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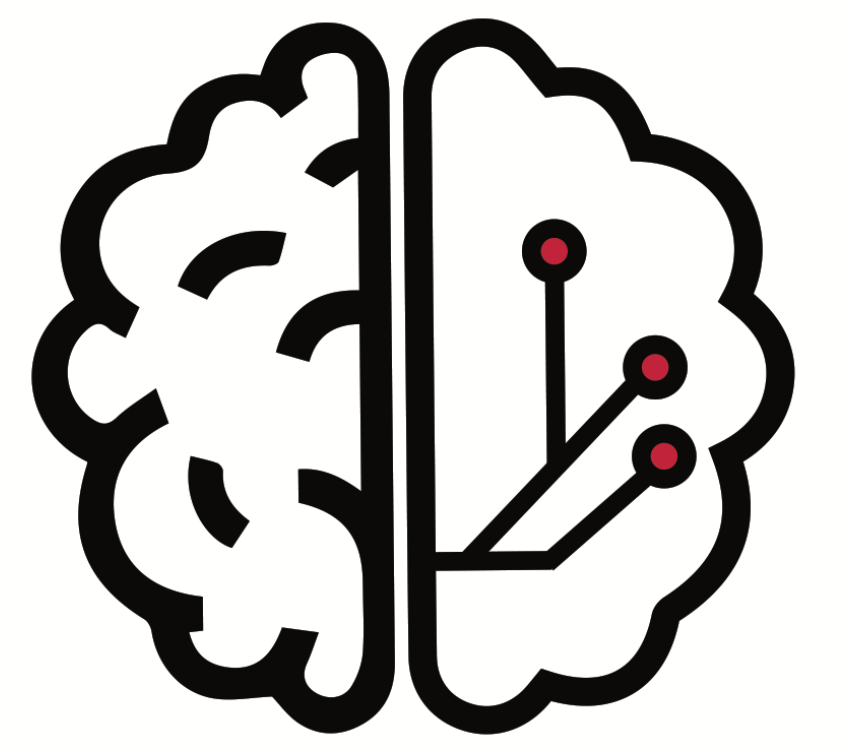
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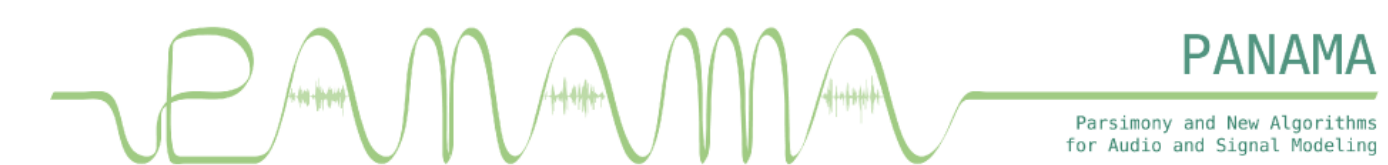
Can we learn from coupling EEG-fMRI to enhance neuro-feedback in EEG only?



