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

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Motivation

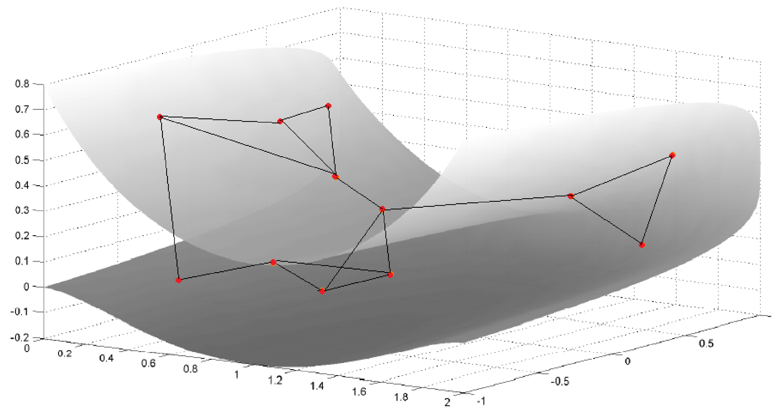
- **Analyze brain activity in natural, complex setting, to assess natural processing**
- **Problems: natural stimuli need expensive labels, fMRI data recording is constrained (time-limit, high demand)**
- **Need to make maximal use of all data obtained**
  - **Resting state activity recorded in absence of task cannot be labeled and acquisition easier**
- **Goal: use resting state data as a source of unlabeled data in semi-supervised regression for dimensionality reduction of cortical activity during visual processing tasks**

1 Methods and Materials

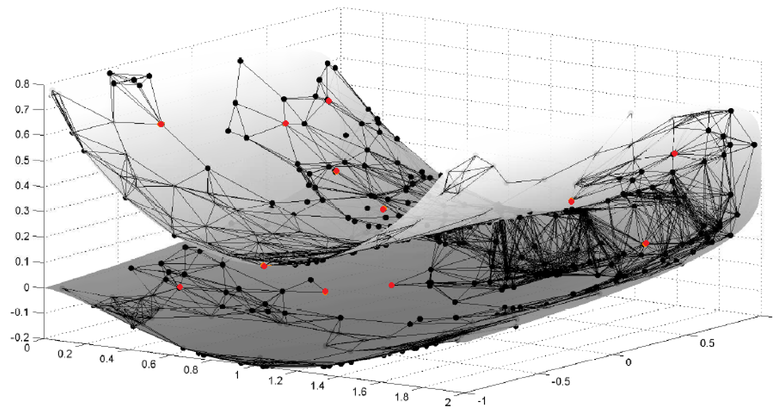
- **fMRI data** of five human volunteers (350 time slices per type):
  - during viewing of **1 labeled** movie and **1 unlabeled** movie
  - **resting state** activity between movies
- 1050 time slices of 3D fMRI brain volumes: Siemens 3T TIM scanner, separated by 3.2 s (TR), spatial resolution of 3x3x3 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 Ridge Regression

- Labeled fMRI data: $\{x_1, \dots, x_n\}$.corresponding labels: $\{y_1, \dots, y_n\}$.
- Paired data (fMRI with labels): $(x_1, y_1), \dots, (x_n, y_n)$.
- Additional data (unlabeled and resting): $\hat{x} = \{x_{n+1}, \dots, x_p\}$.
- 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 Laplacian Regularized Ridge Regression [4]

- **Solve:**

$$\operatorname{argmin}_w \|y - Xw\|^2 + \underbrace{\lambda\|w\|^2}_{\text{Ridge regularizer}} + \underbrace{\frac{\gamma}{m_{\hat{x}}^2} w^T \hat{X}^T \mathcal{L}_{\hat{x}} \hat{X} w}_{\text{Laplacian regularizer}} \qquad (1)$$

