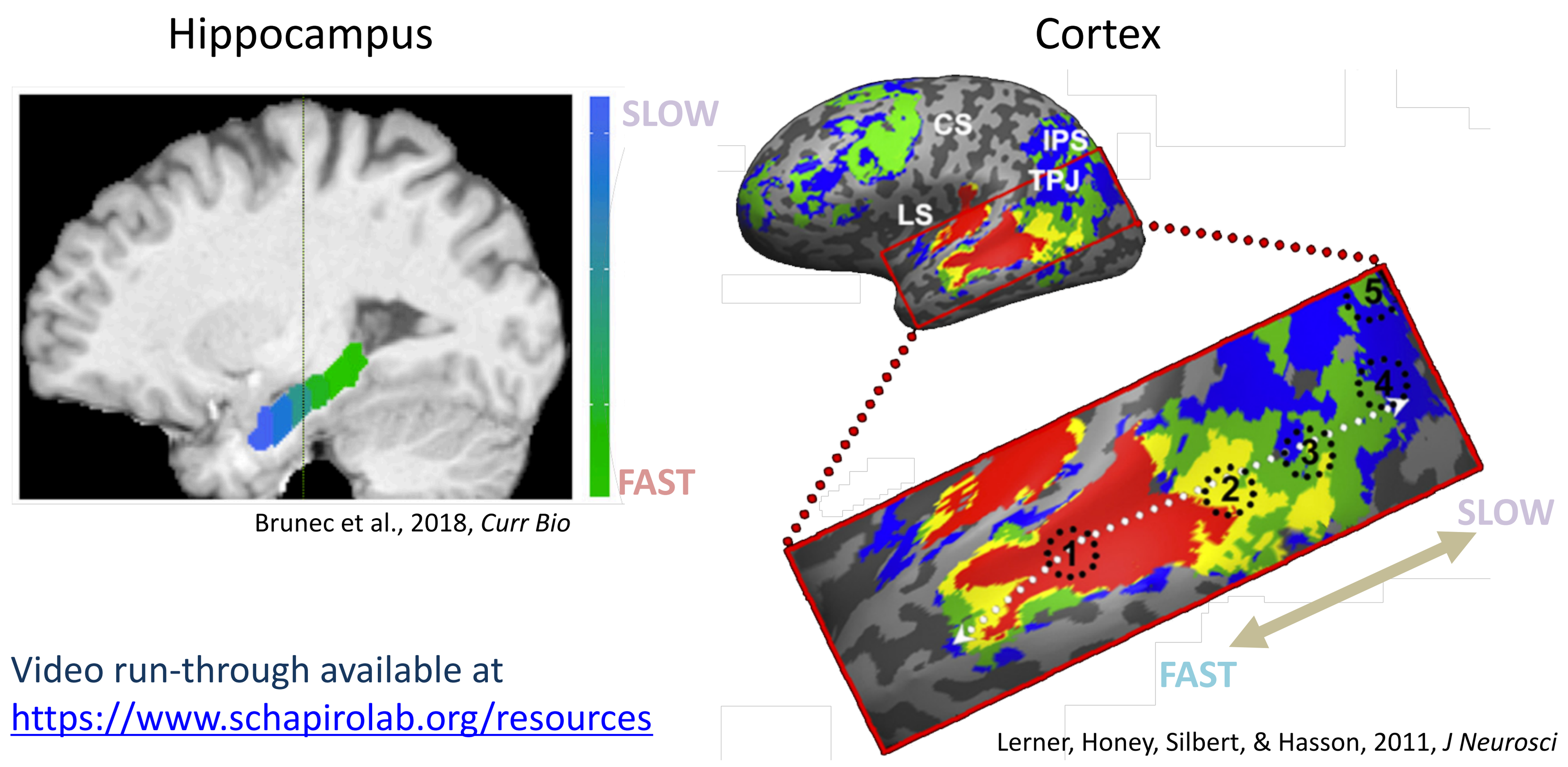
A Hierarchy of Time-Scales in the Brain

- How is sequential structure represented at different hierarchical levels in the brain?
- Combine statistical learning paradigm with neuroimaging: greater control than naturalistic video[1] or audio[2]
- Use finer-grained manipulations to assess cortical encoding of sensory dependencies across time[3]

