Shared Response Model Tutorial

What works? How can it help you?

Po-Hsuan (Cameron) Chen and Hejia Zhang

@ Hasson Lab
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Outline

- SRM Theory
- SRM on fMRI
- Hands-on SRM with BrainIak

SRM Theory

Multi-view representation learning

What is multi-view learning and why is it important?

- Exist an unknown underlying distribution, each view is a realization of it
- Conventional ML models concatenate multiple views into one single view
- Successful multi-view learning leads to better utilization of data with better performance

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

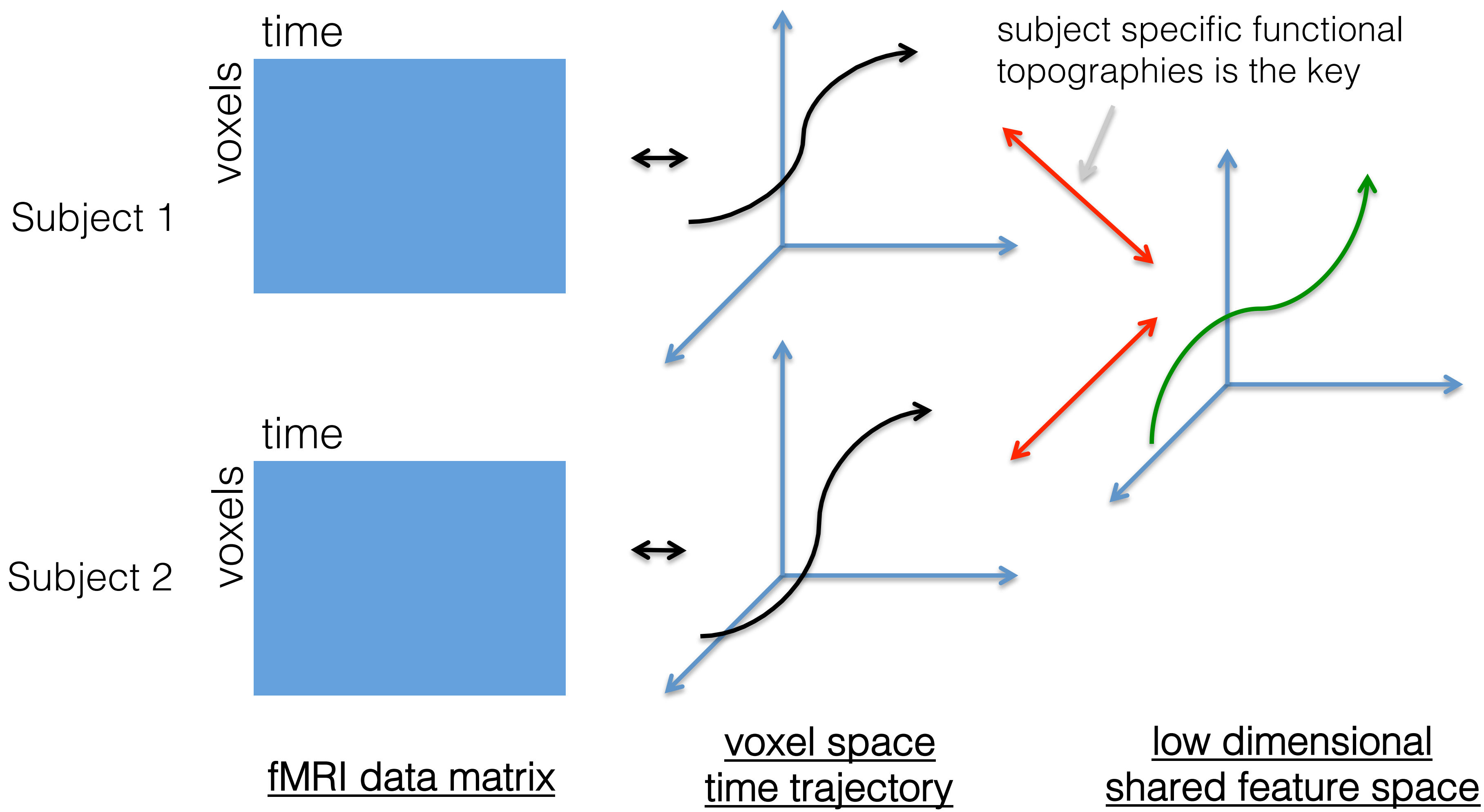
Inter-subject variability in anatomical structure and functional topographies

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

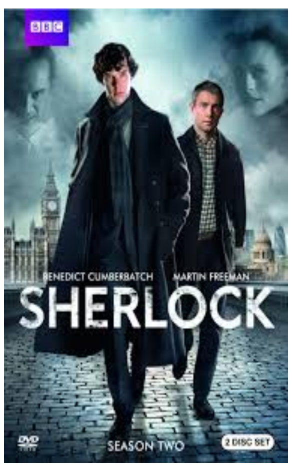


Data collected while subjects receiving stimulus

Temporally synchronized naturalistic stimuli

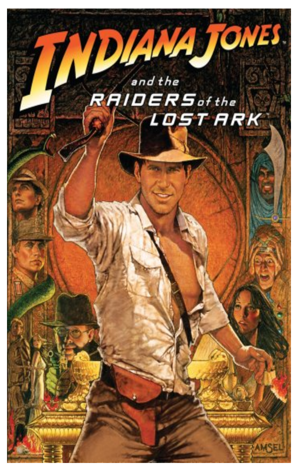
1. Sample a wide range of response from the subject
2. Use time as anchor for learning shared response

