

# Hierarchical statistical learning:

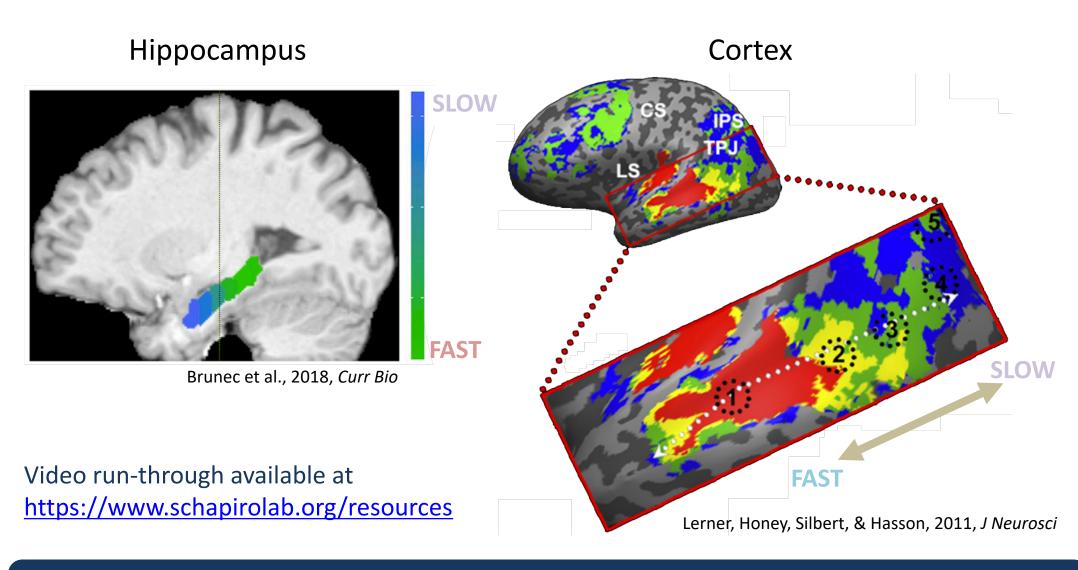
# Behavioral, neuroimaging, and neural network modeling investigations

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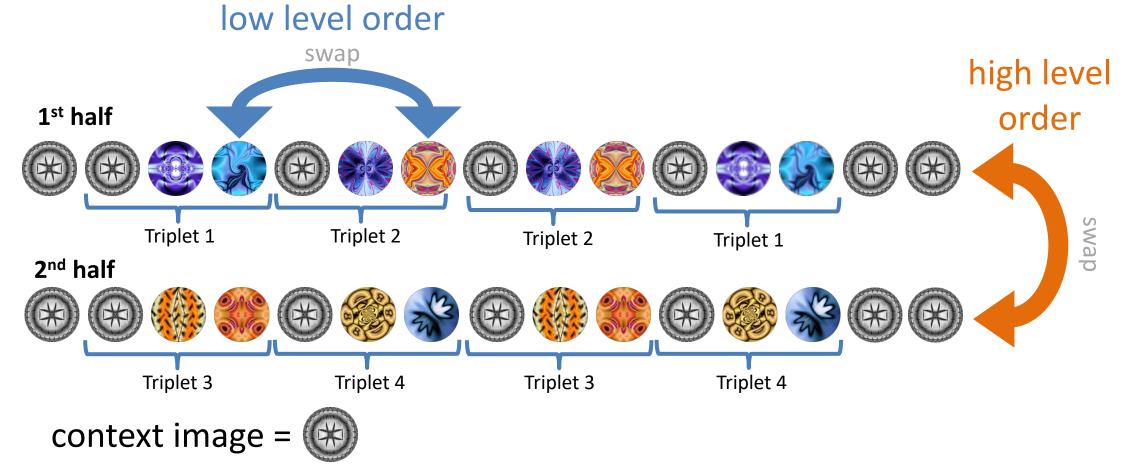
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## A Hierarchy of Time-Scales in the Brain

