Searching for fingerprints of brain activity

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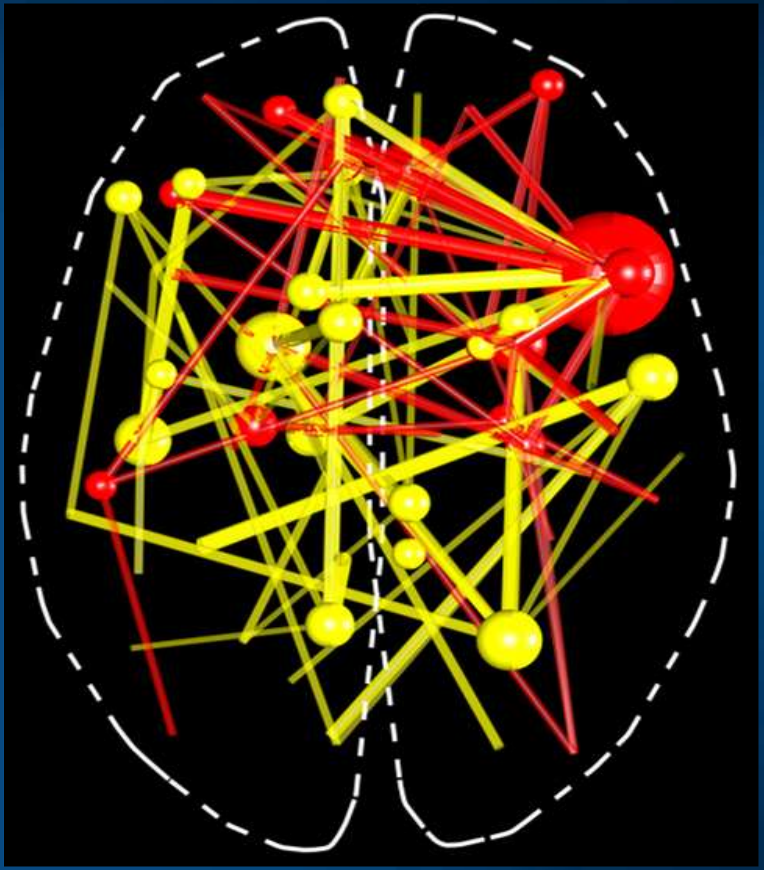
Google: Wlodzislaw Duch

International Symposium on Measurement and Control,
Huazhong University of Science and Technology, Wuhan, Hubei, China. 10.03.2021

Duch W, Mandziuk J (Eds.), *Challenges for Computational Intelligence*. Springer "Studies in Computational Intelligence" Series, Vol. 63, 2007.
Jankowski N, Duch W, Grąbczewski K, *Meta-learning in Computational Intelligence*. Springer 2011.

On the threshold of a dream …



How mental states arise from specific activity of the brain networks?

- Intro: Why is this important: global brain initiatives; human enhancement.
- Mind/Brain at many levels.
- Brain networks – space for neurodynamics.
- Simulation of brain networks.
- Fingerprints of real mental activity.
- Dynamic functional brain networks.

Final goal: Use your brain to the max! Optimization of brain processes?

Duch W. (2012) Mind-Brain Relations, Geometric Perspective and Neurophenomenology, American Philosophical Association Newsletter 12(1)

Human Brain Project, EU Flagship, and Obama BRAIN Initiative (2013):
Brain **R**esearch through **A**dvancing **I**nnovative **N**eurotechnologies.

Total cost of brain disorders in EU estimated in 2010: 798 billion €/year, and in China far greater!

IEEE wants to “Develop new technologies to explore how the brain’s cells and circuits interact at the speed of thought, ultimately uncovering the complex links between brain function and behavior. Explore how the brain records, processes, uses, stores, and retrieves vast quantities of information.
Help bring safe and effective products to patients and consumers.”

This is joint effort of many IEEE Societies.

Neuroscience ⇔ AI

Hassabis, D., Kumaran, D., Summerfield, C., Botvinick, M. (2017). Neuroscience-Inspired Artificial Intelligence. *Neuron*, *95*(2), 245–258.
Collaboration of: Google DeepMind, Gatsby Computational Neuroscience, Institute of Cognitive Neuroscience, Uni. College London, Uni. of Oxford.

Artificial neural networks – simple inspirations, but led to many applications.

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

Amoset 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) Numenta Hierarchical temporal memory (HTM), Jeff Hawkins theory of the neocortex, new book (3/2021) „A thousand brains" with more ideas.

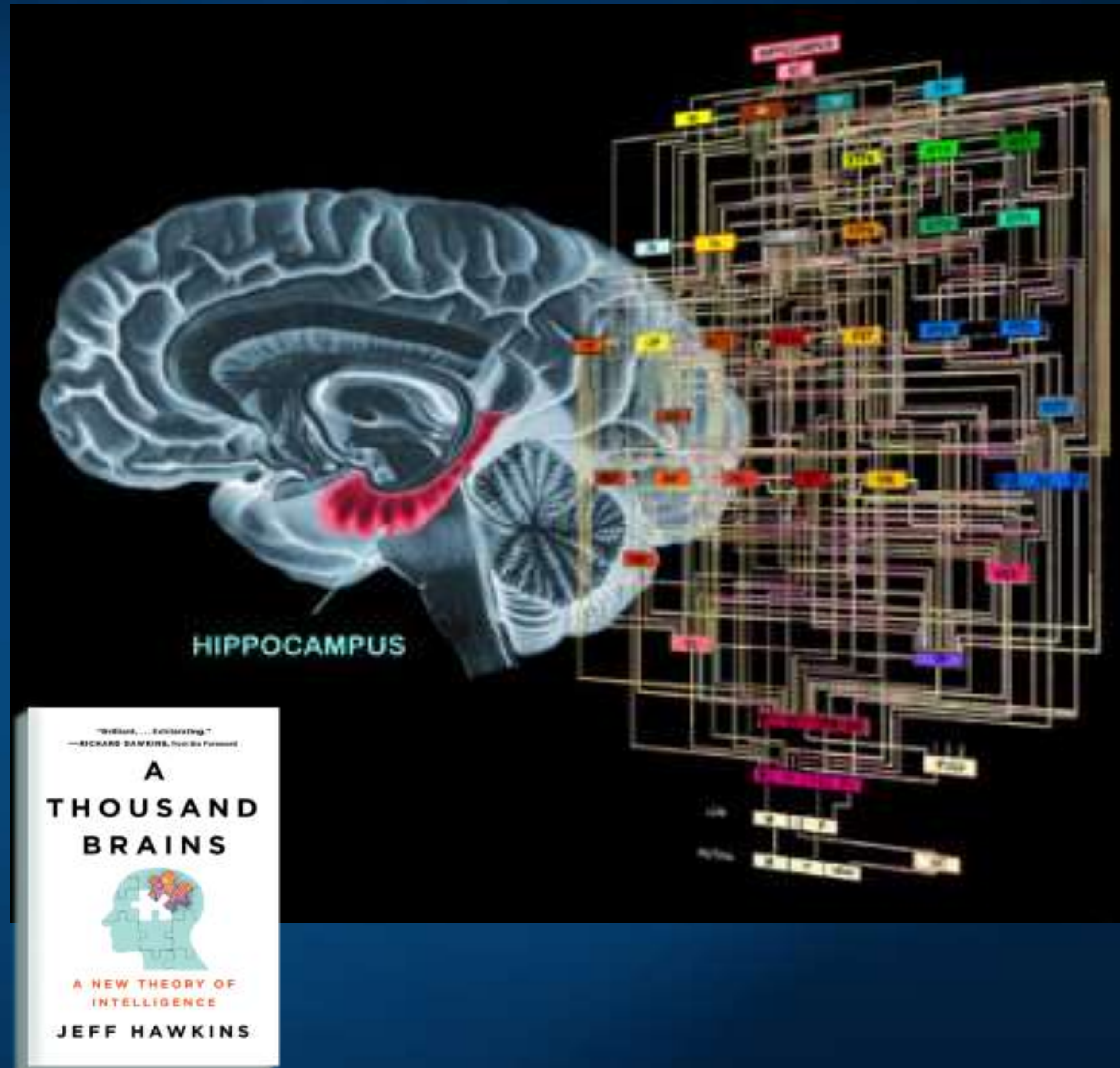
BICA, Brain-Inspired Cognitive Architecture

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

How to create BICA for flexible intelligence?

"We'll never have true AI without first understanding the brain" Jeff Hawkins.

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



Frames, capsules and attractors

Simplification of neurodynamics, model of brain/mental states.

My proposal: Feature Space Mapping neurofuzzy model (1995).

Neurodynamics: characterization of basins of attractors and transitions.

Kozma/Freeman: cinematic theory, metastable states in dynamical systems.

Hawkins: frames, grid cells, cortical columns, sequence learning in HTM.

Hinton: capsule networks for image segmentation and recognition.

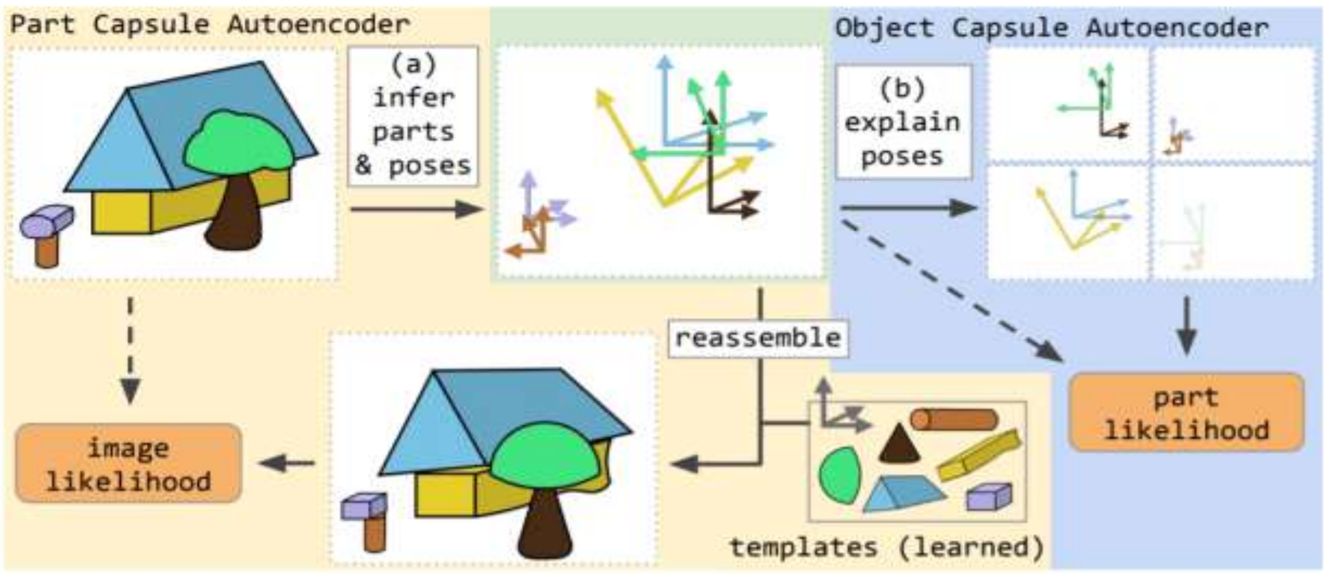
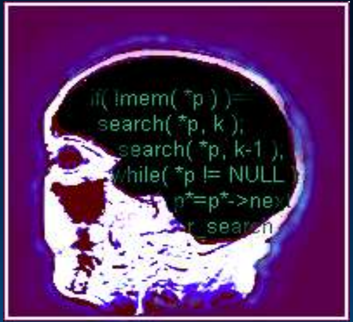


Figure 1: Stacked Capsule Autoencoder (SCAE): (a) *part* capsules segment the input into parts and their poses. The poses are then used to reconstruct the input by affine-transforming learned templates. (b) *object* capsules try to arrange inferred poses into objects, thereby discovering underlying structure. SCAE is trained by maximizing image and part log-likelihoods subject to sparsity constraints.

Simplifying brain functions

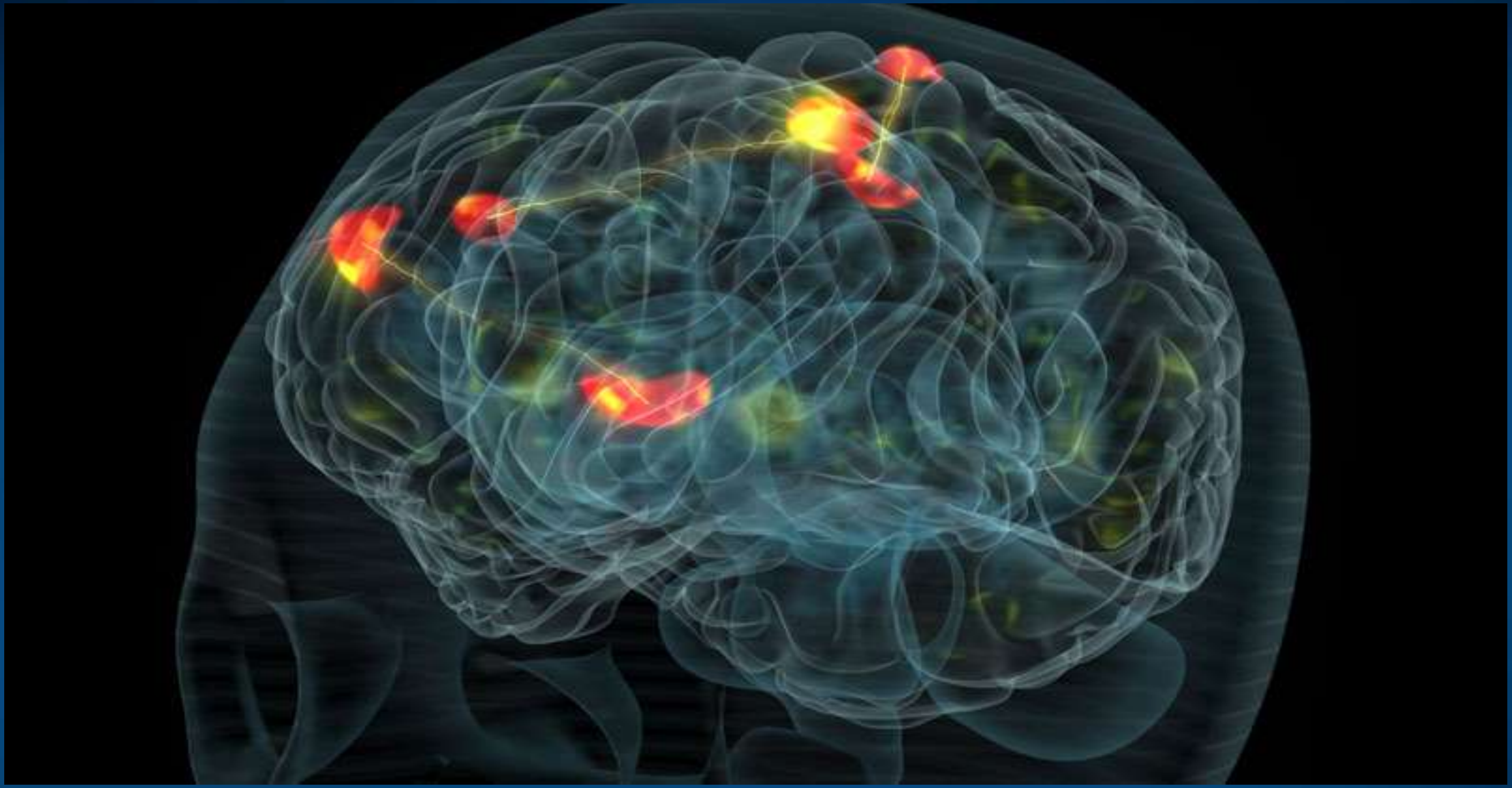
Towards Artificial Brains



Many theories of brain functions. My attempts:

- Duch W (1994) *Towards Artificial Minds* (conf).
- Duch W (1996) *Computational physics of the mind*.
  Computer Physics Communication **97**: 136-153   Metatable states.
- Duch W (1996) *From cognitive models to neurofuzzy systems - the mind space approach.* Systems Analysis-Modelling-Simulation 24 (1996) 53-65
- Duch W (1997) *Platonic model of mind as an approximation to neurodynamics*. In: Brain-like computing and intelligent information systems, ed. S-i. Amari, N. Kasabov (Springer 1997), pp. 491-512
- Duch, W. (2019) *Mind as a shadow of neurodynamics*. Physics of Life Reviews 31: 28-31. Special Issue "Physics of mind", Ed. F. Schoeller (2020)
- Duch. W. (2020) *Experiential Learning Styles and Neurocognitive Phenomics*. PsyArXiv. August 30, 2020. q-bio.NC ArXiv. January 12, 2021.
- Duch W. (2021) *Memetics and Neural Models of Conspiracy Theories*. arXiv.org > q-bio > arXiv:1508.04561, 14 pp..

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?

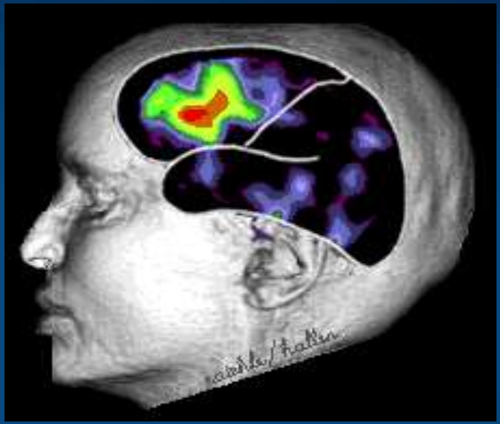
Various subnetworks compete for access to the highest level of control - consciousness, the winner-takes-most mechanism leaves only the strongest. How to extract stable intentions from such chaos? BCI is never easy.

Brains ⇔ Minds

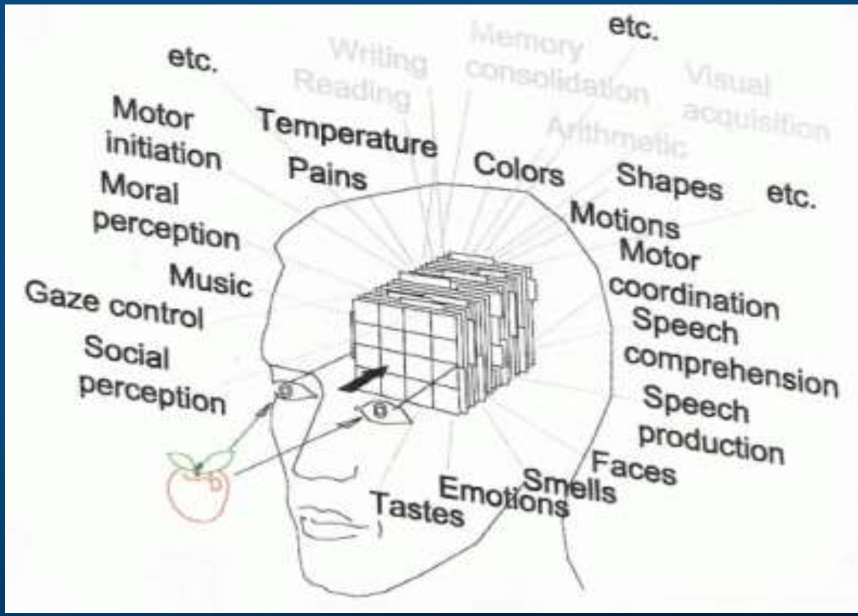
Define mapping S(M)⇔S(B), as in BCI.
How do we describe the state of mind?

Verbal description is not sufficient unless words are represented in a space with dimensions that measure different aspects of experience.

Stream of mental states, movement of thoughts
⇔ trajectories in psychological spaces.



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



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

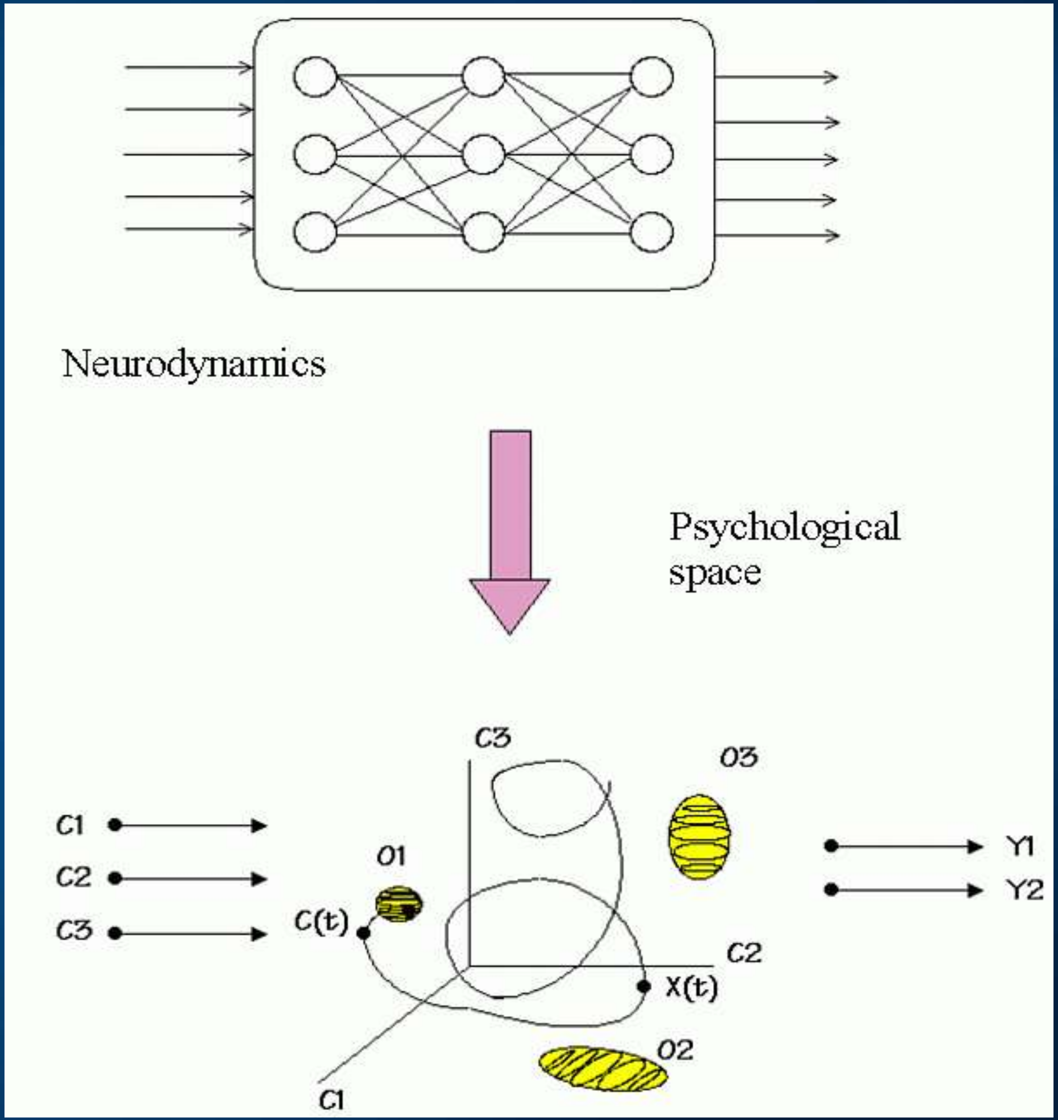
E. Schwitzgabel, Perplexities of Consciousness. MIT Press 2011.

