



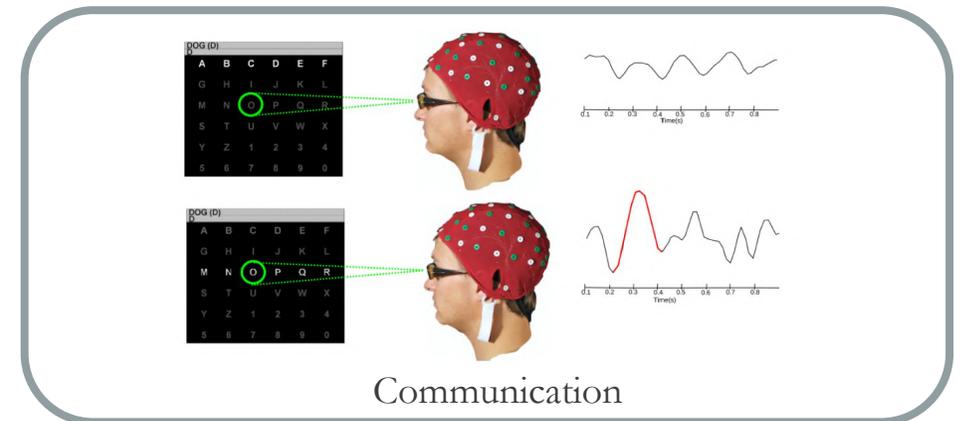
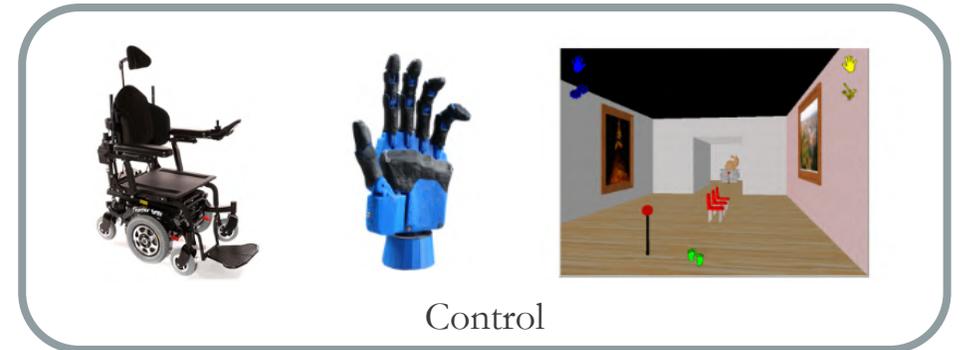
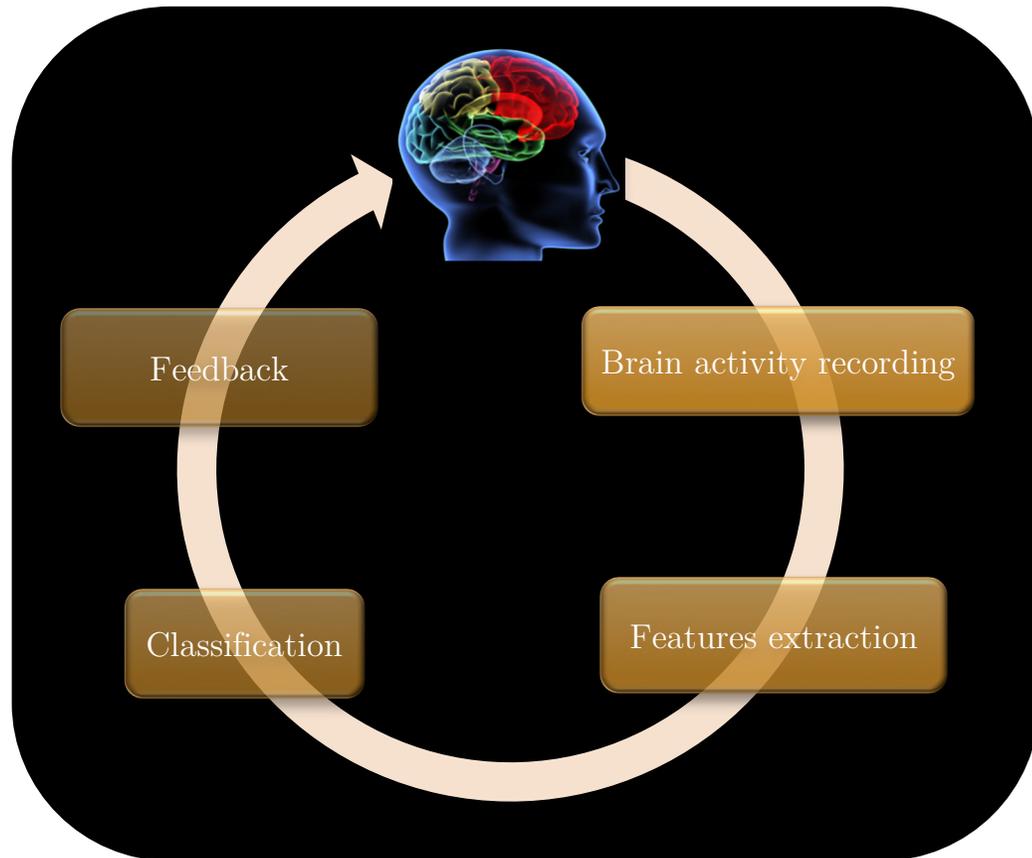
Functional connectivity predicts MI-based BCI learning

