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

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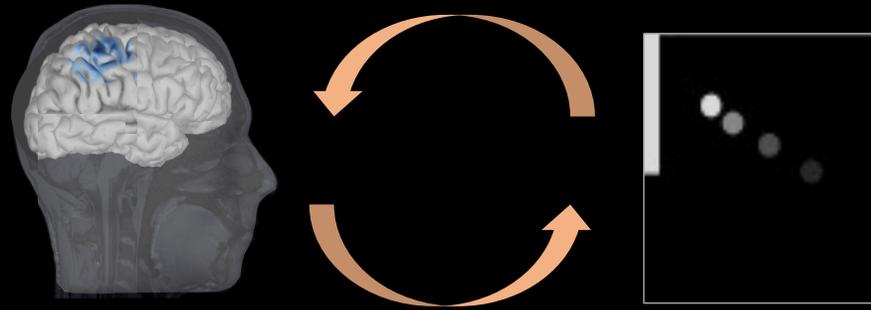
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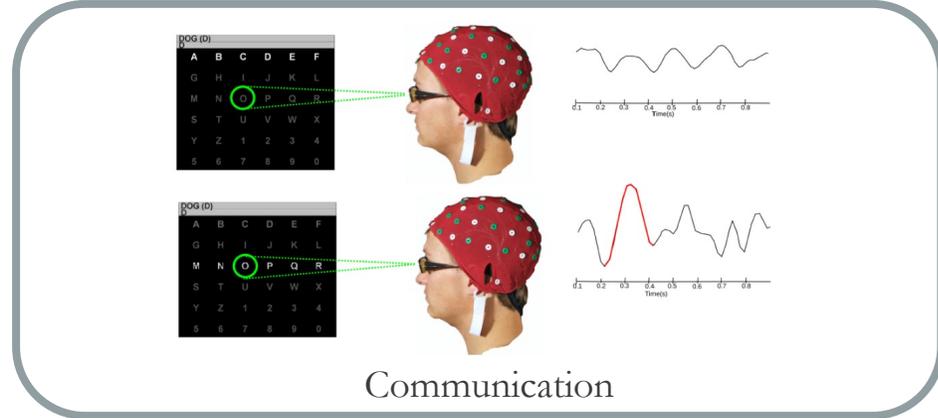
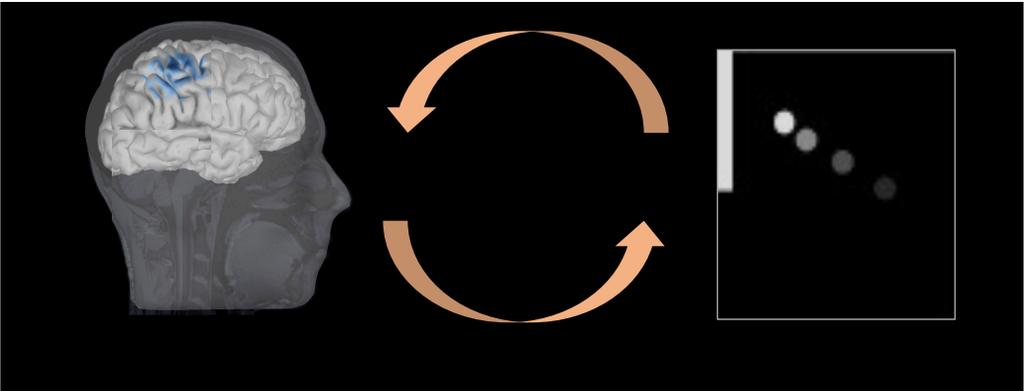
Ensemble of Riemannian classifiers for multimodal data:
FUCONE approach for M/EEG data



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

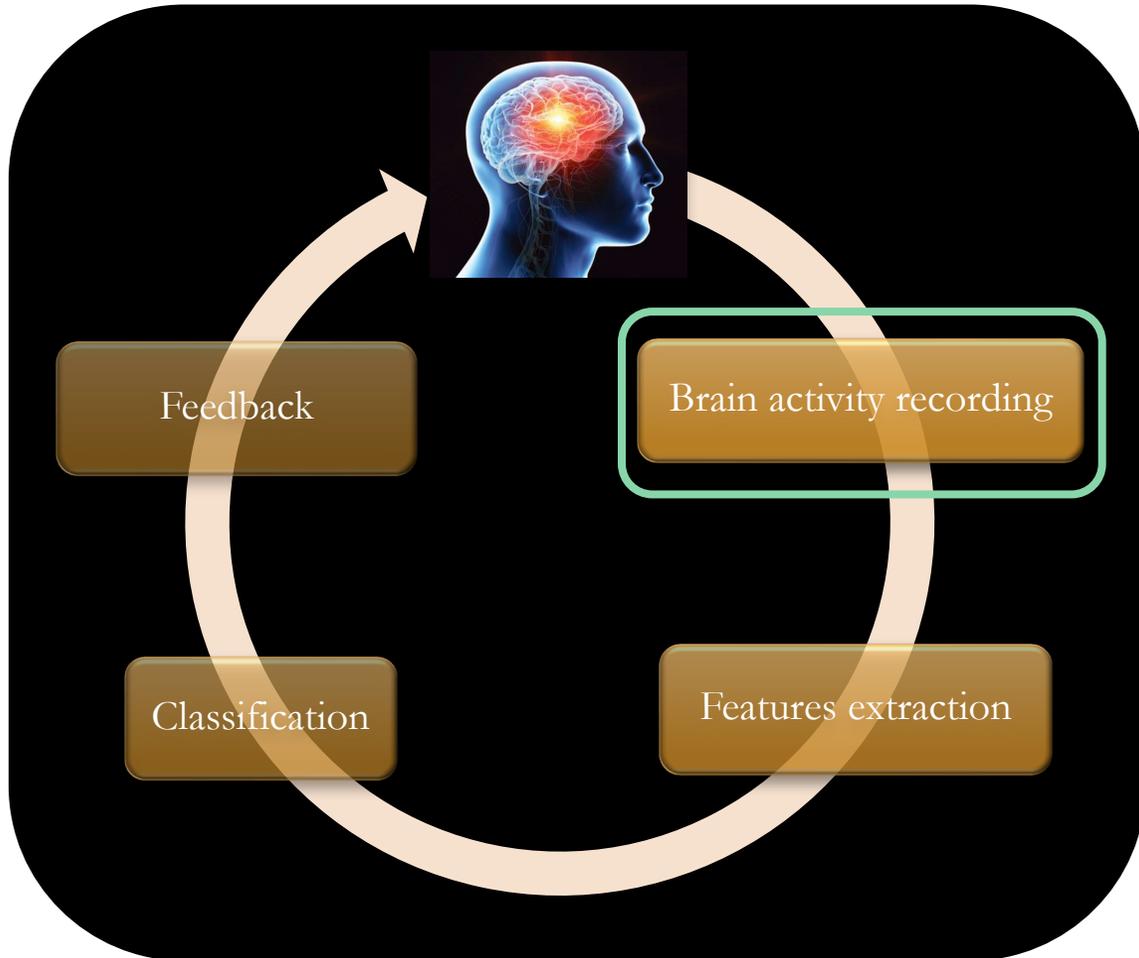
*Inria, Paris Brain Institute, France

Non-invasive Brain-Computer Interface - BCI



Adapted from (Lotte et al, 2015)

Behind the magic...

