Associative learning influences representational structure of objects in the ventral visual pathway

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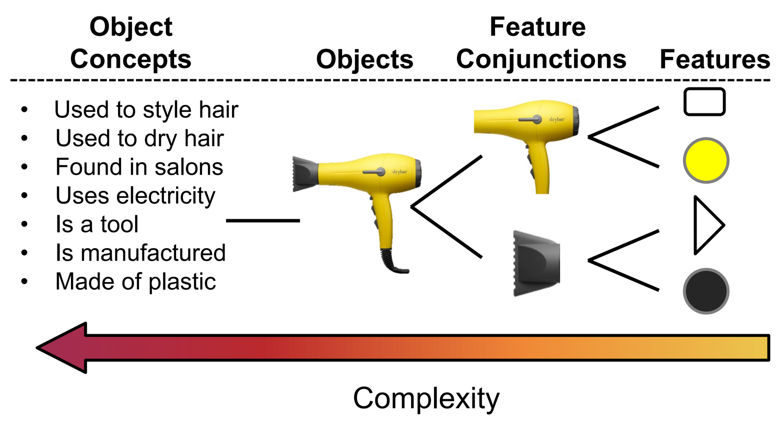
Background

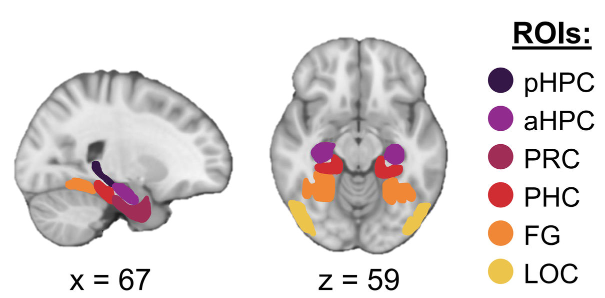
- The ventral visual pathway is an object processing hierarchy that enables adaptive behavior by mapping visual input (e.g., shape) onto semantic knowledge (e.g., function)[1]
- Structures within this pathway, particularly lateral occipital cortex (LOC), fusiform gyrus (FG) and perirhinal cortex (PRC), have been linked to coding of visual and/or semantic object properties[2,3]



The role of these structures in representing visual information and semantic knowledge is thought to be distinct from the role of the hippocampus (HPC)[4] and parahippocampal cortex (PHC)[5,6] which captures arbitrary contextual associations in service of episodic memory

Question

Does learning arbitrary associative structure among visually or semantically similar objects influence how they are represented in the ventral visual pathway, PHC, and in the HPC?



