Unified Generative Latent Representation of Functional Brain Graphs

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NEURAL INFORMATION PROCESSING SYSTEMS

Background

- Whole-brain fMRI produces dense functional connectivity graphs with separate topological and spectral descriptors
- Functional brain graphs may lie on a low-dimensional latent geometry where topology and spectra covary
- We lack a unified generative representation of whole-brain functional graphs connecting this geometry to cognitive states

Aims

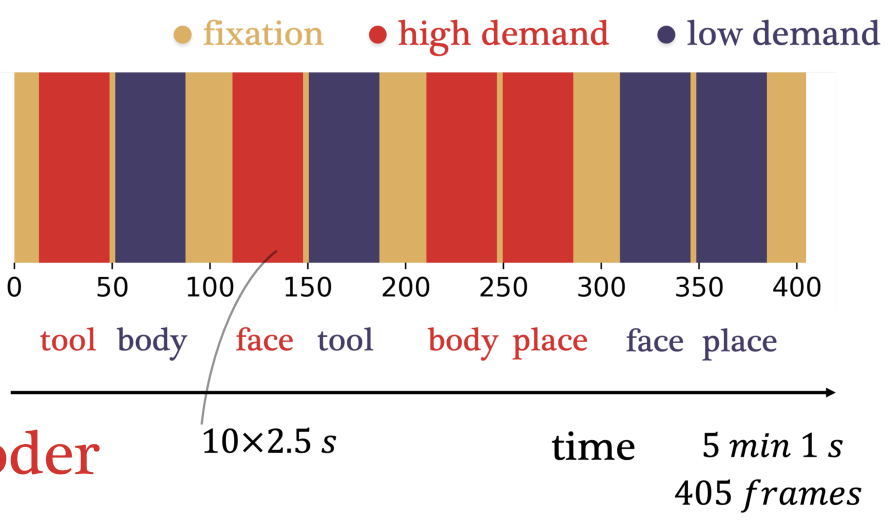
Geometry-aware latent space jointly capturing FC topology and spectral gradients

Use latent diffusion in this space to generate structurally grounded brain graphs

