CORTICAL PARCELLATION WITH GRAPH REPRESENTATION LEARNING ON RESTING-STATE FMRI

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Overall goal

Construct a novel cortical parcellation from resting-state fMRI utilizing *state-of-the-art* graph representation learning.

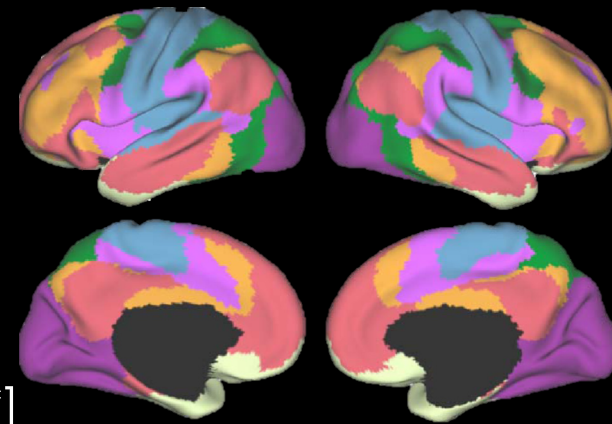
- Existing parcellations are with fixed number of parcels.
- We provide a flexible way to parcellate the cortex with an arbitrary number provided by the user.

Cortical parcellation from resting-state fMRI

Partitioning cerebral cortex (B) into disjoint sets

$$B = B_1 \cup B_2 \ldots \cup B_n$$

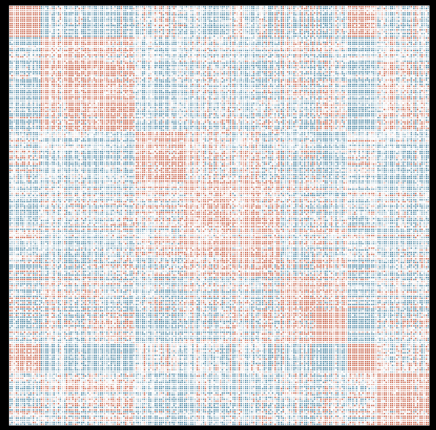
$$B_i \cap B_j = \emptyset,\ i \neq j$$



Yeo-7 [*]

Resting-state functional connectivity (RSFC)

- This representation shows an adjacency matrix of a graph, which measures the synchrony of the brain responses between all pairs of cortical vertices.
- Cortical parcellation can be derived from clustering vertices in this graph.



Vertex-wise RSFC

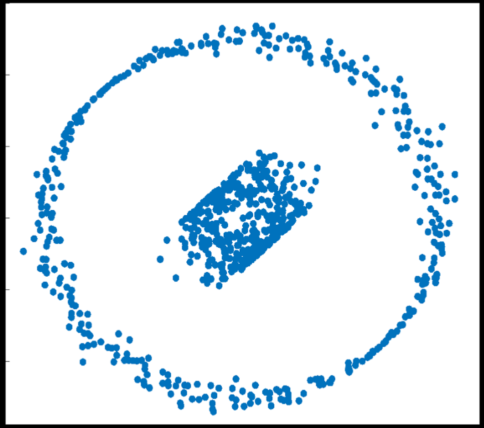
[*] Thomas Yeo, B. T., Krienen, F. M., Sepulcre, J., Sabuncu, M. R., Lashkari, D., Hollinshead, M., ... & Buckner, R. L. (2011). The organization of the human cerebral cortex estimated by intrinsic functional connectivity. *Journal of neurophysiology*, *106*(3), 1125-1165.

Graph representation learning helps clustering

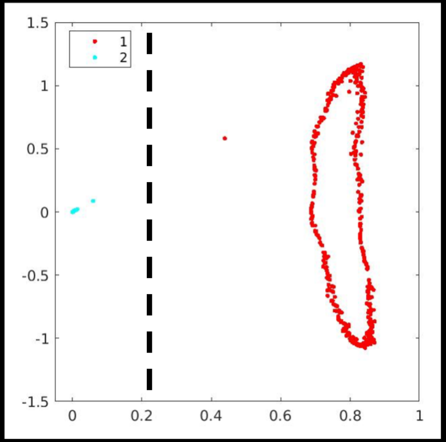
Recent development in graph representation learning

- **Random-walk based:** DeepWalk (KDD, 2014), Node2vec (KDD, 2016)
- **Closed-form:** NetMF (WSDM, 2018) [*]

