Introducing the BrainOwl

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Wolberslab Lab Meeting, 30.1.2019

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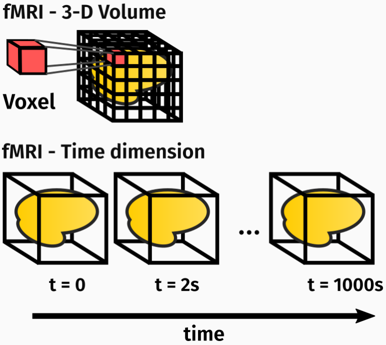
Aging & Cognition Research Group

fMRI univariate data analysis

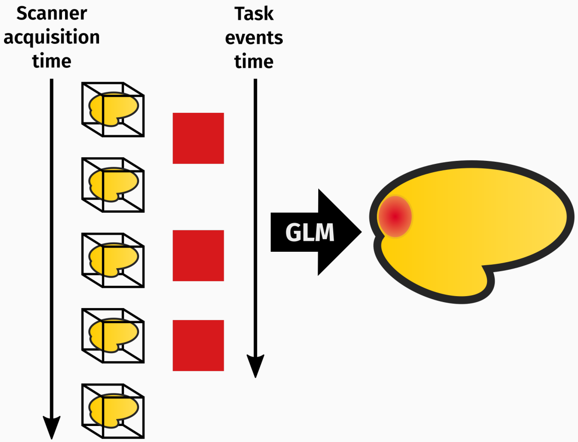
fMRI data

The data resulting from fMRI is 4 dimensional (structural is 3-D). The extra time dimension allows us to analyse how brain activity changes during the task.



Putting it all together

We can analyse the data to detect changes in activation using a General Linear Model (GLM), a massive-univariate analysis.

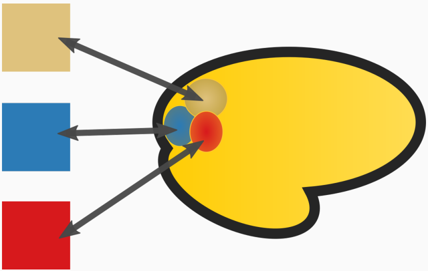


fMRI multivariate analysis: decoding

Asking about categories

Maybe we would like to ask different scientific questions:

1. Can we distinguish categories from the task?
2. Can we find cluster of voxels that discriminate among those categories?



Model

Our proposal to answer those questions is to use a linear model.

$$y = Xw$$

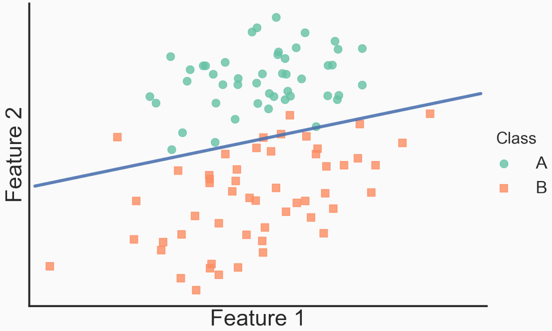
But, we have too many voxels (features) and too few images (samples). That is why we add an extra term to the problem to be solved called regularization, $J(w)$.

$$\hat{w} = \underset{w}{\arg\min}\, \mathscr{L}(y, X, w) + J(w)$$

The solution that we obtain is a vector of weights, $\hat{w}$ with one weight per voxel: the weight map.

If things were this easy...

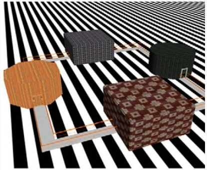
Only two features (e.g., voxels) and many samples:

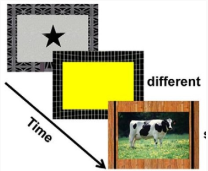


In neuroimaging, we have thousands of features and we cannot plot the data. Instead, we show the weight map.

