Decoding representational spaces with multivariate pattern analysis (MVPA) of fMRI data

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Haxby Lab

Analysis of similarity structure,
representation of biological classes
Andy Connolly
Post-doctoral fellow

Hyperalignment
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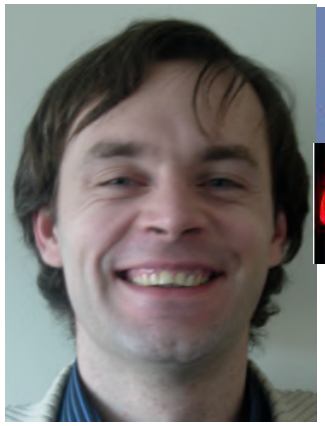
Post-doctoral fellow

Attention
Sam Nastase
Graduate student

Person perception
Dylan Wagner
Post-doctoral fellow

Action representation, computational methods
Nick Oosterhof
Post-doctoral fellow



PyMVPA

NeuroDebian

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Hyperalignment
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Superfish, Israel

Hao Xu
Google

Cameron Chen
current

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- Neural decoding: understanding representational spaces
- 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
- Conclusions

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

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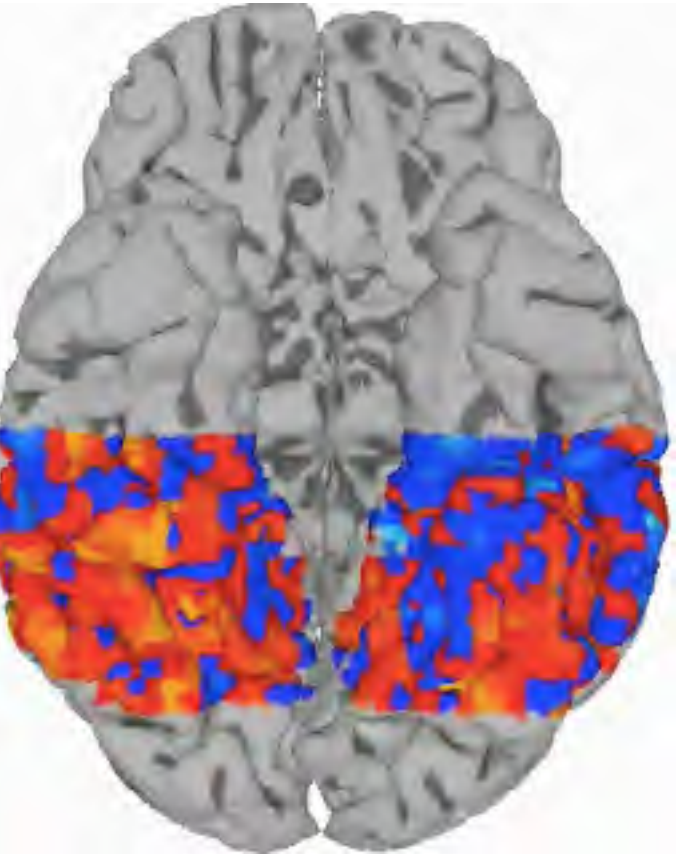
fMRI data matrix



		Voxels				
		v_1	v_2	v_3	...	v_i
Time-points	t_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{i,1}$
	t_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	...	$x_{i,2}$
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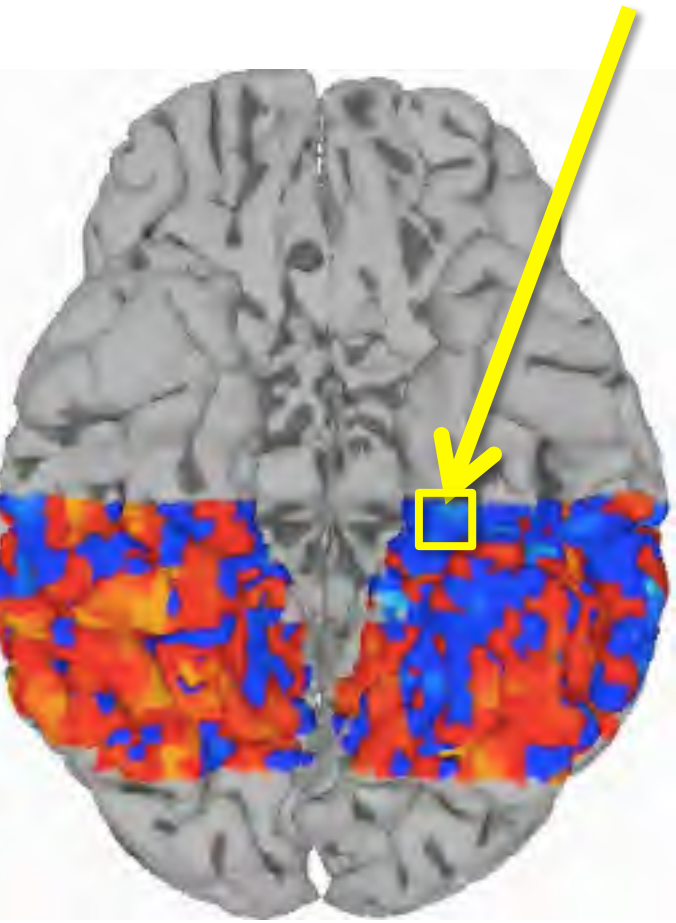
fMRI data matrix
Columns are voxel response tuning profiles



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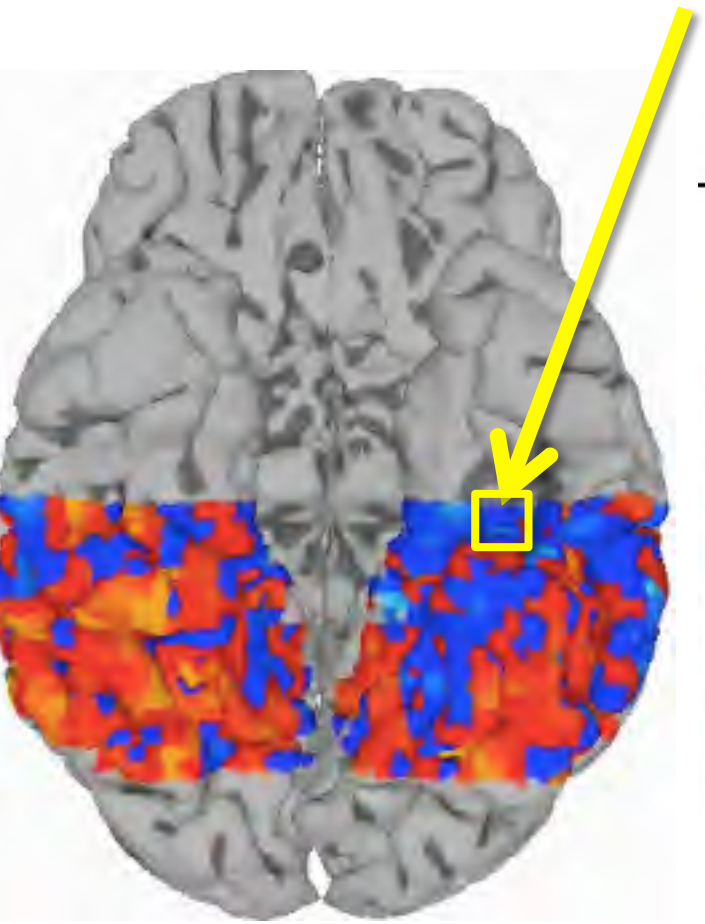

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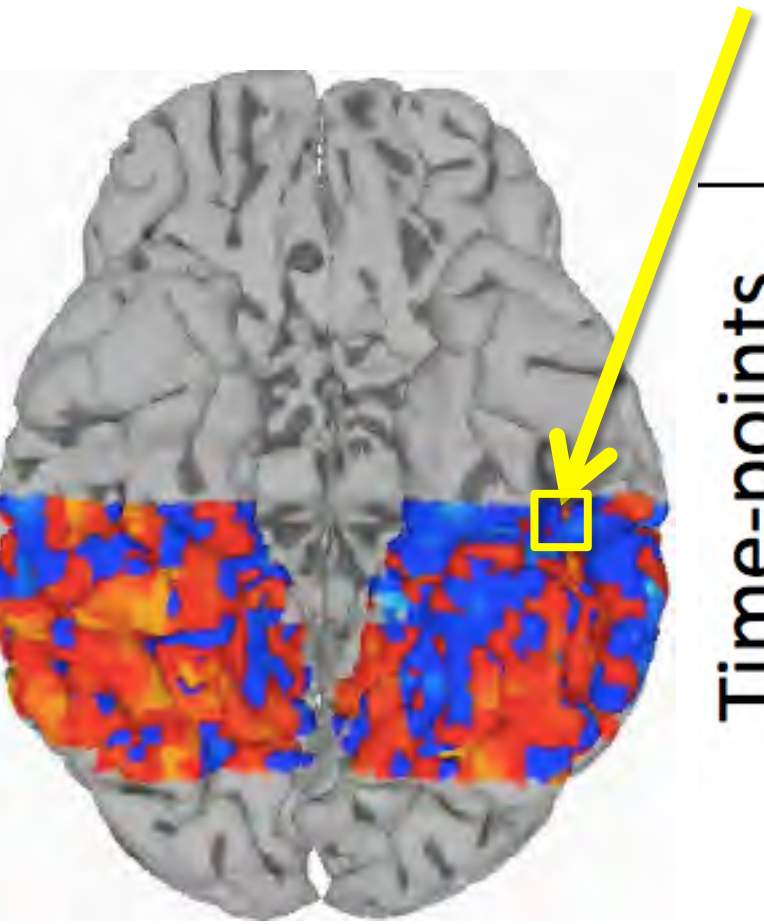

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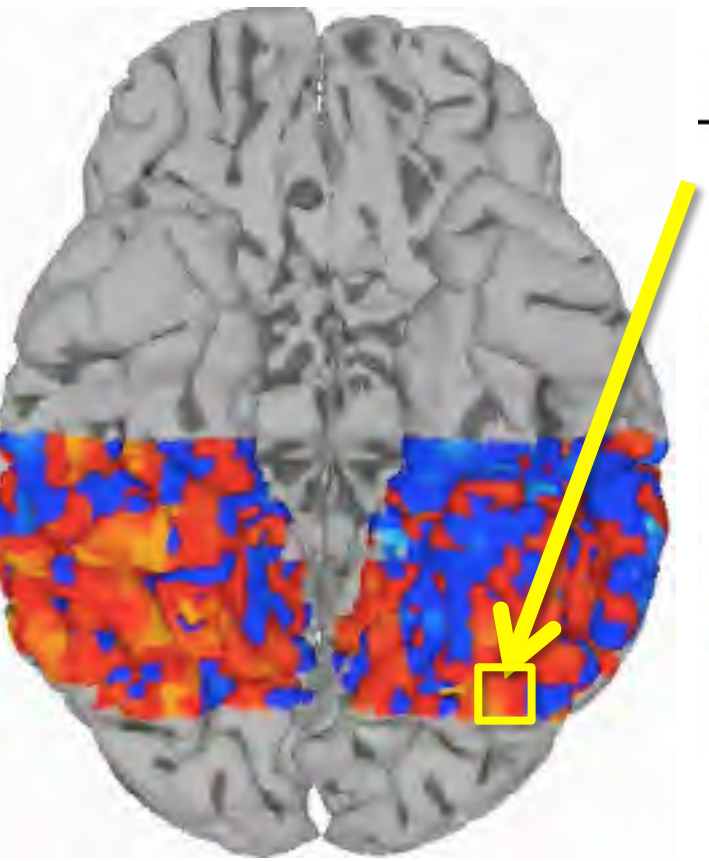

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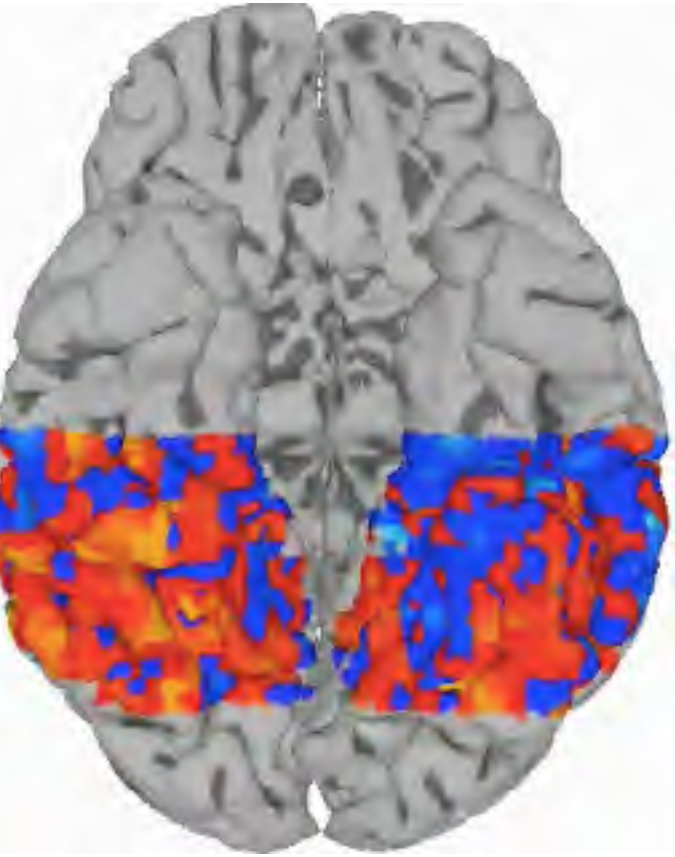
fMRI data matrix
Rows are multivoxel response patterns



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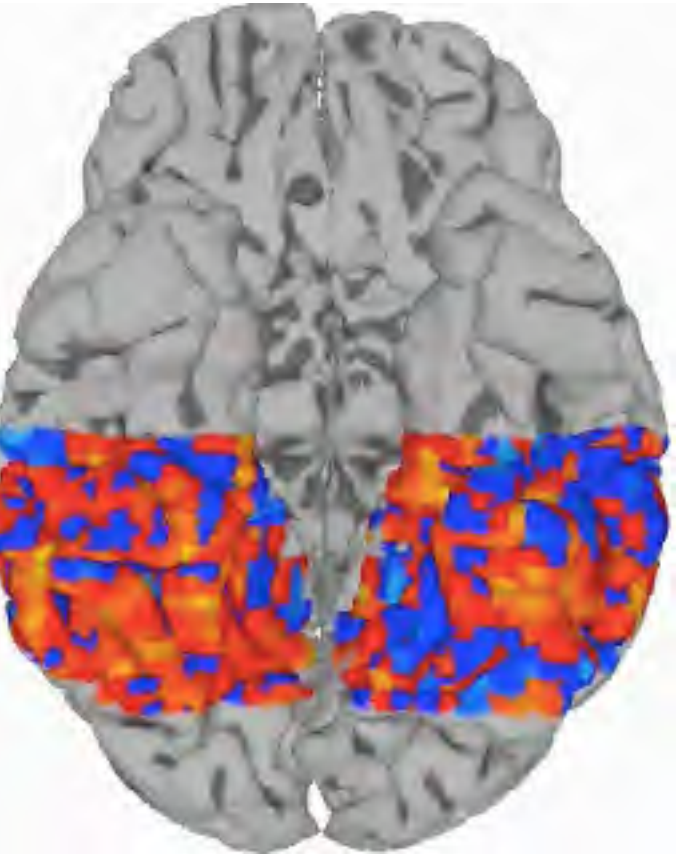

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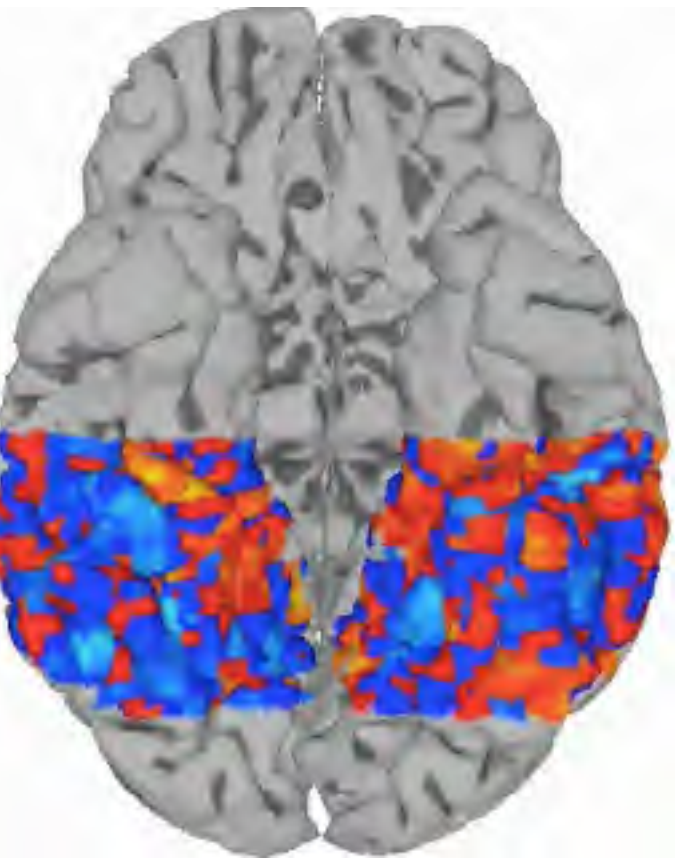

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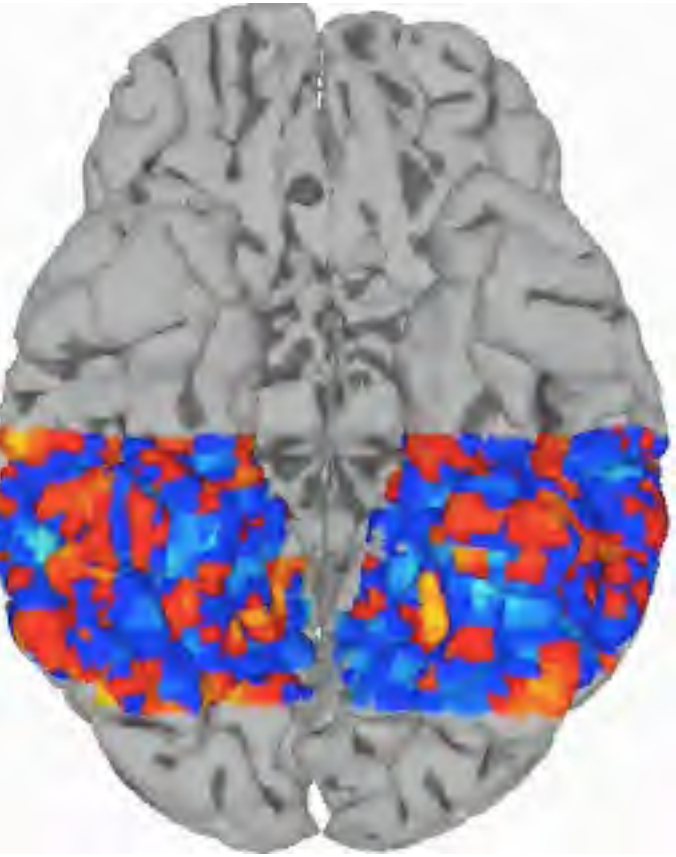

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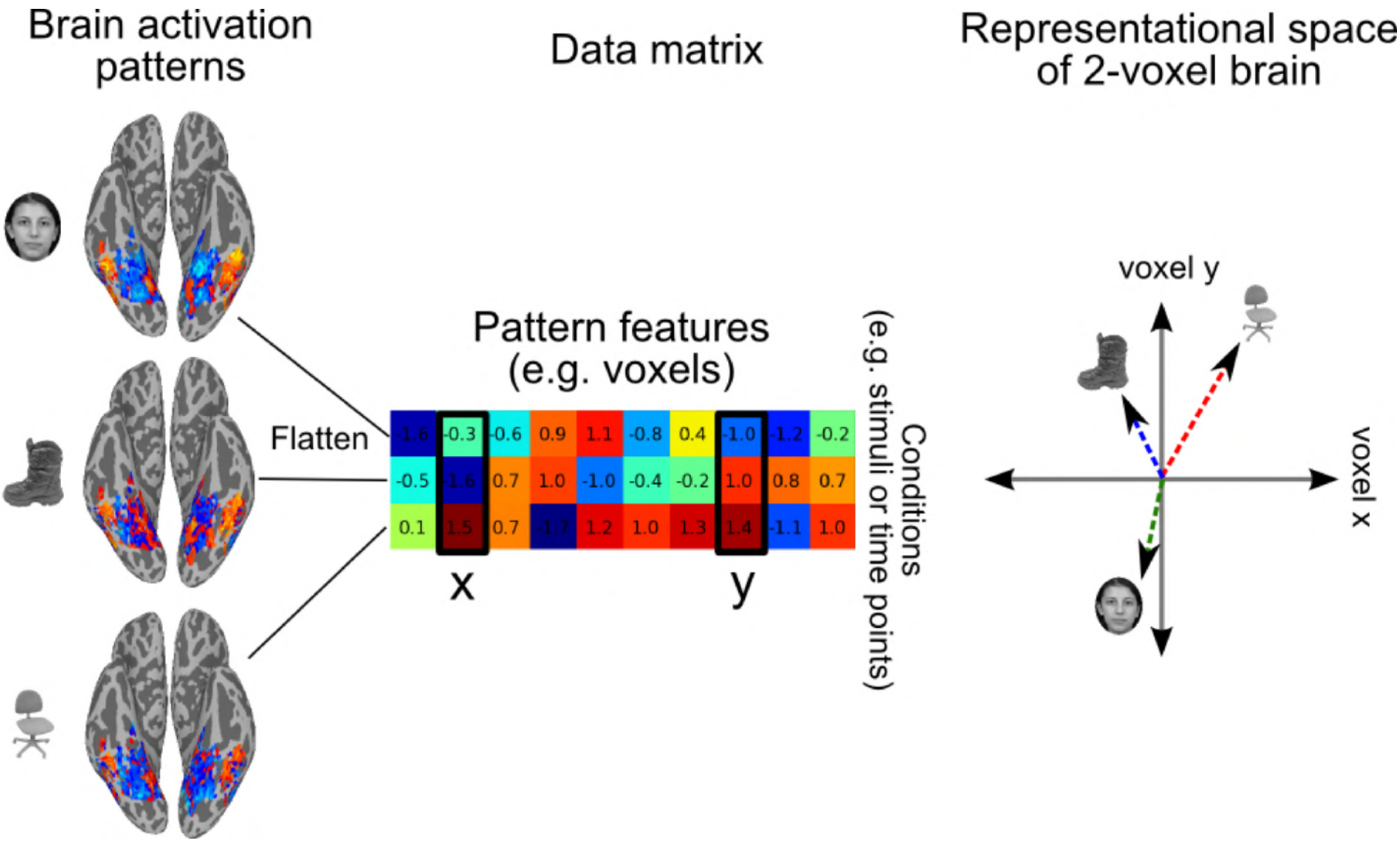
What is a neural representational space?

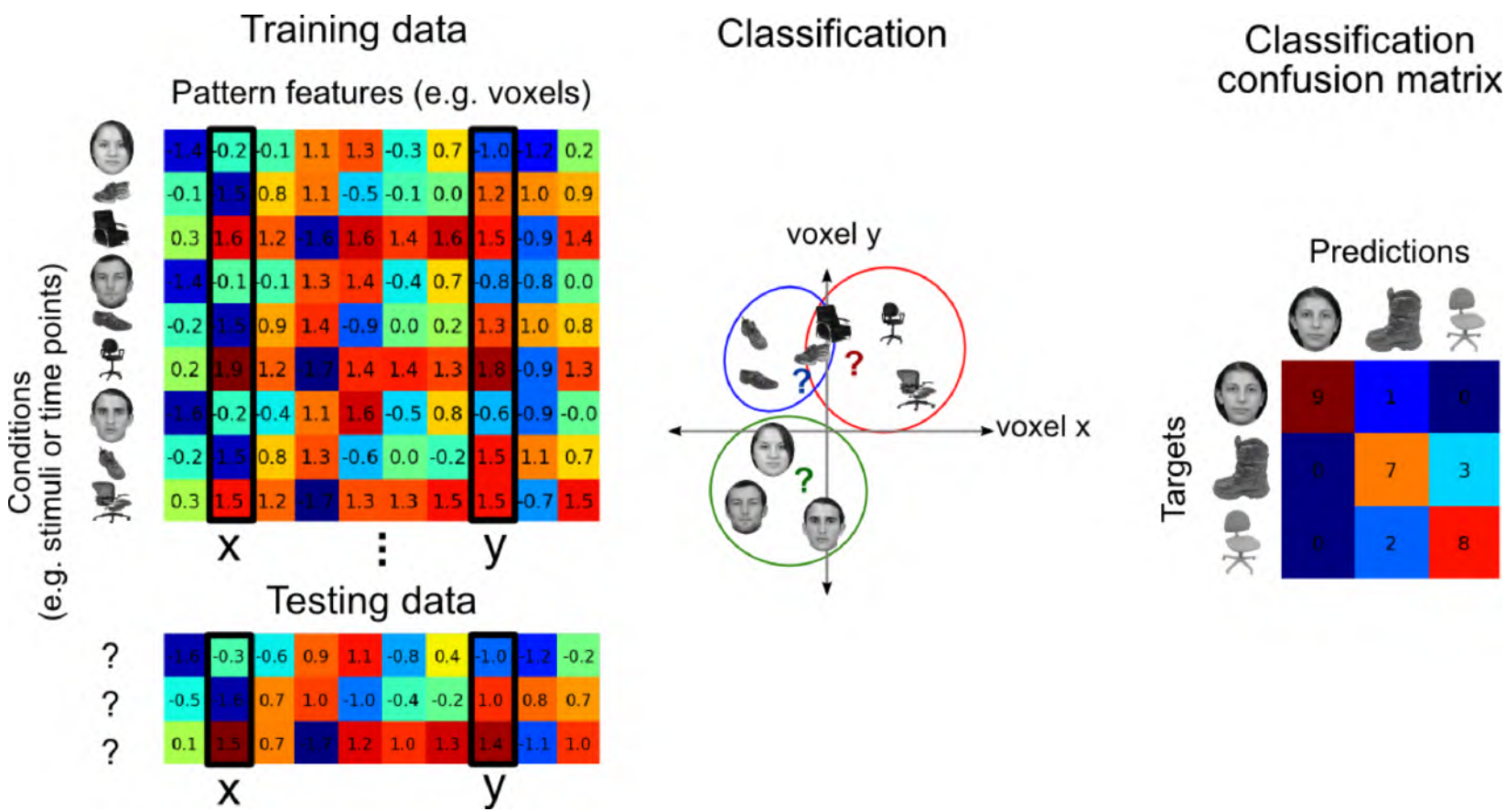
A pattern of activity (distributed over cortex) can be analyzed as a vector in an n-dimensional space, where n = number of voxels (fMRI) or neurons (single unit recordings) or …



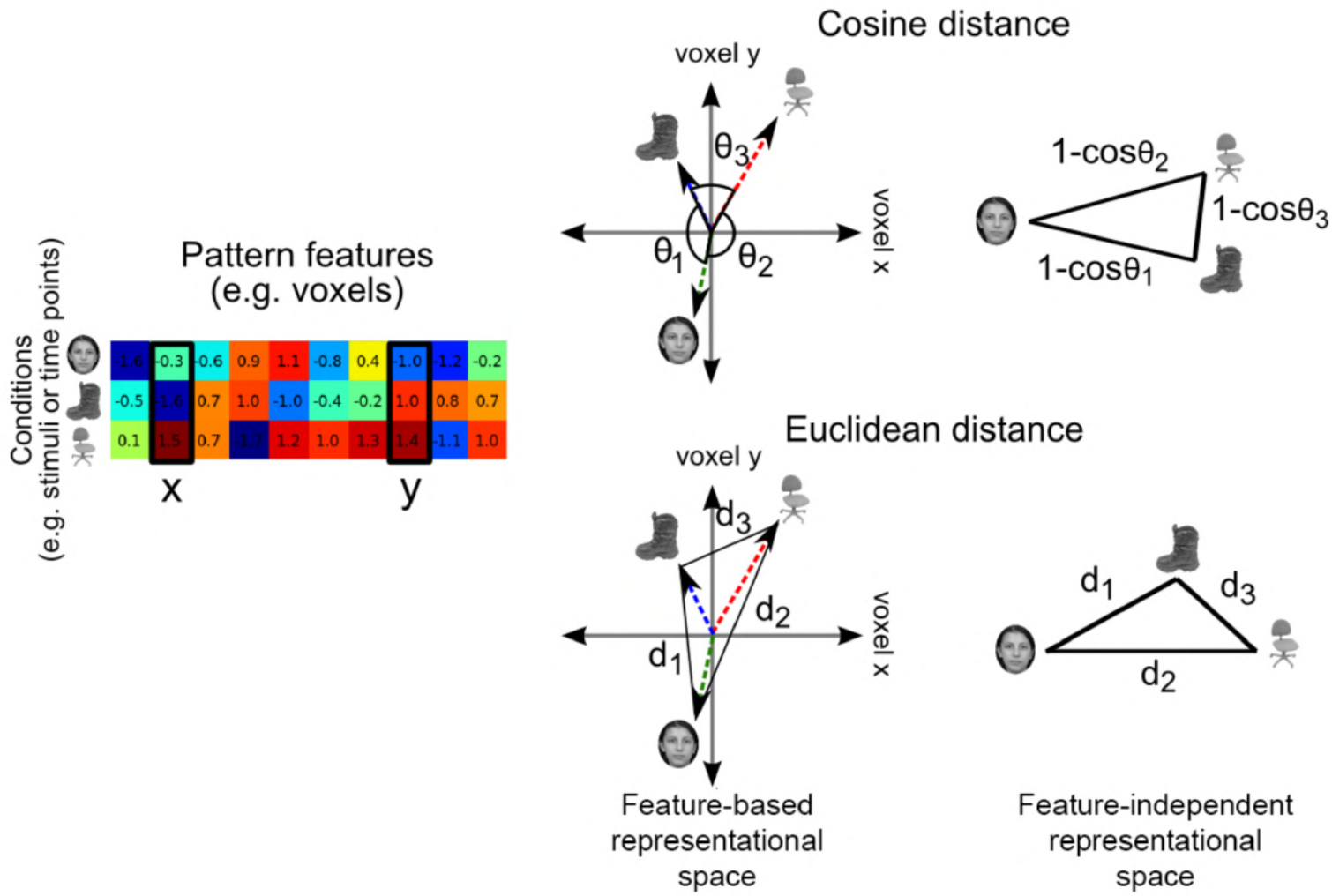
Neural decoding using multivariate pattern analysis (MVPA)

- Pattern classification (MVPC)
- Representational similarity analysis (RSA)

MVP Classification divides the representational space into sectors, each of which is associated with a different category



Representational similarity analysis (RSA) indexes similarities between vectors as distances to analyze *representational geometry*



MVPC of fMRI data

- Each observation (pattern) is treated as a high-dimensional vector
- Each dimension is a single feature - usually a voxel

