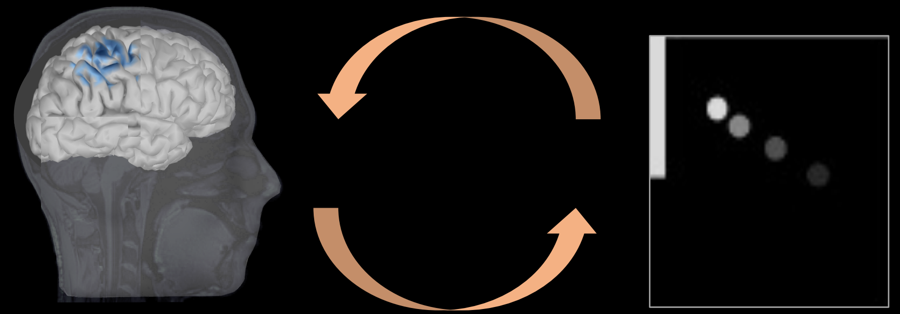
IEEE – ISBI 2023 – Special session

Ensemble of Riemannian classifiers for multimodal data: FUCONE approach for M/EEG data

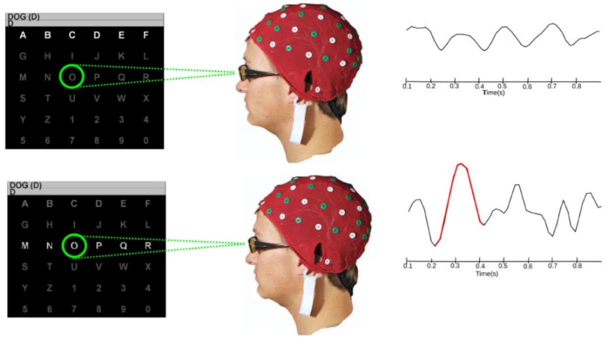


Marie-Constance Corsi*, Sylvain Chevallier, Fabrizio De Vico Fallani, Florian Yger

*Inria, Paris Brain Institute, France

Non-invasive Brain-Computer Interface - BCI

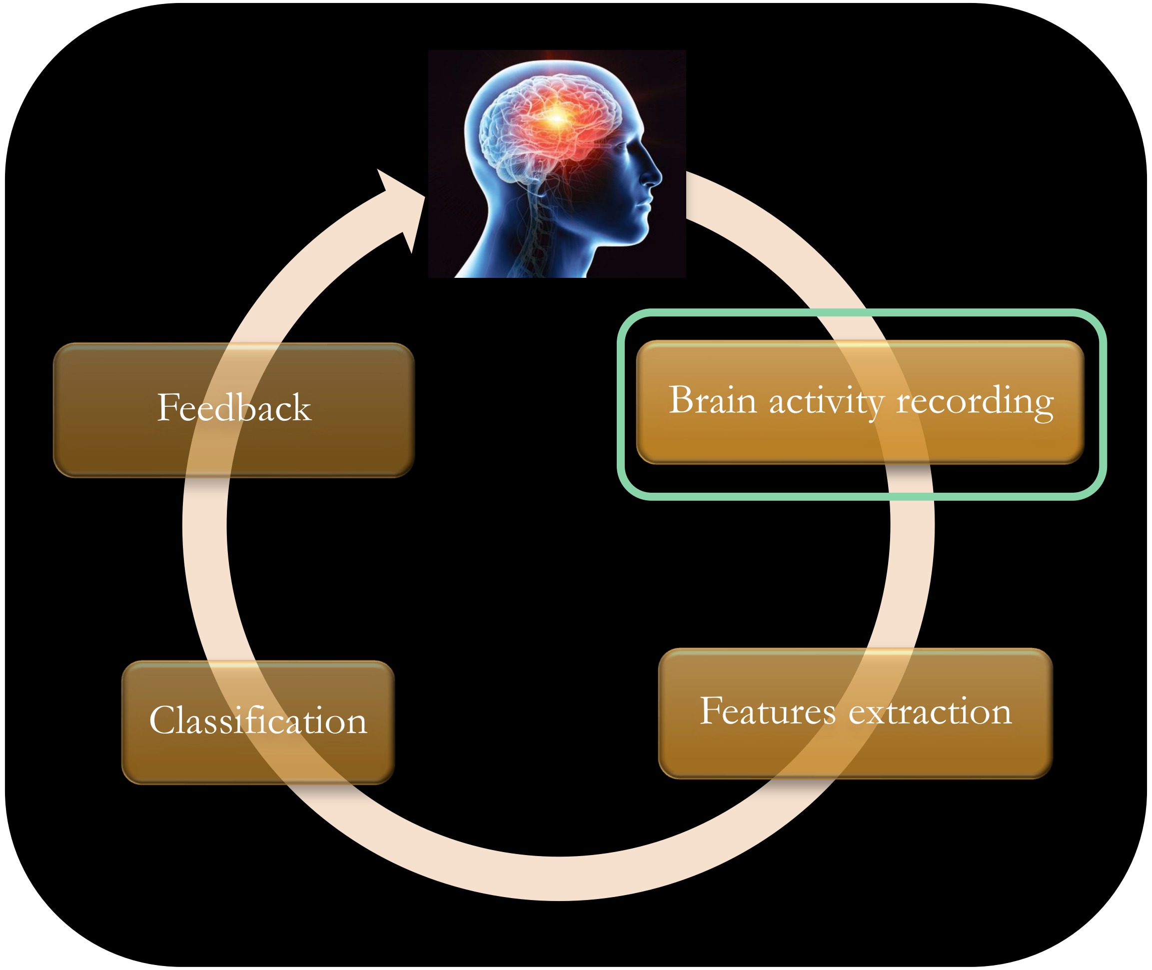
Control



Communication

Adapted from (Lotte et al, 2015)