sherlock



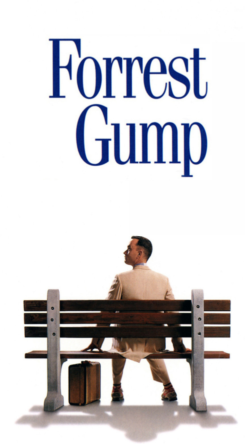
movie watching

raider



movie and image watching

forrest

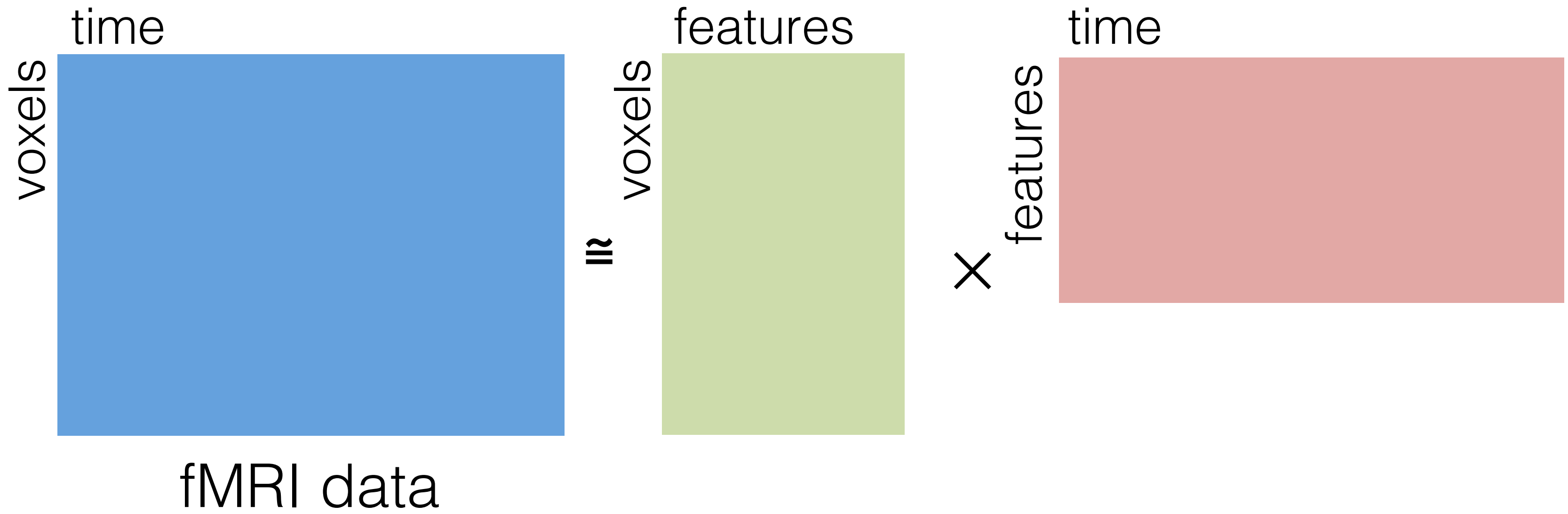


auditory film listening

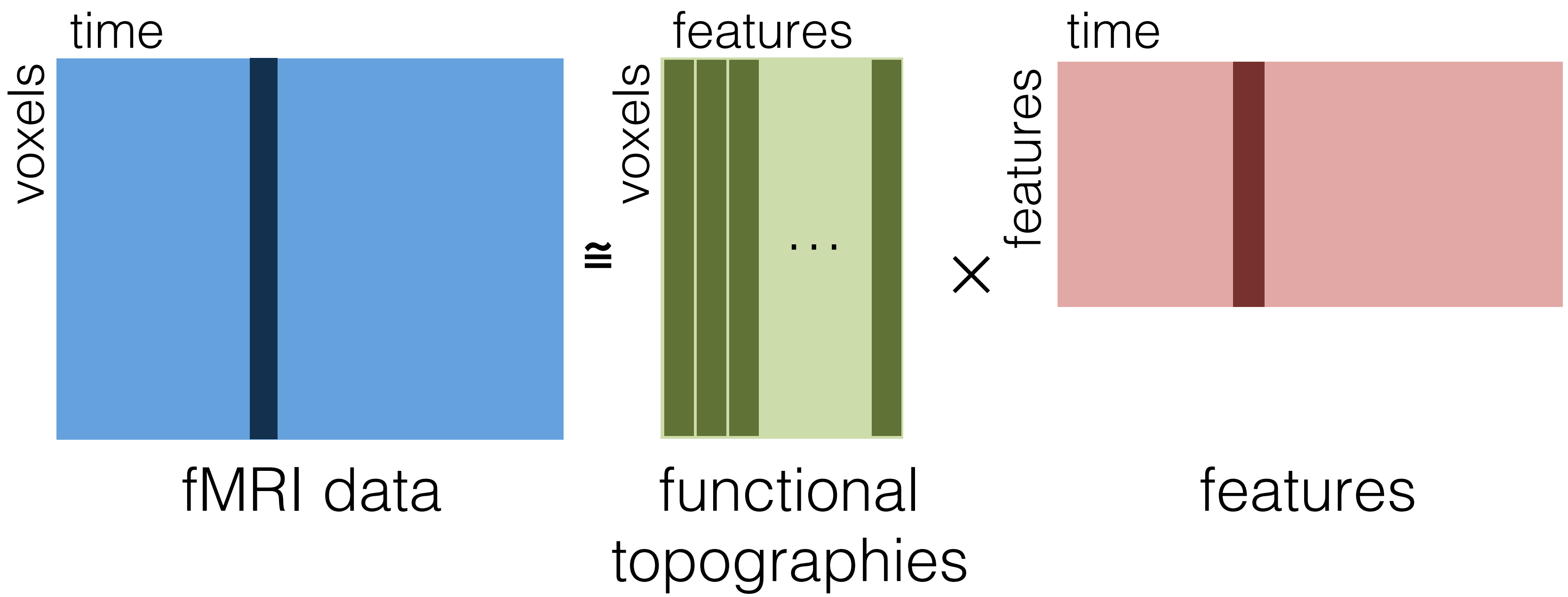
audiobook

audio book listening

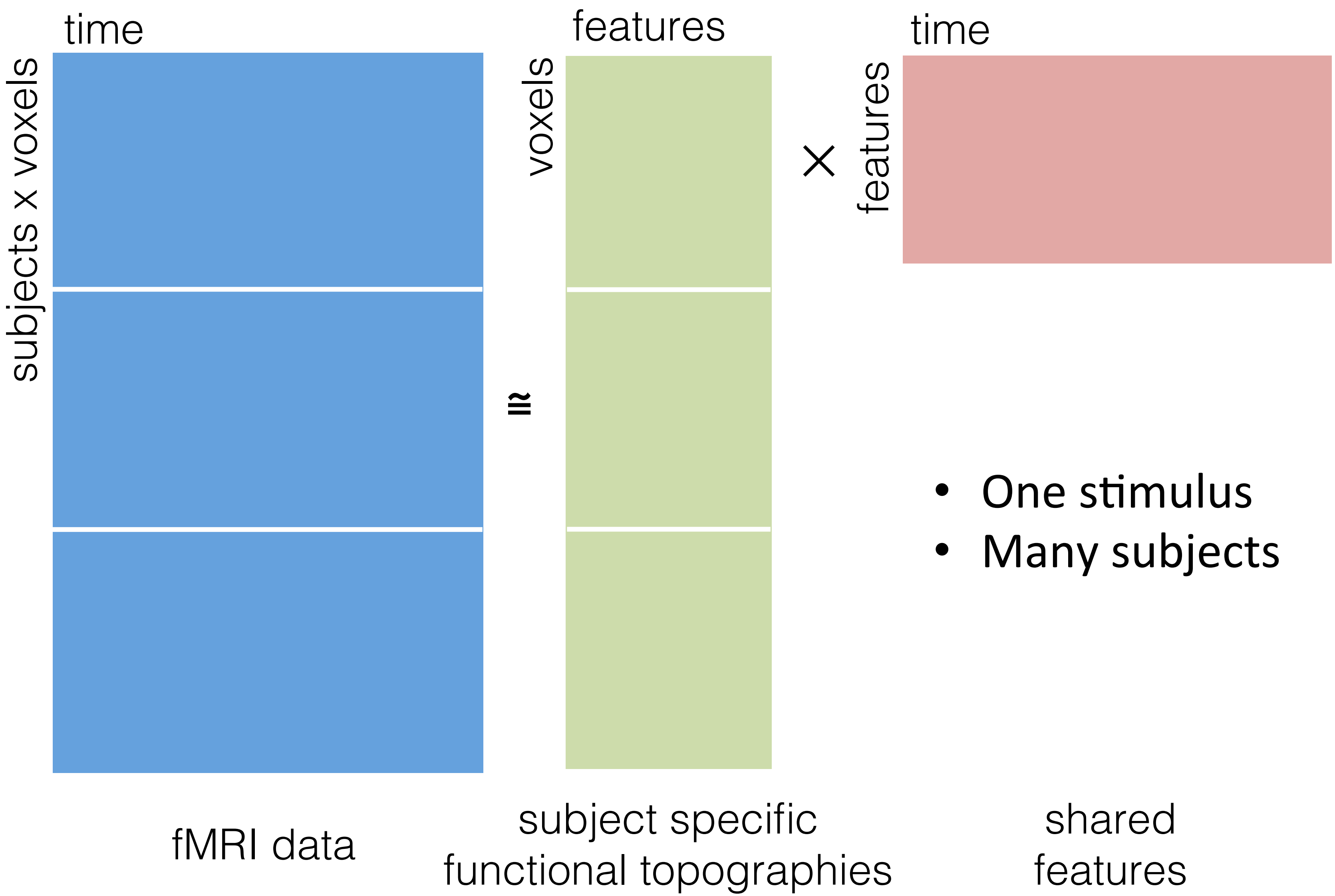
Factor Model



fMRI response as linear combination of functional topographies

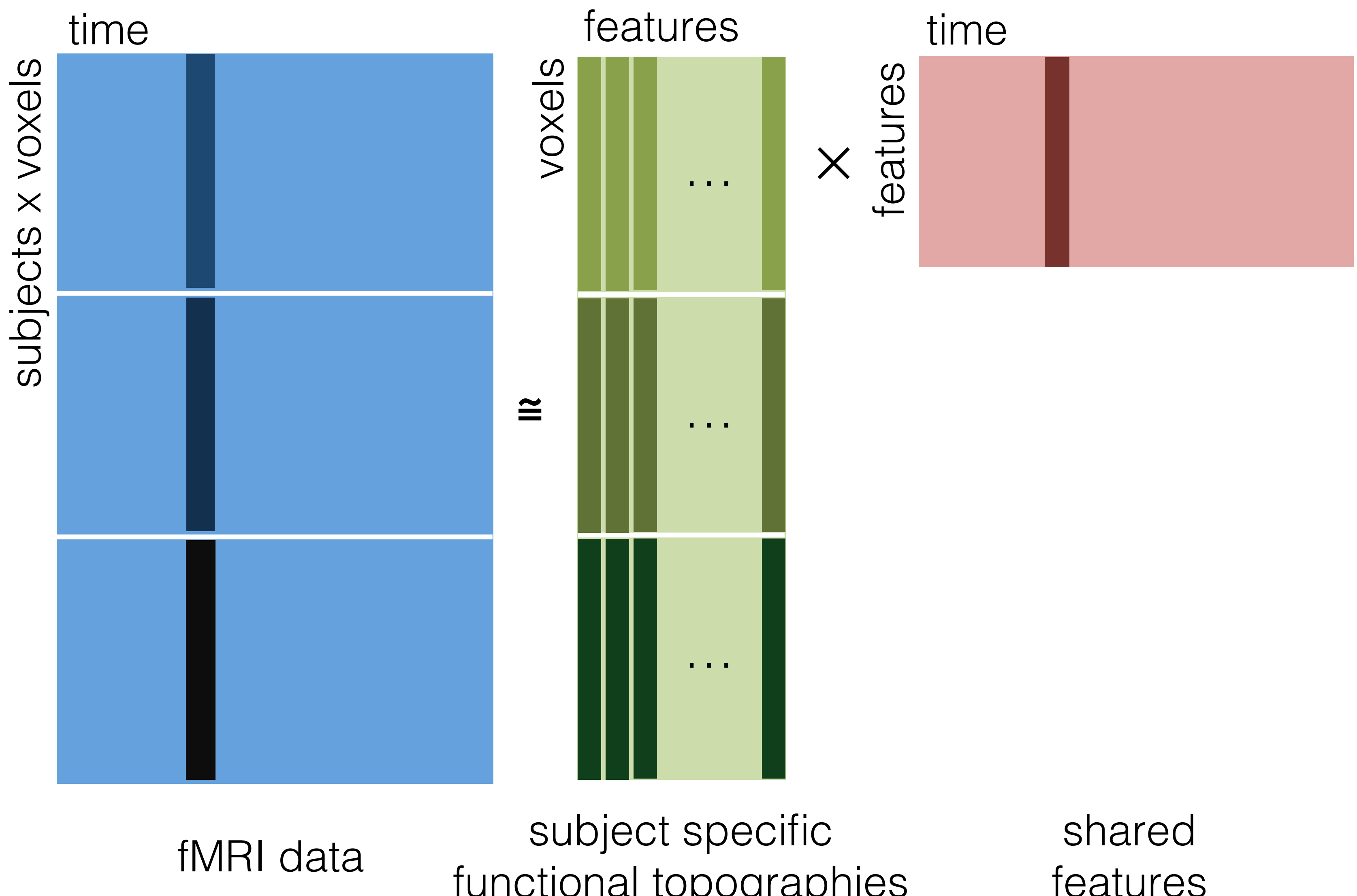


Learning what is shared across subjects

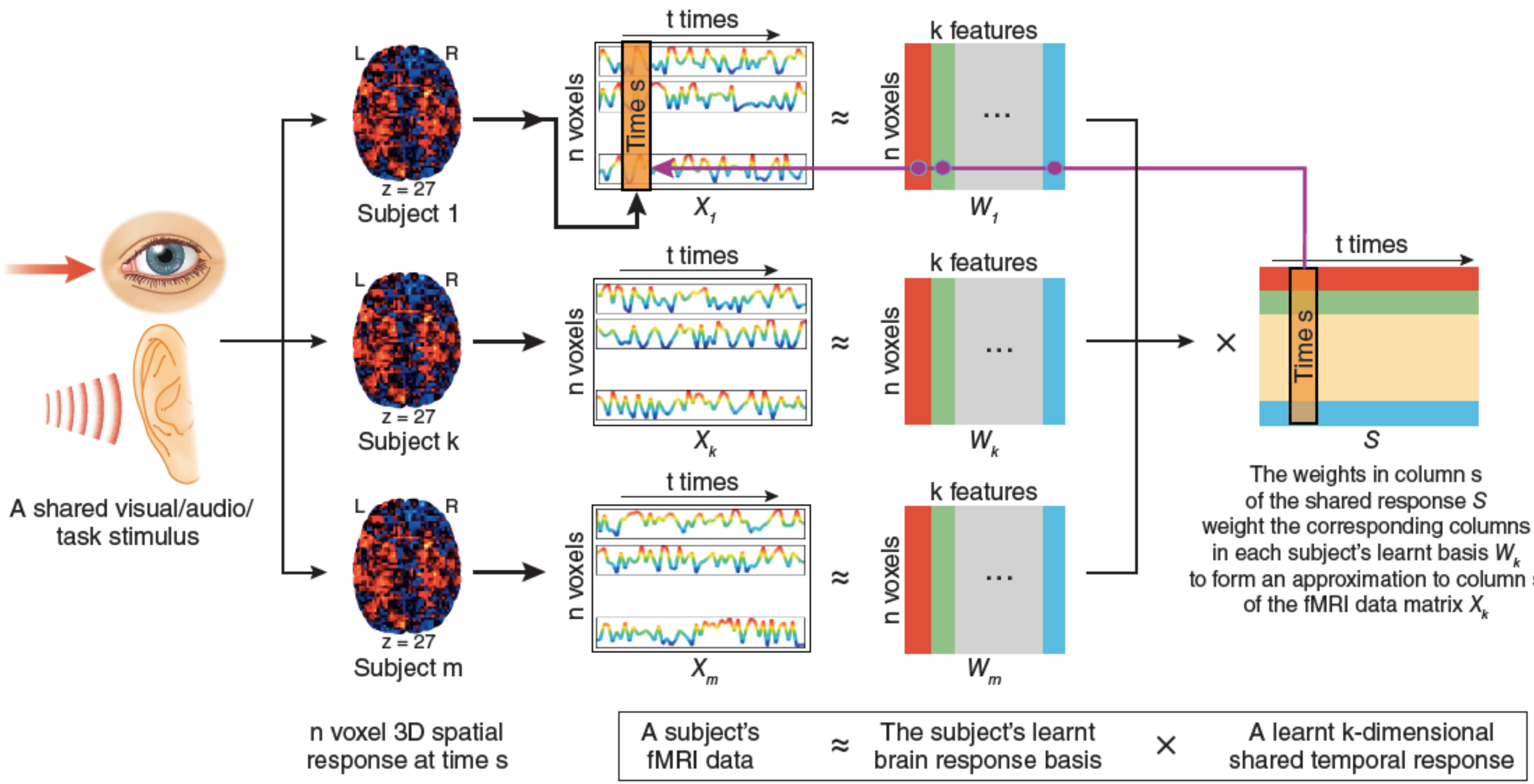


- One stimulus
- Many subjects

fMRI data as linear combination of subject specific functional topographies



Shared Response Model in one figure

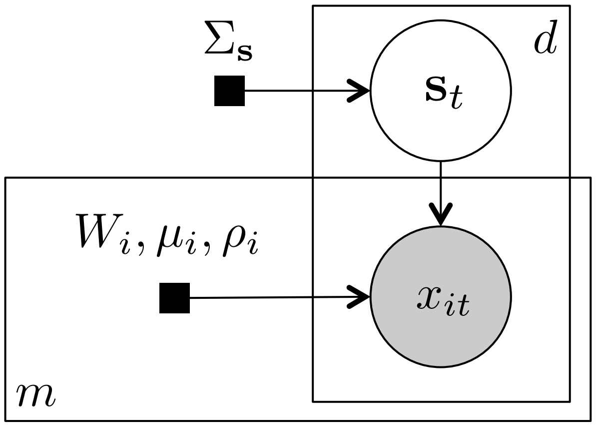


[J. Cohen et al., Nat. Neur., 2017]

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

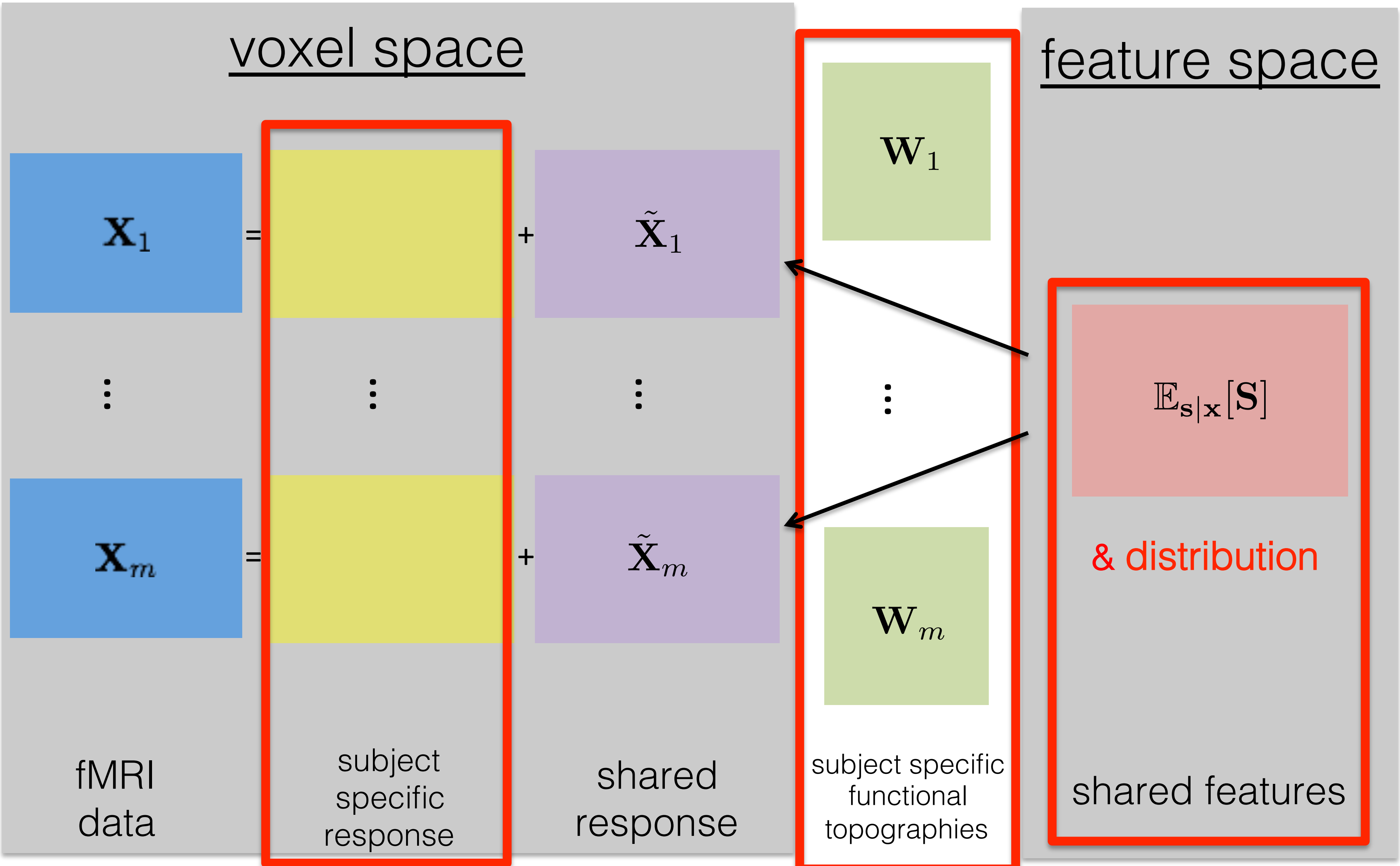
x_{it} observations of subject i at time t

