



# Artificial Intelligence & Neurocognitive Technologies for Human Augmentation

Włodzisław Duch

Neurocognitive Laboratory,  
Center for Modern Interdisciplinary Technologies,  
Dept. of Informatics, Faculty of Physics, Astronomy & Informatics,  
Nicolaus Copernicus University

Google: Wlodzislaw Duch

# Costs of brain diseases

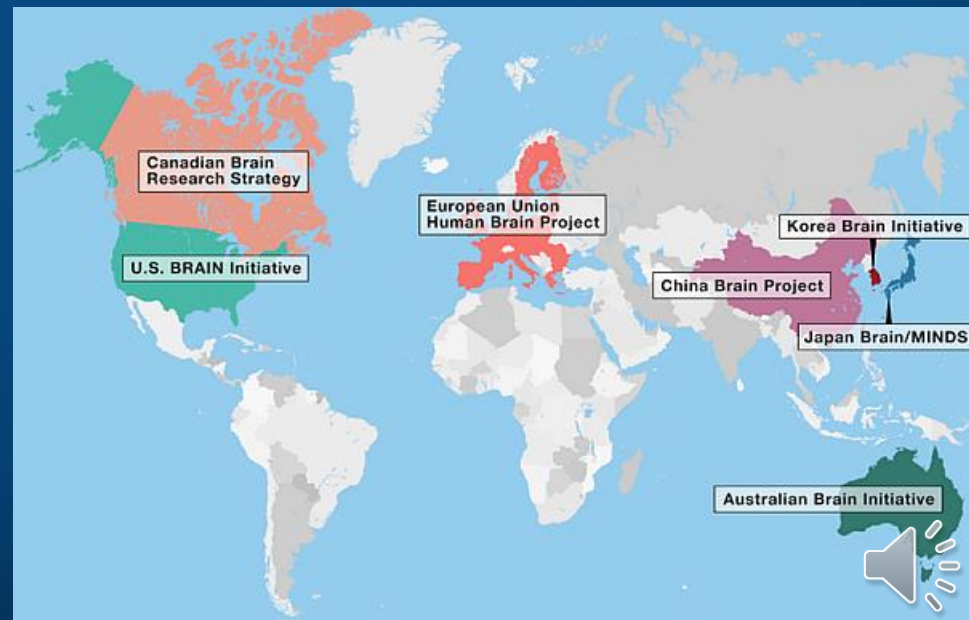
Total cost of brain disorders in EU in 2010: ~ 800 billion €/year, 45% of the total annual health budget of Europe!

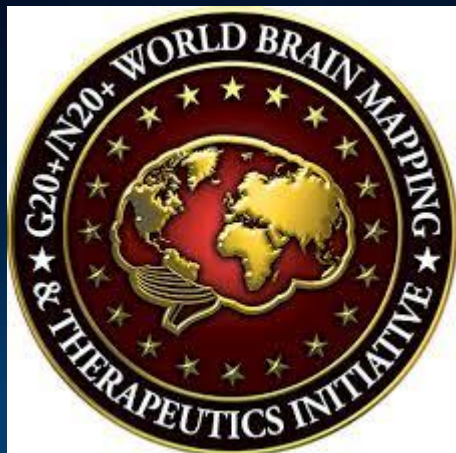
~ 180 millions, or 1/3 of all European citizens with at least one brain disorder during their lifetimes.

Gustavsson et al. (2011). Cost of disorders of the brain in Europe 2010. *European Neuropsychopharmacology*, 21(10), 718–779.

China: > 20% of population (~250 mln) suffering from brain disorders.

Global Brain large initiatives in North America, Europe, China, Korea, Japan and Australia/NZ + a few other countries.





The mission of IEEE Brain is to facilitate cross-disciplinary collaboration and coordination to advance research, standardization and development of technologies in neuroscience to help improve the human condition.

20 IEEE Societies are involved, including: **IEEE Computational Intelligence Society**; Computer Society; Consumer Electronics Society; Digital Senses Initiative; Robotics and Automation Society; Sensors Council; Signal Processing Society; Society on Social Implications of Technology; **Systems, Man, and Cybernetics Society**, Int. Neuroethics Society, and a few other societies.

**Most these societies are also involved in artificial intelligence.**

**Satya Nadella (CEO, Microsoft):** to celebrate National Disability Employment Awareness Month, I'm [sharing examples of how technology can be applied to empower the more than one billion people with disabilities around the world](#)





# Neuro Informatics 2019

International Neuroinformatics Coordination Facility (INCF) goal:  
integrate and analyze diverse data across scales, techniques, and species to understand the brain and positively impact the health and well-being of society.

12th INCF Congress on Neuroinformatics and INCF Assembly, Warsaw 9/2019.  
Neuroimaging, computational neuroscience, artificial intelligence.

Polish INCF Node, established in Warsaw at Nencki Institute,  
since 2017 at our lab at the Nicolaus Copernicus University in Toruń.

Not only ANN models, but EEG/MEG/fMRI and other data from experiments with  
animal and human brains.

Neuroscience ↔ BICA AI



# BICA, Brain-Inspired Cognitive Architecture

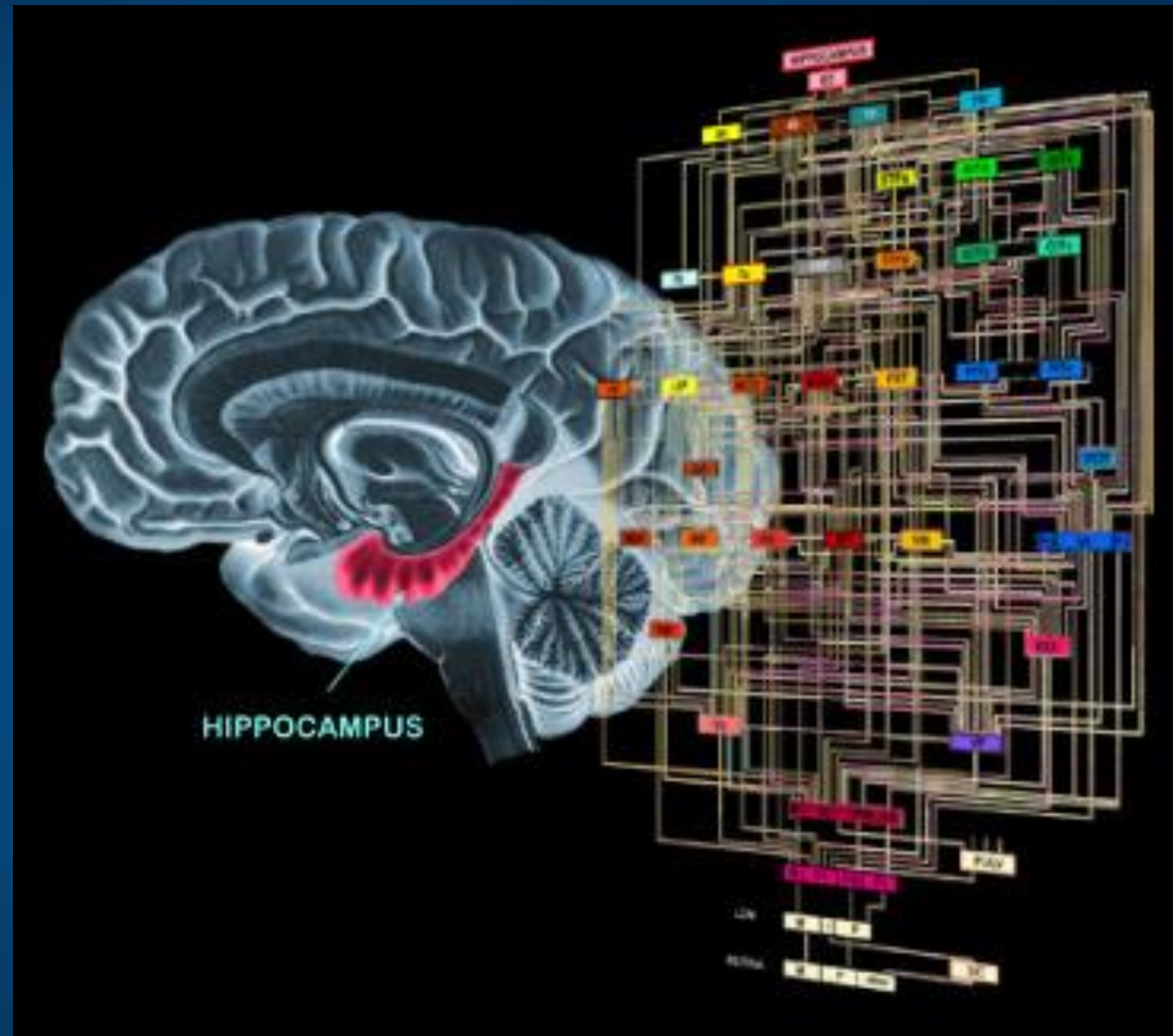
Understanding the brain from engineering perspective means to build a model of the brain showing similar functions.

Cognitive Informatics,  
Neurocognitive Informatics.

Review:

Duch, Oentaryo, Pasquier,  
Cognitive architectures:  
where do we go from here?  
2008

Are brains not too complex?



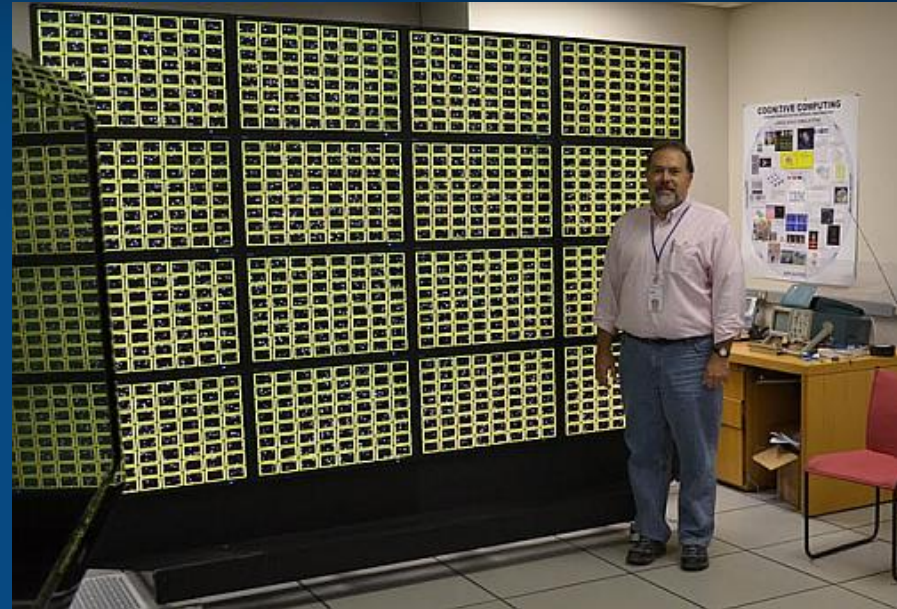
# Neuromorphic future

SyNAPSE Project 2015: IBM TrueNorth chip ~1M neurons i 250M synapses (5.4G transistors),

1 module=16 chips=16M neurons, 4G synapses, needs 1.1 W of power!

Scaling: 256 modules=1024 chips, 4G neuronów, 1T ( $10^{12}$ ) synapses, < 300 W, 48 Gops/Wat!

This wall has  $\frac{1}{4}$  complexity of gorilla brain and  $\frac{1}{20}$  of human brain.



New wave of AI computing: CPU, GPU, ASIC (np. FPGA) now neuromorphic chips. Samsung Dynamic Vision Sensor (DVS) is based on TrueNorth chips.

- Intel Loihi chip (2017), ~ 68 Gops/W, Pohoiki Springs system, available to members of the Intel Neuromorphic Research Community 3/2020.
- Gyrfalcon (2017) DSP small chip, 24.3 Tops/W, processing in memory.

How to use them?



# Neuroscience => AI



Hassabis, D., Kumaran, D., Summerfield, C., Botvinick, M. (2017). Neuroscience-Inspired Artificial Intelligence. *Neuron*, 95(2), 245–258.

Affiliations: Google DeepMind, Gatsby Computational Neuroscience, Institute of Cognitive Neuroscience, Uni. College London, Uni. of Oxford.

**Artificial neural networks** – simple inspirations, but many applications.

Bengio, Y. (2017). The **Consciousness Prior**. *ArXiv:1709.08568*.

Amos et al. (2018). **Learning Awareness Models**. *ArXiv:1804.06318*.

**AI Systems inspired by Neural Models of Behavior:**

- (A) **Visual attention**, foveal locations for multiresolution “retinal” representation, prediction of next location to attend to.
- (B) **Complementary learning systems** and episodic control: fast learning hippocampal system and parametric slow-learning neocortical system.
- (C) Models of **working memory** and the Neural Turing Machine.
- (D) Neurobiological models of **synaptic consolidation** and the elastic weight consolidation (EWC) algorithm.



# Brains $\Leftrightarrow$ Minds

Define mapping  $S(M) \Leftrightarrow S(B)$ , as in BCI.

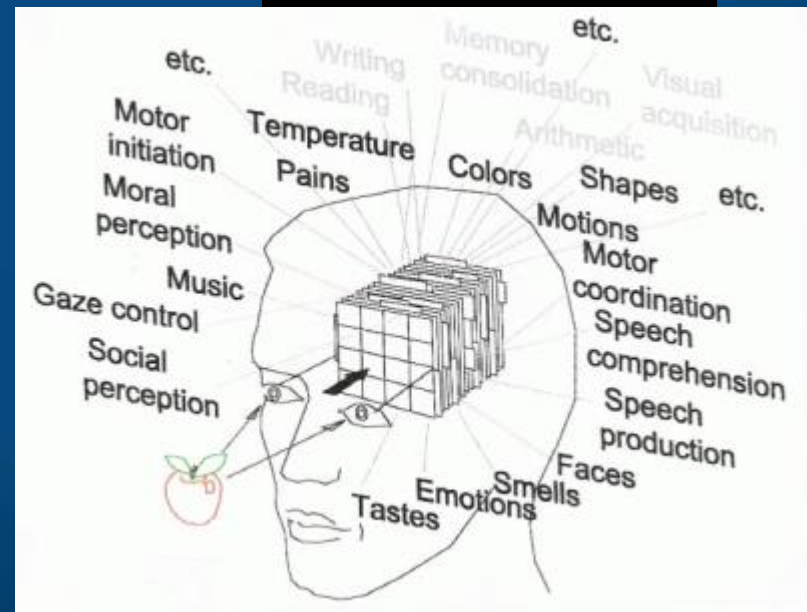
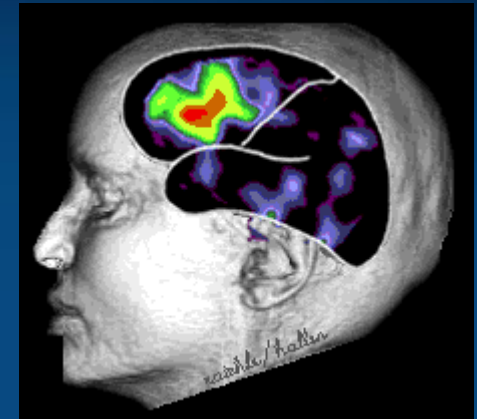
How mental states arise/influence brain states?

Neurodynamics: bioelectrical activity of the brain, neural activity measured using EEG, MEG, NIRS-OT, PET, fMRI ...

Mental states should be represented in a space with dimensions that measure different aspects of inner experience.

Stream of mental states, thought movement  $\Leftrightarrow$  trajectories in some psychological spaces.

**Two problems:** discretization of continuous processes for symbolic models, and lack of good phenomenology – we are not able to describe our mental states.



Duch W. (2019) Mind as a shadow of neurodynamics.  
[Physics of Life Reviews](#) 31: 28

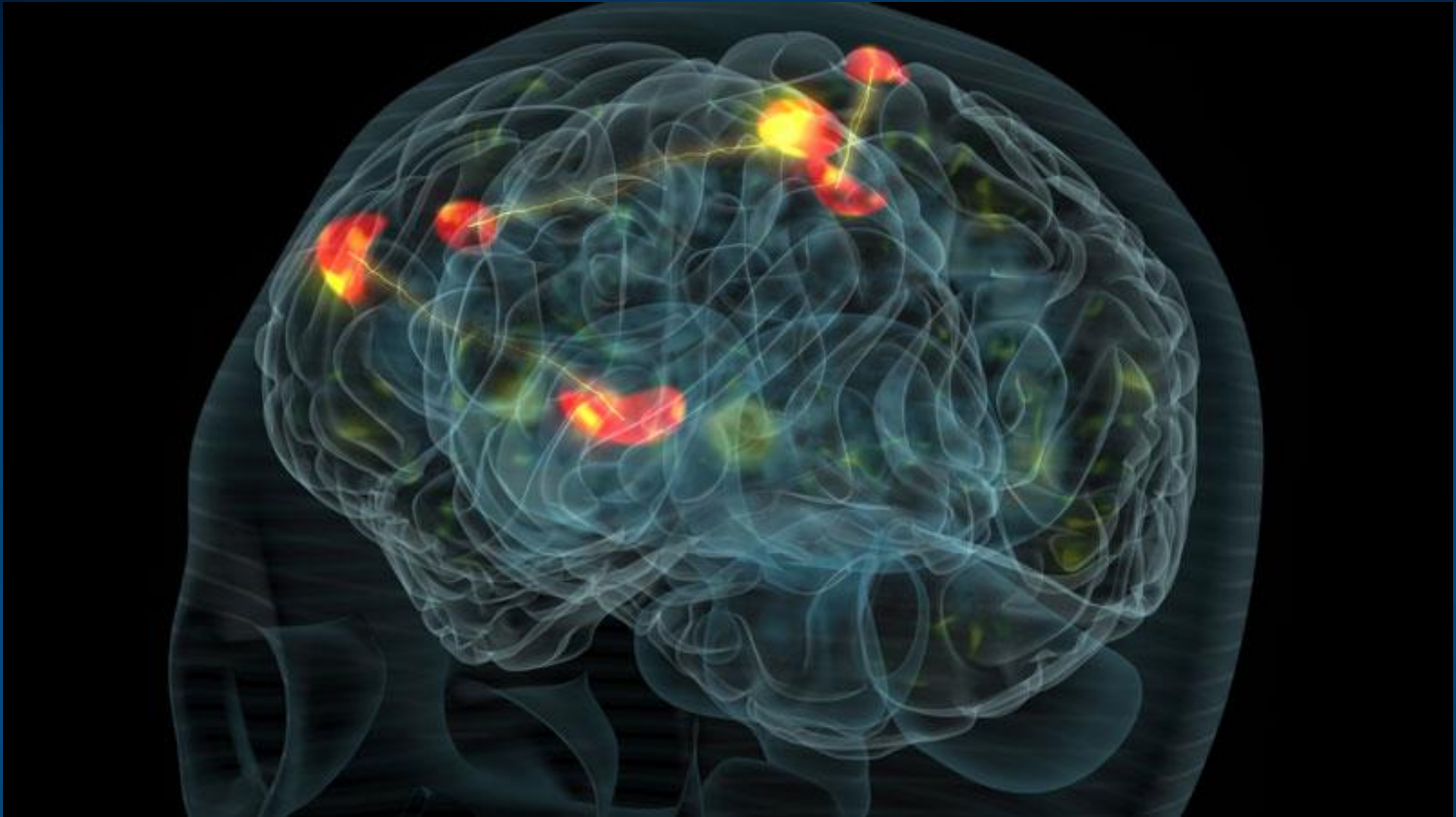




# Brain networks: space for mental states



# Mental state: strong coherent activation

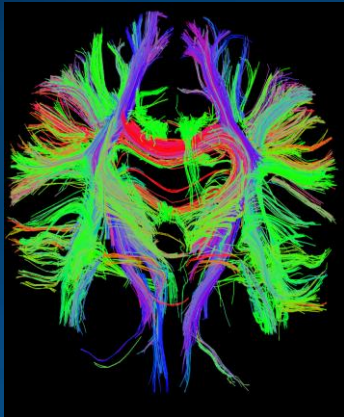


Many processes go on in parallel, controlling homeostasis and behavior. Most are automatic, hidden from our Self. What goes on in my head? Various subnetworks compete for access to the highest level of control - consciousness, the winner-takes-most mechanism leaves only the strongest. How to extract stable intentions from such chaos? BCI is never easy.

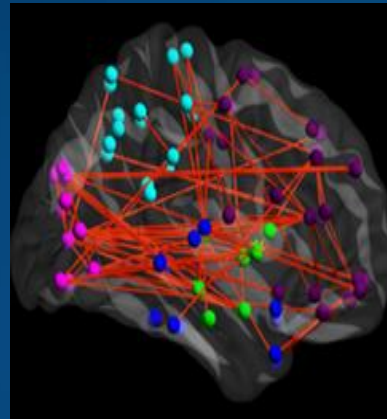


# Human connectome and MRI/fMRI

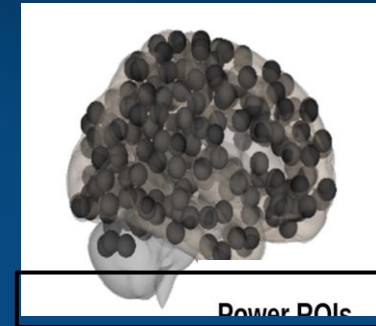
Structural connectivity



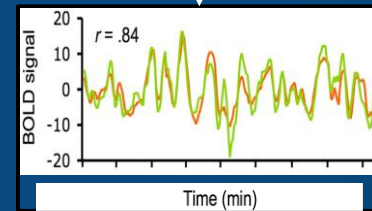
Functional connectivity



Node definition (parcelation)



Signal extraction

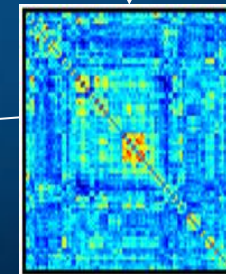


Correlation calculation

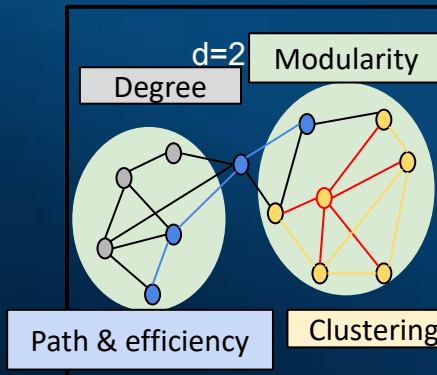
Binary matrix



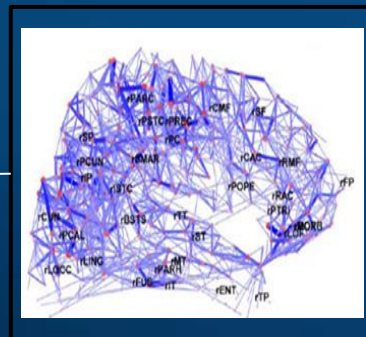
Correlation matrix



Graph theory



Whole-brain graph



Many toolboxes available for such analysis.