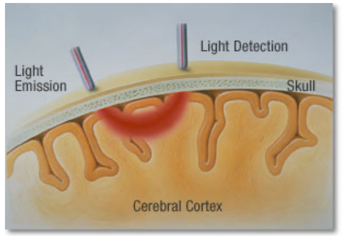
Behind the magic…



Non-invasive tools

EEG

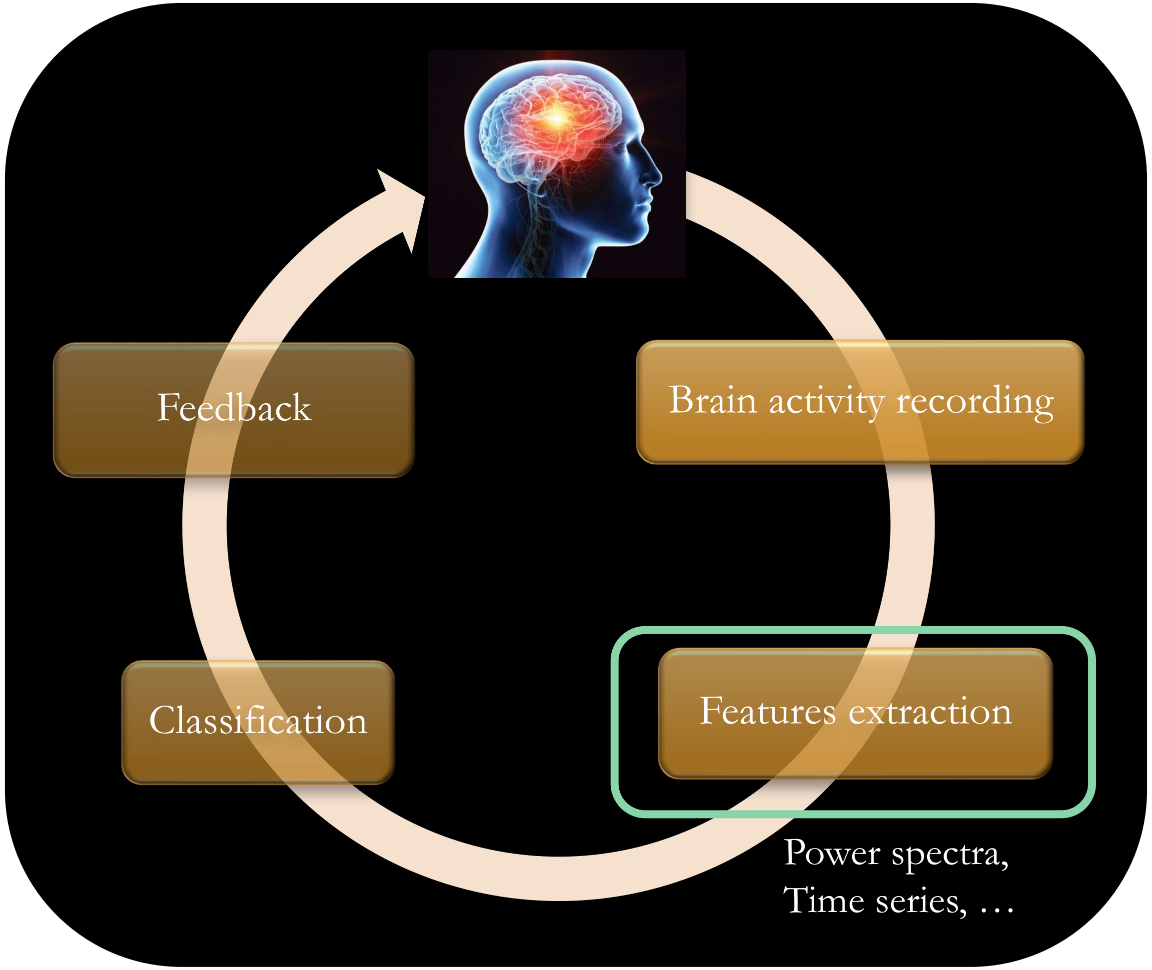
NIRS

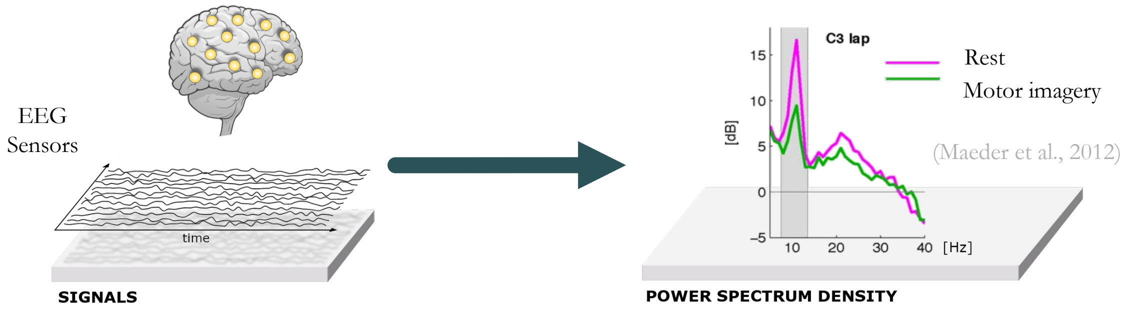


MEG

fMRI

Behind the magic…





Adapted from
[Gonzalez-Astudillo, …, Corsi, & De Vico Fallani, JNE, 2020]

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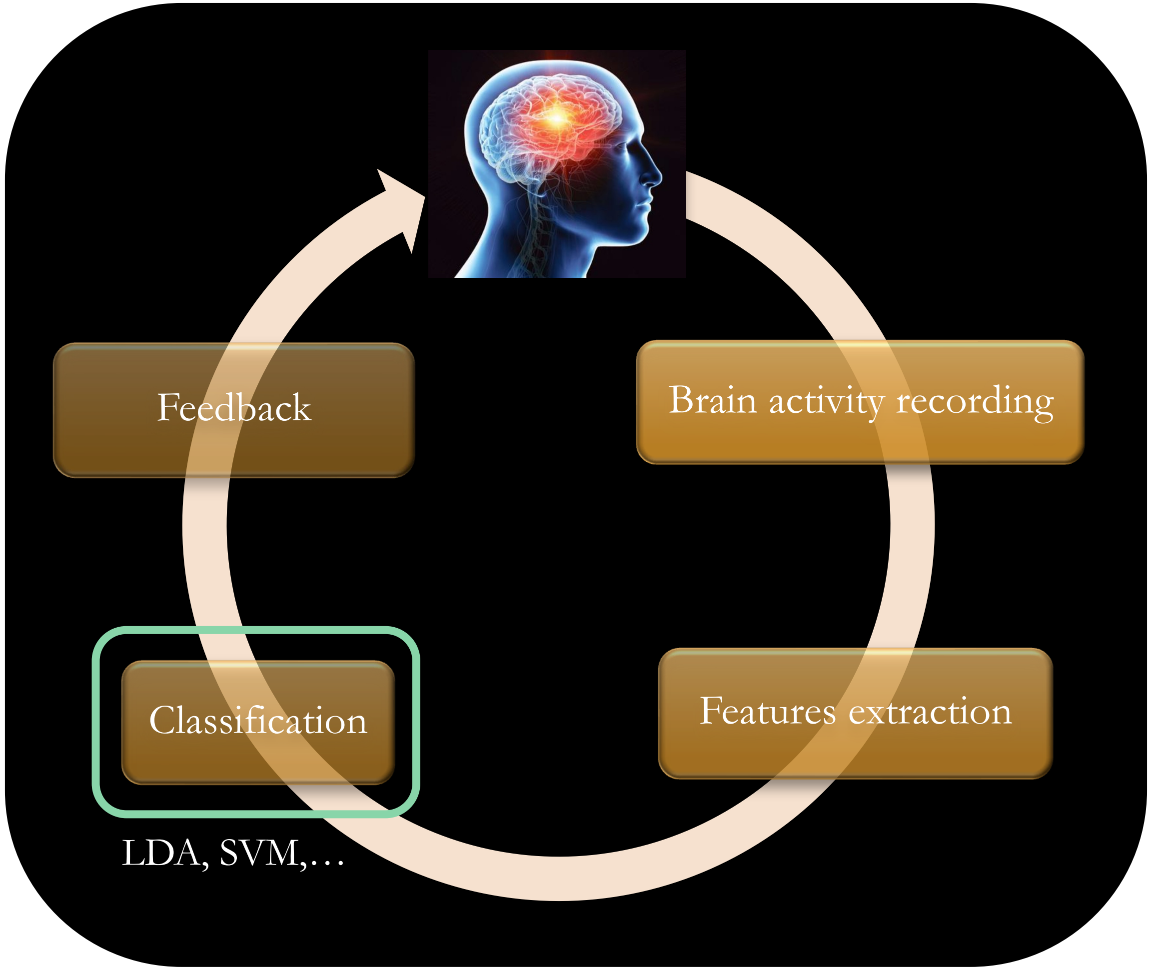