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



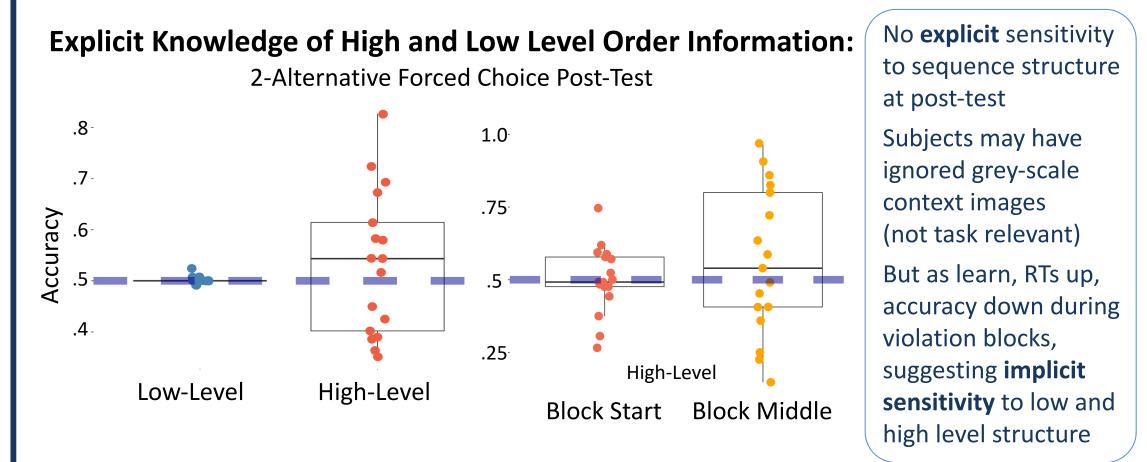
## **Statistical Learning Paradigm**



### Behaviorial Experiment: Methodological Details

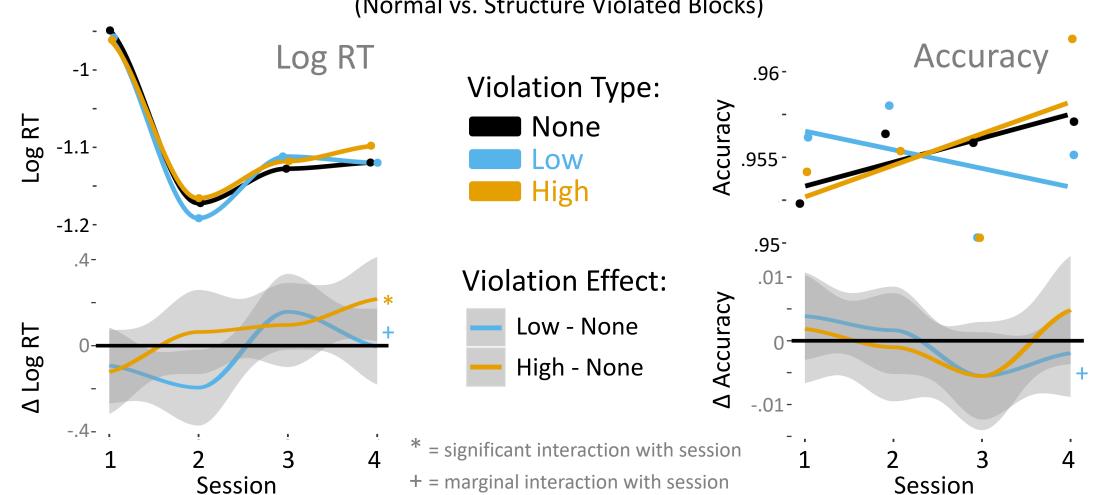
- N = 17, exposed to sequences over 4 sessions (~20,000 images / participant)
- 8 greyscale 'context' images, 8 colored images
- Task = warm/cool color detection (50% warm) on colored images, no button press for greyscale
- For human experiment only: context image appears exactly 4 times at start, middle, end of block, triplets immediately follow each other (for modeling, input more variable to prevent overfitting)
- 90% of blocks follow high and low level order determined by context image
- 10% of blocks follow opposite order rule (high or 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

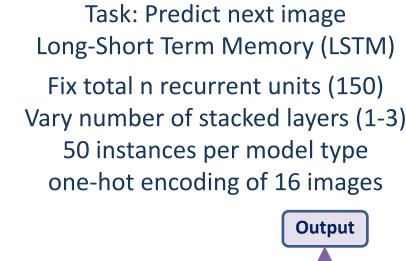


#### Implicit Knowledge of High and Low Level Order Information:

Response Time and Accuracy in Warm/Cool Color Detection Task (Normal vs. Structure Violated Blocks)



