Master Mathématiques Vision Apprentissage

Functional neuroimaging & Brain-Computer Interfaces

Marie-Constance Corsi

Inria research scientist,

NERV team, Paris Brain Institute

Outline

- Magnetoencephalography and electroencephalography (M.-C. Corsi) – 18/01 → 08/02

  - **M/EEG data: where it all begins!** - 18/01 – 9:30-12:30AM

  - **Estimating the sources of M/EEG activity** – w/ Théo Papadopoulo (Inria, Sophia-Antipolis) - 25/01 – 9:30-12:30AM

  - **How to further explore M/EEG data to answer scientific questions?** – 01/02 – 9:30-12:30AM

  - **How to use real-time M/EEG data for clinical purpose?** – 08/02 – 9:30-12:30AM **@ Paris Brain Institute!** (+visit of the neuroimaging platform)

Exam

- Format: Practical work in python & open questions
- Estimated time to complete it: 2 hours
- Probably sent after the third lesson (Feb 1st)
- Deadline: **February 22nd** to avoid overlapping with the exam associated to fMRI & the internship

Information & contacts

- Webpage dedicated to the module (updated w/slides):
  https://project.inria.fr/mvabrainfunctionalimaging/

- For any question related to the module
  - mva-meeg@inria.fr (mailing-list gathering the registered students and the co-lead)

- Co-lead contact info for specific questions
  - fMRI – Bertrand Thirion (Saclay) – bertrand.thirion@inria.fr
  - M/EEG – Marie-Constance Corsi (Paris) – marie-constance.corsi@inria.fr

LESSON 4 – BRAIN-COMPUTER INTERFACES

What is a BCI?

Context

Neuroscience

Physiology

Computer sciences

BCI

Psychology

Engineering

Rehabilitation

Today

1970

1st implanted BCI

2000

~10k publications
3 research groups

2005

> 30k publications
6-8 research groups

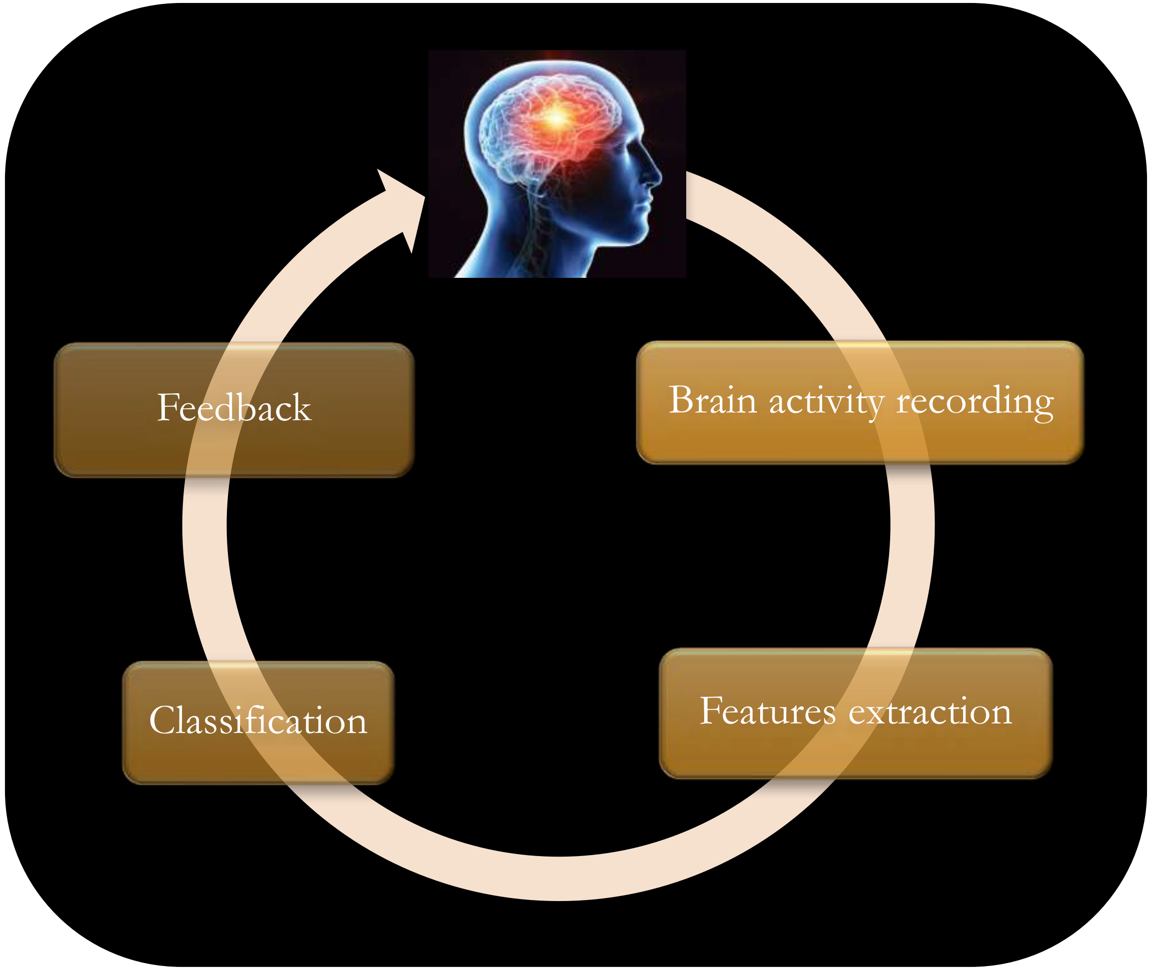
2010

> 50k publications
> 100 research groups

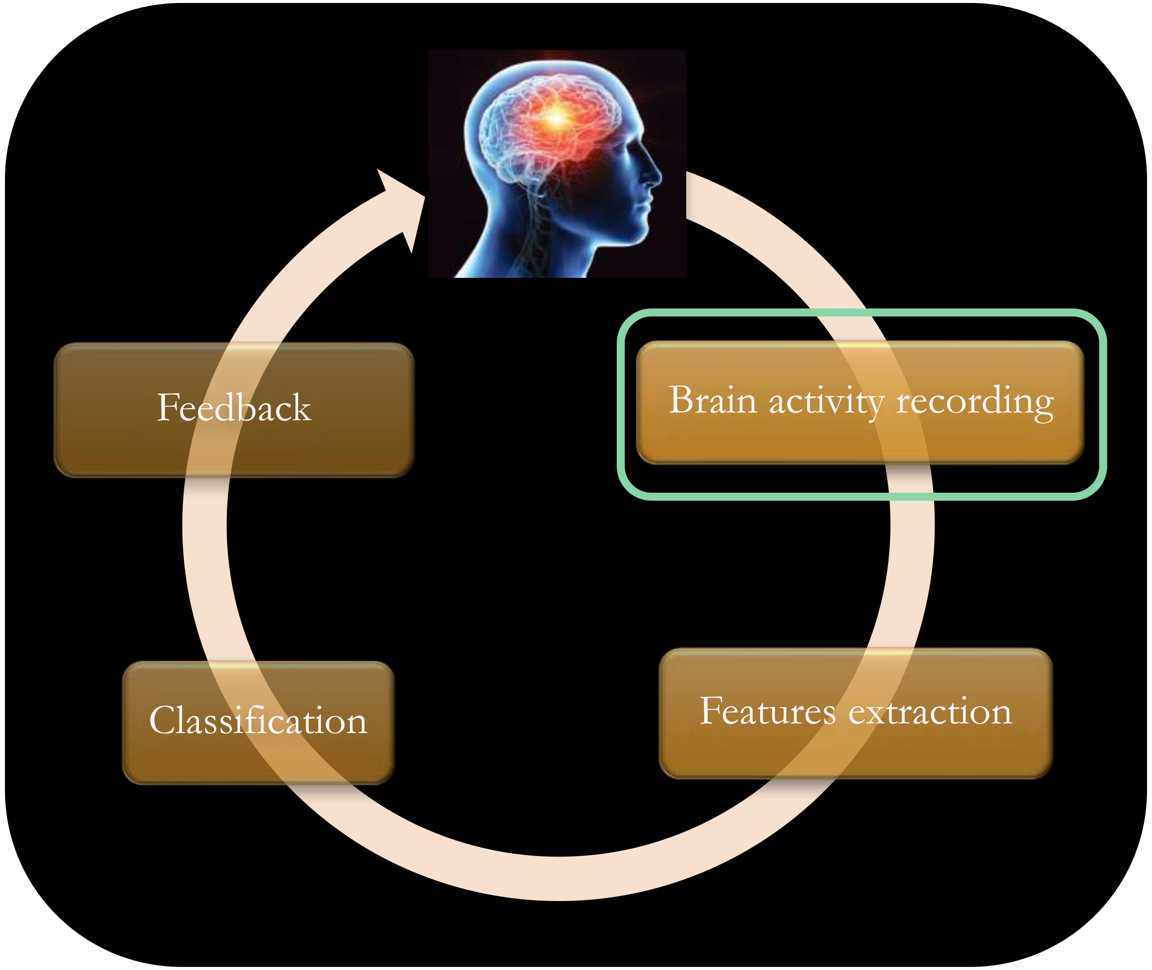
Commercialization of devices oriented to general public

Emotiv, US

Behind the magic…



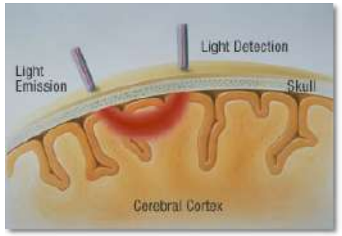
Behind the magic…



Non-invasive tools

EEG

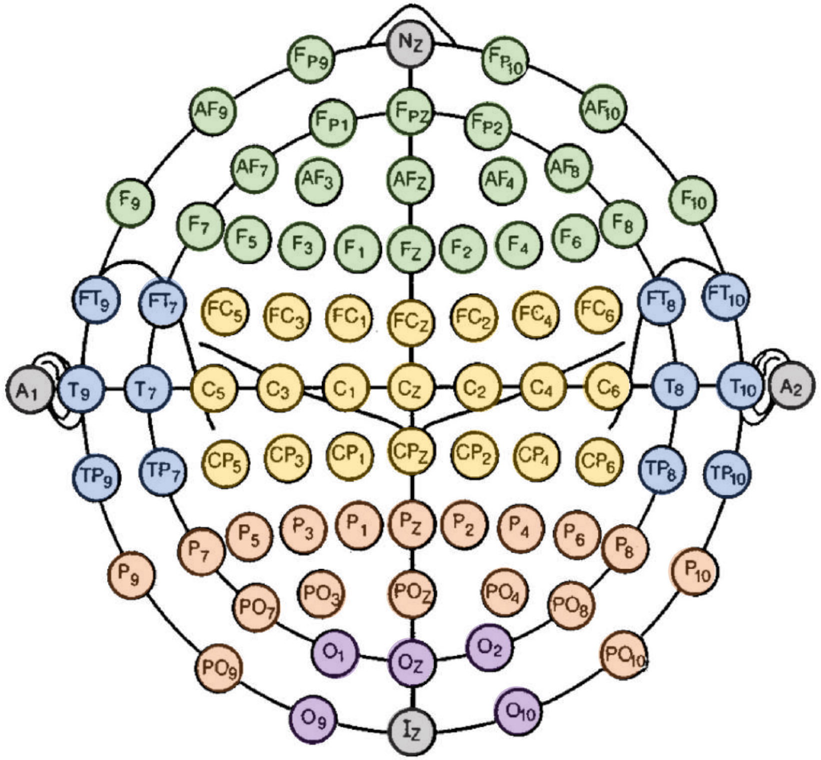
NIRS



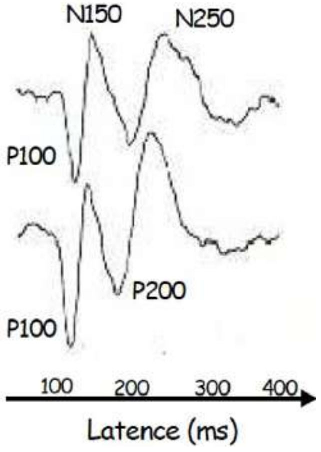
MEG

fMRI

Brain recording – EEG instrumentation



Adapted from (Corsi, 2023)



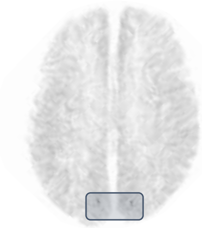
Adapted from [Campagne, 2014]

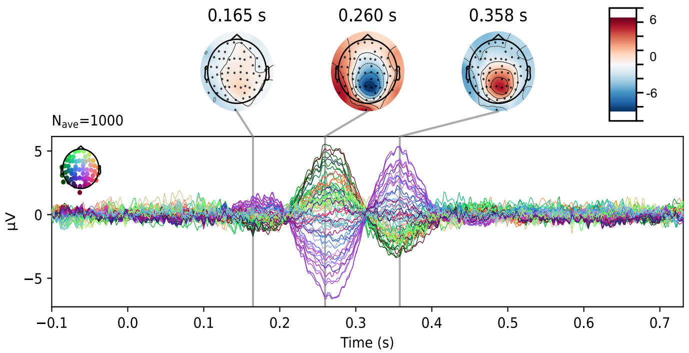
Nomenclature: the latency, the amplitude, the shape and the polarity

- Nxxx: one negative wave @ xxx ms (EEG)
- Pxxx: one positive wave @ xxx ms (EEG)
- Mxxx: one wave @ xxx ms (MEG)

Components

- Early components (exogenous): related to stimulus characteristics
- Late components (endogenous): related to the task, to the subject's stat





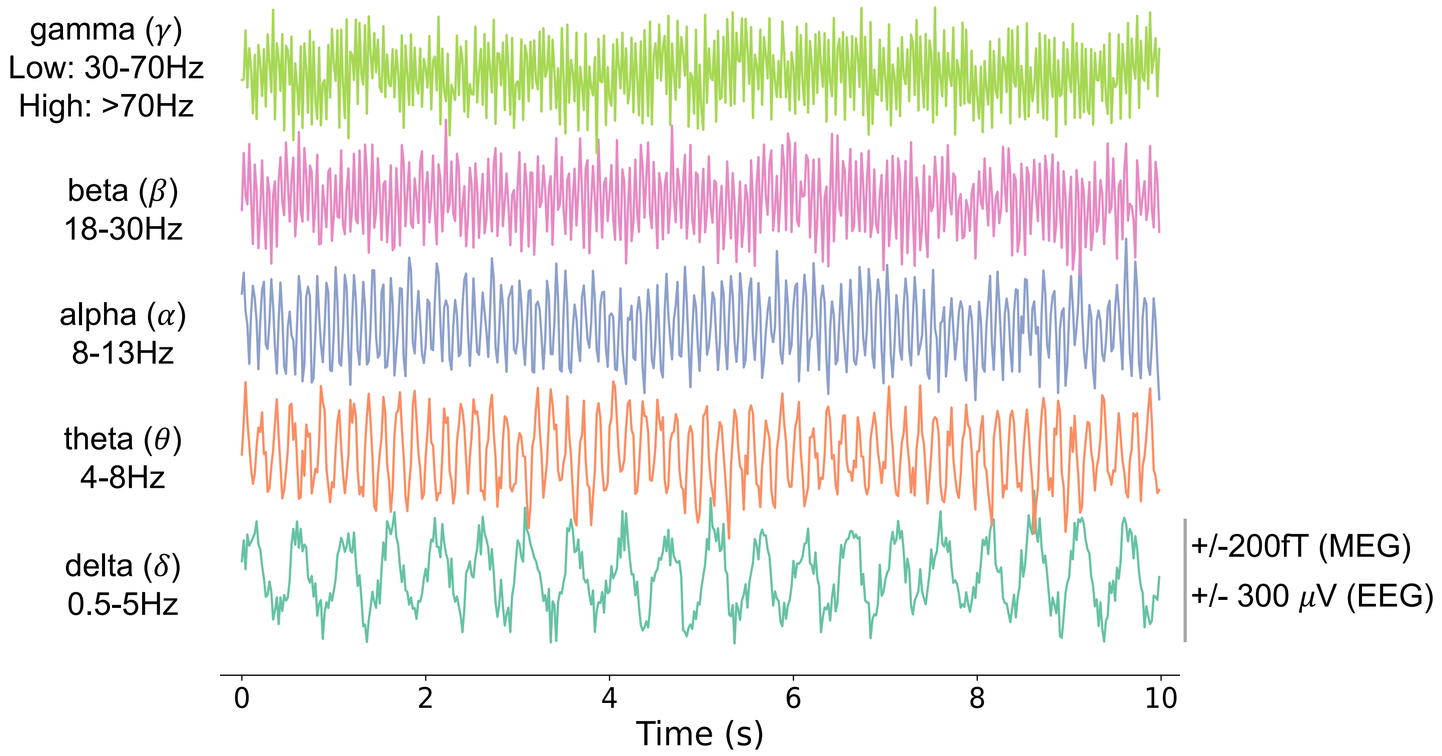
Adapted from [Corsi, 2023]

BCI application: P300 Speller

Brain recording w/ M/EEG – Oscillatory activity

Spontaneous activity, characteristics:

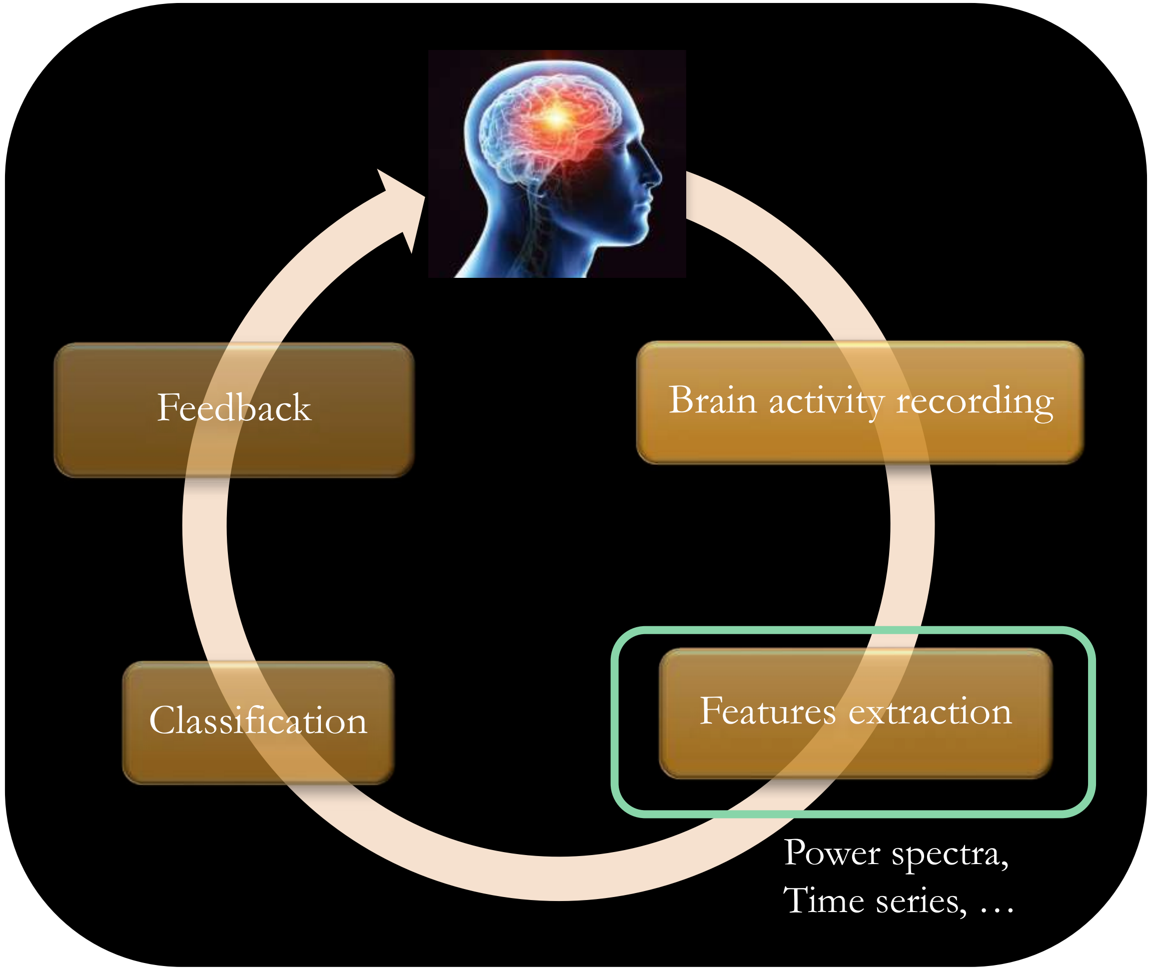
- Frequency
- Amplitude
- Shape
- Localization
- Psychopsychological context
- Duration
- Vanishing



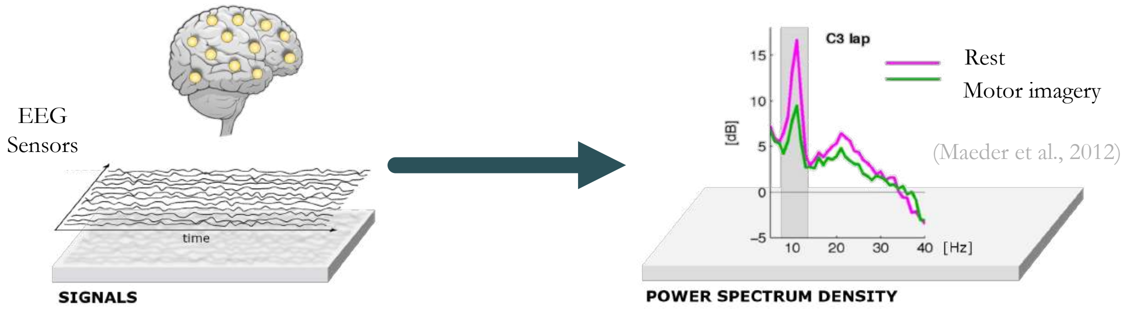
Adapted from [Corsi, 2023]

