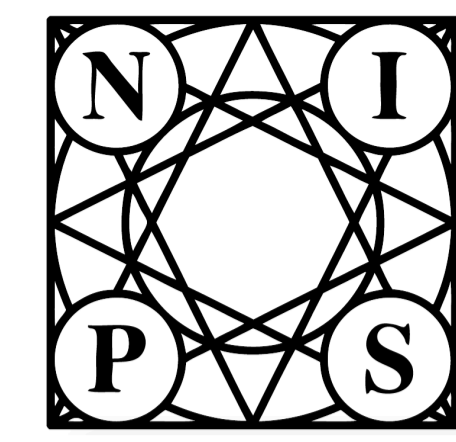


A Reduced-Dimension fMRI Shared Response Model

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Oral Presentation
Dec 9 (Wed)
2:50pm-3:30pm

Introduction

Motivation:

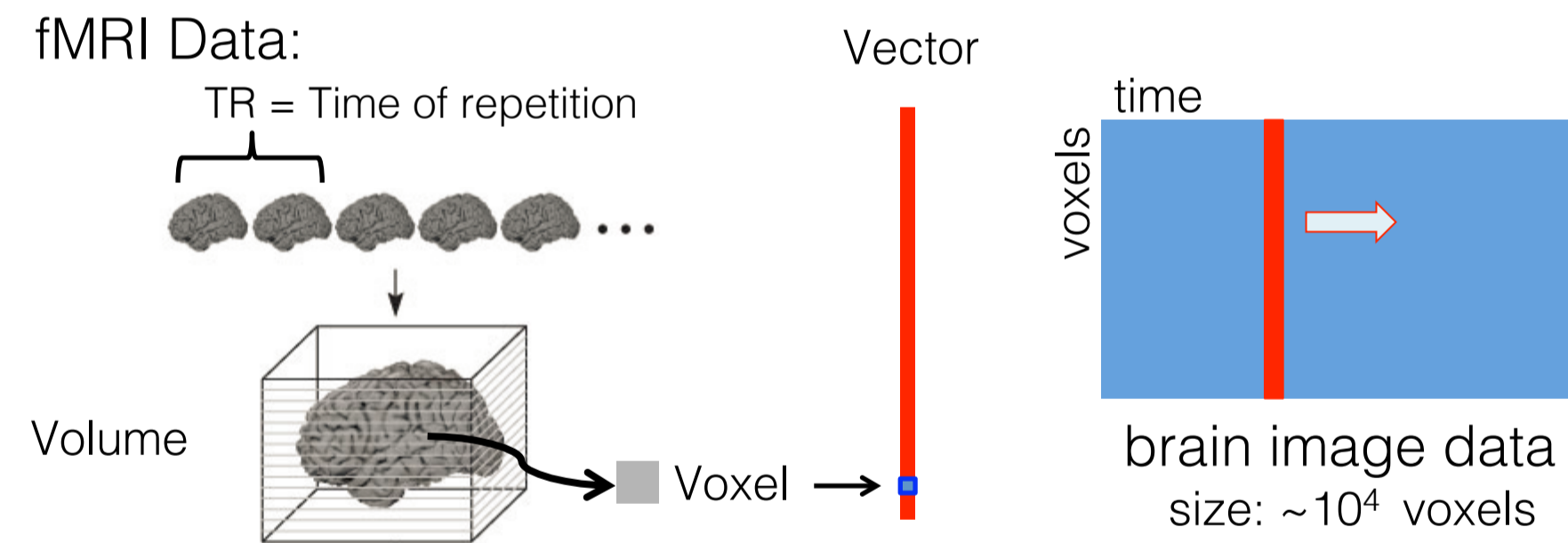
- Modern fMRI studies of human cognition use data from multiple subjects.
- Why? Scientific reasons, and to increase the power of multivariate statistical analysis.

