DISCOVERING VOXEL-LEVEL FUNCTIONAL CONNECTIVITY BETWEEN CORTICAL REGIONS

C. BALDASSANO M.C. IORDAN D.M. BECK L. FEI-FEI

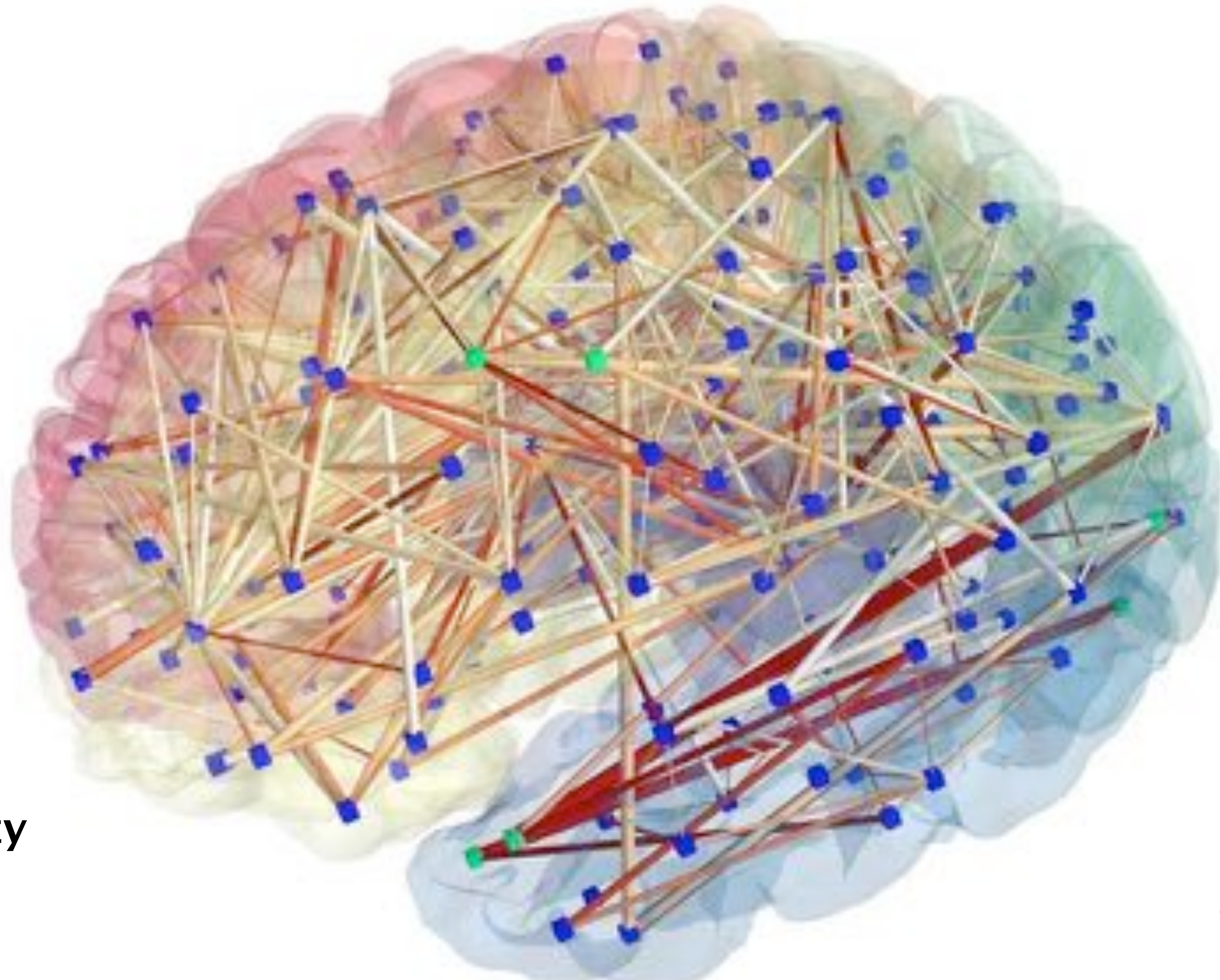



Computer Science Department, Stanford University

Beckman Institute and Psychology Department, University of Illinois at Urbana-Champaign

Attention and Perception Lab

Connectivity

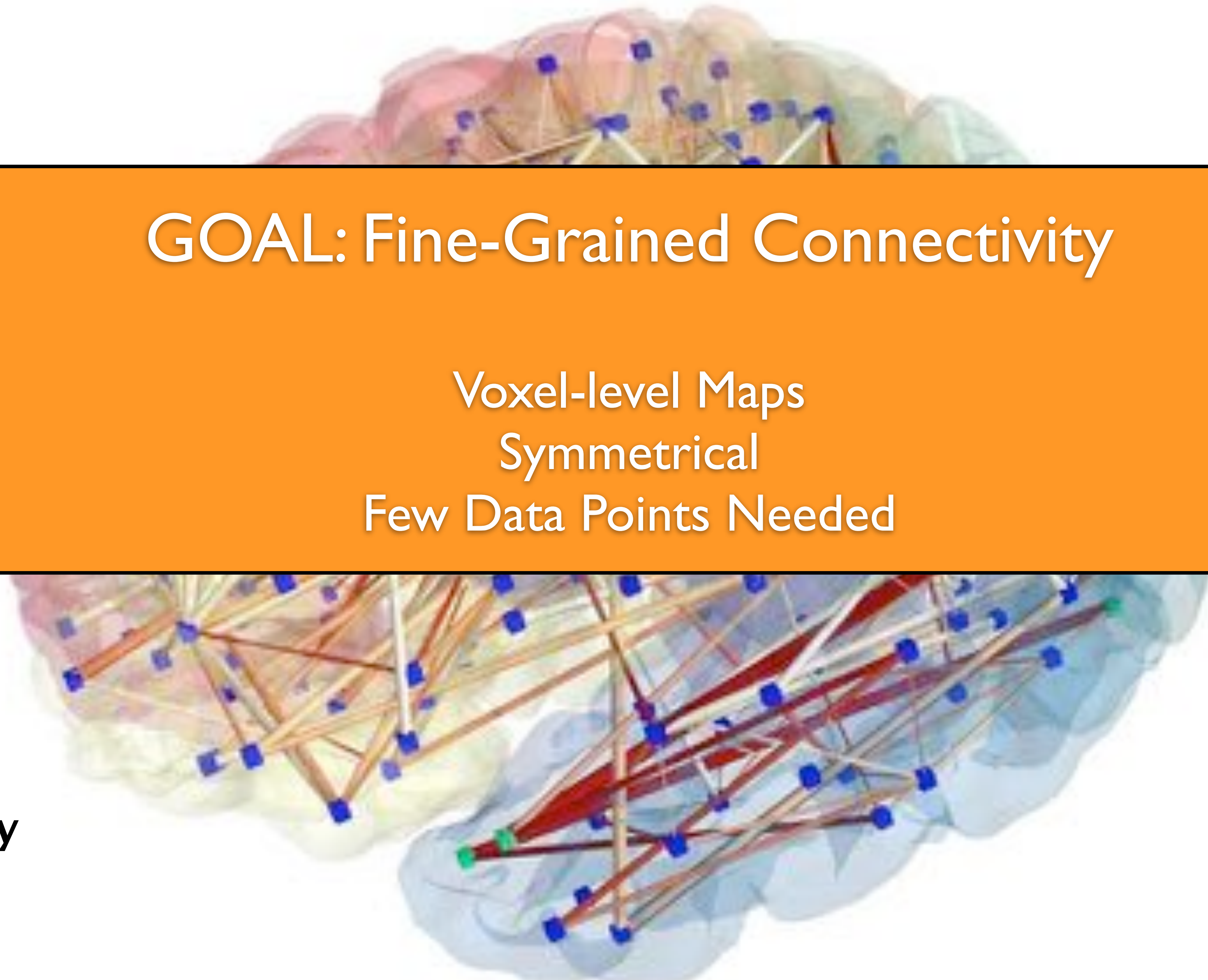


Subregion Connectivity

Precuneus
Amygdala
Thalamus
Lateral occipital complex LOC

Zhang et al. 2008
Kim et al. 2010
Roy et al. 2009
Margulies et al. 2007
Margulies et al. 2009
Heinzle & Haynes 2011