BCI application: motor-imagery based BCI

Behind the magic…

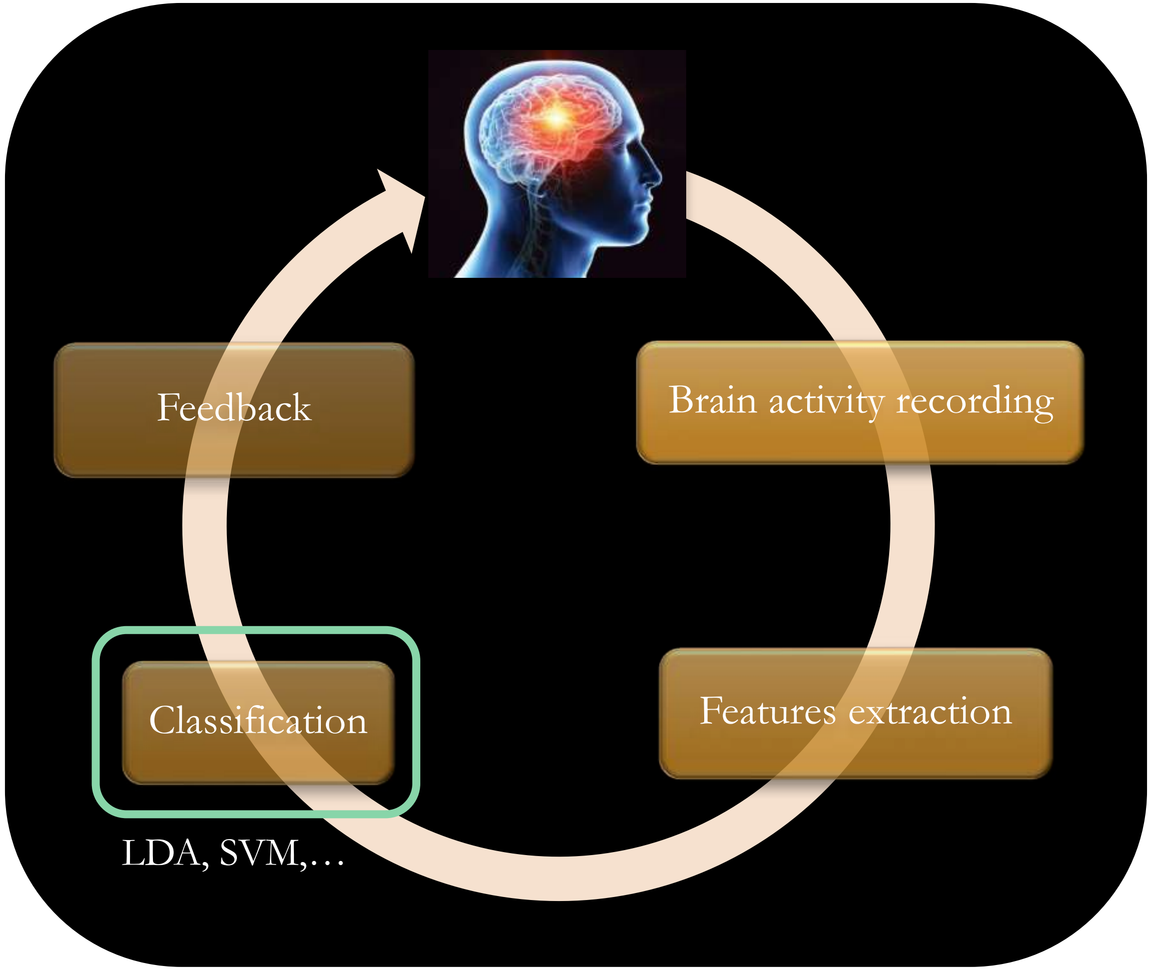


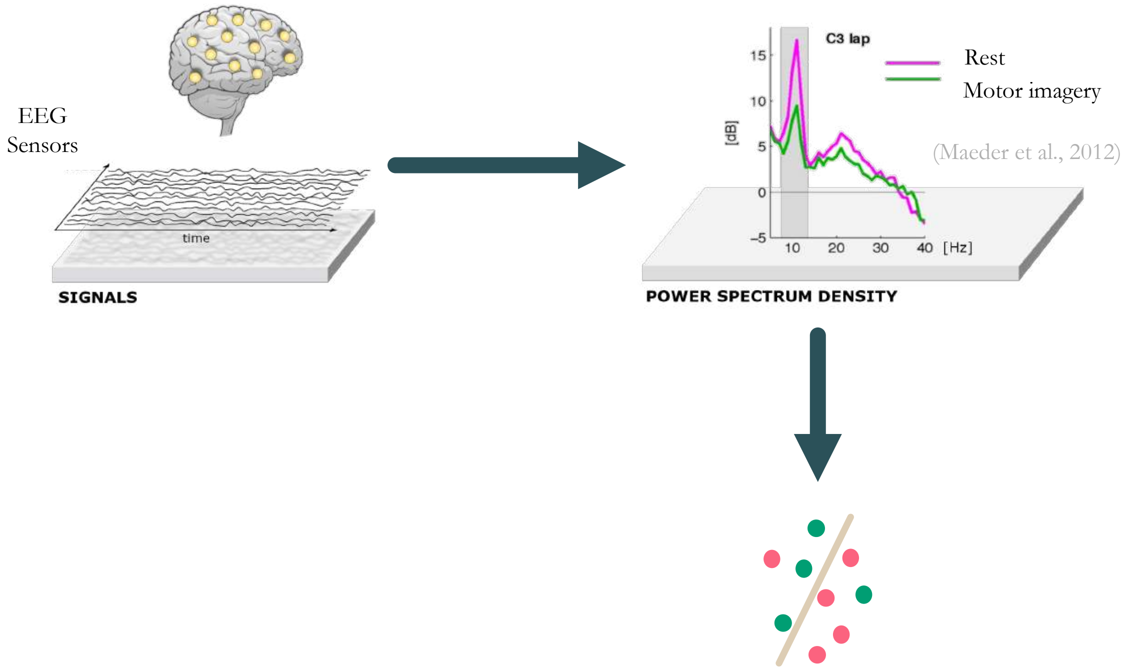
Power spectra,
Time series, …



Adapted from [Gonzalez-Astudillo et al, 2020]

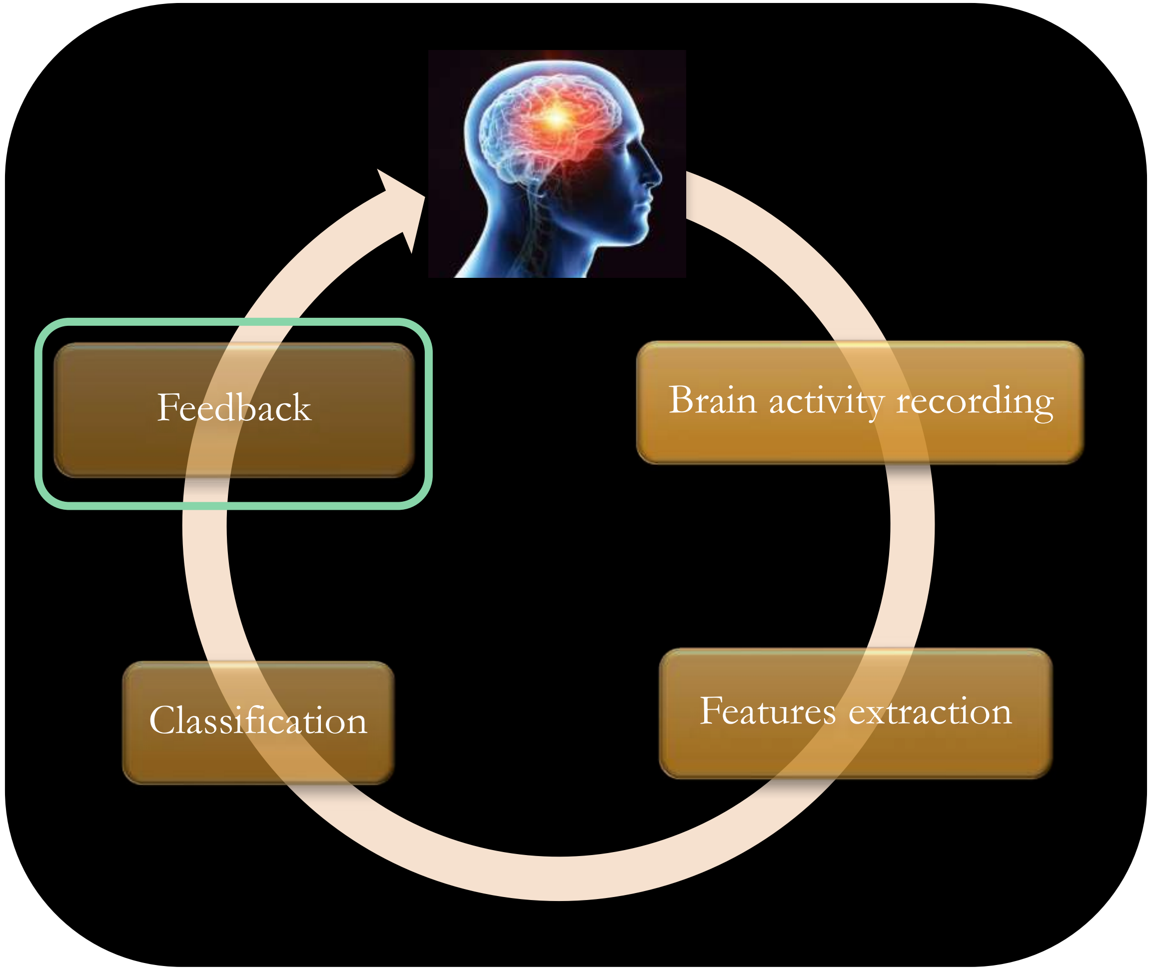
Behind the magic…

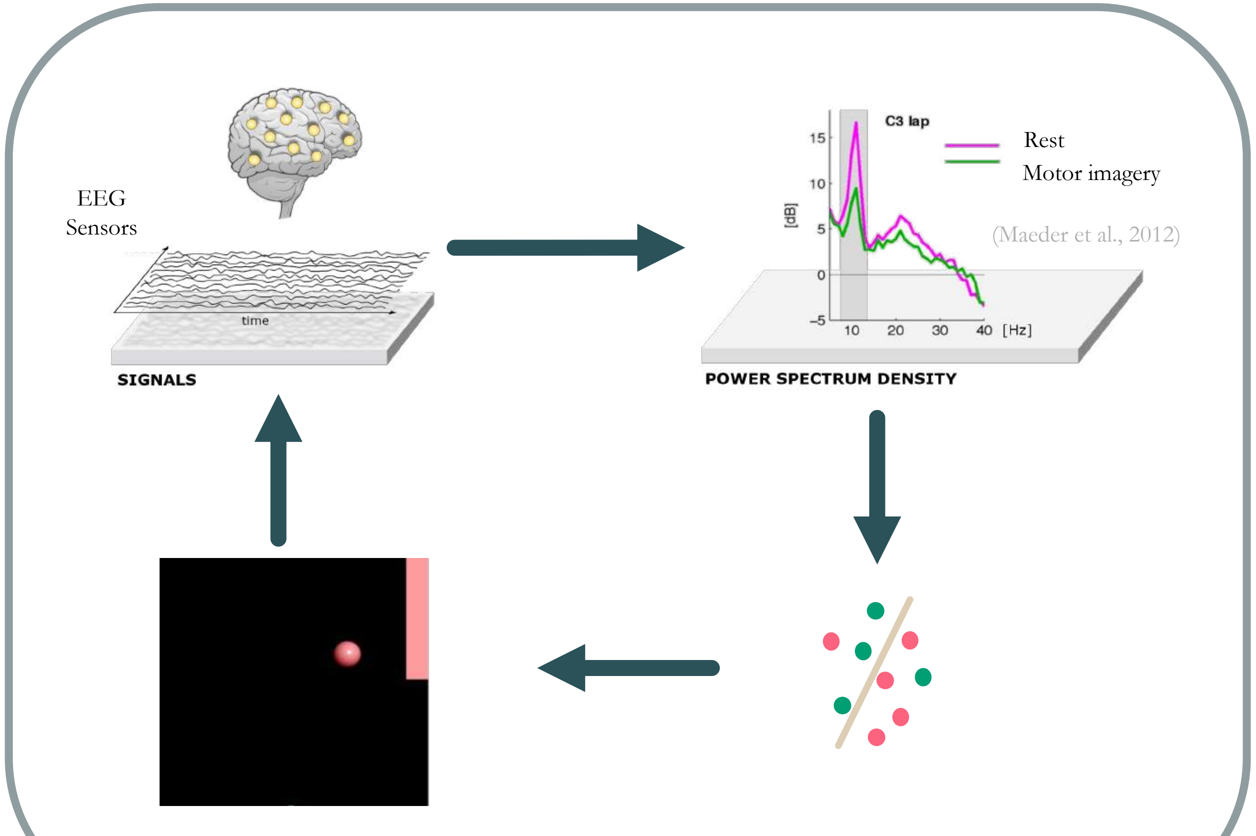




Adapted from [Gonzalez-Astudillo et al, 2020]

Behind the magic…



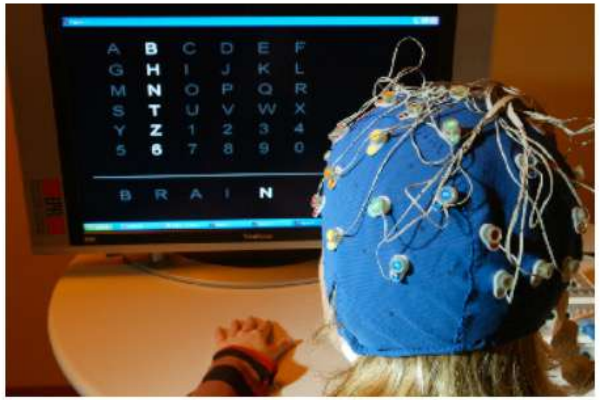


Adapted from [Gonzalez-Astudillo et al, 2020]

Clinical applications

- Control
  - Prosthesis (Fifer et al, 2014)
  - Wheelchair (Carlson & Millan, 2013)
  - Quadcopter (LaFleur et al, 2013)

- Communication
  - Verbal & nonverbal communication (Jin et al, 2012; Hwang et al, 2012; Kashihara, 2014)
  - Silent talk (Naci et al, 2013)

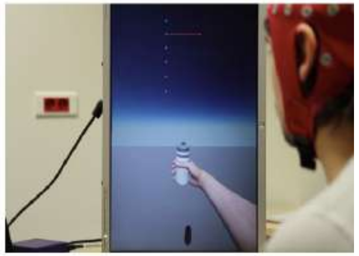


BCI & communication

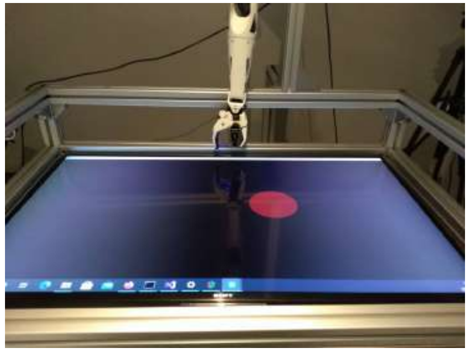
- Neurological disorders treatment
  - Stroke (Prasad et al, 2010)
  - Spinal cord injury (King et al, 2013)
  - Consciousness (Chatelle et al, 2012)
  - Psychiatric disorders (Arns et al, 2017)

Examples of BCI research and clinical applications

- Inria software development w/ OpenViBE for:
  - Robotic device control
  - Stroke rehabilitation
  - Better monitoring general anesthesia



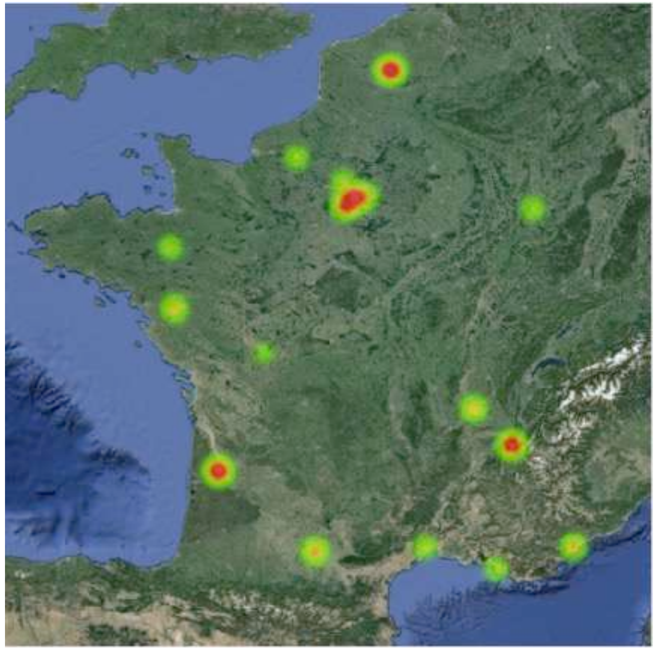
LORIA projects
Courtesy of S. Rimbert



ARAMIS projects
Courtesy of T. Venot

Examples of BCI research and clinical applications

- Examples of French BCI laboratories
  - LORIA team (Nancy, France)
  - Hybrid team (Rennes, France)
  - Potioc team (Bordeaux, France)
  - NERV team (Paris, France)

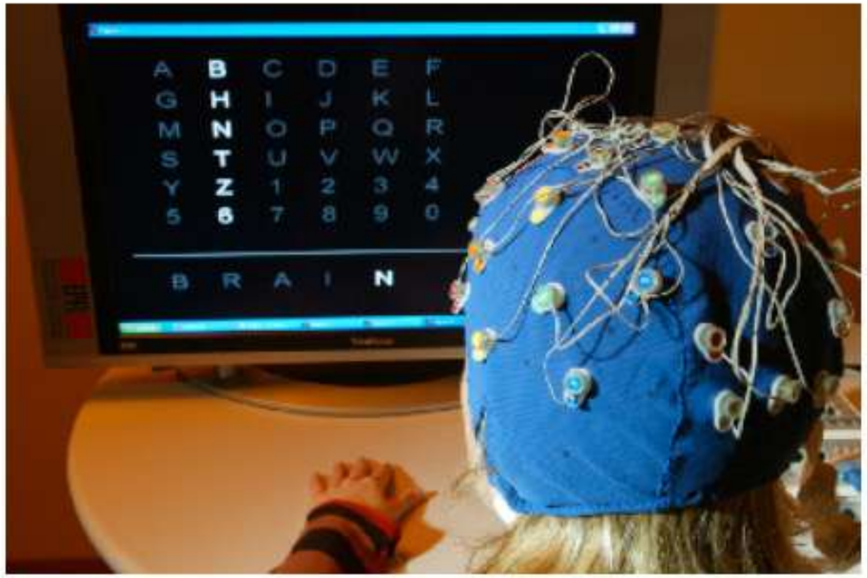


BCI labs localization in France

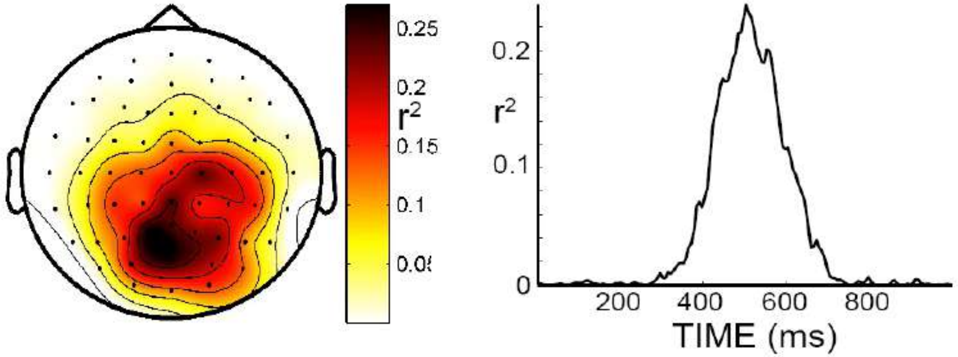
- Most salient disciplines:
  - EEG Signal Processing & Machine Learning
  - Clinical Neuroscience
  - Human-Computer Interaction & BCI
  - Computational Neuroscience
  - Invasive BCI research
  - Ethics

⇒ Access to an interactive map of laboratories: here (work in progress, not exhaustive!)

