A Reduced-Dimension fMRI Shared Response Model


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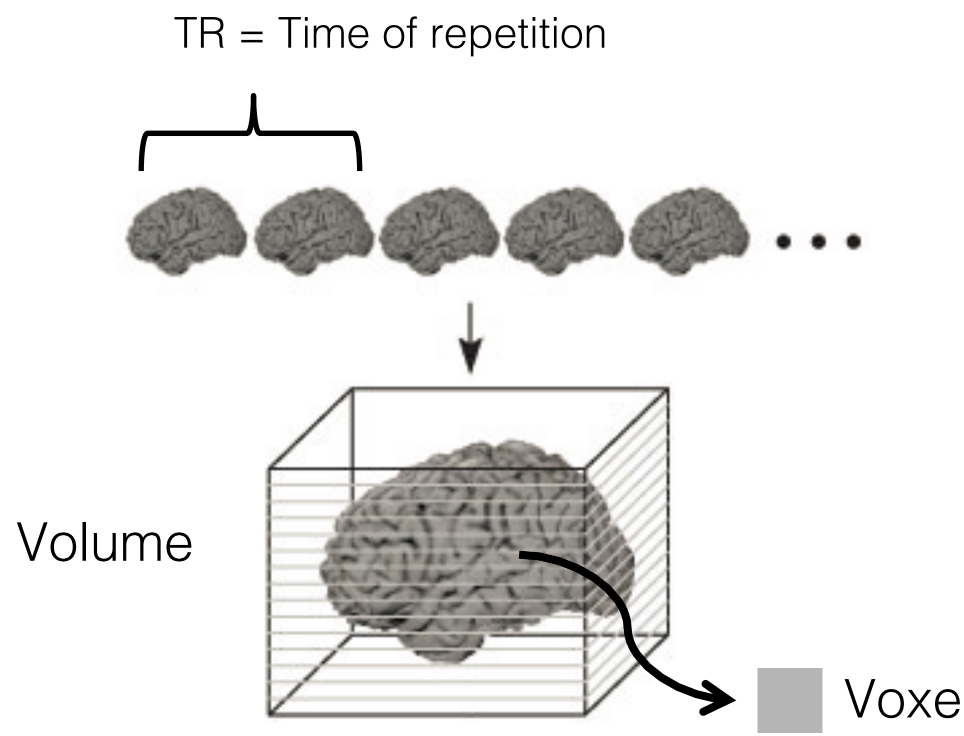
Functional magnetic resonance imaging (fMRI) data



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

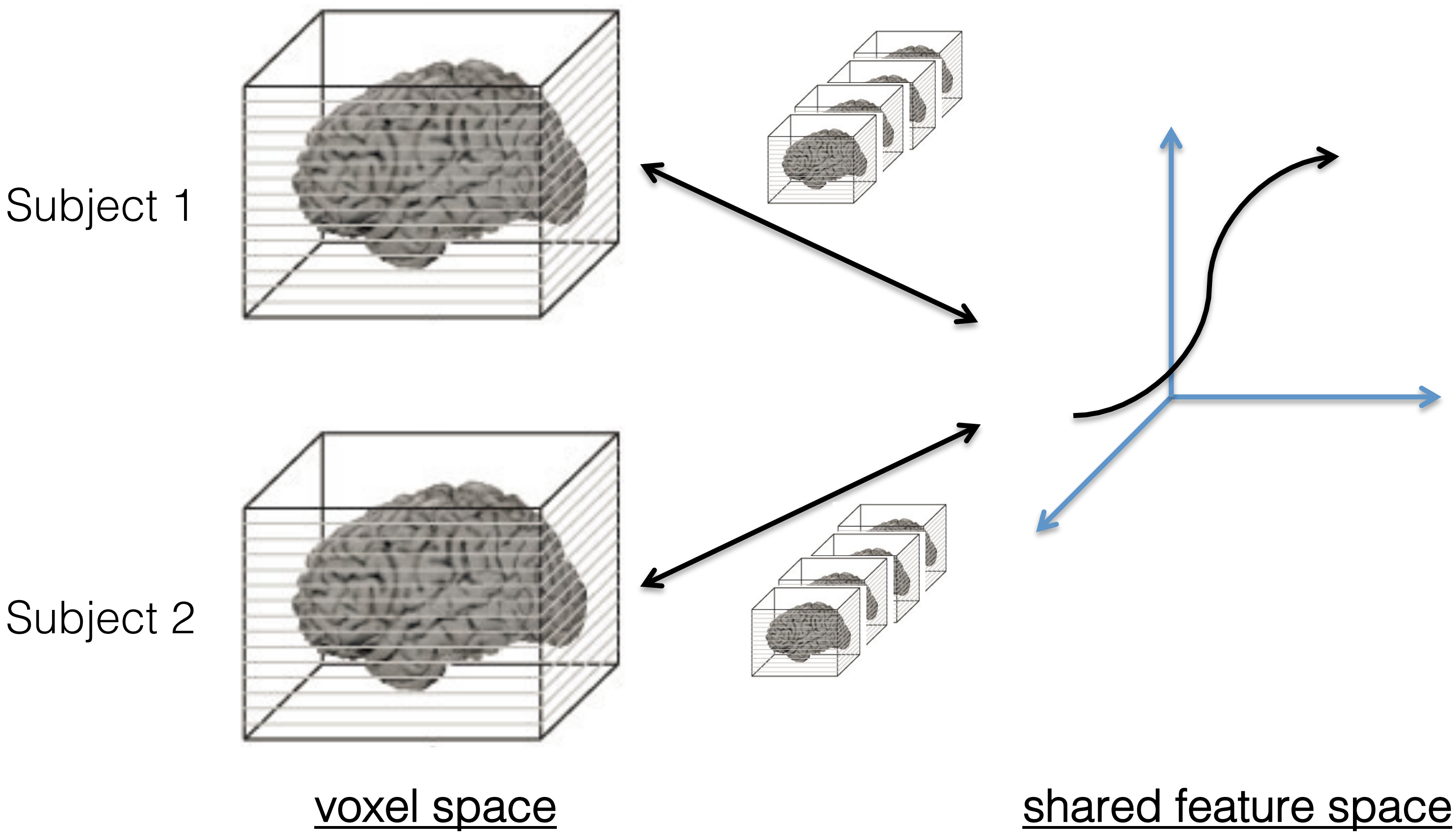
Inter-subject variability in anatomical structure and functional topographies

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?

Learn subject specific functional topographies

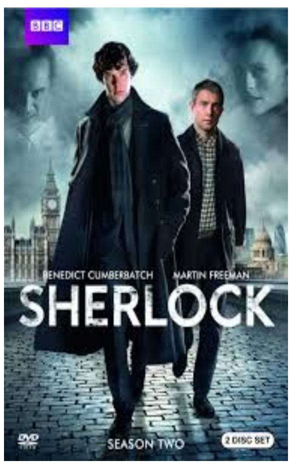


Data collected while subjects receiving stimuli

Temporally synchronized naturalistic stimuli

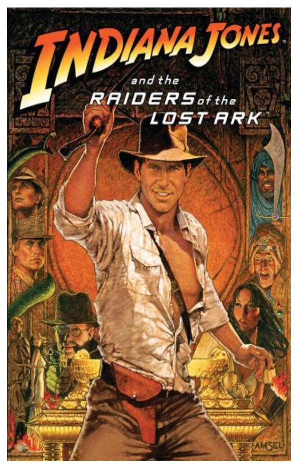
1. Sample a wide range of response from the subject
2. Use time as anchor for learning shared response