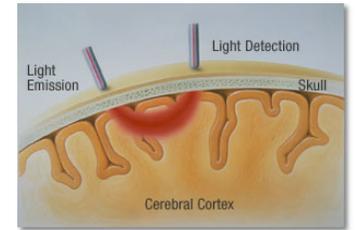


Non-invasive tools

EEG



NIRS



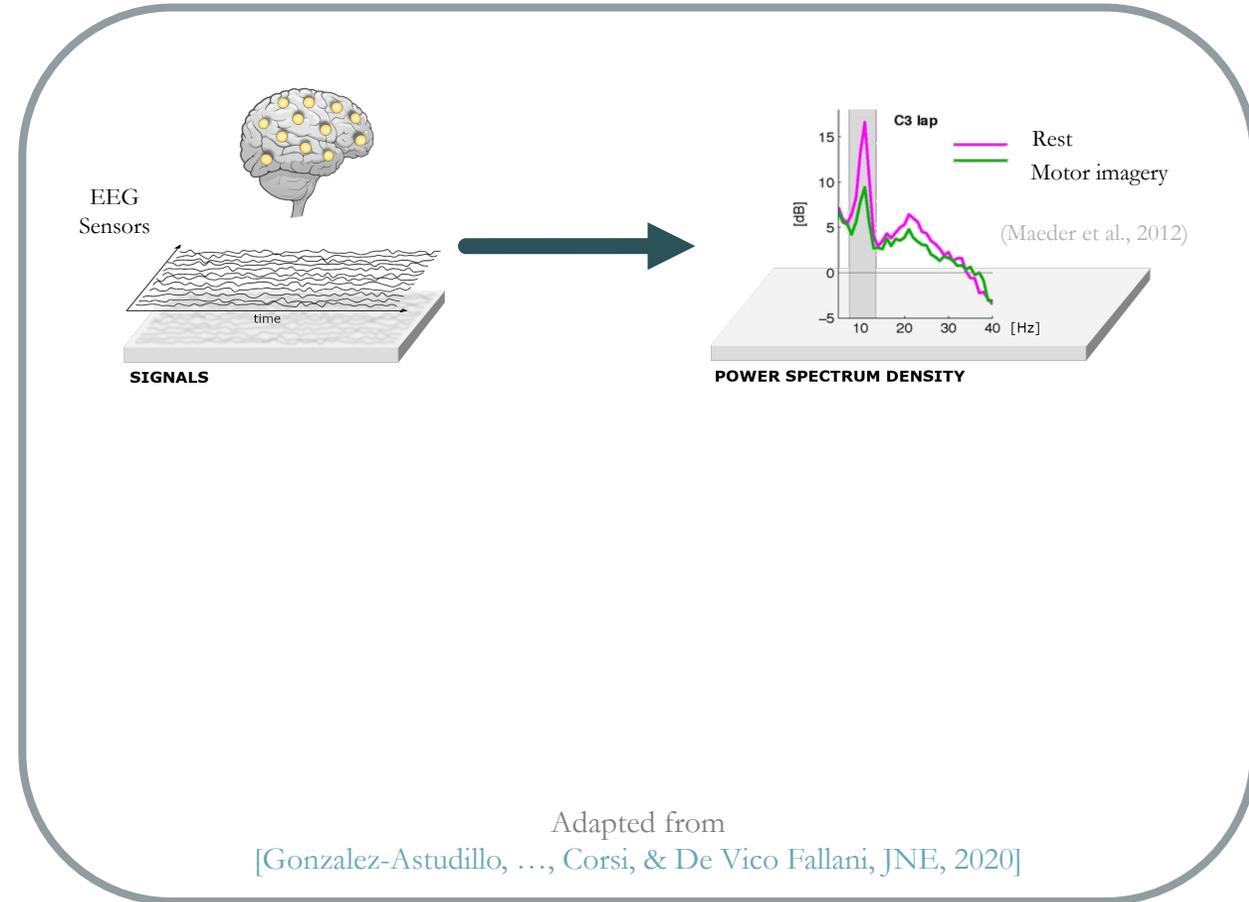
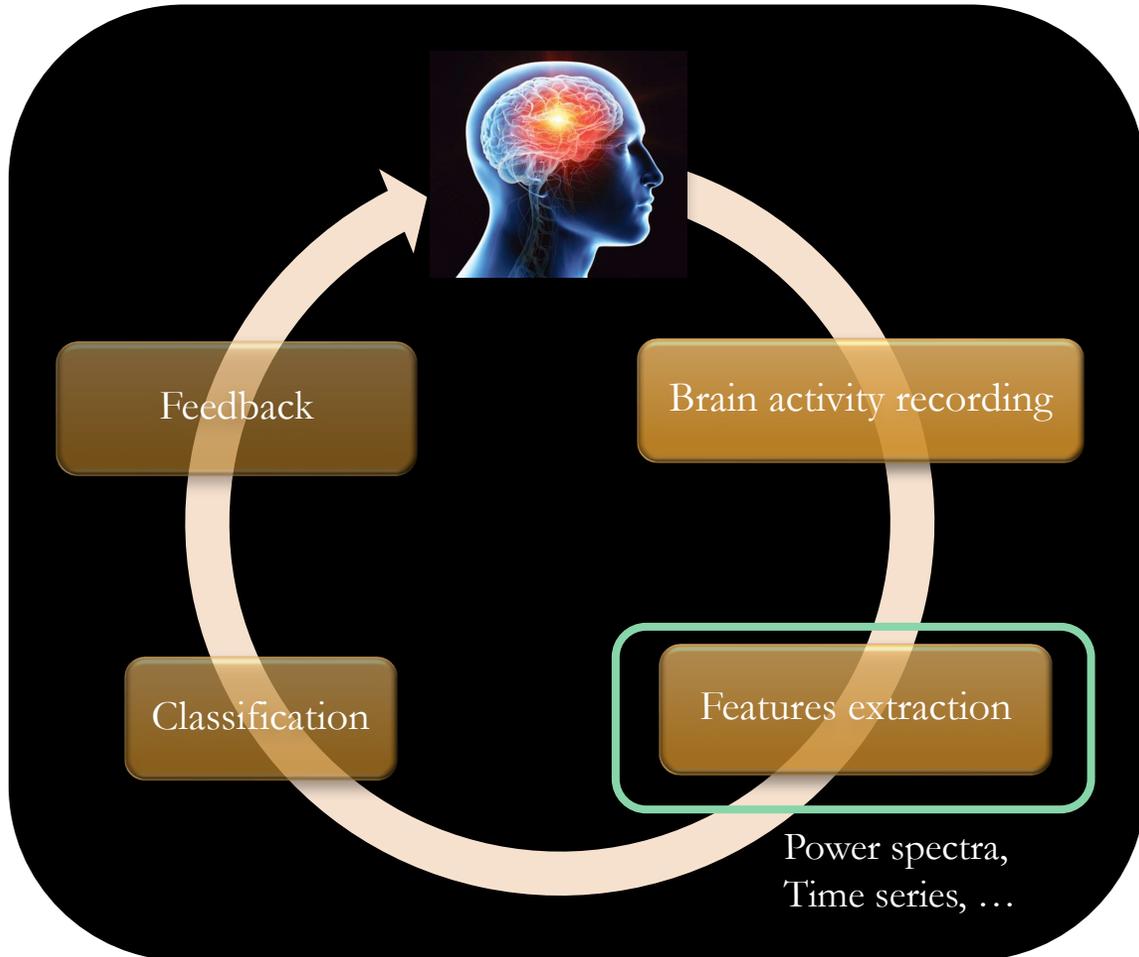
MEG