Marie-Constance Corsi

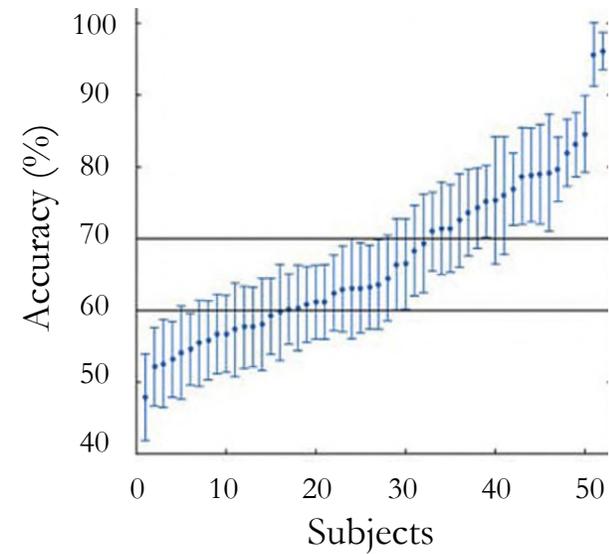
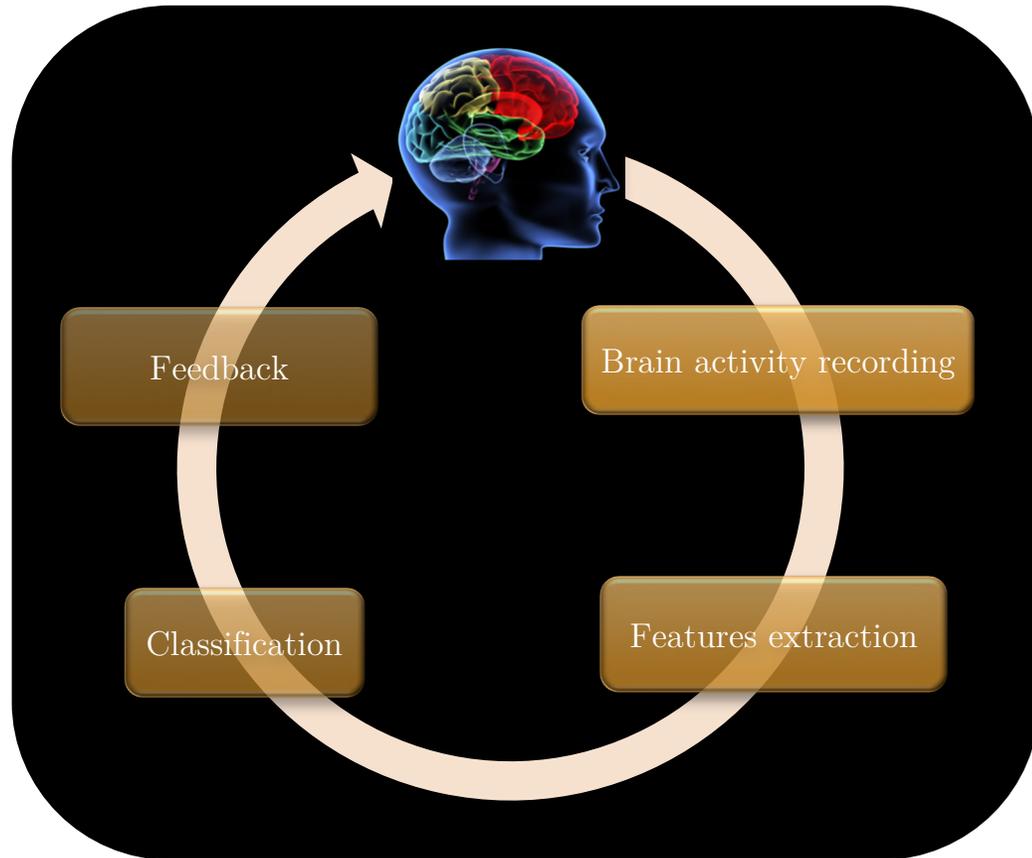
Postdoctoral researcher,

ARAMIS team, Inria-Paris, Paris Brain Institute, France

BCI CHALLENGE



BCI CHALLENGE



Adapted from (Ahn & Jun, 2015)

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

BCI INEFFICIENCY CHALLENGE

- Machine-centered approaches

- Signal processing (Vidaurre et al, 2011)
- Classification algorithms (Lotte et al, 2018)

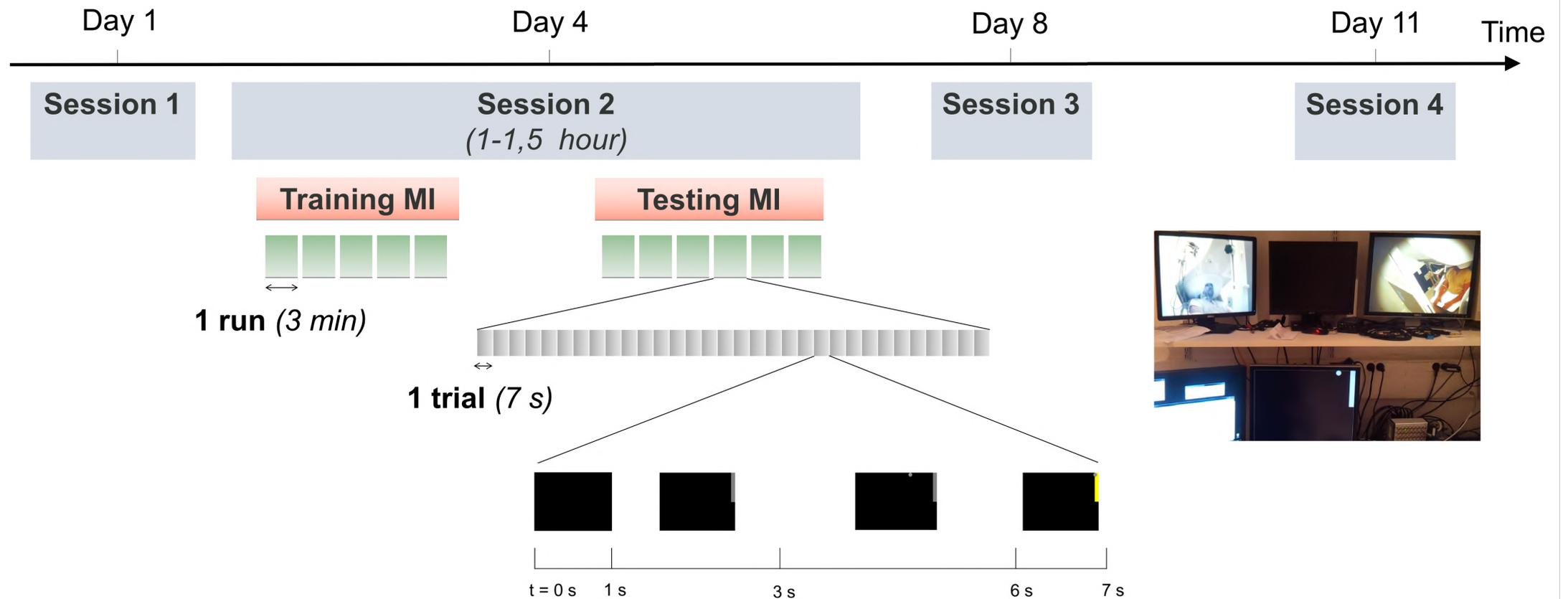
- User-centered approaches

- Search for neurophysiological patterns (Blankertz et al, 2010; Ahn et al, 2015)
- Human factors (Hammer et al, 2012; Jeunet et al, 2015)

