Discrete Representation of Long-Range Brain Network Dynamics via Generative Modelling

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1. Introduction

Motivation

Accurately estimating functional brain networks from electrophysiological data has become a core neuroscientific challenge.

Limitation

While Hidden Markov Models (HMM)[1] and deep learning methods[2] are widely used, they either neglect long-range temporal dependencies or sacrifice interpretability by encoding brain network dynamics into a continuous latent space.

Objective

To address these limitations, we introduce **Dynamic Network States (DyNeStE)**, a novel generative model that learns categorical representations of network dynamics.

2. Data & Methods: Dynamic Network States (DyNeStE) Model

Dataset

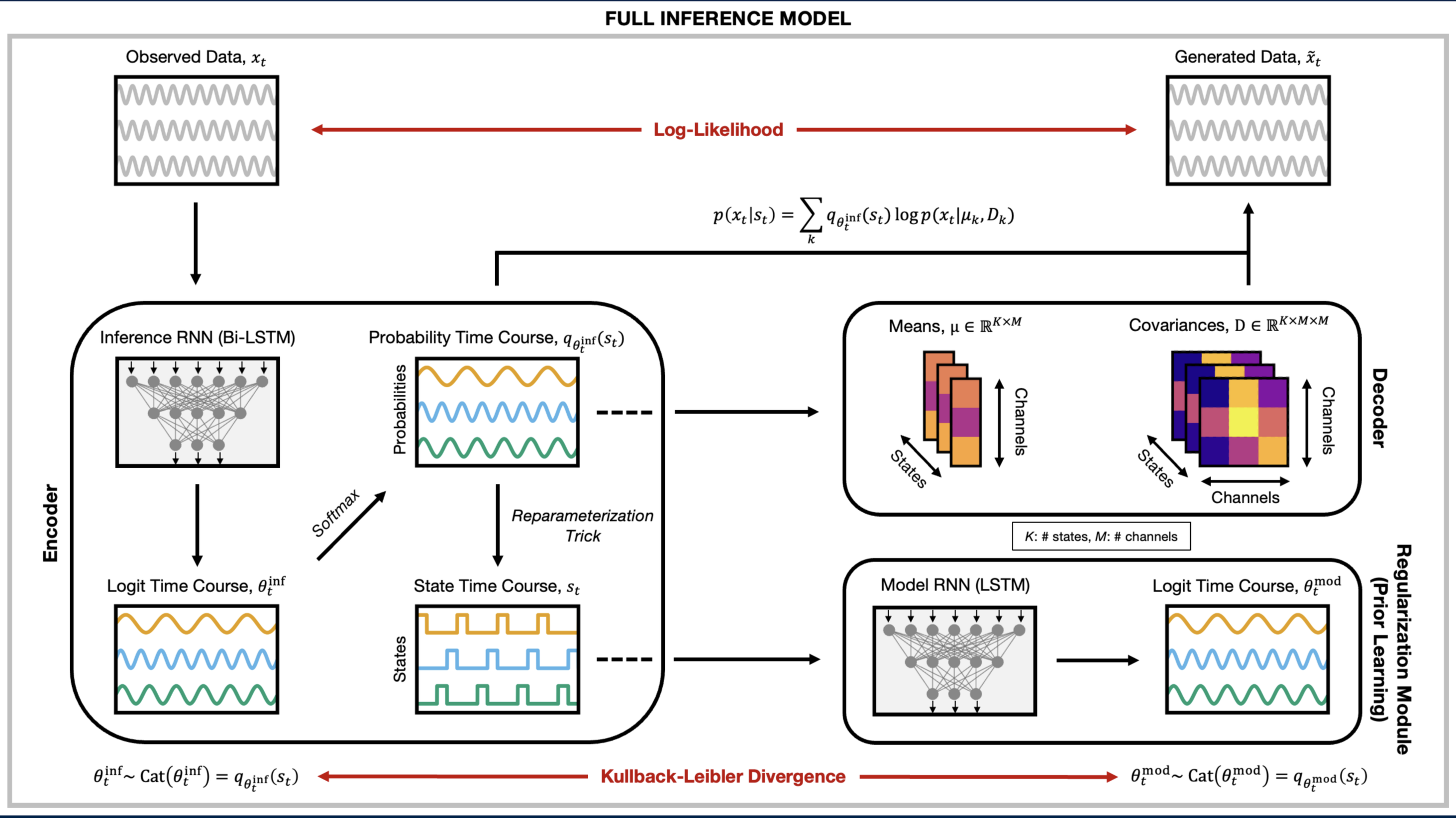
- Nottingham MEGUK[3]
- Resting-state
- Eyes-open
- CTF MEG system

