Estimating human brain organization by fusion across functional imaging datasets

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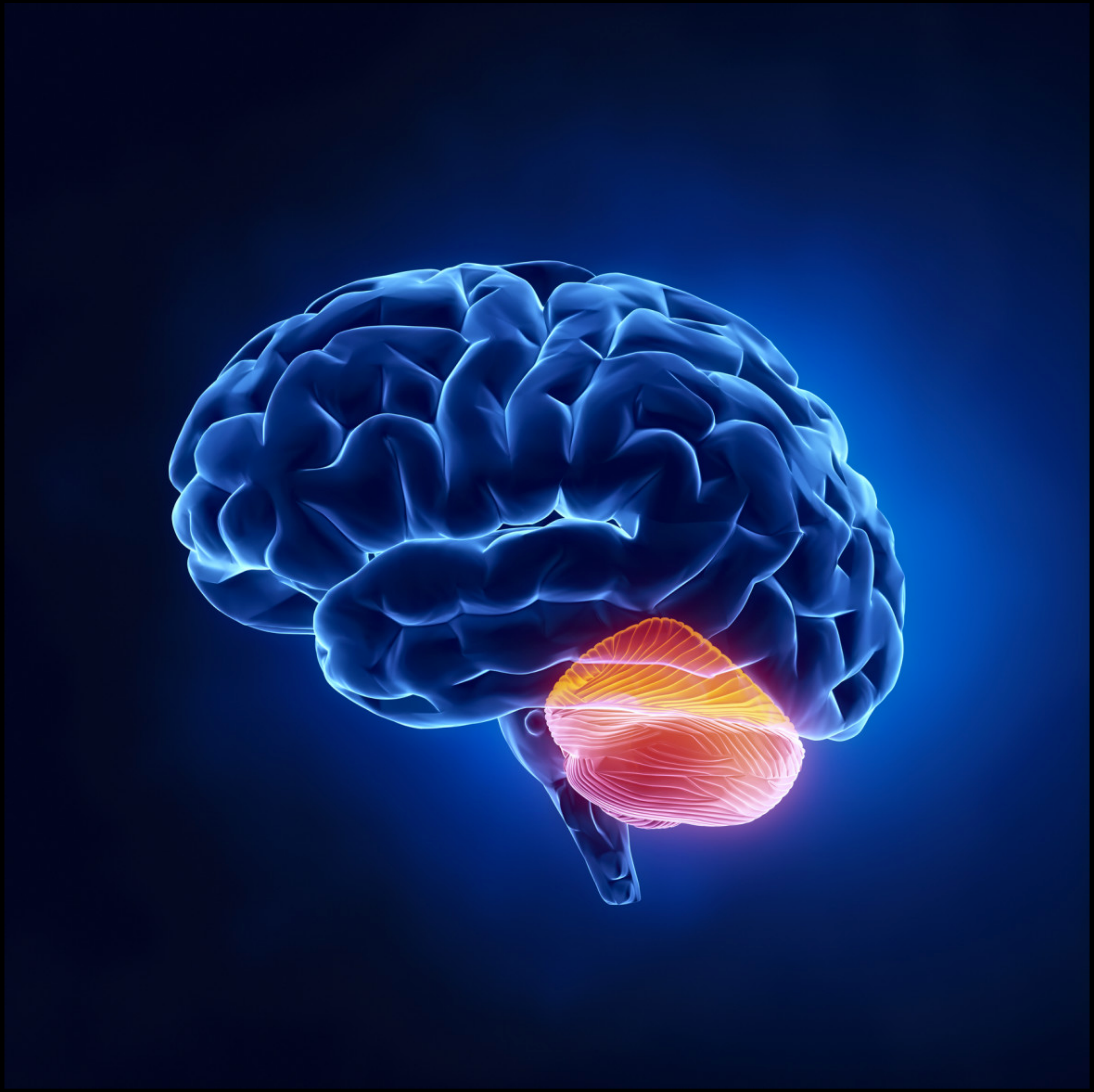
Functional brain organization

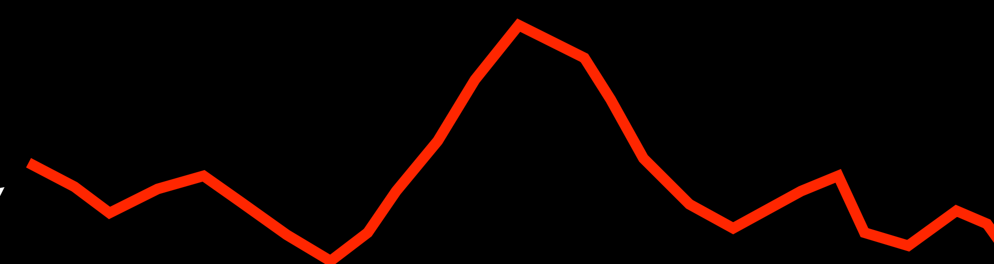


Functional Magnetic Resonance Imaging (fMRI)

Anatomical Image
(5min)

Functional Image
(1s)

3d-pixel
voxel
1-3 mm^3



Images change brightness slightly with different levels of brain activity

Highly multivariate data (~200,000 brain locations across time)

Aims of fMRI research

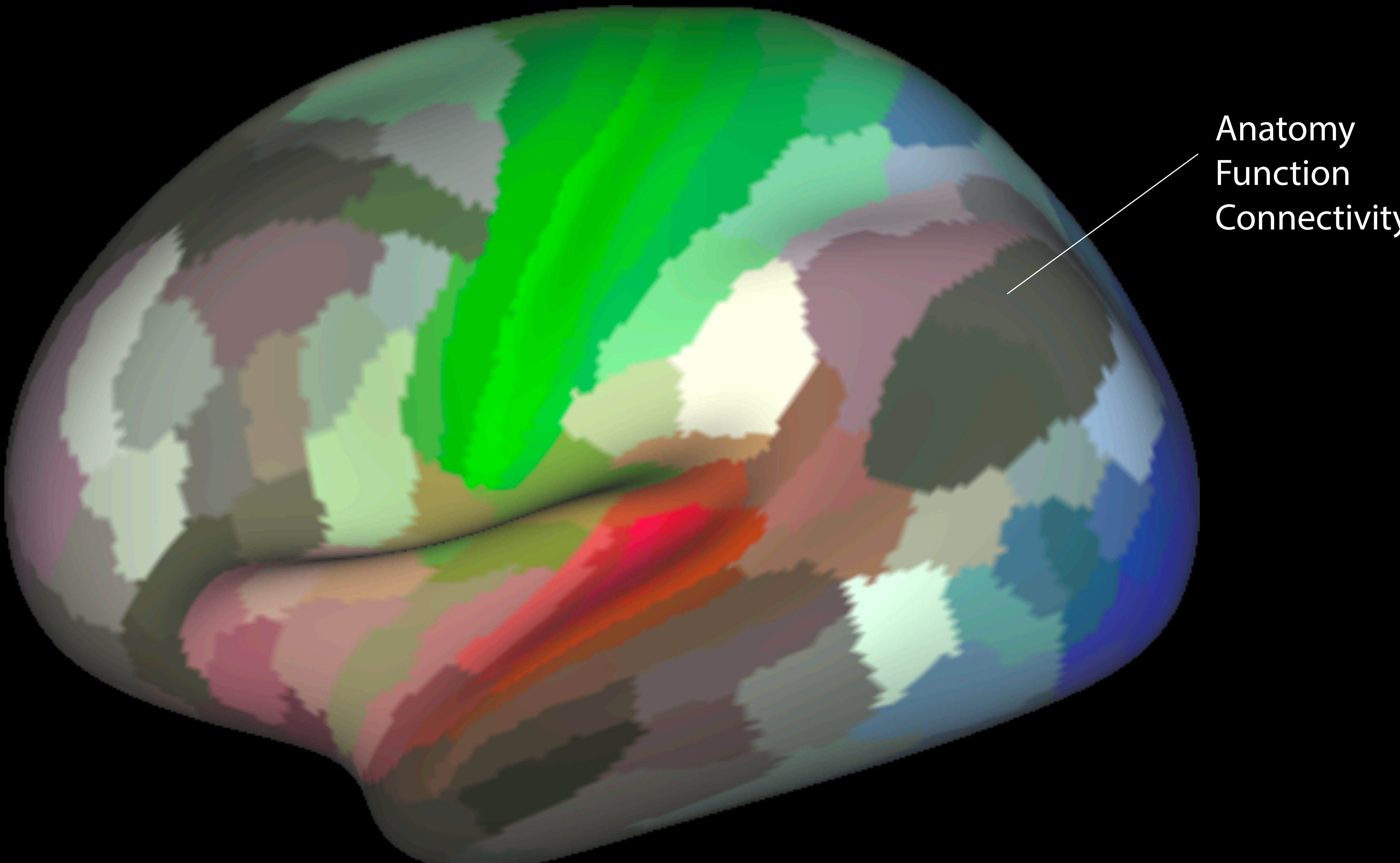
General models of brain function

- Which brain region does what?
- How do brain regions communicate with each other?

Identifying individual brain organization

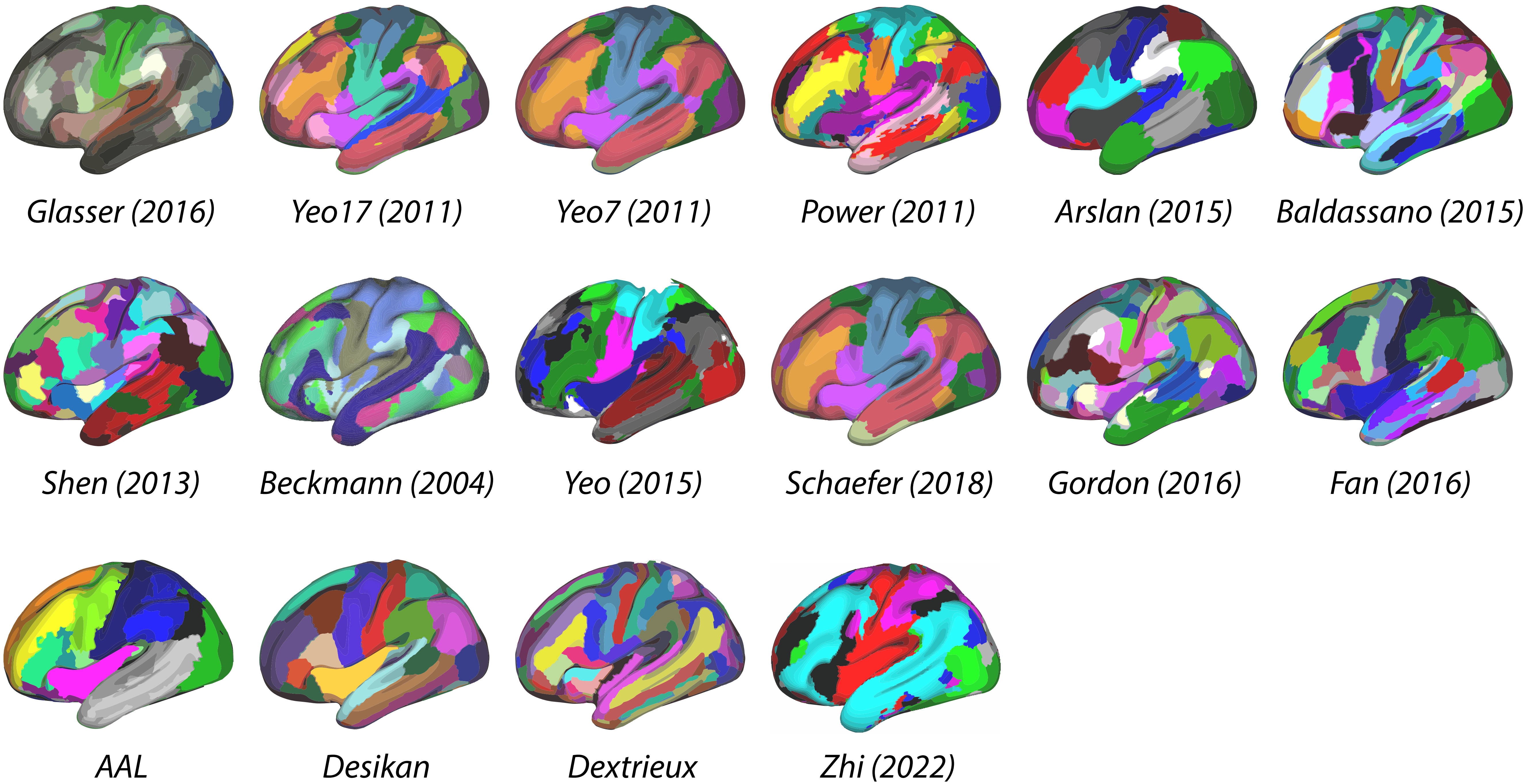
- What aspects of brain organization predict good function or dysfunction?
- Identifying functional brain regions for further study (functional localizer)
- Surgical planning