⇒ Neural mechanisms underlying BCI learning **poorly understood**

⇒ The **interconnected** nature of the brain functioning not considered

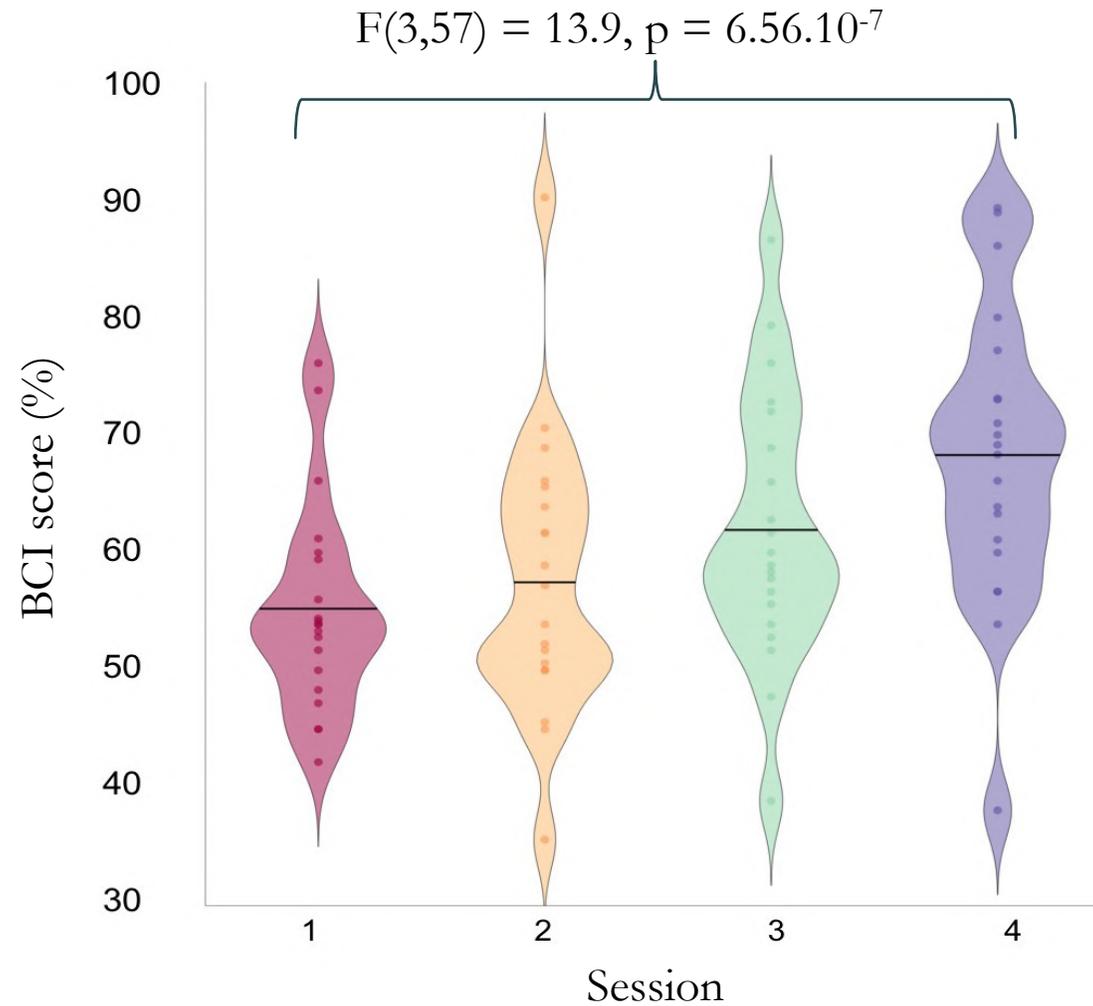
PROTOCOL



PROTOCOL

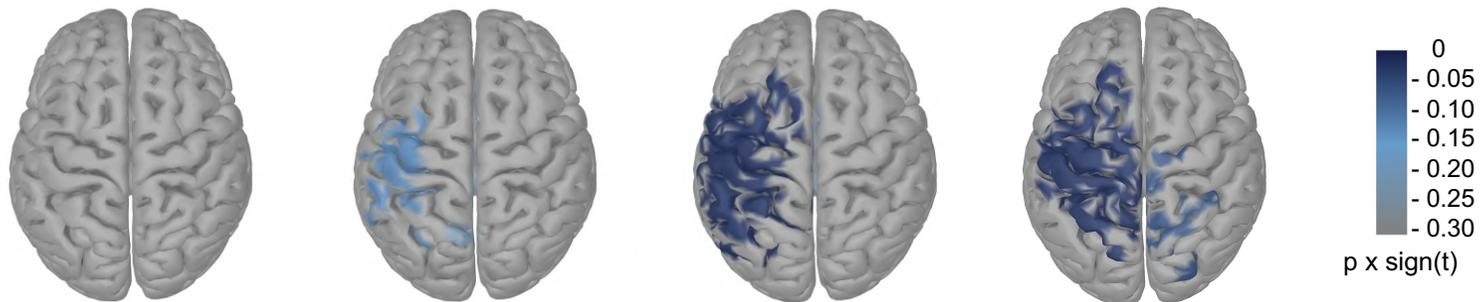
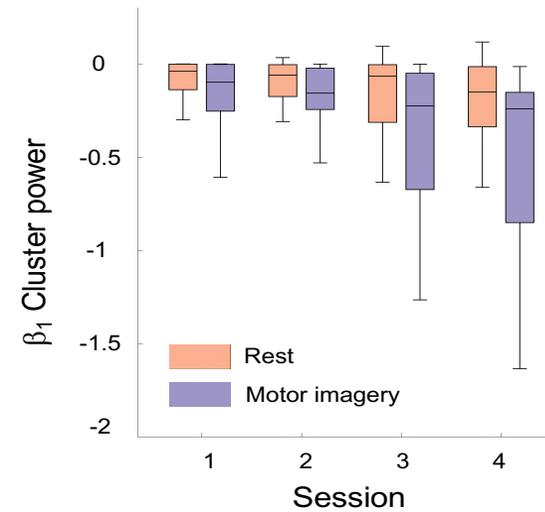
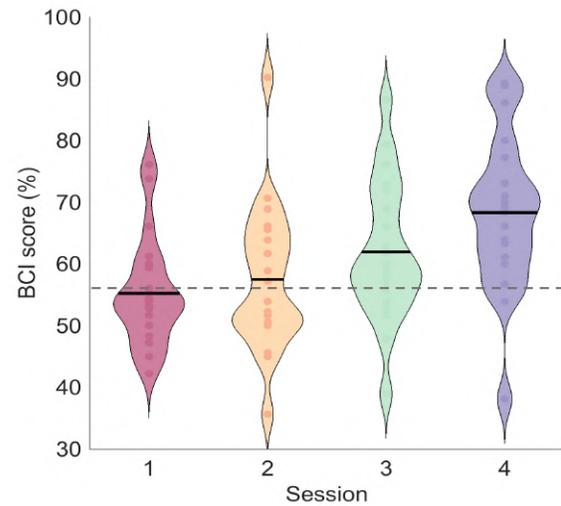


BEHAVIORAL RESULTS – CHANGES OVER SESSIONS

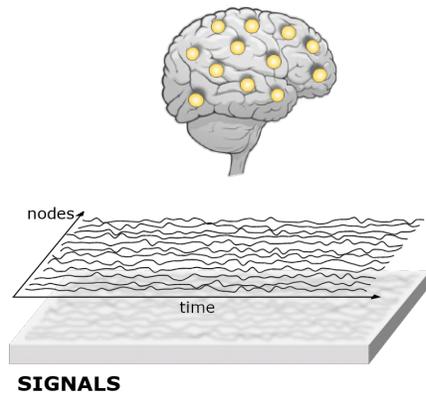


(Corsi et al, NeuroImage, 2020)

REINFORCEMENT OF MOTOR-RELATED ACTIVITY

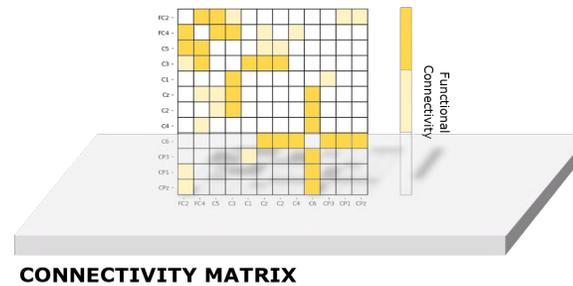
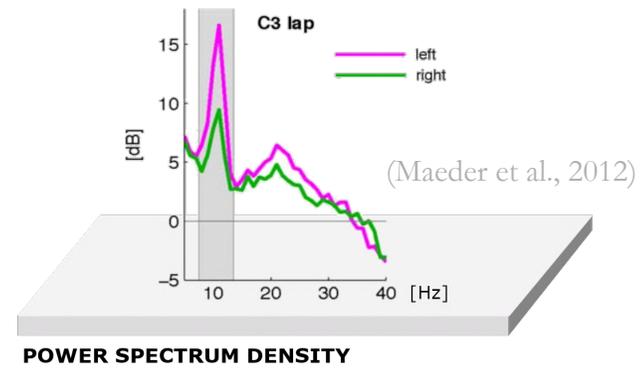