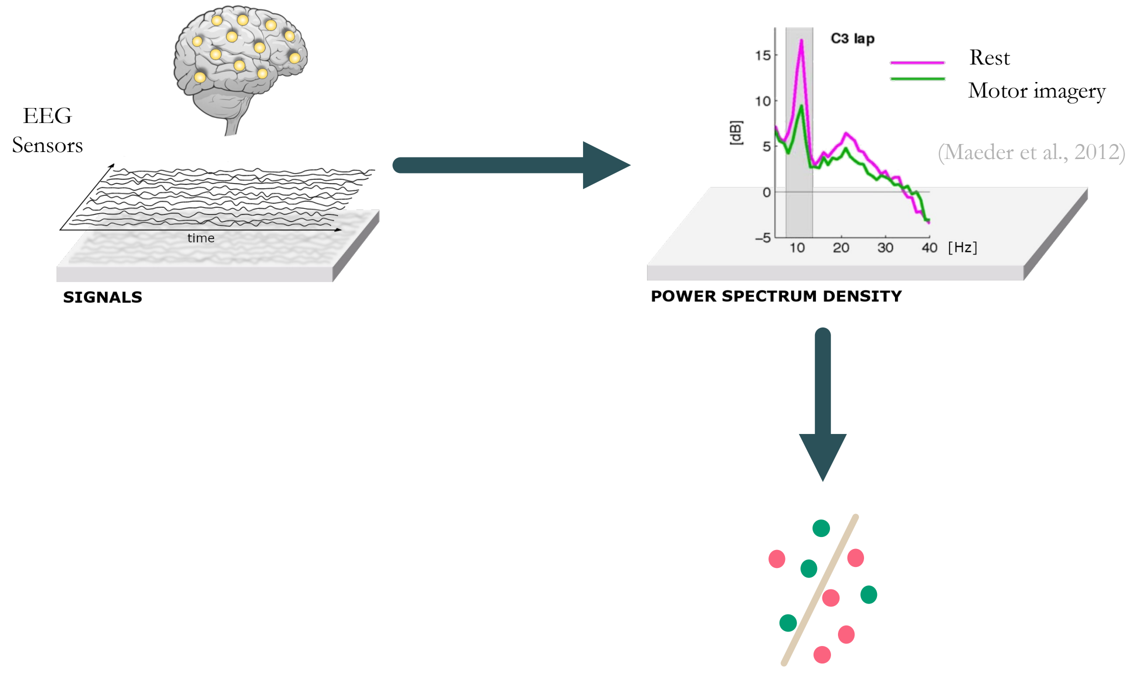

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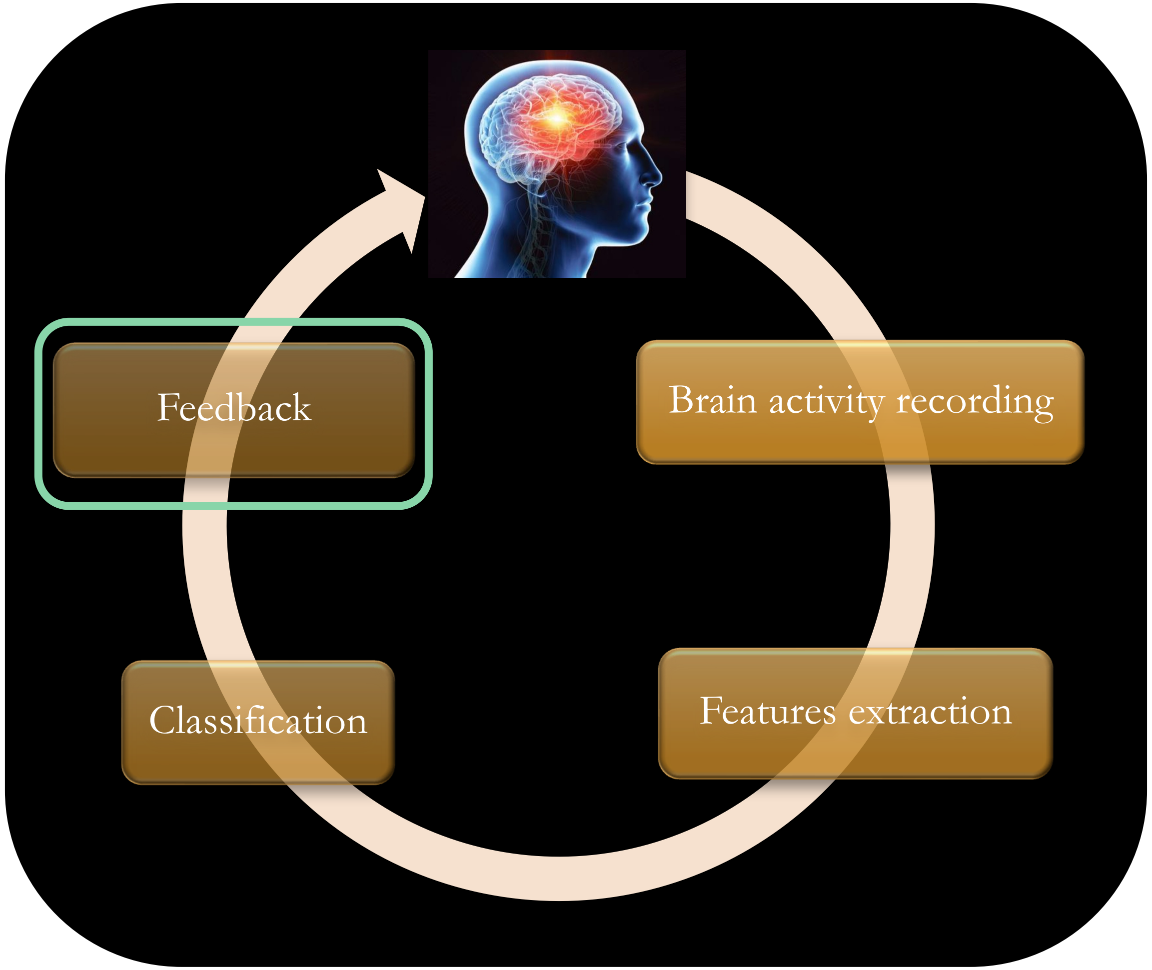