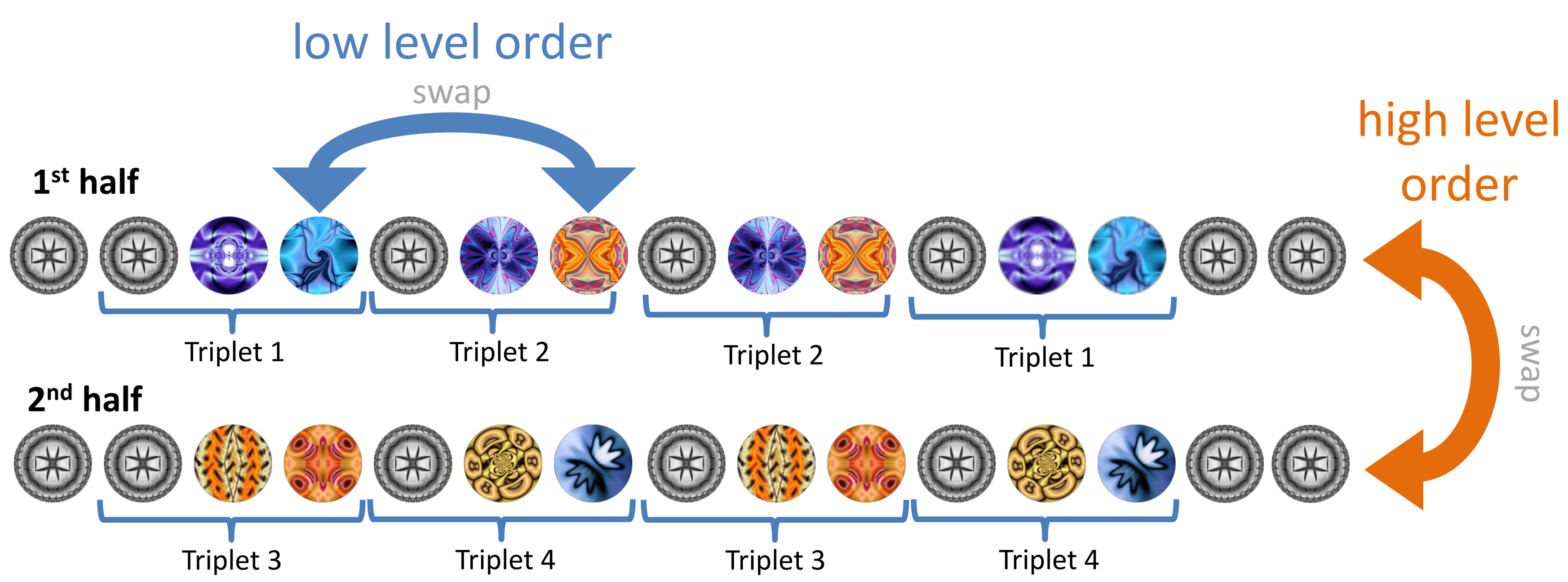


Brunec et al., 2018, *Curr Bio*

Lerner, Honey, Silbert, & Hasson, 2011, *J Neurosci*

Video run-through available at
https://www.schapirolab.org/resources

Statistical Learning Paradigm



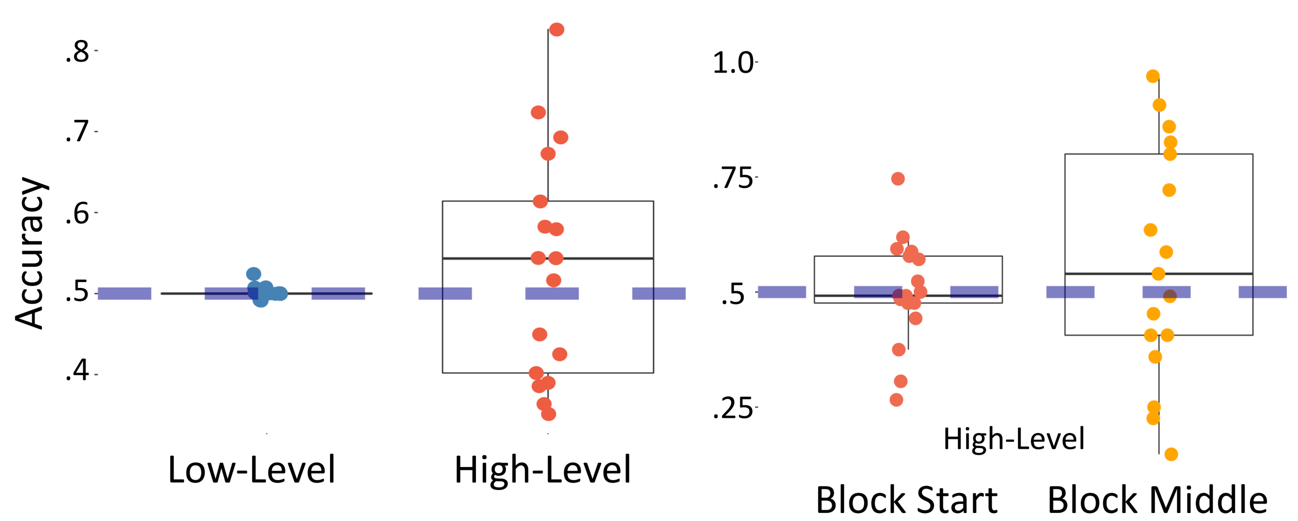
context image = 

Behaviorial Experiment: Methodological Details

- N = 17, exposed to sequences over 4 sessions (~20,000 images / participant)
- 8 greyscale 'context' images, 8 colored images
- Task = warm/cool color detection (50% warm) on colored images, no button press for greyscale
- For human experiment only: context image appears exactly 4 times at start, middle, end of block, triplets immediately follow each other (for modeling, input more variable to prevent overfitting)
- 80% of blocks follow both high and low level order determined by context image
- 20% of blocks follow opposite order rule (10% high level, 10% low level) given context
- Post-test: view a short sequence, choose which of two images comes next -- context (in)congruent
  - Low-level order: view first two images in a triplet
  - High-level order:
    - Block start: view 3x context image A, then 5x context image B
    - Block middle: view triplet (starts with context image A) followed by 5x context image A

Humans Implicitly Learn Low and High-Level Sequential Structure

Explicit Knowledge of High and Low Level Order Information:
2-Alternative Forced Choice Post-Test

