



Ensemble of Riemannian Classifiers for Multimodal Data: FUCONE Approach for M/EEG Data

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

► To cite this version:

Marie-Constance Corsi, Sylvain Chevallier, Fabrizio de Vico Fallani, Florian Yger. Ensemble of Riemannian Classifiers for Multimodal Data: FUCONE Approach for M/EEG Data. ISBI 2023 - IEEE International Symposium on Biomedical Imaging, Apr 2023, Cartagena de Indias, Colombia. hal-04140126

HAL Id: hal-04140126

<https://inria.hal.science/hal-04140126v1>

Submitted on 24 Jun 2023

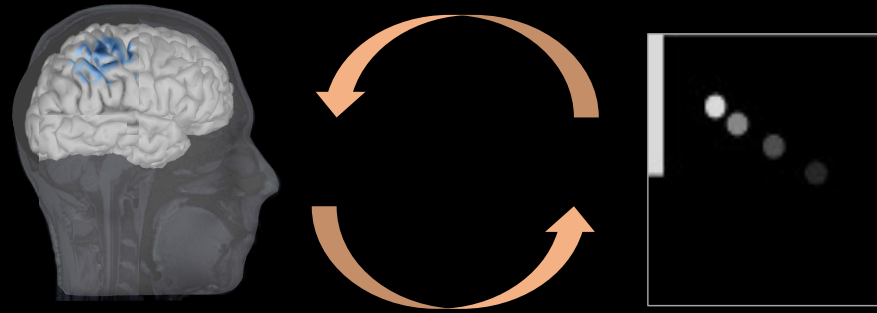
HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

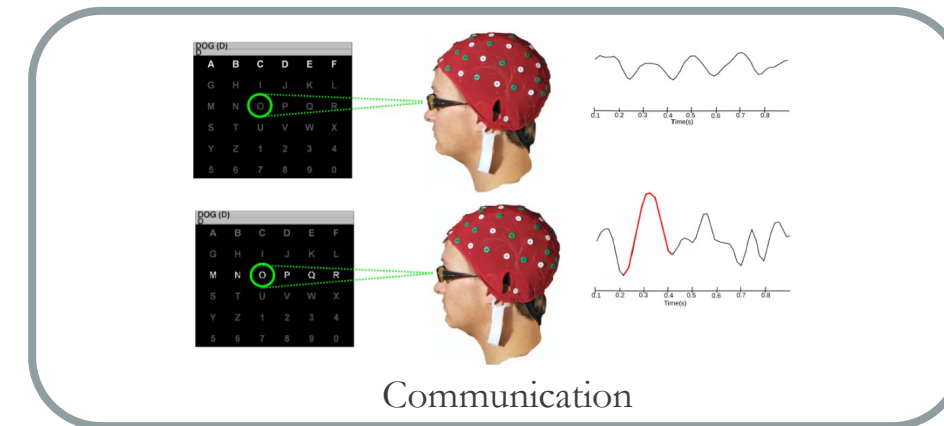
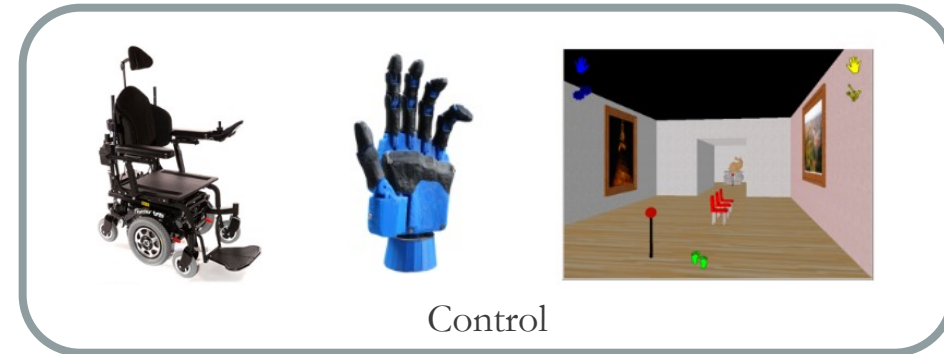
Ensemble of Riemannian classifiers for multimodal data:
FUCONE approach for M/EEG data



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

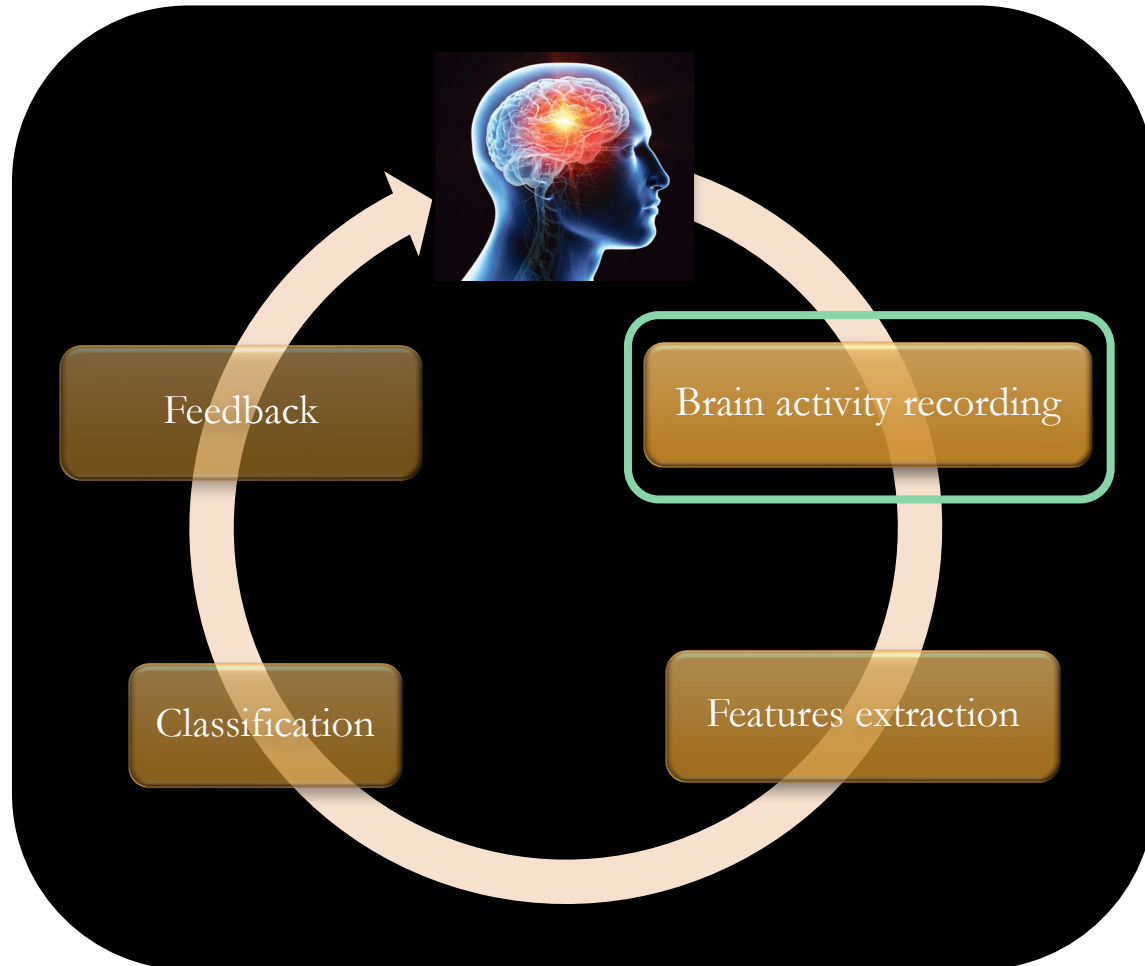
*Inria, Paris Brain Institute, France

Non-invasive Brain-Computer Interface - BCI



Adapted from (Lotte et al, 2015)

Behind the magic...

