An fMRI Shared Response Model

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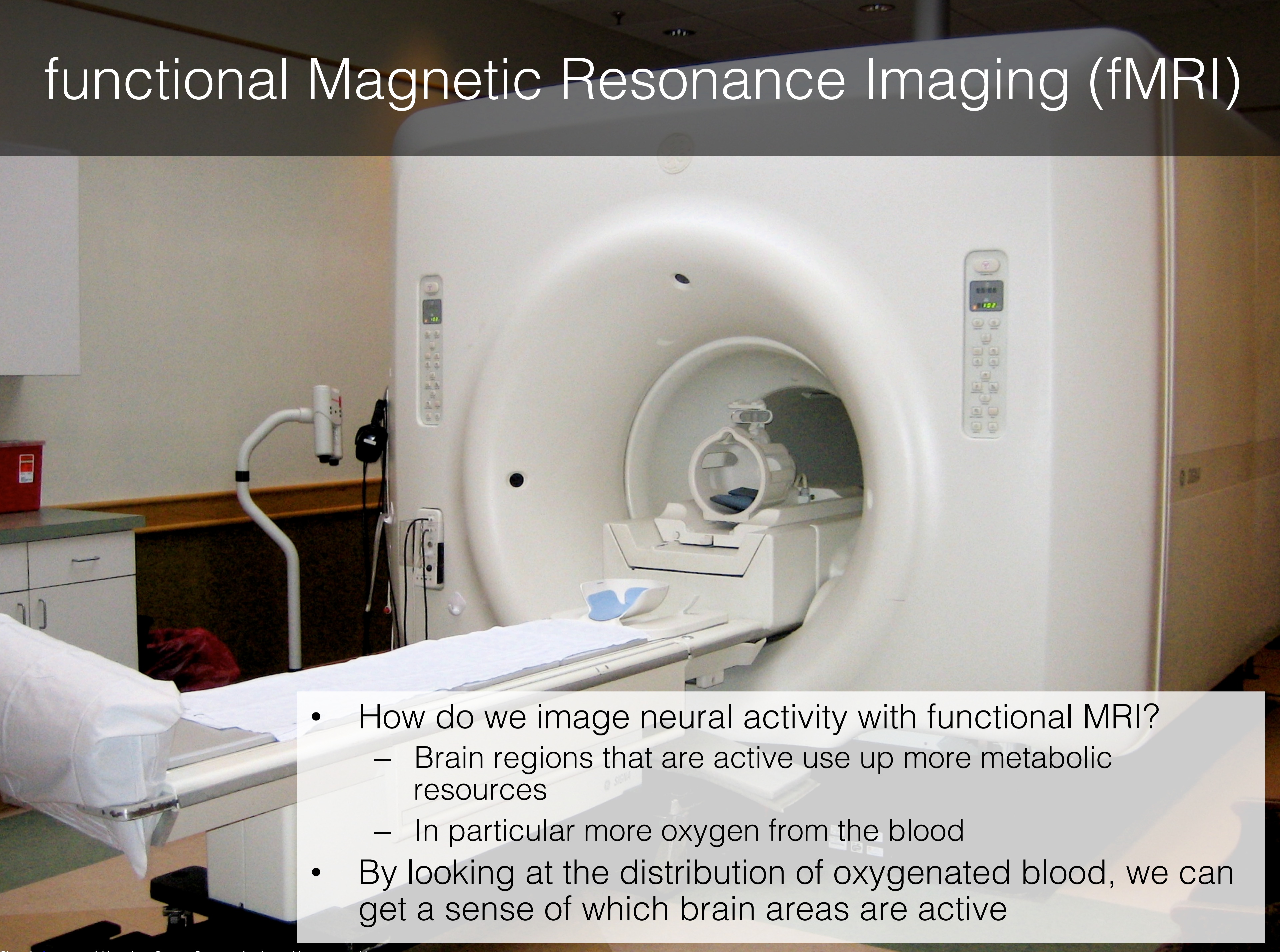
Computer Vision Taiwanese Group Online Meetup
March 25, 2016

Chen et al. "A Reduced-Dimension fMRI Shared Response Model." NIPS 2015.

PRINCETON UNIVERSITY

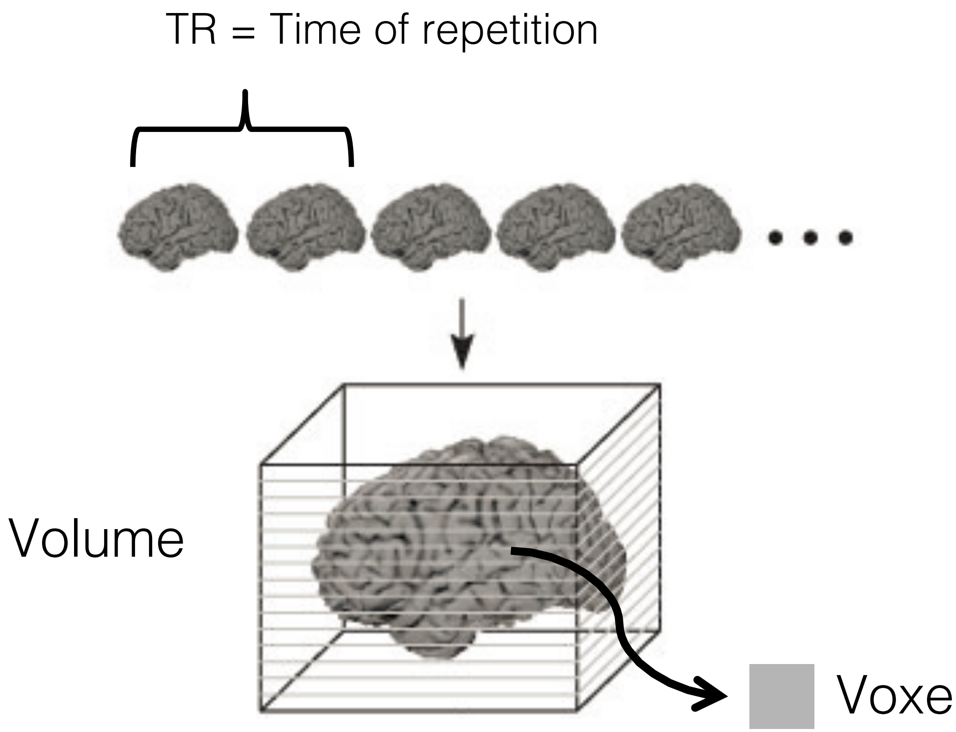
How does the human brain work?

functional Magnetic Resonance Imaging (fMRI)



- How do we image neural activity with functional MRI?
  - Brain regions that are active use up more metabolic resources
  - In particular more oxygen from the blood
- By looking at the distribution of oxygenated blood, we can get a sense of which brain areas are active

Functional magnetic resonance imaging (fMRI) data



Motivation

Modern fMRI studies of human brain use data from multiple subjects

- scientific reason
- statistical reason

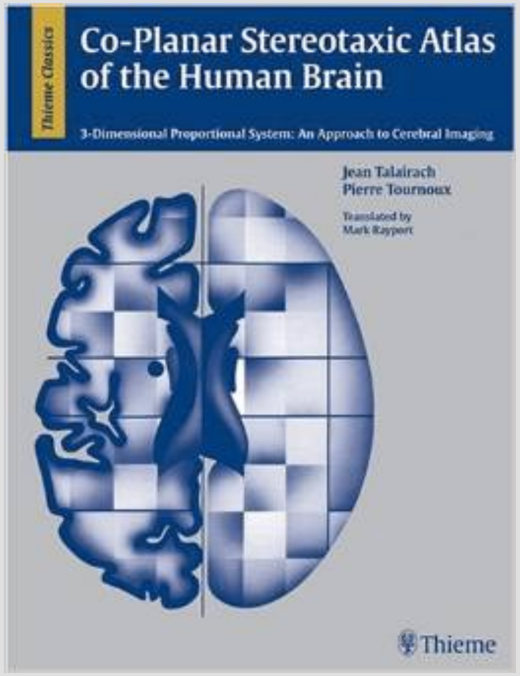
How can we aggregate fMRI data from multiple subjects?

Challenge

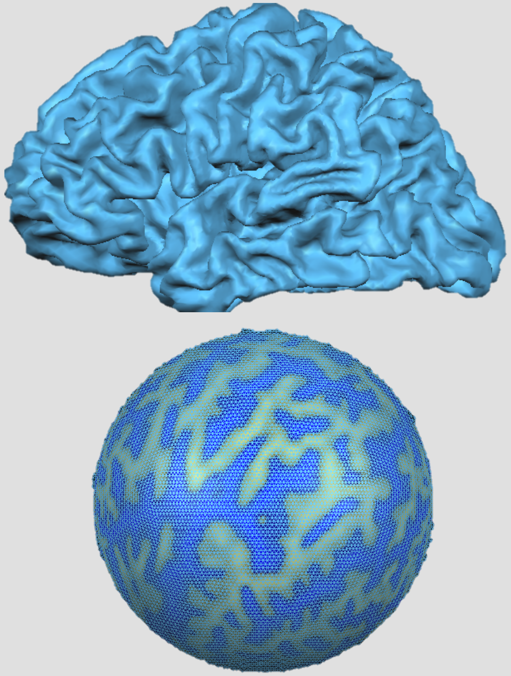
Inter-subject variability in anatomical structure and functional topographies

Anatomical alignment is not sufficient

Tailarach



Cortical Surface

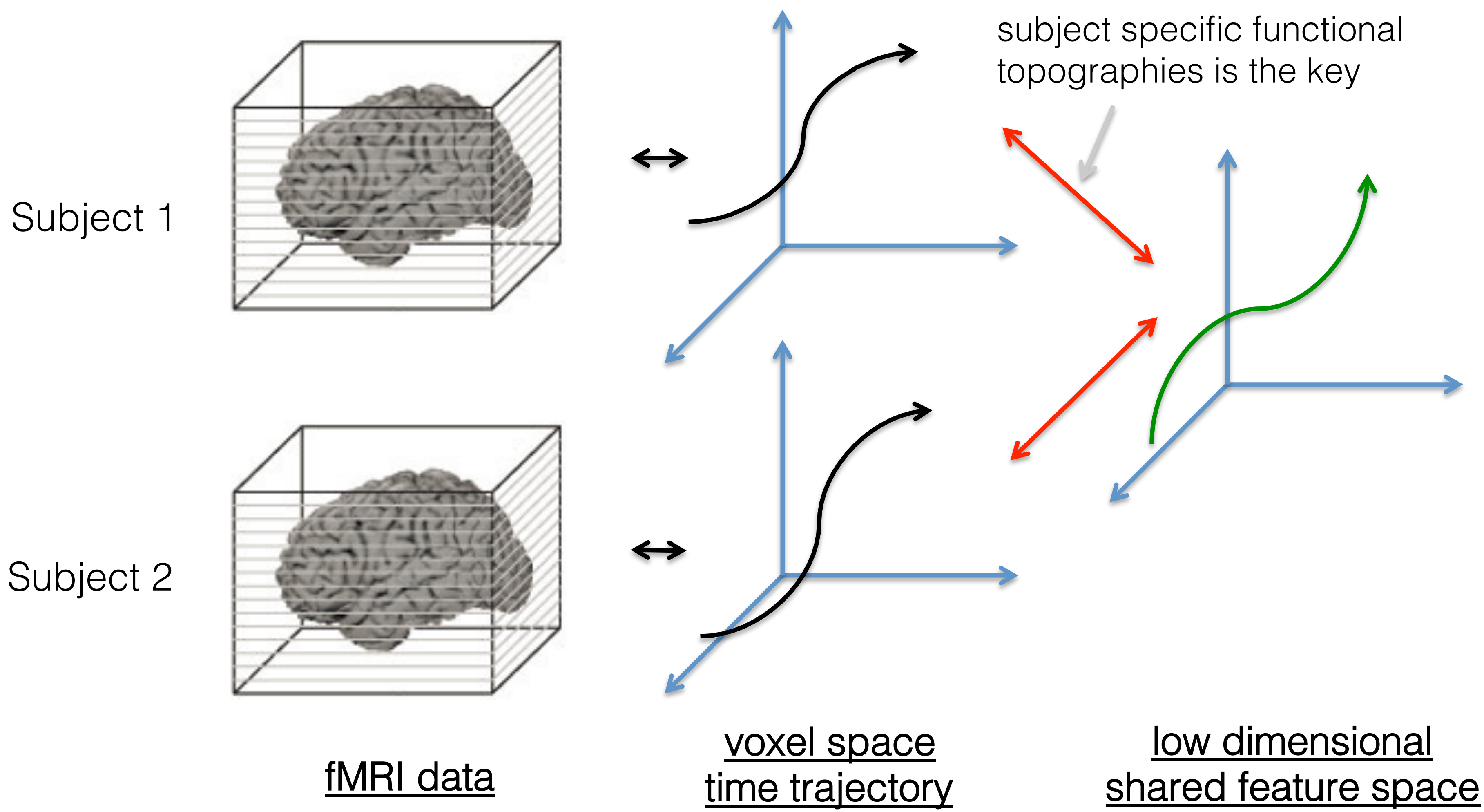


Given data from training subjects,

<u>Prediction:</u>
can we predict the brain response of a test subject?

