The Waisman Laboratory for Brain Imaging and Behavior

University of Wisconsin SCHOOL OF MEDICINE AND PUBLIC HEALTH

Large-scale nested hierarchical structural brain network

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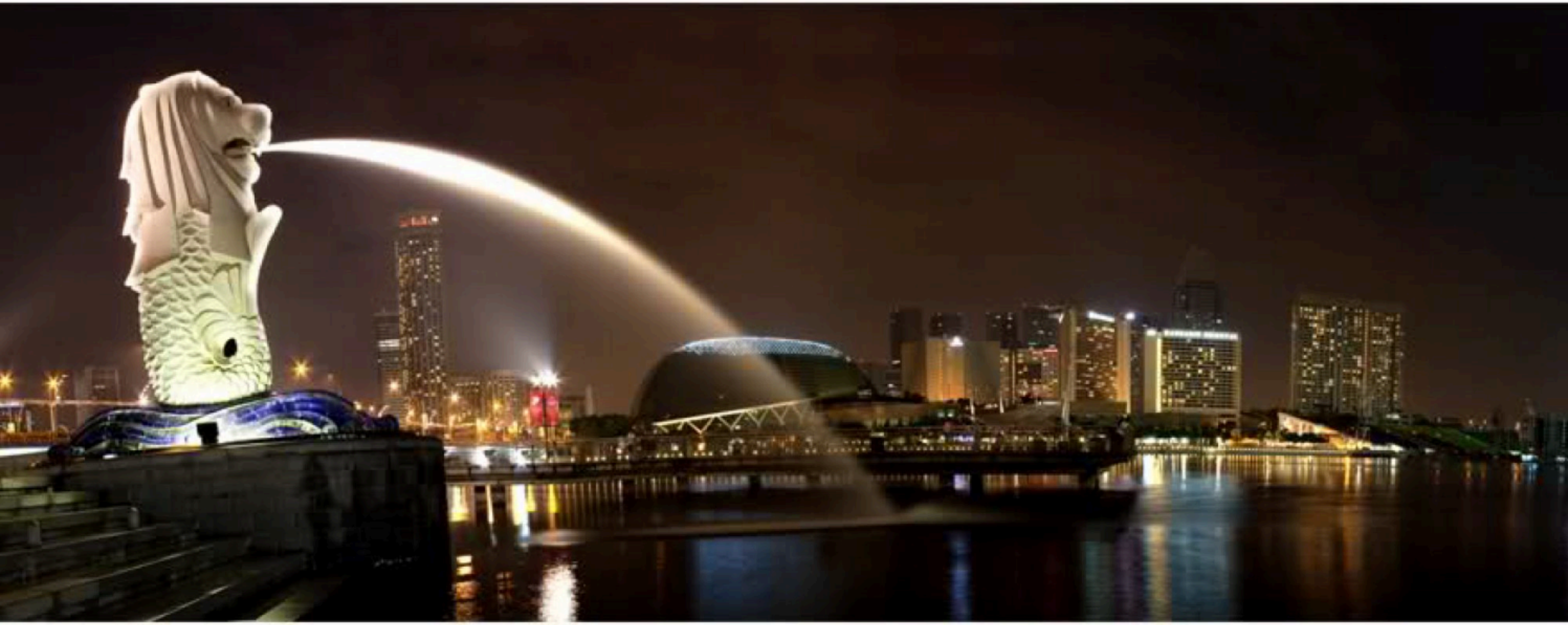
NONSTANDARD BRAIN IMAGE ANALYSIS

ORGANIZERS PROGRAM VENUE REGISTRATION



Satellite Meeting of 2018
OHBM Singapore

June 22-23, 2018

Peter Bandettini (National Institute of Mental Health): **plenary talk**
Jean-Baptiste Poline (University of California – Berkeley, USA): **plenary talk**

Session on Deep Learning
Dinggang Shen (University of North Carolina – Chapel Hill, USA)
Daniel Alexander (University College London, UK)
Jong Chul Ye (Korea Advanced Institute of Science & Technology, Korea)
Jong-Hwan Lee (Korea University, Korea)

Session on Imaging Genetics
Anqi Qiu (National University of Singapore, Singapore)
Li Shen (Indiana University, USA)
Hongtu Zhu (MD Anderson Cancer Center, USA)
Tomas Nichols (University of Oxford, UK)

Session on Nonstandard EEG Analysis
Hernando Ombao (King Abdullah University of Science and Technology, Saudi Arabia)
Hakmook Kang (Vanderbilt University, USA)
Mak Fiecas (University of Warwick, UK)
Tim Johnson (University of Michigan, USA)

Session on Nonstandard fMRI Analysis
Martin Lindquist (Johns Hopkins University, USA)
Alex D. Leow (University of Illinois – Chicago, USA; BiAffect)
Bharat Biswal (New Jersey Institute of Technology, USA)
Christian F. Beckmann (Radboud University Nijmegen, Netherlands)

Session on Nonstandard Brain Connectomics
Moo K. Chung (University of Wisconsin – Madison, USA)
Andrew Zalesky (University of Melbourne, Australia)
James C. Gee (University of Pennsylvania, USA)
Carl-Fredrik Westin (Harvard University, USA)

Poster Session

Acknowledgement

Ross Luo, Nagesh Adluru,
Andrew Alexander,
Richard Davidson, Hill Goldsmith
University of Wisconsin-Madison

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HERITABILITY OF HIERARCHICAL STRUCTURAL BRAIN NETWORK

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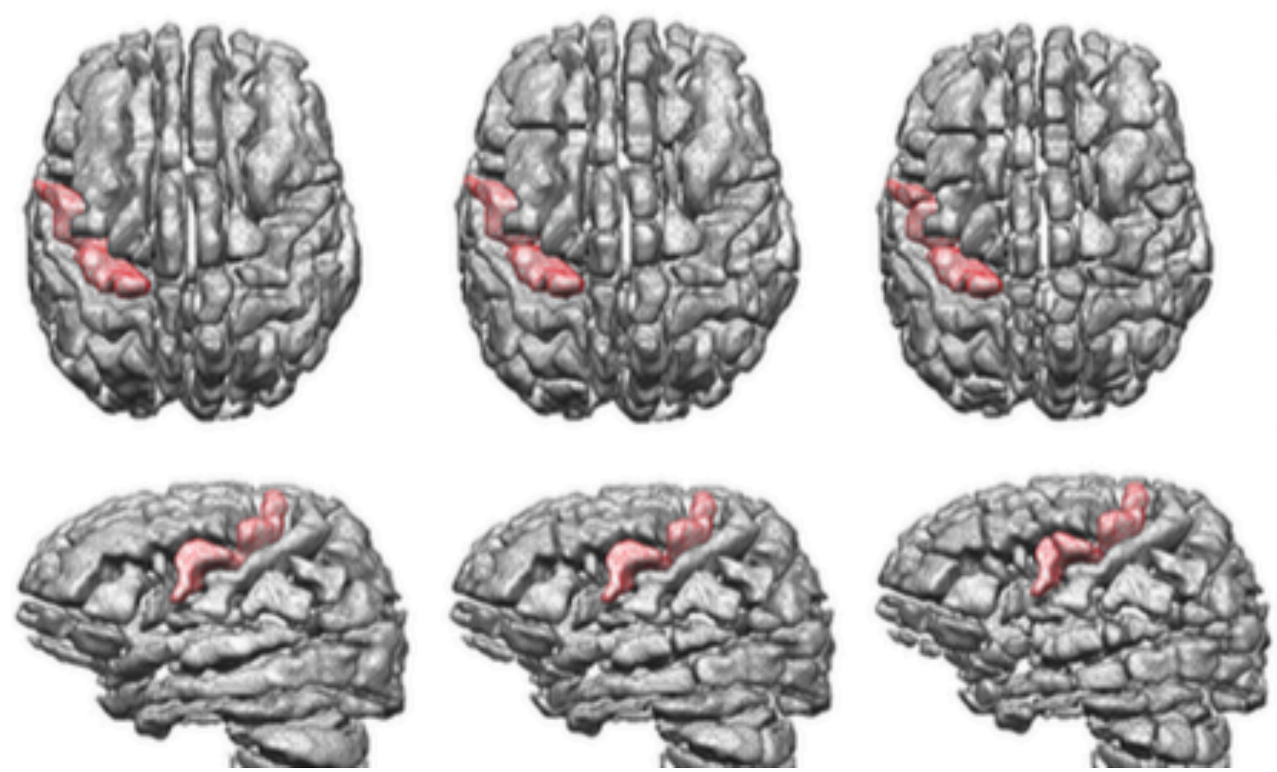
ABSTRACT