Connectivity



GOAL: Fine-Grained Connectivity

Voxel-level Maps
Symmetrical
Few Data Points Needed

Subregion Connectivity

Precuneus
Amygdala
Thalamus
Lateral occipital complex LOC

Zhang et al. 2008
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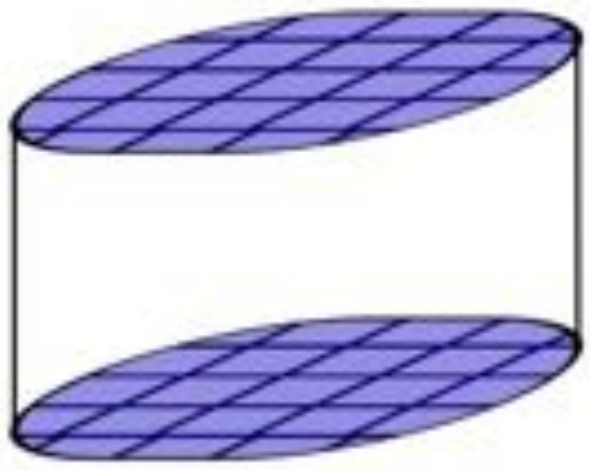
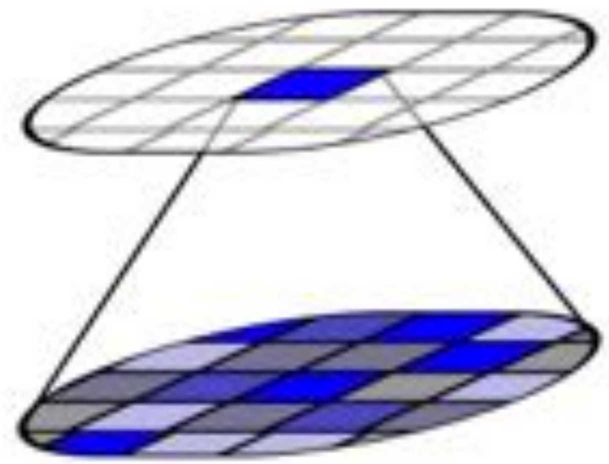
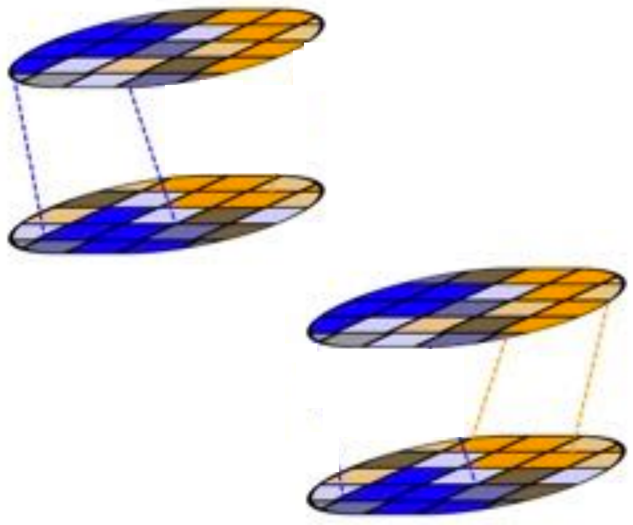
Previous Work

Area 1

Area 2







Traditional

no voxel-level connectivity

cannot identify novel subregions

Rogers et al. 2007

CCRF / FF

treats areas asymmetrically

no continuous maps

post-hoc clustering often needed

Kim et al. 2010
Margulies et al. 2007
Margulies et al. 2009
Haak et al. 2011
Cohen et al. 2007

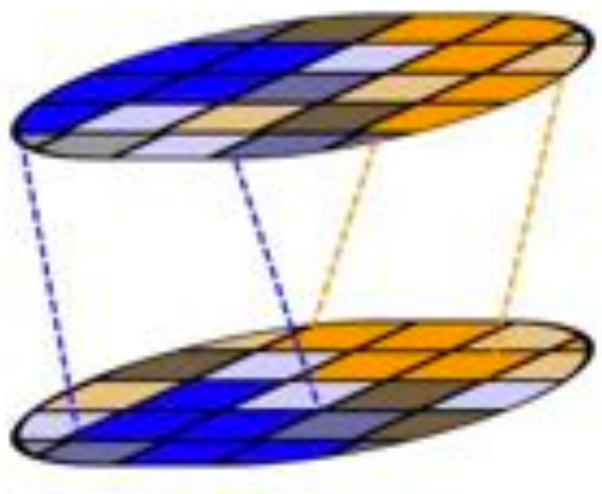
CCA

voxels < # timepoints

cannot identify multiple correlated correspondences

Deleus & Van Hulle 2011

Previous Work



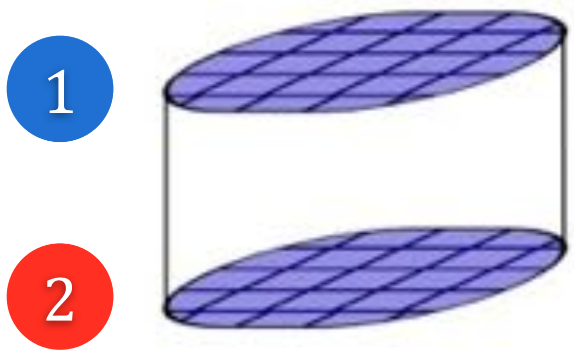
Our Method:
Jointly Learn Continuous Maps over 2 Areas
Multiple Solutions, Even If Correlated

Traditional	CCRF / FF	CCA
no voxel-level connectivity cannot identify novel subregions	treats areas asymmetrically no continuous maps post-hoc clustering often needed	# voxels < # timepoints cannot identify multiple correlated correspondences
Rogers et al. 2007	Kim et al. 2010 Margulies et al. 2007 Margulies et al. 2009 Haak et al. 2011 Cohen et al. 2007	Deleus & Van Hulle 2011

Optimization Problem

Traditional

$$\underset{w}{\text{minimize}} \; ||w \cdot \text{mean}_v(\boldsymbol{A^1}) - \text{mean}_v(\boldsymbol{A^2})||_2^2$$



w ⟶ scalar

mean_v ⟶ mean across voxels

1 2

$\boldsymbol{A} =$ # voxels [...] # timepoints

1 2

timecourse

$$\underset{\boldsymbol{a^1}, \boldsymbol{a^2}, w}{\text{minimize}} \quad ||\boldsymbol{a^1}^T \boldsymbol{A^1} - \boldsymbol{a^2}^T \boldsymbol{A^2}||_2^2$$

$$\text{subject to} \quad \boldsymbol{a^1} = \frac{w}{N_{A^1}} \cdot \mathbb{1}, \; \boldsymbol{a^2} = \frac{1}{N_{A^2}} \cdot \mathbb{1}$$

constant connectivity map $\boldsymbol{a}^T =$ [...]

