

Edge functional connectivity reveals overlapping community structure

Joshua Faskowitz^{1,2}, Farnaz Zamani Esfahlani¹, Younghun Jo^{1,3},
Olaf Sporns¹⁻⁴, Richard F. Betzel¹⁻⁴

Indiana University ¹Department of Psychological and Brain Sciences, ²Program in Neuroscience, ³Cognitive Science Program, ⁴Network Science Institute

Introduction

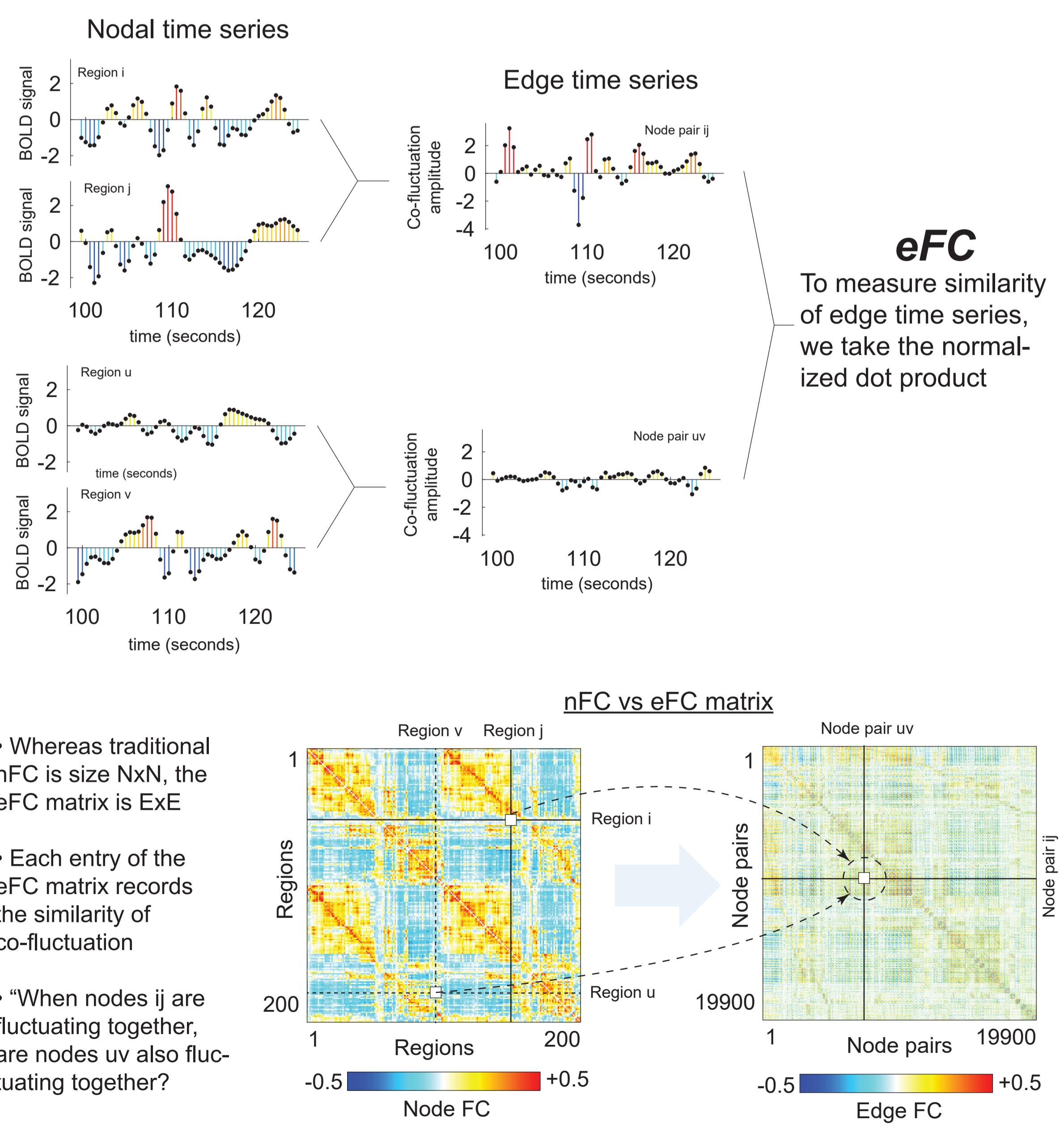
To date, the principal approach in network neuroscience has been node-centric, treating cortical areas as the irreducible units of our network model¹. Here, we present a novel modeling framework that is edge-centric, focusing on the statistical relationships between edges of functional brain networks—a representation we call edge functional connectivity (eFC)².