ρ_i^2 noise level for subject i's data

- Feature identification with dimensionality reduction
- Constrained EM algorithm

[P.-H. Chen et al., NIPS , 2015]

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

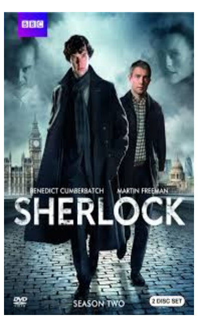


SRM on fMRI

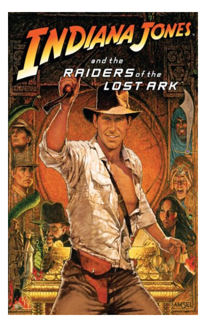
Evaluation with various datasets

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

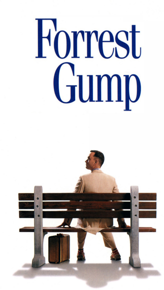
sherlock



raider



forrest



audiobook

SRM on fMRI

- Generalize to new stimulus
- Generalize to new subject
- Decoupling shared and individual response
- SRM with non-temporally synchronized stimulus
- SRM with retinopathy
- Quantifying dimensionality of shared response
- Searchlight SRM

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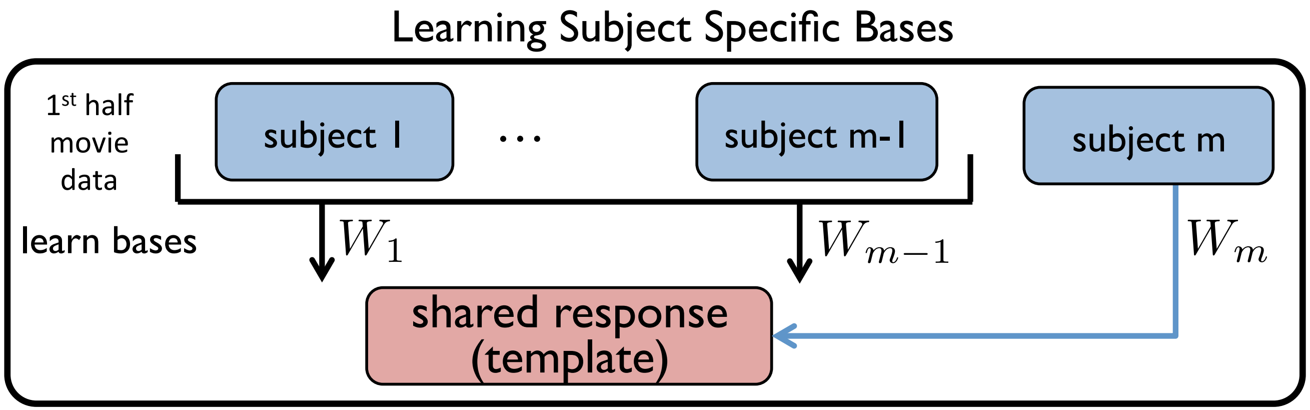
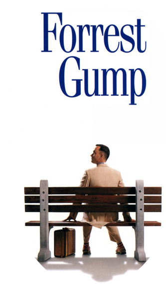
Generalization to new subject with time segment matching



Datasets

sherlock

forrest



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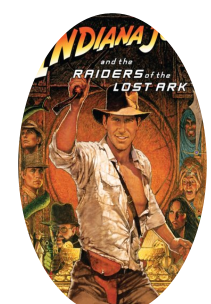
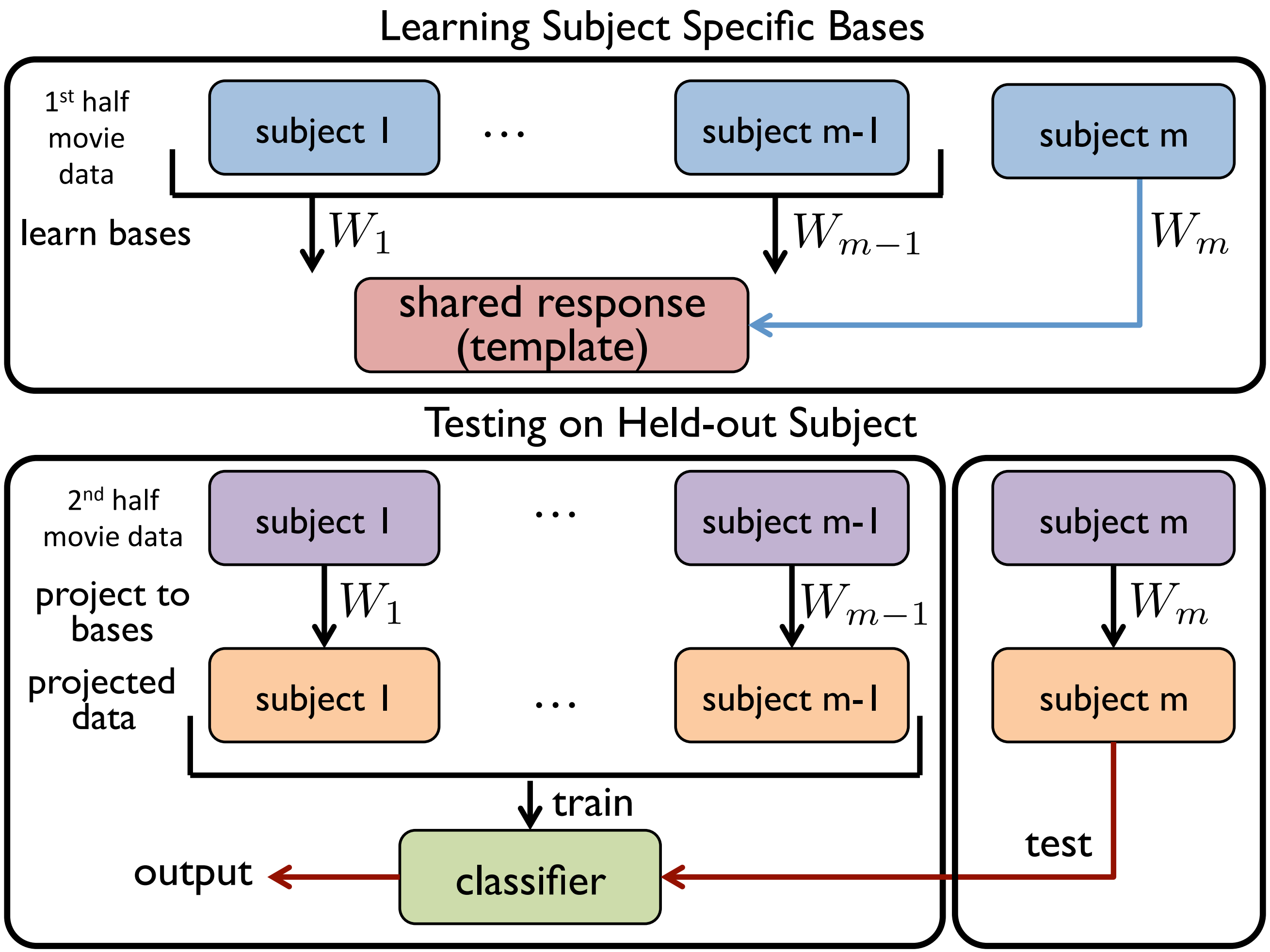


Generalization to new subject with time segment matching



Datasets

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forrest

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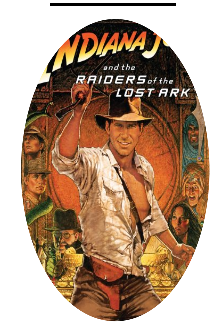

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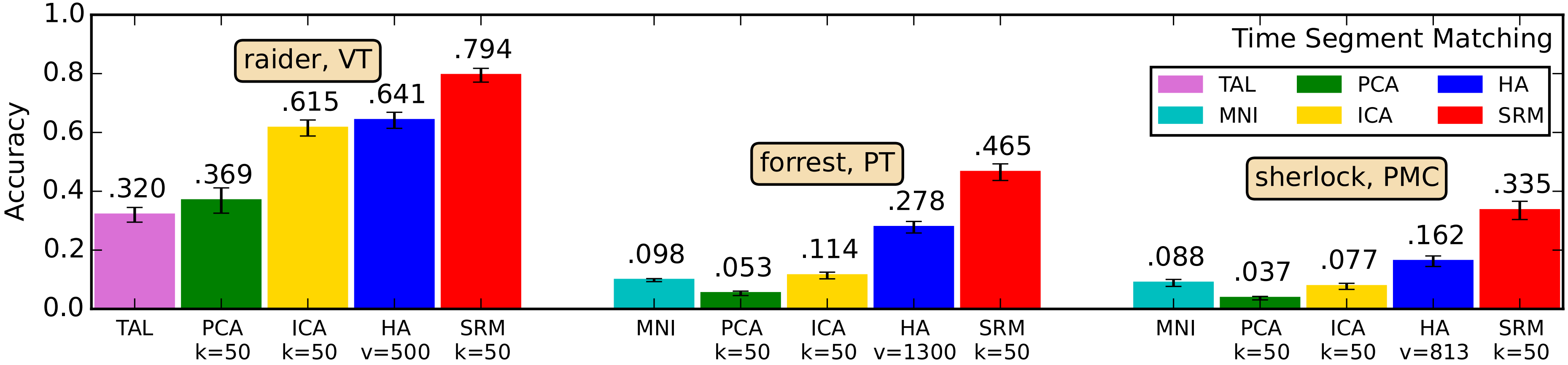
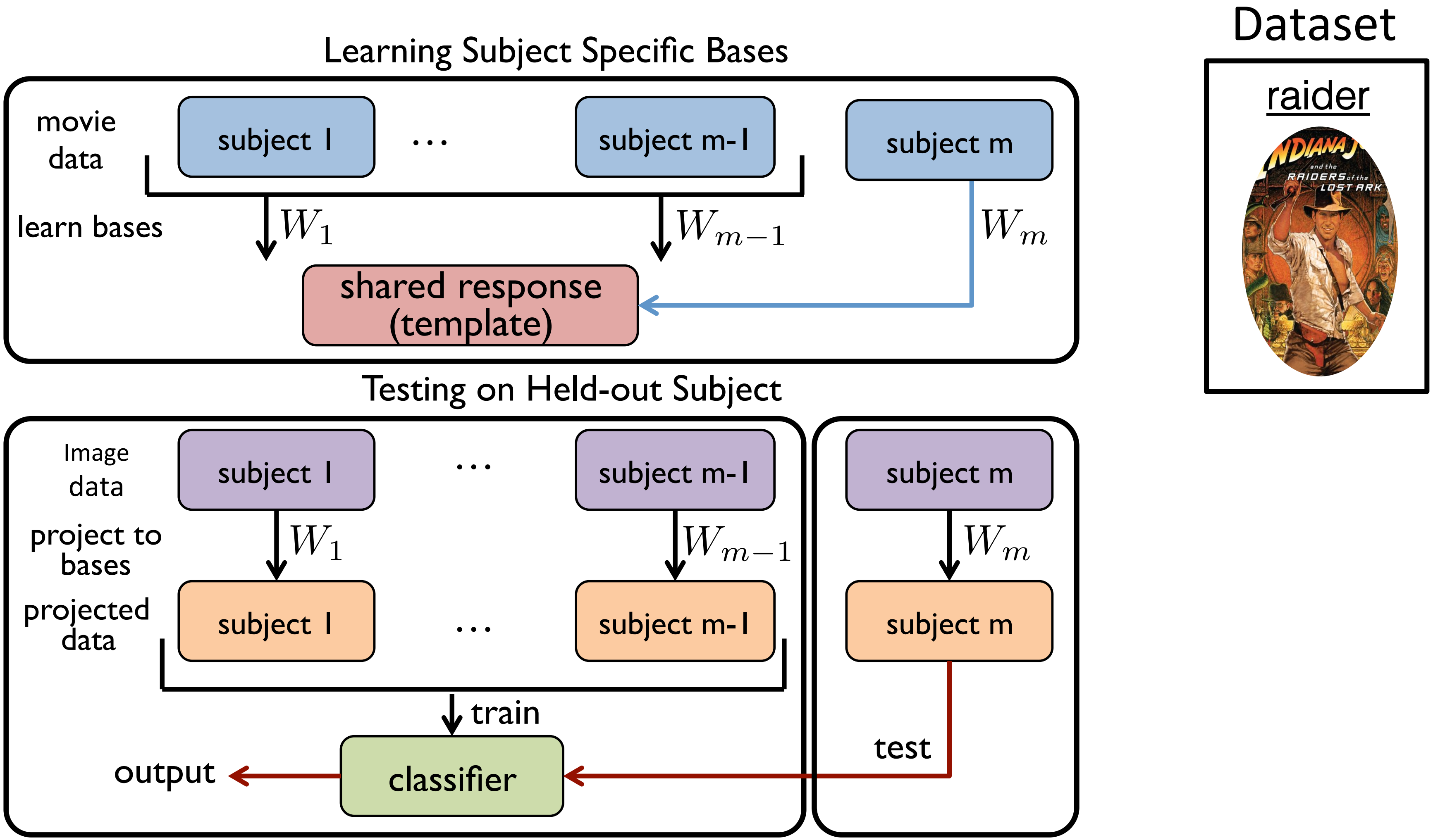
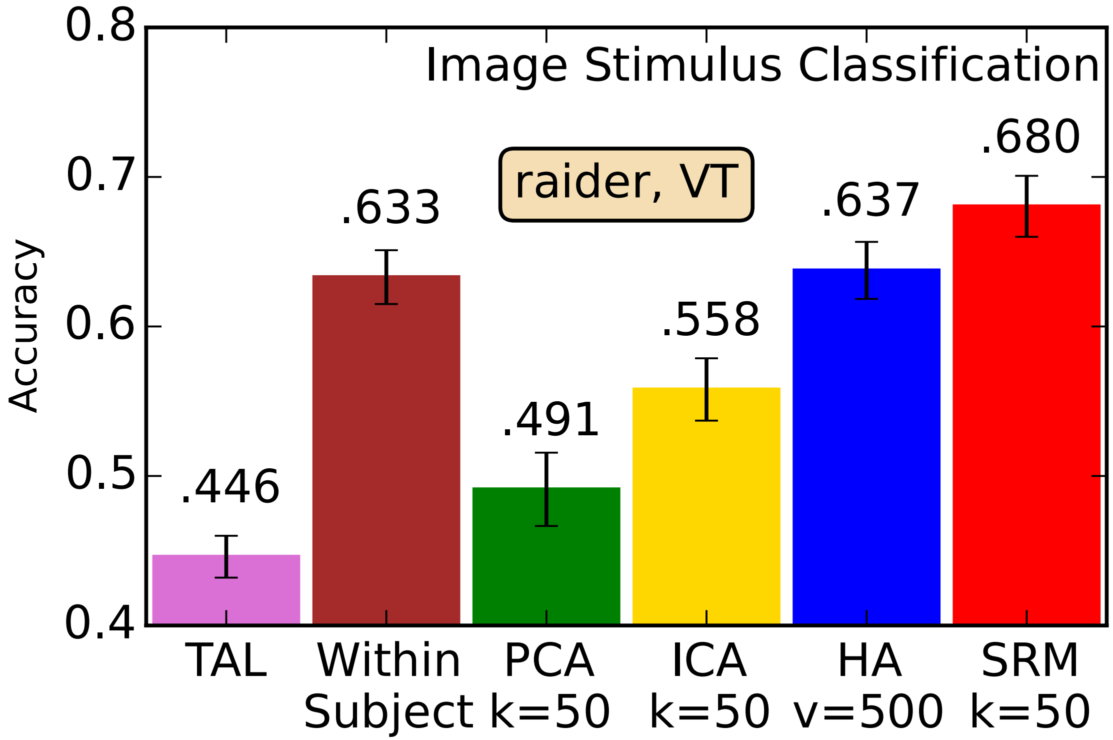