sherlock



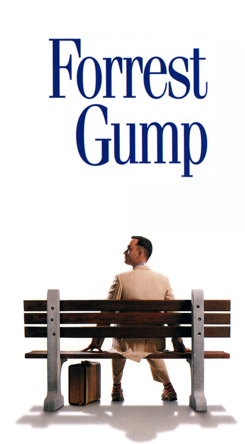
movie watching

raider



movie and image watching

forrest

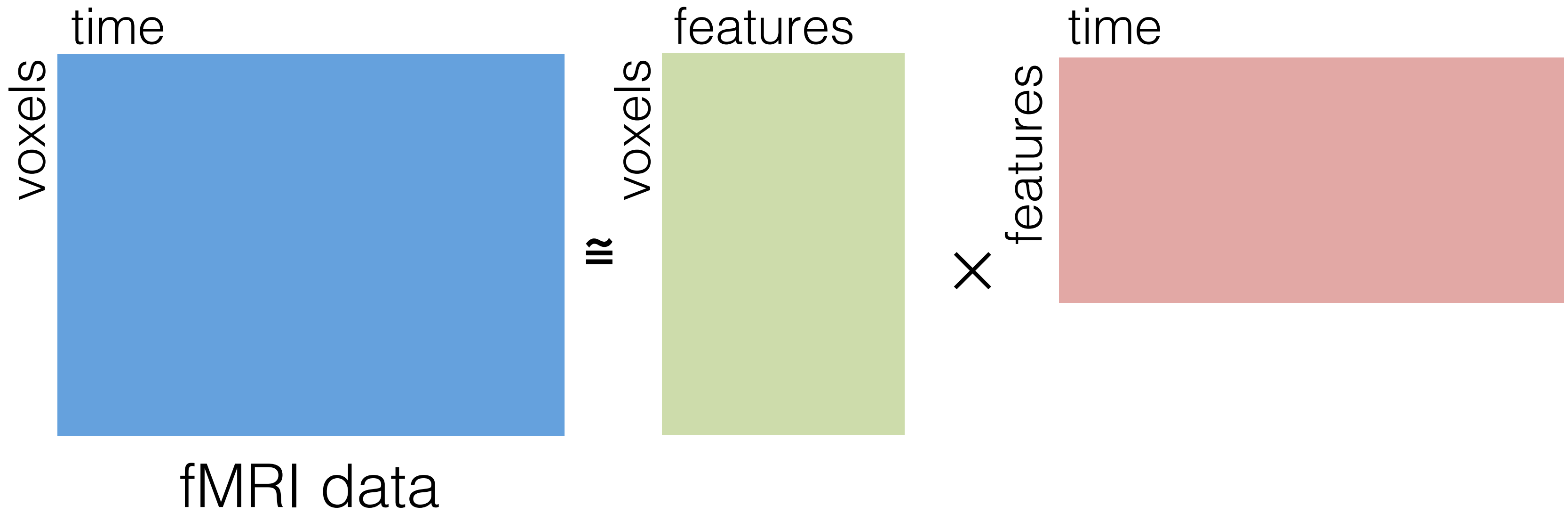


auditory film listening

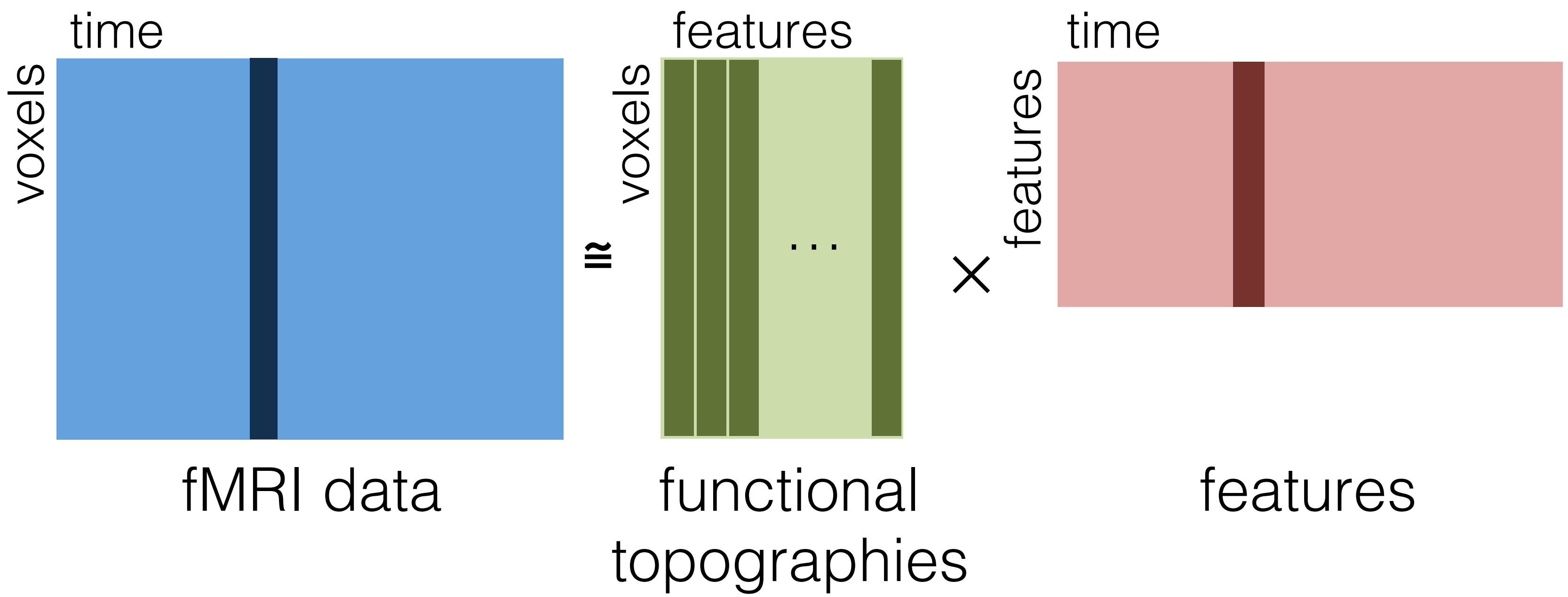
audiobook

audio book listening

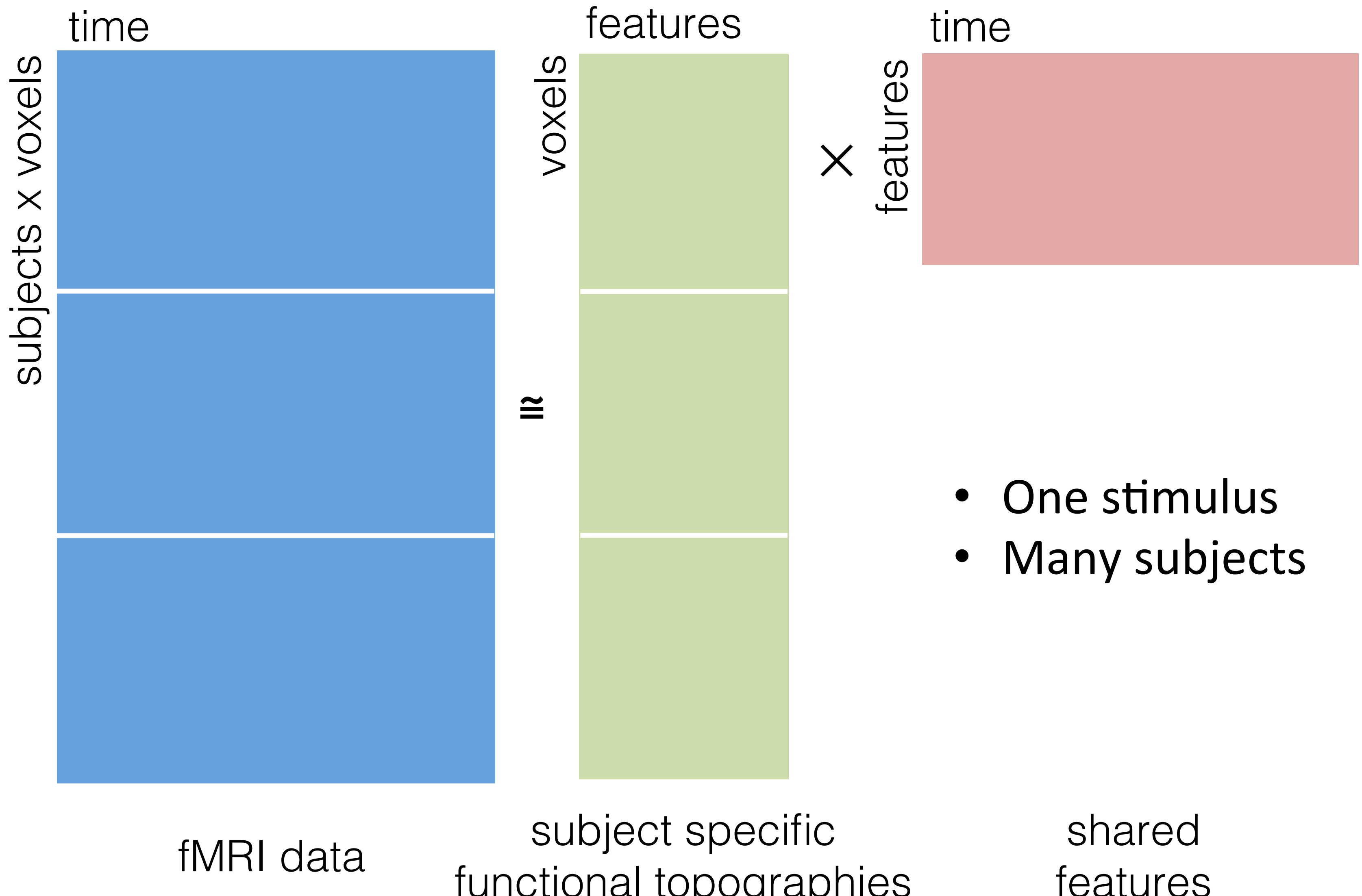