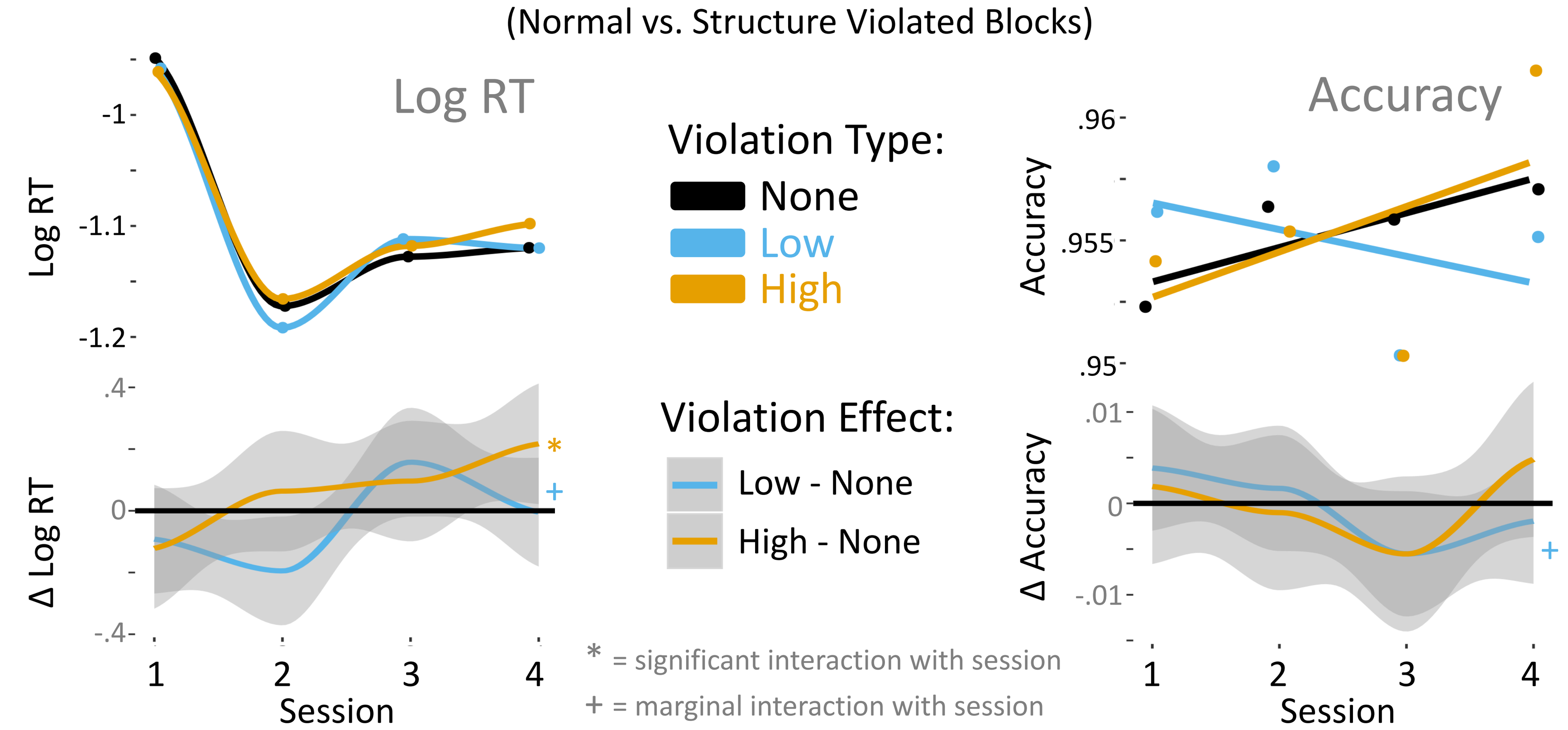


No **explicit** sensitivity to sequence structure at post-test

Subjects may have ignored grey-scale context images (not task relevant)

But as learn, RTs up, accuracy down during violation blocks, suggesting **implicit sensitivity** to low and high level structure

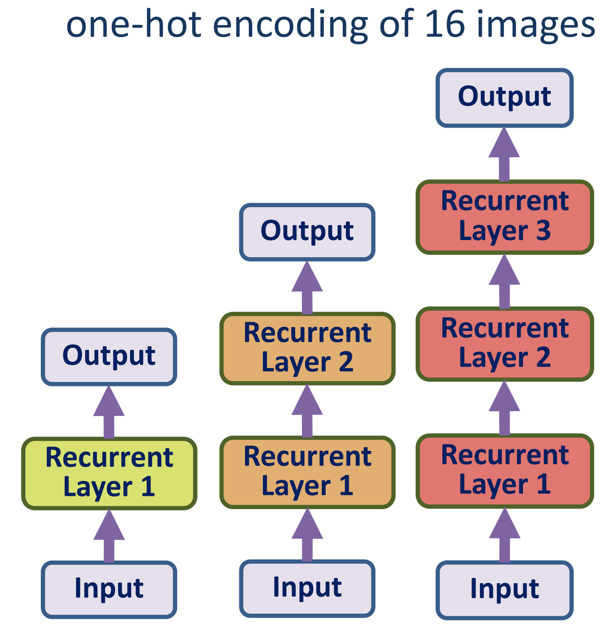
Implicit Knowledge of High and Low Level Order Information:
Response Time and Accuracy in Warm/Cool Color Detection Task
(Normal vs. Structure Violated Blocks)