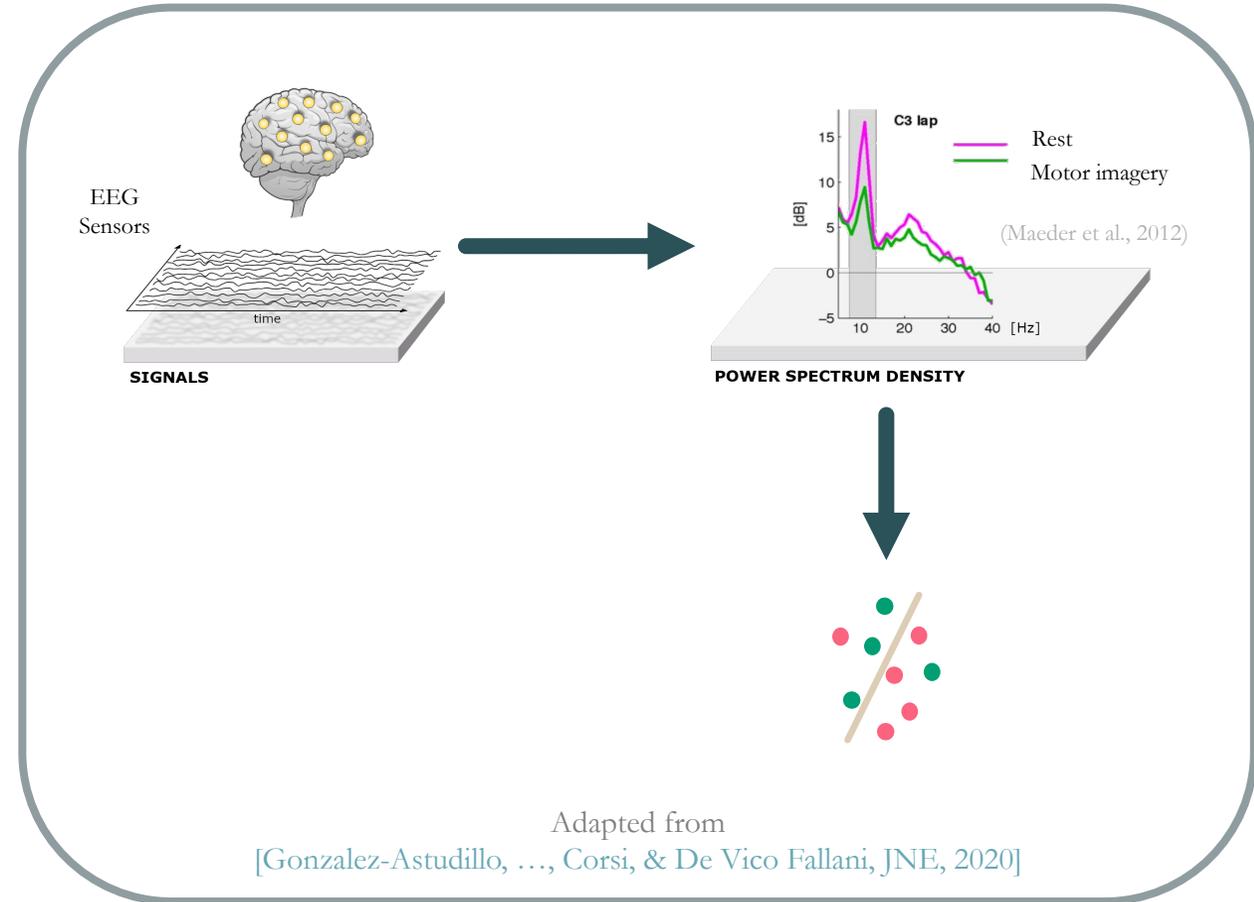
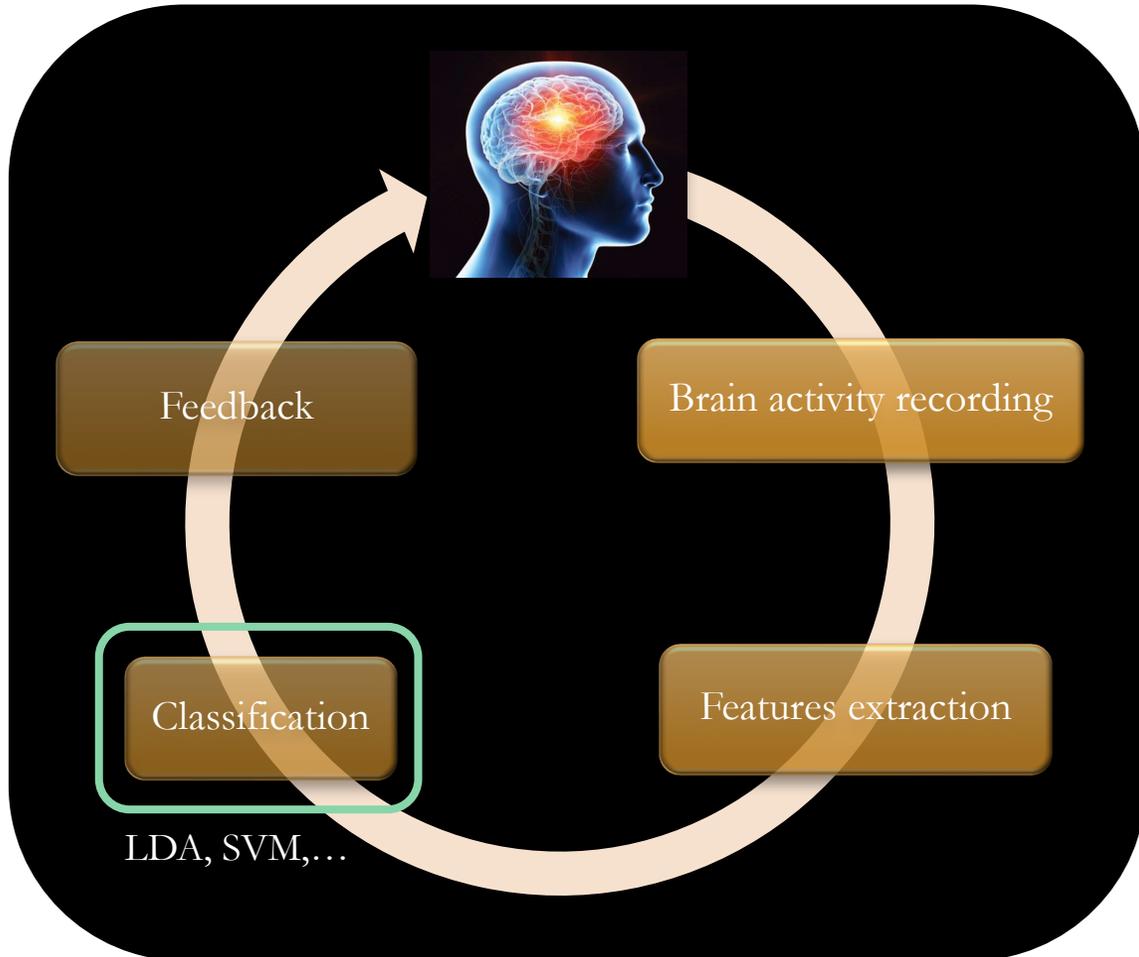
fMRI