FUNCTIONAL CONNECTIVITY

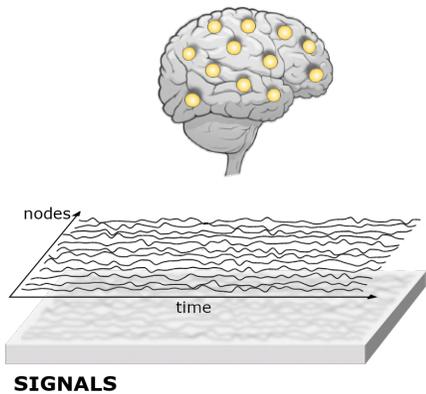


(Gonzalez-Astudillo et al, JNE, 2020)

(De Vico Fallani & Bassett, Physics of Life Reviews, 2019)

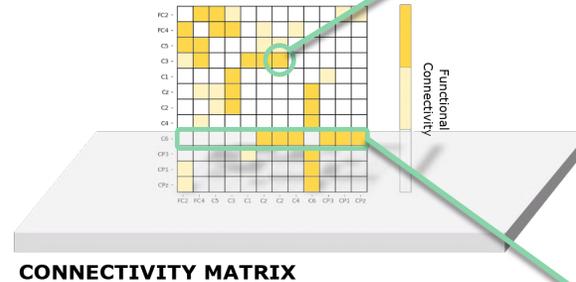


FUNCTIONAL CONNECTIVITY



(Gonzalez-Astudillo et al, JNE, 2020)

(De Vico Fallani & Bassett, Physics of Life Reviews, 2019)



Imaginary coherence

(Nolte et al, 2004; Sekihara et al, 2011)

$$IC_{x,y} = \text{Im} \left(\frac{G_{xy}}{\sqrt{G_{xx} \cdot G_{yy}}} \right)$$

G_{xy} : cross-spectral density between ROIs x and y ;

