# Shared Response Model Tutorial

## What works? How can it help you?

Po-Hsuan (Cameron) Chen and Hejia Zhang

@ Hasson Lab
Feb 15, 2017

PRINCETON UNIVERSITY

# Outline

- SRM Theory
- SRM on fMRI
- Hands-on SRM with Brainlak

# 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

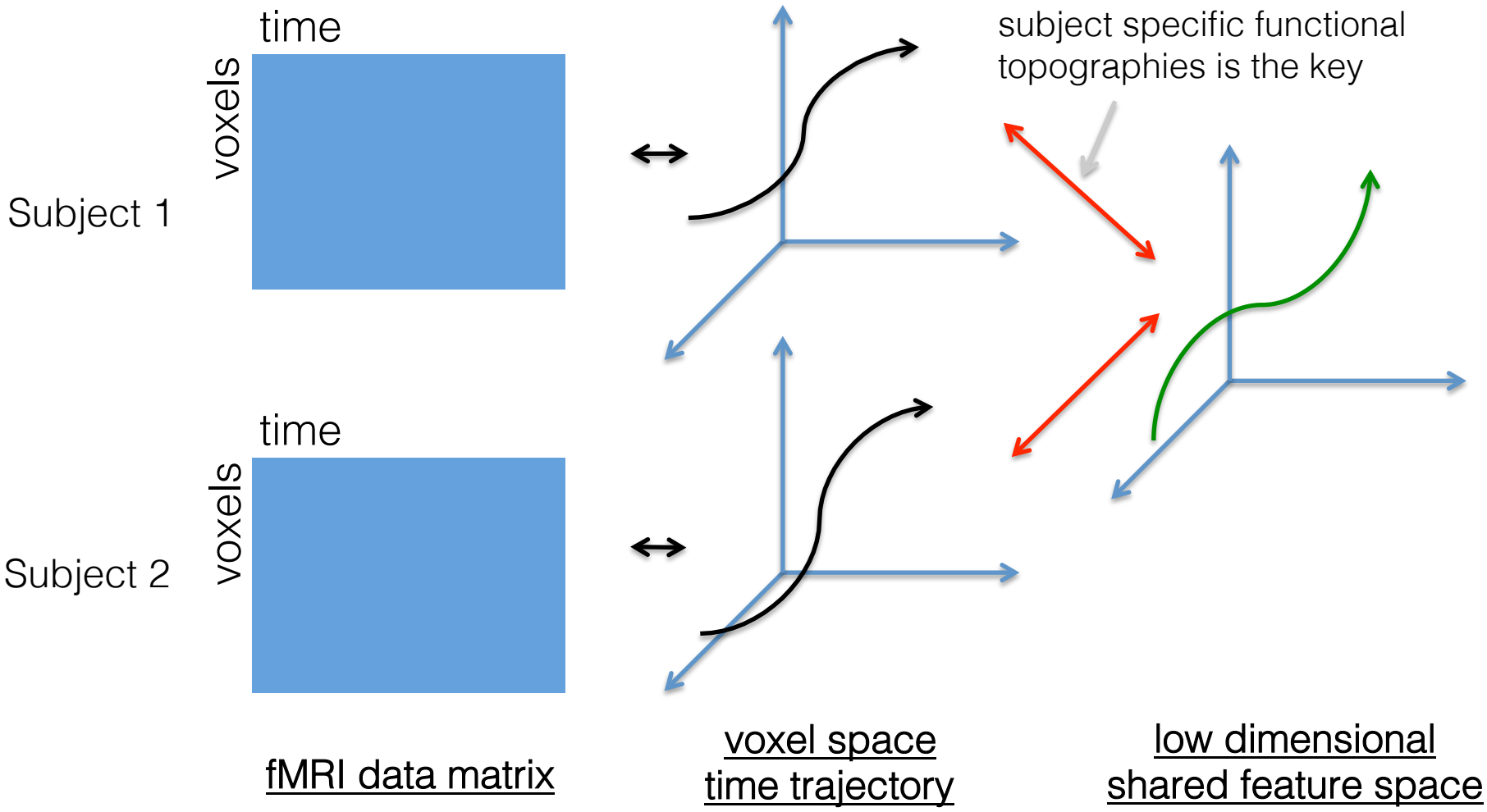
Inter-subject variability in anatomical structure and functional topographies

# Given data from training subjects,

Prediction:
can we predict the brain response of a test subject?

Classification:
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

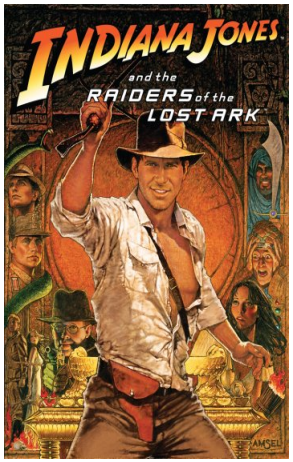
Temporally synchronized naturalistic stimuli

