Classification of fMRI Data

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Abstract

The functional architecture of the object vision pathway in the human brain was investigated using fMRI imaging to measure patterns of response in ventral temporal cortex while subjects viewed categories of objects in Haxby et al. [Science 293 (2001) 2425] [2]. Haxby argued that category related responses in the VT lobe during visual object identification were overlapping and distributed in topography. At the time of Hanson et al. [Elsevier 23 (2004) 156] [1] there were prevailing views that objects codes were focal and localized to specific areas like the fusiform and the parahippocampal gyri. Hanson et al. revisited the Haxby data and provided a crucial test of the former hypothesis using a neural network classifier. The method of Hanson et al. detected more general topographic representations and illustrated that substantially the same VT lobe voxels contribute to classification of all object categories

1 Introduction

Models for the functional architecture of the ventral temporal cortex fall into three categories. One model proposes that VT contains a limited number of areas that are specialized for representing specific categories of stimuli. A second model proposes that different areas in VT are specialized for different types of perceptual processes. The third model proposes that the representations of faces and different categories of objects are widely distributed and overlapping. According to the latter model, VT has a topographically organized representation of attributes of form that underlie face and object recognition meaning that the representation of a face or object is illustrated by a unique pattern of response across a wide expanse of cortex in which primary and secondary regions (i.e. large- and small-amplitude responses) hold information about face and object appearance.

Haxby et al. tested this model by investigating the patterns of response evoked in the ventral temporal cortex by faces and multiple categories of objects (face, house, cat, bottle, scissors, shoe, chair, scrambled image) in a series of runs on six subjects. Patterns of response were defined as those voxels with response that differed significantly by category and will be referred to as POR for future purposes. The data [3] were analyzed to determine whether the stimulus category that a subject was viewing could be identified on examining the similarity between the POR evoked by each category on even and odd runs. Within-category correlations and between-category correlations were compared to determine whether a POR to one category, such as chairs, could be distinguished from the pattern of response to a different category, such as shoes, with and without the exclusion of maximally responsive voxels. For the inclusion of maximally responsive voxels, The POR in object-selective ventral temporal cortex correctly identified the category being viewed in 96 percent of pairwise comparisons. Identification accuracy for faces, houses, and scrambled pictures was at 100 percent and identification accuracy for the small man-made objects (bottles, scissors, shoes, and chairs) was significantly better than chance for each category. For the exclusion of maximally responsive voxels, for example, within the cortex that responded maximally to houses, the POR correctly identified the category being viewed with 93 percent accuracy, 94 percent for small man made objects, and 83 percent for faces. These results demonstrate that POR in VT carries information about the type of object being viewed, even in cortex that responds maximally to other categories.

The work by Hanson et al. established Haxby et al. results while further extending the original analysis. Hanson et al. neural network classifier detected more general topographic representations and achieves an 83 percent correct generalization performance on patterns of voxel response in out-of-sample tests. Using voxel-wise analysis Hanson et al. showed that the same VT lobe voxels contribute to the classification of all object categories, suggesting that the code is combinatorial as Haxby et al. suggested. Our own analysis will adhere to the methods of Haxby et al. and Hanson et al. with the plan of reproducing the Haxby similarity method (comparisons between within-category correlation and between-category correlation) and reproducing and improving upon the POR classification rate with a neural network and homogenous methods. We will make the these studies reproducible in the sense that code used to obtain said results will be easily understandable and readable by others; any graph, statistics, etc. from these studies can be easily simplified and reproduced with the aid of well documented executable and readable code.