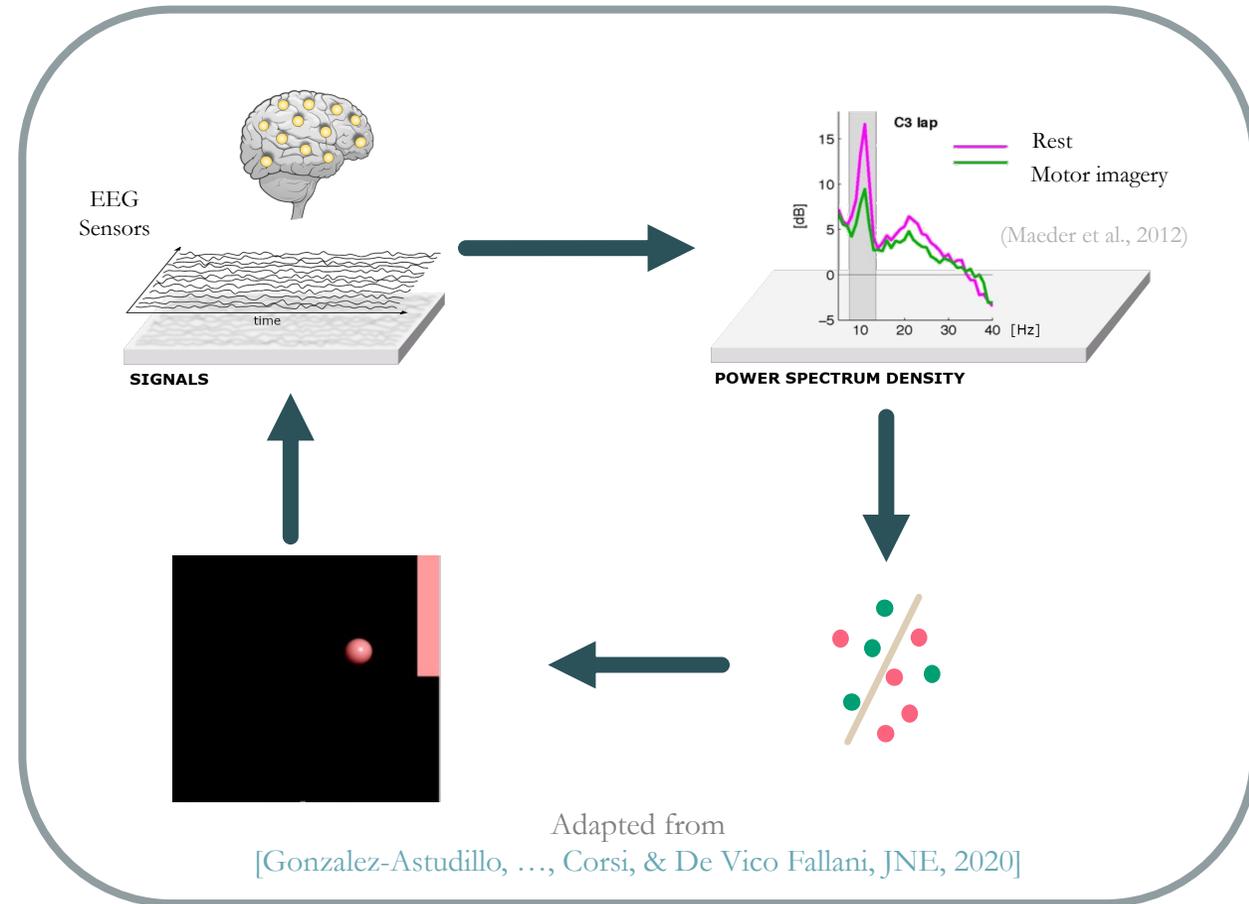
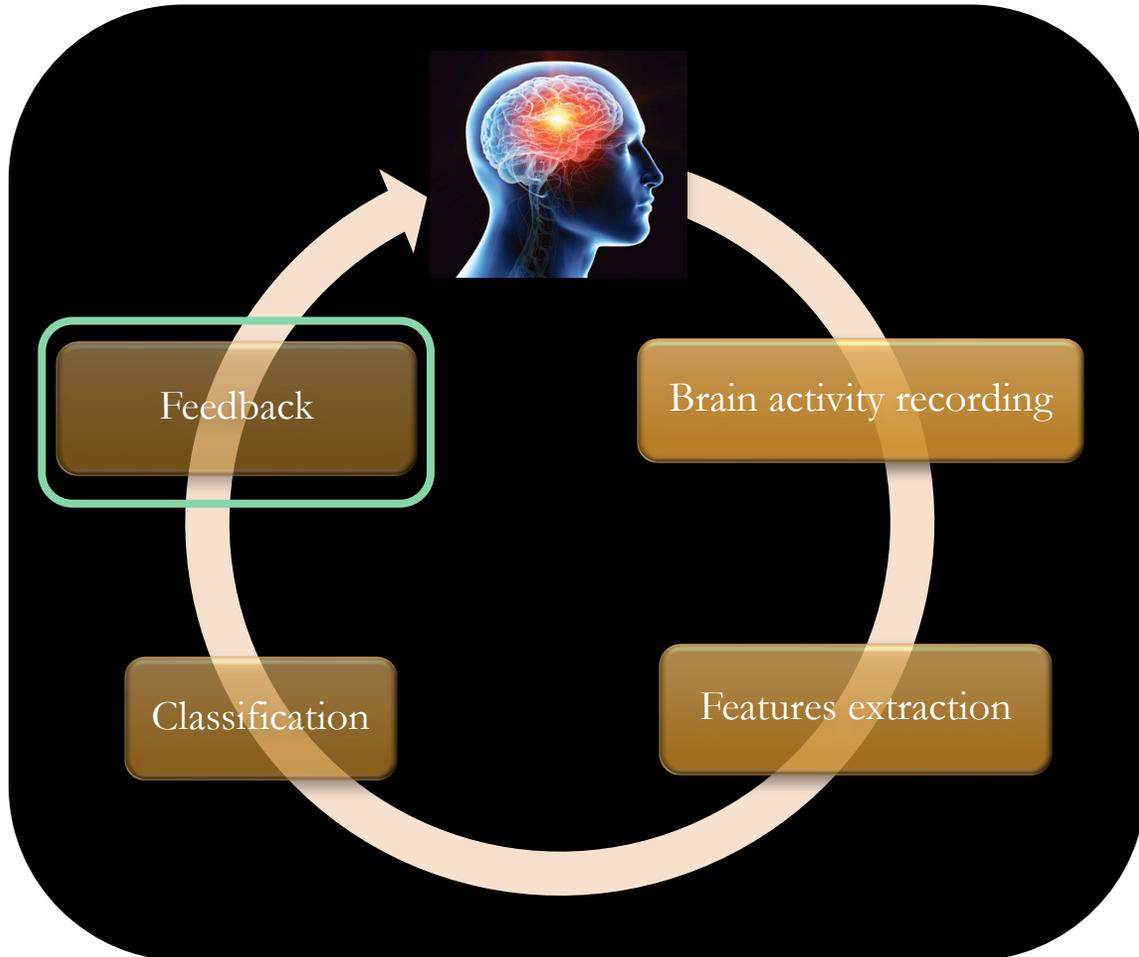
Behind the magic...



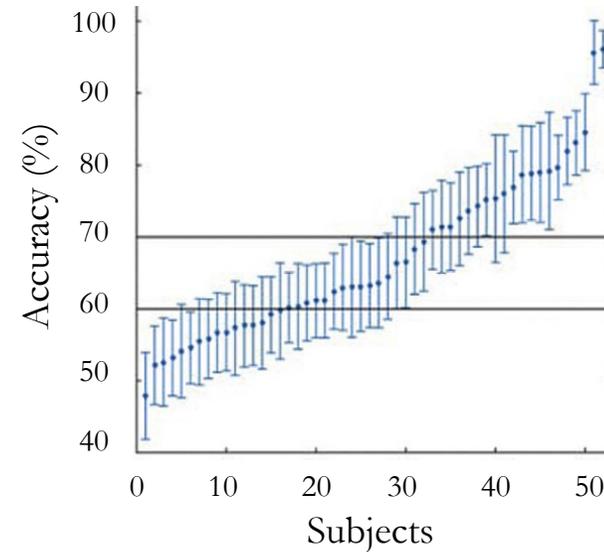
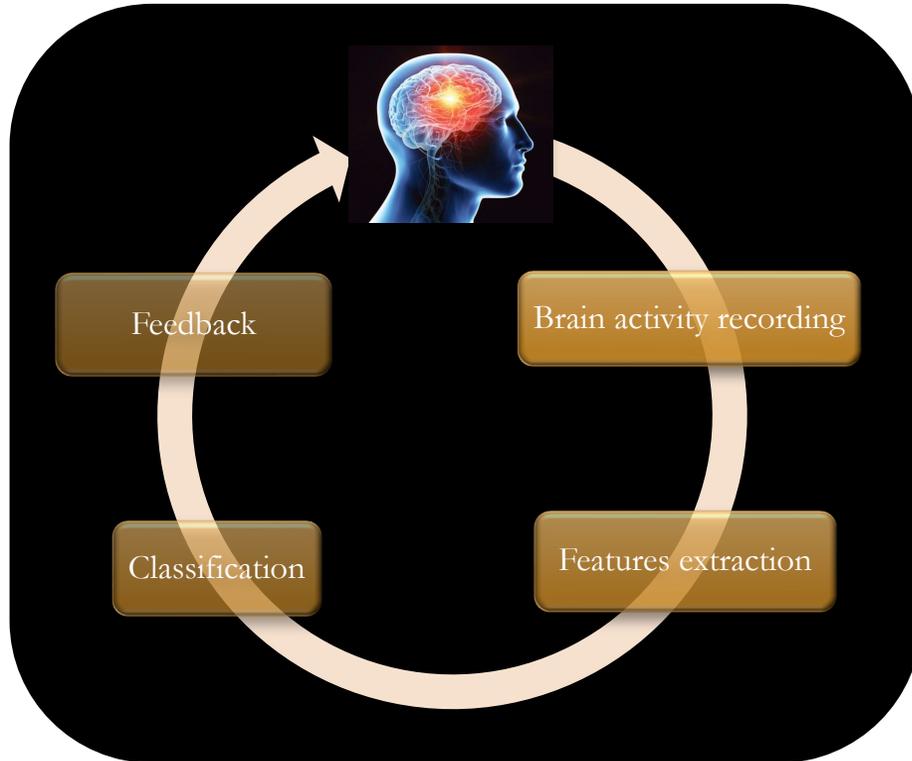
Behind the magic...