Modeling Hierarchical Sequence Learning with Recurrent Neural Networks

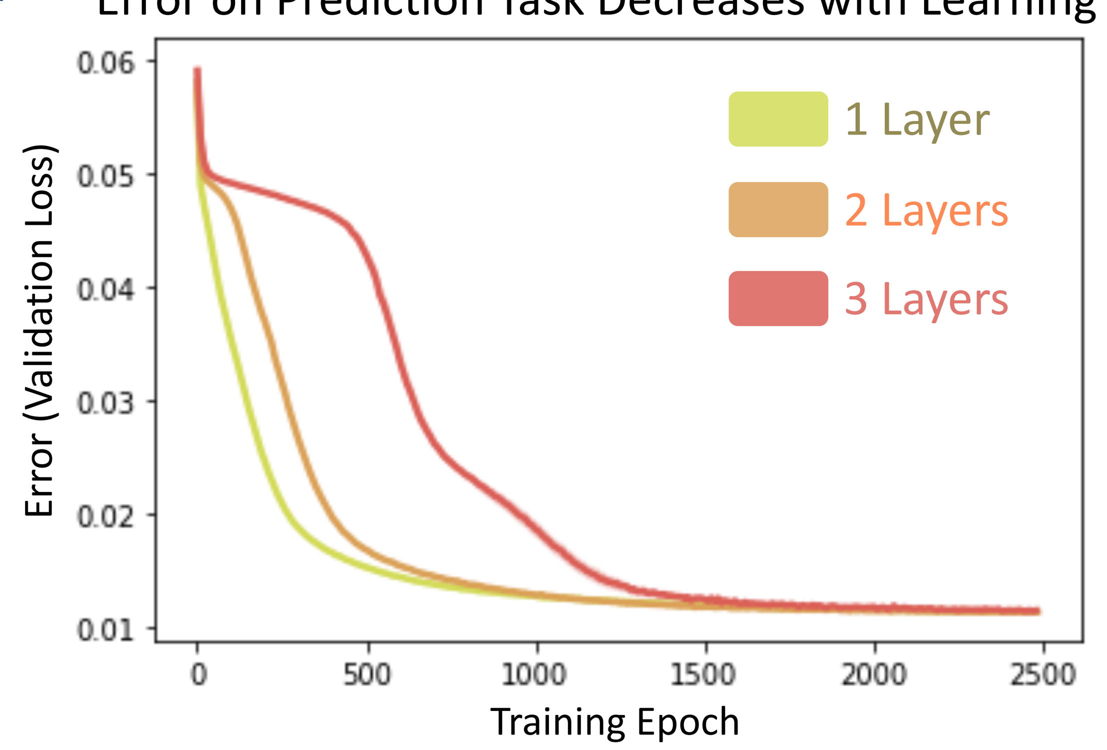
Task: Predict next image
Long-Short Term Memory (LSTM)

Fix total n recurrent units (150)
Vary number of stacked layers (1-3)
50 instances per model type
one-hot encoding of 16 images



All model architectures (1, 2, and 3 recurrent layers) learn to predict the upcoming image.