Brain models: Parcellation into brain regions



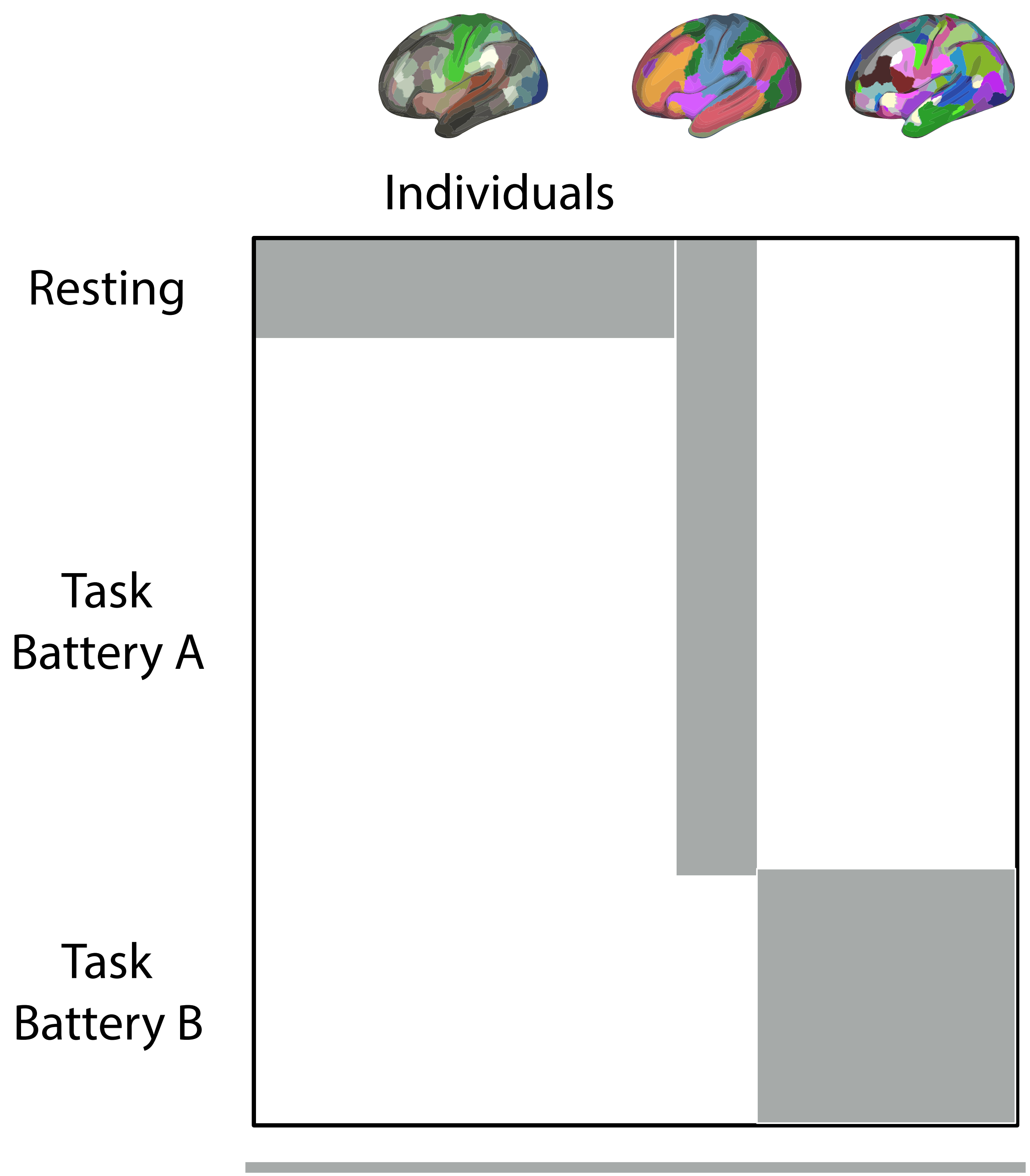
Glasser et al. (2016). Nature.

Different brain parcellations



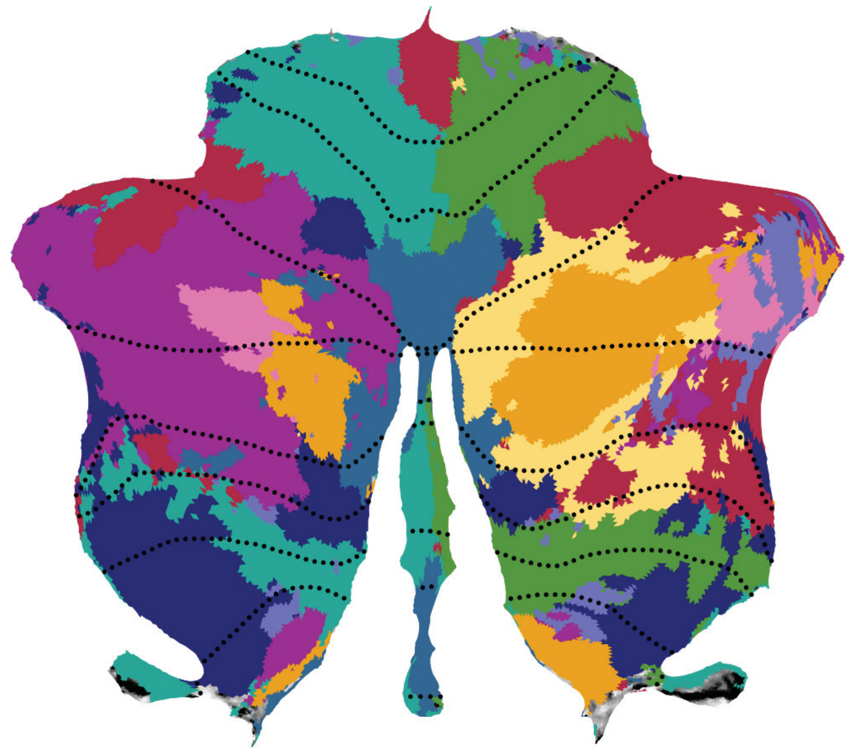
Zhi et al. (2022). Human Brain Mapping.

Wide and deep data sets

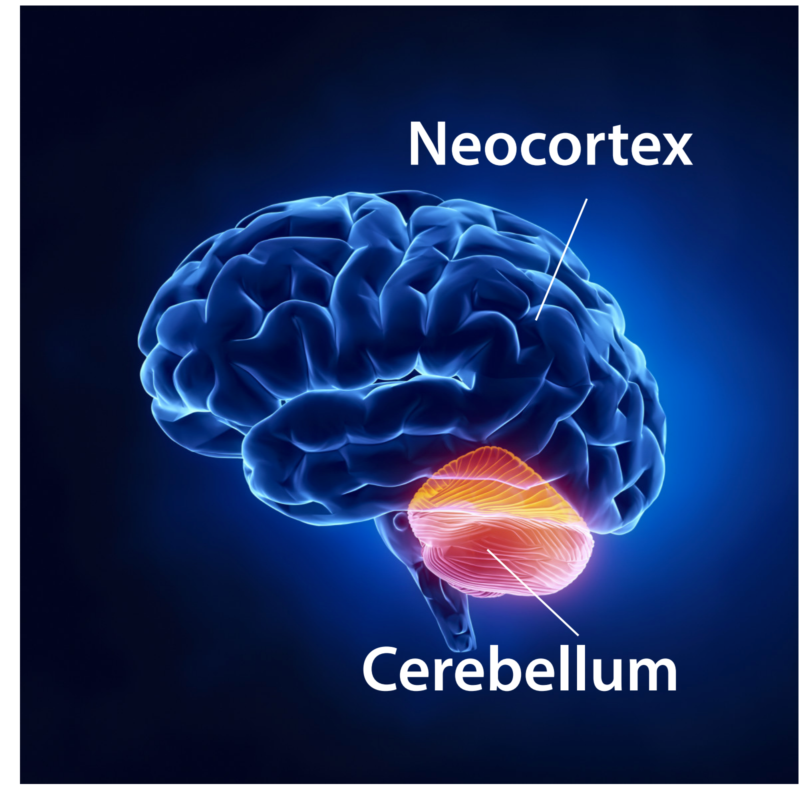


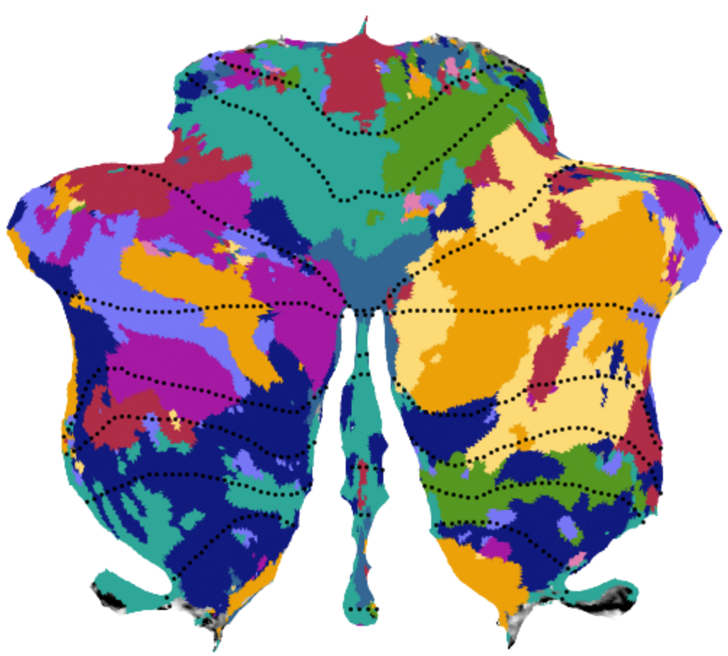
Fusion of information
into single model?