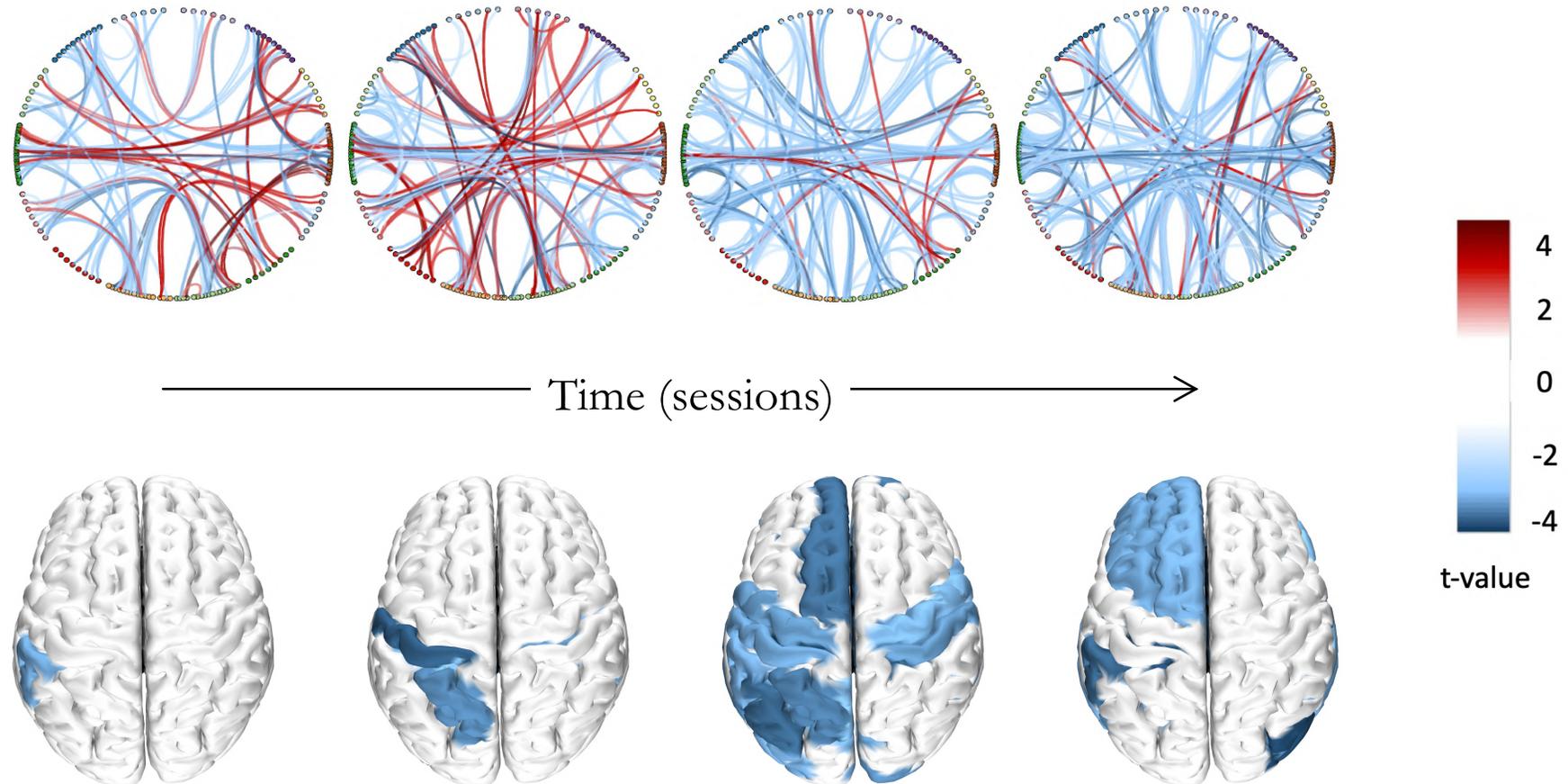
G_{xx} : autospectral density of ROI x

Node strength

For a given ROI x , and a condition j

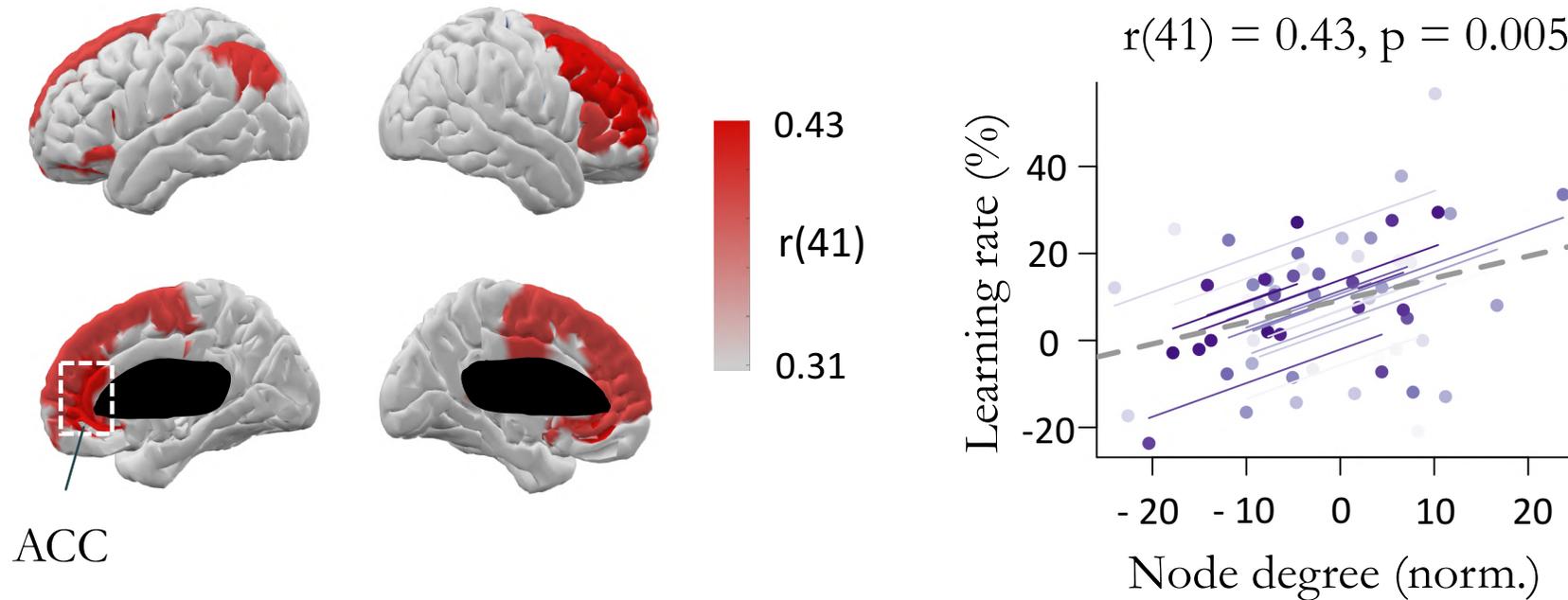
$$N_{x,j} = \sum_{i \in \{\text{ROI}\}} IC_{x,j,i}$$