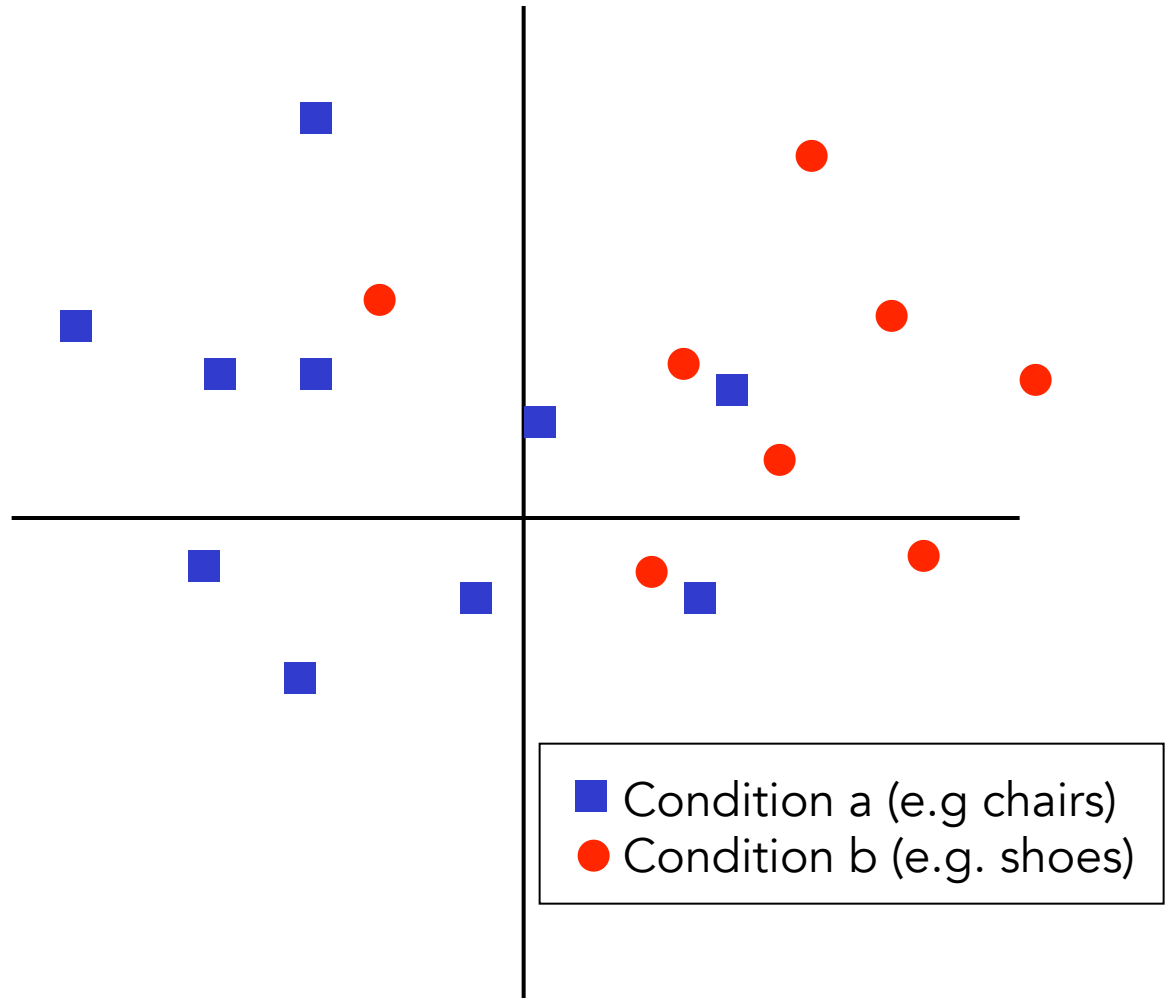


Illustration: 2 voxel pattern classifier

MVPC of fMRI data

- Each observation (pattern) is treated as a high-dimensional vector
- Each dimension is a single voxel (or other feature)
- Classifiers find a rule (e.g. decision surface) that optimally differentiates observations for different conditions

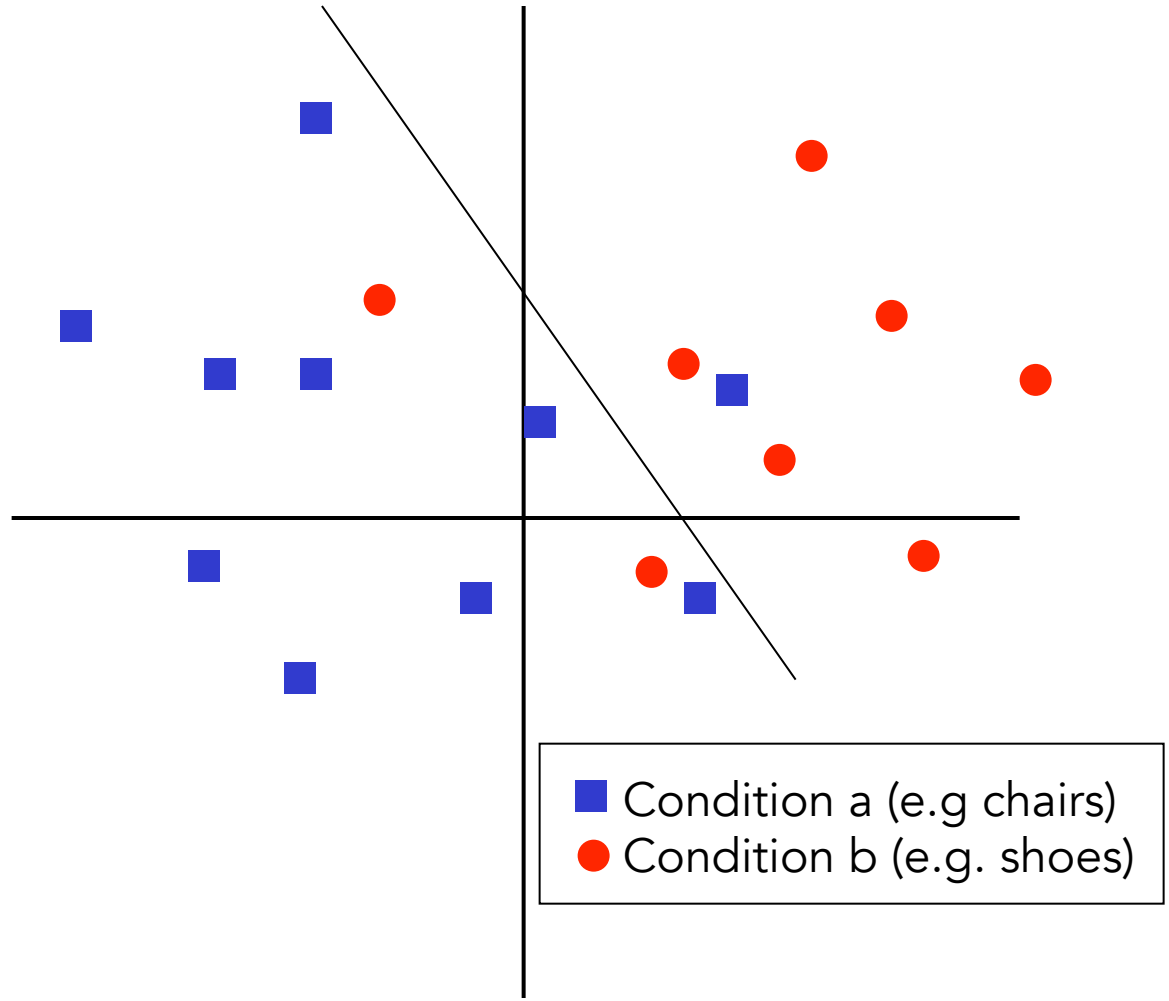
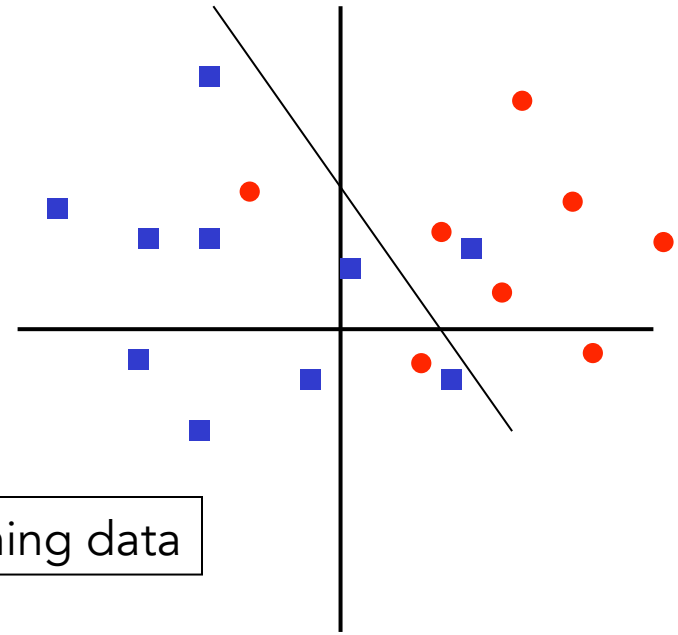


Illustration: 2 voxel pattern classifier

MVPC of fMRI data

- Each observation (pattern) is treated as a high-dimensional vector
- Each dimension is a single voxel (or other feature)
- Classifiers find a rule (e.g. decision surface) that optimally differentiates observations for different conditions
- The validity of that rule is tested on independent test data that played no role in deriving that rule



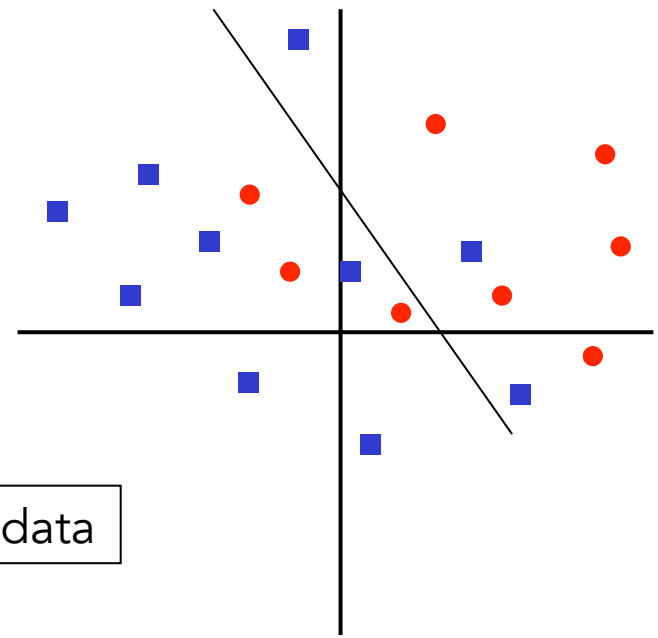


Illustration: 2 voxel pattern classifier

Building and Testing Pattern Classifiers

1. Divide observations into training and test data sets
2. Based on the training data <u>only</u>
   a. Select features (usually voxels)
   b. Develop decision rule
3. Test decision rule on test data set

A new classifier is built for each individual

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

(VT cortex, SVM)

luna moth ladybug

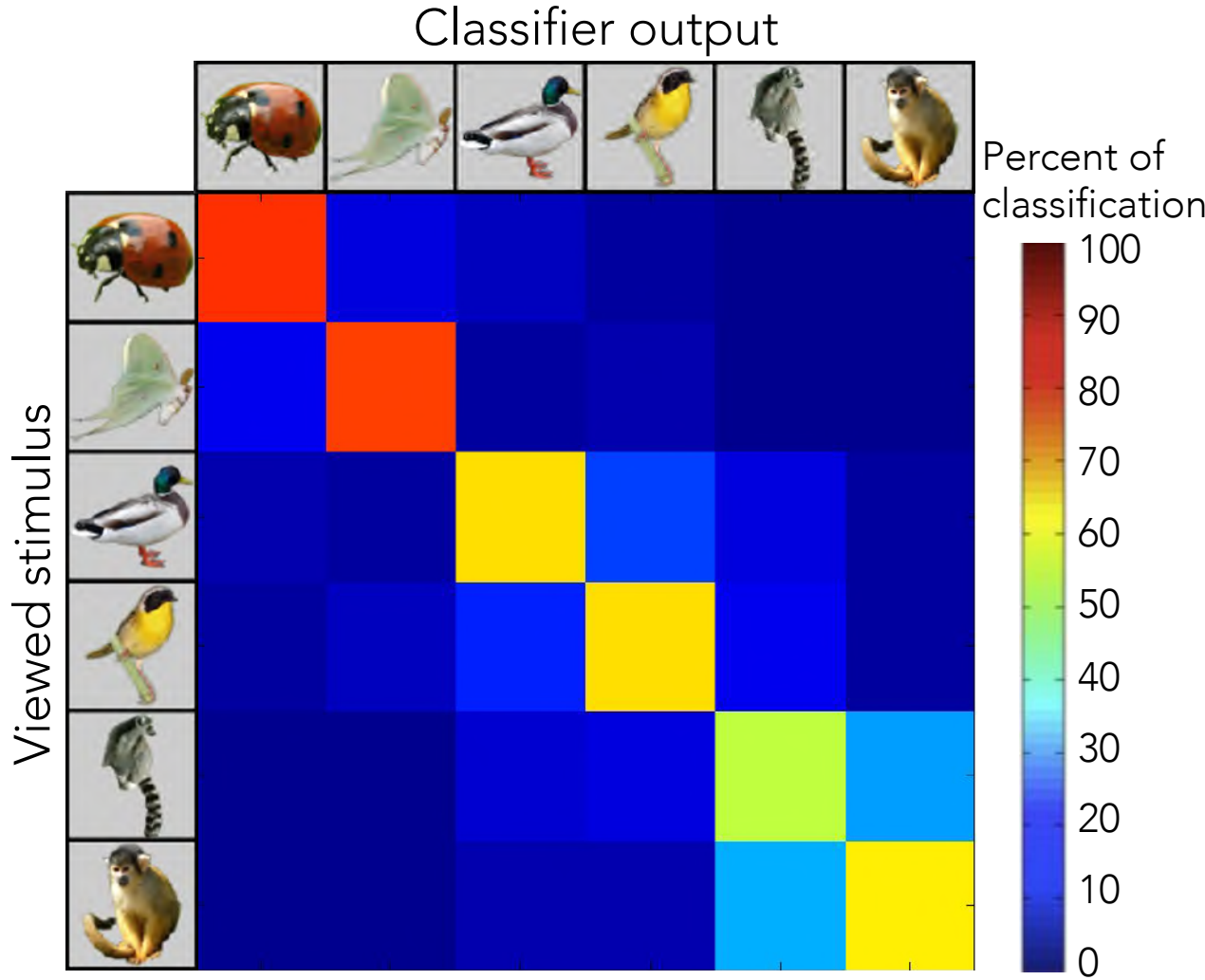
Insects

warbler mallard

Birds

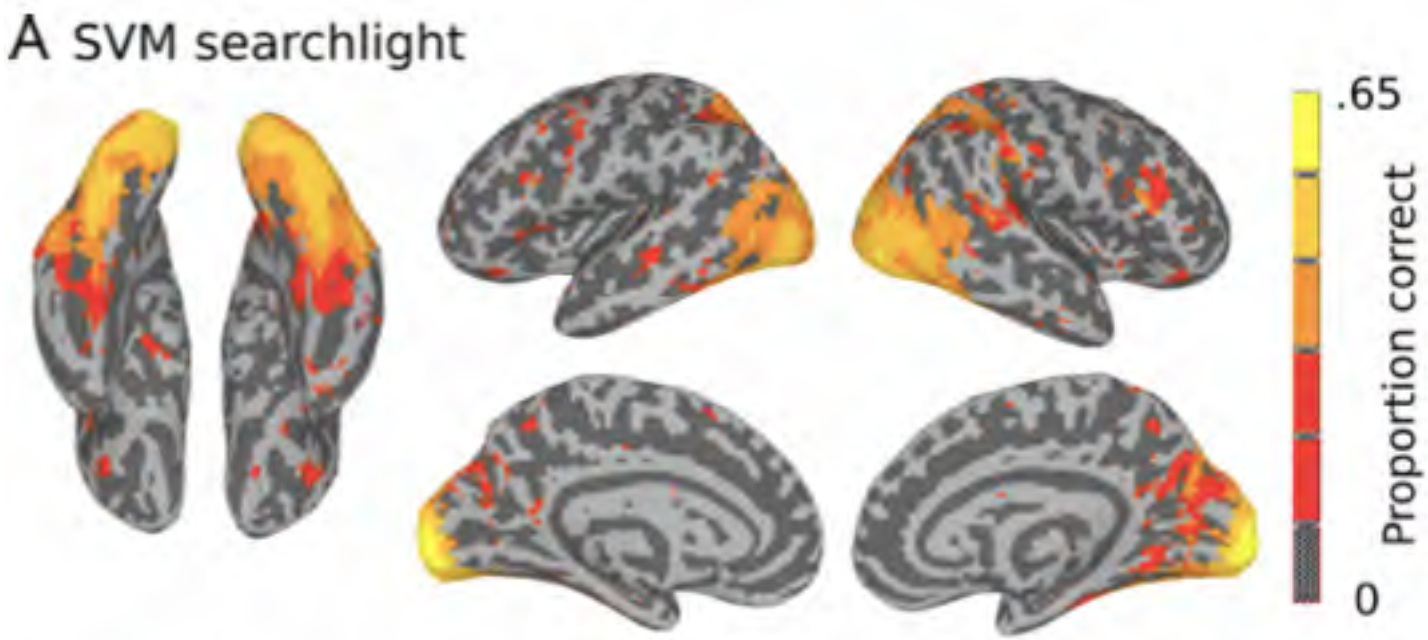
monkey lemur

Primates

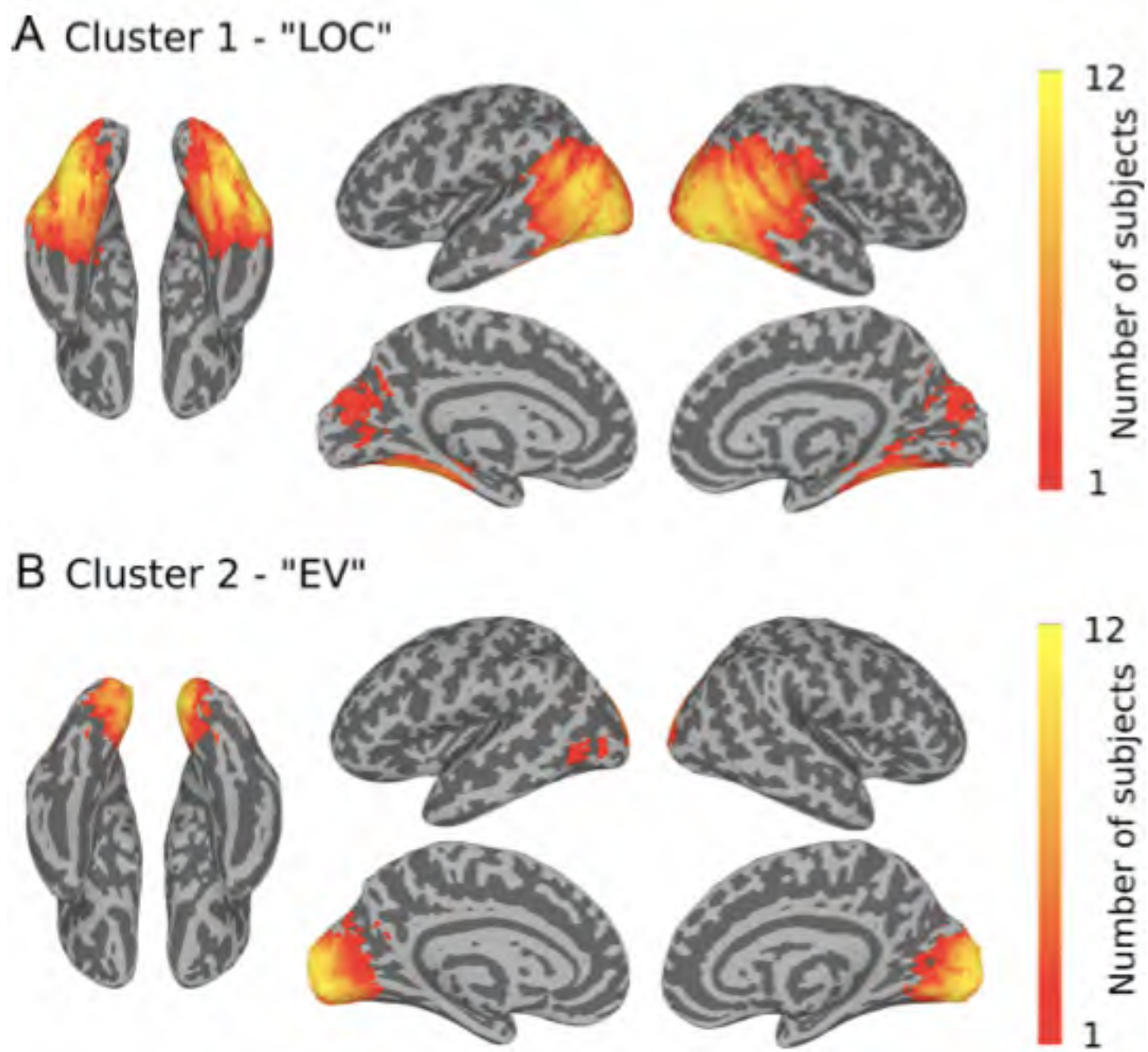


(Haxby et al. 2011; Connolly et al. 2012)

MVP classification of animal species is significant in both early visual cortex and the ventral visual pathway (LOC)
(Connolly et al. 2012)



Data-driven cluster analysis finds distinct representational geometries in the ventral visual pathway (LOC) and early visual cortex (EV)
(Connolly et al. 2012)



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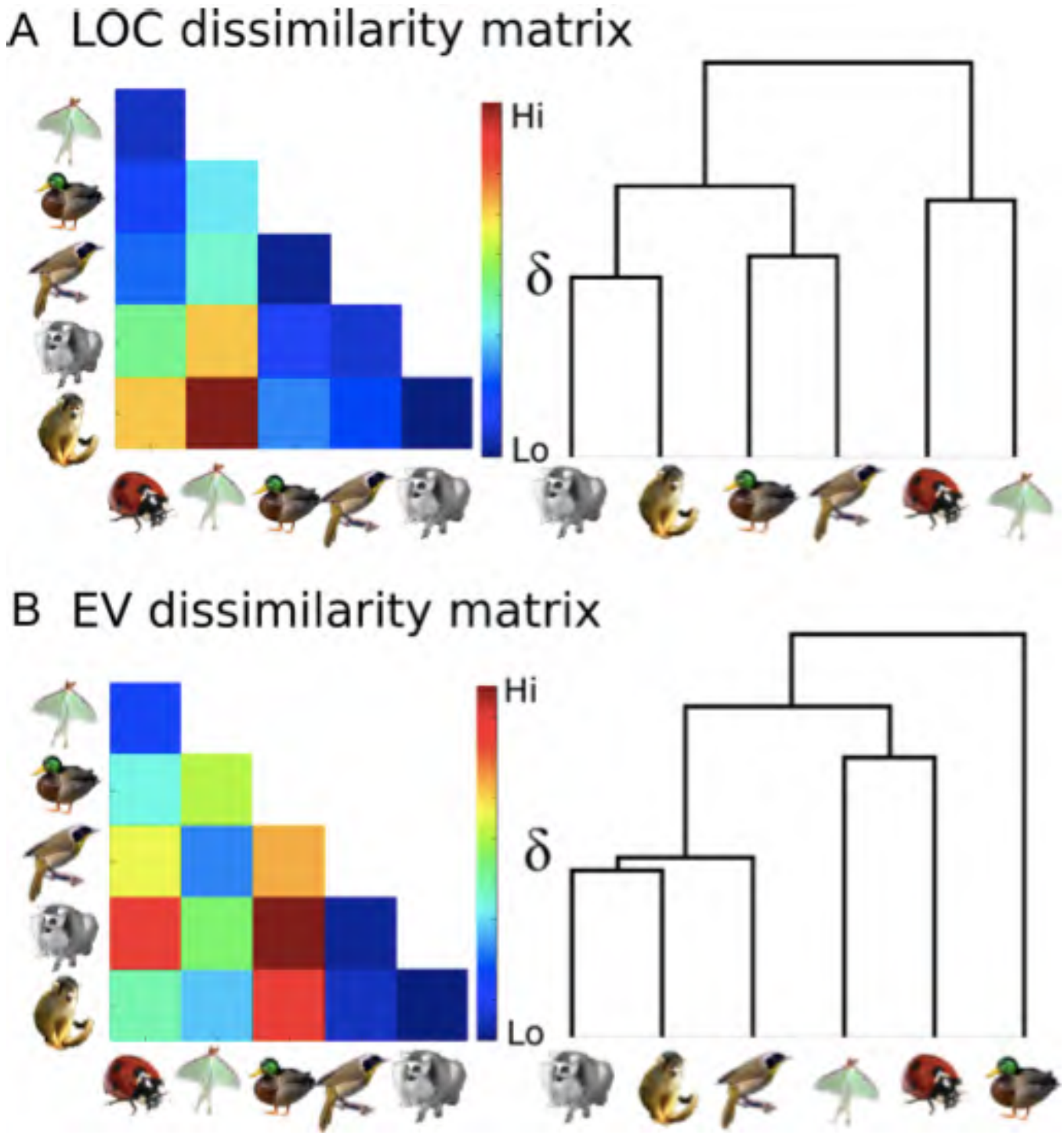
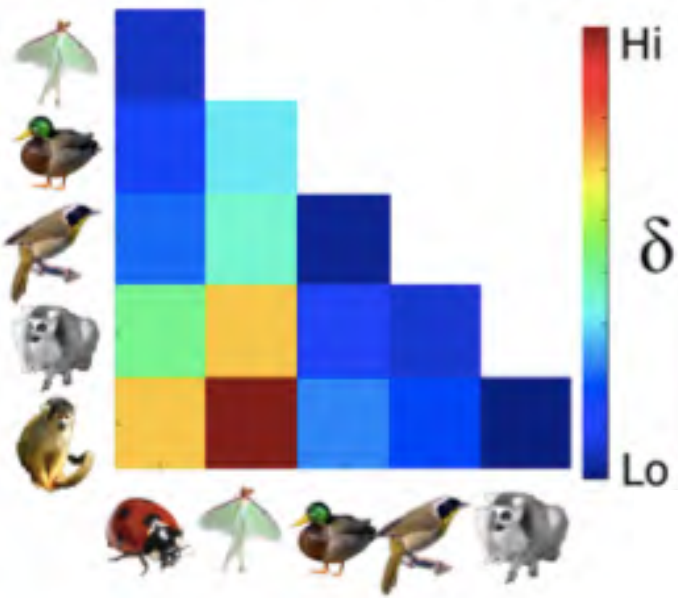


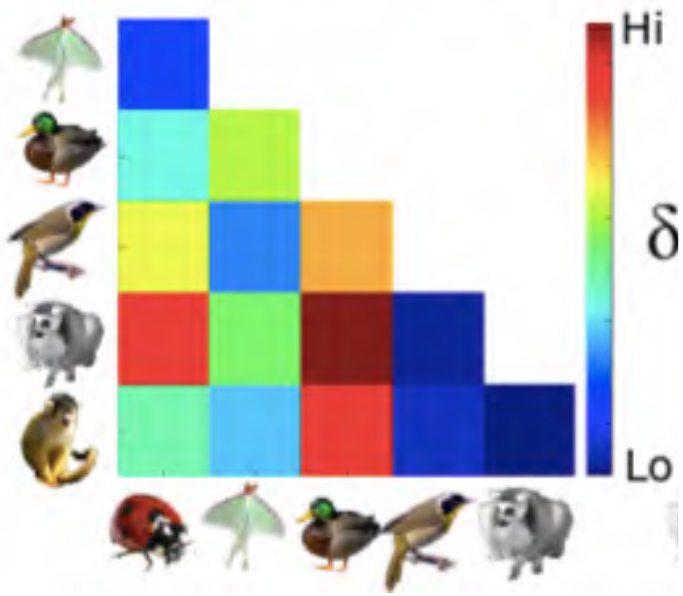
DSMs in early visual and LOC cortices correlate highly with semantic ratings and V1 models but not with each other (Connolly et al. 2012)

A LOC dissimilarity matrix



Correlation with ratings model = 0.76

B EV dissimilarity matrix



Correlation with V1 model = 0.78

Correlation between LOC and EV DSMs = 0.09

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

- Neural decoding: understanding representational spaces
- Statement of the problem: capturing fine-grained distinctions in a common model
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- Validation
- Conclusions

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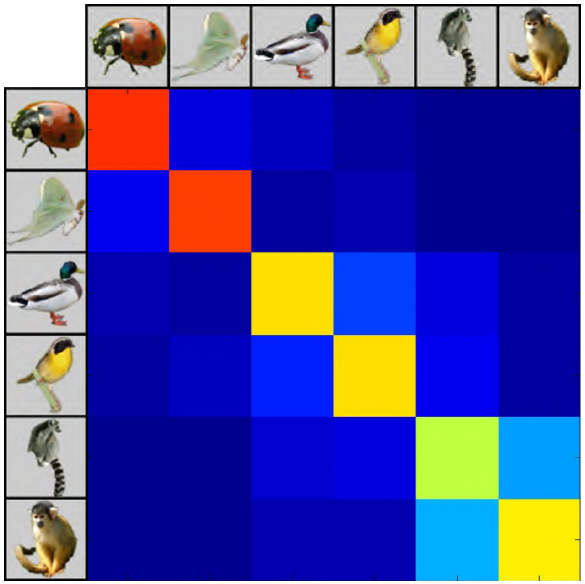
The problem:
Building model representational spaces that are common across brains

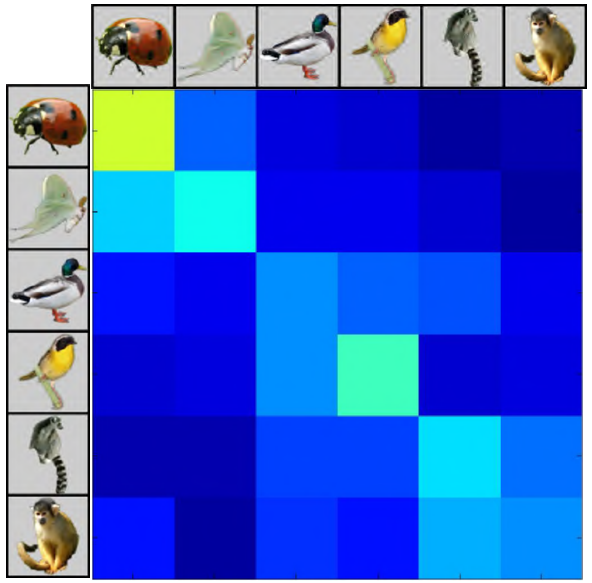
- MVPA detects fine distinctions carried by fine-grained patterns of neural activity
- Anatomical alignment of brain spaces blurs these fine-grained distinctions
- Can a model of functional brain architecture capture these fine-grained distinctions among representations in a common framework?
    - If so, how would such a model be structured?
    - Will it work? Do brains share a common basis for neural coding?