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

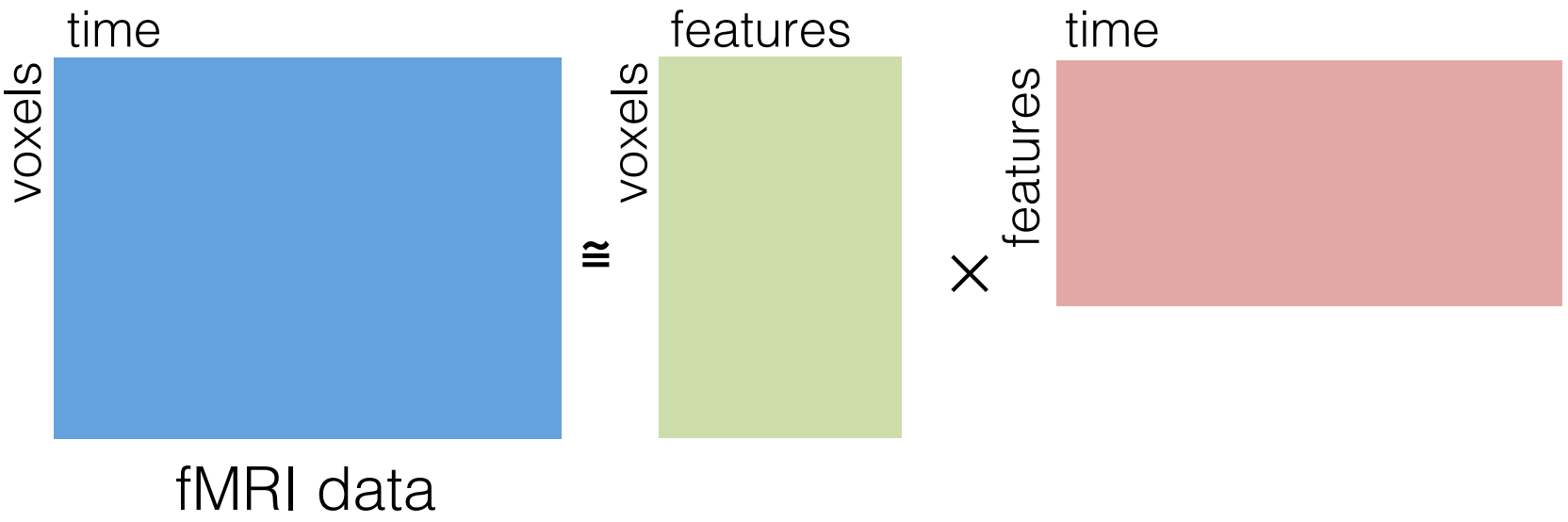
forrest


auditory film listening

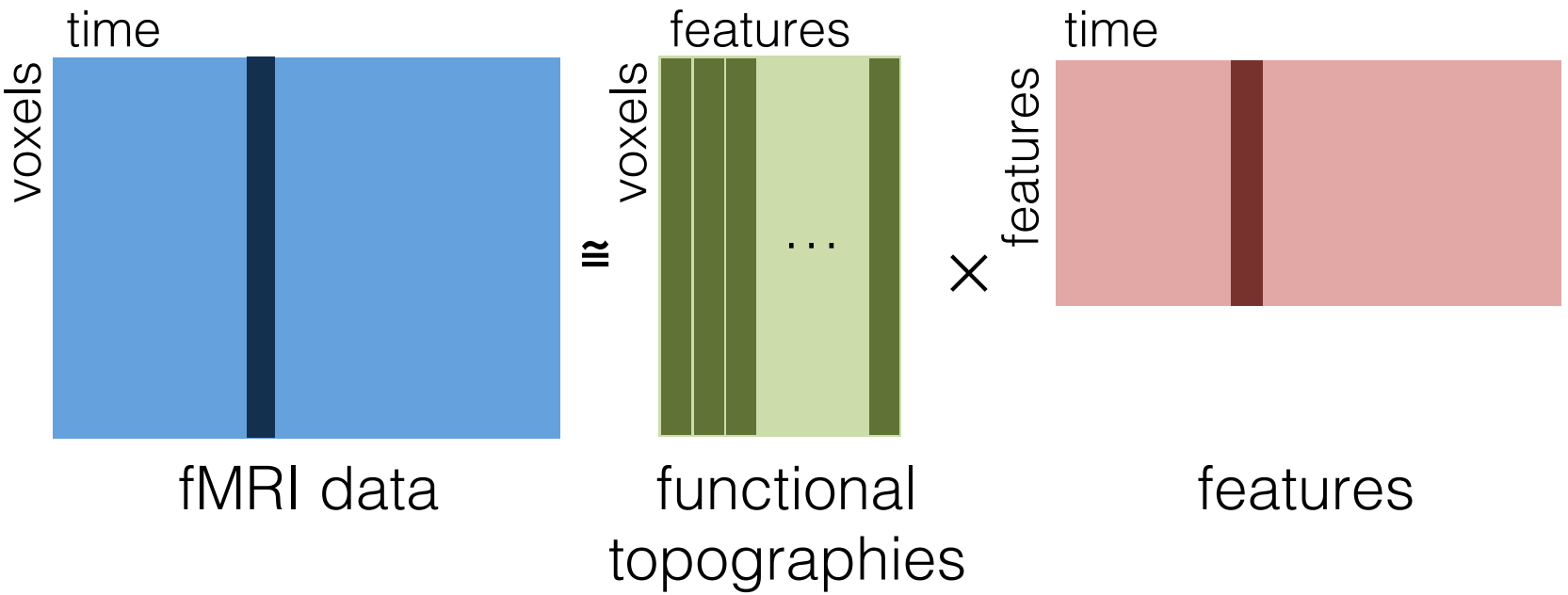
audiobook

audio book listening

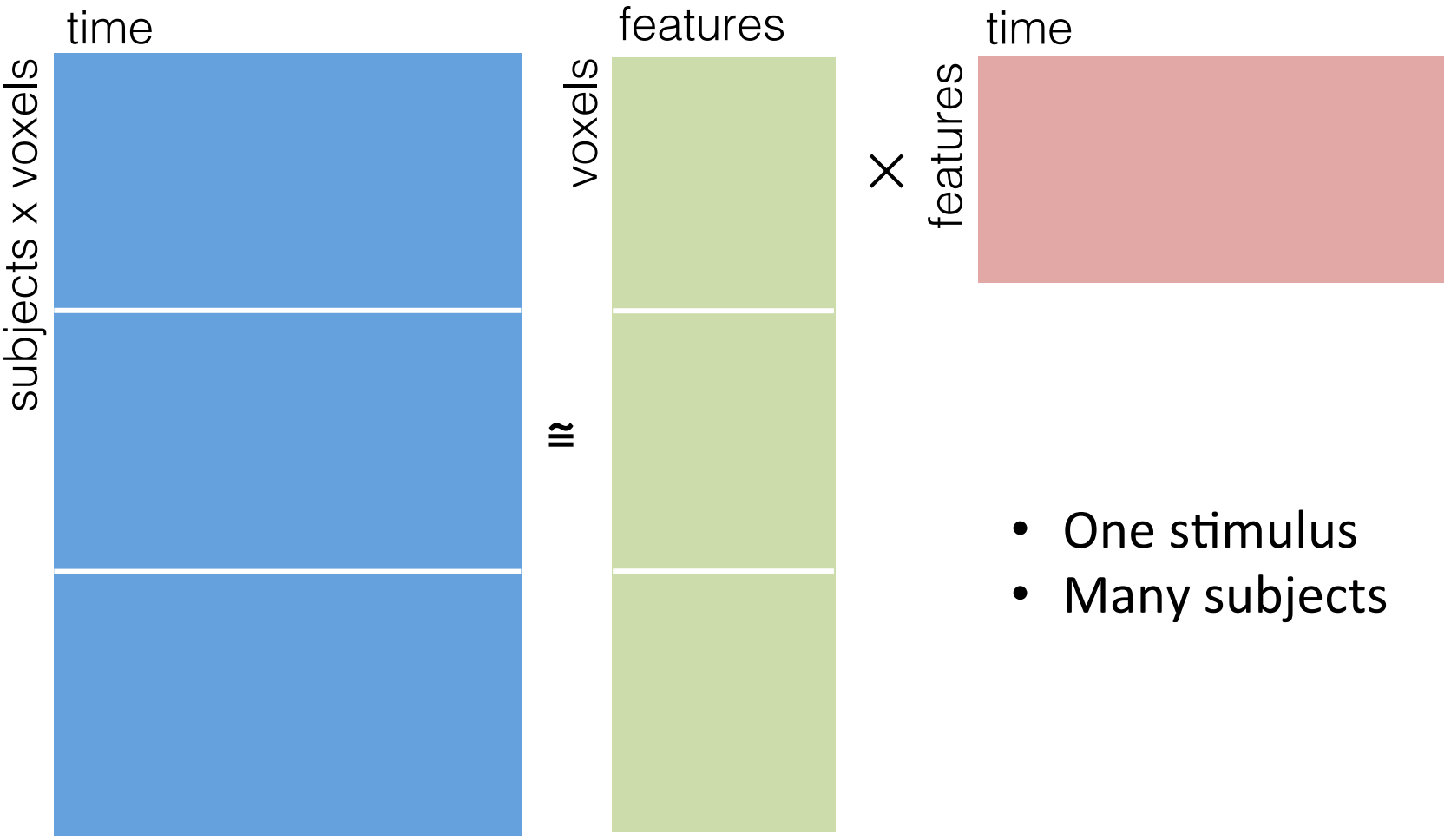
# Factor Model



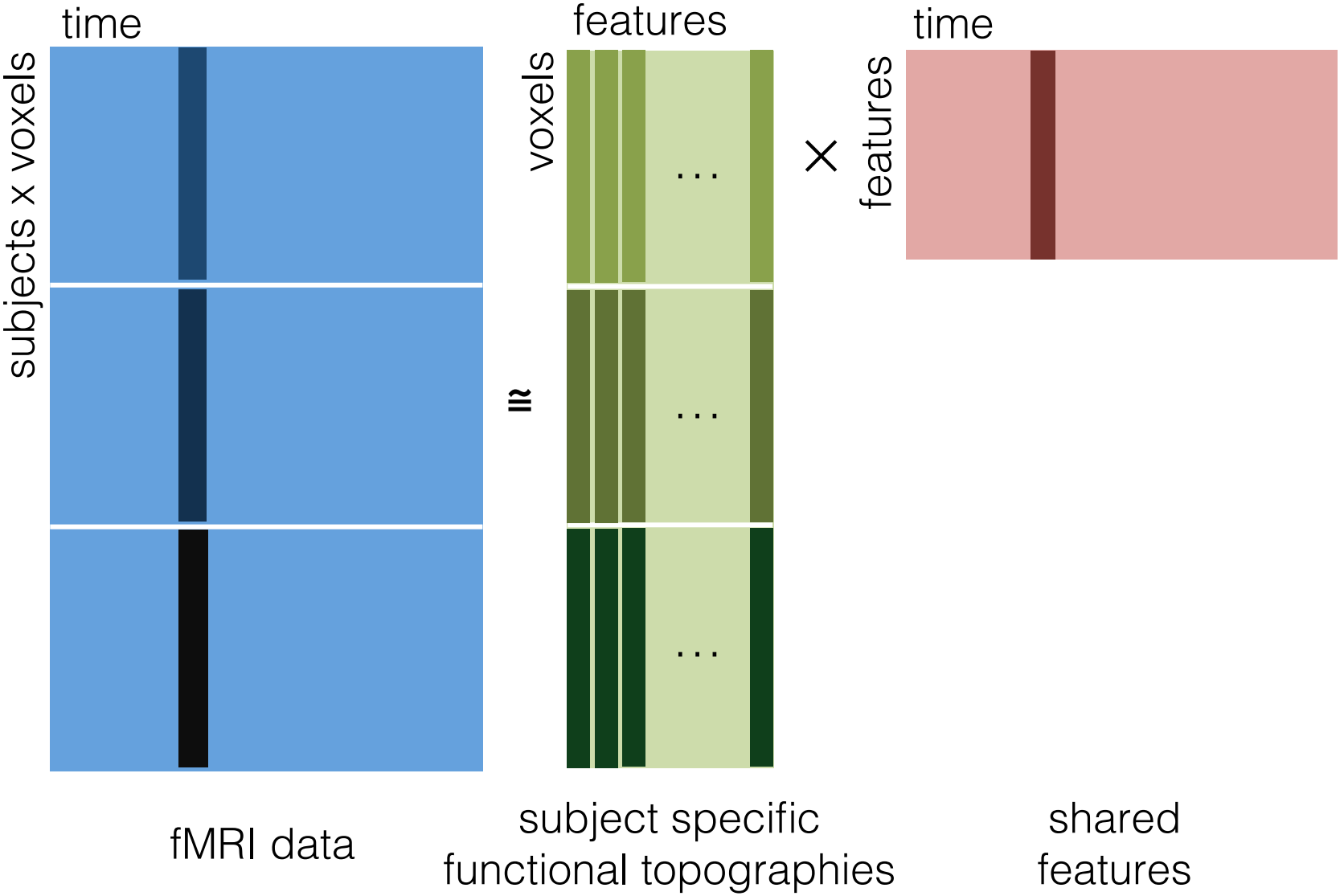
# fMRI response as linear combination of functional topographies



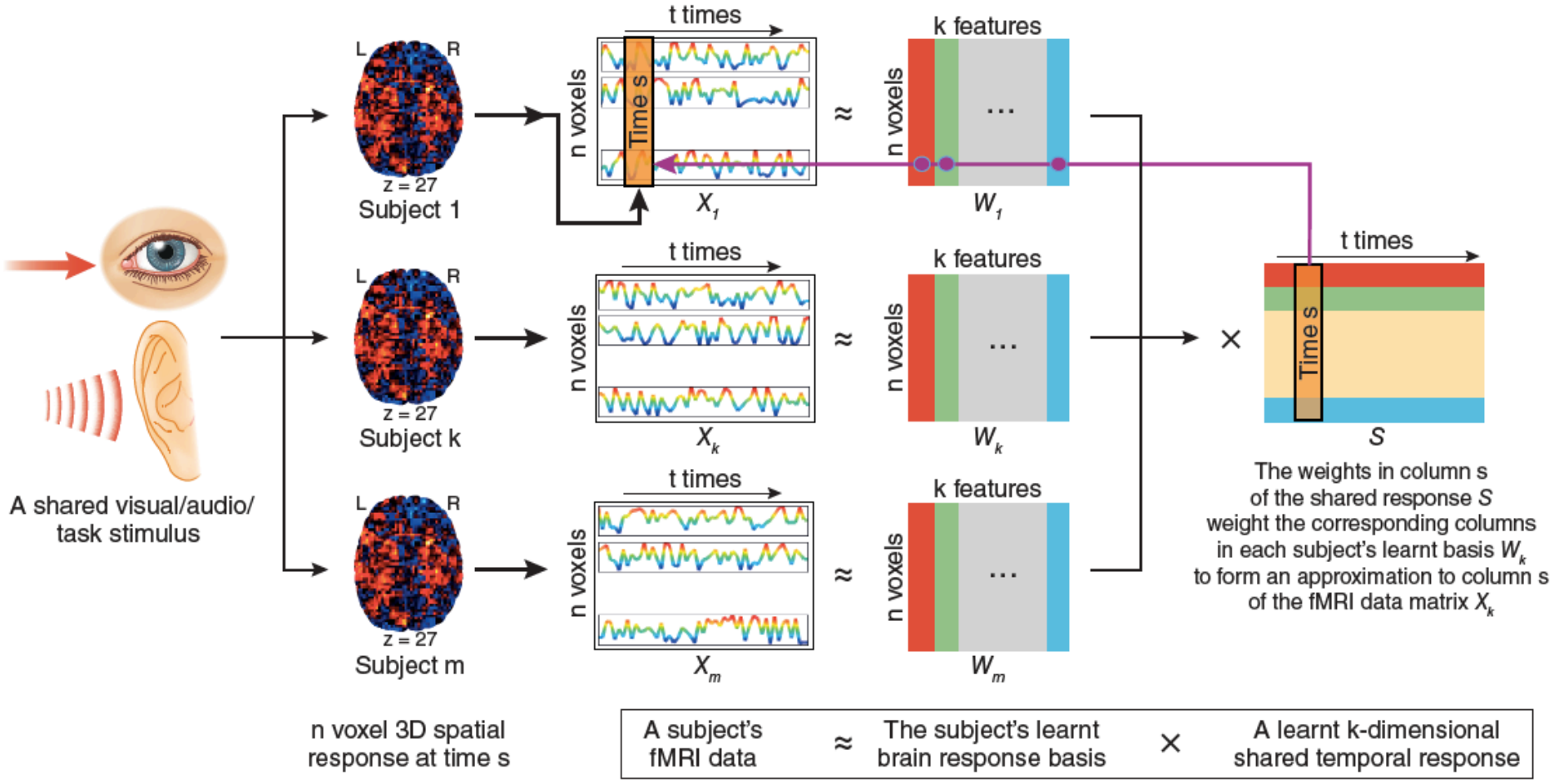
