Functional alignment enhances Electroencephalography (EEG) data' s group analysis

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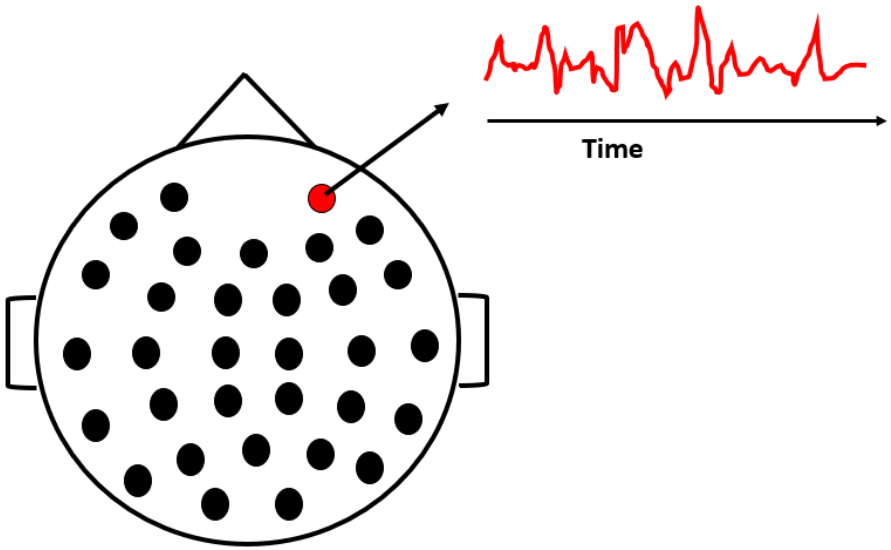
Multi-subjects EEG studies permit to compare studies across subjects, to generalize and to validate the results.

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

ALIGNMENT STEP

- **Anatomical alignment**: MRI;
- **Functional Alignment**: Procrustes Method [1].

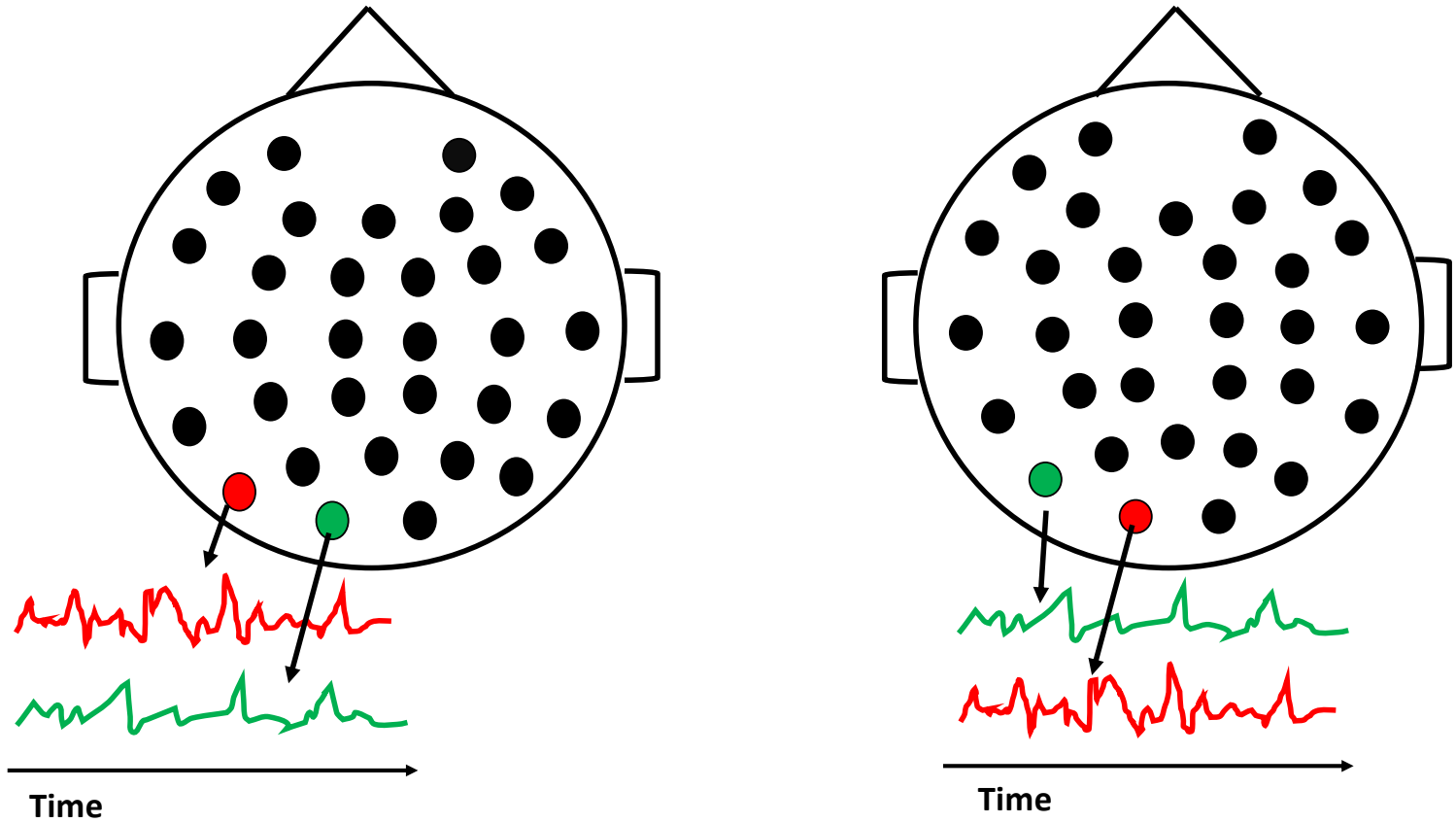
[1] Gower, J.C. and Dijksterhuis, G.B. (2004)