# Multi-level phenomics

M. Minsky, *Society of mind* (1986)

Decompose brain network dynamics into meaningful components of activity related to complex brain functions.

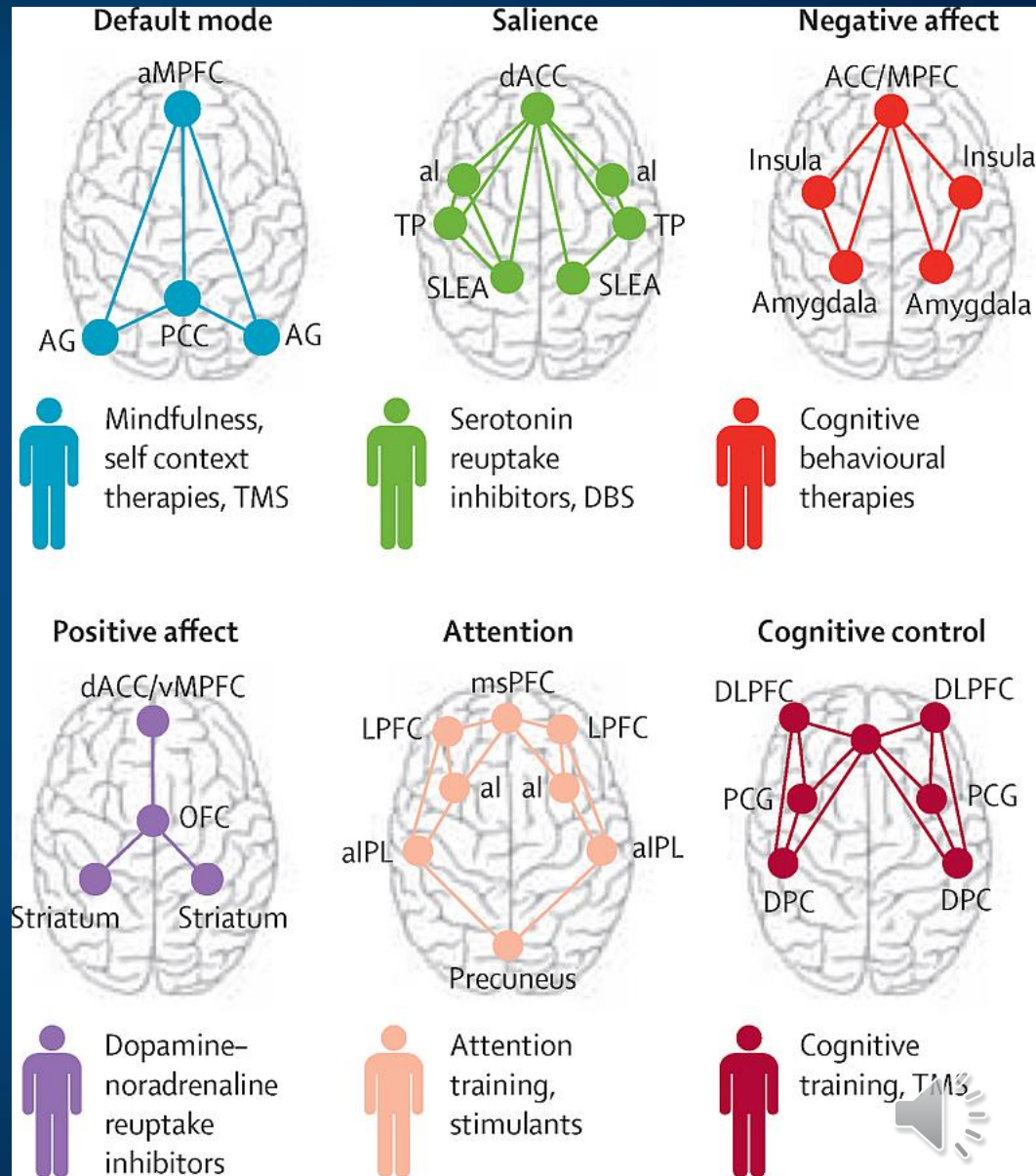
Instead of classification of mental disease by symptoms use **Research Domain Criteria (RDoC)** matrix based on **multi-level**

**neuropsychiatric phenomics**

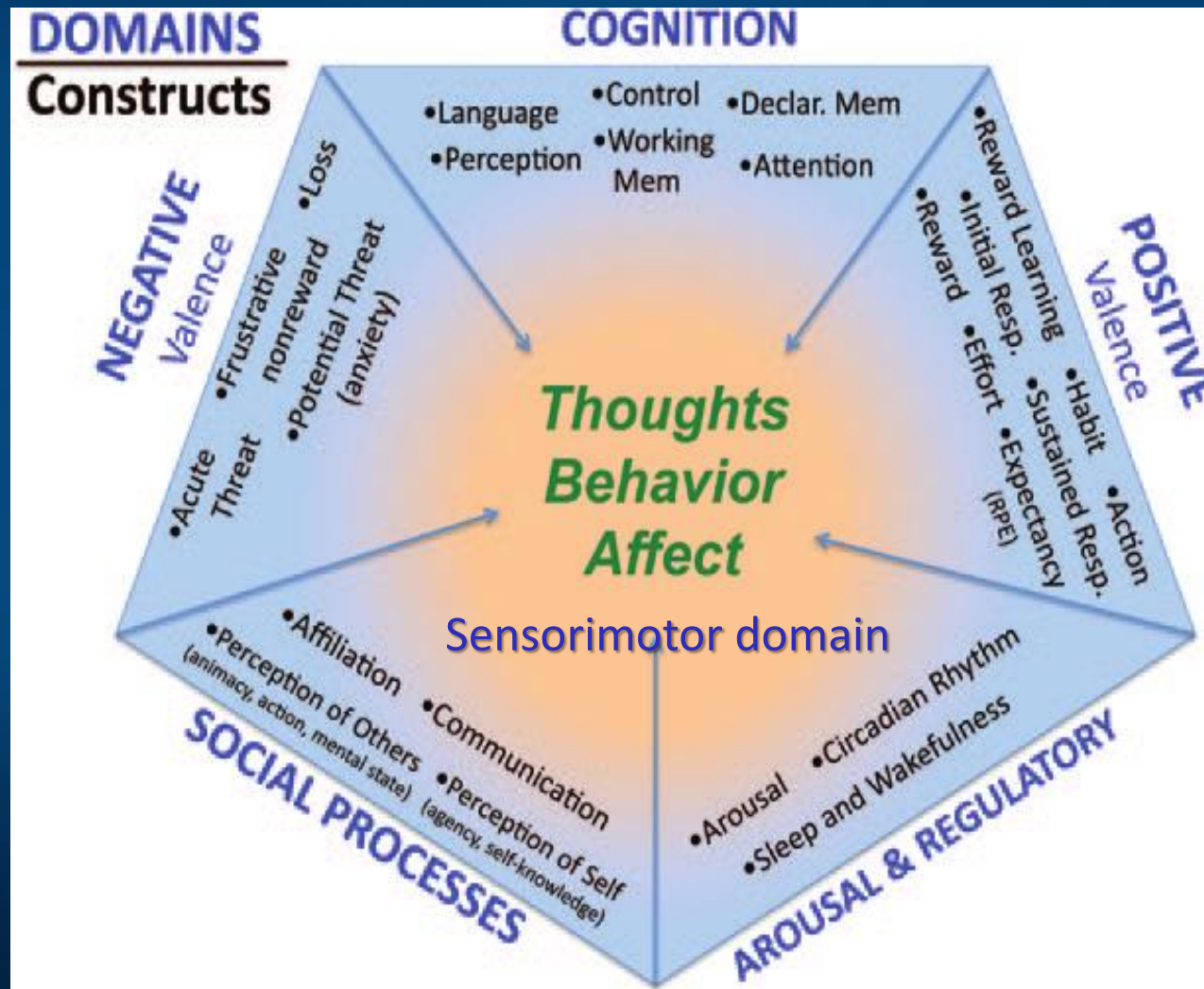
describing large brain systems deregulation.

Include influence of genes, molecules, cells, **neural networks**, physiology, behavior, self-reports on network functions.

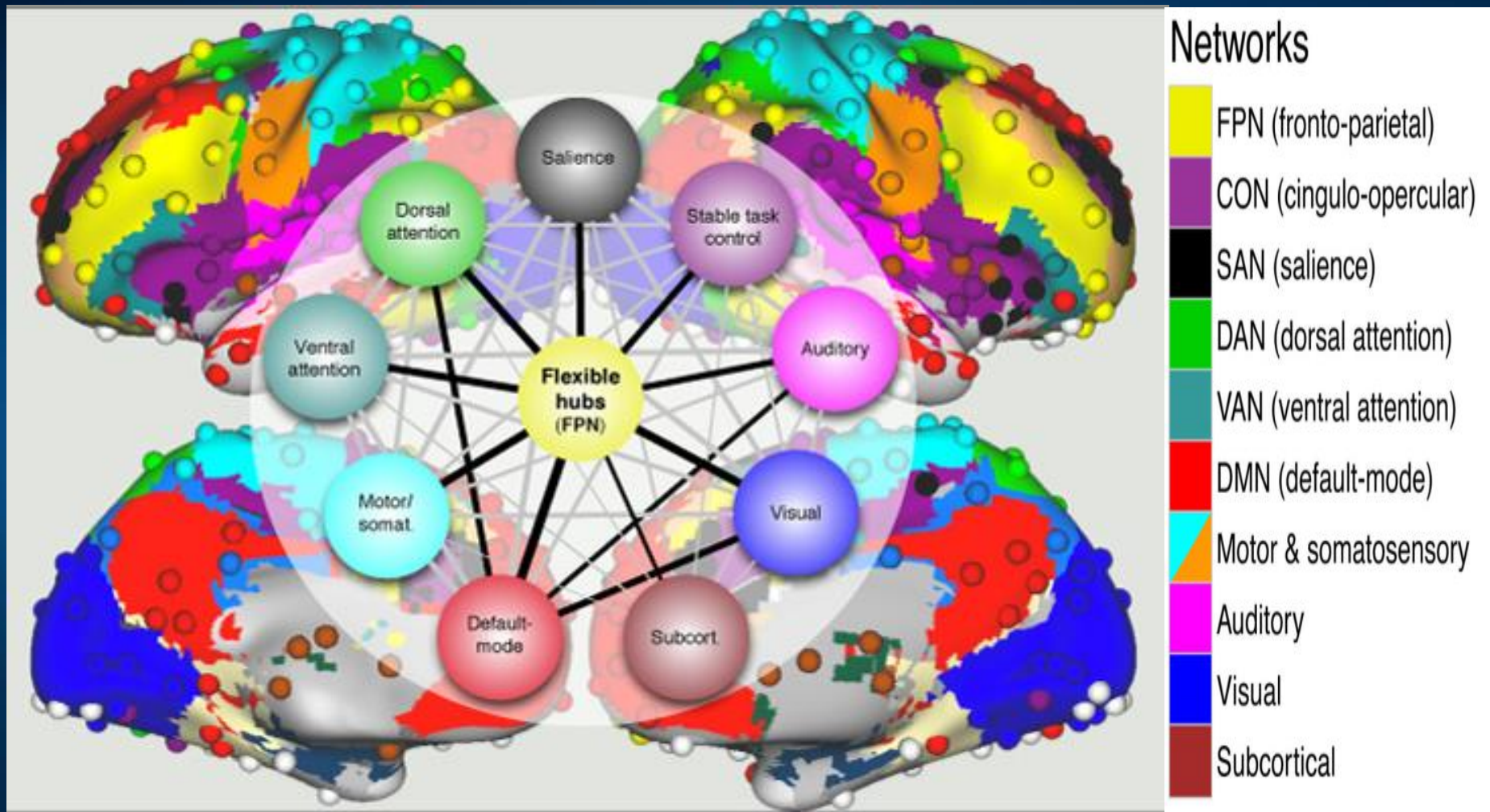
**Neurodynamics is the key.**



# NIMH RDoC Matrix for deregulation of 6 large brain systems.



# Neurocognitive Basis of Cognitive Control



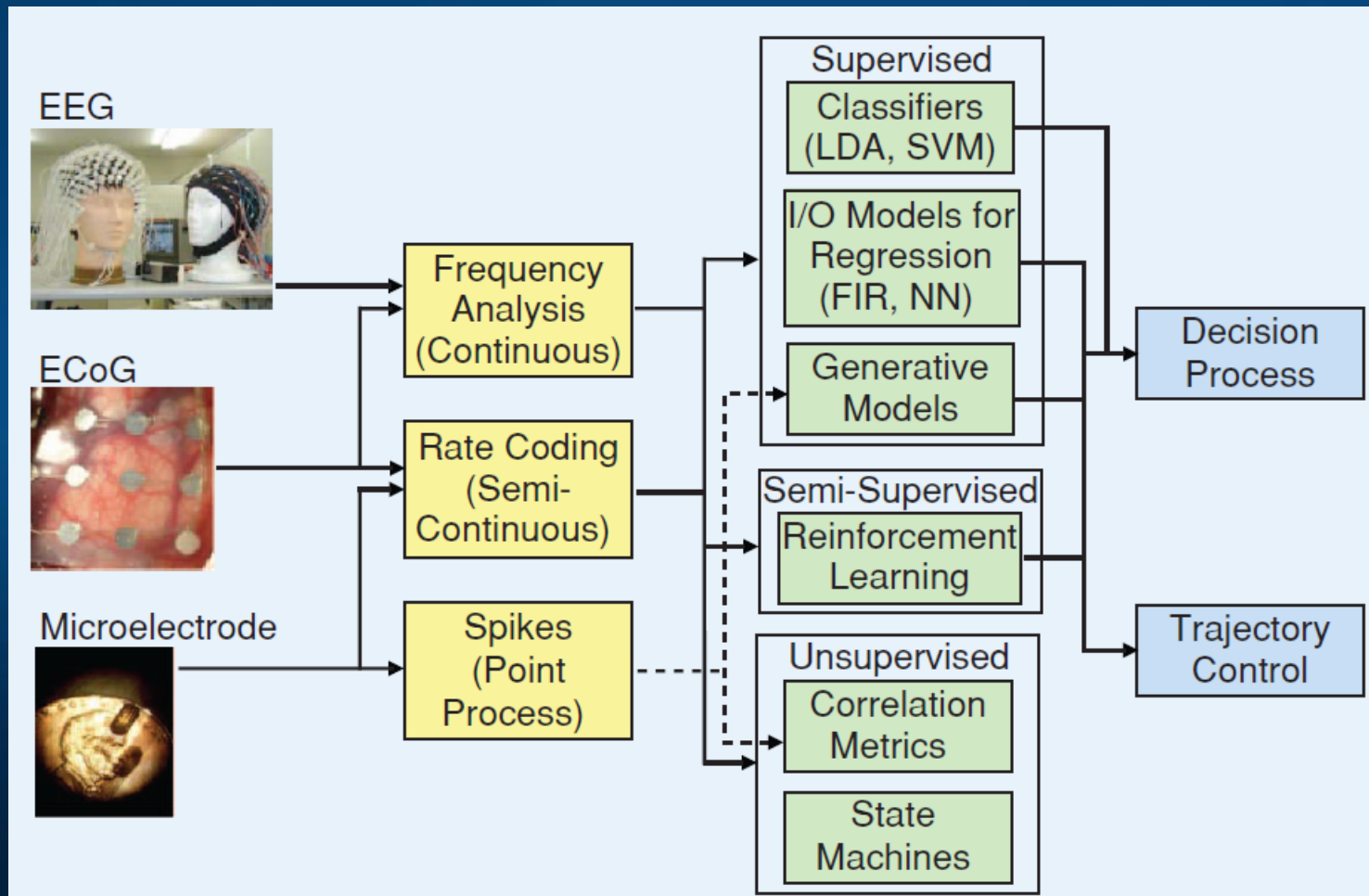
Central role of fronto-parietal (FPN) flexible hubs in cognitive control and adaptive implementation of task demands (black lines=correlations significantly above network average). Cole et al. (2013).

# Human Enhancement and Optimization of Brain Processes



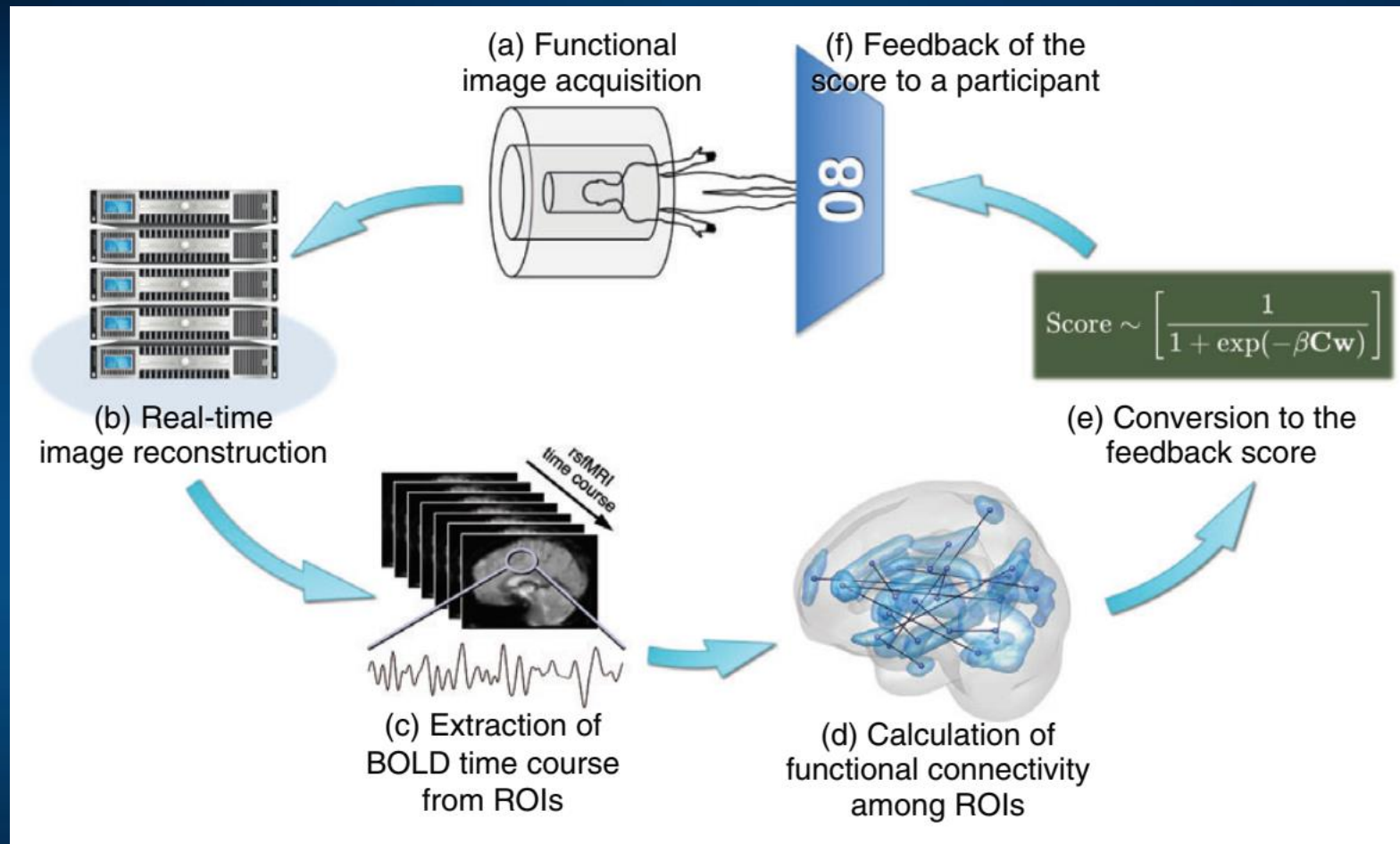
# BCI: wire your brain ...

Non-invasive, partially invasive and invasive signals carry progressively more information, but are also harder to implement. EEG is still the king!





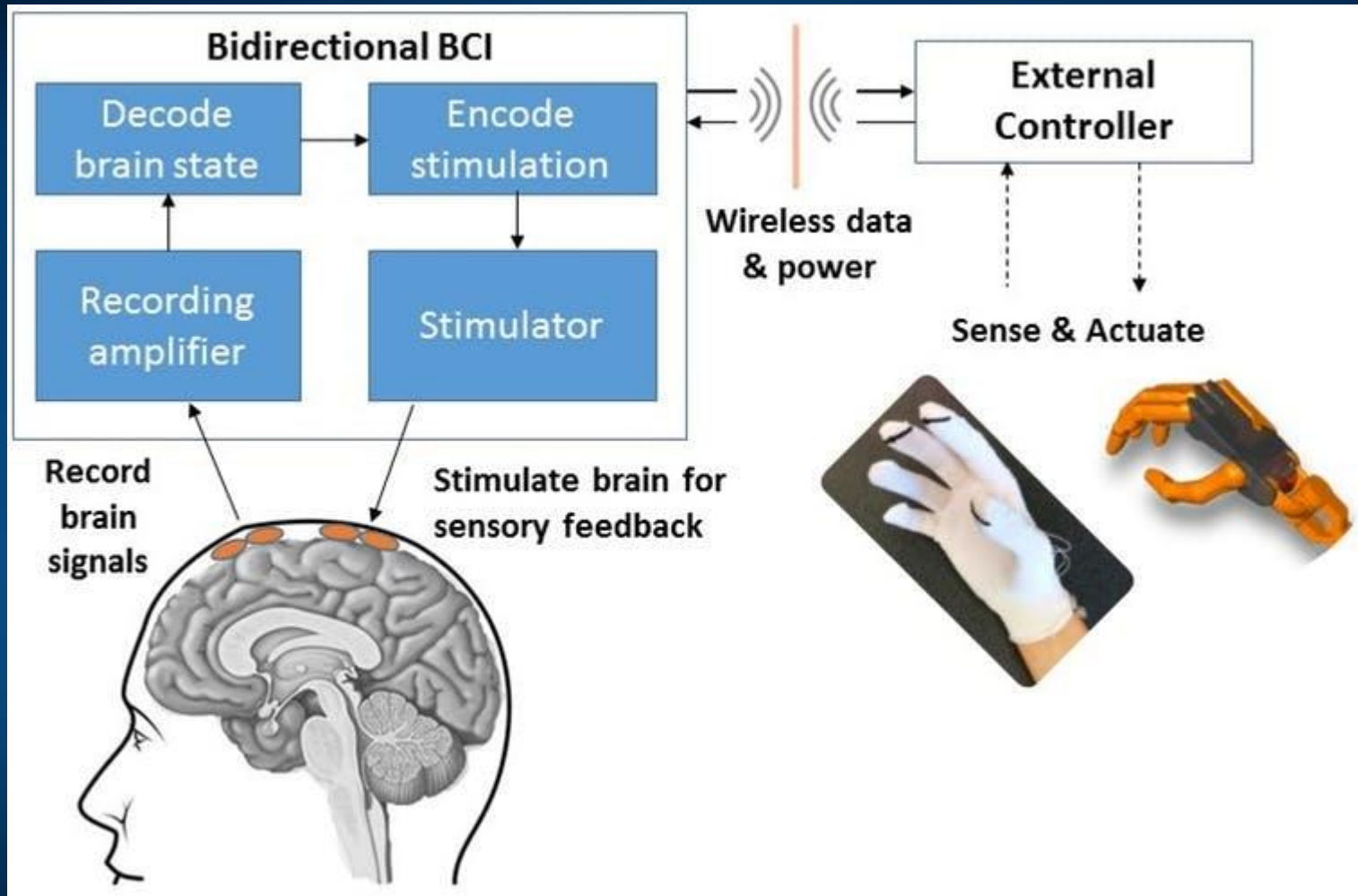
# Neurofeedback may repair network?