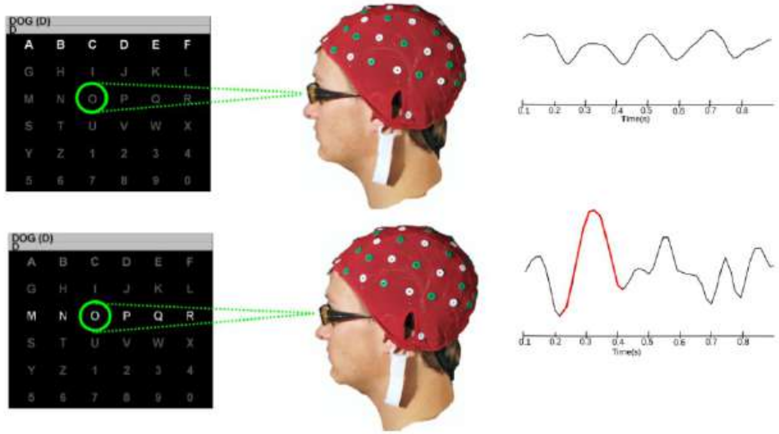
Different types of BCI – P300 Speller



P300 Speller

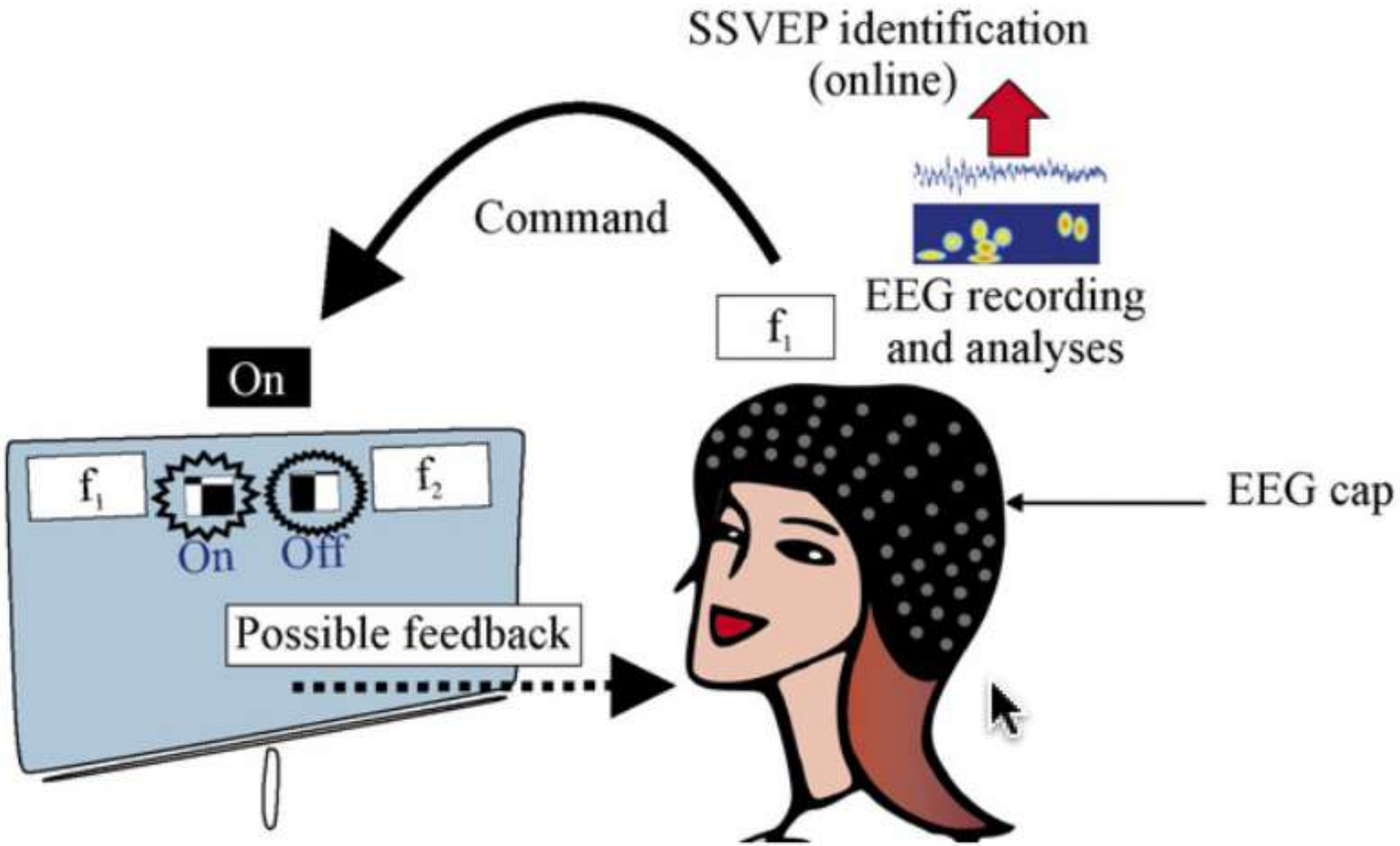


Illustrations from BCI2000 website



Adapted from [Lotte et al, 2015]

Different types of BCI – Visual epoked potential



(Vialatte et al, 2010)

AN EXAMPLE OF BCI EXPERIMENT

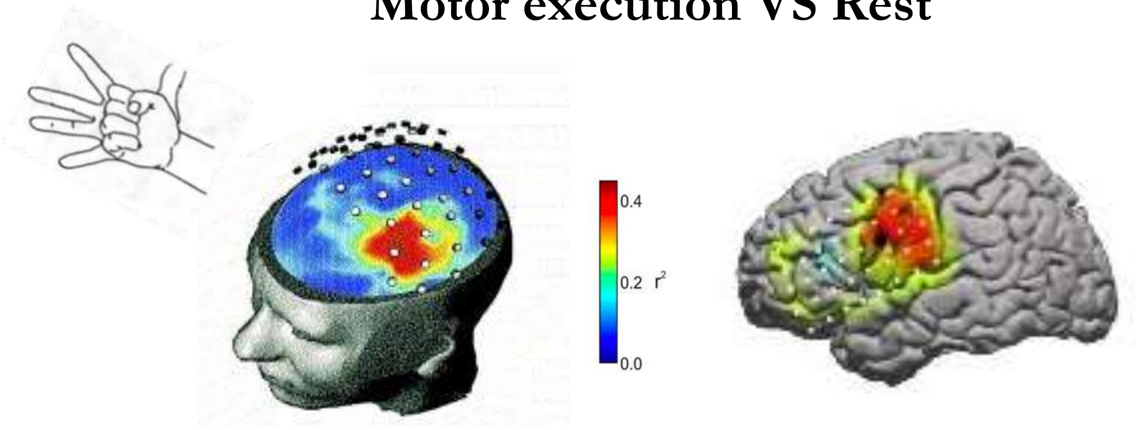
Underlying idea

Taking advantage of a neurophysiological phenomenon to establish a communication between the brain and the computer

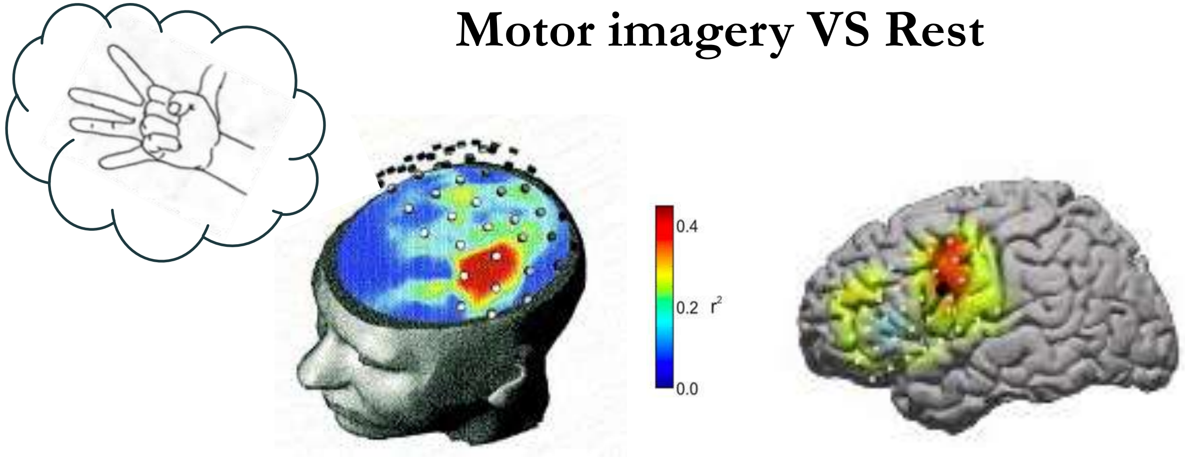
Illustration with Motor imagery-based BCI

Motor imagery – obervations

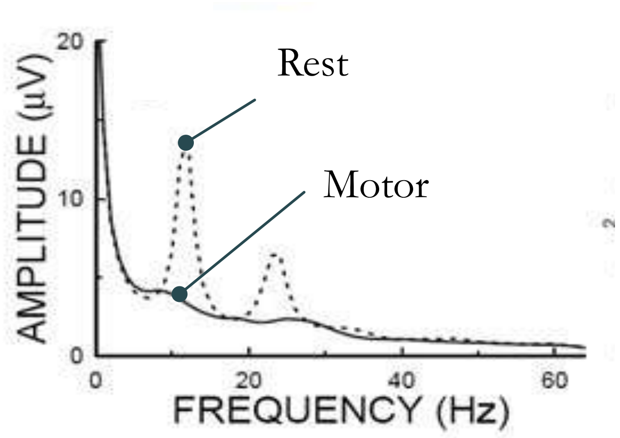
Motor execution VS Rest



Motor imagery VS Rest



Power decrease

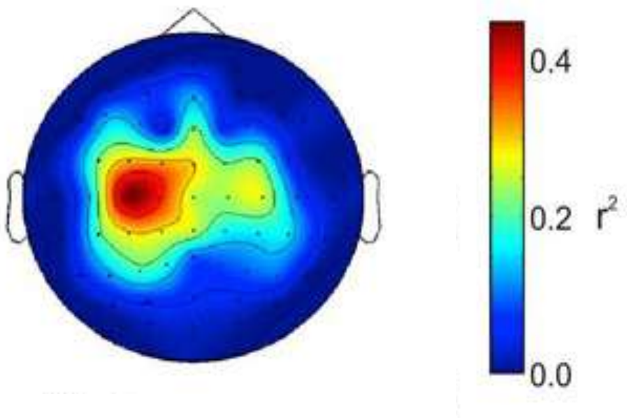


Desynchronization effect
(Pfurtscheller et al, 1999)

Motor imagery – mu & beta rhythms

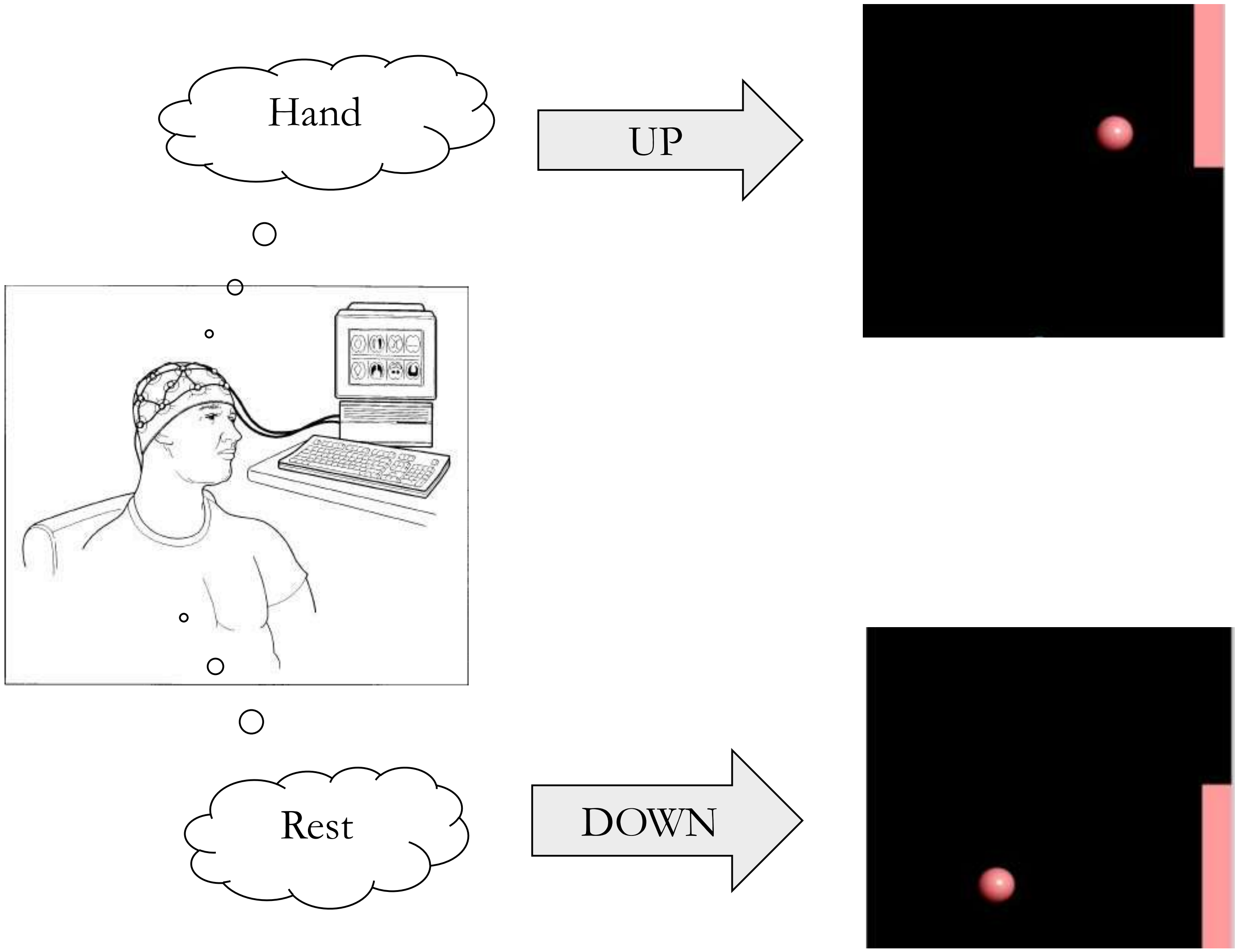
- Behavioral properties
  - Movement / preparation for movement : Event-related desynchronization (ERD) (Pfurtscheller, G, Lopes da Silva, FH, 1999)
  - With relaxation/post-movement period : ERS

- Why using it in BCI ?
  - Mu/Beta activity modulation by motor-imagery, a way to communicate
  - Use of power spectra
  - To establish this communication :
    - Spatial selection
    - Frequency selection



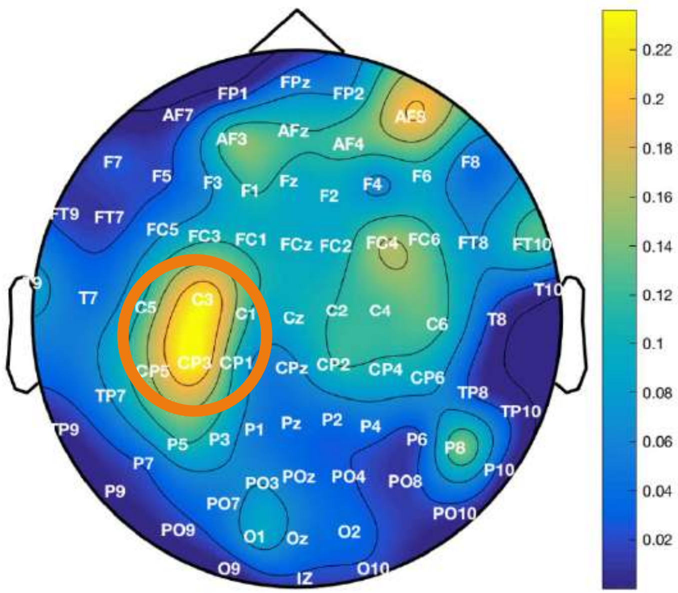
Illustrations from BCI2000 website

Motor imagery – in practice



Motor imagery – in practice

@ 10Hz

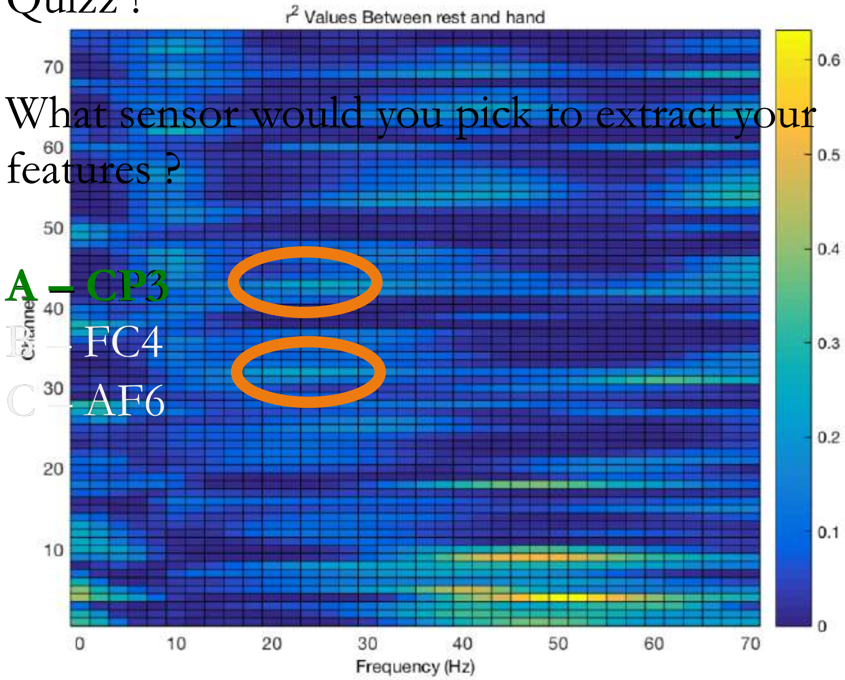


r^2

Quizz !

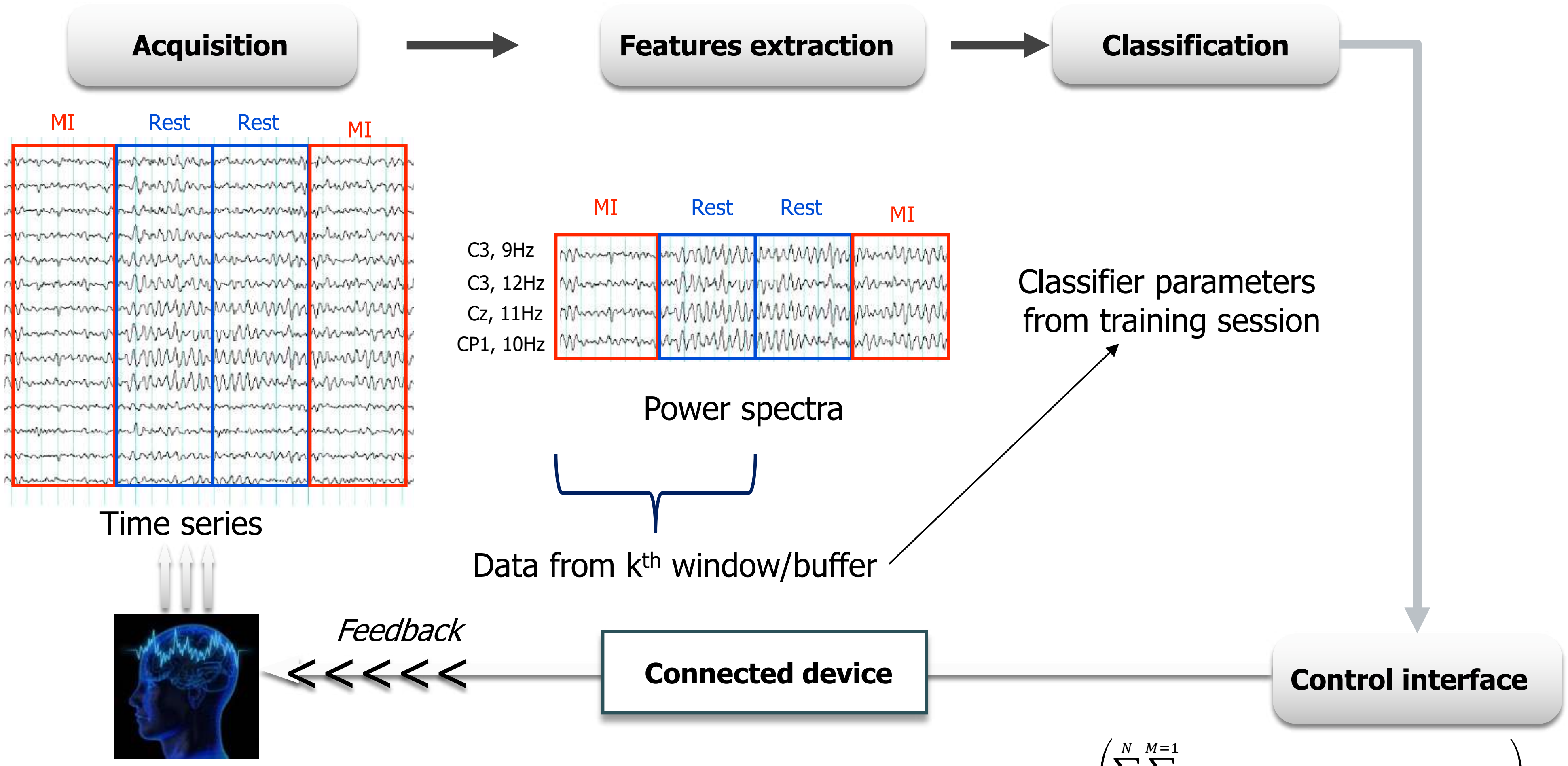
What sensor would you pick to extract your features ?

A – CP3
B – FC4
C – AF6



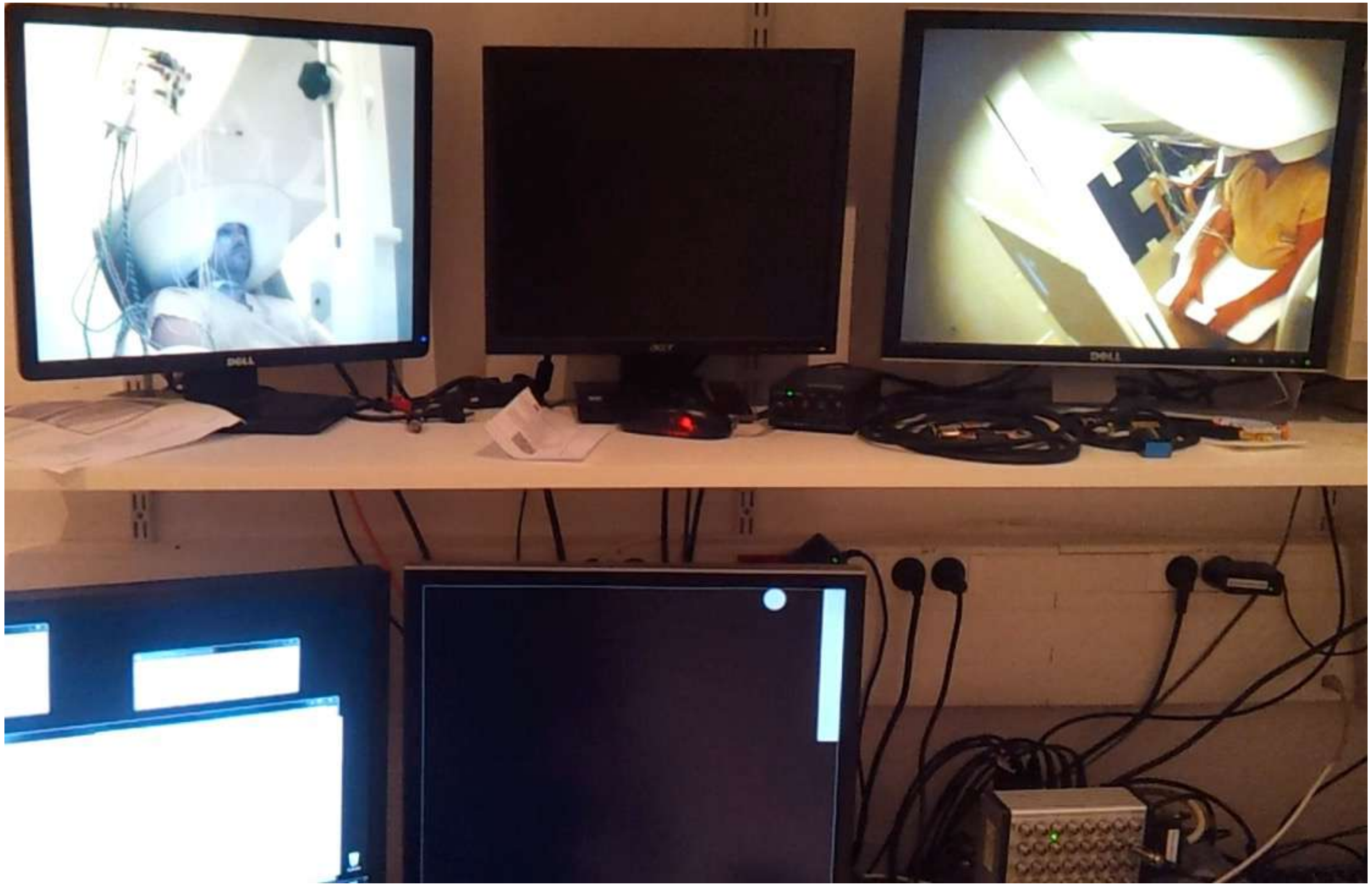
r^2

Motor imagery – in practice



$$cursor\ velocity = \left(\sum_{i=1}^{N} \sum_{j=1}^{M=1} Features_{i,j} Classifier_{i,j,k} - Offset \right) x\ Gain$$