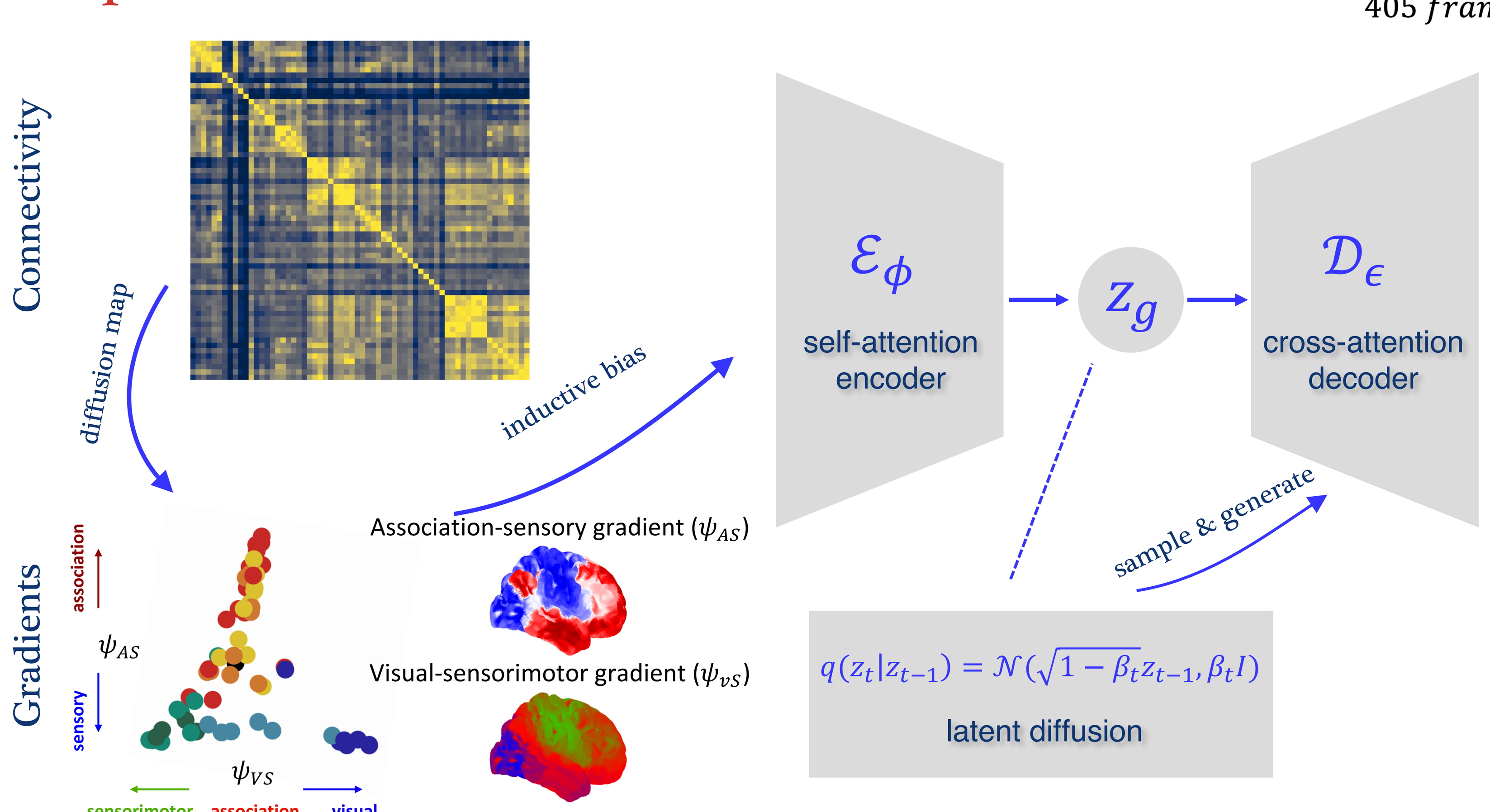
Methods

Human Connectome Project

- Resting-state and **visual working memory** fMRI
- **1078** healthy young adults