Factor Model



fMRI response as linear combination of functional topographies

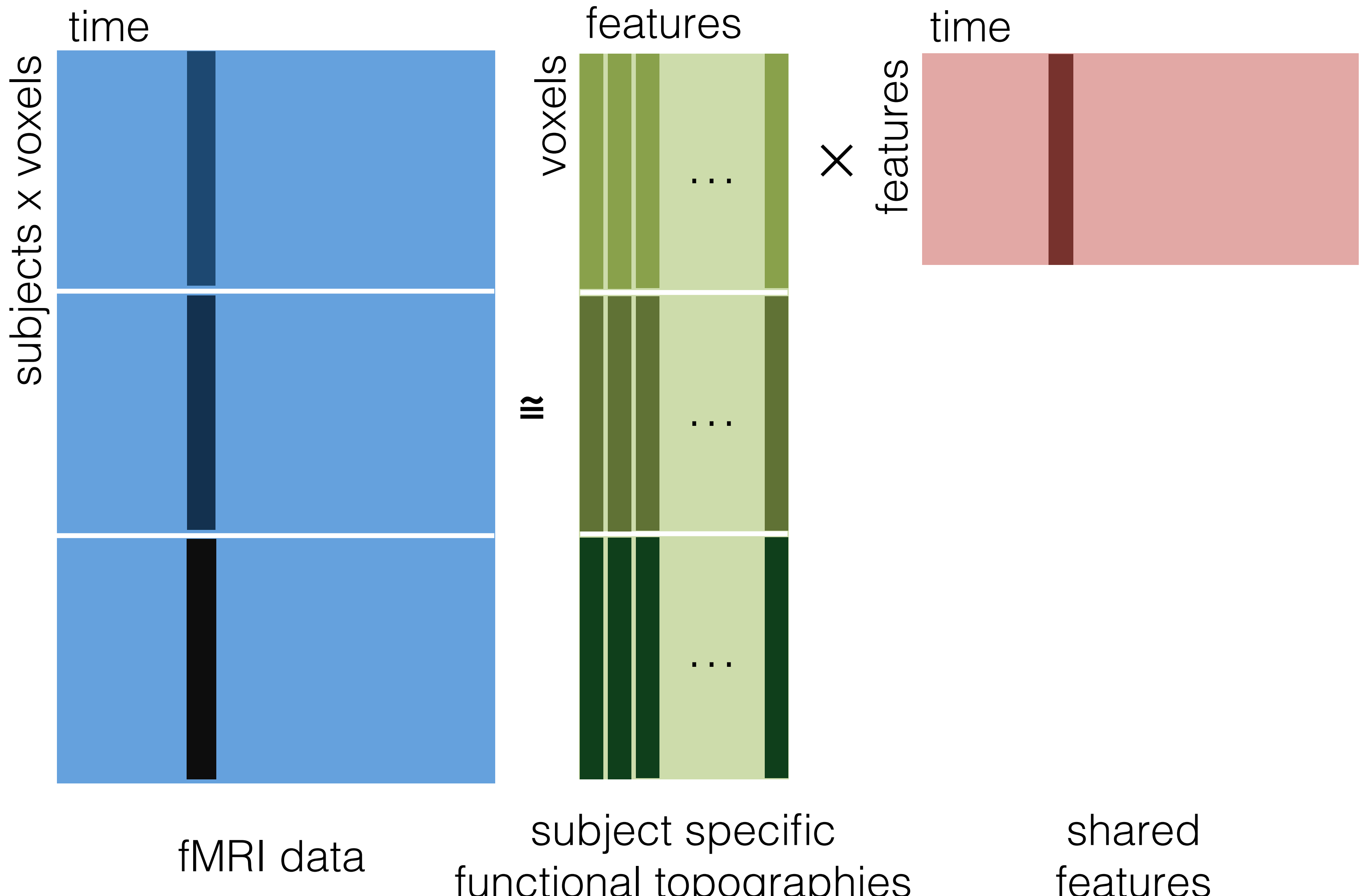


Learning what is shared across subjects

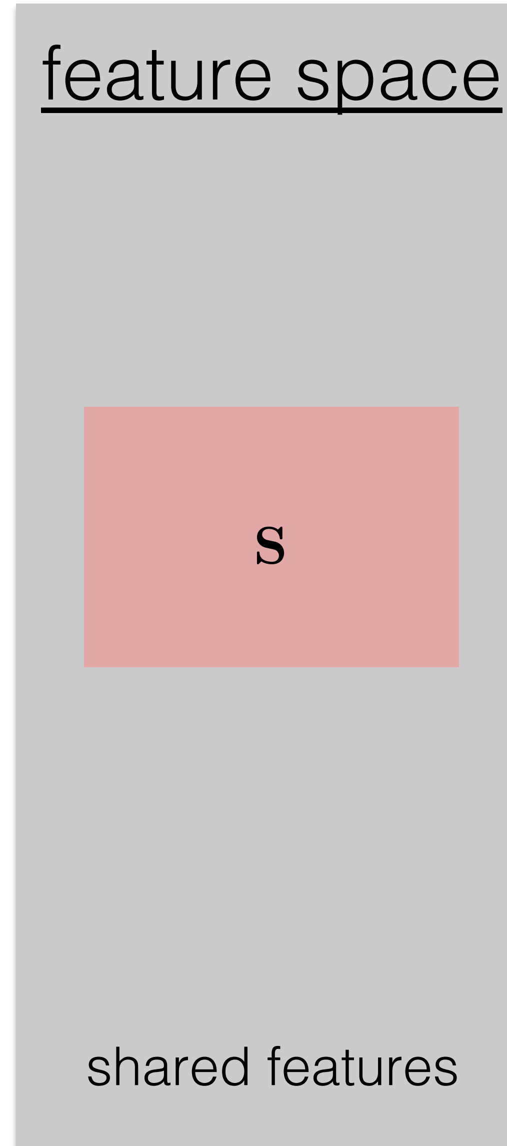


- One stimulus
- Many subjects

fMRI data as linear combination of subject specific functional topographies