# Learning what is shared across subjects



# fMRI data as linear combination of subject specific functional topographies



# Shared Response Model in one figure

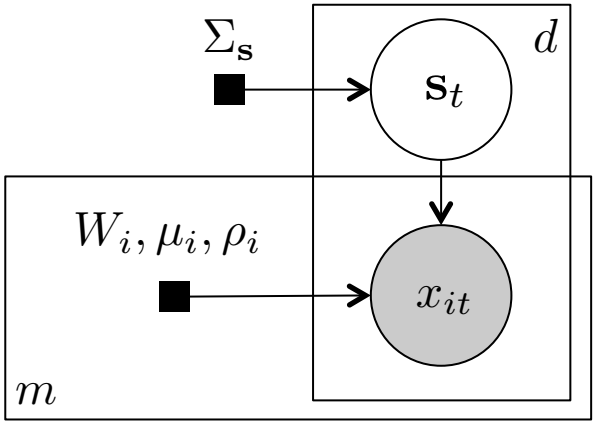



[J. Cohen et al., Nat. Neur., 2017]

# 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

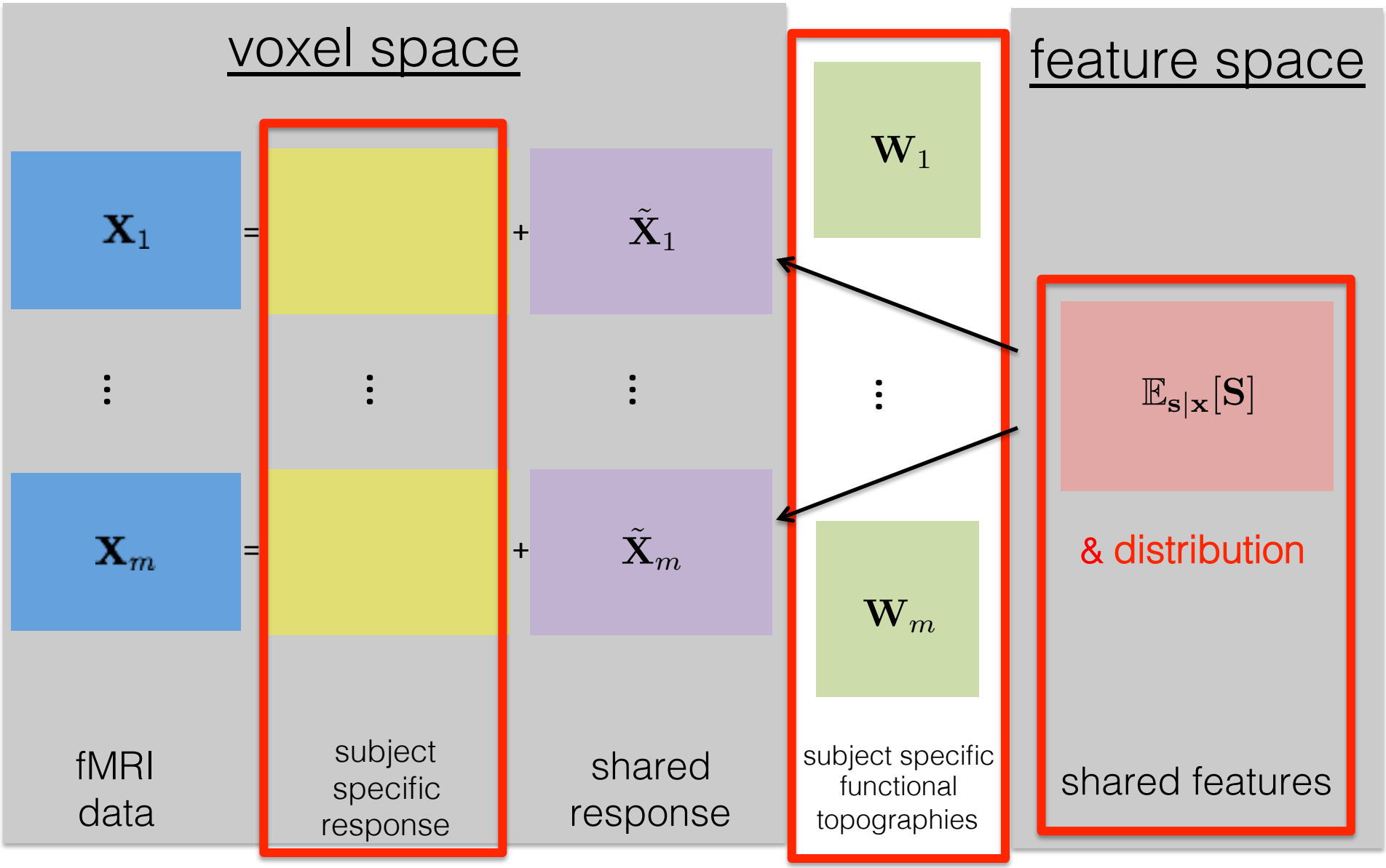



$s_t$ shared elicited response at time t
$W_i$ functional topographies for subject i
$x_{it}$ observations of subject i at time t
$\rho_i^2$ noise level for subject i's data