# **Modeling Hierarchical Sequence Learning** with Recurrent Neural Networks



Recurrent

Layer 2

Recurrent

Layer 1

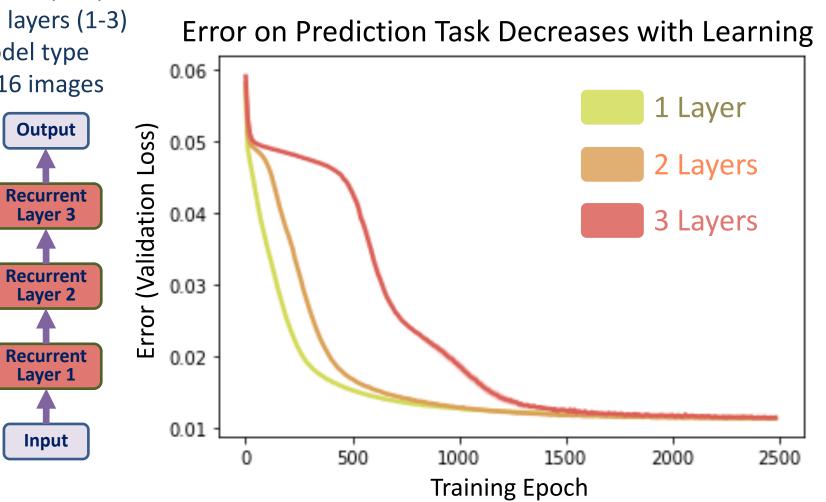
Output

Recurrent

Layer 1

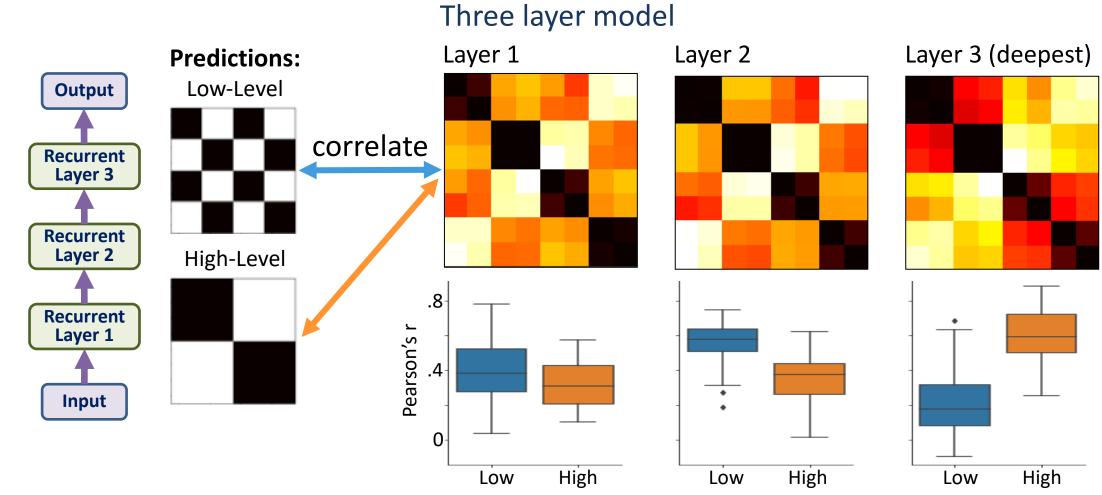
Input

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

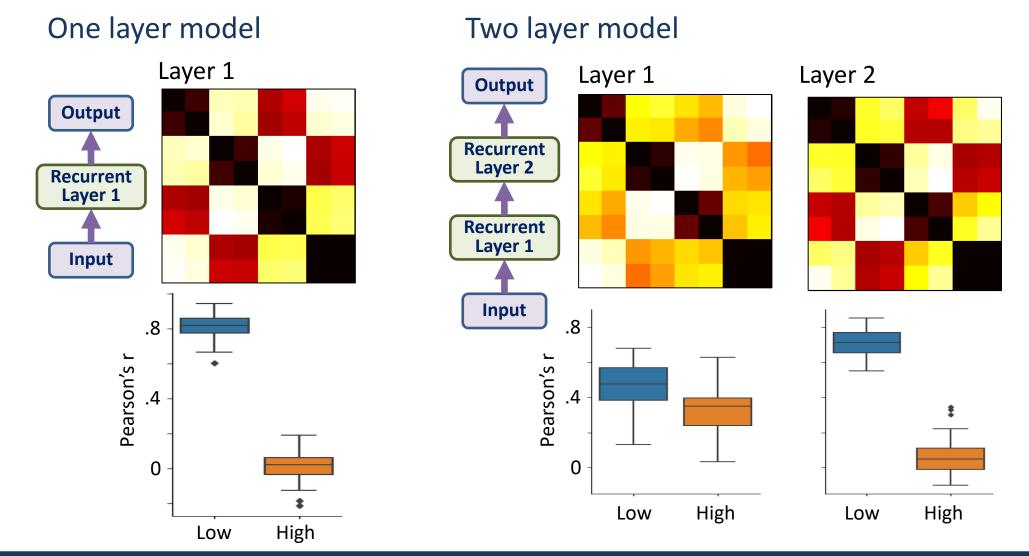


## 'Deep' Neural Networks Show Temporal Gradient

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



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 highlevel 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<sup>[4]</sup>)
- 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

- **Acknowledgements**
- 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.

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.