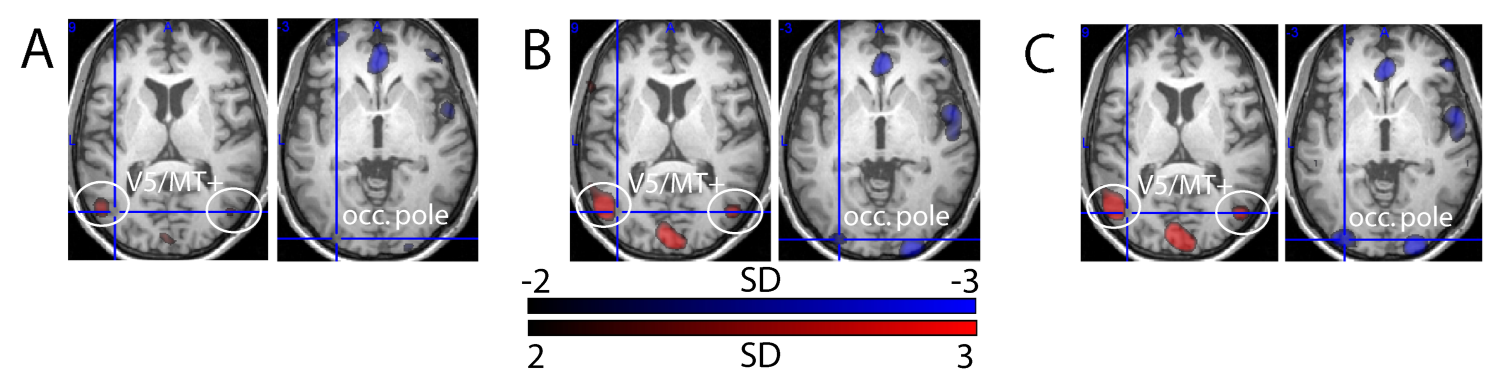
3 Results

- Does semi-supervised Laplacian regularization with resting state data improve regression performance?
- How does resting state data improve regression compared with data acquired during the unlabeled video?

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

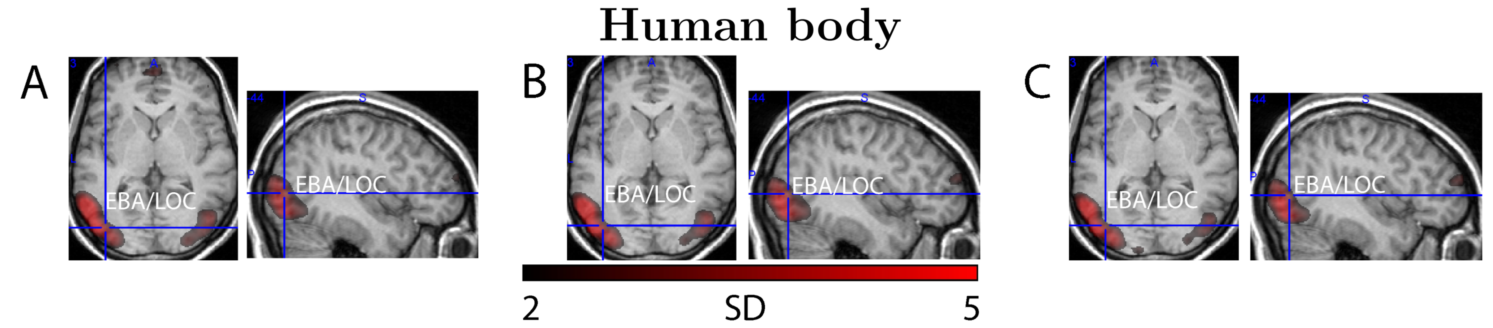
Visualization of learned projections (w) for motion, human body, and language stimuli, following [1,2].

Motion



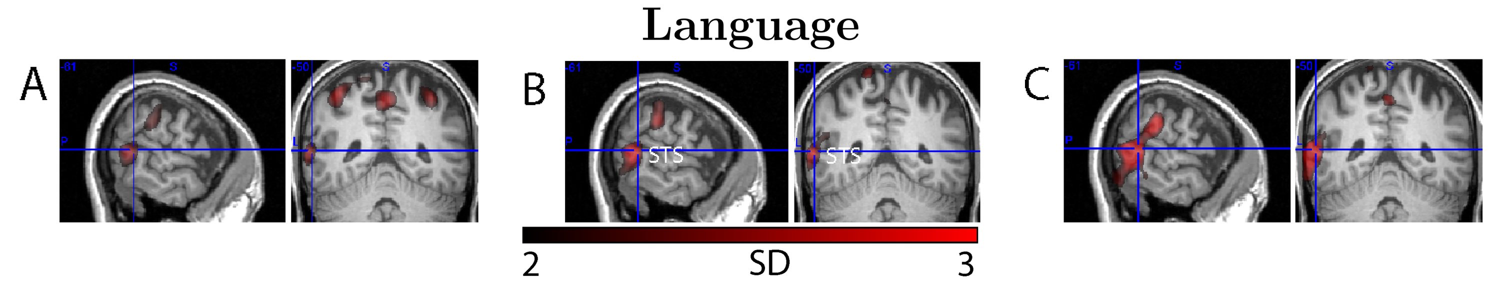
Single subject data show positive weight-maps in the motion processing area V5/MT+, and negative weights in the occipital pole (fovea) of early visual area V1 as in [1]. Note the large improvement from A to B, and the small but noticeable improvement from B to C.