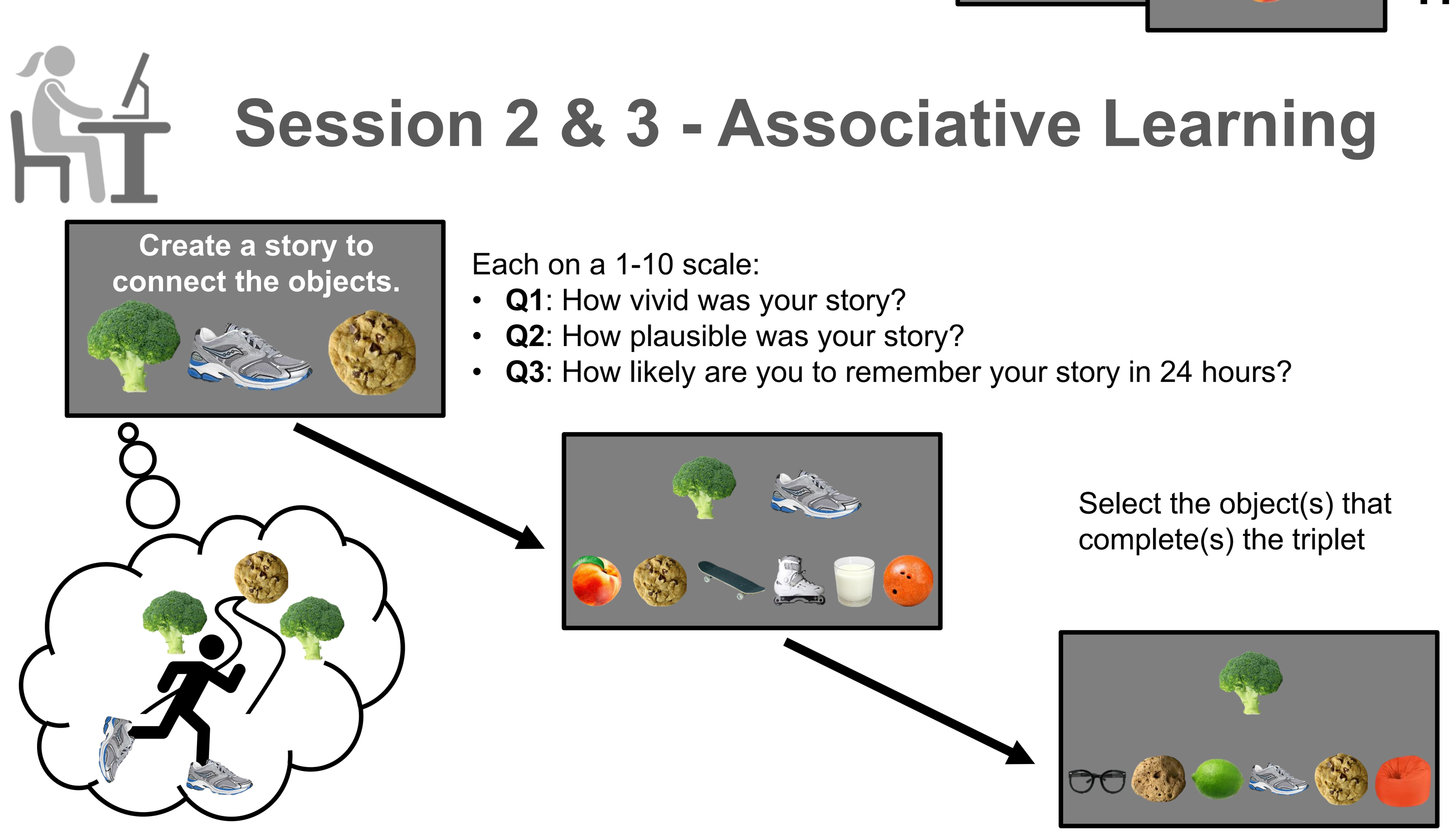
Experimental Design

Each participant (N = 20, M_{age} = 21, Women = 14) engaged in a four-session experiment.

- Day 1: participants completed a scanned 1-back task using images of objects that were either visually similar (e.g., cookie and rock), semantically similar (e.g., cookie and milk), or unrelated (cookie and eyeglasses)
- Day 2 & 3: participants learned arbitrary associations among objects (i.e., 14 triplets with limited visual and/or semantic similarities)
- Day 4: participants completed a second scanned 1-back task, which allowed us to characterize learning-related changes in the representational structure of our targeted areas

