Quot capita, tot sententiae: Don't Forget to Use Anatomical Features into the Alignment of fMRI Data

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Introduction

Multi-subjects fMRI studies permit to **compare** studies across subjects, to generalize and to validate the results.

The anatomical and functional structure of brains vary across subjects even in response to identical sensory inputs.

"Quot capita, tot sententiae"[1]: **ALIGNMENT STEP**

- **Anatomical Alignment** → Talairach space [2];
- **Functional Alignment** → Hyperalignment [3].

[1] Terenzio, Phormio, 161 a.C.
[2] Talairach, J. J, and P. Tournoux. (1988).
[3] Haxby, J. V., et al. (2011).

fMRI data

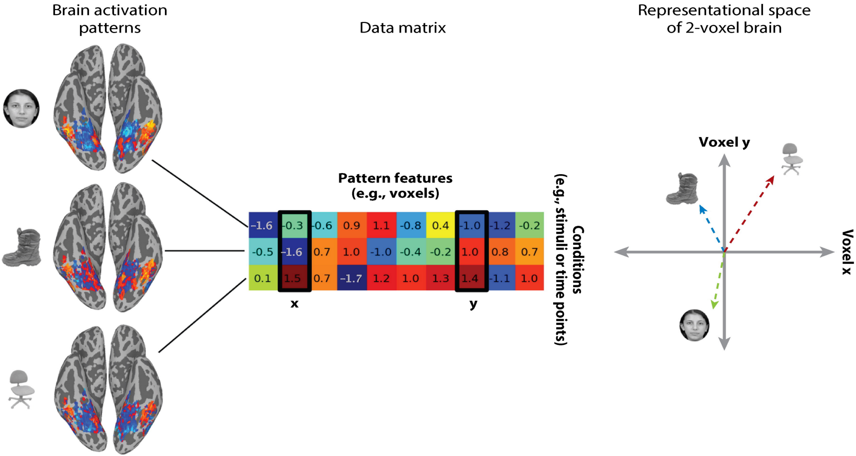
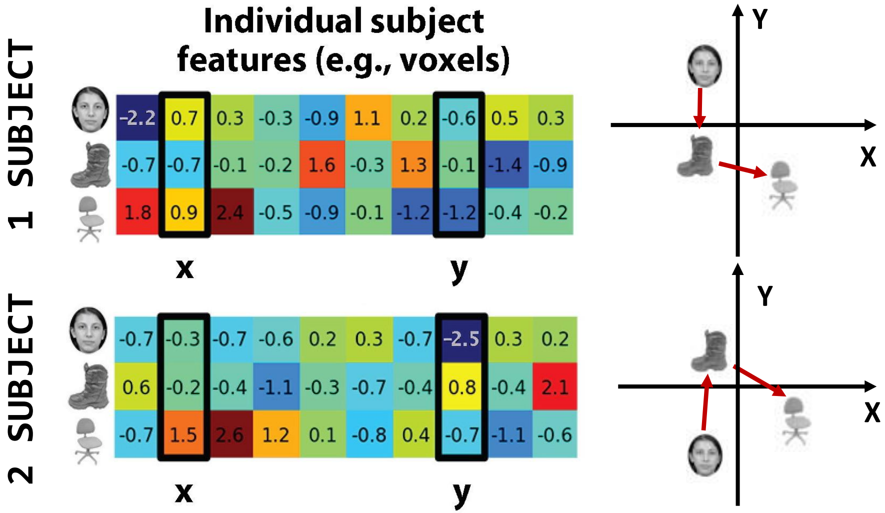


Figure: Haxby, J. V., et al. (2011). "A common high-dimensional model of the representational space in human ventral temporal cortex." Neuron, 72 (1): 404–16.

Misalignment fMRI problem



Misalignment fMRI problem

Each **subject** i is represented by a matrix $\boxed{X_i} \in \mathbb{R}^{n \times v}$:

- the **rows** represent the **response stimuli activation** of voxels

  $\longrightarrow$ the stimuli are time synchronized

- the **columns** represent the **time series of activation** for each v voxel

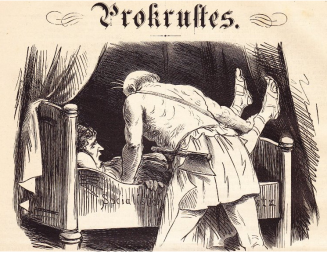
  $\longrightarrow$ not assumed to be in correspondence across N subjects.