A generative model



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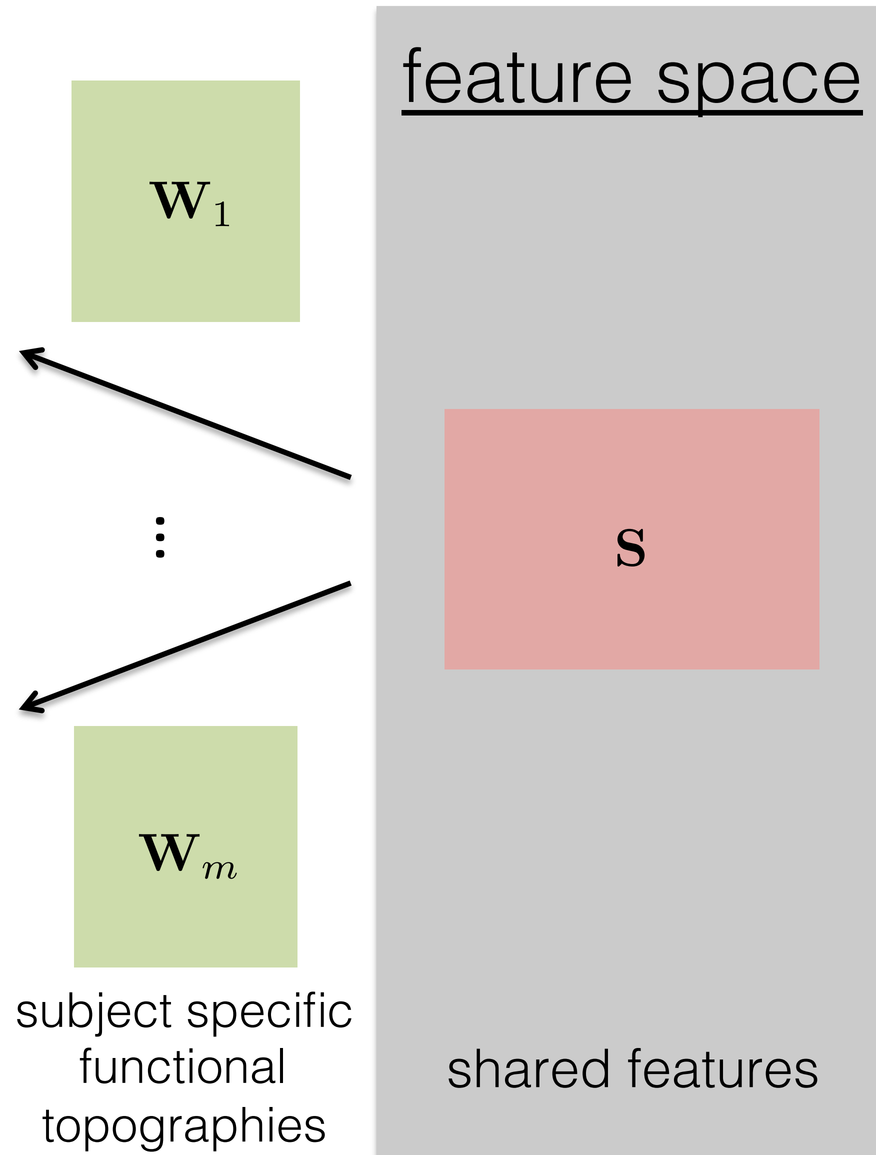

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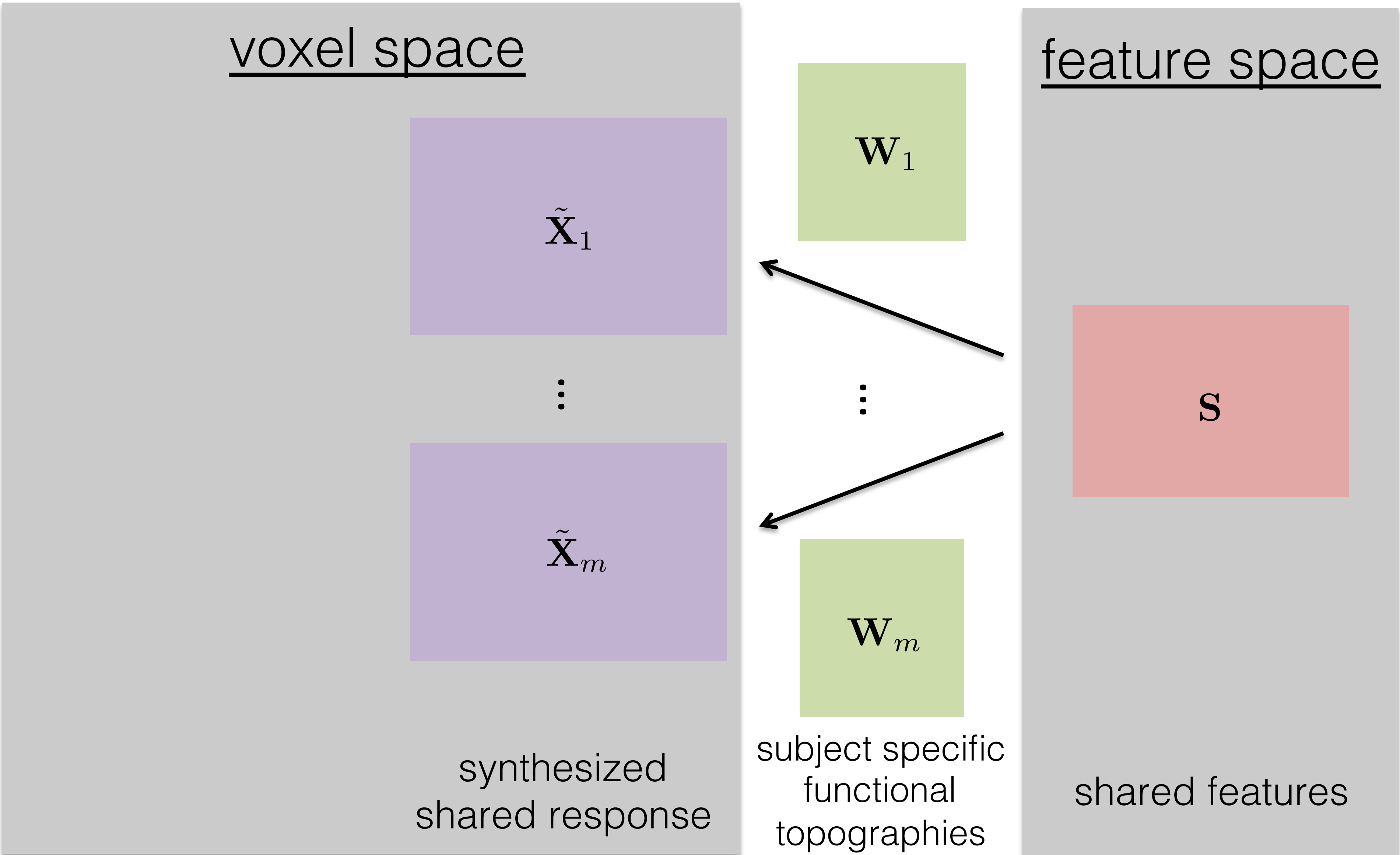
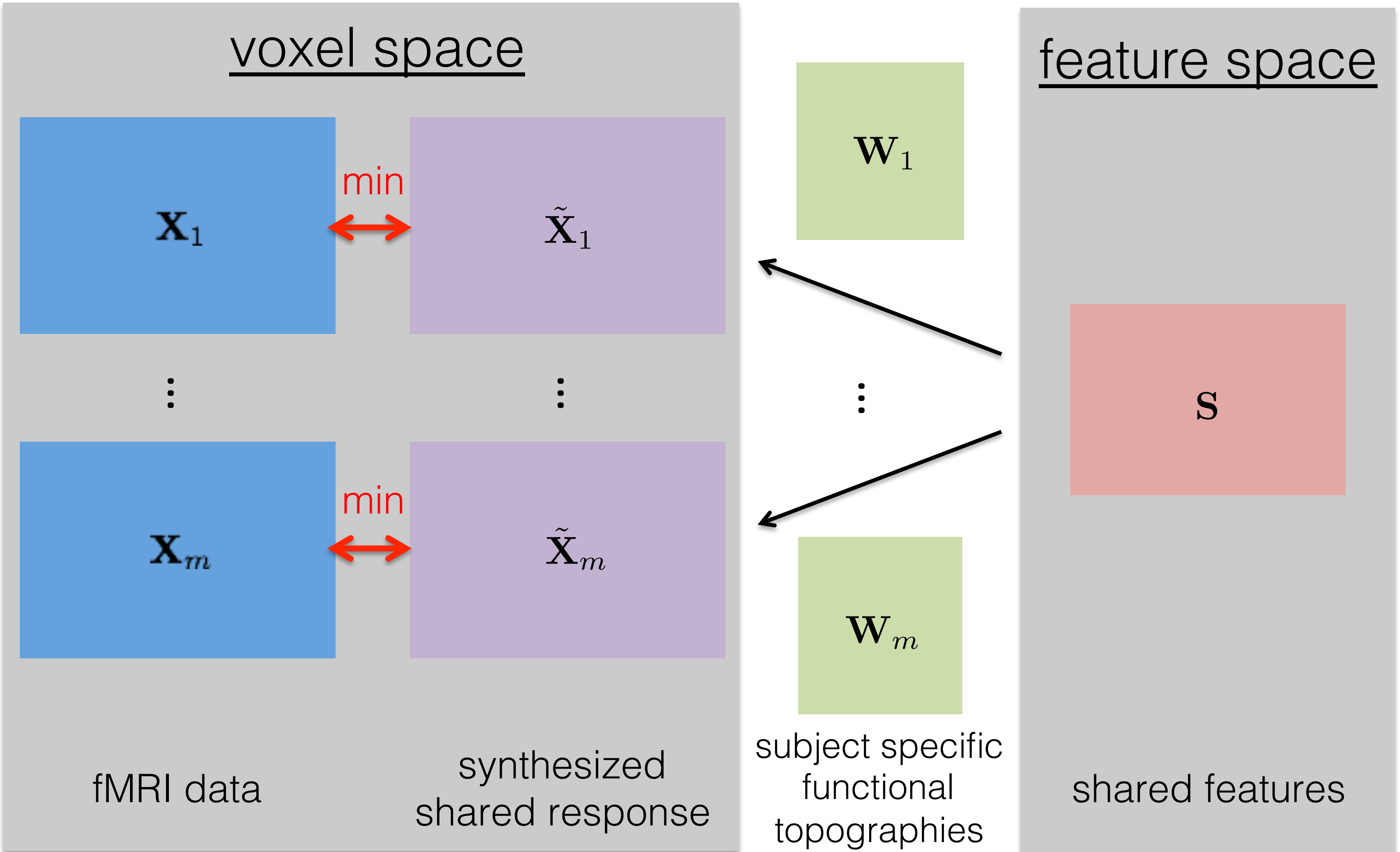


