Categories and Functional Units: An Infinite Hierarchical Model for Brain Activations

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Motivation

- Functional MRI (fMRI) provides noninvasive, large-scale observations of brain activity
  - ➢ At each location (voxel) in the brain, provides time series data as subject performs tasks according to a protocol
  - ➢ Raw data is four-dimensional for each subject: three spatial, one temporal
  - ➢ We convert time to stimuli, and stack all voxels (ignoring spatial information): this results in a two-dimensional dataset
  - ➢ Unfortunately, fMRI data is typically very noisy and very high-dimensional
- Traditional fMRI analysis uses hypothesis-driven methods to find neuroscientifically interesting properties of the brain
  - ➢ e.g. How is it organized? How does it react to different inputs?
  - ➢ Progress in discovering e.g. visually selective areas has been slow
- Use machine learning techniques to help us discover these properties
- Functional specificity:
  - ➢ **Functional units:** What regions of the brain react consistently to groups of stimuli?
  - ➢ **Categories:** Which groups of stimuli/cognitive tasks evoke similar reactions?
- We want to *discover* functional units and categories in an unsupervised fashion using clustering

Approach

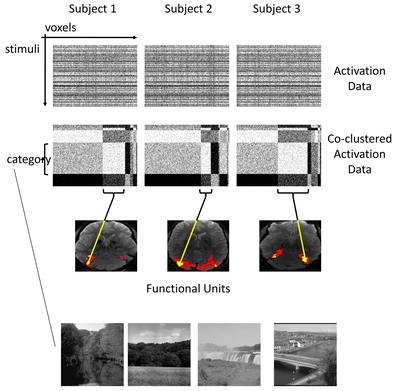
- Coclustering model that jointly learns functional units of voxels, stimulus categories, and how they interact

I. Functional units
- Nonparametric hierarchical clustering model
- Finds groups of voxels across many subjects with similar functional properties, and learns the number of such groups

II. Stimulus categories
- Nonparametric clustering model
- Finds groups of stimuli that evoke similar responses across voxels in all subjects

III. Coclustering model
- Each unit/category pair is associated with a prior probability of activation

IV. Signal model
- Describes the relationship between binary activations (as shown at right) and fMRI time series data



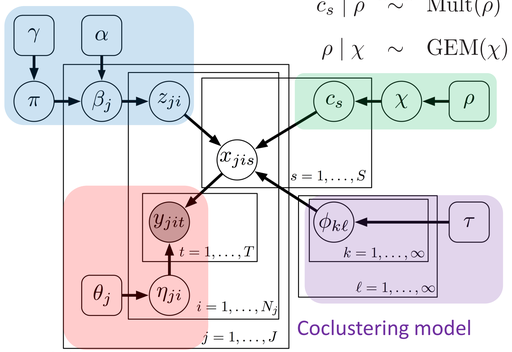
Model

Hierarchical clustering of voxels across subjects (HDP)

$$z_{ji} \mid \beta_j \overset{i.i.d.}{\sim} \text{Mult}(\beta_j)$$
$$\beta_j \mid \pi \overset{i.i.d.}{\sim} \text{Dir}(\alpha\pi)$$
$$\pi \mid \gamma \sim \text{GEM}(\gamma)$$

Clustering of stimuli (DP)

$$c_s \mid \rho \overset{i.i.d.}{\sim} \text{Mult}(\rho)$$
$$\rho \mid \chi \sim \text{GEM}(\chi)$$



FMRI signal model

$$\eta_{ji} = \{a_{ji}, e_{ji}, \lambda_{ji}\}$$
$$\vartheta_j = \{\mu_j^a, \sigma_j^a, \mu_j^e, \sigma_j^e, \kappa_j, \theta_j\}$$
$$e_{jih} \sim \text{Normal}\left(\mu_{jh}^e, \sigma_{jh}^e\right)$$
$$a_{ji} \sim \text{Normal}_+\left(\mu_j^a, \sigma_j^a\right)$$
$$\lambda_{ji} \sim \text{Gamma}\left(\kappa_j, \theta_j\right)$$

Coclustering model

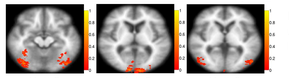
$$x_{jis} \mid z_{ji}, c_s, \phi \overset{i.i.d.}{\sim} \text{Bernoulli}(\phi_{z_{ji}, c_s})$$
$$\phi_{k,l} \overset{i.i.d.}{\sim} \text{Beta}(\tau_1, \tau_2)$$

- Hierarchical Dirichlet Process (HDP) prior over functional units of voxels across different subjects
  - Analogous to Latent Dirichlet Allocation: subjects as documents, voxels as words, topics as functional units
- Dirichlet Process (DP) prior over categories
- FMRI signal model incorporates generative model based on standard analysis (General Linear Model)
  - $y_{ji} = a_{ji} \sum_s G_s x_{jis} + \sum_h F_h e_{jih} + \epsilon_{ji}$
- Coclustering model describes interaction between systems and functional units:
  - $\phi_{k,l}$ describes how likely a voxel in unit k is to respond to a stimulus in category l
- Use variational mean-field inference to find latent variables
  - Use collapsed variational inference scheme for inference on HDP/DP (Teh et al, 2007; Blei et al, 2006)
  - Integrate variational inference scheme for fMRI signal model

Results

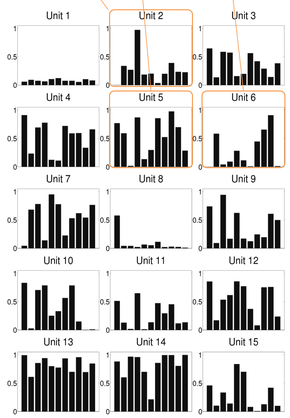
- Applied our model to a study where 8 subjects viewed 69 images
  - ➢ Divide each image into two stimuli, in our analysis to obtain 138 stimuli

Spatial variability of units across subjects



Fraction of subjects for which each voxel was assigned to the corresponding unit: results show spatial **consistency across subjects** while simultaneously highlighting small variations.

Functional units for our model and their responses to each category

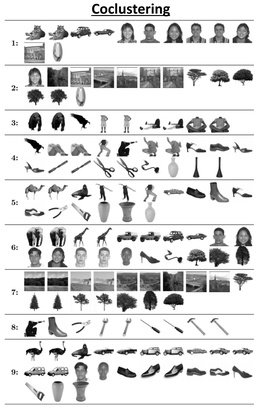


Units are **consistent with neuroscience literature**, and have **meaningful interpretation** with respect to categories

Categories learned by our model

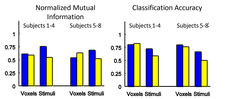
Stimuli corresponding to the same image are **consistently grouped** together, and categories show **coherent patterns** of images

Categories learned by Block-Average Coclustering



Stimuli corresponding to the same image are ***not* consistently grouped** together, and categories are **not coherent**

Robustness comparison with results on full data as ground truth: normalized mutual information and fraction of correct assignments after cluster matching.



Our model is **robust to noise** and tolerates noise as well as or better than BAC.

Contributions

- Novel model for coclustering functional units of voxels and categories of stimuli using fMRI
- Discovery of meaningful structure in both voxel space and stimulus space in real fMRI data
- **Future work:**
  - Experiment with richer space of stimuli
  - Feature-based model for clustering stimuli

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