N_A voxels

Optimization Problem

Traditional

constant map

$$\underset{a^1, a^2, w}{\text{minimize}} \quad ||{a^1}^T A^1 - {a^2}^T A^2||_2^2$$

$$\text{subject to} \quad a^1 = \frac{w}{N_{A^1}} \cdot \mathbb{1}, \; a^2 = \frac{1}{N_{A^2}} \cdot \mathbb{1}$$

CCRF / FF

one non-constant connectivity maps

$$\underset{a^1, a^2, w}{\text{minimize}} \quad ||{a^1}^T A^1 - {a^2}^T A^2||_2^2$$

$$\text{subject to} \quad a^1 = \frac{w}{N_{A^1}} \cdot \mathbb{1}, \; a^2 = \frac{1}{N_{A^2}} \cdot \mathbb{1}$$

Our Method

two non-constant connectivity maps

$$\underset{a^1, a^2, w}{\text{minimize}} \quad ||{a^1}^T A^1 - {a^2}^T A^2||_2^2$$

$$\text{subject to} \quad a^1 = \frac{w}{N_{A^1}} \cdot \mathbb{1}, \; a^2 = \frac{1}{N_{A^2}} \cdot \mathbb{1}$$

Optimization Problem

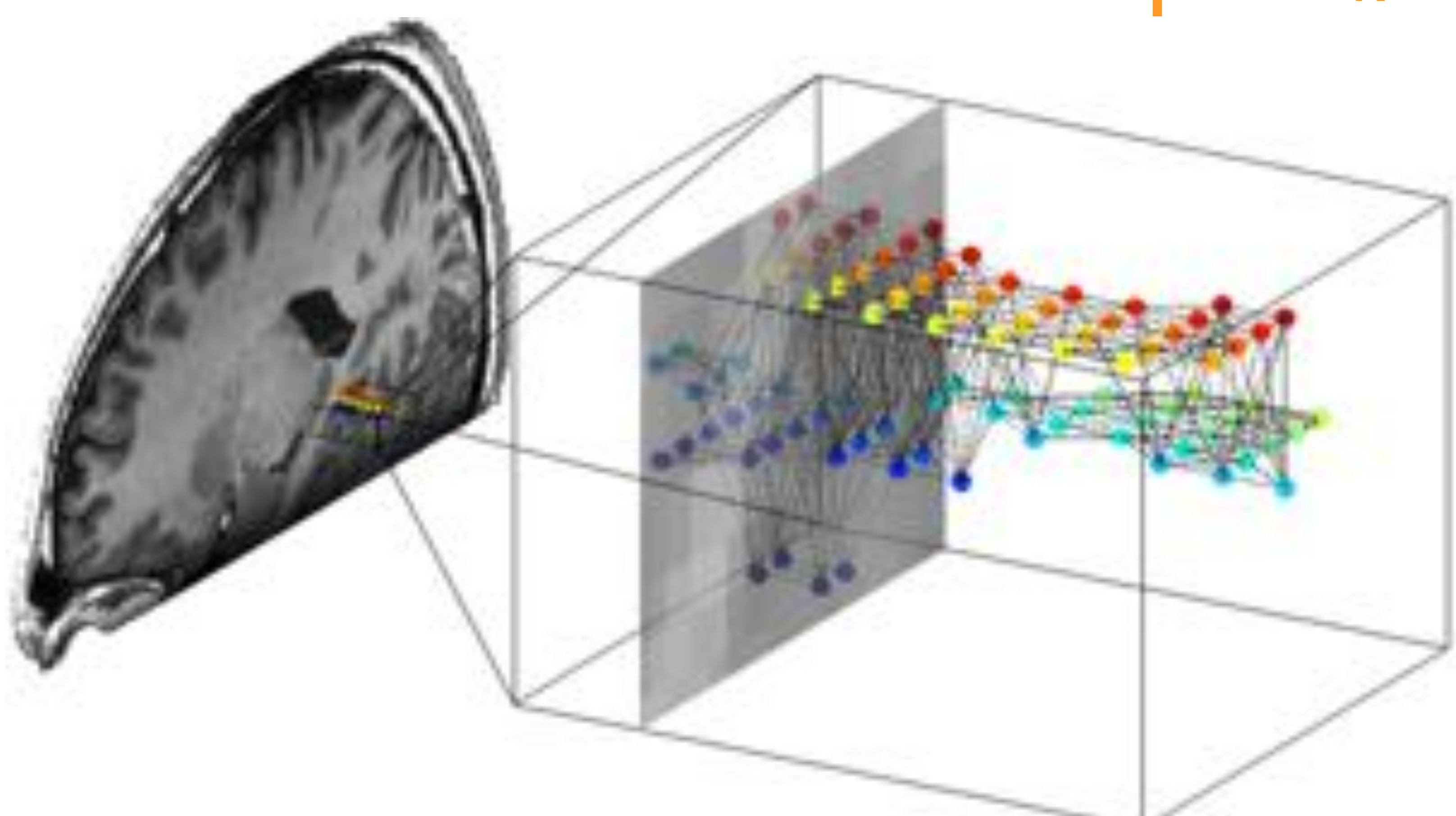
Hyperparameter

Regularization term

$$\underset{\boldsymbol{a^1},\boldsymbol{a^2},w}{\text{minimize}} \quad ||\boldsymbol{a^1}^T\boldsymbol{A}^1 - \boldsymbol{a^2}^T\boldsymbol{A^2}||_2^2 + \lambda \left[\sum_{i \in v_1} \sum_{j \in n(i)} \frac{1}{|n(i)|}(\boldsymbol{a_i^1} - \boldsymbol{a_j^1})^2 + \sum_{i \in v_2} \sum_{j \in n(i)} \frac{1}{|n(i)|}(\boldsymbol{a_i^2} - \boldsymbol{a_j^2})^2 \right]$$

Graph D_k

Sparse Connectivity Graph



Optimization Problem

Hyperparameter

Regularization term

$$\underset{a^1, a^2, w}{\text{minimize}} \quad ||{a^1}^T A^1 - {a^2}^T A^2||_2^2 + \lambda \left[\sum_{i \in v_1} \sum_{j \in n(i)} \frac{1}{|n(i)|} (a_i^1 - a_j^1)^2 + \sum_{i \in v_2} \sum_{j \in n(i)} \frac{1}{|n(i)|} (a_i^2 - a_j^2)^2 \right]$$

$$\underset{a^1, a^2, w}{\text{minimize}} \quad \left\| \begin{bmatrix} \frac{1}{\sqrt{T}} {A^1}^T & -\frac{1}{\sqrt{T}} {A^2}^T \\ \sqrt{\lambda} D_1 & 0 \\ 0 & \sqrt{\lambda} D_2 \end{bmatrix} \begin{bmatrix} a^1 \\ a^2 \end{bmatrix} \right\|_2^2 = ||X_\lambda \cdot \beta||_2^2$$

Our Method

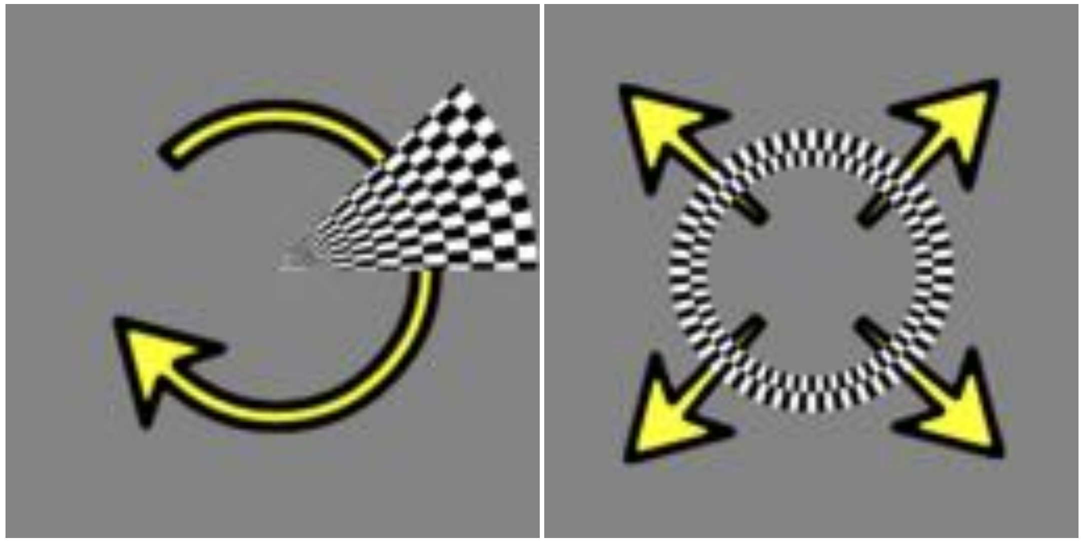
$$\begin{aligned} \underset{\beta}{\text{minimize}} \quad & ||X_\lambda \cdot \beta||_2^2 \\ \text{subject to} \quad & ||\beta||_2 = 1, \ \beta \succeq 0 \end{aligned}$$