Megumi F, Yamashita A, Kawato M, Imamizu H. Functional MRI neurofeedback training on connectivity between two regions induces long-lasting changes in intrinsic functional network. *Front. Hum. Neurosci.* 2015; 9: 160.



# Brain-Computer-Brain Interfaces (BCBI)



Closed loop system with brain stimulation for self-regulation.  
Body may be replaced by sensory signals in Virtual Reality.



# Learning skills

## Engagement Skills

Trainer (EST) procedures are used by USA army.

Intific Neuro-EST uses EEG analysis and multi-channel transcranial simulation (HD-DCS) to pre-activate the brain of the novice in areas where the expert brain is active.

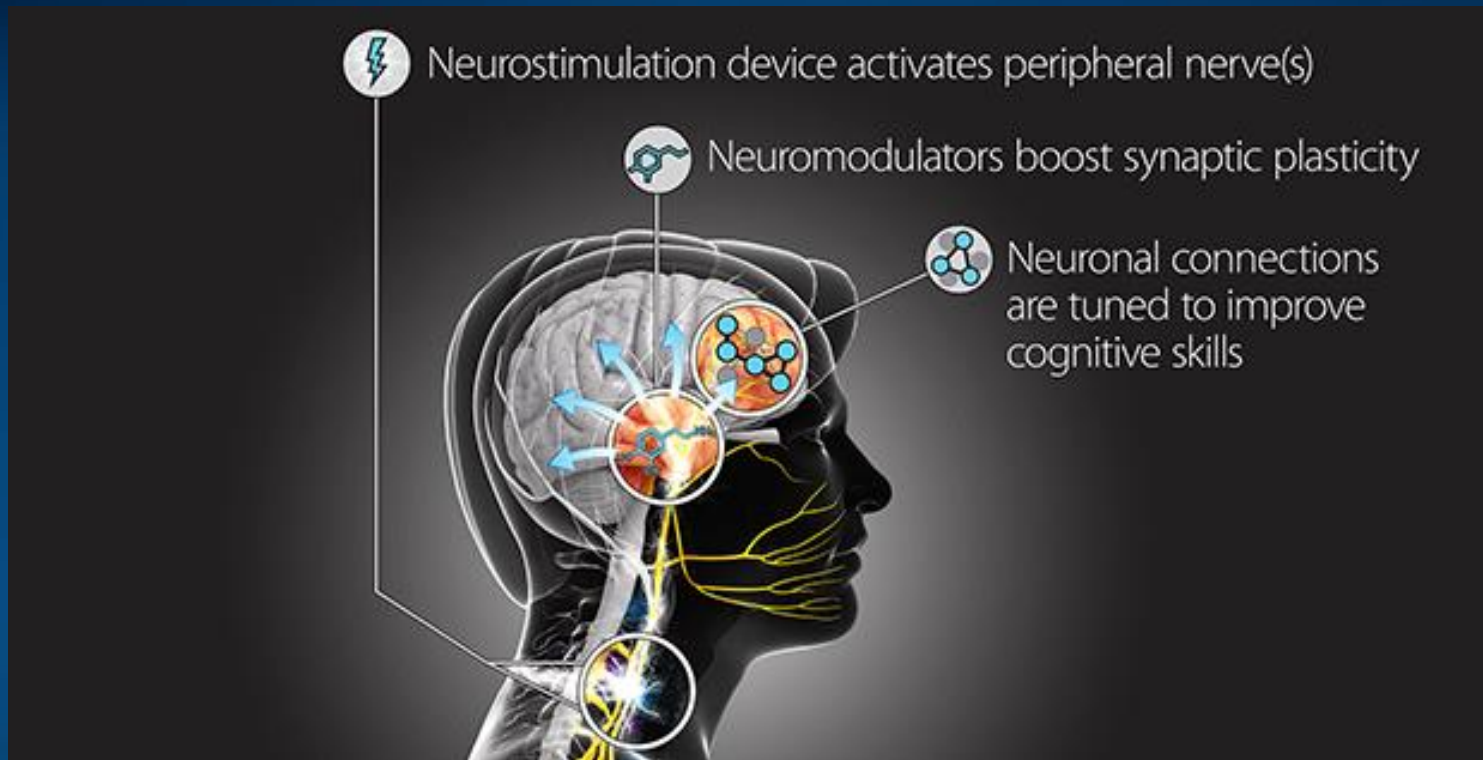
Real-life transfer learning ...

HD-tDCS may have 100 channels, neurolace and nanowires much more.

Inject microcurrents into the motor cortex ...



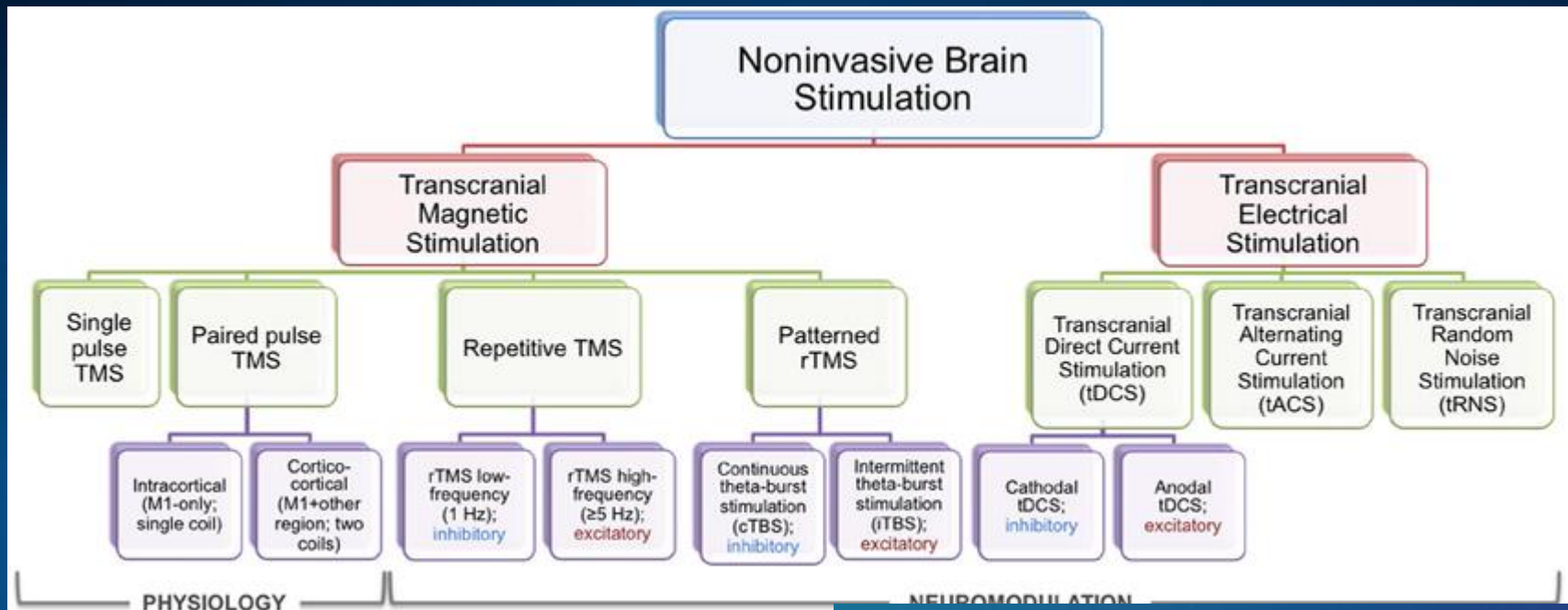
# Targeted Neuroplasticity Training



DARPA (2017): Enhance learning of a wide range of cognitive skills, with a goal of reducing the cost and duration of the Defense Department's extensive training regimen, while improving outcomes. TNT could accelerate learning and reduce the time needed to train foreign language specialists, intelligence analysts, cryptographers, and others.



# Brain stimulation



ECT – Electroconvulsive Therapy

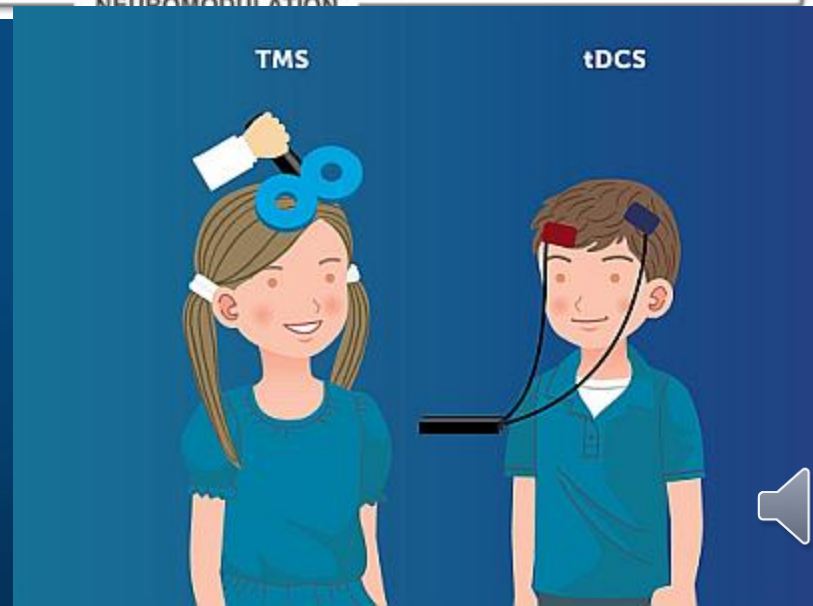
VNS – Vagus Nerve Stimulation

Ultrasound, laser ... stimulation.

Complex techniques?

Smartphones are also complex.

Attention? Just stimulate your cortex,  
no effort is needed!



# HD EEG/DCS?

EEG electrodes + DCS.

Reading brain states

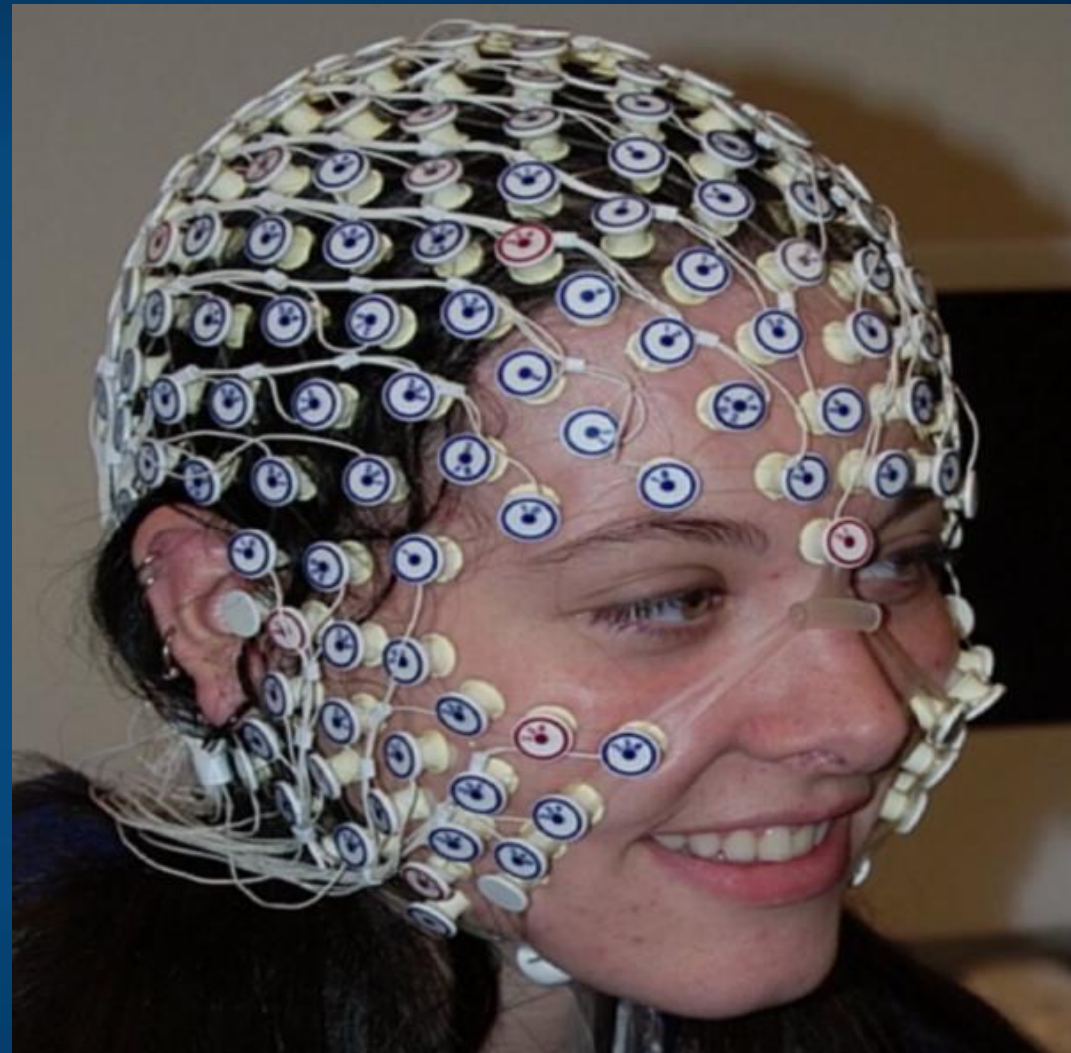
=> transforming to common space

=> duplicating in other brains

Applications:

depression, neuro-plasticity,  
pain, psychosomatic  
disorders, teaching!

Multielectrode DCS  
stimulation with 256  
electrodes induces changes  
in the brain increasing  
neuroplasticity.



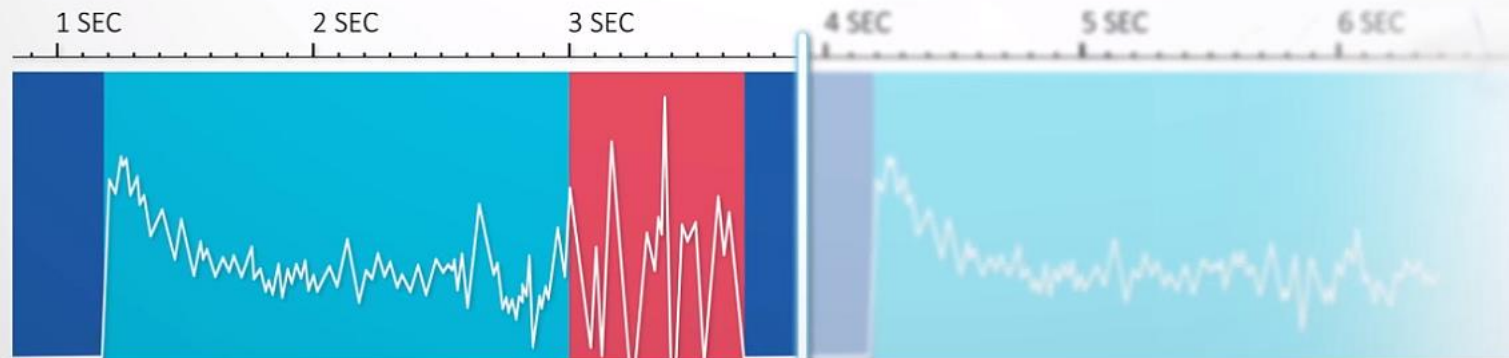
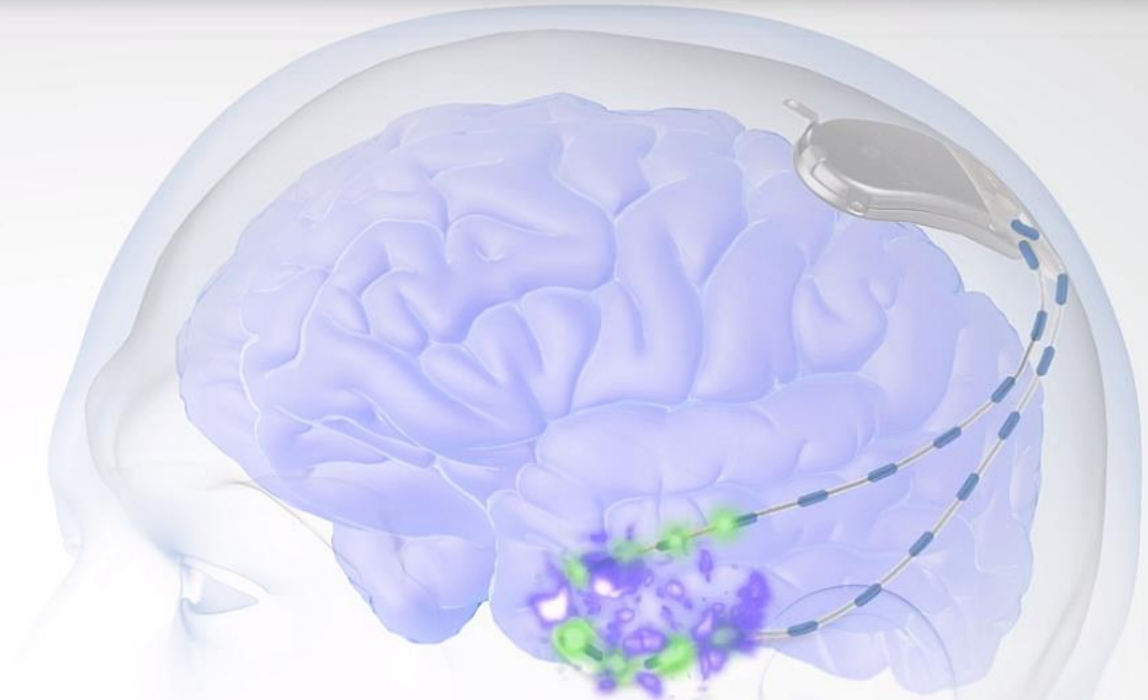
# Epilepsy

## The RNS<sup>®</sup> System

Monitors brainwaves

Detects unusual activity

Responds in real time

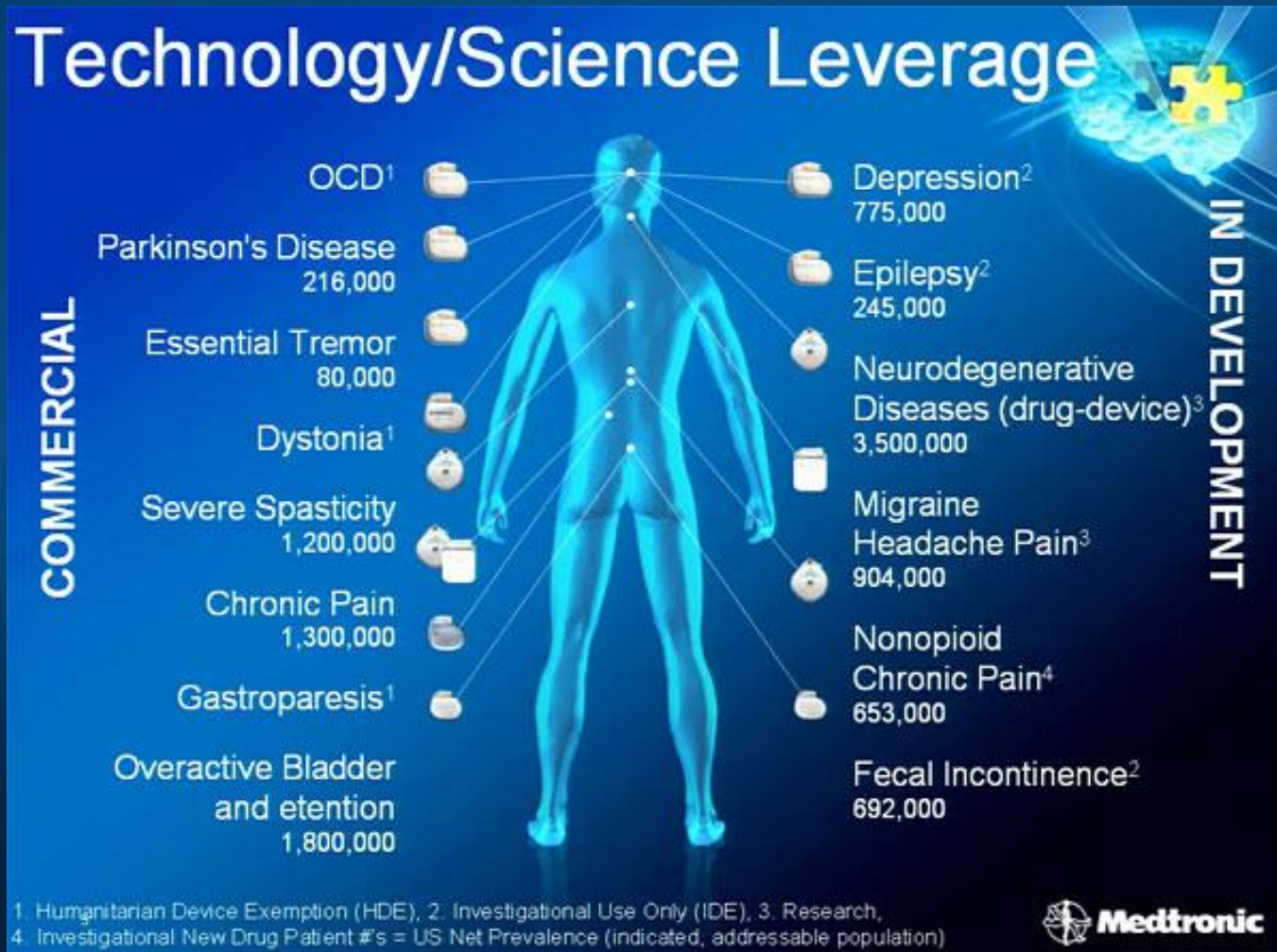


1% of population suffers from epilepsy, if pharmacology does not help neurostimulation based on close loop may help – RNS system is now commercial.



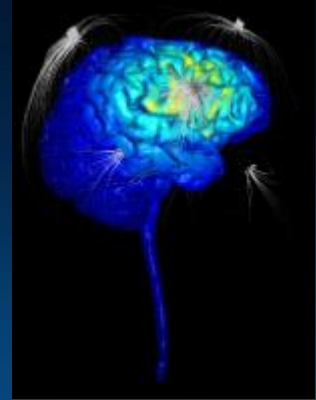
# Neuromodulation

Cochlear implants are common, but deeper implants that stimulate or even replace some brain structures start to appear, not only for deficits at the level of perception, but to regulate neural processes.