- We present **edge time series**, which track frame-wise co-fluctuation³
- The similarity of edge time series is edge functional connectivity (eFC)
- Clustering the eFC matrix yields **overlapping community structure**
 - This structure spans systems, identifies areas of community overlap, highlights diverse systems, and is modulated by task
- eFC is a new method that can be applied to neural time series broadly

Methods

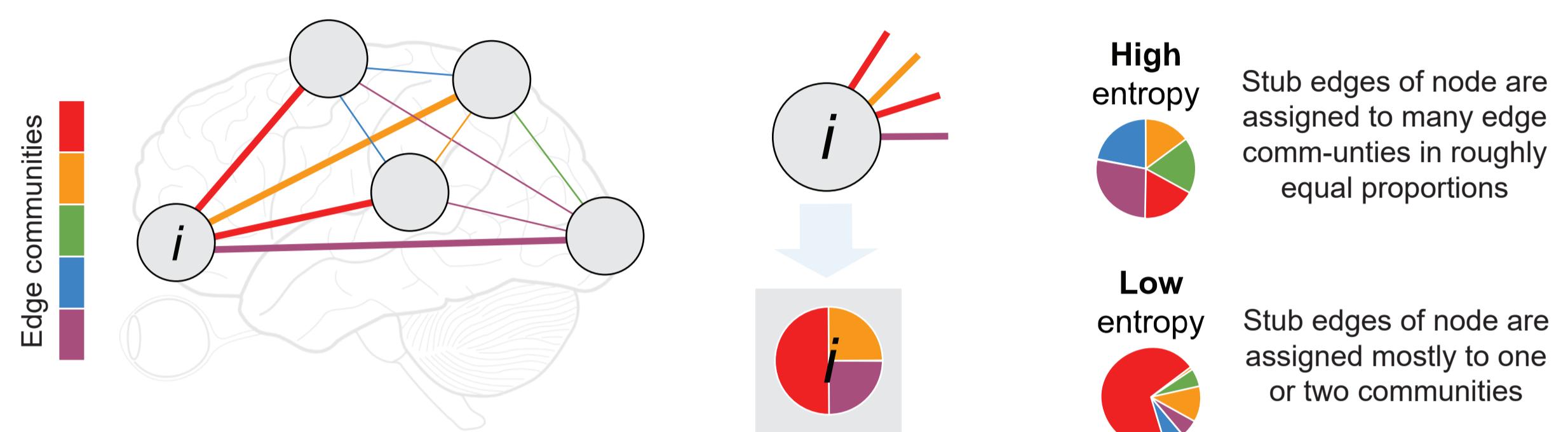
Edge time series and eFC.