The neural actives in different brains are **noisy rotations** of a common space.

Procrustes Method

The **Procrustes** method [4] uses **similarity transformation** to match matrices onto the **reference** one as close as possible.

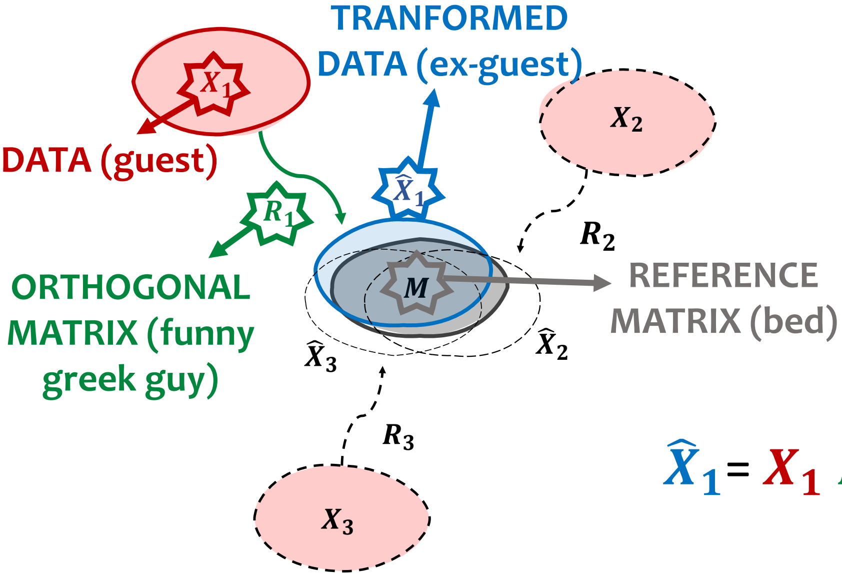
$$\boxed{\min_{R_i} \sum_{i=1}^{N} ||X_i - MR^\top||_F^2 \quad \text{subject to} \quad R^T R = I_v}$$



IN A NUTSHELL

Find the **best orthogonal** matrix-transformation that **MINIMIZE THE DISTANCE** between X_i's (guest) and M (bed)

[4] Schonemann, P. H. (1966). A generalized solution of the orthogonal Procrustes problem. Psychometrika, 31 (1): 1–10



TRANFORMED
DATA (ex-guest)
X_1
DATA (guest)
X_2
$\hat{X}_1$
R_1
R_2
ORTHOGONAL
MATRIX (funny
greek guy)
M
REFERENCE
MATRIX (bed)
$\hat{X}_3$
$\hat{X}_2$
R_3
X_3

$$\hat{X}_1 = X_1 R_1$$

Our method

Hyperalignment is a sequential approach of the Procrustes solution $\rightarrow$ No statistical approach and optimization criteria.

We rephrase it as **statistical model**:

$$\boxed{X_i = MR_i + E_i \qquad \vec{E}_i \sim \mathcal{N}_{nv}(0, \Sigma)}$$

We think that also the **anatomical features** are important!

Use **prior distribution** (Fisher Von Mises[5]) for $\boxed{R_i}$ capturing the 3-dimensional coordinates euclidean distance between voxels.

