

Factor Topographic Latent Source Analysis: Factor Analysis for Brain Images

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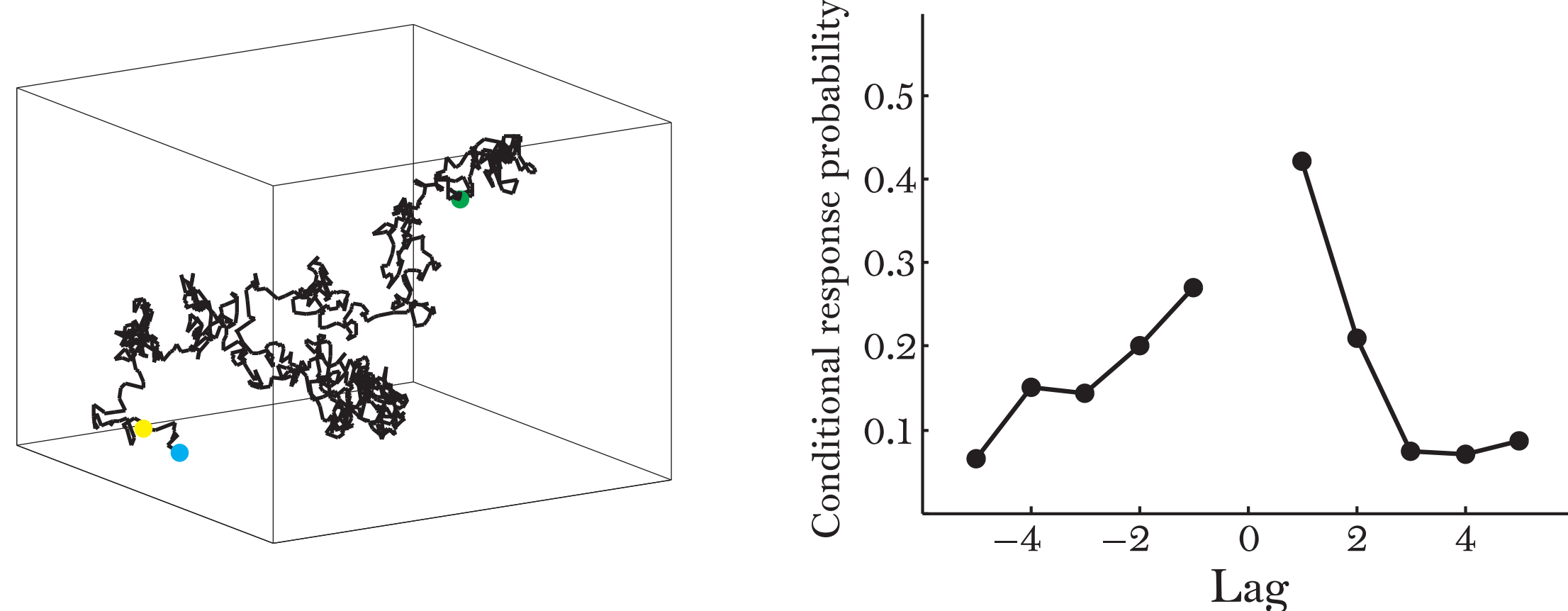
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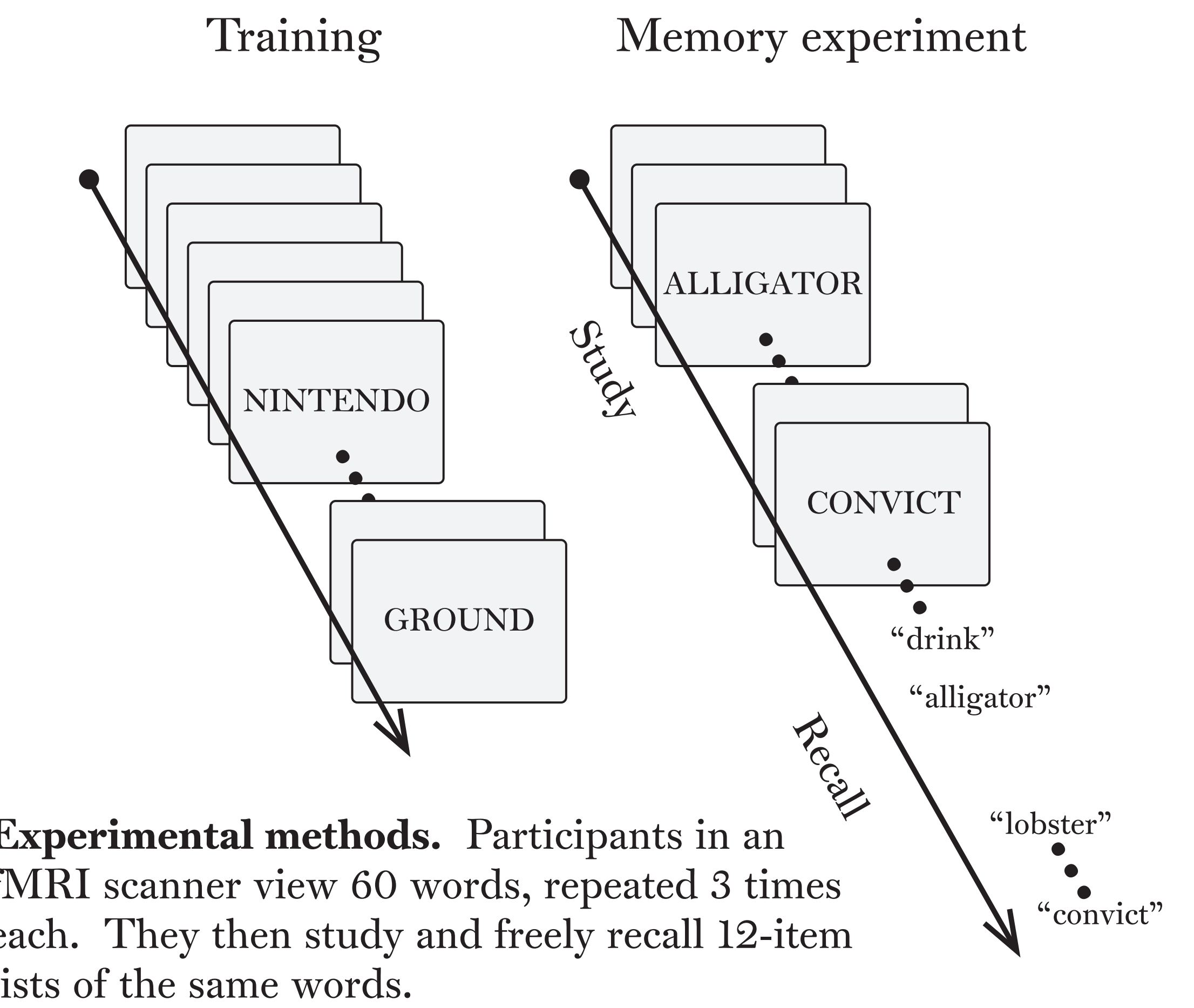
Overview & experimental methods

