Across-Subject Predictive Modeling of fMRI BOLD Responses to Faces

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Motivation and Background

Goal:

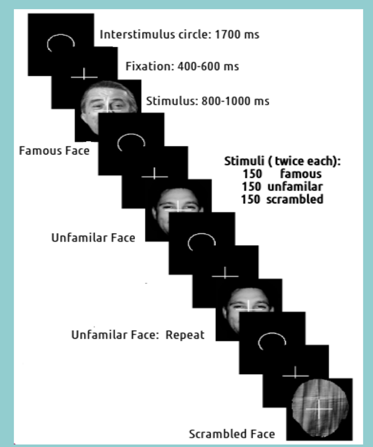
- To predict, across-subjects, the BOLD responses to face image stimuli using a sparse Bayesian latent variable model of multiple fMRI datasets

Dataset:

- Publicly available dataset (www.OpenfMRI.org)[1]
- 210 volumes x 9 runs x 14 subjects
- TR= 2000 ms; voxel size= 3×3×3.75 mm

Experimental Design:

- Rapid event-related design: 9 conditions
- 450 stimuli (famous, familiar, scrambled faces), repeated twice

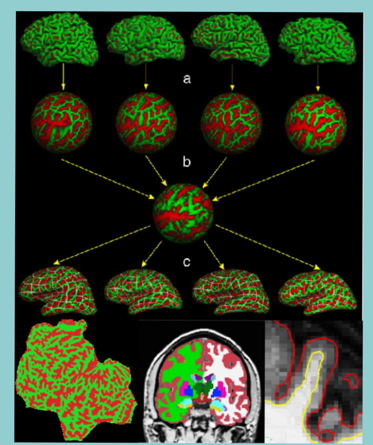


Experiment

Preprocessing Pipeline

Structural (Freesurfer):

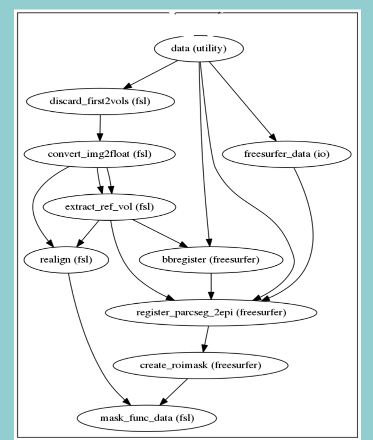
- Cortical surface extraction and flattening
- Anatomical segmentation and ROI labeling
- Surface-based intersubject registration



Freesurfer Pipeline

Functional (Python Nipype):

- Realign all volumes across runs to the 1st volume of first run (reference)
- Compute within-subject registration from anatomical to functional
- Mask functional data with 8 ROIs to obtain ~1800 voxels for each dataset



Nipype Workflow

Methods

Estimation of Beta Weights (activations):

- Deconvolution using separate designs GLM with Finite Impluse Response (FIR) basis [2]
- Local detrending using a Savitsky-Golay filter with a polynomial of degree 3 and a window of 59 s

Predictive Inference:

- A Bayesian Group Factor Analysis (BGFA) model [3] with a hierarchical automatic relevance determination (ARD) sparse prior on the vector components of the weight matrix for 100 factors and 14 datasets
- The BGFA model extends Canonical Correlation Analysis (CCA) to multiple groups and generalizes multi-battery factor analysis (MBFA)[4] by allowing dependencies between subsets of the datasets to be estimated
- The model was fit using variational Bayesian algorithms implemented in the R package CCAGFA

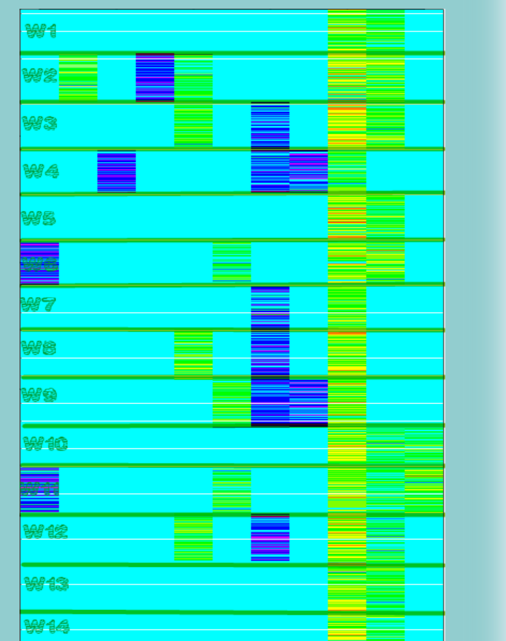
Model:

$$\mathbf{z} \sim N(\mathbf{0}, \mathbf{I}_{100})$$
$$\varepsilon^{(m)} \sim N(\mathbf{0}, \tau_m \mathbf{I}_{D^{(m)}})$$
$$\mathbf{w}_k^{(m)} \sim N(\mathbf{0}, \alpha_{m,k} \mathbf{I}_{D^{(m)}})$$

$$\begin{bmatrix} \mathbf{x}^{(1)} \\ \mathbf{x}^{(2)} \\ \vdots \\ \mathbf{x}^{(14)} \end{bmatrix} = \begin{bmatrix} \mathbf{w}_1^{(1)} & \mathbf{w}_2^{(1)} & \cdots & \mathbf{w}_{100}^{(1)} \\ \mathbf{w}_1^{(2)} & \mathbf{w}_2^{(2)} & \cdots & \mathbf{w}_{100}^{(2)} \\ \vdots & \vdots & & \vdots \\ \mathbf{w}_1^{(14)} & \mathbf{w}_2^{(14)} & \cdots & \mathbf{w}_{100}^{(14)} \end{bmatrix} \mathbf{z} + \begin{bmatrix} \varepsilon^{(1)} \\ \varepsilon^{(2)} \\ \vdots \\ \varepsilon^{(14)} \end{bmatrix}$$

$$\alpha = \begin{bmatrix} \alpha_{1,1} & \cdots & \alpha_{1,100} \\ \vdots & \alpha_{m,k} & \cdots \\ \alpha_{14,2} & \cdots & \alpha_{14,100} \end{bmatrix} = \exp(\mathbf{U}\mathbf{V}^\intercal + \boldsymbol{\mu}_u \mathbf{1}^\intercal + \mathbf{1}\boldsymbol{\mu}_v^\intercal)$$

where $\mathbf{U} \in \mathbb{R}^{M \times R}$, $\mathbf{V} \in \mathbb{R}^{K \times R}$, and rank $R \ll \min(K, M)$