FUNCTIONAL DISCONNECTION OF ASSOCIATIVE AREAS



(Corsi et al, NeuroImage, 2020)

NODE STRENGTH PREDICTS BCI LEARNING RATE

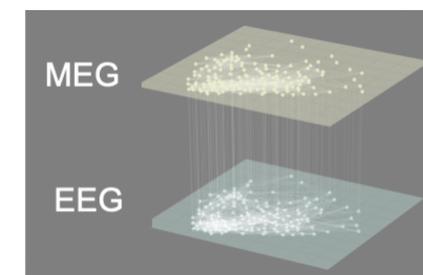
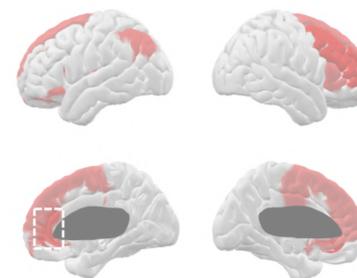


The *reserve* effect

Higher connectivity → higher **potential** to disconnect (learning)

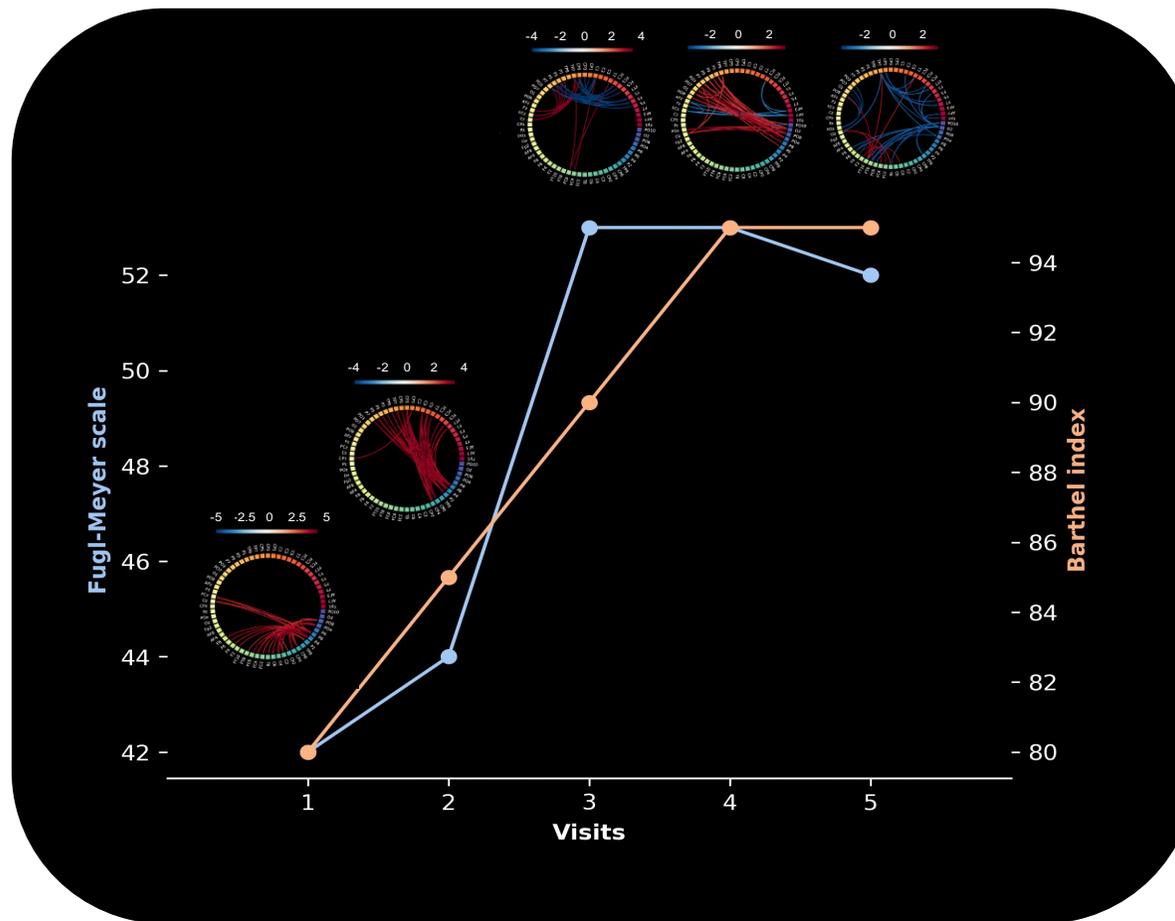
TAKE HOME MESSAGES

- Cortical changes & dynamic reorganization during BCI training
 - Increase of desynchronization & focus on BCI-targeted areas
 - Decrease of connectivity in associative & attentional areas
- Neurophysiological predictors of BCI performance
 - Activations: relative power
 - Functional connectivity: relative node strength
 - Brain networks: multimodal network properties integration



(Corsi et al, 2021)

STROKE – SEARCH FOR ALTERNATIVE FEATURES



Neurophysiological patterns of stroke recovery over 1 year (ongoing project w/ AP-HP)

ACKNOWLEDGEMENTS



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Jennifer Stiso,
Arnold Campbell,
Danielle S. Bassett (PI)



Thank you for your attention !