- 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



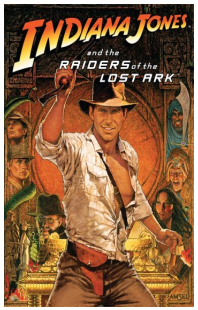
# SRM on fMRI

# Evaluation with various datasets

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

sherlock


raider




forrest


audiobook

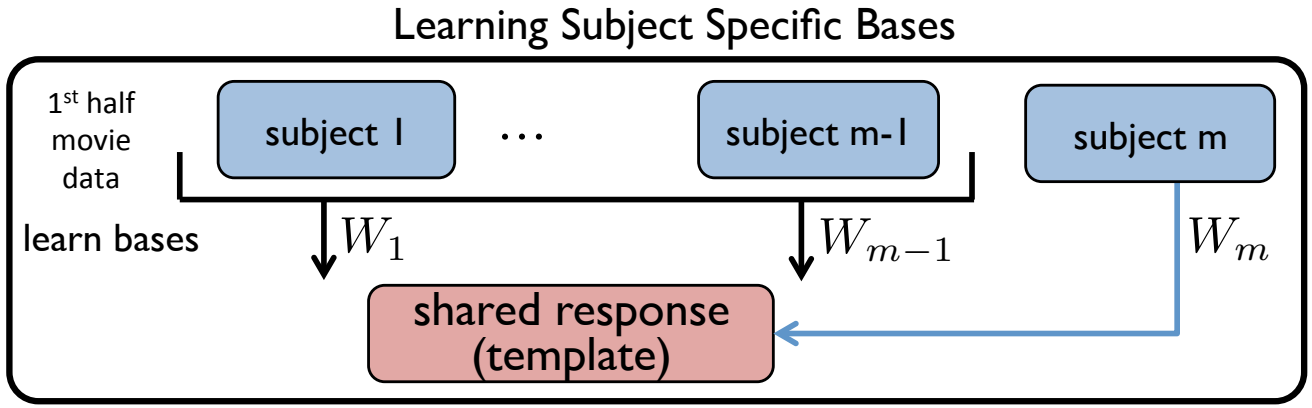
# SRM on fMRI

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

# SRM on fMRI

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

# Generalization to new subject with time segment matching

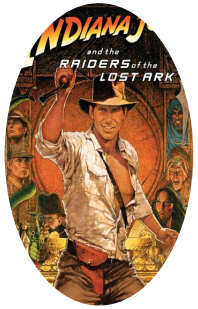



Datasets

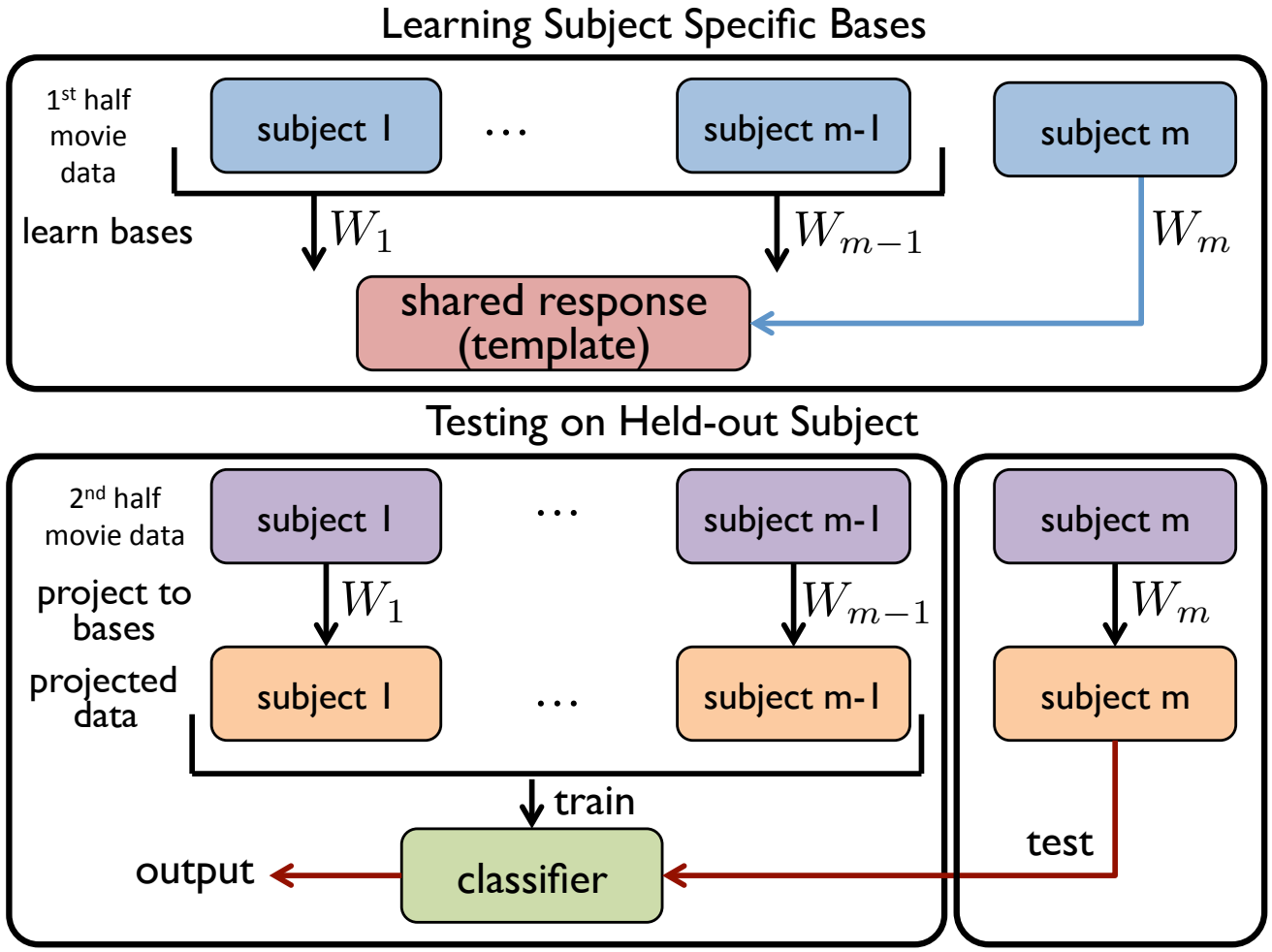
sherlock


forrest


raider



# Generalization to new subject with time segment matching



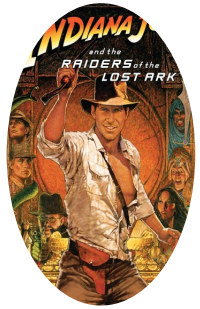

Datasets

sherlock

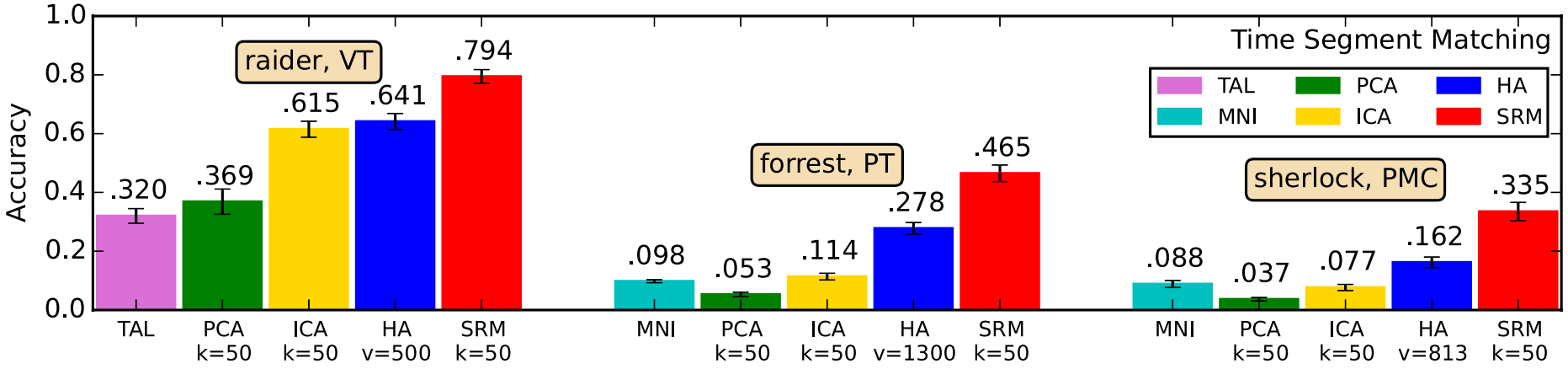

forrest

Forrest Gump

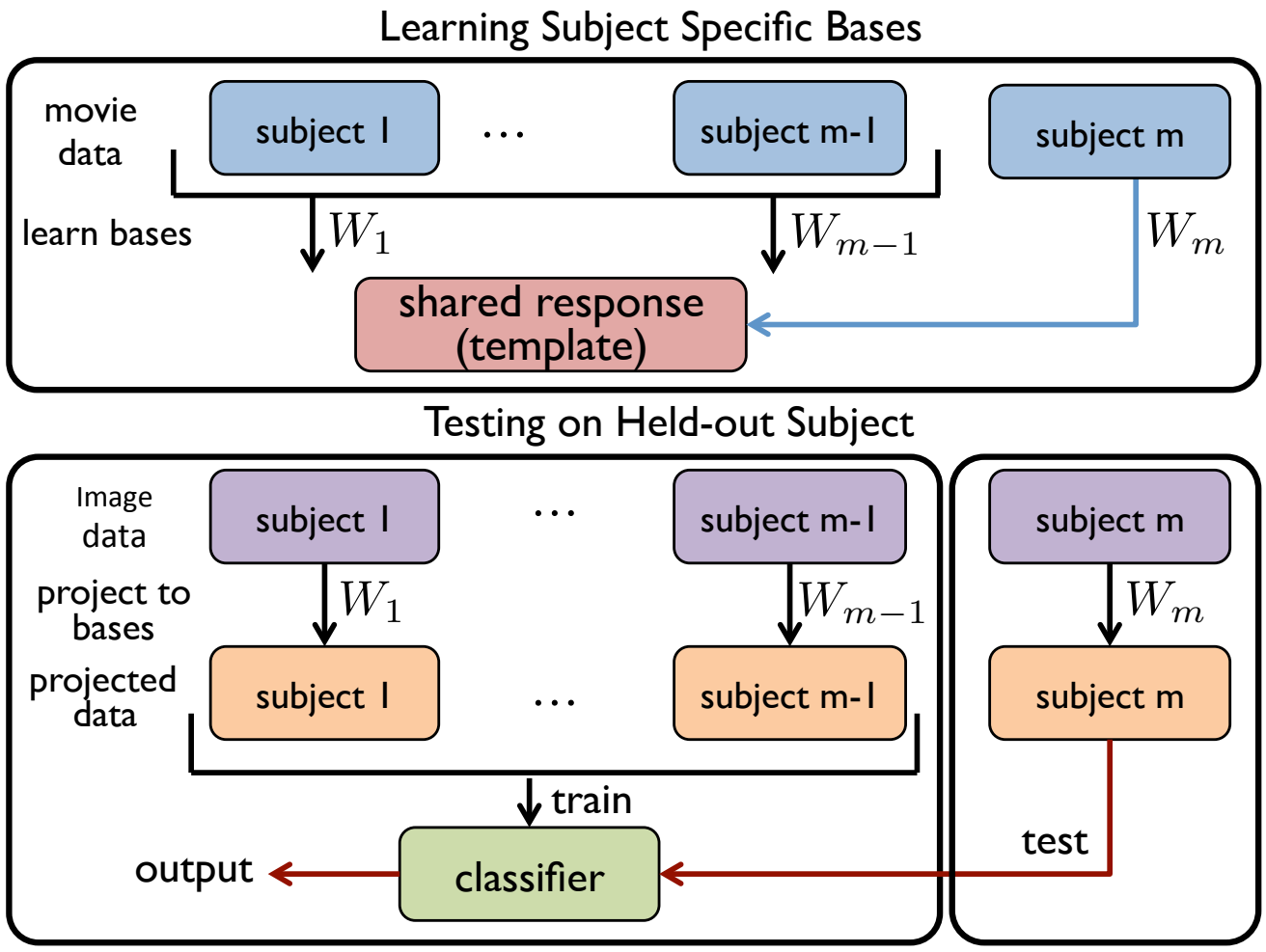
raider



# Generalization to new subject with time segment matching

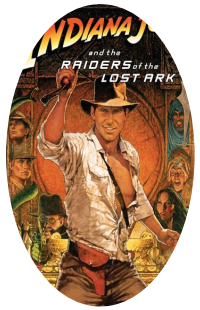


# Generalization to new subject and distinct stimulus with image classification

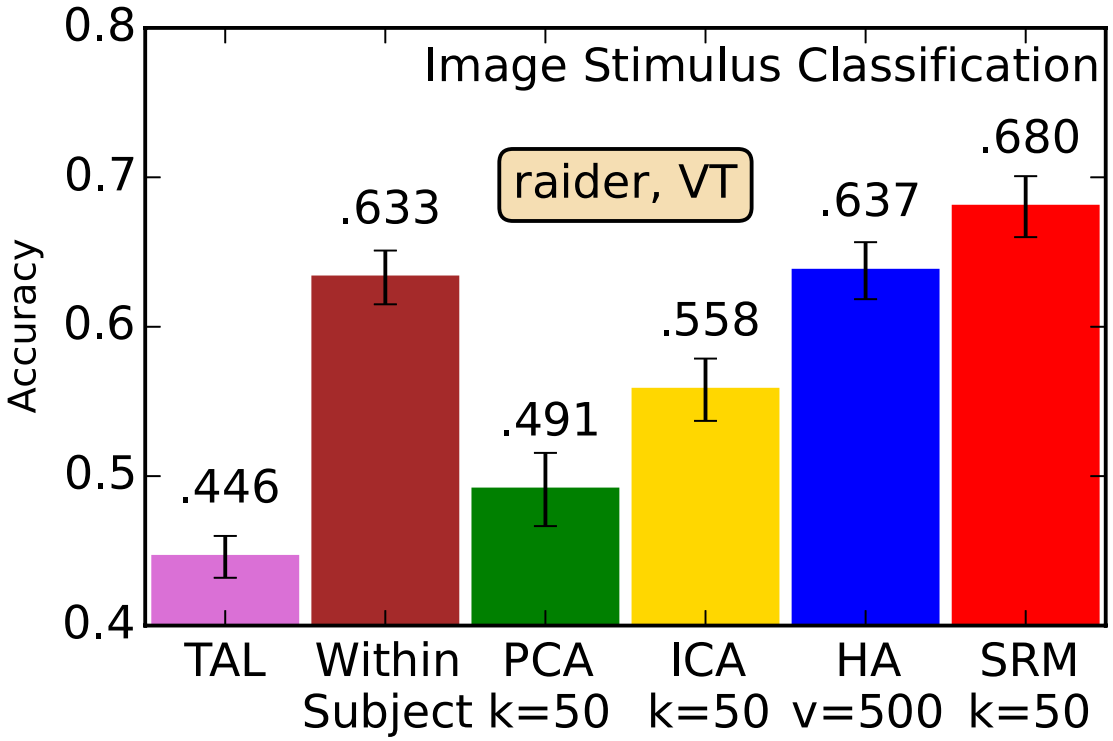



Dataset

raider



# 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 retinotopy
- 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

# Classifying mental states

Group 1

shared by all | within group | individual

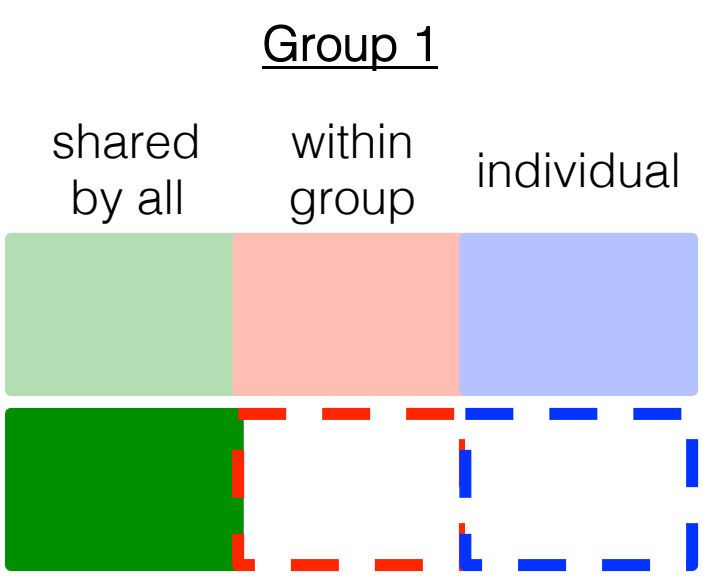
Group 2

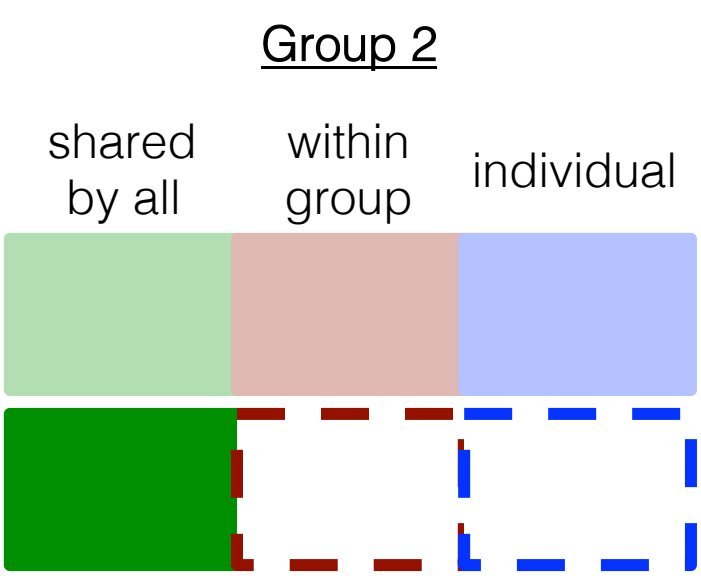
shared by all | within group | individual