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 electrodes
  ⟶ the stimuli are time synchronized
- the **columns** represent the **time series of activation** for each m electrodes
  ⟶ not assumed to be in correspondence across N subjects.

Introduction - Alignment Problem



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

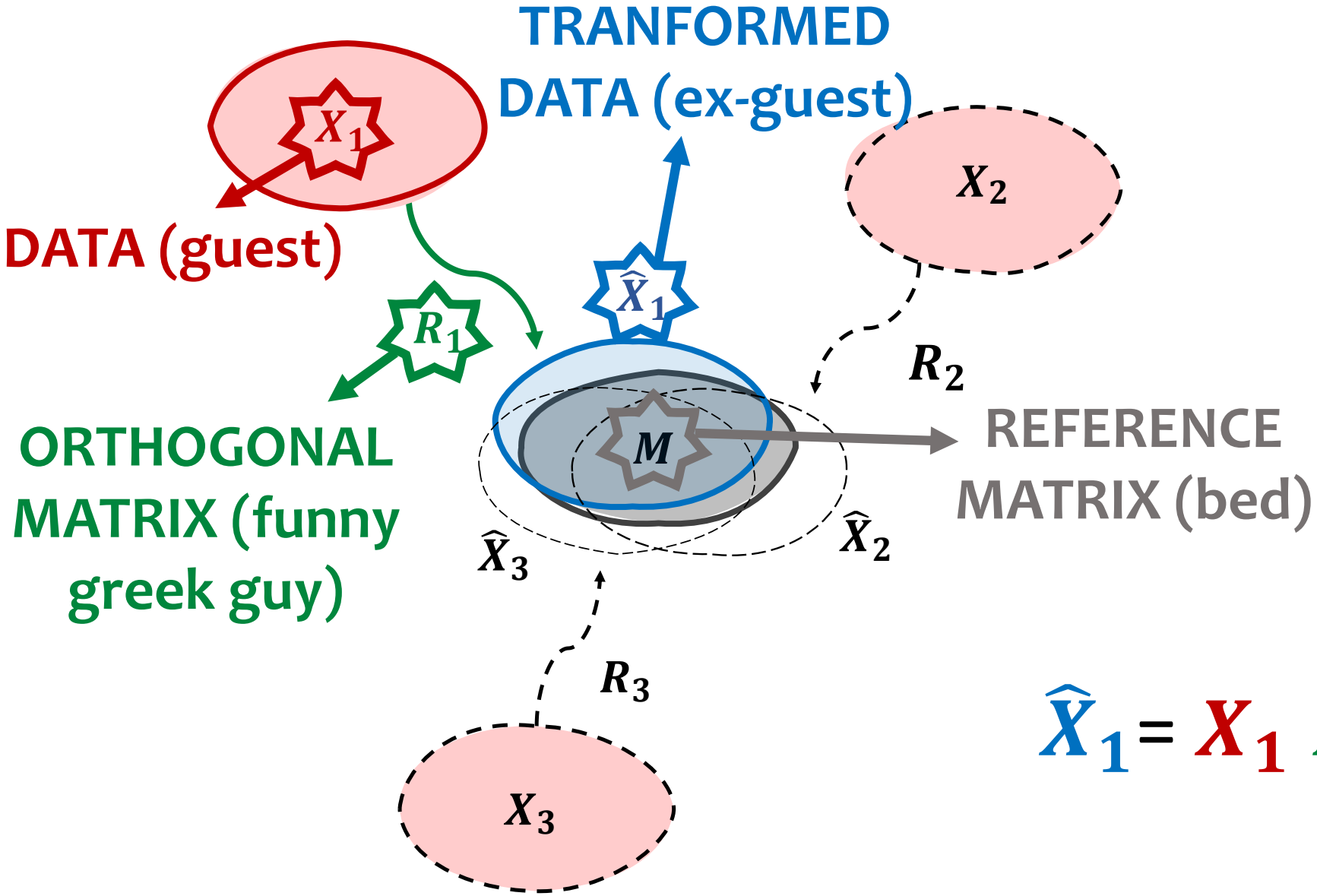
The **Procrustes** method uses **similarity transformation** to match matrices onto the **reference** one as close as possible.