Challenge :

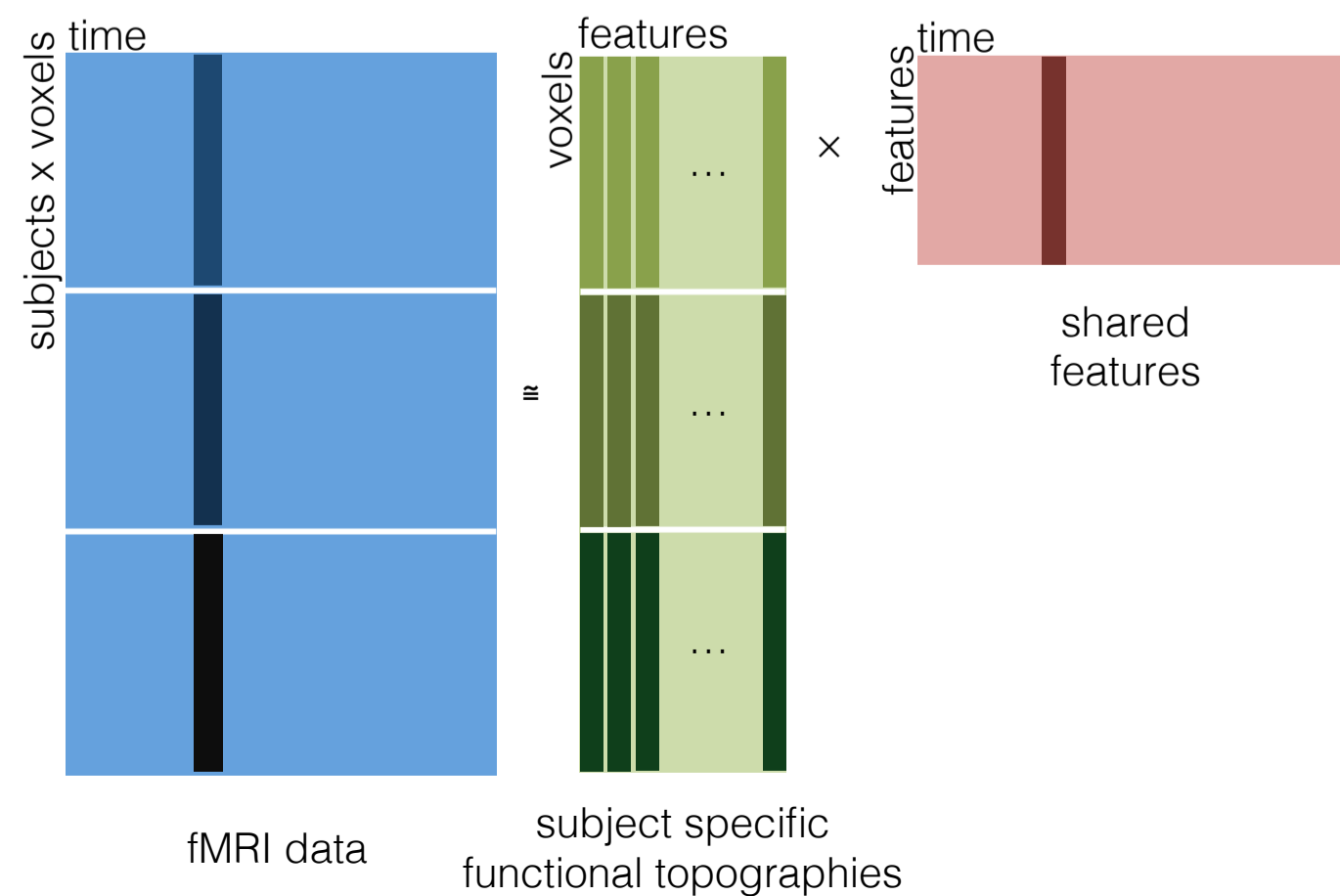
- Inter-subject variability in anatomical structure and functional topographies.
- So how can we aggregate multi-subject fMRI data?