Context-based theories of memory posit that items on a studied list become associated with the mental contexts in which they are experienced.

We present a framework for tracking the neural correlates of individual items⁶ and the contexts in which they are experienced,⁵ during individual study and recall events.



Context-based theories of memory. Context drifts gradually over time and becomes associated with each experienced event, giving rise to the contiguity effect in free recall.

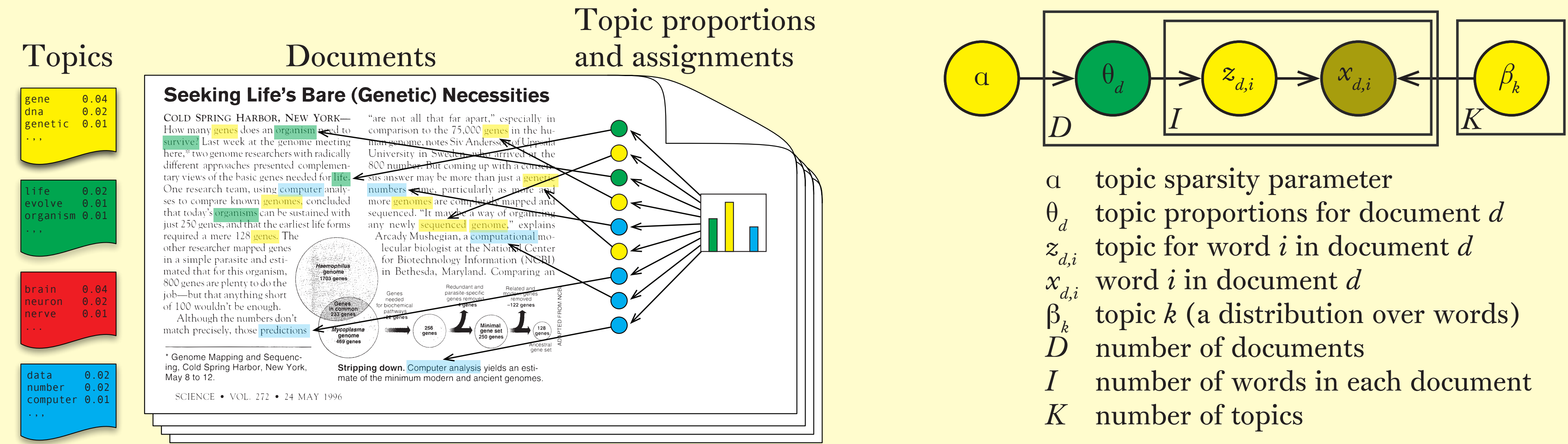


Experimental methods. Participants in an fMRI scanner view 60 words, repeated 3 times each. They then study and freely recall 12-item lists of the same words.



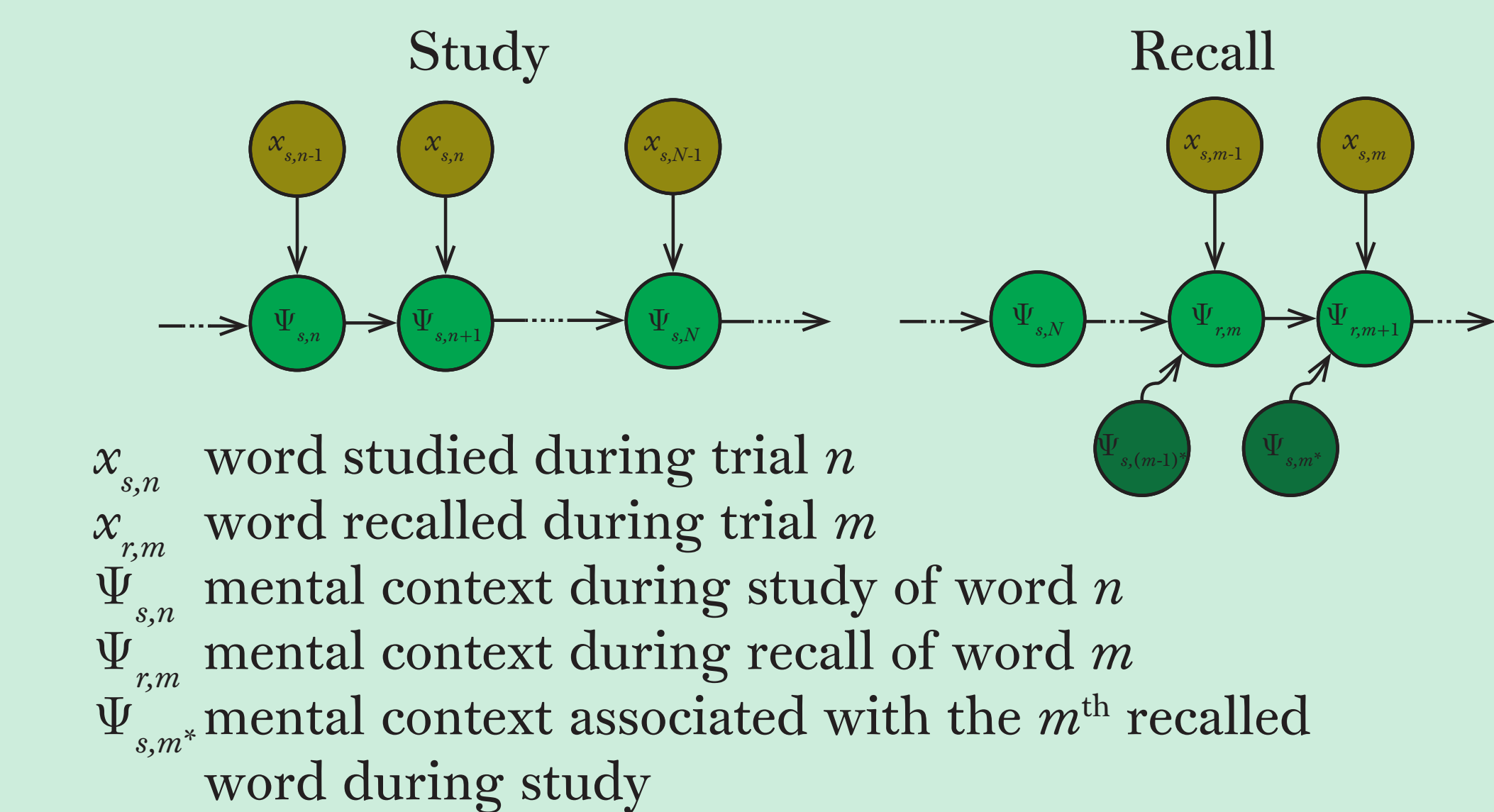
Towards a unified model of corpora and cognition. Our approach attempts to infer the evolving state of mental context using text, behavioral, and neural data.