<u>Classification:</u>
given brain response from a test subject, can we classify what's the stimulus?

Shared latent temporal response + subject specific functional topographies

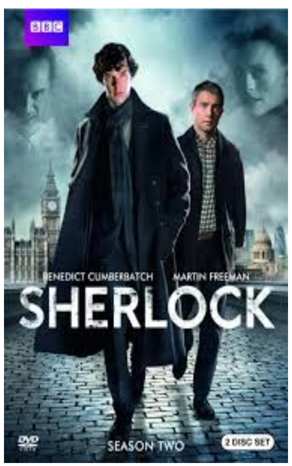


Data collected while subjects receiving stimulus

Temporally synchronized naturalistic stimuli

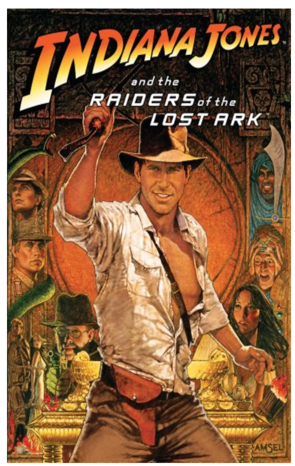
1. Sample a wide range of response from the subject
2. Use time as anchor for learning shared response

<u>sherlock</u>



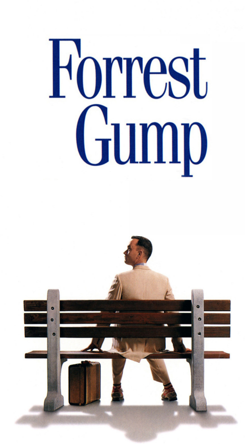
movie watching

<u>raider</u>



movie and image watching