Evaluation :

- Form this as a machine learning question.
- Given test subject's fMRI response, can we successfully classify the stimulus using other subjects' data.



Factor Model



Shared Response Model (SRM)

What are we looking for?

- dimensionality reduction
- better identify the feature space

Approach: generative probabilistic model

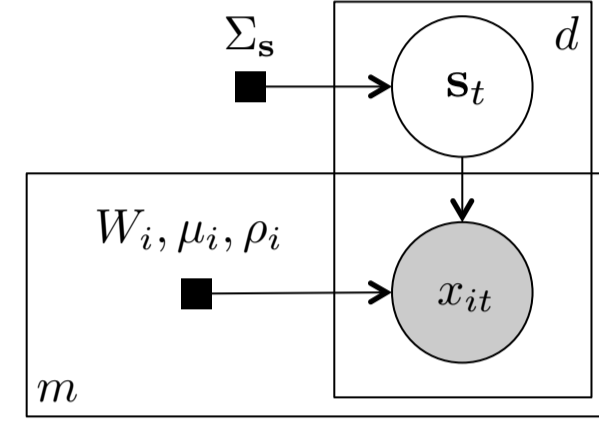
- apply existing statistical tools
- natural incorporation of prior knowledge

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

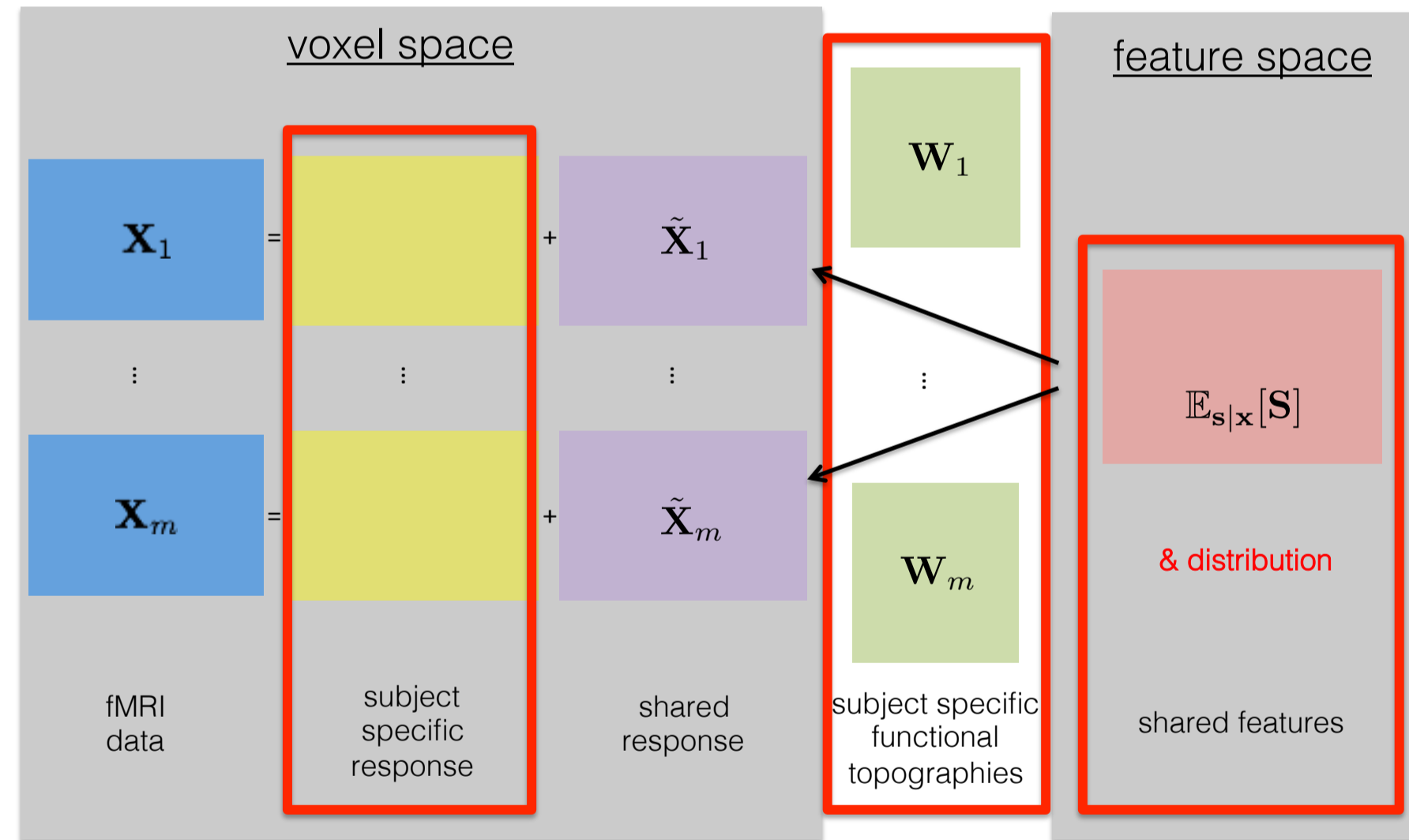
$$x_{it} | s_t \sim \mathcal{N}(W_i s_t + \mu_i, \rho_i^2 I)$$