Individual functional variability

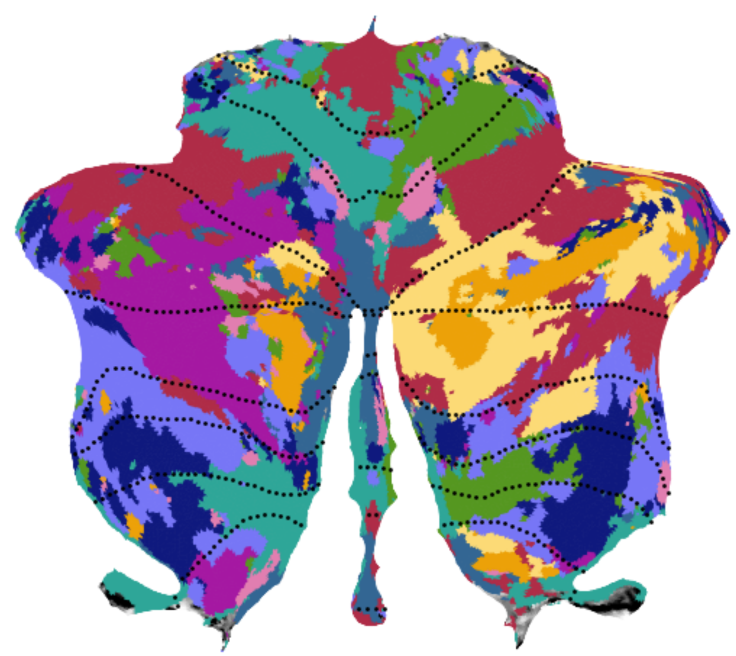


Group probability map

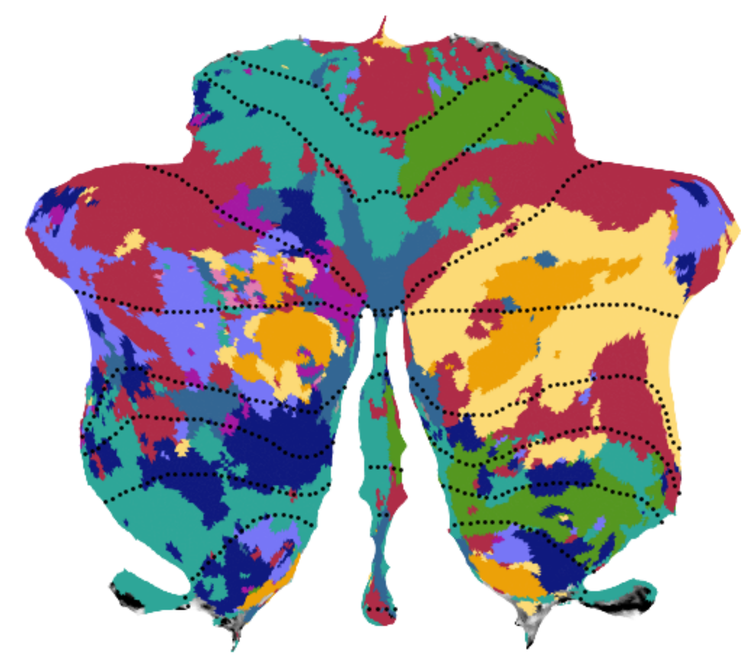




Subject 01



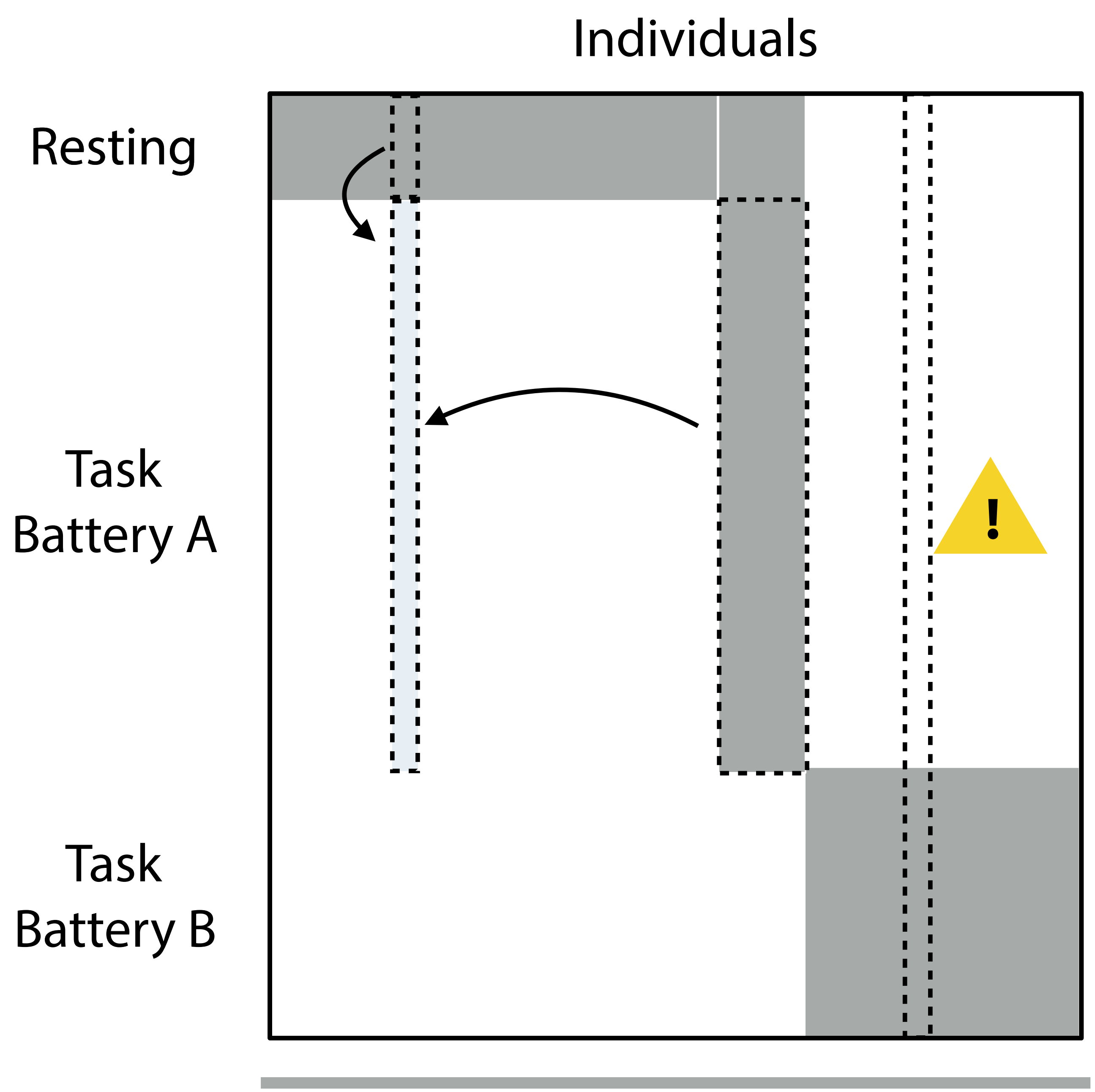
Subject 02



Subject 03

King et al. (2019). Nature Neuroscience.

Probabilistic model of brain organization



Fusion of information into single model?

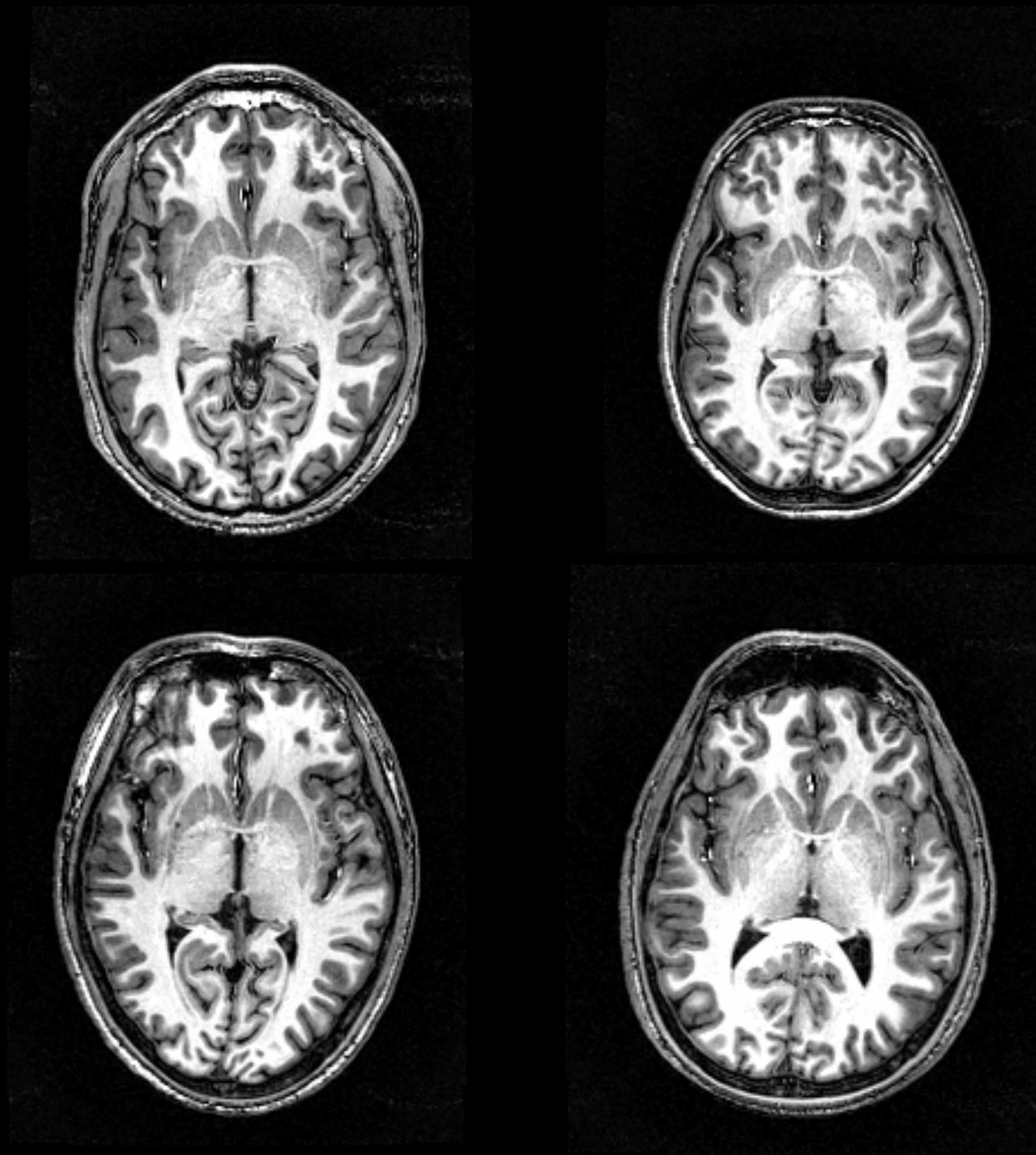
$$p(brain\,|\,\boldsymbol{\theta}_{population})$$

Requires a lot of data

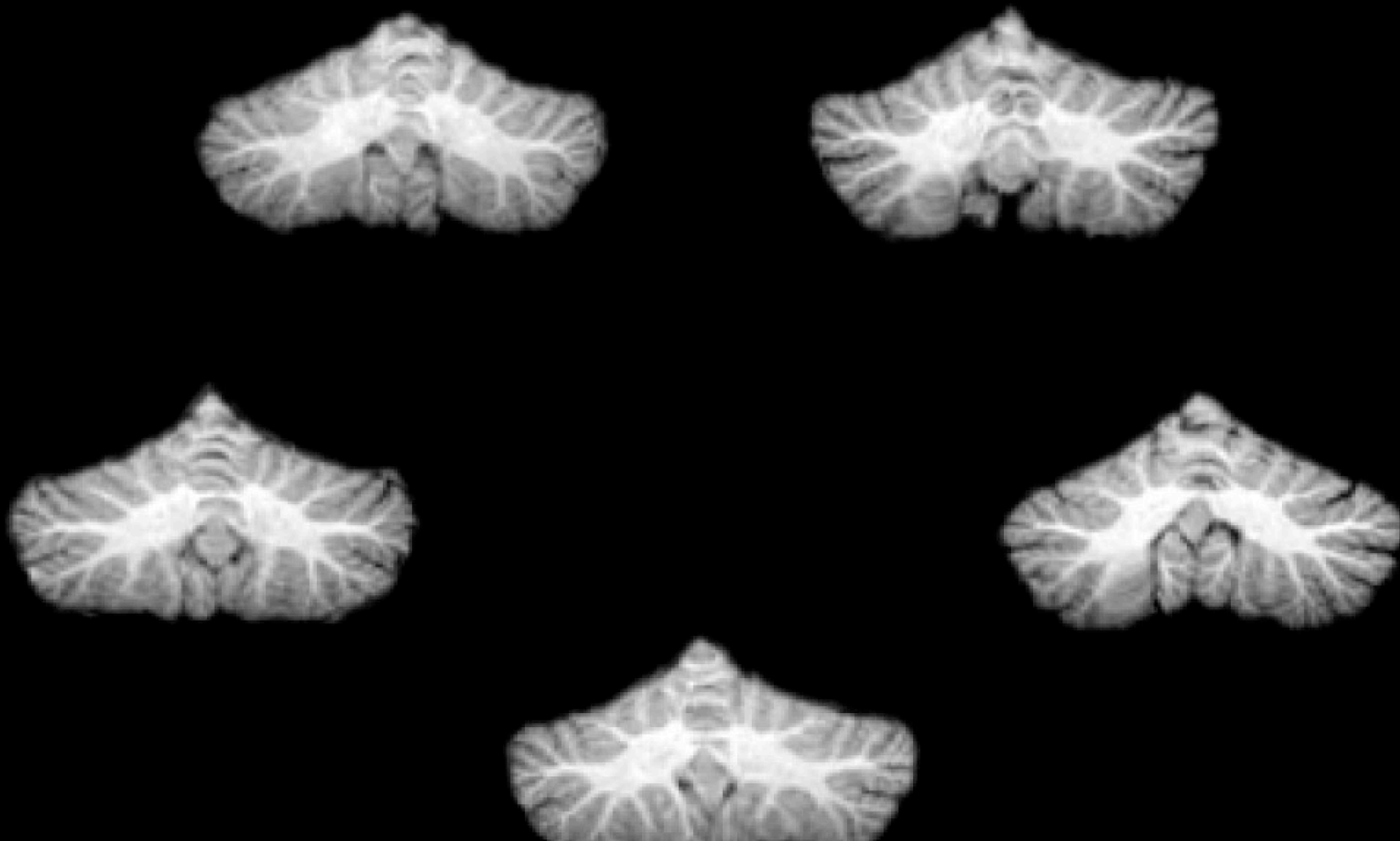
Barriers:

- Techniques
- Models
- Algorithms

Technical problem 1: Anatomical variability

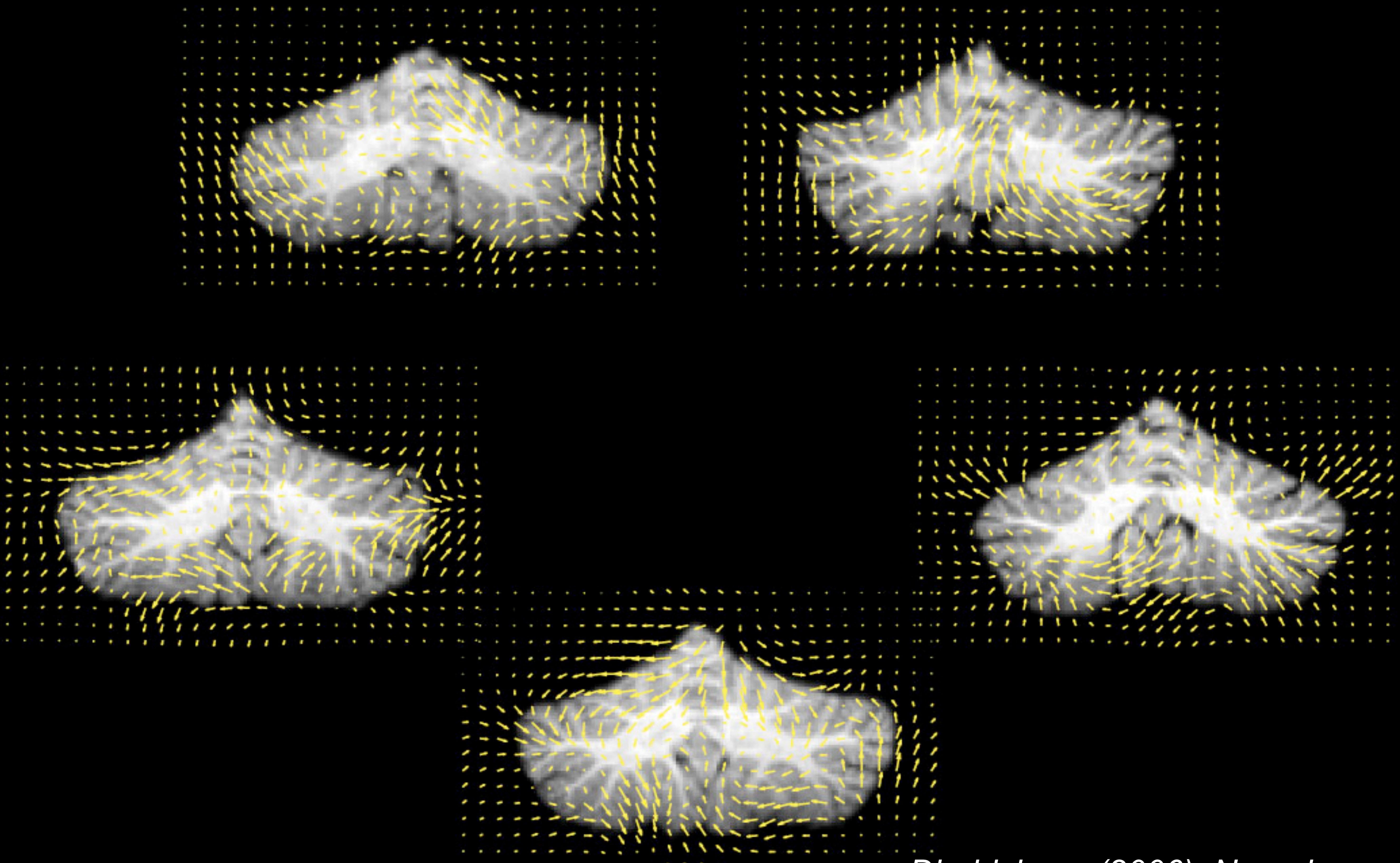


Volume-based registration (cerebellum)