Generalization to new subject and distinct stimulus with image classification



Generalization to new subject and distinct stimulus with image classification



- Outperforms within-subject classification

SRM on fMRI

- Generalize to new stimulus
- Generalize to new subject
- Decoupling shared and individual response
- SRM with non-temporally synchronized stimulus
- SRM with retinopathy
- Quantifying dimensionality of shared response
- Searchlight SRM

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

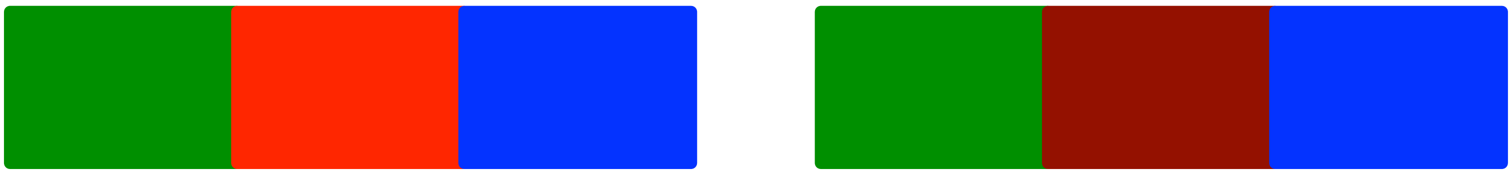
Group 1

shared by all | within group | individual

Group 2

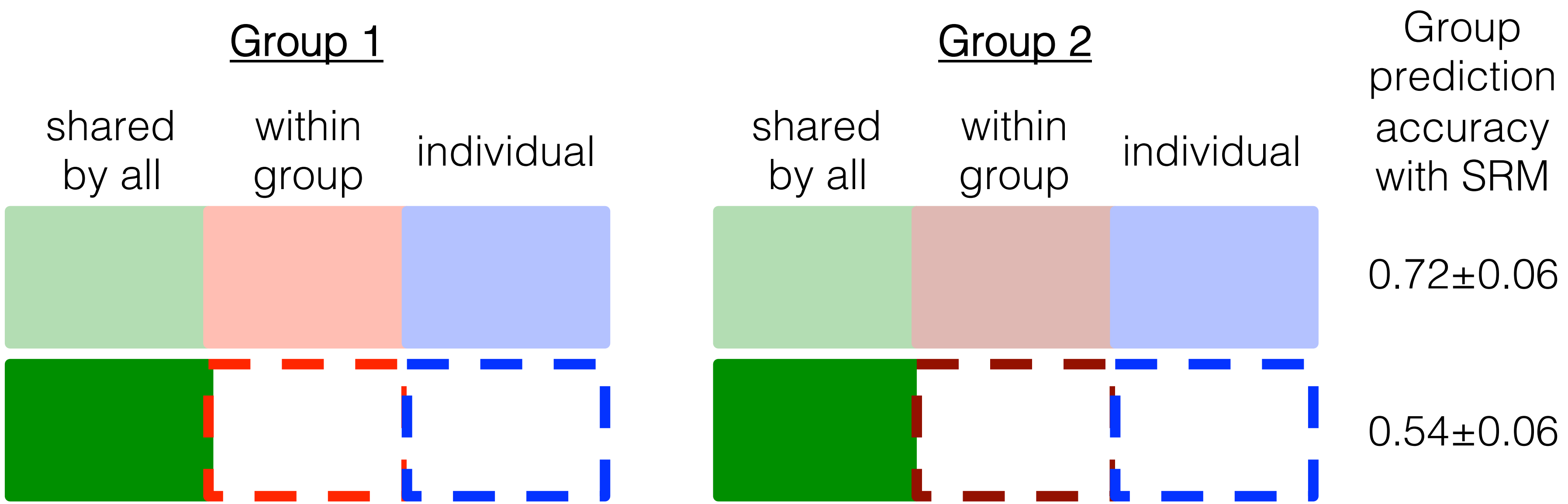
shared by all | within group | individual