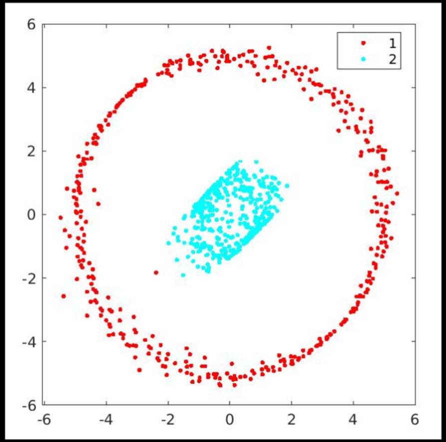
Original data



NetMF representation [*]



K-means on NetMF representation

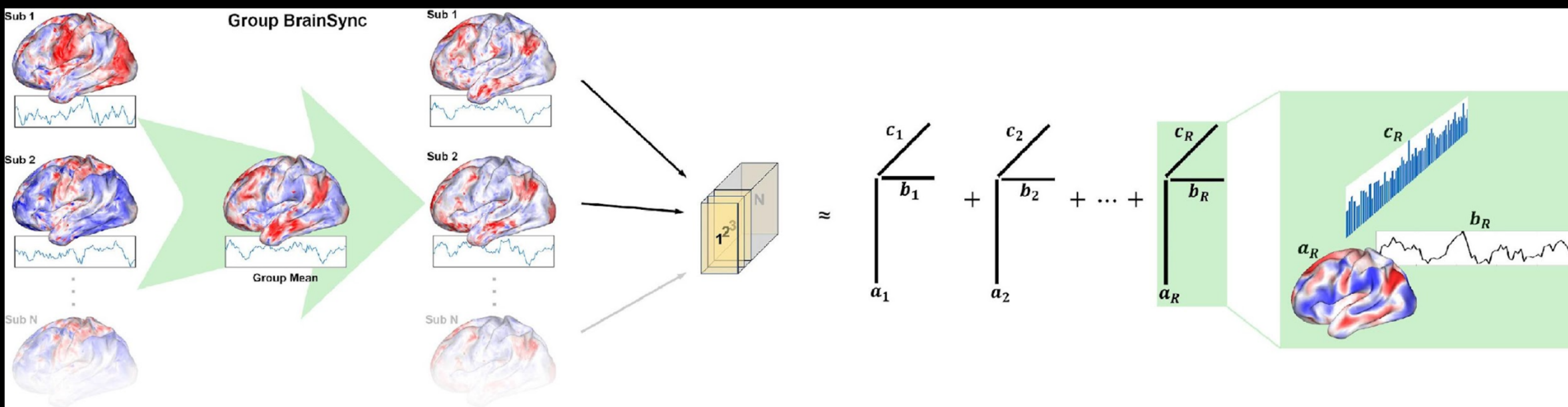


[*] Qiu, J., Dong, Y., Ma, H., Li, J., Wang, K., & Tang, J. (2018). Network embedding as matrix factorization: Unifying deepwalk, line, pte, and node2vec. In *Proceedings of the eleventh ACM international conference on web search and data mining* (pp. 459-467).

From overlapping brain activation maps to non-overlapping partitions

Spatial activation maps from a tensor decomposition method (NASCAR) [*]

- No orthogonal / independent constraints like PCA / ICA
- It generates a feature vector for every surface vertex based on the activation in these spatial maps



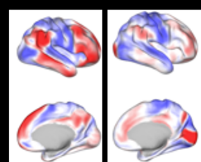
[*] Li, J., Liu, Y., Wisnowski, J. L., & Leahy, R. M. (2023). Identification of overlapping and interacting networks reveals intrinsic spatiotemporal organization of the human brain. *NeuroImage*, *270*, 119944.

Method

NASCAR spatial maps [*]

$$X_{|V|\times n} = \begin{bmatrix} | & | & & | \\ x_1 & x_2 & \cdots & x_n \\ | & | & & | \end{bmatrix}$$

$|V| \approx 59k$
$n = 32$



- Left & right hem separately
- Pearson correlation
  $A = \operatorname{corr}(X) \in \mathbb{R}^{|V|\times|V|}$
- Gaussian kernel
  $\widetilde{A}_{i,j} = \exp\left(\frac{A_{i,j}}{2\sigma^2}\right)$
- Spatial constraint (k-hop)
  $\bar{A}$

$G_L = (V_L, E_L, \bar{A}_L)$
$G_R = (V_R, E_R, \bar{A}_R)$

NetMF Embedding

$B_L \in \mathbb{R}^{|V_L|\times d}$
$B_R \in \mathbb{R}^{|V_R|\times d}$
$d \ll |V|$