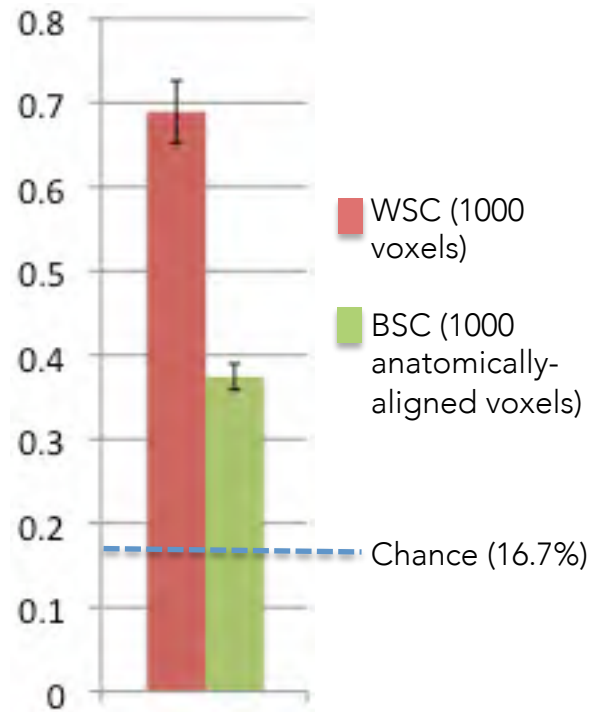
The problem:
Loss of fine-grained distinctions among representations after anatomical alignment of brains

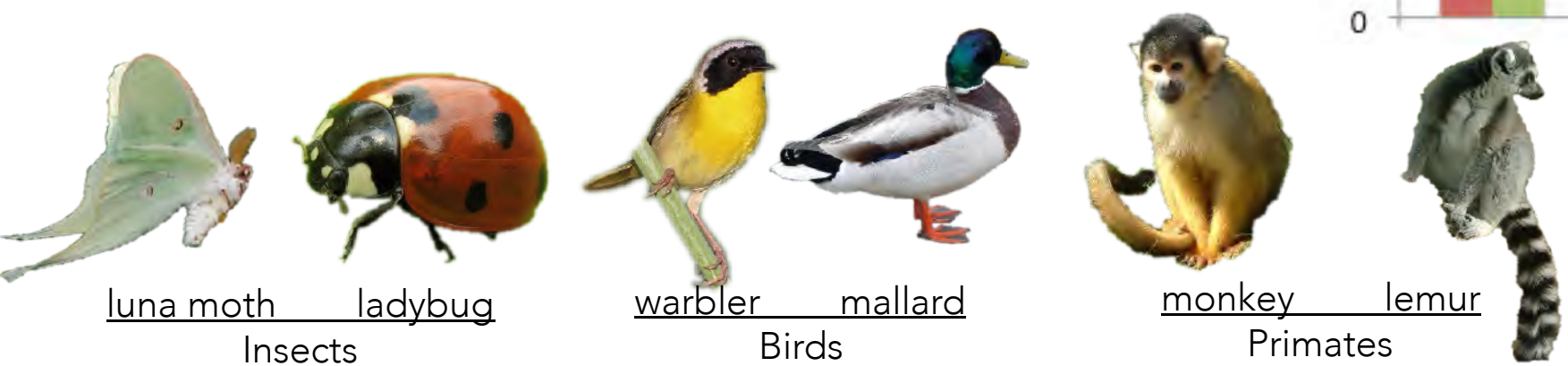
Within-subject classification
(new model for each subject)



Between-subject classification
(common model based on anatomy)







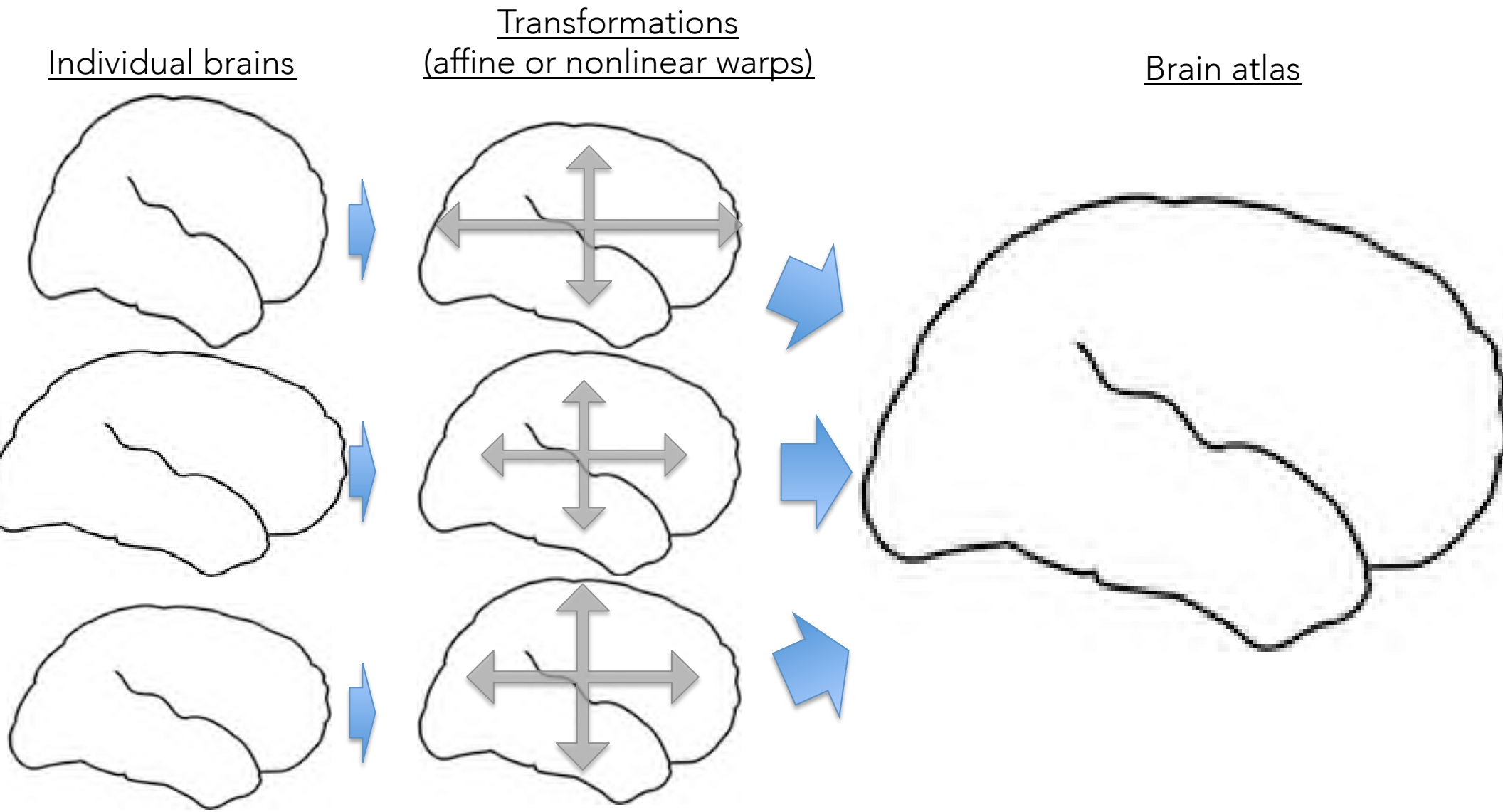
luna moth ladybug
Insects

warbler mallard
Birds

monkey lemur
Primates

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

Modeling functional architecture of the human cortex: Anatomical alignment



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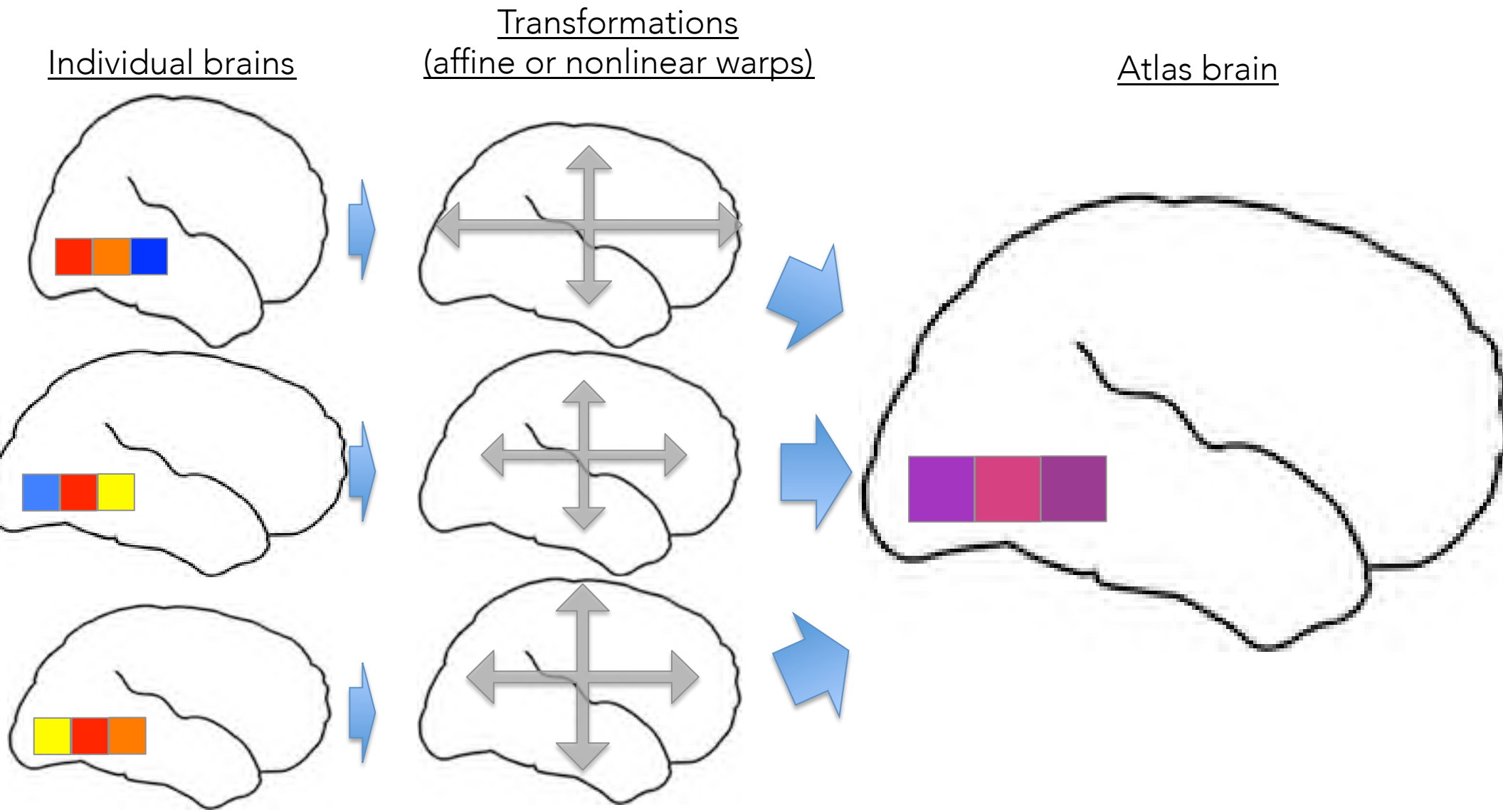

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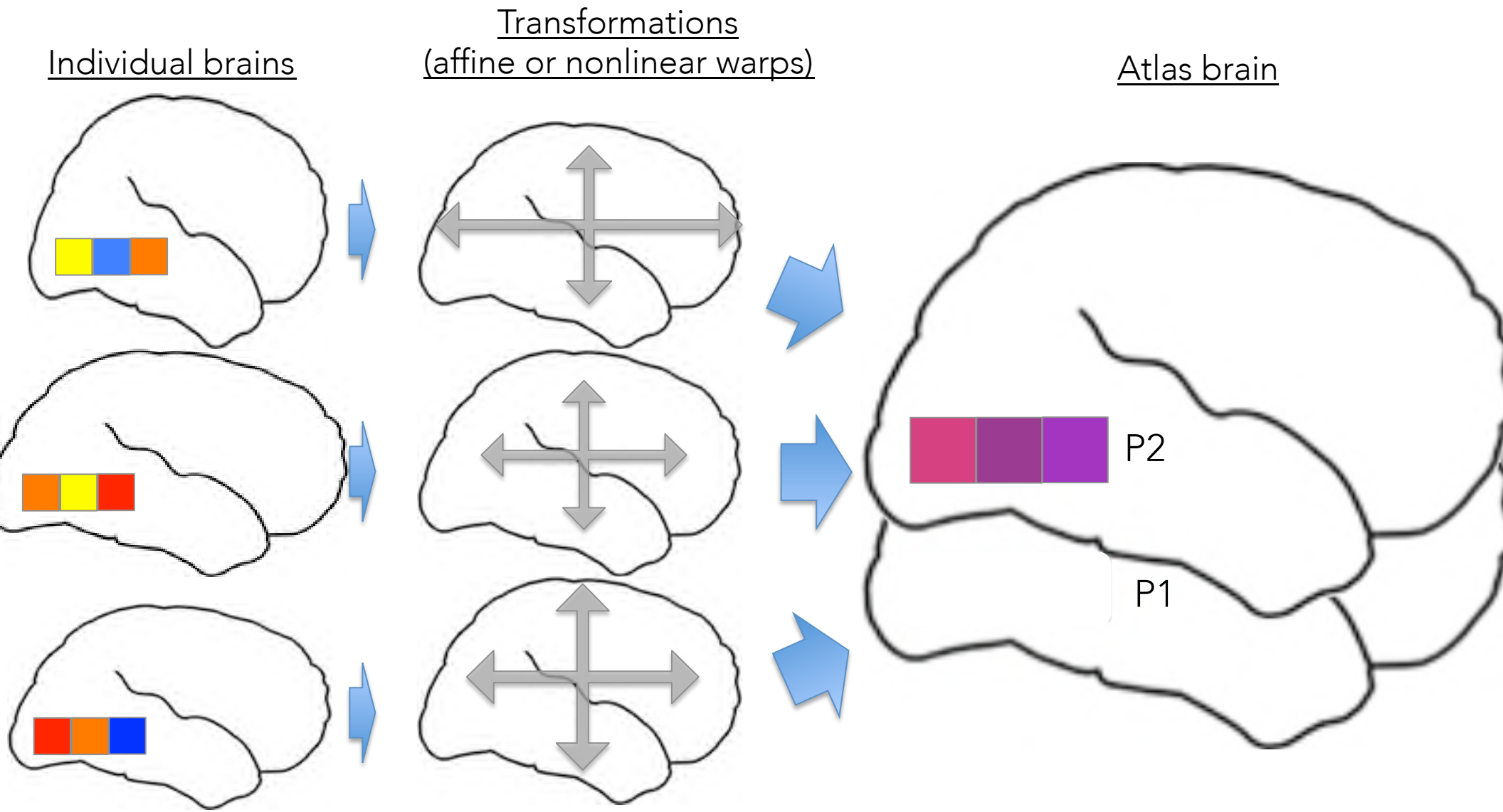
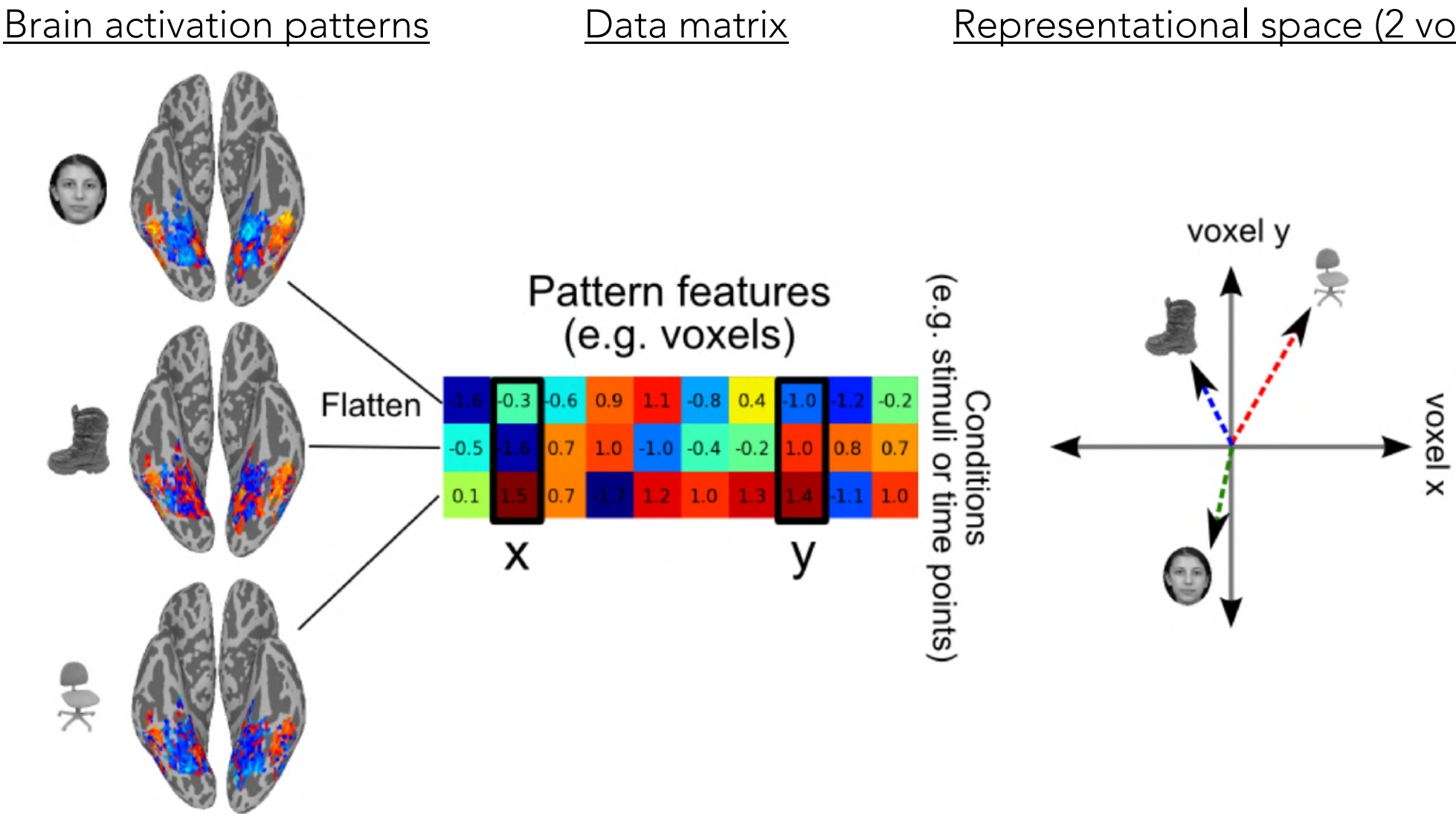
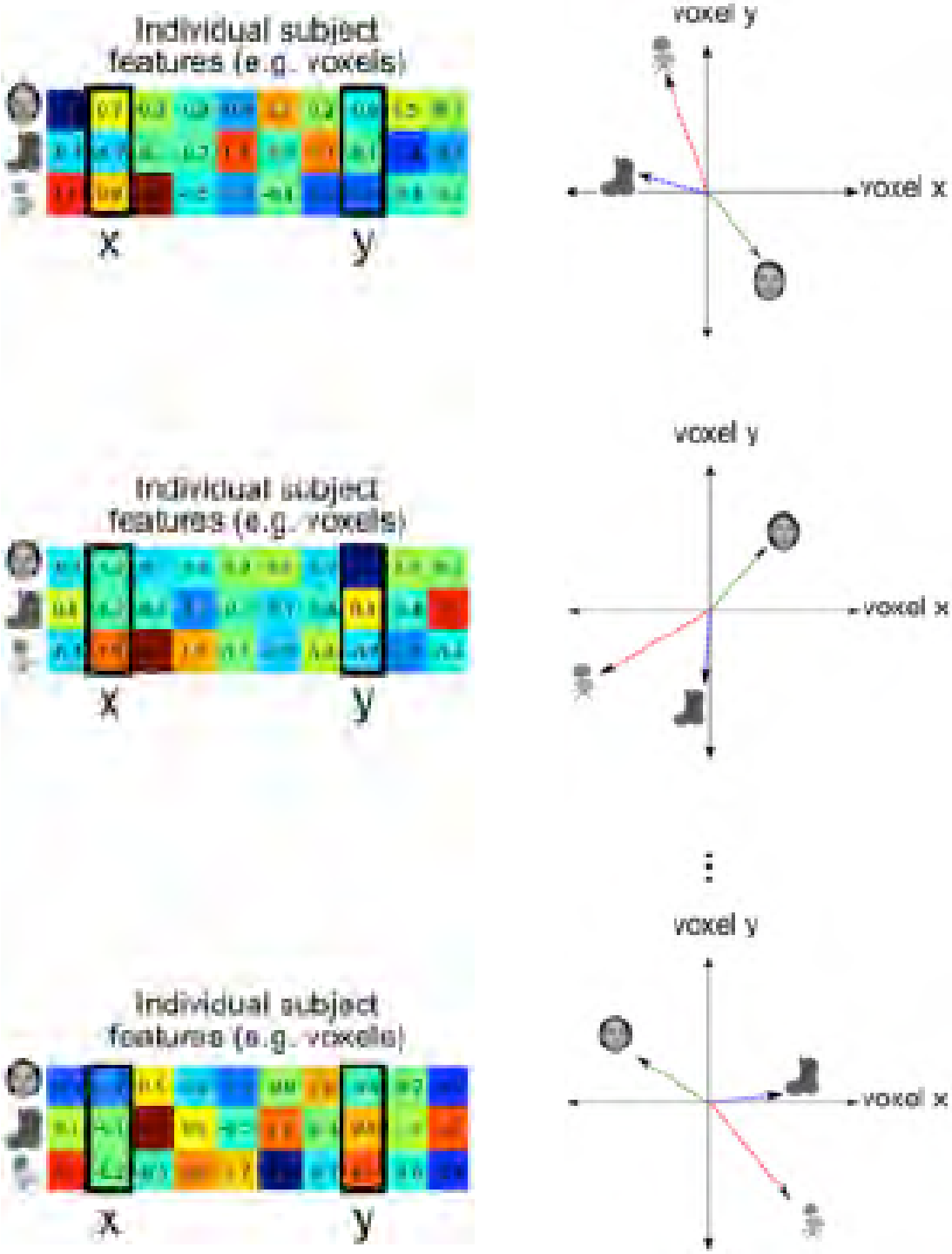


A common high-dimensional linear model of representational spaces in human cortex

- Statement of the problem: capturing fine-grained distinctions in a common model
- Conceptual framework: high-dimensional representational spaces
  - A pattern of activity is a response vector
  - Dimensions are local features, e.g. voxels, of the pattern of activity
  - Model space is based on features (dimensions) with common tuning profiles
- Deriving the common space and individual transformation matrices with hyperalignment
- Validation
- Conclusions

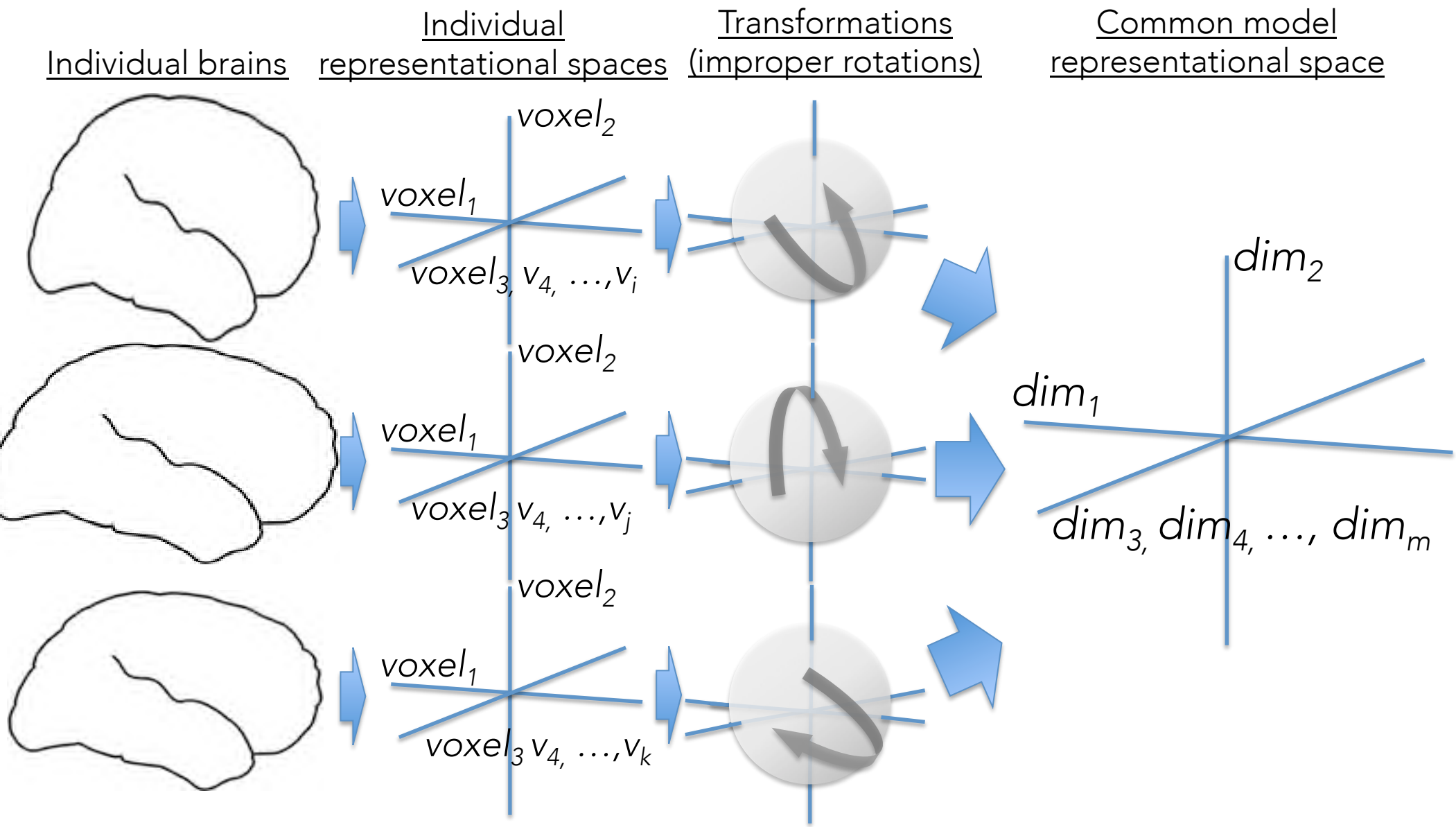
Conceptual framework:
High-dimensional representational spaces



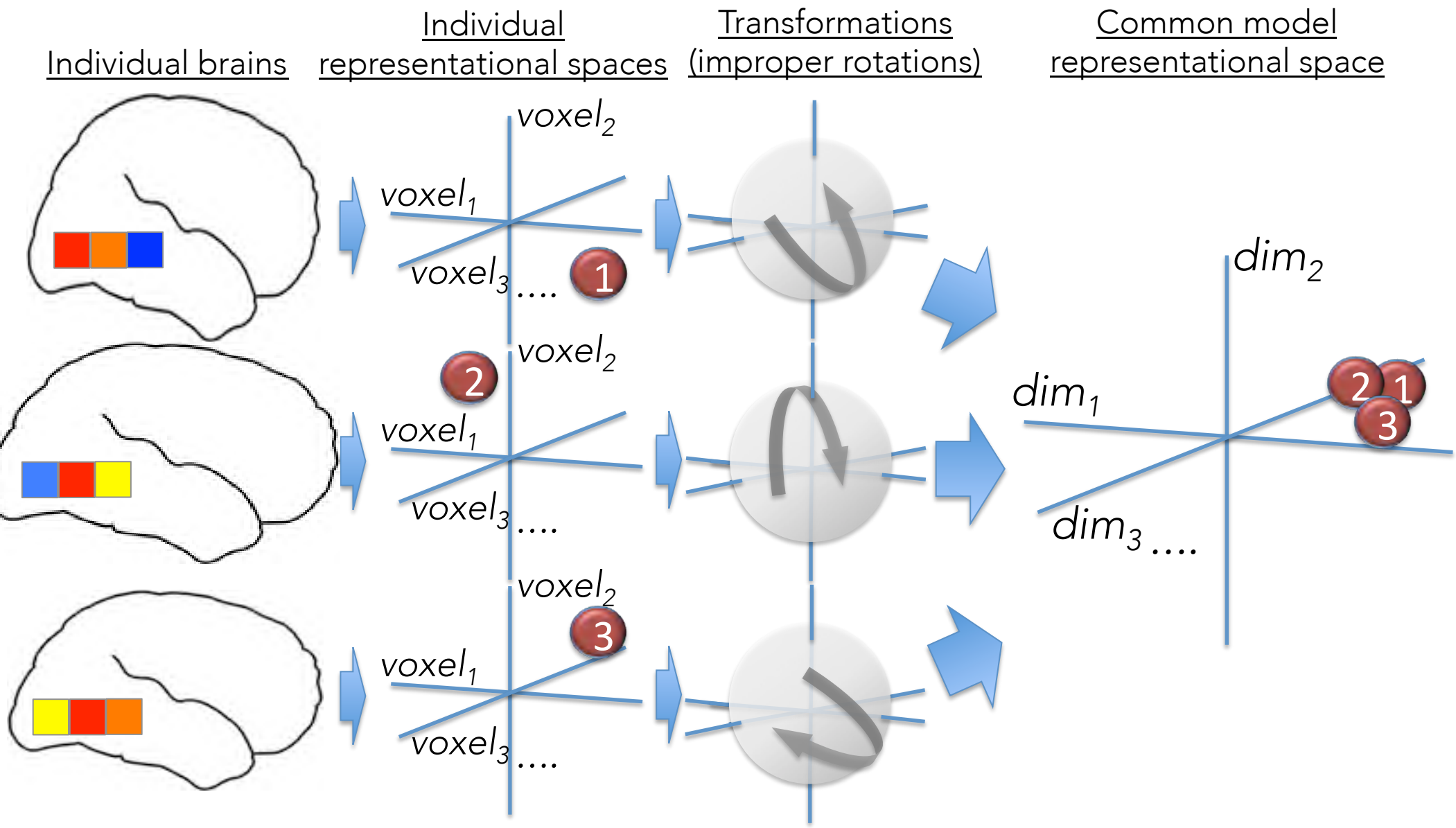


The locations of response pattern vectors for the same stimuli differ across subjects