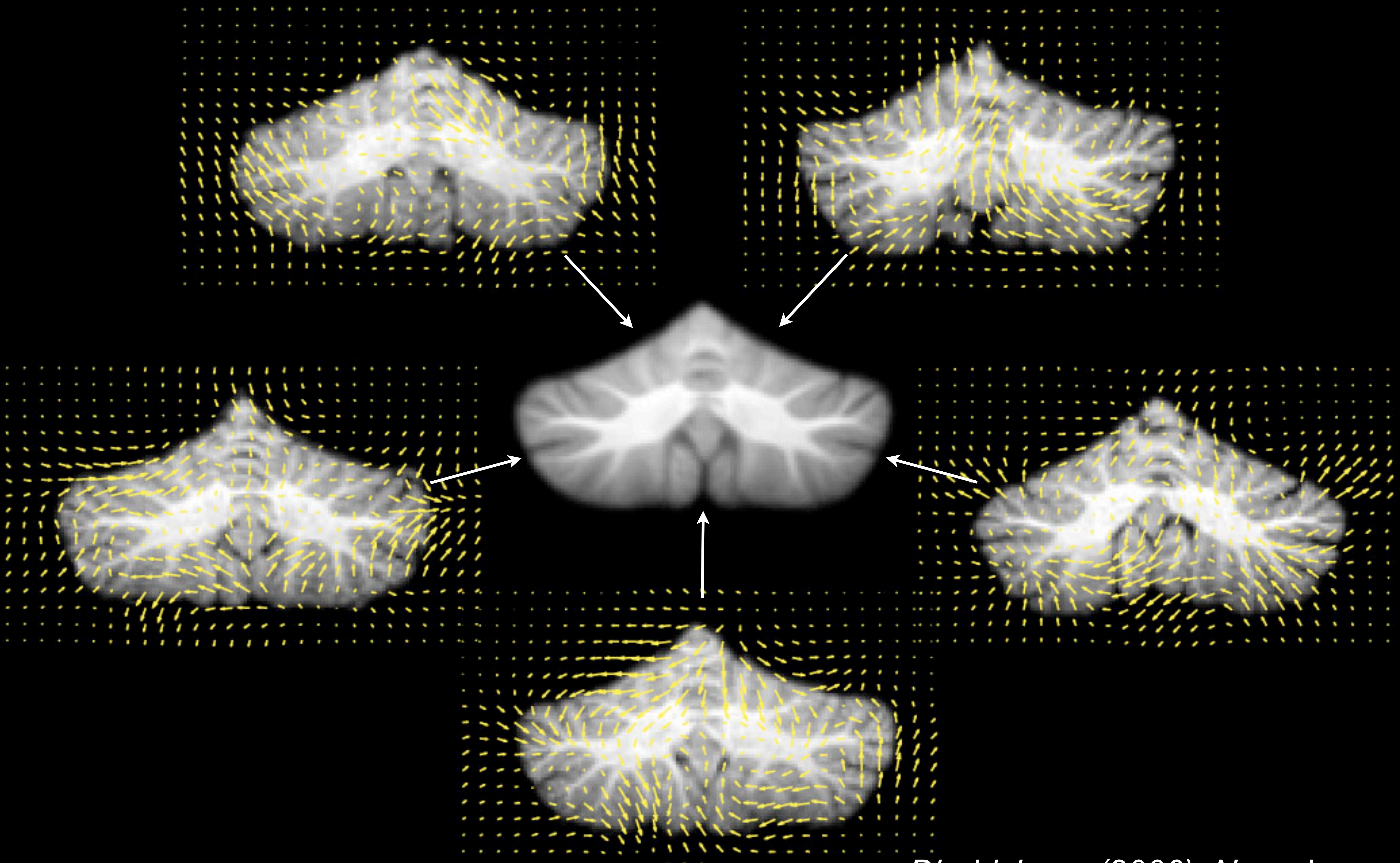
Diedrichsen (2006). Neuroimage.

Volume-based registration (cerebellum)



Diedrichsen (2006). Neuroimage.

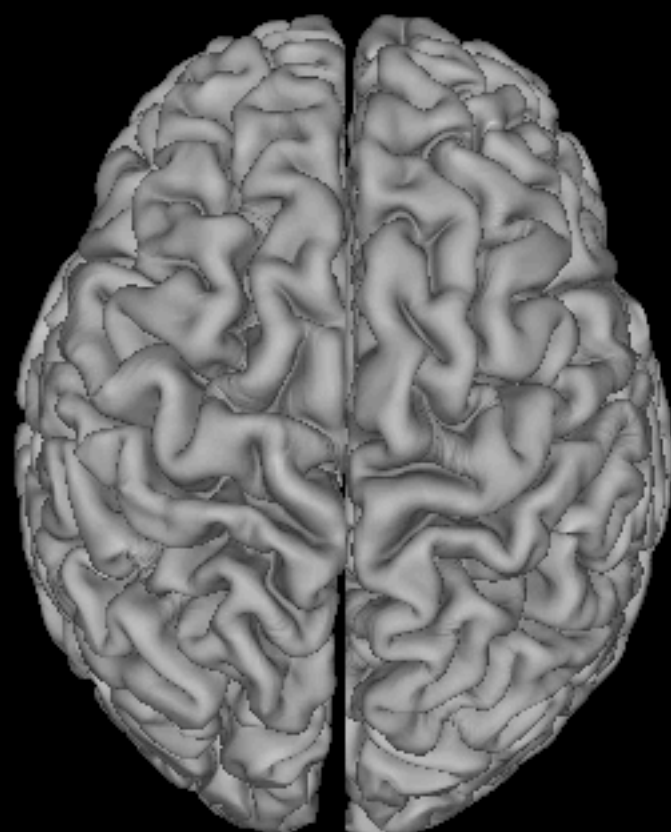
Volume-based registration (cerebellum)



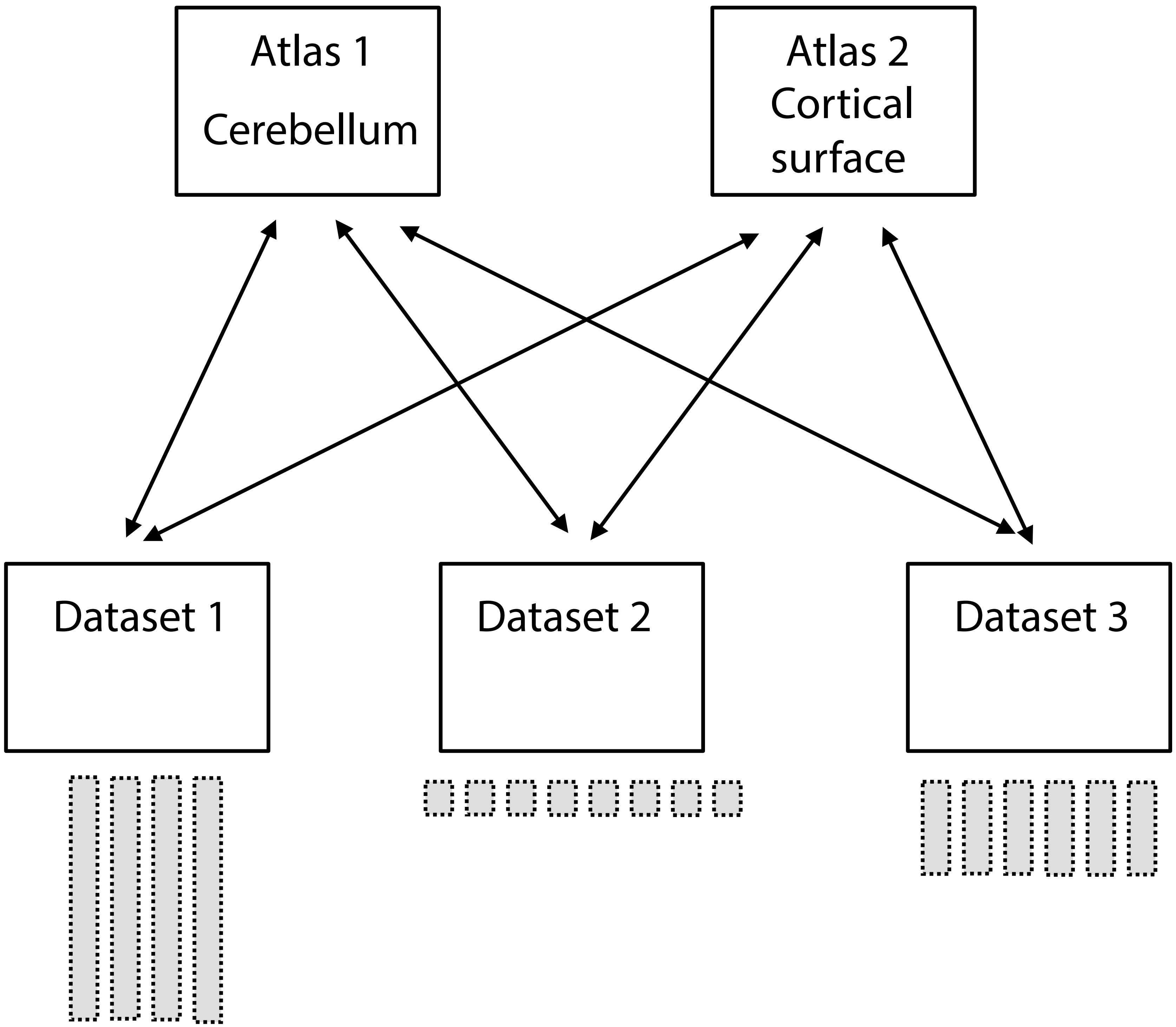
Diedrichsen (2006). Neuroimage.

Surface-based registration (Cortex)

Surface-based registration (Cortex)



Technical problem 2: Data management



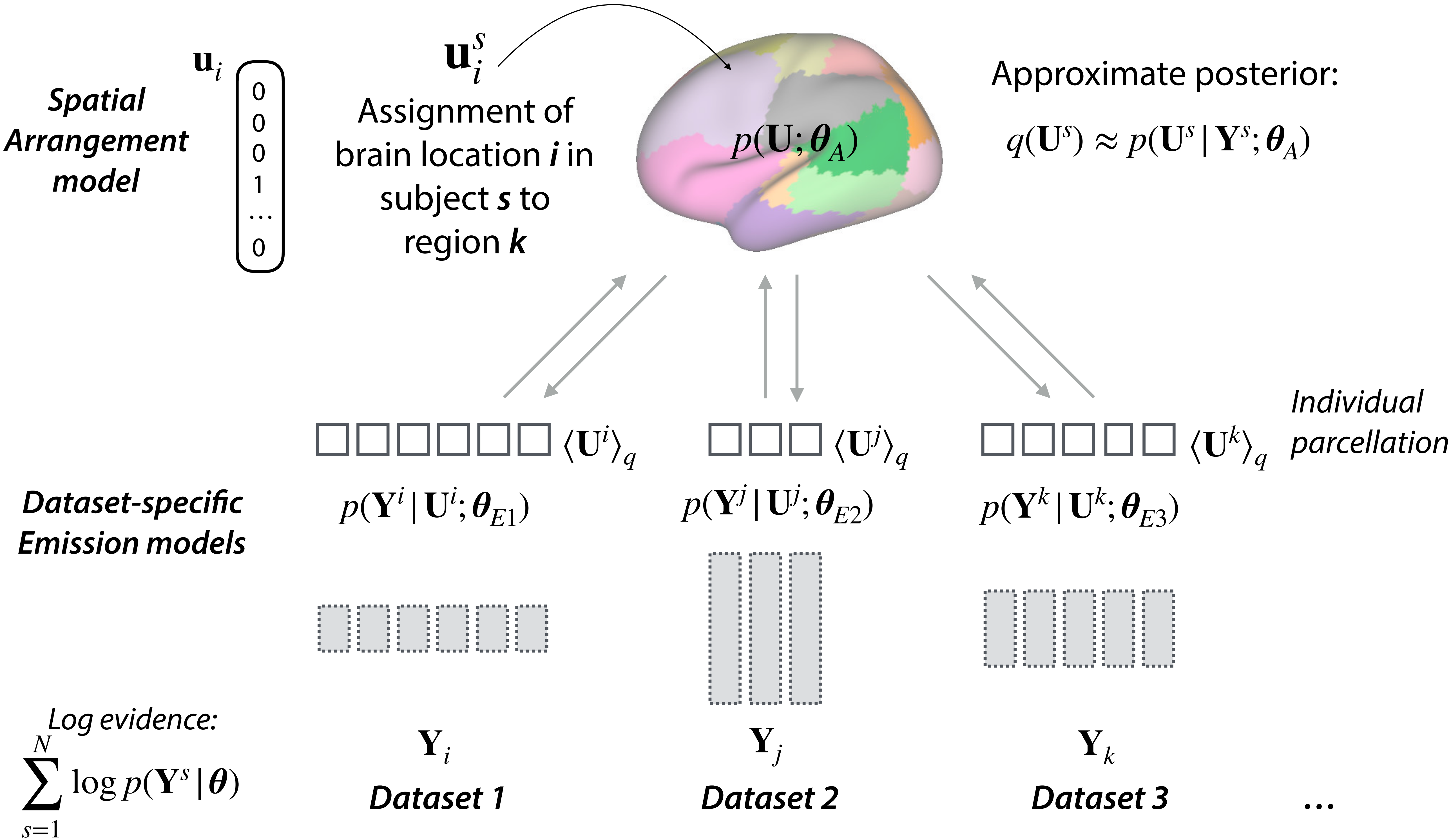
…

Neuroimaging **I**n**F**ormatics
Technology **I**nitiative
(Nifti)