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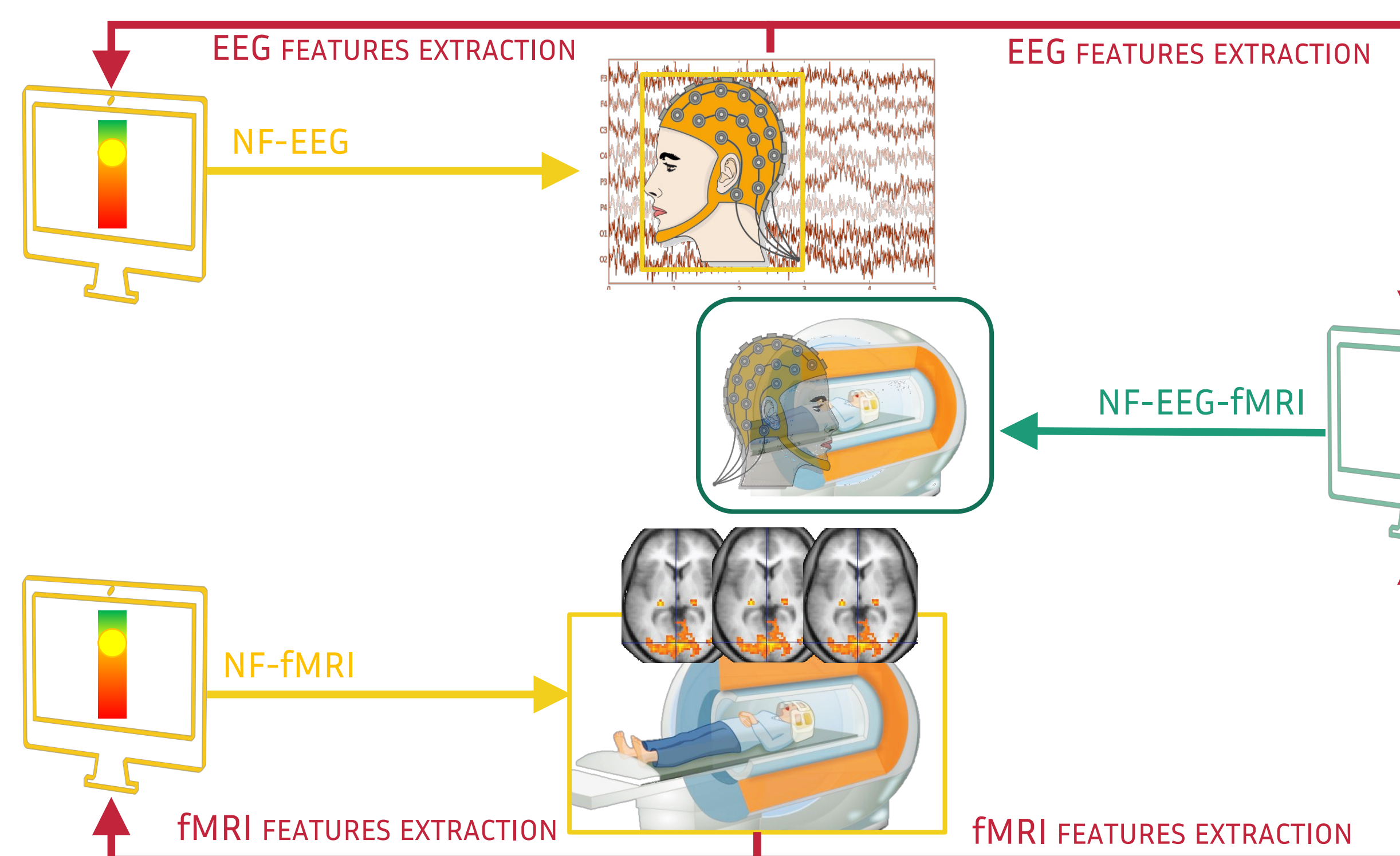
INTRODUCTION

Neuro-feedback (NF) : Learn to control your brain with your brain.

EEG and fMRI, grounds solutions in the context of **brain rehabilitation** protocols.

EEG and fMRI provide complementary information.