A real experiment

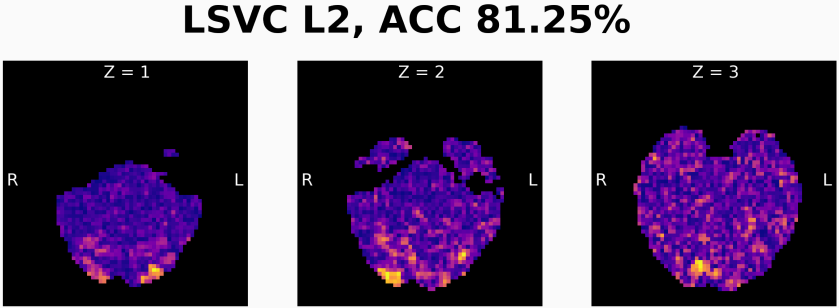
In this task, participants could be in any of four different rooms[1].





[1] Shine, J. P. et al. *Journal of Neuroscience* **2016**, *36*, 6371–6381.

Decoding a real experiment

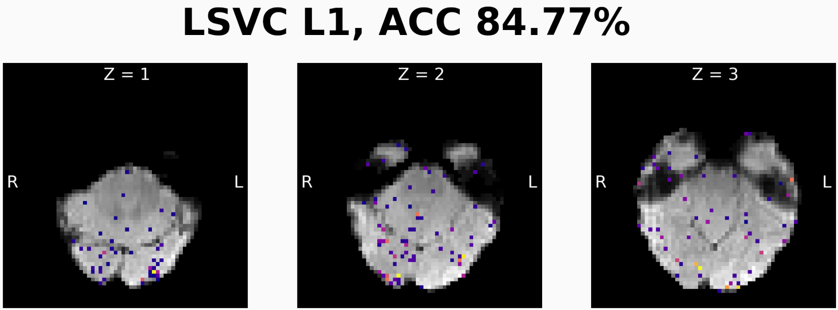


1. The accuracy (ACC) tells us most of the time the right room is identified (25% is random guess).
2. The weight map is *dense*: all weights are $\neq 0$.

Which voxels are the most relevant?

Sparsity

We can also find a *sparse* solution, i.e., many voxel weights are set to 0.

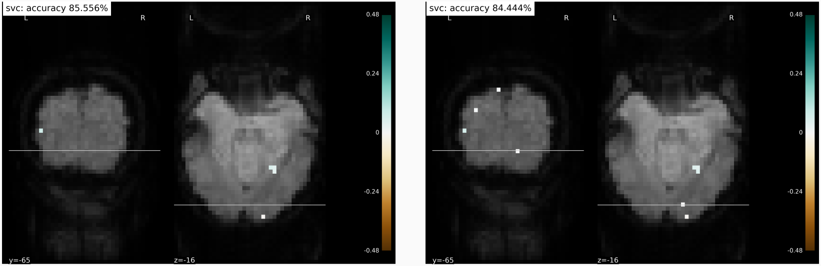


1. Accuracy is even better.
2. Non-relevant voxels are set to 0, but some relevant may be too (e.g., correlated voxels)!

Is the solution unique?

Is the solution unique? Not necessarily

An example of a highly sparse model: SVC with l_1 regularization and Haxby's faces vs. houses



The outcome after running the same analysis with the same conditions: two different weight maps.

Structured sparsity

Why structured sparsity?[2]

Summary so far:

	Pros	Cons
Dense (l_2)	stable	all voxels appear relevant
Sparse (l_1)	few chosen voxels	unstable

[2] Baldassarre, L. et al. *2012 Second Int. Work. Pattern Recognit. NeuroImaging*.

Why structured sparsity?[2]

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Structured sparsity offers a middle ground solution that is stable and selects whole relevant areas.

[2] Baldassarre, L. et al. *2012 Second Int. Work. Pattern Recognit. NeuroImaging*.

Structured sparsity

In a decoding analysis wishlist,

- take into consideration spatial and temporal information,

Structured sparsity

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To favour structured sparsity solutions, we need to use particular regularization terms.

BrainOwl

BrainOwl is a classifier based on the *Ordered Weighted* l_1 (OWL)[3] norm.

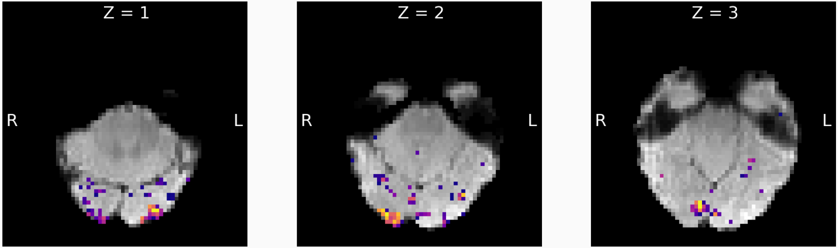
$$J_v(w) = \sum_{i=1}^{n} |w|_{[i]} v_i = v^T |w|_{\downarrow}$$

The OWL norm is robust to correlations and can be implemented efficiently.