Group prediction accuracy with SRM

0.72±0.06

# Classifying mental states



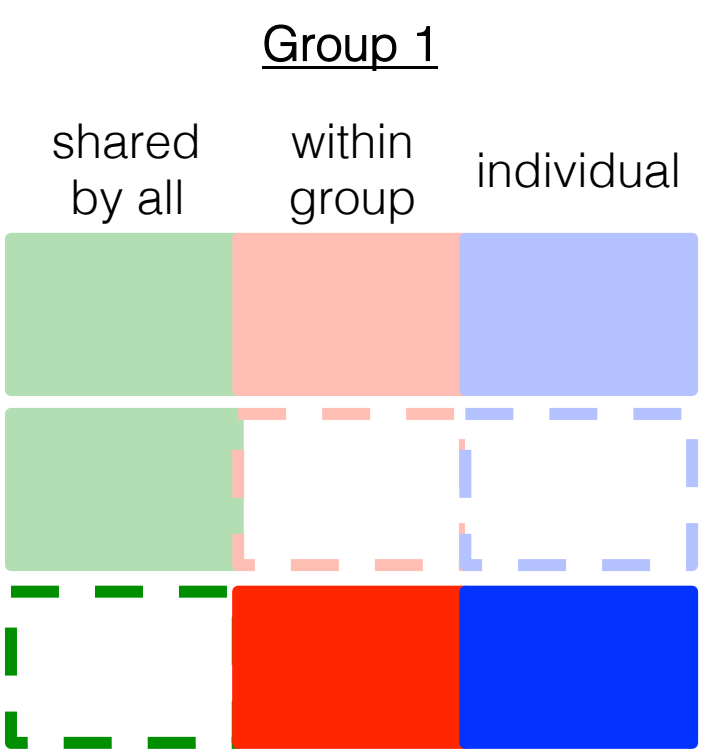



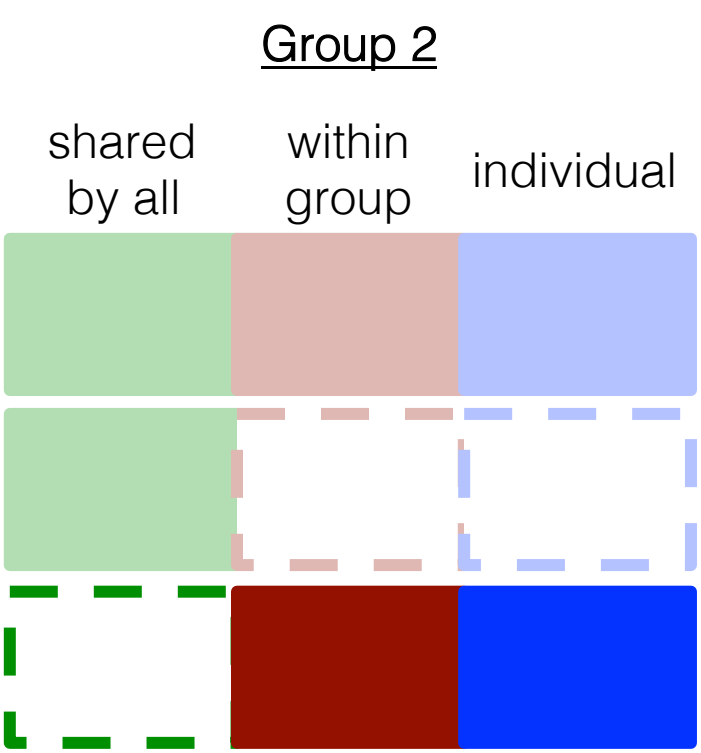

Group prediction accuracy with SRM

0.72±0.06

0.54±0.06

# Classifying mental states



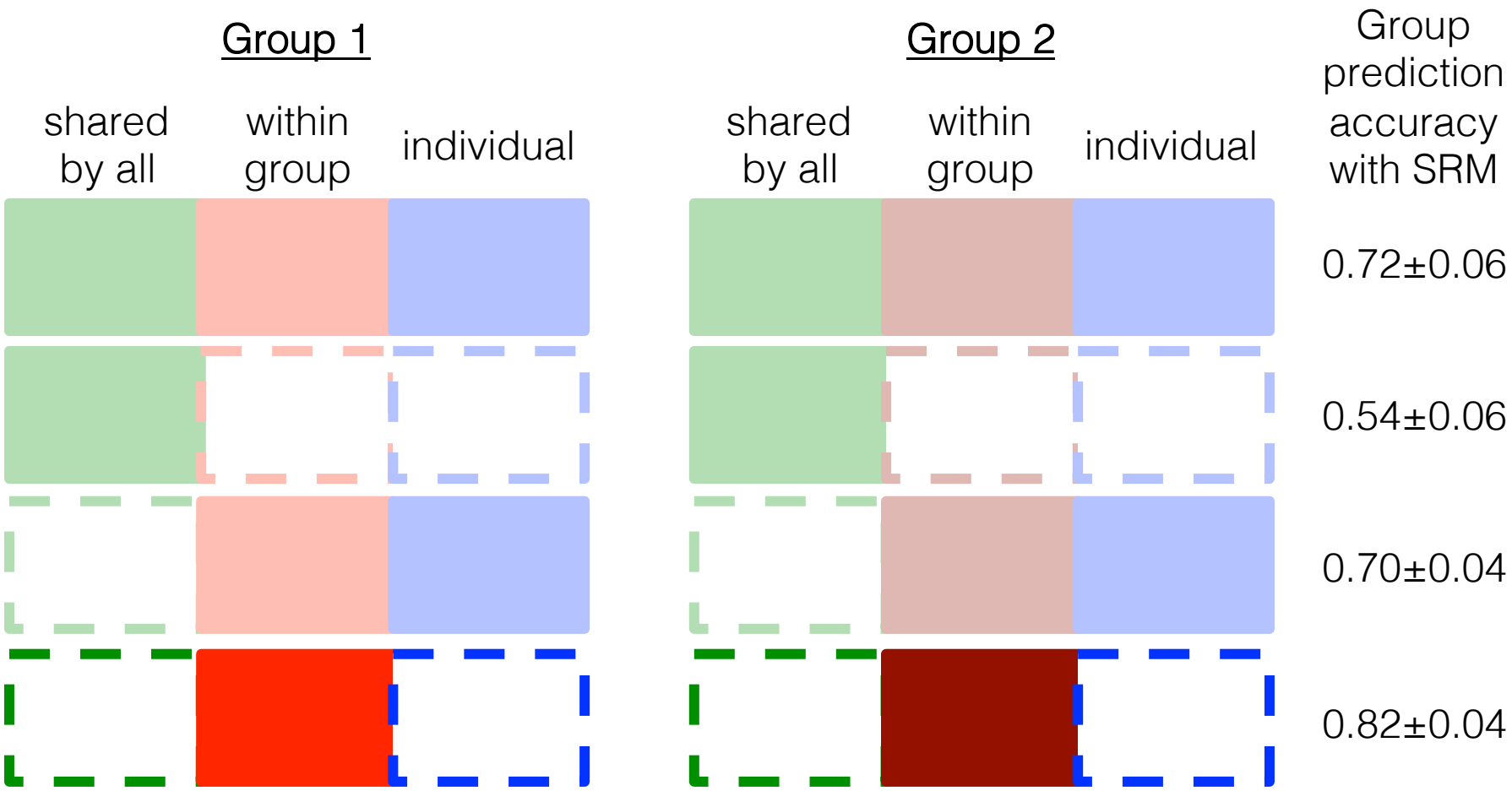

Group prediction accuracy with SRM

0.72±0.06

0.54±0.06

0.70±0.04

# Classifying mental states



# SRM on fMRI

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

# Stimuli

Young Face
Young House

Old Face
Young House

Old Face
Old House

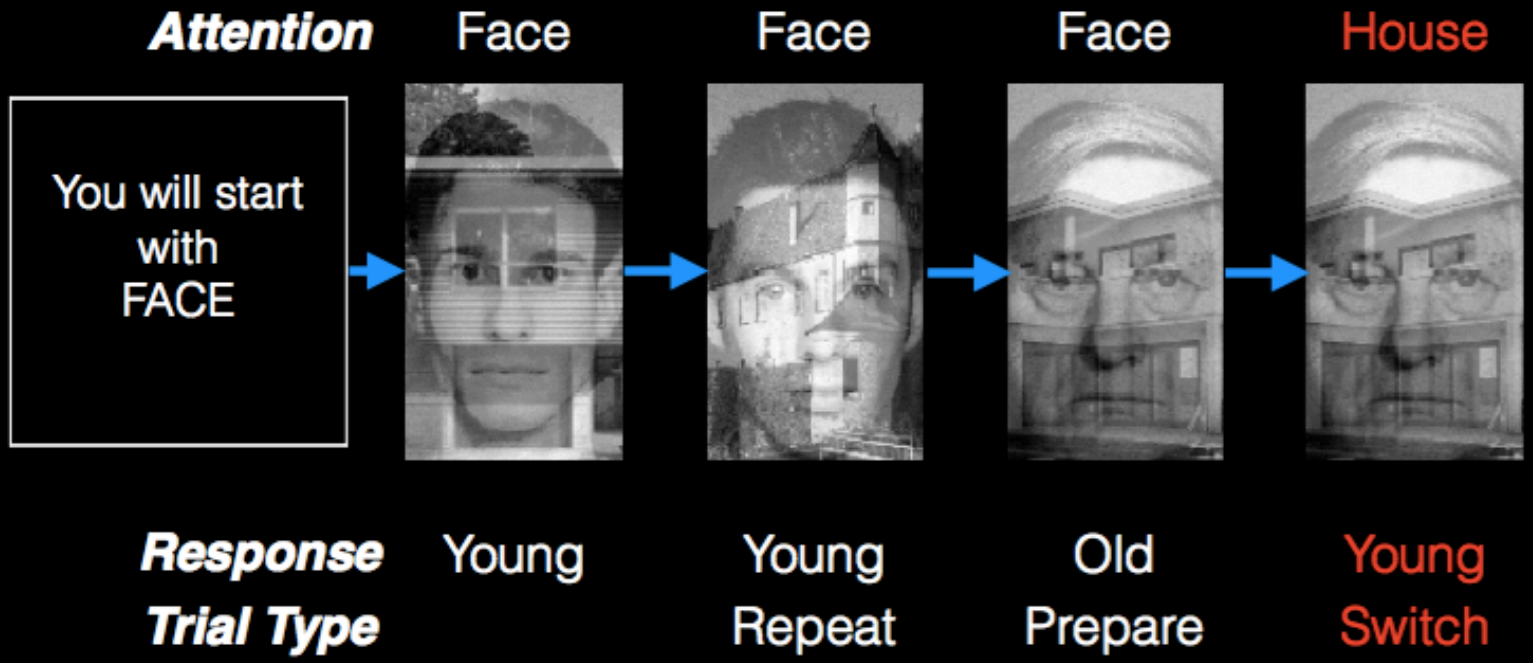
Young Face
Old House

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

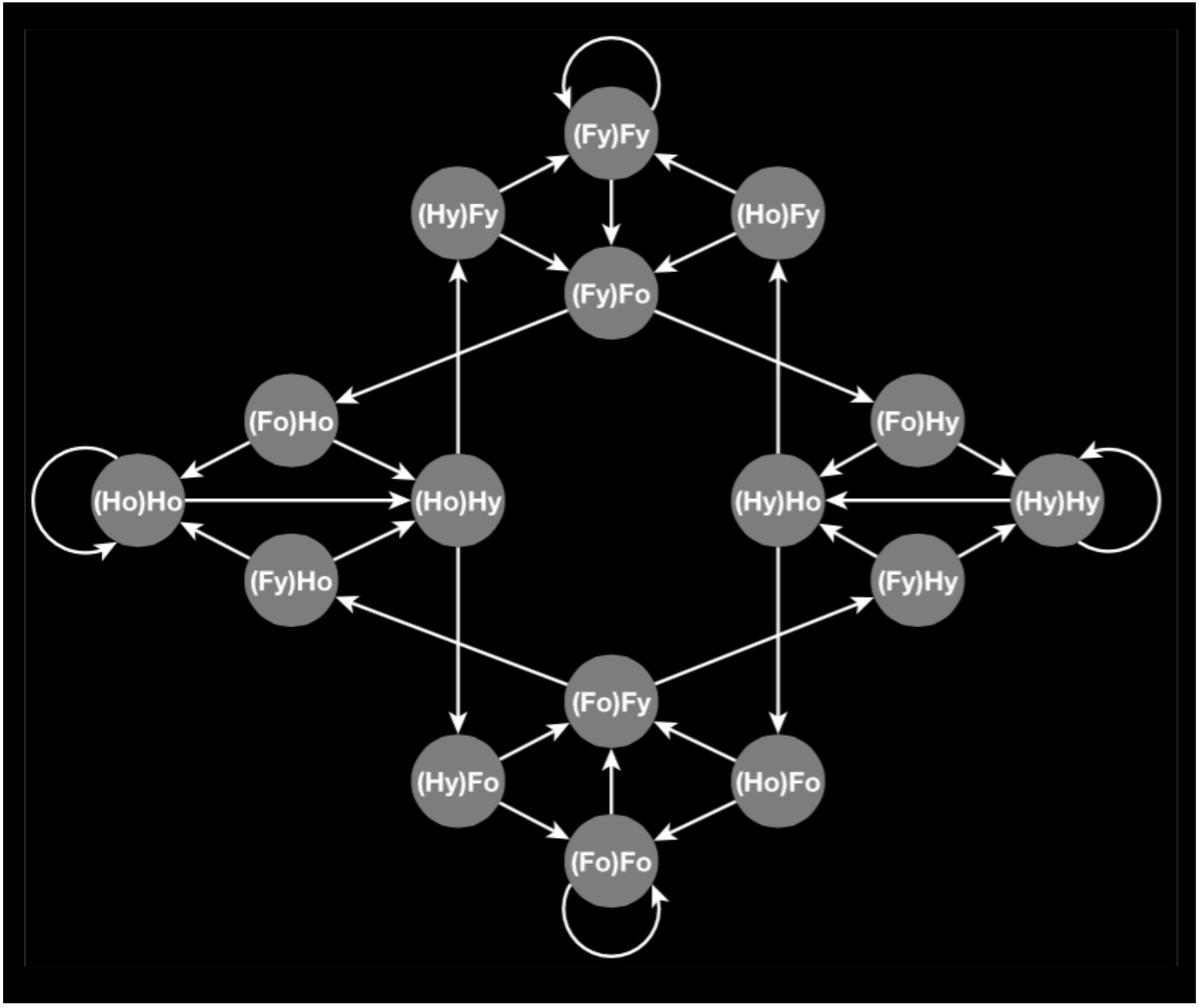
[Slide from Nicolas Schuck]

# Task

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



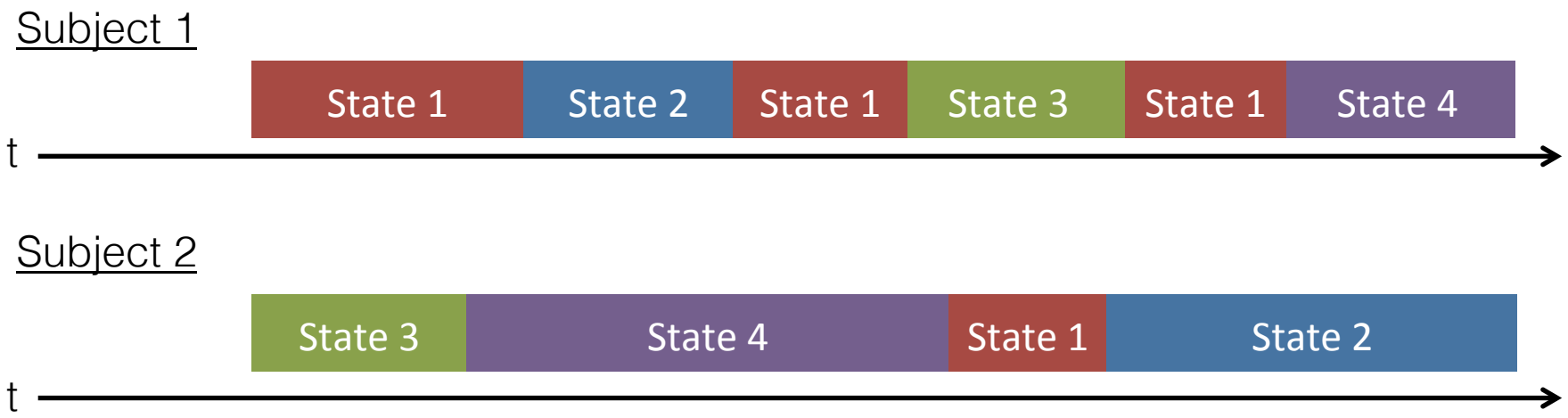

[Slide from Nicolas Schuck]




[Slide from Nicolas Schuck]

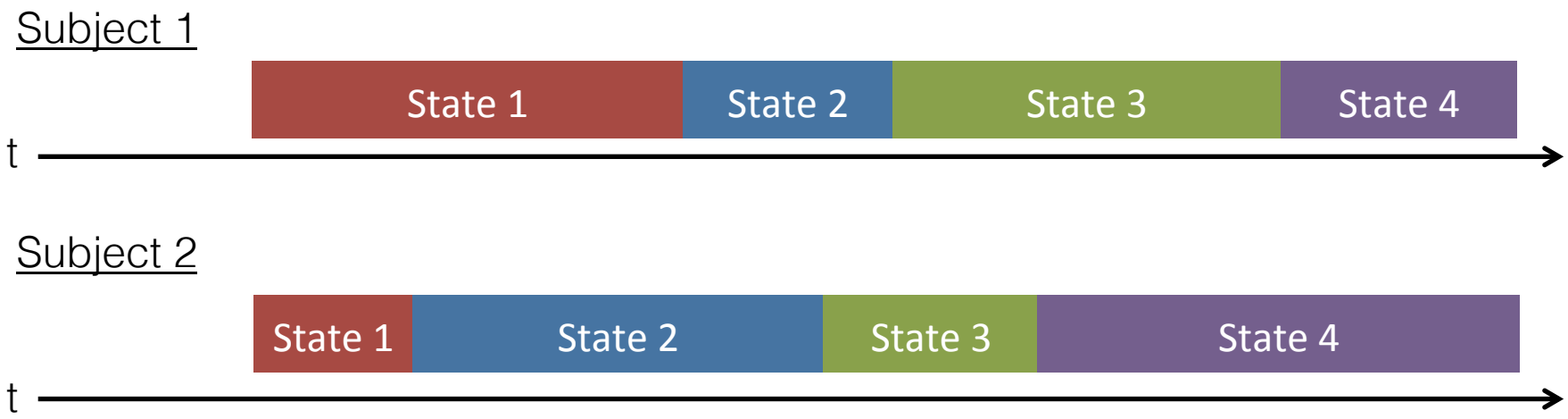
# SRM with non-temporally synchronized dataset

