

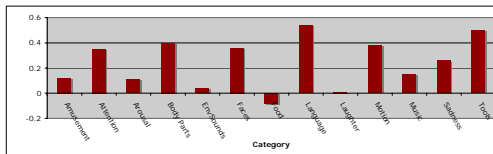


## INTRODUCTION

Inference regarding the neural bases of cognition is predominantly approached by correlating the BOLD signal with various behavioral measures or through cognitive subtraction techniques. Alternatively, an emerging and potentially powerful method involves reverse inference (Poldrack, 2006), that is, to use spatiotemporal information from an individual's BOLD signal as s/he performs a task to predict various aspects of their behavior. Here we describe one novel reverse inference technique that reliably predicted, from the BOLD pattern, how individuals rated 13 real-life features of a popular TV sitcom.

## RESULTS

Our method was very good at predicting some ratings and rather poor at predicting others. The more fundamental a feature is the better the resulting prediction was. As such, the method did quite well for body parts, faces, language, tools, and motion. The method did not fare as well when predicting more subjective vectors, like amusement, arousal, and laughter. The overall best average correlation across all 13 base features in the competition was 0.251.



The most notable aspect of this method is that it relies so heavily on the raw BOLD timecourse for the final prediction. Thus the final predictions are a measure of how well the voxel-level signals in the brain are related to the subjective ratings measures. This is most likely why faces are highly predictable while more esoteric ratings like food are not. Still, our method would most likely generalize to other subjects quite well because it is not overspecified to the data used in the competition.

## NEXT YEAR

Our hope for the future is to develop this method further by bringing in more *a priori* information regarding the relationships between vectors. For example, you will not have a face rating without having a body part rating. As a result many of the ratings vectors are very highly correlated. Additionally, we also hope to use the similarity algorithm on the timeseries itself to determine similarity across periods when the subjective rating is high. This information could then be used as a different method of flatmap pixel selection for generation of the final timecourse.

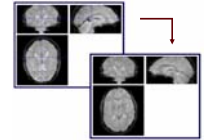
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## METHODS

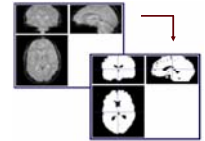
### 1. Reorientation of the data

The Automatic Image Registration package (Woods et al., 1992; Woods et al., 1998) was used to place the volumes in an SPM-compatible neurological orientation. This was a necessary step because the orientation of SPM images requires that the X dimension increase from left to right and the Y dimension to increase from posterior to anterior. Using the 'reorient' command-line program all images were rotated 180 degrees around the z-axis.



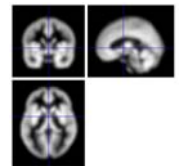
### 2. Creation of brain masks

Images were masked to only include voxels of interest. The anatomical MPRAGE image was first segmented into probabilistic images of cerebral white and gray matter using SPM2 (Ashburner et al., 1997a). These images were then smoothed 1 mm FWHM and recombined to produce a single whole-brain mask. This mask was then used for the removal of cerebrospinal fluid, skull, and other voxels not under investigation.



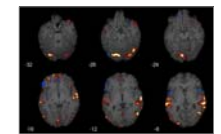
### 3. Spatial normalization

All images were normalized in SPM2 using parameters determined from the segmented gray matter of the anatomical MPRAGE image. Images were normalized into a standard 3D stereotaxic space defined by the International Consortium for Brain Mapping (ICBM)-305 (Ashburner and Friston 1999; Ashburner, et al. 1997b; Mazziotta, et al. 1995).



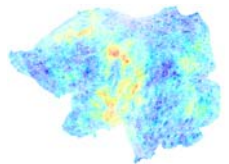
### 4. Generation of covariance volumes

A covariance score was calculated based on the timecourse of each voxel in the EPI images and the hemodynamically convolved behavioral rating. Only periods when a movie was presented to the subject were included in the timecourse for covariance calculation. For both movie1 and movie2 EPI runs each of the 13 base features were covaried against all voxels located within the brain mask. The result of this step was the creation of a volume of covariance values for each of the movie1 and movie2 behavioral ratings.



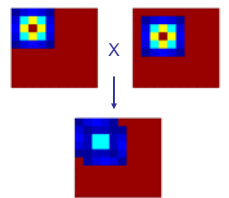
### 5. Flatmapping

All normalized EPI and covariance volumes were made into cortical flatmaps using the Computerized Anatomical Reconstruction and Editing Toolkit (CARET) version 5.3 (VanEssen et al., 2001). The target space used for the flatmapping operation was the human 'Colin' atlas left and right hemispheres (VanEssen, 2002). Grid dimensions for conversion of analyze volumes to Caret metric files were set to the SPM2 default values. A custom MATLAB script loaded the metric file and flatmap coordinate file into memory and assembled a table of node intensity, latitude, and longitude using the node number as a key value. This table of discrete points was then used to create a continuous map of values on a grid using a triangle-based cubic interpolation. Two flatmaps were generated for each volume: one each for the left and right hemisphere.



### 6. Finding Similarity

A custom method was used to identify regions with similarly high covariance between movie1 and movie2. First, a new weighted copy of each covariance map was created. The value of each voxel in the new map was calculated as the average value of the original voxel and its 24 nearest neighbors weighted by a Gaussian filter (sigma = 1) in which the center voxel retained its original value and the surrounding voxels were weighted as a function of their distance from the center of the filter. In this way, robust regions of covariance were amplified, while sparse covariance thought to reflect "noise" in the data was dampened. Next, the two weighted covariance maps for each subject (movie1 and movie2) were multiplied together to enhance the values of voxels that were active in both maps and reduce the values of voxels that were only active in one of the two. The result was a single map for each hemisphere that reflected the areas of peak similarity between two covariance flatmaps.



### 7. Generation of Prediction

The EPI flatmaps were assembled in temporal order to create a flatmap timeseries. Next, an automated peak-search algorithm identified the top 120 pixels from the similarity flatmap. The timeseries of each pixel was z-scored and weighted by the average of the covariance scores for that pixel from movie1 and movie2. The resulting prediction vectors for the left and right hemisphere were then averaged together to yield one final prediction vector. This vector was smoothed using a moving-average method with a span of five data points. For the final (third) competition submission the vectors were also averaged across subjects.