$$W_i^T W_i = I$$

W_i not square



- Closed-form constrained EM algorithm derived.
- Feature identification with dimensionality reduction.



Constrained EM algorithm

E-step :

$$\mathbb{E}_{s|x}[s_t] = (W \Sigma_s)^T (W \Sigma_s W^T + \Psi)^{-1} (x_t - \mu)$$

$$\mathbb{E}_{s|x}[s_t s_t^T] = \text{Var}_{s|x}[s_t] + \mathbb{E}_{s|x}[s_t] \mathbb{E}_{s|x}[s_t]^T$$

$$= \Sigma_s - \Sigma_s^T W^T (W \Sigma_s W^T + \Psi)^{-1} W \Sigma_s + \mathbb{E}_{s|x}[s_t] \mathbb{E}_{s|x}[s_t]^T$$

M-step :

$$\mu_i^{\text{new}} = \frac{1}{d} \sum_t x_{it}$$

$$W_i^{\text{new}} = A_i (A_i^T A_i)^{-1/2}, \quad A_i = \frac{1}{2} (\sum_t (x_{it} - \mu_i^{\text{new}}) \mathbb{E}_{s|x}[s_t]^T)$$

$$\rho_i^{2 \text{new}} = \frac{1}{d} \sum_t (\|x_{it} - \mu_i^{\text{new}}\|^2 - 2(x_{it} - \mu_i^{\text{new}})^T W_i^{\text{new}} \mathbb{E}_{s|x}[s_t] + \text{tr}(\mathbb{E}_{s|x}[s_t s_t^T]))$$

$$\Sigma_s^{\text{new}} = \frac{1}{d} \sum_t (\mathbb{E}_{s|x}[s_t s_t^T])$$

Datasets

sherlock



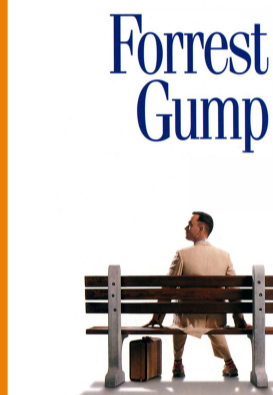
- movie watching
- 16 subjects
- 1976 TRs
- 813 voxels
- Posterior Medial Cortex

audiobook



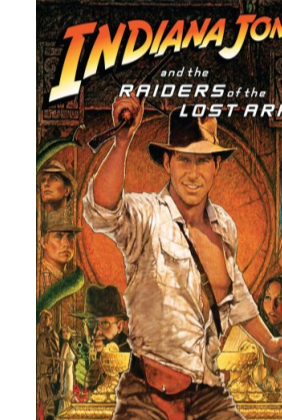
- audiobook listening
- 40 subjects
- 449 TRs
- 5000 voxels
- Default Mode Network

forrest



- auditory feature film listening
- 18 subjects
- 3599 TRs
- 2600 voxels
- Planum Temporale