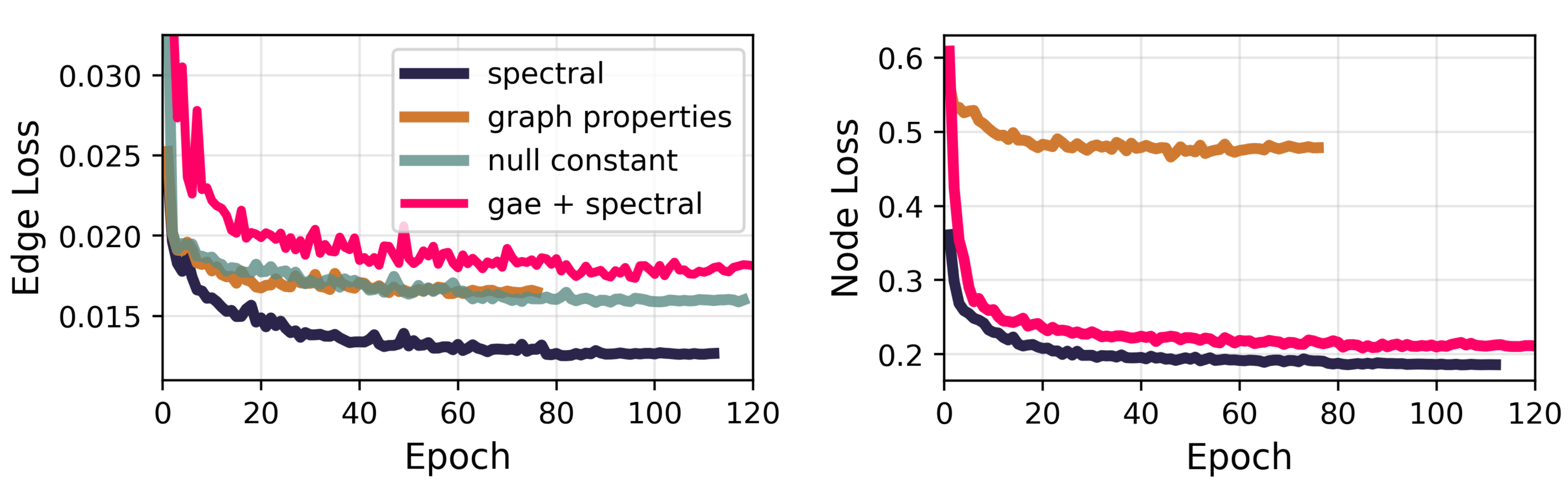


Graph Transformer Autoencoder

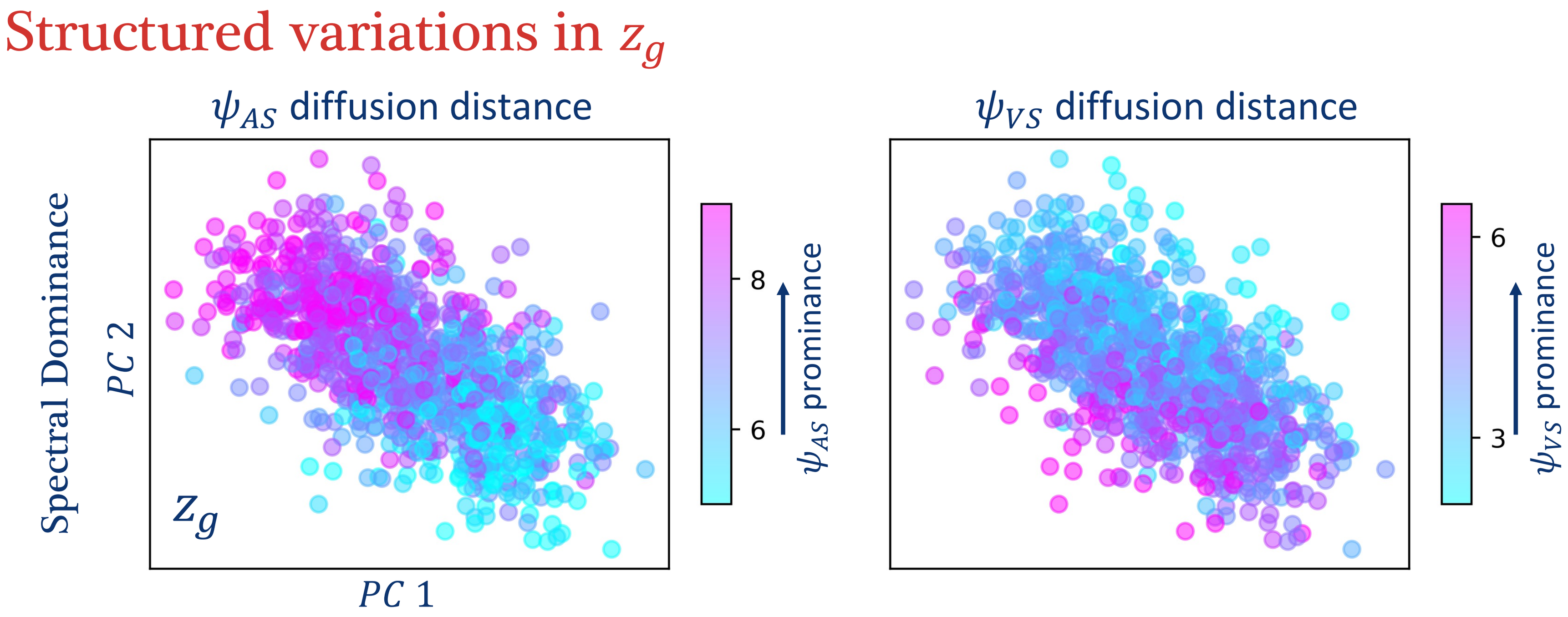


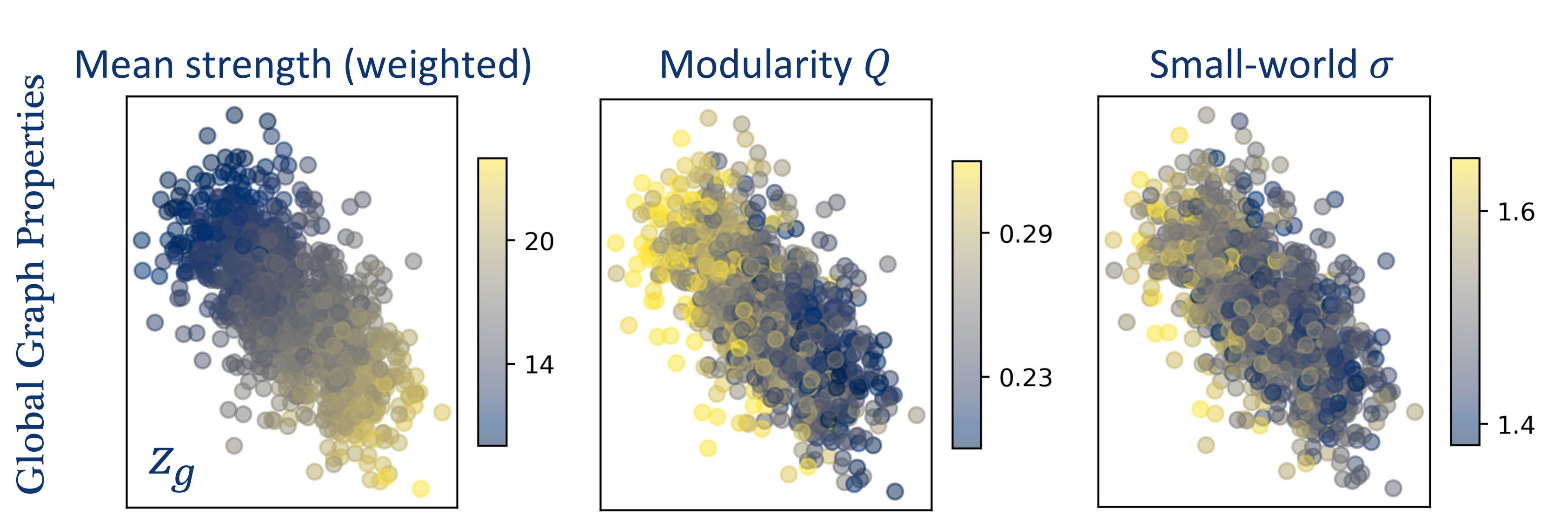