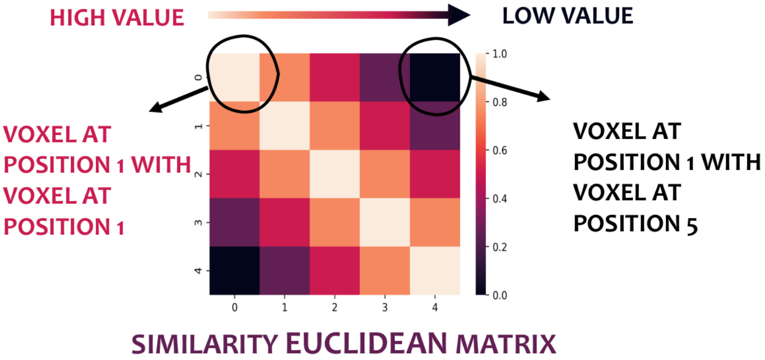
$$\boxed{f(R_i) \propto \exp(k \operatorname{tr}(Q^\top R_i))}$$

[5]Downs, T. D. (1972). Orientation statistics. Biometrika, 59 (3): 665-676

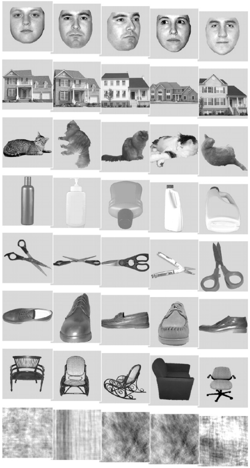
The *magic* matrix $\boxed{R_i}$ performs a **linear combination** of voxel activations to create the new image.

Combine **CLOSER voxels**!

Thanks to the prior distribution, we can exploits this information defining its **location** parameter Q as ...

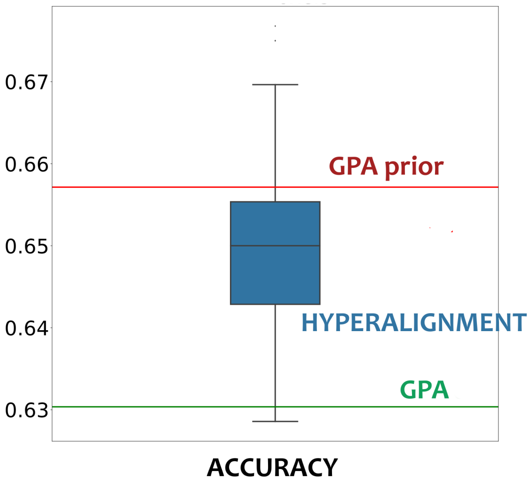


Faces and Objects Data



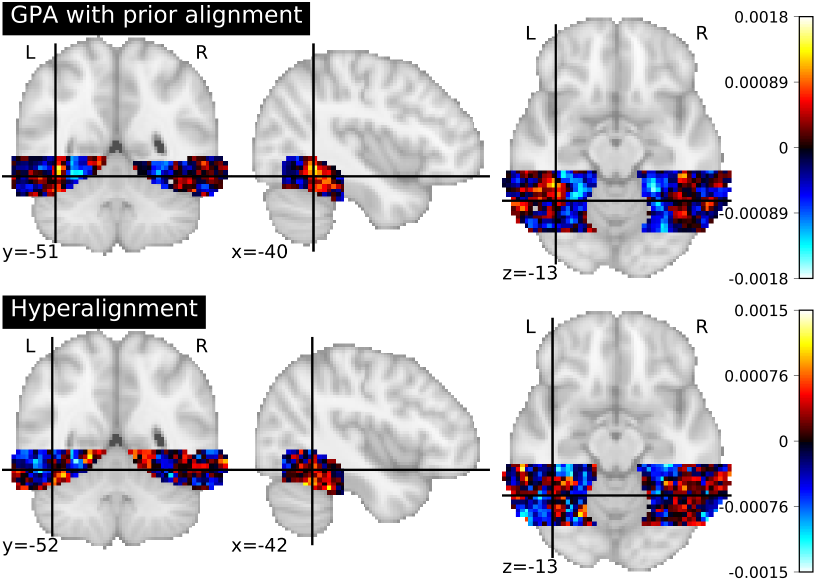
- We align the images of the **Ventral Temporal Cortex** of 10 subjects watching static, grey-scale images of faces and objects;
- The **Multi-class Linear Support Vector Machine** is used as classifier with leave one out subject cross-validation;
- We **permute** 100 times the order of the subjects.

Faces and Objects Data



Using the **anatomical alignment** the accuracy equals to 0.359.