# BCBI for learning



1. **Teaching skills by stimulating cortex:** microstimulation too low to evoke muscle activation, applied in premotor cortex, instructed specific actions.  
Mazurek & Schieber (2017). Injecting Instructions into Premotor Cortex.
2. Eugster et al. (2016). Natural brain-information interfaces: Recommending information by relevance inferred from brain signals. Your brain knows better what is interesting than you do, so use EEG to model search intent while searching, watching or analyzing data.
3. Externally induced frontoparietal synchronization modulates network dynamics & enhances working memory performance (Violante et al 2017).
4. Neuroimaging based assessment strategy may provide an objective means of evaluating learning outcomes in the application of **Universal Design for Learning (UDL)**, an educational framework created to guide the development of flexible learning environments that adapt to individual learning differences.



# Fingerprints of mental activity



# Possible form of Brain Fingerprints

**Fingerprints: patterns of brain activity linked to active regions/networks.**

**fMRI:** BFP is based on  $V(\mathbf{X},t)$  voxel intensity of fMRI BOLD signal changes, contrasted between task and reference activity or resting state.

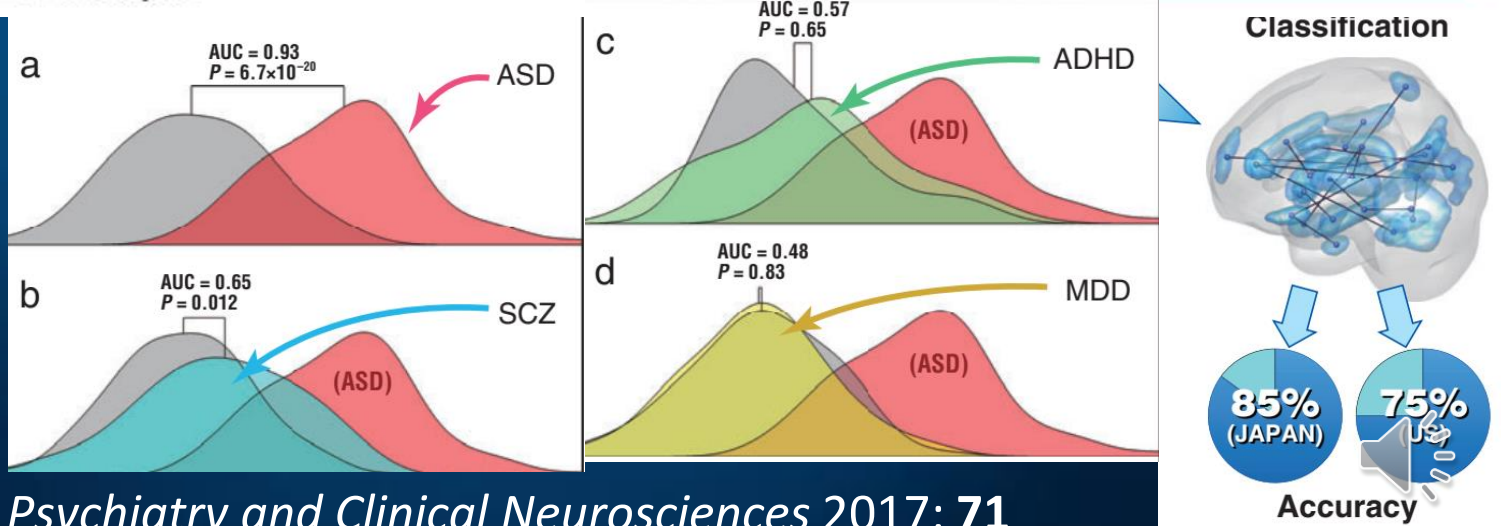
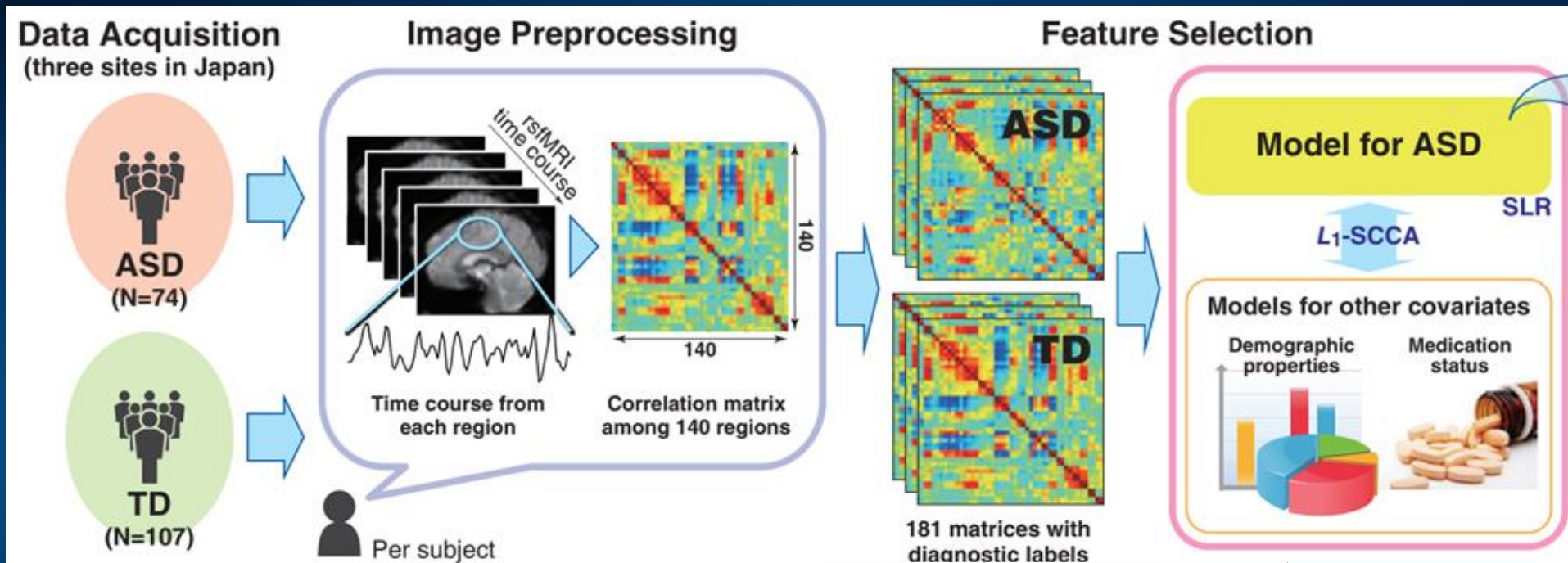
**EEG:** spatial, spatio-temporal, ERP maps/shapes, coherence, various phase synchronization indices.

1. **Spatial/Power:** direct localization/reconstruction of sources.
2. **Spatial/Synch:** changes in functional graph network structure.
3. **Frequency/Power:** ERS/ERD smoothed patterns  $E(\mathbf{X},t,f)$ .
4. **ERP power maps:** spatio-temporal averaged energy distributions.
5. **EEG decomposition into components:** ICA, CCA, tensor, RP ...
6. **EEG microstates, sequences & transitions, dynamics in ROI space.**
7. **Spectral fingerprinting (MEG, EEG), power distributions.**
8. **Model-based: The Virtual Brain,** integrating EEG/neuroimaging data.

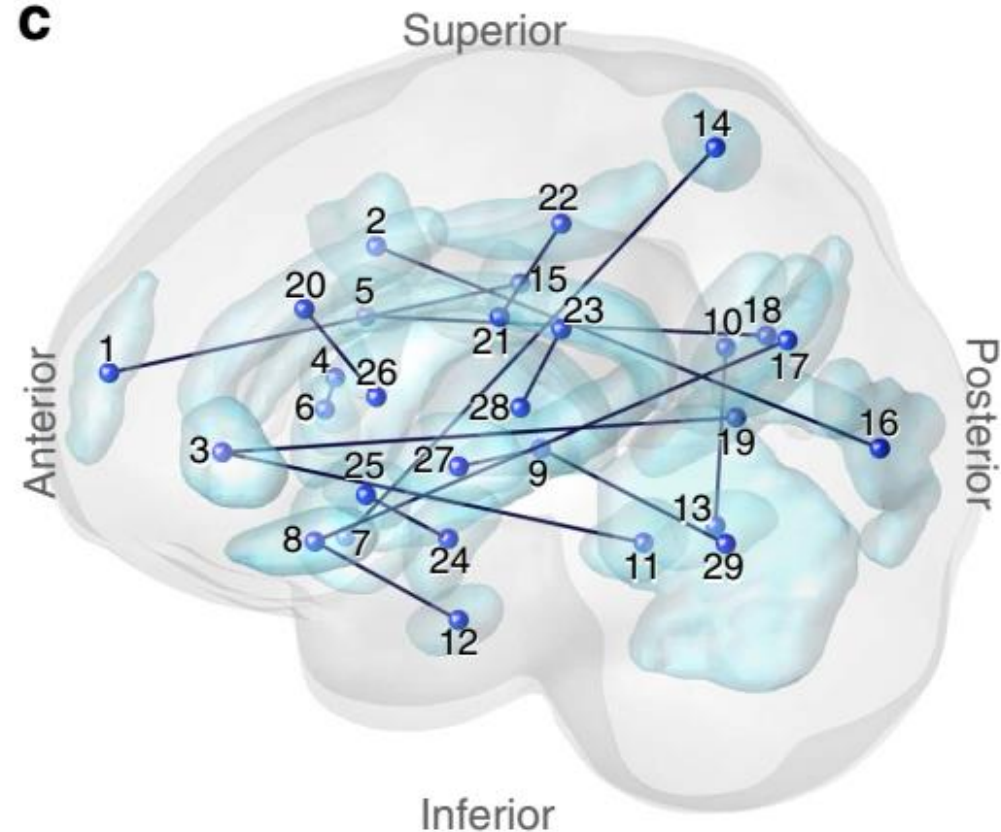
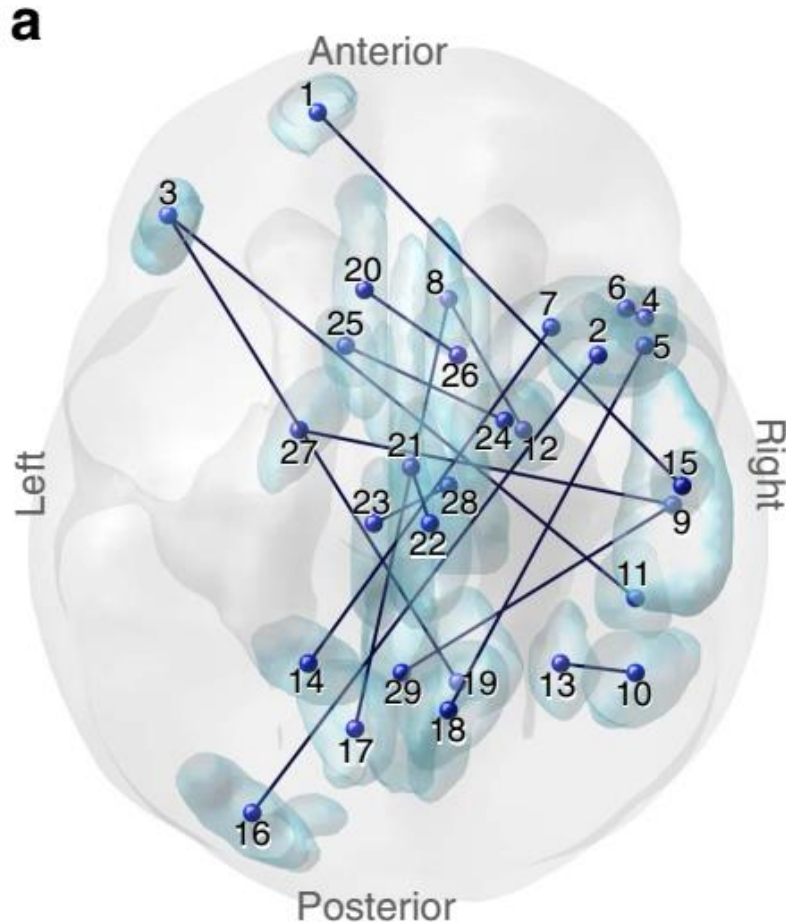
Neuroplastic changes of connectomes and functional connections as results of training for optimization of brain processes.



# Biomarkers from neuroimaging



# Selected connections

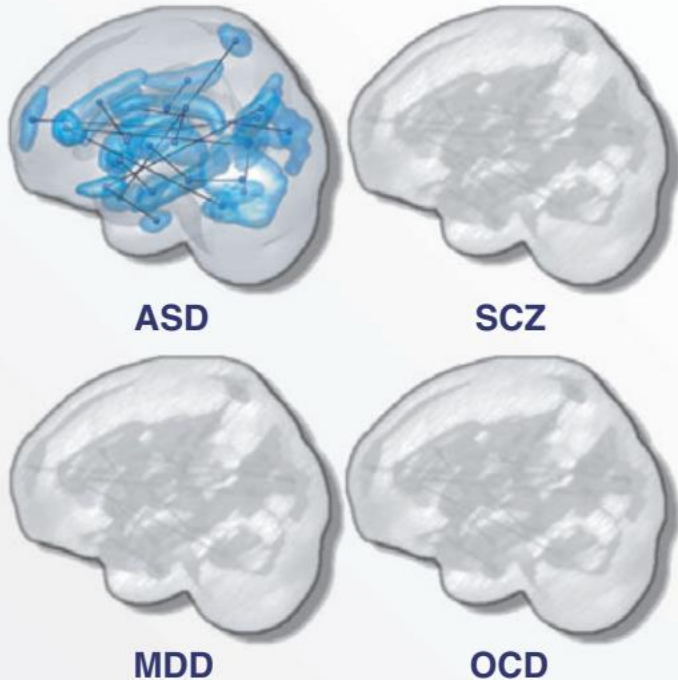


N. Yahata et al (2016): 29 selected regions (ROI) and 16 connections are sufficient to recognize ASD with 85% accuracy in 74 Japanese adult patients vs. 107 people in control group; without re-training accuracy was 75% on US patients.

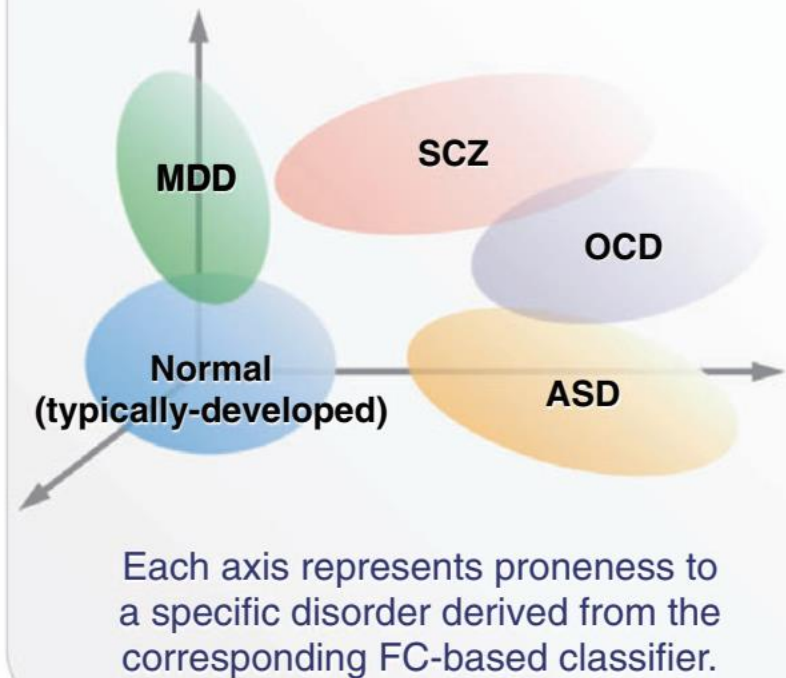


# Biomarkers of mental disorders

## Functional connectivity-based classifiers for mental disorders



## Recasting current nosology in more biologically meaningful dimensions



MDD, deep depression, SCZ, schizophrenia, OCD, obsessive-compulsive disorder, ASD autism spectrum disorder. fMRI biomarkers allow for objective diagnosis.

N. Yahata et al, *Psychiatry & Clinical Neurosciences* 2017; **71**: 215–237

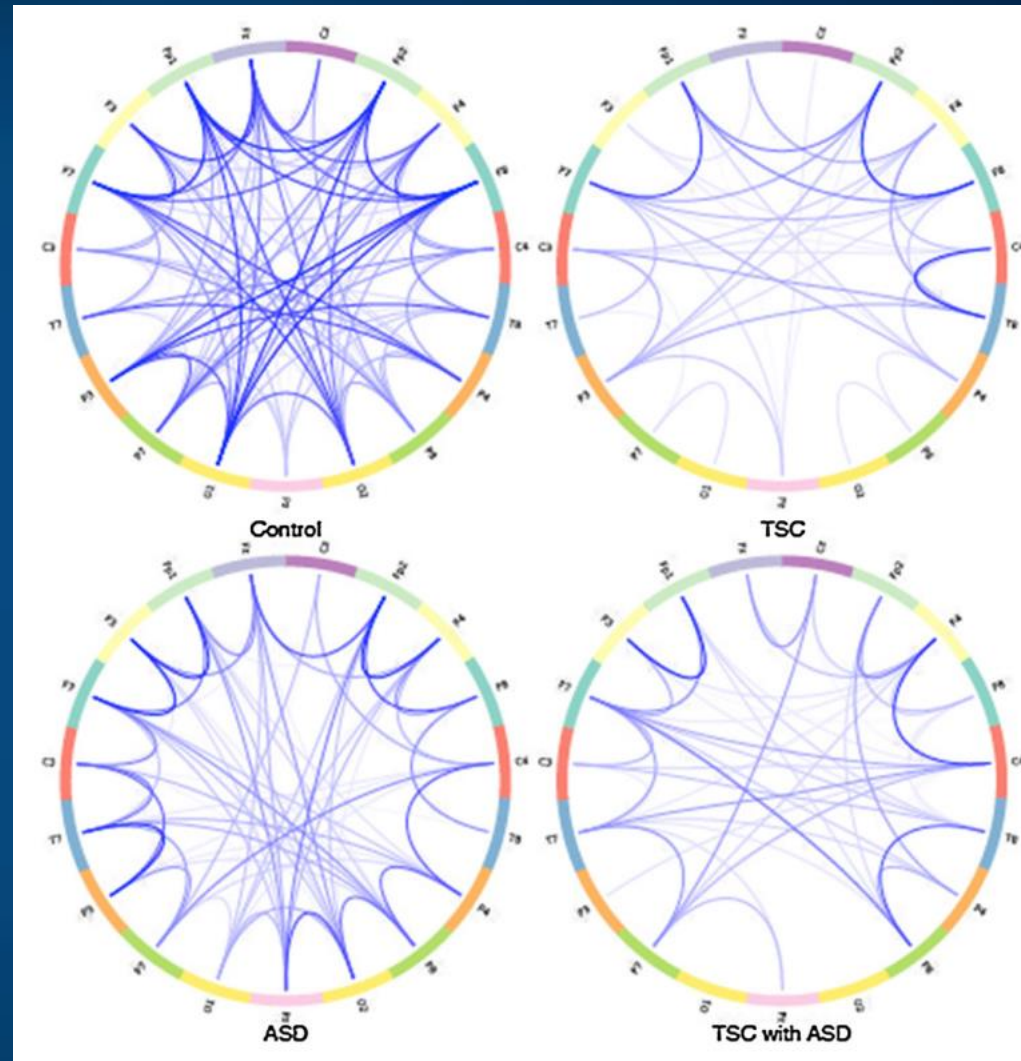


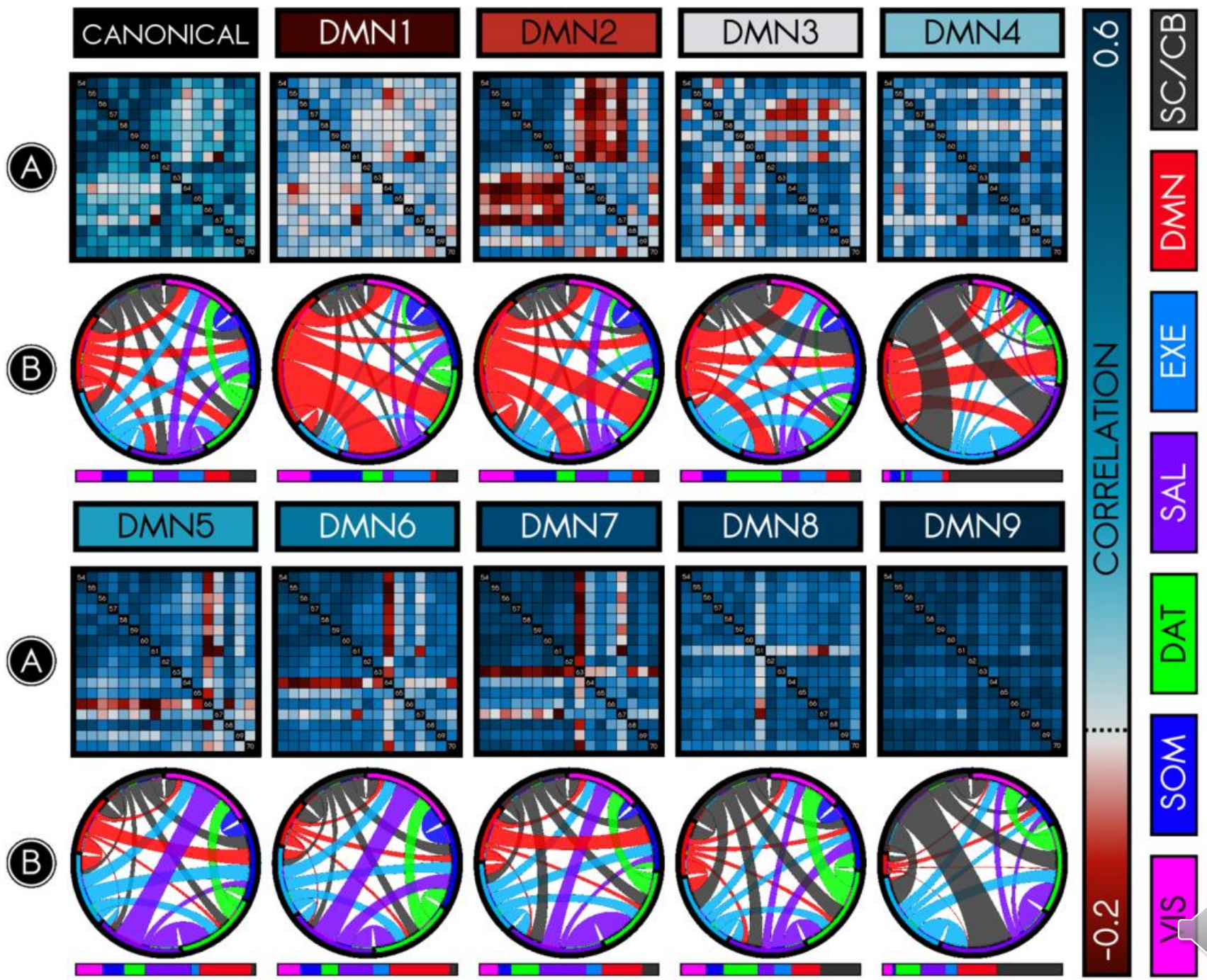
# ASD: pathological connections

Comparison of connections for patients with ASD (autism spectrum), TSC (Tuberous Sclerosis), and ASD+TSC.