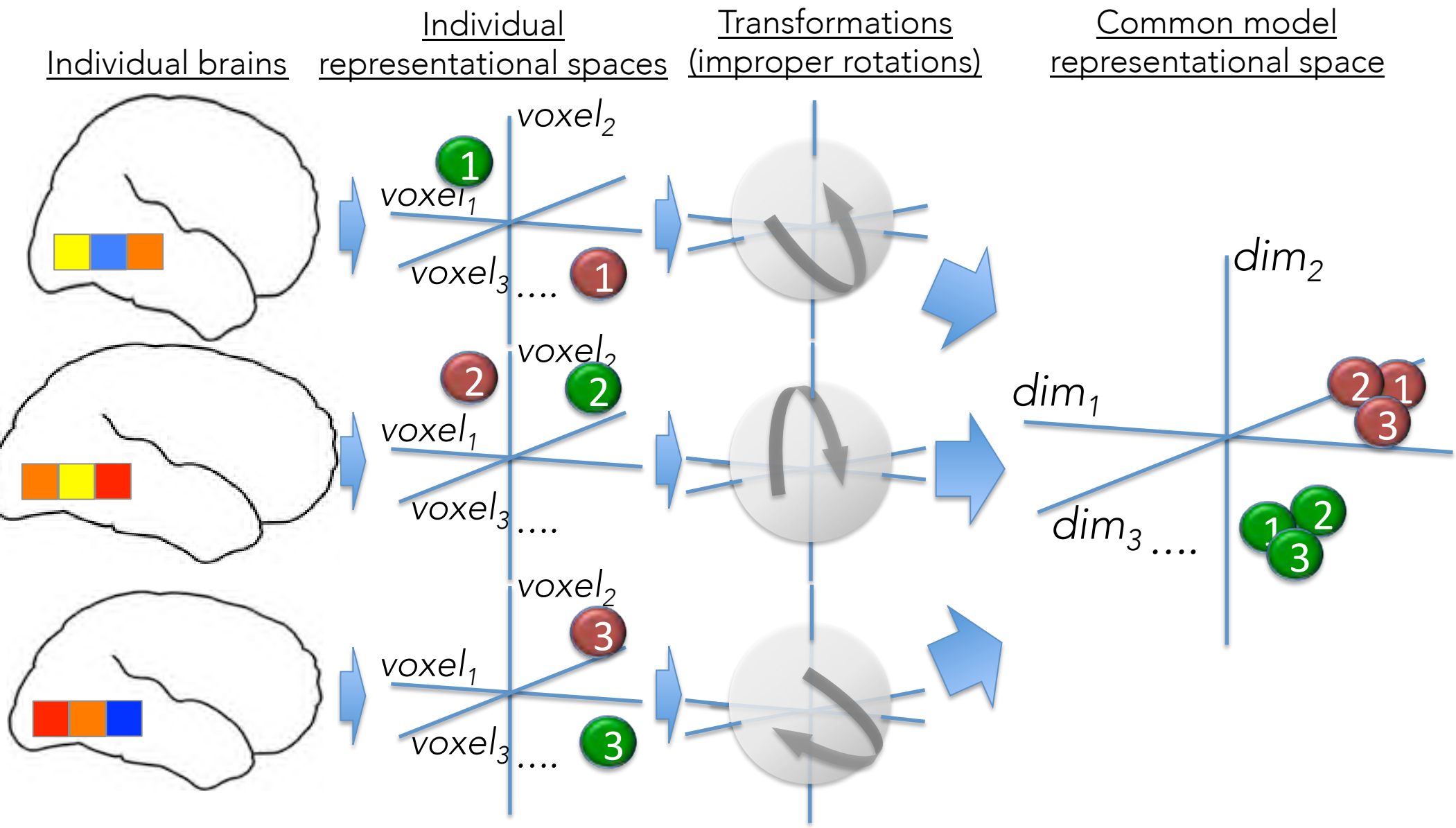
Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space



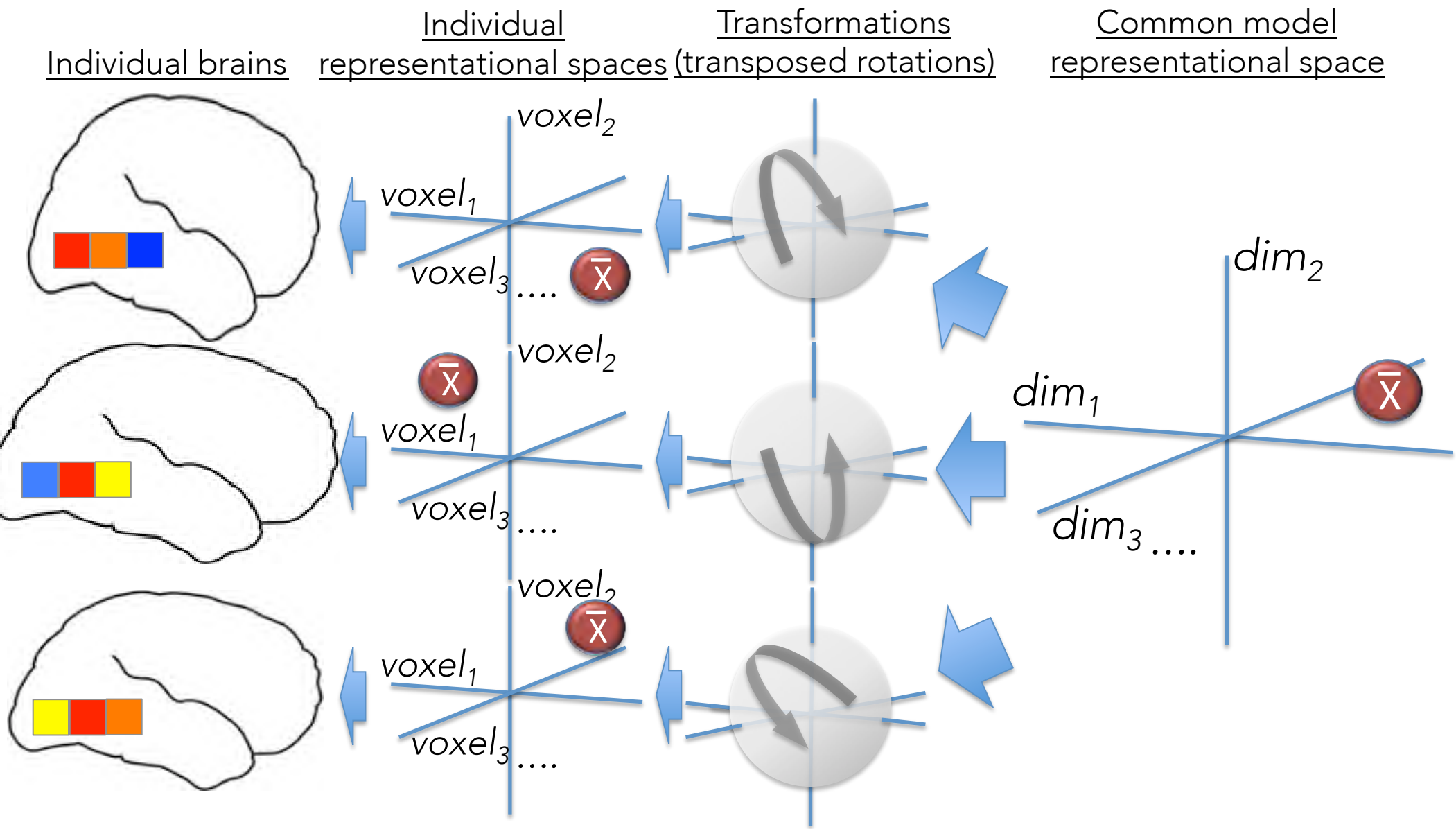
Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space



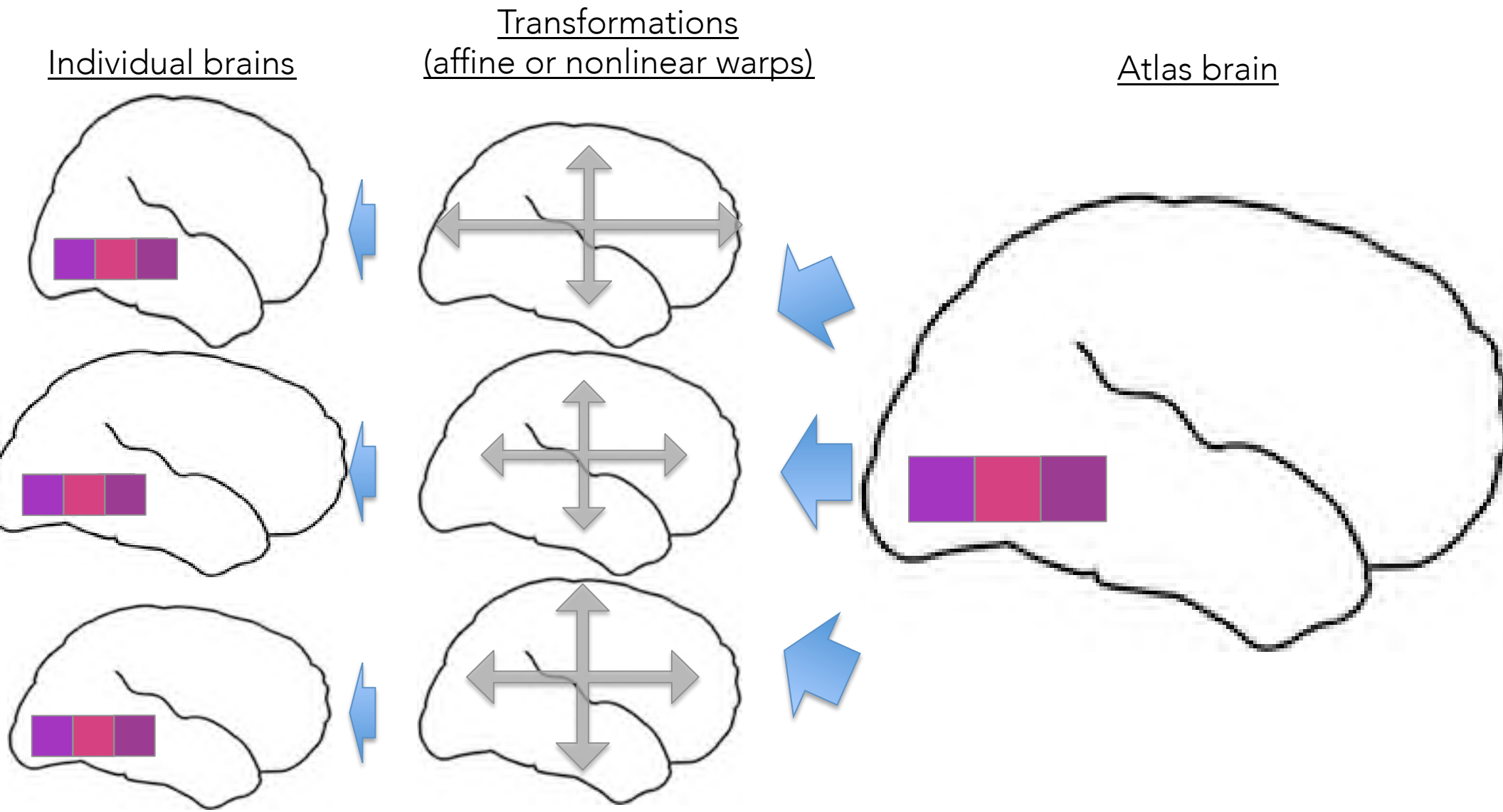
Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space



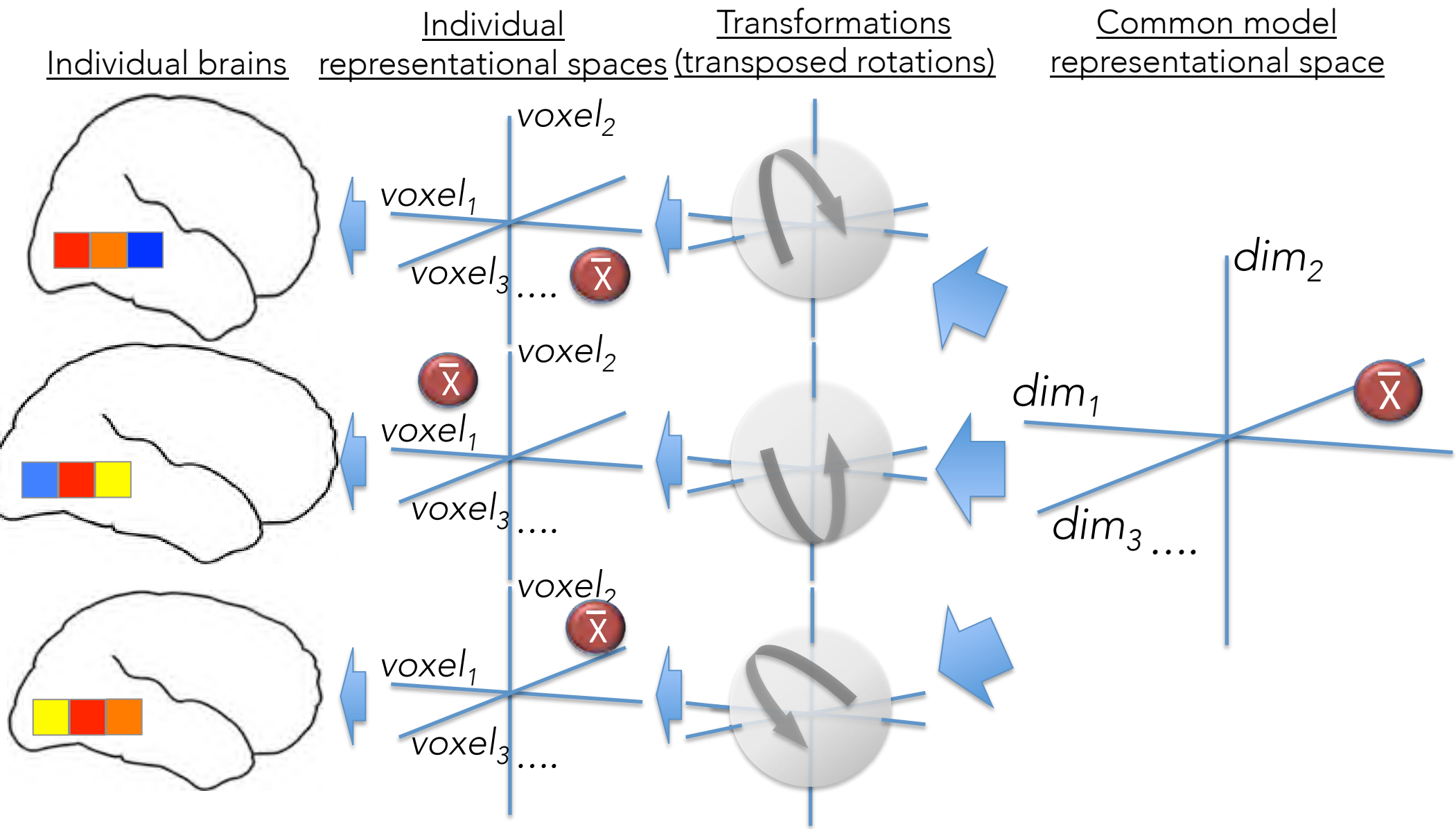
Modeling functional architecture of the human cortex: Individual representational spaces <=> common representational space



Modeling functional architecture of the human cortex: Anatomical alignment



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

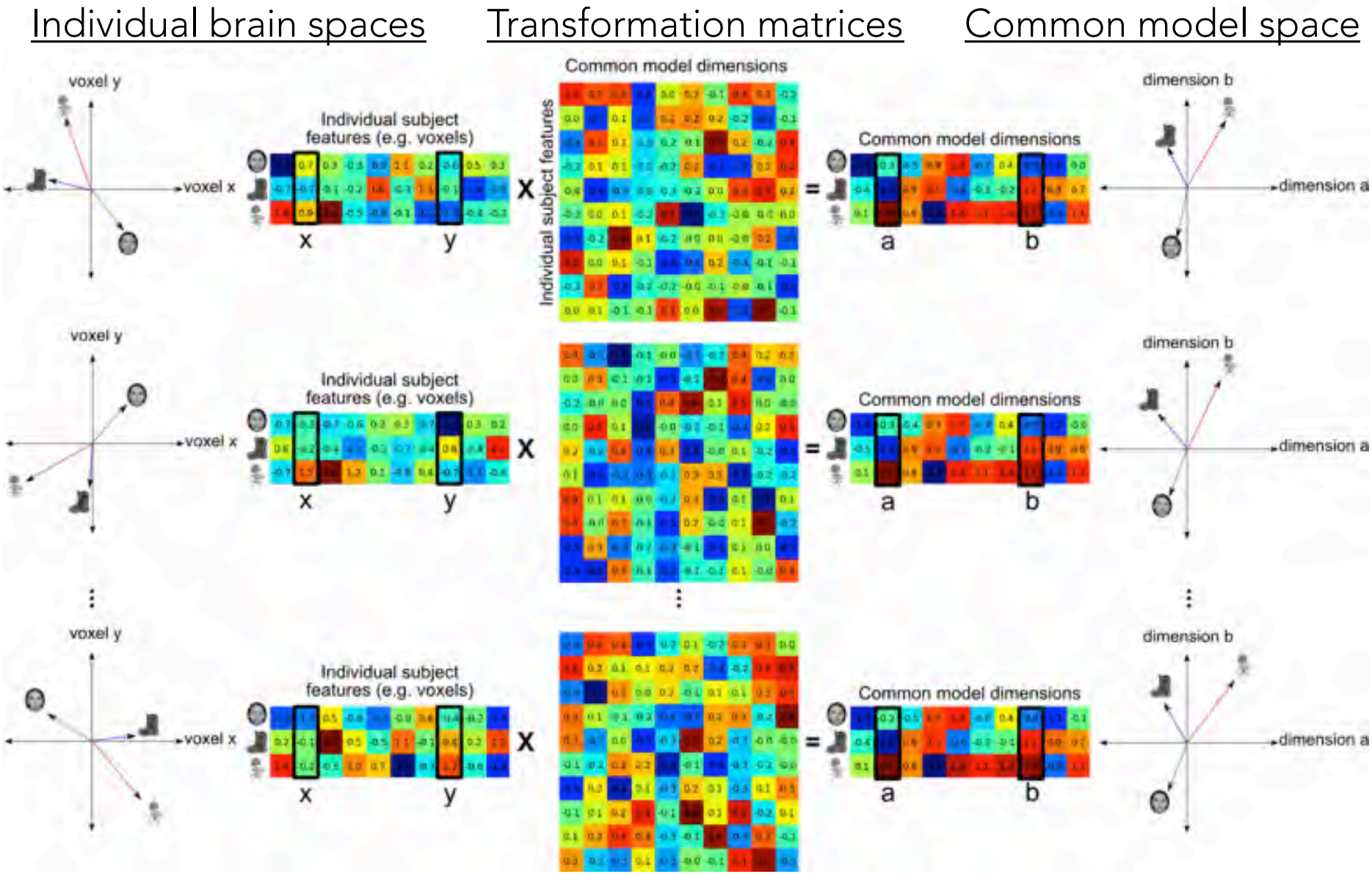


A common high-dimensional linear model of representational spaces in human cortex

- 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

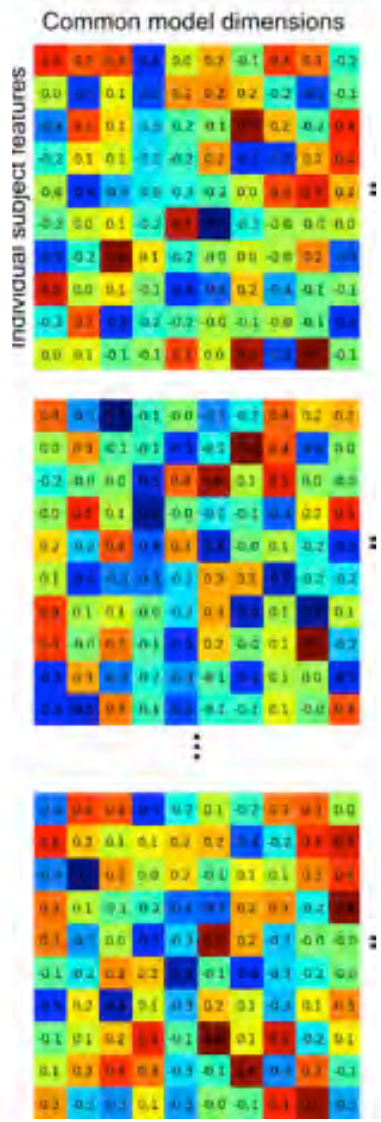
Matrix math:

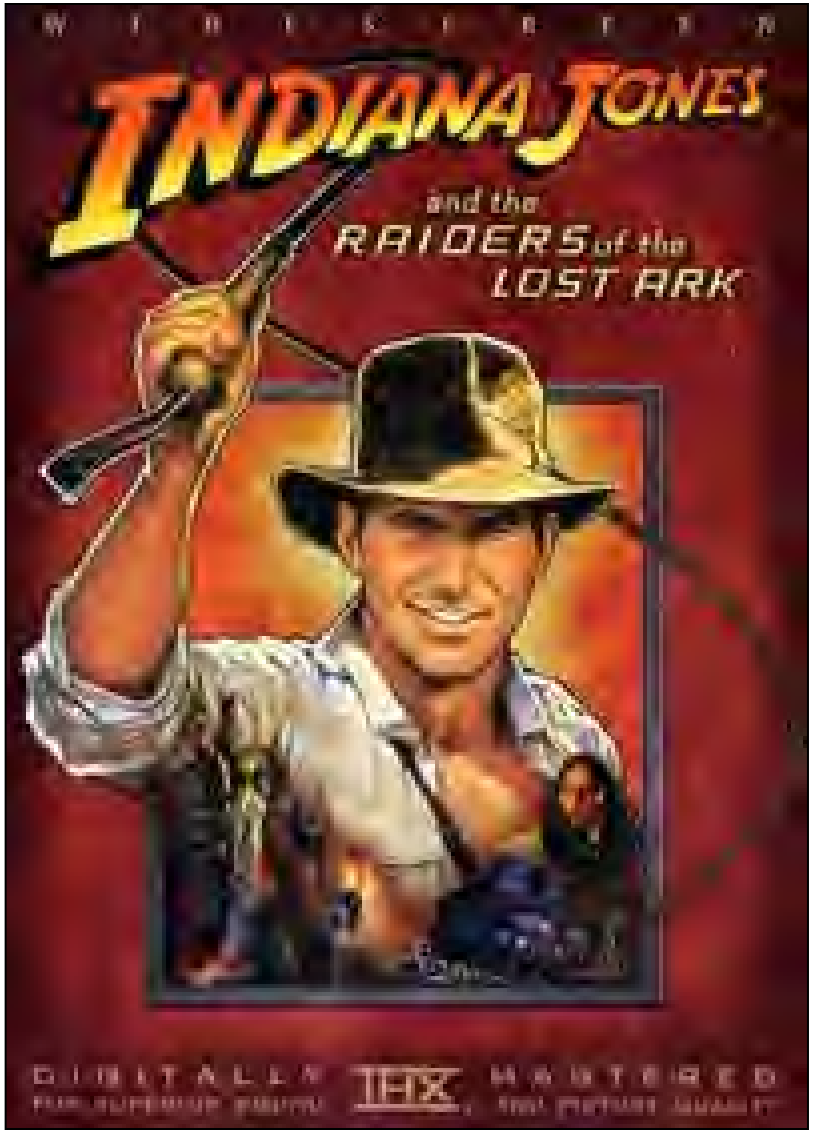
Individual transformation matrices rotate individual brain spaces into common model space coordinates

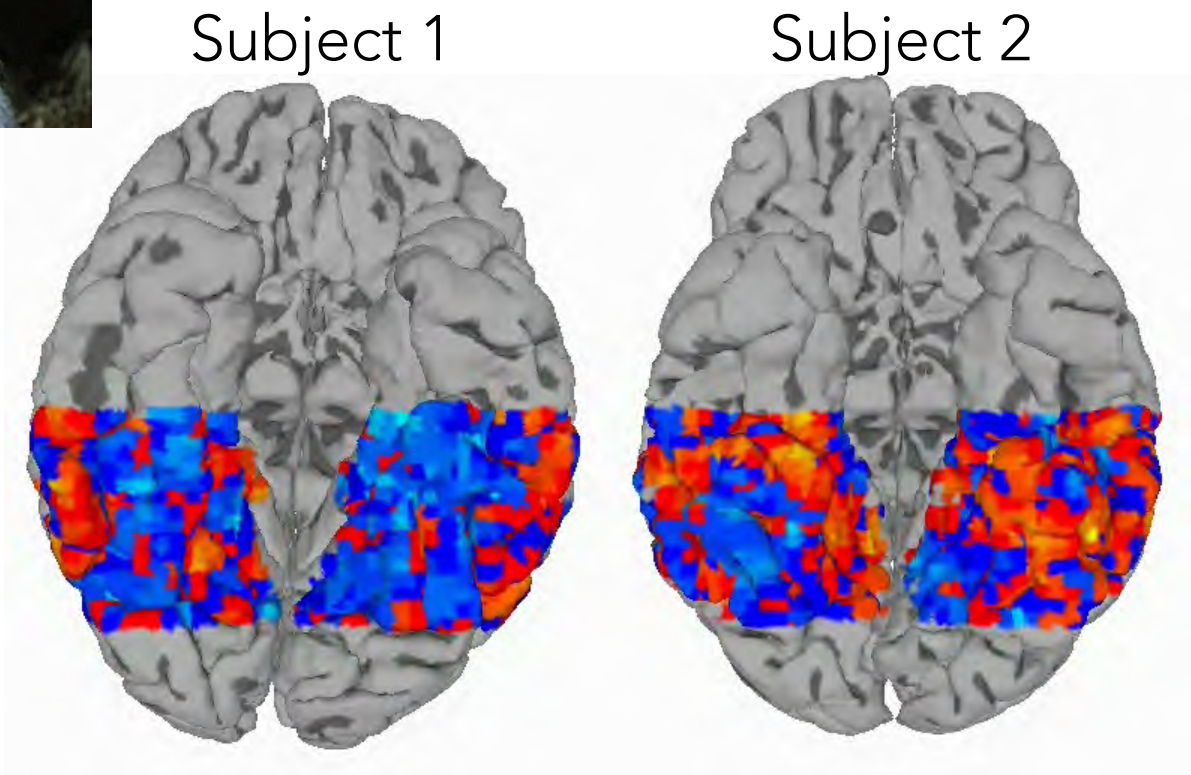


Individual transformation matrices are the key to building the common model: How can the parameters be derived?