<u>forrest</u>

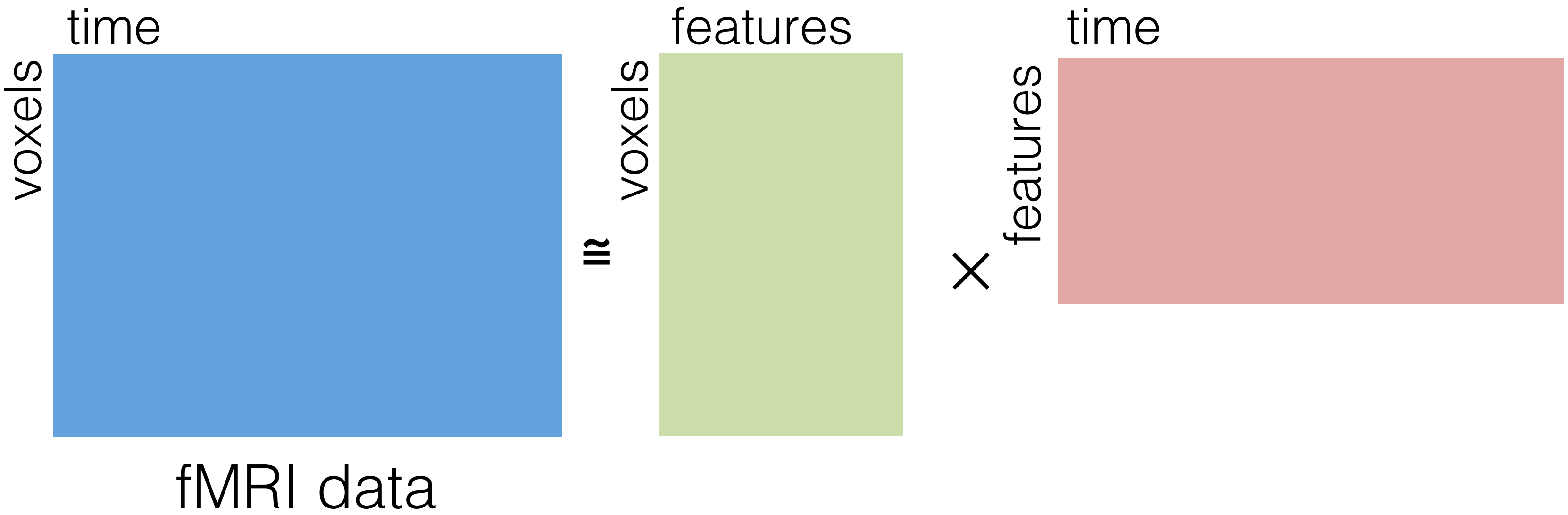


auditory film listening

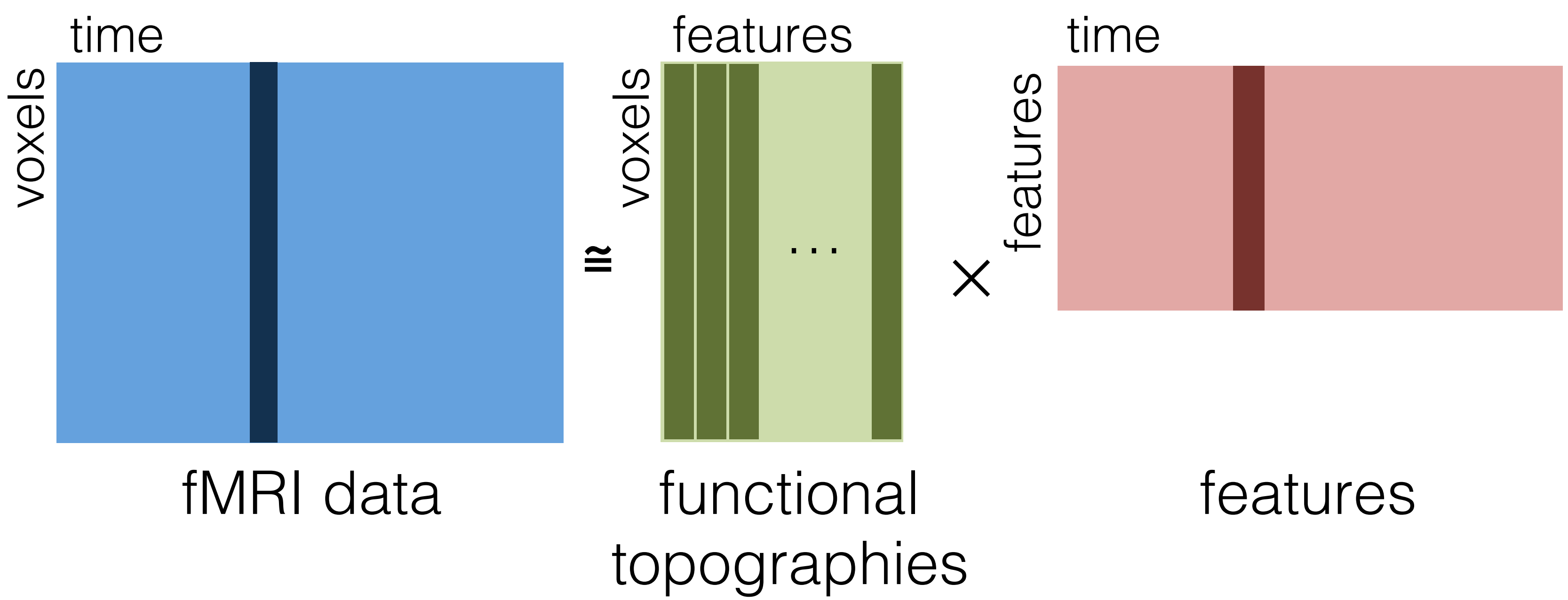
<u>audiobook</u>

audio book listening

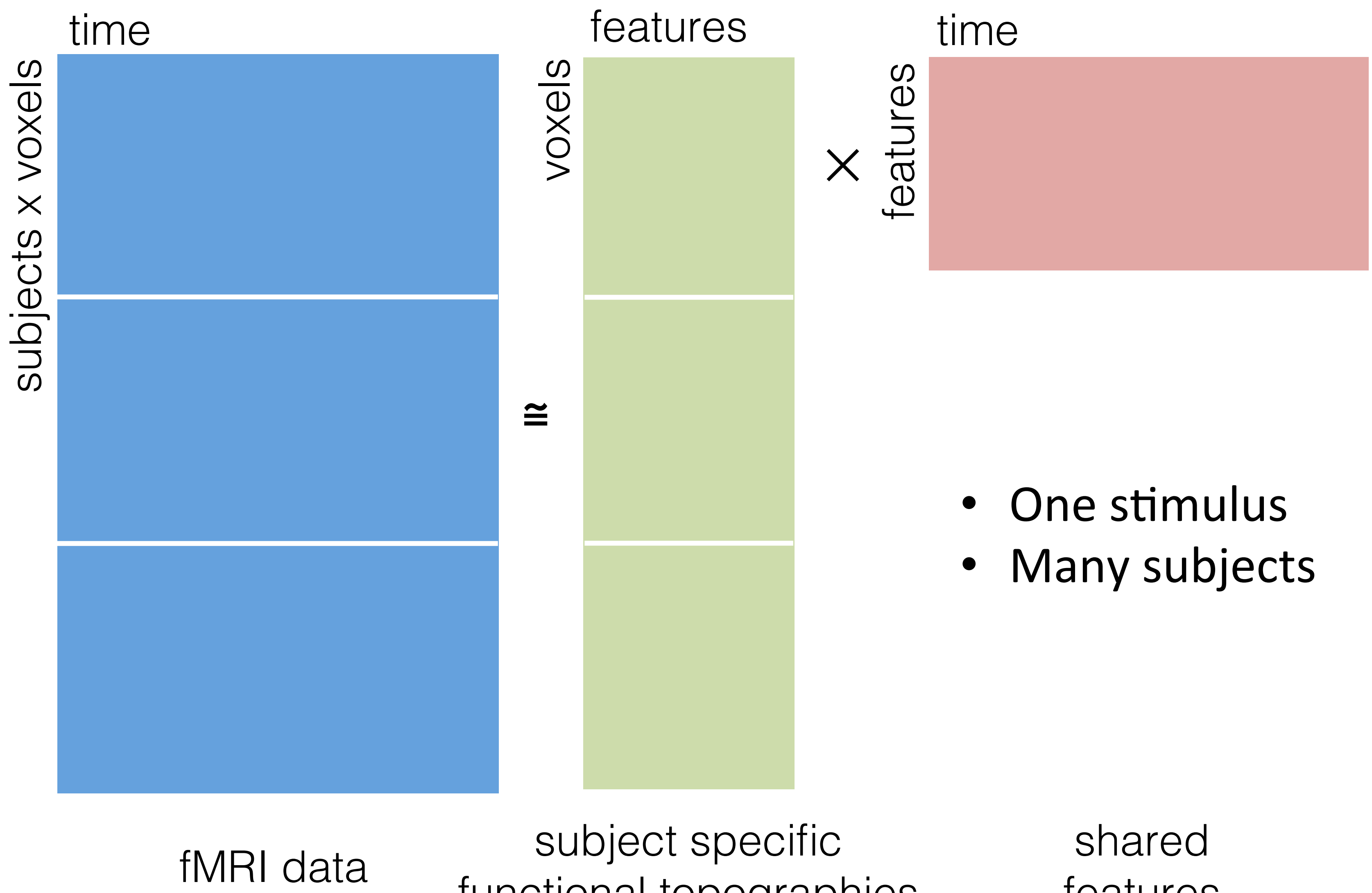
Factor Model



fMRI response as linear combination of functional topographies

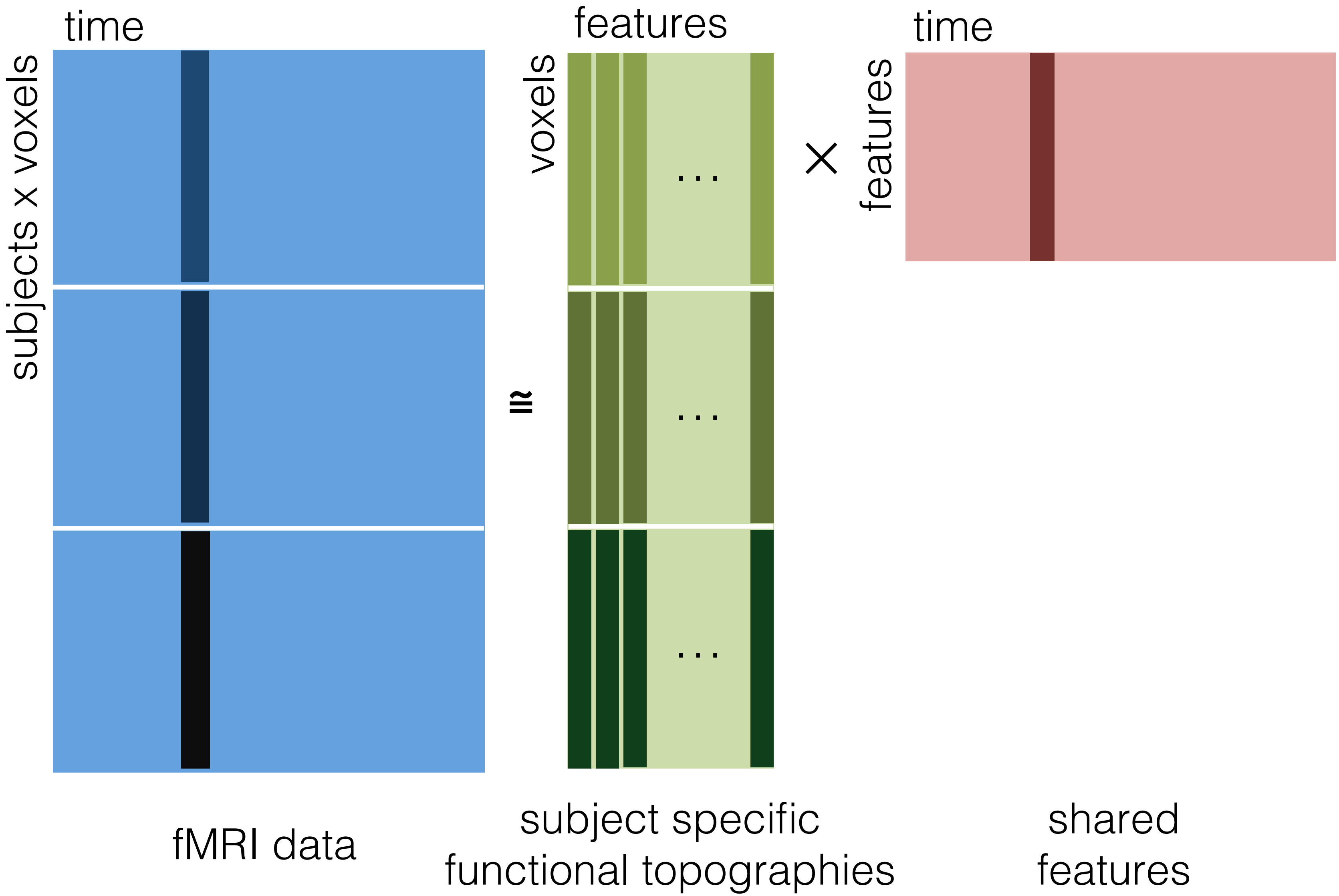


Learning what is shared across subjects

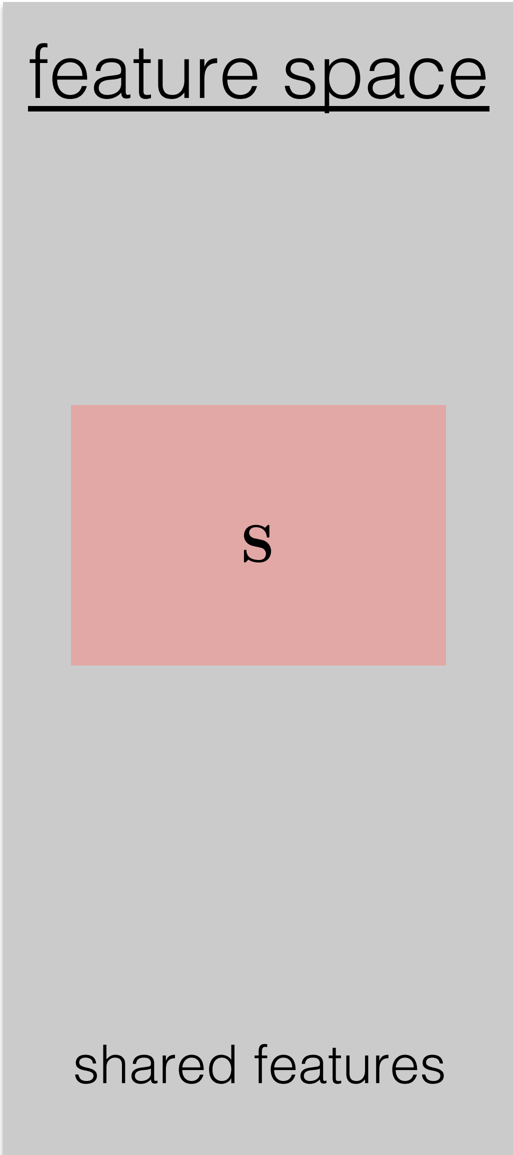


- One stimulus
- Many subjects

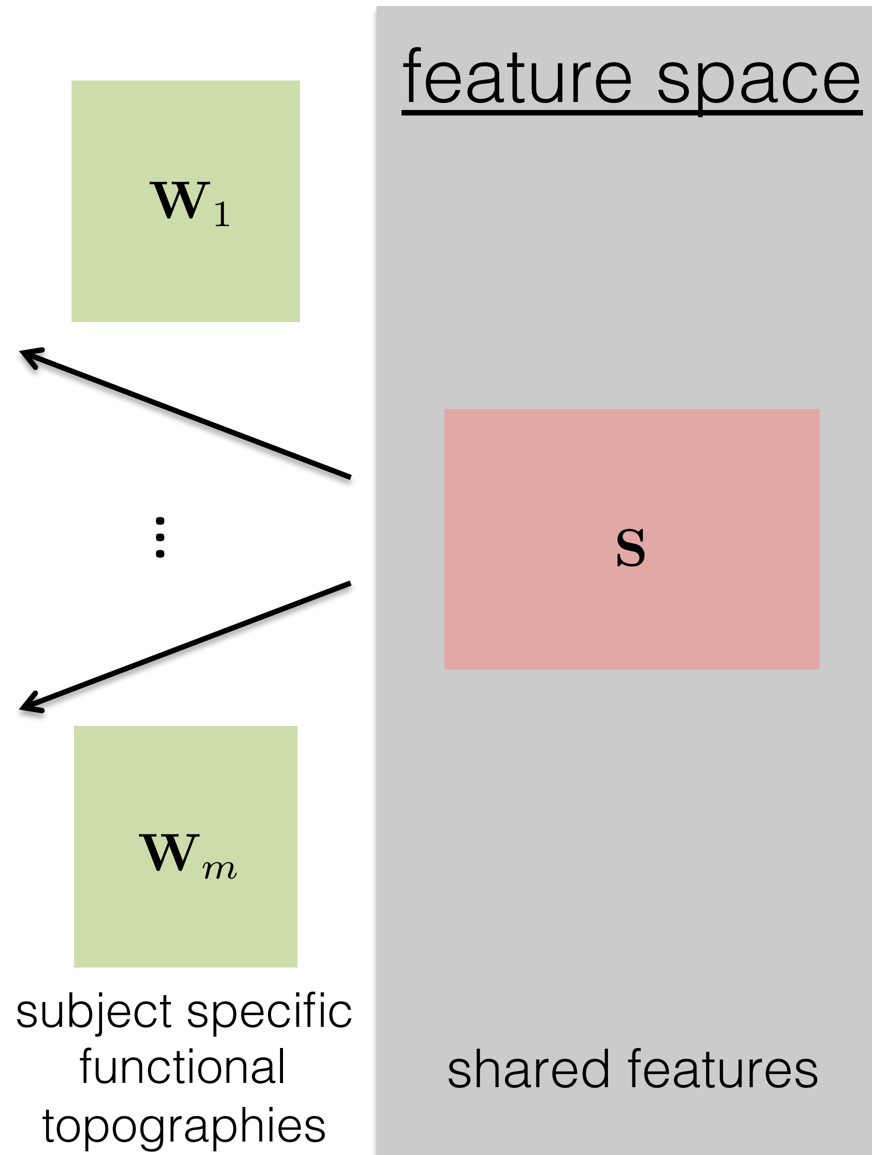
fMRI data as linear combination of subject specific functional topographies