Coherence between electrodes. Weak or missing connections between distant regions prevent ASD/TSC patients from solving more demanding cognitive tasks.

Network analysis becomes very useful for diagnosis of changes due to the disease and learning; **correct your networks!**





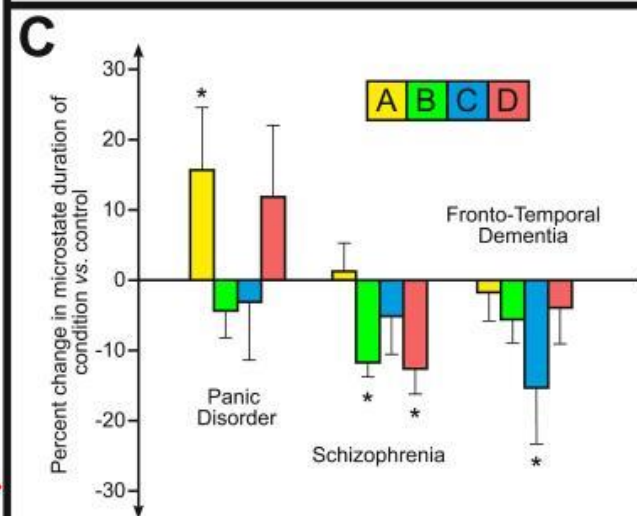
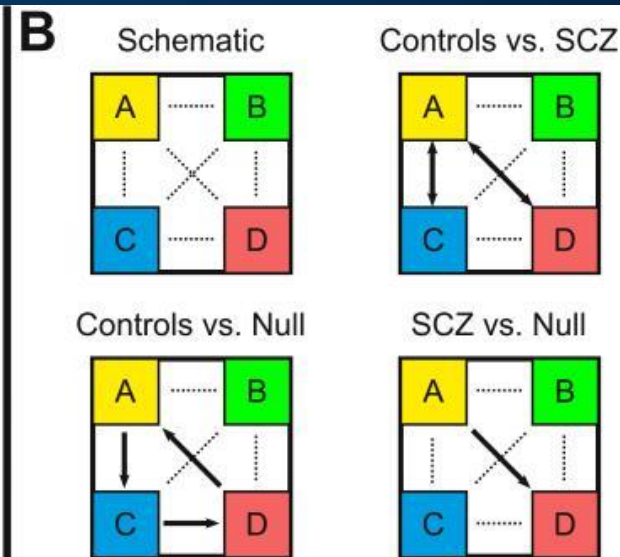
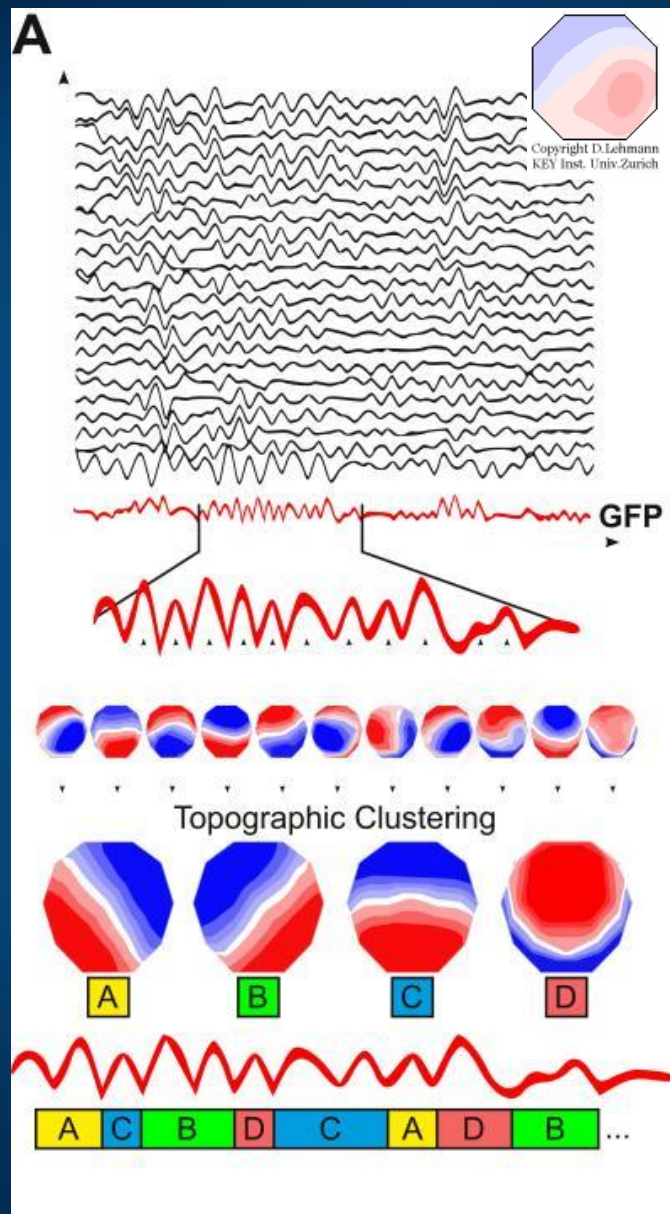


# Microstates

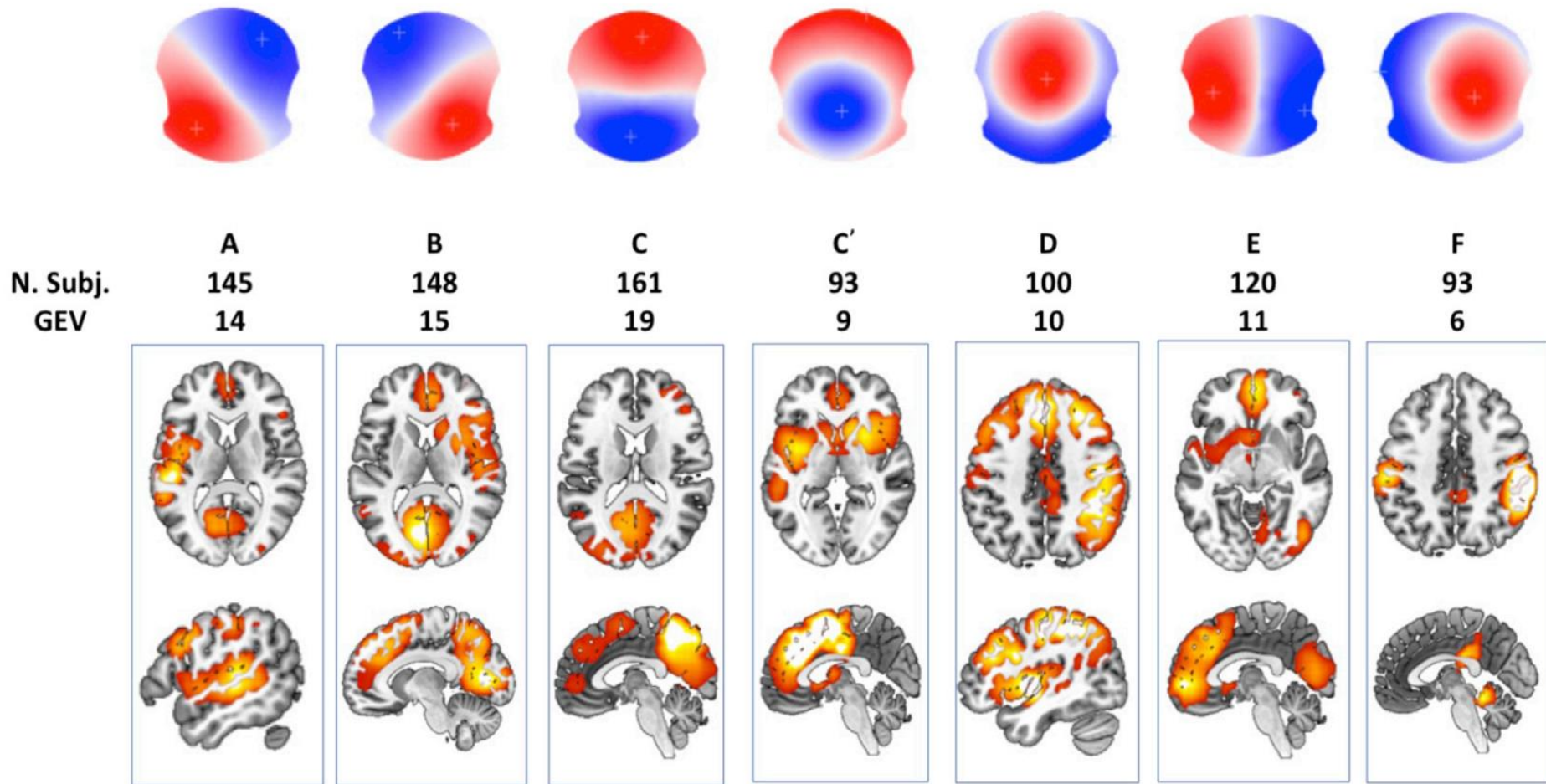
Lehmann et al.  
 EEG microstate duration and syntax in acute, medication-naïve, first-episode schizophrenia. *Psychiatry Research Neuroimaging*, 2005

Khanna et al.  
 Microstates in Resting-State EEG. *Neuroscience and Biobehavioral Reviews*, 2015

4-7 states 60-150 ms  
 Symbolic dynamics.



# Microstates sources

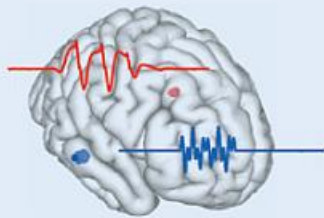


Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. *NeuroImage*, 180, 577–593. <https://doi.org/10.1016/j.neuroimage.2017.11.062>



# EEG localization and reconstruction

ECD



$$\hat{d}_j = \operatorname{argmin} \left\| \phi - \sum_j \mathcal{K}_j d_j \right\|_F^2$$

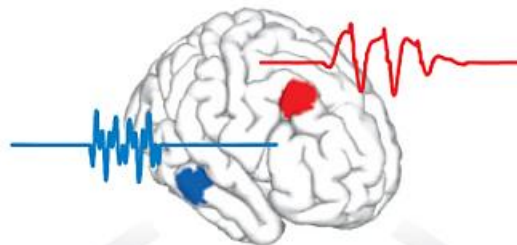
Rotating dipole

- Moving
- Rotating
- Fixed

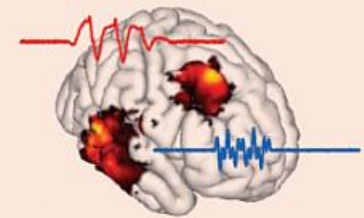
Dipole model



Distributed model



MN ( $\ell_2$ ) family



$$\hat{j} = \operatorname{argmin}_j \left\| \phi - \mathcal{K}j \right\|_2^2 + \lambda \left\| j \right\|_2^2$$

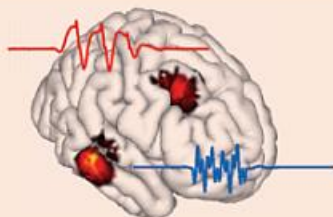
$$\hat{j} = \mathcal{T}\phi = \mathcal{K}^\top (\mathcal{K}\mathcal{K}^\top + \lambda I)^{-1} \phi$$

MN

- MN
- WMN
- LORETA

He et al. Rev. Biomed Eng (2018)

Sparse and Bayesian framework

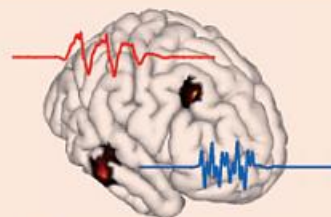


$$\hat{j} = \operatorname{argmin}_j \left\| \mathcal{V}j \right\|_1 + \alpha \left\| j \right\|_1$$

S.T.  $\left\| \phi - \mathcal{K}j \right\|_{\Sigma^{-1}}^2 \leq \epsilon^2$

IRES

Beamforming and scanning algorithms

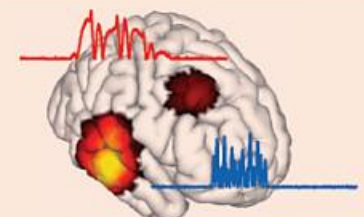


$$\hat{w}_r = \operatorname{argmin}_{w_r} w_r^\top \mathcal{R}_\phi w_r$$

S.T.  $\begin{cases} \mathcal{K}_r^\top w_r = \xi_1 \\ w_r^\top w_r = 1 \end{cases}; \hat{j} = w^\top \phi$

Beamformer (VBB)

Nonlinear post hoc normalization



$$\hat{j}_{mn} = \mathcal{T}_{mn}\phi$$

$$S_j = \mathcal{K}^\top (\mathcal{K}\mathcal{K}^\top + \alpha I)^{-1} \mathcal{K}$$

$$\hat{j}_{sl} = \hat{j}_{mn}(\ell)^\top \left( [S\hat{j}]_{\ell\ell} \right)^{-1} \hat{j}_{mn}(\ell)$$

sLORETA

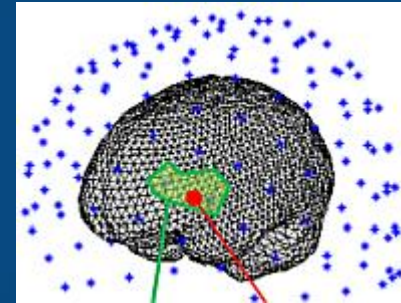
# Spatial filters

LCMV (Linearly Constrained Minimum Variance), classical reconstruction filter is a solution to the following problem:

$$\Phi = K(\theta)j + n, j \approx W\Phi, WK(\theta) \approx I$$

LCMV has large error if:  $K$  - lead-field matrix;  $\theta$  - dipole positions  
 $j$  - activations;  $W$  - spatial filter

- sources are correlated,
- SNR (signal to noise ratio) is low, or
- forward problem is ill-conditioned.



Minimum variance pseudo-unbiased reduced-rank (MV-PURE, Piotrowski, Yamada, IEEE Transactions on Signal Processing 56, 3408-3423, 2008)

$$W = \bigcap_{j \in Y} \arg \min_{\hat{W} \in X_r} \left\| \hat{W}K(\theta) - I_l \right\|_j^2$$

where  $X_r$  is a set of all matrices of rank at most  $r$ , and set  $Y$  denotes all unitary norms. For reconstruction we use 15 000 vertex FreeSurfer brain tessellation with brain atlases that provide parcellation of the mesh elements into 100-240 cortical patches (regions of interest, ROIs), and individual MRI brain scans.



# SupFunSim

SupFunSim: our library/Matlab /toolbox, direct models for EEG/MEG, [on GitHub](#).

Provides many spatial filters for reconstruction of EEG sources: linearly constrained minimum-variance (LCMV), eigenspace LCMV, nulling (NL), minimum-variance pseudo-unbiased reduced-rank (MV-PURE) ...

Source-level directed connectivity analysis: partial directed coherence (PDC), directed transfer function (DTF) measures.

Works with FieldTrip EEG/ MEG software. Modular, object-oriented, using Jupyter notes, allowing for comments and equations in LaTeX.

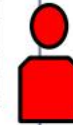
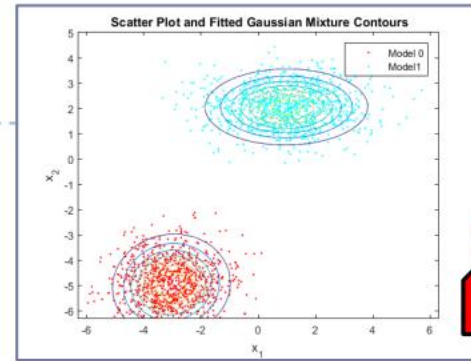
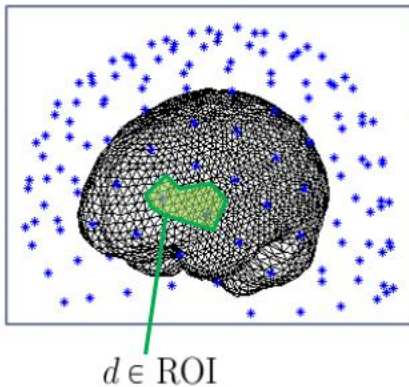
$$A := H_{Src,R} := R^{-1/2} H \quad (34)$$

$$B := H_{Src,N} := N^{-1/2} H \quad (35)$$

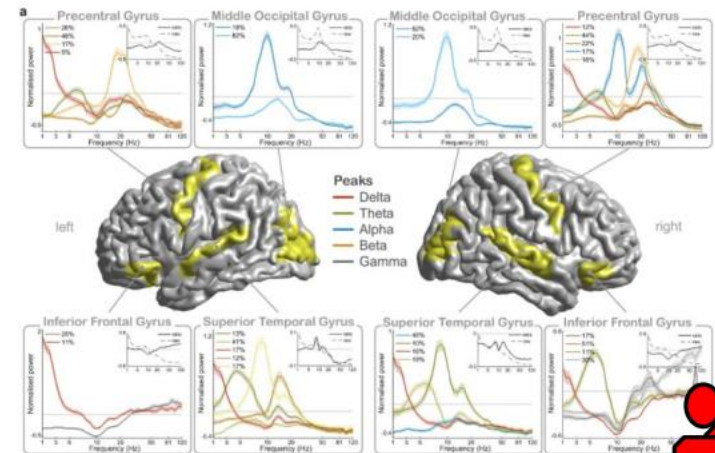
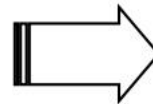
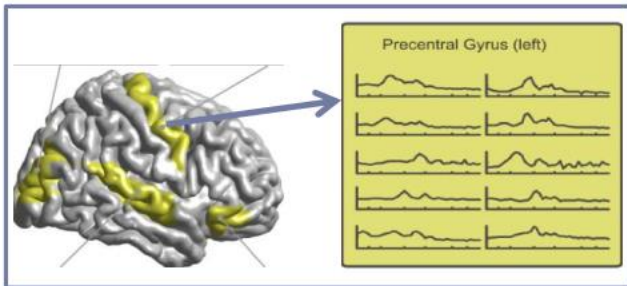
```
1 %%file calculate_H_Src.m
2 function model = calculate_H_Src(MODEL)
3     model = MODEL;
4
5     model.H_Src_R = pinv(sqrtm(model.R)) * model.H_Src;
6     model.H_Src_N = pinv(sqrtm(model.N)) * model.H_Src;
7 end
```



# Spectral fingerprints



Single subject



Group model

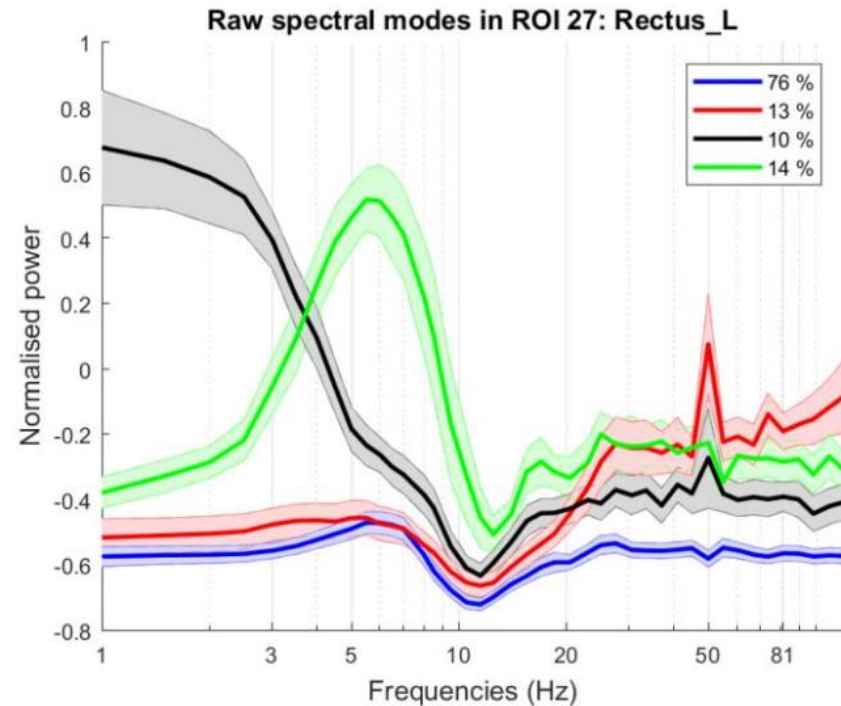
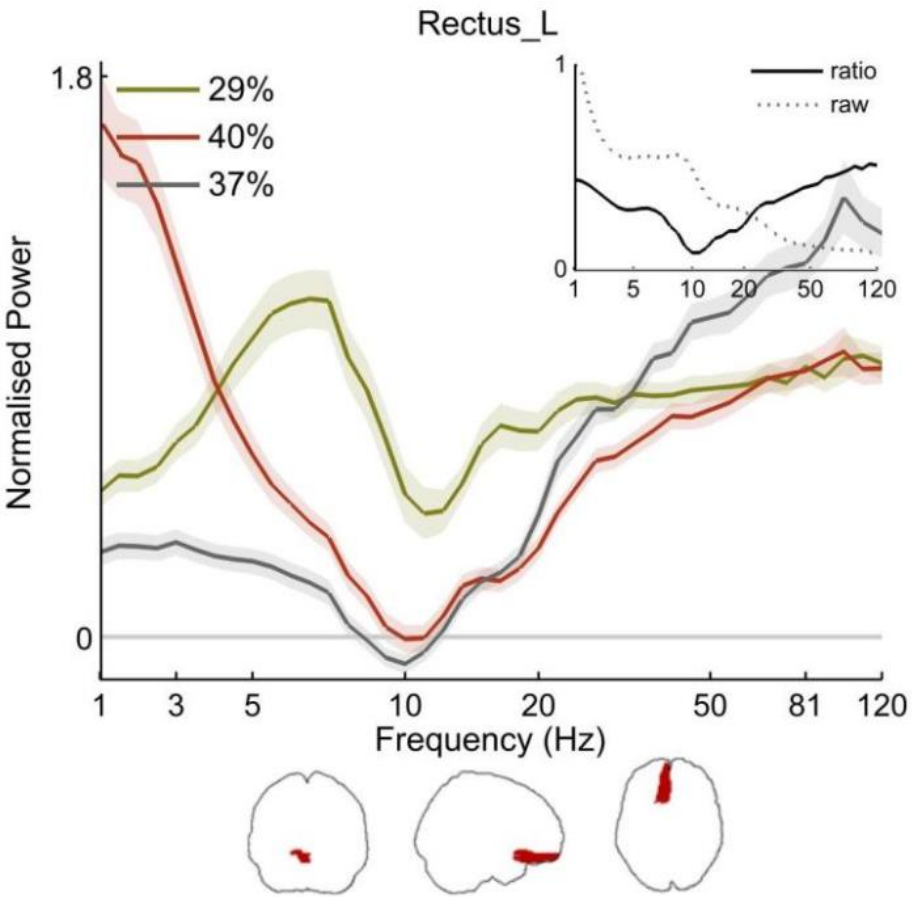
5

