Hierarchical Gaussian Naïve Bayes Classifier for Multiple-Subject fMRI Data

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1 Introduction

The Gaussian Naïve Bayes (GNB) [2] classifier has been successfully applied to fMRI data. However, it is not specifically designed to account for data from multiple subjects and is usually applied to data from a single subject (referred to as GNB-indiv). An extension to the GNB classifier has been proposed ([4], referred to as GNB-pooled), in which the data from all the subjects are combined together naïvely by assuming that they all come from the same subjects. However, this extension ignores subject-specific variations that might exist. Here I describe another extension of the GNB classifier—the hierarchical GNB classifier [3]—that can account for subject-specific variations, and in addition, has the flexibility to increase or reduce the weight of the contribution of the data from the other subjects based on the number of examples available from the test subject.

2 Method

The method assumes that for each feature and conditional on each class, the data y_{si} for a subject s is generated as

$$y_{si} \sim \mathcal{N}(\theta_s, \sigma^2)$$
$$\theta_s \sim \mathcal{N}(\mu, \tau^2).$$

This model is a hierarchical model, more specifically, a hierarchical normal model [1]. Assuming σ^2 as known and using a parametric empirical Bayes approach with uniform prior on (μ, τ^2), we can find that the θ_s that maximizes the conditional posterior $p(\theta_s|\mathbf{y}, \mu_{\mathrm{MP}}, \tau_{\mathrm{MP}})$ is given by

$$\theta_s = \frac{\frac{n_s}{\sigma^2}\overline{y}_{s\cdot} + \frac{1}{\tau^2_{\mathrm{MP}}}\mu_{\mathrm{MP}}}{\frac{n_s}{\sigma^2} + \frac{1}{\tau^2_{\mathrm{MP}}}}, \tag{1}$$

where μ_{MP} and τ^2_{MP} are estimated using maximum likelihood.

We can use equation (1), along with an estimate of σ^2, as parameters of the original GNB classifier.

3 Results

I apply the hierarchical GNB classifier to two datasets. The first dataset consists of fMRI activations of 13 subjects, where in each trial, each subject looked at a configuration of a sentence and a picture

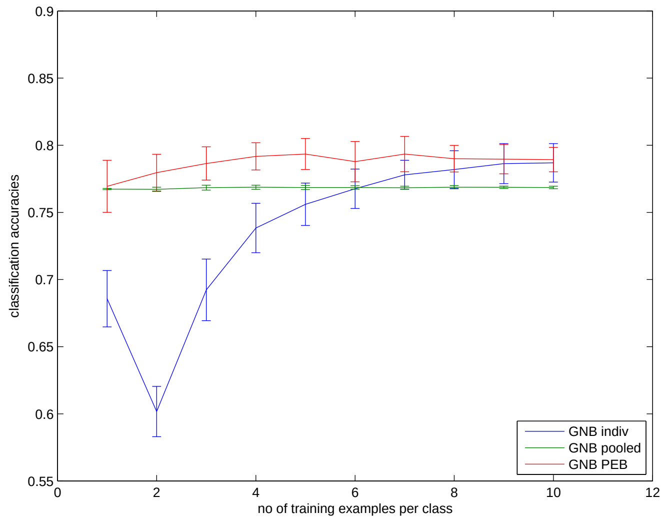

Figure 1: Starplus dataset, classification accuracies vs number of training examples for the hierarchical GNB and the two reference methods (GNB-indiv and GNB-pooled).

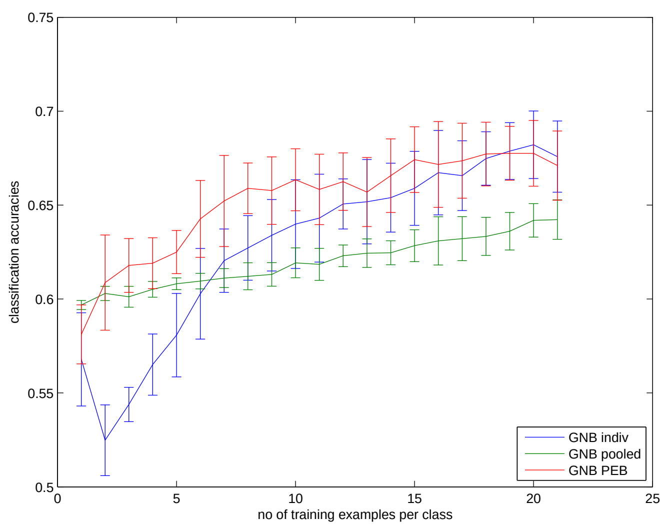

Figure 2: Twocategories dataset, classification accuracies vs number of training examples for the hierarchical GNB and the two reference methods.

or the reverse and had to determine whether they matched; the classification task for this dataset is to determine the class of the first stimulus in each trial based on the fMRI activations, and the result is given in Figure 1. The second dataset consists of fMRI activations of 6 subjects, where in each trial, each subject looked at a word belonging to one of two categories, and had to think about the properties of the word; the classification task for this dataset is to determine the category of the word in each trial based on the fMRI activations, and the result is given in Figure 2.

In the two figures, we can see that the hierarchical GNB classifier (GNB-PEB) is able to utilize the other subjects' data when the number of training examples is small, and at the same time, avoid the problem affecting GNB-pooled of not being able to increase the weight of the contribution of the test subject's data when the number of training examples increases.

References

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