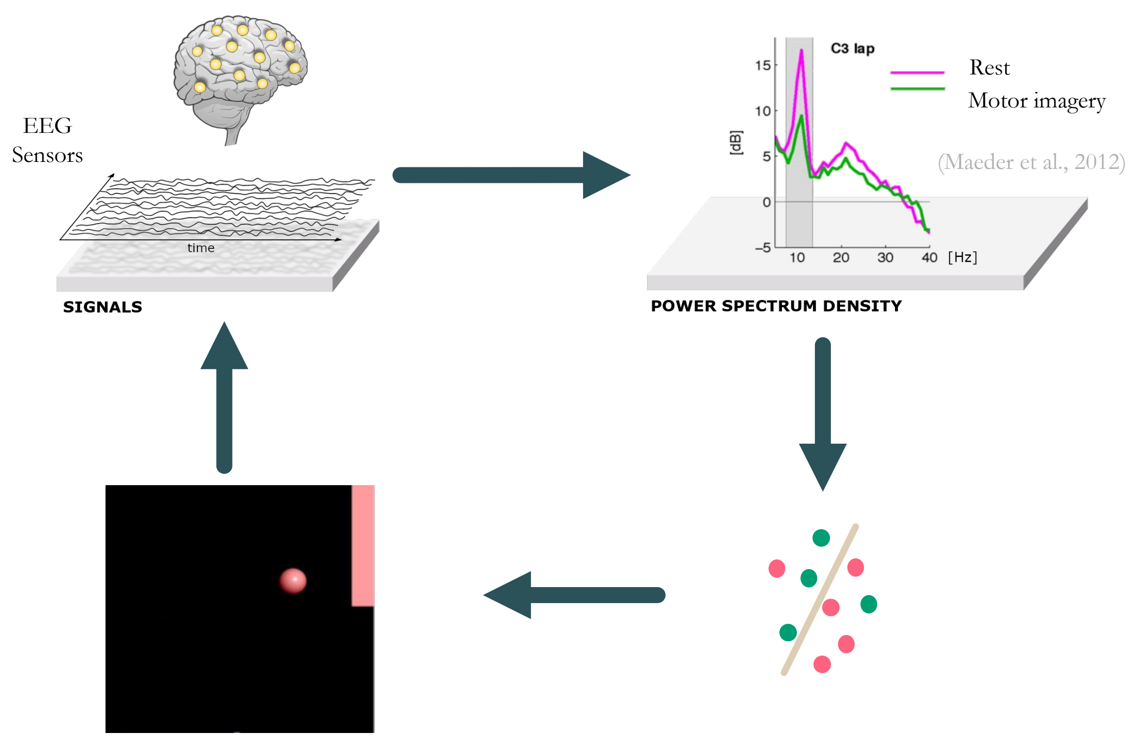

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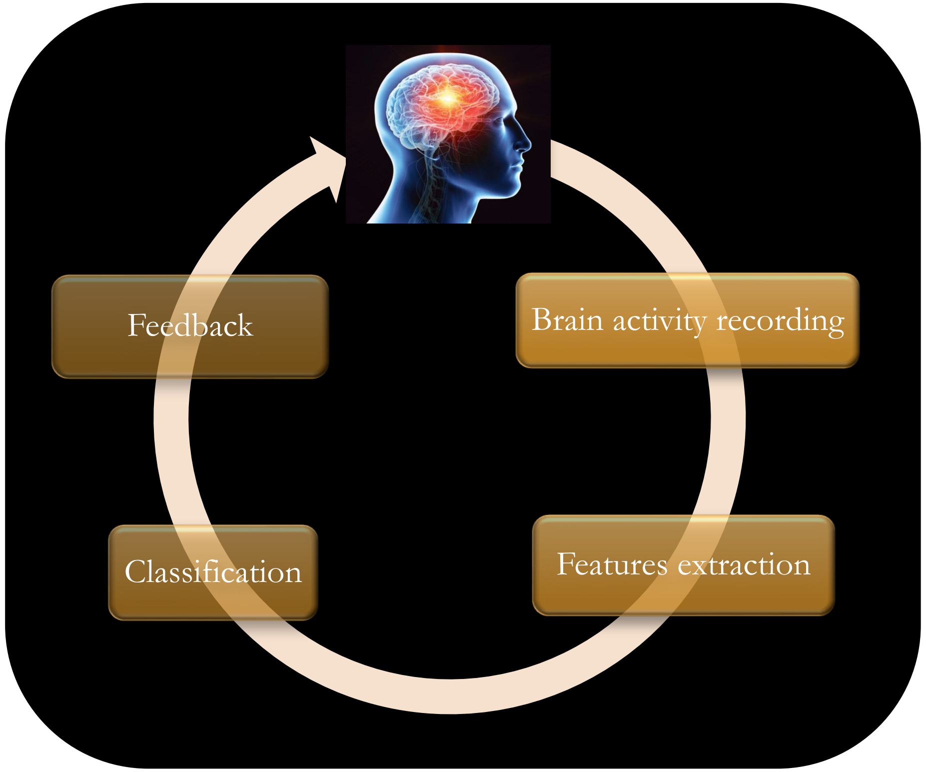
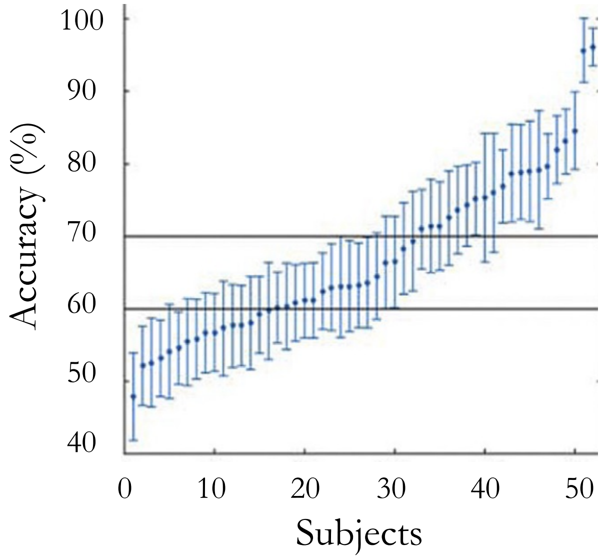
Non-invasive Brain-Computer Interface - BCI



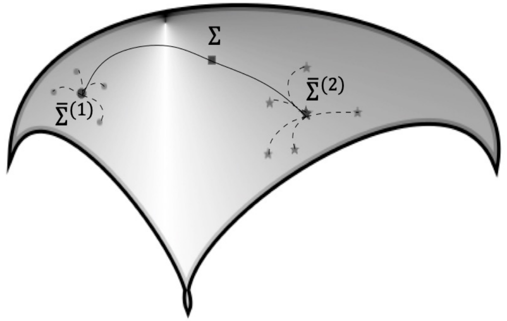


Adapted from (Ahn & Jun, 2015)

Problem: Current BCIs fail to detect the mental intentions in ~30% of users – **BCI inefficiency** (Thompson, 2018)

Geometric methods, gold standard in BCI (Yger et al, 2017)

- Covariance matrices, $\Sigma = \frac{1}{N-1} X X^T$, Σ captures some invariants of the EEG signal
  - Manifold of Symmetric Positive Definite (SPD) matrices
  - Robust & effective classifiers
- Good generalization, compatible with online requirement
- Invariant to affine transformation



Minimum Distance to Mean (MDM)

$$\delta(\Sigma_1, \Sigma_2) = \left\| \log\left(\Sigma_1^{-\frac{1}{2}} \Sigma_2 \Sigma_1^{-\frac{1}{2}}\right) \right\|_{\mathcal{F}}$$

$$\bar{\Sigma} = \mu(\{\Sigma_i\}) = \arg\min_{\Sigma} \sum_{i=1}^{N} \delta^2\left(\Sigma_i, \Sigma\right)$$

Riemannian Geometry (RG) & Functional connectivity (FC)

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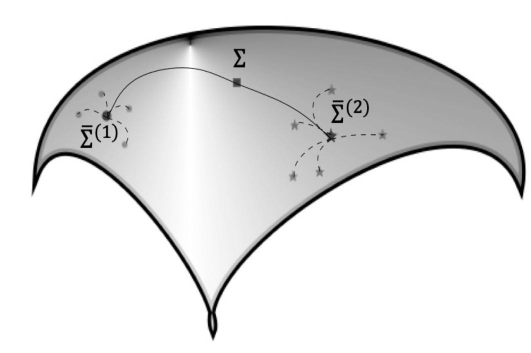

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Problem: RG approaches in BCI rely only on covariance matrices without considering synchronous interactions between brain areas

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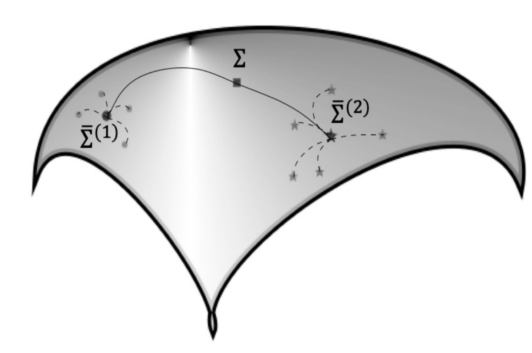

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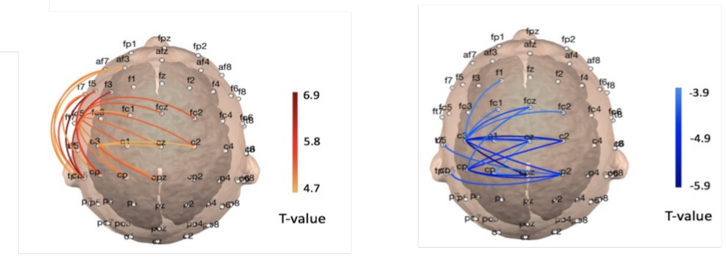
Functional connectivity

- Interconnected nature of brain connectivity & alternative features in BCI
- Use of all the possible information from connectivity matrices
- Regularization methods to make the matrices SPD



Amplitude synchronization Phase synchronization

FC contrast between conditions, adapted from [Cattai, Colonnese, Corsi, et al, IEEE TNSRE, 2021]

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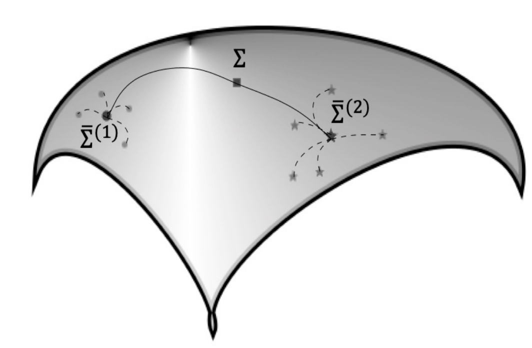

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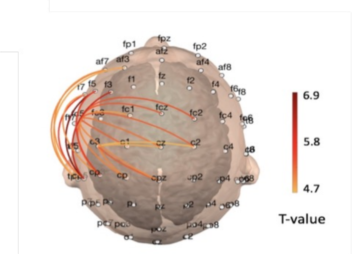
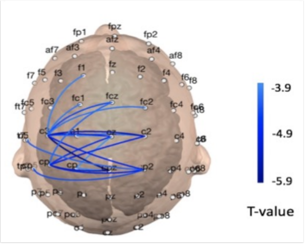


Amplitude synchronization



Phase synchronization

FC contrast between conditions, adapted from [Cattai, Colonnese, Corsi, et al, IEEE TNSRE, 2021]

Hypothesis – Combining functional connectivity estimators and Riemannian geometry will lead to an improvement of classification performance.