EEG is easy to use, fMRI is a costly and exhausting for patients modality



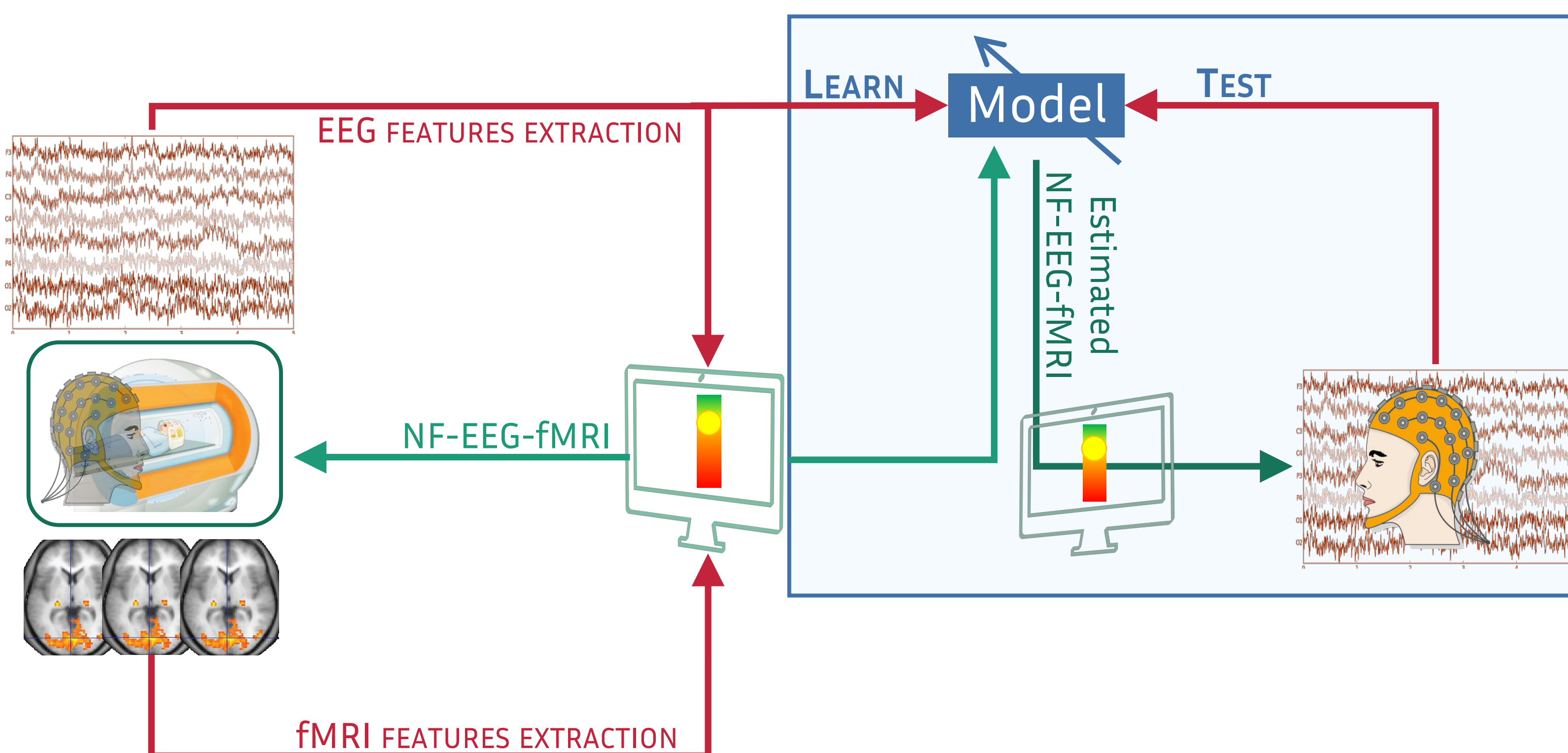
Bi-modal NF :

- Records and synchronises EEG and fMRI signals, in real time (Mano et al).
- Combines NF-EEG and NF-fMRI advantages
- Improve the quality of NF sessions (Perronnet et al).
- It is not portable or easy to use, due to the fMRI modality.

→ Can we enhance NF in EEG only, from a previous bi-modal NF session ?

METHOD

- **Design and strategy** : Machine learning mechanism based on bimodal NF scores and EEG signals.

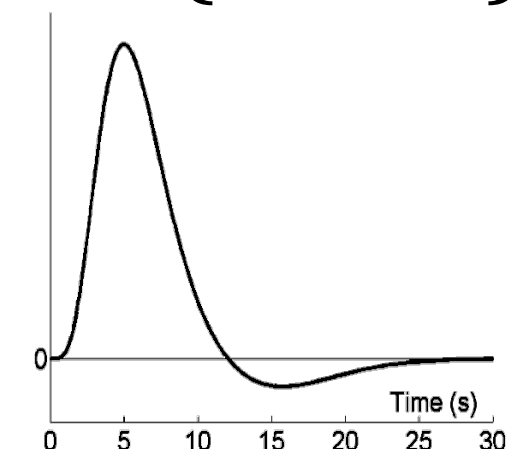


- **Model** : Non linear structured design matrix X

$$X = [X_0; X_3; X_4; X_5], \in \mathbb{R}^{T \times 4E \times B}, \text{ with } X_i \in \mathbb{R}^{T \times E \times B}$$

$$X_0(t, e, b) = \text{Freq}(EEG(e, I_t), F_b), \forall t \in \{1, \dots, T\} \text{ and } \forall b \in \{1, \dots, B\}$$

$$\left. \begin{aligned} X_3(\cdot, e, b) &= X_0(\cdot, e, b) * \text{HRF}(3) \\ X_4(\cdot, e, b) &= X_0(\cdot, e, b) * \text{HRF}(4) \\ X_5(\cdot, e, b) &= X_0(\cdot, e, b) * \text{HRF}(5) \end{aligned} \right\} \forall e \in \{1, \dots, E\}, \text{ and } \forall b \in \{1, \dots, B\}$$