A generative model



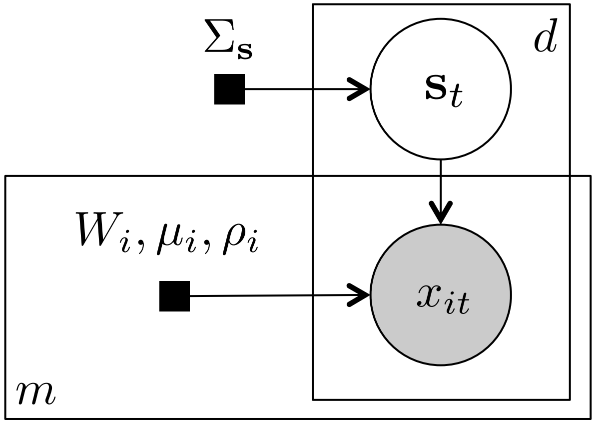
Shared Response Model (SRM) is a latent variable model

$$s_t \sim \mathcal{N}(0, \Sigma_s)$$

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

$$W_i^T W_i = I$$

W_i not square



s_t shared elicited response at time t

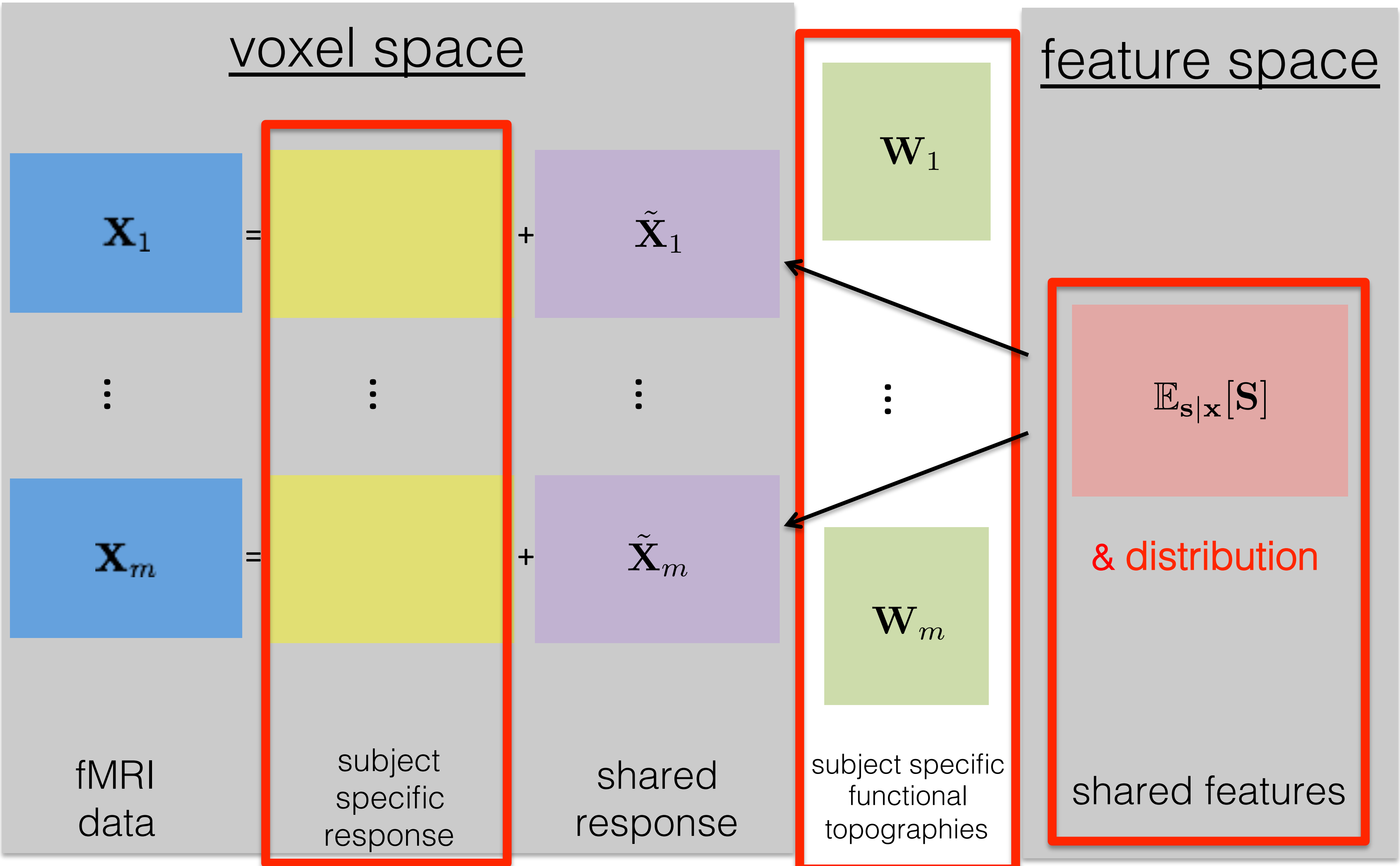
W_i functional topographies for subject i

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

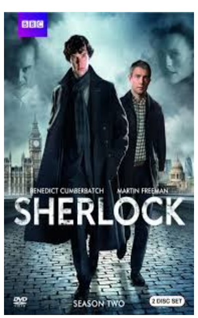
Shared features, subject specific functional topographies, and subject specific response