- FC is time-averaged co-activation between two time courses
- Omit the averaging step → time course of co-fluctuation, edge time series
- Measure the similarity of edge time series to create eFC



Community detection on eFC

- For each node, its $N-1$ edges are assigned to various edge communities
 - Nodes associated with multiple communities
- Distribution of edge communities at each node provides notion of overlap

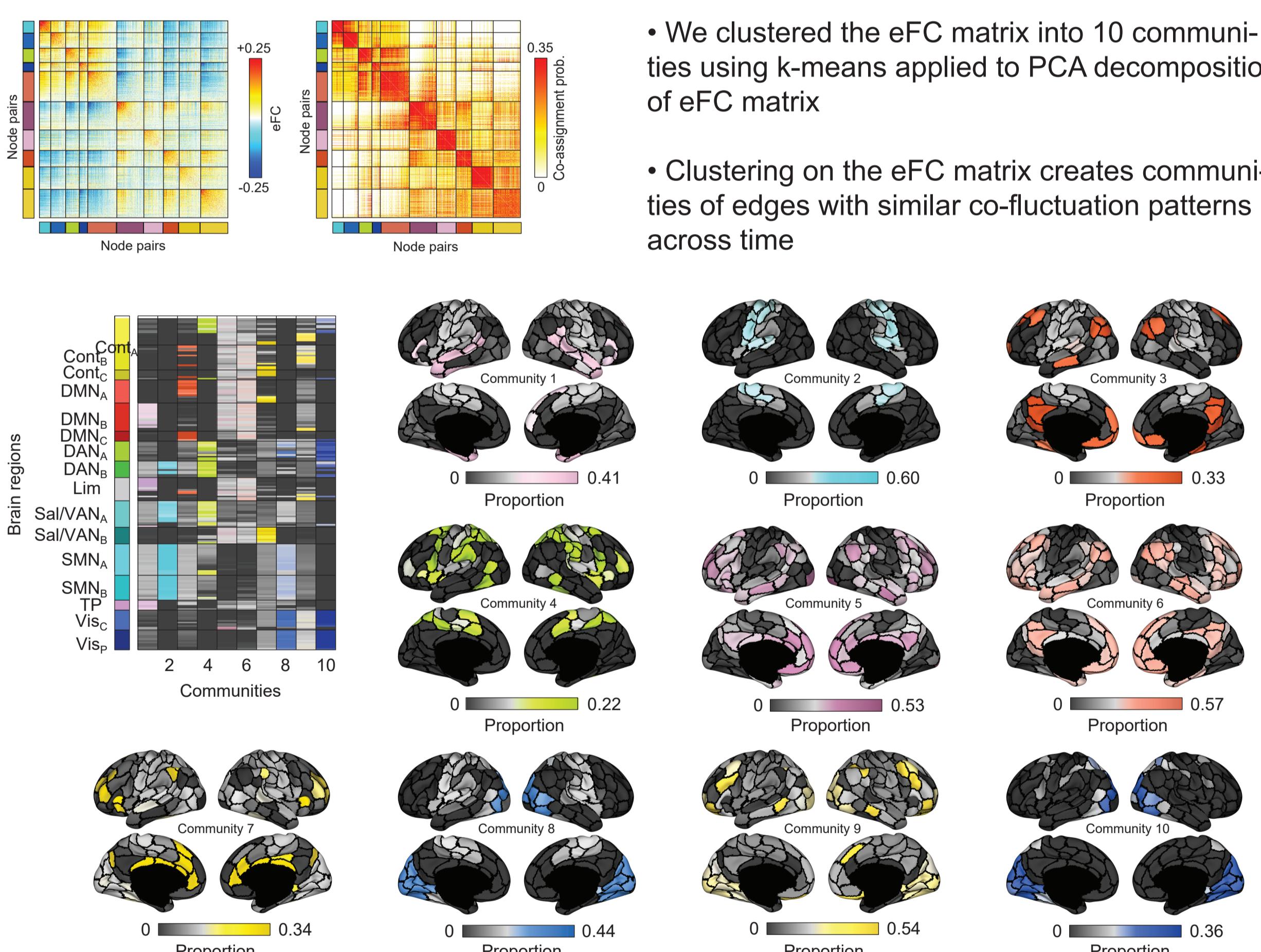


Application to fMRI data

- Human Connectome Project (HCP) unrelated 100, Midnight Scan Club (MSC), Healthy Brain Network Serial Scanning Initiative (HBN)