Behind the magic...



Non-invasive Brain-Computer Interface - BCI



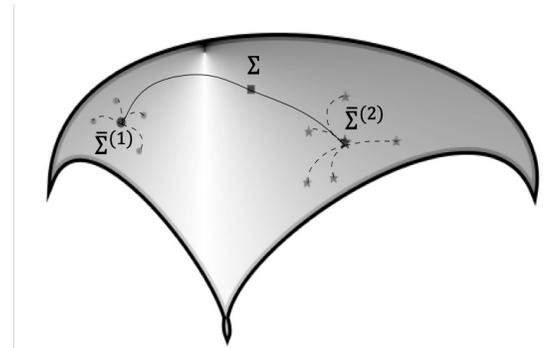
Adapted from (Ahn & Jun, 2015)

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

Riemannian Geometry (RG) & Functional connectivity (FC)

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)

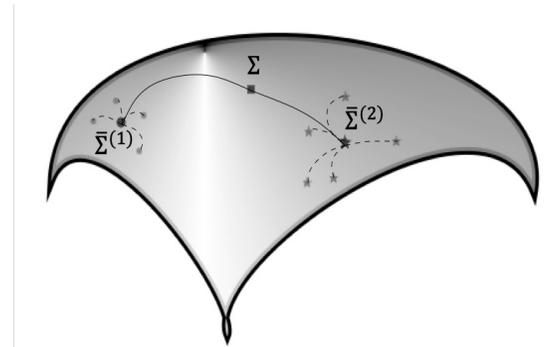
$$\delta(\Sigma_1, \Sigma_2) = \left\| \log(\Sigma_1^{-\frac{1}{2}} \Sigma_2 \Sigma_1^{-\frac{1}{2}}) \right\|_{\mathcal{F}}$$

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

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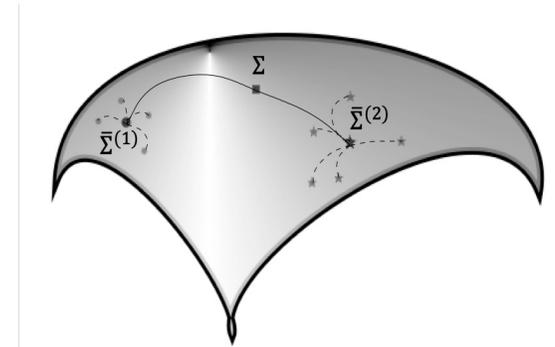
Problem: RG approaches in BCI rely only on covariance matrices without considering synchronous interactions between brain areas

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
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Functional connectivity

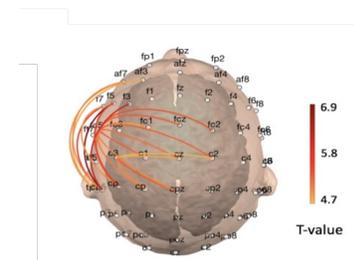
- Interconnected nature of brain connectivity & alternative features in BCI
- Use of all the possible information from connectivity matrices
- Regularization methods to make the matrices SPD



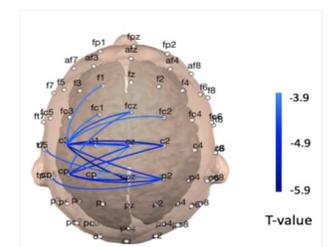
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Amplitude synchronization

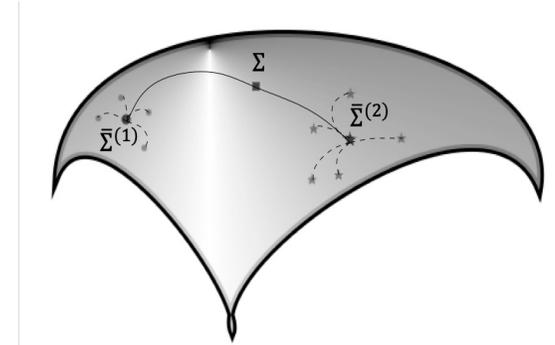


Phase synchronization

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

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

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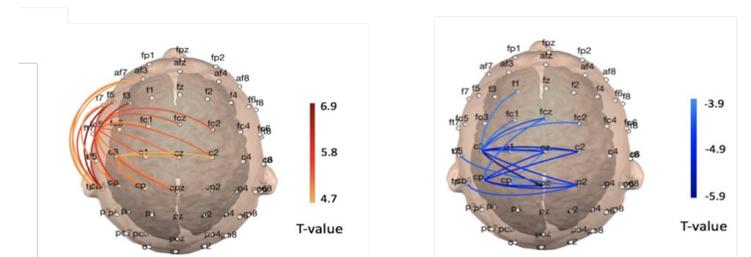
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Amplitude synchronization

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.

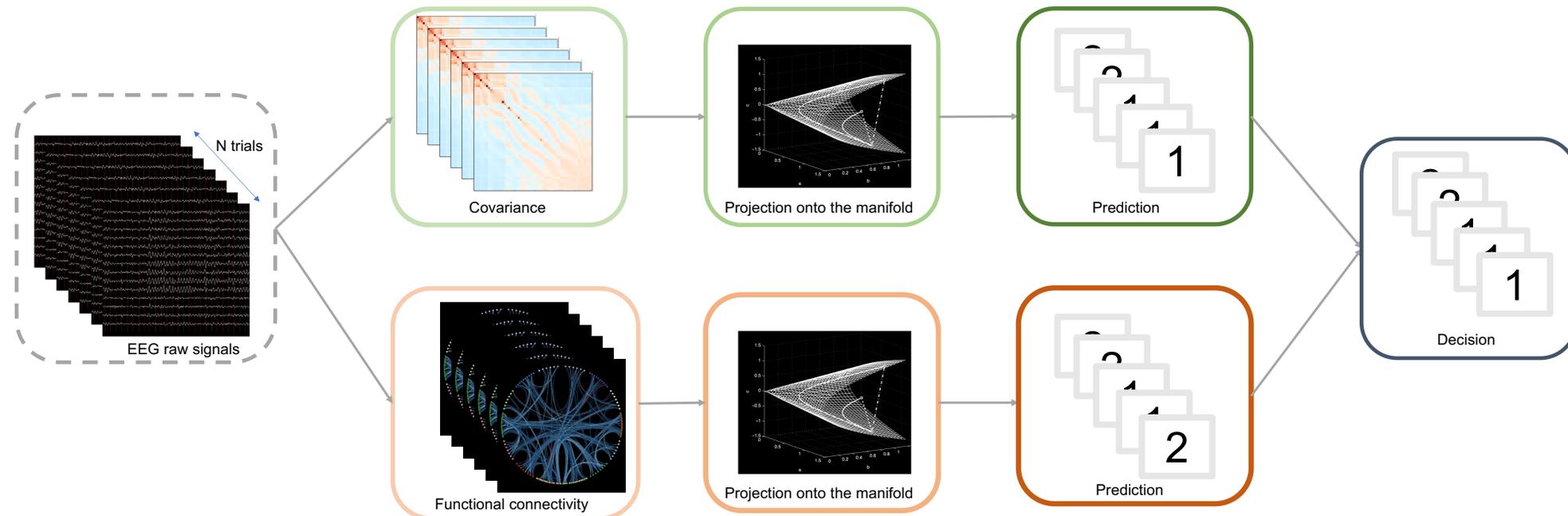
Riemannian Geometry (RG) & Functional connectivity (FC)