[3] Zeng, X.; Figueiredo, M. A. T. *arXiv* **2015**, Bogdan, M. et al. *The Annals of Applied Statistics* **2015**.

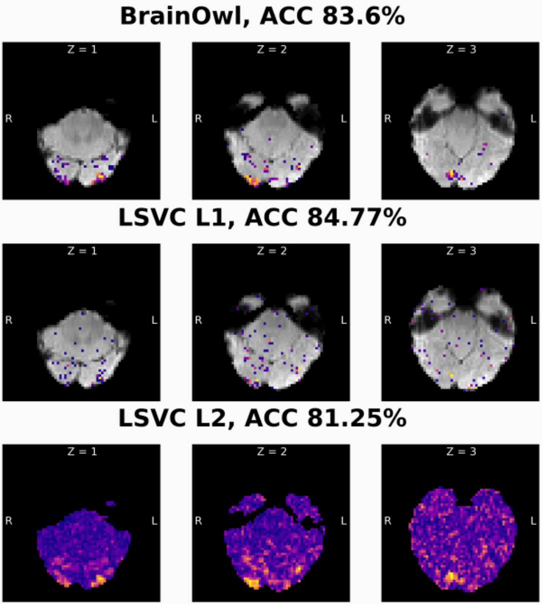
Rooms question revisited

BrainOwl, ACC 83.6%



1. High accuracy ensures we can distinguish rooms.
2. Weight map shows now only selected areas.

Summary: dense, sparse, and structured sparse



Final words

BrainOwl was developed for whole brain decoding, but it is not only limited to that. It can be used with any categorical data (classification) that you have. From other neuroimaging techniques (e.g. MEG, EEG) to behavioral tests, for example.

Useful links:

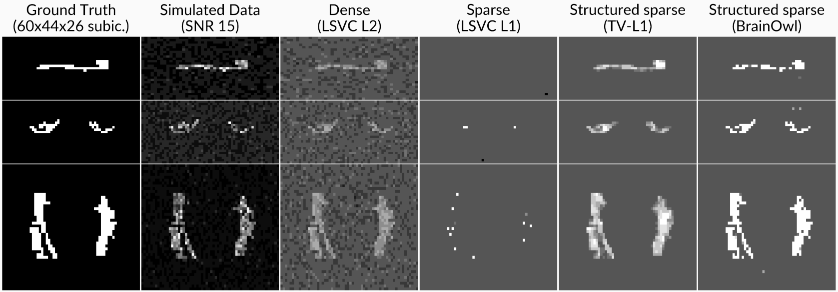
- BrainOwl
  `github.com/jpvaldes/brainowl`
  Soon in `www.wolberslab.net`
  Simply install with `pip install brainowl`
- nilearn contains alternative decoders (TV-L_1, GraphNet)
  `nilearn.github.io`
- scikit-learn, ML library
  `scikit-learn.org`

Thank you!

Now, *live demo time*.

Extra slides

Other structured sparsity decoders



There are other structured sparsity classifiers implemented like *Sparse Total Variation* (TV-l_1)[4] or *Graph-Net*[5].

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[4] Gramfort, A. et al. *2013 Int. Work. Pattern Recognit. Neuroimaging.*
[5] Grosenick, L. et al. *Neuroimage* **2013**, *72*, 304–321.

Structured Sparsity: Graph-Net[6]

Basic idea: look for a regularization term promoting sparsity and imposing structure at the same time.

The starting point is the *Elastic-Net*, a regression problem with

$$J(\mathbf{w}) = \lambda_1 \|\mathbf{w}\|_1 + \lambda_2 \|\mathbf{w}\|_2^2$$

where the l_2 term is substituted by a new term $\lambda_G \|\mathbf{w}\|_G^2$. The new term can incorporate spatial and temporal information, e.g. using the discrete Laplacian.