Subjects (n=65)

- Healthy subjects
- 18 to 60+ years old

Dynamic Modelling

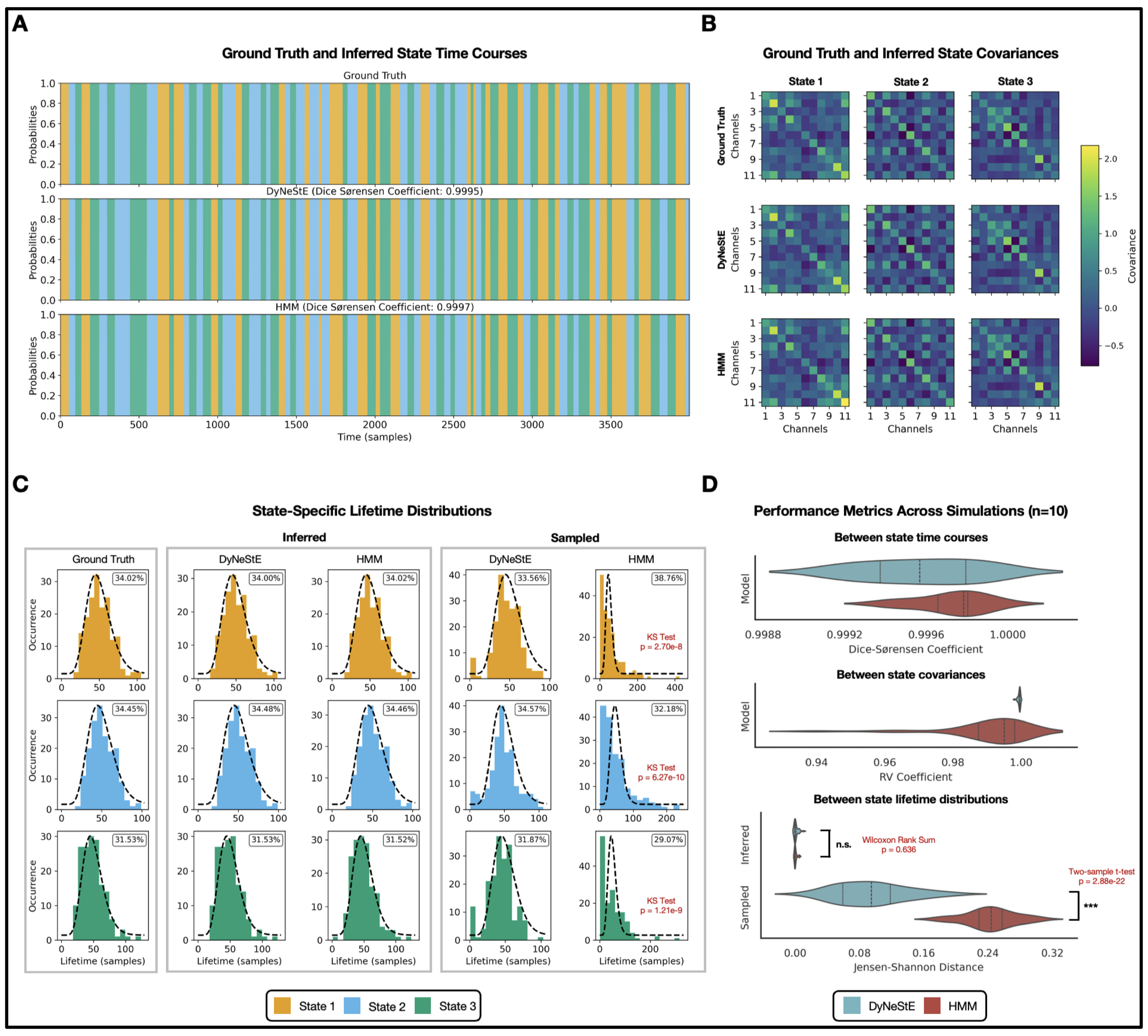
- Categorical VAE with a Gumbel-Softmax distribution[4,5]
- Amortised Bayesian inference
- Learnable categorical prior