\* Pictures from Keitel & Gross 2016 and Fieldtrip beamforming tutorial

A. Keitel & J. Gross, „Individual human brain areas can be identified from their characteristic spectral activation fingerprints”, *PLoS Biol* 14(6), e1002498, 2016



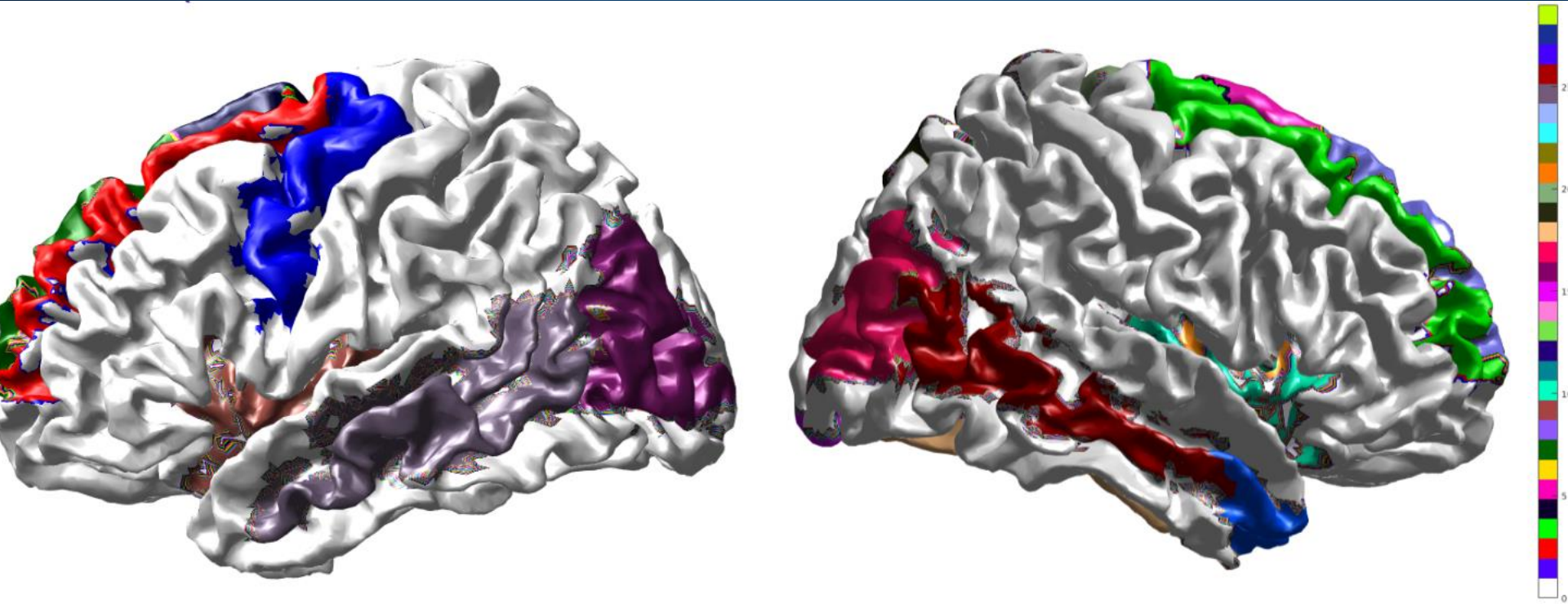
# Spectral fingerprints



A. Keitel i J. Gross, „Individual human brain areas can be identified from their characteristic spectral activation fingerprints”, *PLoS Biol* 14, e1002498, 2016



# Most reliable ROI, homologous $\leq 1.5$



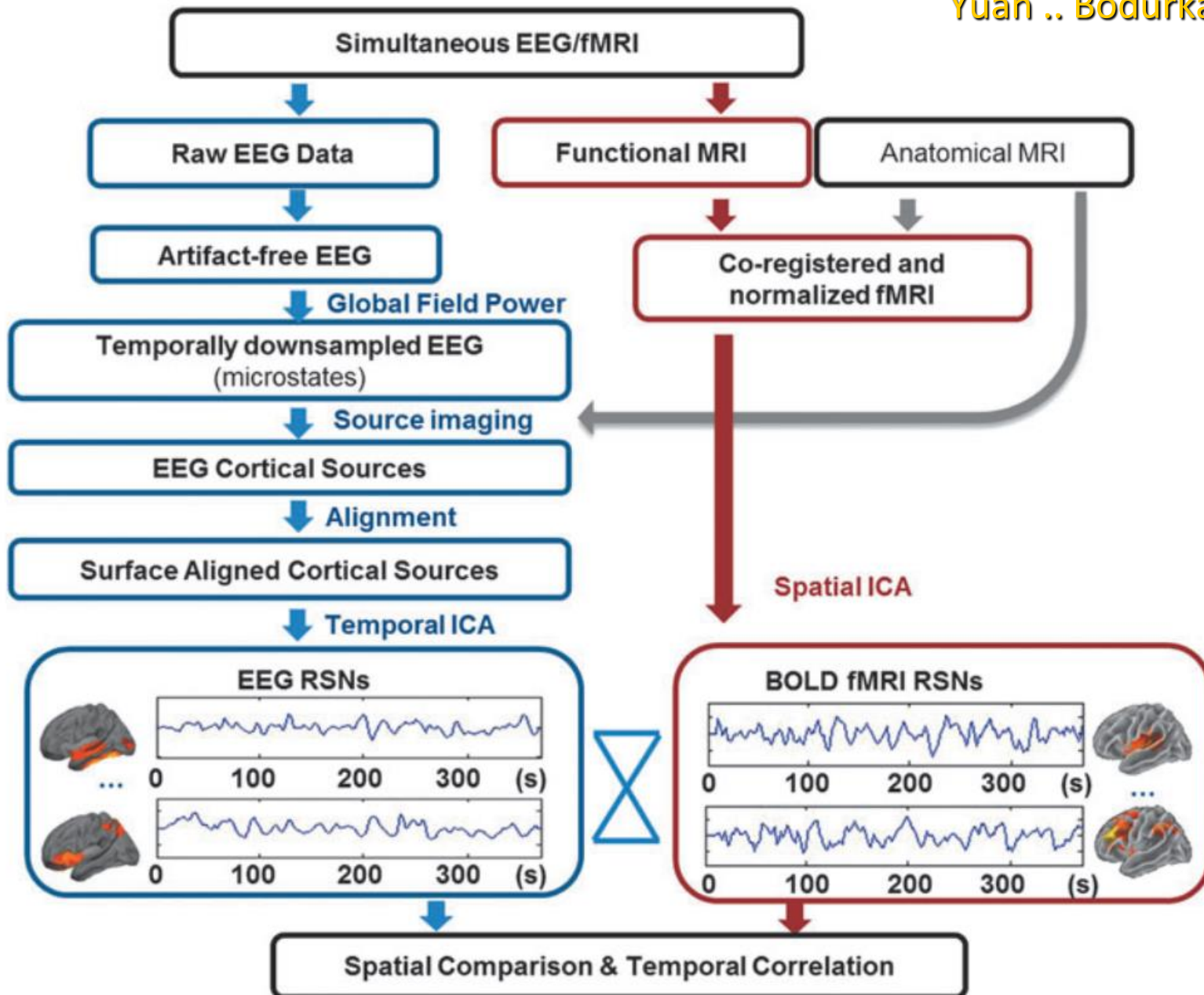
MEG data from the Human Connectome Project (HCP) for 1200 subjects.

Some ROI can be recognized quite reliably.

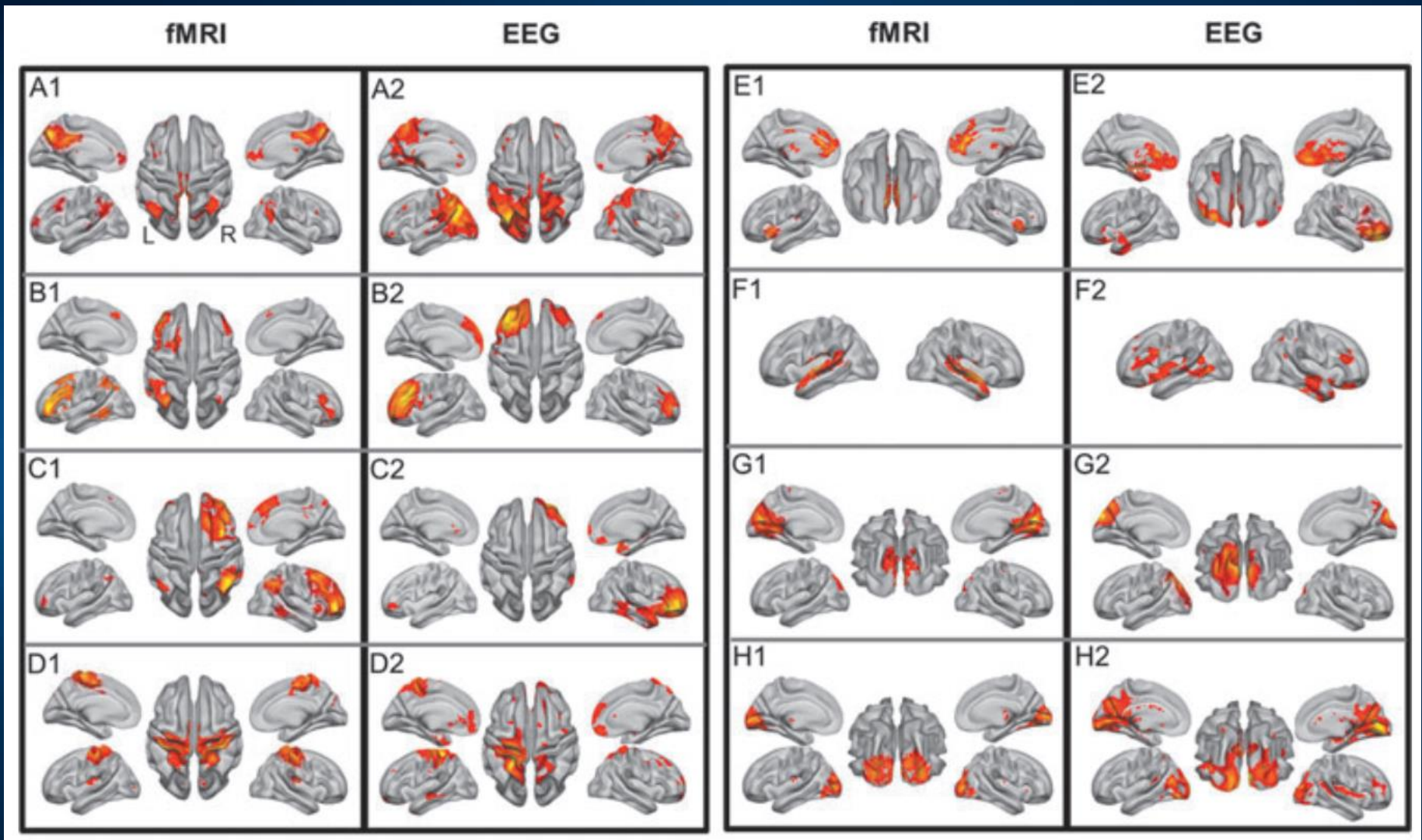
If homologues are not distinguished we have 29 ROIs, many sub-cortical, that can be reliably identified. Still working on EEG data ...





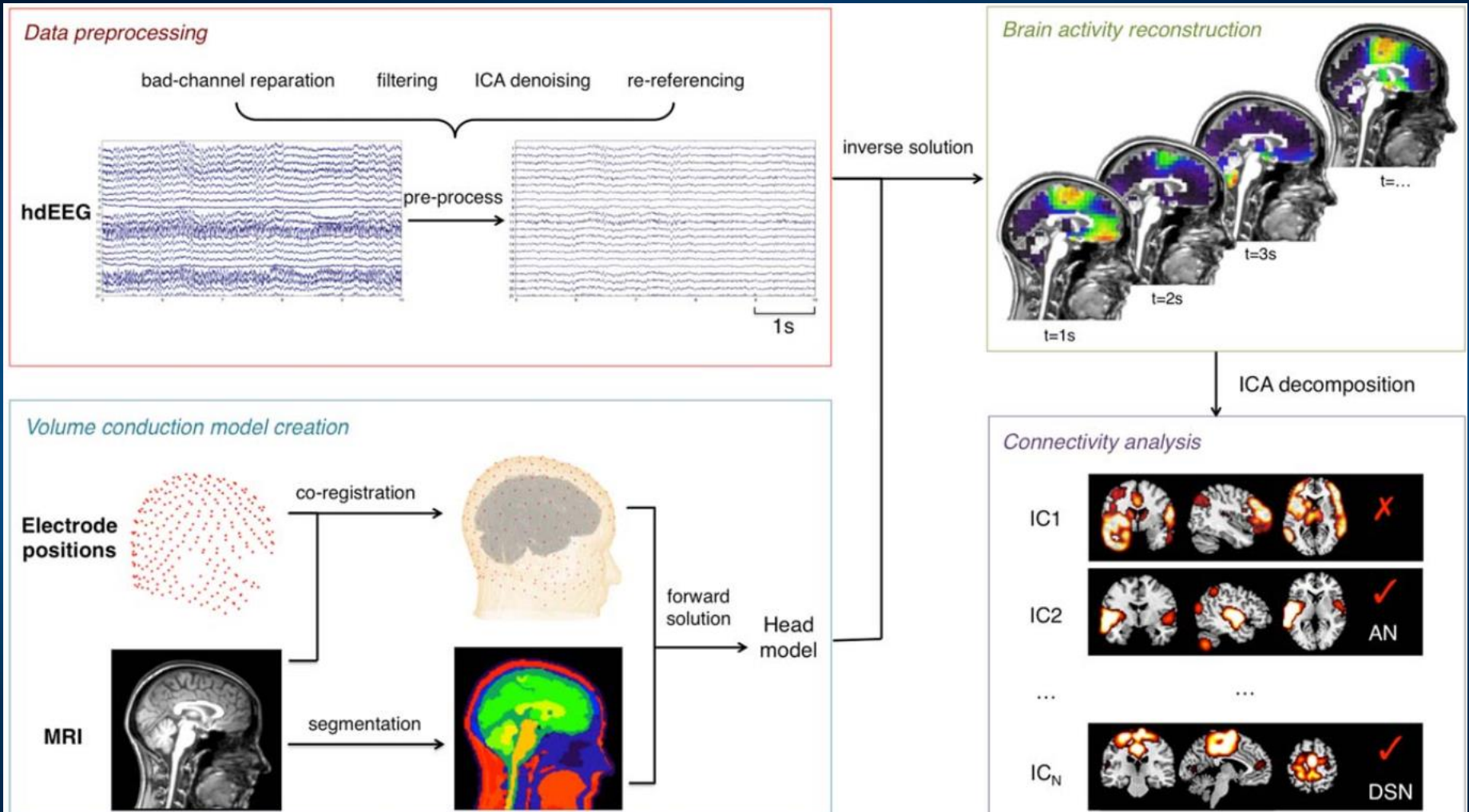


# 8 large networks from BOLD-EEG

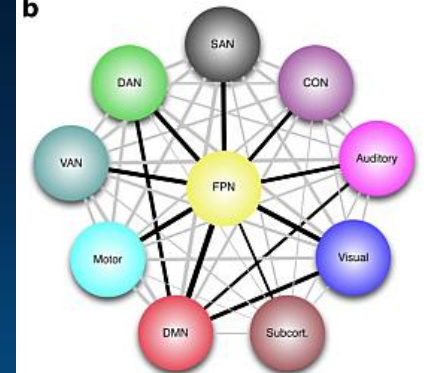


DMN, FP (frontoparietal)-left, right, sensorimotor, ex, control, auditory, visual (medial), (H) visual (lateral). Yuan ... Bodurka (2015)

# 14 networks from BOLD-EEG



# Reorganization of brain nets



**Global Neuronal Workspace Theory (Dehaene et al. 1998):**  
brain processes underlying effortful tasks require:

- Specialized modular processors: perceptual, motor, memory, attentional;
- global workspace for activation patterns composed of distributed and heavily interconnected neurons with long-range axons.

Workspace neurons are mobilized in effortful tasks for which the specialized processors (Kahneman's System 1) do not suffice (System 2).

1. Can the whole-brain network properties change during performance?
2. Do modularity, path length, global, local efficiency and other network measures dependent on the cognitive load?

Finc K, Bonna K, Lewandowska M, Wolak T, Nikadon J, Dreszer J, Duch W, Kühn, S. (2017) Transition of the functional brain network related to increasing cognitive demands. *Human Brain Mapping*, 38(7), 3659–3674.

Finc K, Bonna K, He X, Lydon-Staley D, Kühn S, Duch W, Bassett D.S. (2020) Dynamic reconfiguration of functional brain network during working memory training. *Nature Neuroscience* 2/2020



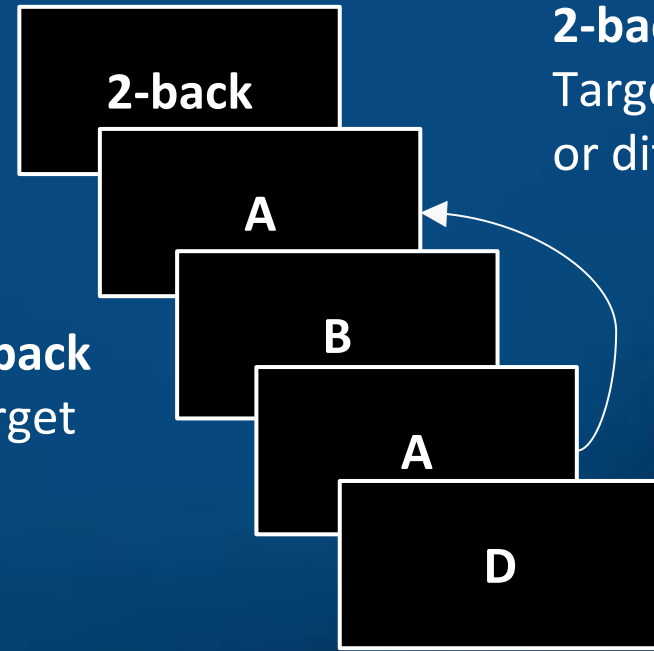
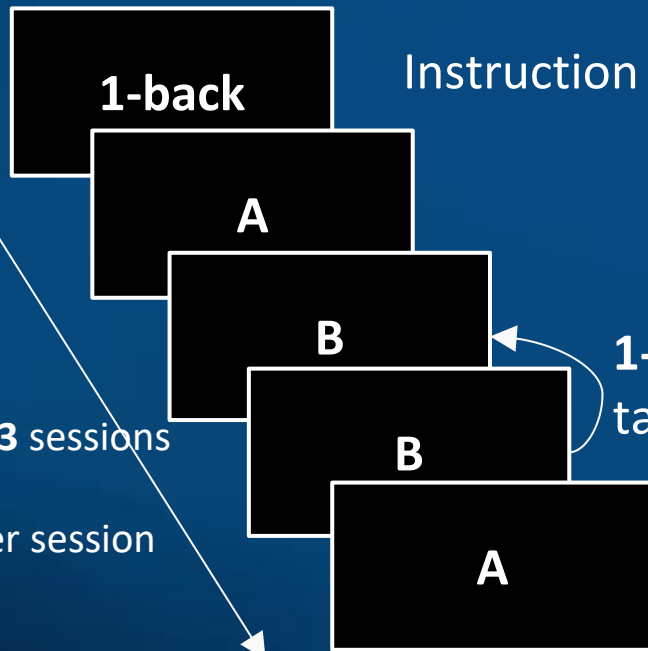
# Cognitive load on whole-brain network

35 participants (17 females; Mean age =  $22.6 \pm 3.1$ ; 19-31).