Brain **I**maging
Data **S**tructure
(BIDS)

OpenNeuro.org

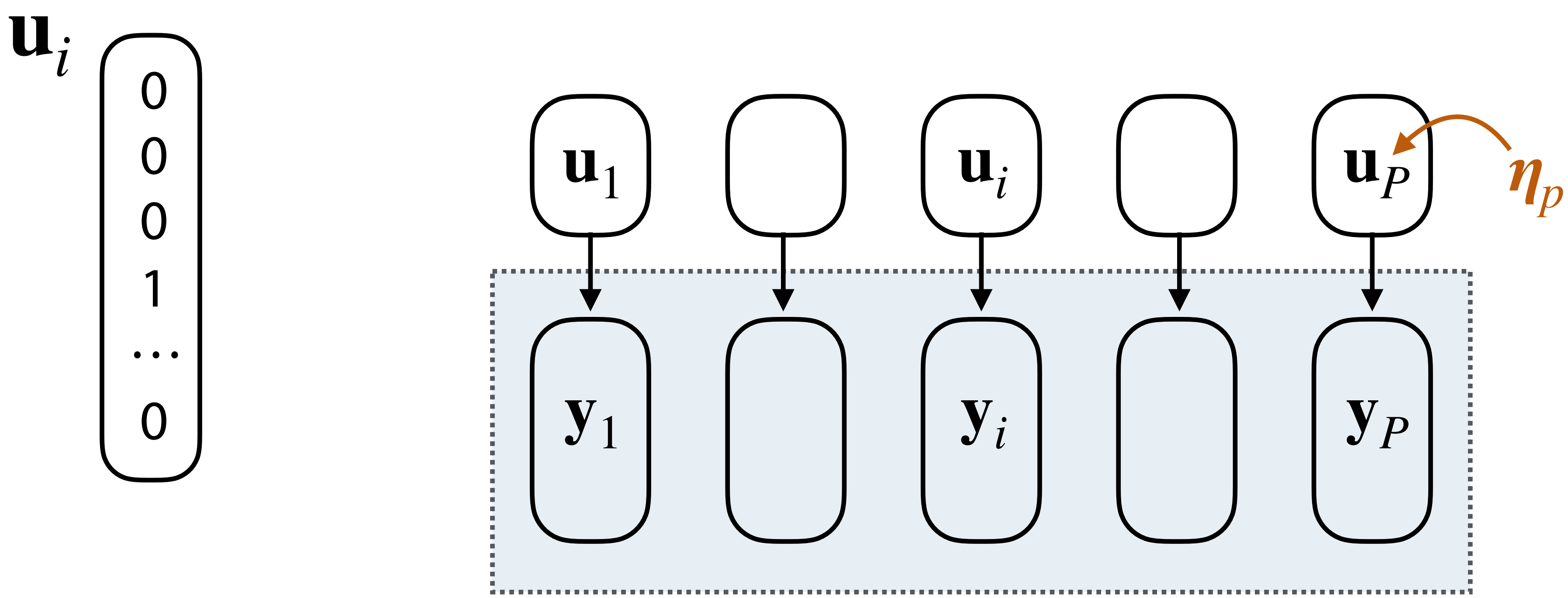
The model: Overall framework



Evidence lower bound (ELBO):

$$\langle \sum_{s=1}^{N} \log p(\mathbf{Y}^s, \mathbf{U}^s;\boldsymbol{\theta}) \rangle_q = \sum_{i=1}^{n_1} \langle \log p(\mathbf{Y}^i \mid \mathbf{U}^i;\boldsymbol{\theta}_{E1}) \rangle_q + \ \ldots + \sum_{s=1}^{N} \langle \log p(\mathbf{U}^s;\boldsymbol{\theta}_A) \rangle_q$$

Independent arrangement



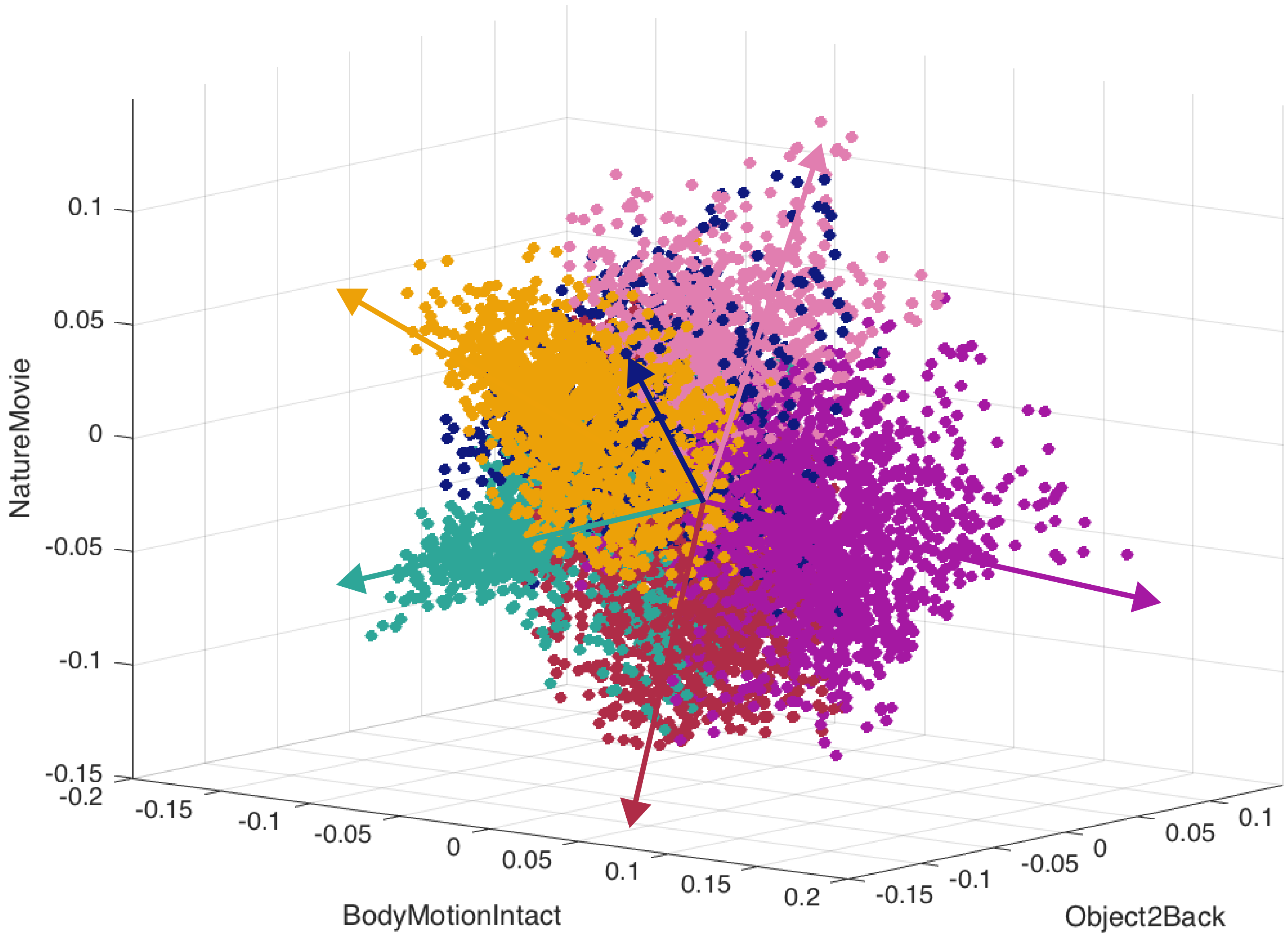
Unnormalized log likelihood:

$$\log \tilde{p}(\mathbf{U}^s \,|\, \boldsymbol{\theta}_A) = \sum_p \log \tilde{p}(\mathbf{u}_p^s) = \sum_p \boldsymbol{\eta}_p^T \mathbf{u}_p^s$$

Expectation:

$$\langle \mathbf{u}_i^s \rangle_q = \mathrm{softmax}(\log(\mathrm{p}(\mathbf{y}_\mathrm{i}^\mathrm{s} \,|\, \mathbf{u}_\mathrm{i}^\mathrm{s}; \boldsymbol{\theta}_{\boldsymbol{E}}) + \boldsymbol{\eta}_\mathrm{i})$$