Group prediction accuracy with SRM

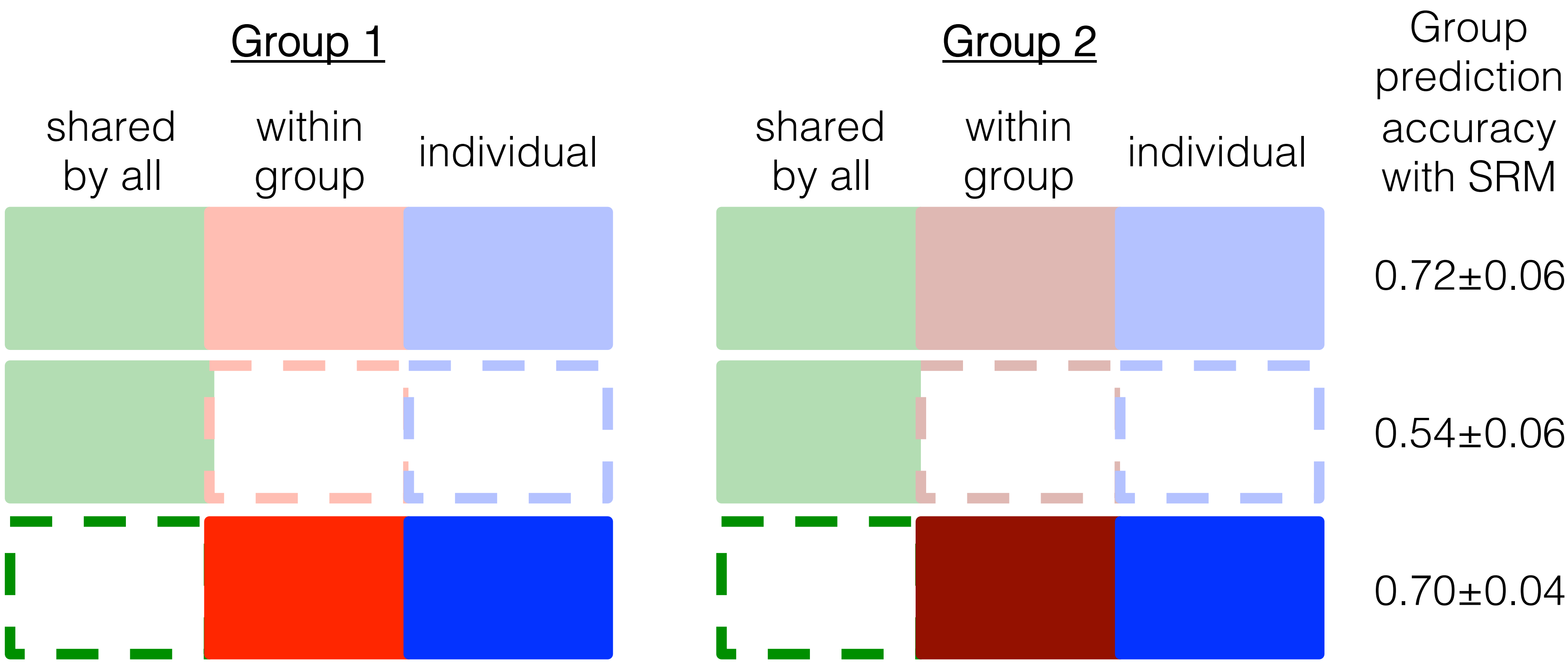


0.72±0.06

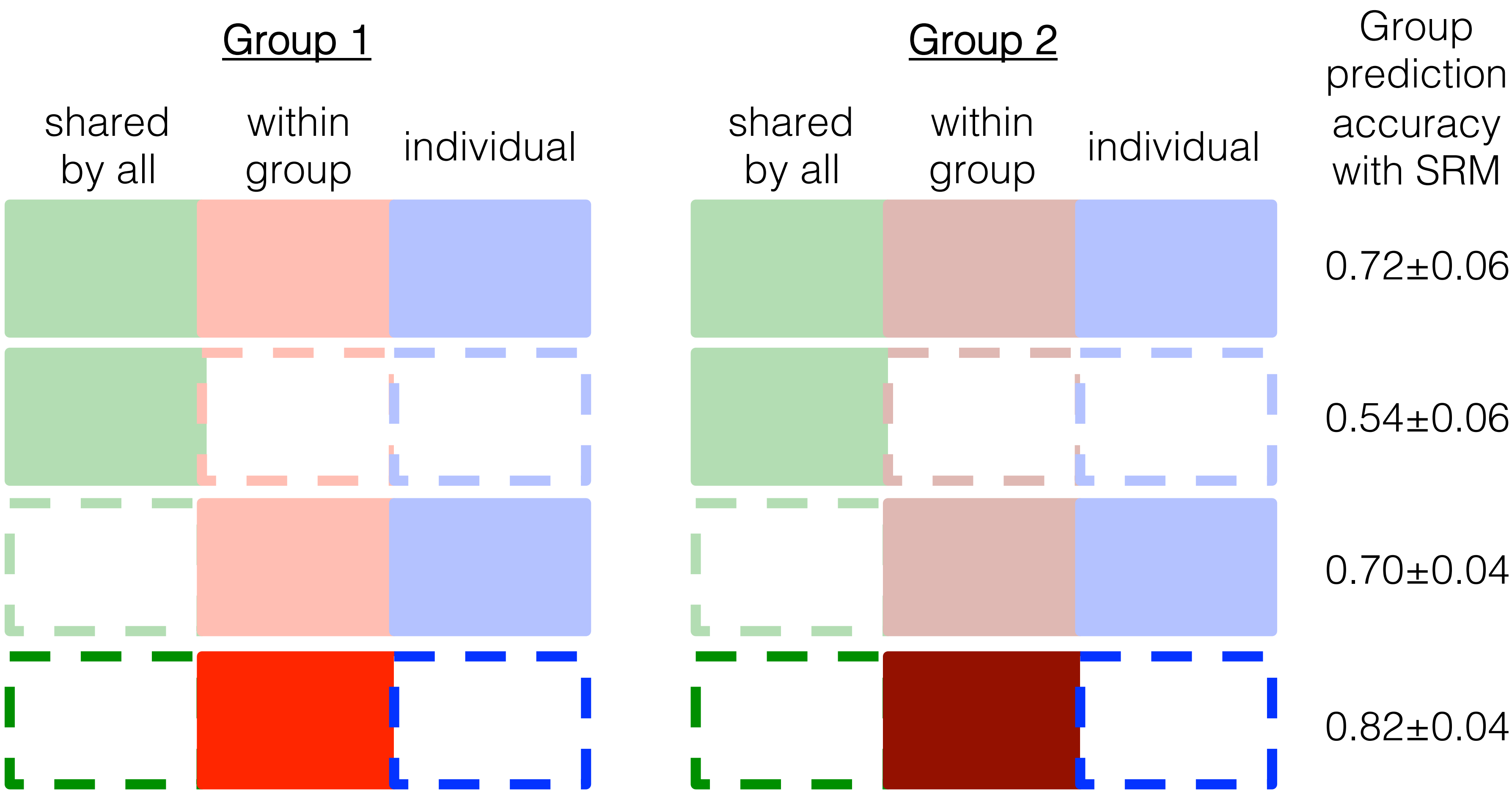
Classifying mental states



Classifying mental states



Classifying mental states



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Stimuli

Young Face
Young House

Old Face
Young House

Old Face
Old House

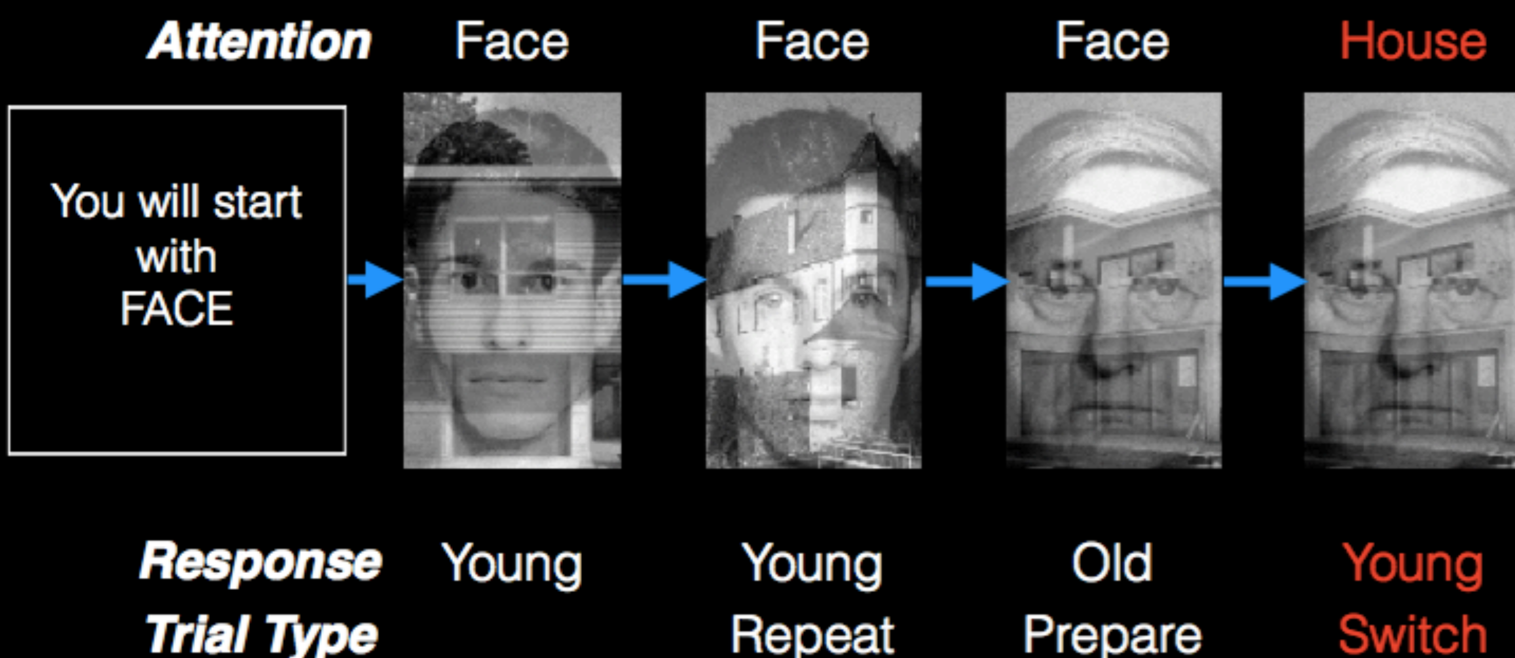
Young Face
Old House

- Each image shows a young or old face and a young or old house

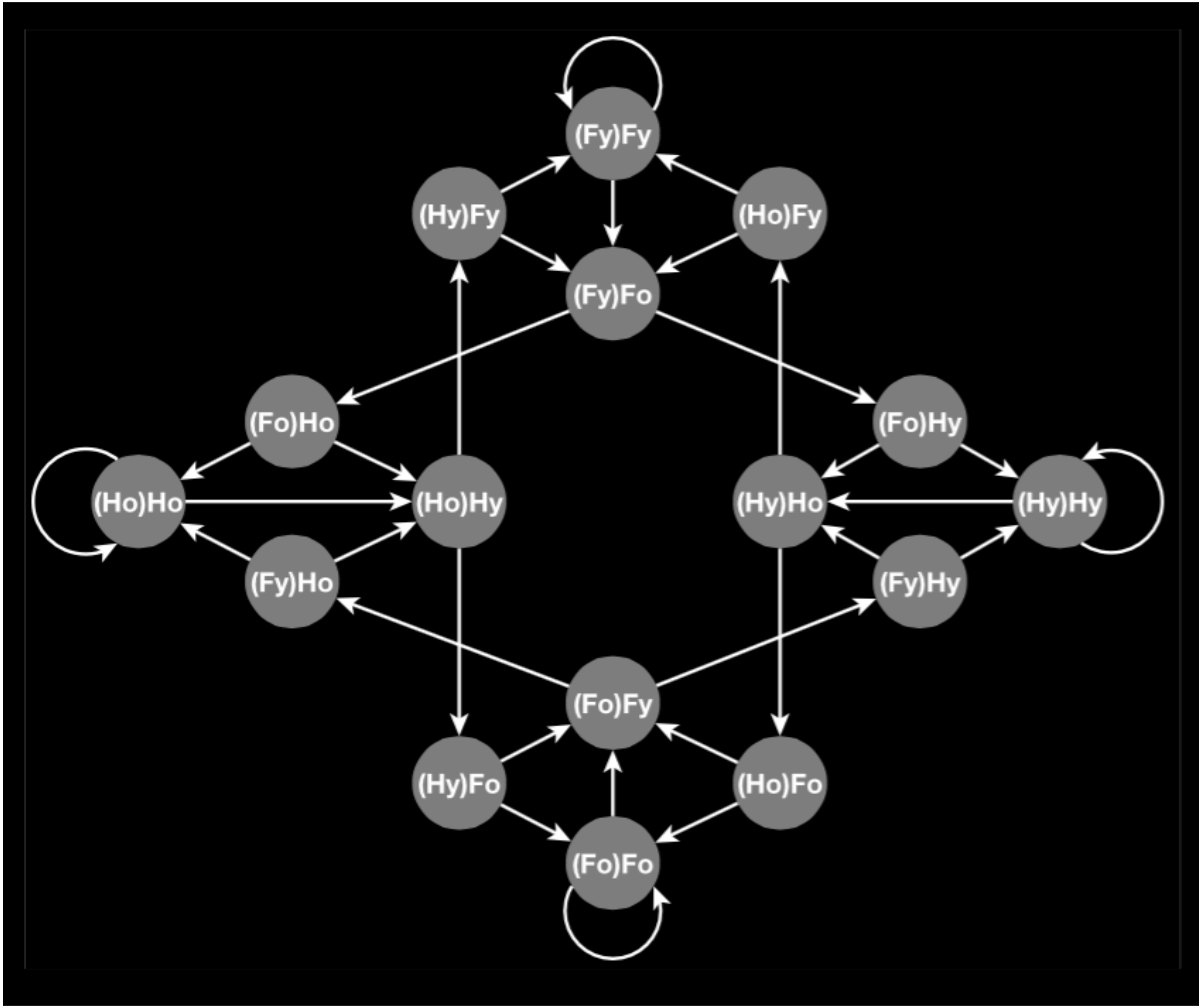
[Slide from Nicolas Schuck]

Task

If the age changes, the switch attention in next trial, otherwise stay



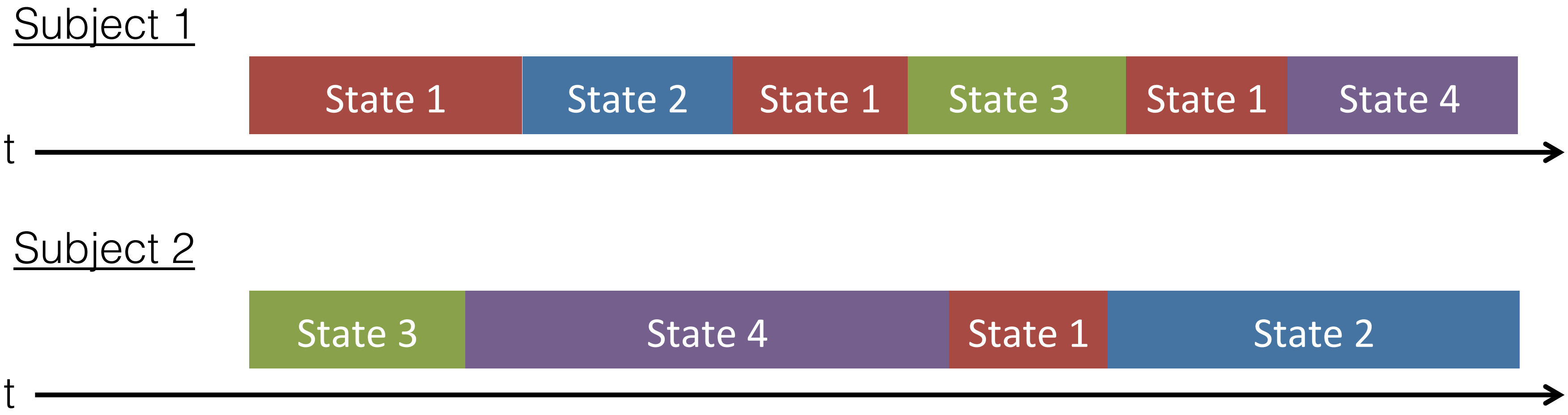
[Slide from Nicolas Schuck]



[Slide from Nicolas Schuck]

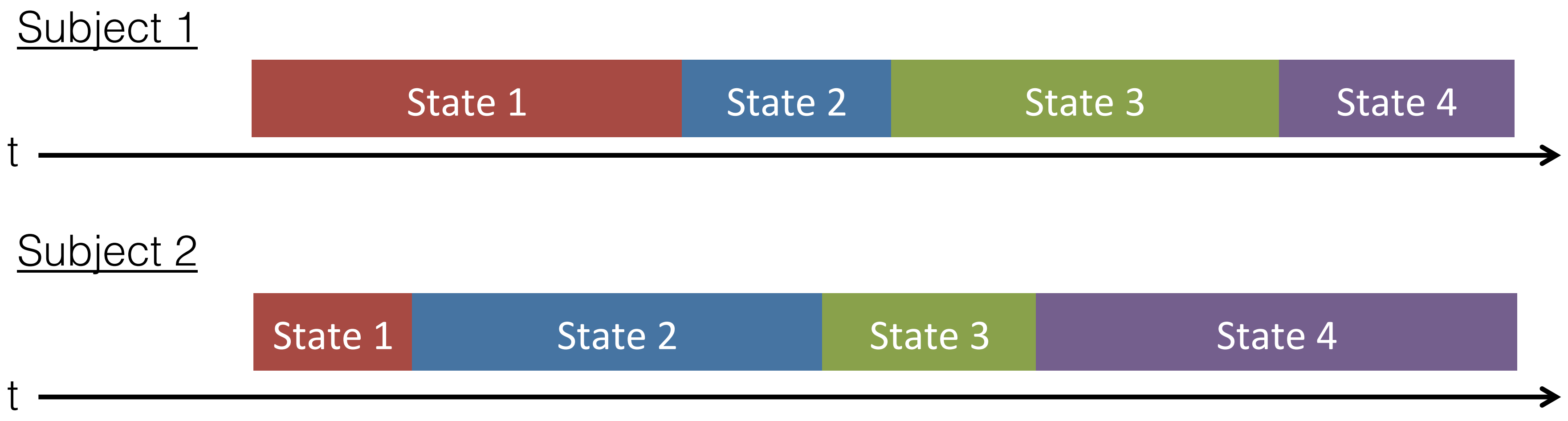
SRM with non-temporally synchronized dataset

