A common model of representational spaces in human cortex: capturing common fine-scale architecture

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Attention
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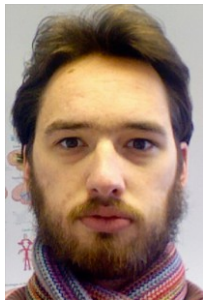

Action representation, computational methods
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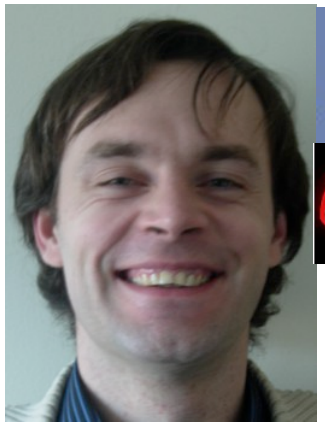

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NeuroDebian

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Analysis of similarity structure,
representation of biological classes
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A common high-dimensional linear model of representational spaces in human cortex

- Statement of the problem: capturing coarse- and fine-grained topographies in a common model
- Conceptual framework: high-dimensional representational spaces
- Deriving the common space and individual transformation matrices with hyperalignment
- Validation
- Conclusions

Multivariate Pattern Classification Example: Classifying responses during viewing of animal species

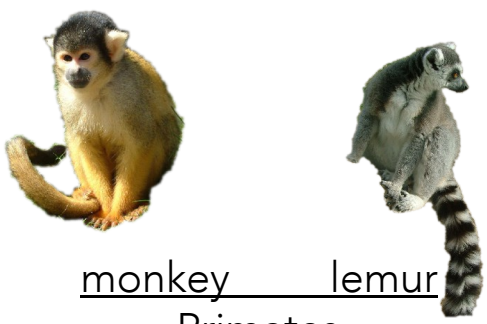
(VT cortex, SVM)

luna moth ladybug

Insects

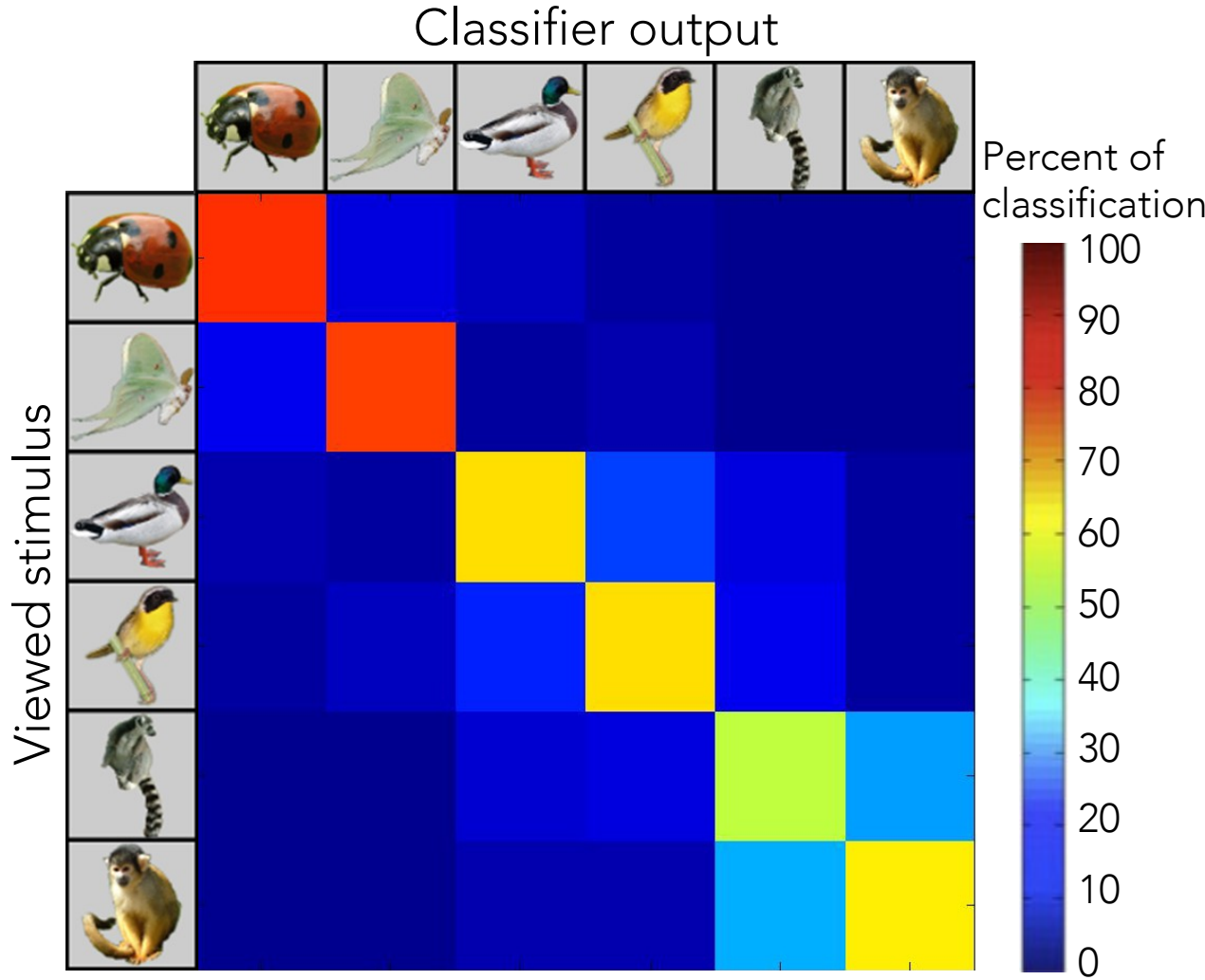
warbler mallard

Birds



monkey lemur

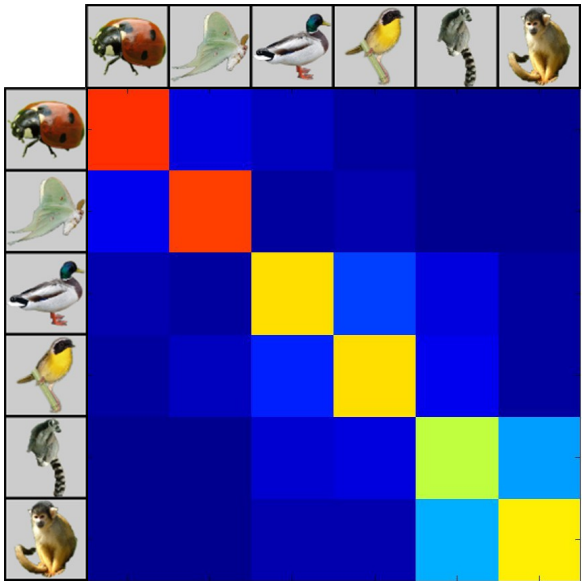
Primates



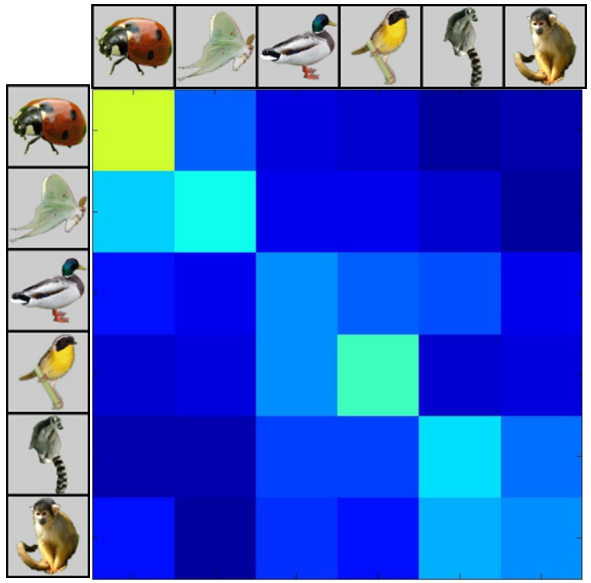
(Haxby et al. 2011; Connolly et al. 2012)

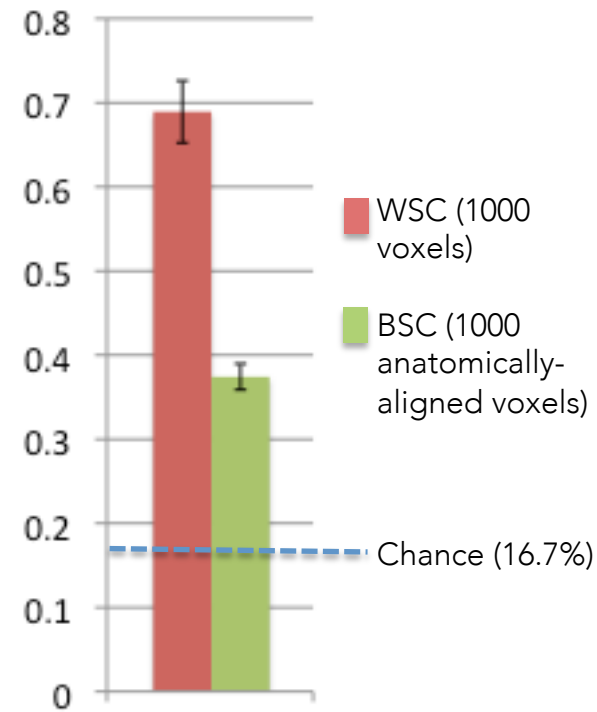
The problem:
Loss of fine-grained distinctions among representations after anatomical alignment of brains

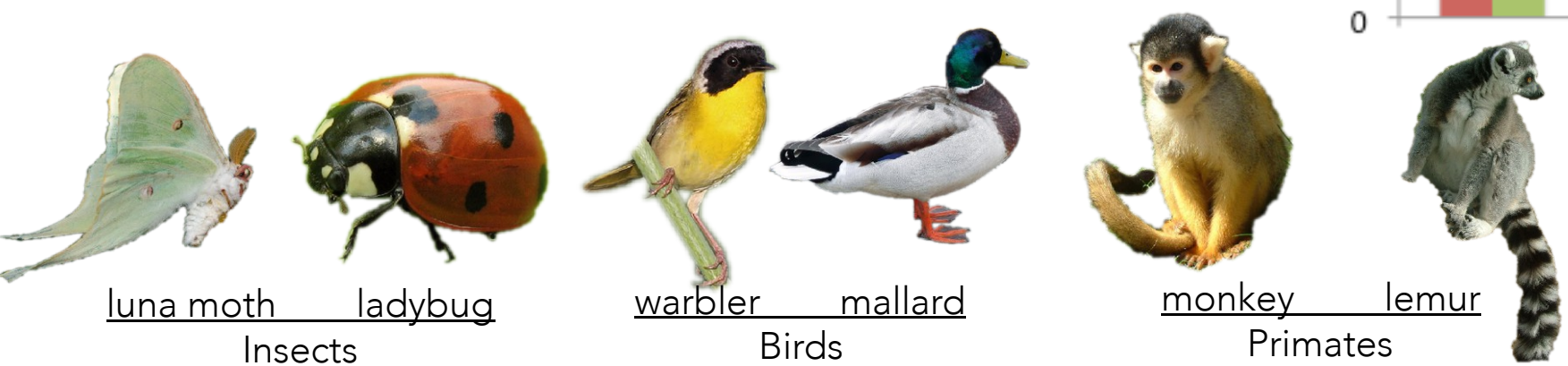
Within-subject classification
(new model for each subject)



Between-subject classification
(common model based on anatomy)







luna moth ladybug
Insects

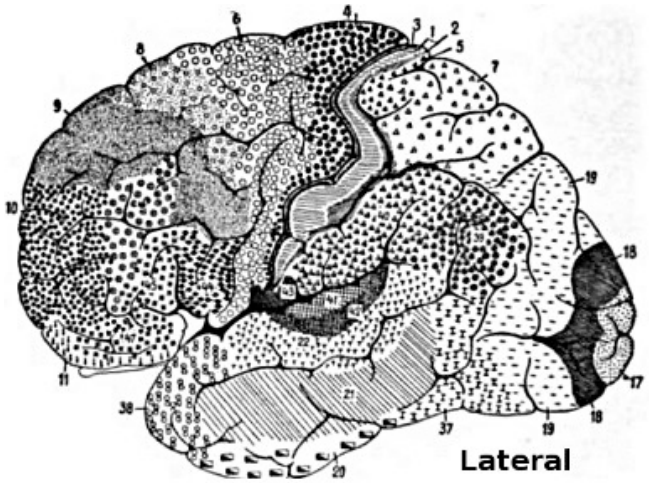
warbler mallard
Birds

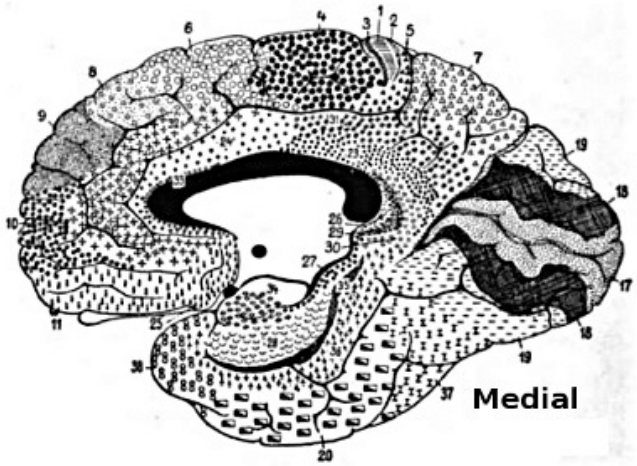
monkey lemur
Primates

(Haxby et al. 2011; Connolly et al. 2012)

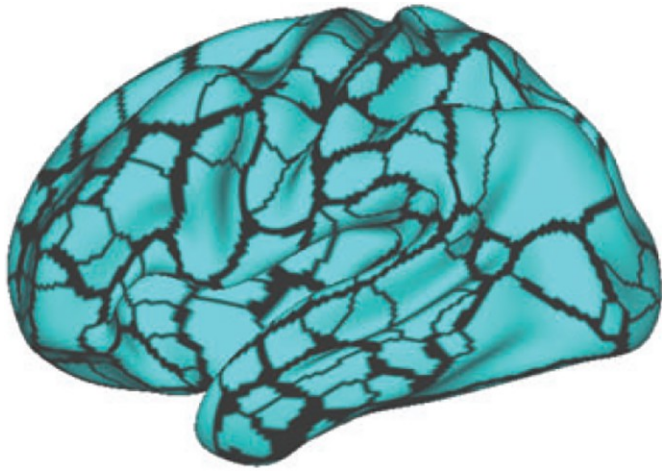
Models of cortical architecture: parcellation of cortex into areas and systems

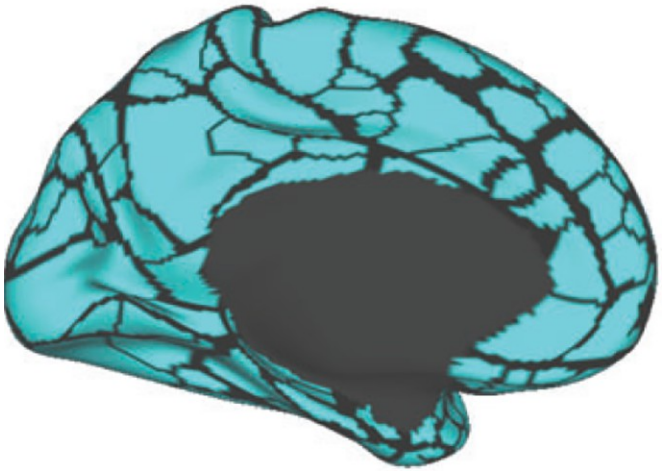
52 areas
(Brodmann, 1909)

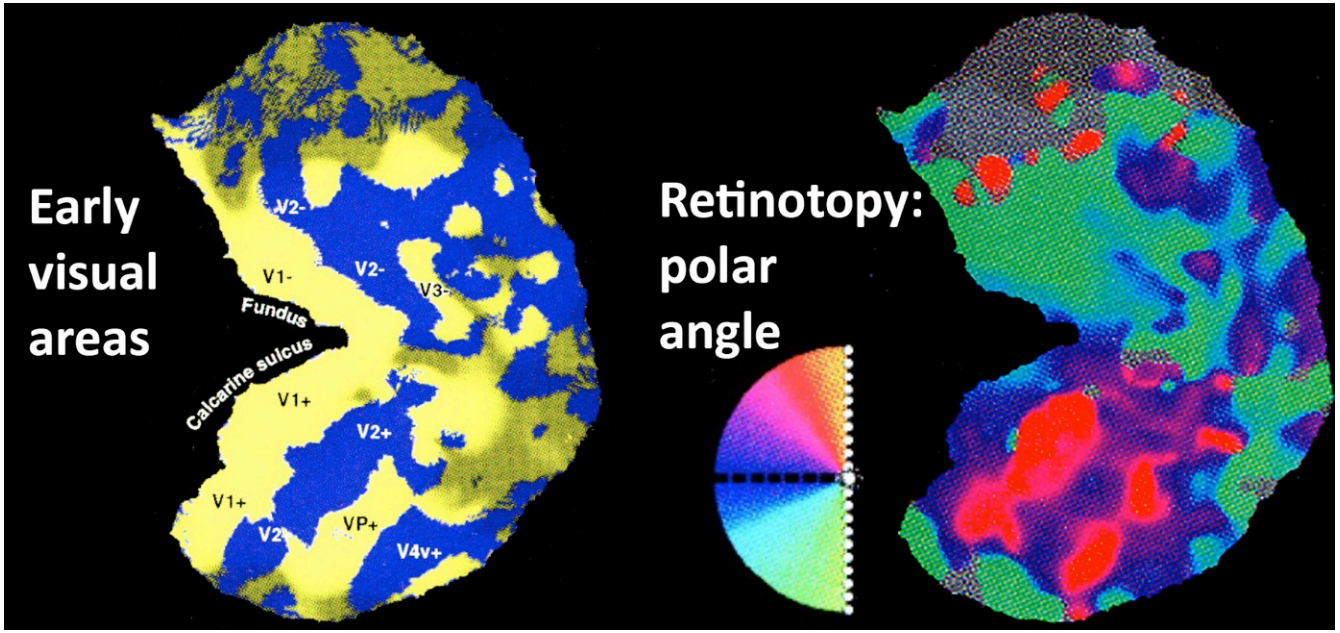




422 areas
(Gordon et al. 2014)

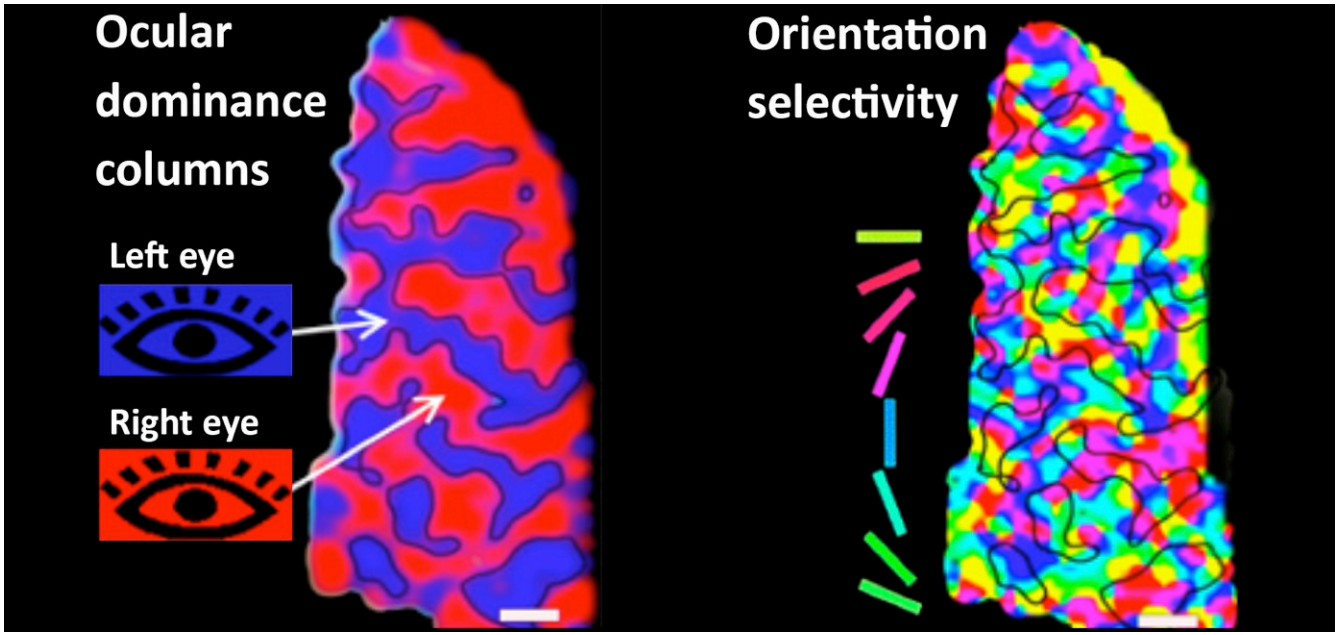






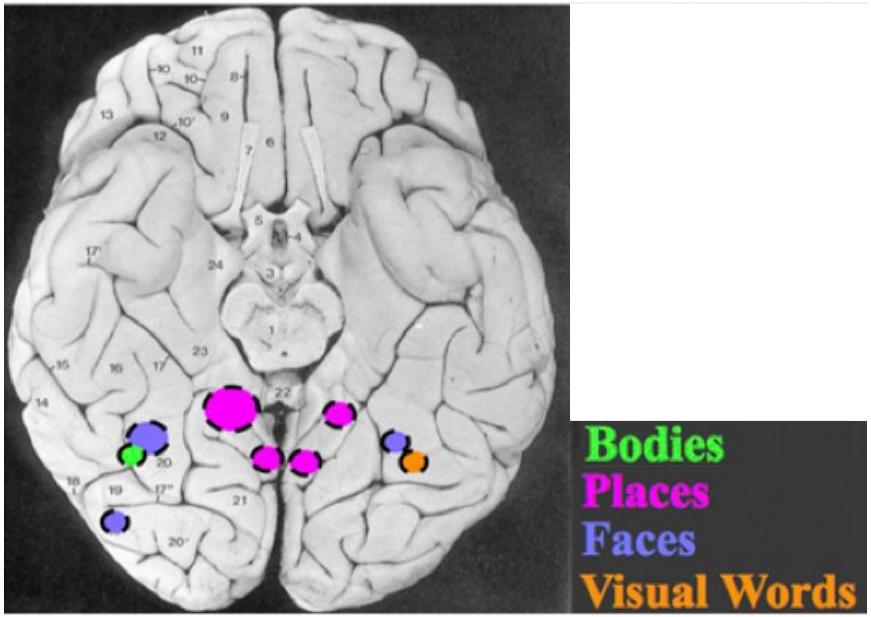
Known topographies of different scales in early visual cortex

Sereno et al. 1995

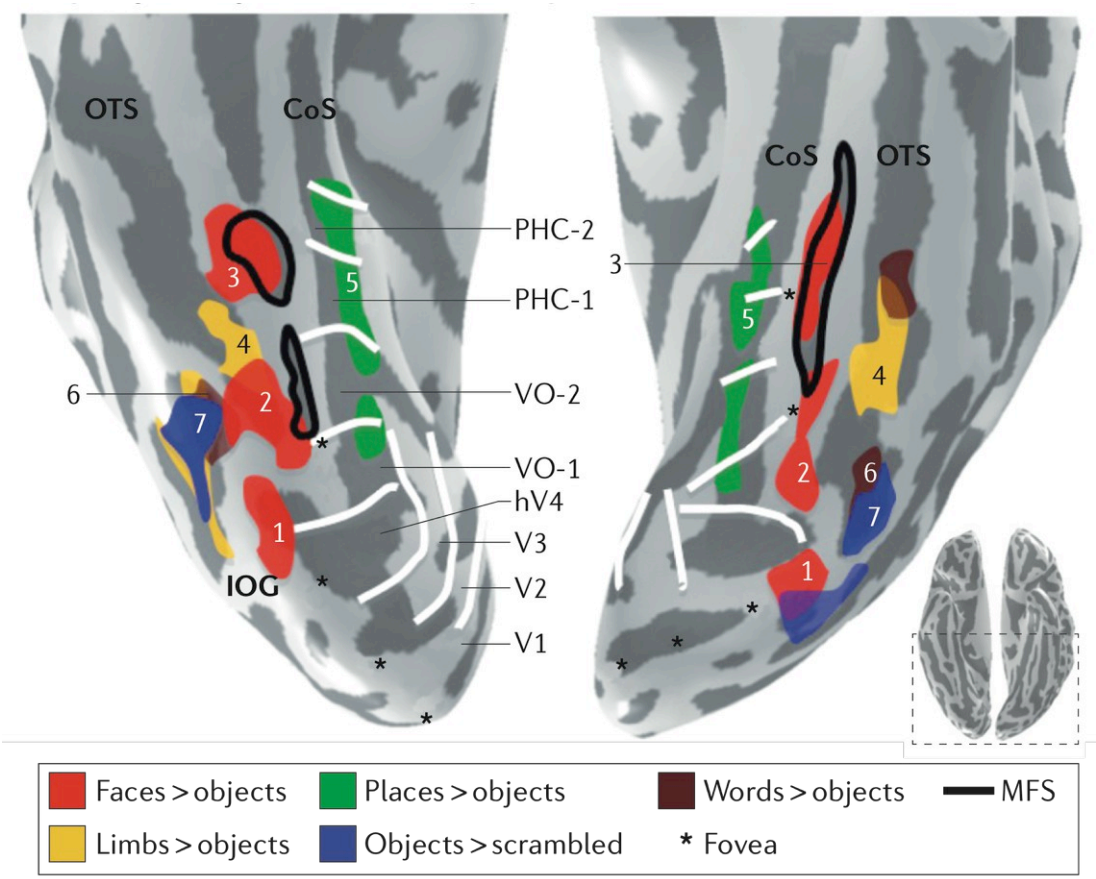


Yacoub et al. 2007, 2008

Category-selective regions in ventral temporal cortex also carry finer distinctions carried by fine-grained topographies



Kanwisher (2010)



Grill-Spector & Weiner (2014)

Category-selective regions in ventral temporal cortex
also carry finer distinctions carried by fine-grained topographies:

Distinctions that can be decoded from response patterns in the FFA

Haxby et al. 2011; Connolly et al. 2012; Guntupalli et al. bioRXiv, 2016 & under review

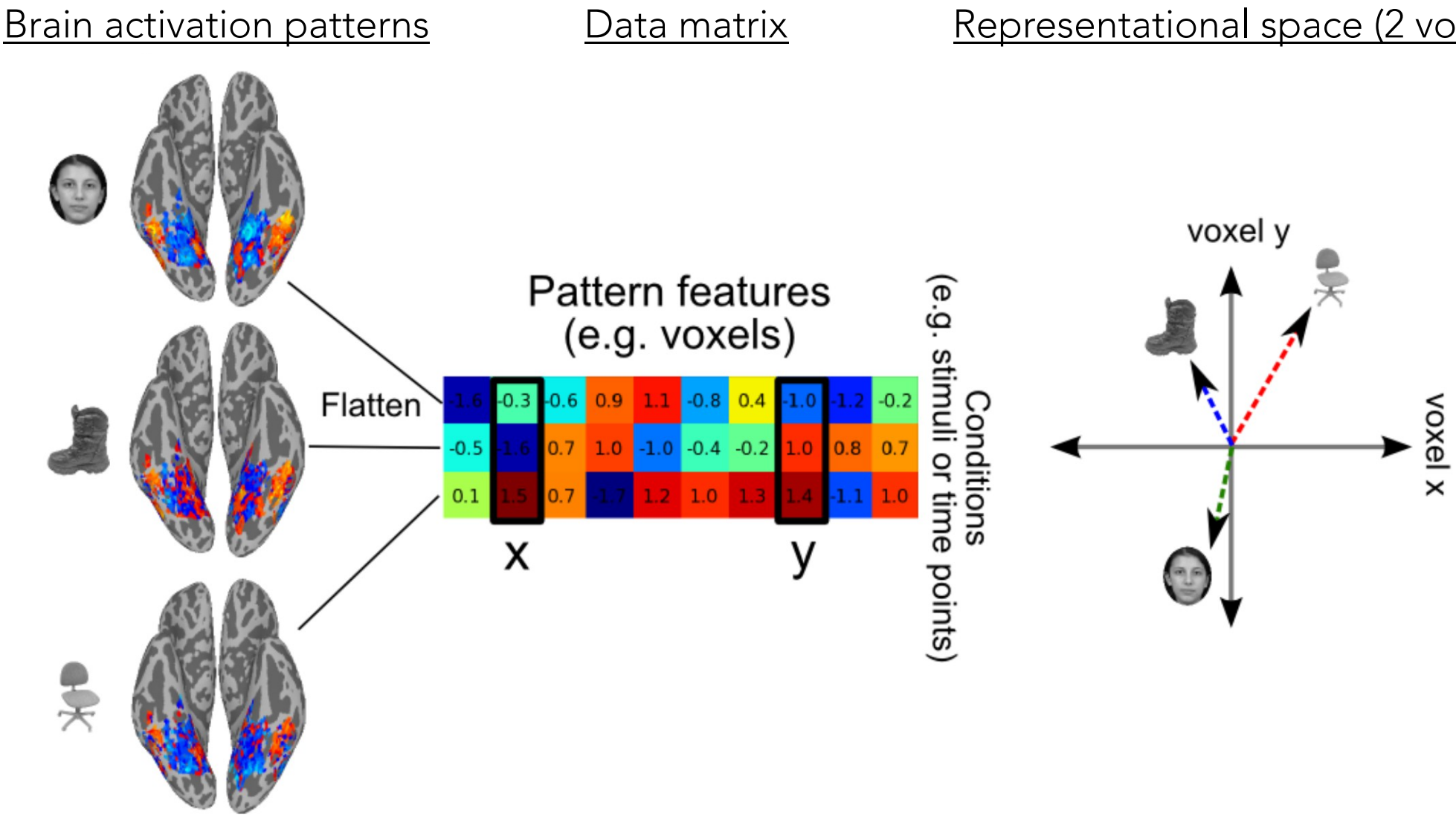
Question

- Can the fine-grained topographies that carry fine distinctions be modeled in a computational framework that is common across brains?
  - i.e. Is there a common basis – shared principles and features - for these population responses, or does each brain develop an idiosyncratic code?

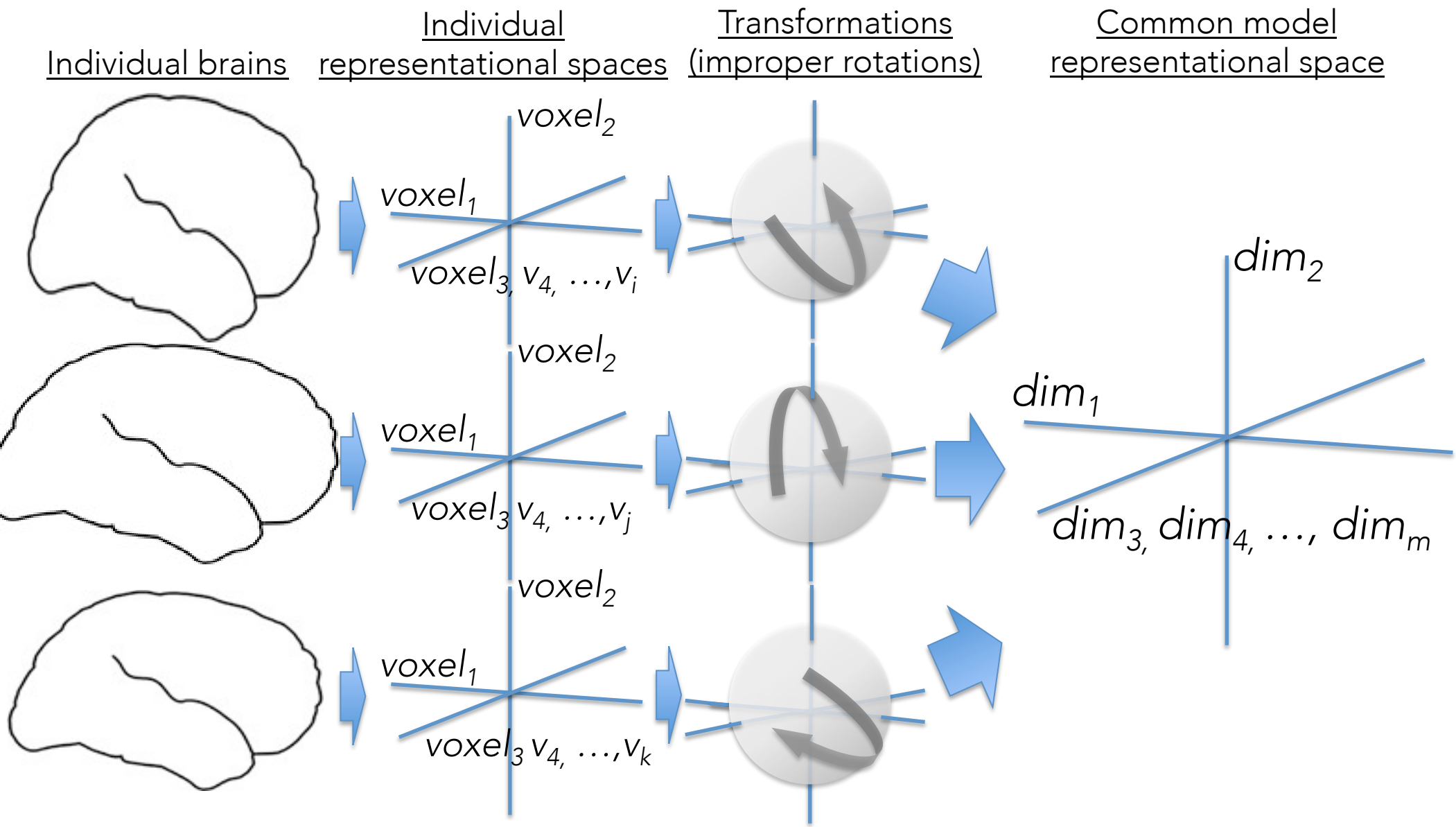
A common high-dimensional linear model of representational spaces in human cortex

- Statement of the problem: capturing fine-grained distinctions in a common model
- Conceptual framework: high-dimensional representational spaces
  - A model space based on features (dimensions) with common tuning profiles
- Deriving the common space and individual transformation matrices with hyperalignment
- Validation
- Conclusions

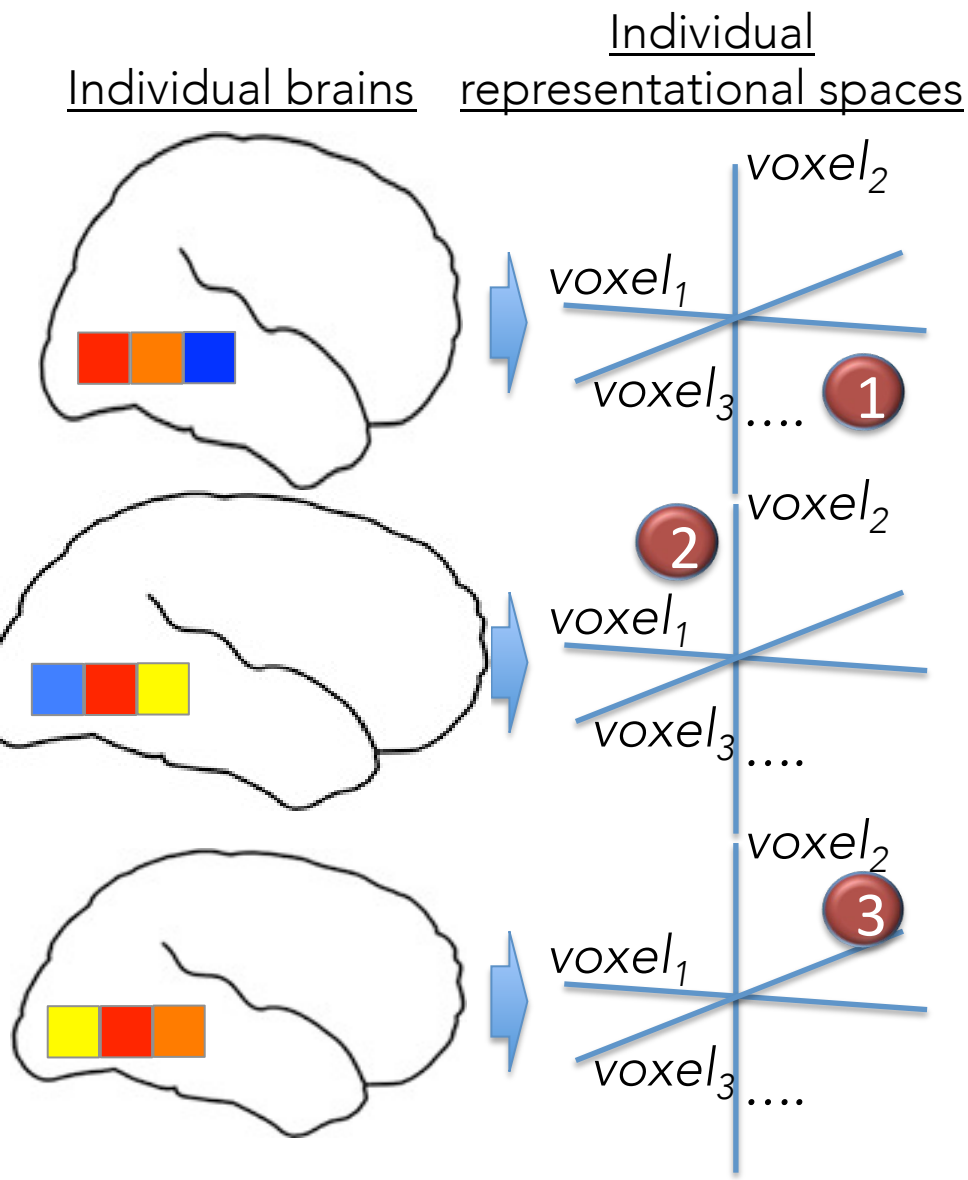
Conceptual framework:
High-dimensional representational spaces



Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space

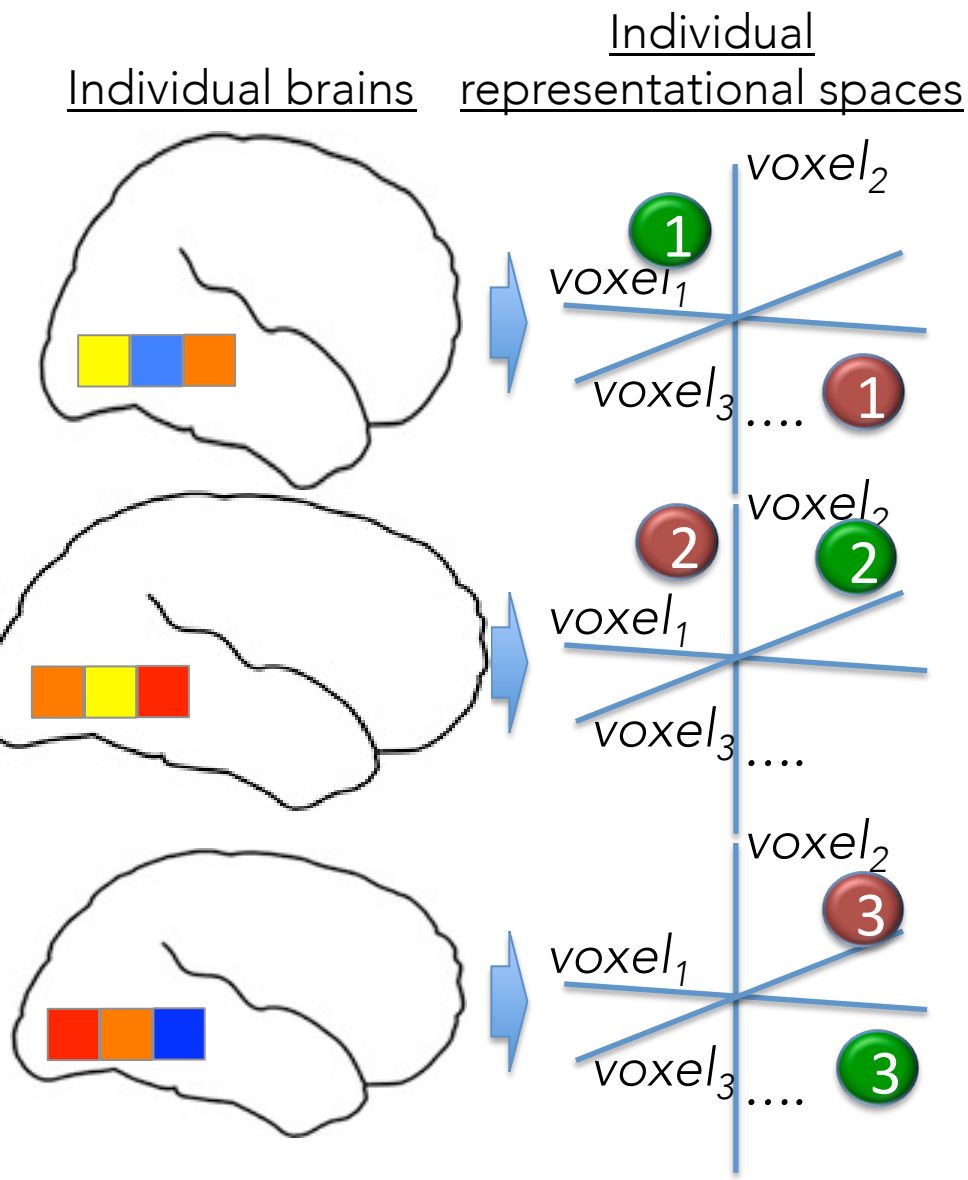


Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space



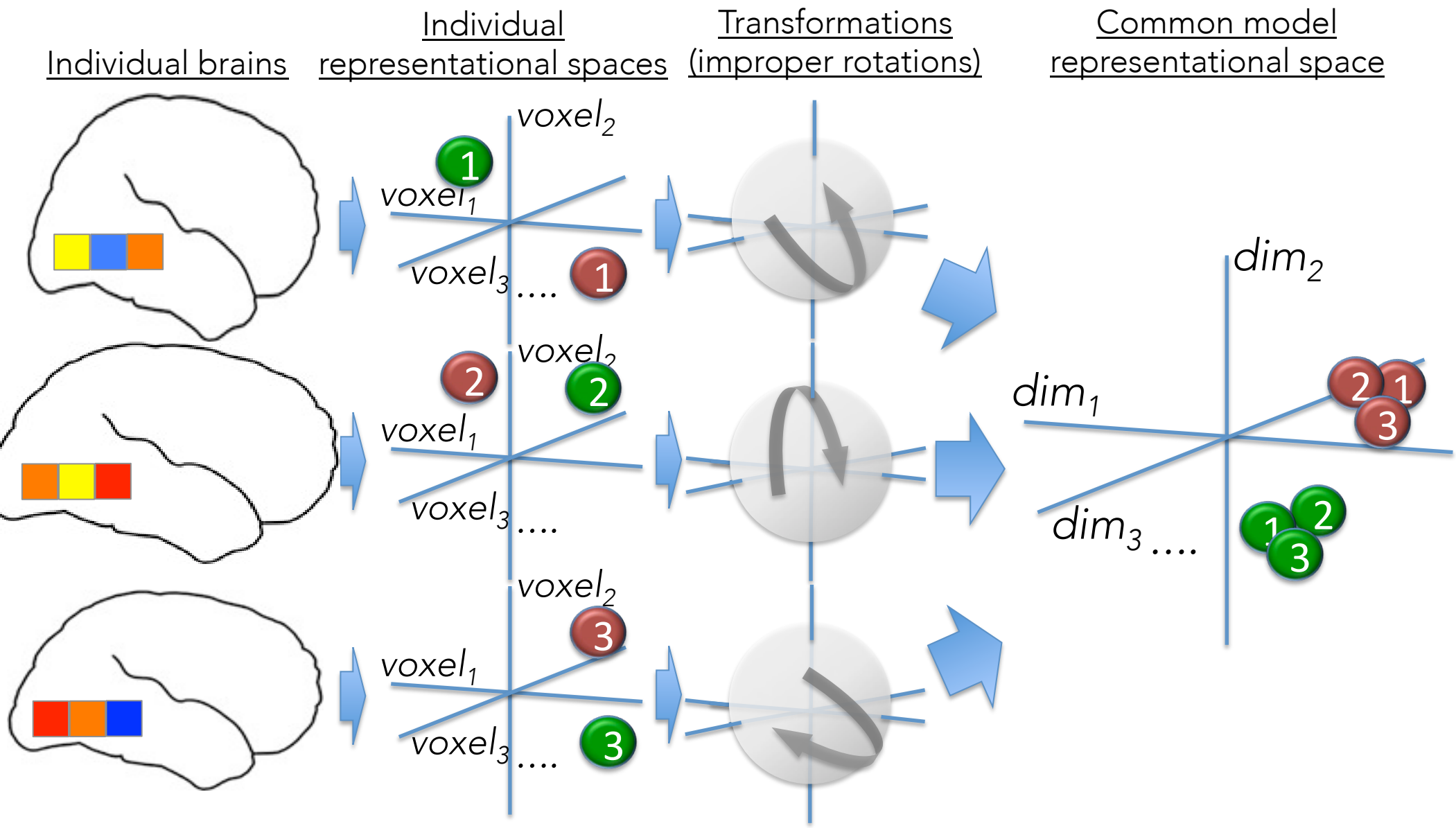
Stimulus

Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space



Another stimulus

Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space

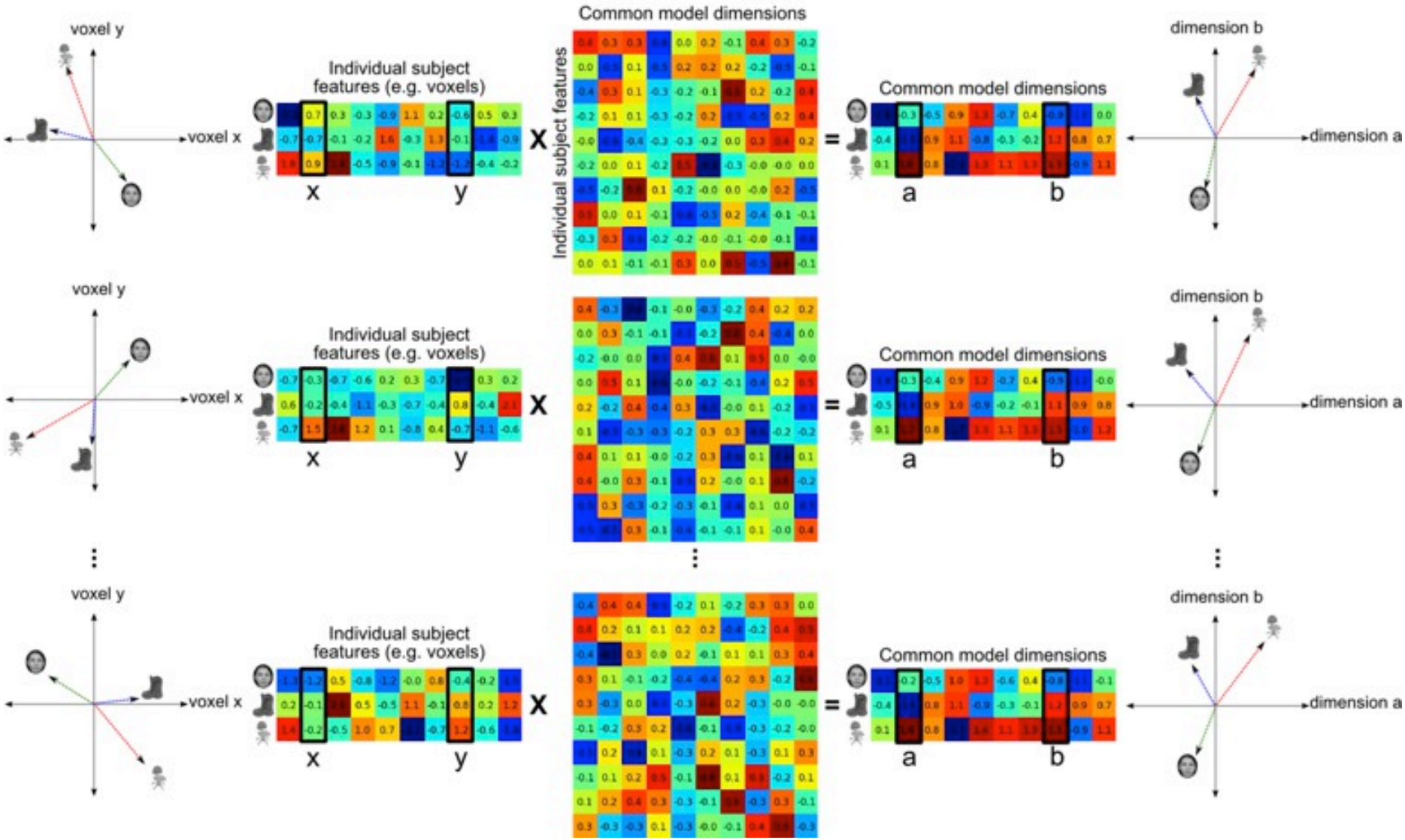


A common high-dimensional linear model of representational spaces in human cortex

- Statement of the problem: capturing fine-grained distinctions in a common model
- Conceptual framework: high-dimensional representational spaces
- Deriving the common space and individual transformation matrices with hyperalignment
  - Hyperalignment algorithm based on Procrustes transformations
  - A rich sampling of response vectors using natural stimulus
- Validation
- Conclusions

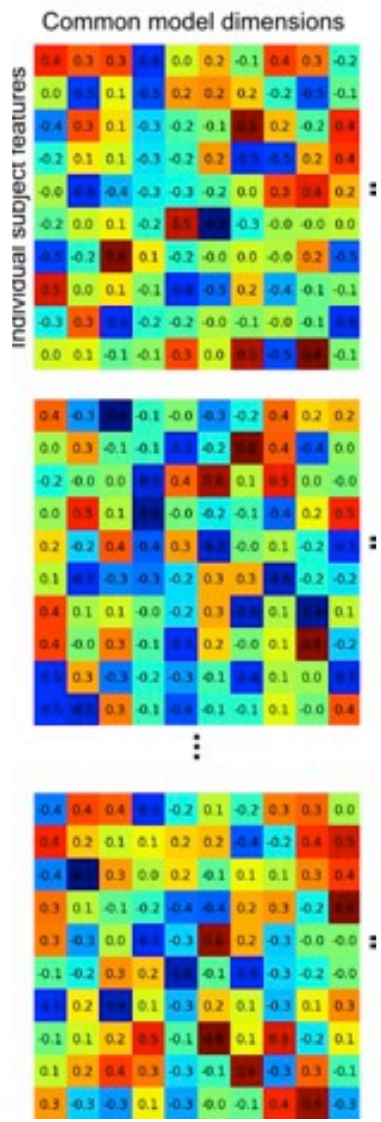
Matrix math:

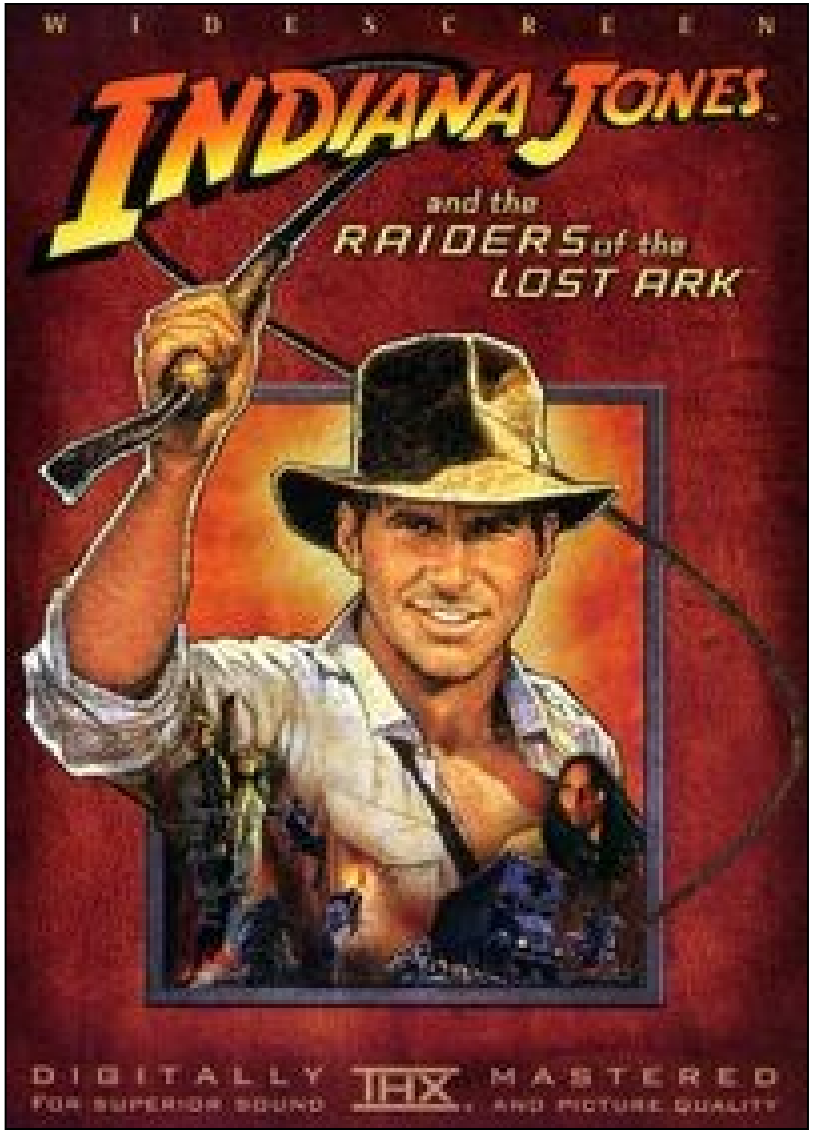
Individual transformation matrices rotate individual brain spaces into common model space coordinates

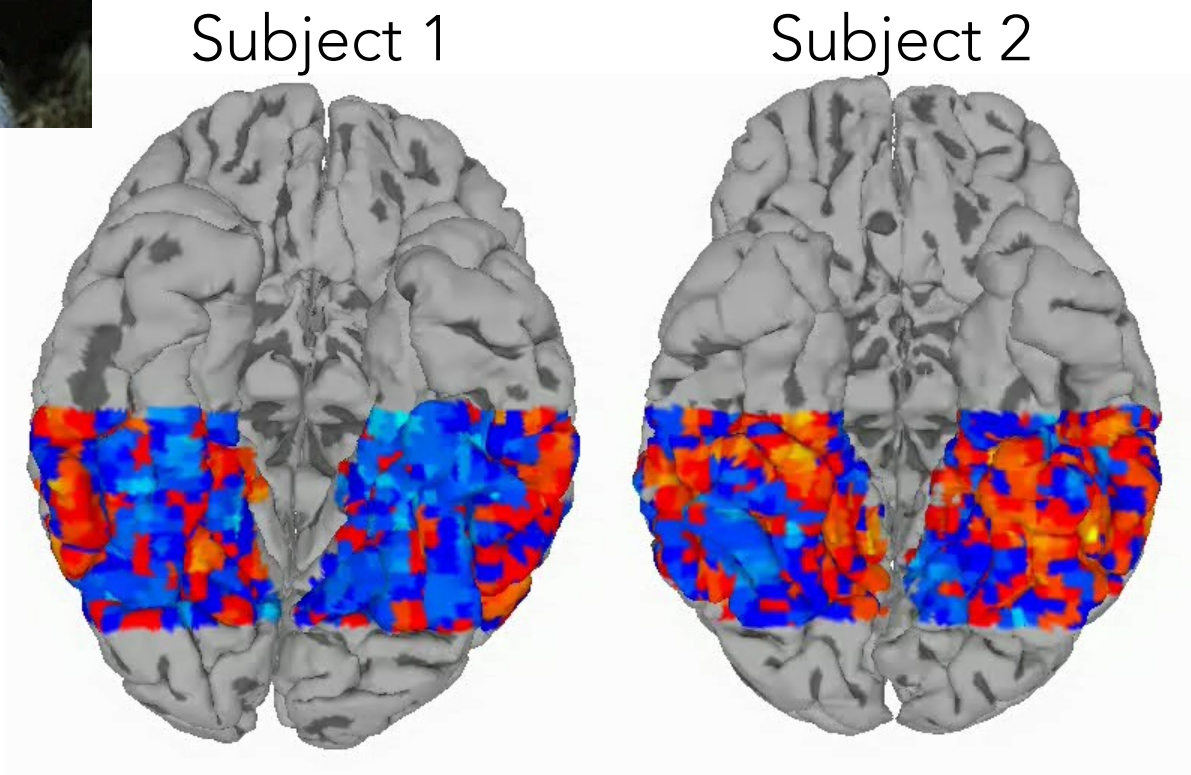


Individual transformation matrices are the key to building the common model: How can the parameters be derived?

<u>Transformation matrices</u>




WIDESCREEN
INDIANA JONES
and the
RAIDERS of the
LOST ARK
DIGITALLY
FOR SUPERIOR SOUND
THX
MASTERED
AND PICTURE QUALITY

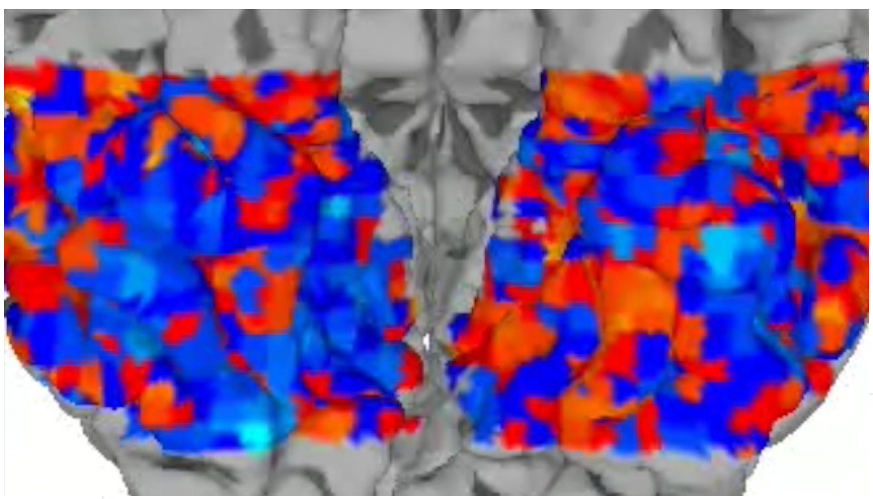

Subject 1
Subject 2

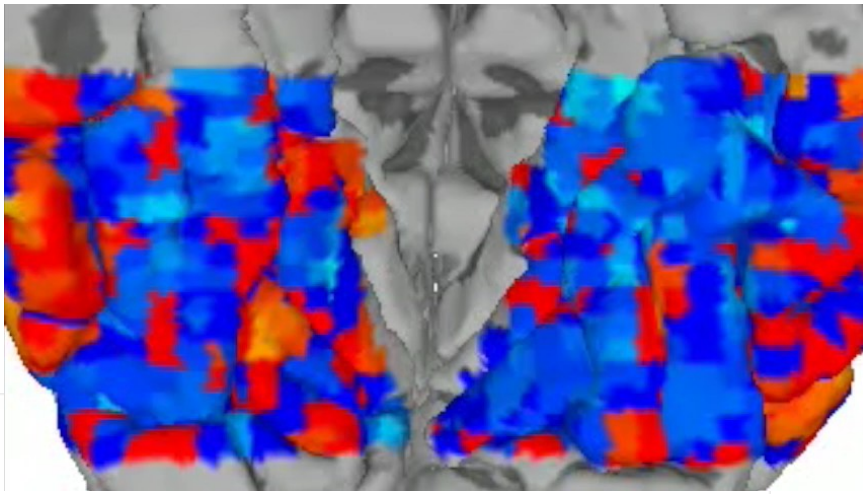
Broad sampling of a neural representational space with a movie

Subject 1

Subject 2

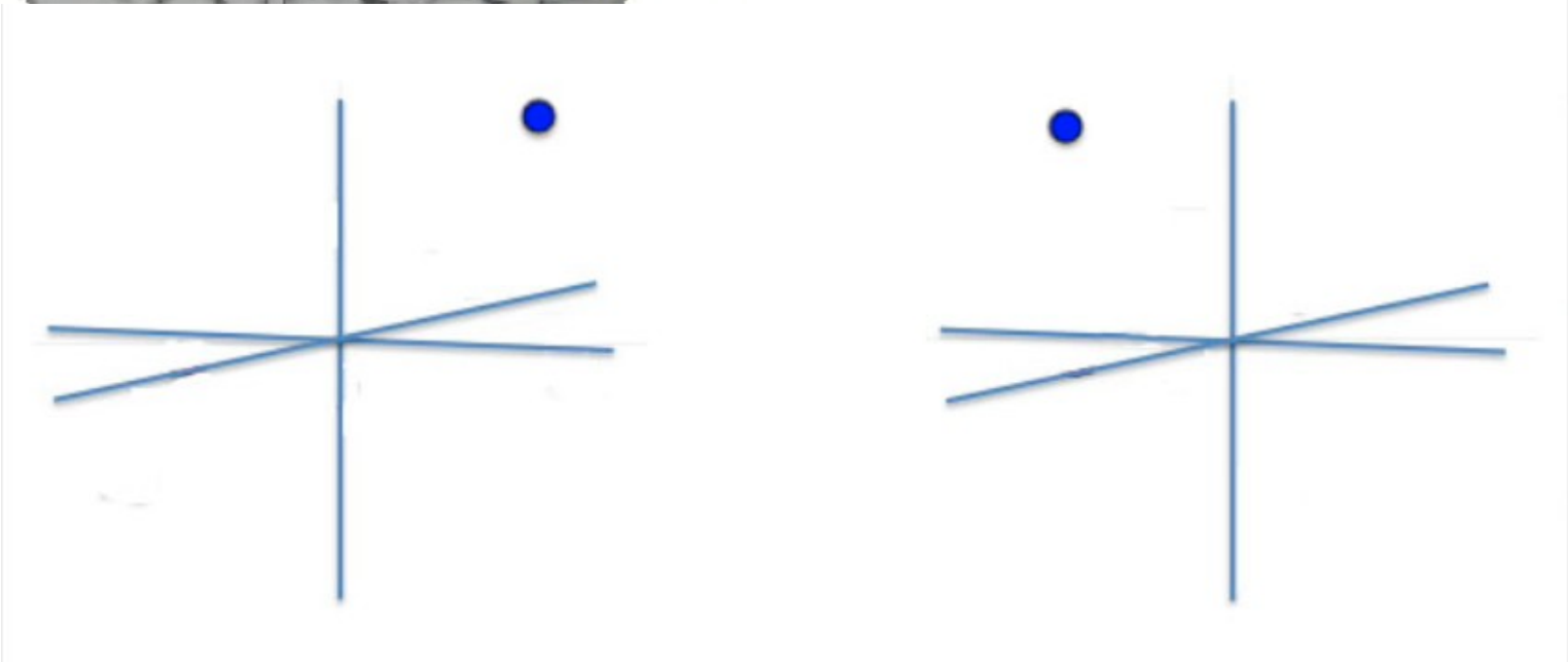
Response patterns in cortex

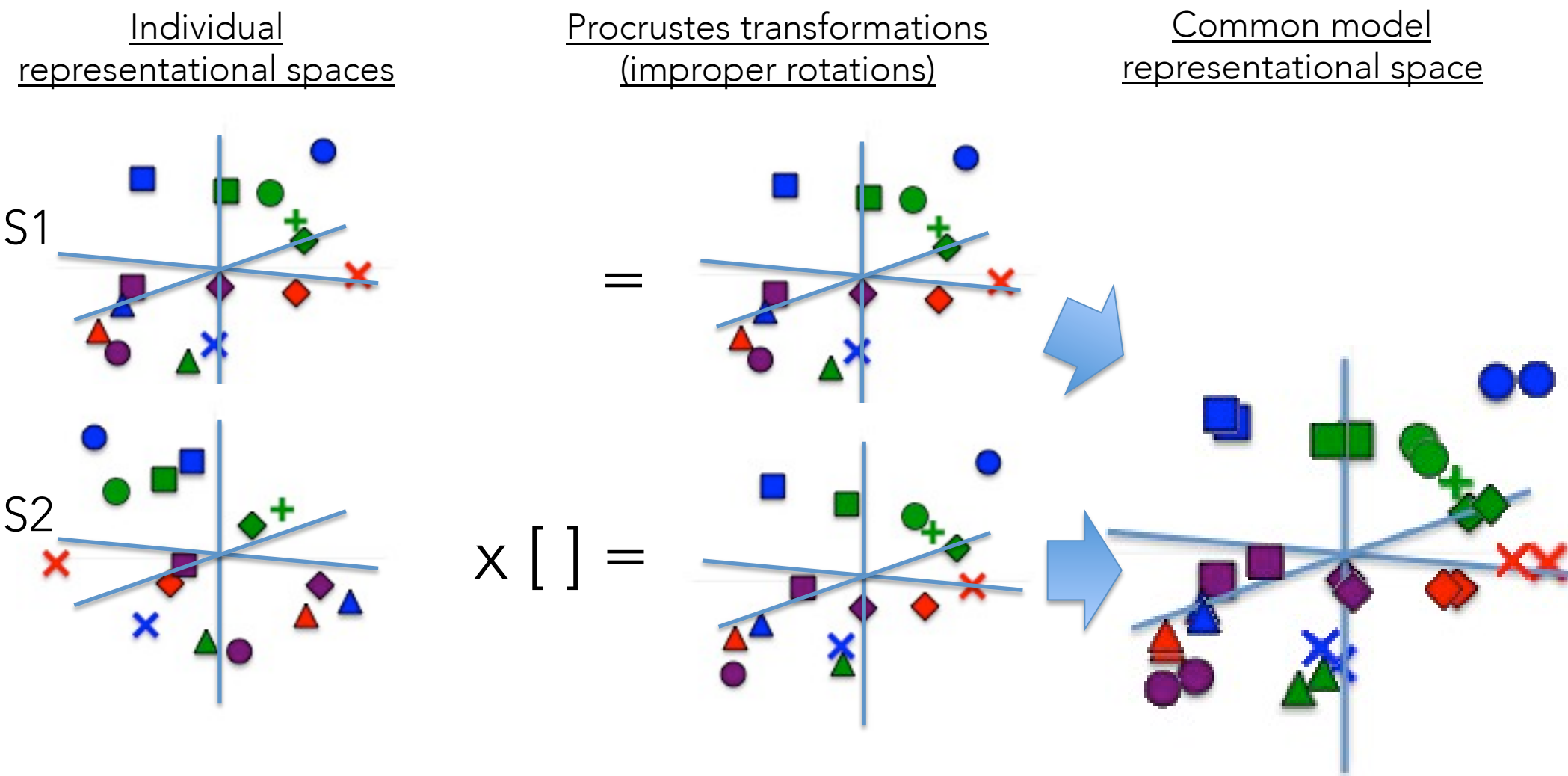


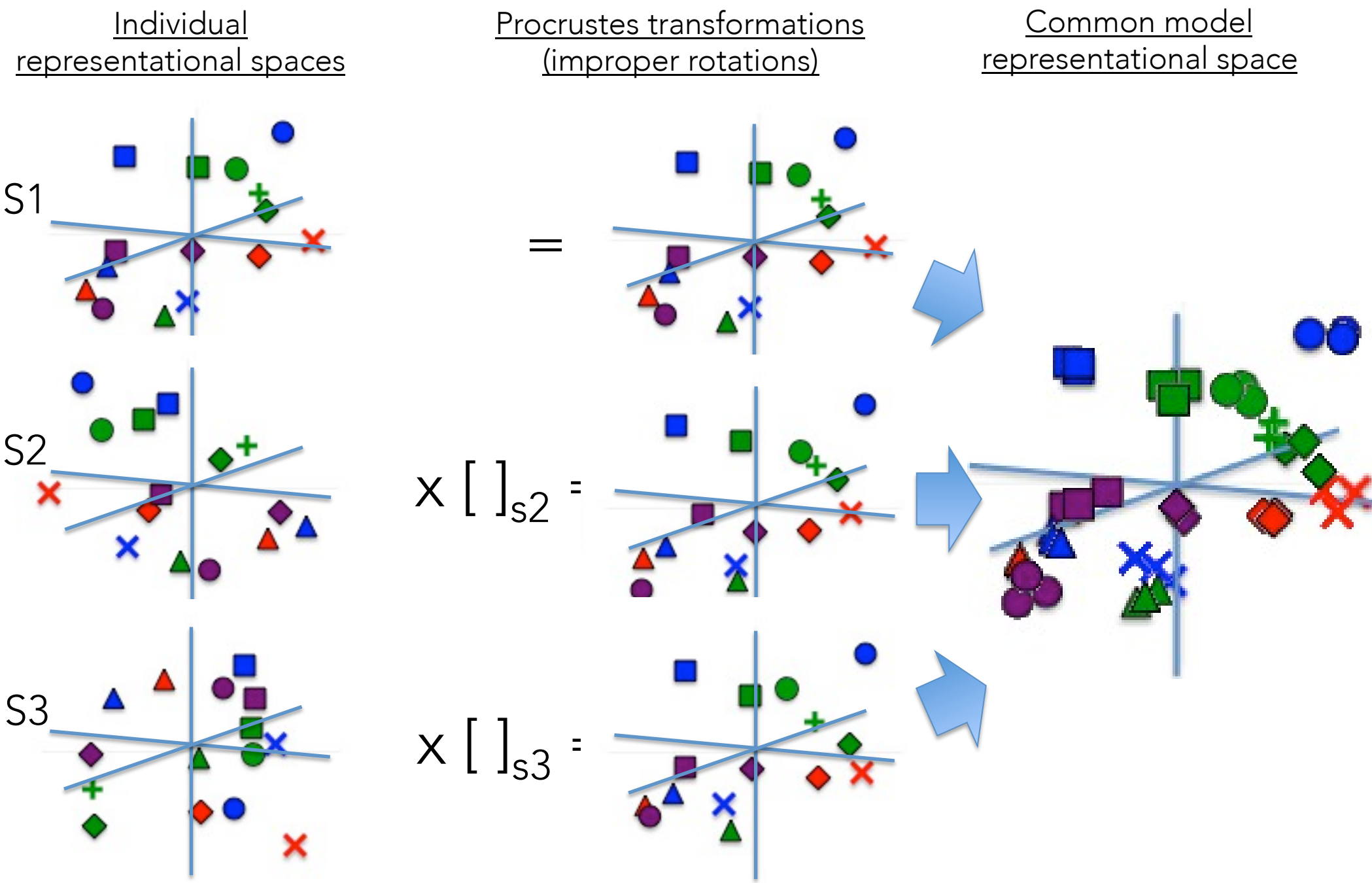


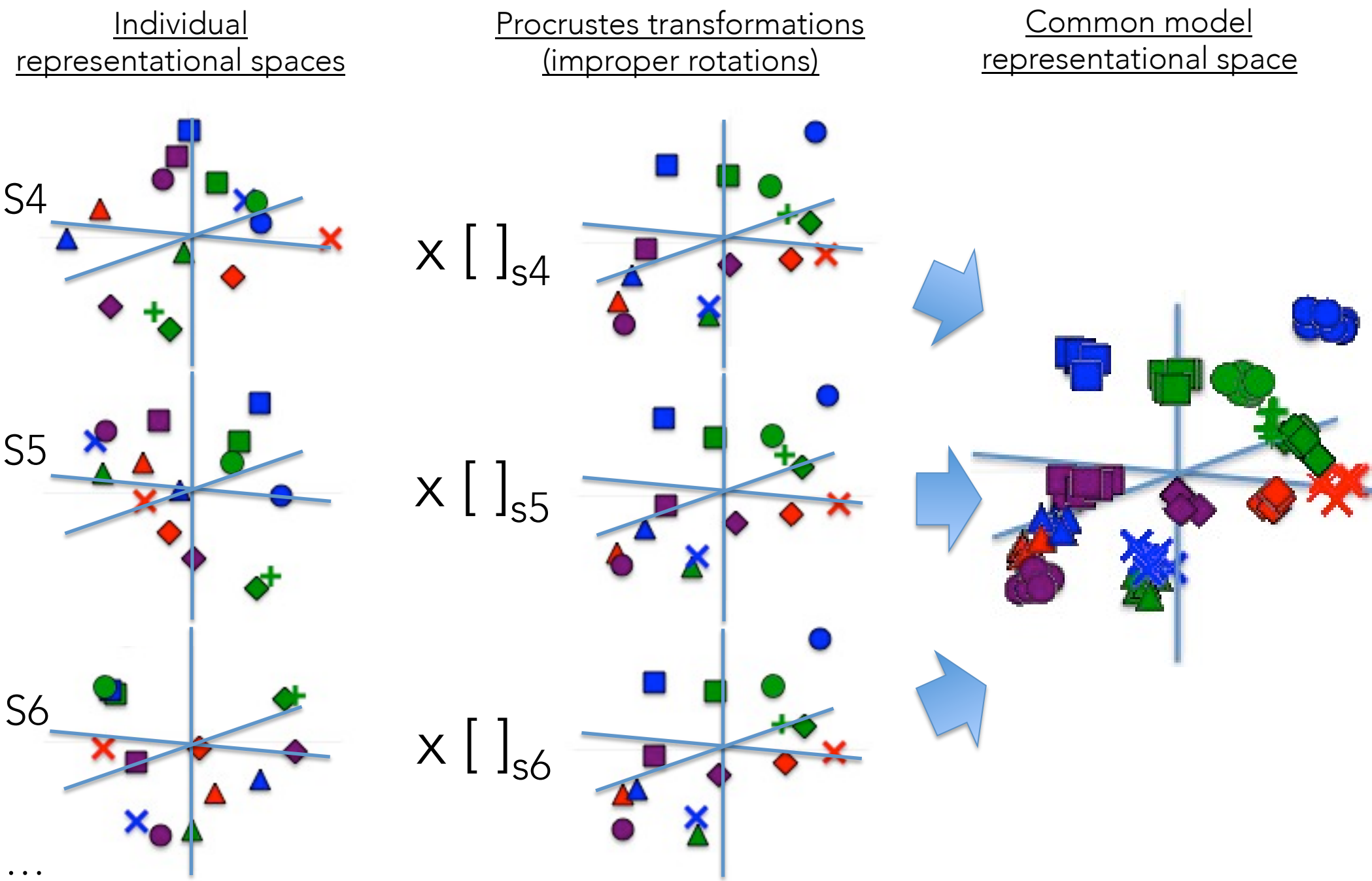
15 response pattern vectors in individual 3D representational spaces

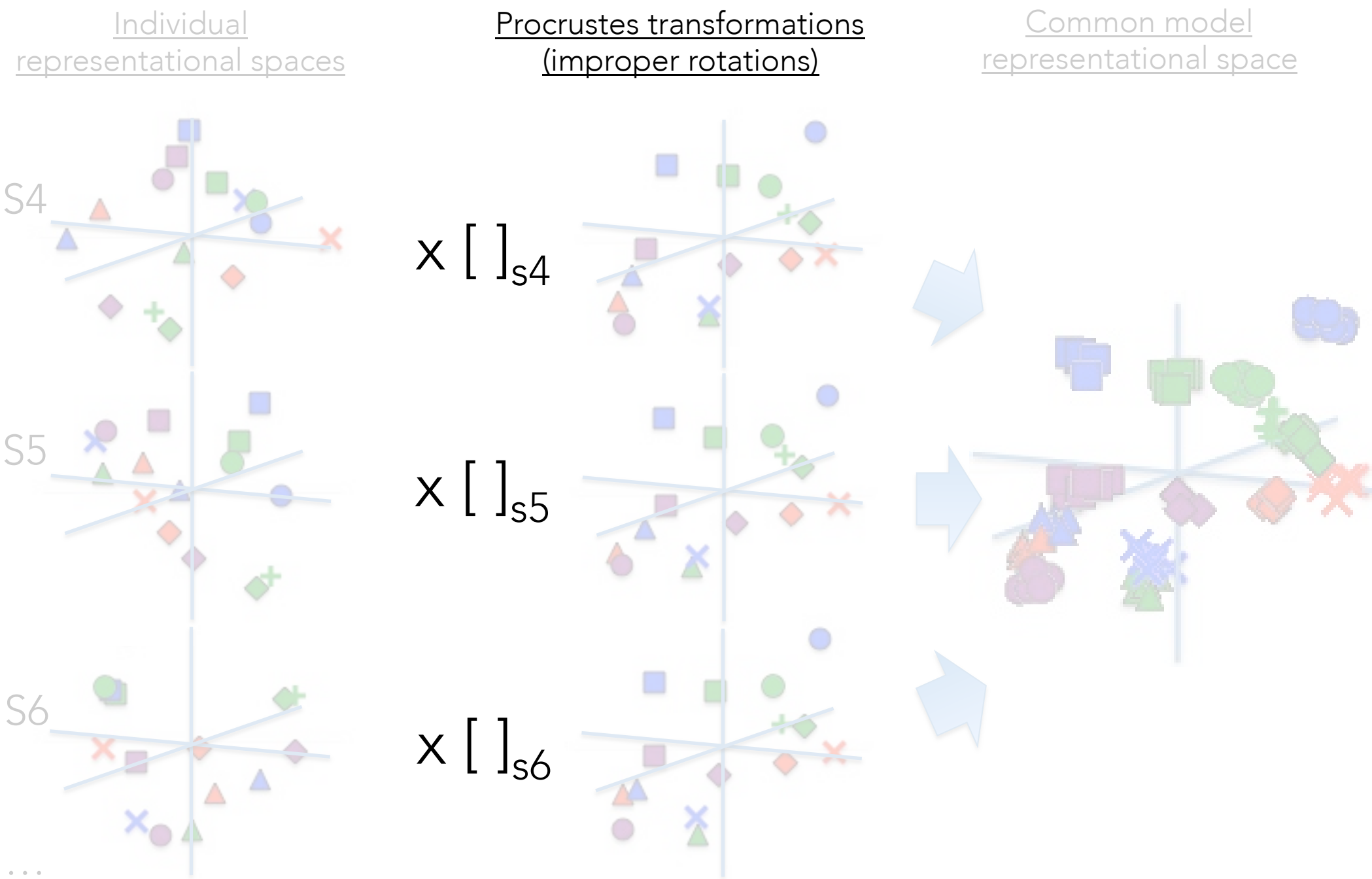
(full exp't has >2600 vectors in >50,000D space)




