Enhanced hyperalignment via spatial prior information

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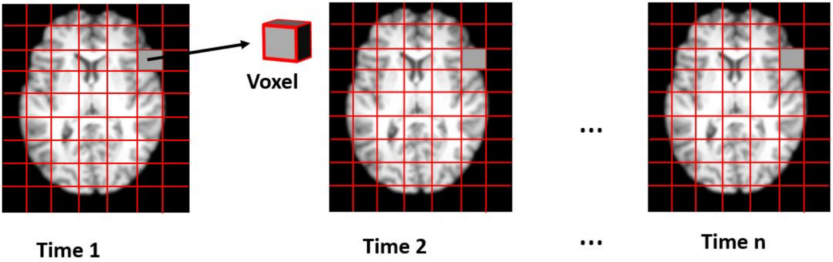
Multi-subjects fMRI data analysis is important as it allows for the identification of shared cognitive characteristics across subjects.

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

ALIGNMENT STEP

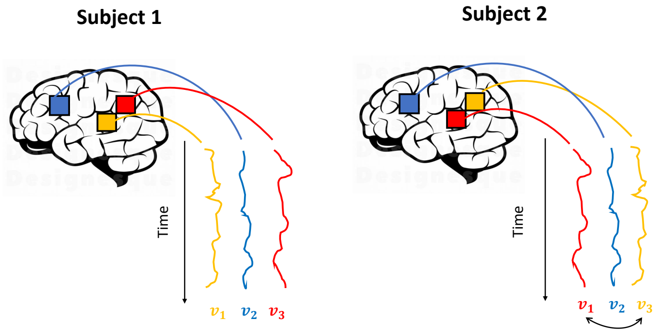
- **Anatomical Alignment**: Align the images with a standard anatomical template (e.g., MNI [1]);
- **Functional Alignment**: Procrustes-based Method (e.g., Generalized Procrustes Analysis [2], Hyperalignment [3]).

[1]Jenkinson et al., 2002
[2]Gower, J.C. and Dijksterhuis, G.B. (2004)
[3]Haxby et al. (2011)



Each subject i is represented by a matrix $\mathbf{X}_i \in \mathbb{R}^{n \times v}$:

- the **rows** represent the **response stimuli activation** of voxels
  → the stimuli are time synchronized
- the **columns** represent the **time series of activation** for each v voxel
  → not assumed to be in correspondence across N subjects.



We can assume that the neural activities in different brains are **noisy rotations of a common space**.

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

Generalized Procrustes Analysis (GPA):

$$\boxed{\min_{\mathbf{R}_i} \sum_{i=1}^{N} \|\mathbf{X}_i - \mathbf{M}\mathbf{R}_i^{\top}\|_F^2 \quad \text{subject to} \quad \mathbf{R}_i^T\mathbf{R}_i = \mathbf{I}_v}$$

IN A NUTSHELL

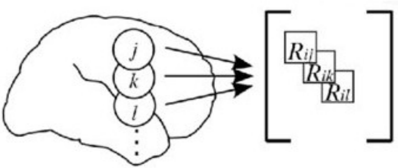
Find the **best orthogonal** matrix-transformation that **MINIMIZE THE DISTANCE** between $\mathbf{X}_i$'s (guest) and M (bed)

Individual-specific and shared functional information is modeled via **high-dimensional transformations** rather than transformations that rely on 3D anatomical space.

Some issues:

- **Hyperalignment** (sequential approach of GPA):
  - **remixes** data across spatial loci → aligning entire cortex may be questionable;
  - **no unique solution** → aligned images and related results do not have a clear topological interpretation;
  - **polynomial** time complexity in v.

- **Searchlight hyperalignment** [4] (overlapping transformations for overlapping searchlights aggregated into a single whole-brain transformation):



  - final transformation is no longer an orthogonal matrix → **not preserve the content of the original data** (similarity/dissimilarity between pairs of voxels response);
  - searchlights imposed **a priori**;
  - voxels outside of the predefined search radius **not influence** the estimation process.

[4] Guntupalli et al., 2016

We rephrase the Procrustes method as **statistical model** called **ProMises model**:

$$\boxed{\mathbf{X}_i = \mathbf{M}\mathbf{R}_i^\top + \mathbf{E}_i \qquad \text{where} \qquad \vec{\mathbf{E}}_i \sim \mathcal{N}_{nv}(0, \Sigma)}$$

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

  ⟶ **Prior distribution** (Fisher Von Mises[5]) for $\boxed{\mathbf{R}_i}$

- The estimation process is computationally heavy; only ROIs can be aligned

  ⟶ **Semi-orthogonal transformation** on $\boxed{\mathbf{X}_i}$

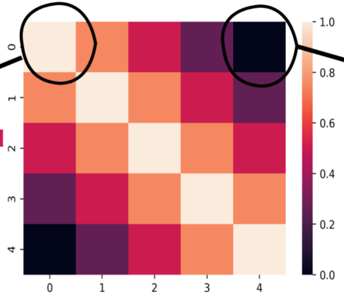
The regularization leads to a unique solution for $\mathbf{R}_i \rightarrow$ **weighted average** between maximum likelihood estimator and the mode of the prior distribution (conjugate prior).