We present a new structural brain network parcellation scheme that can subdivide existing parcellations into smaller subregions in a hierarchically nested fashion. The hierarchical parcellation was used to build multilayer convolutional structural brain networks that preserve topology across different network scales. As an application, we applied the method to diffusion weighted imaging study of 111 twin pairs. The genetic contribution of the whole brain structural connectivity was determined. We showed that the overall heritability is consistent across different network scales.



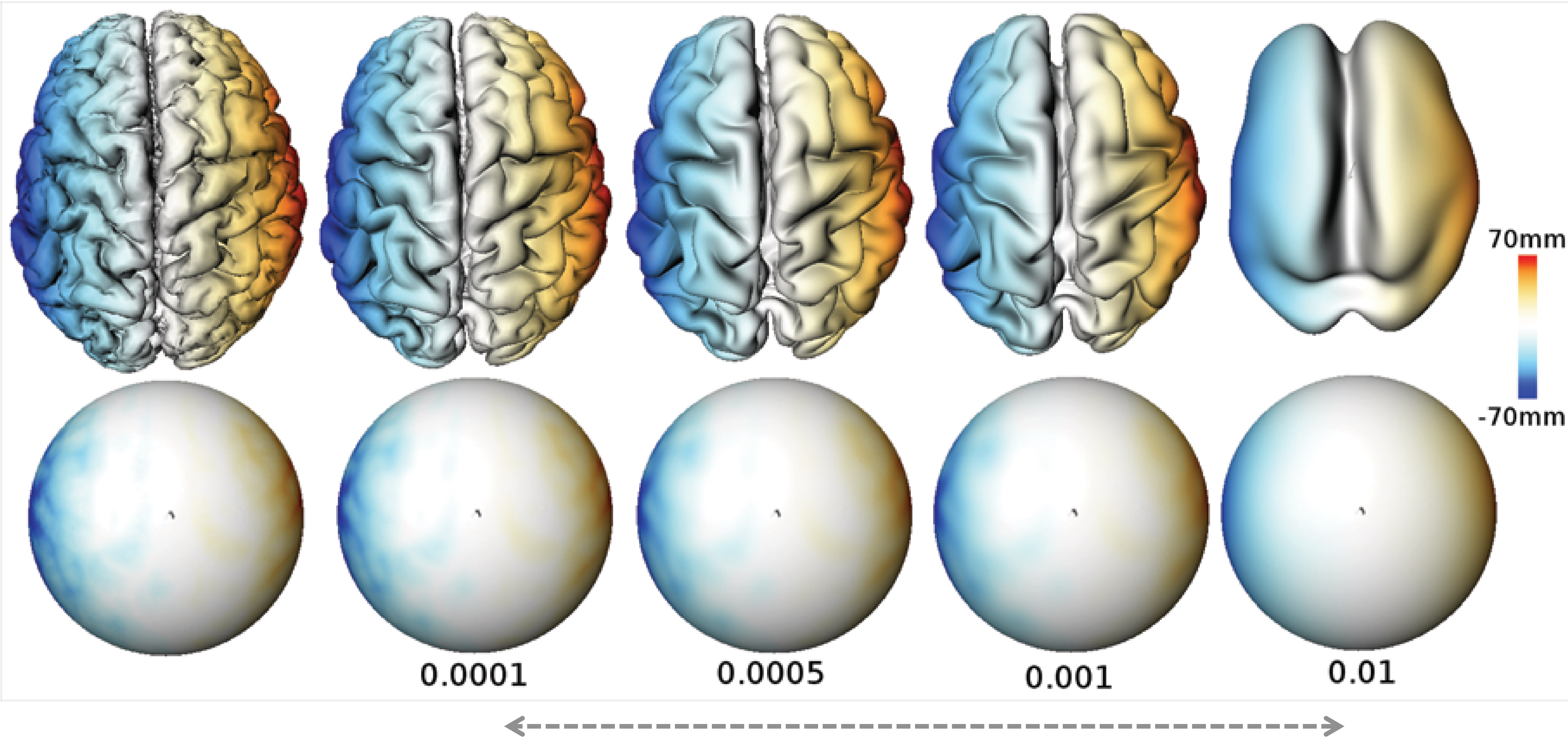
Chung et al. 2018 ISBI *under review*

Preliminary

multiscale image analysis

Weighted-SPHARM

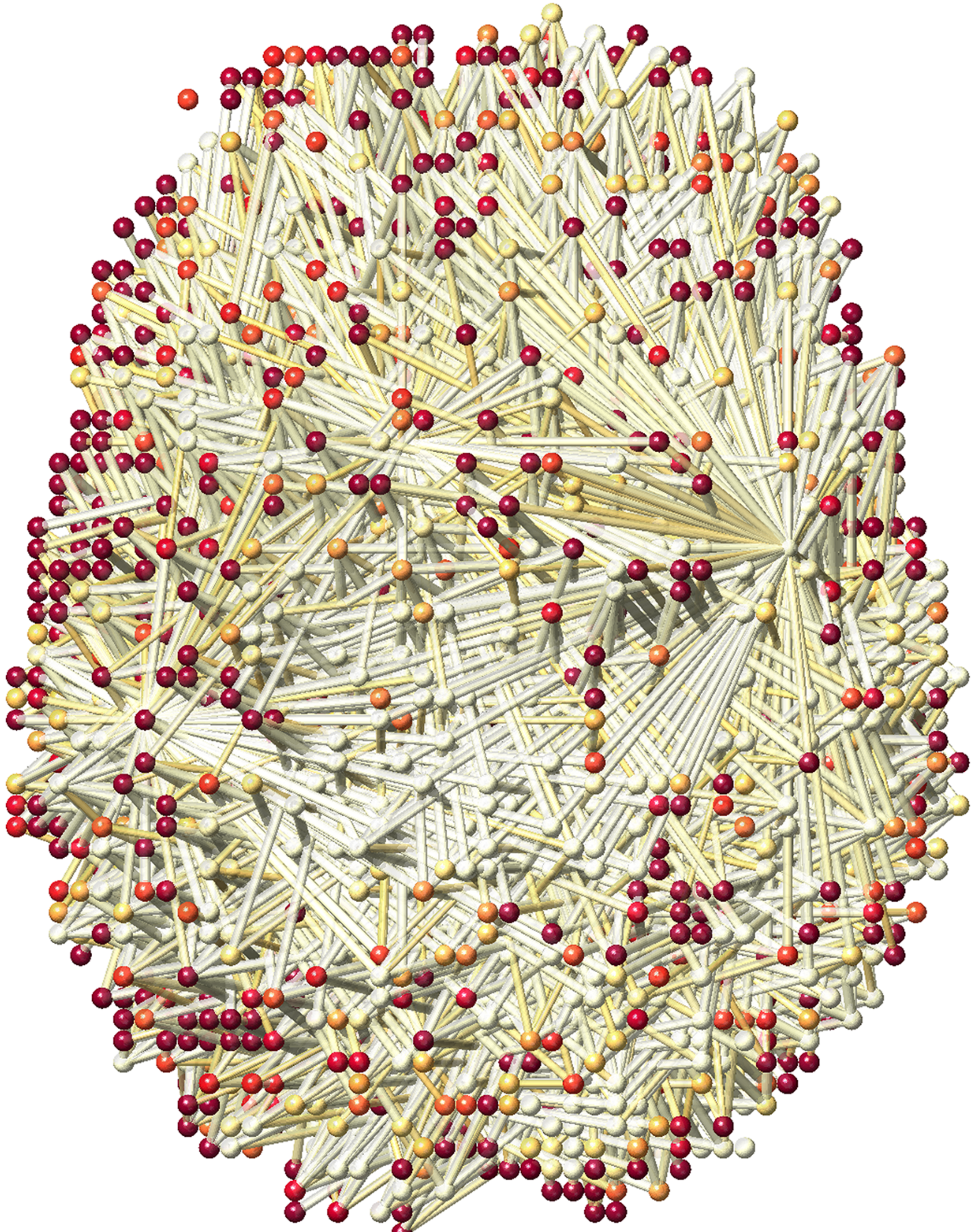
[Chung et al., 2007 IEEE Transactions on Medical Imaging 26:566-581](#)