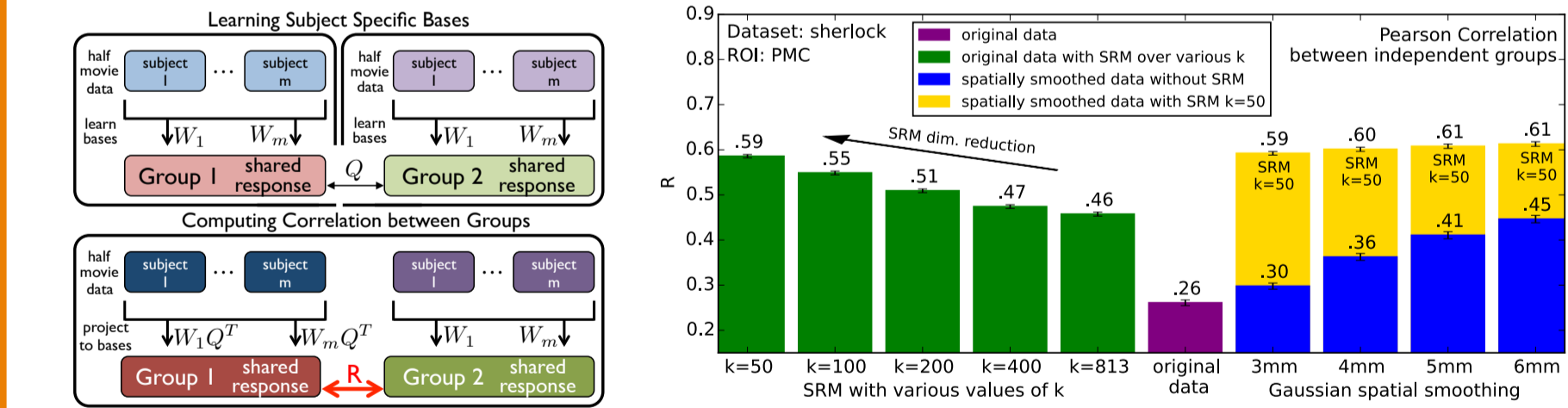
raider



- movie and images watching
- 10 subjects
- 2203 TRs
- 1000 voxels
- Ventral Temporal Cortex

SRM and spatial smoothing

Robustness: Consistent across groups, high correlation between groups, better than anatomical alignment, comparable to 6mm spatial smoothing.