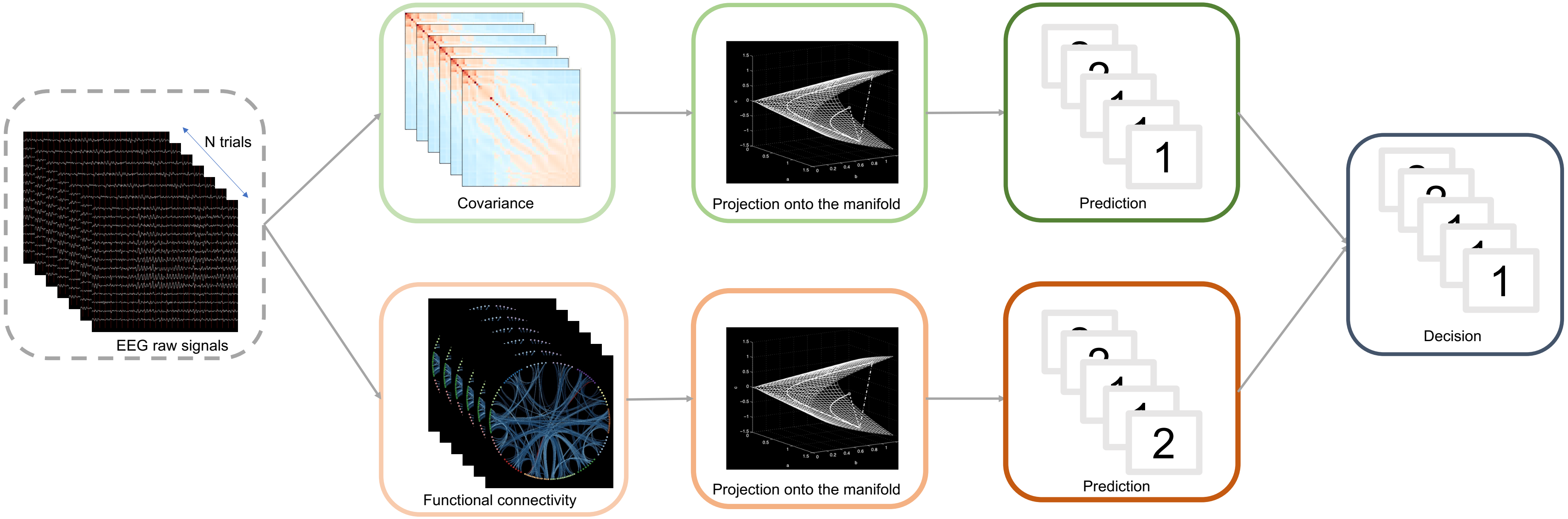
Riemannian Geometry (RG) & Functional connectivity (FC)

Motivation

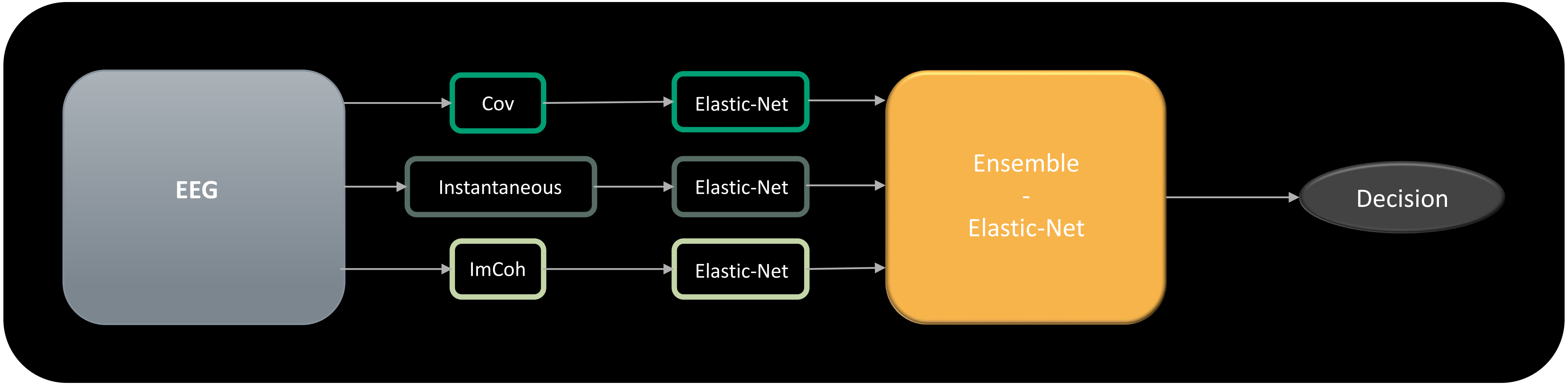
- Considering subjects' specificity
- Improving the robustness

Approach

- Ensemble learning approach – Riemannian Geometry framework relying on covariance matrices & connectivity matrices



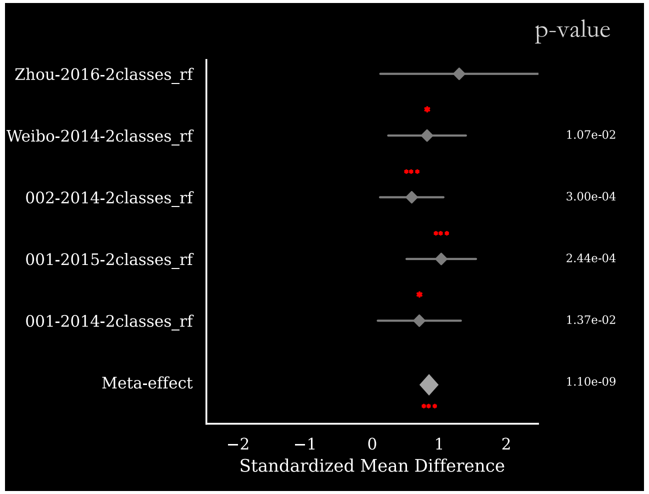
FUCONE approach



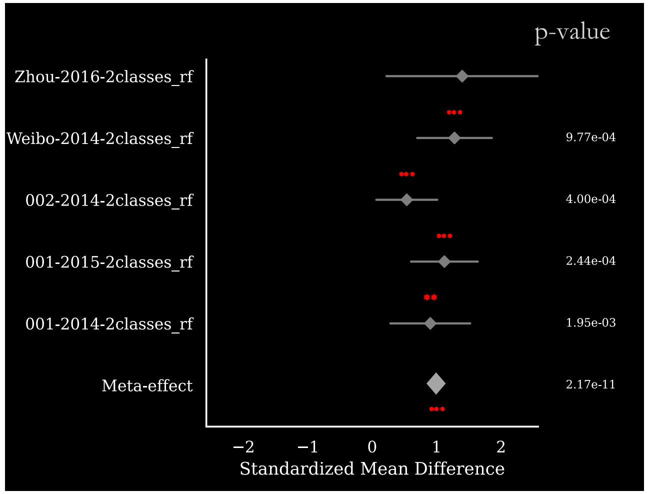
FUnctional CONnectivity Ensemble (FUCONE) approach