heat kernel bandwidth, diffusion time

Matlab: http://www.stat.wisc.edu/~mchung/softwares/weighted-SPHARM/weighted-SPHARM.html

Question: How to build a multiscale network?



+25000 nodes

+0.6 billion connections

Voxel-level functional network

Chung et al. 2017 IPMI

Winsconsin Twin Project

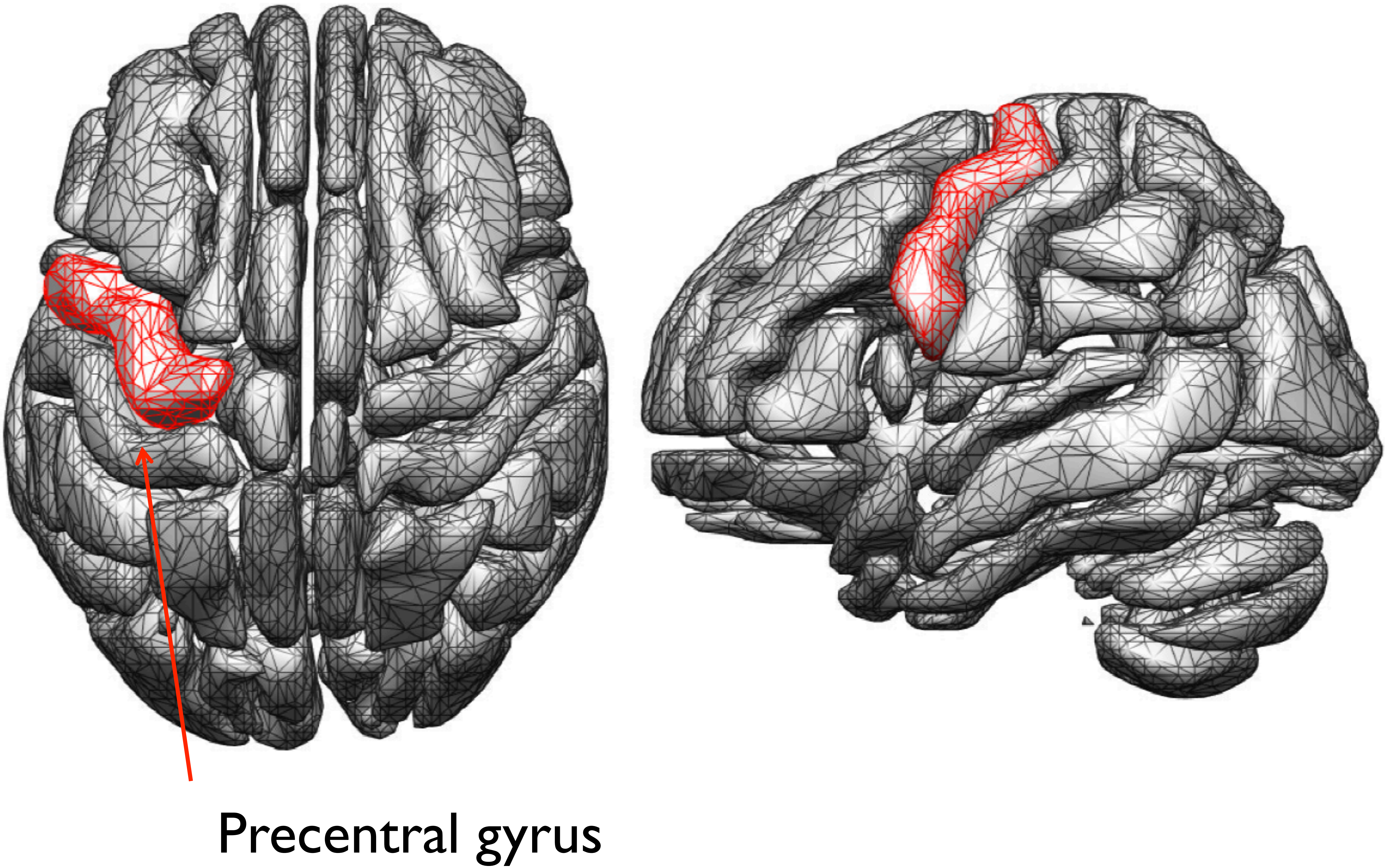
58 Monozygontic (MZ) twin pairs
53 same-sex dizygotic (DZ) twin pairs

111 pairs = 222 subjects

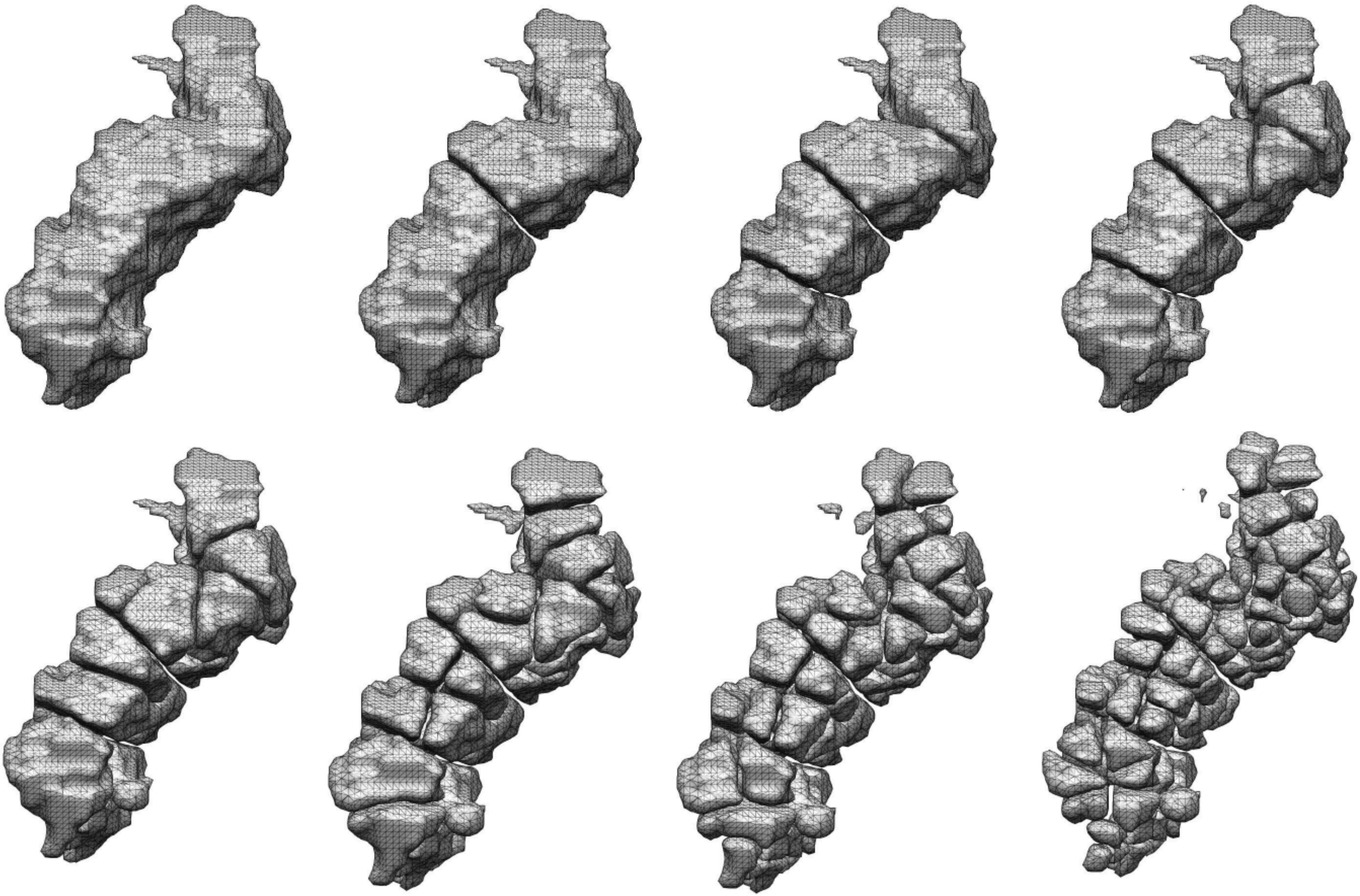
6 non-DWI: b=0
63 DWI: b=500 (9 dir.), 800 (18 dir.) , 2000 (36 dir.)
Isotropic 2mm resolution