Faces and Objects Data



Take-home message

The **Procrustes method with spatial prior**:

- doesn't depend on the **order of the subjects** as Hyperalignment $\rightarrow$ **low replicability**;
- returns a **unique solution** of the rotation matrix having **topological/anatomical meaning** $\rightarrow$ rotation matrices are more understandable;
- improves the **between-subjects classification**, the functional alignment captures the fine-grained patterns of neural activity;
- leads to a **smoother map** of classifier coefficients.

You can find the algorithm on GitHub: angeella/priorGPA.

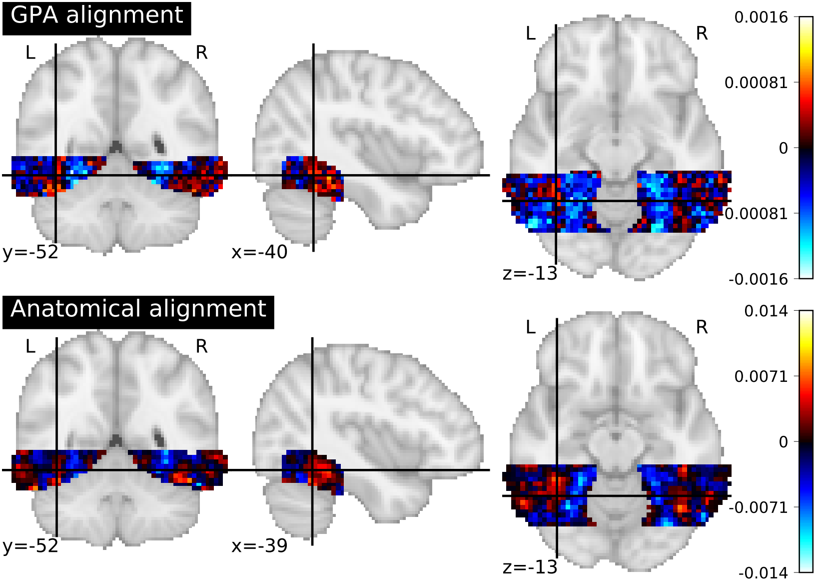
ADDITIONAL MATERIAL

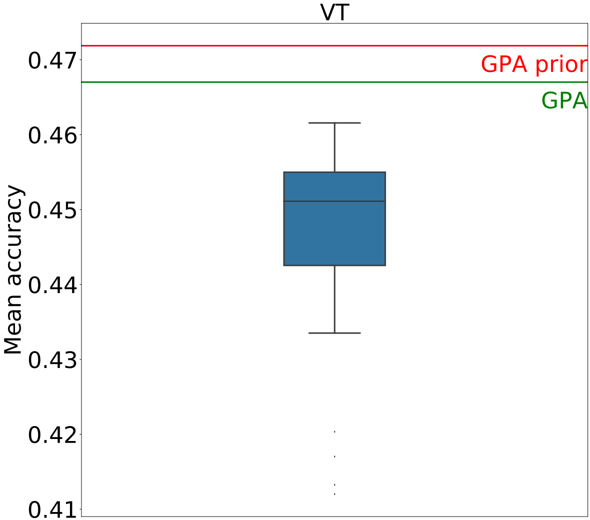
Algorithm

Require: X_i, k, Q, $\mathtt{T}$, $\mathtt{maxIt}$,

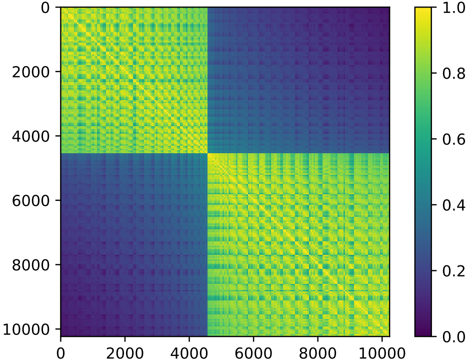
$M \leftarrow \bar{X}$ ▷ Reference = global mean
$\mathtt{count} \leftarrow 0$
$\mathtt{dist} \leftarrow \mathtt{Inf}$
while $\mathtt{dist} > \mathtt{T}$ & $\mathtt{count} < \mathtt{maxIt}$ **do**
  for $i = 1$ to N **do**
    $U, \Sigma, V \leftarrow \mathtt{SVD}(X_i^\top M + k \cdot Q)$
    $\hat{R}_i \leftarrow UV^\top$
    $\hat{X}_i \leftarrow X_i \hat{R}_i$ ▷ Update X_i
  end for
  $M_{\text{old}} = M;$ ▷ Save M
  $M = \bar{\hat{X}};$ ▷ Update M
  $\mathtt{dist} \leftarrow ||M - M_{\text{old}}||_F^2$
  $\mathtt{count} \leftarrow \mathtt{count} + 1$
end while
return $\hat{X}_i$ ▷ $\forall i = 1, \dots, N$

