Random Subspace Methods for Neuroimaging

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Functional Magnetic Resonance Imaging (*fMRI*) allows for a non-invasive indirect measurement of the brain activity with a relatively high spatial resolution. This technology locally records the variation in time of the oxygenated blood flow, called *Blood Oxygenation Level Dependent* (*BOLD*), which is somehow related to the variation of the local brain activity. The measurement is taken as a sequence of volumetric brain images, usually few hundreds, each made of several thousands voxels. The voxels are the smaller portion of brain (usually 2-3 millimeters diameter) where *BOLD* signal can be recorded.

The typical experiment consists in a stimulation protocol with contrasts that maximally activate some cognitive functions. The recorded data is then analyzed to locate the portion of brain related to the specific cognitive task. This analysis, known as *brain mapping*, produces a volumetric image where the voxels are coloured according to their relevance.

In a pattern recognition framework, brain mapping can be conceived as a problem of feature selection. There are basically three approaches to feature selection: *embedded*, *wrapper*, and *filter* methods. Differently from many other domains, the selection of features in the brain mapping framework can not be driven by the performance of a classifier, like in *embedded* and *wrapper* methods. The main requirement here is the redundancy preservation, i.e., all relevant voxels must be retrieved, even if redundant. For this reason, the most appropriate approaches appears to be the *filter* methods, where the features are ranked according to some information-based scores or statistical indices. As a matter of fact, the most common brain mapping approach consists in a uni-voxel linear analysis (commonly referred as *GLM* analysis) with a statistical test over it. The *filters* approach has, however, some limitations: cross-relationships between different parts of the brain may remain undiscovered, moreover, the retrieved features are good descriptors not necessarily allowing for good discrimination between conditions.

The increasing interest on distributed patterns of activity is rising the attention of the neuroscience community to the *Multi-Voxel Pattern Analysis* (*MVPA*) methods, where many voxels are jointly analyzed with discriminative methods. The typical approach aims at predicting the cognitive states with a classifier given the brain activity [1]. This approach, however, does not directly answer the brain mapping issue, which is usually addressed ex post, on the trained classifiers, determining the relevance of the used voxels for the classifier itself.

The main challenge of this approach is to deal with the huge dimensionality of the features space, and the excessive feature-to-instance ratio. There are few *MVPA* solutions directly addressing this task. The *Elastic-Net* [2] and the *Recursive Feature Elimination* [3] perform a whole-brain analysis, finding distributed relationships. These *embedded* approaches, however, suffer of stability problems (i.e., two different runs may produce two completely different solutions). The well known and robust *Searchlight* method [4], on the other side, perfectly copes with the stability issue finding local patterns of activity. The method, however, still suffer some limitations: the spatial bias prevents the detection of distributed pattern of activity; the brain maps overestimate the areas of activation; there is no distinction between correlated and anti-correlated areas; and a whole-brain analysis is not supported.

To cope with all above problems we proposed a wrapper-based solution exploiting a *Random Subset Method* (*RSM*) for feature selection [5]. This multi-variate method is essentially an ensemble method exploiting a bootstrapping principle. Many classifiers are trained with different random subsets of the feature space. It may be considered a *wrapper* method generalizing *Searchlight* to a distributed analysis. The proposed solution presents therefore some advantages. It performs a multi-variate analysis of the whole brain dealing with the unfavorable ratio between voxels and volumes, and it preserves the voxels redundancy. We have proven that under some conditions the method provides results equivalent to the standard *GLM* analysis.

The model has been implemented using python, and exploiting the pyMVPA v 0.4.7 library, both for the management of the neuroimaging data and for the exploitation of the classification framework. The library providing the random subspace method will be deployed as open source software.

References

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