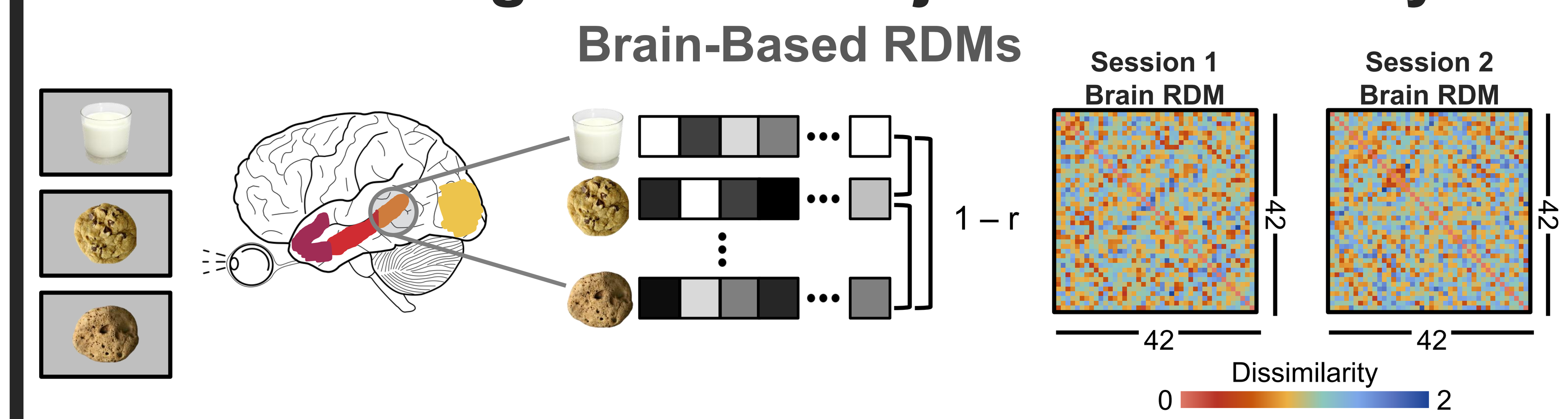
Session 1 & 4 - 1-Back fMRI Task

Session 2 & 3 - Associative Learning



Characterizing Intrinsic Object Dissimilarity

Brain-Based RDMs



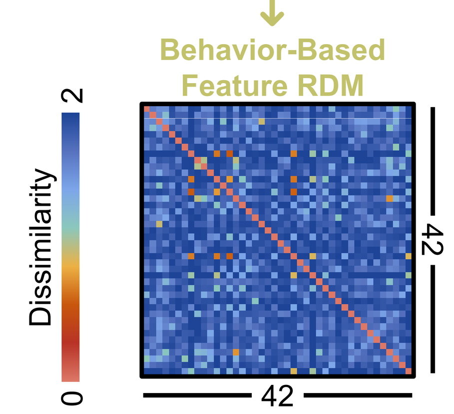
Behavior-Based RDMs

Feature Generation Task

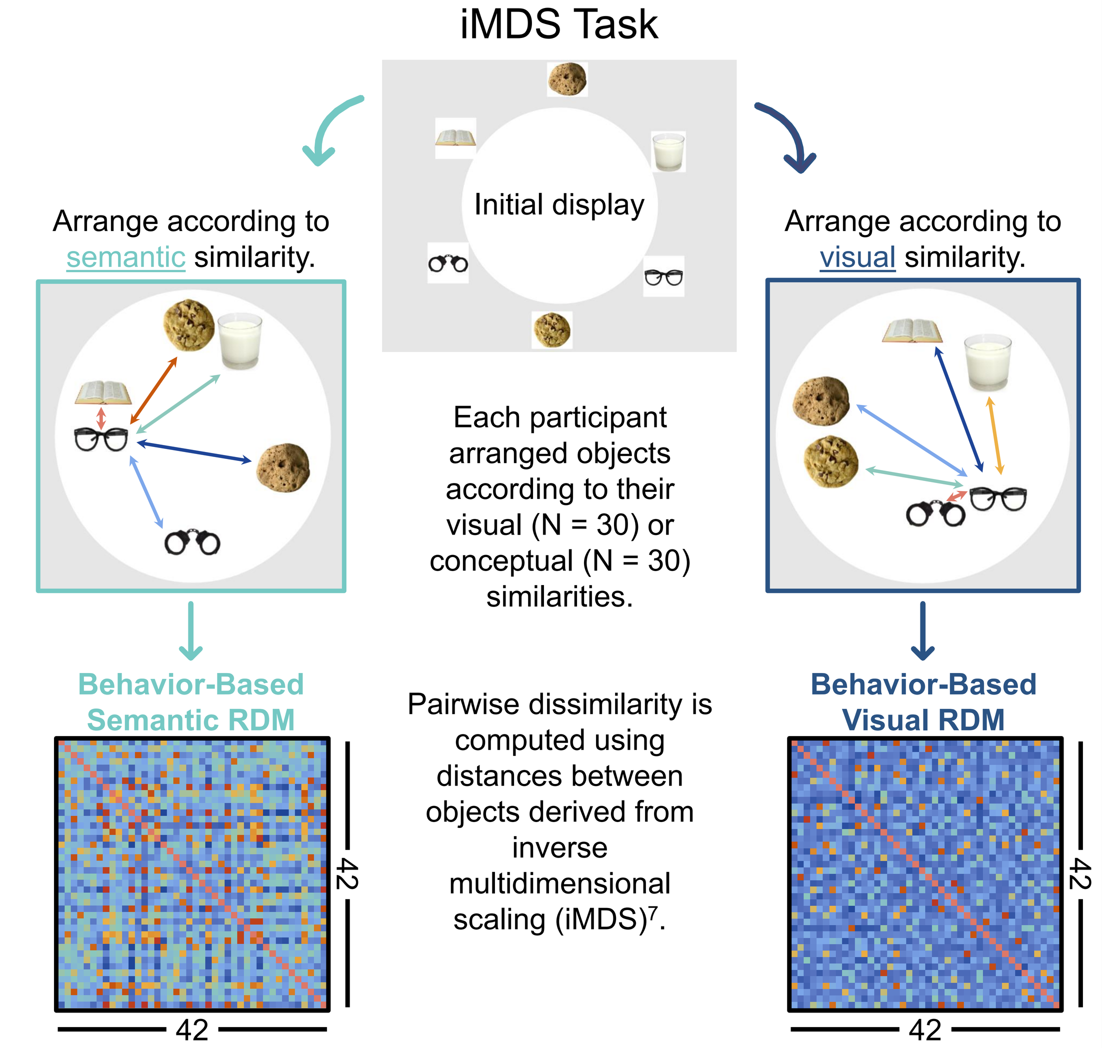
Each participant (N = 840, Mechanical Turk) generated a list of features that characterized a subset of objects.