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

IN A NUTSHELL

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

Procrustes Method



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

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

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

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

  → **Prior distribution** (Fisher Von Mises[2]) for $\mathbf{R}_i$

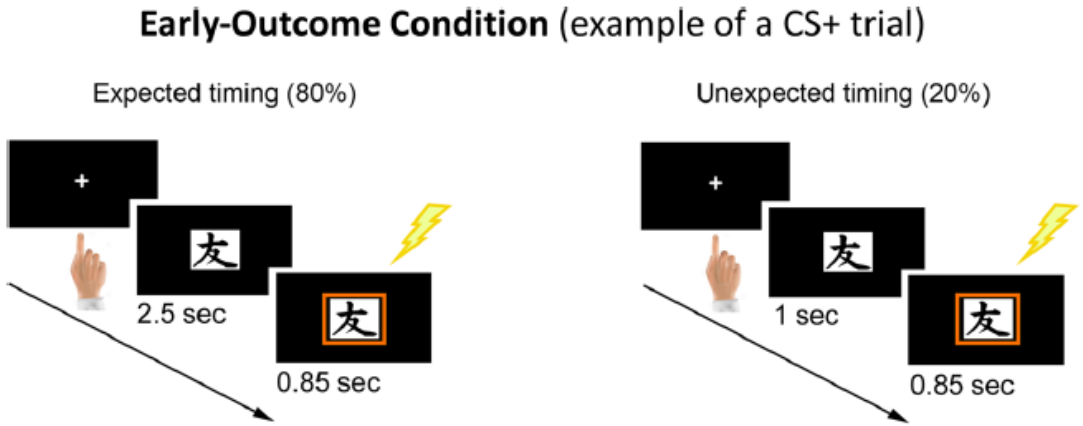
- The estimation process is computationally heavy; only ROIs can be aligned