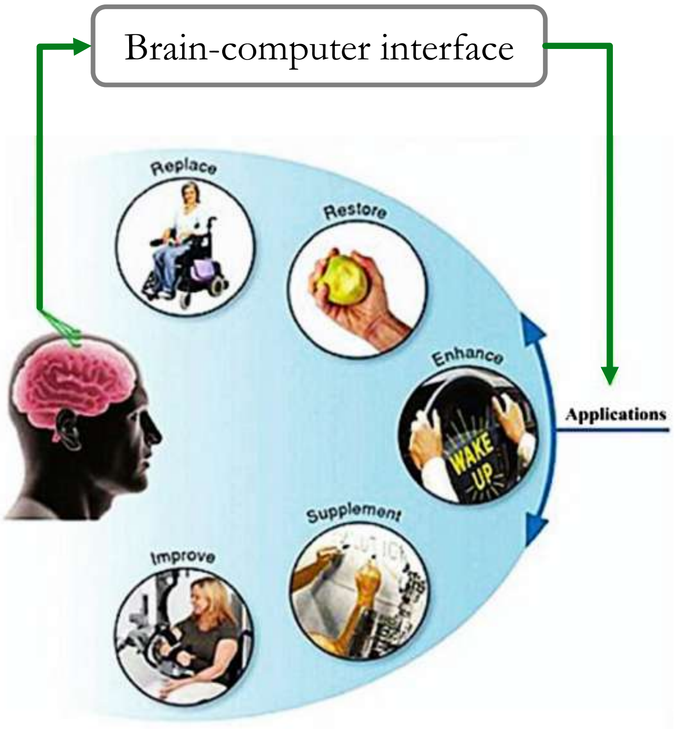
Motor imagery – in practice



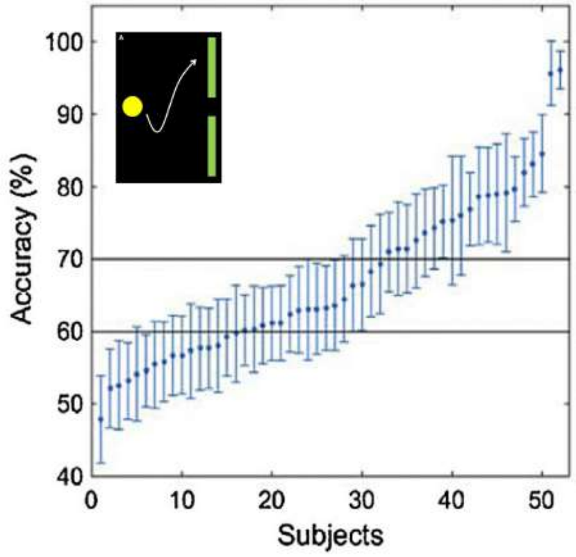
CURRENT CHALLENGES IN BCI RESEARCH

BCI inefficiency challenge

Great potential



Poor usability



(Ahn & Jun, 2015)

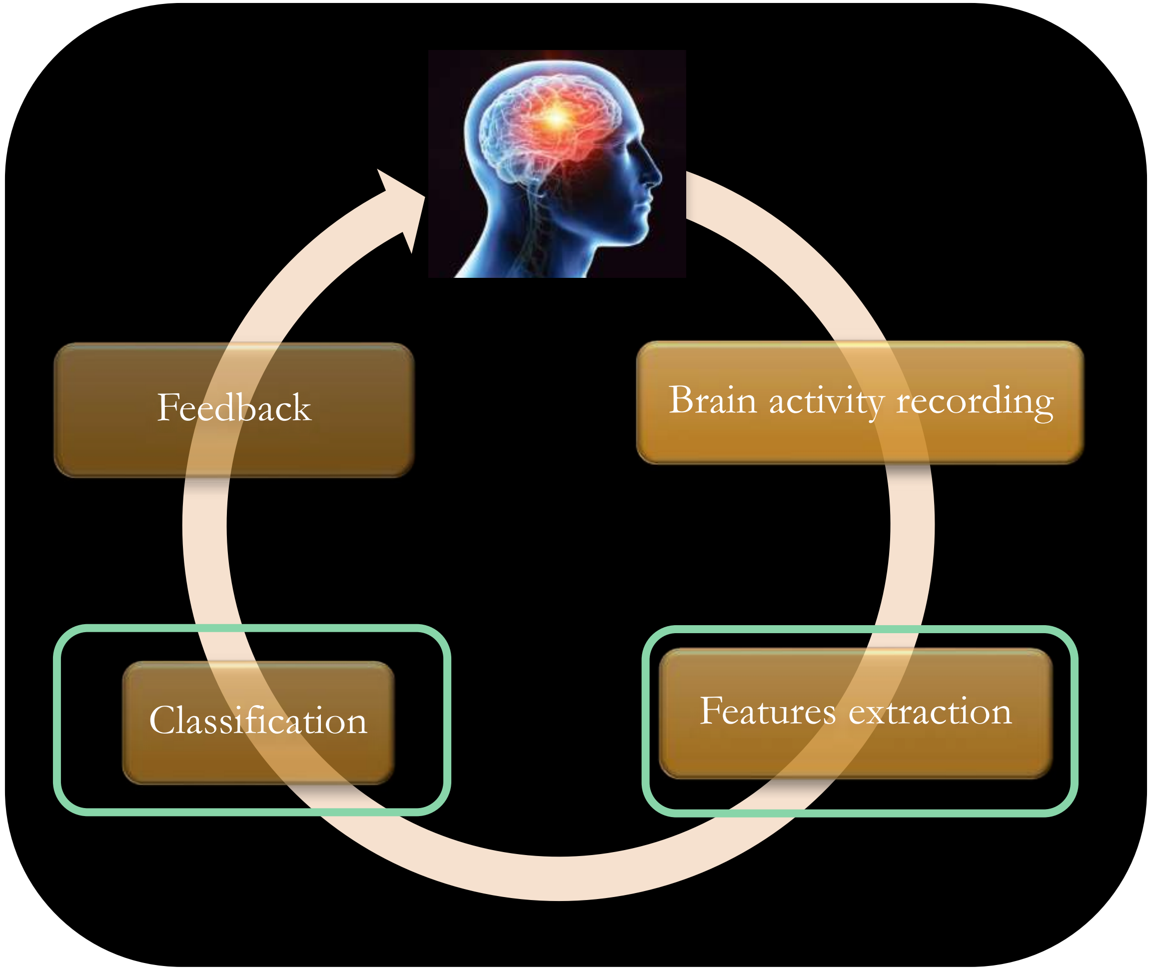
Problem: Current BCIs fail to detect the mental intentions in ~30% of users – **BCI inefficiency** (Thompson, 2018)

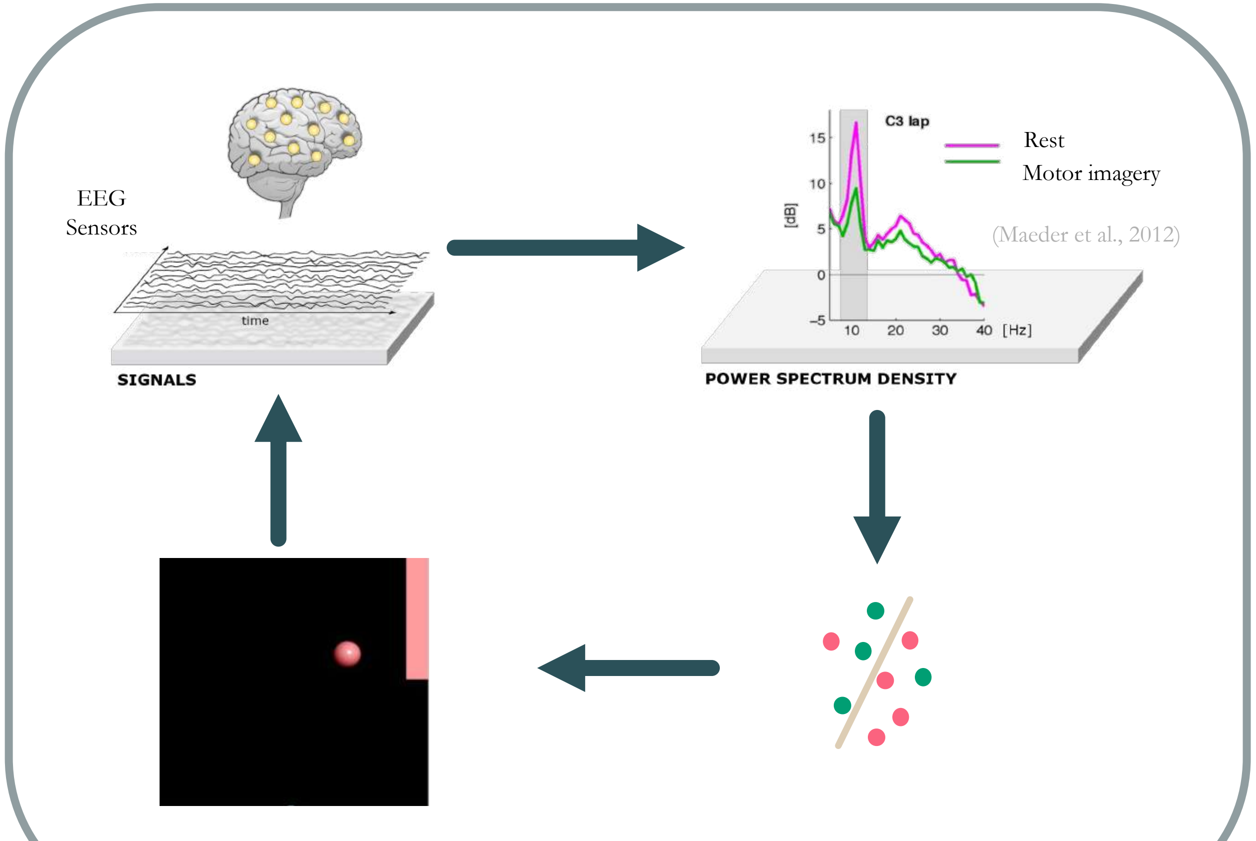
BCI inefficiency challenge – state-of-the-art

- Machine-centered approaches
  - Signal conditioning (Ang et al, 2012)
  - Classification algorithms (Lotte et al, 2018)
- User-centered approaches
  - Search for neurophysiological patterns (Blankertz et al, 2010)
  - Human factors (Jeunet et al, 2015)

MACHINE LEARNING IN BCI RESEARCH

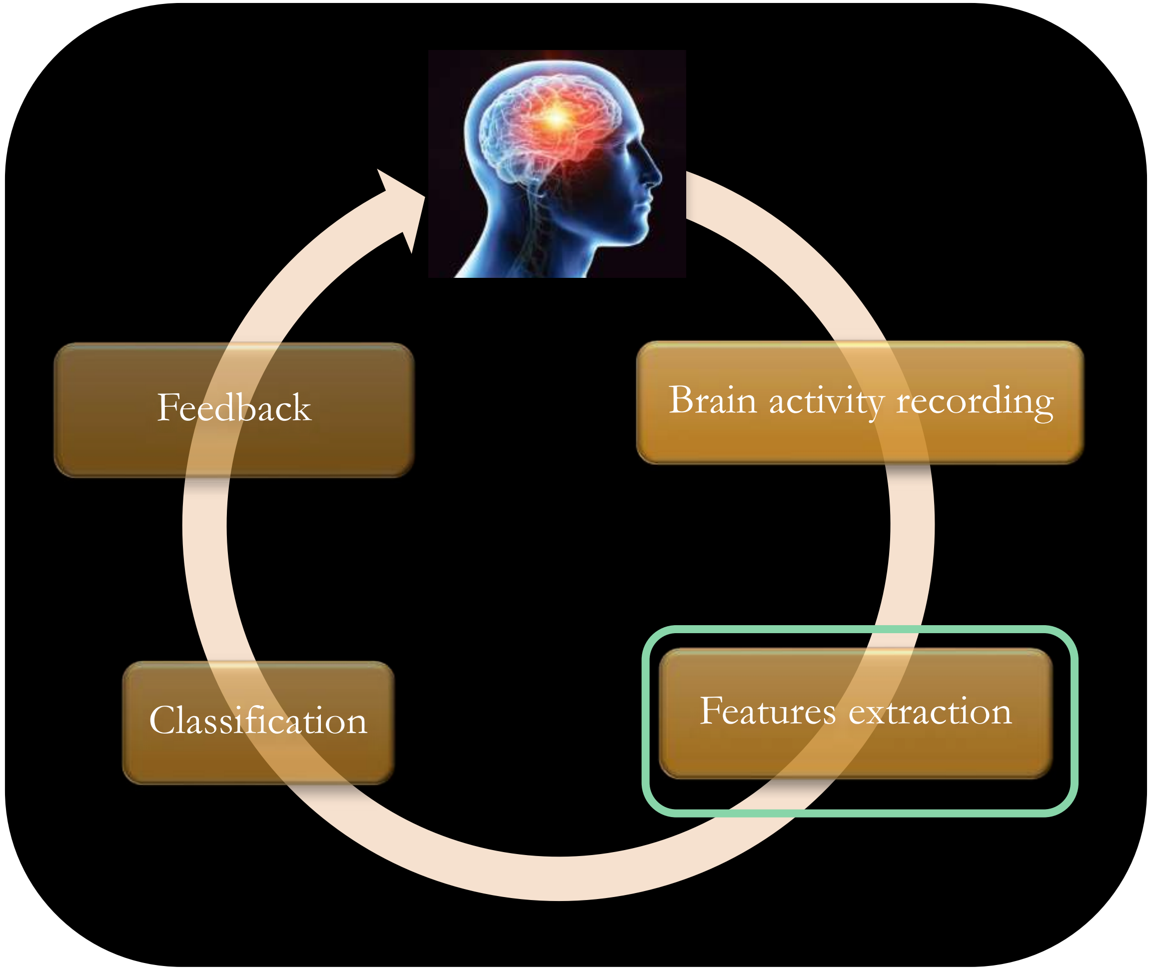
Machine Learning in BCI





Adapted from [Gonzalez-Astudillo et al, 2020]

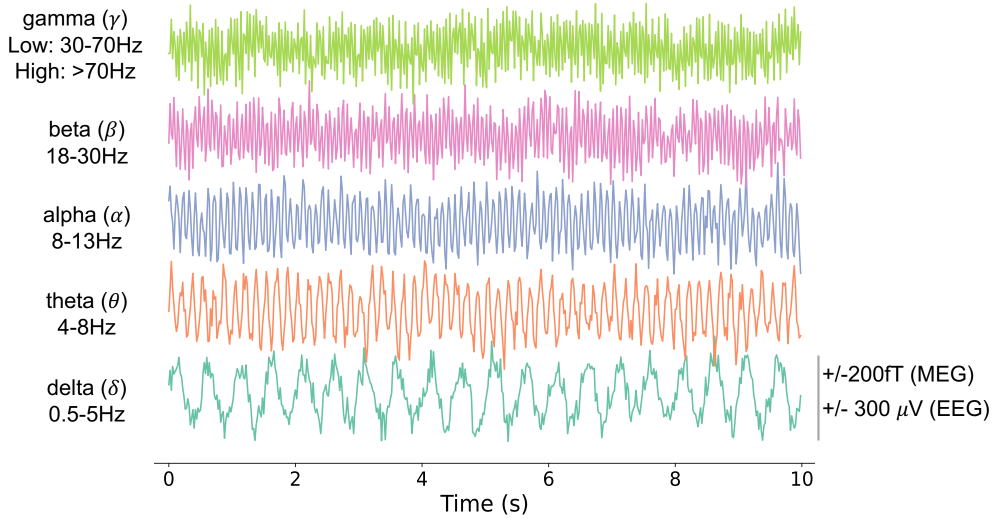
Features extraction in BCI



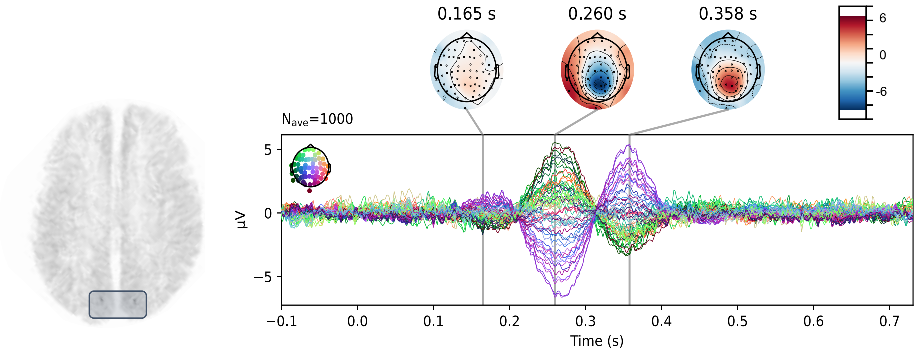
- Properties
  - Noise & outliers
  - High dimensionality
  - Time information
  - Non stationarity
  - Small training sets
- Time variations of M/EEG
  - Concatenation of features from different time segments
  - Combination of classifications at different time segments
  - Dynamic classification

Features extraction in BCI – the most common types

- Frequency band power
  - Power of M/EEG signals
  - Computed in many ways
  - Oscillatory activity
  - BCIs: motor/mental imagery, passive BCI, SSVEP



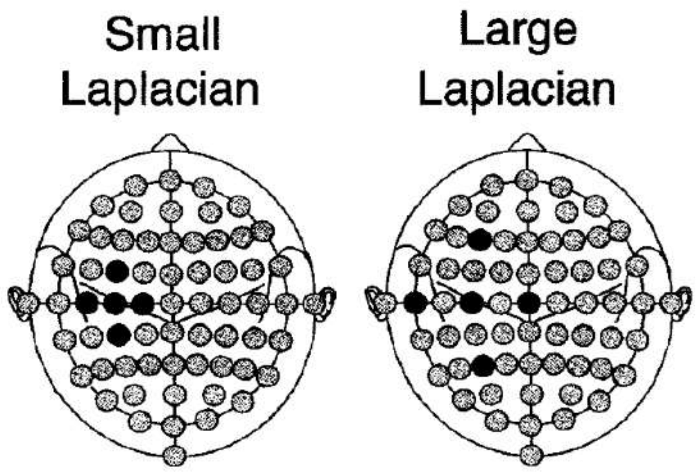
- Time point
  - Concatenation of M/EEG samples
  - Event-Related Potentials (ERPs)
  - BCIs: P300-based BCI



Adapted from [Corsi, 2023]

Features extraction in BCI – spatial filtering

- Spatial filtering
  - Can be data independent
    - based on physicial consideration
    - Examples: Laplacian filter, inverse solution based spatial filtering
  - Can be data driven
    - Supervised spatial learning
    - Example: Common Spatial Pattern (CSP) for oscillatory activity, xDAWN for ERP classification
- Alternative features
  - Functional connectivity – cf lesson 3
  - Covariance matrices & Tensors



Adapted from [McFarland et al, 1997]

Features selection in BCI

- Why selecting features?
  - To reduce redundancy & not relevant information
  - To reduce the number of parameters to be optimized by the classifier
  - To reduce possible overtrianing effects
  - To produce faster predictions -> computational efficiency
  - To reduce data collection and storage

- Different approaches
  - Filtering
  - Wrapper
  - Embedded

Features selection in BCI – Filtering approach

- Relies on measures of relationship between each feature and the target class independently from the classifier used
- Ranking criteria
  - Coefficient of determination
  - Information theory

- Many filters require estimation of the probabiliy densities and the joint density of the feature and class label from the data, possible solutions:
  - Discretize the features and class labels
  - Approximate their densities with a non-parametric method

- Filter approaches have a linear complexity w/ respect to the nb of features

Features selection in BCI – Wrapper & embedded approaches

- Solves the problem of redundancy BUT longer computational time
- Wrapper methods - principle
  - select a subset of features
  - present it as input to a classifier for training
  - observe the resulting performance
  - stop the seach according to a stopping criterion OR propose a new subset if the criterion is not satisfied
- Embedded methods – principle
  - Integrate the features selection and the evaluation in a unique process
  - Example: decision tree

Classification algorithms – classical methods

Type	Examples of methods used in BCI
Linear classifiers	- Linear Discriminant Analysis (LDA) and its regularized version - Support Vector Machine (SVM)
Neural networks (NN)	- Multi-Layer Perceptron (MLP)
Non-linear Bayesian classifiers	- Bayes quadratic classifiers - Hidden Markov Models (HMMs)
Nearest neighbour classifiers	- k-Nearest Neighbour (kNN) - Mahalanobis distance classifiers
Classifier combinations	- Boosting - Voting - Stacking

Current challenges:

- Low signal-to-noise ratio of EEG signals
- Non-stationarity over time of EEG signals
- Inter/intra-subject variabilities
- Limited amount of training data for calibration
- Low reliability and performance of current BCIs

Classification algorithms – recent methods

- Adaptive classifiers
- Classification of matrices
- Classification of tensors
- Transfer learning
- Deep learning

Classification algorithms – recent methods – Adaptive classifiers

- Principles
  - Classifiers whose parameters are incrementally re-estimated and updated over time as new EEG data become available
  - In supervised, unsupervised and semi-supervised maneers

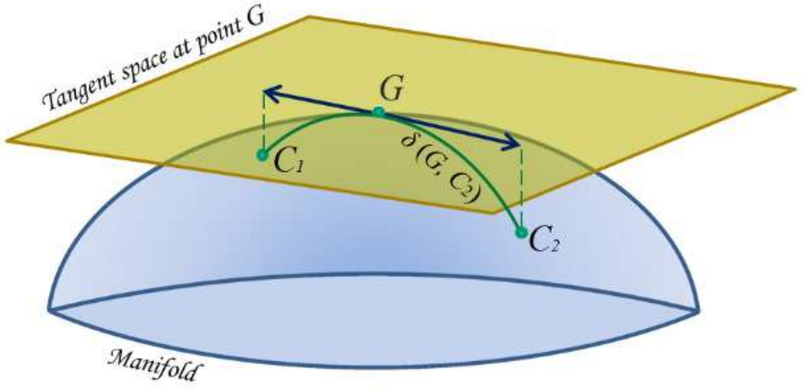
- State-of-the-art
  - Majority based on unsupervised adaptation
  - Mutlitple adaptive classifiers explored offine
  - Multiple sessions that continuously retraining the weights of linear classifiers (supervised manner) to improve performance in SMR but not in P300 – [McFarland et al, 2011]

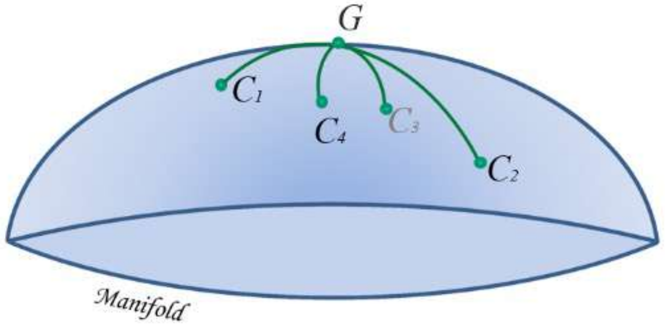
Classification algorithms – recent methods – Adaptive classifiers

Pros	Cons
- Superior to non-adaptive classifiers in MI BCI and some ERP-based BCI - Unsupervised adaptation to shorten/remove the need for calibration - Unsupervised methods based on incremental adaptation – low computational complexity for online exp.	- Unsupervised methods based on full retraining – high computational complexity - Need of more online studies: How adaptation should be performed in practice?