Feature data were obtained from 20 participants for each of the 42 objects.

features	frequency		
	cookie	rock	milk
is edible	20	0	20
rough texture	9	19	0
white in color	0	0	20
a snack	19	0	11
is small	12	18	0



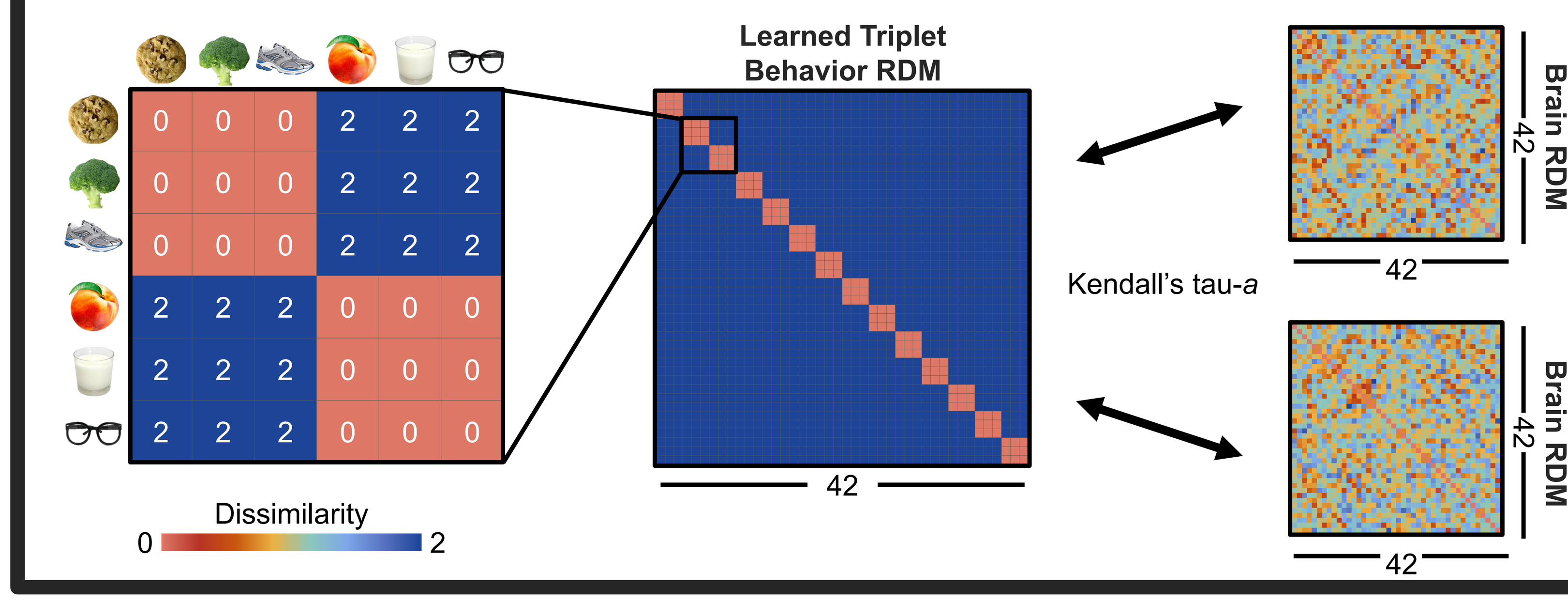
iMDS Task