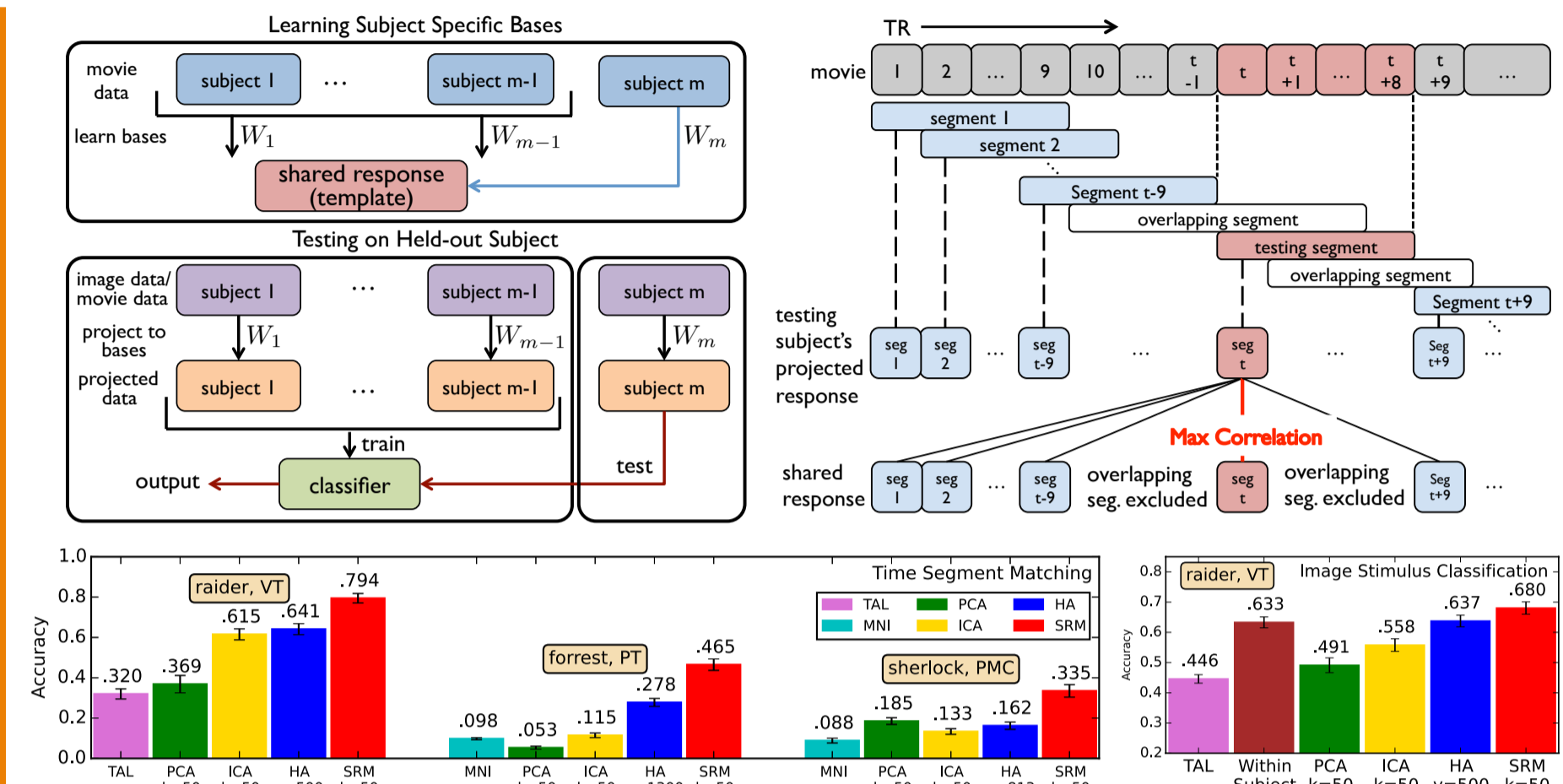


- Identify correlated response between independent groups.
- Increased correlation without dimensionality reduction.

Time segment matching and Image classification

Generalization to new subject and new stimulus:

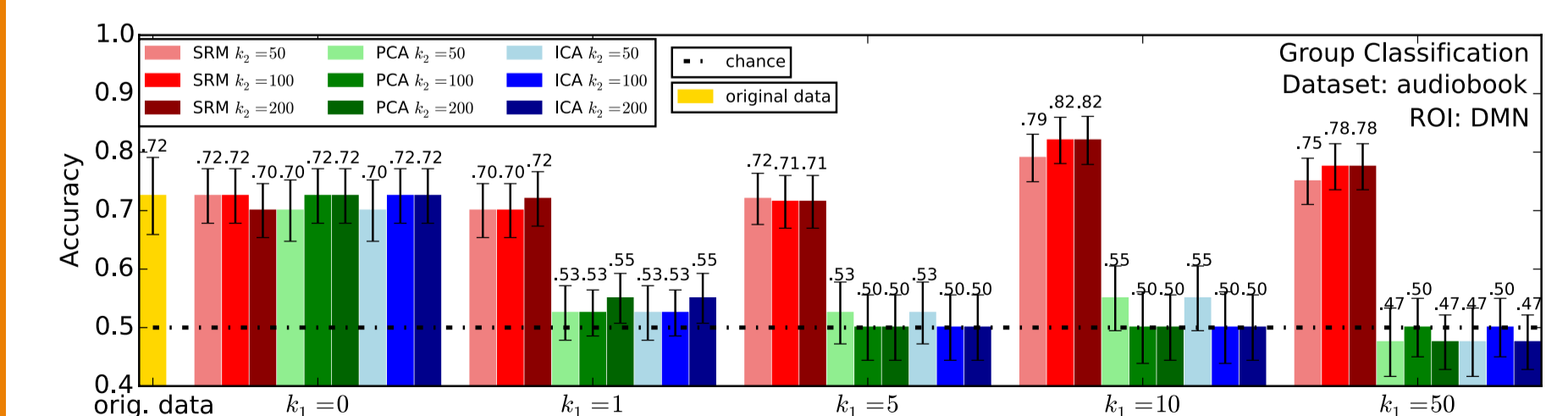
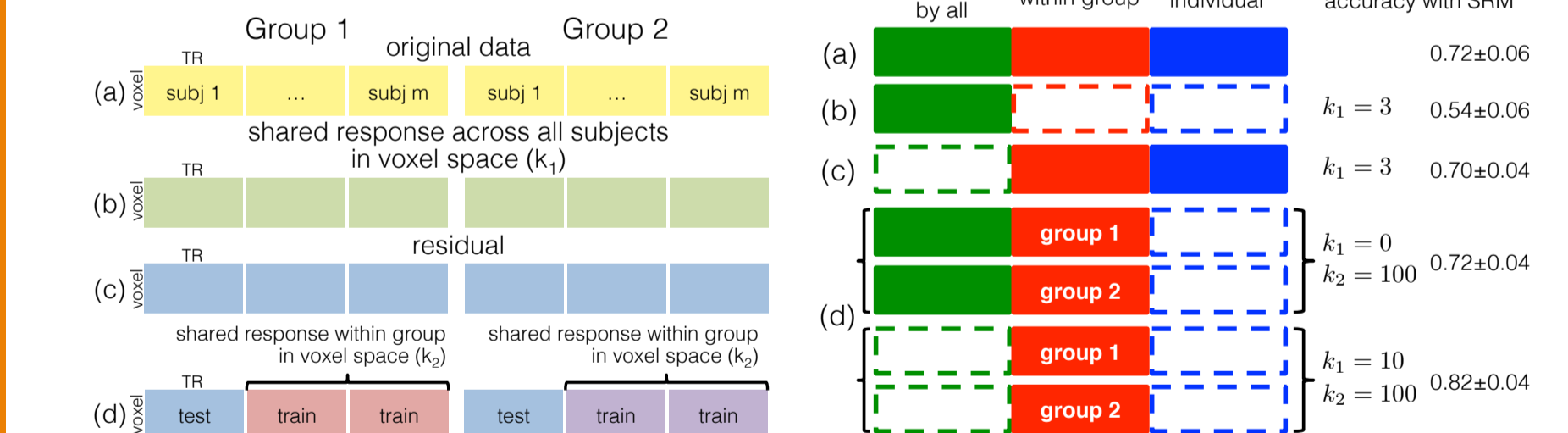
- Given a segment of movie watching response from a test subject, predict the time point of the segment while using other subjects' data for training.
- Given an image watching response from a test subject, predict the image category while using other subjects' data for training.



- State-of-the-art performance in time segment matching and image prediction, suggesting identifying informative shared response.
- Outperforms within subject prediction.

Differentiating between groups

Differentiating two cognitive states : Subjects listen to identical story but different prior context leads to different interpretations.



- Identification of shared and individual responses.
- Ability to detect group specific responses opens up wide range of situations where group differences are the key experimental variable.