Model of word meanings



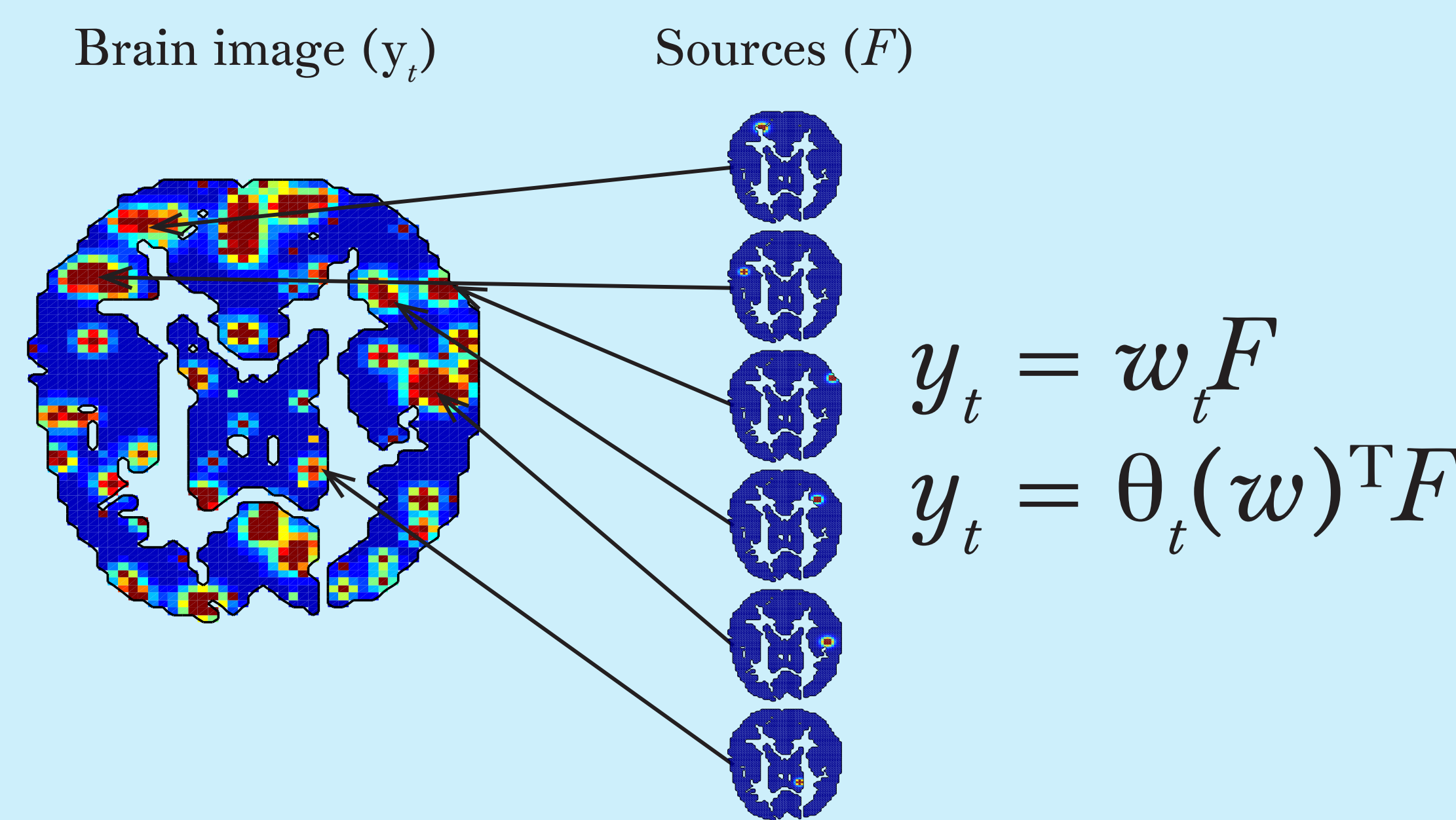
Latent Dirichlet Allocation. Topic vectors are derived by analyzing a collection of documents.¹ LDA entails fitting the latent (lightly shaded) variables given the observed (darkly shaded) words in the documents.