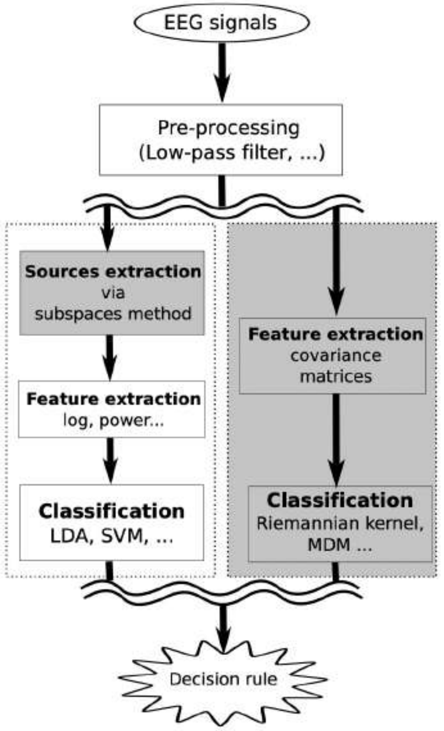
Classification algorithms – recent methods – Riemannian geometry-based classification

- Principles





Adapted from [Lotte et al, 2018]

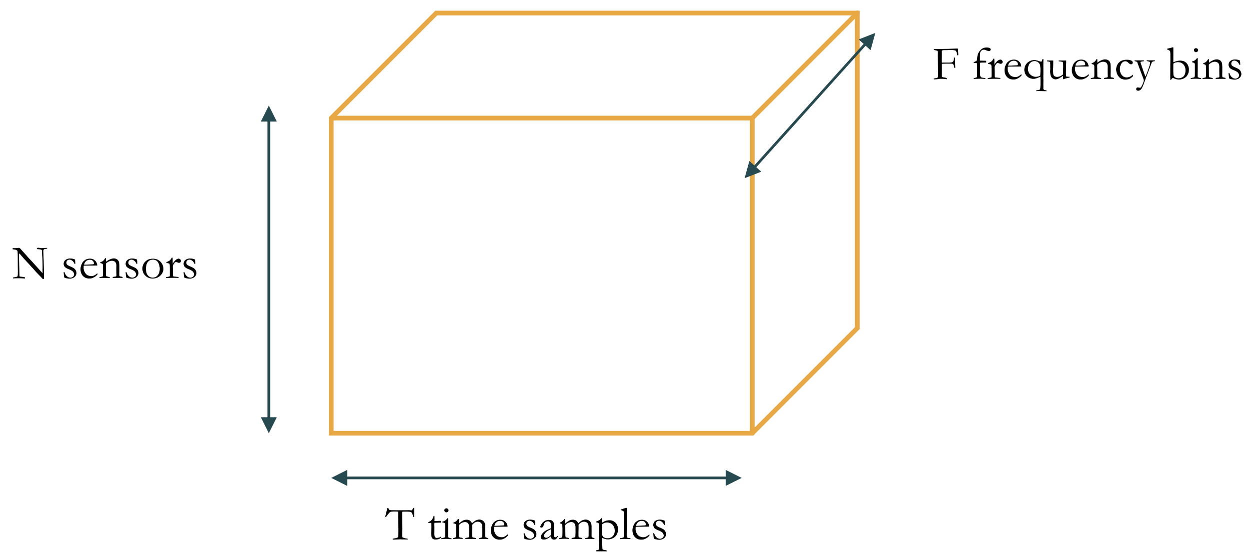


Processing pipelines used in BCI
(Yger et al, IEEE TNSRE, 2017)

Classification algorithms – recent methods – Riemannian geometry-based classification

Pros	Cons
- Processing procedures simpler and with fewer stages - RMDM parameter-free - Robustness towards noise - Invariant to matrix inversion and linear transformation of the data - Not sensitive to the *swelling effect*	- The larger the dimensions the more the distance is prone to noise - Online implementation

Classification algorithms – recent methods – Classification of tensors



EEG pattern	Features/Methods	Classifier	References
Motor imagery	Topographic map, TFR, Connect.	LDA/HODA	[Phan & Cichocki, 2013]
P300	Multilinear PCA	SVM/TSM	[Washizawa et al, 2010]
P300	Tine-space-freq	HODA	[Onishi et al, 2012]
SSVEP	TCCA, MsetCCA, Bayesian	LDA	[Zhang et al, 2010]

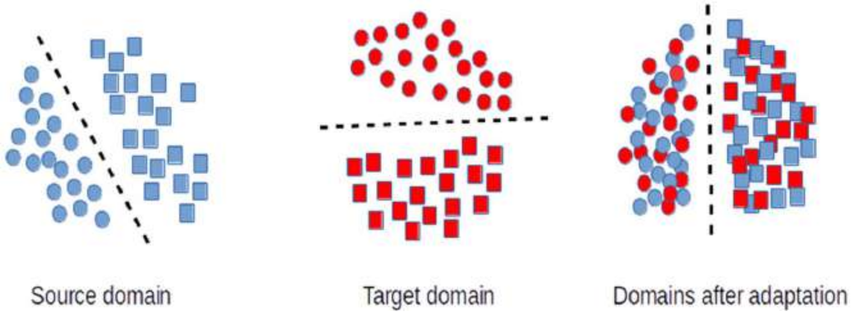
Adapted from [Lotte et al, 2018]

Classification algorithms – recent methods – Classification of tensors

Pros	Cons
- Many data to discover underlying hidden complex (space-time-frequency) data structures - Tensorization to compress largen mutlidim. Data into lower factor matrices (ie reduced features) - Application for pattern recognition, data fusion, dimensionality reduction…	- Complexity of the methids - Algorithms not always mature/optimized

Classification algorithms – Recent methods – Transfer learning

- Principles
  - Exploits knowledge acquired while learning a given task for solving a different but related task
  - Enhancing performance of a learned classifier trained on 1 tasks (domain) based on information obtained while learning another task
  - Especially interesting when abundant labelled data for a given task (source domain) whilst scarce data for the second task (target domain)



Adapted from [Lotte et al, 2018]

- In BCI
  - Homogeneous TL
  - Inductive TL
  - **Transductive TL**

=> reviews – [Jayaram et al, 2016] (TL for BCI) & [Wu et al, 2022] (TL for MI-BCI - tutorial)

Classification algorithms – Recent methods – Transfer learning

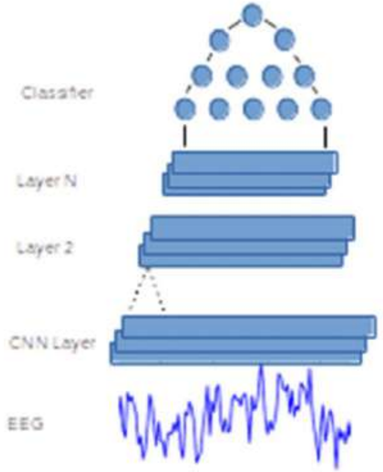
- State-of-the-art
  - Focused on transductive transfer learning
  - Challenges
    - Data scarcity
    - Variability across subjects/sessions
  - Domain adaptation methods:
    - Spatial filters based on ensemble data
    - Sparse representations
    - Model variability across sessions of subjects
    - Transportation

Classification algorithms – Recent methods – Transfer learning

Pros	Cons
- Essential for calibration-free BCI to improve its usability & acceptance - Robust	- Few methods applied online

Classification algorithms – Recent methods – Deep learning

- Principles
  - ML algorithm on which features and the classifier are jointly learned directly from data
  - Architecture of the model based on a cascade of trainable feature extractor modules and non linearities



Adapted from [Lotte et al, 2018]

- Use in BCI
  - Most popular DL approaches in BCI: **convolutional neural**

- New perspectives
  - Data augmentation – review w/ code [Rommel et al, 2022]
  - Towards RG DL
    - Motivation: increasing the robustness and the interpretation
    - Examples: TSMNet by [Kobler et al, 2022] – more resources here
    - Review and comparison of pipelines w/ code [Wilson, et al, 2023]

Classification algorithms – Recent methods – Deep learning

Pros	Cons
- Features extraction (from raw data), - Generalization - Robustness	- Few methods applied online - Parameters to be tuned & training set (less for shallow CNN) reduces the performance - Computational cost (training time) - Interpretation

Classification algorithms – Recent methods – Deep learning

- Key-points when using DL with EEG - [Roy et al, 2019]
  - Architecture – CNN vs RNN
    - Number of layers
    - EEG-specific design choices
  - Training
    - Training procedure
    - Regularization
    - Optimization
    - Hyperparameter search
  - Inspection of trained models

Classification algorithms – Recent methods – Deep learning

- Recommendations & checklist - [Roy et al, 2019]

Table 7. Recommendations for future DL-EEG studies. See appendix B for a detailed list of items to include.

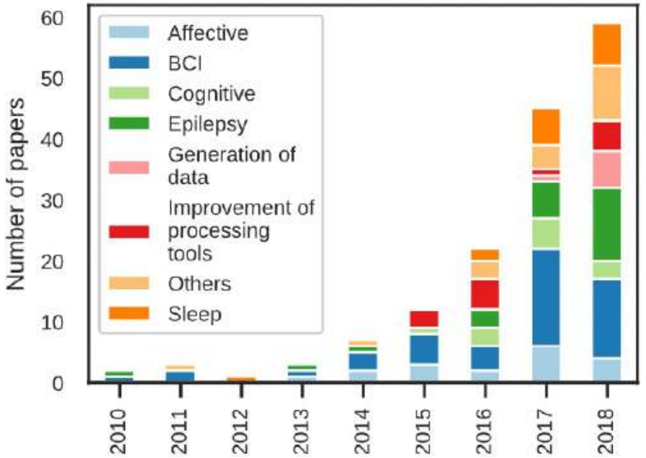
	Recommendation	Description
1	Clearly describe the architecture	Provide a table or figure clearly describing your model (e.g. see [33, 59, 167])
2	Clearly describe the data used	Make sure the number of subjects, the number of examples, the data augmentation scheme, etc are clearly described. Use unambiguous terminology or define the terms used (for an example, see table 1)
3	Use existing datasets	Whenever possible, compare model performance on public datasets
4	Include state-of-the-art baselines	If focusing on a research question that has already been studied with traditional machine learning, clarify the improvements brought by using DL
5	Share internal recordings	Whenever possible
6	Share reproducible code	Share code (including hyperparameter choices and model weights) that can easily be run on another computer, and potentially reused on new data

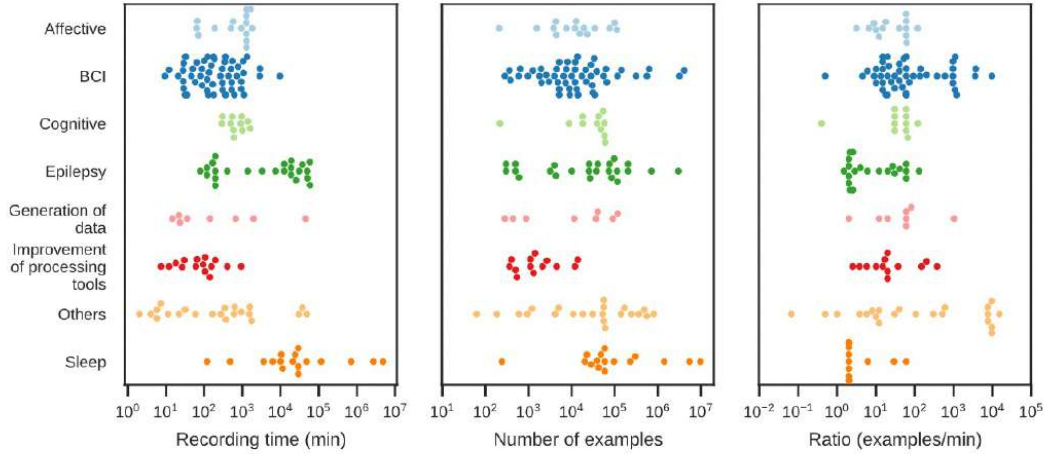
Classification algorithms – Recent methods – Deep learning – beyond BCI…

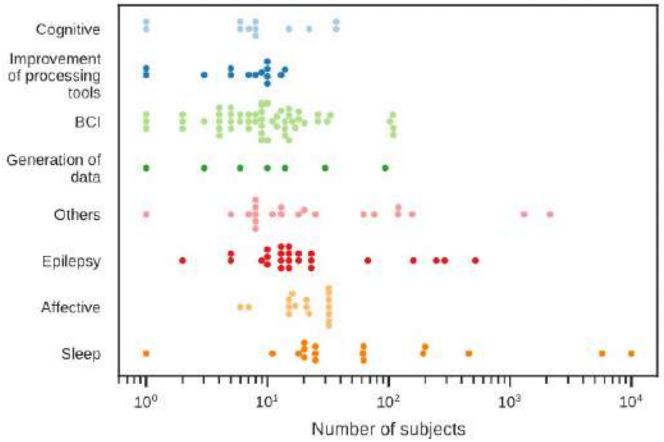
- Main applications - [Roy et al, 2019]
  - Classification of EEG signals
    - BCI
    - Clinical: Alzheimer's disease, anomaly detection, dementia, epilepsy, ischemic stroke, pathological EEG, schizophrenia, sleep
    - Monitoring: affective (emotion), cognitive (engagement…), music semantics…
  - Generation of EEG
  - Improvement of processing tools (signal cleaning…)

Classification algorithms – Recent methods – Deep learning – beyond BCI…

- Main applications - [Roy et al, 2019]

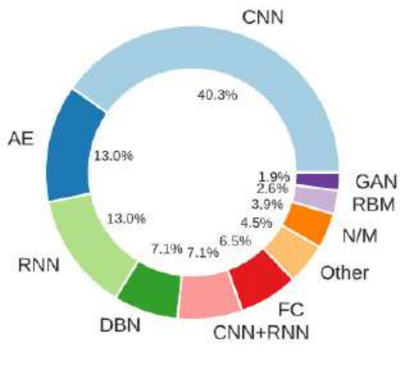




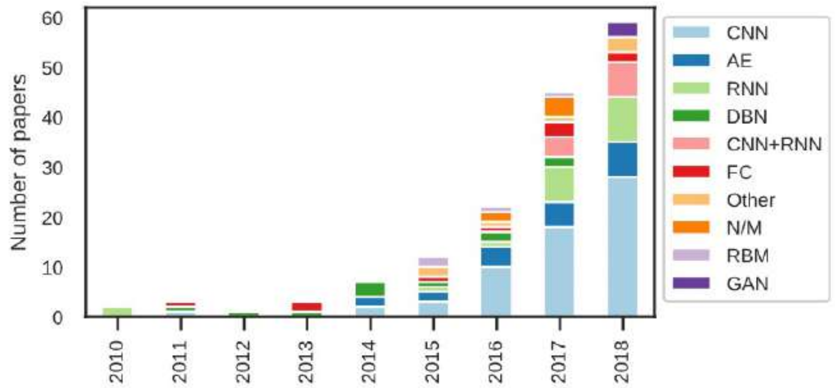


Classification algorithms – Recent methods – Deep learning – beyond BCI…

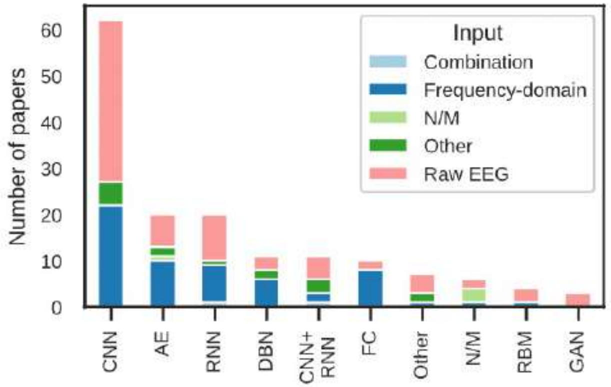
- Main applications - [Roy et al, 2019]



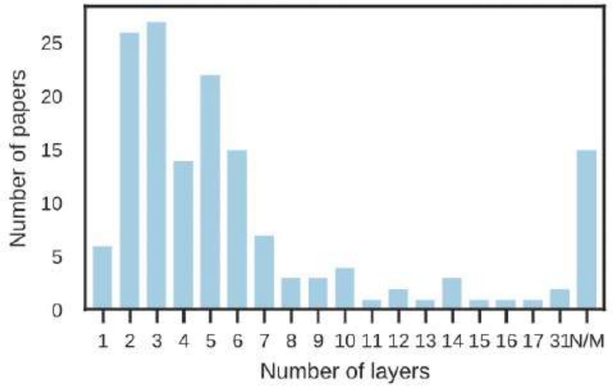
(a)



(b)



(c)



(d)

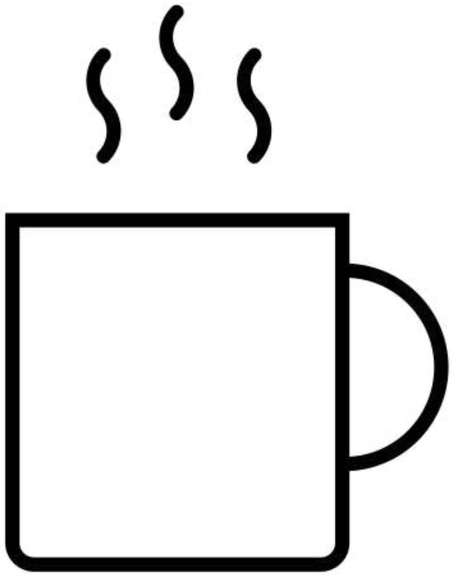
Open challenge – small datasets

- Motivations
  - New subject/protocol – necessity to try out different experimental conditions
  - Working with patients means often short sessions to avoid tiredness and lack of motivation
  - Data change over time (non-stationay feature distributions) – cf rehabilitation training

- Methods
  - LDA variants with domain-specific regularizations [Sosulski et al, 2021]
  - Transfer learning from earlier sessions/other subjects/different tasks [Kobler et al, 2022]
  - Deep Learning and data augmentation [Rommel et al, 2022]

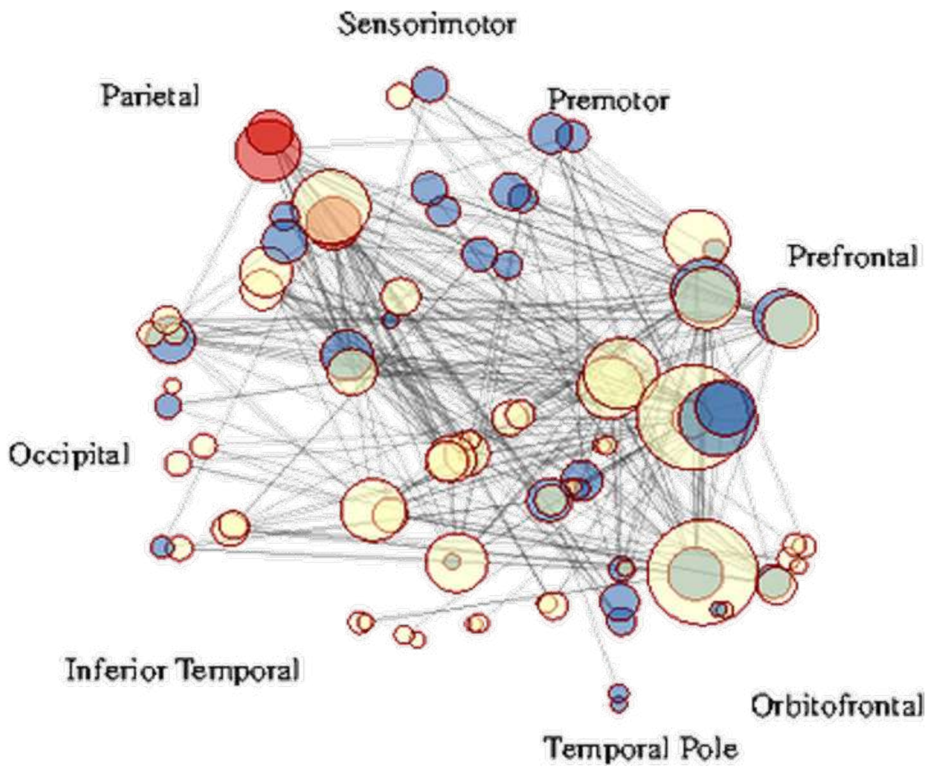
- Resources
  - Workshop dedicated to smal datasets (BCI meeting 2023) by. M. Tangermann – materials (slides and code)

Time for a 15'-break!