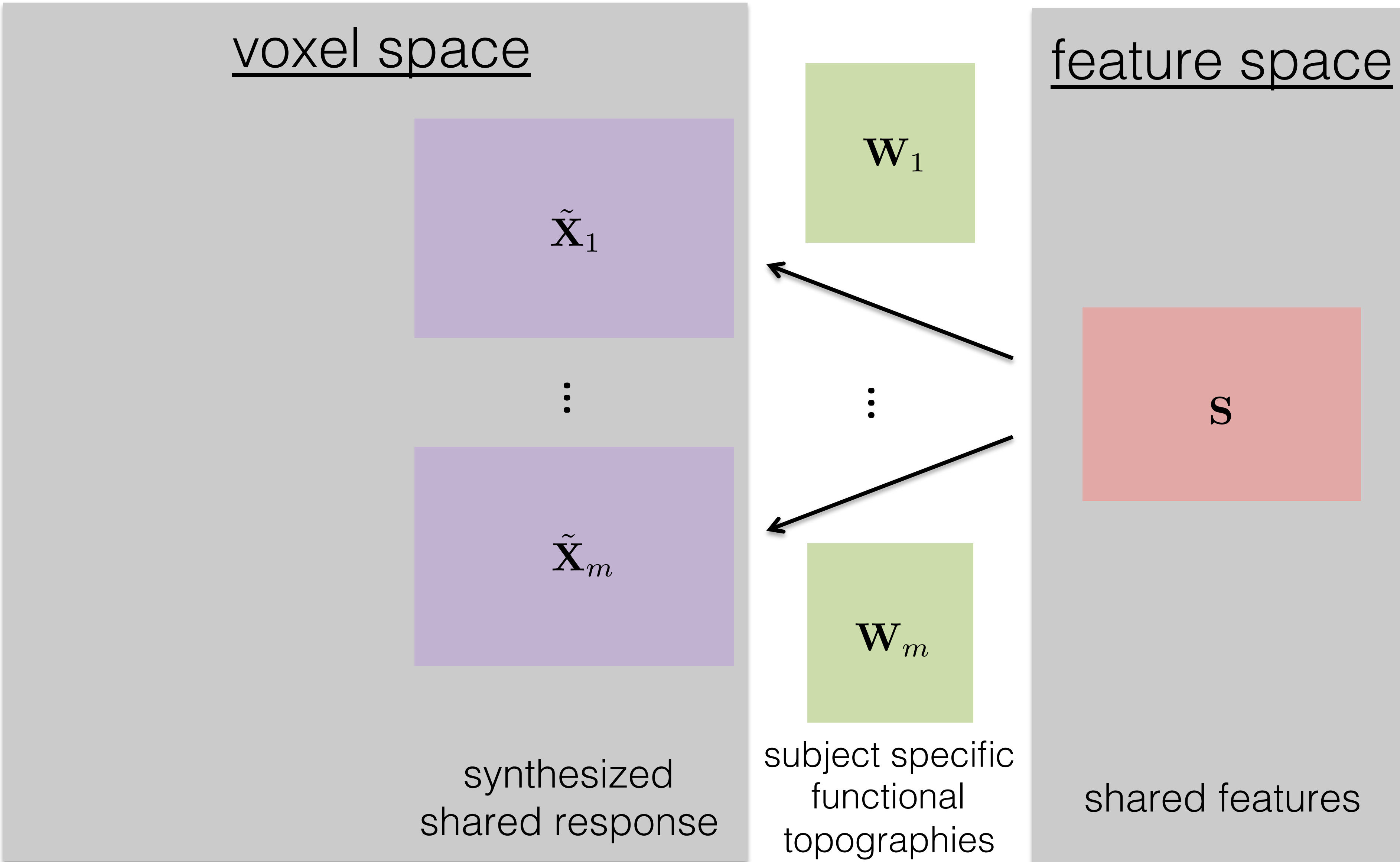
A generative model



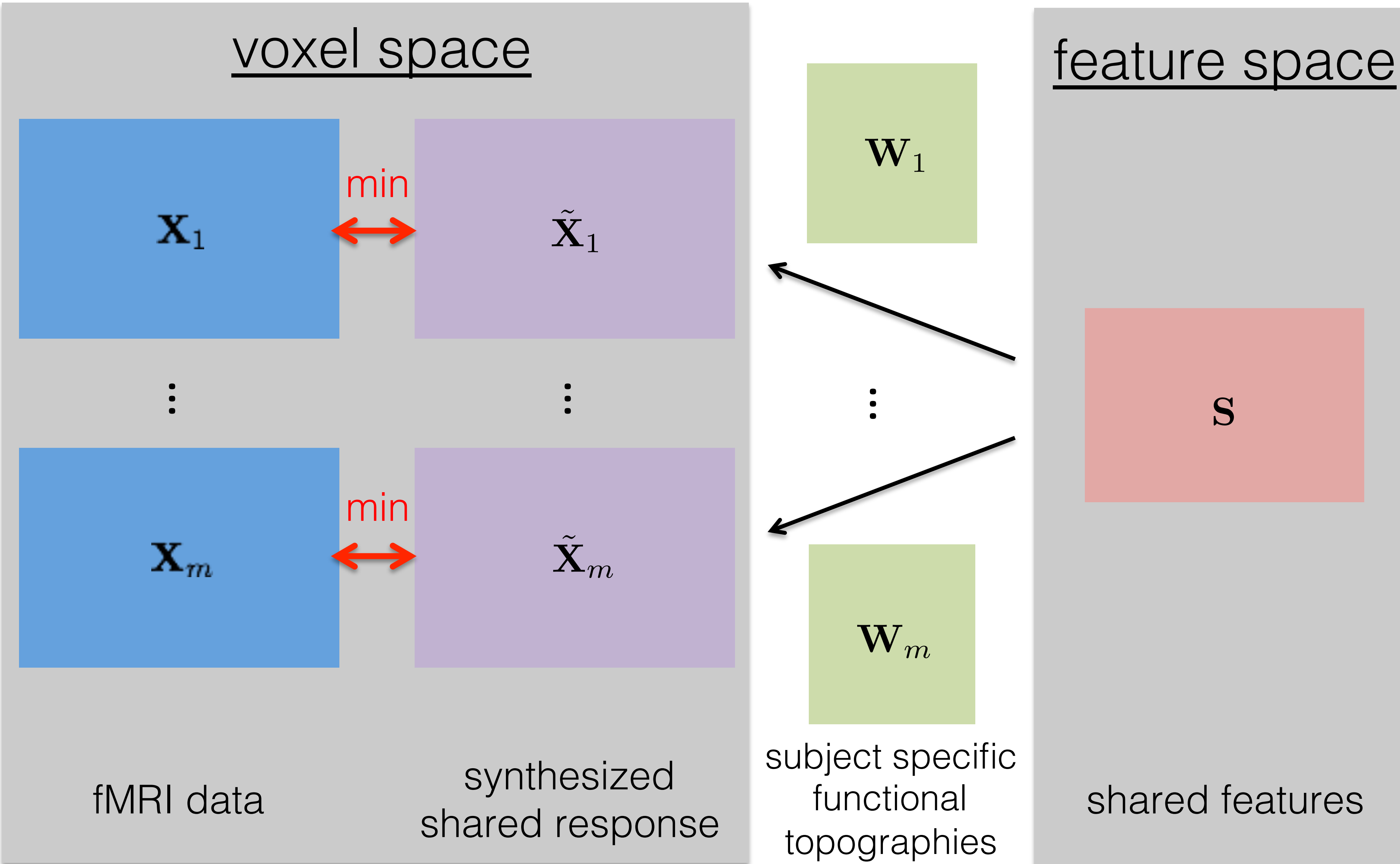
A generative model



A generative model



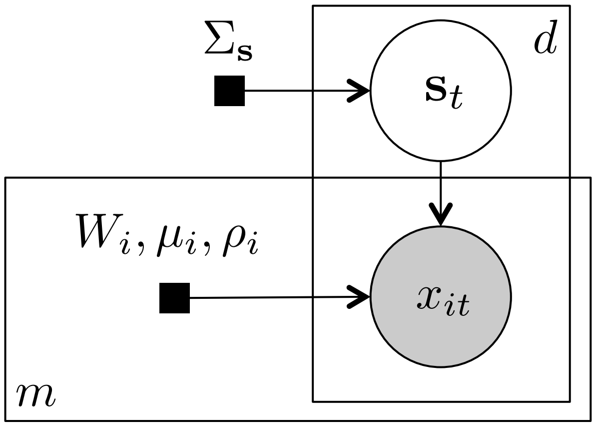
A generative model



Shared Response Model (SRM) is a latent variable model

$$s_t \sim \mathcal{N}(0, \Sigma_s)$$
$$x_{it} | s_t \sim \mathcal{N}(W_i s_t + \mu_i, \rho_i^2 I)$$
$$W_i^T W_i = I$$

W_i not square



s_t shared elicited response at time t

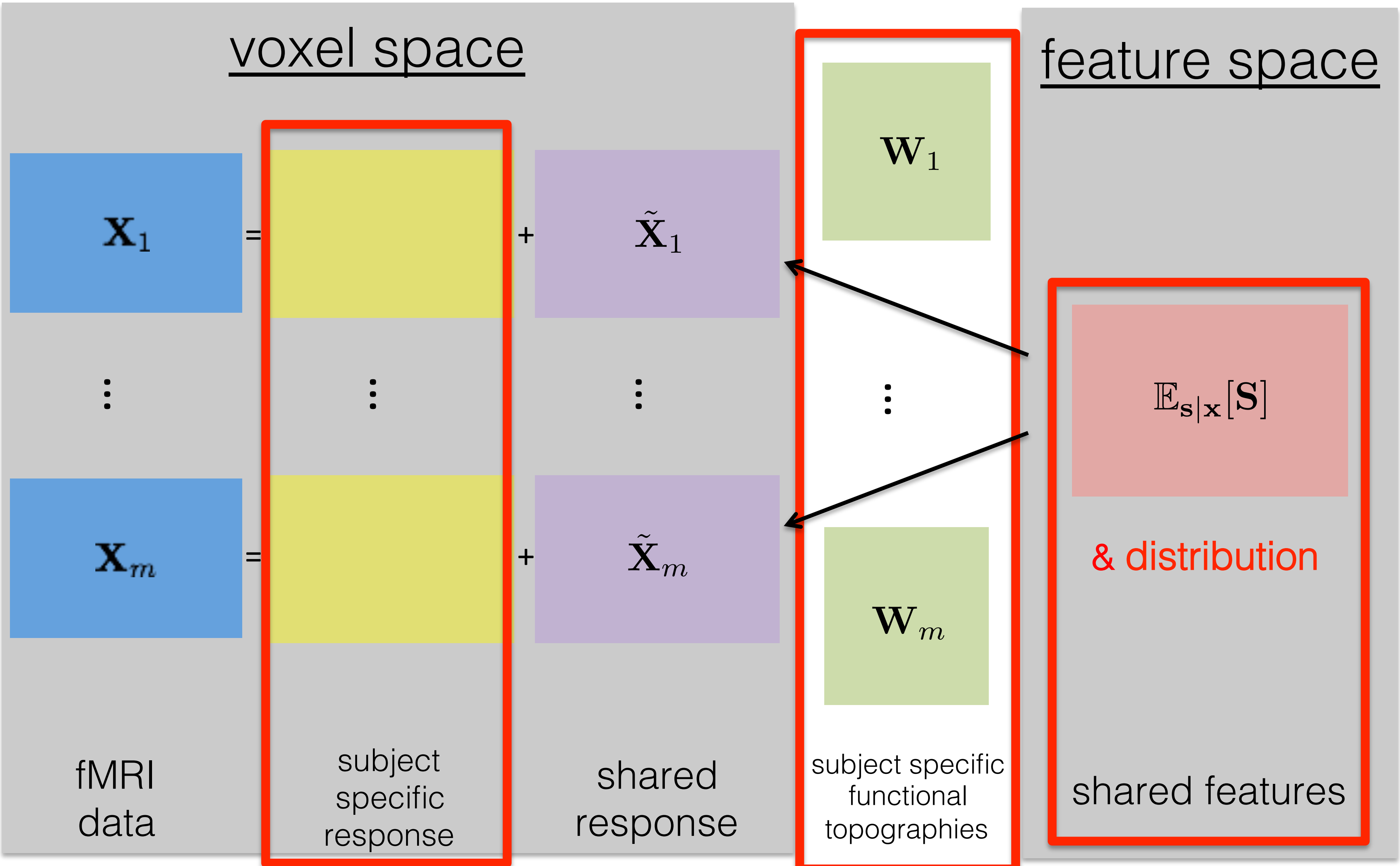
W_i functional topographies for subject i

x_{it} observations of subject i at time t

ρ_i^2 noise level for subject i's data

- Feature identification with dimensionality reduction
- Constrained EM algorithm

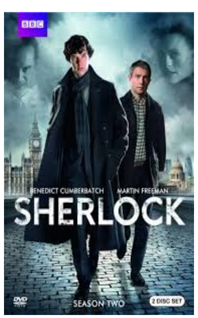
Shared features, subject specific functional topographies, and subject specific response