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

$\boxed{R_i}$ performs a **linear combination** of voxel activations to create the new image. → Combine **CLOSER voxels**!

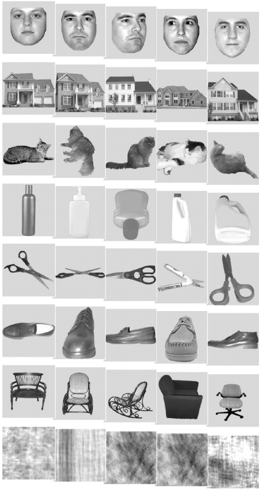
HIGH VALUE → LOW VALUE

VOXEL AT POSITION 1 WITH VOXEL AT POSITION 1



VOXEL AT POSITION 1 WITH VOXEL AT POSITION 5

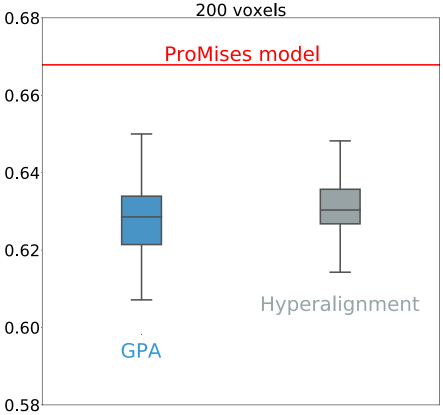
SIMILARITY EUCLIDEAN MATRIX



- We align the images of the **Ventral Temporal Cortex** and **whole brain** from Haxby et. al (2001)[6] 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.

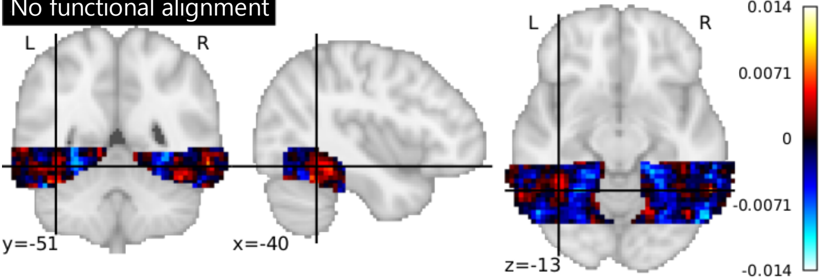
[6] https://openneuro.org/datasets/ds000105/versions/00001

Faces and Objects Data - Ventral Temporal Cortex

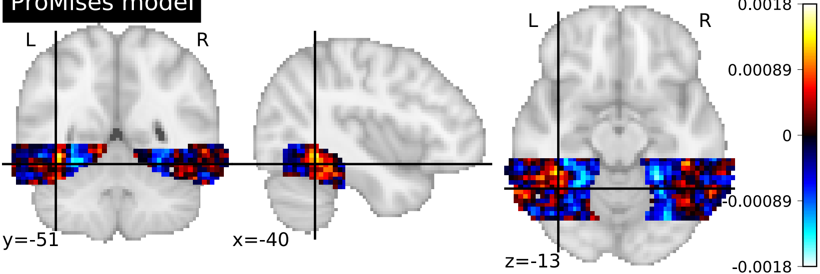


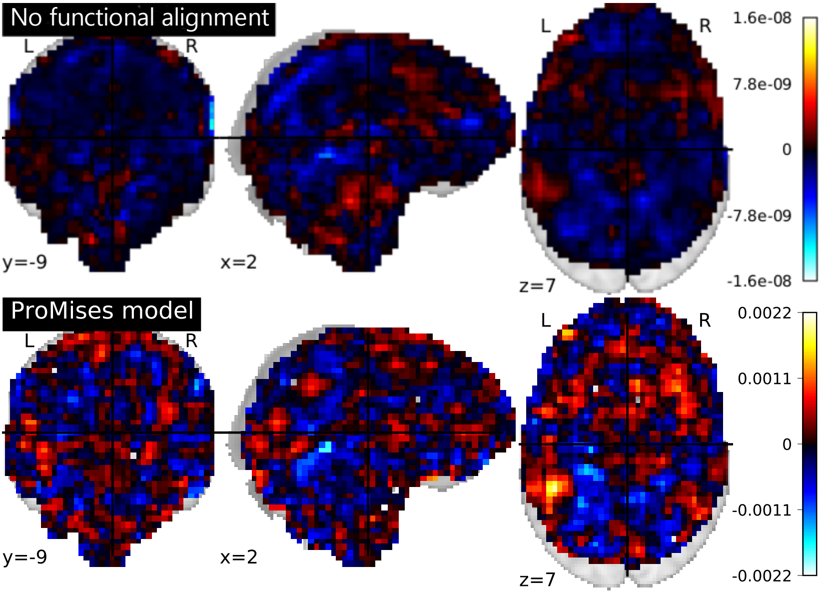
No functional alignment: 0.309.

