Augmenting Feature-driven fMRI Analyses: Semi-supervised Learning and Resting State Activity

Jacquelyn A. Shelton[1,2], Matthew B. Blaschko[3], and Andreas Bartels[1,4]

[1]Max Planck Institute for Biological Cybernetics, [2]Frankfurt Institute for Advanced Studies, [3]University of Oxford, [4]Center for Integrative Neuroscience

Motivation

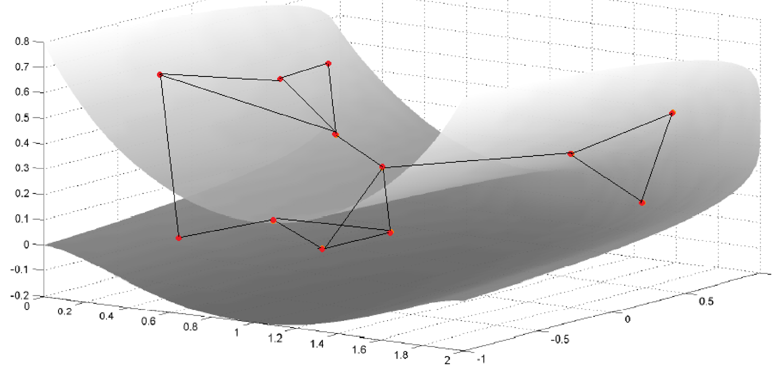
- **Analyze brain activity in natural, complex setting, to assess natural processing**
- **Problems: natural stimuli need expensive labels, fMRI data recording is constrained (time-limit, high demand)**
- **Need to make maximal use of all data obtained**
  - **Resting state activity recorded in absence of task, need no labels and acquisition easier**
- **Goal: resting state data as an unlabeled data source in semi-supervised dimensionality reduction of cortical activity during visual processing tasks**

1 Methods and Materials

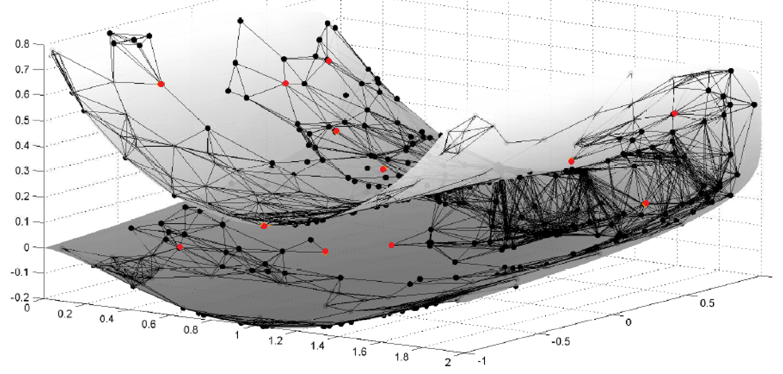
- **fMRI data** of five human volunteers (350 time slices per type):
  - during viewing of **1 labeled** movie and **1 unlabeled** movie
  - **resting state** activity between movies
- 1050 time slices of 3D fMRI brain volumes: Siemens 3T TIM scanner, separated by 3.2 s (TR), spatial resolution of 3x3x3 mm.
- Pre-processed: Statistical Parametric Mapping (SPM) toolbox [6].
- **Labels:** Continuous labels of 1 movie – mean scores from 5 observers: Human faces - Color - Human bodies - Language - Motion [7]

2 Semi-supervised Laplacian Regularized Kernel Canonical Correlation Analysis

- Labeled fMRI data: $\{x_1, \ldots, x_n\}$.corresponding labels: $\{y_1, \ldots, y_n\}$.
- Paired data (fMRI with labels): $(x_1, y_1), \ldots, (x_n, y_n)$.
- Additional data (unlabeled and resting): $\hat{x} = \{x_{n+1}, \ldots, x_p\}$.
- Graph Laplacians [3]: $\mathcal{L}_{\hat{x}} = D^{-\frac{1}{2}}(D - S)D^{-\frac{1}{2}}$ for $(S_{\hat{x}\hat{x}})_{ij} = \exp\left(\frac{-\|x_i - x_j\|^2}{\sigma^2}\right)$ and diagonal $(D_{\hat{x}\hat{x}})_{ii} = \sum_{j=1}^{n+p_x}(S_{\hat{x}\hat{x}})_{ij}$.