Individual representational spaces
Procrustes transformations (improper rotations)
Common model representational space
S1
S2
=
x [ ] =


Individual representational spaces
Procrustes transformations (improper rotations)
Common model representational space
S1
S2
S3
=
x [ ]s2 =
x [ ]s3 =


Individual representational spaces
Procrustes transformations (improper rotations)
Common model representational space
S4
S5
S6
...
x [ ]s4
x [ ]s5
x [ ]s6


Individual representational spaces
Procrustes transformations (improper rotations)
Common model representational space
S4
S5
S6
...
x [ ]s4
x [ ]s5
x [ ]s6

Movie data in Brain Space

Time-points	Voxels				
	v_1	v_2	v_3	...	v_i
t_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{i,1}$
t_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	...	$x_{i,2}$
t_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	...	$x_{i,3}$
t_4	$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	...	$x_{i,4}$
...	...	...	...		...
t_j	$x_{1,j}$	$x_{2,j}$	$x_{3,j}$	...	$x_{i,j}$

X

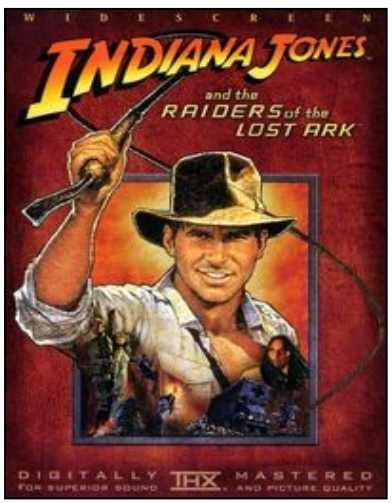
Subject-specific Transformation Matrix

Voxels	Model dimensions				
	d_1	d_2	d_3	...	d_k
v_1	$w_{1,1}$	$w_{2,1}$	$w_{3,1}$	...	$w_{k,1}$
v_2	$w_{1,2}$	$w_{2,2}$	$w_{3,2}$	...	$w_{k,2}$
v_3	$w_{1,3}$	$w_{2,3}$	$w_{3,3}$	...	$w_{k,3}$
...	...	...	...		...
v_i	$w_{1,i}$	$w_{2,i}$	$w_{3,i}$	...	$w_{k,i}$

=

Movie data in Model Space

Time-points	Model dimensions				
	d_1	d_2	d_3	...	d_k
t_1	$y_{1,1}$	$y_{2,1}$	$y_{3,1}$	...	$y_{k,1}$
t_2	$y_{1,2}$	$y_{2,2}$	$y_{3,2}$	...	$y_{k,2}$
t_3	$y_{1,3}$	$y_{2,3}$	$y_{3,3}$	...	$y_{k,3}$
t_4	$y_{1,4}$	$y_{2,4}$	$y_{3,4}$	...	$y_{k,4}$
...	...	...	...		...
t_j	$y_{j,i}$	$y_{j,i}$	$y_{j,i}$	...	$y_{j,k}$



Subject-specific Transformation Matrix

		Model dimensions				
		d_1	d_2	d_3	…	d_k
Voxels	v_1	$w_{1,1}$	$w_{2,1}$	$w_{3,1}$	…	$w_{k,1}$
	v_2	$w_{1,2}$	$w_{2,2}$	$w_{3,2}$	…	$w_{k,2}$
	v_3	$w_{1,3}$	$w_{2,3}$	$w_{3,3}$	…	$w_{k,3}$
	…	…	…	…		…
	v_i	$w_{1,i}$	$w_{2,i}$	$w_{3,i}$	…	$w_{k,i}$

The key that unlocks an individual's neural code

Experiment 2 data in Brain Space

Stimuli	Voxels				
	v_1	v_2	v_3	...	v_i
s_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{i,1}$
s_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	...	$x_{i,2}$
s_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	...	$x_{i,3}$
s_4	$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	...	$x_{i,4}$
...	...	...	...		...
s_m	$x_{1,m}$	$x_{2,m}$	$x_{3,m}$	...	$x_{i,m}$

X

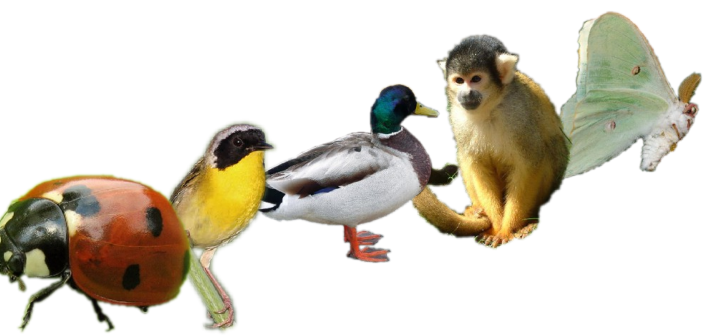
Subject-specific Transformation Matrix

Voxels	Model dimensions				
	d_1	d_2	d_3	...	d_k
v_1	$w_{1,1}$	$w_{2,1}$	$w_{3,1}$	...	$w_{k,1}$
v_2	$w_{1,2}$	$w_{2,2}$	$w_{3,2}$	...	$w_{k,2}$
v_3	$w_{1,3}$	$w_{2,3}$	$w_{3,3}$	...	$w_{k,3}$
...	...	...	...		...
v_i	$w_{1,i}$	$w_{2,i}$	$w_{3,i}$	...	$w_{k,i}$

=

Experiment 2 data in Model Space

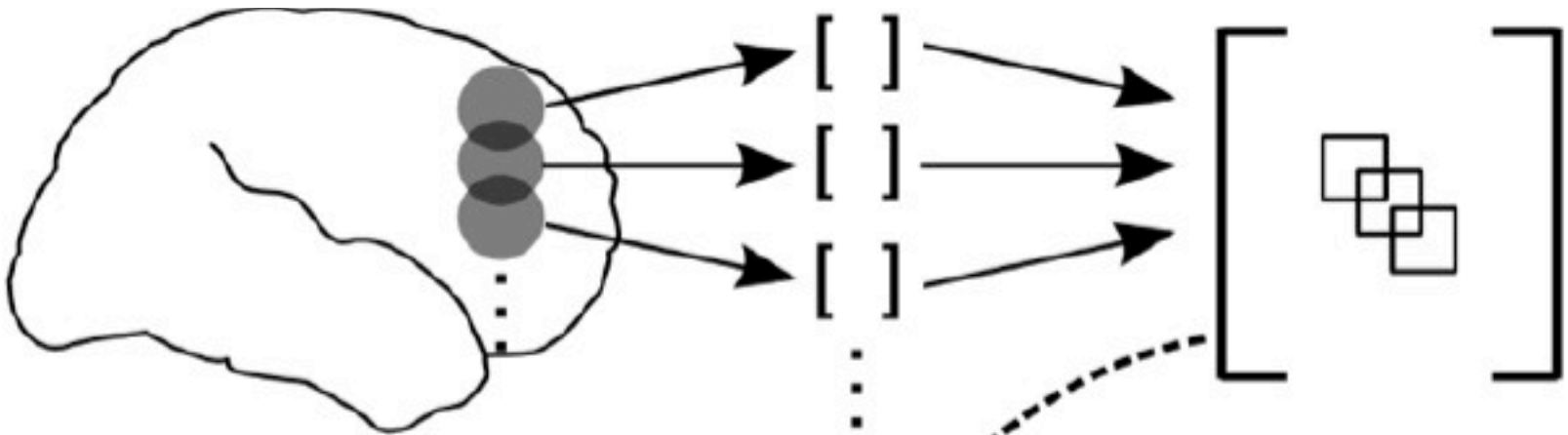
Stimuli	Model dimensions				
	d_1	d_2	d_3	...	d_k
s_1	$y_{1,1}$	$y_{2,1}$	$y_{3,1}$	...	$y_{k,1}$
s_2	$y_{1,2}$	$y_{2,2}$	$y_{3,2}$	...	$y_{k,2}$
s_3	$y_{1,3}$	$y_{2,3}$	$y_{3,3}$	...	$y_{k,3}$
s_4	$y_{1,4}$	$y_{2,4}$	$y_{3,4}$	...	$y_{k,4}$
...	...	...	...		...
s_m	$y_{1,m}$	$y_{2,m}$	$y_{3,m}$	...	$y_{k,m}$



Modeling representational spaces in all human cortex with searchlight hyperalignment

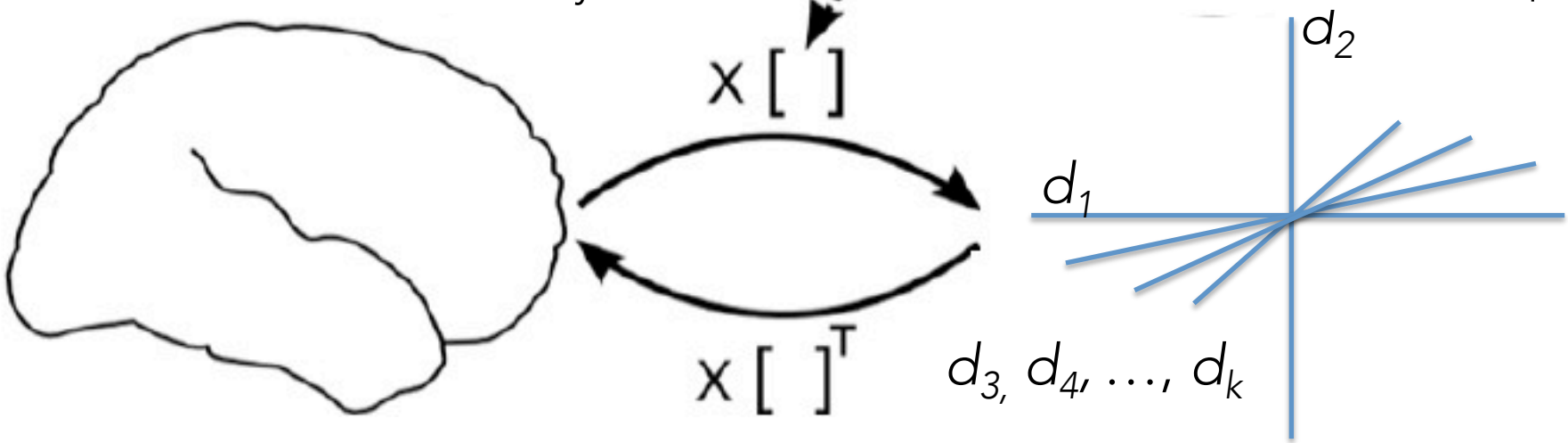
Voxels in overlapping searchlights are hyperaligned across subjects

Overlapping searchlight transformation matrices are aggregated into a whole cortex matrix



Data in individual brain anatomy

Data in common model space



A common high-dimensional linear model of representational spaces in human cortex

- Statement of the problem: capturing fine-grained distinctions in a common model
- Conceptual framework: high-dimensional representational spaces
- Deriving the common space and individual transformation matrices with hyperalignment
- Validation
  - Between-subject classification of movie time segments
  - Between-subject correlations of local similarity structures
  - Estimation spatial granularity of common model features
  - Applying transformation matrices to data from an unrelated experiment
  - Modeling individual variation in coarse features of functional topography
- Conclusions

Movie data in Brain Space

Subject-specific Transformation Matrix

Movie data in Model Space

Time-points	Voxels v_1	v_2	v_3	…	v_i
t_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	…	$x_{i,1}$
t_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	…	$x_{i,2}$
t_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	…	$x_{i,3}$
t_4	$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	…	$x_{i,4}$
…	…	…	…		…
t_j	$x_{1,j}$	$x_{2,j}$	$x_{3,j}$	…	$x_{i,j}$

X

Voxels	Model dimensions d_1	d_2	d_3	…	d_k
v_1	$w_{1,1}$	$w_{2,1}$	$w_{3,1}$	…	$w_{k,1}$
v_2	$w_{1,2}$	$w_{2,2}$	$w_{3,2}$	…	$w_{k,2}$
v_3	$w_{1,3}$	$w_{2,3}$	$w_{3,3}$	…	$w_{k,3}$
…	…	…	…		…
v_i	$w_{1,i}$	$w_{2,i}$	$w_{3,i}$	…	$w_{k,i}$

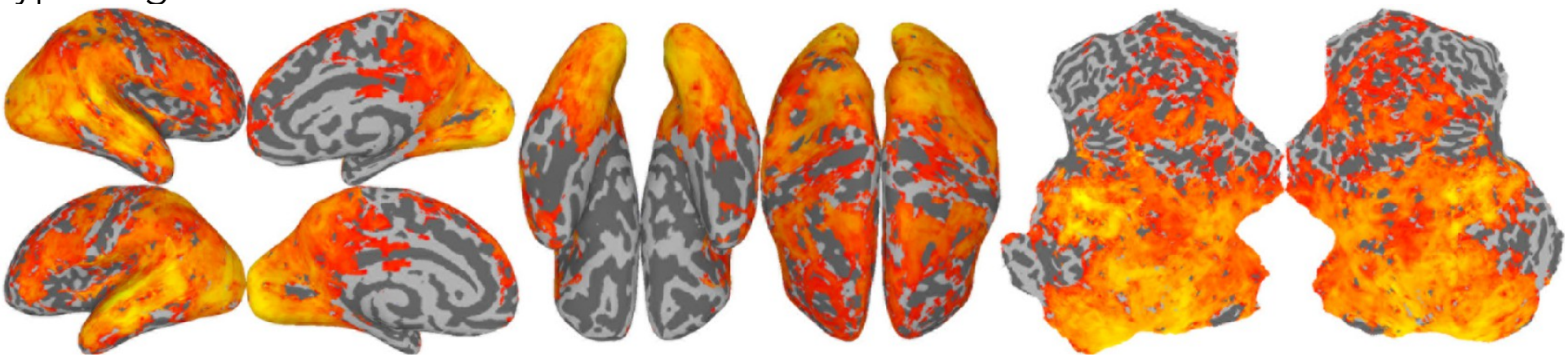
=

Time-points	Model dimensions d_1	d_2	d_3	…	d_k
t_1	$y_{1,1}$	$y_{2,1}$	$y_{3,1}$	…	$y_{k,1}$
t_2	$y_{1,2}$	$y_{2,2}$	$y_{3,2}$	…	$y_{k,2}$
t_3	$y_{1,3}$	$y_{2,3}$	$y_{3,3}$	…	$y_{k,3}$
t_4	$y_{1,4}$	$y_{2,4}$	$y_{3,4}$	…	$y_{k,4}$
…	…	…	…		…
t_j	$y_{j,1}$	$y_{j,2}$	$y_{j,3}$	…	$y_{j,k}$

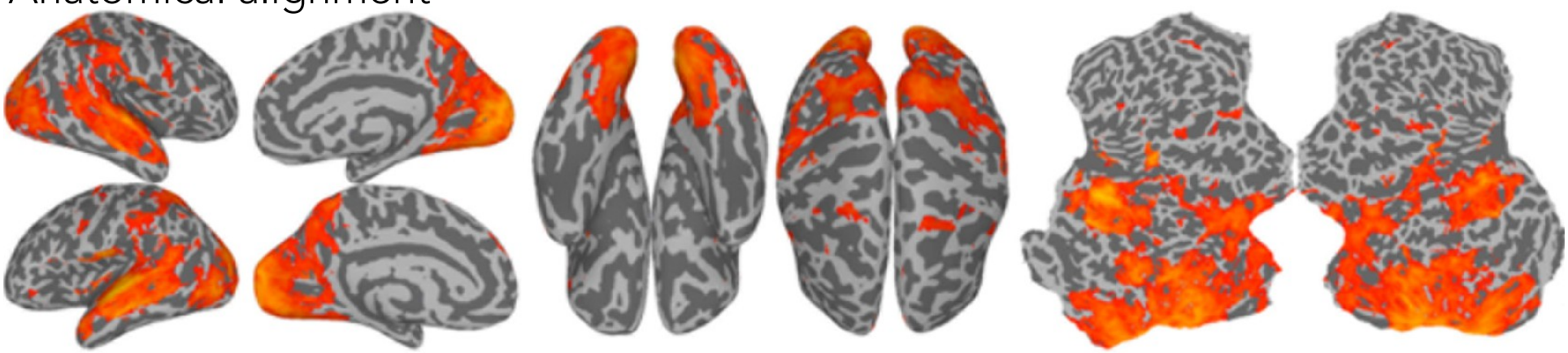
Model dimensions have *common response tuning functions*

Whole-brain hyperalignment increases intersubject correlations of time-series responses to movies in occipital, temporal, parietal and frontal cortices

Hyperalignment



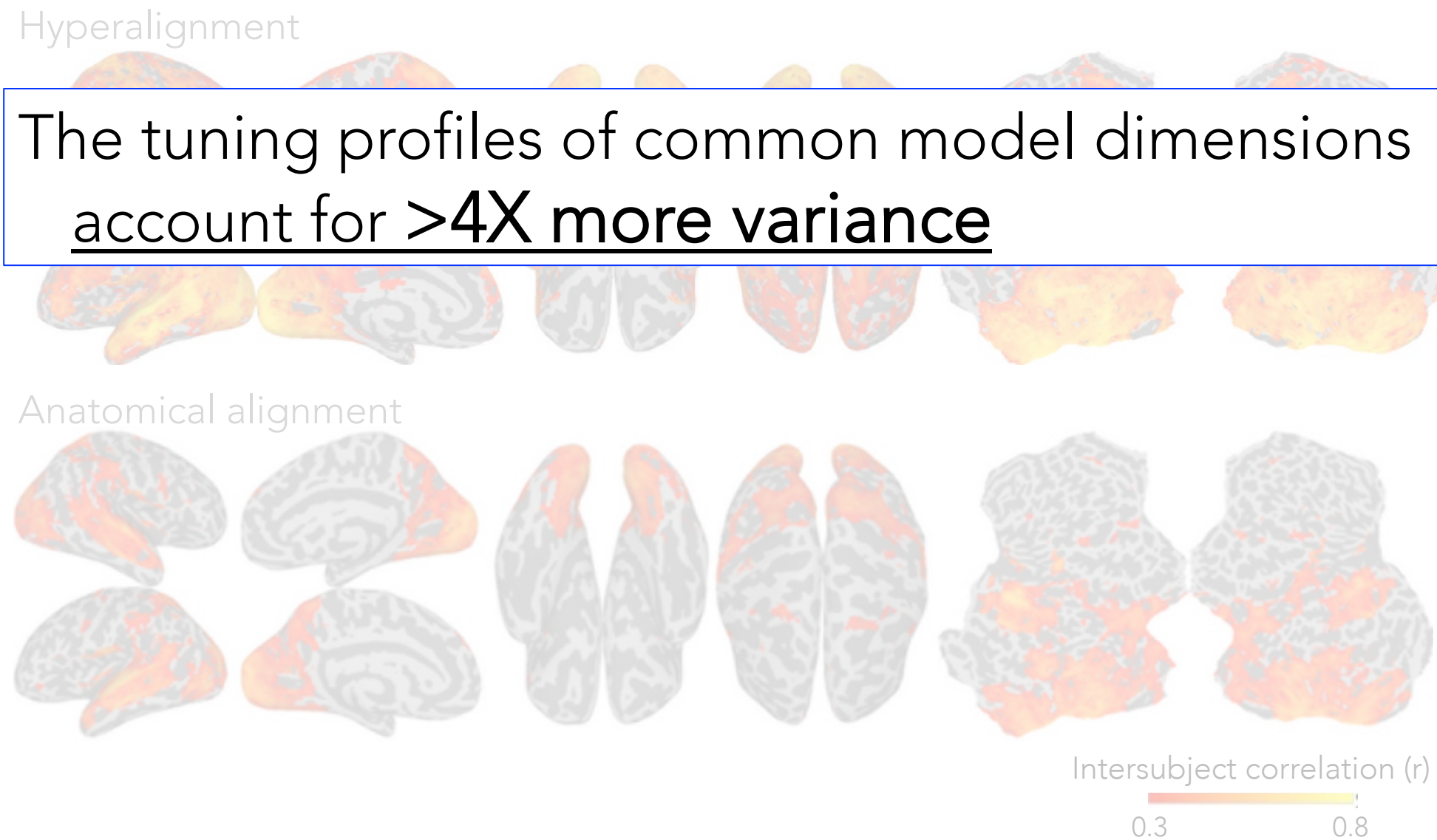
Anatomical alignment



Intersubject correlation (r)

0.3 0.8

Whole-brain hyperalignment increases intersubject correlations of time-series responses to movies in occipital, temporal, parietal and frontal cortices



The tuning profiles of common model dimensions account for >4X more variance

Movie data in Brain Space

Subject-specific Transformation Matrix

Movie data in Model Space

Time-points	Voxels v_1	v_2	v_3	…	v_i
t_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	…	$x_{i,1}$
t_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	…	$x_{i,2}$
t_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	…	$x_{i,3}$
t_4	$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	…	$x_{i,4}$
…	…	…	…		…
t_j	$x_{1,j}$	$x_{2,j}$	$x_{3,j}$	…	$x_{i,j}$

X

Voxels	Model dimensions d_1	d_2	d_3	…	d_k
v_1	$w_{1,1}$	$w_{2,1}$	$w_{3,1}$	…	$w_{k,1}$
v_2	$w_{1,2}$	$w_{2,2}$	$w_{3,2}$	…	$w_{k,2}$
v_3	$w_{1,3}$	$w_{2,3}$	$w_{3,3}$	…	$w_{k,3}$
…	…	…	…		…
v_i	$w_{1,i}$	$w_{2,i}$	$w_{3,i}$	…	$w_{k,i}$

=

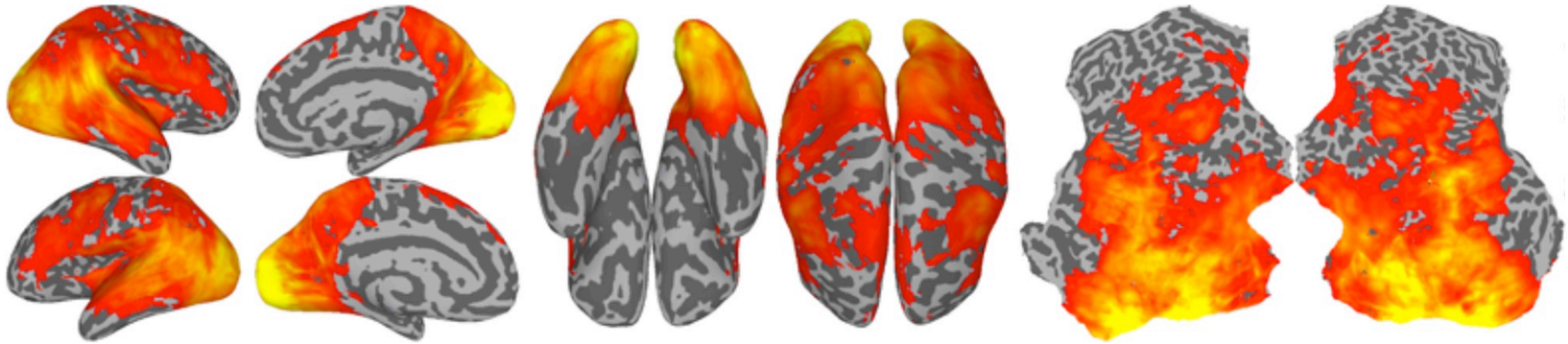
Time-points	Model dimensions d_1	d_2	d_3	…	d_k
t_1	$y_{1,1}$	$y_{2,1}$	$y_{3,1}$	…	$y_{k,1}$
t_2	$y_{1,2}$	$y_{2,2}$	$y_{3,2}$	…	$y_{k,2}$
t_3	$y_{1,3}$	$y_{2,3}$	$y_{3,3}$	…	$y_{k,3}$
t_4	$y_{1,4}$	$y_{2,4}$	$y_{3,4}$	…	$y_{k,4}$
…	…	…	…		…
t_j	$y_{j,1}$	$y_{j,1}$	$y_{j,1}$	…	$y_{j,k}$

In common model space *patterns of response* are more similar across brains, affording

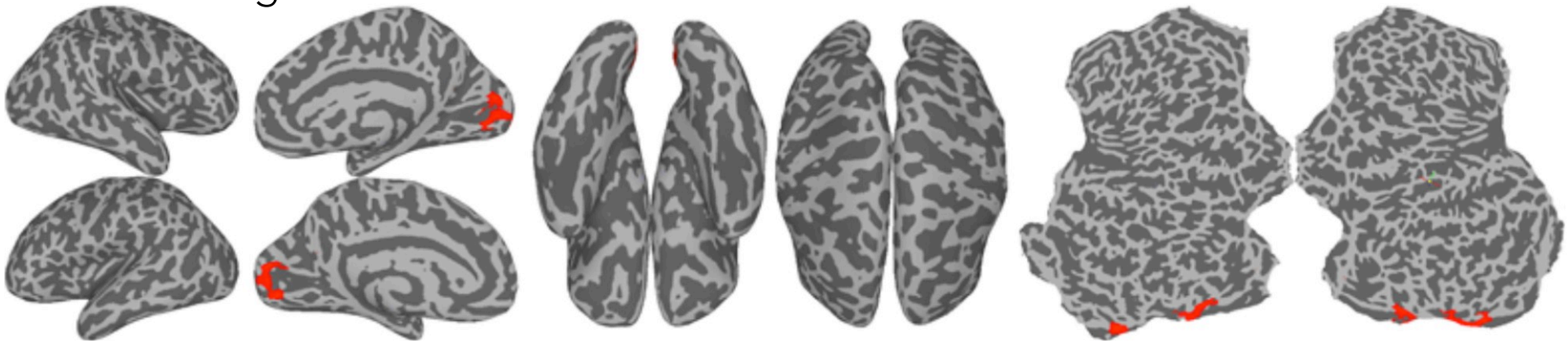
- ? between-subject multivariate pattern classification (bsMVPC)
- ? higher inter-subject correlation of representational geometry

Whole-brain hyperalignment increases between-subject classification of 15 s movie time segments in occipital, temporal, parietal, and frontal cortices

Hyperalignment



Anatomical alignment

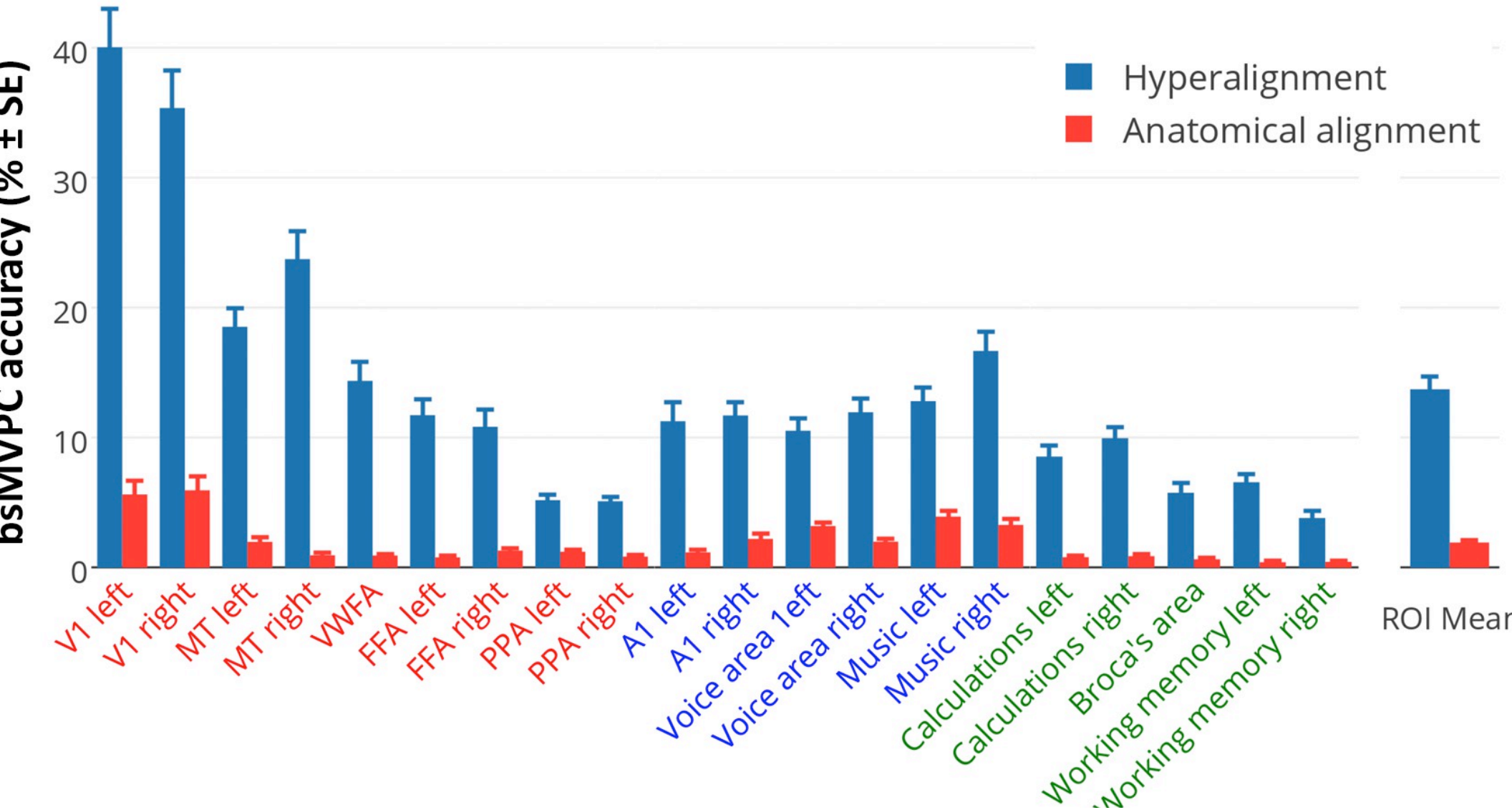


Classification accuracy (%)

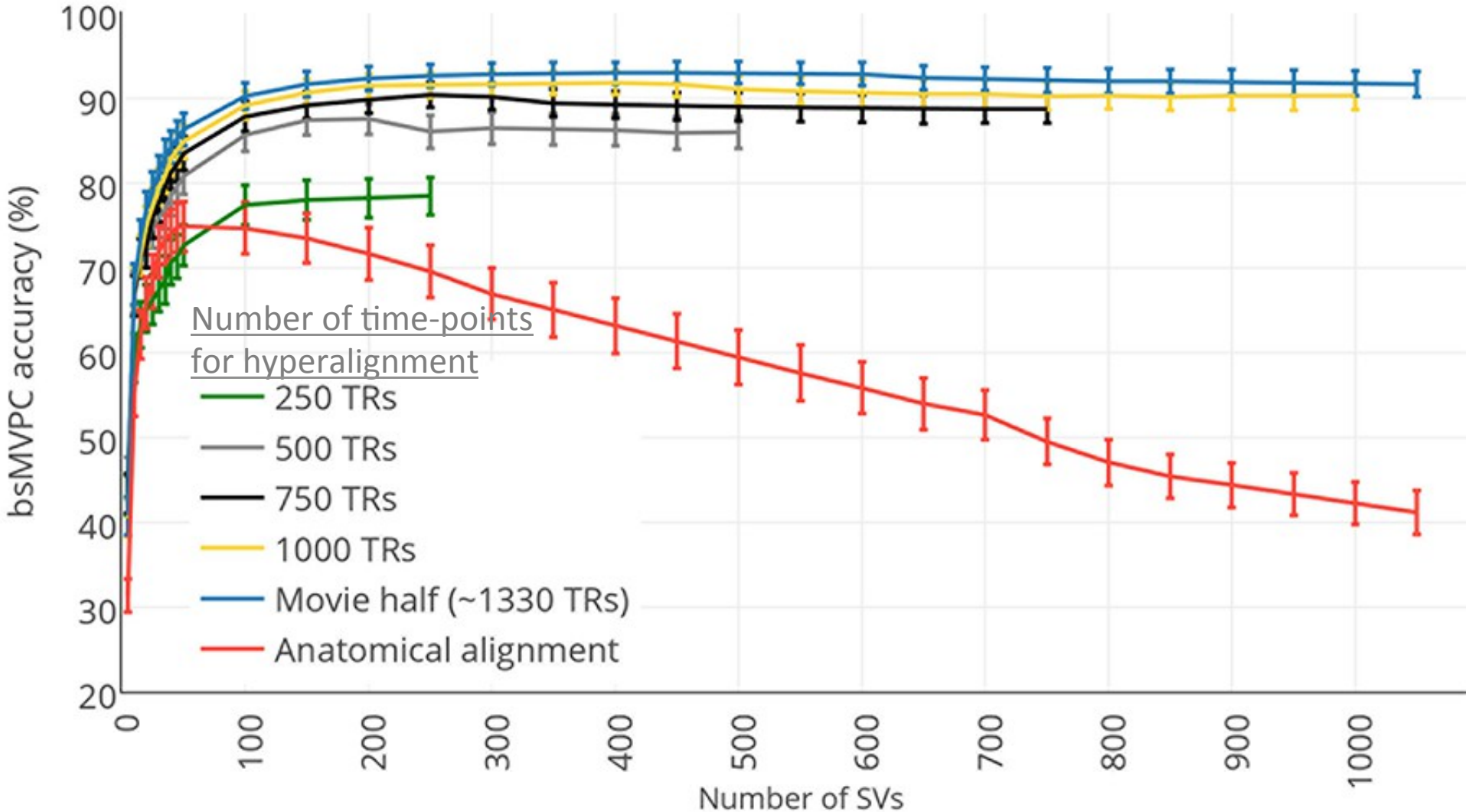
5% 30%

Increased bsMVPC of movie time-segments in visual, auditory, and cognitive regions of interest (ROIs)

(coordinates from NeuroSynth)

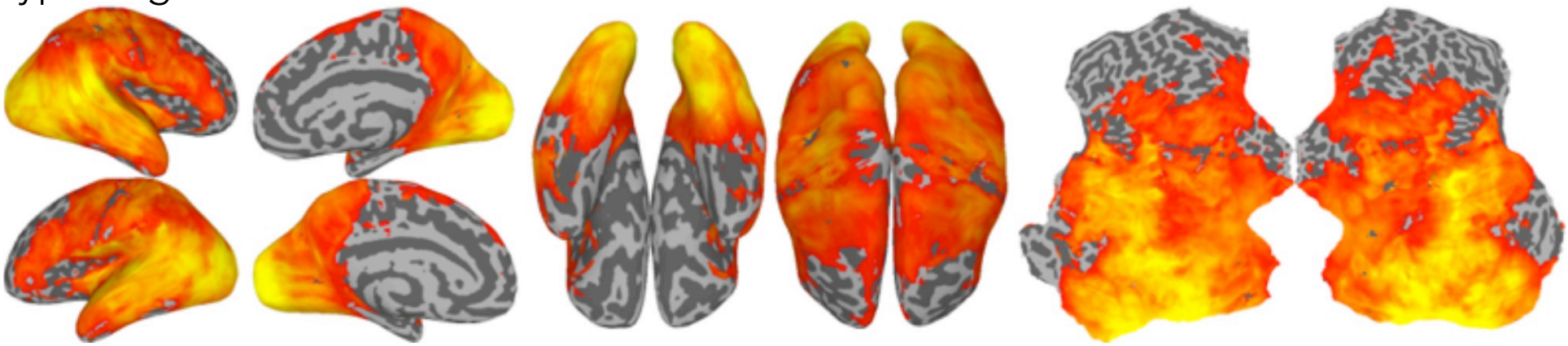


Whole-brain hyperalignment increases between-subject classification of 15 s movie time segments for the whole brain (after SVD dimensionality reduction)

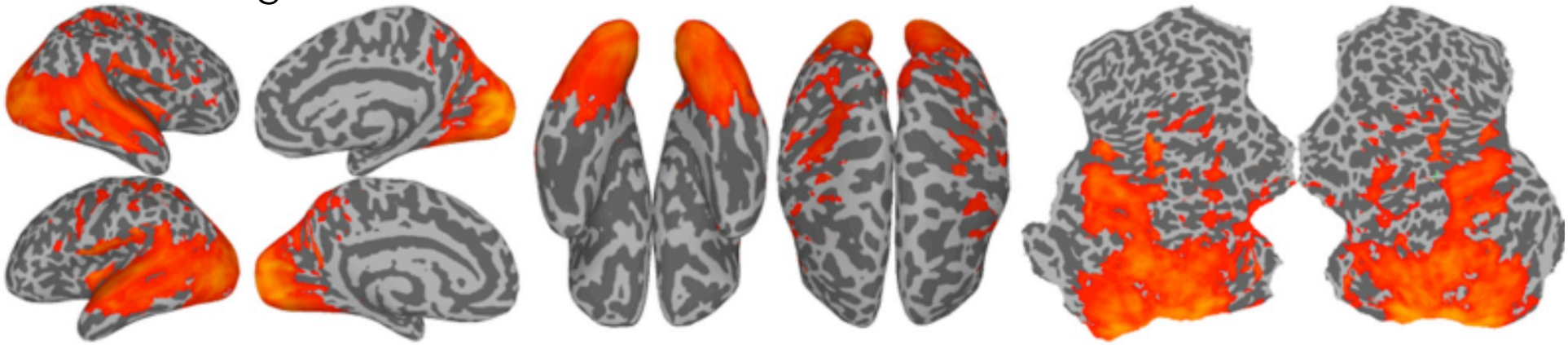


Whole-brain hyperalignment increases intersubject correlation of high-dimensional representational geometries (correlations between movie time-points)