Functional Brain Graph Manifold

Spectral induction augments FC graph learning



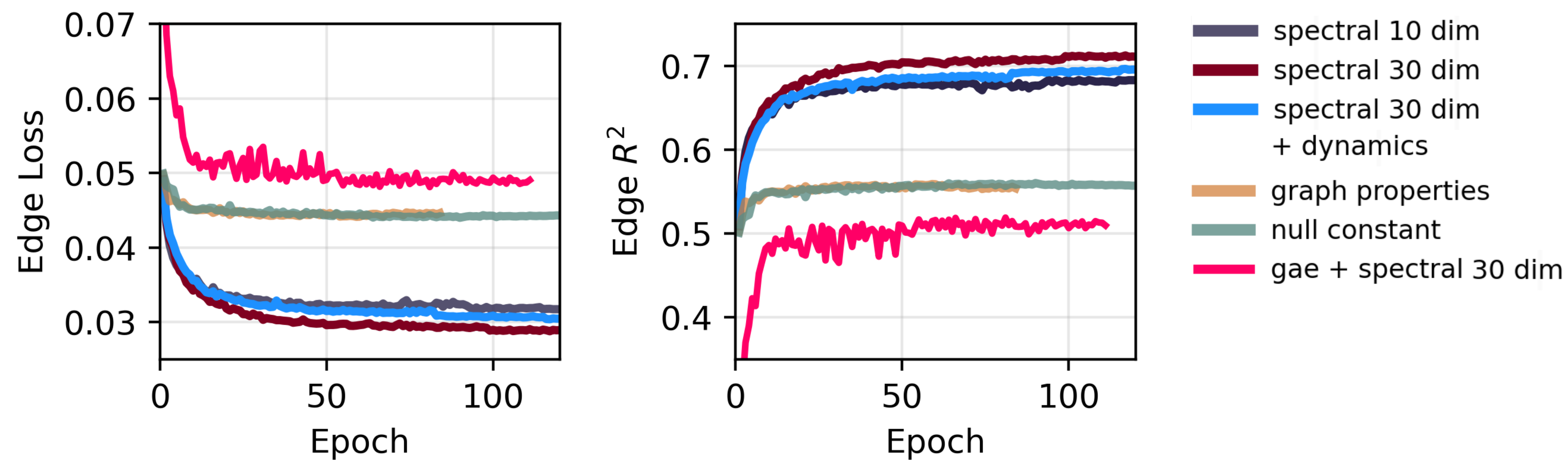
Structured variations in z_g



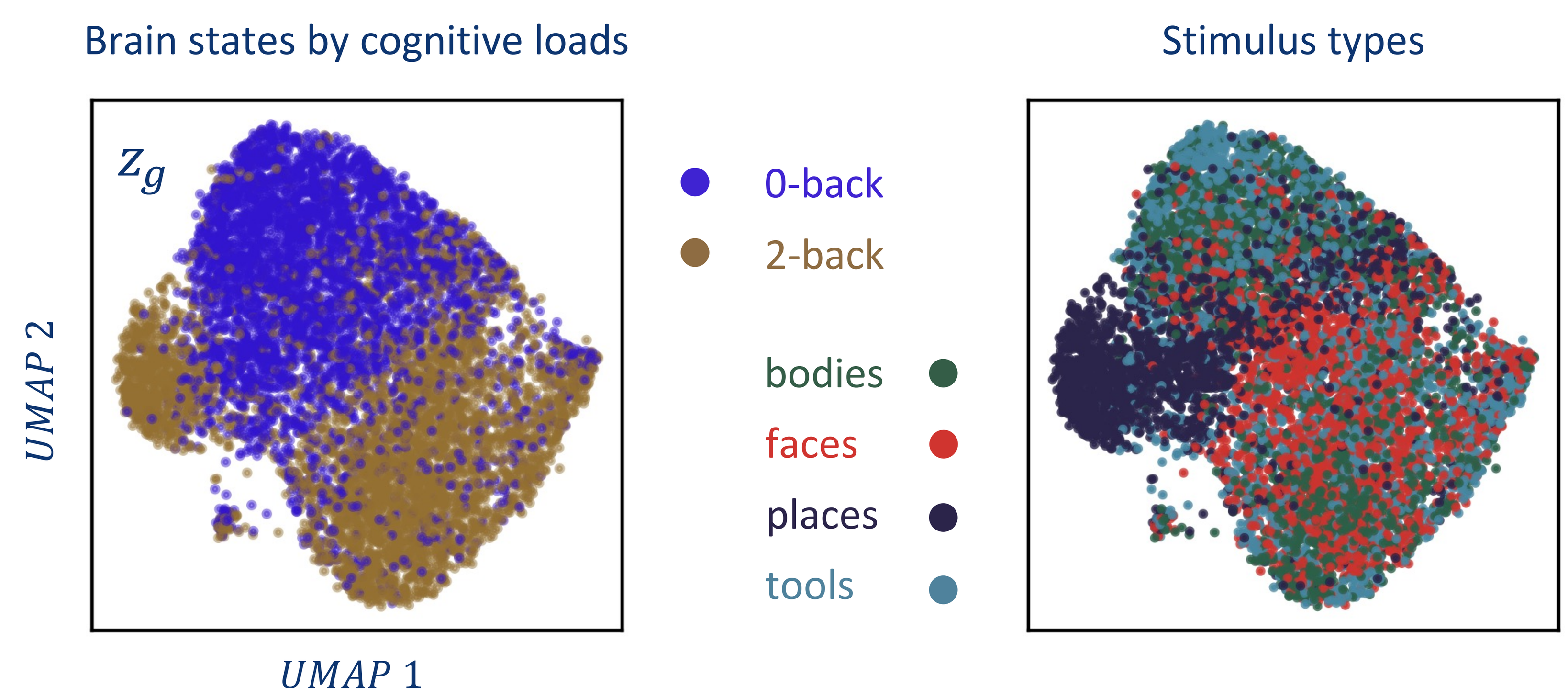