- Each observation is a noisy sample of the brain state



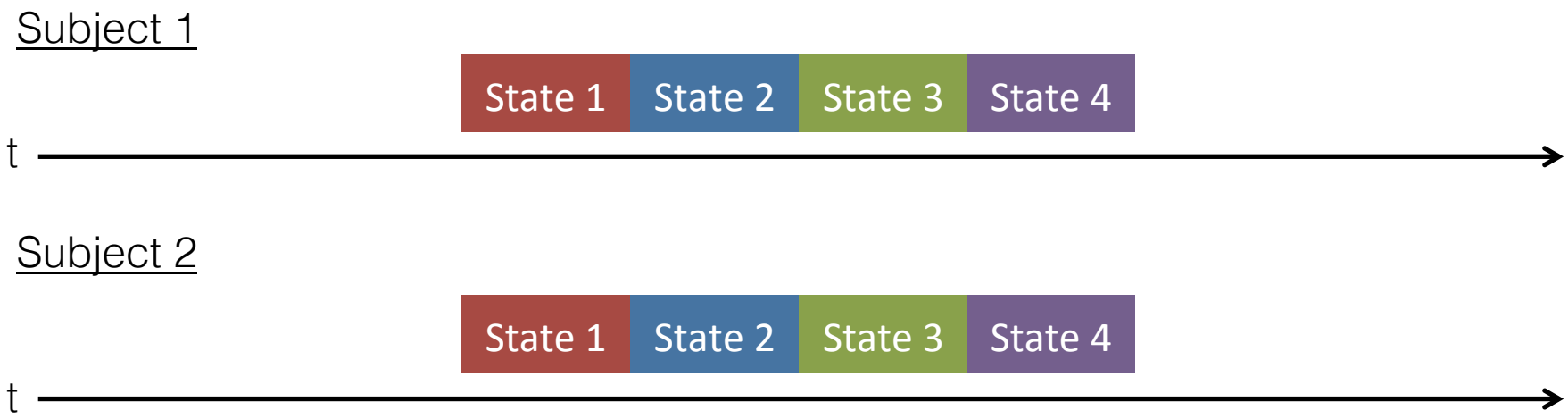
# SRM with non-temporally synchronized dataset

## Step 1: reordering

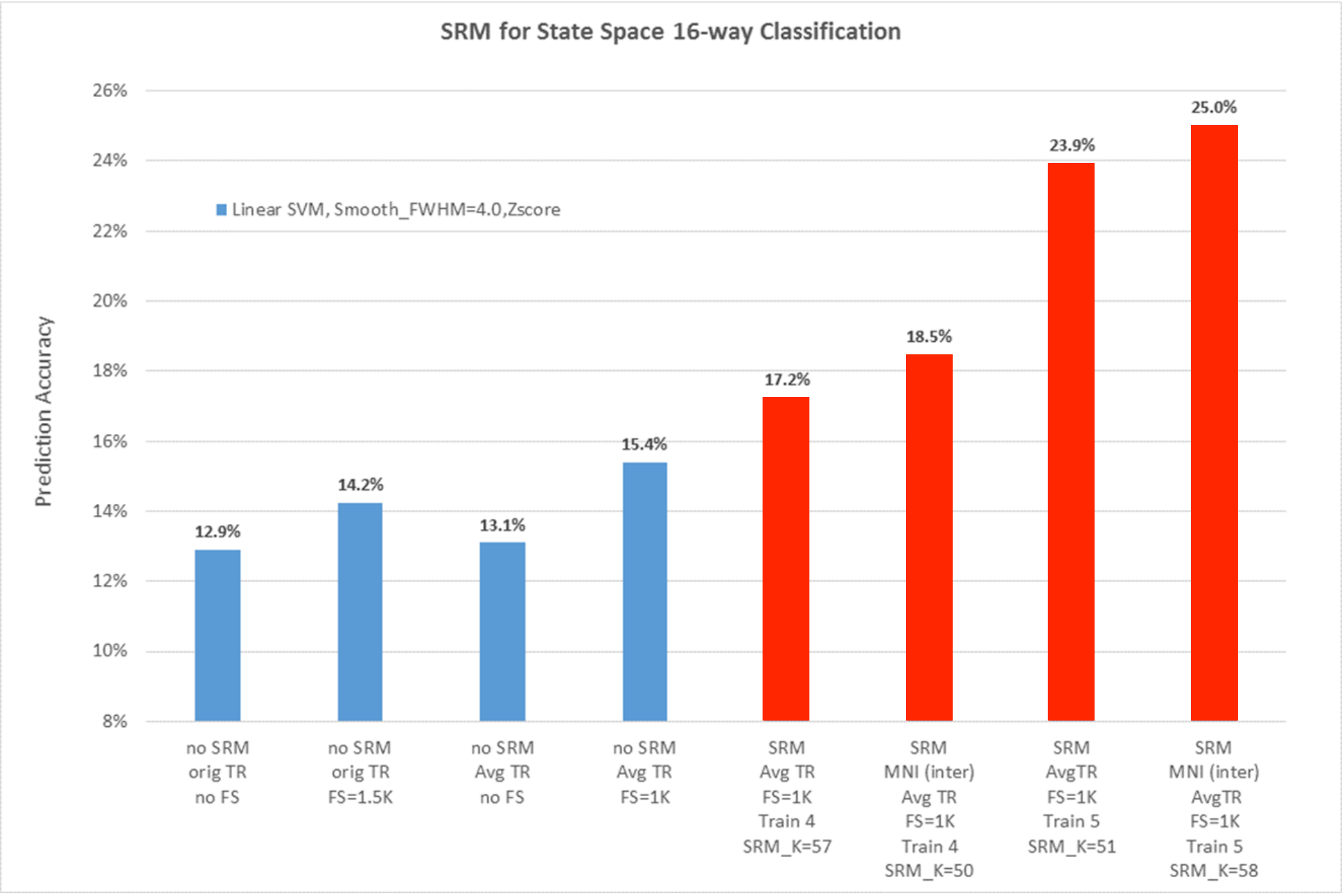


# SRM with non-temporally synchronized dataset

## Step 2: down sampling




## Step 3: fit SRM with preprocessed data

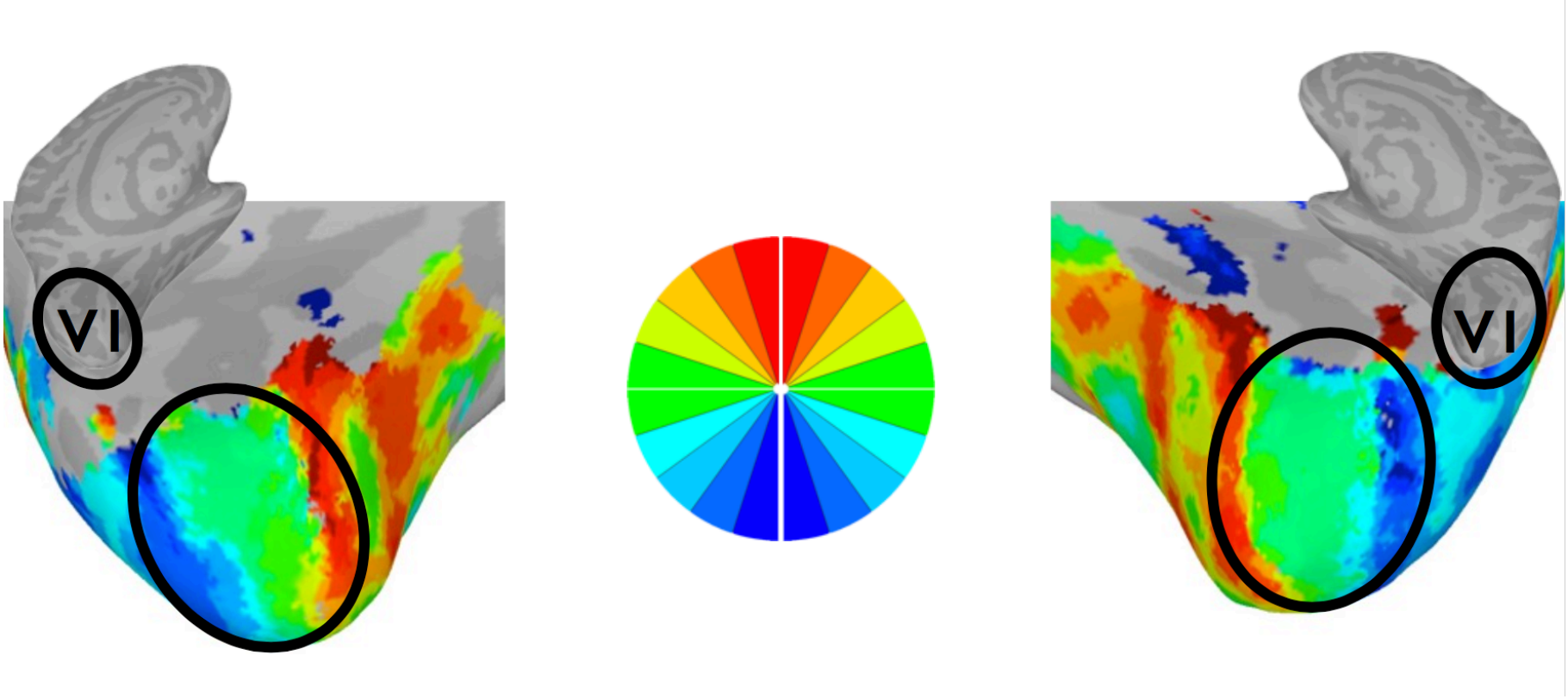



[Work by Ivy Zhu]

# SRM on fMRI

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

# Mapping Visual Field Maps: Retinotopy



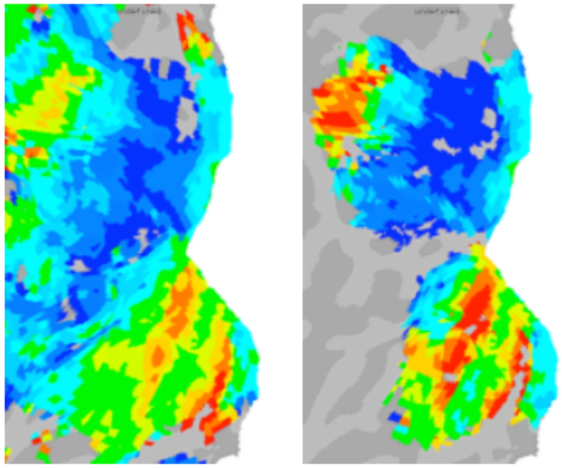

[Work by Michael J. Arcaro]

# Original Phase Maps vs. SRM

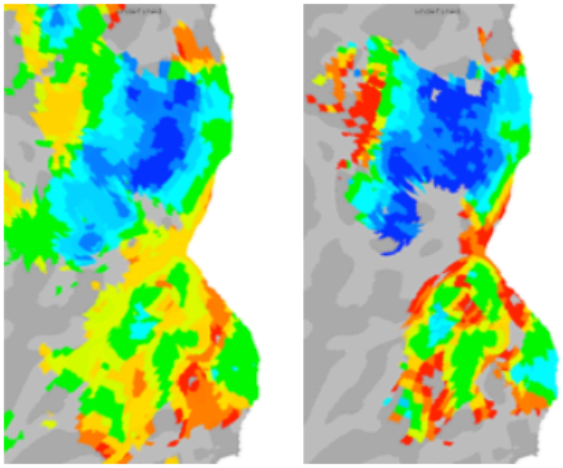
Sanity check: (W_i*transformed_data_i)