3. DyNeStE can learn long-range temporal dependencies from simulated data

Long-range temporal patterns captured by learnable prior in DyNeStE

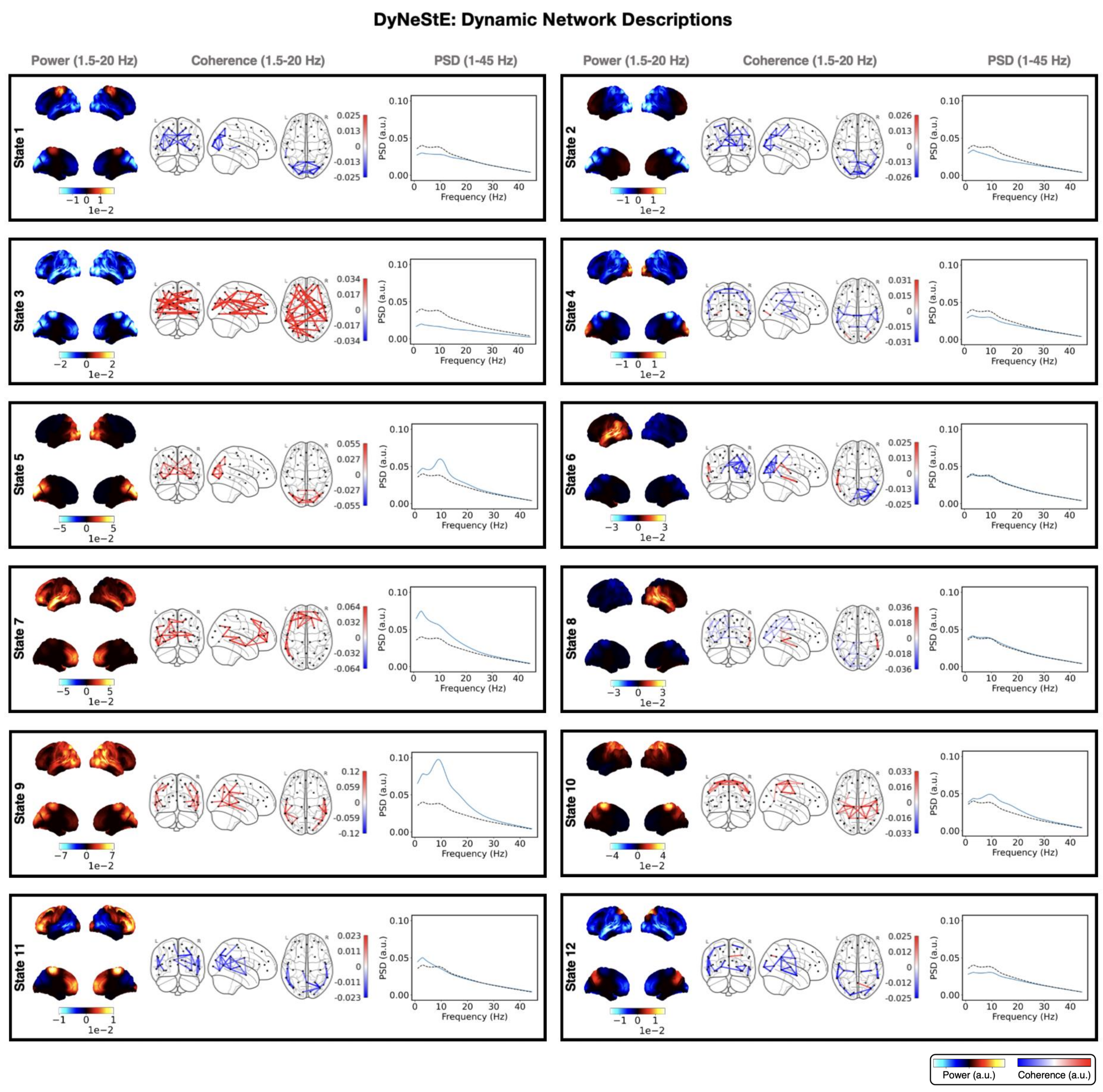
- **Inferred parameters**
  - DyNeStE can accurately infer categorical state activations and state covariance matrices.
- **Lifetime distributions**
  - State lifetime distributions generated by DyNeStE reproduce long-range temporal dependencies, while those generated by HMM do not.