Unsupervised Brain State Decoding

Spectral induction in task graphs



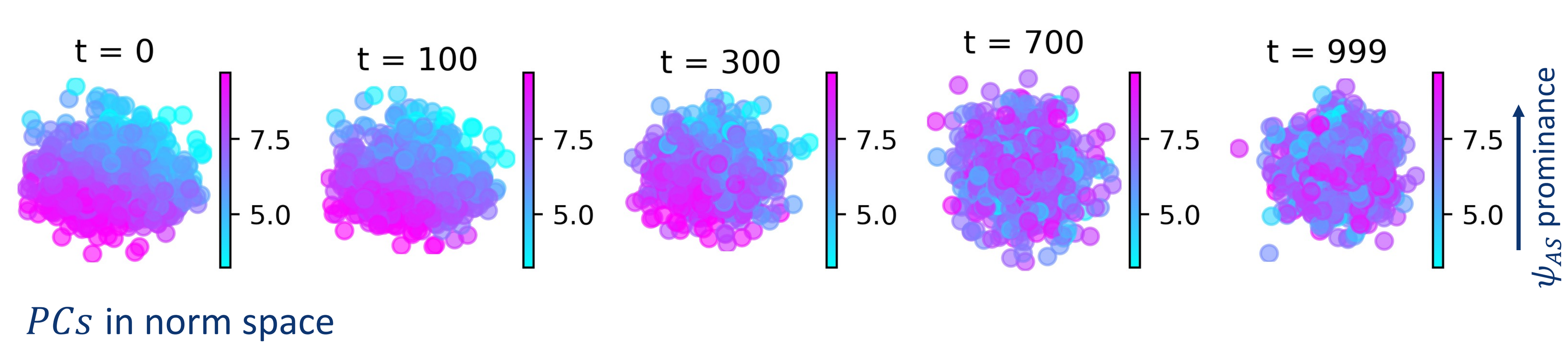
Brain state decoding via linear probe in z_g