Hierarchical Parcellation

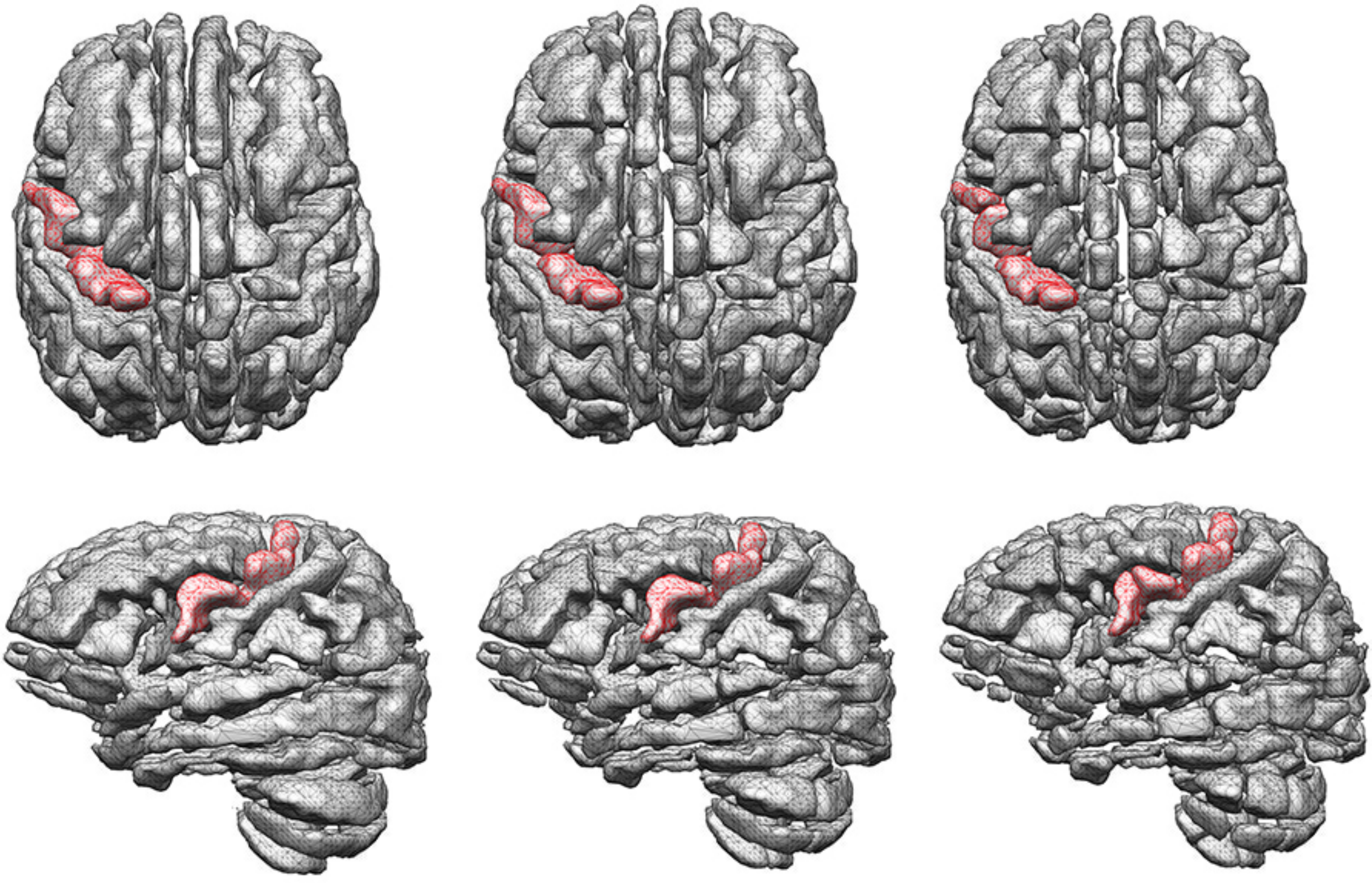
Standard brain parcellation with 116 regions