Networks ⇔ mental objects

Neurodynamics (simulated, observed) may be linked to geometric description of mental states or "objects"
in some "mind space", or
P-space, using attractor networks.

Attractors networks have meta-stable states, patterns of neural activity.

Features of mental objects are coded in cortical columns, variance depends on the size of attractor basin.



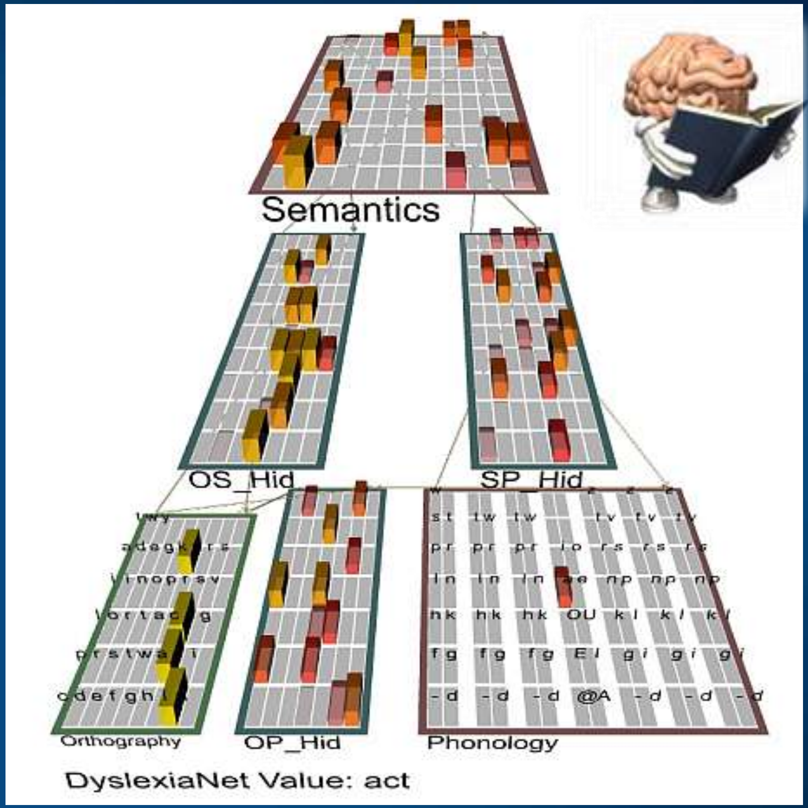
Model of reading & dyslexia

Emergent neural simulator:

Aisa, B., Mingus, B., and O'Reilly, R.
The emergent neural modeling system. Neural Networks, 21, 1045, 2008.
Point neurons with 3 kinds of ion channels.

3-layer model of reading:

orthography, phonology, semantics = distribution of activity over
140 microfeatures defining concepts. Hidden layers OS/OP/SP_Hid in between.
In the brain: microfeature = subnetwork.

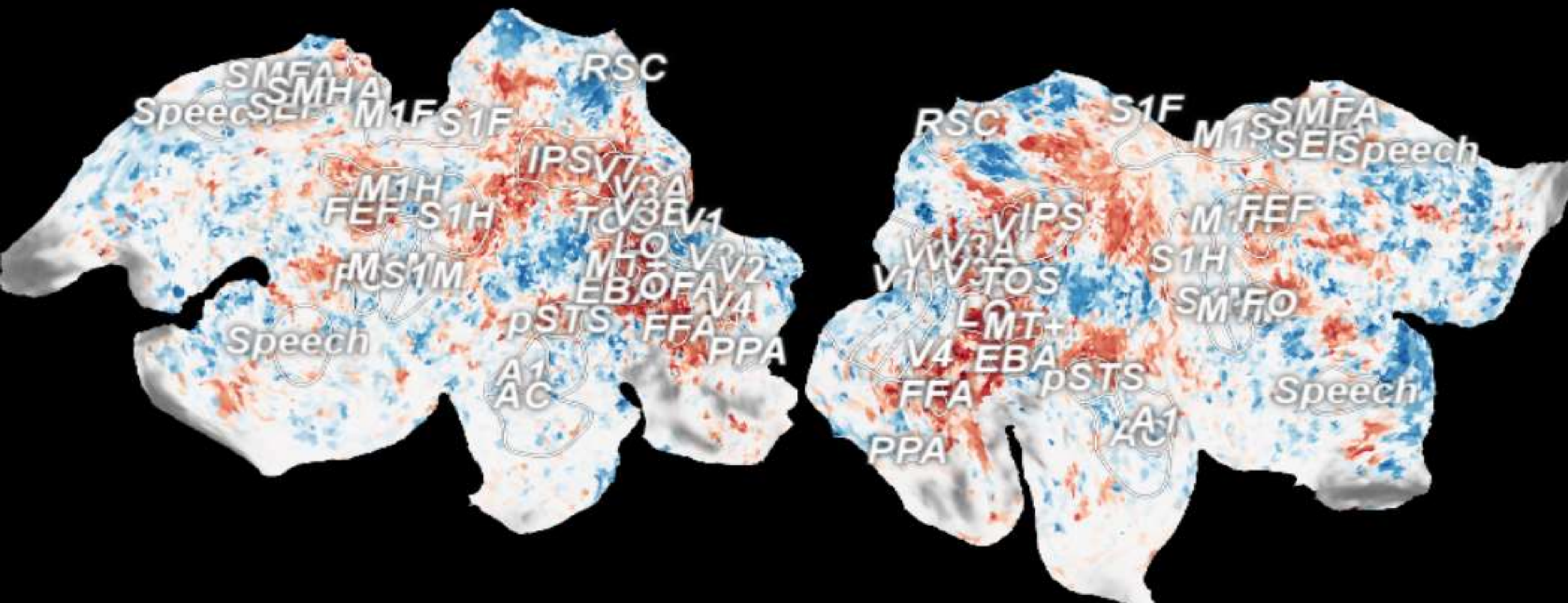


Learning: mapping one of the 3 layers to the other two, LEABRA algorithm.

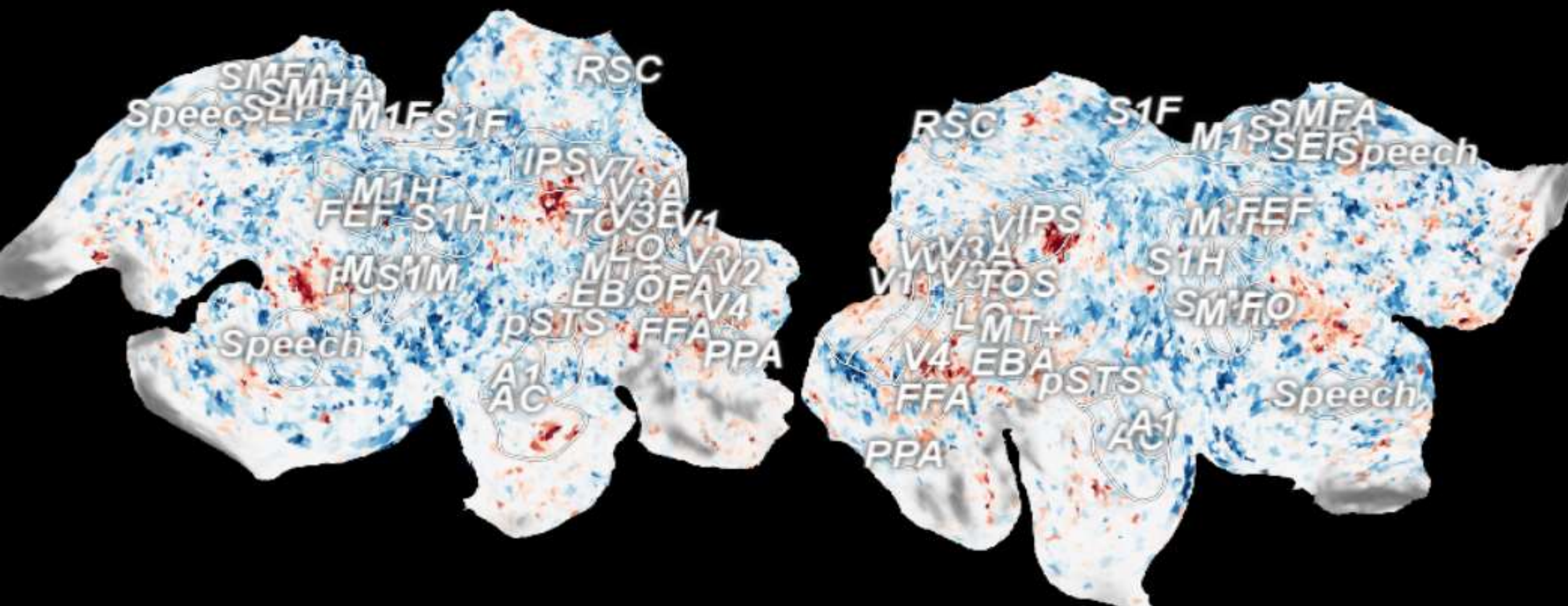
Fluctuations around final configuration = attractors representing concepts.

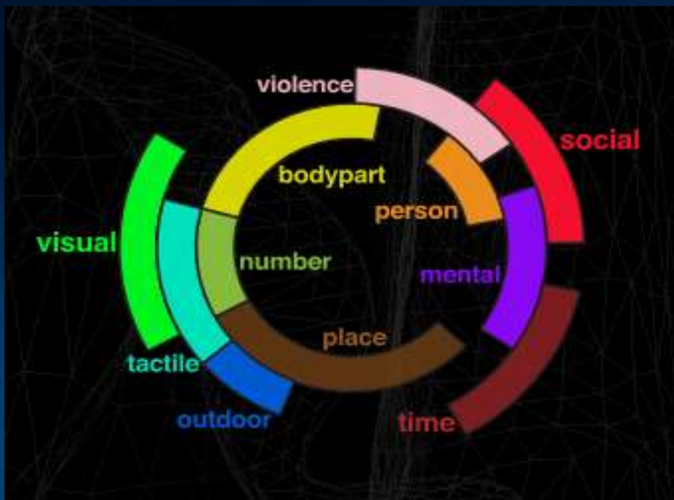
How to see trajectory of neurodynamics, attractor basins, transitions?
Genesis simulator offers more detailed neuron models, but is harder.

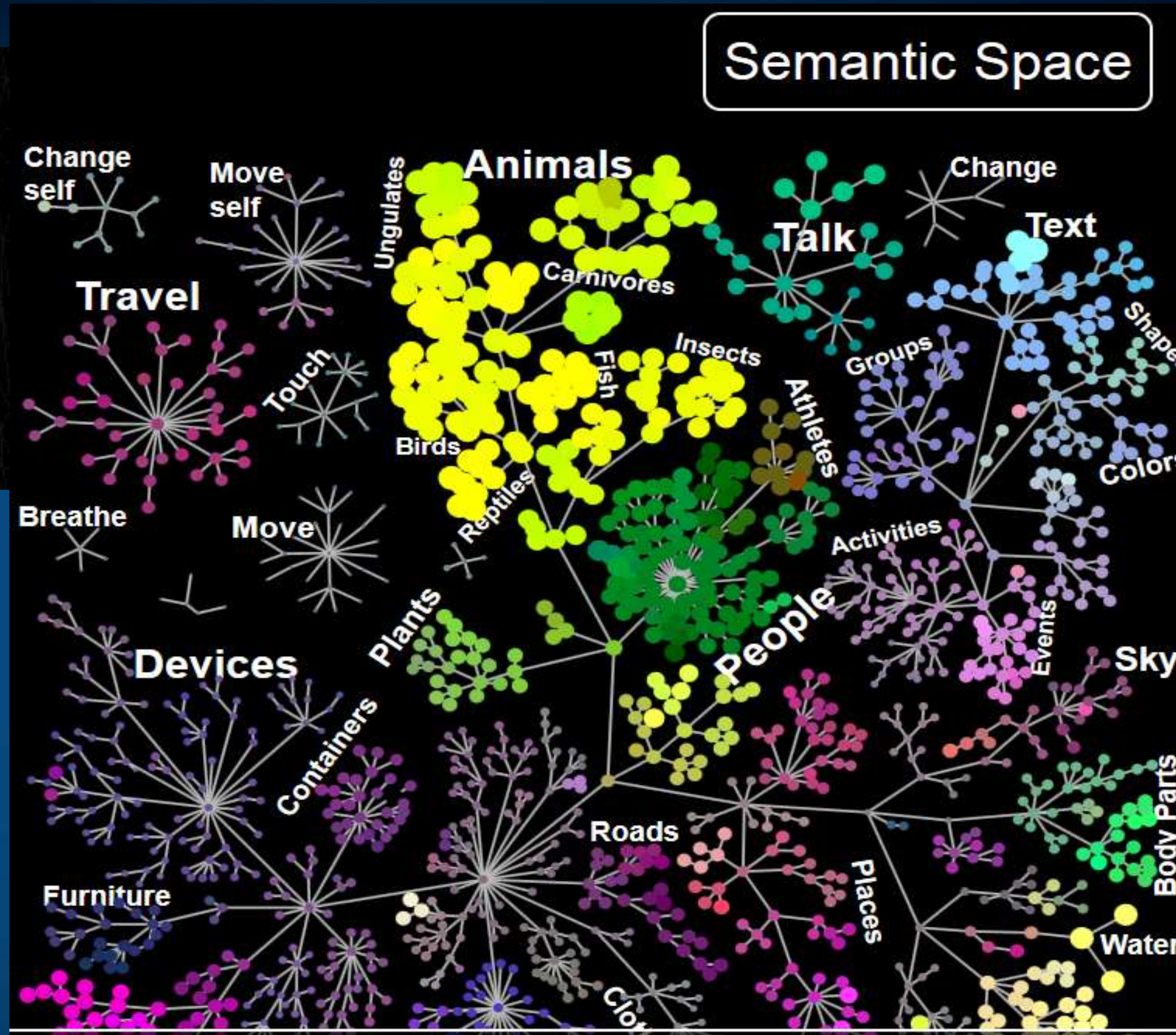
Category zebra: Passive Viewing



Category traffic light: Passive Viewing

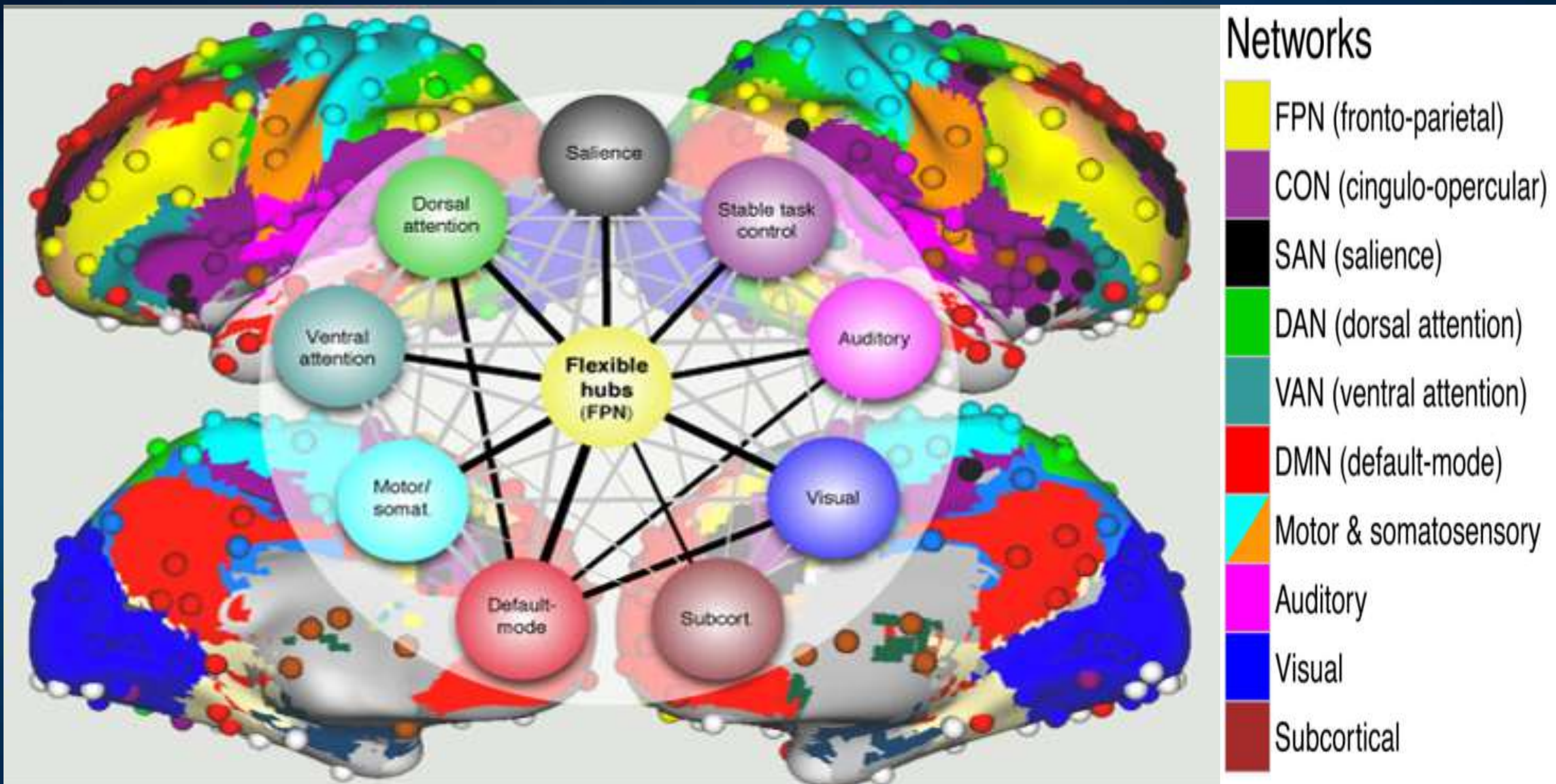






Huth in Gallant lab created maps of fMRI brain activity (60K voxels) for a number of words clustered around different concepts. http://gallantlab.org/

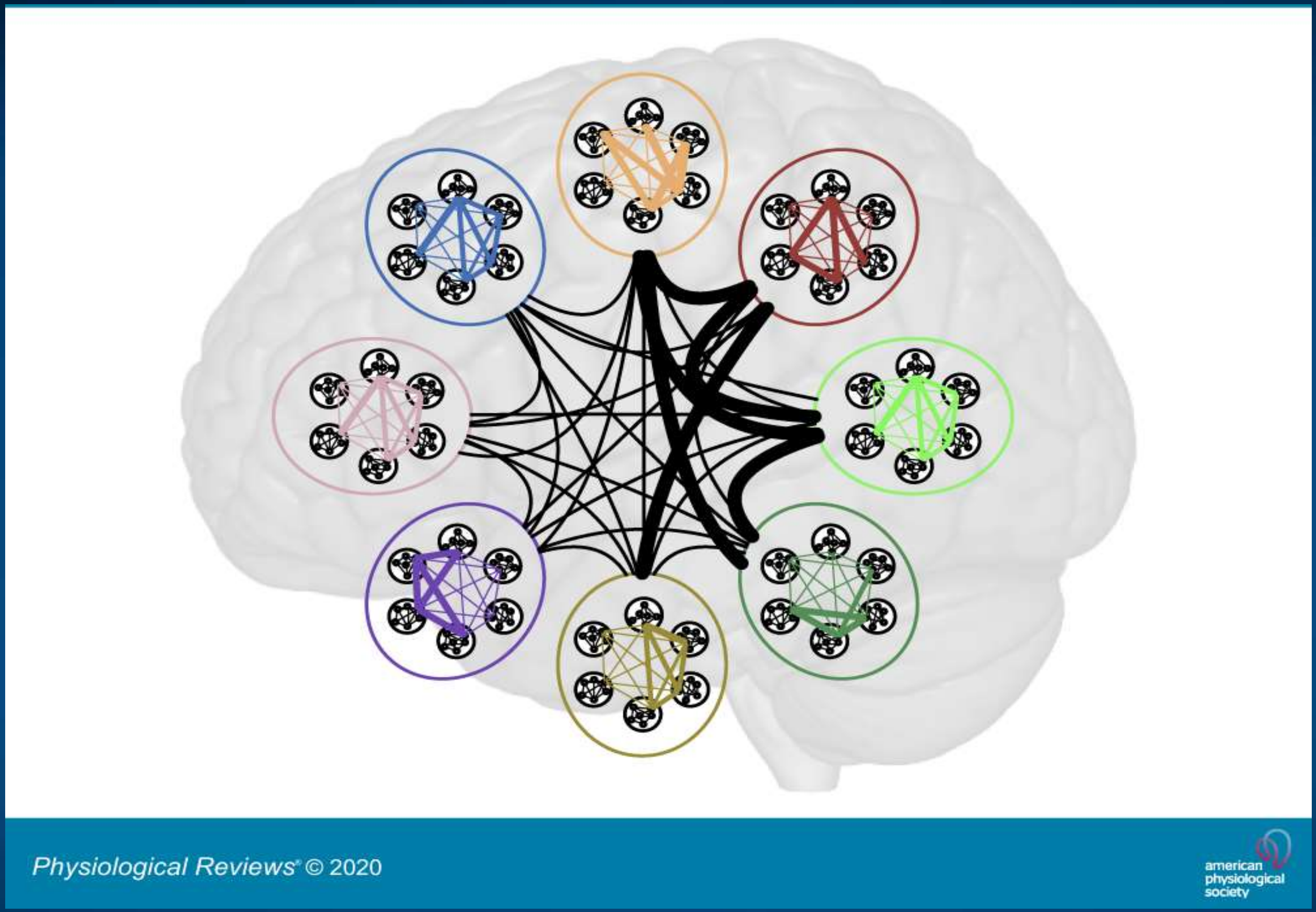
Neurocognitive Basis of Cognitive Control



Central role of fronto-parietal (FPN) flexible hubs in cognitive control and adaptive implementation of task demands.