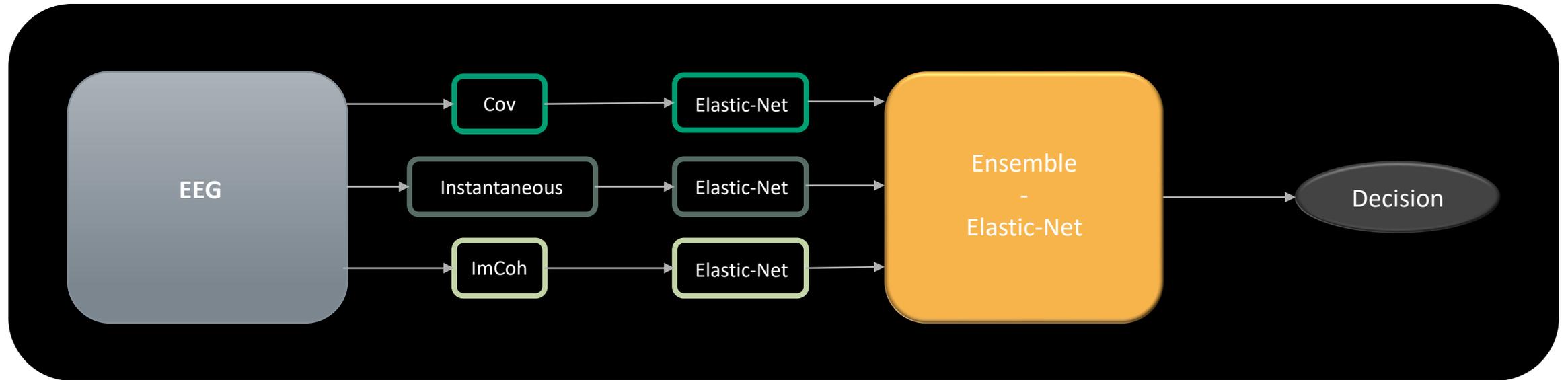
Motivation

- Considering subjects' specificity
- Improving the robustness

Approach

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



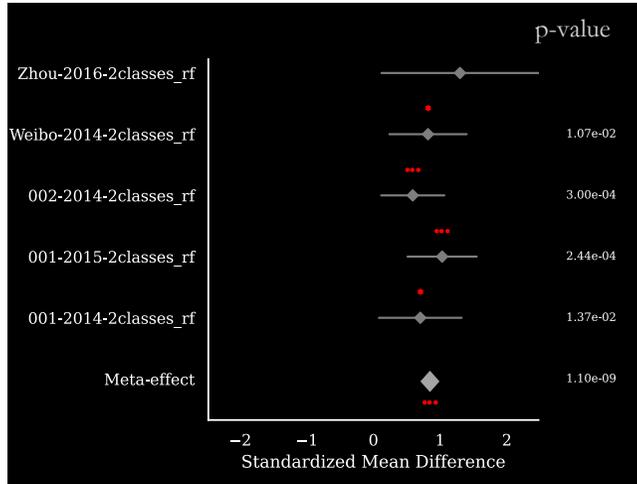


FUunctional CONnectivity Ensemble (FUCONE) approach

FUCONE – A replicable approach

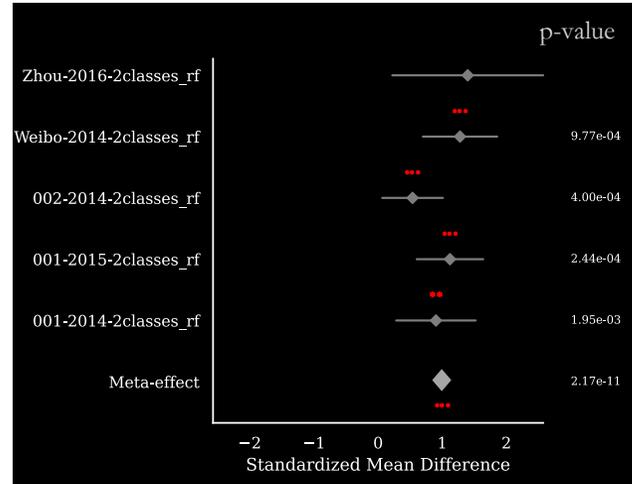
RegCSP+shLDA better

FUCONE better



CSP+optSVM better

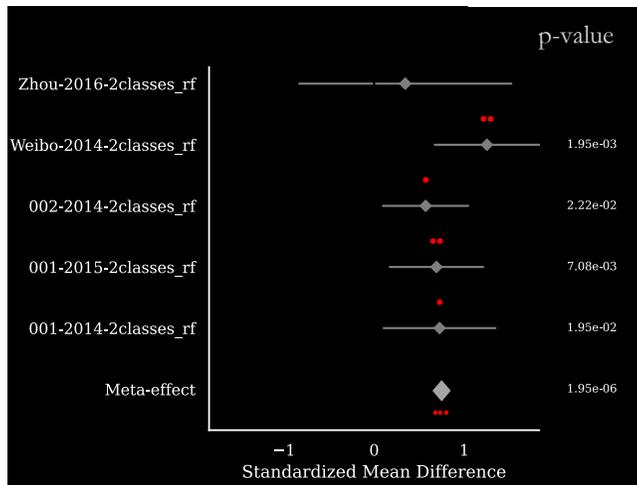
FUCONE better



- Common Spatial Patterns + Shrinkage Linear Discriminant Analysis
- Common Spatial Patterns + Support Vector Machine

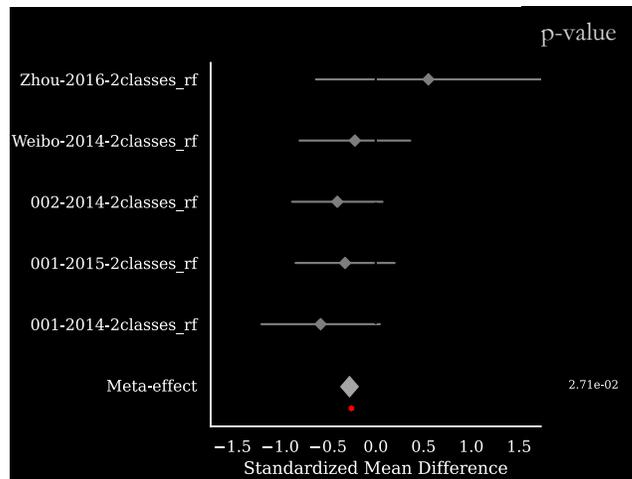
FgMDM better

FUCONE better



FUCONE better

Cov+EN better



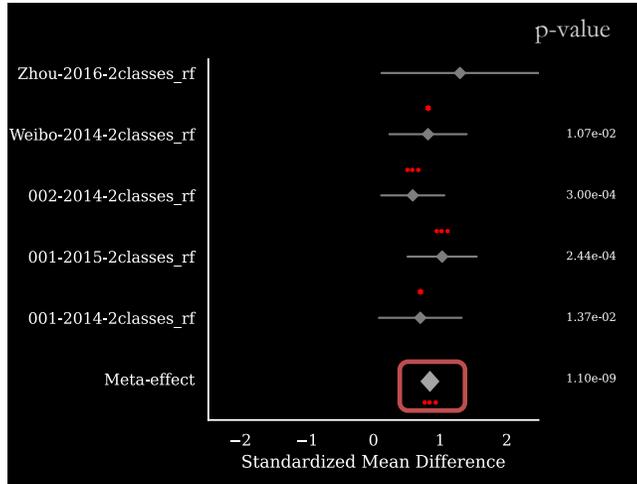
- Geodesic filtering + Minimum Distance to Mean classification
- Covariance + Elastic-Net