Hyperalignment



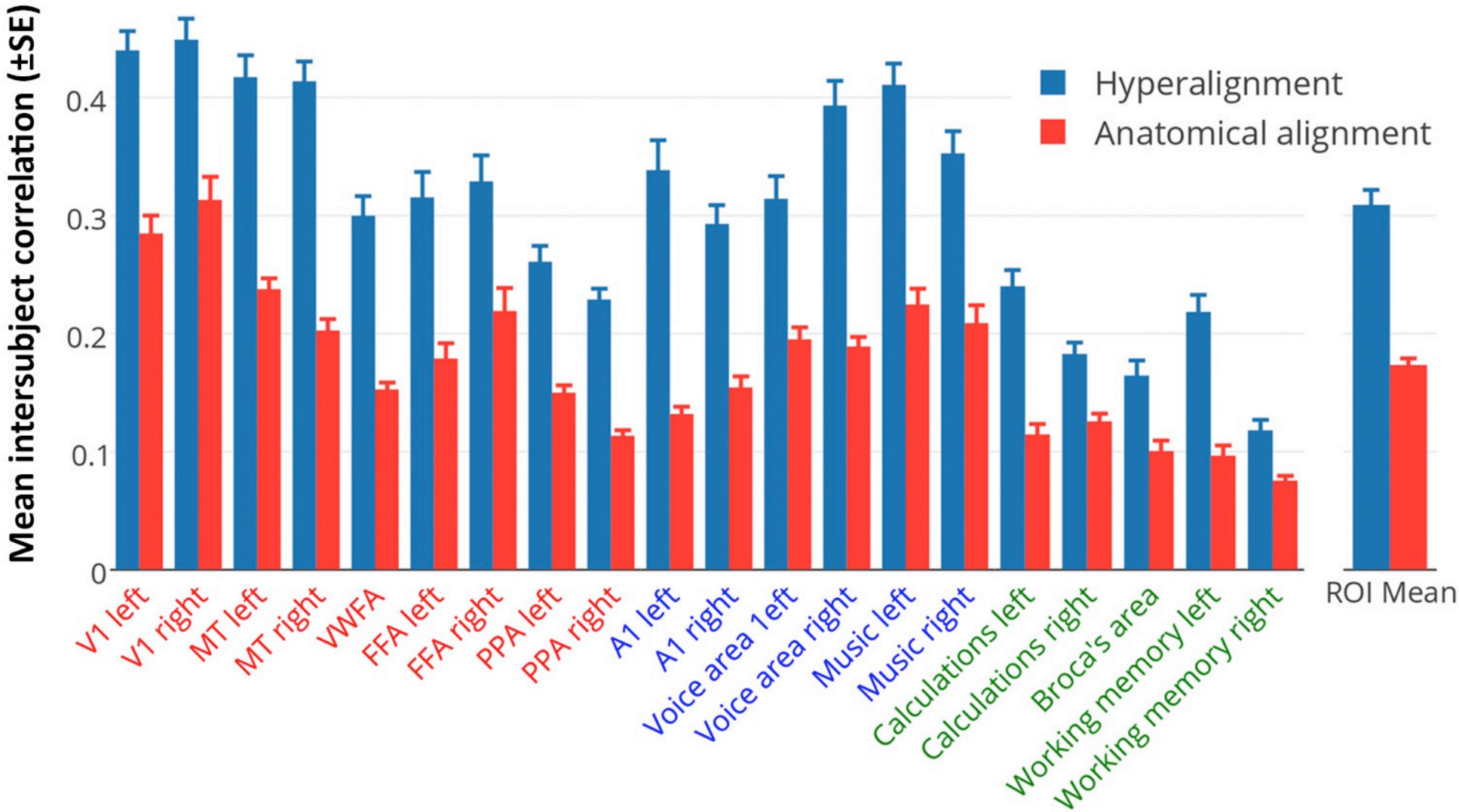
Anatomical alignment



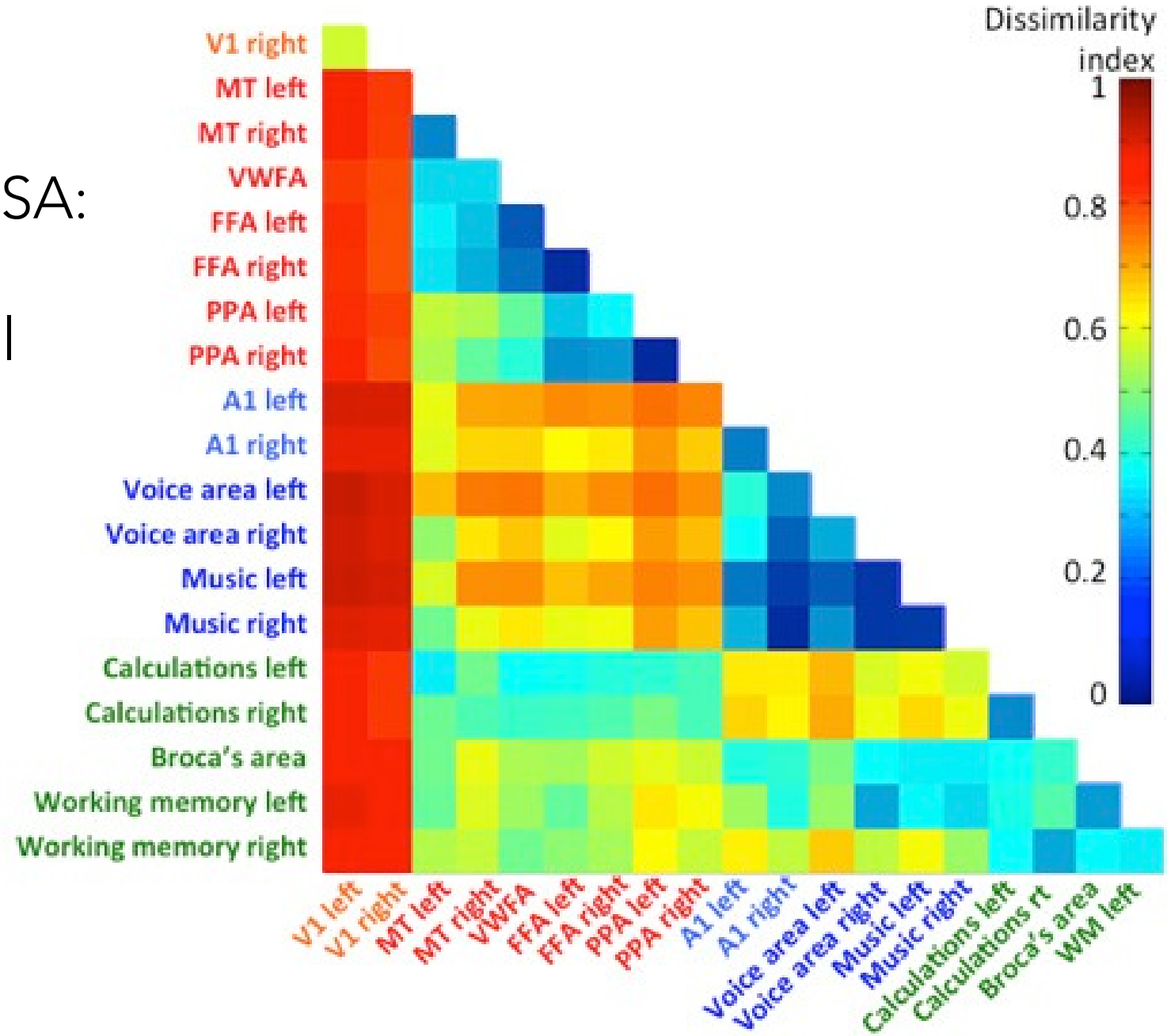
Intersubject correlation

0.15 0.45

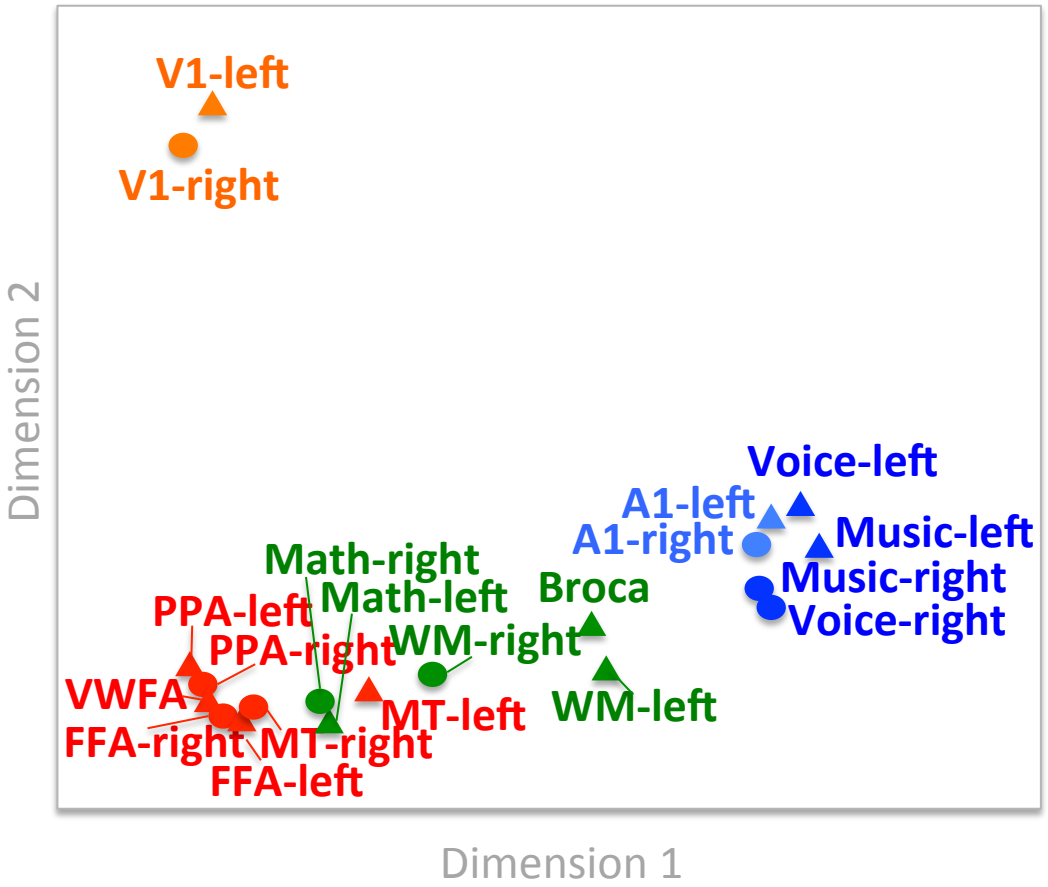
Increased intersubject correlations of representational geometries in visual, auditory, and cognitive regions of interest (ROIs)



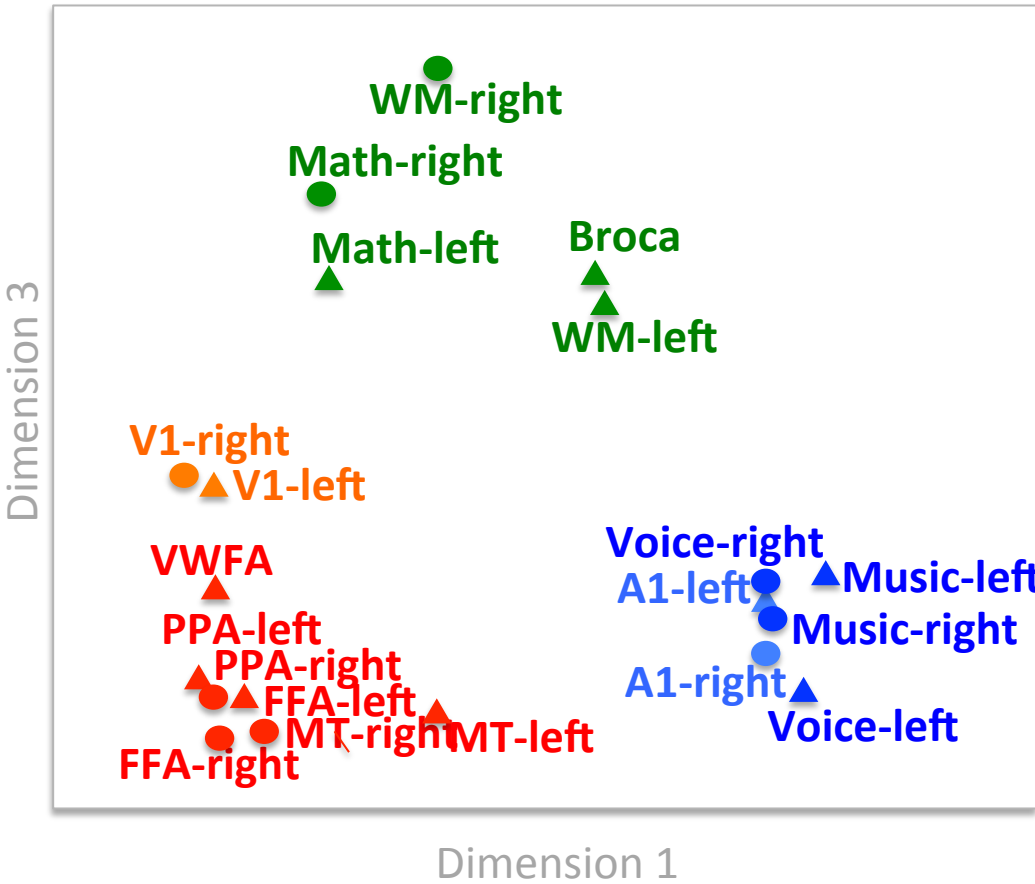
Second-order RSA: Between-ROI representational geometry dissimilarities



Multidimensional scaling (MDS) of similarity structures in visual, auditory, and cognitive regions of interest* (ROIs)



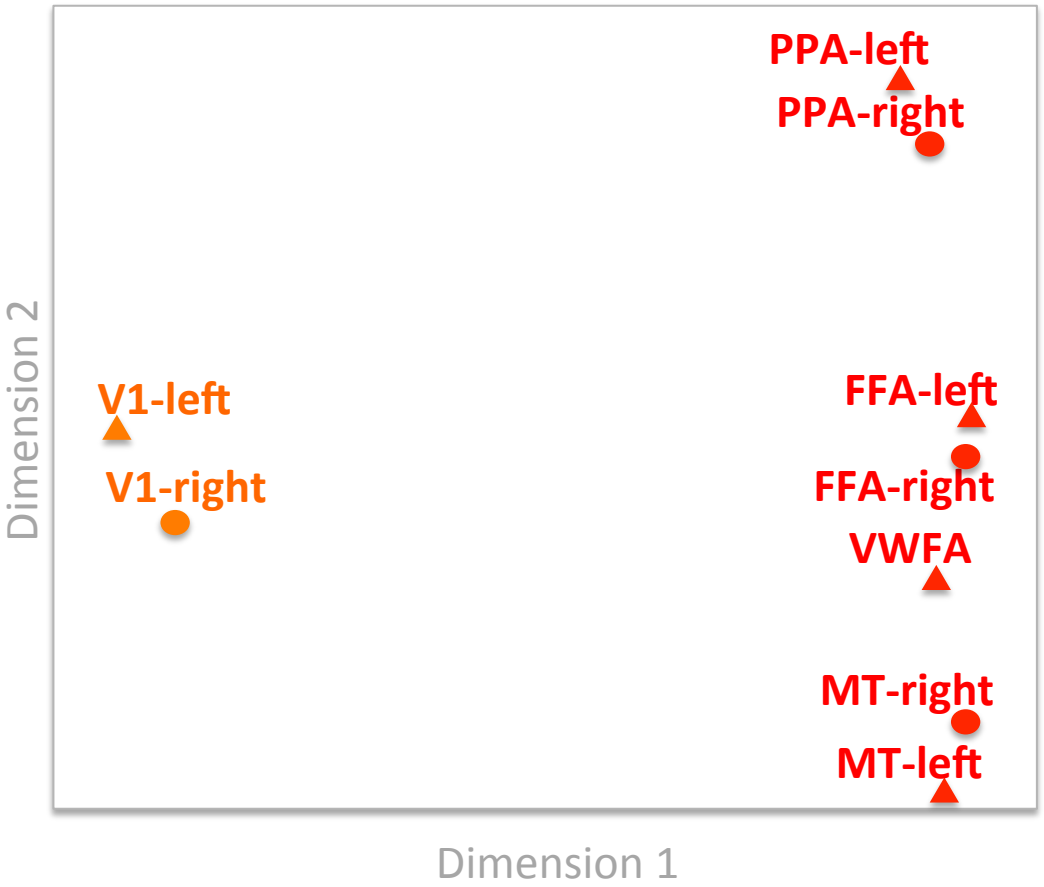
1st subspace (dimensions 1 & 2)



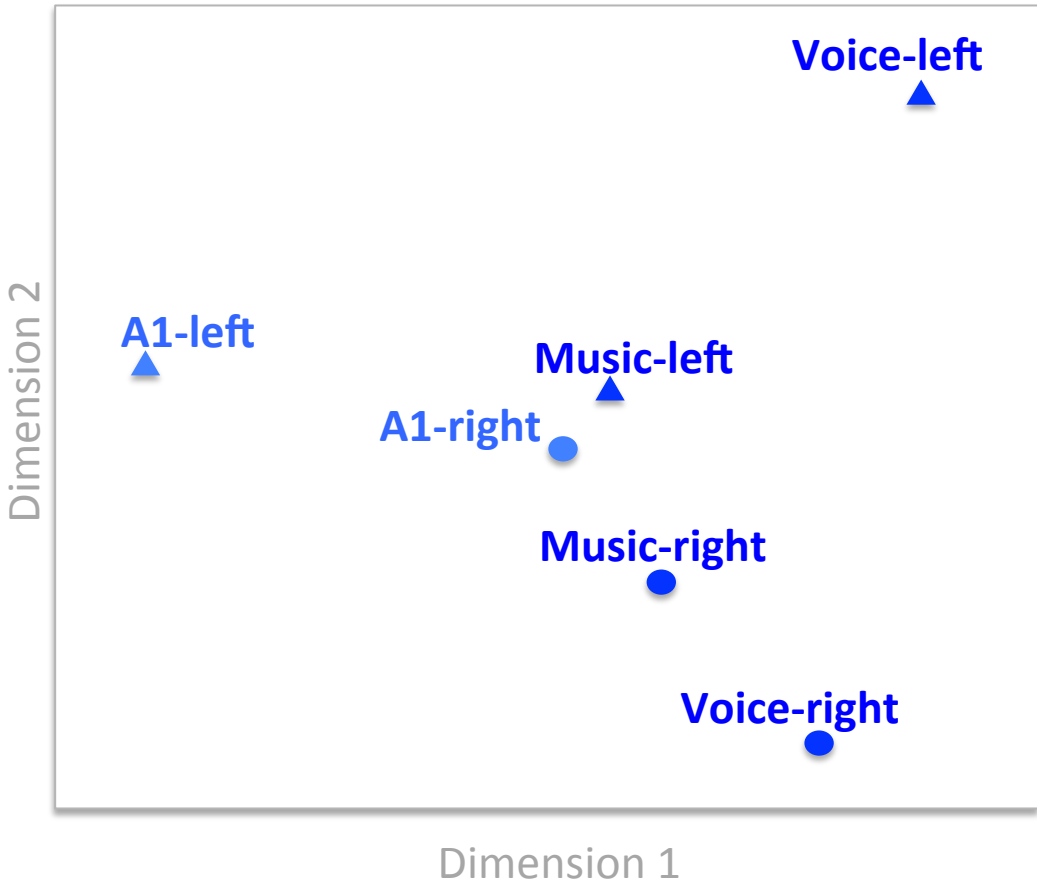
2nd subspace (dimensions 1 & 3)

* ROI coordinates from Neurosynth

Multidimensional scaling (MDS) fit separately to visual and auditory ROIs



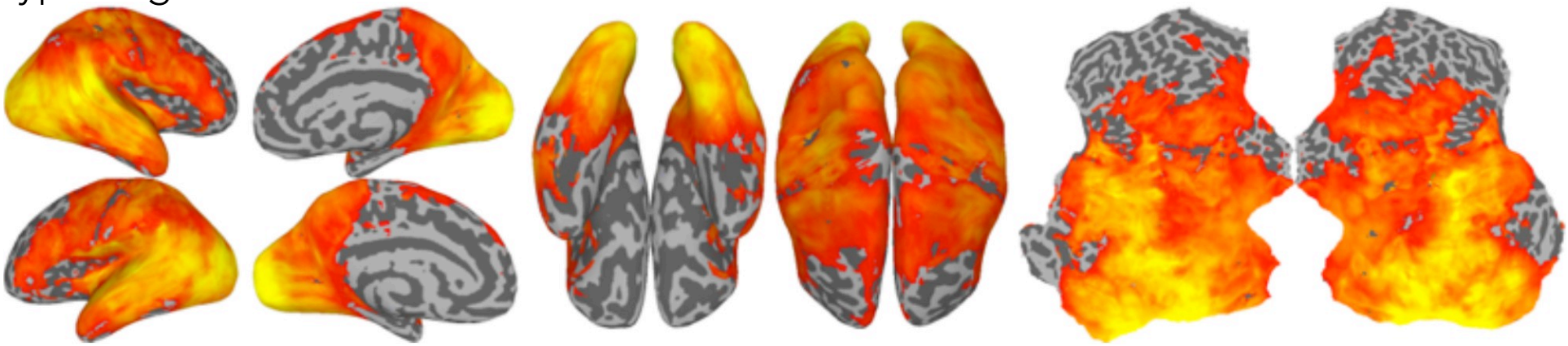
MDS of visual regions only



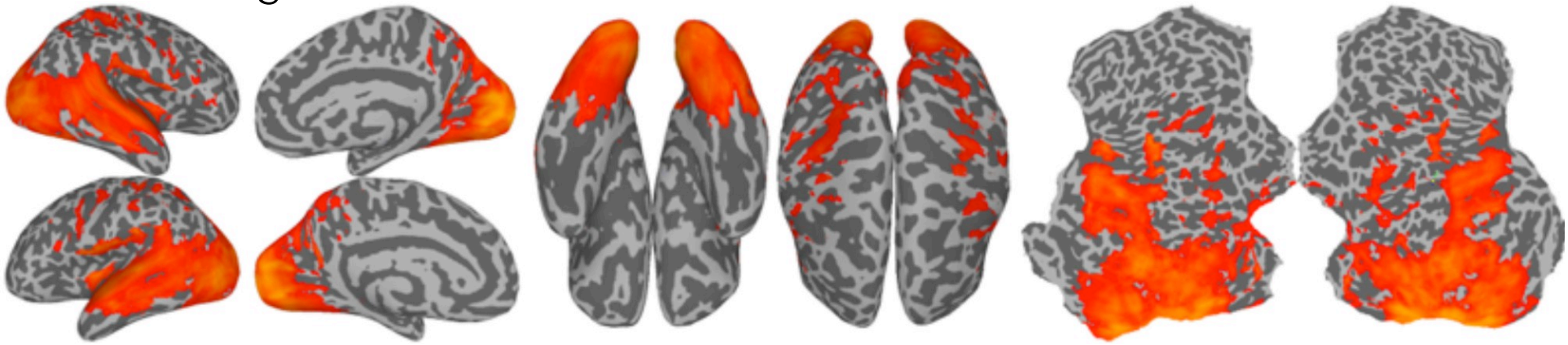
MDS of auditory regions only

Whole-brain hyperalignment increases intersubject correlation of high-dimensional representational geometries *that reflect widely divergent domains of information*

Hyperalignment



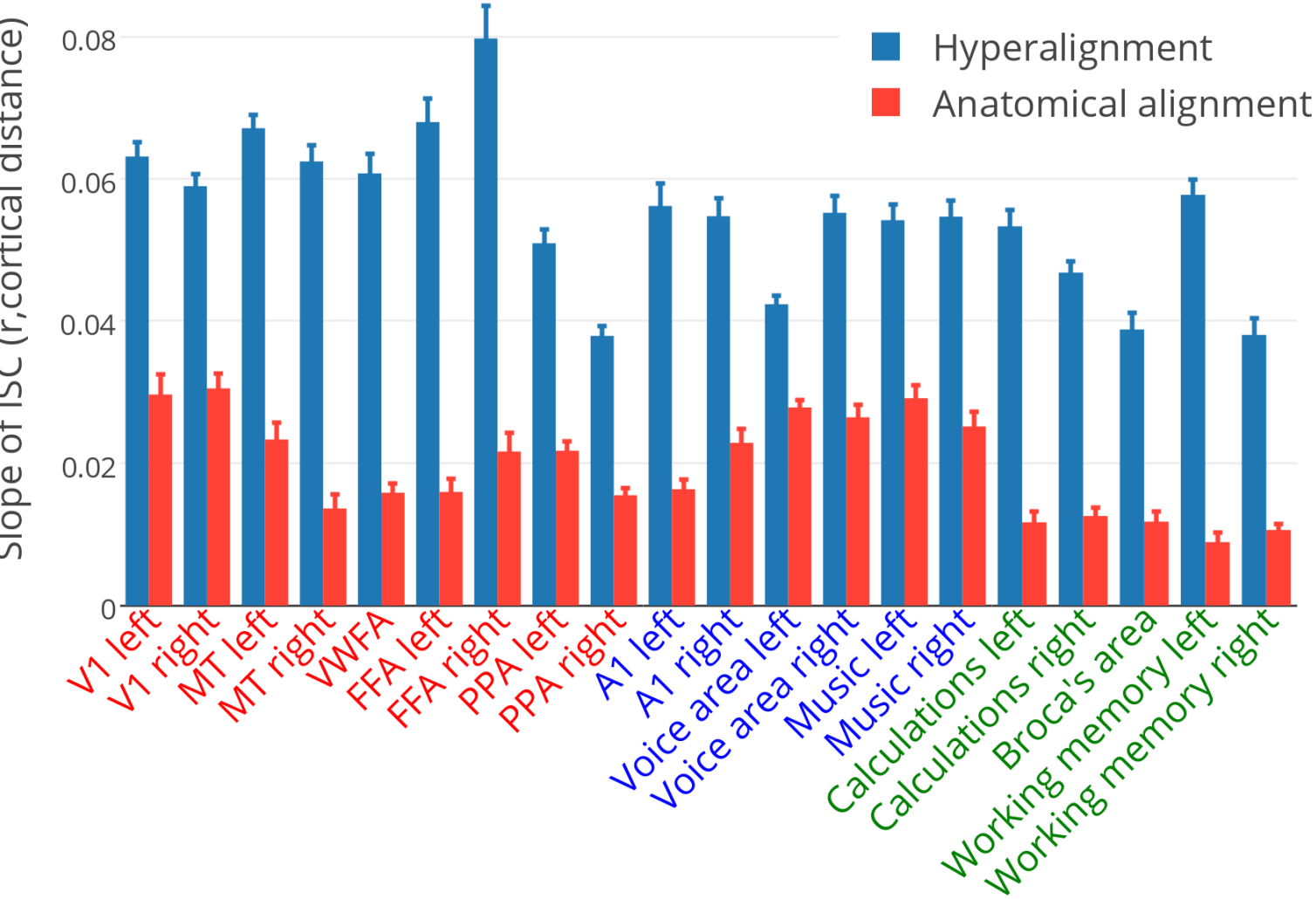
Anatomical alignment

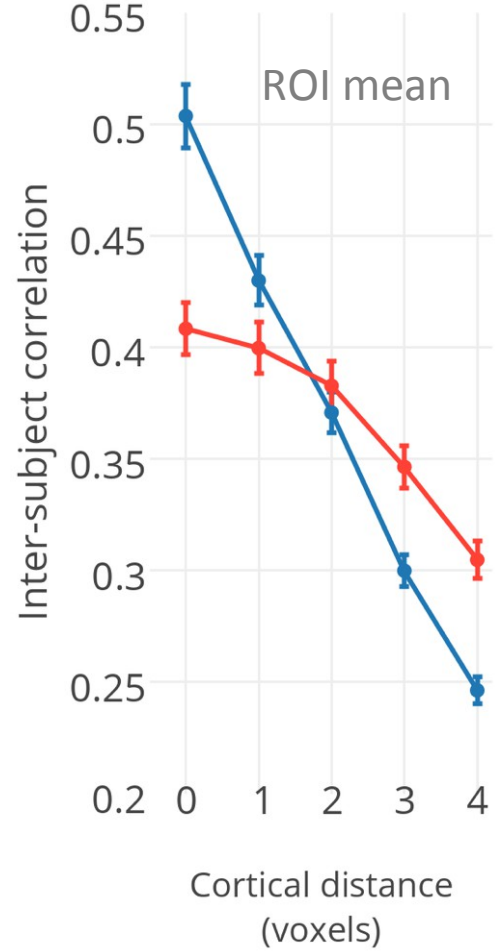


Intersubject correlation

0.15 0.45

Point spread function (intersubject correlations of movie time series): Fine spatial scale of alignment of function





Experiment 2 data in Brain Space

Subject-specific Transformation Matrix

Experiment 2 data in Model Space

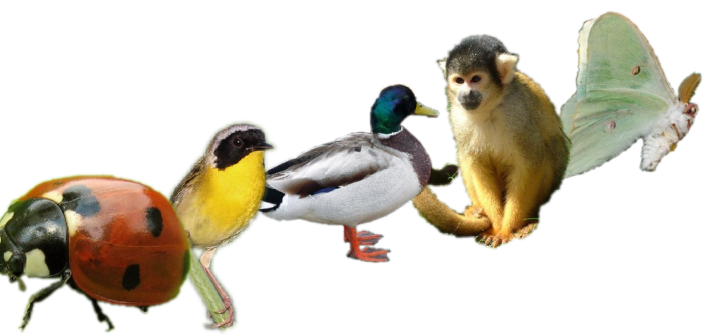
		Voxels				
		v_1	v_2	v_3	...	v_i
Stimuli	s_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{i,1}$
	s_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	...	$x_{i,2}$
	s_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	...	$x_{i,3}$
	s_4	$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	...	$x_{i,4}$
	...	...	...	...		...
	s_m	$x_{1,m}$	$x_{2,m}$	$x_{3,m}$	...	$x_{i,m}$

X

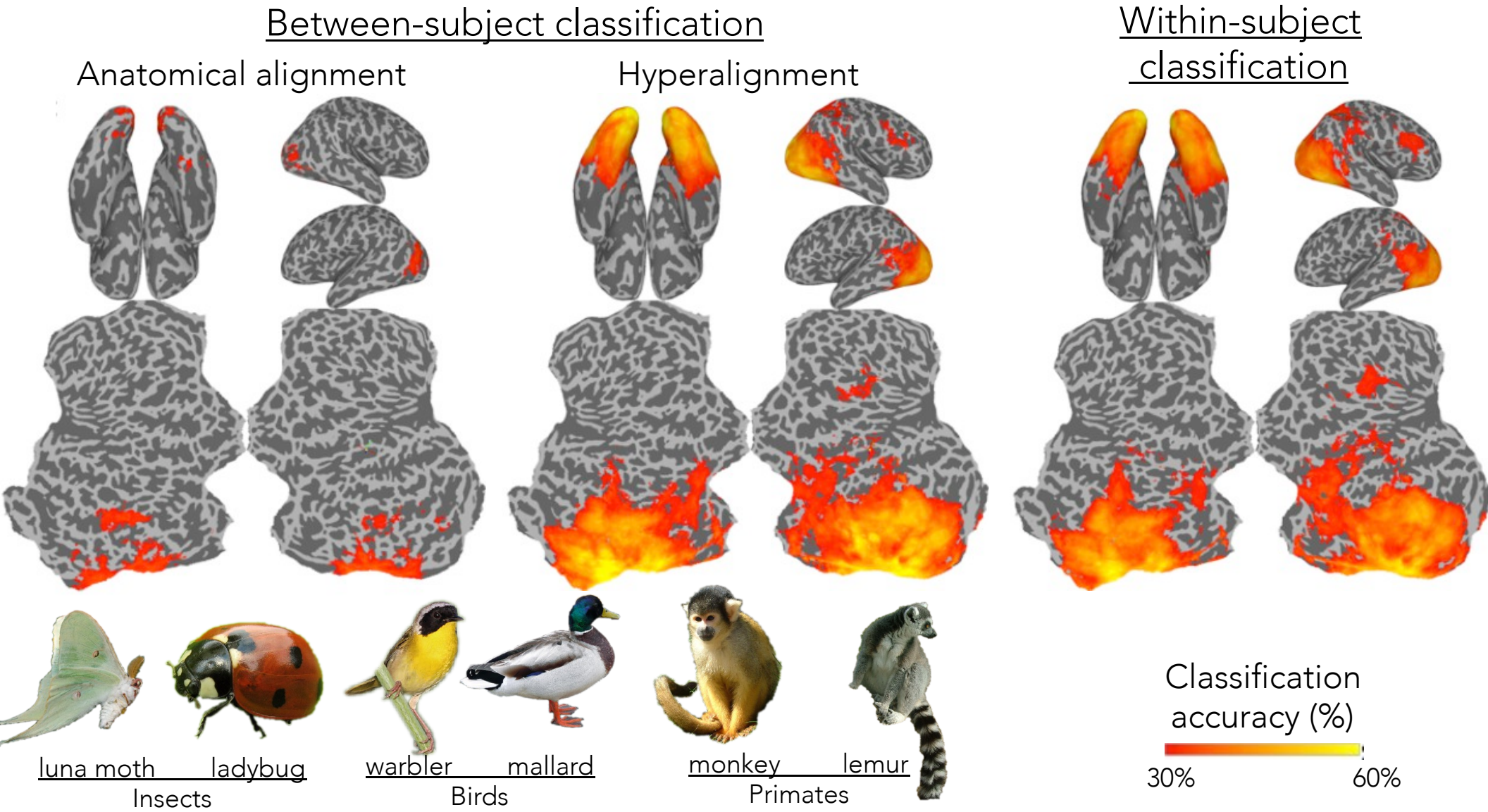
		Model dimensions				
		d_1	d_2	d_3	...	d_k
Voxels	v_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{k,1}$
	v_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	...	$x_{k,2}$
	v_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	...	$x_{k,3}$
	...	...	...	...		...
	v_i	$x_{1,i}$	$x_{2,i}$	$x_{3,i}$	...	$x_{i,k}$

=

		Model dimensions				
		d_1	d_2	d_3	...	d_k
Stimuli	s_1	$y_{1,1}$	$y_{2,1}$	$y_{3,1}$	...	$y_{k,1}$
	s_2	$y_{1,2}$	$y_{2,2}$	$y_{3,2}$	...	$y_{k,2}$
	s_3	$y_{1,3}$	$y_{2,3}$	$y_{3,3}$	...	$y_{k,3}$
	s_4	$y_{1,4}$	$y_{2,4}$	$y_{3,4}$	...	$y_{k,4}$
	...	...	...	...		...
	s_m	$y_{1,m}$	$y_{2,m}$	$y_{3,m}$	...	$y_{k,m}$



Whole-brain hyperalignment based on movie affords between-subject classification of responses in a visual category experiment (6 animal species) *at levels of accuracy that exceed within-subject classification*



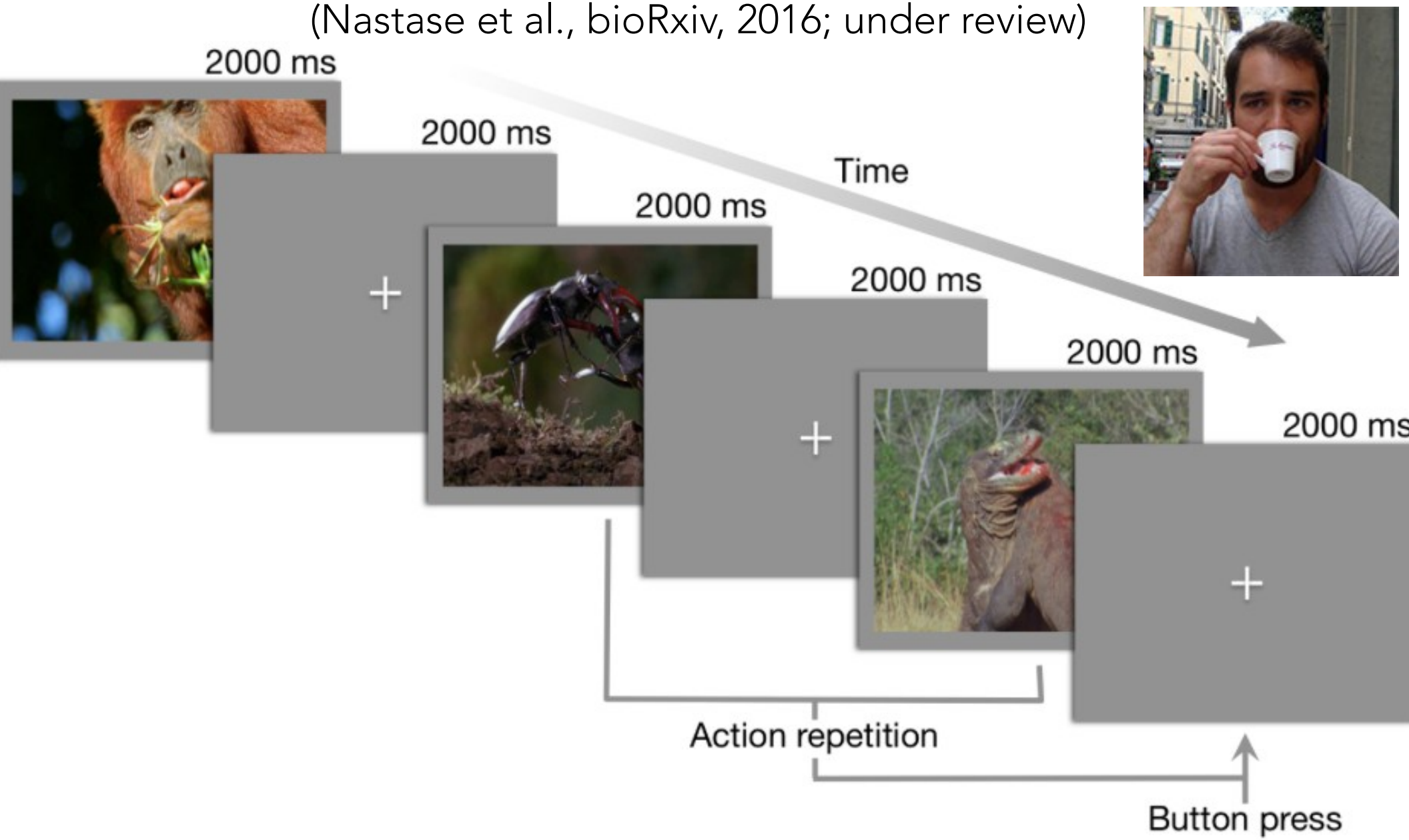
Hyperalignment parameters are estimated from responses recorded during movie viewing

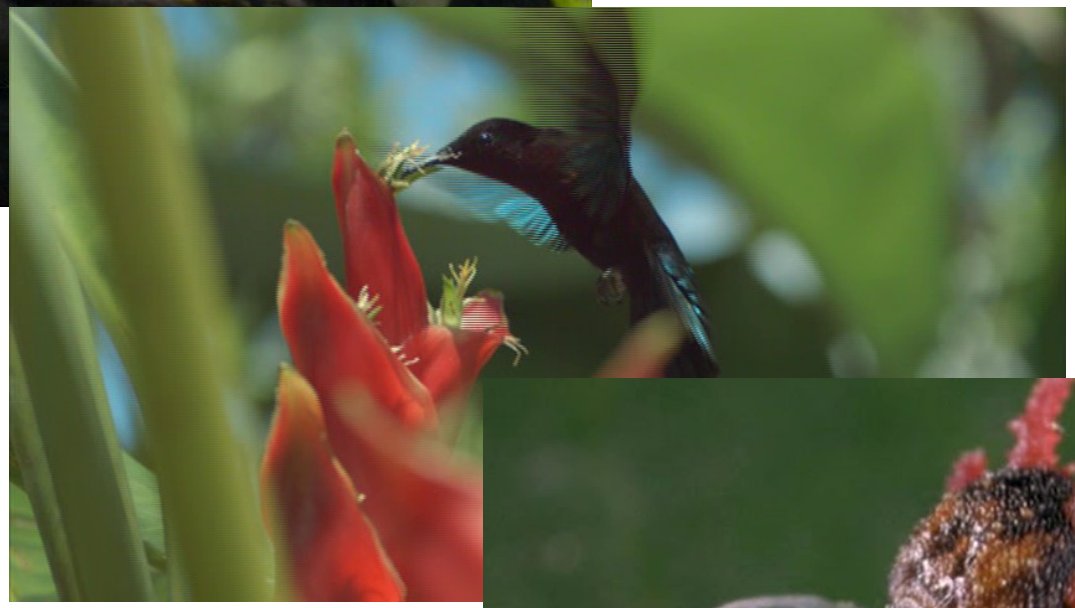
Raiders of the Lost Ark

Life on Earth

The Wire

Study of the effect of attention on the
geometry of representations of animal taxa and animal behaviors
(Nastase et al., bioRxiv, 2016; under review)