Black lines=correlations significantly above network average. From Cole et al. (2013).

~ Small worlds architecture



All complex functions are based on synchronization of many distributed brain areas. Memory, personality or consciousness are collection of functions, like multi-agent systems or the "society of mind". Psychological constructs should be "deconstructed" to connect them with specific brain processes.

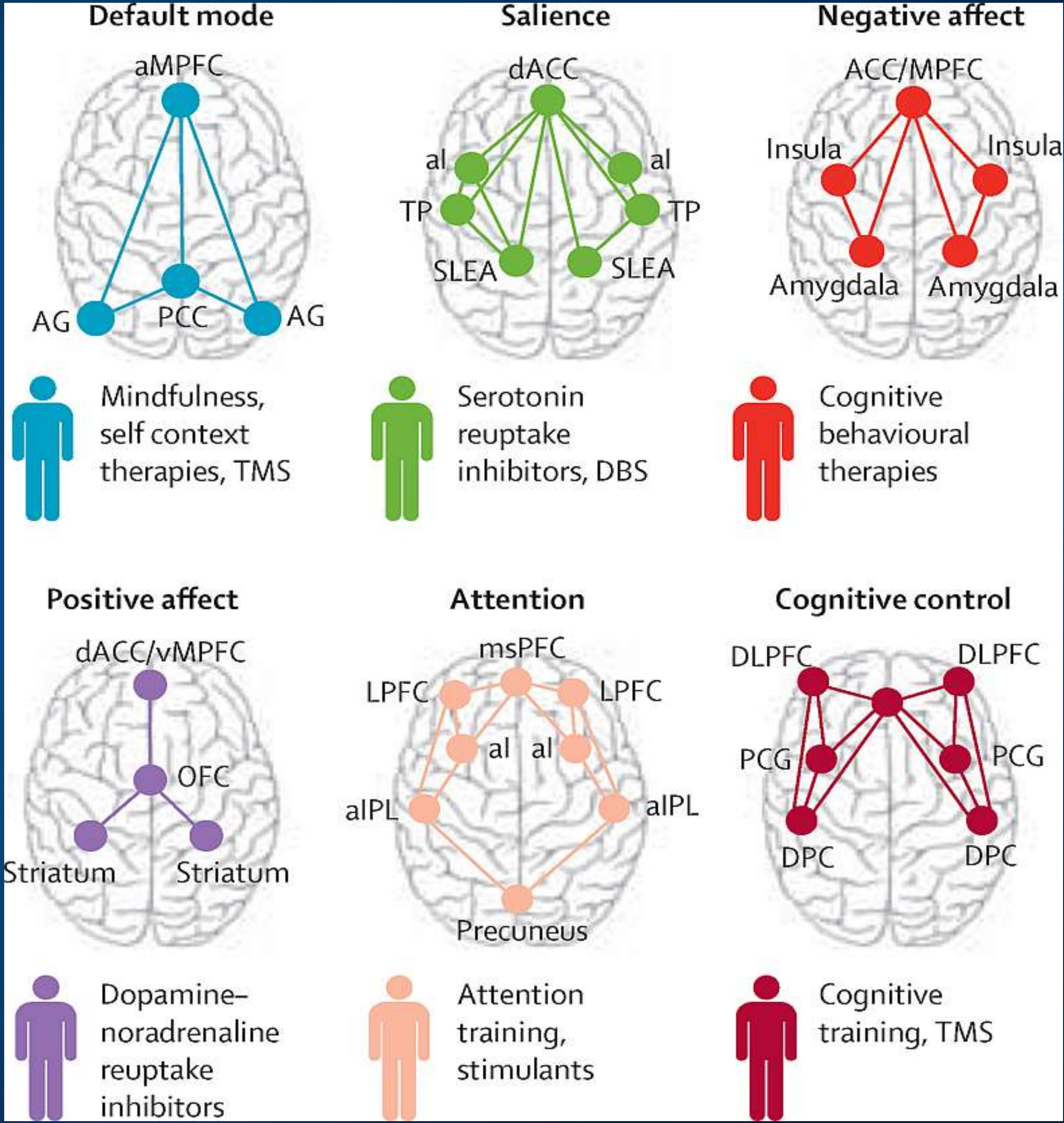
Multi-level phenomics

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.

Decompose brain network dynamics into activity of large-scale networks, meaningful components of activity related to various brain functions.

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

M. Minsky, Society of mind (1986)
Agent = subnetwork implementing specific function.



RDoC
Research Domain Criteria Initiative

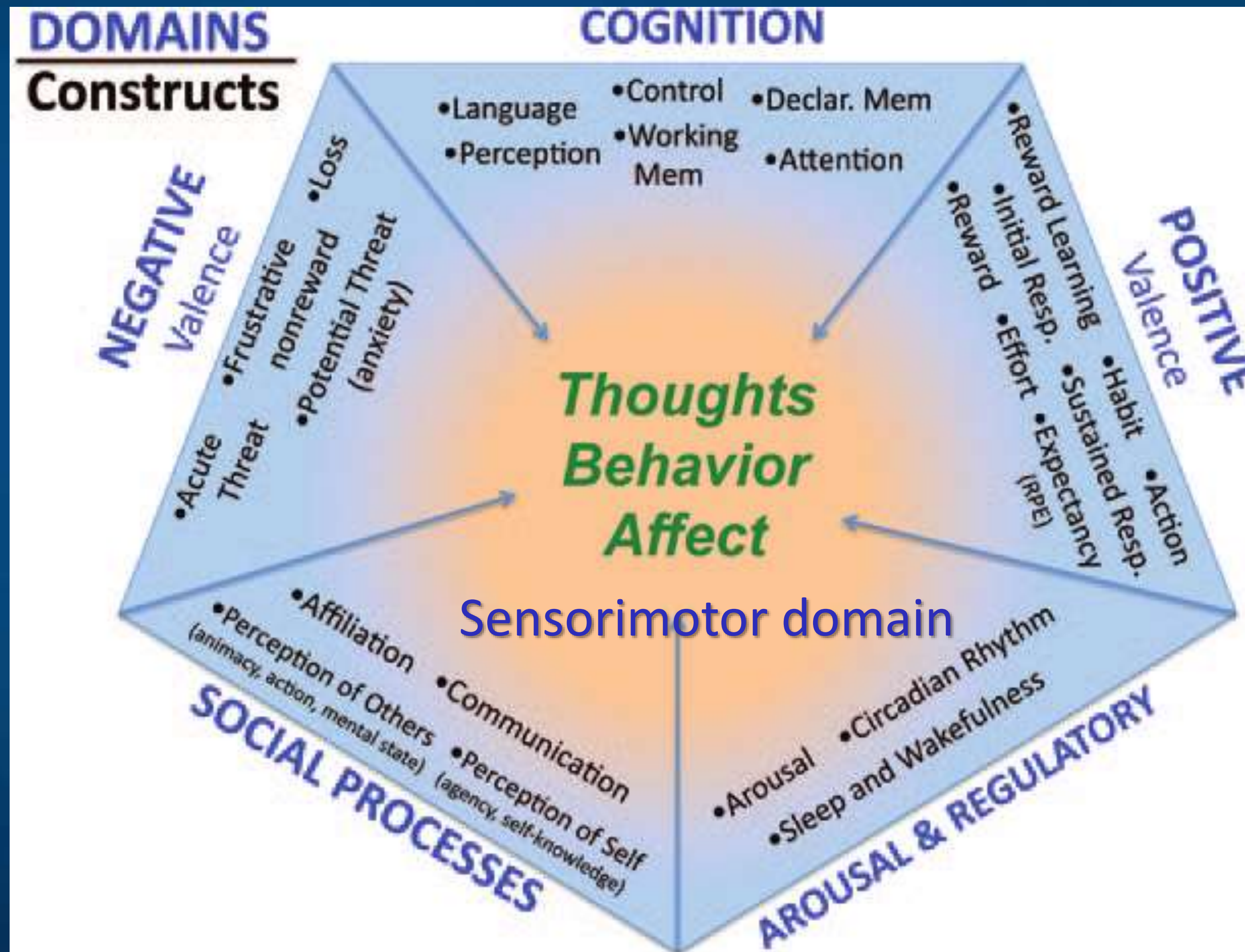
NIMH RDoC Matrix for deregulation of 6 large brain systems.

Psychological constructs are necessary to talk about mental states.

Sensorimotor systems added in Jan. 2019 as sixth brain system.

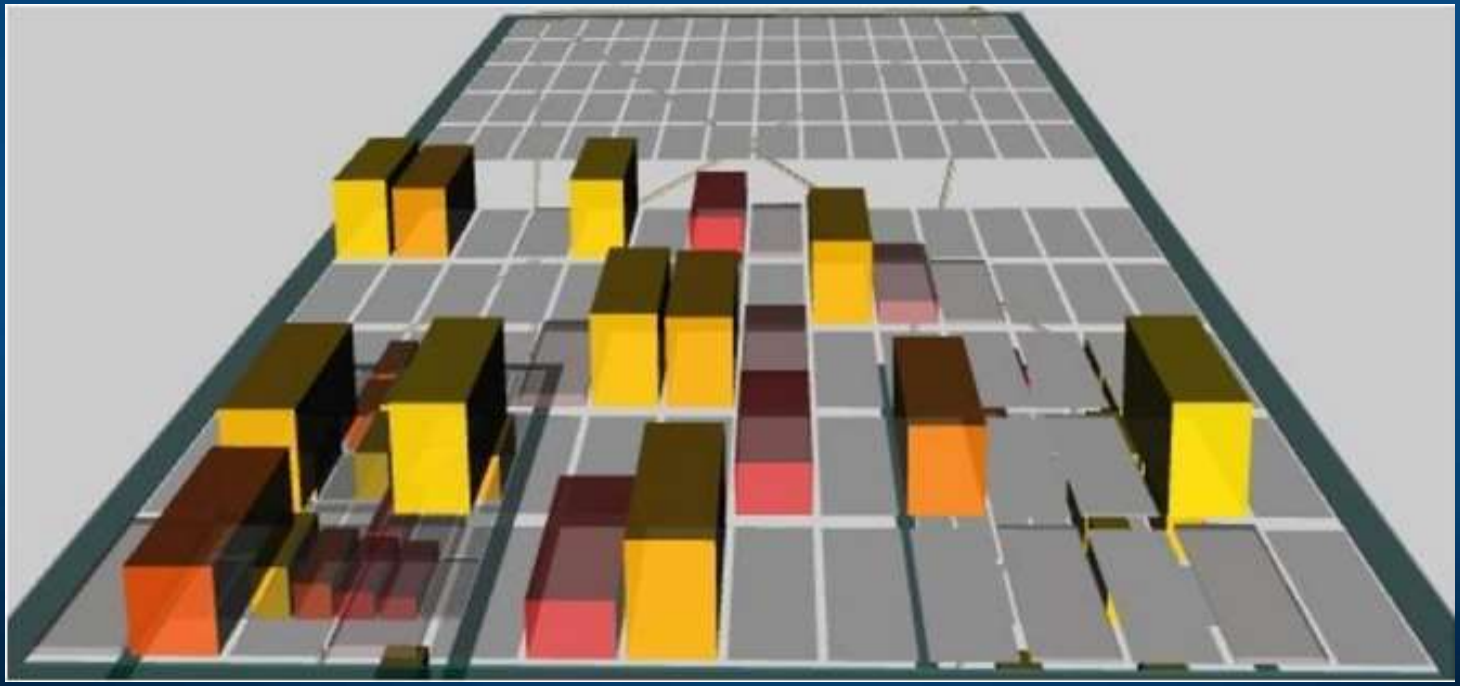
This is the basis of computational psychiatry.

How are these functions implemented in the brain?

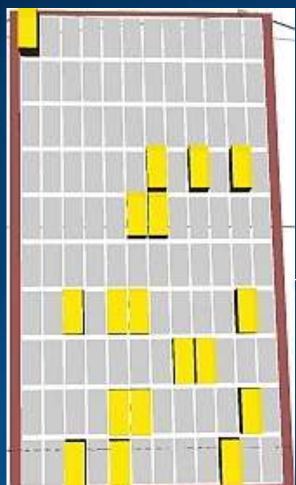


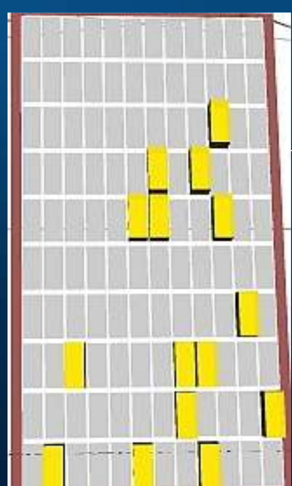
Semantic layer

Semantic layer in our simulations has 140 units.
Here activity for the word "case" is shown, upper 70 units code abstract microfeatures, lower physical properties. Representation is sparse.
Concepts/words are identified by a pattern of active features.
Associations = transitions between patterns, can be formed in many ways.

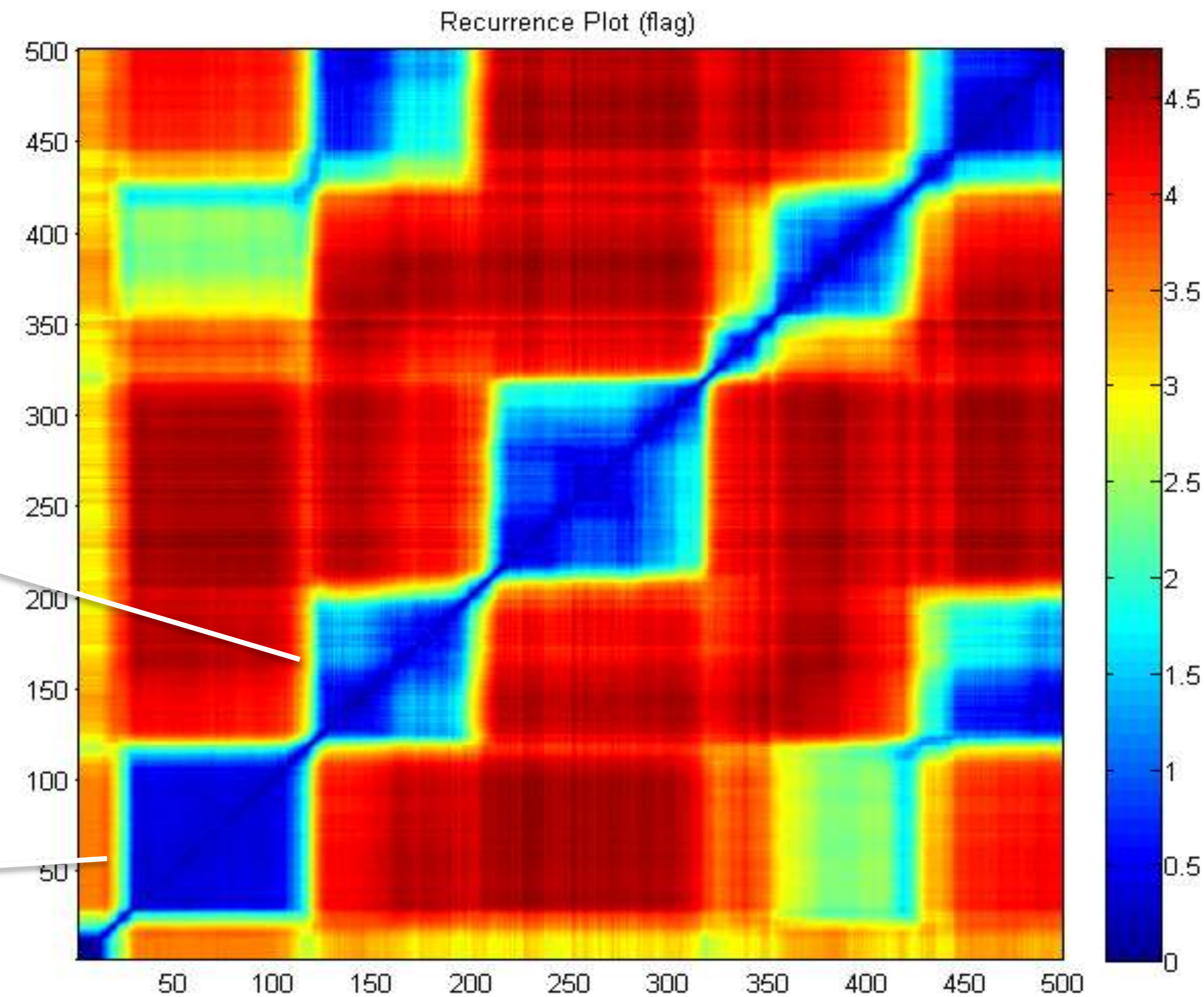


rope



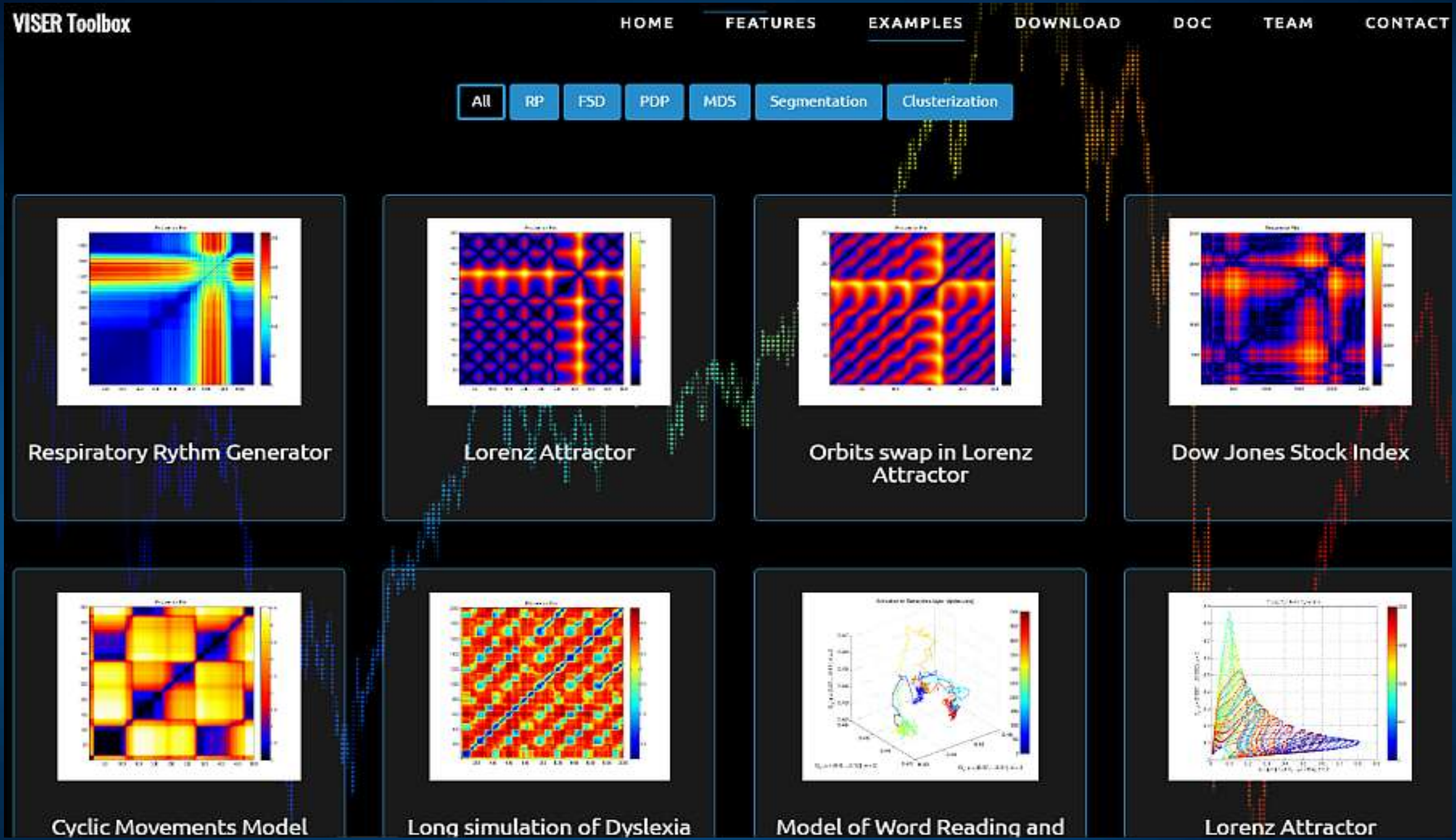


flag



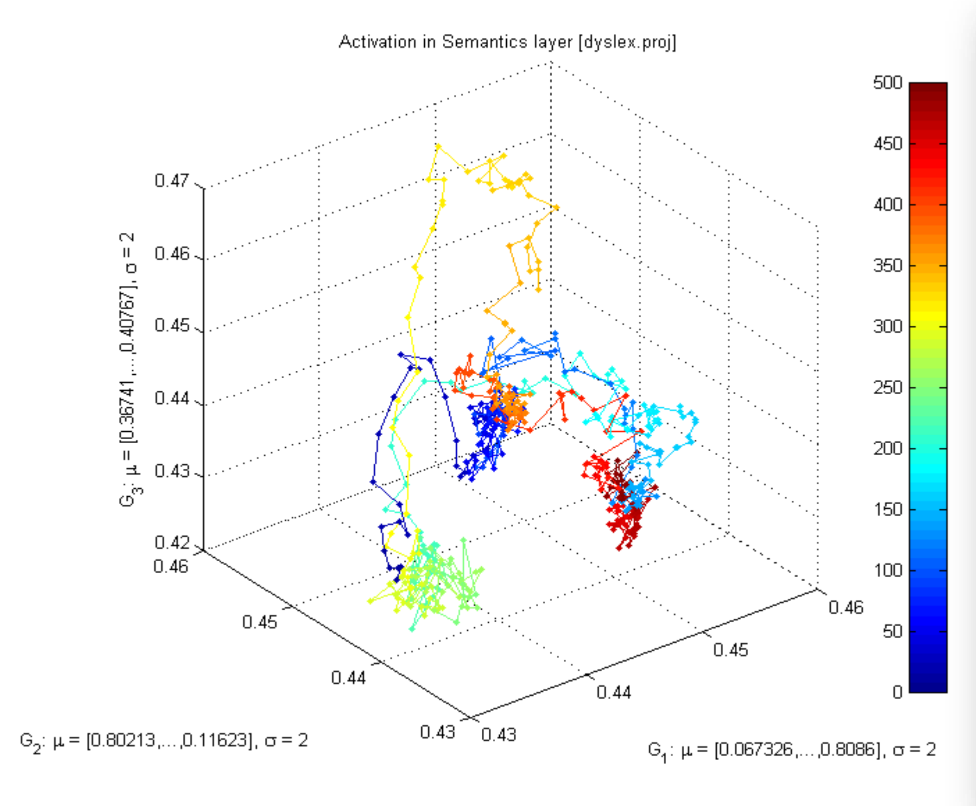
Transitions to new patterns that share some active units (microfeatures); in recurrence plots attractor basins are seen.