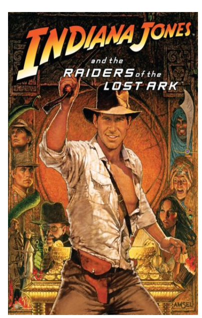
Evaluation with various datasets

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

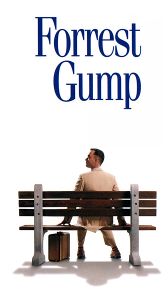
sherlock



raider

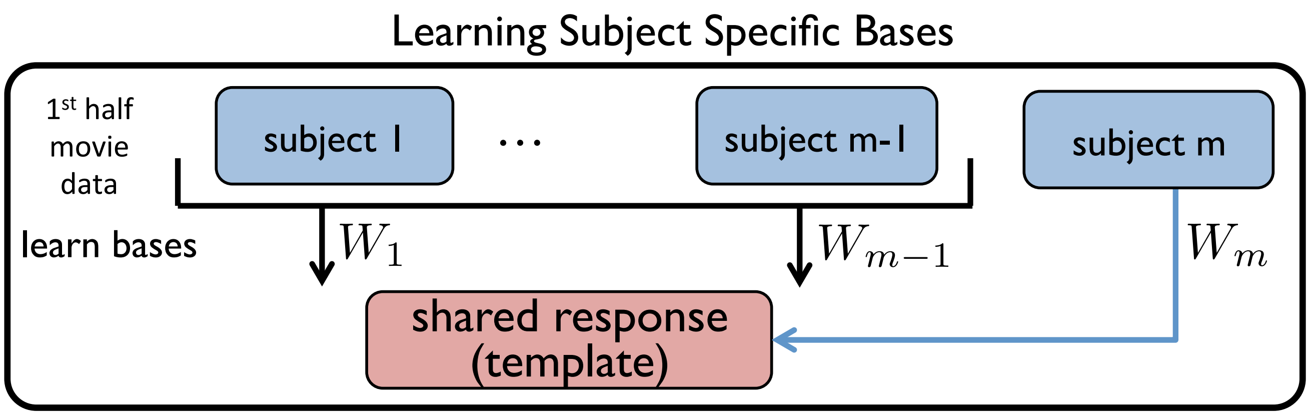


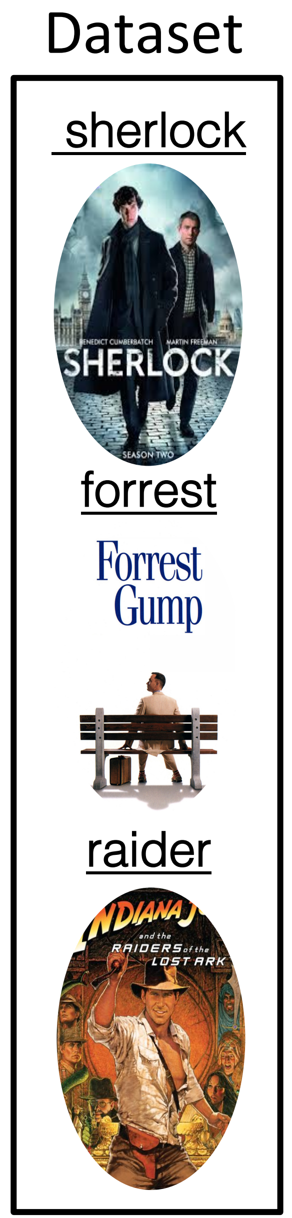
forrest



audiobook

Generalization to new subject with time segment matching





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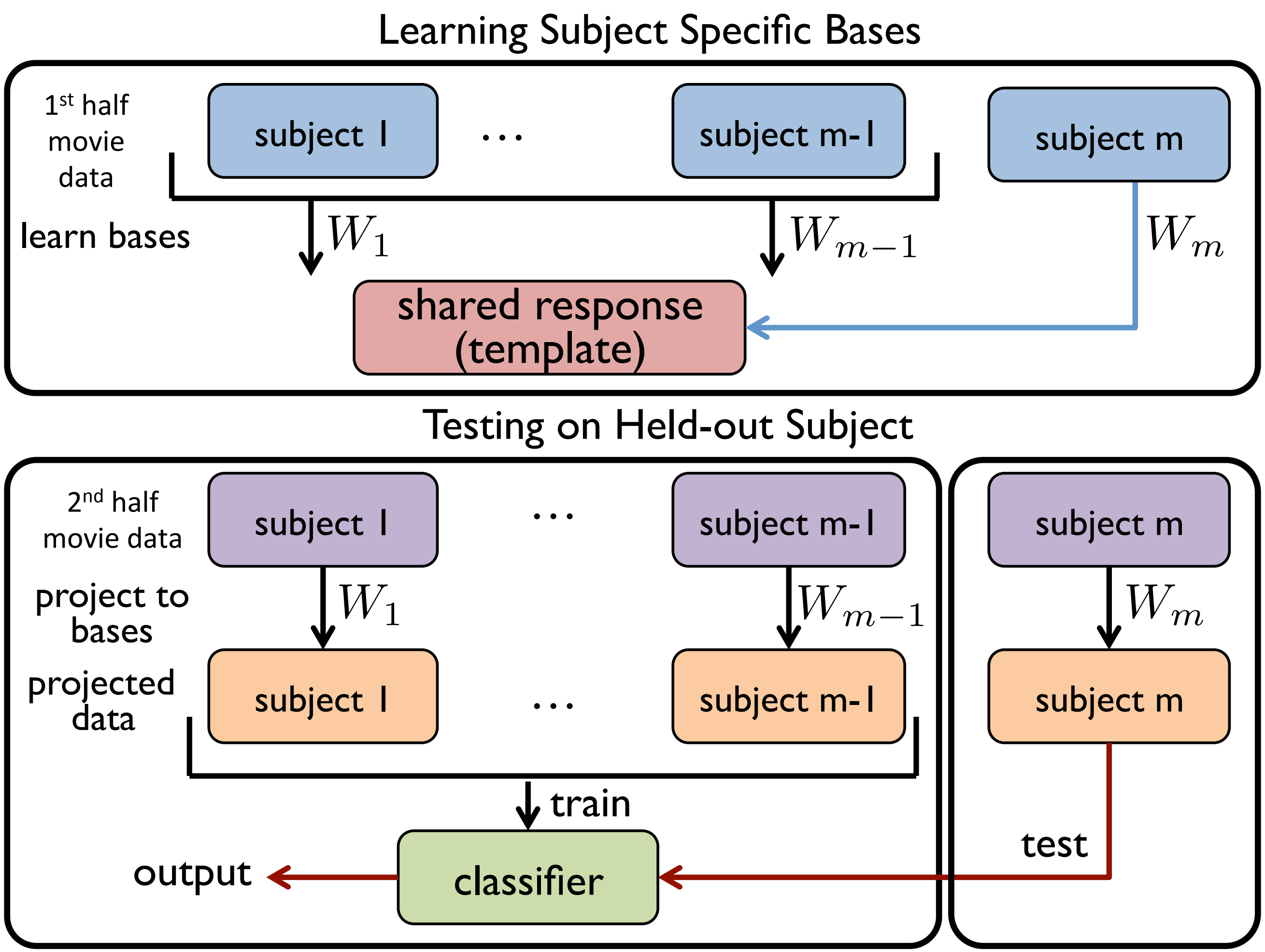
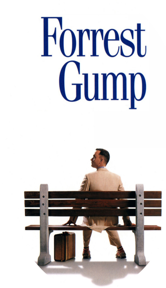


Dataset

sherlock

forrest



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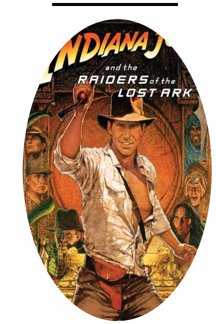