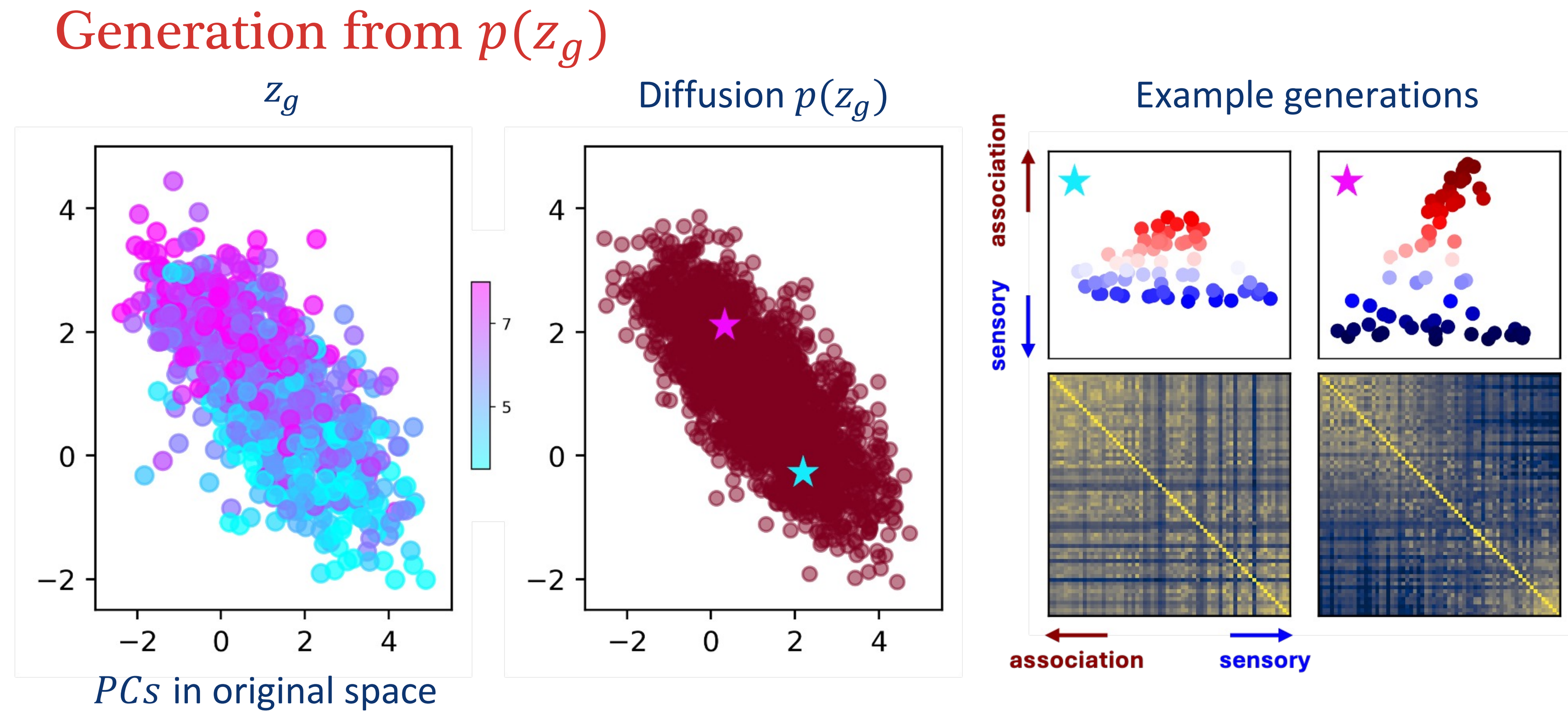
- 0- vs 2-back accuracy **86%**, AUC = **0.93**
- Visual stimuli (4-class) accuracy **73.9%/70.6%** under 0- and 2-back