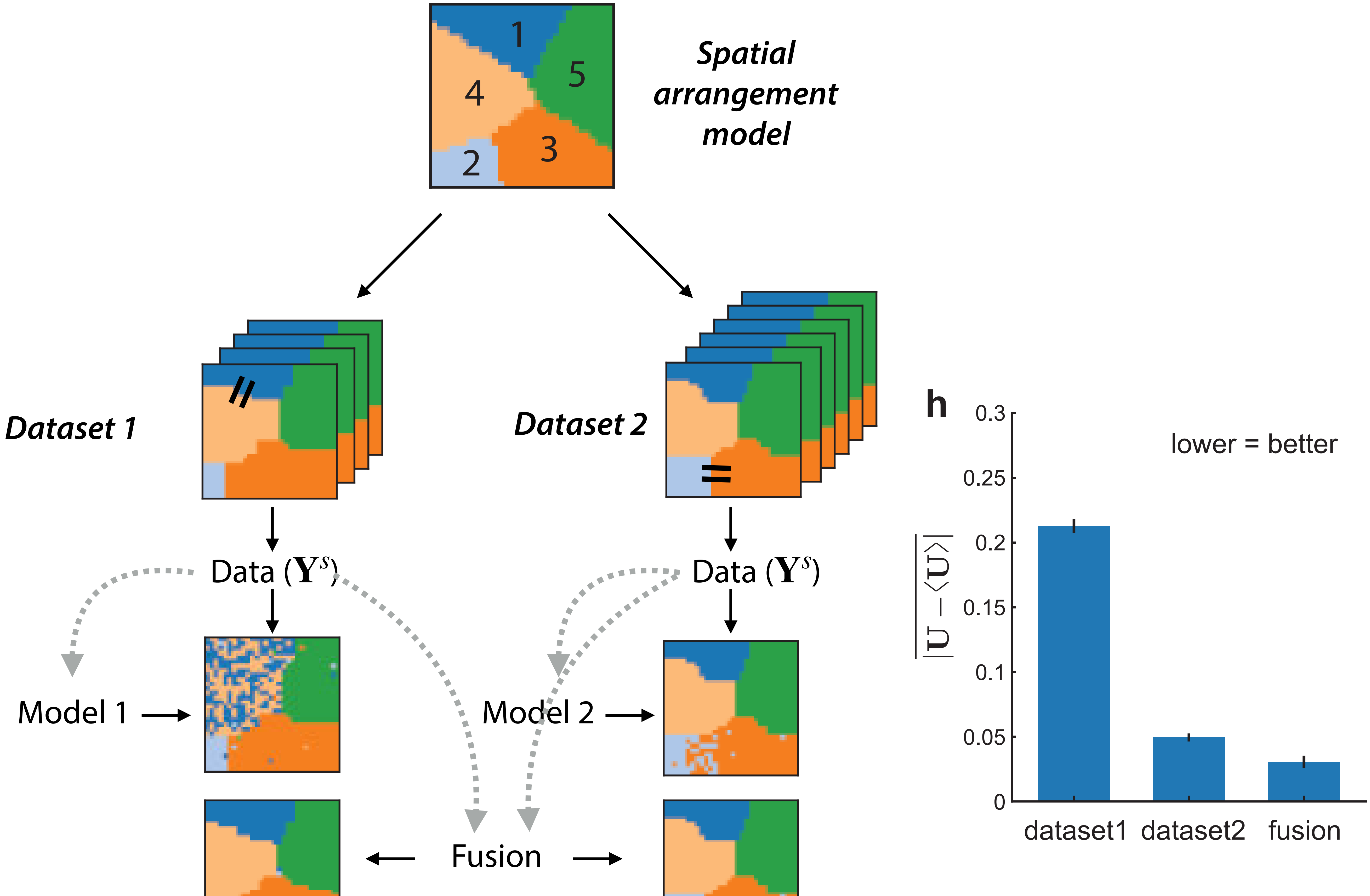
Emission model



K-Mixture of von Mises Fisher distributions

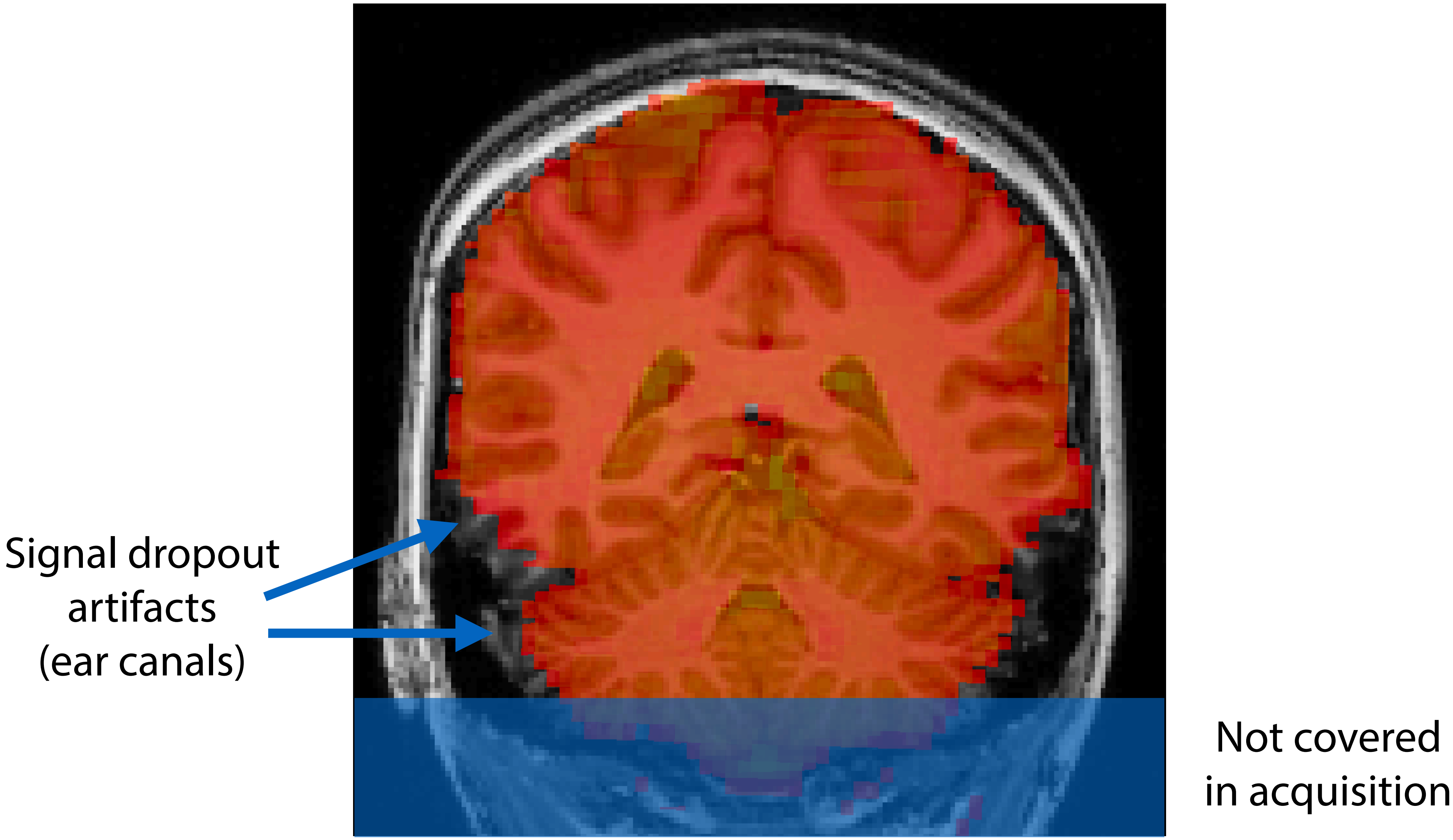
$$\langle \log p(\mathbf{y}_i^s \,|\, \mathbf{u}_i^s; \theta_E) \rangle_q = \log C_N(\kappa) + \sum_k \langle u_i^s(k) \rangle_q \kappa \mathbf{v}_k{}^T \mathbf{y}_i^s$$

Fusion of different data sets

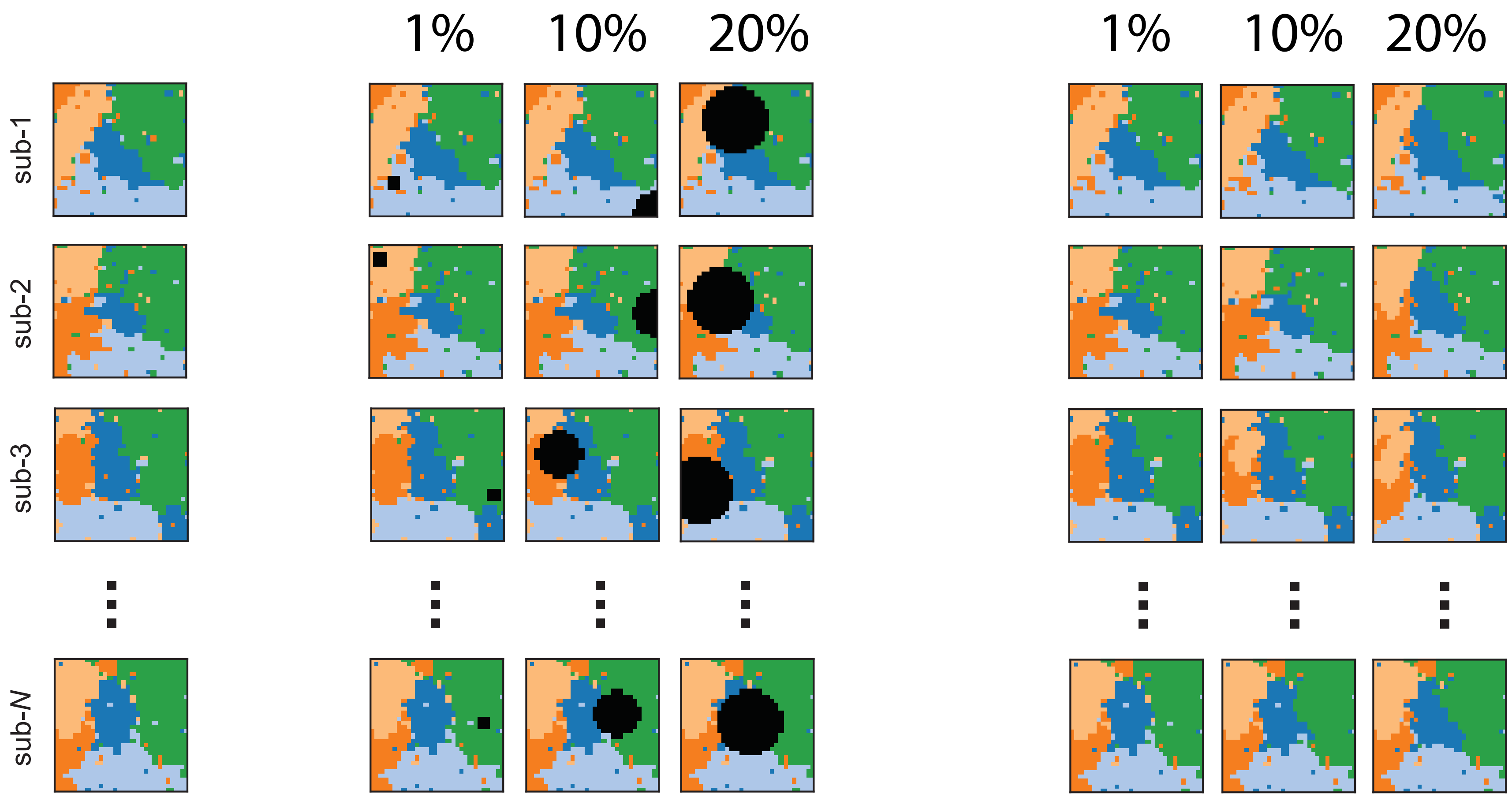


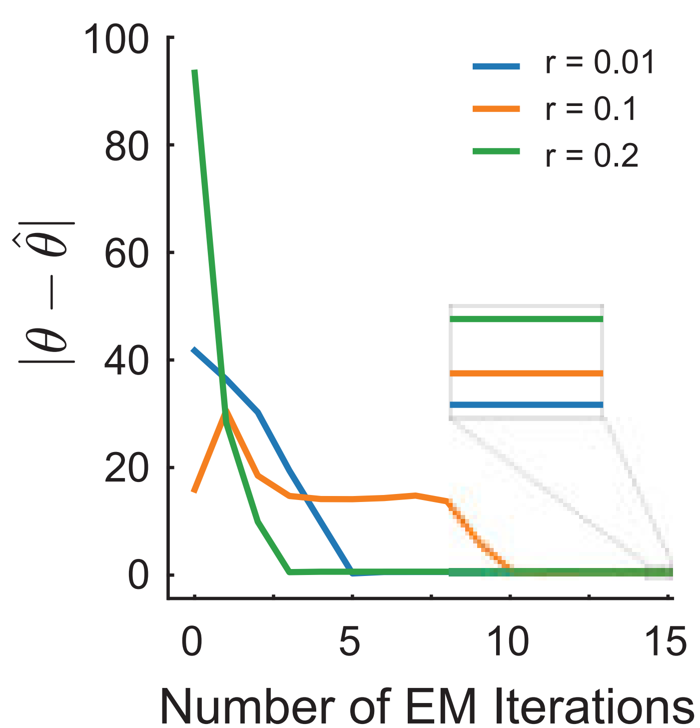
Zhi et al. (2022) Submitted to NIPS.

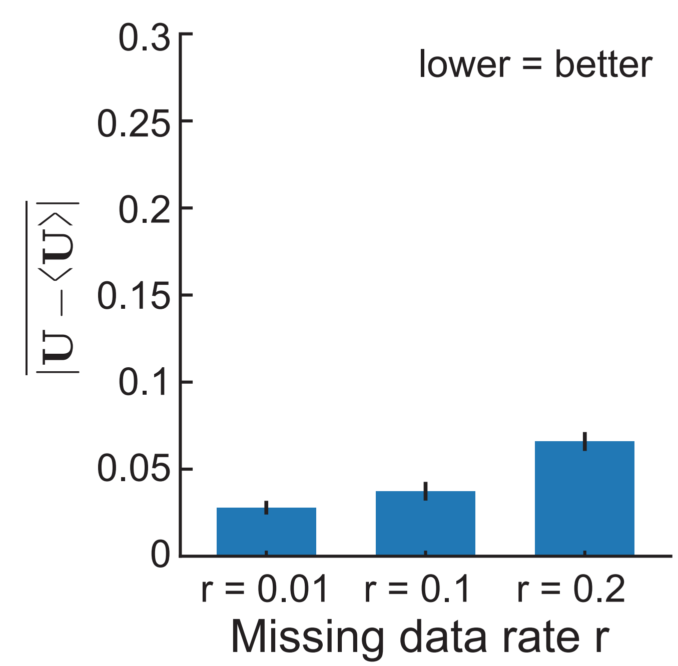
Missing data within subject



Dealing with missing data





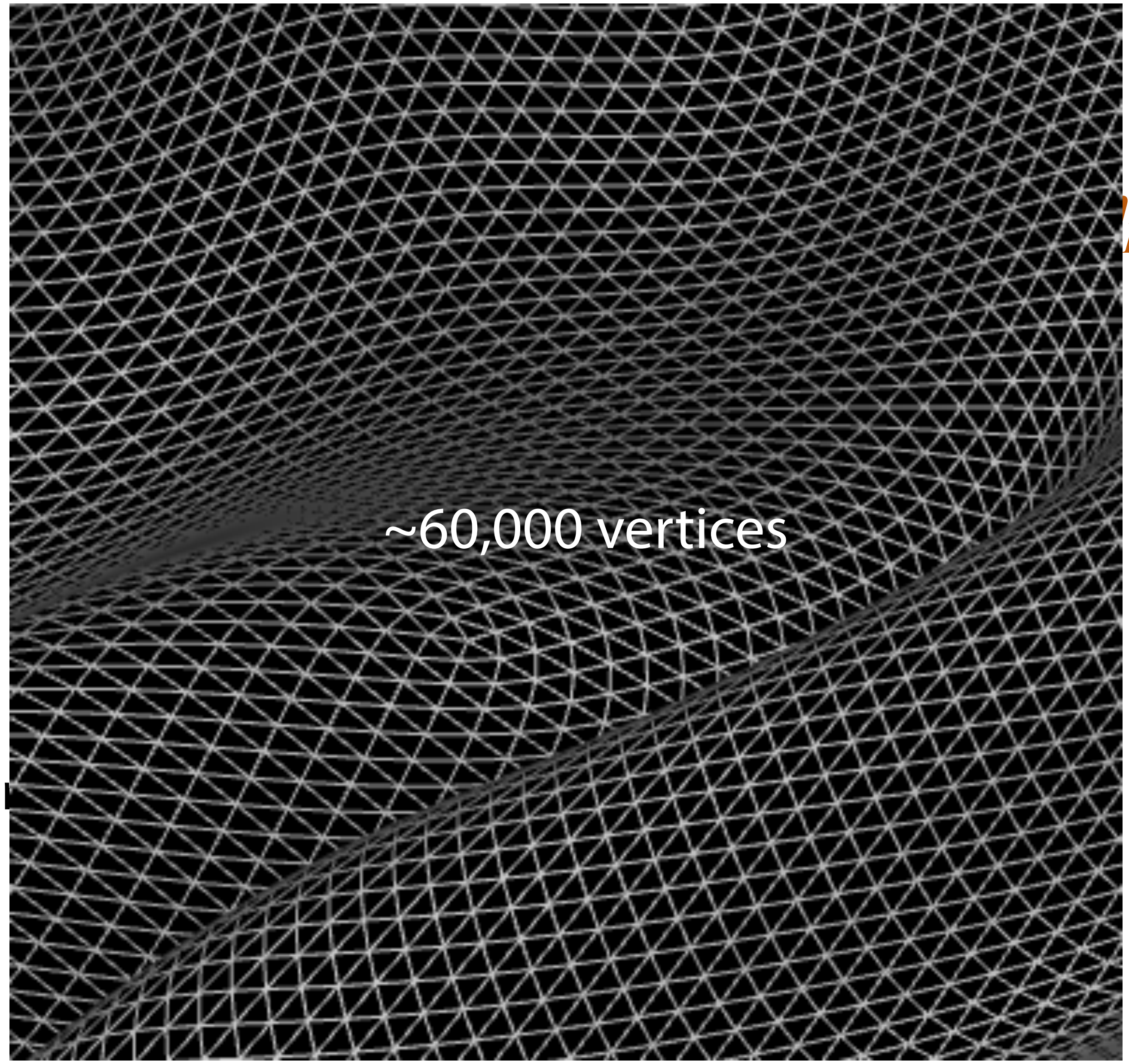


Zhi et al. (2022) Submitted to NIPS.