FUCONE – A replicable approach

RegCSP+shLDA better FUCONE better



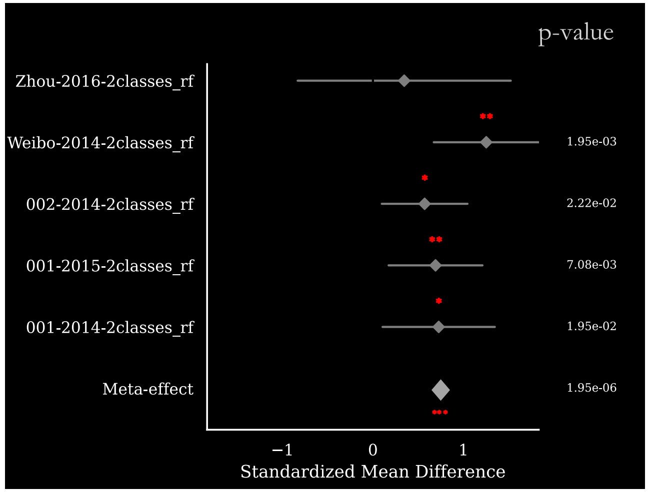
CSP+optSVM better FUCONE better



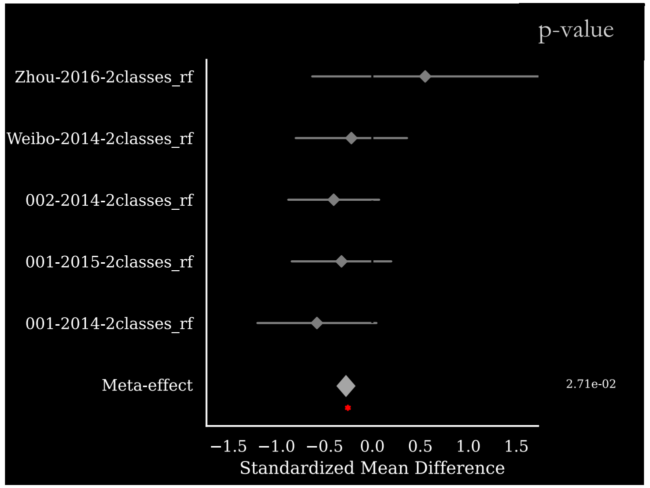
Common Spatial Patterns + Shrinkage Linear Discriminant Analysis

Common Spatial Patterns + Support Vector Machine

FgMDM better FUCONE better



FUCONE better Cov+EN better



Geodesic filtering + Minimum Distance to Mean classification

Covariance + Elastic-Net

[Corsi et al, IEEE TBME, 2022]

FUCONE – A replicable approach

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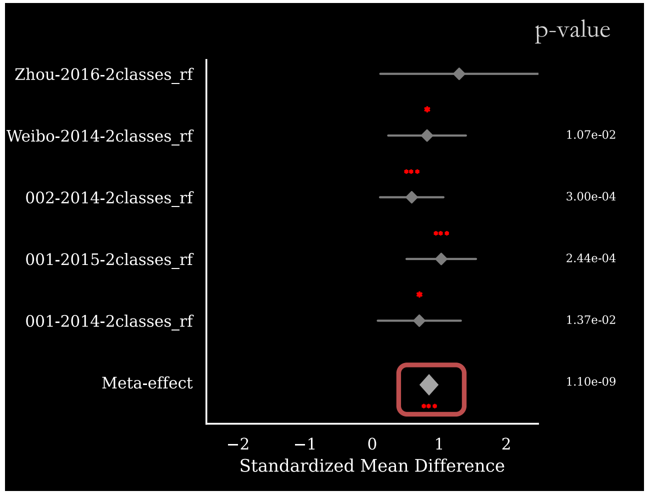

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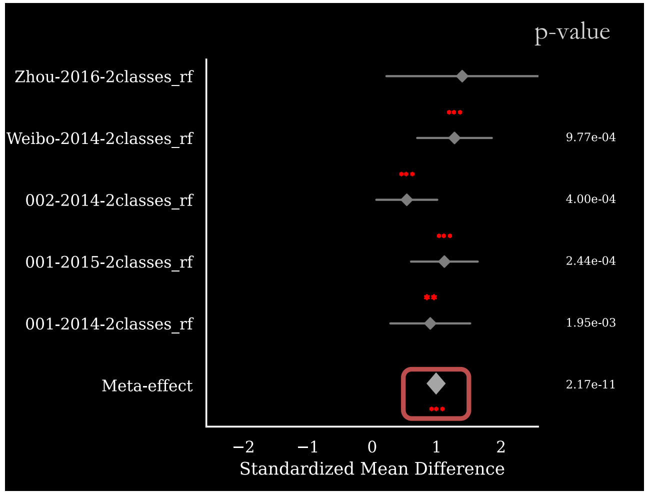

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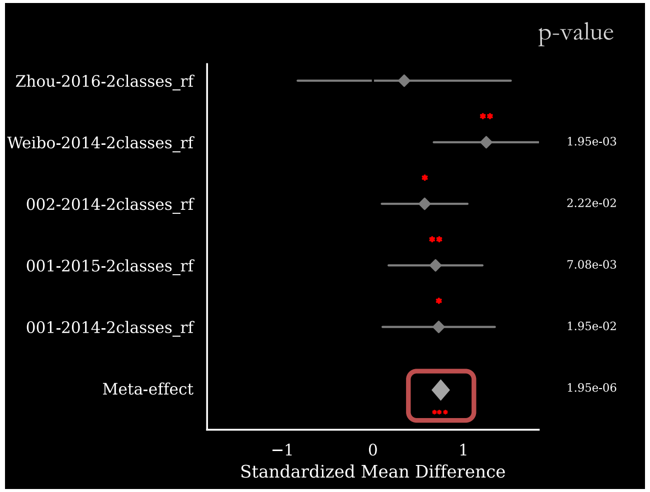

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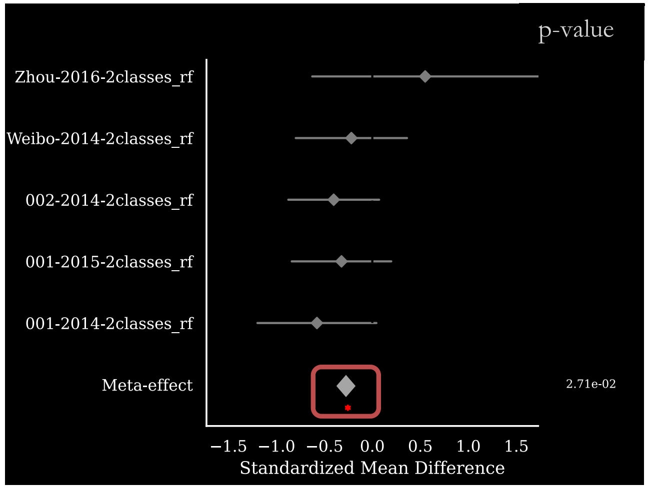