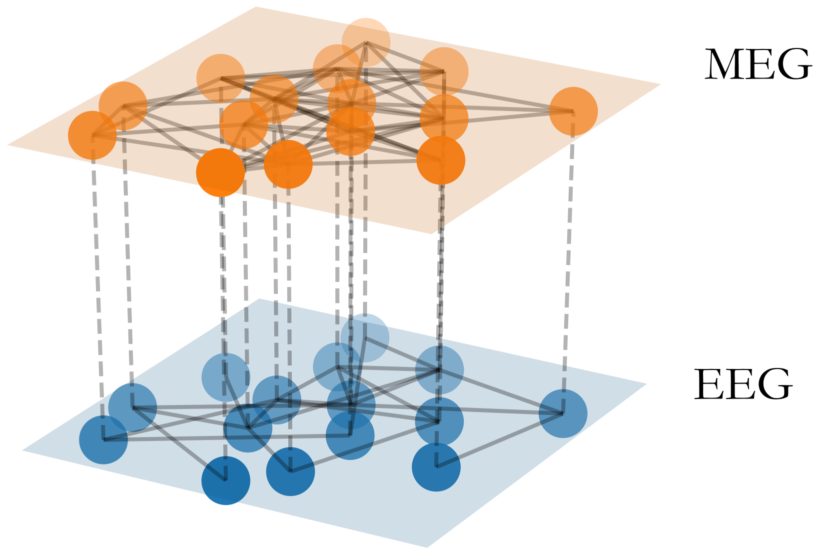


FOCUS – BRAIN NETWORKS & BCI

BCI inefficiency challenge – Network approach

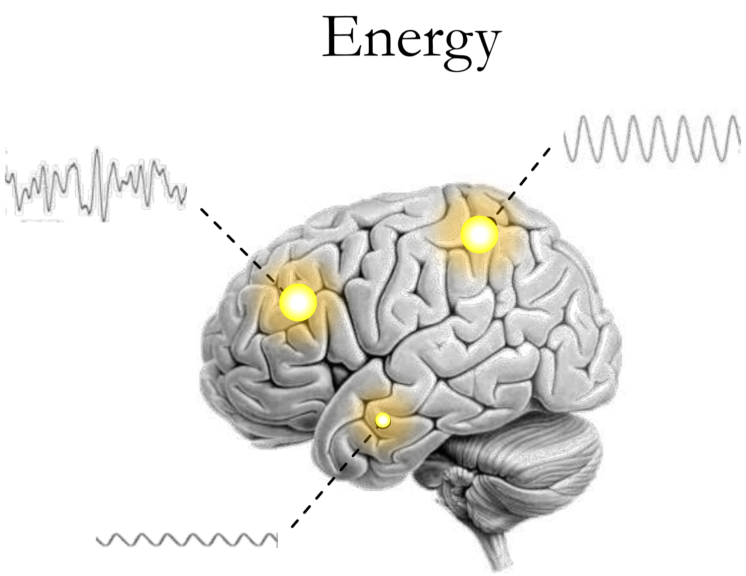


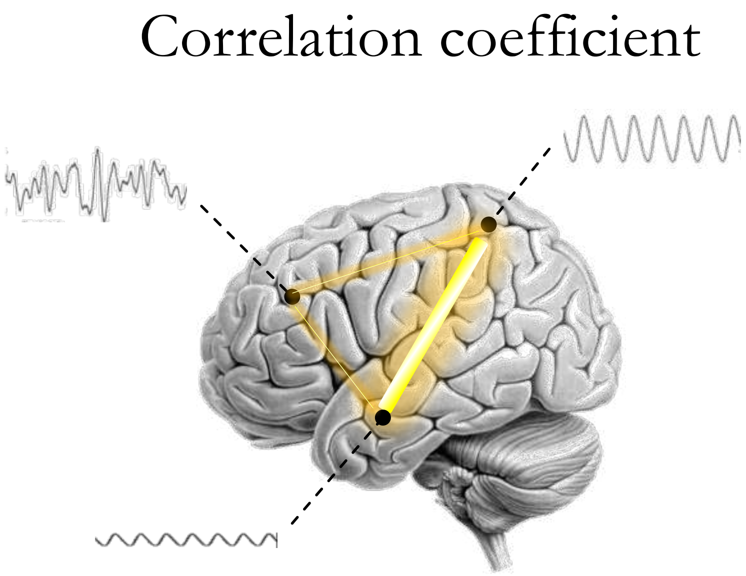
(Varela et al, 1999)



Use of multimodal brain networks to identify alternative features & BCI learning patterns

Activity vs functional connectivity





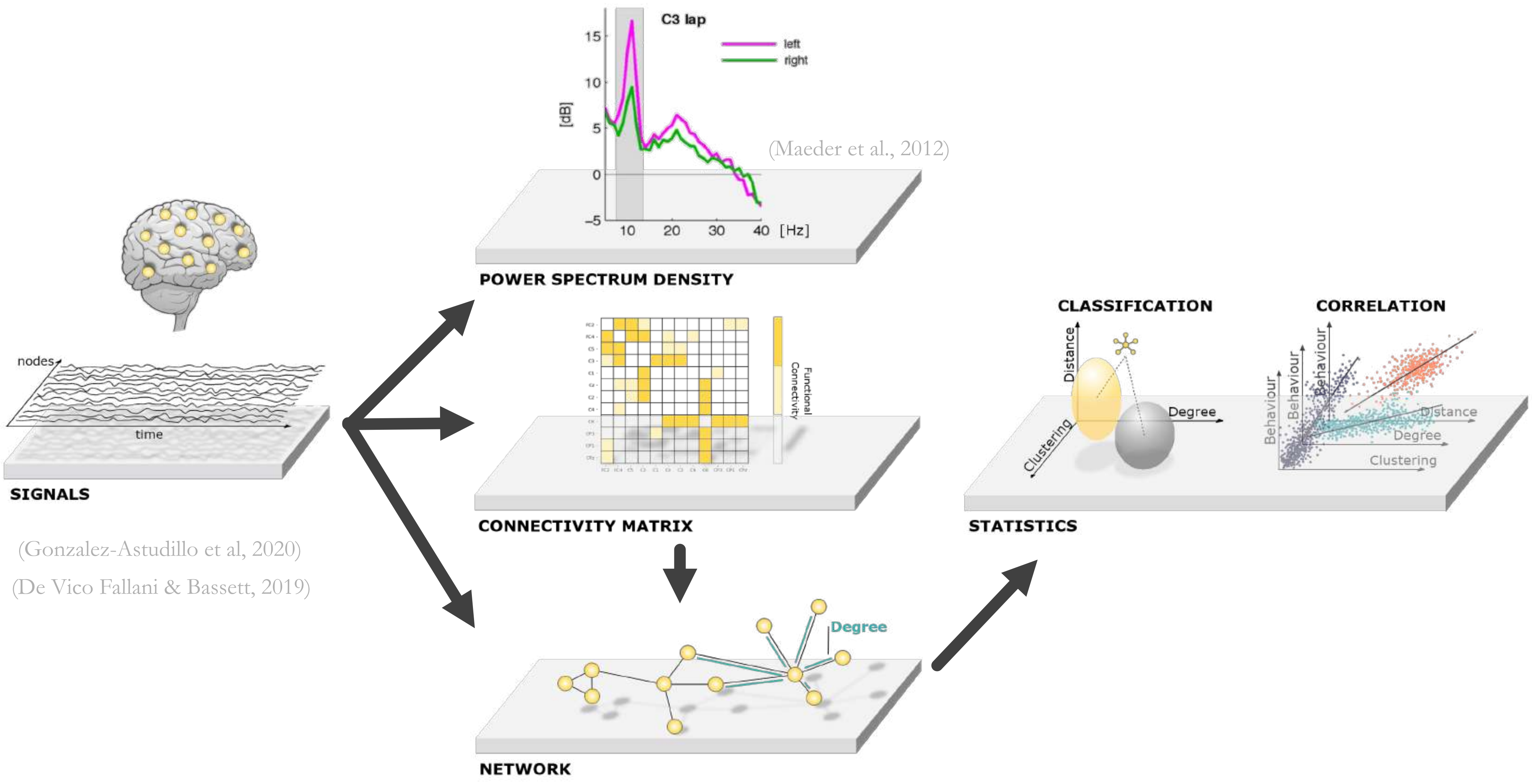
Activity

univariate analysis of signals

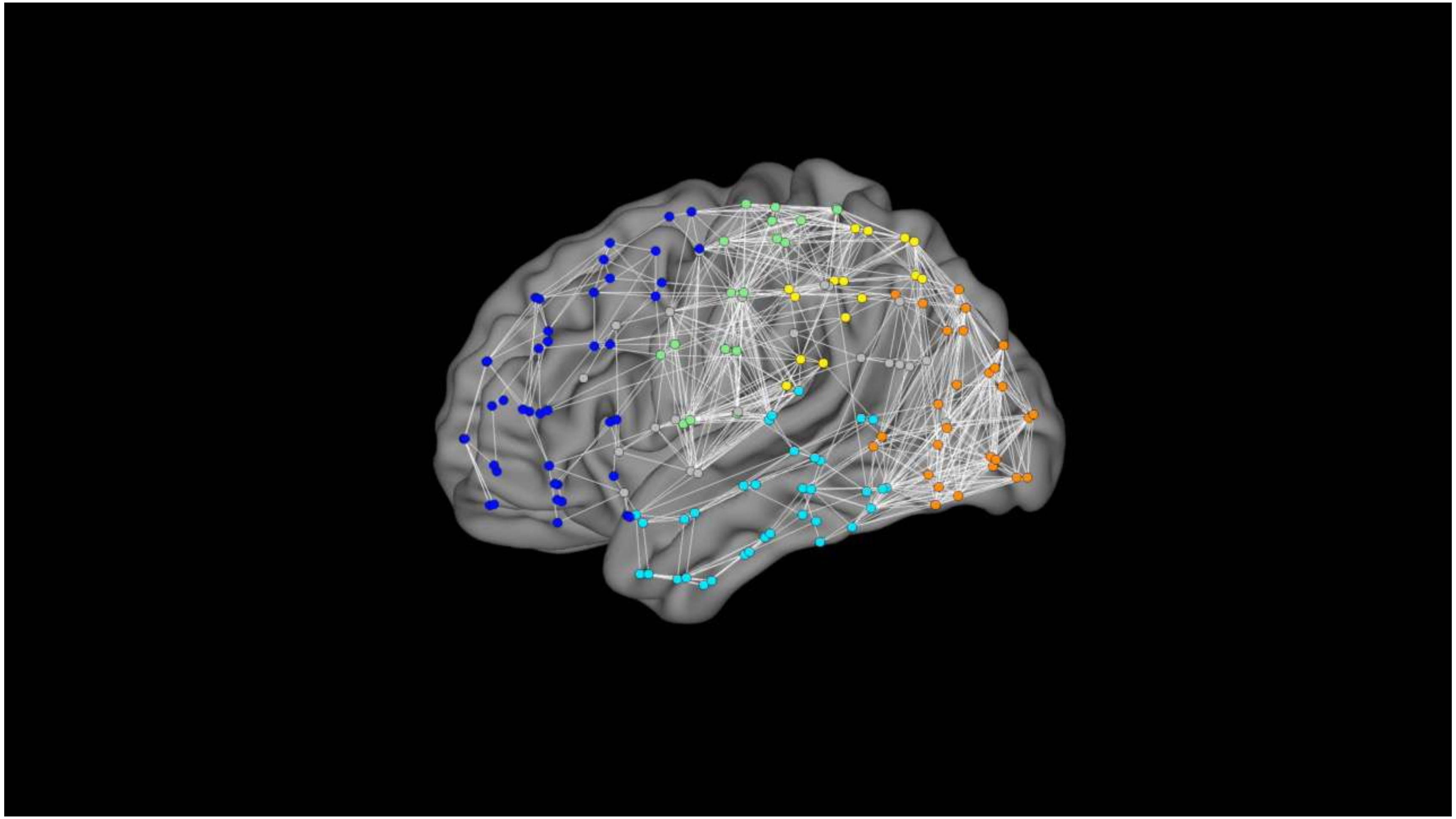
Func. Connectivity

bi/multivariate analysis of signals

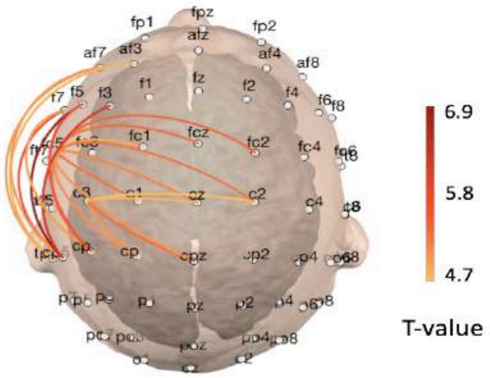
Network metrics for mental states characterization



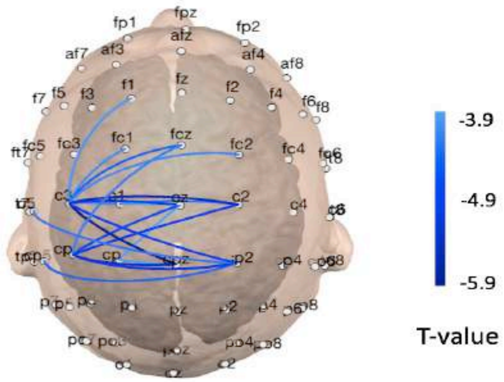
Network metrics for mental states characterization



Brain connectivity changes in MI-BCI

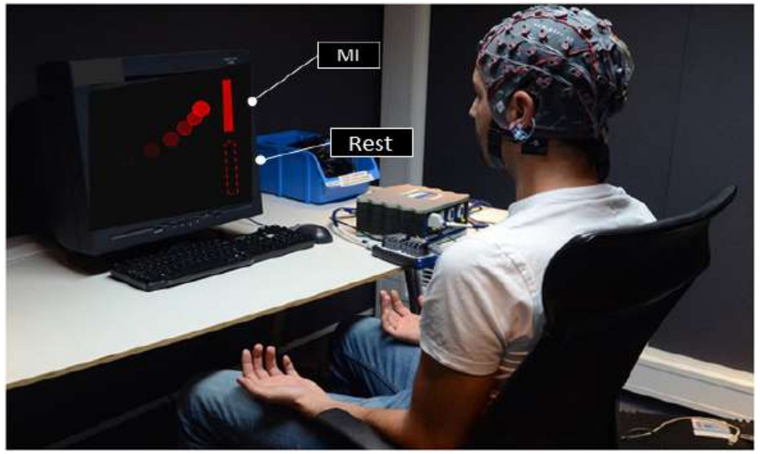


Amplitude synchronization



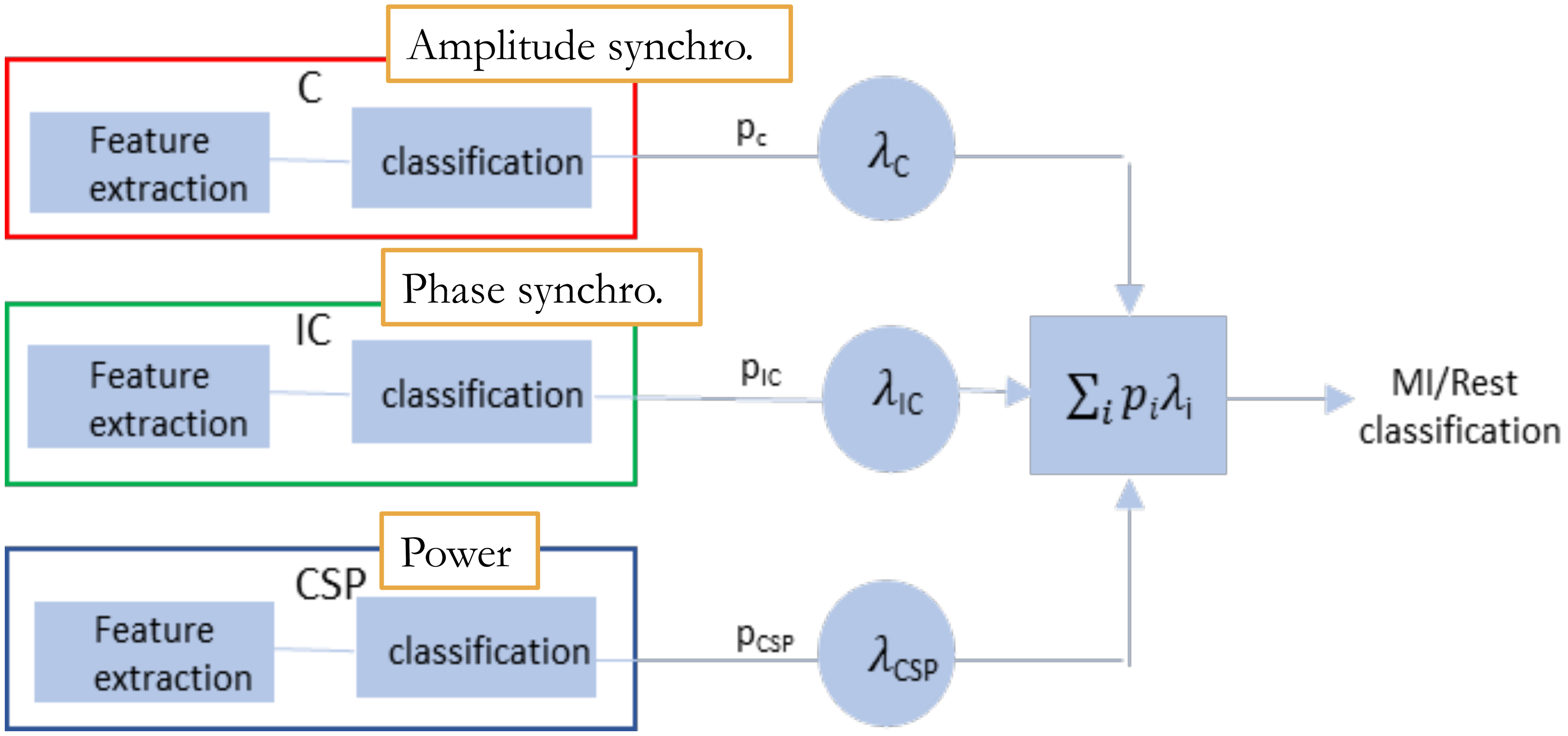
Phase synchronization

Motor imagery
VS
Resting state



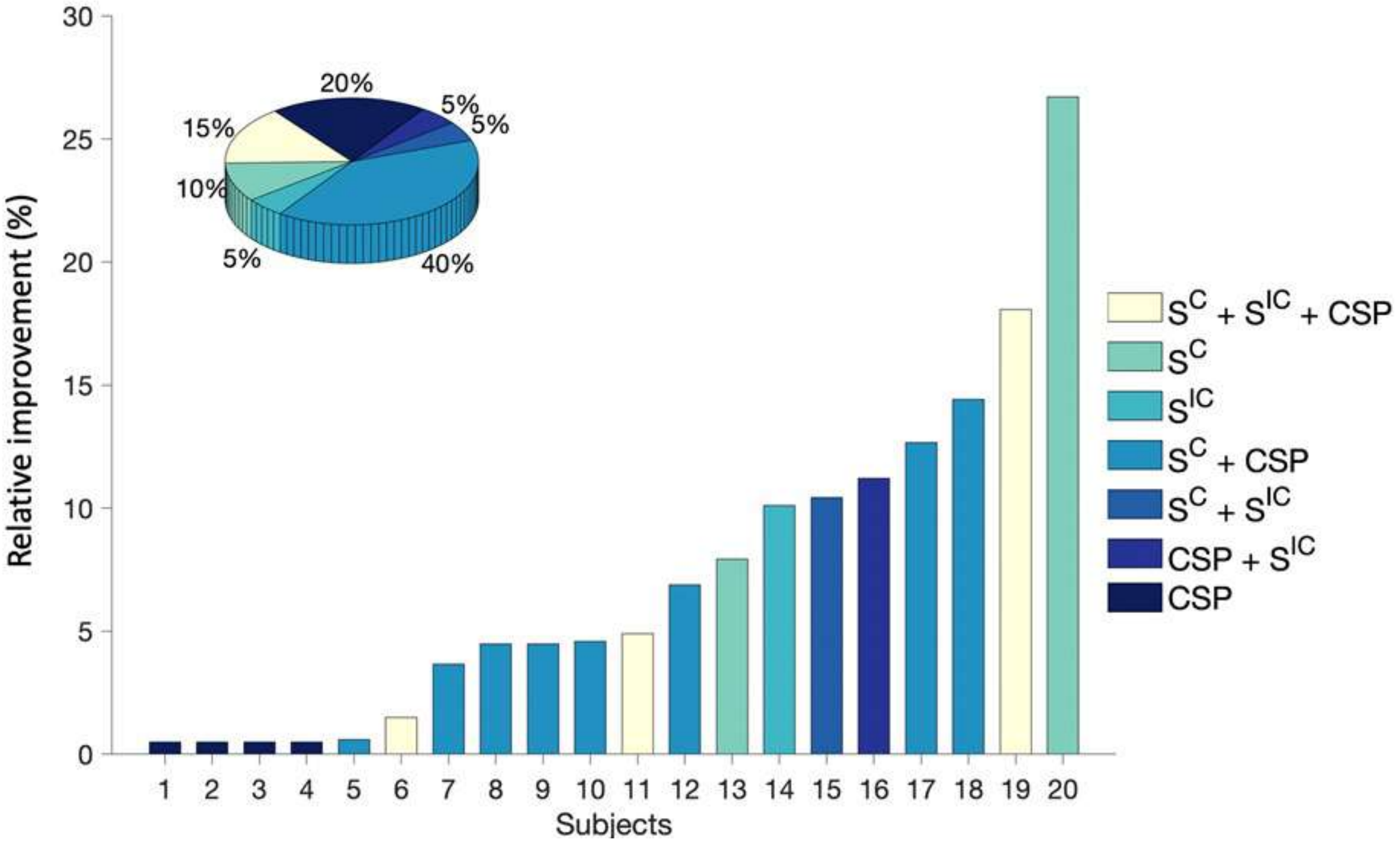
(Cattai et al, , 2021)

Fusing information to improve the classification



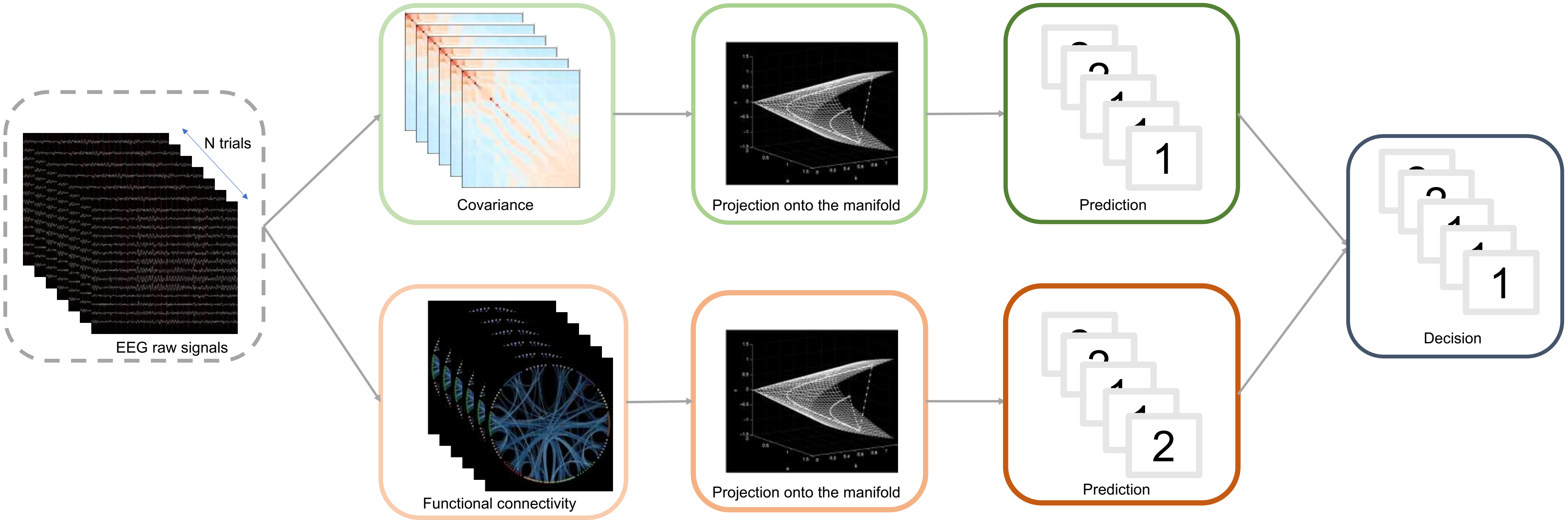
(Cattai et al, , 2021)