20-layer hierarchical parcellation



20-layer hierarchical parcellation



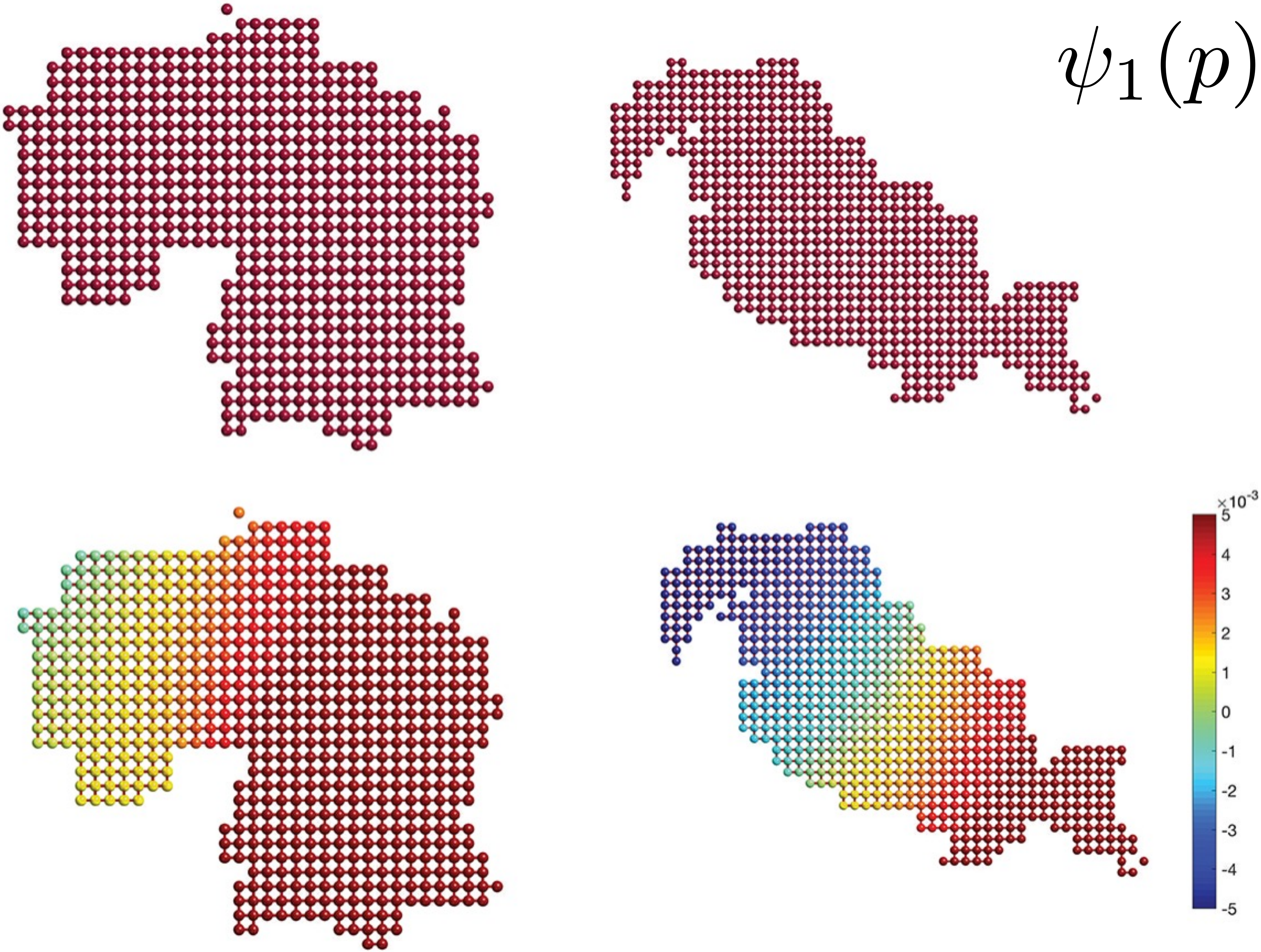
Courant nodal domain theorem

$$\Delta\psi_j(p) = \lambda_j \psi_j(p)$$

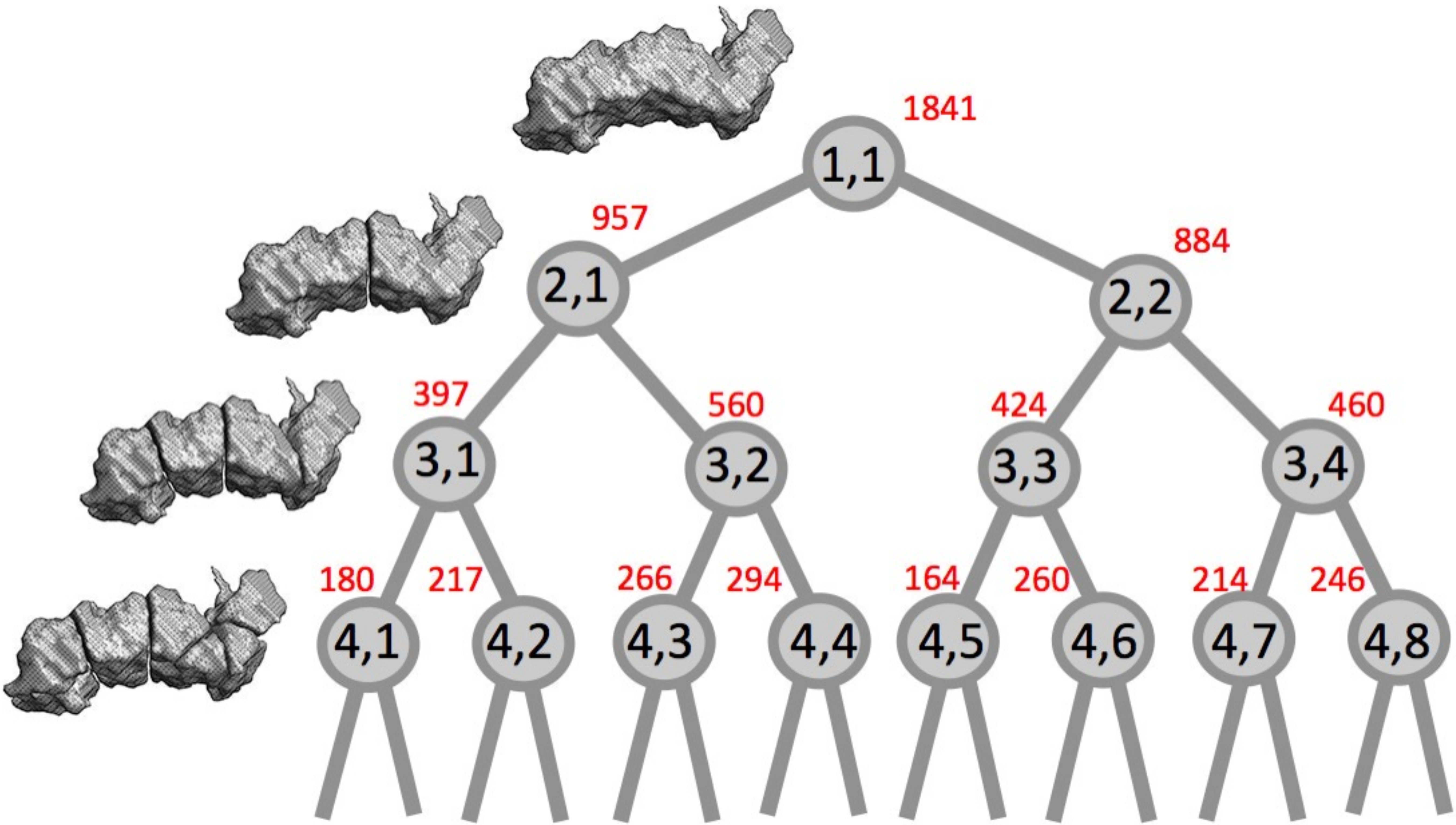
$$0 = \lambda_1 < \lambda_2 \leq \cdots$$