Markov Random Field

$\mathbf{u}_i$

$$\begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \\ \cdots \\ 0 \end{pmatrix}$$



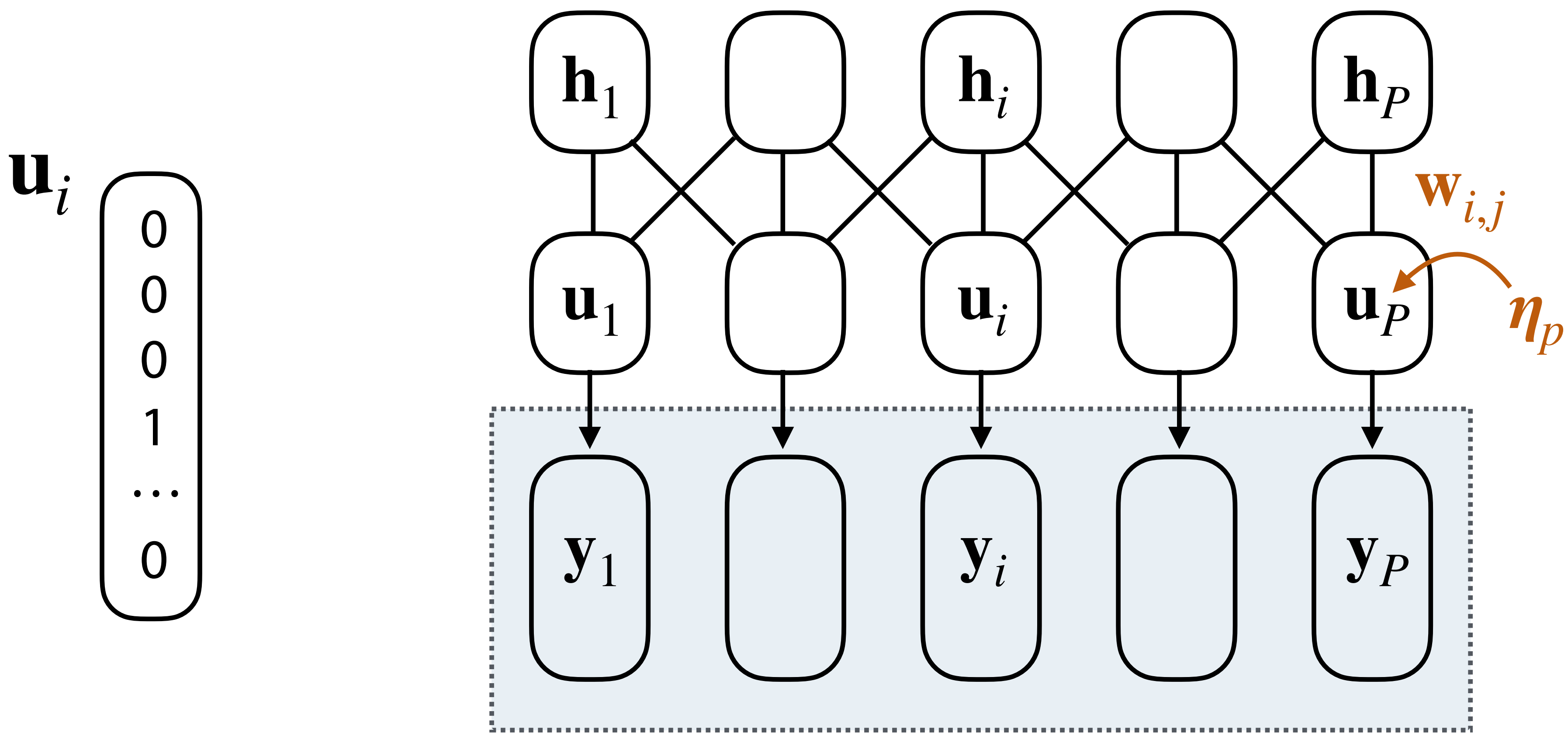
$_p$

Unno

Expectation:

Approximate by node-wise Gibbs sampling :

deep Markov Random Field



Unnormalized log likelihood:

$$\log \tilde{p}(\mathbf{U}^s \,|\, \boldsymbol{\theta}_A) = \sum_i \boldsymbol{\eta}_i^s \mathbf{u}_i + \sum_{i,j,k} w_{i,j} \mathbf{u}_i^s(k) \mathbf{h}_j^s(k)$$

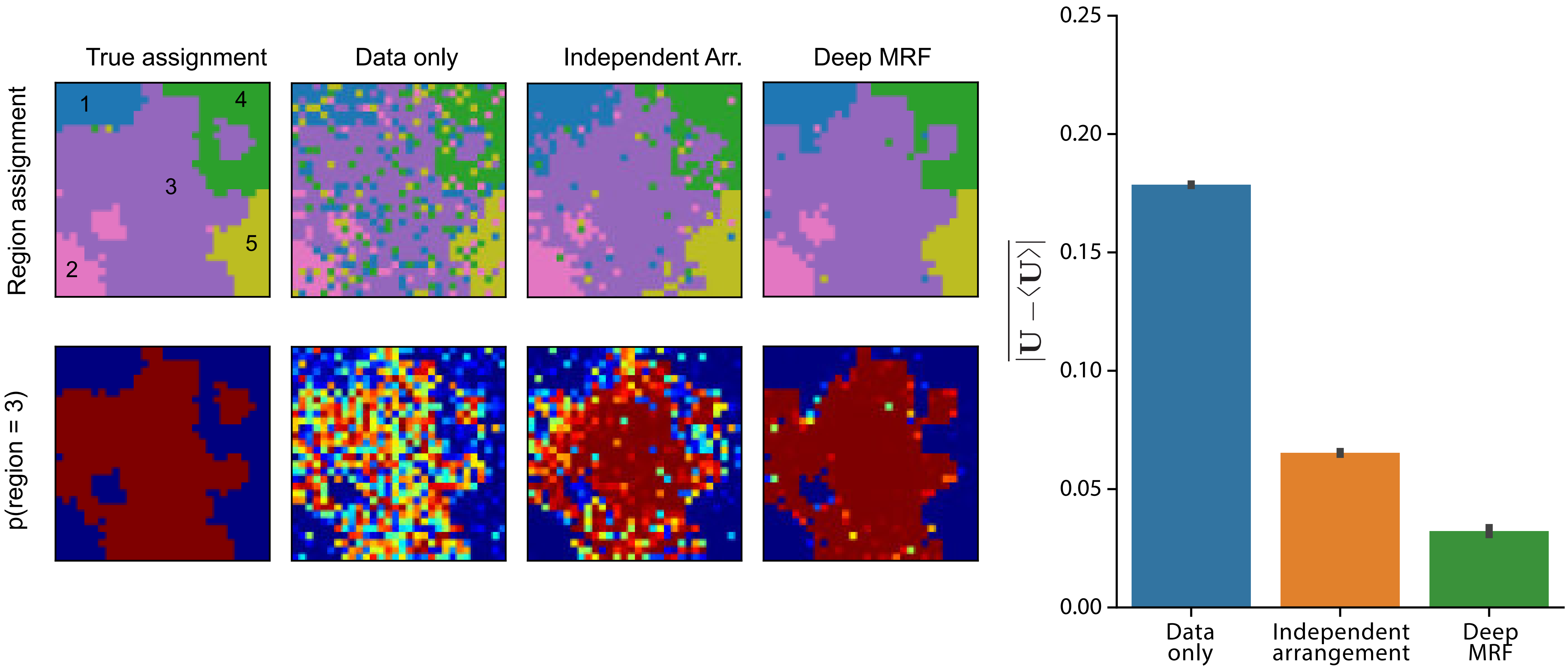
Training:

Mean-field approximation (expectation given data)
Layer-wise Gibbs sampling (expectation given model)
Variational stochastic maximum likelihood

Salakuthdinov et al. (2012). Neural Computation.

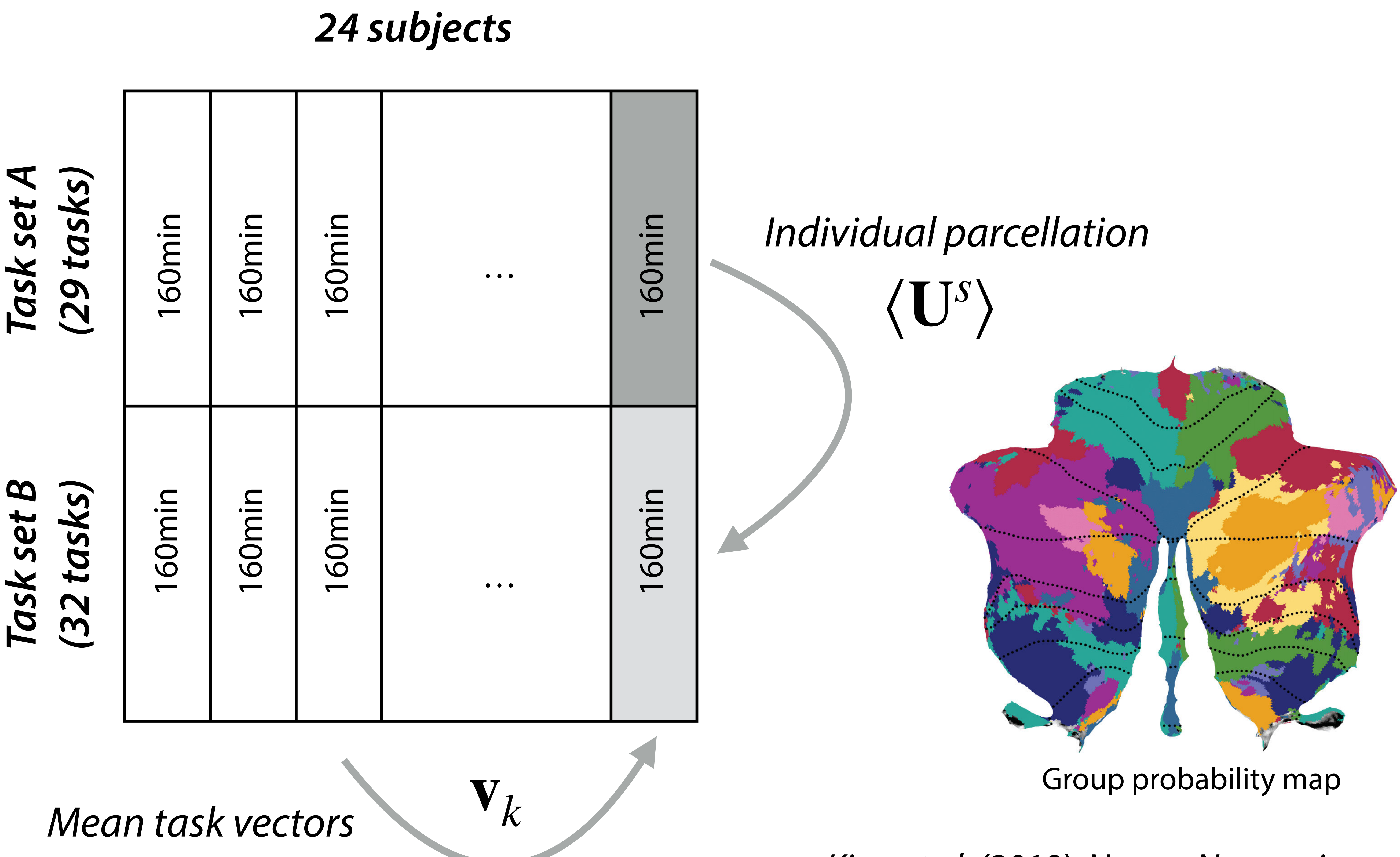
Zhi et al. (2022) Submitted to NIPS.