Not Convex

Use trust region approach and multiple initializations

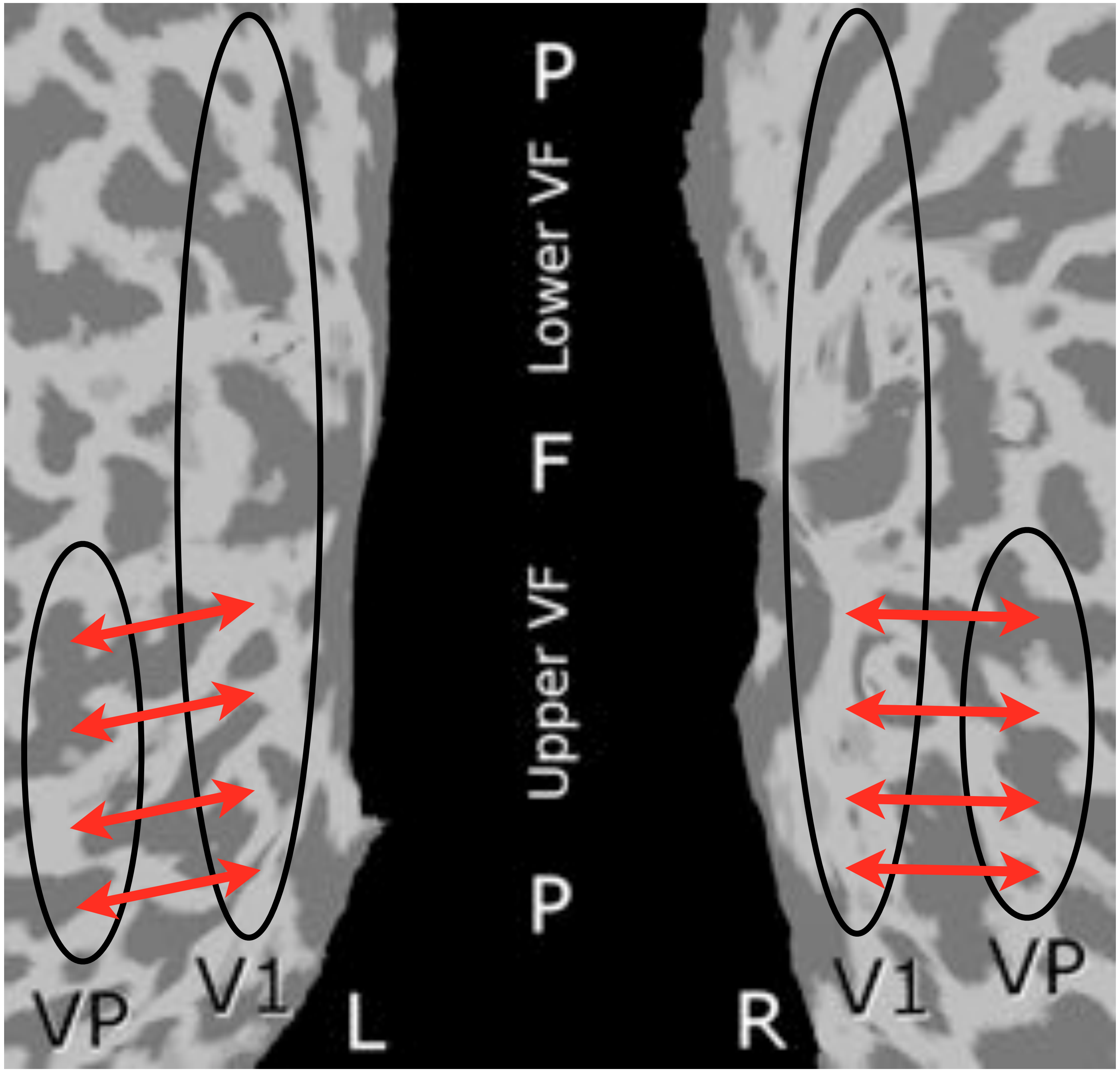
Datasets

Meridian and Eccentricity Mapping
256 timepoints



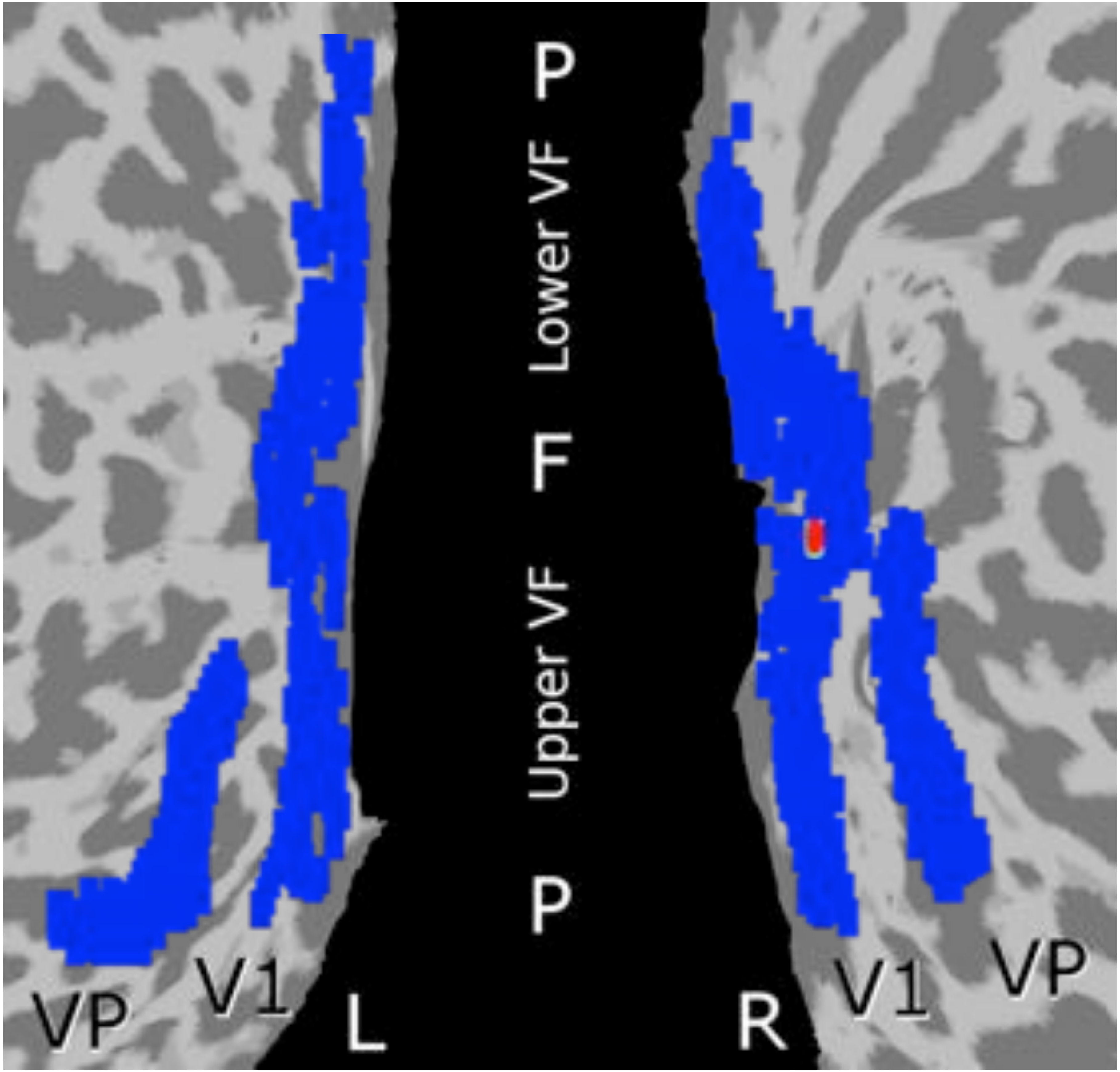
Isolated Objects & Objects in Context
306 timepoints