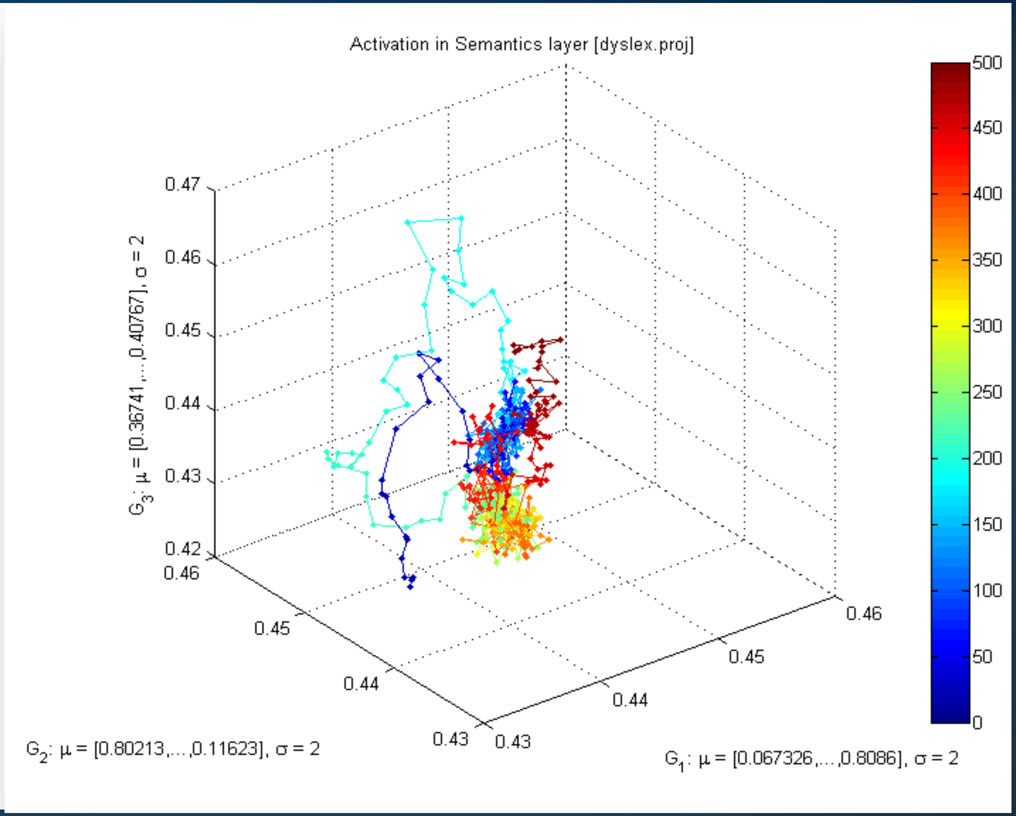
Viser toolbox



Viser toolbox (Dobosz, Duch) for visualization of time series data, including our Fuzzy Symbolic Dynamics (Neural Networks 23, 2010) approach.

Typical Development vs. Autism

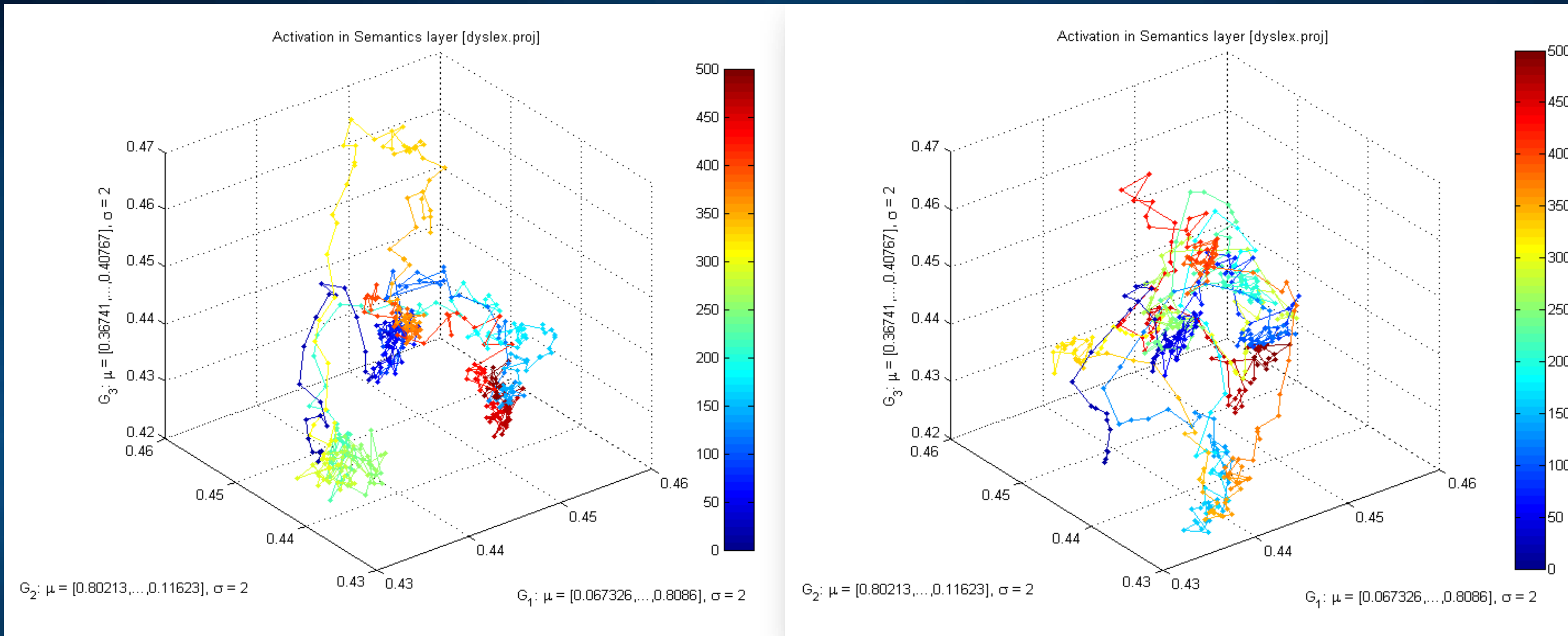




All plots for the flag word, different values of b_inc_dt parameter in the accommodation mechanism. b_inc_dt = 0.01 & b_inc_dt = 0.005

b_inc_dt = time constant for increases in intracellular calcium building up slowly as a function of activation, controls voltage-dependent leak channels.

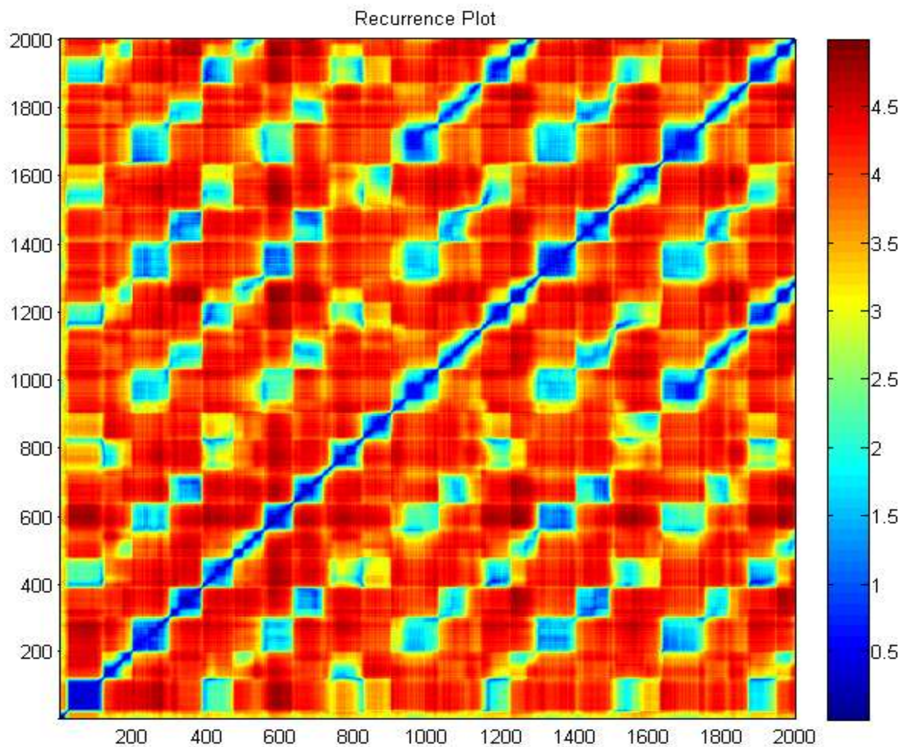
Typical Development vs ADHD

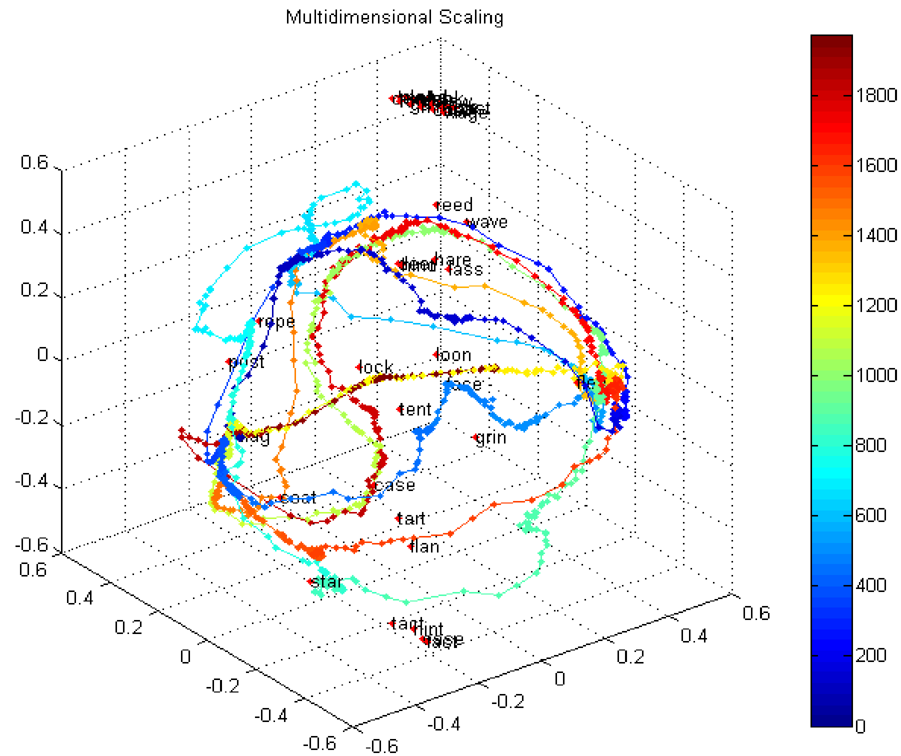


All plots for the flag word, different values of b_inc_dt parameter in the accommodation mechanism. b_inc_dt = 0.01 & b_inc_dt = 0.02.

b_inc_dt = time constant for increases in intracellular calcium which builds up slowly as a function of activation.

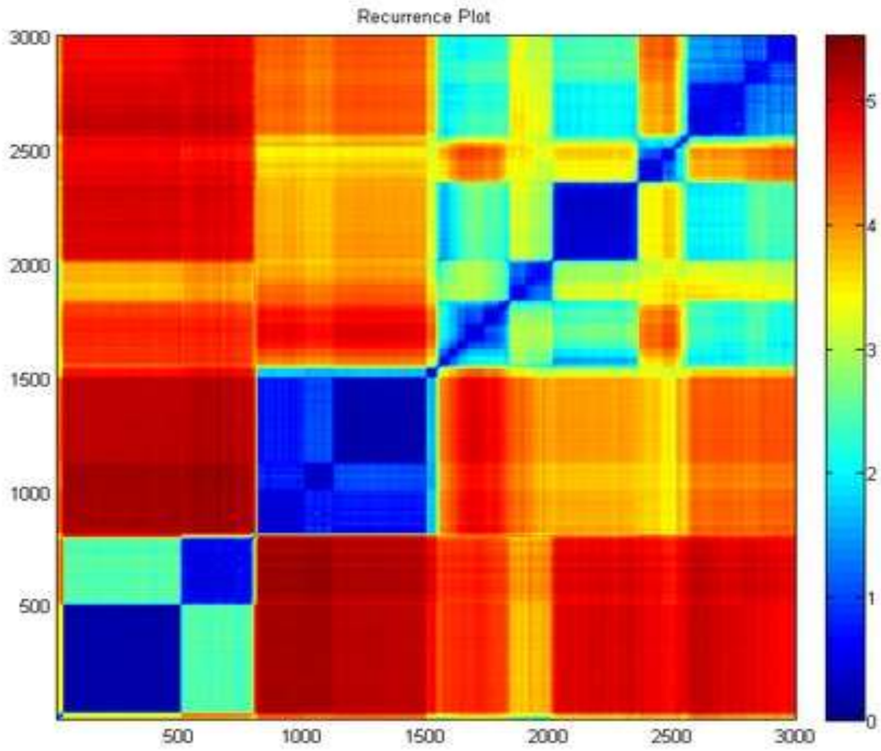
Trajectory visualization

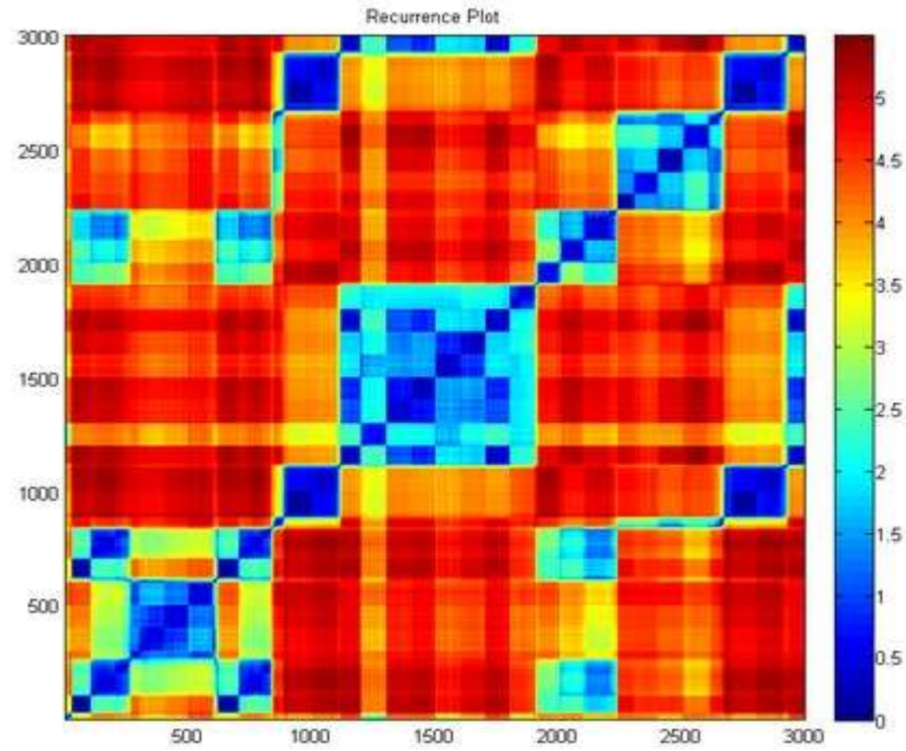




Recurrence plots and MDS visualization of trajectories of the brain activity. Here evolution of 140-dim semantic layer activity during spontaneous associations in the 40-words microdomain is presented, starting with the word “flag”. Trajectories may be displayed using tSNE, UMAP, MDS or our FSD visualization.

Simulations of rapid stimulation in autism

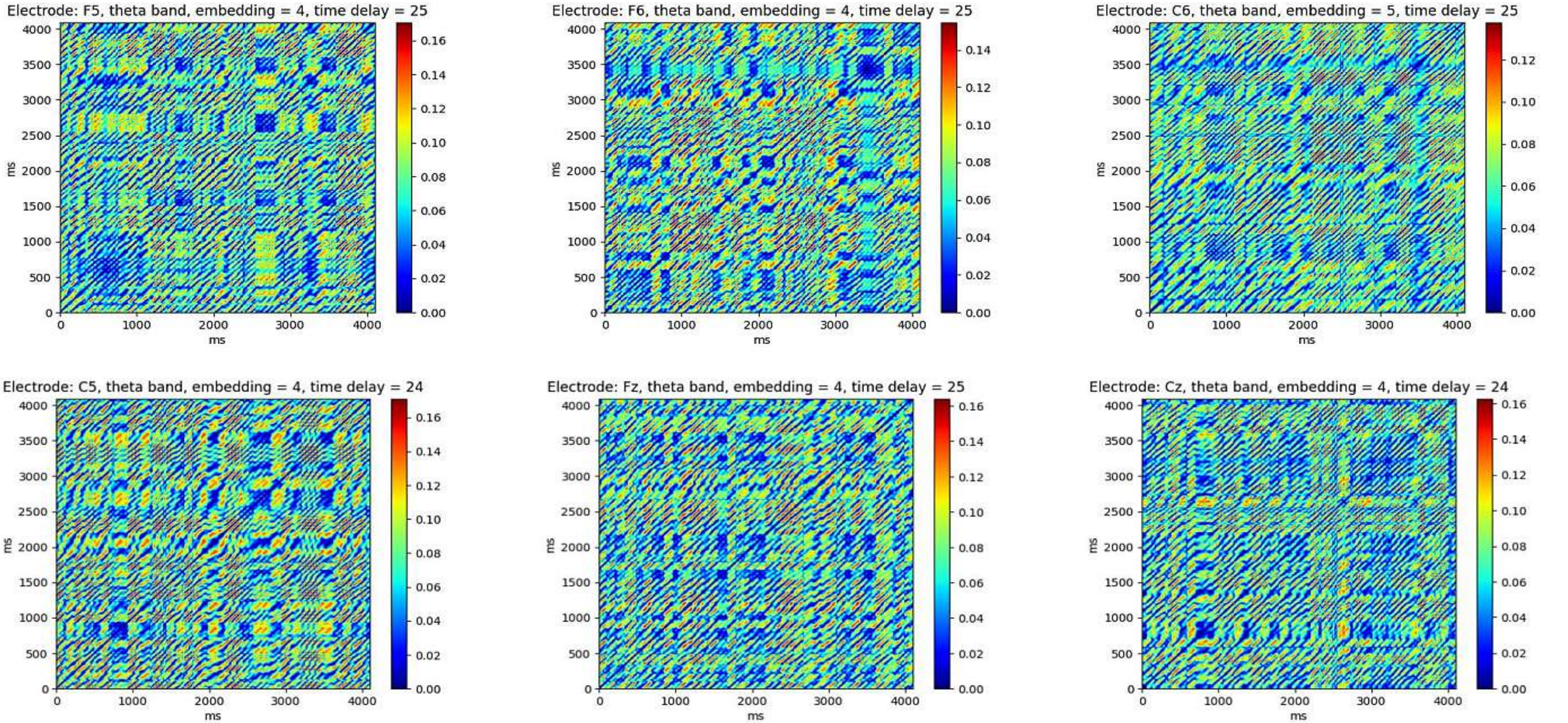




Normal speed
skipping some words,
no associations

fast presentation
more internal states
some associations arise

EEG resting state



HD EEG, selected 6 channels in theta band.
Attractor reconstruction using embedding: $[y(t), y(t-\tau), y(t-2\tau), \ldots, y(t-2n\tau)]$.

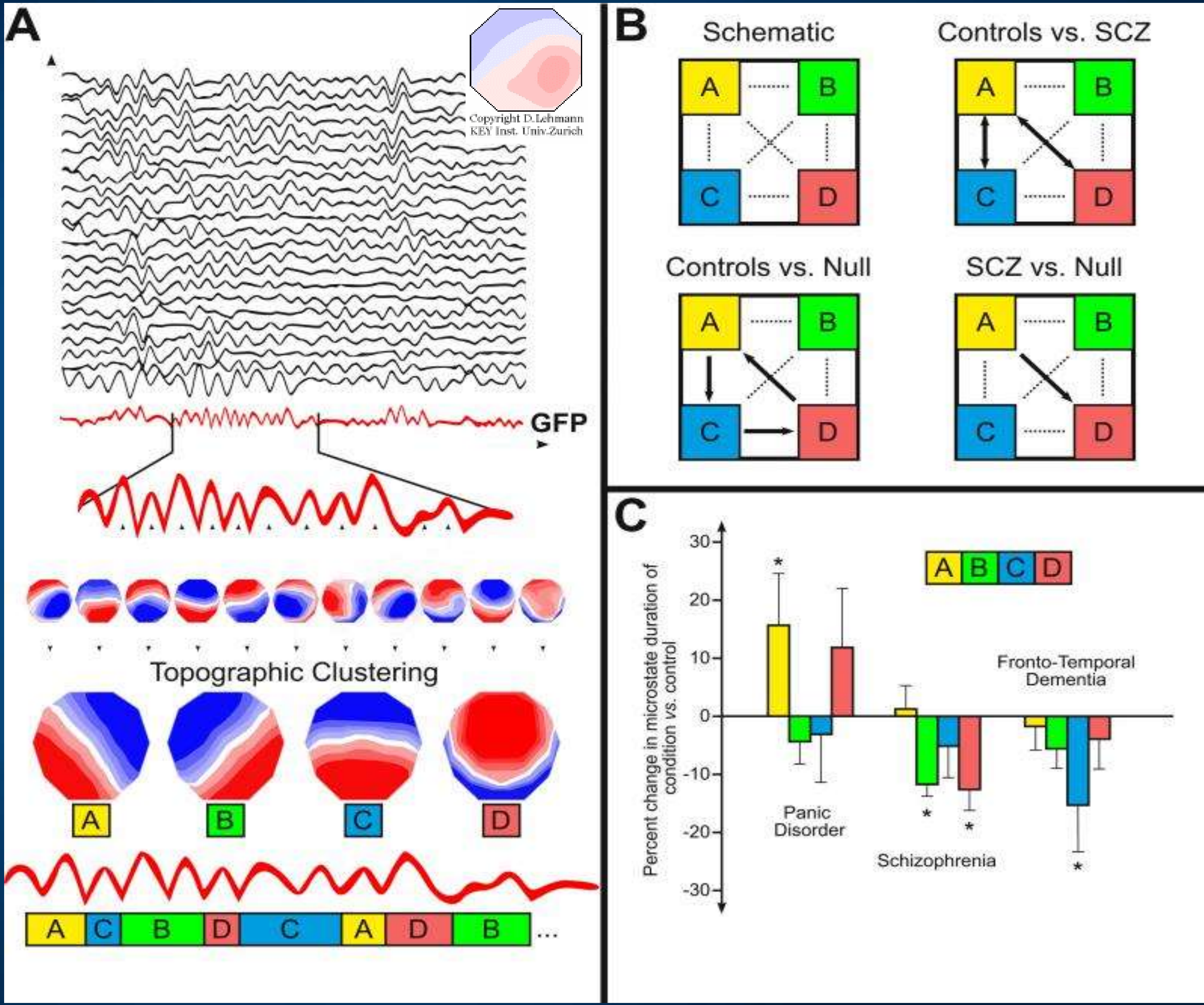
EEG microstates for diagnostics

Global EEG Power.