## Letter *n*-back task

Low cognitive effort

High cognitive effort



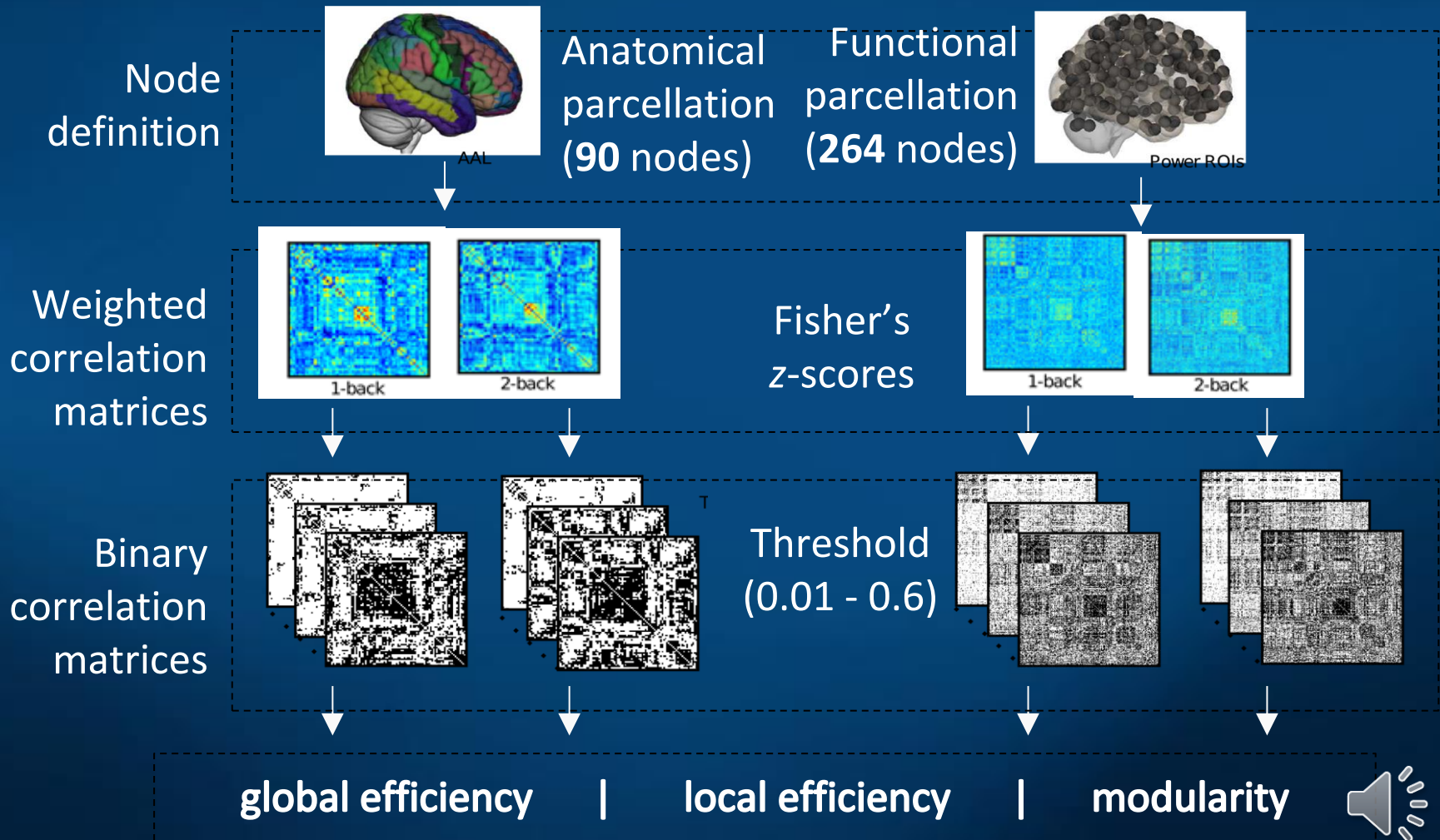
30 s block  
10 blocks x 3 sessions

5:30 min per session



# Data workflow

Two experimental conditions: 1-back, 2-back



# Brain modules and cognitive processes

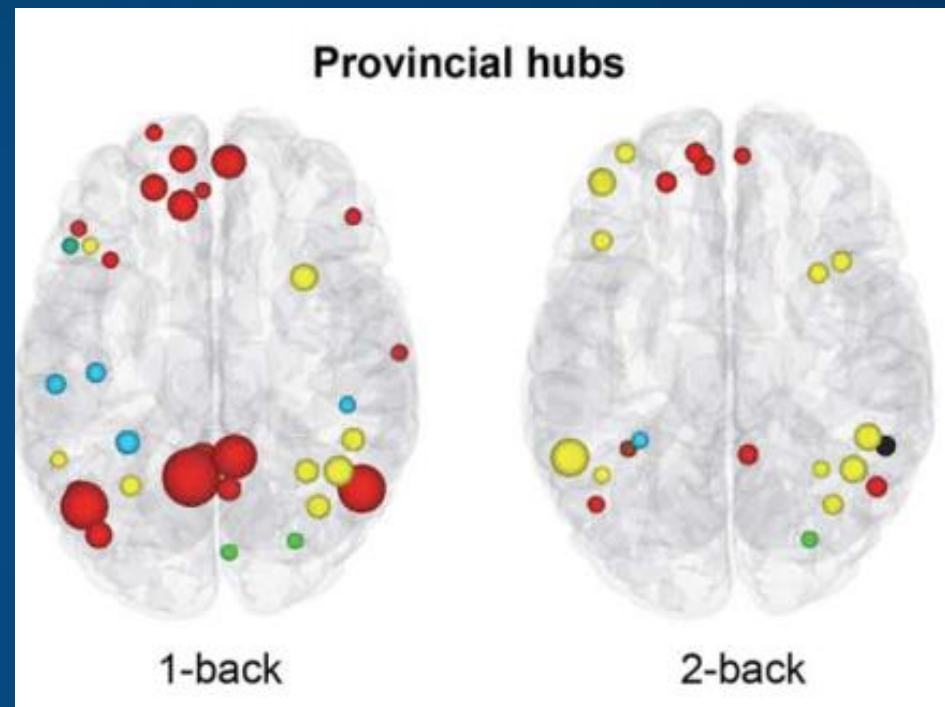
Simple and more difficult tasks, requiring the whole-brain network reorganization.

Left: 1-back local hubs

Right: 2-back local hubs

Average over 35 participants.

Dynamical change of the landscape of attractors, depending on the cognitive load. Less local (especially in DMN), more global binding (especially in PFC).



# Brain modules and cognitive processes

Simple and more difficult tasks, requiring the whole-brain network reorganization.

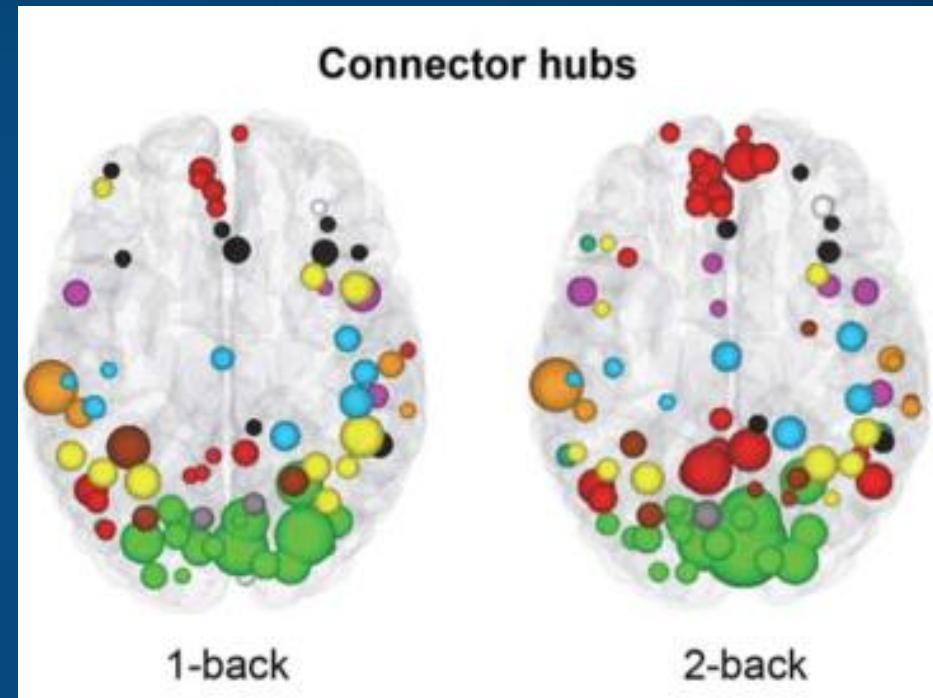
Left: 1-back connector hubs

Right: 2-back connector hubs

Average over 35 *participants*.

Dynamical change of the landscape of attractors, depending on the cognitive load – System 2 (Khaneman).

DMN areas engaged in global binding!

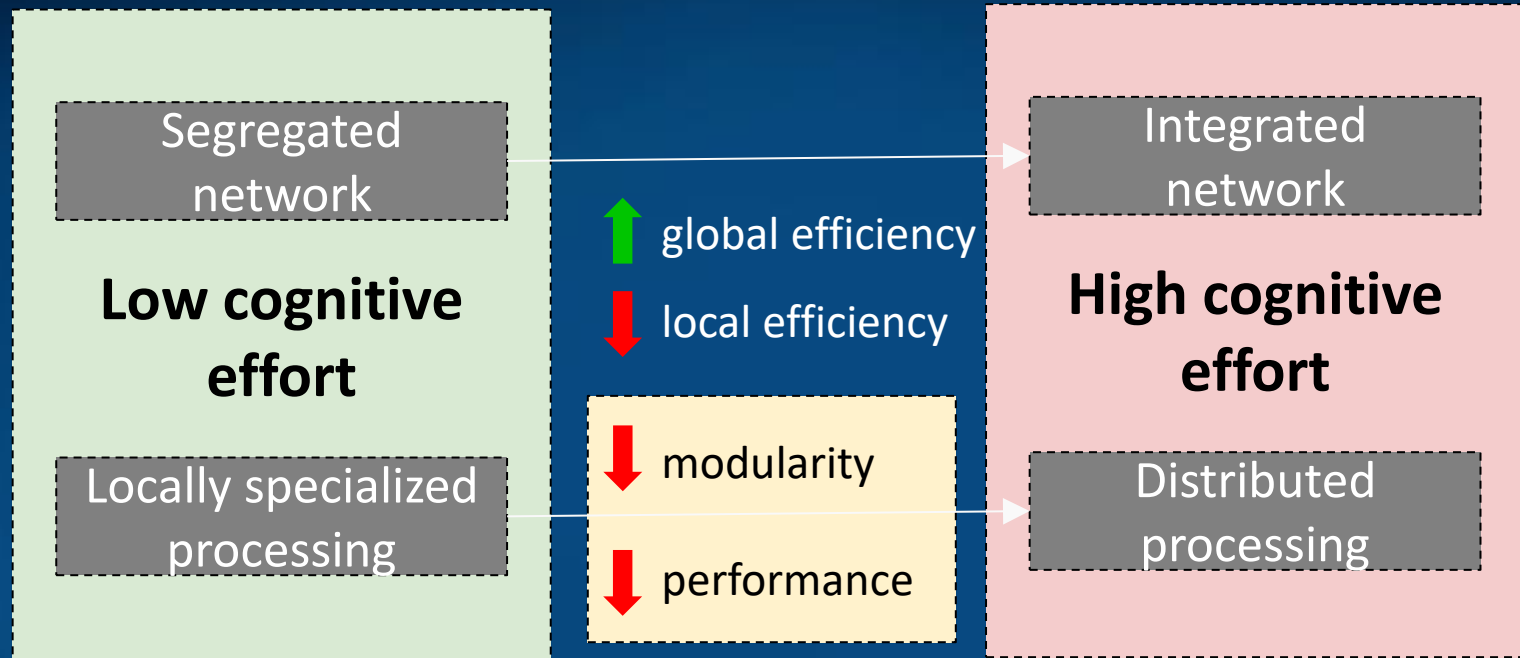


K. Finc et al, HBM (2017).





# Cognitive load



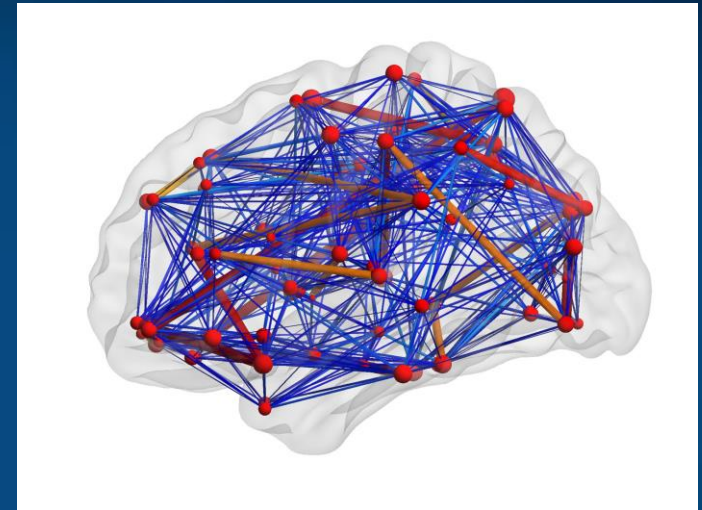
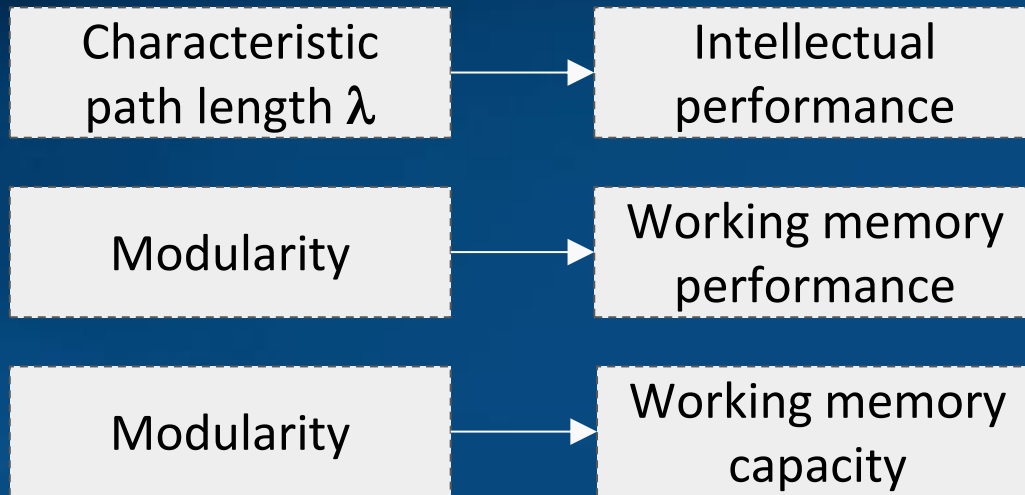
≠



Parcellation into 264 regions (10 mm spheres) shows subnetworks more precisely than for 90 regions; only a small subgroup of neurons in each ROI is strongly correlated.

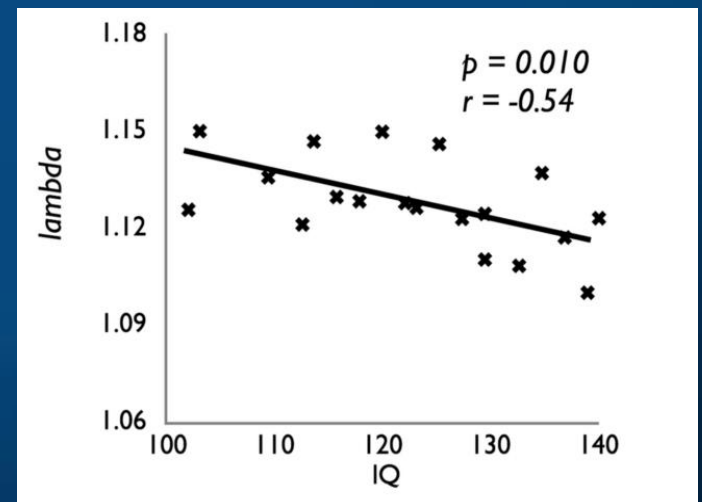


# Resting state/cognitive performance

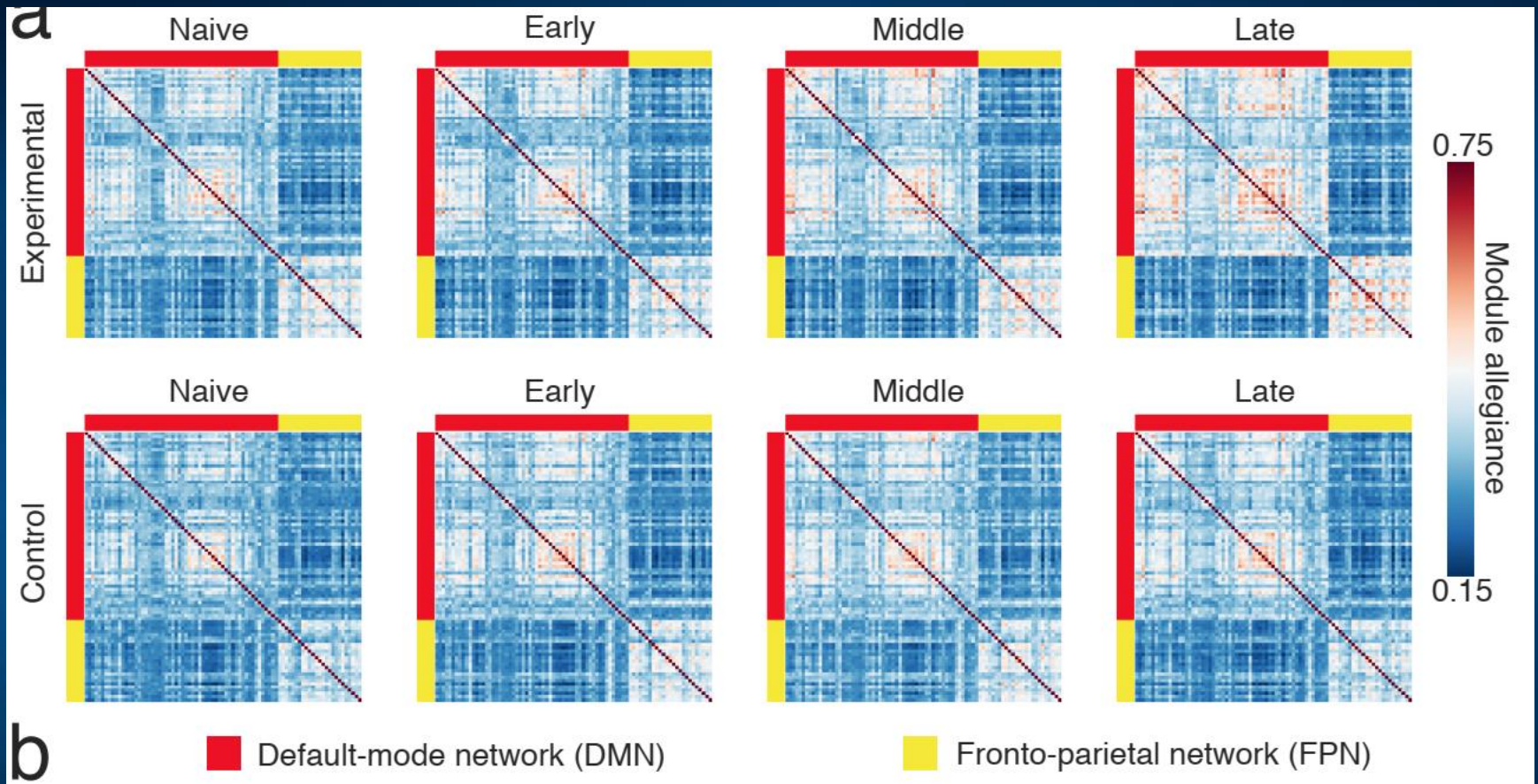


Network modularity  $\Leftrightarrow$  higher working memory capacity and performance.

High connectivity within modules and sparse connections between modules increases effective cooperation of brain regions, is associated with higher IQ.



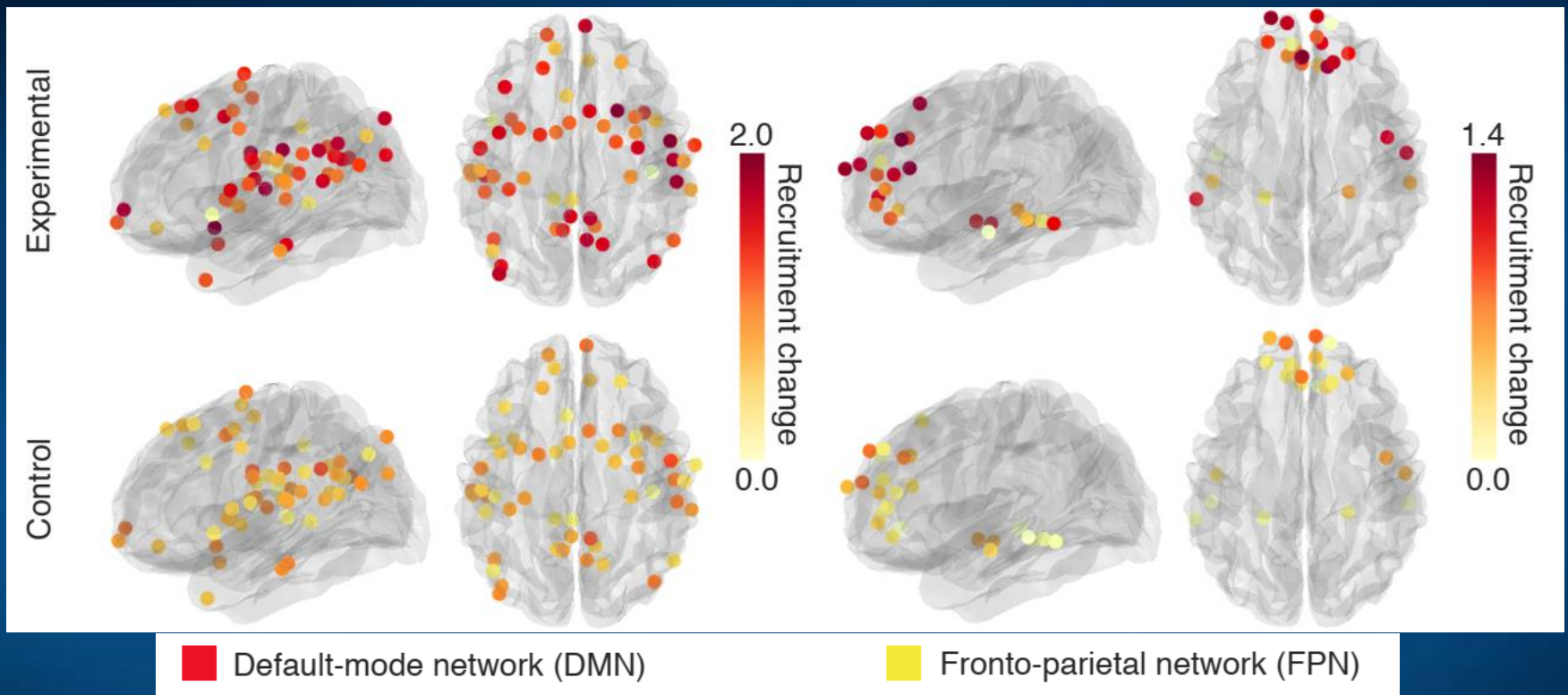
# Working memory training



6-week training, dual n-back task, **changes in module allegiance of fronto-parietal and default-mode networks**. Each matrix element represents the probability that the pair of nodes is assigned to the same community.

Segregation of task-relevant DMN and FPN regions is a result of training and complex task automation. 

# Working memory training



Recruitment changes from the 'Naive' to the 'Late' stage of training. Both control and experimental groups exhibited increase of the DMN recruitment but FPN recruitment only increased in experimental group. No consistent changes in FPN-DMN networks integration was noticed. Finc et al. Nature Neuroscience 2020



# Model of reading & dyslexia

Emergent neural simulator:

Aisa, B., Mingus, B., and O'Reilly, R. The emergent neural modeling system. *Neural Networks*, 21, 1045, 2008.

3-layer model of reading:

orthography, phonology, semantics, or distribution of activity over **140 microfeatures** defining concepts.

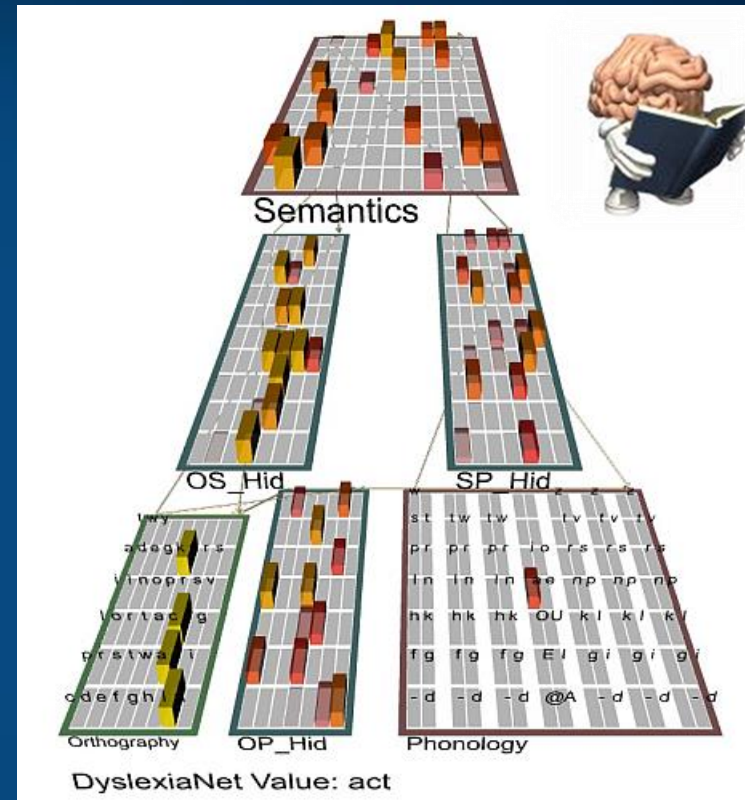
In the brain: microfeature=subnetwork.  
Hidden layers OS/OP/SP\_Hid in between.