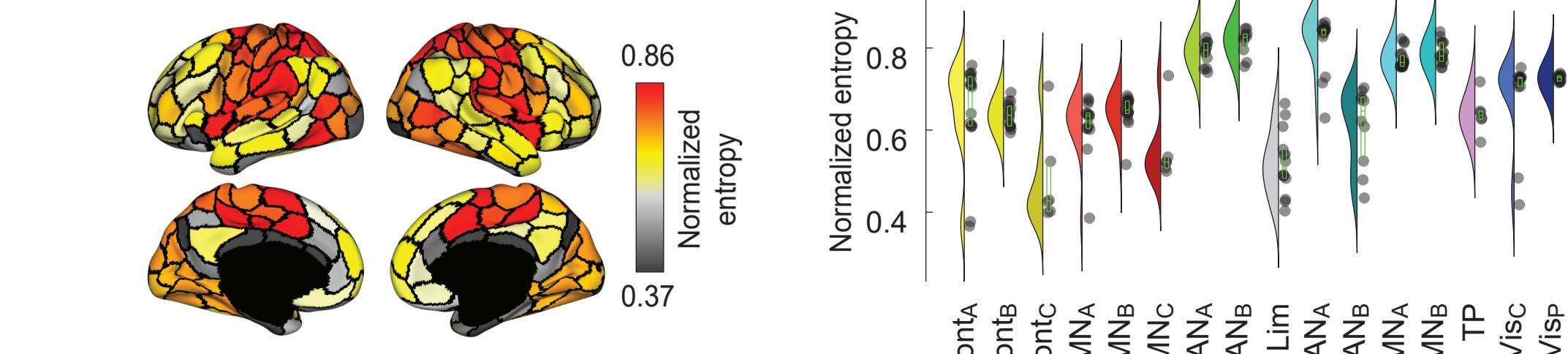
Results

Edge Communities



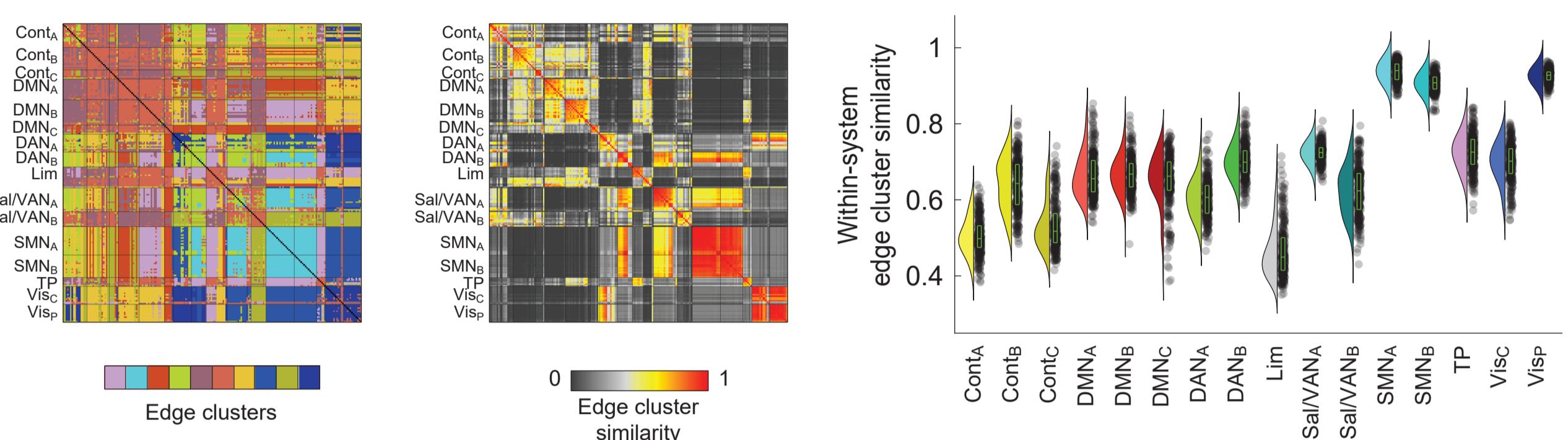
- Nodes are saturated by proportion of edges participating in each community and colored by weighted combination of canonical system⁴