Geodesic filtering + Minimum Distance to Mean classification

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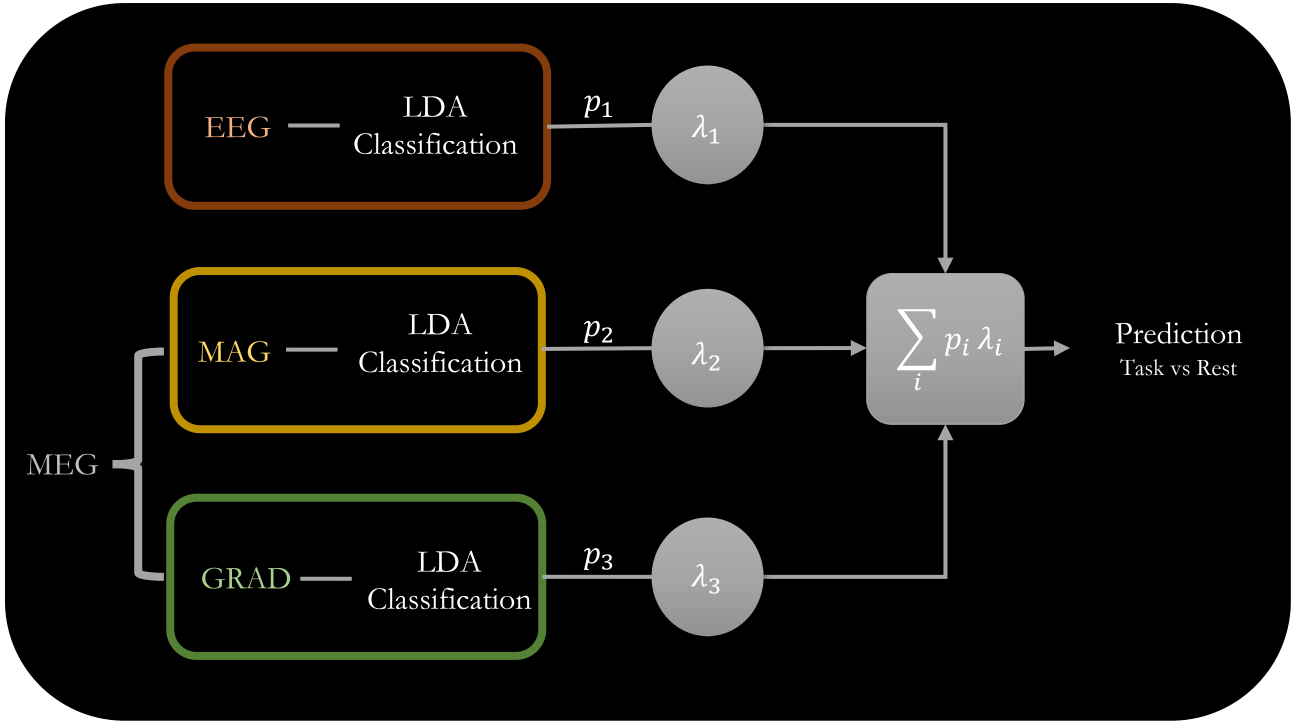
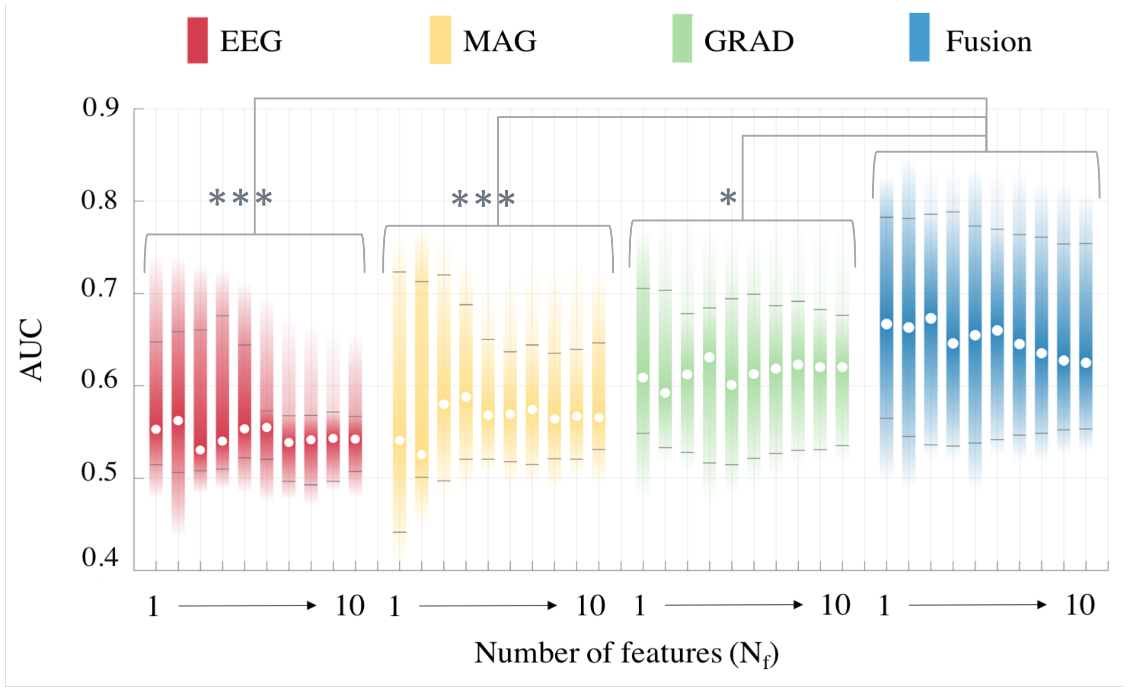
FUCONE approach, extension to multimodal data

Motivation

- Complementarity between MEG and EEG data [Sharon et al, NeuroImage, 2007]
- M/EEG integration led to an improvement of the BCI classification performance (power spectra) [Corsi et al, IJNS, 2018]



$$\lambda_i = \frac{p_i}{p_{EEG} + p_{MAG} + p_{GRAD}}$$



*** $p < 10^{-6}$

* $p < 0.05$

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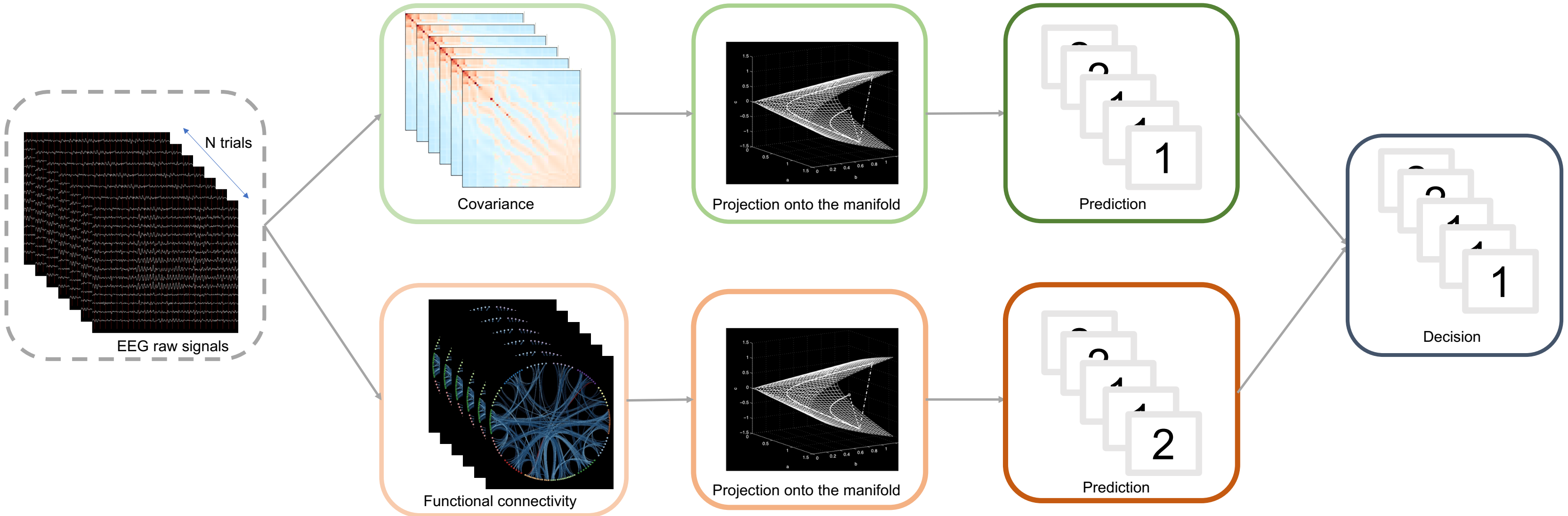
Approach

- Generalization to M/EEG data to exploit their complementarities
- To limit volume conduction effect, work in the source space [Corsi et al, NeuroImage, 2020]