Learning: mapping one of the 3 layers to the other two.

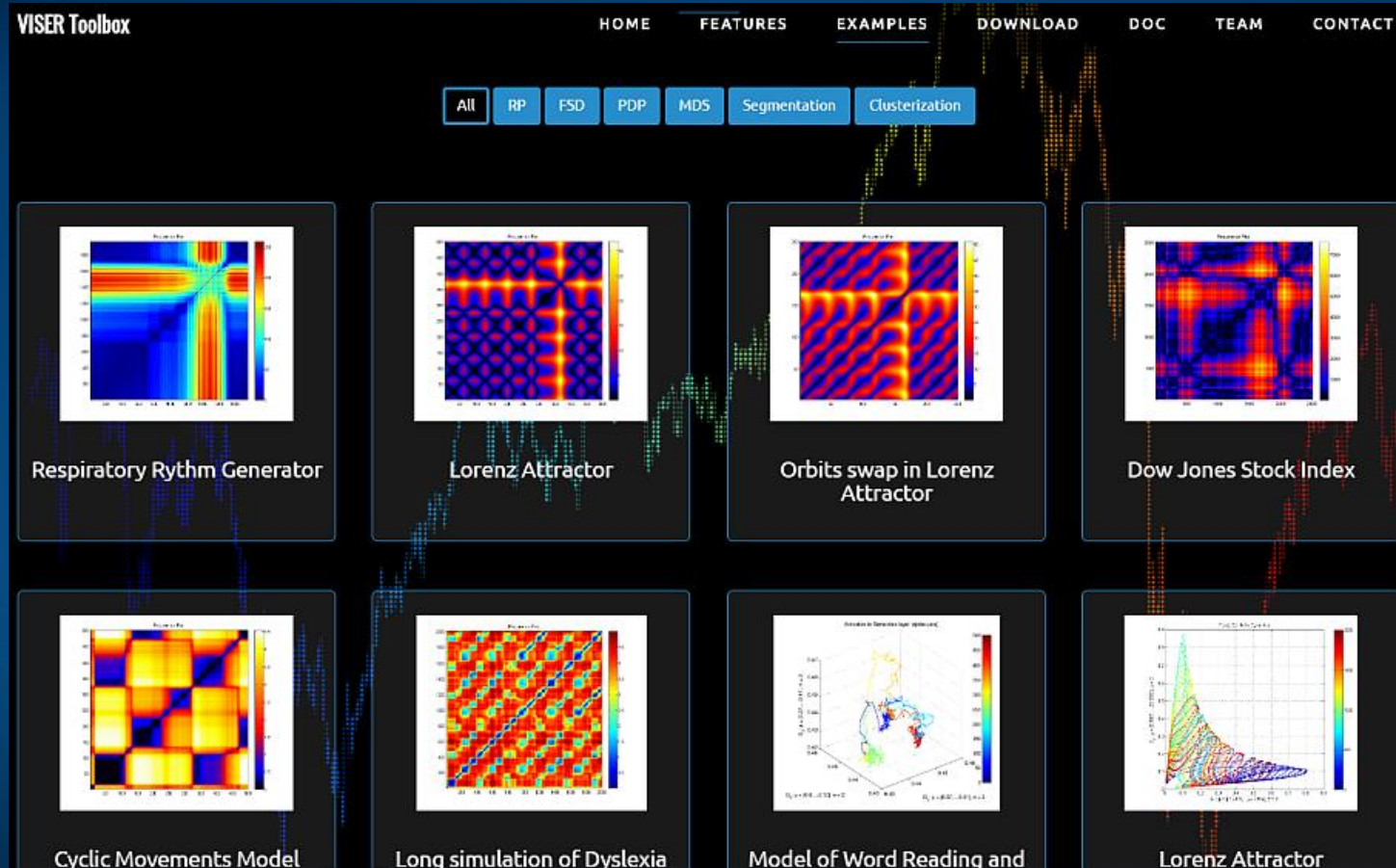
Fluctuations around final configuration = attractors representing concepts.

How to see properties of their basins, their relations?

Model in **Genesis**: more detailed neuron description.



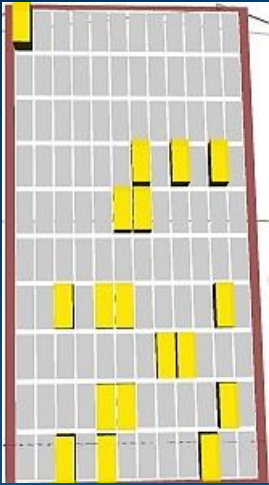
# Viser toolbox



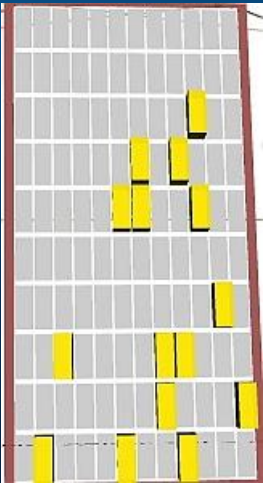
Nasz Viser toolbox (Dobosz, Duch) do wizualizacji szeregów czasowych w wielu wymiarach różnymi technikami.



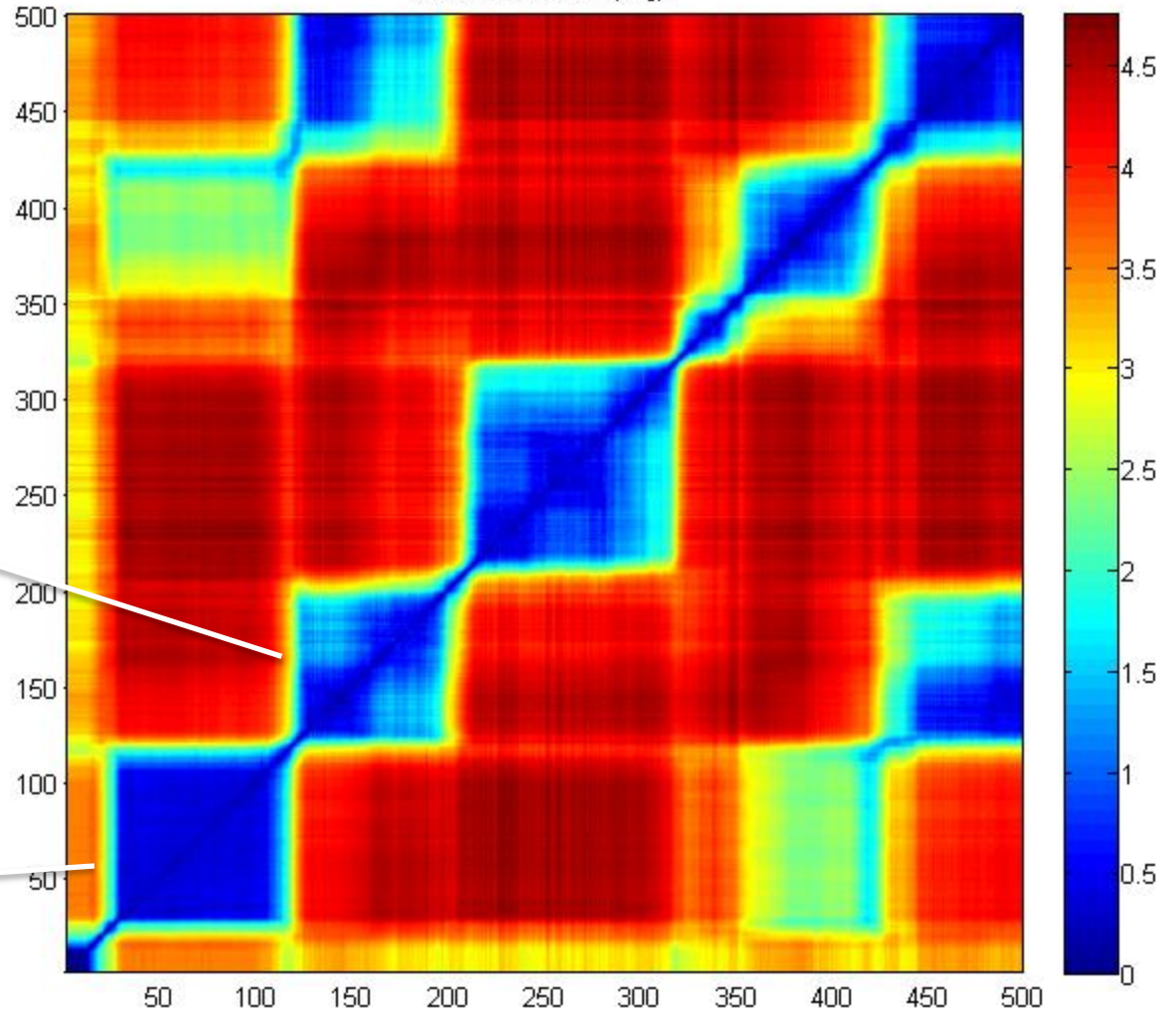
rope



flag



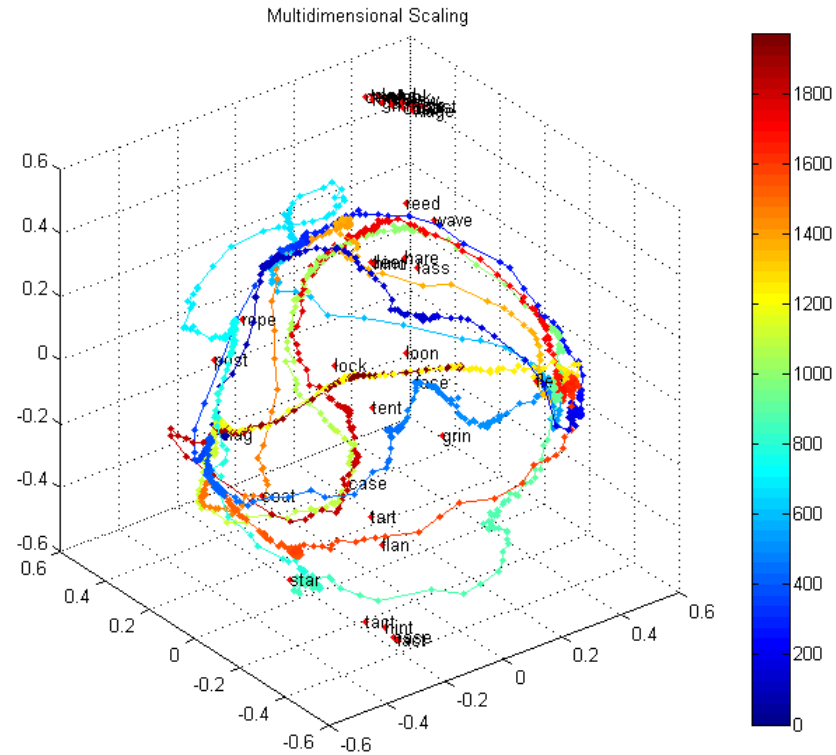
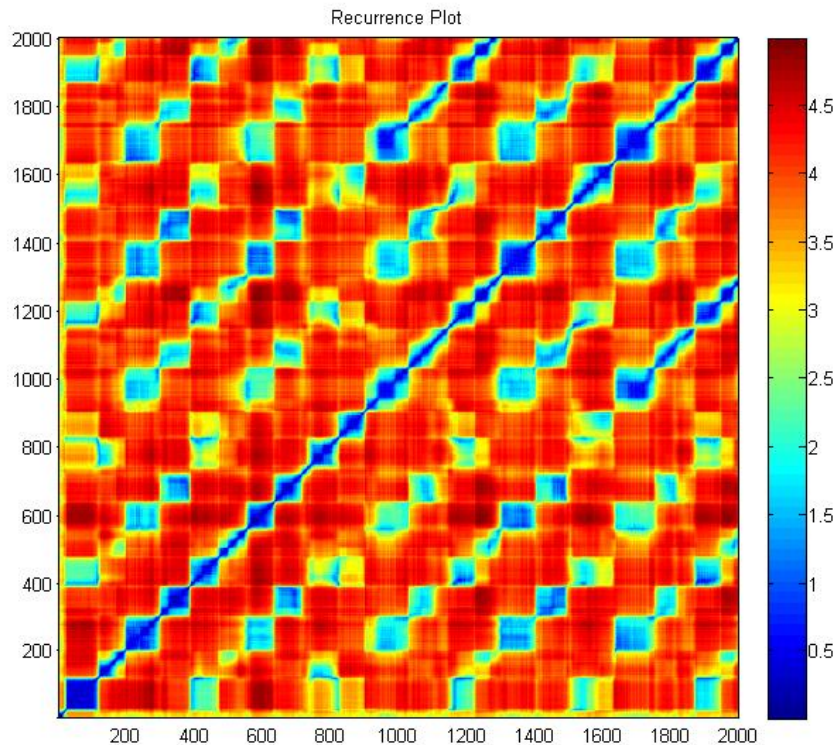
Recurrence Plot (flag)



Transitions to new patterns that share some active units (microfeatures) shown in recurrence plots.



# Trajectory visualization



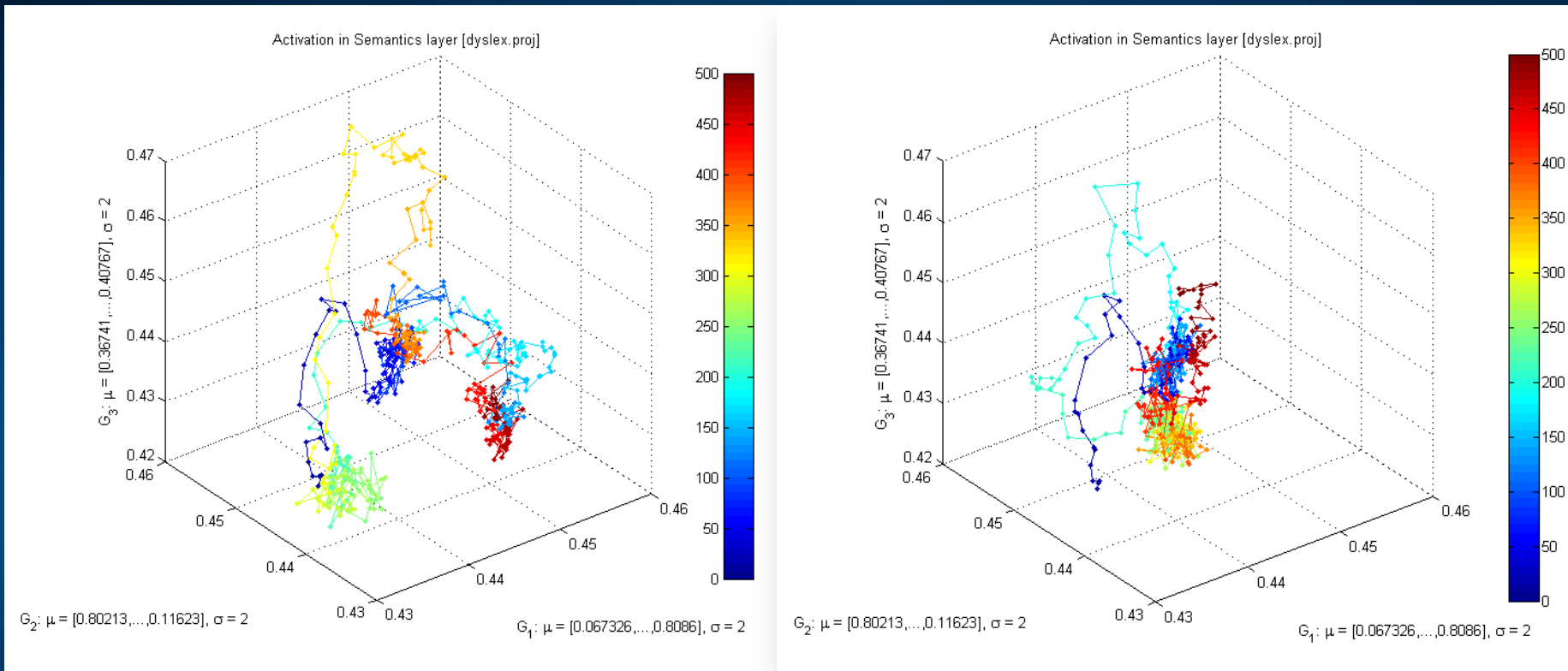
Recurrence plots and MDS/FSD/SNE visualization of trajectories of the brain activity. Here data from 140-dim semantic layer activity during spontaneous associations in the 40-words microdomain, starting with the word “flag”.

Our toolbox: <http://fizyka.umk.pl/~kdobosz/visertoolbox/>





# Typical Development vs. Autism

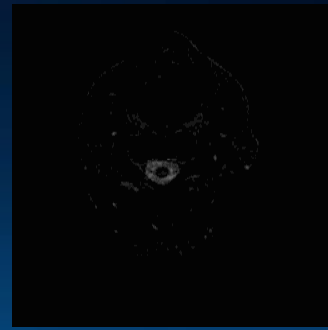


All plots for the flag word, different values of  $b\_inc\_dt$  parameter in the accommodation mechanism.  $b\_inc\_dt = 0.01$  &  $b\_inc\_dt = 0.005$   
 $b\_inc\_dt$  = time constant for increases in intracellular calcium building up slowly as a function of activation, controls voltage-dependent leak channels.

<http://kdobosz.wikidot.com/dyslexia-accommodation-parameters>



# Conclusions



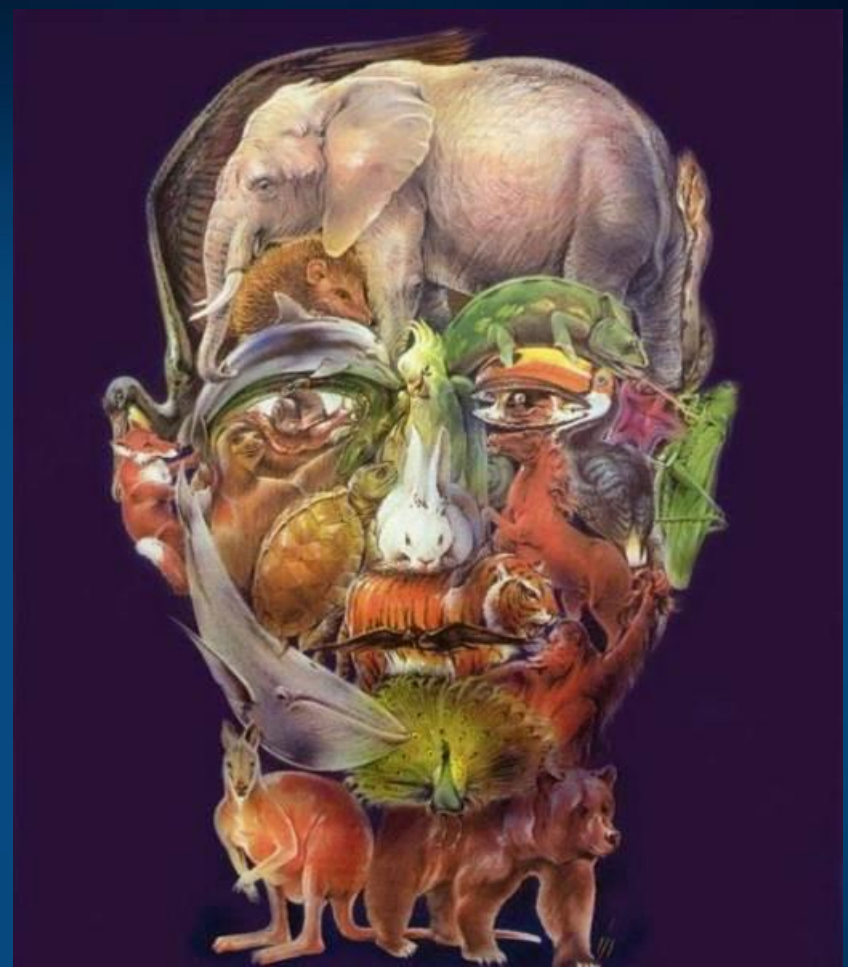
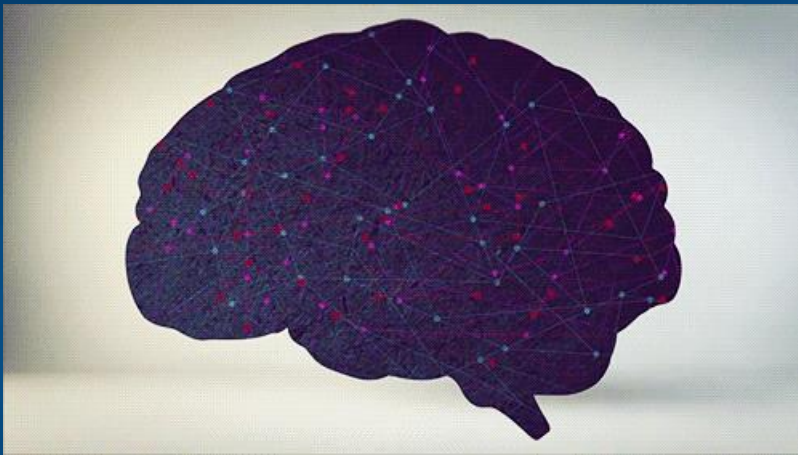
- Many brain states are now linked to specific mental states, and can be transformed into signals that we can understand: motor intentions, plans, images, inner voices ...
- Neuroimaging  $\leftrightarrow$  patterns of activity decomposed to networks, neurodynamics  $\leftrightarrow$  interpretation mental states:  $S(B) \leftrightarrow S(M)$ .
- AI/ML will continue to draw inspirations for BICA from brain research.
- Neurodynamics is the key to understanding mental states, influence of molecular/genetic levels on mental states may be understood indirectly, via changes in neurodynamics. It can be studied analyzing EEG/fMRI and computer simulations.
- Many neurocognitive technologies are coming, helping to diagnose, repair and optimize brain processes, helping in neurorehabilitation, pain management, and facilitating enhancement of human cognition. This seems to be much safer than genetic manipulation.



# My group of neuro-cog-fanatics



Thank you for  
synchronizing  
your neurons



Google: Wlodek Duch  
=> talks, papers, lectures, Flipboard ...

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