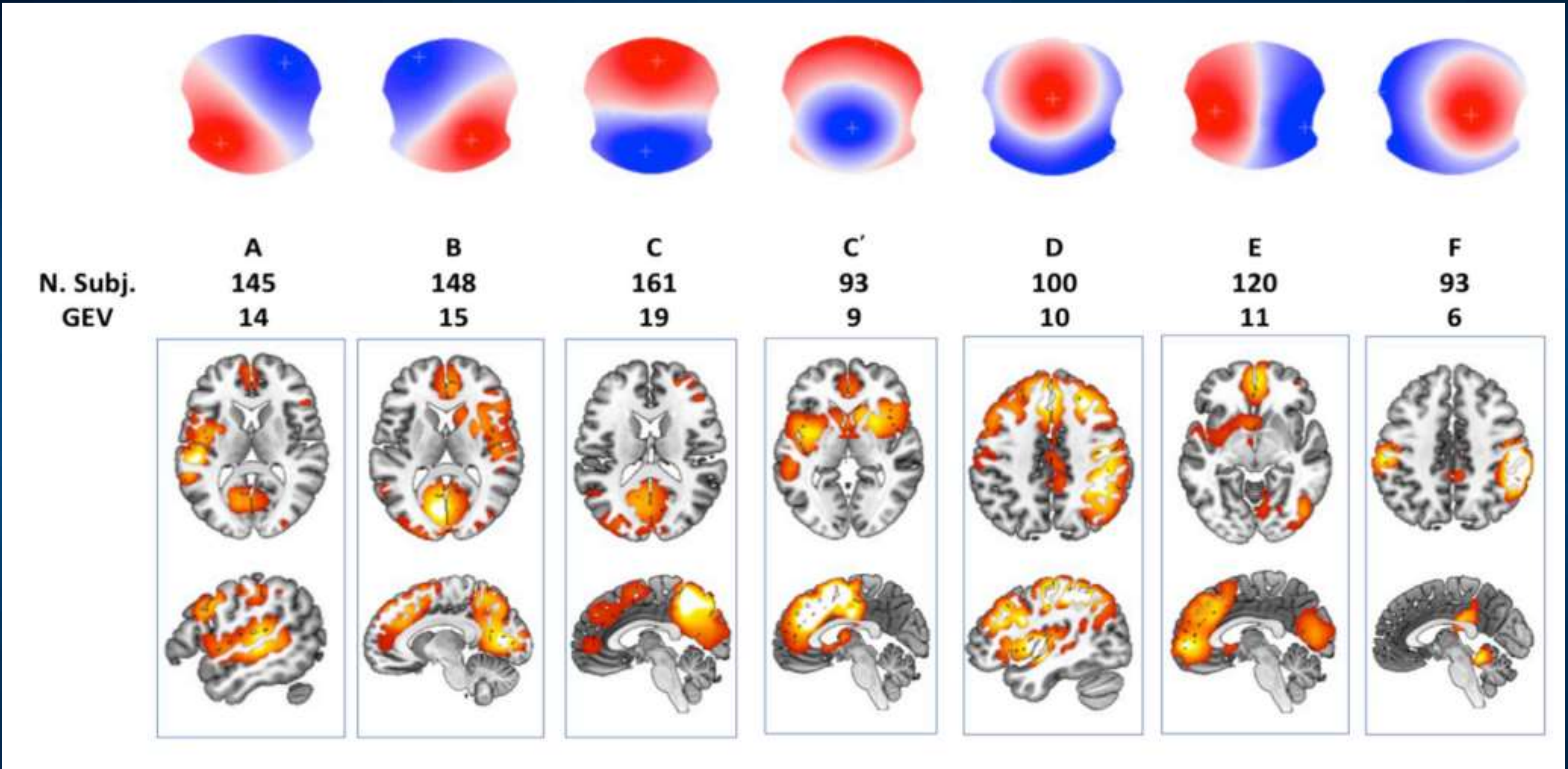
Lehmann et al.
EEG microstate duration and syntax in acute, medication-naïve, first-episode schizophrenia.
Psychiatry Research Neuroimaging, 2005

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

4-7 states 60-150 ms
Symbolic dynamics.

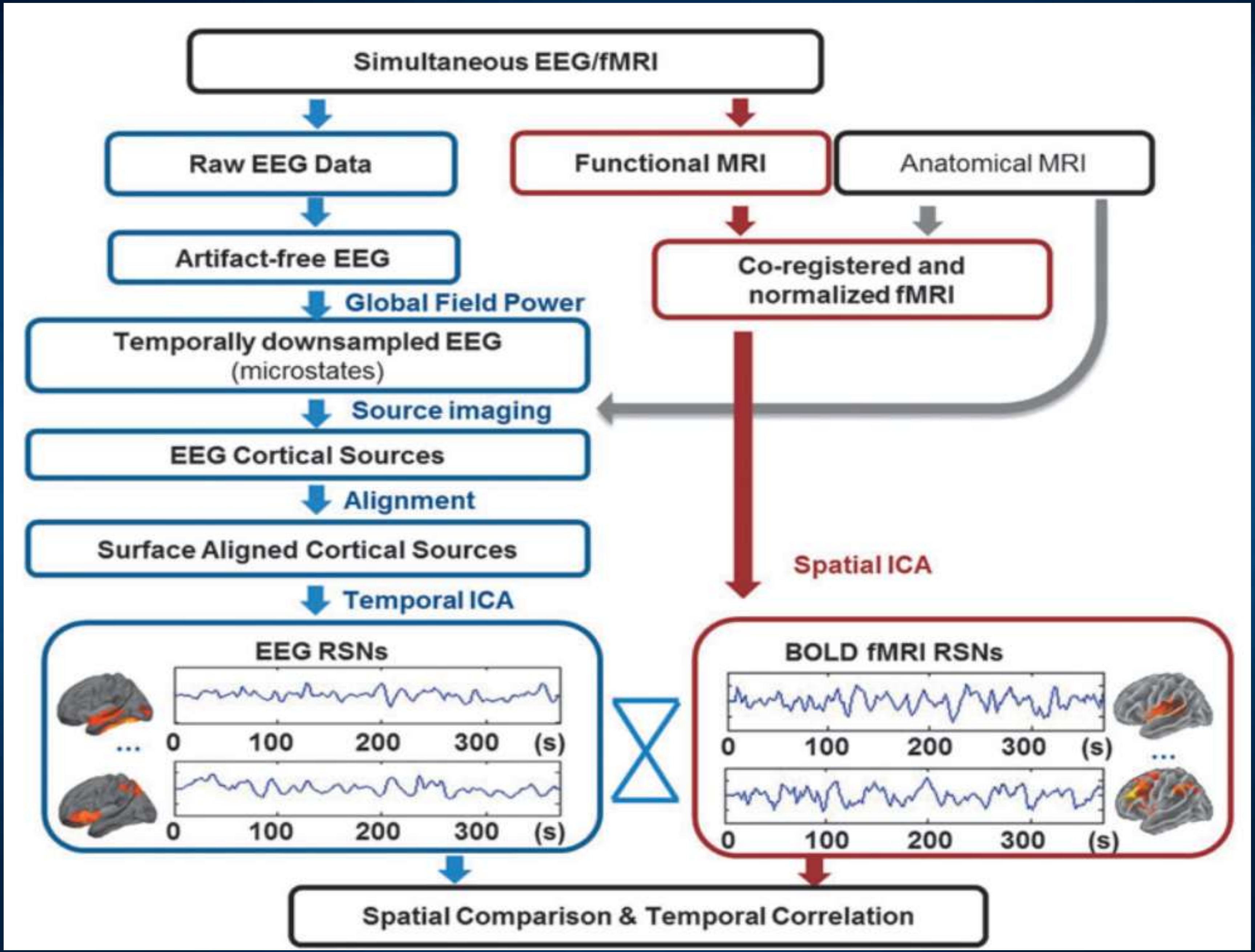


Microstates sources

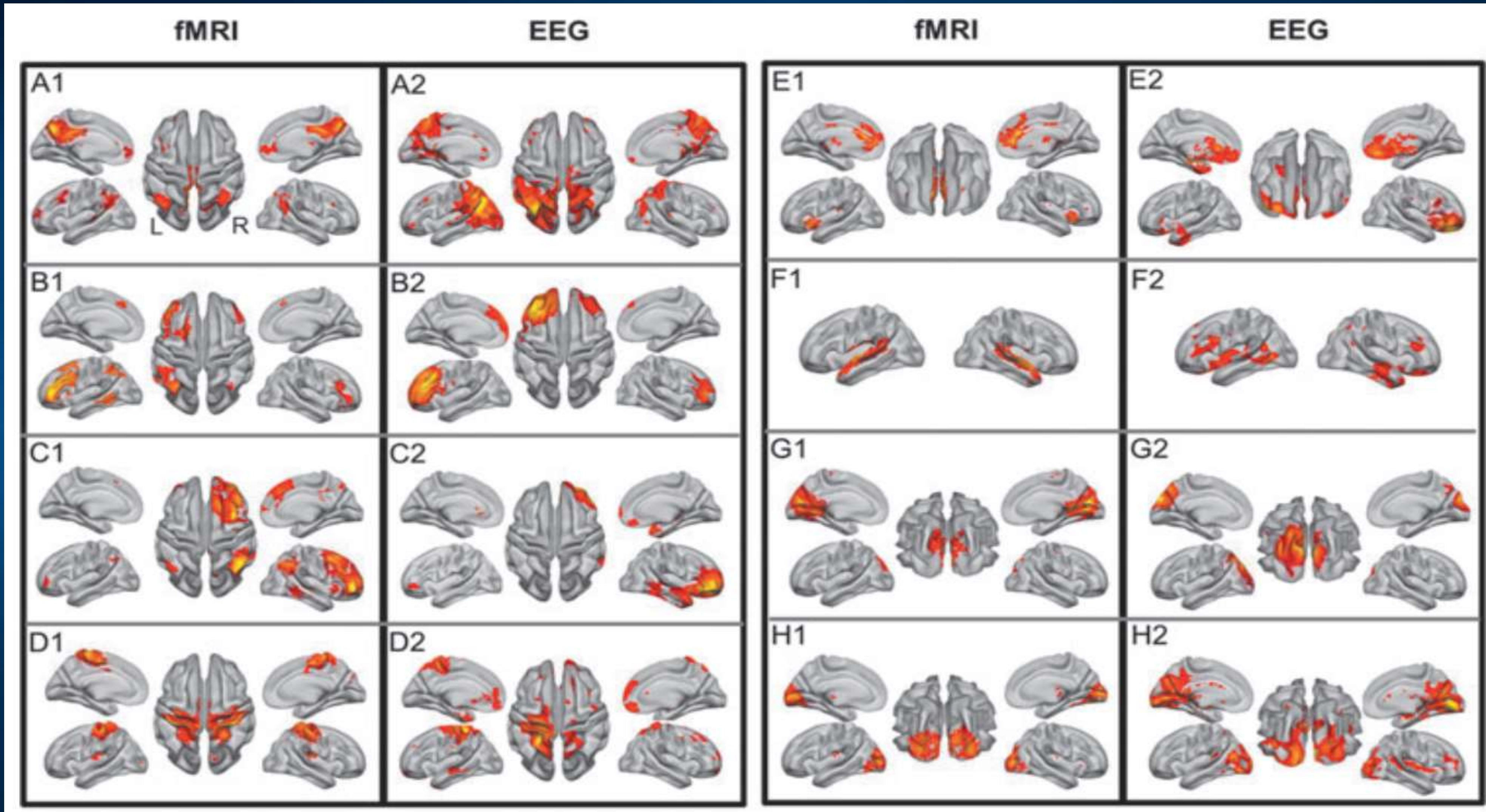


Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. *NeuroImage*, *180*, 577–593. https://doi.org/10.1016/j.neuroimage.2017.11.062

Yuan .. Bodurka, 2015-21

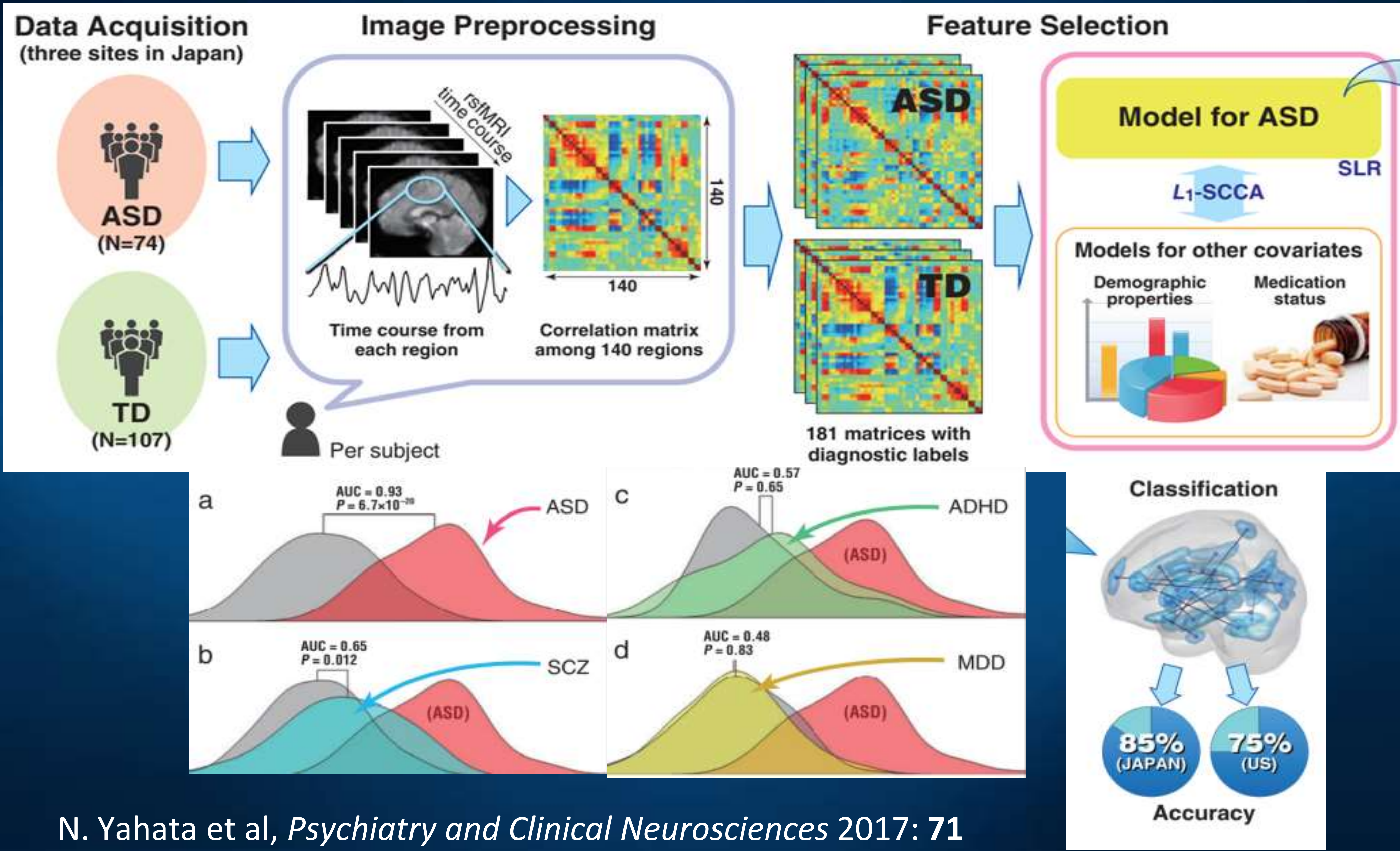


8 large networks from BOLD-EEG



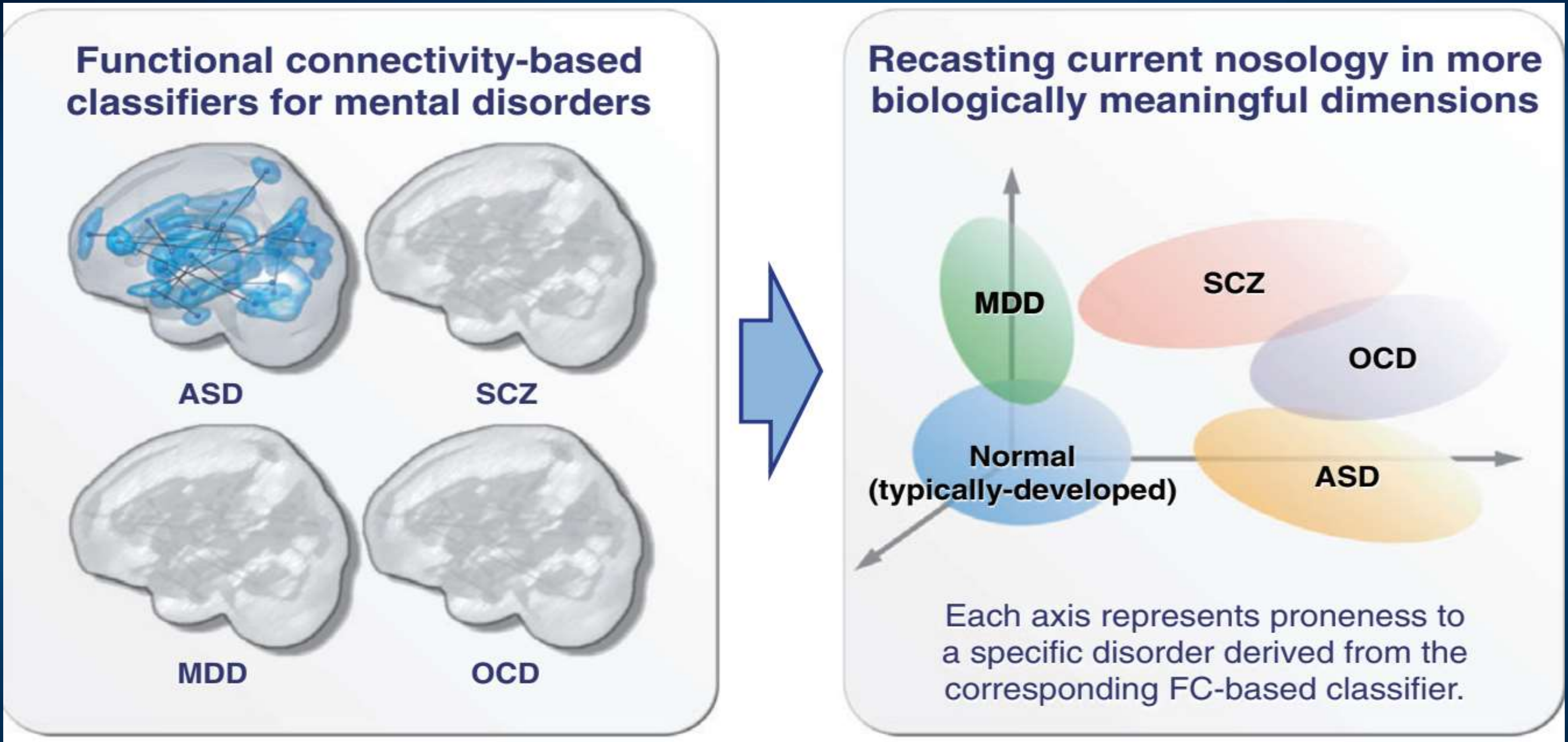
DMN, FP (frontoparietal)-left, right, sensorimotor, ex, control, auditory, visual (medial), (H) visual (lateral). Yuan, Ding, Zhu, Zotev, Phillips & Bodurka (2015)

Biomarkers from neuroimaging



N. Yahata et al, *Psychiatry and Clinical Neurosciences* 2017: **71**

Biomarkers of mental disorders



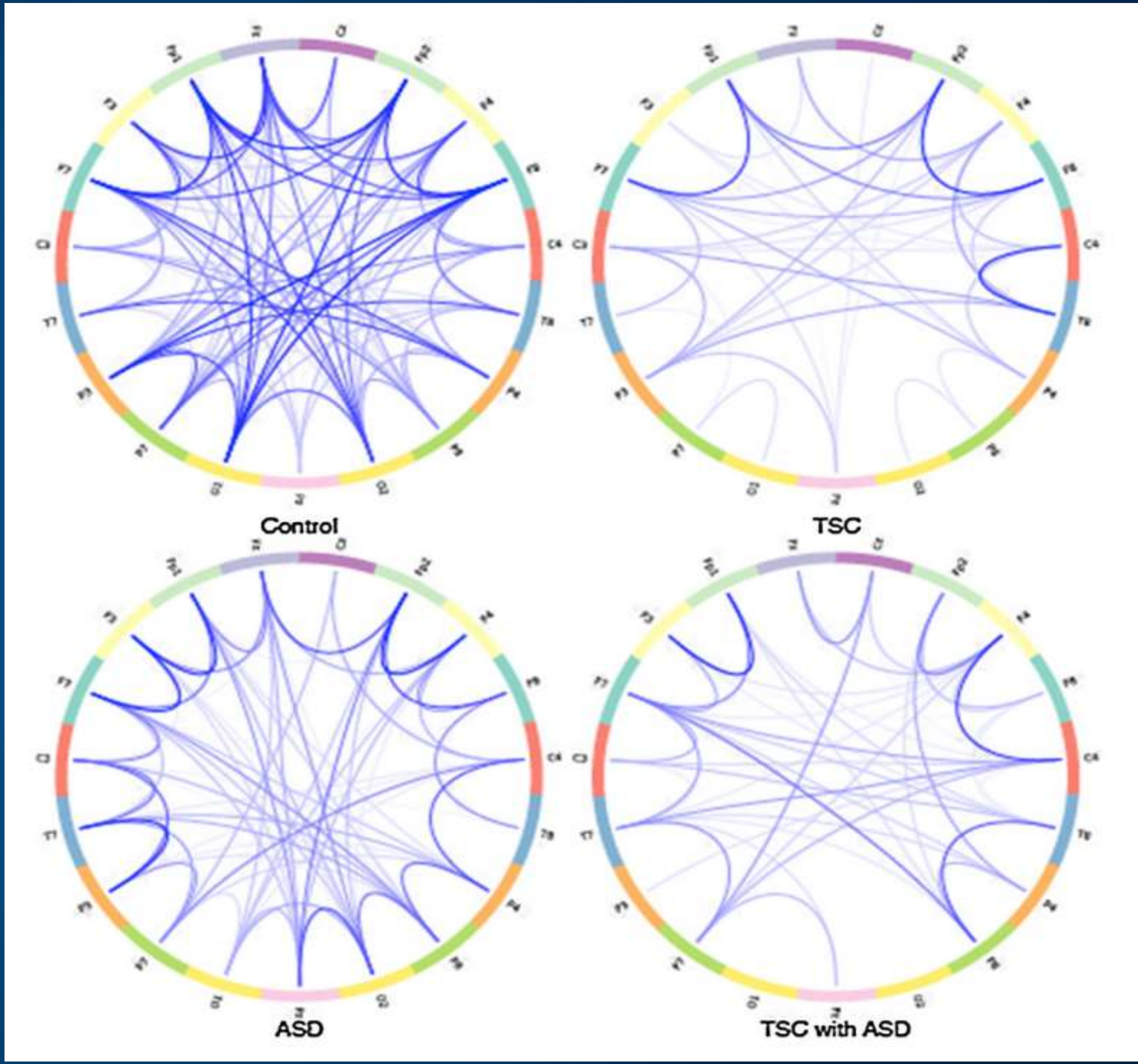
MDD, deep depression, SCZ, schizophrenia, OCD, obsessive-compulsive disorder, ASD autism spectrum disorder. fMRI biomarkers allow for objective diagnosis.
N. Yahata et al, *Psychiatry & Clinical Neurosciences* 2017; **71**: 215–237

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**!