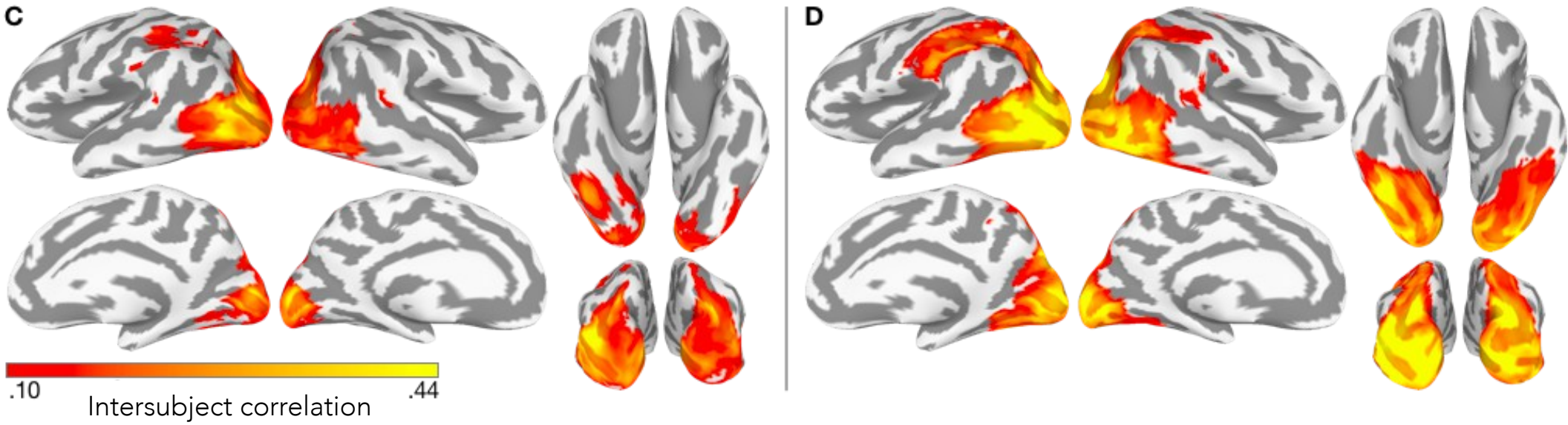




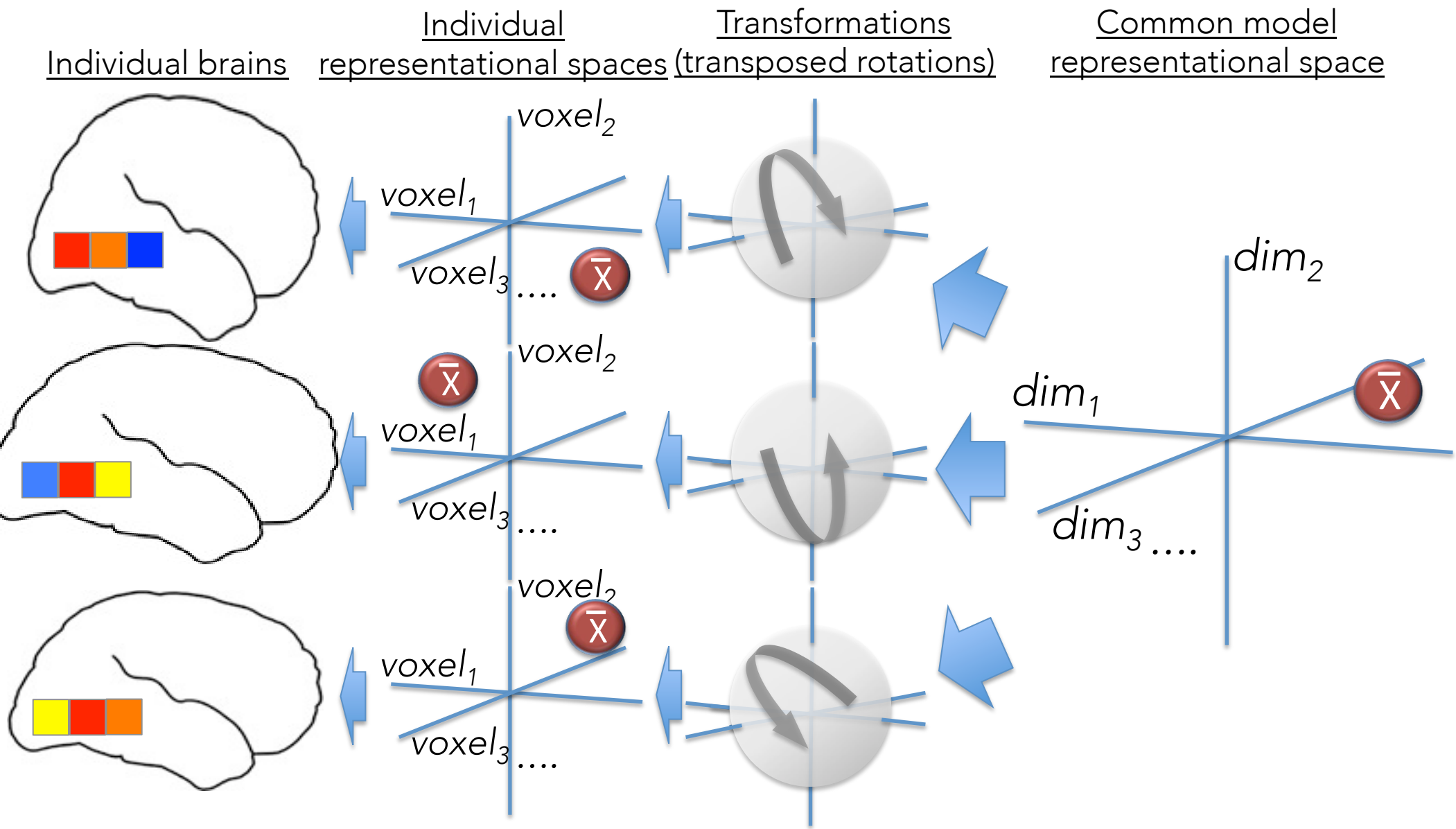
Higher inter-subject correlation of representational geometries for animal behaviors and taxa after hyperalignment
(Nastase et al., bioRxiv, 2016; under review)

Anatomical alignment

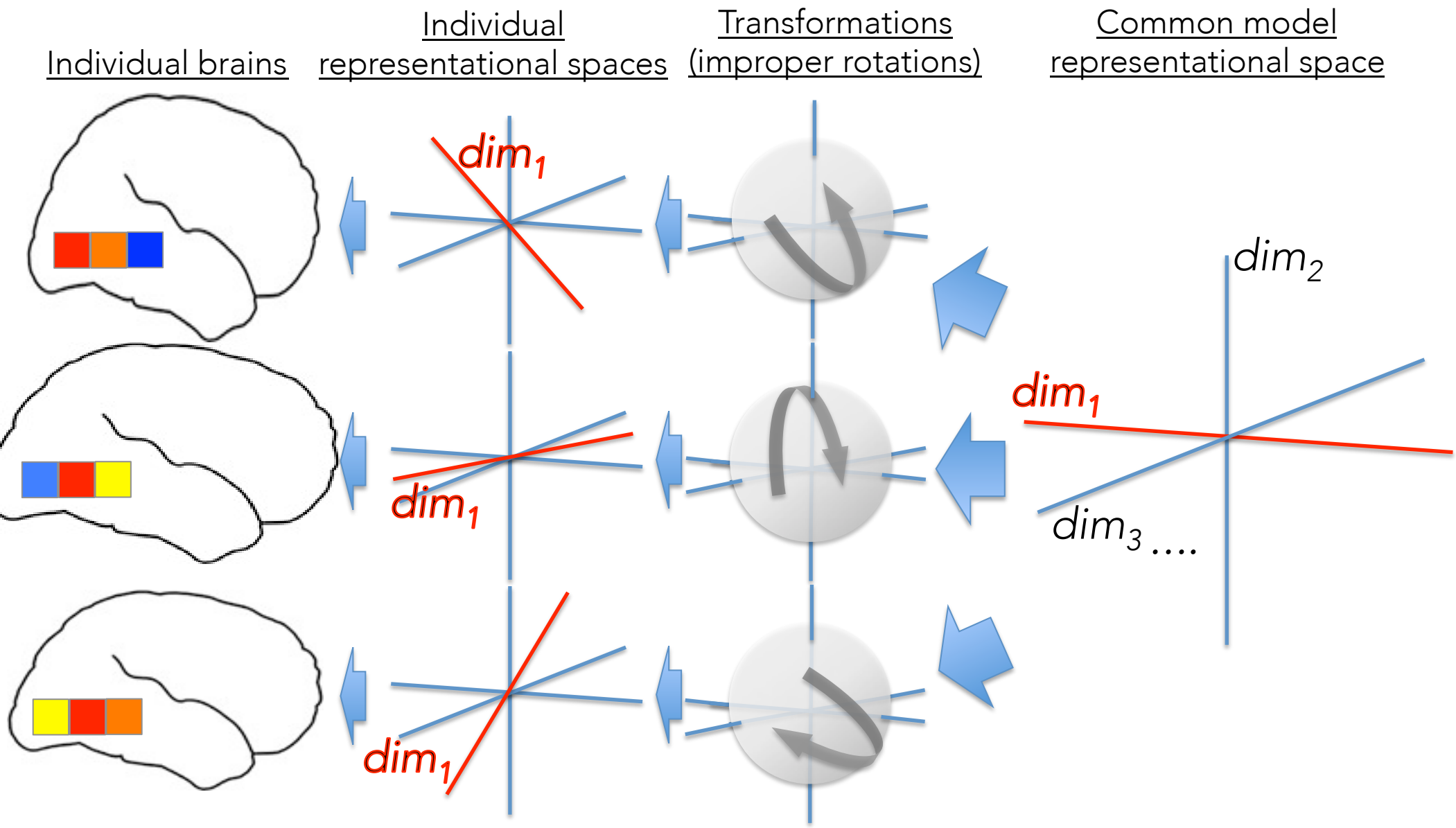
Hyperalignment



Projecting group data from common model space into individual subject's anatomy



Modeling functional architecture of the human cortex: common model dimensions ≠ voxels



Movie data in Brain Space

Subject-specific Transformation Matrix

Movie data in Model Space

Time-points	Voxels v_1	v_2	v_3	…	v_i
t_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	…	$x_{i,1}$
t_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	…	$x_{i,2}$
t_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	…	$x_{i,3}$
t_4	$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	…	$x_{i,4}$
…	…	…	…		…
t_j	$x_{1,j}$	$x_{2,j}$	$x_{3,j}$	…	$x_{i,j}$

X

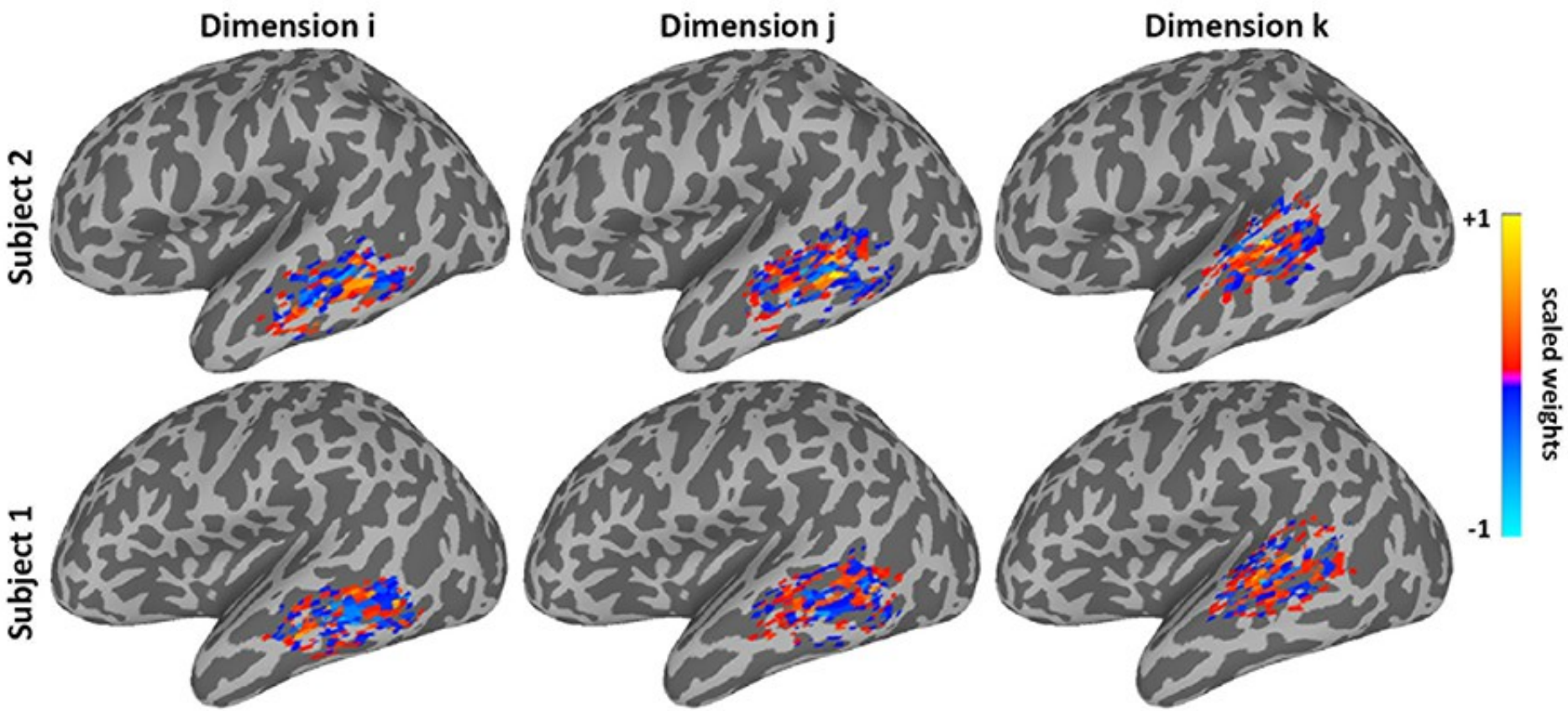
Voxels	Model dimensions d_1	d_2	d_3	…	d_k
v_1	$w_{1,1}$	$w_{2,1}$	$w_{3,1}$	…	$w_{k,1}$
v_2	$w_{1,2}$	$w_{2,2}$	$w_{3,2}$	…	$w_{k,2}$
v_3	$w_{1,3}$	$w_{2,3}$	$w_{3,3}$	…	$w_{k,3}$
…	…	…	…		…
v_i	$w_{1,i}$	$w_{2,i}$	$w_{3,i}$	…	$w_{k,i}$

=

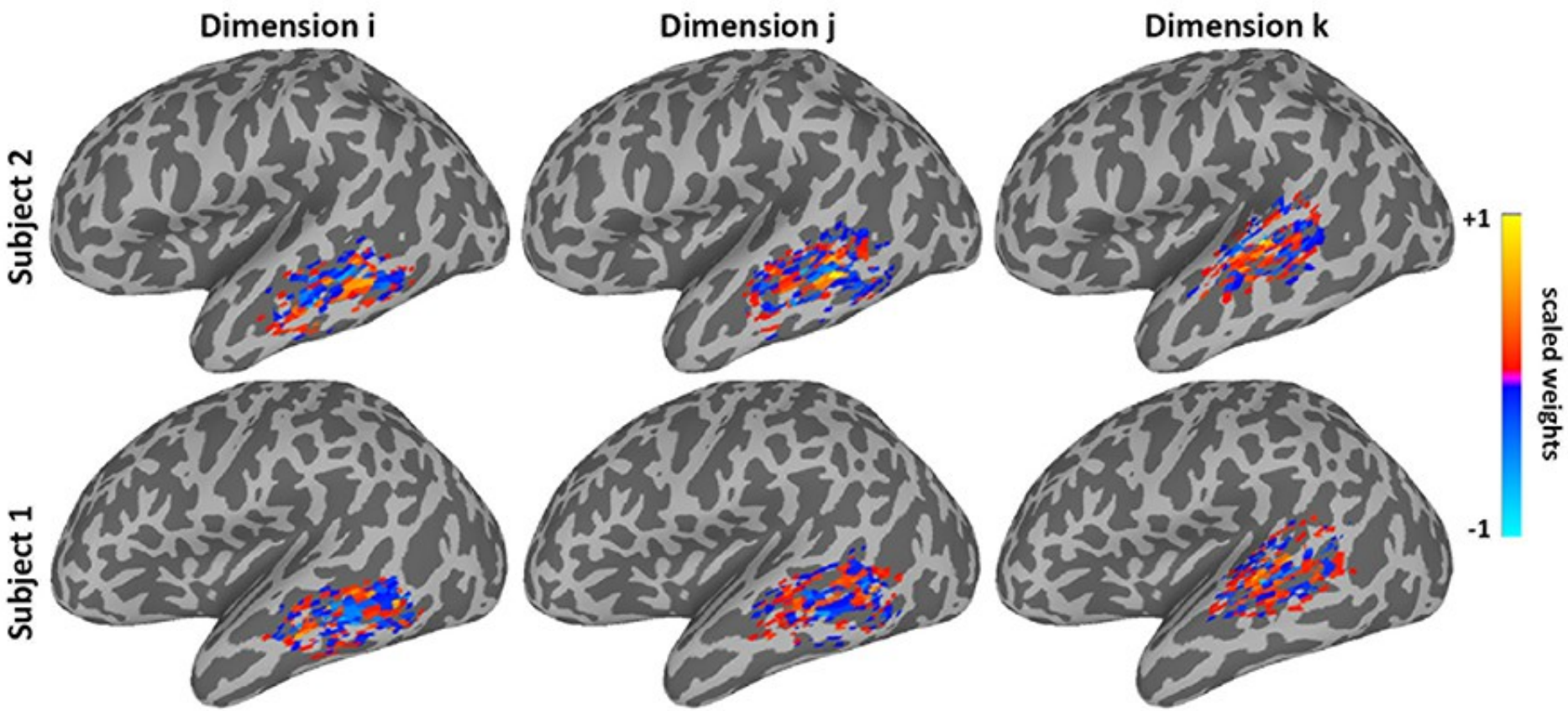
Time-points	Model dimensions d_1	d_2	d_3	…	d_k
t_1	$y_{1,1}$	$y_{2,1}$	$y_{3,1}$	…	$y_{k,1}$
t_2	$y_{1,2}$	$y_{2,2}$	$y_{3,2}$	…	$y_{k,2}$
t_3	$y_{1,3}$	$y_{2,3}$	$y_{3,3}$	…	$y_{k,3}$
t_4	$y_{1,4}$	$y_{2,4}$	$y_{3,4}$	…	$y_{k,4}$
…	…	…	…		…
t_j	$y_{j,1}$	$y_{j,2}$	$y_{j,3}$	…	$y_{j,k}$

Model dimensions have *individual-specific topographic basis functions*

Topographies of weights for three model dimensions in two subjects

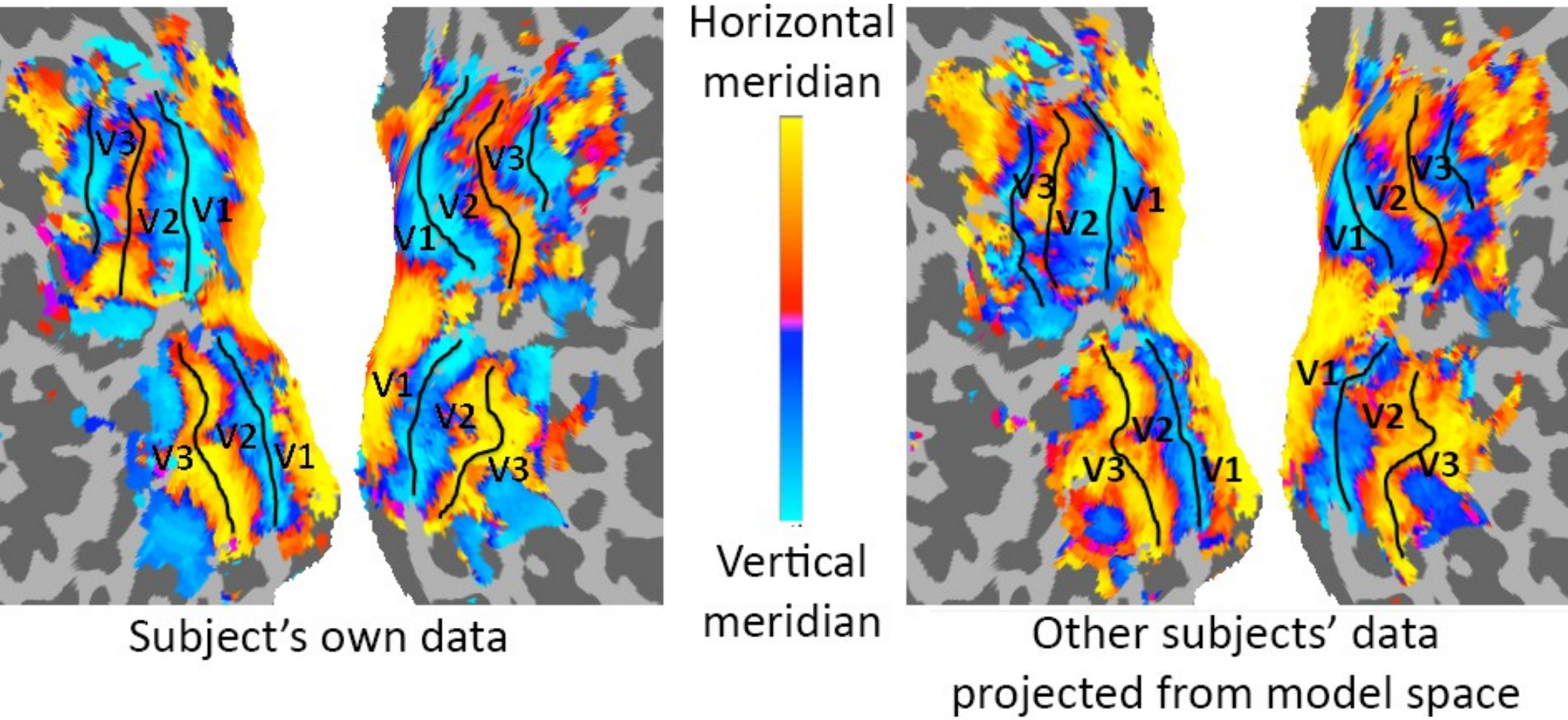


Topographies for response patterns can be modeled in different brains with these <u>individual-specific topographic basis functions</u> using <u>the same weights for for all subjects</u>



$$\sum \beta_1 * T_{1Sx} \ldots + \beta_i * T_{iSx} \quad + \beta_j * T_{jSx} \quad + \beta_k * T_{kSx} \ldots$$

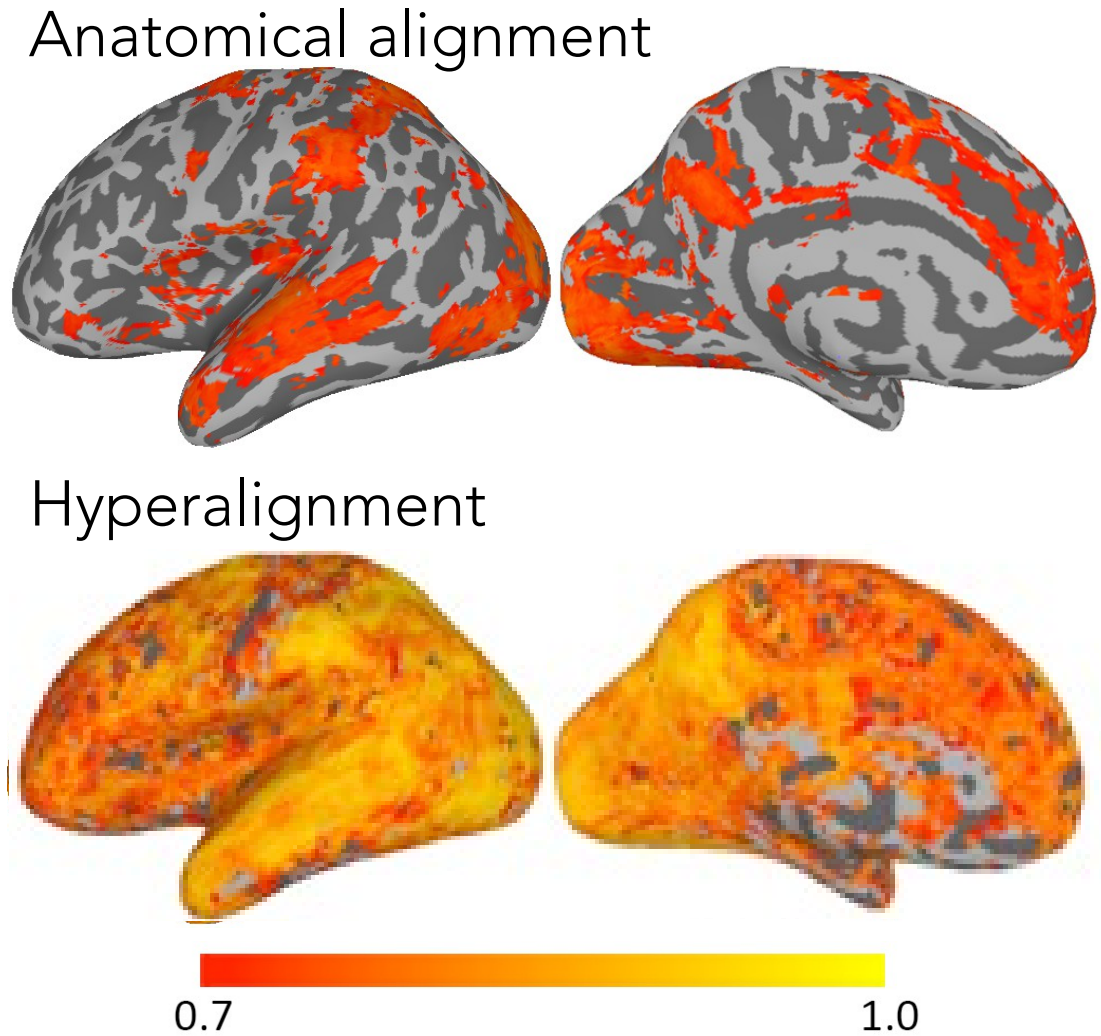
Mapping retinotopy by projecting other subjects' polar angle maps into a different subject's occipital topography



Subject's own data

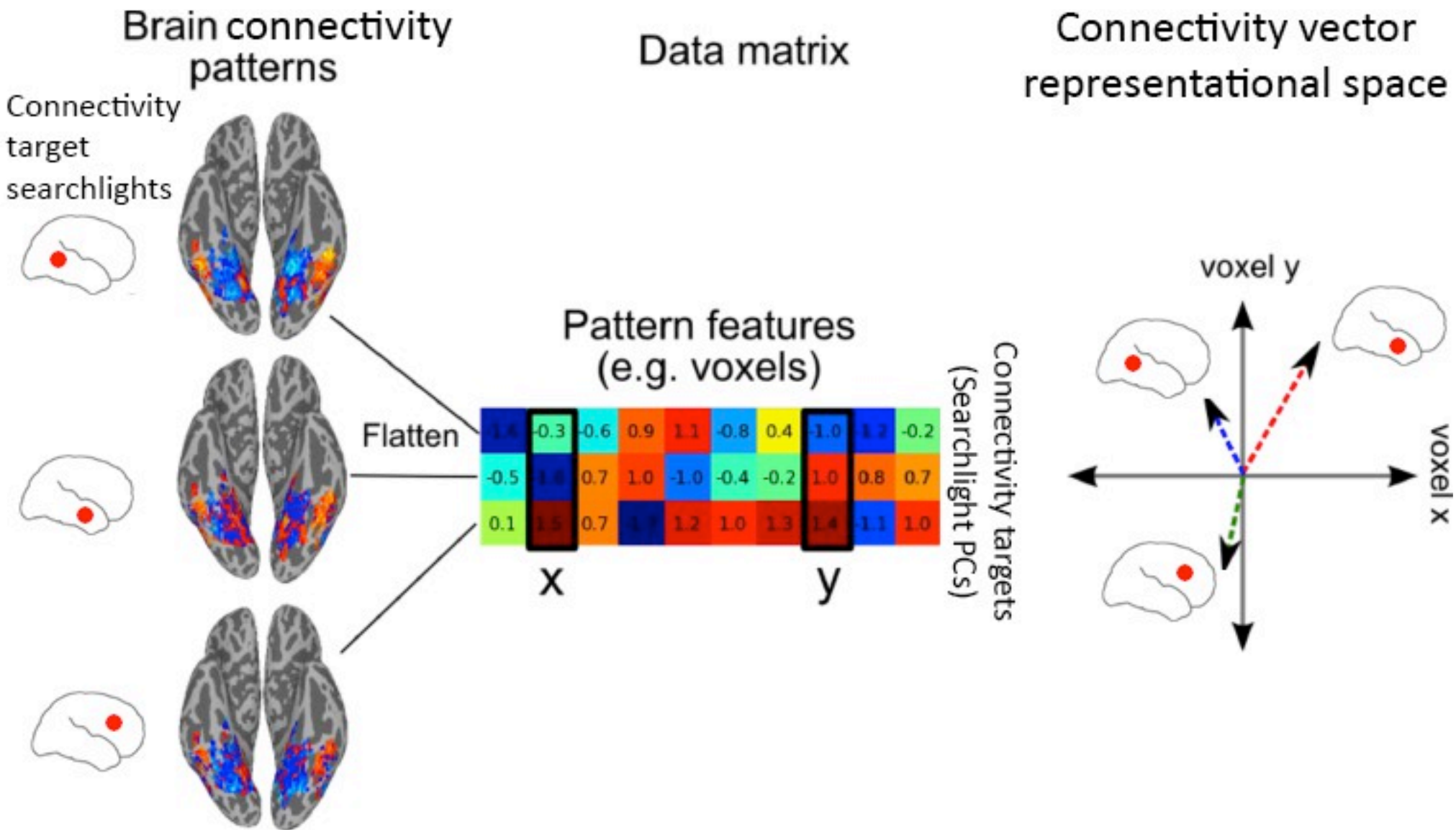
Other subjects' data projected from model space

Brain connectivity patterns are better aligned in the common model space

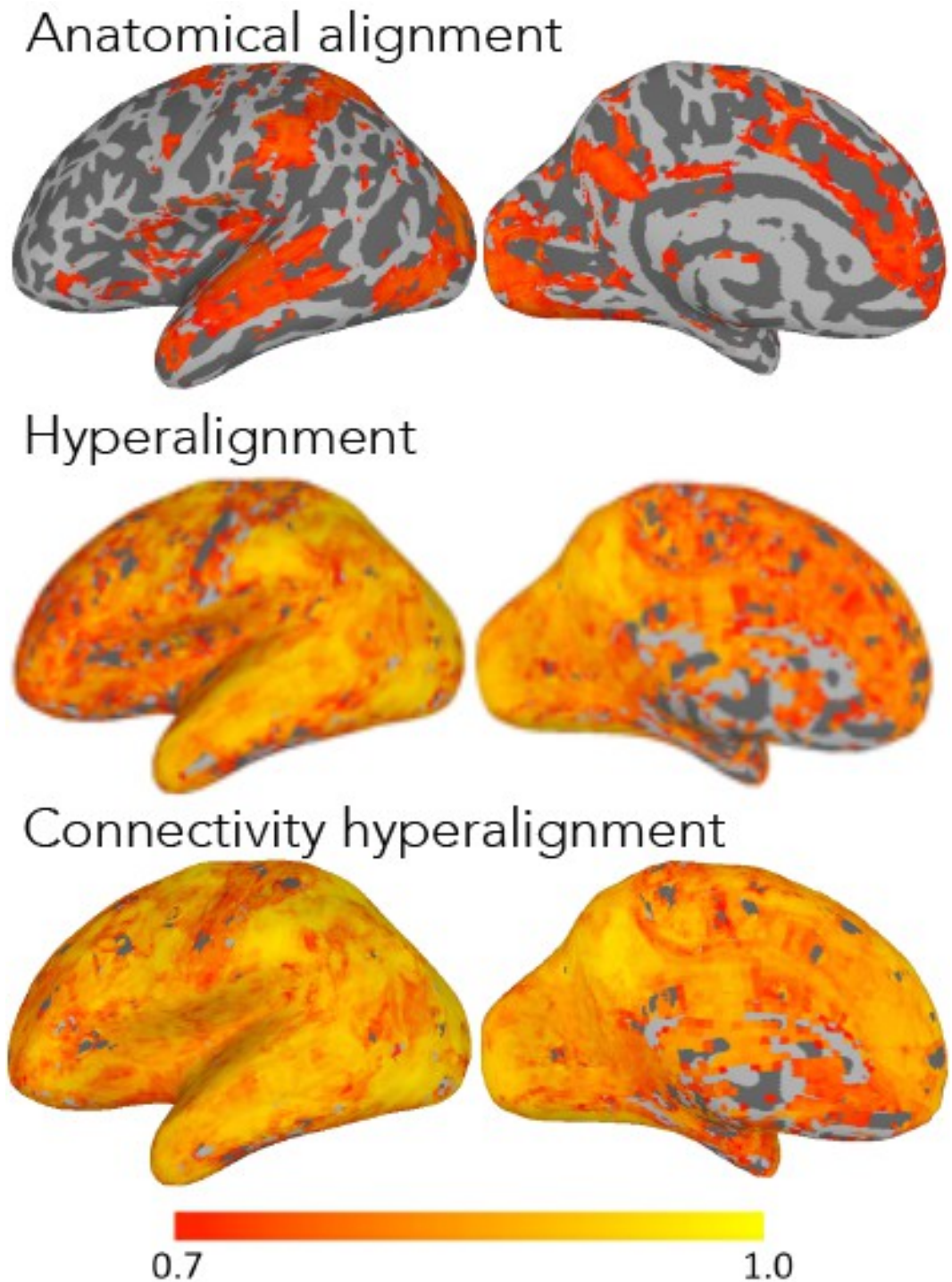


Inter-subject correlation of connectivity vectors

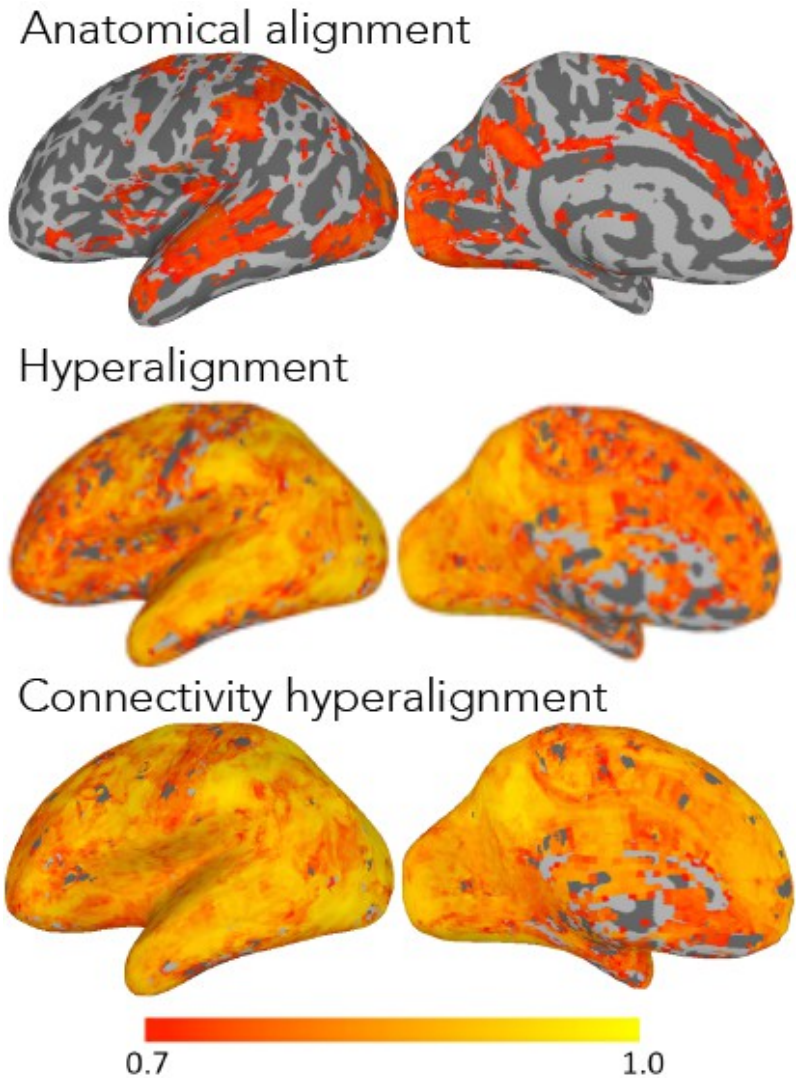
Connectivity hyperalignment

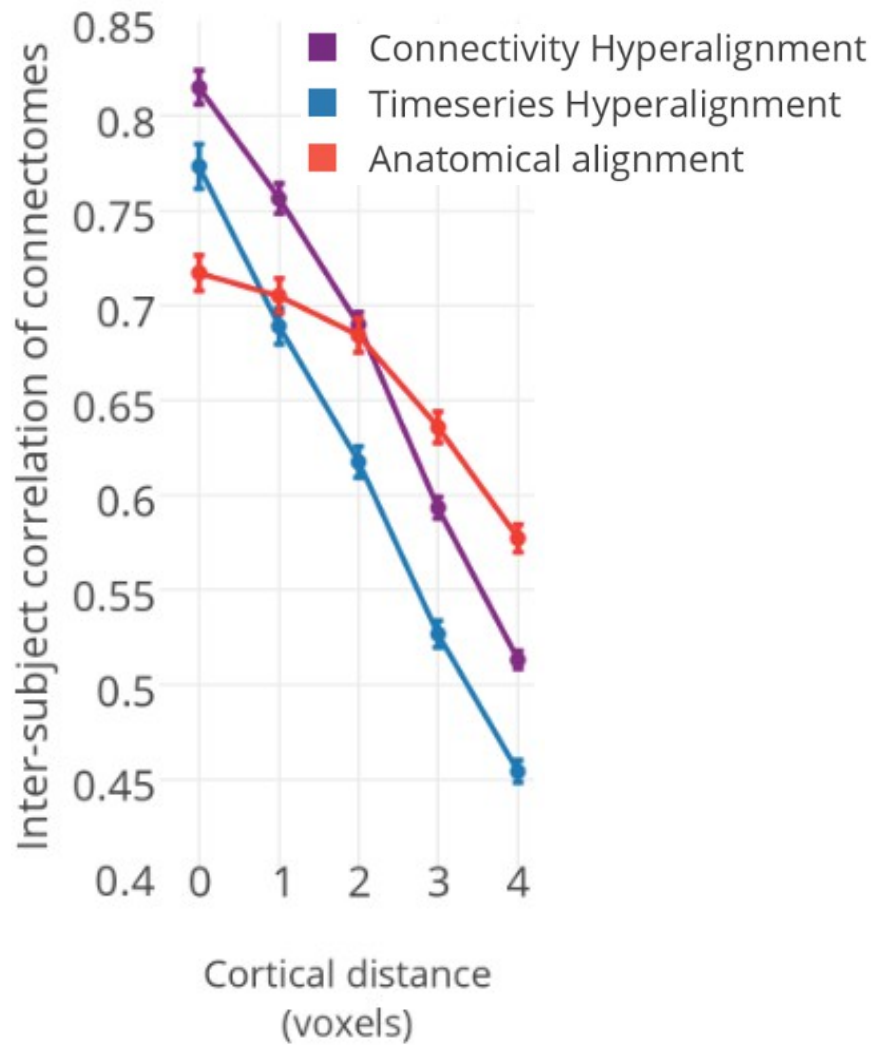


Brain connectivity patterns are better aligned in the common model space

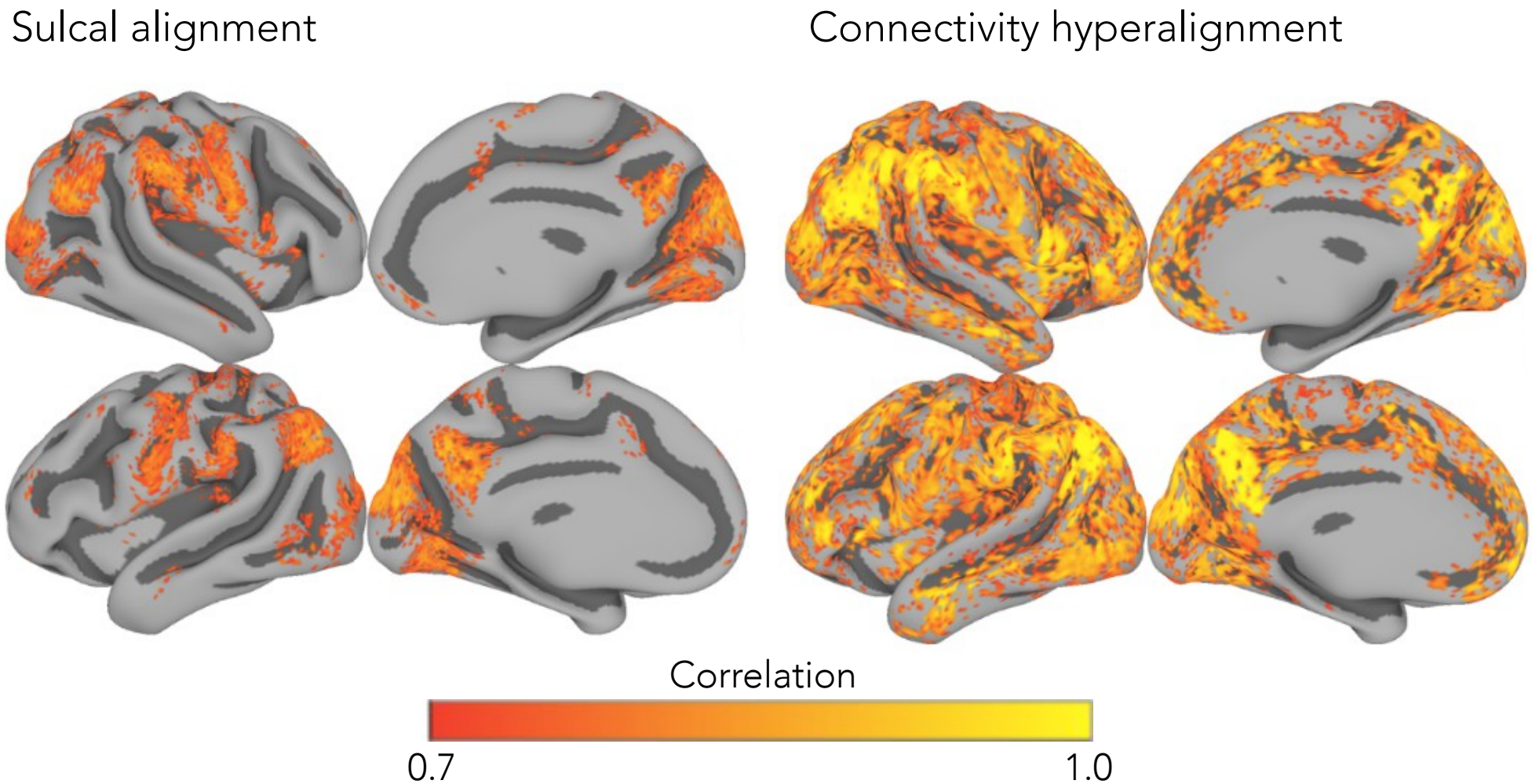


Brain connectivity patterns are better aligned in the common model space
<u>and</u> have a surprisingly fine-scale granularity (PSF)