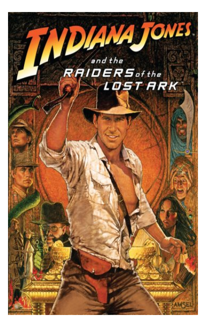
Evaluation with various datasets

- Different MRI machines
- Different institutes
- Different subjects
- Different preprocessing protocols
- Different brain regions
- Different data size

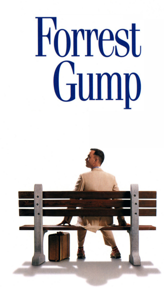
sherlock



raider



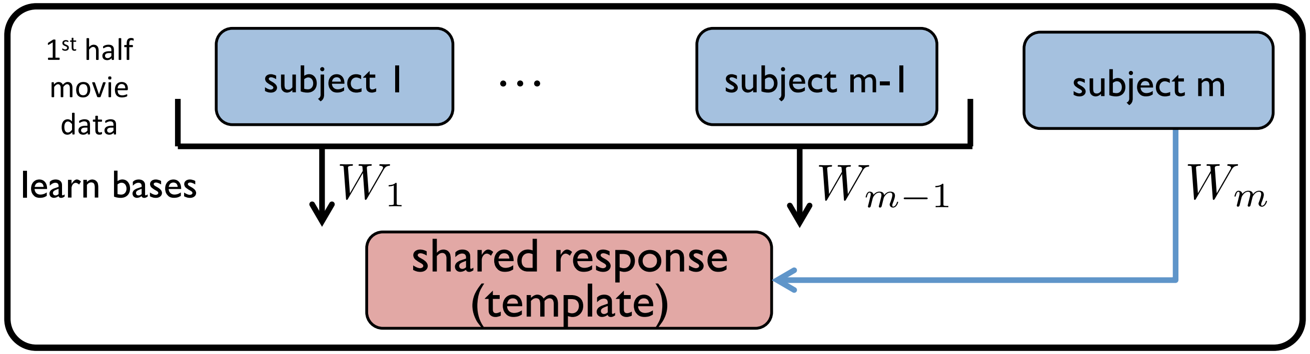
forrest



audiobook

Generalization to new subject with time segment matching

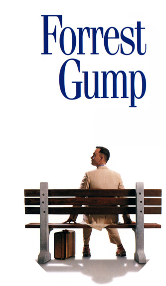
Learning Subject Specific Bases



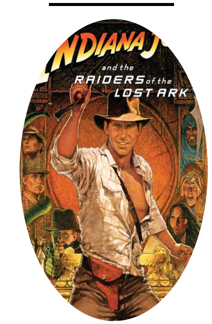
Datasets

sherlock

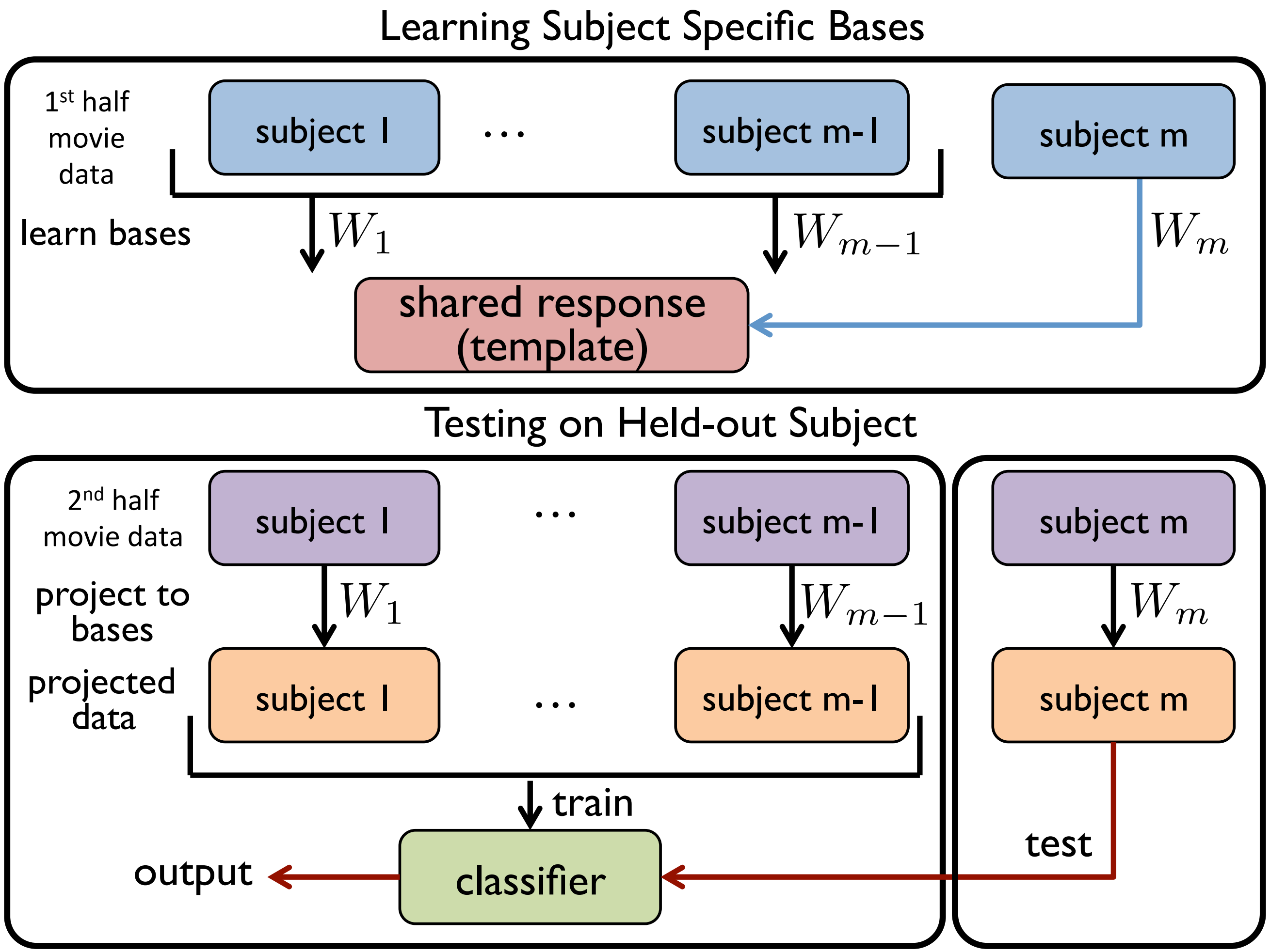
forrest



raider



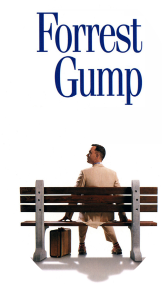
Generalization to new subject with time segment matching



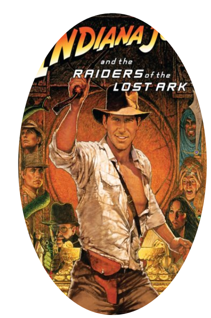
Datasets

sherlock

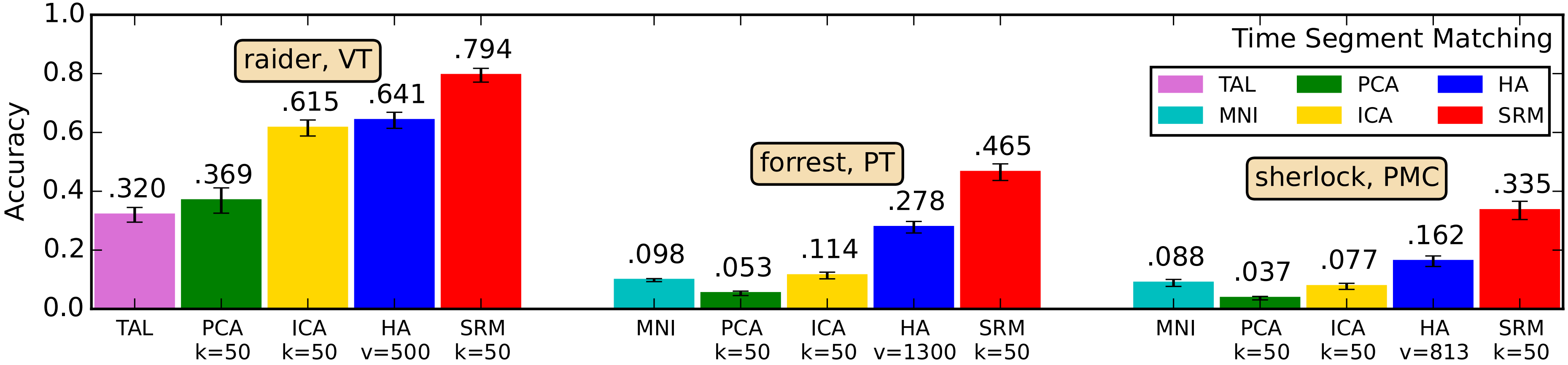
forrest



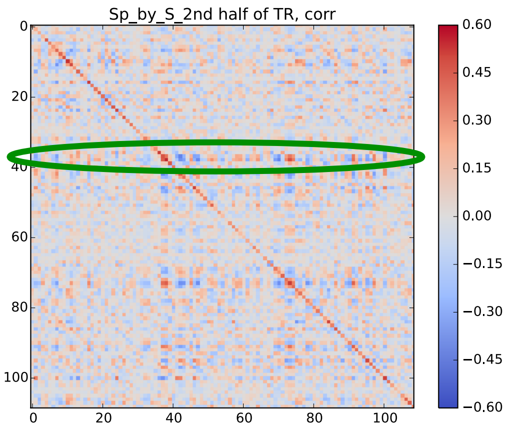
raider



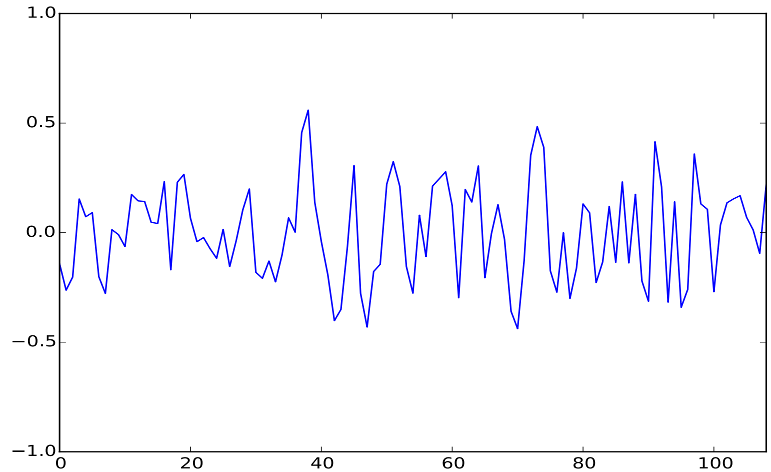
Generalization to new subject with time segment matching



Similarity structure leads to interesting results

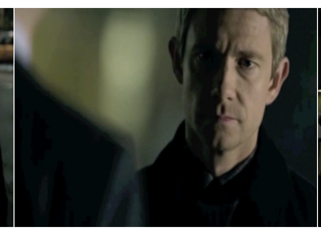


Look at row 38 only



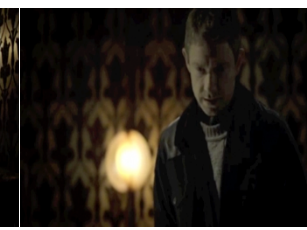
rank	correlation	frame
1	0.56	38
2	0.48	73
3	0.46	37
4	0.41	91
5	0.39	74
6	0.36	97
7	0.35	72
8	0.32	51
9	0.31	45
10	0.30	64