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

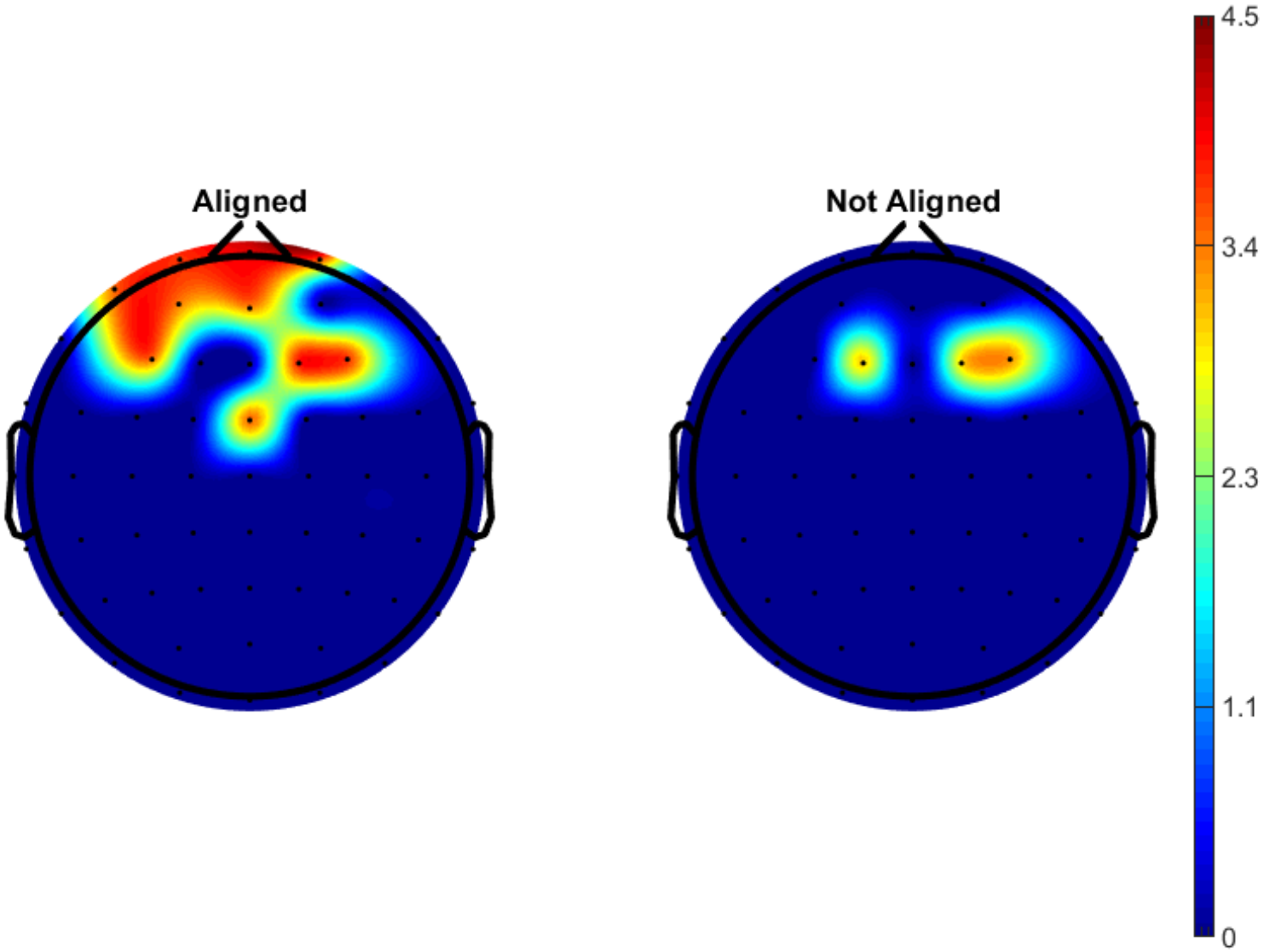
The regularization leads to a unique solution for $\mathbf{R}_i$.

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

Aim: Test whether unexpected timing of salient (i.e., aversive) outcomes, as compared with neutral outcomes, can trigger ACC/mPFC activity expressed as mediofrontal negativity.
Study: Pavlovian aversive conditioning task. 48 participants press a button to start a new trial: the stimuli *CS+* were followed by a visual outcome indicating an imminent shock delivery. Such outcomes occurred on 80% of the trials at an expected timing (left) and were shifted in time on 20% of the trials (right).



Application



Take Home messages

The **ProMises Model**:

- leads to a **unique** solution of the transformation → unique representation/interpretation of the final result;
- allows alignment of the **whole brain**;
- exploits the information of voxels' **spatial position**;
- yields more **reliable** measures of individual differences both:
  1. by reducing confounds from topographic idiosyncrasies;
  2. by capturing variation around shared functional and anatomical response across individuals;
- allows to find **groups** of individuals sharing patterns of neural brain activation.

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