Multivariate pattern interpretation using PRoNTo

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Introduction

Recently, machine learning models have been applied to neuroimaging data [1], allowing to make predictions about a variable of interest based on the pattern of activation or anatomy over a set of voxels. The main drawback of multivariate machine learning models is that local inference with respect to the brain neuroanatomy is complex: although linear models generate weights for each voxel, the model predictions are based on the whole pattern and therefore one cannot threshold the weights to make regional statistical inferences as in univariate analysis.

Aim: Facilitate the interpretation of weight maps from linear kernel machines.

Methods

Data and Design

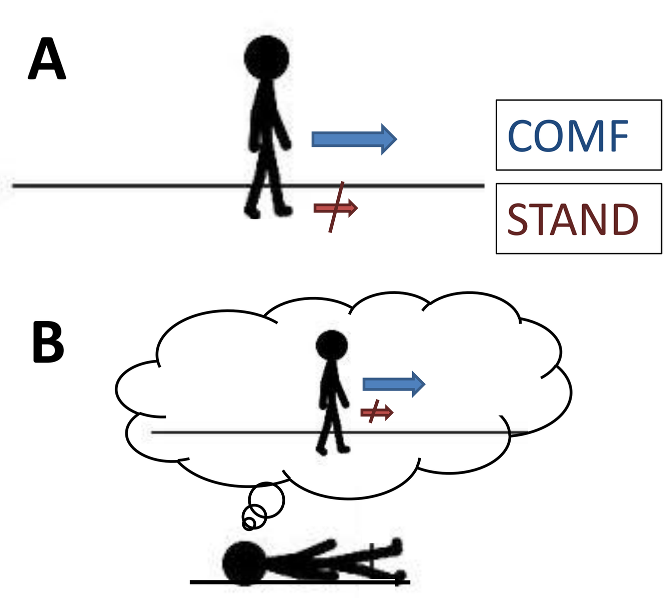
15 controls (7M, 63.8 ± 8.1 y): CTRL

(**A**) *Before* fMRI:

- Walk at comfortable pace along a 25m path.

(**B**) *During* fMRI: Imagery of

- Standing on the path (STAND, 8 trials)
- Walking at a comfortable pace (COMF, 8 trials)



Analysis

- Pre-processing using SPM8.
- The parametric maps of each condition were computed using a General Linear Model [2]
  → 2 contrast images (STAND/COMF) per subject.

Classification performed with PRoNTo [3] :

- Binary Support Vector Machines (SVM, [4]) for between tasks comparison (STAND/COMF).
- Balanced and class accuracies were obtained using leave-one-subject out cross-validation.
- The significance of the results was assessed by random permutations (n=1000).

Weight maps

- Regional average of the weights NW_{ROI} using anatomical atlas (AAL, Figure 1): $$NW_{ROI} = \frac{\sum_{v \in ROI} |W_v|}{N_v}$$
  W_v: weight of voxel v, N_v: number of voxels in region ROI.
- Rank the regions according to their proportion of NW_{ROI}
- Expected rank cross folds:
  $$E(Rank_{ROI}) = 1 \times f(1) + 2 \times f(2) + \ldots + N_{ROI} \times f(NROI)$$
  $f(x)$: frequency that region ROI was ranked x^{th}
  N_{ROI}: number of regions

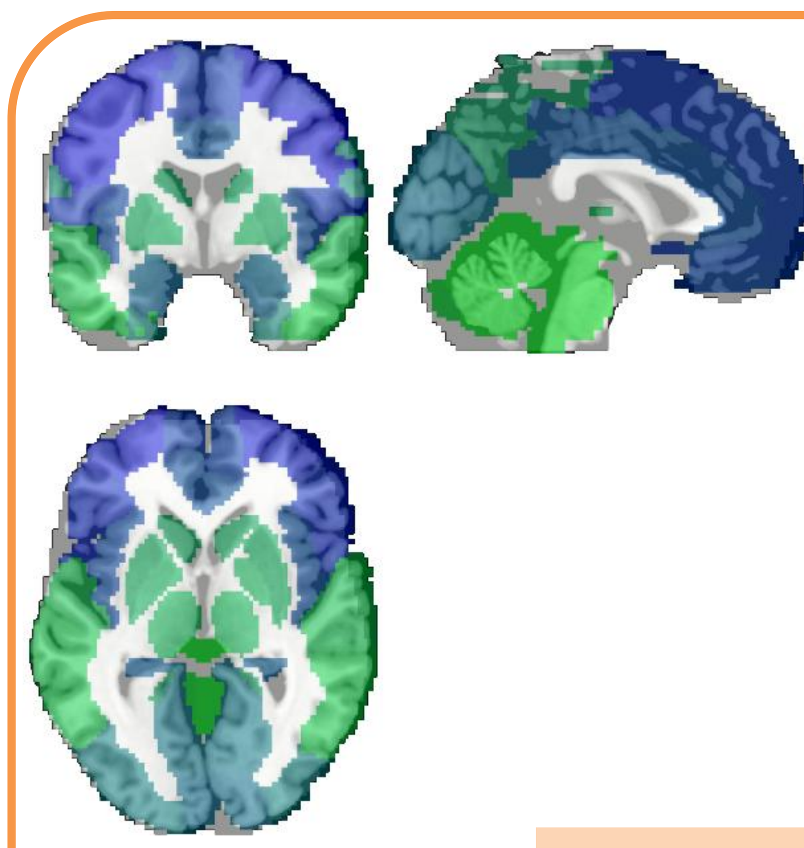


Figure 1: Mask considered for the discrimination between the COMF and STAND conditions overlaid with the labelled anatomical template (in colour) used to compute *NW*. Please note that weights corresponding to voxels not associated with any labelled region (in grayscale) are pooled together in a supplementary region called 'others'.