<u>Transformation matrices</u>




INDIANA JONES
and the
RAIDERS of the
LOST ARK
THX

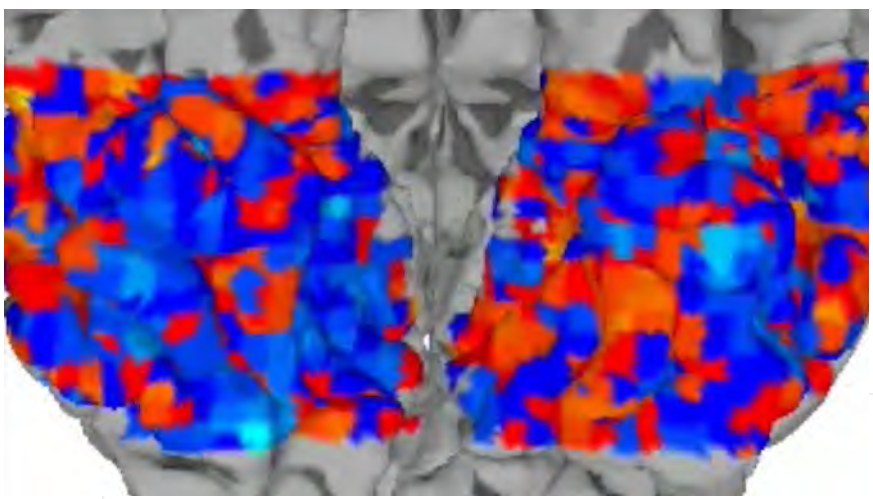

Subject 1
Subject 2

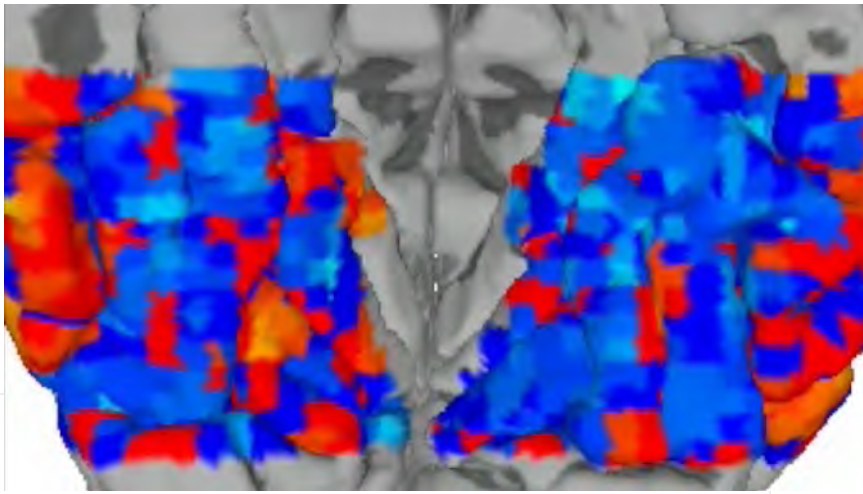
Broad sampling of a neural representational space with a movie

Subject 1

Subject 2

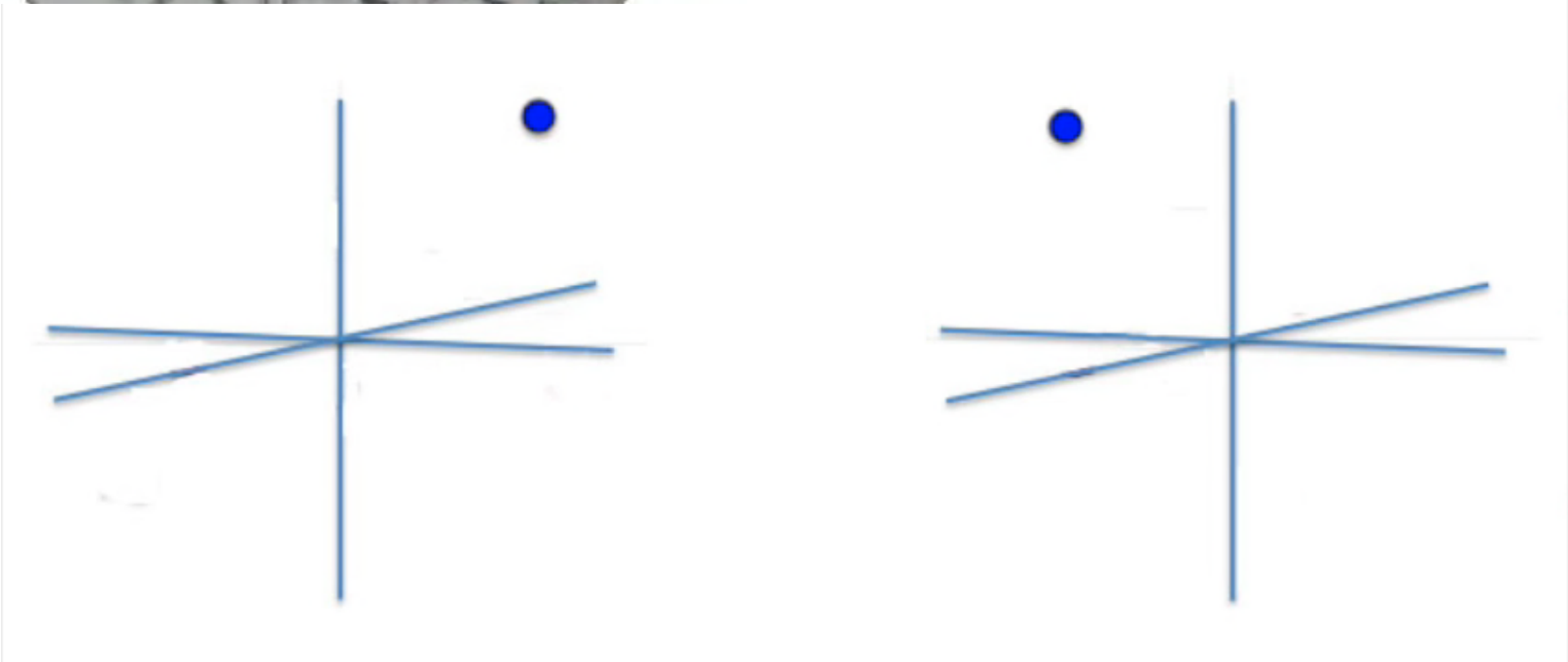
Response patterns in cortex

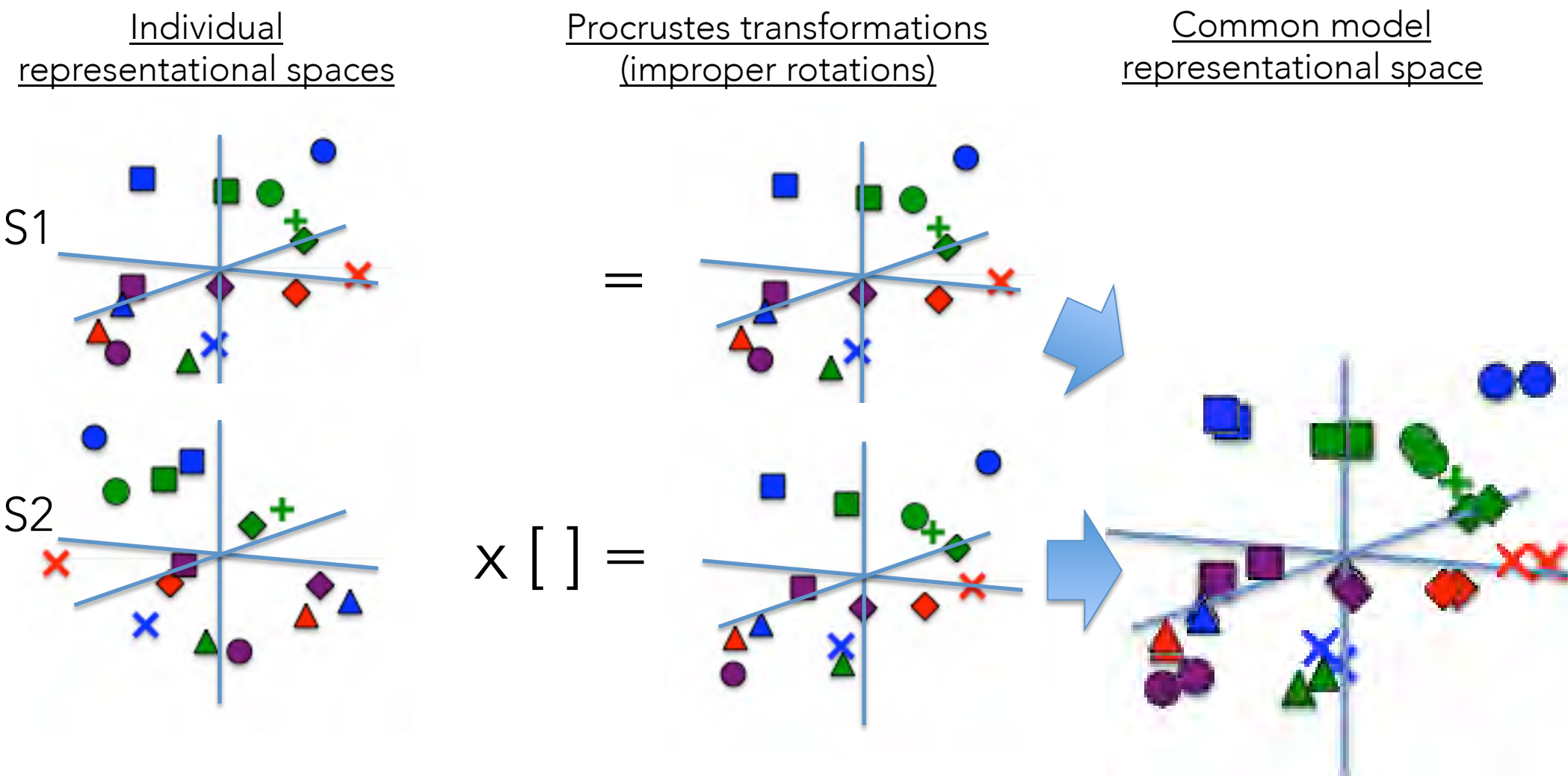


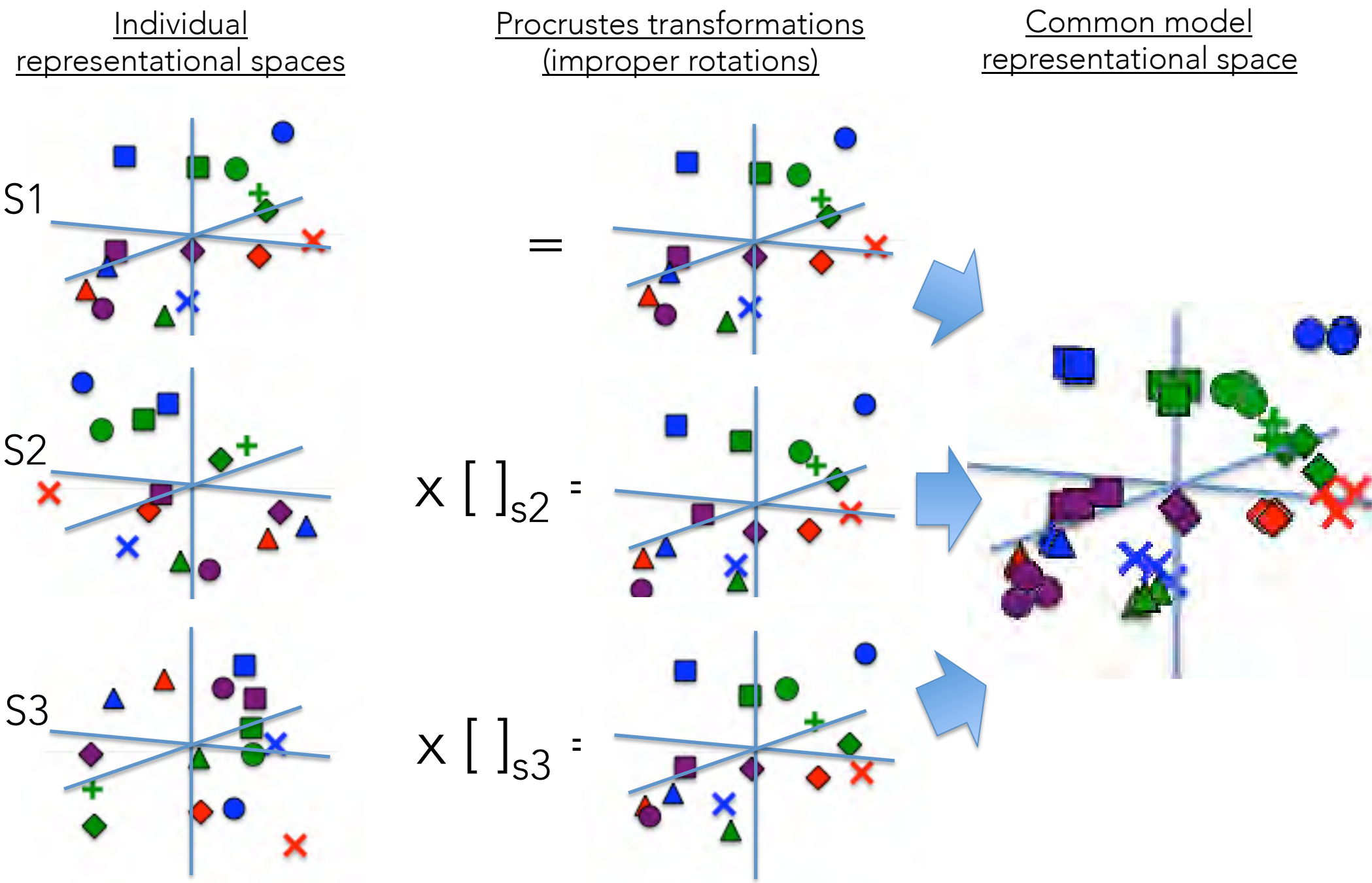


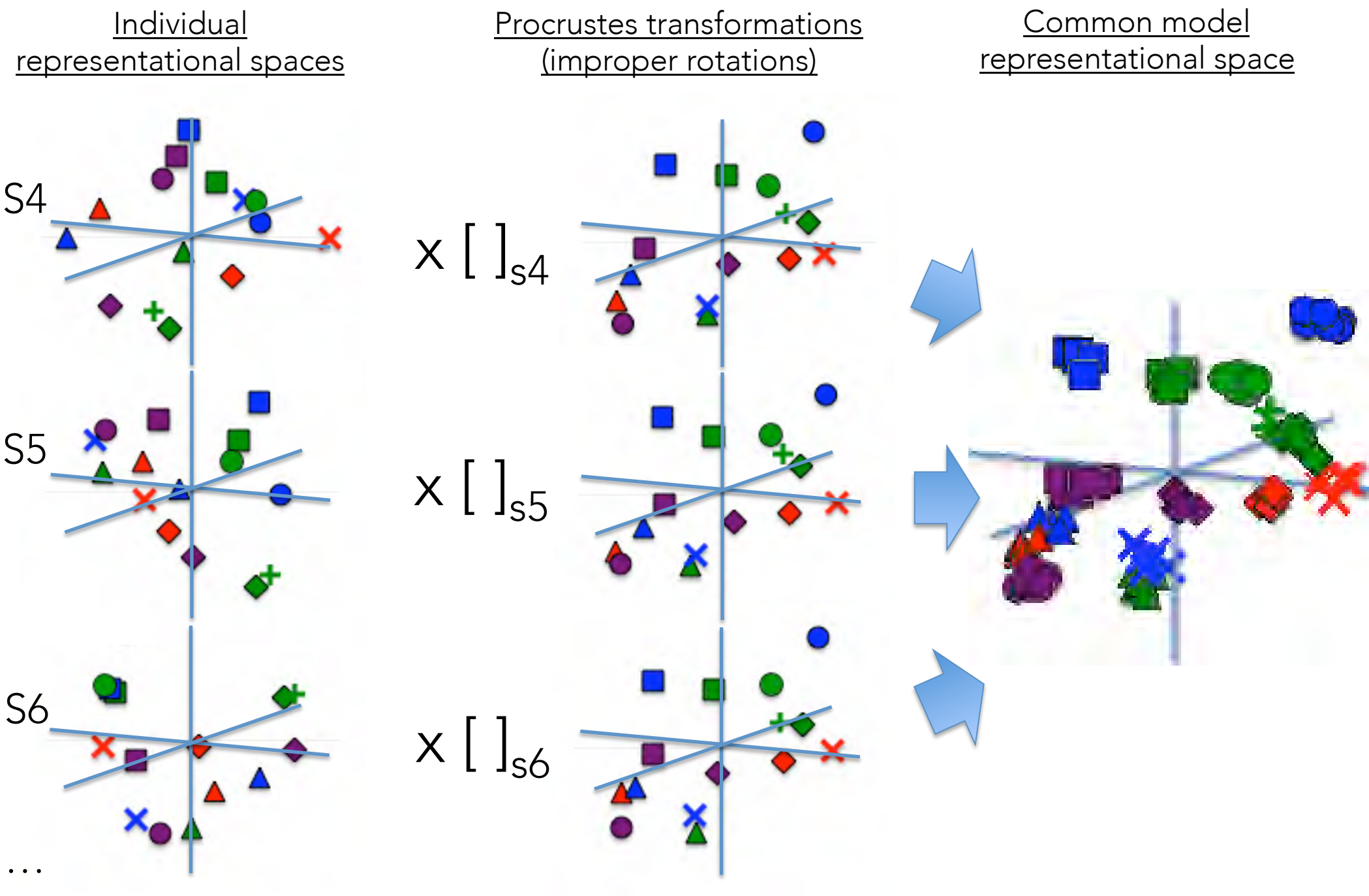
15 response pattern vectors in individual 3D representational spaces

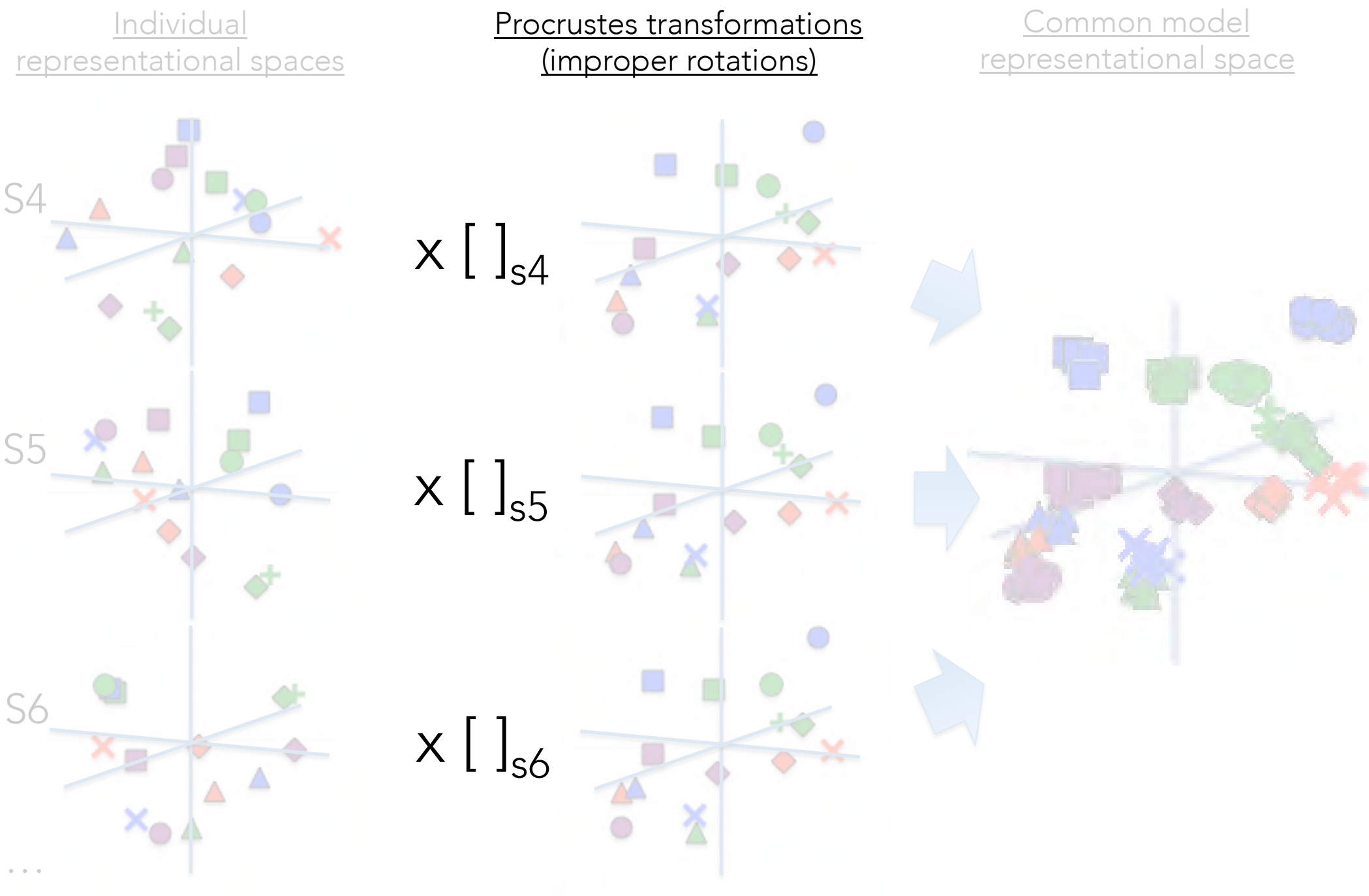
(full exp't has >2600 vectors in >50,000D space)




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

Subject-specific Transformation Matrix

Movie data in Model Space

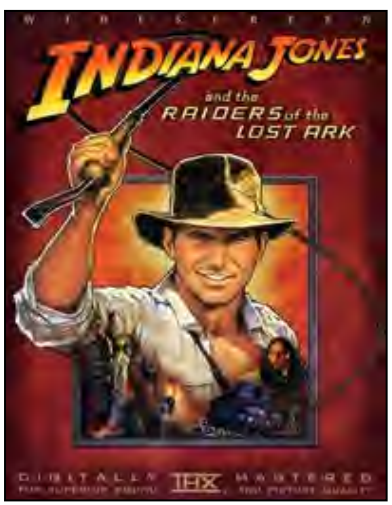
		Voxels				
		v_1	v_2	v_3	...	v_i
Time-points	t_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{i,1}$
	t_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	...	$x_{i,2}$
	t_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	...	$x_{i,3}$
	t_4	$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	...	$x_{i,4}$
	...	...	...	...		...
	t_j	$x_{1,j}$	$x_{2,j}$	$x_{3,j}$	...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

X

		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
Time-points	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	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{k,1}$
	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	$x_{1,i}$	$x_{2,i}$	$x_{3,i}$	...	$x_{i,k}$

The key that unlocks an individual's neural code

Experiment 2 data in Brain Space

Subject-specific Transformation Matrix

Experiment 2 data in Model Space

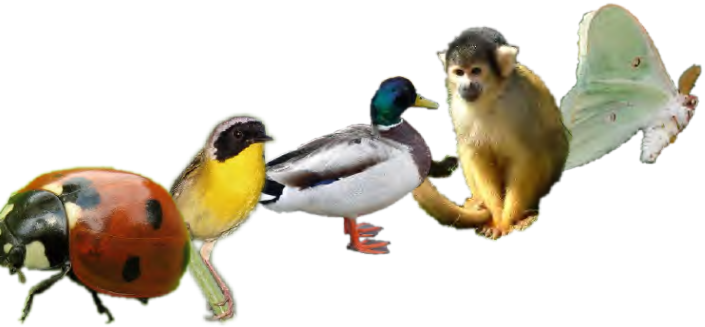
		Voxels				
		v_1	v_2	v_3	...	v_i
Stimuli	s_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{i,1}$
	s_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	...	$x_{i,2}$
	s_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	...	$x_{i,3}$
	s_4	$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	...	$x_{i,4}$
	...	...	...	...		...
	s_m	$x_{1,m}$	$x_{2,m}$	$x_{3,m}$	...	$x_{i,m}$

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	$x_{1,i}$	$x_{2,i}$	$x_{3,i}$	...	$x_{i,k}$

=

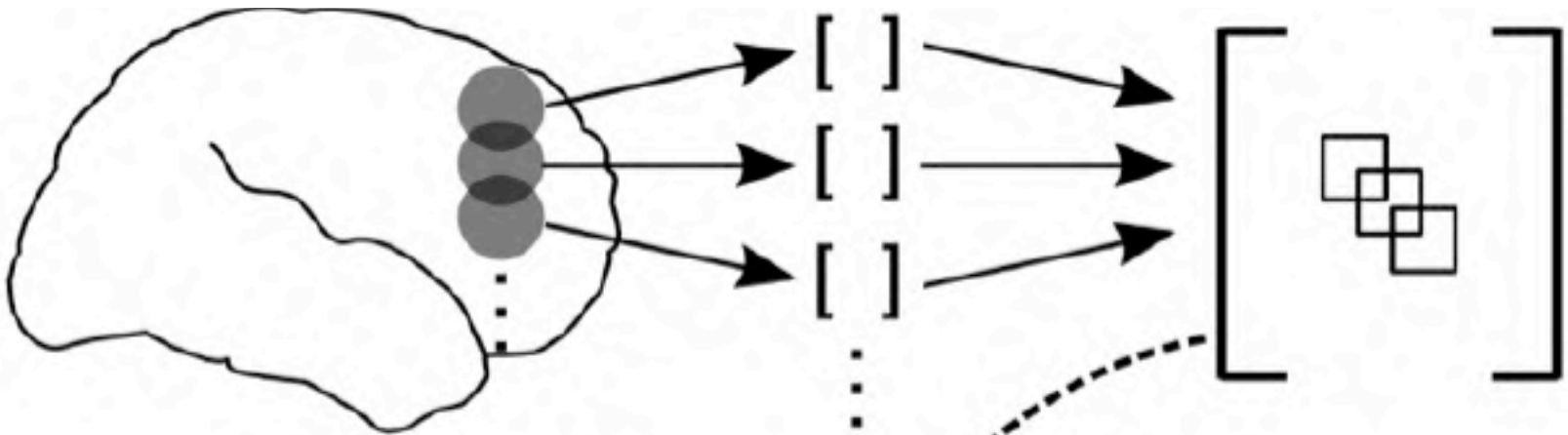
		Model dimensions				
		d_1	d_2	d_3	...	d_k
Stimuli	s_1	$y_{1,1}$	$y_{2,1}$	$y_{3,1}$	...	$y_{k,1}$
	s_2	$y_{1,2}$	$y_{2,2}$	$y_{3,2}$	...	$y_{k,2}$
	s_3	$y_{1,3}$	$y_{2,3}$	$y_{3,3}$	...	$y_{k,3}$
	s_4	$y_{1,4}$	$y_{2,4}$	$y_{3,4}$	...	$y_{k,4}$
	...	...	...	...		...
	s_m	$y_{1,m}$	$y_{2,m}$	$y_{3,m}$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



Modeling representational spaces in all human cortex with searchlight hyperalignment

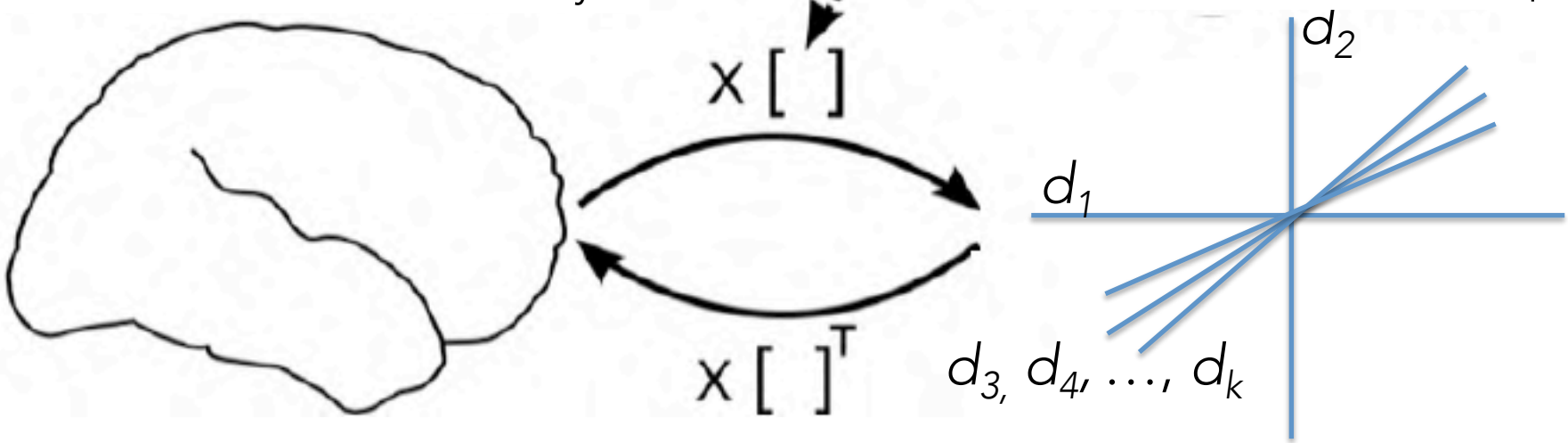
Voxels in overlapping searchlights are hyperaligned across subjects

Overlapping searchlight transformation matrices are aggregated into a whole cortex matrix



Data in individual brain anatomy

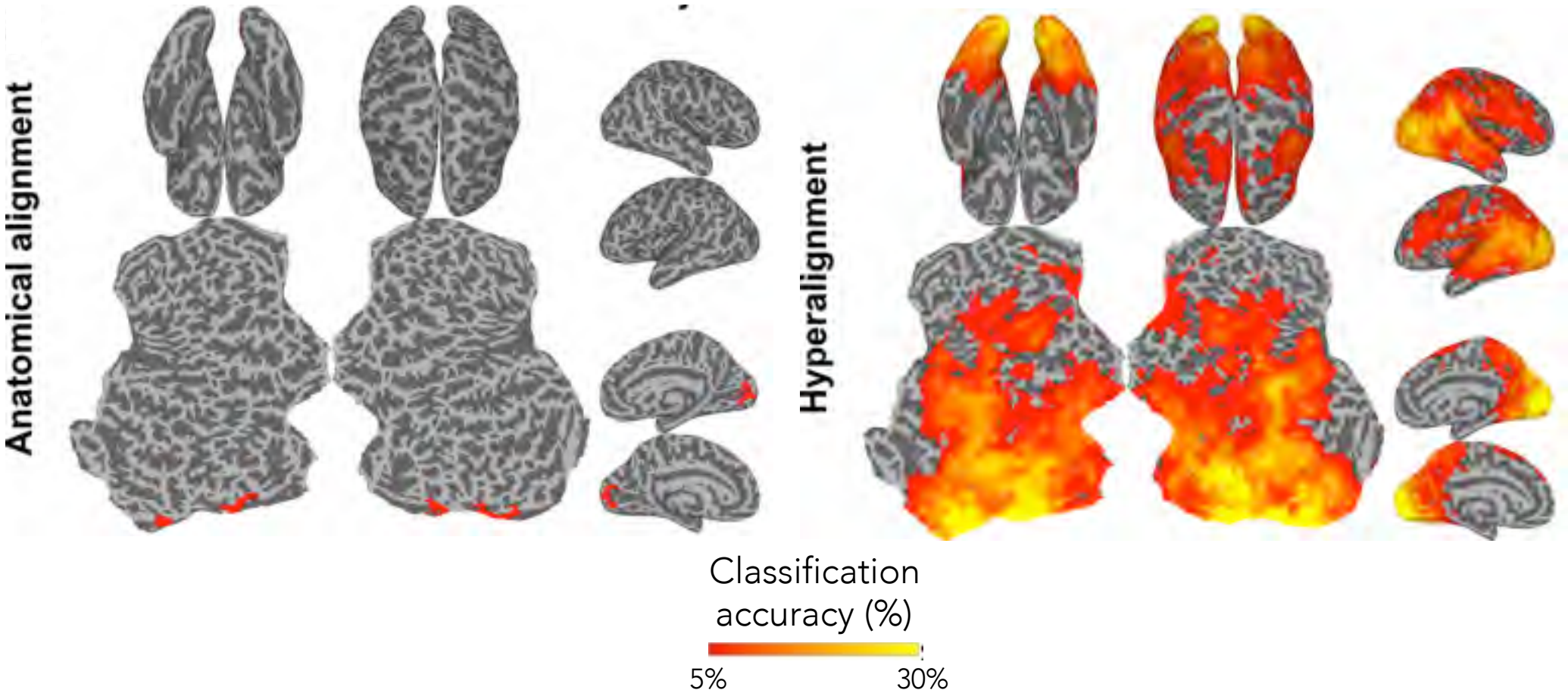
Data in common model space



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

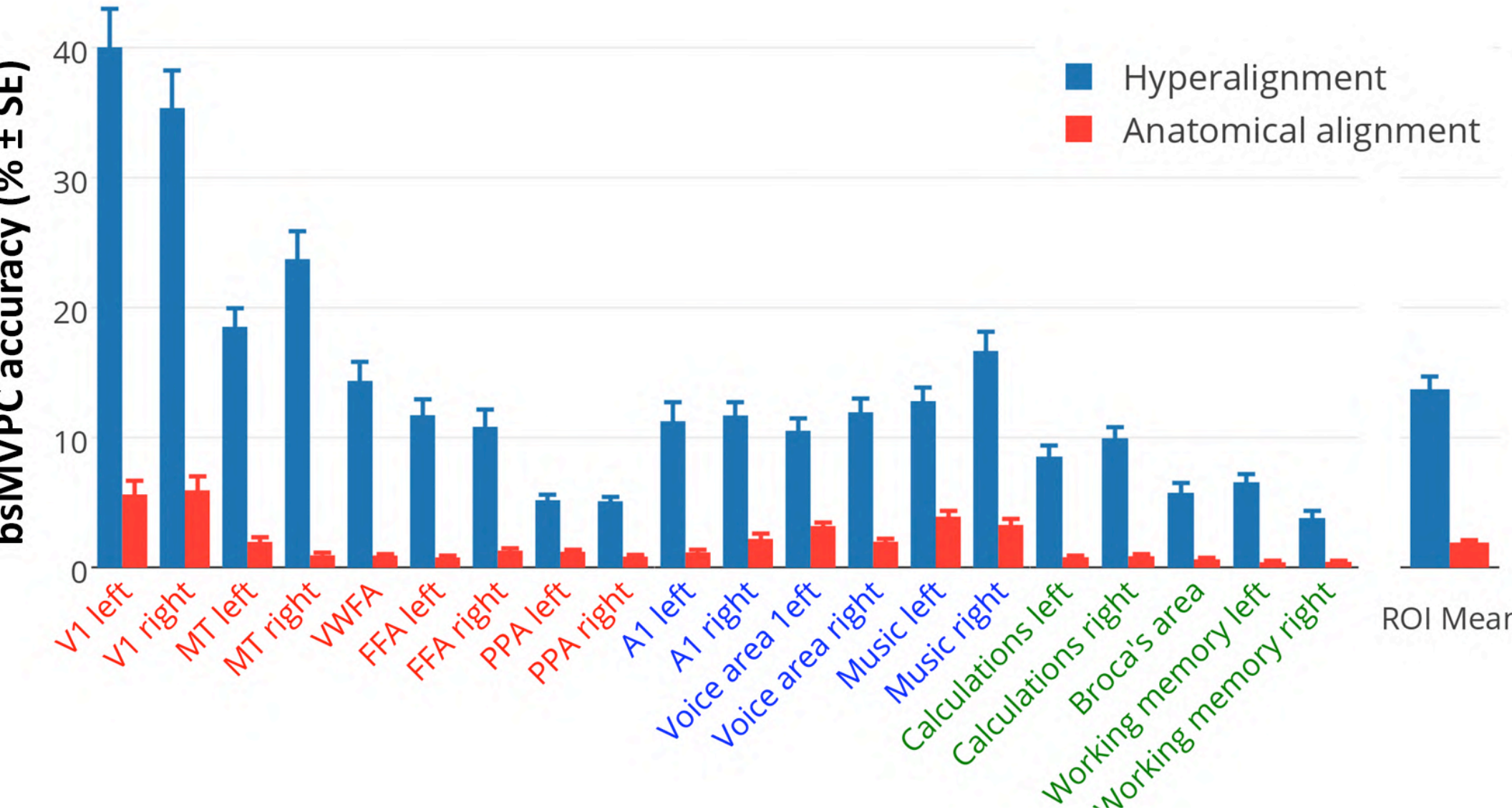
- Statement of the problem: capturing fine-grained distinctions in a common model
- Conceptual framework: high-dimensional representational spaces
- Deriving the common space and individual transformation matrices with hyperalignment
- Validation
  - Between-subject correlations of time-series
  - Between-subject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