[Webpage & contact](#)

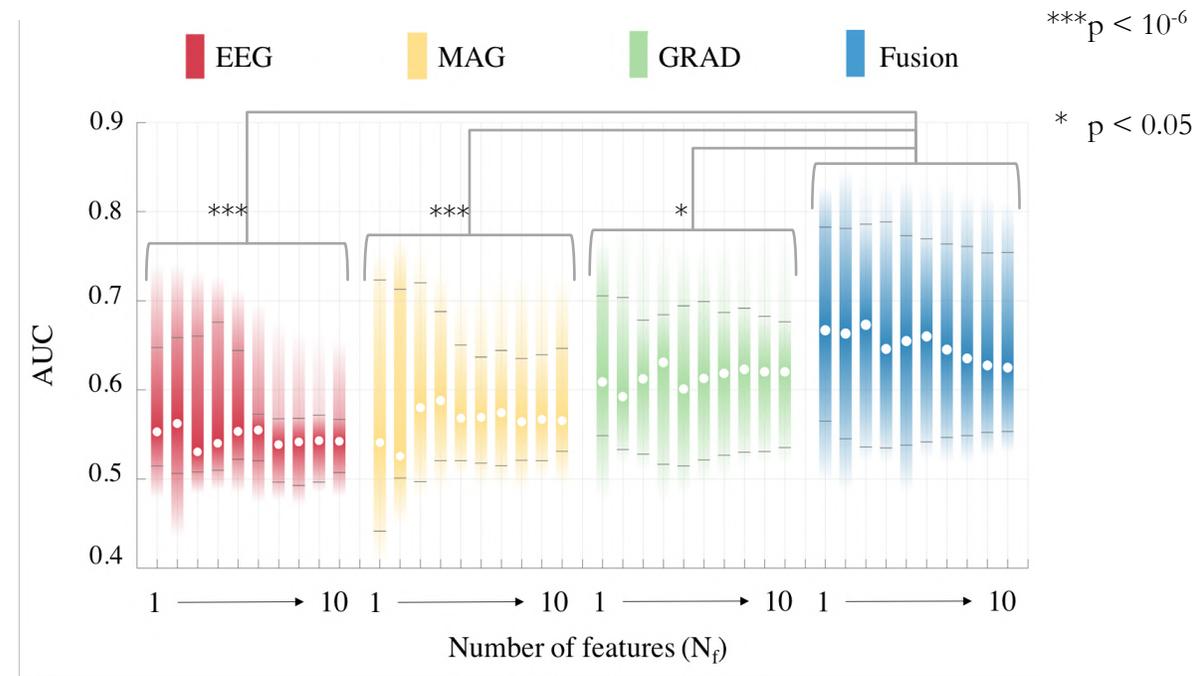
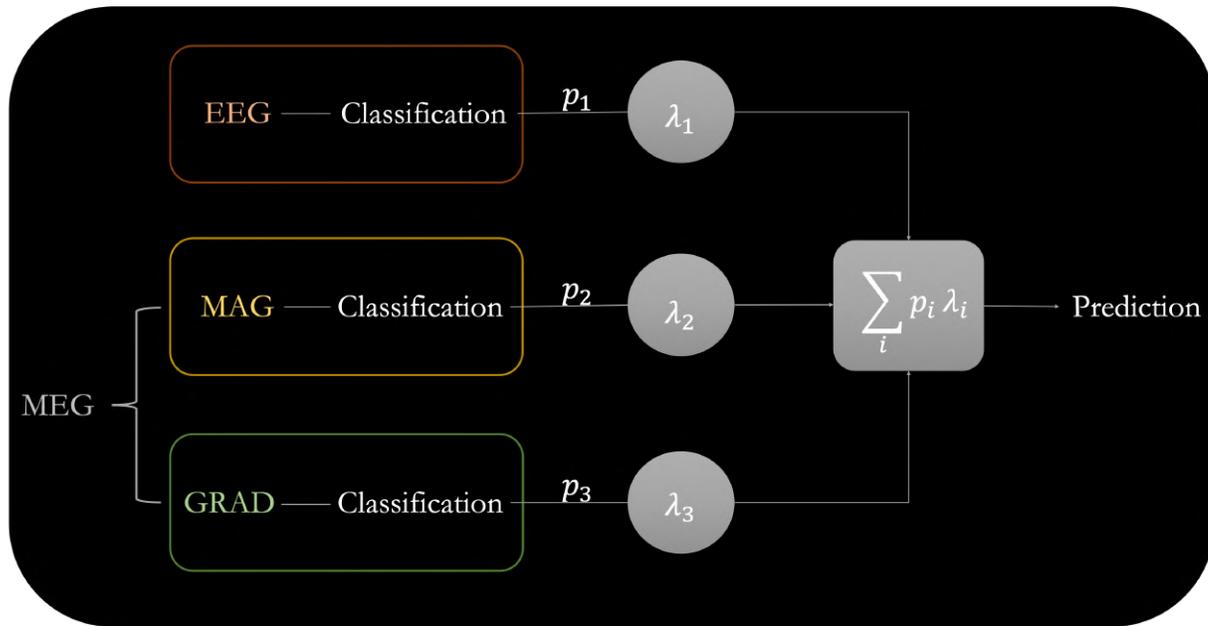


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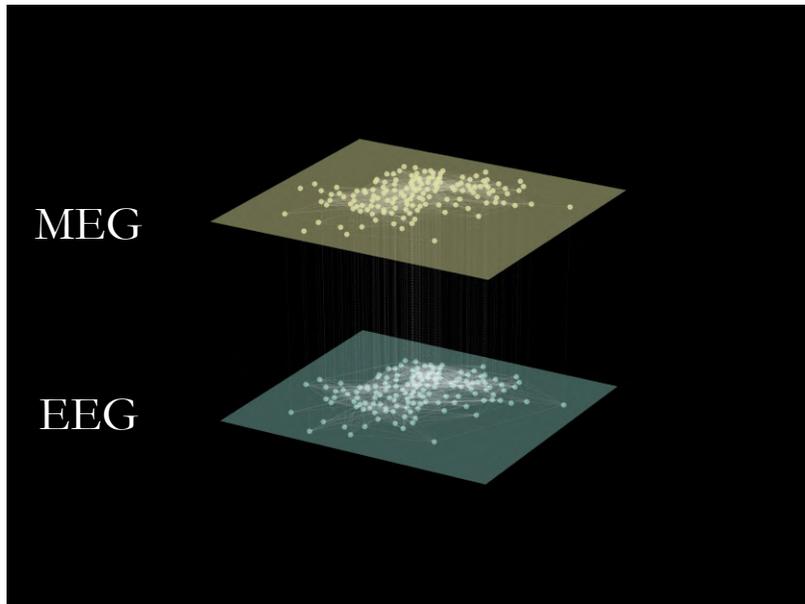
[MConstanceCorsi](#)