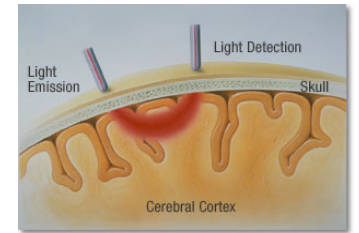


Non-invasive tools

EEG



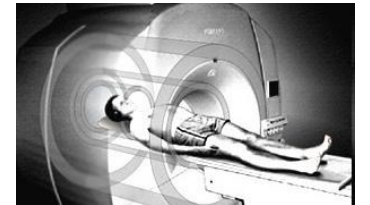
NIRS



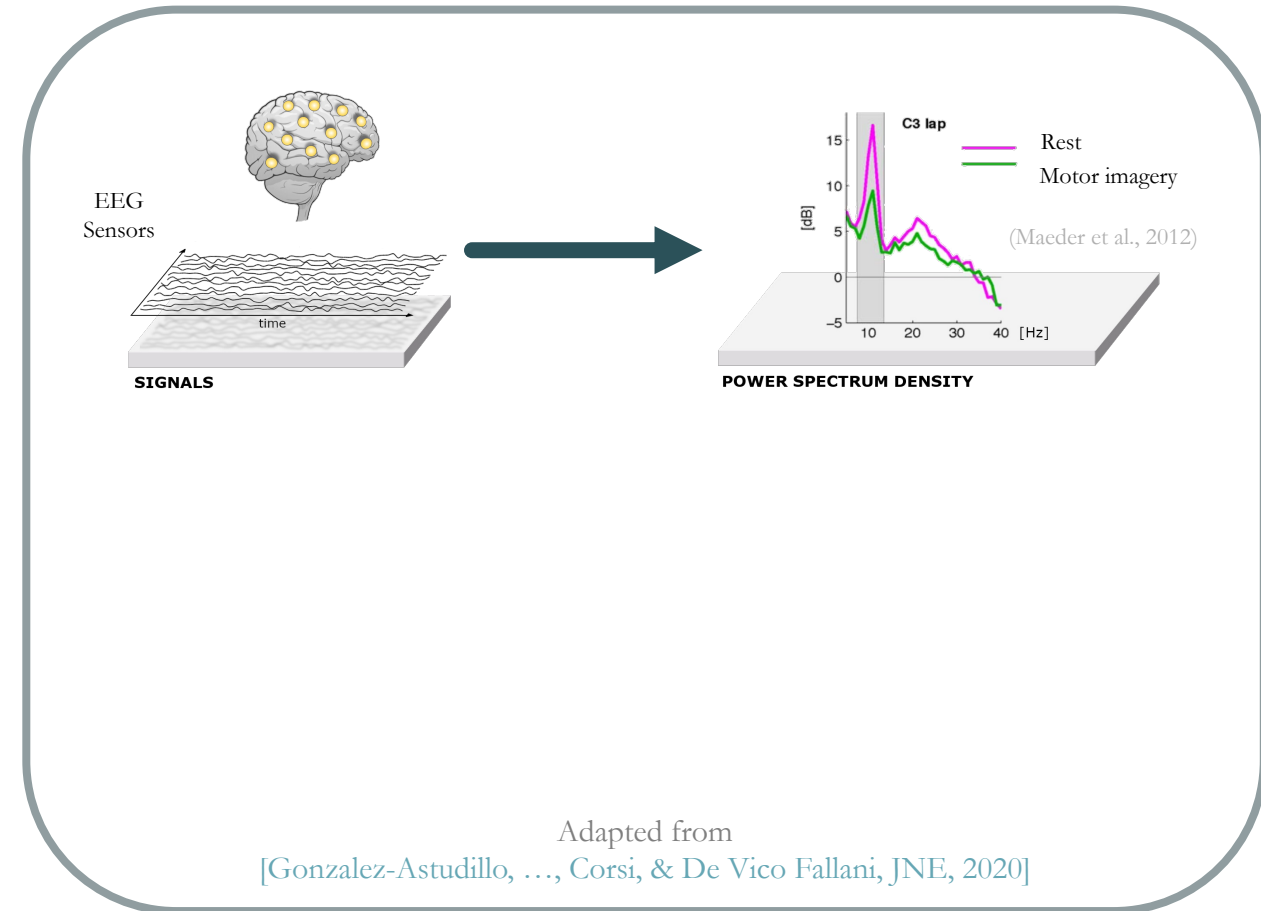
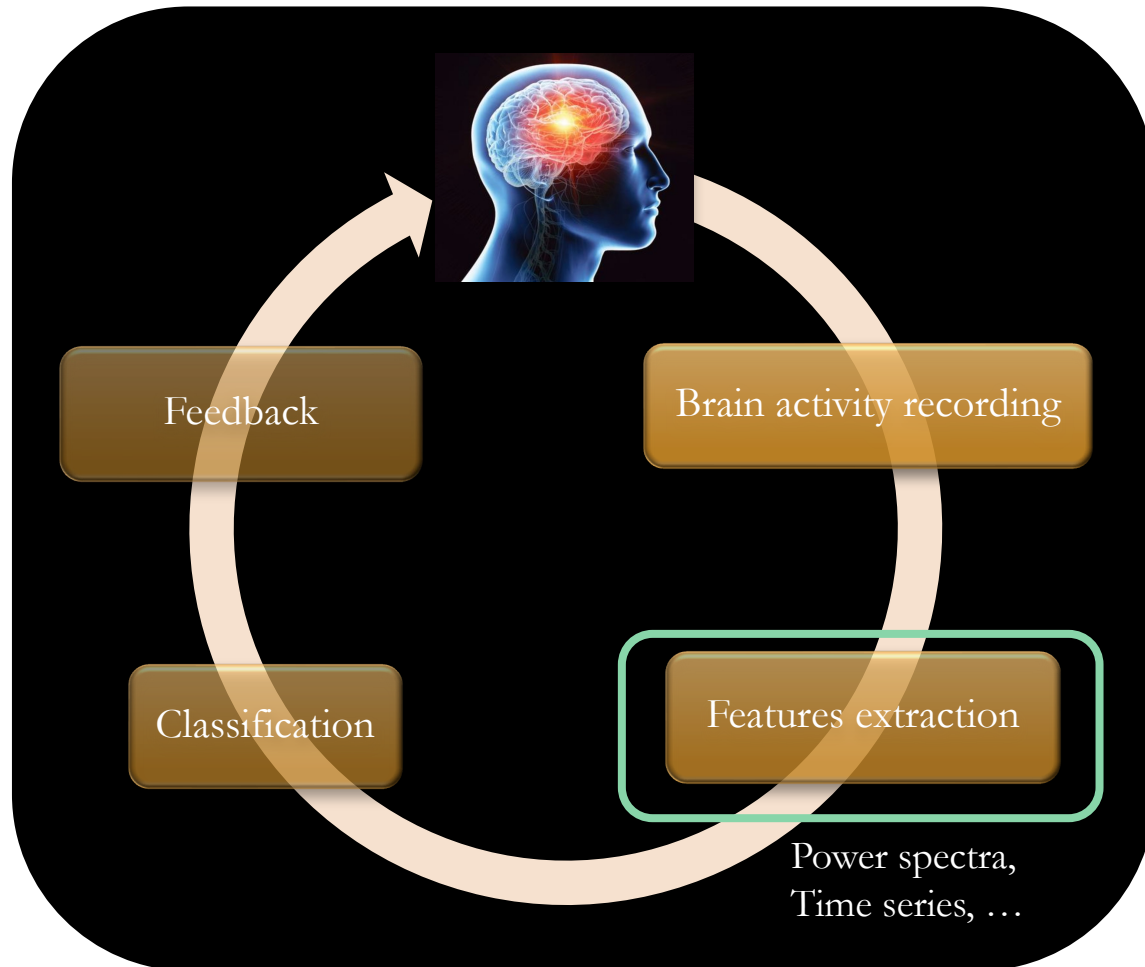
MEG