Fusing information to improve the classification



(Cattai et al, , 2021)

Fusing information to improve the classification

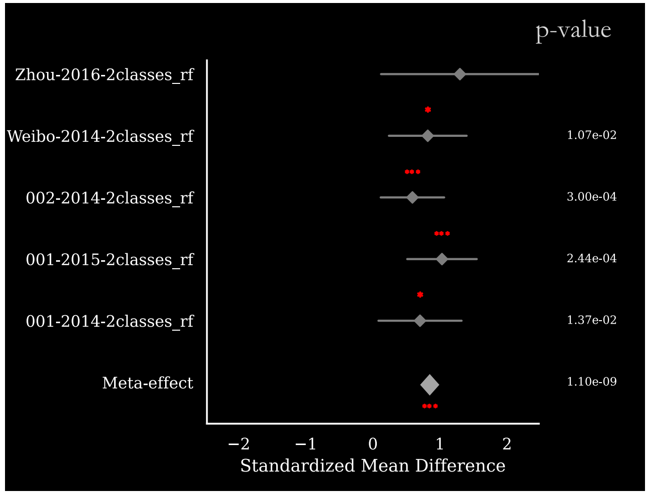


Functional CONnectivity Ensemble (FUCONE) approach adapted from
[Corsi et al, ICASSP, 2021], [Chevallier, Corsi et al, Software Impacts, 2022], & [Corsi et al, IEEE TBME, 2022]

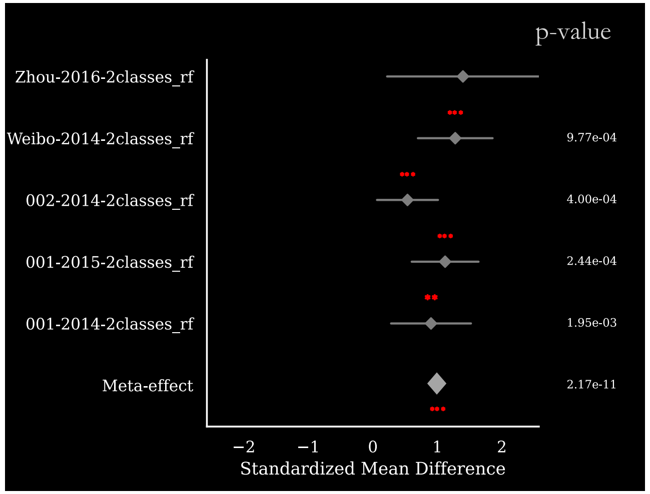
mccorsi/FUCONE

Fusing information to improve the classification

RegCSP+shLDA better FUCONE better



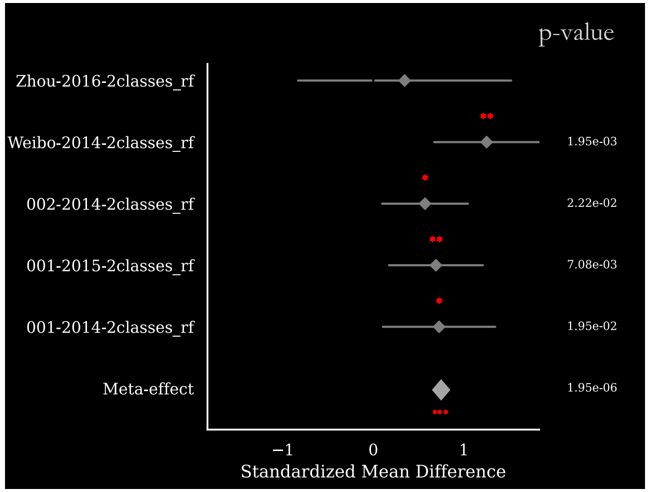
CSP+optSVM better FUCONE better



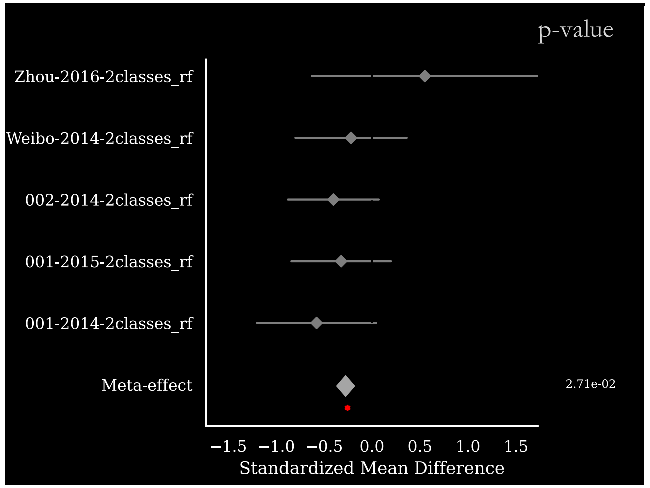
Common Spatial Patterns + Shrinkage Linear Discriminant Analysis

Common Spatial Patterns + Support Vector Machine

FgMDM better FUCONE better



FUCONE better Cov+EN better

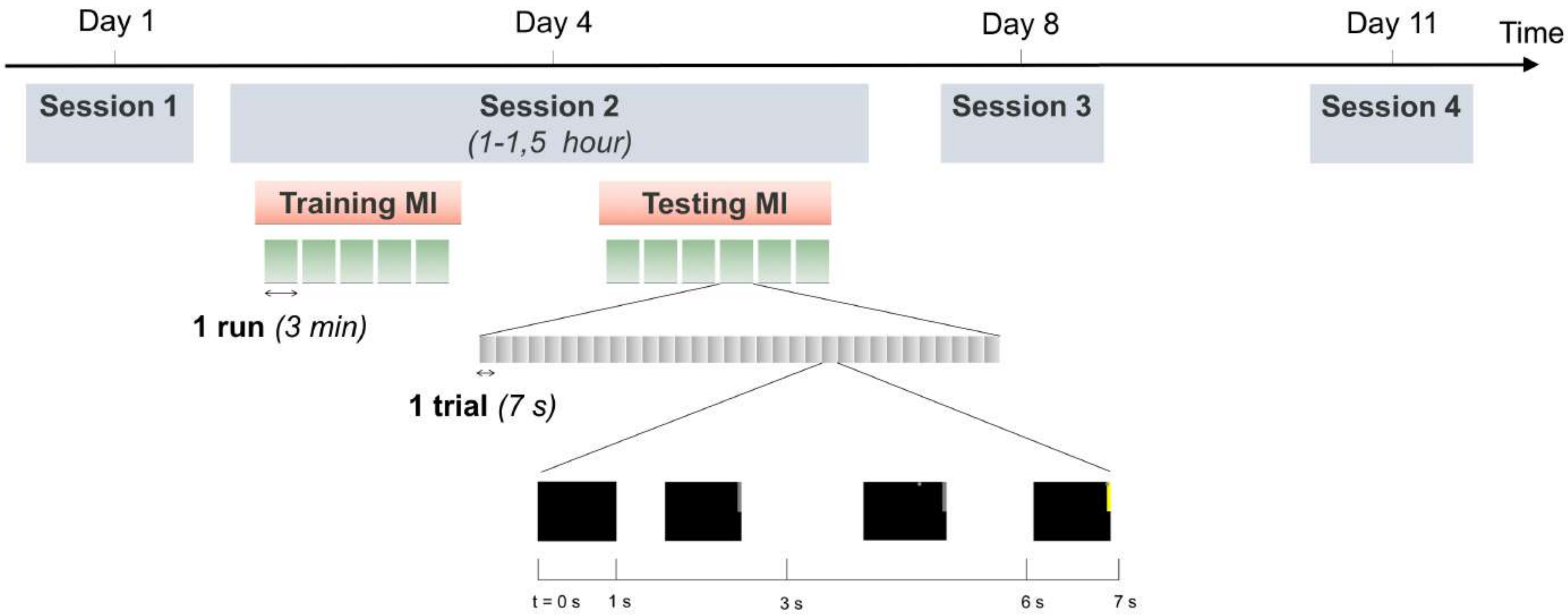


Geodesic filtering + Minimum Distance to Mean classification

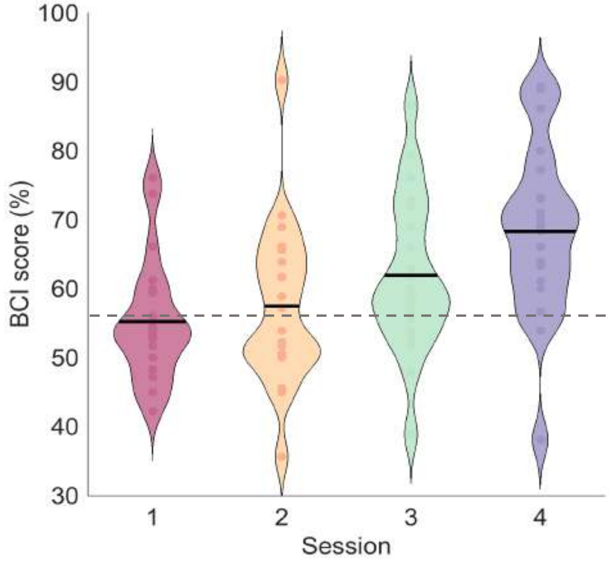
Covariance + Elastic-Net

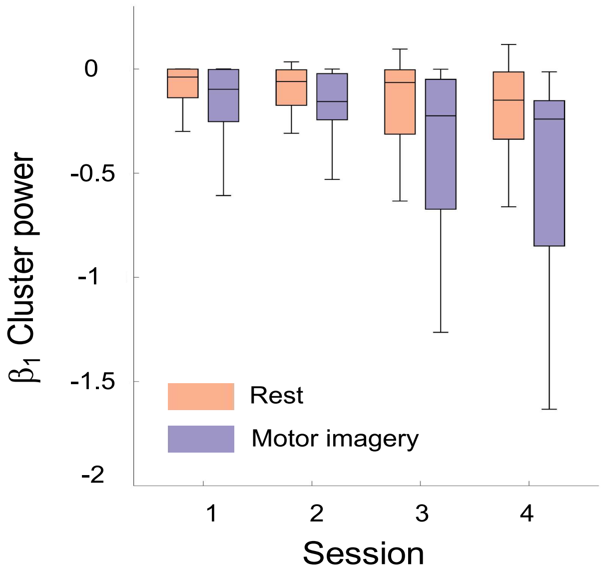
How do we learn to control a BCI?

NETBCI project



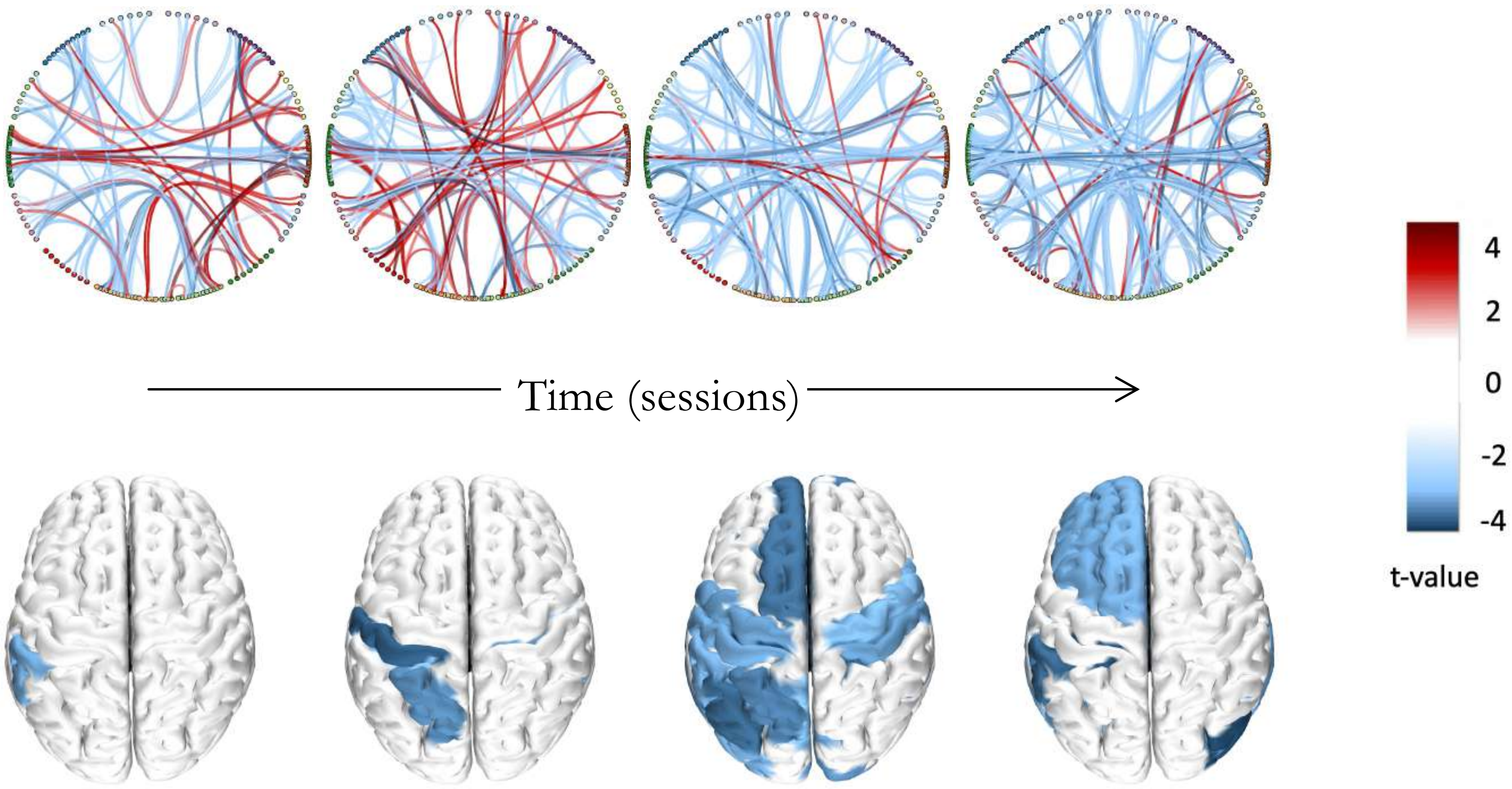
Reinforcement of motor-related activity





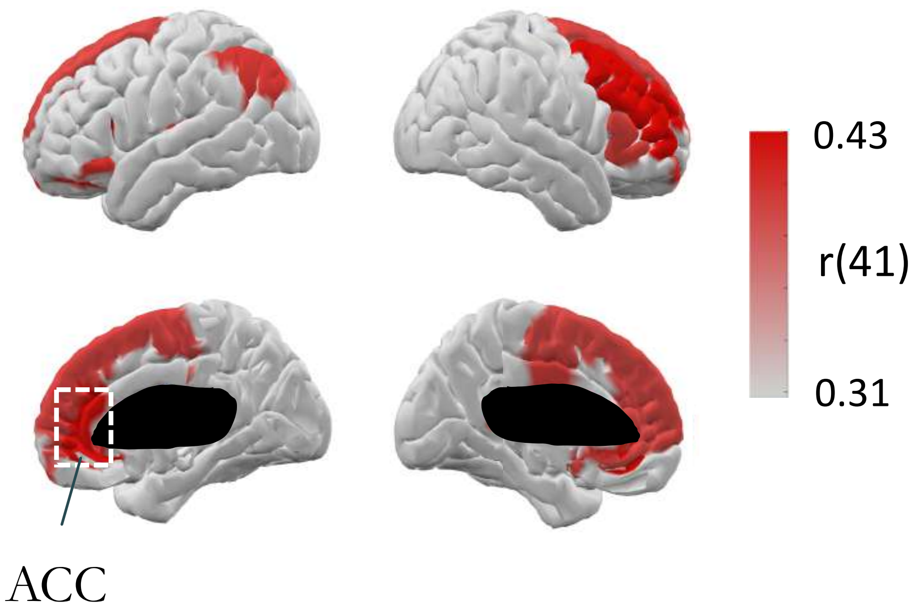
(Corsi et al, 2020)

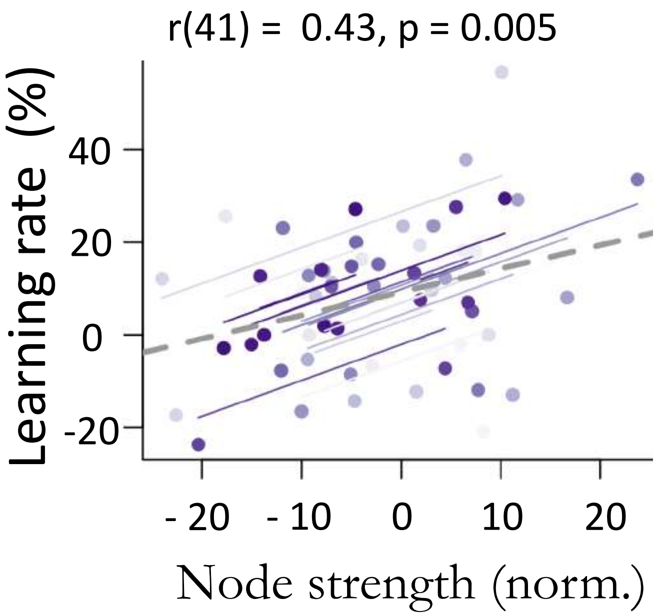
Functional disconnection of associative areas



(Corsi et al, 2020)

Node strength predicts BCI learning rate



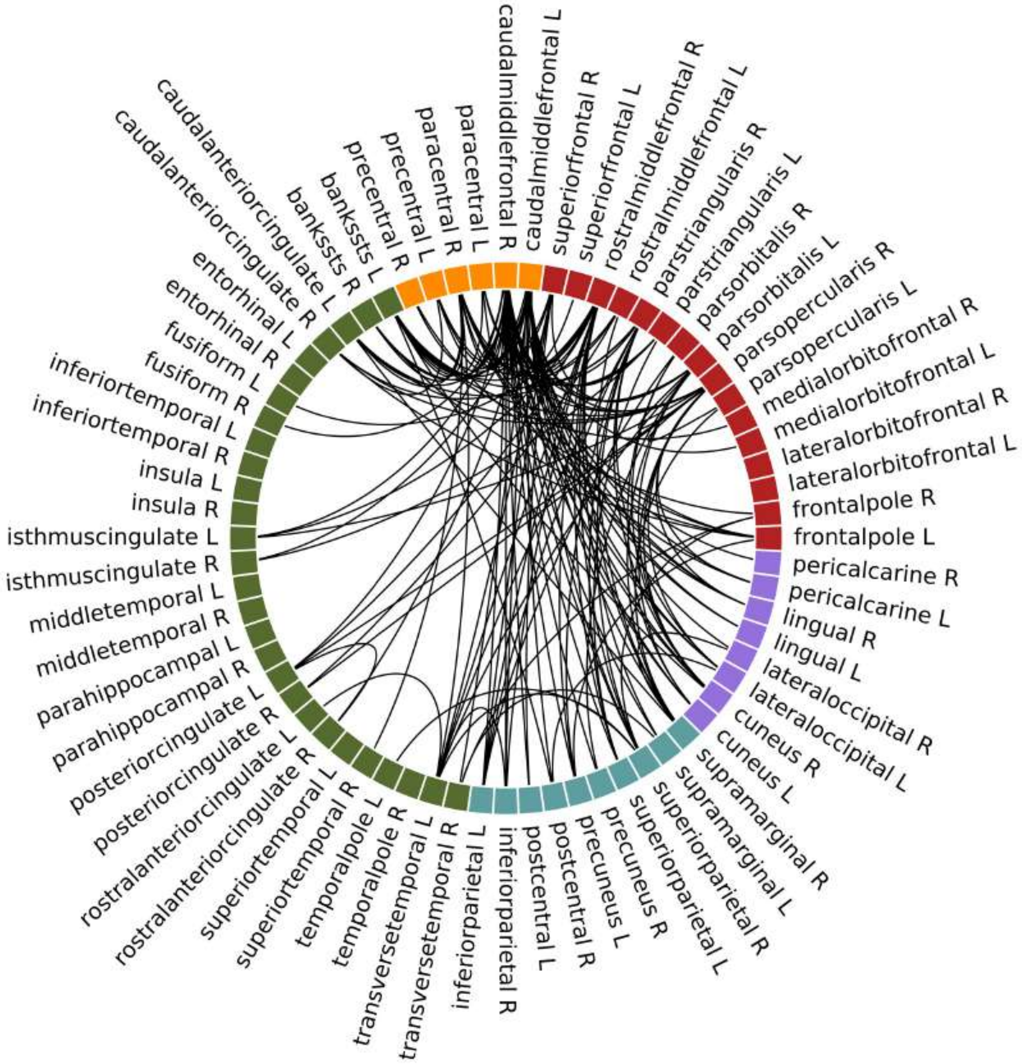


The *reserve* effect

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

(Corsi et al, 2020)