Model of mental context



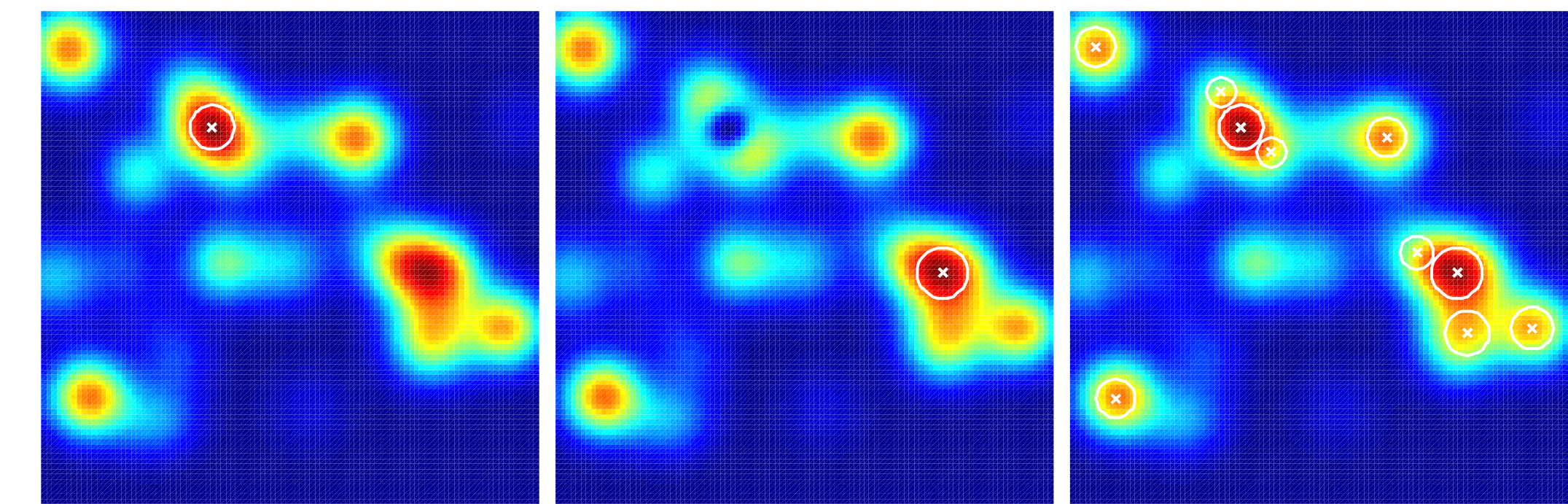
Temporal Context Model. Mental context vectors are weighted averages of topic vectors for studied and recalled words.^{3,8}