Normalized entropy map



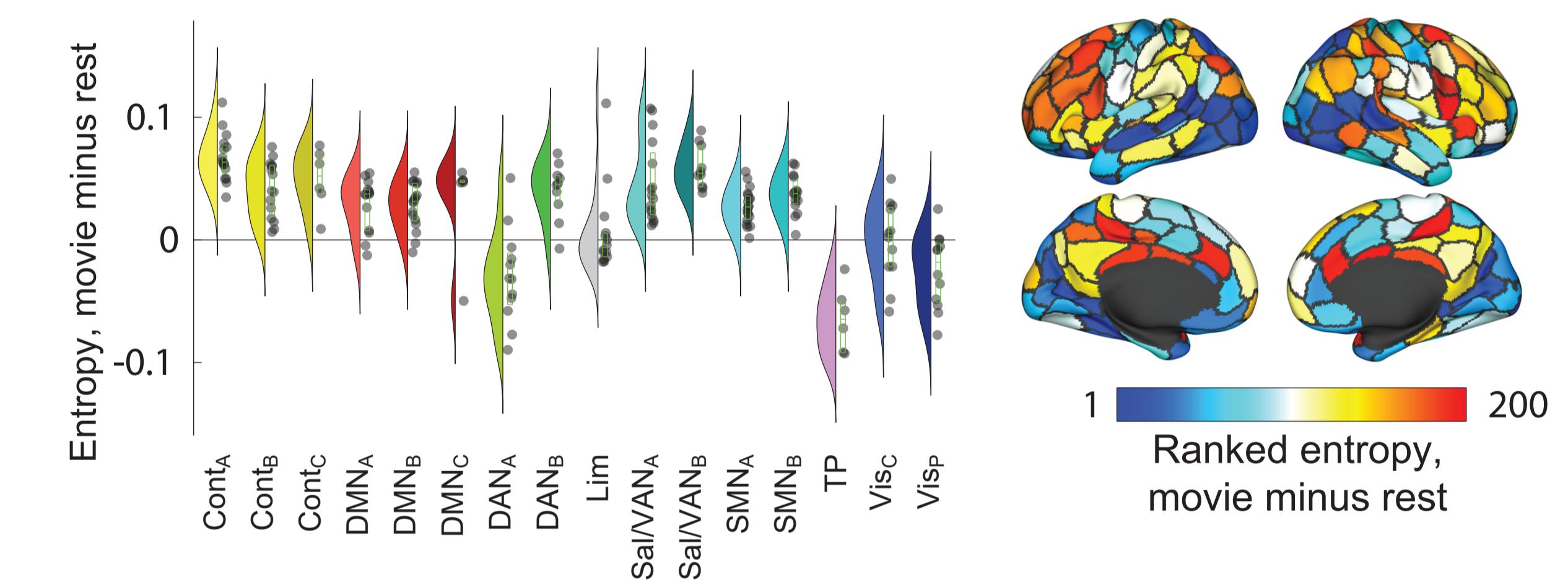
- Normalized entropy is highest dorsal-attention, somato-motor, and visual nodes, indicating that stub edges to these nodes are distributed across a variety of communities