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

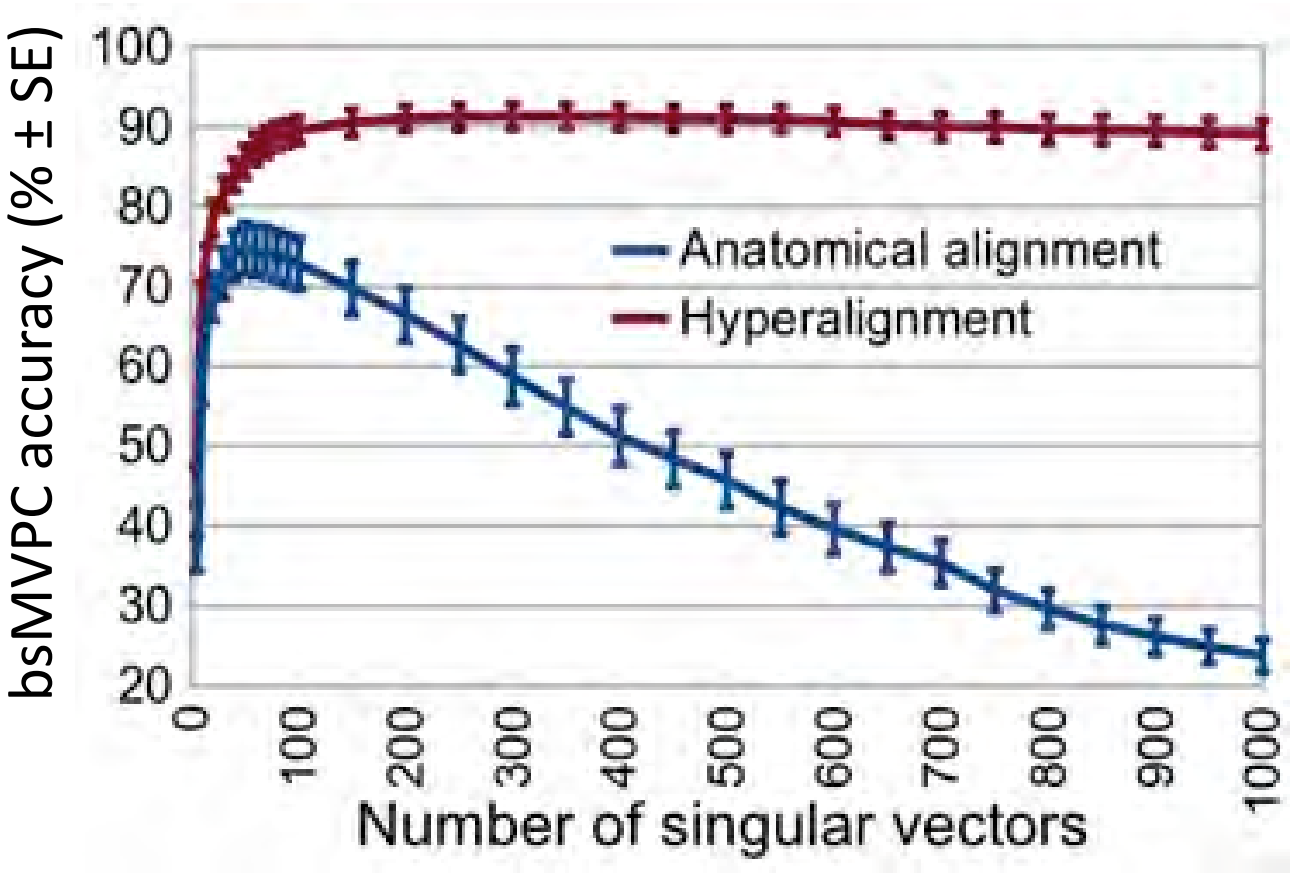


Increased bsMVPC of movie time-segments in visual, auditory, and cognitive regions of interest (ROIs)

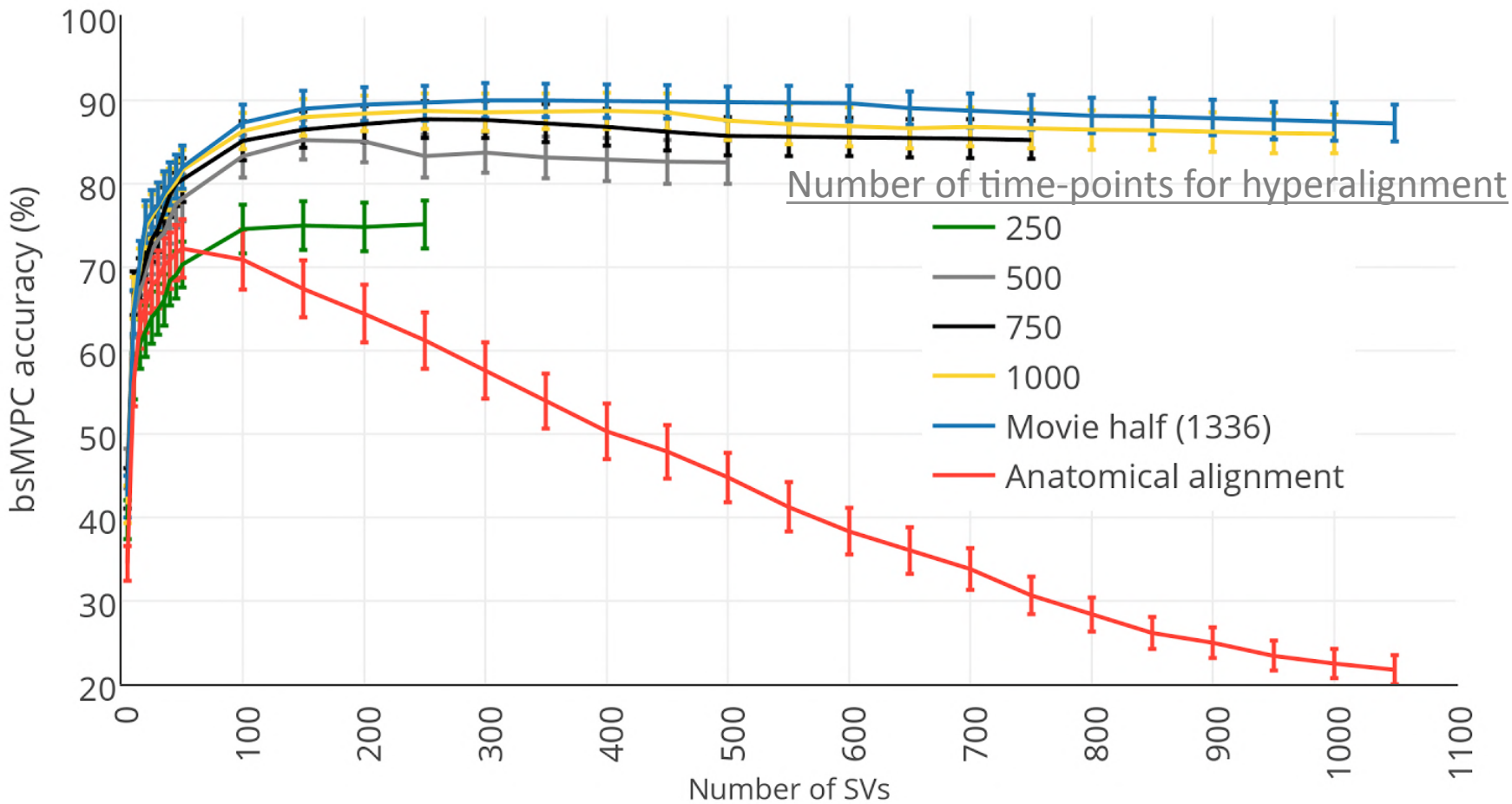
(coordinates from NeuroSynth)



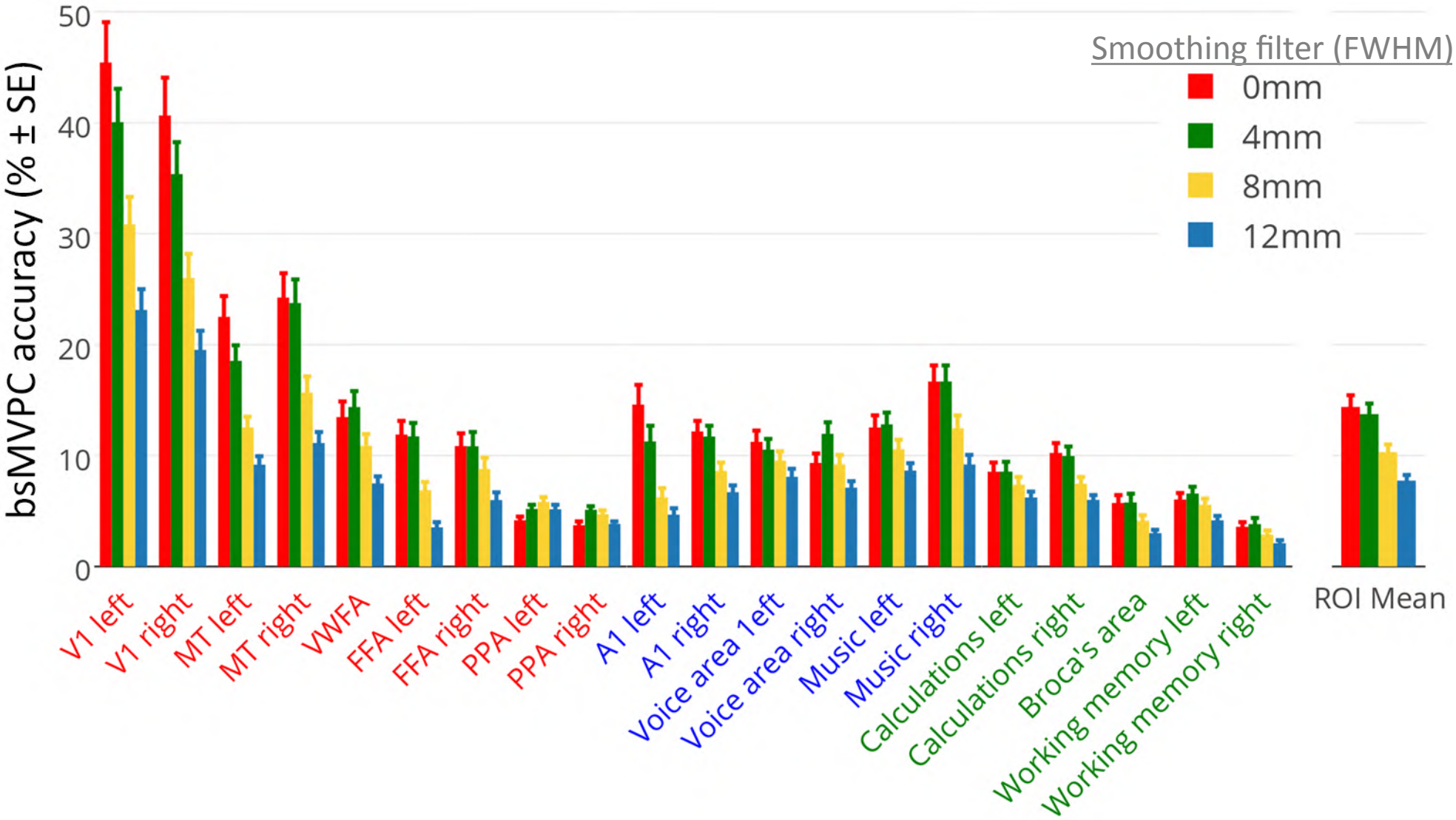
Whole-brain hyperalignment increases between-subject classification of 15 s movie time segments for the whole brain (after SVD dimensionality reduction)



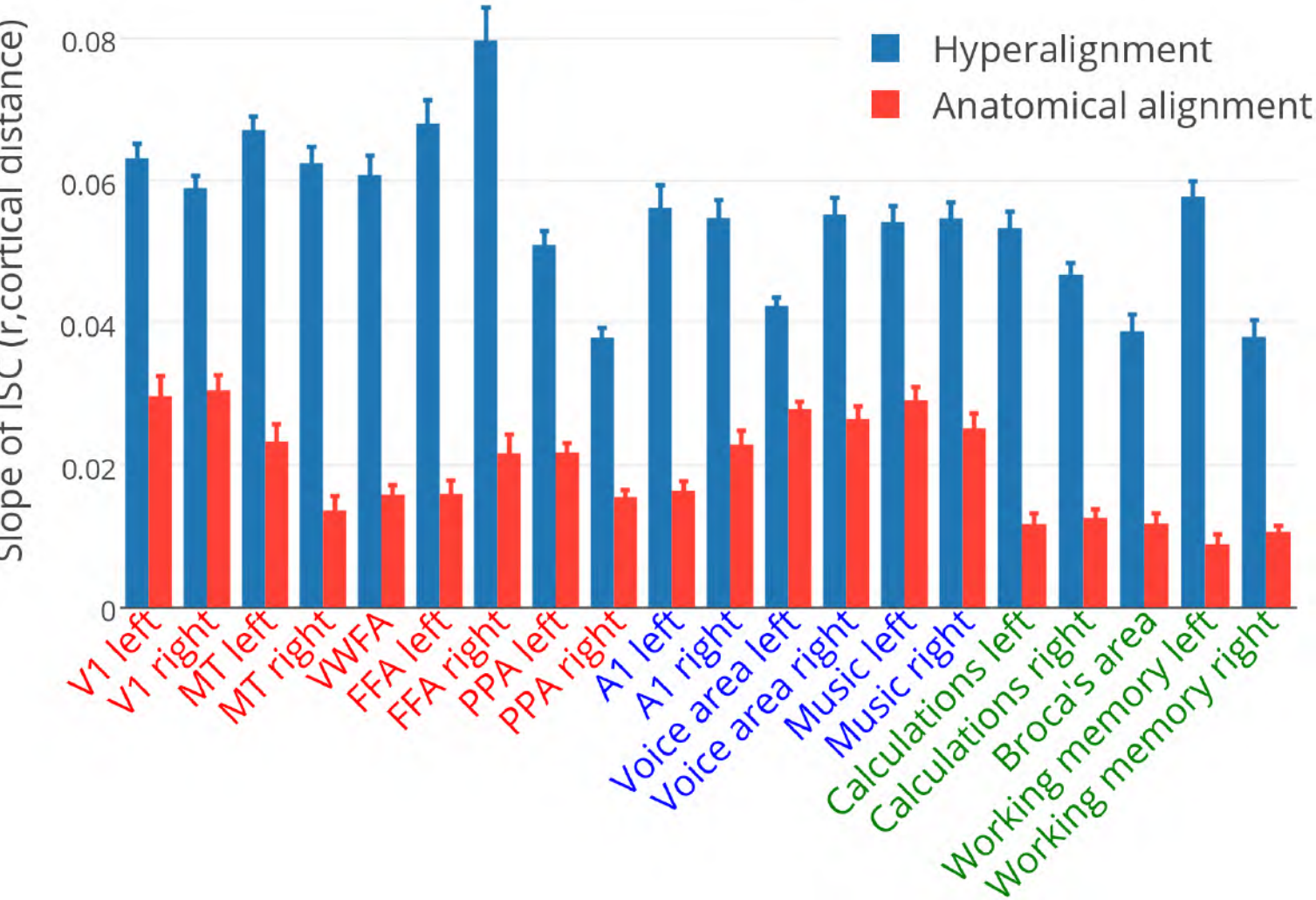
How much movie data is necessary to calculate transformation matrices?
Answer – the more the better, but ~20 minutes isn't too bad

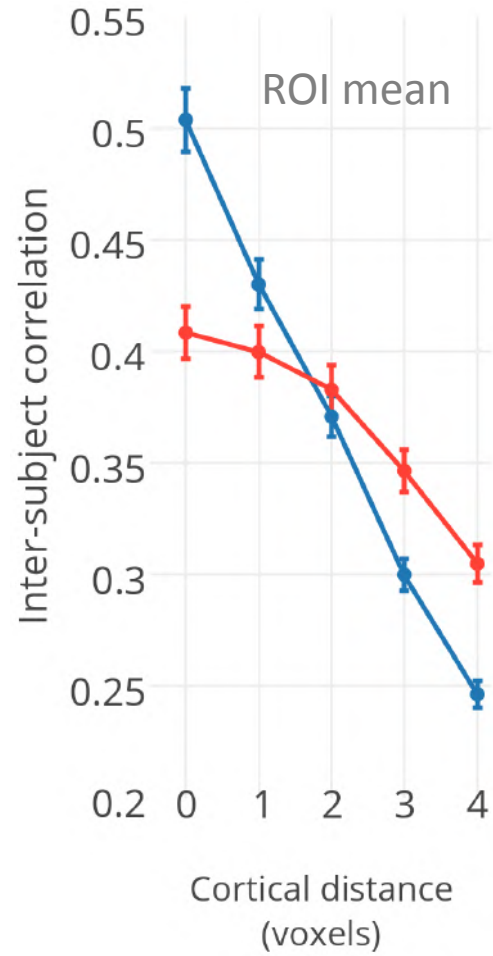


Smoothing reduces BSC accuracies
In all visual, auditory, and cognitive regions of interest (ROIs)

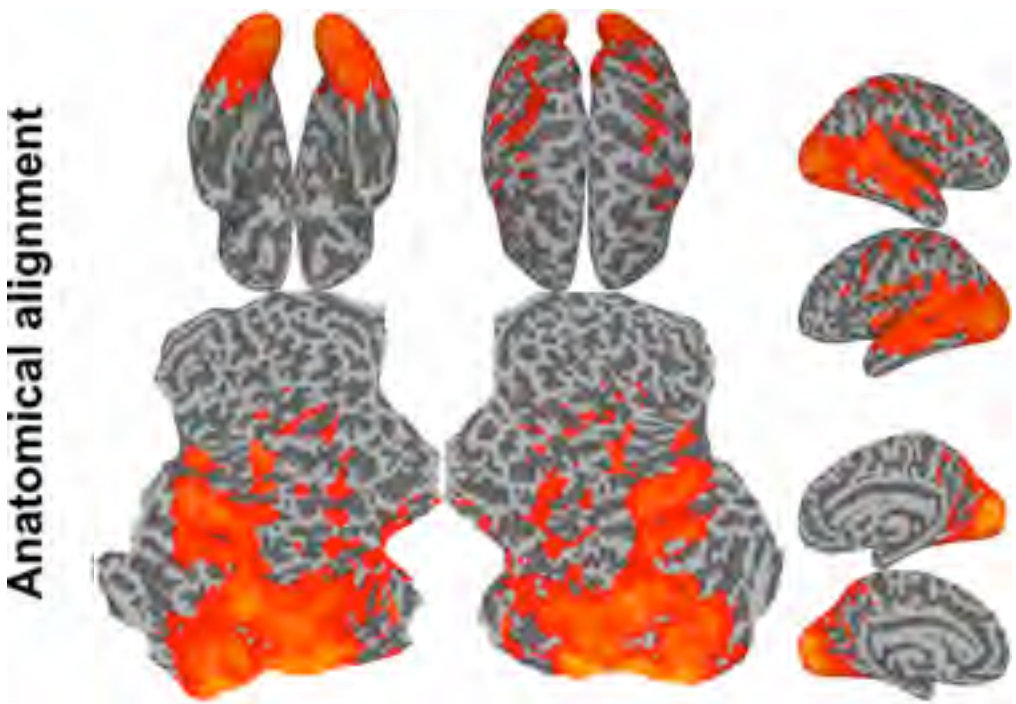


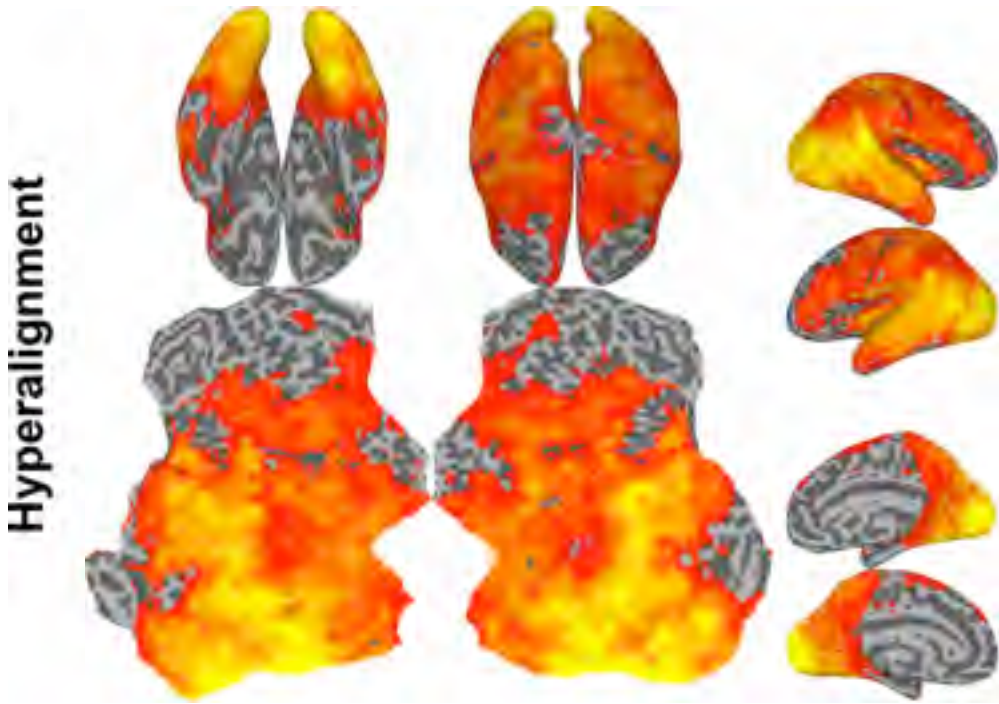
Point spread function (intersubject correlations of movie time series): Fine spatial scale of alignment of function





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

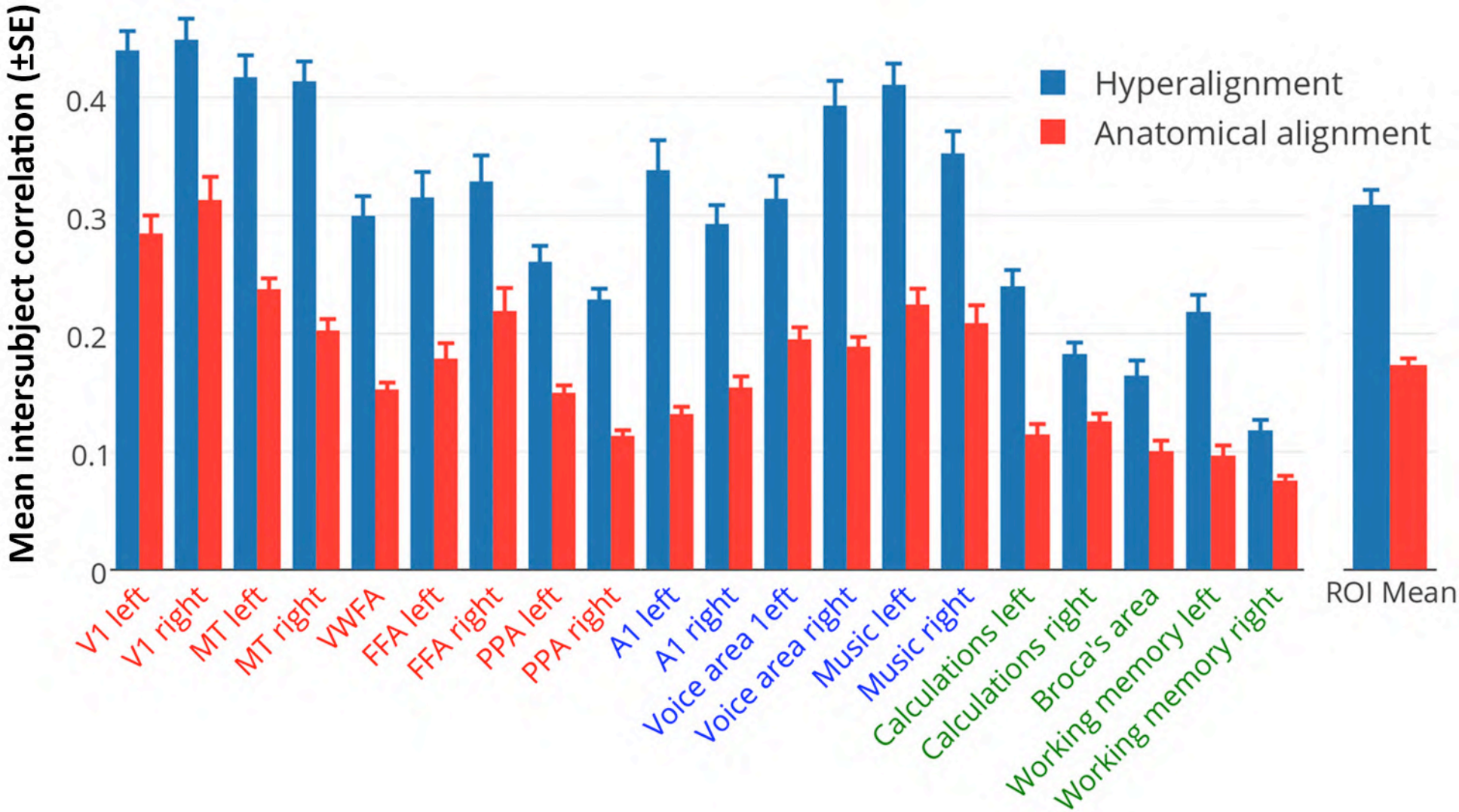




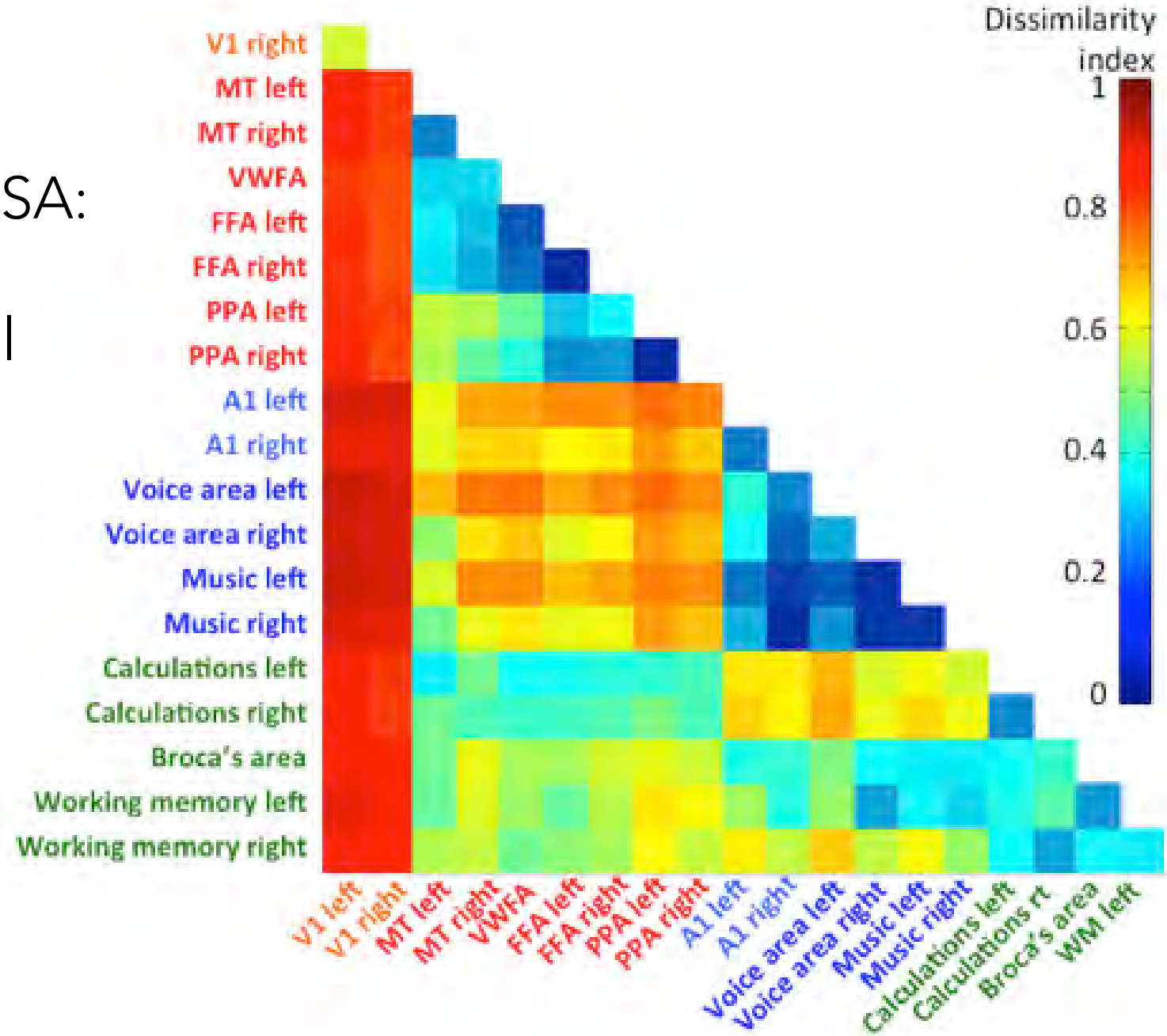
Correlation

0.15 0.45

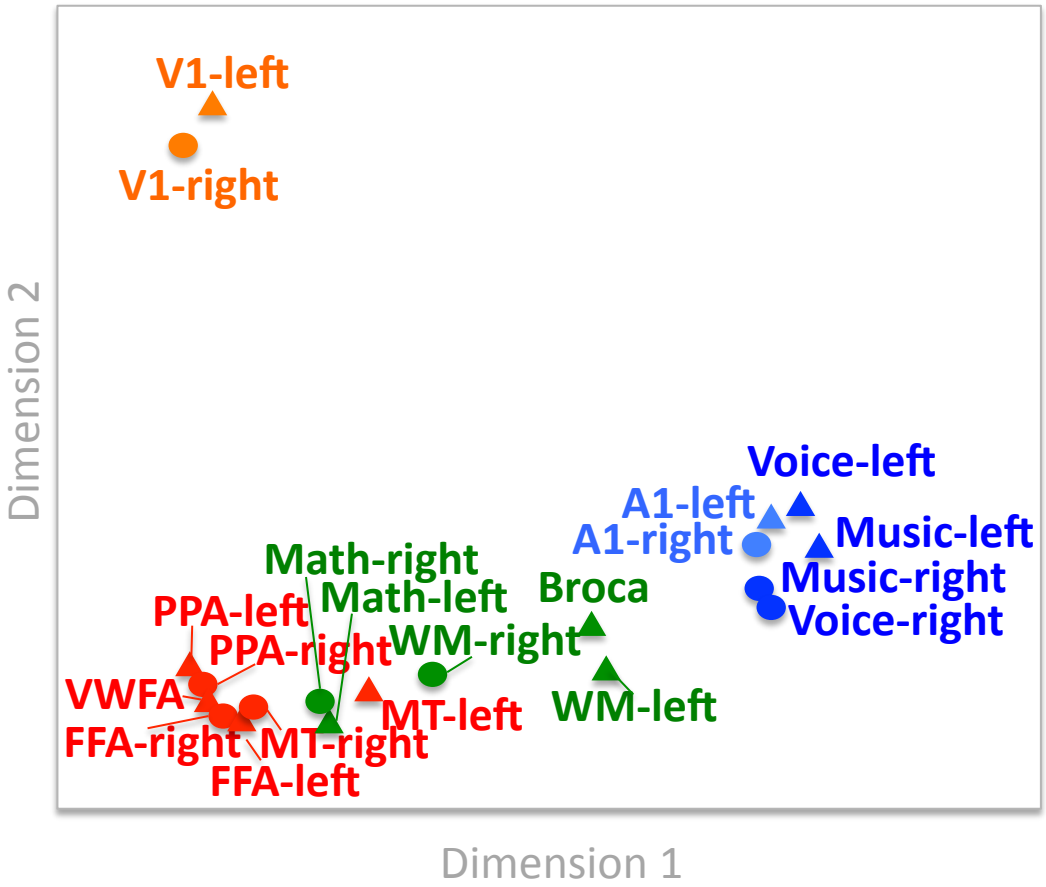
Increased intersubject correlations of representational geometries in visual, auditory, and cognitive regions of interest (ROIs)