37， 38

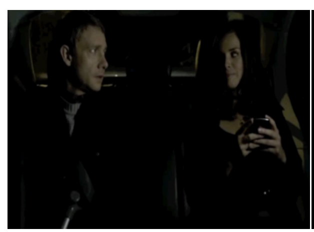


72， 73， 74

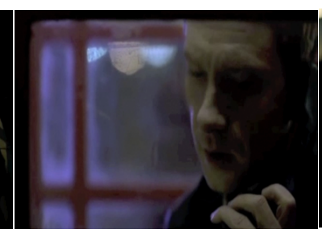
91



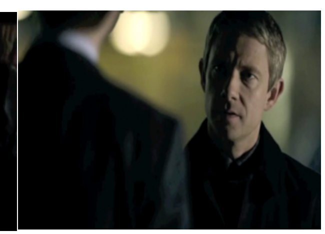
97
talking with Sherlock



51



45

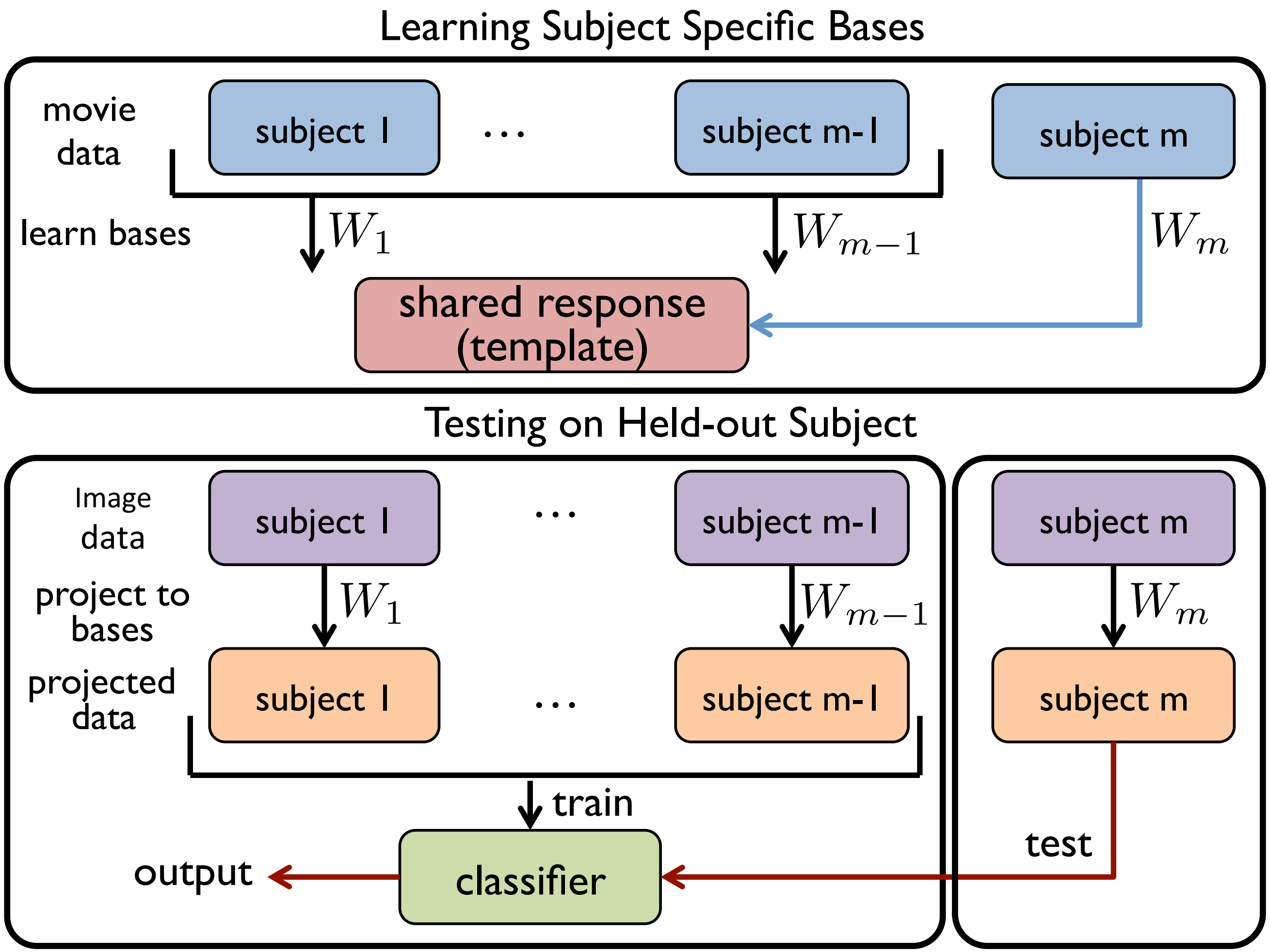


64

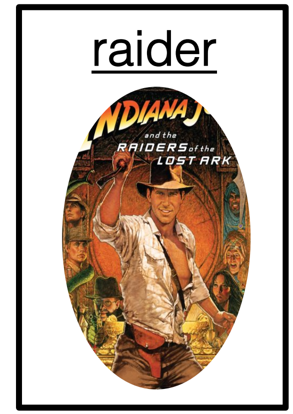
High correlation time segments correspond to similar scenes: Watson talking to somebody in a stressful circumstance

[Work by Hejia Zhang]

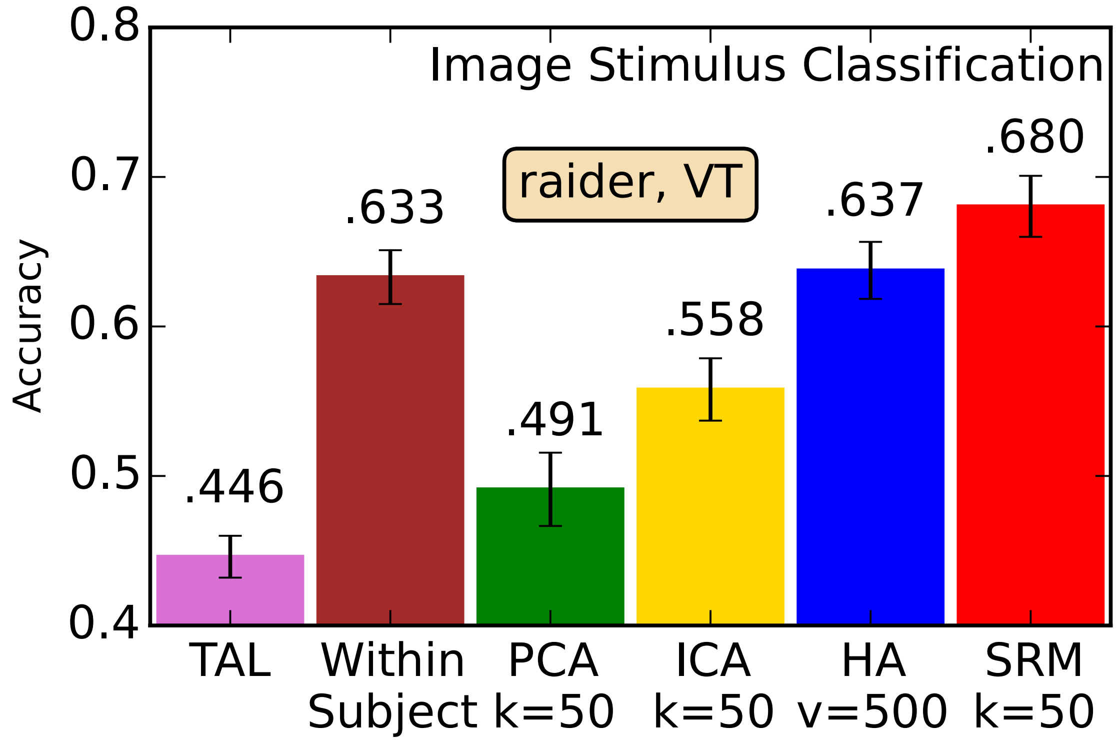
Generalization to new subject and distinct stimulus with image classification



Dataset



Generalization to new subject and distinct stimulus with image classification



- Outperforms within-subject classification

Classifying mental states

- 40 subjects listening to narrated story
- Separate 40 subjects into 2 groups
- Two groups receive different prior contexts
- Leading to different interpretations of the story
- Predict prior context of a left-out subject

Dataset

audiobook

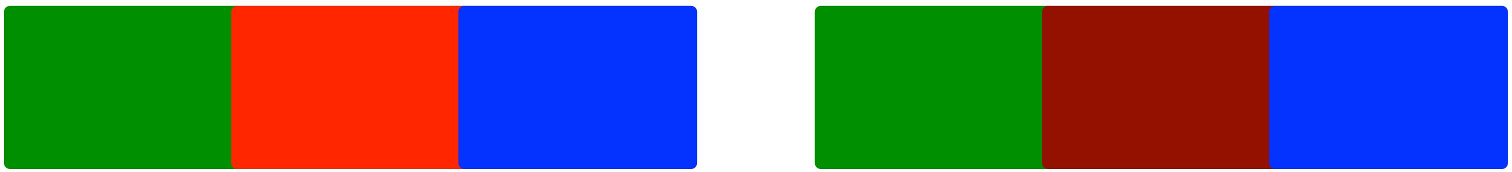
Classifying mental states

Group 1

shared by all | within group | individual

Group 2

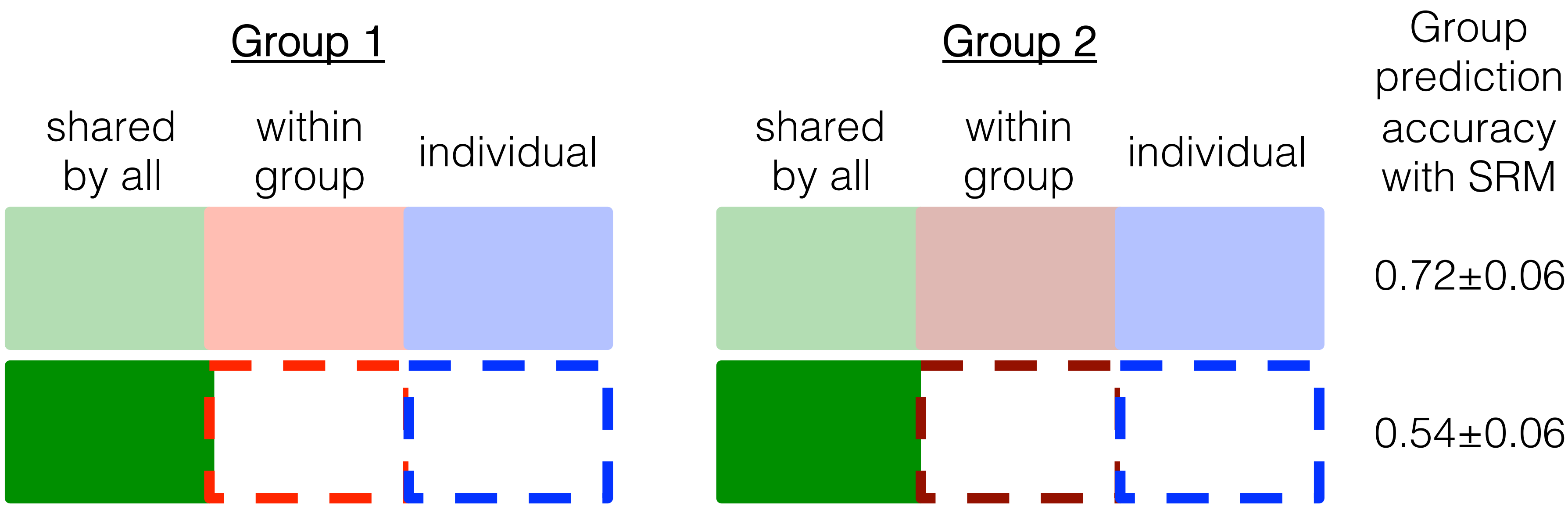
shared by all | within group | individual