Edge cluster similarity

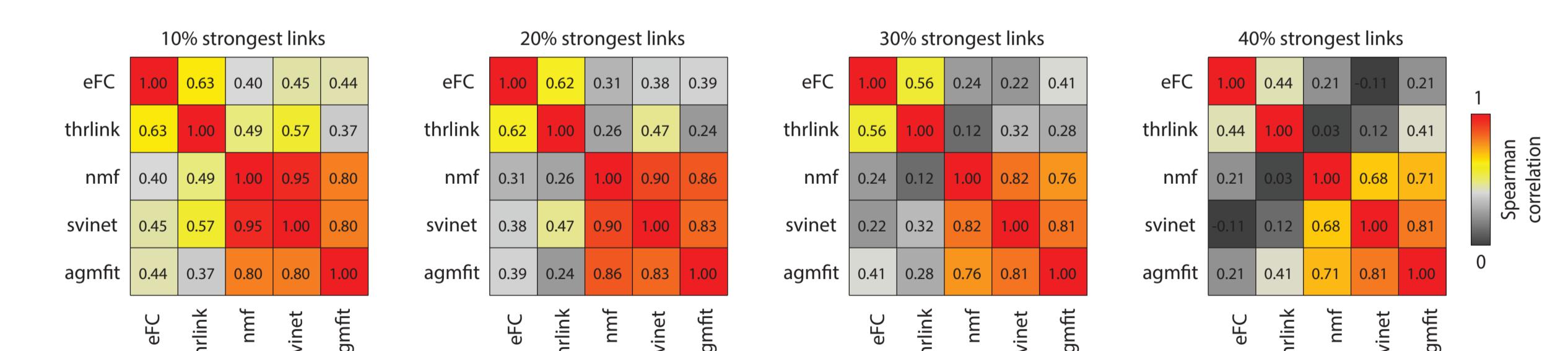


- As each edge is assigned to a cluster, we can project communities into the space of adjacency matrix
- Similarity of edge community assignment illustrates node-level systems with varying diversity⁵; control network → diverse edge community patterns

Entropy differences in rest vs. task



Comparison to alternative overlapping algorithms



- Comparison of entropy patterns across methods and thresholds show eFC yields dissimilar overlap patterns; most similar is *thrlink*, which is based on line graphs; *nmf*: non-negative matrix factorization⁶, *svinet*: an overlapping blockmodel⁷; *agmfit*: tiled overlapping algorithm⁸

Conclusion

The edge-centric approach allows us to uncover a pervasively overlapping⁹ community structure by assigning communities to functional brain network **edges**. In fact, all nodes are associated with multiple edge communities. We demonstrate that this structure is modulated by task-based input. These patterns of overlap provide a different, yet complementary, account of functional brain network organization.

¹Bassett, D. S. & Sporns, O. (2017). Network neuroscience. *Nature neuroscience*, 20(3), 363.

²Faskowitz, J., Esfahlani, F. Z., Jo, Y., Sporns, O. & Betzel, R. F. (2019). Edge-centric functional network representations of human cerebral cortex reveal overlapping system-level architecture. *bioRxiv*, 79924.

³Zamani Esfahlani, F., Faskowitz, J., Jo, Y., Sporns, O. & Betzel, R. F. (2020). Edge-centric functional network representations of human cerebral cortex reveal overlapping system-level architecture. *bioRxiv*, 20200045.

⁴Soriano, M. V., Kivimaki, M., Monti, M. M., Cai, X., Giedd, J. N., Heath, A. C., ... & Neale, B. T. (2018). Large-scale brain-wide detection of the functional organization of the human cerebral cortex from intrinsic functional connectivity MRI. *Cerebral Cortex*, 28(9), 3095-3114.

⁵Parsakian, I., Roberts, S., Ebden, M. & Sheth, R. (2011). Overlapping community detection using bayesian non-negative matrix factorization. *Physical Review E*, 83(6), 065114.

⁶Gillis, N. P. & Lim, J. S. (2014). Nonnegative matrix and tensor factorizations: Applications to topics modeling and blind source separation. *Proceedings of the IEEE*, 111(36), 14534-14539.

⁷Yang, Y. & Leskovec, J. (2014). Overlapping community detection via graph partitioning of networks. *nature*, 496(7407), 761-764.

⁸Agapiou, J., Betzel, R. F. & Sporns, O. (2019). Link communities reveal complex modularity in networks. *bioRxiv*, 4687307, 761-764.

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