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

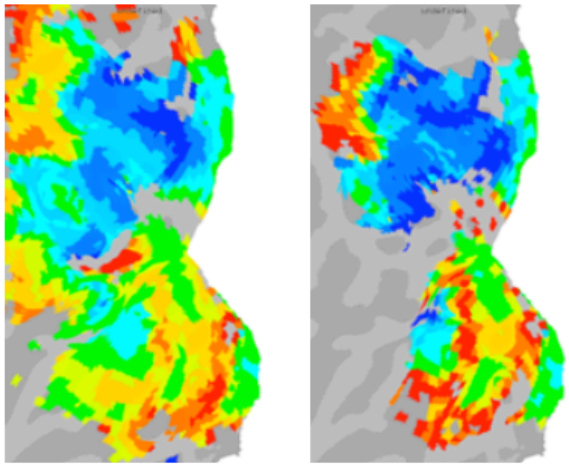
Orig SRM



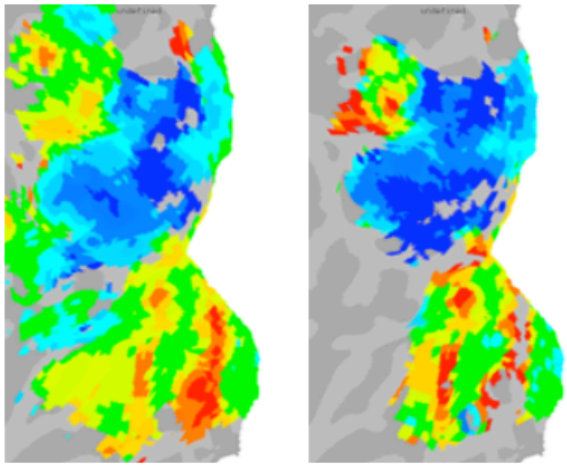
Orig SRM



Orig SRM

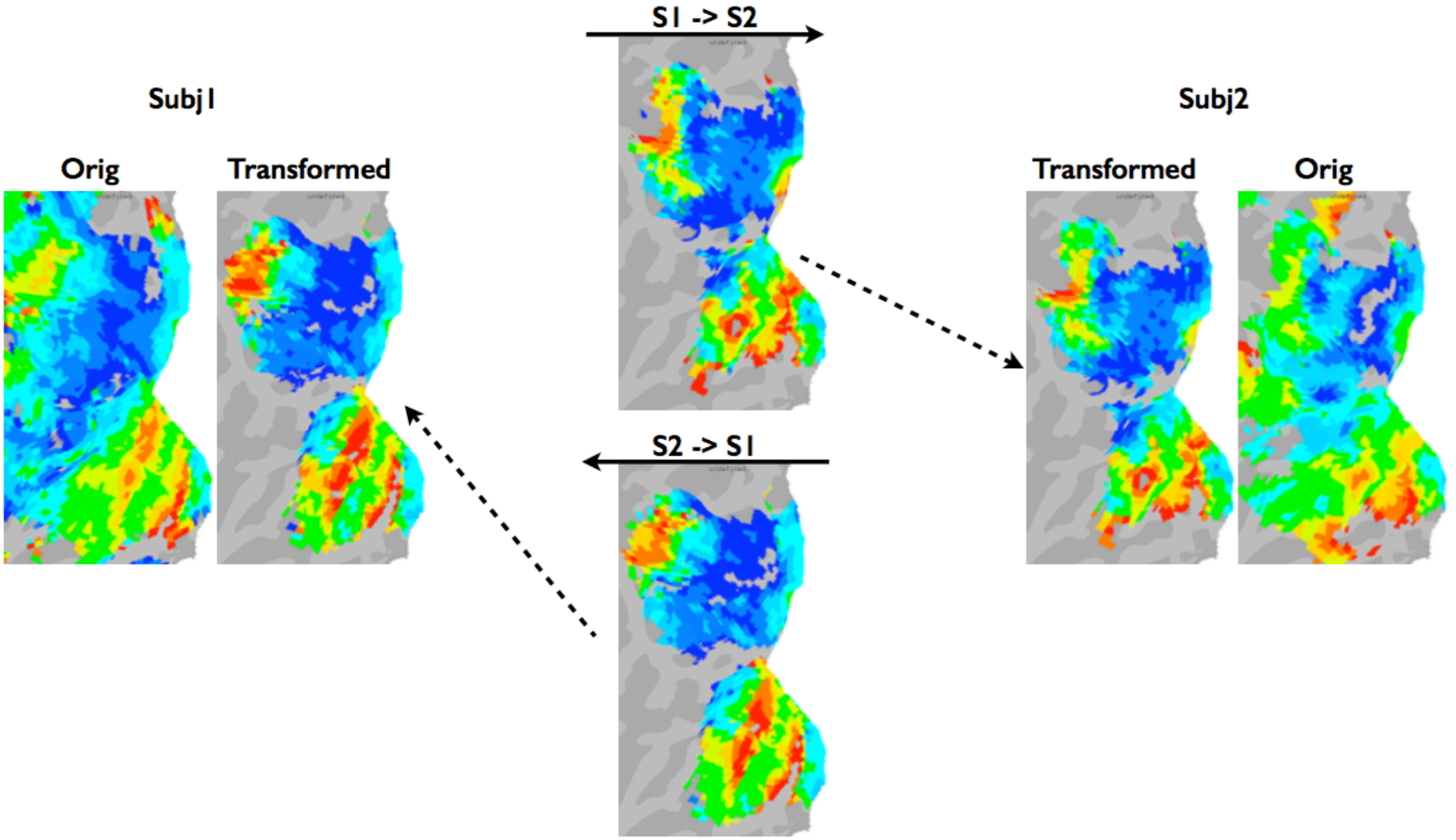


Orig SRM

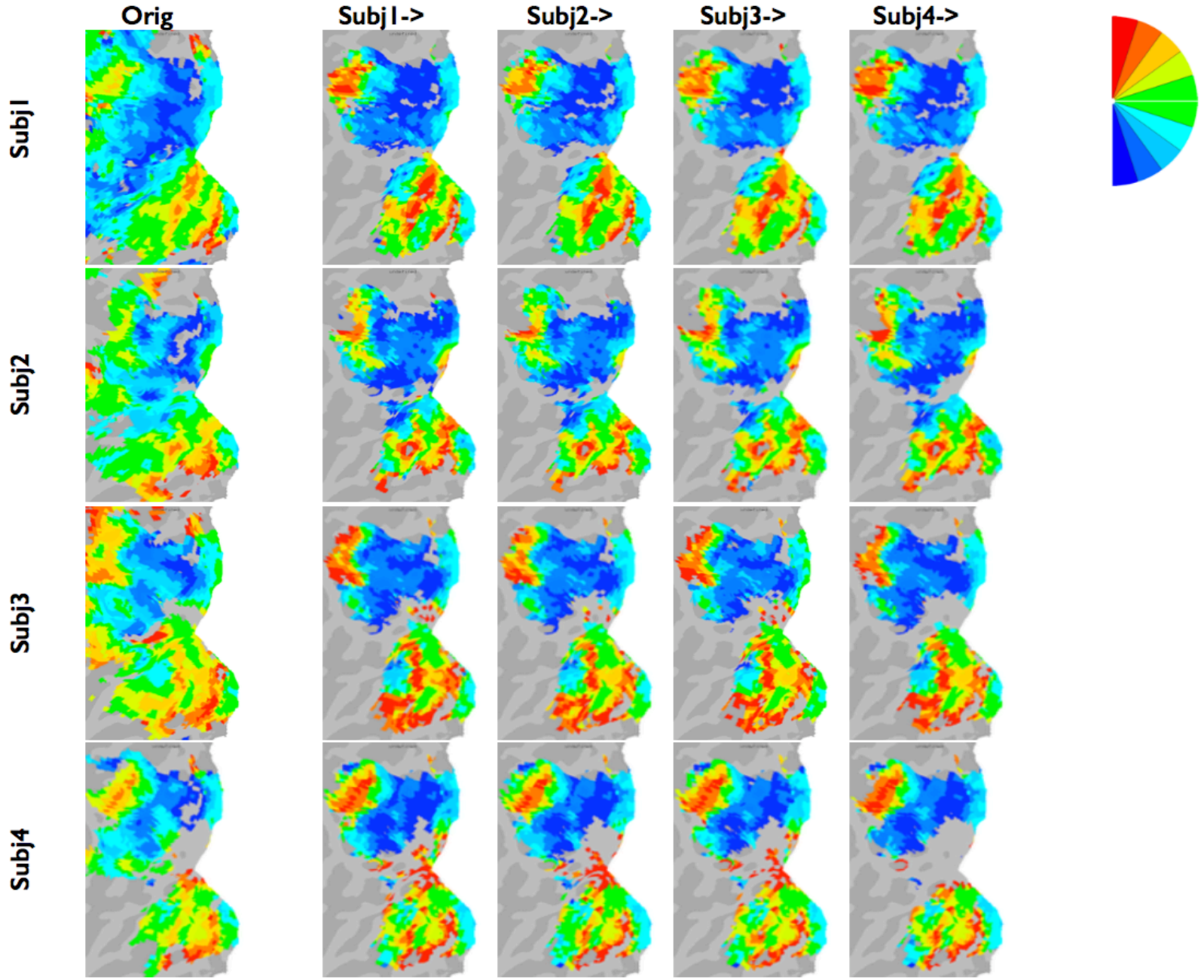


[Work by Michael J. Arcaro]

# Transformation between subjects




[Work by Michael J. Arcaro]

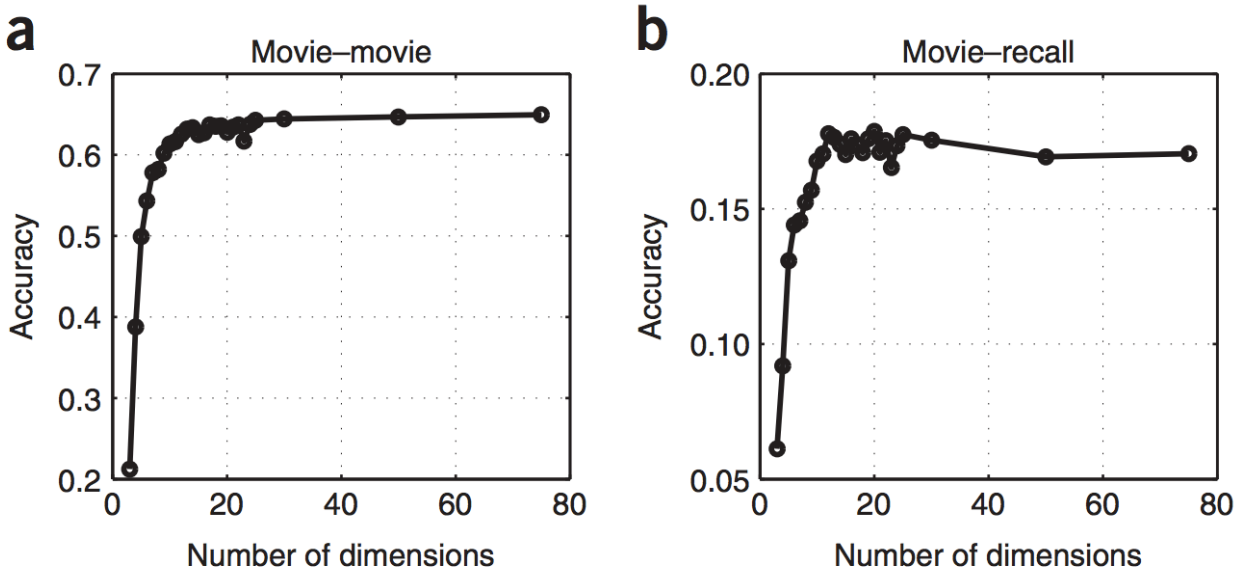



[Work by Michael J. Arcaro]