(a) Poor estimate: Labeled data



(b) Better estimate: Labeled and additional data

Semi-Supervised KCCA [4]

- **Solve (e.g. as generalized eigenproblem):**

$$\max_{\alpha,\beta} \frac{\alpha^T K_{\hat{x}x} K_{y\hat{y}} \beta}{\sqrt{\alpha^T \left(K_{\hat{x}x} K_{x\hat{x}} + R_{\hat{x}}\right) \alpha \beta^T \left(K_{\hat{y}y} K_{y\hat{y}} + R_{\hat{y}}\right) \beta}}, \qquad (1)$$

$$R_{\hat{x}} = \varepsilon_x K_{\hat{x}\hat{x}} + \frac{\gamma_x}{m_x^2} K_{\hat{x}\hat{x}} \mathcal{L}_{\hat{x}} K_{\hat{x}\hat{x}}$$

$$R_{\hat{y}} = \underbrace{\varepsilon_y K_{yy}}_{\text{Tikhonov Regularization}} + \underbrace{\frac{\gamma_y}{m_y^2} K_{yy} \mathcal{L}_y K_{yy}}_{\text{Laplacian Regularization}}$$

- **Finds projections that are smooth w.r.t. manifold structures of $\hat{X}, Y$ instead of ambient spaces.**

3 Results

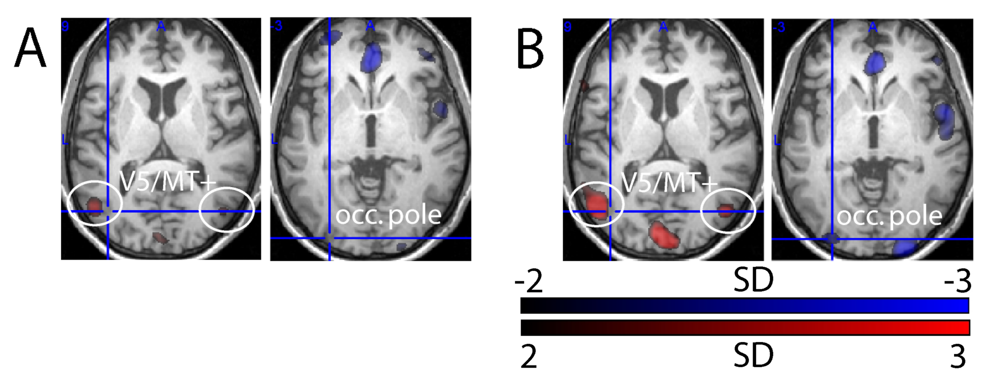
- Semi-supervised Laplacian regularization with resting state data
- Unlabeled data improvements: *Resting state* vs. *active viewing*

Experiments:

Experiment	Labeled	Laplacian	Resting state	Unlabeled
A	X			
B	X	X		
C	X	X	X	
D	X	X		X
E	X	X	X	X

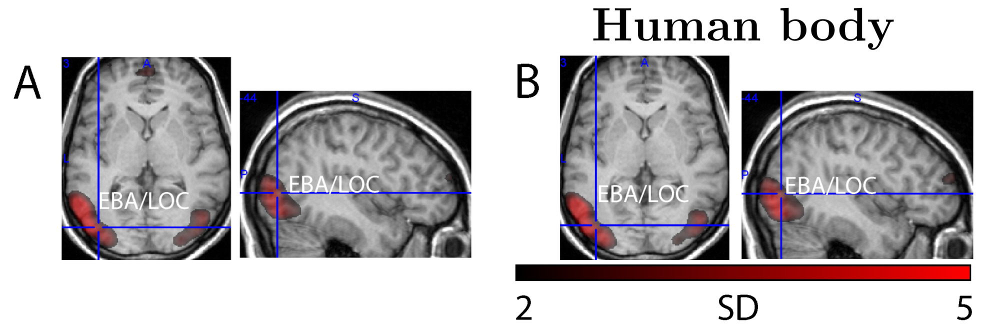
Visualization of learned projections (w) for motion, human body, and language stimuli, following [1,2].

Motion



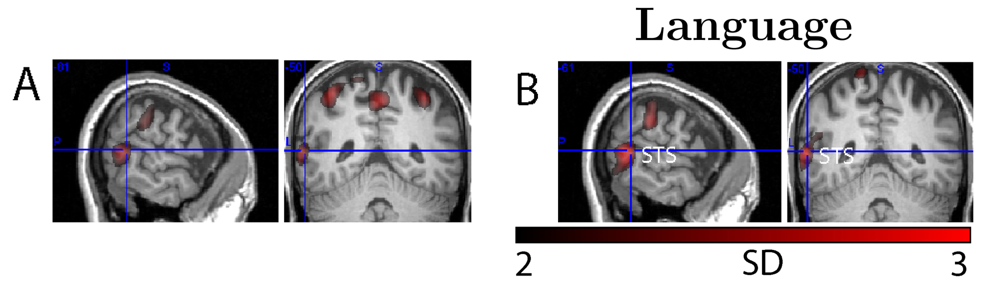
Positive weight-maps in the motion processing area V5/MT+, and negative weights in the occipital pole (fovea) of early visual area V1 as in [1].