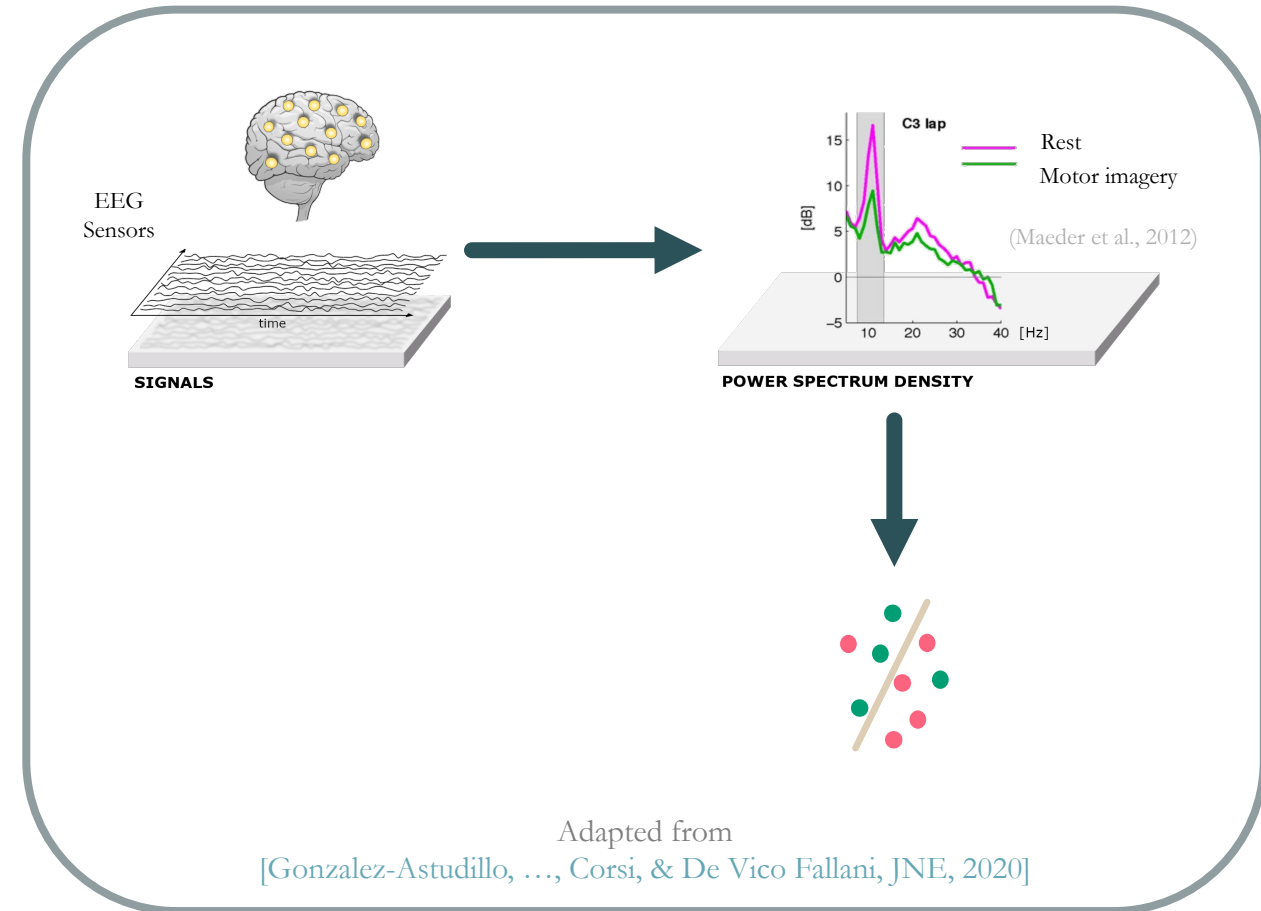
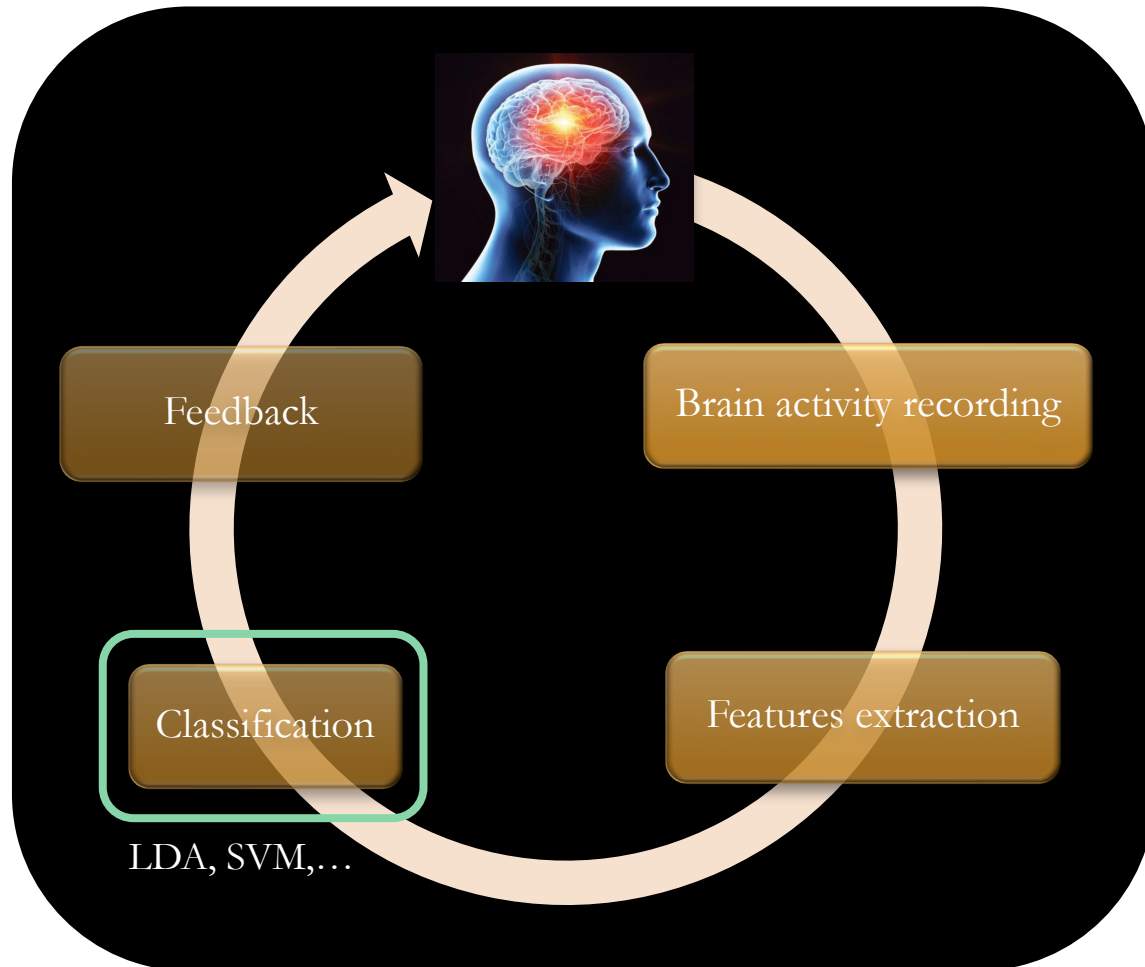
fMRI