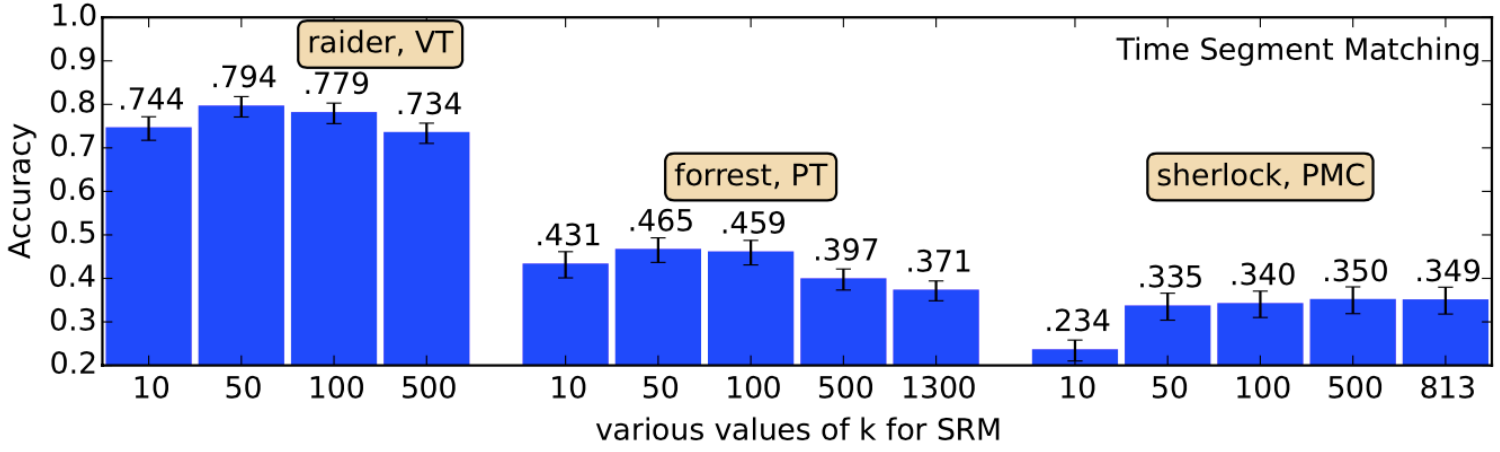
# SRM on fMRI

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

# Quantifying dimensionality of shared response

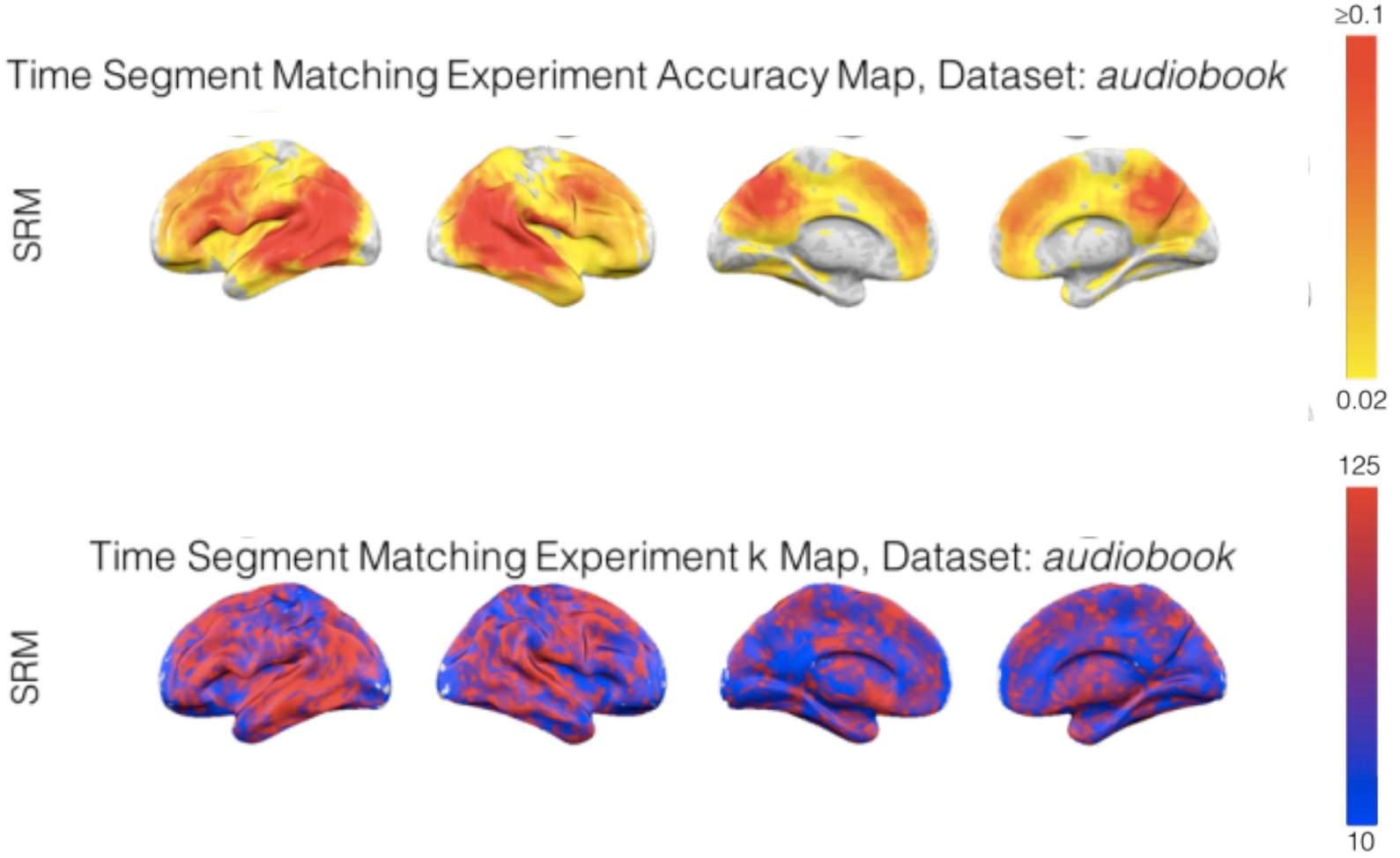



[J. Chen et al., Nat. Neur., 2017]




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

# Quantifying dimensionality of shared response



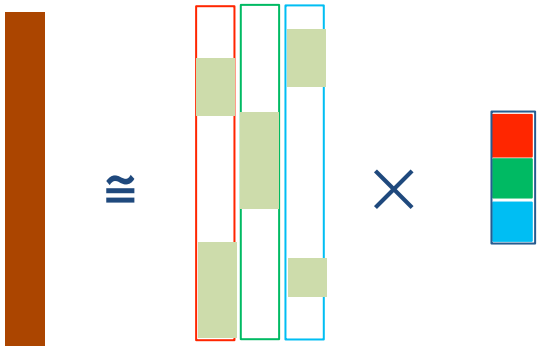

[H. Zhang et al. ArXiv, 2016]

# SRM on fMRI

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

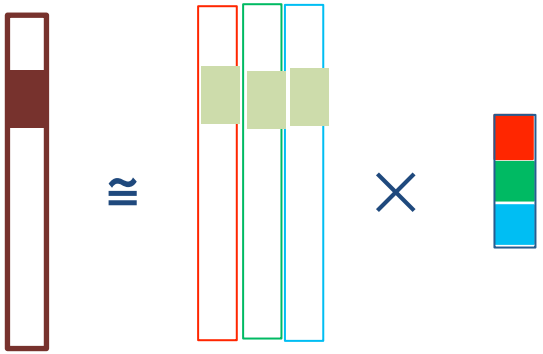
# Why searchlights?

Structured Sparsity



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

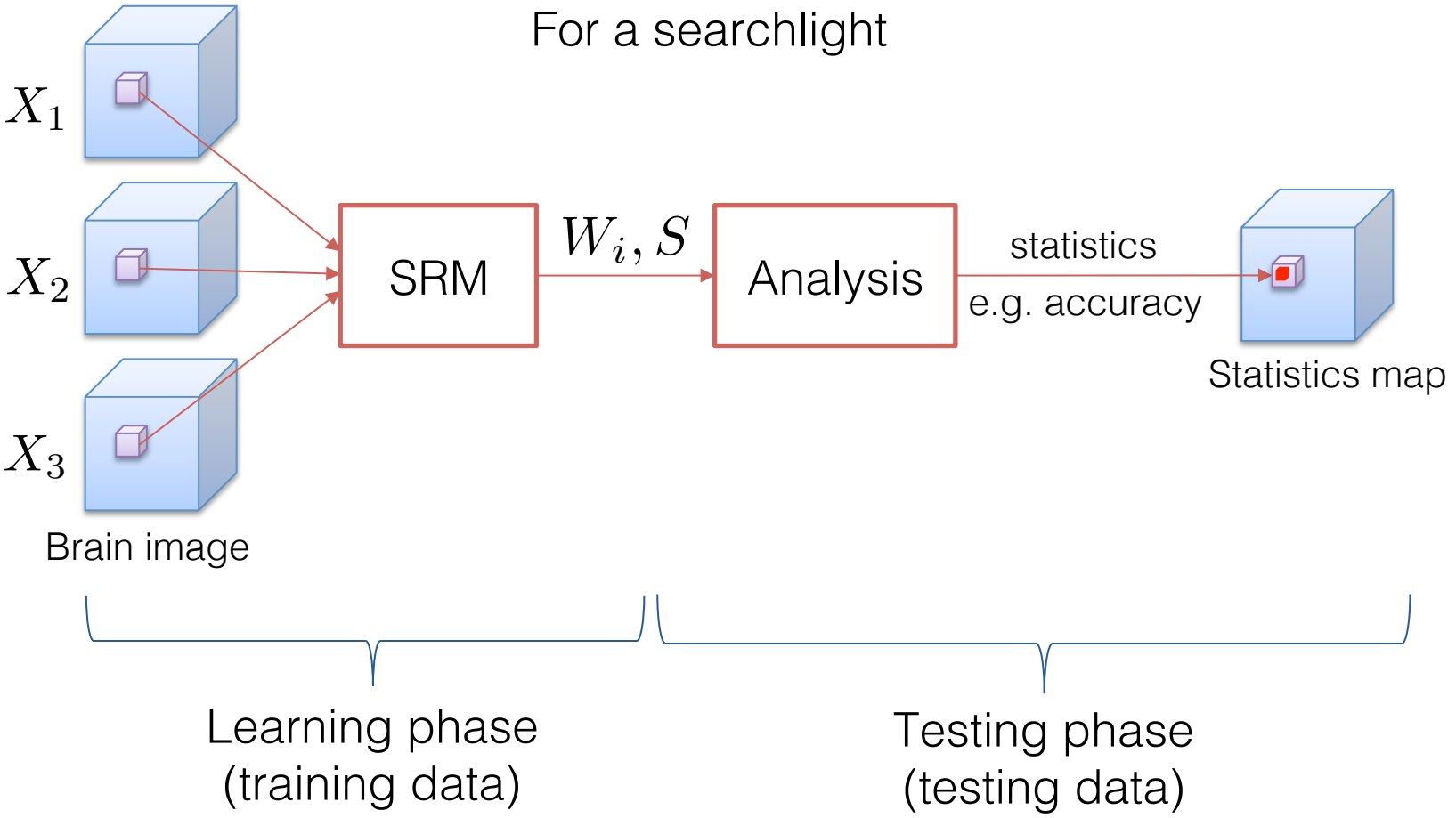
Searchlight



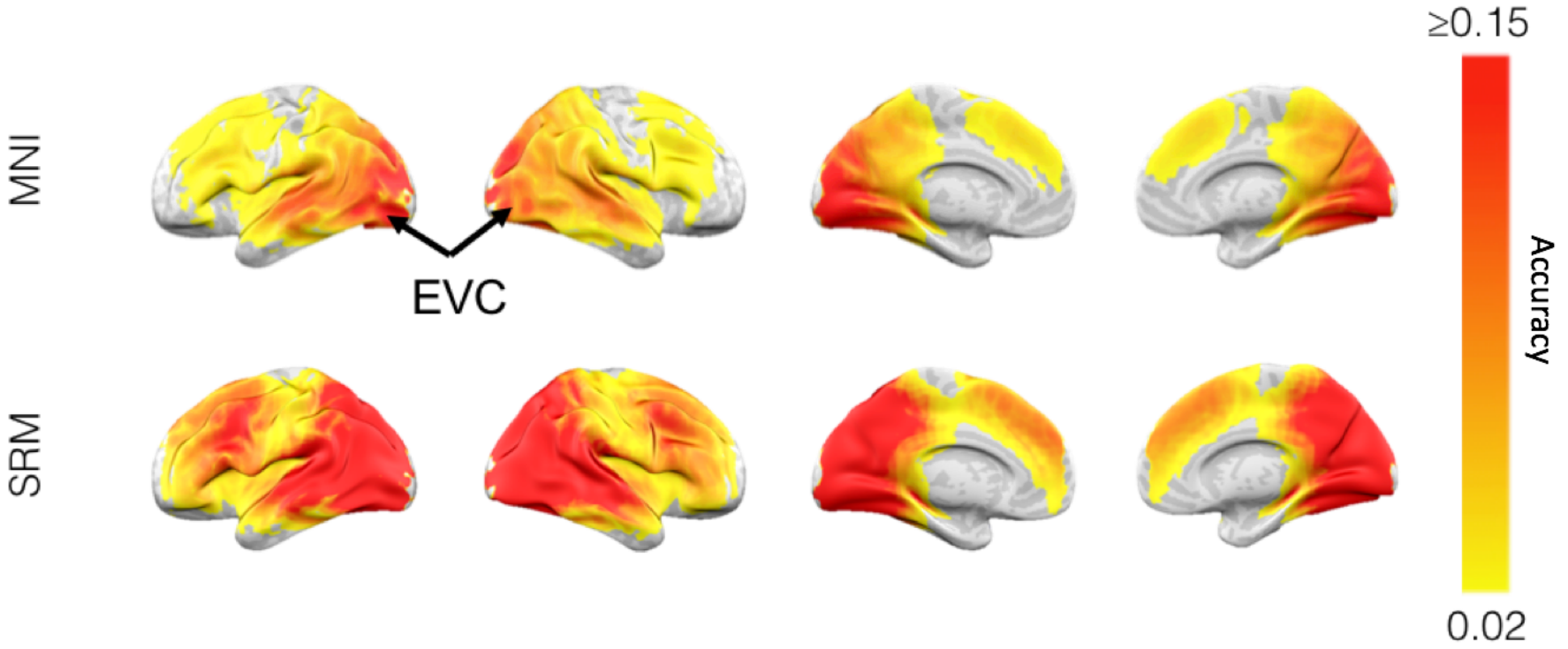
t-th column of $X_i$ $W_i$ t-th column of $S$

# 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