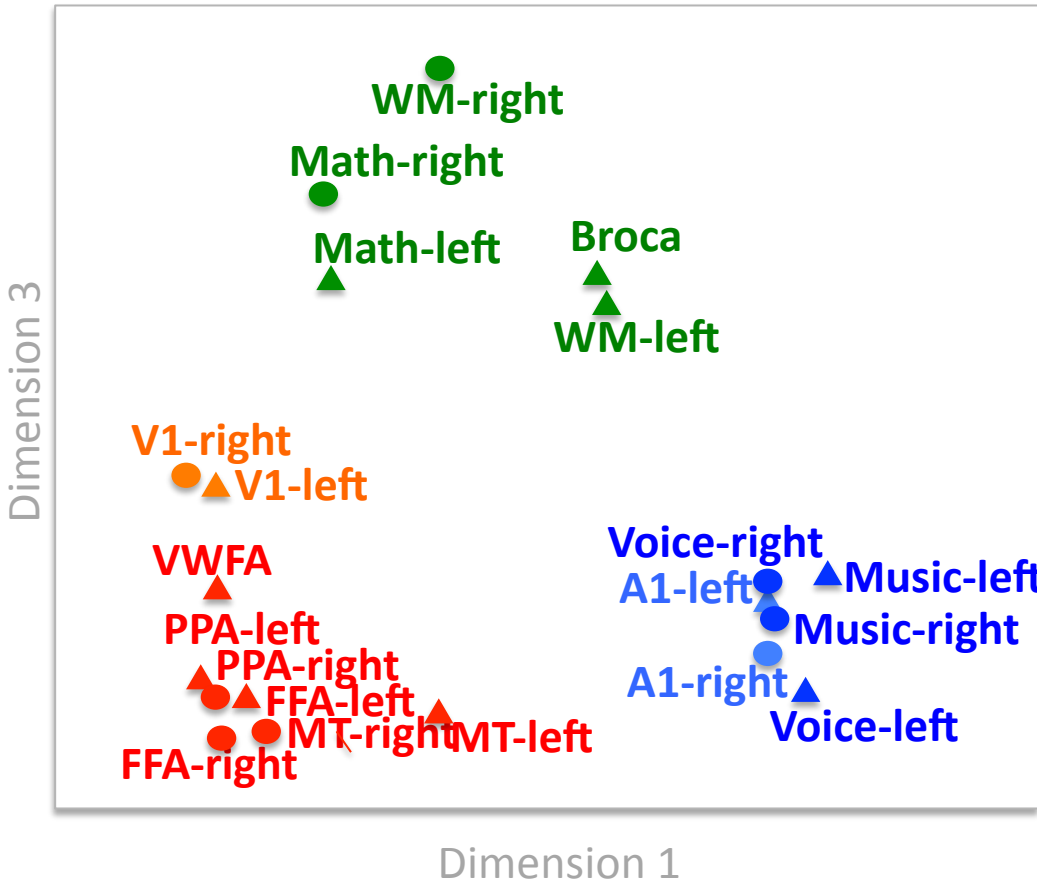
Second-order RSA: Between-ROI representational geometry dissimilarities



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



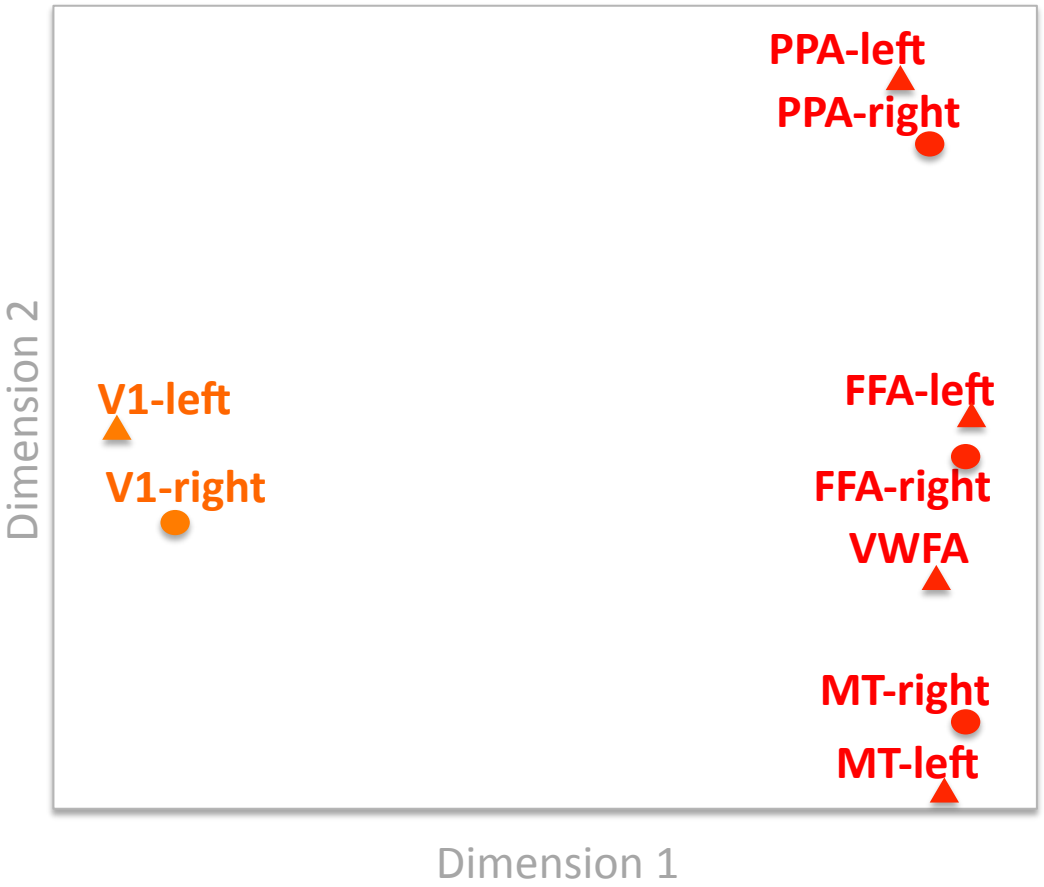
1st subspace (dimensions 1 & 2)



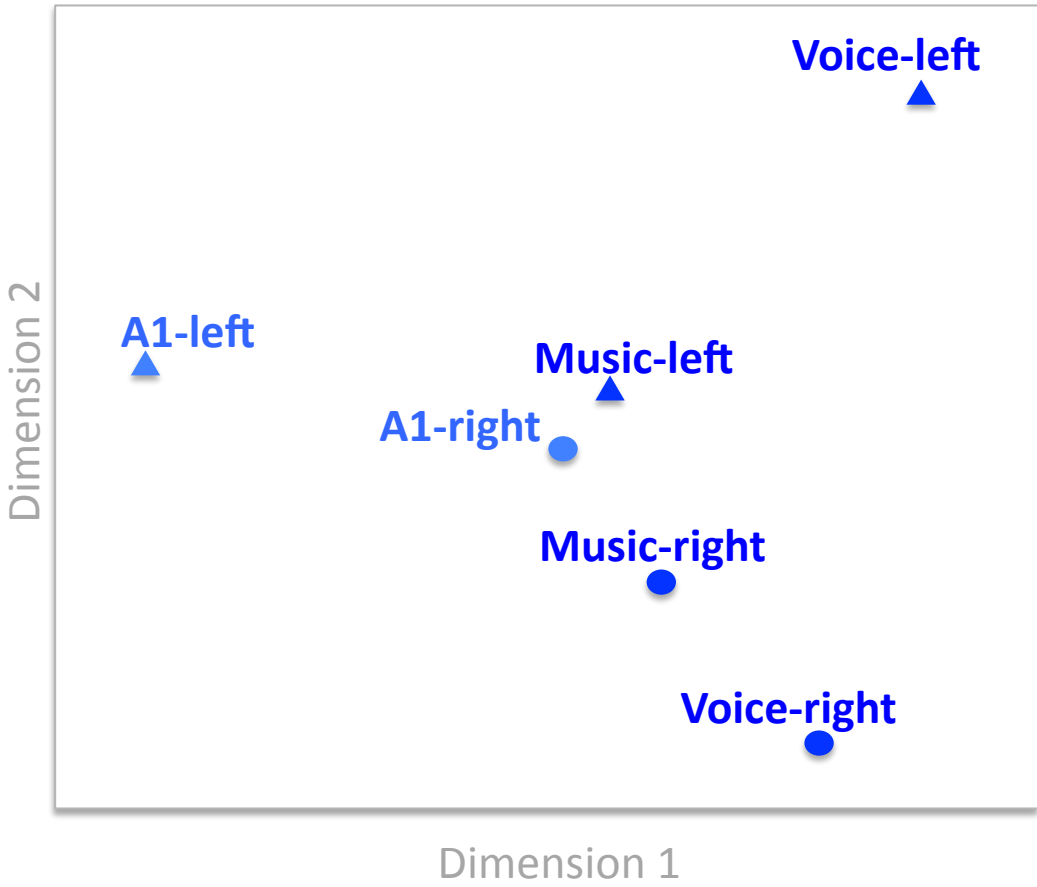
2nd subspace (dimensions 1 & 3)

* ROI coordinates from Neurosynth

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

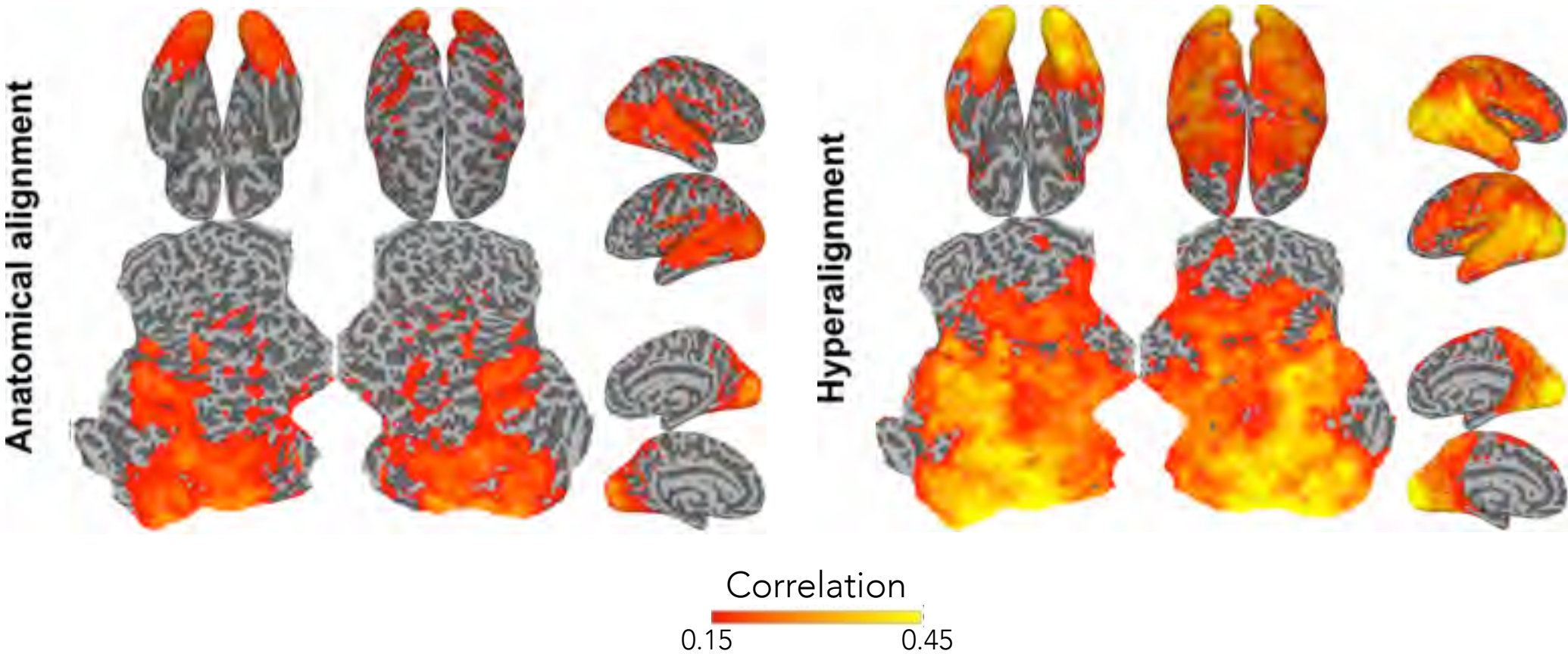


MDS of visual regions only

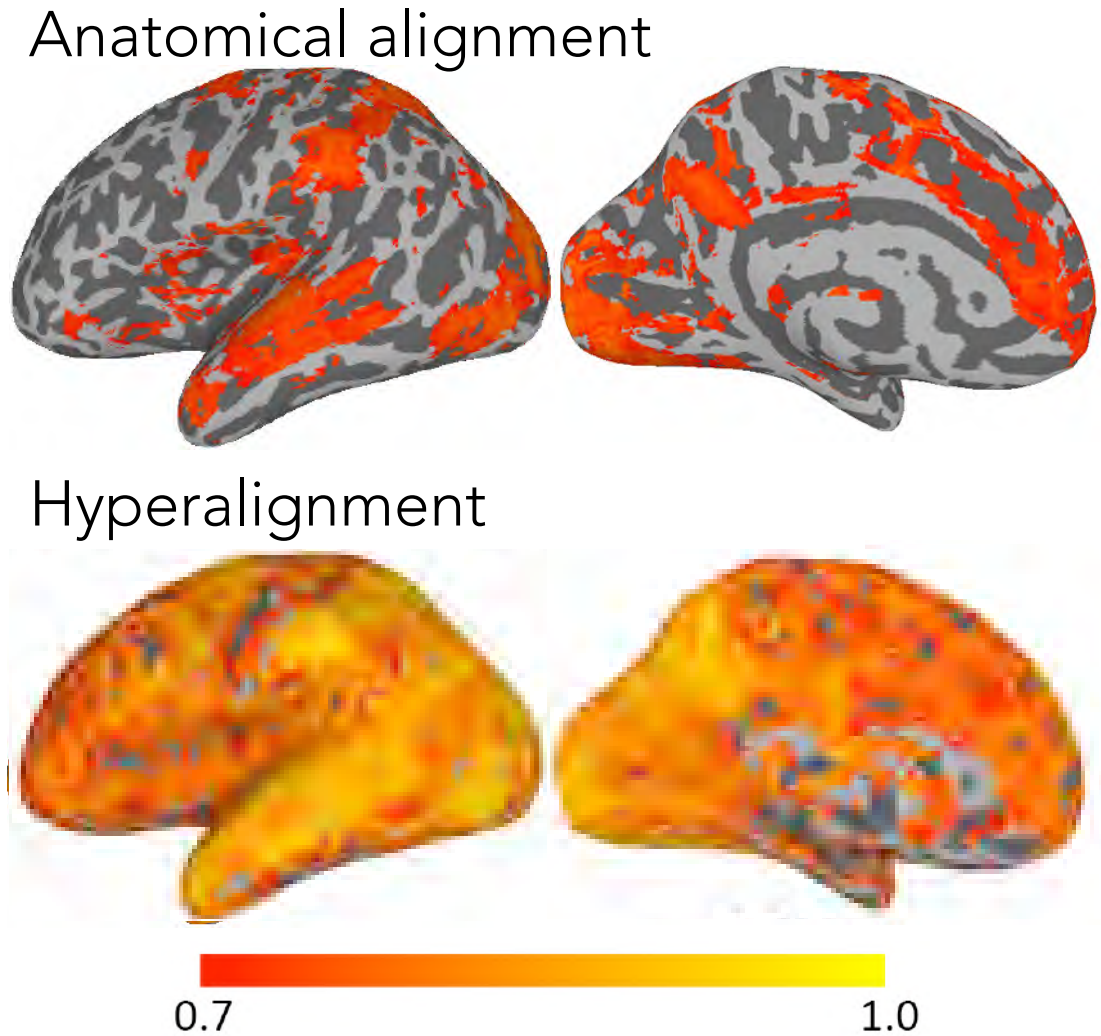


MDS of auditory regions only

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



Brain connectivity patterns are better aligned in the common model space



Inter-subject correlation of connectivity vectors

Experiment 2 data in Brain Space

Subject-specific Transformation Matrix

Experiment 2 data in Model Space

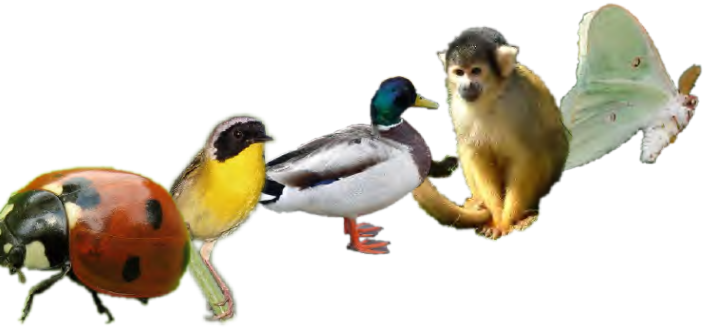
		Voxels				
		v_1	v_2	v_3	...	v_i
Stimuli	s_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{i,1}$
	s_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	...	$x_{i,2}$
	s_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	...	$x_{i,3}$
	s_4	$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	...	$x_{i,4}$
	...	...	...	...		...
	s_m	$x_{1,m}$	$x_{2,m}$	$x_{3,m}$	...	$x_{i,m}$

X

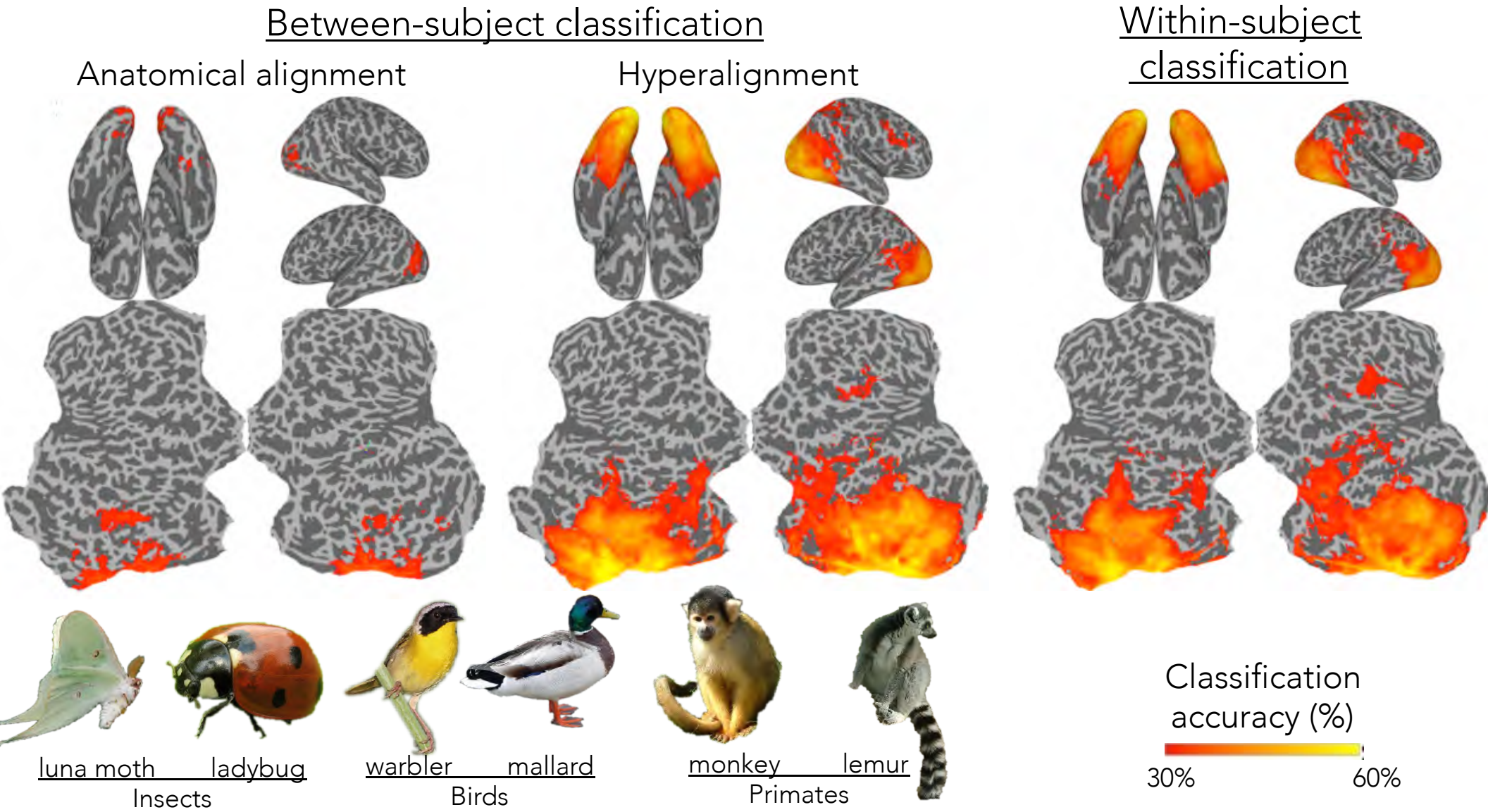
		Model dimensions				
		d_1	d_2	d_3	...	d_k
Voxels	v_1	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	...	$x_{k,1}$
	v_2	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	...	$x_{k,2}$
	v_3	$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	...	$x_{k,3}$
	...	...	...	...		...
	v_i	$x_{1,i}$	$x_{2,i}$	$x_{3,i}$	...	$x_{i,k}$

=

		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	$y_{1,m}$	$y_{2,m}$	$y_{3,m}$	...	$y_{k,m}$

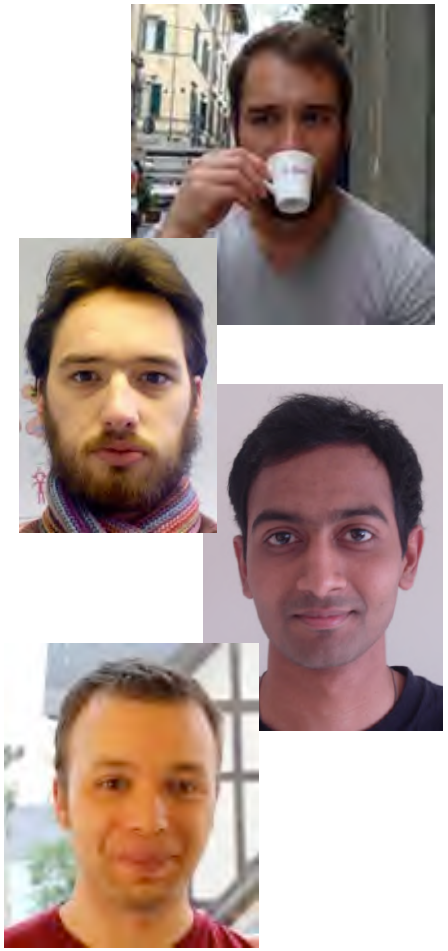


Whole-brain hyperalignment based on movie affords between-subject classification of responses in a visual category experiment (6 animal species) *at levels of accuracy that exceed within-subject classification*



Further validation testing and algorithm development

Similar results for other domains



- Action observation and attention (Sam Nastase, Dartmouth)
- Action execution (Nick Oosterhof, CIMeC, University of Trento)
- Connectivity hyperalignment and Music (Swaroop Guntupalli, Dartmouth, Caltech)
- Person knowledge (Dylan Wagner, Dartmouth, now Ohio State)

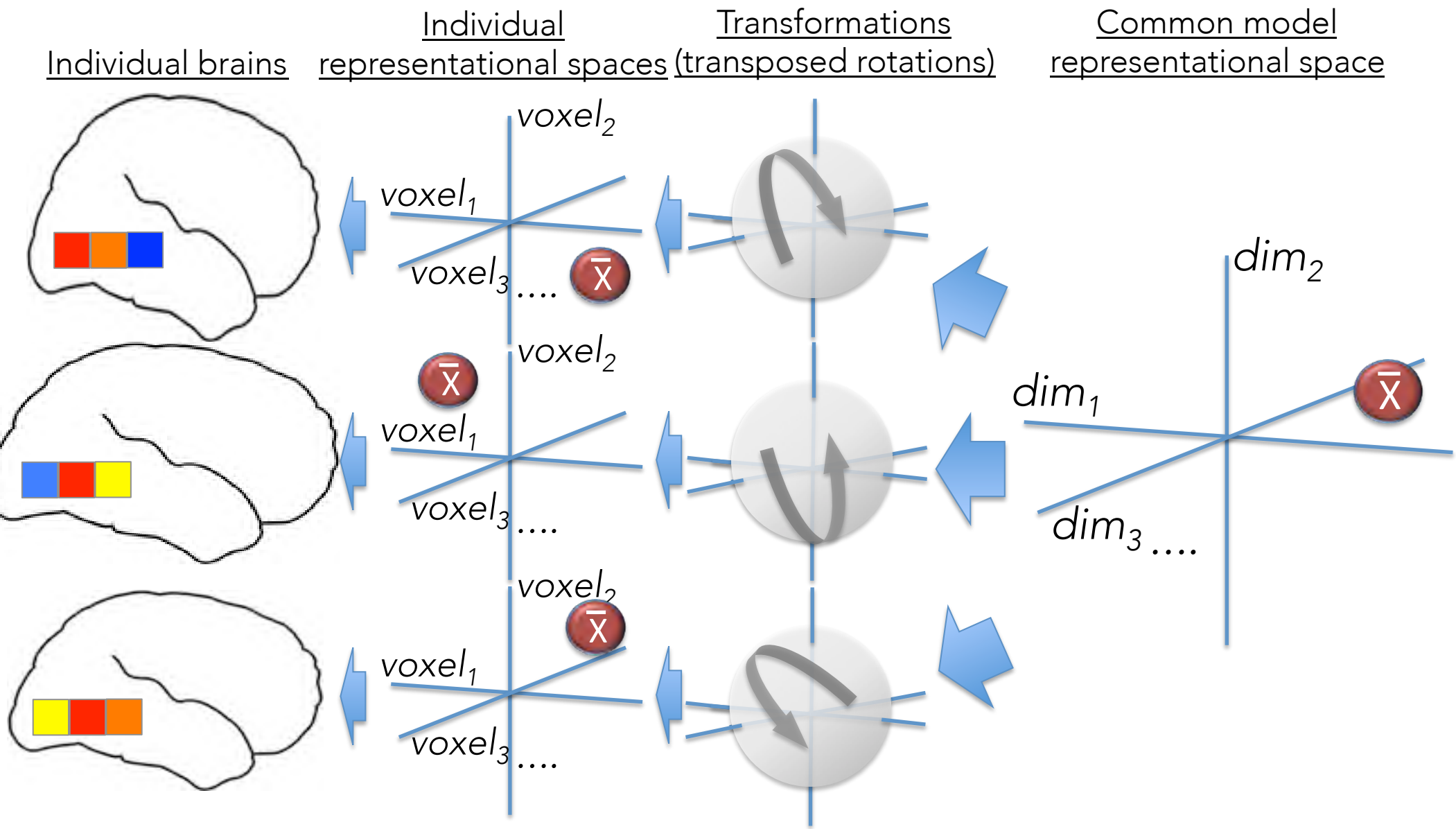
Hyperalignment parameters are estimated from responses recorded during movie viewing