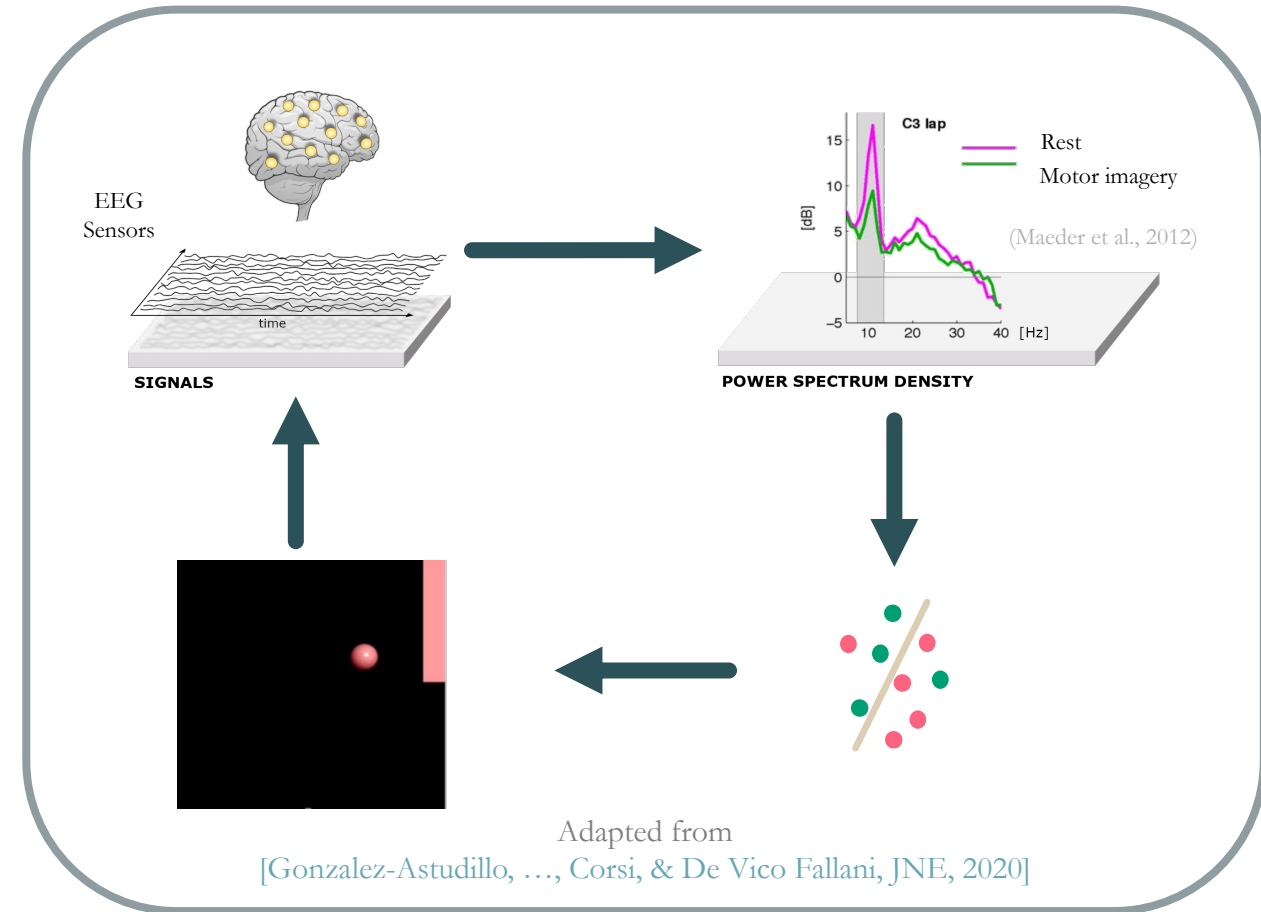
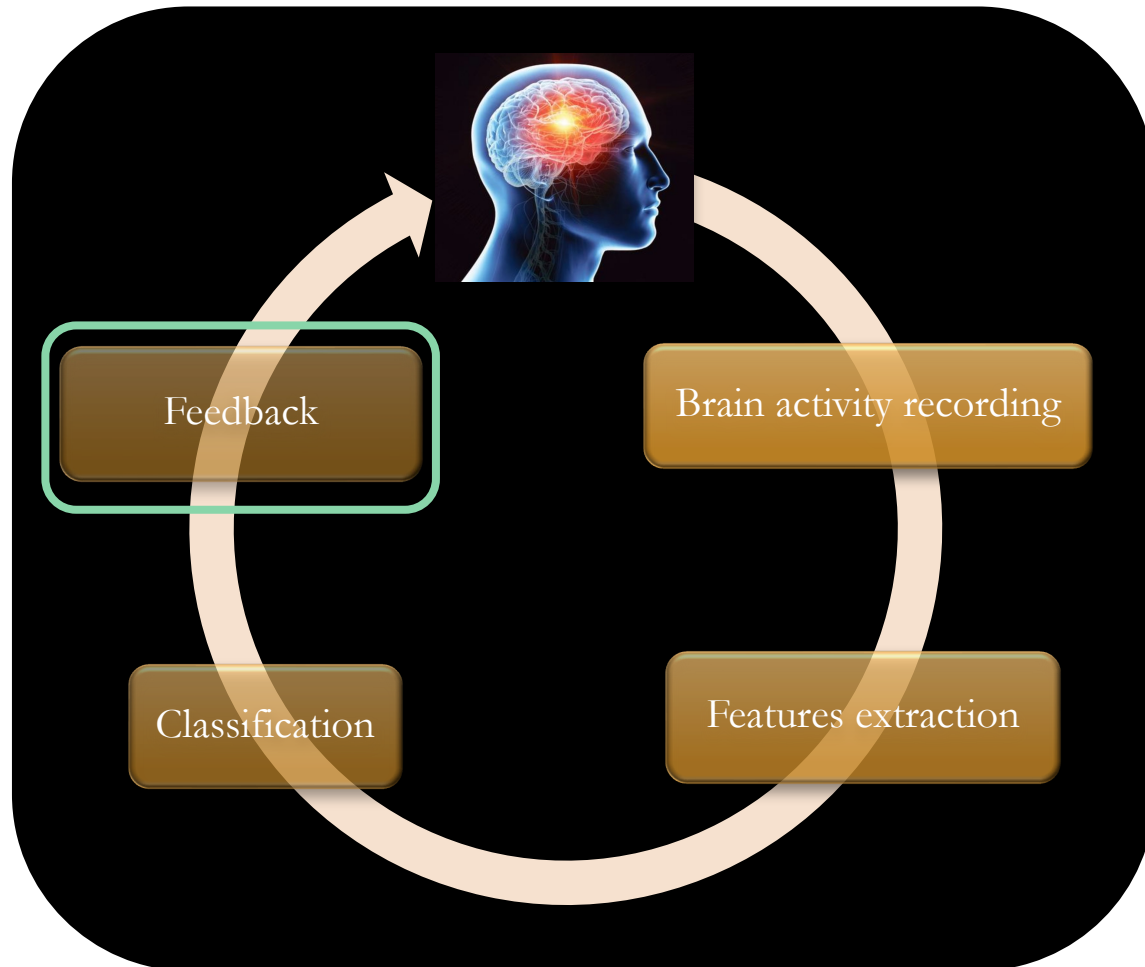
Behind the magic...



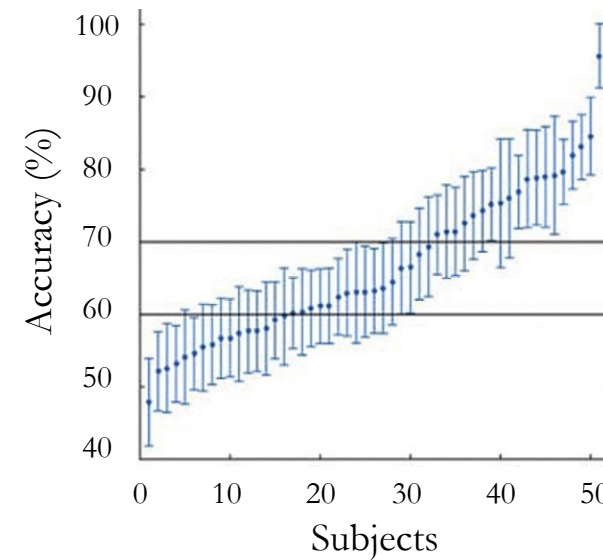
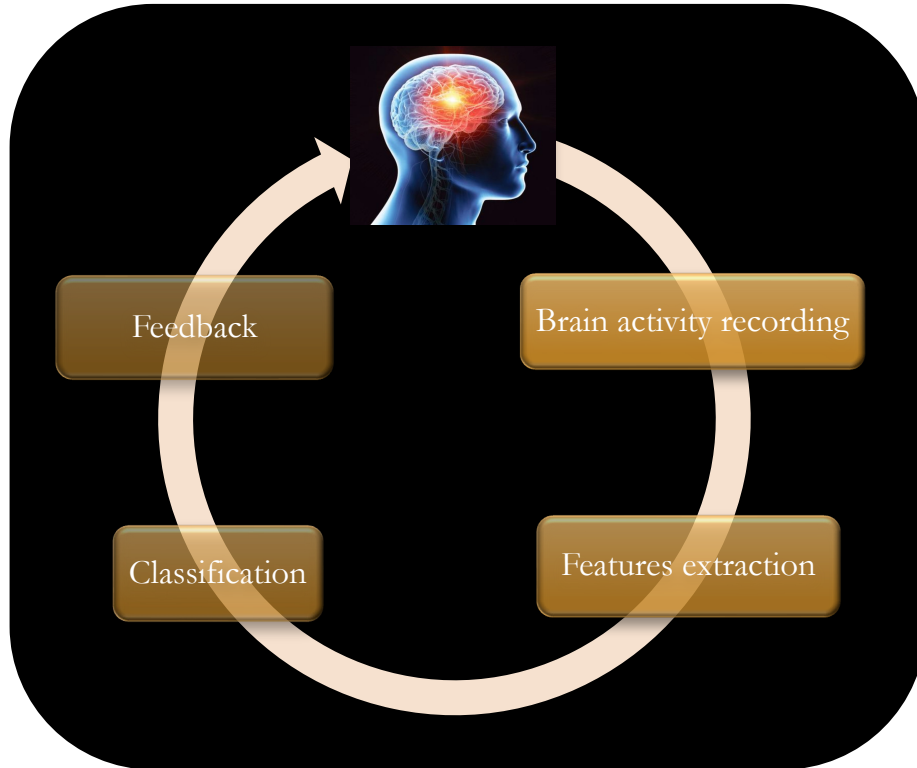
Behind the magic...