- Each observation is a noisy sample of the brain state



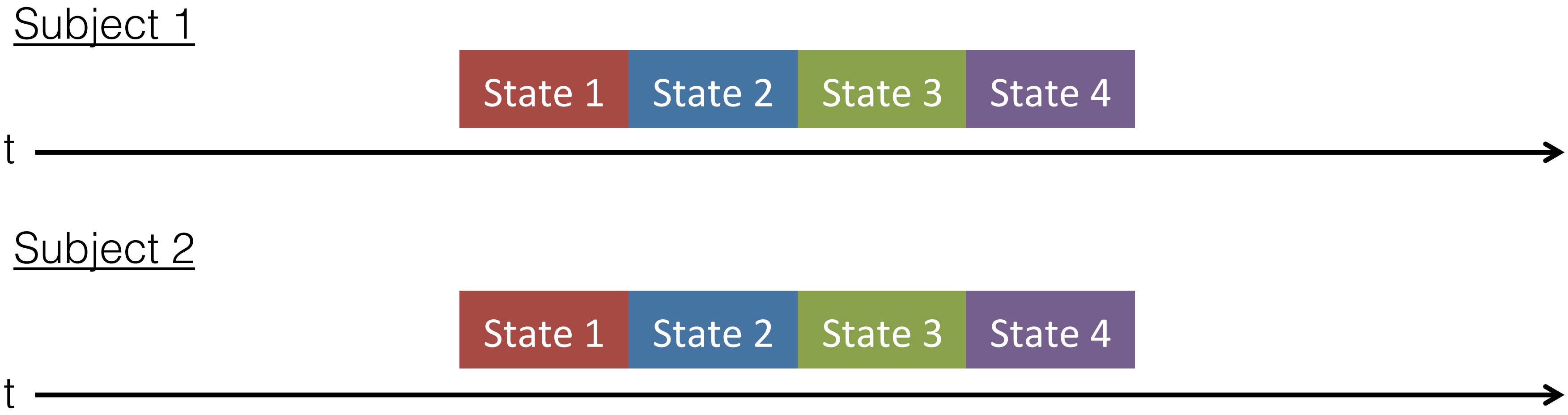
SRM with non-temporally synchronized dataset

Step 1: reordering

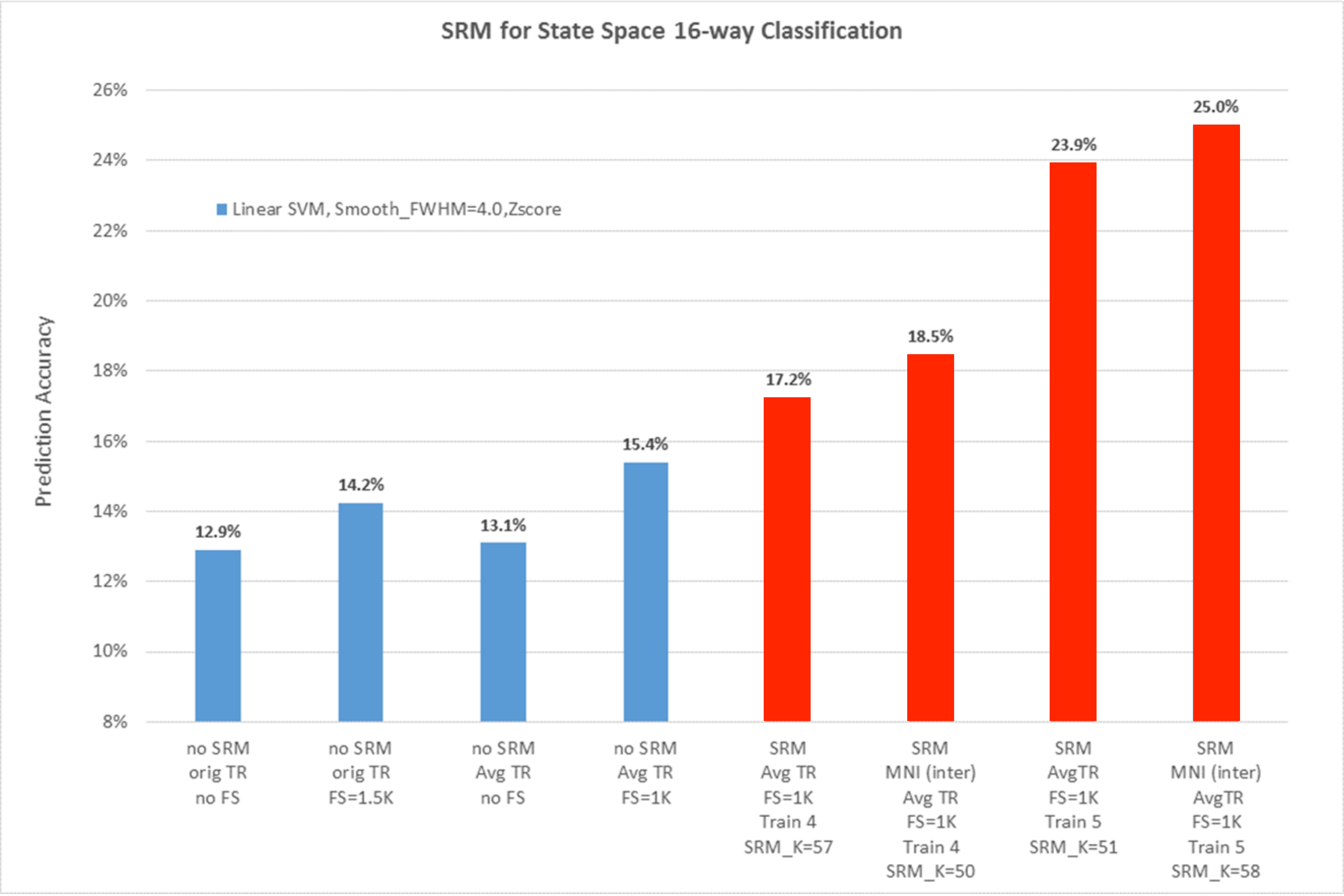


SRM with non-temporally synchronized dataset

Step 2: down sampling



Step 3: fit SRM with preprocessed data



[Work by Ivy Zhu]

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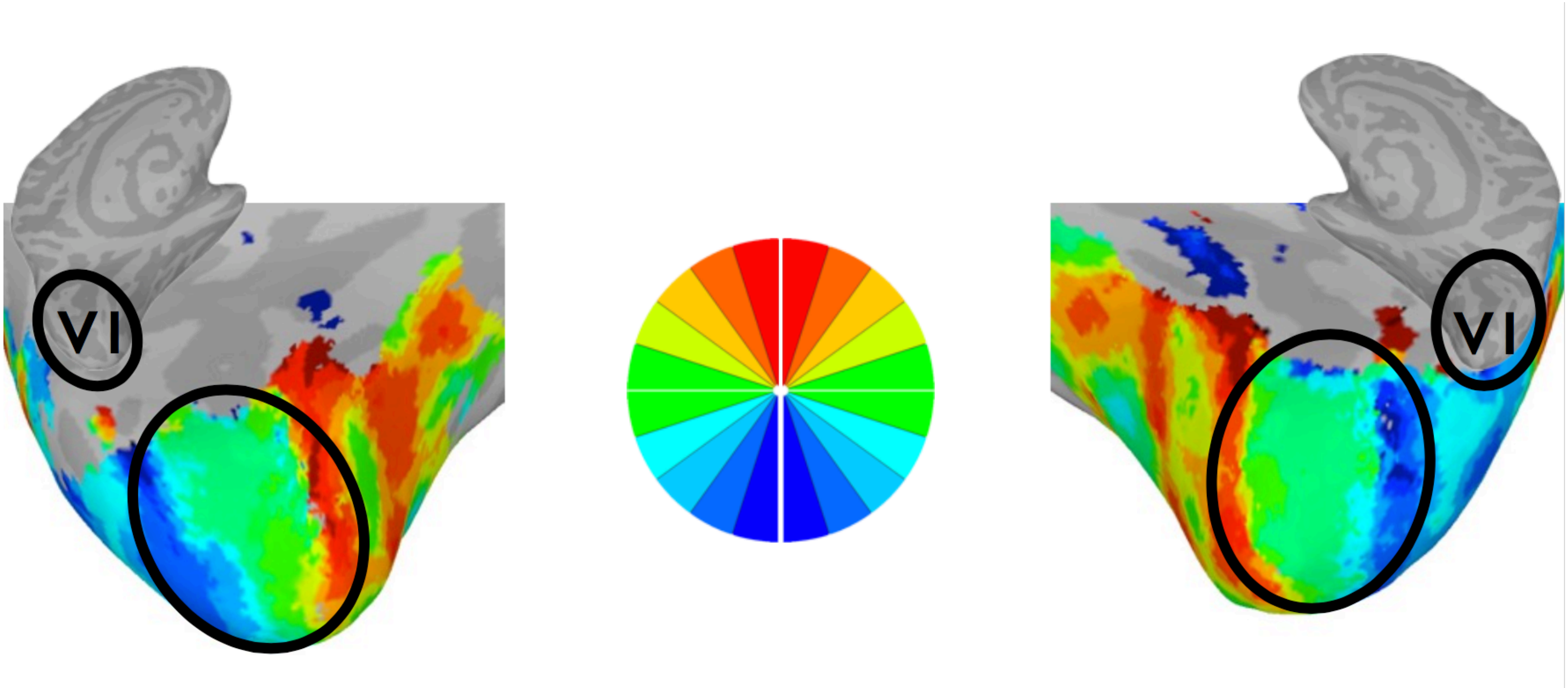
Mapping Visual Field Maps: Retinotopy



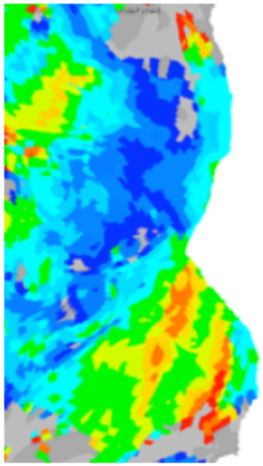
[Work by Michael J. Arcaro]

Original Phase Maps vs. SRM

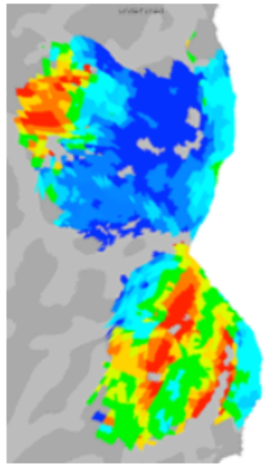
Sanity check: (W_i*transformed_data_i)

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



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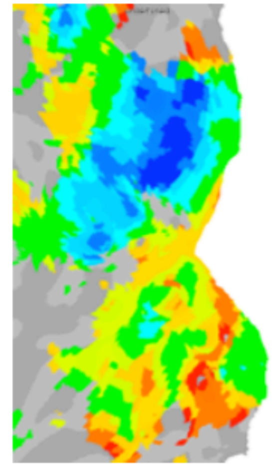
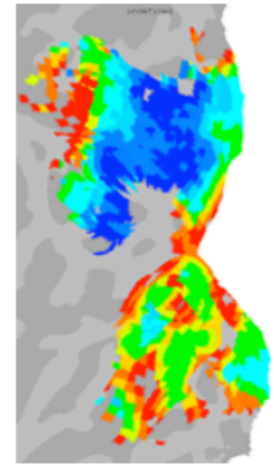


SRM



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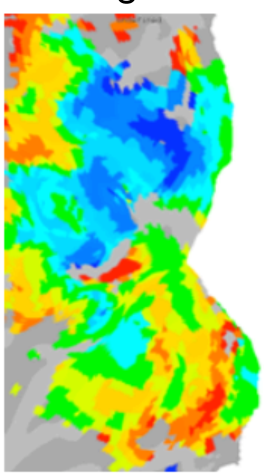

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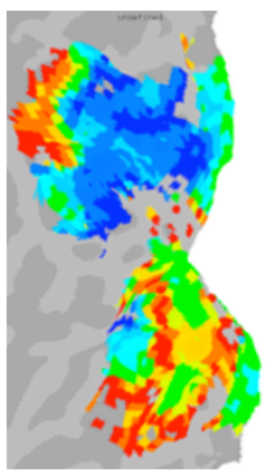