Raiders of the Lost Ark

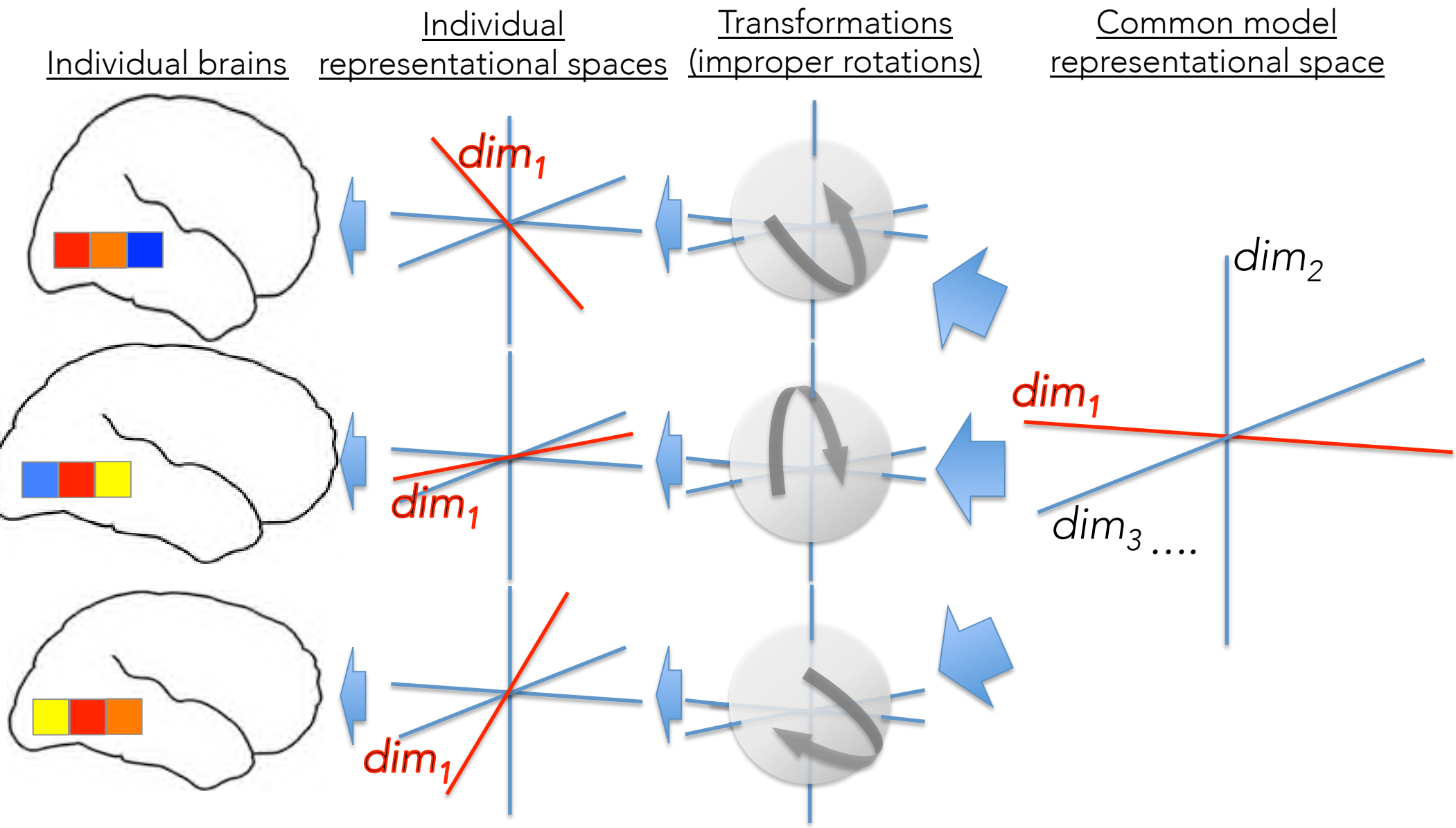
Life on Earth

The Wire

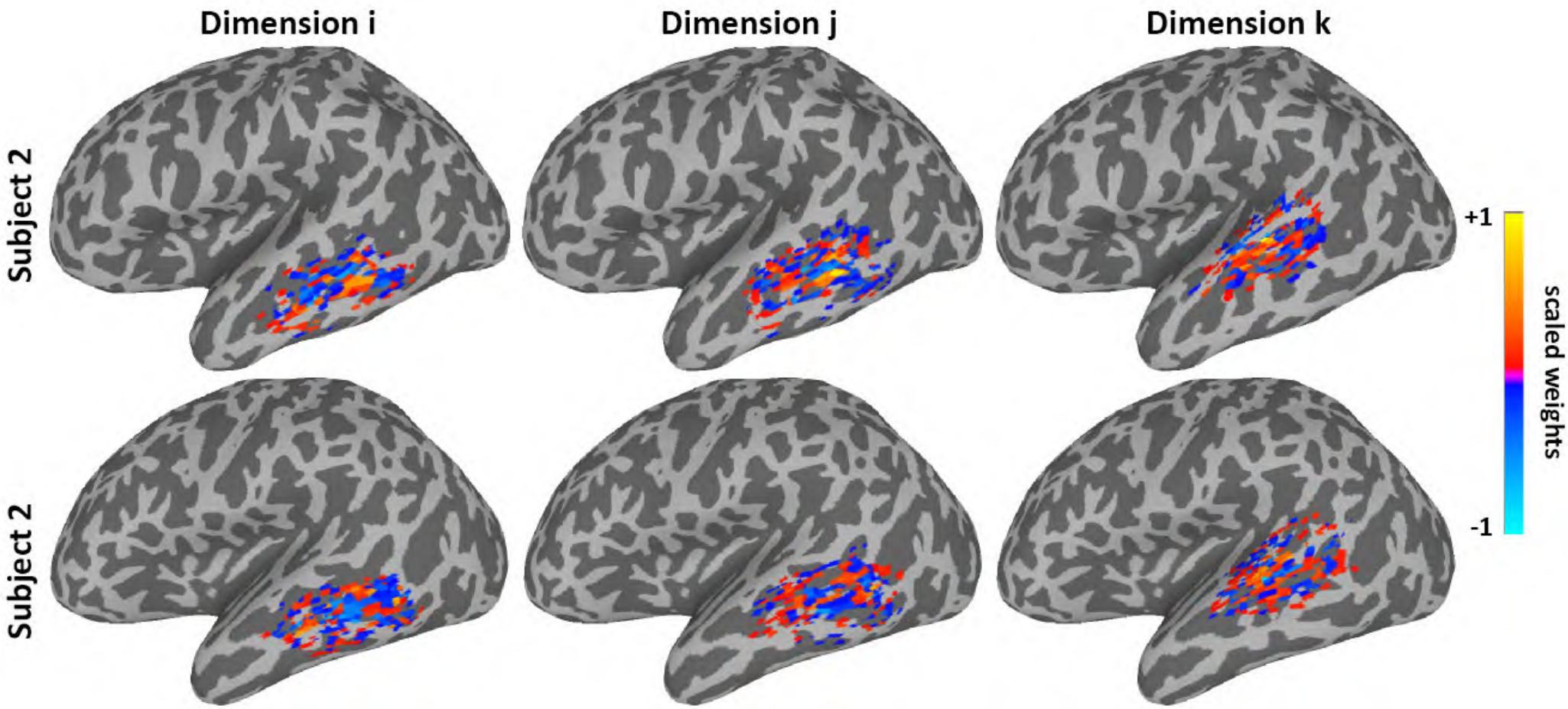
Projecting group data from common model space into individual subject's anatomy



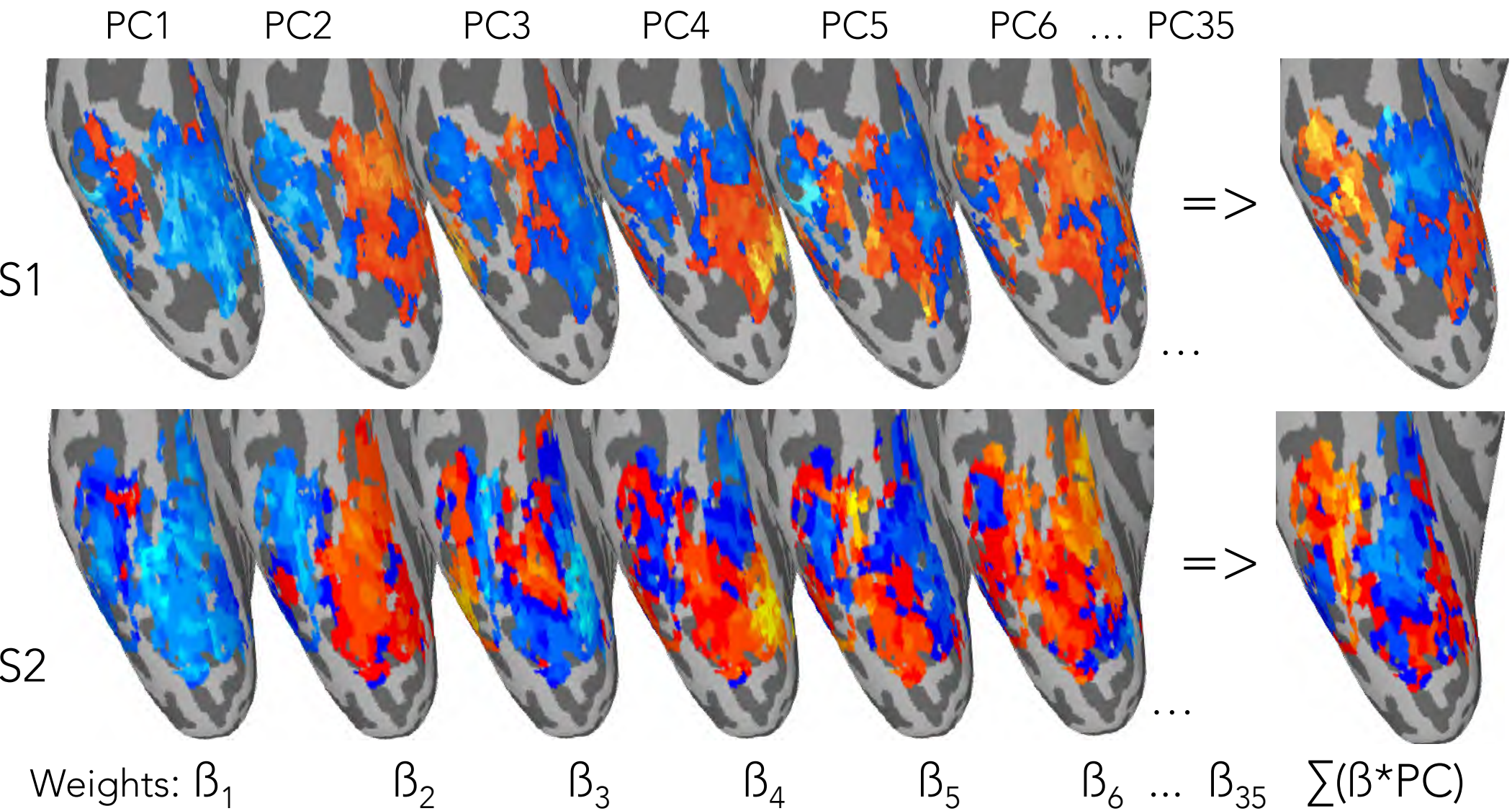
Modeling functional architecture of the human cortex: common model dimensions ≠ voxels



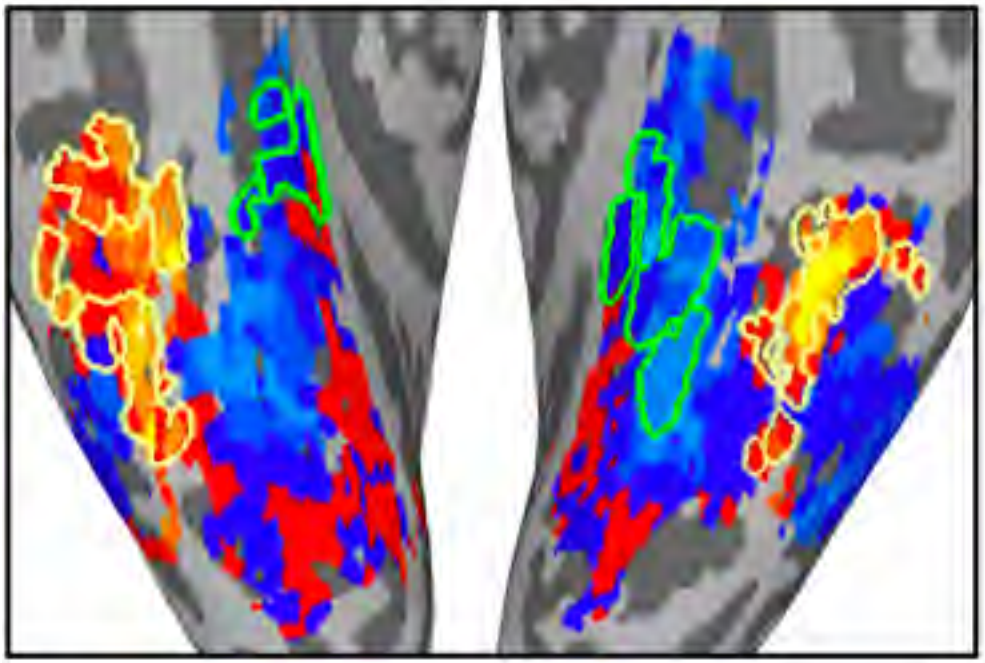
Topographies of weights for three model dimensions in two subjects



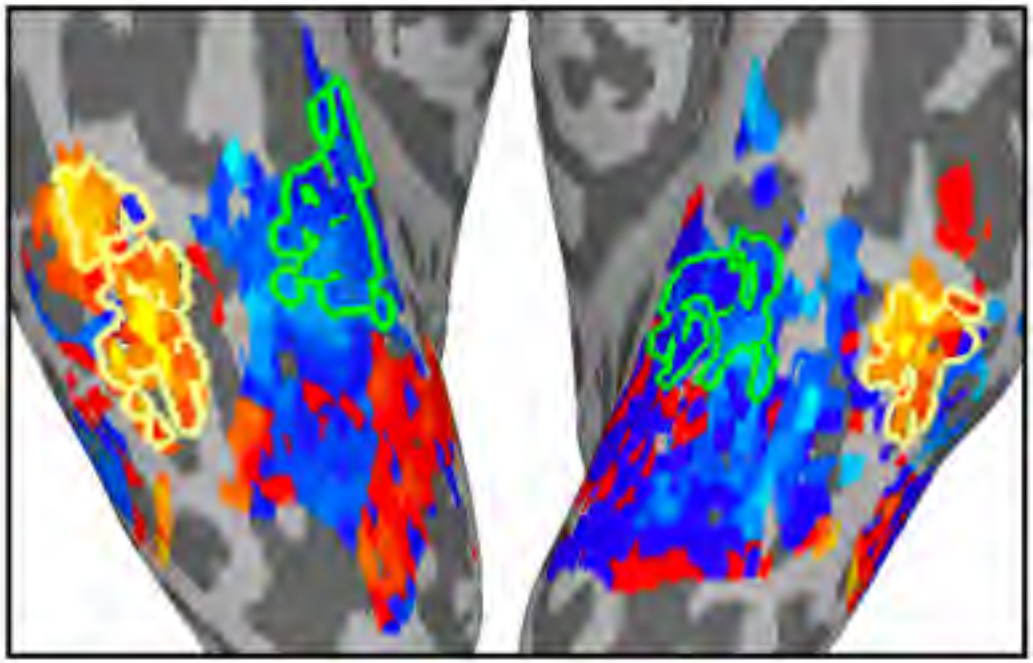
Topographies for response patterns are modeled in different brains as weighted sums of individual-specific topographic basis functions using <u>the same weights for common model dimensions</u>



Individual VT topographies for face vs object dimension in the model agrees well with the topographies of individually-defined FFAs

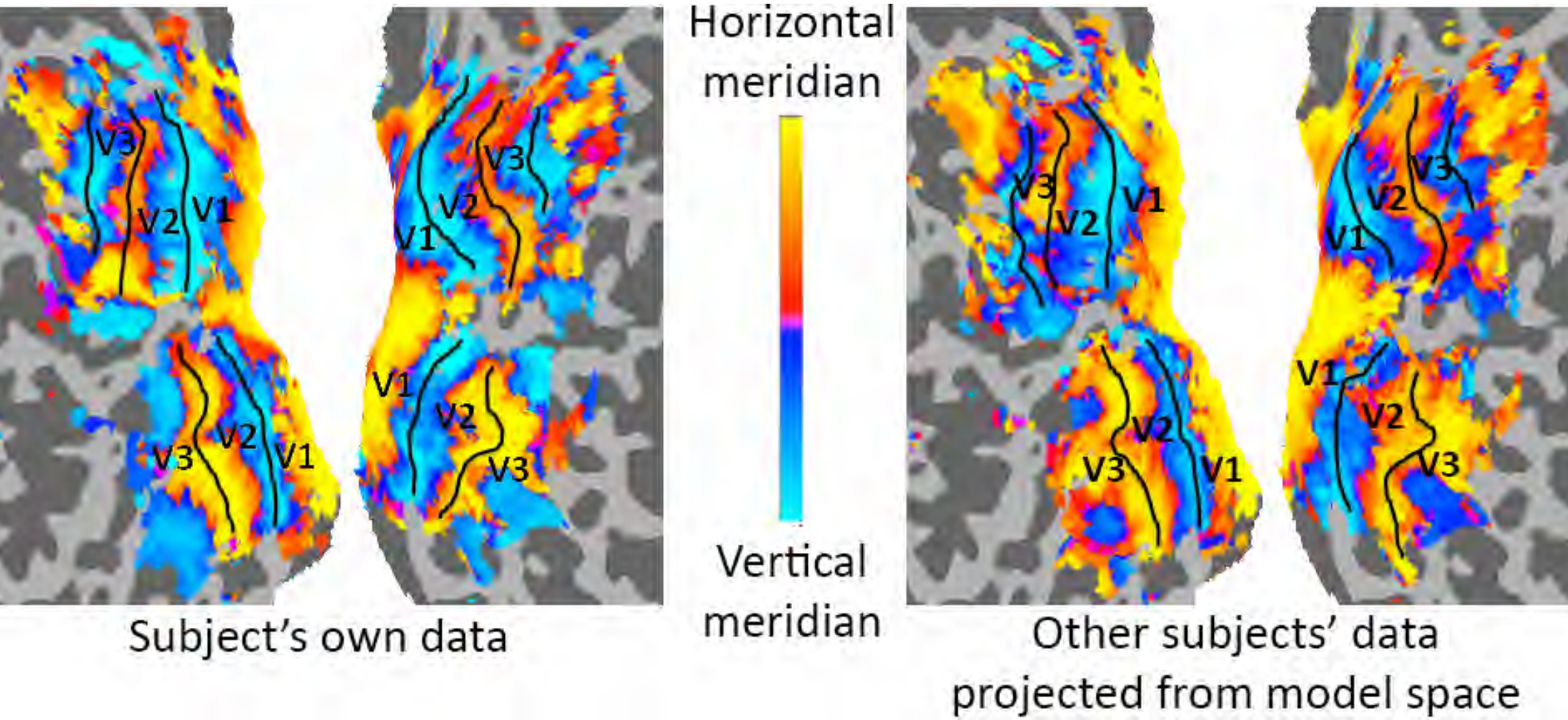


Subject 1



Subject 2

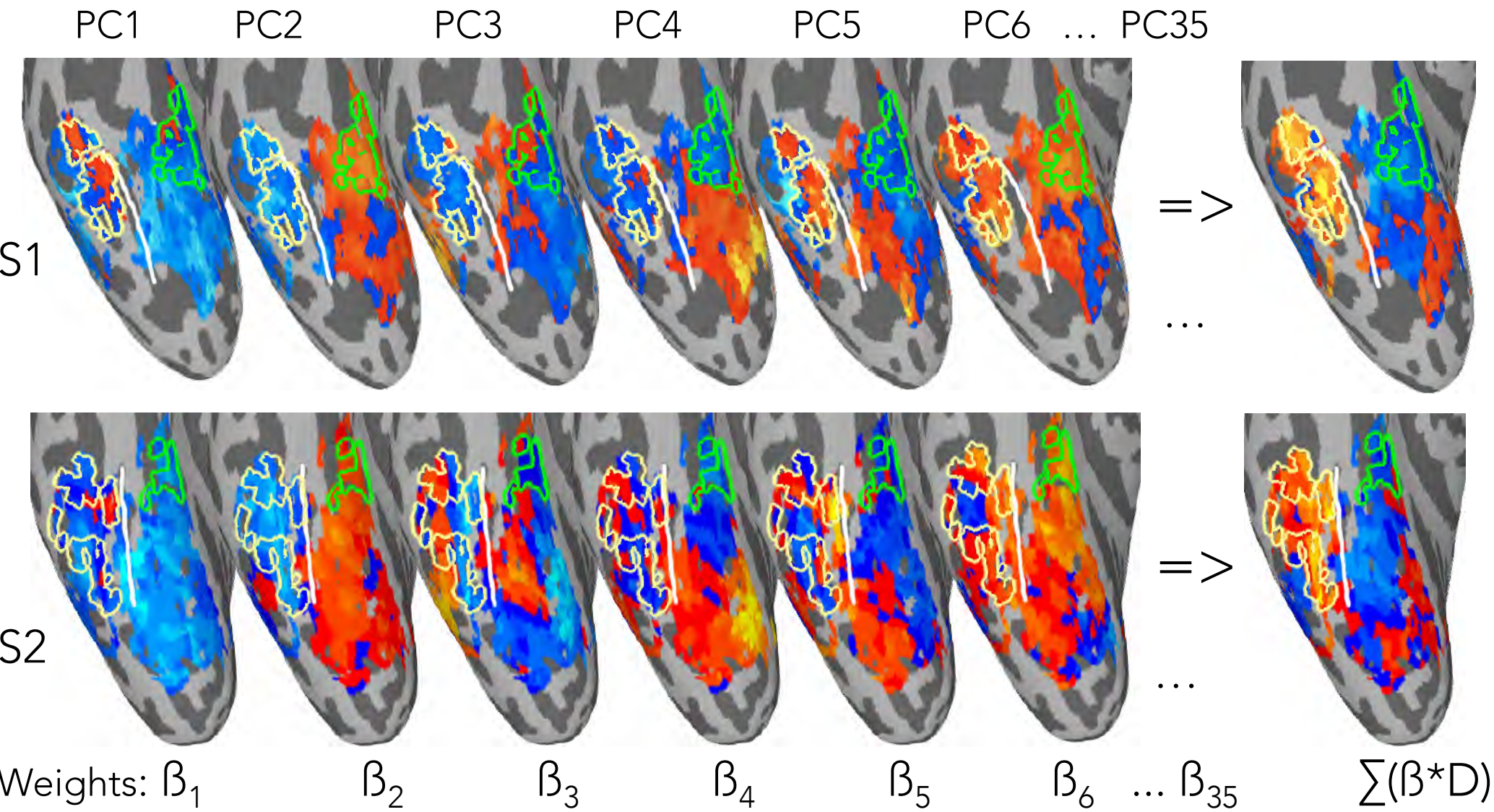
Mapping retinotopy by projecting other subjects' polar angle maps into a different subject's occipital topography



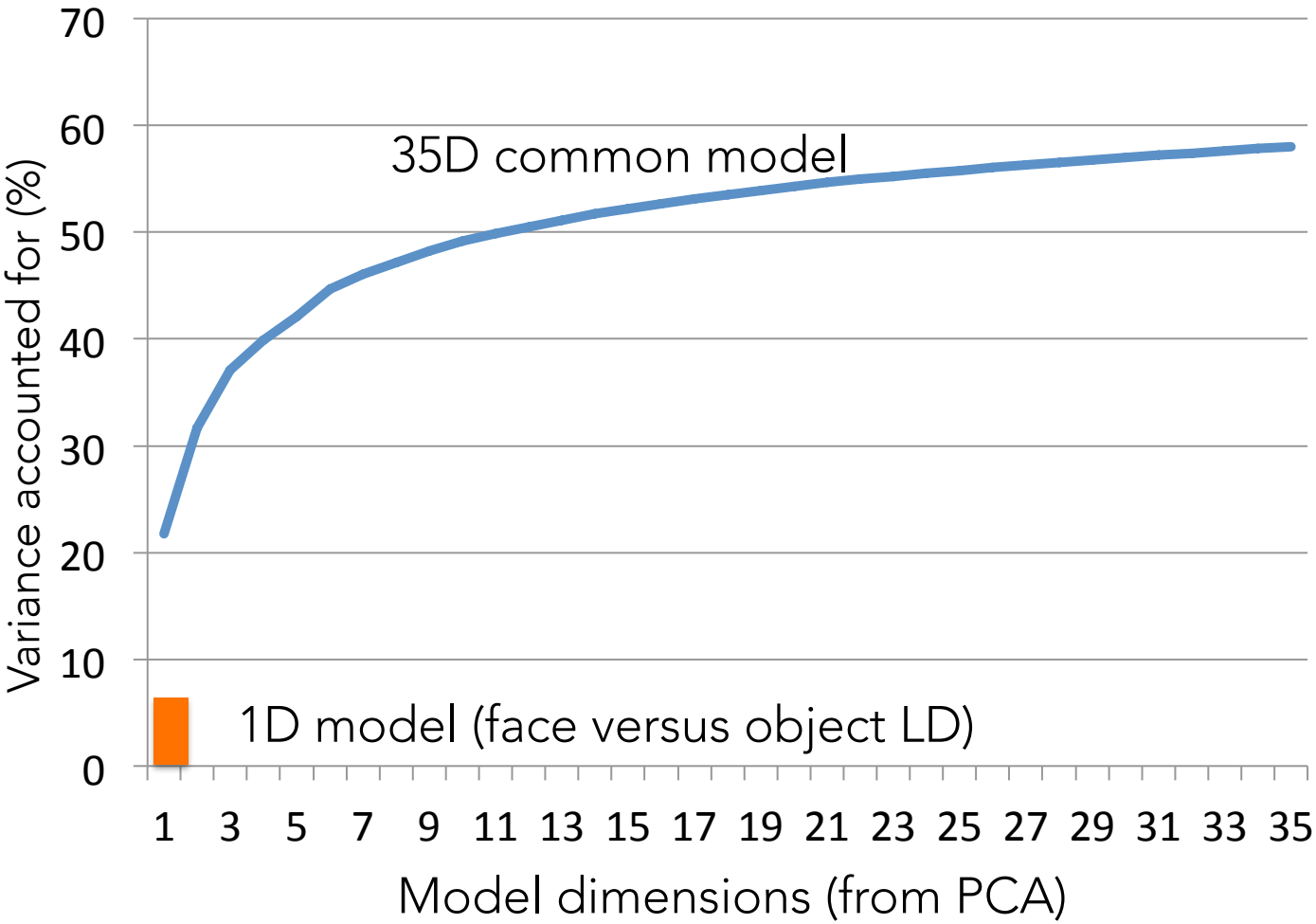
Subject's own data

Other subjects' data projected from model space

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

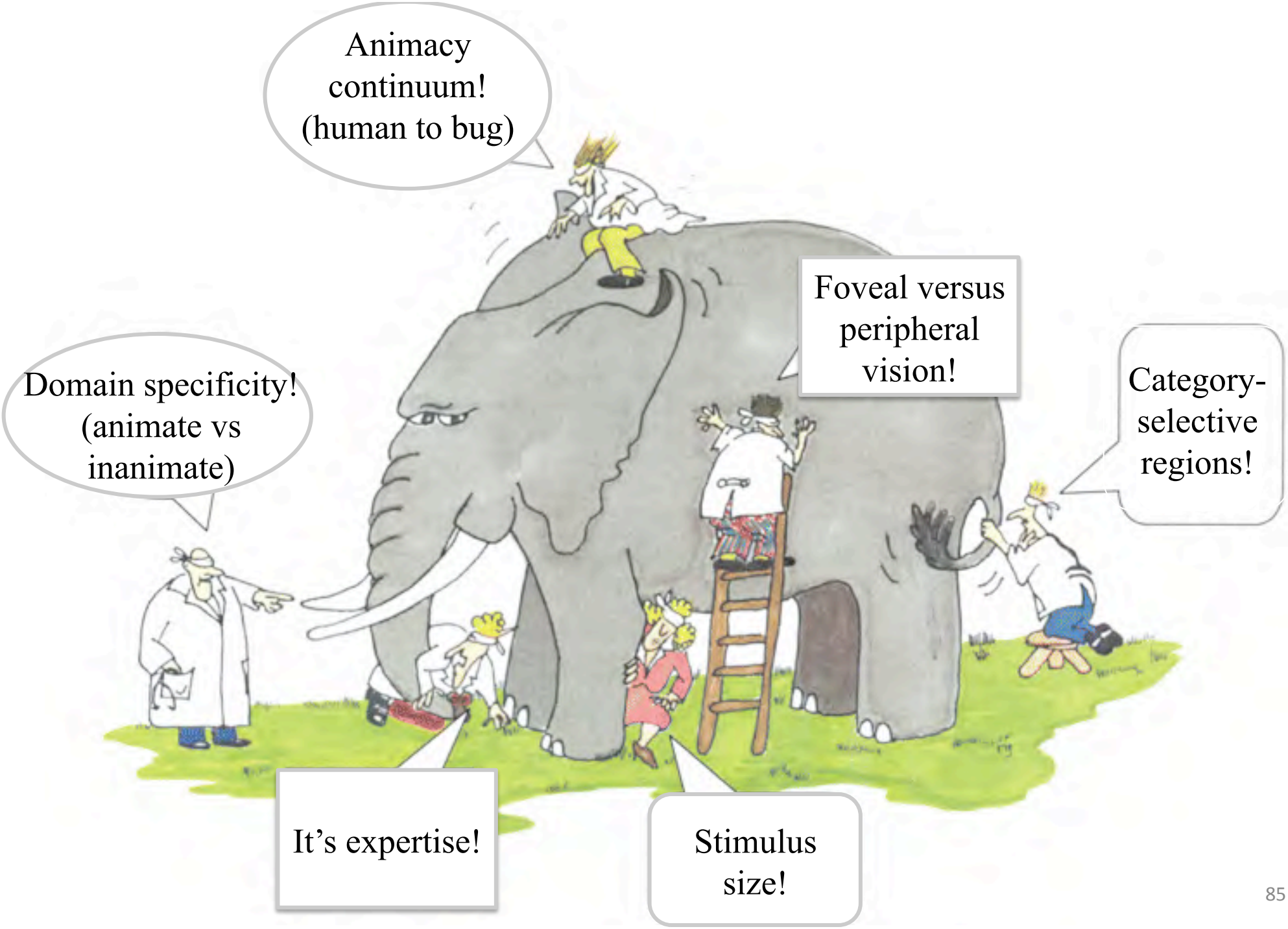


Single dimensions (simple contrasts) are inadequate for modeling the functional architecture of cortex



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!

Common model: Structure and validation testing

- Our model captures fine distinctions among neural population responses in a high-dimensional representational space based on response tuning functions that are common across brains
  - Valid for diverse domains of information
- Functional cortical topographies are modeled with basis functions that are grounded in common tuning functions
  - Accounts for structure-function relationships in individual brains with high fidelity
- Single dimensions (or small numbers of dimensions) are inadequate to capture fine distinctions and the fine-grained structure of topographies that carry these distinctions

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).

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

See the NeuroDebian/PyMVPA booth in exhibits

New massive data release of 7T fMRI with natural stimulus and lots more:

data website: http://www.studyforrest.org

paper: Hanke et al. (2014) *Nature Scientific Data, 1: 140003.*