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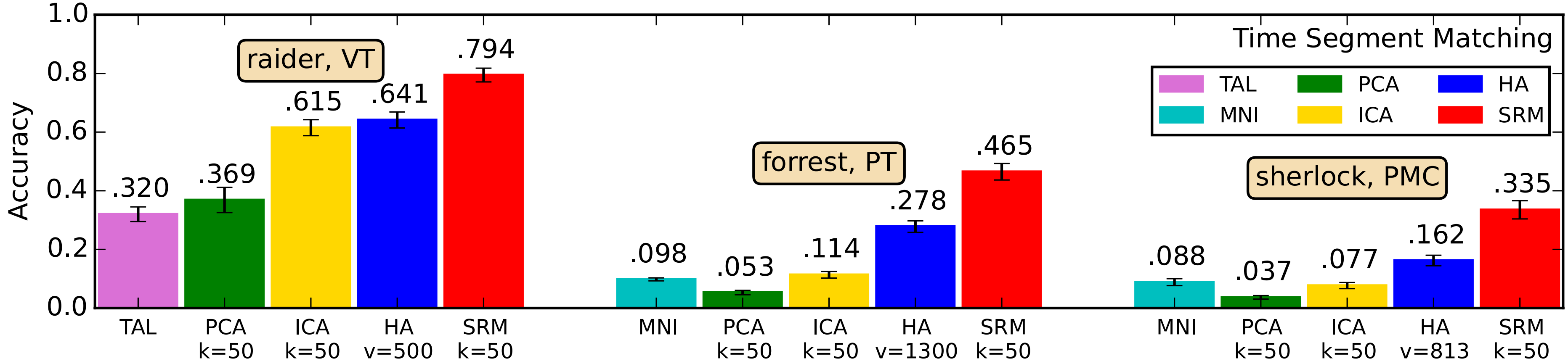
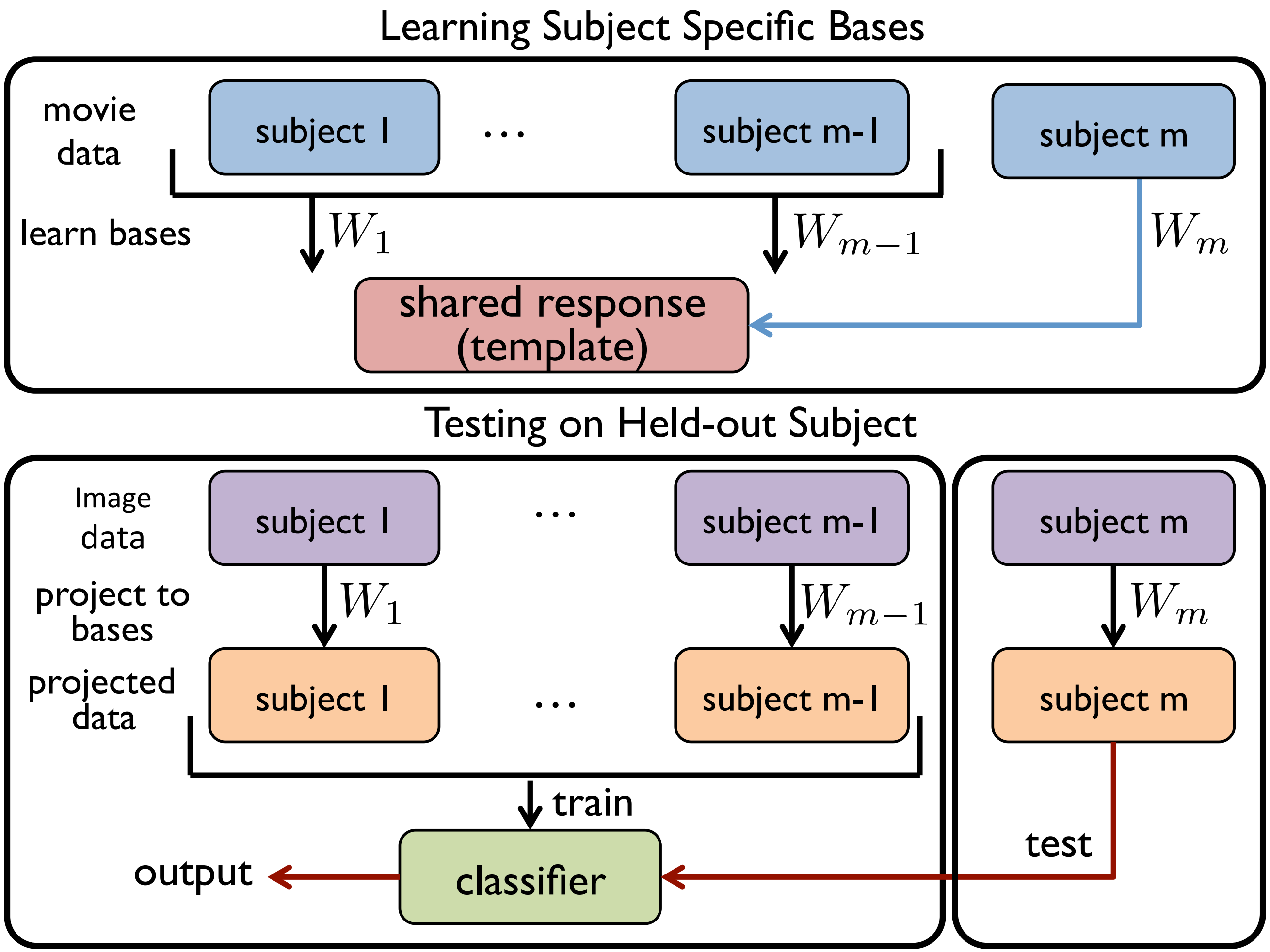
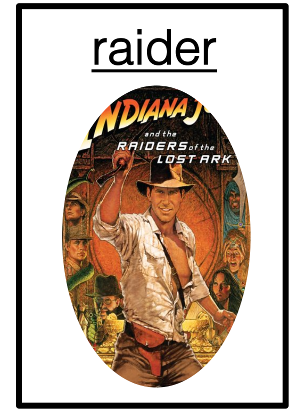


Generalization to new subject and distinct stimulus with image classification



Dataset



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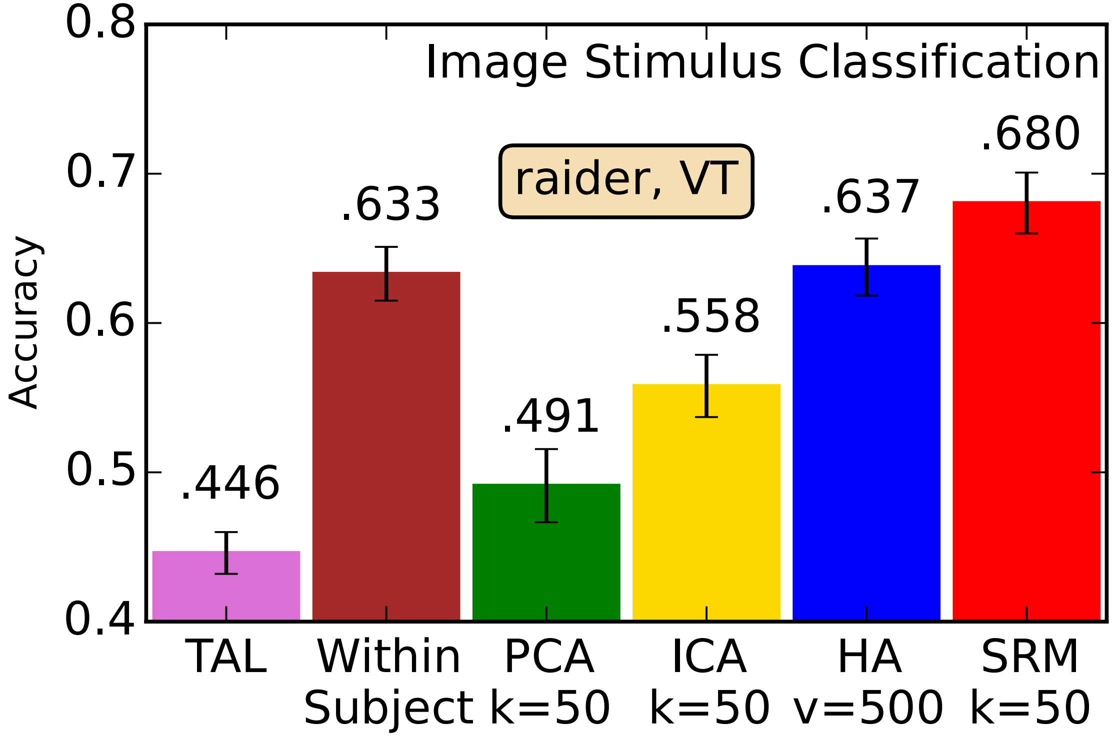