- **Optimisation** : structured sparse regularisation following 3 conditions:

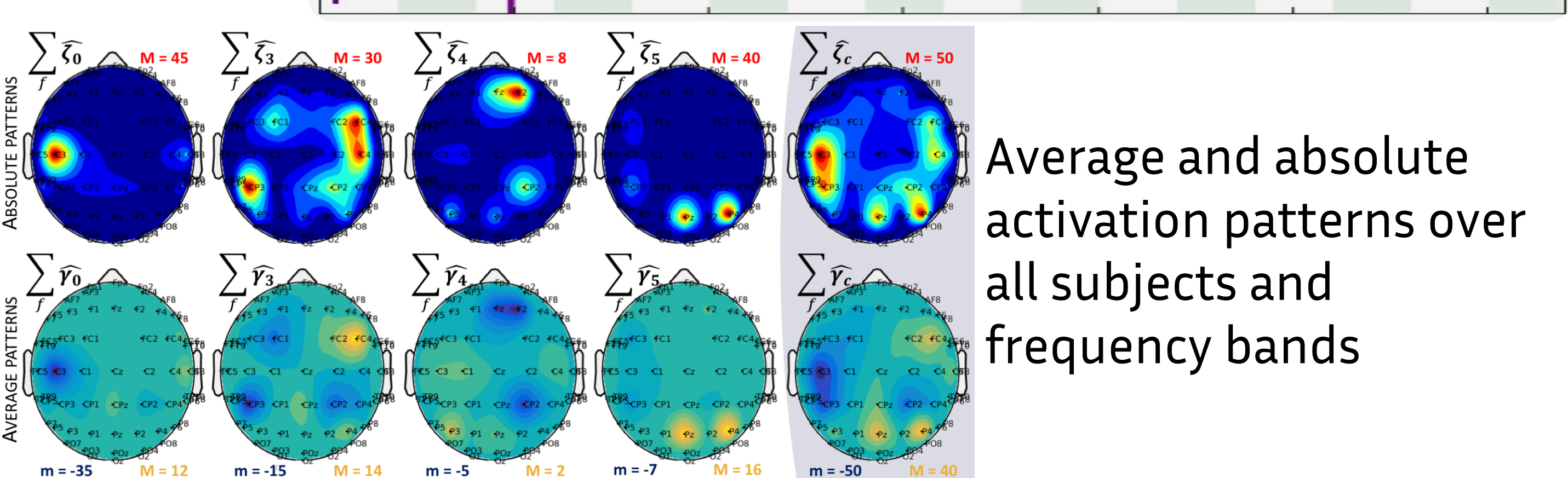
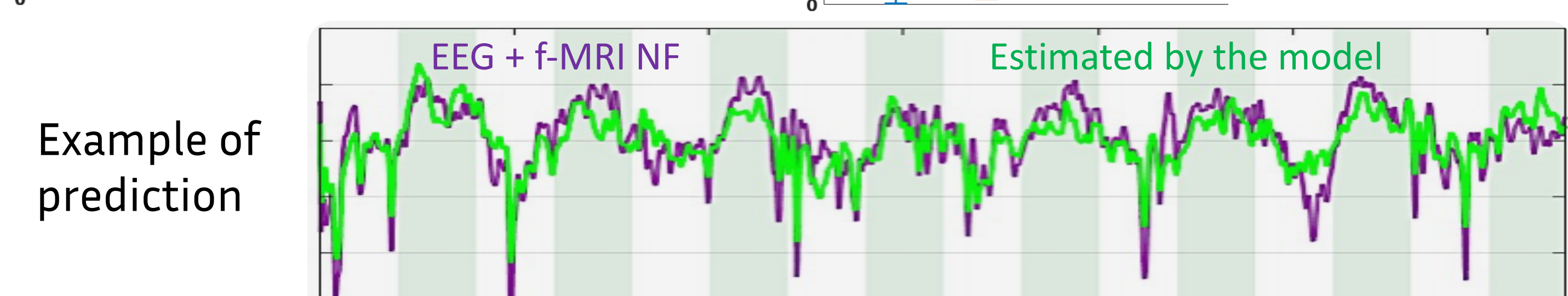
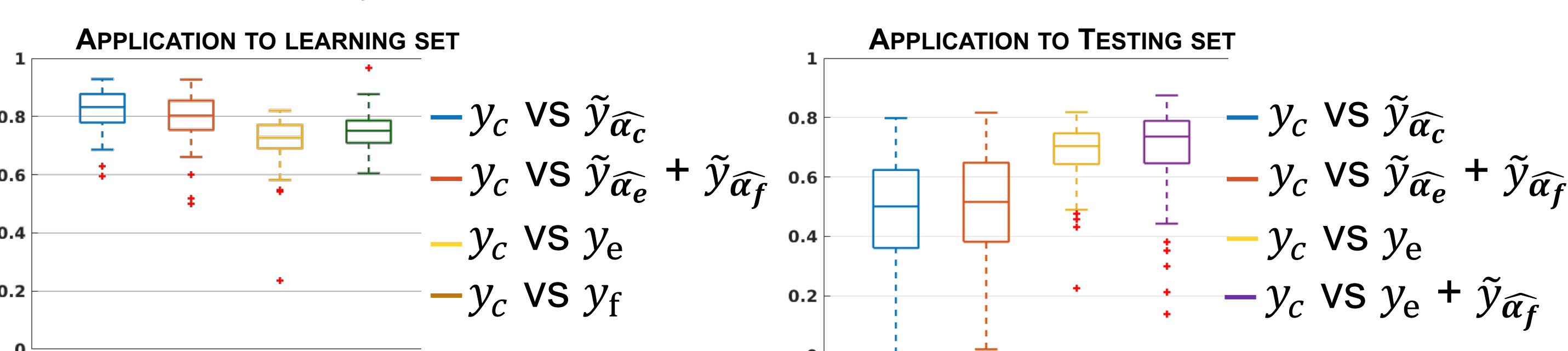
1. Spatial sparsity
2. Smooth across frequency bands
3. Group selection of frequency bands.