Model of neural activity

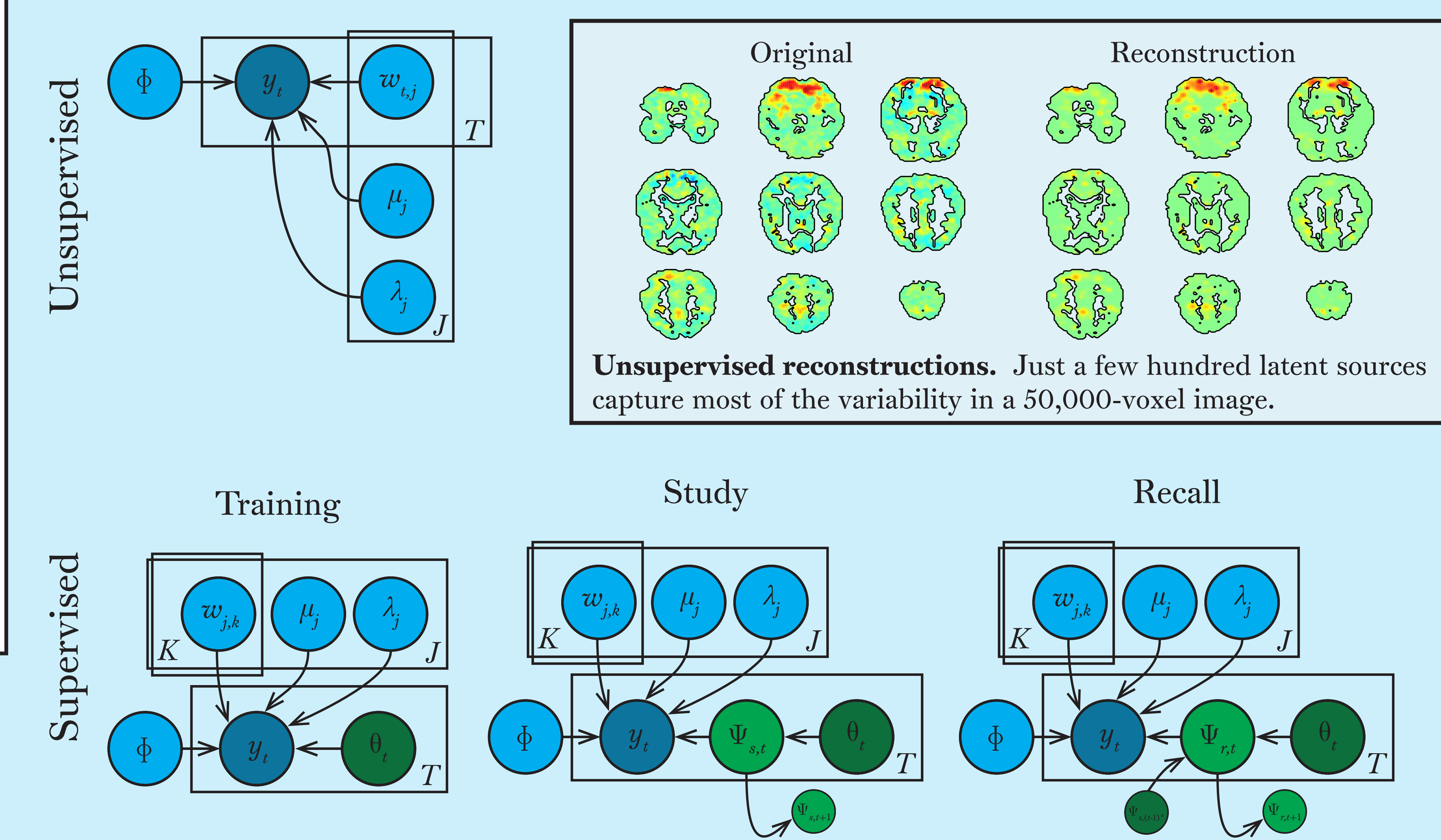


Topographic Latent Source Analysis. Neural patterns are represented as linear combinations of spherical sources.^{2,4} Unsupervised (top) and supervised (bottom) equations are shown.