FUCONE – A replicable approach

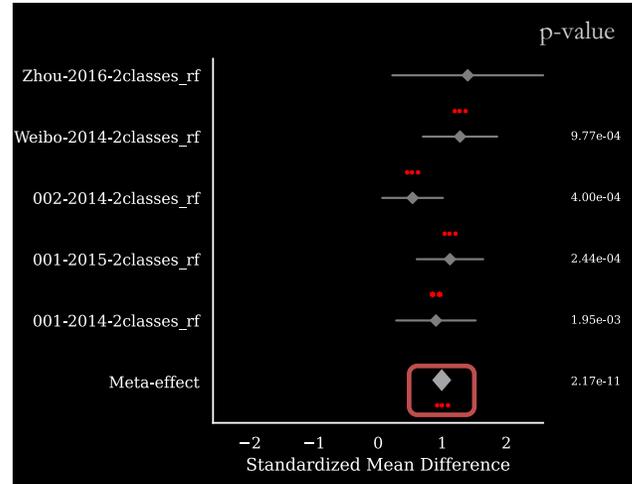
RegCSP+shLDA better

FUCONE better



CSP+optSVM better

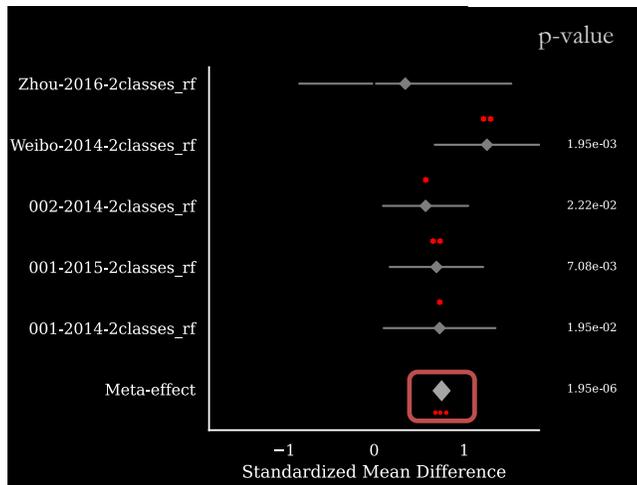
FUCONE better



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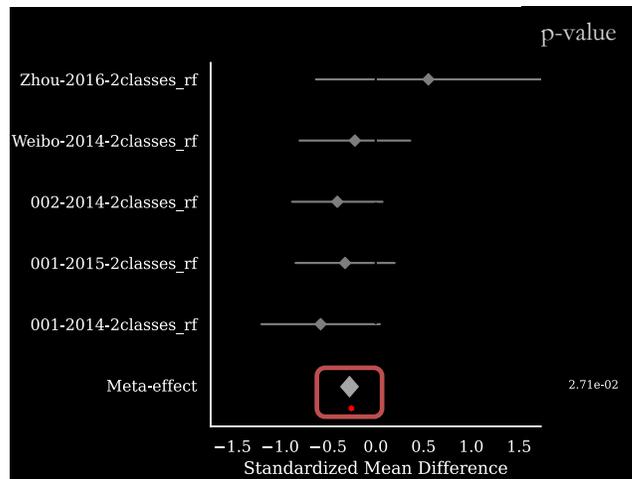
FgMDM better

FUCONE better



FUCONE better

Cov+EN better

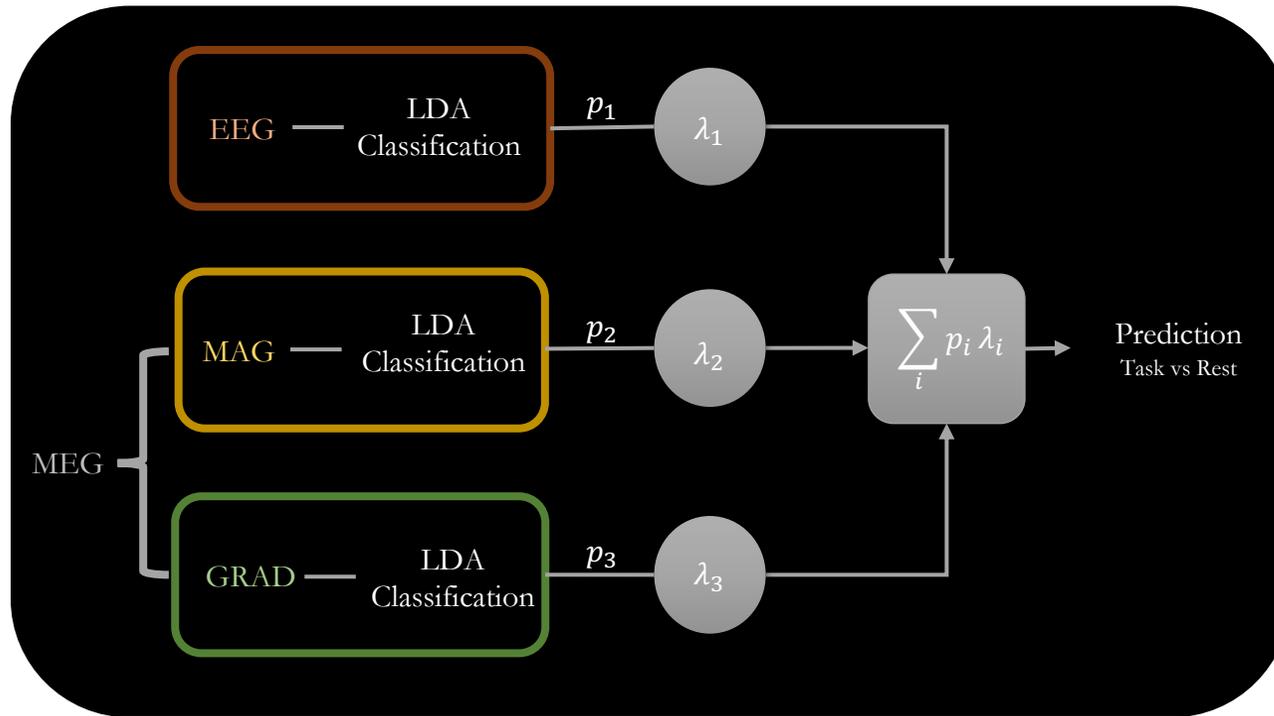


- Geodesic filtering + Minimum Distance to Mean classification
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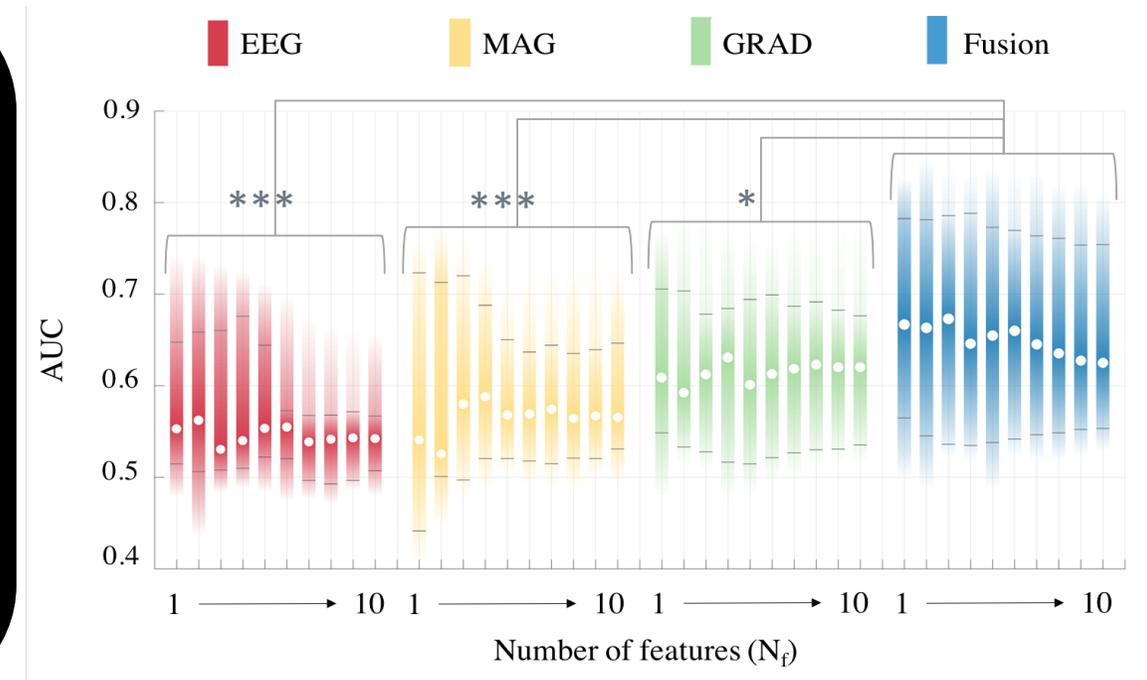