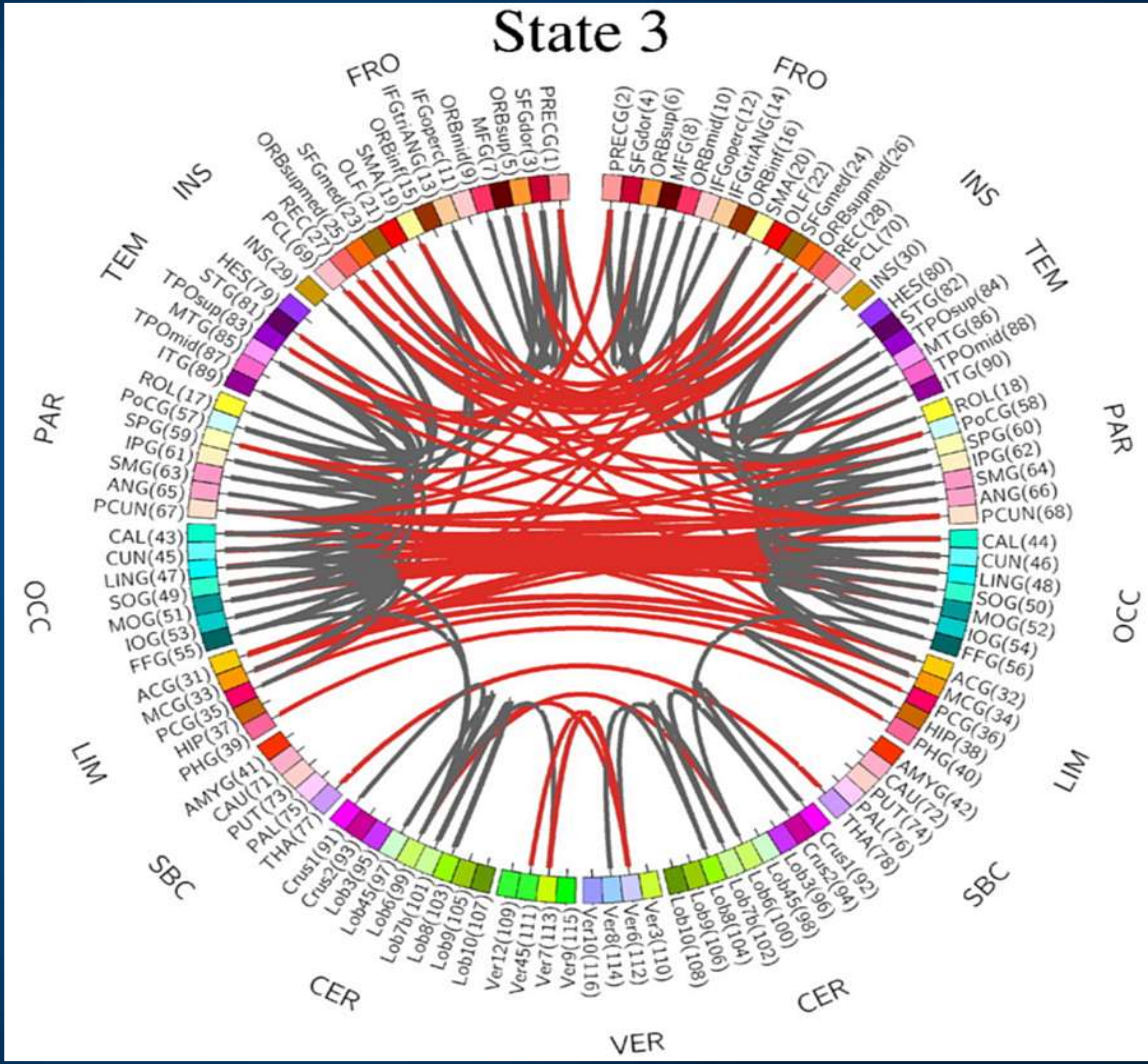
J.F. Glazebrook, R. Wallace, Pathologies in functional connectivity, feedback control and robustness. Cogn Process (2015) 16:1–16

Functional connections in healthy people

Healthy people, positive and negative functional connections in one of the 5 states of the Deep Auto-Encoder (DAE) + HMM models.

Connections |W|>0.65.

Suk et al. Neuroimage (2016)



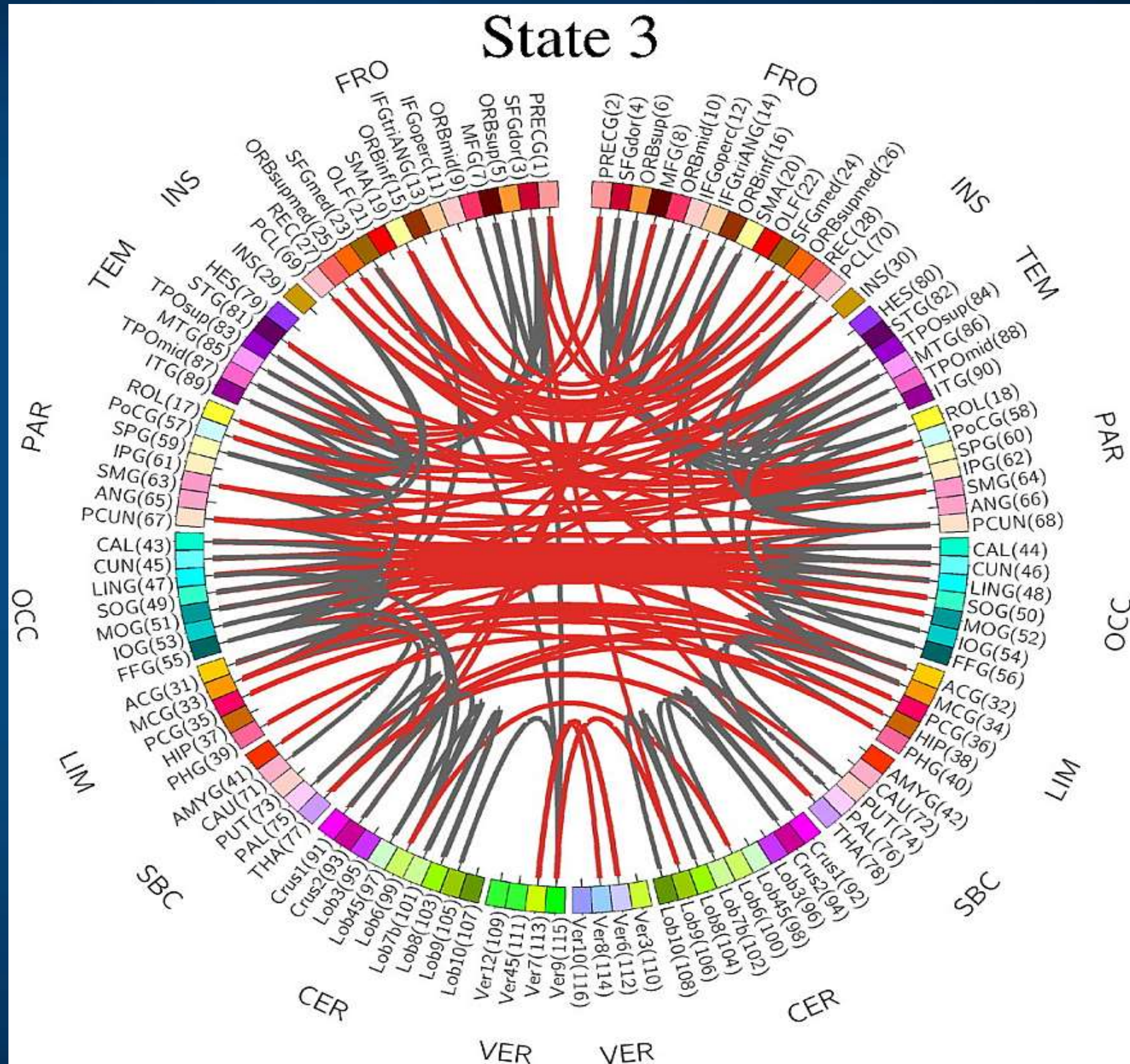
Negative connections in MCI patients

MCI patients, positive and negative functional connections in one of the 5 states of the Deep Auto-Encoder (DAE) + HMM models.

Connections |W|>0.65.

MCI patients have greater number of strong connections but smaller number of weak connections due to compensation effects.

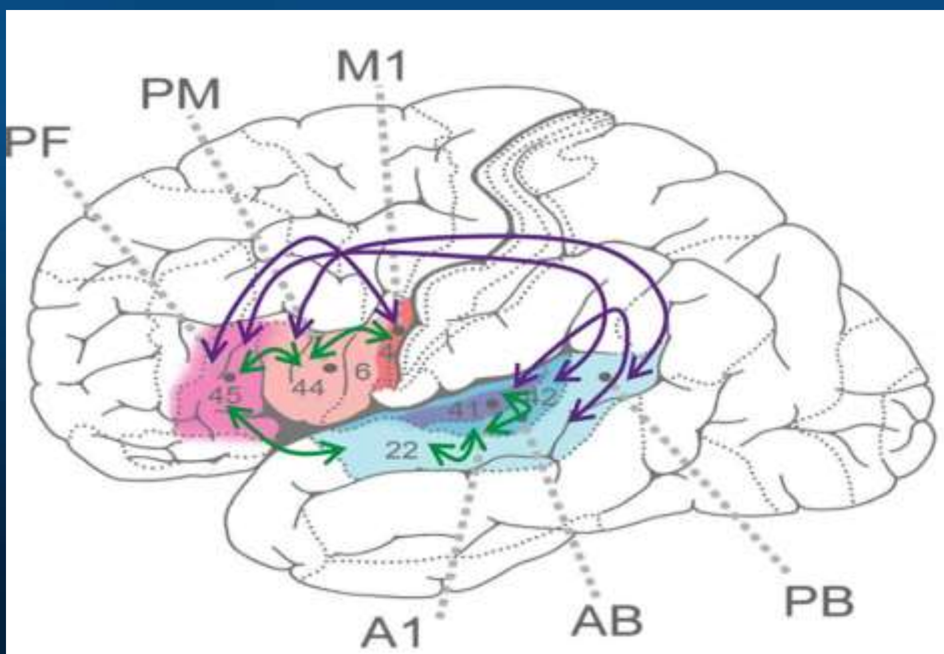
Suk et al. Neuroimage (2016)

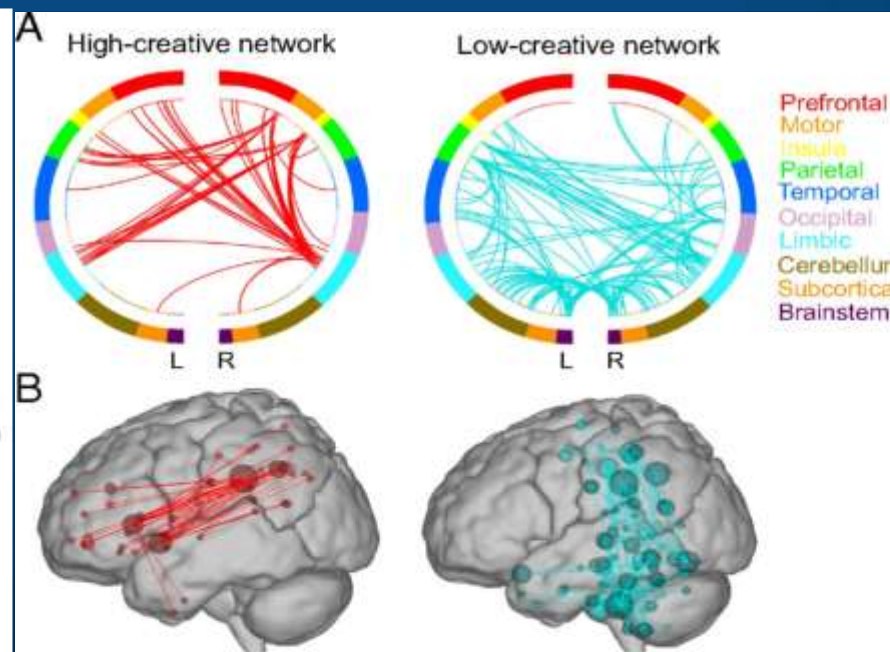


Fluid nature

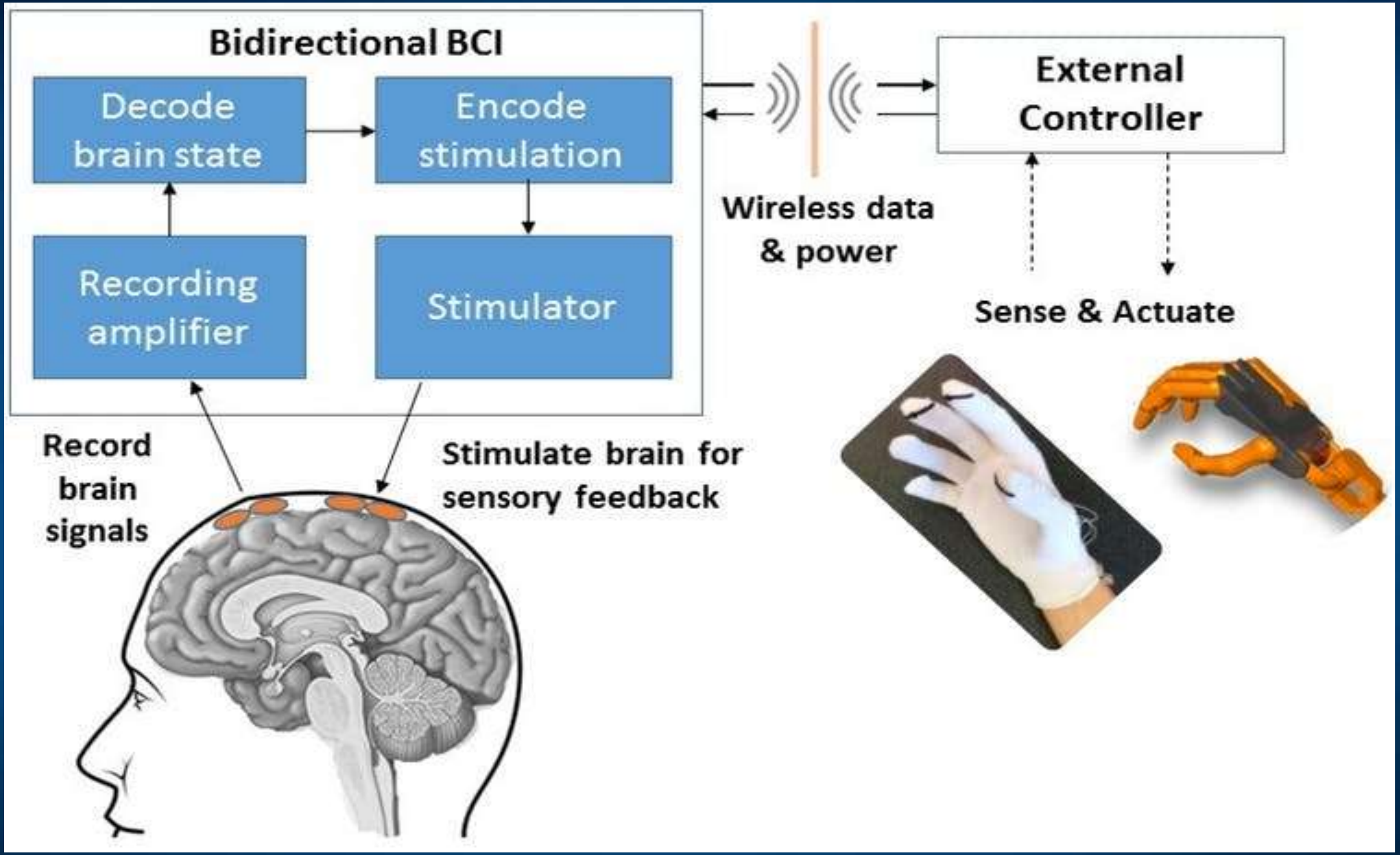
Development of brain in infancy: first learning how to move, sensorimotor activity organizes brain network processes.

The Developing Human Connectome Project: create a dynamic map of human brain connectivity from 20 to 44 weeks post-conceptional age, which will link together imaging, clinical, behavioral, and genetic information.
Pointing, gestures, lead to connectome development in pre-linguistic children (our BabyLab has a lot of EEG recordings).





Brain-Computer-Brain Interfaces



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

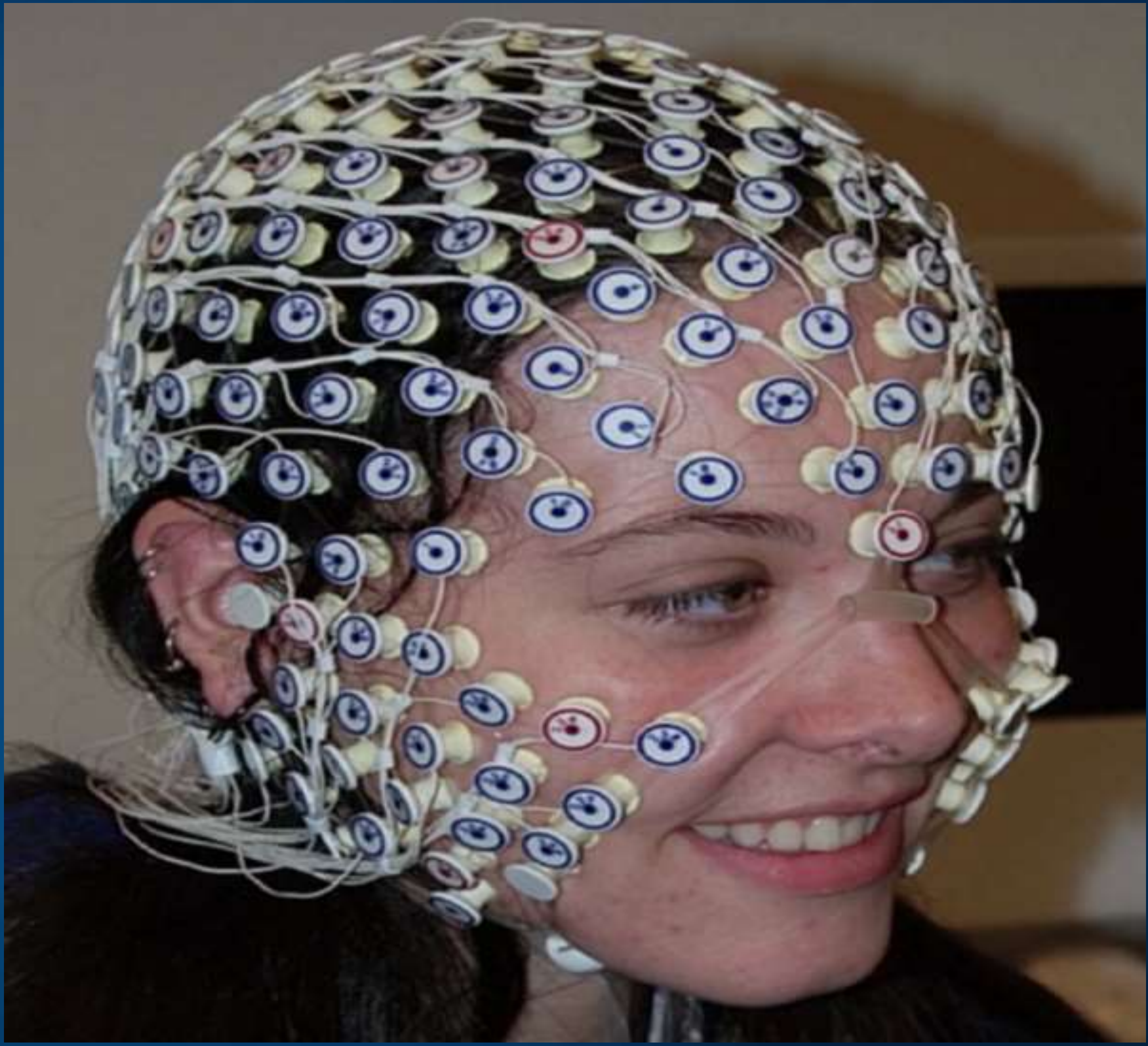
HD EEG/DCS?