Fitting the models



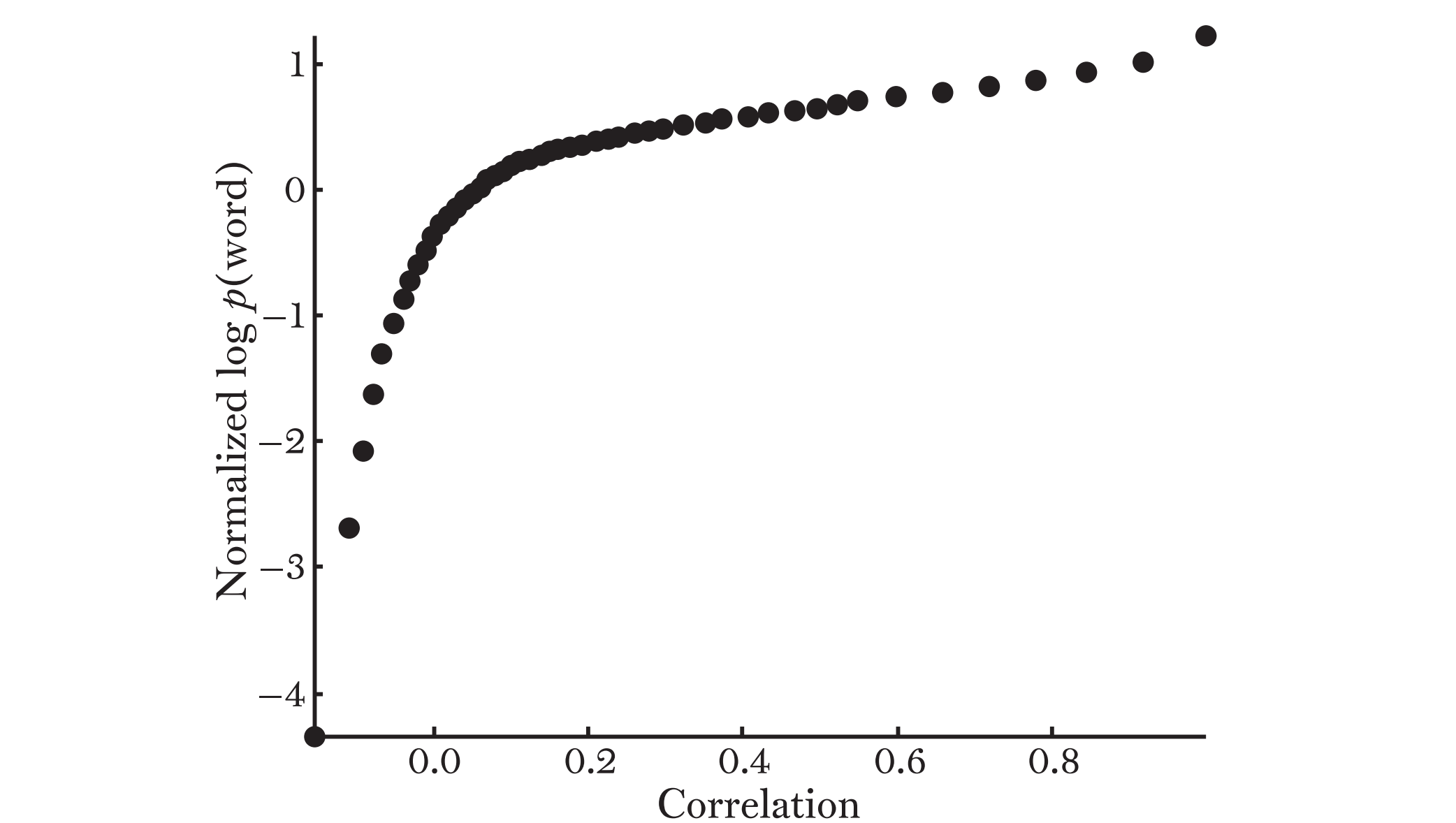
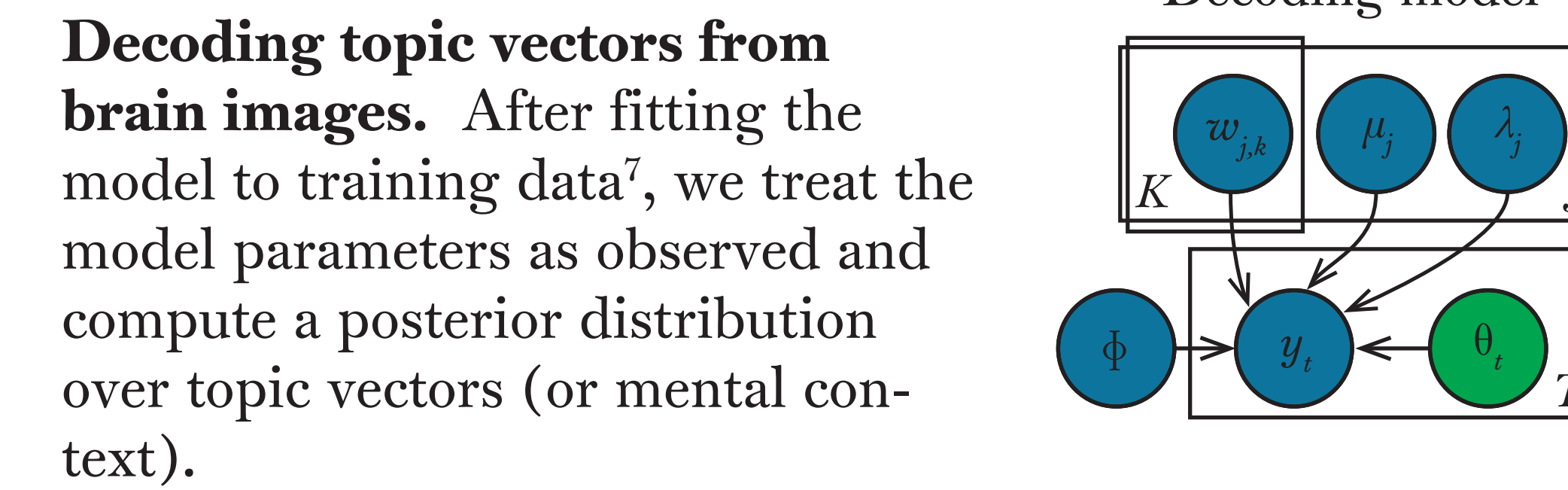
Initializing source locations and widths. We use “hotspots” in the neural images to estimate the locations and widths of the sources. We can then solve for the source weights using linear regression. **Honing the parameter estimates.** We use a scalable stochastic variational inference-based fitting procedure to hone the parameter values given the observed neural and behavioral data.