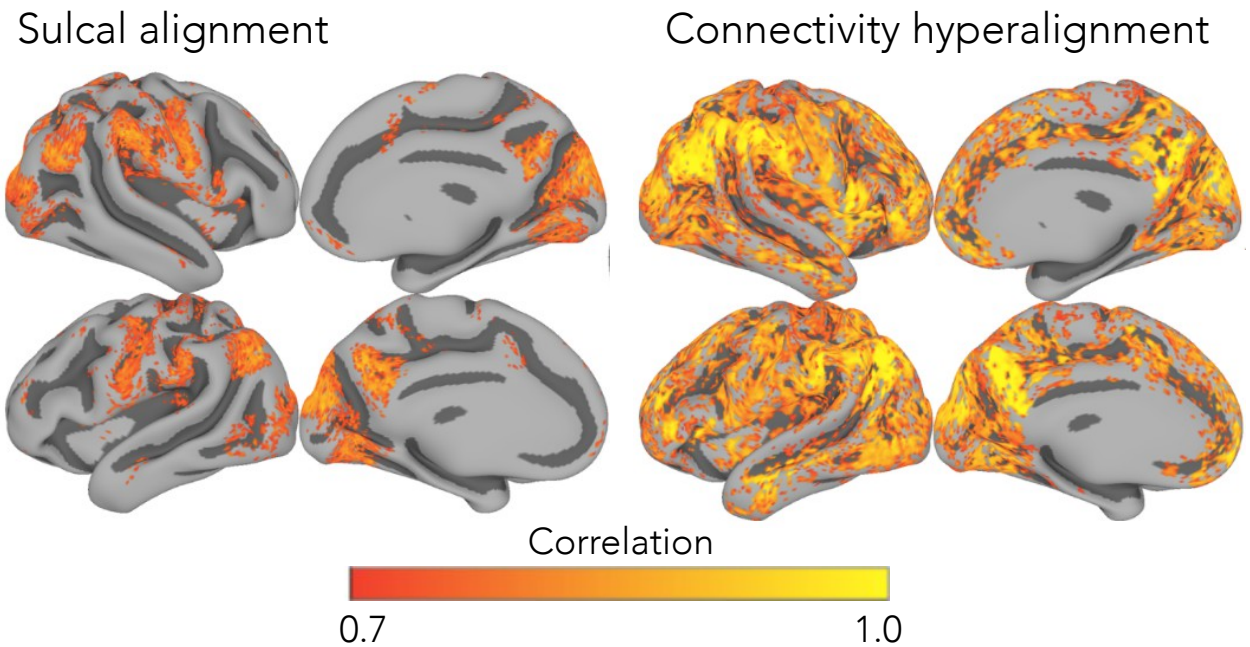


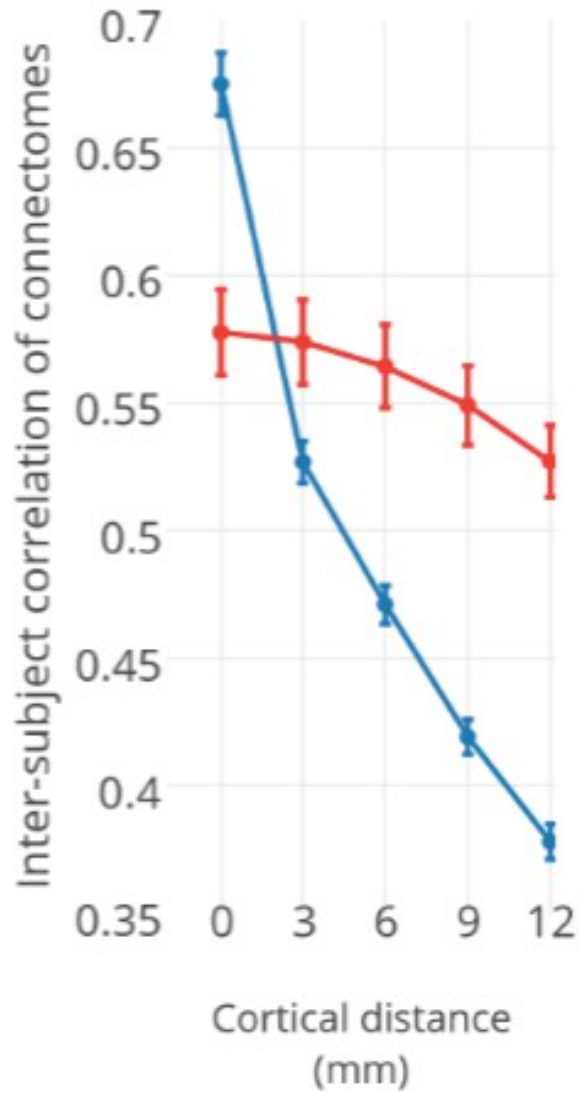


Connectivity hyperalignment of Human Connectome Project (HCP) resting state fMRI data (n=20) increases ISC of connectivity vectors



Connectivity hyperalignment of Human Connectome Project (HCP) resting state fMRI data (N=20) increases ISC of connectivity vectors <u>and</u> reveals a fine-scale architecture





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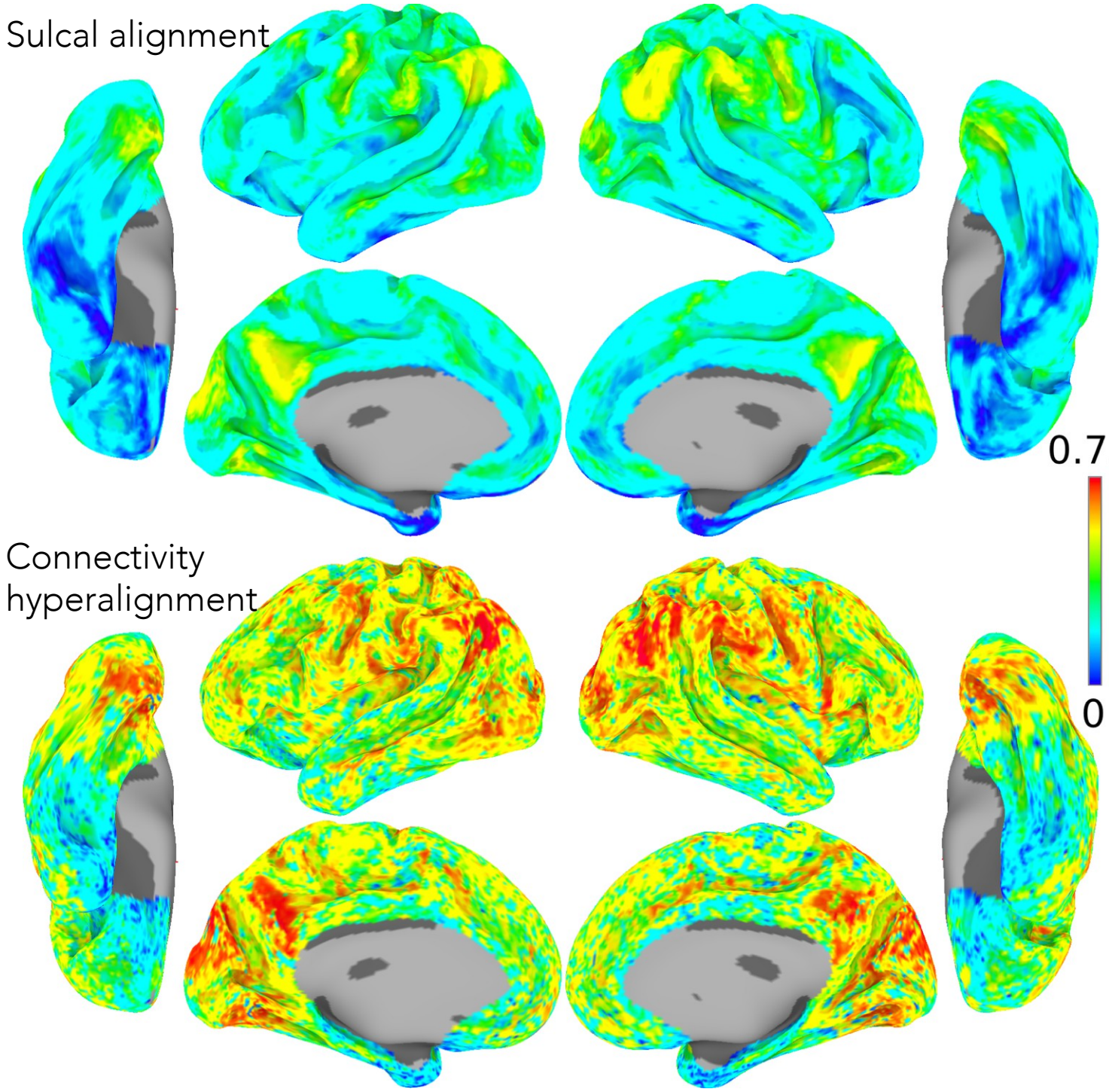
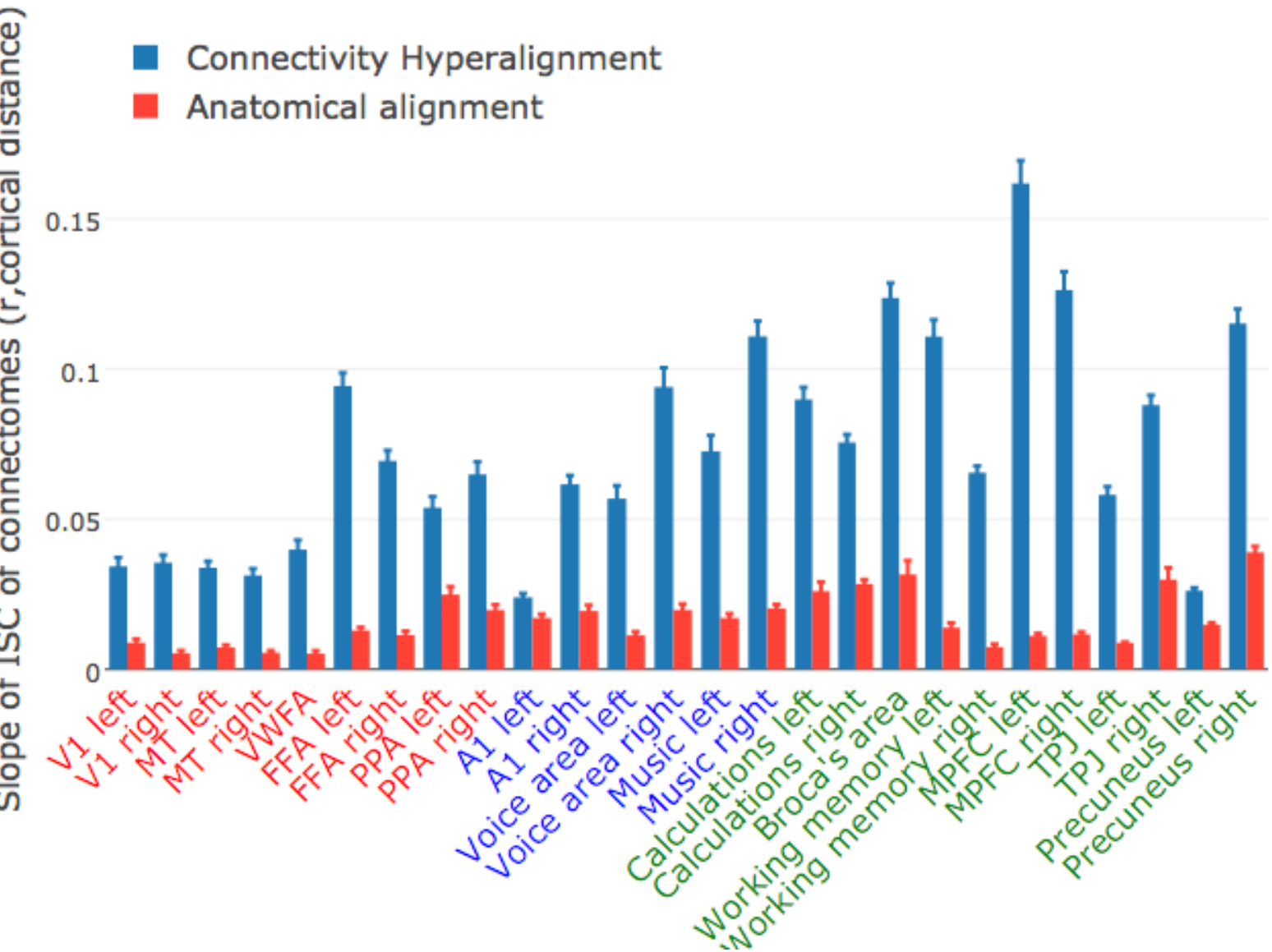
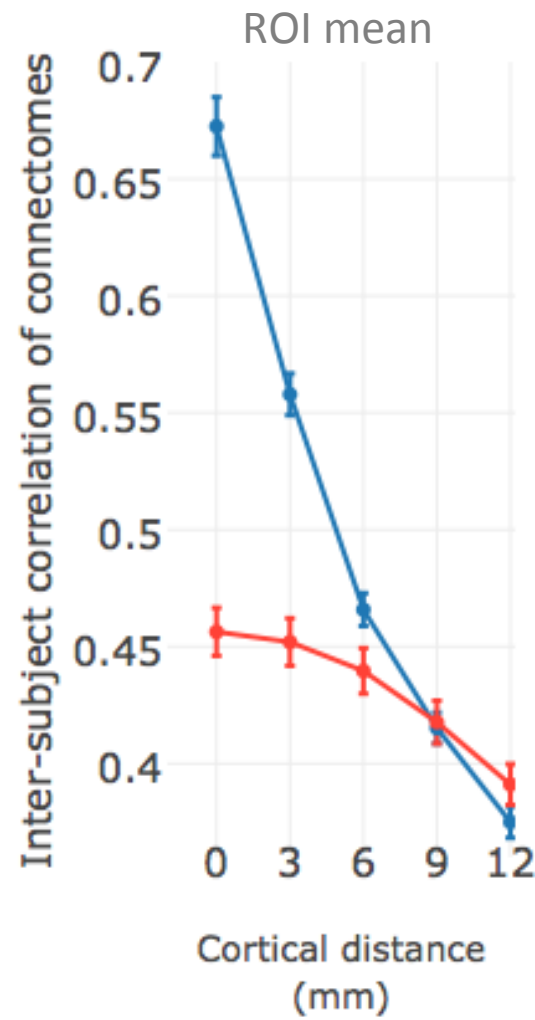


Do variations in connectivity profiles also have a fine spatial scale? YES

Point spread function (intersubject correlations of connectivity vectors, HCP data)





A common high-dimensional linear model of representational spaces in human cortex

- Statement of the problem: capturing coarse- and fine-grained topographies in a common model
- Conceptual framework: high-dimensional representational spaces
- Deriving the common space and individual transformation matrices with hyperalignment
- Validation
- Conclusions

Common model: Basic components

- Common, high-dimensional representational space
- Individual transformation matrices
- Algorithm for calculating transformation matrices and deriving the common model space (hyperalignment)

Common model dimensions

- Response tuning basis functions
  - Common across brains
  - Model population responses that carry fine distinctions
  - Capture variations with a fine spatial granularity
  - Valid for diverse domains of information
- Functional connectivity vectors
  - Common across brains
  - Capture variations with a fine spatial granularity
- Topographic basis functions
  - Individual specific
  - Model individual variations in functional topography with high fidelity

The Common Model accounts for the fine-grained structure of cortical architecture <u>and</u> coarse-grained areal topography

- Captures common bases for the fine-grained structure of local variations in response tuning and functional connectivity profiles

- Preserves and models individual variation of coarse-grained areal topography

Fine-scale structure in cortical functional architecture: How big a factor is it?

The common model

- accounts for <u>4X more variance</u>
- affords <u>7X higher bsMVPC accuracies</u>

Software for hyperalignment and data are on PyMVPA (www.pymvpa.org)

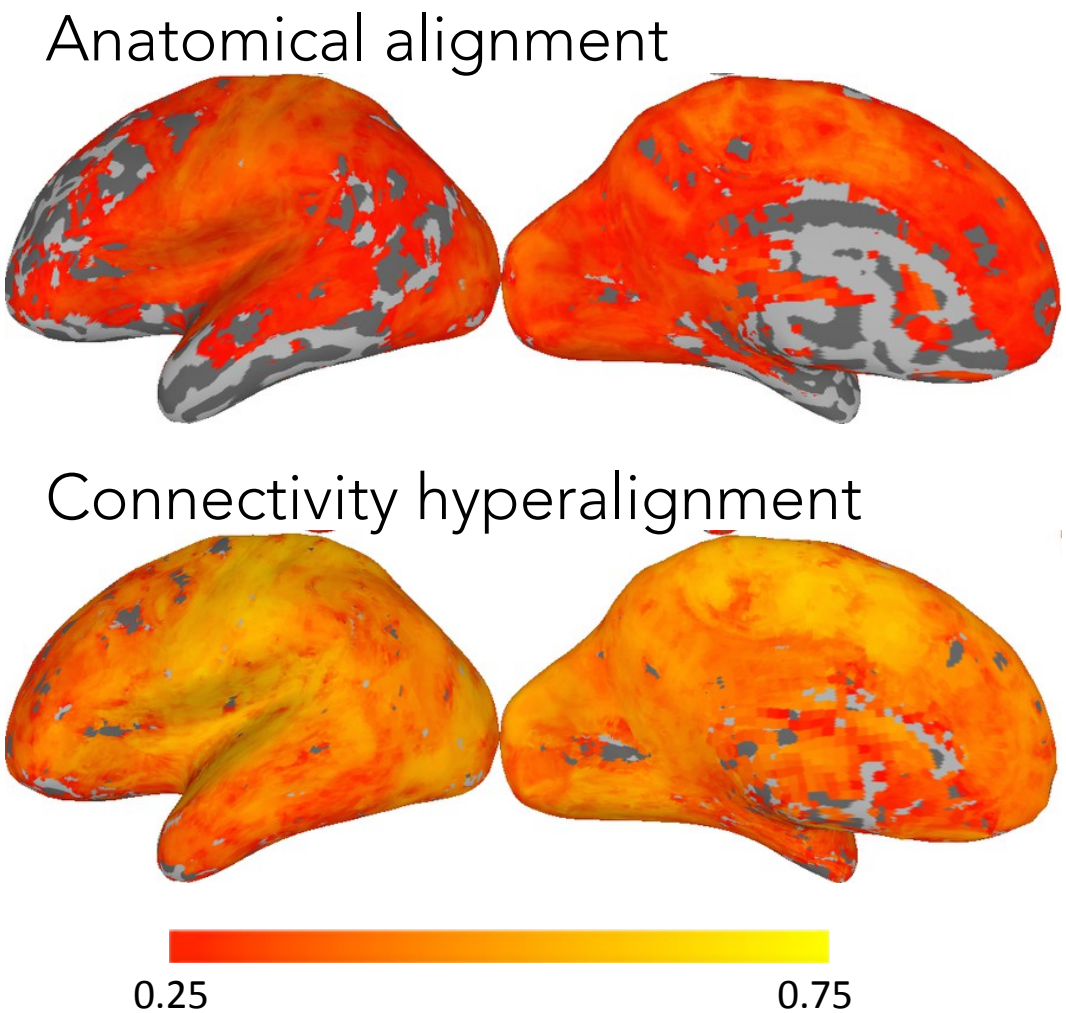
PyMVPA

http://neuro.debian.net

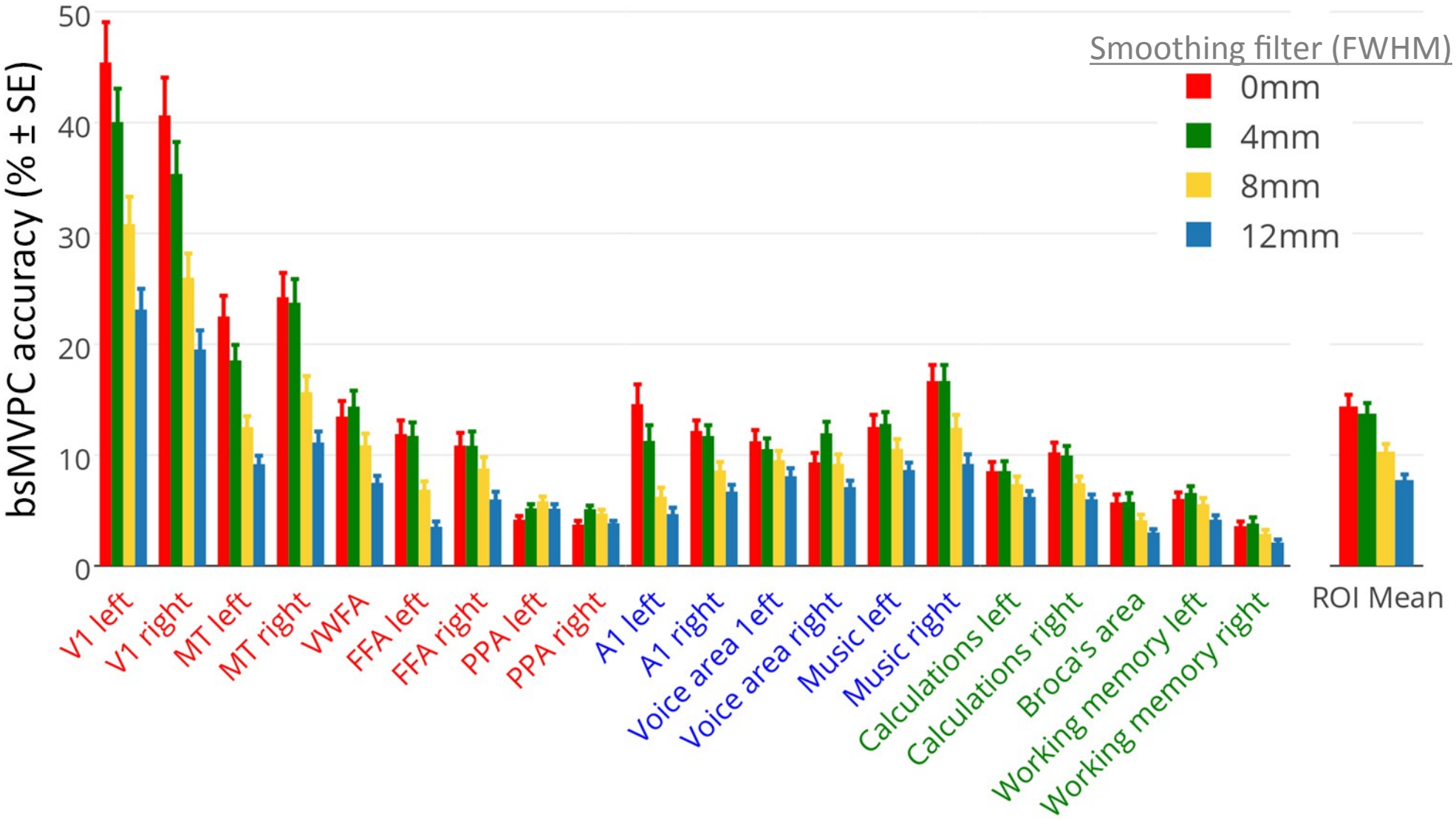
neurodebian

Guntupalli et al. (2016) A model of representational spaces in human cortex. *Cerebral Cortex*, epub ahead of print, open access.

Connectivity hyperalignment of resting state fMRI increases ISC of connectivity vectors



Smoothing reduces bsMVPC accuracies
In all visual, auditory, and cognitive regions of interest (ROIs)



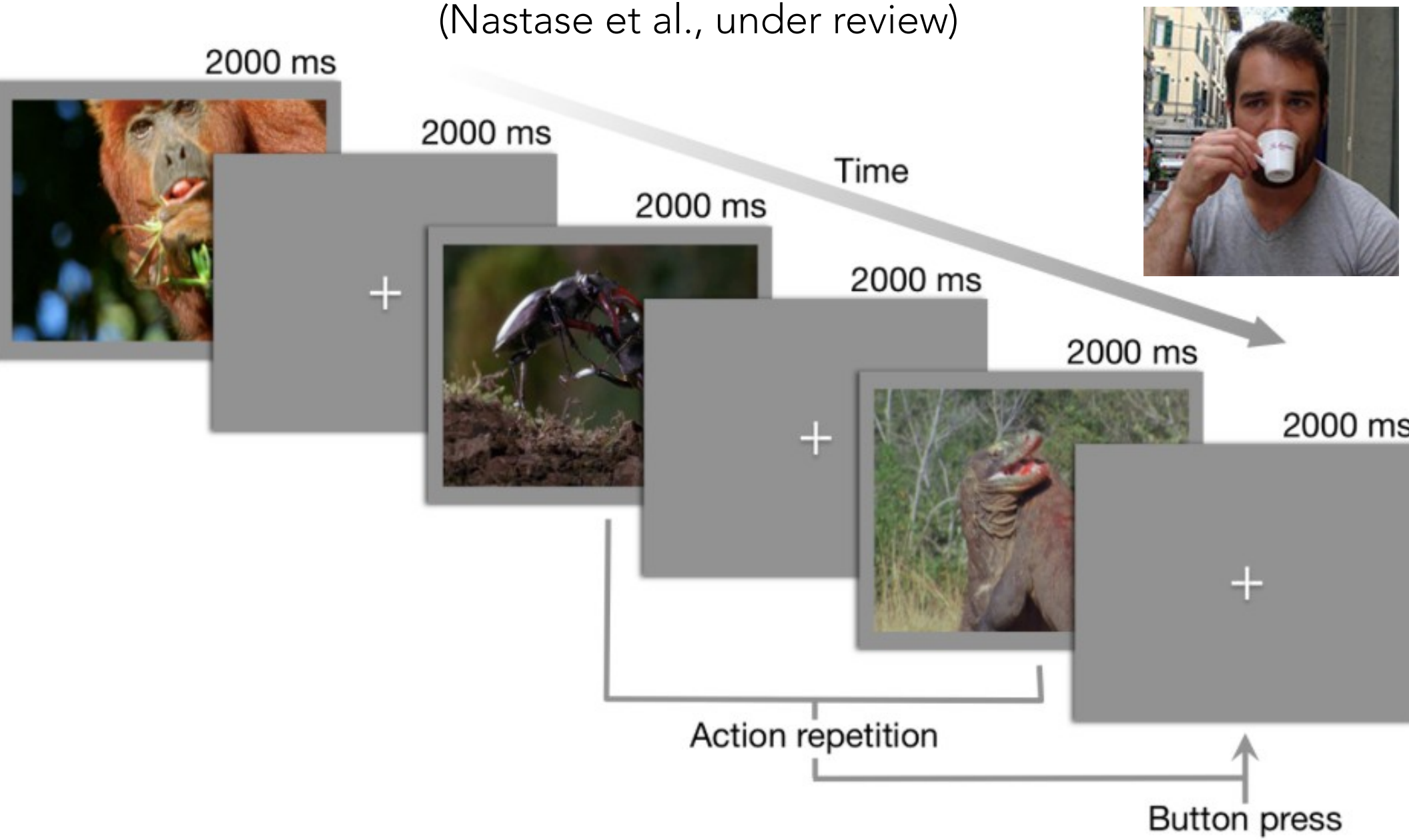
Hyperalignment parameters are estimated from responses recorded during movie viewing

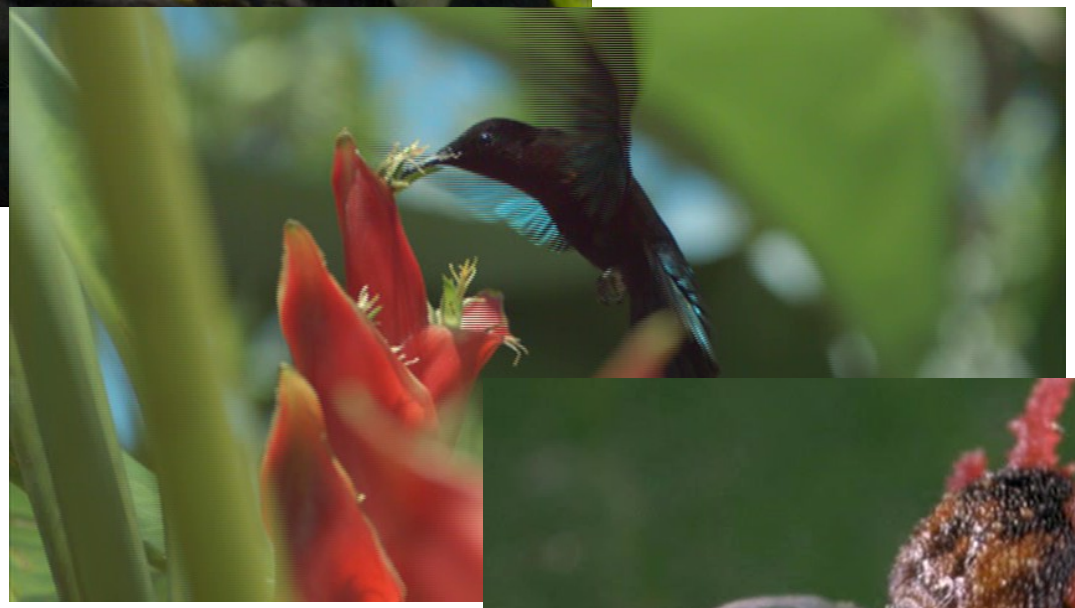
Raiders of the Lost Ark

Life on Earth

The Wire

Study of the effect of attention on the
geometry of representations of animal taxa and animal behaviors
(Nastase et al., under review)

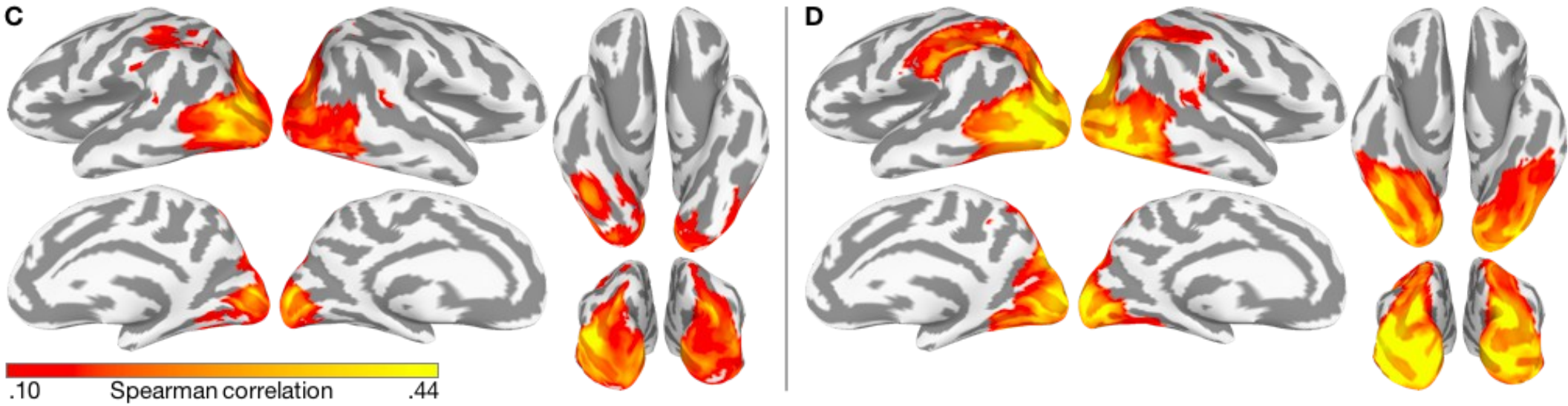




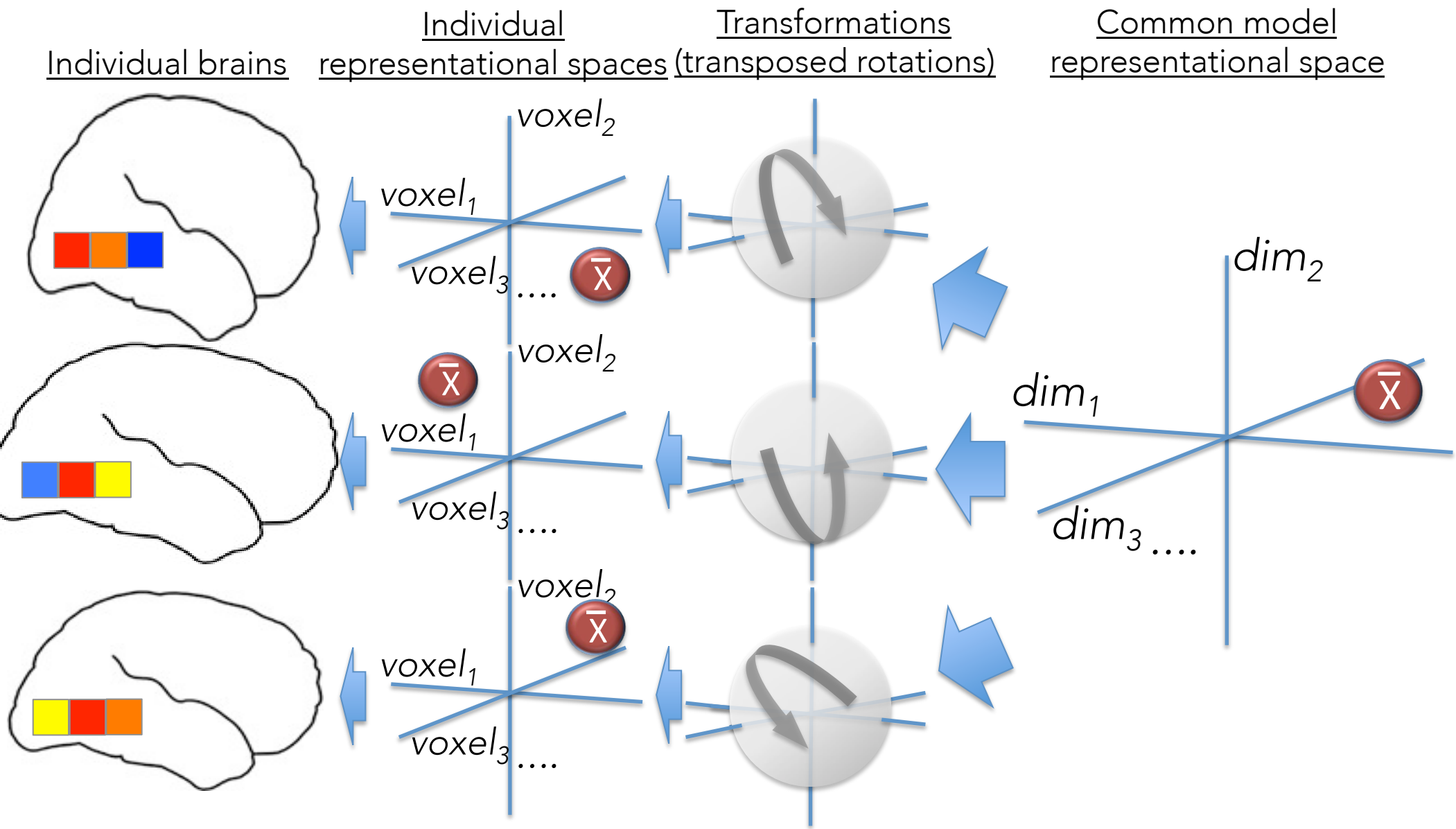
Higher inter-subject correlation of representational geometries for animal behaviors and taxa after hyperalignment
(Nastase et al., bioRxiv, 2016; under review)