EEG electrodes + DCS.

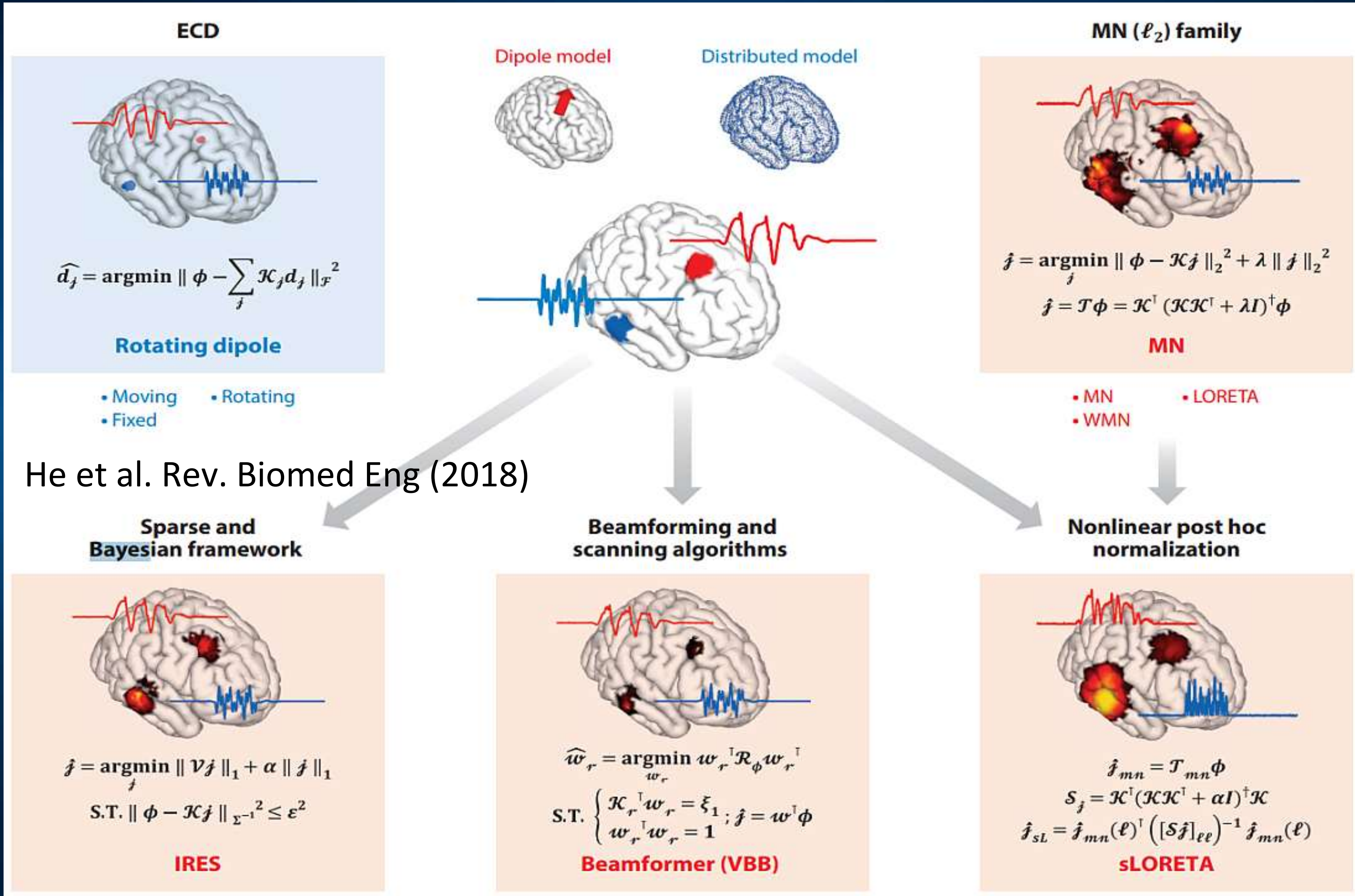
Reading brain states
 => transforming to common space
=> duplicating in other brains
Applications:

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

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



EEG localization and reconstruction

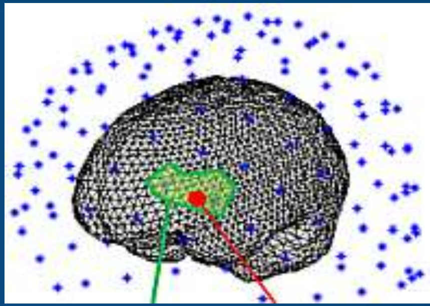


He et al. Rev. Biomed Eng (2018)

Spatial filters

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

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



LCMV has large error if:

- sources are correlated,
- SNR (signal to 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)

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

where X_r is a set of all matrices of rank at most r, and set Υ denotes all unitary norms. We use 15000 vertex FreeSurfer brain tessellation together with brain atlases that provide parcellation of the mesh elements into 100-240 cortical patches (regions of interest, ROIs).

SupFunSim

SupFunSim: our library/Matlab /tollbox, 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.

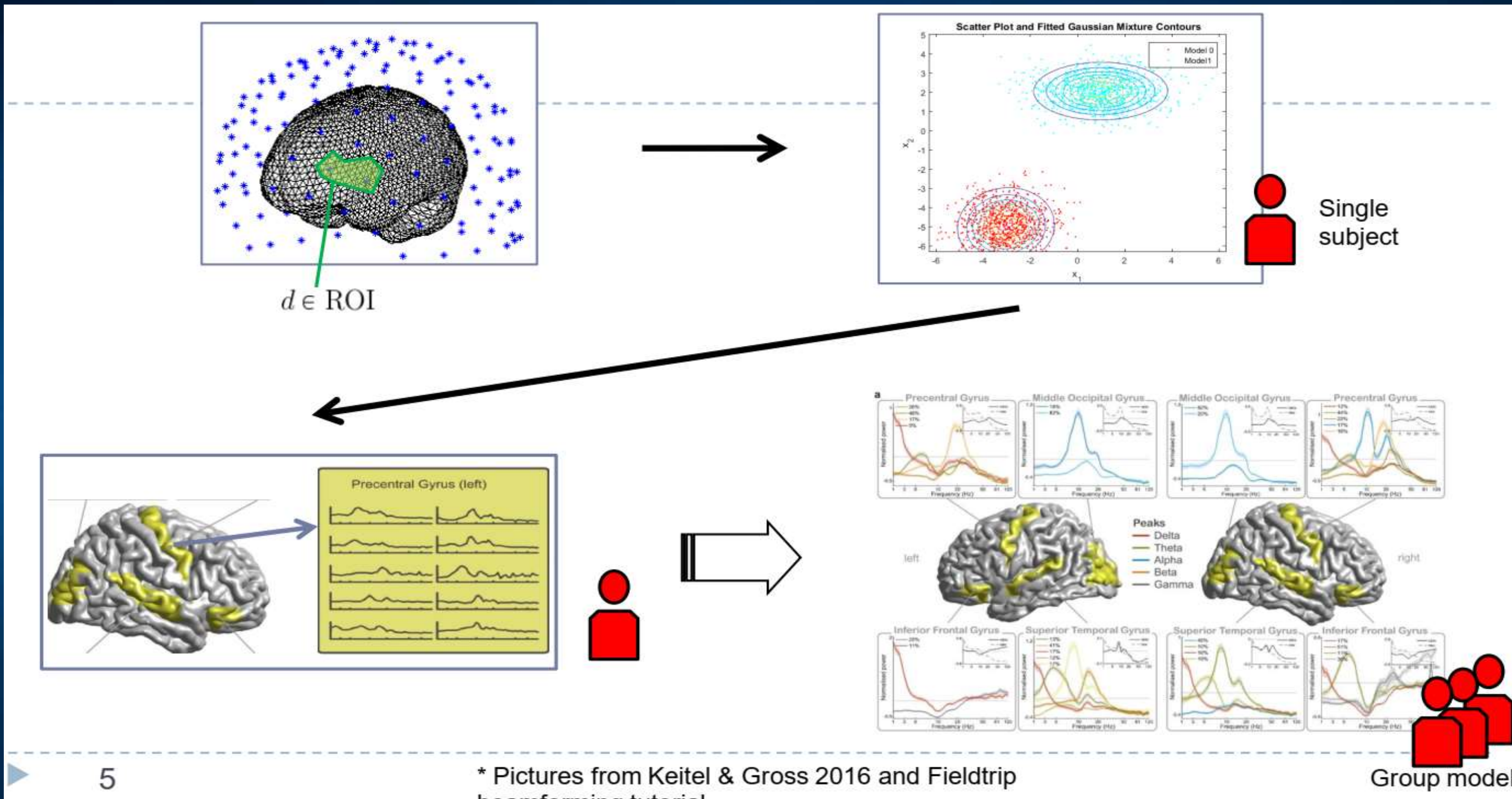
$$A := H_{Src,R} := R^{-1/2}H \tag{34}$$
$$B := H_{Src,N} := N^{-1/2}H \tag{35}$$

```
%%file calculate_H_Src.m
function model = calculate_H_Src(MODEL)
    model = MODEL;

    model.H_Src_R = pinv(sqrtm(model.R)) * model.H_Src;
    model.H_Src_N = pinv(sqrtm(model.N)) * model.H_Src;
end
```

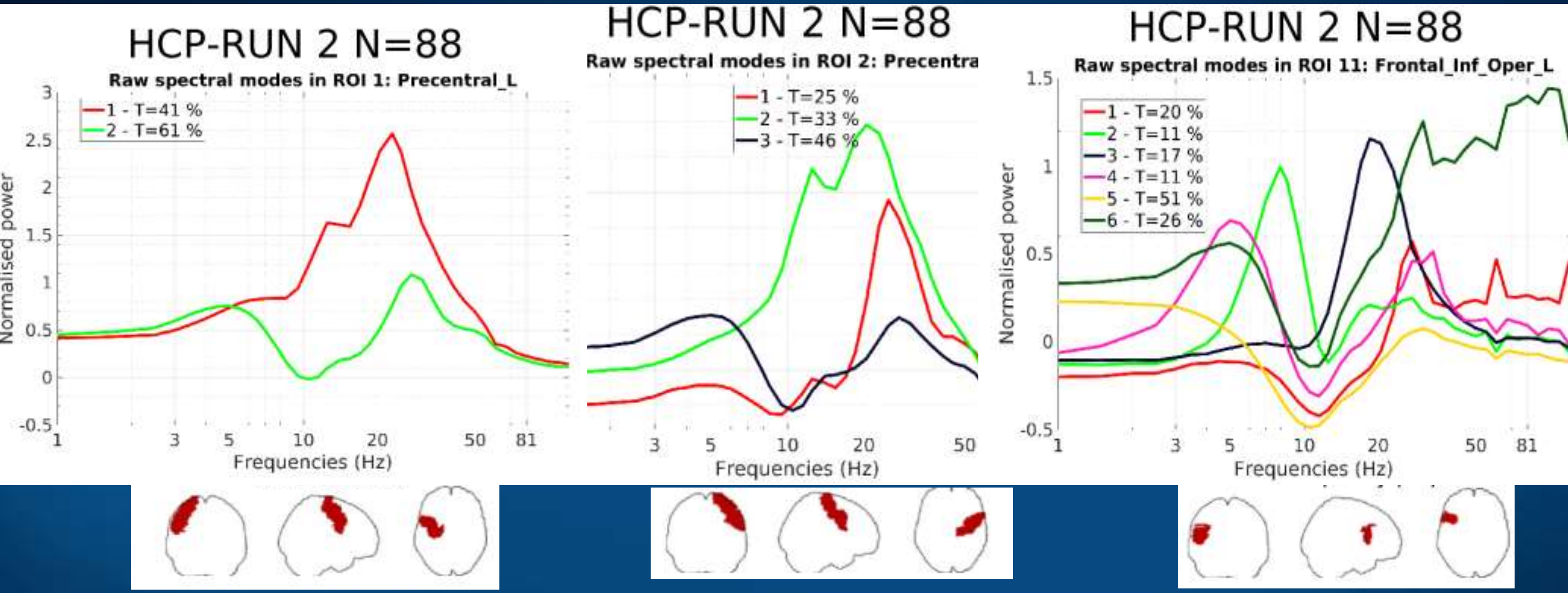
Rykaczewski, Nikadon, Duch, Piotrowski, *Neuroinformatics* **19**, 107-125, 2021.

Spectral fingerprints



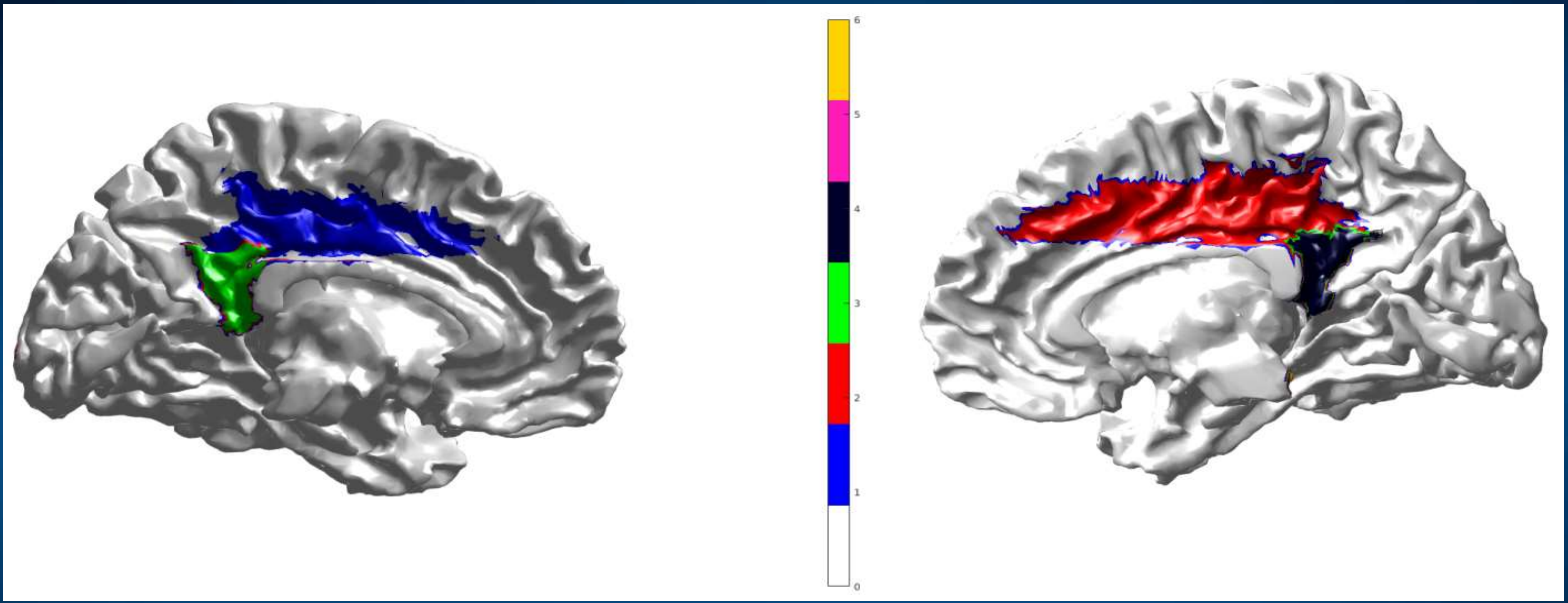
A. Keitel, J. Gross, „Individual human brain areas can be identified from their characteristic spectral activation fingerprints", *PLoS Biol* 14(6), e1002498, 2016

Spectral fingerprints



Example of spectra showing modes of oscillation characteristic to precentral left and right gyrus, and much more complex opercular part of inferior frontal gyrus.
MEG data from the Human Connectome Project (HCP).

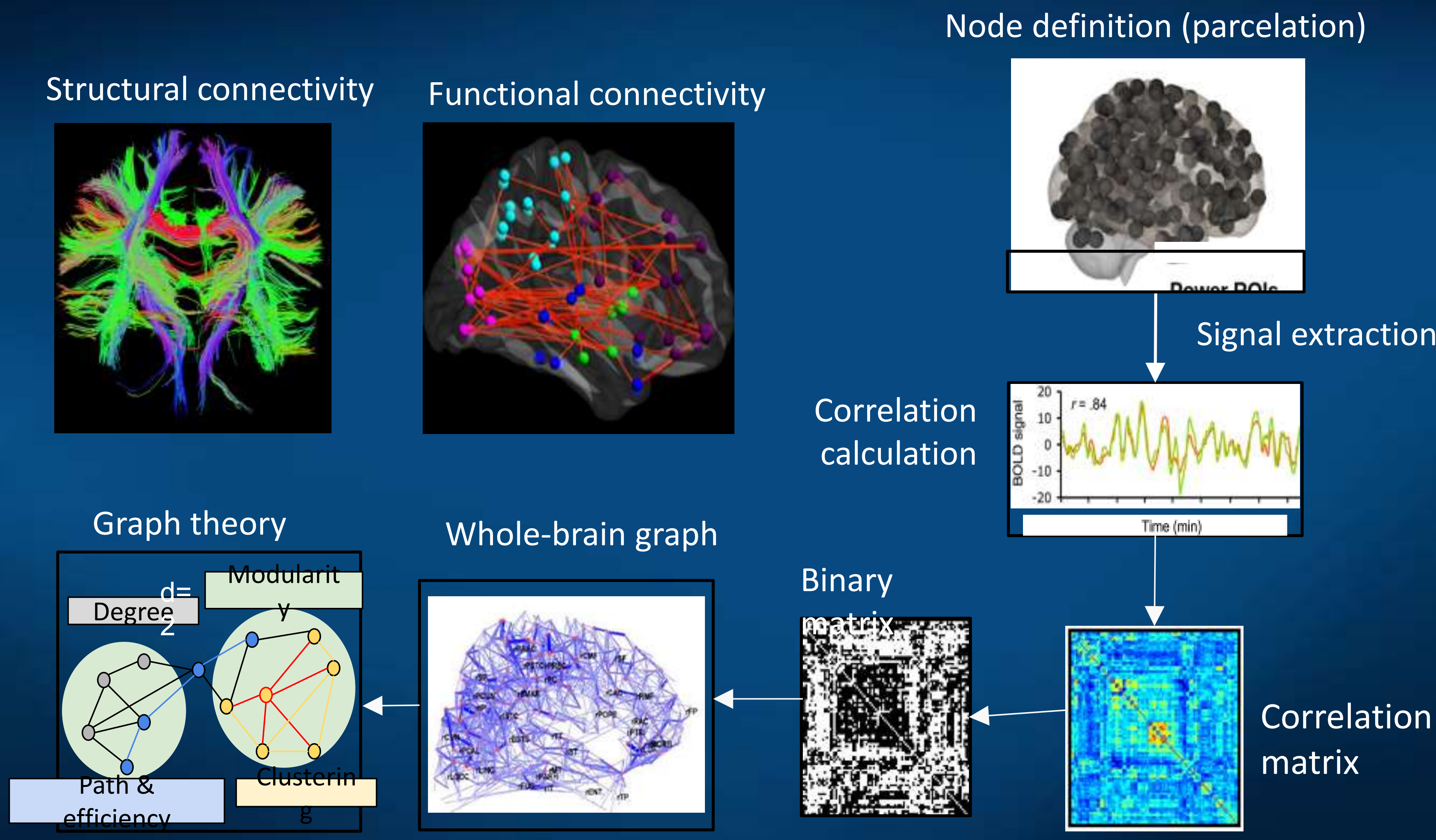
Most reliable ROI



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

ROI that we can recognize quite reliably.
33 1 Cingulum_Mid_L, 34 2 Cingulum_Mid_R, 35 3 Cingulum_Post_L,
36 4 Cingulum_Post_R, 51 5 Occipital_Mid_L, 110 6 Vermis_3

Human connectome and MRI/fMRI



Many toolboxes available for such analysis.

Bullmore & Sporns (2009)

Effect of cognitive load on info flow

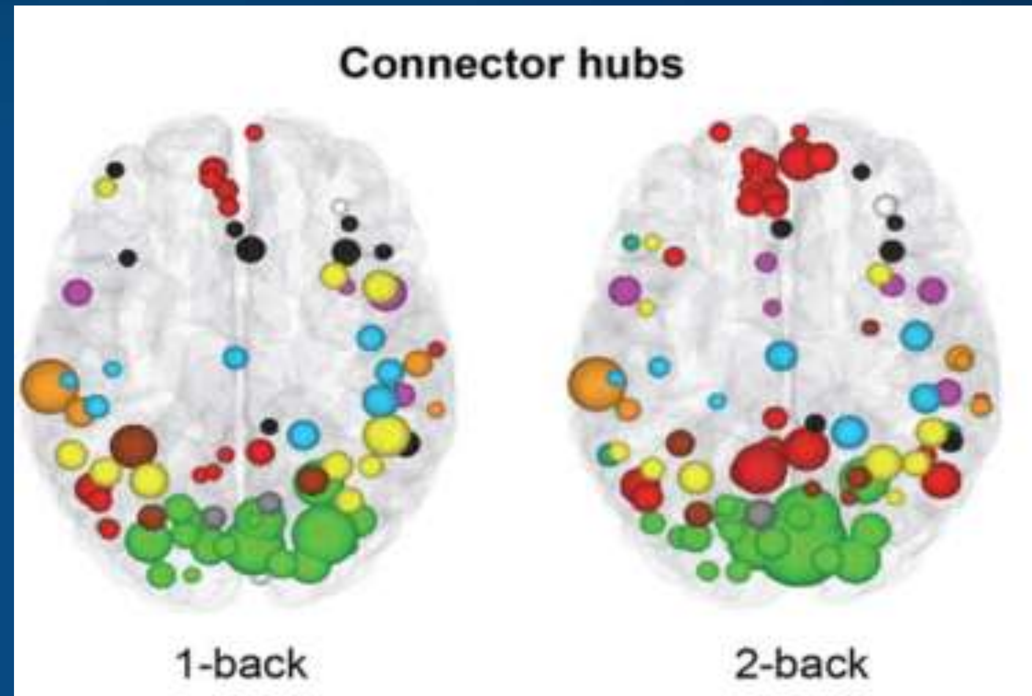
Simple and more difficult tasks, requiring the whole-brain network reorganization.