- Outperforms within-subject classification

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

<u>Group 1</u>

shared by all | within group | individual

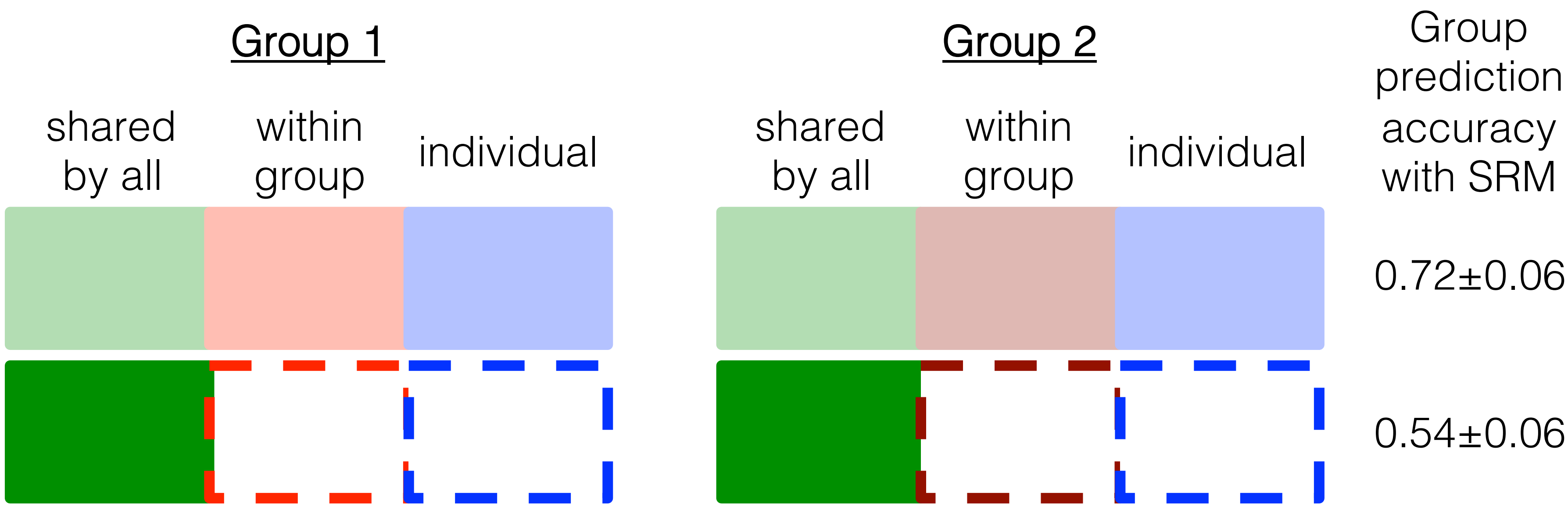
<u>Group 2</u>

shared by all | within group | individual

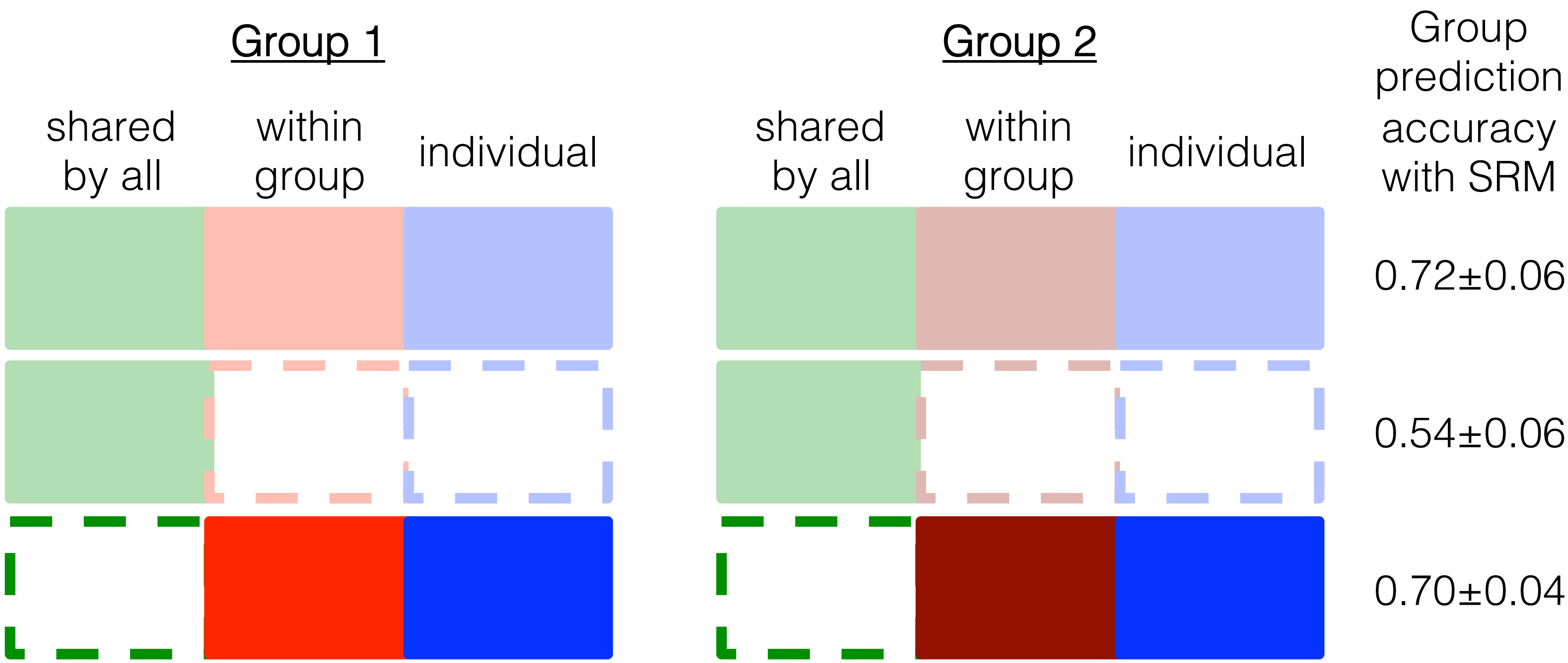
Group prediction accuracy with SRM

0.72±0.06

Classifying mental states



Classifying mental states



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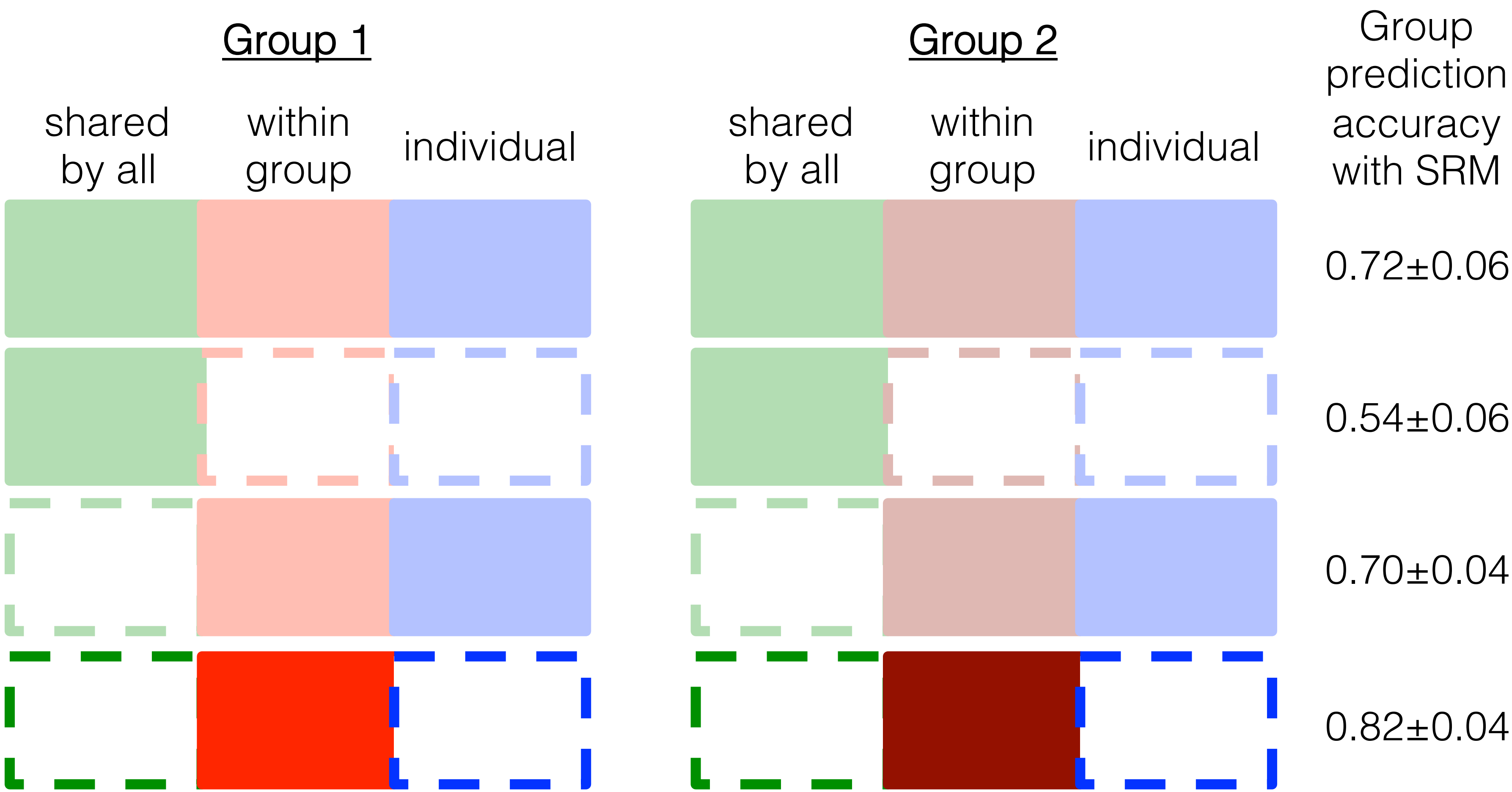

Conclusion

- SRM achieves state-of-the-art performance using multi-subject data, demonstrates higher sensitivity
- SRM outperforms within subject classification
- Low dimensional representation of brain response
- SRM decouples shared and individual responses, allowing detection of group specific responses

Recent Extensions:

- Kernel version of SRM to unlock information in higher order statistics from fMRI data
- Information theoretic based SRM

A Reduced-Dimension fMRI Shared Response Model

Poster 23


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