2 Data

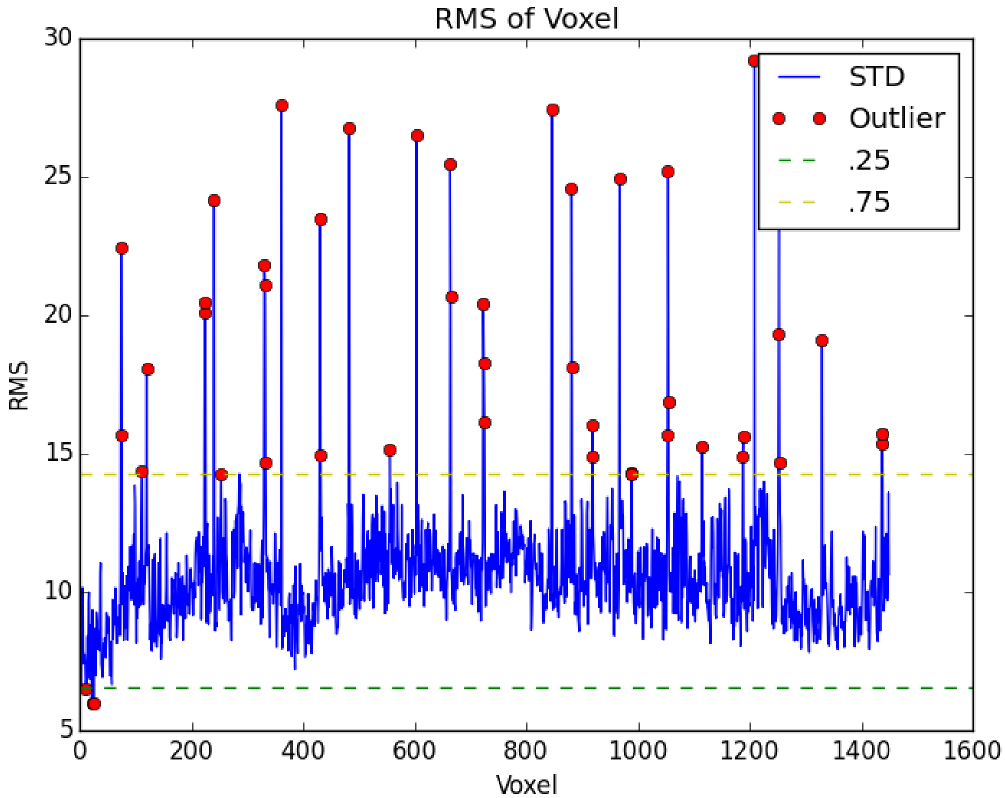
The data consists of 64 slices 64 X 40 BOLD collected from a GE 3T (repetition time = 2500 ms, forty 3.5-mm-thick sagittal images, field view of = 24 cm, echo time = 30 ms, flip angle = 90 percent). Patterns of neural response were measured with functional magnetic resonance imaging (fMRI) in six subjects while they viewed pictures of faces, cats, five categories of manmade objects. Twelve time series were obtained for each subject. Each time series began and ended with 12-s rests and contained eight stimulus blocks of 24-s duration, one for each category, separated by 12-s interval of rest. Stimuli were presented for 500 ms with an inter stimulus interval of 1500 ms. Repetitions of meaningful stimuli were pictures of the same face or object photographed from different angles; stimuli for each meaningful category were four images each of 12 different exemplars. The data shape for any particular run is (40, 64, 64, 121) that can be read as 64 slices 64 X 40 BOLD for 121 contiguous slices in time (i.e. 121 volumes of time).

3 Methods

3.1 Preprocessing/ EDA

The Haxby data consists of six folders for each individual subject. Each of these folders contains the fMRI data along within 12 folders, one for each run. The structure of the data is cumbersome and for reasons of reproducibility, and for our own sake, we implemented code to merge these 12 runs by calling on a function and passing through the argument of subject name (i.e. 'sub001', 'sub002',..., 'sub012'). This code conveniently merges the 12 runs for any specified subject. fMRI can have a considerable degree of noise. There are often volumes with an unusual degree of noise and for that reason these volumes can produce outliers in voxel time-courses. Another sign of an artifact in a volume is that a given volume is very different from the preceding volume. This would imply a sudden wide-spread shift in signal.

We calculated the standard deviation of every volume, 121x12 = 1452 volumes, for each subject and identified outliers with two methods. The first method was the interquartile range which is the value of the 75th percentile minus the 25th percentile. We might decide to declare a value as an outlier, if the value (i.e. voxel standard deviation) is greater than 1.5 * IQR added to the 75th percentile, or lower than 1.5 * IQR subtracted from the 25th percentile. The second method assesses outliers by taking the square root of the mean of the squared voxel values where these voxel values correspond to the difference of a subject's 3D volume from the subsequent volume. The interquartile range method is applied to these values to obtain outliers.



If we have done a good job of identifying and removing outliers, we would expect a drop in the residuals from a statistical model (e.g. linear model).

4 Results

4.1 Discussion

Most of our analysis consisted of exploring the structure of our data, comprehending the analysis of Haxby et al. and Hanson et al., and formulating and setting up major groundwork for the reproducibility aspect of our code for analysis. This left us with some time to preprocess the data by performing simple outlier identification; we also performed some rough convolution which needs some touching up. The scikit-learn package for machine leaning package we wish to use on the data requires a merging of a subjects 12 runs of data. A good amount of time was spent on merging the data and in understanding the ways of the package. The Git workflow further extended this time as those unfamiliar to the workflow practiced to become familiarized to it. The structure and study of the fMRI data itself is something new and unfamiliar territory; therefore, we made it a priority to understand the basics of previous analyses and structures of our data. Our future work will contain more analysis, for we are set to begin. In our next step we will reduce the dimension of our data (i.e. perform PCA or PLR), we will then produce a sparse model (i.e. perform ridge/lasso and cross validation to identify crucial voxels and appropriate tuning parameters), and determine the best way to split our data (i.e. perform cross validation on different statistical models).

References

[1] S. J. Hanson et al., *Combinatorial codes in ventral temporal lobe for object recognition*, NeuroIm-

age, 23 (2004), pp. 156–166.

[2] J. V. Haxby, *Distributed and overlapping representations of faces and objects in ventral temporal cortex*, Science, 293 (2001), pp. 2425–2430.

[3] J. V. Haxby et al., *Visual object recognition.* https://openfmri.org/dataset/ds000105, 2001.