$$\hat{\alpha} = \arg \min_{\alpha} \sum_{t=1}^T \frac{1}{2} (NF(t) - \langle X(t), \alpha \rangle)^2 + \lambda \underbrace{\|\alpha\|_{21}}_{\text{Cond 1. and 2.}} + \rho \underbrace{\|\alpha\|_1}_{\text{Cond 3.}}$$

RESULTS

- **SIGNIFICANT INFORMATION FROM NF-fMRI CAN BE CAPTURED BY THE MODEL, AND ENHANCE EEG ONLY NEUROFEEDBACK.**
 - PREDICTION WITH **NF-PREDICTOR 5** WITH A MEDIAN CORRELATION OF 0.74

- Method tested on 17 subjects with 3 bimodal neuro-feedback sessions of motor imagery tasks.
- We tested 5 NF-predictors:
 1. $\tilde{y}_{\alpha_c}(t) = \langle X, \hat{\alpha}_c \rangle$, learned from X and $NF_c = NF\text{-EEG} + NF\text{-fMRI}$
 2. $\tilde{y}_{\alpha_e}(t) = \langle X, \hat{\alpha}_e \rangle$, learned from X_0 and $NF\text{-EEG}$
 3. $\tilde{y}_{\alpha_f}(t) = \langle X, \hat{\alpha}_f \rangle$, learned from X_d and $NF\text{-fMRI}$
 4. $\tilde{y}_{\alpha_e}(t) + \tilde{y}_{\alpha_f}(t)$
 5. $y_e(t) + \tilde{y}_{\alpha_f}(t)$, with $y_e(t) = NF\text{-EEG}(t)$



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