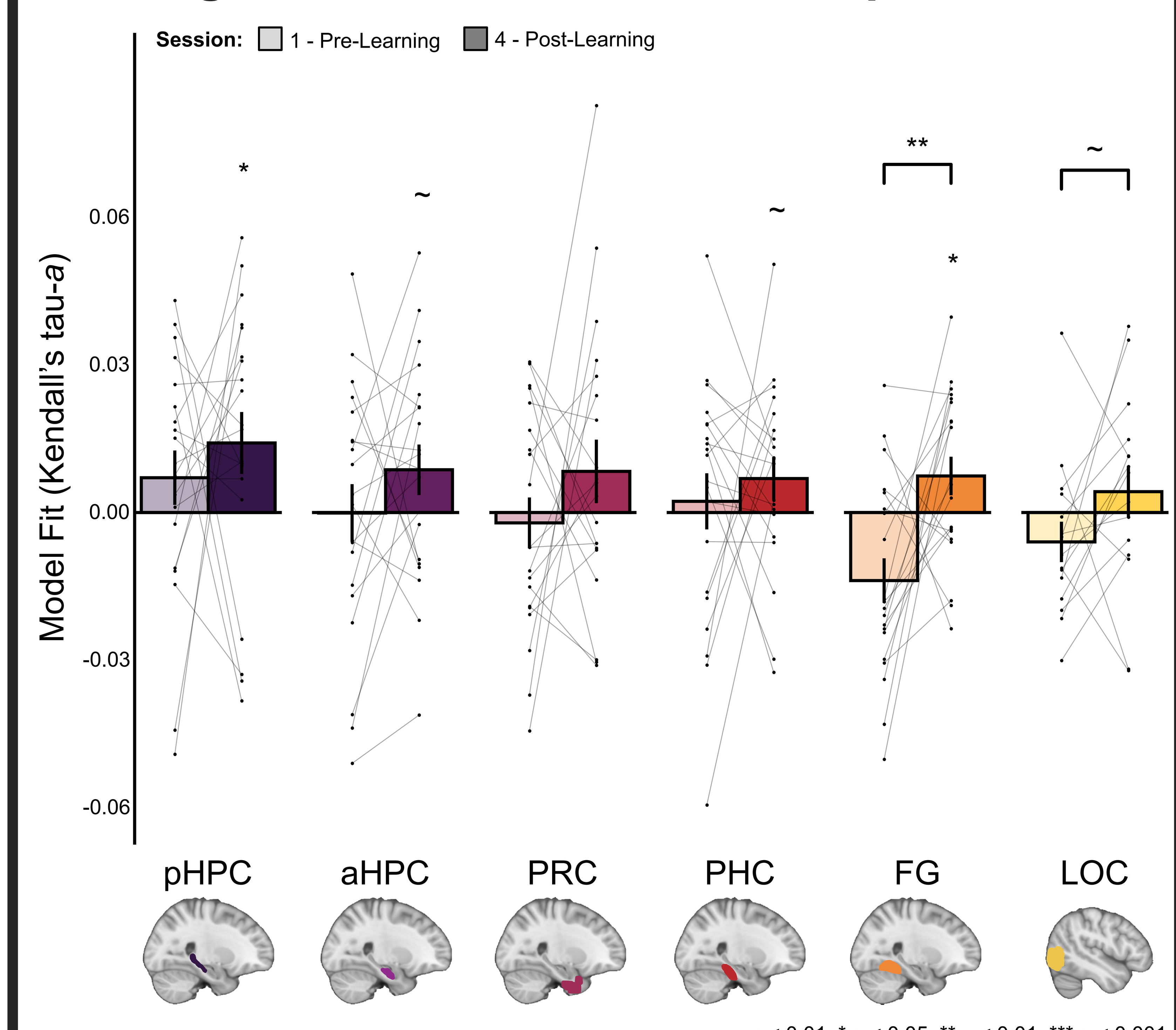
Each participant arranged objects according to their visual (N = 30) or conceptual (N = 30) similarities.

Pairwise dissimilarity is computed using distances between objects derived from inverse multidimensional scaling (iMDS)[7].