4. DyNeStE can provide plausible dynamic resting-state network descriptions

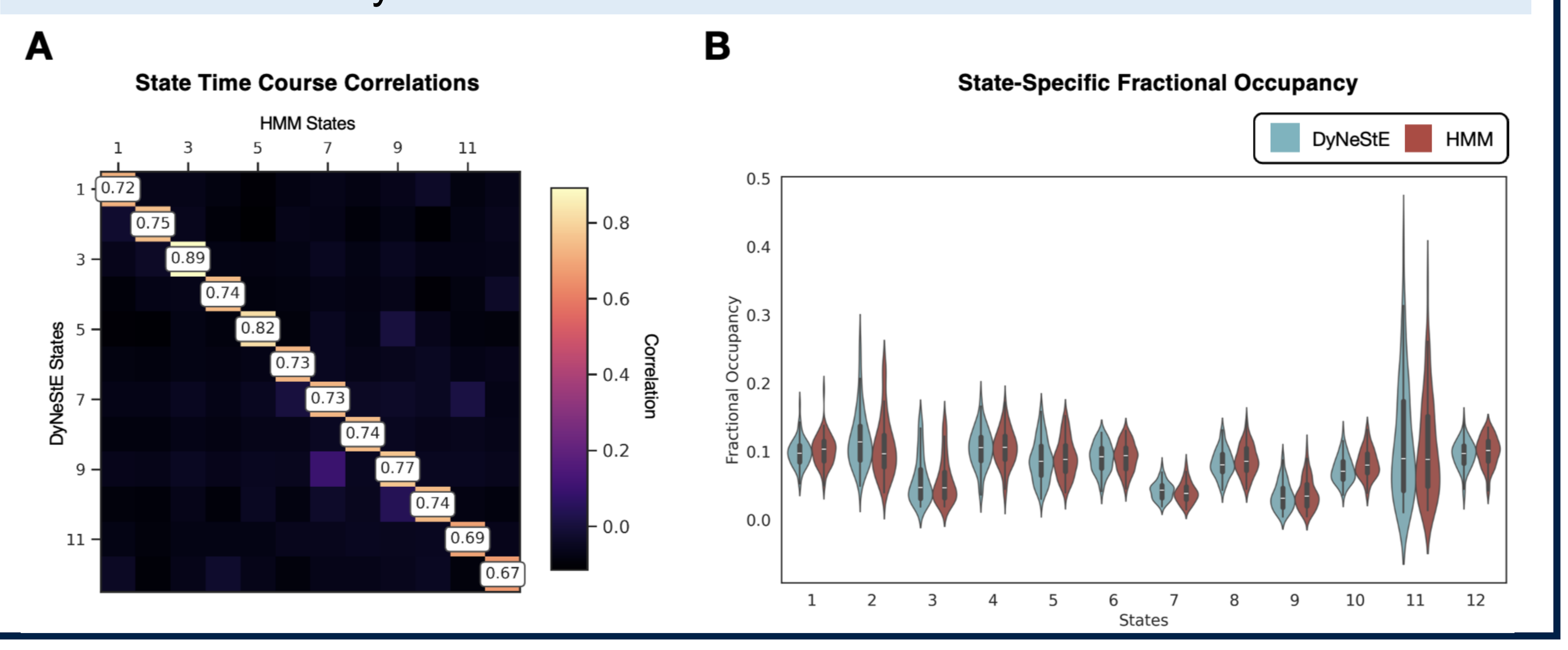
12-state dynamic resting-state networks (RSNs) inferred by DyNeStE

- DyNeStE produces categorical and mutually exclusive RSNs that are comparable to the canonical RSNs inferred by the HMM.