Behind the magic...



Non-invasive Brain-Computer Interface - BCI



Adapted from (Ahn & Jun, 2015)

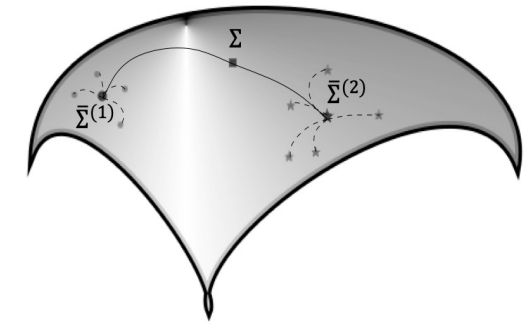
Problem: Current BCIs fail to detect the mental intentions in ~30% of users –
BCI inefficiency (Thompson, 2018)

Riemannian Geometry (RG) & Functional connectivity (FC)

8

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

- Covariance matrices, $\Sigma = \frac{1}{N-1}XX^T$, 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)

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

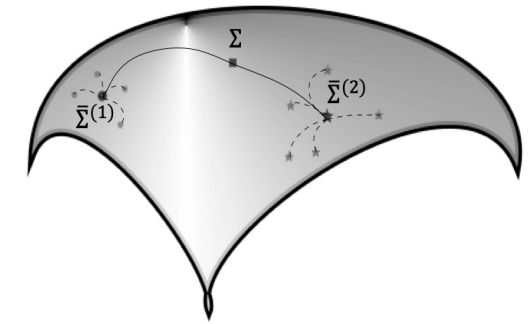
$$\bar{\Sigma} = \mu(\{\Sigma_i\}) = \arg \min_{\Sigma} \sum_{i=1}^N \delta^2(\Sigma_i, \Sigma)$$

Riemannian Geometry (RG) & Functional connectivity (FC)

9

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

- Covariance matrices, $\Sigma = \frac{1}{N-1}XX^T$, 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)

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

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

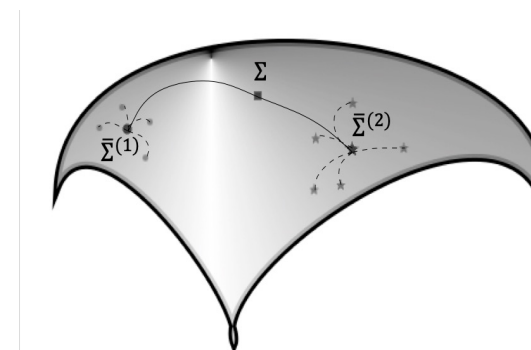
Problem: RG approaches in BCI rely only on covariance matrices without considering synchronous interactions between brain areas

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

- Covariance matrices, $\Sigma = \frac{1}{N-1}XX^T$, 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

Functional connectivity

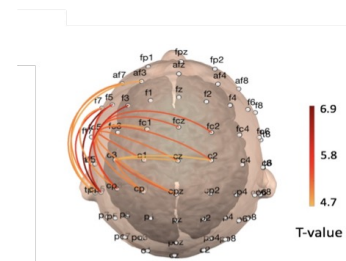
- Interconnected nature of brain connectivity & alternative features in BCI
- Use of all the possible information from connectivity matrices
- Regularization methods to make the matrices SPD



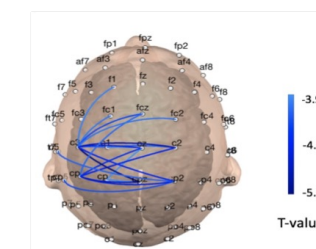
Minimum Distance to Mean (MDM)

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

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



Amplitude synchronization



Phase synchronization

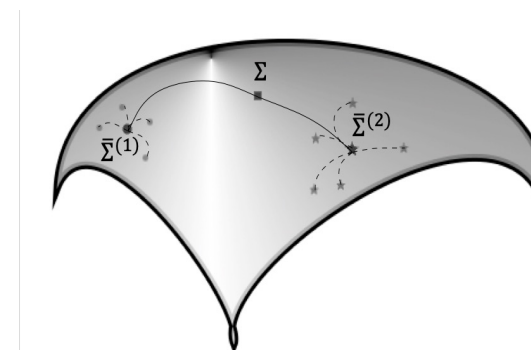
FC contrast between conditions, adapted from
[Cattai, Colonnese, Corsi, et al, IEEE TNSRE, 2021]

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

- Covariance matrices, $\Sigma = \frac{1}{N-1}XX^T$, 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

Functional connectivity

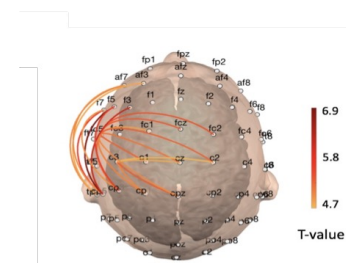
- Interconnected nature of brain connectivity & alternative features in BCI
- Use of all the possible information from connectivity matrices
- Regularization methods to make the matrices SPD



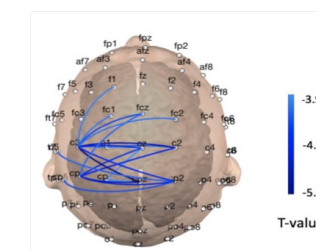
Minimum Distance to Mean (MDM)

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

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



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)