M/EEG INTEGRATION TO IMPROVE BCI ACCURACY



M/EEG integration improves accuracy → **subject's specificity** taken into account

MULTIPLEX CORE-PERIPHERY PREDICTS BCI PERFORMANCE



Multiplex coreness of node (ROI) i – C_i

$$C_i = \frac{1}{N-1} \sum_{k=1}^{N-1} \delta_i^k ; \delta_i^k = 1, \text{ if nodes } i \text{ in the core, } 0 \text{ otherwise}$$

Optimization of the contribution c of each layer/modality

$$F(c) = \frac{(\langle C^{MI}(c) \rangle - \langle C^{Rest}(c) \rangle)^2}{(s^{MI})^2 + (s^{Rest})^2}$$

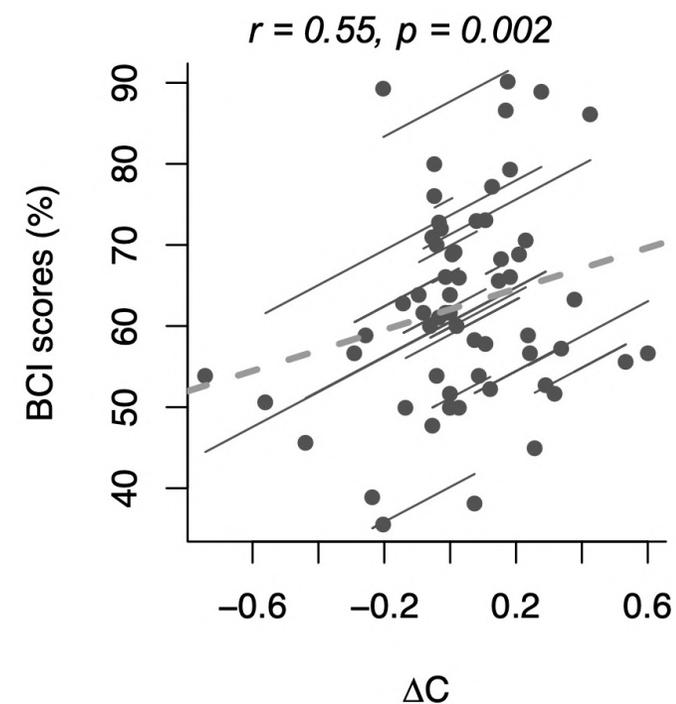
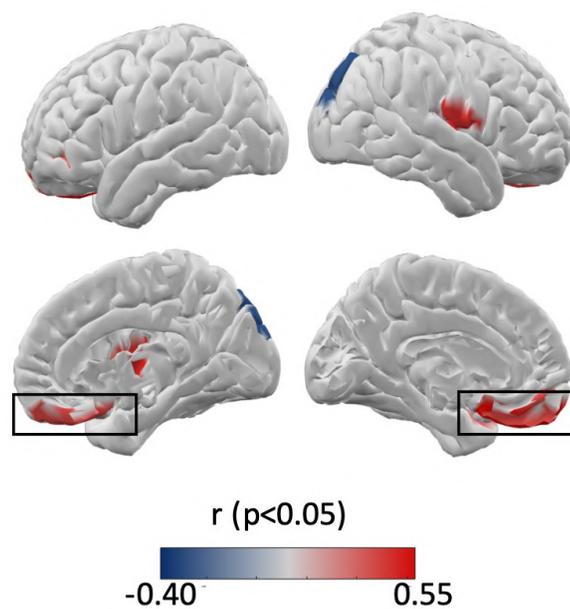
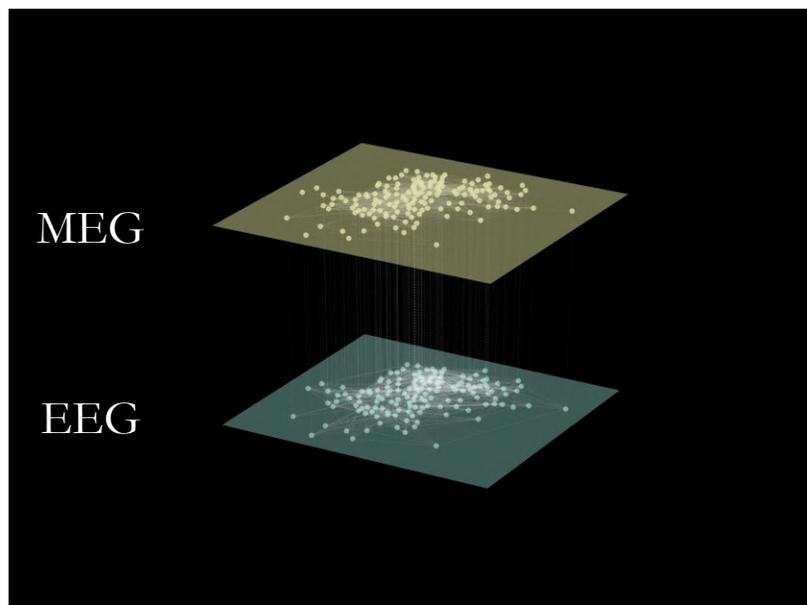
Where:

$$(s^{cond})^2 = \sum_{i \in \{1 \dots N\}} (\langle C_i^{cond}(c) \rangle - \langle C^{cond}(c) \rangle)^2$$

$\langle C^{cond}(c) \rangle$, averaged coreness over the nodes i

C_i^{cond} , coreness computed in node i , condition $cond$

MULTIPLEX CORE-PERIPHERY PREDICTS BCI PERFORMANCE



(Corsi et al, JNE, 2021)