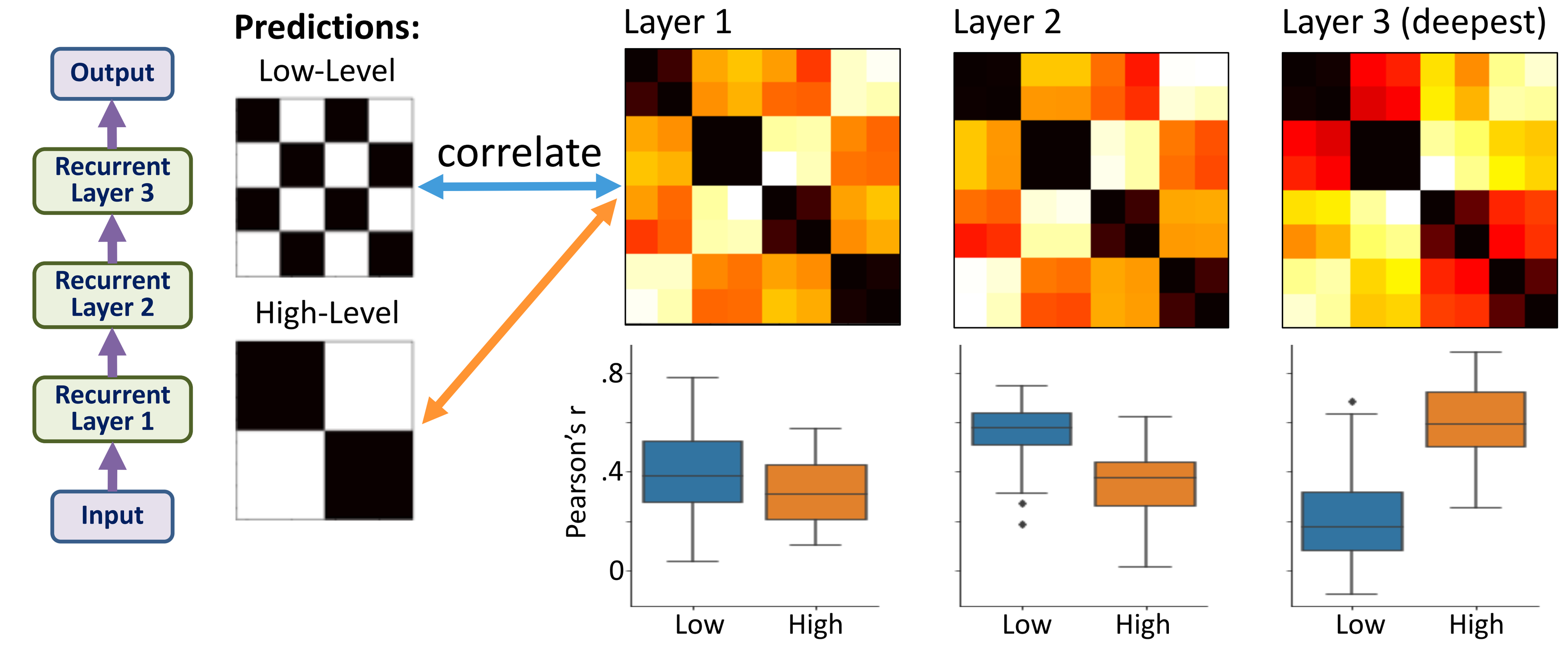
Error on Prediction Task Decreases with Learning