Characterizing Associative Learning

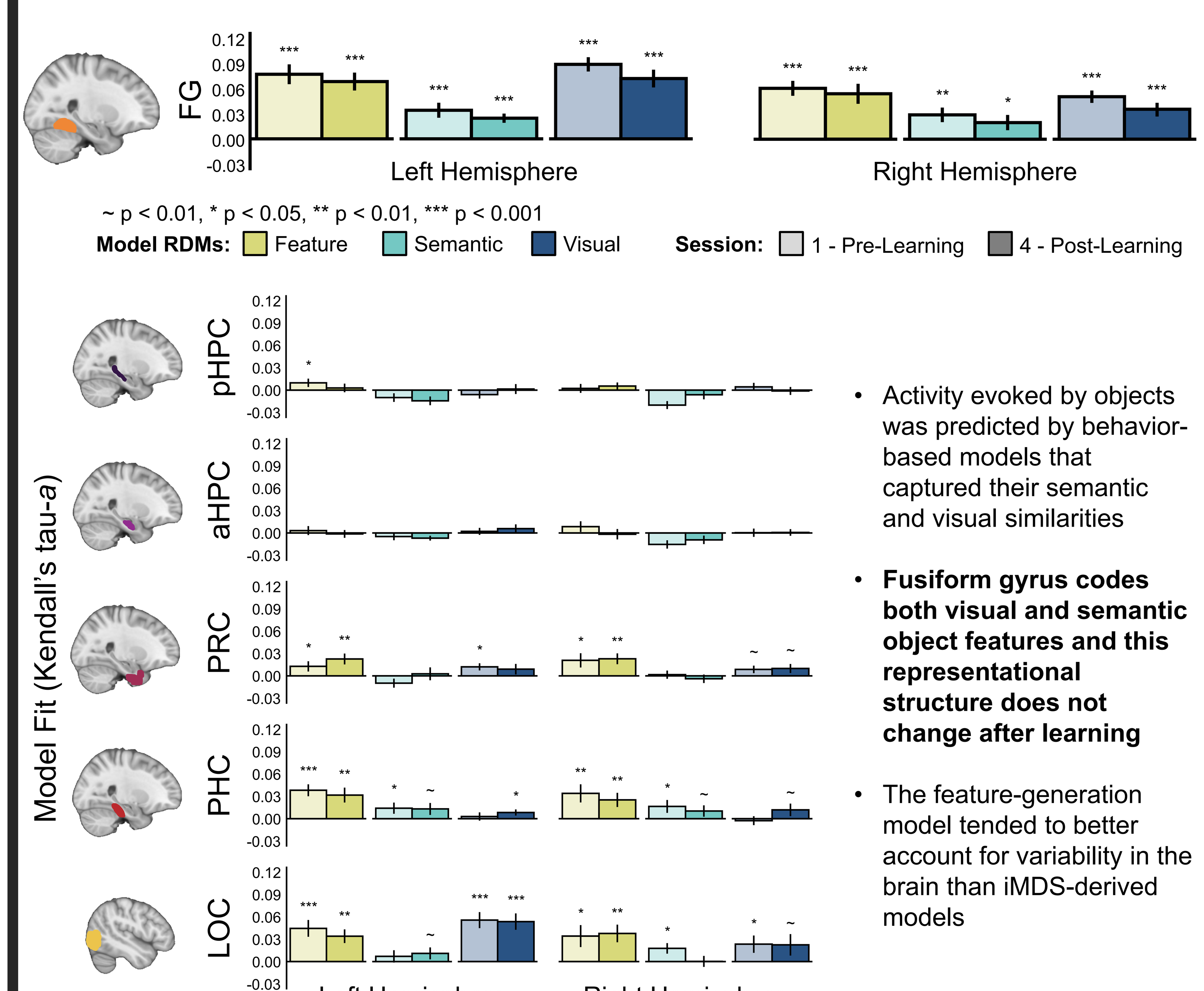


Coding of Associative Relationships



- **Representational structure in left fusiform gyrus captures associations among arbitrary triplets**
- Regions in the right hemisphere did not express evidence of learning

Coding of Semantic and Visual Features



- Activity evoked by objects was predicted by behavior-based models that captured their semantic and visual similarities
- **Fusiform gyrus codes both visual and semantic object features and this representational structure does not change after learning**
- The feature-generation model tended to better account for variability in the brain than iMDS-derived models

Summary

- Activity patterns in left fusiform gyrus simultaneously capture the semantic, visual, and learned relationships among arbitrarily associated objects, despite the fact that these properties are fundamentally different (abstract, sensory, and associative).
- Fusiform gyrus incorporated associative relationships learned on days 2 and 3 while preserving the representation of intrinsic semantic and visual features.
- Overall pattern of results is suggestive of a complex, multidimensional code that can flexibly accommodate acquired knowledge that is orthogonal to its pre-existing structure.

References: [1]Martin, C.B., & Barense, M.D. (2023). *Annu. Rev. Vis. Sci.*, [2]Martin, C.B., et al., (2018). *eLife*, [3]Clarke, A., & Tyler, L. K. (2014). *J Neurosci.*, [4]Davachi, L. (2006). *Curr. Opin. Neurobiol.*, [5]Solomon, S.H., et al., (2024). *bioRxiv*, [6]Aminoff, E.M., Kveraga, K., & Bar, M. (2013). *TiCS*, [7]Kriegeskorte, N., & Mur, M. (2012). *Front. psychol.*