Results

Classification

The discrimination between COMF and STAND led to a significant balanced accuracy of 86.7% (STAND: 100%, COMF: 73.3%).

Weight maps & Pattern localization

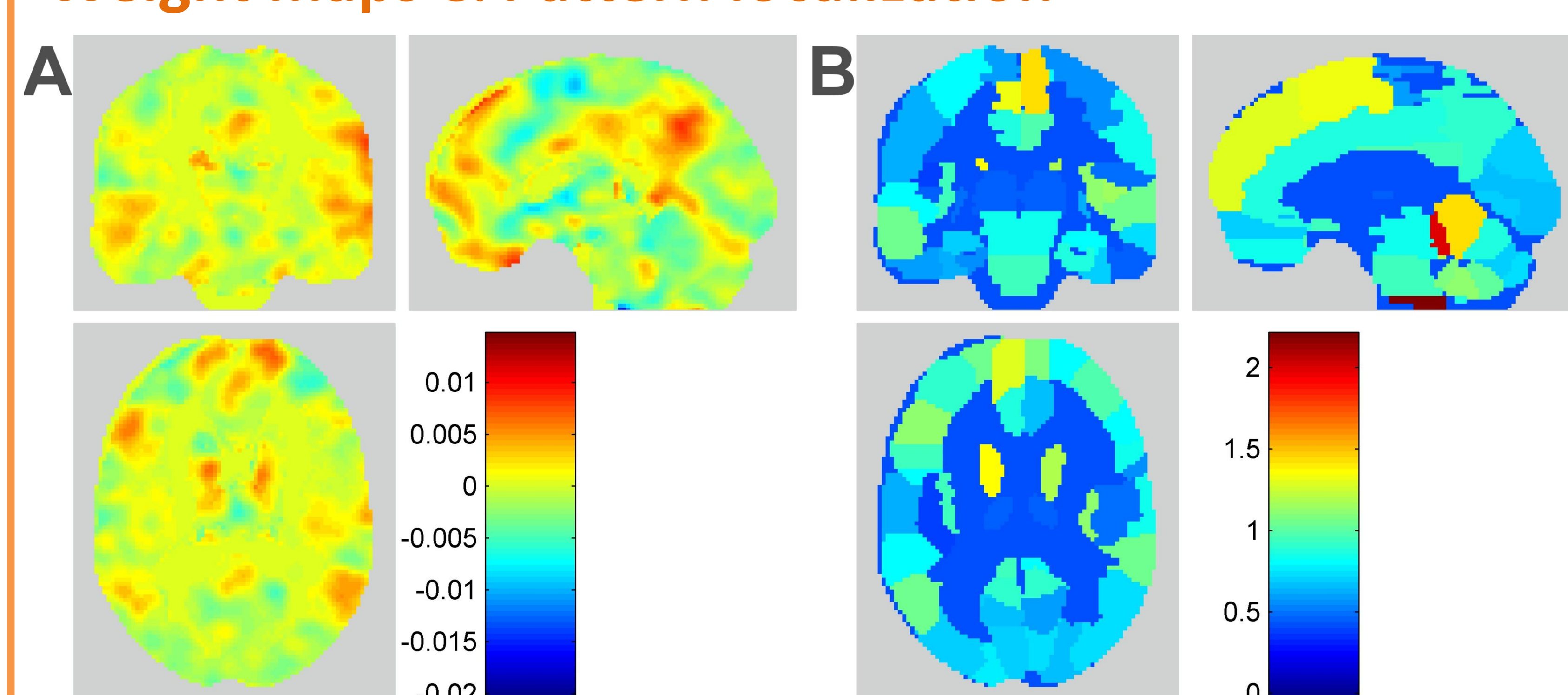


Figure 2: Weights (**A**) and proportions of *NW* for each labeled region (**B**), corresponding to the COMF versus STAND comparison. Displays: PRoNTo.

The univariate results of [5], and the computed ranking (according to NW) showed a nice overlap (Table 1), with the cerebellum vermis, cerebellum cortices, caudate nuclei, medulla and supplementary motor area regions listed in the top 15.

	Top 10 NW_{ROI}	NW_{ROI} (in %)	Reported in [5]
1	Medulla	2.0694	Yes
2	Vermis 3	1.9593	Yes
3	Cerebellum 3 (L)	1.6953	Yes
4	Vermis 4-5	1.4690	Yes
5	SMA (R)	1.4312	Yes
6	Sub-temporal (L)	1.3835	-
7	Caudate (L)	1.3383	Yes
8	SMA (L)	1.2835	Yes
9	Inf frontal (L)	1.2667	Yes
10	Angular (L)	1.1899	-

Table 1: Top 10 (arbitrarily fixed number for illustration) of the labelled regions according to NW_{ROI}. The right column indicate whether each region was previously reported in univariate results ([5], Yes) or not (-). SMA stands for Supplementary Motor Area, and L and R for lateralization.

Conclusions

1. Methodology to ease the interpretation of weight maps obtained from linear kernel machine learning models.
2. Based on a priori anatomical knowledge according to atlases → atlas dependent
3. Could be applied to sparse models in voxel space, accuracy maps from searchlight [6] or to the "source" pattern instead of the model weights [7].
4. Implemented in PRoNTo [8].

References

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Acknowledgments

Fonds de la Recherche Scientifique (FRIA-FNRS), the University of Liège.
Wellcome Trust Centre for NeuroImaging.
Pascal II Harvest Project.