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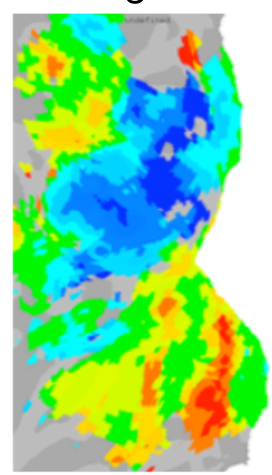
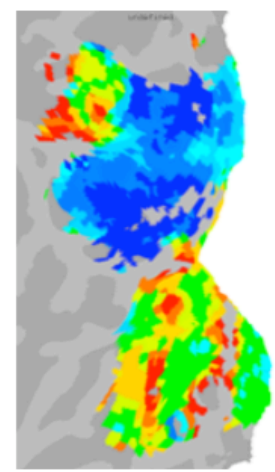
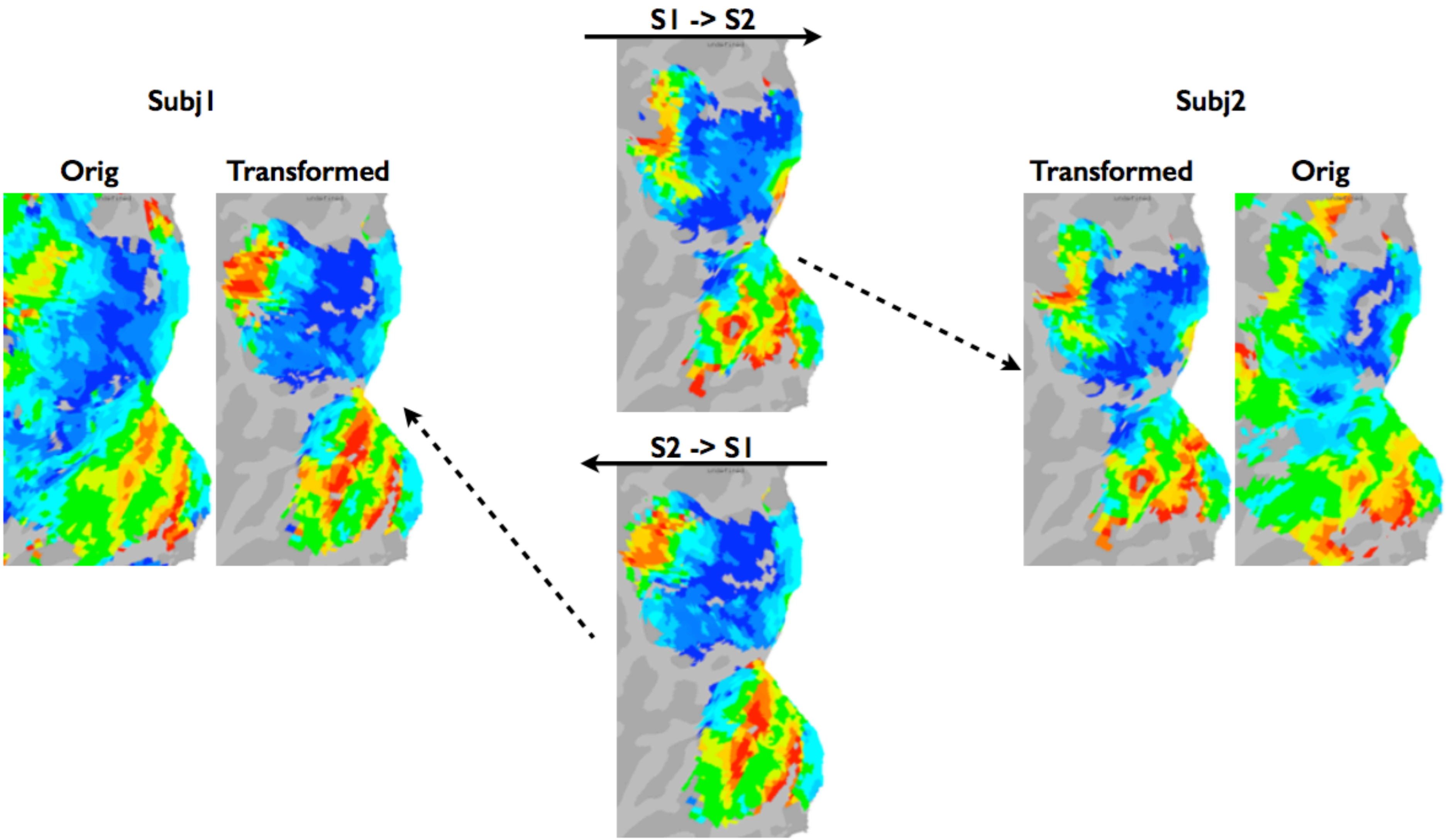


SRM



[Work by Michael J. Arcaro]

Transformation between subjects



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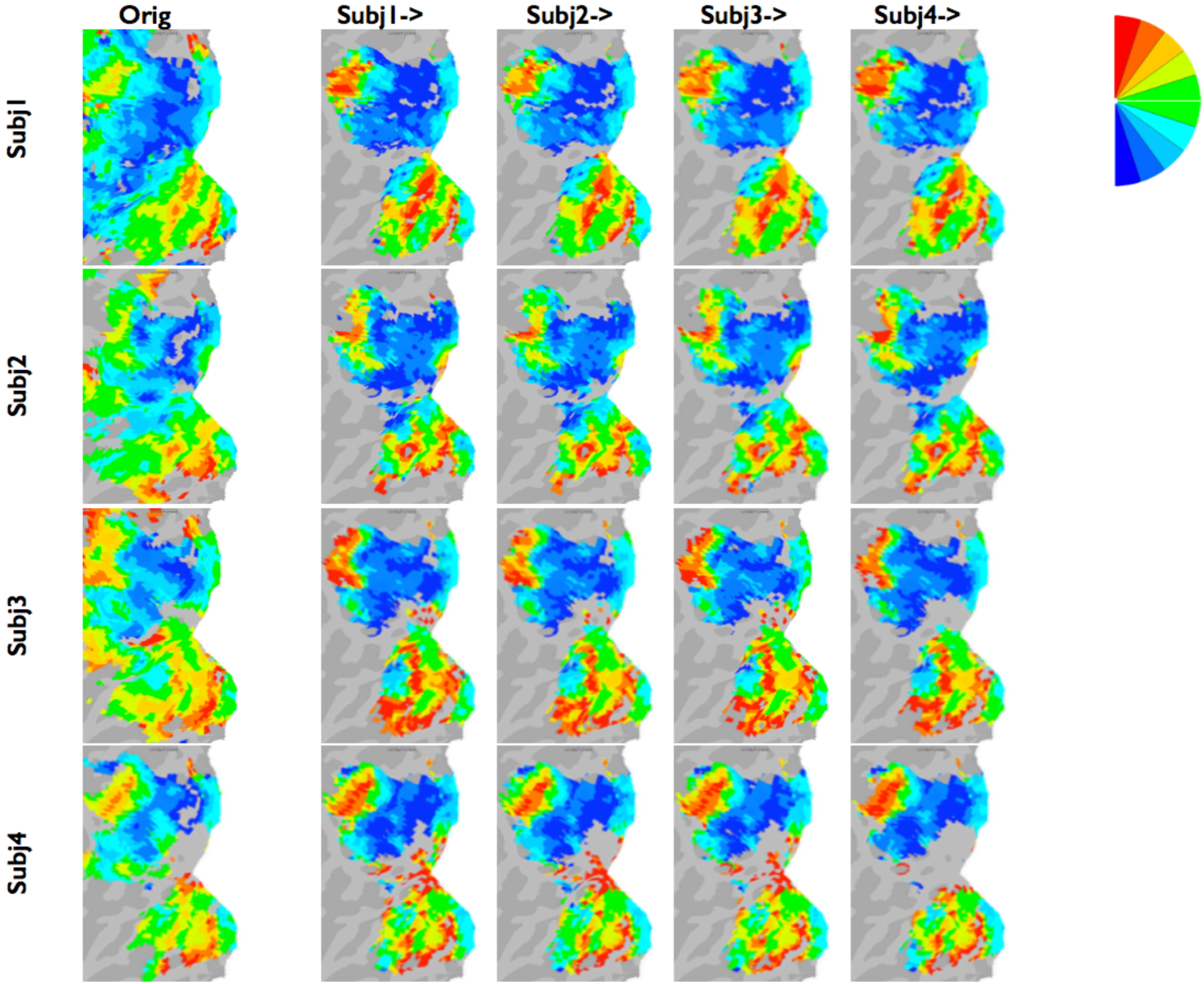

[Work by Michael J. Arcaro]

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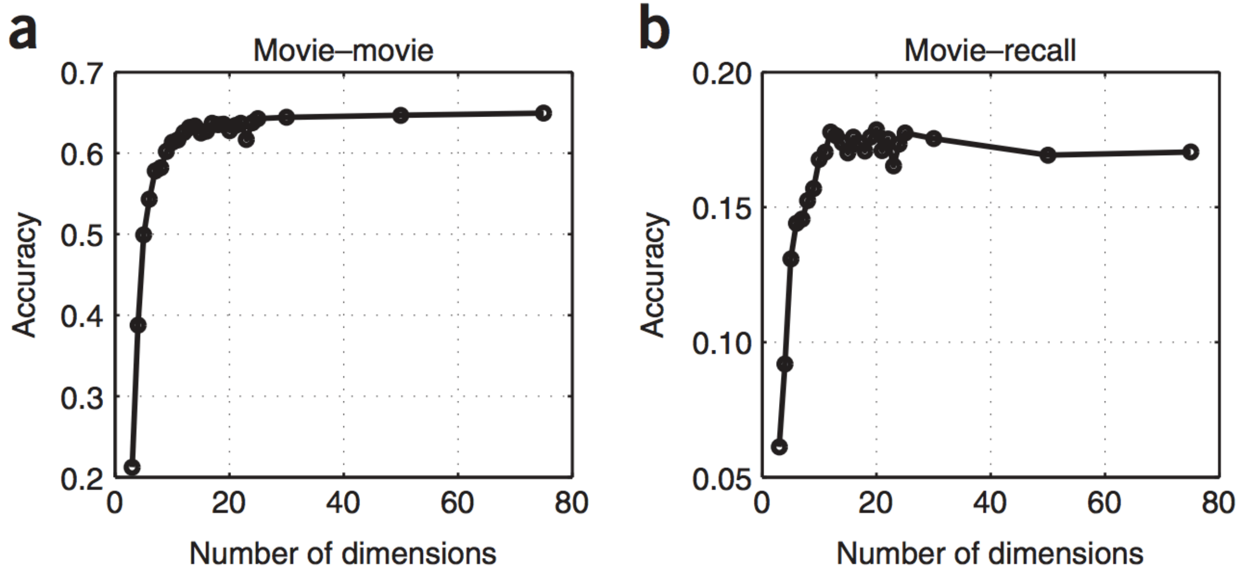
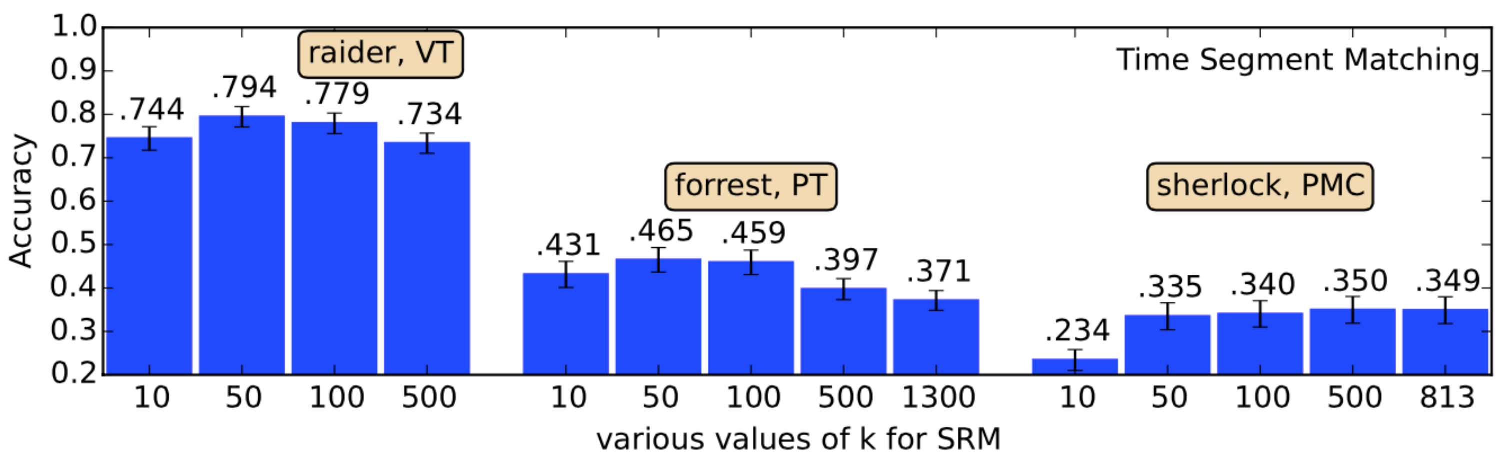
Quantifying dimensionality of shared response

