Co-Clustering Approach to Neural Representation of Objects

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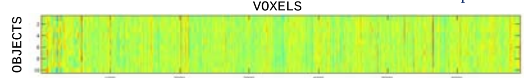
Introduction

How are individual objects encoded and represented in the brain? Multi-voxel pattern analysis has been successfully applied to fMRI data to identify the cognitive states associated with viewing categories of objects as well as object exemplars. In this work we further investigated object representation (e.g. *tools* and *dwellings*) using an exploratory co-clustering approach that associates groups of objects with networks of voxels.

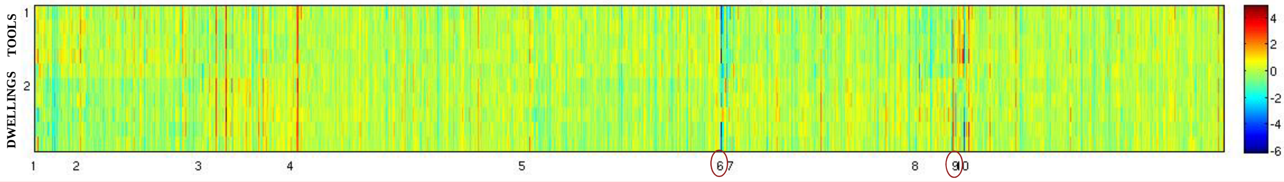
Results

We illustrate the co-clustering algorithm on data from one participant. The algorithm was run with two object clusters and ten voxel clusters. The number of object clusters was selected based on the number of semantic categories (*tools* and *dwellings*). The number of voxel clusters was selected to avoid singleton clusters.

Input data



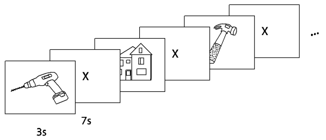
Co-clustered data



Methods

Experimental paradigm

Participants viewed line drawings of ten objects, for six presentations each, from *tools* and *dwellings* categories[1].



fMRI procedure

Siemens Allegra 3.0T scanner; TR = 1000 ms, TE = 30 ms, 60 flip angle; 17 5-mm thick oblique-axial slices, with 1-mm gap; 64 x 64 acquisition matrix with 3.125 x 3.125 x 5-mm voxels

fMRI processing and analysis

The data were corrected for slice timing, motion, linear trend, and were temporally smoothed with a high-pass filter using a 190s cutoff. Preprocessed data for each participant were spatially normalized into MNI space using a 12-parameter affine transformation and resampled to 3x3x6 mm^3 voxels (SPM99).

The percent signal change relative to the fixation condition was computed for each stimulus presentation at each voxel. The mean of four images acquired within a 4s window, offset 4s from the stimulus onset, provided the main input measure for the analysis. A representative fMRI pattern of brain activity for each stimulus was created by computing the mean fMRI response over its six presentations. To reduce the number of voxels in the analysis, only gray matter voxels were included in the analysis. The data is presented in $m \times n$ matrix, where the rows represent objects, and the columns represent voxels. The (i, j) entry corresponds to the mean percent signal change for the i^{th} object in the j^{th} voxel.

Information-Theoretic Co-Clustering

Co-clustering algorithms seek to *simultaneously* group random variable X into k disjoint clusters, and random variable Y into l disjoint clusters:

$$C_X : \{x_1, x_2, \ldots, x_m\} \to \{\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_k\}$$
$$C_Y : \{y_1, y_2, \ldots, y_n\} \to \{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_l\}$$

Where $\hat{X}, \hat{Y}$ represent the clustered variables. Here an information theoretic approach to co-clustering[2] has been implemented and the clustered variables were found iteratively by minimizing the mutual information function for the representations:

$$\Delta MI = I(X;Y) - I(\hat{X};\hat{Y}) = KL(p(x,y) \,\|\, q(x,y))$$

The Kullback-Leibler divergence, $KL(\cdot \,\|\, \cdot)$ may be expressed as follows:

$$\Delta MI = \sum_{\hat{x}} \sum_{\hat{y}} \sum_{x \in \hat{x}} \sum_{y \in \hat{y}} p(x,y) \log \frac{p(x,y)}{q(x,y)}$$

where $q(x,y) = p(\hat{x},\hat{y}) p(x \mid \hat{x}) p(y \mid \hat{y}),$ and $x \in \hat{x}, y \in \hat{y}$

The algorithm monotonically decreases the loss in mutual information :

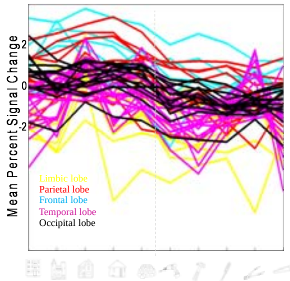
1. *Start with random assignment of co-clusters*
2. *Assign rows to row-cluster with closest KL divergence*
3. *Recompute column-clusters*
4. *Assign columns to column-cluster with closest KL divergence*
5. *Recompute row-clusters*
6. *Iterate until convergence*

Dhillon et al. (2003)

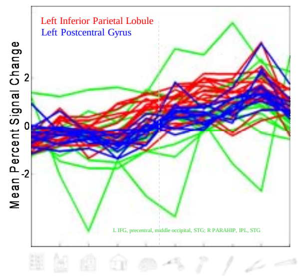
Rows and columns of the data matrix were reordered to reflect co-cluster membership. Objects were successfully clustered into the two categories - perfect accuracy for the visualized example. On average, classification accuracy was significantly above chance over multiple runs of the algorithm.

OBJECT PROFILES FOR SMALL VOXEL CLUSTERS

Cluster 6



Cluster 9



The smallest cluster for the representation of the *dwellings* category (cluster 6) contained voxels that were widely distributed throughout the cortex .

The smallest cluster shown to be important for the representation of the *tools* category (cluster 9) grouped voxels with similar profiles together. Most voxels in that cluster were located in the left inferior parietal and postcentral gyri – areas previously associated with activation for tools.

Summary

Both objects and voxels were simultaneously grouped to study how semantic information about objects is represented in the cerebral cortex (a novel application of co-clustering).

Simultaneous grouping of objects and voxels allows extraction of biologically meaningful information, since multiple objects can be represented by the same network of voxels. The method allowed us to reveal the similarity structure in object representations in terms of their neural signature, and, at the same time, identify the most relevant subsets of voxels for object representation.

References

1. Shinkareva S.V., Mason, R.A., Malave, V.L., Wang, W., Mitchell, T.M. et al. (2008). Using fMRI Activation to Identify Cognitive States Associated with Perception of Tools and Dwellings. PLoS ONE 3(1): e1394.
2. Dhillon, I.S., Mallela, S., & Modha, D.S. (2003). Information-Theoretic Co-clustering. *ACM SIGKDD, 89-98.*

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