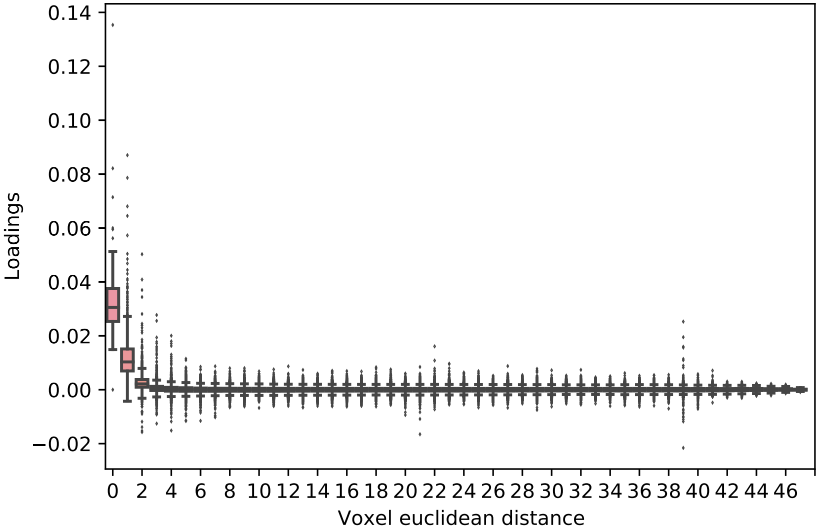
No functional alignment



ProMises model




No functional alignment
L
R
y=-9
x=2
z=7
1.6e-08
7.8e-09
0
-7.8e-09
-1.6e-08
ProMises model
0.0022
0.0011
-0.0011
-0.0022


0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
−0.02
Loadings
0 2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40 42 44 46
Voxel euclidean distance

The **ProMises Model**:

- leads to a **unique** solution of the transformation → unique representation/interpretation of the final result;
- **outperforms** the other functional alignment techniques in all permutations of these approaches;
- allows alignment of the **whole brain**;
- insert the information of voxels' **spatial position** directly into the estimation process → flexibility;

You can find the `Python` module and the `R` package on my GitHub profile `https://github.com/angeella`.

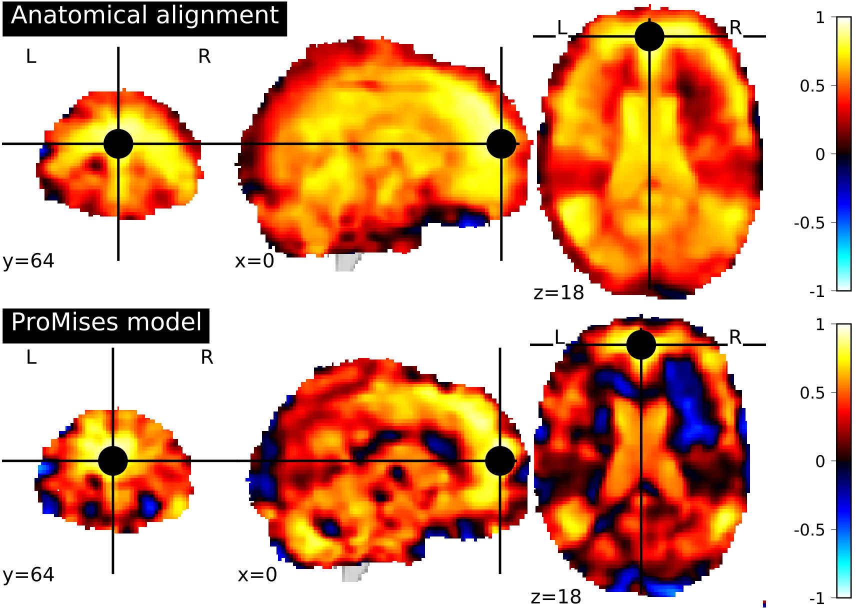
We align the brain images from Pernet et al. (2015)[6] of 18 subjects passively listening to vocal, i.e., speech, and non-vocal sounds.

After the $\mathbf{X}_i$ matrices' alignment:

- **Seed-based correlation analysis**;
- **ROI correlation analysis**;

[4]https://openneuro.org/datasets/ds000158/versions/1.0.0

Auditory Data - Seed-based correlation analysis



Auditory Data - ROI correlation analysis