$$\psi_0(p) = 1/\sqrt{\mu(\mathcal{M})}$$

$$\int_{\mathcal{M}} \psi_1(p)\ d\mu(p) = 0$$

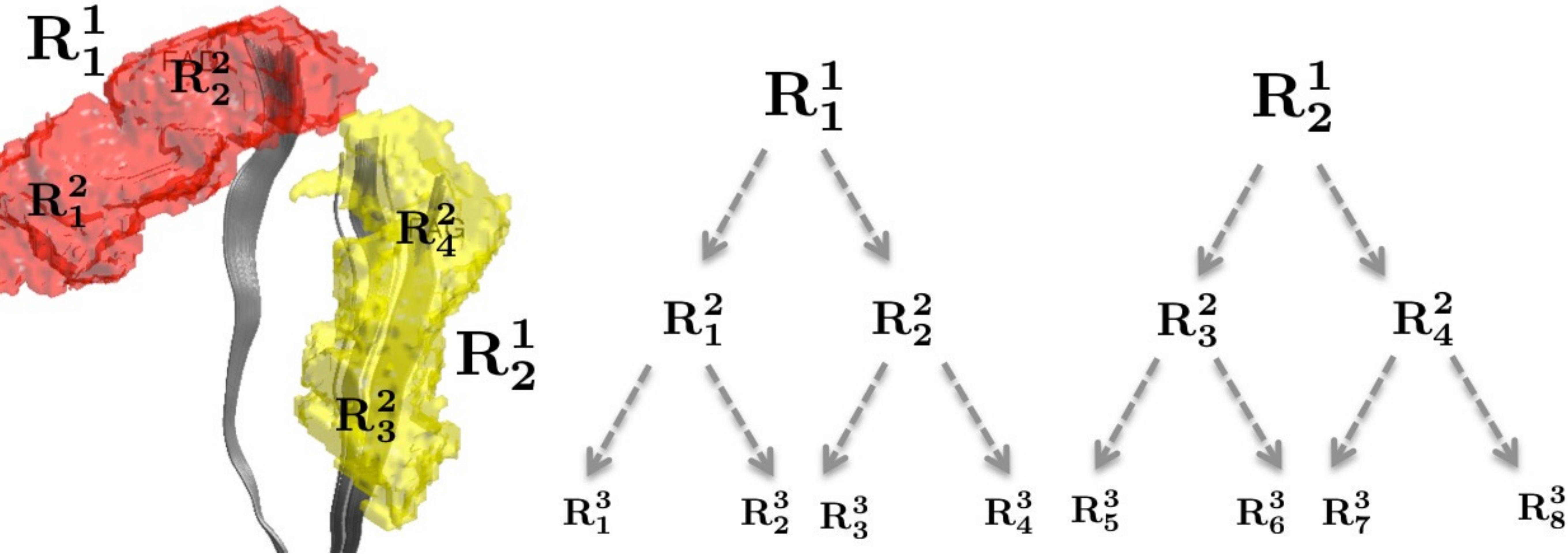

$\psi_1(p)$
×10-3
5
4
3
2
1
0
-1
-2
-3
-4
-5

Number of voxels in each layer



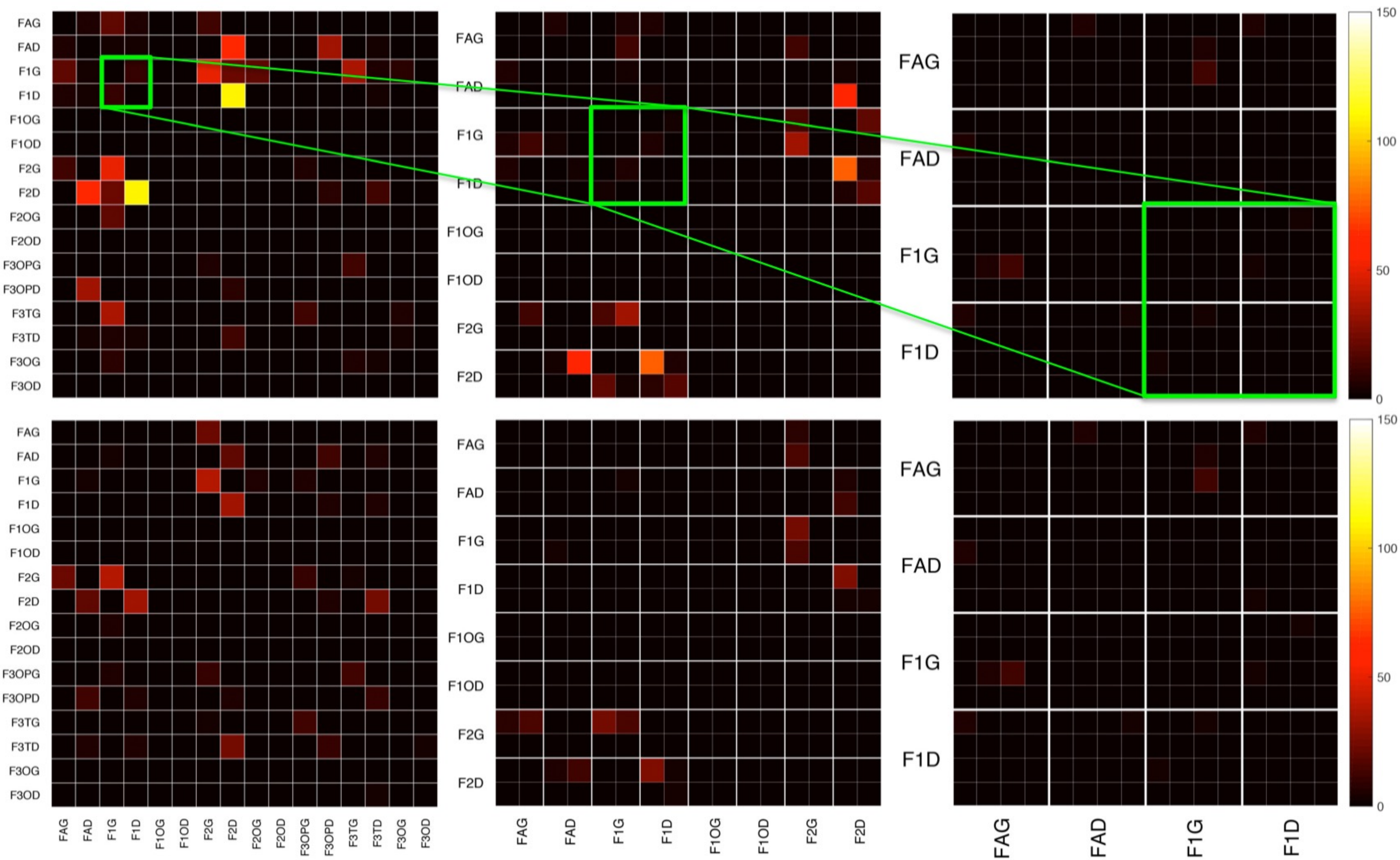
Hierarchical Connectivity

Hierarchical connectivity S^i_{jk}



$$S^i_{jk} = \sum_{\mathbf{R}^{i+1}_l \subset \mathbf{R}^i_j} \sum_{\mathbf{R}^{i+1}_m \subset \mathbf{R}^i_k} S^{i+1}_{lm}$$

Hierarchical connectivity matrix



Heritability of structural network

Heritability Index

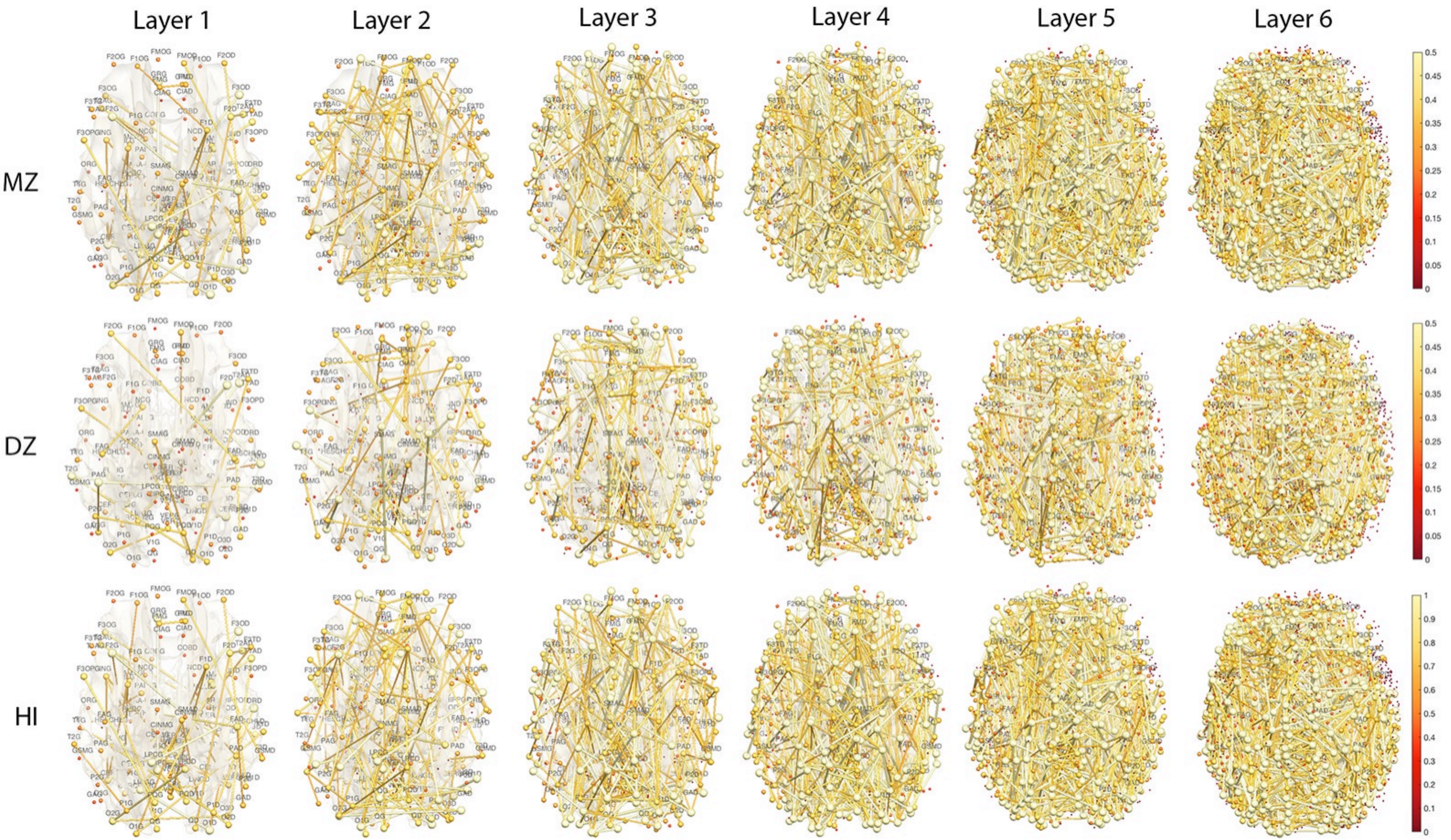
$$\mathrm{HI} = 2(\rho_{\mathrm{MZ}} - \rho_{\mathrm{DZ}})$$