Left: 1-back connector hubs

Right: 2-back connector hubs

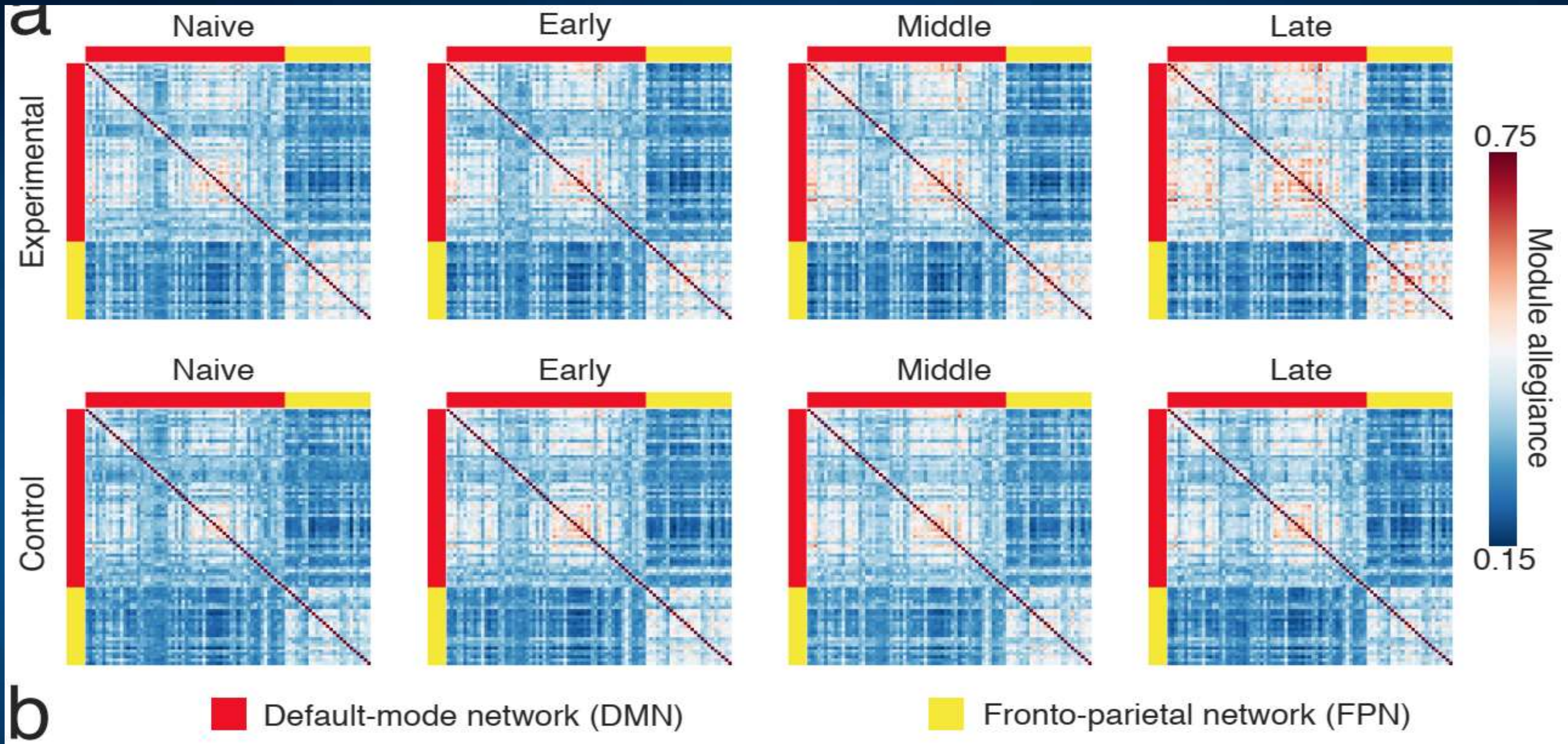
Average over 35 *participants.*

Dynamical change of the landscape of attractors, depending on the cognitive load – System 2 (Khaneman).
DMN areas engaged in global binding!



Finc, Bonna, Lewandowska, Wolak, Nikadon, Dreszer, Duch, Kühn, Human Brain Mapping (2017). Transition of the functional brain network related to increasing cognitive demands.

Working memory training



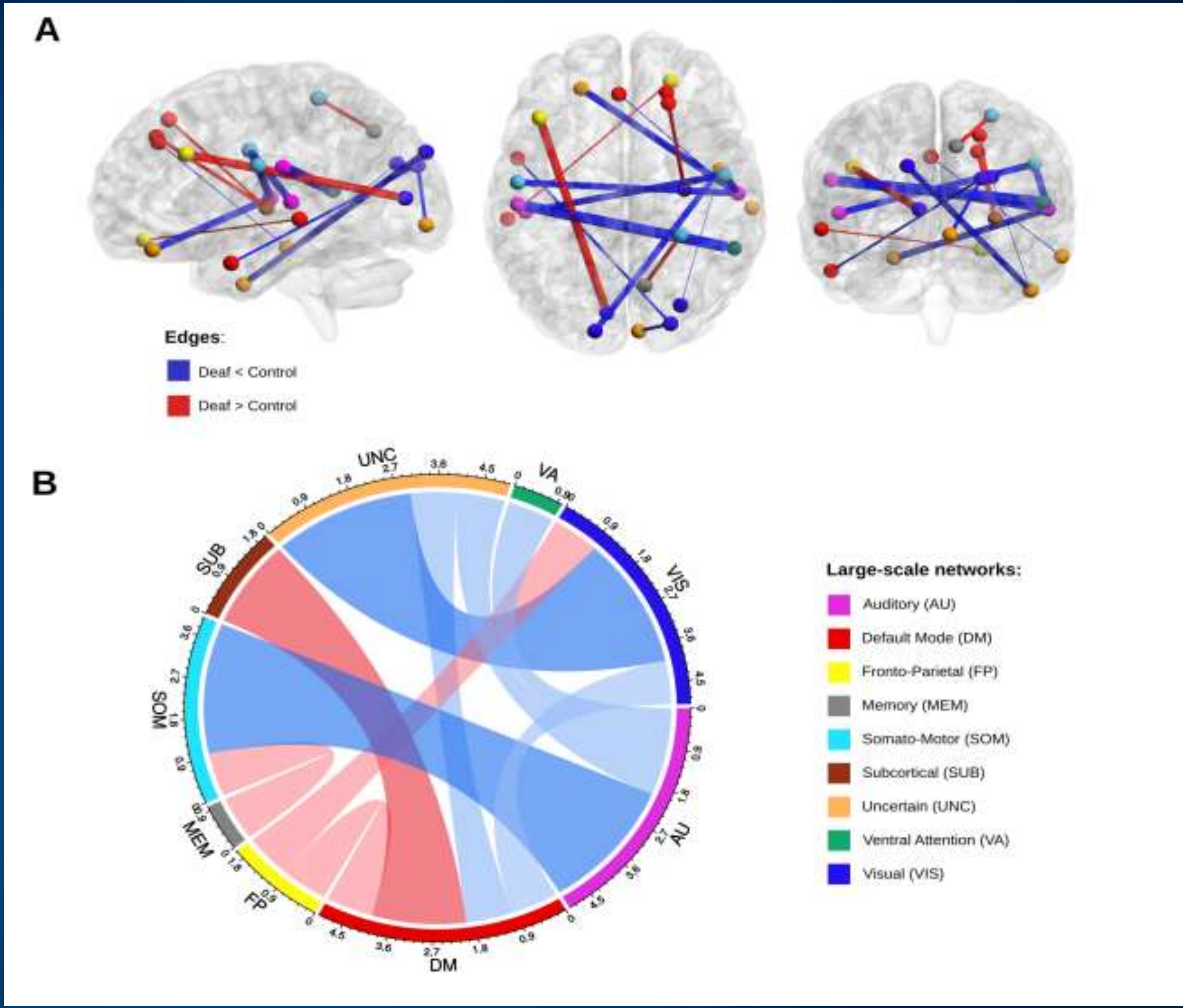
6-week training, dual n-back task, c**hanges in module allegiance of fronto-parietal and default-mode networks.** Each matrix element represents the probability that the pair of nodes is assigned to the same community.

Segregation of task-relevant DMN and FPN regions is a result of training and complex task automation, i.e. from conscious to automated processing.

Deaf vs. Control

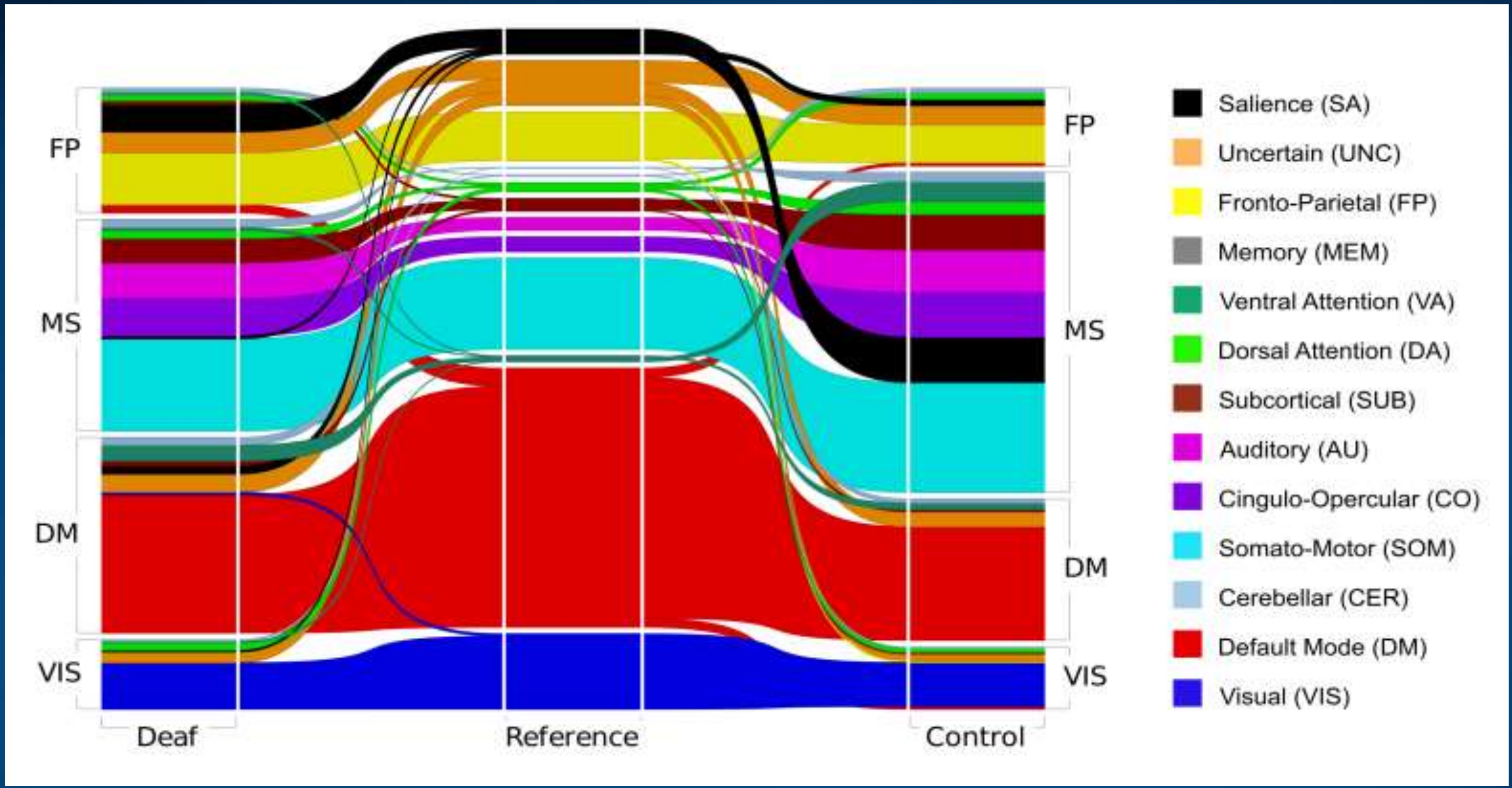
Edge-wise functional connectivity network differences visualized in the brain space.
(A). Connections that are significantly stronger (red) or weaker (blue) in deaf. Edge thickness reflects t-test statistic strength.
(B) Number of significant edges between different large-scale networks.

Red bands = edges stronger in the deaf vs. hearing control, blue bands with weaker functional connectivity.



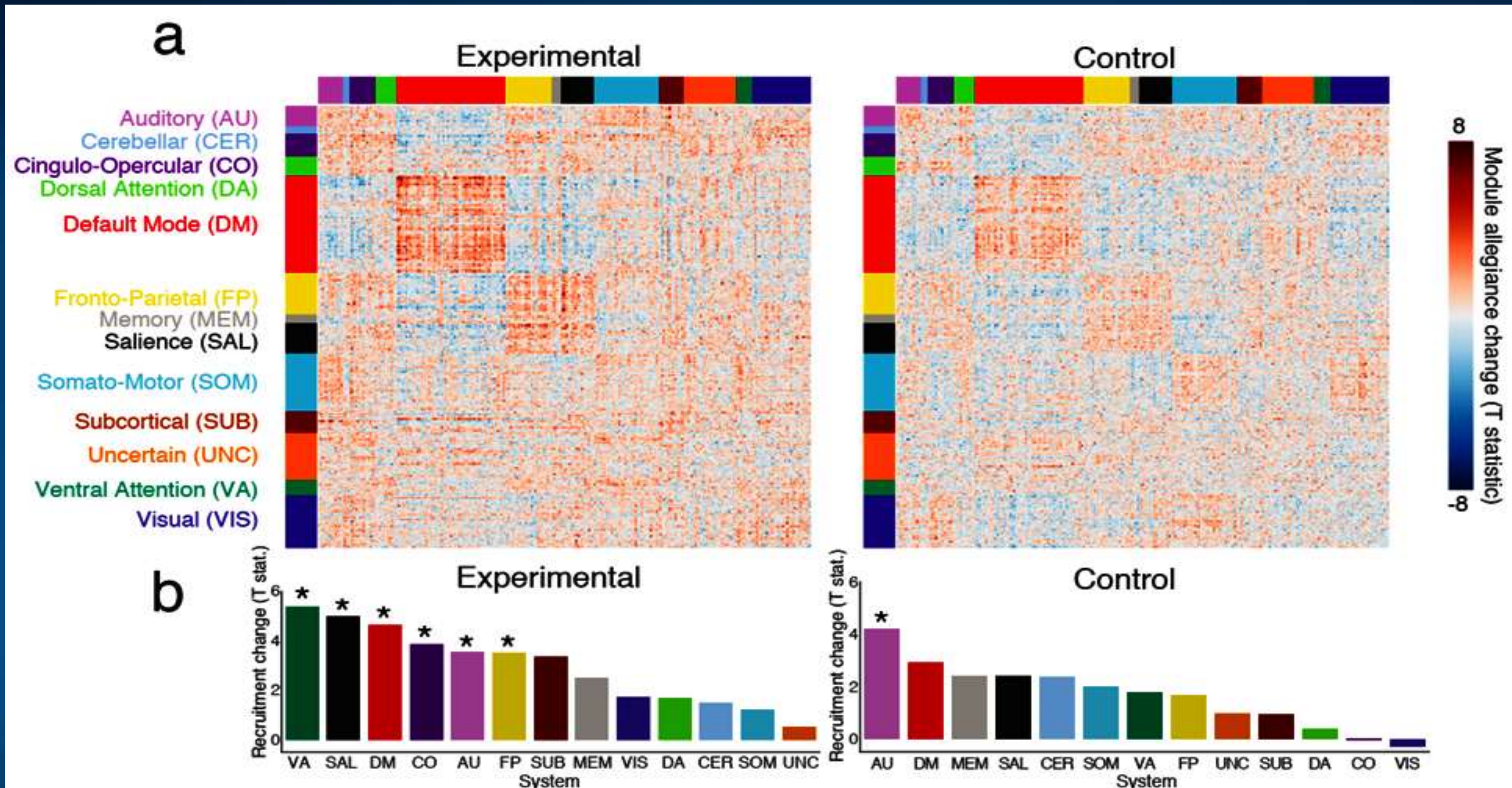
Bonna, Finc et al. Early deafness leads to re-shaping of global functional connectivity beyond the auditory cortex. Brain Imaging and Behavior 2020).

Deaf-Control



Modular organization of mean functional networks in deaf (left) vs control group (right) and reference network division into large-scale brain systems (Power et al., 2011). Salience nodes (black) are part of fronto-parietal (FP) module in the deaf group but fall into **multi-system (MS**) module in the control group. Ventral-attention nodes (dark green) are part of MS module in control group but in deaf group they are part of default mode module (DM).

Working memory training



Whole-brain changes in module allegiance between the start and after 6-week of working memory training.

(a) Changes in node allegiance as reflected in the two-tailed *t*-test.

(b) Significant increase * in the default mode DM, fronto-parietal ventral attention VA, salience SAL, cingulo-opercular CO, and auditory systems AU recruitment.

Finc, Bonna, He, Lydon-Staley, Kühn, Duch, Bassett, Nature Communications (2020).

Conclusions

- Flexible AI should be based on brain principles, we need BICA architectures. Simplified description of brain functions and processes is the key. This is our GREAT challenge! Time to do something good!
- AI/ML draws inspirations from brain research, but also neural network models and learning algorithms (recurrence networks, reinforcement learning, capsule nets) help to interpret information processing in the brain.
- Neurodynamics is the key to understanding mental states. Neuroimaging & analysis of EEG/MEG ⇔ helps to understand network neurodynamics ⇔ interpretation, mental states: S(B) ⇔ S(M).
- Although many things are still not well understood neurocognitive technologies are coming, helping to diagnose, repair and optimize brain processes. Great progress in EEG analysis has been achieved in recent years.
- Potential of such methods is enormous, disorders of the brain are one of the greatest burdens on the society in every country.

In search of the sources of brain's cognitive activity

Project „Symfonia”, 2016-21

FACULTY OF PHYSICS, ASTRONOMY AND INFORMATICS

CENTRE FOR MODERN INTERDISCIPLINARY TECHNOLOGIES

INSTITUTE OF PHYSIOLOGY AND PATHOLOGY OF HEARING

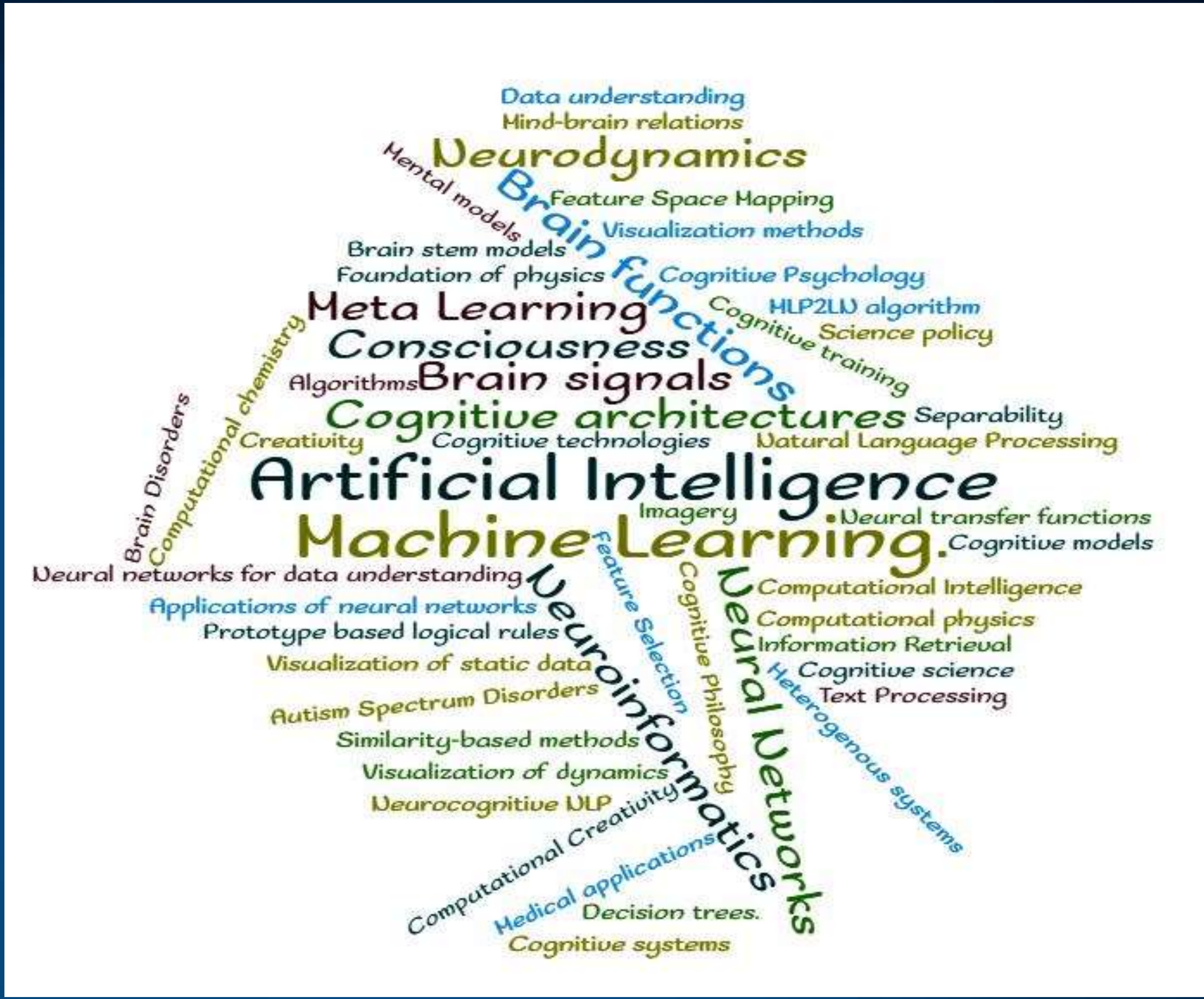
nencki institute of experimental biology

We have many interesting topics in ML/neuro research.

Our group "Neuroinformatics and Artificial Intelligence" in the University Centre of Excellence in Dynamics, Mathematical Analysis and Artificial Intelligence (DAMSI) is looking for students and visiting professors, please see:

Grants for experienced researchers from abroad.

Grants for young researchers from abroad.



Google: Wlodzislaw Duch
=> talks, papers, lectures, Flipboard …