K-means clustering

- The number of clusters are matched to a range of existing atlases

$c \in \mathbb{R}^{|V|}$
Label at vertex i:
$c_i \in \{1, 2, \cdots, \#\text{cluster}\}$

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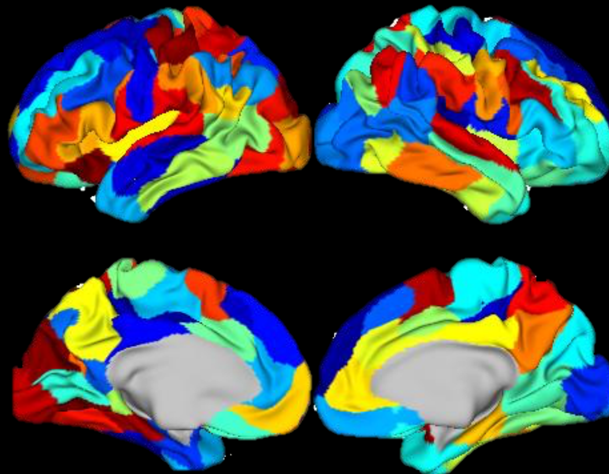
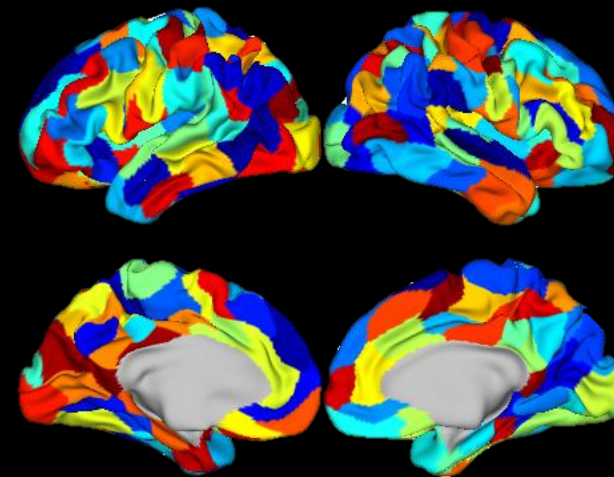
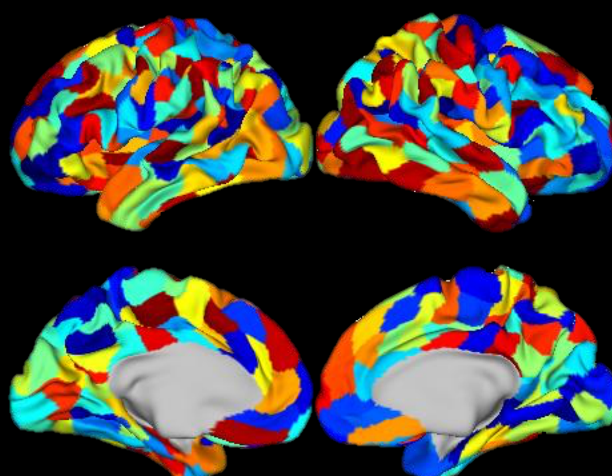