Derivatives of the coefficients encourage smooth solutions (i.e., penalize roughness) while the l_1 term promotes sparse solutions.

[6] Grosenick, L. et al. *Neuroimage* **2013**, *72*, 304–321.

Structured Sparsity: TV-l_1[7]

The idea behind *Sparse Total Variation* (TV-l_1) is similar to Graph-Net.

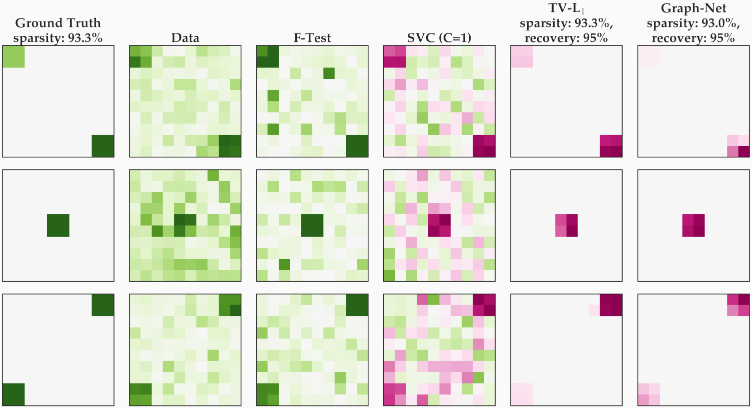
$$J(\mathbf{w}) = \lambda \left(\|\mathbf{w}\|_1 + \|\nabla \mathbf{w}\|_1 \right)$$

This time, the TV term, $\|\nabla \mathbf{w}\|_1$ favors sharp contours and piece-wise constant solutions to the regression problem, in contrast with the Graph-Net that prefers smoother solutions.

[7] Gramfort, A. et al. *2013 Int. Work. Pattern Recognit. Neuroimaging*.

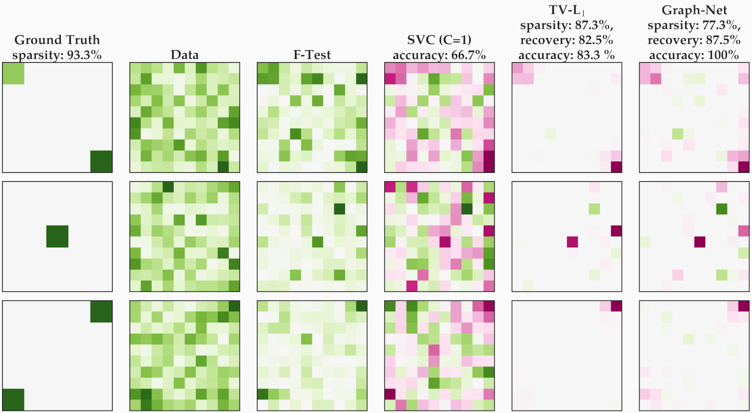
Example: Noisy Data

A set of simulated noisy data consisting of 30 samples and 2 clases.



Example: Noisier Data

Same ground truth but noisier data.



Regularization: Purpose

Regularization

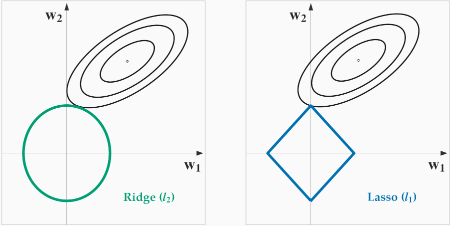
- helps with overfitting,
- can do feature selection ($\rightarrow$ sparsity),
- and is necessary to solve the mathematical problem when the number of dimensions is very high (because it is ill-posed).

Regularization: How does it do it?

Regularization is a term, $J(\mathbf{w})$, added to the optimization problem:

$$\hat{\mathbf{w}} = \arg\min_{\mathbf{w}} \|\mathbf{y} - \mathbf{X}\mathbf{w}\|_2^2 + \lambda J(\mathbf{w})$$

	$J(\mathbf{w})$	Effect
Ridge, l_2	$\|\mathbf{w}\|_2^2 = \sum_{i=1}^N w_i^2$	Shrinkage
Lasso, l_1	$\|\mathbf{w}\|_1 = \sum_{i=1}^N \lvert w_i \rvert$	Sparsity



Regularization: Effect on Coefficients