Machine learning in fMRI

Feature Extraction

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Outline

1. Motivation
   - The feature extraction problem
   - Feature extraction examples

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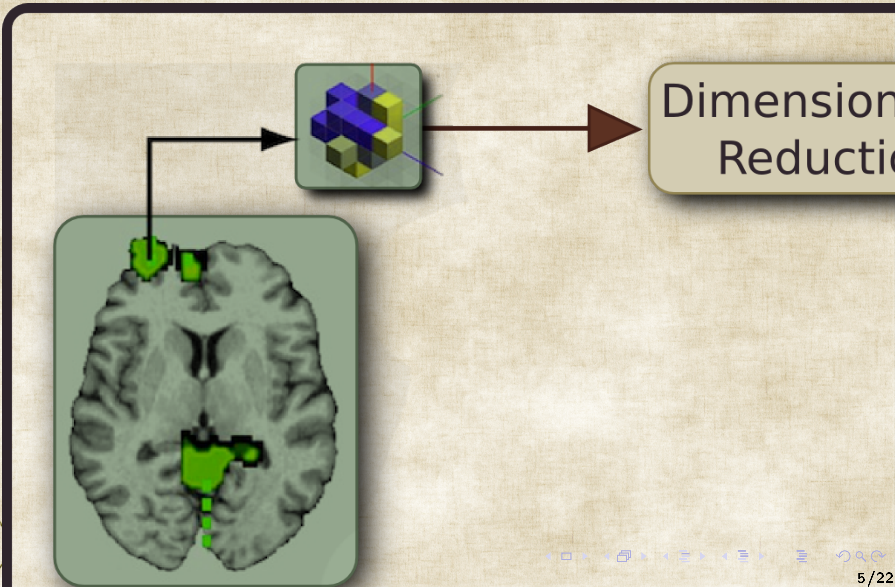
The feature extraction problem I

- Feature extraction is a special form of dimensionality reduction.
- There are common algorithms for dimensionality reduction which can be applied to reduce the dimensionality of the data:
  - Principal component analysis (PCA)
  - Independent Component Analysis (ICA)
- Feature extraction methods can be more specific to the type of data we are analysing.
  - The meaning of the data is implicit to the feature extraction method.

The feature extraction problem in fMRI



The feature extraction problem in fMRI I

- The number of possible feature sets we can extract from fMRI acquisitions of a determined group is very large.

The feature extraction problem in fMRI II

- It can depend on:
  - Experimental design
  - Number of subjects
  - Type of experiment we want to perform
  - The techniques we can use
  - The techniques used in the literature for similar situations

The feature extraction problem in fMRI III

- Group normalization is an issue in fMRI.
  - Finding a feature set with the same meaning and the same size for all the subjects in our data set is not an easy task.
  - In addition, the algorithm should be able to extract the same features from new unseen subjects.

Examples I

- Dimension reduction and feature extraction using ICA[1]

Examples II

- Use average intensity in multiple TRs [2]
    - a drawback of this method is a reduction in the number of samples available for training.

Examples III

- [3] At each stimulus presentation, a trial $t\,(t = 1, \ldots, T)$ is formed considering N_{pre} and N_{post} temporal samples (before and after stimulus onset respectively) of the pre-processed time course of activity.
- A trial estimate of the response at every voxel $v\,(v = 1, \ldots, V)$ is then obtained by fitting a General Linear Model (GLM) with one predictor coding for the trial response and one linear predictor accounting for a within-trial linear trend.
- The trial-response predictor is obtained by convolution of a boxcar with a double-gamma hemodynamic response function (HRF)

Examples IV

- Firstly, let S and R be the sets of selected features and the group of features that might be chosen: we start with $S = \emptyset$ and $R = \{x_i\}, i = 1..N$ and the algorithm will stop when R is empty.
- This algorithm uses an hybrid stepwise selection.
  - The forward strategy adds at each step the most informative feature given the previously selected ones.
  - The backward strategy removes from R all the features which are not informative at this step: we indeed assume that those features will not be informative in the next steps.
- In order to select a feature, we compute at each step, for each dimension x in R, the value $MI1 = MI(S\{x\}, Y)$, which yields the amount of information about Y present in S and x. [4]

Examples V

- To break the complexity of the problem, we first perform a hierarchical clustering of the voxel-based signals, under connectivity constraints, so that only spatially connected clusters are created.
- At that stage, we ignore the target information, but use the variance-minimizing approach of Ward's algorithm [12] in order to ensure that cluster-based averages provide a fair representation of the signal within each cluster. Only adjacent clusters can be merged together.
  - The purpose of this procedure is to use the hierarchical parcellation to guide the search of informative regions within the volume of interest.
- Thus, at a given level in the hierarchy, the data is reduced to NC cluster-based averages, which significantly decreases the computational complexity compared to a voxel-based approach with $N_v \gg NC$ voxels. [5]

Examples VI

- Thus, in order to further reduce the dimensionality of the data, we parcellate this region in 200 parcels with a variant of Ward's algorithm, and we average the signal within each parcels.[6]

Examples VII

- We used PCA to find the bases of reduced dimensionality.
- In the present work, we did not exclude any PC in the analysis, that is, the PCA step is loss–less dimension reduction and represents only a change of the coordinate system to the subspace spanned by the measured brain volumes. [7]

Examples VIII

- After realignment of the functional volumes using SPM5,1 we use the IBASPM toolbox (Tzourio-Mazoyer et al., 2002; Alemán-Gómez et al., 2006) to build an individual brain atlas based on the structural MRI, containing $M = 90$ anatomical regions.
- While this is a relatively coarse atlas, it is an essential step to allow for inter-subject variability and enable inter-subject decoding with good generalisation ability to unseen subjects — using group-level normalisation and atlasing is not an option in this setting.
- Furthermore, the structural atlas serves only as a basis for computing a much lower resolution functional atlas. Using a more fine-grained atlas might result in some regions disappearing completely in the functional atlas.

Examples IX

- Another benefit of using the AAL atlas is that it offers a way of comparing results with several other studies [8]

Summary

- Feature extraction methods is a special form of dimensionality reduction.
- In fMRI there are many different algorithms for feature extraction in the literature.
- The difficulty of a good feature extraction method lies on finding:
  - Common features for all the subjects in the data set (due to spatial normalization problems)
  - The best fit to the experimental design and classification objective of our experiment.

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