V1 – VP Connectivity

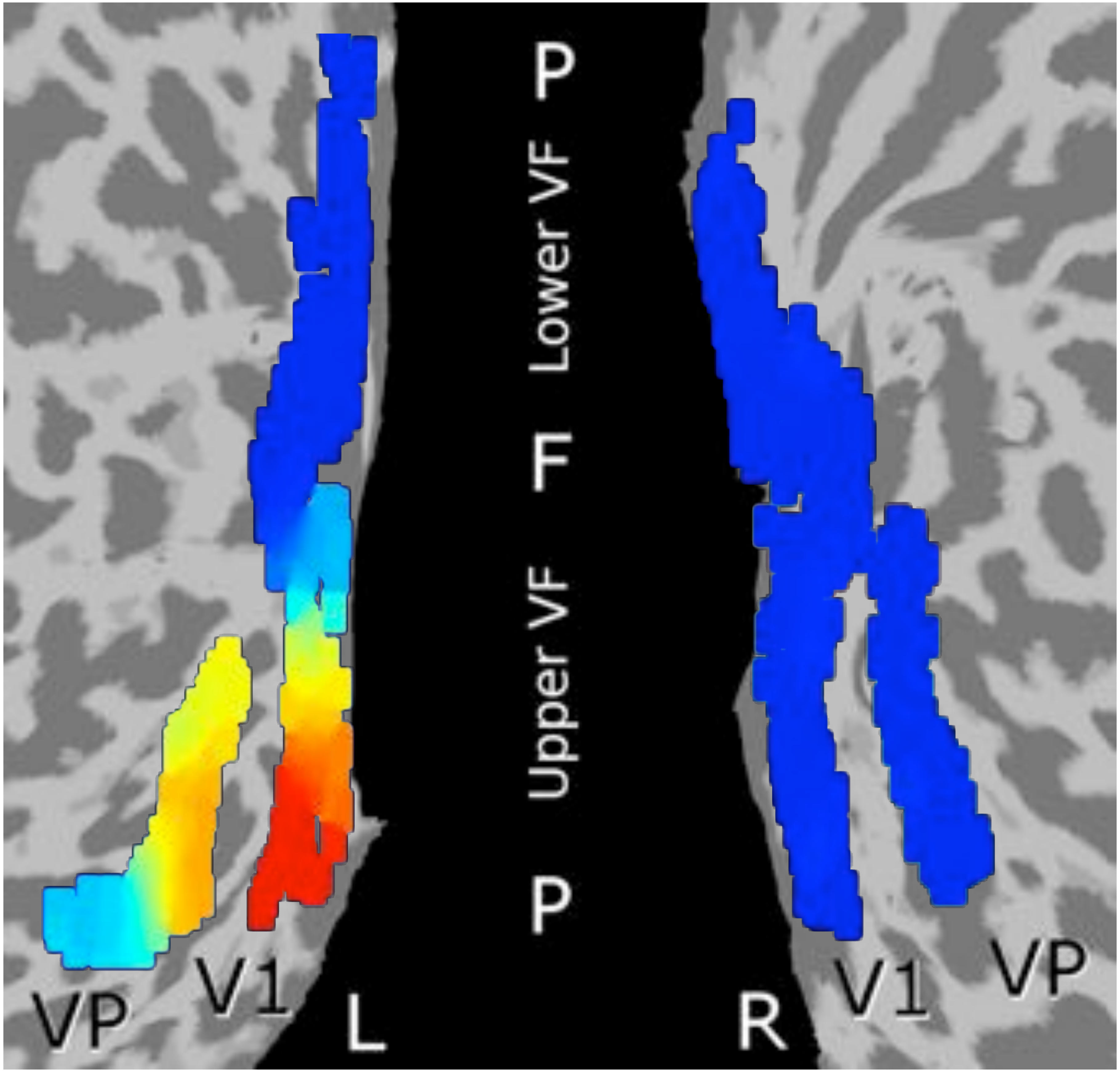


Expected Connectivity

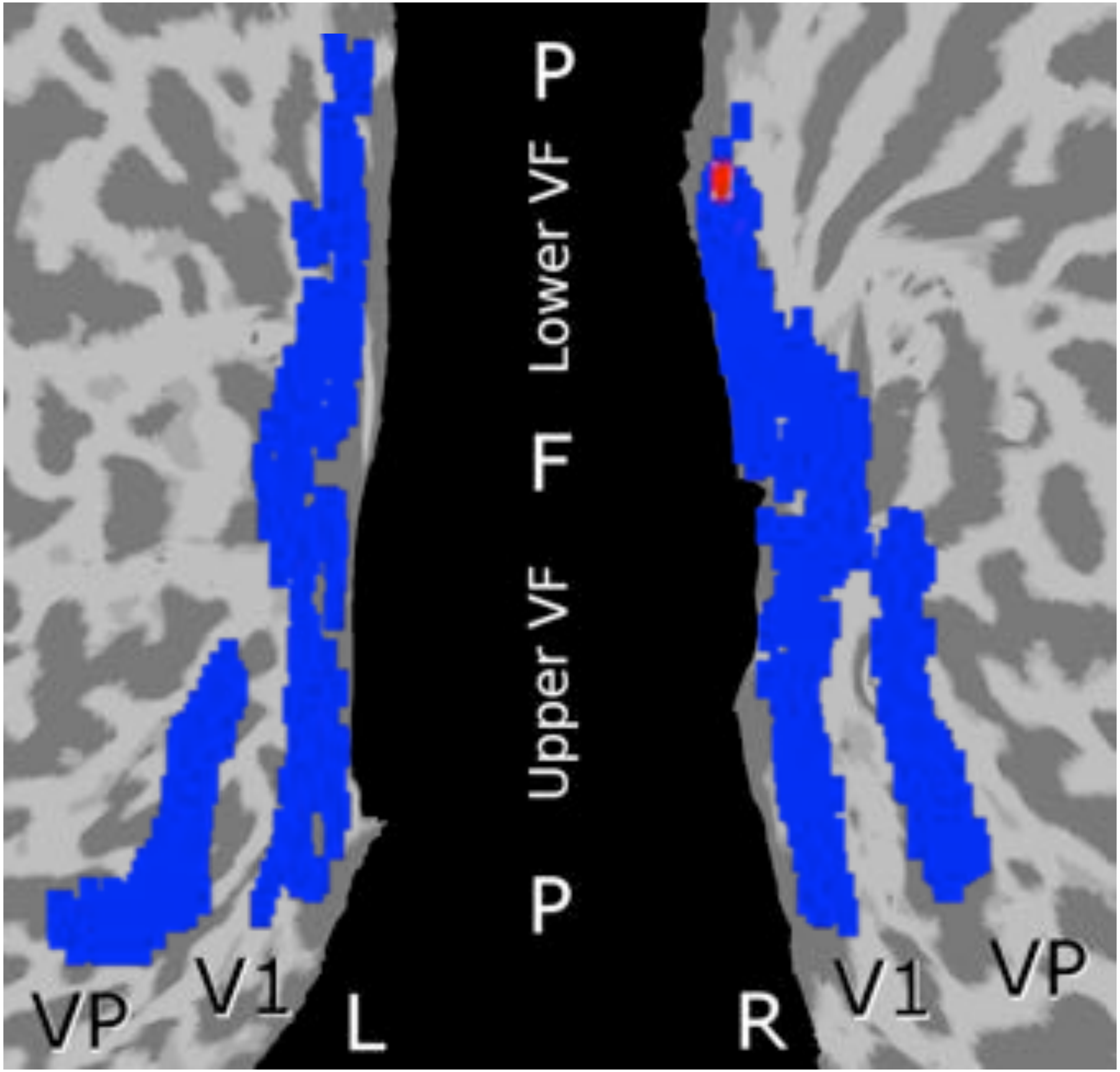
V1 – VP Connectivity



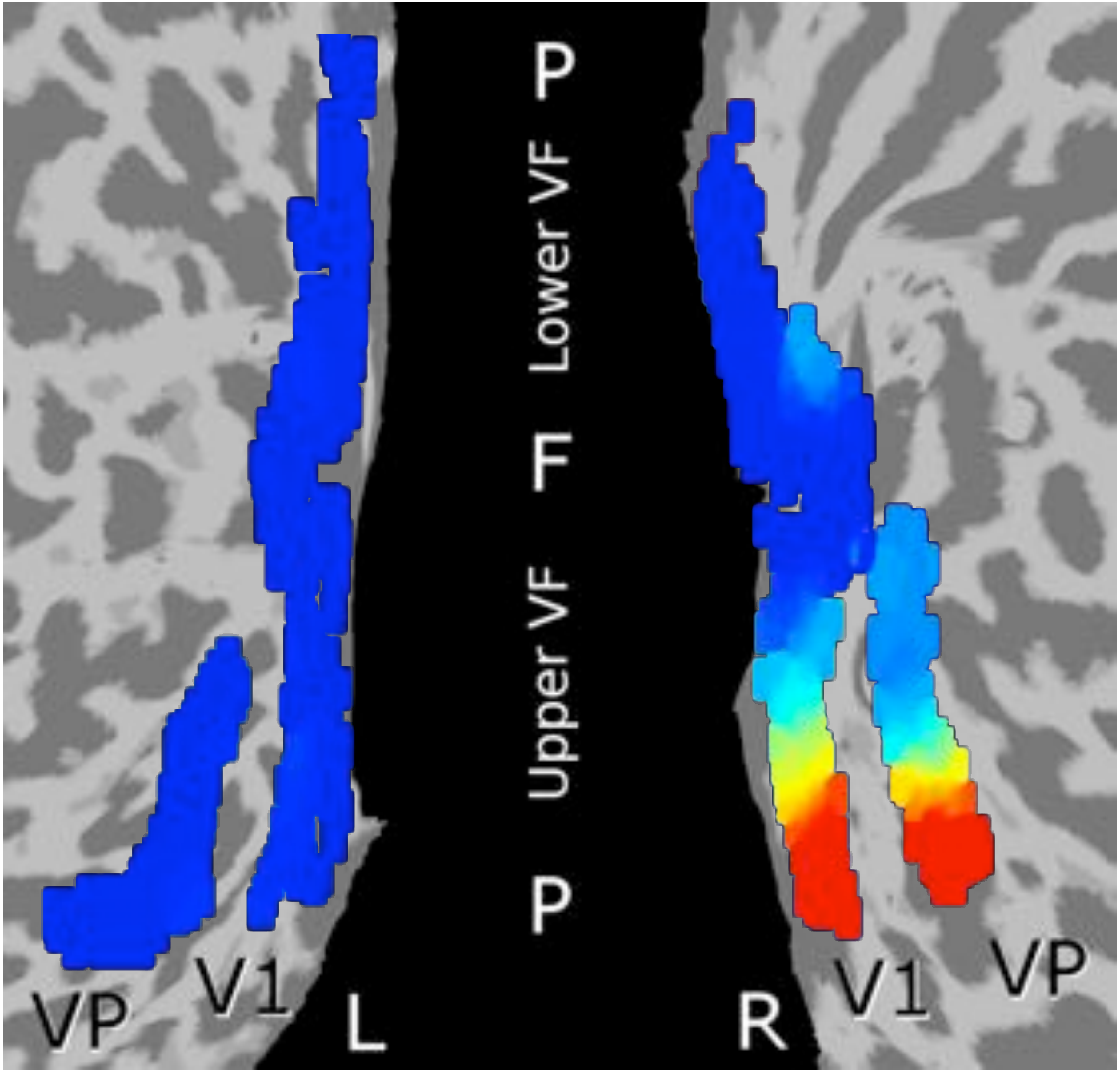
V1 – VP Connectivity



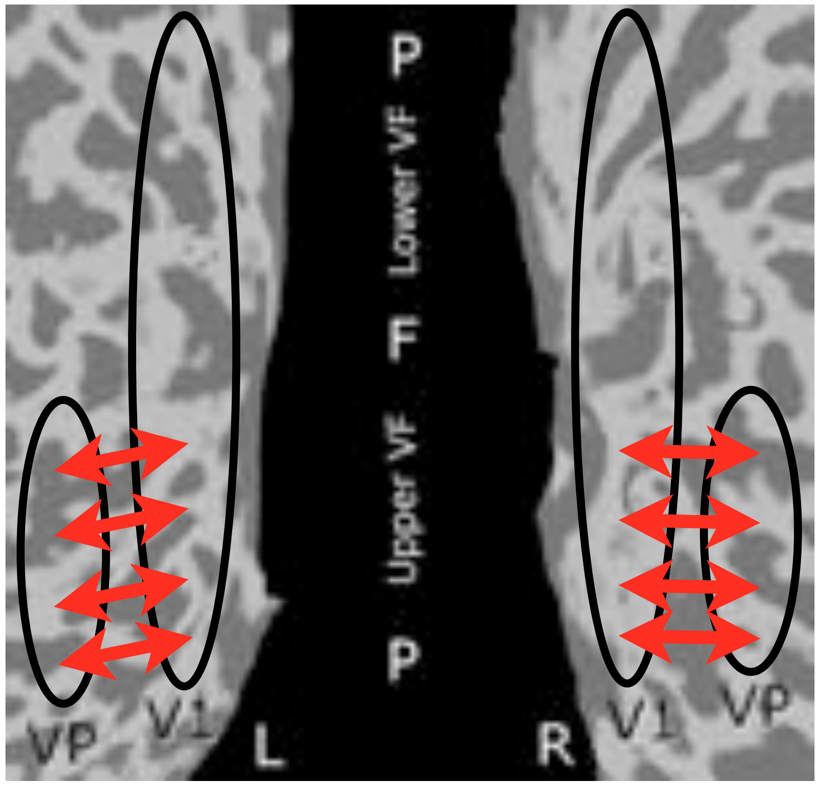
V1 – VP Connectivity



V1 – VP Connectivity

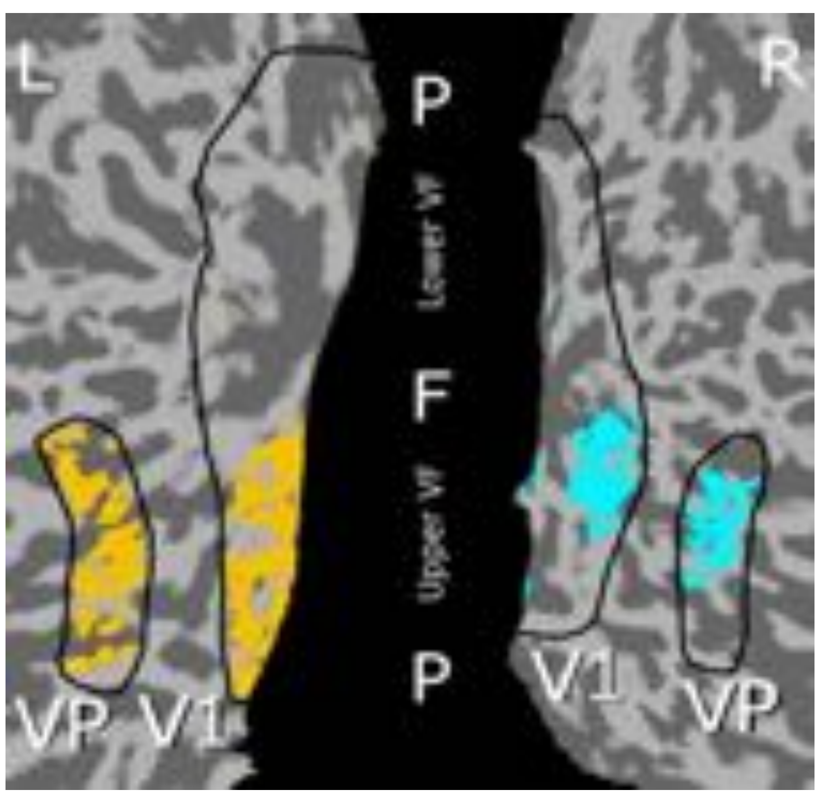


V1 – VP Connectivity