Anatomical alignment

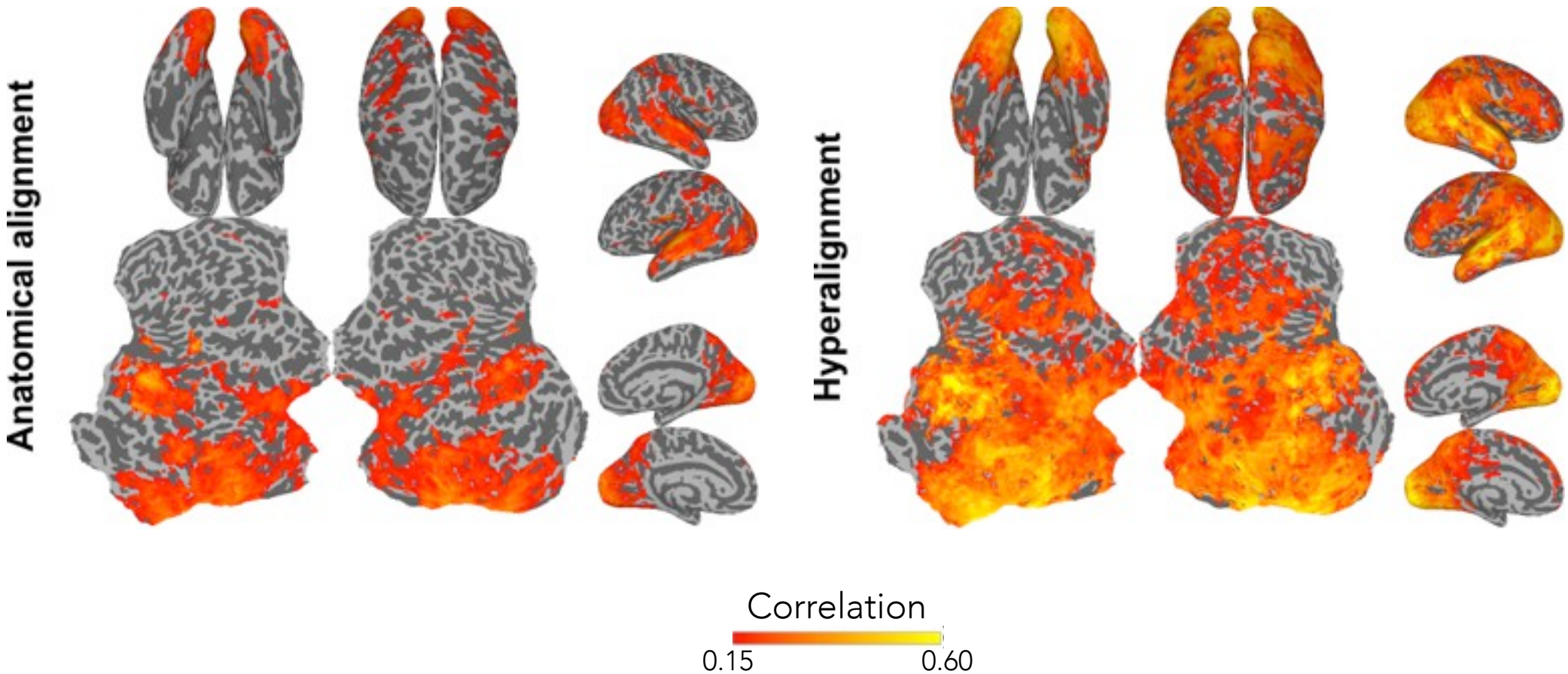
Hyperalignment



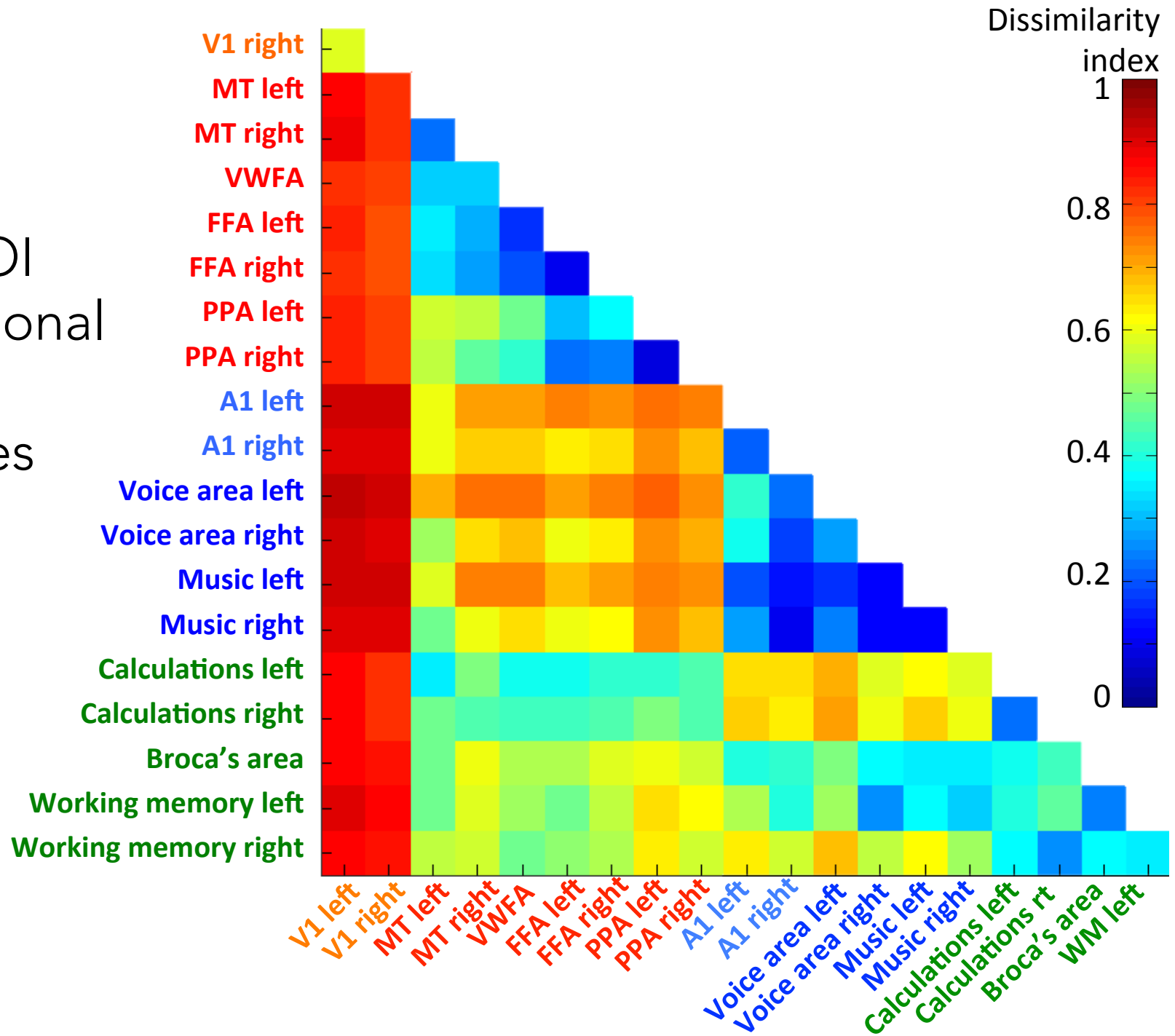
Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space



Whole-brain hyperalignment increases between-subject correlations of time-series in occipital, temporal, parietal, and frontal cortices



Between-ROI representational geometry dissimilarities



HyperCortex
Proposal for a new functional brain atlas
based on a high-dimensional common representational space

- *Brain responses can be analyzed as pattern vectors* with response basis functions that are shared across brains.

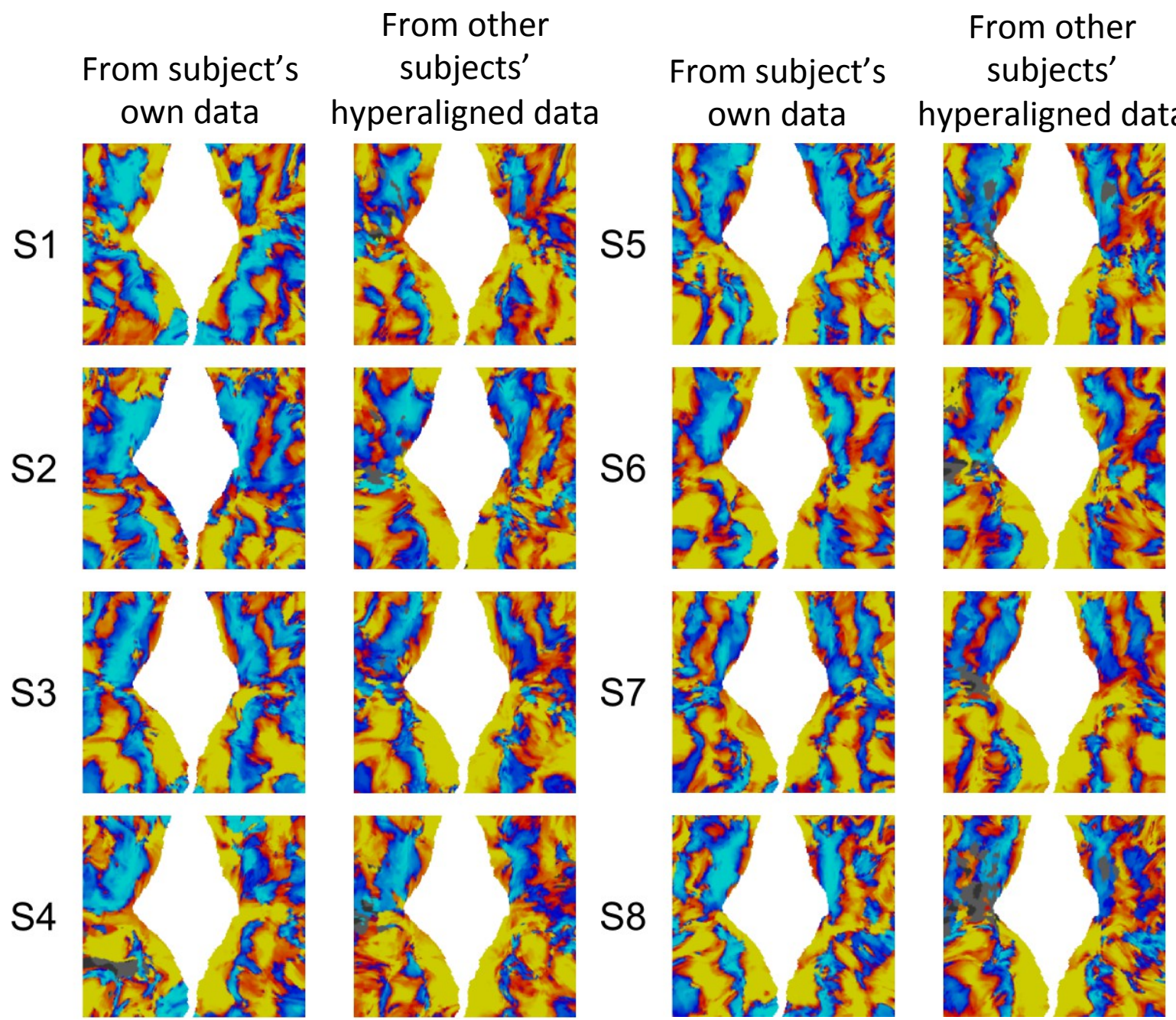
- *Captures and preserves fine-scale topographies* and models variability across individual brains.

- Data can be shared, interpreted, and subjected to meta-analysis in *a computational structure that captures fine-scale patterns of activity that encode fine distinctions.*

Concluding comments

- Extensibility and caveats
  - Vectors can be based on other functional indices (e.g. connectivity)
  - General validity can be increased with better stimulus and task paradigms (e.g. motor execution and music)
  - Model can incorporate other modalities (e.g. MEG, ECoG)
  - Hyperalignment may be improved with better algorithm (e.g. probabilistic hyperalignment, Chen et al. submitted)

Mapping retinotopy from other subjects' hyperaligned polar angle maps



Concluding comments

- Extensibility
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- Caveats

Concluding comments

- Extensibility
- Caveats
  - General validity can be increased with better stimulus and task paradigms (e.g. motor execution and music)
  - Hyperalignment may be improved with better algorithm (e.g. probabilistic hyperalignment, Chen et al. in prep)

Concluding comments

- Basis for a new kind of functional brain atlas
  - Report results as vectors in common model space rather than as anatomical coordinates
  - Afford comparison and interpretation of results at a far more fine-grained level
  - Allow arbitrarily large, multi-subject data sets for MVPA
- Extensibility
- Caveats

HyperCortex
Proposal for a new functional brain atlas
based on a high-dimensional common representational space

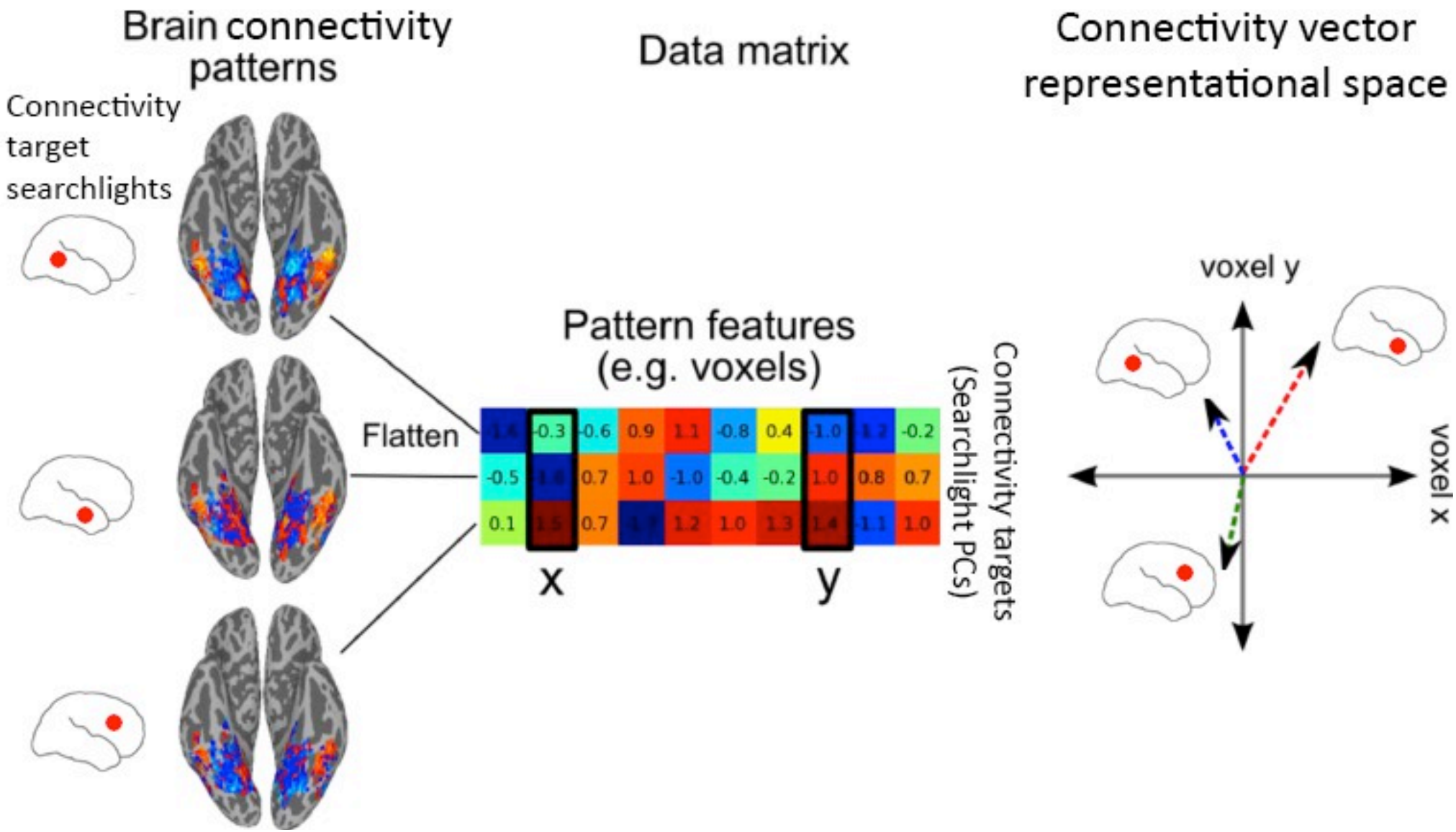
- Model dimensions have *response tuning functions* that are *highly similar across brains.*

- *Brain responses are captured as pattern vectors*, reflecting population codes with response basis functions that are shared across brains.

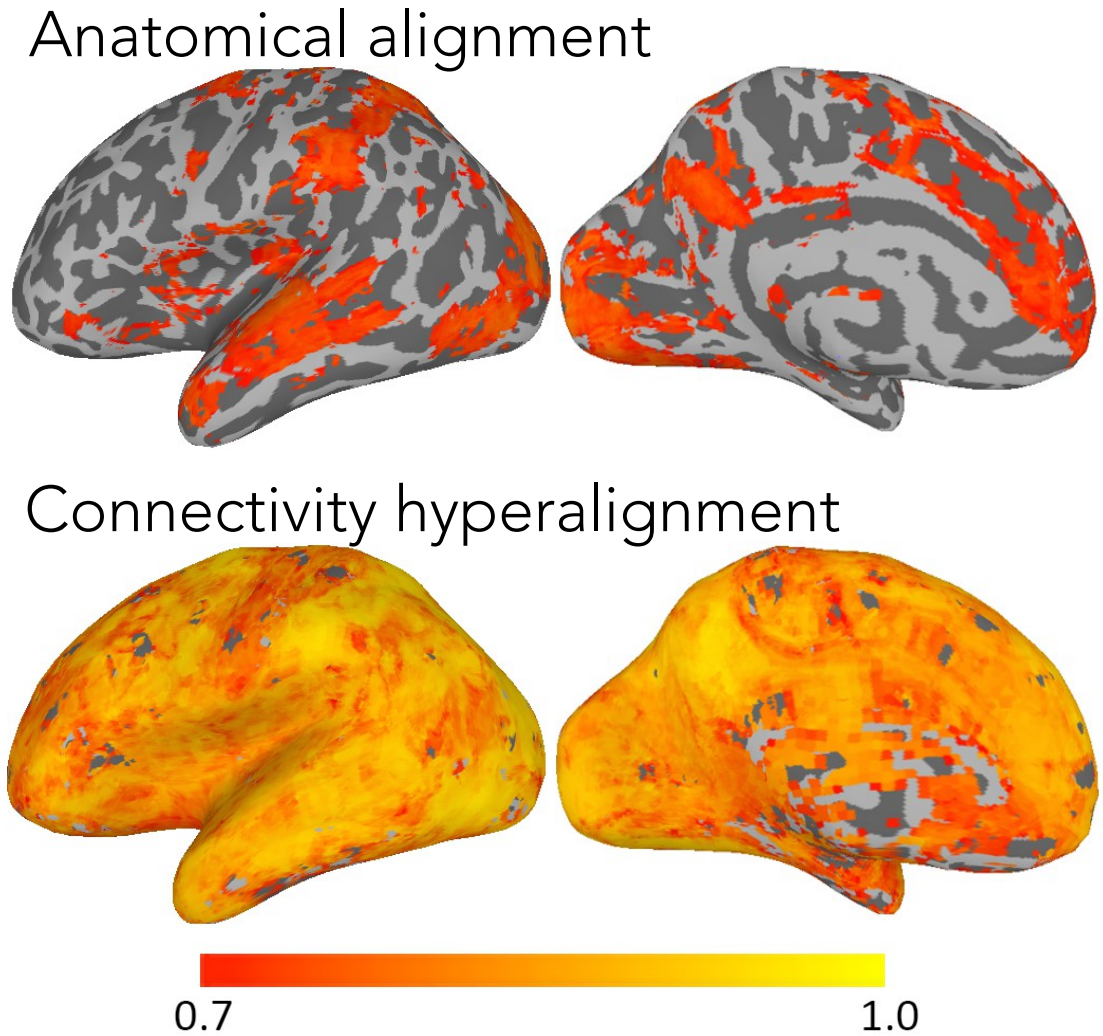
- *Fine-scale topographies are preserved* and can be recreated in each individual brain.

- Data can be shared, interpreted, and subjected to meta-analysis in *a computational structure that captures fine-scale patterns of activity that encode fine distinctions.*

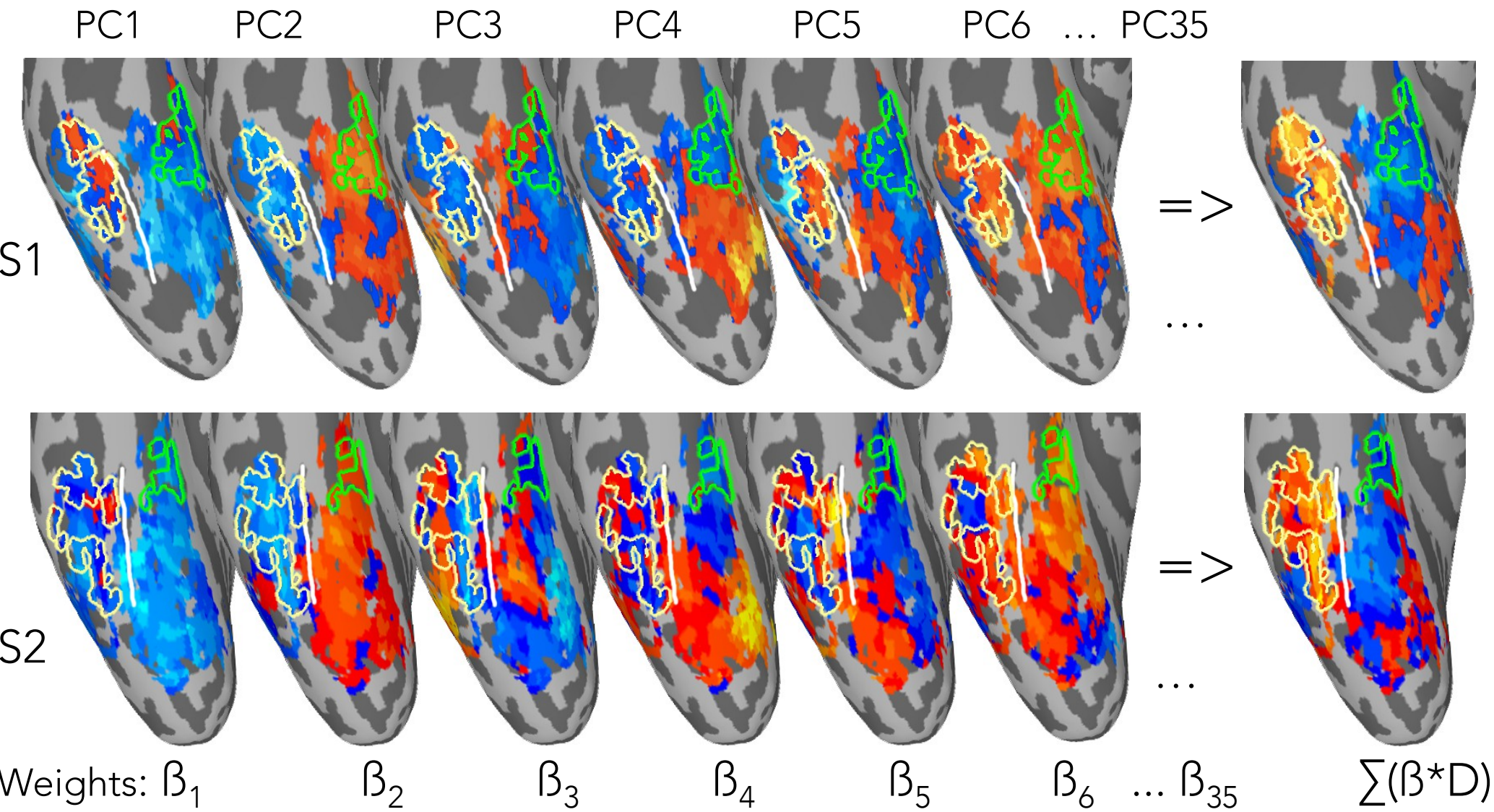
Connectivity hyperalignment



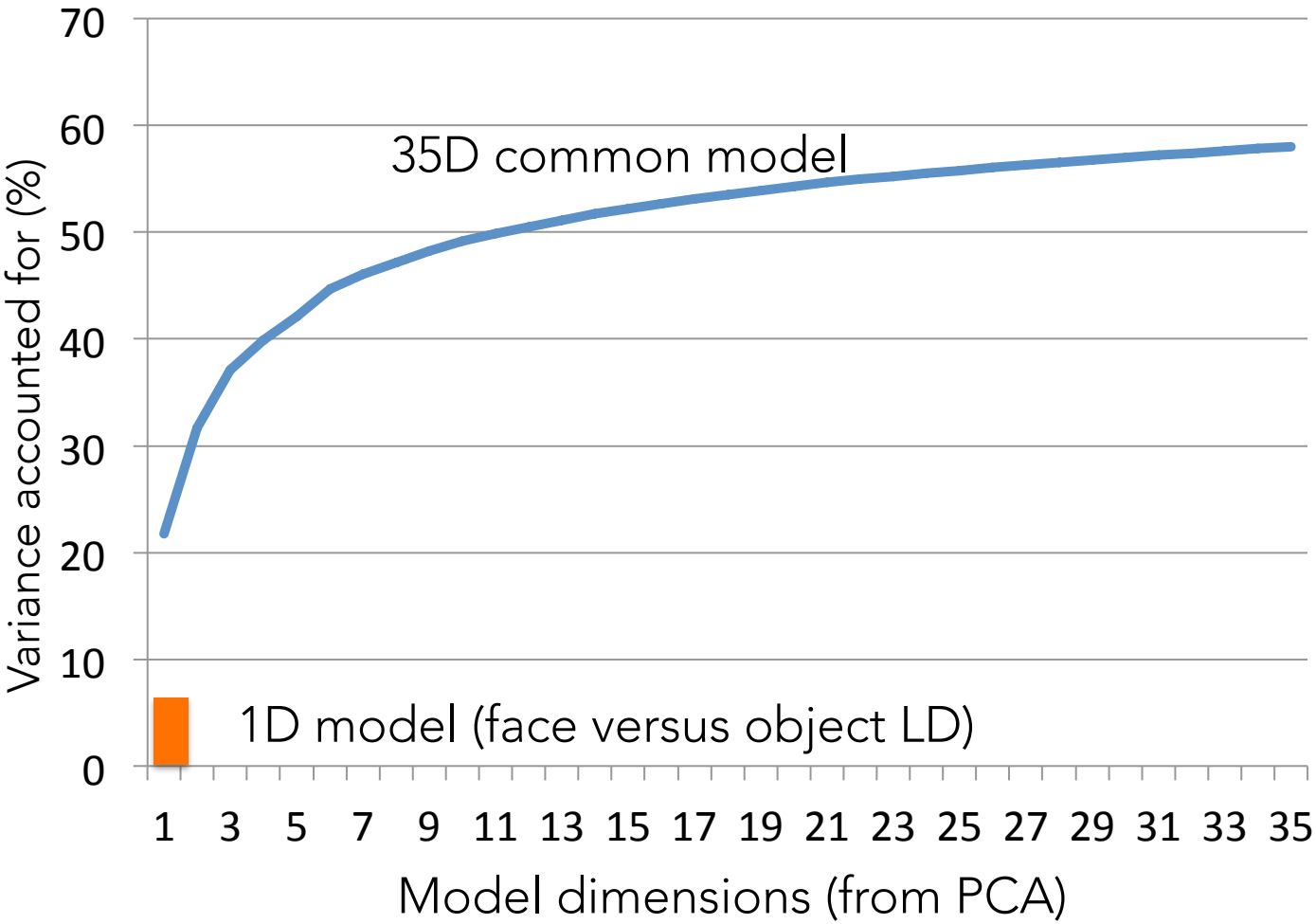
Intersubject correlations of connectivity vectors



The topographic basis functions for PCs individually show little correspondence to category-selective face and place areas or the domain-specific divisions for animate and inanimate stimuli

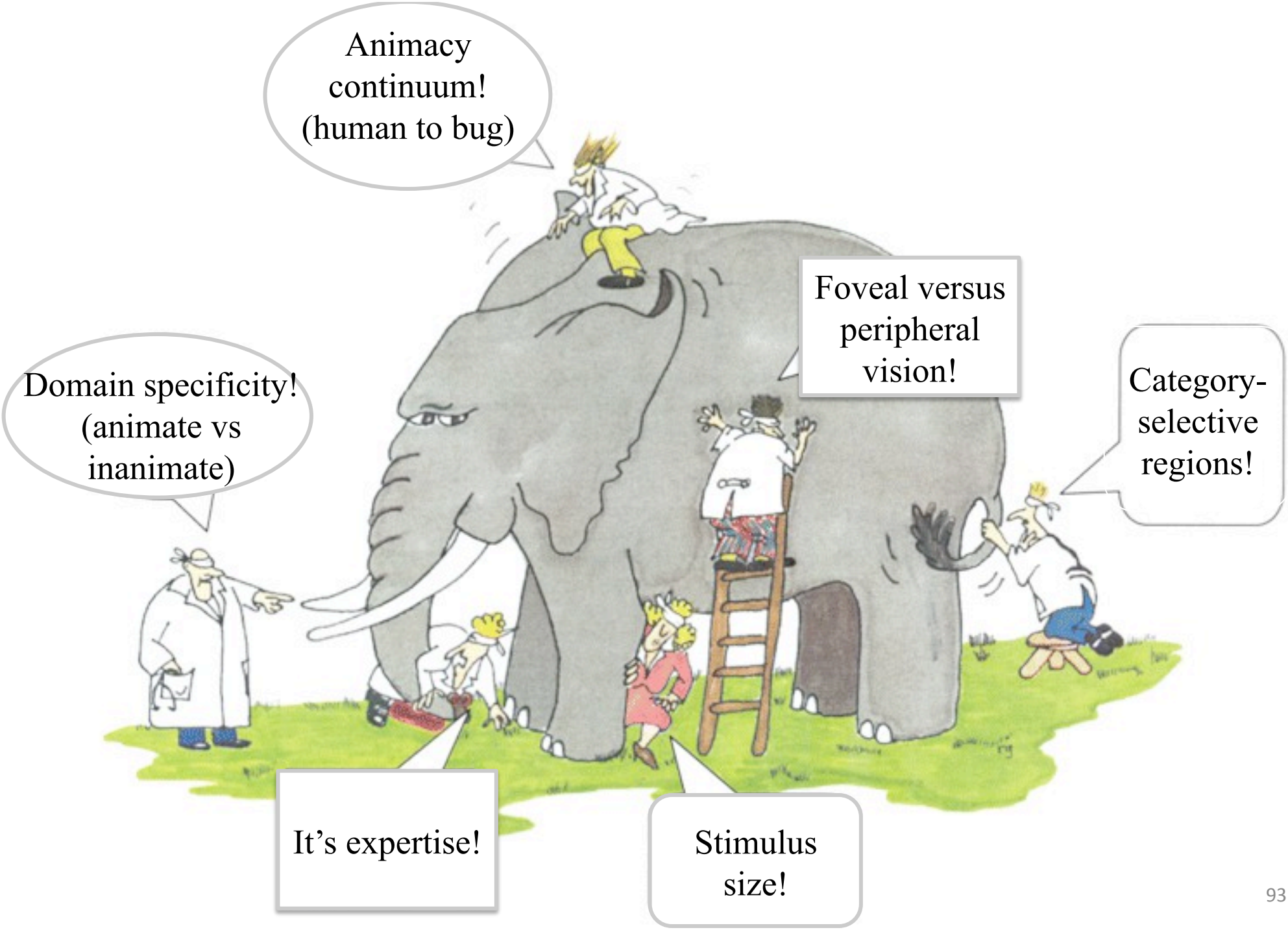


Single dimensions (simple contrasts) are inadequate for modeling the functional architecture of cortex



The face vs object LD accounts for only 7% of movie response variance in VT cortex

- <20% of VAF by top 3 model dimensions
- <13% of VAF by 35 model dimensions


Animacy continuum! (human to bug)
Foveal versus peripheral vision!
Domain specificity! (animate vs inanimate)
Category-selective regions!
It's expertise!
Stimulus size!

Can a high-dimensional common model of human cortex be leveraged to build a new type of functional brain atlas?