Deep MRF models



Zhi et al. (2022) Submitted to NIPS.

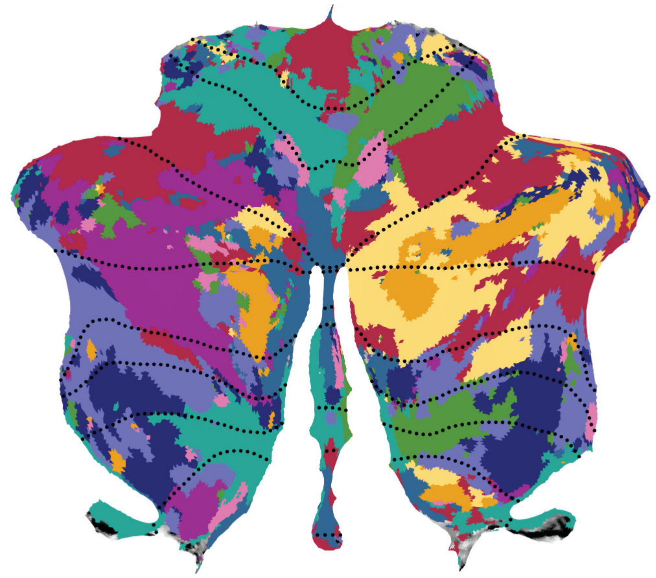
Multi-domain task battery dataset



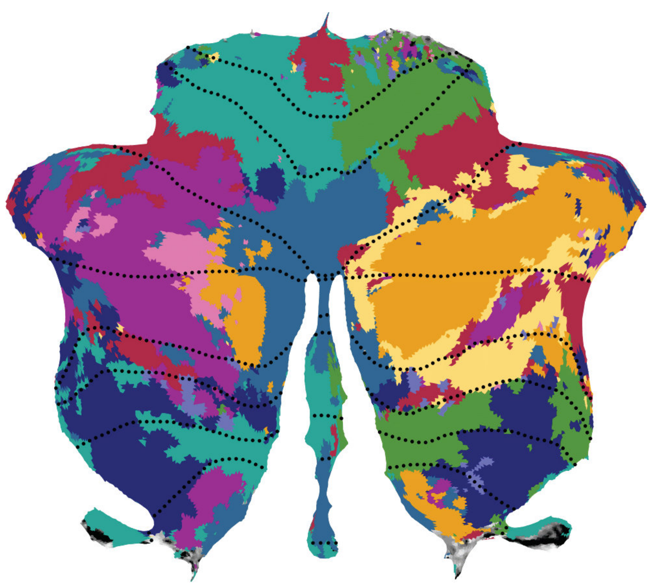
King et al. (2019). Nature Neuroscience.

Improvements on real data

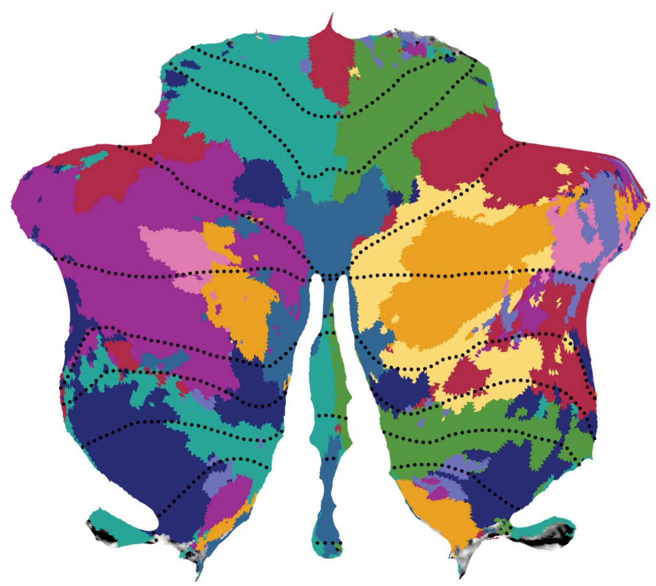
Data Likelihood (10min)



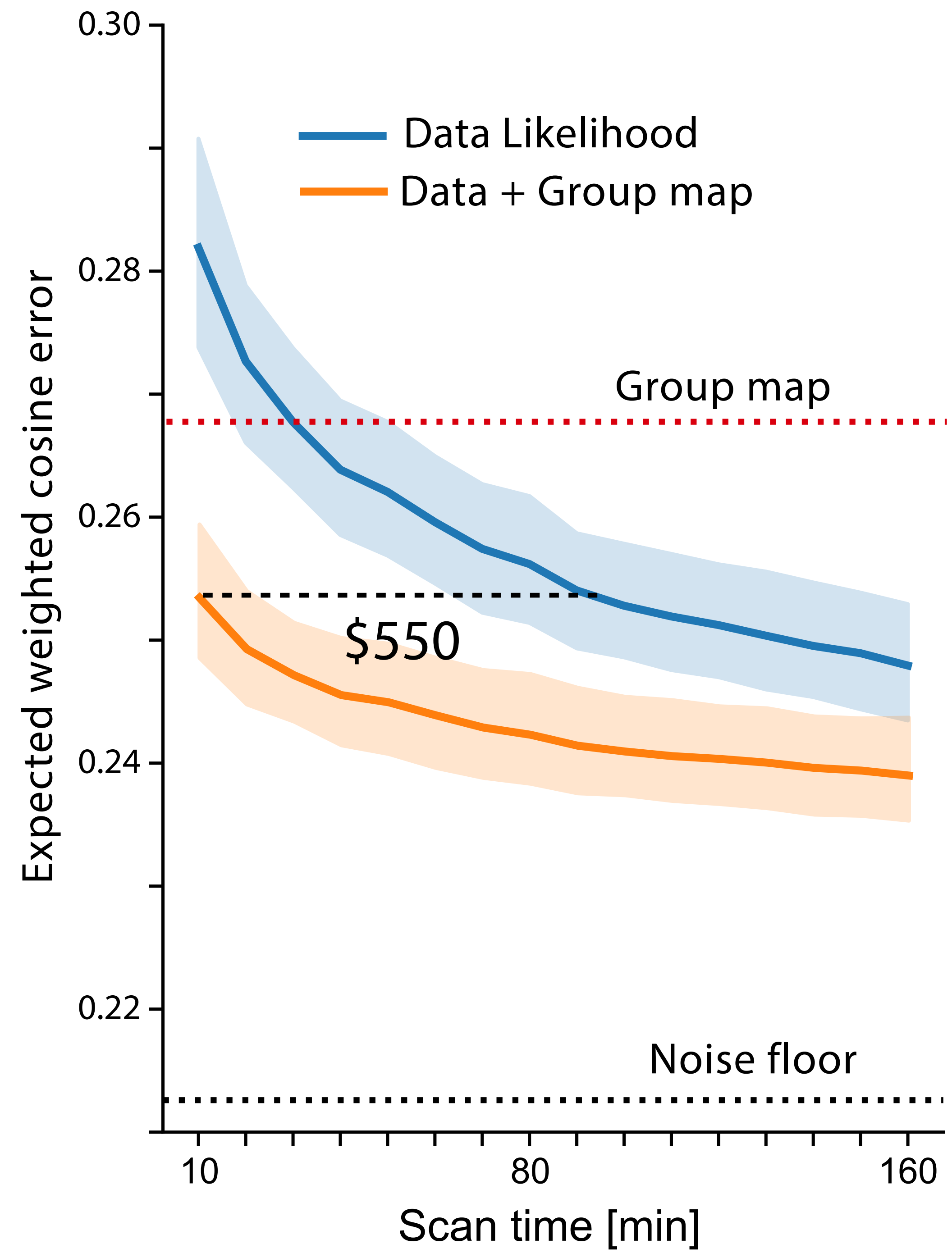
Data Likelihood (160min)



10 min data + Group

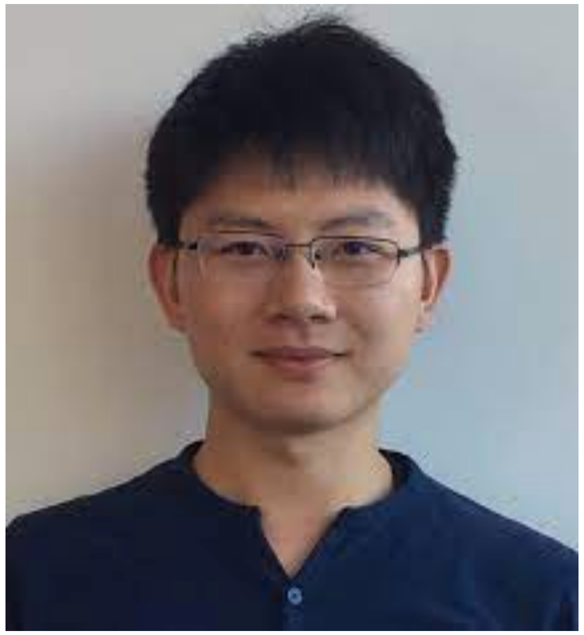


Group probability map



Zhi et al. (2022) Submitted to NIPS.

Computational Neuroscience lab



Da Zhi

Western:
- Da Zhi
- Caro Nettekoven
- Ana Luisa Pinho
- Ladan Shahahani
- Mahidyar Shabazi
- Linglin Lin
- Jingyu Cui
- Grace Yi

UC Berkeley:
- Richard Ivry
- Maedbh King

McGill / Mila:
- Danilo Bzdok

Dalhousie:
- Carlos Hernadez Castillo

Harvard:
- Randy Buckner

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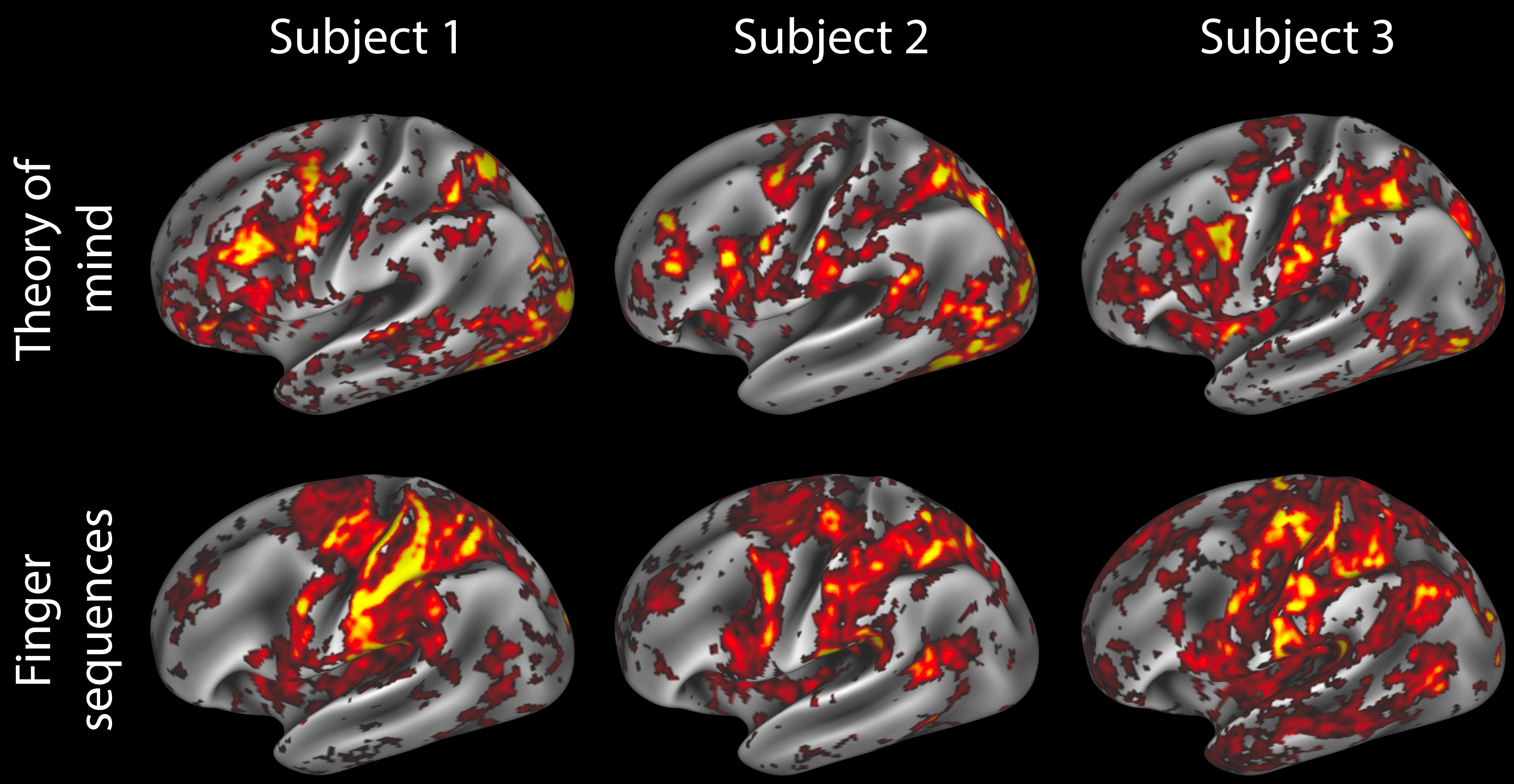
NSERC CRSNG

CIHR IRSC Canadian Institutes of Health Research / Instituts de recherche en santé du Canada

Western BrainsCAN Transforming brain research.

Functional variability



Independent arrangement