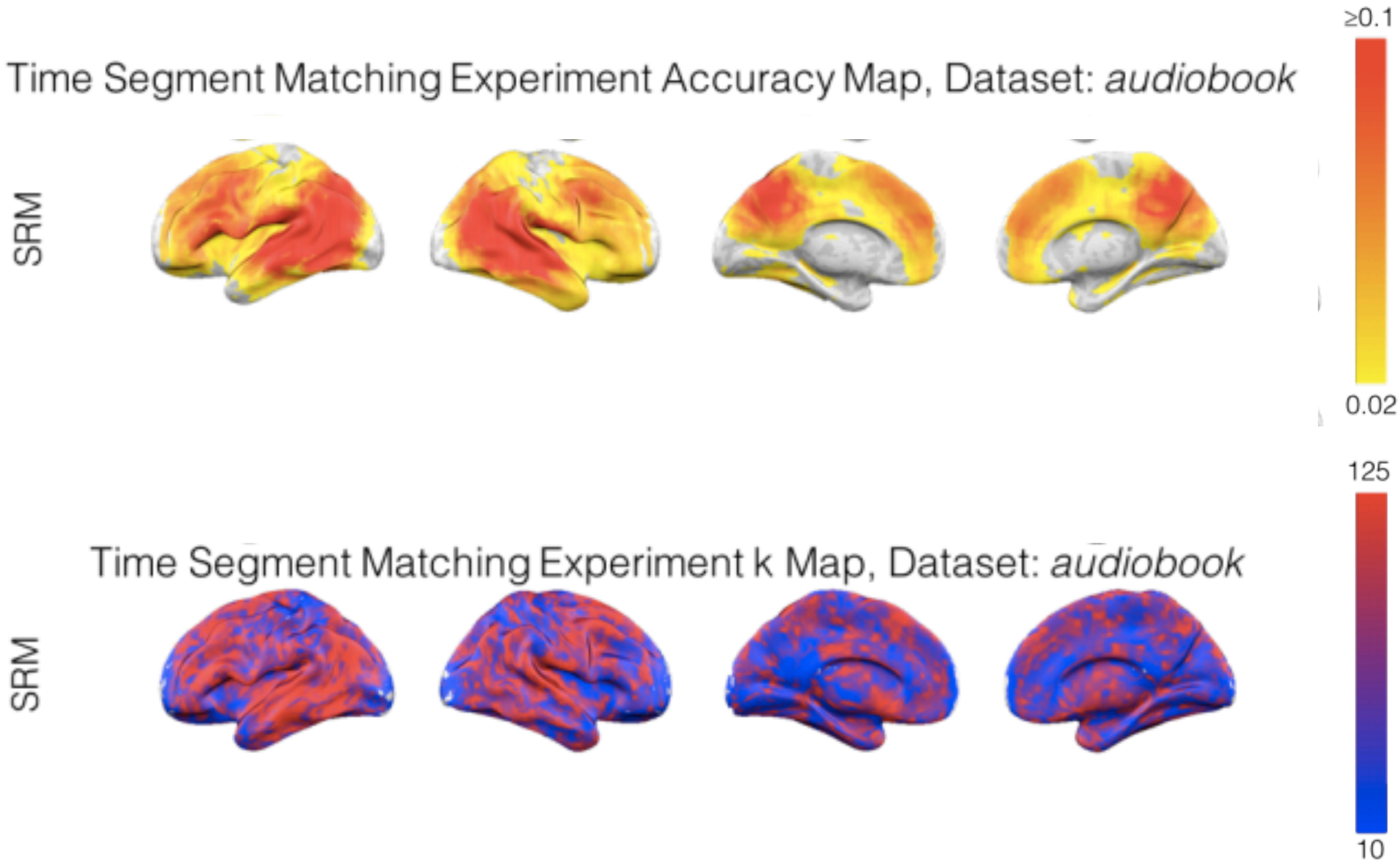


[J. Chen et al., Nat. Neur., 2017]



[P.-H. Chen et al. NIPS, 2015]

Quantifying dimensionality of shared response



[H. Zhang et al. ArXiv, 2016]

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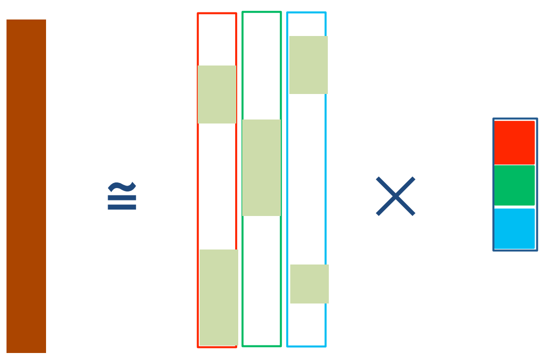
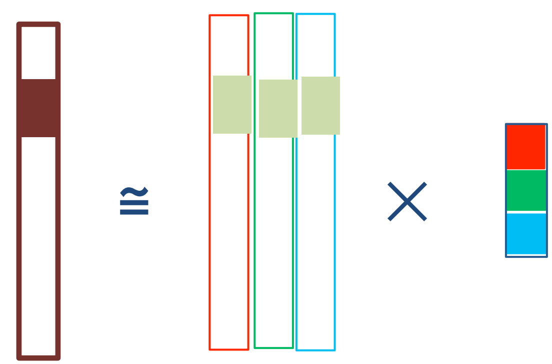
Why searchlights?

Structured Sparsity



t-th column of X_i W_i t-th column of S

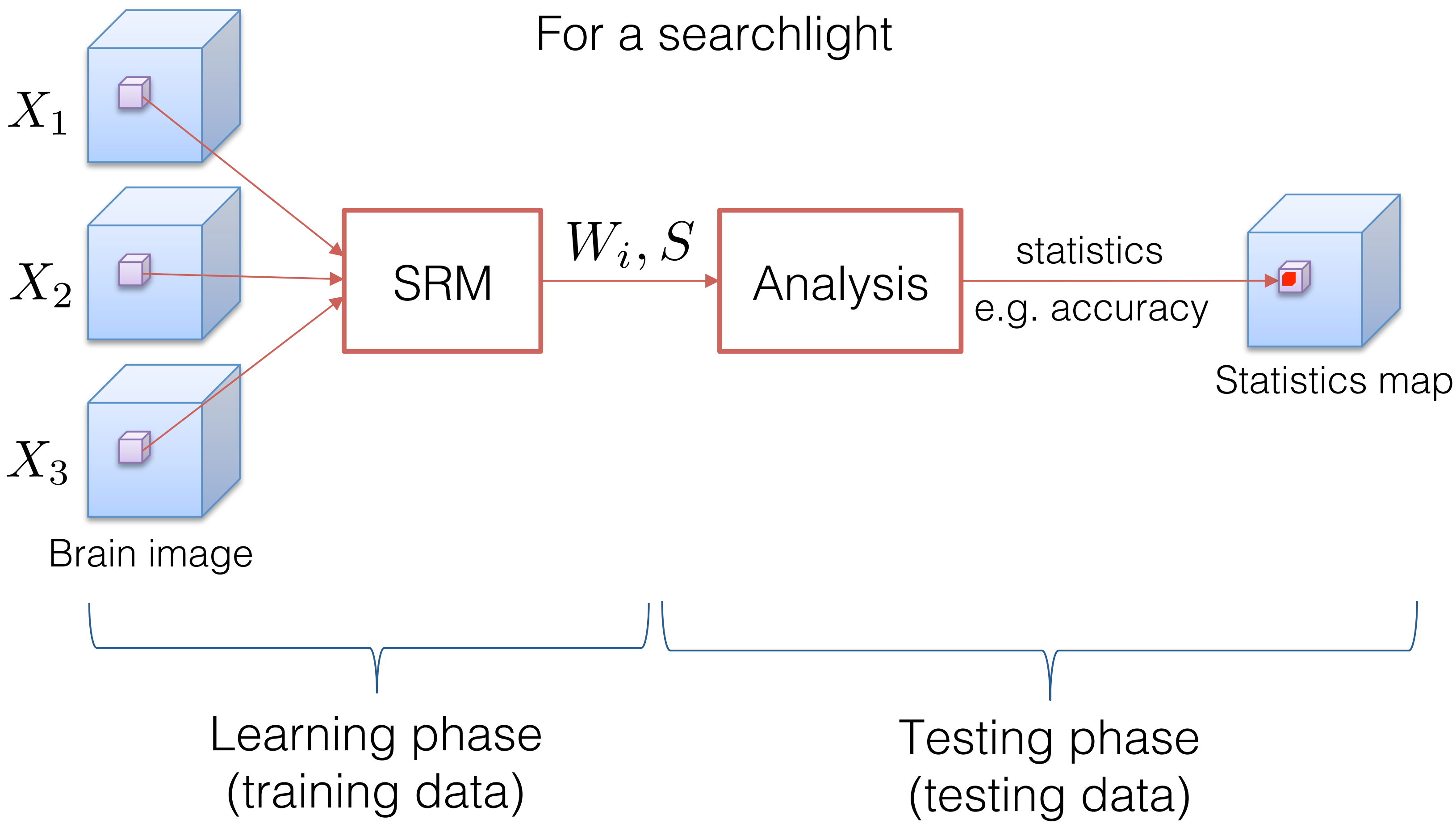
Searchlight



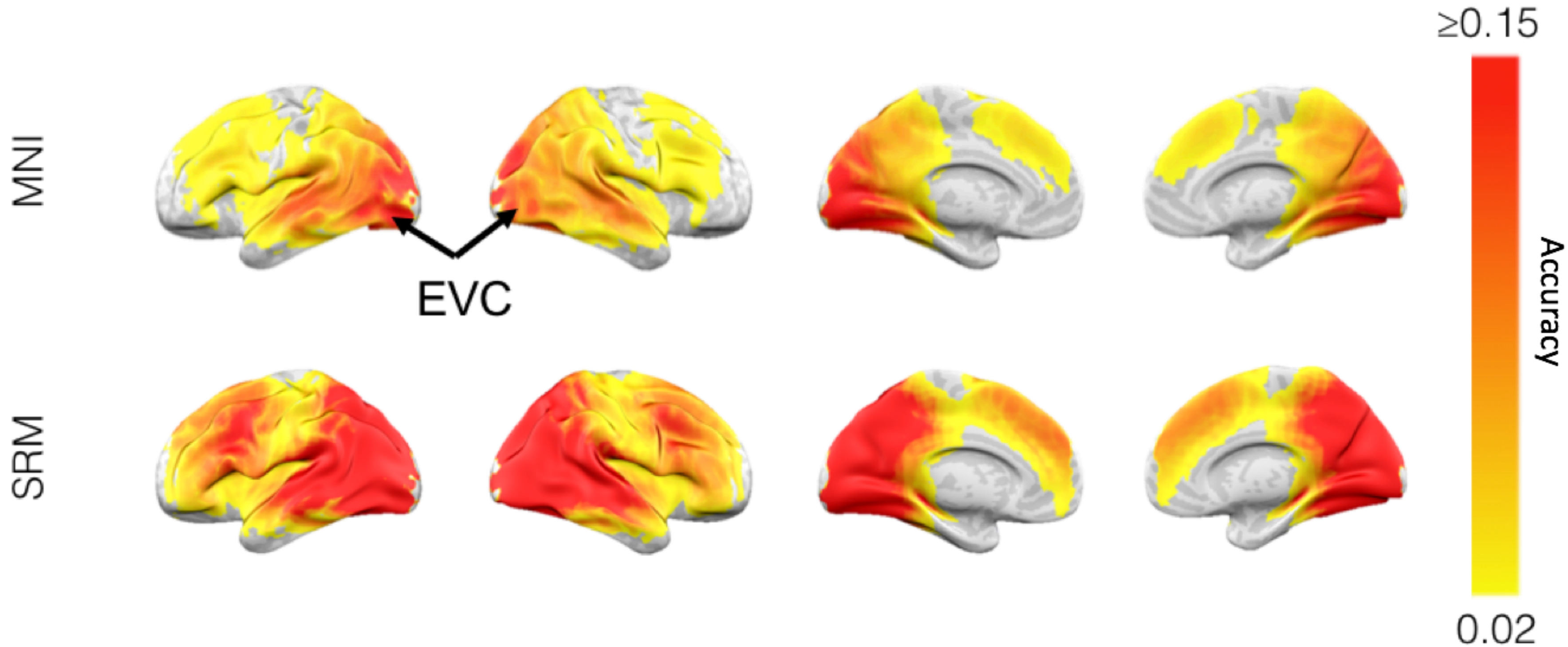
t-th column of X_i W_i t-th column of S

Searchlight SRM

- localized analysis across the whole brain



Time segment matching with searchlight SRM



Accuracy map from time segment matching experiment (Sherlock)

How can SRM help?

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

Can I use SRM on my data?

- Temporally synchronized stimuli
  - No problem!
- Non-temporally synchronized stimuli
  - Can also work with preprocessing!

List of extensions

- SRM with word embedding
- Semi-supervised SRM
- Distributed SRM
- Convolutional Autoencoder SRM
- Spatial SRM
- Kernelized SRM
- Gaussian Process SRM
- Information theoretic SRM
- Matrix Normal SRM

Key Takeaways

When should you consider using SRM?

1. I want to figure out what’s shared/not shared in my multi-set data (multi-subject, multi-modality, multi-region, etc)

2. I have multi-set data, I want better prediction accuracy!!

Hands-on SRM with BrainIak

Code ready to use on your dataset

https://github.com/IntelPNI/brainiak

- Simple setting, one line command to fit SRM on your data
- Handles different numbers of voxels across subjects/views

Jupyter notebook examples

Need jupyter notebook and brainiak properly installed with python 3

1. git clone https://github.com/cameronphchen/SRM_tutorial.git
2. cd SRM_tutorial
3. chmod +x download-data.sh
4. ./download-data.sh
5. jupyter notebook

Thank you!

{pohsuan,hejiaz}@princeton.edu

cameronphchen.github.io