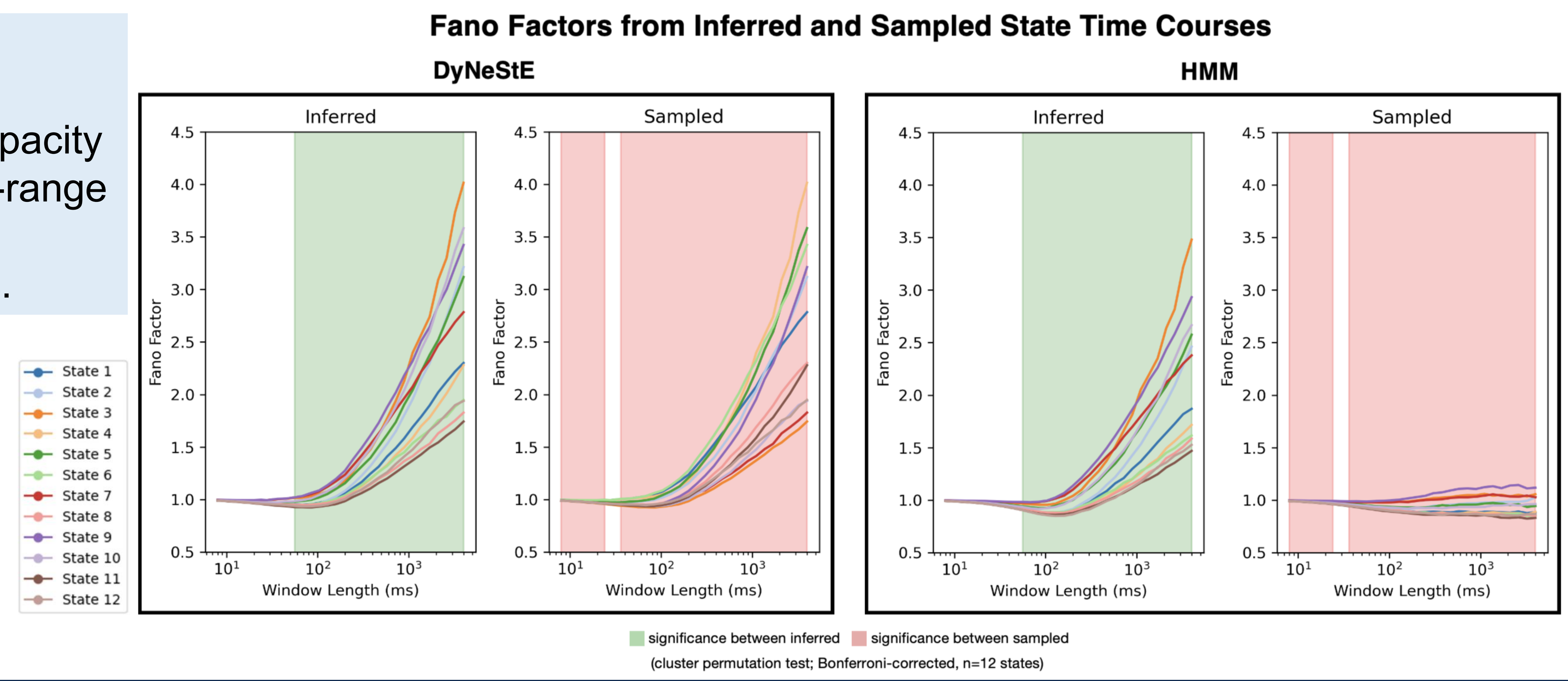
5. DyNeStE models categorical network dynamics

- State activations inferred by DyNeStE are categorical and analogous to HMM network dynamics.



6. DyNeStE captures long-range dependencies in real data

- Fano factors demonstrate DyNeStE's capacity to model long-range temporal dependencies.



7. Discussion & Conclusion

Key Takeaways

- We introduce DyNeStE, a novel model for representing dynamic brain networks as discrete states capable of capturing long-range temporal dependencies.
- Our model:
  - Provides interpretable dynamic network descriptions comparable to HMMs.
  - Effectively captures long-term dependencies in both simulated and empirical data.
- Our results indicate that DyNeStE can be a viable alternative to traditional HMM approaches, offering enhanced insights into neural mechanisms and neuroimaging analysis.

8. References

[1] Vidaurre D et al. (2018). Spontaneous cortical activity transiently organises into frequency specific phase-coupling networks. *Nature Communications*, 9(1):2987.

[2] Gohil C et al. (2022). Mixtures of large-scale dynamic functional brain network modes. *NeuroImage*, 263:119595.

[3] The MEG UK dataset. https://meguk.ac.uk/database/.

[4] Jang E et al. (2017). Categorical Reparameterization with Gumbel-Softmax. *ICLR 2017*.

[5] Maddison CJ et al. (2017). The Concrete Distribution: A Continuous Relaxation of Discrete Random Variables. *ICLR 2017*.

For the open-source software for DyNeStE and HMM, please visit OSL Dynamics Toolbox (https://osl-dynamics.readthedocs.io/en/latest/).

See here for the electronic version of the poster!