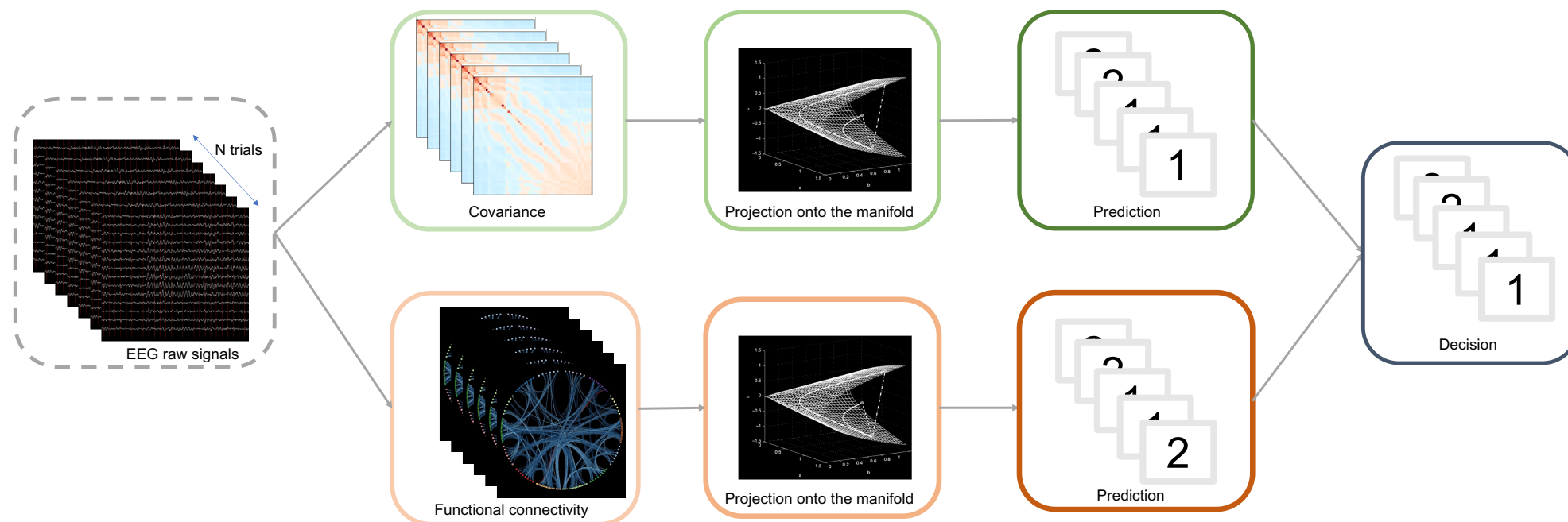
12

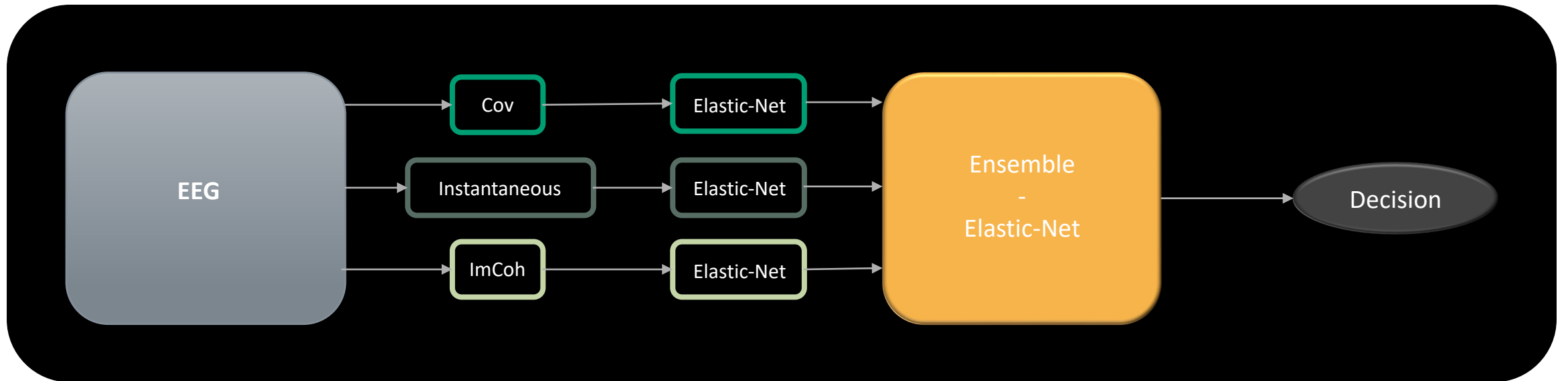
Motivation

- Considering subjects' specificity
- Improving the robustness

Approach

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





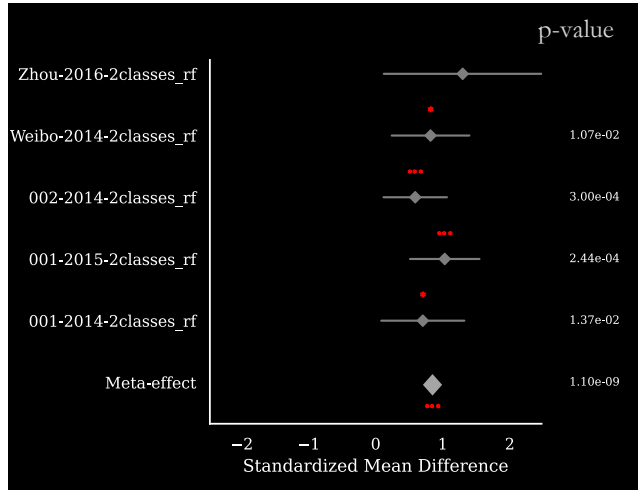
FUnctional CONnectivity Ensemble (FUCONE) approach