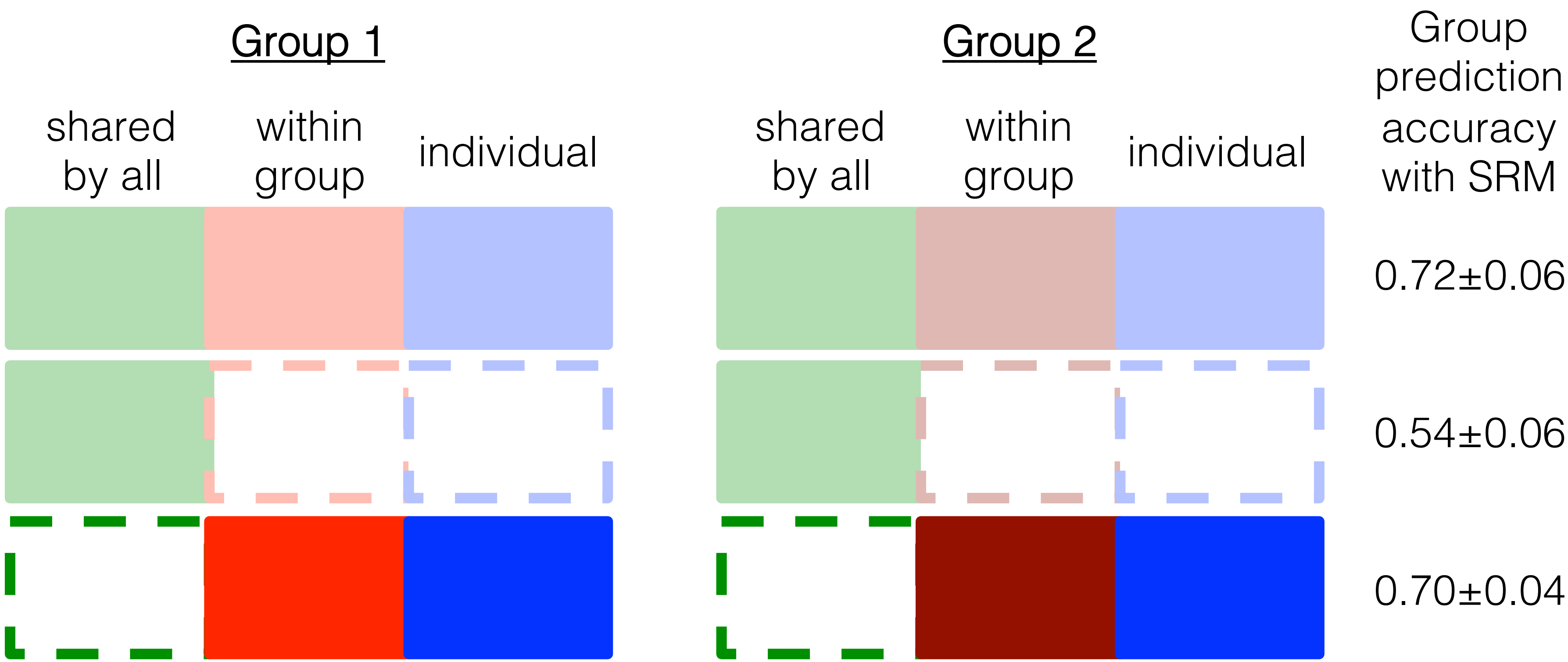
Group prediction accuracy with SRM

0.72±0.06

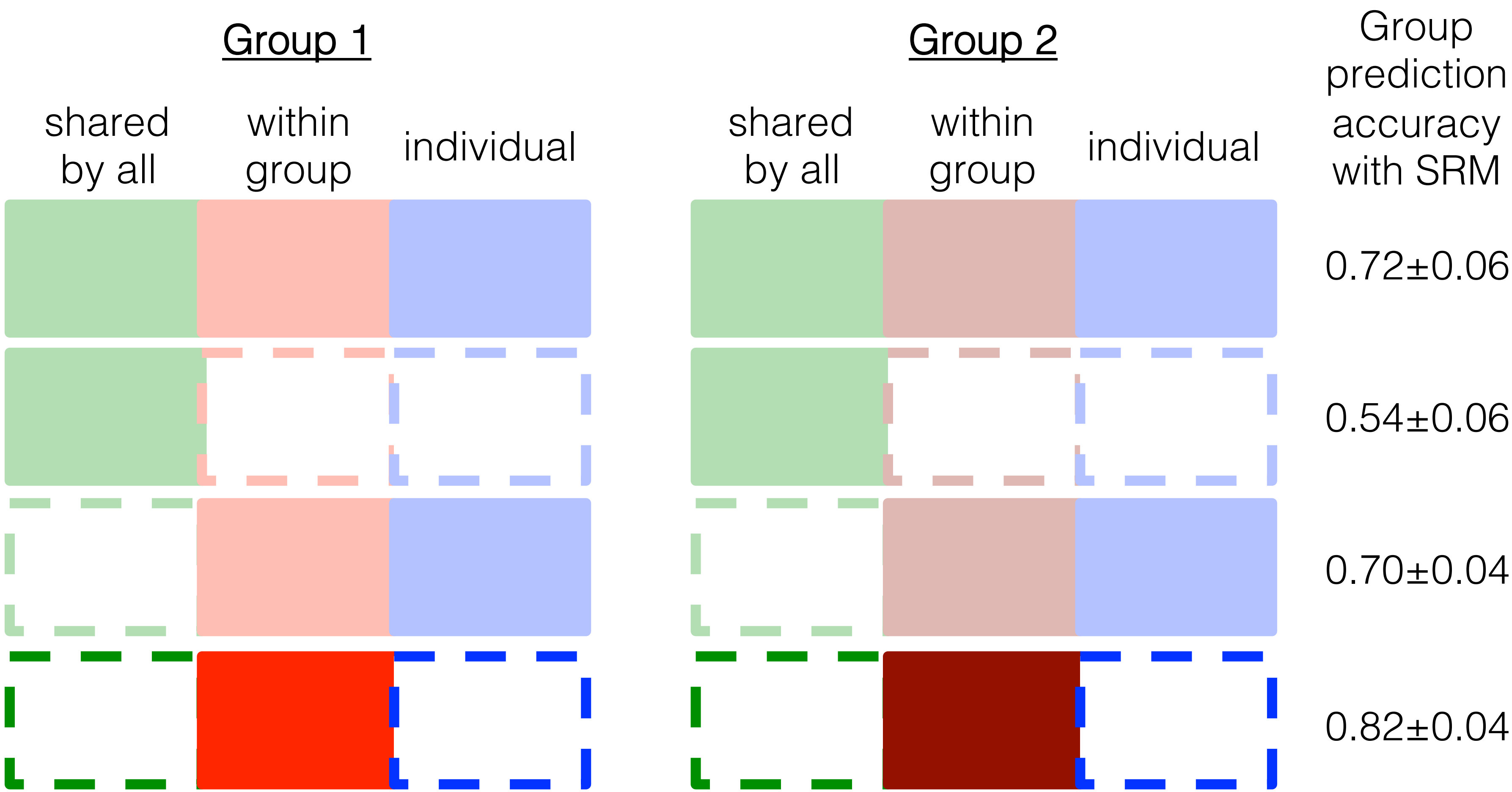
Classifying mental states



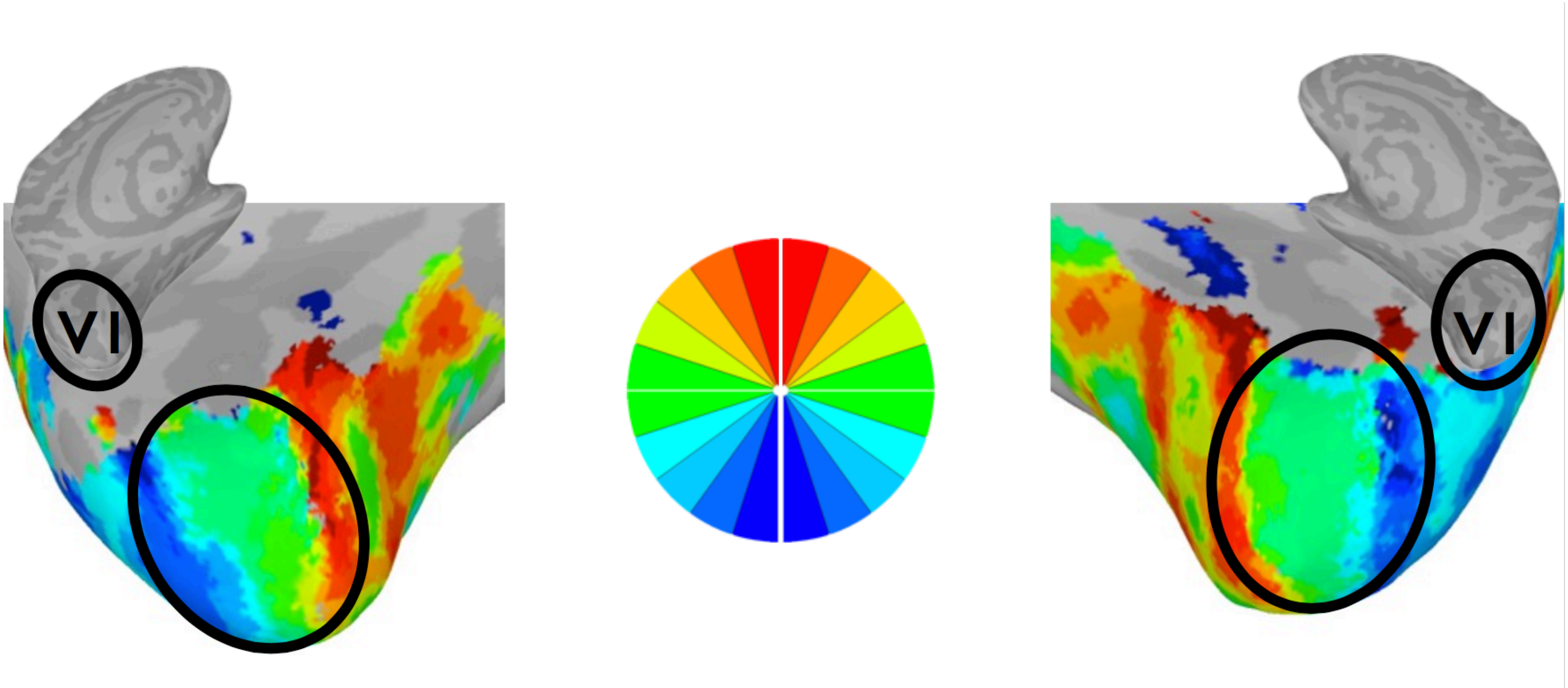
Classifying mental states



Classifying mental states



Mapping Visual Field Maps: Retinotopy



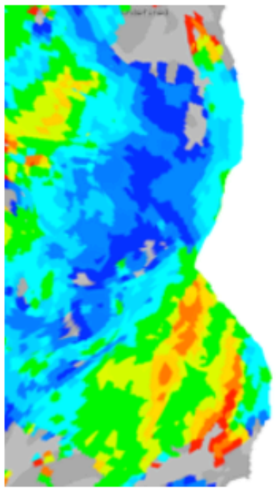
[Work by Michael Arcaro]