Expected Connectivity

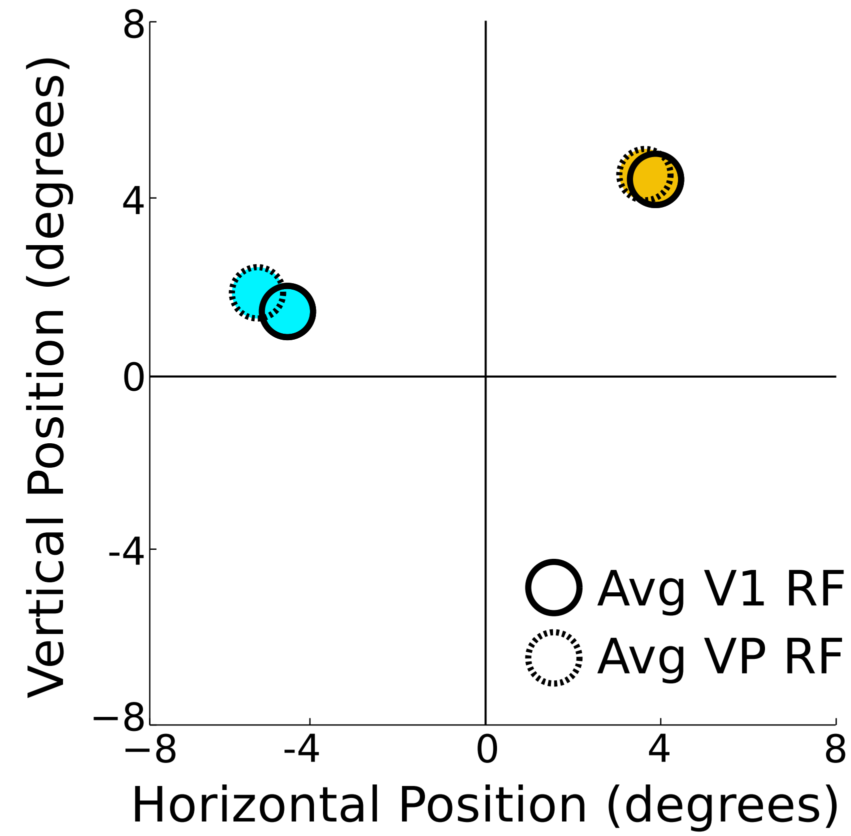
Solutions Found

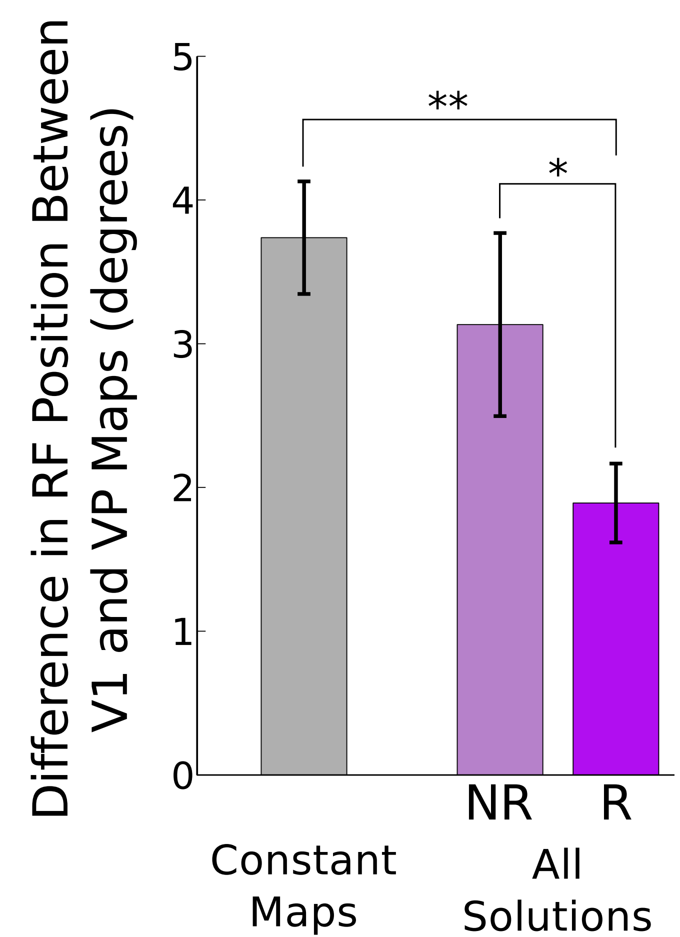


Solution Maps Consistent with Retinotopic Organization

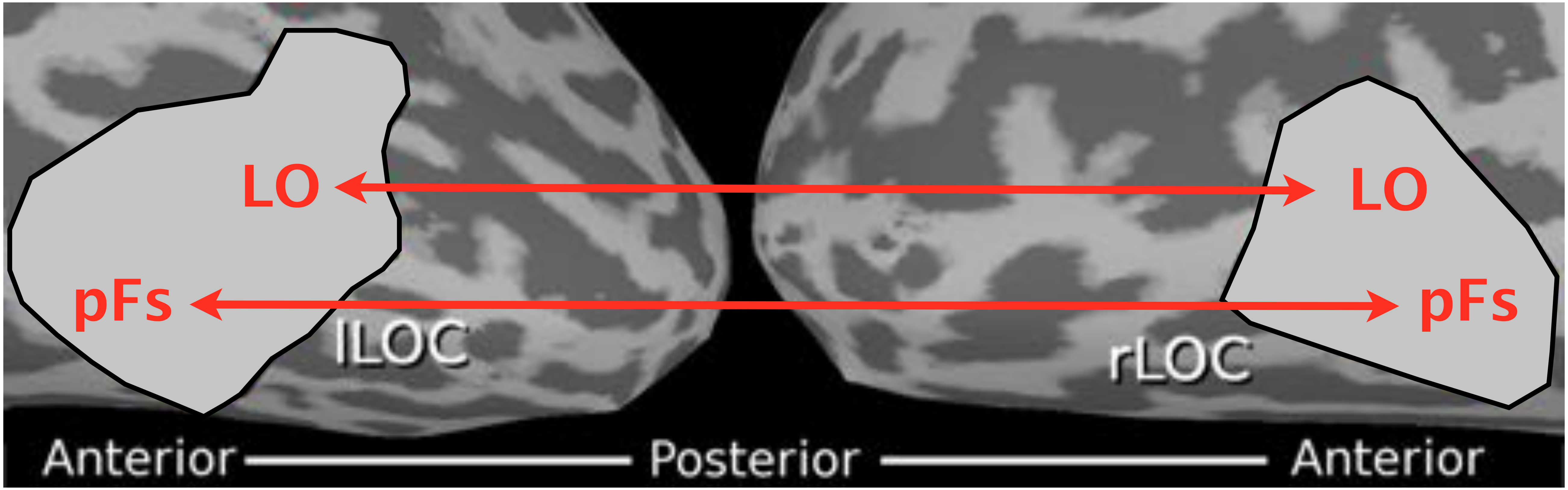
Regularization Improves RF Localization

256 Timepoints



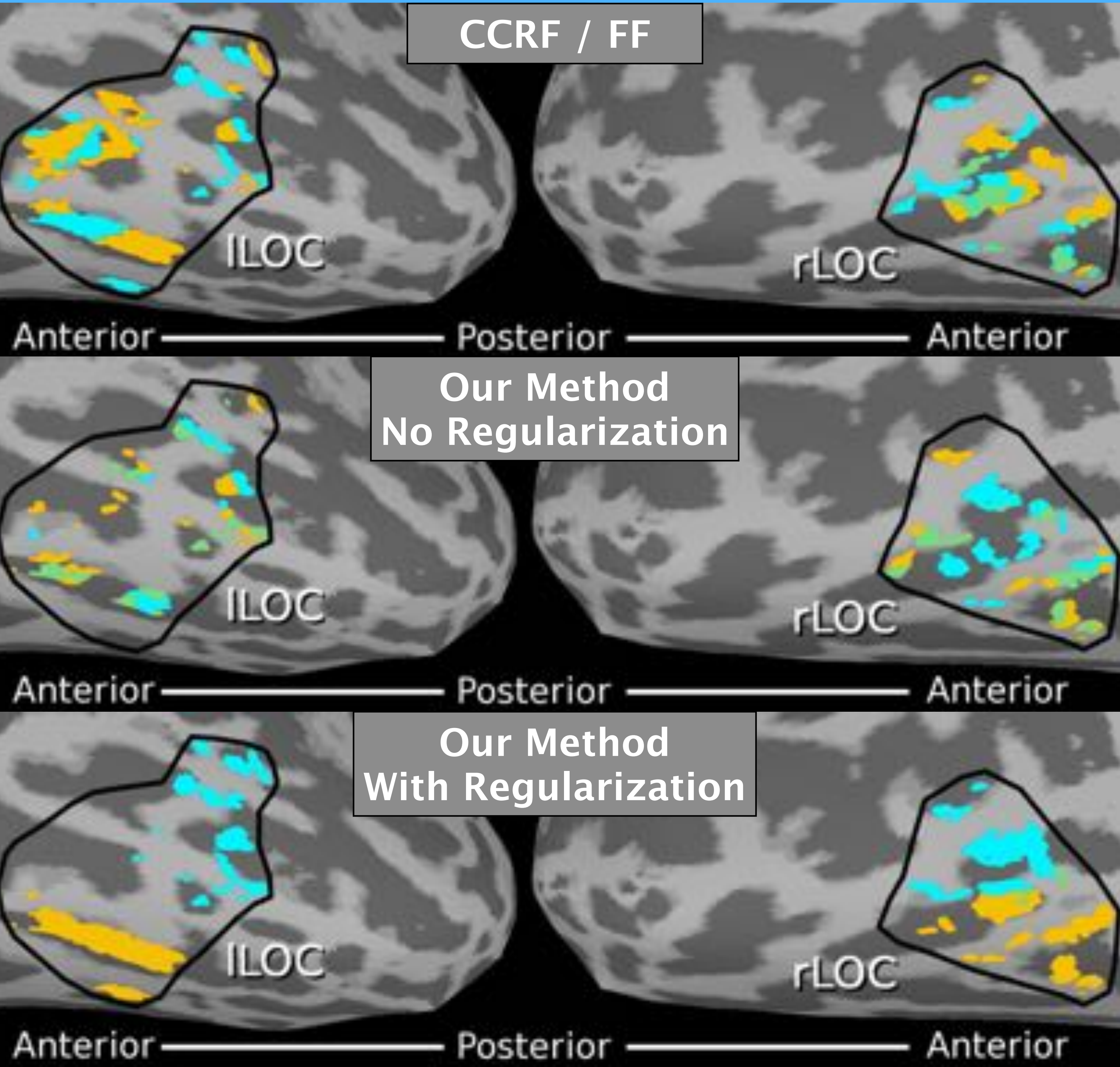


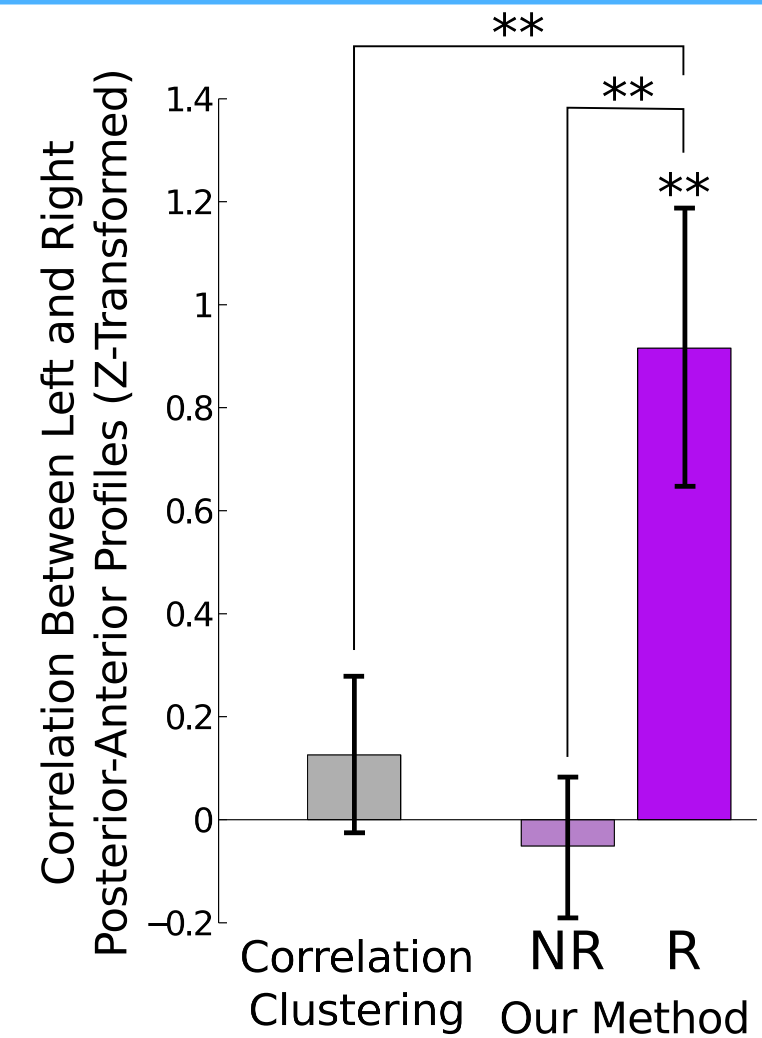
Left LOC – Right LOC Connectivity