FUCONE – A replicable approach

14

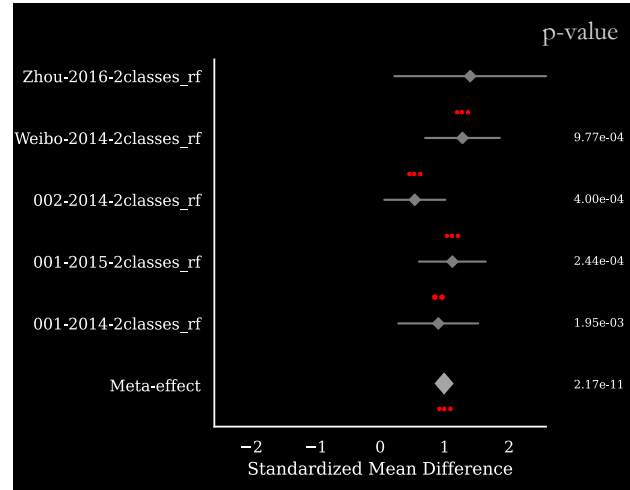
RegCSP+shLDA better

FUCONE better



CSP+optSVM better

FUCONE better

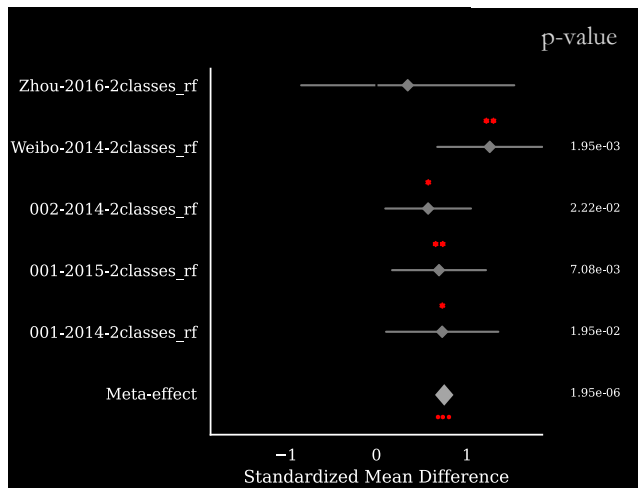


Common Spatial Patterns + Shrinkage Linear Discriminant Analysis

Common Spatial Patterns + Support Vector Machine

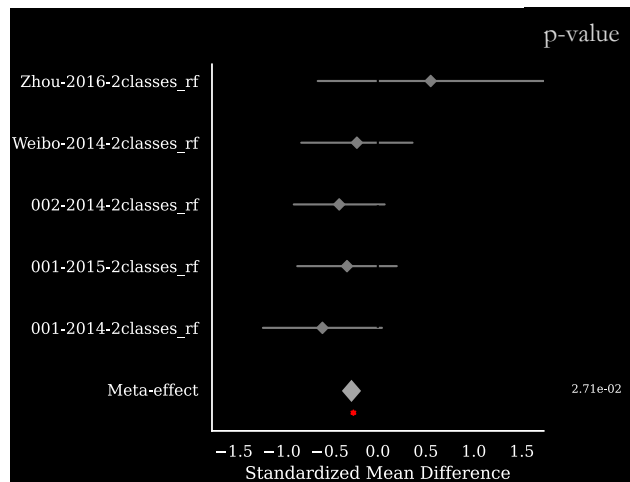
FgMDM better

FUCONE better



FUCONE better

Cov+EN better



Geodesic filtering + Minimum Distance to Mean classification

Covariance + Elastic-Net

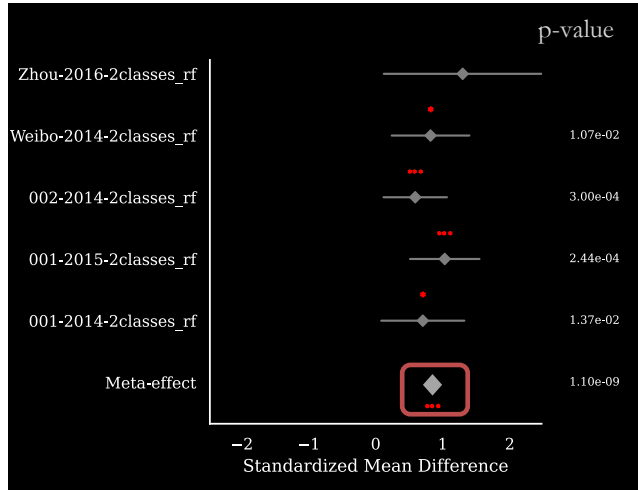


FUCONE – A replicable approach

15

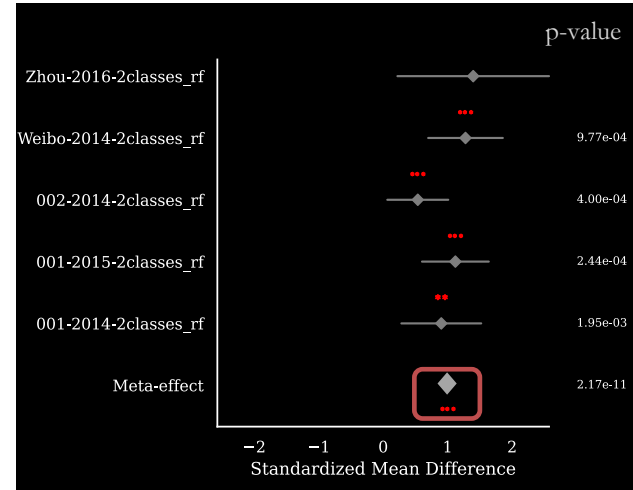
RegCSP+shLDA better

FUCONE better



CSP+optSVM better

FUCONE better

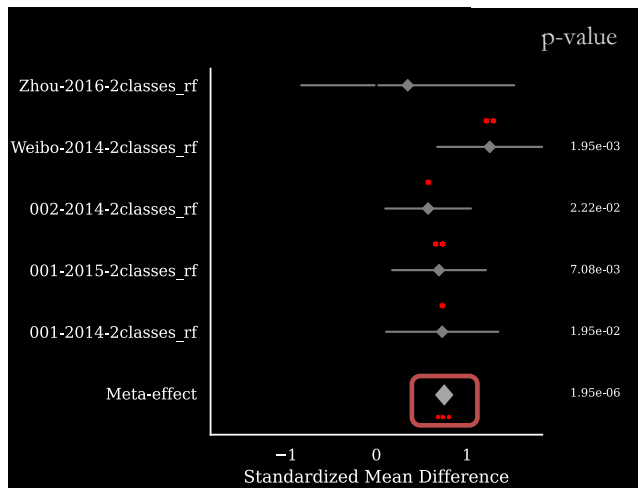


Common Spatial Patterns + Shrinkage Linear Discriminant Analysis

Common Spatial Patterns + Support Vector Machine

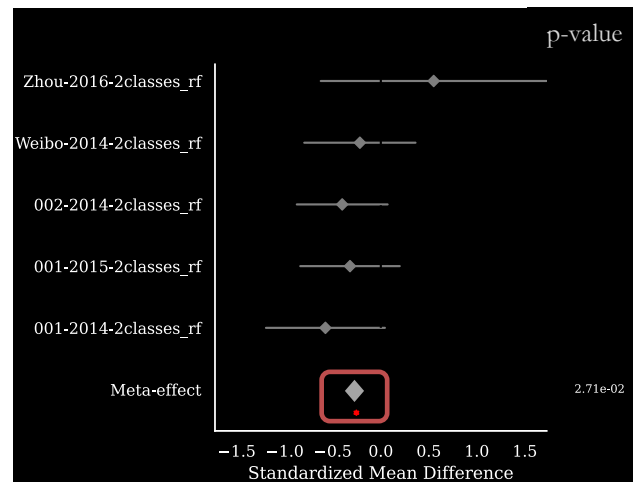
FgMDM better

FUCONE better



FUCONE better

Cov+EN better



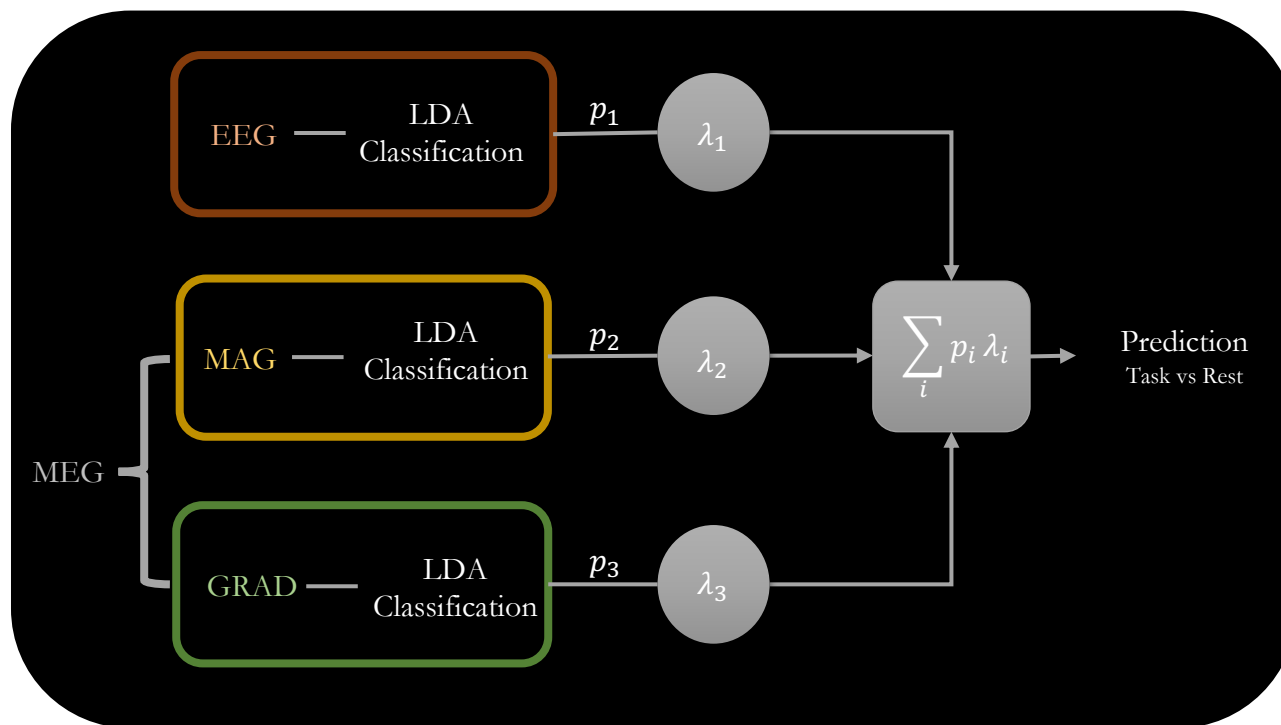
Geodesic filtering + Minimum Distance to Mean classification

Covariance + Elastic-Net

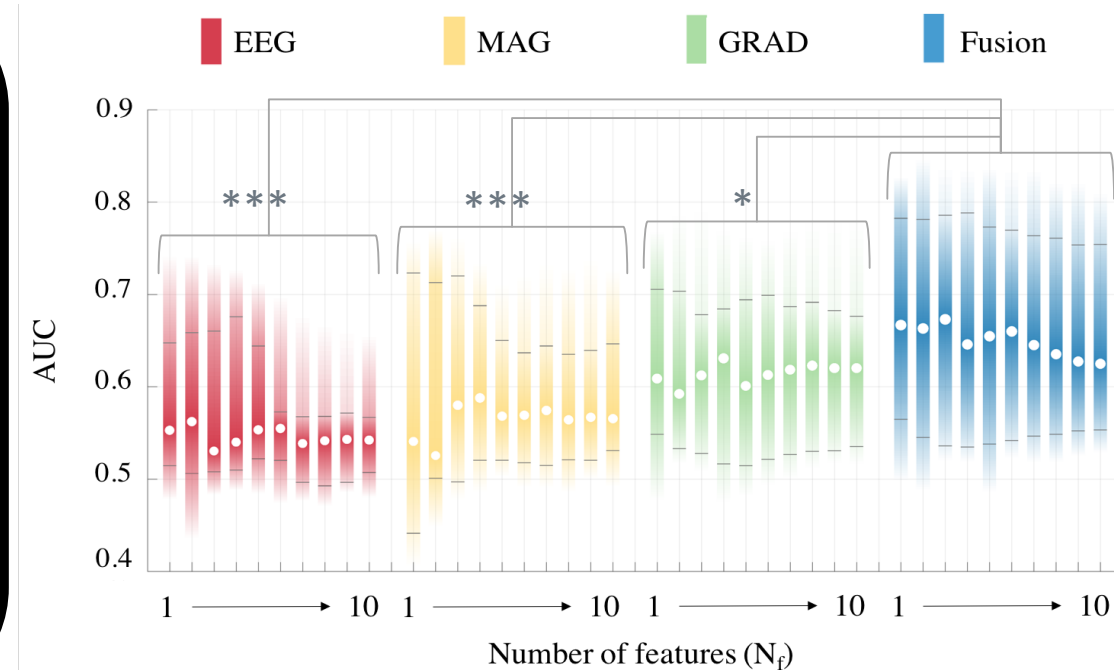


Motivation

- 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]