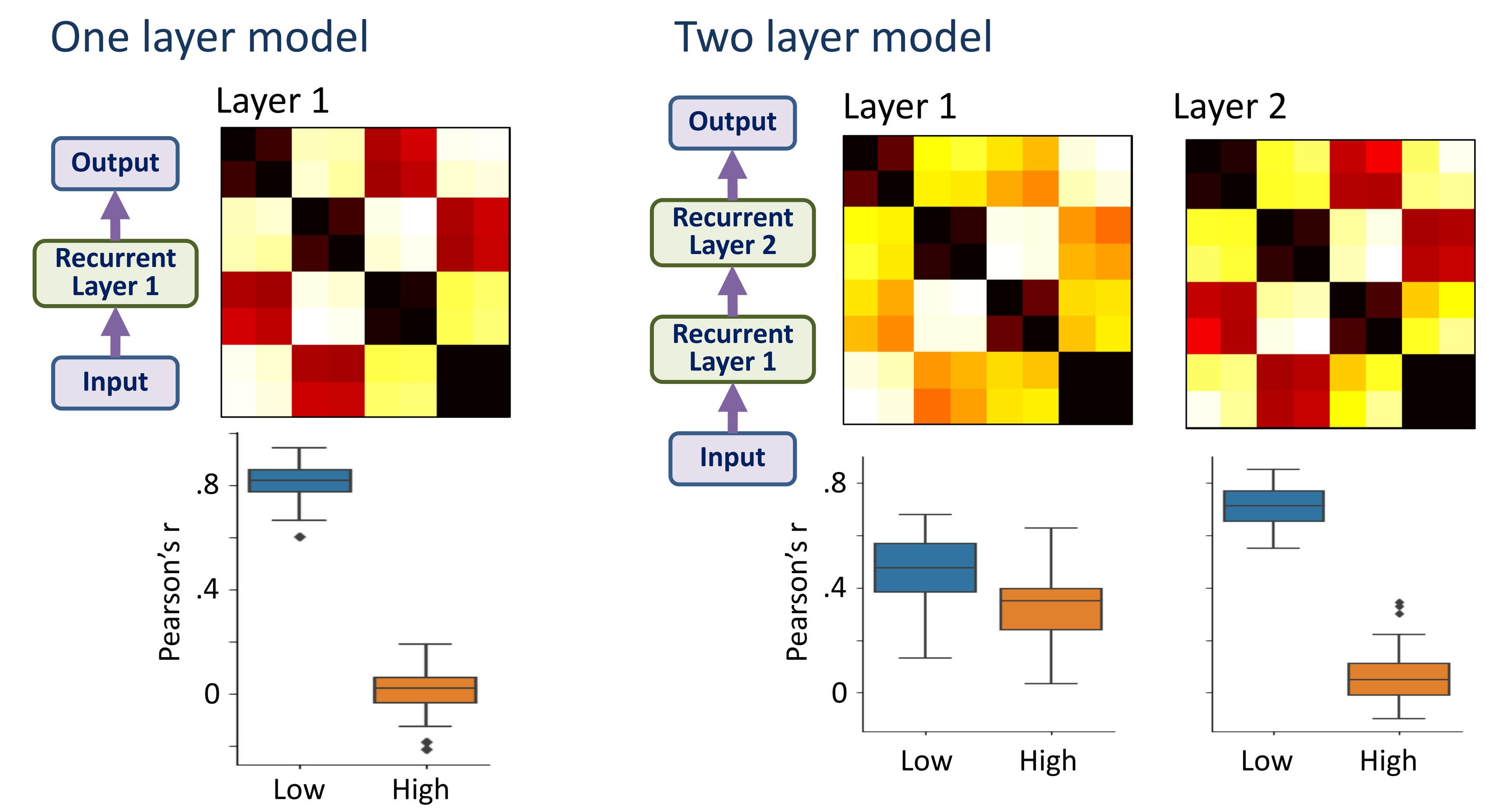
'Deep' Neural Networks Show Temporal Gradient

Deeper layers group context images based on **longer** time-scale order information

Three layer model



Pattern similarity to high-level structure is contingent on sufficient network depth



Conclusions

- Humans show implicit sensitivity to both low and high level sequential structure after extended learning (~20,000 images)
- Deep layers in neural network (LSTM) more sensitive to high-level structure of input, but need sufficient depth

Future directions:

- Further behavioral piloting to improve learning of low & high-level structure
- Model comparison with existing sequential learning models (e.g. HAT[4])
- Collection of fMRI + EEG data
  - EEG during learning – implicit measures of learning low and high level structure
  - fMRI pre-post learning response to context cue images (pattern similarity)
- Comparison with auditory sequence data

References

1. Hasson, U., et al., (2008). *J Neurosci*, *28*(10), 2539-2550.
2. Lerner, Y., Honey, C. J., Silbert, L. J., & Hasson, U. (2011). *J Neurosci*, *31*(8), 2906-2915.
3. Hasson, U., Chen, J., Honey, C. J. (2015). *Trends Cog Sci*, *19*(6), 304-313.
4. Chien, H.-Y. S. & Honey, C. J. (2020). *Neuron*, 106, 1-12.

Acknowledgements

This work was supported by NIH grant R01DC00920 awarded to S.T-S. and by NIH grant 1F32MH123002-01 awarded to C.M.S. Thank you to Elisabeth Karuza for valuable support in developing this project.