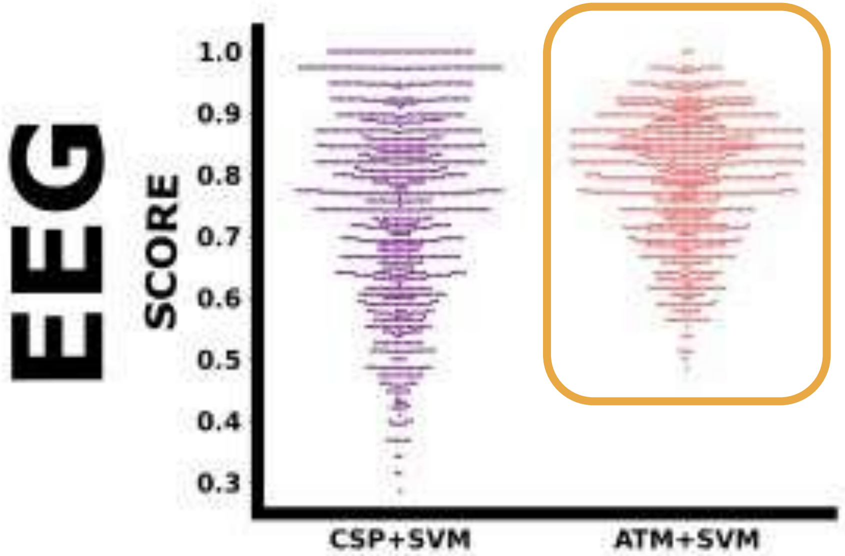
Neuronal avalanches to inform BCI



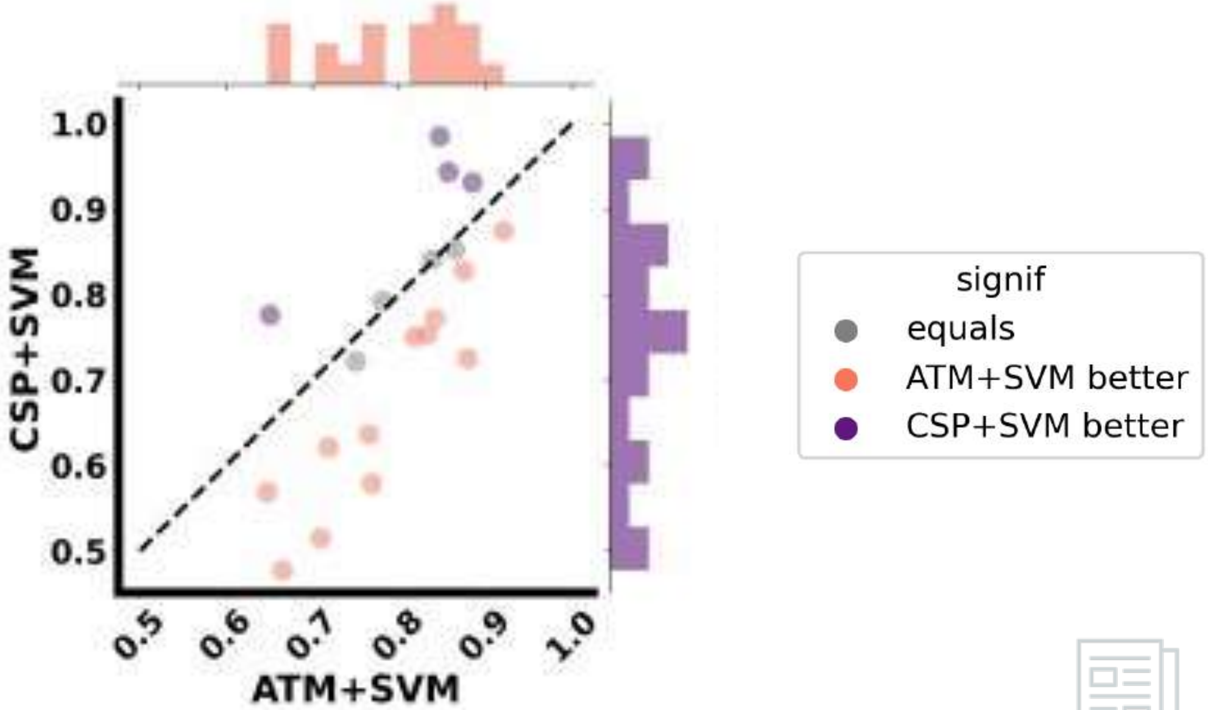
Adapted from [Corsi*, Sorrentino* et al, iScience, 2024]

Neuronal avalanches to inform BCI

Group-level

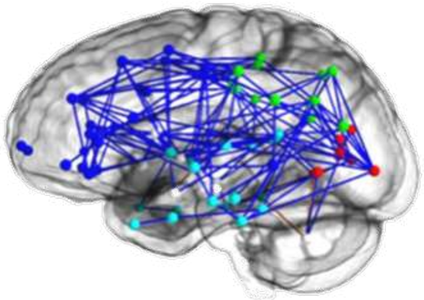


Individual-level

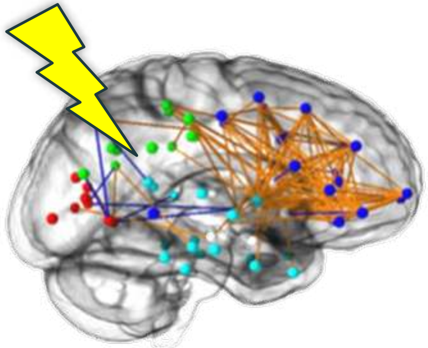


Adapted from [Corsi*, Sorrentino* et al, iScience, 2024]

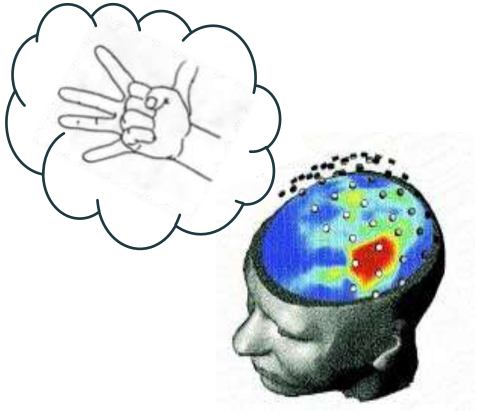
Stroke – cortical reorganization



Disability

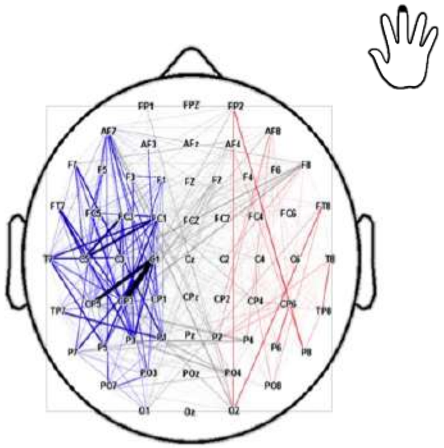


Motor Imagery

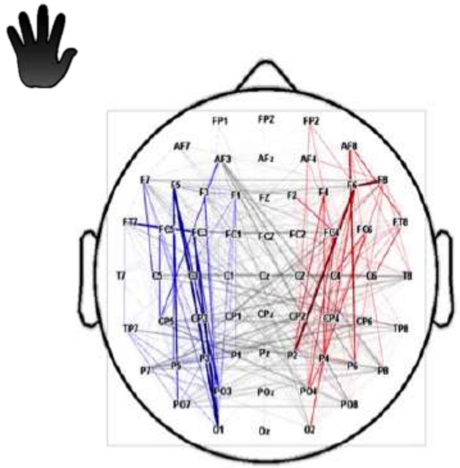


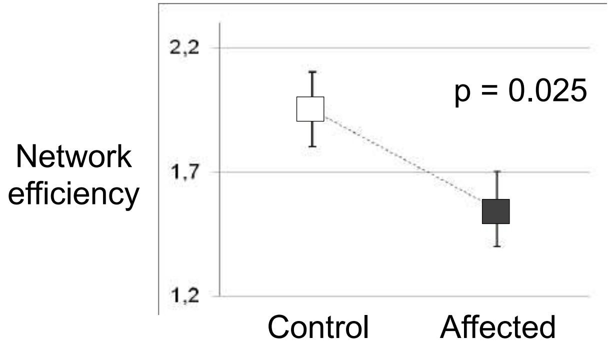
Stroke – inter-hemispheric connectivity & efficiency

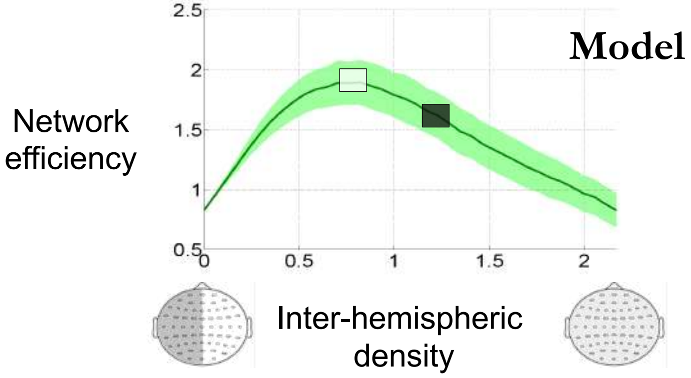
Control



Affected

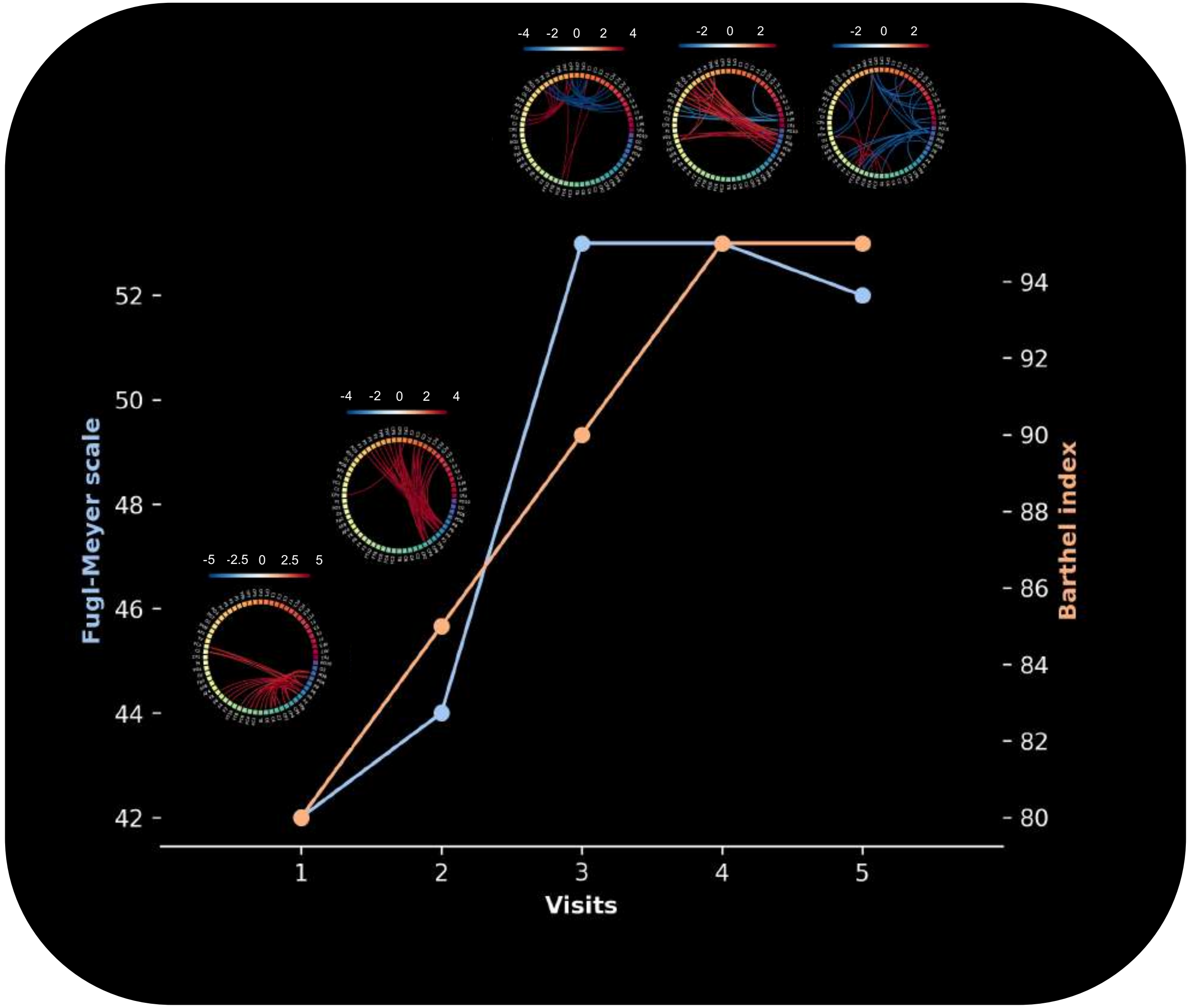






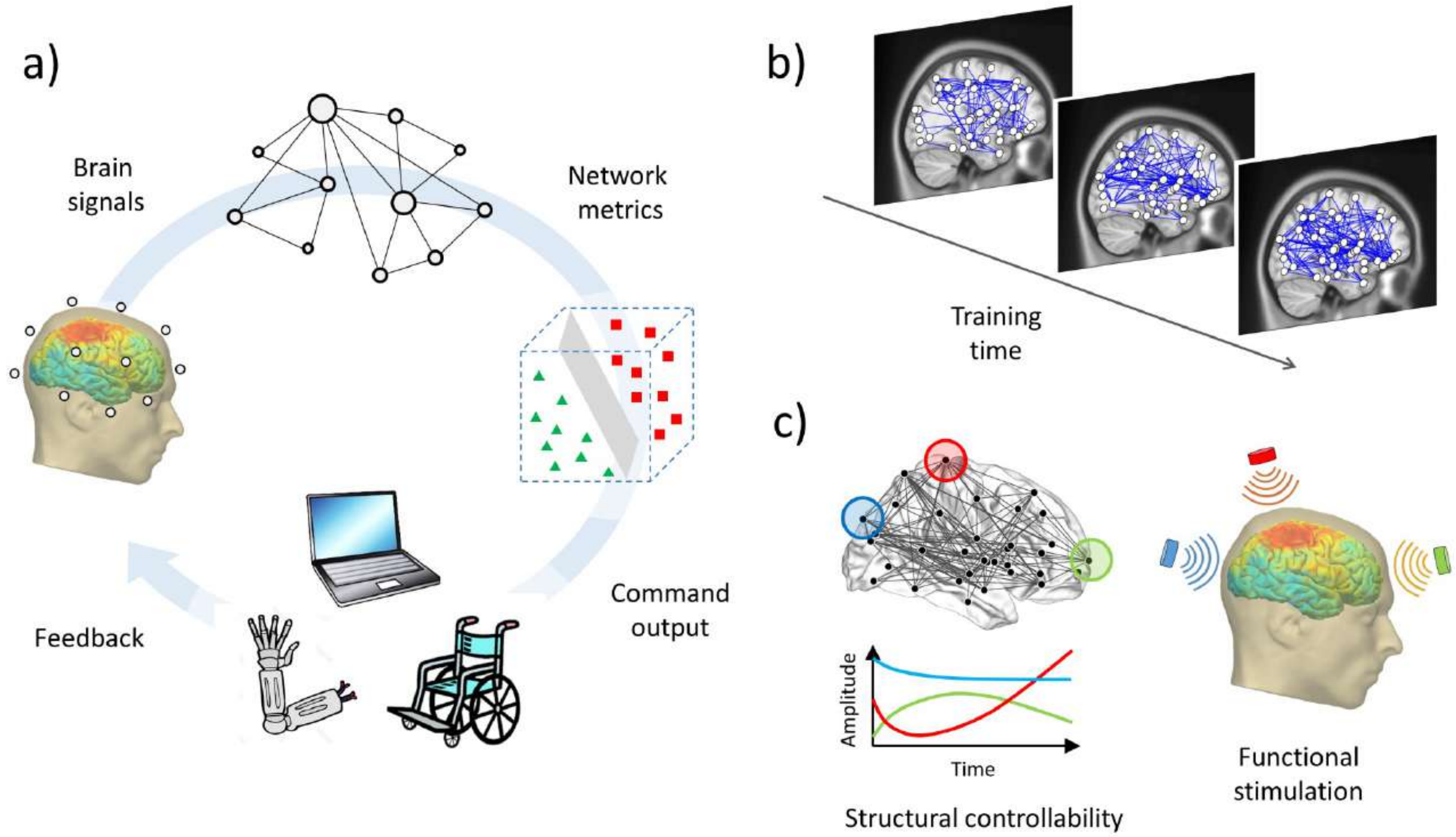
(De Vico Fallani et al, 2013)

Stroke – search for alternative features



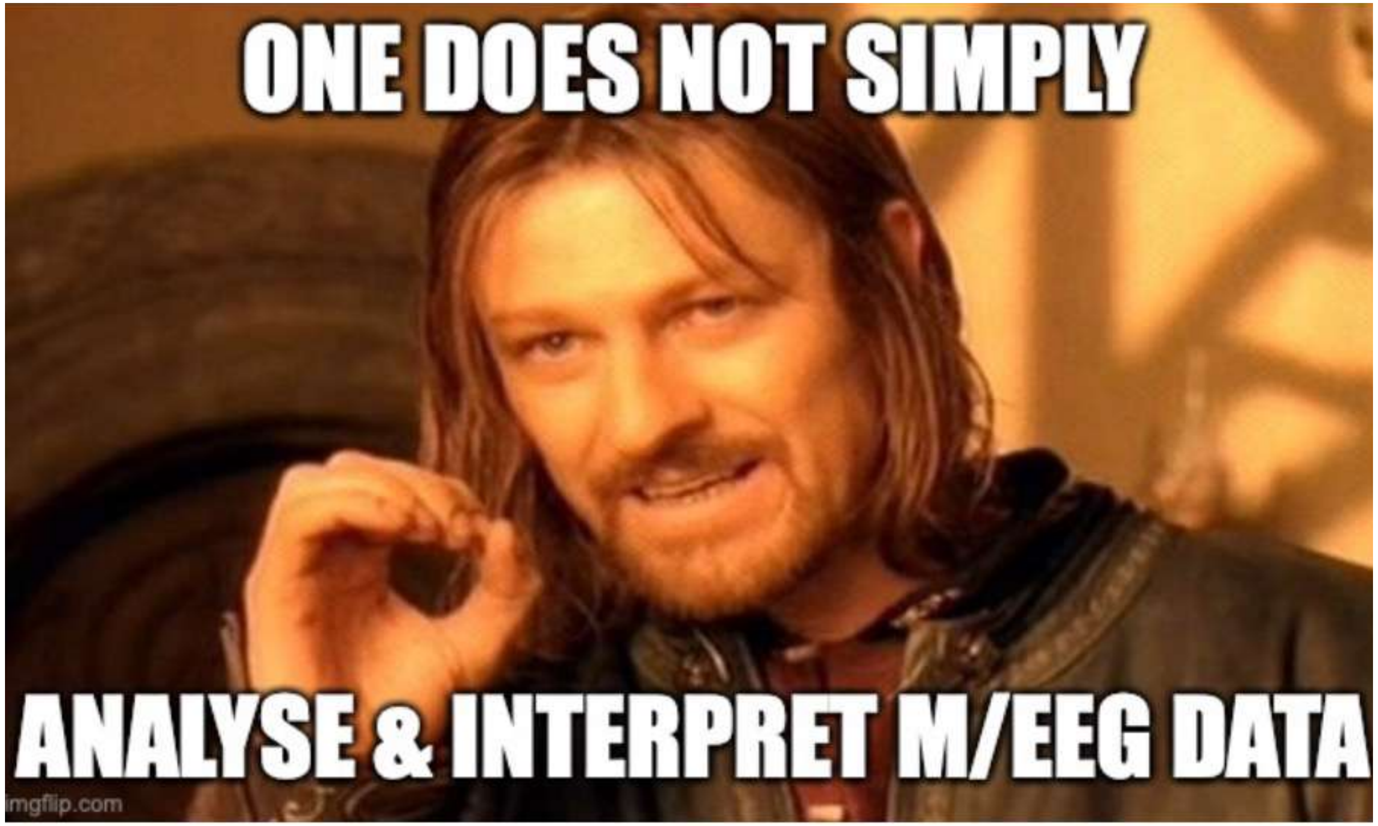
Neurophysiological patterns of stroke recovery over 1 year (ongoing project w/ AP-HP)

New perspectives for optimizing BCIs



(De Vico Fallani & Bassett, 2019)

Since…



Let's see together an example & visit the M/EEG platform!

CONCLUDING REMARKS

Take home messages

- BCI
  - Promising tool for clinical applications
  - **Multidisciplinary** domain
  - Growing interest in the last few years with the AI

- BCI learning & inter-subject variability
  - Improving the classifier / signal processing
  - Improving instructions
  - Finding (new) subject-related predictors

- Groups & events
  - International: BCI society, international society
  - Cybathlons: competitions to promote BCI and to test the finest algorithms with **end users !**
  - In France: CORTICO, French association to promote BCI

To go further…

- Tools – with many tutorials
  - Performing online experiments : OpenViBE, an Inria software
  - Open datasets to test algorithms & check their replicability: MOABB
  - M/EEG data analysis : MNE-Python
  - Classification tools : Scikit-learn
  - Extracting and selecting features in BCI: HappyFeat an Inria software

To go further…

- Tools – with many tutorials
  - Performing online experiments : OpenViBE, an Inria software
  - Open datasets to test algorithms & check their replicability: MOABB
  - M/EEG data analysis : MNE-Python
  - Classification tools : Scikit-learn
  - Extracting and selecting features in BCI: HappyFeat an Inria software

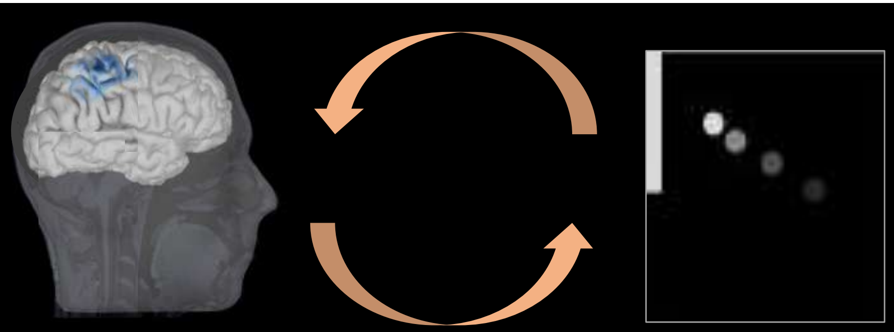
- M/EEG
  - Chapter book
    - Origins of the signals,
    - M/EEG experiments,
    - Data analysis,
    - Features extraction & selection,
    - Brain disorders

To go further…

- Tools – with many tutorials
  - Performing online experiments : OpenViBE, an Inria software
  - Open datasets to test algorithms & check their replicability: MOABB
  - M/EEG data analysis : MNE-Python
  - Classification tools : Scikit-learn
  - Extracting and selecting features in BCI: HappyFeat an Inria software

- M/EEG
  - Chapter book
  - Github repo
    - E/MEG data visualization,
    - Data extraction (ERD/S),
    - Classification

Lesson 4: ✓



marie-constance.corsi@inria.com

MConstanceCorsi

mccorsi