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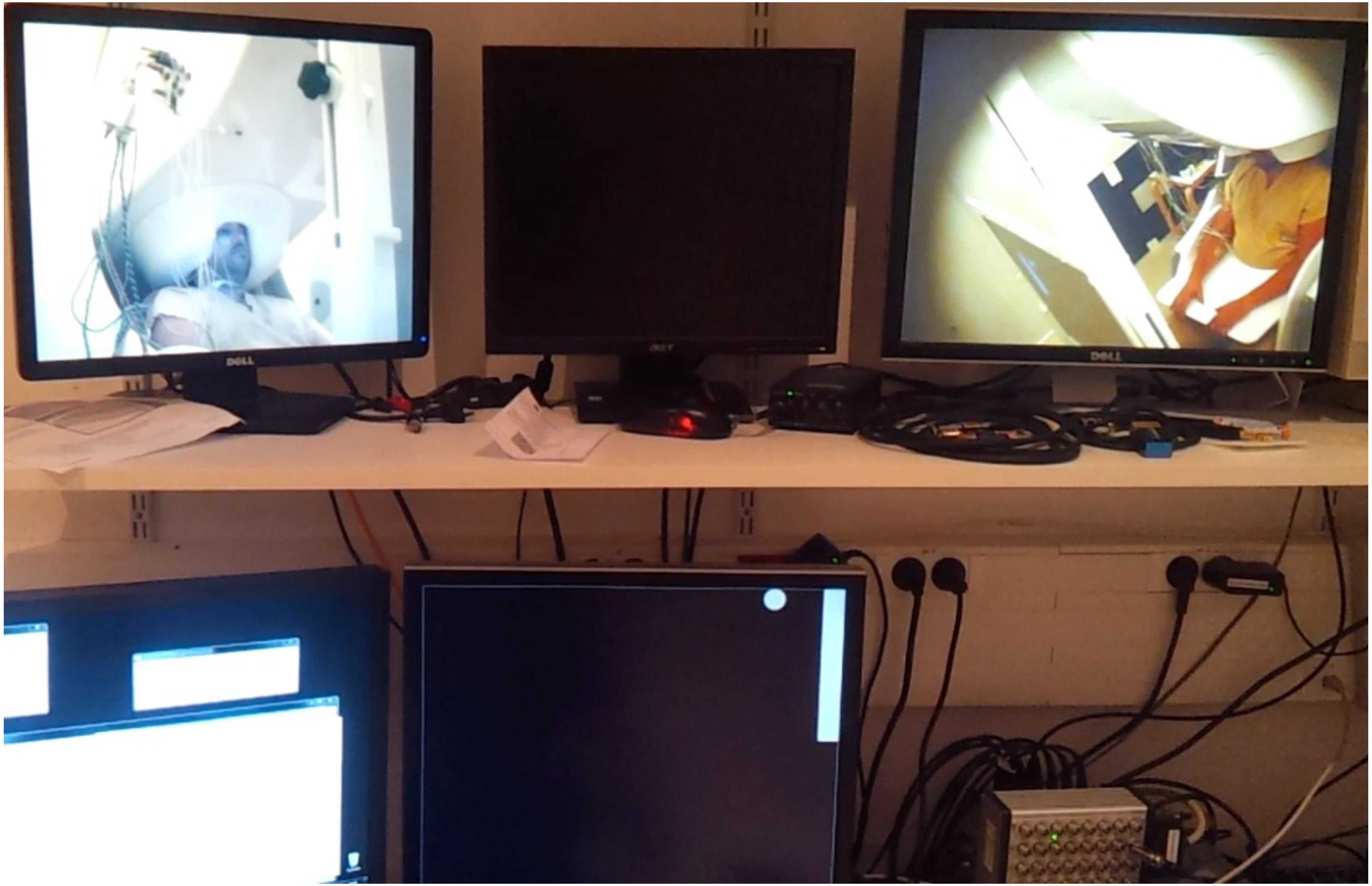

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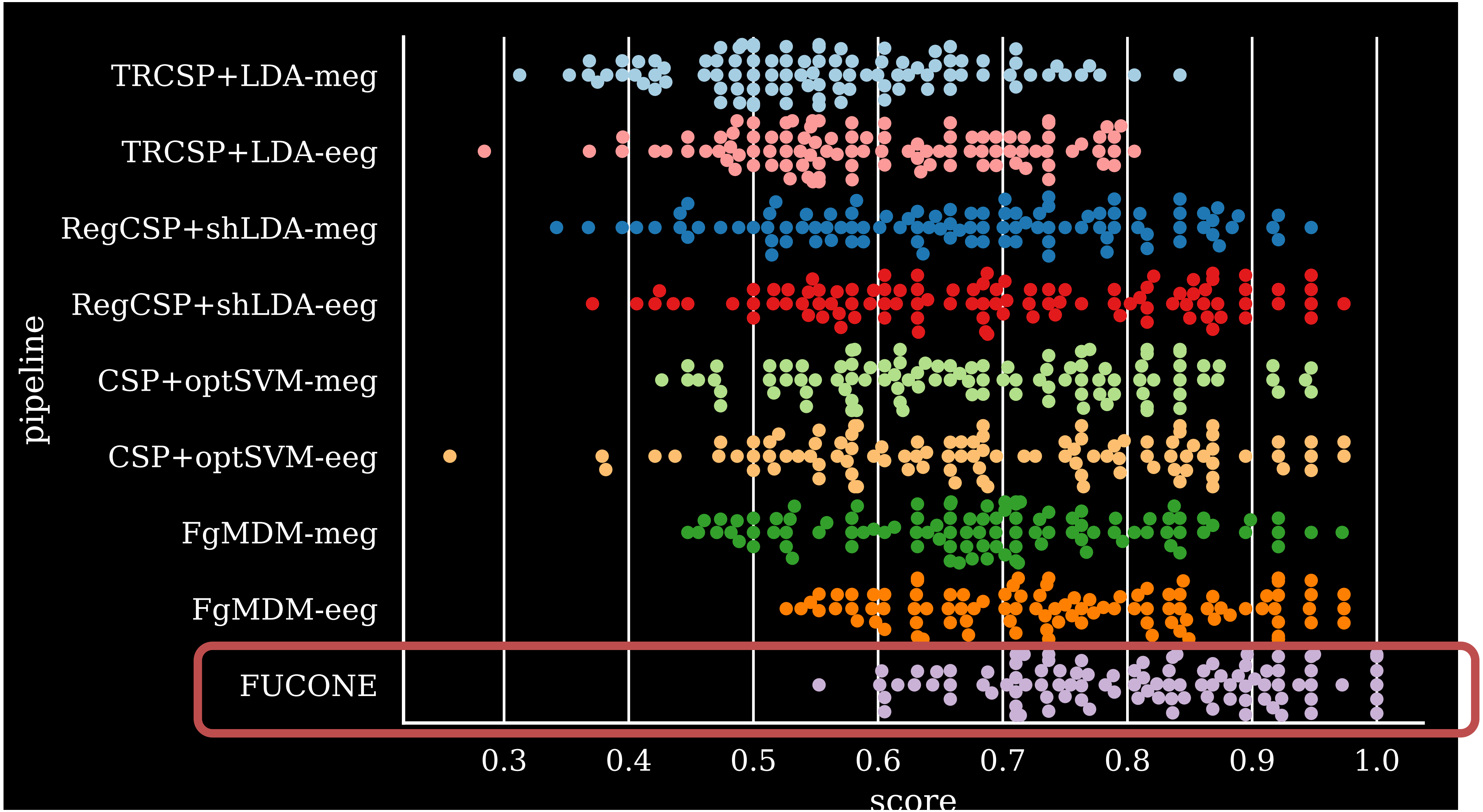

$p<10^{-4}$

Discussion

FUCONE approach

- Possibility to consider the users' specificity
- Replicable approach
  - From 2 to 4-classes configuration
  - Within and Cross-sessions

Extension to multimodal data, M/EEG

- Possibility to consider their complementarities
- Outperforms the state-of-the art method

Next steps

- Dimensionality reduction & interpretability of the chosen ROIs
- Features extraction

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Univ. Paris Dauphine – GREYC

Florian Yger

CNRS, Univ. Paris Saclay

Sylvain Chevallier

Interested in this study?

Scan the QR code to get access to the associated paper!

mccorsi/FUCONE

Thank you for your attention!

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MConstanceCorsi