100 clusters



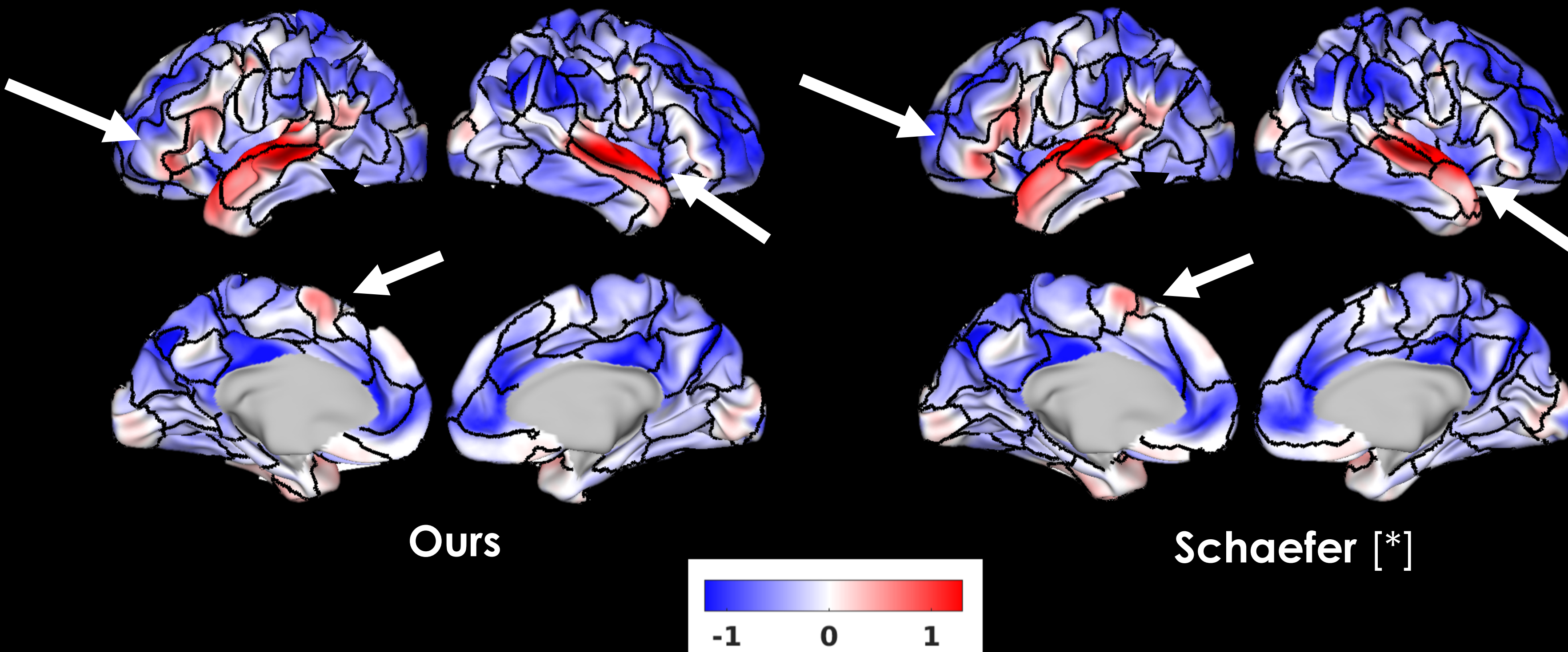
200 clusters



400 clusters

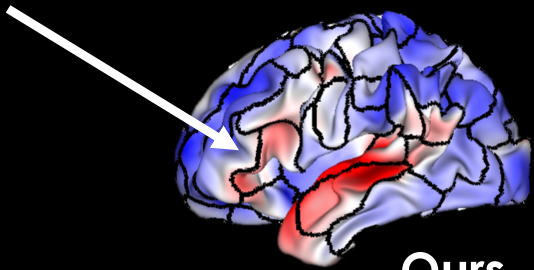
but how do we know these are useful/correct?

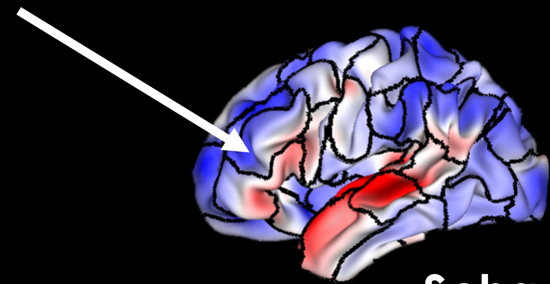
Parcellation overlaid on story task activation map



[*] Schaefer, A., Kong, R., Gordon, E. M., Laumann, T. O., Zuo, X. N., Holmes, A. J., ... & Yeo, B. T. (2018). Local-global parcellation of the human cerebral cortex from intrinsic functional connectivity MRI. *Cerebral cortex*, *28*(9), 3095-3114.

Quantitative metric for evaluating alignment with activation map





σ_i^2: variance of activation values within parcel i

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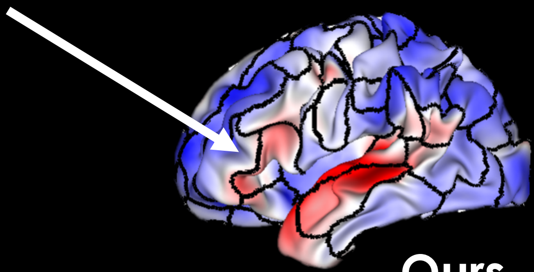
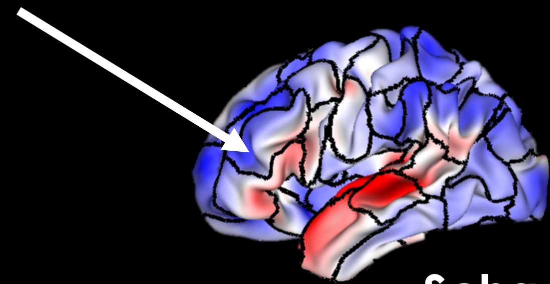