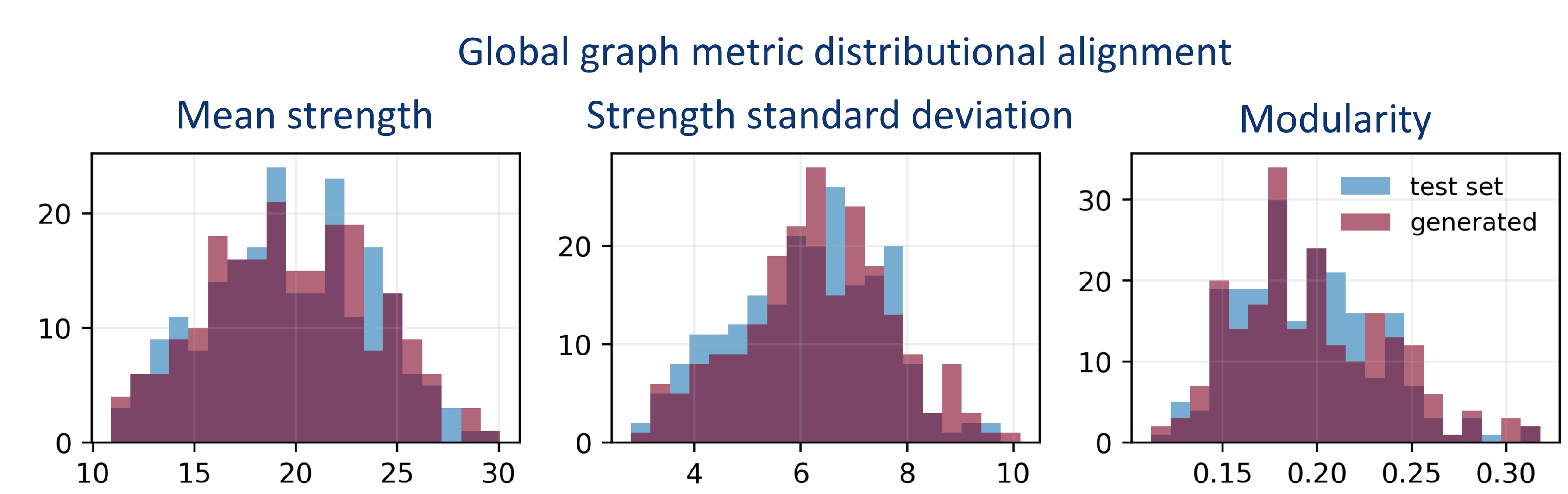
Latent Diffusion and Generation

Diffusion in z_g



Generation from $p(z_g)$





Conclusion

- Learned a geometry-aware latent space z_g that jointly captures FC topology, spectral gradients; enables unsupervised state decoding
- Latent diffusion on z_g provides a generative prior that samples functional brain graphs preserving empirical network properties

Future work

Fuse with encoder-decoder RNN to jointly embed neural dynamics and functional graphs

Map the behavioural, cognitive, and clinical significance of the neural geometry in z_g