Faces and Object Dataset

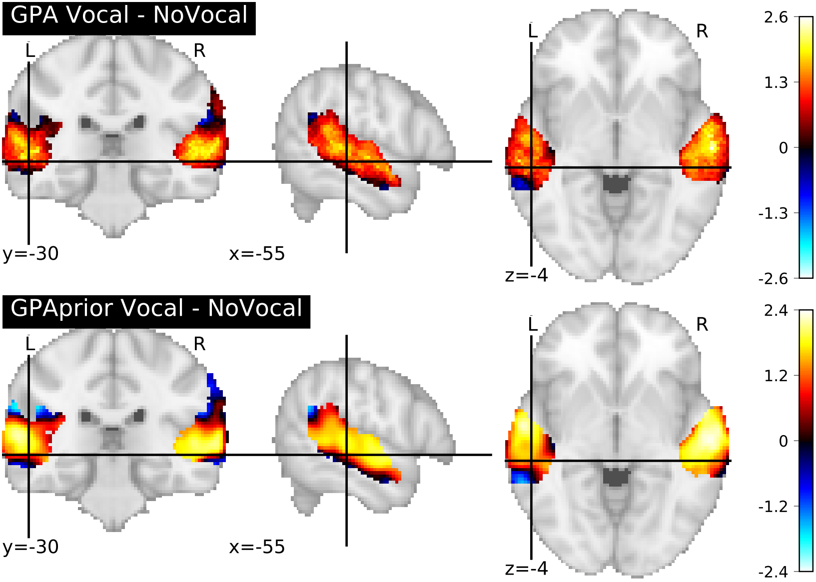



VT
GPA prior
GPA
Mean accuracy
0.47
0.46
0.45
0.44
0.43
0.42
0.41

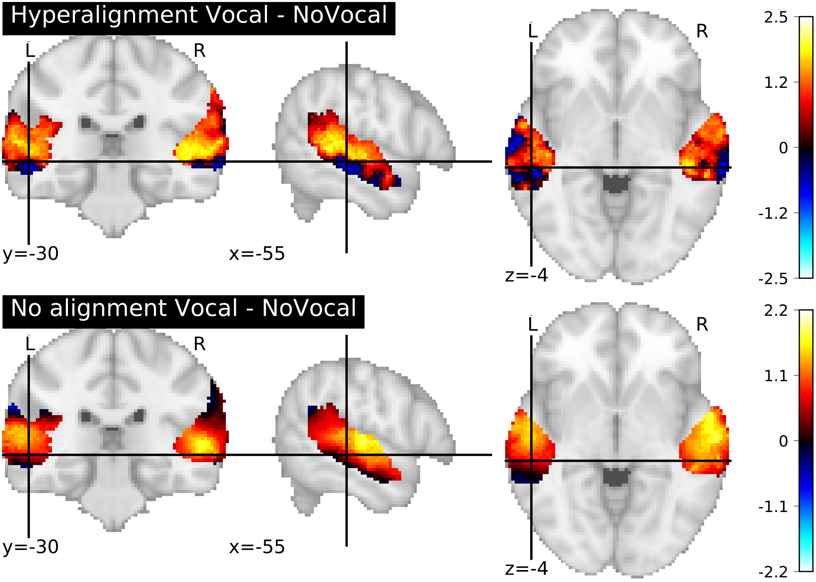
Auditory Data



Auditory data



Auditory data



Auditory data