Spearman's rank correlation was used on tract counts.

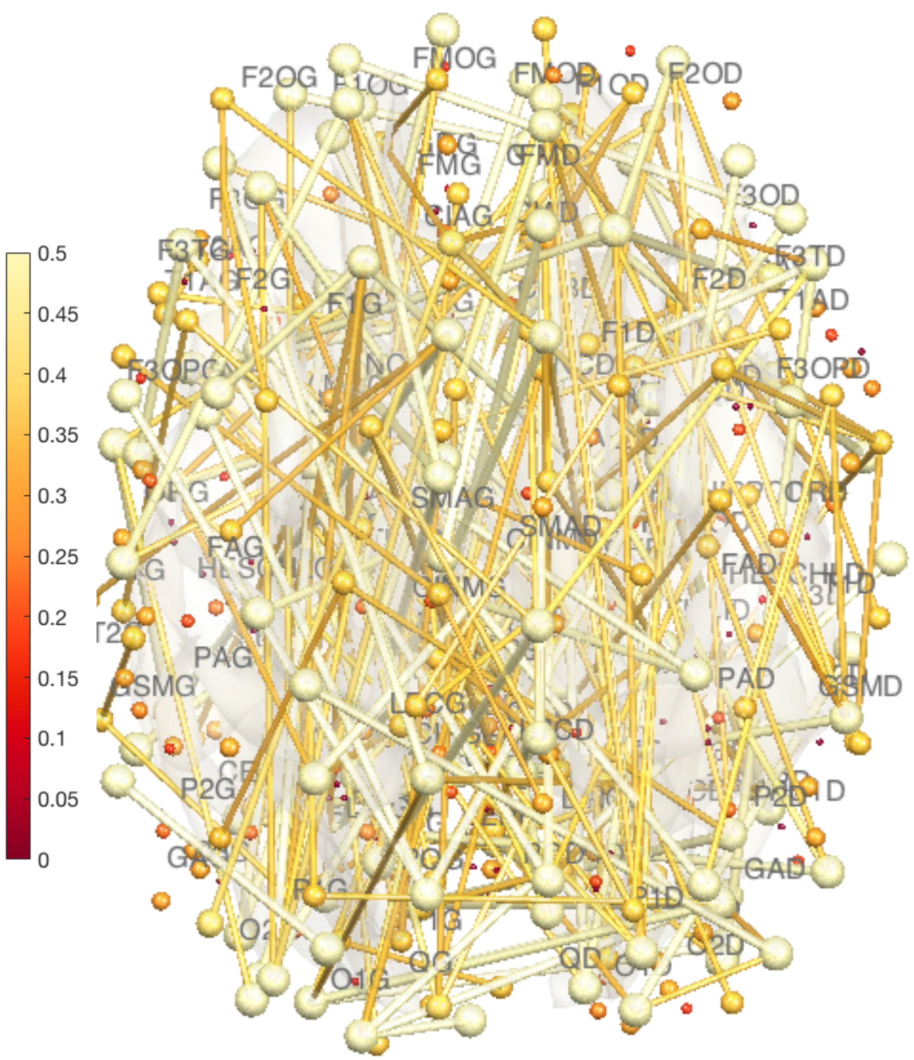
(1 2 3) (2 3 10)