Expected Connectivity

Left LOC – Right LOC Connectivity

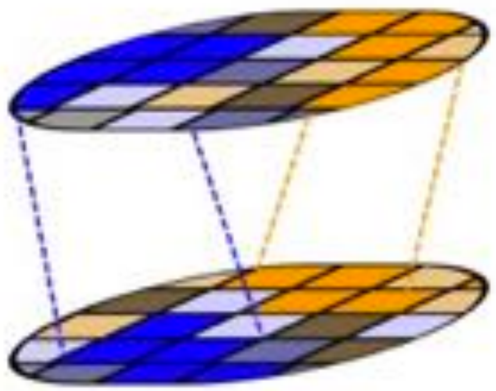




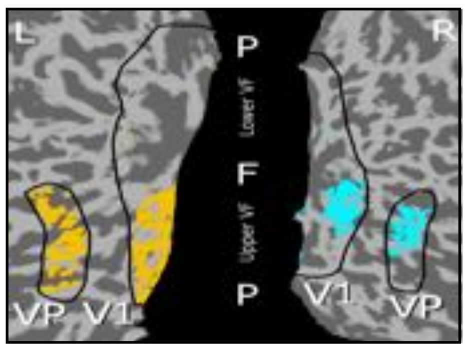
Regularized Method Recovers Anterior-Posterior Connectivity

Timecourse Correlation
$r = 0.8$

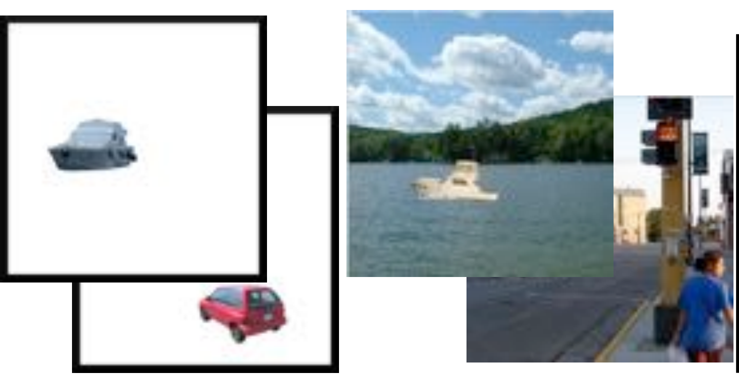
Summary



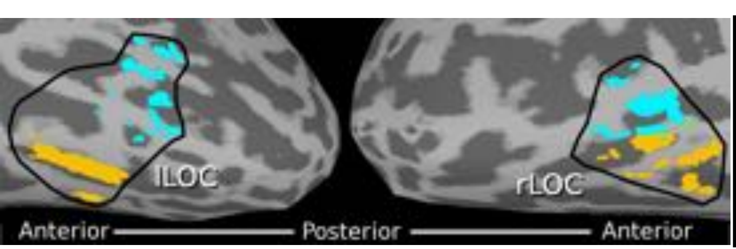
Jointly Learns Continuous Connectivity Maps



Can Recover Retinotopic Organization
and Anterior-Posterior Differences in LOC



No Specialized Datasets,
Fewer Timepoints than Voxels!



Can Recover Correlated Distinct Solutions

Implementation Available at:
vision.stanford.edu/resources_links.html

C. BALDASSANO M.C. IORDAN D.M. BECK L. FEI-FEI




MCI@STANFORD.EDU CHRISB33@STANFORD.EDU

Acknowledgements: NSF, SGF, NIH