Weight matrix of the top 11 factors

Computation:

- Most of the analyses were run on the Oakley supercomputer at the Ohio Supercomputer Center

Oakley

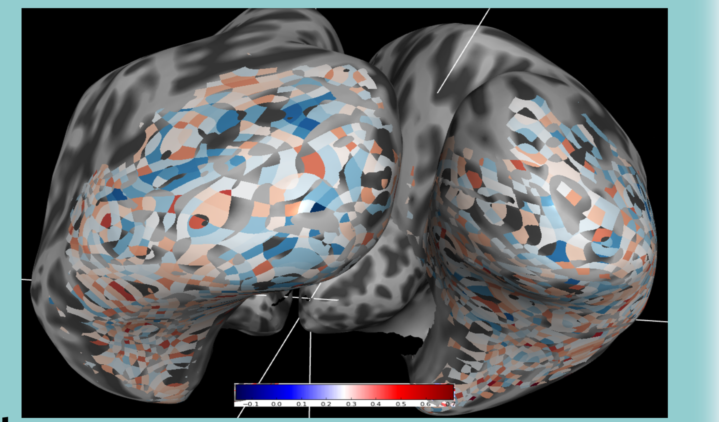
Results

Predictive Performance:

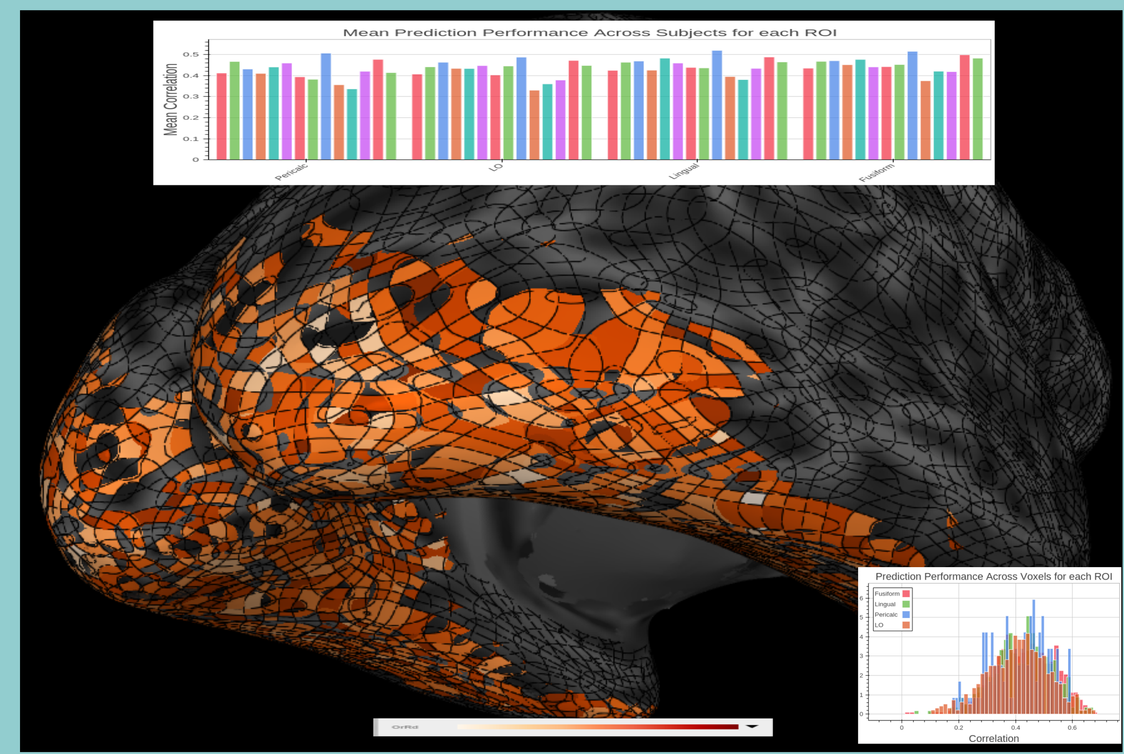
- Leave-one-run-out data folding gave the best low rank solution: R=3 with prediction RMSE=0.9045

Data Visualization (Pycortex):

- Right: Subject 2's projection weights corresponding to the 9th factor
- Below: correlation between predicted data and test data across voxels



Projection Weights (loadings)



Correlation Cortical Map

References

[1] Wakeman, D. G., & Henson, R. N. (2015). A multi-subject, multi-modal human neuroimaging dataset.Scientific Data, 2

[2] Mumford, J. A., Turner, B. O., Ashby, F. G., & Poldrack, R. A. (2012). Deconvolving BOLD activation in event-related designs for multivoxel pattern classification analyses. NeuroImage

[3] Klami, A., Virtanen, S., Leppaaho, E., & Kaski, S. (2014). Group Factor Analysis. Neural Networks and Learning Systems, IEEE Transactions

[4] Browne, M. W. "Factor analysis of multiple batteries by maximum likelihood."

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