Brain atlases are an essential tool for functional neuroimaging research

- Provide a common basis for reporting results
- Allow comparisons across studies affording
    - Replication testing
    - Interpretation
    - Meta-analysis
- More generally, afford accrual of knowledge about the functional organization of the human brain

Functional Brain Atlas: Current State of the Art
Results are reported in tables with anatomical x,y,z coordinates

Table 1. Group-Average Activation for the Biological Motion Display

	Talairach Coordinates				
Region	X	Y	Z	Mean T	mm^3
R. ITS	44	−69	−7	4.63	2101
R. ITS	52	−51	3	4.49	920
R. STS	57	−41	21	4.17	112
R. Fusiform	36	−39	−19	4.72	748
R. Fusiform	34	−68	−18	4.32	174
R. Post. Occipital	14	−96	−4	4.43	151
L. ITS	−42	−70	−4	4.59	2544
L. Supramarginal	−56	−39	25	4.37	388

from Peelen & Downing, Neuron, 2006

Functional Brain Atlas: Current State of the Art

Results are aggregated across studies based on x,y,z coordinates

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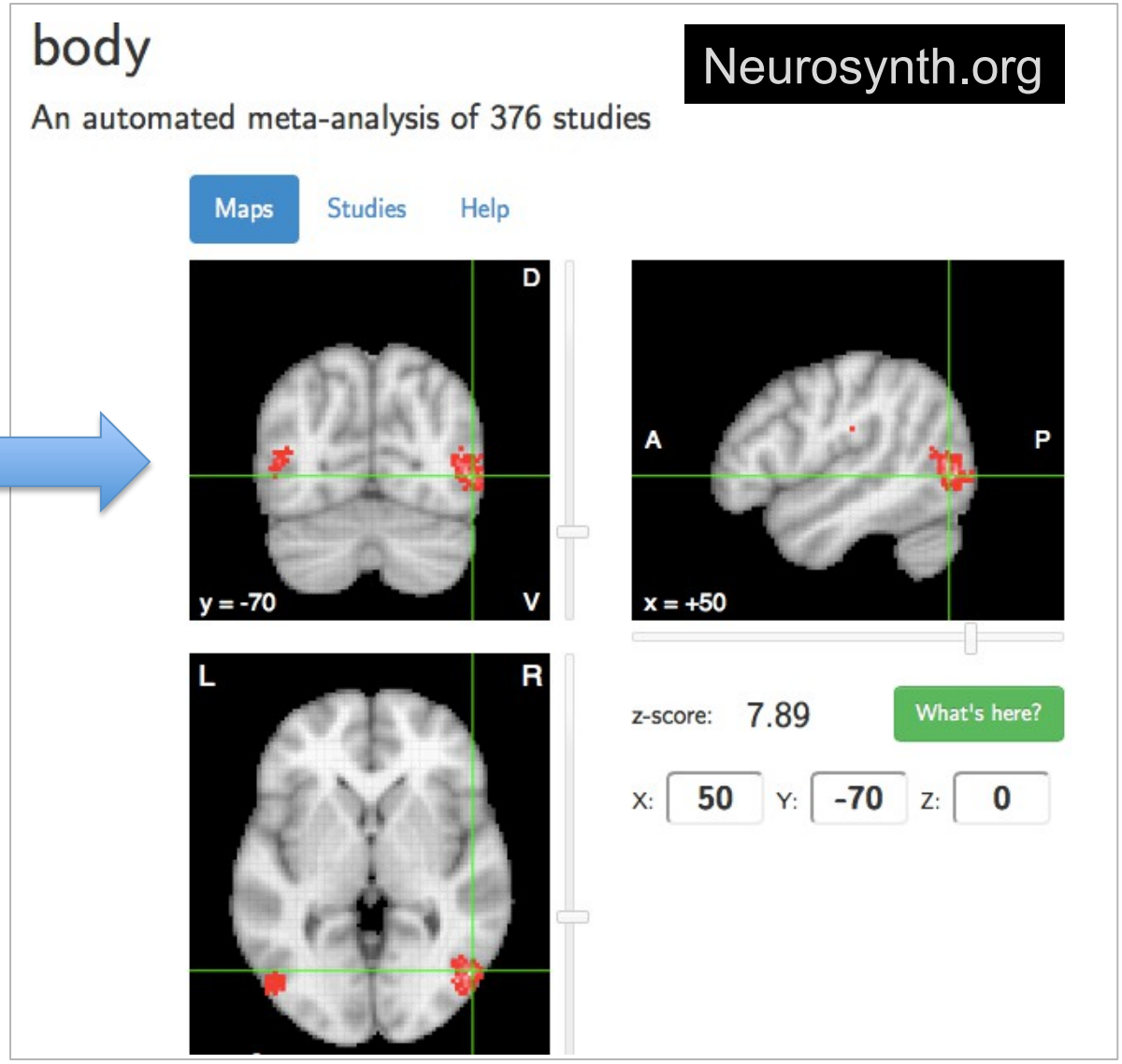

Functional Brain Atlas: Current State of the Art
The function of a locus is described as a "word-cloud"

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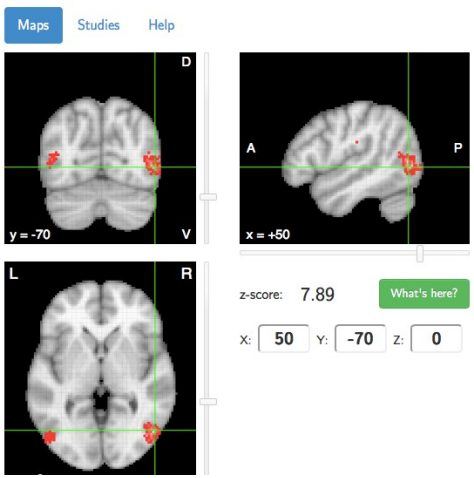
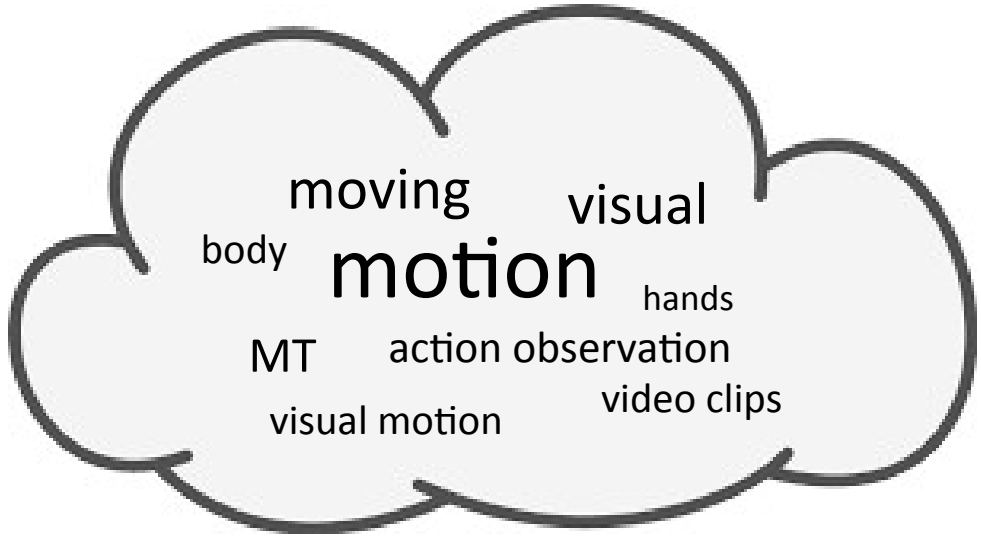
body

An automated meta-analysis of 376 studies

Neurosynth.org





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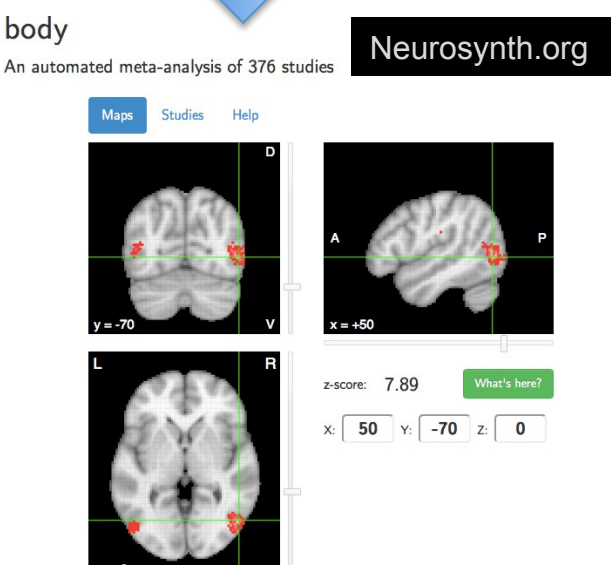
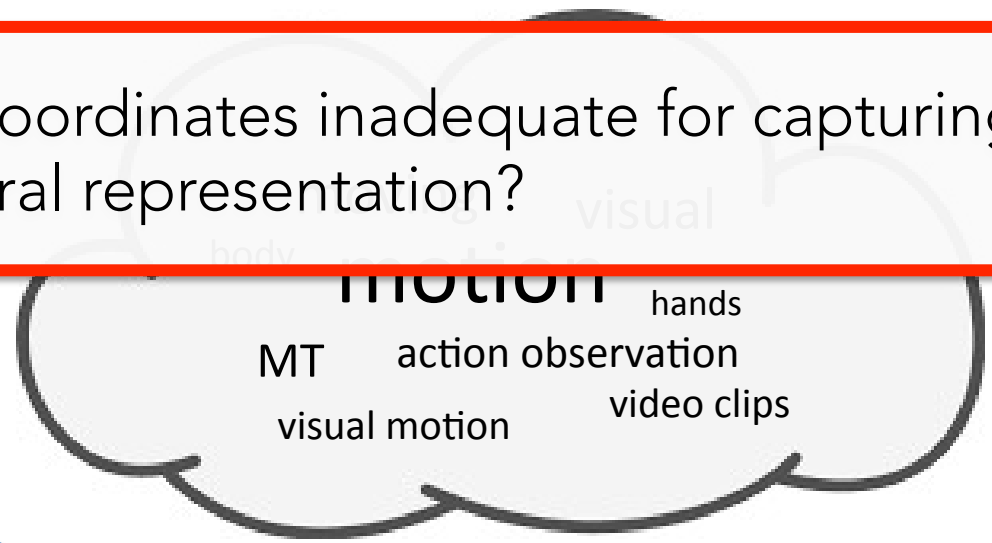
Why are anatomical coordinates inadequate for capturing neural representation?





Real-life cognition challenge

(Hanke et al., Poster #3672, OHBM 2014)

- **2 hours of 7-Tesla fMRI** (0.5Hz, 1.4mm), large sample of **natural language processing**
- Simultaneous respiratory and cardiac trace (200Hz)
- 0.7mm T1w, T2w
- SWI, angiography, DTI
- 20 human participants, plus phantom

http://studyforrest.org

Data in the public domain

No registration needed

Participate in the challenge and win 5000 Euro

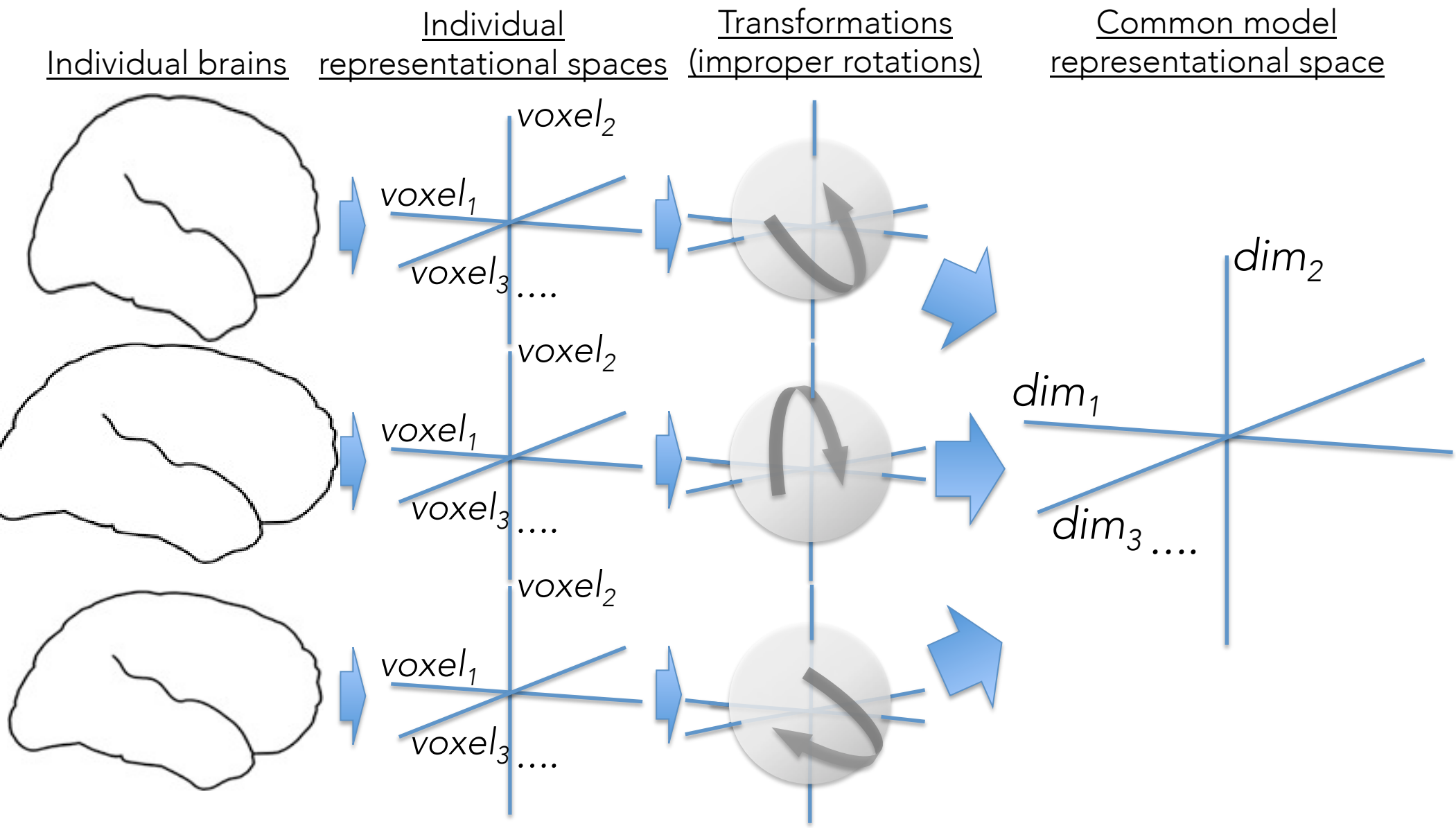
binc germany-usa

SPONSORED BY THE Federal Ministry of Education and Research

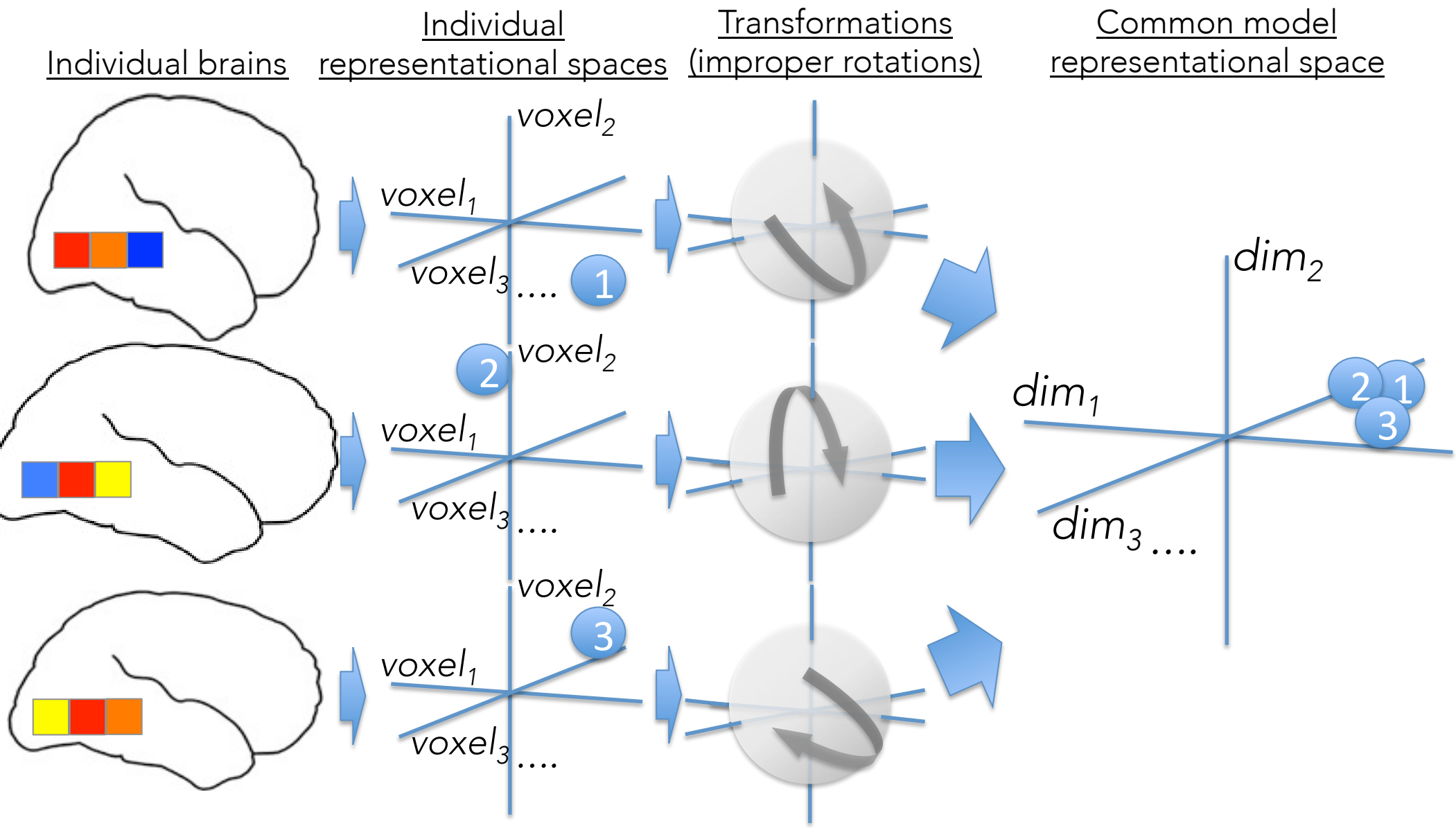
NSF

cbbs center for behavioral brain sciences

Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space



Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space



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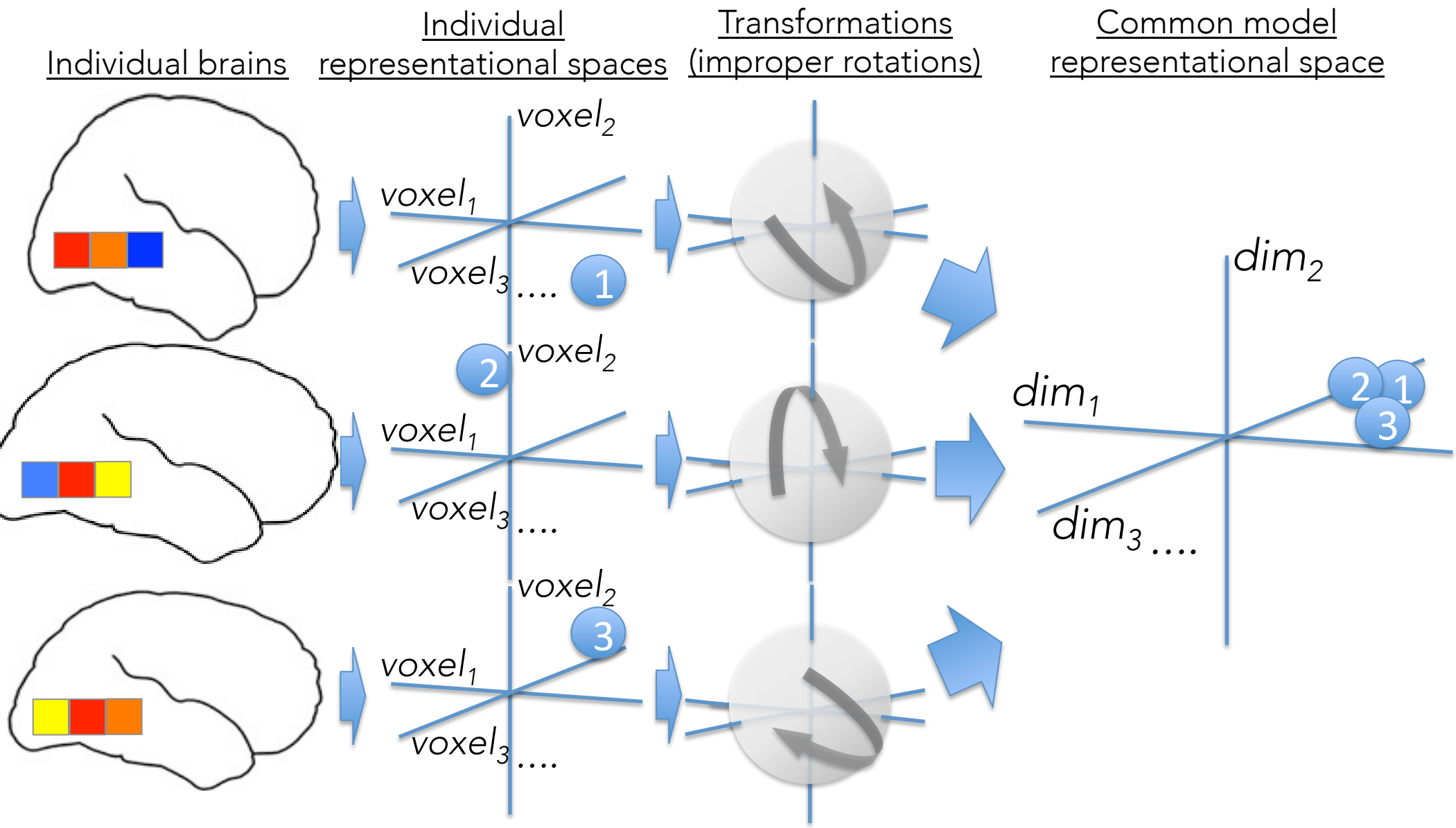
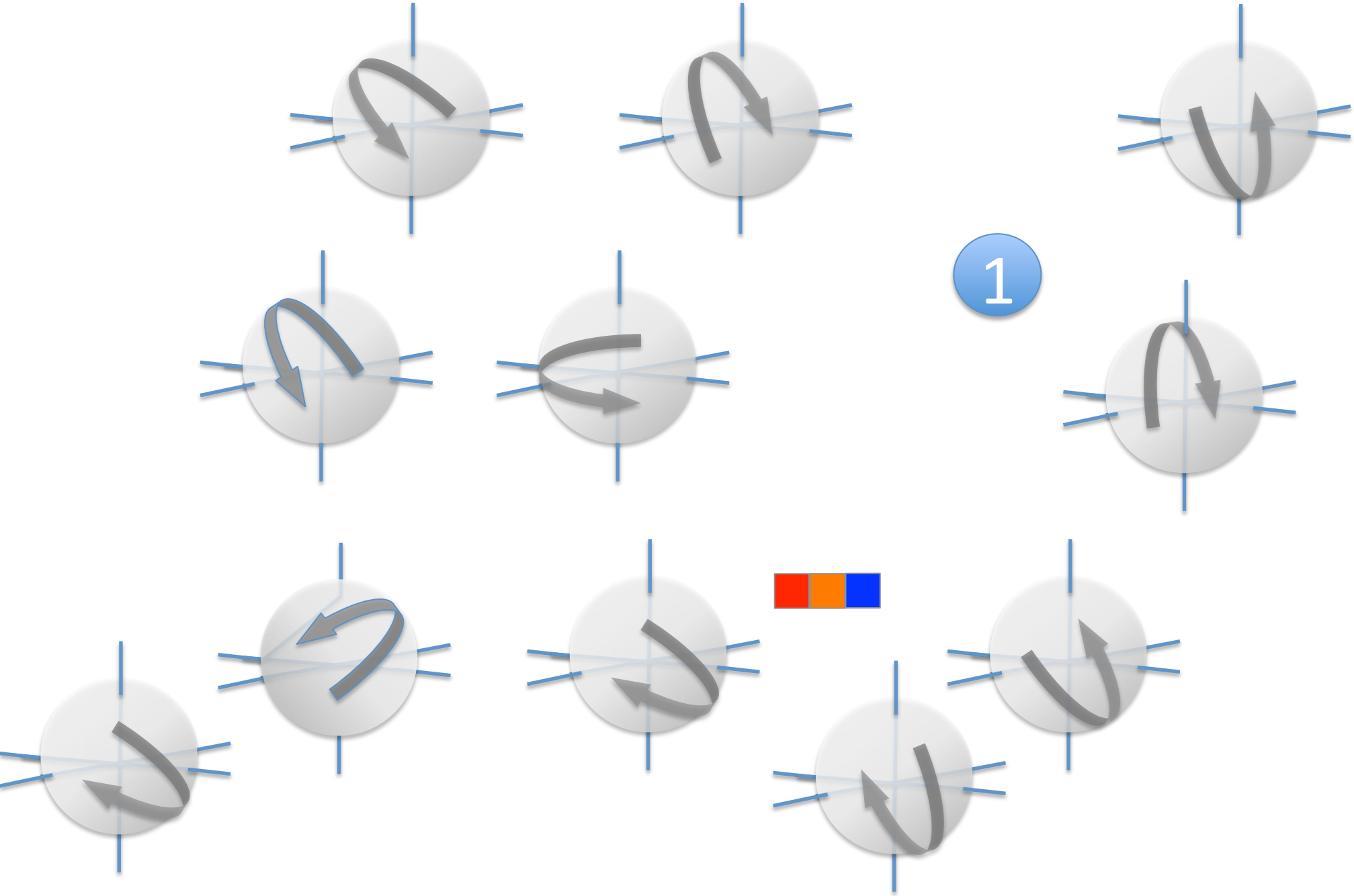



1

Validation

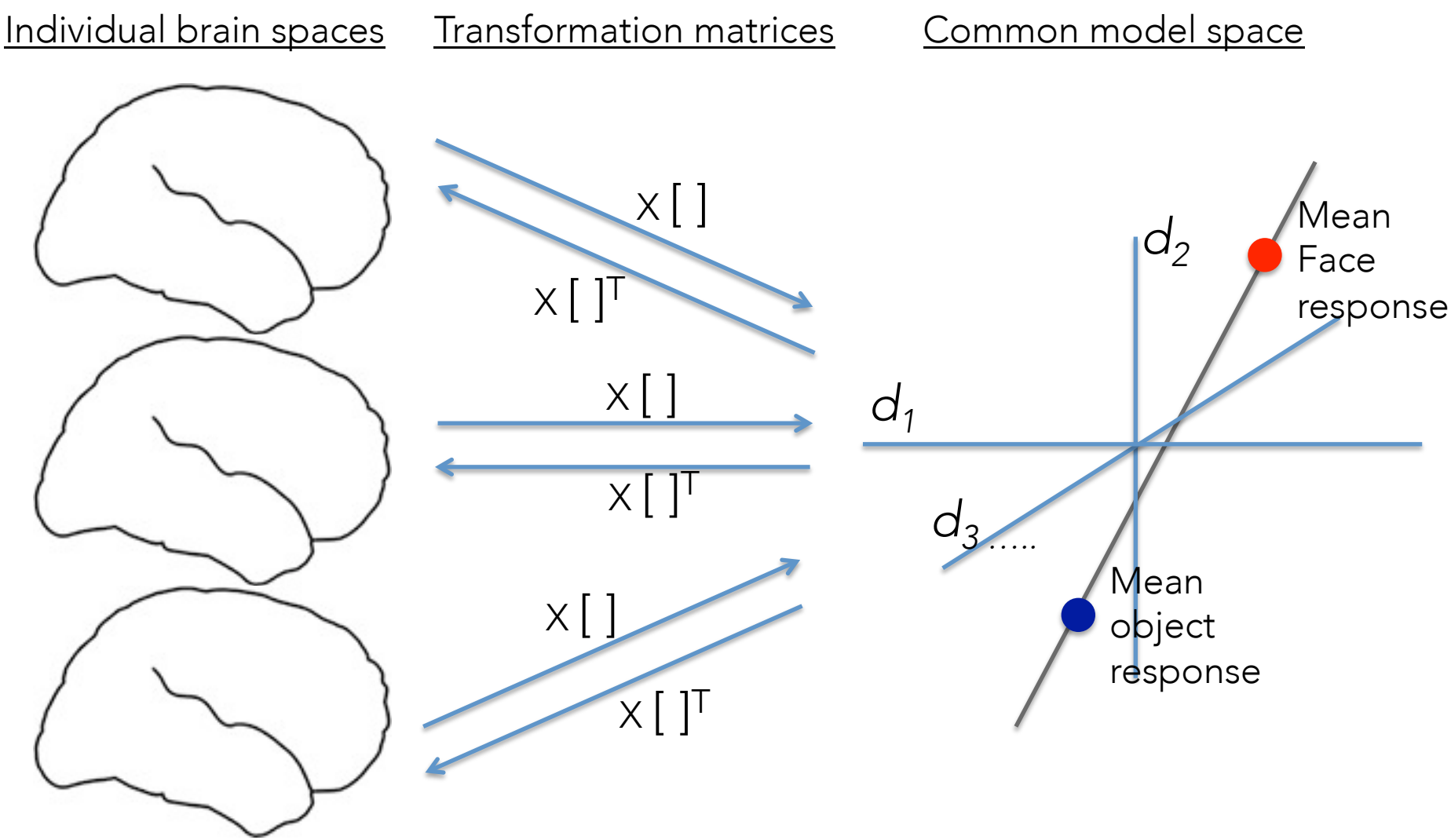
Modeling fine distinctions in a model space based on response tuning functions that are are common
Modeling topographies with basis functions that are grounded in common tuning functions
Single dimensions (or small numbers of dimensions) are inadequate to capture fine distinctions and the fine-structure of topographies that carry these distinctions

Functional brain atlas

Extensibility

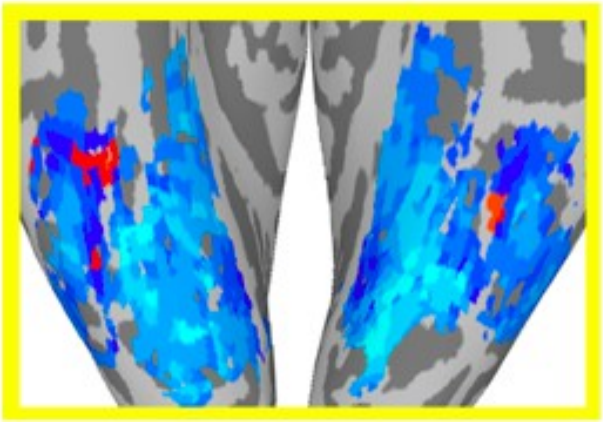
Caveats
Other methods for hyperalignment
Other stimulus or task paradigms for sampling representational spaces

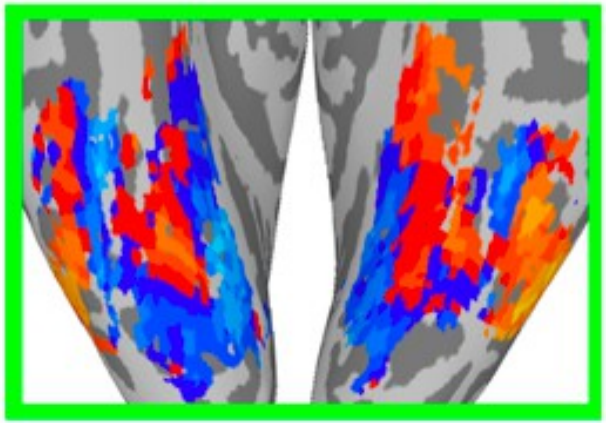
The face versus object topography can be found in common model space by projecting it into the cortical topography of individual brains



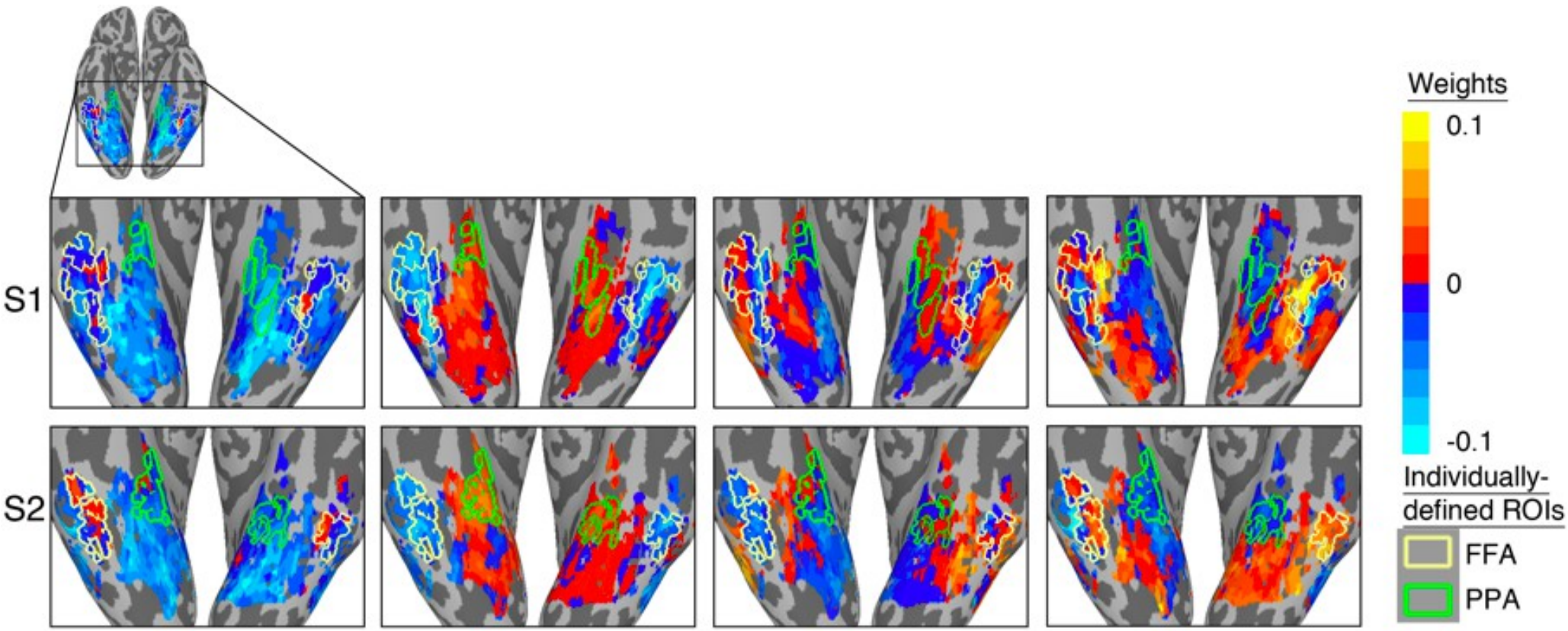
Each model dimension has an individual-specific cortical topography (weights in individual transformation matrix columns)

P		Principal components				
		pc_1	pc_2	pc_3	...	pc_{35}
Voxels	v_1	$w_{1,1}$	$w_{2,1}$	$w_{3,1}$	...	$w_{35,1}$
	v_2	$w_{1,2}$	$w_{2,2}$	$w_{3,2}$	...	$w_{35,2}$
	v_3	$w_{1,3}$	$w_{2,3}$	$w_{3,3}$	...	$w_{35,3}$
	...	...	...	...		...
	v_{1000}	$w_{1,1000}$	$w_{2,1000}$	$w_{3,1000}$	...	$w_{35,1000}$





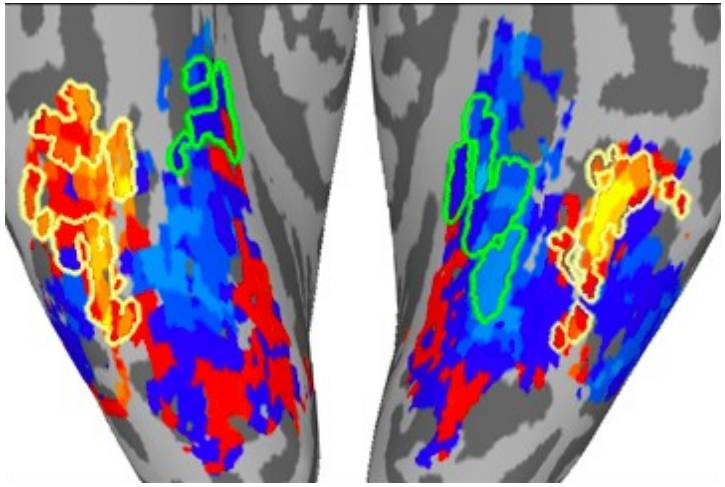
VT topographies for 4 Top Principal Components
A face-specific topography is not evident



PC1 PC2 PC3 PC5

Faces vs objects is a simple contrast that can be modeled as a weighted sum of model dimension topographies

Face vs object contrast in Subject 1



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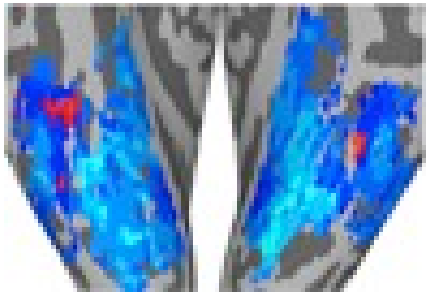
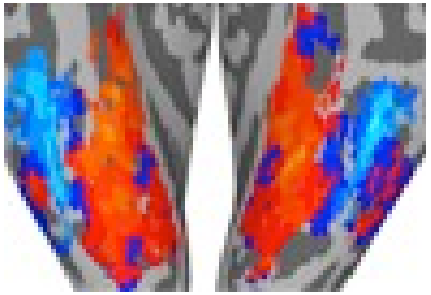
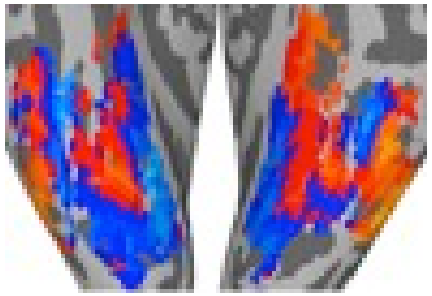
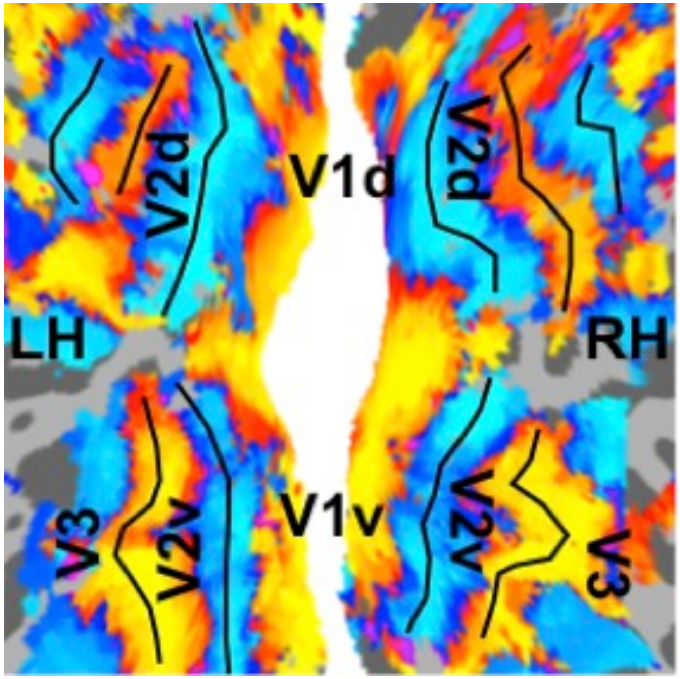
Pattern basis functions for each model dimension

β_1 *  + β_2 *  + … + β_k * 

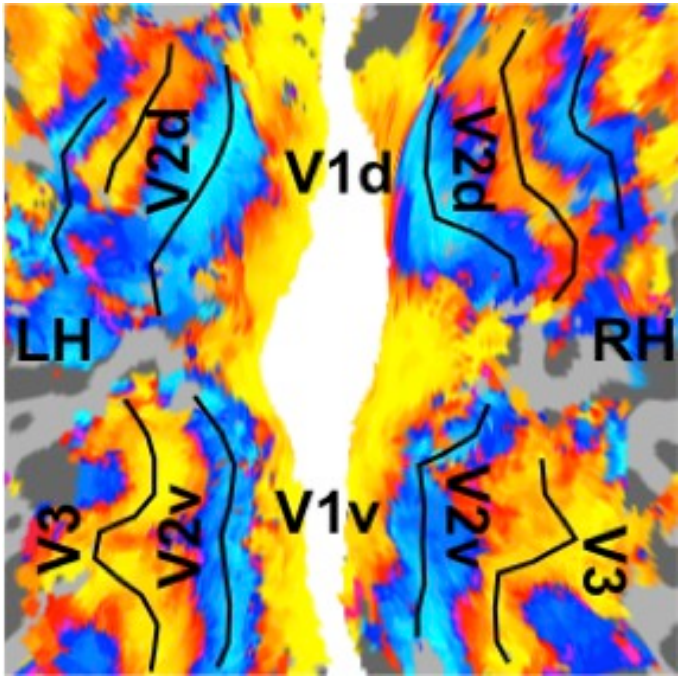
d_1 d_2 d_k

Mapping retinotopy by projecting other subjects' polar angle maps into a different subject's occipital topography

Polar angle from subject's own retinotopy data



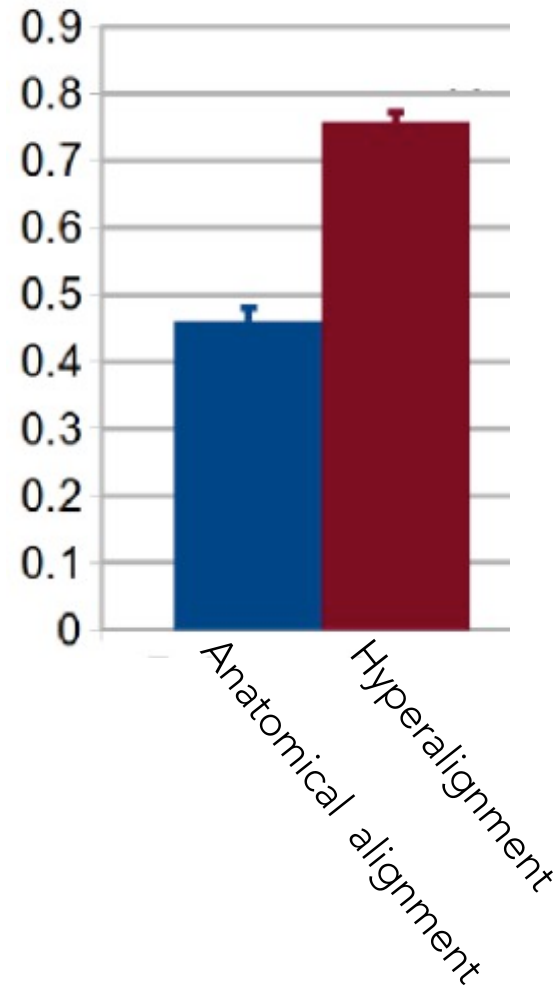
Polar angle from other subjects' retinotopy data



Horizontal meridian

Vertical meridian

Correlation between measured and projected



Why are anatomical coordinates inadequate for capturing neural representation?

- *Response tuning functions* for voxels with the same anatomical coordinates *are highly variable across brains.*
- The *basic unit for neural representation is the population response*, not the responses of single voxels (or single neurons).

Hyperalignment
Swaroop Guntupalli
Post-doctoral fellow

Parcellation using resting state fMRI connectivity

17 systems
(Yeo et al. 2011)

422 areas (group)
(Gordon et al. 2014)

616 areas (individual)
(Laumann et al. 2015)