Human body



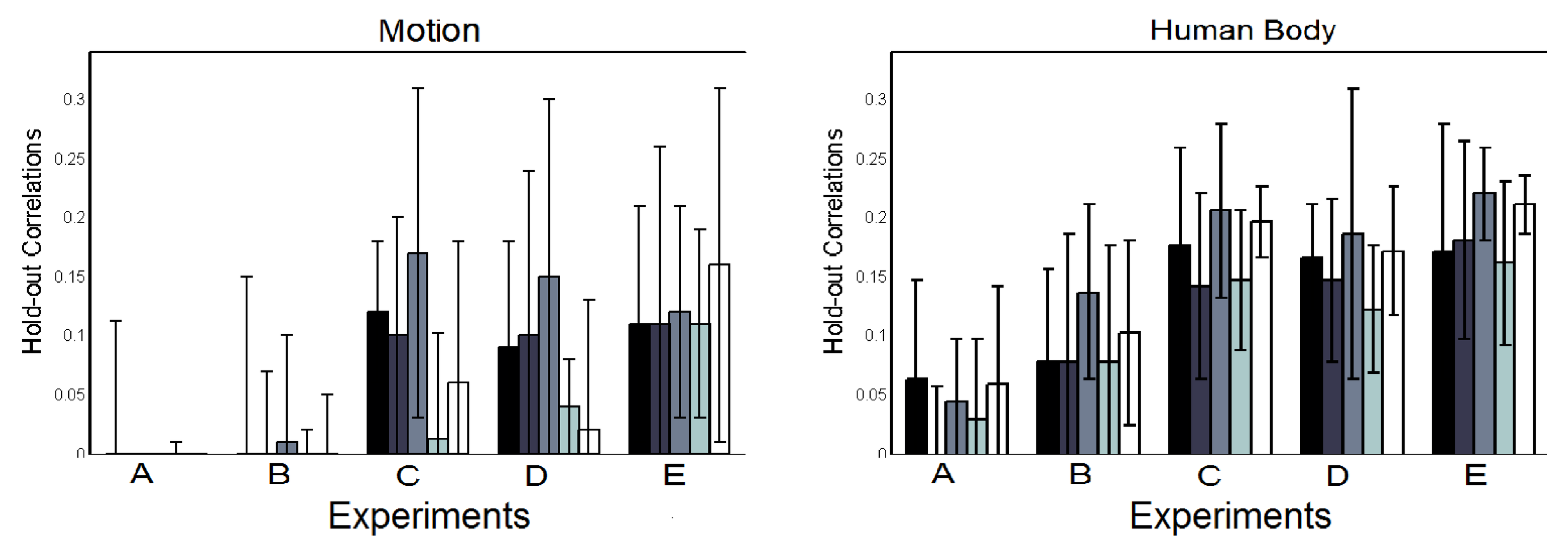
Activity involves the object-responsive lateral occipital cortex (LOC) extending dorsally into the region responsive to human bodies, dubbed extrastriate body area (EBA) [9]. The weights in all experiments are very strong for this feature; very little in the extent of activation is visible across experiments.

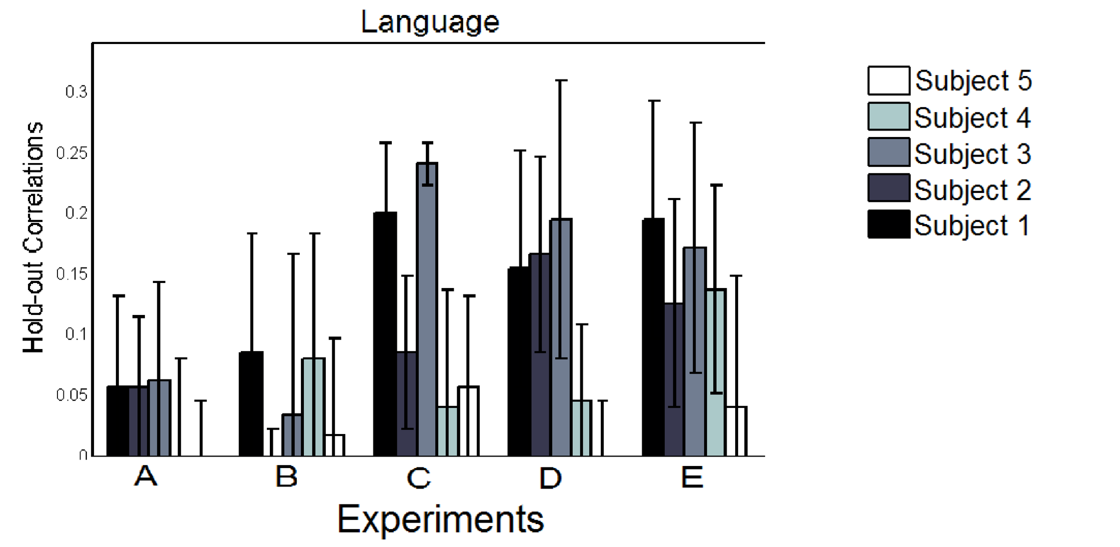
Language



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, and posteriorly, the object-responsive region LOC, involved in analyzing facial features (in accord with [2]).

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





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

Conclusions

- **Laplacian regularization improves Regression 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**

References

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