Motivation

- 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]



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



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

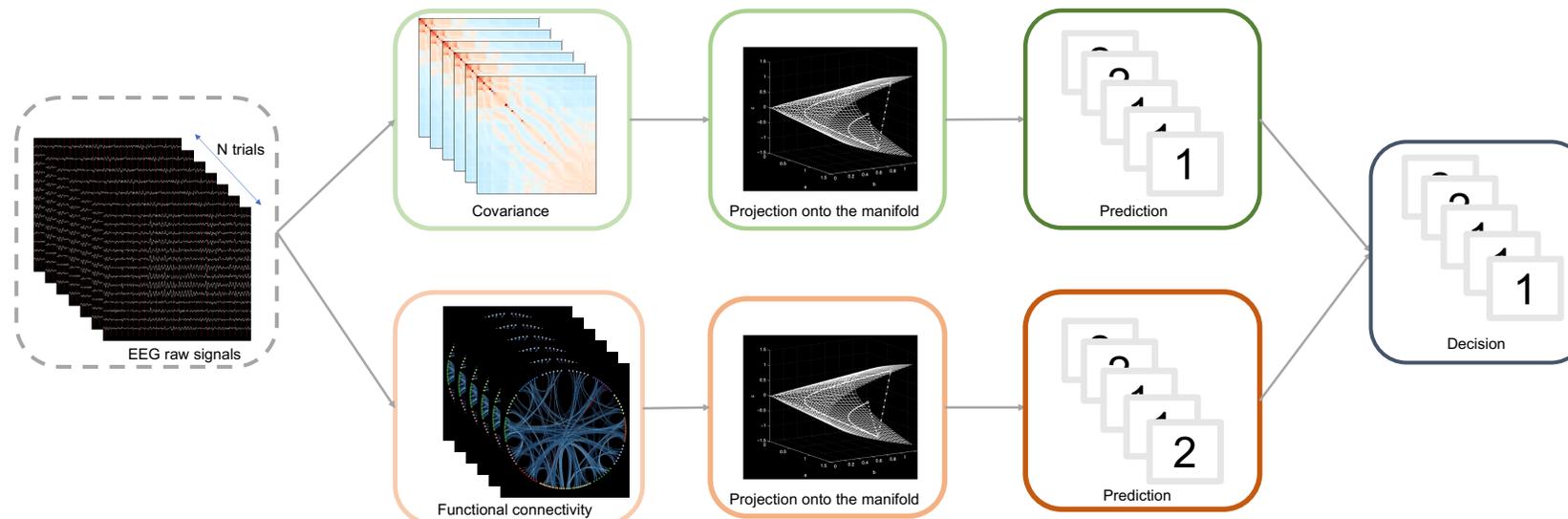
* $p < 0.05$

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Approach

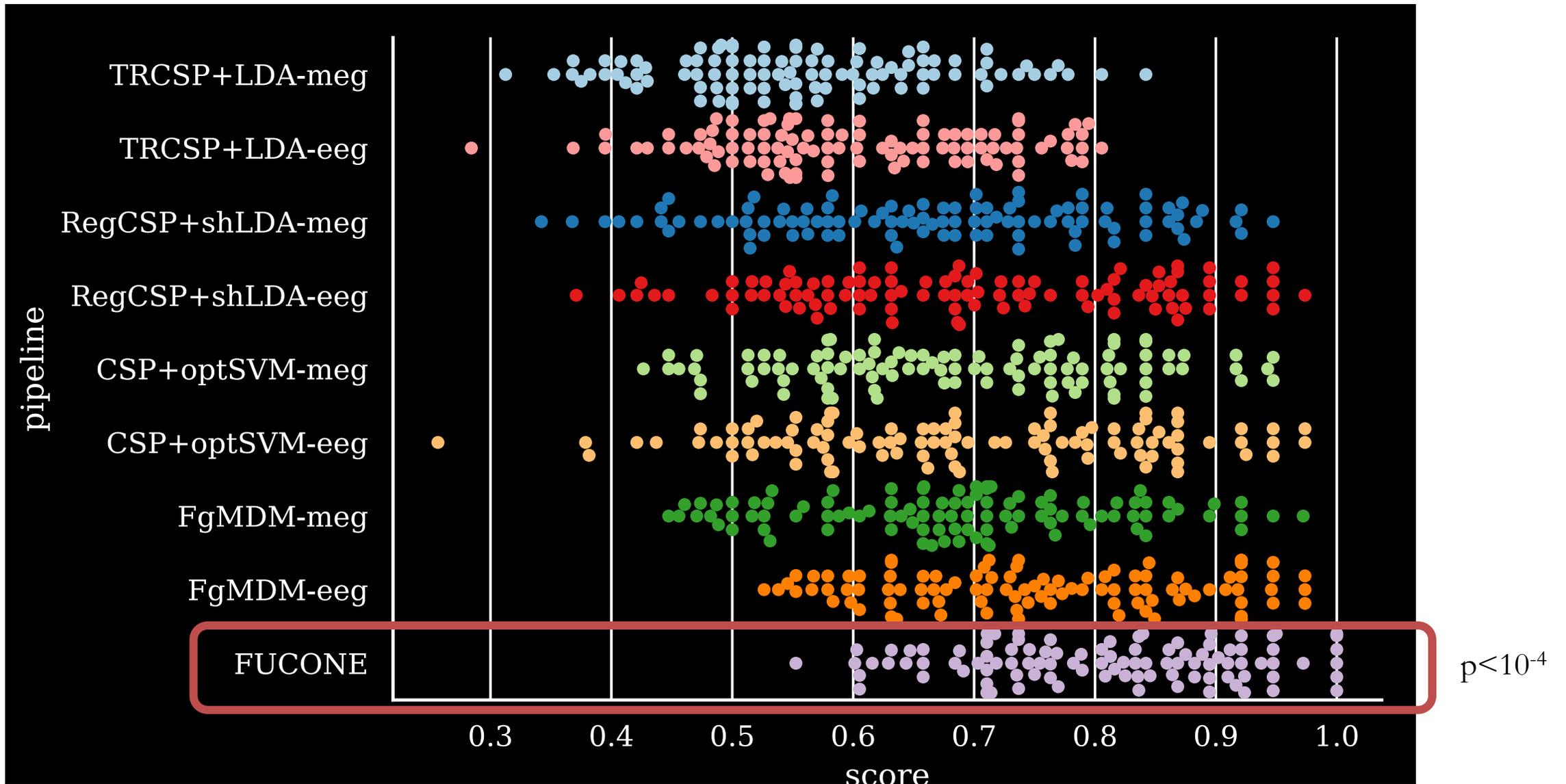
- Generalization to M/EEG data to exploit their complementarities
- To limit volume conduction effect, work in the source space [Corsi et al, NeuroImage, 2020]



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



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

Penn University

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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](#)

Thank you for your attention!



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[MConstanceCorsi](#)