Pearson's : 0.92
Spearman's : 1

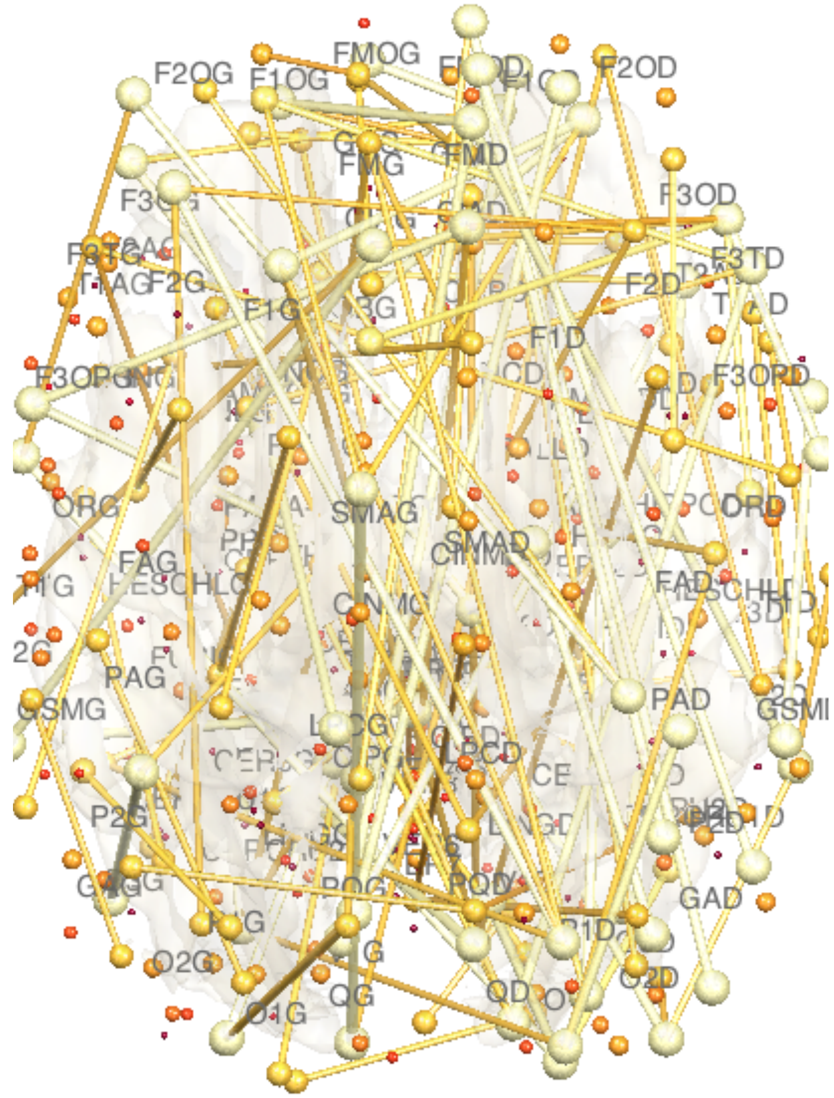
Twin correlations & heritability index



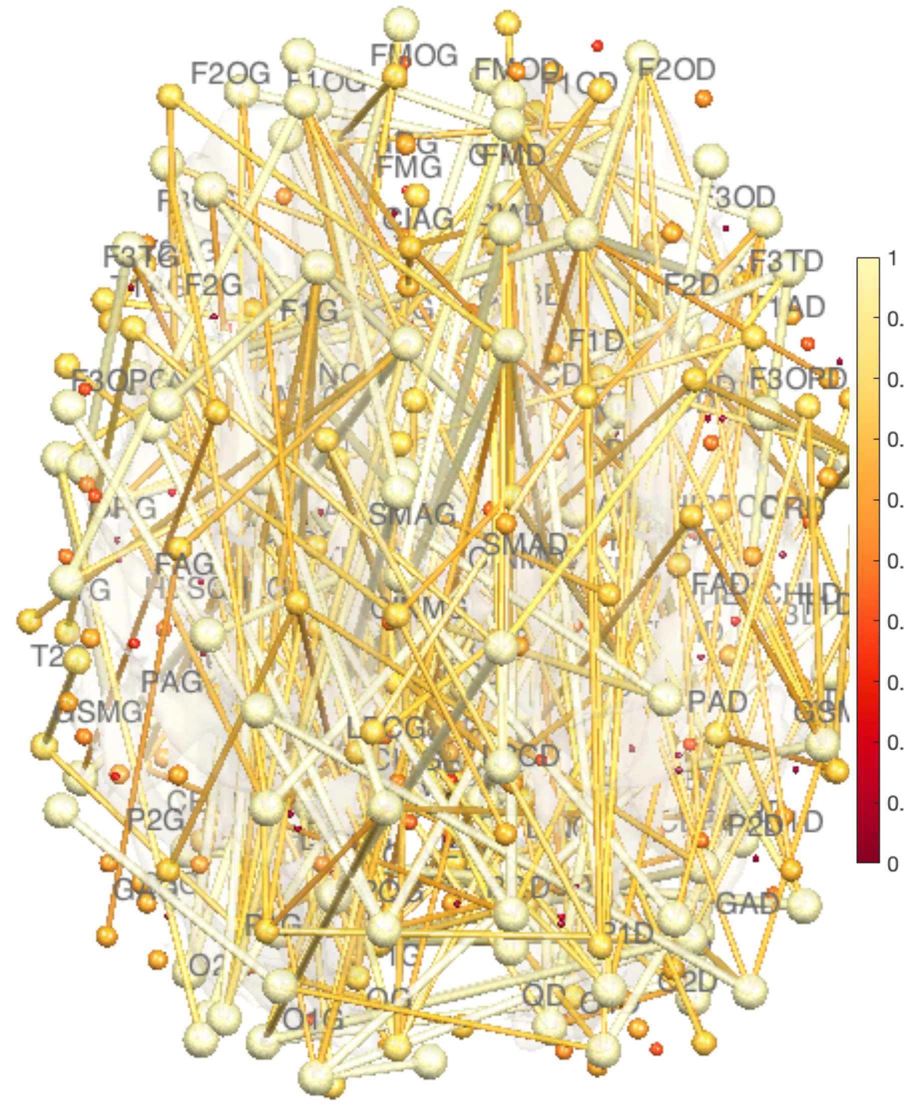
Twin correlations & heritability index



MZ



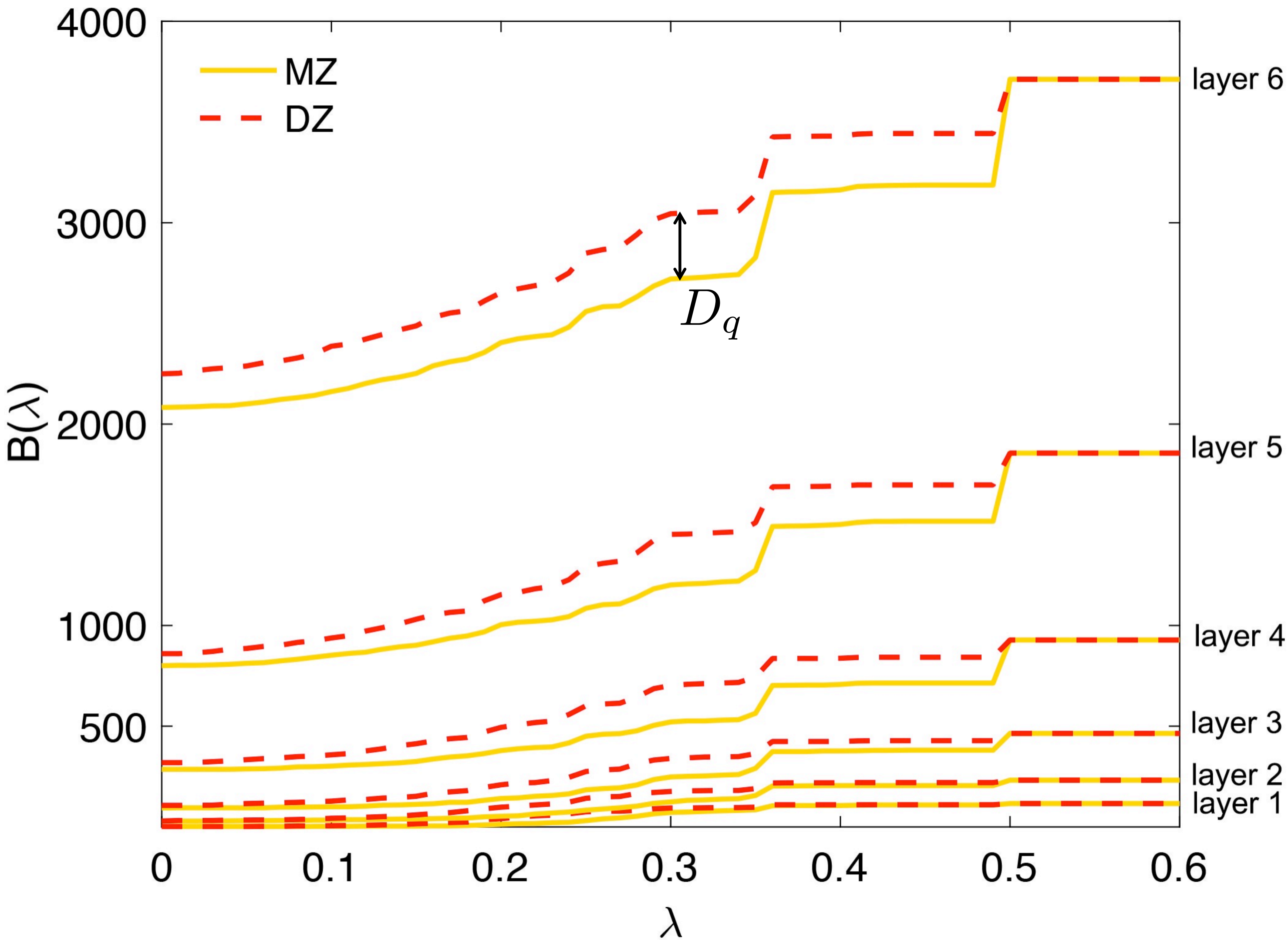
DZ



HI

Exact Topological Inference

Betti-0 plot (# of connected components)



Exact topological inference

Maximum gap between plots

$$D_q = \sup_{1 \leq j \leq q} \left| B(G^1_{\lambda_j}) - B(G^2_{\lambda_j}) \right|$$

$$P\left(D_q / \sqrt{2q} \geq d \right) \approx 2 \sum_{i=1}^{\infty} (-1)^{i-1} e^{-2i^2 d^2}$$

Chung et al. 2017 IPMI