Human body



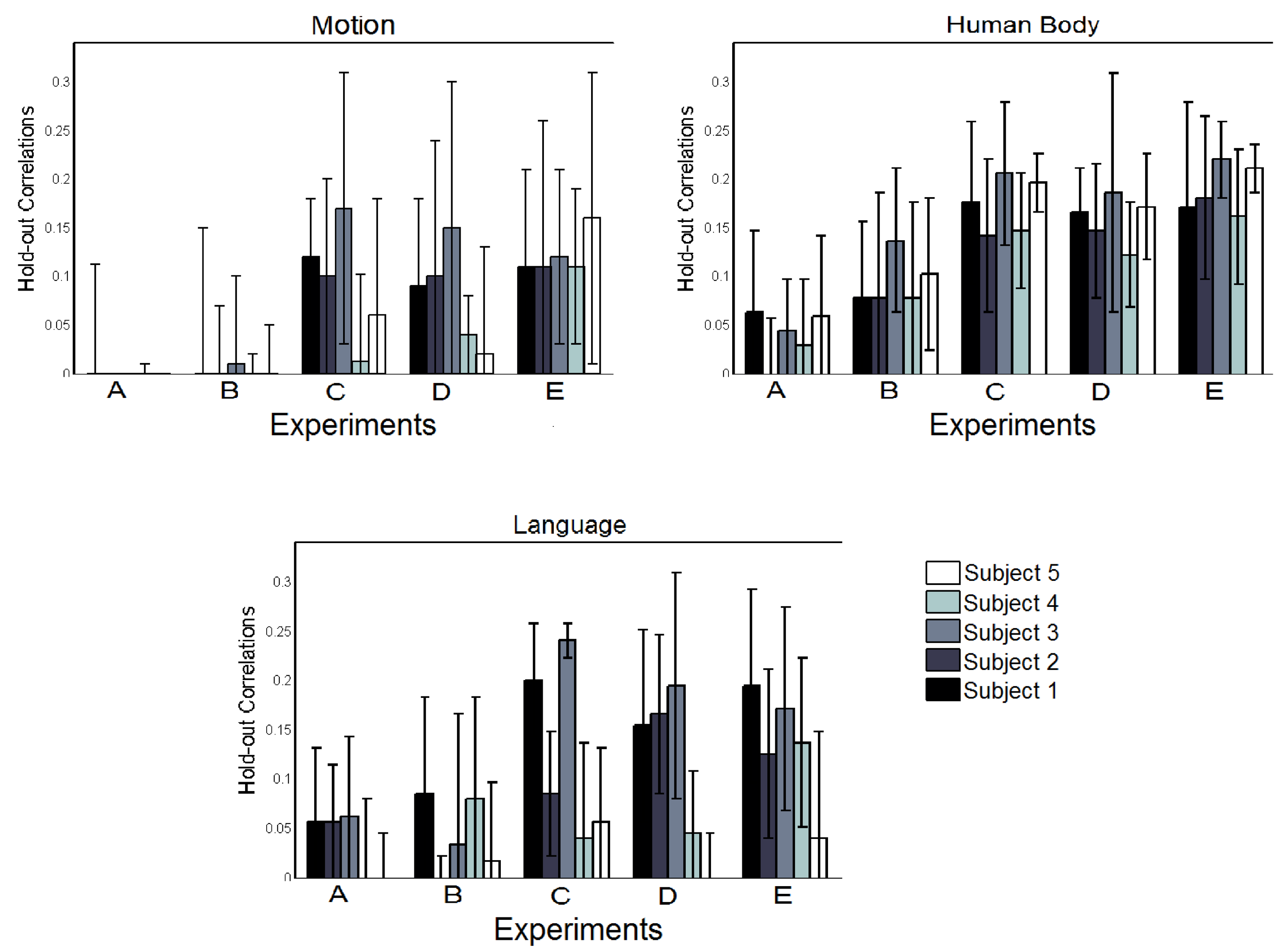
Activity involves the object-responsive lateral occipital cortex (LOC) extending dorsally into the region responsive to human bodies, (EBA) [9].

Language



The activation (*increasing* with experiments A, B and C) involves the superior temporal sulcus (STS) and extends anteriorly to include parts of Wernickes speech processing area.

Mean holdout correlations [8] from five-fold cross validation across the motion, human body, and language features in all experiments.



→ Semi-supervised KCCA using resting state data (Exp C) improves over KCCA using only labeled data (Exp A).

Conclusions

- **Laplacian regularization improves KCCA without unlabeled data → manifold assumption holds for fMRI**
- **Resting state data seem to have a similar marginal distribution to data recorded during a visual processing task → similar types of activation**
- **Resting state data can be broadly exploited to improve the robustness of empirical inference in fMRI studies, an inherently data poor domain**

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