Original Phase Maps vs. SRM

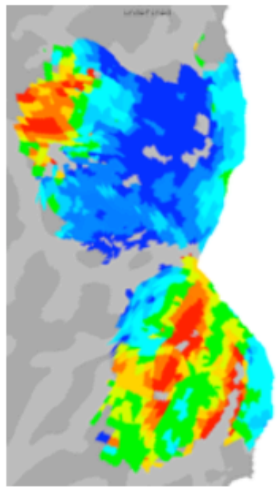
Sanity check: (W_i*transformed_data_i)

Phase map comparison between original phase maps and phase maps derived from data reconstructed in same subject post hyperalign. NOTE: original data was not masked and includes more of cortex. Data threshold a $p < .0001$

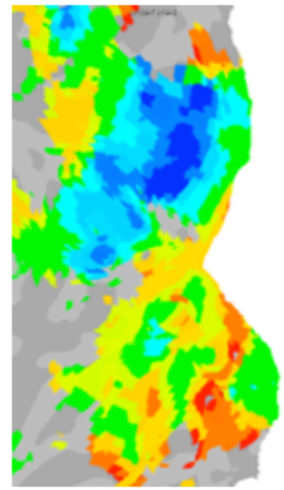
Orig



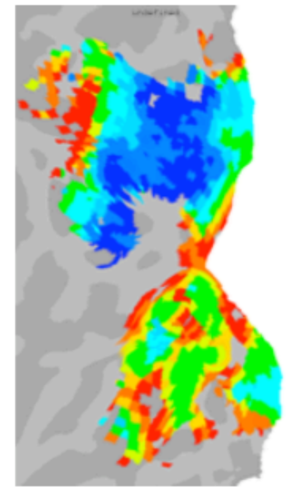
SRM



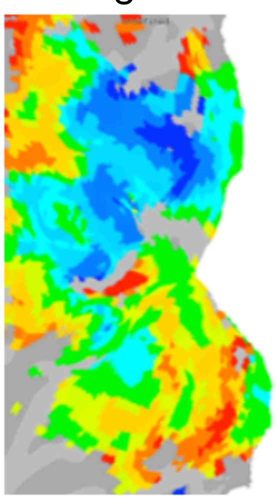
Orig



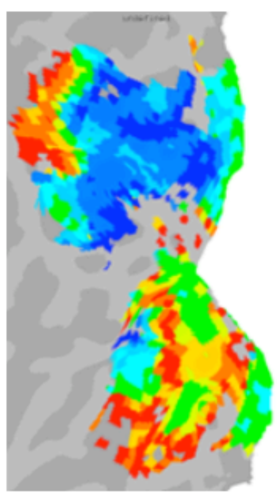
SRM



Orig



SRM



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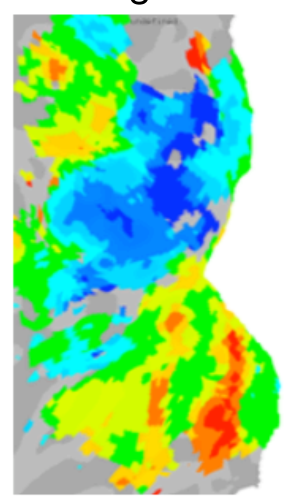
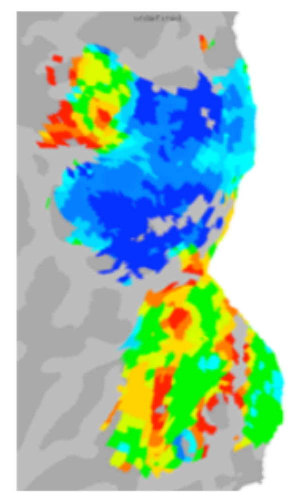
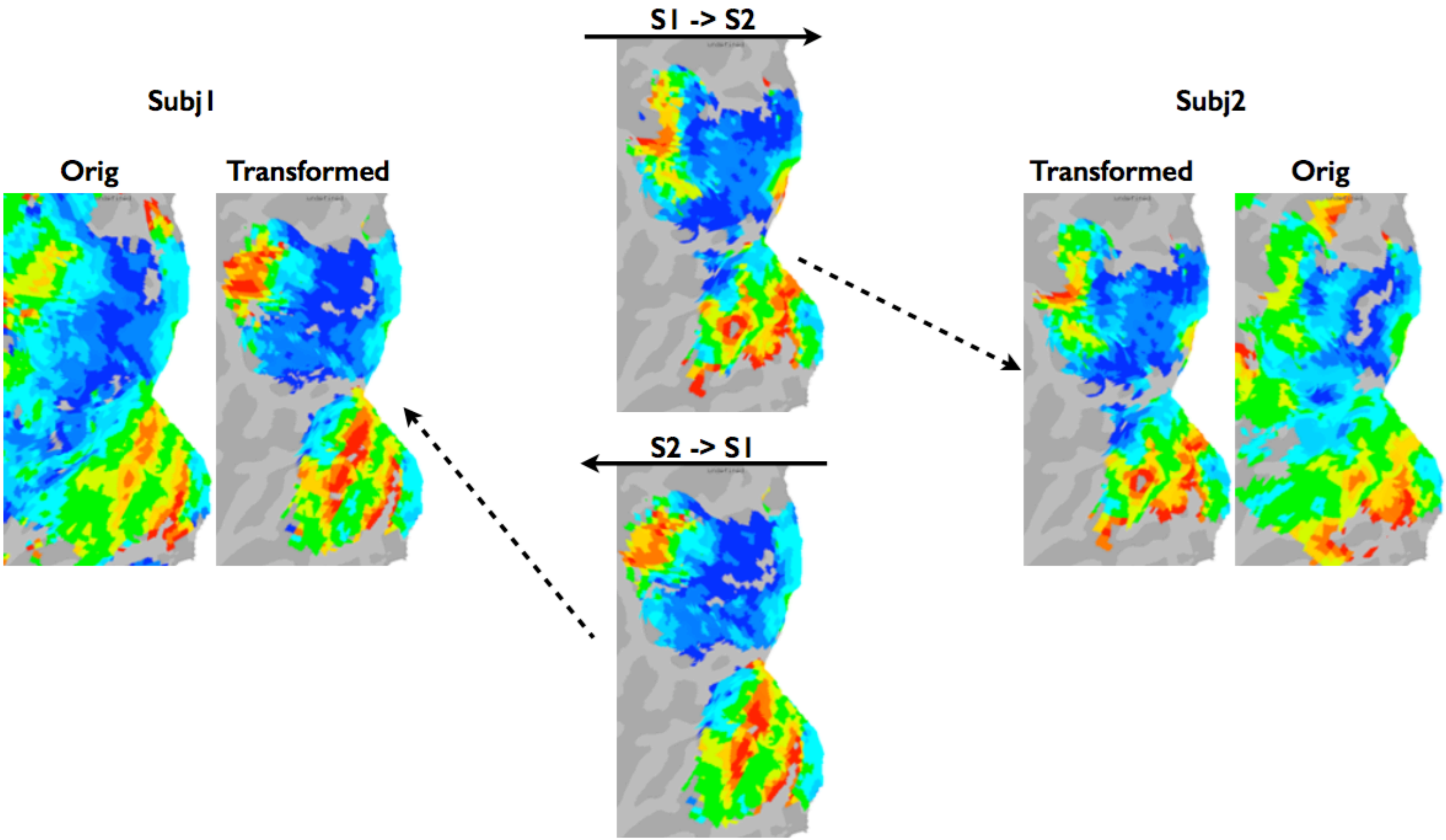
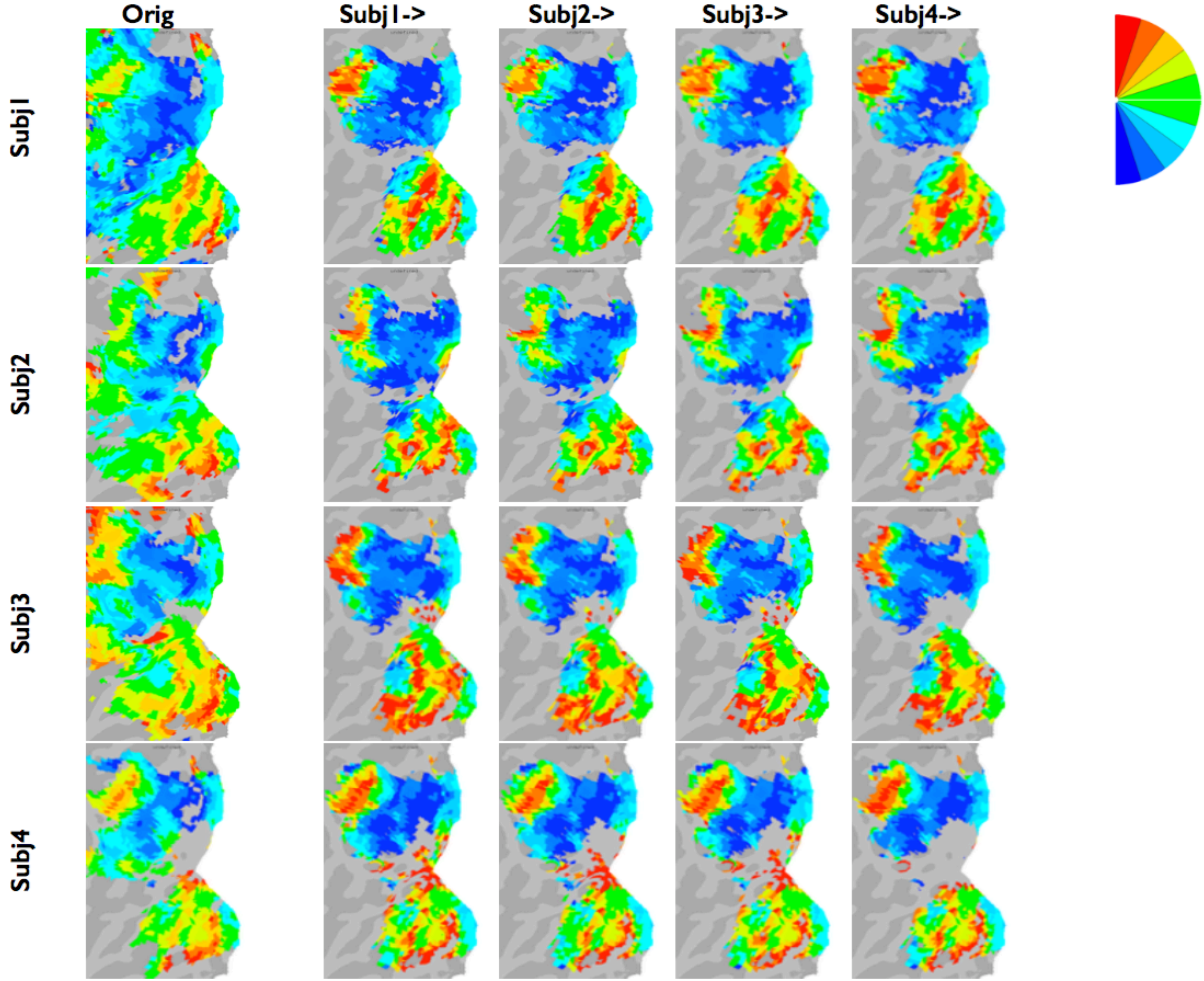


SRM



Transformation between subjects




Orig
Subj1->
Subj2->
Subj3->
Subj4->
Subj1
Subj2
Subj3
Subj4

Summary

What can SRM do?

- Multi-subject data driven de-noising
- Aggregation of multi-subject data
- Generalizable to new subject and new stimulus
- Outperform within subject classification
- Decoupling of shared and individual response

How can it help us learn how the brain work?

- Increase sensitivity in statistical test
- Discover information pathway
- Compare group differences