

Classifying single trial fMRI: What can machine learning learn?

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Abstract

We describe three experiments combining neuroimaging and machine learning. The first experiment compares the performance of maximum likelihood and neural net classifiers for "brain reading" of fMRI data in the visual cortex. The second experiment applies the optimal classifier to measure the development of the face region in children and adolescents. While the previous experiments used block designs, the third experiment describes an event-related experiment where the classification algorithm learned something real, but not what was planned. The corroboration and validation of the classification results with brain images will be demonstrated.

Object classification by imaging of the distributed representation in the visual cortex was shown first shown by Haxby [1], and demonstrated on a per block basis by Cox and Savoy [2]. In adults, regions of the ventral-occipital cortex are involved in visual processing of faces, objects, and places. The first experiment attempted to classify the visual input of faces, scrambled faces, scenes, objects, and textures on a trial by trial basis for adults. Two classifiers were studied in a "train and test" paradigm. We used a maximum likelihood method with a leave-one-out approach, clipping outliers in the training data, selected features based only on the training set, and sequentially tested against all the cases in the data set. The Widrow-Hopf neural net approach started with a large superset of features selected by the maximum likelihood approach (from 500 to 2000 features), used four layers of hidden nodes, and learned the connection strengths by gradient descent and back propagation. The training sets were chosen at random in the data, and training continued until the maximum error was below threshold. Since the default SPM high pass filter left a bias at each end of the data that lowered classification accuracy, a new signal processing filter was developed to correctly pad the ends of the data. After this correction, both classifiers discriminated face from non-face with an average accuracy of 90% accuracy in adult subjects. Visual displays (Fig. 1) showed there was usually a clear difference in spatial distribution of BOLD signals for faces and non-faces in the slice through the fusiform gyrus. Conversely, classification errors could often be traced to temporal artifacts in the data.

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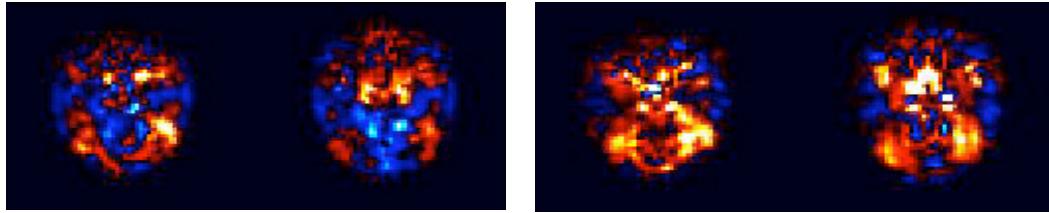


Figure 1: Two slices of single trial response to face (Left) and object (Right)

Next we asked whether face processing undergoes a prolonged development in children before reaching the adult level. Thus, in the second experiment we tested how the spatial pattern of BOLD signals within an anatomically specified ROI classified the nature of the input to the subject (G. Golarai [3,4]). A total of 40 subjects were divided into age ranges of 8-11 (children), 12-16 (adolescents), and 19-27 (young adults). The neural net classifier from the first experiment was used. Face classification accuracy was significantly lower among children compared to adolescents ($P<0.02$ 2-tailed t-test) and to adults ($P<0.01$, 2-tailed t-test, Fig. 2), consistent with continued face area specialization up to adolescence.

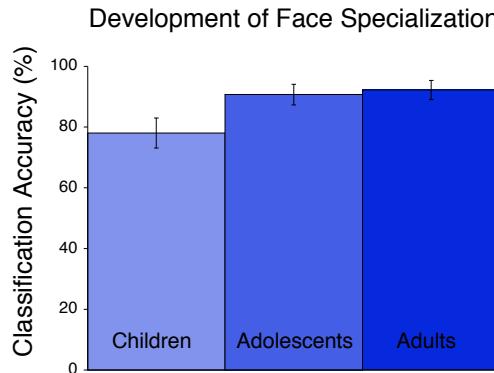


Figure 2: Face region classification accuracy is lowest for 8-11 year old children.

In the third experiment, we attempted to classify from fMRI images whether visual stimuli were successfully encoded in a subsequent memory paradigm [5]. Twelve subjects were scanned while observing images, and asked later if they recalled them. Using the same adaptive classifier method, accuracies were above the 50% level predicted by random chance. However, it appears that the classifier actually learned the subject specific average performance accuracy, rather than finding an accurate signature for trial by trial encoding of memory. We found this false effect could be eliminated by requiring the input training set to have an equal number of trials for each condition.

Our experience has shown that (i) machine learning algorithms can successfully learn to classify states in neuroimaging applications, (ii) they can help understand cognitive specialization, but that (iii) it is important to optimize the preprocessing steps of the fMRI analysis pipeline, and to use visual displays to review the spatial distribution of results.

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