Ours



Schaefer [*]

σ_i^2: variance of activation values within parcel i

Weighted average variance across all parcels $\sigma^2 = \sum_{i=1}^{N} \sigma_i^2 \frac{|\boldsymbol{V}^i|}{|\boldsymbol{V}|}$

- N: number of parcels
- $|\boldsymbol{V}^i|$: number of vertices within parcel i
- $|\boldsymbol{V}|$: number of vertices over the whole cortex

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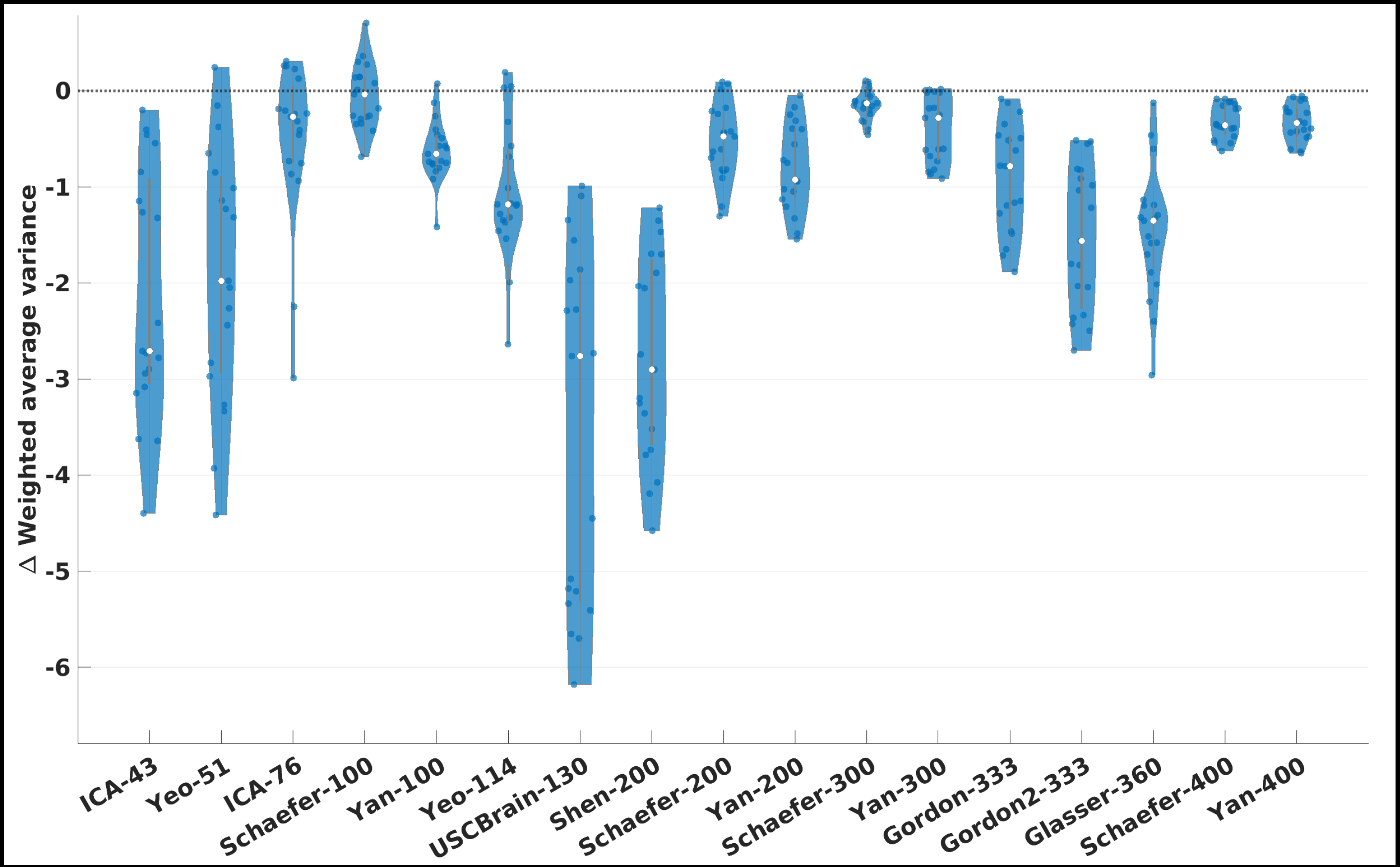
Difference of weighted average variance between our parcellation and baselines



Acknowledgement

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THANKS!