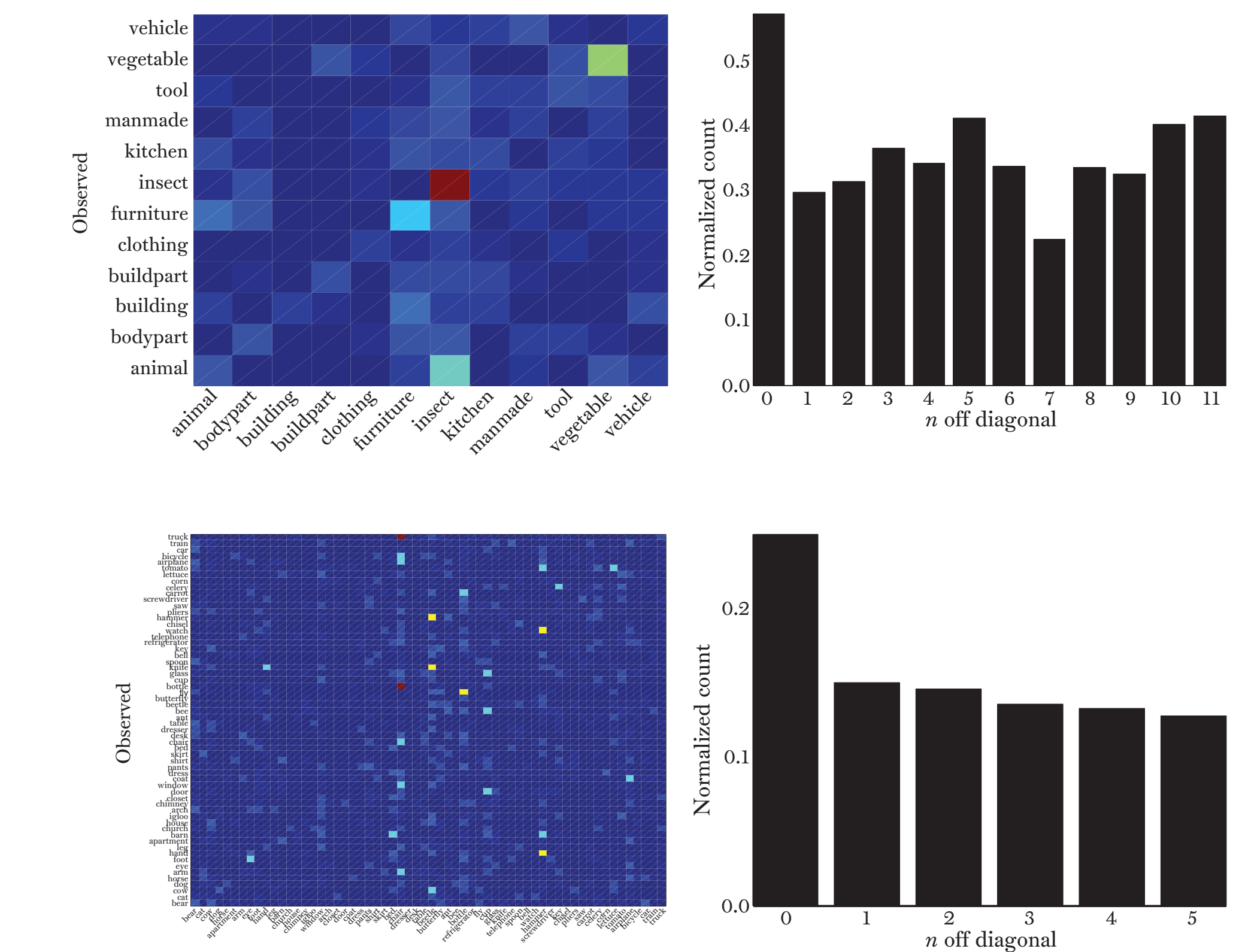
Unsupervised reconstructions. Just a few hundred latent sources capture most of the variability in a 50,000-voxel image.

Models of evolving neural activity. The sources’ center and width parameters are held fixed across trials. In the unsupervised model, the source weights vary independently to explain each image. In the supervised model, the source weights vary as a function of the semantic attributes of the word experienced as the images were collected. The study and recall models account for drifting mental context by introducing an additional autocorrelated latent variable. In the recall model, the mental context associated with the word being recalled is reinstated and influences the way in which mental context drifts.

Results



Posterior probability as a function of correlation. Correlations are between the actual word’s topic vector and the topic vector for each alternative word.



Confusion matrices. These panels summarize decoding errors by category (top) and word (bottom). The right panels display the mean (normalized) counts as a function of the positional distance from the diagonals of the confusion matrices.

Bibliography

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