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



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

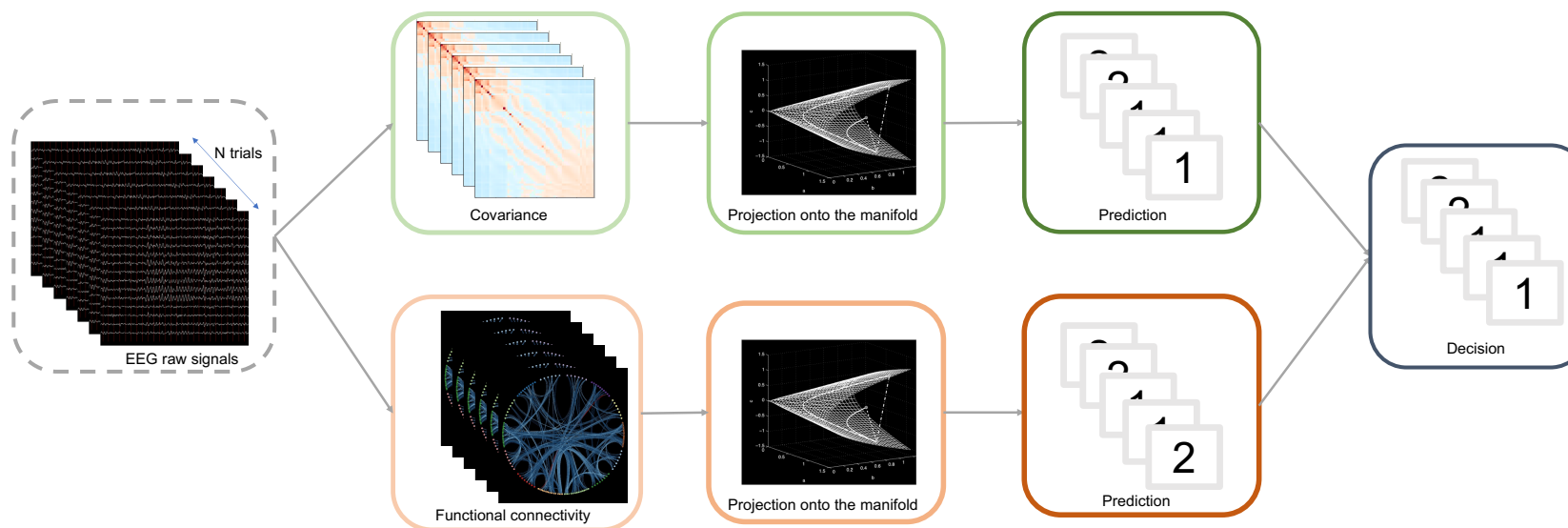
* $p < 0.05$

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]

Approach

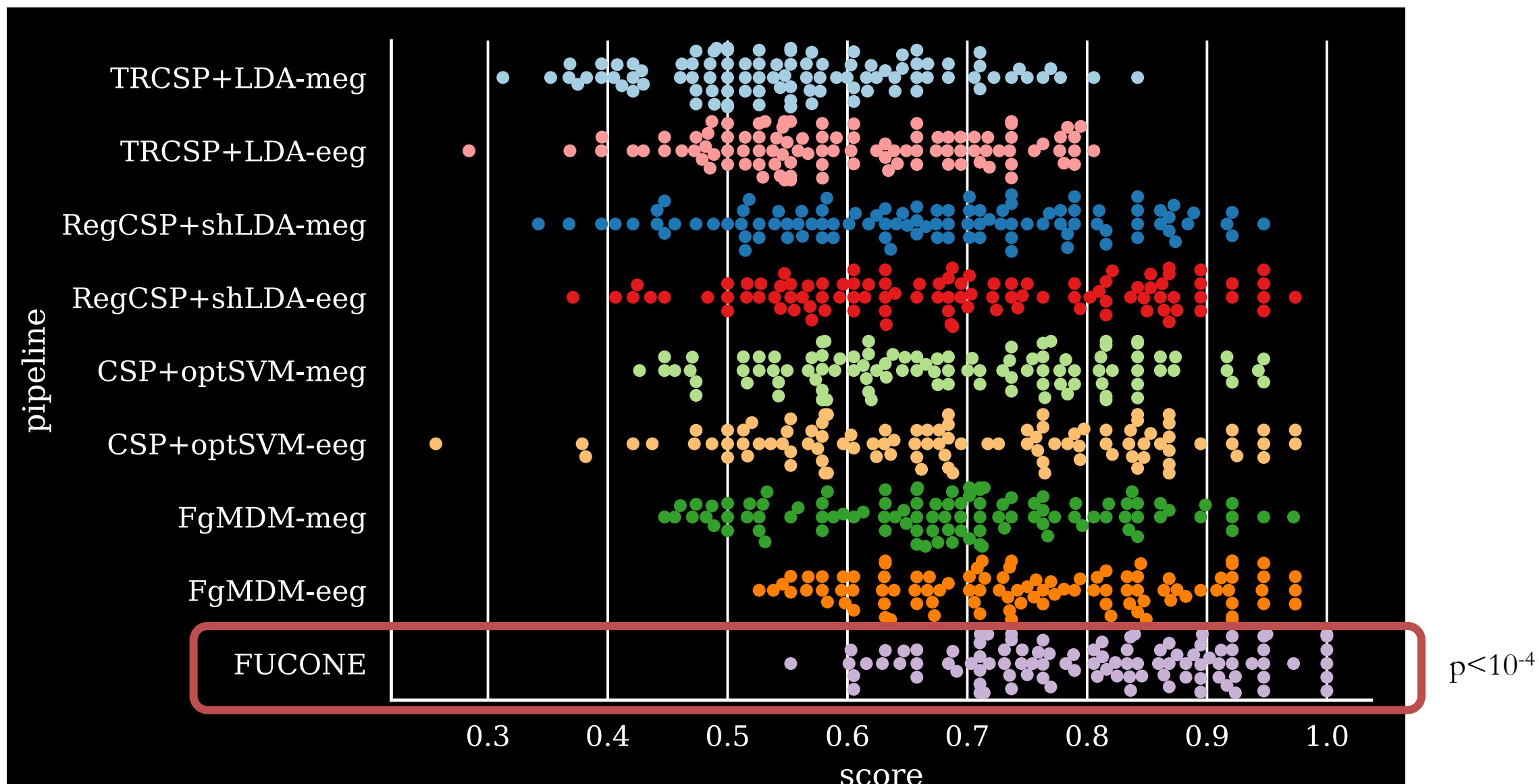
- Generalization to M/EEG data to exploit their complementarities
- To limit volume conduction effect, work in the source space [Corsi et al, NeuroImage, 2020]



FUCONE approach, extension to multimodal data

18





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



Paris Brain Institute



Denis Schwartz,
Nathalie George,
Laurent Hugueville,
Christophe Gitton
Sophie Dupont,
Juliana Gonzalez-Astudillo,
Fabrizio De Vico Fallani (PI)

Penn University

Ari E. Kahn,
Ankit Khambhati,
Jennifer Stiso,
Arnold Campbell,
Danielle S. Bassett (PI)



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](https://github.com/mccorsi/FUCONE)

Thank you for your attention!



marie-constance.corsi@inria.fr



MConstanceCorsi